# An optimality assessment methodology for Home Energy Management System approaches based on uncertainty analysis

Von der Fakultät für Elektrotechnik und Informationstechnik
der Rheinisch-Westfälischen Technischen Hochschule Aachen
zur Erlangung des akademischen Grades eines Doktors
der Ingenieurwissenschaften genehmigte Dissertation

vorgelegt von

Baptiste Feron, Master of Science
aus
Ottignies, Belgien

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Tag der mündlichen Prüfung: 09. July 2018

**Bibliographische Information der Deutschen Nationalbibliothek**
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über
http://dnb-nb.de abrufbar.
D 82 (Diss. RWTH Aachen University, 2018)

Herausgeber:
Univ.-Prof. Dr.ir. Dr.h.c. Rik W. De Doncker
Direktor E.ON Energy Research Center

Institut für Automation of Complex Power Systems
E.ON Energy Research Center
Mathieustraße 10
52074 Aachen

E.ON Energy Research Center | 62 Ausgabe der Serie
ACS | Automation of Complex Power Systems



Printed in Germany

ISBN: 978-3-942789-61-5
1. Auflage 2018

Verlag:
E.ON Energy Research Center, RWTH Aachen University
Mathieustraße 10
52074 Aachen
Internet: www.eonerc.rwth-aachen.de
E-Mail: post_erc@eonerc.rwth-aachen.de

# Abstract

The emergence of ICT based devices enables houses and buildings to become an active part of their environment, by shifting their thermal or electrical consumption/production at different time period according to the grid requirements. Considering the rise of interests for time-dependent electricity tariffs, Home Energy Management System (HEMS), a computer-aided tool with communication ability, is a promising tool for helping prosumers to optimize their device operation accordingly to their comfort and the given electricity price.

This dissertation first delivers an overview on the different HEMS approaches, their typical objective functions, their formulations and the considered flexible devices in the literature. This literature review highlights the various HEMS forms and the difficulty to compare them because of the specificity of their evaluation conditions.

For this purpose, this dissertation presents an assessment methodology which considers the HEMS evaluation conditions, typically time-series, as uncertain parameters. An uncertainty analysis method for uncertain time-series is developed for fast uncertainty analysis according to stochastic optimization theory. It is shown that for a HEMS approach, the results of 10 000 Monte Carlo simulations can be achieved by 3 simulation runs per uncertain parameters with an appropriated selected set of representative scenarios.

Finally, this assessment method is used for comparing and quantifying the saving potential of two different HEMS: an optimization and a market-based control, which both are compared to a conventional control, taken as reference case. The specific saving potential associated to each flexible devices is also studied as well as the sensitivity of these results to a forecast error. All the presented results take into account different user profiles for electrical and domestic hot water demand and consider 5 years of historical data for the temperature and the irradiation in Germany.

# Acknowledgments

First, I would like to thank my supervisor Univ.-Prof. Ph.D. Antonello Monti for his confidence and for giving me the opportunity to write my dissertation at the institute for Automation of Complex Power System, RWTH Aachen University. I really appreciated the freedom he gave me and the fruitful discussion we had. At the same time, I would like to thank Univ.-Prof. Ph.D Ferdinanda Ponci for her many reviews and her valuable comments.

Secondly, I would like to thank all the students with whom I had the chance to work: Jan Schlageter, Julian Vossen, Guillermo Moraleda, Andjey Hartl, Artur Niederfhrenhorst, Silvia Giudice, Dimitar Stanev, Markus Erwert, Arsam Aryandoust, Philipp Theile, Julius Rakow, Manoel Brunnen, Avichal Malhotra, Lucia Martin, Margarita del Castillo and my different Hiwis: Marvin Garbade, Nikolaos Savvopoulos, Nisar Khan, Georgii Tishenin, Subhodeep Chakraborty. Thanks for your collaboration and the valuable contribution to this work.

In addition, I would like to thank all my colleagues from the Institute for Automation of Complex Power System for the exchanges all along my dissertation, the friendly and multi-cultural atmosphere and the nice memories. Without forgetting the EON ERC music band composed by Prof. Monti, Markus, Jan, Nina and Edoardo and my amazing roommates in Aachen: Felix, Dany, Amelie, Alex, Tabea, Alicja and Anshuman. I thank also the Belgian Rail for providing me with a frequent moving office between Aachen and Brussels.

Finally I would like to express all my gratitude and my love to my family, my supportive and loving parents Eric and Anne, my reliable brothers: Emilien and Jean-Brieuc and their wives: Laurence and Doriane and my cute nieces: Albane, Capucine and Isaline, my amazing and unwavering friends, Thomas, Matthias, Olivier, Sylvain, Gilles, Thomas "Buddy", Pierre-Yves, Marie, Eleonore, Fanny, Maxime, Boris, Tim, Kanali and Max. Last but not least, I would like to express all my love and my gratitude to my kind, supportive and beautiful life partner Savina. Thank you all of you for being always there for me.

**Baptiste Feron**, July 2018, Aachen

# Contents

# List of Abbreviations

| | |
|---|---|
| ANN | Artificial Neural Networks |
| ARMA | Auto Regressive Moving Average |
| CPP | Critical Peak Pricing |
| DHW | Domestic Hot Water |
| DR | Demand Response |
| DSO | Distribution System Operator |
| FiT | Feed-in Tariff |
| HEMS | Home Energy Management System |
| IBR | Inclining Block Rate |
| ICT | Information and Communication Technology |
| MAPE | Mean Average Percentage Error |
| MAS | Multi Agent System |
| MC | Monte Carlo |
| PDF | Probability Density Function |
| PV | Photovoltaic |
| RTP | Real Time Pricing |
| SOTAFE | State-Of-The-Art Forecast Error |
| SRT | Scenario Reduction Technique |
| SVR | Support Vector Regression |
| TOU | Time Of Use tariff |
| TSO | Transmission System Operator |

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# Introduction

The known limit capacity of fossil fuel and the ongoing climate change has mainly driven political choices the last decade. The European Union (EU) targets a decrease by 20% of greenhouse gas emission compared to 1990 and an increase up at least to 20% of renewable energy production by 2020. Furthermore, it envisions a decrease by 40% of greenhouse gas and an increase by 27% of energy from renewable sources by 2030. These changes bring major challenges to the EU states and grid operators:

- EU states have to incentive the installation of renewable energy while ensuring a competing electricity price
- Distribution System Operators (DSO) have to accommodate the increase of decentralized sources of production while avoiding large invest in the grid
- Transmission System Operators (TSO) have to ensure the security of supply in spite of the volatility and non-controllability of the decentralized production units

One possible component of the solution is to benefit from the electrical consumption flexibility of domestic and commercial consumers. Indeed, the emergence of ICT based appliances changes the position of houses and buildings in their environments, by enabling them to become an active part of it: by shifting their consumption/production at different time period accordingly to the power grid requirement. For this purpose, different time-varying electricity tariffs such as Time-of-Use (TOU), Critical-Peak Pricing (CPP), Feed-in Tariff (FiT) and Real-Time Pricing (RTP) are proposed in literature to solve specific challenges:

decrease the peak load demand, reduce greenhouse gas emission or maximize the self-consumption. The emergence of these time-dependent pricings rises the interest of customer in managing load and generation units for environmental and economical purposes. Considering this, Home Energy Management System (HEMS), a computer-aided tool with communication ability, is a promising tool for helping customers to optimize their domestic device operation accordingly to their comfort and the given electricity price.

## Research motivation

The mentioned facts illustrate a future reality where there is a need for HEMS to support the energy transition. According to literature, there are various HEMS approaches that can be differentiated according to their objective formulation, their parameters and the solver used. Unfortunately, *the specificity of the considered assessment scenarios in literature does not allow identifying the most optimal HEMS approaches.*

For this reason, there is a need for an assessment method which:

- brings generality in its conclusion
- is achieved in a limited number of simulation runs
- shows a good accuracy

## Contribution of this thesis

This dissertation addresses these challenges by:

- Identifying the main sources of specificity in the HEMS assessment process, according to literature.
- Presenting an innovative HEMS approach based on the economic theory applied at a household level, so-called market-based control.
- Presenting an assessment method, formalized as an uncertainty analysis for uncertain time-series parameters inspired by stochastic optimization theory that deals with identical challenges.

- Assessing the accuracy of the proposed uncertainty analysis with the state of the art uncertainty analysis: Monte Carlo.
- Applying this optimality assessment methodology to different HEMS approaches and highlight their sensitivity to forecast errors. In addition, the specific saving associated to each considered devices is also studied.

## Dissertation outline

The dissertation is structured as follows:

**Chapter 1** classifies the various HEMS approaches presented in literature according to their objective functions, their objective formulations and the different scheduling approaches. Based on this, the main sources of specificity in HEMS assessment process are then identified.

**Chapter 2** introduces and formulates the different optimization approaches studied in this dissertation, i.e. the optimization-based and the market-based approaches, and the reference control: the rule-based approach. This includes the optimization approach formulation and the modelling of the different flexibilities considered.

**Chapter 3** introduces the state-of-the-art uncertainty analysis approaches and presents their advantages and limitations. Then, the proposed uncertainty analysis is described in detail and compared to the Monte Carlo approach for a practical case.

**Chapter 4** presents a comparison of the different HEMS approaches based on the uncertainty analysis proposed. This comparison highlights the impact of different forecast errors on the objective function and the benefit brought by different flexibility sources.

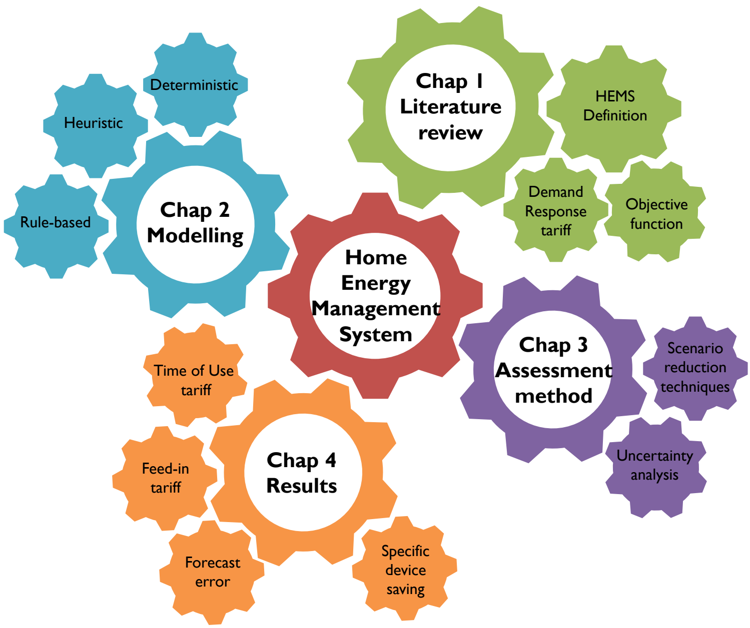


Figure 0.1: Illustrative description of the thesis content.

# Chapter 1

# Home Energy Management System: a literature review

The emergence of ICT based appliances changes the position of houses and buildings in their environments, by enabling them to become an active part of it: by shifting its consumption/production at different time period accordingly to the power grid requirement. Different time-varying electricity tariffs such as TOU, CPP, FiT and RTP are proposed in literature to solve the different challenges faced by grid operators (Section 1.2). These time-dependent pricings rises the interest of customer in managing load and generation units using HEMS for environmental and economical purposes.

This chapter describes the state of the art of Home Energy Management System approaches at a household level: typical objective functions, considered flexibilities, optimization problem formulation and challenges for HEMS.

This chapter answers to the following questions:
Section 1.1: *What is the definition of a HEMS?*
Section 1.2: *What are the HEMS objective functions?*
Section 1.3: *What are the different ways to formulate the scheduling problem?*
Section 1.4: *What are the different scheduling approaches to solve the problem?*
Section 1.5: *What are the different sources of specificity in the assessment approaches proposed in literature?*

## 1.1 HEMS definition

A home energy management system -HEMS- is a computer-aided tool that shifts and curtails electrical demand according to a specific objective function, a given electricity price and the consumer comfort. The HEMS can communicate with domestic devices and the utility to receive external information, e.g. solar power production or demand response (DR) electricity prices. In that way, it can improve the energy consumption and production schedule of domestic devices [1].

In literature, ”home energy management system” (HEMS) [2–6] is also typically called ”energy management system” (EMS) [7–9] and ”residential energy management system” (REMS) [10, 11]. The HEMS purpose is to control the electricity consumption within a home on behalf of a consumer. This is made possible by the emergence of ICT based devices, differentiated electricity tariffs and energy optimization algorithms that allow an automatic and effective control of different domestic appliances. To achieve an optimal decision, several challenges have to be addressed: the diversity of the devices to control, the problem complexity and finally the uncertainty of the future.

## 1.2 HEMS objective function

According to literature (Table 1.1), the most typical objective function is to minimize the energy costs at a household level while ensuring the user comfort, expressed as constraints (Costs) or explicitly in the objective function (Costs + Comfort).

| **Objectives** | **References** |
|---|---|
| Costs | [3, 12–25] |
| Comfort | [26] |
| Peak Demand | [25] |
| Costs + Comfort | [9, 27–29] |
| Costs + Battery Life | [30] |

Table 1.1: HEMS optimization objectives

### 1.2.1 Minimization of operation costs

The optimization aims at minimizing the operation costs of the different flexibility sources (Table 1.8) according to the considered electricity price scheme and/or the feed-in tariff. The cost formulation and the constraint ensuring a power balance are expressed according to equations 2.1 and 2.2. It can be noticed that they depend explicitly on different forecasts:

- Photovoltaic production: $P_{PV}(t)$
- Uncontrollable electrical demand e.g. lights or television: $P_{dem}(t)$

Depending on the considered devices, additional forecasts can be required e.g. outside temperature or domestic hot water (DHW) demand.

The total costs and the power balance constraints can be expressed in a general way:

$$C(\mathbf{x}) = \Delta t \sum_t \overbrace{P_{imp}(\mathbf{x}(t))C_{imp}(t)}^{\text{import cost}} - \overbrace{P_{exp}(\mathbf{x}(t))C_{exp}(t)}^{\text{export revenue}} + \overbrace{C_{discomfort}(t)}^{\text{discomfort costs}} \tag{1.1}$$

$$\begin{aligned} &\forall t, \underbrace{P_{imp}(\mathbf{x}(t)) + P_{PV}(t)}_{\text{electrical production}} = \\ &\underbrace{P_{exp}(\mathbf{x}(t)) + \sum_{d=0}^{D} P_d(\mathbf{x}(t)) + P_{dem}(t)}_{\text{electrical consumption}} \end{aligned} \tag{1.2}$$

$\mathbf{x}(t)$ is the vector of decision variables for the flexible devices considered at time $t$. $P_d(\mathbf{x}(t))$ is a continuous variable associated to the power consumption of the scheduled device $d$. $P_{imp}(\mathbf{x}(t))$ and $P_{exp}(\mathbf{x}(t))$ are respectively the imported and exported power from/to the grid, constant over a time interval $\Delta t$ and depending implicitly on the decision variable vector $\mathbf{x}(t)$. $C_{imp}(t)$ and $C_{expt}(t)$ are respectively the importing cost and exporting revenue in €/kWh which depend on the electrical pricing considered. $P_{PV}(t)$ and $P_{dem}(t)$ represents the uncontrollable photovoltaic (PV) production and electrical demand.

In literature, many different pricing schemes are proposed to achieve one or several objectives at a global level.

a) Minimize the energy costs

b) Minimize the peak load demand

c) Maximize the global welfare

d) Maximize the self-consumption

e) Minimize the CO2 emission

Table 1.2: Different pricing schemes and their global objectives.

| Pricing | | Objectives | literature |
|---|---|---|---|
| Time-differentiated tariff | TOU | b), c) | [31–34] |
| | CPP | b), c) | [35–37] |
| | RTP | a) , b) , c) | [38–40] |
| Incentive payments | | a), b), c), d), e) | [41, 42] |
| Feed-in tariff | | d) | [3, 43] |

Time-differentiated tariff and incentive payments are part of the DR mechanism because they incentive consumption at a given period of time whereas feed-in tariff is a policy mechanism which incentivizes the investment in renewable energy.

### 1.2.2 Demand response tariff

Customer acceptance and legislation are sine qua non conditions for the effective deployment of DR programs. Empirical results show that consumers are open to dynamic pricing, but prefer simple programs to complex and highly dynamic ones [44]. In literature, different studies highlight the elasticity of house consumption to electricity price in USA [45] or Italy [46]. According to [47], DR allowed for cutting 7% of the seasonal peak in PJM interconnection (USA). In 2011, the demand response market in the United States generated approximately $6 billion in direct revenues.

DR programs can take two main forms: time-differentiated electricity rates or incentive payments. Each of this form has a huge number of variants.

#### 1.2.2.1 Time-differentiated electricity rates

Time-differentiated electricity rates are classified into time of use (TOU) and dynamic pricing.

**TOU pricing** are known to user well in advance i.e. months ahead and are fixed for a long period (i.e. 3 months) [6]. It is divided into different unit prices for usage during different blocks of time in order to encourage customers to shift consumption when demand is low, e.g. during night time or off peak period [29, 41].

**Dynamic pricing** can have different time granularity i.e. minutes or hours block and are known to customers in advance.
- *Critical peak pricing (CPP)* considers additional cost during high demand peak on a small fraction of the days in the year in order to encourage load shifting and shedding. According to [35], residential CPP customers achieve 15% of peak reduction while residential with TOU pricing achieve 5% reduction.
- *Real time pricing (RTP)* aims at reflecting the actual generation costs of electricity to the customers on an hourly or sub hourly basis. Customers are typically notified of the wholesale market prices on a day-ahead or hour-ahead basis [6, 29] such as to adjust demand according to the notified price. RTP can take different forms to protect the customer from the market volatility [48] or to prevent rebound effect with inclining block rate (IBR) [49].

#### 1.2.2.2 Incentive payments

The customer allows the central entity e.g. utility or aggregator, to control its loads according to a pre-defined agreement in exchange of incentive payments. There are different strategies developed to control residential loads, using direct load control (DLC) or large industrial load using interruptible load management (ILM) [41]. Other derived pricing exists for playing in wholesale market using Demand Bidding Programs (DBP), Capacity Bidding Programs (CBP) and ancillary services market programs (ASMP) [42].

### 1.2.3 Feed-in tariff

Feed-in tariff is a policy mechanism which incentives the investment in renewable energy by offering cost compensation and long-term price contract to renewable energy producers. Feed-in tariff are characterized by a differentiated price for importing and exporting electricity from a household point of view. These prices are depending on the country regulation [43] and drives directly the user behaviour. The feed-in tariff often decreases over the time to incentive technological costs reduction.

## 1.3 Objective formulation

Depending on the available forecast information and the sensitivity to the forecast error, the HEMS objective function can be formulated differently by considering either explicitly forecasts uncertainty: optimization under uncertainty or not: deterministic optimization.

| Objective formulation | References |
|---|---|
| **Deterministic** | |
| With point forecast | [3, 9, 13–16, 19, 20, 24, 25, 27–30] |
| **With uncertainty** | |
| Stochastic | [18, 21–23, 26] |
| Chance constrained | [8, 17] |
| Robust | [21] |

Table 1.3: Objective formulation in literature

### 1.3.1 Deterministic optimization

Deterministic optimization is the most typical formulation in literature (Table 1.3) because of its intuitive formulation and the absence of uncertainty modelling.

$$\mathrm{Min}_{\mathbf{x}} C(\mathbf{x})$$

where $C(\mathbf{x})$ is the costs expression (Eq. 2.1) and $\mathbf{x}$ is the vector of decision variables for the flexible devices considered.

Nevertheless, irradiation, space heating, residential electricity or DHW demand are highly dynamic and variable, which make them very challenging to forecast. This implies that the forecast error can be large and lead to sub optimal control. To mitigate the impact of forecast errors, optimization under uncertainty methods are introduced in literature [50, 51].

### 1.3.2 Optimization under uncertainty

Unlike deterministic optimization, optimization under uncertainty aims at benefiting from the probabilistic forecast information. Incorporating forecast uncertainty in the scheduling process has the potential to improve the algorithm optimality despite of an increase of complexity due to the high number of scenarios considered. The most prominent works in literature implement mainly a *stochastic optimization* and few other works consider *robust optimization* or *chance constrained optimization* (Table 1.3).

**Stochastic optimization**

Stochastic optimization is explicitly accounting for the forecast uncertainty by considering the forecast probability in the objective formulation. It aims at minimizing the expected value of the costs under the forecast scenarios considered. This implies that for some scenarios, the schedule will not be optimal or feasible but in average, this schedule will minimize the costs. The feasibility can be increased only at the expense of increasing the number of scenarios considered.

The general formulation of a stochastic optimization problem [51] is:

$$\mathbf{min}_{\mathbf{x}}\mathbb{E}[C(\mathbf{x})] = \mathbf{min}_{\mathbf{x}} \int_{\Omega} C(\mathbf{x}, \omega) dP(\omega) \tag{1.3}$$

where $\mathbb{E}$ is the expected value with respect to $P$, which is a distribution defined on the probability space $\Omega$. $C(\mathbf{x}, \omega)$ is the cost function (Eq. 2.1) and the considered random variable defined on $\Omega$. Let $\omega$ denote a discrete-time stochastic process e.g. the electrical or DHW demand probabilistic forecast.

There are different ways of formulating a stochastic optimization: one stage, two stages or multiple stages, depending on the availability of the required information as function of time. Some decisions need to be made at a given time, while some can be made at a later time period as more information becomes available. For this reason, the schedule is corrected all along the considered horizon through *recourse variables*, accordingly to the realization of the uncertainties. This introduces one of the major challenge of stochastic optimization with multiple stages: problem complexity. The number of variables grows exponentially with respect to the number of recourse stages. For this reason, a two-stage stochastic optimization approach is more common in the literature [18, 21–23, 26].

**Chance-constrained optimization**
Chance-constrained optimization aims at minimizing the worst-case scenario with a desired confidence interval. Unlike robust optimization, chance-constrained optimization can use unbounded distributions of uncertainty since it only covers the majority of cases accordingly to the desired confidence interval. For example, [8] minimizes costs while ensuring that the probability of outage is below a given interval. Chance constrained optimization requires to invert the PDF, which is only feasible for few class of PDFs.

**Robust optimization**
Robust or worst-case optimization uses bounded distribution of uncertainty and focuses on minimizing the impact of the worst-case scenario. For example, if the objective is to reduce the cost of electricity, a robust optimization problem would minimize the upper-bound that a consumer would pay. For this reason, robust optimization is necessarily conservative [1].

## 1.4 Scheduling process

Three different approaches are used in the literature to schedule energy consumption: mathematical optimization, heuristic and meta-heuristic approaches. The use of one of these approaches depends on

- the problem complexity impacting directly the solving time
- the required solution optimality: global or local optimum
- the device models used

The table 1.4 summarizes the different scheduling processes in the literature.

| Scheduling approaches | References |
|---|---|
| **Mathematical optimization** | |
| Linear Programming | [29] |
| Mixed Integer Linear Programming | [17, 19, 21, 24, 25, 28] |
| Quadratic Programming | [8, 26, 52, 53] |
| Convex Programming | [9, 53, 54] |
| Dynamic Programming | [22, 23, 30] |
| Non Linear Programming | [9, 16, 18, 25] |
| **Heuristic** | |
| Fuzzy-Logic controller | [24] |
| Two-Step LSOEM | [15] |
| Market-based | [3, 55, 56] |
| Q-Learning | [30] |
| **Meta-Heuristic** | |
| Genetic algorithm | [20, 27] |
| Particle Swarm Optimization | [14, 17, 30] |

Table 1.4: HEMS scheduling approaches in the literature

### 1.4.1 Mathematical optimization

Mathematical optimization leads to a global optimum. The mathematical formulation of the problem depends on 1) the objective function considered (Section 1.2), 2) the way how forecasts uncertainty is taken into account (Section 1.3) and 3) the device models considered.

- *Linear Programming (LP)*: is the simplest form of mathematical optimization. It is characterized by mature algorithms requiring linear objective function and constraints. LP can be solved in a polynomial-time, but requires a linear form, restricting the HEMS problem formulation.

- *Mixed Integer Linear Programming (MILP)*: is like a LP but it includes integer variables that makes it a non-polynomial-complete problem. This a very common approach in the literature because of the presence of flexible devices requiring a binary variable e.g. uninterruptible loads such as washing machine.

- *Quadratic Programming*: is a mature algorithm that requires a quadratic formulation of the objective function, unlike LP.

- *Convex Programming*: is defined by convex objective function and constraints. There is no analytical solution but they can be solved effectively. The solver cannot be defined yet as a mature algorithm method. The main challenge is the problem formulation, requiring more mathematical transformation than linear programming.

- *Dynamic Programming*: breaks the initial problem into simpler subproblems and solves them recursively by storing their solutions.

- *Non Linear Programming*: is used for optimization problem whose constraints and objective function are not linear and not known to be convex. There is no effective methods for solving such problems.

Aside these mathematical optimizations, heuristic and meta-heuristic approaches solve the HEMS problem with less computational effort than optimization approach but lead to local optimum solution.

### 1.4.2 Heuristic approach

Heuristic methods limit the number of searches based on experience and knowledge about specific problem and are tailored to the specific problem. For example, a simple heuristic method is to charge the battery if the RTP pricing is below a given threshold, defined by experience and knowledge about the specific problem.

### 1.4.3 Meta-heuristic approach

Meta-Heuristic approaches treat the problem as a black box and may be applied to a broad range of problems without change of the algorithm. Typically, genetic or evolutionary algorithms use a large set of possible schedules until to converge near an optimum. The most typical meta-heuristic approaches are genetic algorithms and particle swarm optimization algorithms [14,17,20,27,30].

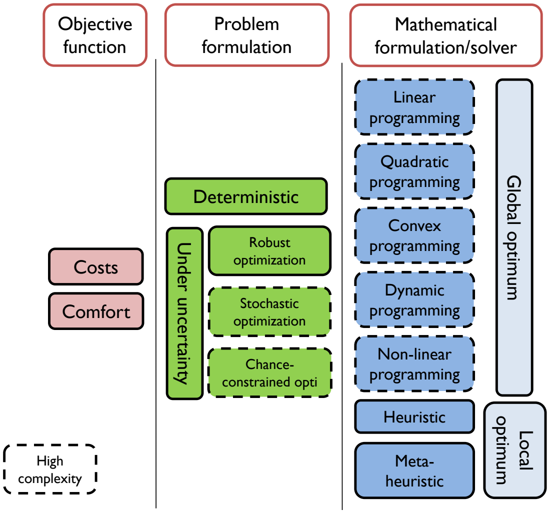


Figure 1.1: Optimization approaches classification, according to literature.

## 1.5 Optimality of HEMS approaches

As presented before, HEMS optimization can be implemented in various ways depending on the objective function, its formulation and the scheduling approach followed (Figure 1.1). In the literature, authors assess typically their HEMS approaches with specific assessment conditions that lacks generality. This section presents the achieved results in the literature and the identified sources of specificity in the assessment.

### 1.5.1 Results in the literature

Table 1.5 presents different results in the literature. It shows that results vary strongly and that no clear outcome can be extracted out of this literature study. Authors consider different and specific assessment conditions that do not allow comparing fairly different HEMS approaches.

| References | DR tariff | Costs reduction |
|---|---|---|
| [16] | RTP | 68% |
| [27] | RTP + IBR | 7.25% |
| [15] | RTP | 20% |
| [3] | Feed-in tariff | 10.7% |
| [18] | TOU tariff | 6.2 - 10.7% |
| [30] | RTP | 16 - 26.6% |
| [19] | TOU tariff | 4.1 - 18.8% |
| [29] | RTP + IBR | 25% |
| [20] | RTP | 8 - 21.7% |
| [21] | RTP | 24.4 - 26.4% |
| [22] | RTP | 11% |
| [23] | RTP | 30 - 40% |
| [24] | RTP, max threshold | 10.4 -12% |
| [2] | TOU tariff | 25 - 28 % |
| [57] | RTP/Feed-in tariff | 4.2 - 11% |
| [58] | TOU + Feed-in tariffs | up to 49,7% |
| [59] | TOU tariff | 7% |

Table 1.5: HEMS costs reduction in the literature

### 1.5.2 Assessment conditions in the literature

The various cost reduction results in the literature are mainly due to the specificity of the assessment conditions. In the literature, the presented results are valid for specific case: one given house location, with specific DR pricing and over a limited simulation time. Sometimes forecast errors are considered but in most of the case, it is not the case. This leads to a lack of generality. The sources of specificity in the literature are presented in this section.

#### 1.5.2.1 User behaviour

User behaviour affects mainly the uncontrollable electricity and DHW demand profiles.

The uncontrollable electrical demand is defined by the electrical demand that cannot be controlled by the HEMS, e.g. television, lights. The uncontrollable associated energy consumption impacts directly the final costs.

Whereas the DHW demand is defined by the hot water need i.e. shower or washing up. DHW demand impacts indirectly the costs, only if it is produced by an electrical source.

First, this implies that electrical and DHW demand is correlated and linked to the presence of users in the house. Second, specific electrical and/or DHW demand conditions bring specificity in the conclusion.

#### 1.5.2.2 Demand response pricing

The demand response pricing considered, defined in Section 1.2 and Table 1.2, affects directly the control strategy followed. For example, if there is a feed-in tariff, the appliances are driven to be started when sun is shining whereas if there is a Real Time Pricing, they are driven to start at low price periods.

| References | Simulation time | Location |
|---|---|---|
| [27] | 24 hours | Taiwan:1 house |
| [16] | 24 hours | UK: 30 houses |
| [15] | 24 hours | USA: 1 house |
| [3] | 7 days | Germany |
| [18] | 24 hours | China: office building |
| [30] | 7 days | USA: 1 house |
| [19] | 24 hours | UK: 1 house |
| [29] | 4 months | USA: 1 house |
| [20] | 24 hours | Spain: 1 house |
| [21] | 24 hours | USA: 1 house |
| [22] | 1 year | Australia: 1 house |
| [23] | 1 year | USA: 1 house |
| [24] | 2 days | USA: 1 house |
| [2] | 290 days | Turkey: 1 house |

Table 1.6: Simulation scenarios

#### 1.5.2.3 House location

The weather profiles i.e. temperature, irradiation or humidity is linked to the house location. Based on that, it can be concluded that the space heating demand flexibility and the PV production is directly impacted by the house location and its associated meteorological conditions. If simulations consider only a specific period of the year, as often in the literature (Table 1.6), the results are not representative.

#### 1.5.2.4 Forecast error

HEMS problem require typically forecasts for scheduling the appliances (Eq .2.1). Nevertheless, most of papers consider perfect forecasts in the assessment process, leading to an over-estimation of the cost savings.

In the literature (Table 1.7), the current forecasting methods under investigations are typically Auto Regressive Moving Average (ARMA), Support Vector Regression (SVR) or Artificial Neural Networks (ANN). The presented results in Table 1.7 have to be taken with caution, given that the forecast results are very sensitive to the considered data set, as shown in [60]. Therefore, some authors [60, 61] present the results for a large number of data sets. In addition, current researches concentrate on probabilistic forecasts which give more insights about the forecasted value probability and can be used with stochastic optimization [60, 62–64].

#### 1.5.2.5 Flexible devices

Authors consider different source of flexibility (Table 1.8) The sources of flexibility mainly considered from a residential point of view are the thermo-electrical devices such as air conditioners or water heaters, the energy storages and the uninterruptible loads such as washing machines or clothes dryer [1].

These different domestic sources of flexibility can be classified into classes [1]:

- Uninterruptible loads which must run for a given time period once started e.g. dishwasher or clothes dryer
- Interruptible loads which can be interrupted and resumed at a later time with associated constraints or penalties linked to the users comfort e.g. Plug-in Electric Vehicles (PEVs) or heat pumps
- Regulating loads that must maintain a device energy state in proximity of a desired state e.g. electro-thermal devices
- Energy storage that can be used to store and dispense energy when needed without restriction.

| Forecast methods | Error | References |
|---|---|---|
| **Ambient T°** | | |
| ARMA | MAPE: 14% | [65] |
| | MAPE: 10% | [20] |
| **Irradiation** | | |
| ARMA | NRMSE: 40% | [65] |
| SVR | NRMSE: 50% | [65] |
| **Electricity demand** | | |
| ARMA | MAPE: 50-70% | [61] |
| | MAPE: 100% | [65] |
| | MAPE: 25% | [14] |
| SVR | MAPE: 80% | [65] |
| ANN | MAPE: 28% | [14] |
| **Hot water demand** | | |
| ARMA | MAPE: 65% | [65] |
| SVR | MAPE: 70% | [65] |
| **Market price** | | |
| ARMA | MAPE: 10% | [20] |
| | MAPE: 10% | [15] |
| Weighted average | MAPE: 13% | [29] |
| **Wind power** | | |
| ARMA | MAPE: 20% | [20] |

Table 1.7: Forecast error in the literature. MAPE: Mean Average Percentage Error, NRMSE: normalized root mean square error.

### 1.5.3 Limits of assessment approaches in the literature

As discussed before, authors consider different assessment conditions which do not allow comparing fairly these different approaches according to results presented in the literature. Table 1.9 refers the different sources of specificity in the literature.

| Flexible devices | References |
|---|---|
| **Uninterruptible loads** | |
| Clothes dryer | [9, 13–15, 22, 24–26, 29] |
| Dishwasher | [13–15, 17, 21, 22, 25, 29] |
| Washing machine | [9, 13–16, 21, 22, 25–29] |
| **Interruptible loads** | |
| PHEV/EV | [12, 16, 20–22, 24–26, 29] |
| Swimming pool pump | [9, 22] |
| **Regulating loads** | |
| Air conditioner | [9, 14, 15, 17, 20–22, 24–28] |
| Electric heater | [3, 9, 16, 25, 28] |
| Heat pump | [3, 55, 57, 66–69] |
| Refrigerator | [9, 28] |
| Water heater | [3, 9, 14, 15, 21, 22, 24, 25, 27, 28] |
| **Energy storage** | |
| Battery/energy storage | [9, 12, 17–19, 24, 28, 30] |

Table 1.8: Flexible devices considered in the literature

| Influencing inputs | Depending on |
|---|---|
| Electrical profile | User presence, devices |
| DHW demand profile | User presence |
| Weather profile | Location, calendar |
| Forecast profile | Forecast method, error |
| Building/house | Year of construction |
| Flexible devices | Choices, year of construction |
| Pricing scheme | Legislation |

Table 1.9: Sources of specificity for HEMS assessment

| Ref. | Simu time | Forecast errors | Pricing | Objectives achieved | Location |
|---|---|---|---|---|---|
| [27] | 24 hours | Electricity demand: MAPE: 13.32% | RTP + IBR | Electricity costs reduction: 7.25%<br>PAR reduction: 8.65% | Taiwan:1 house |
| [16] | 24 hours | - | RTP | Electricity costs reduction: 68%<br>Peak demand reduction: 57%<br>Load factor increase: +13% | UK: 30 houses |
| [15] | 24 hours | Electricity price: MAPE:10% | RTP | Electricity costs for water heating reduction: 20% | USA: 1 house |
| [3] | 1 week | - | Feed-in tariff | Electricity costs reduction: 10.7% | 1 house |
| [18] | 24 hours | - | TOU tariff | Electricity costs reduction: 6.2-10.7% | China: office |
| [30] | 1 week | - | RTP | Electricity costs reduction: 16-26.6% | USA: 1 house |
| [19] | 24 hours | - | TOU tariff | Electricity costs reduction: 4.1-18.8% | UK: 1 house |
| [29] | 4 months | Electricity price: MAPE: 13% | RTP + IBR | Electricity costs reduction: 25% | USA: 1 house |
| [20] | 24 hours | 1) Ambient T°: MAPE: 10%<br>2)Electricity demand: MAPE: 2%<br>3)Electricity price: MAPE: 10%<br>4)Wind power: MAPE: 20% | RTP | Costs reduction: 8-21.7% | Spain: 1 house |
| [21] | 24 hours | - | RTP | Costs reduction: 24.4-26.4% | USA: 1 house |
| [22] | 1 year | - | RTP | Costs reduction:11% | Australia: 1 house |
| [23] | 1 year | Electricity price: ME: 0 | RTP | Costs reduction: 30-40% | USA: 1 house |
| [24] | 2 days | - | RTP + max threshold | Costs reduction: 10.4-12% | USA: 1 house |
| [2] | 290 days | - | TOU tariff | Costs reduction: 25-28% | Turkey: 1 house |

Table 1.10: Literature review summary: simulation time, considered pricing, objective function and building location

# Chapter 2

# Modelling

The different HEMS approaches implemented and studied in this work are presented in this chapter. First the deterministic optimization and its associated models are formulated. Second, the heuristic optimization approach based on a market mechanism is presented. Finally the benchmarking control, to which the other HEMS are compared, is briefly introduced. This chapter is mainly based on the work presented by Feron et al. [3, 5].

## 2.1 Deterministic optimization approach: Mixed Integer Linear Programming

This section aims at introducing the domestic devices model used in the optimization based HEMS. As stated in the literature review (table 1.4), the most typical HEMS optimization formulation is a MILP problem, a mature solving algorithm which ensures a global optimal solution. In the following, the objective function is presented, then the modelling of the different flexible devices is formulated.

### 2.1.1 Objective function

The optimization aims at minimizing the operation costs of the different flexibility sources according to the considered electricity price scheme and the feed-in tariff. Based on the cost and the constraints expressed in Section 1.2.1, the optimization problem can be expressed as:

$$\text{Minimize } \Delta t \sum_{t} \overbrace{P_{imp}(\mathbf{x}(t))C_{imp}(t)}^{\text{import cost}} - \overbrace{P_{exp}(\mathbf{x}(t))C_{exp}(t)}^{\text{export revenue}} + \overbrace{C_{discomfort}(t)}^{\text{Discomfort costs}} \quad (2.1)$$

$$\text{Subject to } \forall t, \underbrace{P_{imp}(\mathbf{x}(t)) + P_{PV}(t)}_{\text{electrical production}} = \underbrace{P_{exp}(\mathbf{x}(t)) + \sum_{d=0}^{D} P_d(\mathbf{x}(t)) + P_{dem}(t)}_{\text{electrical consumption}} \quad (2.2)$$

| | |
|---|---|
| $\mathbf{x}(t)$ | vector of decision variables for the flexible devices in $t$ |
| $P_{imp}(\mathbf{x}(t))$ | imported power from the grid [kW] |
| $P_{exp}(\mathbf{x}(t))$ | exported power to the grid [kW] |
| $C_{imp}(t)$ | importing cost depending on the considered tariff [€/kWh] |
| $C_{exp}(t)$ | exporting revenue depending on the considered tariff [€/kWh] |
| $C_{discomfort}(t)$ | discomfort costs [€/h] |
| $P_{PV}(t)$ | photovoltaic power (PV) production [kW] |
| $P_{dem}(t)$ | uncontrollable electrical demand [kW] |

$P_d(\mathbf{x}(t))$ is a continuous variable associated to the power consumption of the scheduled device $d$, classified according to their constraints [1]. In the following the different linear models used are presented. The objective of this work is not to study the impact of modelling error on optimality. Therefore, state-of-the-art low order models are considered.

### 2.1.2 Interruptible load model

An interruptible load is characterized by the possibility to be interrupted and to be resumed later according to constraints or penalties defined by the user comfort, e.g. a thermo-electrical device supplying space heating demand and constrained by room temperature. The following linear constraints describe the interruptibility condition under user comfort constraint.

$$\text{if } d \in \{\text{interruptible}\}, \forall t$$
$$P_d(x_d(t)) = x_d(t) \cdot P_{d,max}$$

$$P_{comfort}^{min}(x_d(t-1),y(t)) \leq P_d(x_d(t)) \leq P_{comfort}^{max}(x_d(t-1),y(t)) \qquad (2.3)$$

| | |
|---|---|
| $x_d(t)$ | continuous variable element of the variable vector $\mathbf{x}(t)$ |
| $P_{d,max}$ | maximum load power [kW] |
| $P_{comfort}^{min}$ | minimum consumption level to fulfil the user comfort [kW] |
| $P_{comfort}^{max}$ | maximum consumption level to fulfil the user comfort [kW] |

$x_d(t)$ states the consumption level of the considered interruptible load. The minimum and maximum consumption level that the load can support to fulfil the user comfort depend on the previous state of the device $x_d(t-1)$ and the external variables $y(t)$ such as outside temperature or irradiation.

### Heat pump -HP-

The heat pump is a very efficient thermo-electrical device which extracts heat power from a low temperature source such as air or water, using an inverse fridge cycle. The heat pump supplies typically a water tank storage which can supply DHW and/or space heating (SH) needs. The heat power output of a heat pump is governed by the coefficient of performance (COP) which is a function of ambient temperature and the flow temperature for hot water supply.

$$Q_{HP}(t) = COP \cdot P_{HP}(t) \qquad (2.4)$$

$$P_{HP}(t) = x_{HP}(t) \cdot P_{HP}^{max}(t) \qquad (2.5)$$

| | |
|---|---|
| $P_{HP}$ | electrical power of HP [kW] |
| $Q_{HP}$ | thermal power of HP [kW] |
| $COP$ | coefficient of performance [-] |
| $x_{HP}$ | binary element of the decision variable vector $\mathbf{x}(t)$ describing the HP operation |

### Electrical heater -EH-

The electrical heater is a fast heating device constituted by an electrical resistance which can be installed in rooms to provide SH or in the water tank to supply DHW demand. The heat power output of electrical heater is governed by the efficiency of the electrical heater.

$$Q_{EH}(t) = \eta_{EH} \cdot P_{EH}(t) \tag{2.6}$$

$$P_{EH}(t) = x_{EH}(t) \cdot P_{EH}^{max}(t) \tag{2.7}$$

| | |
|---|---|
| $P_{EH}$ | electrical power of EH [kW] |
| $Q_{EH}$ | thermal power of EH [kW] |
| $\eta_{EH}$ | EH efficiency [-] |
| $x_{EH}$ | binary element of the decision variable vector $\mathbf{x}(t)$ describing the EH operation |

In this work, the HP and EH operation is restricted to on-off operation.

### 2.1.3 Uninterruptible load model

An uninterruptible load is characterized by a must-run condition: if switched on, it must finish its task, e.g. washing machine. The following linear constraints describe this condition.

$$\text{if } d \in \{\text{uninterruptible}\}, \forall t$$

$$x_d(t) \cdot P_{d,min} \leq P_d(x_d(t)) \leq x_d(t) \cdot P_{d,max}$$

$$x_d(t) \leq x_d(t+1) + \frac{\Delta t}{T} \sum_{\tau=1}^{t} x_d(\tau) \tag{2.8}$$

$$\sum_{t=1}^{T_{flex}} x_d(t) \geq 1 \tag{2.9}$$

| | |
|---|---|
| $x_d(t)$ | binary variable equals to one if device is on |
| $T$ | time for a load cycle [s] |
| $T_{flex}$ | ultimate time interval when the load must be run [-] |
| $\sum_{\tau=1}^{t} x_d(\tau) \cdot \Delta t$ | the current cycle time [s] |

According to Eq. 2.8, $x_d(t+1) = 1$ only if $x_d(t) = 1$ and $\sum_{\tau=1}^{t} x_d(\tau) \cdot \Delta t < T$ (Table 2.1). Furthermore, it ensures that the load is on for its full cycle $T$. Finally, Eq. 2.9 ensures that the device will run before the time limit given by the user.

Table 2.1: Truth table of uninterruptible load constraints (Eq. 2.8)

| $x_d(t)$ | $\sum_{\tau=1}^{t} x_{d,\tau} \cdot \Delta t$ | $x_d(t+1)$ |
|---|---|---|
| 0 | 0 or T | 0 |
| 1 | $<$ T | 1 |
| 1 | T | 0 |

### 2.1.4 Energy storage model

An energy storage is characterized by the possibility to store and restore energy when required. From a modelling point of view, its constraints are described by equation 2.3 where $P_{d,min}$ and $P_{d,max}$ define respectively the minimum and maximum consumption/production level that the storage can support to fulfill its physical constraints such as its state of charge boundaries.

#### 2.1.4.1 Battery

In this work, a lithium ion battery model is considered. The continuous decision variables are the discharging $P_{discharge}$ and charging power $P_{charge}$ constrained by the power limitation due to the maximum admissible current in the cells and the inverter power.
The state of the art of the charging strategy is the Constant Current Constant Voltage (CCCV) which implies a maximum power charge or discharge depending on the current battery voltage, i.e. the state of charge [70].

$$0 \leq P_{charge}(t) \leq P_{charge,max}(SOC(t)) \tag{2.10}$$

$$0 \leq P_{discharge}(t) \leq P_{discharge,max}(SOC(t)) \tag{2.11}$$

The evolution of the stored energy in the battery is depending on its previous energy state, the charge/discharge power and the combined battery-inverter system efficiency (Eq. 2.12)

$$E(t+\Delta t) = E(t) + \Delta t \left( \eta_{batt} P_{charge}(t) - \frac{P_{discharge}(t)}{\eta_{batt}} \right) \tag{2.12}$$

| | |
|---|---|
| $E$ | energy stored [kWh] |
| $E_{max}$ | battery capacity [kWh] |
| $P_{charge}$ | charge power [kW] |
| $P_{discharge}$ | discharge power [kW] |
| $\eta_{batt}$ | system efficiency (battery and inverter) [-] |
| $SOC$ | battery state of charge [-] |

The state of charge of the battery is defined as

$$SOC(t) = \frac{E(t)}{E_{max}} \in [0,1] \tag{2.13}$$

#### 2.1.4.2 Water tank storage

Water tank storage is used for storing thermal energy typically used for DHW or SH demand. Its energy balance is formalized in Equation 2.14.

$$E(t + \Delta t) = E(t) + \Delta t \left(Q_{in}(t) - Q_{out}(t) - Q_{loss}(t)\right) \tag{2.14}$$

| | |
|---|---|
| $E$ | thermal energy stored in the water tank [kWh] |
| $Q_{in}$ | input thermal power from heating system [kW] |
| $Q_{out}$ | output thermal power i.e. DHW or SH demand [kW] |
| $Q_{loss}$ | heat losses function of the WT temperature [kW] |

The energy stored in a water tank storage is function of the average of the inside temperature ($T$).

$$E(t) = \rho(T(t)) \cdot m \cdot c_p(T(t)) \cdot T(t) \tag{2.15}$$

The water parameters $\rho$ and $c_p$ describe respectively the density and the heat capacity of water, in function of its temperature. $m$ denotes the mass of water in the WT. The storage is empty ($SOC = 0$) when $T$ equals to $T_{min}$ whereas it is full ($SOC = 1$) when $T$ equals to $T_{max}$.

$$SOC(t) = \frac{E(t) - E(T_{min})}{E(T_{max}) - E(T_{min})} \in [0,1] \tag{2.16}$$

The heat losses are function of the water tank temperature and is typically formalized as a linear function of the energy stored.

$$Q_{loss}(t) = q_{loss} \cdot E(t) \tag{2.17}$$

#### 2.1.4.3 Building wall mass storage

In the frame of this work, a first-order thermal model of the house according to international standard EN ISO13790 is implemented [71]. This model is characterized by a one-zone model i.e. parameters and variables are averaged and represent the overall house behaviour. According to [71], the house temperature is expressed as:

$$T(t+\Delta t) = T(t) + \frac{\Delta t}{C_{house}} \left( Q_{in}(t) + \overbrace{\eta_{h,gn}(Q_{sol}(t) + Q_{int}(t))}^{\text{external and internal gains}} - \overbrace{Q_{loss}(t)}^{\text{thermal losses}} \right) \tag{2.18}$$

| | |
|---|---|
| $T$ | internal temperature of the house [°C] |
| $Q_{in}$ | heat power input of the space heating system [kW] |
| $C_{house}$ | thermal house capacitance [kWh/°C] |
| $\eta_{h,gn}$ | gain utilization factor [-] |
| $Q_{sol}$ | solar heat gains [kW] |
| $Q_{int}$ | internal heat gains [kW] |
| $Q_{loss}$ | heat losses by transmission and ventilation [kW] |

The house temperature depends on the input power: respectively the space heating system and the gains. Two different type of gains are considered, the external and internal: respectively irradiation and the heat produced internally by electrical devices, e.g. micro-wave, oven.

Standard values are used for the operating conditions (room temperature, air exchange rate, internal heat sources) and for the solar radiation reduction factors (shading). The calculation of this different parameters are based on a harmonized approach in the framework of the Intelligent Energy Europe project DATAMINE [72].

The use of a first-order model leads to approximations:

- all thermal masses are combined to one representative thermal capacitance

- the different material characteristics are combined to one representative thermal resistance

The use of a higher-order model will bring finer resolution about the temperature in the different rooms and about the house dynamic, at the expense of a more complex problem to solve. The calculation of the different terms in Equation 2.18 are presented in details in [73].

### 2.1.5 Implementation details

In the frame of this work, the presented MILP optimization approach is implemented in the Python environment. More specifically, the problem was modelled using the Pulp package [74] which allows changing easily from one solver to another one. The presented results are achieved using the MILP solver Gurobi [75], because of its good performance and its availability for academic purpose.

## 2.2 Heuristic optimization approach: a market-based approach

The heuristic optimization approach is based on the energy market mechanism, where each flexible device is a market player, bidding its flexibility. As the optimization-based approach, the market-based approach takes place in the house and controls the domestic electrical or thermo-electrical devices with flexibility in order to minimize the energy costs according to the considered electricity price scheme i.e. feed-in or DR tariffs (Eq. 2.1).

It is based on a bottom up approach: every controllable device in the house is a market participant which negotiates its demand or offer of electricity and/or thermal energy (heat or cooling) on a virtual domestic market in the house to fulfill economically its need. The agents interact among them (Fig. 2.1) via a bidding process on this domestic market in order to balance energetically the system i.e. the house, through an internal market equilibrium price. This in-house market price steers the devices and differs from the residential electricity price scheme such as DR tariffs.

This market approach extends the well-known Powermatcher approach [55] by introducing in addition to the electricity market, one or more *local heat and/or cooling markets* which accounts for the thermal flexibilities in the considered subsystem, formed by a thermal sink and a thermal source e.g. a room and its associated space heating system (Fig. 2.1). In addition to the electricity equilibrium price, additional local thermal equilibrium prices are determined in order to ensure a thermal balance in the subsystem.

This section presents first the market-based optimization and its theoretical background. Based on this, the bidding strategies for interruptible loads and energy storages are then derived. Finally, its possible implementation in a distributed way as a multi-agent system is described.

### 2.2.1 Microeconomic theory

This section discusses the market-based optimization conditions which lead to system cost minimization.

Economy is stated as a constrained optimization where the resources are scarce. On one hand, the consumer's objective is to maximize its utility subjected to a budget constraint whereas on the other hand, the producer's objective is to optimize its production in order to maximize its profit. Finally, the global objective of economy is to maximize the consumer and producer surplus, called global welfare, in spite of the fact that the two objectives are competing. Therefore, economy can be described as an optimization problem with a local goal achieved at consumer/producer level and a global goal achieved at the market level.

To this regard, a *competitive market* achieves a global welfare maximiziation and is defined by four hypotheses, which drive the market-based optimization [76]:

- Products homogeneity: electricity and heat do not take various forms and are well defined worldwide according to standard energy unity
- Free entrance in the market: no barrier to enter in the market
- Transparency: everyone has the same information from the market, namely the current and past market prices.
- Actors are price takers: actors do not consider in their bidding strategy that they have influence over market price.

The first economy theorem states that a competitive market leads to a Pareto optimal solution, corresponding to solution which does not allow to make a participant better off without making any another one worse off. Furthermore, a competitive equilibrium leads to a solution maximizing the consumer and producer surplus [76]. In addition to this, the consumer's objective, maximize utility, leads to a minimization of its utility costs (dual problem) whereas the producer's objective, maximize profit, leads to a minimization of the production cost [77]. Based on these results and the first economy theorem, it can be stated that a competitive market leads to a minimization of the global costs, defined by the utility costs and the production costs.

In summary and according to competitive market theory, the minimization of global costs is achieved if each producer bids at its marginal costs and each consumer bids for minimizing its utility costs. Table 2.2 refers to literature presenting optimal bidding strategies according to the microeconomic theory for different types of domestic flexibility. More details about these bidding strategies are given in the following.

Table 2.2: Bidding strategy in the literature

| | | |
|---|---|---|
| Interrupible loads | Electrical heater | [3] |
| | Combined heat power | [56] |
| | Heat pump | [3], [56] |
| | Plug in hybrid vehicle | [78] |
| Energy storage | Water tank storage | [3] |
| | Battery energy storage system | [67] |

## 2.2.2 Interruptible loads

The interruptible load can be interrupted and resumed at a later time with associated constraints or penalties linked to the user comfort. The interruptible loads bidding strategies presented in this work are appropriated for thermo-electrical devices such as heat pump (HP) or electrical heater (EH), characterized by an electrical consumption and a thermal production. For this reason, its associated bid has to tender an electrical power demand on the electrical market and a heat power supply on the heat market, both of them depending on the electricity and heat price [3, 56].

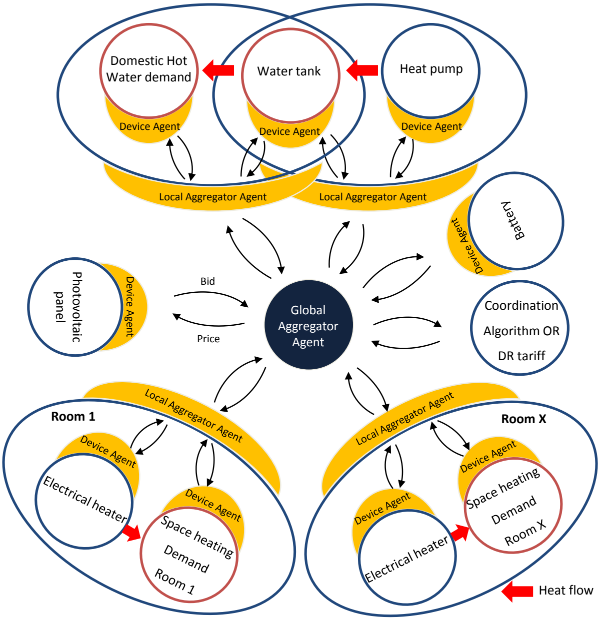


Figure 2.1: Electro-thermal market-based Multi-Agent System at a household level: agent interactions and information exchange.

#### 2.2.2.1 Heat pump

Based on the microeconomic theory, the heat pump has to maximize its profit on the markets whereas considering it is a price taker.

$$\mathbf{max} \quad \overbrace{p_h \cdot Q - C(Q)}^{\text{Profit [€/h]}} \tag{2.19}$$

$$\mathbf{s.t.}$$

$$\forall t, \quad P = \frac{Q}{COP} \tag{2.20}$$

where the costs can be expressed as

$$C(Q) = p_e \cdot P + C_{fixed} = p_e \cdot \frac{Q}{COP} + C_{fixed} \tag{2.21}$$

| | |
|---|---|
| $Q$ | produced thermal power [kW] |
| $P$ | consumed electrical power [kW] |
| $p_h$ | heat price [€/kWh] |
| $p_e$ | electrical price [€/kWh] |
| $C_{fixed}$ | fixed costs, e.g. maintenance [€/h] |
| $COP$ | coefficient of performance of the HP [-] |
| $\eta_{EH}$ | EH efficiency [-] |

In the case of a competitive market, the market participant is a price taker ($dp_h/dQ = 0$), meaning that it does not consider in its bidding strategy that it can potentially influence the market price, even it could. Indeed, *if a large consumer/producer considers in its bidding strategy that it influences the market price to maximize its profit, the market is no more competitive but oligopolistic and does not lead to an operating cost minimization* [76]. Considering a competitive market, the maximization (Eq. 2.19) leads to:

$$Q \overbrace{\frac{dp_h}{dQ}}^{=0} + p_h \frac{dQ}{dQ} - \frac{dC(Q)}{dQ} = 0 \tag{2.22}$$

$$p_h = \frac{dC(Q)}{dQ} \tag{2.23}$$

From there, the optimal HP bidding strategy is to bid its thermal power on the thermal market and its associated electrical consumption on the electrical market if:

$$p_h = \frac{p_e}{COP} \tag{2.24}$$

#### 2.2.2.2 Electrical Heater

Identically, the EH bids can be derived by considering a slightly different cost function.

$$C(Q) = p_e \cdot P + C_{fixed} = p_e \cdot \frac{Q}{\eta_{EH}} + C_{fixed} \tag{2.25}$$

Based on equation 2.25, the optimal EH bidding strategy is to bid its thermal power on the thermal market and its associated electrical consumption if:

$$p_h = \frac{p_e}{\eta_{EH}} \tag{2.26}$$

As stated in equations 2.24 and 2.26, the bidding strategy of thermo-electrical devices is depending on the electrical and the thermal prices. Given that they produce heat and consume electricity, they have to bid in two markets: thermal and electrical. Note that if a HP and EH compete in the same thermal market, the HP will be more likely used because of its smaller heat price (COP is in the range of 3 while EH efficiency is around 1). Furthermore, additional constraints can influence the bidding strategy, e.g. a minimum must-run time, which avoids too close switch on/switch off of the unit.

### 2.2.3 Energy storage

The energy storage units can be used to store and dispense energy when needed, e.g. water tank or battery. In a market, they maximize their profit by buying energy when prices are cheap and by selling energy when prices are high, while being constrained by their state of charge. The optimal bidding strategy for storage unit is formulated in equation 2.27, while considering that the storage unit is a price taker to achieve a competitive market.

$$\textbf{max} \quad \Delta t \sum_{t=1}^{T} \left( \overbrace{P_{discharge}(t) \cdot p(t)}^{\text{Sold energy}} - \overbrace{P_{charge}(t) \cdot p(t)}^{\text{Bought energy}} \right) \tag{2.27}$$

$$\textbf{s.t.}$$

$$\forall t, \quad SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{2.28}$$

$$\forall t, \quad T_{house}^{min} \leq T(t) \leq T_{house}^{max} \tag{2.29}$$

The state of charge of the battery and water tank energy storage is defined as:

$$SOC(t) = \frac{E(t)}{E_{max}} \in [0,1] \tag{2.30}$$

The same models are considered than with the optimization-based approach.

| | |
|---|---|
| $P_{discharge}$ | optimal discharging power at the considered time step $t$ [kWh] |
| $P_{charge}$ | optimal charging power at the considered time step $t$ [kWh] |
| $SOC$ | state of charge [-] |
| $T(t)$ | internal temperature of the house [°C] |
| $E$ | stored energy [kWh] |
| $p$ | internal market price [€/kWh] |
| $\Delta t$ | time step duration between decisions [h] |
| $T$ | number of scheduling time interval [-] |
| $E_{max}$ | maximum stored energy [kWh] |

#### 2.2.3.1 Battery

The considered battery model is described in section 2.1.4.1. $P_{charge}$ and $P_{discharge}$ are the continuous decision variables describing respectively the charging and discharging battery power.

#### 2.2.3.2 Water tank

The considered water tank model is described in section 2.1.4.2. In contrast with the battery, the water tank cannot intentionally be discharched. $P_{charge}$ is the continuous decision variable that describes the charging power, i.e. heat production from the EH.

#### 2.2.3.3 Thermal wall mass

The thermal wall mass of a house can also be used as a thermal storage. In contrast with the battery, the thermal wall mass cannot intentionally be discharched. The considered thermal wall mass model is described in section 2.1.4.3. $P_{charge}$ is the continuous decision variable describing the charging power, i.e. the heat production from the HP.

#### 2.2.3.4 Optimization problem

The maximization problem formulated in equation 2.27 requires knowing upfront the price to determine the optimal charge and discharge power in function of the current market price. Given the challenge of forecasting the market price, [67] proposes to use a naive forecast with a heuristic approach for optimizing the storage units bidding strategy: buy at periods of low prices and resell it in periods of high prices in function of the SOC and the market price knowledge. Where the maximum and the minimum market price is determined according to the considered forecast. This work follows this approach.

### 2.2.4 Market price determination

Each flexible device optimizes locally its tender and bids on the associated market so that an equilibrium price can be determined. This work considers the electrical and thermal consumers/producers as source of flexibility. For this reason, thermal and electrical equilibrium market prices, ensuring the electrical and thermal power balance, have to be determined subsequently at each time step.

#### 2.2.4.1 Thermal market price

The thermal flow in the house are physically constrained, e.g. the electrical heater installed in a given room cannot supply the space heating demand in another room. Note that heat transfer between rooms is assumed to be negligible and is not considered from a market exchange point of view. The elements that can exchange physically thermal energy, have to trade in the same local thermal market, annotated $i$. According to microeconomic theory, the local thermal market $i$ determines a thermal equilibrium price $p^*_{h,i}$ according to a merit order, for each electrical price (Eq. 2.31). The resulting electrical bid is then considered in the electrical market price determination.

$$\forall p_e,\ \mathbf{Min}_{p^*_{h,i}} |Q_{supply,i}(p_e, p_h) - Q_{demand,i}(p_e, p_h)| \tag{2.31}$$

$$\text{Subject to } p_e, p_h > 0 \tag{2.32}$$

where $Q_{supply,i}$ and $Q_{demand,i}$ are the sum of all the bids respectively supplying and consuming thermal energy in the local heat market $i$. The equation 2.31 minimizes the difference between the demand and the supply and leads for this reason, to an equilibrium between thermal demand and supply.

#### 2.2.4.2 Electrical market price

An electrical equilibrium market price has to be then determined according to a merit order approach, formalized as [77]:

$$\mathbf{Min}_{p_e^*} |P_{supply}(p_e) - P_{demand}(p_e)| \tag{2.33}$$

$$\text{Subject to} \qquad p_e > 0 \tag{2.34}$$

$$P_{tot}(p_e) \quad = 0, \text{ if } p_e > p_{grid}(t) \tag{2.35}$$

where $P_{supply}$ and $P_{demand}$ are the sum of all the electrical bids respectively supplying and consuming electrical energy in the house. Therefore, the market price, formulated as a minimization problem in equation 2.33, leads to an equilibrium between electrical demand and supply. The grid constraints in equation 2.35 expresses that the grid can provide all the required power if the internal electrical market price is larger or equal to the current grid pricing $p_{grid}$, e.g. TOU.

The optimal thermal and electrical prices are determined thanks to a merit order approach which leads to a global minimization of the thermal and electrical demand and supply mismatch, for given bids. The merit order has a low complexity and does not suffer from convergence issue (the bidding and pricing process takes less than 1s).

The major advantages of the presented market-based approach is its low complexity of the algorithm that allows a reactive control to an unexpected event or a wrong forecast.

On the other hand, because of the considered naive price forecasts and the heuristic nature of energy storage bidding strategies, the market-based approach leads to suboptimal solutions. One of the objective of the work is to determine if its reactive control feature can counterbalance the suboptimality of its solution.

### 2.2.5 Multi-agent system implementation

A multi-agent system (MAS) is characterized by several physical or virtual entities, which communicate, interact, sense and act. Each agent has a local objective whereas the group of entities forming the MAS have a global objective.

In a market case, the local objective is to minimize the utility costs for consumers or to bid at marginal costs for producers whereas the global market objective is to maximize the global welfare or in other words minimize the total costs while ensuring the power balance.

In the frame of this work, a MAS platform developed in Python [79] according to the IEEE Foundation for Intelligent Physical Agents (FIPA) [80] was implemented. FIPA releases number of standards specifying how agents can communicate between each others. Python was chosen given that it enables an easy integration into low power hardware with basic python interpreter, e.g. Raspberry Pi Zero or Arietta G25. In constrast with the existing MAS software e.g. JADE [81] or osBrain [82] , the developed python library is compatible with different domestic communication technologies, e.g. Wifi, Zigbee, Bluetooth LE, Z-Wave, Thread or DigiMesh.

The objective of the MAS implementation is to minimize the hardware energy usage while keeping a robust, reliable and scalable system. For these reasons, the MAS is designed with [55]:

- **tree topology** which stands out because of its low number of sent messages per market cycle, equals to the number of agents and by its tractable and intuitive tree creation that follows the physical layout of the network.
- **resilience against hardware failure** thanks to the self-organized election of the aggregator, Section 2.2.5.2.
- **plug and play** thanks to the dynamic tree topology creation, Section 2.2.5.2.
- **low energy usage** given i) the limited number of messages sent per market cycle and ii) the idle mode of every agents between each market cycle.

#### 2.2.5.1 Agents

For achieving this, three different types of agents are defined (Fig. 2.1):

- *The device agent* acts on behalf of a physical device on the market and computes the optimal bid with respect to its constraints and the microeconomic theory.

- *The local aggregator agent* extends specifically the Powermatcher approach. It calculates the thermal market equilibrium price according to the merit order formulated in equation 2.31 in function of the electrical price. In doing so, a local equilibrium heat/cooling price ensures a thermal balance of the subsystem considered, as demonstrated in [3, 56].

- *The global aggregator agent* aggregates the different electrical bids and determines the electricity market price accroding to the merit order formulated in equation 2.33. The electrical market price ensures an electrical power balance in the system [55]. This entity is also the link with outside such as a larger coordination algorithm which could optimize the residential energy usage or provide grid services e.g. balancing or congestion management. This agent can indeed offer the current domestic flexibility using bids to an upper layer of the residential coordination algorithm, as in [83, 84].

#### 2.2.5.2 Tree topology and self-organized aggregator election process

The global aggregator agent is elected with a bully algorithm. After its election, it broadcasts a proposal for a patent-child relationship to its neighbors to build the tree topology. This proposal will be accepted by its neighbors if it has no parent yet. Once accepted, this node proposes as well to its neighbors and the process continues until that each node is the child of another one. This process enables a dynamic integration or removal of any agents in a plug and play way. At the beginning of a market cycle, all the agents wait for a proposal of the aggregator of the last market cycle. If it proposes then, no election is carried out and the network is considered as operative. Once elected, the aggregator broadcasts a market initiation request to its neighbors, that they forward to their neighbors as well. Based on this request, each node aggregates the bids from its children and sends it to its parent. A market cycle takes place every minute.

This work does not investigate in detail the MAS features and the presented results consider a perfect MAS operation.

## 2.3 Rule-based approach: conventional control

The rule-based approach is the considered benchmarking control, based on the current system states. It is a robust approach because it does not require communication infrastructure between the different devices given that each of them maximize independently the user comfort. This is the less optimal but the most commonly implemented control in house.

### 2.3.1 Objective function

The objective function is local at the device level and maximize the user comfort and the house self-consumption if there are PV and domestic BESS.

### 2.3.2 Interruptible loads

The interruptible loads are controlled to maximize the user comfort. For example, a space heating device will be controlled to keep the temperature at a given reference value, independently of the other system states.

### 2.3.3 Uninterruptible loads

The uninterruptible load are started as soon as possible such as to maximize the user comfort.

### 2.3.4 Energy storage

The domestic BESS is controlled independently such as to maximize the self-consumption of the house. If the house is exporting electricity because of a high PV production, then the battery is charged whereas when the house is importing electricity, the battery is discharged until to reach its minimum state of charge.

## 2.4 Discussion and summary

In this chapter, three different HEMS approaches were described: the optimization-based approach formulated as a Mixed Integer Linear Programming; the heuristic approach based on market approach and the benchmarking control: the rule-based approach.

This chapter presents the mathematical formulation of a HEMS as a MILP with different types of flexibility: interruptible loads, uninterruptible loads and energy storage units. Secondly the market-based optimization is presented: the associated microeconomic theory, the optimal bidding strategy for interruptible loads and energy storage units and the equilibrium market price determination. Finally, the reference control maximizing the user comfort and the self-consumption is presented.

These presented approaches can be distinguished according to their

- **Communication infrastructure**: centralized, decentralized or distributed. In centralized approaches, the algorithm is computed in one master entity which controls the slave entities, e.g. schedulable devices. Centralized architectures, typically an optimization-based method e.g. MILP, provide theoretically the best results because it is omniscient but it could suffer highly from privacy and scalability issues [85]. Decentralized architectures, like the rule-based control, are characterized by independent optimization computed by every entities leading to a scalable, robust and flexible system which suffers from convergence problems due to the lack of inter-communication [86]. The distributed architecture, like the market-based approach, is a trade-off solution in terms of convergence, privacy and robustness. It is characterized by an architecture that comprise organizational entities called concentrators or aggregators, which have also computing capabilities, allowing decomposition algorithms for problem complexity reduction (e.g. Dantzig-Wolf decomposition) [87].

- **Theoretical optimality and associated complexity**: optimality and complexity are often competing. In theory, the MILP formulation leads to a global optimum at the expense of a longer solving time because of the problem complexity. Specifically, its complexity increases with the number of decision variables, depending on the number of devices and timestamps considered. Whereas the market-based optimization leads to a local optimum but is a fast algorithm which allows reacting to forecast error. Finally, the rule-based approach leads to a local optimum and is a fast and robust approach because it does not require communication infrastructure between the different devices given that each of them maximize independently the user comfort and the self-consumption.

| | Communication | Optimality | Complexity |
|---|---|---|---|
| MILP | Centralized | Global optimum | $\propto n, k$ [1] |
| Market-based | Distributed | Local optimum | Constant |
| Conventional control | Decentralized | Local optimum | Constant |

Table 2.3: Comparison of implemented HEMS approaches with $n$ the number of controlled loads and $k$ the number of timestamps.

In theory, the MILP performs a better control because of its optimal solution. Nevertheless, in practice this can be different because of the forecast error and its limited solving time. While the market-based approach leads to sub optimal solution because of its heuristic nature, that can be counterbalanced by a fast reaction to an unexpected event or a wrong forecast. So, only practical cases can highlight the most optimal HEMS algorithm. Given the impact of the considered conditions (Chapter 1) and the forecast errors on the HEMS optimality, an effective comparison of HEMS approaches has to be performed. For this reason, the next chapter presents a methodology for comparing HEMS under uncertain time-series such as weather conditions, user behaviours or wrong forecasts.

# Chapter 3

# HEMS assessment methodology based on uncertainty analysis

As seen in Chapter 1, HEMS approaches can take a large number of forms according to the *objective function*, *the mathematical formulation* and *the solver* used. In literature, most authors consider short-term and specific evaluation conditions that lacks generality. This does not help to identify easily the most optimal or appropriated HEMS approach.

The focus of this chapter is to present an assessment methodology that allows comparing different HEMS approaches in spite of their various forms and in the most general way from a testing conditions point of view, e.g. temperature, irradiation, DHW or electrical demand.

This problem can be formalized as an uncertainty problem whose main sources of uncertainties considered are:

- the scenarios, e.g. electrical and domestic hot water demand, irradiation, temperature
- their associated forecasts with errors

The state-of-the-art uncertainty analysis are not applicable to this problem because of the assessment time and the nature of the uncertain parameters, discrete time-series.

For these reasons, this chapter introduces an uncertainty analysis methodology inspired by stochastic optimization which allows considering discrete time-series as uncertain parameters while requiring a small number of system evaluation.

This chapter is organized as the following:

- Section 3.1: presentation of the uncertainty analysis problem formulation and of the state-of-the-art methods in the literature;

- Section 3.2: description of the proposed assessment approach, formalized as an uncertainty analysis and inspired by stochastic optimization approaches;

- Section 3.3: application of the proposed method to a HEMS approach and validation of its performance;

## 3.1 Uncertainty analysis fundamentals

This section introduces some basic terms of probability theory and describes the state-of-the-art of uncertainty analysis approaches.

### 3.1.1 Probability fundamentals

#### 3.1.1.1 Random variables and distribution functions

The probability space $\Omega$ of a random experiment is defined as the set of all possible outcomes of the considered experiment. Any subset $A \subseteq \Omega$ will be called an event, whose the probability is noted $P(A)$.

$$\begin{aligned} \forall A \in \Omega, P(A) &\geq 0 \quad (3.1) \\ P(\Omega) &= 1 \quad (3.2) \end{aligned}$$

For a continuous random variable $X$ defined on $\Omega \subseteq \mathbb{R}$, the probability distribution function (PDF) is defined as:

$$g_X : x \to P[X \leq x] \quad (3.3)$$

The cumulative distribution function (CDF) can be defined in function of $g_X$.

$$G_X : x \to \int_{-\infty}^{x} g_X(t)dt \tag{3.4}$$

#### 3.1.1.2 Characterization of random variables

The expected value of a random variable $X$ given on a probability space $\Omega$ is defined as:

$$E[X] := \int_{\Omega} X(\omega) \cdot dP(\omega) \tag{3.5}$$

Two random variables $X_1$ and $X_2$ are not correlated if for all positive measurable function $f_1$ and $f_2$, we have:

$$E[f_1(X_1)f_2(X_2)] = E(f_1(X_1))E(f_2(X_2)) \tag{3.6}$$

The variance of a random variable $X$ is defined as:

$$Var[X] := E(X - E[X])^2 \tag{3.7}$$

More details about these and other concepts can be found in [88, 89].

### 3.1.2 Uncertainty analysis formalization

Uncertainty analysis methods give information on the statistical distribution of the system response in function of the uncertainty in parameters or inputs. In the literature, the uncertainty analysis problem is formulated as an estimation of the expected value of a system response in function of the uncertainty in parameters or inputs [89, 90]. The common way to model uncertainty is to interpret it as a random variable with a probability density function (PDF) that matches its statistical distribution. Based on the expected value formulation, uncertainty analysis is formalized as an integral estimation problem, stated in equation 3.5.

Because the random variable $X$ and its probability is not known, the integral (Eq. 3.5) is not easy to evaluate. For this reason, the following presents different methods in the literature which deal with this integral estimation problem, so called uncertainty analysis:

- Monte Carlo method

- Quasi Monte Carlo method
- Quadrature method
- Advanced uncertainty analysis methods

These methods can be differentiated in terms of the error associated to the integral estimation, the required form of uncertainty model (continuous or discrete) and their scalability with the number of uncertain parameters $d$.

In the following, we consider

- $X$ a continuous random variable defined on $\Omega \subseteq \mathbb{R}^d$.
- $\omega$ an element of $\Omega$ and which represents the different realizations of $\Omega$.

### 3.1.3 Monte Carlo method

The most widely applied approach is the Monte Carlo (MC) method, firstly introduced by N. Metropolis and S. Ulam [91]. MC methods are characterized by the repetition of a deterministic simulation with random input samples generated from the uncertain parameters. Its principle is based on two major theorems:

1. *The law of large numbers* which justifies the convergence of the method. Average of all the results obtained from a repeated and independent stochastic experiment converges to the theoretical expected value. The MC estimation can be formalized as:

$$E[X] \approx \frac{1}{N} \sum_{i=1}^{N} X(\omega_i) \tag{3.8}$$

2. *The central limit theorem* which gives the rate of convergence. The error of the estimated integral of $X$ with Monte Carlo approach converges to a Gaussian distribution centered in 0 and with a standard deviation equals to $\sigma/\sqrt{N}$, where $\sigma$ is the standard deviation of the $X$ distribution. This means that the error is a random number, independent of the number of uncertain parameters which can take large values even if $N$ is large. Nevertheless, the probability of such event tends to 0 when $N$ tends to infinity.

Because the MC rate convergence is of the order $\sigma/\sqrt{N}$, there are various MC techniques, so-called reduction variance techniques, to reduce the value of $\sigma$ to improve the MC convergence rate.

More details about these theorems and MC methods can be found in [89–91].

### 3.1.4 Quasi Monte Carlo method

Quasi Monte Carlo (QMC) [92–94] method can be formalized like a MC approach (Eq. 3.8) with the difference that the inputs are deterministic instead of random ones. QMC selects a limited number of deterministic samples with low-discrepancy sequences such as the Halton sequence [95] or the Sobol sequence [96]. It estimates the integral with a convergence rate of $O(\frac{log(N)^d}{N})$, depending on the number of uncertain parameter $d$, unlike MC. For this reason, QMC is efficient for a moderate number of uncertain parameters but its convergence rate decreases drastically when this number $d$ becomes large [97].

### 3.1.5 Quadrature method

Quadrature methods estimate the integral according to weighted ($m_i$) function evaluation (Eq. 3.9).

$$E[X] \approx \sum_{i=1}^{N} m_i \cdot X(\omega_i) \tag{3.9}$$

Many quadratures are presented in the literature but the Gaussian quadrature is the most typical [92,94]. Quadrature methods scale badly with an increase of uncertain parameters: its number of evaluation points increases exponentially with the number of uncertain parameters.

### 3.1.6 Other uncertainty analysis methods

More sophisticated methods which imply less samples include Stochastic Collocation and Polynomial Chaos. Both approaches describe the randomness of the considered parameters through an approximate polynomial expansion. The former represents a random parameter with known coefficient (polynomial fitting the uncertainty). While the latter captures the randomness of the considered parameter in an orthogonal expansion with well-known polynomials. Nevertheless, both of them suffer from a curse of dimensionality and require an analytical representation of the uncertain parameters. [98] proposes a combination of both methods, so-called non-intrusive polynomial chaos.

### 3.1.7 Requirements of HEMS assessment approach

HEMS approaches are characterized by discrete time-series inputs and a high complexity, implying a time-consuming evaluation.

For this reason, there is a need for an uncertainty analysis which:

- takes into account discrete time-series as uncertain parameters
- requires a small number of evaluation
- shows a good accuracy

Monte Carlo method is not suitable because of the high number of required runs to achieve an accurate estimation. While the QMC, the quadrature and the advanced methods are not applicable because they require a continuous representation of the uncertainty.

These facts lead to the need for an uncertainty analysis approach which is specifically designed for:

- discrete parameters: typically time-series
- time-consuming process evaluation like optimization approaches

| Method | Error convergence | uncertainty form |
|---|---|---|
| Monte Carlo | $O(\frac{1}{\sqrt{N}})$ | continuous or discrete |
| Quasi Monte Carlo | $O(\frac{log(N)^d}{N})$ | continuous |
| Quadrature methods | Method dependent | continuous |
| Proposed method | Problem dependent | continuous or discrete |

Table 3.1: Comparison of integral estimation for uncertainty analysis with $d$ uncertain parameters

## 3.2 Assessment method for scheduling process with correlated and discrete uncertain parameters

As seen in the previous section, this integration problem can be solved in many different ways: Monte Carlo methods, Quasi Monte Carlo methods or Quadrature methods. Because of the number of required runs and/or the discrete nature of uncertain parameters, the previously presented methods are not applicable.

The presented method is inspired by stochastic optimization theory and is designed for studying the impact of uncertain discrete time-series on a system, in this case a HEMS.

### 3.2.1 Prerequisites

The proposed uncertainty analysis method requires:

- the description of the considered uncertainty $\omega$, which has to be a discrete time-serie derived from historical data or stochastic model. $\omega$ is a time-dependent vector containing the different considered scenarios which can be also correlated.
- a description of the system response $X$, a continuous random variable defined on $\Omega \subseteq \mathbb{R}^d$, where $d$ is the number of uncertain parameters considered.

### 3.2.2 Step 1: Reducing the set of scenarios with an appropriated scenario reduction technique

The proposed uncertainty analysis is inspired by stochastic optimization problems which minimize the expected value of the objective function over a set of uncertain time-series, so-called scenarios. Stochastic optimization faces the same challenge: calculate an integral over a set of uncertain time-series parameters in a limited number of system evaluations.

#### 3.2.2.1 Stochastic optimization fundamentals

Stochastic programming problems are formalized as a minimization or maximization of the expected value of the objective function under uncertainty according to equation 3.10 [51, 89]. Except under special circumstances, this problem cannot be solved analytically, so its solution can only be approximated using a reduced number of uncertain scenarios $\omega_i$.

$$E[X] = \int_{\Omega} X(\omega) \cdot dP(\omega) \approx \sum_{i=1}^{S} X(\omega_i) \cdot P(\omega_i) \tag{3.10}$$

The fundamental idea of optimal scenario reduction consists in determining a probability distribution $X(\omega_i)$ which is the best approximation of $X(\omega)$, with respect to a given probability measures and whose support consists of a subset of $X(\omega)$. The subset $X(\omega_i)$ has to ensure that the solution of Eq. 3.10 does not change much if $X(\omega)$ is replaced by $X(\omega_i)$.

#### 3.2.2.2 Scenario reduction techniques

The following classification is inspired by [99–102]. Scenario reduction techniques are classified into four main categories:

- Important sampling-based techniques
- Moment matching-based techniques
- Clustering techniques
- Optimal scenario reduction based on probability metrics.

In **important sampling-based techniques** [103,104], scenarios are selected from an initial set of scenarios according to a sampling criterion that typically reflects the importance/impact of a scenario on the objective function of the stochastic optimization, e.g expected value of perfect information (EVPI). In its simplest form, i.e. when scenarios are of the same importance, it is equivalent to a Monte Carlo sampling.

With **moment matching-based techniques** [105, 106], scenarios are selected to minimize a distance measure, e.g. a norm between the reduced set and the original set of scenarios. This problem is often non-convex and requires heuristic that does not guarantee convergence, i.e. increasing the number of selected scenarios does not improve solution stability.

With **clustering techniques** [107, 108], scenarios are grouped into a predefined number of clusters, based on an index or a metric that characterizes the scenario impact on the solution of the stochastic problem. This typically results into a NP-hard optimization problem that can be solved using local-search algorithms. The quality of the selected scenarios is highly depending on the chosen metric. A typical clustering approach is the *k-means* methods which seeks to minimize the squared distance in the same cluster [109].

In **optimal scenario reduction techniques (SRT) based on probability metric** [100, 110–113], scenarios are selected according to a specific probability metric such as the Kantorovich distance, which expresses the difference between two distinct scenarios. The solution of this minimization problem is a reduced set of scenarios that minimizes the probabilistic difference with the original set of scenarios. Nevertheless, this problem is a non-differentiable non-convex combinatorial optimization that is often too large in scale to be practical in many applications [100, 102]. For this reason, heuristics have been developed for approximating this problem:

- the forward algorithm: selects the scenario minimizing the probabilistic distance and includes this scenario into the set of representative scenarios. It stops when a given number of scenarios is selected or if a given probabilistic distance is reached
- the backward algorithm: eliminates the scenario maximizing the probabilistic distances from the initial set of considered scenarios.

Note that these heuristic approaches do not guarantee the SRT performance. Nevertheless, empirical results reported in the literature [100, 111–113] indicate that forward algorithms perform well in practice.

More information about scenario reduction techniques can be found in [102, 114].

### 3.2.3 Step 2: Evaluate the scheduling process with the reduced set of scenarios

Considering $\omega_{SRT}$ the reduced set of scenarios from step 1, the optimal solution distribution obtained with the considered scheduling process $X$, can be evaluated. The performance of the proposed uncertainty method can be assessed, by comparing the results with the state-of-the-art uncertainty analysis approach: the Monte Carlo method.

### 3.2.4 Step 3 (optional): Evaluate the assessment methodology performance

In the literature, the accuracy of the stochastic optimization solution obtained with the reduced scenarios is compared to the true solution obtained from the continuous description of the random variable using the stability and bias evaluation criteria. Nevertheless, this is not always possible to obtain it because of the discrete nature of the random variable or the lack of information about the uncertainty input. Therefore, a Monte Carlo method is typically used to approximate the true solution [98, 114].

#### Bias and stability criteria for stochastic optimization problem

According to stochastic optimization theory [99, 114–116], the expected value of the optimal solution obtained with the reduced scenarios should be *unbiased* with respect to the true solution obtained with the continuous description of the stochastic variable or a Monte Carlo approach [98, 99, 114]. This is formalized as:

$$e_F(\omega_{SRT}, \omega) = F(\omega_{SRT}) - F(\omega) \tag{3.11}$$

where $F(\omega)$ and $F(\omega_{SRT})$ are the expected value of the solution distribution obtained with the stochastic optimization respectively with the true distribution of $\omega$ and the reduced set of scenarios $\omega_{SRT}$.

In addition, the solution should exhibit *stability* with the reduced set of scenarios, indicating that additional scenarios does not change the value of the optimal objective function [99]. This criterion is used for comparing the quality of different scenario reduction techniques. [115] argues that stability can be tested by solving the considered problem with several different scenarios, generated by the same method. If the assessment indicator does not change too much, the stability can be claimed.

The stability criterion is formalized as:

$$\forall i, \forall j : |F(\omega_{SRTi}) - F(\omega_{SRTj})| < \epsilon \tag{3.12}$$

where $\omega_{SRTi}$ and $\omega_{SRTj}$ are different reduced scenarios of increasing cardinality, generated with the same deterministic SRT method. And where $\epsilon$ defines the stability threshold.

Given the bias definition (Eq. 3.11), the stability criterion can be also formalized as:

$$\forall i, \forall j : |e_F(\omega_{SRTi}, \omega) - e_F(\omega_{SRTj}, \omega)| < \epsilon \tag{3.13}$$

**Bias and stability criteria for uncertainty analysis**

The bias and stability criteria cannot be used as such for uncertainty analysis because of the different nature of the process outputs:

- with the stochastic optimization, it is a deterministic value: the expected value of the solution distribution, i.e. the objective function.

- with the uncertainty analysis, it is a distribution estimation.

For this reason, we propose to use the energy distance metric to evaluate the bias criteria. It is a statistical metric which measures the "distance" between two distributions and which states how similar they are. The expected value and the variance could be also used but it requires to evaluate them conjointly, which is less convenient than evaluating and analysing one single metric.

The energy distance metric is formalized as [117]:

$$e(F,G) = \int_{-\infty}^{\infty} (F(x) - G(x))^2 dx \tag{3.14}$$

$F$ and $G$ are the cumulative distribution functions of $X$ obtained respectively with the true distribution of scenarios and the reduced set of scenarios. The energy distance has the same unit than the optimality metric $X$. According to [118], this is a suitable metric because it:

- is a proper metric: non-negativity, symmetry, sub-additivity.

- equals zero if and only if the distributions are identical, thus it characterizes equality of distributions and provides a theoretical foundation for statistical inference and analysis.

Finally, the stability criterion is formalized according to Equation 3.15:

$$\forall i, \forall j : |e(F, G_i) - e(F, G_j)| < \epsilon \tag{3.15}$$

where $G_i$ and $G_j$ are the cumulative distribution functions of $X$ obtained with a reduced set of scenarios of increasing cardinality.

## 3.3 Application example

Having introduced the theoretical aspects of uncertainty analysis and the proposed method, this section aims at presenting a practical application with a HEMS assessment approach.

A basic HEMS approach is considered for a house with a battery, a heat pump providing the space heating and an electrical heater providing the DHW (more details in section 4.1.3 and on Figure 4.4). In the frame of the performed assessment approach, the considered uncertain parameters are the domestic electricity and the DHW demand.

In this case, the continuous description of the stochastic variable is not available and a Monte Carlo sampling with 10 000 scenarios is used to assess the results of the proposed method.

### 3.3.1 Step 1: scenario reduction technique selection

Recently, [119] compared four different scenario reduction techniques: 1) an importance sampling technique 2) a clustering method based on *k-means* algorithm 3) the fast forward and 4) backward heuristic based on probability metrics. It concludes that the fast forward scenario approach yields in the most optimal solution and is the most computationally efficient. In addition, these results are confirmed by other empirical results [100, 112] which point out also its robustness. Although importance sampling, moment-matching or clustering techniques have their merits, optimal scenario reduction techniques (SRT) is implemented in this work. Indeed, importance sampling techniques is not supported by theoretical background and its results depend mainly on sampling rule. Moment-matching techniques will not be considered as they do not guarantee convergence towards the stable solution of the stochastic program, by design [115]. Finally, clustering techniques typically require an additional scenario reduction method to select one or multiple scenarios within a cluster.

Optimal SRT is easy to implement and a widely used approach. Furthermore, SRT based on Kantorovich probability distance is supported by the theory of

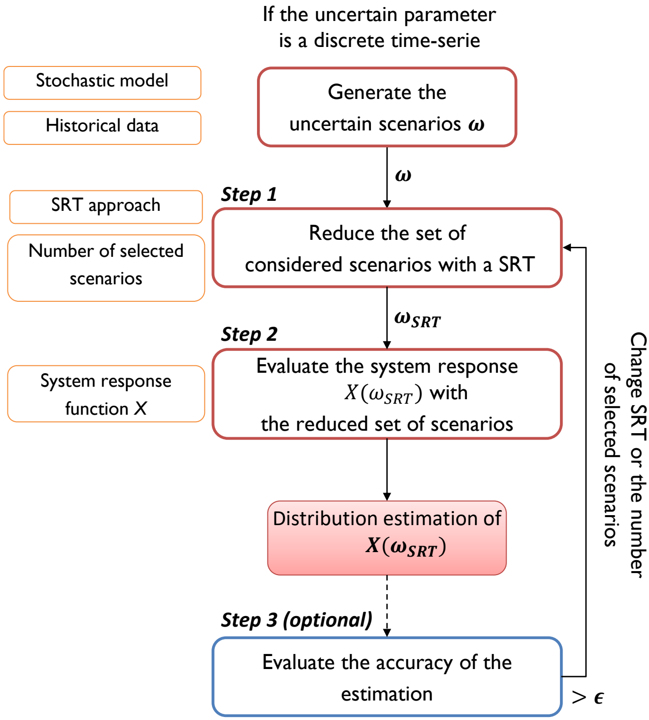


Figure 3.1: Illustration of the assessment method proposed.

stability of stochastic optimization problems with regard to changes in the probability measure. Theory demonstrates that the change in the solution can be approximated using a probabilistic metric, independent on the optimization problem. By minimizing this distance, the stability can be ensured [99–101].

The implemented optimal scenario reduction techniques based on probability metric -forward algorithm- is described in [50].

As mentioned before, the considered scenarios are correlated, e.g. the electrical demand and the DHW demand. For this reason, the scenario reduction of the correlated scenarios has to be achieved together, not to lose their correlated information. To do so, for each normalized correlated scenarios, e.g. electrical and DHW demand, the Kantorovich probability distance is calculated independently. The two distances of each corresponding electrical and DHW scenarios are then summed up and the representative scenarios are selected based on this summed Kantorovich distance. On that way, the scenario reduction select the joint electrical and DHW scenario that is the most representative from the initial set of scenarios point of view.

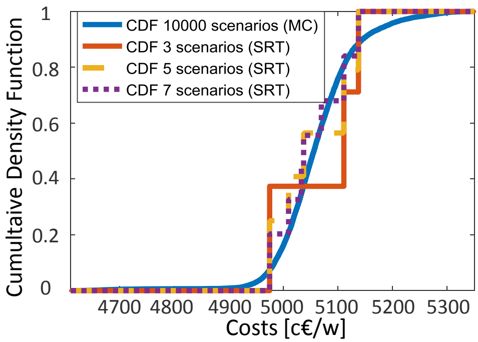


Figure 3.2: Cumulative density function of the HEMS weekly costs compared to Monte Carlo method with 10 000 scenarios and the proposed method with 3, 5 and 7 selected scenarios with the optimal SRT based on Kantorovich distance.

### 3.3.2 Step 2: evaluation of the scheduling process

Based on the reduced set of scenarios, the HEMS approach can be evaluated and compared to the Monte Carlo method. Figure 3.2 presents the cumulative density function of the costs with the Monte Carlo method and the results obtained with the optimal SRT based on the Kantorovich distance for different number of selected scenarios. The proposed method allows reducing by a factor 2000, the number of process evaluation compared to a MC method.

### 3.3.3 Step 3: evaluation of the assessment methodology

As presented in Section 3.2.4, the performance of the SRT has to be studied using the bias and stability criteria.

#### Bias and stability

Figure 3.3 presents the stability and bias analysis with the energy distance metric (Eq. 3.14).

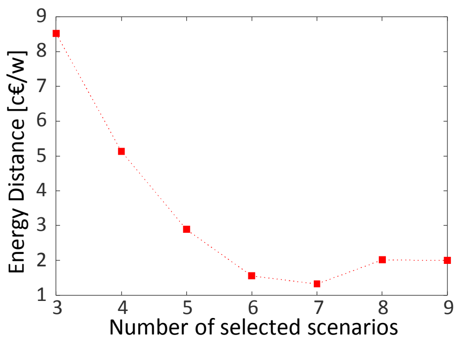


Figure 3.3: Energy distance of the distribution estimation with different scenario reduction cardinality compared to the true distribution evaluated using the Monte Carlo method.

*Bias* (Eq. 3.11): the distribution error decreases with an increasing scenario reduction cardinality until to converge to about 2 c€/w, for more than 5 selected scenarios. This represents an error of only 0.05% of the true expected value.

*Stability* (Eq. 3.15): the stability can be claimed if the stability threshold $\epsilon$ is above 3 c€/w. Beyond this, the energy distance seems to converge with an increasing number of selected scenarios.

So based on these, it can be concluded that the optimal scenario reduction based on Kantorovich distance seems to be stable (Equation 3.12) and slightly biased.

### Expected value bias

Figure 3.4 presents the expected value bias of the proposed method compared to the true expected value, estimated with the Monte Carlo approach and 10 000 samples. The maximum expected value error is 21 c€/kWh which represents only 0.4% of the true expected value. Based on these results, it seems that the proposed method with a SRT based on Kantorovich distance is accurate.

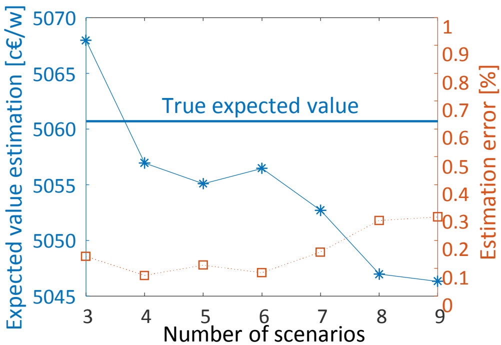


Figure 3.4: Estimated expected value and its error for different number of selected scenarios based on Kantorovich distance compared to the true expected value.

### Number of required simulation runs

The main objective of the presented methodology is to reduce the number of simulation runs, while keeping a good accuracy of the expected value estimation. Given that the domestic electricity and the DHW demand are correlated, the number of considered uncertainty $d$ is equal to 1. The presented methodology leads to $c^d$ simulation runs. Where $c$ is the number of selected scenarios with the SRT. With $c = 5$, this reduces by a factor 2000, the number of simulation runs, given that Monte Carlo uncertainty analysis requires 10 000 simulation runs to achieve an expected value estimation error under 0.1%.

## 3.4 Range of applicability

To apply the proposed method, some considerations need to be made about its advantages and disadvantages. The advantages are all attributed to usability aspects, while disadvantages need special attention since they are associated with the applicability of the method.

### 3.4.1 Advantages

#### Number of simulation runs

The main advantage of the proposed method compared to a MC method is the small number of required simulations, for a system with few uncertain parameters.

#### Independent input scenarios

A benefit shared with MC method is the fact that the process evaluation can be parallelised, since the input scenarios are independent of each other. This can be an important advantage for complex process simulations.

#### Type of uncertainty

This method can be used to analyse systems with uncertain parameters characterized by discrete time-series, unlike Quasi Monte Carlo or quadrature methods. Continuous time-series models can be also studied if they are first discretized with a sufficient number of samples.

### 3.4.2 Disadvantages

#### Curse of dimensionality

The number of required simulation runs grows exponentially with the number of considered uncertain time-series. Therefore, there is a necessity to consider a tradeoff between the accuracy of the distribution estimation and the number of simulation $s$ compared to a MC method.

$$s = c^d \tag{3.16}$$

where $c$ is the number of selected scenarios with the SRT and $d$ is the number of uncertain parameters considered. This implies that it pays off to apply this method while the simulation runs $s$ is smaller than the number of desired MC simulations.

### Method accuracy

The proposed method is implemented with the optimal SRT based on Kantorovich distance solved using a heuristic approach. The heuristic approaches do not guarantee the SRT performance. Nevertheless, empirical results reported in the literature [100, 111–113] indicate that forward algorithms perform well in practice. So the optimality of the selected scenarios is not proved formally. For this reason, the accuracy of the proposed method cannot formally bounded and has to be investigated for each studied case, unlike MC method. The accuracy investigation is time-consuming for complex process. To reduce this, the accuracy boundaries can be determined with an identical but less complex process, e.g. identical optimization problem with relaxed constraints or continuous variables rather than integers.

## 3.5 Discussion and summary

This chapter presented an assessment methodology, which allows comparing different HEMS approaches in spite of their various forms and on the basis of their objective function distribution. The main source of uncertainties considered in the frame of this work are the discrete time-series parameters, e.g. scenarios and their associated forecast, typically required in the HEMS evaluation process (Chapter 4).

Uncertainty analysis based on Monte Carlo approach requires a large number of evaluation of the studied process. While the Quasi Monte Carlo and quadrature methods require a continuous representation of the uncertain parameters, which is not the case in this case, with the discrete scenarios.

These facts lead to the need for an uncertainty analysis approach which is specifically designed for

- **discrete parameters**: typically time-series
- **time consuming process evaluation** like HEMS optimization approaches.

For this reason, the proposed uncertainty analysis is inspired by stochastic optimization theory which faces the same challenge. The proposed method is based on an optimal scenario reduction based on probabilistic metric. This scenario reduction technique is supported by theory, widely used and shows the best results in practice.

The proposed assessment methodology can be summarized as:

1. select the uncertain time-series parameters considered in the assessment approach/uncertainty analysis

2. generate representative discrete distribution of these uncertain time-series $\omega$ e.g. electrical and domestic hot water demand

3. suppose $X(\omega)$ a continuous random variable representing the metric under consideration in function of the considered uncertain time-series, e.g. the HEMS costs

4. Step 1: reduce the set of scenarios to $\omega_{SRT}$ with an appropriated scenario reduction techniques, e.g. optimal SRT based on the Kantorovich distance

5. Step 2: evaluate the metric under consideration $X$ with the reduced set of scenarios and obtain an estimated distribution $X(\omega_{SRT})$

6. Step 3 (optional): evaluate the accuracy of the estimated distribution by comparing it with the true distribution or with the Monte Carlo method using the energy distance metric.

Finally, the presented method is applied to a HEMS approach with an uncertain electrical and DHW demand input. The proposed method allows reducing by a factor 2000, the number of process evaluation compared to a Monte Carlo method while the results show a small bias (excpected value error under 0.5% of the true expected costs) and a good stability for 5 or more selected scenarios.

The main advantage of this approach compared to a MC method is the small number of simulation runs with few uncertain parameters. While its main drawbacks is that its associated error cannot be bounded in a formal way and has to be investigated for each case.

In the next chapter, the presented assessment approach is used to compare the different HEMS approaches under different DR tariffs and forecast errors.

# Chapter 4

# Results analysis

This chapter applies the assessment method proposed in Chapter 3 to the different HEMS approaches: optimization-based, market-based and conventional control (Chapter 2). In accordance with the assessment method, the considered uncertainties are discrete time-series:

- the scenarios: uncontrollable electrical demand, irradiation, temperature and domestic hot water (DHW) demand

- their associated forecasts with errors

It considers a specific house, selected according to German statistics and under two different DR pricing schemes, feed-in and time of use tariffs.

This chapter is organized as the following:

- Section 4.1: presentation of the assessment conditions: scenarios and forecasts generation, considered house configuration, assessment metric presentation and considered DR pricing;

- Section 4.2: illustration of the control with the different approaches under the same conditions for one specific week.

- Section 4.3: analysis and comparison of the different HEMS performance according to their total costs, the specific savings associated to each considered flexibilities and their sensitivity to forecast errors;

## 4.1 Assessment conditions

The assessment follows the proposed assessment method presented in Chapter 3. This section presents the considered assessment conditions: scenarios and their forecasts, the comparison metric and the DR pricings.

### 4.1.1 Uncertain parameters: scenarios and associated forecasts

In the literature, most authors [3,15,19,56,120] consider perfect forecasts and specific evaluation scenarios over a short-time period, neglecting the dependency on seasonal and user behaviours.

The uncertain parameters considered in the frame of this study are time-series:

- scenarios: uncontrollable electrical demand, irradiation, temperature and domestic hot water demand

- their associated forecasts with errors

As stated in section 3.3, the considered uncertain scenarios have to be firstly generated according to historical data or a stochastic model.

#### 4.1.1.1 Scenarios generation

In this work, the electrical and DHW demand is based on a stochastic model using the user occupancy and stochastic behaviour models. In that way, a dependent electrical demand [121] and DHW profiles [122] are generated, based on an identical occupancy profiles. In the frame of this work, 10 000 different weekly profiles of electrical and DHW demand are generated with a granularity of 1 minute. Finally, each scenario is rescaled according to the average consumption in Germany [73]. While the temperature and irradiation are based on 5 years of historical data from the German National Meteorological Service (Deutscher Wetterdienst) [123].

The assessment method takes into account all these scenarios as an uncertain parameters. A forecast error associated to each scenario is generated according to the state-of-the-art forecasting method Auto Regressive Moving Average (ARMA).

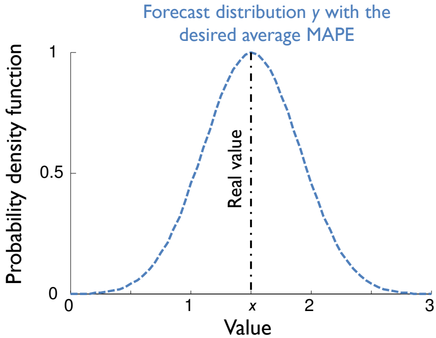


Figure 4.1: Forecast generation process based on the ARMA forecasting method and the average MAPE forecast error.

#### 4.1.1.2 Forecast generation

The Autoregressive Moving-Average (ARMA) method was introduced by Box and Jenkins in 1970 and has become a very popular approach for short-term forecasting [124] in many different fields such as economics or scheduling problems. ARMA models represents random variable as a linear function of its past values. ARMA can be classified as a special type of linear regression for time series data. A comprehensive discussion of general linear regression can be found in [125].

ARMA models are characterized by a Gaussian distribution of error and a linear dependence to previous real value [124]. The forecast distribution, a Gaussian $f()$ defined by the real value $x$ and the standard deviation $\sigma$, is derived from the equation 4.1. In accordance with literature (Section 1.5.2), this work considers the Mean Average Percentage Error (MAPE) as forecast error metric. For each bins of the forecast, the MAPE is calculated and weighted accordingly to its probability as defined by:

$$\widehat{MAPE}(x,\sigma) = \int_{-\infty}^{\infty} \overbrace{f(y|\mu = x,\sigma^2)}^{\text{probability of forecast y}} \quad \overbrace{\frac{|y-x|}{x}}^{\text{MAPE of forecast y}} \, dy \tag{4.1}$$

In that way, the considered generic forecast:

- corresponds to the ARMA forecasts error distribution: Gaussian
- captures the dependence with previous value because forecasted values are based on the real value, embedding implicitly this dependence
- unbiased: the expected value of the generated forecast corresponds to the real value
- compatible with methods requiring probabilistic forecasts

In the following, different forecast errors are considered in the optimization approach. The reference forecast error is based on the state-of-the-art forecat error (SOTAFE) according to literature[(i)], Section 1.5.2. For example, the case with a SOTAFE-50% corresponds to a case where the forecast error is improved by 50% for all the considered forecasts.

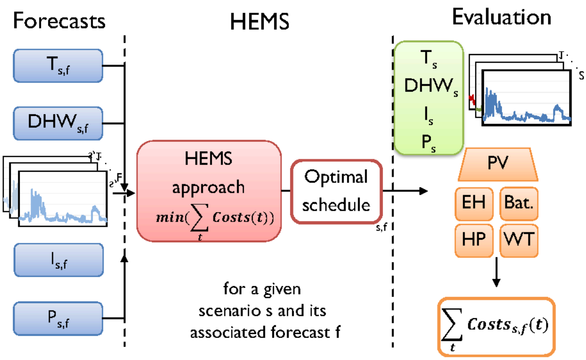


Figure 4.2: HEMS cost evaluation for a given scenario $s$ and its associated forecast $f$ with a given forecast error.

### 4.1.2 Assessment metric

The optimization approach considers these generated forecasts with a given error associated to the temperature ($T_{s,f}$), DHW ($DHW_{s,f}$), irradiation ($I_{s,f}$) and electrical demand ($P_{s,f}$). Based on these, the considered HEMS approach

(i) Electrical and DHW demand: 60% MAPE and irradiation: 30% MAPE [65].

calculates an optimal schedule. The produced schedule is then evaluated with the real profiles with a time discretization of 1 minute (green in Fig. 4.2) such as to highlight the impact of decision time interval (typically, 15 minutes for optimization) and the forecasting errors. To each considered scenario is associated 1000 forecasts generated according to the Gaussian distribution defined in Eq. 4.1. In this way, the uncertainty associated to the forecast model is embedded in the uncertainty analysis.

#### 4.1.2.1 Average total costs

For a given HEMS approach, the weekly average total costs $\widehat{C}_{HEMS}$ are derived for given evaluation scenarios $s$ and its associated forecasts $f$. $S$ and $F$ are respectively the number of considered evaluation scenarios and their associated forecasts. $p_s$ and $p_f$ are respectively the probability associated to the scenario and the considered forecast and are equal to $\frac{1}{S}$ and $\frac{1}{P}$ with a MC method. $Cost_{s,f}$ is the derived costs for one specific evaluation scenario (Fig. 4.2).

$$\widehat{C}_{HEMS} = p_s \sum_{s=1}^{S} \left( p_f \sum_{f=1}^{F} Cost_{s,f} \right) \tag{4.2}$$

The weekly average cost [c€/w] allows an easy performance comparison between different HEMS approaches.

#### 4.1.2.2 Specific device cost

Nevertheless, the weekly average total cost metric is sensitive to the final states of the storing elements which can differ from simulation to simulation and lead to wrong conclusion. A different final state increases or decreases the total energy consumption, e.g. final battery SOC or temperature of the house or water tank.

Therefore, this work introduces an additional comparison metric: the specific average cost associated to each considered flexible devices in c€/kWh.

First, a cost associated to the device consumption is calculated at each time step in function of the electricity price and the proportion of PV consumed. The sum of all the device costs is equal to the weekly total average costs, introduced in the previous section.

Second, this cost is normalized by its associated energy consumption.

Thanks to the energy normalization, these costs are no more directly depending on the final states of the storing elements. It allows a better comparison of the the saving potential from specific devices.

The specific average cost is

- close to the minimum electricity price if it consumes electricity when price is cheap, i.e. the device is flexible and its consumption can be shifted.

- close to the maximum electricity price if it consumes regardless of the electricity price, i.e. the device has a small flexibility and its consumption cannot be shifted.

Based on this cost, the saving potential of different devices can be investigated. And the optimality of the different control approaches can be fairly compared as well.

For the *electrical storage device* such as domestic battery, the specific battery gain is used as a metric and is defined as

$$\frac{C_{batt,discharge} - C_{batt,charge}}{E_{batt,disch}} \tag{4.3}$$

In contrast with the specific average cost of a consuming device, larger is the specific battery gain value, better is the control.

### 4.1.3 House set up

This study considers the most representative house in Germany according to the German statistical data. According to [128], the most typical German family houses are occupied by an average number of 3.57 persons, rounded to 4. The thermal model of the considered household (Table 4.1) is based on average value according to an European study about the building stock in Germany [73]:

- House type: Single Family House -SFH- (57% of building stocks) with 2 floors (56% of the SFH) and a tilted roof (91.3%).

- Construction period: 1958-1968 with usual refurbishment (15.31% of SFH were built during this period)

Table 4.1: parameters used in the simulation

| | |
|---|---|
| Number of inhabitants | 4 persons |
| Location | North Germany |
| Grid electricity price | 30 c€/kWh |
| Feed-in tariff | 12 c€/kWh |
| Yearly uncontrollable electrical demand [126] | 4200 $kWh_e/y$ |
| Yearly space heating demand (norm VDI4656) [73] | 16120 $kWh_{th}/y$ |
| Yearly DHW demand [126] | 1815 $kWh_{th}/y$ |
| Heat power production of EH | 5 kW |
| EH efficiency | 0.98 |
| Water tank for DHW | 200 l |
| Heat power production of HP | {0, 7.5, 15} kW |
| HP Coefficient of Performance | 3 |
| House temperature constraints | [17.5, 19.5] °C |
| Photovoltaic installation [127] | 6.2 kWp |
| BESS installed [127] | 4 kWh |
| Maximum forecast error for electrical demand [61, 65] | MAPE 60 % |
| Maximum forecast error for DHW demand [65] | MAPE 60 % |
| Maximum forecast error for irradiation [65] | MAPE 30 % |
| MILP time interval & scheduling horizon | 15 min over 24h |
| MILP rescheduling time | 12h |
| Conventional control frequency | 15 min |
| Market-based control frequency | 1 min |

The typical house-type identified in [73] is assumed refurbished with a standard refurbishment according to German statistics. The house geometry and its insulation characteristic have been based on this study as well.

The first order house model and the house parameters are derived from seasonal average value based on [73] and according to the EN ISO 13790 standard [129].

The considered heating units in the house (Fig. 4.4) are based on the most typical installation in Germany [73] which provides electrical flexibility, i.e. gas or oil based units are not considered as a possible configuration. Based on this, the space heating demand is provided by a heat pump with 2 levels of output power to fulfil the peak demand. Whereas the DHW is produced by an electrical

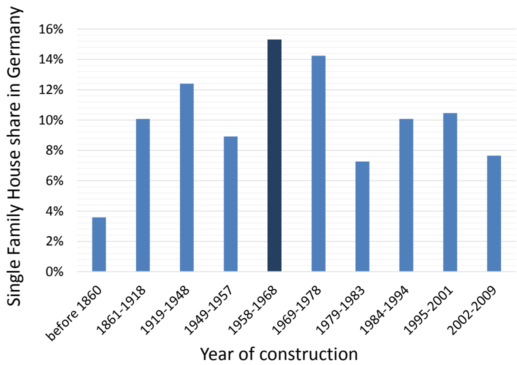


Figure 4.3: Yearly share of single family house built in Germany.

boiler supplying a water tank [73]. The storage capacity of the water tank is dimensioned according to the number of inhabitants and follows typically a rule of thumb: 40-50 l/pers. Based on an economical study, the photovoltaic system and the domestic battery are dimensioned according to the yearly electrical consumption. The most typical PV installation in Germany is considered: 6.2 kWp [73]. Based on this PV installation and the domestic yearly consumption, the most cost-efficient solution according to [127] was derived: 4kWh.

### 4.1.4 Demand response tariffs considered

**Feed-in tariff (FiT)** is based on the current tariff in Germany in 2017: the importing electricity costs is 30 c€/kWh and exporting price is 12 c€/kWh. As presented in Chapter 1, this FiT should continue to decrease in the future to incentivize the reduction of the technology cost.

**Time of use (TOU)** is divided into different unit prices for usage during different blocks of time in order to encourage customers to shift consumption when demand is low. The multiple TOU tariffs in the literature (Section 1.2.2) does not enable to extract a typical TOU. Therefore, the considered TOU tariff in this work (Table 4.2) is based on actual TOU tariffs which implement a three period tariff [34]. Based on the price ratio in the literature [31–34], the peak demand and the off peak prices are adapted according to the current tariff in

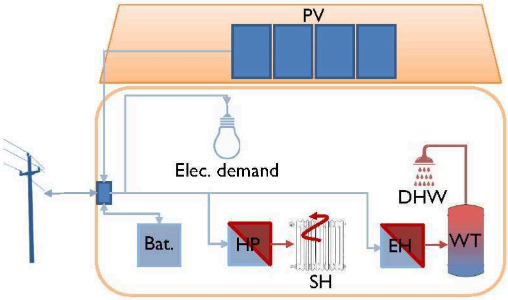


Figure 4.4: Thermal (red) and electrical (blue) representation of the considered house set up with a heat pump (HP) supplying the space heating (SH), an electrical heater (EH) supplying a water tank (WT) for domestic hot water demand (DHW), photovoltaic panels (PV) and domestic battery.

Germany (30 c€/kWh), whereas feed-in tariff is still considered.

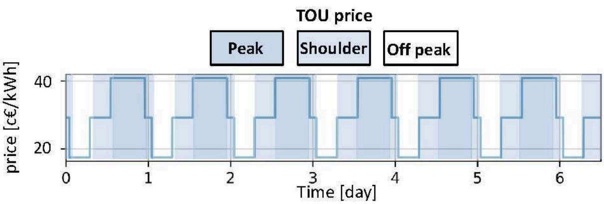


Figure 4.5: Illustration of the considered TOU pricing in simulation.

| Period | Time | Ratio | Cost [c€/kWh] |
|---|---|---|---|
| Off peak | 01:00-07:00 | 0.6 | 18 |
| Shoulder | 07:00-13:00 & 23:00-01:00 | 1.0 | 30 |
| Peak | 13:00-23:00 | 1.4 | 42 |

Table 4.2: TOU tariff according to the literature.

## 4.2 Illustrative control

This section illustrates the different control achieved with the different HEMS approaches.

### 4.2.1 Optimization-based

Figure 4.6 presents the results of the MILP control with perfect forecasts. This figure highlights that

- EH and HP never consume in peak price period and concentrate their consumption in off-peak price period.
- when EH and HP consume in shoulder price period, it is because of the PV production or because of the constrains, e.g. the WT state of charge is too low or the house temperature reaches the temperature limit.
- the battery maximizes first the self-consumption given that the feed-in tariff (12c€/kWh) is cheaper than the off-peak price (17c€/kWh). When there is PV production (day 0 to day 5), the battery is only charged by the PV production in spite of the shoulder price period. When there is no PV production, it charges in period of off-peak price while it discharges only in period of peak price period.

MILP with perfect forecasts anticipates perfectly the PV production, the electrical and DHW demand. For this reason, the MILP can perfectly adapt its control in function of the conditions. With forecast error, the control is based on wrong information. It will capture then less PV production or will be forced to turn on the EH or the HP during the peak price period because of constraints violation, leading to higher total costs.

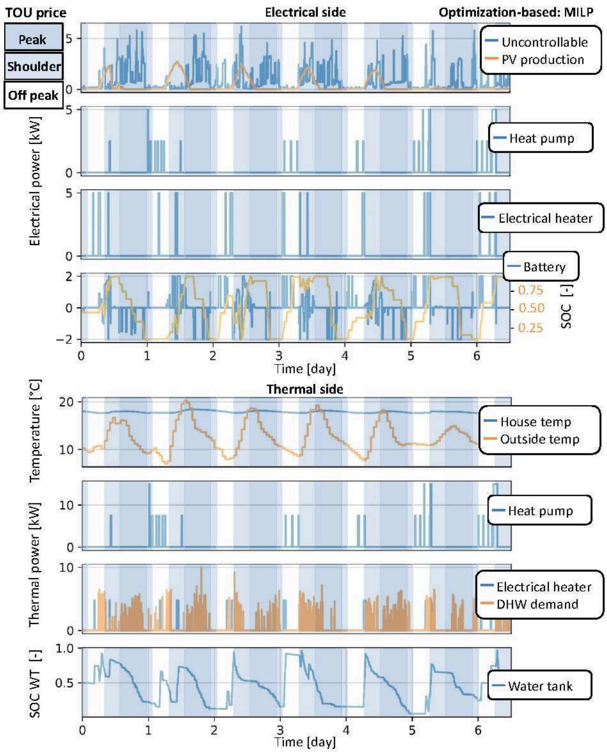


Figure 4.6: Illustration of MILP control with TOU tariff and perfect forecasts.

### 4.2.2 Market-based

Figure 4.7 presents the results of the market-based control. The market-based control is based on the current system states and naive forecasts. It highlights that

- as with the MILP, EH and HP consume mainly during off peak price period and consume in shoulder price period only if the constraints are violated.

- The battery charges only during off peak price period and discharges during the peak price. In contrast with FiT, the battery under TOU tariff

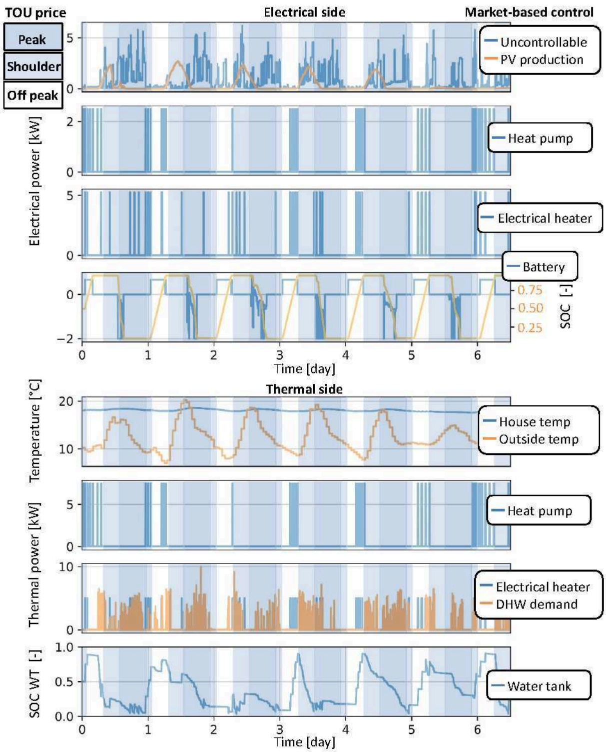


Figure 4.7: Illustration of market-based control with TOU tariff.

stores a very small amount of PV production.

The market-based control occurs every minute and allows well capturing fast PV variation. On the other hand, it leads to a more dynamic control leading to more switch on/switch off of the HP or the EH. It anticipates less the future than the optimization-based control but is able to react very fast to a unexpected event, in contrast with the optimization. All in all, the market-based control outperforms the conventional control and is outperformed by optimization-based approaches with or without forecast errors (Fig. 4.9).

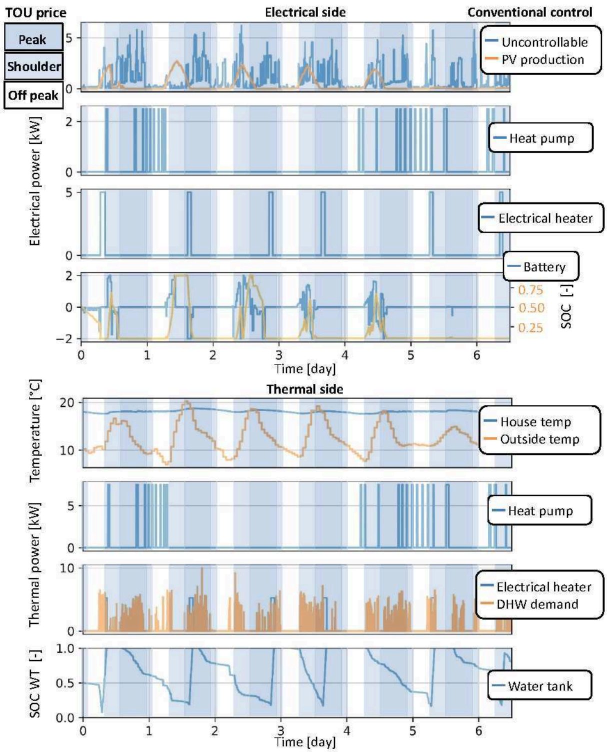


Figure 4.8: Illustration of conventional control with TOU tariff.

### 4.2.3 Conventional control

Figure 4.8 presents the results of the conventional control that is based on the local information and the current system states. The conventional control is the common control implemented in house given that there is no need of communication and that it optimizes locally the user comfort. Control graphs highlight that

- EH and HP consume regardless of the electricity price or the PV production. Nevertheless, one can observe that the HP is mainly switched on in off-peak price period which occurs during the night and corresponds, by chance, to the high heat demand.

- the battery is controlled to maximize the self-consumption. It is discharged during the consumption period which follows the PV production and corresponds to peak price period.

Despite that the conventional control follows a local objective, one can observe that it seems to lead to a kind of meaningful control with TOU. The battery charges during off peak price or PV production period and discharge during the peak period. Nevertheless, this is not sufficient to outperform the two others presented HEMS approaches.

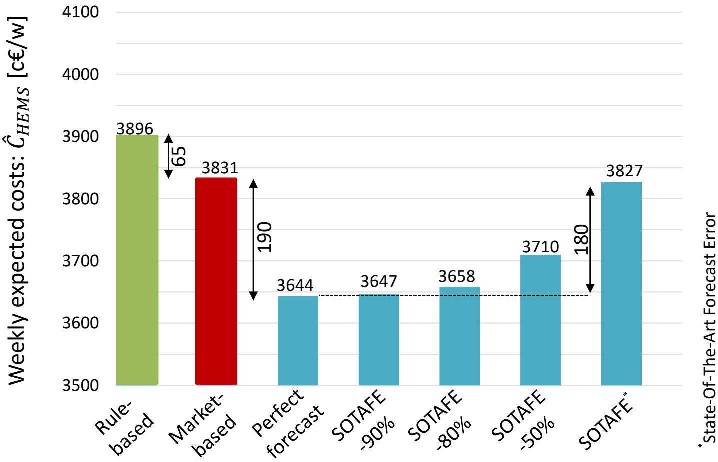


Figure 4.9: FiT tariff: weekly average costs for the different approaches with different forecast errors.

## 4.3 Results analysis

In this section, the different HEMS approach are compared according to their average cost results under two different tariffs:

- **Feed-in tariff**: the HEMS saving potential is mainly driven by the PV production and the ability of the HEMS control to shift the consumption during PV production period. The results highlight a saving potential of

255c€/w and 65c€/w respectively with the perfect optimization approach and with the market-based control compared to the conventional control (Fig. 4.9).

- **Time of Use tariff**: the HEMS saving potential is mainly driven by the electricity pricing, the PV production and the ability of the HEMS control to shift the consumption during the off peak price period or PV production period. The results highlight a much larger saving potential of 1000 and 430 c€/w respectively with the perfect optimization approach and with the market-based control compared to the conventional control (Fig. 4.10).

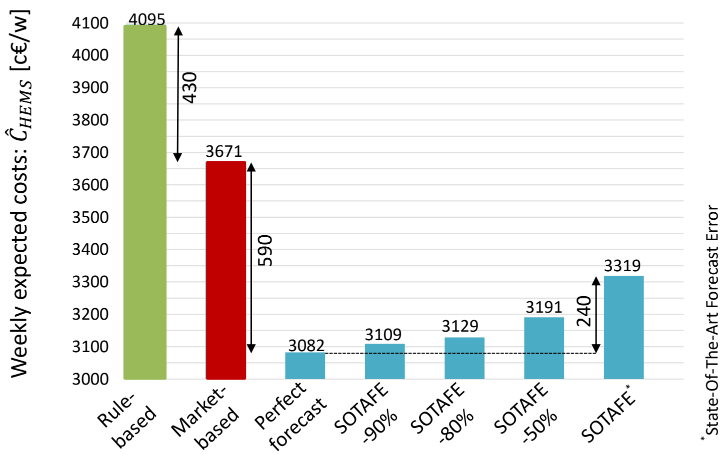


Figure 4.10: TOU tariff: weekly average costs for the different approaches with different forecast errors.

In both cases, the additional savings with the optimization-based control can be mainly explained by the **optimal consumption shift** due to the better anticipation of the PV production/electricity pricing and a better coordination of the thermal production with its consumption, **decreasing the total energy consumption** because of the reduced energy losses.

Note that the market-based and the conventionnal control approaches do not consider implicitly forecasts. The market-based approach considers implicitly naive forecasts [3, 5, 67] whereas rule-based does not base its decision on forecasted value.

All the results comparison is based on the assessment methodology presented in Chapter 3. For this reason, the presented cost or energy results are averaged value, defined in section 4.1.2. For the two considered tariffs, the following sections

- compare the optimality of the three considered approaches with errors and perfect forecasts.
- quantify the specific saving potential from the different devices and their sensitivity to forecast errors.

## 4.3.1 Performance comparison of HEMS approaches

This section presents a comparison of optimality performance between the three different HEMS approaches based on their weekly average total costs.

### 4.3.1.1 Feed-in tariff

Based on the Figure 4.9, the optimization-based with perfect forecasts saves about 255c€/w compared to the reference case for the considered house with FiT. In addition, the same optimization-based control with the state-of-the-art forecast (SOTAFE) still saves 75c€/w, compared to the conventional control case. Whereas the market-based control saves 65 c€/w.

Based on these results, the optimization-based control is competitive regardless of the forecast error, compared to the conventional or the market-based control.

### 4.3.1.2 Time of Use tariff

The presented TOU results are derived with the same assessment conditions than the previous results with FiT. Only the electricity pricing policy is different. In addition, according to literature (Section 1.2.2), the TOU tariff is perfectly known in advance and does not suffer from forecast error.

The results on Figure 4.10 highlight a saving potential of 1000c€/w with an optimal HEMS. This is about 4 times the saving potential achieved with an optimization-based approach under FiT. This can be explained by the presence of period of time with very cheap electricity price (off peak), offering more potential to shift the consumption. In spite of forecast error (SOTAFE), the optimization-based approach still outperforms largely the conventional control. Nevertheless, the forecast error increases the costs by 240c€/w compared to the perfect forecast case. The market-based control performs well and leads to costs savings of 430c€/w compared to the conventional control.

The two studied cases, respectively FiT and TOU, highlight the saving potential brought by the optimization-based control regardless of the forecast error and the good performance of the market-based approach. The TOU allows larger savings because of the presence of well-known period of time with very cheap electricity price. Finally, this study highlights also the impact of the tariff on a 4 persons house without advanced HEMS, i.e. with a conventional control, they will pay weekly 300c€more with the TOU tariff than with the FiT.

The following section gives insights about the presented results. Specifically, it investigates the specific saving potential of the considered flexible devices and their sensitivity to the forecast errors. For doing so, this work compares the specific average costs of each devices, as explained in Section 4.1.2.

### 4.3.2 Saving potential of flexible devices

This section studies the saving potential of each specific device, defined in Section 4.1.2, on the basis of a specific cost comparison with the optimal HEMS approach. Note that the considered reference for the percent calculation is the optimization-based approach with perfect forecasts.

This study is based on the FiT and TOU tariffs results presented before.

The specific average costs allows identifying i) the contribution of each device to the total cost savings ii) the impact of a control approach on the device saving potential.

Based on the specific average costs comparison on Table 4.3, the device with the largest saving potential is not surprisingly the battery, given that it earns about 8c€per kWh stored. The device with the the second largest saving potential is the electrical heater: each consumed kWh costs 26 (FiT) or 18 (TOU) c€. Finally, each kWh consumed by the heat pump costs around 29 (FiT) or 20 (TOU) c€.

| Feed-in tariff | Optimization | | Conv. control | |
|---|---|---|---|---|
| | [c€/kWh] | [kWh/w] | [c€/kWh] | [kWh/w] |
| Heat pump | 29.63 | 71.56 | 29.8 (+0.5%) | 75.5 |
| Electrical heater | 26.2 | 22.7 | 29 (+10%) | 24.2 |
| Battery gain | 8.1 | 15.2 | 5.20 (-35%) | 13.5 |
| **TOU tariff** | | | | |
| Heat pump | 19.8 | 80.2 | 30.0 (+51%) | 75.5 |
| Electrical heater | 17.8 | 23.3 | 24.9 (+40%) | 24.2 |
| Battery gain | 7.8 | 22.8 | 7.3 (-7%) | 13.5 |

Table 4.3: Specific device costs [c€/kWh] and weekly consumed energy [kWh/w] associated to the conventional control and the optimization approach with feed-in and TOU tariffs.

This cost comparison highlights the average saving potential of each device in an optimal case with perfect forecasts. Note that the presence of a device in the house impacts the costs of the others. For example, the presence of the battery makes that the electrical heater can be switched on when the battery is discharged, decreasing in that way, the specific cost of the electrical heater.

Based on Table 4.3, the effective saving potential of each device can be highlighted:

- **Heat pump control** with the optimization brings from 1% (FiT) to 50% (TOU) of average cost reduction compared to the conventional control. As a reminder, the heat pump provides the space heating demand and is constrained by the user comfort, i.e. indoor temperature. Under FiT, the saving potential is mainly driven by the consumption shift during PV production. Based on this, the smaller saving potential of the heat pump with FiT can be explained by the small space heating demand during PV production due to the solar gains.

- **Electrical heater (EH) control** with the optimization reduces by 10% (FiT) to 40% (TOU) its average costs compared to the conventional control. As a reminder, the electrical heater heats up the water used for domestic hot water needs. The effective flexibility of EH and the WT is larger than the heat pump. As explained in Section 4.3.5, this is due to the constant hot water demand, its large operating temperature range and paradoxically its bad efficiency.

- **Battery control** with the optimization brings 7 to 35% of additional gains. This can be explained by the better anticipation of the PV production or the electricity price with the optimization approach. In addition, the optimal control stores 10 to 40% more energy in the battery than the conventional control.

### 4.3.3 Sensitivity to forecast error

| **Feed-in tariff** | Optimization | | Optimization with SOTAFE | |
|---|---|---|---|---|
| | [c€/kWh] | [kWh/w] | [c€/kWh] | [kWh/w] |
| Heat pump | 29.63 | 71.5 | 29.7 (+0.5%) | 71.6 |
| Electrical heater | 26.2 | 22.7 | 27.3 (+4%) | 25.7 |
| Battery gain | 8.1 | 15.2 | 2 (-75%) | 15.6 |
| **TOU tariff** | | | | |
| Heat pump | 19.8 | 80.2 | 19.8 (+0%) | 80.4 |
| Electrical heater | 17.8 | 23.3 | 19.7 (+11%) | 26.0 |
| Battery gain | 7.8 | 22.8 | 0.6(-92%) | 24.42 |

Table 4.4: Specific device costs [c€/kWh] and weekly consumed energy [kWh/w] associated to the optimization approach with and without forecast errors.

Based on Table 4.4, it can be seen that larger is the saving potential of the device, more sensitive it is to forecast errors. This is logical given that the saving potential of a device is coming from its ability to shift its consumption when the electricity price is the cheapest. The devices with more flexibility shift their consumption in function of the electricity price and are much more affected by a forecast error, given that they will consume at a wrong period of time than devices consuming electricity regardless of the electricity price, i.e. without consumption flexibility.

So based on the conclusion from the previous section, the battery is logically the most affected by the forecast error: decrease of 75 to 90% of gains. Then the electrical heater is affected by a cost increase of 5 to 10% and the heat pump by a cost increase under 1% (Table 4.4). In addition, the forecast error leads to a slight increase of the energy consumed by each device, due to the wrong anticipation of the thermal or electrical consumption.

As a reminder, forecast errors are considered in the irradiation, the electrical and DHW demand.

### 4.3.4 Market-based control analysis

Based on Figures 4.9 and 4.10, the market-based control beats the conventional control with FiT: costs decrease by 65c€/w or TOU: costs decrease by 430c€/w. While it is outperformed by the optimization-based with FiT: 190c€/w of additional costs or TOU: 590c€/w of additional costs.

| **Feed-in tariff** | Optimization [c€/kWh] | Conv. Control [c€/kWh] | Market-based [c€/kWh] |
|---|---|---|---|
| Heat pump | 29.63 | 29.8 (+0.5%) | 29.65 (+0.1%) |
| Electrical heater | 26.2 | 29 (+10%) | 26.5 (+1%) |
| Battery gain | 8.1 | 5.20 (-35%) | 10.9 (+35%) |
| **TOU tariff** | | | |
| Heat pump | 19.8 | 30.0 (+51%) | 27.7 (+40%) |
| Electrical heater | 17.7 | 24.9 (+40%) | 20.0 (+12%) |
| Battery gain | 7.8 | 7.3 (-7%) | 12.7 (+60%) |

Table 4.5: Specific device costs [c€/kWh] associated to the optimization approach, the conventional control and the market-based.

Table 4.5 gives insights about the performance of the market-based control:

- **Heat pump control** with market-based control and under TOU, reduces by 10% its average specific costs compared to the conventional control.(Section 4.3.2). Without surprise the market-based under FiT does not bring additional saving potential compared to the conventional or the optimization-based control (See Section 4.3.2).

- **Electrical heater (EH) control** with the market-based reduces by 10 to 25% its average specific costs compared to the conventional control.

- **Battery control** with the market-based brings 35 to 60% of additional gains compared to the optimization-based control. This can be explained by the frequency control. Optimization-based control takes a control decision every 15 minutes and does not change it during this time interval. While the market-based control takes a decision every minute and can better capture the feed-in or the consumption of the house by discharging or charging with a good accuracy.

The market-based control seems to perform well because of its smaller time interval between its control. The reduction of the time interval of the optimization-based control could be an option but it will lead to a more complex problem because of the increase of the number of decision variables. In the literature, the typical control interval for a scheduling problem is about 15 to 60 minutes (Section 1.4).

### 4.3.5 Factors influencing the saving potential of thermo-electrical devices

This section presents the main factors influencing the effective saving potential of the thermo-electrical devices and their associated storages i.e. electrical heater and its water tank and the heat pump and the thermal wall mass of the house. It gives insights to better understand the results from previous section which highlight a larger saving potential with an electrical heater compared to a heat pump, while the battery outperforms them.

Intuitively, the saving potential of thermo-electrical devices is mainly associated to the thermal storage capacity but this not completely true because there are other impacting factors:

- *The associated thermal demand*: the DHW demand is quite constant all over the year while the space heating demand is only required one third of the year because of the temperature seasonality. In addition, there is typically no thermal demand when the sun is shinning (Fig. 4.6) because of the solar gain. If there is no thermal demand, there is logically no potential for savings at that time.

- *The efficiency of the thermo-electrical device*: the thermo-electrical devices allow using the thermal storage as an electrical flexibility. But paradoxically, an efficient device leads to a smaller electrical consumption, and thus less consumption flexibility. For example, the heat pump uses in average one $kW_e$ to produce three $kW_h$, therefore the capacity of the house equipped with a HP is three times smaller than its storage capacity from an electrical point of view.

- *The capacity of the associated thermal storage*: defined by the thermal wall mass or the water tank capacity $C$, and their operating temperature range ($E = C \cdot (T_{max} - T_{min})$). Larger is the storage capacity and the temperature range, larger is the saving potential. In the case of the house with optimization-based control, the temperature exceeds the minimum allowed temperature by one degree at the maximum while it could be increased by two. So only the half of the capacity is used in reality.

- *The thermal losses of the thermal storage*: a storage with large losses decreases the saving potential of using the storage capacity, given that storing energy, i.e. increasing the temperature, leads to additional losses costs.

The combination of these different factors explains the previous results: the device with the largest cost saving potential is the battery, followed by the electrical heater and then the heat pump.

### 4.3.6 Study limitation

The results presented in this work compare the optimality of different HEMS approaches while it includes generality in the operating conditions and the forecast scenarios. Nevertheless, the results are only valid for

- a typical German house according to statistics [73]

- a house equipped with battery, electrical water heater and heat pump

- the current German FiT and the most typical TOU tariff according to literature

All the presented results consider the identical low order energy models in simulation, neglecting the impact of thermal dynamic on the results.

In addition, the presented simulation consider a perfect signal transmission between the different devices and the HEMS unit as well as hardware failure is not considered. So, the loss of control of a device is not taken into account in this work.

More specifically, the presented results with the optimization-based approach are the upper bound of the cost savings given that perfect models of the house, heat pump, battery and electrical heater are considered in the problem formulation. More information about the impact of model error can be found in [65].

## 4.4 Discussion and summary

This section presents an optimality comparison of two different HEMS approaches: the market-based and the optimization-based approaches compared to the conventional control. The simulation results comparison is achieved according to the assessment method presented in the previous chapter. It takes into account different user profiles for electrical and DHW demand and considers 5 years of historical data for the temperature and the irradiation in Germany. All the results presented are averaged values. The considered forecaster is the ARMA model and its associated forecast error is considered for the irradiation, electrical and DHW demand according to the current literature.

Two different prices are considered in the frame of this work. With FiT, the HEMS saving potential is mainly depending on the PV production. Without PV production, there is then no saving potential. While with TOU tariff, the HEMS saving is mainly depending on its capacity to shift consumption during period of time with cheap electricity price and PV production.

From the results analysis, the main conclusions (yearly costs considered here) are:

- the added value of a HEMS is highly depending on the adopted tariff. Results shows that the optimal saving potential brought by a HEMS compared to a conventional control is in average 130€/y with FiT, and 500€/y with TOU tariff. The larger saving potential with TOU tariff can be explained by the presence of well-known period of time with very cheap electricity price.

- the forecast error decreases this potential by 100 and 130€/y in average for both tariffs with the state-of-the-art forecaster (SOTAFE). Nevertheless, the optimization-based with forecast errors still outperforms the conventional-control and the market-based control.

- the market-based control outperforms the conventional control and leads to average costs saving of 35€/y with FiT and 220€/y under TOU.
- the market-based control of the battery outperforms the optimization-based control because of its control frequency: every minute vs. every 15 minute which allows the battery to better capture the feed-in or the consumption of the house.
- the battery has the largest saving potential, followed by the electrical heater and finally the heat pump. This can be mainly explained by the unconstrained battery consumption. The larger potential of the electrical heater is explained by the associated thermal energy demand, the thermo-electrical device efficiency and the effective thermal storage capacity.
- the forecast errors impact mainly the devices with the largest saving potential.

This study quantifies the averaged saving potential brought by the considered HEMS approaches under different user behaviours, meteorological conditions and forecast errors. Besides the total saving potential study, this work introduces and studies the specific costs associated to each flexible devices to understand its specific impact on the total costs. This enables to identify which devices bring the largest cost saving potential and to quantify their sensitivity to forecast errors.

# Chapter 5

# Conclusion and future work

## 5.1 Conclusion

This thesis presents an uncertainty analysis method appropriated for uncertain time-series parameters with a limited number of process evaluation according to stochastic optimization theory. In addition, the proposed uncertainty analysis is applied to compare different HEMS approaches by taking into account different user profiles, forecast errors and several years of meteorological data.

Chapter 1 delivers an overview on the different HEMS approaches in the literature: their typical objective functions, their formulations and the considered flexible devices. The main challenges for comparing HEMS approaches are identified as i) the various form of the HEMS formulation as well as ii) the specificity of the evaluation conditions in literature, e.g. evaluation profiles and forecast errors.

In Chapter 2, the three different HEMS approaches considered in this work are described: the optimization-based, the market-based and the conventional control approaches. The considered HEMS approaches exploit the thermal and the electrical flexibilities at a household level according to the user comfort and the considered DR pricing. The objective function and the models are formalized for each approach. In addition, the specific theory supporting the market-based formulation is presented in details.

In Chapter 3, the assessment methodology is introduced and formalized as an uncertainty analysis for uncertain time-series according to the stochastic optimization theory. This methodology consists in the following steps. Once the uncertain time-series parameters are selected, a representative discrete distribution of these scenarios is generated. Then, the system response is evaluated with a reduced set of scenarios, selected according to the scenario reduction techniques (SRT), e.g. the forward algorithm based on the Kantorovich probability distance. Finally, the error associated to this distribution estimation can be evaluated using the true distribution, evaluated with the Monte Carlo method. According to required method accuracy, the SRT method or the number of selected scenarios can be adapted. The presented method is applied to a HEMS and stands out from the state-of-the-art uncertainty analysis methods because of the small number of simulation runs required and its good accuracy compared to the Monte Carlo method. It reduces by a factor 2000, the number of simulation runs compared to a Monte Carlo method, while the results show a small estimation error, under 0.5% of the true expected costs and a good stability for 5 or more selected scenarios. Neverthless, this method suffers from the curse of dimensionality given that the number of runs grows exponentially with number of uncertain time-series parameters. Furthermore, its associated error cannot be bounded in a formal way and has to be investigated for each studied case.

In Chapter 4, the different HEMS approaches are compared according to the uncertainty analysis introduced in Chapter 3. It takes into account different user profiles for electrical and DHW demand and considers 5 years of historical data for the temperature and the irradiation in Germany. All the presented results are the mean values from the achieved uncertainty analysis. The considered forecaster is the ARMA model and its associated forecast error is considered for the irradiation, electrical and DHW demand according to the current literature. Two different prices are considered in the frame of this work. With feed-in tariff (FiT), the HEMS saving potential is mainly depending on the photovoltaic production. Without photovoltaic production, there is then no saving potential. While with time of use (TOU) tariff, the HEMS saving is mainly depending on its capacity to shift consumption during period of time with cheap electricity price and photovoltaic production. According to German statistics, a 4-persons house with a heat pump, a domestic battery and an electrical heater is considered. The results show that:

1. The optimization-based approach with perfect information leads to a cost saving potential of 130€/y with FiT, and 500€/y with TOU tariff compared to the conventional control. The larger saving potential with TOU tariff can be explained by the presence of well-known period of time with very cheap electricity price which can be exploited to shift consumption.

2. The optimization-based approach with the state-of-the-art forecast error (SOTAFE) decreases respectively this potential by 100 and 130€/y. In this case, the optimization with forecast error still outperforms the conventional control and the market-based control.

3. The market-based approach outperforms the conventional control and leads to costs close to the optimization-based with forecast error. Its good performance can be mainly explained by its control frequency: every minute vs. every 15 minute for the optimization, which allows the battery to better capture the feed-in or the consumption of the house.

Besides the total saving potential study, this work introduces and studies the specific costs associated to each flexible devices to understand their specific impacts on the total costs. The results show that:

1. The battery has the largest saving potential, followed by the electrical heater and finally the heat pump. This can be mainly explained by the unconstrained battery consumption. The larger saving potential of the electrical heater is mainly explained by its constant thermal energy demand all along the year, its thermo-electrical device efficiency and its effective thermal storage capacity.

2. The forecast errors impact mainly the devices with the largest saving potential, respectively the battery followed by the electrical heater and finally the heat pump.

Although the assessment approach considers various user profiles and several years of historical data, the presented results are valid specifically for i) a typical

German house according to statistics ii) equipped with battery, electrical water heater and heat pump and iii) under the two studied tariff: the feed-in and TOU tariffs.

Finally, the implementation of the presented approaches in real life application is foreseen to affect these results because of the model uncertainties embedded in the optimization formulation or because of technical failure in operation: loss of device control, critical latency in communication or measurement errors.

Therefore, hardware-in-the-loop (HiL) based results are required to assess the real potential of HEMS approach and give additional insights about its implementation challenges in real life. In addition, the running time of a HiL setup is equivalent to real time which makes them very time consuming, e.g. a HiL simulation of one week takes one week in real time as well. Given this, the application of the proposed assessment methodology to the HiL test will give additional value to these results, given its representativity through the inclusion of different user behaviours or meteorological conditions and its small number of required runs.

To conclude this dissertation, the proposed assessment method was designed for the enhancement of HEMS approaches comparison through simulations. Nevertheless, this method could be as well applied in many other domains, provided that the uncertain parameters are time-series and that a limited number of runs is required.

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