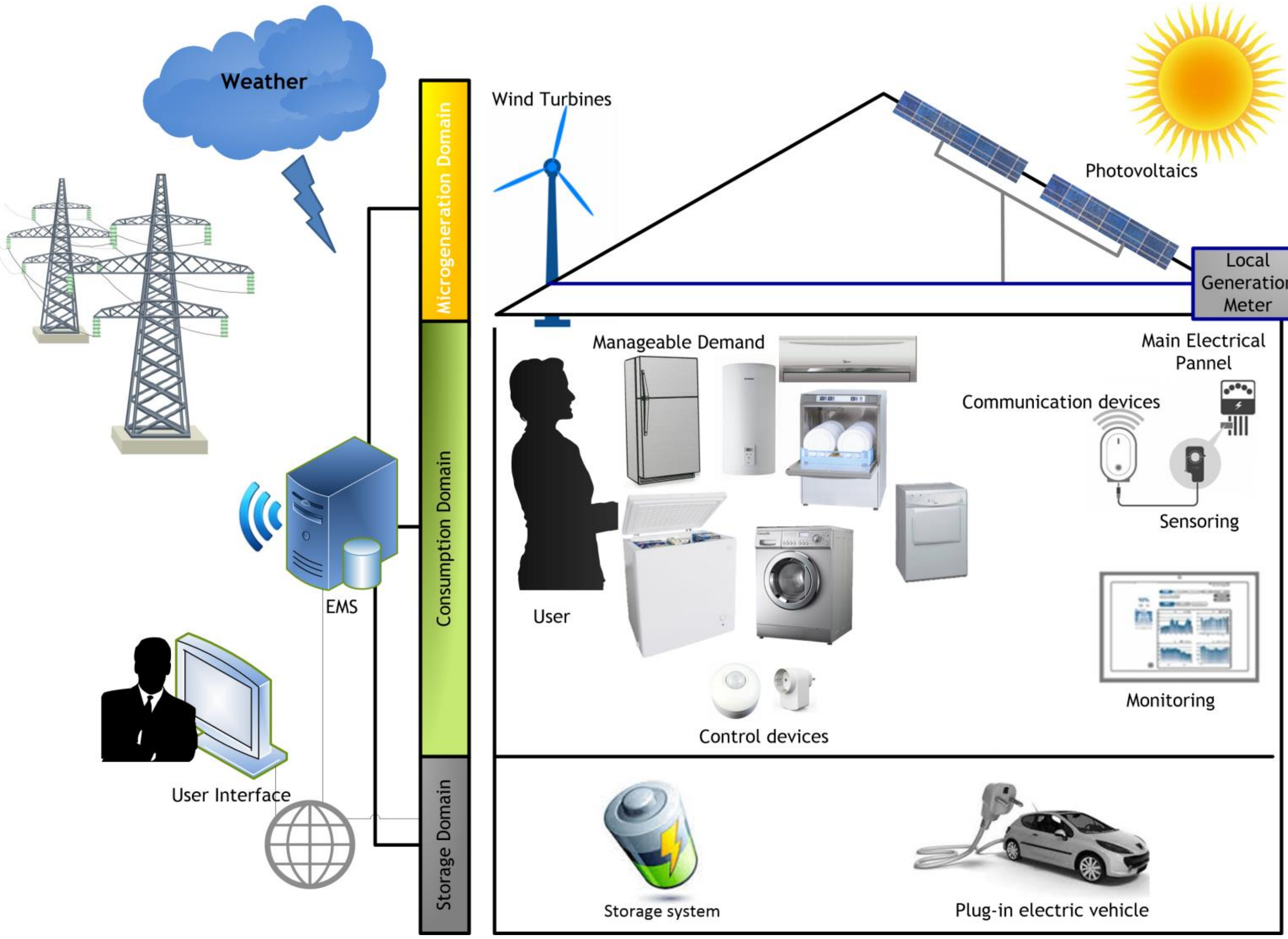

Adapted from: Poster presentation (Lopes et al., 2012) at IEEE International Symposium on Sustainable Systems and Technology

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Integrated Management of Residential Energy Resources: Models, Algorithms and Application

PhD Thesis in Sustainable Energy Systems supervised by Professor Álvaro Gomes and Professor Carlos Henggeler Antunes, submitted to the Department of Mechanical Engineering, Faculty of Sciences and Technology of the University of Coimbra

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Universidade de Coimbra

UNIVERSIDADE DE COIMBRA

INTEGRATED MANAGEMENT OF RESIDENTIAL ENERGY RESOURCES: MODELS, ALGORITHMS AND APPLICATION

by

Ana Raquel Gonçalves Soares

PhD Thesis in Sustainable Energy Systems

in the framework of the Energy for Sustainability Initiative of the University of Coimbra and MIT Portugal Program

submitted to the Department of Mechanical Engineering, Faculty of Sciences and Technology of the University of Coimbra

Thesis Supervisors

Professor Doutor Álvaro Gomes

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ABSTRACT

The gradual development of electricity networks into smart(er) grids is expected to provide the technological infrastructure allowing the deployment of new tariff structures and creating the enabling environment for the integrated management of energy resources. The suitable stimuli, for example induced by dynamic tariffs, i.e. energy prices varying in short periods of time, and an adequate technological infrastructure for metering, controlling and data communication are expected to become major tools to foster a more active role of demand-side resources and facilitating the penetration of distributed generation based on renewable sources. In this setting, active residential load management can play an important role to help end-users optimizing the usage of energy resources to minimize the overall energy cost without compromising comfort. This load management asks for the development of optimization models of combinatorial nature and able to account for multiple objectives, given the diversity of comfort requirements, technical constraints, appliances to be scheduled, etc., in a near real-time framework, to decide which automated demand response action should be implemented. The decisions are influenced by energy costs, end-users' preferences and requirements, potential dissatisfaction when the operation cycle of loads is changed, technical constraints, weather forecasts, the existence of local generation and storage systems.

Evolutionary algorithms have been used to solve a variety of complex optimization problems, coping with large and irregular search spaces, and also multiple objectives of different nature. Due to these features and the ability to provide good solutions in a reasonable computational time, an evolutionary algorithm approach has been developed to solve a multi-objective optimization model for managing residential energy resources. The energy resources to be considered include local generation, storage systems (stationary and plug-in electric vehicle) and manageable demand. Demand resources can be categorized under shiftable loads, reparameterizable loads and interruptible loads.

The evolutionary algorithm developed makes the most of the physical characteristics of the problem to obtain results that can be implemented in practice with a mild computational effort. For the different types of loads, customized solution encoding and operators are used since the detailed knowledge of the physical characteristics of the problem is essential to obtain better results. The bi-objective model considers as objective functions the minimization of the energy cost and the minimization of end-user's dissatisfaction associated with management strategies. The consideration of a bi-objective model enables to study the trade-offs between the competing objective functions and then select a compromise solution more in accordance with the end-user profile.

The use of the tailored evolutionary algorithm proposed in this research, though not directly aiming at an overall reduction of energy consumption, allows minimizing the electricity bill and end-user's dissatisfaction through an optimized use of energy resources. According to the results obtained, the contracted power level can also be lowered. Savings in the electricity bill are usually between 5-16%, although higher ones can be attained since savings are strongly dependent on the tariff structure, end-user's preferences and willingness to accept a higher level of control. Results show the higher the flexibility of the end-user regarding the usage of the different energy services, the higher the savings.

This evolutionary algorithm approach endows the Energy Management System with a reliable method to automatically make decisions concerning the optimal integrated use of multiple residential energy resources according to the end-user profile and has a high flexibility concerning the integration of a high diversity of manageable resources.

Keywords:

Residential Integrated Energy Resources Management; Demand Response; Evolutionary Algorithms; Smart Grids.

RESUMO

A evolução gradual das redes de energia no sentido de redes mais inteligentes expectavelmente fornecerá a infraestrutura tecnológica necessária permitindo a implementação de novas estruturas tarifárias, criando um ambiente favorável para a gestão integrada de recursos energéticos. Os estímulos adequados induzidos, por exemplo, por tarifas dinâmicas, em que o preço de energia é variável ao longo de intervalos de tempo curtos, assim como a infraestrutura tecnológica para monitorização, controlo e comunicação de dados tornar-se-ão ferramentas importantes para fomentar um papel mais ativo dos recursos do lado da procura e promover a penetração da geração distribuída baseada em fontes renováveis. Neste contexto, a gestão ativa das cargas no setor residencial pode desempenhar um papel importante para permitir aos utilizadores a otimização da utilização de recursos energéticos, com o intuito de minimizar o custo total de energia, sem comprometer o nível de conforto. Esta gestão de cargas requer o desenvolvimento de modelos de otimização de natureza combinatória e tendo em conta múltiplos objetivos, dada a diversidade de requisitos em termos de conforto, restrições técnicas, quantidade de cargas a escalonar, entre outros, num ambiente em tempo quase real, para decidir que ações de gestão da procura devem ser implementadas. As decisões são influenciadas pelos custos de energia, pelas preferências e requisitos do utilizador, pela potencial insatisfação quando o ciclo de funcionamento das cargas é alterado, pelas restrições técnicas, pelas previsões meteorológicas e pela existência de sistemas de geração local e de armazenamento.

Os algoritmos evolucionários têm sido usados para resolver problemas de otimização complexos, devido à sua capacidade para trabalhar com espaços de procura grandes e irregulares, e com vários objetivos de natureza diversa. Devido a estas características e ainda à capacidade para encontrar boas soluções num tempo computacional razoável, foi desenvolvida uma abordagem baseada num algoritmo evolucionário para resolver um modelo de otimização multi-objetivo para a gestão de recursos energéticos no setor residencial. Os recursos energéticos a considerar incluem geração distribuída local, sistemas de armazenamento (estacionários ou veículos elétricos) e a procura controlável. A procura controlável pode ser dividida em cargas ajustáveis no tempo (ou que permitem reagendamento), cargas reparametrizáveis e cargas cujo funcionamento pode ser interrompido.

O algoritmo evolucionário desenvolvido tira partido do conhecimento das características físicas do problema de modo a obter resultados que podem ser implementados na prática, com um esforço computacional moderado. Assim, para os diferentes tipos de cargas, é feita uma adaptação da codificação da solução e dos operadores, pois um conhecimento detalhado das caraterísticas físicas do problema permite obter melhores resultados. O modelo bi-objetivo considera como funções objetivo a minimização do custo de energia e a minimização da insatisfação associada à implementação das ações de gestão da procura. A consideração de um modelo bi-objetivo permite a análise dos *trade-offs* entre as duas funções objetivo e a seleção de uma solução de compromisso de acordo com o perfil do utilizador.

O uso do algoritmo evolucionário proposto neste trabalho, embora não tenha como intenção essencial a redução global do consumo de energia, permite minimizar a fatura de eletricidade, assim como a insatisfação do utilizador, através de uma gestão otimizada dos recursos energéticos. De acordo com os resultados obtidos, o escalão da potência contratada também pode ser reduzido. As poupanças na fatura de eletricidade variam geralmente entre 5 e 16%, apesar de poderem ser atingidas poupanças mais elevadas uma vez que estas são fortemente dependentes da estrutura tarifária, das preferências do utilizador e da sua predisposição para aceitar um nível de controlo mais elevado. Os resultados mostram que quanto maior a flexibilidade do utilizador relativamente à utilização dos diferentes serviços de energia, maior é a poupança.

Esta abordagem, baseada num algoritmo evolucionário, permite dotar o sistema de gestão de energia de um método confiável para gerir automaticamente e de modo integrado os vários recursos energéticos existentes no setor residencial de acordo com o perfil do utilizador. Esta abordagem apresenta ainda uma flexibilidade elevada em termos de integração de uma elevada diversidade de recursos controláveis.

Palavras-chave:

Gestão Integrada de Recursos Energéticos no Sector Residencial; Gestão da Procura; Algoritmos Evolucionários; Redes Inteligentes.

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ABBREVIATIONS

AC	-	Air Conditioner
ADR	-	Automated Demand Response
BA	-	Battery-Assisted Appliances
COP	-	Coefficient of Performance
CPU	-	Central Processing Unit
DR	-	Demand Response
DSO	-	Distribution System Operator
DW	-	Dishwasher
EA	-	Evolutionary Algorithm
EER	-	Energy Efficiency Ratio
EMS	-	Energy Management System
EWH	-	Electric Water Heater
G2V	-	Grid-to-Vehicle
GA	-	Genetic Algorithm
GHG	-	Greenhouse Gases
IBR	-	Inclining Block Rate
ICT	-	Information and Communication Technologies
IDGA	-	Iterative Deepening Genetic Algorithm
LM	-	Laundry Machine
LSEA	-	Load Scheduling Evolutionary Algorithm
MA	-	Model-Based Appliances
MCP	-	Monitoring and Control Plug
MILP	-	Mixed Integer Linear Programming
MOGA	-	Multiple Objective Genetic Algorithm
NSGA	-	Nondominated Sorting Genetic Algorithm
PBM	-	Physically-Based Models
PGA	-	Parallel Genetic Algorithm

PHEV	-	Plug-in Electric Vehicle
PSO	-	Particle Swarm Optimization
PV	-	Photovoltaic
SA-IL	-	Schedule-Based Appliances with Interruptible Load
SA-UL	-	Schedule-Based Appliances with Uninterruptible Load
SoC	-	State of Charge
SOGA	-	Single Objective Genetic Algorithm
TD	-	Tumble Dryer
V2G	-	Vehicle-to-Grid

OBJECTIVES

The aim of the research leading to this PhD thesis was to design a methodology for optimizing the usage of multiple energy resources in a single household while simultaneously considering variable energy prices, end-users' needs and the variability associated with both the electricity demand and local generation. The residential energy resources comprise manageable loads, energy storage systems, including plug-in electric vehicles, micro-generation systems and energy drawn from the grid. The approach includes an adequate framework to take into consideration end-users' preferences, the models to reproduce the power profile of the energy resources and the optimization algorithms to be implemented in a residential Energy Management System (EMS).

The models are aimed to reproduce the regular behavior of loads, i.e, without interference of an automated management system and, when aiming at an optimized use of energy resources, should also be able to reproduce their behavior when subjected to management actions. An evolutionary approach able to cope with the multiple objectives, combinatorial nature and nonlinear features of the model, is responsible for computing solutions aiming at the optimal integrated management of the available energy resources. This optimization is aimed at deriving the Pareto optimal set associated with minimizing the electricity bill and the potential end-users' dissatisfaction due to the implementation of Automated Demand Response (ADR) actions.

In order to accomplish the objectives of this PhD research, the following steps have been followed:

1. Categorization of loads to be the target of ADR actions through the identification of the characteristics that allow demand to be treated as a manageable and responsive resource;
2. Design of the main features of the different possible ADR actions;
3. Development of the simulation environment to reproduce residential electricity demand, micro-generation and energy storage systems, and assess the impact of ADR actions on different energy resources;
4. Development of optimization models;
5. Integration of optimization models in the simulation environment to be tackled by evolutionary algorithms coping with multiple objectives and the combinatorial nature of the search space, taking into account end-users' requirements and preferences;
6. Evaluation of the impacts of the optimal integrated management of energy resources on the residential load diagram, the end-users' electricity bill and potential dissatisfaction caused by changes in habitual load operation schedules.

1. INTRODUCTION

1.1. CONTEXT AND MOTIVATION

The adequate operation of the electrical power grid requires a balance between demand and supply. According to a "supply follows load strategy", which assumes that electricity demand is almost inelastic, utilities[1] need to accurately estimate demand and schedule their energy supply portfolio for a given planning period and cannot rely on end-users' response to meet direct requests for increasing or decreasing demand (Albadi and El-Saadany, 2008; Chrysopoulos et al., 2014; Ipakchi and Albuyeh, 2009; Katz et al., 2011). In recent years, with the need to reduce simultaneously external energy dependence and Greenhouse Gases (GHG) emissions and the increasing investment in renewable sources, existing power supply systems have been facing new changes and challenges, in particular the need to fully integrate generation from renewable energy sources (Directorate-General for Research Sustainable Energy Systems, 2006). At the same time the power grid has been also facing several modifications, namely the integration of smart embedded systems combining instrumentation, analytics and control to increase grid's efficiency. Driven by security of supply, sustainability and competitiveness concerns, this grid will become self-diagnosing, self-healing, more distributed and bidirectional (Brown et al., 2010; European Commission, 2006; Moshari et al., 2010). European countries are currently moving towards the development of a smart(er) grid, which will make possible the setting of an efficient market where end-users' flexibility concerning electricity usage may play an important role (D'hulst et al., 2015; Jacobsen et al., 2015).

Nowadays this demand flexibility, when existent, takes place usually in industry and requires bilateral agreements. Usually in this scenario large electricity users are paid to reduce their consumption in critical periods to avoid grid congestion (Jacobsen et al., 2015) while residential end-users have a flat, dual or triple time-of-use tariff and independently manage their energy usage without direct external interference. In the context of smart grids, a paradigm change is expected to occur mainly due to the presence of bidirectional communication and the more intense use of computing, control and information and communication technologies (ICT) which will contribute to increase the system's overall efficiency, reliability, flexibility and sustainability (Kahrobaee et al., 2013). Bidirectional communication enables the adoption of dynamic tariff schemes and consequently encourages end-users to have a more active role concerning electricity usage. In the smart grid scenario, instead of the traditional strategy, a "load follows supply" strategy can be implemented (Katz et al., 2011). This strategy aims to stimulate end-users to make a more informed and wise usage of energy resources, through the use of adequate technical and economic approaches (Molderink et al., 2010a). It is widely acknowledged that demand-side

[1] An utility is seen in this context as a company engaged in activities necessary for delivery of electric energy to consumers.

resources active participation is one of the ways to enhance the economic efficiency of electricity markets, reduce peak demand and improve the reliability of electric power systems (Hirst and Kirby, 2001), besides the direct advantages to the end-user concerning the reduction of the electricity bill. In this scenario all the electricity chain participants, from generation to consumption, may participate actively in the functioning of the power system.

Incentive-based schemes are an option which can be used in this context to enroll consumers voluntarily in programs in which the grid operator or energy retailers may control some of the end-use loads according to a pre-established contract. On the other hand, time-based rates schemes can induce changes in the way end-users use their resources and may include scheduled time-of-use pricing, peak-pricing and time varying/dynamic tariffs (Tsui and Chan, 2012).

Dynamic tariff schemes, known a certain time in advance, which more accurately reflect the real costs of energy, can be used instead of flat tariffs to induce behavior change and influence electricity usage (Deng et al., 2013; Vanthournout et al., 2015). Nonetheless, the effort required to end-users to be aware of energy price variation and make decisions concerning the way electricity is used can be too high. Decisions such as:

- the best scheduling for appliances to be turned on/off (laundry machines, tumble dryers, dishwashers, etc.);
- the temperature change in thermostats set points and/or the curtailments to be applied over thermostatically controlled loads, such as air conditioners and electric water heaters or even refrigerators and freezers;
- what to do with the energy produced locally (store/use/sell to the grid);
- how to manage electricity storage devices, including a Plug-in Electric Vehicle (PHEV) which may be used in both Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) modes;

should be done continuously and in a near real-time environment thus requiring the help of decision support tools such as EMS (Lopes et al., 2012; Paterakis et al., 2015). These systems can thus be responsible for making decisions concerning which ADR actions should be implemented and how, while respecting technical and comfort constraints.

Recent works concerning EMS have focused on the management of appliances under real-time electricity pricing mainly aiming at reducing end-users' electricity bill (Allerding et al., 2012; Braun et al., 2016; Mauser et al., 2014). The most common ADR action is shifting energy consumption from periods of higher prices to periods of lower prices. Bidirectional exchange of information between the utility or even an aggregator entity[2] and end-users encompasses energy prices and power requested to the grid in each period of time.

[2] Aggregators in this context are seen as energy players whose main role is gathering flexibility in electricity usage from consumers and intermediate transactions with other energy players (Agnetis et al., 2011; Carreiro et al., 2015; Giordano and Fulli, 2012; Gkatzikis et al., 2013)

Demand Response endows the end-user with the possibility to participate in the operation of power systems by enabling to increase, reduce or shift electricity usage during a given period of time in response to external signals, for example energy prices (Federal Energy Regulatory Commission, 2011). Furthermore, Demand Response (DR) programs can help improving the stability of the distribution grid and a more efficient integration of renewables and thus contributing to a future lower carbon economy. End-users engaging in these programs are expected to have a certain degree of flexibility regarding the usage of a group of appliances and be willing to trade-off convenience in daily energy services usage (e.g., accepting small and brief changes in indoor temperature range of a room or hot water).

In the smart grids context, DR has re-emerged as a tool that helps energy suppliers minimizing peak load demand while allowing end-users to reshape their energy consumption by making informed decisions regarding consumption and storage (Gomes et al., 2011). DR can be seen in this framework as an alternative to build (or reinforce) power plants and network infrastructures since it contributes to increase the utilization of existing generation capacity and network assets by inducing end-users to modify their demand patterns according to real-time and estimated information concerning generation availability (namely renewables) and energy prices (Salinas et al., 2013). DR programs are also useful to Distribution System Operators (DSOs) since they can take into account grid constraints and induce electricity consumption changes. Accordingly these programs can provide means for flattening peak demand or changes in the load curve if needed and hence postponing investments in grid infrastructure (Jacobsen et al., 2015).

The buildings sector is currently one of the largest energy consumers representing 32% of the global energy use (IEA, 2012). In Europe, this percentage achieved 41% in 2010 (European Commission, 2012), enhancing the importance of this sector to reach GHG emissions goals and the desired improvement in energy efficiency by 2020 (European Comission and Eurostat, 2015). Concerning electricity, the residential and tertiary sectors together represented more than 50% of the electricity consumption in EU-27 in 2010 (Bertoldi et al., 2012) and the residential sector by itself accounted for 30% of total final electricity consumption in EU-27. This sector has been showing an increasing consumption trend therefore justifying the need to promote and implement energy efficiency policies and actions to change energy behaviors (Bertoldi et al., 2012; INE, 2011; Lopes et al., 2012a).

Although it may be argued that appliances are becoming more efficient, the ownership rate of some of them has also been rising as well as their use (Bertoldi et al., 2012). Considering the residential sector as a target to achieve a smarter use of electricity due to the existence of a certain degree of flexibility regarding the usage of appliances, adequate algorithms should be designed to be at the core of EMS to help end-users responding to energy price variations.

Concerning the final aim of the EMS, different energy systems stakeholders may have distinct aims. From the residential end-user's point of view the final aim is optimally managing energy resources to decrease the electricity bill without degrading the quality of the energy services provided. For prosumers (simultaneously producers and consumers), the objectives also include maximizing the use of local renewable energy resources and maximizing the profits with selling of electricity. As for the utility, the main goals lay on the maximization of profits and the maximization of savings in both capital and operational expenditures. For the grid operator, a major motivation is the maximization of the reliability of supply and the minimization of congestions and losses in the electrical grid, postponing the investments in increasing grid infrastructure. The adoption of an EMS requires the clear identification of the actors and the objectives to be pursuit to adequately design and configure the embedded optimization algorithms. Table 1 shows some entities who may be interested in such a system and some of their main goals. In this PhD research the end-user's perspective was chosen and therefore the objectives are twofold: minimization of the electricity bill and minimization of the potential dissatisfaction sensed by the end-user. Despite of adopting the end-user perspective for the development of this work, other perspectives (such as the ones of retailers and DSOs) can be considered together with the end-user perspective if adequate mechanisms are used to create convergence of interests, such as suitable tariff schemes. EMS already used in the services sector and even in the residential sector can have their functionalities upgraded by including the option of automatically adapt demand to supply on behalf of the end-users (Miorandi and De Pellegrini, 2012).

Table 1: Example of different actors and goals

Actors	Goals
End-user consumer	Minimize the electricity bill Minimize the degradation of the quality of energy services provided
Prosumer	Maximize the use of local renewable energy resources Maximize the profits with selling of electricity Minimize the electricity bill Minimize the degradation of the quality of energy services provided
Utility	Maximize profits Maximize savings in both capital and operational expenditures
Grid Operator	Maximize the reliability of supply Minimize congestions and losses in the electrical grid
Retailer	Maximize profits

In the smart grids context, the introduction of new services by utilities is also expectable such as bundled up services and new contract options, which may already include technologies and strategies for engaging end-users in DR programs, remote management of home temperature, battery leasing for PHEVs, among others (Giordano and Fulli, 2012; Logenthiran et al., 2012). DSOs and energy traders actors can take advantage from trading end-users flexibility and capacity regarding the usage of energy services on energy markets, although the revenues, investment payoff and savings achieved are strongly dependent on the amount of manageable loads engaged in load management programs (Carreiro et al., 2015; Soares et al., 2014b). In the case of residential users, the level of involvement is expected to be high for most manageable loads, since what will most influence the end-user behavior is the trade-off between the quality of the energy service provided, e.g. meet comfort requirements and preferences, and the potential savings in the electricity bill resulting from using the energy service under different conditions (Stamminger and Anstett, 2013).

From the point of view of network companies, the implementation of ADR strategies with impact on the peak load demand decreases the network congestion and losses. There is then a reduction of the need to build new under-used power plants and consequently no need to expand neither the transmission lines nor the distribution networks, thus decreasing the overall costs, reducing the carbon emission levels and consequently improving the grid sustainability.

The dissemination of PHEVs is also expected to gain an additional impetus and the charging of a multitude of PHEVs may pose some new burdens on the grid, mostly due to the creation of new power peaks (Eppstein et al., 2011; Guille and Gross, 2009; Salinas et al., 2013; Shao et al., 2011; Weiller, 2011; Zhang et al., 2012). End-users' flexibility for charging these PHEVs in different time slots or to interrupt their charging cycle, as long as the desired state of charge (SoC) of the PHEV battery is achieved by a given time, makes possible to manage these loads individually or using some type of aggregating entity (Bessa et al., 2012). From the grid's perspective, lowering those power peaks, which most likely occur a few hours per day only, will contribute to extend the usage of the available grid capacity and postpone the investments needed to expand it.

1.2. CONTRIBUTIONS AND RESEARCH QUESTIONS

The problem addressed in this work consists in designing and implementing an evolutionary approach, aiming at the integrated management of residential energy resources, to be embedded in a residential EMS. This EMS will explore the flexibility that residential end-users have concerning electricity usage.

The targeted energy resources include local generation, shiftable loads, thermostatically controlled loads, storage systems (either stationary or a PHEV) and energy drawn from the grid. For the different groups of loads, customized solution encoding and operators are used since the detailed knowledge of the physical characteristics of the problem allows tailoring the algorithm to obtain effective results that can be implemented in practice. The multi-objective model considers as objective functions the minimization of the energy cost and the minimization of end-user's dissatisfaction associated with management strategies, in order to make solutions acceptable to the typical end-user who does not want to jeopardize comfort. Results have shown that significant savings can be achieved although they are strongly dependent on the end-user's willingness to accept automated control.

The main research questions to be answered by this research are therefore:

- *in a smart grid context how can the use of different residential energy resources be optimized?*
- *how should the algorithmic approach be customized to optimally manage the distinct energy resources?*

The main highlights from this PhD research are:

- the inclusion of two conflicting objectives: minimization of the electricity bill and minimization of the potential dissatisfaction sensed by the end-user;
- development of an EA approach able to deal with the bi-objective and combinatorial nature of this optimization problem;
- the customization of the solution encoding and operators used to obtain effective results;
- diversity of the energy resources considered in the model;
- variety of ADR actions considered;
- ability to quickly re-compute new solutions if the context changes during the optimization process.

1.3. ORGANIZATION

The presentation of the PhD thesis is based on three journal papers and book chapters, which describe the several stages of this research[3]. The thesis is structured in seven chapters. Chapter 1 presents a brief introduction to the research problem and the research objectives. Chapter 2 focuses on the identification of responsive resources in the residential sector and its features. Chapter 3 provides a detailed overview of evolutionary approaches that may be used to deal with combinatorial multi-objective models to optimize the management of residential energy resources in the smart grids context. Aiming at presenting the most recent works in this area, this review addresses papers published in the 21st century only. This chapter also includes a small section presenting other optimization techniques that have also provided good results. The problem to be solved is formulated and modelled in Chapter 4. The methodology, based on an evolutionary algorithm, used to solve this model is presented in Chapter 5. Simulation results and the possible choice of the final solution according to distinct residential end-user profiles are depicted and analyzed in Chapter 6. Conclusions are drawn and future research directions are outlined in Chapter 7.

[3] Copyright has been granted to reuse all of the published papers.

2. Resources in the Residential Sector[4]

2.1. Residential Resources Overview

Residential loads are devices that consume energy and have frequently been seen as passive, displaying inelastic demand (Lui et al., 2010). However, the way appliances are perceived is changing since they can be managed up to a certain degree, aiming at changing their electricity consumption during specific periods of time. The change of normal operation of manageable loads can contribute to maximize the integration of renewables (Lui et al., 2010; Timpe, 2009) and the accommodation of new end-use loads, such as PHEVs, becomes easier. The flexibility in using the different services makes manageable demand able to be adequately managed according to different objectives and interests.

The design of algorithms to optimize the use of residential resources requires their characterization. For example, it is necessary to know:

- which energy resources are able to be controlled and in what extent;
- what kind of control actions can be applied over each resource;
- which technical constraints and comfort preferences are associated with the services provided by each resource.

The knowledge of the disaggregated electricity consumption in the residential sector as well as the typical patterns of usage of the appliances and user's day activities, plus the previous itemized information allow identifying responsive loads to be the target of ADR actions within certain conditions (Lopes et al., 2016b; Rosin et al., 2010). Technical constraints and end-user's preferences that frame the way loads can be controlled also play an important role and should be included in the optimization process.

Although the way electricity is used in the residential sector may differ among different countries (e.g., in some countries air conditioner systems are widely used while in other countries their ownership rate is very low) as well as the end-user's willingness and flexibility concerning the implementation of ADR actions, loads have common features and are used to achieve similar goals. People's daily activities include gainful work and study, residential work, meals, personal care, travel, free time and sleep. Even if some of the previous activities are performed outside people's home, others are done at home and require the activation of energy services, namely food preparation, dish washing, cleaning, laundry, watching television, among others (Lopes et al., 2015). Therefore the first step is to clearly identify the energy services and responsive demand.

[4] This chapter is partially based on Soares, A., Gomes, Á., Antunes, C.H., 2014b. Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions. Renew. Sustain. Energy Rev. 30, 490–503 .

To achieve that goal, a detailed analysis of how electricity is used in the Portuguese residential setting is conducted based on a study from the Directorate General for Energy and Geology in Portugal (DGEG) / IP-3E (DGGE /IP-3E, 2004) with:

- the disaggregation of residential load profile by end-uses (Figure 1);
- the contribution of end-use loads to the total electricity consumption and electricity bill (Figure 2).

Other studies concerning end-users habits, daily's activities (Lopes et al., 2016a) and users' willingness to change behavior concerning the utilization of energy services (Gyamfi and Krumdieck, 2011; Lopes et al., 2012a; Stamminger, 2008; Timpe, 2009) also provide useful information (Figure 3) that can be crossed with the previous study (DGGE /IP-3E, 2004).

This analysis enables extracting the regular periods of usage of end-use loads and making some assumptions concerning residential end-users' habits and the potential of operating some of the appliances in different schedules or under different settings.

From the end-user's point of view and in order to accept the implementation of ADR actions, the control should be done by taking advantage of usage flexibility of manageable end-use loads, without reducing comfort or depreciating the quality of the energy services provided.

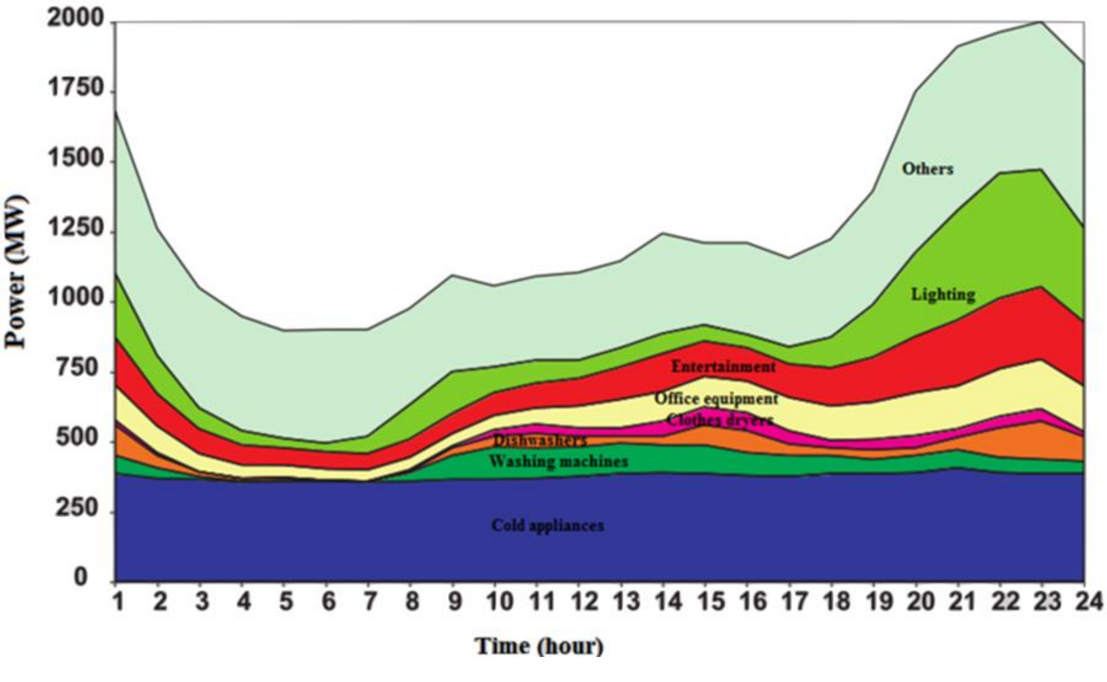

Figure 1: Demand profile of the residential sector in Portugal (DGGE /IP-3E, 2004)

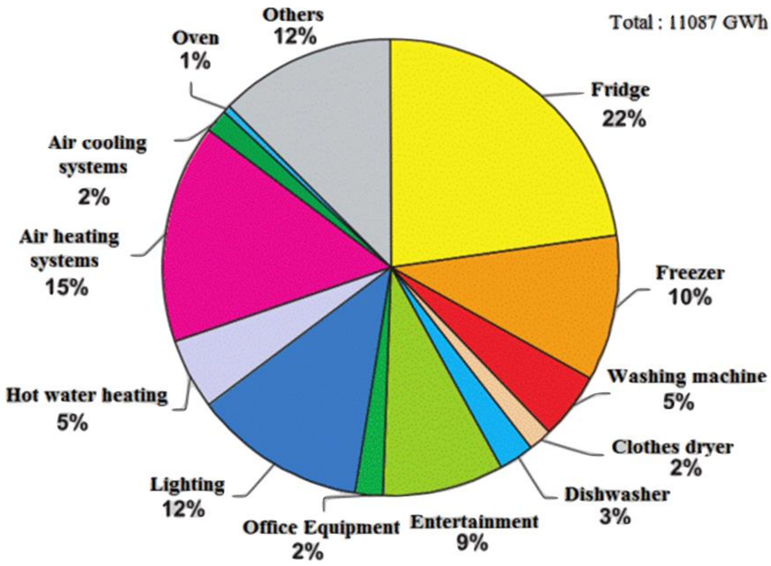

Figure 2: Disaggregated electricity consumption in the residential sector in Portugal (DGGE /IP-3E, 2004)

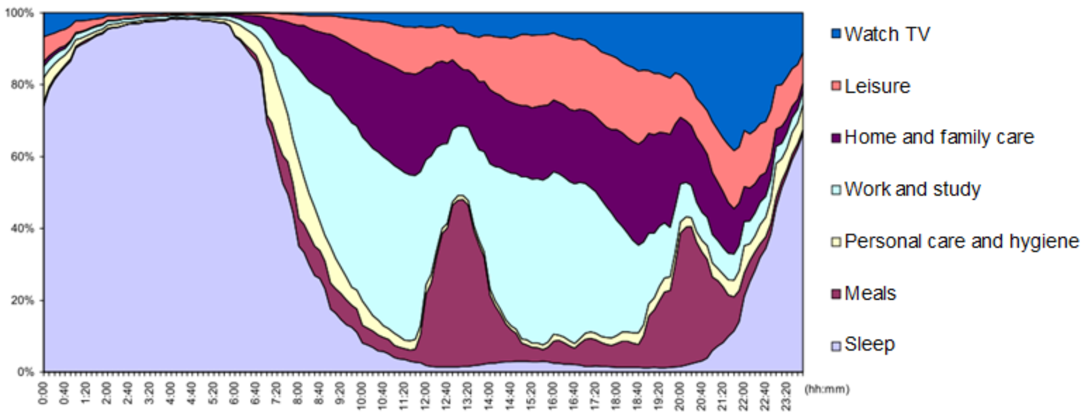

Figure 3: Average day activities from portuguese residential users (INE, 1999; Lopes et al., 2016b)

2.2. Load Categorization

In a broad sense, each household has non-manageable loads, manageable loads with different degrees of control and, in some cases, small renewable generation systems and some form of storage systems, including PHEVs. The non-manageable loads typically comprise loads associated with entertainment, cooking, cleaning or lighting activities such as audio visual, office, cooking and cleaning appliances, among others. Manageable loads are usually associated with an energy service that may be not coincident with electricity consumption or may be provided in different periods of time, including:

- dishwashers, laundry machines; tumble dryers;
- thermostatically controlled loads:
  - fridges and freezers;
  - electric water heaters (EWH);

  - air conditioner (AC) systems.
- storage systems (either stationary or PHEVs).

2.2.1. Shiftable Loads

There are loads such as laundry machines (LM), dishwashers (DW) and tumble dryers (TD), for which the energy services may be provided in different periods of the day when there are economic advantages for the end-user without decreasing their quality of service as long as end-users needs and requirements are fulfilled (Albadi and El-Saadany, 2008; Meyers et al., 2010). These loads can be classified as shiftable loads.

Figure 4 shows energy use during a typical operation cycle for a residential laundry machine at two different washing programs and the average pattern of use in Portugal. This type of load is mainly put into service in the morning and after lunch period. The information of load usage together with the characteristics of these loads plus end-user's willingness to accept control makes them suitable for postponement or anticipation actions. In terms of energy consumption, most electricity is consumed in the water heating phase, being advisable to use low temperature programs. Interruptions should not occur during this stage due to possible heat losses and the need to re-heat water.

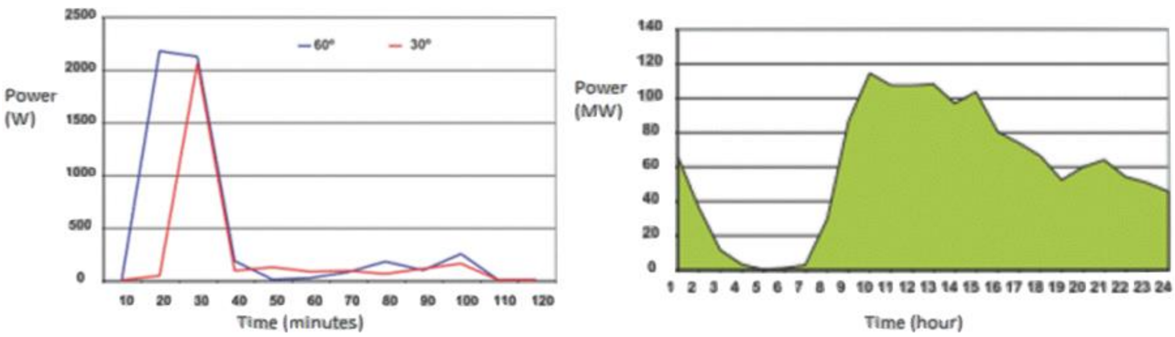

Figure 4:Typical working cycle of laundry machine and average daily pattern of use (DGGE /IP-3E, 2004)

Figure 5 provides information about energy and time of use for residential tumble dryers. As for the laundry machines, tumble dryers also offer a significant opportunity to reduce the traditional electricity peak presented in Figure 1 and shift that consumption to other period of the day. However, it is important to highlight that usually these loads are operated after the working cycle of the laundry machine is over, which strongly influences their flexibility concerning the time shifting window. Although the ownership rate of these appliances is not very high in Portugal (around 19%), the possibility of controlling them without causing discomfort to the end-user is easily achieved either by shifting the consumption or even interrupting it to take advantage of the residual heat. From an end-user perspective and since the tumble dryer cycle time and energy consumption are linked, the interruption of the cycle will not affect drying performance, but will lengthen the duration of the total working cycle by increasing the time that the heater is shut off (Lui et al., 2010).

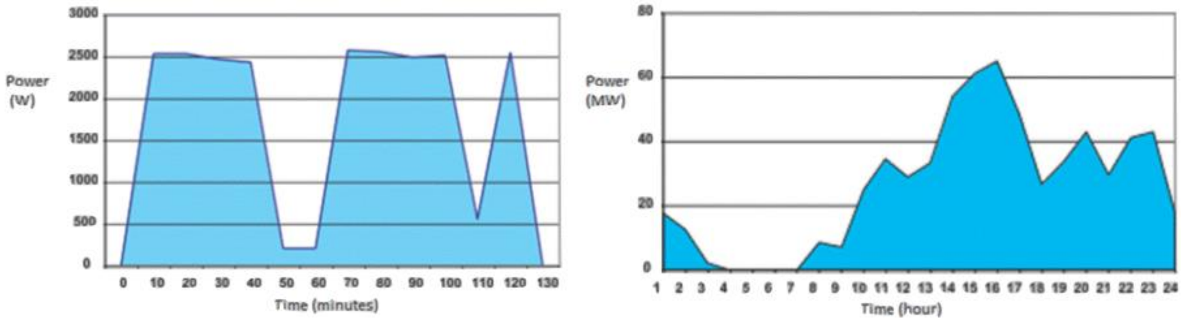

Figure 5: Typical working cycle of a tumble dryer and average daily pattern of use (DGGE /IP-3E, 2004)

Dishwashers are usually used after meals, being ideal to be managed since their electricity consumption can be deferred without bringing discomfort to the end-user as long as the dishes are washed and dried at a stipulated time (Figure 6). Normally the peak of use of this type of loads occurs after dinner, being coincident with current peak electricity demand in the residential sector in Portugal (Figure 1). If these loads are used when the price of electricity is lower or there is energy being produced locally, then economic advantages of using these appliances at the adequate schedule are expected. Also, along with the possibility to defer the operation cycle, there can also be a power and energy reduction by eliminating the heated drying portion of the cycle pointed out in Figure 6 (Lui et al., 2010) in extreme situations.

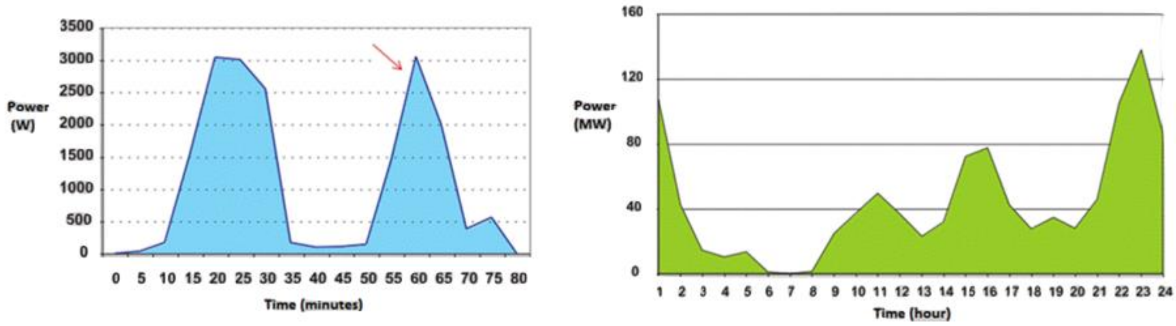

Figure 6: Typical working cycle of a dishwasher and average daily pattern of use (DGGE /IP-3E, 2004)

2.2.2. Thermostatically Controlled Loads

Some dissociation may exist between the energy services and electricity consumption since the final objective of the usage of those appliances can be conserving food, heating water or keeping room temperature within a given range. These loads can be generally categorized under the label thermostatically controlled loads, since the level of some of these energy services, i.e. temperature set points, can be slightly changed during short periods of time leading to changes in energy consumption without noticeable changes in the quality of the energy service provided. Additionally, the normal working cycle of these loads may also be interrupted during short periods of time without decreasing the quality of the energy service provided as long as temperature restrictions are taken into account. It is possible to group under this category cold appliances, EWHs and ACs systems.

Cold appliances are present in almost every household, sometimes even more than one per house, and accounted for more than 30% of the annual residential electricity consumption in Portugal (Figure 2) according to (DGGE /IP-3E, 2004). This load has a working cycle controlled by a thermostat (Figure 7) and can have the thermostat settings changed or even be the target of short interruptions without causing the deterioration of the energy service as they can act as energy storage devices (Xu et al., 2011). In practical terms, a difference of 1°C is not, in general, problematic for conserving food while for electricity consumption it represents a non-negligible difference (Kupzog and Roesener, 2007). Therefore, ADR actions targeting small changes of the thermostat settings and short time interruptions with consequent small changes of temperature parameters are possible (Molderink et al., 2010a; Perfumo et al., 2012).

Although one may argue that the power drawn from the power system by cold appliances is relatively low, the fact that they are working all day long in almost every house, meaning the overall energy consumed may be high, along with their storage characteristics, makes them an attractive load to be controlled. This control, either re-set of thermostat parameters or short time interruptions, should not originate temperature variations that may negatively impact on service provided, being important to establish the adequate ADR actions and temperature boundaries.

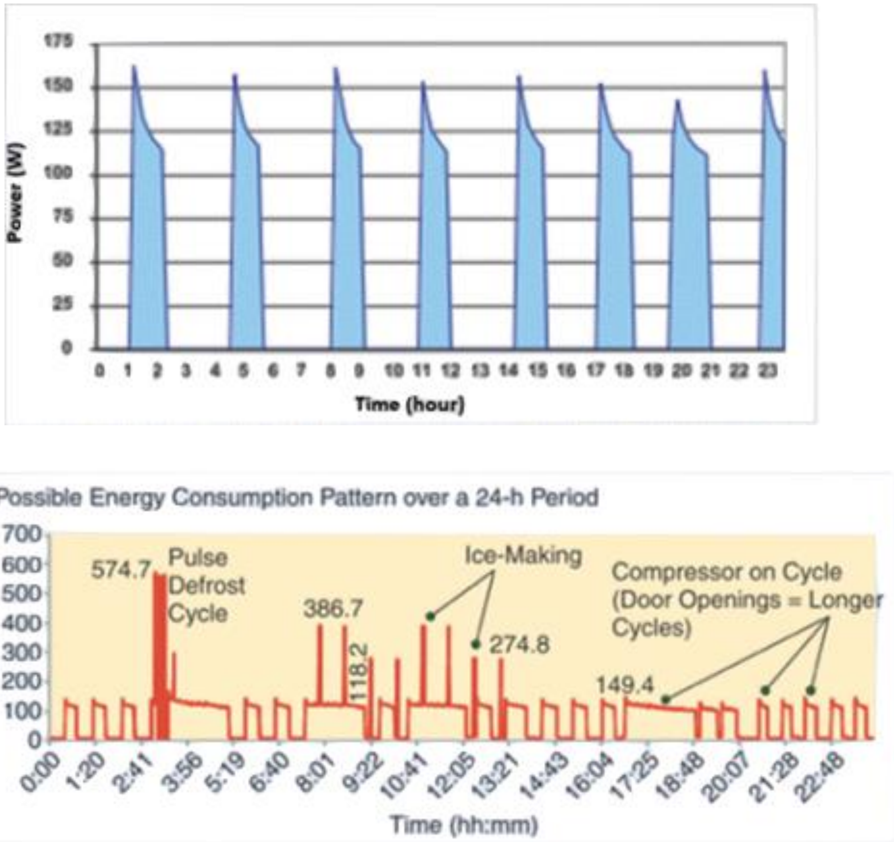

Figure 7: Typical working cycle of a refrigerator (DGGE /IP-3E, 2004; Lui et al., 2010)

According to (DGGE /IP-3E, 2004) EWHs represented more than 5% of the annual residential electricity demand in Portugal (DGGE /IP-3E, 2004). This electricity consumption is strongly dependent on the routines and habits but also on the number of people using them and hence the amount of hot water needed. In this type of thermostatically controlled load there is some dissociation between the period during which electricity is used to heat water and the effective use of hot water (Vanthournout et al., 2012). Therefore, it is possible to reduce energy costs by taking advantage of variable electricity prices through the implementation of ADR actions such as the anticipation/postponement of the working cycle and short interruptions (Ericson, 2009; Goh and Apt, 2004). It is also possible to redefine thermostat settings by lowering the desired temperature when the electricity price is high and increase it when the price is low or when electricity is available from local generation or storage system. These ADR actions should be implemented without noticeable degradation of the quality of the energy service.

Figure 8 displays the typical day average electricity consumption of EWHs whose data was gathered in energy audits for weekdays, Saturdays and Sundays (Jorge, 2010). Typically, the peaks are found in the early morning and evening for weekdays and, with peaks not so high, a bit later in the morning and in the evening for the weekend. So as long as hot water is assured when needed, the impact in comfort of the ADR actions implemented is minimized.

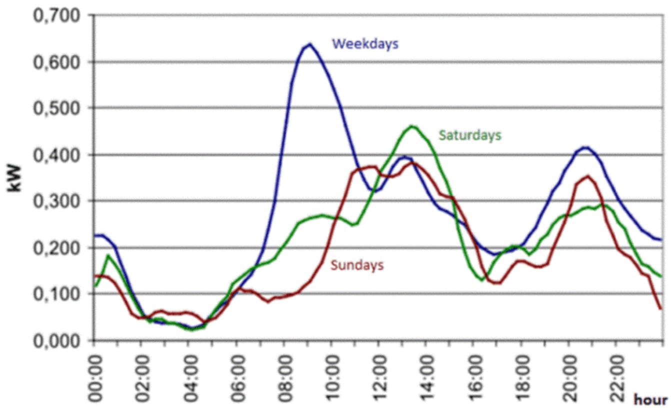

Figure 8: Daily average consumption of EWHs of representative consumers (Jorge, 2010)

Electric room heating and cooling systems are responsible for more than 15% of the annual electricity consumption in the residential sector in Portugal (Figure 2) although only AC systems are well suited for the implementation of ADR actions. However, the ownership rate of AC systems in Portugal is still not too significant even though showing an increasing trend (Shahbaz et al., 2011).

The main objective of an AC system is to provide thermal comfort to the user (Chu and Jong, 2008) and the main difficulty associated with this type of load is the correct regulation of the temperature when aiming to reduce energy consumption (Figure 9). Due to the energy storage capacity existing in rooms being heated/cooled, ADR actions are possible over this load. (Chu and Jong, 2008) showed that DR can be used in this context to re-shape the system peak load profile, when the reliability of the system is jeopardized, and the load diagram. Most energy used in an AC system (in the cooling function) in the refrigeration cycle is for compressing the refrigerant and transfer indoor heat outdoors, and it can increase or decrease depending on weather conditions and indoor heat load. ADR actions over these type of systems, either the re-set of thermostat parameters or short time interruptions must assure thermal comfort to the end-user (Chu and Jong, 2008) without neglecting the associated payback effect (Chen et al., 1995; Ericson, 2009; Gomes et al., 2013; Newsham and Bowker, 2010). The payback effect is an increase in peak demand during the restoration of loads after a period of forced supply interruption when compared with the regular demand when no ADR actions are implemented (Gomes et al., 2009).

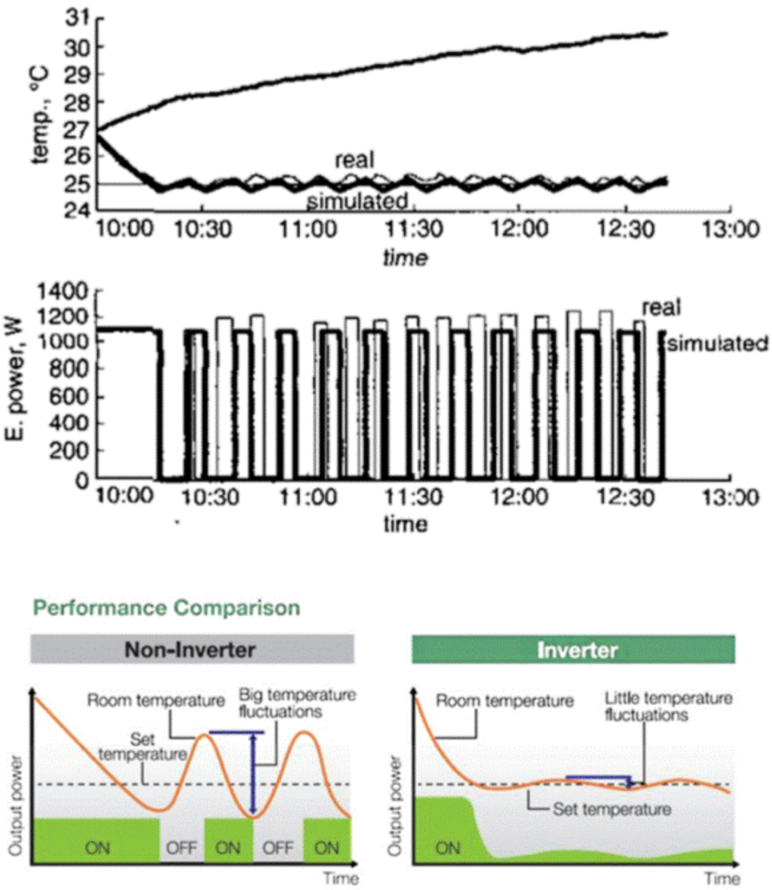

Figure 9: Temperature variation and typical working cycle of an AC system (Molina et al., 2003; Panasonic, 2012)

2.3. Final Remarks

Demand Response actions must be tailored to each manageable load and input signals, respecting technical constraints, and adapted to fulfill end-users' preferences and achieve their objectives (e.g. minimize electricity bill and minimize end-user's potential dissatisfaction).

The analysis of residential energy resources, typical patterns of usage and technical constraints allows the identification of four main load categories according to the degree/type of control (Soares et al., 2012a):

1. non-manageable loads: loads that when controlled may cause discomfort to the user or perturbation to ongoing activities (lighting, office and entertainment equipment, cooking appliances);
2. thermostatically controlled loads which can be also called reparameterizable loads: loads that are thermostatically controlled and allow a re-set of thermostat settings changing energy consumption (cold appliances, AC systems and EWHs);
3. interruptible loads: loads which can be interrupted during a short period of time without decreasing in a perceived way the quality of the energy services provided (cold appliances, AC systems and EWHs);
4. shiftable loads: loads whose functioning can be postponed or anticipated according to end-users' preferences (laundry machines, tumble dryers, dishwashers and EWHs).

According to this categorization, and the typical annual consumption of those loads in Portugal, it is possible to trace the relation between the potential degree of load control and annual electricity consumption (Figure 10):

- the x-axis refers to the annual electricity consumption (GWh);
- the y-axis refers to the potential degree of control (1 – non-manageable loads, 2 – reparameterizable loads, 3 – interruptible loads, 4 – shiftable loads);
- the circle or/and the ellipse represent all the possible types of control, being the most typical control represented by the circle;
- each circle has a radius proportional to the average electricity consumption per year.

It is important to point out that although the same type of control may be applied to several loads, the characteristics of the ADR actions (duration of the interruption, new temperature settings, time deferral, etc.) are different and may differ along the day (D'hulst et al., 2015). This means that each control strategy must be tailored to each end-use and therefore take into consideration the energy service to be provided and the end-users' flexibility and requirements.

According to this analysis, the loads that present higher annual consumption are fridges, air heating systems and freezers. Fridges and freezers are on during all day and thus present a high annual electricity consumption (Soares et al., 2012b). Room heating, despite the seasonality of its use, also has high electricity consumption and one of the reasons may be the poor insulation in buildings and the high ownership rate of these systems. Nonetheless, it is not easy to actuate over these systems, contrariwise to AC systems, which can be seen as a strong candidate to the implementation of ADR actions.

As far as control is concerned, EWHs may be the target of different actions: they can have the temperature re-set, the working cycle interrupted and even have some flexibility concerning the working cycle operation, as long as water is hot at a certain hour. Also fridges and freezers may have the temperature re-set or be interrupted during a short time period. These different ADR actions to be implemented are represented in Figure 10 using ellipses that cover different possible types of control. PHEVs are not represented since their annual electricity consumption is still not significant but it could be categorized under interruptible and shiftable load categories.

Ovens, lighting, office and entertainment equipment cannot be managed, since their control strongly interferes with end-users' comfort and activities thus strongly depreciating the quality of the energy services provided.

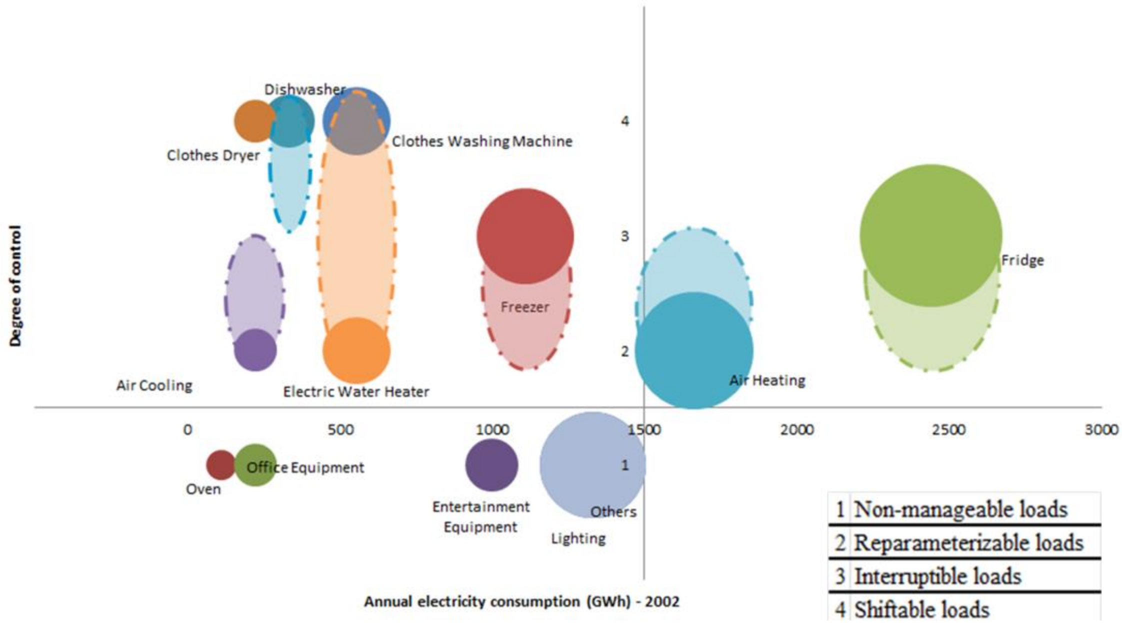

Figure 10: Load categorization according to its degree of control and annual electricity consumption (Soares et al., 2012b)

For the adequate control and coordination of responsive residential demand, the integrated monitoring of electricity consumption at the household level must be assured. The continuous monitoring of demand and load control cannot, however, be entirely left to the end-users due to their complexity either concerning the variety of decisions to be made or the requirements in terms of time availability to implement ADR actions. ADR actions are responsible for:

- modifying the power profile of thermostatically controlled loads by changing the reference temperature;
- postponing/anticipating the working cycles of shiftable loads;
- deciding when to charge/discharge storage systems;
- interrupting the operation of interruptible loads;

in response to input signals such as energy prices, direct incentives (due to emergency requests) and residential end-users' requests and requirements (Federal Energy Regulatory Commission, 2011).

Leaving all the decisions to the end-user would lead to response fatigue and loss of willingness to continue participating in DR programs (Vanthournout et al., 2015). Thus the importance of EMS which are needed to decide, on behalf of the end-users, the control actions to implement, how and when (Lopes et al., 2012). Accordingly, EMS should be able to manage residential energy resources without negatively impacting the quality of the energy services provided (e.g., room temperature below/above a pre-specified comfort threshold, completion of the washing machine operation cycle before a given instant) (Soares et al., 2014a, 2013b). Operational aspects linked to the functioning of each energy resource must therefore be adequately considered and included in the optimization process. Thus the previous characterization of manageable energy resources and assessment of the potential effect of ADR actions in the residential load diagram is of utmost importance (Soares et al., 2014b).

The deployment of EMS endowed with adequate optimization algorithms will give DR schemes a more important role in the electricity market. Demand responsive programs allow the management of load operation in order to benefit from dynamic tariffs and renewables availability (Gyamfi and Krumdieck, 2011; Strbac, 2008; Tsui and Chan, 2012). They also can contribute to increase reliability, mitigate the impact of generation shortfalls and decrease transmission congestion as well as drop of financial risks such as wholesale price spikes (Heffner and Grayson, 2001).

Several studies already focus on the control of different loads, mainly thermostatically controlled loads like AC systems and EWHs and shiftable loads, with a special emphasis on the PHEV (Amato et al., 2007; Du and Lu, 2011; Ericson, 2009; Goh and Apt, 2004; Heleno et al., 2015; Ilic et al., 2002; Lee et al., 2014; Mohsenian-Rad and Leon-Garcia, 2010; Molina et al., 2011; Pedrasa et al., 2010; Schweppe et al., 1989). In this thesis the manageable loads are shiftable loads (Soares et al., 2014b), a PHEV, a stationary storage system and thermostatically controlled loads, namely a fridge, an EWH and an AC system.

The management of such loads, particularly thermostatically controlled loads, may present conflicting objectives: on one hand, the end-user wants to reduce the electricity bill while, on the other hand, he/she does not want to have the quality of the energy services depreciated and may therefore impose restrictions on the control actions. Thus, when implementing ADR actions, the end-user should be allowed to previously define restrictions regarding the quality of the energy service provided by loads and associate a penalty to its violation as a result of a certain control action. The end-user should be able to define:

- a temperature range for the acceptable variation around the reference temperature of thermostatically controlled loads and interruptible loads;
- the most suitable time slots for the operation of shiftable loads;
- the desired SoC of the PHEV battery.

The proposed algorithmic approach differs from previous works in the methodology used, range of loads being managed, the different type of ADR actions that may be implemented to achieve an integrated optimization of all energy resources, the type of models used to reproduce their regular behavior and the impact of ADR actions, the ability to keep the maximum power requested to the grid below the contracted power, and to react to external emergency requests or modification of end-user's preferences and non-manageable demand.

The final aim is finding solutions which minimize the cost of the energy consumed and the potential end-user's dissatisfaction associated with the management strategies. This dissatisfaction is computed by considering an objective function consisting in penalties associated with:

- the end-users' preferences not entirely satisfied concerning the allowable time slots for the operation of each load (Soares et al., 2014a);
- changing the temperature set-point of thermostatically controlled loads;
- the closeness of the actual peak power with respect to the contracted power (as a surrogate for the risk of supply).

3. APPROACHES TO MANAGE RESIDENTIAL ENERGY RESOURCES[5]

Evolutionary algorithms (EAs) have been widely used to solve a variety of complex optimization problems, namely with combinatorial or/and nonlinear features in engineering areas. After a comparison with other techniques, some of which are briefly presented in section 3.6, EAs were identified as an adequate approach to deal with the integrated optimization of residential energy resources. This is a multi-objective optimization problem, with combinatorial characteristics with a very large search space. EAs showed to be able to provide very good solutions in a reasonable computational time and also have the ability to quick re-compute new solutions whenever the conditions suddenly change, namely end-user's manageable resources availability, comfort preferences or preferred periods of time for allocating shiftable loads. In case these changes occur, there is no need to re-introduce information concerning the current power demand, temperatures etc., since the approach computes new solutions using as inputs the information contained in the optimization process just before the event happened. Therefore, this chapter is mainly focused on EAs, although other relevant optimization techniques are also briefly described in section 3.6.

3.1. BRIEF DESCRIPTION OF EAS

A general overview of EAs, with a special focus on multi-objective optimization, and several examples of the most representative algorithms and their applications can be found in (Coello Coello, 2006). EAs have revealed as useful approaches, namely to address combinatorial problems with multiple conflicting objectives. In the energy sector EAs can be used to solve problems such as network planning, unit commitment and dispatch (Mashhadi et al., 2003), scheduling appliances working cycles (Omara and Arafa, 2010; Soares et al., 2013b), grid reconfiguration (Chittur Ramaswamy et al., 2012), minimization of power losses (Possemato et al., 2013; Ramaswamy and Deconinck, 2011), among many others (Antunes and Henriques, 2016).

EAs are based on Darwin's evolution theory of survival of the fittest and commonly used in search and optimization processes. In this methodology a group of potential solutions (population) to the problem evolve during several generations through the use of specific operators inspired on genetic mechanisms offering the strongest individuals a higher chance of survival. This evolution will hopefully lead to the "fittest" individual in single objective optimization or the identification of a Pareto frontier in multi-objective optimization. Solution encoding is an important step when designing EAs and the detailed knowledge of the physical characteristics of the optimization problem to be solved can bring some insights. Nevertheless, there are no general rules to be followed to produce an effective representation scheme. In Figure 11 the chromosome

[5] This chapter is based on Soares, A., Gomes, Á., Antunes, C.H., 2015. Integrated management of energy resources in the residential sector using evolutionary computation – a review. Soft Computing Applications for Renewable Energy and Energy Efficiency edited by M. Cascales, J. Lozano, A. Arredondo et al. Copyright 2012, IGI Global, www.igi-global.com.

representing each solution uses binary encoding to represent whether a given manageable load is on (“1”) or off (“0”) in each instant of time. The operators typically used are:

- Selection: used to select individuals, either for generating offspring or being included in the next generation;
- Crossover: used to combine characteristics of different individuals;
- Mutation: used to insert changes and consequently diversity in the population.

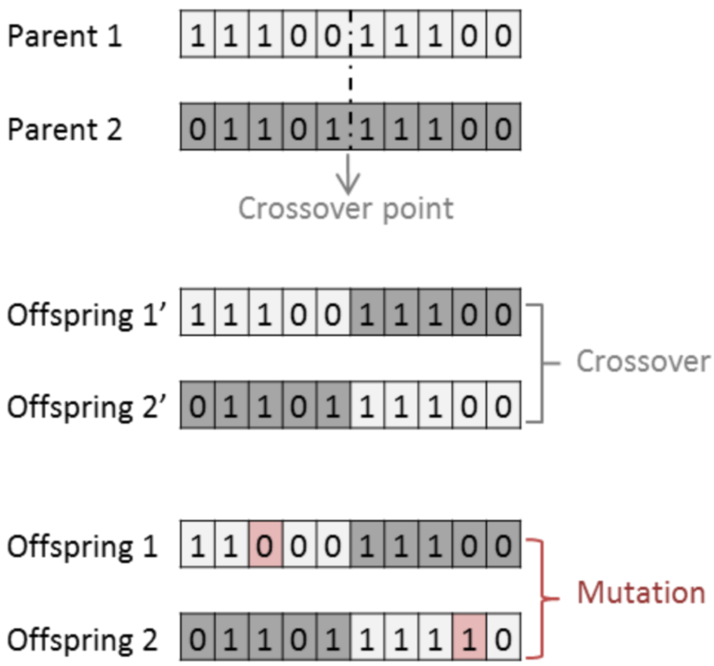

Figure 11: Example of a solution encoding and impact of the operators in the offspring (one-point crossover and mutation of one gene in each offspring)

The initial population usually consists of random candidate solutions or solutions created using problem domain expertise. The fitness function, used to evaluate solutions, is generally based on the objective function(s) but may incorporate additional merit evaluation issues, such as a penalty term accounting for model constraints violation. Solutions are chosen to seed the next generation using a selection procedure, such as tournament or roulette wheel, usually based on their fitness. The crossover operator is then used over the selected parents to generate offspring by combining the parents’ genetic material (i.e. solution components). The mutation operator is aimed at introducing further changes in some solutions, thus promoting diversification in the search space. The successive application of these probabilistic operators leads to (hopefully better) solutions in subsequent generation populations. The use of crossover, mutation and selection operators allows combining, modifying and choosing possible solutions iteratively until a good approximation of the optimal solution/Pareto frontier to the single/multi objective optimization model is found. The transmission and improvement of some characteristics of the solutions from one generation to the next one can be perceived as a form of memory allowing the population to evolve to regions in the search space where better solutions reside (Dréo et al., 2006). The stop condition is typically attaining the maximum number of generations, a satisfactory value for the fitness function, or the time elapsed. During the evolution process an elitist strategy can be used to keep a given number of the best solutions preserved and avoid their loss with the aim of facilitating the convergence of the process, although the risk of premature convergence may exist if an excessive elitist pressure is imposed.

Concerning the smart grids context, evolutionary approaches have been used to optimize the management of residential energy resources at the household's individual level according to different aims. Considering the existence of EMS such as the one proposed in (Livengood and Larson, 2009; Lopes et al., 2016b, 2012b), decisions can be implemented in an automated way as long as previous information about end-users' requirements and preferences is known. External signals reflecting the grid's state, such as emergency signals, may also be received by the EMS and interpreted to derive optimal decisions in almost real-time.

Concerning the management of the energy resources and implementation of DR actions, two levels of aggregation may be defined:

- an upper level where loads under control are not disaggregated since this depends on which households respond to the signals and requests coming from the utility;
- a lower level where the algorithms are aimed at controlling specific manageable loads within the household.

Most approaches embedded in EMSs have the same common goal - the minimization of the electricity bill - and use energy prices as input (Allerding et al., 2012; Antunes et al., 2013; Conte et al., 2010; Morganti et al., 2009; Penya, 2003; Salinas et al., 2013; Soares et al., 2013b; Zhao et al., 2013b). Nevertheless in (Logenthiran et al., 2012) instead of using directly the energy prices, the input consists in a load curve to be attained, which is inversely proportional to the electricity market prices. The constraints considered depend on who makes the request to implement DR actions: in the case of utilities, specific grid constraints are included in the model (Yao et al., 2005), whereas in the case of residential end-users the constraints are mainly focused on their preferences regarding availability for letting a system controlling specific loads, within certain time bounds, and the variation of the energy price. The algorithmic approaches mainly comprise hybrid and parallel genetic algorithms (GAs), tailored and heuristic-based EAs and non-dominated sorting GAs. GAs are the most common option and they are used in (Penya, 2003; Soares et al., 2014a, 2013b; Yao et al., 2005; Zhao et al., 2013b). (Conte et al., 2010; Morganti et al., 2009) combine GAs with multi-agent theory to schedule the operation of multiple loads aiming at minimizing a performance index composed by the number of overloads (overload happens when the requested power in a given instant of time overcomes a certain limit) and the relative delay (represents the amount of time between the actual completion of the energy service and the time it would have finished if the operation cycle have started as soon as the on instruction is given). (Allerding et al., 2012; Logenthiran et al., 2012; Salinas et al., 2013) use EAs to solve the optimization model.

Although some studies clearly state the controlled loads and thus a disaggregated level is considered (Antunes et al., 2013; Conte et al., 2010; Morganti et al., 2009; Penya, 2003; Soares et al., 2013b; Yao et al., 2005; Zhao et al., 2013b), other studies request a certain amount of energy to be shedded but do not identify the loads to be managed (Carreiro et al., 2015; Logenthiran et al., 2012; Salinas et al., 2013). Typically, thermostatically controlled loads such as ACs are one of the targets of DR actions.

The next sections present a more detailed analysis of the several approaches used in this context of smart grids for the optimization of load management along with their main features.

3.2. PARALLEL GENETIC ALGORITHM

(Penya, 2003) presents a parallel GA, commonly called island model PGA or coarse grained PGA, to schedule the energy consumption of several loads according to three objectives:

- minimization of power peaks;
- minimization of energy acquisition cost;
- maximization of comfort associated with the preferred load operation time and the actually planned execution time.

The algorithm developed can be at the core of an EMS installed mainly in buildings to control lighting, AC and heating systems. However, the loads to be controlled are discussable, since the management of lighting cannot be done in the same way as the control of an AC system as it depends on the level of natural light coming in from outdoors together with the activity of the household's occupants (Richardson et al., 2009). In fact, although lighting is responsible for a reasonable part of electricity consumption in the residential sector - about 10% of the residential electricity consumption in EU-27 (Bertoldi et al., 2012) -, feasible DR actions on lighting are quite reduced and clearly do not include deferral in time. Supply interruptions can only be implemented when combined with occupancy sensors, thus not requiring the use of an EMS for an integrated management of this energy service. Dimming options are unsuitable for some types of lamps and are not mentioned as a DR action (Penya, 2003).

The main features of an island model PGA are the division of the population into demes (set of partners which any individual in a population may mate - semi-independent sub-populations), which evolve separately, and the potential migration that allows demes receiving the best solutions from other islands and consequently incorporating better features along the evolution process. Migratory movements can occur between demes as long as they belong to adjacent islands. However, even in this situation migration should not be too high otherwise the demes may overlap. When the load scheduling process begins, individuals are grouped into islands so that each group can explore a part of the search space. Communication concerning the expected consumption of the devices along the planning period is an important piece of this strategy. The parameters, which are tuned by experimentation, include how often a device must share its expected consumption, the frequency of migrations between islands and the maximum number of generations. When the maximum number of generations is attained, the candidate solutions are compared and the best one is chosen, although the authors are not very clear how this final choice is made.

3.3. Iterative Deepening Genetic Algorithm

Motivated by the high percentage of energy demand in Taiwan due to AC systems during summer, (Yao et al., 2005) present a methodology to help Taiwan's power company to implement DR actions over these specific loads. The implementation of these actions is done at an aggregate level.

The proposed approach uses a modified GA, called iterative deepening genetic algorithm (IDGA), to optimize the scheduling of DR actions over groups of AC systems. In the solution encoding each gene represents a group of loads. The objective is minimizing the utility company's revenue loss due to the implementation of DR actions, also minimizing the number of loads to be shedded. To assure the participation of customers in this type of programs and avoid complaints, the accumulated shedding time of each load group should be levelled off. For each group the minimum time to keep loads running before any shedding action is implemented is considered as a constraint. This constraint assures that mechanical weariness due to frequently turning on and off these loads is reduced and the system performance is not affected. The proposed IDGA finds a sub-optimal solution with the best set of status (on/off) combinations for the AC group of loads under control. The payback effect associated with these loads is considered in the model, thus avoiding the creation of new (and possible worse) power peaks when supply is restored to loads.

The IDGA uses a two-level strategy where a master GA evaluates the status combinations by iteratively calling a slave GA at each of the subsequent time steps and evaluating possible forward status combinations. This modified GA differs from the typical GA since the search process begins in the current sampling interval down to a pre-defined number of time steps instead of searching from the beginning until the end of the control interval. In order words, the proposed algorithm, aiming at minimizing the required load to be shed, looks ahead for the load difference at each of the subsequent time steps beginning at the current time step.

Another difference between the IDGA and the typical GA is the gene selection scheme used to keep the total amount of shedding time for each AC group close to the average. In this strategy the accumulated time under control and off control for each one of the groups is stored and used to compare with the accumulated time under and off control of a group of ACs. According to the result of this comparison, the probability of that group being selected for shedding or for exemption in the next time step may increase or decrease. Thus, the chance of a gene being selected depends on the deviation of its corresponding accumulated shedding time from the average value. In the typical GA each gene has the same probability of being selected. Although not guaranteeing to reach the optimal solution, in general a less time-consuming but satisfactory sub-optimal solution is found with this IDGA strategy.

3.4. GENETIC ALGORITHMS AND MULTI-AGENT SYSTEMS

(Conte et al., 2010; Morganti et al., 2009) combine two approaches to manage electricity demand at a lower level. Multi-agent systems theory (Niazi and Hussain, 2011) is used to reproduce the behavior of appliances while GAs are used to tune important parameters associated with the operation of the loads under control. Two different agent categories are considered:

- the domotic agents, which receive information such as the power level at a given instant and adapt their behavior accordingly;
- the domotic objects, which are not capable of interpreting information and whose operation cannot be neither interrupted nor shifted to another time slot.

Since the domotic agents need electricity to complete their operation cycles, there is a competition with the domotic objects for this resource. The power available may, however, not be sufficient to satisfy all the agents at the time of request due to the power limit of 3 kW. This threshold may be exceeded for a few minutes without the occurrence of a blackout.

The domotic agents to be allocated according to previous established priorities are the dishwasher and the laundry machine and compete with the boiler and non-manageable devices for electricity. The boiler has the highest priority in the use of electricity and is followed by the use of non-manageable devices. The overall power requested to the grid by these two agents does not exceed the 3 kW threshold, but if these domotic agents are running and an overload occur then one of them must be turned off.

Concerning the allocation of the dishwasher and laundry machine, two parameters are used to account for the end-user satisfaction: the overload and the suspension times for the two machines. While the overload time represents the time the appliance must wait before interrupting its operation, the suspension time represents the time the appliance waits before restarting its operation after having interrupted its working cycle. These two parameters were tuned using single and multiple objective GAs (SOGA and MOGA, respectively). The step for the increase or decrease of the parameters is 10 seconds for the overload time and 100 seconds for the suspension time.

The representation of the solutions is the same for SOGA and MOGA with each solution being encoded by an array of four integers (overload and suspension time for the dishwasher and laundry machine). The objective function to be minimized in SOGA is the overall performance index, which has two weighted components: the number of overloads and the relative delay. The relative delay for each of the manageable appliances, which should be as close to 0 as possible to assure end-user's satisfaction, depends on the priority assigned to the task. For simulation purposes the value chosen for the weights is equal to 1, thus assigning the same "importance" to both tasks. One of the main disadvantages of SOGA is precisely the use of weights, especially in the aggregate objective function with the consequent need to refine them and their sensitivity to changes.

Considering MOGA, the non-dominated sorting genetic algorithm NSGA-II (Deb et al., 2002) is used to find a set of solutions aiming at minimizing the relative delay and the number of overloads. In both approaches a tournament selection is used and the probability for the mutation and crossover operator are the same.

Both approaches present satisfactory results although SOGA tends to converge faster but with the disadvantage of only presenting a single optimal solution, instead of a variety of potential solutions.

None of these approaches include thermostatically controlled loads or the solution encoding is flexible enough to include other control alternatives than anticipating, postponing or interrupting working cycles.

3.5. EVOLUTIONARY AND GENETIC ALGORITHMS

(Allerding et al., 2012) propose an evolutionary algorithm with local search to minimize the residential electricity bill of a residential end-user who is willing to accept the intervention of an EMS to schedule his/her dishwasher, laundry machine, tumble dryer and electric vehicle. The problem is formulated as a nonlinear integer programming problem where the objective function consists in minimizing the total costs associated with energy acquisition and the extra costs resulting from the violation of a pre-defined load limitation curve. The constraints ensure that the managed loads cannot have their operation interrupted (hard constraint) and the load limitation curve is not exceeded (soft constraint with an associated penalty). The end-user is able to assign degrees of freedom to the several loads to be managed. These degrees of freedom consist in the span between the earliest starting time and the point in time when the task has to be finished (release time and deadline, respectively). The algorithm calculates the optimal starting point for the different appliances, which is constrained by the release time and the deadline.

The solution encoding is done using a Boolean matrix sized $j \times T$ (j = number of tasks to be scheduled and T = intervals of the planning period). The proposed EA uses a rank-based selection procedure where individuals are ranked according to their fitness. The probability of an individual to be chosen to generate a new offspring depends on that rank, as well as the selection of the individuals to be part of the next generation. The crossover operator decides for each appliance whether the offspring adopts the starting point inherited from parent 1 or 2. The mutation operator randomly changes the starting point of some of those loads as long as it is still constrained by the release time and deadline, guaranteeing that all new individuals satisfy the time constraints for the completion of the task. The local search is done by calculating the fitness of each solution after shifting the starting time of a single appliance by plus or minus one time unit. Solutions presenting cost improvements (i.e., lower overall costs) are stored and the solution with the single change of the starting time presenting the higher improvement is selected.

The authors also state that extensions are possible, namely the inclusion of thermostatically controlled loads into the model although more variables and constraints are required. Also, depending on the type of DR actions the solution encoding might have to be changed. Accordingly, to include those features, (Mauser et al., 2015) designed a modular building EMS able to handle energy flows and optimize the operation of several devices, while respecting any existent interdependency. The main difference of (Mauser et al., 2015) work when compared to (Allerding et al., 2012) is the simultaneous optimization of multiple energy carriers, more specifically electricity and hot water and the consequent inclusion of more loads.

Targeted loads include a photovoltaic system, a gas-fired condensing boiler, a hot water storage tank, a hob, an oven, a dishwasher, a laundry machine, a tumble dryer and a battery storage system. Machines may use hot water from the tank or heat up the water using electricity and thus the importance of interdependencies. The hob and the oven have to decide between electricity and natural gas. External inputs include energy prices, weather forecasts and end-user's goals. Solution encoding is done through a bit string whose length depends on the diversity of devices. In this way, the string may not be homogeneous since some parts of the string represent control sequences while others represent parameter settings or even time periods for which a given appliance may be deferred or interrupted. The main features of the EA comprise binary tournaments for selection, single-point crossover with two offspring, and bit-flip mutation using an elitist strategy with a rank based survivor selection.

In (Logenthiran et al., 2012) a heuristic-based EA using a generalized day-ahead DR management strategy is proposed to solve an optimization problem where the aim is minimizing the distance between a desired load demand curve and the forecasted load demand curve. The proposed approach is able to schedule the connection time of multiple manageable devices in the residential, commercial and industrial sectors, bringing the load consumption curve as close to the objective load consumption curve as possible. This approach differs from related work since it uses the objective load curve as an input. Nonetheless, considering that the final goal is to reduce the end-users' electricity bill and the desired load curve chosen is "inversely proportional" to electricity market prices, energy prices still play an important role although not so direct. Solution encoding is done using a bit string and the length of the chromosome is equal to the number of time steps × the number of bits required to represent the loads shifted in each time step. The inputs to the simulation include the control period, consumption patterns of the manageable devices and the power consumption at each time step. The population is randomly initialized and evolution is carried out using single point crossover and binary mutation operators, and tournament to select the parents to produce the offspring. The use of a large rate for the crossover operator assures fast convergence while the low mutation rate avoids premature convergence. An elitist strategy is used to keep good solutions in the population. The rates of the operators were tuned by experimentation. When a specified number of generations is attained or no significant changes occur in the fitness value for a certain amount of generations the algorithm stops.

Linking the stages of this strategy to its implementation in a real environment aimed at attaining a desired load consumption curve, the proposed DR strategy analyzes the required load actions and automatically schedules the operation of the manageable loads while respecting the previously stipulated acceptable time delay and the number of time steps that appliances can be shifted. One of the drawbacks that can be pointed out to this approach is the lack of DR actions anticipating the working cycles (the DR action only considers delaying the working cycle). The control actions are supposed to be executed in real-time based on the power demand. Hence, when the end-user tries to turn on a manageable load, the request is sent to a controller implementing the EA to make decisions concerning the DR action. Since this strategy is intended to schedule the operation of loads a day-ahead, the final decision can then be a new operation time or the immediate operation of the load. While in the residential sector the power requested to the grid is relatively low when compared to the industrial sector and the duration of the working cycles of the manageable loads is also limited, simulation results show significant savings for the three types of users varying between 5 and 10%. The commercial sector, which is characterized in this study by having slightly higher energy consumption than the one verified in the residential sector, has a reduction of around 5.8% in the electricity bill.

None of the approaches presented so far prevent the occurrence of an aggregate peak load demand. (Zhao et al., 2013b) introduced a feature in the input signals to avoid the occurrence of that situation. The aim of the proposed methodology, based on a GA, is to schedule residential electricity usage while simultaneously reducing the electricity bill and the power peak-to-average ratio (PAR). This approach uses a pricing structure different from the works previously presented since it incorporates a real-time tariff scheme combined with the inclining block rate (IBR) model to decrease the PAR. This model is also used by (Mohsenian-Rad and Leon-Garcia, 2010; Reiss and White, 2005; Zhao et al., 2013a). The main advantage of using this price structure is the possibility to avoid situations in which the use of a real-time pricing structure may cause a significant shift in demand to periods of the day presenting a lower electricity price, leading therefore to a higher peak demand and even to instability in the system. Combining the real-time pricing structure and the IBR model, the energy price during a time slot increases if the electricity consumption overcomes a pre-defined threshold. Therefore, potential solutions allocating several appliances in the same time slot, and possibly causing an undesirable power peak, will have an increase in the energy price impacting their fitness and forcing the algorithm to find solutions that do not cause an increase of the PAR and consequently maximize the stability of the entire system.

The approach used to solve the optimization problem is based on a GA and schedules residential electricity demand using as input information the energy price combined with the IBR pricing scheme. Similarly to other approaches focused on the disaggregated level, the loads to be scheduled belong to the category of manageable appliances and allow the deferral or anticipation in time of their working cycle. The end-user is responsible for setting the parameters concerning the time slot during which the load may be scheduled, the duration of the working cycle and the energy requested. Authors state that the time resolution used (12 minutes) is short enough for the operation of the considered loads and more convenient to solve the optimization problem. However, some drawbacks are associated with the use of the chosen time step: the length of the working cycle of thermostatically controlled loads, like an AC, and shiftable loads, such as laundry machine, tumble dryer and dishwasher, has to be set to integer multiples of the time step. The problem to be solved is a single-optimization problem that aggregates in a single objective function to be minimized the costs associated with energy acquisition and the difference between the release time (i.e., first instant when the appliance can start its operation) and the actual start of operation. Weights are associated with each objective, which means that similarly to what happens in (Morganti et al., 2009) those weights should be duly defined.

(Salinas et al., 2013) designed two EAs to obtain the Pareto front solutions and approximate ε-Pareto front solutions to solve the load scheduling problem. These algorithms are to be used by an external entity responsible for managing energy consumption of a group of end-users, and thus an aggregate level is considered. The objectives are the minimization of electricity bill and the maximization of a utility function, which differs according to the external entity. Hence, while in the case of a company aiming to manage its energy consumption, the objective is minimizing the energy acquisition cost and maximizing the gross income, for a community manager what matters is the maximization of comfort of the people living in that community. Usually these utility functions are non-decreasing regarding the energy consumed (Samadi et al., 2011). All energy requests are submitted to this external entity responsible for optimally scheduling the demand according to the two conflicting objectives. The constraints for this optimization problem include the users' tolerance for the daily energy consumption (i.e., the deviation from the amount of energy he/she intends to consume, which is linked to the loads to be operated), assure that the user's energy request to complete a specific energy service is satisfied between the requested starting time and deadline, and the total energy consumption does not exceed the maximum generation capacity of the system. Input signals include a three-piece price function where the energy price increases significantly when the total energy consumption exceeds a certain threshold. The total amount of energy allowed to be used by the external entity is also limited and if the threshold is exceeded an arbitrarily high energy price is assigned. Solution encoding is done using a vector that represents the complete energy consumption schedule for each user during one day with time slots with equal length. NSGA-II (Deb et al., 2002) is used in this approach to obtain a set of Pareto-optimal solutions and the trade-offs between energy acquisition costs and the utility function value. It is important to highlight that the initial population does not have to meet the constraint associated with the maximum value for the total energy consumption but the evolution of the population guarantees that all constraints are met.

Although the results using NSGA-II are satisfactory, the required computation time is high and a dense Pareto front where adjacent solutions provide similar trade-offs is provided. Since neither the external entity nor the end-user benefit from finding different solutions with approximate trade-offs, an ε- load scheduling EA (ε-LSEA) that provides a less densely populated Pareto-front is proposed. The major difference between this latter approach and the previous one is based on the choice of the parents and the offspring. The ε-LSEA chooses one parent from an archived population with variable size and another one from the fixed sized population, and only one offspring is generated per iteration.

For this specific optimization problem, the authors state that ε-LSEA presents a higher efficiency when compared to LSEA using NSGA-II, especially when the number of users becomes larger. (Salinas et al., 2013) do not provide any information concerning the type of users, the managed loads, amount of energy available for being managed or even the characteristics of DR actions.

It is important to note that in any case the allocation of manageable loads should not follow static rules and must be capable of evolving and adapting according to the dynamics of the planning environment (consumption, generation and storage availability at a given instant) while maximizing the possibility for every residential load to satisfy its demand in the preferred time slot, maximizing end-user's satisfaction regarding the quality of energy services, minimizing electricity bill and maximizing the use of local generation/storage.

Most approaches presented so far focus on the control of manageable demand, or at least request the implementation of DR actions, but do not include a dynamic relation with distributed local generation and storage capabilities, with the exception of electric vehicles. These optimization problems are typically subject to several technical and user-defined constraints and therefore present a significant complexity (Molderink et al., 2012). For instance, thermostatically controlled loads may be switched off or have temperature settings re-parameterized depending on the end-user's preferences. Also, the use of laundry machines in different time slots is dependent on user's acceptance. Nevertheless, in the literature other approaches besides EAs are proposed to optimize electricity consumption and exploit the benefits of distributed generation and storage systems.

Considering that in the smart grid context a deployment of local generation systems based on renewables is expected and these sources are generally intermittent, attention should be paid to their incorporation in this type of studies, especially if used together with storage systems. Electricity generated locally, for example during the night by a micro wind turbine, can be stored and used later or sold to the grid (Molderink et al., 2010b). The amount of energy withdrawn from a battery or charging a battery is also influenced by the user's needs and may vary along the day. The optimization process should then encompass the integrated optimization of all energy resources to obtain usable solutions.

A summary of the main features of each model described is presented in Table 2. For sake of comparison, the table also presents the contributions of this PhD research which will be further detailed in Chapters 4 and 5.

Table 2: Summary of model structure

	Reference	(Allerding et al., 2012)	(Conte et al., 2010)	(Morganti et al., 2009)	(Penya, 2003)	(Salinas et al., 2013)	(Zhao et al., 2013b)	(Logenthiran et al., 2012)	(Yao et al., 2005)	(Mauser et al., 2015)	(Soares et al., 2013b)	(Soares et al., 2014a)	(Soares et al., in press)
Perspective	grid					x							
	consumer	x	x	x	x	x	x	x		x	x	x	x
	utility					x			x				
Optimization problem	single-objective	x	x	x	x		x	x	x		x		
	multi-objective		x	x		x						x	x
Algorithmic approach	GAs						x				x	x	x
	GAs + Multi-agent systems		x	x									
	EAs	x				x		x		x			x
	Parallel GA				x								
	IDGA								x				
Evaluation aspects	minimize electricity bill	x	x	x	x	x	x	x		x	x	x	x
	minimize no. of overloads		x	x									x
	minimize delay associated with load operation		x	x			x						
	minimize power peaks				x		x						x
	maximization of a utility function					x							
	maximize comfort/minimize dissatisfaction				x							x	x
	minimize company's revenue loss								x				
	minimize no. of shedded loads								x				
	minimize difference between objective load and forecasted load curves							x					
Inputs	energy price	x	x	x	x	x	x			x	x	x	x
	end-user's preferences	x					x				x	x	x
	objective load curve							x					
Constraints	equipment	x							x			x	x
	grid					x		x	x			x	x
	residential end-users	x				x	x	x			x	x	x
	contracted power	x	x	x							x	x	x
Loads controlled	disaggregated	x	x	x	x		x		x		x	x	x
	aggregated					x		x		x			

3.6. Other Optimization Techniques

The advantages of residential energy management in the context of smart grids have been addressed in recent studies and several researchers have developed different methodologies to solve that problem. Accordingly, other approaches besides EAs have been used, such as:

- linear programming (Conejo et al., 2010; Kishore and Yener, 2011; Mohsenian-Rad and Leon-Garcia, 2010; Molderink et al., 2010a);
- mixed linear programming (Paterakis et al., 2015);
- convex programming (Tsui and Chan, 2012);
- game theory (Mohsenian-Rad et al., 2010a);
- dynamic programming (Livengood and Larson, 2009);
- tabu search (Abras et al., 2008);
- bi-level optimization (Safdarian et al., 2014);
- dual decomposition plus stochastic gradient (Deng et al., 2013);
- other population-based meta-heuristics such as particle swarm optimization (PSO) (Kahrobaee et al., 2013; Kishore and Yener, 2011; Pedrasa et al., 2009, 2010).

Without aiming to do an extensive analysis of these approaches, some of them are briefly presented.

(Molderink et al., 2010a) propose a three-step control methodology to manage generation, storage and consumption. The main goal is to optimize the use of residential resources, by supplying heat and electricity demand and shaving power peaks without compromising the end-users' comfort. The problem of finding the optimal combination of sources to minimize costs and matching heat and electricity demand is dealt with by means of an integer linear programming model. This model can be used at a neighborhood level with distributed micro-generation based on renewables contributing to the materialization of a virtual power plant. The control strategy consists in determining the local profile, offline global planning and real-time local control. The approach enables the control of residential electricity and heat demand, generation and storage of heat and electricity (Molderink et al., 2010b, 2009). In the first step a neural network approach is used for predicting energy demand and generation mainly focusing on heat demand while the second step uses heuristics for the planning based on local and global objectives. While local objectives may include minimizing the electricity bill by shifting electricity demand to more beneficial periods and minimizing PAR through peak shaving, global objectives can comprise the maximization of revenue from managing a large group of micro-generators with a total capacity comparable to a conventional power plant. The last step consists in deciding which appliances are switched on/off.

(Mohsenian-Rad and Leon-Garcia, 2010) aim to achieve a desired trade-off between two objectives: the minimization of the electricity bill and the minimization of the spanning time for the operation of the loads under control. Although the problem is stated as multi-objective model, the objectives are aggregated into a single objective function by assigning a cost to the spanning time. Similar to (Zhao et al., 2013b) a real-time tariff combined with the IBR model is used to avoid the concentration of a high demand in low-priced periods. Additionally, a really short random starting delay is used to avoid different appliances from starting simultaneously. The optimization approach is based on linear programming and uses price forecasts.

Another approach proposed by the same authors uses game-theory to design a novel pricing model to be incorporated into an EMS responsible for finding the optimal energy consumption schedule for the end-user (Mohsenian-Rad et al., 2010a). The aim is minimizing the electricity bill as well as the PAR. Game theory is also used by the same authors to formulate an energy consumption scheduling game where the players are the residential end-users and the strategies are the daily schedule of the managed loads (Mohsenian-Rad et al., 2010b).

Mixed linear programming is used in (Paterakis et al., 2015) in a day-ahead context to determine the optimal schedule of manageable loads under an hourly varying tariff structure while assuring that the contracted power limit is not overcome. This approach also encompasses a photovoltaic-based system (PV), a PHEV and an energy storage system. Concerning the managed loads, thermal models were used to mimic the behaviour of thermostatically controlled loads, previous known duty cycles for shiftable loads and a group of equations describing the behaviour of the PHEV and storage system. According to the authors, the average solution time is quite low and therefore the model may be effectivelly deployed in an EMS.

In order to coordinate DR provided by residential customers (Safdarian et al., 2014) use bi-level optimization. In this approach, models used for load management are seen as independent agents endowed with bidirectional communication and responsible for receiving information from the grid concerning energy prices and total load profile and sending to the grid the daily schedule of their loads. The objective is minimizing the electricity bill while flattening the overall load profile. In this approach, there is a continuous data exchange and load profile updates untill no further improvement is achieved, attaining therefore a Nash equilibium point in the final solution. According to the concept of bi-level optimization, the problem to be solved is divided into a upper and lower subproblems, from the utility and end-user's perspective, respectively. Hence the upper subproblem aims to flatten total load profile, whereas the the lower subproblem goal is minimizing end-users' electricity bill.

(Tsui and Chan, 2012) propose a convex programing optimization framework to automatically manage residential appliances in the context of smart grids using an EMS. The focus is the optimal allocation in time of the manageable appliances in a single home under a real-time pricing structure known in advance, subject to the appliances operating constraints. The objective function to be minimized comprises the total cost of using the appliances and the users' dissatisfaction. The technical constraints and users' dissatisfaction depend on the appliance. The dissatisfaction can be measured using a utility function or a monetary cost derived from the end-user information associated with the operation of each appliance.

In this approach the appliances are classified under four categories:

1. Schedule-based appliances with interruptible load (SA- IL): appliances that should have the working cycle allocated within a user-defined time interval and may have their operation interrupted (e.g., pool pump);
2. Schedule-based appliances with uninterruptible load (SA- UL): appliances that should have the working cycle allocated within a user-defined time interval but cannot have their operation interrupted (e.g., laundry machine);
3. Battery-assisted appliances (BA): appliances with an internal battery or stationary storage systems;
4. Model-based appliances (MA): appliances whose working cycle may be described by physically-based models (e.g., thermostatically controlled loads).

For the first group of loads, the approach only needs to schedule when the load is "on" or "off" within a user's preferred time period, since the amount of energy consumed is fixed and interruptions are allowed. Concerning schedule-based appliances with uninterruptible load, additional constraints must be considered to avoid the interruption of the working cycle ensuring that the appliance operates consecutively once it starts. The amount of energy to be supplied to or withdrawn from a BA is bounded as well as the total energy stored in the battery, so values outside these boundaries are not allowed. In the case of MA the amount of electrical energy consumed may be managed according to the desired temperature to be achieved.

The way end-users' dissatisfaction is measured also depends on the appliance category. Thus, this monetary value may be added to the cost of the objective function if the working cycle of a SA-IL/SA-UL is not allocated, the energy used by the BA is reduced too much, or the variation of the indoor temperature with respect to a pre-defined comfort temperature is perceived by the user. The final aim is to prevent the EMS from sacrificing the users' comfort by:

- not allocating some appliances;
- withdrawing too much energy from a battery;
- setting temperatures outside the desired range in order to minimize the electricity bill.

Simulations carried out by the authors schedule the operation of four types of appliances in one-day time horizon (time step 1 hour) using as input the energy price. The possible utilization of distributed renewable energy sources was considered by including a photovoltaic panel, which can deliver a maximum energy in a certain time interval. Simulation results have shown that the proposed convex programming optimization framework efficiently solves the problem. Nevertheless, actions such as selling back electricity to the grid or even decisions concerning whether to sell, store or use electricity in a given instant considering the status of the system were not considered.

In a complementary way and already including storage, (Kahrobaee et al., 2013) focus on the determination of the optimal size of a wind generation-battery system with the aim to minimize the overall household electricity bill. The approach uses a hybrid stochastic method based on Monte Carlo simulation to capture the long-term stochastic electricity consumption of loads, electricity tariffs and the expected wind generation, and PSO to solve the optimization model. Initial capacities for the battery and generation systems are selected and a population of particles is generated to evolve them. The decision variables are battery and wind generation capacities and the set of constraints include power balance (energy demand must be equal to the energy bought from the grid minus the energy sold plus the energy withdrawn from the battery), operational limits of the battery and the maximum capacities for the wind generator and the battery. The output of the wind generation may be either used to match demand or to charge the electricity storage system. If the amount of local generation exceeds the demand, then the remainder can be directly sold to the grid based on a contract between the two parties. The results for the case-study showed that the optimal values for the capacity of the wind generator and battery would decrease peak demand by 25% compared to a conventional home with the same average load without any wind generation-battery system installed.

(Du and Lu, 2011) present an appliance commitment scheme, similar to unit commitment, to schedule residential loads over a given period of time based on price and consumption forecasts. Although there are similarities with the unit commitment problem, the main differences lay on the:

- stochastic usage of loads impacting on their electricity consumption;
- existence of few power output levels for each load (i.e., each load has just a few specific demand profile and its operation should be done accordingly);
- formulation of the constraints associated with the loads to be scheduled, namely thermostatically controlled loads whose set of linear or nonlinear constraints must reflect end-users comfort settings.

The illustration of the proposed approach uses an EWH and forecasts concerning the use of hot water. Authors state that the inclusion of other types of loads, distributed generators and energy storage systems is also possible. The objective function is to minimize the electricity bill over 24 hours meeting the expected hot water demand. The end-user's satisfaction concerning the use of hot water is tackled transforming the admissible temperatures in different periods of the planning period into a set of linear constraints. The appliance commitment is formulated as a nonlinear optimization problem and solved using a multiple-looping algorithm similar to the one proposed by (Lu et al., 2004) improved with the introduction of linear sequential optimization. This enhancement makes the approach robust to uncertainties associated with the forecasted prices and flexible to deal with comfort constraints. A two-step adjustment process is used to solve the deterministic problem based on forecasted spot prices and hot water usage and then make adjustments in real-time according to updated information.

(Abras et al., 2008) use a multi-agent system to minimize the electricity cost consisting of several types of agents decomposed into two main mechanisms responsible for:

- keeping end-users' satisfaction above a certain threshold and the power consumption below a given value;
- compute global consumption and production plans.

A tabu search algorithm is used to compute the global consumption and production plan. However, and differently from the previous approaches, this optimization is done by solving sub-problems involving different agents. The advantage of this strategy is the reduction of the complexity associated with the number of devices being managed and the number of periods of each sub-problem. The division into sub-problems is done respecting end-user's satisfaction concerning the use of the energy services. The global plan is obtained by merging the solutions to the sub-problems (i.e., the individual allocation of each load) as long as the contracted power is not exceeded. The search for the solution to each sub-problem begins with the initial solution found by the energy distribution step (i.e., the division of the available energy per load assuring end-users' maximum satisfaction). In the following iterations, the agent responsible for managing the loads decreases the end-users' satisfaction progressively and sends that information to the agents that will seek new schedules respecting the given satisfaction level. When the agent responsible for managing loads receives the proposed schedules, only the solutions violating constraints as less as possible are chosen. The search process stops when the schedules generated do not exceed the contracted power and the global satisfaction level has reached a steady value.

(Pedrasa et al., 2009) use binary PSO to satisfy a schedule of required hourly curtailments aiming to minimize the electricity bill and the number of interruptions. The targeted users can be either residential or industrial as long as previous agreements concerning the interruption of their energy supply under certain conditions were established. The multi-objective problem was tackled by aggregating the two objectives into a single objective function using a penalty associated with the number of interruptions. The PSO approach was preferred over GAs by the authors due to the contribution of all particles history to the search process without discarding poor solutions. The optimal solution found presents a schedule with the total hourly curtailments although no detailed information about the specific managed loads is computed. In a more recent study, the same authors use a co-evolutionary PSO to schedule the operation of residential distributed energy resources aiming to maximize the end-user net benefit (Pedrasa et al., 2011).

(Azar et al., 2015) use an optimization algorithm based on the knapsack problem for managing residential appliances. In some intervals of the planning period, the algorithm selects a subset of loads to start or continue operation and shifts the other ones to the next time slot. The aim is to maximize end-users satisfaction while flatening the demand curve.

4. PROBLEM DESCRIPTION [6]

The optimization of the operation of residential energy resources in the context of smart grids requires the adequate design of algorithms to identify and select ADR actions, on behalf of end-users, for managing residential energy resources in face of dynamic tariffs to be embedded in EMS. The aim is optimizing the integrated usage of the resources: a selected group of loads, with a special focus on shiftable loads, thermostatically controlled loads and stationary storage systems, local generation and energy drawn from the grid. The ADR actions comprise:

- allocating the working cycles of the manageable loads according to the most favorable time slots previously specified by the user;
- regulating temperature settings of cold appliances, EWHs and AC systems, within a given range, which may change along the scheduling period;
- deciding when to store, sell or buy electricity and how to use the stationary storage systems accordingly.

From the residential end-user's perspective the goals of this management are twofold:

- the minimization of the electricity bill;
- the minimization of potential dissatisfaction due to the implementation of ADR actions.

Not depreciating comfort, at least in a perceived way, is a basic requirement to enable the participation of end-users in DR programs (Vanthournout et al., 2015). Therefore the algorithmic approach responsible for the identification of the ADR actions must take this aspect duly into account. Accordingly, the aim is finding non-dominated solutions balancing the two objectives. The electricity bill results from the energy acquisition cost, subtracting the revenue from both injecting energy into the grid or the rewards from responding to grid signals whenever required. The dissatisfaction sensed by the end-user is computed by considering an objective function consisting of penalties associated with:

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[6] This chapter is partially based on:

Soares, A., Gomes, A., Antunes, C.H., (in press). A Customized Evolutionary Algorithm for the Optimization of Residential Energy Resources, in: Advances in Energy System Optimization. Springer.;

Soares, A., Oliveira, C., Gomes, A., Antunes, C.H., 2015b. Analysis of solutions provided by a residential energy management system, in: Proceedings of Energy for Sustainability 2015 - Sustainable Cities: Designing for People and the Planet. Coimbra, Portugal.

Soares, A., Antunes, C.H., Oliveira, C., Gomes, Á., 2014a. A multi-objective genetic approach to domestic load scheduling in an energy management system. Energy 77, 144–152.

- the end-users' preferences concerning the time slots specified for the operation of each load;
- changing the temperature set-point of thermostatically controlled loads when compared to the regular set-point;
- the closeness of the actual peak power with respect to the contracted power (as a surrogate for the risk of supply).

The aim is reshaping the electricity consumption pattern during the planning period, by changing the normal operation of load working cycles and simultaneously making the most of the integration of local generation, to optimize the two objectives. If the end-user also owns a local generation system based on renewables, namely PV systems, and storage systems, the EMS should also include in the optimization process energy exchanges with these systems (Figure 12).

The implementation of ADR actions should not, however, jeopardize the quality of energy services provided; thus the importance of the categorization presented in Chapter 2 which was based on loads' typical usage and technical features. Accordingly, models able to reproduce the power profile of all manageable loads and the impact of ADR actions over controlled loads and storage systems are also essential and therefore they have been embedded in the approach for solving this bi-objective optimization problem.

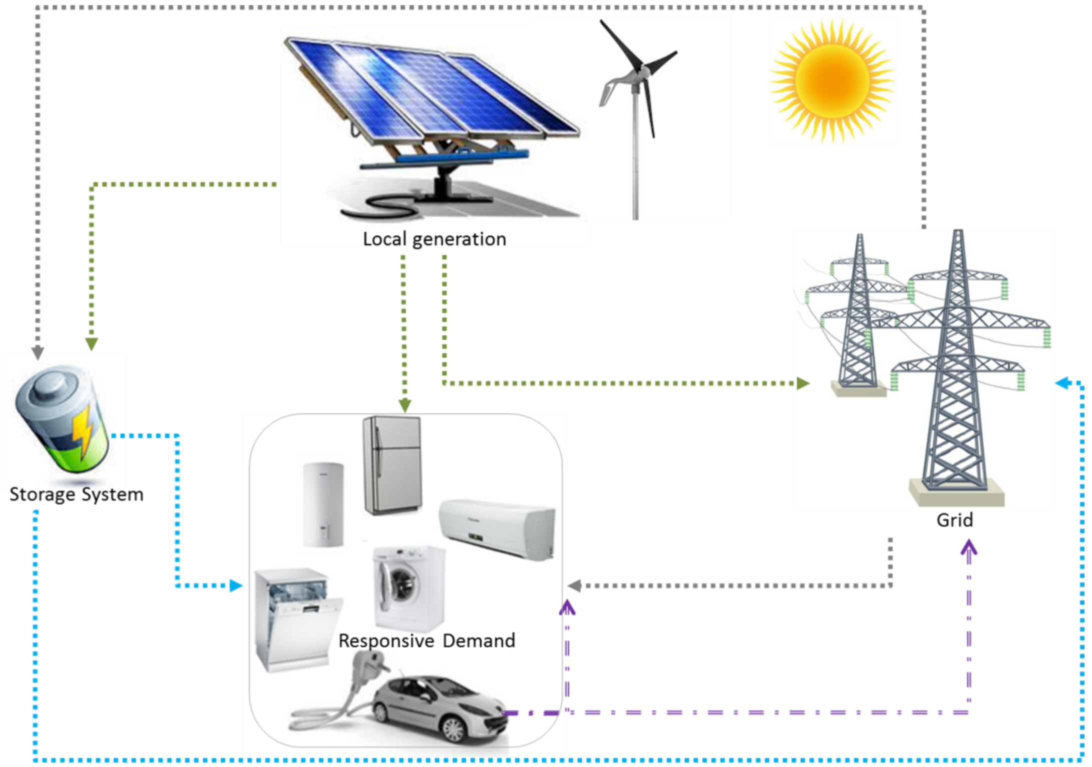

Figure 12: Energy exchanges to be optimized by the EMS

Given the diversity of resources that may exist (shiftable loads, thermostatically controlled loads, storage systems, local generation and power from the grid), different scenarios can be explored. Table 3 shows some of those scenarios.

Table 3: Example of scenarios of resources and ADR actions

Resources	Actions
Responsive Demand • Thermostatically controlled loads • Shiftable loads Grid	• allocating the working cycles of the manageable loads according to the most favorable time slots previously specified by the user; • regulating temperature settings of cold appliances, EWHs and AC systems, within a given range, which may change along the scheduling period;
Responsive Demand • Thermostatically controlled loads • Shiftable loads • PHEV Grid	• allocating the working cycles of the manageable loads according to the most favorable time slots previously specified by the user; • regulating temperature settings of cold appliances, EWHs and AC systems, within a given range, which may change along the scheduling period; • how to use the PHEV: deciding when to store, sell or buy electricity.
Responsive Demand • Thermostatically controlled loads • Shiftable loads • PHEV Grid Local Generation	• allocating the working cycles of the manageable loads according to the most favorable time slots previously specified by the user; • regulating temperature settings of cold appliances, EWHs and AC systems, within a given range, which may change along the scheduling period; • how to use the PHEV: deciding when to store, sell or buy electricity; • how to use the energy locally produced: store, sell or self-consumption.
Responsive Demand • Thermostatically controlled loads • Shiftable loads • PHEV Grid Local Generation Storage	• allocating the working cycles of the manageable loads according to the most favorable time slots previously specified by the user; • regulating temperature settings of cold appliances, EWHs and AC systems, within a given range, which may change along the scheduling period; • how to use the PHEV and the stationary storage system: deciding when to store, sell or buy electricity; • how to use the energy locally produced: store, sell or self-consumption.

4.1. MODELS FOR SIMULATION OF MANAGEABLE LOADS

Data collected during audits is used for modeling shiftable loads since the power profile considered is the same even if the working cycles are allocated in different time slots of the planning period. Although different power profiles can be used to characterize the operation of shiftable loads, after a profile is selected it remains the same whatever the operating period. Adequate physically-based models (PBM) (Gomes et al., 2013, 2009; Jorge et al., 2000) and a dynamic model are used to reproduce the behavior of thermostatically controlled loads and storage systems, respectively, in order to extract the power profile resulting from the implementation of the ADR actions and the temperature or SoC variation (Gomes et al., 1999; Soares et al., 2012b).

PBMs have the ability to reproduce the physical behavior of storage-type loads by tracking the temperature of the fluid being cooled/heated and consequent identification of the load profile (Gomes et al., 2013). Additionally they capture changes induced by the ADR actions. These models are based on expressions to compute temperature and power (Eq. 1 to Eq. 12). The required input information is presented in Table 4. The storage system dynamic model used in this work is based on the one developed by (Tremblay and Dessaint, 2009).

Table 4: Information to be inserted for thermostatically controlled loads (Soares et al., 2013a)

<table>
<tr><th>Thermostatically controlled load</th><th>Specific information</th><th>Common information</th></tr>
<tr><td>Fridges / Freezers</td><td>• Internal temperature at the beginning of the simulation
• COP (coefficient of performance)
• Capacity</td><td rowspan="3">• Power
• Reference temperatures (minimum and maximum)
• External temperature
• Characteristics of the insulation</td></tr>
<tr><td>EWHs</td><td>• Water temperature at the beginning of the simulation
• Temperature of the water coming from the supply system
• Capacity
• Hot water consumed</td></tr>
<tr><td>AC (conventional and inverter)</td><td>• Room temperature at the beginning of the simulation
• COP / EER (energy efficiency rating)
• Volume of the room and number of air changes per hour
• Characteristics of the room (insulation material, windows, doors, solar radiation, orientation, air renewal rate, etc.)
• Number of people in the room
• Internal heat load due to lighting and equipment</td></tr>
</table>

4.1.1. THERMOSTATICALLY CONTROLLED LOADS

4.1.1.1. AC SYSTEMS

Concerning AC systems, the PBMs assess the total heat load of a space imposed to these systems:

$$Q_T(t) = Q_L(t) + Q_S(t) \ \ [W] \quad \text{Eq. 1}$$

where $Q_L(t)$ [W] represents the latent load and $Q_S(t)$ [W] is the sensible load, at time t.

The main contributors for the thermal load of the space considered are (Gomes et al., 2013, 2009):

- the heat transmission through the envelope (walls);
- heat transfer through the windows (insolation);
- internal heat sources;
- renewal of the indoor air.

The heat transfer through the envelope depends on the physical characteristics of the walls and the difference between indoor and outdoor temperatures. The insolation load is the thermal load "due to the solar energy going through windows or stored and released by an opaque element of the envelope" and therefore linked to the element of the envelope and its orientation (Gomes et al., 2013). Therefore, the heat gain through the opaque elements of the envelope has a delay which is considered in the assessment of its contribution to the heat load by using a reduction factor. Concerning windows and since their thermal capacity is quite low, almost all insolation load goes through those elements although the final amount is dependent on the glazing and type of shading used (which impacts on the shading coefficient). These contributions are strongly dependent on the time of the year and solar hour. The internal heat load resulting from people's presence in the room, lighting and equipment is also considered and variable along the planning period.

When using a conventional AC for cooling down the room, temperature in the room can be computed through:

$$T_{room}(t+\Delta t) = T_{room}(t) - \frac{(y.P_{AC}(t) - Q_T(t)).\Delta t}{m.c_p} \quad \text{Eq. 2}$$

where $T_{room}(t)$ [°C] is the indoor temperature of the room being cooled at time t.

$$y = \begin{cases} 1, & if\ [T_{room}(t) \geq \mathrm{Tref_L} \wedge T_{room}(t) < T_{room}(t-1)] \bigvee [T_{room}(t) \geq \mathrm{Tref_H}] \\ 0, & otherwise \end{cases} \quad \text{Eq. 3}$$

where $\mathrm{Tref_L}$ is the minimum reference temperature of the thermostat, and $\mathrm{Tref_H}$ is the maximum reference temperature of the thermostat.

$$P_{AC}(t) = P_{AC} * COP(t) \qquad \text{Eq. 4}$$

where P_{AC} is the power of the AC, and

$COP(t)$ is the coefficient of performance of the AC, which varies with the temperature.

m is the air mass [kg].

c_p is the specific heat of air $\left[{}^{J}/_{kg^oC}\right]$.

Δt is the elemental time interval [s].

$Q_T(t)$ is the total heat load [W] at time t.

While the working cycle of the conventional AC is determined by the thermostat, which switches "on" or "off" the AC (Eq. 3) making it run at full power or not run at all, the inverter AC withdraws from the grid the amount of power needed to compensate for the heat gains/losses of the room (Gomes et al., 2013). Therefore, room temperature is kept more stable with an inverter AC than when using a conventional AC system (Figure 9).

When using an inverter AC, although Eq. 1 and Eq. 2 remain the same, Eq. 3 will now depend on the room and reference temperatures to define the way the AC is operated. In the heating mode (Figure 13), when the AC is switched on it is operated in what is called "instability mode" and if T_{room}-T_{ref}≤A (for example -1°C) the AC runs at full power until the T_{room}-T_{ref}>A when it switches to "stability mode". When the difference T_{room}-T_{ref}>B (for example 2°C) the AC is turned off and when C≤T_{room}-T_{ref}≤B runs at variable speed thus withdrawing a variable power from the grid. In the cooling mode (Figure 14) it starts in "instability mode" and, when T_{room}-T_{ref}≥A (for example 1°C) the AC runs at full power until switching to "stability mode". In this mode, when the difference T_{room}-T_{ref}<C (for example -1.5°C) the AC is turned off and when C≤T_{room}-T_{ref}≤B runs at variable speed thus withdrawing a variable power from the grid. The PBM of the inverter AC is based on the model presented in (Gomes et al., 2013).

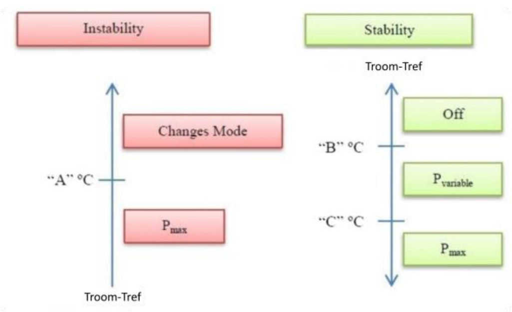

Figure 13: Inverter AC – heating mode (Gomes et al., 2013)

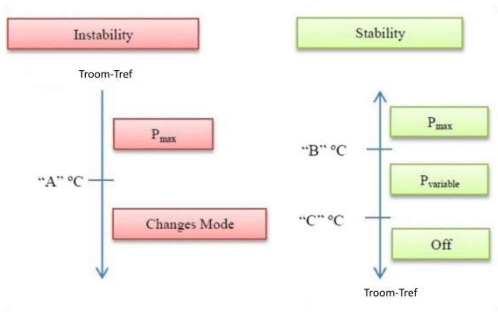

Figure 14: Inverter AC – cooling mode (Gomes et al., 2013)

4.1.1.2. EWHs

For EWHs, the PBM model computes the losses per unit of time and the available energy during the time interval to heat the water:

$$P_{losses}(t) = A \times U \times \Delta T' \ [W] \qquad \text{Eq. 5}$$

where A is the surrounding area of the EWH [m^2].

U is the element heat transfer coefficient $\left[{}^{W}\!/_{(m^2 \, . \, {}^{o}C)} \right]$.

$\Delta T'$ is the difference between the temperature of water inside the EWH and the outdoor temperature [^{o}C].

$$Q(t) = [P_R(t) - P_{losses}(t)] \times \Delta t \ [J] \qquad \text{Eq. 6}$$

where $P_R(t)$ [W] is the power of the heating element in the EWH at time t.

The hot water temperature can be computed through:

$$T_{water}(t + \Delta t) = T_{water}(t) + \frac{v.P_R(t) - P_{losses}(t)}{M \times c_p} . \Delta t \ [^{o}\text{C}] \qquad \text{Eq. 7}$$

$$\text{where } T_{water}(t) = \frac{M - m(t)}{M} \times T_{hot}(t) + \frac{m(t)}{M} \times T_{grid}(t) \ [^{o}\text{C}] \qquad \text{Eq. 8}$$

M is the total mass of water to be heated [kg].

c_p is the specific heat of the water $\left[{}^{J}\!/_{kg^{o}C} \right]$.

$m(t)$ is the amount of hot water consumed in each instant of time t [kg].

$T_{hot}(t)$ is the desired temperature of the hot water [^{o}C] at time t.

$T_{grid}(t)$ is the temperature of the water coming from the grid [^{o}C] at time t.

$$v = \begin{cases} 1, & if \ [T_{water}(t) \leq \text{Tref}_{\text{L}}] \\ & \bigvee [T_{water}(t) \leq \text{Tref}_{\text{H}} \ \land \ T_{water}(t) > T_{water}(t-1)] \\ 0, & otherwise \end{cases} \qquad \text{Eq. 9}$$

where Tref_{L} is the minimum reference temperature of the hot water, and

$\mathrm{Tref_H}$ is the maximum reference temperature of the hot water.

The consumption of hot water and the temperature of the water coming from the grid strongly impacts on the working cycle of the EWH and on the resulting temperature (Figure 15).

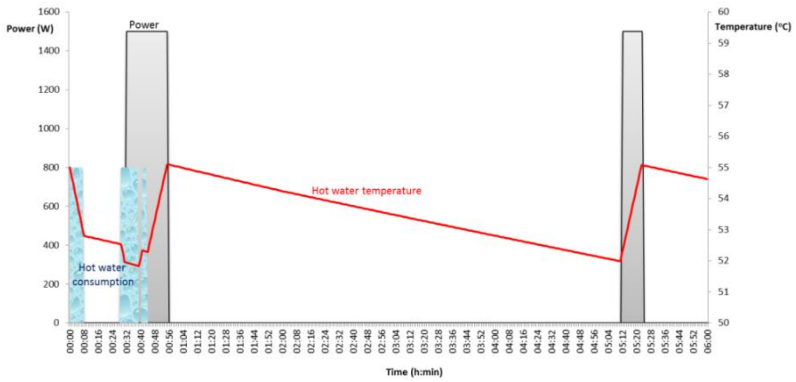

Figure 15: Close-up of the impact of hot water consumption.

4.1.1.3. Cold Appliances

Concerning cold appliances, a simplified PBM can be deduced from more detailed studies (Hovgaard et al., 2012; Laguerre and Flick, 2010) and the temperature is computed by the expression (Eq. 10) as long as the several variables have been previously identified, namely concerning the intrinsic characteristics of the cold appliance to be modelled:

$$T_{cold_{ap}}(t+\Delta t) = T_{cold_{ap}}(t) - \frac{w.P_{t_{cold_{ap}}(t)} - AU\left[T_{room}(t) - T_{cold_{ap}}(t)\right]}{M.c_p}.\Delta t \qquad \text{Eq. 10}$$

where A is the surrounding area of the cold appliance [m^2].

U is the heat transfer coefficient $\left[{W}/{(m^2.\,^oC)}\right]$.

M is the mass of air inside the cold appliance [kg].

c_p is the specific heat of the air $\left[{J}/{kg^oC}\right]$.

$T_{room}(t)$ is the room temperature where the cold appliance is placed at time t [^{o}C].

$$P_{t_{cold_{ap}}(t)} = P_{app} \times COP \text{ is the compressor power [W].} \qquad \text{Eq. 11}$$

COP is the coefficient of performance of the cold appliance

$$w = \begin{cases} 1, & if \ \left[T_{cold_{ap}}(t) \geq \mathrm{Tref_L} \wedge T_{cold_{ap}}(t) < T_{cold_{ap}}(t-1)\right] \\ & \qquad \bigvee \left[T_{cold_{ap}}(t) \geq \mathrm{Tref_H}\right] \\ 0, & otherwise \end{cases}$$ Eq. 12

where $\mathrm{Tref_L}$ is the minimum reference temperature of the cold appliance, and

$\mathrm{Tref_H}$ is the maximum reference temperature of the cold appliance.

4.2. Models for Storage Systems and Local Generation

The model used for simulation of the stationary storage system and PHEV in both G2V and V2G modes is based on (Tremblay and Dessaint, 2009) and thus the SimPowerSystems battery model in MatLab is used. The equivalent circuit of the storage system is represented in Figure 16. The expressions for the discharge and charge models depend on the battery type (lead-acid, lithium-ion, nickel-cadmium, etc).

In our approach the lead-acid battery was used as the stationary storage system while the lithium-ion was selected for the PHEV. One of the main differences of these two types of batteries is the typical charge characteristic curve (Figure 17). The degradation of the battery, although not directly considered in this model, can be taken into account in the evolutionary approach through the use of a specific term in the objective function concerning end-user's dissatisfaction associated with the number of charge and discharge cycles.

Concerning local generation, a PV system is considered and the production is forecasted through a model previously implemented in Netlogo (Wilensky, 1999) and based on the model presented by (DenHerder, 2006; Renato and Pompéia, 2009). The output of this model is further used as an input to the algorithm presented in Chapter 5.

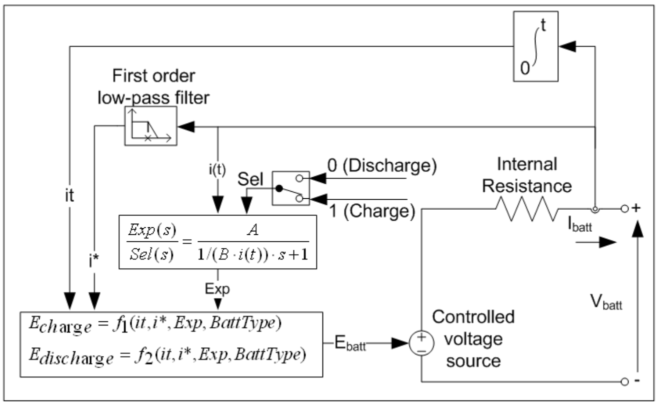

Figure 16: Equivalent circuit of the storage system (Tremblay and Dessaint, 2009)

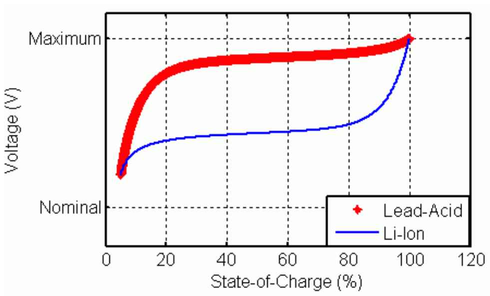

Figure 17: Typical charge characteristics (MathWorks Support, 2008)

4.3. SHIFTABLE LOADS FEATURES, END-USERS' PREFERENCES AND CONSTRAINTS

Concerning shiftable loads, although it is not possible to change their power consumption profile in order to lower electricity bill, savings in the electricity bill may be achieved if the tariff structure is not a flat rate. Thus, under a dynamic tariff, the cost of operation of those loads is not constant though the energy requested to the grid might be the same. Assuming there is some flexibility concerning the use of these loads (D'hulst et al., 2015), residential EMS can be used in this context to optimize the scheduling of shiftable loads while respecting end-user's preferences.

These preferences may include time slots for load operation and hence a (dis)utility function is used to establish the penalties associated with not meeting the preferred time slots specified by the end-user for the operation of each load. For penalties associated with time slots it is important to note that the degree of dissatisfaction may vary for the same load along the day. For that reason, there are continuous dissatisfaction levels along the day which can be assigned to the multiple shiftable loads, including the PHEV when used in the G2V mode only.

Preferences associated with different time slots for the functioning of shiftable loads are based on end-users' availability to carry out associated tasks, such as hanging out clothes to dry or load the tumble dryer. In this context, a zero penalty corresponds to the timeframe in the planning period where the end-user clearly prefers the allocation of a given load, while a maximum penalty corresponds to the timeframe where the end-user does not want the load to operate under any circumstance. Decreasing, increasing and in-between penalties are also possible and have different meanings (Figure 18).

However, the end-user generally does not have complete information about the overall consumption at a given instant or about the potential consequences of turning on more appliances. By assigning time slot preferences to the shiftable loads, in an extreme situation it may occur that the preferred time slots are coincident and the operation of those loads in that timeframe in addition to the non-manageable loads originates a power peak which drastically decreases the difference between the contracted power and the power currently being requested to the grid or even makes this difference negative. This event might lead to the interruption of energy supply and therefore the importance of also considering in the model power constraints to account for that risk. Unexpected variations of the non-manageable base load and contracted power constraint are therefore included in the model to deal with the risk of interruption of energy supply.

The use of the contracted power as a hard constraint, which cannot be violated under any circumstances, is an important feature to keep this approach as close to reality as possible. For the same reason, a time step of one minute is used: this time resolution ensures that power peaks too close to the contracted power or even exceeding it are taken into account and not smoothed in the aggregated load diagram (Soares et al., 2013b). In a real setting, sensoring equipment can be used to monitor power in each instant of time and help computing the closeness to the contracted power level. The planning period of one day and a half was chosen since it includes a normal 24 hour day plus 12 hours allowing the inclusion of more time slots for the operation of shiftable loads and a more accurate management of the storage systems and thermostatically controlled loads.

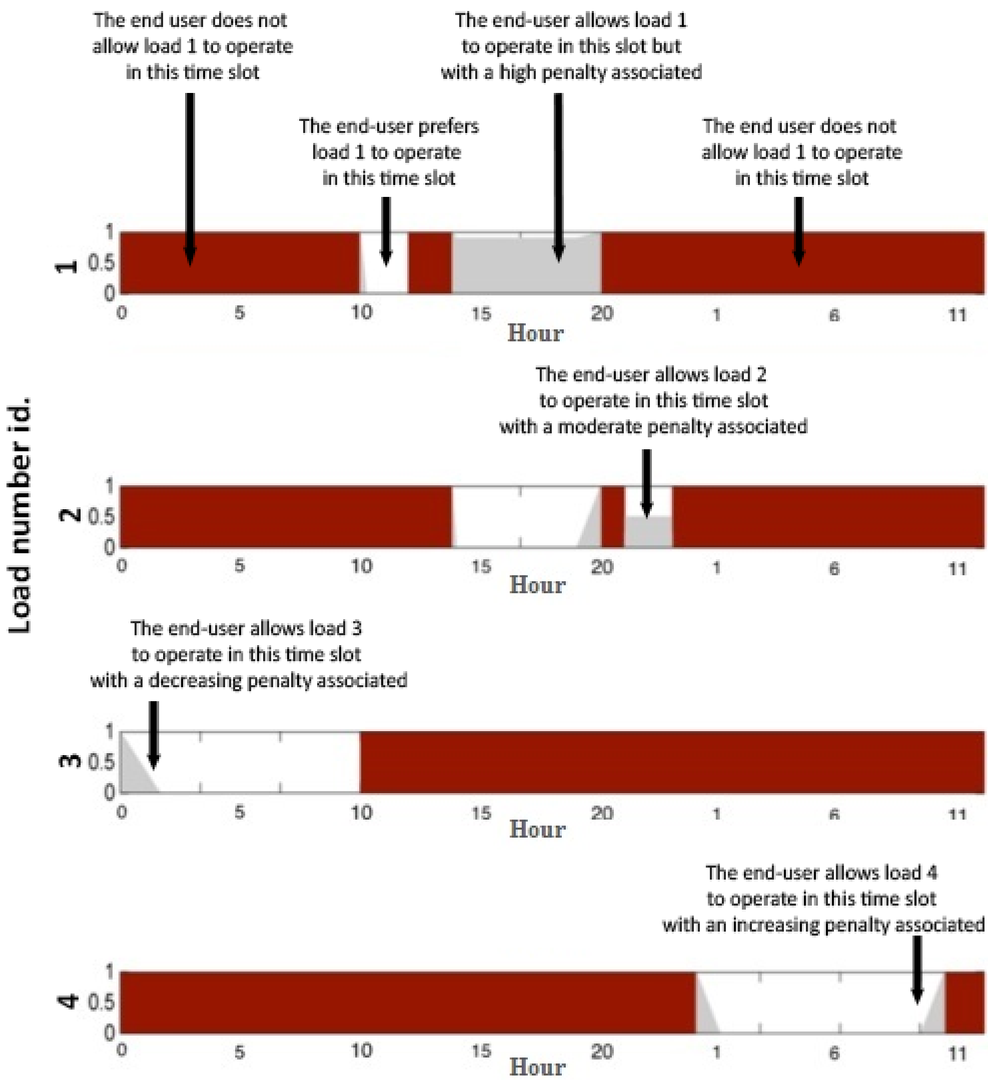

Figure 18: Example of end-user time slot preferences (Soares et al., 2013b)

Concerning thermostatically controlled loads, demand can be shaped through the modification of temperature set points and thus the importance of the PBMs previously mentioned in section 4.1.1. The freedom given to the EMS for modifying the set points must be limited to a certain temperature range, otherwise the most effective way to minimize the electricity bill would be choosing a temperature not requiring the load to work (e.g., for cold appliances the set point temperature meeting the room temperature). Changes in thermostat temperature can be for example $\pm 0.5\,^{o}$C or $\pm 1^{o}$C and have a penalty associated. This penalty increases when the absolute difference between the reference and the new temperature increases.

Accordingly, preferences associated with these loads are given by an allowable temperature modification range and a penalty is embedded in the dissatisfaction objective function to avoid the choice of extreme ADR actions requiring less energy but negatively impacting end-users' satisfaction. An example of the evolution of thermostatically controlled loads penalties for two extreme solutions, which minimize individually each one of the objective functions, can be found in Figure 19. Is it possible to see from this example that penalties over thermostatically controlled loads are not constant during the planning period and differ between solutions.

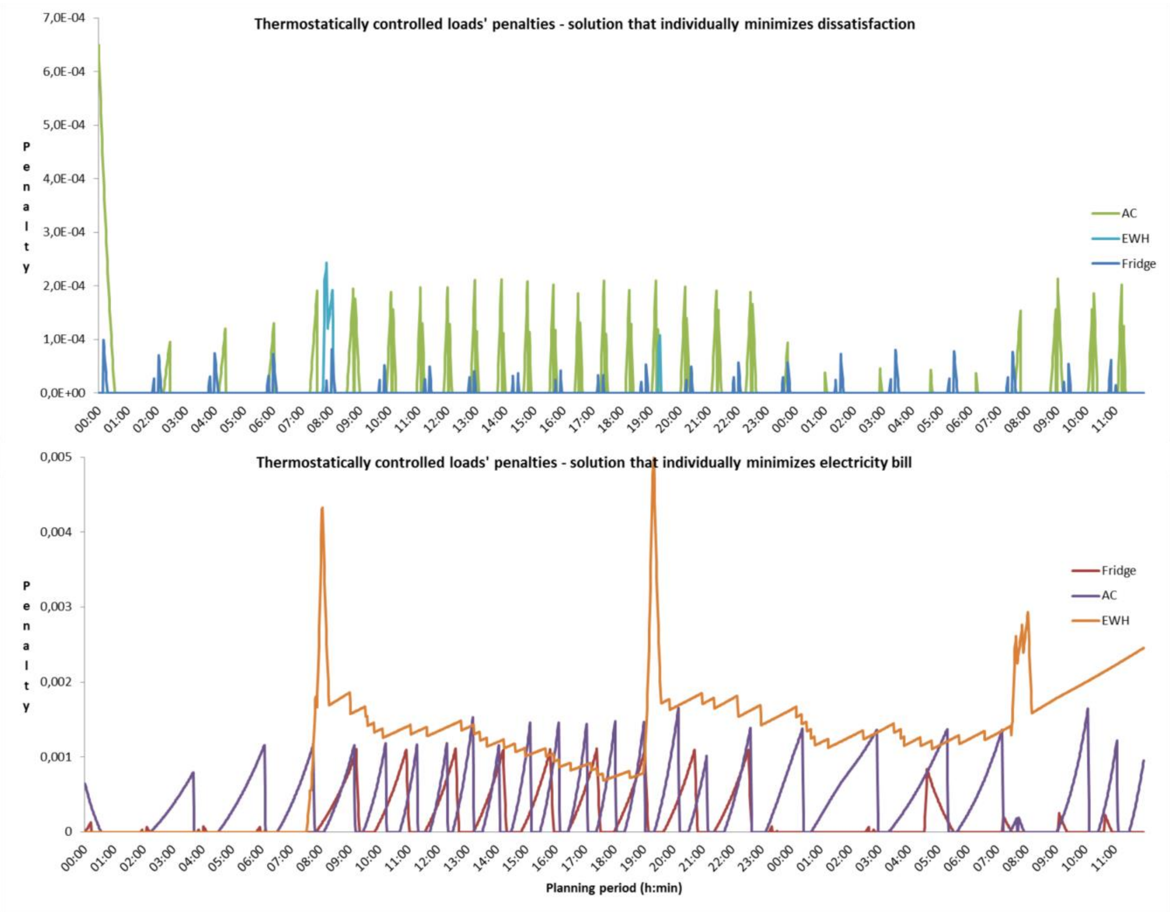

Figure 19: Example of penalties associated with thermostatically controlled loads for the solutions that individually optimize each objective function (Antunes et al., 2015)

In addition to these constraints and in order to avoid the interruption of energy supply, it is important that the EA also comprises the ability to quickly re-compute solutions as a response to changes in the operation environment. For example, if there is a sudden increase of non-manageable load that would lead to the interruption of energy supply, then ADR actions such as short time interruptions in shiftable and thermostatically controlled loads can be used to avoid the energy supply interruption and thus minimizing end-user's dissatisfaction. Also the hypothesis of the end-user wanting to change the initial manageable loads and/or preferences should also be considered. Therefore the ability to pick up near real-time information and make subsequent optimization based on that information is a major advantage of this approach.

5. METHODOLOGY[7]

The approach used in this research was developed to deal with simpler scenarios, in which only shiftable loads are managed, or with more elaborated scenarios where multiple energy resources of different nature exist (Table 3). When dealing just with shiftable loads, a GA can be used to schedule the use of shiftable loads according to previously identified technical and user-defined constraints such as the one presented in (Soares et al., 2013b). The selection of ADR actions (postponement or anticipation) considers penalties, in the form of costs associated with time slot preferences for the operation of loads. Such penalties vary according to the type of load and along the 36 hours of the planning period. Input signals comprise energy prices, known a day and a half in advance, and a two level contracted power. In (Soares et al., 2013b) the aim is minimizing a single objective function comprising the aggregate cost of the energy consumed by the loads scheduled, the monetized penalty associated with the risk of interruption of energy supply and monetized penalties for load operation outside specific time slots. The decision variables are the starting minute of the working cycle for each load in the planning period. The (soft and hard) constraints include the contracted power levels and end-users' preferences for the allocation of the loads in the time slots.

The discomfort caused by the interruption in the energy supply, requiring the end-user to turn off some loads to go back under the contracted power limitation, is considered and penalized. The risk of interruption of energy supply is considered in the model by penalizing solutions that give origin to high demand peak power and a small amount of available energy in the considered time slots. Accordingly, a zero penalty is assigned to the maximum value of power available (i.e. farther from the contracted power – C_t) and a maximum penalty (value 1) to the minimum value of power available (Figure 20).

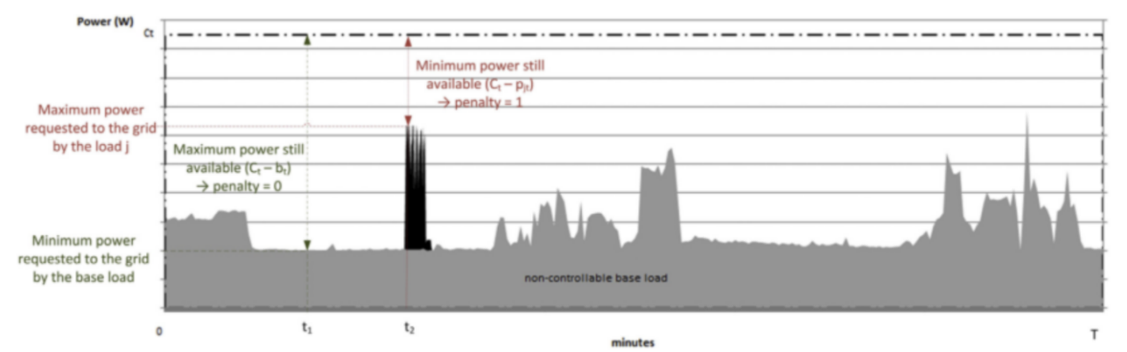

Figure 20: Example of extreme values for available and requested power to be used in the computation of the penalty associated with the risk of interruption of energy supply

[7] This chapter is partially based on Soares, A., Gomes, A., Antunes, C.H., (in press). A Customized Evolutionary Algorithm for the Optimization of Residential Energy Resources, in: Advances in Energy System Optimization. Springer.

Since the objective function previously mentioned gathers energy costs and monetized penalties and already anticipating the need to include other kind of penalties hardly monetized, a multi-objective genetic approach is presented in (Soares et al., 2014a). In this approach there are two objective functions to be minimized: the electricity bill and the end-user's dissatisfaction concerning the preferred time slots for load operation also including the risk of interruption of the energy supply. Similarly to what was done in (Soares et al., 2013b), penalties are assigned to the operation of the loads outside their preferred time slots using a (dis)utility function. Also, penalties associated with the power requested by the operation of each load being too close to the contracted power are considered. The contracted power is modelled as a hard constraint and thus cannot be violated. The decision variables are the starting minute of each load working cycle. Auxiliary binary variables state whether the working cycle of each load is on or off at a given minute of the planning period.

When considering other energy resources besides shiftable loads, a more elaborate formulation should be used to consider all the constraints and features (Table 5). The bi-objective model is solved by an EA tailored to the physical characteristics of this problem. The use of a customized EA is justified by its ability to deal with:

- this multi-objective problem of combinatorial nature in which a population of solutions converges to the non-dominated (Pareto optimal) frontier where compromise solutions between the competing objective functions are located;
- diversity regarding energy resources which have different features and require distinct ADR actions.

This approach differs from previous works in the range of loads being managed, the type of models used to reproduce their regular behavior, the different type of ADR actions that may be implemented, the assessment of the impact of ADR actions (mainly through the use of PBMs), the incorporation of end-users' preferences for each type of load and the ability to keep the peak power requested to the grid as low as possible below the contracted power. Moreover this approach has the capability to quickly react to external emergency requests or modifications of end-user's preferences and non-manageable demand by re-computing new solutions without the need to restart the process and with a mild computation effort.

Considering the objectives of the optimization model, there are advantages for displaying the behavior of each managed load in the solution encoding. These advantages are mainly linked to the positive impact on the computation time needed to find the Pareto front. Thus, for shiftable loads, considering the previous knowledge of their working cycle, what really matters is the starting minute within the planning period. For thermostatically controlled loads, their operation depends on the indoor temperature and the desired temperature and hence this load is represented by the maximum allowable temperature in each instant of time. The electric vehicle and the stationary storage system power profile in each instant of time are encoded by -2,-1,0 or 1, representing each one of these codes a different state (self-consumption and selling electricity to the grid; selling electricity to the grid; battery not in use; or electricity storage, respectively).

Table 5: Bi-objective problem formulation

Objective functions		Observations
1. Minimization of the energy bill		The energy bill is determined by the acquisition cost from the grid, subtracting the revenue from injecting energy into the grid and responding to grid signals.
2. Minimization of end-users' dissatisfaction	Shifting loads to non-preferred time slots	(Dis)utility functions establish the penalties associated with not meeting end-users' preferences. Demand response actions requiring the change of temperature settings of thermostatically controlled loads, which are different from the normal functioning of these appliances, are penalized using an exponential function.
	Proximity to contracted power threshold	
	Changing temperature set points	
	Not ensuring a minimum SoC of the PHEV battery by the end of the planning period	
Constraints		
1. End-users' time slot preferences for allocating shiftable loads	Laundry machine, tumble dryer, dishwasher Electric vehicle if only used in G2V mode	Modelled as hard constraints: time slots with a shorter duration than the working cycle of the load to be allocated are excluded.
2. End-users' temperature range for thermostatically controlled loads	EWH, AC, fridge	Modelled as constraints: solutions outside the allowable temperature range are penalized to make them uninteresting.
3. End-users' preferences for the use of storage systems	Stationary storage system and the PHEV in both G2V and V2G modes	The SoC of the stationary storage system is checked by the physically-based model in each instant of time and kept not lower than 0.2. The SoC of the PHEV battery at the end of the planning period must be in accordance with the minimum SoC requested by the end-user.
4. Usage of local generation	PV systems to generate electricity	The power generated in each instant of time can be used for self-consumption, stored in the storage system or injected in the grid.
5. Contracted power threshold	A contracted power level is assumed to exist and there are economic advantages from keeping it as low as possible.	The contracted power is considered as a constraint: a very high penalty is considered when exceeding the contracted power to make those solutions uninteresting.

Technical restrictions		
Technical restrictions are associated with every managed load and allowable demand response actions.	Laundry machine, tumble dryer, dishwasher	Although these loads may be technically interrupted, this possibility is only considered if the contracted power exceeds the power threshold.
	Thermostatically controlled loads: fridge, EWH, AC	Small changes of the thermostat settings are considered without compromising the quality of service. The temperature range variation depends on the end-user's preferences.
	Storage systems	The SoC of the stationary storage system is kept not lower than 0.2 in each instant of time. The charging of the PHEV may be modelled by considering more than one power level as long as the total amount of energy requested is provided to the PHEV. The EMS can freely stop and start the charging of the PHEV, but must always make sure that the car has the minimum SoC requested by the end-user before the specified departure time or at the end of the planning period.

The solution encoding translates into the genes of the chromosome representing each solution the ADR actions that are physically feasible (Figure 21). As a result the length of the chromosome is strongly dependent on the planning period and the number of managed loads.

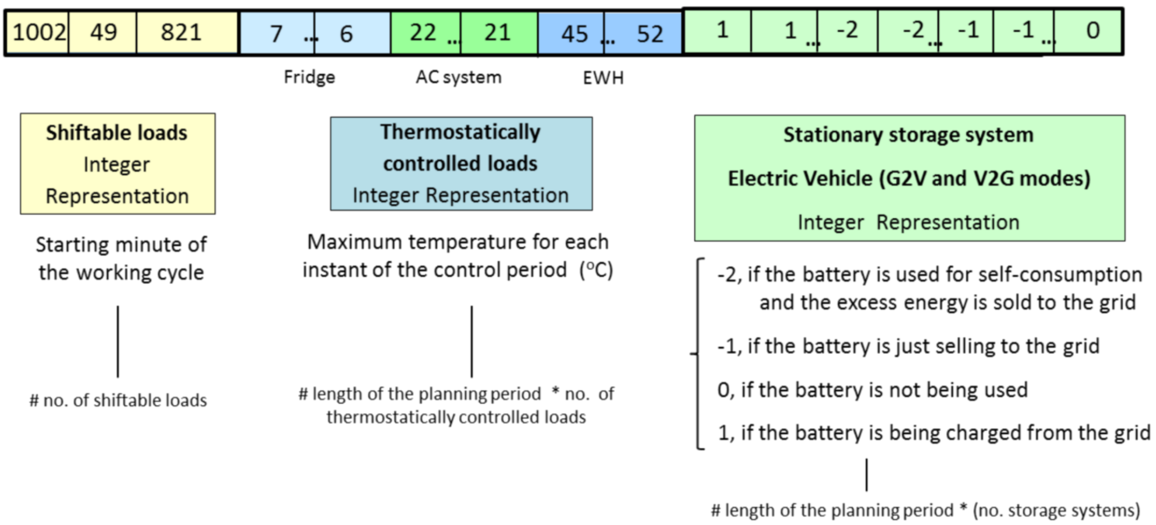

Figure 21: Solution encoding

Other important feature of this approach is the generation of the initial population according to the type of loads being managed, which strongly influences the computation time needed to obtain good results. Thus, while for shiftable loads the corresponding genes are randomly generated as long as the starting minute is included in the allowed time slots for the operation of those loads, for thermostatically controlled loads the genes are randomly generated within the thermostat temperature deadband variation when ADR actions are not implemented (and therefore no temperature penalty is associated) except for two individuals (solutions). These two individuals represent extreme solutions, each of them with very good values for one objective function at the expense of very bad values for the other objective function and are generated in order to enhance the diversity of the population during the evolutionary process. For the individual with a zero penalty associated with changing temperature settings, the desired temperature is always maintained within the admissible range. For the individual with maximum penalty associated with changing temperature settings, these settings are established as the maximum allowable value for cold appliances and AC systems, and to the minimum allowable value for the EWH.

Concerning the PHEV used in the G2V mode only, the corresponding genes in individuals of the initial population are set to fully charge the battery without any interruptions during that charging period.

For the stationary storage system or the PHEV in both G2V and G2V modes, the decision for each gene is generated according to the energy price:

- if the buying energy price is above the average for the scheduling period, then the decision may be self-consumption or sell the electricity to the grid;
- if the buying energy price is below the average for the scheduling period, then the decision may be buying electricity from the grid to charge the battery or do nothing.

The crossover and mutation operators are also customized according to the type of load being managed (Figure 22) and the particularities of each one are detailed in Table 6.

The flowchart of the optimization approach, based on NSGA-II, is displayed in Figure 23. At the beginning of the simulation and considering the planning period of 2160 minutes (one day and a half – 36h), the input information relevant to the integrated load management is read. This information includes:

- contracted power threshold;
- energy prices;
- weather forecast;
- expected base load demand;
- forecast of energy locally produced.

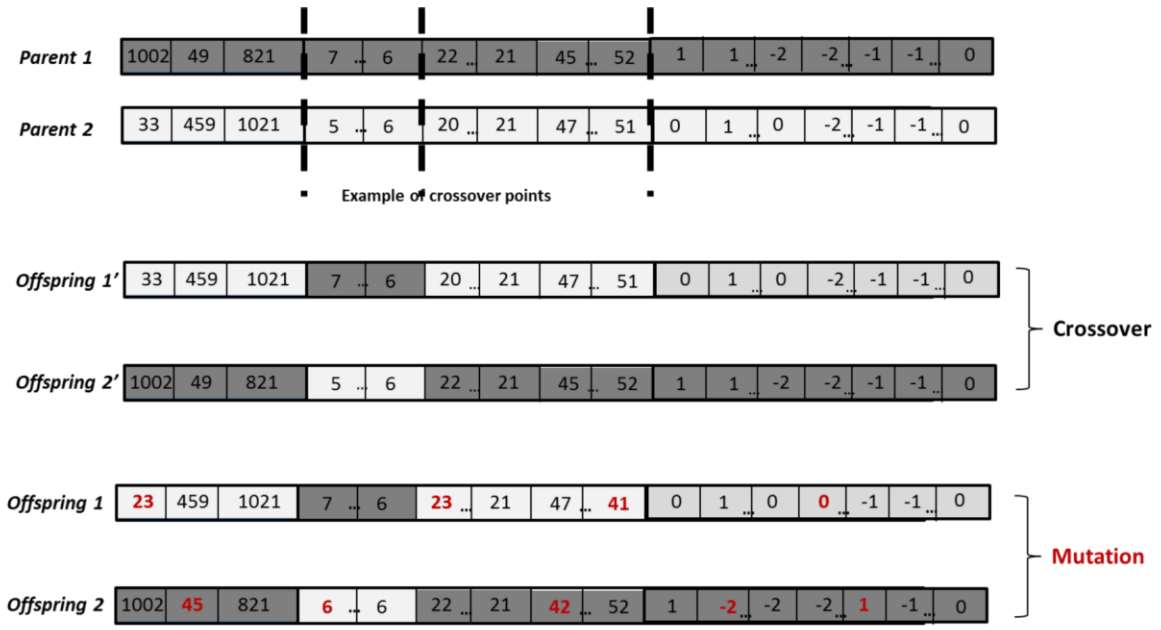

Figure 22: Example of the use of the crossover and mutation operators

Table 6: Customized operators to be applied over the managed loads

Load managed	Mutation operator	Crossover operator
Shiftable load	Changes the starting minute of the working cycle according to a previously defined deviation bound, while respecting the time slot allowed for this cycle operation.	Swaps the starting minute of the same load between two different individuals.
Thermostatically controlled load	Changes the maximum temperature within a given deviation bound. This deviation is different for cold appliances, EWHs and AC systems. Changing the maximum temperature will also impact the minimum temperature since the difference between the maximum and minimum temperatures (deadband variation) is supposed to remain constant.	The maximum temperature value is exchanged between two individuals preserving its location in the solution encoding. One or more genes may be changed.
Electric vehicle	Sets interruptions in the charging cycle according to a defined number of maximum interruptions, while respecting the time slot allowed for the charging operation.	Interchanges the power withdrawn from the grid between two individuals in a variable number of genes.
Stationary storage system	Changes the decision made for the battery (self-consumption and selling electricity to the grid; selling electricity to the grid; battery not in use; or electricity storage).	Interchanges decisions in a variable number of genes between two individuals.

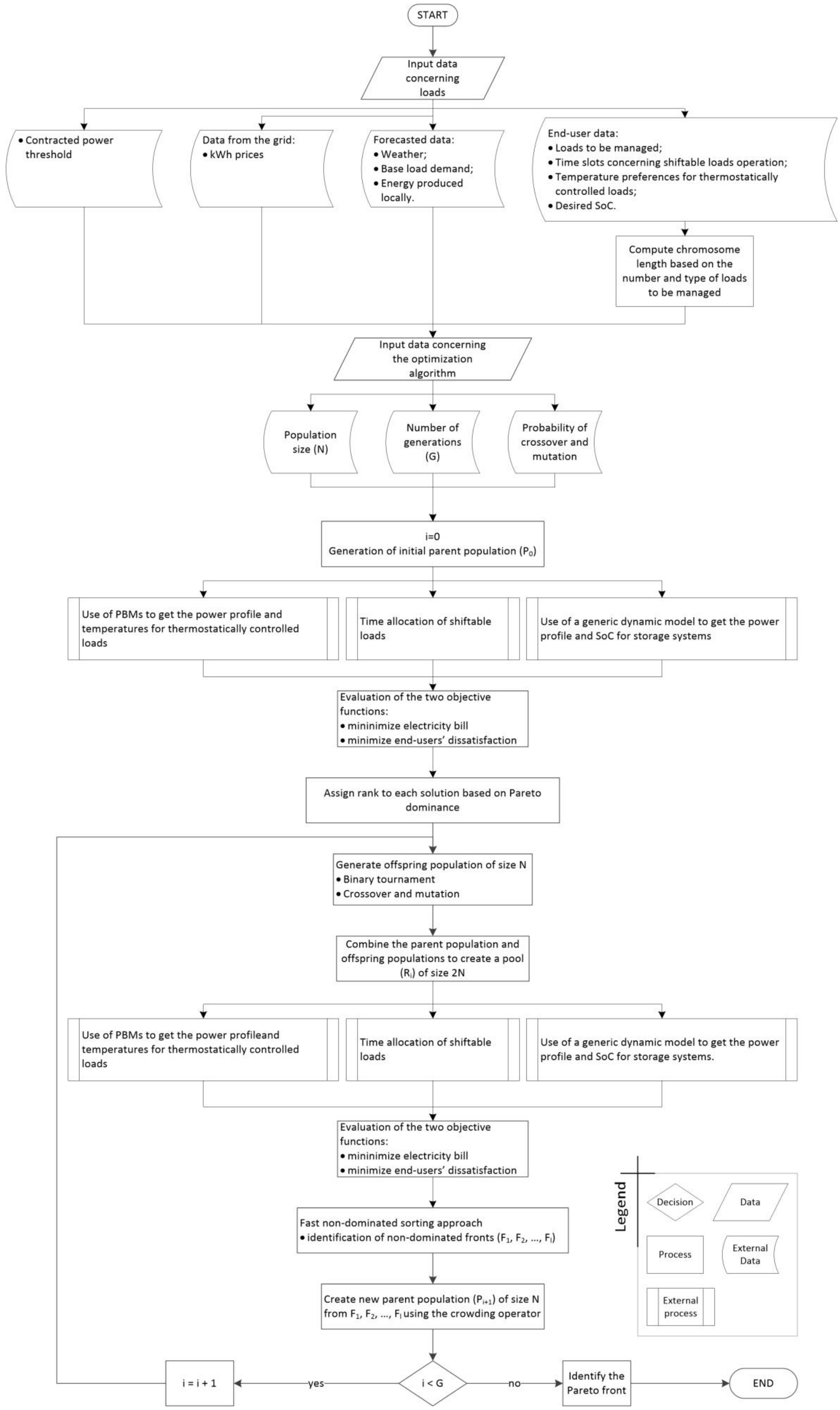

Figure 23: Algorithmic approach flowchart

Information concerning the diversity of loads to be managed and end-users preferences are also considered at this step including:

- time slots for the allocation of shiftable loads;
- temperature preferences for thermostatically controlled loads;
- desired SoC for the PHEV battery if used in both G2V and V2G modes.

The features of the EA such as population size (N), number of generations (G) and probability of the crossover and mutation operators are specified to run the optimization process. The process begins with the generation of the initial parent population according to the features of the managed loads and the consequent:

- use of PBMs to obtain the power profile and temperatures for thermostatically controlled loads;
- time allocation of shiftable loads according to the solution encoding for this part of the chromosome;
- use of a generic dynamic model to get the power profile and SoC for storage systems.

Through the compilation of the previous information and the identification of power profile and temperatures it is possible to assess the fitness function. This assessment is carried out for each individual of the population and allows assigning a rank to it based on Pareto dominance. The next step consists of generating the offspring through a binary tournament to choose the two parents and then using of the crossover and mutation operators.

Parents and offspring population are then combined to create a pool of solutions ($R_{i,}$, i represents the generation number) with twice the size of the initial population (2N). The allocation of shiftable loads in the planning period, the use of both the PBMs for the thermostatically controlled loads and a generic dynamic model for the storage system allow the evaluation of the two objective functions. Then, a non-dominated sorting approach is used to identify the non-dominated front and the population size is reduced again to N individuals to obtain the mating pool for the next generation. The crowding operator is used in this step to assign a crowding distance to each solution within the same front (Deb et al., 2002; Salinas et al., 2013), which measures how close an individual is to other individuals. If there are two individuals presenting the same rank during the non-dominated sorting approach, then the one with larger crowding distance is selected.

This procedure is repeated until the intended number of generations is performed. When this stop condition is attained, the Pareto front is identified and the final solution can be chosen at this final step according to the end-user’s profile. The solutions individually optimizing the electricity bill or the end-user’s dissatisfaction would correspond to a more cost-oriented or a more quality of service-oriented end-user, respectively. Other profiles can be identified, such as an end-user who prefers:

- the operation of shiftable loads as soon as possible;
- the PHEV fully charged as soon as possible;
- minimal changes in the room temperature.

5.1. Problem Formulation

The problem of integrated management of residential energy resources can be formulated by means of the following model (Eq. 13-Eq. 29) which has been coded in MatLab. As it is presented here this model cannot be directly used in a mathematical programming solver such as CPLEX since it is not a mixed integer linear programming (MILP) model because of the way decision variables are represented as a function of the operation cycle of shiftable loads (Eq. 15 and Eq. 23). The transformation of this model into a MILP model is presented in (Alves et al., 2016). However, transforming the model into a standard MILP requires a very high number of auxiliary binary variables (number of minutes of the planning period X number of minutes of the load operation cycle X number of loads) and additional constraints (almost five times the total number of auxiliary variables detailed below). Note that this is only necessary if a solver, such as CPLEX, is to be used. The model representation below is adequate to be tackled by the EA and results in a simpler formulation.

5.1.1. Notation

T = number of minutes of the planning period (t =1,…,T) (T=2160)

n = number of shiftable loads to be managed (j=1,..,n)

m = number of thermostatically controlled loads to be managed (b=1,..,m)

τ_{bt} = temperature of thermostatically controlled load b at minute t of the planning period determined by the PBM according to the reference temperature and the end user's preferences.

C_t = contracted power at minute t of the planning period (kW)

u_t = non-manageable base load at minute t of the planning period (kW)

Z = amount of energy required by the electric vehicle to fulfill end-user's needs (kWh)

d_j = duration of the operation cycle of load j (minutes)

$€_t$ = kWh price at minute t of the planning period (€/kWh)

$f_j(r)$ = power requested by shiftable load j at minute r of its working cycle (r =1,…,d_j) (kW) (Figure 24)

g_{jt} = penalty associated with the risk of interruption of energy supply to load j at minute t of the planning period

h_{jt} = penalty associated with the time slots assigned to shiftable load j at minute t of the planning period

r_{bt} = penalty associated with the variation of temperature in thermostatically controlled load b at minute t defined by the PBM r_{bt}={0, R_{bt}}; R_{bt} calculated in Eq. 29

T_{refLb} = minimum reference temperature of load b

T_{refHb} = maximum reference temperature of load b

w_b = allowable deadband variation for load b

LP_t = local generation at minute t of the planning period

Q = maximum capacity of battery (kWh)

Q_0 = energy stored in the battery at the beginning of the planning period (kWh)

T_I = starting minute at which the PHEV is available for charging

T_F = end minute at which the PHEV is available for charging

<u>*Decision variables:*</u>

x_j = starting minute of the working cycle of shiftable load j

s_t = total power injected into the grid at minute t of the planning period (kW)

s_{LPt} = power from local production injected into the grid at minute t of the planning period (kW)

s_{Bt} = power from battery injected into the grid at minute t of the planning period (kW)

a_t = total power used for self-consumption at minute t of the planning period (kW)

a_{LPt} = power from local generation used for self-consumption at minute t of the planning period (kW)

a_{Bt} = power from battery used for self-consumption at minute t of the planning period (kW)

v_t = power requested to the grid by the stationary storage system at minute t of the planning period (kW)

v_{LPt} = power from local production used for feeding the stationary storage system at minute t of the planning period (kW)

y_{jt} = binary variable representing whether the working cycle of shiftable load j is "on" ($y_{jt} = 1$) or "off" ($y_{jt} = 0$) at minute t of the planning period

p_{jt} = power requested to the grid by shiftable load j at minute t of the planning period (kW), including the PHEV

p_{bt} = power requested by thermostatically controlled load b at minute t of the planning period (kW) p_{bt}={0, P_b}; P_b is the rated power of load b.

5.1.2. Model

$$\min \sum_{t=1}^{T}\left(\sum_{j=1}^{n}\frac{€_t\, p_{jt}}{60}+\sum_{b=1}^{m}\frac{€_t\, p_{bt}}{60}+\frac{€_t v_t}{60}-\frac{0.8€_t s_t}{60}+\frac{€_t u_t}{60}\right) \quad \text{Eq. 13}$$

$$\min \sum_{t=1}^{T}\left(\sum_{j=1}^{n}(g_{jt}+h_{jt})y_{jt}+\sum_{b=1}^{m} r_{bt}\right) \quad \text{Eq. 14}$$

s. t.

$$y_{jt}=\begin{cases}1, & \text{if } x_j \le t \le x_j+d_j\\ 0, & \text{otherwise}\end{cases} \qquad j=1,\dots,n \quad t=1,\dots,T \quad \text{Eq. 15}$$

$$\sum_{j=1}^{n} p_{jt}+u_t+\sum_{b=1}^{m} p_{bt}+v_t-a_t \le C_t \qquad \forall t \quad \text{Eq. 16}$$

$$a_t = a_{LPt}+a_{Bt} \qquad \forall t \quad \text{Eq. 17}$$

$$s_t = s_{LPt}+s_{Bt} \qquad \forall t \quad \text{Eq. 18}$$

$$a_{LPt}+s_{LPt}+v_{LPt}=LP_t \qquad \forall t \quad \text{Eq. 19}$$

$$Q_0+\frac{1}{60}\sum_{k=1}^{t}\left(v_k+v_{LBk}-(a_{Bk}+s_{Bk})\right)\le Q \qquad \forall t \quad \text{Eq. 20}$$

$$\frac{1}{60}\sum_{t=T_i}^{T_F} p_{jt}=Z \qquad \forall t \quad j=EV \quad \text{Eq. 21}$$

$$p_{jt}=f_j(t-x_j+1)y_{jt} \qquad j=1,\dots,n \quad t=1,\dots,T \quad \text{Eq. 22}$$

$$1\le x_j \le T-d_j+1 \qquad j=1,\dots,n \quad \text{Eq. 23}$$

The penalty coefficients g_{jt}, h_{jt} and r_{bt} are expressed in the same scale, in order to be aggregated in the dissatisfaction objective function.

The state of charge (SoC) of the stationary storage system is checked by the model in each instant of time and kept not lower than 0.2.

Concerning thermostatically controlled loads, in each iteration the algorithm guarantees that the deadband of every thermostatically controlled load lies in the interval defined by the corresponding lower and upper reference temperature. These lower and upper temperature reference values may change during the execution of the algorithm according to the end-user's preferences, although there is a penalty associated with this temperature variation.

$$Tref_{\mathrm{H}b} - w_b = Tref_{Lb} \qquad \forall\, b \qquad \text{Eq. 24}$$

For b=fridge and b=AC:

$$\begin{cases} p_{bt} = P_b, \tau_{bt} < \tau_{b(t-1)} \\ p_{bt} = 0, \tau_{bt} \geq \tau_{b(t-1)} \end{cases} \qquad \forall\, t \qquad \text{Eq. 25}$$

$$\begin{cases} r_{bt} = 0 \quad , \quad Tref_{Lb} \leq \tau_{bt} \leq Tref_{\mathrm{H}b} \\ r_{bt} = R_{bt} \; , \quad \tau_{bt} < Tref_{Lb} \vee \tau_{bt} > Tref_{\mathrm{H}b} \end{cases} \qquad \forall\, t \qquad \text{Eq. 26}$$

For b=EWH:

$$\begin{cases} p_{bt} = P_b \quad , \tau_{bt} > \tau_{b(t-1)} \\ p_{bt} = 0 \quad , \quad \tau_{bt} \leq \tau_{b(t-1)} \end{cases} \qquad \forall\, t \qquad \text{Eq. 27}$$

$$\begin{cases} r_{bt} = R_{bt} \; , \quad \tau_{bt} < Tref_{Lb} \vee \tau_{bt} > Tref_{\mathrm{H}b} \\ r_{bt} = 0 \quad , \quad Tref_{Lb} \leq \tau_{bt} \leq Tref_{\mathrm{H}b} \end{cases} \qquad \forall\, t \qquad \text{Eq. 28}$$

For the three thermostatically controlled loads (b=fridge, AC, EWH), the penalty associated with the variation of temperature is given by:

$$\begin{cases} R_{bt} = e^{\frac{|(\tau_{bt} - \mathrm{TrefHb})|}{w_b}} - 1 \, , \tau_{bt} > \mathrm{TrefHb} \\ R_{bt} = e^{\frac{|(\tau_{bt} - \mathrm{TrefLb})|}{w_b}} - 1, \tau_{bt} < \mathrm{TrefLb} \end{cases} \qquad \forall\, t \qquad \text{Eq. 29}$$

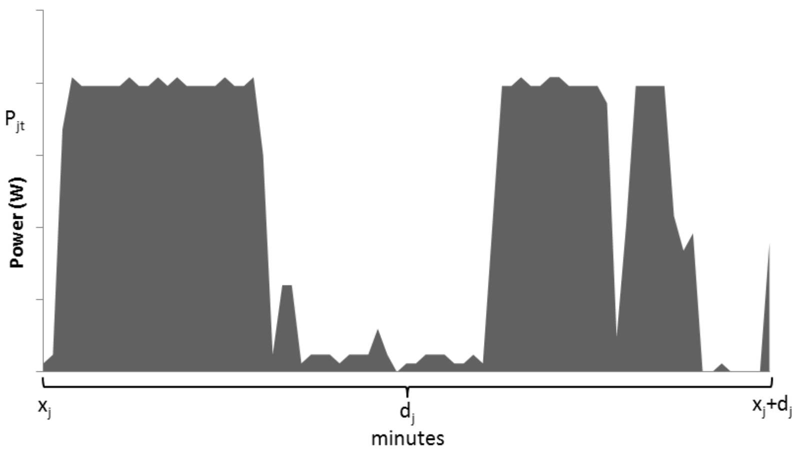

Figure 24: Example of power requested by shiftable load j initiating its working cycle, with a duration d_j, at minute x_j of the planning period

Consumption data for every manageable load and weather forecasts are embedded in the input data to the PBM and used in the optimization process to shape the household's load profile. Information such as electricity prices, emergency signals and requests for load reduction/augmentation coming from the utility can also be transmitted to the EMS and ADR decisions will be performed accordingly.

In order to offer the ability to make decisions without the need to continuously interact with the end-user, the EMS must correctly interpret end-user's preferences concerning time slots for the use of shiftable loads, admissible variations in temperature settings for thermostatically controlled loads, minimum SoC required by a given time in the planning period. Thus the importance of using PBMs to reproduce the power profile of thermostatically controlled loads and stationary storage systems with the aim of providing information to guide the EMS determining the ADR actions to be implemented. PBMs allow assessing the impact of an ADR action in terms of power requested to the grid and comfort (temperature) (Gomes et al., 2013). Each type of thermostatically controlled load (cold appliance, AC system or EWH) uses a specific PBM as presented in section 4.1.1. As the same type of ADR action may have different impacts over different loads, it is thus important to consider this aspect in the optimization process whenever evaluating the objective functions or assessing the satisfaction of constraints.

Solutions are evaluated concerning two axes: the electricity bill and the dissatisfaction perceived by the end-user concerning the energy services provided. The electricity bill includes the cost of energy consumed by the loads, the ones being managed and the non-manageable load, and the revenue from injecting energy into the grid.

Although end-user's dissatisfaction is difficult to measure, several key criteria were included in this assessment. The detailed knowledge of the physical characteristics of the problem and the possible impacts of ADR actions allowed the identification of the following key aspects that directly influence end-user's dissatisfaction, which is modelled by means of penalty coefficients:

- allocation of shiftable loads, including the PHEV, outside the time slots specified by the end-user;
- room temperature resulting from AC operation being outside the admissible temperature range;
- unavailability of hot water at the desired temperature when the end-user needs it;
- not attaining the minimum SoC of the PHEV battery.
- not keeping a safety margin to prevent the interruption of energy supply due to overcoming the contracted power.

For the cold appliance or the AC system, the temperature penalty is computed according to the difference between the maximum/minimum reference temperature and the temperature set due to the implementation of the ADR action. If the temperature setting resulting from the implementation of the ADR action is kept within the reference range $[\mathrm{TrefLb};\ \mathrm{TrefHb}]$, the penalty is equal to zero. When the temperature setting resulting from the implementation of the ADR action is outside that range, the exponential term Eq. 26 is used. If the temperature resulting from the implementation of the ADR actions is lower than the minimum reference temperature, then there is also an extra amount of energy consumed leading to an increase in the electricity cost.

For the EWH, when the difference between the temperature setting resulting from the implementation of the ADR action and the minimum reference temperature is negative, or the difference between the temperature setting resulting from the implementation of the ADR action and the maximum reference temperature is positive, then the exponential term Eq. 29 is used.

The temperature penalties were balanced to prevent a thermostatically controlled load with a wider range of temperature variation (such as the EWH) from having a higher impact on the overall dissatisfaction objective function.

6. SIMULATION RESULTS

The algorithmic approach developed (Chapter 5) requires the following inputs:

- the energy resources to be managed;
- end-users' preferences concerning time slots for the allocation of shiftable loads;
- allowable temperature range for thermostatically controlled loads;
- minimum SoC in the PHEV battery when used in both the G2V and V2G modes;
- energy price for buying and selling energy from/to the grid, which may be different;
- weather conditions (temperature and insolation forecasts);
- the existence of any type of local generation system and the associated forecasted production.

Energy supply from the grid is assumed to be always available and emergency signals may be triggered. The emergency signals considered in this approach can be used by utilities to induce consumption changes, for example if the reliability of the system is jeopardized for some reason or due to lack or surplus of energy.

The degree of difficulty concerning the optimization process depends on the amount of resources being managed. The computational effort is lower when only shiftable loads are considered as manageable resources; further complex cases may include thermostatically controlled loads, storage systems, either the PHEV or stationary systems, and the existence of local generation from different sources.

Considering a real setting implementation, some inputs come from the grid, others from the use of adequate sensoring equipment and the remaining information should be specified by the end-user. A prototype is under development incorporating this algorithmic approach. Communication between the multiple residential manageable loads, microgeneration and storage systems and the gateway, responsible for coordinating the information exchange between the Monitoring and Control Plug (MCP) devices and the EMS where the optimization algorithms are running, can be done using RF or a ZigBee stack as presented in (Soares et al., 2015b) (Figure 25).

6.1. Case Study 1

In order to show the capability of this algorithmic approach to deal simultaneously with multiple manageable resources and the corresponding end-user's preferences, the first case study includes:

- three shiftable loads (dishwasher – DW, laundry machine – LM and tumble dryer – TD);
- three thermostatically controlled loads (fridge, conventional AC system, EWH);
- one PHEV which may be used in both G2V and V2G modes;
- a local generation system.

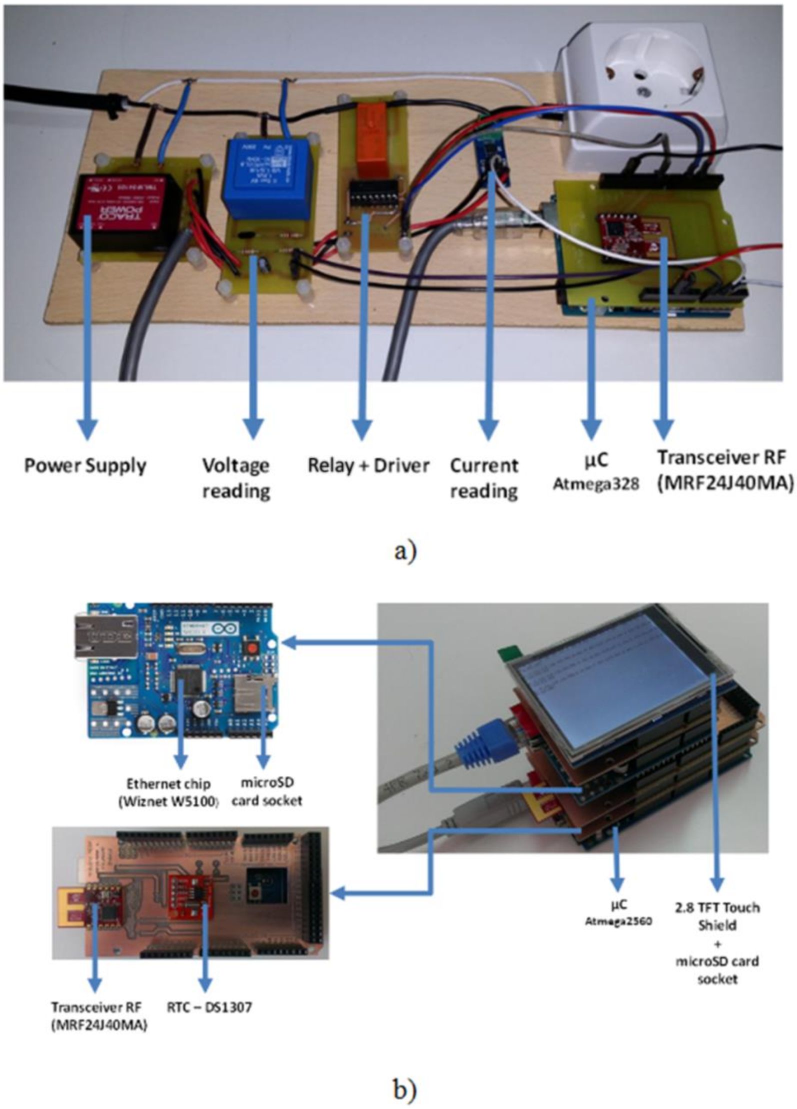

Figure 25: Prototype under development: a) Monitoring and Control Plug. b) Information Gateway

The working cycles of the shiftable loads are known in advance, since they mainly depend on the program chosen, and are plotted in Figure 26. The PHEV needs around 9.6 kWh to be fully charged, assuming that the initial SoC is 20% (Figure 27). (Soares et al., 2015a) presented a PHEV charger topology and AC/DC converter controller architecture for V2G and G2V operation which may be used in a real setting to control the PHEV.

Temperature and PV local generation forecasts for a hot day are represented in Figure 28. The prices for buying and selling energy from/to the grid are different, with the kWh selling price always below the buying price (Figure 29). This assumption is in accordance with actual Portuguese legislation concerning distributed generation, self-consumption and the injection of energy in the power grid (*Decreto-Lei n.º 153/2014 de 20 de outubro*, 2014). The energy buying price is based on a three level time-of-use tariff in which the lowest price corresponds to the night period and the peak price is achieved during late morning and early night (Figure 29). The lowest energy price is 0.11 €/kWh, peak price is 0.19 €/kWh and the intermediate price is 0.16 €/kWh. For illustrative purposes, the energy selling price is 80% of the energy buying price.

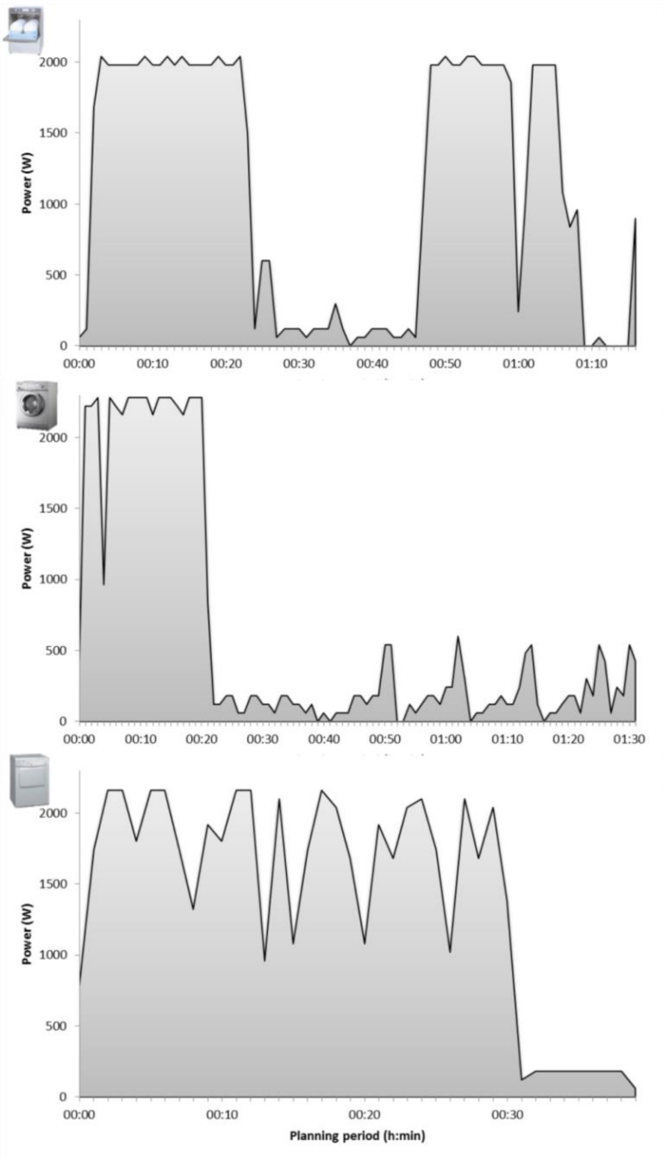

Figure 26: Working cycles of the three shiftable loads (DW, LM and TD)

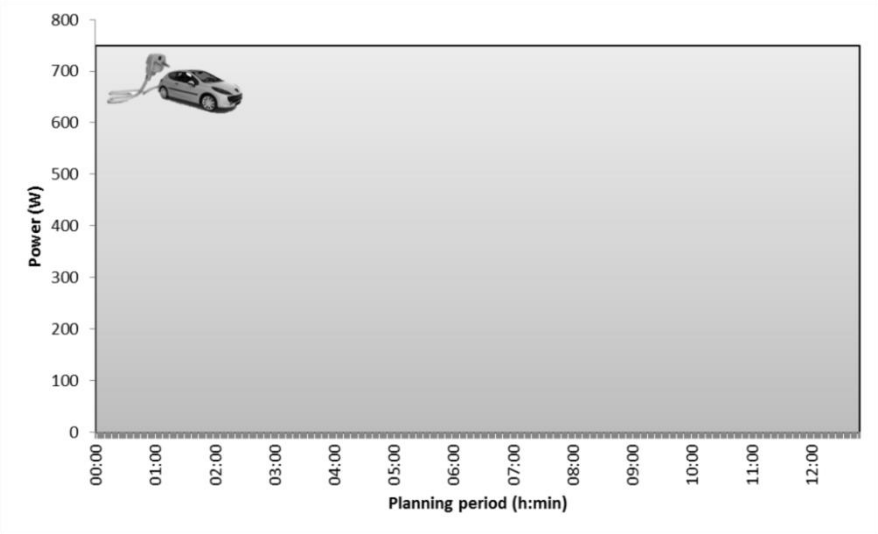

Figure 27: Working cycle of the PHEV when used only in the G2V mode and charged from 20% until 100% (total amount of energy needed 9.6 kWh)

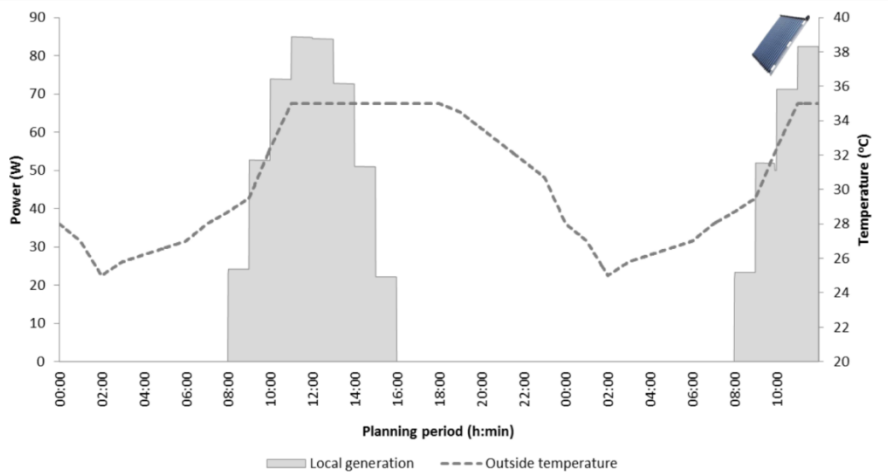

Figure 28: Temperature and local generation (photovoltaics) forecast

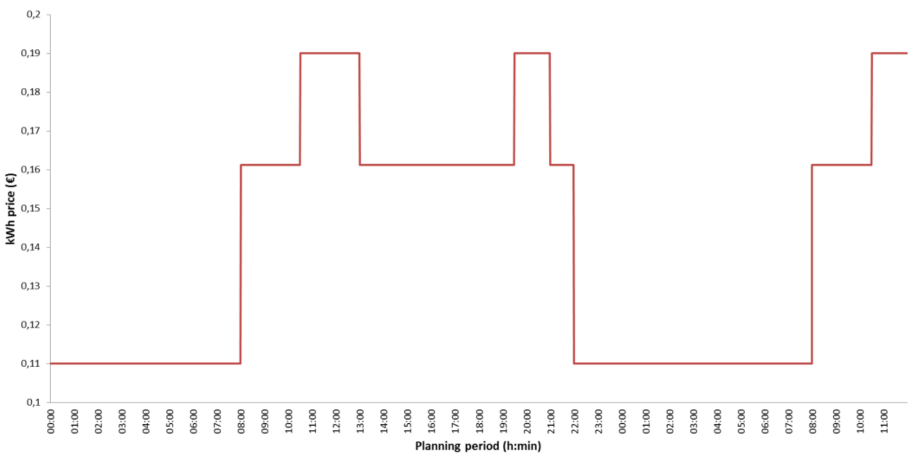

Figure 29: Tariff structure considered (buying price)

Time slots preferences for shiftable loads such as dishwashers, laundry machines and tumble dryers are dealt with in the same way as depicted in section 4.3 and (Soares et al., 2014a, 2013b), considering time slots with different penalties for the scheduling of their working cycles (Figure 30). The preferable time slot for operation of the DW is during the night period, between 12 am until 7 am, and later in the next day during dawn. There are other admissible time slots which have, however, a dissatisfaction penalty: a constant dissatisfaction penalty around 12 pm till 4:30 pm, a decreasing penalty beginning around 10 am till 12 pm and an increasing penalty from 4:30 pm till 3 am. For the LM, the preferable time slots, i.e., without any dissatisfaction penalty associated are linked to the end-users' availability to hang clothes or place them in the TD. Therefore two time slots are considered: the first one during early morning of the first day of the planning period and the other one from lunch time till around 4 pm. Increasing and decreasing penalties are also associated with other time slots, namely before 6 am, between 8:30 am and 12 pm, and after 4 pm until midnight. The TD is supposed to work only after the LM and thus the preferable time slots starts after 4 am. This does not mean that the end-user is loading the TD during late night. In fact, clothes may be placed in the TD as soon as the LM has completed its working cycle, but the preferable time slot for its operation occurs later at night/early dawn.

For the sake of comparison, a reference scenario with a plausible instantiation of these inputs should be established to assess savings and impacts of solutions corresponding to ADR actions. Thus, in the reference case:

- shiftable loads are allocated according to the time slots allowed for load operation and the kWh buying price;
- no ADR actions are implemented over thermostatically controlled loads;
- the PHEV is used in both V2G and G2V modes, but the SoC must have already achieved 100% before the end of the planning period;
- the PHEV is charged mainly during the periods of time when the energy price is lower and the energy stored is consumed when the energy price is higher; the energy selling price is 80% of the kWh buying price; the degradation induced by charging/discharging cycles is not taken into account.

Concerning thermostatically controlled loads, the evolution of the working cycle and the temperature without the implementation of ADR actions together with the admissible variation range are represented in Figure 31 and Figure 32. The admissible temperature variation range is associated with the interval of comfort for each thermostatically controlled load and changes with the end-user's needs and preferences. Thus, for each household, the temperature limits of these loads may be chosen and inserted as input information.

For the electric water heater, temperature must be kept ideally in the range [50; 55] ^{o}C so no dissatisfaction penalty is incurred. Nevertheless, in order to achieve savings in the electricity bill, the end-user allows the [45; 60] ^{o}C variation range with a dissatisfaction penalty (Eq. 28 and Eq. 29). The AC system should work between [19;21] ^{o}C with no penalty and may have a more flexible allowable temperature range variation [17;23] ^{o}C with the corresponding dissatisfaction penalty (Eq. 26 and Eq. 29). Considering the fridge, and although temperature is not constant inside the fridge, the normal temperature variation range is [4; 6] ^{o}C while the allowable variation is [2;8] ^{o}C with the corresponding dissatisfaction penalties (Eq. 26 and Eq. 29).

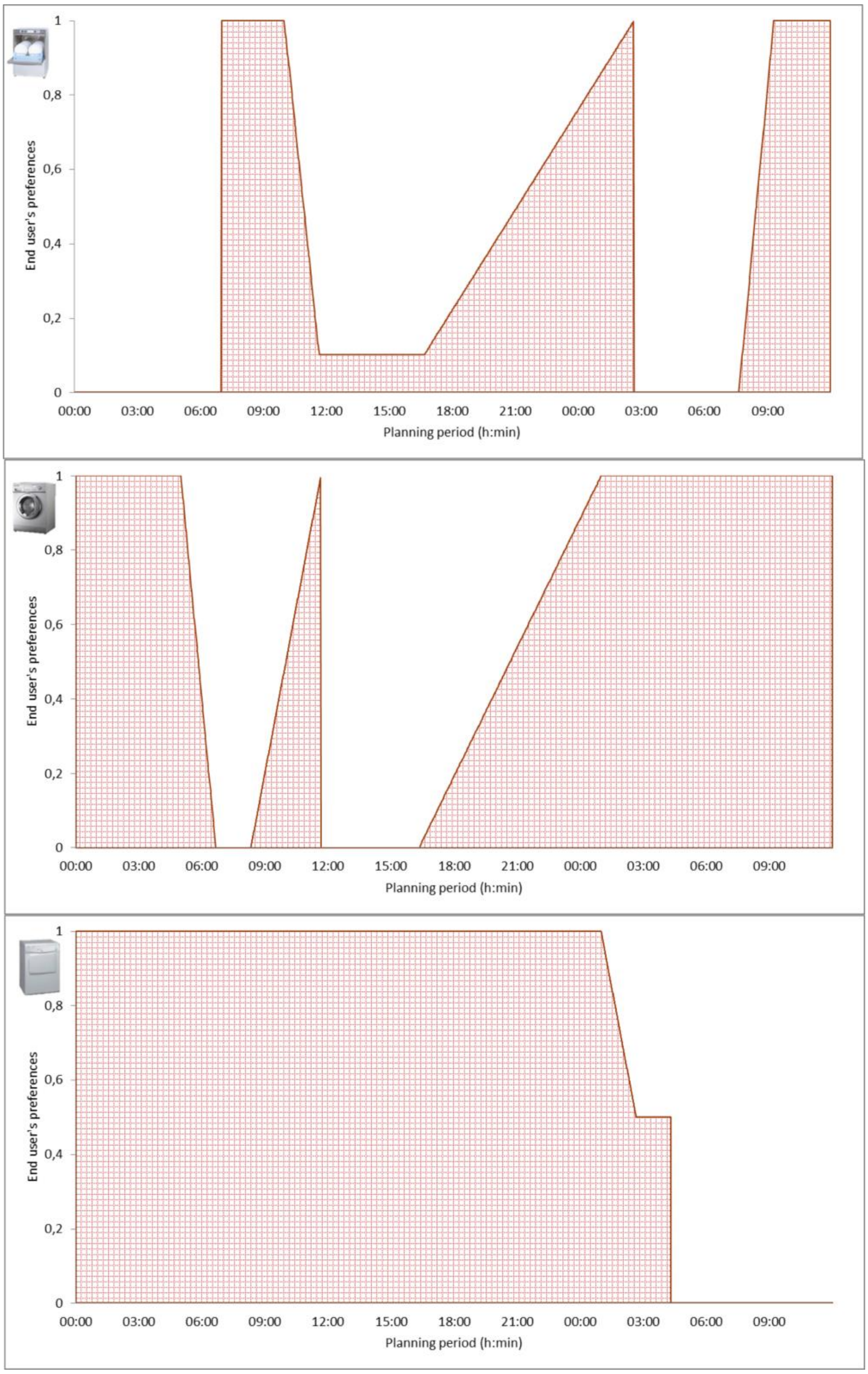

Figure 30: Time slot preferences for shiftable loads (DW, LM and TD)

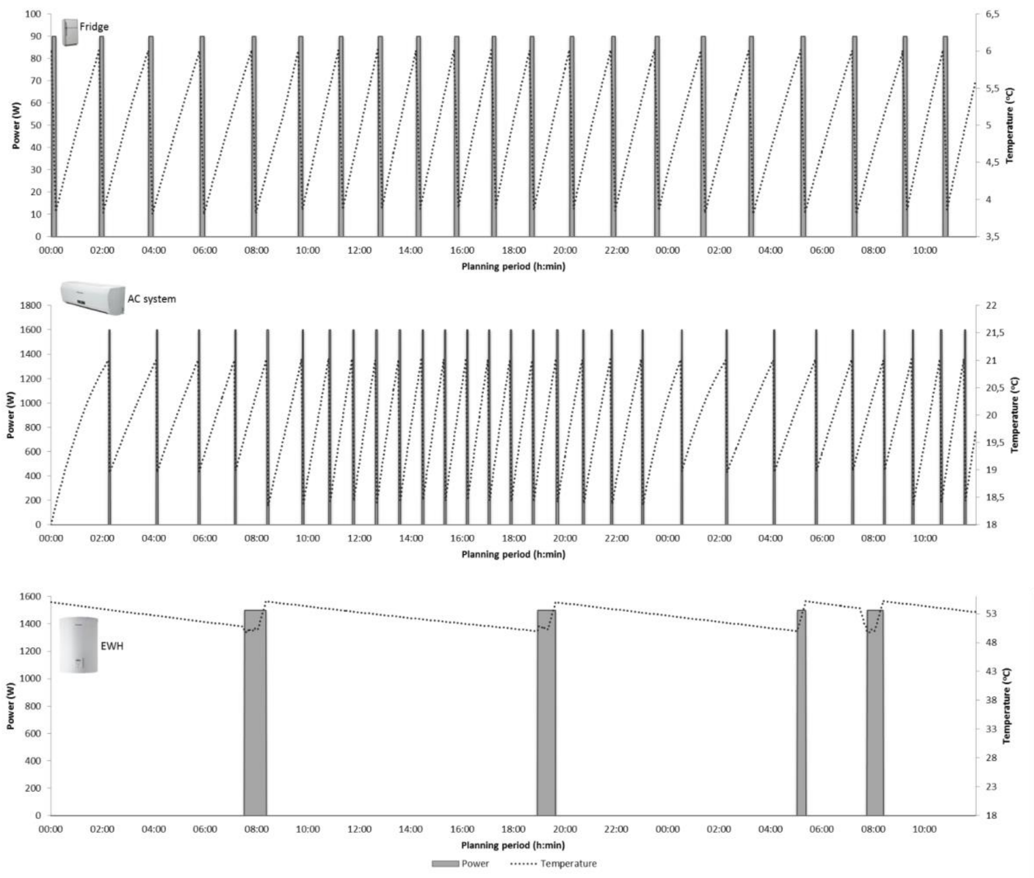

Figure 31: Power and temperature evolution of thermostatically controlled loads without the implementation of ADR actions (reference case) for the planning period

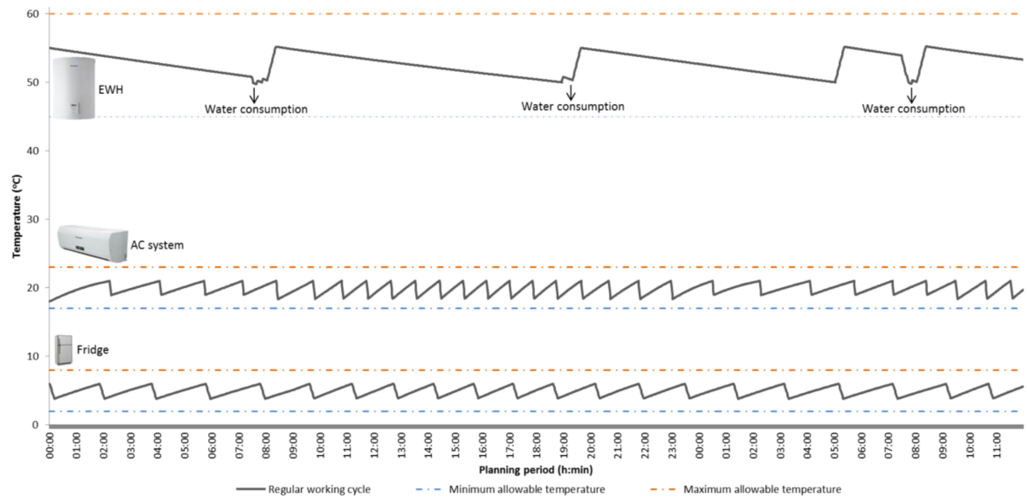

Figure 32: Normal behavior of thermostatically loads and admissible variation range (no ADR actions)

The resulting load diagram for the reference case considering a planning period of one day and a half is depicted in Figure 33 and the corresponding electricity bill is 3.47 €. The SoC variation is represented in Figure 34 and it is possible to see that the PHEV is charged when the energy price is at its minimum value and some of the stored energy is used for self-consumption or injected in the grid when the energy price is higher. A profit of 0.12 € is achieved from the injection of energy into the grid.

Although the end-user does not own any type of EMS in this reference case, the operation of shiftable loads is avoided when the energy price is higher, similarly to what the end-user would do if he knew in advance the energy prices. Also the SoC of the PHEV battery is controlled by the end-user in such a way that after 10 pm the battery cannot be used in the V2G mode so it can be fully charged in the morning of the second day and preferably before the end of the planning period. Temperature variation of thermostatically controlled loads is shown in Figure 32, since no ADR actions are used and thus the normal working cycle of these loads remains unchanged.

The optimization approach is launched using the same inputs as the reference case but allowing the EMS to do an integrated management of the multiple energy resources. The minimum energy acquisition cost, and the minimum dissatisfaction caused to the end-user are used to compare the results when different parameters are used. The best combination of parameters were tuned through extensive experimentation and is shown in Table 7, while results obtained for each run are summarized in Table 8. Note that the true Pareto optimal front for this bi-objective optimization problem is not known.

The different values, resulting from the tuning process, for the operators are due to the features of each load. The mutation operator has a:

- higher value in thermostatically controlled loads since changing one temperature degree in some genes of the chromosome generally leads to better results;
- very low value in the PHEV since randomly changing some genes can impose a high frequency of charging and discharging decisions.

Results have shown that the crossover operator did not produce so good results when the integrity of each segment of the chromosome component associated with some type of loads, namely thermostatically controlled loads, was not respected. This is explained since any interchange of information between individuals concerning these loads would strongly impact on the power required by each load and the temperature because the temperature of the fluid being heated/cooled depends on the recent operation of the load. Also the rate for the mutation operator has different values according to the load categorization. Thus the mutation operator used in thermostatically controlled loads has a higher value, while for the PHEV (when used in G2V and V2G modes) this value is quite low. The reason is that occasionally changing one or several genes in the components of the chromosome associated with thermostatically controlled loads may slightly change the temperature and consequently the power required from the grid for these loads, while the decision of charging/discharging or doing nothing for the stationary storage system may have an unwanted impact in energy flows (for instance, quick changes imposing a high frequency of charging and discharging decisions).

Concerning the results obtained for 30 runs with 50 individuals and 1000 generations, the worst solution that individually optimizes end-user's dissatisfaction is due to not reaching the 100% SoC by the end of the planning period. In fact, in this specific run, none of the solutions reached 100% SoC, although all the solutions reached the minimum desired SoC (at least 50%) and 22% of the solutions achieved a SoC above 72%. Additionally, the quality of the energy services provided are not jeopardized since the minimum SoC is always attained. In the 30 runs, 73% of the solutions that individually optimize end-user's dissatisfaction achieve 100% of the SoC by the end of the planning and 90% achieve 80% of the SoC.

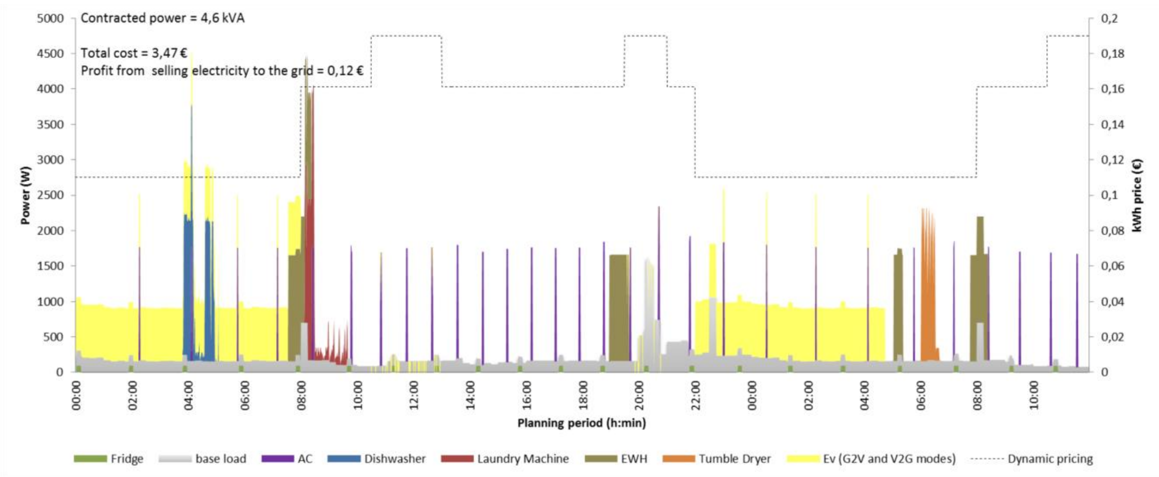

Figure 33: Reference case

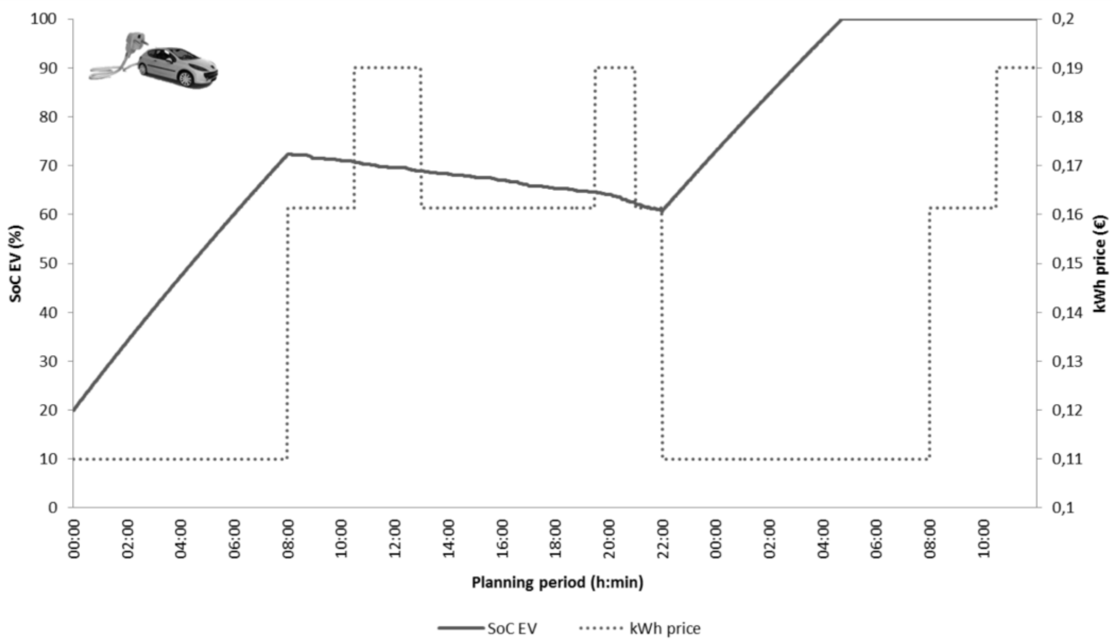

Figure 34: SoC variation of the PHEV battery during the planning period

Table 7: Probabilities of operators over different loads

	Mutation	Crossover
Shiftable loads	0.2	0.5
Thermostatically controlled loads	0.6	0
PHEV (G2V and V2G modes)	0.02	0.5

Table 8: Results obtained considering 30 EA runs (50 individuals and 1000 generations)

	Energy cost (€)	Dissatisfaction
Best	2.156	0.048
Worst	2.268	3.182
Median	2.185	0.060
Average	2.194	0.717
Std Deviation	0.025	1.063

Figure 35 displays the non-dominated solution set in the bi-objective space: costs associated with energy purchase, including the profit from selling energy to the grid, and end-user's dissatisfaction. These illustrative results correspond to a randomly chosen run. The Pareto front is uniformly spread-out except for a specific zone where solutions A and B are represented. The difference verified is mainly due to the physical characteristics of the multi-objective problem and the impacts of the ADR actions over the electricity bill and end-user's dissatisfaction, especially due to the impact of the ADR actions over the EWH which causes a high dissatisfaction (Figure 36).

The solutions that individually optimize the electricity bill (solution I) and the end-user's dissatisfaction (solution J) are represented in Figure 37 and Figure 38. An intermediate solution K is displayed in Figure 39. The main differences between these three solutions are the ADR actions implemented over thermostatically controlled loads (Figure 40) and the energy flows between the PHEV, as well as the other energy resources and the grid which directly impact on the SoC and consequently on end-user's dissatisfaction (Figure 41). Solutions are consistent in terms of allocating as far as possible shiftable loads in periods of time where the energy price is lower and the penalty associated with the time slots is zero, as well as charging the battery during the period of time where energy price is lower to use the energy stored for self-consumption when the energy price is higher.

All the solutions of the Pareto front present savings when compared to the reference case. Nevertheless, some of them present higher savings since the SoC of the PHEV does not attain 100%. Thus, in order to have a direct fair comparison, solutions presenting 100% SoC by the end of the planning period allow savings between 5-11%. The EMS with this EA approach embedded allows a better integrated management of all resources and consequently a better use of the PHEV in V2G mode.

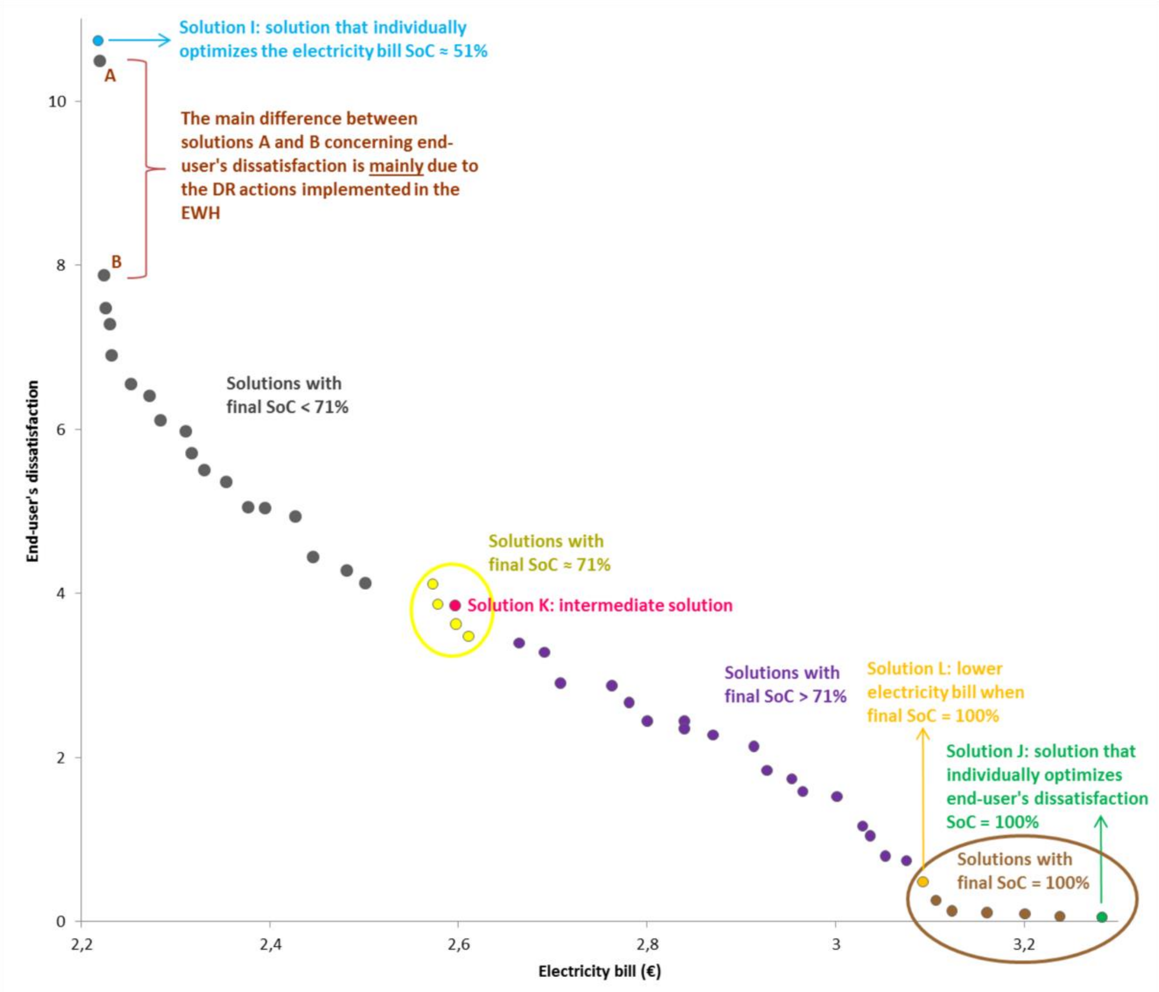

Figure 35: Pareto front for case study 1

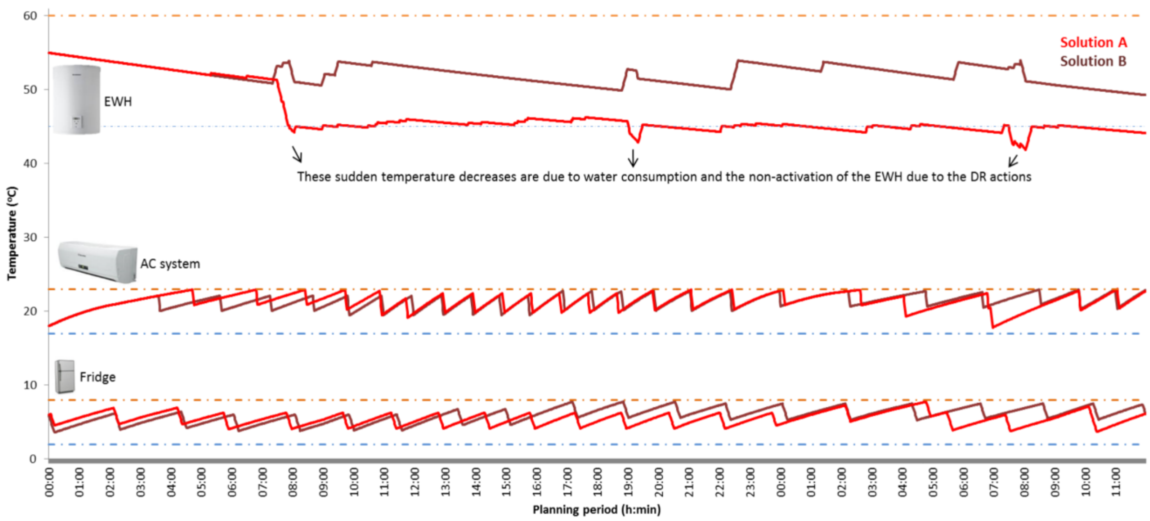

Figure 36: Main differences between solutions A and B

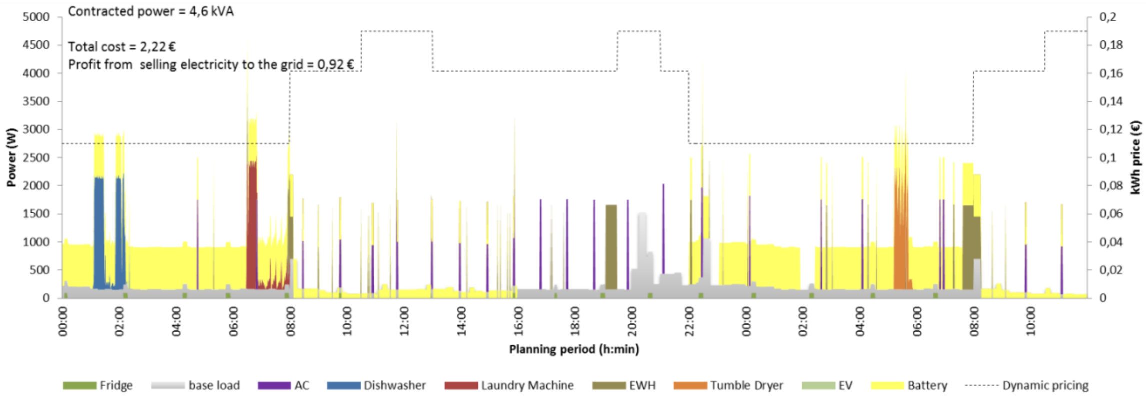

Figure 37: Solution that individually optimizes the electricity bill – solution I

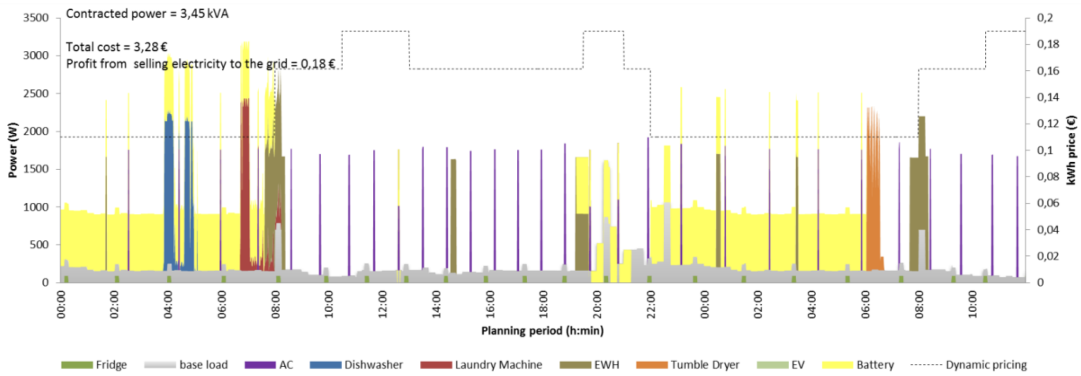

Figure 38: Solution that individually optimizes end-user's dissatisfaction – solution J

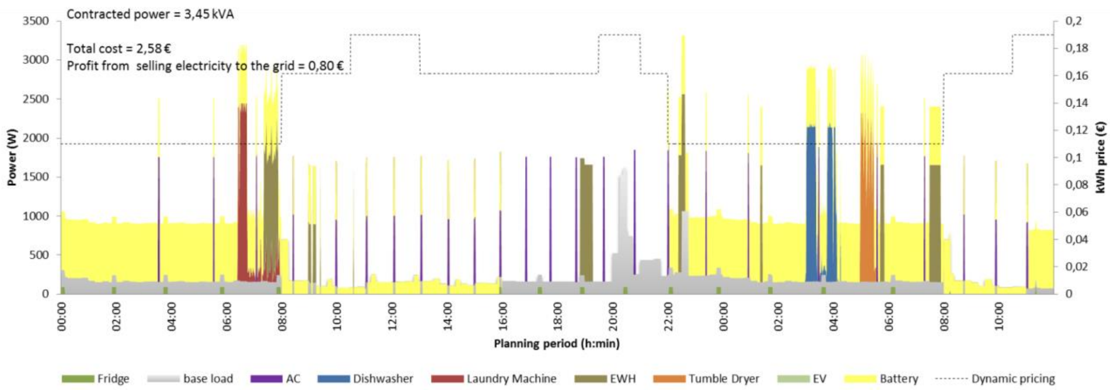

Figure 39: Intermediate solution K

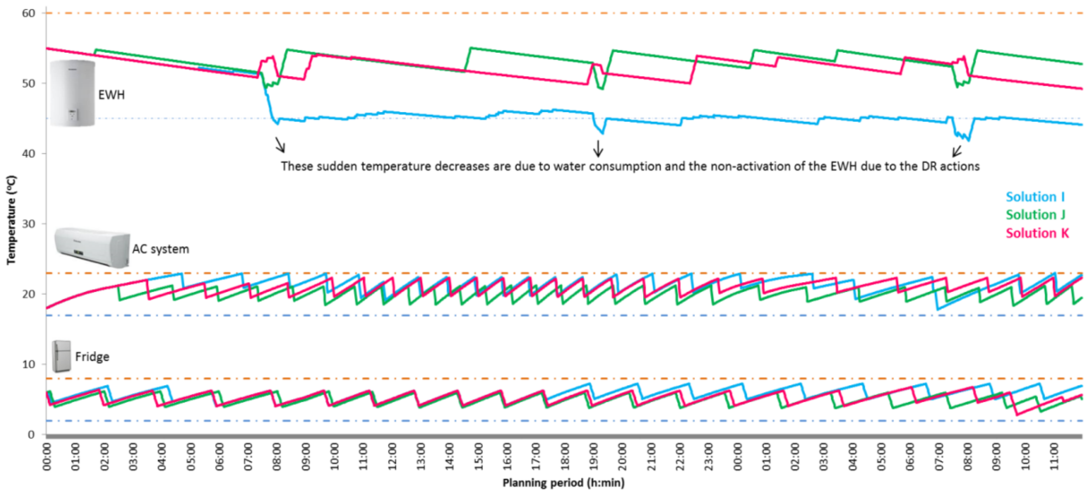

Figure 40: Impact of ADR actions over thermostatically controlled loads – solutions I, J and K

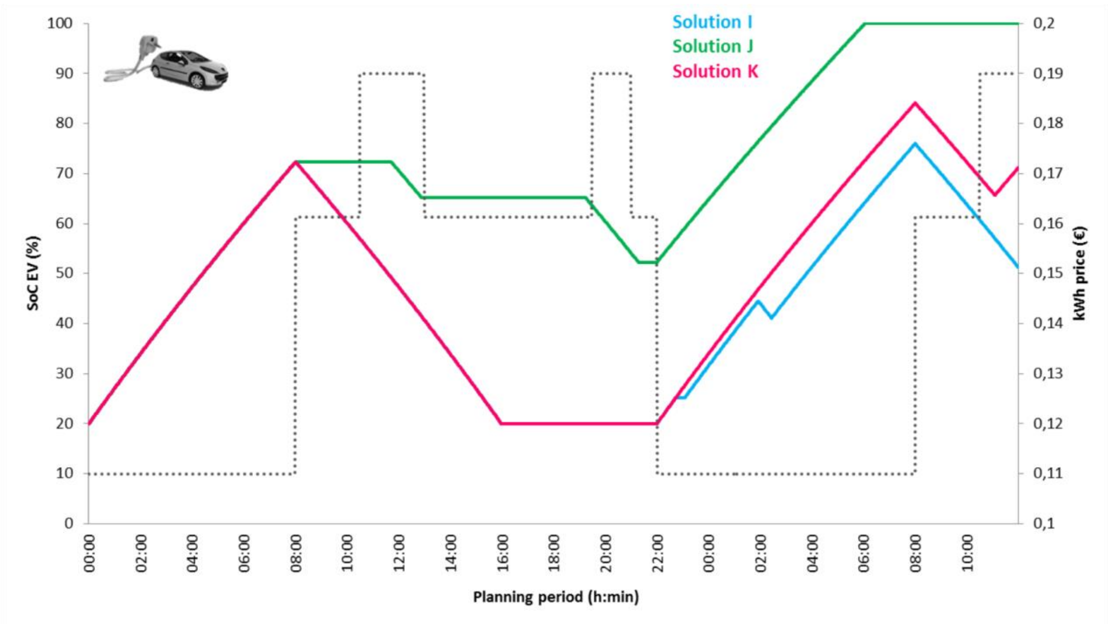

Figure 41: Impact of ADR actions over the SoC of the PHEV battery – solutions I, J and K

Solutions in the Pareto front have different features. The choice of the final solution depends on the end-user profile. An end-user who privileges savings in the electricity bill can choose solution I (Figure 35). However, if the end-user wants to simultaneously minimize electricity bill but having 100% final SoC level in the PHEV battery, then solution L is a good candidate to be chosen (Figure 35 and Figure 42). On the other hand, if the end-user wishes to favor solutions with lower impact on dissatisfaction, then solution J is the choice.

This approach allows establishing trade-offs between the electricity bill and the quality of service evaluation dimensions. For instance, solution A is 0.02 € cheaper than solution B but has a much higher dissatisfaction penalty associated with mainly due to the hot water temperature which is kept at a lower value.

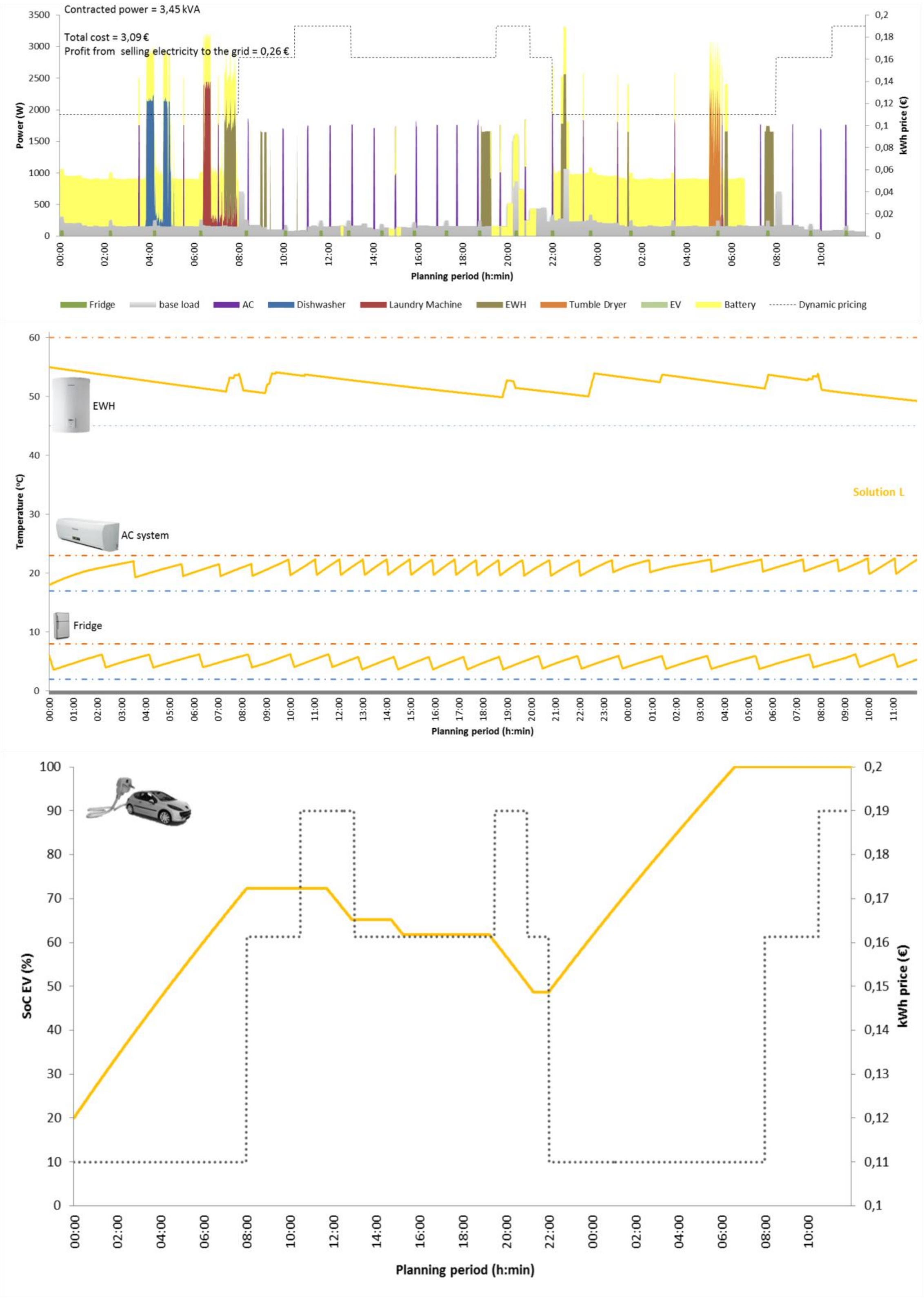

Figure 42: Solution L: lower electricity bill when final SoC = 100%

6.2. CASE STUDY 2

In case study 1, the level of contracted power is the same as in the reference case (4.6 kVA). The desired level of contracted power can be entered as a constraint and force the EA to find solutions requiring a lower level of contracted power (since this implies a lower fixed term power tariff).

Case study 2 uses a 3.45 kVA contracted power level as a constraint, which means that all solutions require one power level below the reference case presented in Chapter 6.1. An illustrative example of the solution that individually optimizes end-user’s dissatisfaction (solution J) considering 3.45 kVA for the contracted power level is represented in Figure 43. The load diagram for the solution that individually optimizes the electricity bill (solution I) is represented in Figure 44. Differences concerning temperature variation of thermostatically controlled loads and SoC of the PHEV battery are summarized in Figure 45. Solution I (that individually optimizes the electricity bill) keeps most of the time AC and fridge temperatures closer to the maximum reference temperature and hot water temperature in the EWH closer to the minimum reference temperature, in comparison with solution J (that individually optimizes end-user’s dissatisfaction) which keeps temperature within the normal range as far as possible. Concerning the SoC of the PHEV battery, solution I attains around 51% by the end of the planning period while solution J fully charges the battery.

The Pareto front for this run is presented in Figure 46 and the main differences between solutions A and B are shown in Figure 47 and Figure 48. The main differences between these solutions are the ADR actions over thermostatically controlled loads, the energy flows between stored energy in the PHEV battery, the grid and the other residential resources, and the final SoC of the PHEV battery. Solution A presents a lower electricity bill at the expense of a higher dissatisfaction. The allocation of the dishwasher, laundry machine and tumble dryer is also done in a different time slot between solutions A and B, which also impacts on end-user’s dissatisfaction. For instance, in solution A the allocation of the dishwasher has a penalty associated with the allocation in a time slot which is not the most preferred; while in solution B no penalty is assigned.

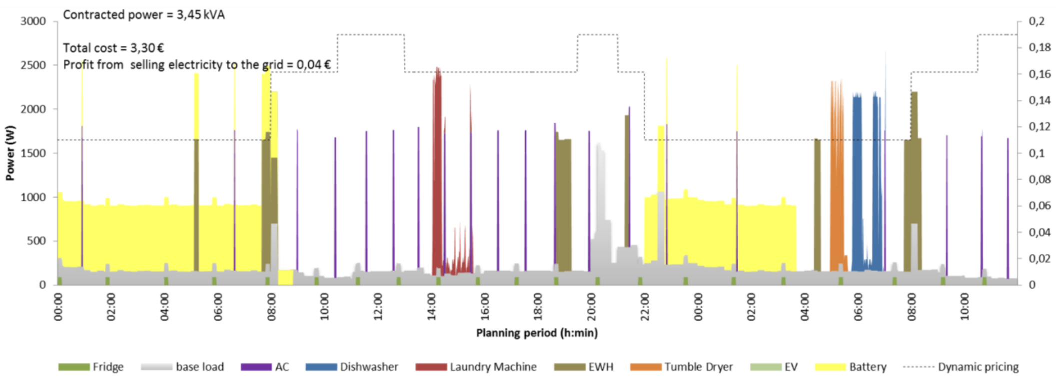

Figure 43: Solution J that individually optimizes end-user’s dissatisfaction considering as constraint 3.45 kVA for the contracted power level

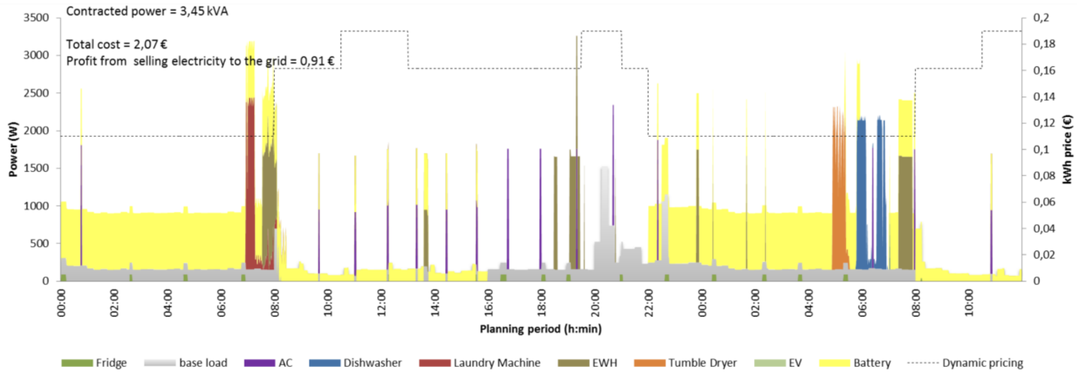

Figure 44: Solution I that individually optimizes the electricity bill considering as constraint 3.45 kVA for the contracted power level

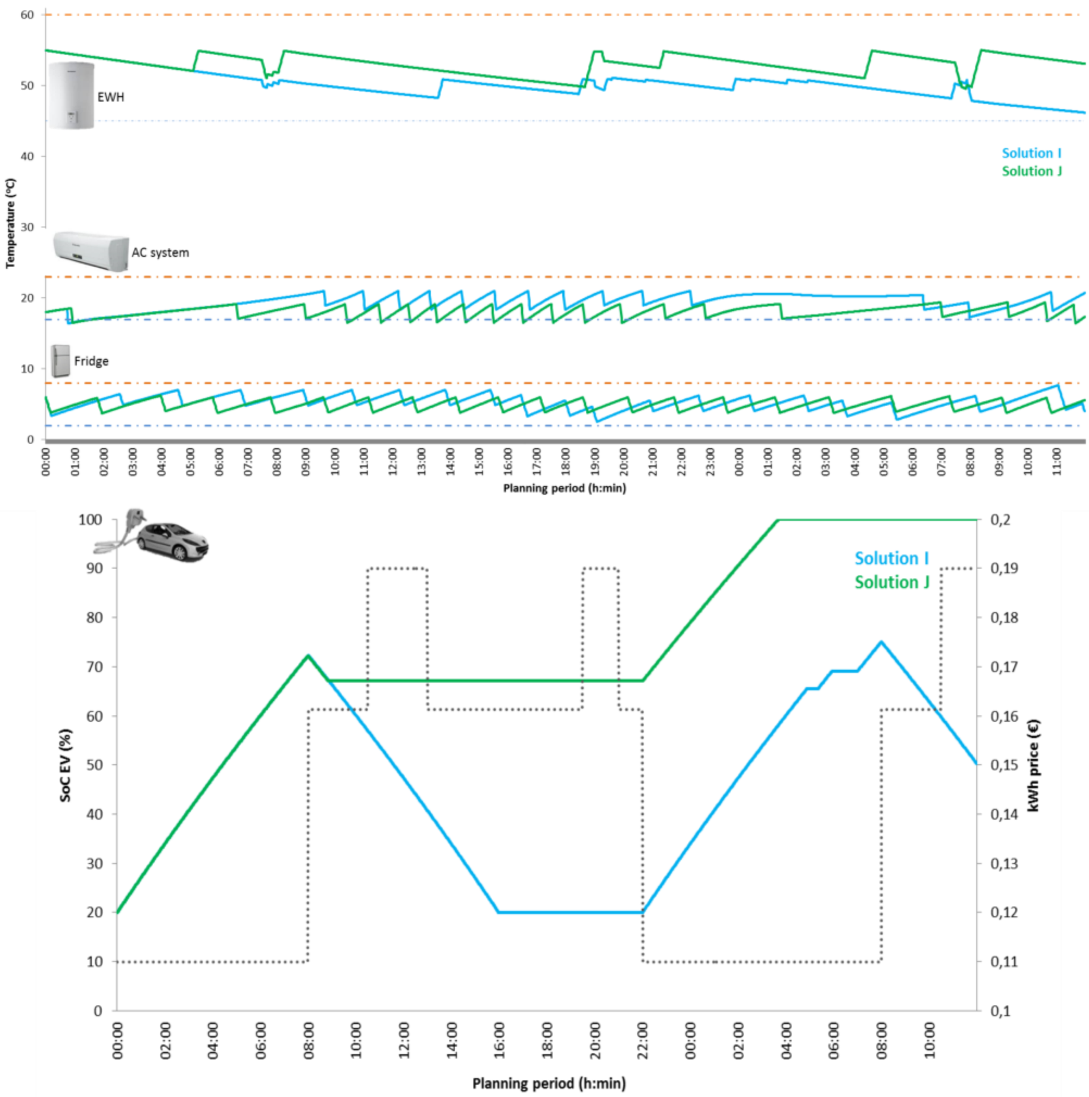

Figure 45: Main differences in thermostatically controlled loads and the PHEV between solutions I and J

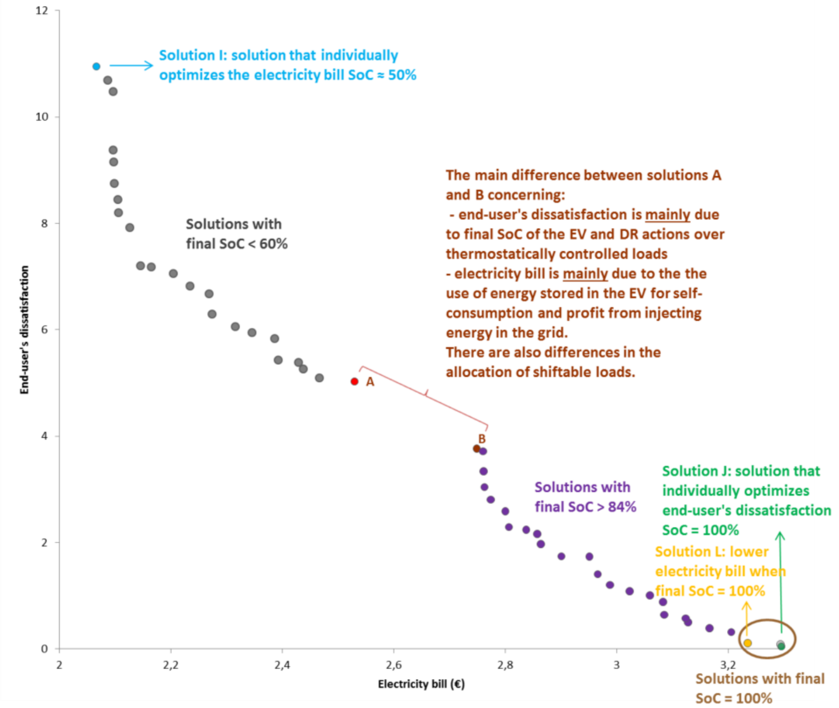

Figure 46: Pareto front for case study 2 considering 3.45 kVA as the contracted power

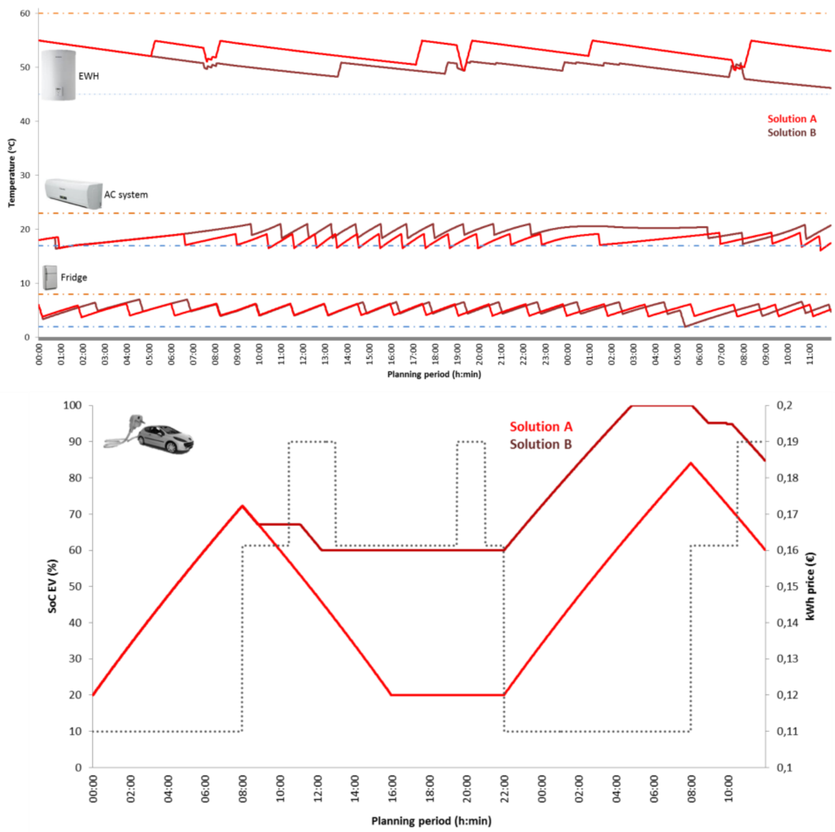

Figure 47: Main differences in thermostatically controlled loads and the SoC of the PHEV battery between solutions A and B

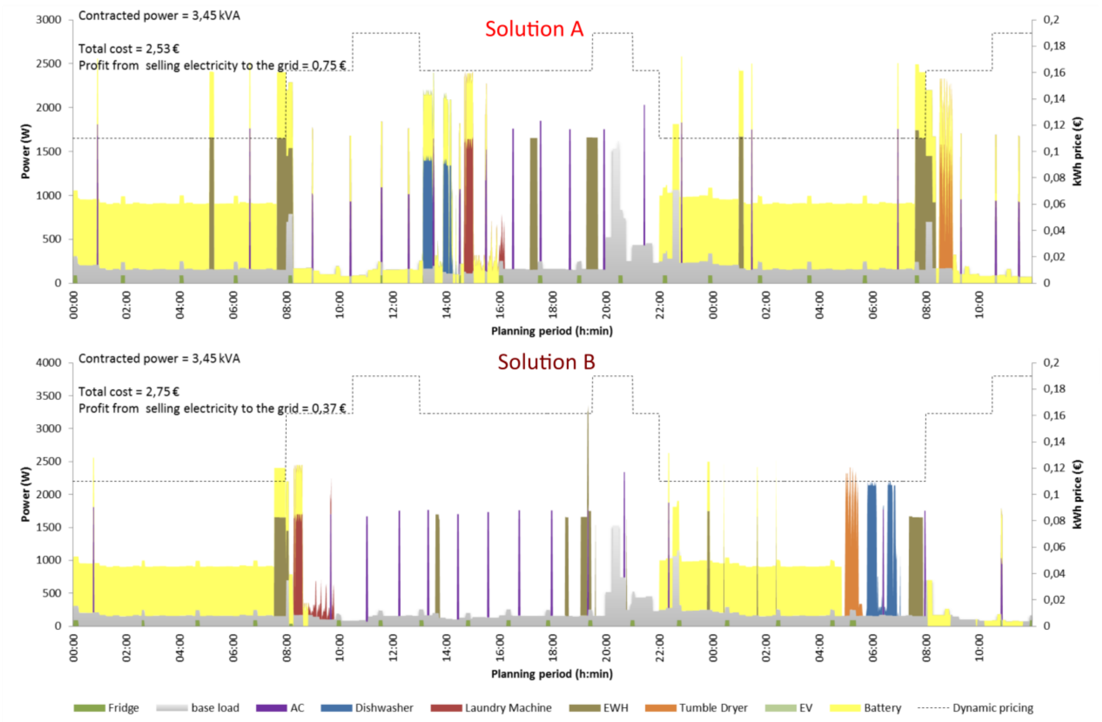

Figure 48: Main differences in the load diagram between solutions A and B

Considering the scenario presented in case study 1 in terms of resources, preferences and input data, and modifying the contracted power level constraint to one level below, as it is presented in this case study 2, it is possible to find solutions with a decrease in the fixed term paid per day corresponding to the contracted power.

6.3. Case Study 3

This third case study differs from the previous ones with respect to:

- lower temperature forecast input (Figure 49) and consequently the need to use the inverter in heating mode;
- the use of the PHEV in the G2V mode only;
- the inclusion of a stationary storage system.

The room temperature variation when no ADR actions are implemented over the inverter is displayed in Figure 50. It can be seen that the AC system is able to keep temperature constant and quite close to 21°C as desired by the end-user between 1 pm and 11 pm and close to 19°C from 0 am to 1 pm as well as on the morning of the second day of the planning period.

The time slot preferences for shiftable loads are the ones already displayed in Figure 30. Since the PHEV cannot be used in the V2G mode, this load is also considered as a shiftable one and its time slot preferences are presented in Figure 51.

Since in the reference case no ADR actions are implemented over the fridge and EWH, the working cycles and temperature variation are the ones previously presented in Figure 31.

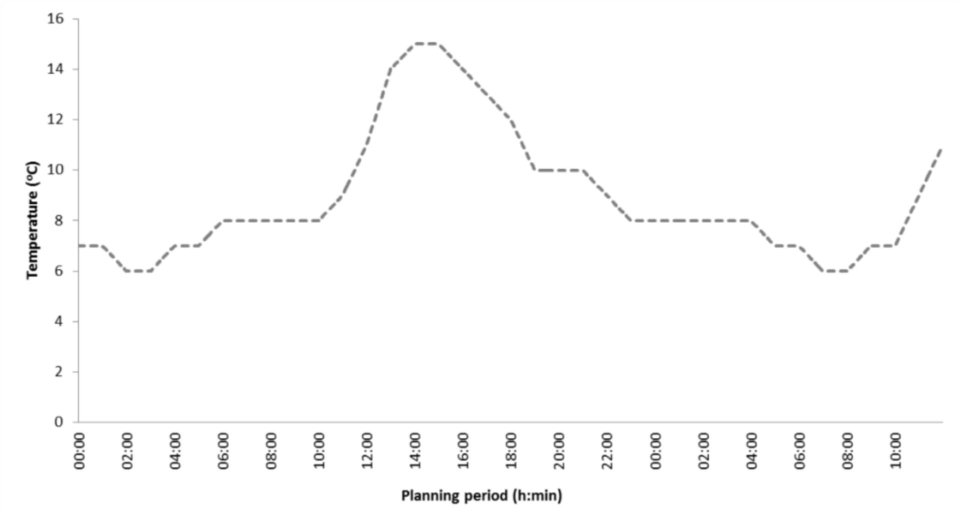

Figure 49: Outside temperature forecast used as input

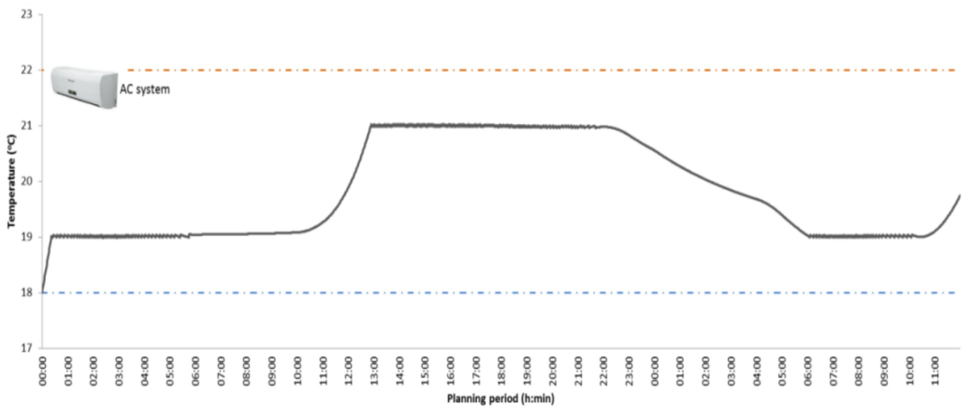

Figure 50: Room temperature

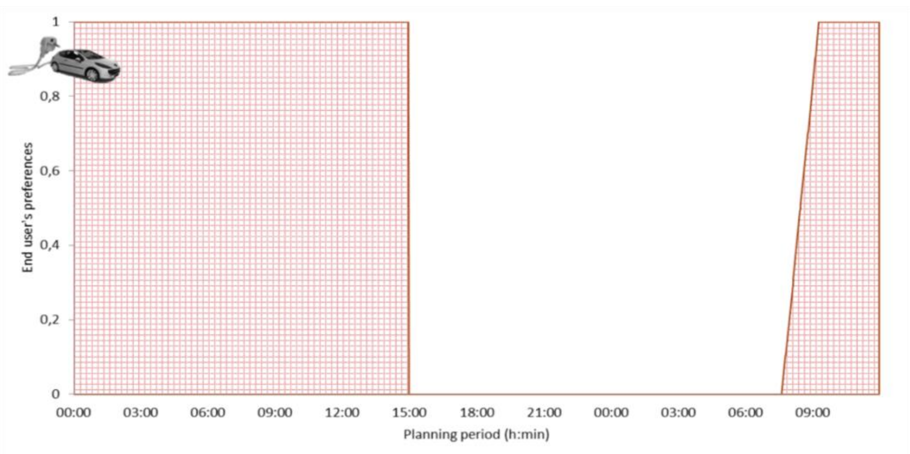

Figure 51: Time slot preferences for the PHEV when used in the G2V mode only

The load diagram for the reference case is displayed in Figure 52. In this scenario, shiftable loads are allocated according to the end-user's availability to perform some associated tasks if needed (such as loading the LM and TD) and the PHEV is charged after the end-user arrives home, considering the deadline set for achieving full charge. The stationary storage system is charged when the energy price is at its minimum, and used for self-consumption or injection into the grid when the energy price is higher. In this situation, the end-user is not concerned with the final SoC of the storage system. The only restriction is keeping the SoC above 20% to avoid detrimental effects in the battery.

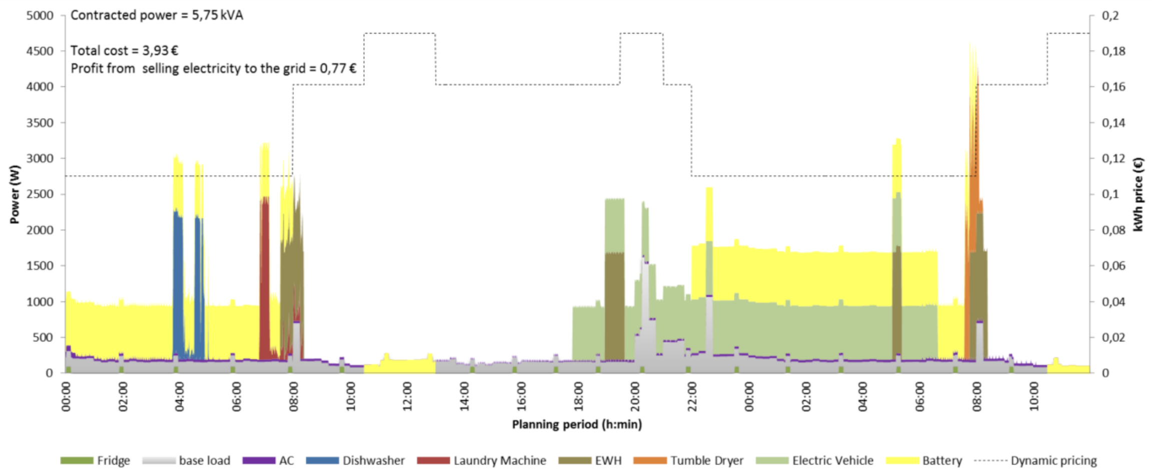

Figure 52: Reference case

The parameters used in the EA are displayed in Table 9. The only difference in comparison with parameters in case study 1 is the use of customized operators over the part of the chromosome representing the PHEV, which is used in the G2V mode only. In this situation, the mutation operator has a very high value since there are only two decisions (charging or not charging) and the modification of the decision in a given instant of time for a defined interval generally leads to better solutions. The results obtained in 30 runs are summarized in Table 10. It is possible to conclude that a lower power level can be contracted when compared to the reference case.

Table 9: Probabilities of operators over different loads

	Mutation	Crossover
Shiftable loads	0.2	0.5
Thermostatically controlled loads	0.6	0
PHEV (G2V mode)	0.9	0.3
Stationary storage system	0.02	0.5

Table 10: Results obtained considering 30 EA runs (50 individuals and 1000 generations)

	Energy cost (€)	Dissatisfaction
Best	2.748	0.032
Worst	3.002	0.075
Median	2.800	0.052
Average	2.827	0.053
Std Deviation	0.072	0.010

The Pareto front is displayed in Figure 53 and corresponds to a randomly chosen run. The main differences between the extreme solutions are the PHEV and dishwasher allocation, the profit from injecting energy in the grid and the impact of ADR actions over thermostatically controlled loads (Figure 54). In solution I (solution that individually optimizes the electricity bill) the PHEV is charged when energy price is at its minimum and more energy is injected in the grid, making a different use of the stationary storage system in comparison with solution J (that individually optimizes end-user's dissatisfaction). Nevertheless, while the PHEV allocation has a different cost in solutions I and J, the dishwasher allocation does not impact neither on the difference in the electricity bill nor on the end-user's dissatisfaction. ADR actions over thermostatically controlled loads also contribute to a higher electricity bill and end-user's dissatisfaction.

Concerning solutions A and B, the main issue justifying the difference in the electricity bill is the profit obtained from injecting energy into the grid (Figure 55 and Figure 56).

When comparing the whole range of Pareto optimal solutions with the reference case, savings between 10-29% may be achieved and the contracted power can be decreased in one level. Since the contracted power is payed per day by adding a fixed term to the monthly electricity bill, higher savings can then be achieved.

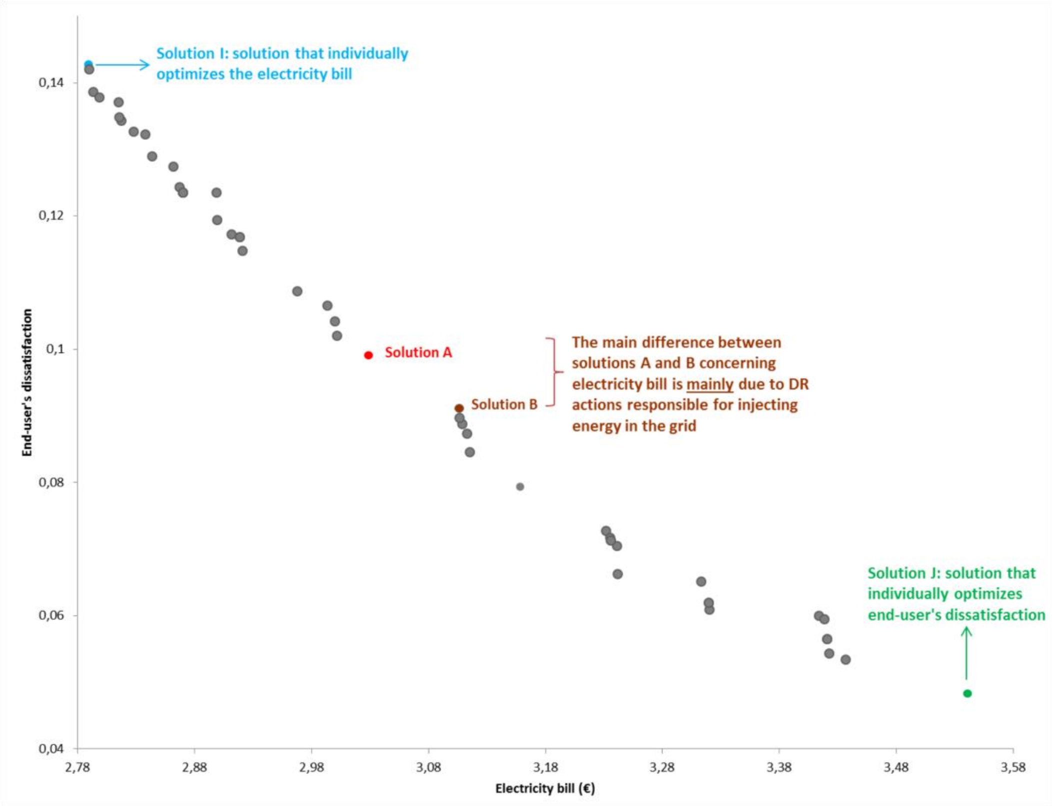

Figure 53: Pareto front for case study 3

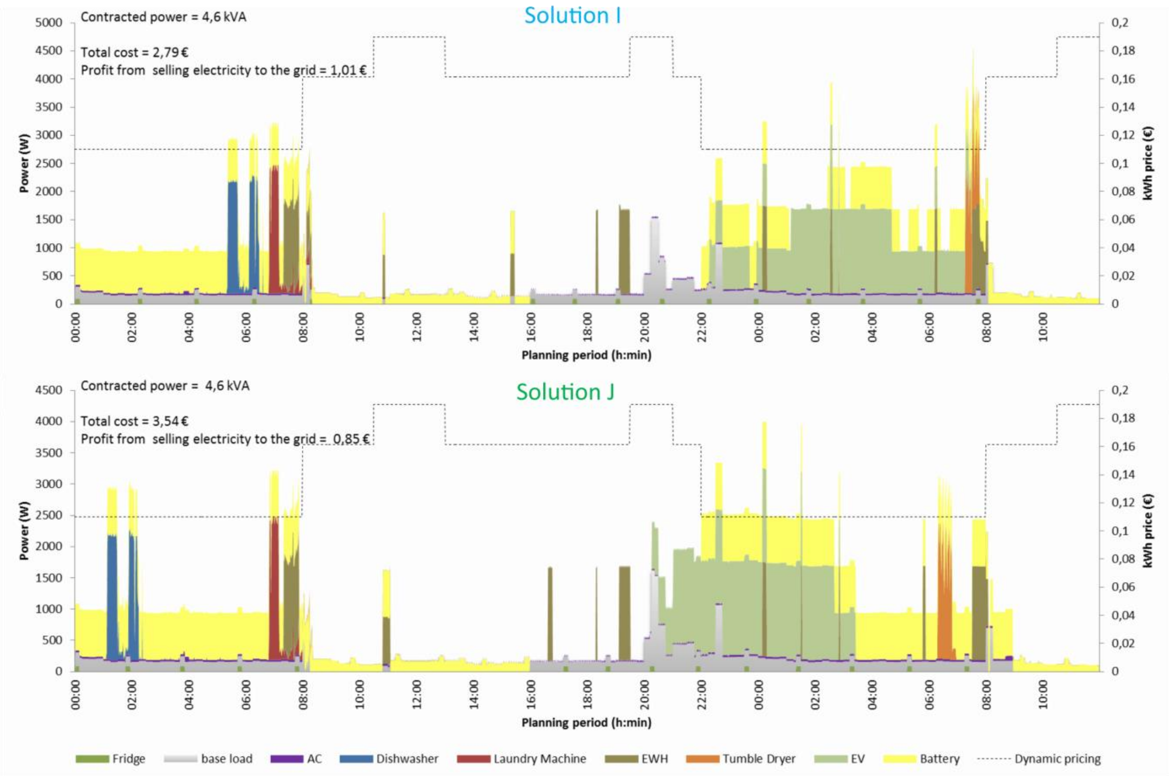

Figure 54: Load diagram of solutions I (solution that individually optimizes the electricity bill) and J (solution that individually optimizes end-user's dissatisfaction)

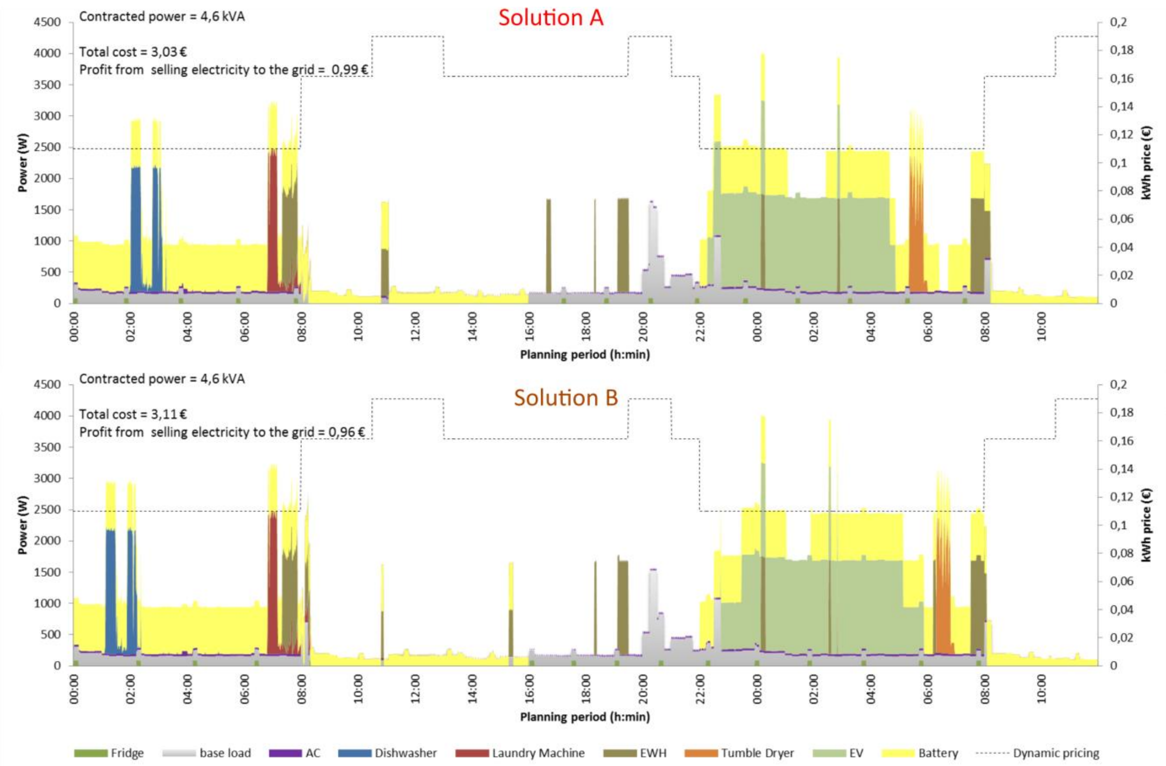

Figure 55: Load diagram of solutions A and B

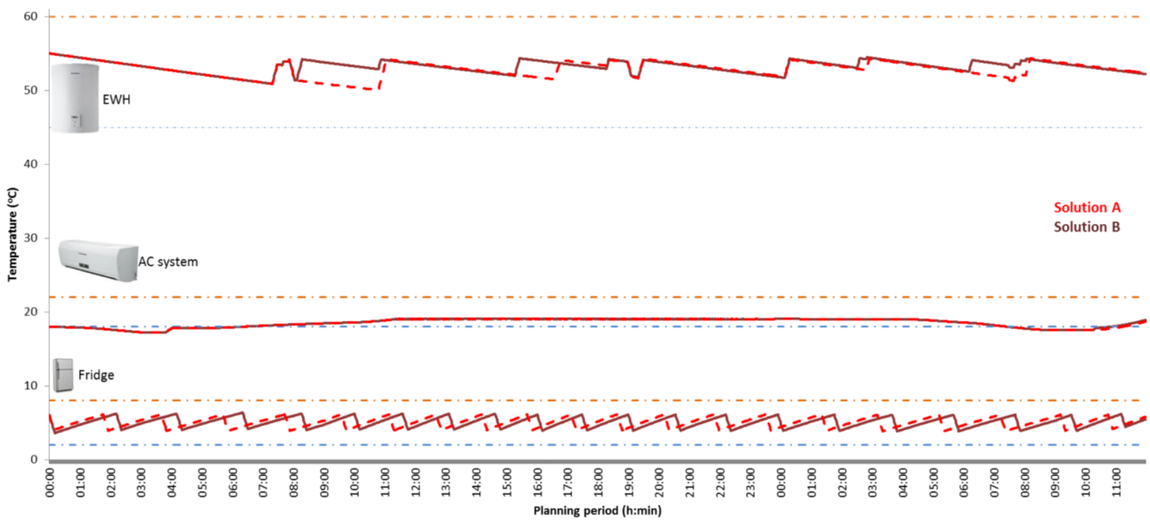

Figure 56: Impact of ADR actions over thermostatically controlled loads – solutions A and B

6.4. CASE STUDY 4

Variability[8] is an important issue that should also be taken into account when developing the EA approach for the integrated management of energy resources. The ability to deal with unexpected events is a key aspect to guarantee the acceptance of the EMS. The algorithmic approach is able to re-optimize the management of energy resources if changes occur in any of the following inputs:

- tariff structure;
- insertion or removal of energy resources;
- changes in comfort or time slots preferences;
- changes of non-manageable load;
- requests from the utility asking for a decrease or increase of power and corresponding economic incentive if a response is provided.

Considering that there is a modification in any of the previous inputs, a new solution is sought to the remaining of the planning period. Thus, when information concerning changes is received, the approach is able to check:

- which loads already ran and have the operation cycle completed;
- current temperatures of thermostatically controlled loads;
- actual SoC of the PHEV battery when used in G2V and V2G modes;

and swiftly compute a new Pareto front for the remaining of the planning period. The resulting optimization is a combination of the initial optimization until the arrival of information concerning changes and the re-optimization in face of input changes.

This re-optimization is crucial in several scenarios. An example is a situation in which the end-user suddenly unplugs the PHEV and returns later with a lower SoC then expected if no changes had occurred. Modifications in time slot preferences for one or more shiftable loads can also occur as well as unexpected variations of tariffs.

For illustrative purpose, an initial scenario similar to the one described in case study 1 is considered, but with a few modifications:

[8] Variability is understood in this context as the modification of one or more inputs: tariff structure, end-user's needs and preferences and needs, non-manageable loads, requests from the utility, among others.

- the end-user unplugs the PHEV at 7:30 am and only returns at 1 pm with 20% of SoC;
- time slots preferences for the tumble dryer are modified and the end-user prefers the operation of this load after 10 am and until 12 pm of the second day;
- the end-user changes the AC admissible temperature range variation to [19; 23]^{o}C (higher maximum temperature compared with case study 1);
- the end-user changes the fridge admissible temperature range variation to [2; 9]^{o}C (higher maximum temperature compared with case study 1);
- the end-user changes the EWH admissible temperature range variation to [50; 60]^{o}C (higher minimum temperature compared with case study 1);
- there is an unexpected rise of energy price in a given period.

When changes occur, the algorithmic approach re-runs and re-computes a new solution. During the first stage of the EA run (i.e., before the end-user unplugs the PHEV, modifies time slots and temperature preferences and variations in the tariff structure are communicated):

- the energy resources are the ones already presented in case study 1 (Figure 26, Figure 27);
- comfort and time slot preferences remain equal to case study 1 (Figure 30 and Figure 32);
- the tariff structure is kept the same (Figure 29);
- there are no modification in weather and local generation forecasts (Figure 28).

The load diagram corresponding to the solution that individually optimizes electricity bill would have been the one presented in Figure 57.

According to the moments when changes occur, two different periods can be identified at:

1. 7:30 am the end-user unplugs the PHEV, changes time slots and temperature preferences for some loads and the tariff is modified;
2. 1 pm the end-user plugs the PHEV back.

As a consequence of unplugging the PHEV, modifying time slots preferences for the tumble dryer and temperature preferences for thermostatically controlled loads and rise of the energy tariff, a first re-optimization is done. Then, when the end-user plugs the PHEV back again at 1 pm, another re-optimization is promptly carried out and a new Pareto front is presented for the remaining of the planning period. The selected solution still individually optimizes the electricity bill (Figure 58), according to the end-user profile and the initial solution chosen before changes have occurred. Since there is an increase of the energy tariff during some periods of time of the first day, the resulting electricity bill is higher.

The main differences between the initial solution (Figure 57) and the final solution (Figure 58) are:

- charging the PHEV only after 10 pm (when the energy price is lower) and use energy stored in the PHEV for self-consumption or injection into the grid close to the end of the planning period, assuring a minimum SoC of 50% as requested by the end-user since that between 7:30 am and 1 pm the PHEV is not avaliable;
- the allocation of the laudry machine around 9 pm when the energy price is not so high and time slot penalties are still acceptable (although the energy price is lower later, those time slots have a higher penalty);
- reducing the frequency that the AC system and the fridge are turned on during the period when energy prices are higher;
- increasing the energy used by the EWH to keep water temperature within the admissible range;
- delaying the operation of the tumble dryer.

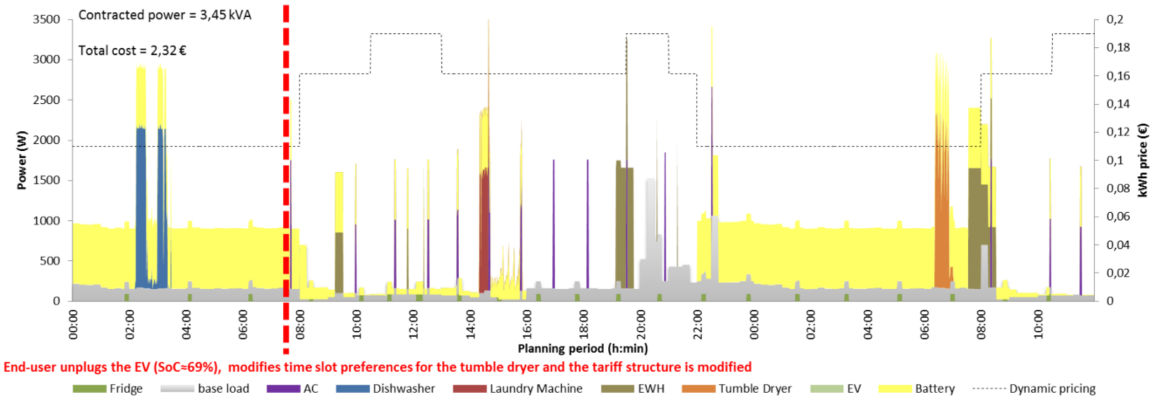

Figure 57: Load diagram for the solution which individually optimizes electricity bill before a modification of some inputs requiring a re-optimization

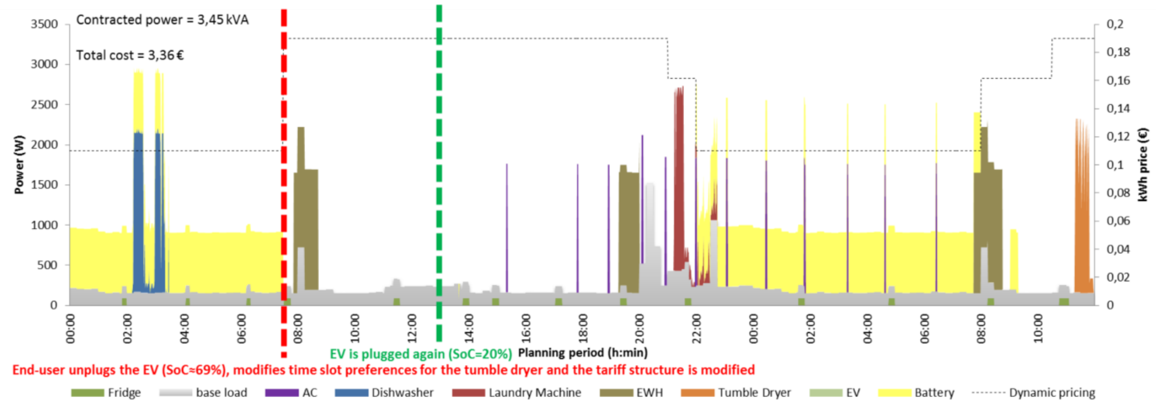

Figure 58: Resulting load diagram for the solution which individually optimizes end-user's dissatisfaction after a modification of some inputs requiring a re-optimization

6.5. FINAL REMARKS

The aim of this chapter was:

1. presenting different scenarios in which the EA approach developed can be used and analyzing the results;
2. showing its flexibility concerning the:
   a) diversity of manageable energy resources;
   b) ability to deal with different types of preferences (time slots for allocating shiftable loads, range of temperature for thermostatically controlled loads and desired SoC for the PHEV battery when used in G2V and V2G modes);
   c) changes in the input data.

The application of this approach is not, however, limited to the case studies herein reported. All input information can be modified, including manageable resources, tariff structure, end-users' preferences, local generation and weather forecasts. It can be used with a dual-tariff scenario and just shiftable loads and it can be used under a dynamic tariff structure with multiple energy level prices, different levels of contracted power and all the manageable resources analyzed in Chapter 4. According to extensive experiments performed, realistic savings in the electricity bill can range from 5% to 16% even when using a dual tariff and not owning a PHEV. The savings attained depend on the tariff structure, end-users' preferences and the choice of the final solution, which is strongly dependent on the end-user profile (Soares et al., 2015c). Local generation from sources other than PV, such as wind, can also be easily added.

The ability to react to changes is of particular interest in situations in which power demand suddenly approaches the contracted power (due to unpredictable use of non-manageable loads) and is necessary to reduce demand in order to prevent the main circuit breaker of shutting down the power supply.

The computation time required for running this EA using Matlab on an Intel Core i7, 3.4-GHz CPU with 32 GB of RAM varies from 5-10 minutes on average, which shows the ability to achieve results usable in practice for the 2160 minutes scheduling time. This range of computation time is due to the diversity of manageable resources.

7. CONCLUSIONS

The expected evolution of the power grid together with the integration of smart embedded systems combining instrumentation, analytics and control will contribute to deliver electricity in a more reliable and efficient way. Features such as the ability of self-diagnosing, self-healing, increased accommodation of renewables and bidirectional communications will have a relevant role towards this achievement. The deployment of two-way communications between the grid and end-users is also expected to foster the implementation of new tariff structures. In this smart grid context, instead of using a flat rate or a dual tariff rate, changes in the wholesale electricity price can be reflected on the energy price and transmitted to the end-user. This price information enables to influence demand up to a certain degree, aiming at reshaping demand profile and reducing unwanted power peaks.

ADR actions can be used in this context to manage demand according to energy price information in order to obtain electricity bill savings. The integrated management of energy resources, including distributed generation, storage systems and manageable demand will make possible the adoption of a load follows supply strategy in which end-users benefit from monitoring and controlling electricity consumption. To achieve this goal, adequate technologies with the aim to help end-users managing demand should be used. An effective technology are EMSs endowed with optimization algorithms to respond to dynamic tariffs and other input data and manage the use of energy resources while minimizing end-users' dissatisfaction caused by the implementation of ADR actions.

With these EMSs, electricity end-users become responsive customers and economically motivated users, who consume and produce energy, and simultaneously make an active management of existent energy resources. This management has also advantages from different perspectives. In addition to economic incentives and reduced electricity bill for the individual end-user who is able to decrease costs by performing an integrated management of electricity consumption, storage systems and micro-generation, society also benefits since the need to invest in new power plants and network infrastructure is postponed. Moreover, the reshaping of demand with the increased accommodation of renewables can also contribute to decrease environmental impacts. Different power system sector players, including retailers, can also have advantages namely through the increase of profits and the creation of new business opportunities, including new technologies and services, besides contributing to alleviate power system stresses.

This integrated management, through the use of EMS, requires the design of suitable optimization algorithms to address combinatorial problems with conflicting objectives. An approach based on EAs has been used to solve a variety of complex optimization problems and provide good solutions in a reasonable computational time. The approach developed is able:

- to deal with distinct scenarios regarding:
    - energy resources being managed;
    - end-users' preferences;
    - stimuli for changing consumption patterns.
- sudden changes in the input data;

making it suitable to be used for (near) real-time management of residential energy resources.

This PhD research aimed at developing an approach for managing residential energy resources and making energy use decisions on behalf of users in a smart grid context in which dynamic tariffs are used. Before developing the algorithmic approach, manageable residential energy resources have been characterized. The characterization of residential demand enabled the identification of four types of loads:

- non-manageable loads: loads that when controlled may cause too much discomfort to the user or perturbation to ongoing activities;
- thermostatically controlled loads: loads that allow a re-set of temperature settings within a certain range without causing discomfort to the user but changing energy consumption;
- shiftable loads: loads whose operation can be postponed or anticipated according to end-users' preferences;
- interruptible loads: loads which can be interrupted during a short period of time not impacting on the quality of the energy services provided.

Accordingly, three control options can be implemented, individually or in combination depending on the load:

- re-set of temperature settings;
- postponement or anticipation of working cycles;
- interruption of electricity supply.

Thermostatically controlled loads, such as cold appliances, ACs and EWHs may be subject to one or more of these control options depending on the users' preferences (including flexibility and level of comfort desired). Laundry machines, tumble dryers, and dishwashers are often among the loads whose operation can be anticipated or delayed, as long as the task is accomplished by a certain deadline. Thermostatically controlled loads and storage systems, including PHEVs, can also be the target of short interruptions. ADR actions modify the power profile of thermostatically controlled loads or postpone/anticipate the working cycles of shiftable loads in response to input signals such as energy prices, incentives and residential end-users' requirements.

For the end-user, what really matters is the minimization of the electricity bill as long as energy services provided are not jeopardized. So although control might be accepted up to a certain degree for shiftable loads, it can be argued that the willingness to accept the control of thermostatically controlled loads based on the temperature settings is not straightforward from the end-user's point of view. This acceptance relies thus on showing that the quality of the energy services provided by end-loads is not jeopardized and that significant savings can be attained through the management of demand and storage systems and integration of local generation.

The ADR actions to be carried out by the EA approach should then smoothly manage energy resources in such a way that end-user's preferences, in terms of time slots for allocation of shiftable loads, temperature settings and charging of the PHEV, are respected and the control discretely done. Additionally, since there is some uncertainty linked to the use of energy resources and even end-user's needs, which may vary during the same day, the approach must be able to cope with modifications of parameters and input information. This includes changes in end-user's manageable and non-manageable resources, comfort preferences or preferred periods of time for allocating shiftable loads, new energy prices or even requests for decreasing/increasing energy consumption for a given period of time. In case of these events the approach computes new solutions using at this stage as inputs the information provided just before the event happened.

The deployment of EMS with the proposed EA approach embedded in a real environment requires some adaptions. PBMs can be replaced by adequate sensoring equipment and a rule-based system can be used to limit ADR actions. Monitoring technologies can also be used to provide information about:

- current power demand by shiftable and non-manageable loads;
- local generation;
- SoC of the storage systems (PHEV and stationary batteries).

The use of the customized EA proposed in this research, though not aiming at an overall reduction of energy consumption, allows minimizing the electricity bill and end-user's dissatisfaction through an optimized use of energy resources. The customization includes an adequate solution encoding and operators acting according to the physical characteristics of the resources being managed. The consideration of a bi-objective model enables to study the trade-offs between the competing objective functions and then select a compromise solution more in accordance with the end-user profile (e.g., more cost oriented or more quality of service oriented). Savings in the electricity bill are usually between 5-16%, although higher ones can be attained. Another advantage is the possibility to define a lower level of contracted power with the corresponding economic benefits.

This EA approach endows the EMS with a reliable method to automatically make decisions concerning the optimal integrated use of multiple residential energy resources according to the end-user profile. Although the economic savings for each residential end-user may seem limited, the aggregation of several houses can drive to substantial benefits at national level in the whole electrical energy chain, contributing to postpone the need to reinforce the network infrastructures and improving the grid efficiency.

7.1. FUTURE RESEARCH DIRECTIONS

The aim of this PhD thesis was to design an approach based on evolutionary algorithms to optimize the use of residential energy resources. The objective functions included the minimization of the electricity bill and potential dissatisfaction sensed by the end-user. Although this work has already included innovative aspects, namely concerning the diversity of ADR actions, the incorporation of power constraints and the way end-users' preferences are dealt with, future developments should encompass new features such as:

- learning algorithms able to capture preferences, habits, renewable generation and consumption;
- inclusion of interdependencies between appliances without the end-user's intervention in order to define time slot preferences;
- minimization of the time span associated with the allocation of shiftable loads outside the most preferred time slots;
- being capable of detecting and signaling malfunctions or failures;
- capability to propose other time slots for shiftable loads and reasonable temperature set points aiming at reducing the electricity bill and dissatisfaction;
- the inclusion of other energy carriers (such as gas) in the optimization process for hybrid appliances;
- tariff structures in which energy prices increase according to the rise of demand in a given instant of time, indulging solutions with lower power peaks.

Alongside, the design of adequate tariff structures to induce smart behaviors concerning the use of electrical energy is also an interesting topic to be explored and further integrated. In this context, retailers can use this algorithmic approach to assess the potential impact of energy prices in the residential demand profile and efficiently compute the price levels aiming to design dynamic tariff schemes which lead to responsive demand.

Concerning the parameterization of the evolutionary algorithm, this may be done in the future in an automated way through the use of adaptive techniques including customized genetic operators.

Additionally, other strategies to attain the same goals and a comparative assessment of the distinct algorithmic approaches should also be carried out.

A pilot study can also be used to evaluate the integration of the hardware and firmware based on the EA approach developed. An user-friendly interface facilitating the interaction with the end-user concerning the introduction of preferences can be developed to assist the pilot study.

REFERENCES

Abras, S., Pesty, S., Ploix, S., Jacomino, M., 2008. An Anticipation Mechanism for Power Management in a Smart Home using Multi-Agent Systems, in: 2008 3rd International Conference on Information and Communication Technologies: From Theory to Applications. IEEE, pp. 1–6.

Agnetis, A., Dellino, G., De Pascale, G., Innocenti, G., Pranzo, M., Vicino, A., 2011. Optimization models for consumer flexibility aggregation in smart grids: The ADDRESS approach. 2011 IEEE First Int. Work. Smart Grid Model. Simul. 96–101.

Albadi, M.H., El-Saadany, E.F., 2008. A summary of demand response in electricity markets. Electr. Power Syst. Res. 78, 1989–1996.

Allerding, F., Premm, M., Shukla, P., Schmeck, H., 2012. Electrical Load Management in Smart Homes Using Evolutionary Algorithms, in: Hao, J.-K., Middendorf, M. (Eds.), Evolutionary Computation in Combinatorial Optimization. Springer Berlin / Heidelberg, pp. 99–110.

Alves, M.J., Antunes, C.H., Carrasqueira, P., 2016. A Hybrid Genetic Algorithm for the Interaction of Electricity Retailers with Demand Response, in: Applications of Evolutionary Computation. pp. 459–474.

Amato, A., Di Lecce, V., Piuri, V., 2007. A Smart Distributed Measurement Data Management System for DSM, in: 2007 IEEE Instrumentation & Measurement Technology Conference IMTC 2007. IEEE, pp. 1–5.

Antunes, C.H., Henriques, C.O., 2016. Multi-Objective Optimization and Multi-Criteria Analysis Models and Methods for Problems in the Energy Sector, in: Multiple Criteria Decision Analysis. pp. 1067–1165.

Antunes, C.H., Soares, A., Gomes, Á., 2013. An evolutionary algorithm approach to an integrated energy management system, in: J.Krope, A. G. Olabi, D.G. (Ed.), Proceedings of the 6th International Conference on Sustainable Energy and Environmental Protection - SEEP 2013. Maribor, Slovenia.

Antunes, C.H., Soares, A., Gomes, Á., 2015. An Integrated Building Energy Management System, in: Med Green Forum – Mediterranean Green Buildings and Renewable Energy Forum 2015. Florence, Italy.

Azar, A.G., Jacobsen, R.H., Zhang, Q., 2015. Aggregated load scheduling for residential multi-class appliances: Peak demand reduction, in: 2015 12th International Conference on the European Energy Market (EEM). IEEE, pp. 1–6.

Bertoldi, P., Hirl, B., Labanca, N., 2012. Energy Efficiency Status Report 2012 - Electricity Consumption and Efficiency Trends in the EU-27. Italy.

Bessa, R.J., Matos, M.A., Soares, F.J., Lopes, J.A.P., 2012. Optimized Bidding of a EV Aggregation Agent in the Electricity Market. IEEE Trans. Smart Grid 3, 443–452.

Braun, M., Dengiz, T., Mauser, I., Schmeck, H., 2016. Comparison of Multi-objective Evolutionary Optimization in Smart Building Scenarios, in: Applications of Evolutionary Computation. pp. 443–458.

Brown, H.E., Suryanarayanan, S., Heydt, G.T., 2010. Some Characteristics of Emerging Distribution Systems Considering the Smart Grid Initiative. Electr. J. 23, 64–75.

Carreiro, A.M., Oliveira, C., Antunes, C.H., Jorge, H.M., 2015. An Energy Management System Aggregator Based on an Integrated Evolutionary and Differential Evolution Approach, in: Applications of Evolutionary Computation - 18th European Conference, EvoApplications 2015, Copenhagen, Denmark, April 8-10, 2015, Proceedings. Springer International Publishing, pp. 252–264.

Chen, J., Lee, F., Breipohl, A., 1995. Scheduling direct load control to minimize system operation cost. Power Syst. IEEE 10, 1994–2001.

Chittur Ramaswamy, P., Deconinck, G., Ramaswamy, P.C., 2012. Smart grid reconfiguration using simple genetic algorithm and NSGA-II, in: Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on. IEEE, Berlin, pp. 1–8.

Chrysopoulos, A., Diou, C., Symeonidis, A.L., Mitkas, P. a., 2014. Bottom-up modeling of small-scale energy consumers for effective Demand Response Applications. Eng. Appl. Artif. Intell. 35, 299–315.

Chu, C., Jong, T., 2008. A Novel Direct Air-Conditioning Load Control Method. IEEE Trans. Power Syst. 23, 1356–1363.

Coello Coello, C.A., 2006. Evolutionary multi-objective optimization: a historical view of the field. IEEE Comput. Intell. Mag. 1, 28–36.

Conejo, A.J., Morales, J.M., Baringo, L., 2010. Real-Time Demand Response Model. IEEE Trans. Smart Grid 1, 236–242.

Conte, G., Perdon, A.M., Scaradozzi, D., Morganti, G., Rosettani, M., 2010. Resource management in home automation systems. 18th Mediterr. Conf. Control Autom. MED'10 154–160.

D'hulst, R., Labeeuw, W., Beusen, B., Claessens, S., Deconinck, G., Vanthournout, K., 2015. Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium. Appl. Energy 155, 79–90.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6, 182–197.

Decreto-Lei n.º 153/2014 de 20 de outubro, 2014. . Diário da República.

Deng, R., Yang, Z., Chen, J., 2013. Load scheduling with price uncertainty and coupling constraints. IEEE Power Energy Soc. Gen. Meet. 29, 2823–2834.

DenHerder, T., 2006. Design and Simulation of Photovoltaic Super System Using Simulink. California Polytechnic State University.

DGGE /IP-3E, 2004. Eficiência energética em equipamentos e sistemas eléctricos no sector residencial [WWW Document]. URL www.p3e-portugal.com

Directorate-General for Research Sustainable Energy Systems, 2006. EUR 22040 - European Technology SmartGrids Platform - Vision and Strategy for Europe's Electricity Networks of the Future.

Dréo, J., Pétrowski, A., Siarry, P., Taillard, E., 2006. Metaheuristics for Hard Optimization. Springer-Verlag, Berlin/Heidelberg.

Du, P., Lu, N., 2011. Appliance commitment for household load scheduling. IEEE Trans. Smart Grid 2, 411–419.

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39, 3789–3802.

Ericson, T., 2009. Direct load control of residential water heaters. Energy Policy 37, 3502–3512.

European Comission, Eurostat, 2015. Smarter, greener, more inclusive? – Indicators to support the Europe 2020 strategy.

European Commission, 2006. Green Paper. A European strategy for sustainable, competitive and secure energy.

European Commission, 2012. EU transport in figures 2012. Luxembourg: Publications Office of the European Union, Luxembourg: Publications Office of the European Union.

Federal Energy Regulatory Commission, 2011. Assessment of Demand Response and Advanced Metering.

Giordano, V., Fulli, G., 2012. A business case for Smart Grid technologies: A systemic perspective.

Energy Policy 40, 252–259.

Gkatzikis, L., Koutsopoulos, I., Salonidis, T., 2013. The role of aggregators in smart grid demand response markets. IEEE J. Sel. Areas Commun. 31, 1247–1257.

Goh, C., Apt, J., 2004. Consumer strategies for controlling electric water heaters under dynamic pricing (No. Carnegie Mellon Electricity Industry Center Working Paper CEIC-04-02), Carnegie Mellon Electricity Industry Center Working Paper CEIC-04-02. Pitsburgh, PA.

Gomes, A., Antunes, C.H., Martinho, J., 2013. A physically-based model for simulating inverter type air conditioners/heat pumps. Energy 50, 110–119.

Gomes, A., Antunes, C.H., Martins, A.G., 2009. Physically-based load demand models for assessing electric load control actions, in: 2009 IEEE Bucharest PowerTech. IEEE, pp. 1–8.

Gomes, A., Martins, A.G.G., Figueiredo, R., 1999. Simulation-based assessment of electric load management programs. Int. J. Energy Res. 23, 169–181.

Gomes, A., Soares, A., Antunes, C.H., 2011. Impacts of demand side management and micro-generation units on low voltage distribution radial networks, in: 11th International Conference on Electrical Power Quality and Utilisation. IEEE, Lisbon, pp. 1–7.

Guille, C., Gross, G., 2009. A conceptual framework for the vehicle-to-grid (V2G) implementation. Energy Policy 37, 4379–4390.

Gyamfi, S., Krumdieck, S., 2011. Price, environment and security: Exploring multi-modal motivation in voluntary residential peak demand response. Energy Policy 39, 2993–3004.

Heffner, D., Grayson, C., 2001. Demand responsive programs-an emerging resource for competitive electricity markets? Proc. Int. Energy Progr. Eval. Conf.

Heleno, M., Matos, M.A., Lopes, J.A.P., 2015. Availability and Flexibility of Loads for the Provision of Reserve. IEEE Trans. Smart Grid 6, 667–674.

Hirst, E., Kirby, B., 2001. Retail-load participation in competitive wholesale electricity markets, Policy Analysis. Edison Electric Institute / Project for Sustainable FERC Energy Policy.

Hovgaard, T.G., Larsen, L.F.S., Edlund, K., Jørgensen, J.B., 2012. Model predictive control technologies for efficient and flexible power consumption in refrigeration systems. Energy 44, 105–116.

IEA, 2012. World Energy Outlook 2012, World Energy Outlook. OECD Publishing.

Ilic, M., Black, J.W., Watz, J.L., 2002. Potential benefits of implementing load control, in: Power Engineering Society Winter Meeting, 2002. IEEE. Ieee, pp. 177–182.

INE, 1999. Use of time - Information to Media.

INE, 2011. Inquérito ao Consumo de Energia no Sector Doméstico 2010 (Residential sector energy consumption survey).

Ipakchi, A., Albuyeh, F., 2009. Grid of the future. IEEE Power Energy Mag. 7, 52–62.

Jacobsen, R.H., Gabioud, D., Basso, G., Alet, P., 2015. SEMIAH : An Aggregator Framework for European Demand Response Programs, in: Proceedings of 18th Euromicro Conference on Digital Systems Design. Madeira.

Jorge, H., 2010. Characterization of Residential Energy Consumption (in Portuguese: Caracterização dos Consumos no Sector Residencial) [WWW Document]. Work. Standby Energy Consum. (in Port. Work. sobre Consum. Energ. nos modos standby e desligado).

Jorge, H., Antunes, C., Martins, A.G., 2000. A multiple objective decision support model for the selection of remote load control strategies. IEEE Trans. Power Syst. 15, 865–872.

Kahrobaee, S., Asgarpoor, S., Qiao, W., 2013. Optimum Sizing of Distributed Generation and Storage Capacity in Smart Households. IEEE Trans. Smart Grid 4, 1791–1801.

Katz, R.H., Culler, D.E., Sanders, S., Alspaugh, S., Chen, Y., Dawson-Haggerty, S., Dutta, P., He, M., Jiang, X., Keys, L., Krioukov, A., Lutz, K., Ortiz, J., Mohan, P., Reutzel, E., Taneja, J., Hsu, J., Shankar, S., 2011. An information-centric energy infrastructure: The Berkeley view. Sustain. Comput. Informatics Syst. 1, 7–22.

Kishore, S., Yener, A., 2011. Smart (in-home) power scheduling for demand response on the smart grid, in: ISGT 2011. IEEE, pp. 1–7.

Kupzog, F., Roesener, C., 2007. A closer Look on Load Management, in: 2007 5th IEEE International Conference on Industrial Informatics. IEEE, pp. 1151–1156.

Laguerre, O., Flick, D., 2010. Temperature prediction in domestic refrigerators: Deterministic and stochastic approaches. Int. J. Refrig. 33, 41–51.

Lee, S., Kwon, B., Lee, S., 2014. Joint Energy Management System of Electric Supply and Demand in Houses and Buildings. IEEE Trans. Power Syst. 1–9.

Livengood, D., Larson, R., 2009. The Energy Box: Locally Automated Optimal Control of Residential Electricity Usage. Serv. Sci. 1, 1–16.

Logenthiran, T., Srinivasan, D., Shun, T.Z., 2012. Demand Side Management in Smart Grid Using Heuristic Optimization. IEEE Trans. Smart Grid 3, 1244–1252.

Lopes, M., Antunes, C.H., Martins, N., 2012a. Energy behaviours as promoters of energy efficiency:

A 21st century review. Renew. Sustain. Energy Rev. 16, 4095–4104.

Lopes, M., Antunes, C.H., Martins, N., 2015. Towards more effective behavioural energy policy: An integrative modelling approach to residential energy consumption in Europe. Energy Res. Soc. Sci. 7, 84–98.

Lopes, M., Antunes, C.H., Martins, N., 2016a. Estimating behavioural savings in dwellings using Building Energy Performance Simulations. Build. Res. Inf. in print.

Lopes, M., Antunes, C.H., Soares, A., Carreiro, A., Rodrigues, F., Livengood, D., Neves, L., Jorge, H., Gomes, A., Martins, A.G., Dias, L., Pereirinha, P., Trovao, J.P., Larson, R., Leow, W.L., Monica, A., Oliveira, M., Breda, S.J., Viegas, R., Peixoto, P., 2012b. An automated energy management system in a smart grid context, in: 2012 IEEE International Symposium on Sustainable Systems and Technology (ISSST). IEEE, Boston, USA, pp. 1–1.

Lopes, M., Soares, A., Antunes, C.H., Gomes, Á., 2016b. From energy behaviours to energy resources optimisation in smart(er) grids: development of an energy management system, in: Proceedings of the International Conference "Smart Energy Regions." Cardiff, Wales, UK, pp. 1–26.

Lu, N., Chow, J.H., Desrochers, A.A., 2004. Pumped-storage hydro-turbine bidding strategies in a competitive electricity market. Power Syst. IEEE Trans.

Lui, T., Stirling, W., Marcy, H., 2010. Get Smart. IEEE Power Energy Mag. 8, 66–78.

Mashhadi, H.R., Shanechi, H.M., Lucas, C., 2003. A new genetic algorithm with lamarckian individual learning for generation scheduling. IEEE Trans. Power Syst. 18, 1181–1186.

MathWorks Support, 2008. Battery [WWW Document]. URL http://www.mathworks.com/help/physmod/sps/powersys/ref/battery.html;jsessionid=2980190eaaf913caa70f29c56df5?refresh=true

Mauser, I., Dorscheid, M., Allerding, F., Schmeck, H., 2014. Encodings for Evolutionary Algorithms in smart buildings with energy management systems. 2014 IEEE Congr. Evol. Comput. 2361–2366.

Mauser, I., Müller, J., Allerding, F., Schmeck, H., 2015. Adaptive building energy management with multiple commodities and flexible evolutionary optimization. Renew. Energy 1–11.

Meyers, R.J., Williams, E.D., Matthews, H.S., 2010. Scoping the potential of monitoring and control technologies to reduce energy use in homes. Energy Build. 42, 563–569.

Miorandi, D., De Pellegrini, F., 2012. Demand-Side Management in Smart Grids: an Evolutionary Games Perspective, in: Proceedings of the 6th International Conference on Performance

Evaluation Methodologies and Tools. IEEE, pp. 178–187.

Mohsenian-Rad, A.-H., Leon-Garcia, A., 2010. Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments. IEEE Trans. Smart Grid 1, 120–133.

Mohsenian-Rad, A.-H., Wong, V.W.S., Jatskevich, J., Schober, R., 2010a. Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid, in: 2010 Innovative Smart Grid Technologies (ISGT). IEEE, pp. 1–6.

Mohsenian-Rad, A.-H., Wong, V.W.S., Jatskevich, J., Schober, R., Leon-Garcia, A., 2010b. Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid. IEEE Trans. Smart Grid 1, 320–331.

Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L., Smit, G.J.M., 2009. Domestic energy management methodology for optimizing efficiency in Smart Grids, in: 2009 IEEE Bucharest PowerTech. IEEE, pp. 1–7.

Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L., Smit, G.J.M., 2010a. Management and Control of Domestic Smart Grid Technology. IEEE Trans. Smart Grid 1, 109–119.

Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L., Smit, G.J.M., 2010b. A three-step methodology to improve domestic energy efficiency, in: 2010 Innovative Smart Grid Technologies (ISGT). IEEE, pp. 1–8.

Molderink, A., Bakker, V., Hurink, J.L., Smit, G.J.M., 2012. Comparing demand side management approaches, in: 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe). IEEE, pp. 1–8.

Molina, A., Gabaldon, A., Fuentes, J.A., Alvarez, C., 2003. Implementation and assessment of physically based electrical load models: application to direct load control residential programmes. IEE Proc. - Gener. Transm. Distrib. 150, 61.

Molina, D., Lu, C., Sherman, V., Harley, R., 2011. Model predictive and genetic algorithm based optimization of residential temperature control in the presence of time-varying electricity prices, in: 2011 IEEE Industry Applications Society Annual Meeting. IEEE, pp. 1–7.

Morganti, G., Perdon, A.M., Conte, G., Scaradozzi, D., Brintrup, A., 2009. Optimising Home Automation Systems: A comparative study on Tabu Search and Evolutionary Algorithms, in: 2009 17th Mediterranean Conference on Control and Automation. IEEE, pp. 1044–1049.

Moshari, A., Yousefi, G., Ebrahimi, A., 2010. Demand-side behavior in the smart grid environment. Innov. Smart Grid Technol. Conf. Eur. (ISGT Eur. 2010 IEEE PES 1–7.

Newsham, G.R., Bowker, B.G., 2010. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. Energy Policy 38, 3289–3296.

Niazi, M., Hussain, A., 2011. Agent-based computing from multi-agent systems to agent-based models: a visual survey. Scientometrics 89, 479–499.

Omara, F. a., Arafa, M.M., 2010. Genetic algorithms for task scheduling problem. J. Parallel Distrib. Comput. 70, 13–22.

Panasonic, 2012. www.panasonic.co.in [WWW Document]. URL www.panasonic.co.in

Paterakis, N.G., Erdinc, O., Bakirtzis, A.G., Catalao, J.P.S., 2015. Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies. IEEE Trans. Ind. Informatics 11, 1509–1519.

Pedrasa, M., Spooner, T.D., MacGill, I.F., 2009. Scheduling of Demand Side Resources Using Binary Particle Swarm Optimization. IEEE Trans. Power Syst. 24, 1173–1181.

Pedrasa, M.A., Spooner, E.D., MacGill, I.F., 2011. Robust scheduling of residential distributed energy resources using a novel energy service decision-support tool, in: ISGT 2011. IEEE, pp. 1–8.

Pedrasa, M.A.A., Spooner, T.D., MacGill, I.F., 2010. Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services. IEEE Trans. Smart Grid 1, 134–143.

Penya, Y.K., 2003. Last-generation applied artificial intelligence for energy management in building automation, in: D. Dietrich, J. P. Thomesse, Dietmar Dietrich, P.N. (Ed.), Fieldbus Systems and Their Applications 2003. Elsevier Science, pp. 79–83.

Perfumo, C., Kofman, E., Braslavsky, J.H., Ward, J.K., 2012. Load management: Model-based control of aggregate power for populations of thermostatically controlled loads. Energy Convers. Manag. 55, 36–48.

Possemato, F., Storti, G.L., Paschero, M., Rizzi, A., Mascioli, F.M.F., 2013. Two evolutionary computational approaches for active power losses minimization in Smart Grids. IFSA World Congr. NAFIPS Annu. Meet. (IFSA/NAFIPS), 2013 Jt.

Ramaswamy, P.C., Deconinck, G., 2011. Relevance of voltage control, grid reconfiguration and adaptive protection in smart grids and genetic algorithm as an optimization tool in achieving their control objectives, in: 2011 International Conference on Networking, Sensing and Control. IEEE, pp. 26–31.

Reiss, P., White, M., 2005. Household electricity demand, revisited. Rev. Econ. Stud.

Renato, J., Pompéia, C., 2009. Análise do comportamento da bateria utilizada em sistemas fotovoltaicos de pequeno porte. Universidade Estadual Paulista "Júlio de Mesquita Filho."

Richardson, I., Thomson, M., Infield, D., Delahunty, A., 2009. Domestic lighting: A high-resolution energy demand model. Energy Build. 41, 781–789.

Rosin, A., Hoimoja, H., Moller, T., Lehtla, M., 2010. Residential electricity consumption and loads pattern analysis, in: Proceedings of the 2010 Electric Power Quality and Supply Reliability Conference. IEEE, pp. 111–116.

Safdarian, A., Fotuhi-Firuzabad, M., Lehtonen, M., 2014. A Distributed Algorithm for Managing Residential Demand Response in Smart Grids. IEEE Trans. Ind. Informatics 10, 2385–2393.

Salinas, S., Li, M., Li, P., 2013. Multi-Objective Optimal Energy Consumption Scheduling in Smart Grids. IEEE Trans. Smart Grid 4, 341–348.

Samadi, P., Schober, R., Wong, V.W.S., 2011. Optimal energy consumption scheduling using mechanism design for the future smart grid, in: 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm). IEEE, pp. 369–374.

Schweppe, F.C., Daryanian, B., Tabors, R.D., 1989. Algorithms for a Spot Price Responding Residential Load Controller. IEEE Power Eng. Rev. 9, 49–50.

Shahbaz, M., Tang, C.F., Shahbaz Shabbir, M., 2011. Electricity consumption and economic growth nexus in Portugal using cointegration and causality approaches. Energy Policy 39, 3529–3536.

Shao, S., Pipattanasomporn, M., Rahman, S., 2011. Demand Response as a Load Shaping Tool in an Intelligent Grid With Electric Vehicles. IEEE Trans. Smart Grid 2, 624–631.

Soares, A., Antunes, C.H., Oliveira, C., Gomes, Á., 2014a. A multi-objective genetic approach to domestic load scheduling in an energy management system. Energy 77, 144–152.

Soares, A., Gomes, A., Antunes, C.H., 2012a. Integrated Management of Residential Energy Resources. EPJ Web Conf. 33, 05005.

Soares, A., Gomes, A., Antunes, C.H., 2012b. Domestic load characterization for demand-responsive energy management systems, in: 2012 IEEE International Symposium on Sustainable Systems and Technology (ISSST). IEEE, Boston, USA, pp. 1–6.

Soares, A., Gomes, A., Antunes, C.H., n.d. (in press) A Customized Evolutionary Algorithm for the Optimization of Residential Energy Resources, in: Advances in Energy System Optimization. Springer.

Soares, A., Gomes, Á., Antunes, C.H., 2013a. An agent-based modelling approach for domestic load simulation, in: Eceee 2013 Summer Study Proceedings: Rethink, Renew, Restart. Belambra Presqu'île de Giens, France, pp. 1631–1636.

Soares, A., Gomes, Á., Antunes, C.H., 2014b. Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions. Renew. Sustain. Energy Rev. 30, 490–503.

Soares, A., Gomes, Á., Henggeler Antunes, C., Cardoso, H., 2013b. Domestic Load Scheduling Using Genetic Algorithms, in: Esparcia-Alcázar, A. (Ed.), Applications of Evolutionary Computation SE - 15, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Vienna, Austria, pp. 142–151.

Soares, A., Melo, H., Antunes, C.H., Trovao, J.P., Gomes, A., Jorge, H., 2015a. Integration of the Electric Vehicle as a Manageable Load in a Residential Energy Management System, in: 2015 IEEE Vehicle Power and Propulsion Conference (VPPC). IEEE, Montréal, Canada, pp. 1–6.

Soares, A., Melo, H., Gomes, Á., Antunes, C.H., Oliveira, C., Trovão, J., Pereirinha, P., Santos, V., 2015b. A Residential Energy Management System, in: Proceedings of the IT4Energy 2015. Lisbon.

Soares, A., Oliveira, C., Gomes, A., Antunes, C.H., 2015c. Analysis of solutions provided by a residential energy management system, in: Proceedings of Energy for Sustainability 2015 - Sustainable Cities: Designing for People and the Planet. Coimbra, Portugal.

Stamminger, P.R., Anstett, V., 2013. Effectiveness of demand side management by variable energy tariffs in the households – results of an experimental design with a fictive tariff model, in: Eceee 2013 Summer Study Proceedings: Rethink, Renew, Restart. pp. 2159–2166.

Stamminger, R., 2008. Synergy potential of smart appliances, d2. 3 of wp 2 from the smart-a project.

Strbac, G., 2008. Demand side management: Benefits and challenges. Energy Policy 36, 4419–4426.

Timpe, C., 2009. Smart Domestic Appliances Supporting the System Integration of Renewable Energy. Intelligent Energy Europe.

Tremblay, O., Dessaint, L.A., 2009. Experimental validation of a battery dynamic model for EV applications. World Electr. Veh. J. 3, 1–10.

Tsui, K.M., Chan, S.C., 2012. Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing. IEEE Trans. Smart Grid 3, 1812–1821.

Vanthournout, K., D’hulst, R., Geysen, D., Jacobs, G., 2012. A Smart Domestic Hot Water Buffer. IEEE Trans. Smart Grid 3, 2121–2127.

Vanthournout, K., Dupont, B., Foubert, W., Stuckens, C., Claessens, S., 2015. An automated residential demand response pilot experiment, based on day-ahead dynamic pricing. Appl. Energy 155, 195–203.

Weiller, C., 2011. Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States. Energy Policy 39, 3766–3778.

Wilensky, U., 1999. NetLogo.

Xu, Z., Ostergaard, J., Togeby, M., 2011. Demand as Frequency Controlled Reserve. IEEE Trans. Power Syst. 26, 1062–1071.

Yao, L., Chang, W.-C., Yen, R.-L., 2005. An Iterative Deepening Genetic Algorithm for Scheduling of Direct Load Control. IEEE Trans. Power Syst. 20, 1414–1421.

Zhang, P., Qian, K., Zhou, C., Stewart, B.G., Hepburn, D.M., 2012. A Methodology for Optimization of Power Systems Demand Due to Electric Vehicle Charging Load. IEEE Trans. Power Syst. 27, 1628–1636.

Zhao, Z., Choi, J., Park, K., Lee, W.C., 2013a. A cognitive scheduling method for demand response ensured home energy management, in: 2013 Fifth International Conference on Ubiquitous and Future Networks (ICUFN). IEEE, pp. 137–138.

Zhao, Z., Lee, W.C., Shin, Y., Song, K., 2013b. An Optimal Power Scheduling Method for Demand Response in Home Energy Management System. IEEE Trans. Smart Grid 4, 1391–1400.