Demand response implementation in smart households

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ABSTRACT

Home energy management system (HEMS) is essential for residential electricity consumers to participate actively in demand response (DR) programs. Dynamic pricing schemes are not sufficiently effective for end-users without utilizing a HEMS for consumption management. In this paper, an intelligent HEMS algorithm is proposed to schedule the consumption of controllable appliances in a smart household. Electric vehicle (EV) and electric water heater (EWH) are incorporated in the HEMS. They are controllable appliances with storage capability. EVs are flexible energy-intensive loads, which can provide advantages of a dispatchable source. It is expected that the penetration of EVs will grow considerably in future. This algorithm is designed for a smart household with a rooftop photovoltaic (PV) system integrated with an energy storage system (ESS). Simulation results are presented under different pricing and DR programs to demonstrate the application of the HEMS and to verify its' effectiveness. Case studies are conducted using real measurements. They consider the household load, the rooftop PV generation forecast and the built-in parameters of controllable appliances as inputs. The results exhibit that the daily household energy cost reduces 29.5%-31.5% by using the proposed optimization-based algorithm in the HEMS instead of a simple rule-based algorithm under different pricing schemes.

KEYWORDS: controllable load; demand response; home energy management system; smart household; thermal storage

Nomenclature

Indices

t	Time intervals.
h	Hours.
k	Tariff categories of time-of-use (TOU) pricing schemes.
v	EVs.
s	ESSs.

Variables

$\mathrm{Cost}_{\mathrm{RTP}}$	Daily electricity cost under real-time pricing (RTP) scheme [€].
$\mathrm{Cost}_{\mathrm{TOU}}$	Daily electricity cost under TOU pricing scheme [€]
P_t^{buy}	Power to be purchased from the grid at each time interval t [kW].
P_t^{sell}	Power to be sold to the grid at each time interval t [kW].
P_t^{EWH}	Power consumption of EWH in time interval t [kW]
$P_t^{\mathrm{PV,home/sell}}$	Photovoltaic (PV) generation for household consumption/selling to grid at each time interval [kW].
$P_t^{v,\mathrm{Ch/Dch}}$	Charging/discharging power of EV v [kW].
$P_t^{s,\mathrm{Ch/Dch}}$	Charging/discharging power of ESS s [kW].
$P_t^{v,\mathrm{home/sell}}$	EV discharging power for household consumption/selling to the grid at each time interval [kW].
$P_t^{s,\mathrm{home/sell}}$	ESS discharging power for household consumption/selling to the grid at each time interval [kW].
$x_t^{v,\mathrm{Ch}}$	Charging status of EV v in period t (1 if the EV is charging in $t \in \mathrm{T}^v$and 0 otherwise).
$x_t^{v,\mathrm{Dch}}$	Discharging status of EV v in period t (1 if the EV is discharging in $t \in \mathrm{T}^v$and 0 otherwise).
$x_t^{s,\mathrm{Ch}}$	Charging status of ESS s in period t (1 if the ESS is charging in time interval t and 0 otherwise).
$x_t^{s,\mathrm{Dch}}$	Discharging status of ESS s in period t (1 if the ESS is charging in time interval t and 0 otherwise).
x_t^{EWH}	Operating status of EWH in period t (1 if the EWH is operating in time interval t and 0 otherwise).
θ_t^{EWH}	Water temperature at time interval t [°C].
SoC_t^v	State of charge (SoC) of EV v in the end of time interval t [kWh].
SoC_t^s	SoC of ESS s in the end of time interval t [kWh].

DR_h	Consumption of the customer below the baseline load in hour h [kWh].
E_d	Daily peak demand [kWh].

Parameters

C^k	Electricity TOU tariff for category k.
τ	Time interval duration [h].
π_t^{buy}	Price of buying electricity from the grid at time interval t [€/kWh].
π_t^{sell}	Price of selling electricity to the grid [€/kWh].
π^{DPT}	Daily power-based network tariff [€/kW].
$\eta_{\text{Ch/Dch}}^v$	Charging/discharging efficiency of EV v.
$\eta_{\text{Ch/Dch}}^s$	Charging/discharging efficiency of ESS s.
SoC_{d}^v	Expected SoC of EV v at the departure time [kWh].
α^v	Arrival time of EV v.
β^v	Departure time of the EV v.
$SoC_{\text{Min/Max}}^v$	Minimum/Maximum SoC level of EV v [kWh].
$SoC_{\text{Min/Max}}^s$	Minimum/Maximum SoC level of ESS s [kWh].
m_t	Average hourly hot water usage at time interval t.
M	Capacity of the water tank of the EWH [L]
R	Thermal resistance of EWH [°C/kW]
C	Thermal capacitance of EWH [kWh/°C]
Q	EWH power rate [kW]
θ_t^a	Ambient temperature at time interval t [°C].
$\theta_{\text{Low/Up},t}^{\text{EWH}}$	Lower/Upper bound of the hot temperature of the EWH at time interval t [°C].
l_t^{firm}	Firm load at time interval t [kW].
P_t^{PV}	PV generation forecast at time interval t [kW].
l_h^{baseline}	Baseline load [kW].
FI_h	Financial incentives offered to the customer for consuming below the baseline load (€/kWh)
P^{Max}	Maximum demand power from the grid [kW].

Sets

T	Set of time periods in the scheduling horizon.
Ω^k	Set of time periods that belong to tariff category k.
Ω^h	Set of time periods in each hour h.

Ω^{DR}	Set of hours that the retailer has offered incentives for demand reduction.
Ω^{s}	Set of ESSs in the household.
Ω^{v}	Set of EVs in the household.
K	Set of tariff categories in TOU pricing scheme.
H	Set of hours in the scheduling horizon.
T^{v}	$\mathrm{T}^{v} \subseteq \mathrm{T}$ is the set of periods in which EV v is connected to the grid; $\mathrm{T}^{v} = \left\{ t \in \mathrm{T} : \alpha^{v} \leq t \leq \beta^{v} \right\}$.

1. Introduction

The rise in power generation volatility and the uncertainty of the electric grid, which are caused by the high penetration of renewable energy sources, can be tackled effectively by implementing DR programs. Employing DR programs enables the demand-side to closely follow the variable generation [1]. DR represents the demand-side capability to alter the consumption pattern in response to price changes or financial incentives [1]. DR programs induce customers to reduce electricity consumption during the periods with high electricity prices or the periods in which an incentive is considered for voluntary demand reduction [2]. DR prevents the operation of high-cost/emission generating units and defers the capital intensive reinforcements [3].

In central demand-side management, the peak load of the grid is controlled by a separate entity rather than the consumers, while in an individual demand-side management the households can proactively control the consumption [4]. Optimization of consumption scheduling is the core part of the demand-side management in both cases, which is done externally in the first case and carried out internally by the consumer itself in the second case. In one classification, DR programs are divided to two categories of price-responsive and controllable DR programs. In price-responsive DR programs, consumption is adjusted by the consumer in response to dynamic rates, while in controllable DR programs, the consumer accepts load curtailment by another entity under specific circumstances.

There are several obstacles for the widespread utilization of DR programs for households and residential customers. The main obstacle is the lack of appropriate smart metering infrastructure. Overcoming this primary obstacle enables the implementation of dynamic pricing schemes by utility companies, but does not ensure considerable improvements in demand-side activity. The next barrier is customers' limitations to effectively respond to the pricing or incentive signals. By addressing this issue, we can expect active electricity consumers to be able to be seen as resources for the power system. An acceptable solution for this problem is employing an optimization-based or a rule-based control system that automatically responds to these signals. This automated system that usually operates with an optimization algorithm is generally referred as a HEMS [5]. It provides automatic responses to price changes and incentive signals. Therefore, it is envisioned as one of the necessary means of successful implementation of smart grids [6]. Deployment of smart meters, sensors and automatic control systems at the consumers' level through a two-way communication network, and the market liberalization reforms in parallel with these technological advancements are the enablers for consumption scheduling [7]. They have an effective role in utilizing the DR strategies [8]. The residential customers that are equipped with HEMS, can actively participate in price-based and incentive-based DR programs [5]. In other words, implementing HEMS increases the price responsiveness of the electricity consumers in general.

A smart household within the context of smart grids refers to an active electricity consumer that is equipped with an intelligent HEMS [9]. Smart meters provide the possibility of monitoring the energy consumption in real-time for utilities and customers. The combination of a smart metering system and HEMS enables the consumers to reduce their electricity bill by using an optimal consumption schedule [8]. The HEMS can optimally schedule the operation of household controllable loads and storage units. It can also determine the amount of surplus energy from distributed generation (DG) units in order to sell to the grid for those customers who have installed DG units and have had an opportunity of selling electricity to the grid.

Different entities of electricity markets have been motivated by the potential benefits of DR programs to plan for activating DR programs [3]. Traditionally in power systems, scheduling and unit commitment were done by the system operator to operate generating units. Conventional loads were not controllable and the measuring system at the end-use points was not developed to a level of maturity that would enable consumption scheduling and load commitment [7]. Development of smart grid technologies motivated different entities in electricity markets to offer their clients the DR programs. Those entities that may benefit from DR implementation are the companies which are conducting retailing business in electricity markets. DR programs offered by the retail electricity providers to the customers reward both sides; it is a tool for retailers to manage the financial risks and reduce peak load and acts as a means for consumers to reduce the energy cost [2]. The optimal operation of a HEMS under DR programs depends on the information received from the retail companies, which requires the coordination and interaction of the HEMS and the retailers. Retailers share the price data and the incentive-based DR programs with the HEMS to obtain the optimal schedule for the appliances in a home [9]. In addition, the consumer preferences should significantly influence the operation of the HEMS.

1.1. Objectives

The main purpose of the present paper is to develop an optimization-based HEMS that schedules the appliances and resources in a smart household. The proposed HEMS algorithm can be embedded in the load control unit of smart meters or incorporated into automated decision-making technologies, such as home automation systems [2]. It optimally controls the operation of appliances in response to dynamic price signals or the financial incentives of the DR programs that have been offered under time-of-use (TOU) pricing schemes [10]. In this paper, the financial incentive plans [11,12] offered to households under DR programs are used as inputs of the proposed HEMS model. The focus of the decision-making framework is on reducing the costs associated with the electricity bill of the customers. Scheduling is carried out in response to the price signals that are received from the retailers while taking into account the preferences of the customers [5]. The results of this study show how the responsive customers can benefit from using an optimization-based HEMS and the time-varying electricity prices.

Controllable loads are used in the smart household model to implement different types of DR programs. EVs have the possibility of storing energy, and the thermostatically controlled appliances like EWHs have thermal storage capabilities. These loads are good candidates for DR implementation [7]. In this model, the detailed dynamic models of EWH and EV loads are used for potential DR applications. The possibility of selling electricity to the grid at variable prices is also considered for the customers. Consumers use EVs, ESS, photovoltaic (PV) systems to sell energy to the grid. Different operating modes of EVs in the discharging status, such as vehicle-to-home (V2H) and vehicle-to-grid (V2G) are modeled in this paper [9]. In V2G and V2H operating modes, EV serves as a DG resource for the grid rather than just serving as a vehicle [8,13]. The EV owners can sell the excess energy stored in the battery back to the grid or use it for the household consumption. Selling electricity to the grid from V2G requires the essential equipment, such as bidirectional chargers and communication devices, as well as the legislation and regulations that allow this trade. In V2G mode, the electricity flows from the battery to the distribution network. Another market opportunity for EV owners is participating in ancillary service markets [14].

The priorities of customers are also taken into account in scheduling process. Consumers can update arrival and departure time of the EVs, their expected initial storage level and the required charge at departure time. Users' choices on thermostat settings of EWH are considered with a time-varying temperature band.

1.2. Related work

In order to clarify unique contributions of this paper, a survey on reported research on implementing DR programs via HEMS in smart households is outlined here. Designing load scheduling programs to control the consumption of appliances on a daily basis has drawn much interest in the literature recently. The reasons of this interest are the concept of non-emergency ancillary services provision through demand-side, the possibility of buying electricity at dynamic prices for residential customers, and the emerging market of EVs [15]. The mechanism proposed by Alizadeh et al. [15] can be used to strategically compensate the customers who allow retail companies to directly schedule their consumption, whenever the retailers want to use an eligible appliance. Retailers compute the incentives and post them as publicly available menus, allowing the customers to decide whether to participate or not [15].

The HEMS models developed by Erdinc et al. [8] and Paterakis et al. [9] determine the optimal day-ahead appliance scheduling of a smart household. The consumption and production scheduling of various types of controllable appliances and DG units are performed under real-time pricing (RTP) scheme. The model proposed by Erdinc et al. [8] allows an electricity customer to change the priority of the sources that can provide electricity to the grid. Hard and soft peak power-limiting-based DR strategies are also taken into account by Paterakis et al. [9].

The operation of household appliances during a DR event is modeled by Fernandes et al. [16]. A dynamic load priority method is proposed to change the load priority during the DR event. The operation of controllable appliances within a price-based HEMS is prioritized from the customer's viewpoint by Rastegar et al. [5]. The operational priority of each appliance is indicated with the value of lost load. The HEMS minimizes energy and reliability costs by considering the appliances' value of lost load, electricity tariffs, and operational constraints of appliances. A HEMS model that controls a residential battery system which is connected to a rooftop PV system is presented by Marzband et al. [17]. The main focus in this model is to examine the impact of PV generation and energy load forecast errors on household economics.

Bozchalui et al. [2] developed a decision-making framework for a residential energy hub. The proposed mathematical optimization model can be incorporated into automated decision-making technologies in smart grids to optimally control residential loads, storage and production components in real-time. The customers' preferences and expected comfort levels were also considered in the model [2].

Electrification of the transport sector has potential to reduce CO_2 emissions from this sector, while reducing the mobility operating costs [18]. It is expected that in the future, EVs will become one of the high energy consuming appliances at homes [19]. Therefore, it is essential to include them in energy management models at different levels of scheduling in power systems, particularly for load management at the consumer level. Rassaei et al. [19] have proved that for certain practical distribution of EV's usage, it is possible to accommodate EVs for all users in the system and still keep the same peak demand as when there is no EV in the system. The problem of scheduling the EVs' charging is formulated by Jin et al. [20] as a mixed integer linear programming (MILP) model. It investigates the utilization of EVs and ESSs together. The aggregators' revenue is maximized by using this approach. The cost of EV owner and the discharging capability of the EVs' battery for injecting energy to the grid or using at households are not taken into account in this model.

Thermal loads, such as heating, ventilation and air conditioning (HVAC) and water heating systems constitute a significant share of the household energy consumption [21]. The energy scheduling problem of a residential building with solar assisted HVAC and water heating system is investigated by Nguyen et al. [21]. The objective was to minimize the electricity cost under RTP environment while maintaining the thermal comfort requirements of the user. In this model, the thermal solar water tank is used as a dynamic storage facility to support the thermal demand of water heating and the HVAC system [21].

The price-based DR program for electric storage space heating loads is modeled by Kilkki and Seilonen [1]. The electricity retail company seeks the optimal consumer electricity price for these loads. The problem of price determination is formulated within a game-theoretic framework, where the procurement and consumption profiles of the retailer and customer are based on the set price [1].

The HEMS algorithm that is developed by Du and Lu [7] for consumption scheduling of households with thermostatically loads, optimizes the payment while taking into account the individual requirements of the customers. Customers can specify the acceptable range of temperature changes, and these requirements are considered as operational constraints during the process of scheduling. In this model, the EWH is used as an example of a thermostatically load. The predicted hot water demand of the users is taken into account as the input of the model. The comfort zone of the EWH reflects the range of the hot water temperature set by the customers.

The DR potential of residential EWH and HVAC loads is studied by Safdarian et al. [3]. It develops a distributed framework to iteratively coordinate the operation cycle of residential consumers' HVAC and EWHs, and shows how this coordination can in practice bring considerable peak reductions. In this direct load control (DLC) model, the operator that serves multiple domestic consumers can control the operating cycle of EWH and HVAC loads without overriding the users' thermal preferences [3]. DLC program has been the most frequently used DR program since the 1960s. It was usually used for emergency purposes such as reducing demand quickly due to a supply-demand mismatch in the system. EWHs, HVAC systems and pool pumps are the most eligible appliances for DLC programs [22].

The multi-scale rule-based energy management system proposed by Pourmousavi [6] is developed for an islanded MG that operates independently in a remote area. The operation of controllable appliances, such as ON/OFF control of EWHs and battery's charging/discharging is modeled with a rule-based algorithm. Compared to optimization-based approaches, they are easy to implement, incredibly fast and computationally efficient, but obtaining the minimum cost is not guaranteed in this approach [6].

1.3. Contributions

From a detailed review of the technical literature, it is clear that most of the existent work only consider the RTP schemes for the scheduling of appliances. They are mostly designed to minimize the daily household energy cost, without properly taking into account the incentive-based DR programs and the impact of network charges for the peak demand. RTP still has not been applicable in many retail markets and requires the state legislation in those markets. In this situation, the retail companies are more interested in independently offering incentive-based DR programs to their clients in order to manage their own payoff in the volatile electricity market. Therefore, an essential need of consumers is energy management systems in demand-side which are also compatible with TOU pricing schemes and the incentive-based DR programs that are offered under these pricing programs. To fill the gap present in the literature, this paper proposes an optimization-based HEMS that can be employed by the consumers under both RTP and TOU pricing schemes. It also takes the incentive-based DR programs as inputs and schedules the electricity consumption based on price and DR signals. In addition, a rule-based HEMS model is developed in the paper to validate the performance of the proposed optimization-based algorithm. Another contribution of this work is considering the impact of the network charges. To accomplish this, the cost of peak demand is incorporated in scheduling procedure. Consequently, the HEMS cannot simply shift the consumption from the high price periods to periods with lower prices, and it should consider the charges of the network due to the peak consumption.

2. Problem description

Implementation of advanced metering infrastructure largely depends on the effective operation of information technology and communication systems. Information and communication technologies in the smart grid context can provide the access of both utilities and customers to metering data of the smart meters. As a result, various utility applications, such as billing, load forecast, load profiling and customer information services, can be enhanced [23]. Managing the household energy cost requires smart decisions about consumption, which is far beyond only providing the access to price and demand information in real-time. End-users need some tools to help them make optimal consumption choices [24]. Requesting domestic electricity consumers to create an optimal consumption schedule based on price and incentive signals is impractical when they are not using appropriate energy management systems [7]. Thus, some intelligent algorithms are required to determine the optimal consumption schedule of household appliances. The attempt in this paper is to design an intelligent algorithm for a HEMS to operate under TOU pricing and RTP schemes, considering DR programs.

Household appliances have different levels of demand flexibility [15]. DR can not be applied to appliances that need on-demand power supply without deteriorating the users' comfort levels. The primary focus for consumption scheduling purposes in smart households is on flexible and controllable loads. EVs and EWHs that respectively provide electricity and thermal storage are considered in the proposed HEMS model. They can be scheduled without having major effects on customer comfort levels [2]. Controlling these time-shiftable loads can significantly increase the residential demand elasticity [19]. The proposed load profile control performed under price- or incentive-based DR programs is an alternative to DLC programs.

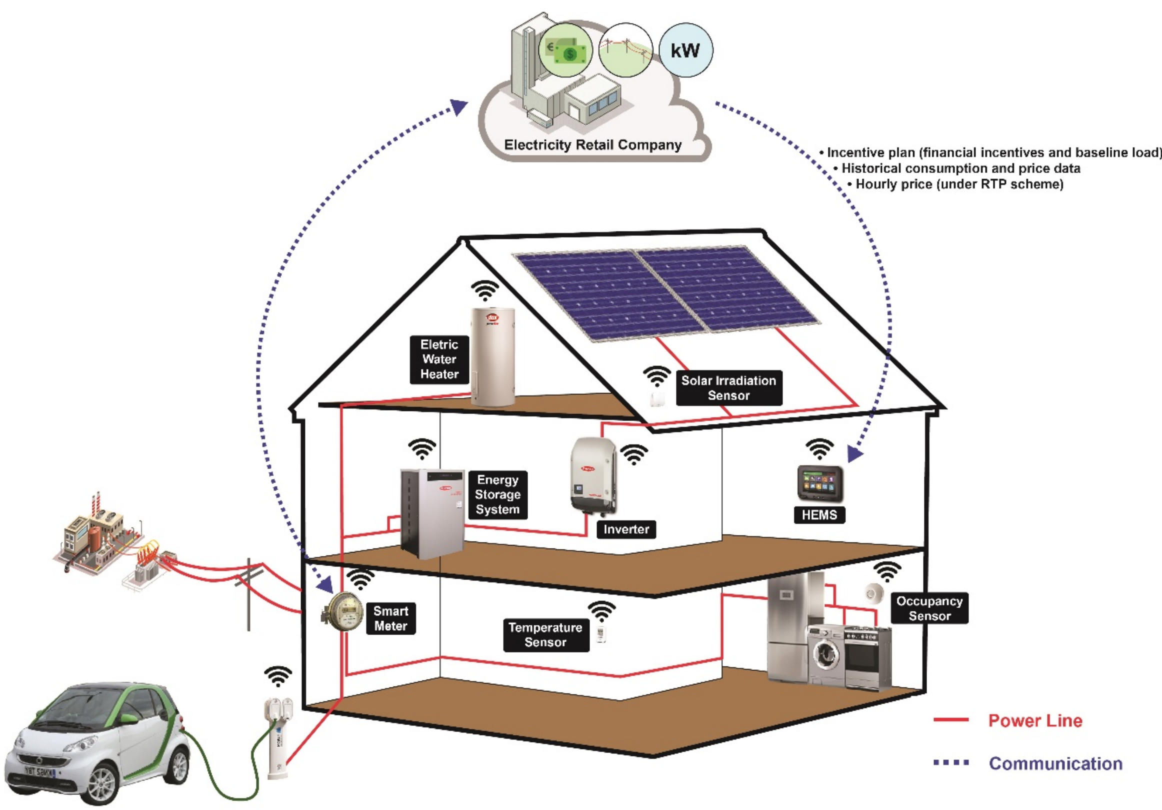


Figure 1. A schematic representation of a smart household.

Figure 1 represents a schematic of the smart household model used in this paper. The electricity retail company sends the price and incentive data to the HEMS on a daily basis and receives the consumption data in real-time from smart meters. The historical data and price data are also provided to the HEMS. The ON/OFF status, charging, cycling, or mode switching of the appliances are controlled and monitored wirelessly through the HEMS. Customers' preferences are a priority for HEMS, and the consumption scheduling should not deteriorate defined comfort levels. The built-in parameters of the appliances are stored in HEMS and the customer is allowed to update several settings of the HEMS before each scheduling.

HEMS models can be classified on the basis of different aspects. One of the aspects is choosing the target of controllable appliances for the HEMS and adjusting the model to incorporate their dynamic conditions. There is a wide range of controllable loads, such as thermostatically controllable loads [7,25–29], non-thermostatically controllable loads (e.g., washing machine and dishwasher) [5,30,31] and EVs [8,9], which can provide the required flexibility for the demand-side [32]. EVs and EWHs are considered as the target appliances in this study, due to their storage capability. Utilizing the storage capability of EVs and EWHs can prevent households from investing on expensive battery technologies for ESSs. However, the current model can be easily extended to incorporate more categories of appliances. It can be done by including the dynamic behavior of each load. The operation of HEMS models also depends on the type of the decision-making entity, whether it is the consumer itself or the aggregator. The HEMS model is developed from the perspective of an individual consumer in this model, which receives the price signals from the retailer.

2.1. Retailers' interaction with consumers

The residential electricity customers that can not or do not want to directly take part in energy markets make contracts with an intermediary, such as a retailer or an aggregator [19]. The retailer or aggregator conducts the price and demand negotiations with market operators and generation companies on behalf of their clients [19]. The retailer plays the role of a mediator in the electricity market, allowing residential consumers to associate with the market and participate in DR programs efficiently [19]. In deregulated markets, retail companies submit demand bids to the day-ahead market. The bids contain demand and price components. It means that the retailer is buying energy only if the market clearing price is less than the desired price [19].

The development of smart grids can significantly influence the relationship between retailers and electricity consumers [33]. Smart grid solutions can enable the active participation of consumers, which are modeled in the form of DR programs. The retailer seeks to influence its customers' demand profile for several reasons. Demand flexibility has a time-varying value because the retailers purchase electricity in the wholesale markets at variable prices [15]. This concept is practically demonstrated when the retailers are offering incentive-based DR programs to their customers. For some periods they pay incentives for demand reduction and for other periods they may promote the demand rise. Retailers convince customers to voluntarily change their consumption pattern by offering DR programs to them. Incentives can vary dynamically with time and appliance cluster.

In electricity market, several entities can offer DR programs to consumers. Purposes of these entities are not necessarily similar to each other, although all of them may expect similar reactions from the consumers, which are shifting the electric usage from peak to off-peak periods [8]. Controlling and shifting the electricity consumption through DR programs reduces the electricity demand during peak times when the use of older less efficient generating units is required. Therefore, DR implementation reduces the release of CO_2 emissions that contribute to global warming [24]. Retail companies offer DR programs to obtain higher profits in the market, while the operators usually implement DR program to maintain the stability of the network by reducing the stress on utility-handled assets.

Some retail companies or smart meter operators provide additional services for customers to manage the costs with hourly pricing. These services are offered to guide the client to take control of the electricity costs, and they consist of real-time high price alerts, online bill comparison tool and mobile applications [24]. Usually, the customers have to pay the delivery service charges regardless of the electric supply choice (RTP or TOU pricing) [24].

2.2. Pricing schemes

Retailers offer time-varying electricity prices, such as TOU and RTP to influence and guide energy consumption [34]. In some markets the end-use customers sign up for hourly electricity pricing scheme based on market prices [35]. The customers that purchase electricity under RTP tariffs, which represents a dynamic pricing scheme in the retail market, pay hourly prices for electricity. It is based on the day-ahead or hour-ahead market prices, and thus the variations of the electricity prices in this scheme depend on the variations of the wholesale market price. [35]. RTP is considered as one of the most efficient price-based DR programs [36].

HEMS is needed when a consumer with flexible demand faces variable electricity rates. The more price variations, the more intelligent algorithms are needed to schedule the consumption. Tariff structures with price variations can motivate customers to schedule their consumption. The proposed HEMS in this paper is designed to operate under RTP and TOU pricing schemes.

2.3. Energy storage

Implementing some sorts of energy storage is expected to become highly prevalent in households. Electrical energy storage at the household level can play several roles. Its' unique capability is to cope with the critical characteristics of electricity markets, such as hourly variation of electricity price [37]. The produced energy can be captured when the price is lower to use at the periods with higher prices [37]. Apart from the ESSs, some loads can also be utilized to store energy.

EVs are becoming the new appliances in households, which have higher consumption than any other electricity-powered device in a home. Charging level of a small sized EV may even exceed the total installed power of many households [8]. Several solutions are proposed to enable the charging of EVs in homes. In many cases, the electrical supply of the home should be upgraded to support higher operating currents. Some EV manufacturers offer connector to the EV owners to provide the possibility of charging the car at home [38].

EVs need a certain amount of energy stored in their batteries during a specified time frame. During this time frame, they potentially can give energy back in order to be used locally in home or to be injected into the grid [19]. They can also be considered as a resource for the grid when they are used in V2H and V2G modes. The EV's DR can help to reduce the household electricity cost, especially under dynamic pricing schemes. It also contributes to peak demand reduction by shaping the daily demand profile. Some utility companies install new meters specifically for the EV, which allows applying different rates for the charging of the EVs [39].

Figure 2 shows the EV load model which is used by the proposed HEMS model. There are some built-in parameters within these loads, which do not require updating before each consumption scheduling. They are permanent characteristics of the EVs. Other inputs should be updated before each load scheduling. However, the consumer may use some intelligent algorithms to estimate these inputs, for instance, the initial level of battery stored energy can be estimated based on the historical data of the EV owner.

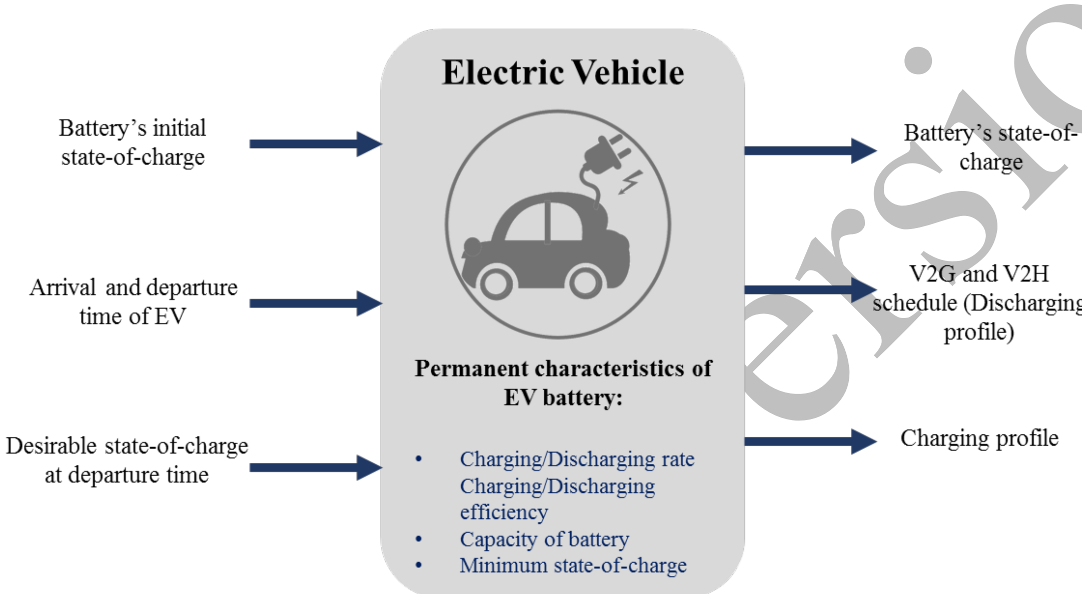


Figure 2. Block diagram of EV load model.

Electric heating is another major residential electricity load. Heating loads can be curtailed or deferred easily, without sacrificing users' comfort [1]. Water heating is an energy-intensive load for households, which is shiftable in time without influencing the comfort levels. EWHs represent a significant load demand in modern grids and have a capacity for energy storage in form of heat [40]. The controllable residential EWH loads are used in this paper to model the implementation of DR programs through HEMS. Compared with other loads in households, they are less time critical loads and can be shed first [41]. EWHs are responsive loads that have the energy storage capability [6]. Controlling the water heating is easy, due to the large specific heat capacity of water and the fact that the users are not sensitive to small changes in the set point temperature [42]. Currently, most of the hot water tanks maintain the water temperature at a constant set point temperature. This archaic way consumes a lot of energy [42]. Using smart energy storage by water heaters can defer the consumption to more inexpensive periods without deteriorating the comfort levels [1]. Utilities or aggregators can also control the grid-interactive EWHs in order to perform several grid services such as DR, grid stabilization, and peak load shavings [40]. Grid-interactive EWHs send the temperature and status of the appliance and can be remotely controlled by the utility or the aggregator [41].

Figure 3 shows the block diagram of an EWH load. The built-in parameters are shown in the gray box and the inputs are the parameters that require updates before each load scheduling. Hot water consumption profile and the desirable temperature range of hot water are the most important inputs.

An average hourly hot water consumption profile can be estimated for each household [43]. Hot water usage can be predicted by historical data that has been provided from the flow meter or from the hourly electricity consumption of an EWH. Average hourly consumption refers to the mean volume of the hot water consumed during the specified time interval [44]. Several studies on hot water consumption have developed forecasting methods to forecast the individual hot water usage profile [42]. Forecasting hot water usage pattern is useful for demand-side management.

The bounds on temperature reflect individual needs of the users. They are considered as operational constraints in the scheduling process [7]. Customers can provide more flexibility in scheduling by increasing the temperature range of the EWHs. This behavior can decrease their energy costs [7]. The setpoint temperature can be adjusted according to the hourly price changes [42]. Considering a wide range of the comfortable temperature provides more flexibility for the EWH for DR implementation [42].

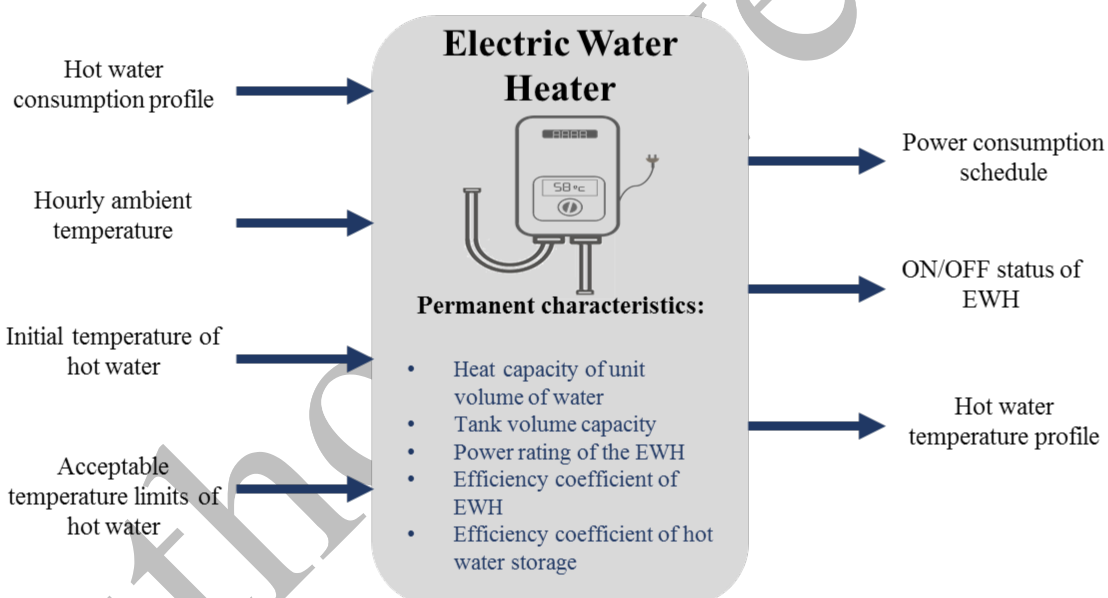


Figure 3. Block diagram of EWH load model.

3. Mathematical model

Optimization models have been widely used in resources management problems, especially when there is a lack of sufficient resources or the considerable cost variations highly depend on the decision maker's strategies. Several similarities can be found between energy resources management and water resources management problems. In water resources management, the decision-making model is developed for different purposes such as irrigated agriculture [45–49]. In the proposed energy resources management model at demand-side, the energy resources and the demand are optimally scheduled to reduce the household energy cost. In contrast to water resources management problems, in which the decision-maker has to deal with shortages of the resources, the main purpose here is to reduce the electricity bill of the consumer.

The consumption schedule of controllable household appliances and decisions for selling the surplus energy to the grid are the main outputs of the proposed optimization-based HEMS. In this model, the consumer can benefit from several sources for selling energy to the grid. The optimization model decides when to sell the PV production to the grid or when to consume it in the household. Similar decisions are made for the energy stored in ESSs and EVs. The scheduled household demand for the next day helps the owner to find out the dispatch of the local energy sources and the load in advance. In this optimization model, minimizing the daily energy cost of the household is the main objective.

This optimization problem requires technical data of EWHs and EVs, outdoor temperature, and consumers' hot water demand as inputs. Whereas the hot water temperature, operating cycle of EWH, charging and discharging power of the EVs and ESSs are decision variables. The implementation of incentive-based DR programs for EWH and EV loads under TOU pricing programs is overlooked in the proposed HEMS models in the literature. Therefore, introducing this optimization model can be considered as the main contribution of the paper. A simple rule-based HEMS is also introduced at the end of this part. This algorithm is used in the case studies to verify the benefits of the intelligent HEMS algorithm for the end-users.

The proposed model is based on the following assumptions:

- The charging of the EVs takes place at homes.
- The EV owner connects the EV to the grid when it arrives, but this does not mean that the charging starts immediately. An intelligent algorithm and the dedicated charger controls the charging process, namely the power injection flowing from the outlet [19].
- Since our focus is on EV and EWH loads, all other appliances either flexible or inflexible are considered firm.
- The temperature of the inlet water in EWH is near to the ambient temperature.
- The forecasts of daily water consumption and the PV production with sufficient level of accuracy is available.

The principal objective of the HEMS is to minimize the cost function of the customer while taking the preferences and the priorities of the customer into account. The main purpose of this paper is to demonstrate the operation of HEMS and the optimal consumption scheduling while implementing DR programs. Therefore, two cost functions for the HEMS are formulated here, one as a price-based DR program and the other as an incentive-based DR program.

In order to implement the price-based DR program, the daily household energy cost under RTP scheme is calculated using the following equation:

$$\mathrm{Cost}_{\mathrm{RTP}} = \sum_{t\in\mathrm{T}}\left(P_t^{\mathrm{buy}}\cdot\tau\cdot\pi_t^{\mathrm{buy}} - P_t^{\mathrm{sell}}\cdot\tau\cdot\pi_t^{\mathrm{sell}}\right) + E_d\cdot\pi^{\mathrm{DPT}}, \tag{1}$$

where P_t^{buy} is the electricity that the customer buys at variable prices (π_t^{buy}) and τ is the duration of each time period. The customer can also sell the excess electricity (P_t^{sell}) to the grid at variable prices (π_t^{sell}). The last term in (1) refers to the cost of daily power-based network tariff (DPT), which is determined by the daily peak demand of the household (E_d) [35]. The customer is charged (π^{DPT}) for each kW of the daily peak demand. Shifting the load to periods with lower electricity prices may be achieved at the expense of increasing the peak demand. This term shows that considering the network tariff associated with the peak demand will avoid this impact.

The energy cost of the household under TOU pricing scheme ($\mathrm{Cost}_{\mathrm{TOU}}$) is formulated as:

$$\mathrm{Cost}_{\mathrm{TOU}} = \sum_{k\in\mathrm{K}}\left(C^k\cdot\sum_{t\in\Omega^k}P_t^{\mathrm{buy}}\cdot\tau\right) - \sum_{t\in\mathrm{T}}P_t^{\mathrm{sell}}\cdot\tau\cdot\pi_t^{\mathrm{sell}} - \sum_{h\in\mathrm{H}}DR_h\cdot FI_h + E_d\cdot\pi^{\mathrm{DPT}}. \tag{2}$$

The first term of the cost function (2) indicates the cost of energy with regard to the tariff category. The price of electricity under category k is shown with C_k. The second term shows the revenue from selling electricity to the grid. The third term is the potential revenue of the household from participating in incentive-based DR programs. $DR_h$is the difference between the baseline load and the and the actual demand from the grid, which will receive the financial incentive of FI_h for each kWh of consuming below the baseline load. Consumptions above the baseline load will be penalized with FI_h for each kWh of consumption above the baseline load. The last term in this function refers to the cost of DPT.

The constraint below enforces that the hourly purchases from the grid is always below the daily peak demand E_d

$$\sum_{t\in\Omega^h}\tau\cdot P_t^{\mathrm{buy}} \le E_d, \qquad \forall h. \tag{3}$$

The set of time periods that are defined in each hour is shown with Ω^h. Constraint (4) enforces a limit on the power that can be purchased from the grid during each time interval by P^{Max}

$$P_t^{\mathrm{buy}} \le P^{\mathrm{Max}}, \qquad \forall t. \tag{4}$$

The amount of electricity that the consumer purchases from the grid or sells to the grid can be respectively expressed as follows:

$$P_t^{\mathrm{buy}} = l_t^{\mathrm{firm}} + P_t^{\mathrm{EWH}} + \sum_{\forall v\in\Omega^v}\left(P_t^{v,\mathrm{Ch}} - P_t^{v,\mathrm{home}}\right) + \sum_{\forall s\in\Omega^s}\left(P_t^{s,\mathrm{Ch}} - P_t^{s,\mathrm{home}}\right) - P_t^{\mathrm{PV,home}}; \qquad \forall t, \tag{5}$$

$$P_t^{\mathrm{sell}} = \sum_{\forall v\in\Omega^v}P_t^{v,\mathrm{sell}} + \sum_{\forall s\in\Omega^s}P_t^{s,\mathrm{sell}} + P_t^{\mathrm{PV,sell}}; \qquad \forall t. \tag{6}$$

The difference between the household consumption and local production expresses the amount of power purchase from the grid. Household consumption is composed of the firm load (l_t^{firm}), the consumption of the EWH (P_t^{EWH}) and the charging power of EVs ($P_t^{v,\mathrm{Ch}}$) and ESSs ($P_t^{s,\mathrm{Ch}}$). The local production consists of the power discharged from the EVs ($P_t^{v,\mathrm{home}}$) and the ESSs ($P_t^{s,\mathrm{home}}$) and the power production of PV ($P_t^{\mathrm{PV,home}}$), which are considered for internal consumption. The selling power consists of the discharging power of EVs ($P_t^{v,\mathrm{sell}}$) and ESSs ($P_t^{s,\mathrm{sell}}$) and the production of PV ($P_t^{\mathrm{PV,sell}}$), which are considered to be injected to the grid. The set of the EVs and ESSs of the household are respectively illustrated with Ω^v and Ω^s.

Incentive-based DR programs influence the consumption scheduling in HEMS. The consumer can decrease its daily energy cost by reducing the consumption. The equation below sates that the DR_h is the difference between the baseline load ($l_h^{baseline}$) and the total purchase from the grid at hour h:

$$DR_h = l_h^{\mathrm{baseline}} - \sum_{t \in \Omega^h} \tau \cdot P_t^{\mathrm{buy}}, \qquad \forall h \in \Omega^{\mathrm{DR}}. \tag{7}$$

It is positive when the consumer reduces the load below the baseline load, and therefore reduces the daily household energy cost in (2). $DR_h$is negative when the end-user is consuming above the baseline load, which means that the consumer will receive penalty for those hours according to the difference between the baseline load and the actual demand from the grid. The set of hours that the retailer has offered incentives for demand reduction is shown with Ω^{DR}.

3.1. ESS operational constraints

The following constraints (8) and (9) enforce that the charging and discharging power of the ESS should be respectively lower than $P_{Max}^{s,\mathrm{Ch}}$ and $P_{Max}^{s,D\mathrm{ch}}$

$$0 \le P_t^{s,\mathrm{Ch}} \le P_{\mathrm{Max}}^{s,\mathrm{Ch}} \cdot x_t^{s,\mathrm{Ch}}; \qquad \forall s \in \Omega^s, \forall t \in \mathrm{T}, \tag{8}$$

$$0 \le P_t^{s,\mathrm{Dch}} \le P_{\mathrm{Max}}^{s,\mathrm{Dch}} \cdot x_t^{s,\mathrm{Dch}}; \qquad \forall s \in \Omega^s, \forall t \in \mathrm{T}, \tag{9}$$

where the binary decision variable $x_t^{s,Ch}$and $x_t^{s,Dch}$ respectively express whether the ESS is in charging or discharging modes [50].

The restriction over simultaneous charging and discharging of the ESS is applied with

$$x_t^{s,\mathrm{Ch}} + x_t^{s,\mathrm{Dch}} \le 1, \qquad \forall s \in \Omega^s, \forall t \in \mathrm{T}. \tag{10}$$

The discharged power of ESSs can be used to serve the household loads or to be sold to the grid:

$$P_t^{s,\mathrm{Dch}} \cdot \eta_{\mathrm{Dch}}^s = P_t^{s,\mathrm{sell}} + P_t^{s,\mathrm{home}}, \qquad \forall s \in \Omega^s, \forall t \in \mathrm{T}. \tag{11}$$

The stored energy in the ESS in the end of time interval t depends on the remaining energy from the previous period and the charging and discharging in that period. The following equations are used to calculate the state of charge (SoC) update function respectively in the first time interval and the remaining time periods:

$$SoC_t^s = SoC_{\mathrm{Initial}}^s + \tau \cdot \left[\eta_{\mathrm{Ch}}^s \cdot P_t^{s,\mathrm{Ch}} - P_t^{s,\mathrm{Dch}} \right]; \qquad \forall s \in \Omega^s, t = 1, \tag{12}$$

$$SoC_t^s = SoC_{t-1}^s + \tau \cdot \left[\eta_{\mathrm{Ch}}^s \cdot P_t^{s,\mathrm{Ch}} - P_t^{s,\mathrm{Dch}} \right]; \qquad \forall s \in \Omega^s, \forall t \in \mathrm{T}, t \ne 1. \tag{13}$$

The SoC of the ESS must be within a certain range represented by its minimum storage level (SoC_{Min}^s) and its capacity (SoC_{Max}^s) [50]. This limitation is imposed on the problem by the following constraint:

$$SoC^{s}_{\text{Min}} \le SoC^{s}_{t} \le SoC^{s}_{\text{Max}}, \qquad \forall s \in \Omega^{s}, \forall t \in \mathrm{T}. \tag{14}$$

3.2. EV operational constraints

The charging power and discharging power of EVs should be within the range of the charging and discharging rates of the EVs. This limitation is formulated as follows:

$$0 \le P^{v,\text{Ch}}_{t} \le P^{v,\text{Ch}}_{\text{Max}} \cdot x^{v,\text{Ch}}_{t}; \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}, \tag{15}$$

$$0 \le P^{v,\text{Dch}}_{t} \le P^{v,\text{Dch}}_{\text{Max}} \cdot x^{v,\text{Dch}}_{t}; \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}, \tag{16}$$

where $P^{v.\text{Ch/Dch}}_{\text{Max}}$ is the maximum charging/discharging rate. The simultaneous charging and discharging of the EVs is avoided with the following constraint:

$$x^{v,\text{Ch}}_{t} + x^{v,\text{Dch}}_{t} \le 1, \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}. \tag{17}$$

The energy stored in the EV, while it is parked at home (i.e., during T^{v}), can be used for household needs or can be sold to the grid at market prices, i.e.,

$$P^{v,\text{Dch}}_{t} \cdot \eta^{v}_{\text{Dch}} = P^{v,\text{sell}}_{t} + P^{v,\text{home}}_{t}, \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}. \tag{18}$$

Constraint (18) states that during the periods that the EV is plugged in at home, the discharging power ($P^{\text{EV.Dch}}_{t}$) is used in home (V2H mode) or injected to the grid (V2G mode).

The SoC update function is represented as follows:

$$SoC^{v}_{t} = SoC^{v}_{\text{Initial}} + \tau \cdot \left[\eta_{\text{Ch}} \cdot P^{v,\text{Ch}}_{t} - P^{v,\text{Dch}}_{t}\right]; \qquad \forall v \in \Omega^{v}, t = \alpha^{v}. \tag{19}$$

$$SoC^{v}_{t} = SoC^{v}_{t-1} + \tau \cdot \left[\eta_{\text{Ch}} \cdot P^{v,\text{Ch}}_{t} - P^{v,\text{Dch}}_{t}\right]; \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}, t \ne \alpha^{v}, \tag{20}$$

where equation (19) calculates the SoC of the EV at the end of the first time period after the arrival and equation (20) calculates it for the remaining time periods. The SoC of the EVs' battery should always be within a certain range

$$SoC^{v}_{\text{Min}} \le SoC^{v}_{t} \le SoC^{v}_{\text{Max}}, \qquad \forall v \in \Omega^{v}, \forall t \in \mathrm{T}^{v}. \tag{21}$$

Constraint (21) guarantees high battery efficiency during its' lifetime [51]. Although an EV is very similar to an ESS, in terms of operational scheduling, a few extra constraints should be enforced on the charging/discharging status of EVs [51]. For instance, they are only available between the arrival and departure time of the EV (T^{v}) or the SoC of the EV should be at the specific amount by the departure time. These two characteristics are mathematically described as:

$$x^{v,\text{Ch}}_{t} + x^{v,\text{Dch}}_{t} = 0; \qquad \forall v \in \Omega^{v}, \forall t \notin \mathrm{T}^{v}, \tag{22}$$

$$SoC^{v}_{t} = SoC^{v}_{\text{d}}; \qquad \forall v \in \Omega^{v}, t = \beta^{v}, \tag{23}$$

where SoC^{v}_{d} is the required energy level of the battery at the departure time. Constraint (22) shows that during the periods that the EV is not connected to the grid, charging and discharging tasks cannot be performed.

Constraint (23) enforces that the EV should be charged to a specific amount when the user is taking the car for daily trips (23).

3.3. EWH operational constraints

The model introduced by Du and Lu [7] is used to show the scheduling aspects of an EWH in a household. The thermal dynamics of the EWH, considering the heat exchange with environment and with the cold water inflows is formulated as follows [7]:

$$\theta_t^{\mathrm{EWH}} = \theta_t^{\mathrm{a}} + R \cdot P_t^{\mathrm{EWH}} - \left(\frac{M - m_t}{M}\right)\left(\theta_t^{\mathrm{a}} - \theta_{t-1}^{\mathrm{EWH}}\right)\exp\left(-\tau / R \cdot C\right), \qquad \forall t \in \mathrm{T}. \tag{24}$$

The thermal dynamics of the EWH is considered as a function of hot water usage, temperature of the ambient, thermal parameters and the ON/OFF status of the EWH [7]. The impact of heat exchange with the environment and cold inlet water on the water temperature inside the tank is also taken into account [9]. In this equation, water temperature and the ambient temperature at period *t* are respectively shown by θ_t^{EWH} and θ_t^{a}. The average hourly hot water usage is shown with m_t, and *M* denotes the capacity of water tank.

EWH is turned on to compensate the heat loss via the tanker walls and the heat losses due to the cold water inflows, which are always followed by the hot water usage. Thermal resistance (*R*) and capacitance (*C*) are used to model the thermal behavior of EWH. These parameters can be calculated with statistical and regression techniques [7]. Another way is to obtain these values from the 2015 ASHRAE Handbook [7,52].

The load profile of the EWH is zero during the periods that it is in the OFF status and operates at its capacity (*Q*) during the ON periods ($x_t^{EWH} = 1$):

$$P_t^{\mathrm{EWH}} = Q \cdot x_t^{\mathrm{EWH}}, \qquad \forall t. \tag{25}$$

The permissible limits of hot water temperature at each time interval are set by

$$\theta_{\mathrm{Low},t}^{\mathrm{EWH}} \le \theta_t^{\mathrm{EWH}} \le \theta_{\mathrm{Up},t}^{\mathrm{EWH}}, \qquad \forall t. \tag{26}$$

$\theta_{\mathrm{Low}}^{\mathrm{EWH}}$ and $\theta_{\mathrm{Up}}^{\mathrm{EWH}}$ define the acceptable temperature range. They are chosen by the customer according to their thermal preferences [3]. Wider ranges provide more flexibility, while tighter ranges are desirable for consumers whose thermal comfort is their first and foremost priority [3].

3.4. Rule-based HEMS

A simple rule-based approach is introduced for consumption scheduling. The main purpose of using this approach for load scheduling is to have a benchmark for measuring the effectiveness of implementing the proposed intelligent HEMS algorithm.

Algorithm 1. EWH scheduling.

for $t = 1$ to $t = n(\mathrm{T})$ with *step* 1 **do**
    $load_t \leftarrow load_t^{\mathrm{firm}} - P_t^{\mathrm{PV}}$
    $x_t^{\mathrm{EWH}} \leftarrow 1$
    $P_t^{\mathrm{EWH}} \leftarrow x_t^{\mathrm{EWH}} \cdot Q$
    Calculate θ_t^{EWH} with (24)
        if $\theta_t^{\mathrm{EWH}} \ge \theta_{\mathrm{Up}.t}^{\mathrm{EWH}}$ **then**

$x_t^{\mathrm{EWH}} \leftarrow 0$
end if
$P_t^{\mathrm{EWH}} \leftarrow x_t^{\mathrm{EWH}} \cdot Q$
$a \leftarrow load_t + P_t^{\mathrm{EWH}}$
if $a > P^{\mathrm{Max}}$ **then**
$x_t^{\mathrm{EWH}} \leftarrow 0$
end if
$P_t^{\mathrm{EWH}} \leftarrow x_t^{\mathrm{EWH}} \cdot Q$
$load_t \leftarrow load_t + P_t^{\mathrm{EWH}}$
Calculate θ_t^{EWH} (24).
end for

Algorithm 2. EV charging scheduling.

for $t = 1$ to $t = n(\mathrm{T})$ with *step* 1 **do**
if $t \in T^v$ **then**
if $SOC_{t-1}^v = SOC_{\mathrm{d}}^v$ **do**
$SOC_t^v \leftarrow SOC_{t-1}^v$
$P_t^{v.Ch} \leftarrow 0$
else
$R \leftarrow SOC_{\mathrm{d}}^v - SOC_{t-1}^v$
if $R \leq \tau \cdot \eta_{\boldsymbol{ch}}^v \cdot P_{\mathrm{Max}}^{v.\mathrm{Ch}}$ **then**
$P_t^{v.Ch} \leftarrow R \cdot (1/\eta_{\boldsymbol{ch}}^v)$
$SOC_t^v \leftarrow SOC_{\mathrm{d}}^v$
else
$P_t^{v.Ch} \leftarrow P_{\mathrm{Max}}^{v.\mathrm{Ch}}$
$SOC_t^v \leftarrow SOC_{t-1}^v + \tau \cdot \eta_{\boldsymbol{ch}}^v \cdot P_t^{v.Ch}$
end if
if $P_t^{v.Ch} + load_t \leq P^{Max}$ **then**
$P_t^{v.Ch} \leftarrow P_t^{v.Ch}$
else
$P_t^{v.Ch} \leftarrow P^{Max} - load_t$
$SOC_t^v \leftarrow SOC_{t-1}^v + \tau \cdot \eta_{\boldsymbol{ch}}^v \cdot P_t^{v.Ch}$
end if
else
$P_t^{v.Ch} \leftarrow 0$
$SOC_t^v \leftarrow 0$
end if
$load_t \leftarrow P_t^{v.Ch} + load_t$
end for

In this rule-based approach the PV generation is used in household and the surplus is sold to the grid. In the first step the EWH load is scheduled as shown in algorithm 1. The cardinality of set T is illustrated by $n(\mathrm{T})$. The main constraints for scheduling are not violating the maximum water temperature and the maximum power limit of the household.

Algorithm 2, which runs after the EWH scheduling is a heuristic algorithm for scheduling of the EVs' charging. The EV that arrives first is charged first up to the desirable energy level by the departure time, and again the main constraint here is not to violate the maximum household power limit.

4. Test system

Load scheduling of a smart household with 17.25 kVA contracted power is carried out in this paper to show the performance of the proposed intelligent algorithm. It is considered in this paper that the household includes a small-scale PV system of 5 kW. The expected household firm load is obtained from the public data sets provided by the Intelligent Systems Subcommittee of the PSACE IEEE PES [53] and were also used by Fernandes et al. [54]. The PV generation over the scheduling horizon is presented in Figure 4. The PV generation profile is taken from the installed rooftop PV system of GECAD research center. The scheduling horizon is 24 hours and begins at 9:00 AM. The main reason for starting the scheduling horizon at 9:00 AM is the arrival and departure of EVs, assuming that these actions happen chronologically in this time horizon, and therefore the total connection time is within the scheduling horizon. The selected time slot for optimization is 5 min. Thus, the 24 hours scheduling horizon consists of 288 time intervals.

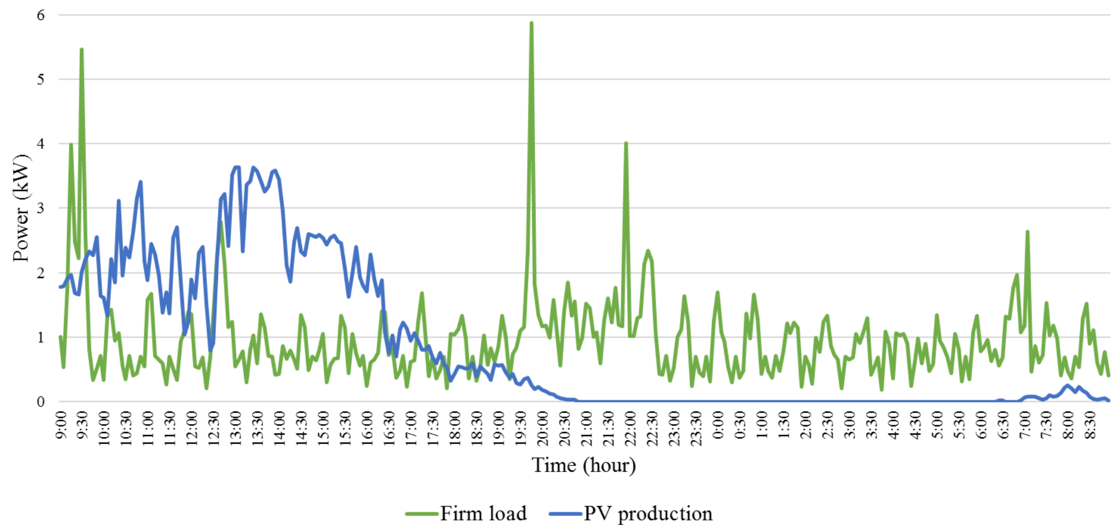


Figure 4. Expected firm load and PV production of the smart household during the scheduling horizon

The prices under RTP and TOU pricing are shown in Figures 5 and 6 respectively. The prices under RTP scheme reflect price changes of a typical day in the Iberian electricity market (MIBEL) [55]. The day-ahead prices are modified by assuming a fixed markup for the retail company. The tri-hourly price scheme of the EDP Comercial, the incumbent Portuguese electricity retailer in the liberalized market, for a typical weekday is considered with few modifications for the TOU pricing program [56]. This scheme consists of prices in three categories of: normal, economic, and super economic. In Figure 6 normal prices are illustrated in red, economic prices in blue, and super economic prices in green.

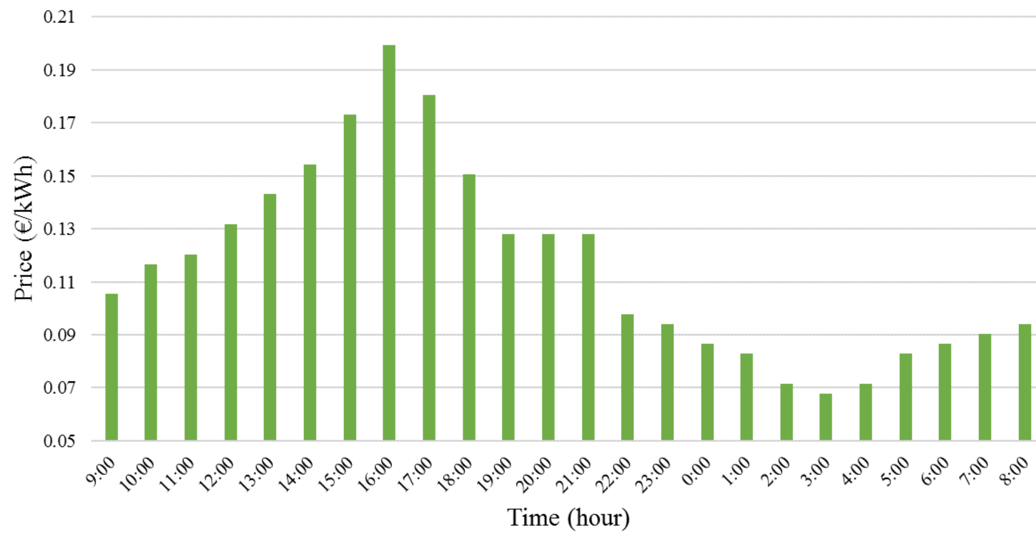


Figure 5. Prices under the RTP scheme.

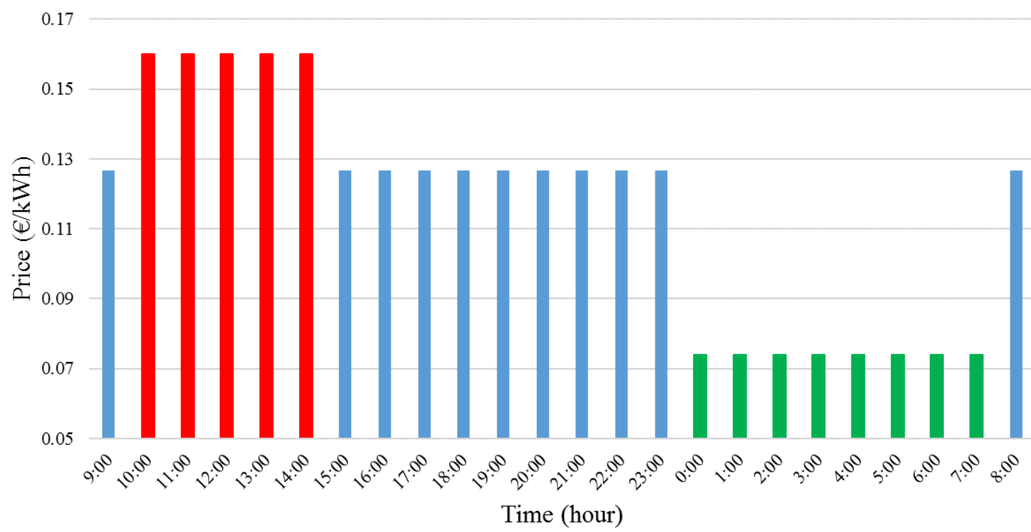


Figure 6. Prices under the TOU pricing scheme [56].

By participating in incentive-based DR programs, the consumer receives the incentive plan in advance. The proposed HEMS algorithm uses the incentive plan shown in Table 1. The plan indicates that the incentives are assigned to the hours when the consumption is below the baseline load, and penalties are assigned when the consumption is above the baseline load. Consumers can benefit from the opportunity of receiving financial incentives for each kWh demand reduction below the baseline load. They are charged with the TOU prices for other hours during the scheduling horizon.

Table 1. Incentive plan.

Hours	Incentive/Penalty (€/kWh)	Baseline load (kWh)
19:00	0.030	6.5
20:00	0.025	6.0

0:00	0.020	9.0
1:00	0.042	8.5
2:00	0.035	8.1
5:00	0.026	7.5
7:00	0.032	8.0

The controllable household appliances are 2 EVs and an EWH. Characteristics of the EVs and the ESS are shown in Table 2. EV 1 has less capacity and less charging/discharging rate compared to EV 2. In Table 3, the built-in parameters of the EWH is shown.

Table 2. Built-in characteristics of the EVs and the ESS.

	Brand	Capacity (kWh)	Charging rate (kW/h)	Discharging rate (kW/h)	Charging efficiency	Discharging efficiency
EV 1	Chevy Spark EV	19	3.3	2.805	0.89	0.91
EV 2	Ford Focus Electric	23	6.6	4.818	0.94	0.92
ESS	-	46	4.5	3.8	0.86	0.85

Table 3. Built-in characteristics of EWH [7].

Capacity (kW)	Water tank capacity (L)	Thermal resistance (^{o}C/kW)	Thermal capacitance (kWh/^{o}C)
4.5	400	1.52	863.4

The HEMS optimal load scheduling depends on the data that the user updates in a daily basis. This data refers to some temporary features of the controllable loads. These parameters are not permanent and change day to day. The arrival and departure time of the EVs and the expected SoC of the EVs' batteries at the arrival and departure time should be updated in daily basis by the consumer or through some interfaces that may operate with intelligent algorithms to predict these parameters. Table 4 shows the characteristics of EVs at arrival and departure. The HEMS requires the forecasts of water consumption and ambient temperature, in order to schedule the EWH for the following day. Figure 7 shows the forecasts of ambient temperature [57] and the expected daily water consumption [58].

Table 4. EVs' expected SoC at arrival and departure.

	Arrival time	Departure time	EVs' SOC (percentage of the total capacity	
			Arrival	Departure
EV 1	10:15	21:35	14%	87%
EV 2	17:05	8:25	19%	91%

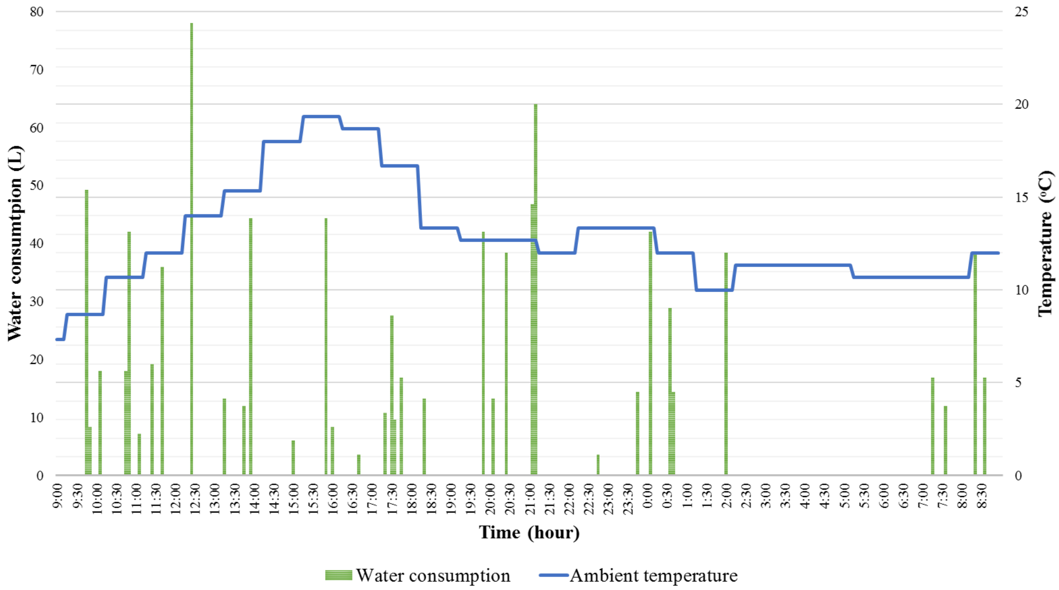


Figure 7. Forecasts of water consumption and ambient temperature.

5. Case studies

The main reason for using HEMS in households is to ensure customer benefits. This section provides simulation results to demonstrate the performance and the efficiency of the proposed framework. The proposed algorithm can be used in HEMS and aims to minimize daily electricity cost of the users, without violating their comfort levels.

5.1. Cases

In order to show the performance of the automated HEMS and the benefits of using an intelligent algorithm to control the EV charging and consumption scheduling, 5 case studies are carried out. The main features of the case studies are summarized in Table 5. In cases 1 and 2, the electricity consumer employs the rule-based algorithm rather than the proposed intelligent algorithm to schedule the consumption and to manage the charging of EVs. The only difference between these two case studies is the pricing scheme: case 1 is under RTP scheme and case 2 is under TOU pricing program. In cases 3 and 4, the proposed intelligent algorithm for the HEMS is employed respectively for RTP and TOU pricing. Therefore, the first 4 cases are representing the two HEMS models under the two pricing schemes. The outcomes of the 2 HEMS models can be compared with each other when they operate under similar pricing program. In case 5, the customer is paying under TOU pricing scheme and the incentive plans are also taken into account. It is also assumed that in all cases the consumer can also sell electricity to the grid. The selling price can also be time variable, but for all case studies a fixed price of 0.10443 €/kWh is considered for the selling price. This price is below the average price that the consumer is buying electricity from the grid.

Table 5. Features of the case studies.

	HEMS algorithm	RTP	TOU	Incentive-based DR	V2H	V2G	PV	ESS
Case 1	Rule-based	✓	-	-	-	-	✓	✓
Case 2	Rule-based	-	✓	-	-	-	✓	✓
Case 3	Optimization	✓	-	-	✓	✓	✓	✓
Case 4	Optimization	-	✓	-	✓	✓	✓	✓
Case 5	Optimization	-	✓	✓	✓	✓	✓	✓

5.2. Results

The HEMS model is developed as a MILP problem. In MILP problems only some of the variables are constrained to be integers, while the rest are allowed to be non-integers. In this problem, the integer variables are used to model the charging and discharging status of the EVs and the ESSs and the ON/OFF status of the EWH during the scheduling horizon. The computational complexity of the case studies is illustrated in Table 6. In this table, the cardinality of sets is denoted by $n(\cdot)$. Obviously, the size of the problem changes under incentive-based DR programs, since the number of variables and constraints to be considered changes. The MILP optimization problems are modeled in GAMS 24.4.6 with the execution time of few seconds in a computer with an Intel Xeon E5-2620 2.10 GHz processor with 16 GB of RAM and Windows 8.1. The problems are solved by the commercial solver CPLEX 12 [59]. CPLEX uses a branch-and-cut search to obtain the global optimal solution of a linear problem with integer variables. The branch-and-cut procedure manages a search tree consisting of nodes, where each node is associated with a linear programming subproblem [59,60].

Table 6. Computational complexity of case studies.

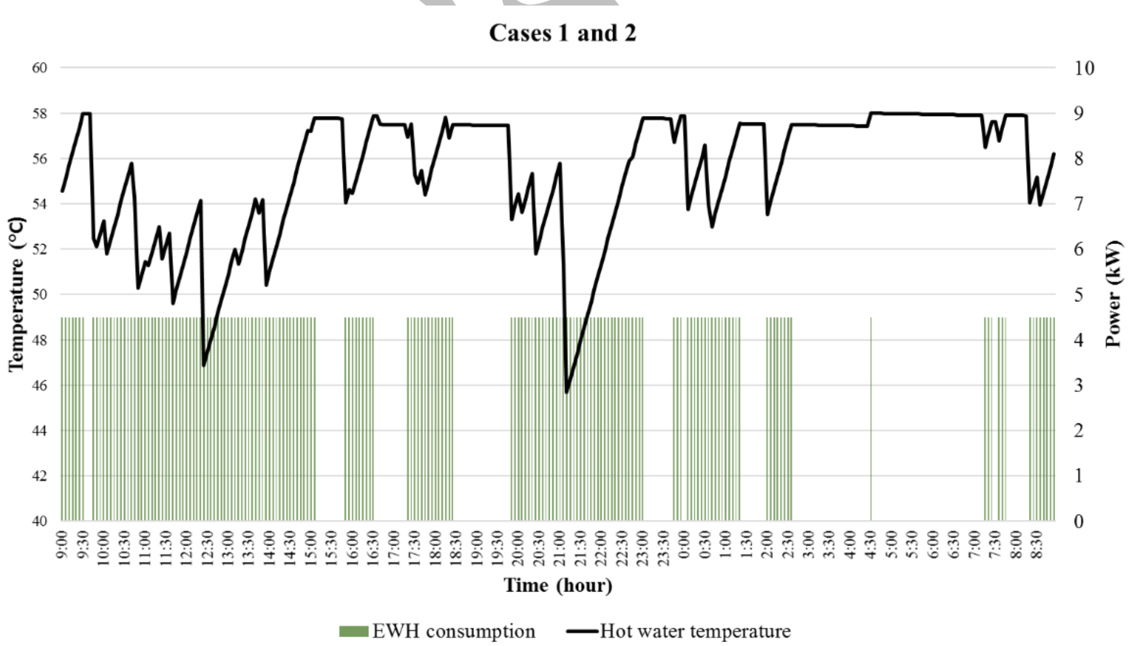
	Number of continuous variables	Number of binary variables	Number of constraints
Case studies 3 and 4	$n(\mathrm{T})\cdot\left(5+2n(\Omega^s)\right)+3\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)+1$	$n(\mathrm{T})\cdot\left(1+2n(\Omega^s)\right)+2\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)$	$n(\mathrm{T})\cdot\left(7+10(\Omega^s)+n(\Omega^v)\right)+8\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)+n(\mathrm{H})+n(\Omega^v)$
Case study 5	$n(\mathrm{T})\cdot\left(5+2n(\Omega^s)\right)+3\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)+n\left(\Omega^{DR}\right)+1$	$n(\mathrm{T})\cdot\left(1+2n(\Omega^s)\right)+2\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)$	$n(\mathrm{T})\cdot\left(7+10(\Omega^s)+n(\Omega^v)\right)+8\sum_{v\in\Omega^v} n\left(\mathrm{T}^v\right)+n(\mathrm{H})+n(\Omega^v)+\mathrm{n}(\Omega^{DR})$

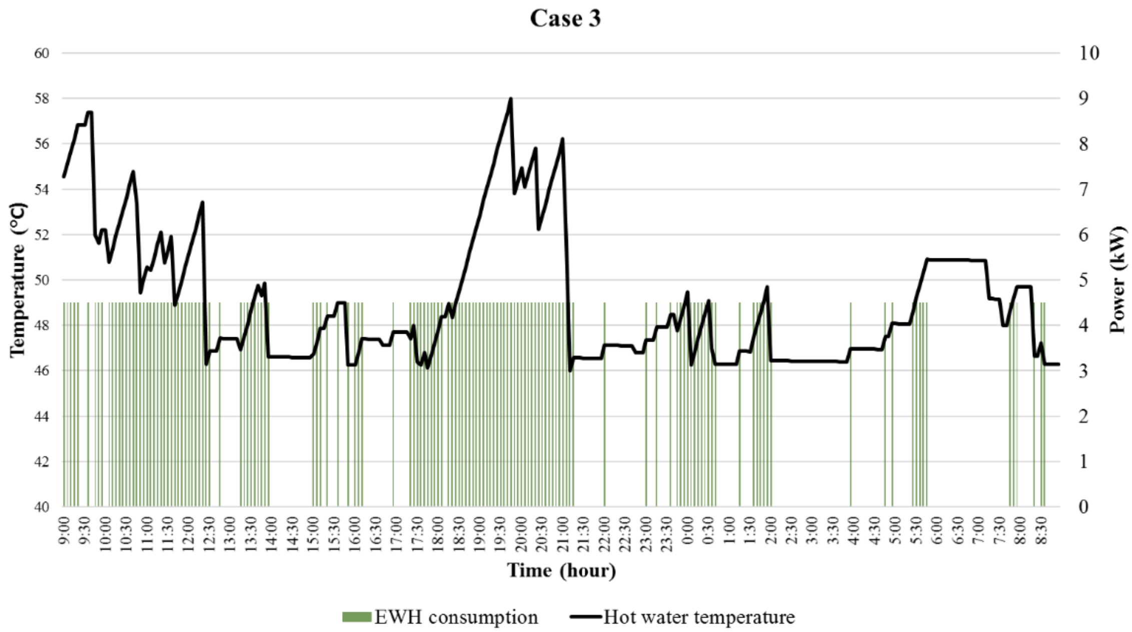
Table 7 shows the main outcomes for all case studies. The highest household energy cost with the lowest peak hourly demand is identified in the first two cases, where the customer is using a rule-based HEMS to schedule the consumption. The optimization-based approach obtains lower daily costs for the household energy consumption under each pricing scheme, compared to the rule-based algorithm. The daily energy cost reduces 29.5% under the RTP scheme by using the optimization-based algorithm instead of the rule-based approach, and under TOU pricing scheme the cost reduces by 31.5% when the optimization-based algorithm is implemented in the HEMS. The minimum cost and the highest peak hourly demand is observed in case 5, when the consumer is buying electricity at TOU tariffs and participates in incentive-based DR programs.

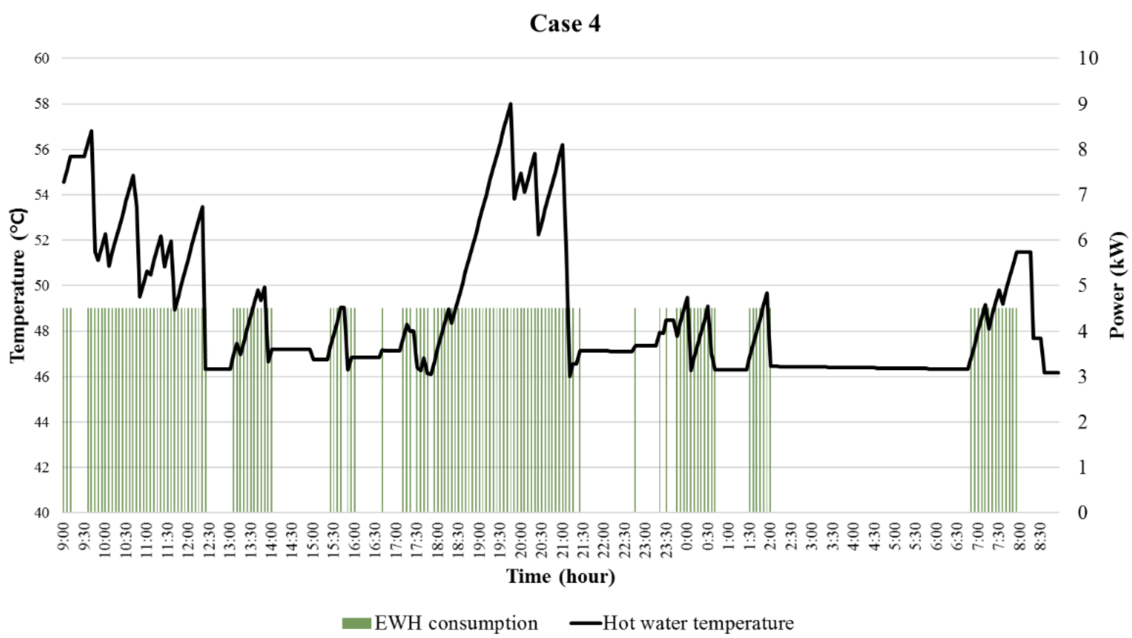
Table 7. Comparison of case study outputs.

	Cost [€]	Peak hourly demand [kW]	EWH daily energy consumption [kWh]	Total V2G energy transaction [kWh]	Total V2H energy transaction [kWh]
Case 1	13.20	9.14	66.00	-	-
Case 2	13.42	9.14	66.00	-	-
Case 3	9.30	11.43	53.63	10.33	2.28
Case 4	9.19	9.41	53.63	12.95	2.91
Case 5	8.63	12.29	54.00	0.02	6.97

The hot water temperature in the cases that the intelligent algorithm is used for the HEMS can vary in a range between 46°C and 58°C. In the rule-based approach, the only characteristic that should be taken into account is the maximum demand, which should not be violated. Figure 8 shows the ON periods of the EWH and the changes of the water temperature. Although in cases 1 and 2, the EWH consumes more energy (about 23% more) compared to other cases, the temperature goes below 46°C at 21:10, which means that the comfort levels are also not maintained when the HEMS is not operating with an intelligent algorithm.




Case 3
Temperature (°C)
Power (kW)
Time (hour)
EWH consumption
Hot water temperature


Case 4
Temperature (°C)
Power (kW)
Time (hour)
EWH consumption
Hot water temperature

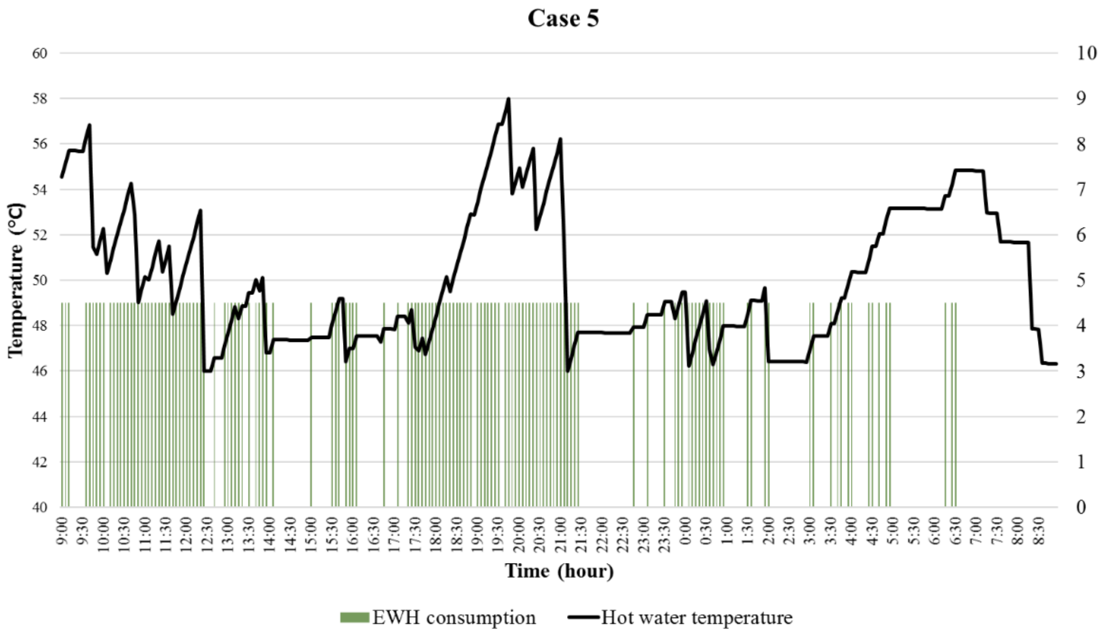
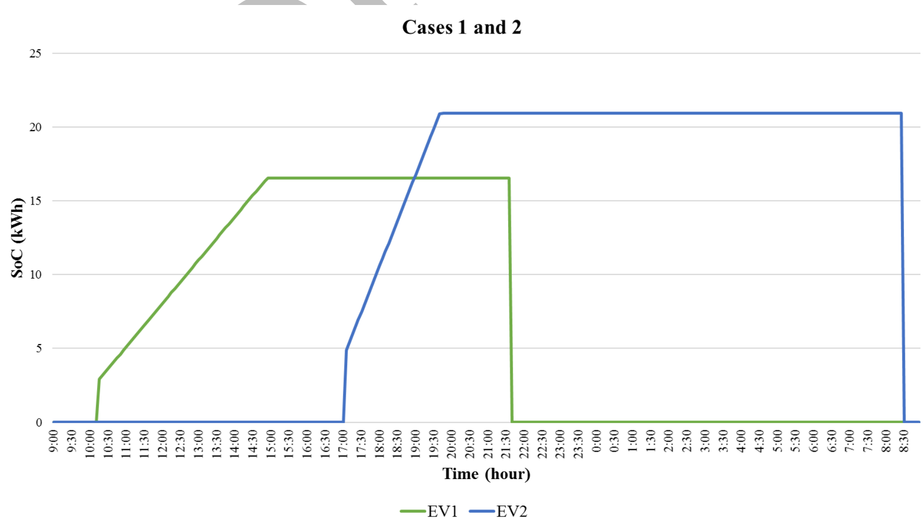


Figure 8. EWH's temperature and consumption schedule.

The SoC of the EVs is shown in figure 9. In cases 1 and 2, which V2G and V2H is not possible, the curve is only rising. In other case studies, the energy level of the EVs' battery decreases in some periods due to the power injected to the grid or to the house. As shown in Table 7, highest amount of V2G and V2H energy transaction are scheduled respectively for cases 4 and 5. In case 5 a significant decrease in the SoC of EV2 is observed during hours 19 and 20. During these hours the firm load is high and the EWH is also ON, therefore the HEMS schedules the energy stored in the EV2's battery for V2H.



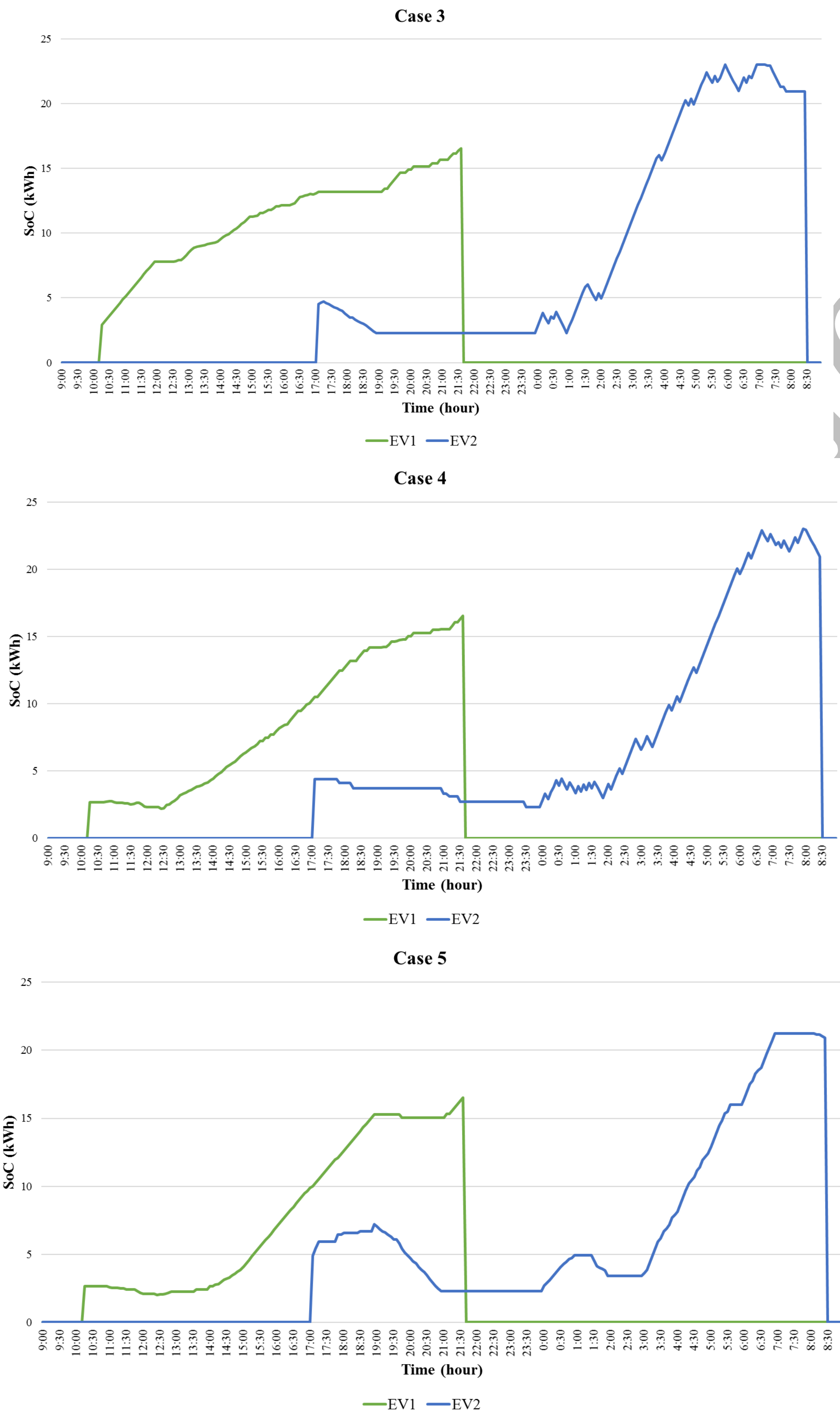


Figure 9. EVs' SoC during the connection time.

The potential gain of the consumer from participating in incentive-based DR programs can be calculated from the hourly load profile of the periods that the incentives have been assigned. Figure 10 shows the difference between the baseline load and the scheduled consumption. Positive values that are shown by green bars denote the periods that the consumption is below the baseline load and the negative values demonstrated with red bars refer to the periods that scheduled consumption is above the baseline load. The consumer gains 1.07 € from participating in incentive-based DR programs. The amount of electricity that is scheduled to be purchased from the grid is shown in Figure 11. In case 5, during the periods that the retailer offers the incentives for demand reduction, the scheduled power profile to be purchased from the grid significantly reduces. The amount of energy purchase from the grid under each case study is shown in Table 8. In the rule-based approach, energy purchases from the grid during the charging process of each EV, which begins after the arrival of the EV and ends when the EV is charged to the requested amount, is higher than the optimization-based approach in the same time window, though there is not significant difference among different case studies in terms of the total daily purchase from the grid. EV1 arrives at 10:15 and is charged to 87% of the total battery capacity until 14:55 with the rule-based HEMS, and during this period 28.20% of the total purchase from the grid occurs. EV2 arrives at 17:05 and is charged to 91% of the total battery capacity until 19:45 with the rule-based approach, and during this period 22.69% of the total purchase from the grid occurs.

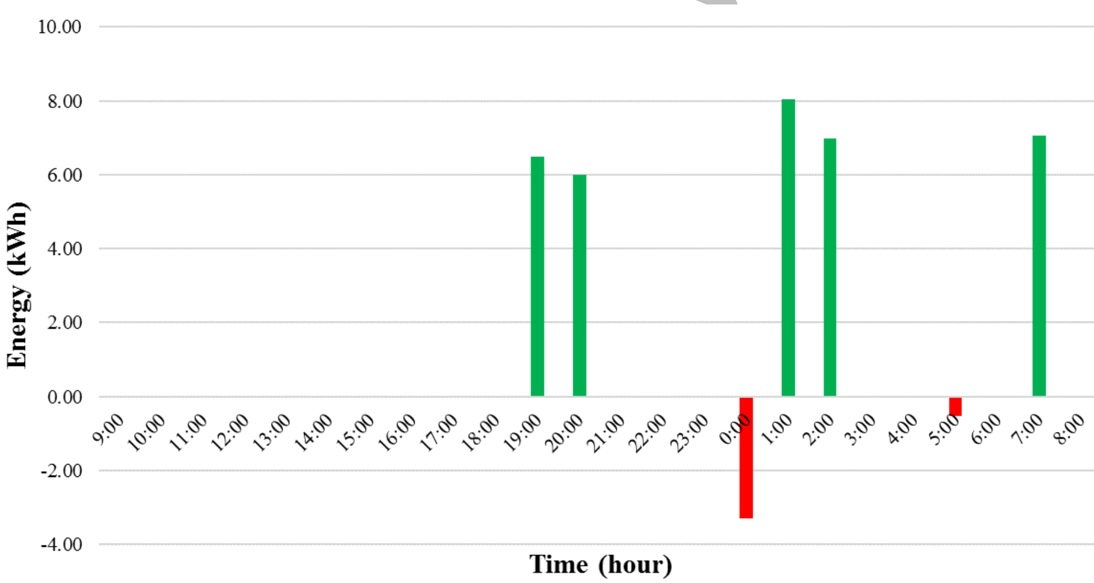
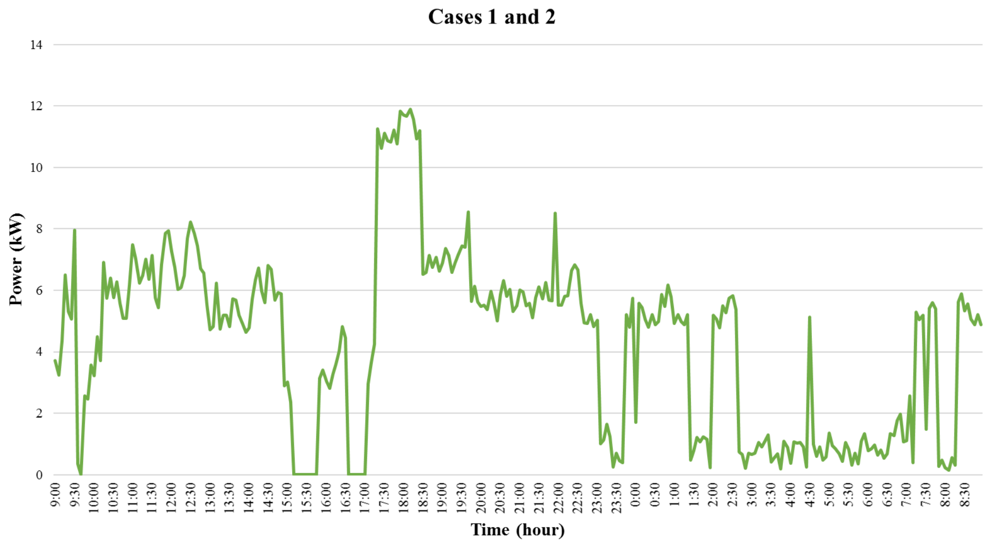
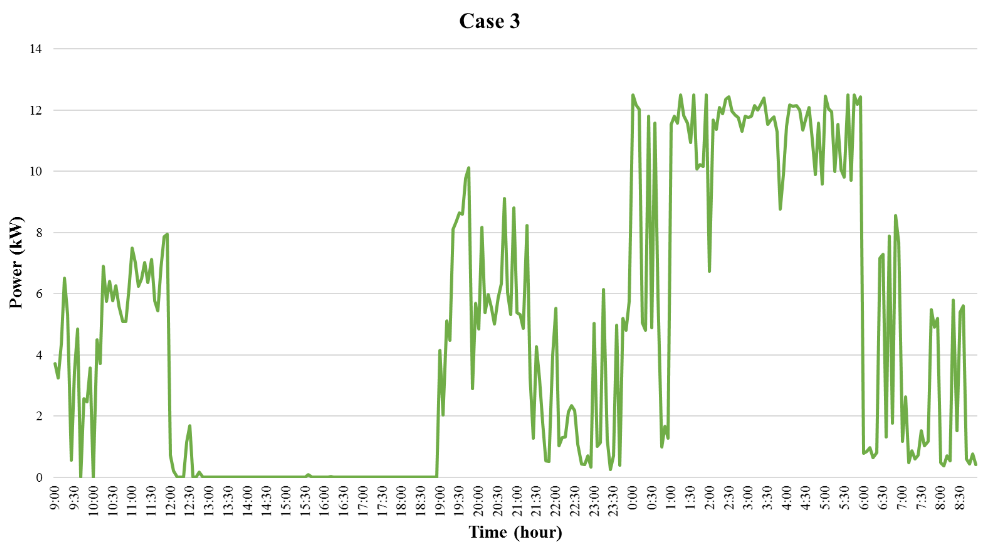
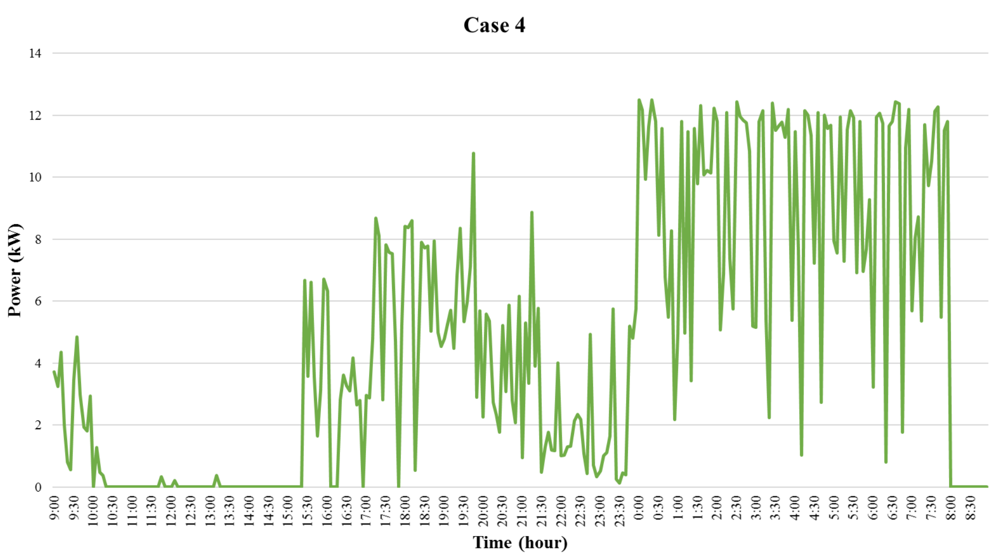


Figure 10. Difference between the baseline load and the scheduled consumption.


Cases 1 and 2
Power (kW)
Time (hour)


Case 3
Power (kW)
Time (hour)


Case 4
Power (kW)
Time (hour)

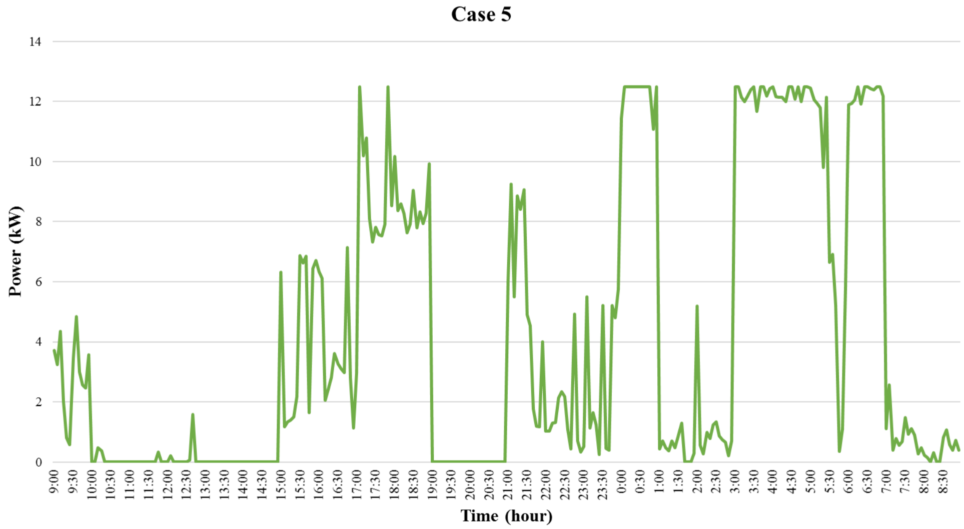


Figure 11. Power purchase from the grid.

Table 8. Variations of power purchase from the grid.

		Cases 1 and 2	Case 3	Case 4	Case 5
Daily purchase from grid (kWh)		102.89	108.70	111.80	97.75
Purchase during 10:15-14:55 (charging period of EV1 in rule-based HEMS)	**kWh**	29.02	11.55	0.11	0.21
	Percentage of the daily purchase	28.20%	10.63%	0.10%	0.22%
Purchase during 17:05-19:45 (charging period of EV2 in rule-based HEMS)	**kWh**	23.35	5.78	16.74	16.92
	Percentage of the daily purchase	22.69%	5.32%	14.98%	17.31%

The quality and accuracy of modeling the dynamic behavior of appliances are crucial to obtain optimal solutions in a HEMS. Solving an optimization-based HEMS model with high levels of accuracy based on a not enough accurate model for the controllable appliances is useless [61]. However, there should be always a trade-off between realism and complexity. In the proposed HEMS for instance, a linear model is used to represent the thermostatic behavior of EWHs. The purpose was to keep the linearity of the optimization problem. Nevertheless, in some cases, the linearized models might not be able to fully represent the features of a thermostatically controllable EWH.

Updating the HMES inputs based on the daily preferences of the customers also complicates the designing process of the model. The proposed model has been tested to be robust enough to operate under different feasible requests of the consumer and make the optimal decisions while limiting the consumer in advance to make impracticable requests. For instance, requesting the HEMS to schedule the full charging of the vehicle in a short time or high water temperature despite using large amounts of water.

6. Conclusions and future work

In this paper, an intelligent algorithm is proposed to manage the consumption of controllable loads with energy storage capability, such as EVs and EWHs. This algorithm can be integrated into HEMS to help household owners to automatically schedule the optimal load consumption and to ensure lower energy costs while maintaining the comfort levels of the consumers and suiting their preferences. The performance of the algorithm was verified by applying to a smart household and comparing the outputs with a rule-based approach. The smart household model used in this study had a rooftop PV with an ESS in addition to the controllable loads. The operation of the controllable appliances was controlled under RTP and TOU pricing programs. The incentive-based DR programs were also taken into account when the customer is buying electricity under TOU pricing scheme.

The proposed optimization-based HEMS, which was applied to an individual smart household, was able to illustrate the impact of adopting an intelligent algorithm for consumption scheduling. The results verified that under TOU pricing scheme, which is common in most retail electricity markets, the implementation of incentive-based DR programs can be an alternative to RTP program. The household experienced lower energy costs under this pricing scheme. EVs' controlled charging influenced the power purchase pattern from the grid. In the rule-based approach, the EVs are charged at the maximum charging rate after connection until being charged to the required amount, but with the intelligent algorithm charging power can vary during the scheduling horizon and the charging process can be scheduled for the whole connection period to minimize the total energy costs. Automated DR programs may influence the load diversity and potentially result in creating new peaks at least price intervals. This effect has been controlled in the proposed model by considering the network charge for peak demands. The inclusion of network tariffs in HEMS models is an element to avoid high peak demands in periods with lower energy costs. Despite the higher energy costs in the rule-based approach, the results show that the comfort levels were also not maintained.

Load management in this paper is entirely dependent on the signals received from the retailers in order to decrease the energy costs. The proposed HEMS can be developed in the future works to incorporate the operators' requests, which are to cope with power quality, power imbalance, and network congestion challenges. Future efforts will be mainly focused on developing the HEMS architecture by adding the dynamic models of other controllable household appliances into the current model. The model also requires being further improved by considering the uncertainty of the forecasted values used in the model. The effectiveness of the proposed framework will be more investigated by carrying out more tests on the various categories of residential consumers.

Acknowledgment

The present work was done and funded in the scope of the following projects: H2020 DREAM-GO Project (Marie Sklodowska-Curie grant agreement No 641794); AVIGAE Project (P2020 - 3401); UID/EEA/00760/2013 funded by FEDER funds through COMPETE program and by national funds through

Fundação para a Ciência e a Tecnologia (FCT); and SFRH/BD/94688/2013 (Mohammd Ali Fotouhi Ghazvini PhD grant).

Rui Castro was supported by national funds through FCT with reference UID/CEC/50021/2013.

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