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An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands

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Abstract

The increasing trends of energy demand and renewable integration call for new and advanced approaches to energy management and energy balancing in power networks. Utilities and network system operators require more assistance and flexibility shown from consumers in order to manage their power plants and network resources. Demand response techniques allow customers to participate and contribute to the system balancing and improve power quality. Traditionally, only energy-intensive industrial users and large customers actively participated in demand response programs by intentionally modifying their consumption patterns. In contrast, small consumers were not considered in these programs due to their low individual impact on power networks, grid infrastructure and energy balancing. This paper studies the flexibility of aggregated demands of buildings with different characteristics such as shopping malls, offices, hotels and dwellings. By using the aggregated demand profile and the market price predictions, an aggregator participates directly in the day-ahead market to determine the load scheduling that maximizes its economic benefits. The optimization problem takes into account constraints on the demand imposed by the individual customers related to the building occupant comfort. A case study representing a small geographic area was used to assess the performance of the proposed method. The obtained results emphasise the potential of demand aggregation of different customers in order to increase flexibility and, consequently, aggregator profits in the day-ahead market.

Keywords: demand flexibility, demand response, load scheduling, electricity market

1. Introduction

Demand side flexibility is gaining importance due to the rise in distributed renewable generation, increasing energy demand, and lower predictability in the electricity markets. A high level of demand flexibility is crucial in order to cope with less predictable energy flows, and mitigate against price volatility. It is also required to create a level playing field for emergent market services and to maintain a secure network and a high-quality supply of electricity [1]. The economic benefit of DR is based on its ability to substitute peak power generation capacity and on its competitiveness compared with short to medium-term storage technologies [2]. Moreover, temporal variations in DR application highlight the particular importance of load profiles in the assessment of DR potential.

Traditionally, only large industrial customers had access to Demand Response (DR) schemes, selling their flexibility and participating in the electricity market on an individual basis. In contrast, smaller residential and commercial customers generally have not participated in the markets to date, as their individual demands were considered too low to have an effect at the system level. However, the demand flexibility offered to the electrical system can be greatly increased by aggregating these smaller loads. In this way, an aggregator may act as a market intermediary [3] that encourages smaller customers to increase their DR contributions (or to directly control their flexible loads) and trades their flexibility (as portfolio optimization) in electricity markets.

A good overview on the most common DR methodologies can be found in [4, 5, 6]. Demand flexibility

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Nomenclature

Indices

k	time interval to compensate flexible load, h
t	time interval, h

Variables

$P_{k,t}^{pback}$	payback power at k from non-residential flexible energy taken at t, kW
P_t^{flex}	non-residential flexible demand taken at t, kW
P_t^{load}	total demand bid in the market at t, kW
P_t^{nresi}	net flexible non-residential demand from heating and cooling loads at t, kW
P_t^{resi}	shiftable demand from residential electrical devices at t, kW

Constants and data

π_t	electricity market price at t, €/kWh
d	duration of the market time period, h
E_{resi}	daily shiftable residential energy, kWh
N_h	optimization horizon
N_k	maximum time for flexible load payback
N_s	number of periods for residential load shifting
P_t^{comf}	Non-residential demand from the use of the comfort temperature in period t, kW
$\overline{P_t^{agnr}}$, $\underline{P_t^{agnr}}$	upper and lower limits of the aggregate non-residential demand at t, kW
$\overline{P_t^{agr}}$, $\underline{P_t^{agr}}$	upper and lower limits of the aggregate residential demand at t, kW
$\overline{P_t^{tag}}$, $\underline{P_t^{tag}}$	upper and lower limits of the total aggregate demand at t, kW

in the residential sector can be achieved by using common household appliances (e.g. washing machines, dryers, dishwashers, etc.), electric vehicles or heating systems [7]. Previous research has examined the provision of demand flexibility through scheduling of home appliances [8, 9], or through user responses to time-of-use electricity pricing [10, 11]. Domestic thermal loads such as electric water heaters have also been applied as flexible demand resources, particularly in colder climates [12, 13].

In commercial buildings heating, ventilation and air-conditioning (HVAC) demands represent suitable candidates for DR [14, 15]. Building thermal dynamics allows demand flexibility to be introduced by temporarily changing indoor temperature conditions without reducing occupant comfort. A number of papers focus on demand flexibility from HVAC systems in both residential and non-residential buildings. In [16], the electricity consumption during specific hours of a day is either maximized or minimized by adjusting the HVAC load, while maintaining thermal user comfort. In [17], the potential impacts of the individual responsive appliances were studied and the results revealed that almost all the benefits could be achieved by harnessing the flexibility of heating and ventilation systems, although this study was conducted in a Nordic country.

A key consideration in such studies is the impact of adjustments in HVAC control setpoints on user comfort. The international standards ISO 7730:2005 [18] and ASHRAE 55:2013 [19] deal with indoor climate and the range of factors which influence user comfort levels. These standards provide guidelines on acceptable building temperature levels, and also provide information on what temporary excursions from the standard temperature ranges are can be allowed without adversely impacting user comfort.

Many works quantify flexibility from commercial buildings (e.g. offices), but few of them use it in the electricity market. In [20], a methodology for computing the flexibility of buildings and its cost is proposed and a case study on an office building reveals a large variation in both flexibility and cost depending on time, weather, utility rates, building use and comfort requirements. In [21], a coordination framework for leveraging demand flexibility from buildings is proposed, and the demand flexibility of an office building is quantified, finding difficulties in achieving tasks' shift-ability and lack of significant price differentiation between off-peak and peak periods.

In [22], the aggregation of detached houses is carried out to investigate the benefit of heating load flexibility for the aggregator and the consumers in the Nordic day-ahead market. Consumer participation is rewarded with flexibility or comfort based bonuses. However, the results are optimistic because it assumes perfect forecasts for demand, spot prices, and residual supply curves. Also, it shows that flexibility provides more benefit when it is optimized with inflexible demand and that massive building structures receive more bonus, whereas efficient insulation tends to decrease the amount of bonus.

In this work, the aggregator is assumed to be an entity representing the role of a retailer, a flexibility manager and a balance responsible party or market agent. A more detailed explanation of these functions can be found in [23, 24, 25]. This entity agrees with its customers to directly control their electricity consumption of their flexible loads (HVAC loads from commercial customers and smart appliances from residential customers) [26, 27]. These flexible demands can be shifted along a given time period depending on the nature of the process [28], but the amount of daily energy to be consumed is known and previously agreed between the aggregator and its customers. This type of agreement is not considered in the work proposed here. At last, it is assumed the non-residential customer thermal comfort is ensured by the control of the indoor temperature that depends on the building thermal inertia, time, weekday, season and occupancy pattern.

To measure the demand flexibility of the aggregation of different buildings, we use the demand flexibility ratio that is the difference between the upper and lower limits of the aggregated demand regarding the total flexible demand at a certain time. The demand flexibility ratio and the aggregator daily average profit from its participation in the day-ahead market will be analysed by using a case study based on the aggregation of different building types. The optimal demand will be disaggregated to simulate the impact of the optimal load scheduling on individual buildings. It will be shown the indoor temperatures remain within the desired range even when there is no linear relation between the energy demand and the indoor temperature. The results will demonstrate that an adequate aggregation of different building types allows the aggregator to achieve significant economic profits in the day-ahead market.

The main topics addressed in this work are listed as follows: 1) flexibility modelling of aggregated demands from buildings with different characteristics such as shopping malls, offices, hotels, and dwellings. Although the flexibility could be obtained from real data, the aggregator needs to forecast the possible hourly bounds of the flexible load types (HVAC and washing machines), since every building demand has different consumption profiles and dynamics (consumer behaviour, weather, season, etc). In this case the minimum and maximum temperatures are used only to obtain the estimation of the demand flexibility used for the next day offer. However, once either positive or negative flexibility is used the energy must be compensated during the following hours (as explained in the optimal scheduling section). Obviously, during this interval the demand flexibility does not coincide with the profile generated for the purpose of providing the demand flexibility offer. 2) An effective optimization model that takes into account the constraints over demand related to the building occupant comfort, and provides the optimal load scheduling for the aggregator into daily markets. The principal contribution of the paper is the combination of points 1) and 2). At last, the performance of the proposed method is assessed in a case study representing a small geographic area. The demand flexibility ratio and the aggregator daily average profit from its participation in the day-ahead market are analysed for 16 days during summer and winter periods, respectively.

This paper is structured as follows. Section 2 presents the methodology used in this work. Section 3 provides a brief description of the Spanish day-ahead electricity market and the participation rules. Section 4 describes the simulation models used to determine the available demand flexibility in residential and non-residential buildings. Section 5 defines the mathematical optimization problem to be solved by the aggregator for the optimal demand scheduling. The considered case study with different building types is presented in Section 6 and the obtained results are presented in Section 7. Finally, in Section 8 the most important conclusions are drawn.

2. Methodology

In this paper, statistical data has been used to model the residential energy consumption as well as architectural characteristics, building usage, location, on-site facilities, occupancy and economic data to model the non-residential energy consumption. In order to simulate a real market environment, the forecasted prices used in the paper were taken from Iberian day-ahead market data.

In the proposed method, the aggregator firstly models and aggregates the flexible consumption of certain processes from their users to obtain the reference demand profile with its upper and lower bounds in order to manage the flexibility according to its objectives. Then the aggregator uses the flexibility and the wholesale market price predictions as inputs in the optimization problem that derives an optimal load scheduling. Finally, the aggregator submits the optimal load scheduling to the day-ahead market in order to minimize the energy cost or maximize its profit.

3. Electricity market

Approximately two thirds of the energy consumed in the Spanish peninsular system is managed in the day ahead market by OMIE (OMI-Polo Español S.A., Spanish electricity market operator). This body is in charge of collecting orders, clearing the markets and publishing results. The Spanish market is a part of the EU's Internal Electricity Market, where electricity prices are set on a daily basis (every day of the year) at 12 noon, for the twenty-four hours of the following day. As described in [29], "the price and volume of energy over a specific hour are determined by the point at which the supply and demand curves meet, according to the marginal pricing model adopted by the EU, based on the algorithm approved for all European markets (EUPHEMIA)". Both results and rules can be found in [30, 31, 32].

In the day ahead market, purchase and sale bids for day D must be sent to OMIE before the gate closure at 12 a.m. of day D-1. After the daily market, six sessions of an adjustment (intraday) market take place along the day. The average interval between the gate-closure and the physical delivery of energy is 4.5 hours for these intraday markets.

According to the current rules, the agents that can participate in these markets are producers, retailers, direct consumers and international traders. Consumers and retailers can only buy energy in the daily market, although they can sell or buy energy in the intraday market to fit their actual consumption to the energy traded. If there is a difference between the two an imbalance occurs that must be paid at a higher price than the marginal price.

Retailers must submit a bid for the energy they are interested in buying with the price assigned. Most of the demand is traded at the cap price from the Spanish market, 180 €/MWh, which means that it is inflexible demand, not changing with price. Only a part of the consumption is offered at a price close to that of the market.

4. Flexibility modelling

Demand flexibility describes the customers' ability to modify their energy consumption in response to an external signal. Two simulation models have been used to determine the demand flexibility offered by residential and non-residential buildings.

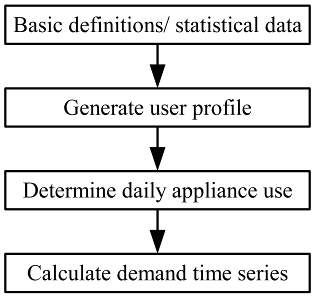

Figure 1: Principal steps in the applied residential energy consumption modelling.

4.1. Flexibility in the residential sector

Demand flexibility in the residential sector is considered as relevant because of significant daily and seasonal variations of the observed loads. Nowadays, residential demand depends directly on the customer habits where comfort plays a decisive role in energy consumption. Flexibility in the energy demand can be achieved by incentivising changes in customer habits while reducing negative impacts on comfort as much as possible. In the present paper the effects of a modified user behaviour have been determined by using a residential energy consumption model based on statistical data [33, 34].

The model used estimates energy consumption of a household in three phases (see Fig. 1): generation of the household configuration, computation of the daily use of each appliance and calculation of the exact energy demand of each appliance. The different steps of the consumer energy demand model are based on a probabilistic approach by using basic appliance definitions and statistical data for the generation of the consumption data. The appliance definitions are not considered part of the model and have to be supplied externally.

In the first step the consumer energy demand model determines the configuration of one or several households. The number of devices of a certain appliance type in a household is computed by using a binomial distribution in order to obtain certain variation around a desired average value. In the second step the consumer energy demand model computes the daily usage for each appliance in the household, i.e. if and how many times a device is used on a particular day. The frequency of use of some appliances is influenced by seasonal factors and has been considered in the consumer energy demand model. In the third step the model determines the exact time-of-use for the appliances by exploiting the statistical data. At this stage, the power curve of each appliance and the overall consumer energy demand of

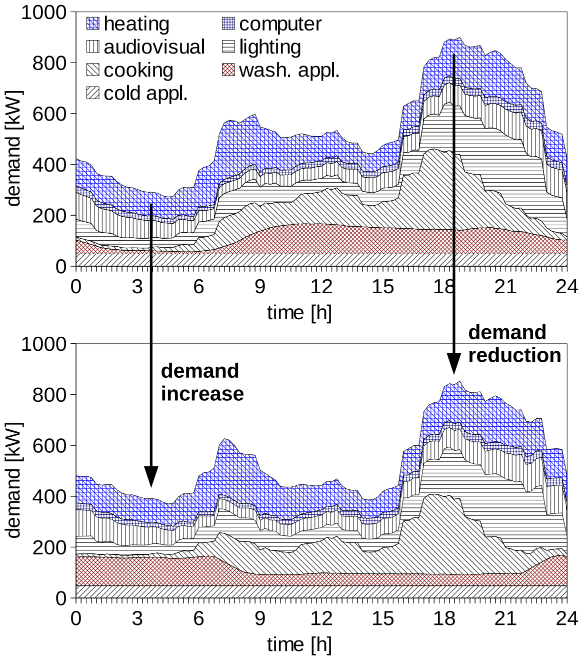

Figure 2: Energy consumption of a group of 1000 residential customers with average usage patterns (top) and modified usage patterns with increased use of washing appliances at night hours (bottom).

a household are calculated with a sampling time of 15 minutes.

Flexibility in the residential sector can be then modelled as the difference between the demand of an ordinary customer and the demand of a user which has been incentivised to modify its energy consumption habits (commonly by providing economic benefits through time-of-use tariffs of dynamic pricing schemes). The previously described energy consumption model can be used to determine the possible demand variation resulting from such a change in user behaviour (see Fig. 2 for an example based on modified usage patterns). The demand consists of a fixed part – the minimum demand, which does not depend on the considered changes in user habits – and a variable part represented by the flexibility as a consequence of changed customer consumption patterns (see Fig. 3).

In the residential sector, demand flexibility is frequently obtained by changing the operation time of energy intensive appliances such as washing appliances. Other approaches include modifications in the duty cycle of cold devices (e.g. freezers or refrigerators) or variations in the power level of lighting and other appliances.

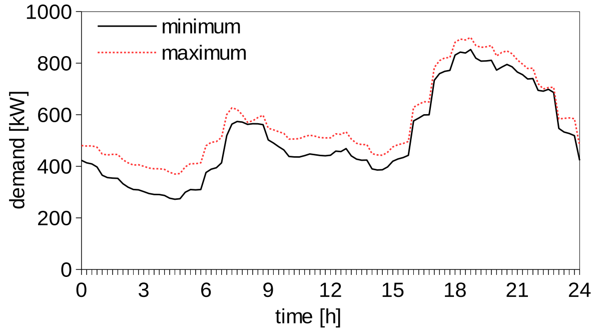

Figure 3: Demand flexibility of a group of 1000 residential customers obtained from modified usage patterns for washing appliances.

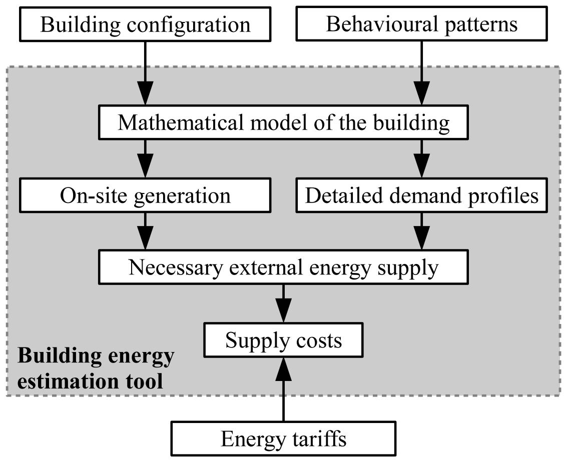

Figure 4: Structure of the building energy estimation tool [36] used to determine the non-residential building energy consumption.

4.2. Flexibility in non-residential sector

Non-residential buildings contribute significantly to the total energy demand and account for up to 20 % of primary energy consumption [35]. Demand flexibility in the non-residential sector is frequently achieved by modifying the building operation conditions (such as HVAC temperature setpoints) within a certain predefined range. In this paper, the building energy estimation tool developed in [36] is used to provide detailed demand profiles for commercial buildings (see Fig. 4). This tool includes a physical model of the building structure and a model of the behavioural patterns of its users, considering architectural characteristics, building usage, location, on-site facilities, presence of people and economic data. This flexible configuration allows modelling of a wide range of different building types such as shopping malls, office buildings and hotels.

The building energy estimation tool outlined in [36] has been modified to include the building's temperature dynamics and thermal capacity in the energy demand estimation. Heating, ventilation and air conditioning (HVAC) systems represent good candidates for demand side management (DSM) strategies in the non-residential sector because of their most significant impact on energy consumption. Indoor temperature regulation takes advantage of thermal inertia of buildings and can be used for prolonged load changes [37].

The simulation tool can be used to determine the primary energy demands of a non-residential building for different indoor temperature references (see Fig. 5 for an example). The applied indoor temperature reference has an important impact on the energy demand and allows regulating the energy consumption of the building. The building manager is who chooses the indoor temperature references to guarantee a high comfort level taking into account the energy consumption and the associated costs, for instance, from 09:00 to 22:00 for a commercial center, there is a more comfortable indoor temperature but, the remaining hours of the day it allows a higher indoor temperature for summer or lower for winter, which reduces the consumption. The energy demands achieved with the minimum and maximum indoor temperature references represent the limits of the available demand flexibility (see Fig. 6), i.e. the controllable range of the building energy demand. It should be noted that the maximum building energy demand does not necessarily correspond to the maximum indoor temperature reference.

Building occupant comfort (as defined in [18] and [19]) is the limiting factor for demand flexibility in the non-residential sector when HVAC systems are used. Any temporary modifications in heating, cooling and air conditioning have to be later compensated in order to preserve suitable indoor conditions. The relatively slow thermal dynamics of buildings can be exploited for peak load reduction or load shaping.

Once all the individual flexibilities of all residential and non-residential loads are aggregated, the total demand flexibility and its maximum and minimum limits are known to the aggregator and can be used for the optimal scheduling according to the predicted market prices.

5. Optimal Scheduling of Aggregate Demand

This section introduces the mathematical formulation of the optimal scheduling for the aggregate demand. The optimization carried out by the local aggregator maximizes the economic benefit taking into account the available demand flexibility and the predicted market

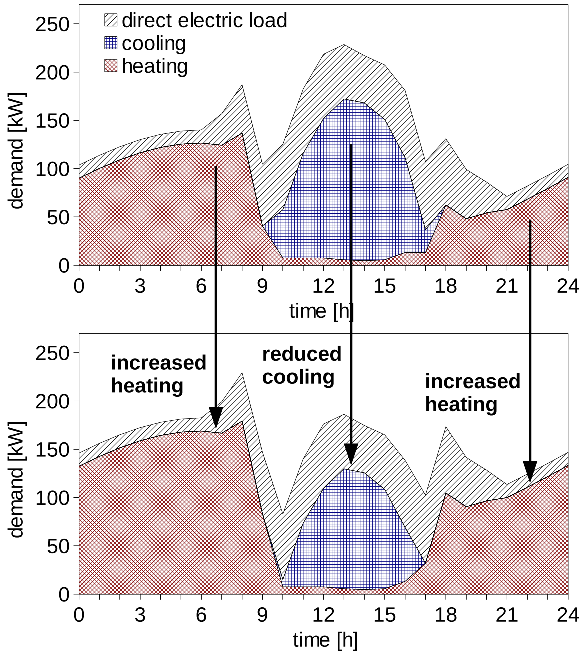

Figure 5: Energy demand of an office building on a workday with low indoor temperature reference (top) and high indoor temperature reference (bottom).

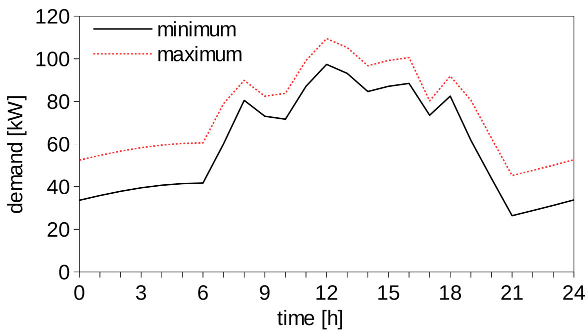

Figure 6: Demand flexibility of an office building obtained from variations of the indoor temperature reference.

prices. The aggregator participates directly in the daily electricity market and orders the required energy according to the obtained optimal scheduling.

The optimization of the aggregate demand takes into consideration the flexibility previously modelled and calculated in Section 4 from residential and non-residential customers with their upper and lower bounds for each time period. Even though it is difficult to predict the flexibility beforehand, it must be known by the aggregator in order to manage it in the day-ahead market, minimize the energy cost or maximize its profit. Although this flexibility can be calculated by different methods, the optimization of the aggregate demand considers the following two types of flexible demands:

- Flexible residential demand: some electrical appliances can be connected and disconnected at different moments in a day depending on the market prices forecast and the consumer behaviour forecast (flexibility bounds). Some part of the demand can be, therefore, shifted along a given period of time, but the amount of the daily energy to be consumed is known and previously agreed between the aggregator and the residential consumers.

- Flexible non-residential demand: loads that admit temporal variations within a certain range, mainly heating and cooling demands. These loads have a payback interval of a few hours [28], i.e. any load reduction or increase has to be compensated in the following hours. This type of demand has an implicit relation with the comfort temperature of several different non-residential buildings controlled by a thermostat device. Thus, consumer behaviour, building dynamics and weather conditions considered in the forecast flexibility model together with the forecast market prices must be taken into account to minimize the energy cost in the daily market.

The optimization process determines the most favourable purchase cost of the energy made by the aggregator in the daily market. Throughout the paper, we assume that 1) the aggregator is a price taker, because the energy purchased does not significantly affect the resulting market price; and 2) the aggregator buys and sells energy at the same price, i.e., network access tariffs and taxes have not been included. The used formulation is linear:

$$\min \sum_{t=1}^{N_h} \pi_t P_t^{load} d \tag{1}$$

subject to the following constraints for $t = 1, \ldots, N_h$ and $k = 1, \ldots, N_k$:

$$\sum_{t=1}^{N_s} P_t^{resi} d = E_{resi} \tag{2}$$

$$P_t^{nresi} = P_t^{comf} - P_t^{flex} + \sum_{k=1}^{N_k} P_{k,t}^{pback} \tag{3}$$

$$P_t^{load} = P_t^{resi} + P_t^{nresi}, \quad t = 1, \ldots, N_h \tag{4}$$

$$P_t^{flex} = \sum_{k=1}^{N_k} P_{k,t+k}^{pback}, \quad \forall\, k = 1, \ldots, N_k \tag{5}$$

$$\sum_{t=1}^{N_h} P_t^{flex} d = \sum_{k=1}^{N_k} \sum_{t=1}^{N_h} P_{k,t}^{pback} d \tag{6}$$

$$\underline{P_t^{ag}} \leq P_t^{load} \leq \overline{P_t^{ag}}, \quad t = 1, \ldots, N_h \tag{7}$$

$$\underline{P_t^{agr}} \leq P_t^{resi} \leq \overline{P_t^{agr}}, \quad t = 1, \ldots, N_h \tag{8}$$

$$P_t^{comf} - \overline{P_t^{agnr}} \leq P_t^{flex} \leq P_t^{comf} - \underline{P_t^{agnr}} \tag{9}$$

$$P_{k,t}^{pback} = 0, \quad \forall\, k \geq t \tag{10}$$

$$P_{N_h}^{flex} = 0 \tag{11}$$

The minimization problem (1) is based on the objective function represented by the total energy costs over the optimization horizon considering variable market prices. The optimal scheduling allows the aggregator to reduce the cost of the purchased energy in the electricity market. Here, P_t^{load} includes flexible and non-flexible components that are represented by the upper and lower limits of the aggregate load.

It is followed by the constraints of the process. Equation (2) formulates the condition that the shiftable residential demand should be provided in a given number of hours, N_s, here E_{resi} is considered as a fixed amount of energy per day that was agreed between the aggregator and their residential consumers through a previous contract. Equation (3) defines the optimal net flexible non-residential demand that comes from electrical heating and cooling loads. Here, P_t^{comf} is the hourly consumption if the comfort temperature has been set for the day, P_t^{flex} is the non-residential flexible load that could be positive or negative if a load reduction or a load increase is required and is equivalent to delaying or advancing the operation of heating and cooling processes and, the last term corresponds to the paid back power that is divided in N_k variables at a certain period t, i.e., if $N_k = 3$ we have the variables $P_{1,t}^{pback}$, $P_{2,t}^{pback}$ and $P_{3,t}^{pback}$.

Equation (4) defines the optimal total load P_t^{load}, which is the result of the optimization process and is formed by residential and non-residential demands.

The condition that the non-residential flexible power taken in a specific period t should be paid back in the next $t + k$ hours for the N_k variables is formulated in equation (5); for example if $t = 1$ and $N_k = 3$, then we have $P^{pback}_{1,2}$, $P^{pback}_{2,3}$ and $P^{pback}_{3,4}$. To ensure that the non-residential flexible energy taken for the day is balanced in the same day, the equation (6) is introduced. The rest of the equations set the limits of the variables, except the last two, which set the initial and final conditions. One should note that P^{nresi}_t includes a non-flexible component that is its lower limit and corresponds to the case where there is no heating or cooling consumption. Although the time slot has been one hour, according to the Spanish market features, the formulation could be applied to any other time slot, d.

6. Case study

The performance of the proposed flexibility scheduling method (see Section 5) has been assessed in a case study representing a small geographic area. The region under consideration consists of 4000 residential customers, 12 hotels, 8 office buildings and 2 malls. The aggregator combines the individual demands of the energy users and participates directly in the Spanish electricity market [38]. The regional energy demand is optimized by the aggregator with respect to economic objectives (see Section 5) taking into account the real-time energy prices of the electricity market and the available aggregated flexibility of the customers.

The simulations were carried out in the Matlab environment by using realistic demand profiles obtained from the models of the residential and non-residential sector (see Section 4). In the case study, a maximum payback of three hours ($N_k = 3$) was used, i.e. load variations induced by the optimization procedure had to be compensated within 1 to 3 hours. This value of N_k is in the range of other previous research [28, 39] and agrees with our own conclusions.

Note that the flexibility model and the case study considers different sampling times of 15 minutes and 1 h, respectively. It is worth saying that for each house we used the average power value of the household consumption over one hour period and then aggregated a large number of houses providing an excellent approximation. Thus, the models are independent but not incompatible.

6.1. Demand Flexibility Considerations

The individual demands in the considered area exhibit significant differences depending on the type of consumer connected. The admissible maximum and minimum loads define the flexibility that can be offered by each energy user.

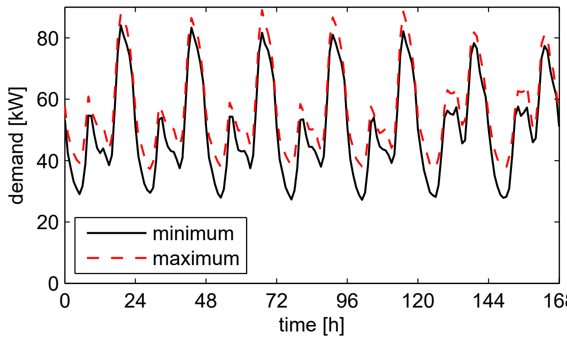

Figure 7: Demand flexibility in the residential sector (100 customers) for one week in winter obtained from modified energy consumption patterns.

Residential customers usually have a moderate energy consumption during daytime hours with a minor increase in the morning and a peak demand around dinner time. During weekends energy consumption of residential customers is generally higher while the afternoon peak is substantially lower. In the case study demand flexibility in the residential sector has been achieved by modifying energy consumption patterns (see Fig. 7). It was assumed the users were incentivized to shift operation of energy intensive appliances (i.e. washing machines, clothes dryers and dishwashers) to low demand periods (off-peak hours). Domestic thermal loads such as electric water heaters are important flexible resources, particularly used in colder climates [12, 13]. Nevertheless, our case study focuses on Spain, where their use is not very widespread and therefore they have been excluded from our analysis.

The geographic area contains several hotels that have been modelled as typical medium-sized hotels focussed on city tourism with a high occupation throughout the year. Each hotel is located in a five storey building (15 m high, 35 m long, 20 m wide) with a modest thermal insulation. Each building is equipped with a heat pump, an additional electric space heating, a chiller and a solar water heating system. The indoor temperature is maintained every day of the year from 8 am to 9 pm between 20 °C and 24 °C. At other times, indoor temperature limits are reduced by 2 °C in winter and increased by 2 °C in summer. Indoor temperature regulation within the given intervals is employed to add demand flexibility (see Fig. 8) to the hotel's energy system.

The office buildings in the simulated region are represented by seven storey buildings (21 m high, 43 m

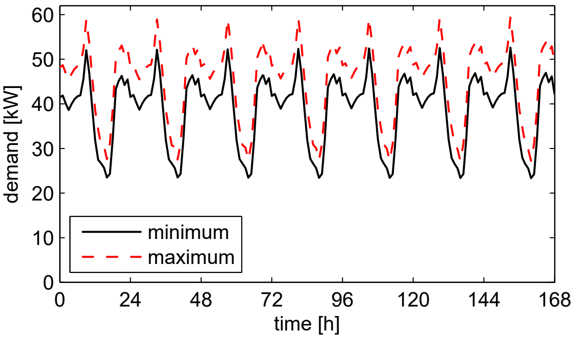

Figure 8: Demand flexibility of a medium-sized hotel for one week in winter obtained by using indoor temperature variations.

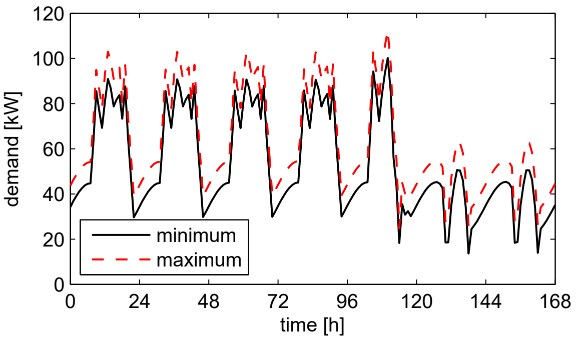

Figure 9: Demand flexibility of an office building for one week in winter obtained by using indoor temperature variations.

long and 15 m wide) with two additional basement levels used as a parking. On an ordinary workday approximately 300 people do their work in each office building. Walls and roofs are well insulated and 60 % of the façades are covered by solar control windows. The installed HVAC systems include energy efficient heat pumps and chillers. During working hours indoor temperature is maintained between 20 °C and 24 °C. Outside office hours the permitted indoor temperature is reduced by 3 °C in winter and increased by 3 °C in summer. Indoor temperature variations within the mentioned intervals convert part of the building load in a flexible demand (see Fig. 9).

Large shopping malls are the third type of non-residential buildings considered in the simulation of a small geographic area. These buildings have only few windows in the external walls and a good thermal insulation to minimize the effect of variable ambient conditions. Each mall opens seven days a week from 9 am to 10 pm with a noticeable higher number of customers on holidays and weekends than on workdays. Heating, cooling and residential hot water is supplied by heat

Table 1: Non-residential building data

	Hotel	Office	Mall
Storey Buildings	5	7	–
High x Long x Wide (m^3)	15x35x20	21x43x15	–
Thermal Insulation	Modest	Medium	High
Indoor Temperature in Opening Hours	20-24°C	20-24°C	18-22°C
Indoor Temperature in Closing Hours (Winter)	18-22°C	17-21°C	15-19°C
Indoor Temperature in Closing Hours (Summer)	22-26°C	23-27°C	21-25°C

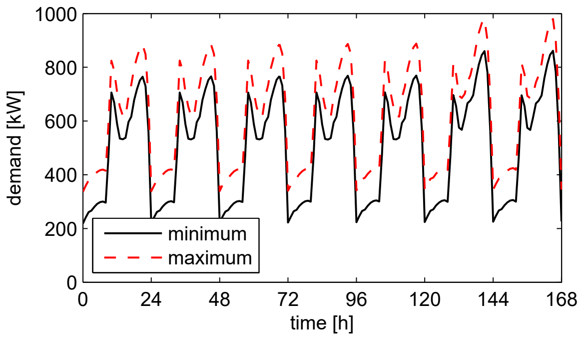

Figure 10: Demand flexibility of a mall for one week in winter obtained by using indoor temperature variations.

pumps, chillers and solar collectors on the building roof. During opening hours the temperature in the malls is maintained in the range from 18 °C to 22 °C. When the malls are closed, i.e. from 10 pm to 9 am, the indoor temperature limits are reduced by 3 °C in winter and increased by 3 °C in summer. Flexibility in the mall's energy demand is achieved by modifying indoor temperature between permitted minimum and maximum temperature (see Fig. 10).

A data summary is shown in Tab. 1. Note that opening hours for a hotel corresponds from 8 am to 9 pm.

6.2. Aggregated energy demand

The optimization algorithm has been developed for groups of buildings or local areas that include customers from various sectors. The aggregation of residential and commercial users with different energy consumption patterns allows increasing demand flexibility[1] throughout the day.

The overall demand considered in the case study is obtained by aggregating the individual loads of the energy users (see Section 6.1 for the demands of the different building types) in the simulated geographic area.

[1]With the permitted maximum and minimum power at a certain time the ratio of demand flexibility can be defined formally as:

$$F(t) = \frac{\max(P(t)) - \min(P(t))}{\max(P(t)) + \min(P(t))} \tag{12}$$

which ranges from 0 (no flexibility) to 1 (high flexibility).

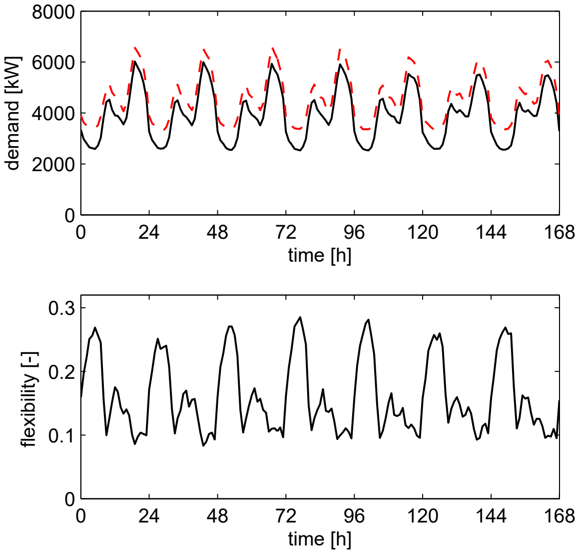

Figure 11: Aggregated demand with lower and upper limits (top) and resulting ratio of demand flexibility (bottom) for one week in winter.

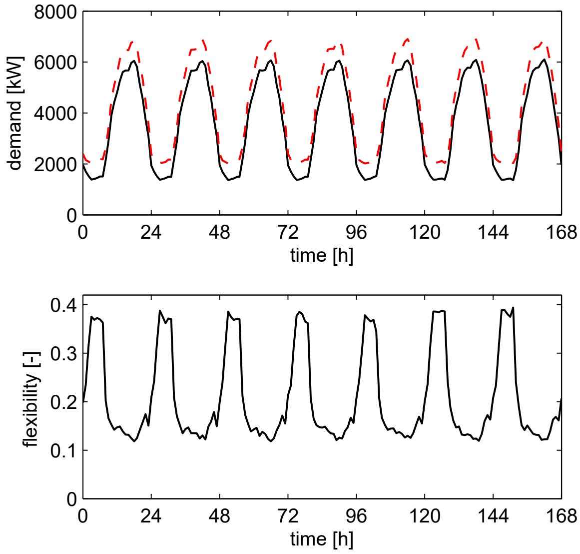

Figure 12: Aggregated demand with lower and upper limits (top) and resulting ratio of demand flexibility (bottom) for one week in summer.

The aggregate demand and the resulting flexibility for one week in winter is shown in Fig. 11. The lower and upper limits of the demand present two large peaks in the morning hours and in the late afternoon/early night hours. The corresponding flexibility varies between 0.1 and 0.3 with maximum values during night.

The minimum and maximum values of the aggregate demand for one week in summer are given in Fig. 12. The demand shows large variations over the day with low values at night and high values during the day, especially in the afternoon. In contrast, the obtained flexibility is high at night (up to 0.4) and relatively low during the day (approximately 0.12). For the considered area, a generally higher demand flexibility can be observed in summer than in winter.

6.3. Real-time pricing

The real-time prices used in this case study are the wholesale market prices. In this case they are used as the market price predictions by the aggregator a day before the actual time of energy delivery to the consumer. Note that these prices differ to the final prices paid by the end-users, which have not been addressed in this work, since the objective of it is to minimize the energy procurement cost for the aggregator in the wholesale market. The final price should include access fees and taxes, and the aggregator must take them into account for the contractual arrangement with the customers. The design of these conditions is out of the scope of this paper. In response to changes to energy prices, the aggregator tries to adjust the aggregate consumption to maximize its own welfare. The day-ahead energy prices that correspond to the periods of the aggregate load on typical winter and summer days (January 14-29 and July 1-16, 2013) are used from data of the Spanish wholesale electricity market [40]. The average energy prices during the 16 days analyzed in winter and summer were 5 c€/kWh and 4.5 c€/kWh, respectively.

7. Results

Given the aggregate flexible loads, the solution to the optimization problem is the optimal scheduling that minimizes the cost of the purchased energy in the daily electricity market for the considered operation processes.

The detailed results obtained with the proposed optimization procedure applied to the aggregate demand of a small geographic area are given in Tab. 2. The economic profit shown represents the daily energy cost difference between the non-optimized and the optimized case. The daily average profit for the considered area, achieved with the load scheduling based on flexibility, adds up to 97.9 € in winter and 36.4 € in summer. In addition to that, the ratio of demand flexibility determined with (12) is displayed for each building cluster. It can be observed that the considered hotels, office buildings and malls have a higher demand flexibility during summer. In contrast, residential customers exhibit a slightly increased demand flexibility in winter.

Table 2: Daily Average profit and rate of flexible consumption per cluster of building

		Winter			Summer		
Building	Nro.	Profit		Flex.	Profit		Flex.
		€	%	1×10^{-2}	€	%	1×10^{-2}
Hotels	12	10.7	11	1.9	4.8	13.1	3.1
Offices	8	10.4	10.6	2	4.4	12.2	2.8
Malls	2	31.4	32.1	5.7	13.4	36.9	8.8
Dwellings	4000	45.4	46.3	6.5	13.8	37.8	6.2
Total	–	97.9	100	16.1	36.4	100	20.9

The electricity market price and its daily variations play an important role in the energy cost reduction based on optimal load scheduling. In the analyzed case study the observed difference between minimum and maximum prices is 2.4 c€/kWh in summer and 5.56 c€/kWh in winter. The larger market price variations during winter led directly to higher economic profits for each building type and the entire area. The higher demand flexibility of hotels, office buildings and malls during summer did not compensate the lower market price variations resulting in smaller benefits during the summer season.

The aggregation of buildings is another factor to take into account for increasing flexibility and profits. The aggregation of 4000 dwellings results in a higher profit than 2 malls for the considered operation processes (electrical appliances for dwellings and heating and cooling loads for malls) as the consumption of heating and cooling of one mall is equivalent to the consumption of electrical appliances of 1854 and 3595 dwellings in winter and summer respectively. In the case of the aggregation of non-residential buildings as malls, hotels and offices (only heating and cooling loads), it can be observed in Tab. 2 that flexibility and profit of 2 malls are higher than flexibility and profit of 12 hotels and 8 offices together. Moreover, there are more hotels than offices but the flexibility of one hotel is lower than the flexibility of one office. This why the profit and flexibility of the aggregation of these buildings do not differ much. Then, we can say that profit is proportional to the flexibility affected by the aggregation of buildings.

Finally, the profit is affected by the flexibility, the aggregation of buildings and the market price. Additionally, the type of building that contributes more to the reduction of the energy cost is the shopping mall followed by the office, hotel, and dwellings. In Fig. 13 and 14 the optimal scheduling for a sample day of winter and summer are shown, it can be seen that the optimal aggregated load follows the market price within its set limits.

Although, in reality, the disaggregation does not only depend on the result of the optimization problem but also on the contract between the aggregator and each

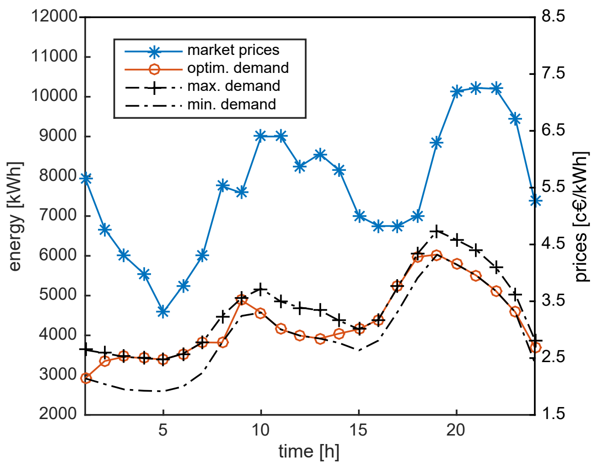

Figure 13: Optimal aggregated flexible consumption and market price for one workday in winter.

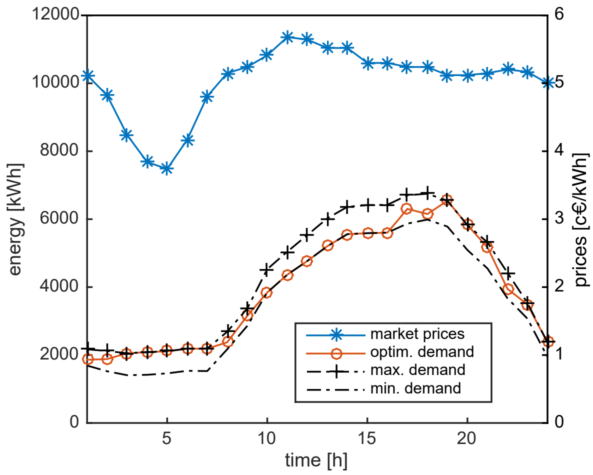

Figure 14: Optimal aggregated flexible consumption and market price for one workday in summer.

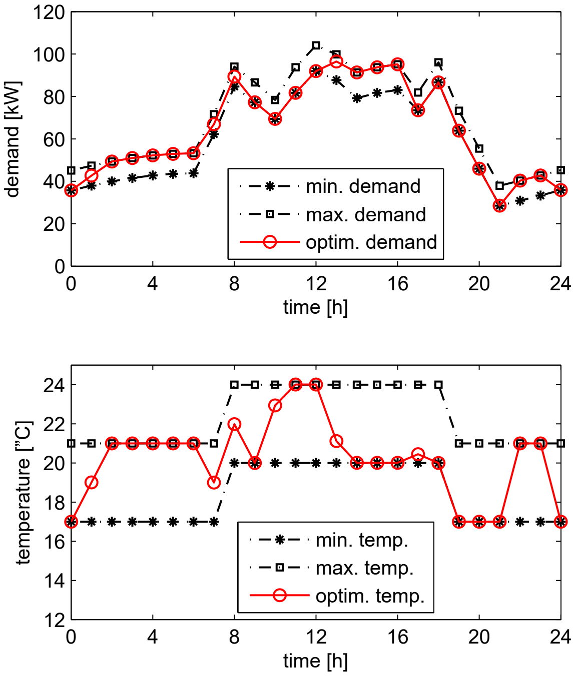

Figure 15: Optimal demand (top) and indoor temperature (bottom) of an office building for a workday in winter.

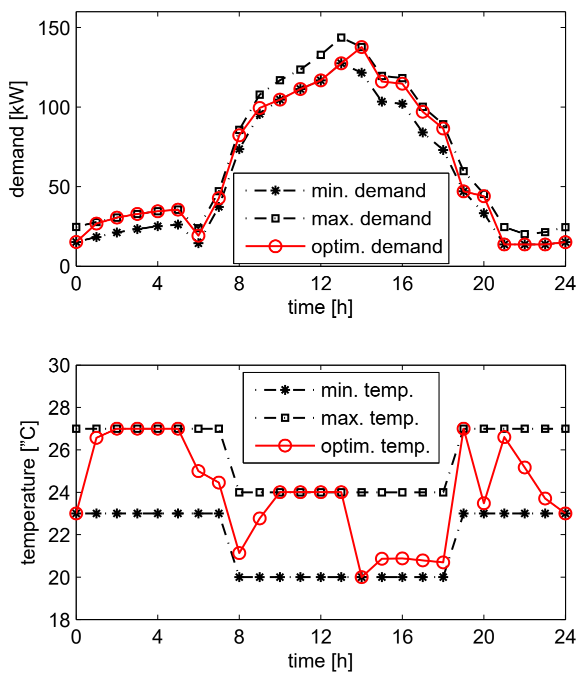

Figure 16: Optimal demand (top) and indoor temperature (bottom) of an office building for a workday in summer.

type of building. Here the optimal aggregated demand for the small geographic area under consideration was disaggregated and applied to the different building types. A ratio between the gap of the optimal aggregated demand and its lower bound regarding the gap of their upper and lower bounds was taken for the disaggregation. This ratio is assumed constant for each aggregated building. Then, the disaggregated demands were used to simulate the effect of the optimal load scheduling on individual buildings. The obtained optimal demand and corresponding indoor temperature of an office building for workdays in winter and summer are given in Fig. 15 and Fig. 16, respectively. It can be observed that the optimal load scheduling induces indoor temperatures variations within the permitted range. It has to be underlined that the energy demand and the indoor temperature do not have a linear relationship, i.e. depending on the time of day and season a higher demand can lead to a temperature increase or temperature reduction. This phenomenon can be observed in the summer results (see Fig. 16) where the permitted maximum demand between 2 am and 5 am leads to a high temperature (heating phase) while the high demand between 2 pm and 6 pm results in a relatively low temperature (cooling phase).

8. Conclusions

This paper presents a method for optimal scheduling of aggregated demands based on an economic criterion. The optimization method uses the demand flexibility to optimally distribute the energy consumption of the customers. It was demonstrated the demand aggregation of buildings with different usage and properties leads to a more equally distributed flexibility and allows users with relatively small loads to participate in the scheme. The aggregator participates directly in the wholesale electricity market and determines the optimal load scheduling to maximize its profits.

The proposed method was validated by using a case study with different buildings located in the same small geographic area. The shopping malls, hotels, offices and dwellings were included with their specific consumption patterns dependent on the time, weekday and season. In the residential sector demand flexibility was achieved by shifting the operation of energy-intensive appliances. In case of commercial buildings (malls, hotels and offices) indoor temperature variations within a given interval were used to obtain certain flexibility in the demand. The flexibility with respect to the aggregated demand was between 10 % and 30 % in winter and between 12 % and 40 % in summer. The results showed that the optimal scheduling shifts part of the aggregated demand from peak to off-peak periods. The economic benefit was considerably larger in winter than in summer due to the high intraday price variations during the cold season of the year.

The obtained results underline the potential of combining demand aggregation and optimal scheduling. The aggregator provides the option to close the traditional gap between the day-ahead wholesale market and the individual customer. The proposed method helps the actual costs of power production to be passed on to the consumers and ensures access to fair electricity tariffs for all users.

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