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Optimum residential load management strategy for real time pricing (RTP) demand response programs

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ABSTRACT

This paper presents an optimal load management strategy for residential consumers that utilizes the communication infrastructure of the future smart grid. The strategy considers predictions of electricity prices, energy demand, renewable power production, and power-purchase of energy of the consumer in determining the optimal relationship between hourly electricity prices and the use of different household appliances and electric vehicles in a typical smart house. The proposed strategy is illustrated using two study cases corresponding to a house located in Zaragoza (Spain) for a typical day in summer. Results show that the proposed model allows users to control their diary energy consumption and adapt their electricity bills to their actual economical situation.

1. Introduction

Energy demand is increasing in many countries as a result of economic and industrial developments; consequently, many governments are working to provide reliable electrical energy. However, problems related with restrictions in electricity prices by means of a price ceiling and flat rates have produced a difference between marginal electricity generation costs and energy consumption cost of electricity. This increases the growth of demand faster than the growth of generation capacity. In addition, the volatility of wholesale electricity prices affects the retailer's ability to generate profit and increase the investment uncertainty (Kim and Shcherbakova, 2011). The demand response (DR) is defined as changes in the electricity consumption patterns of end consumers to reduce the instantaneous demand in times of high electricity prices. A change in consumption patterns could be made by means of a change in the price of electricity (Price-Based Programs) or incentive payments (Incentive-Based Programs Albadi and El-Saadany, 2008). Time-of-Use (TOU) is a particular type of Price-Based Program whereby peak periods have higher prices than prices during off-peak periods; consequently, the users change their use of electricity. This type of DR program is particularly convenient for residential users (Eissa, 2011).

Recently, many studies have been carried out to determine how end-users can adjust their load level according to a determined DR program. Molderink et al. (2010) developed an algorithm for the control of energy streams on a single house and a large group of houses. It is assumed that every house has microgenerators, heat and electricity buffers, appliances, and a local controller. In this approach, global and local controllers are used in three steps. First, a prediction is made for production and consumption for one day ahead, and then the local controller determines the aggregated profile and sends it to the global controller. Second, the plan for each house is made for the next day. Third, the algorithm decides how the demand is matched. Two examples were analyzed, and the results showed that it is possible to plan for a fleet of houses based on a one-day prediction; however, any forecasting error affects the outcomes of this approach. Houwing et al. (2011) analyzed the importance of the micro-Combined Heat and Power systems (micro-CHP) as a special type of distributed generation (DG) technology. The model-predictive control (MPC) proposed to make a demand response, minimizing the cost of the domestic energy use, subject to operational constraints and assuming the perfect prediction of energy demand and electricity prices. The results showed that the costs are between 1% and 14% lower than the standard control strategies.

Mohsenian-Rad and Leon-Garcia (2010) developed a residential load control for real-time pricing (RTP) environments where the electricity payment and the waiting time for the operation of each appliance are minimized in response to the variable real-time prices. First, a price prediction is made for a determined scheduling horizon. Next, an objective function that considers the total electricity payment and the total cost of waiting (cost of using appliances at later hours) into the scheduling horizon is minimized. Mohsenian-Rad et al. (2010) presented a demand side

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management model where, for a fleet of residential consumers, the optimal energy consumption schedule for each consumer is determined by minimizing the energy cost in the system based on game theory. Conejo et al. (2010) presented a demand response model that minimizes the cost of energy consumption considering the load-variation limits, hourly load, and price prediction uncertainty. This model assumes that prices and decisions in the prior $t-1$ h are known; in the actual moment (hour t), the price and power demand are known, and the prices in the next $24-t$ h are estimated using an autoregressive integrated moving average (ARIMA)-based model with a confidence interval. Using this information, the optimization model establishes a floor for daily consumption, and ramping down/up limits are solved, obtaining the energy consumption in the current hour t and the demand at the beginning of hour $t+1$. Finally, this procedure is repeated each hour on a scheduling horizon of 1 day.

Sianaki et al. (2010) proposed a methodology for demand response that considers the customers' preferences for the use of certain appliances during peak hours by means of the Analytic Hierarchy Process. This quantification of customer preferences is used to decide what appliances must be used during the peak hours, solving the Knapsack Problem, wherein the numerical priority obtained by the Analytic Hierarchy Process for a certain appliance is considered as a measure of the profit obtained by its use. The authors conclude that this method allows improvement both in customers' budgets and the global energy consumption on the electrical grid. Tanaka et al. (2011) presented a methodology to minimize the power flow fluctuation in the smart grid with a fleet of houses using optimally a battery bank and a heat pump, concluding that this methodology allows for the reduction of the electric power consumption and the cost of electricity.

An important aspect is that the success of a determined DR program depends widely on awareness, attitude, and behavioral adaptation of consumers (Bartusch et al., 2011). However, according to results obtained by Gyamfi and Krumdieck (2011), customers are very sensitive to the energy prices. In scientific articles previously mentioned, the motivation and intention of consumers to participate in the DR program is represented in different ways. For example, Mohsenian-Rad and Leon-Garcia (2010) use a factor that is equal to 1 when a strict cost reduction is required, slightly higher than 1 when a medium cost reduction is required, and much higher than 1 when a cost reduction is not required. However, this type of representation might be a simplistic way to effectively reflect the relationship between the reduction in the electricity bill and the economic situation of the consumers. Based on this reasoning, this paper proposes a load management strategy that considers the power-purchase of energy of the consumers in a real-time pricing DR program optimizing the negotiation between the consumer and retailer.

The paper is organized as follows. Section 2 explains the smart grid infrastructure required for the real-time pricing demand response program implementation, and the mathematical modeling of household appliances and electric vehicles. Section 3 describes in detail the load management strategy proposed. Section 4 analyzes two study cases of a residential consumer in a real-time pricing demand response in the Iberian Peninsula. Finally, Section 5 gives conclusions.

2. Mathematical model of system

The load management based on the real-time prices requires an electricity grid that allows for active participation of consumers in demand response programs to supply electricity economically and efficiently. This electricity grid is known as the "smart grid." Future smart grids will be provided with a communication infrastructure that can be categorized into three classes: wide area network (WAN), field area network (FAN), and home area network (HAN). A WAN is used to exchange real-time measurements between the control center and electric devices located in power plants, substations, and distributed storage. A FAN allows communication between distribution substations, distribution feeders, transformers, and customers' homes. A HAN allows communication between loads, sensors, and appliances in homes. An Energy Services Interface (ESI) is a secure two-way communication interface between the utility and the customers. An ESI can receive hourly prices from the utility and inform the customers; using a web-based Energy Management System (EMS) or In-Home Display (IHD) connected to the ESI, customers can respond to the pricing signal (Wang et al., 2011). For a typical house provided with a smart meter, wind turbine, photovoltaic (PV) panels, several household appliances, and an electric vehicle (EV), the technique proposed in this paper consists of using information about wholesale energy prices, the power of renewable sources and temperature, energy demand, and user behavior to determine optimal demand response for the following day, considering the power-purchase of energy of the consumers. Fig. 1 describes the load management strategy proposed, where, using ESI, the user is informed about the actual and forecasted values of energy prices, energy consumption, and renewable power. Then, using a diary planner for the next day—expressed by means of the user's power-purchase of energy and predictions of wholesale energy prices, renewable power productions, and energy demand—the EMS can determine the optimal use of household appliances for the next day and the best time to use the electric vehicle, subject to the conditions imposed by a specific trip.

The next section describes a mathematical model of household appliances and electric vehicles of a typical residential consumer.

2.1. Energy demand modeling

2.1.1. Household appliances

Let $n=1,2,3,\ldots,N$ be the household appliances. In this paper, it is assumed that a typical household appliance n can be modeled by means of an idealized load profile, as shown in Fig. 2. Here, h_n is the possible hour at which the appliance will start its operation, P_n is its power required, and d_n is the duration of its operation. The matrix of all possible load profiles for this appliance $PDCA_n$ (Possible Demand Curve of the Appliance n) can be obtained using the algorithm shown in Fig. 3. The matrix $PDCA_n$ will have 24 columns, and its number of rows will be a variable value called R_n, while the variables r and l are counters used by the algorithm.

Additionally, a row with zeros must be added to the matrix $PDCA_n$ to consider the option of shutting down the appliance n.

2.1.2. Electric vehicle

Environmental factors related to greenhouse gas emissions, petroleum-based transportation, and air pollution are promoting

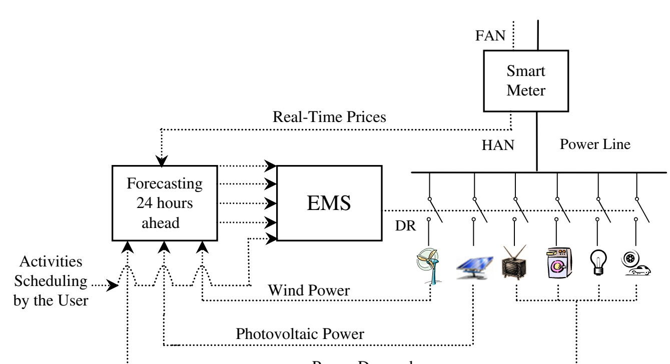

Fig. 1. Smart house and load management strategy.

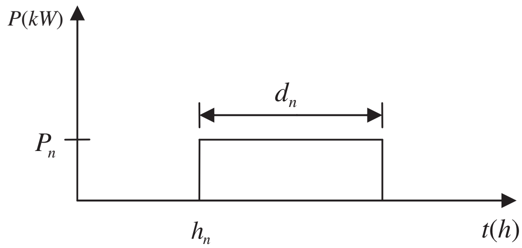

Fig. 2. Idealized load profile of household appliances.

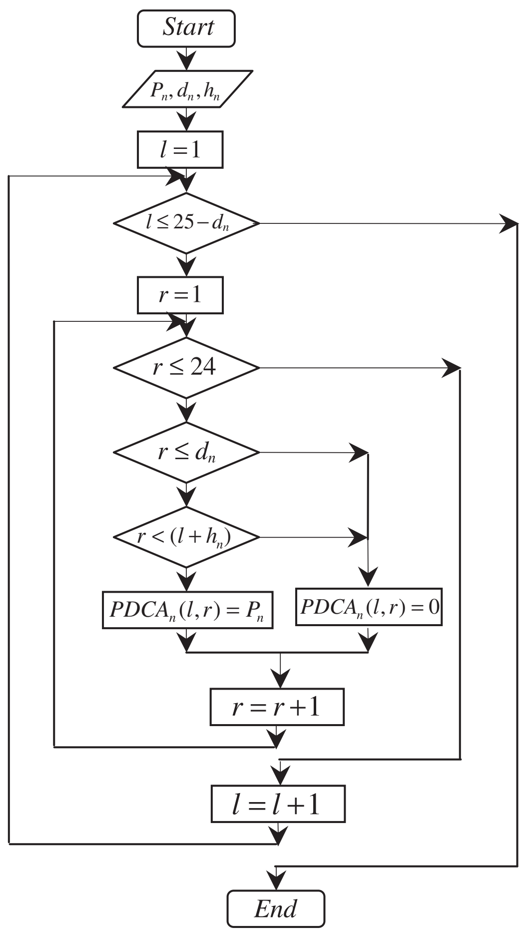

Fig. 3. Algorithm to find $PDCA_n$.

the development of EVs. For these reasons, it is expected that EVs will be an important electric load in the urban environments; therefore, this is considered in our analysis. Recently, there are plug-in hybrid electric vehicles that use nickel-metal hydride and lithium ion batteries (Bradley and Frank, 2009); however, for simplicity and illustrative purposes, in our optimal load management strategy, a lead acid battery model will be considered.

Copetti and Chenlo (1994) developed a general lead acid battery model to represent the complex battery behavior; however, its mathematical formulation is complex because we need to solve a nonlinear equations system for each hour of simulation; for this reason, a simplification is used. The following Equations represent the capacity model normalized with respect to the total ampere-hours that might be charged or discharged in 10 h at 25 °C (C_{10} capacity):

$$C_T = 1.67C_{10}(1+0.005\Delta T_a) \tag{1}$$

$$C = \frac{C_T}{1+0.67(|I|/I_{10})^{0.9}} \tag{2}$$

where $\Delta T_a = T_a - 25$ is the temperature variation from the reference of 25 °C, T_a is the ambient temperature in °C, C_T is the maximum capacity of the battery and C is the ampere-hours capacity at the charge or discharge constant current I.

The Coulombic efficiency (η_b) during the discharge ($I<0$) and charge ($I>0$) processes is calculated using the following equation (Copetti et al., 1993):

$$\eta_b = \begin{cases} 1-\exp\left[\left(\frac{20.73}{I/I_{10}+0.55}\right)(SOC-1)\right], & I>0 \\ 1, & I<0 \end{cases} \tag{3}$$

where I_{10} is the charge or discharge current in 10 h at 25 °C. The state of charge (SOC) of the battery is calculated by

$$SOC = \begin{cases} \frac{Q}{C}\eta_b, & I>0 \\ 1-\frac{Q}{C}\eta_b, & I<0 \end{cases} \tag{4}$$

where $Q=|I|t$ is the charge supplied by the battery (discharge) or to the battery (charge) during time t. During the charge process, the battery voltage at which the charge controller disconnects the power source is assumed to be 2.5 V/cell; during this process, the battery voltage per cell might be approximated by (Copetti and Chenlo, 1994)

$$V = \left(2+0.16\frac{Q}{C}\right) + \frac{I}{C_{10}}\left(\frac{6}{1+I^{0.6}} + \frac{0.48}{(1-Q/C_T)^{1.2}} + 0.036\right)(1-0.025\Delta T_a) \tag{5}$$

Eq. (5) allows us to estimate the Q value at which the battery voltage is 2.5 V per cell and, therefore, the state of charge in the moment at which the charge controller disconnects the power sources. During the discharge process, when the state of charge is equal to the minimum value specified by the battery manufacturer, the charge controller disconnects the traction system to prevent over-discharge.

Let $k=1,2,3,\ldots,K$ be the number of electric vehicles in the house. A matrix $PDCEV_k$ (Possible Demand Curve of the Electric Vehicle k) can be made similar to the one used to represent all possible load profiles of household appliances ($PDCA_n$) but using the lead acid battery model presented above to estimate power required from the electric grid to charge the battery bank of EV considering a determined level of autonomy. The matrix $PDCEV_k$ will have 24 columns, and its number of rows will be a variable value called F_k.

3. Optimum load management strategy

As explained in Section 2, the optimum load management strategy requires forecasting of renewable power production, load, and electricity prices for the next day. Then, using the activity scheduling by the user—expressed as the power-purchase of energy—the negotiation between utility and user is optimized. The next sections present a survey about predictions of interest, show users how to express the activities scheduling, and describe the optimization problem and its solution methodology to determine the optimal demand response of the user for the next day.

3.1. Ensemble forecasting

Several models have been developed to forecast wind speed and power using different types of information. Lei et al. (2009) divided the forecasting methods into four categories: physical model, conventional statistical model, spatial correlation model, and artificial intelligence model. The *physical model* uses information about terrain, obstacles, pressure, and temperature to predict wind speed. The result obtained with this model can be used as the auxiliary input of a *statistical model*, which is based on analyzing historical data. *Spatial correlation* models consider the spatial relationship between the wind speeds at different places. The models based on *artificial intelligence* use an artificial neural network (ANN), fuzzy logic, or a support vector machine to make predictions of wind speed and wind power. The photovoltaic power prediction can be made using models based on artificial intelligence and statistical analysis such as ANNs, autoregressive moving average (ARMA) process, Bayesian inference, and Markov chains (Paoli et al., 2010).

However, other approaches based on analyses of satellite data and numerical weather predictions present greater accuracy for horizons of more than 5 h (Kleissl, 2010). Aggarwal et al. (2009) divided the electricity price forecasting methodologies in three main categories: game theory-based models, simulation-based models, and time series analysis-based models. *Game theory* models consider the strategies of the market participants to maximize their benefits. *Simulation* models consider system operational conditions by means of optimal power flow. *Time series* classification includes statistical techniques such as ARMA models, ANNs, and data mining. Artificial intelligence models have been applied to analyze the relationship between energy consumption patterns and temperature behavior. Some examples of this type of approach have been proposed by Abdel-Aal (2004a, 2004b) and Fan et al. (2009). Electric vehicles will be an important load whose patterns of use must be known. In the load management strategy proposed in this paper, the home-arrival time of the EV must be predicted. Wang et al. (2011) have developed a probability distribution of this variable to analyze the impact of plug-in hybrid electric vehicles on power systems; however, statistical analysis could also be considered.

3.2. Activity scheduling by user

An example of the power-purchase of energy of the user is shown in Table 1. For the household appliance n, the column VUA_n (Value to User of the household Appliance n) contains the hourly values assigned by the consumer to use this appliance during a determined hour of the following day. According to Table 1, the consumer could pay €0.05 per kWh to use the household appliance n from 16:00 to 18:00 h. Similarly, the column $VUEV_k$ (Value to User of the Electric Vehicle k) contains the hourly values assigned by the consumer to use the electric vehicle k during a determined hour of the next day. According to Table 1, the consumer would pay 7 cents of euro per kWh to travel with the EV k from 11:00 to 15:00 h. It is assumed that the energy required for an EV k to travel from 11:00 to 15:00 h is bought previously between the 1:00 and 10:00 h; when the consumer comes back home (16:00 h), the EV is reconnected, and consequently, the consumer must negotiate with the utility again. Other possibilities of use of EVs can be included in the model simply by changing the value to use the EV in determined hours of the following day. Additionally the user must express the required level of autonomy for future travel with the EV. This methodology allows us to express the diary planning consumption for one day ahead in terms of the interest shown in using a determined household appliance or EV at a determined time—this interest is conveniently expressed in €/kWh. Table 1 shows the input information to EMS, which optimizes the negotiation between retailer and consumer.

Table 1
Activities scheduling by the user for the next day.

t (h)	VUA_1 (€/kWh)	VUA_n (€/kWh)	$VUEV_1$ (€/kWh)	$VUEV_k$ (€/kWh)
1	0	0	0.15	0.07
2	0	0	0.15	0.07
3	0	0	0.15	0.07
4	0	0	0.15	0.07
5	0	0	0.15	0.07
6	0	0	0.15	0.07
7	0	0	0.15	0.07
8	0	0	0	0.07
9	0	0	0	0.07
10	0	0	0	0.07
11	0	0	0.15	0
12	0.1	0	0.15	0
13	0.1	0	0.15	0
14	0.1	0	0.15	0
15	0.1	0	0.15	0
16	0.1	0.05	0.15	0.07
17	0.1	0.05	0.15	0.07
18	0	0.05	0.15	0.07
19	0	0	0.15	0.07
20	0	0	0.15	0.07
21	0	0	0.15	0.07
22	0	0	0.15	0.07
23	0	0	0.15	0.07
24	0	0	0.15	0.07

3.3. Optimization problem

The optimal demand response for the next day, considering the power-purchase of energy of the user, could be determined by maximizing the difference between the amount of money the user can pay and the cost of obtaining the required energy from the grid, which is related to the energy market prices.

Let $n=1,2,3,\ldots,N$ be the number of household appliances and $k=1,2,3,\ldots,K$ the number of electric vehicles in the house. The matrix $PDCA_n$ with R_n rows and 24 columns, and the matrix $PDCEV_k$ with F_k rows and 24 columns, are determined according to the Sections 2.1.1 and 2.1.2, respectively. Let α_n be an integer number contained in the interval $[1,R_n]$ and β_k an integer number contained in the interval $[1,F_k]$. For a specific combination of load profiles for different household appliances indicated by the row α_n in the matrix $PDCA_n$, and the different charge profiles for the electric vehicles indicated by the row β_k in the matrix $PDCEV_k$, the objective function described above could be represented mathematically using

$$f=\sum_{i=1}^{i=24}\left[\begin{array}{l}\left(\sum_{n=1}^{n=N}VUA_n(i)PDCA_n(\alpha_n,i)+\sum_{k=1}^{k=K}VUEV_k(i)PDCEV_k(\beta_k,i)\right)\\ -EP(i)\left(\sum_{n=1}^{n=N}PDCA_n(\alpha_n,i)+\sum_{k=1}^{k=K}PDCEV_k(\beta_k,i)\right)\\ +EP(i)(WP(i)+PVP(i))\end{array}\right] \quad (6)$$

where f is the difference between the amount of money that the user can pay and the cost of obtaining the required energy from the grid, $VUA_n(i)$ is the user value of household appliance n in the hour i, $PDCA_n(\alpha_n,i)$ is the power demanded by household appliance n in the hour i, $VUEV_k(i)$ is the user value to travel in electric vehicle k in the hour i, $PDCEV_k(\beta_k,i)$ is the power demanded by electric vehicle k during charge process in the hour i, $EP(i)$ is the forecasted electricity prices in the hour i and $WP(i)$ and $PVP(i)$ are the forecasted wind power and photovoltaic power in the hour i, respectively. In Eq. (6), the first term represents the power-purchase of energy of the consumer, while the second term represents the cost of the required energy, and the third term represents the benefits obtained due to selling wind and photovoltaic energy back to the grid. The number of possible combinations (N_c) in the optimization problem to maximize the objective function of Eq. (6) depends on the operation time of the different appliances (d_n) and on the number of appliances according to

$$N_c=(26-d_1)(26-d_2)\cdots(26-d_n)\cdots(26-d_N) \quad (7)$$

Fig. 4 shows in a semi-logarithmic graph the behavior of the number of possible combinations when the number of appliances is between 1 and 20, and their operation time ($d_1,d_2,\ldots,d_n,\ldots,d_N$) is

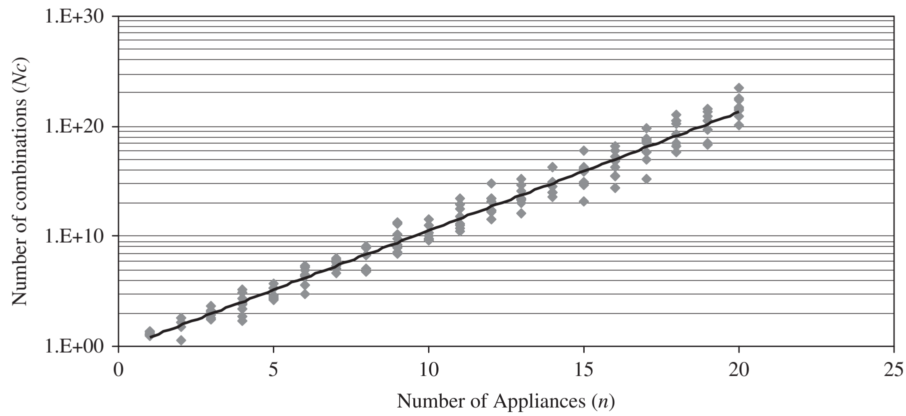

Fig. 4. Relationship between number of combinations (N_c) and number of appliances (N).

represented as a integer random variable between 1 and 24. According to these results, the number of possible combinations grows exponentially (N_c=0.5566e$^{2.4809n}$, R^2=0.9765) with the number of appliances considered.

Considering the nonlinear nature of the optimization problem and the number of possible combinations, we concluded that heuristic optimization techniques should be applied. Heuristic optimization techniques do not ensure finding a global optimal solution, but they can find very good solutions while consuming a low computational time. The proposed methodology requires solving the optimization problem at the end of the present day in order to reduce uncertainty in the ensemble of forecasting. Thus, the problem of finding the combination of household appliances' load profiles and EV trips that maximize the objective function of Eq. (6) can be solved using a heuristic optimization technique. In this case, we used a genetic algorithm (Goldberg, 1989) that, for a determined number of individuals in the population (P_o), number of generations (G_o), crossing rate (C_o) and mutation rate (M_o), can be implemented in the following way:

1. The initial population is obtained randomly, where an individual is an integer vector such as this: $|\alpha_1|\alpha_2|\ldots|\alpha_n|\ldots|\alpha_N|$ $\beta_1|\beta_2|\ldots|\beta_k|\ldots|\beta_K|$ with n=1,2,3,…,N; k=1,2,3,…,K and $\alpha_1, \alpha_2,\ldots,\alpha_n,\ldots,\alpha_N \in [1,R_n]$; $\beta_1,\beta_2,\ldots,\beta_k,\ldots,\beta_K \in [1,F_k]$.
2. For each individual in the population, the objective function (f) of Eq. (6) is evaluated.
3. The fitness function (F_{it}) of individual p is determined according to its rank in the population (rank 1 is assigned to the best individual, which maximizes f defined by Eq. (6), and rank P_o to the worst individual, which minimizes f). The fitness function is shown as

$$F_{it} = \frac{(P_o+1)-p}{\sum_{p=1}^{P_o}(P_o+1-p)} \quad \text{with} \quad p=1,2,\ldots,P \tag{8}$$

4. Reproduction, crossing, and mutation are carried out on the obtained solutions, defining the next generation. Reproduction is made using the roulette-wheel method, where the selection probability of a determined individual is proportional to its fitness. The crossing between two individuals is made by the "one crossing point" method with a crossing rate C_o ($0<C_o<1$), which defines how many descendants will be produced in each generation. The mutation is made by randomly changing the components of some individuals, whose quantity is defined by the mutation rate M_o ($0<M_o<1$), which determines the number of individuals which will be mutated in each generation.
5. The process in steps 2–4 is repeated until G_o generations are reached. The best solution obtained is the one that has the highest value of f, and then the optimal load profile of each household appliance and travel with the EV fitted to the power-purchase of energy of the consumer is determined.

4. Study cases

To illustrate the load management strategy proposed in this paper, a residential house located in Zaragoza (Spain) is analyzed. The house has a television of 0.12 kW (n=1), air conditioner of 1 kW (n=2), computer of 0.1 kW (n=3), 15 bulbs of 10 W (n=4), other household appliances with total consumption of 0.15 kW (n=5), a wind turbine of 3 kW, and an EV with a battery bank of C_1=53 Ah and 312 V (k=1). Two cases have been considered, as presented in the next sections.

4.1. Case study determining the best time to use EV

During the previous day of our analysis, the user specified his plan to EMS using Table 1 linked to ESI. Specifically for this day, the user, according to his power-purchase, could pay 1 c€/kWh to watch television between 14 h and 23 h, 10 c€/kWh to use the air conditioner for 5 h between 13 h and 22 h, 10 c€/kWh to use the computer between 9 h and 20 h, 10 c€/kWh to use the lights between 21 h and 23 h, 10 c€/kWh to use the other household appliances during the 24 h period, and 5 c€/kWh to use the EV for 5 h at any time of the day. According to Section 3, predictions 24 h ahead of electricity prices, ambient temperature, and wind power are simulated. Analyzing information published by Foley et al. (2012), Aggarwal et al. (2009), Hahn et al. (2009), and Abdel-Aal (2004a), wind power forecasting error of 20%, energy prices forecasting error of 10%, ambient temperature forecasting error of 10% and load forecasting error of 2% have been considered.

The household appliances and EV were modeled according to Section 2. For example, for the air conditioner (n=2, P_2=1 kW, and d_2=5 h), the matrix of all possible load profiles derived from all possible uses ($PDCA_2$) is built using the algorithm presented in Fig. 3. The transpose matrix of $PDCA_2$ is shown in Table 2. Note that a row with zeros in $PDCA_2$ has been included to consider the option of shutting down the air conditioner (R_2=21).

Initially, the battery bank of the EV has an SOC of 35%, and then the user connects the EV to the grid to increment the SOC to 60% or higher. It is estimated that 11.7% of energy stored in the battery bank is spent during travel, and when the user returns with the EV, he will reconnect it to the grid to recharge its battery bank. The transpose matrix of the load for each possible travel with the EV ($PDCEV_1$) under these autonomy requirements is shown in Table 3, assuming that the EV is charged optimally, maintaining the voltage at a constant value. Note that a row with zeros in $PDCEV_1$ has been included to consider the option of no travel with the EV ($F_1=13$).

Tables similar to Table 2 were built for other household appliances, and then the optimum load management strategy, explained in Section 3, was implemented in MATLAB considering $P_o=1000$, $G_o=30$, $C_o=95\%$, and $M_o=1\%$. The evolution of the genetic algorithm is shown in Fig. 5. The total number of possible combinations is 2,812,992, and the implemented program evaluates about 28 combinations per second.

Table 2
Transpose matrix $PDCA_2$.

Possible load curves																				
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	**1**	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	**1**	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	**1**	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0

Fig. 6 shows forecasted and actual values of electricity prices and ambient temperature 24 h ahead of a typical summer day based on information provided by the Spanish electrical market operator OMEL (http://www.omel.es) and the Spanish meteorological agency AEMET (http://www.aemet.es). Typically, the residents of this house use their air conditioner between 18 h and 22 h—assuming that this house has a good thermal insulation—so the air conditioner could be used in the daytime hours, during which electricity prices are low. In this sense, Fig. 7 shows the load shifting recommended by load management strategy regarding the use of the air conditioner for this day.

The user of the EV typically travels between 8:00 h and 13:00 h. However, in the plan, the user has expressed flexibility to use the EV on this day. Under the travel conditions explained above, Fig. 8 shows the results obtained by the load management strategy about the use of the EV; note that if the user travels with the EV at 8:00 h ($SOC=61.7\%$) and returns at 13:00 h ($SOC=50\%$), electricity to recharge the battery bank will be bought when electricity prices will be high. However, if the user travels with the EV at 19:00 h ($SOC=77.7\%$) and returns at 23:00 h, the autonomy of EV is incremented and its battery bank is charged when energy prices are low.

The user has specified a value of 1 c€/kWh to watch television between 14 h and 23 h, which, according to the hourly prices shown previously in Fig. 6, is a very low value, and the load management strategy recommends shutting down the television. Fig. 9 shows a comparison between typical and optimal load profiles, which allows the reduction of the electricity bill of 21.7%. These results could be shown by EMS through ESI to give the users an incentive to change their energy consumption pattern. Note that according to Fig. 9, the load management strategy allows users to reach an important reduction of energy consumption in hours of high electricity prices.

4.2. Case study selecting time to use EV

In a typical situation, we can consider that the consumer needs to use EV from 8:00 to 13:00 h and can pay 5 c€/kWh for the

Table 3
Transpose matrix $PDCEV_1$.

Possible travel												
1	2	3	4	5	6	7	8	9	10	11	12	13
3.42	3.42	3.42	3.42	3.42	3.42	3.42	3.42	3.42	3.42	3.42	3.42	0.00
3.36	3.36	3.36	3.36	3.36	3.36	3.36	3.36	3.36	3.36	3.36	3.36	0.00
3.02	3.02	3.02	3.02	3.02	3.02	3.02	3.02	3.02	3.02	3.02	3.02	0.00
2.24	2.24	2.24	2.24	2.24	2.24	2.24	2.24	2.24	2.24	2.24	2.24	0.00
1.99	1.99	1.99	1.99	1.99	1.99	1.99	1.99	1.99	1.99	1.99	1.99	0.00
1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	1.68	0.00
1.65	1.65	1.65	1.65	1.65	1.65	1.65	1.65	1.65	1.65	1.65	1.65	0.00
0.00	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	0.00
0.00	**0.00**	1.31	1.31	1.31	1.31	1.31	1.31	1.31	1.31	1.31	1.31	0.00
0.00	**0.00**	**0.00**	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	0.00
0.00	**0.00**	**0.00**	**0.00**	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	0.00
0.00	**0.00**	**0.00**	**0.00**	**0.00**	1.07	1.07	1.07	1.07	1.07	1.07	1.07	0.00
2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.81	0.81	0.81	0.81	0.81	0.81	0.00
2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.82	0.82	0.82	0.82	0.82	0.00
1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.84	0.84	0.84	0.84	0.00
1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.78	0.78	0.78	0.00
1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.56	0.56	0.00
1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.48	0.00
1.13	1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00
1.10	1.13	1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	**0.00**	0.00
0.95	1.10	1.13	1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	**0.00**	0.00
0.82	0.95	1.10	1.13	1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	**0.00**	0.00
0.85	0.82	0.95	1.10	1.13	1.10	1.29	1.35	1.76	2.07	2.45	**0.00**	0.00
0.83	0.85	0.82	0.95	1.10	1.13	1.10	1.29	1.35	1.76	2.07	2.45	0.00

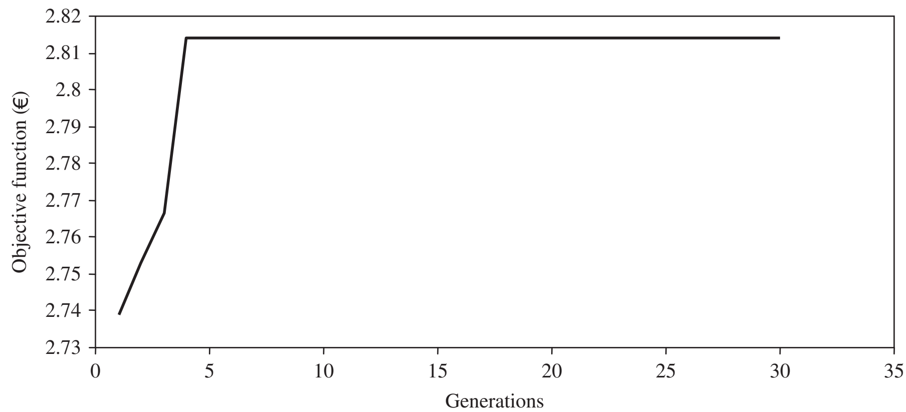

Fig. 5. Evolution of genetic algorithm optimization.

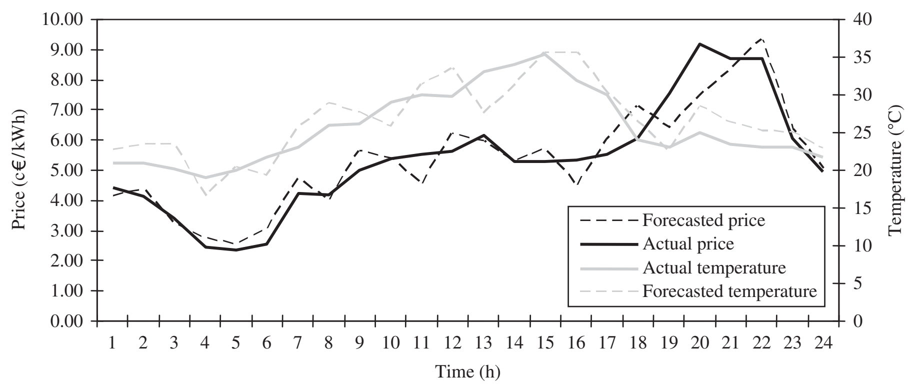

Fig. 6. Energy prices and temperature for a typical day of summer.

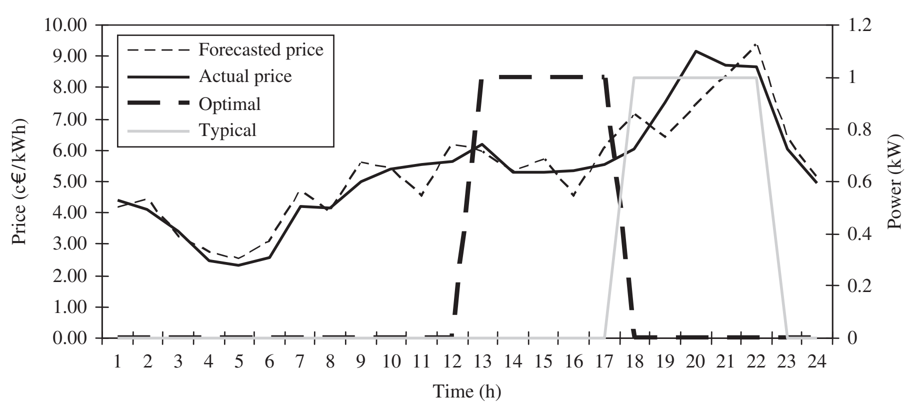

Fig. 7. Comparison of typical and optimal use of air conditioner.

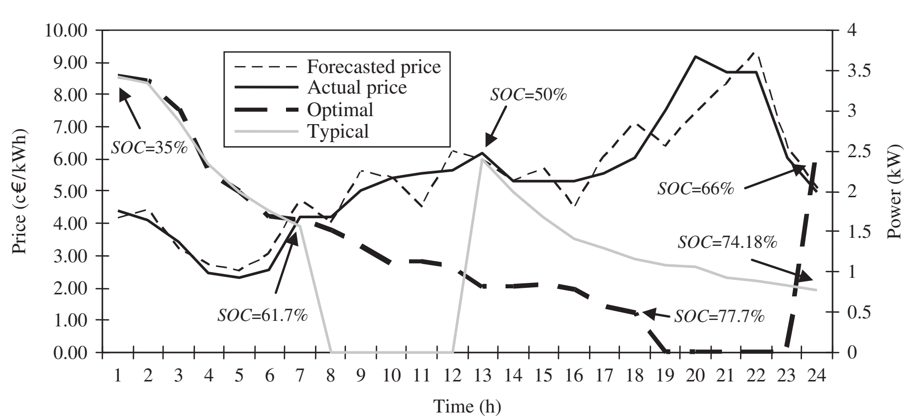

Fig. 8. Illustration of optimal use of EV for 5 h.

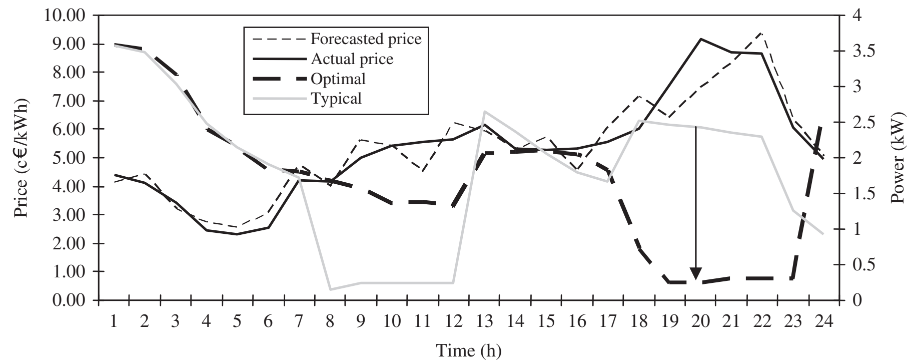

Fig. 9. Comparison between typical and optimal load profiles.

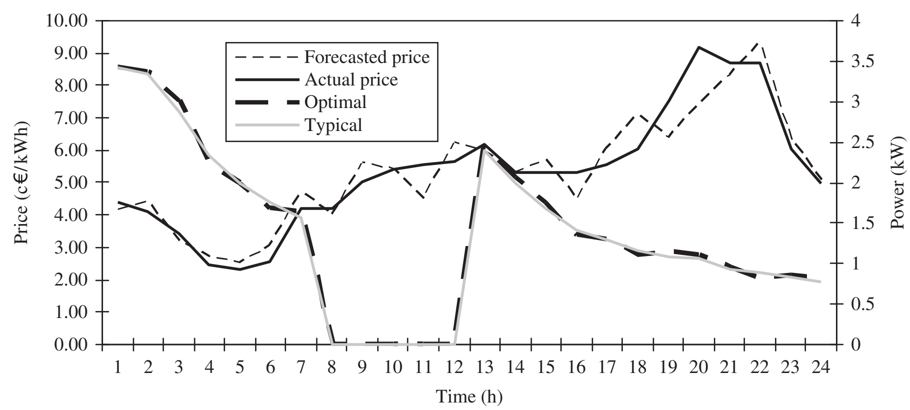

Fig. 10. Illustration of the required use of EV during 5 h.

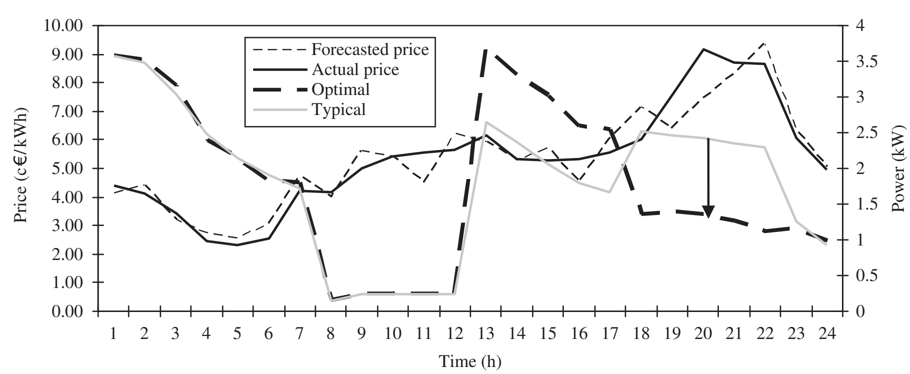

Fig. 11. Comparison between typical and optimal load profiles under typical use of EV.

energy required from the grid to charge its battery bank. It is expected that the user comes home and reconnects the EV at 13:00 h. The conditions for the other appliances are the same as previously analyzed in Section 4.1. Fig. 10 shows the results obtained from the optimization process, where the use of EV is required by the consumer. Fig. 11 shows a comparison between the typical and optimal load profiles. Under these conditions, the reduction of the electricity bill is 8%, mainly due to air conditioner use.

An important aspect to consider is that a forecasting error of electricity prices could affect the ability of the load management strategy to determine optimal scheduling for different appliance usages and traveling with EVs, while a forecasting error of renewable power could affect the estimation of benefits obtained from selling renewable energy to grid.

5. Conclusions

In this paper, an optimal load management strategy for residential consumers is shown that utilizes the communication infrastructure of the future smart grid, predictions of electricity prices, energy demand, renewable power production, and power-purchase of energy of the consumer to determine—through the negotiation between retailer and consumer—the optimal utilization of different appliances and EVs. Two study cases, of a residential consumer in Zaragoza (Spain), have been analyzed. Results show that the proposed model allowed users to reduce their electricity bill between 8% and 22% for the typical summer day analyzed and adapt the electricity bill to their actual economical situation.

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