Adaptive model predictive control for electricity management in the household sector

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Abstract

This paper focuses on the optimisation of electricity consumption in residential buildings. To deal with the increase in electricity consumption, the intermittency of renewable energy generation and grid contingencies, a greater effort is required towards residential management optimisation. A novel adaptive model predictive control algorithm is proposed to achieve this objective. The challenges for this research included recognising and modelling the economic and technical constraints of the sources and appliances and addressing the uncertainties concerning the weather and user behaviour. Data-driven models are developed and trained to predict the user behaviour and buildings. Artificial neural networks and statistical models based on the weighted moving average are proposed to capture the patterns of deferrable and non-deferrable appliances, battery storage, electric vehicles, photovoltaic modules, buildings and grid connections. A dual optimisation method is devised to minimise the electricity bill and achieve thermal comfort. The proposed optimisation solver is a two-step optimisation method based on genetic algorithm and mixed integer linear programming. A comprehensive simulation study was carried out to reveal the effectiveness of the proposed method through a set of simulation scenarios. The results of the quantitative analysis undertaken as part of this study show the effectiveness of the proposed algorithm towards reducing electricity charges and improving grid elasticity.

Keywords: Adaptive Model Predictive Control; Home Energy Management System; Smart Grid; Demand Response; Distributed Energy Resources; Artificial Neural Network; Genetic Algorithm

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Nomenclature	
AI	Artificial Intelligence
AMPC	Adaptive Model Predictive Control
ANN	Artificial Neural Network
BESS	Battery Energy Storage Systems
DER	Distributed Energy Resources
DR	Demand Response
EV	Electric Vehicle
GA	Genetic Algorithm
GHG	Green House Gas
HEMS	Home Energy Management System
HVAC	Heating, Ventilating and Air Conditioning
IoT	Internet of Things
LP	Linear Programming
MAE	Mean Absolute Error
MILP	Mixed-Integer Linear Programming
MPC	Model Predictive Control
PID	Proportional Integral Derivative
PLC	Power-line Communication
PV	Photovoltaic
RES	Renewable Energy Sources
RTP-DA	Real-Time Pricing – Day-Ahead
SoC	State of Charge
ToU	Time of Use
V2G	Vehicle to Grid
WMA	Weighted Moving Average

1. Introduction

Energy sector reform is an essential input towards attaining the goal of GHG reduction. The European Union (EU) has undertaken a thorough reform of its energy model for realising a low-carbon society [1]. The changes that are underway in the energy sector together with the integration of more variable renewable energy sources (RES) will increase the need for demand flexibility [2]. Some key components that can support the intermittency and the non-dispatchable nature of wind and solar energy production are demand-side resources and storage technologies that can transfer flexibility from generation to consumption. Electricity demand in residential markets will undergo a transformation due to the demand response (DR) programmes, distributed energy resources (DER) and new battery storage capacities. DR programmes concern the changes in electricity usage by the end users of their normal consumption patterns in response to changes in the price of electricity or incentive payments by improving grid elasticity. Distributed energy is the generation and storage of energy performed by a variety of small, grid-connected devices referred to as DER. They are located within the electricity distribution system at or near the end user, and they can provide services to fill the flexibility gaps at the local and transmission levels. DER, DR and electric vehicles (EVs) play an important role for a gradual transition to a green economy.

According to Eurostat [3], in 2018, energy consumption in households represented 26% of the total energy consumption. In the EU-28, the consumption of electricity by the household sector increased by 12.6% from 2000 to 2017, and because of fossil fuel depletion, it is more than probable that there would be an increase in electricity demand in the subsequent decades. The major potential in the household sector's demand flexibility remains untapped. Smart home services is a key part of smart grid development [4]. EVs, battery energy storage systems (BESS) and roof-top photovoltaic (PV) systems combined with time-varying prices can accomplish positive results for the environment and consumers [5]. The introduction of BESS is an effective solution to use energy on demand [6], and deferrable appliances and EVs are suitable for DR [7]. Smart appliances include white goods, heating, ventilation and air conditioning (HVAC) systems, and storage systems.

In a smart home, domestic appliances are intelligent and networked together. The communication infrastructure of the grid and smart homes can comprise wireless or wired connections. The internet of things (IoT) technology has the potential for connecting devices through the Internet and providing a robust information infrastructure [8]. A multitude of protocols, standards and configurations are possible for communication; therefore, an open interface communication system to ensure interoperability is a key factor in IoT appliances. Wireless technologies such as ZigBee, WLAN, 4G/5G, WiMAX are suitable for the deployment of smart homes. The power-line communication (PLC) technology uses power transmission conductors to simultaneously transmit data and AC electric. The products based on the PLC technology are also suitable for home automation, energy monitoring and energy storage systems' management.

The present paper proposes a novel adaptive model predictive control (AMPC) for modelling electricity consumption and creating control strategies to optimise the household sector using learning-based approaches. The AMPC is suitable for deploying the home energy management system (HEMS) in residential buildings. The proposed algorithms take into account vehicle to grid-electric vehicle (V2G-EV), PV arrays combined with BESS, smart appliances and heat pump-based HVAC systems. This novel approach addresses energy optimisation for the calculation of economic dispatch based on the price of electricity. About 50 publications were reviewed for the purpose of this study. These articles despite being substantial in number and a representative sample of the literature available on state-of-the-art technology, is not the total number of articles on the subject.

1.1. Background and literature review

In this section, a bibliographic review of previous works related to the subject of this study has been presented. First, the model predictive control (MPC) approach for buildings has been reviewed followed by an analysis of the models and management of HVAC and household electrical devices.

1.1.1. MPC

MPC is, in essence, an advanced method of process control in which a model is used to predict the performance of the controlled plants over a finite time horizon. The models predict the change in the dependent variables caused by changes in the independent variables. The main advantage of this method is that it allows the current timeslot to be optimised, simultaneously taking into account future timeslots, while only implementing the current timeslot and then optimising it repeatedly. MPC requires an energy flow model to perform forecasts, a cost function *'J'* and an optimisation algorithm to minimise the cost function.

The state-of-the-art technology in forecasting models for HEMS are physics-based mathematical models, autoregressive models like AR, ARX, ARIMA, artificial neural networks (ANNs), deep learning networks, fuzzy models, support vector machines and hybrid structures. These are some of the most representative methods that have been reviewed. Previous works about HEMS's optimisation developed rule-based energy-scheduling methods, but the lack of a logical design methodology in these methods caused other optimal energy management strategies, such as linear programming (LP), mixed integer linear programming (MILP), stochastic optimisation, GA and self-scheduling, to gain more attention.

Driven by the objective of price reduction in electricity storage and the improvements in communication and computing devices, several strategies that stimulate an efficient use of energy have been studied. In [9], a comparison was made between an MPC, the ON/OFF and proportional integral derivative (PID) controls of an air conditioning unit (AC system) controlling the temperature inside a room. A strategy for battery use in households with grid-connected PV systems via MPC for peak shaving was studied in [10]. An occupancy prediction method was presented in [11]. Several papers assessed energy management systems for buildings [12]–[20], and two of them dealt with the integration of a plug-in EV, PV array and heat pump [21], [22]. Another study [23] proposed an MPC method which allows EVs to participate in the grid voltage regulation and keeps EVs charged to the desired state. This research deals with linear appliances' objective function and non-linear devices such as HVAC or PV [24]. Hence, this approach implements an AMPC with hybrid non-linear programming and LP methods that are suitable for cost-effective HEMS based on the energy-pricing scheme that can have uncertainties, non-linear models and constraints.

1.1.2. HVAC modelling and optimisation

The power consumption by HVAC systems to obtain the suitable conditions for thermal comfort in buildings is almost half of the building's total energy consumption. Modelling and optimising energy consumption for HVAC is being widely studied. White-box models employ a method derived by using the laws of physics, thermodynamic principles and technical features of the HVAC system. Analytical models are highly developed to simulate and optimise the energy consumption profile of the building. Physics-based models provide reliable results for the management of HVAC systems. However, it is not easy to obtain parameters such as thermal coefficients, irradiance or occupancy, which makes it difficult for these models to be implemented in real-time applications [25] as the problem of uncertainty remains.

Nowadays, artificial intelligence (AI) methods are attracting an increasing interest due to the complexity and non-linearity of HVAC systems. Numerous black box data-driven approaches have been proposed to capture the thermal behaviour. AI includes several techniques such as regression algorithms, ANNs, fuzzy logic, support vector machine, genetic programming or their combinations. These are well-known hybrid systems [26]. ANNs can be used to predict energy consumption more consistently than traditional simulation models and regression techniques. Several studies have established the superiority of ANN models over linear and physical models in modelling the non-linear HVAC systems. However, to build models using ANN, a significant amount of controlling parameters are required, and above all, ANN suffers from generalisation capability [27] .

An extensive analysis of the modelling techniques used in building HVAC systems was performed in [27] and [28]. This analysis provides a state-of-the-art review of ANN based on the MPC and the optimisation of residential HVAC systems. Most researchers have focused on predicting the electric load profile of an HVAC system to be used as an ANN model for building energy control schemes [25], [26], [37], [29]–[36]. The objective of these studies was to exploit the operational flexibility of HVAC systems for the energy optimisation concerning price-based DR, while ensuring grids' voltage stability and occupants' thermal comfort. Other research approaches use the combination of ANNs and genetic algorithm (GA) to optimise the operating point of an HVAC system for minimising power consumption under the constraints of indoor temperatures [38] [39] or to introduce a heating setpoint scheduler that aims to minimise the energy consumption for heating [40]. Some papers suggest ANNs for control purposes. A fuzzy neural PID controller with self-tuning parameters for temperature and humidity control in HVAC systems is proposed in [41] and [42]. This controller focuses on the prevention of overheating in buildings, taking into consideration future weather conditions. A data-driven approach to intelligently learn an effective strategy for operating HVAC systems in buildings was developed in [43]. A demand management system to improve the performance in changing (weather or occupancy) conditions was suggested in [44]. In this approach, ANN modelling was performed to predict HVAC systems' thermal behaviour, which was then combined with GA to optimise the cost function.

1.1.3. Household electric devices' modelling and optimisation

An analysis of the electricity consumption pattern in the household sector is one of the most important steps for instituting energy management systems in buildings. Load forecasting is a vital component for smart grid energy optimisation. Towards enabling energy optimization processes, several papers have addressed methods for estimating the electricity consumption patterns of buildings. The deployment of smart meter has promoted studies like [45], which combine consumption data with weather and temporal variables and [46] that uses data mining to discover households' different energy use patterns over a month from their daily-electricity-consumption data. A mathematical estimation approach was proposed in [47] and [48]. A model including energy behaviours, personality traits, demographic information, building features and weather indicators of an individual household and accurately predicting the electricity consumption was studied in [49]. For the present research, mathematical models based on the weighted moving average (WMA) were developed to capture the patterns of deferrable and nondeferrable appliances, after which an MILP optimised the cost function.

1.2. Contribution of this research

Different approaches can improve elasticity to ensure a greener household sector in Europe. Several studies deal with HEMS; however, more efforts are needed to harness the potential of households' demand flexibility. This paper expands the knowledge concerning smart grid with a general-purpose HEMS based on AMPC.

In this context, the contribution of this paper can be summarised as follows:

- It proposes a novel AMPC methodology to find a quasi-optimal solution for the elasticity of electricity consumption in the residential sector, taking into account the cooling, heating and electricity demand. (Very few of the papers reviewed in the course of this research address this issue.)
- It develops a hybrid model methodology based on ANNs for determining buildings' thermal behaviour and electricity consumption statistics.
- It implements a two-step optimisation solver based on GA and MILP, which has been formulated as a dual optimisation method.
- It tests the proposed AMPC methodology using actual data obtained from residential buildings.

1.3. Organisation of this paper

This paper is organised as follows: Section 1 introduces the objective to harness the potential of household demand flexibility to deal with future challenges in energy, and considers AMPC for HEMS in dealing with DER and DR. Some approaches have been revised to provide a theoretical background. Section 2 describes the general framework of the proposed approach and presents the modelling techniques that can be used for predictions. The formulation of energy optimisation is explained in detail in Section 3. Section 4 addresses AMPC validation, training the algorithm with real data to capture the building's operational patterns and simulating energy management strategy. A discussion about the impact of management control on comfort and electricity bill is mentioned in Section 5. Finally, Section 6 presents the main conclusions of this research vis-à-vis the proposed approach.

2. Modelling methodology

This section details the methodology used to model the energy flow for electric devices in a residential building. The system under study consists of a household with an EV, a PV array combined with battery storage, smart appliances and a heat pump HVAC system, as depicted in Figure 1.

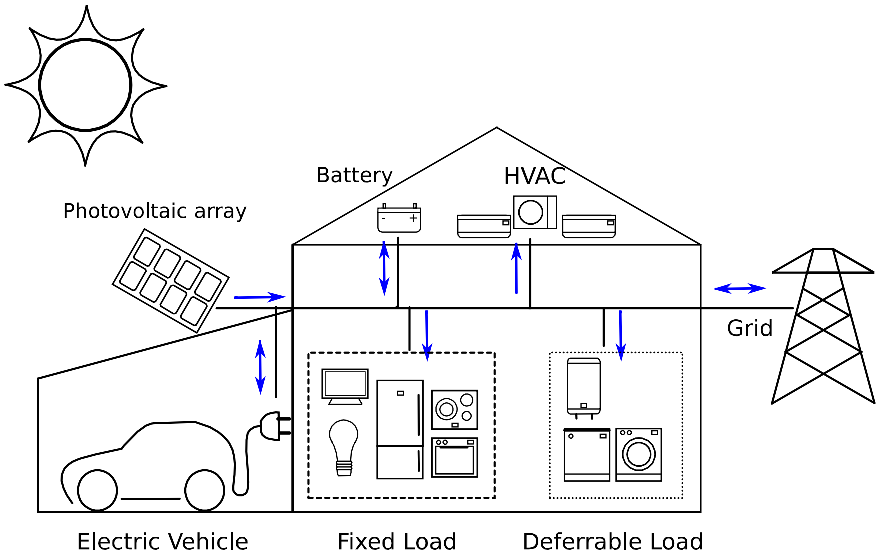

Figure 1. Household under study: an illustration

This approach incorporates a set of data-driven models based on the analysis of the data on the specified system. The data-driven models find relationships between variables without explicit knowledge about the physical behaviour of the system, facilitating its application to buildings with different characteristics.

2.1 AMPC framework

A model of the household's energy flow captures how system behaviour is affected over a horizon time by controlled inputs and disturbances. Therefore, the model can predict the future energy flow response in the building as a function of a set of control decisions. The adaptive feature is implemented via model recalculation using data feedback. In this approach, a hybrid GA and MILP solver is employed. The developed custom optimisation solver uses these predictions to find an optimised control sequence in accordance with the cost function and system constraints. The energy flow is calculated at the beginning of each timeslot *'k'* for the 48h prediction horizon. The real energy flow is updated hourly at the end of each timeslot and then repeatedly optimised. Inconsistencies between the real and forecasted energy flow can be overcome through repetitive optimisation calculations and the updating of its control signals in every step. In our research, we found that AMPC manages an HVAC system, deferrable appliances, battery storage, EV, grid power and predicts fixed load and PV generation to minimise electricity costs as shown in Figure 2. Moreover, AMPC ensures that the electric vehicle's state of charge (SoC), thermal comfort and load demand requirements are taken into account while the grid's energy flow is subjected to the time of use (ToU) electricity tariff with three price levels.

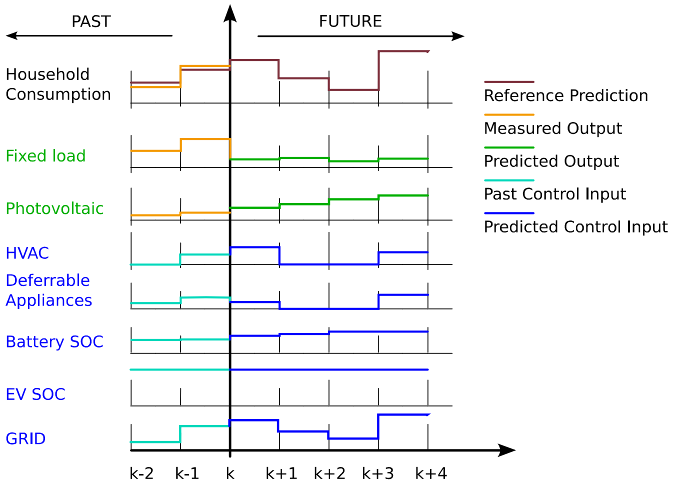

Figure 2. The household's MPC scheme

Figure 2 shows an example of a quasi-optimal control sequence, which is obtained by an AMPC algorithm. At every step *'k'*, AMPC uses models to predict electric consumption and generation, and a cost-minimising control strategy is computed over a finite horizon. When the first step of the control strategy is implemented, the household state is measured again to overcome the disturbances in the predicted state, and the optimisations are repeated, starting from the new current state.

2.2 Modelling electricity consumption

Predicting the household electricity consumption and generation represents a key step for implementing energy management systems in buildings. This approach predicts the energy flow based on previous measured data and energy consumption patterns, as shown in Figure 3. Different types of electrical devices have different load patterns, which makes the load type an important factor in modelling. Loads pertaining to household electrical consumption are categorised according to their characteristics in terms of use or connection arrangement:

- Deferrable load is an electrical load that requires a certain amount of energy within a given time period, although the exact timing is not important. Therefore, it can be scheduled during off-peak hours.
- Interruptible loads are those that can be interrupted momentarily.

- Fixed loads are non-deferrable and non-interruptible.

For household customers, the HVAC system uses the most power-intensive load, so heat pumps and air conditioners are critical in the optimisation process. An HVAC system is classified as an interruptible, but non-deferrable, load; however, the thermal inertia of buildings allows to carry out a management strategy that takes advantage of the electricity periods with low rates. Buildings' thermal behaviour will be captured by a trained ANN that deploys a management strategy based on a GA.

Washing machines, dish washers and clothes dryers are considered as deferrable loads, while water heaters are considered deferrable and interruptible. These household appliances can either be scheduled for electricity periods with low rates and periods with PV overproduction or shifted to reduce peak demand. The infrastructure for charging EVs provides great flexibility opportunities. A V2G-EV is suitable for DR, avoiding EV charging from peak demand; this also applies to energy storage, which increases flexibility on the consumer's side. EV charging is deferrable as well as interruptible. In this research, deferrable appliances and EVs were considered smart and manageable. All other loads, associated with fridges, lights, ovens, stoves and multimedia devices are considered non-flexible. The model to estimate the availability and electrical load profile was based on mathematical calculations using one month's WMA from the data collected for the building under analysis. The calculations were performed on an hourly basis to capture the weekly load patterns.

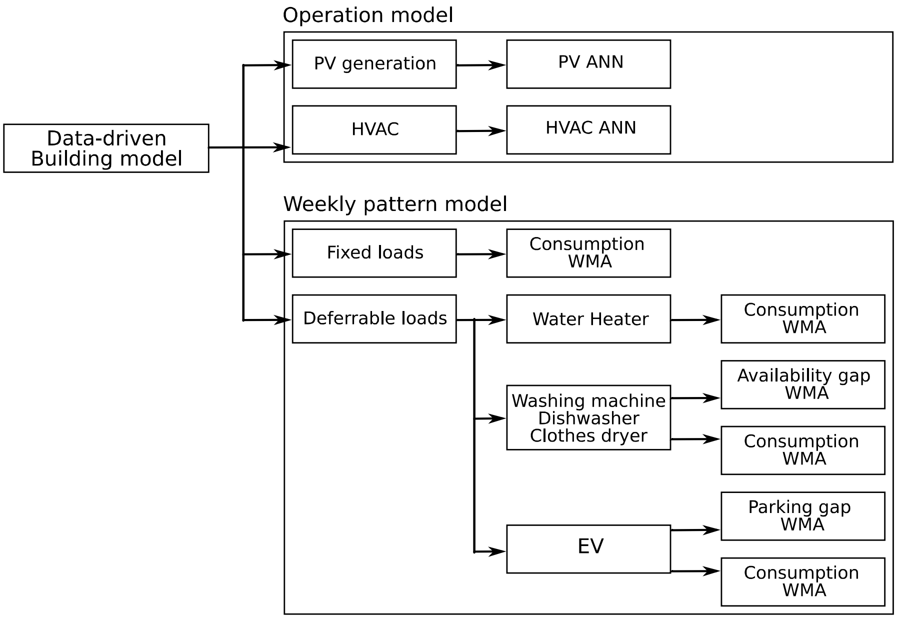

Figure 3. Building model

Modelling HVAC

The indoor temperature data according to the HVAC energy consumed is modelled using an ANN. Physical models require a detailed study of the building's characteristics, thus making it difficult to extrapolate the model for different buildings. Data-driven models are proposed to deal with the problem of parameterisation, facilitating their deployment in buildings. Another important reason to apply an ANN is that it performs better with non-linear data such as that generated by HVAC. That is due to its influential feature in handling non-linear data. The use of ANNs for HVAC modelling has been supported by several studies that establish the superiority of ANN models over linear and physical models in modelling non-linear HVAC systems [27]. ANNs are retrained on a weekly basis to adapt and capture the thermal behaviour of the building at different occupancy rates, weather conditions and energy efficiency. The training process is carried out using a backpropagation algorithm that searches through multiple iterations values for the neural network model's weights, which results in good performance based on the training dataset. Backpropagation tunes the weights of a neural network based on the error rates obtained in the previous epoch to reduce error rates and makes the model reliable by increasing its generalisation. Inputs of raw datasets are normalised before the training and testing process. The whole process is shown in Figure 4. The measured error in the mean absolute error (MAE) is used for evaluation, making a comparison between the predicted and observed values in the training and testing tasks.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \tag{1}$$

where y_i is the predicted value and x_i is the true value.

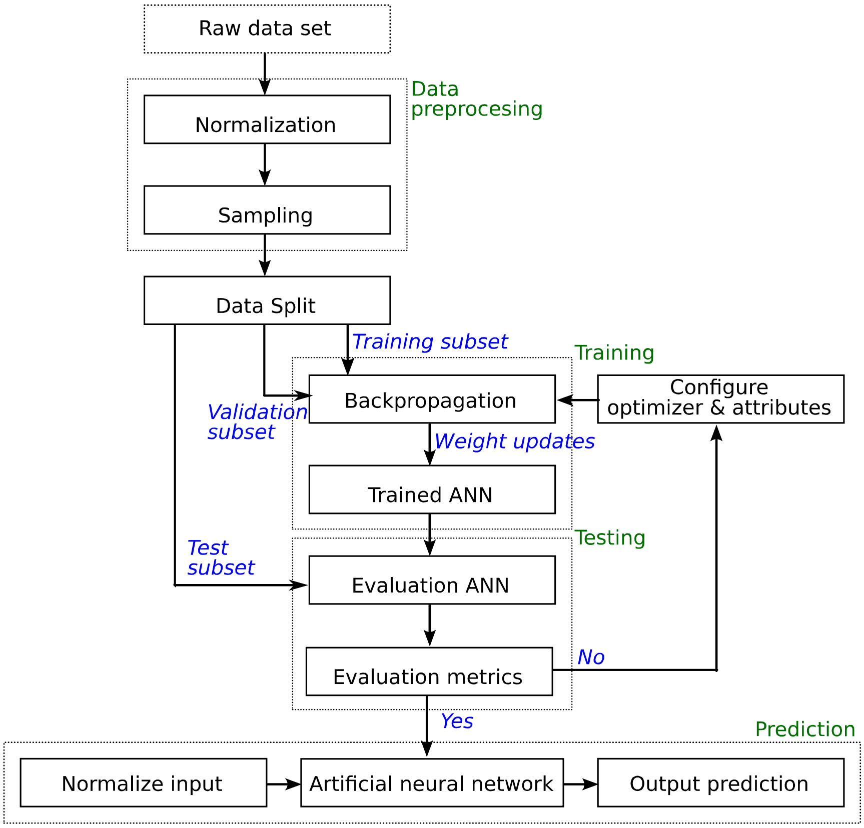

Figure 4. Neural network operations

In this research, the key factors affecting indoor temperature and buildings' thermal behaviour were identified to be fed into the ANN. Some specific requirements such as a trade-off between accuracy and input simplicity were considered. Weather forecast data, including irradiance, temperature and humidity were used in the predictions. Further, the solar altitude and azimuth were included to determine the effect of seasonal solar irradiance on thermal load in conjunction with occupancy. The influence of thermal inertia on the building is represented by the 48-hour outdoor air temperature average and the present and previous room temperature data. Figure 5 illustrates the HVAC system's neural network.

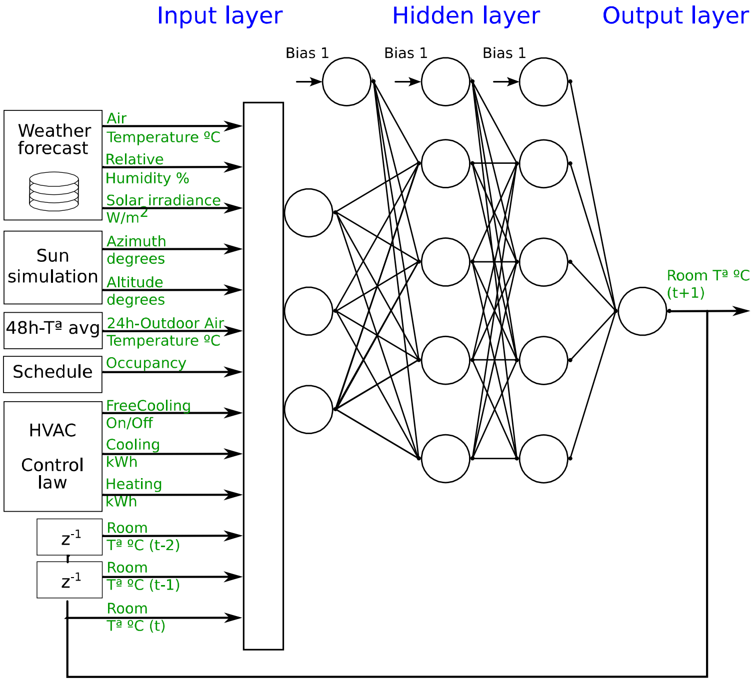

Figure 5. An HVAC system's neural network model

An HVAC model was implemented with four dense layers ANN, consisting of an input layer, 128 sigmoid neurons in both the hidden layers and one sigmoid neuron in the output layer. The number of neurons in the input layer is determined by the identified input variables. The network topology's definition has been based on the performance of a set of candidates. This topology was selected due to its best performance when compared with the other candidates. An ANN was implemented with Keras [50] based on TensorFlow and codified using Python. The solar altitude and azimuth data was calculated with the help the opensource library, Pysolar [51]. The weather forecast data was collected from the State Meteorological Agency. The data on occupancy, HVAC's consumption and indoor temperature were collected by HEMS. The measured and collected input values were normalised to obtain a uniform one-hour sampling time in the training process.

2.2.1 Modelling the fixed load consumption

Fixed loads are those loads for which electric consumption does not have to be deferred or interrupted under normal grid circumstances. Usually, there is a close relationship between fixed loads' consumption patterns and hourly occupancy. A WMA is proposed to represent the fixed load's pattern. Every previous value is weighted with a factor from the weighting group in the univariate forecast profile. The WMA assigns a greater weight to the most recent data and less weight to data in the distant past. It is obtained by multiplying each number in the dataset by a predetermined weight and then summing up the resulting values. It is for this reason that the prediction model is more sensitive to adapt itself to the changes in the load's pattern. The WMA for the fixed load consumption is calculated using the following equation:

$$Cf_{[d,h]} = \frac{\sum_{w=1}^{n} W_w * C_{[w,d,h]}}{\sum_{w=1}^{n} W_w} \tag{2}$$

In the equation, the fixed load consumption $Cf_{[d,h]}$ for the forecast profile model is calculated every day *'d'* and for hour *'h'*, where $C_{[w,d,h]}$ correspond to the last-stored-consumption data from every week *'w'*, day of the week *'d'* and hour *'h'*. The constant *'n'* is the number of weeks used in the calculation of the WMA. The weight W_w is the number of weeks, where *'n'* corresponds to the last week and value 1 to the oldest week. For the present research, the gap selected was four weeks. The calculations were performed weekly to adapt to the weekly consumption pattern for the model's forecasting purposes. According to work and occupancy schedule, the algorithm adapted its forecasting to consider the days off.

2.2.2 Modelling the deferrable load consumption

Deferrable loads are suitable for changes in the electricity usage by customers from their normal consumption patterns in response to demand optimisation. The control algorithm optimises deferrable load scheduling under the constraints of electricity supply and demand forecast. When deferrable appliances are activated, the MILP scheduler creates the optimal plan in a limited amount of time to adjust to the appliance's deadlines. Modelling the time availability and consumption of deferrable load allows week-ahead predictions about deferrable appliances' demand, as illustrated in Figure 6.

This approach models the weekly availability pattern and consumption for the washing machine, dish washer and clothes dryer. A WMA is proposed to model the availability pattern and consumption. Equation 3 calculates the availability requirements for appliances following a four-week gap. The model calculations are performed weekly to achieve adaptive requirements. The availability for the deferred state is defined by '1';otherwise it is '0'.

$$Ad_{[d,h]} = \frac{\sum_{w=1}^{n} W_w * \mathrm{A}_{[w,d,h]}}{\sum_{w=1}^{n} W_w} \tag{3}$$

$Ad_{[d,h]}$ corresponds to the timeslot the appliance is available, where it is supposed to be either of the following:

- $\text{Active or standby appliance, if } Ad_{[d,h]} \geq 0.5$
- $\text{Inactive appliance, if } Ad_{[d,h]} < 0.5$

The appliance's consumption model is estimated in Equation 4 by the WMA of 20 last active periods.

$$Cd_{[h]} = \frac{\sum_{w=1}^{n} W_w * C_{[h]}}{\sum_{w=1}^{n} W_w} \tag{4}$$

where *'n'* corresponds to the number of four timeslots of hourly consumption data. Predictions for the actual availability, deadline and consumption values are replaced when the smart deferrable appliances are activated.

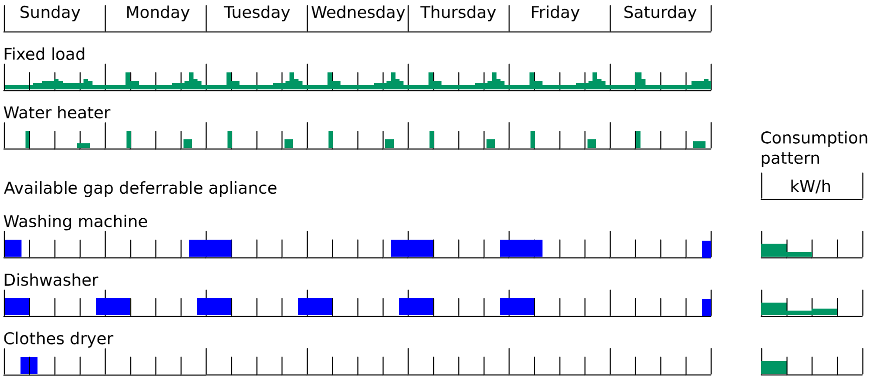

Figure 6. Household appliances' consumption pattern models

The water heater can store heat at any time; therefore, the MILP scheduler optimises consumption mainly to periods of low electricity rates or solar overproduction. Hot water consumption reduces the temperature of water in the tank, so the temperature should be kept in an acceptable range T_r. A simple model represented in Figure 7 is proposed to illustrate the stored energy in the water heater E_{WH}, multiplying the hot water tank volume *'V'* by the temperature range T_r and converting de unit into Wh, considering that 1 Wh is equal to 3600 J, and the water specific heat is 4180J/(kg ºC)

$$E_{WH} = \frac{T_r * V * 4180}{3600} \tag{5}$$

where the temperature range T_r is the subtraction between high T_h and low T_l temperature parameters.

$$T_r = T_h - T_l \tag{6}$$

The water heater's SoC for water temperature T is defined by next equation.

$$SoC_{WH} = \frac{T - T_l}{T_r} \tag{7}$$

Then, the energy consumption is calculated by multiplying the negative SoC variation by energy capacity.

$$C_{WH} = |\nabla SoC_{WH} * E_{WH}| \tag{8}$$

The water heater's consumption pattern is calculated according to the temperature variation by Equation 9. This equation estimates the delivered hot water and standby and distribution losses. The energy conversion efficiency to transform electrical energy into heat energy is assumed to be equal to 1.

$$C_{WH[d,h]} = \frac{\sum_{w=1}^{n} W_w * C_{WH[w,d,h]}}{\sum_{w=1}^{n} W_w} \tag{9}$$

The SoC in the water tank is the variable for optimisation. The model used to define the SoC of time '*k+1*' according to the energy consumption C_{WH} and electrical heating H_{WH} at time k is depicted in Equation 10.

$$SoC_{WH}(k+1) = SoC_{WH}(k) - C_{WH}(k) + H_{WH}(k) \tag{10}$$

The water heater's operation must maintain a high SoC over time to ensure hot water availability and comfort. To overcome this constraint, it is necessary that the SoC must be equal to SoC_{WHmax} every early morning. The SoC_{WHmin} makes sure that water heater's SoC is over a threshold to deal with the uncertainty between the real and predicted values. SoC_{WHmax} is equal to E_{WH}

$$Water\ Heater \rightarrow SoC_{WHmin} \leq SoC_{WH} \leq SoC_{WHmax} \tag{11}$$

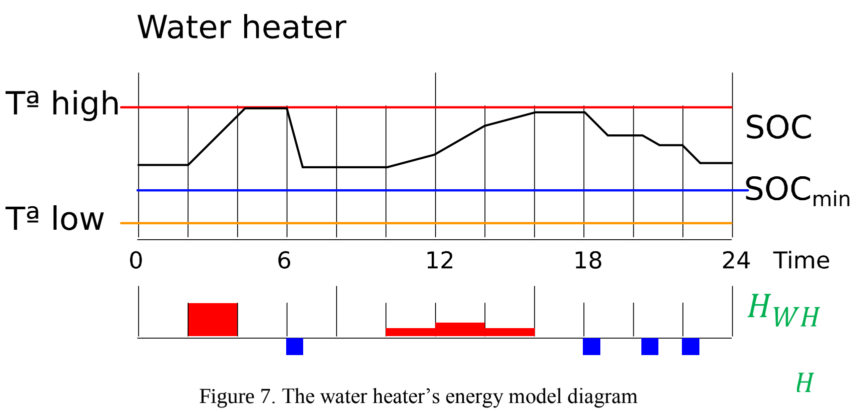

Figure 7. The water heater's energy model diagram

2.2.3 Modelling EVs and defining constraints

EVs using V2G technology enable energy to be bought or sold to the power grid from the battery. With vehicle-to-grid technology, a car battery can be charged and discharged based on the rates, load consumption and PV generation intermittency. The SoC in the vehicle's battery is the variable for optimisation. The battery model used to define the SoC of time *'k+1'* when battery is charging or discharging at time *'k'* is captured by Equation 12.

$$SoC_{EV}(k+1) = SoC_{EV}(k) + ef_{EVch} * P_{EVch}(k) * \frac{1}{\Delta t} - ef_{EVdis} * P_{EVdis}(k) * \frac{1}{\Delta t} \tag{12}$$

where P_{EVch} and P_{EVdis} are the energy flows when charging and discharging the battery, ef_{EVch} and ef_{EVdis} are the efficiencies of charging and discharging and *'Δt'* is the timeslot duration in hours. Up and low boundaries are defined for the SoC and charging and discharging power.

$$SoC_{EVmin} \leq SoC_{EV} \leq SoC_{EVmax} \tag{13}$$

$$P_{EVch\,min} \leq P_{EVch} \leq P_{EVch\,max} \tag{14}$$

$$P_{EVdis\,min} \leq P_{EVdis} \leq P_{EVdis\,max} \tag{15}$$

This paper proposes the model represented in Figure 8 to determine the weekly availability pattern and SOC requirements. This model is based on four EV parameters: plugged-in time, plugged-out time, the SoC at the plugged-in time and the SoC required at the plugged-out time. The gap selected is four weeks, and the adaptive model calculations are performed weekly. The cost function in the optimisation section includes the cycling ageing when the battery is discharged to improve the battery's lifetime through a trade-off between the optimal performance and battery-ageing cost.

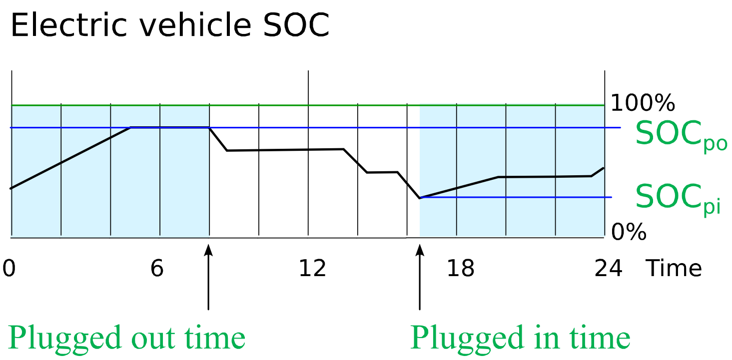

Figure 8. EVs' energy & params model diagram

A WMA is proposed in Equation 16 to calculate the EV's availability. The EV's plugged state is defined by '1' and is otherwise '0'.

$$A_{EV[d,h]} = \frac{\sum_{w=1}^{n} W_w * A_{EV[w,d,h]}}{\sum_{w=1}^{n} W_w} \quad (16)$$

$A_{EV[d,h]}$ corresponds to the availability where the following is supposed:

- EV plugged '1' if $A_{[d,h]} \geq 0.5$
- EV unplugged '0' if $A_{[d,h]} < 0.5$

The WMA for predicting the SoC at the plugged-in time and the SoC required at the plugged-out time are calculated by Equations 17 and 18 respectively.

$$SoC_{po} = \frac{\sum_{w=1}^{n} W_w * SoC_{po[w,d]}}{\sum_{w=1}^{n} W_w} \quad (17)$$

$$SoC_{pi} = \frac{\sum_{w=1}^{n} W_w * SoC_{pi[w,d]}}{\sum_{w=1}^{n} W_w} \quad (18)$$

2.2.4 *Modelling PV generation*

To forecast PV's power output accurately, an ANN has been proposed as depicted in Figure 9. The ANN is trained weekly through backpropagation with previous measured data. The methodology for the training and testing process is explained in Figure 4. The available data is used to train the PV's ANN, to forecast generation and to evaluate the performance of the trained ANN. The correlation data analysis in this previous study [52] identifies the global radiation, air temperature and humidity for the forecasting tasks with exogenous variables, whereas solar irradiance is considered to be the most critical parameter in solar power generation units. Furthermore, in [53], it was identified that the incorporation of azimuth and zenith parameters in the model significantly improves the performance of forecasting via ANNs.

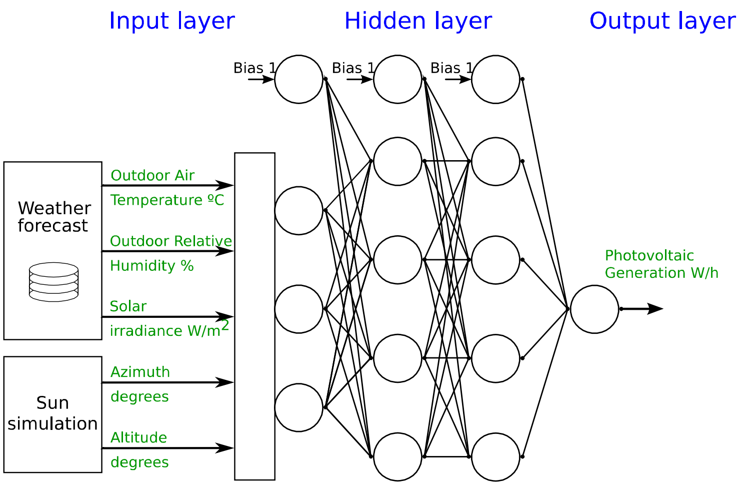

Figure 9. PV neural network model

2.3 Defining battery storage constraints

Storage technology provides flexibility to integrate renewable energy sources and improve the grid operation. The main physical parameter of the battery storage is its SoC. The battery model used to define the SoC of time *'k+1'* when the battery is charging or discharging at time *'k'* is calculated by Equation 19.

$$Battery \rightarrow SoC_B(k+1) = SoC_B(k) + ef_{Bch} * P_{Bch}(k) * \frac{1}{\Delta t} - ef_{Bdis} * P_{Bdis}(k) * \frac{1}{\Delta t} \tag{19}$$

where P_{Bch} and P_{Bdis} are the energy flows when charging and discharging the battery, ef_{Bch} and ef_{Bdis} are the efficiencies of charging and discharging and 'Δt' is the timeslot duration in hours. The up and low boundaries are defined for the SoC, charging and discharging power, in

$$Battery \rightarrow SoC_{Bmin} \leq SoC_B \leq SoC_{Bmax} \tag{20}$$

$$Battery \rightarrow P_{Bch\,min} \leq P_{Bch} \leq P_{Bch\,max} \tag{21}$$

$$Battery \rightarrow P_{Bdis\,min} \leq P_{Bdis} \leq P_{Bdis\,max} \tag{22}$$

The SoC_{min} sets the battery's SoC over a threshold to deal with the uncertainty between the real and predicted values and to prevent deep discharge. The cost function in the optimisation section includes cycling ageing when the battery is charged or discharged to improve the battery's lifetime through a trade-off between the optimal performance and the battery-ageing cost.

2.4 Defining the grid and power balance constraints

A grid's power constraints are defined by Equation 23.

$$P_{Grid\,min} \leq P_{Grid} \leq P_{Grid\,max} \tag{23}$$

where, $P_{Grid\,min}$ can be a negative value when selling electricity and $P_{Grid\,max}$ corresponds to the electrical capacity hired. The power balance in the building under study, shown in Figure 1, is described by Equation 24.

$$P_{Grid} + P_{PV} + P_{Bat} + P_{EV} - P_{Load} = 0 \tag{24}$$

where P_{Grid} is the power from/to the main grid, P_{PV} is the PV power generation, P_{Bat} is the power of the battery, which can be calculated by ($Battery \rightarrow P_{ch} - P_{dis}$), P_{EV} is the power of the EV, which can be calculated by ($EV \rightarrow P_{ch} - P_{dis}$) and P_{Load} is the sum of the HVAC systems', deferrable appliances' and fixed power's consumption.

3 Optimisation methodology

This section addresses the methodology used to carry out the control strategy to optimise the household's electricity flow. A two-step optimisation algorithm has been proposed to minimise the household spending for electricity and improve the self-consumption ratio while ensuring thermal comfort. The algorithm uses two objective functions, one for the GA and the other for the MILP. First, the objective function defined by Equation 26 was formulated as a dual optimisation level, considering the minimisation of electricity costs for the HVAC system and the minimisation of the deviation from the comfort temperature. The MILP's cost function defined by Equation 27 focuses on minimising electricity costs for the rest of electricity consumers. The model's constraints were defined for each one in the previous section. The constraints were defined to determine the discrete nature of some decisions such as storage capacity, technical limits of the grid, appliances and EVs and the time sequence of the appliances. AMPC solves at each hourly control step an optimisation problem to determine which actions should be taken over a 48-hour prediction horizon that are subject to consumption and PV generation's predictions. At each timeslot, the optimisation calculates a sequence of optimised actions after taking into account the household's behaviour over the time horizon. The calculations are repeated in every timeslot with new measurements and updated predictions.

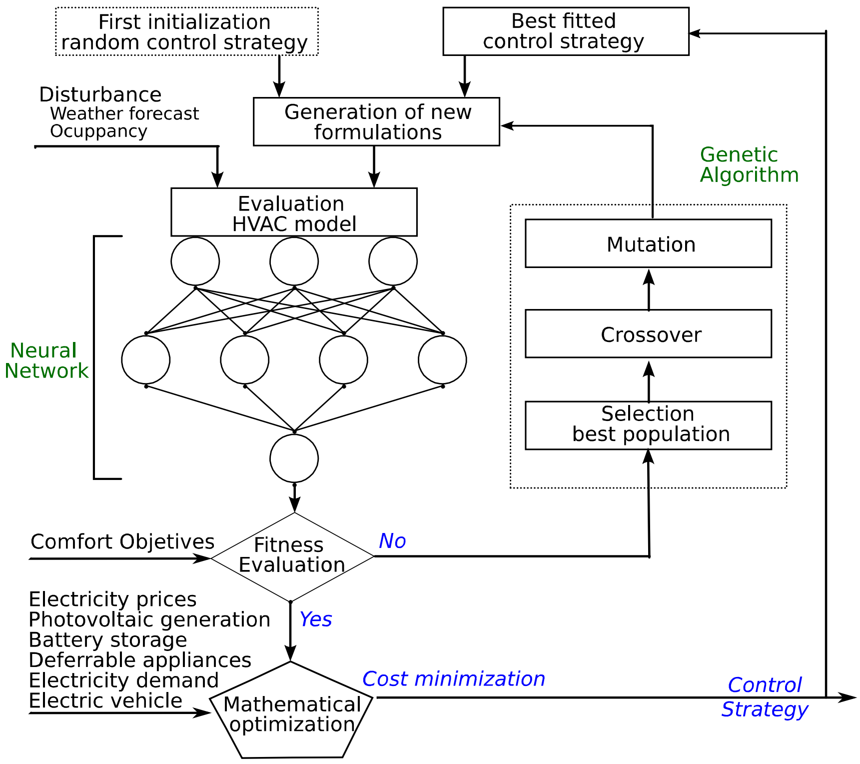

Figure 10. The optimisation solver's approach

The proposed framework in Figure 10 introduces two optimisation levels to achieve thermal comfort and cost minimisation. An HVAC control sequence set is first generated using a GA and then evaluated to fit with the comfort objectives and electric costs. Strategies that accomplish the pre-selected objectives are evaluated with regard to the electric home appliances and EV using a MILP algorithm. The PV generation and charging operation of the storage and EV battery are also considered. The AMPC strategy is proposed to control the electric devices accounting for the operational constraints to achieve comfort and cost reduction for the consumer. The prediction horizon is divided into slots. The timeslot duration is defined as Δt = 60 minutes each, in accordance with the weather forecast, where one day is partitioned into 24 numerated slots. The electricity tariff used is a dynamic electricity tariff with different electricity costs during specific time intervals (on-peak, mid-peak and off-peak) denoted by ToU.

3.1 GA's optimisation

A GA is a metaheuristic search and optimisation technique that has been inspired by natural evolution. Every timeslot, crossover and mutation functions generate a set of potential offsprings for the HVAC control of the previous population. Fitness proportionate selection, also known as roulette wheel selection, is used for selecting potentially useful solutions for recombination. So, evolution will find a suboptimal solution by selecting the best control strategies after several successive generations. A GA is used to find a thermal setting that fits with the comfort directives. Every individual in a population of *'n'* elements defines a set of HVAC strategies for a 48-hour prediction horizon and each is restricted to integer values between 0 and 10.

$$HVAC_{control}^{n} = \{x_1, x_2, x_3, \dots, x_n\}$$

where

$$x_n = \{0,1,2,3,4,5,6,7,8,9,10\}$$

HVAC systems' consumption is calculated by:

$$HVAC_{consumption}^{n} = HVAC_{control}^{n} * \frac{HVAC_{power}}{10} \qquad (25)$$

Then HVAC set of strategies are evaluated in the economic and thermal cost optimisation using Equation 26 to calculate a set of J_{HVAC}. This optimisation process involves variables with opposed objectives, because generally more comfort means more cost and vice versa; therefore, a trade-off between the power consumption and thermal comfort is required. This is formulated as a dual optimisation level to find the optimal strategy adding the electricity cost and the temperature error cost. The hybrid optimisation problem is formulated as follows:

$$J_{HVAC} = min\left\{\sum_{n=1}^{horizon} HVAC_{consumption}^{n} * Electricity\ cost^{n} + \sum_{n=1}^{horizon} (T_{in}^{n} - T_{d}^{n})^2\right\} \qquad (26)$$

where T_{in}^{n} is the predicted temperature of the household, and T_{d}^{n} is the desired setpoint. The strategy with the lowest overall cost from the evaluated set is implemented. The thermal deviation is evaluated in *'n'* timeslot with defined setpoints, and the electricity cost is determined considering the ToU, PV generation and fixed load.

In the first initialisation of the algorithm, a random population of HVAC control strategy is performed. A roll sequence control function was developed to deal with the progress of the timeline. Elements that roll beyond the first position are re-introduced in the end to be fed into the GA every new timestep as shown in Figure 11. This technique allows the best-fitted population to be reused and reduces computational effort.

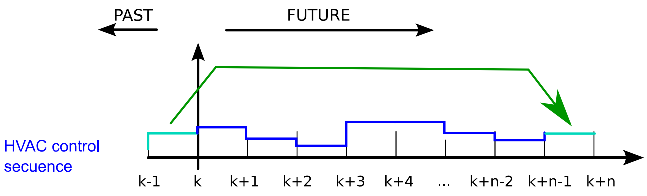

Figure 11. GA population roll function

GA is combined with the HVAC neural network to predict household temperature. This feature makes it possible to store thermal energy during low price hours or PV overproduction.

3.2 *Mixed integer programming's optimisation*

The objective of optimising the mixed integer programming is to minimise operation costs depending on the price for importing electricity, the price at which electricity could be sold, and the battery-ageing cost in a discrete time model over a finite time horizon. Self-consumption takes priority over the sale of PV electricity. The power balance of energy flow in the building under study is described in Equation 24; then, the cost function at the time horizon *n* was defined by the difference between the power bought and sold to the grid and the battery-ageing cost when discharging. The objective function to minimise it, as depicted in Equation 27.

$$J_E = min \sum_{n=1}^{horizon} \left(P_{Grid\ buy}^{n} * C_{TOU}^{n} + P_{Grid\ sell}^{n} * C_{sell}^{n} + PB_{dis}^{n} * CB_{cicle}^{n} + PEV_{dis}^{n} * CEV_{cicle}^{n}\right) * \frac{1}{\Delta t} \tag{27}$$

where the cost of energy J_E is calculated for every control step with a predictive horizon n; $P_{Grid\ buy}$ is the grid energy demand; C_{TOU} is the ToU electric tariff which either can be TOU or real-time-pricing–day-ahead (RTP-DA); PB_{dis} and PEV_{dis} are the battery and EV discharge energy respectively; CB_{cicle} and CEV_{cicle} are the estimated battery and EV cycle ageing cost; Δt is timeslot duration in hours. The PVs' cost was excluded in the cost function to prioritise generation for self-consumption. Renewable power should always be consumed, stored or sold, according to electric price and constraints.

The household operational constraints defined in the models are considered during the operation. Deferrable appliances as well as charge/discharge battery storage are scheduled based on a MILP approach. The purpose of optimising the scheduling is to shift the usage of appliances to off-peak periods. When an EV is also available in a household, its charging is scheduled to achieve the desired SoC by its departure time. The EV's battery is also considered as energy storage. Water heater, storage battery and EV are described and solved as a LP optimisation problem.

A mixed-integer programming is performed to capture the discrete nature of the washing machine, dish washer and clothes dryer. The running of these appliances is defined by a binary-integer LP, ensuring the development of the sequence in the proper order. The optimiser can turn on the smart appliances, so the phases of the power loads are executed sequentially based on its operation duration. Every deferrable appliance *'d'* is characterised by its power consumption array $Cd_{[d,p]}$ that operates over *'h'* time slots. The scheduling is divided into a sequence of *'p'* uninterruptible phases that is correlated with consumption array. Let the binary variables array $ON_{[d,p]}^{n}$ be the decision variable; then, every array for phase *'p'* of the deferrable appliance *'d'* defines the state of the appliance for the timeslot prediction horizon *'n'*, where each element is restricted to integer values between 0 and 1.

$$ON_{[d,p]}^{n} = \{x_1, x_2, x_3, \dots, x_n\}$$

where

$$x_n = \{0,1\}$$

Next, the constraints are defined. If the deferrable appliance *'d'* must be turned on for a 48-hour prediction horizon, an x_n on every phase p will be active once and 0 otherwise.

28

$$\sum_{n=1}^{horizon} ON_{[d,p]}^{n} = 1; \quad \text{for every phase p in appliance d}$$

The first appliance phase is turned on within the availability time window.

29

$$ON_{[d,1]}^{n} \leq Ad_{[d]}^{n}; \quad \text{for every n time slot}$$

The next set of constraints define the sequence will run in the proper order.

30

$$ON_{[d,2]}^{n}(n+1) = ON_{[d,1]}^{n}(n); \quad \text{for every n time slot}$$
$$\dots$$
$$ON_{[d,p]}^{n}(n+1) = ON_{[d,p-1]}^{n}(n); \quad \text{for every n time slot}$$

Deferrable appliances' consumption for power balance is calculated using the next equation.

31

$$Deferrable\ appliances\ consumption = \sum_{d=1}^{Napp} \sum_{p=1}^{Nphases} \left(ON_{[d,p]}^{n} * Cd_{[d,p]} * \frac{1}{\Delta t} \right)$$

3.3 Household AMPC

A two-level optimisation approach is adopted to deal with thermal comfort and economic optimisation. The overall process of the algorithm implemented is illustrated in the following figure.

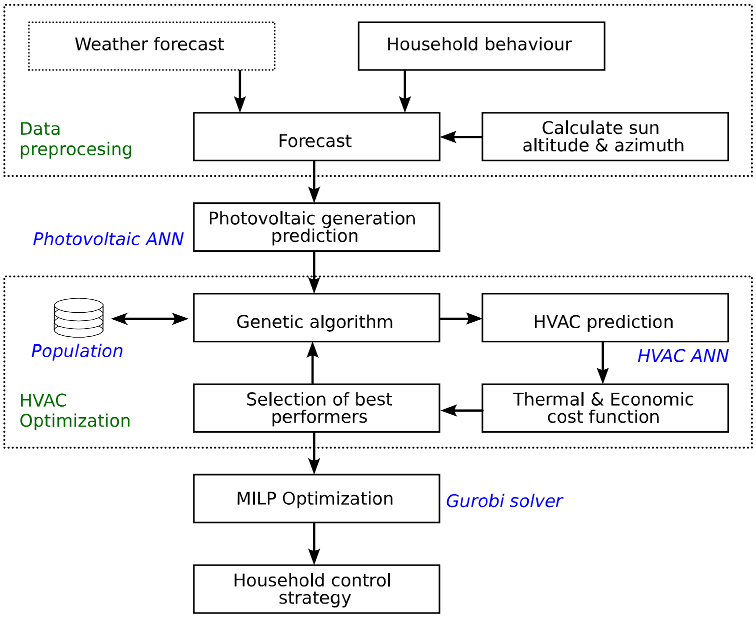

Figure 12. AMPC algorithm

The GA and MILP algorithm minimise at each timestep *'k'* the cost functions using the control variables over the receding horizon without violating constraints. At each *'k'*, the algorithm uses model predictions for making its control decision. GA combined with an ANN model deal with the non-linear HVAC system. The MILP problem involves real and binary variables; therefore, it is classified as linear. The AMPC algorithm calculates the next control inputs for each prediction step, which is iterative until converging to a sub-optimal solution. Nonetheless, only the first control output step is sent to the system. The minimisation process is repeated for every timeslot. A mixed integer linear programme was codified in Python using Gurobi mathematical optimisation solver [54].

4 Simulation

In this section, the proposed methodology is tested in a study case. Figure 13 shows the residential building's scenario. Device parameters and constraints for the study scenario are presented in Table 1.

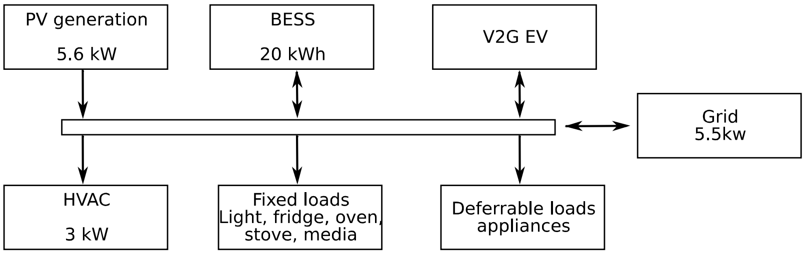

Figure 13. Simulation plant's diagram

Parameter	Value	Description
PmaxGrid	5.5	[kW] max. power input/output on grid connection
BatPmaxChg	3.5	[kW] BESS max. charge power
BatPmaxDis	3.5	[kW] BESS max. discharge power
BatSoCmax	20	[kWh] BESS capacity
BatSoCmin	5	[kWh] BESS min. SOC to overcome power disturbances
BatCost	360	[€] BESS amortisation cost
BatLife	3600	[cycles] BESS cycle ageing
BatEfChg	0.95	BESS charge efficiency
BatEfDis	0.95	BESS discharge efficiency
EVPmaxChg	20	[kW] EV max. charge power
EVPmaxDis	20	[kW] EV max. discharge power
EVSoCmax	60	[kWh] EV battery capacity
EVSoCmin	20	[kWh] EV min. SOC (V2G use threshold)
EVBatCost	600	[€] EV amortisation cost
EVbatLife	4000	[cycles] EV cycle ageing
EVEfChg	0.95	EV charge efficiency
EVEfDis	0.95	EV discharge efficiency
WHCapacity	100	[litre] Weather heater capacity
WHTmax	80	[ºC] Water heater max. Tª
WHTmin	40	[ºC] Water heater min. Tª
WHSoCmin	20	[%] SoC min. to overcome disturbances
WHHeatP	1	[kWh] Water heater heating power
EfInvPV	0.95	PV inverter efficiency
HVACPmax	3	[kW] HVAC max power in electricity consumption
latitude	41.682533	
longitude	-0.872732	

Table 1. Simulation plant's parameters

The AMPC approach requires data-driven models that can learn and make predictions from the data. First, the data-driven models were trained with a set of actual data from some single-family households in Spain. Data was collected in the summer of 2020. Historical weather data was obtained from the State Meteorology Agency, AEMET. The datasets were normalised on an hourly basis, according to the weather data layout.

4.1 Training PV generation model

The PV data was collected from a residential 5.6 kW PV array, which was installed on the building's rooftop. It had paralleled subarrays that consisted of 17 PV series panels. The ANN model for PV generation described in section 182.2.4 was trained and tested with the collected data. A 48-h horizon forecast test was then performed, as show in Figure 14, with a MAE 91 and 105.8 each one.

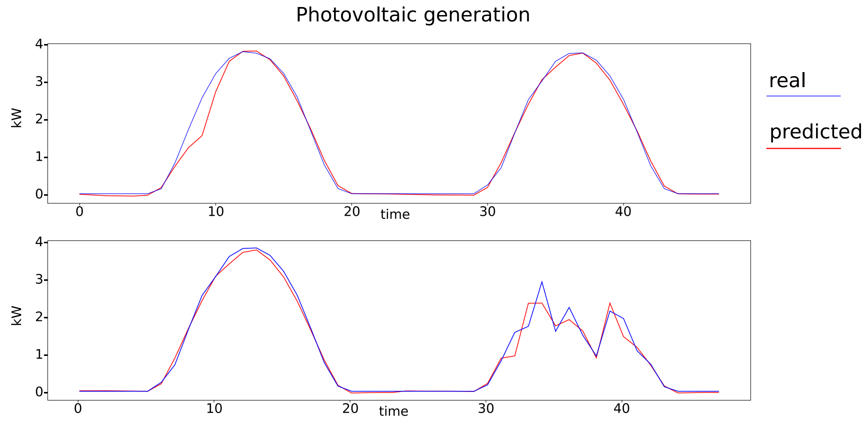

Figure 14. PV ANN

Some deviations in electricity generation were observed. This was because of the solar irradiance error, due to the distance between the state weather station and the location of the building.

4.2 Training HVAC model

The data-driven model for the HVAC system, described in Section 0, based on an ANN was trained to capture the building's thermal behaviour. Indoor temperature, house occupancy and the HVAC system's operational and consumption data was collected from a single-family household. The weather dataset (air temperature, relative humidity and solar irradiance) was obtained from the State Meteorology Agency. The sun azimuth and altitude were calculated according to the altitude and longitude parameters for every date and time. The ANN model was trained with 30.000 epochs. Figure 15 shows the ANN test plot with a high correlation between the predicted and actual values. Test data was assessed with a MAE 0.2062.

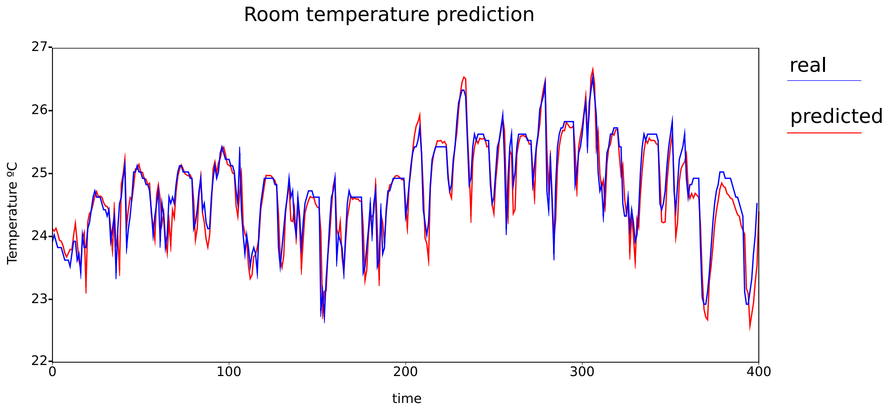

Figure 15. HVAC ANN

4.3 Training the fixed consumption model

Fixed loads' consumption model, described in Section 2.2.1, was trained with the data obtained from the electricity consumption in a single-family household in summer. A close relationship was observed between fixed loads' consumption for each week. A WMA captured the household fixed loads' consumption pattern.

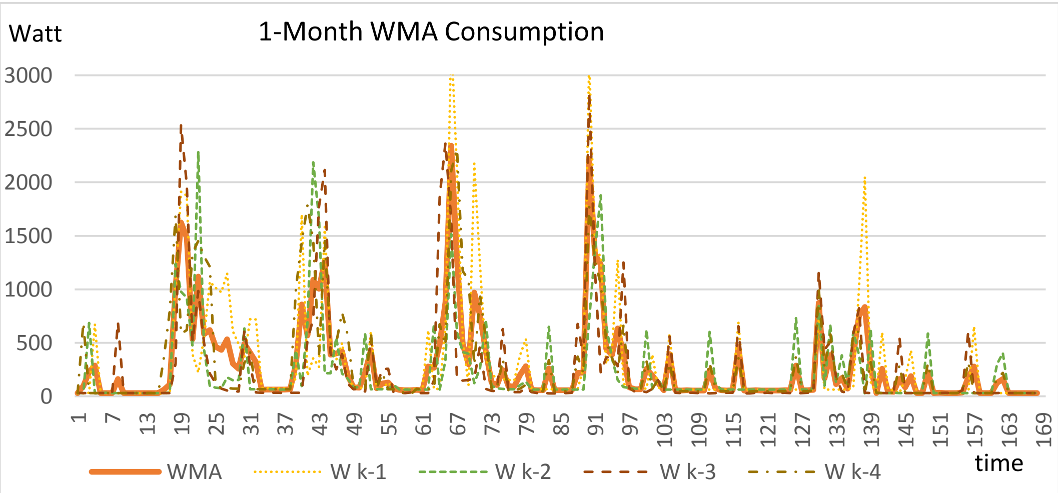

Figure 16. The household's energy balance

4.4 The AMPC' scenario

A 48h-time horizon simulation scenario of the inputs for the AMPC algorithm was defined. The inputs set (Figure 17) included weather and solar irradiance forecast, calculations pertaining to the sun, model predictions and electricity rates. The initial simulation parameters, deferrable appliances' and EV's availability and consumption were also defined.

Parameter	Value	Description
BatSoCini	5	[kWh] BESS SoC
WHSoCini	40	[%] Water heater SoC
Year	2020	
Month	8	
Day	6	
Hour	0	

Table 2. Initial parameters simulation scenario

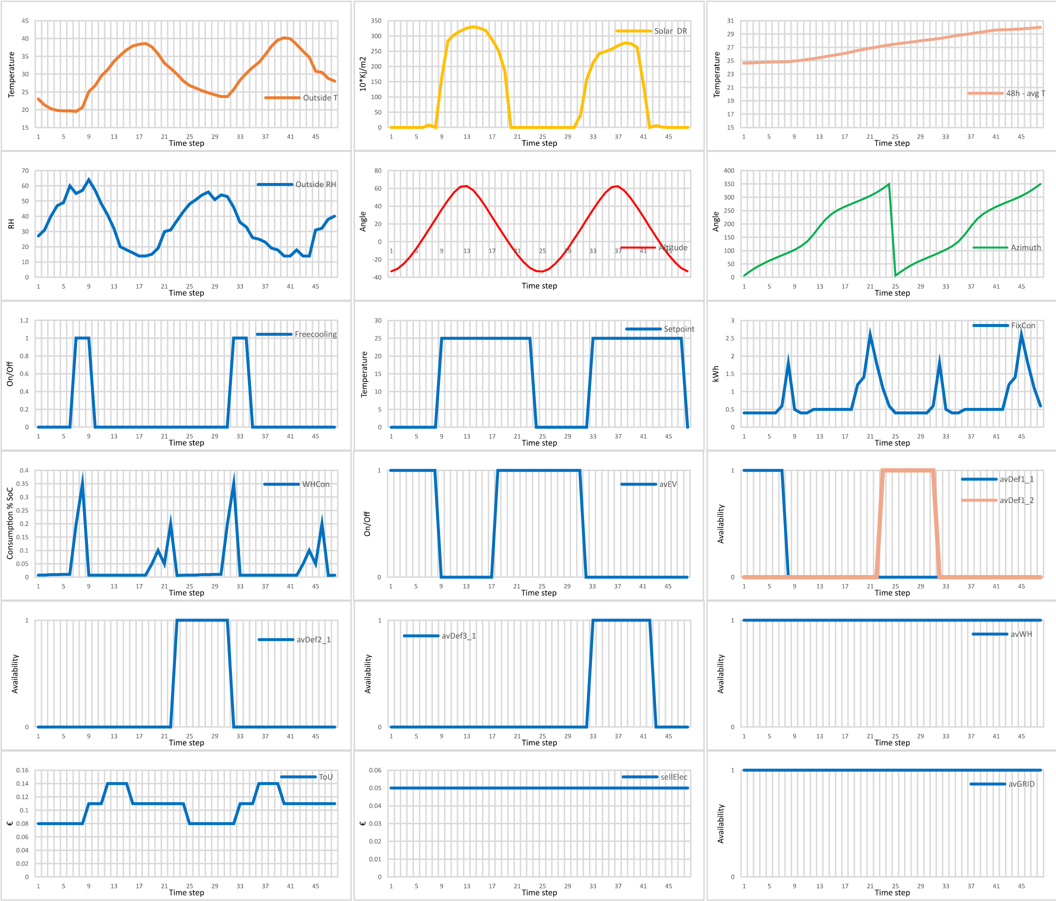

Figure 17. Weather forecast, predictions and electricity rates in the simulation scenario

5 Result and discussion

In this section, the simulation results are provided to evaluate the performance of the proposed AMPC algorithm for deferrable loads' scheduling under the constraint of electricity supply in the power systems. The assessment has been developed by developing a simulated household. The horizon time of the predictive control is from twelve o'clock at night for 48 hours; however, the previous population of GA is set beforehand. The simulated household is considered connected to the grid and equipped with fix loads, (lights, TV, PC, refrigerator, stove and oven) deferrable smart appliances, (washing machine, dish washer, clothes dryer and electric water heater), heat pump-based HVAC system, EV, storage battery and PV array. The household's behaviour and consumption pattern is considered to schedule the appliances usage, and a given ToU and battery cost is assumed, as defined in previous section.

The control strategy for optimisation converges to a solution in a few minutes. The smart appliances schedule is distributed based on off-peak and PV peak. The optimal control algorithm minimises electricity cost under the constraint of electricity supply in the power systems and induces the pre-cooling of the HVAC system. The optimal schedule of household power consumption and the energy sources for every timeslot is given in Figure 18. The diagrams show the balance between consumption and the energy sources with the EV's demand included.

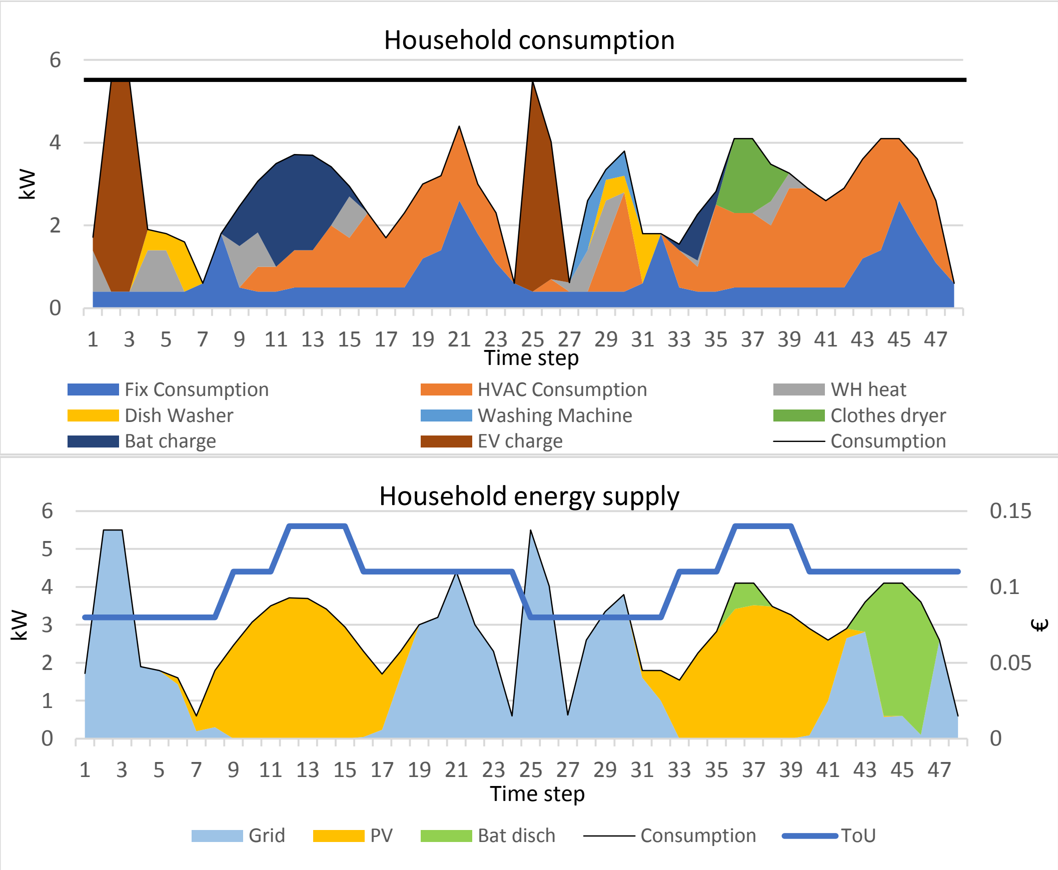

Figure 18. Household energy balance

The algorithm ensures electricity consumption before the on-peak price period and storage PV overproduction to reduce peak demand or support consumption anticipating future changes. Due to this fact, households can profit from the periods with lower electricity rates to lower their daily energy costs. The proposed method balances and economises the total electricity consumption according to operational constraints. The management during peak demand allows to fulfil the maximum grid power available (black line) and battery charge and discharge range. It also schedules most of the household appliances consumption in off-peak periods, as shown Figure 19, which allows the consumer to pay an optimal electricity cost while maintaining the requested services.

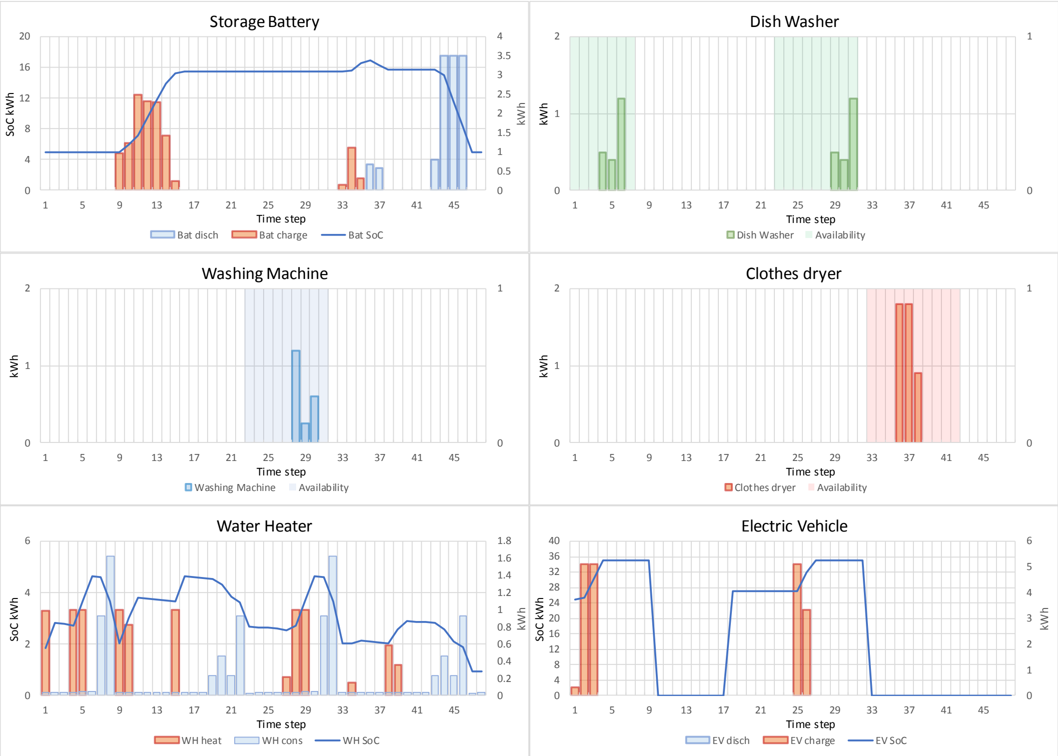

Figure 19. Electricity consumption elasticity

5.1 *Assessment of the GA*

To assess the GA's performance, tree setpoint temperature scenarios were developed. The base scenario is shown in the next figure in the middle column where the input for setpoint room temperature was defined at 24ºC. The additional scenarios with the cooling mode for the HVAC system in summer were calculated with 23ºC and 25ºC room setpoint and are shown in left and right column. The results are shown in the figure below. The cost for buying energy for the 48h horizon time with 23ºC, 24ºC and 25ºC were 8.05€, 6.41€ and 4.92€ respectively.

Figure 20. HVAC optimisation

The GA controls the cooling system to maintain the indoor temperature close to the comfort level setpoint. When the electricity price is high, the AMPC pre-cools the building to maintain the desired temperature and optimise cost. When the exterior temperature decreases, the free-cooling is activated. Thus, the GA manages the cooling system to benefit from the falling temperature and to support the extra cooling demand.

5.2 The MILP algorithm's assessment

To assess the MILP algorithm's performance, three PV generation scenarios were developed. The first is on the left, with 80% PV generation; the base scenario is in represented in the middle column, and finally on the right is the third scenario with 120% PV generation. The results are shown in the figure below.

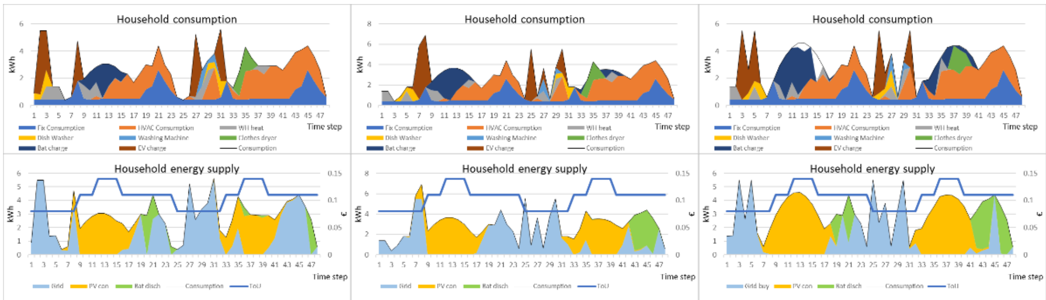

Figure 21. MILP's optimisation

The energy exchange from/to the grid and battery for each PV generation scenario is shown in the following figure. In the 120% PV generation scenario, when the battery is fully charged, PV overproduction is sold to the grid as shown in the figure. The cost in buying energy for the 48h-horizon time with 80%, 100% and 120% PV generation were 7.41€, 6.41€ and 5.09€ respectively.

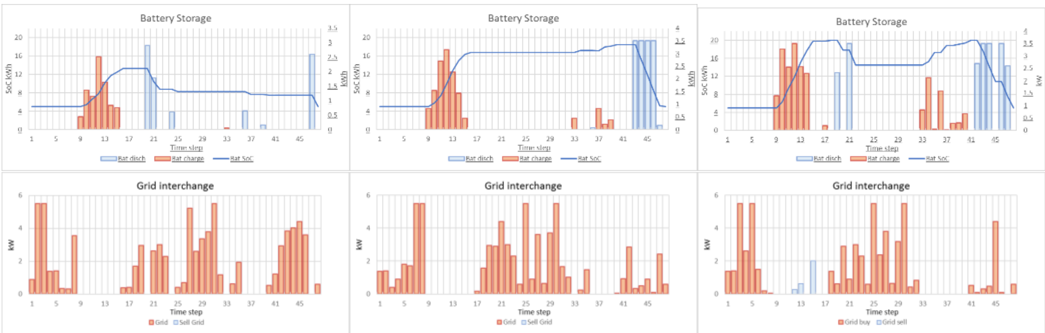

Figure 22. Grid energy interchange and battery storage

5.3 *The AMPC algorithm's assessment*

To evaluate the AMPC optimisation algorithm, an uncontrolled scenario is performed (Figure 23). In this context, the appliance's load cycle is turned on and off without taking into consideration the time-varying prices except for the EV, which is recharged taking advantage of the nightly rate. The controlled and uncontrolled scenarios were developed with the same requirements of electrical appliances and PV generation. The energy cost for the 48h-horizon time in the uncontrolled scenario was 7.22€, in contrast with 6.5€ obtained with the AMPC, which is more than 11% of economic cost difference. On the other hand, the uncontrolled scenario reported higher grid consumption during peak hours. To support the uncontrolled appliances' consumption, at least a 7-kW grid connection is required. In the demand flexibility case, the AMPC algorithm implements a valley-filling approach, as many loads are shifted to the least expensive hours, lowering the customers' bills, shifting consumption away from the grid peak and flattening the demand profile. In the AMPC scenario, household consumption does not exceed 5.5-kW. This represents a 27% cut in the power hired, lowering the overall system cost.

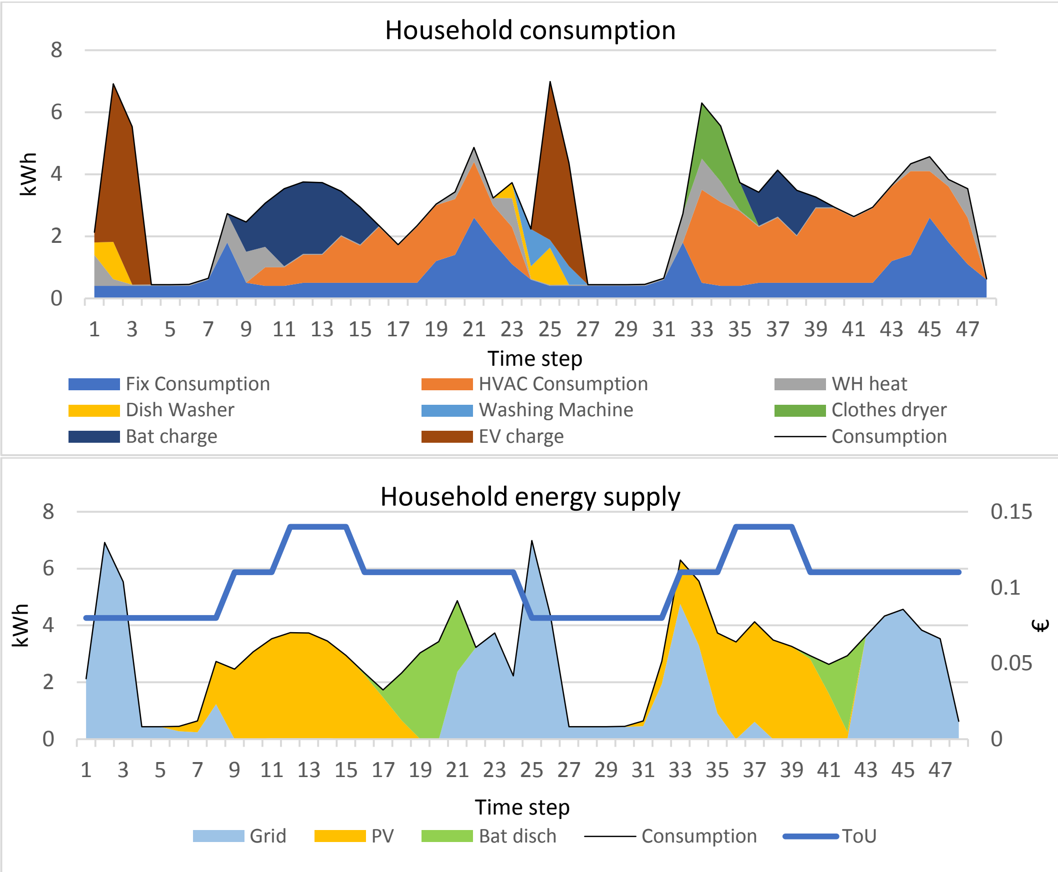

Figure 23. Household energy balance uncontrolled scenario

5.4 AMPC's stability analysis

A crucial requirement in control theory for the design of management strategies is their ability to deal with the changes in system inputs and show robustness in diverse conditions. MILP algorithm used to solve LP problems assumes that tiny changes to the system lead to small changes in the solution. This condition is true for the appliances' scheduling problem, guaranteeing stability and time-convergence. Gurobi [54] solver has been tested thoroughly for numerical stability and correctness using an internal library of over 10,000 models from industry and academia. The MILP algorithm is well-suited for optimising a building, but it inherently involves different challenges to achieving scalability. Thermal comfort's cost function is optimised by a custom metaheuristic procedure based on GA. The algorithm selects the best-fitted strategy performed in each timeslot. The algorithm performs calculations based on the preceding strategies' population, improving the optimisation performance and adapting to the disturbances. To verify

AMPC's stability, it was given to compute a set of 100 diverse scenarios with different weather conditions, appliances and EV consumption patterns, PV generation and room temperature setpoints. All feasible data sets were stable.

6 Conclusions

In this study, the scheduling problem of smart home energy resources was solved in several scenarios applying an AMPC approach. The novelty of the present paper can be summarised as follows:

- The proposal of a novel AMPC methodology to find a quasi-optimal solution for the elasticity of residential electricity consumption, considering the cooling, heating and electricity demand.
- Development of a novel hybrid model methodology based on ANNs for buildings' thermal behaviour and electricity consumption statistics.
- Implementation of a two-step optimisation solver based on GA and MILP formulated as a dual optimisation method.

The proposed AMPC was tested using the data obtained from actual residential buildings. The algorithm's stability was tested with a set of diverse parametric simulations. The numerical results demonstrated the capability of the proposed algorithm to support a quasi-optimal and cost-effective power management strategy as well as increase grid elasticity. The broad steps involved in the optimisation approach and its results are summarised as follows:

- Deferrable appliances' usage was shifted to valley-filling with low TOU rates or high PV generation periods.
- The comfort temperature of the room was addressed with diverse weather conditions, taking advantage of the building's thermal storage.
- BESS optimal charging and discharging was performed for peak shaving in the smart home.
- Electricity consumption was flattened, minimising the requirements for the power hired.
- DER self-consumption condition was satisfied. PV overproduction was first stored at BESS and sold only when the battery is full.

Further research is required, particularly on the application of the proposed AMPC algorithm for testing its long-lasting performance in buildings. Some aspects such as the initial data collection and computational effort for training neural networks and optimising GA to acquire the HVAC solution and the consumption pattern's prediction to the optimisation problem will be of special interest. Also, smart appliances and V2G charger that support smart grid communication with AMPC algorithm must be defined and developed.

Acknowledgement

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