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Fiorini, L.; Aiello, M.

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Predictive CO₂-efficient Scheduling of Hybrid Electric and Thermal Loads

Laura Fiorini

Department of Distributed Systems
University of Groningen
Groningen, The Netherlands
l.fiorini@rug.nl

Marco Aiello

Department of Service Computing
University of Stuttgart
Stuttgart, Germany
marco.aiello@iaas.uni-stuttgart.de

Abstract—The current energy transition leading towards decentralized generation and low emission sources challenges our energy systems. With multiple energy sources available, the complexity of households as energy systems increases, while growing energy consumptions imply a higher environmental impact that, in the context of decarbonization, needs to be addressed. We investigate the potential for smart homes to lower their environmental impact in terms of CO₂ emissions through a home energy management system (HEMS). This is achieved by adopting a model predictive control (MPC) to minimize CO₂ emissions due to the consumptions of gas and electricity by scheduling the operation of time-flexible appliances and by changing the energy carriers to supply electric and thermal loads. The scheduling problem is formulated as a mixed-integer linear programming (MILP) program subject to constraints that reflect the users' preferences in operation and allowed delays of individual appliances, as well as main characteristics of different household technologies. Using statistical data available for German households and emission factor of the German power grid, we show that the proposed approach can reduce the daily emissions of a group of 300 households by up to 27% (i.e., 599 kgCO₂ eq), while satisfying users' comfort preferences.

Index Terms—Carbon emissions, Hybrid appliances, Thermal load, Optimal scheduling, Model predictive control

I. INTRODUCTION

Increasing concerns on climate change have brought the attention to the environmental impact of building energy consumptions; in Europe, residential and commercial building are attributed 36% of CO₂ emissions [1]. Increasing diffusion and use of appliances have significantly raised the households' need for electricity, and controlling the residential energy use has become an important aspect of the power grid management. A great deal of research has focused on cost optimal scheduling of consumptions and generation in households [2]. From an environmental point of view, a mere price-based shifting of the demand over time may not lead to the solution with the lowest environmental impact [3]. The CO₂ emissions tied to the use of electricity depend on how the electricity is generated, and they may have a negative relation with electricity prices, i.e., lower prices correspond to higher electricity CO₂ intensity; as a consequence, a decrease in

electricity bills may correspond to an increase in emissions and vice versa [4], [5]. The integration of diverse energy carriers, such as electricity and gas, has shown potential economic and energetic benefits. Multi-energy systems take advantage of variations over time of both price and CO₂ intensity of different energy carriers. Space heating and hot water demands can be supplied by gas-burning boilers or combined heat and power (CHP) systems, as well as by electric heaters and electric heat pump (EHP) [6], [7]. Although their availability is still limited, hybrid cooking and wet appliances integrating more energy carriers are gaining adoption [8], [9], thanks to their potential synergies with sustainable energy sources [10]. A HEMS aims at monitoring and controlling energy consumption and production of a household, while scheduling the use of available resources. The optimal scheduling problem involves multiple factors subject to uncertainty, such as energy demand, weather conditions, and price signals, the forecasts of which are never fully accurate [11]. An effective way of dealing with such uncertainties is the use of MPC, which approximates a long-horizon problem by a short-horizon one, making short-term decisions when new, more accurate forecasts are available [12]–[14].

In this work, we propose a MPC-based HEMS for CO₂-efficient scheduling of hybrid electric and thermal loads in smart homes, that, to the best of our knowledge, is a novel enterprise. We show that one can reduce CO₂ emissions by 27% with minimal discomfort for a large group of households with different preferences in terms of shifting loads in time and use of energy carriers. We model households realistically by considering, depending on size and the season, them having up to six common appliances and varying thermal loads (including space and cooling demand, as well as domestic hot water (DHW) demand). Such smart homes are configured as multi-energy systems, which supply hybrid electric and thermal loads by means of multiple technologies, namely a gas-fired boiler, an EHP, an electric water heater (EWH), a thermal store (TS), and a home energy storage (HES). The remainder of the paper is organized as follows: Section II provides a description of the MPC approach and an overview of different household loads, while the optimization problem is formulated in Section III. The data used to model the households are presented in Section IV. The simulation setup

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is described in Section V, while Section VI presents the results. Section VII summarizes the main findings and discusses future work.

II. MODEL DESCRIPTION

A. Model predictive control

The scheduling takes the dynamic CO₂-equivalent intensity factor of the power grid as the input signal, which is determined by the following equation [9]:

$$EF_{e,t} = \frac{\sum_{pp} E_{t,pp} \cdot EF_{pp}}{\sum_{pp} E_{t,pp}} \quad (1)$$

where $E_{t,pp}$ is the energy produced by power plant pp in time step t , and EF_{pp} is the life-cycle greenhouse gases (GHG) emission factor of power plant pp . Our approach follows the so-called electricity mix method for CO₂ emission quantification, which is a good indicator for the share of renewables and the carbon intensity of the energy sector [15]. Currently, generation mix data are not always available in real-time and CO₂ signals are subject to forecasting errors, mainly due to unplanned power plant outages, changes in weather conditions, renewable production, and total electricity demand. To be able to ensure self-balancing while minimizing the environmental impact of energy consumption and satisfying user's preferences, the HEMS has to reschedule the loads and change the operating point of flexible units as new information on uncertain parameters becomes available. To adjust the demand-supply scheduling in real-time, our MILP model employs MPC, which iteratively finds an optimal scheduling over finite overlapping prediction horizons [13]. The HEMS of each smart home will use MPC to minimize the environmental impact expressed in CO₂ emissions of its daily energy consumptions. The optimization problem is formulated and solved at discrete time steps of 15 minutes and over a pre-defined prediction horizon (e.g., 6 hours). Only the actions for two time steps are implemented, and the process is then repeated for the following time step considering new CO₂ signals and external temperature information.

B. Electric and thermal loads

The smart home model we employ is an extension of the one we proposed in [9]. Traditional household appliances use a single energy carrier to operate, usually electricity or gas. Devices featuring modern technologies can be supplied by multiple energy carriers, either in parallel or alternatively. Such appliances are referred to as *hybrid* and their environmental and economic potential benefits have been recently investigated, e.g. in [16], [17], although their general public availability is still limited. For instance, some washing machines (WMs) take electricity and pre-heated hot water as inputs [18]; dual-fuel cookers combine electricity and gas, even in the same cooking device [19]. Part of the electricity needed for heating processes in tumble dryers could be saved by transferring energy from hot water to air in a heat exchanger [10], [20]. With a broader approach, a microwave oven (MO) or a gas hob can be interchangeably used for several cooking activities, e.g.,

Fig. 1. Domestic hot water demand profiles according to household size

boiling water, cooking rice, or heating food [21]. Similarly, space heating and DHW demand can be satisfied by a gas boiler or an electric heater, as well as by a combination of technologies, e.g., an EHP coordinated with a gas boiler [22].

Our model includes a gas-fired boiler, an EHP, an EWH, a TS, a HES, and six appliances, namely, WM, tumble dryer (TD), dish washer (DW), oven (OV), cooker hob (HB), and MO. The gas-fired boiler contributes to both space heating and hot water production; the EHP supplies space heating and cooling power, whereas the EWH produces hot water. The TS is charged by both the gas boiler and the EWH.

The house temperature is determined by a simplified thermal model according to the following equation [23]:

$$T_{in,t} = T_{in,t-1} \cdot e^{\frac{\Delta t}{R \cdot C_a}} + (R \cdot H_{air,t-1} + T_{out,t-1}) \cdot (1 - e^{\frac{\Delta t}{R \cdot C_a}}) \quad (2)$$

where $H_{air,t}$ is the thermal power required to set the indoor temperature at time step t , and it is determined by the thermal output of the gas boiler for space heating and the thermal output for both space heating and cooling of the EHP, i.e., $H_{air,t} = H_{BOI,t}^{SH} + H_{EHP,t}^{SH} - H_{EHP,t}^{SC}$. $T_{out,t}$ is the external temperature; R is the thermal resistance of building shell; C_a is the heat capacitance of the building, and Δt is the time step.

The hot water temperature in the TS at each time step is calculated from the following equation [6]:

$$T_{TS,t} = T_{TS,t-1} - a \cdot (T_{TS,t-1} - T_{in,t-1}) + b \cdot (H_{BOI,t-1}^{DHW} + H_{EWH,t-1}^{DHW} - P_{hw,t-1}) \quad (3)$$

where $H_{BOI,t}^{DHW}$ and $H_{EWH,t}^{DHW}$ are the thermal output of the boiler and EWH for DHW production, respectively. $P_{hw,t}$ is the total demand for hot water and it is defined as follows:

$$P_{hw,t} = \sum_{a \in A_{hw}} P_{hw,a,t} + D_{DHW,t} (T_{TS,t} - T_{cold}) c_w \quad (4)$$

where $P_{hw,t}$ is the hot water consumption of appliance a , A_{hw} is the set of appliances using hot water when in hybrid mode, and $D_{DHW,t}$ is the demand for DHW in liter/hour (see Fig. 1). The parameters a and b are calculated as follows:

$$a = \frac{\Delta t A}{\rho V R_{TS} c_w}, \quad b = \frac{\Delta t}{\rho V c_w} \quad (5)$$

where A is the surface area of the TS, V is its volume, R_{TS} is its thermal resistance, ρ is the water density, and c_w is the specific heat of water.

III. MODEL FORMULATION

The proposed HEMS for a smart home serves to schedule the demand and supply of electrical and thermal power, while minimizing the total CO₂ emissions and is formulated as follows:

$$\min \left[\Delta t \cdot \sum_{t=k}^{k+H-1} \left(EF_{e,t} P_{e,t} + EF_g P_{g,t} \right) \right] \quad (6)$$

where H is the prediction horizon, k is the time step the optimization is run at, $P_{e,t}$ and $P_{g,t}$ (kW) are the electricity and gas imported from the distribution grids at t , respectively, and EF_g is the gas emission factor, which we set to 288 gCO₂eq/kWh as suggested in [24]. The imported electricity and gas are defined as follows:

$$P_{e,t} = \sum_{a \in A} \left(P_{e,a,t} + P_{eh,a,t} \right) + P_{EES,t}^{ch} - P_{EES,t}^{dis} + \frac{H_{EHP,t}^{SH} + H_{EHP,t}^{SC}}{COP_{EHP}} + \frac{H_{EWH,t}^{DHW}}{\eta_{EWH}} \quad (7)$$

$$P_{g,t} = \sum_{a \in A_g} P_{g,a,t} + \frac{H_{BOI,t}^{SH} + H_{BOI,t}^{DHW}}{\eta_{BOI}} \quad (8)$$

where A is the set of all appliances and A_g is the set of appliances using gas when in hybrid mode. $P_{e,a,t}$ and $P_{eh,a,t}$ are the electric power consumptions of appliance a at time step t when operating in electricity-only and hybrid modes, respectively, while $P_{g,a,t}$ is the gas consumption. COP_{EHP} , η_{EWH} , and η_{BOI} are the coefficients of performance of the EHP [7], and the efficiency factor of the EWH and the boiler, respectively. $P_{HES,t}^{ch}$ and $P_{HES,t}^{dis}$ are the charging and discharging power of the HES. The power and/or heat demands at each time step t for each appliance a are defined as follows:

$$P_{s,a,t} = \sum_{l=1}^{\gamma_a} \delta_{s,a,t,l} \cdot P_{s,a,l} \quad \forall s \in S, \forall a \in A, \forall t \in [k, k+H-1] \quad (9)$$

where $P_{s,a,l}$ is the demand for source s equal to level l for appliance a ; $\delta_{s,a,t,l}$ is a binary variable indicating the operation status (0 or 1) of appliance a requiring level l from the energy carrier s at time step t . S is the set of energy carriers (electricity-only e , gas g , hot water hw , electricity in hybrid mode eh). Given the demand profile of a device during its operation of duration γ_a , the required power or heat in each quarter of hour corresponds to a level l . The operation of (hybrid) appliances is based on our previously proposed model [9].

The thermal output of the boiler, the EHP, and the EWH are assumed continuous and constrained between zero and a maximum value depending on the technology (see Table I).

TABLE I
PARAMETERS FOR THE CONSIDERED TECHNOLOGIES

Technology	Parameter	Value
Gas boiler	Max thermal output	20 kW
	η_{BOI}	0.96
EHP	Max thermal output	10 kW
	COP_{EHP}	3.51 at 20°C; 1.97 at -4°C
EWH	Max thermal output	1.5 kW
	η_{EWH}	0.85
TS	V	150 L
	T_{TS}	0.33 m ² K/W
	A	1.8 m ²
HES	$\frac{\eta_{HES}^{ch} - \eta_{HES}^{dis}}{P_{HES}^{ch} - P_{HES}^{dis}}$	0.90 - 0.90
	$\frac{P_{HES}^{ch} - P_{HES}^{dis}}{SoC_{HES} - \bar{SoC}_{HES}}$	5 kW - 5 kW
	SoC_{HES}	0 kWh - 13.5 kWh

TABLE II
LEVELS OF LOAD FLEXIBILITY

Level	dT _{in}	dT _{TS}	Cooking appl.	Wet appl.
None (N)	2°C	2°C	-	-
Low (L)	2.5°C	3°C	15 min	2 h
Medium (M)	3°C	4°C	1 h	4 h
High (H)	3.5°C	5°C	2 h	8 h

Additional constraints are set to model the thermal load behavior described in (3) and (2). $T_{TS,t}$ and $T_{in,t}$ have to be kept within a range, as follows:

$$T_{x,t} - dT_x \leq T_{x,t} \leq T_{x,t}^* + dT_x \quad (10)$$

where x stands for either TS or in , $T_{x,t}^*$ is the preferred temperature, and dT_x determines the acceptable range. Table II shows the levels of load flexibility on the basis of indoor and thermal store temperature; allowed delays for cooking and wet appliances.

The electrical power demanded by the smart home at time t is supplied by the battery output $P_{HES,t}^{dis}$ and the distribution grid. The HES is modeled via an auxiliary binary variable $y_{HES,t}$ to prevent charging and discharging at the same time. Formally,

$$\sum_{t=k}^{k+H-1} y_{HES,t} \leq H \quad (11)$$

The charging and discharging power are limited by the maximum charging $\overline{P_{HES}^{ch}}$ and discharging $\overline{P_{HES}^{dis}}$ power capacity of the HES, while the stored energy $SoC_{HES,t}$ is constrained between the minimum $\underline{SoC_{HES}}$ and maximum $\bar{SoC_{HES}}$ state of charge, as follows:

$$P_{HES,t}^{ch} \leq \overline{P_{HES}^{ch}} \cdot y_{HES,t} \quad (12)$$

$$P_{HES,t}^{dis} \leq \overline{P_{HES}^{dis}} \cdot (1 - y_{HES,t}) \quad (13)$$

$$\underline{SoC_{HES}} \leq SoC_{HES,t} \leq \bar{SoC_{HES}} \quad (14)$$

$$SoC_{HES,t} = SoC_{HES,t-1} + \Delta t \cdot \left(P_{HES,t}^{ch} \cdot \eta_{HES}^{ch} - \frac{P_{HES,t}^{dis}}{\eta_{HES}^{dis}} \right) \quad (15)$$

Fig. 2. Dynamic CO₂-equivalent intensity factors for five representative days, given German generation mix data

where $\eta_{\text{HES}}^{\text{ch}}$ and $\eta_{\text{HES}}^{\text{dis}}$ are the charging and discharging efficiency of the HES, respectively.

IV. HOUSEHOLD CLASSES AND DATA

To calculate the dynamic CO₂-equivalent intensity factor we consider the generation mix data for the German grid available on the European Network of Transmission System Operators for Electricity (ENTSO-E) Transparency Platform [25]. Without loss of generality, we assume that the forecasts of the generation mix and, hence, of the CO₂ signals are perfect and equal to the available historical data. To take into account seasonal variability and according to the criteria used by ENTSO-E in drawing its *Monthly Statistics Reports* [26], we use the generation data available for the third Wednesday of four months of 2018, namely, January, April, July, and October. The dynamic CO₂-equivalent intensity factors are calculated based on (1) and shown in Fig. 2.

To simulate realistically the behavior of a large group of users, we model several types of households differentiating on the basis of their electric and thermal loads, flexibility, and operation preferences. Statistical data on German household are available from [27], where ownership probabilities of the most common household appliances are reported depending on household size (see Table III). As for the thermal load, several DHW demand profiles are generated with [28] (see Fig. 1), whereas the preferred indoor temperature $T_{\text{in},t}^*$ is set equal to 22 °C in July and to 20 °C in the other months [29]. Considering the chosen days of 2018, the external temperature is assumed perfectly forecasted and equal to the historical data available for the city of Stuttgart, Germany [30].

The energy consumption and standard running time of the household appliances are adapted from [8], [10] and summarized in Table IV, according to the operation mode. The appliances are classified in wet (i.e., DW, WM, and TD) and cooking (i.e., HB, OV, and MO) appliances. The former group uses only electricity, when operating in traditional mode, or both electricity and hot water, when hybrid. The latter group uses either only electricity or both electricity and gas; in this case, energy consumptions are assumed to be +30% higher, due to additional distribution losses, heat dissipation, and water-air heat exchange process [8]. To diversify the users,

Fig. 3. Average usage probability of major household appliances

TABLE III
APPLIANCE OWNERSHIP PROBABILITIES BASED ON HOUSEHOLD SIZE

	Household size				
	1 (32%)	2 (39%)	3 (14%)	4 (11%)	5+ (4%)
HB	99 %	100 %	100 %	100 %	100 %
OV	87 %	87 %	87 %	87 %	87 %
MO	63 %	75 %	81 %	82 %	79 %
DW	52 %	85 %	90 %	95 %	94 %
WM	90 %	98 %	99 %	100 %	99 %
TD	25 %	48 %	59 %	67 %	72 %

we randomly generate starting time preferences, according to the probability appliance usage in [16] (see Fig. 3). Moreover, we define four levels of user flexibility with respect to range temperature for both indoor and hot water temperature, and allowed delay of cooking and wet appliances (see Table II).

We also define four possible household operation modes.

- *Electricity-based operation (E)*: all appliances run in traditional mode, using only electricity; no boiler is installed; and the maximum importable power is 8 kW;
- *Gas-based operation (G)*: all appliances run in traditional mode; the thermal load is supplied by the gas boiler, while neither the EHP nor the EWH are installed. The maximum importable electrical power is 8 kW;
- *Hybrid operation (H)*: all appliances run in hybrid mode, i.e., using both electricity and gas or hot water; gas boiler, EHP, and EWH are installed; the maximum importable electrical power is 4.5 kW; and
- *Optimal operation (O)*: it is defined as the *hybrid operation*, but all appliances are optimally scheduled with

TABLE IV
ENERGY CONSUMPTIONS PER OPERATION CYCLE OF HOUSEHOLD APPLIANCES

Appliance	Electricity-only mode kWh	Hybrid mode kWh
HB	1.650	0.006 + 2.135 (gas)
OV	2.500	0.150 + 3.055 (gas)
MO	0.375	0.0015 + 0.479 (gas)
DW	1.193	0.160 + 1.343 (hot water)
WM	0.888	0.213 + 0.878 (hot water)
TD	2.460	0.400 + 2.808 (hot water)

TABLE V
SIMULATION MATRIX. COLUMNS: % LOAD FLEXIBILITY (N/L/M/H).
ROWS: % OPERATION MODE (E/G/H/O)

E/G/H/O	N/L/M/H		
	50/50/0/0	25/25/25/25	0/0/50/50
50/50/0/0	Case A1	Case A2	Case A3
25/25/25/25	Case B1	Case B2	Case B3
0/0/50/50	Case C1	Case C2	Case C3

TABLE VI
TOTAL DAILY CARBON EMISSIONS (KG) AND VARIATIONS IN PERCENTAGE
FROM REFERENCE CASE. COLUMNS: % LOAD FLEXIBILITY (N/L/M/H).
ROWS: % OPERATION MODE (E/G/H/O) AND MONTH

E/G/H/O		N/L/M/H		
		50/50/0/0	25/25/25/25	0/0/50/50
50/50/0/0	Jan	1494	1452 (-3%)	1411 (-6%)
	Apr	1967	1909 (-3%)	1853 (-6%)
	Jul	1813	1759 (-3%)	1706 (-6%)
	Oct	2172	2110 (-3%)	2049 (-6%)
25/25/25/25	Jan	1501 (-)	1460 (-2%)	1421 (-5%)
	Apr	1797 (-9%)	1748 (-11%)	1702 (-13%)
	Jul	1699 (-6%)	1653 (-9%)	1608 (-11%)
	Oct	1910 (-12%)	1861 (-14%)	1813 (-17%)
0/0/50/50	Jan	1506 (+1%)	1467 (-2%)	1428 (-4%)
	Apr	1634 (-17%)	1594 (-19%)	1557 (-21%)
	Jul	1593 (-12%)	1553 (-14%)	1515 (-16%)
	Oct	1658 (-24%)	1620 (-25%)	1584 (-27%)

respect to energy carriers according to CO₂ signals.

V. SIMULATIONS AND IMPLEMENTATION

To evaluate the proposed HEMS, we consider a group of 300 households of increasing sizes. We compare several configurations with varying percentages of load flexibility and operation mode, which are summarized in Table V. Case A1 is assumed as the reference case, featuring low levels of load flexibility and common operation modes. The MILP model and MPC framework are implemented in Python 3.7.1 and solved by GUROBI optimizer, which provides a free academic version. To speed up the execution of the simulations, we use the Multiprocessing package. We use the Beautiful Soup package for pulling data out of XML files provided by the ENTSO-E platform. For data analysis and data structure, we use the Numpy package and the Pandas package. Results are stored and manipulated by using the H5py package, while Matplotlib is used to visualize the results. These simulations were run on one node Intel Xeon, 2.5 GHz of the Peregrine cluster of the University of Groningen.

VI. RESULTS

Solving the proposed optimization problem entails the scheduling of the electrical and thermal loads of 300 households, in turn minimizing the carbon emissions due to the energy generation. The total daily carbon emissions for four days and nine configurations are summarized in Table VI.

Taking Case A1 as the reference case, one can immediately notice the seasonality effect on the total daily emissions (see

TABLE VII
DAILY IMPORTED ENERGY FROM DISTRIBUTION GRIDS: PERCENTAGE OF
ELECTRICITY AND GAS.

E/G/H/O		Electricity	Gas
50/50/0/0	Any	59%	41%
25/25/25/25	Jan	41%	59%
	Apr	34%	66%
	Jul	36%	64%
	Oct	30%	70%
0/0/50/50	Jan	24%	76%
	Apr	10%	90%
	Jul	14%	86%
	Oct	3%	97%

Table VI). With high use of electricity, low dynamic CO₂-equivalent emission factors on a windy day like the 17th of January reduce the total daily emissions of up to 31% (roughly 700 kg) compared to days when renewable sources have lower share of the generation mix. On such a windy day, traditional operation modes with higher user of electricity, i.e., electricity-only (E) and gas (G) operation modes, are the most sustainable choices. On the other days, operation modes featuring hybrid loads with larger use of heat and gas are shown to enable between 6% and 24% emission savings, considering low levels of load flexibility. With an increasing share of households running in either hybrid (H) or optimal (O) operation, the import of electricity decreases in all days, although the seasonality effect is still evident for the day of January, as shown in Table VII. On the other hand, different percentages of load flexibility cause only minor variations in energy consumptions. On 17th of October, when the dynamic CO₂-equivalent intensity factors are significantly higher than the gas emission factor, the HEMSs limit the use of electricity to only 3% of the total energy consumptions. When households are equipped with an EHP, the space heating relies solely on it, given its good performances in terms of COP; on the other hand, the DHW demand is mainly satisfied by the gas boiler, while the use of the EWH is limited to the households running in electricity-only operation. Overall, because hybrid appliances are assumed to consume 30% more when in hybrid mode, the total energy consumptions over four days in case C are 1.5% higher than in the other operation modes, due to additional heat losses in such devices. As for the load flexibility, wider temperature ranges and longer allowed delays for appliances always improve the emissions and energy consumptions savings, especially when households run in electricity-only operation, although to a minor extent, i.e., from +2% to +5%. Furthermore, considering the 18th of April and a middle level of load flexibility, we also evaluate the effect of introducing HESs in 50% of the households with varying percentage of operation modes. Additional emissions and energy consumptions savings of around 1% are achieved, although the benefits may be limited if the final state of charge of the HES is set to be at least equal to the initial one.

TABLE VIII
DAILY IMPORTED ENERGY FROM DISTRIBUTION GRIDS OVER FIVE DAYS.
COLUMNS: % LOAD FLEXIBILITY (N/L/M/H). ROWS: % OPERATION
MODE (E/G/H/O).

E/G/H/O	N/L/M/H	50/50/0/0	25/25/25/25	0/0/50/50
50/50/0/0	Electr	12642	12378	12114
	Gas	8863	8607	8363
	Total	21503	20896	20477
25/25/25/25	Electr	7657	7584	7485
	Gas	14012	13555	13145
	Total	21668	21139	20630
0/0/50/50	Electr	2801	2937	3021
	Gas	19036	18352	17747
	Total	21838	21291	20771

VII. CONCLUSIONS

We propose a CO₂-efficient scheduling of hybrid electric and thermal load within a MPC framework with the goal of improving the sustainability of homes. We simulate the behavior of a group of 300 users realistically by modeling several types of households having different electric and thermal loads, flexibility, and operation preferences. The results show that the proposed HEMS can significantly reduce CO₂ emissions, while satisfying users' comfort preferences in terms of temperature and allowed delay of main household appliances. Considering configurations with increasing levels of load flexibility and integration of energy carriers, emission savings vary between 2% and 27%, compared to the reference case with low flexibility and traditional operation modes. The presence of more technologies allows for the improvement of supply's efficiency for space heating and DHW demand, maintaining the total energy consumptions mostly unchanged. Further emission and energy consumption savings can be achieved with the use of HES, whose potential benefits and operation modeling require additional analysis. Future works include the integration of a forecasting model for CO₂ signals.

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