A Multi-Objective Home Energy Management System based on Non-Intrusive Load Monitoring and Heat Pump Control

Christos L. Athanasiadis
Dept. of Electr. & Comp. Eng.
Democritus University of Thrace
Xanthi, Greece
cathanas@ee.duth.gr

Theofilos A. Papadopoulos
Dept. of Electr. & Comp. Eng.
Democritus University of Thrace
Xanthi, Greece
thpapad@ee.duth.gr

Georgios C. Kryonidis
Dept. of Electr. & Comp. Eng.
Aristotle University of Thessaloniki
Thessaloniki, Greece
kryonidi@ece.auth.gr

***Abstract*—Grid modernization and digitalization gradually alter the traditional operation of power systems. Demand side management has attained significant attention and the deployment of smart meters creates opportunities for new data-driven services. Towards this direction, home energy management systems (HEMS) can play a pivotal role by enabling residential demand response applications. This paper introduces a HEMS aiming at low energy cost, improved thermal comfort and scheduling of appliance operation according to end-user habits. To this end, a multi-objective optimization problem is formulated by employing a non-intrusive load monitoring mechanism and a control scheme for heat pumps. The conducted analysis investigates the effect of each objective on the overall system performance under different dynamic tariff schemes.**

***Index Terms*—Demand side management, heat pump, home energy management system, non-intrusive load monitoring, multi-objective optimization, thermal comfort.**

I. Introduction

Traditionally, in power systems large generation units optimize their operation to achieve a match between supply and demand. Nonetheless, nowadays grid modernization and digitalization not only enable residential end-users to become active parts of the energy sector exploiting photovoltaics (PV) and battery energy storage (BES) but also provide new advanced data-driven services through the deployment of smart meters (SMs). Demand response (DR) is one such service and refers to the change of the end-user consumption to match demand with supply. Typically, utilities broadcast signal demand requests to their customers containing information about the electricity price or commands for load shedding [1]. This way end-users may adjust their power demand by shifting selected tasks that require large amounts of electric power or changing the temperature set-points of the electrical heating system. To exploit this load flexibility, home energy management systems (HEMS) that combine hardware and software components are required for monitoring and controlling efficiently and most importantly in an automatic way the household under DR schemes.

Christos L. Athanasiadis is also with NET2GRID B.V., Thessaloniki, Greece (e-mail: christos@net2grid.com).

Residential DR and HEMS have been widely investigated in the literature [2], [3]. Various approaches rely on the direct appliance control by programming the set-points of water heaters and heating, ventilation, and air-conditioning (HVAC) units to provide hot water and thermal comfort, to end-users [4]–[6]. Appliance scheduling under day-ahead pricing has also been investigated [7], [8] to plan the operation of specific appliances for the next day aiming to minimize the cost and maximize the thermal comfort of end-users. Nevertheless, these solutions neglect the discomfort that may be posed to the end-users by not aligning the scheduling of the appliances with their habits.

To overcome this issue, non-intrusive load monitoring (NILM) techniques have been integrated to HEMS to identify and include the end-user habits in the optimal day-ahead scheduling [9], [10]. NILM refers to the process of energy consumption breakdown (disaggregation) on appliance or activity level for residential or commercial-industrial consumers [11]. Sub-measurements from appliances within the household are not required; instead only the total measured demand at the main power service is used [12]. In [9], SM data are analyzed with a multi-task deep neural network (DNN), and appliance-level information regarding the consumption and operating status is extracted. The NILM model is integrated within HEMS to create an efficient and user-centered system to schedule the appliance usage of a household microgrid with residential wind turbines, PV, and BES units. A similar approach has been followed in [10], where NILM is used to extract the end-user habits and schedule the operation of the household appliance without user intervention by employing an automated genetic multi-objective algorithm.

Based on the above, it is evident that most HEMS studies [4]–[8] formulate the optimization problem on the basis of cost and thermal comfort objectives. Few works incorporate in their analysis the end-user habits [9], [10], but still do not consider all aspects, e.g., the impact of thermal comfort. Additionally, all these solutions pose restrictions only to the netted active power exchanged with the grid, neglecting reactive power. To fill these gaps, and introduce a holistic

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approach in this paper a HEMS for smart active/reactive power control and management of households based on SM data analysis and heat pump (HP) control is presented. The proposed system aims to i) minimize the energy cost by employing a PV/BES system, ii) schedule the operation of various appliances tailored to end-user habits by means of NILM, and, iii) maximize thermal comfort by controlling the indoor temperature via a HP. Therefore, a multi-objective optimization problem is formulated and solved through mixed-integer non-linear programming (MINLP). Finally, from the conducted parametric analysis the impact of each objective on the final result is evaluated and discussed under different electricity cost tariffs.

II. Proposed HEMS System

The target of the proposed HEMS is the optimal day-ahead electricity scheduling of a household. The HEMS is depicted in Fig. 1 and consists of two main operational modules, namely the optimization and the NILM, as well as of a number of sub-systems, i.e., PV/BES, HP, and flexible load (appliances that their operation can be shifted throughout the day). A distinct feature of the proposed HEMS is the NILM module that extracts the end-user habits in terms of flexible load usage by analyzing historical SM data. The HEMS collects the resulting information from NILM, the day-ahead tariff and the forecasts of the outdoor temperature, the PV production, and the uncontrollable load. By utilizing the above data, schedules the operation of the flexible load according to the end-user preferences and controls the HP and BES to provide thermal and habit comfort alongside minimizing the total cost.

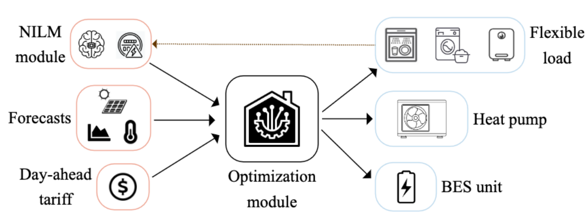

Fig. 1. Architecture of the proposed HEMS.

III. NILM Module

To extract end-user habits and create an end-user-oriented HEMS, NILM analysis is applied by using a multi-task DNN. The model is appliance-specific, i.e., for each target appliances, a new model is created. The network utilizes SM measurements of active (P_{load}) and reactive (Q_{load}) power at a sampling rate of 6 s to estimate the corresponding active and reactive power of the target appliance k, denoted as $\hat{P}_k$ and $\hat{Q}_k$, respectively. The model input consists of sliding non-overlapping windows of P_{load} and Q_{load} with a length of 15 min (150 samples) and the outputs are $\hat{P}_k$ and $\hat{Q}_k$ for the same time window along with the target appliance status (on/off), $\hat{s}_k$. The model architecture is presented in Fig. 2 and consists of two combinations of convolutional/pooling layers, two long-short term memory (LSTM) cells, a common dense layer, and three separate dense layers for each output.

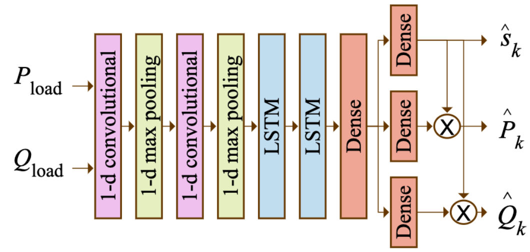

Fig. 2. Architecture of the NILM model.

The selected target appliances are dishwasher, washing machine, dryer, and water heater due to their high energy consumption and flexibility [13]. To train, validate and evaluate the models, three distinct datasets were created. In particular, by using the bottom-up modeling approach presented in [14], the aggregated active/reactive timeseries of a single household were created for 90 days, including all target appliances. From this dataset, 60 days were used for training, 15 for validation, and 15 for testing. All timeseries were normalized to speed up learning and achieve faster convergence.

During the training process, a backpropagation algorithm was used to optimize the loss function. Since the problem concerns multi-task learning with three outputs, three different loss functions are combined. The loss functions L_P and L_Q defined in (1) and (2) refer to the mean squared error (MSE) of the active and reactive power for T samples, respectively, and L_s in (3) to the binary cross-entropy of the appliance status.

$$L_{\mathrm{P}} = \frac{1}{T} \cdot \sum_{t=1}^{T} (P_k(t) - \hat{P}_k(t))^2 \tag{1}$$

$$L_{\mathrm{Q}} = \frac{1}{T} \cdot \sum_{t=1}^{T} (Q_k(t) - \hat{Q}_k(t))^2 \tag{2}$$

$$\begin{aligned} L_{\mathrm{s}} = -\frac{1}{T} \sum_{t=1}^{T} [&s_k(t) \log_2 \hat{s}_k(t) \\ &+ (1 - s_k(t)) \log_2 (1 - \hat{s}_k(t))] \end{aligned} \tag{3}$$

Therefore, the total loss is calculated in (4):

$$L = \frac{1}{3} L_{\mathrm{P}} + \frac{1}{3} L_{\mathrm{Q}} + \frac{1}{3} L_{\mathrm{s}} \tag{4}$$

Adam optimizer [15] was selected assuming an initial learning rate of 10^{-4}. To avoid over-fitting, early stopping with patience was used; the training process is stopped once the validation error does not decrease after three consecutive iterations.

Once the models have been trained, the end-user habits are determined from the testing set based on the following four appliance-specific operating parameters:

- mean active power consumption ($\overline{P}_k$),
- mean reactive power consumption ($\overline{Q}_k$),
- mean operation time (OT_k), and
- the preferred operation period (POP_k), i.e., the time period when the end-user usually operates the appliance.

To estimate POP_k, the probability density function (PDF_k), i.e., the probability of the appliance operating at each timestep, is calculated. The POP_k is defined as the period between the first and last index when PDF_k is higher than 0.5·max(PDF_k), similarly to [9].

IV. Optimization Module

The optimization module aims to minimize the total household energy cost and maximize the end-user thermal and habit comfort under three objective functions. This way, the day-ahead scheduling of the flexible load is formulated as a MINLP problem.

A. Objective Functions

1) Operation cost (OC): This objective function represents the total household energy cost in terms of dynamic tariff:

$$OC = \sum_{n=1}^{N} DAP(n) \cdot P_{\text{net}}(n) \cdot \Delta n \tag{5}$$

where n denotes a specific timestep, N is the number of timesteps, Δn is the length of timestep in hours, DAP is the day-ahead electricity pricing, and P_{net} is the power exchanged with the grid. A timestep of 15 min. is assumed, thus $N = 96$ and Δn = 0.25. It should be indicated that OC is normalized to $OC_{norm} = OC/c_{proxy}$; c_{proxy} is an approximated day-ahead cost (BES and HP units are neglected), and is calculated as:

$$c_{proxy} = \left[\sum_{n=1}^{N} DAP(n) \cdot (P_{\text{un}}(n) - P_{\text{PV}}(n)) + mean(DAP) \cdot \sum_{k=1}^{K} OT_k \cdot \overline{P}_k\right] \cdot \Delta n. \tag{6}$$

The generated power of the PV unit, P_{PV}, and the active power of the uncontrollable loads, P_{un}, are assumed as known inputs that can be provided from advanced forecasting models.

2) Habits discomfort (HD): The second objective refers to the habits of the end-user regarding appliance operation. The aim is to minimize the discomfort by scheduling the appliance operation during periods when the end-user usually uses them by utilizing the information provided by the NILM module.

To this end, a satisfaction degree, SD_k, for each timestep n is calculated per appliance. If the appliance is scheduled to operate within POP_k, then $SD_k = 1$; as the scheduled period deviates from POP_k, the value of SD_k decreases. An indicative example is shown in Fig. 3 with a POP_k from 16:00 ($n = 64$) to 20:00 ($n = 80$). In this context, HD is expressed as follows:

$$HD = 1 - \frac{\sum_{k=1}^{K} \sum_{n=1}^{N} SD_k(n) \cdot u_k(n)}{\sum_{k=1}^{K} OT_k} \tag{7}$$

where $u_k(n)$ is a binary value indicating the status (on/off) of the appliance k at timestep n. Note that, the following constraints should be met regarding the appliance operation duration and ensure that the appliance works continuously without any interruption [9]:

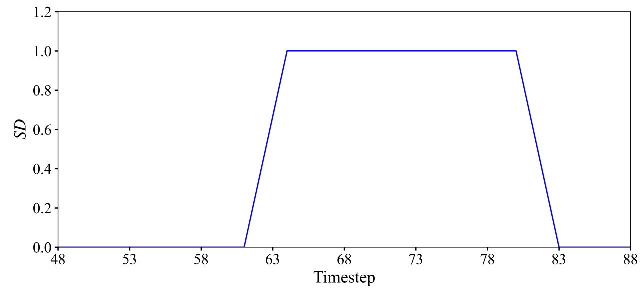

Fig. 3. Example of satisfaction degree.

$$\sum_{n=1}^{N} u_k(n) = OT_k \tag{8}$$

$$\sum_{n=2}^{N} |u_k(n) - u_k(n-1)| = 2 \tag{9}$$

3) Thermal discomfort (TD): The third objective aims to maintain the indoor temperature, T_{in}, close to the desired level, T_{c}, by adjusting the HP set-points. In this sense, the objective is to minimize TD:

$$TD = \frac{\sum_{n=1}^{N} |T_{\text{in}}(n) - T_{\text{c}}|}{N} \tag{10}$$

Considering, the three objective functions, the overall multi-objective function is formulated as:

$$min\{\alpha_1 \cdot OC_{norm} + \alpha_2 \cdot HD + \alpha_3 \cdot TD\} \tag{11}$$

where α_1, α_2 and α_3 are the corresponding weights.

B. Operational and Technical Constraints

The aim of the optimization is to schedule the operation period of each appliance (u_k), and determine the BES (P_{bat}) and HP (P_{HP}) unit power in terms of (11) considering that the aggregated active and reactive power is:

$$P_{\text{net}}(n) = P_{\text{un}}(n) + \sum_{k=1}^{K} \overline{P}_k \cdot u_k(n) + P_{\text{HP}}(n) + P_{\text{bat}}(n) - P_{\text{PV}}(n) \tag{12}$$

$$Q_{\text{net}}(n) = Q_{\text{un}}(n) + \sum_{k=1}^{K} \overline{Q}_k \cdot u_k(n) + tan(cos^{-1}(pf_{\text{HP}})) \cdot P_{\text{HP}}(n) \tag{13}$$

where Q_{un} is the reactive power of the uncontrollable loads and pf_{HP} is the HP power factor; for PV and BES units a unity power factor is assumed. The constraints regarding the connection with the grid are the following:

$$P_{\text{min}} \leq P_{\text{net}}(n) \leq P_{\text{max}} \tag{14}$$

$$Q_{\text{net}}(n) \leq Q_{\text{max}} \tag{15}$$

aiming to prohibit large injections of active power into the grid and at the same time limit the active and reactive power consumption of the end-user.

V. Sub-Systems Modeling

In this section, the modeling of each HEMS sub-system is described.

A. Uncontrollable Loads

The bottom-up modeling approach presented in [14] is used to create the total active and reactive power consumption by aggregating the elementary load components, i.e., individual appliances. The appliances under consideration are the four flexible appliances and a number of non-flexible uncontrollable loads, i.e., always-on, TV, fridge, iron, toaster, range. The extracted timeseries are used to train and test the corresponding NILM models. In the context of day-ahead scheduling, only the non-flexible appliances are modeled since the operation of the flexible appliances is determined by the HEMS.

B. Heat Pump

An air-source HP is modeled by considering the relationship between indoor temperature (T_{in}), outdoor temperature (T_{out}), and HP active power, P_{HP}, as [8]:

$$T_{\mathrm{in}}(n+1) = T_{\mathrm{in}}(n) + \eta \cdot (T_{\mathrm{out}}(n+1) - T_{\mathrm{in}}(n)) + \gamma \cdot P_{\mathrm{HP}}(n) \cdot \Delta n \tag{16}$$

where η and γ are coefficients denoting the thermal conditions of the HP. Moreover, the following limitations are applied:

$$0 \leq P_{\mathrm{HP}}(n) \leq P_{\mathrm{HP,max}} \tag{17}$$

where $P_{\mathrm{HP,max}}$ is the maximum permissible power.

C. PV/BES Sub-system

Regarding renewables, a PV is considered as the main generation source. The PVGIS platform [16] is employed to obtain hourly PV generation profiles along with the corresponding outdoor temperatures. The Akima interpolation [17] is used for upsampling to 15 min.

To cope with the intermittent nature of PVs, improve the self–sufficiency of the end-user, and reduce the electricity tariff costs, a BES unit is also incorporated. The BES state-of-charge, SoC, is estimated as [9]:

$$SoC(n+1) = SoC(n) + \left[\eta_{\mathrm{ch}} \cdot P_{\mathrm{bat}}^{\mathrm{ch}}(n) - \frac{P_{\mathrm{bat}}^{\mathrm{dch}}(n)}{\eta_{\mathrm{dch}}}\right] \cdot \frac{\Delta n}{E_{\mathrm{bat}}} \tag{18}$$

where $P_{\mathrm{bat}}^{\mathrm{ch(dch)}}$ and $\eta_{\mathrm{ch(dch)}}$ are the charging (discharging) power and efficiency of BES unit, respectively; E_{bat} is the energy capacity. To increase the BES lifetime, upper and lower state of charge and charging/discharging power limits are assumed according to (19), (20), and (21):

$$SoC_{\min} \leq SoC(n) \leq SoC_{\max} \tag{19}$$

$$P_{\mathrm{bat}}^{\mathrm{ch}}(n) \leq P_{\mathrm{ch,max}} \cdot u_{\mathrm{bat}}(n) \tag{20}$$

$$P_{\mathrm{bat}}^{\mathrm{dch}}(n) \leq P_{\mathrm{dch,max}} \cdot (1 - u_{\mathrm{bat}}(n)) \tag{21}$$

TABLE I
NILM Results

Metric	Water heater	Dishwasher	Washing machine	Dryer
Active power MAE (W)	3.986	16.121	6.612	18.181
Reactive power MAE (VAr)	0.000	1.753	3.548	1.212
Precision	0.954	0.687	0.917	0.973
Recall	0.973	0.846	0.939	0.965
F1-score	0.964	0.758	0.928	0.969

TABLE II
Operating Parameters

	Parameter	Water heater	Dishwasher	Washing machine	Dryer
Actual	$\overline{P}_k$ (kW)	4.023	0.981	0.435	1.292
	$\overline{Q}_k$ (kVAr)	0.000	0.068	0.218	0.059
	OT_k (min.)	17.314	70.784	48.430	57.100
	POP_k	20:11-20:52	14:53-16:09	09:47-10:14	11:35-12:32
Estimated	$\overline{P}_k$ (kW)	3.815	1.111	0.478	1.254
	$\overline{Q}_k$ (kVAr)	0.000	0.034	0.116	0.042
	OT_k (min.)	17.714	68.269	48.225	57.400
	POP_k	20:11-20:52	15:00-16:10	09:45-10:15	11:35-12:34

where $P_{\mathrm{ch(dch),max}}$ is the maximum charging (discharging) power. Moreover, u_{bat} is a binary variable indicating charging or discharging. Based on these, P_{bat} is defined as:

$$P_{\mathrm{bat}}(n) = P_{\mathrm{bat}}^{\mathrm{ch}}(n) - P_{\mathrm{bat}}^{\mathrm{dch}}(n). \tag{22}$$

VI. Numerical Results

A. NILM Analysis

The performance of the NILM system is tested by evaluating the accuracy of the target appliance estimated active and reactive power by means of the mean absolute error (MAE). Accordingly, for the assessment of the appliance status the precision, recall, and F1-score [11] metrics are adopted. All metrics are calculated for the testing set presented in Table I and the results are on par with other approaches [9], [18], [19]. It can be seen that the proposed NILM model can accurately estimate both active and reactive power as well as the status of all target appliances.

The actual and the estimated operating parameters of the target appliances are compared in Table II. The calculated POP_k is very close to the real operational period for all appliances indicating that the developed NILM systems can indeed determine the period where HD can be minimized.

B. Day-ahead Scheduling

To evaluate the proposed day-ahead scheduling and the impact of the three objectives, the test case with parameters summarized in Table III is examined. The input timeseries, i.e., the solar production for a 3kWp PV system, the active power of the uncontrollable loads, the outdoor temperature, and DAP are depicted in Fig. 4. In order to solve the MINLP problem, the APOPT solver of GEKKO package [20] is used.

TABLE III
PARAMETERS

Parameter	Value	Parameter	Value	Parameter	Value
$P_{\text{HP,max}}$	3 kW	E_{bat}	8 kWh	η_{ch}	0.9
pf_{HP}	0.85	$SoC_{\min}$	0.1	η_{dch}	0.9
η	0.9	$SoC_{\max}$	0.9	$P_{\min}$	-4 kW
γ	-2.0	$P_{\text{ch,max}}$	3 kW	$P_{\max}$	5 kW
T_{c}	25	$P_{\text{dch,max}}$	3 kW	$Q_{\max}$	4 kVAr

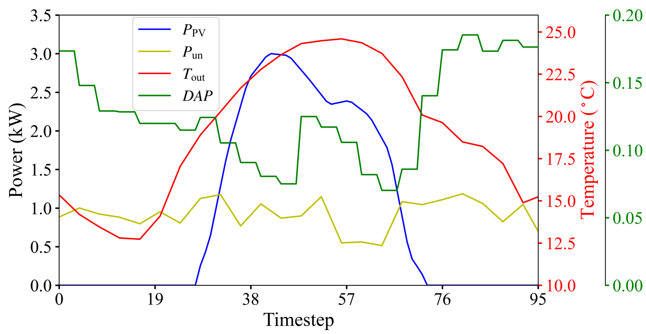

Fig. 4. Input timeseries

The scope of this test case is to evaluate the relative impact of HD and TD on OC. Assuming that $\alpha_1 = 1$, the day-ahead scheduling is performed by varying α_2, α_3. This way the effect of HD and TD with respect to OC is investigated. The resulting OC, HD, and TD are presented in Fig. 5 by means of heat maps.

It is evident that low values of α_2 and α_3 (habit and thermal comfort are not significant) result into low OC. This is because the operation of the flexible loads is scheduled during low-cost hours and the HP operation is trivial. By increasing α_2, habit comfort becomes more important, and flexible loads are scheduled during specific periods. This results into slightly increasing OC. On the other hand, high values of α_3 dictate the necessity for thermal comfort. Therefore, the optimization module intensifies the operation of the HP aiming to heat the household up to the specified temperature and consequently significantly increasing the operation cost, OC.

To further evaluate the results, a greedy HEMS is considered. In this case, the HEMS schedules the operation of each appliance separately (in descending order regarding the total energy consumption) at the cheapest available timeslot that guarantees uninterrupted operation without violating the maximum power constraints. Subsequently, the HP operation aims to provide optimal thermal comfort by means of (16) with respect to the maximum active/reactive power constraints. Note that, in this case, the BES control strategy target is to maximize the self-consumption ratio (SCR) [21]. Under the SCR strategy, any surplus of generated power is used for charging; discharging is activated when the PV generation is lower than the active power demand. The results of the greedy HEMS are presented in Table IV. It can be seen that $HD = 1$ since the scheduling of the appliances is based solely on minimizing the energy cost without considering end-user habits. Moreover, TD is lower and OC higher than the proposed HEMS, even when the latter provides maximum thermal and habit comfort.

TABLE IV
RESULTS OF GREEDY HEMS

Objective	Value
OC	8.056
HD	1.000
TD	1.323

C. Investigation of Other Billing Mechanisms

Two additional test cases (TCs) are examined and compared to the original scenario. In both test cases, the imported energy is charged according to DAP and:

- TC1: the exported energy is compensated by a 10% increase, i.e., $1.1 \cdot DAP$, and
- TC2: the exported energy is compensated by a 10% decrease, at $0.9 \cdot DAP$.

The obtained results for TC1 and TC2 are presented in Fig. 6 and Fig. 7, respectively. In TC1, the optimization module leverages the highly compensated exported energy leading to marginally profit-oriented solutions. Thus, the OC decreases significantly compared to the original scenario at the expense of higher HD and TD. In TC2, the opposite effect is observed. The low compensation of exported power leads to a smaller margin for financial benefit and thus to comfort-oriented solutions. In this context, the proposed HEMS provides lower HD and TD than the original scenario, but higher OC.

VII. CONCLUSIONS

A NILM-based HEMS is presented aiming to minimize the energy cost of the household, schedule the operation of flexible loads based on the end-user habits and maximize the thermal comfort by controlling the indoor temperature via a HP. Moreover, active assets, i.e., PV and BES units, are considered to provide additional flexibility. The operation of the HEMS is formulated as a multi-objective optimization problem. A parametric analysis is performed regarding the effect of each objective and different dynamic tariffs are examined by modifying the price of the exported energy.

From the analysis, it can be deduced that the employed NILM model can effectively profile end-user habits based on SM data. The extracted habits and accurate forecasts of temperature and PV production enable the proposed HEMS to plan the day-ahead operation of flexible loads, BES, and HP units under a win-win strategy in terms of cost and comfort. Finally, according to the obtained results, it can be realized that higher and lower compensation for exported energy leads to profit-oriented and comfort-oriented solutions, respectively.

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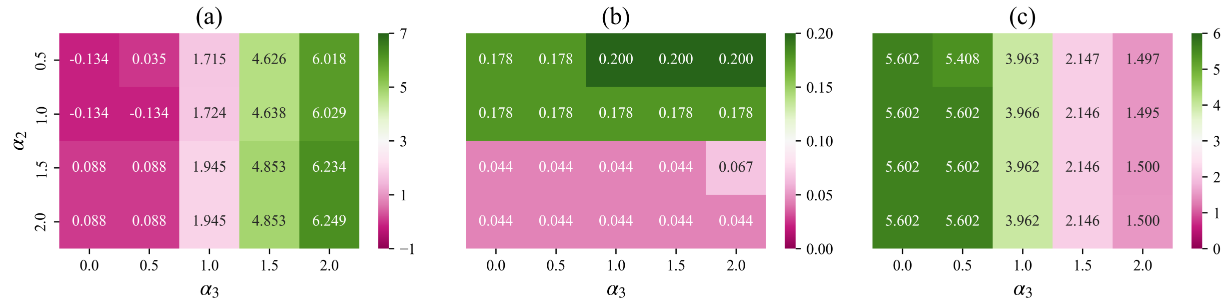

Fig. 5. Results for day-ahead scheduling: (a) OC, (b) HD, (c) TD

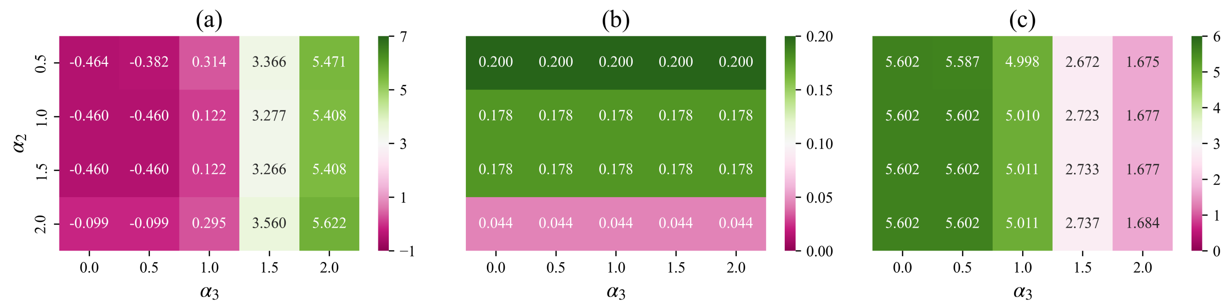

Fig. 6. Results for day-ahead scheduling with 10% higher feed-in tariff: (a) OC, (b) HD, (c) TD

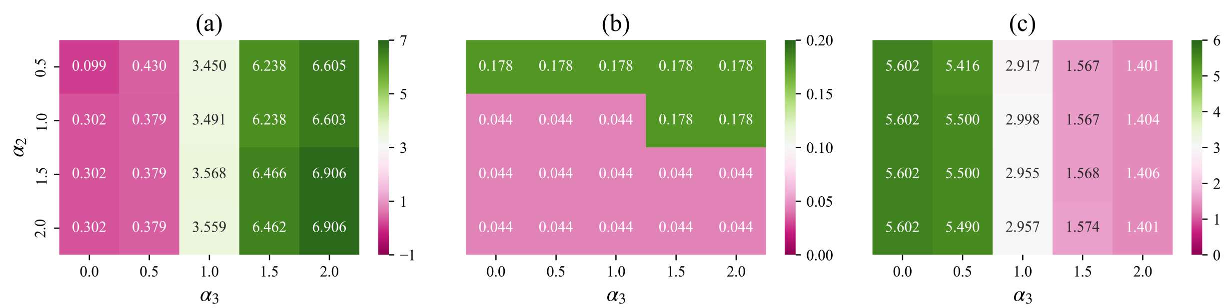

Fig. 7. Results for day-ahead scheduling with 10% lower feed-in tariff: (a) OC, (b) HD, (c) TD

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