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Integrated Household Appliance Scheduling With Modeling of Occupant Satisfaction and Appliance Heat Gain

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With the prevalence of building automation and Internet-of-Things technologies, home energy management has become an active area in recent years. This paper proposes an integrated, multi-objective Home Energy Management System (HEMS), which optimally schedules controllable electric household appliances to balance three objectives: 1) home energy cost; 2) the occupant's use satisfaction of controllable appliances; and 3) the occupant's thermal comfort. In particular, the HEMS models the coupling operational relationship between the non-thermostatically controlled appliances and the air conditioner by investigating the impact of heat gains released by the appliances on the indoor temperature. An advanced multi-objective optimizer is applied to solve the home energy management model. Simulations are conducted to validate the proposed method.

Keywords: demand response, smart home, building energy, smart grid, demand side management

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INTRODUCTION

Modern buildings are characterized by the penetration of renewable energy sources, Internet-of-Things (IoT) facilities, and building automation technologies. These have been driving buildings transition from static civil infrastructures to be complex cyber-physical entities that are capable of actively interacting with external physical systems, e.g., smart grids. In particular, the demand response (DR) flexibility of buildings (Mathieu et al., 2011), which refers to reducing or shifting building's energy consumption subjected to grid-side incentive and/or pricing signals, has been recognized as an affordable way for accommodating renewable energy and deferring the grid's infrastructure investment.

The advances of automation technologies in residential buildings drive the research and development of home energy management systems (HEMSs) (Inoue et al., 2003). A HEMS is an expert system that provides decision-making support to the occupant on scheduling and controlling household energy resources, such as rooftop photovoltaic solar panels and wind turbines, controllable appliances, energy storage devices, and plug-in electric vehicles. Depending on the managed objects, HEMSs can have different designs, which have been extensively studied in the literature. The following are some representative ones: Some research efforts and industrial demonstrations study the operation strategy for home energy storage devices, mainly including battery energy storage systems (BESSs) (Zhang et al., 2020) and the batteries in plug-in electric vehicles (known as the "vehicle-to-home" integration (Liu et al., 2013)). These efforts optimize battery's charging/discharging power to accommodate the residential renewable energy and provide energy to the household locally. For example, Iwafune et al. (2015) designed a rule-based controller to determine the charging/discharging power of residential BESSs based on the real-time power output of the rooftop photovoltaic (PV) solar panel. The Nissan Motor Company Ltd. demonstrated its "Smart Home of the Future concept" by using a Nissan Leaf vehicle to supply electricity to a house while operating off the power grid (Hornyak, 2011). Some literature study the energy management of air conditioning systems. For example, Jo et al. (2013) propose a coordinated scheduling method for a home BESS and an air conditioning system, aiming at minimizing the household's energy cost (both electricity cost and gas cost) while maintaining an acceptable indoor thermal comfort level. Dorokhova et al. (2020) propose an occupancy-based air conditioner (AC) control method. It firstly applies machine learning techniques to infer the room's occupancy from the smart meter data profile. Based on the occupancy state and the building's heat load, the work designs a rule-based controller to decide the ON/OFF state and operation mode (i.e., heating mode or cooling mode) of the AC.

The increasing prevalence of building IoT devices further lays a foundation to automatically control a wider range of household appliances besides the AC and energy storage systems. Such appliance scheduling methodologies have been actively studied in the literature in recent years. Jindal et al. (2020) propose a heuristic-based scheduling method which schedules both the time shiftable and interruptible appliances in a smart home environment to accommodate the power output of the rooftop PV solar panel and minimize the home net-load. Zhao et al. (2013) optimally schedule a residential BESS and a group of controllable household appliances to maximize the utilities of the appliances to the occupant while reducing the home's energy cost when subjected to a time-varying electricity tariff. (Ozturk et al. (2013) propose a HEMS, which dynamically schedules appliances in each dwelling unit based on the power demand of the whole community which was forecasted and reported to the utility to make day-ahead grid operation plans. In the authors' previous work (Luo et al., 2018), a coordinated scheduling model is proposed, which coordinately makes operation plans for an AC, a group of plug-in time shiftable appliances, and a plug-in EV. The authors also develop a multi-stage HEMS (Luo et al., 2019), which schedules a residential BESS and multiple controllable appliances in a PV solar power-penetrated home environment: in the day-ahead forecasting stage, an artificial neural network-based forecasting system is developed to predict the PV solar power output; in the day-ahead scheduling stage, a scheduling model is formulated to determine the BESS's charging/discharging plan and the appliances' operation plans; in the actual operation stage, a predictive control-based model is applied to real-time update the charging/discharging actions of the BESS and the appliances' operation states.

When designing HEMSs, the occupant's dwelling satisfaction is one of the primary considerations. While the occupant's satisfaction is a general concept that can be measured in various aspects, two satisfaction categorizes are commonly considered in a typical home environment: (i) usage satisfaction for the household appliances (except for the AC), which is directly related to the appliances' operation time and/or power consumptions; and (ii) indoor thermal comfort, which is influenced by the indoor air temperature, and the indoor temperature is affected by the outdoor climate and the AC's operation. These two aspects of satisfaction have been addressed in the state-of-the-art HEMS designs. For the usage satisfaction for typical time shiftable appliances (i.e., the appliances whose operation time is deferrable), it is usually reflected in the constraints that strictly restrict each appliance to operate in an allowable time range that is pre-specified by the occupant (Rastegar et al., 2012; Zhao et al., 2013; Luo et al., 2019). For indoor thermal comfort, the most commonly practiced approach is to control the AC to ensure the indoor temperature within a pre-specified comfort band (Jo et al., 2013; Dorokhova et al., 2020). These approaches can be considered to be "rigorous", as they use rigid constraints to restrict the appliance's operation.

Such a rigorous dwelling satisfaction modeling approach shows a major limitation in accurately representing the occupant's satisfaction. For example, if the occupant sets up an allowable time range for a washing machine (say, 2–8 pm), will the occupant really feel unsatisfied if the washing machine is scheduled to complete its task at 8:01 pm? To overcome the limitation, some research (e.g., the authors' previous work (Luo F. J. et al., 2017)) proposes linear models to model the relationship between the variation of the occupant's satisfaction and the deviation between the schedules of the appliances determined by the HEMS and the ones desired by the occupant. But a recent small-scale survey carried out by the authors on three Australian households indicates that the residents' satisfaction on the appliances' task completion time follows a non-linear pattern. The residents are asked to provide their subjective satisfaction feeling on the operation of several major household appliances (washing machine, dish washer, clothes dryer, and lighting bulbs). Their feedback is intuitive: if a deferrable appliances' actual task completion time (or a bulb's brightness) is close to the desired one, the residents feel it is acceptable; however, their dissatisfaction rapidly increases with the increase of the deviation between the actual and desired task completion time (or bulb's brightness). This indicates that nonlinear models are more desirable for modeling the occupant's dwelling satisfaction on appliance operations.

The issue of "rigorous dwelling satisfaction modeling" is also seen in controlling AC systems to maintain the occupant's thermal comfort. The literature usually uses the "temperature dead band" approach to strictly control the indoor temperature within a pre-specified comfort range of $T^{set} \pm \Delta T$, where T^{set} is the set temperature of the AC system and ΔT is the temperature variation band. For example: Gupta et al. (2015) develop a consensus-control based method to determine the optimal set-point of the AC system in a building subjected to the diverse set-point preferences of multiple occupants. An evolutionary programming method is applied to optimize the chilled water and supply air temperatures of an AC system to maintain the indoor temperature below a pre-set temperature point (Fong et al., 2006). With such a strict temperature band control approach, it is unreasonable to judge whether the occupant would feel "comfortable" or "uncomfortable" if the indoor temperature just temporarily varies out of the pre-specified comfort band a little bit. Gupta et al. (2018) design an incentive-based mechanism to enable each occupant in a building to spend credits to "purchase" his/her personalized thermal comfort preference in his/her occupancy zone. Despite the fact that this approach provides a more flexible way to facilitate the occupant to compromise thermal comfort and financial cost, it is more suitable for commercial building environments where spaces are shared by financially independent occupants rather than residential environments. For residential energy management, it is still necessary to develop models that can be more flexible than the "rigorous representations" to represent the occupant's satisfaction variation when subjected to different appliance schedules. Such satisfaction models would have a direct impact on the household's energy cost and thus would affect the design principle and operational performance of the HEMS.

In addition, there is another limitation that can be identified in the literature. When determining control strategies for the AC, the internal heat gain produced in the building environment is usually considered as a constant parameter (e.g., (Jo et al., 2013)). However, this approach can hardly be applied to HEMS designs where the AC is scheduled with other household appliances. This is because many appliances release heat in their operations. Different schedules of appliances would lead to different temporal variations of their heat gain productions, which would affect the indoor temperature variation and subsequentially influence the AC's operation. To the best of the authors' knowledge, coordinately scheduling the AC and other household appliances by considering the appliances' heat gains is never considered in the existing HEMS designs.

Based on the above discussion, the main contribution of this study is to develop a new HEMS that is centered on an integrated scheduling model for a group of controllable household appliances. The controllable appliances include an AC, multiple time shiftable appliances (TSAs), and multiple power adjustable appliances (PAAs). To overcome the aforementioned limitations of the existing work, the HEMS incorporates a new occupant satisfaction representation method, which uses nonlinear models and adjustable parameters to represent the occupant's comfort degree when subject to the operation of the different categories of appliances. Further, the developed HEMS links the heat gain produced by the appliances' operations with the building's thermal model to implement integrated scheduling for the AC and other appliances by simultaneously considering the household's energy performance and the occupant's dwelling satisfaction. In this study, we deliberately do not consider the penetration of energy storage systems and renewable power. This makes the proposed HEMS applicable for many apartment units where these devices are not available. Meanwhile, the models of renewable power sources and energy storage systems can be easily integrated into the proposed HEMS without significant modifications (e.g., following the modeling methodology in our previous work (Luo et al., 2018, 2019)).

This paper is organized as follows. *Modeling of Home Energy Resources* presents the modeling methodology of home energy resources managed by the HEMS. *Modelling of Occupant's Dwelling Satisfaction* and *Formulation of Home Energy Management Model* present the proposed occupant satisfaction models and the HEMS, respectively. *Solving Approach* presents the solving approach. *Simulation Study* discusses the numerical simulation result. Finally, the conclusion is drawn in *Conclusion and Future Work*.

MODELING OF HOME ENERGY RESOURCES

Figure 1 illustrates the operational environment of the HEMS. In this study, we consider that the HEMS manages three types of controllable appliances that are typically seen in current home environments: 1) multiple time shiftable appliances (TSAs, or known as deferrable appliances), whose power consumptions are constant, but operation time can be shifted to a certain extent. Typical appliances in this category include washing machines, clothes dryers, etc.; (b) multiple power adjustable appliances (PAAs), whose operation time is fixed, depending on the occupant's life requirements; but their power consumptions can be adjusted to a certain extent. Typical appliances in this category include lights, amplifiers, etc.; and (c) an AC, whose operation is driven by the indoor air temperature and the occupant's thermal comfort preference.

Denoting there are a total of T time slots over the energy management period and the duration of each time slot is Δt (hour), then the models of each type of these home energy resources are presented as below.

Modeling of Time Shiftable Appliances

Time shiftable appliances represent the appliances whose operation time can be shifted to an extent. Considering there are a total of N^{tsa} TSAs managed by the HEMS, then the ith TSA ($i = 1\!:\ N^{tsa}$) can be modeled to be with the following properties:

1) Operating power (P_i^{tsa}, kW). Each TSA is considered to consume constant operating power in its operation.
2) Task duration (d_i^{tsa}), expressed as the number of time slots. It represents the time needed for the TSA to complete the task.
3) Desired task completion time ($t_i^{tsa,*}$). $t_i^{tsa,*}$ is expressed as a time slot index, representing the time when the occupant most intends to complete the appliance's operation.
4) Heat gain value (h_i^{tsa}, kW), representing the heat gain released by the TSA in its operation.

Therefore, each TSA can be modeled as a 4-turple vector: $< P_i^{tsa}, d_i^{tsa}, t_i^{tsa,*}, h_i^{tsa} >$. **Figure 2** provides an illustrative example to depict the model representation of a TSA.

Modeling of Power Adjustable Appliances

Considering there are N^{paa} power adjustable appliances managed by the HEMS. For the jth PAA ($j = 1\!:\ N^{paa}$), it has the following properties:

1) Operation time. Each PAA is associated with one or multiple occupant-specified time points when it is requested to run. The operation time can be represented as a vector $\mathbf{t}_j^{run} = [t_{j,1}^{run}, t_{j,2}^{run}, \cdots, t_{j,M_j}^{run}]$, where M_j is the total number of operation time points of the jth PAA; $t_{j,m}^{run} (m = 1\!:\ M_j)$ is the time slot index of the mth operation time point of the jth PAA.
2) Desired power consumption. For each PAA, there is an occupant-specified desirable power consumption value at each operation time point, denoted as

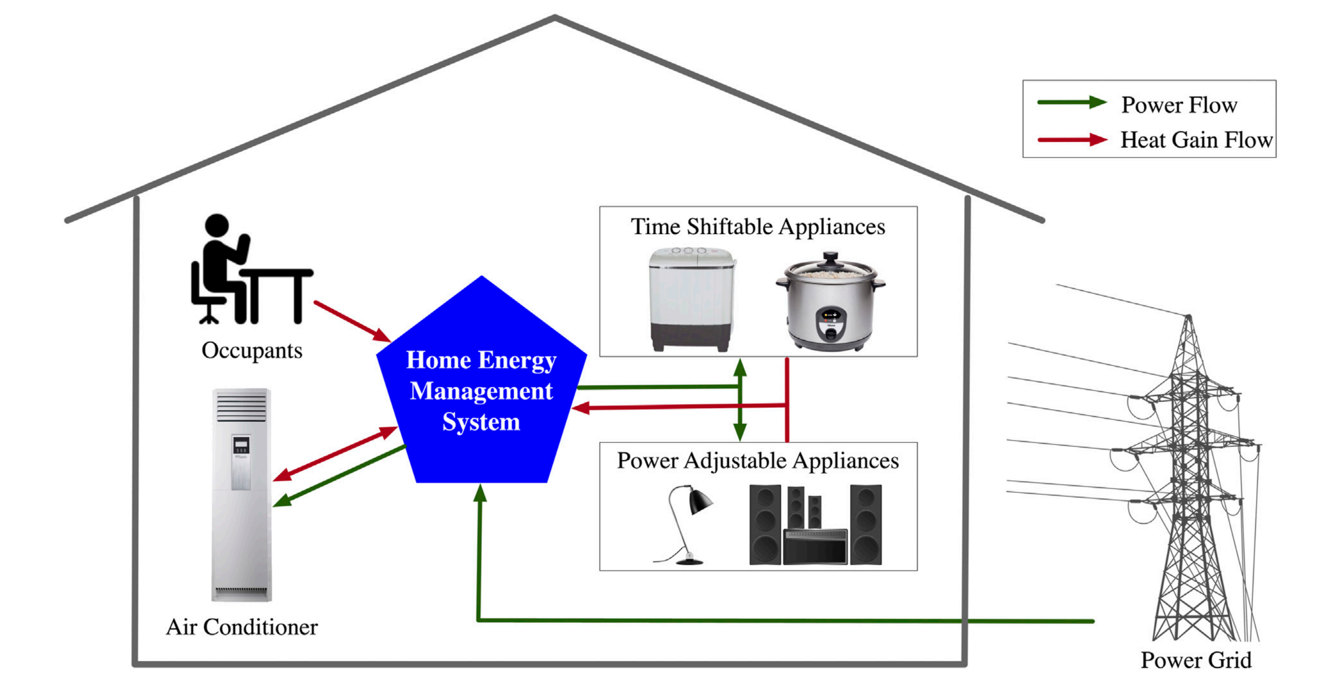

FIGURE 1 | Illustration of the HEMS.

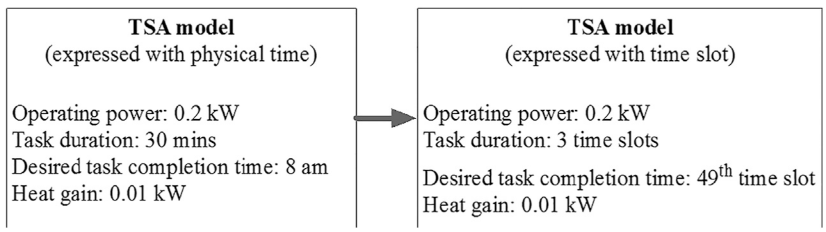

FIGURE 2 | Illustration of a TSA model (considering that the scheduling period starts from 7:30 am and the duration of each time slot is 10 min).

$\mathbf{P}_j^{dsr} = \left[P_{j,1}^{dsr}, P_{j,2}^{dsr}, \cdots, P_{j,M_j}^{dsr}\right]$, where $P_{j,m}^{dsr}$ is the occupant's desired power consumption for the jth PAA at the time point of $t_{j,m}^{run}$ (kW). In practice, the occupant would specify his/her desired level of the appliance's certain function (e.g., an amplifier's sound level), and then the HEMS maps it to the corresponding power level.

3) Adjustable power range. Each PAA has a lowest power level, denoted as P_j^{low} (kW). In this study, we consider the PAA's power to be continuously adjustable. That is, its adjustable power range at the time point of $t_{j,m}^{run}$ is $\left[P_j^{low}, P_{j,m}^{dsr}\right]$. For PAAs whose power consumption can only be adjusted at discrete levels, they can be easily integrated into the proposed HEMS model without significant modifications (i.e., specifying the value boundary of the decision variables representing the PAAs' power consumptions as discrete values instead of continuous values, see *Encoding Scheme*).
4) Heat gain value (h_j^{paa}, kW), representing the heat gain released by the jth PAA in its operation.

Based on the properties mentioned above, **Figure 3** provides an example to illustrate the model representation of a PAA.

Model of Air Conditioner

The operation of AC is directly related to the room's thermal model. This section presents the room's thermal model and the AC's operation model.

Room's Thermal Model

There are a number of models in the literature that can be used to model the room's thermal transition process. In this study, we follow the building thermal model in Ryder-Cook (2009). This thermal model has also been used in other literature about AC energy management (e.g., (Ding et al., 2019)). With this model, the indoor temperature trajectory of the room is described as:

$$c \times \rho \times V^{room} \times \frac{dT^{ind}}{dt} = H_t^{gain} - H_t^{loss} \tag{1}$$

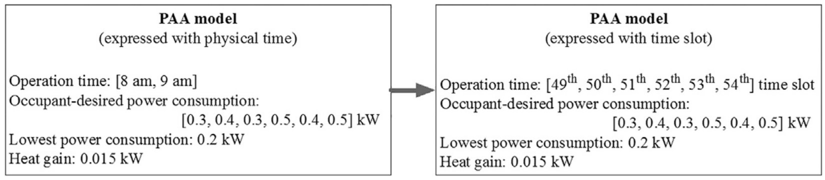

FIGURE 3 | Illustration of a PAA model.

The heat gain H_t^{gain} is calculated by **Eq. 2**. It consists of the heat gains from the following sources at the tth time slot: 1) from the AC (H_t^{ac}); (b) from the internal appliances and occupants (H_t^{apo}); and (c) from the Sun (H_t^{solar}).

$$H_t^{gain} = H_t^{ac} + H_t^{apo} + H_t^{solar} \tag{2}$$

$$H_t^{ac} = P_t^{ac} \times COP_t \tag{3}$$

For air-sourced ACs, COP is mainly related to the indoor and outdoor temperature difference and can be approximately expressed as a linear equation:

$$COP_t = -\theta \times \left| T_t^{ind} - T_t^{out} \right| + \delta \tag{4}$$

where θ and δ are the fitted coefficients. In Ryder-Cook (2009), the heat gain from the appliances and occupants are simplistically estimated with the product of the room's area and a coefficient. Such simplified estimation cannot be applied to the proposed HEMS, because the power consumption and operation time of the appliances are scheduled by the HEMS and thus lead to different temporal internal heat gain distributions to the room. Therefore, in this study H_t^{apo} is calculated from the appliances' schedules:

$$H_t^{apo} = \sum_{i=1}^{N^{tsa}} \left(h_i^{tsa} \times s_{i,t}^{tsa} \right) + \sum_{j=1}^{N^{paa}} g\left(P_{j,t}^{paa} \right) + \zeta_t \tag{5}$$

where the function $g(\cdot)$ returns the heat gain value of a PAA according to the power consumption level of the PAA at that time. Due to the fact that the relationship between a PAA's power consumption and its heat gain depends on the appliance's internal mechanical design and usually varies for different appliance models, it is hard to establish a generic and explicit form for $g(\cdot)$. The output of $g(\cdot)$ should be based on measurements or the appliance's manufacture configuration. ζ_t is the heat gain released by the occupant at time t, which is related to the occupant's indoor activity level. H_t^{solar} is calculated as:

$$H_t^{solar} = P_t^{ins} \times A^{window} \tag{6}$$

The heat loss of the room is estimated based on the losses through the building envelope and air leakages (Ryder-Cook, 2009):

$$H_t^{loss} = K \times A^S \times \left(T_t^{ind} - T_t^{out} \right) + c \times \rho \times V^{room} \times \left(T_t^{ind} - T_t^{out} \right) \times n \tag{7}$$

Operation Model of Air Conditioner

The operation of the AC is driven by the indoor temperature and the occupant's thermal comfort preference that is presented in *Modelling of Occupant's Dwelling Satisfaction*. The AC has two states: operation state and standby state. Denoting the AC's state at time t as s_t^{ac} ($s_t^{ac} = 1$and 0 represent the AC in its operating and standby states at the tth time slot, respectively), the AC's power consumption at the tth time slot (denoted as P_t^{ac}, kW) is then expressed as:

$$P_t^{ac} = \begin{cases} P^{rate} & \textbf{if } s_t^{ac} = 1 \\ P^{stdb} & \textbf{if } s_t^{ac} = 0 \end{cases} \tag{8}$$

The positive value of P^{rate} indicates the heating mode of the AC and the negative value indicates cooling mode.

MODELING OF OCCUPANT'S DWELLING SATISFACTION

Given a schedule of the home energy resources, this study evaluates the occupant's dwelling satisfaction in three aspects as follows.

Modeling of Occupant's Satisfaction on Time Shiftable Appliances

For the schedule of the ith TSA ($i = 1{:}\ N^{tsa}$) that is determined by the HEMS, we propose to model the occupant's use dissatisfaction on it (D_i^{tsa}) as a normalized value:

$$D_i^{tsa} = \frac{D_i'}{D_i^{\max}} \tag{9}$$

$$D_i' = \left(\left| \left(\bar{t}_i^{tsa} + d_i^{tsa} - 1 \right) - t_i^{tsa,*} \right| \times \Delta t \right)^{\alpha_i} \tag{10}$$

$$D_i^{\max} = \left(\max\left(\left| 1 - t_i^{tsa,*} \right|, \left| T - t_i^{tsa,*} \right| \right) \times \Delta t \right)^{\alpha_i} \tag{11}$$

where the function $\max(\cdot)$ returns the maximum value of the inputs; α_i is the occupant-specified comfort factor for the ith TSA. It reflects the occupant's subjective satisfaction of using the ith TSA. As an example, **Figure 4** plots the occupant's dissatisfaction degree when a TSA finishes its task on different time points with two comfort factor values of α_i. The curves show that at the time when the TSA is scheduled to complete its task close to the desired task completion time, then the dissatisfaction degree is close to zero. The larger distance between the scheduled and desired task completion time points, the larger the dissatisfaction degree is. The satisfaction factor α_i controls the shape of the curve, which may vary in different occupants, depending on the occupant's subjective preference.

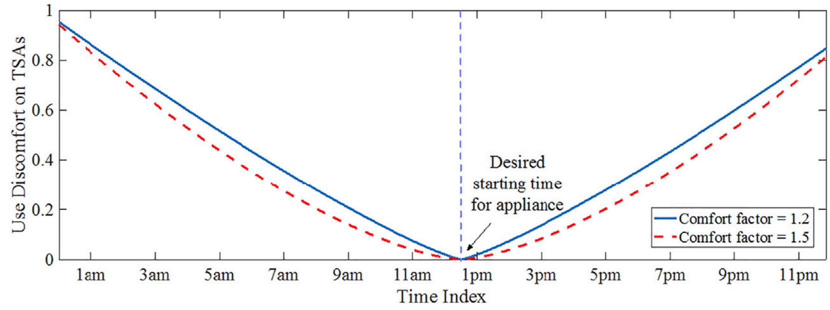

FIGURE 4 | Illustration of the occupant's varying dissatisfaction degree on the operation of a TSA (settings: T = 144, Δt = 10 minutes $t_i^{tsa,*}$ = 1pm, and d_i^{tsa} = 40 minutes).

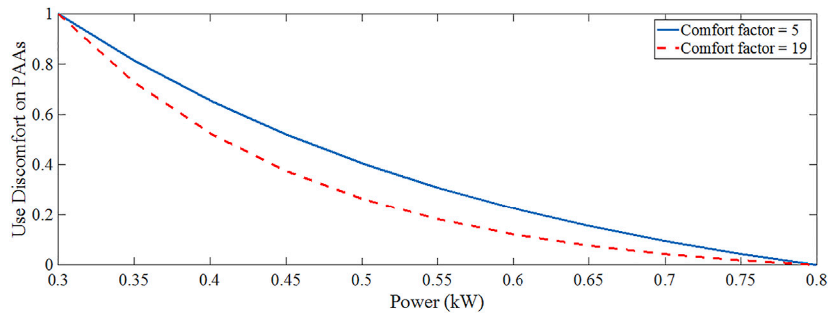

FIGURE 5 | Illustration of the variation of the occupant's dissatisfaction degree on a PAA's operation at one time slot ($P^{dsr}_{i,t^{run}_{i,m}}$ = 0.8 and P_i^{low} = 0.3).

Modeling of Occupant's Satisfaction on Power Adjustable Appliances

For the schedule of the jth PAA ($j = 1{:}\ N^{paa}$) that is determined by the HEMS, we propose to model the occupant's use dissatisfaction degree on it (D_j^{paa}) as a normalized value:

$$D_j^{paa} = \frac{\sum_{m=1}^{M_j} D_{j,m}^{paa}}{M_j} \tag{12}$$

$$D_{j,m}^{paa} = \frac{\left(\beta_j\right)^{\psi_{j,m}} - 1}{\beta_j - 1} \tag{13}$$

$$\psi_{j,m} = \frac{P^{dsr}_{j,t^{run}_{j,m}} - P_{j,t^{run}_{j,m}}}{P^{dsr}_{j,t^{run}_{j,m}} - P_j^{low}} \tag{14}$$

As an example, **Figure 5** plots the occupant's dissatisfaction degree for a PAA at one time slot subjected to β_j = 5 and 19, respectively.

Indoor Thermal Comfort Model for the Occupant

Indoor thermal comfort is an important aspect of the occupant's dwelling satisfaction. It has a direct relationship with the indoor temperature. Distinguished from many literature papers that set up a rigorous indoor temperature band, we propose to evaluate the occupant's thermal comfort using the following nonlinear function:

$$D_t^{ac} = \begin{cases} 0, & \text{if } T^{dsr,low} \le T_t^{ind} \le T^{dsr,up} \\ \left(\dfrac{T_t^{ind} - T^{dsr,up}}{T^{set,up} - T^{dsr,up}}\right)^{\gamma}, & \text{if } T^{dsr,up} < T_t^{ind} \le T^{set,up} \\ \left(\dfrac{T^{dsr,low} - T_t^{ind}}{T^{dsr,low} - T^{set,low}}\right)^{\gamma}, & \text{if } T^{set,low} \le T_t^{ind} < T^{dsr,low} \\ 1, & \text{otherwise} \end{cases} \tag{15}$$

where γ is the occupant-specified comfort factor for the AC. **Figure 6** illustrates the variation of the occupant's thermal comfort with the settings of γ = 2 and 4, respectively.

As mentioned in the introduction section, the proposed nonlinear satisfaction models (the ones presented in *Modelling of Occupant's Satisfaction on Time Shiftable Appliances–Indoor Thermal Comfort model for the Occupant*) can better represent the nonlinear variation of the occupant's dissatisfaction. The proposed models also incorporate adjustable satisfaction parameters (α_i, β_j, and γ) that allow different occupants to shape the nonlinear models based on their subjective satisfaction requirement.

FORMULATION OF HOME ENERGY MANAGEMENT MODEL

Based on the home energy resources models and occupant comfort models presented in *Modelling of Home Energy*

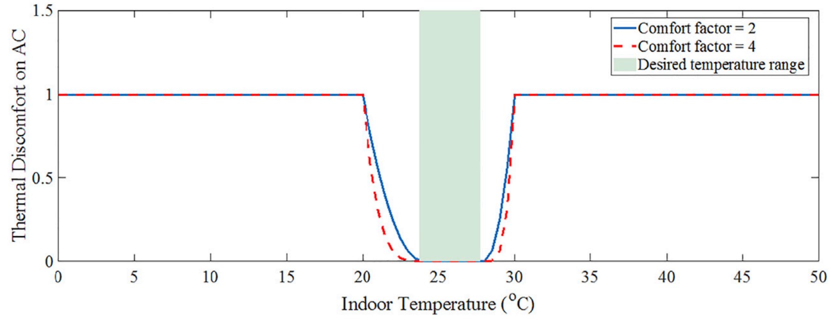

FIGURE 6 | Illustration of the variation of the occupant's discomfort degree on the AC's operation ($T^{dsr,low}$ = 24, $T^{dsr,up}$ = 28, $T^{set,low}$ = 20, $T^{set,up}$ = 30).

Resources and *Modelling of Occupant's Dwelling Satisfaction*, this section formulates the home energy management model. The model is formulated as a 3-objective optimization problem, in which the HEMS determines the schedules of the controllable appliances to balance the three aspects of considerations in a smart home environment: (i) the home energy cost; (ii) the occupant's use satisfaction for TSAs and PAAs; and (iii) the occupant's indoor thermal comfort.

The decision variables of the home energy management model include: (i) start operation time of each TSA, i.e., $\tilde{t}_i^{tsa}$, $i = 1{:}\ N^{tsa}$; (ii) power consumption of each PAA at each of its operation time slots, i.e.,$P^{paa}_{j,t^{run}_{j,m}}$, $j = 1{:}\ N^{paa}$, $m = 1{:}\ M_j$; and (iii) status of the AC at each time slot, i.e., s_t^{ac}, $t = 1{:}\ T$. The three objectives of the home energy management model are:

Objective 1—Minimization of the household energy cost:

$$\min F_1 = \sum_{t=1}^{T}\left(P_t^{home}\cdot\Delta t\cdot pr_t\right) \tag{16}$$

$$P_t^{home} = \sum_{i=1}^{N^{tsa}}\left(P_i^{tsa}\cdot s_{i,t}^{tsa}\right) + \sum_{j=1}^{N^{paa}} P_{j,t}^{paa} + P_t^{ac} \tag{17}$$

Objective 2—Minimization of the Occupant's Use Dissatisfaction for TSAs and PAAs:

$$\min F_2 = \sum_{k=1}^{N^{tsa}+N^{paa}} w_k\cdot D_k \tag{18}$$

$$D_k = \begin{cases} D_k^{tsa}, & \text{if } 1\le k\le N^{tsa} \\ D_{k-N^{tsa}}^{paa}, & \text{if } \mathbf{k} > N^{tsa}\end{cases} \tag{19}$$

Objective 3—Minimization of the Occupant's Thermal Discomfort:

$$\min F_3 = \sum_{t=1}^{T} D_t^{ac} \tag{20}$$

The home energy management model **Eqs. 16**-**20** is subjected to the following operational constraints:

$$P_j^{low} \le P^{paa}_{j,t^{run}_{j,m}} \le P^{dsr}_{j,t^{run}_{j,m}} \tag{21}$$

$$s_{i,t}^{tsa} = \begin{cases} 1 & \text{if } \tilde{t}_i^{tsa}\le t\le \tilde{t}_i^{tsa} + d_i^{tsa} - 1 \\ 0 & \text{otherwise}\end{cases}, i = 1{:}\ N^{tsa} \tag{22}$$

$$P_{j,t}^{paa} = 0 \text{ if } t\notin \mathbf{t}_i^{run},\ j = 1{:}\ N^{paa} \tag{23}$$

Constraint (**Eq. 21**) restricts the adjustable power range of each PAA at each of its operational time slots. Constraint (**Eq. 22**) ensures that each TSA can only be in the "ON" state in its task execution period. Constraint (**Eq. 23**) ensures that each PAA does not consume power except at its operational time slot.

SOLVING APPROACH

The proposed home energy management model (*Modelling of Home Energy Resources–Formulation of Home Energy Management Model*) is a mixed-integer, nonlinear multi-objective optimization problem over a finite time horizon. Evolutionary computation has been proved to be an effective technique for solving multi-objective optimization problems and obtaining the Pareto Frontier. In this study, we apply the Multi-Objective Natural Aggregation Algorithm (MONAA) previously proposed by the authors (Luo et al., 2016) to solve the proposed model. MONAA roots from the Natural Aggregation Algorithm (Luo F. et al., 2017)—a swarm-based heuristic algorithm. MONAA mimics group living animals' self-aggregation intelligence by distributing a group of candidate solutions (called "individuals") into multiple sub-populations and using a biology-rooted stochastic migration model to migrate the individuals among the sub-populations. It also designs heuristic searching rules to produce mutants of the individuals to search for the global/near global optimal solution in the high dimensional problem space.

The major reasons of using MONAA to solve the proposed home energy management model are two-fold: firstly, by inheriting NAA's stochastic searching mechanism, MONAA shows satisfactory performance in finding the Pareto Frontier of several engineering optimization problems (e.g., Luo F. et al., 2017; Deng et al., 2020); secondly, the authors have developed a well-packaged MONAA solver, which can be easily interfaced to demand side optimization models. The well-defined interfaces mean the solver can be efficiently and conveniently applied to the proposed home energy management model. Since the

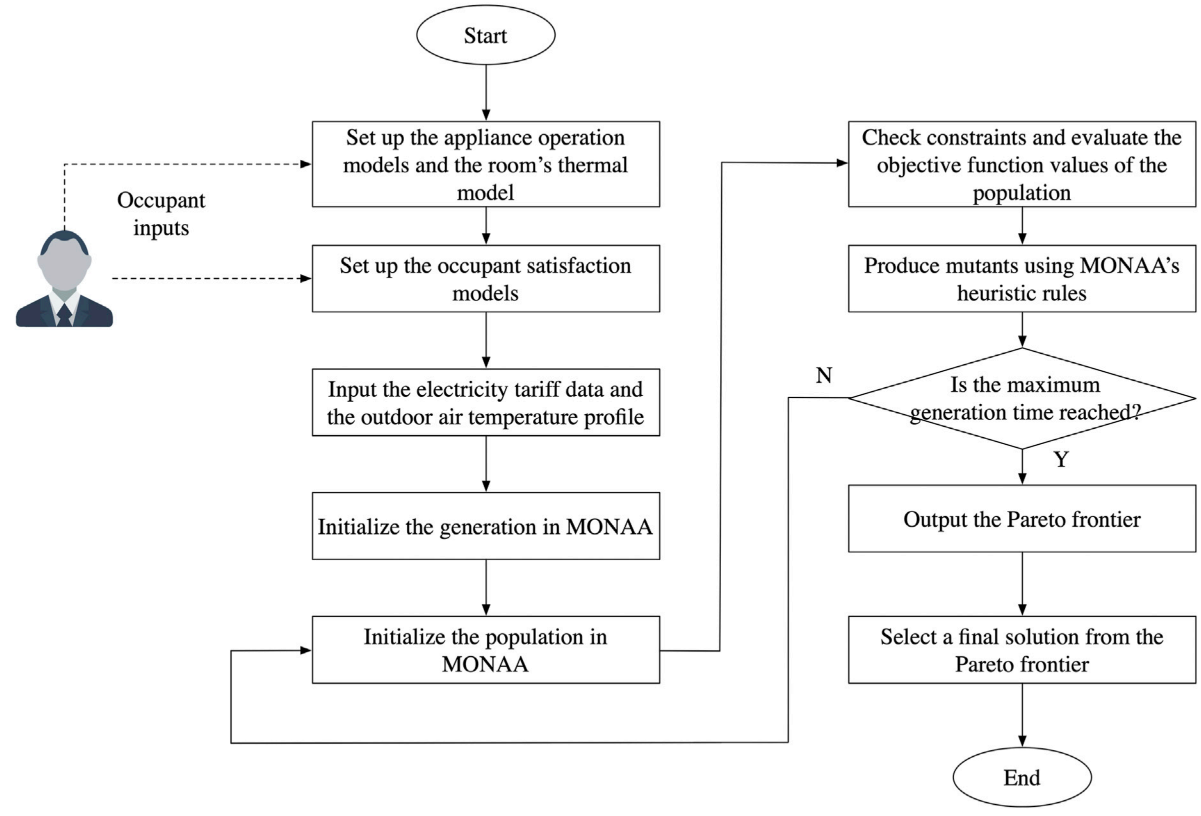

FIGURE 7 | Solving workflow for the proposed HEMS.

optimization algorithm itself is not the primary focus of this paper, other multi-objective optimizers (such as NSGA-II) can also be applied to solve the proposed model with little modifications to the proposed system.

Encoding Scheme

In MONAA, each individual is encoded as a vector with the dimensionality of $N^{tsa} + \sum_{j=1}^{N^{paa}} M_j + T$ representing a candidate home energy management solution. The encoding scheme for each individual is as follows:

1) The first N^{tsa} dimensions represent the starting operation time slot index of the TSAs, where each dimension represents that of one TSA;
2) the next $\sum_{j=1}^{N^{paa}} M_j$ dimensions represent the power consumptions of the PAAs, in which every sequential M_j dimension represents the power consumptions of one PAA at each of its operation time slots;
3) the last T dimensions represent the room's set temperature at each time slot.

Solving Workflow

The solving workflow is shown in **Figure 7**. Firstly, the models of the appliances (TSAs, PAAs, and the AC), the room model, the occupant satisfaction models, the electricity tariff data, and the predicted outdoor air temperature profile are inputted into the system. Then, MONAA initializes a population of individuals and iteratively produce mutants to perform heuristic searching. After the maximum generation time is reached, the algorithm outputs a set of non-dominated individuals (called the Pareto Frontier).

Since the solutions in the Pareto Frontier are non-dominated with each other, it is unreasonable to say which solutions are "better"; they just represent different compromises of the three optimization objectives. Choosing the final solution from the Pareto Frontier can be completely based on the user's subjective preference, or can be generated based on certain criteria. The latter approach is useful especially when the number of solutions in the Pareto Frontier is large, which would mean the user would find it difficult to choose. In *Simulation Study* of this paper, we will discuss the final solution that is selected by a compromise-solution method (Marler and Arora, 2004), shown in **Eqs. 24, 25**:

$$\min_{y \in Y} \sqrt{\sum_{o=1}^{3} \left| F(y,o) - F_o^* \right|^2} \tag{24}$$

$$F(y,o) = \frac{Y_o^{\max} - y_o}{Y_o^{\max} - Y_o^{\min}} \tag{25}$$

where Y is the set of non-dominated solutions; $Y_o^{\max}$ and $Y_o^{\min}$ represent the maximum value and minimum value of the oth objective among the non-dominated solutions, respectively; y_o is the value of solution y on the oth objective; F_o^* is the utopia point,

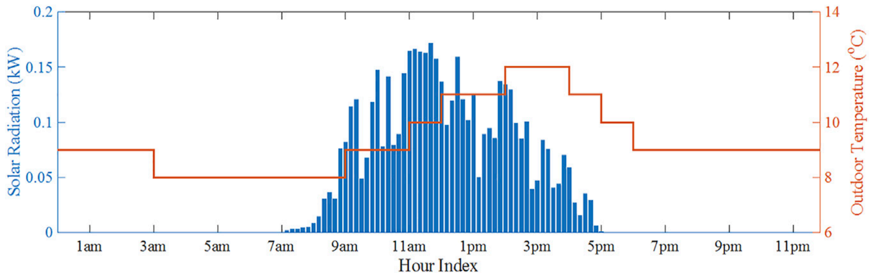

FIGURE 8 | Profiles of outdoor temperatures and solar radiation in a typical winter day.

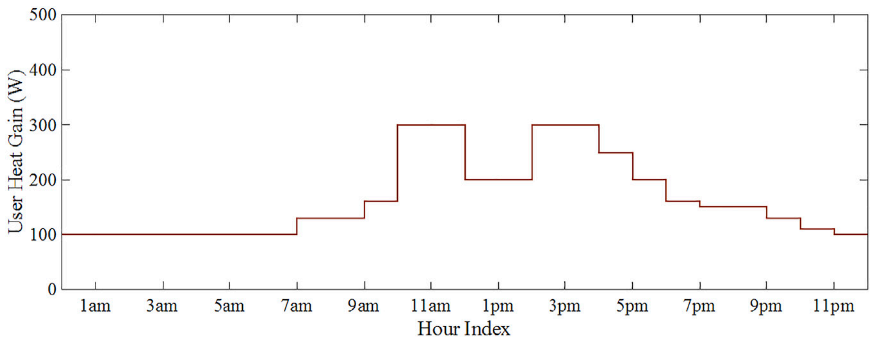

FIGURE 9 | Heat gain released by the occupant.

TABLE 1 | Settings of major parameters in the home environment.

Parameters of occupant	
Desired indoor temperature ($[T^{dsr,low}, T^{dsr,up}]$)	[20°C,28°C]
Range of set temperature ($[T^{set,low}, T^{set,up}]$)	[16°C,30°C]
Thermal comfort factor (γ)	0.5
Parameters of room	
The volume of the room (V^{room})	$(10\times10\times3)\text{m}^3$
The initial indoor temperature	10°C
Parameters of AC	
Standby power (P^{stdb})	0.025kW
Operating power (P^{rate})	2kW
The bandwidth of set temperature	+/- 2°C

which is set as one on all of the three objectives to make all objective functions as close as possible to the minimum value.

SIMULATION STUDY

This section reports the numerical simulation that is conducted for validating the proposed HEMS. All the programs are implemented on Matlab and are executed on a PC with macOS Catalina, Intel Core i9, with 16 GB memory.

Simulation Setup

We consider a home energy management scenario on a typical cold winter day, where the AC operates in heating mode. The profiles of 1-day solar radiation and outdoor air temperature (**Figure 8**) are based on the meteorological data of Zhengzhou City, China on a day in March 2021, collected from the "Weather" application on iPhone. The profile of the room's internal heat gain due to the occupant's activity is shown in **Figure 9**, based on the data provided in Heat Gain from People, Lights, and Appliances. The parameters of the room's thermal model and AC are set as **Table 1**.

Six TSAs and two PAAs are simulated for being managed by the HEMS. The configurations of these appliances are given in **Table 2**, note that the heat gain released by the jth power adjustable appliance at the tth time slot can be calculated by **Eq. 26**, where η_j is the heat emission coefficient of the jth power adjustable appliance. In this experiment, the heat emission coefficient of these two PAAs are obtained from Suszanowicz (2017):

$$h^{paa}_{j,t} = g\left(P^{PAA}_{j,t}\right) = \eta_j \times P^{PAA}_{j,t} \tag{26}$$

The home is considered to be charged by a real-time electricity pricing (RTP) scheme, shown as **Figure 10**. A 24-h scheduling period is considered with the duration of each time slot (Δt) as 10 min. Therefore, there are a total of 144 time slots, i.e., $T = 144$. The control parameters of MONAA are set as follows: population

TABLE 2 | Settings of controllable appliances.

	Time shiftable appliances						Power adjustable appliances	
	Coffee heater	Dish washer	Oven	Kettle	Hot plate	Washing machine	LED bulb	Incandescent light bulb
Heat gain	210 W	380 W	20 W	21 W	3,170 W	150 W	0.08 W/W[a]	0.95 W/W[a]
Duration	20 min	50 min	30 min	20 min	30 min	60 min	-	-
Comfort factor	1.5	1.2	2	2	1.8	1.6	1.1	1.5
Weight	0.5	0.8	0.6	0.5	0.6	0.7	0.8	0.6
Rated power	0.67 kW	0.38 kW	1.2 kW	0.13 kW	4 kW	1 kW	[0.00 5kW, 0.015 kW]	[0.108 kW, 0.112 kW]
Completion time	8:10	12:30	11:40	15:00	18:40	17:00	[18:10, 23:10]	[18:00, 21:00]

[a]*Heat emission coefficient of power adjustable appliances.*

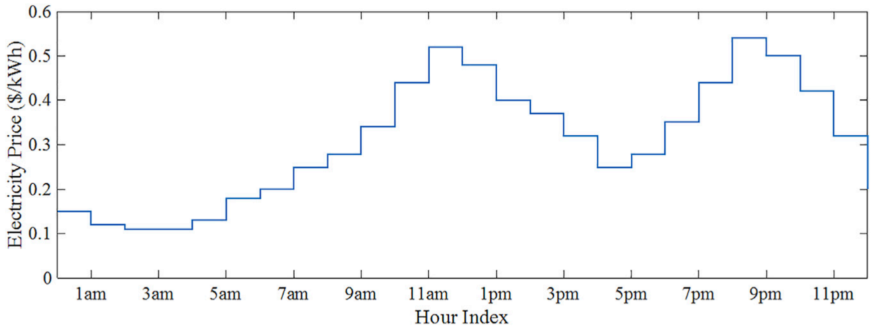

FIGURE 10 | Profile of the real-time electricity prices.

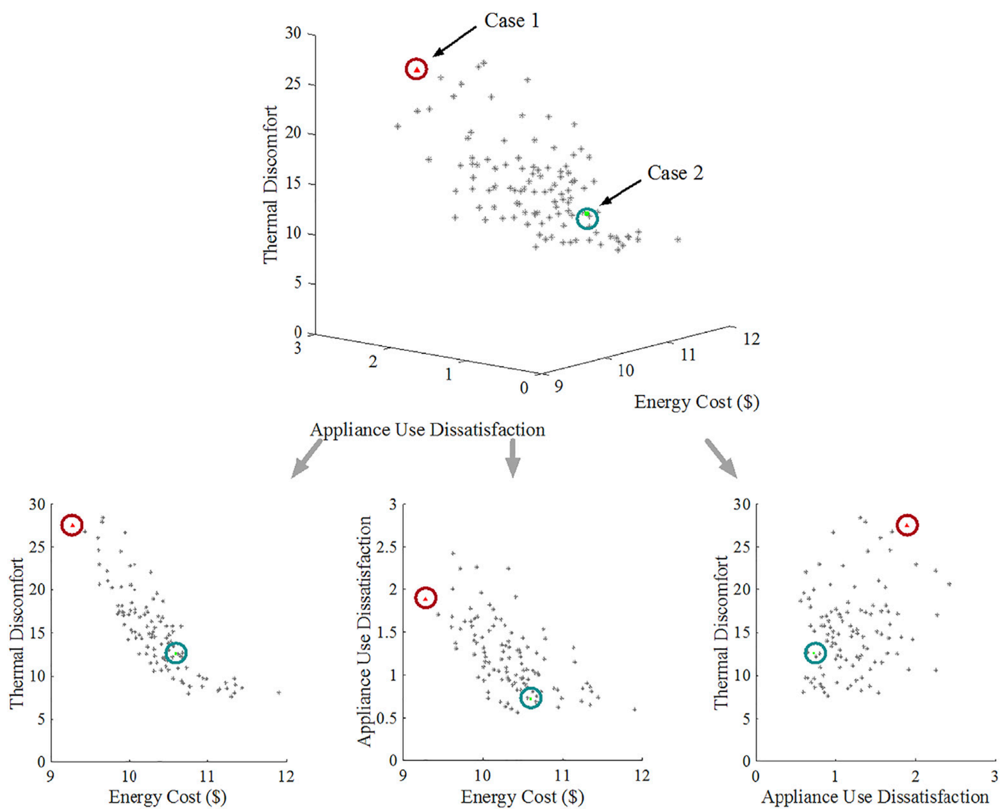

FIGURE 11 | Obtained non-dominated home energy management solutions.

TABLE 3 | Objective values under three cases.

	Energy cost ($)	Appliance use dissatisfaction value	Indoor thermal discomfort value	Total energy consumption (kWh)
Case 1	9.28	1.89	27.52	34.14
Case 2	10.60	0.73	11.61	36.77
Case 3	13.87	0.00	3.08	45.35

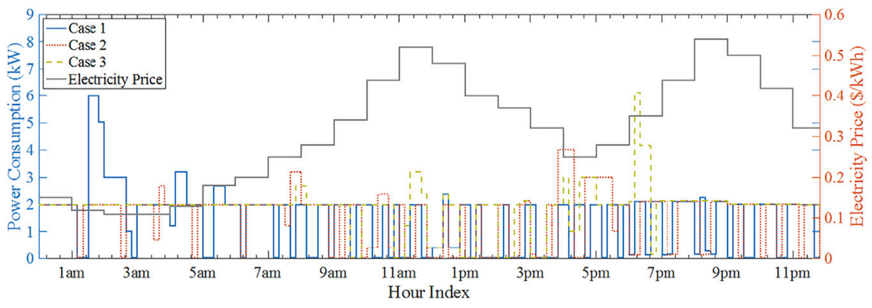

FIGURE 12 | Total power consumption profiles under the three cases.

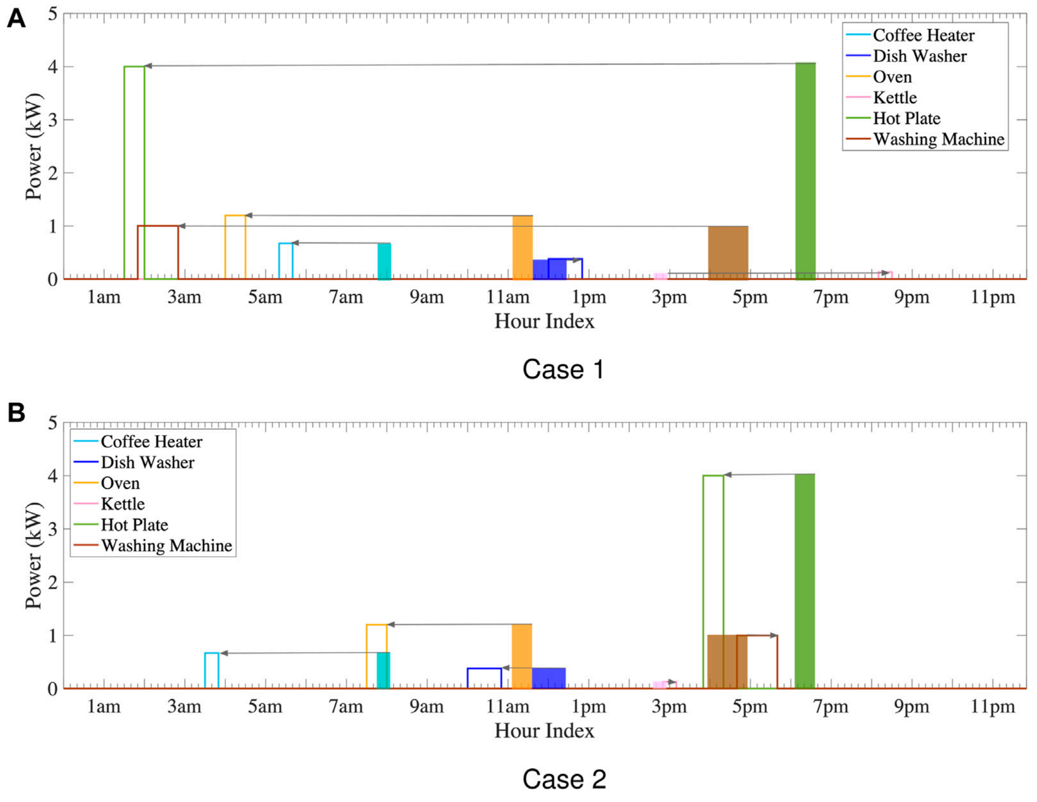

FIGURE 13 | Planned schedule of TSAs under Case 1 and Case 2 (lines: optimized completion time of each TSA by MONAA; blocks: user-specified completion time of each TSA).

size—500; maximum generation time—1,000; number of shelters—4; shelter capacity—125; scaling factor—1.0; located crossover factor—0.9; movement amplification—1.2; generalized crossover factor—0.1. These settings are based on the authors' trials of NAA and MONAA on benchmark functions and other engineering problems (e.g., Luo et al., 2016; Luo et al., 2018;

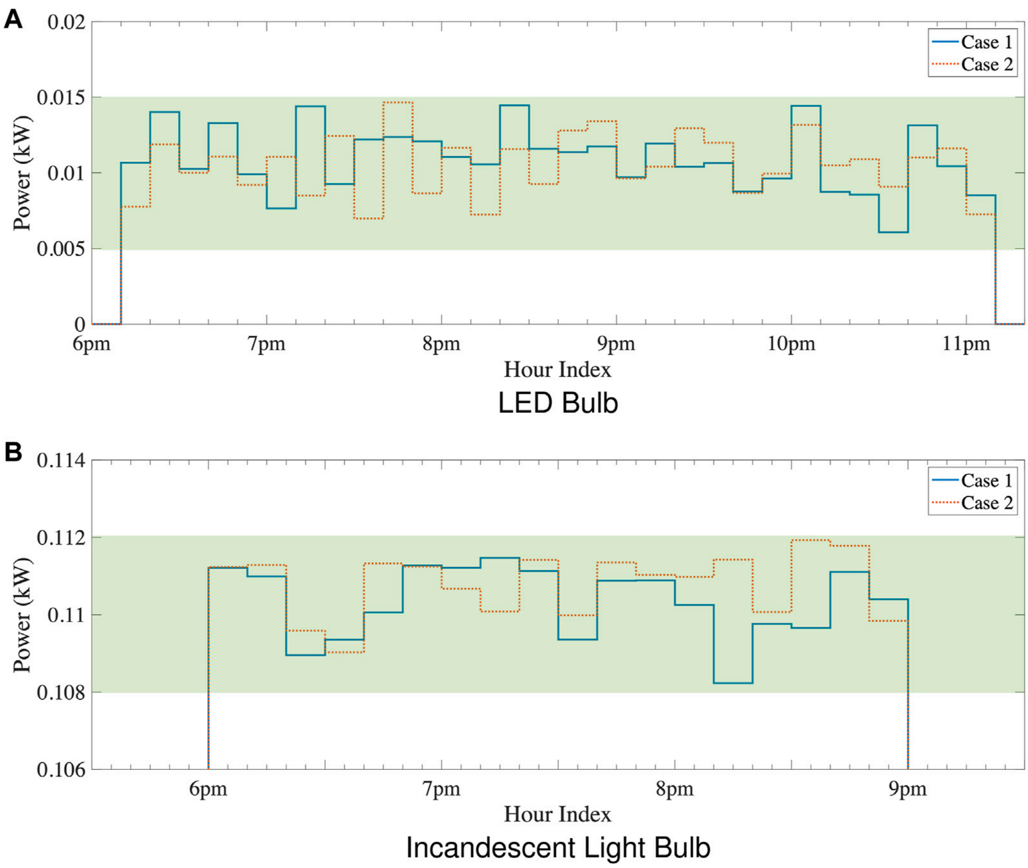

FIGURE 14 | Power consumptions of the PAAs under two cases.

TABLE 4 | Appliance use dissatisfaction values.

	Appliance use discomfort values								Total discomfort value (weighted)
	Coffee heater	Dish washer	Oven	Kettle	Hot plate	Washing machine	LED bulb	Incandescent light bulb	
Case 1	0.063	0.013	0.338	0.138	0.829	0.759	0.398	0.376	1.885
Case 2	0.143	0.091	0.088	0.000	0.024	0.006	0.439	0.268	0.728
Case 3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Luo et al., 2019), which show a good searching performance on the majority of the trials.

Result and Discussion

Following *Solving Approach*, the MONAA is applied to solve the proposed HEMS. The execution time of the optimization depends on various factors, including the pre-specified maximum generation time and population size, the pre-specified control interval, the number of TSAs, the number and configuration of PAAs, and the hardware configuration of the processor that executes the optimization. With the simulation settings reported in this paper, a total of 15 min is spent on performing the optimization, which is acceptable for an ex-ante appliance scheduling task. The Pareto Frontier consisting of 112 non-dominated solutions is obtained, where each solution represents a home energy management scheme. **Figure 11** shows these non-dominated solutions as well as their projections on each 2-objective space.

Figure 11 generally shows that the proposed HEMS effectively generates diverse solutions to achieve different compromises among the three energy management objectives. To demonstrate the home energy management effect with more detail, we select two specific cases from the generated Pareto Frontier and compare the two cases with another benchmark case:

1) Case 1—the home energy management solution with lowest energy cost, denoted by the red spot in **Figure 11**.

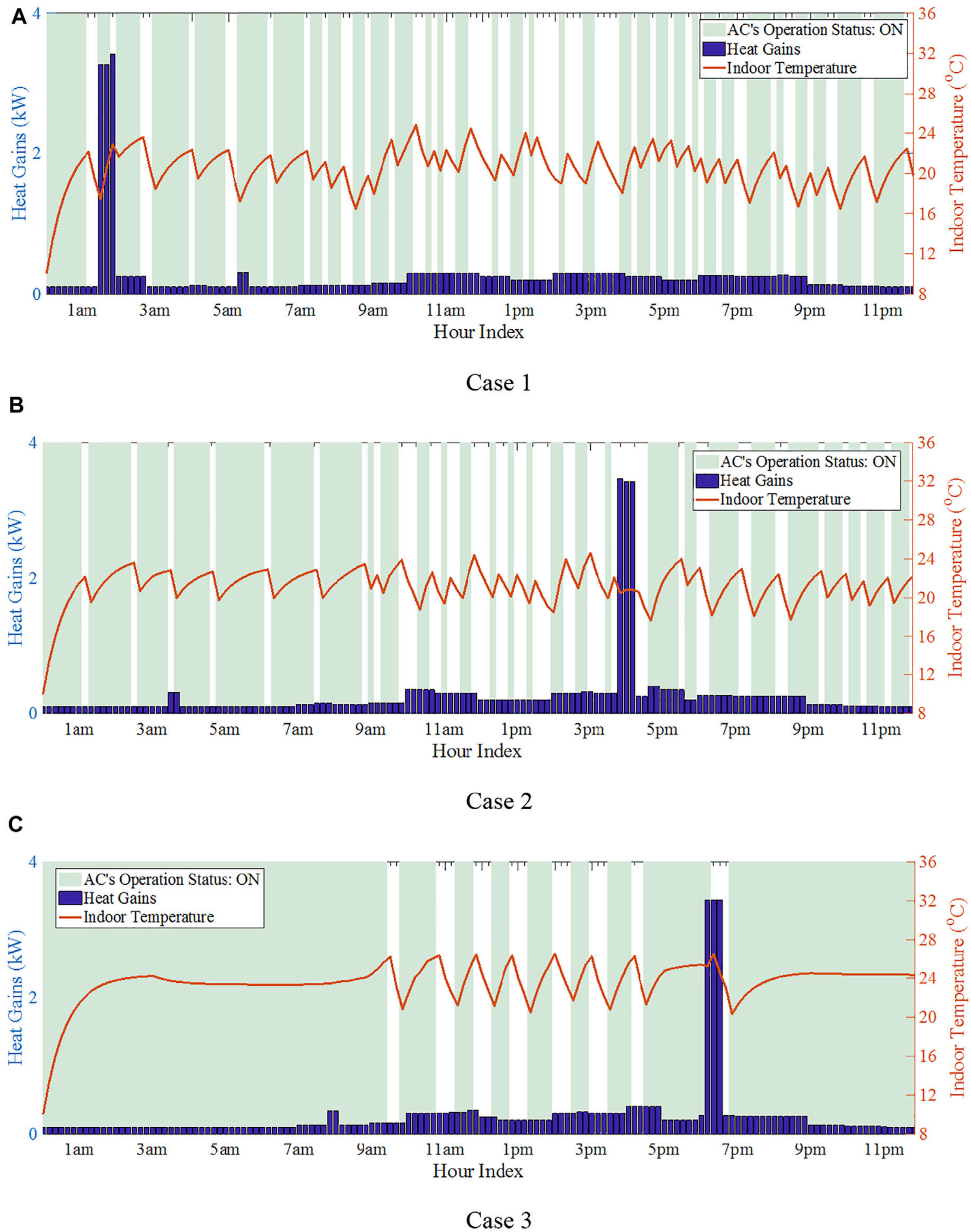

FIGURE 15 | Indoor thermal environment and AC operation status.

2) Case 2—the home energy management solution chosen from the Pareto Frontier using the compromise-solution method (*Solving Approach*), denoted by the green spot in **Figure 11**.

3) Case 3—the benchmark case without energy management. That is, each TSA completes its task at the desired time slot; each PAA operates at the desired power level; the AC operates in a natural heating cycling mode: when the indoor

temperature achieves $T^{dsr,low}$, the AC is turned on to heat up the room until the indoor temperature reaches $T^{dsr,up}$ at that time, the AC is turned off to cool down the room until the indoor temperature reaches $T^{dsr,low}$.

Table 3 shows the objective values under the three cases. It can be seen that the home energy management solution in Case 1 can produce approximately \$1.30 and \$4.50 cost savings comparing with Cases 2 and 3 at the expense of a higher dissatisfaction level to the occupant. For the case without energy management (Case 3), it produces little dissatisfaction to the occupant, but also leads to a very large energy cost (\$13.87). **Figure 12** shows the corresponding profiles of the home's total power consumption under the three cases. Obviously, in the case without energy management measures (Cases 3), more energy is consumed in the peak (at noontime) and moderate electricity price hours. In Cases 2 and 3, not only are the power consumptions in these hours less than Case 3, but the total energy consumption over the day is also reduced. This is mainly because of the reduced AC operation in Cases 1 and 2, as further discussed in the rest of this section.

Figure 13 visualizes the schedule for TSAs with and without energy management. The arrows in the figure denote shifting of the appliances' operation time from the occupant's desired completion time to the optimized completion time. The optimized results of the LED bulb and incandescent light bulb under Case 1 and Case 2 are shown in **Figure 14A,B**, respectively, where the green block represents the power range of the LED bulb. While in Case 3, the power of the LED bulb is 0.015 kW and the power of the incandescent light bulb is 0.112 kW. Detailed appliance use discomfort values of these controllable appliances (calculated following *Modelling of Occupant's Dwelling Satisfaction*) are listed in **Table 4**.

It can be seen that the optimized completion time of TSAs and the power consumptions of PAAs are different with the ones originally desired by the occupant, due to the consideration of reducing the home energy cost. Particularly, in Case 1 that produces the least home energy cost, it can be seen that a majority of the TSAs (e.g., washing machine and hot plate) are scheduled to operate at midnight, and this also yields significant dwelling dissatisfaction to the occupant. In contrast, the appliance schedules in Case 2 produce a larger energy cost but a lower dissatisfaction level than Case 1.

Figure 15 shows the resulted indoor thermal environments under the three cases. It can be seen that in the natural heating cycling mode (Case 3), the AC keeps running almost the whole late evening and midnight time due to the low outdoor air temperature; as a result, the indoor temperature is kept around 24 Celsius to maintain the maximum thermal comfort level to the occupant. Without performing energy management when subjected to the time-varying electricity tariff, the energy cost due to the AC's operation is \$12.19. For Cases 1 and 2, compared with Case 3, the AC's operation time is reduced in the peak electricity price hours (i.e., 11 am-1 pm and 8–10 pm), leading to a lower energy cost for AC operation (\$8.46 in Case 1 and \$9.28 in Case 2, respectively). For the exchange of the reduced energy cost, the indoor temperature under Cases 1 and 2 deviate from the comfort temperature range more frequently, leading to a lower thermal comfort degree for the occupant.

Figure 15 also shows that the internal heat gain distribution of the room has an impact on the AC's operation. Taking Case 3 as an example, when there is high internal heat gain released by the appliances and the occupant (around 6–7 pm, mainly because of the operation of the hot plate), the room is warmed, meaning the AC can be turned off temporarily even though the outdoor temperature at that time is low. A similar phenomenon is also observed in Cases 1 and 2. Such an impact indicates that heat gain-aware coordinated scheduling of AC and other appliances would be meaningful for optimizing the energy performance of a home, which is less investigated in the existing literature.

CONCLUSION AND FUTURE WORK

This paper studies the home energy management problem when subjected to a real-time electricity price environment. Flexible satisfaction and comfort models are established, which use adjustable parameters to reflect individual occupants' appliance usage and thermal comfort preferences. Based on these models, a new multi-objective home energy management model is established. Numerical simulations demonstrate that when comparing the existing literature, the proposed system can model the home energy management process in a more realistic manner in terms of balancing the different considerations in a home environment and accounting for the impact of the room's internal heat gain on the AC's operation.

The HEMS proposed in this paper is expected to enhance automation and energy efficiency in the residential sector. Future work can be conducted in two directions. Firstly, the authors are planning a user survey and field testing to collect data to fit the parameters in the theoretical satisfaction models proposed in this paper. Secondly, the HEMS proposed in this paper can be expanded to integrate renewable energy sources and energy storage systems. More sophisticated thermal models can also be integrated into the proposed home energy framework without significant modifications.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary files, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

FL designed experiments; ZZ carried out experiments. YZ analyzed experimental results. YZ approved the final version of the paper for publication. SS made important revisions to the paper. ZZ and FL. wrote the article.

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NOMENCLATURE

Parameters

T Number of time slots over the energy management period

Δt Duration of each time slot (hour)

N^{tsa} Number of time shiftable appliances

P_i^{tsa} Operating power of the ith time shiftable appliance (kW)

d_i^{tsa} Task duration of the ith time shiftable appliance

$t_i^{tsa,*}$ Desired task completion time of the ith time shiftable appliance

h_i^{tsa} Heat gain of the ith time shiftable appliance

N^{paa} Number of the power adjustable appliances

$\mathbf{t}_j^{run}$ Operation time of the jth power adjustable appliance

M_j The total number of operation time slot of the jth power adjustable appliance

$\mathbf{P}_j^{dsr}$ Occupant-desired power consumption of the jth power adjustable appliance (kW)

P_j^{low} The lowest power level of the jth power adjustable appliance (kW)

h_j^{paa} Heat gain of the jth power adjustable appliance

c The heat capacity of air

ρ The density of air

V^{room} The volume of the room (m^3)

T^{ind} The indoor temperature (°C)

T^{out} The outdoor temperature (°C)

ζ_t The heat gain released by the occupant at the tth time slot

P_t^{ins} The coefficient of heat absorbed from the Sun at the tth time slot

A^{window} The area of the window (m^2)

P^{rate} The rated power of the air conditioner (AC) when it is under the operating state (kW)

P^{stdb} The power of the AC when it is under the standby state (kW)

P_t^{ac} The real power of the AC at the tth time slot (kW)

α_i The occupant-specified comfort factor for the ith time shiftable appliance

β_j The occupant-specified comfort factor for the jth power adjustable appliance

γ The occupant-specified comfort factor for the AC

$T^{dsr,low}$ The desired lowest indoor temperature (°C)

$T^{dsr,up}$ The desired highest indoor temperature (°C)

$T^{set,low}$ The lowest temperature the user can tolerate (°C)

$T^{set,up}$ The highest temperature the user can tolerate (°C)

pr_t Electricity price at the tth time slot

K Heat transfer coefficient

A^S The surface area of the building envelope (m^2)

n The air exchange times

w_k Weight of the kth controllable appliance

Variables

s_t^{ac} The state of the AC at the tth time slot, $s_t^{ac}=0$ and 1 represent the standby and operating state, respectively

$\tilde{t}_i^{tsa}$ The start time of the ith time shiftable appliance

$P_{j,t}^{paa}$ The real power of the jth power adjustable appliance at the tth time slot (kW)

$s_{i,t}^{tsa}$ The state of the ith time shiftable appliance at the tth time slot