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Distributed Optimization Framework for Energy Management of Multiple Smart Homes With Distributed Energy Resources

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ABSTRACT This paper proposes a distributed optimization algorithm for scheduling the energy consumption of multiple smart homes with distributed energy resources. In the proposed approach, the centralized optimization problem for home energy management is decomposed into a two-level optimization problem, corresponding to the local home energy management system (LHEMS) at the first level and the global home energy management system (GHEMS) at the second level. The controllable household appliances (e.g., air conditioner and washing machine) are scheduled in the LHEMS within the consumer's preferred appliance scheduling and comfort level, while the energy storage system and power trading between households are scheduled in the GHEMS. In the simulation study, the proposed distributed algorithm shows almost equivalent performance to the centralized algorithm in terms of the electricity cost and the consumer's comfort level. The impact of different network topologies on the proposed algorithm is also analyzed, and the result provides insight into the selection of the optimal network configuration in view of the consumer's electricity cost saving.

INDEX TERMS Home energy management system (HEMS), energy consumption scheduling, demand side management, distributed algorithm.

I. INTRODUCTION

As home energy consumption has increased considerably due to population growth and housing expansion along with the deployment of smart home appliances (e.g., air conditioners, washing machines, and refrigerators), home energy management is becoming increasingly important for consumers to reduce their electricity costs and maintain the efficiency of their home appliances. With an increasing energy consumption in the residential sector, the emerging smart grid technologies including distributed energy resources (DERs) (e.g., rooftop solar photovoltaic (PV) and residential energy storage system (ESS)), advanced metering infrastructure (AMI) with smart meters, and demand side management (DSM), have rendered home energy management more complex.

A home energy management system (HEMS) is the key solution to the efficient and economical management of the residential energy usage of the future smart grid. The main functions of HEMS are to monitor the real-time energy usage of consumers using a smart meter and to schedule the optimal energy consumption of home appliances for reducing consumers' electricity costs in the consumers' comfortable and preferred environments. According to a report on [1], the global HEMS market is expected to grow from USD 864.2 million in 2015 to USD 3.15 billion by 2022 due to factors such as increasing real-time energy conservation approach, cloud computing technologies and data analytics, and increased device interconnectivity. It is worth noting that this market forecast would be correct when HEMS has computational capability to efficiently process very large amounts of heterogeneous data from various sources such as DERs, smart meters, smart home appliances, consumer preferences, and weather centers.

One approach to reduce the increasing computational complexity due to overwhelming data is to distribute the centralized computation to decentralized entities that are capable of managing the energy consumption of the corresponding households. The aim of this paper is to develop a distributed two-level optimization framework, where the energy consumption scheduling for individual households is conducted at the local level and the control of energy trade

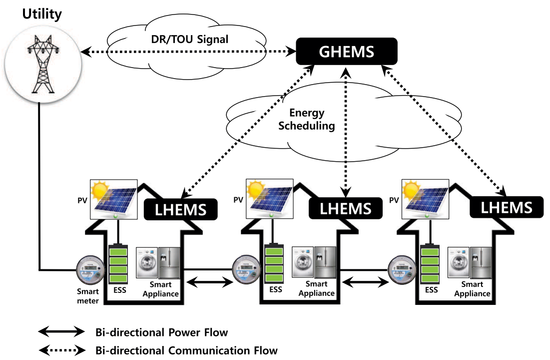


FIGURE 1. Conceptual architecture of the distributed HEMS (DHEMS).

between neighboring households is coordinated at the global level. Fig. 1 illustrates the system model for the proposed distributed HEMS (DHEMS) that comprises the local home energy management system (LHEMS) and the global home energy management system (GHEMS).

A core technology in HEMS is the optimization method for an economic load reduction and load shifting. A considerable amount of literature has been published recently on the development of the HEMS optimization algorithm, including the scheduling of electric vehicles (EVs) and various types of residential loads using linear programming (LP) [2], [3], the load scheduling within consumer comfort level using mixed integer nonlinear programming (MINLP) [4], the efficient calculation of load scheduling using relaxed MINLP method with an L1 regularization term [5], community load scheduling for a neighborhood with multiple consumers using mixed integer linear programming (MILP) [6], [7], the MILP method-based demand response (DR) aggregation framework in wholesale electricity markets [8], and an interdisciplinary approach between optimization and machine learning [9], [10]. Joint optimization approaches have been developed for HEMS and the building energy management system (BEMS) [11]. A new HEMS algorithm with voltage control was proposed for minimizing the load shifting operation [12]. A method for the prediction of the energy consumption of appliances was presented based on a stochastic approach [13]. The HEMS was designed with the Internet of things (IoT) technology [14] and load disaggregation algorithm, namely non intrusive load monitoring (NILM) [15], in order to improve the accuracy of the load scheduling. A data sensitivity analysis framework was developed to quantify the impact of erroneous data on the HEMS using the perturbed Karush-Kuhn-Tucker (KKT) conditions from the HEMS optimization formulation [16]. The general optimization problem and the architecture of the HEMS are summarized in [17] and [18]. While much work has focused on the development of centralized HEMS (CHEMS) optimization algorithms, several studies have been conducted recently to develop distributed HEMS (DHEMS) optimization algorithms to reduce the computational complexity of CHEMS. In general, these DHEMS optimization algorithms were designed in a two-level architecture, where each consumer's energy scheduling obtained at the local level is coordinated at the global level with a focus on (i) sharing a single community ESS among consumers in a cooperative manner [19] and (ii) tracing the desired aggregate scheduled load [20], [21]. However, these works have not explicitly considered consumer comfort level and power trade between households in the distributed optimization framework.

In comparison with existing DHEMS optimization algorithms, our proposed approach provides a two-level optimization framework, where each consumer's preferred home appliance scheduling is executed and the consumer comfort level is adjusted at the local level (LHEMS), while the scheduling of each consumer's ESS operation and power transactions between consumers are conducted at the global level (GHEMS), subsequently reducing the total electricity cost. Compared to the CHEMS optimization algorithm, the proposed DHEMS optimization algorithm is beneficial in several ways as follows. The computation complexity of DHEMS can be reduced significantly by decentralizing the computation burden to multiple LHEMSs. In addition, the proposed algorithm is developed based on an efficient data exchange scheme that requires minimum communication between GHEMS and LHEMSs. In terms of smart grid cyber security, a single point of failure due to a cyber attack on CHEMS can be eliminated. Furthermore, a strong privacy protection of each consumer can be ensured because the GHEMS schedules the operation of only ESS, the operation of which does not reveal the consumer's energy usage patterns to attackers. Specifically, the three main contributions of the proposed approach are as follows.

- We present a two-level distributed system model consisting of the local home energy management system (LHEMS) and global home energy management system (GHEMS), where the computation time can be significantly reduced by distributing the centralized computation to local systems as shown in Fig. 1.
- We propose a distributed home energy management optimization algorithm with the following two scheduling steps: i) the controllable household appliances are scheduled at the LHEMS, while the consumer's preferred appliance scheduling and comfort level are maintained through the participation of the consumer and ii) each consumer's ESS and power trade between neighboring households are scheduled at the GHEMS, consequently leading to the optimal electricity cost for all households.
- Simulation results confirm that the proposed distributed algorithm shows almost equivalent performance to the centralized algorithm in terms of the electricity cost and the consumer's comfort level under various comfort level settings. In addition, we analyze the impact of different network topologies (e.g., radial, ring, and mesh networks) with varying line flow limits on the proposed algorithm, and verify that the mesh network yields the maximum electricity cost saving among the three networks.

This paper is organized as follows. Section II defines the various types of smart home appliances and introduces the optimization formulation for the centralized home energy management. Section III presents the proposed distributed home energy management optimization algorithm using MILP in the time of use (TOU) pricing tariff where the electricity price varies according to a different time block. Section IV presents the simulation of the proposed optimization algorithm with four households equipped with smart home appliances and DERs. Finally, concluding remarks are presented in Section V.

TABLE 1. Notations.

$\mathcal{U}$	Set of households
$\mathcal{A}_u$	Set of appliances in household u ($\mathcal{A}_u = \mathcal{A}_u^c \cup \mathcal{A}_u^{uc}$)
$\mathcal{A}_u^c$	Set of controllable appliances in household u ($\mathcal{A}_u^c = \mathcal{A}_{u,r}^c \cup \mathcal{A}_{u,s}^c$)
$\mathcal{A}_{u,r}^c$	Set of reducible appliances in household u
$\mathcal{A}_{u,s}^c$	Set of shiftable appliances in household u ($\mathcal{A}_{u,s}^c = \mathcal{A}_{u,s}^{c,NI} \cup \mathcal{A}_{u,s}^{c,I}$)
$\mathcal{A}_{u,s}^{c,NI}$	Set of shiftable appliances with non-interruptible load in household u
$\mathcal{A}_{u,s}^{c,I}$	Set of shiftable appliances with interruptible load in household u
$\mathcal{A}_u^{uc}$	Set of uncontrollable appliances in household u
$\mathcal{T}$	Set of time slots
$\mathcal{T}_{\text{DR}}$	Set of DR time slots ($\mathcal{T}_{\text{DR}} \subset \mathcal{T}$)
$\mathcal{L}$	Set of distribution lines
$P_{u,t}^{\text{net}}$	Net power consumption in household u at time slot t
$P_{u,a,t}$	Power consumption of appliance a in household u at time slot t
$P_{u,a}^{\text{max(min)}}$	Maximum(Minimum) power consumption of appliance a in household u
$P_{u,a,t}^{\text{c}}$	Charging power of ESS a in household u at time slot t
$P_{u,a,t}^{\text{d,home}}$	Discharging power of ESS a in household u at time slot t
$P_{u,t}^{\text{imp}}$	Import power of household u from neighbors at time slot t
$P_{u,t}^{\text{exp}}$	Export power of household u to neighbors at time slot t
$P_{u,a}^{\text{c,max(min)}}$	Maximum(Minimum) charging power of ESS a in household u
$P_{u,a}^{\text{d,max(min)}}$	Maximum(Minimum) discharging power of ESS a in household u
$SOC_{u,a,t}$	State of charge of ESS a in household u at time slot t
$SOC_{u,a}^{\text{max(min)}}$	Maximum(Minimum) state of charge of ESS a in household u
$\eta_{u,a}^{\text{c}}$	Charging efficiency of ESS a in household u
$\eta_{u,a}^{\text{d}}$	Discharging efficiency of ESS a in household u
$E_{u,a}^{\text{max}}$	Maximum energy capacity of ESS a in household u
$T_{u,t}^{\text{in}}$	Indoor temperature in household u at time slot t
$T_u^{\text{max(min)}}$	Maximum(Minimum) comfortable temperature in household u
α_u, β_u	Thermal characteristics for air conditioner in household u
$F_{l,t}$	lth line power flow at time slot t
$F_l^{\text{max(min)}}$	Maximum(Minimum) capacity of line l
$b_{u,a,t}^{s,I}$	Binary charging and discharging state of ESS a in household u at time slot t, "1" for charging, "0" for discharging
$b_{u,a,t}^{s,NI}$	Binary consumption state of non-interruptible shiftable appliance a in household u at time slot t, "1" for consumption, "0" otherwise
$b_{u,t}^{\text{flow}}$	Binary power exchange state of household u at time slot t, "1" for power import, "0" for power export
$\widehat{P}_{u,a}$	Predicted daily energy consumption of appliance $a \in \mathcal{A}_{u,s}^{c,NI}$
$\widehat{P}_{u,t}^{\text{solar}}$	Predicted solar power at time slot t
$\widehat{T}_{u,t}^{\text{out}}$	Predicted outdoor temperature in household u at time slot t
π_t	Electricity price at time slot t
$\delta_{u,t}$	Temperature relaxation variable in household u at time slot t
ϵ_u	Penalty for the relaxation variable in household u

II. BACKGROUND

The notations used in this paper are summarized in Table 1. Other undefined symbols are explained within the text.

A. TYPE OF SMART HOUSEHOLD APPLIANCES

Automatic energy management is conducted by HEMS, which schedules and controls the following types of household appliances.

- Uncontrollable appliance ($\mathcal{A}_u^{uc}$): An uncontrollable appliance such as a TV, PC, or lighting cannot be scheduled and operated by the HEMS. $\mathcal{A}_u^{uc}$ thus follows the fixed energy consumption scheduling.
- Controllable appliance ($\mathcal{A}_u^c$): A controllable appliance includes an appliance of which the operation is scheduled and controlled by the HEMS. Their operation characteristic categorizes controllable appliances into incentive-based reducible appliances ($\mathcal{A}_{u,r}^c$) and price-based shiftable appliances ($\mathcal{A}_{u,s}^c$). An example of a reducible appliance is an air conditioner in which the energy consumption can be curtailed during the DR period. On the other hand, under the TOU pricing scheme, the energy consumption of a shiftable appliance can shift from one time slot to another time slot to minimize the total electricity cost. A shiftable appliance has two types of loads: (1) a non-interruptible load ($\mathcal{A}_{u,s}^{c,NI}$); and (2) an interruptible load ($\mathcal{A}_{u,s}^{c,I}$). The operation of shiftable appliances with non-interruptible loads must not be stopped by the HEMS control during the task period of the appliance. For example, a washing machine must perform a washing cycle prior to drying. A shiftable appliance with interruptible load can be allowed to be interrupted at any time. For example, the HEMS should be able to terminate the discharging process of ESS and initiate the charging process instantly when the PV power generation is greater than the load demand.

B. CENTRALIZED HOME ENERGY OPTIMIZATION PROBLEM

In general, an algorithm for HEMS that solves the optimal operating schedule of home appliances and DERs is formulated as a MILP optimization problem with the following linear objective function ($J(\mathbf{x}, \mathbf{a})$) and the linear equality/inequality constraints ($\mathbf{Fx} = \mathbf{a}$, $\mathbf{Gx} \le \mathbf{a}$):

$$\min_{\mathbf{x}} J(\mathbf{x}, \mathbf{a}) = J_1(\mathbf{x}, \mathbf{a}) + J_2(\mathbf{x}, \mathbf{a}) \tag{1}$$

$$\text{s.t. } \mathbf{Fx} = \mathbf{a} \tag{2}$$

$$\mathbf{Gx} \le \mathbf{a}. \tag{3}$$

The goal of this optimization problem is to compute the optimal operating schedule $\mathbf{x}$ of home appliances (e.g., continuous energy consumption, the on/off status of a washing machine) and DERs (e.g., the binary charging/discharging status of ESS) by minimizing the electricity cost ($J_1(\mathbf{x}, \mathbf{a})$) and the consumer's discomfort ($J_2(\mathbf{x}, \mathbf{a})$) in (1) while satisfying the operating constraints of appliances, network, and consumer comfort preference in (2) and (3). $\mathbf{a}$ represents the data vector that includes the operation parameter of the appliance, consumer's comfort setting, weather information, etc. From the aforementioned optimization formulation, the optimization problem for the centralized home energy management system (CHEMS) is formulated in the following subsections where the vector $\mathbf{x}$ includes the decision variables ($P_{u,t}^{\text{cost}}, P_{u,t}^{\text{net}}, P_{u,t}^{\text{imp}}, P_{u,t}^{\text{exp}}, P_{u,a,t}, T_{u,t}^{\text{in}}, \delta_{u,t}, SOC_{u,a,t}, b_{u,a,t}^{s}, v_{u,a,\tau}, b_{u,a,t}^{s,I}$). The other parameters and data belong to the vector $\mathbf{a}$.

1) OBJECTIVE FUNCTION

The objective function (1) for the CHEMS optimization problem consists of two parts, each of which has different decision variables ($P^{\text{cost}}_{u,t}$, $\delta_{u,t}$):

$$\min_{P^{\text{cost}}_{u,t},\delta_{u,t}} \underbrace{\sum_{u\in\mathcal{U}}\sum_{t\in\mathcal{T}} \pi_t P^{\text{cost}}_{u,t}}_{J_1(P^{\text{cost}}_{u,t})} + \underbrace{\sum_{u\in\mathcal{U}} \epsilon_u \sum_{t\in\mathcal{T}} \delta_{u,t}}_{J_2(\delta_{u,t})}. \tag{4}$$

In (4), $J_1\left(P^{\text{cost}}_{u,t}\right)$ is the total electricity cost that is computed using the TOU price π_t and $P^{\text{cost}}_{u,t}$ during the time period $\mathcal{T}$ (24 hours with one hour scheduling resolution). $P^{\text{cost}}_{u,t}$ consists of two types of power consumptions: 1) the net consumption $P^{\text{net}}_{u,t}$ (the total energy purchased from the grid) and 2) the trade consumption (the total energy purchased $P^{\text{imp}}_{u,t}$ or sold $P^{\text{exp}}_{u,t}$ from or to the neighborhood, respectively). $J_2\left(\delta_{u,t}\right)$ is the total amount of penalty that involves the consumer's discomfort cost. The discomfort implies the deviation of the consumer's preferred temperature from the indoor temperature. $\delta_{u,t}$ is a relaxation variable to ensure the feasibility of the CHEMS optimization problem. ϵ_u is a penalty for the relaxation variable. A smaller ϵ_u yields a larger $\delta_{u,t}$ and hence burdens the consumer with increasing discomfort, yet prevents the optimization problem from becoming infeasible due to more relaxed constraints. The value of ϵ_u can be determined by the HEMS operator to satisfy the consumer's preferred comfort level. The following subsections illustrate equality/inequality constraints (2) and (3) for the CHEMS optimization problem.

2) NET POWER CONSUMPTION AND POWER TRADE CONSTRAINTS

Equation (5) is the constraint on the energy consumption for the total electricity cost, i.e. the sum of the net energy consumption and the gap between the energy purchased from the neighborhood and sold to the neighborhood. Equation (6) is the constraint on the net energy consumption, i.e. the difference between the total consumption for all appliances and the generated solar output along with the energy purchased from neighborhood. In (7), the total consumption for all appliances in (6) is decomposed into four different types of reducible appliances ($a \in \mathcal{A}^c_{u,r}$), for shiftable appliances with non-interruptible load ($a \in \mathcal{A}^{c,NI}_{u,s}$), shiftable appliances with interruptible load ($a \in \mathcal{A}^{c,I}_{u,s}$), and uncontrollable appliances ($a \in \mathcal{A}^{uc}_u$).

$$P^{\text{cost}}_{u,t} = P^{\text{net}}_{u,t} + P^{\text{imp}}_{u,t} - P^{\text{exp}}_{u,t} \tag{5}$$

$$P^{\text{net}}_{u,t} = \sum_{a\in\mathcal{A}_u} P_{u,a,t} - \widehat{P}^{\text{solar}}_{u,t} - P^{\text{imp}}_{u,t} \tag{6}$$

$$\begin{aligned}\sum_{a\in\mathcal{A}_u} P_{u,a,t} = &\sum_{a\in\mathcal{A}^c_{u,r}} P_{u,a,t} + \sum_{a\in\mathcal{A}^{c,NI}_{u,s}} P_{u,a,t}\\ &+ \sum_{a\in\mathcal{A}^{c,I}_{u,s}} \left(P^c_{u,a,t} - P^{\text{d,home}}_{u,a,t}\right) + \sum_{a\in\mathcal{A}^{uc}_u} P_{u,a,t}\end{aligned} \tag{7}$$

The energy trade balance of all households is described by (8). Equation (9) ensures that the energy from only shiftable appliances with interruptible load can be sold to neighbors. Constraints (10) and (11) limit the energy trade between households, where $b^{\text{flow}}_{u,t}$ represents the binary decision variable that determines the status of the energy import and export. Without the energy trade limit, the parameter N is set to be a very large number.

$$\sum_{u\in\mathcal{U}} P^{\text{imp}}_{u,t} = \sum_{u\in\mathcal{U}} P^{\text{exp}}_{u,t} \tag{8}$$

$$P^{\text{exp}}_{u,t} = \sum_{a\in\mathcal{A}^{c,I}_{u,s}} P^{\text{exp}}_{u,a,t} \tag{9}$$

$$0 \le P^{\text{imp}}_{u,t} \le N b^{\text{flow}}_{u,t} \tag{10}$$

$$0 \le P^{\text{exp}}_{u,t} \le N(1 - b^{\text{flow}}_{u,t}) \tag{11}$$

3) CONTROLLABLE APPLIANCE CONSTRAINTS

Equation (12) is the constraint for temperature dynamics of the reducible appliance (e.g., air conditioner) at time t ($T^{\text{in}}_{u,t}$), which is expressed in terms of $T^{\text{in}}_{u,t-1}$ at time $t-1$, the predicted outdoor temperature at time $t-1$ ($\widehat{T}^{\text{out}}_{u,t-1}$), the power consumption of the reducible appliances ($P_{u,a,t}$), and the environmental parameters (α_u, β_u) that specify the indoor thermal condition. Equation (13) presents the range of relaxed indoor temperatures. The relaxation variable $\delta_{u,t}$ in (13) is limited by $\delta^{\max}_u$ in (14).

$$T^{\text{in}}_{u,t} = T^{\text{in}}_{u,t-1} + \alpha_u(\widehat{T}^{\text{out}}_{u,t-1} - T^{\text{in}}_{u,t-1}) + \beta_u P_{u,a,t} \tag{12}$$

$$T^{\min}_u - \delta_{u,t} \le T^{\text{in}}_{u,t} \le T^{\max}_u + \delta_{u,t} \tag{13}$$

$$0 \le \delta_{u,t} \le \delta^{\max}_u \tag{14}$$

Equation (15) is the constraint on the predicted daily energy consumption for controllable appliances with non-interruptible load.

$$\sum_{t\in\mathcal{T}} P_{u,a,t} = \widehat{P}_{u,a}, \quad \forall a \in \mathcal{A}^{c,NI}_{u,s} \tag{15}$$

Equations (16), (17), and (18) guarantee the desired operation of shiftable appliances with non-interruptible load (e.g., washing machine): i) for the operation period $L_{u,a}$ hours during a day in (16), ii) for the starting time with the binary value once a day in (17); and iii) a consecutive operation period $L_{u,a}$ hours in (18).

$$\sum_{t\in\mathcal{T}} b^s_{u,a,t} = L_{u,a} \tag{16}$$

$$\sum_{\tau\in\mathcal{T}} v_{u,a,\tau} = 1 \tag{17}$$

$$b^s_{u,a,t} = \sum_{\tau\in\mathcal{T}_\tau} v_{u,a,\tau}, \quad \mathcal{T}_\tau = [t - L_{u,a} + 1,\ t] \tag{18}$$

The capacity of power consumption for the shiftable appliances with non-interruptible load and reducible appliances is described by

$$P^{\min}_{u,a} \le P_{u,a,t} \le P^{\max}_{u,a} \tag{19}$$

Equation (20) defines the operational dynamics of the state of charge (SOC) for ESS at the current time t in terms of the SOC at the previous time t-1, battery capacity $E^{\max}_{u,a}$, charging and discharging efficiency, $\eta^{c}_{u,a}$ and $\eta^{d}_{u,a}$, charging and discharging power for the consumer u, $P^{c}_{u,a,t}$ and $P^{d,home}_{u,a,t}$, respectively, and discharging power for his or her neighbor households, $P^{exp}_{u,a,t}$. Equation (21) gives the capacity constraint of SOC for ESS. Equations (22) and (23) present the constraints on charging ($P^{c}_{u,a,t}$) and discharging power ($P^{d,home}_{u,a,t} + P^{exp}_{u,a,t}$) of the ESS, respectively, where $b^{s,I}_{u,a,t}$ represents the binary decision variable that determines the on/off status of ESS.

$$SOC_{u,a,t} = SOC_{u,a,t-1} + \frac{\eta^{c}_{u,a} P^{c}_{u,a,t}}{E^{max}_{u,a}} - \frac{\left(P^{d,home}_{u,a,t} + P^{exp}_{u,a,t}\right)}{\eta^{d}_{u,a} E^{max}_{u,a}}, \quad \forall a \in \mathcal{A}^{c,I}_{u,s} \tag{20}$$

$$SOC^{min}_{u,a} \le SOC_{u,a,t} \le SOC^{max}_{u,a} \tag{21}$$

$$P^{c,min}_{u,a} b^{s,I}_{u,a,t} \le P^{c}_{u,a,t} \le P^{c,max}_{u,a} b^{s,I}_{u,a,t} \tag{22}$$

$$P^{d,min}_{u,a}(1 - b^{s,I}_{u,a,t}) \le P^{d,home}_{u,a,t} + P^{exp}_{u,a,t} \le P^{d,max}_{u,a}(1 - b^{s,I}_{u,a,t}) \tag{23}$$

4) DR CONSTRAINTS

Consumers who participate in a DR program receive a DR signal from a utility via the smart meter and curtail their energy demand based on the signal. This could help to reduce peak demand, thus resulting in the alleviation of power system stress conditions. The DR constraint is described by

$$\sum_{t \in \mathcal{T}_{DR}} P^{net}_{u,t} \le \mathrm{DR}(\mathrm{Q}_u, \mathrm{D}_u) \tag{24}$$

where the DR signal ($\mathrm{DR}(\mathrm{Q}_u, \mathrm{D}_u)$) consists of a demand reduction request Q_u (kW) and DR period D_u (hours).

5) POWER FLOW CONSTRAINTS

Equation (25) gives the relationship between the power associated with consumer u's electricity cost and power flows to his/her neighbors under different types of network topologies (e.g., radial, ring, and mesh). In (25), $a_{u,l}$ is the element of a node-branch matrix $\mathbf{A}$: $a_{u,l} = \pm 1$ if node u is the receiving or sending terminal of branch l; otherwise $a_{u,l} = 0$. Equation (26) simply states that the total power flow from the grid is the sum of the net consumption of all consumers. The constraint (27) ensures that the power flow between households remains within the line capacity limit.

$$P^{cost}_{u,t} = \sum_{l \in \mathcal{L}} a_{u,l} F_{l,t} \tag{25}$$

$$F_{1,t} = \sum_{u \in \mathcal{U}} P^{net}_{u,t} \tag{26}$$

$$-F^{max}_{l} \le F_{l,t} \le F^{max}_{l}, \quad l \ne 1 \tag{27}$$

III. PROPOSED DISTRIBUTED HOME ENERGY MANAGEMENT ALGORITHM

In this section, we propose a distributed optimization algorithm to schedule the energy consumption of home appliances

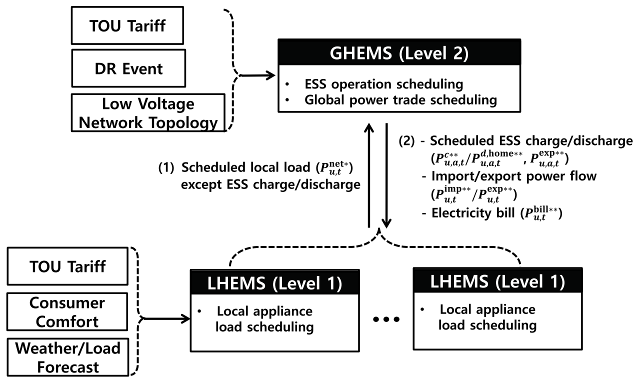


FIGURE 2. Conceptual system model for HEMS.

with ESSs and power trades in multiple smart households. As shown in Fig. 2, in the proposed algorithm, the CHEMS optimization problem illustrated in subsection II-B is decomposed into a two-level hierarchical optimization problem that consists of local optimization problem for LHEMS and a coordinator problem for GHEMS, corresponding to subsections III-A and III-B, respectively. In the first level, the LHEMS problem for each household is optimized independently to schedule the consumption of appliances, given the consumer's preferred appliance scheduling and comfort level. In the second level, using the solution obtained from LHEMS and the additional information such as DR signal from a utility, GHEMS schedules the charge/discharge of ESSs for all households, coordinates the power trade between neighboring households, and calculates their electricity costs, which are finally returned to the households. More detailed formulations for LHEMS and GHEMS optimization problems are illustrated in the following two subsections.

A. LOCAL HEMS OPTIMIZATION MODEL: LEVEL 1

The goal of the LHEMS optimization problem is to find the optimal net power consumption and deviation of the consumer's preferred indoor temperature by minimizing the following electricity cost and consumer discomfort:

$$\min_{P^{net}_{u,t}, \delta_{u,t}} \sum_{t \in \mathcal{T}} \pi_t P^{net}_{u,t} + \epsilon_u \sum_{t \in \mathcal{T}} \delta_{u,t} \tag{28}$$

$$\text{s.t. } P^{net}_{u,t} = \sum_{a \in \mathcal{A}_u} P_{u,a,t} - \widehat{P}^{solar}_{u,t} \tag{29}$$

$$\sum_{a \in \mathcal{A}_u} P_{u,a,t} = \sum_{a \in \mathcal{A}^{c}_{u,r}} P_{u,a,t} + \sum_{a \in \mathcal{A}^{c,NI}_{u,s}} P_{u,a,t} + \sum_{a \in \mathcal{A}^{uc}_{u}} P_{u,a,t} \tag{30}$$

$$\text{Eqn. } (12) - (19). \tag{31}$$

In the LHEMS formulation, the net power constraint (6) and the total power consumption constraint for all appliances (7) in the CHEMS formulation are modified to constraints (29) and (30), where the power trade and ESS operation are excluded, respectively. All the constraints of controllable appliances (air conditioner, washing machine) (12) – (19) are added to the LHEMS problem.

B. GLOBAL HEMS OPTIMIZATION MODEL: LEVEL 2

In the second level, the GHEMS optimization algorithm computes the optimal electricity cost of each household in the following optimization problem:

$$\min_{P_{u,t}^{\text{cost}}} \sum_{u \in \mathcal{U}} \sum_{t \in \mathcal{T}} \pi_t P_{u,t}^{\text{cost}} \tag{32}$$

$$\text{s.t. } P_{u,t}^{\text{cost}} = P_{u,t}^{\text{net}} + P_{u,t}^{\text{imp}} - P_{u,t}^{\text{exp}} \tag{33}$$

$$P_{u,t}^{\text{net}} = P_{u,t}^{\text{net}^*} + P_{u,a,t}^{\text{c}} - P_{u,a,t}^{\text{d,home}} - P_{u,t}^{\text{imp}} \tag{34}$$

$$0 \leq P_{u,t}^{\text{imp}} \leq P_{u,t}^{\text{net}^*} - P_{u,a,t}^{\text{d,home}} \tag{35}$$

$$\text{Eqn. (8)} - (11) \tag{36}$$

$$\text{Eqn. (20)} - (27). \tag{37}$$

Compared to constraints (5) and (6) in the CHEMS formulation, the constraints of electricity cost (33) and net power consumption (34) in the GHEMS formulation involve the scheduling of only the ESS operation and power trade with $P_{u,t}^{\text{net}^*}$ obtained from LHEMS. Constraint (35) illustrates the limit of import power from consumer u's neighbors. Finally, the constraints for power trade (8) – (11) and the constraints for ESS operation, DR, and power flow (20)–(27) in CHEMS are also included in the GHEMS formulation.

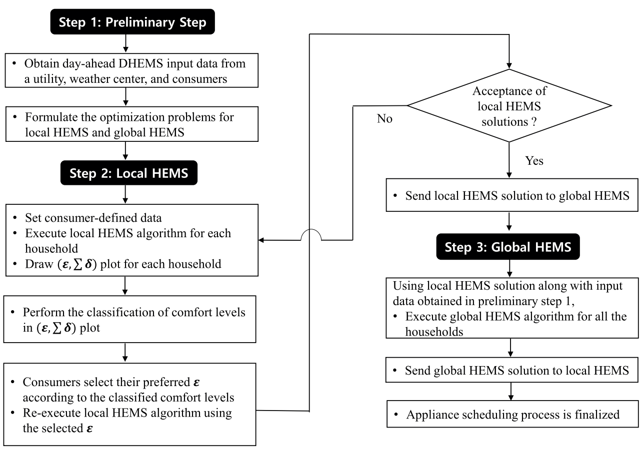


FIGURE 3. Flowchart of the procedure of the DHEMS algorithm.

Finally, as shown in Fig. 3, the procedures of the proposed DHEMS algorithm at the local level and the global level involve the following three steps.

Step 1): Before the recursive step, in this preliminary step, all input data that are required for the DHEMS operation are prepared, and the optimization problems for the LHEMS and the GHEMS are formulated.

Step 2): Each consumer u sets its own data such as preferred indoor temperature range and the corresponding LHEMS performs the scheduling of energy consumption of home appliances. Then, using the solution obtained from LHEMS, the plot of $(\epsilon_u, \sum \delta_{u,t})$ can be obtained (e.g., Fig. 8(b) in Section IV). According to the value of ϵ_u, the consumer's thermal discomfort is classified into several levels in the plot. Each consumer u chooses their preferred ϵ_u in the classified discomfort levels, and the LHEMS algorithm is executed again with the selected ϵ_u. If the consumer is satisfied with the indoor temperature and the schedule of appliances calculated by LHEMS, the procedure moves to Step 3). Otherwise, the procedure returns to the initial stage in Step 2)

Step 3): Using the optimal solution from LHEMS with additional data such as DR information, the GHEMS algorithm is carried out. The solution calculated by the GHEMS is returned to all LHEMSs, which provide the final operation schedules of home appliances, ESSs, power trade, and the total electricity cost to all consumers.

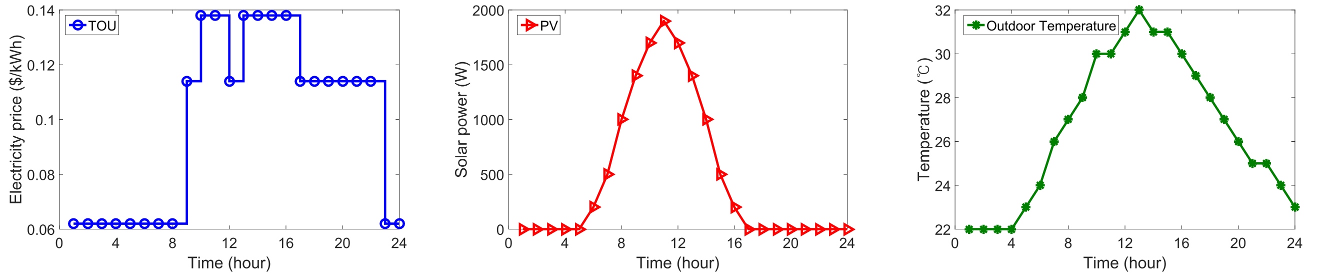
TABLE 2. Appliance type ratings for four households.

Appliance type	Rated Power (W)			
	House A	House B	House C	House D
Air conditioner	1,050	1,050	1,050	1,050
Washing machine	500	500	500	500
Uncontrollable appliance	1,700	1,500	1,000	700

IV. SIMULATION RESULTS

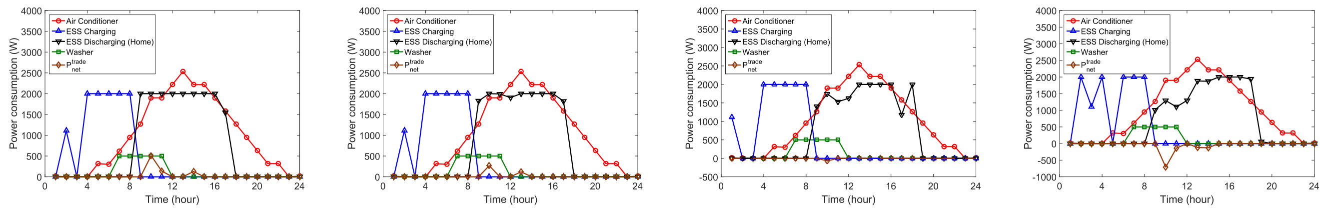
A. SIMULATION SETUP

Under the TOU tariffs shown in Fig. 4(a), we consider four smart households where the proposed DHEMS optimization algorithm schedules the operation of two tasks: i) two major controllable appliances (air conditioner and washing machine) at the local level (LHEMS); and ii) the residential ESS and the power trade between households at the global level (GHEMS). The simulations are carried out for 24 hours with one hour scheduling resolution. Table 2 shows the maximum power consumption of an air conditioner, washing machine, and aggregated uncontrollable appliances. It is assumed that the predicted PV generation output $\widehat{P}_{u,t}^{\text{solar}}$ and the outdoor temperature $\widehat{T}_{u,t-1}^{\text{out}}$ in Figs. 4(b) and 4(c) as well as the predicted daily consumption of appliances $\widehat{P}_{u,a}$, can be accurately obtained. For each household, the comfortable temperature range prior to the relaxation is assumed to be [22°C,24°C] with the maximum relaxed temperature $\delta_u^{\max} = 3$°C. The parameters α and β, which illustrate the thermal characteristics of the air conditioner, are set as 0.9 and -0.012, respectively. For ESS, the battery capacity $E_{u,a}^{\max}$ is 10 kWh, the maximum charging and discharging powers are both 2 kW, the initial, minimum, and maximum SOC are 0.5, 0, and 1.0, respectively, and the charging and discharging efficiencies $\eta_{u,a}^{\text{c}}$ and $\eta_{u,a}^{\text{d}}$ are both 95%. The capacity limits of all lines between households $F_l^{\max}$ are set to be identical at 9 kW. For simplicity, all houses are equipped with appliances that have the same specifications, and the preferred indoor temperature ranges of all consumers are also the same under identical temperature relaxation. Numerical testing is performed with the optimization toolbox in MATLAB R2015b.



(a) (b) (c)

FIGURE 4. Profiles of electricity price and weather. (a) TOU price. (b) Solar power. (c) Outdoor temperature.



(a) (b) (c) (d)

FIGURE 5. CHEMS-based optimized appliance schedules of four households throughout the day. (a) Household A. (b) Household B. (c) Household C. (d) Household B.

TABLE 3. Impact of different topologies on DHEMS.

Line capacity limit (W)	Total electricity cost during a day ($)		
	Radial	Ring	Mesh
9,000	12.104	12.104	12.104
7,000	12.309	12.104	12.104
3,000	Infeasible	12.533	**12.104**
2,000	Infeasible	13.473	**12.533**

B. CASE 1: NO RELAXED TEMPERATURE CONDITION

In Case 1, the algorithms for CHEMS and DHEMS are simulated and compared when no relaxation of the consumer preferred temperature constraint is allowed with a large value of ϵ. Through a comparison between Figs. 5 and 6, we observe that the operating schedules of ESS and net power trade ($P^{\text{net,trade}}_{u,t} = P^{\text{imp}}_{u,t} - P^{\text{exp}}_{u,t}$) in each household differ between CHEMS and DHEMS, whereas the operations of the air conditioner and washing machine are scheduled identically. This implies that without the relaxed indoor temperature constraint, the proposed DHEMS algorithm maintains the same operating schedules of the air conditioner and washing machine of each house as those of the CHEMS algorithm. However, Figs. 5 and 6 show that the scheduling of the operations of the ESS and net power trade differs in both algorithms. This is because, in CHEMS, all appliances, ESSs, and power trades are scheduled considering all operating constraints simultaneously, whereas in DHEMS, the scheduling of ESS and the power trade at GHEMS are carried out separately with the scheduling of appliances at LHEMS. In general, ESS is charged when the TOU price is low during off-peak periods and is discharged when the TOU price is high during high peak periods in order to reduce the electricity cost. In this simulation, the ESS of each household u becomes fully charged at 8 am (i.e., $SOC_{u,a,8} = 1$) in both algorithms because ESS charges the maximum possible power during the low price period (1 $\sim$ 8 am), as shown in Fig. 4(a). Therefore, we can observe from Figs. 5 and 6 that charge of all ESSs finishes at 8 am with different and irregular charging patterns between households. On the other hand, we verify that the amount of fully discharged status of ESS decreases from house A with the largest load to house D with the smallest load from 9 am to 22 pm. This is expected because a higher (or lower) load demand requires more (or less) discharging power of ESS. It is noted that the remaining electricity of ESS after discharging ends can be exported to neighboring households of which the energy demand is higher than the energy supply, which are illustrated in Figs. 5(c), 5(d) and 6(d).

Finally, the simulation results show that even though the scheduling of ESS and the net power trade differ in each household between the aforementioned CHEMS and DHEMS algorithms, the optimal electricity cost of each house in both algorithms becomes identical: the optimal electricity costs of houses A, B, C, and D are listed in decreasing order of \$4.15, \$3.65, \$2.51, and \$1.78, respectively. In summary, under the scenario without indoor temperature relaxation, the scheduling of the ESS and power trade yielded by the proposed distributed approach differs from that yielded by the centralized approach, although the proposed distributed approach achieves the same value as that of the objective function in the centralized approach. This conclusion is also verified under fully relaxed indoor temperature conditions.

Next, we study the impact of different network topologies on the performance of the proposed DHEMS algorithm.

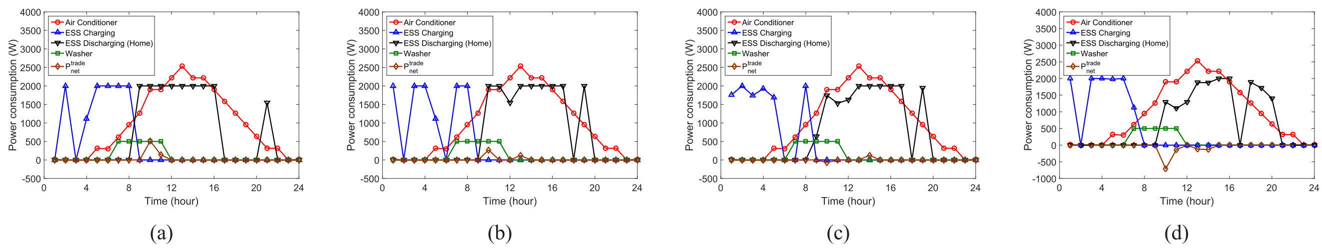


FIGURE 6. DHEMS-based optimized appliance schedules of four households throughout the day. (a) Household A. (b) Household B. (c) Household C. (d) Household B.

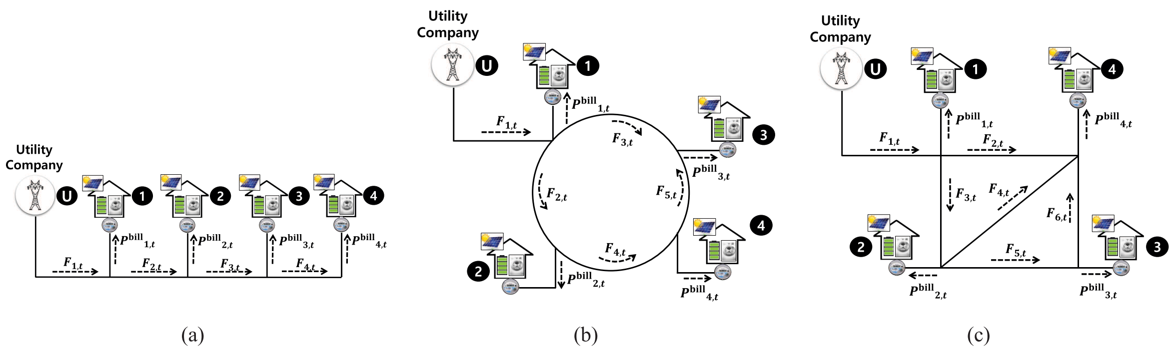


FIGURE 7. Three types of network topology. (a) Radial. (b) Ring. (c) Mesh.

TABLE 4. Comparison of the performance between CHEMS and DHEMS under same ϵ_u setups.

House(ϵ_u)	CHEMS		House(ϵ_u)	DHEMS	
	$\sum_{t=1}^{N_t} \delta_{u,t}$ (°C)	Cost (\$)		$\sum_{t=1}^{N_t} \delta_{u,t}$ (°C)	Cost (\$)
A(40)	12	3.63	A(40)	18	3.40
B(40)	9	3.26	B(40)	18	2.92
C(40)	6	2.25	C(40)	18	1.82
D(40)	5	1.57	D(40)	18	1.12
Total	32	10.71	Total	72	9.26

In this study, three network topologies (radial, ring, and mesh) are considered, as shown in Fig. 7. The radial, ring, and mesh topologies have three, four, and five interconnected lines among neighboring households, respectively. Table 3 shows the total electricity cost of each network topology with varying line flow capacity limit (2, 000W $\sim$ 9, 000W).

From this table, we first observe that as the limit of the line flow decreases, the electricity cost increases in all network topologies due to the tighter restriction of power trade between neighboring households. In particular, when the line limit decreases to 3,000W, the proposed algorithm becomes infeasible in only a radial topology. In addition, in Table 3, comparing the values in the columns for each row, the mesh, ring, and radial topologies are listed in ascending order of the total electricity cost. This is because an increasing number of interconnections among neighboring households provide additional operation flexibilities to households by exchanging power in order to reduce the electricity cost. Based on the aforementioned observations, we can conclude that in view of electricity cost saving for consumers, the mesh network is more effective than the ring and radial networks. As the LV network size increases with more deployed ESSs, the electricity cost saving for consumers becomes more significant in the mesh network.

C. CASE 2: PARTIALLY RELAXED TEMPERATURE CONDITION

In Case 2, the performance of both the CHEMS and DHEMS algorithms is compared under a partially relaxed temperature condition with some value of ϵ. Figs 8 (a) and 8(b) show the impact of varying ϵ on the performance of both algorithms for all four households in terms of the electricity cost and the discomfort cost. In these figures, the plots appear to be

TABLE 5. Comparison of the performance between CHEMS and DHEMS under different ϵ_u setups.

House(ϵ_u)	CHEMS $\sum_{t=1}^{N_t} \delta_{u,t}$ (°C)	CHEMS Cost (\$)	House(ϵ_u)	DHEMS $\sum_{t=1}^{N_t} \delta_{u,t}$ (°C)	DHEMS Cost (\$)
A(35.85)	37	2.71	A(35)	37	2.71
B(35.85)	37	2.23	B(35)	37	2.23
C(35.85)	30	1.39	C(36)	31	1.35
D(35.85)	19	1.08	D(38)	18	1.12
Total	123	7.41	Total	123	7.41

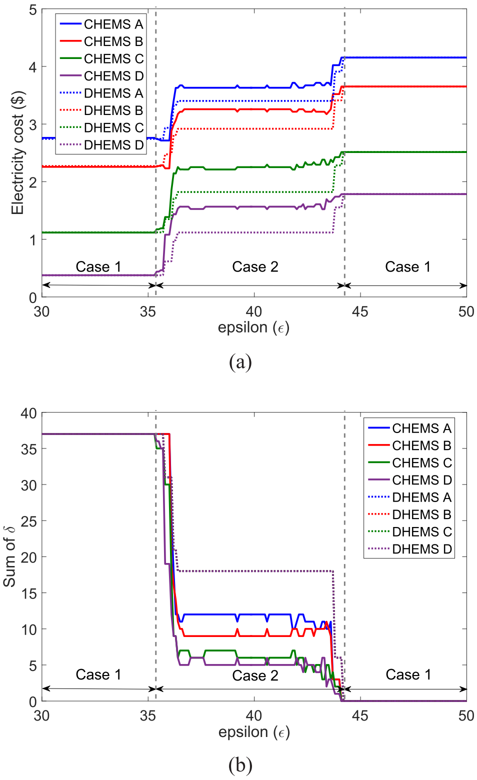


FIGURE 8. Comparison of the performance between CHEMS and DHEMS with varying ϵ. (a) Electricity cost. (b) Discomfort cost.

step functions, which are divided into two cases according to the interval of ϵ: (1) $\epsilon = [30, 36]$ and $[44, 50]$ in Case 1, as illustrated in the previous subsection, and (2) $\epsilon = [37, 43]$ in Case 2. As expected, we observe that for houses A, B, C, and D (with total load in descending order), both the electricity cost and the discomfort cost in CHEMS appear in descending order. That is, as the electricity load of the house increases, the electricity cost increases and the violation of preferred indoor temperature range also increases. Fig. 8(b) also verifies that the discomfort costs of all households in DHEMS reaches the same value. This is expected because the preferred indoor temperature range of each consumer is assumed to be identical. If this range is set differently for each consumer, the plots of the discomfort costs for all consumers differ.

It is noted that the plots in DHEMS have constant amplitudes, while the plots in CHEMS generally have fluctuating amplitudes. We conclude from this observation that the operator in the DHEMS can adjust the individual consumer comfort level more easily than in the CHEMS because in the DHEMS, the change of ϵ in one house does not affect that of another house. We also observe that, in Case 2, at the same ϵ, the electricity cost of DHEMS is less than that of CHEMS, whereas the discomfort cost of DHEMS is larger than that of CHEMS. This is because the LHEMS problem in DHEMS is formulated without considering the scheduling of the ESSs and energy trade, consequently leading to further reduction of the electricity cost than GHEMS at the expense of a larger ϵ. Table 4 shows the trade-off between the electricity cost and the discomfort cost for both CHEMS and DHEMS with the same ϵ.

Next, we investigate the impact of different ϵ in each household on the performance of the DHEMS. Table 5 shows the result of the comparison of the performance between the CHEMS and the DHEMS when they have an identical and different setup of ϵ_u, respectively. In this simulation, ϵ_u for houses A and B in the DHEMS is smaller than that in the CHEMS, whereas ϵ_u for houses C and D in the DHEMS is larger than that in the CHEMS. From this table, we observe that the DHEMS achieves an equivalent performance to that of the CHEMS by setting different ϵ_u for each household u. We can conclude from this observation that delicate tuning of the parameter ϵ_u could decrease the performance gap between the CHEMS and the DHEMS mentioned in the previous paragraph. The optimal ϵ_u could be selected by the operator heuristically, using Fig. 8. A theoretical analysis for calculating ϵ_u is beyond the scope of this paper and will be considered in future work.

V. CONCLUSIONS

In this paper, we propose a distributed two-level HEMS optimization algorithm that minimizes the total electricity cost of multiple households with distributed energy resources while maintaining the consumer's thermal comfort level. In the first level, the local home energy management system for each household schedules the energy consumption of the home appliances in each household through the selection of the consumer's preferred thermal comfort level. In the second level, the global home energy management system coordinates the operation of ESSs for all households and the power trade between neighboring households, and then calculates the optimal electricity cost for all consumers. Numerical results demonstrate that the proposed distributed algorithm achieves almost equivalent performance to that of the centralized optimization algorithm in terms of consumer's electricity cost and comfort level. Furthermore, we verify that the mesh network is more economical than the radial and ring networks in terms of the consumer's electricity cost saving. Finally, in comparison with the centralized optimization algorithm for home energy management, the proposed algorithm has the following advantages: 1) the computation time can be reduced significantly by distributing the centralized computation to local systems; 2) the comfort level of each consumer can be adjusted more readily and accurately; 3) a single point of failure due to cyber attacks can be avoided; and 4) a consumer's privacy can be further enhanced by conducting the scheduling of home appliances at only local home energy management system.

In future work, a theoretical framework to investigate the effect of the consumer's discomfort parameter ϵ_u on a distributed HEMS as well as tune it optimally will be developed. Also, the practical implementation of the proposed distributed algorithm will be tested in large-scale realistic low voltage network.

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