# A Real-time Cyber-physical Energy Management System for Smart Houses

Wei Wu[1], Muhammad Khalid Aziz[1], Hantao Huang[1], Hao Yu[1*], Hoay Beng Gooi[1]

***Abstract*-- The substitution of non-renewable energy by renewable energy as electricity supply is an emerging trend for development of smart houses nowadays. For example, solar photovoltaic (PV) panels, rechargeable batteries, external power supply, and power-consuming houses have formed a distributed micro-smart-grid. The traditional energy management system (EMS) for such a micro-smart-grid is, however, based on static demand model. As such, the resource (solar energy) cannot be optimally allocated to each house with real-time adjustment when the battery profile is different. In order to achieve high utilization rate of solar-energy, we propose a cyber-physical controller for real-time EMS of smart houses in this paper. Based on physically sensed battery profile, one cyber-physical controller enables the resource to be shared between different houses. The micro-smart-grid is modeled by decentralized multi-supplier and multi-customer system. The proposed real-time EMS is formulated based on the modified minority-game (MG) algorithm such that the task (or EU load) can be allocated with balanced distribution and hence improved utilization rate. The experiment results show that the proposed EMS can increase the solar energy utilization rate by 12.78% on average (up to 20%) when compared to the traditional design under the static demand model. Moreover, the load balancing of tasks (or customers) on each battery (or supplier) is significantly improved. For example, the average standard deviation of the load of tasks on batteries in each month is reduced from $45.36\,KWh$ (static demand model) to $5.19\,KWh$ (proposed model). The improved load balancing can further prolong lifetime of batteries.***

***Index Terms*-- Solar energy, batteries, energy management, smart grids.**

## I. INTRODUCTION

According to the estimation by Harvey in 2010, the future primary power requirement will reach up to 10 Tera-watt (TW) [1]. The transition from traditional energy to renewable energy has now become a real demand for sustainability. A significant portion of 21,000 MW solar photovoltaic (PV) has been installed globally in 2010 and is still increasing [2]-[3]. As shown in Fig. 1, the typical application of small-scale solar energy system is targeted to supply houses. This system acquires the solar energy by solar PV, supplies for electrical utilities (EUs), and stores the extra energy into battery or battery pack. The electrical grid servers as back-up supplier in case energy stored in the battery is used up [1]-[3].

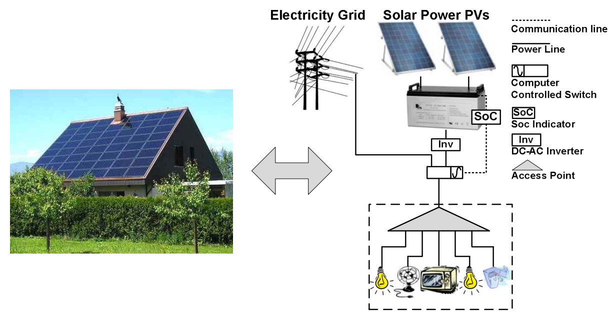


Figure 1. Traditional separated house with separated solar-power supply

Such a hybrid energy system requires a high efficiency energy management system (EMS) to improve the solar energy utilization rate. A number of EMSs have been developed for large-scale power-grid [4]-[6]. The micro-grid-level EMS solutions are also studied in [7]-[8]. Nevertheless, all approaches assume a static demand model. However, as discussed below, the static demand model has two physical constraints.

Firstly, different houses usually have different total requirements on solar energy. Thus, when the energy stored in the battery of one house is used up, one may not need to use the electricity grid immediately, but to use the remaining energy from other houses in the same community. The distinct energy-supply and requirement of individual house is, however, ignored by the static demand model and hence leads to a low utilization rate.

Secondly, different houses also have distinct energy-customer profiles. Note that the efficiency factor ($\mu$) of the battery degrades as low as 60% with a large discharge current [9]. To ensure the battery life-time, people usually set the maximum limitation ($current_{Max}$) on the discharge current. As such, one needs to use the electricity grid immediately once the total required current from EUs exceeds $current_{Max}$ of the battery. This information has to be sensed in real-time fashion as well for higher energy utilization rate.

In this paper, we propose one real-time EMS with cyber-physical controller for the utilization of solar-energy from many smart houses in a community. A modified minority-game (MG) algorithm is developed to realize the cyber-physical controller for real-time EMS. In our problem formulation, the smart houses are modelled by a multi-supplier and multi-customer system. The MG algorithm is

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implemented as a cyber-physical controller for fairly allocating multiple customers to multiple suppliers. As such, the renewable solar-energy is fairly utilized from different houses given different real-time energy profiles with the consideration of the maximum current limitation. A set of task models are designed [10]-[12], according to the EU power, solar and load profile, as benchmark for the evaluation. The numerical experiment results show that the proposed EMS can consider the maximum current of battery, and the solar energy utilization rate is increased by 12.78% on average when compared to the traditional design under the static demand model. Especially, from Apr. to Nov., the utilization rate improvement can be as high as 20%. Moreover, better load balancing performance can be achieved on the proposed EMS. The standard derivation of the load on each battery is reduced from $45.36\,KWh$ (Max: $81.54\,KWh$, Min: $11.21\,KWh$) to $5.19\,KWh$ (Max: $12.42\,KWh$, Min: $0.48\,KWh$). Especially from Apr. to Sep., the proposed EMS reduces the average standard deviation from $67.47\,KWh$ (traditional one) to $7.70\,KWh$ (proposed one). The better load balancing can further prolong the battery lifetime.

The rest of this paper is organized as follows. The background of smart-house microgrid system is introduced in Section II. Our EMS problem formulation is presented in Section III. In Section IV, the solution by minority-game based solution is illustrated. In Section V, experiments are performed to compare our EMS solution with the traditional houses without using the cyber-physical EMS. Finally, the paper is concluded in Section VI.

## II. BACKGROUND

In this section, we discuss the underlying physical system of smart houses. As shown in Fig. 2, the physical system is divided into three parts: power bundle, electrical utilities (EUs) and the interconnections between them.

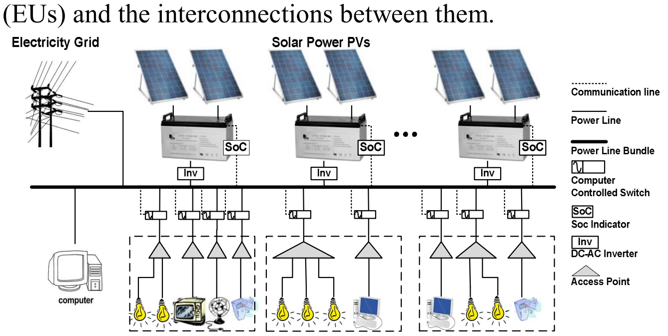


Figure 2. Physical system diagram for smart houses with shared soloar-power supply and electricty grid

The power bundle here is designed in a decentralized fashion similar to [13]-[14]. It is composed of both the battery and the external electricity-grid. All power lines to connect suppliers are integrated as one power bundle. We deploy batteries to store the solar-power and prepare them for the usage of EUs. When the stored solar energy is used up, the smart houses can consider the energy from the external electricity-grid. The EUs in Fig. 2 access the supplier through accessing points at the power bundle. The EUs with low-power consumption in one house may share the same accessing point controlled by one switch. Other EUs, especially the EU with high-power consumption, such as air conditioner, have their own power bundle accessing point. The accessing points connecting EUs to the power bundle can be realized by a computer-controlled switch. One central computer is equipped to decide which supplier in the power bundle to use, and then send the control signal to the computer-controlled switch for the execution.

Moreover, the electrical energy is delivered from batteries in direct current (DC) mode, which cannot be directly used by EUs. To facilitate the access of EUs to batteries, power converters are also assumed to convert the power from DC to AC [15]-[16]. Note that each solar-charged battery is equipped with a smart power meter to sense state of charge (SoC) [17]-[18] as energy supplier profile. Similarly, each EU is also equipped with a smart power meter to sense the energy customer profile. The communication signal, such as the SoC information collected from batteries, and the control signal from the central computer to the computer controlled-switch are carried by the power line communication [19]-[20].

## III. REAL-TIME EMS

According to the physical system structure just discussed, the smart houses can be modeled as a multi-supplier and multi-customer allocation problem, in which batteries act as supplier, while accessing points for EUs are considered as customers. We also discussed how this EMS can be applied to larger scale decentralized energy supplier systems.

### *A. Multi-supplier Model*

Since our objective is to use the battery as much as possible to reduce the utilization of the external electricity-grid, EUs will not turn to the external electricity-grid only if all batteries are unavailable.

In our system, the supplier is used to model the battery on each house. The battery model from [18] is adopted with solar energy to be charged to the battery according to the solar radiation profile, which will be introduced later in Section V. To avoid over-discharge of the battery, batteries are characterized into two different states, available and unavailable. There are two SoC thresholds used to control the battery state between these two states. For all available batteries, once SoC of a battery is lower than $T_1(5\%)$, all the customers using this battery will be allocated with new suppliers, and that battery will turn to the state of unavailable. For batteries in unavailable state, once the battery is charged to more than $T_2(10\%)$ SoC, that battery will become available to customers again. We use two thresholds rather than one to avoid the continuously switching between the two states, so as to reduce the overhead. The state switching between the two states is described as Fig. 3. Note that another 2 thresholds, $T_3(90\%)$ and $T_4(95\%)$ can be used to achieve over-charge protection. The functionality of over-charge protection is similar to over-discharge.

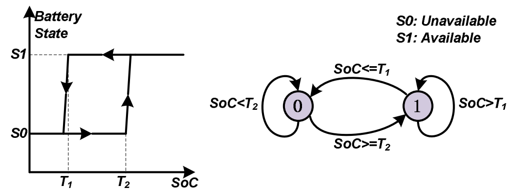


Figure 3. State transisions of battery to prevent over-charge/discharge

### B. Multi-customer Model

Furthermore, in our system, customers are referred to the EUs connected to the power line bundle. EUs that share the same accessing point are considered as one customer, and must be allocated with the same supplier, because they share a same computer-controlled switch. To model different EUs, we refer to the power consumption profile of EUs from [10]. The power consumptions of each EU used in our model are shown in Table I in terms of power and current consumption based on one $48V$ battery pack.

TABLE I. POWER CONSUMPTION OF DIFFERENT EUS

| *Electrical Utilities* | *Power (Watts)* | *Current (Amps)* |
|---|---|---|
| Air-Conditioning (Summer) | 1000 | 20.8 |
| Lighting (x12) | 240 | 5.0 |
| Desktop PC | 152 | 3.2 |
| Laptop | 50 | 1.0 |
| Personal Printer | 100 | 2.1 |
| Television | 150 | 3.1 |
| Electric Oven | 1178 | 24.5 |
| Blender | 300 | 6.3 |
| Heater (Winter) | 1200 | 25.0 |

We define the activeness of EU or EUs in one customer as tasks. If the EU of a customer is turn on, we say the task for this customer is activated. Similar to the battery modeling, we define four states to describe the task, 1) inactive; 2) active but unallocated; 3) allocated to battery; and 4) allocated to grid. The active task will require electrical energy from the suppliers. In other words, once a task is detected as state 2), the EMS needs to assign a supplier for this task in real-time fashion, and change its state into 3) or 4). Since our objective is to use as less energy from the external electricity-grid as possible, it is clear that we should find tasks in states 2) and 4), and try to allocate the solar energy (battery) to these tasks.

Finally, the active time and EU type in the tasks are adjusted and gathered together to match the household electricity load profile [12]. In future, if the system is enlarged to village level or block level, we can consider the entire house as a task. The modeling of tasks to match the household electricity load profile will be discussed in Section V.

### C. Cyber-physical Controller

PROBLEM FORMULATION We regard batteries, $\{B_k\}$ $k \in (1, N_B)$, as suppliers, while tasks $T_i$ $i \in (1, N_T)$ from EUs are models as customers. Since the discharge current of each battery cannot exceed the limitation of $current_{Max}$, if there are many tasks requiring for one battery, we need to allocate them fairly to the each battery, so as to avoid the concentrating the current on one battery and to exceed $current_{Max}$.

The overview of the cyber-physical EMS is described in Fig. 4. The central-computer checks the battery data (SoC, current) from different smart power meters in real-time periodically. Once there are tasks requiring the battery, the EMS will find an available battery to map tasks based on one real-time task mapping schemes. In the meantime, sensed battery data are used as feedback during the mapping. One minority-game (MG) based mapping is introduced later in this paper with history to record the sensed battery data. If no battery is available, this task will be allocated to the external electricity-grid. To perform the mapping, control signals are sent to computer-controlled switches to for the execution.

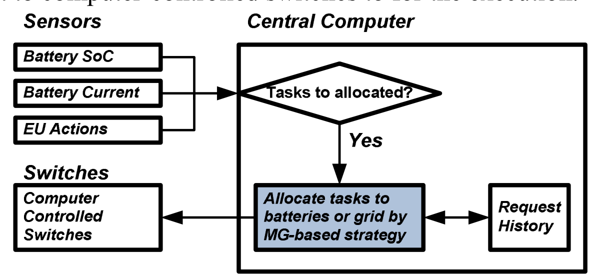


Figure 4. Cyber-physical energy management system

## IV. MINORITY GAME BASED CYBER-PHYSICAL CONTROLLER

In this section, minority game (MG) algorithm is implemented as the cyber-physical controller for the real-time EMS. The primary motivation is that the MG algorithm can perform the real-time and fair mapping of tasks to batteries.

### A. Minority Game Overview

Minority game (MG) is an algorithm widely adopted [21]-[25] for fair allocation of limited resource in multi-agent system, which is similar to balancing customers to multiple suppliers of our problem. This algorithm was first proposed by Challet and Zhang [21]. In the original MG algorithm, $n$ players make decisions to bar A or bar B independently. After that, the players in the minority side will win obtain a $Payoff$. Meanwhile, each player here will record the total requesting times $Req(i)$, and the times of successes to win the point on bar $k$, $s(i,k)$. This leads to the definition of *history*: $H(i,k) = s(i,k)/Req(i)$. In every iteration, a group of parameters, defined as *attractiveness* ($Attr$) of each bar to the player, is calculated. The player will choose the bar based on $Attr$. The calculation of $Attr$ is indicated in (3) [25]

$$Attr(i,k) = a_P * Payoff(k) + a_h(1 - H(i,k)) \quad . \quad (3)$$

In (3), $a_P$ and $a_h$ are defined to weight $Payoff$ and the *history* factors.

### B. Modified Minority Game for EMS

The game-play situation in our problem of multi-supply multi-customer EMS is more complicated than the original MG. Similar to the original MG, when we model the competition of multiple batteries $\{B_k\}$ $k \in (1, N_B)$, and for tasks $T_i$ $i \in (1, N_T)$, we calculate the attractiveness ($Attr$) of all available batteries to one task in order to facilitate the decision on which battery to use. We then map this task to the battery according to the calculated $Attr$. Different from the original MG algorithm, in our problem formulation the $Attr$ is calculated from three factors: the priority of battery, the feedback of battery and the history.

DEFINITION1 EMS PRIORITY: we introduce priority ($P_k$) for each battery as the first decision factor, which is similar to the $Payoff$ in the original MG. It is obvious that the larger discharge current on the battery, the fewer tasks can be allocated to the battery. In our modified MG, we use the $current_{Max}$ (with value of 100A) to normalize the priority, as shown in (4).

$$P_k = 1 - current_{Present}/current_{Max} \quad (4)$$

DEFINITION2 EMS HISTORY: we use the history of the times of successful mappings as the second decision factor. We record successful mapping times on battery $k$ in $Suc(i,k)$ and the total requesting times in $Req(i)$. Then the history $H(i,k)$ in our problem is defined in (5).

$$H(i,k) = Suc(i,k)/Req(i) \quad i \in (1, N_T), k \in (1, N_B) \quad (5)$$

DEFINITION3 EMS FEEDBACK: we further add the sensed battery feedback $SoC$ as the third factor. Since tasks can be supplied by one battery, it is necessary to consider the $SoC$ when the battery $B_k$ makes its decision in a real-time fashion as SoC acts as the feedback. For example, when the feedback indicates one battery with high $SoC$, it is reasonable to allocate more tasks on that battery.

DEFINITION4 EMS ATTRACTIVENESS: After introducing these three factors, we define the $Attr$ according to expression (6) under our problem

$$Attr(i,k) = a_{TP} * P_k + a_S * SoC(k) + a_H * \left(1 - H(i,k)\right) \quad i \in (1, N_t), k \in (1, N_b) \,. \quad (6)$$

In expression (6), $a_{TP}$, $a_S$ and $a_H$ are designed as control-knob parameters for the three factors. If $a_{TP}$ and $a_S$ are set as zero, the algorithm becomes the history-based decision similar to the equal-distribution algorithm. On the other hand, if $a_H$ and $a_S$ are set zero, the algorithm becomes the greedy algorithm.

### *C. Flow of Modified Minority Game*

The detailed flow of the MG-based cyber-physical controller is illustrated as a flowchart in Fig. 5. The MG algorithm will be invoked when the controller detects any EU is turn on, in other words, when any task is activated. If there is no invoking signal, the controller will iterate the MG within certain period. One decision table is formed for the ranking.

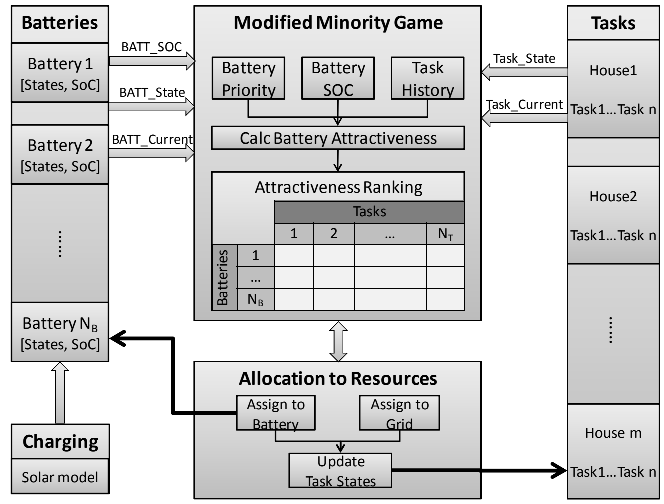


Figure 5. Task Flow of Modified Minority Game

**Algorithm: Modified Minority-game**

```
// Update the SoC of all batteries
For all batteries ∀B_k ∈{Battery}
    SoC(k) = GetSoC(k);
End For
// Update the battery states
For all batteries ∀B_k ∈{Battery}
    Update battery states, available or unavailable
End For
// Game Start
For all unallocated tasks and tasks allocated to grid ∈{T_I}
    //Calculate Attractiveness
    For all available batteries ∈{B_K}
        Attr(T_i, j) = CalcAttractiveness();
    End For
    // Sort Attractiveness
    SortedAttr(T_i, :) = SortAttractiveness(Attr);
    // Map Task to Battery
    For all available batteries according to sorted sequence
        Current(k)+= TaskCurrentConsumption;
        If Current(k) < Current_Max
            Map this task to Battery k;
            break;
        End If
    End For
    If This task is not mapped to battery
        Map this task to Grid
    End If
End For
// Game End
```

Figure 6. Task battery mapping based on MG algorithm

In Fig. 6, we also show the pseudo-code of modified MG in each iteration. The algorithm first gets the battery SoC from the sensors and updates the battery states. Then, it will process all the tasks in state 2) and state 4). For these tasks, we calculate the $Attr$ of all available batteries to the task, and rank the batteries by their $Attr$. Afterwards, the algorithm will check if there is any battery can afford this task, which requires that the total discharge current does not exceed $current_{Max}$, from the most attractive one to the least, until a battery is found to supply this task. If no battery is available to supply the task, this task will be assigned to the external electricity-grid.

## V. EXPERIMENTS

### A. Experiment Configuration

In the experiment, we set up a small scale smart-house system with four houses under MG-based cyber-physical EMS, and compare it to the case with four separated solar-powered houses under static demand. We generate a set of tasks based on various EUs, and apply tasks to the aforementioned two systems. The objective here is to obtain the electrical energy from solar-power supplier as much as possible and reduce the access of external electricity-grid energy. We need to verify if the MG-based cyber-physical controller can demonstrate this advantage as the real-time EMS, and how much the solar energy utilization rate can be improved by fairly allocating these tasks to the shared multiple batteries. Below, we further show the detailed configuration of experiments on how the battery and solar energy modeled and how task is applied.

1) *Solar energy collection:* For the solar energy supplier, we model it in accordance with the solar radiance data during different period of the year. The solar radiance data, which differ by month, are obtained from National Renewable Energy laboratory (NREL) in USA [11]. The maximum average daily acquired solar energy per square meter in one month (5.93 $KWh/m^2$ in Aug.) can be about 3.8 times to the minimum (1.57 $KWh/m^2$ in Nov.). Fig. 7a shows the profile of daily acquired solar energy per square meter in three months of summer and their average value respectively. The corresponding profile in winter is shown in Fig. 7b.

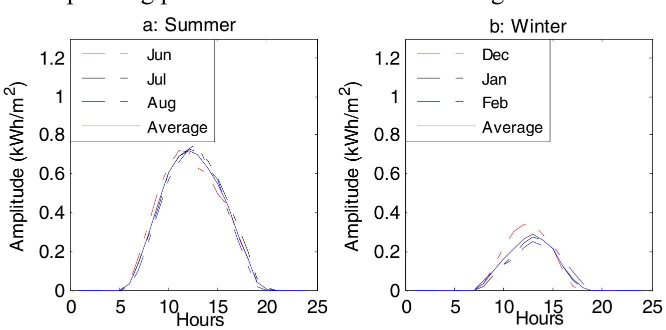


Figure 7. Daily solar radiance profile in different months

According to [8], the conversion efficiency from solar irradiance to AC conversion is about 15%. Assuming that the applicable area to install solar PV on the house roof is 25 $m^2$, the daily acquired energy ranges from 5.89$KWh$ to 22.24 $KWh$, which is comparable to the average daily power consumption per house.

2) *Batteries:* As mentioned before, we use the battery model proposed in [18] to simulate the battery. The parameter in this model is configured according to Sanyo's 48$V$ battery [26]. To enlarge the battery capacity for storing the collected solar energy, we configure 12 parallel connected batteries as a battery pack for each house. This battery pack can be continuously charged by solar PV for more than 5 hours without overcharge. To ensure the efficiency factor ($\mu$) of the battery, we set the maximum discharge current, $current_{Max}$, as 100$A$ for each battery pack.

*3) Tasks:* Tasks are modeled according to not only the EU power but also to people's habits on using EUs. For example, the light is usually inactive in the midnight; the microwave oven is more likely to be active at the dinning time. Moreover, tasks in one house are gathered together to match the electricity load profile of residential house [12]. Similar to the solar radiance profile, the electricity load profile varies by season. To be more realistic, we model task combinations in accordance to the electricity load profiles in different seasons, as illustrated in Fig. 8.

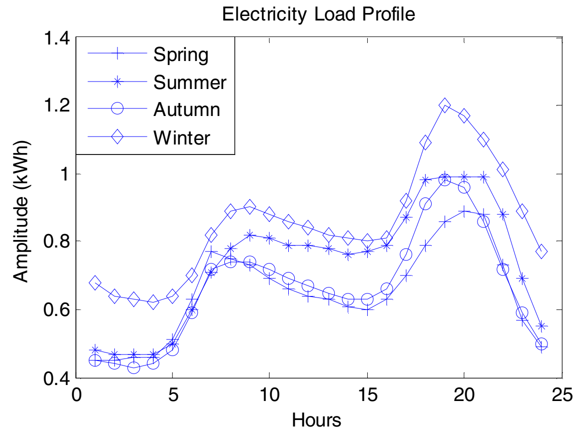


Figure 8. Electricity load profile in different seasons

Generally, there are two peaks in the electricity load profile of residential houses: one small peak occurs at the morning, while the other bigger one turns out in the evening. If we examine carefully, we can notice that the area below the winter profile is the largest. In other words, the average electricity load consumption in winter is the highest. Following the winter, are the summer, autumn and spring.

### B. Results and Analysis

1) *Solar energy utilization rate comparison:* As mentioned above, we modeled the task combinations in each seasons and solar radiance profiles in each month to compare the smart-house system and the separated-house system. Furthermore, for each season, we create two set of task combinations, as shown in Fig. 9, for comparison. In Fig. 9a, the load profiles of the 4 houses are similar to each others. In other words, the variance of each load profile is small. On the contrary, in Fig. 9b, the load profiles vary by houses, which is more realistic since people have different habits on using EUs.

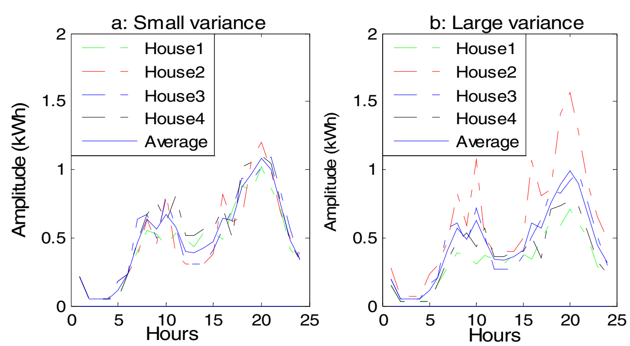


Figure 9. Load profiles with different variances

The duration of the simulation is configured as one week. To simulate the higher load in weekend, we simply increase the power of each EU by 20%. During simulation of smart-house system, all active tasks in 4 houses are dynamically assigned to different batteries according to the modified MG algorithm, whereas in the separated-house system, they are statically mapped to the battery of their own houses.

The simulation results of the aforementioned two task combinations on smart-house system and separated-house system are shown in Fig. 10 and Fig. 11, respectively. There are three types of columns in these figures: 1) the total energy consumption of these tasks; 2) the solar energy utilized by smart-house system; 3) the solar energy consumed by separated-house system. The result shown in Fig. 10 is simulated by several houses with similar task profile, as illustrated in Fig. 9(a). In Fig. 10, the solar energy utilization ratios of smart-house and separated-house system are very close to each other, and the solar energy utilized by smart-house is only 1.12% more than the separated-house. That is because the task profile of each house is similar to others but this situation is rare for realistic applications.

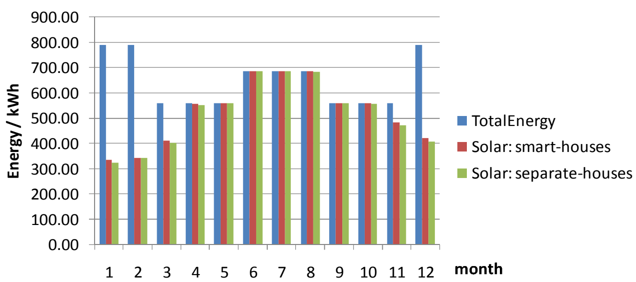


Figure 10. Energy consumption on tasks with small variance

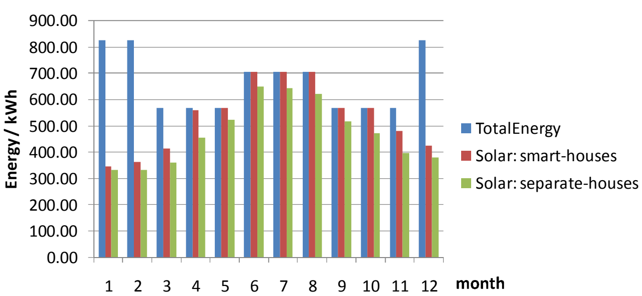


Figure 11. Energy consumption on tasks with large variance

On the contrary, the result in Fig. 11 reveals that the smart-house can achieve higher solar energy utilization rate compared with the separated one. 12.78% more solar energy can be utilized by smart-house. Furthermore, to compare the performance in different season, we can notice that in three winter months from Dec. to Feb., the electricity load is much higher than the available solar energy, such that it will use up all the solar energy, even if the tasks are not fairly distributed on each battery. As a result, the total utilized solar energy of smart-house is only 8% more than separated-house in these three months. However, in the other months, especially Apr. and Nov., the smart-house can make use of 20% more solar energy compared with separated-house.

2) *Fair resource allocation analysis:* To further validate the fair allocation merit of our MG-based cyber-physical controller for real-time EMS, we calculate the energy consumption on each battery. The energy consumptions per battery of smart-house and separated-house in 12 month are illustrated in Fig. 12 and Fig. 13 respectively.

In Fig. 12, although there is slightly unbalancing among each battery for smart-house system, it is much better than the separated-house system, which is shown in Fig. 13. In the separated-house system, the energy consumption on each supplier, the battery, is much different from each other. To analyze the resource allocation in quantitative fashion, we calculate the standard deviation of the load (energy consumption) on each supplier in different months. The results show that the average standard deviation in smart-house is 5.19 $KWh$ (Max: 12.42 $KWh$; Min: 0.48 $KWh$), while that of separated-house is 45.36 $KWh$ (Max: 81.54 $KWh$ ; Min: 11.21 $KWh$). Especially from Apr. to Sep., the smart-house reduces that average standard deviation from 67.47 $KWh$ (separated-house) to 7.70 $KWh$.

According to the quantitative analysis, we can claim that the smart-house system equipped with MG-based cyber-physical controller for the real-time EMS can allocate the tasks more fairly to multiple batteries. This fair resource allocation can balance the load on each battery to prolong its lifetime. Moreover, that also explains why a higher solar-power utilization rate can be achieved when compared to the separated-house system with static demand model.

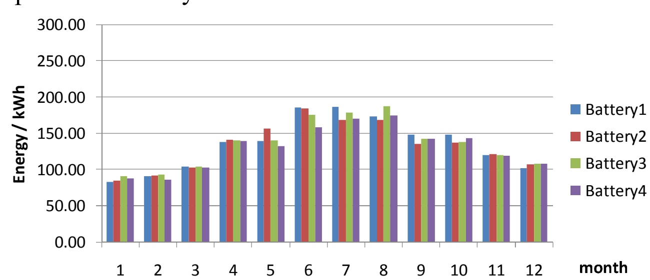


Figure 12. Distribution of energy consumption for smart-house

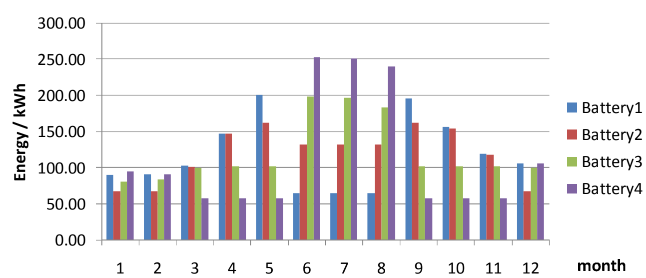


Figure 13. Distribution of energy consumption for separated-house

## VI. CONCLUSION

With the emerging implementation of hybrid energy network with both renewable solar-energy and non-renewable electricity, there is a need to develop the new energy management system (EMS) algorithm to improve energy unitization rate. The traditional EMS is mainly based on static demand and a real-time EMS is required to consider the varying profiles of energy-suppliers and energy-customers.

In this paper, we propose a multi-supplier and multi-customer problem formulation with a solution by minority-game (MG) based cyber-physical controller. With the physically sensed profiles of batteries and EUs, one can fairly allocate the tasks from EUs to multiple batteries of smart houses with the consideration of the maximum current of battery. Experiments show that our approach can increase the utilization rate of solar energy by 12.78% on average when compared with the static demand based EMS and up to 20% improvement. Moreover, considering the fair resource allocation, the average standard deviation of load on each battery can be very low in the smart-house system, which is only 5.19 $KWh$ (Max: 12.42 $KWh$; Min: 0.48 $KWh$) in our proposed method, while that of the traditional method is 45.36 $KWh$ (Max: 81.54 $KWh$ ; Min: 11.21 $KWh$ ). Especially, from Apr. to Sep., the smart-house reduces that average standard deviation from 67.47 $KWh$ (separated-house) to 7.70 $KWh$. This fair allocation leads to the load balancing on each battery with prolonged lifetime.

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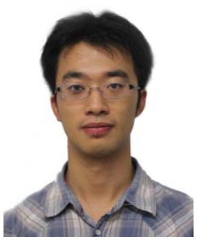

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