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利用粒子群最佳化演算法於智慧電網社區  
電力需求管理

Power Demand Side Management Using   
Particle Swarm Optimization in Smart Grid Community

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1. 中文摘要

近年來，由於能源過度使用造成的環境問題，讓節能減碳成為世界各國最為關切的焦點議題之一。隨著世界的快速發展，傳統電力網正面臨用電需求大幅提升的挑戰。因應用電需求的改變，能夠提供需求端管理的次世代電網，智慧電網，是相當重要的發展。例如：能夠讓家庭進行家中能源管理。透過智慧電網與需求端管理，不但可以有效地減少家中電費還可以同時降低電力負載的波動性。在智慧電網的架構下，同時考慮再生能源、儲能設備與動態電價進行〝日常活動排程的最佳化〞，如此可以達到節省電費的最佳化。另一方面，透過社區中多戶家庭互相合作進行電能管理，則可以最小化電力負載的波動性，如此不但可以有效地降低契約容量還可以使整體的電力系統更穩定。然而過去對於這方面的研究都專注於家電本身的資訊來進行分別的排程，卻忽略了家電狀態與家中日常活動之間的關係，事實上人在家中特定的空間使用某些家電會形成活動，例如：有人在客廳且大燈與電視皆為開啟的狀態，則很高的機率此人正在從事的活動為〝看電視〞。

本研究的主要貢獻有以下三點: 第一，本研究透過建立家中活動與電器之間的關係，先了解家中的日常生活習慣，再以活動進行排程，如此能更親近使用者的直覺。第二，當了解每戶家庭不同的活動的電器偏好，我們將日常活動的排程問題轉換成一種最佳化排程問題，對於單一家庭來說，我們將流動電費的節省達到最佳化，對於社區中多戶家庭來說，我們同時進行最佳化電費的節省與最小化電力負載的波動性，且不犧牲家庭使用者的偏好。第三，我們導入解決最佳化問題的方法，並將本研究提出的最佳化排程問題利用該法找出近似最佳之活動排程。

**關鍵字**:智慧電網、需求端管理、再生能源、電力負載波動

1. ABSTRACT

The issues of energy conservation and carbon reduction have been discussed for years. Because the world evolves rapidly, conventional power grid suffers from the increasingly high power demand. For the next generation power grid, a.k.a. Smart Grid, being able to perform Demand Side Management (DMS) is crucial, *i.e.* capable of managing the energy demand at residences. With both DSM and Smart Grid, the residents not only can minimize their electricity cost but also can alleviate Peak-to-Average Ratio (PAR) of their total power consumption distribution. Here, minimization of electricity cost is achieved through optimal scheduling of daily activities, which simultaneously takes into account the distributed generation from Renewable Energy (RE) sources, the energy storage devices, and the dynamic pricing. In addition, an optimal PAR that makes the power system stabler can be achieved via cooperation among multiple homes in a community. However, most of the prior works focus on exchanges of appliance-level information but ignore the potential of context-awareness, *e.g.* disregarding the relation between activity and associated power consumption.

There are three major contributions in this thesis. Firstly, the context related to an activity is considered while optimization of the power demand is being performed. Secondly, we formulate the power demand side management into an optimization problem. For individual home power, the electricity cost is minimized. For multiple homes, electricity cost and PAR are minimized simultaneously without compromising the preference of residents. Thirdly, a method for scheduling daily activity is proposed for both individual home and the environment with multiple homes, *i.e.* community.

**Keyword:** Smart Grid, Demand Side Management, Renewable Energy, Peak-to-Average Ratio

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# Introduction

## Motivation

Energy conservation and carbon reduction are important issues nowadays, and according to [[1](#_ENREF_1)], approximately 40% of global power consumption is from residential building. As a consequence, Demand Side Management (DSM) becomes crucial for power saving in the residential sectors, and Home Energy Management (HEM)[[2](#_ENREF_2)] serves as an important example under this viewpoint. DSM, proposed in late 1970s[[3](#_ENREF_3)] for the purpose of energy saving, plans the utility company’s activities in order to influence customer’s electricity usage pattern that will produce desired changes in the utilities load shape[[4](#_ENREF_4)]. An important support for DMS is from Smart Grid, which tries to overcome the disadvantages of the conventional power grid by incorporating the Information and Communication Technology (ICT)[[5](#_ENREF_5)]. With the increasingly high penetration of Advance Metering Infrastructure (AMI), Smart Grid promises to provide two-way communication so that residents can exchange information with utility company. As a result, with the help of Smart Grid and AMI, DSM is achieved by carrying out Demand Response (DR) mechanism, which usually motivates residents to change their electricity demand in response to *dynamic pricing*, aiming to reduce the electricity cost over time[[6](#_ENREF_6)]. However, for DSM to achieve an optimal daily activity schedule for residents, it is important to exploit *distributed generation from Renewable Energy (RE)*, which has drawn growing interest recently. According to the prediction in [[7](#_ENREF_7)], 33% of the energy supply will come from RE by 2020 in California. With the support of RE, the energy demand for Smart Grid can be alleviated. A result from [[8](#_ENREF_8)] has also shown that HEM with RE can obtain good performance in reducing *electricity cost*. Furthermore, provided that *energy storage devices* are deployed, RE can be utilized in a flexible way so as to achieve a better utilization by scheduling usage of RE in proper time periods of each day. In sum, an optimal DSM helps residents reduce their electricity cost via less energy usage during peak times, shift of power load from peak to off-peak period as well as better utilization of RE. It also results in alleviated Peak-to-Average Ratio (PAR) defined as the highest power load over the average power load[[9](#_ENREF_9)], which helps the energy providers to save power generation cost since less energy will be needed from power plants to meet the peak electricity demand. Generally, PAR is used to represent the dynamic range of the power load, and hence its alleviation can contribute to lowering of the degree of power load fluctuation and in turn stabilize the power system.

## Challenges

In order to achieve optimal DSM for both individual home and community consisting of multiple homes, two primary challenges have to be addressed. The first challenge is to achieve better utilization of RE for each home. The second challenge is to achieve power demand side optimization in community, *i.e.* the environment with multiple homes.

### Challenges of Utilizing the Renewable Energy

With the advance of technology, the cost of RE is descending in recent years[[7](#_ENREF_7)] and equipment of RE, *e.g.* solar panel or wind turbine, is getting popular. In accordance with the experiment conducted by [[8](#_ENREF_8)], better utilization of RE is able to increase the performance of Home Energy Management System (HEMS). Traditionally, RE is utilized in a straightforward way, *i.e.* directly consume RE whenever it is available. However, this method cannot guarantee the optimal usage of RE because it will be more efficient if RE is able to be consumed during the proper time slot, e.g. time slots when electricity prices are higher.

Due to the intermittent characteristic of RE and for the purpose of better exploiting RE, the energy storage device such as rechargeable battery needs to be taken into account so that all of the RE will first be charged into battery before it is distributed to home later. While considering dynamic pricing, utilization of RE and operation of energy storage device, the problem of power demand optimization becomes more difficult and complicated. In order to achieve optimal DSM, when will the storage device is charged/discharged and how much should be charged/discharged needs to be decided clearly. Generally speaking, not only homes can save their electricity bills but also power plants can alleviate their power loads during the peak period if RE can be efficiently utilized during the proper time slots.

### Challenges of Optimizing Power Demand in Community

One of the most important issues in Smart Gird is to maintain the stability and reliability of the power system. In order to achieve the goal, PAR of community needs to be alleviated. The key idea is to keep the fluctuation of power supply from utility company as low as possible, so the utility company does not have to address the sudden increase or decrease of the power demand, which might make the power system unstable or cause unexpected damage to the power system. Note that, PAR of community could be unpredictable if power demand optimization is done by each home individually. Thus, power demand optimization should take all homes in the community into account simultaneously. Since, gaining lower PAR and reducing electricity cost might be conflicting with each other, power demand optimization considering the two above in a community with multiple homes is apparently more sophisticated than in a individual home. Additional challenges of power demand optimization are how not to let the results compromise the user’s daily living preference and cost benefit of individual home gained from individual-home power demand optimization, *i.e.* , electricity cost of each home should be lower when community is the base for optimization. Given their constraints/concerns, the power demand optimization in community, which is tackled in this thesis, can be a tough challenge.

Actually, most of the prior works in the related area only consider how to reduce electricity cost. Since the problem of optimization within a community is hard to be formulated, most of prior researches only consider the schedule optimization in individual-home. Some works choose to ignore part of the features while alleviating PAR of multiple homes so as to simplify the problem formulation. For instance, how to utilize the RE is not taken into account, or only a few appliances are considered.

## Related Work

Due to the increasingly high power consumption, traditional power grid is no longer able to provide sufficient electricity efficiently. A concept of novel power system, also known as Smart Grid, has been brought up several years ago. Recently, there has been a significant growth in Smart Grid technology development and it provides new opportunities to realize the program of Demand Response (DR). Therefore, so far many previous works on addressing the power demand optimization have been proposed. Basically, the primary goal of these works is to simultaneously save the electricity bill and lower the power demand during the peak period. There are several pricing schemes used in these works, but the most common schemes are Time-Of-Use (TOU), Critical Peak Price (CPP), Real Time Price (RTP) and Inclining Block Rate (IBR). Among these former works, different optimization algorithms are adopted depending on the problem formulation and the pricing schemes, for instance, Integer Linear Programming (ILP)[[10](#_ENREF_10), [11](#_ENREF_11)], Game Theory[[9](#_ENREF_9), [12](#_ENREF_12)], Genetic Algorithm (GA)[[13](#_ENREF_13)], Particle Swarm Optimization (PSO)[[14](#_ENREF_14)], and Breath-First Search (BFS)[[15](#_ENREF_15)].

### Smart Grid

In recent years, the power consumption level of the whole world keeps growing. However, the cost for meeting the increasingly high power demand under the infrastructure of traditional power grid is extremely high. According to [[16](#_ENREF_16)], reliability of power system is highly important for power delivery and economic development of a community. An unexpected high power demand might jeopardize the power system, make it unstable and cause black out in a community. In order not to put damage into the power system, the ability to be aware of the power usage of residential home is significant. Because traditional power gird is not capable of supporting Wide Area Situation Awareness (WASA)[[17](#_ENREF_17), [18](#_ENREF_18)], the risk of having abrupt surge of power demand is extremely high due to overly similar life-styles of many residents. For example, a large group of the residents usually get off their duty at 5 pm and start to prepare dinner around 6 pm, and then the electrical appliances used for cooking or in kitchen would probably be turned on from 6 pm to 7 pm. Following what has been mentioned, to address the concern, a possible solution is to develop a novel power grid system, which consists of a better infrastructure and transmission system that allows good communicating with residential homes.

For constructing a more reliable, powerful and smarter power grid, the concept of the next generation power grid, also known as Smart Grid, is proposed. In accordance with [[18](#_ENREF_18)], Smart Grid generally consists of seven basic domains that include bulk generation, transmission distribution, customer, markets, operations, and service provider. Fig. 1‑1 shows the architecture defined by National Institute of Standards and Technology (NIST)[[19](#_ENREF_19)]. People expect Smart Grid is capable of addressing the disadvantages of the conventional power gird by incorporating Information and Communication Technology (ICT)[[5](#_ENREF_5)]. With the increasingly high penetration of Advance Metering Infrastructure (AMI), Smart Grid promises to provide two-way communication so that residents can exchange information, *e.g.* electricity price and power demand, with utility company.

|  |
| --- |
| Macintosh HD:Users:LeeChu:Desktop:Screen Shot 2014-05-16 at 4.46.53 PM.png |
| Fig. ‑ Smart Grid architecture proposed by NIST |

### Demand Response

Smart Grid, characterized by two-way communication, advance metering infrastructure, and dynamic pricing, provides the opportunity to realize the program of Demand Response (DR). According to [[6](#_ENREF_6)], DR is defined as the program to motivate residents to change their electricity demand in response to the electricity price over time. Furthermore, DR is classified into two general categories, incentive-based DR and price-based DR, according to two different motivations[[20](#_ENREF_20)]. For incentive-based DR, utility company will establish ways to negotiate with customers about their reward on power usage pattern change. For example, when the utility company issues a special event, which needs customers to adjust their power usage pattern, customers have to respond following the contract. If they fail to do so, the utility company has the right to inflict the punishment on customers. For the price-based DR, the customers adjust their power consumption in response to variation of electricity price. There are several pricing schemes used in this group but the most common schemes are Time-Of-Use (TOU), Critical Peak Price (CPP), Real Time Price (RTP), and Inclining Block Rate (IBR). For TOU, different electricity price is defined over the 24 hour period. In contrast, electricity price for shorter time periods is usually defined by RTP. On the other hand, CPP specifies the electricity price for some special conditions, *e.g.* 20 days during summer time to prevent customer from overusing the air-conditioner. For IBR, the electricity price is increased according to how much power has already been consumed, *i.e.* the accumulated consumed power. Usually, a hybrid version of electricity tariff will be applied, *e.g.* integrating the basic program of TOU with the special conditions specified by CPP.

### Demand Side Management

The method of power demand optimization proposed by [[10](#_ENREF_10)] schedules the appliances to lower electricity cost. There are two kinds of appliances, namely, shiftable and nonshiftable ones. A shiftable appliance can be scheduled by the optimization method, *e.g.*, shift the start-time of washing machine from the time slot with higher electricity price to the one with lower electricity price. On the other hand, a nonshiftable appliance cannot be scheduled since it has fixed operation period. The shiftable appliances are further classified into two kinds, *i.e.*, time-shiftable and power-shiftable. For time-shiftable appliances, operation’s start-time can be scheduled on the condition that the power consumption pattern is satisfied. For power-shiftable appliances, the system only needs to guarantee that the energy resource can sustain the total power demands during the desired period. The result shows the power load is reduced during peak period, but PAR unfortunately is not. Besides, this work does not take RE and energy storage device into account. On the other hand, in [[11](#_ENREF_11)], single user and multi-user scenarios are tackled and compared. Furthermore, the effect of different number of batteries and photovoltaic panels are also discussed. However, the approach in [[11](#_ENREF_11)] only focuses on minimizing user’s electricity bill for both single user and multi-user scenarios, which results in higher PAR unfortunately.

In order to achieve a better electricity tariff for both residents and service providers, the Stackelberg Game is used in [[12](#_ENREF_12)] where service providers, *i.e.*, utility company, play the role as the leader and residents as the follower. An Energy Management Controller (EMC) is implemented in each resident’s home. Once the game begins, the follower issues a power request first, and then accordingly the leader calculates the electricity price as the reply to the corresponding follower. However, this method seems unfair for the follower who issues the request later, and only three kinds of the appliances are used in their evaluation. Another game theory approach that [[9](#_ENREF_9)] adopted can achieve lower PAR and reduce the electricity cost. There is an Energy Consumption Scheduler (ECS) deployed inside the smart meter in each home, forming a distributed architecture. Those ECSs are able to interact with each other through smart meters and find optimal energy consumption schedule for every resident. The distributed algorithm however still needs a centralized controller to determine each selected user’s priority of execution, and hence it takes longer time to converge when the number of residents becomes huge.

Genetic Algorithm (GA) is adopted in [[13](#_ENREF_13)], aiming to reduce the electricity cost and alleviate the PAR. When dynamic pricing is concerned, the approach uses the scheme that combines Real Time Pricing (RTP) with Inclining Block Rate (IBR). RE is mentioned but it is not formulated there. Furthermore, the way how to do cooperate among several homes is not addressed. Therefore, the global optimality of reducing the electricity cost and allocating the PAR is not guaranteed to be reached simultaneously. Another approach proposed by Azad *et al*. [[14](#_ENREF_14)] considers each residential home independently. The appliances are divided into two kinds: shiftable and nonshiftable ones. The electricity cost is minimized by scheduling the shiftable loads over 24 hours a day. Nevertheless, since each home is independent from the others, PAR will become higher if most homes have similar schedules.

In [[15](#_ENREF_15)], an electricity cost minimization strategy for office is proposed. Initially, the devices are categorized into many types to represent different usage patterns with constraints. Next, the strategy schedules the operation period for all the devices. While generating the schedule, the guiding principle is that the energy with the lowest price will always be used first and RE is considered cost-free, *i.e.*, it will be consumed whenever it is available. However, conceivably the usage of RE will be more efficient if RE is consumed during the time with higher electricity price. Although some of the above works have simultaneously taken electricity cost and PAR as their optimization targets, they focus more on exchanges of appliance-level information but ignore the potentials of context-awareness, *e.g.*, the potential relation between resident related contexts and the associated power consumption is disregarded. In contrast, the proposed approach in this thesis intends to optimize the schedule of residents’ daily activities, which is believed to be more intuitive to users than scheduling various appliances. Since our proposed scheduling method is activity based, all the appliances involved in the same activity of a user will be scheduled at the same time. In contrast to the former cases where appliances are scheduled respectively, our method in turn guarantees feasibility of the resulting schedule. For example, residents will turn on the TV and light if they do the activity "watching TV". TV and light may not be scheduled in the same periods if the schedule perspective is appliance.

Table 1‑1 shows the differences between the previous works and our approach from several perspectives, including features of Smart Grid, multiple homes and target of scheduling.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table ‑ Comparison among different approaches in the literature and ours | | | | | |
|  | Features of Smart Grid | | | Multiple  Homes | Schedule  Perspective |
| Dynamic Pricing | Renewable Energy | Energy Storage Device |
| Z. Ziming *et al.* [[10](#_ENREF_10)] | ✓ | ✓ | − | − | Appliance |
| Georgievski *et al.* [[15](#_ENREF_15)] | ✓ | ✓ | − | − | Appliance |
| Azad *et al.* [[14](#_ENREF_14)] | ✓ | ✓ | − | − | Appliance |
| Z. Zhuang *et al.* [[13](#_ENREF_13)] | ✓ | − | − | ✓ | Appliance |
| Our Approach | ✓ | ✓ | ✓ | ✓ | Activity |

## Objective

For the purpose of addressing the aforementioned challenges, the objective of this thesis is to develop an Energy Management System (EMS) with power demand optimization engine for both individual home and community. For individual home, the system aims to minimize the electricity cost; for community, the system aims to minimize the electricity cost and PAR simultaneously. The contributions of this thesis are listed as follow:

* **Minimize Electricity Cost for Individual home**

In the environment connected to Smart Grid, small solar penal, wind turbine and battery are assumed to be deployed in each residential home. While considering RE, energy storage devices and dynamic pricing, we propose a power demand optimization method to minimize the electricity cost of individual home.

If the power generated by solar penal and wind turbine is directly distributed to the home and consumed directly, it will not be able to reduce the power supply from utility company during peak period. The aforementioned problem will lower the performance of the EMS, which means the electricity cost will cannot be reduced to a desired level. Therefore, how to efficiently manage the RE is an important issue while building an EMS in Smart Grid. Because when and how much to charge/discharge the battery is hard to decide in a straightforward strategy, we formulate it into an optimization problem and develop an activity scheduling engine in HEMS so that it is able to automatically manage the battery in an optimal way. As a result, HEMS can minimize the electricity cost and maximize the efficiency of utilization of RE at the same time.

* **Minimize Electricity Cost and PAR for Community**

Community is the environment consisting of multiple homes and the life patterns of most of them are probably similar. For example, most people used to do the laundry from 8 p.m. to 10 p.m. after all the family members take the shower. If the power demand optimization is done by each residential home independently, there will be a peak load during the period from 8 p.m. to 10 p.m. in this example. Although the electricity cost can be minimized by doing individual-home power demand optimization, PAR of the community should be high and cannot be improved at all. Since the higher PAR here implies the higher maximum power demand from the community, the Contract Capacity (CC) has to be set to a higher value, which may lead to an even more expensive demand charge. Therefore, we propose the power demand optimization requiring cooperation among multiple homes in a community to reduce the electricity cost and PAR at the same time. Note that the better reduction of PAR helps reducing the maximum demand, and hence obtaining better CC and lower demand charge, which in turn contributes to reduction of electricity cost of individual homes in the community.

## System Overview

In order to address the uncertainty of electricity price and Renewable Energy (RE) at the same time, a real-time schedule optimization mechanism is proposed. Thus, the proposed system can be separated into two parts. First part is for one-day ahead schedule optimization and second part is for real-time schedule optimization. The system flow is shown in Fig. 1‑2.

The predicted optimal schedule will be generated in the previous day. When the day comes, the real-time data, *i.e.,* real-time solar production and electricity tariff, will be compared with the predicted data at the beginning of each time slots. If there is difference between real-time and predicted data, the real-time optimization will regenerate the optimal schedule from the current time slot to the end of the day, *i.e.,* the updated optimal schedule, in accordance with predicted optimal schedule. After that, the predicted optimal schedule will be replaced by updated optimal schedule.

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| C:\Users\LeeChu\Desktop\123.png |
| Fig. ‑ System Overview |

## Thesis Organization

This thesis consists of six chapters, and they are organized as follows.

**In chapter2**, we introduce some preliminary knowledge of the thesis, such as Particle Swarm Optimization (PSO), which is an optimization algorithm used to quickly and easily solve the non-linear optimization problem, Multi-Objective Particle Swarm Optimization (MOPSO), which is an extended version of PSO used to solve the optimization problem with multiple objectives, and M2M-based Context-aware Home Energy Saving System (M-CHESS), which is the energy saving system proposed by the previous work, consists of three core engines[[21](#_ENREF_21)].

**In chapter 3,** initially, the individual-home environment will be introduced. Next, we give the overview of the proposed HEMS based on M-CHESS. Finally, Schedule Optimization Engine (SOE) for HEMS will be described, which includes data preprocessing and PSO-based schedule optimization.

**In chapter 4**, the environment with multiple homes, *i.e.* community, will be introduced in the beginning. Then, the technical details of power demand optimization in a community will be described, which includes problem formulation and MOPSO-based schedule optimization.

**In chapter 5**, we will show the details of the experiment environment and the evaluation metrics. The experimental results are discussed and analyzed in this chapter as well.

**In chapter 6**, we give a conclusion and discuss the future work

# Preliminaries

## Particle Swarm Optimization

Particle Swarm Optimization (PSO), which was firstly proposed by James Kennedy and Russell Eberhart in 1995[[22](#_ENREF_22)]. PSO is a population-based stochastic optimization method. The population is formed by numbers of particles/swarms and each of them occupies a position, which represents one possible solution with a corresponding fitness value calculated by fitness function in the search space. Based on the movement of those particles, PSO searches the optimal solution in the search space by simulating the social behavior of fish schooling, bird flocking and swarming theory in particular. In other words, each particle will move around the search space according to its position and velocity to look for the position/solution with best fitness value. This algorithm can be separated into four parts, which include initialization, particle evaluation, velocity update and particle update.

### PSO Initialization

In the initialization phase, the size of the population has to be predefined, i.e. the number of particles needs to be specified beforehand. Then, PSO algorithm will generate initial set of particles according to the size of the population by sampling around the search space randomly. Each one of them will be located in one position that represents one possible solution in the search space. An example is shown in Fig. 2‑1. Numbers of initialized particles are randomly distributed in a two-dimensional search space.

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| Macintosh HD:Users:LeeChu:Desktop:particle.png |
| Fig. ‑ Initialized particles in a two-dimensional search space |

### PSO Particle Evaluation

According to different goals, there is a corresponding objective function that needs to be minimized or maximized. Such function is to guide one to efficiently search for the position corresponding to the optimal solution in the search space through the movement of particles. Unfortunately, PSO algorithm does not guarantee that the optimal solution can always be found. Actually, it can only find the near optimal solution instead of the real optimal one in most scenarios.

The position of each particle that represents one possible solution can be evaluated with the fitness function, which is usually similar to the objective function. After that, each particle will be associated with a fitness value to show how good the particle is. For example, the smaller the fitness value the better the corresponding particle will be if the goal is trying to minimize the objective function. Furthermore, some optimization problems might have some constraints that need to be satisfied. Therefore, the particle possess the infeasible solution are usually penalized by the evaluation process. An example of penalization is to let the evaluation process add a constant positive value to the fitness values of those infeasible particles in the minimization problem, subtract a constant positive value from the fitness value in the maximization problem.

After the evaluation, the position of particle with best fitness value among all the particles will be chosen as global best, *i.e.,* *gbest*. Then, each particle will update the position that it has ever been through as local best, *i.e., pbest*.

### PSO Velocity Update

The velocity of a particle is updated by considering *the global best*, the best solution experienced by whole particles until now, *the local best*, the best solution achieved by individual particle, and *the current velocity*. The following equations are used to update velocity.

|  |  |
| --- | --- |
|  | (2‑1) |

where, represents the velocity of the *ith* particle at the *kth* iteration. The parameter stands for inertia of the particle, which means the weight of previous velocity. The constants *c1*, *c2* are the degrees of effectiveness of the local best and global best, respectively. If *c1* is greater than *c2*, the particles will learn more knowledge from *the local best* and then move like isolated individual. If it is on the contrary, the particles will trust *the global best* moreand will probably move toward local optimum. As a result, it is better to let *c1* and *c2* be approximately equal. For *rand1* and *rand2*, they are uniformly distributed random number from 0 to 1, which will be regenerated in every new iteration. The local best of the *ith* particle at iteration *k-1* and the global best are respectively denoted as and. Fig. 2‑2 illustrates the idea of velocity of particle and how *gbest* and *pbest* influence the movement/velocity of a particle.

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| Macintosh HD:Users:LeeChu:Desktop:velocity.png |
| Fig. ‑ Influence of *gbest* and *pbest* to a particle |

### PSO Particle Update

According to the previous step, each particle has its own velocity. In this phase, PSO will update the position of particles by using their velocity information. The new position of each particle can be calculated by the following equation.

|  |  |
| --- | --- |
|  | (2‑2) |

where and denote the current and previous positions of particle *i*, andrepresents the velocity of particle *i*. The idea of updating the position of particle is shown in Fig. 2‑3.

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| Macintosh HD:Users:LeeChu:Desktop:UpdateParticle.png |
| Fig. ‑ Updating the position of a particle |
| C:\Users\LeeChu\Desktop\Thesis chart\flow chart of pso.png |
| Fig. ‑ The flow chart of Particle Swarm Optimization |

The PSO algorithm will terminate when the ceiling number of iteration is achieved, otherwise, it will update the velocity and position of each particle. After updating the velocity and position of each particle, the PSO algorithm finishes the current iteration and starts the next iteration. The flow chart of the whole PSO process is shown in Fig. 2‑4.

### Multi-Objective Particle Swarm Optimization

Multi-Objective Particle Swarm Optimization (MOPSO) was first proposed by [[23](#_ENREF_23)]. MOPSO is extended from PSO for solving the problem with multiple objectives. There are three primary differences between PSO and MOPSO. First, MOPSO has multiple objectives, *i.e.*, at least two objectives. Second, MOPSO naturally has a set of global best particles, each of which is not dominated by the others, rather than only on particle. Third, MOPSO needs an additional mechanism to select which global best particle should be the guidance for each particle because there are more than one global best particles. For all the particles in MOPSO, it is said to be global best if and only if it is Pareto optimal. The definition of Pareto optimality, Pareto dominance and Pareto front in the minimization problem are described as follows[[24](#_ENREF_24)]:

* **Pareto** **Optimality:**

From all of the feasible solutions in the search space, given a solution , which is Pareto optimal if and only if there is no other feasible solution that dominates .

* **Pareto** **Dominance:**

Given two vectors and , is said to dominate if and only if , and .

* **Pareto Front:**

Pareto front is formed by the set of Pareto optimal solutions.

The flow chart of MOPSO is similar to PSO, but there is another step before one sets the velocity to select which global best particle should be the guidance for each particle. Fig. 2‑5 shows the flow of process of MOPSO.

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| C:\Users\LeeChu\Desktop\Thesis chart\mopso flow chart.png |
| Fig. ‑ The flow chart of Multi-Objective Particle Swarm Optimization |

## M-CHESS Overview

M-CHESS is the abbreviation of M2M-based Context-aware Home Energy Saving System[[21](#_ENREF_21)]. For achieving home energy saving, it is important to understand how residents interact with their surrounding environment. A Context-aware system indicates that the system is always aware of the surrounding contexts, *e.g.*, the on-going users’ activities and the status of appliances. In order to make the system context-aware, different types of sensors are deployed inside the home to form the M2M Home Area Network (HAN). For example, the integrated sensor for measuring temperature, humidity, and illumination is as shown in Fig. 2‑6(a); the smart socket for measuring the current of appliance is as shown in Fig. 2‑6(b); the current sensor for detecting the on/off state of appliance is as shown in Fig. 2-6(c); the microphone sensor for detecting the sounds in the environment is as shown in Fig. 2‑6(c); and the depth-camera for locating the residents is as shown in Fig. 2‑6(d).

|  |  |
| --- | --- |
|  | C:\Users\LeeChu\Desktop\S__4440072.jpg |
| (a) | (b) |
|  | 描述: 描述: E:\台大\M2M\DSC_0025.jpg |
| (c) | (d) |
|  | |
| (e) | |
| Fig. ‑ The sensor deployed in the home environment | |

Based on the M2M infrastructure, three core engines are developed to minimize the energy consumption and to keep the user comfort simultaneously. The functions of three engines are briefly described as follows. Energy Responsive Context (ERC) for describing the relation between activity and its associated appliances is proposed. Then, the process of modeling ERC is done by the so-called Energy Responsive Context Inference Engine (ERCIE). In order to know what activity the user(s) is(are) doing, a model called The job of measuring the comfort level is done by the so-called User Comfort Evaluation Engine (UCEE). For the user comfort, the system adopts comprehensive comfort index that consists of three sub-indices. Last but not the least, the process of deciding how to control the appliance is done by the so-called Energy Saving Decision Support Engine (ESDSE). For the purpose of fine-grain control, the problem of how to control the appliance is formulated as an optimization process. Fig. 2‑7 shows the system diagram of M-CHESS, and all the details of three core engines are depicted in the following paragraphs.

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|  |
| Fig. ‑ System diagram of M-CHESS |

### Energy Responsive Context Inference Engine

Activity is an important context when home energy saving is concerned since one activity usually involves several different appliances. Some of them might have strong relation with the activity coheres some of them might not. For example, fan and light may be turned on to a certain status or may not be turned on while residents are playing the video games. But, TV and XBOX must be turned on while they are playing the video games. As mentioned earlier, ERC is proposed to model the aforementioned relation between activity and its associated appliances, [[21](#_ENREF_21)], which thus contains the information on energy consumption from usage of all involved appliances. Based on the M2M infrastructure, the power consumption of an appliance can be measured by a smart meter and the data will be collected by the smart home system. Then, the ERC model can in fact be learnt from historical data.

For each activity, the power consumption state of an appliance will have a state (either "on", "off", or "standby") which is the most related to that activity. According to how this state of appliance is affected by the corresponding activity, ERCs are generally classified into the following two categories.

* **Explicit Power Consumption**

The appliances in this category are highly related to the associated activity or context, *i.e.*, the power state of the appliance is triggered on by the mentioned activity. In other words, the power consumption states of all of the explicit appliances will change their operation states (*e.g.* "off"🡪"on", "standby"🡪"off", …, *etc.*) when an activity takes place. For example, for the activity context, "Playing XBOX", XBOX is the appliance belonging to "explicit power consumption" type, because XBOX is turned on and off when the activity starts and ends. Another example is about the context "Go Out", where all the “explicit power consumption” appliances of this context are those with "standby" mode, because the power consumption states of these appliances can be changed from "standby" to "off" when the context "Go Out", take place.

* **Implicit Power Consumption**

The appliances in this category are only fairly related to the associated activity. The power consumption state of the appliance is not triggered on directly or indirectly by an activity. In other words, the time duration over which these appliances are at the "on" state are usually longer than or unrelated to the time duration over which the activity takes place. For example, the light in the living room could be an "implicit power consumption" appliance for the activity: "Playing XBOX" in the living room, since it is turned on while residents are playing XOBX, but not necessarily turned off when playing stops. More observations show that light is not a necessary appliance to compose the

|  |
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|  |
| (a) |
|  |
| (b) |
| Fig. ‑ The concept of explicit and implicit power consumption |
| (a) explicit power consumption and (b) implicit power consumption |

activity context, "Playing XBOX", because residents would probably not turn on the light if they paly XOBX during daytime and they would not turn off the light after they finish playing XBOX at night.

The concepts of explicit and implicit power consumption depicted above are illustrated in Fig. 2‑8.

### User Comfort Evaluation Engine

In a home environment, energy saving and user comfort could conflict each other, and hence how to achieve energy saving while maintaining user comfort is an significant and worthy issue. In User Comfort Evaluation Engine (UCEE), a multi-agent architecture is introduced to evaluate the comprehensive comfort index. Based on the M2M infrastructure, UCEE is able to extract the environmental sensor data, *e.g.* temperature, humidity, illumination, and the status of every appliance to perform the comprehensive comfort evaluation. The comfort index consists of three sub-indices, which are visual comfort, thermal comfort, and comfort for energy saving decision, which is based on the appliances-usage preference of resident.

In order to optimize the energy saving while considering residents’ comfort, a utility function formed by the comfort sub-indices and energy consumption has been proposed and then an optimization problem is formulated.

### Energy Saving Decision Support Engine

After receiving all the environmental sensor data, Energy Responsive Context Inference Engine (ERCIE) will infer the Energy Responsive Context (i.e. activity). The details of ERC are illustrated in Section 2.2.1. After the ERC is inferred by ERCIE, the activity and its corresponding Energy Usage Signature (EUS) will be passed to User Comfort Evaluation Engine (UCEE) and Energy Saving Decision Support Engine (ESDSE). After receiving the information of activity and its associated EUS, UCEE will generate one possible control decision for every appliance, which possesses the lowest power consumption and keeps all of the three comfort sub-indices within the respective constraints at the same time. The control decisions of all appliances will be passed to ESDSE. After receiving the context and control decisions from ERCIE and UCEE, respectively, ESDSE will send out the control signals to trigger the actuators in the environment and change the status of relevant appliances.

# Individual-home Power Demand Optimization

## Smart Energy Saving Home

* **Environment Overview**

Under the framework of a Smart Grid, one assumes that a set of solar panels or wind turbines have been deployed on the roof top of every home. Furthermore, energy storage devices, *e.g.* rechargeable batteries, are usually also deployed in the basement of every home. According to [[25](#_ENREF_25)], the configuration of grid-hybrid system is assumed to be built as the one shown in Fig. 3‑1, and hence the power demand at home can be supplied by grid and battery at the same time. Advance Metering Infrastructure (AMI), is an important part of Smart Grid, which requires every home to deploy the Smart Meter, additionally. It is worthwhile to mention that the smart meter realizes the concept of two-way communication so that the information, *e.g.*, power load at demand side or electricity price given by utility company, can be transmitted from residential home to utility company, vice versa.

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| C:\Users\LeeChu\Desktop\Thesis chart\configuration.png |
| Fig. ‑ Grid-hybrid system configuration |

* **Home Energy Management System (HEMS)**

Based on the aforementioned home environment, a novel Home Energy Management System (HEMS) is capable of optimizing power usage and eliminating energy wastage energy for individual home. HEMS should know how to control the power consumption states of home appliances in an optimal manner, which brings many benefits, *e.g.,* reducing the electricity cost. Based on the energy saving system in the previous work, *i.e.* M-CHESS[[21](#_ENREF_21)], we further extend it to a HEMS for a residential home connected to Smart Grid. Based on the M2M infrastructure developed in M-CHESS, the new HEMS is also a context-aware system, which can be aware of all necessary information, like status of battery, state of appliances and residents’ location. The goal of the proposed HEMS is to minimize the electricity cost, and conserve energy usage without compromising user comfort and residents’ activity preference at the same time.

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| C:\Users\LeeChu\Desktop\HEMS.png |
| Fig. ‑ Home environment with HEMS |

The proposed HEMS consists of four core engines. Three of them are ERCIE, UCEE and ESDSE from M-CHESS[[21](#_ENREF_21)], and the 4th one is Schedule Optimization Engine (SOE) proposed in this thesis. The engine SOE is responsible for optimizing schedules of daily activities and battery usage at home while considering Renewable Energy (RE) from solar power, characteristics of energy storage device, and dynamic pricing. As in M-CHESS, the home server provides execution platform for the four engines and connected to smart meter so that various information can be sent and retrieved through it, like electricity price and power load. For the purpose of interacting with residents, the In-Home Display (IHD) is an important component of HEMS. It is a friendly web user interface developed for residents to perceive the current status of HEMS, the context in the environment, and to input their preference of daily activities. Residents are able to provide the relation between activity and appliances by filling the table through IHD. On the other hand, Energy Responsive Context (ERC) model can also be learnt from long-term historical data. Fig. 3‑2 shows the home environment with the proposed HEMS.

## Schedule Optimization Engine (SOE)

### Optimization Flow

The goal of SOE is to minimize the electricity cost and optimize activity and battery schedules. One way to minimize the electricity cost is to shift some activities to some proper time slots (*e.g.*, to the time slot with the lowest electricity price) and maximize the efficiency of utilization of RE. Another way is to minimize the Contract Capacity (CC), which will be tackled in the next chapter, *i.e.,* community schedule optimization. The flow of optimization can be separated into four parts.

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| C:\Users\LeeChu\Desktop\Thesis chart\system diagram.png |
| Fig. ‑ Flow chart of Schedule Optimization Engine |

First of all, the properties of each activity will be specified by residents through web interface. SOE will preprocess the information of each activity retrieved from residents including the earliest start time, the latest end time, operation duration, and associated appliances. After preprocessing the activity property, an activity profile will be generated as an input to the schedule optimizer. Second, it is necessary to have the prediction of solar power production since activity scheduling needs to be optimized in one-day ahead. In the thesis, we adopt the method of forecasting of solar power production proposed by [[26](#_ENREF_26)] for simplicity. The forecasting method will take the historical data of solar radiation as input. Based on the historical data, Auto-Regressive Moving Average (ARMA) model is trained for the forecasting of solar power production. Third, the electricity tariff, namely, Time-of-Use (TOU), is referenced from Taiwan Power Company. Fourth, activity optimizer will optimize the schedules of activity and battery usage in accordance with the activity profile, forecasting of solar power production, and the electricity tariff. Both of schedules will be shown on the IHD as a recommendation. The details of flow chart of proposed SOE is as shown in Fig. 3‑3.

### Data Preprocessing

* **Forecasting of Solar Power Production**

In order to optimize activity and battery schedules in one-day ahead, prediction of daily solar production is necessary. For simplicity, we adopt the method proposed by [[26](#_ENREF_26)]. The forecasting method of solar power production will take the historical solar radiation as input. In the thesis, the historical solar radiation data consisting of Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), and Global Horizontal Radiation (GHI) are referenced from [[27](#_ENREF_27)]. DNI is the amount of solar radiation received by a solar panel held perpendicular to the radiation modeled as a straight line originated from the sun. Thus, the solar panel is able to receive the maximum amount of radiation provided it is always perpendicular to the incoming radiation. DHI is the amount of solar radiation scattered by cloud or particles in the atmosphere received by the solar panel. The relation between these three radiations is shown in the following equation, where GHI is the amount of solar radiation that includes both DNI and DHI. Given the angle between the direction of sun and that of the solar panel surface, the relation among the three radiations is formulated as follows:

|  |  |
| --- | --- |
|  | (3‑1) |

In the aforementioned home environment, we assume that solar panel deployed at the roof top is fixed, which means the solar panel is not able to change its angle to face directly to the sun. Thus, GHI is considered as the major incoming radiation. Based on the historical data, Auto-Regressive Moving Average (ARMA) model is trained for the forecasting of solar power production. ARMA model was first introduced in 1951 by Peter Whittle[[28](#_ENREF_28)]. ARMA is a combination version of Autoregressive (AR) and Moving Average (MA). The model of AR and MA is shown as (3‑2) and (3‑3), respectively.

|  |  |
| --- | --- |
|  | (3‑2) |

In (3‑2), are parameters, *c* is a constant value, and represents white noise. White noise is a random value with a constant power spectral density in signal processing[[29](#_ENREF_29)].

|  |  |
| --- | --- |
|  | (3‑3) |

In (3‑3), are parameters of the model, indicates the expectation of , which is usually assumed to be zero, and stands for the white noise.

In most cases, ARMA is used to predict the trend of signal in the next phase based on the cyclic historical data. Since the solar power production has cyclic characteristic, ARMA is able to perform well on forecasting the solar power production. For example, the solar power production in each season is usually similar to the same season in other years, and hence solar power production will be like a cycle year by year.

ARMA model consists of AR and MA models. Two important parameters in ARMA are *p* and *q* in the AR and MA models, respectively. ARMA model can be shown as follow:

|  |  |
| --- | --- |
|  | (3‑4) |

According to ARMA model, we implement the forecasting algorithm in MATLAB. For simplicity, the embedded ARMA function in MATLAB is adopted. The forecasting algorithm of solar power production is shown in the following. Several variables are described first, followed by descriptions of the input, output and algorithm.

|  |  |  |
| --- | --- | --- |
| **Algorithm** Forecasting Algorithm of Solar Power Production | | |
| **Variable** | | **Meaning** |
| data2010 | | Solar radiation data in 2010 |
| data2011 | | Solar radiation data in 2011 |
| z | | data2010 in frequency-domain |
| bestP | | a parameter in AR model that makes AIC the smallest |
| bestQ | | a parameter in MA model that makes AIC the smallest |
| AIC | | Akaike’s Information Criterion that is used to estimate model |
| armaModel | | an ARMA model |
| result | | result of prediction |
| **Input:** one year historical solar radiation information | | |
| **Output:** predicted solar power production | | |
| 1: | data2010 = csvread('single\_2010.csv'); | |
| 2: | data2011 = csvread('single\_2011.csv'); | |
| 3: | z = iddata(data2010); | |
| 4: | **for** p = 1:10 | |
| 5: | **for** q = 1:10 | |
| 6: | [bestP bestQ] combination of p, q such that AIC is the smallest | |
| 7: | **end for** | |
| 8: | **end** for | |
| 9: | armaModel Build ARMA model by **armax(z, [bestP bestQ])** | |
| 10: | yp Predict solar power production by **predict(armaModel, data2011, 24)** | |
| 11: | Truncate negative values | |

Note that the two important parameters *bestP* and *bestQ*, they are chosen to be 10 and 9, respectively, from empirical experience we take the radiation data in 2010 in Philadelphia for example, in Fig. 3‑4(a), and the prediction result for the year 2011 is shown in Fig. 3‑4(b). The red part is the forecasted data of ARMA and the blue part is the radiation data in 2011. For both figures, x-axis stands for hours in a year and y-axis stands for watts. From Fig. 3‑4(b), one can see that the prediction is quite promising.

|  |
| --- |
| C:\Users\LeeChu\Desktop\2010_trainingdata.png |
| (a) |
| C:\Users\LeeChu\Desktop\predict_result.png |
| (b) |
| Fig. ‑ Training data and result of solar forecasting algorithm |

* **Activity Profile**

Each activity possesses many important features, like whether it is schedulable or not. An activity is schedulable means it can be scheduled by ASE. In other words, the start time of the activity can be shifted from one time slot to another; otherwise the activity is nonschedulable. For the purpose of maintaining the user preference, it is necessary to collect the activity related information from residents. For example, when is the earliest time for an activity to be started and when is the latest time for an activity to be finished. In order to let residents provide their activity preference, a friendly web interface is developed. This web interface can be browsed by any devices as long as it has browser embedded. The web interface browsed by Google Chrome is shown in Fig. 3‑5.

|  |
| --- |
| C:\Users\LeeChu\Desktop\Screen Shot 2014-05-27 at 4.52.17 PM.png |
| Fig. ‑ Web interface for activity preference inputs |

The parameters include the name of activity, (earliest) start time, (latest) end time, operation duration, and associated appliances. The activity will not be scheduled by activity optimizer if it is nonschedulable. Thus, if the activity is nonschedulable, the earliest start time and latest end time will automatically change to the start time and end time, and accordingly, the operation duration will be determined. For each activity, all of the parameters need to be set before schedule optimizer starts, so as to make sure the optimization result (activity and battery schedules) is appropriate and user preference is not compromised. In Table 3‑1 Parameters of activity profile, name and meaning of each parameter are described.

|  |  |
| --- | --- |
| Table ‑ Parameters of activity profile | |
| **Parameter** | **Meaning** |
| Name | What this activity is, e.g. watching TV or washing dishes. |
| Schedulability | Activity is schedulable if it can be scheduled for the need for optimization; otherwise it is nonschedulable. |
| The (earliest) start time  The (latest) end time | For each schedulable activity, at least one schedulable period from the earliest start time till the latest end time needs to be specified. For each nonschedulable activity, the deterministic start time and end time are needed. |
| Activity duration | Residents need to specify how long each activity will last for if the activity is schedulable. The activity duration will equal to the duration from start time to end time if it is nonschedulable. |
| Appliance | Appliances corresponding to the specified activity need to be provided, i.e. the ERC model, which will be learnt from historical activity data in the future. |

After residents submit the data, all of the information will be transferred to our cloud platform and be processed it into an XML file. In the XML file, all of the tags are bounded by the tag named "schedule". The tag in next level called "activity" with attribute "name", which stands for the name of activity. Inside the "schedule" tag, we have "times" tag with "id" attribute that represents how many times this activity will takes place in this day. For example, "Sleeping" only occurs once in this day as show in Fig. 3‑6. In each tag of "time", there are tags of "periodList", "duration", "schedulable" and "applianceList". All the valid periods specified by residents are represented under the "period" tag and each period will hold an earliest start time and latest end time. The content of "duration" tag stands for the period over which this activity takes place. For the content of "schedulable" tag, it is "true" if the activity is schedulable; otherwise, it is "false", like the one in Fig. 3‑6. Finally, all of the appliances related to this activity will be stored in "applianceList" tag. For instance, the activity, "Sleeping", only involves night lamp, which means residents only turn on the night lamp while they are sleeping. Since the XML formatted activity file is very long, a portion of it is shown in Fig. 3‑6.

|  |
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| C:\Users\LeeChu\Desktop\Screen Shot 2014-06-16 at 5.02.13 PM.png |
| Fig. ‑ XML formatted activity profile |

### PSO-based Schedule Optimization

* **Activity Model**

Based on our previous work [[21](#_ENREF_21)], the potential relation between activity and its associated power consumption from various home appliances is learnt as Energy Responsive Context (ERC), which is introduced in Section 2.2.1. According to the ERC model, some of the appliances are often turned on when residents start to do the activity and turned off after residents finish the activity. These appliances are classified as explicit-on related appliances of this activity. For example, TV is explicit-on related appliance in the ERC model of "Watching TV". Since the proposed power demand optimization is activity based, the power consumption of each activity needs to be specified. Therefore, we define *PAi* as the power consumption of activity *i*, the sum of the power consumption of the explicit-on related appliances in its ERC model.

|  |  |
| --- | --- |
|  | (3‑5) |

In (3‑5), *APP* represents the set of all electric appliances; means the number of appliances; *pj* indicates the power consumption of appliance *j*. The parameter *appi,j* shows whether appliance *j* is explicit-on related to activity *i*, *i.e.,* it is equal to one if the relation is explicit-on; otherwise, it equals zero.

In the thesis, activities are categorized into schedulable and nonschedulable. Only the schedulable activities can be scheduled by the optimization method. Let *S* denote the "schedulable vector" that contains all schedulable activities’ start-times and *NS* denote the "nonschedulable vector" that contains the deterministic start-times of all the nonschedulable activities, as follows:

|  |  |
| --- | --- |
|  | (3‑6) |
|  |  |

In (3‑6), *sch* and *nsch* indicate the numbers of schedulable and nonschedulable activities, respectively. In addition, there are constraints of each entry in *S*. Let *ESi* and *LEi* denote vectors of the available earliest start-times and latest end-times of activity *i*. Each *ESi* and *LEi* is paired, and hence each legal period is set from *esk* in *ES*i till its corresponding *lek* in *LEi*, so the dimension of both vectors is equal to the amount of available periods. For example, and, which means activity *i* must be taken place either from 1 a.m. to 5 a.m. or from 9 p.m. to 11 p.m.. In order to satisfy the residents’ preference, the following constraint must hold.

|  |  |
| --- | --- |
|  | (3‑7) |
|  |  |

where *di* represents the duration of activity *i*. The constraint shows that the start-time cannot be earlier than nor being later than ; otherwise, the activity is scheduled in illegal period.

According to (3‑6) and the duration of each activity, we can construct the activity scheduling matrix, *AS*, which contains all of the schedulable and nonschedulable activities.

|  |  |
| --- | --- |
|  | (3‑8) |

where *A* denotes the number of activities, which is equal to the sum of *sch* and *nsch*; *T* indicates the total time slots in one day. For each entry, the value is one if activity *i* happens at the *tth* time slot, and zero otherwise.

* **Battery Model**

Next, two of the three factors affecting the optimal Home Energy Management (HEM) for a individual home are formulated, which are *distributed generation from RE* and *energy storage devices*. For the purpose of sound utilization of RE, we assume that the solar power generated at the current time slot will be stored in the temporary capacitance, and charged into the battery at the end of the current time slot before it can be consumed. In addition, it is necessary to decide when and how much the battery should be discharged or charged, but not to utilize it directly. As a result, the utilization of RE can be treated as the management of the battery.

In the following, the constant indicates the maximum capacity of battery, which is reasonably set to nearly 20kWh according to[[30](#_ENREF_30)], and represents the state of battery at the beginning of time slot. In order not to cause damage to the battery, should always be more than. The amount of power of discharge from battery to home and charge from grid to battery, is modeled as and, respectively. For discharge, two constraints need to be sustained. First, cannot be greater than, otherwise, will be less than. Second, should be less than Total Power Consumption at time slot (), which is defined as the sum of power consumption of all activities at time slot, otherwise, the power will be wasted. Thus, we choose the one with smaller value to be the upper bound of. For charge, two constraints need to be sustained as well. Frist, we know that solar power generated at the time slot, which is denoted as, will be charged into the battery at the end of the time slot, and hence cannot be greater than, otherwise, some of will be wasted. Second, should be restricted by the Maximum Charge Power (*MCP*), which is defined as the maximum amount of power can be charged while battery is operating by its maximum charge rate. The charge rate are defined by *C-rate*[[31](#_ENREF_31)]. For a 65Ah battery *C* = 65A and 1C means to charge with 65A. So, if the charge rate is, it would take two hours to fully charge the battery from an empty state. For a realistic battery, maximum charge rate is usually less than one, and hence we are not able to fully charge the battery within a time slot, *i.e.,* one hour. The constraints of both of them are shown as follow:

|  |  |
| --- | --- |
|  | (3‑9) |
|  |  |
|  |  |

According to the grid-hybrid system configuration, power demand can be supplied by grid and battery at the same time. Thus, discharge and charge are not necessary to take place simultaneously within a time slot. For example, and , one scenario is that the amount of power of charge and discharge are 5kWh and 3kWh, *i.e.,*  and . Thus, power supplied by grid is (4-3) + 5 = 6kWh, and. Another scenario is that the amount of power of charge is 2kWh but not discharging. Power supplied by grid is 4 + 2 = 6kWh, and. For both scenarios, the power supplied by grid and final state of battery is the same. As a result, battery needs only be in either discharge or charge mode within a time slot. Therefore, we use one parameter,, to model discharge (positive value of, ) or charge (negative value of, ). So, can be formulated as follow:

|  |  |
| --- | --- |
|  | (3‑10) |
| *subject to* |  |

where, indicates the state of battery from the end of previous day. The parameter *T* represents the total time slots in one day. For different application, *T* can be extended to any suitable positive integer.

* **Electricity Cost**

With (3‑6), (3‑9), (3‑10), the electricity cost of a individual home can be calculated as follows, which formulates the third factor affecting optimal HEM for a individual home, *Dynamic Pricing*.

|  |  |
| --- | --- |
|  | (3‑11) |

where *T* indicates the total time slots in one day; *A* denotes the number of activities, which is equal to the sum of *sch* and *nsch*. For each entry,, the value is one if activity *i* happens at the *tth* time slot, and zero otherwise. represents the power consumption of activity *i* and stands for the amount of power of discharge when it is positive value, otherwise it is the amount of power of charge. For *Dynamic Pricing*, *ct* indicates the electricity price at time slot *t*. Given *S, NS,* and *R,* which represent the battery schedule in one day, the optimization problem can be formulated as follows.

|  |  |
| --- | --- |
|  | (3‑12) |
| *where*  , , |  |

* **PSO-based Optimization**

The proposed optimization problem is solved by using Particle Swarm Optimization (PSO). The flow chart of PSO-based optimization is shown in Fig. 3‑7. Here, the position of every particle is represented by *S, NS,* and *R*. The way to evaluate the fitness of particle is to calculate the electricity cost, *i.e.,* fitness function in (3‑11). After the particle evaluation, *i.e.,* calculation of electricity cost of every particle, the one with lowest electricity cost will be chosen as global best particle, *i.e.* *gbest*. Then we update local best of every particle, *i.e.,* *pbest*, if the new position of particle is the best one that this particle has ever been through. After that, we check whether the termination condition is reached or not. If it is reached, we output the optimal daily schedule, which is hold by global best particle as the result, consists of activity and battery schedules. Otherwise, we update the velocity and position of every particle according to (2‑1) and (2‑2), respectively.

|  |
| --- |
| C:\Users\LeeChu\Desktop\flow chart.png |
| Fig. ‑ PSO-based optimization flow chart |

In the phrase of velocity update, the weight of previous velocity, *i.e.,* inertia, could significantly influence the result. There are many methods of deciding the inertia. The one proposed by [[32](#_ENREF_32)] is adopted since it results in better result in the most cases. The idea is to let inertia be the maximum value in the beginning, and make it decrease as the iteration goes on. The updating equation is shown as follow:

|  |  |
| --- | --- |
|  | (3‑13) |

where, and represents the maximum and minimum values of the inertia, which are decided at the beginning. *k* indicates the current iteration; *N* indicates the maximum iteration.

After updating the position of particles, some particles might be in the infeasible position, *e.g.,* start time of some activities are invalid. Following, we will introduce how to do constraint handling. For activity schedule, we shift the invalid start time of activity to the closest valid start time. For example, represents the start time of activity *i*, which is invalid is as shown in Fig. 3‑8(a). Assume the time period in two red rectangles are valid periods and duration of activity is 2 hours. According to (3‑7), it is clear that two valid start times are 7 a.m. and 1 p.m.. Because is even closer to 1 p.m., it is shift to 1 p.m. as.

For battery schedule, the state of battery needs to be checked from the first time slot. At each time slot *t,* the upper and lower bounds of, *i.e.*, and, will be calculated first. If the upper and lower bounds are not sustained by, it will be reset to the boundary as shown in Fig. 3‑8(b). For example, if is greater than, it will be reset to.

|  |
| --- |
| C:\Users\LeeChu\Desktop\activity constraint handling.png |
| (a) |
| C:\Users\LeeChu\Desktop\123.png |
| (b) |
| Fig. ‑ Constraint handling of activity and battery schedule |

# Residential Community Power Demand Optimization

## Smart Grid Community

* **Environment Overview**

According to the individual-home environment in Smart Grid mentioned in Section 3.1, a set of solar panels or wind turbines have been deployed on the roof top of every home. Furthermore, energy storage devices, *e.g.* rechargeable batteries, are usually also deployed in the basement of every home. In this chapter, the environment will be extended from individual home to community. A Smart Grid community is an environment with multiple homes and each home has the aforementioned layout. We assume that Home Energy Management System (HEMS) is deployed in every home. Through HEMS each home is able to be connected with a centralized server, and hence the information can be shared. It is worthy because the schedule of all homes can be optimized together to gain more benefits not only for residents but also for utility company. For residents, Contract Capacity (CC) can be lower so as the electricity cost. For utility company, a stabler power load is achieved so as the cost of generating power. The Smart Grid community is as shown in Fig. 4‑1.

|  |
| --- |
| C:\Users\LeeChu\Desktop\community_1.png |
| Fig. ‑ Typical Environment of Community |

* **Contract Capacity**

In Taiwan, Contract Capacity (CC) is the quantity of essential power demand that a community needs to decide and sign a contract with Taiwan Power Company. CC is highly related to the demand charge, which is part of the electricity cost, of homes in the community. If CC is higher, the demand charge will get higher as well. The reason to have demand charge is that utility company needs to do equipment maintenance so as to guarantee the power system is reliable and stable. Thus, there is essential electricity cost, *i.e.*, demand charge, even if residents do not consume power. Furthermore, if the highest demand, which is defined by Taiwan Power Company as the maximum power demand within 15 minutes, is higher than the CC, community will be punished by doubling the demand charge for the exceeding part under 10% of CC, or tripling the demand charge for the exceeding part over 10% of CC. For example, CC = 20kW and the highest demand is 30kW, and hence exceeding part is 10kWh. Thus, the cost of exceeding part under 10% of CC, *i.e.*, , will be doubled, and the cost of exceeding part over 10% of CC, *i.e.*, , will be tripled. In summary, lowering the highest demand is able to get a better CC, and hence it can reduce the demand charge of every home, so the electricity cost of each home in the community becomes even lower. From the perspective of benefiting utility company, it can reduce the cost of generating power in order to meet the power demand during peak period.

* **Community Energy Management System (CEMS)**

According to [[33](#_ENREF_33)], Community Energy Management (CEM), also called community energy planning, means to combine scheduling concepts and demand side management in residential communities or green cities. Based on the aforementioned community environment, a novel Community Energy Management System (CEMS) is capable of managing the power demand of community in an optimal manner. The benefits of extending from individual home to community are depicted as follows. For residents, reduction of the electricity cost is achieved by reducing CC through CEMS. For utility company, CEMS is able to alleviate the Peak-to-Average Ratio (PAR), which helps the energy providers to save power generation cost since less energy will be needed from power plants to meet the peak electricity demand. Generally, PAR is used to represent the dynamic range of the power load, and hence its alleviation can contribute to lowering of the degree of power load fluctuation and in turn stabilize the power system. Additionally, utility company can achieve Wide Area Situation Awareness (WASA) and control the power flow in a more efficient way.

In order to gain the aforementioned benefits, every home in the community needs to cooperate with one another, and attain an optimal power demand for the entire community. The proposed HEMS introduced in Section 3.1. is assumed to be deployed in every home in the community. Then, a centralized server connecting all the HEMS for data collection, data preprocessing, data analysis, and demand optimizing is indispensable. For example, there is a centralized cloud platform with several computers and all the HEMSs can upload data to the database of cloud platform. After data preprocessing and data analysis, optimization of community power demand will be tackled and community activity and battery schedules will be generated according to community activity and battery models. The system overview is as shown in Fig. 4‑2.

|  |
| --- |
| C:\Users\LeeChu\Desktop\CEMS.png |
| Fig. ‑ Overview of CEMS |

## Community Schedule Optimizer

### Optimization Flow

The goal of power demand optimization in community is to minimize the total electricity cost of a community and alleviate PAR of a community at the same time. In order to achieve both these two objectives, the system needs to take the following things into account in a community simultaneously. First, choose proper start time slot for each activity in each home. Second, decide when and how much amount of power to discharge or charge for battery. Third, keep the total electricity cost and PAR of the community in a low level. According to the aforementioned objectives, the optimization flow is as designed in follow.

|  |
| --- |
| C:\Users\LeeChu\Desktop\Thesis chart\community system diagram.png |
| Fig. ‑ Flow chart of community schedule optimizer |

The flow of system can be separated into four parts. Firstly, the forecasting method of solar power production using ARMA model mentioned in Section 3.2.2 is adopted again. The historical data of solar radiation is assumed to be the same for all homes since they are in the same community. Secondly, residents lived in different homes need to specify their activity preference through web interface, also mentioned in Section 3.2.2. Right after the submission, HEMS will automatically upload it to the centralized server for further data preprocessing and data analysis. CEMS will aggregate the data and generate two sets of XML files, which are community daily solar production and community activity profile. Thirdly, the electricity tariff will be taken into account. Here, Time-Of-Use (TOU) from Taiwan Power Company is adopted. Finally, the proposed community schedule optimizer will take outputs from aforementioned three parts as its inputs and generate optimal daily schedule for the community, which consists of the schedule for activity and battery of each home in the community. The flow chart of community schedule optimizer is as shown in Fig. 4‑3.

### MOPSO-based Schedule Optimization

The goal of power demand optimization in a community is to alleviate PAR and to minimize the electricity cost at the same time. These two objectives are conflict with each other, but they need to be achieved simultaneously, and hence the optimization problem is formulated as a multi-objective one. In order to solve the nonlinear multi-objective optimization problem in a high dimensional solution space, Multi-Objective Particle Swarm Optimization (MOPSO) is adopted.

* **Community Activity & Battery Model**

Here, we model the schedule of activity and battery for all the homes in a community. For activity schedule, we gather schedulable vectors and nonschedulable vectors of all the homes in a community as the activity schedule of community,, each of which is as shown in (4‑1).

|  |  |
| --- | --- |
|  | (4‑1) |
|  |  |

where represents the schedulable vector of home *m*; represents the nonschedulable vectors of home *m*; *H* indicates the number of homes in a community.

For battery schedule, we use a matrix, *CR,* to represent the battery schedule in a community. Each row,, of *CR* indicates the battery schedule of home *m* in one day, *i.e.*, stands for the amount of power charged into or discharged from the battery of home *m* at time slot. The whole matrix *CR* is as shown in (4‑2).

|  |  |
| --- | --- |
|  | (4‑2) |

* **Objectives**

|  |
| --- |
|  |
| (a) |
|  |
| (b) |
| Fig. ‑ Example of high and low PAR |

The first objective is to alleviate the PAR of a community, which is defined as the highest power load over the average power load, so as to lower the fluctuation degree of power load, and to stabilize the power system. PAR also helps the energy providers to save power generation cost since less energy will be supplied by grid to meet the peak electricity demand. To simply illustrate the concept of PAR, Fig. 4‑4(a) shows two examples of power load, each of which with high and low PAR, respectively. Fig. 4‑4(b) shows their corresponding PAR. As shown in Fig. 4‑4(a), power load in solid line changes significantly and thus has higher PAR than that in dotted line. Let indicates the power supplied by utility company of home at the time slot. PAR of the community can be formulated as follows:

|  |  |
| --- | --- |
|  | (4‑3) |
|  |  |

The second objective is to minimize the electricity cost of community. Here, we take demand charge into account. As mentioned before, demand charge is the essential part of electricity cost, which is highly related to the value of CC. Demand charge per day per home is defined as, which is formulated as follow:

|  |  |
| --- | --- |
|  | (4‑4) |
| *where* |  |

where, indicates the cost of one kW of CC per month; *CC* indicates the value of Contract Capacity whose unit is kW. In this thesis, it is set to the value of highest demand in one day; *H* stands for the number of homes in the community; *DAYS* means the number of days in one month. It is assumed the demand charge of community is equally afforded by each home in a community, so is divided by *H*.

The other part of electricity cost is formulated as (3‑11) in individual-home schedule optimization. Here, we call it electricity charge. Since there are multiple homes in a community, an additional index *m* is added to represent the cost of different homes. Let represent the electricity charge of home, which is formulated as follow:

|  |  |
| --- | --- |
|  | (4‑5) |

where, *T* is the number of time slots in a day; *A* is the number of activities; means whether activity happens at the time slot at home *m*; indicates the power consumption of activity at home *m*; stands for the electricity price at time slot.

According to (4‑4) and (4‑5), the electricity cost per day of a community,, is formulated as the sum of and as follow.

|  |  |
| --- | --- |
|  | (4‑6) |

According to (4‑1), (4‑2), (4‑3), and (4‑6), the optimization problem with two objectives can be formulated as follow:

|  |  |
| --- | --- |
|  | (4‑7) |
|  |  |
|  |  |

* **MOPSO-based optimization**

The proposed multi-objective optimization problem is solved by using Multi-Objective Particle Swarm Optimization (MOPSO). The corresponding flow chart of optimization is shown in Fig. 4‑5. After initialization, the position of each particle is represented by,, and *CR, i.e.,* schedule of activity and battery for each home in a community. The way to evaluate the fitness of each particle is to calculate its PAR and electricity cost, *i.e.*, fitness functions in (4‑3) and (4‑6). Since one particle possesses two fitness values, global best could be an archive. By using the idea of Pareto dominance that mentioned in 2.1.5, all the particles with Pareto optimality property will be put into the global best archive, which forms the Pareto front.

|  |
| --- |
| C:\Users\LeeChu\Desktop\flow chart mospo.png |
| Fig. ‑ MOPSO-based optimization flow chart |

The other particles that are not Pareto optimal will be guided by one of the particles in the Pareto front. In the Pareto front, some particles have higher electricity cost but lower PAR, whereas the others possess lower electricity cost but higher PAR. Selecting one appropriate solution from them is necessary, otherwise it might compromise residents’ benefit gained from individual-home schedule optimization, *i.e*. the lowest electricity cost. Before doing the optimal daily activity scheduling for multiple homes, each home needs to set the elastic rate of electricity cost, which is defined as the percentage of the additional cost each home is willing to pay due to the adjustment of schedule. The way to do guidance selection is illustrated in Fig. 4‑6. Assume we are selecting guidance for particle *x,* and *Y* represents the set of particles in global best archive. The way to select the guidance for particle *x* is to find *Z,* a set of candidate particles which satisfy the constraint of electricity cost, *i.e.,* *constraint(x)*, from *Y*, and then choose a particle *w* with the lowest PAR from that set as the guidance.

|  |
| --- |
| C:\Users\LeeChu\Desktop\Thesis chart\guidance selection.png |
| Fig. ‑ Approach of guidance selection |

# System Evaluation

## Simulated Environment

The evaluation of power demand side management for an individual home and a residential community are shown in this chapter. For both scenarios, it is assumed that every home is a smart energy saving home, and connected to Smart Grid. For Renewable Energy (RE), every home is equipped with a small-scaled solar panel whose size is 1. For energy storage device, a battery of 12V and 65Ah is taken into account, and the charge rate is 0.3C. According to [[30](#_ENREF_30)], the capacity of the battery is reasonably set to nearly 20 kWh. Thus, 25 batteries are connected in series, and hence the maximum capacity of battery is 19.5 kWh. According to the aforementioned spec of battery, the Maximum Charge Power *(MCP), i.e.,* the maximum power can be charged in a hour, is calculated by the following equation:

|  |  |
| --- | --- |
|  | (‑) |

For dynamic pricing, Time-Of-Use (TOU) from Taiwan Power Company is adopted, which is as shown in Fig. 5‑1.

|  |
| --- |
|  |
| Fig. ‑ TOU from Taiwan Power Company |

In Fig. 5‑1, three different types of TOU corresponding to weekday, Saturday and Sunday, are provided. In the experiments, electricity price of weekday is adopted.

For solar power production, a forecasting method of solar power production with Auto Regression Moving Average (ARMA) model[[26](#_ENREF_26)] is applied, an example prediction on June 1, 2012 is shown in Fig. 5‑2.

|  |
| --- |
|  |
| Fig. ‑ Predicted solar power production on Jun. 1, 2012 |

For the daily activity and home appliance, 12 activities and 20 appliances are considered. The list of all activities and power consumption of appliances are shown in Table 5‑1 and Table 5‑2, respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table ‑ Daily activity list | | | | | |
| Watching TV | Playing XBOX | Reading | Using PC | Using  Laptop | Washing Dishes |
| Laundry | Drying Clothes | Cleaning | Cooking | Making Coffee | Sleeping |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table ‑ Power consumption of appliances | | | | | |
| **Appliance Name** | **Power (W)** | | **Appliance Name** | **Power (W)** | |
| **standby** | **on** | **standby** | **on** |
| TV | 2.16 | 160 | Dishwasher | 1.2 | 680 |
| XBOX | 0 | 1056 | Oven | 0 | 1200 |
| Radio | 2.95 | 40 | Rice Cooker | 0.95 | 860 |
| Water Cold Fan | 6.52 | 110 | Microwave | 2.25 | 1000 |
| Fan | 0 | 52 | Coffee Maker | 0 | 140 |
| Air-conditioner | 2.41 | 1025 | Range Hood | 0 | 310 |
| Light | 0 | 240 | Vacuum Cleaner | 0 | 1000 |
| Lamp | 0 | 23 | Tumble Dryer | 0 | 1420 |
| Night Lamp | 0 | 5 | Washing Machine | 0.7 | 430 |
| PC | 4.93 | 500 | Laptop | 0 | 60 |

Five different daily activity schedules are collected from five different subjects, and are listed in Table 5‑3 to Table 5‑7. The table includes the information of name of activity, schedulability, duration, the earliest start time, and the latest end time. Some activities take place more than once in one day are listed in the same row, like "Cooking" in Table 5‑3. Some activities take place once but have multiple available durations are listed in the same row as well, like "DryingClothes" in Table 5‑3. For simplicity, the ERC model of each activity is obtained from [[21](#_ENREF_21)] initially, and then is customized for each subject according to his/her own preference.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 5‑3 Daily activity profile of subject\_1 | | | | |
| **Activity** | **Schedulability** | **Duration(h)** | **Earliest  Start time** | **Latest  End time** |
| Sleeping | Nonschedulable | 9 | 00:00 | 09:00 |
| Cooking | Schedulable | 1 | 09:00 | 11:00 |
| Schedulable | 1 | 12:00 | 14:00 |
| Schedulable | 1 | 17:00 | 19:00 |
| MakingCoffee | Schedulable | 1 | 09:00 | 11:00 |
| Schedulable | 1 | 12:00 | 14:00 |
| WatchingTV | Nonschedulable | 2 | 09:00 | 11:00 |
| UsingPC | Schedulable | 1 | 10:00 | 12:00 |
| Reading | Schedulable | 2 | 14:00 | 17:00 |
| PlayingXBOX | Schedulable | 1 | 14:00 | 17:00 |
| WashingDishes | Schedulable | 1 | 19:00 | 23:00 |
| Laundry | Schedulable | 1 | 19:00 | 23:00 |
| DryingClothes | Schedulable | 1 | 00:00 | 12:00 |
| 19:00 | 23:00 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table ‑ Daily activity profile of subject\_2 | | | | |
| **Activity** | **Schedulability** | **Duration(h)** | **Earliest  Start time** | **Latest  End time** |
| Sleeping | Nonschedulable | 8 | 00:00 | 08:00 |
| Schedulable | 2 | 11:00 | 15:00 |
| Cooking | Nonschedulable | 1 | 11:00 | 12:00 |
| Nonschedulable | 1 | 18:00 | 19:00 |
| MakingCoffee | Nonschedulable | 1 | 08:00 | 09:00 |
| WatchingTV | Schedulable | 1 | 14:00 | 16:00 |
| 19:00 | 22:00 |
| UsingPC | Schedulable | 2 | 11:00 | 15:00 |
| Schedulable | 3 | 18:00 | 22:00 |
| Reading | Schedulable | 2 | 10:00 | 14:00 |
| Schedulable | 3 | 19:00 | 23:00 |
| UsingLaptop | Schedulable | 2 | 14:00 | 16:00 |
| 20:00 | 22:00 |
| WashingDishes | Schedulable | 1 | 14:00 | 16:00 |
| 19:00 | 22:00 |
| Laundry | Schedulable | 1 | 21:00 | 23:00 |
| Cleaning | Schedulable | 1 | 10:00 | 14:00 |
| 16:00 | 19:00 |
| 21:00 | 23:00 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table ‑ Daily activity profile of subject\_3 | | | | |
| **Activity** | **Schedulability** | **Duration(h)** | **Earliest  Start time** | **Latest  End time** |
| Sleeping | Schedulable | 6 | 00:00 | 08:00 |
| Cooking | Schedulable | 1 | 11:00 | 13:00 |
| Schedulable | 1 | 17:00 | 19:00 |
| WatchingTV | Schedulable | 1 | 08:00 | 10:00 |
| 18:00 | 23:00 |
| UsingPC | Schedulable | 2 | 18:00 | 23:00 |
| Reading | Nonschedulable | 1 | 22:00 | 23:00 |
| UsingLaptop | Schedulable | 1 | 18:00 | 23:00 |
| Schedulable | 1 | 10:00 | 12:00 |
| 14:00 | 17:00 |
| WashingDishes | Schedulable | 1 | 18:00 | 23:00 |
| Laundry | Schedulable | 1 | 06:00 | 08:00 |
| 18:00 | 23:00 |
| DryingClothes | Schedulable | 1 | 06:00 | 08:00 |
| 18:00 | 23:00 |
| PlayingXBOX | Schedulable | 1 | 10:00 | 12:00 |
| 14:00 | 17:00 |
| 19:00 | 23:00 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table ‑ Daily activity profile of subject\_4 | | | | |
| Activity | Schedulability | Duration(h) | Earliest  Start time | Latest  End time |
| Cooking | Schedulable | 1 | 09:00 | 12:00 |
| Schedulable | 1 | 16:00 | 18:00 |
| WatchingTV | Schedulable | 1 | 07:00 | 09:00 |
| Schedulable | 1 | 11:00 | 13:00 |
| Schedulable | 1 | 18:00 | 22:00 |
| UsingPC | Schedulable | 3 | 09:00 | 12:00 |
| Schedulable | 2 | 14:00 | 17:00 |
| Reading | Schedulable | 1 | 09:00 | 12:00 |
| Schedulable | 1 | 14:00 | 16:00 |
| Schedulable | 3 | 13:00 | 18:00 |
| UsingLaptop | Schedulable | 2 | 19:00 | 22:00 |
| Schedulable | 1 | 09:00 | 12:00 |
| WashingDishes | Schedulable | 1 | 13:00 | 17:00 |
| Schedulable | 1 | 19:00 | 23:00 |
| Laundry | Schedulable | 1 | 00:00 | 23:00 |
| DryingClothes | Schedulable | 1 | 00:00 | 23:00 |
| PlayingXBOX | Schedulable | 1 | 14:00 | 17:00 |
| MakingCoffee | Schedulable | 1 | 06:00 | 08:00 |
| Schedulable | 1 | 10:00 | 12:00 |

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| Table ‑ Daily activity profile of subject\_5 | | | | |
| **Activity** | **Schedulability** | **Duration(h)** | **Earliest  Start time** | **Latest  End time** |
| Cooking | Schedulable | 1 | 11:00 | 13:00 |
| Schedulable | 1 | 17:00 | 19:00 |
| WatchingTV | Schedulable | 1 | 07:00 | 09:00 |
| Schedulable | 1 | 18:00 | 21:00 |
| UsingPC | Schedulable | 1 | 08:00 | 12:00 |
| 14:00 | 17:00 |
| Schedulable | 2 | 19:00 | 22:00 |
| Reading | Schedulable | 1 | 09:00 | 11:00 |
| Schedulable | 1 | 14:00 | 17:00 |
| 19:00 | 22:00 |
| UsingLaptop | Schedulable | 1 | 08:00 | 12:00 |
| 14:00 | 17:00 |
| WashingDishes | Schedulable | 1 | 07:00 | 08:00 |
| Schedulable | 1 | 12:00 | 14:00 |
| Schedulable | 1 | 19:00 | 22:00 |
| Laundry | Schedulable | 1 | 17:00 | 21:00 |
| DryingClothes | Schedulable | 1 | 21:00 | 23:00 |
| MakingCoffee | Schedulable | 1 | 07:00 | 09:00 |
| 18:00 | 20:00 |
| Schedulable | 1 | 13:00 | 16:00 |
| Cleaning | Schedulable | 1 | 19:00 | 23:00 |

## Individual Home Electricity Cost

In the evaluation of individual-home schedule optimization, two evaluation results are shown. First, with dynamic pricing and Renewable Energy (RE) being considered, the impact on saving electricity cost with/without considering energy storage device is shown. Second, the result with/without schedule optimization are shown while dynamic pricing, RE, and energy storage device are considered.

* **With/Without Energy Storage Device**

The result shows that energy storage device (battery) can increase the saving rate of electricity cost significantly. The reason is that RE can be efficiently utilized with discharge/charge of the battery being considered. In accordance with the daily activity profile listed in Table 5‑3, we apply the proposed PSO algorithm for the same scenario, with/without considering battery, respectively. The evaluation result, which includes the details of power consumption, the portion of power supplied by the utility company for each slot as well as the electricity cost, is shown and compared. In the following figures, only the higher value is shown on the top of each bar at every time slots.

Fig. 5‑3 shows the total amount of power consumption, which includes power charged into battery and consumed by appliances if in the case with battery, at each time slots. For the case without battery, power consumption is supplied by RE and the utility company. For the case with battery, it is supplied by the battery and the utility company. Fig. 5‑4 shows the portion of power supplied by the utility company. It is clearly that power supplied by the utility company is shifted to the time slots with lower electricity price (*i.e.,* the first, second, forth, and twenty-three time slots) while taking battery into account, and power supplied by RE is also stored into the battery and is utilized later to achieve better efficiency. Fig. 5‑5 shows the electricity cost at each time slot.

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| Fig. ‑ Power consumption with/without battery |
|  |
| Fig. ‑ Power supplied by the utility company with/without battery |
|  |
| Fig. ‑ Electricity cost with/without battery |

The results of electricity cost of five different subjects with/without battery are compared and shown in Fig. 5‑6. According to the schedules provided by five different subjects in this thesis, the saving rate of electricity cost ranges from 20% () to 47% () compared with the result of not taking battery into account. In average, the saving rate of electricity could reach 31.3%, which is quite a promising result.

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| Fig. ‑ Electricity cost of five subjects with/without battery |

* **With/Without Schedule Optimization**

In the following, three scheduling algorithms listed in Table 5‑8 are compared. The first one, called first fit, is to schedule activity without optimization. The second one, called best fit, is a simple heuristic algorithm, which schedules activities to the period with lowest electricity cost, *i.e.*, only consider minimizing the electricity cost but not efficiently utilizing the battery. The last one is our proposed method, which minimizes the electricity cost and maximizes the efficiency of utilization of RE, and battery.

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| Table ‑ Different scheduling algorithms and its meaning | |
| **Scheduling Algorithm** | **Meaning** |
| First fit | Activities are scheduled for the first available period, and the RE is utilized straightforward, *i.e.,* directly use RE whenever it is possible |
| Best fit | Activities are scheduled for the period with the lowest electricity cost, and the RE is utilized straightforward |
| Our method | Activities are scheduled while optimizing the battery schedules, *i.e.,* the amount of power to charge into or discharge from the battery at every time slots. |

The details of power consumption, which includes power charged into battery and consumed by appliances, among three scheduling algorithms are shown in Fig. 5‑7. Fig. 5‑8 and Fig. 5‑9 show that our method can fully utilize the battery by charging it at the time slot with a lower electricity price (*i.e.,* the 1st and the 4th time slots in Fig. 5‑9), and discharging it when the price is higher (*i.e.,* from 10th to 18th time slots in Fig. 5‑8). Furthermore, the schedule generated by our method is more distributed than the other two methods. The reason behind this distributed pattern in our method is that the battery might not be able to afford the need if there are too many activities scheduled at the same time slot, which will increase electricity cost even at the time slot with a lower electricity price, and therefore our schedule optimization method will shift some activities to some other time slots with a higher electricity price, which actually results in lower electricity cost because there is enough support from RE at that time slot.

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| Fig. ‑ Power consumption with/without schedule optimization |
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| Fig. ‑ Power supplied by battery with/without schedule optimization |
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| Fig. ‑ Power supplied by utility company with/without schedule optimization |
|  |
| Fig. ‑ Electricity cost with/without schedule optimization |

The results of electricity cost of five different subjects with three different scheduling algorithms are compared and shown in Fig. 5‑11. According to the schedules provided by five different subjects in this thesis, the saving rate of electricity cost ranges from 20.4% to 47.8% compared with the result of first fit, and 13.2% to 42.8% compared with best fit approach. Saving rate of electricity cost for five homes is shown in Table 5‑9. In average, the saving rate of electricity cost could reach 28% compared with best fit approach, which is quite a promising result.

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| Fig. ‑ Electricity cost of three different scheduling algorithms |

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| --- | --- | --- | --- | --- | --- |
| Table ‑ Saving rate of electricity cost for five homes | | | | | |
|  | Subject 1 | Subject 2 | Subject 3 | Subject 4 | Subject 5 |
| First Fit | 45.1% | 37.2% | 24.6% | 20.4% | 47.8% |
| Best Fit | 42.8% | 33% | 13.2% | 19.7% | 41.7% |

## Multiple Homes Electricity Cost & PAR

In the evaluation of residential community, five homes cooperate to alleviate the Peak-to-Average Ratio (PAR) of a community for the purpose of increasing the stability of the entire power system, and the total electricity cost of the community is also minimized.

* **PAR & Electricity Cost**

The total electricity cost is further separated into two parts, demand charge and electricity charge. In this thesis, demand charge and electricity charge is calculated by (4‑4) and (4‑5), respectively. In order not to sacrifice the benefit gained from individual-home optimization, the resident who is willing to pay more electricity charge can gain more benefit from demand charge. The corresponding electricity cost of a community and its PAR in one day is shown in Table 5‑10. The result shows that PAR is reduced 63.1% , and the total electricity cost is also reduced 5.1% compared to the individual-home schedule optimization. The detailed curve of the PAR and the power are shown in Fig. 5‑12 and Fig. 5‑13, respectively.

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| Table ‑ Electricity cost and PAR of community | | | | |
| **Optimization** | **Electricity cost** | | | **PAR** |
| **Demand charge** | **Electricity charge** | **Total** |
| Individual Home | 157.464 | 250.086 | 407.55 | 4.67 |
| Residential Community | 70.863 | 315.947 | 386.81 | 1.72 |

The following table shows the details of total electricity cost of each home. It is clear that our method can benefit all homes together.

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| --- | --- | --- | --- | --- | --- |
| Table ‑ Details of total electricity cost of each home | | | | | |
| **Optimization** | **Home 1** | **Home 2** | **Home 3** | **Home 4** | **Home 5** |
| Individual Home | 149.27 | 74 | 61.22 | 62.92 | 60.13 |
| Residential Community | 143.62 | 70.79 | 56.48 | 57.57 | 58.36 |

The detailed change of PAR curve, and the power supplied by the utility company are shown in Fig. 5‑12 and Fig. 5‑13, respectively. It is clear that our method can evenly schedule the power supplied by the utility company to the time slots with lower electricity price, and hence the PAR is alleviated significantly.

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| Fig. ‑ Details of PAR |
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| Fig. ‑ Details of power supplied by the utility company |

The power supplied by the utility company for the five homes is shown in Fig. 5‑14 and Fig. 5‑15, respectively. It is clear that our method can arrange power load of five homes to different time slots to achieve lower PAR.

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| Fig. ‑ Power supplied by the utility company for individual home |
|  |
| Fig. ‑ Power supplied by the utility company for resident community |

In the following, the result of the PAR for 7 days, *i.e.,* 168 hours is shown as Fig. 5‑16. Because the value of the PAR is not stable for the first two days, *i.e.,* during hour 1 to hour 48, the result is shown from hour 49. Compared with the power demand optimization for individual home, *i.e.,* without coordination among multiple homes, the result shows that our method for residential community can alleviate PAR effectively. With our method for residential community, the PAR of a community is maintained at about 2.5. Without our method for residential community, PAR can be very unpredictable and increase to about 6.6 in the last day.

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| Fig. ‑ Detailed change of PAR in 7 days |

# Conclusion

## Summary

In this thesis, a DSM method based on optimal daily activity scheduling is proposed for an individual home and a residential community with multiple homes in Smart Grid. Most of features, *i.e.,* dynamic pricing, Renewable Energy (RE), and energy storage device (battery), which can efficiently improve the performance of energy management in Smart Grid, are taken into account. For individual home, the experimental results show that we achieve 28% of saving rate of electricity cost while maintaining user activity preference. For residential community, the experimental results show that we achieve 63.2% of alleviation of PAR, and save 5.1% more on electricity cost than individual-home schedule optimization.

* **Utilizing dynamic pricing, RE, and battery for schedule optimization**

Utilization of RE and battery are modeled as management of battery, *i.e.,* deciding when and how much to charge (discharge) into (from) the battery. With dynamic pricing, our method can efficiently utilize renewable energy and battery by charging in the time slots with lower electricity price, and discharging while the electricity price becoming higher.

* **Introducing multi-objective for community schedule optimization**

. In order to create a win-win situation for residents and utility company, we propose a multi-objective optimization problem, *i.e.*, Peak-to-Average Ratio (PAR) and electricity cost of community are optimized simultaneously. Then, we solve it by using Multi-Objective Particle Swarm Optimization (MOPSO) efficiently.

## Future Work

Many further research works can be done to improve this work, some of which are listed below:

* **Modeling the behavior of energy market among homes and utility company**

In this thesis, residents can only purchase electricity from utility company. In the future Smart Grid environment, residents could gain more benefits if the electricity can be provided by other homes. Modeling and optimizing the behavior of bargaining in the energy market could achieve this goal.

* **Developing cloud-based algorithm to improve computation efficiency**

A cloud-based algorithm could reduce the computational time by paralleling the optimization process, and hence the environment is able to be scaled up to higher level, *e.g.,* city. Thus, the activity and battery schedules are able to be optimized in a very short time, *e.g.,* 10 minutes, even if the total number of homes is growing very fast.

* **Deployment of smart energy saving home in semi-real home**

We already deployed our M2M-based Context-aware Home Energy Saving System in a semi-real home experimental environment. Reconstructing the infrastructure of power line, and deploying solar panel and rechargeable battery could make the semi-real home become a smart energy saving home mentioned in this thesis. Then, the proposed system is able to be evaluated in a semi-real environment.

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