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Investigation of Electric Water Heaters as Demand Response Resources and Their Impact on Power System Operational Reliability

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INVESTIGATION OF ELECTRIC WATER HEATERS AS DEMAND RESPONSE RESOURCES AND THEIR IMPACT ON POWER SYSTEM OPERATIONAL RELIABILITY

by

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ABSTRACT

INVESTIGATION OF ELECTRIC WATER HEATERS AS DEMAND RESPONSE RESOURCES AND THEIR IMPACT ON POWER SYSTEM OPERATIONAL RELIABILITY

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Under the Supervision of Dr. Lingfeng Wang

The electricity consumption has increased dramatically in past decades due to the improvement of people's life standard and the increase of their incomes. Some uncertainties have occurred because of an increasing electricity consumption at the household level. As a result, the high power consumption of massive households will affect power system reliability. Recently, the traditional power grid is being transformed to the smart grid, which is an effective way to deal with these issues. The electricity utility could manage the demand side resources using different kinds of Demand Response (DR) methods. Residential resource is an important part besides industrial resource and commercial resource. With the deployment of Home Energy Management System (HEMS) and smart household devices, users' behavior could be adjusted to respond to the utility signal. Electric Water Heaters (EWHs) account for a huge percentage of energy consumption among all the home appliances. Aggregated EWHs are idea candidates as demand response resources whose power consumption pattern can be modified because they not only consume lots of energy but also have heat storage capability. Therefore, EWHs can react to the optimal operation signal without affecting customers' daily needs. In this way, electricity utility

could treat EWHs as a kind of interruptible load to provide operating reserves to improve power system reliability.

In this thesis, a Binary Particle Swarm Optimization (BPSO) algorithm is utilized to perform the optimization of EWHs. The goal of each EWH optimization using BPSO is to minimize the customers' electricity cost. Therefore, Time-Of-Use (TOU) electricity rate is utilized as the DR incentive. Meanwhile, the customers' daily need for hot water should be guaranteed, so a comfort level index is enforced in the optimization process. The thermal model of EWH and water usage profile are used to calculate the real-time hot water temperature. Aggregating thousands of EWHs will have positive influences on power system reliability when massive EWHs are utilized as interruptible loads. EWHs could compensate for the Unit Commitment Risk (UCR) considering the operating reserve capacity they can provide. The UCR reduction is used to calculate and analyze the influence of aggregated EWHs.

A Reliability Test System is modified to test the capacity of aggregated EWHs in this study. Based on the simulation results, the proposed optimization strategy for EWHs is proved to be practical. The customers' electricity bill has declined effectively and the user's comfort level, considering different water temperature set point ranges, is ensured. This thesis provides a practicable scheme for residential customers to arrange their EWHs more reasonably. The simulation results show the aggregated EWHs' load curve and indicate that the proposed method shifts aggregated EWHs load effectively during some peak hours. According to the calculation results of UCR reduction, the aggregated EWHs is turned out to be a great candidate for power system to improve the reliability during peak-hours.

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Chapter 1 Introduction

1.1 Background of Smart Grid

Over the past few years, the consumption of electricity energy has increased dramatically. Through the statistics published by the U.S. Department of Energy that the energy expenditure has increased approximately by 20%–40% in residential and commercial buildings among the total expenditure each year [1]. As reported by Energy Information Administration (EIA, U.S) [2], the electricity generation worldwide will increase by 69% from 2012 to 2040, which is 21.6 trillion kWh in 2012. Due to economic increase and living standard improvement, the residential electricity consumption will increase by 2.1 percent on average in this period [2].

With the increasing electricity demand, compensating for the power of peak-load hour needs lots of capital investment which is very expensive and can only satisfy a limit number of hours. Therefore, using some effective techniques to reduce the peak load is imperative, such as demand side management (DSM). The most critical issue overall is related to the power grid reliability as well as coordination of demand and supply capacities. In a way, the utility should not only install more and more generation but also adjust the demand side load to improve the electricity utilization because the energy resources are limited.

Nowadays, the power system infrastructure is facing an important change from the conventional scheme to the intelligent smart grid. Smart grid is a concept that refers to the future electric power grid which upgrades the way to manage electricity consumption as well as distribution by involving some high-level bi-directional communications and widespread computing techniques for advanced control, safety, reliability and efficiency [3]. It has some novel characters just like the inclusion of consumers' participation. For instance, DSM is enabled by smart grid which aims to improve the efficiency and reliability of power system. DSM generally refers to the electrical utilities' energy management programs aiming at adjust energy consume behavior through smart meters from customers' side [4]. Totally, energy protection, efficiency, load management and fuel replacement programs are all belonging to DSM programs [5]. An infrastructure of Smart Grid composition is shown in Figure 1.1.

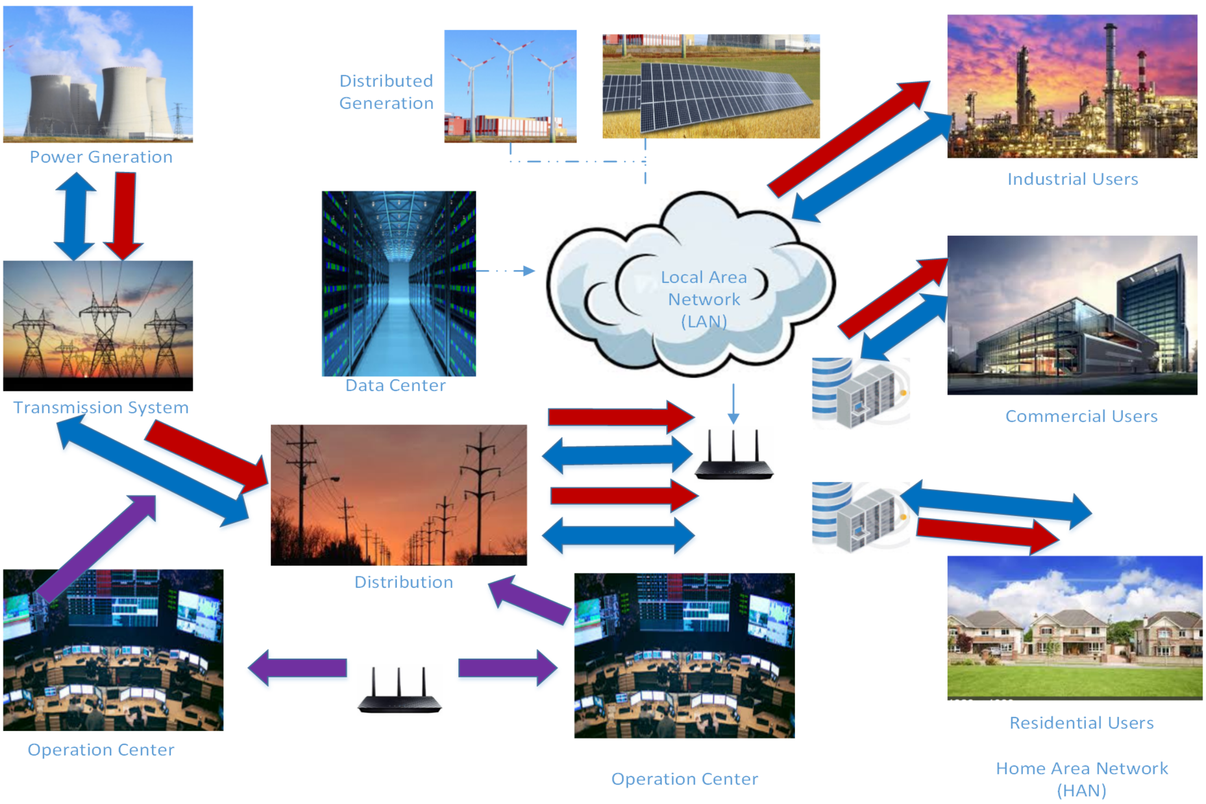


Figure 1.1 Infrastructure of Smart Grid Composition

1.2 Introduction of DR

The goal of load management programs is to cut down the peak-hour load or sometimes shift the peak-hour load to nonpeak-hour. Simply curtailing loads to specific off-peak hours would cause a new peak-load-time sometimes, but it could be useful if peak load can be separated to many different off-peak hours in case of a new peak-load-time. Therefore, some novel technologies are deployed in power grid. Recently, the smart grid technologies have been developed and deployment of smart meters, advanced meter infrastructure (AMI), Home Energy Management System (HEMS) and others has increased, it becomes possible to make a reasonable schedule of end-use customers to benefit electrical utility as well as customers. For example, some smart appliances, using pattern of HVAC devices (Heating, Ventilation and Air Conditioning) could be cut down during some time or could be shifted by executing intelligent strategies.

Over the past decade, Demand Response (DR) has been developed significantly in power grid. As reported from the U.S. Department of Energy, DR refers to electricity consumption changes made by end-users to respond the electricity price changes or other stimulus in order to reduce electricity use as well as increase energy efficiency and power system reliability[6]. Retail customers participated in electricity markets by monitoring and reacting to electricity prices. Basically, DR programs can be classified into two types: the first one is related to incentive, the second one is related to time [7]. Furthermore, DR programs can be divided into several subgroups which are shown in Table 1.1.

Table 1.1 Classification of Demand Response Program

Program types	Subgroup	Characteristics
incentive-based programs	Direct Load Control (DLC)	Customers' load will be cut down or cycled by utility directly through short notice to make sure system reliability, sometimes incentive price is used as exchange benefit.
	Interruptible/curtailable service (I/C)	Customers receive dynamic EP if they agree to change their behavior. They'll pay penalty rate if they refused to reduce load during system contingency time.
	Demand Bidding (DB)	Big customers can offer the accepted EP and the load quantities they would like to be curtailed.
	Emergency Demand Response Program (EDRP)	Customers receive dynamic EP if they agree to change their behavior. This event is voluntary.
	Capacity Market Program (CAP)	Customers reduce their load during system contingency, and are subject to be punished if they do not respond.
	Ancillary Service Market (A/S)	Customers will be paid for bidding shaving load as operating reserves if they're approved in ISO markets.
time-based programs	Time-of-Use (TOU)	Utility sets different EP during different periods based on system load. For example, if the system load is high, the EP will be high.
	Real Time Pricing (RTP)	Dynamic EP reflected changes in power directly.
	Critical Peak Pricing (CPP)	An increase on existed EP during extreme peak hour.

1.3 Introduction of EWHs load

Residential Electric Water Heaters (EWHs) can be ideal candidates for DR program because the water tanks can be regarded as thermal energy storage equipment and EWHs consume a big quantity of energy which could not be ignored among daily consumption. As shown in Figure 1.2, EWHs account for about 18% of the electricity among residential consumption in the U.S. What's more, EWH load has clear similarity with the power grid load in peak-load hours [9].

Group of EWHs load benefit to utilities as they can provide ancillary services and could be acted as interruptible loads to provide service for power grid. IL (interruptible loads) are those loads which are able to be interrupted considering required condition and constraints, in order to keep power system reliability as well as to reduce financial prices. Sometimes, IL could be compensated by electricity tariffs [10]. Relief of load can be achieved by turning on or off of individual EWH when there's a need. Economic benefits for both residential users and utilities can be realized by aggregating a certain number of household appliances and shifting their peak load to separate periods of time. Moreover, maintaining the users' comfortable preference is also an important factor in adjustment.

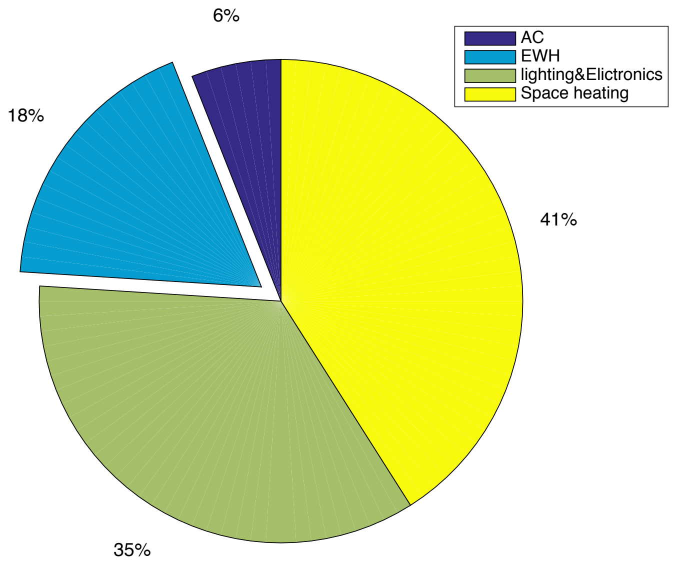


Figure 1.2 Residential energy distribution in the U.S. (Aug. 2013)

The most necessary factor in power system is to provide customers a reliable and economic electricity supply [11]. The time phase is divided into two stages in power system, which is the planning phase and the operating phase. In operating phase, reserve generation must be considered accounting for generation outage and some uncertainty situation. Generally, there are two kinds of reserve: spinning reserve and operating reserve. Spinning reserve, literally, is the reserve which is spinning and ready for putting into operation. Operating reserve is the total capacity additionally added up to spinning reserve, such as hydro-plant, gas turbine and interruptible loads [12].

Increasing investing in planning phase or operating phase can reduce the probability of customers' disconnection with power system. Standby generation capacity, for example, rapid start units, can contribute to the power system reliability. In this level, EWHs can be regarded as a kind of resources from the demand side that can compensate the generation shortage. Loads of EWHs are considered to be interruptible to relieve capacity shortage as long as the heat limits of customers can be fulfilled in some time periods.

1.4 Objective and thesis layout

The EWH optimal objective in this thesis is not only to minimize residential users' electricity costs but also to stabilize the system load as well as keep residential users comfortable. The optimization method in this thesis is Binary Particle Swarm Optimization (BPSO) algorithm considering EWH only has two operation status (on and off). For individual EWH, we only consider the economic benefits and comfortable preference because only single EWH has limit capability to the system stabilization.

For aggregated EWHs, we involve the reliability indices calculation to analysis the influence of them on power grid reliability considering the total consumption of group EWHs is high. In some degree, aggregated EWHs can be regarded as interruptible load in power system for reducing the load demand. In other words, it can provide operating reserve for power system to relief the load stress. This is one of the first paper considering the influence of EWHs load on power grid system reliability in the literature, which is the basic novelty of this thesis.

The thesis is arranged as follows. The first part will describe the thermal and physical model of single EWH and water usage profiles needed for further optimization. After that, the optimization strategy for household EWH based on BPSO algorithm is proposed in second part. Next, the third part proposes the method used to calculate power system reliability indices which is specifically unit commitment risk (UCR) of EWHs loads. Finally, the conclusion of this thesis is presented in fourth part.

Chapter 2 Model of Electric Water Heater

2.1 Introduction of HEMS

Home Energy Management System (HEMS) aims to monitor and schedule the residential devices in an optimizing way. By HEMS, some information could be collected, for example, the ambient environment condition (temperature), Electricity Price (EP) from utility and so that HEMS can make decision about energy consumption pattern of residential users based on this information.

There are some existing studies about HEMS, in [13], the control algorithm was proposed to manage residential household loads and to participate in DR program considering some priority indexes and comfort levels that customers set in advance and to make sure the electricity need below limit levels during certain time period. A DR model for household appliances based on EP was proposed by Chen Z et al. in [14], which aimed to balance the electricity efficiency and financial benefits. The appliances loads are classified into three types of operation task: curtailable and deferrable load, non- curtailable and deferrable load and non-curtailable and non-deferrable load. De Angelis et al. discussed an HEMS control strategy in which incorporate both electrical consumption constraints and thermal character limits as well as customers' comfort preference [15]. A HEMS structure is shown in Figure 2.1, which is used to optimize home appliances schedule considering hourly EP and peak-hour load constraint [16].

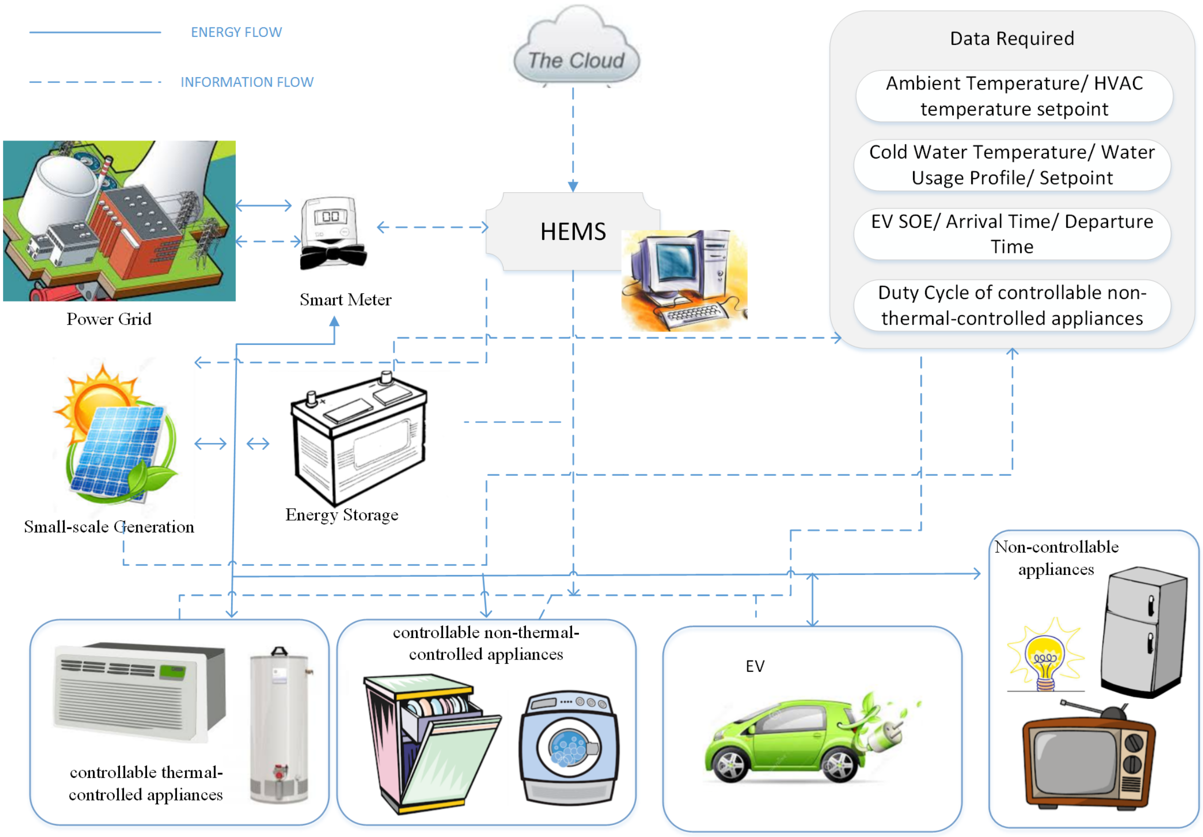


Figure 2.1 Home Energy Management Structure

This Chapter discusses the system structure, thermal model of EWH and customers' behavior of water usage.

2.2 The structure of the EWH control system

The optimization goal is to minimize the residential electricity bill of EWHs by rescheduling the operation time of EWH subjecting to the specific temperature limits set by users. The first thing of the optimization process overall is to get useful information. The infrastructure enabled customers' participation is required.

It's assumed that each EWH installed a smart meter, which is connected to both power line and the local area network (LAN) using bi-directional communication. Furthermore, the EWH can receive the latest EP information from the utility and the ambient environment information through smart meter via LAN. Meanwhile, the utility could get the load data of EWHs. The operation scheduler is deployed in each smart meter to make decision. BPSO algorithm is used to optimize the users' electricity cost as well as the electricity consumption of every single EWH. The overall EWH operation management system came up in this paper is shown in Figure 2.2.

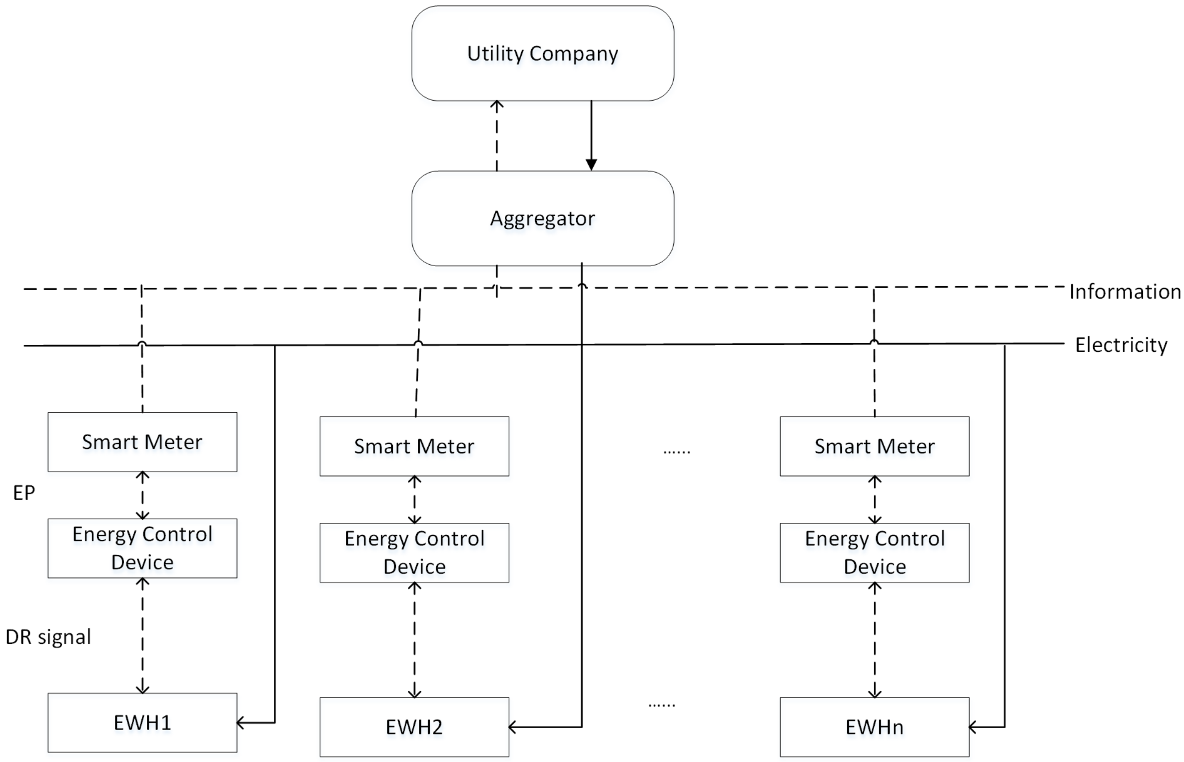


Figure 2.2 Overall EWH Operation Management System Structure

Assuming that the EWH has two heating scenario, which is under-heating scenario and over-heating scenario. In the EWHs under-heating scenario, EWHs load is considered as interruptible load to help relieve a capacity shortage as long as heat requirements set by customers can be fulfilled in some time periods. In the EWHs over-heating scenario, it's supposed that extra electrical energy can be stored in EWHs regarded as heat, water can be pre-heated to absorb excess power generation.

2.3 The classification of home appliances

Over past few years, the extensive deployment of automatic control device and smart meters in residential systems has made it possible for operating residential devices in an smart and efficient pattern considering both customers' economic effectiveness and constraints of power grid operation. There're lots of household appliances in residential level. Basically, we could classify the home devices into two categories, which are controllable devices and non-controllable devices. Furthermore, controllable devices can be classified into two types, which are controllable thermal-controlled type and controllable non-thermal-controlled type [17].

Some examples of different kinds of appliances are shown in Table 2.1 [18]. Non-controllable appliances are those appliances whose status could not be changed easily because of its electricity consumption characteristics. As a result, they could not be schedule. Usually, they can be modeled using load profile which is forecast by historical users' data. The characteristics of controllable non-thermal-controlled appliances are usually discrete and can be scheduled directly during appliances operation control period. For example, once washers and dryers open, they could not be stopped, but the start time can be schedule flexibly by controller. Controllable thermal-controlled appliances have specific thermal needs and they can be scheduled flexibly as long as their needs could be fulfilled, some appliances also have thermal reservation ability. Therefore, they are ideal candidates for residential DR program. To better schedule the controllable thermal-controlled appliances, some thermal settings, dynamics, randomness and customers comfort level should be considered.

Table 2.1 Classification of Different Kinds of Home Appliances

Non-controllable appliances	**controllable appliance**	
	controllable thermal-controlled appliances	non-thermal-controlled appliances
Lighting, Television, Refrigerator	Air-conditioner, Space Cooling & Heating, Water Heater	Clothes washer & dryer, Dishes washer

Actually, not all of household appliances is DR automated, and some of appliances is manually operated or semi-automatic operated [19]. To make a reasonable schedule for home appliances operation, a precise DR-enabled model for control objective is necessary. Several studies have focused on the EWH model and simulation. Shad M, et al. present a method for modeling the status of individual EWH from thermal dynamics models in[20]; Lu N , et al. discuss an uncertainty model for thermal loads by a discrete state queueing (SQ) model in [21]. The operation circle time of thermal loads is influenced by the appliances types and some dynamic parameters. This ideology of state queue proposed by [13] is also adopted in this thesis in Chapter 3.

2.4 Thermal Model and Physical Model of EWH

The traditional EWH model has two heating units and two thermostats up and down, shown in Figure 2.3 [22]. During each heating event, only one heating element will work.

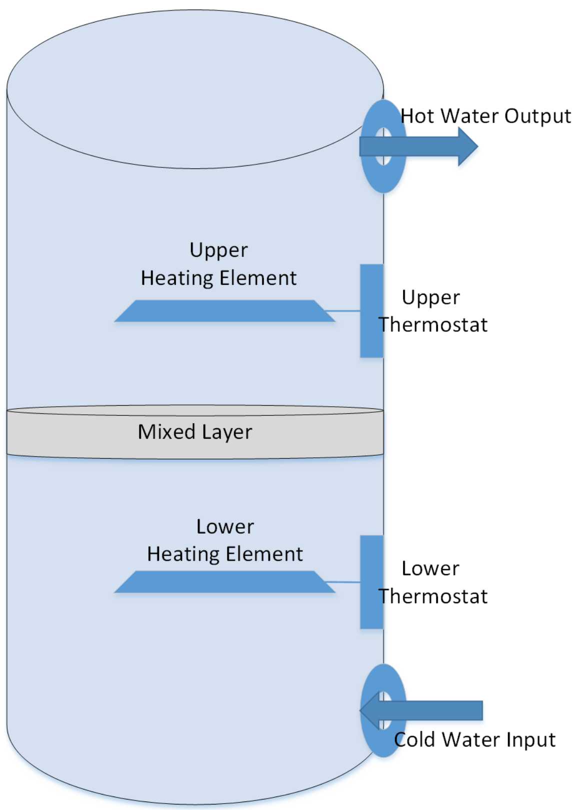


Figure 2.3 Inside Structure of EWH

The cold water will be injected to the water tank at the bottom when there's a water draw. This is because the density of cold water is higher than hot water. Then the low temperature of water inside will trigger the lower thermostat, then the lower heating element will start to work. If the water draw is big enough, the cold water will rise to the high level and trigger the higher thermostat. Meanwhile, the lower heating element will turn off. Unless water in both higher unit and lower unit is already heated, the thermostat will turn off [22].

To stimulate the model, some needed parameters of an EWH as input is shown in Figure 2.4, which includes the rated power of EWH, ambient tank temperature, inlet cold water temperature, hot water temperature, set point and tank size, et al.

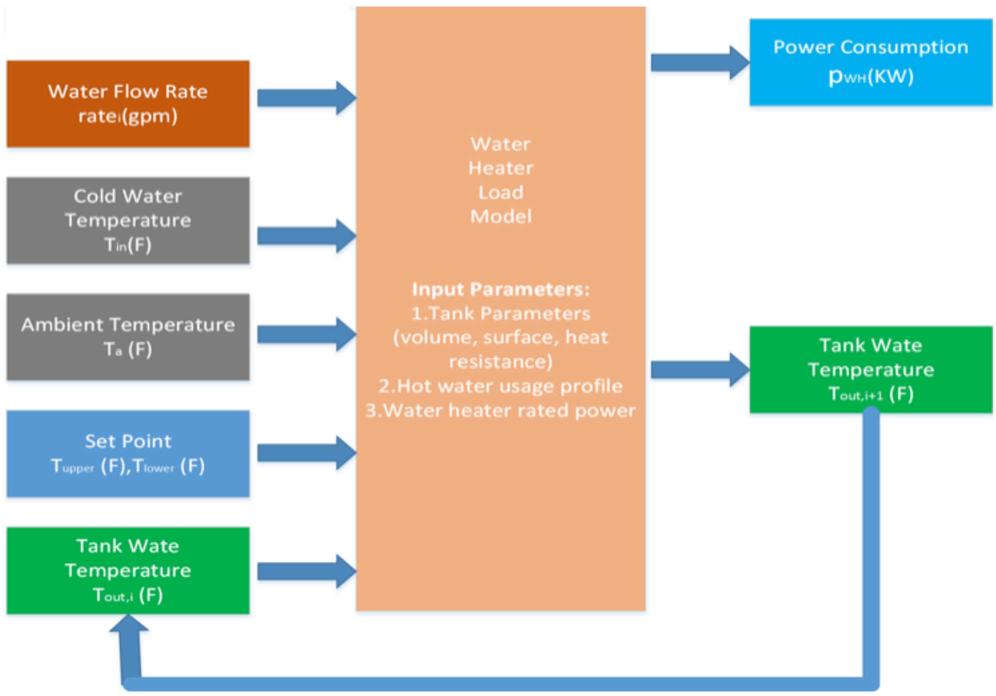


Figure 2.4 Diagram chart of EWH

For every time step, the water heating unit electricity demand at time i is calculated as follows [23],

$$p_{WH,i} = w_{WH,i} * P_{WH} * \eta_{WH} \tag{2.1}$$

$w_{WH,i}$ represents on and off status of the EWH;

P_{WH} represents the rated power of EWH(KW);

η_{WH} represents the efficiency factor, is usually assumed to be 1.

c_{WH} represents sent from smart controller and it affects the status of EWH. The on/off status of water heater is decided by the following procedure: if the water temperature is over the upper set point limit, then it stays in off status (0); if the temperature is below the lower set point limit, then it stays in on status (1) until the temperature reaches the limited value; if the temperature in the tank is between these two limits, then it stays the same status as the last time interval.

$$\omega_{WH,i} = \begin{cases} 0 & T_{out,i} > T_{upper} \\ 1 & T_{out,i} < T_{lower} \\ \omega_{WH,i-1} & T_{lower} < T_{out,i} < T_{upper} \end{cases} \tag{2.2}$$

$T_{out,i}$ represents the maximum value of temperature set point at time i;

T_{lower} represents the minimum value of temperature set point;

T_{upper} represents the maximum value of temperature set point;

To simplify the optimization process, we just calculate the mixed hot water temperature out from the EWH tank, the calculation is shown in Equation (2.3),

$$T_{out,i+1} = \frac{T_{out,i}\ (V_{tank} - rate_i * \Delta t)}{V_{tank}} + \frac{T_{in} * rate_i * \Delta t}{V_{tank}} + \frac{1\ gal}{8.34\ lb} * \left[p_{WH,i} * \frac{3412\ Btu}{Kwh} - \frac{A_{tank} * (T_{out,i} - T_a)}{R_{tank}}\right] * \frac{\Delta t}{60 * \frac{min}{h}} * \frac{1}{V_{tank}} \tag{2.3}$$

T_{in} represents the temperature of the injected cold water (F);

$rate_i$ represents the hot water flow rate outside the tank during time interval i(gallon/minute);

Δt represents the time interval(minutes);

V_{tank} represents the EWH tank volume (gallon);

A_{tank} represents the EWH tank surface area (ft2);

R_{tank} represents the EWH tank heat resistance (F*ft2*h/Btu);

T_a represents the ambient room temperature(F);

The unit is equal to F, which is Btu/lb. in the third term. 1 Btu is the total value of required energy that 1 lb water needs to be heated by 1F. Based on the proposed model below, we could get the temperature curve of a single EWH which temperature set point range belongs to [135,150] is as shown in Figure 2.5.

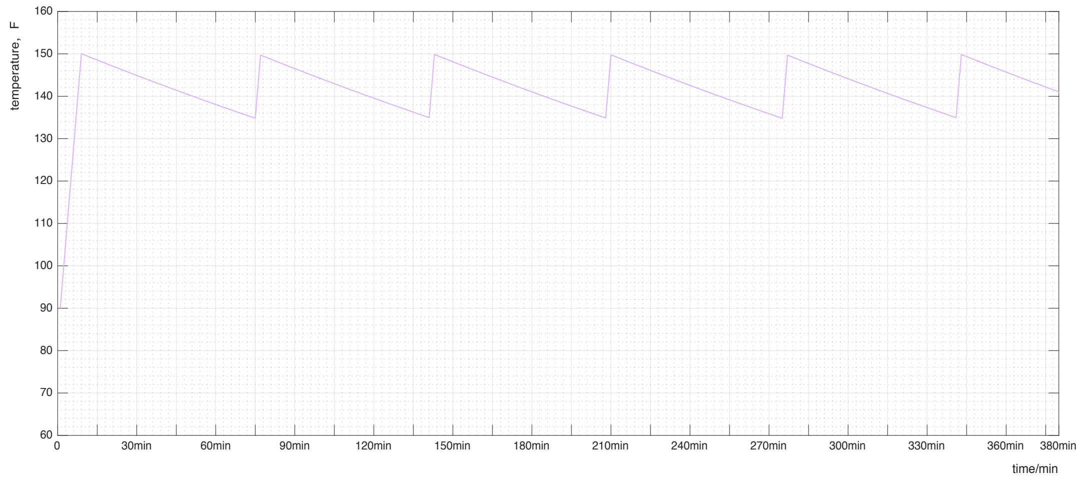


Figure 2.5 EWH Water Temperature Curve Without Consumption

As to some settings, some assumptions were proposed to simplify the calculation process based on the EWH model.

- The hot water temperature mixed in tank was supposed to be equivalent.
- The ambient temperature of tank is assumed to be the same temperature as the ambient air.
- The cold water temperature injected into water tank is assumed as the ground temperature.
- The set point of demand hot water temperature is assumed to be generated by a uniform function based on some data from [24].
- Some typical parameter values for individual EWH is taken into account from [25] and the most common tank size is 50 gal.

The parameters assumption is shown in Table 2.2.

Table 2.2 Parameters Assumption of EWH Model

Item	Symbol	Value	Unit
Water tank volume	V_{tank}	50	gallon
Cold water temperature injected	T_{in}	60	F
Ambient room temperature	T_a	50	F
Average upper set point	T_{upper}	170	F
Average lower set point	T_{lower}	105	F
Rated power	P_{WH}	4	KW/h
Surface area of the tank	A_{tank}	50	ft^2
Heat resistance of the tank	R_{tank}	15	F*ft^2*h/Btu
time interval	Δt	15	minutes

2.5 Hot water usage profile

The input data of EWH model discussed below include: water temperature, water heater setting parameters and hot water usage profile. The electricity household consumption can vary greatly based on the behavior of each customer. Therefore, figuring out the hot water usage information accounting for users' behavior is very important. As to hot water usage profile, from [26], some hot water draw events can be classified into several types. For convenience, each hot water draw events could be divided using water flow rate whose unit is gallon per minute. In [27], it shows that the daily average water usage varies from 5 to 20 gallons per person considering the mixed hot water temperature is 140 °F.

Sometimes, users can be classified into different kinds considering different consumption patterns. For example, a multi-family home has much less-consistent hot water consumption patterns than a single-family home. A week family has good potential to shift load during the weekend while a weekend family has good potential during the week days.

Table 2.3 Classification of Different Water Draw Event

Water usage event type	Value of water draw
Activity 1 (L)	0-0.53 gal/draw
Activity 2 (M)	0.53-5.23 gal/draw
Activity 3 (H)	>5.23 gal/draw

Roughly, the water draw events are divided into three categories as shown in Table 2.3, which is low-level water draw, medium-level water draw and high-level water draw based on a survey in Germany [28]. Low-level water draws basically include some small water usage events such as hand washing and dish washing. Medium-level water draws are shower and clothes washing and high-level water draws involve large water usage, for example, taking a bath.

On account of some load surveys, some data are gathered from End-Use Load and Consumer Assessment Program (ELCAP) and Bonneville Power Administration (BPA) [29]. Average hourly residential EWHs load profiles are used to generate individual EWH water consumption behavior. The typical hot water usage events in the U.S. [30] and Sweden [31] are given below in Table 2.4 and Table 2.5. Even though the amounts for hot water needed in these two tables are different, both of them show that the demand for each event is more than 2 KW. Both tables are calculated assuming that the cold water temperature injected into tank is 60 F.

Table 2.4 Hot water need for residential water usage events in the U.S. [31]

Event	Usage(gallon)	Energy(KWh)
Shower	30	5.9
Bath	20	3.9
Laundry	20	3.9
Dishwasher	15	2.9

Table2.5. Hot water need for residential water usage events in Sweden [31]

Event	Usage(gallon)	Energy(KWh)
Shower (5min)	10.6	2.1
Bath	26.4	5.2
Dishwasher	10.2	2.0

Chapter 3 Investigation of Electric Water Heaters as Demand Response Resources

3.1 Introduction of PSO & BPSO algorithm

Particle Swam Optimization (PSO) Algorithm was initially proposed by J. Kennedy and R.C.Eberhart in 1995[32]. PSO algorithm basically imitate animal population social behavior, for example, bird flocking. This algorithm is utilized to search for the optimal solution of a problem by coding both particles and behaviors. Each particle on behalf of a possible solution for the aimed problems which is represented by a vector and a multiple-dimension searching area.

All particles will eventually adapt to the optimal solution, considering a fitness function and some extra constraint conditions designed in advance[5]. The movement of each particle is affected by other particles as well as their own historical situations.

The updating rules of the location and velocity are as follows [33].

$$\vec{v}_i^{(t+1)} = w * \vec{v}_i^{(t)} + c_1 * \mathrm{rand}() * \left(\vec{x}_{Pbest}^{(t)} - \vec{x}_i^{(t)}\right) + c_2 * \mathrm{rand}() * \left(\vec{x}_{Gbest}^{(t)} - \vec{x}_i^{(t)}\right) \quad (3.1)$$

$$\vec{x}_i^{(t+1)} = \vec{x}_i^{(t)} + \vec{v}_i^{(t+1)} \quad (3.2)$$

$\vec{x}_i^{(t)}$ represents particle i ‘s location at time t;

$\vec{x}_i^{(t+1)}$ represents particle i 's location at time $t+1$;

$\vec{v}_i^{(t)}$ represents particle i 's velocity at time t;

$\vec{v}_i^{(t+1)}$ represents particle i 's velocity at time $t+1$;

w represents the inertia weight number;

c_1 and c_2 are learning factors.

The updating rules of personal good location and global good location is shown below:

$$\vec{x}_{Pbest}^{(t)} = \begin{cases} \vec{x}_i^{(t)}, & if\ f\left(\vec{x}_i^{(t)}\right) < f(\vec{x}_{Pbest}^{(t-1)}) \\ \vec{x}_{Pbest}^{(t-1)}, & otherwise \end{cases} \tag{3.3}$$

$$\vec{x}_{Gbest}^{(t)} = \begin{cases} \vec{x}_i^{(t)}, & if\ f\left(\vec{x}_i^{(t)}\right) < f(\vec{x}_{Gbest}^{(t-1)}) \\ \vec{x}_{Gbest}^{(t-1)}, & otherwise \end{cases} \tag{3.4}$$

PSO algorithm is a good method for global optimization problem and has plenty of advantages. Compared to other heuristic algorithms, PSO is much easier to reach convergence and has less variables, and the influence of variables on the optimization process is also less [34].

The PSO algorithm can be summarized using the follow chart shown in Figure 3.1.

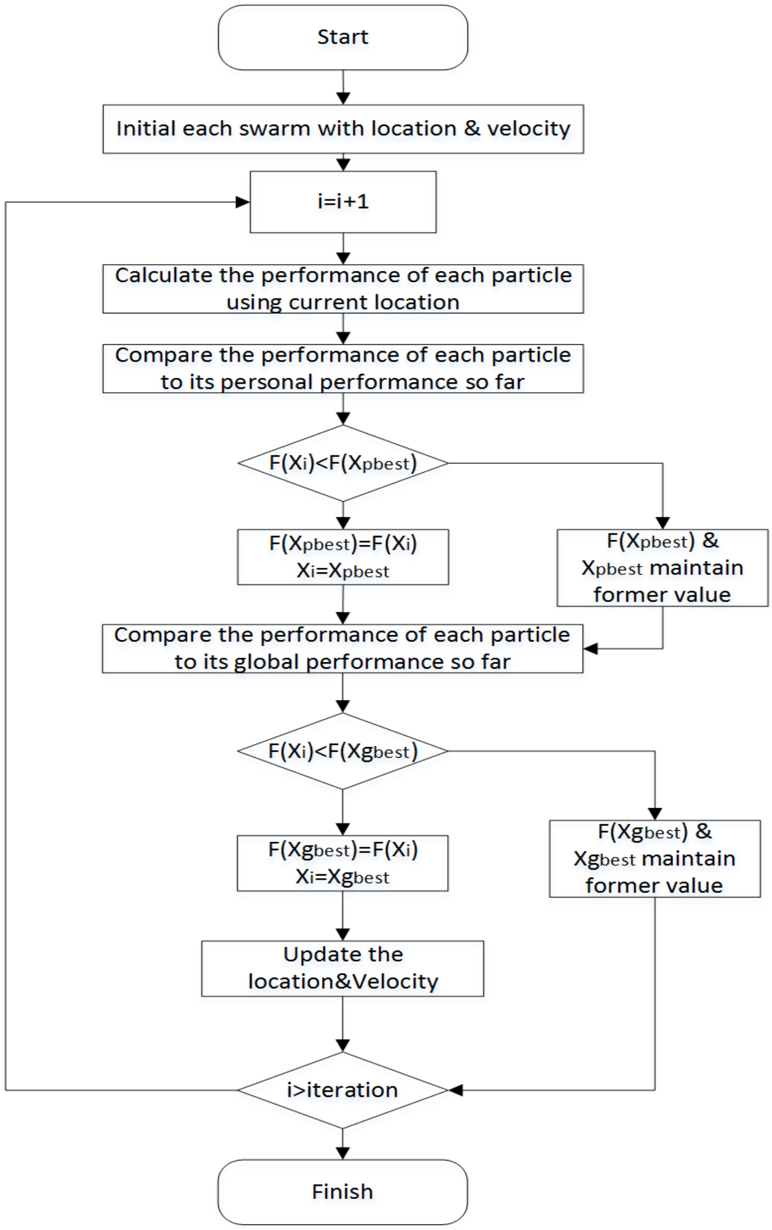


Figure 3.1 The PSO Algorithm Follow Chart

BPSO is binary particle swarm optimization, it's used for optimization problems whose variables are discrete. For example, the operation status of a generator is whether dispatched or not. BPSO algorithm has been proved a good way for solving optimization problems and network allocation problems [35]. In [36], a mixed PSO method was used to generator dispatching problem and BPSO method was used in the unit commitment area. In BPSO method, the updated rules of personal best value and global best value is the same as original

PSO shown above in equation (3.3) and (3.4). The only difference between traditional PSO and Binary PSO is the updating rule of the location considering the probabilities. In BPSO, there are only two kinds of status, which is 1 and 0. Particle location is updated only in discrete space by comparing the velocity factor with a random number belonging to [0,1]. The velocity must be constrained into a certain range, once the velocity is too big or too small, it needs to be reset. The sigmoid function used here is a normalization function:

$$v_i'^{(t)} = \mathrm{sig}\left(\vec{v}_i^{(t)}\right) = \frac{1}{1+e^{-v_i^{(t)}}} \tag{3.5}$$

$$\vec{x}_i^{(t+1)} = \begin{cases} 1 & \text{if } (\mathrm{rand}() < v_i'^{(t)} \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

$$V_{min} < v_i^{(t)} < V_{max} \tag{3.7}$$

where,

$\mathrm{rand}()$ represents a uniform-distributed random number which is in belonging to [0,1];

V_{min} and V_{max} is the lower and upper boundary of velocity.

The detailed process of using the BPSO algorithm is shown below, which is similar to PSO:

(1) Generate lots of particles randomly in the whole searching area at first. For each particle, calculate the location and velocity of next time using the initial locations and velocities.

(2) Calculate the fitness function of each particle.

(3) Compare the fitness function of each particle passing through the personal searching area with the current value of personal optimal solution.

(4) Compare the current value of personal optimal solution passing through the whole searching area with the value of global best solution so far, finally get the global best solution. Set the personal best value and global best value so far.

(5) Update the velocity of each particle using the current velocity and both the current personal best location and global best location, equation (3.3) and (3.4).

(6) Update the each particle' location using updating rules, equation (3.5) to (3.7).

(7) Repeat steps (2) to (6) until reaching the convergence or any criterion.

3.2 Optimization Strategy for individual EWH using BPSO Algorithm

Using Time-of-use (TOU) electricity price could make the EWHs loads more sensitive to the utility decision. The reason why electricity price (EP) is chosen as an incentive to shift the EWHs load is that the EP curve is related to the power system load curve. If the system load is high, then the EP will be high in the upcoming hours and vice versa. For residential users, electricity costs can be reduced through shifting their loads. Therefore, customers will react to EP changes to avoid high-price hours and as a result, they can shift their loads to non-peak hours as well as save money on their electricity bill.

For each EWH, a queue state vector is used to describe the operation status as follows:

$$\overrightarrow{X_a} = [x_a^1, x_a^2, x_a^3, \ldots . x_a^n] \tag{3.6}$$

n represents the total time intervals that being considered into optimization process. Two discrete value 0&1 is used to represent the operation status of each operation task. The EWH will have 1 value if the operation status is on while 0 value denotes the operation status is off once the water temperature reached the expected value.

The optimization is aimed to minimize the residential EWH electricity bill by rescheduling the operation time of EWH subjected to the expected temperature constraints. The problem can furthermore be formulated shown below.

1) Minimum electricity cost function

The input incentive used in this optimization is TOU price. Considering EP at each time interval is different, we use a vector to represent EP. The basic fitness function of EWH optimization then can be represented below:

$$\min\{\mathrm{Cost} = \sum_{i=1}^{n} P_{WH} * \overrightarrow{EP}(i) * \vec{X}_a(i)\} \tag{3.7}$$

where,

n represents total time intervals;

i represents the index of time intervals;

EP represents the electricity price vector;

$X_a(i)$ represents the operation status vector of EWH.

Based on the electricity price, we can find some low-price-period for EWH to work. At each time, the fitness function will be calculated and compared using the updating equations and information above. The value of fitness function is the most important factor that needed to be considered during the whole optimization procedure. The TOU price used in this paper is summarized from [37], which is shown in Figure 3.2.

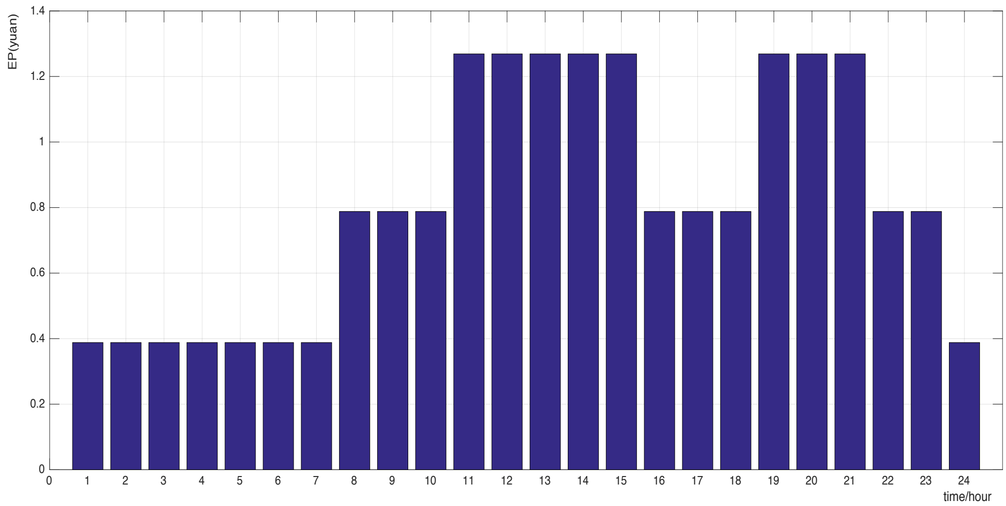


Figure 3.2 Time of Use Electricity Price

2) Minimum and maximum temperature limits

The constraint condition here is to make sure certain temperature expectation is achieved during certain periods. The certain periods refer to time intervals in which a water usage event occurs based on customers' water usage behavior. Also, during the optimization process, the water temperature is not allowed to be too high. The error allowed for the upper and lower limited temperature is 10F. Therefore, the upper limit in optimization process is set to be 10 F higher than the higher set point. And the lower limit is set to be 10 F lower than the lower set point. The constraint condition of EWH optimization can be represented below:

$$\forall t = i \text{, if } rate_i \sim= 0 \quad \text{then } T_{out,i} \geq T_{lower} - 10 \tag{3.8}$$

$$X_a(i+1) = \begin{cases} 0 & \text{if } T_{out,i} > T_{upper} + 10 \\ X_a(i) & \text{if } T_{out,i} \leq T_{upper} + 10 \end{cases} \tag{3.9}$$

3.3 Simulation results and Analysis

The optimization process of single EWH using BPSO is given in flow chart:

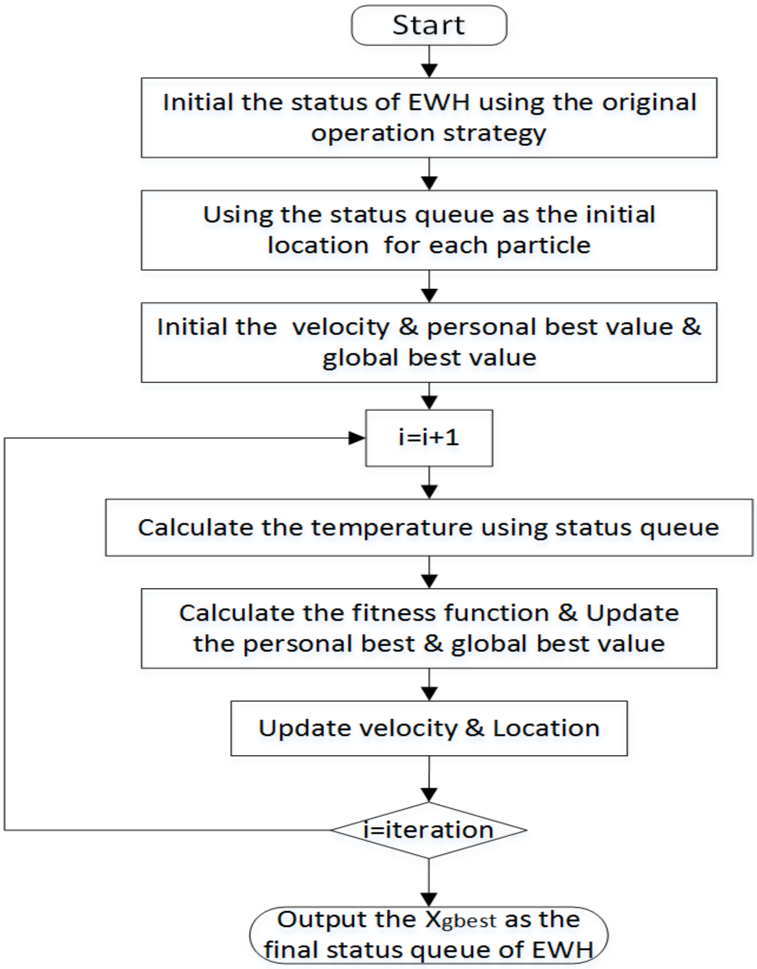
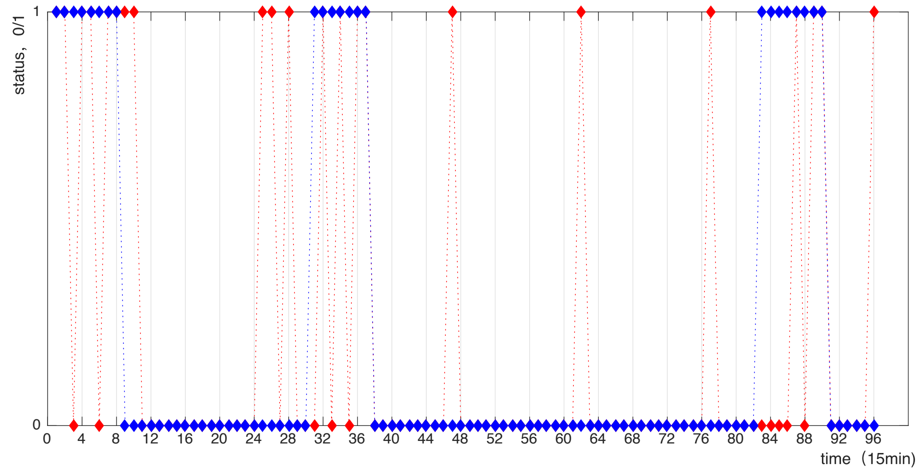


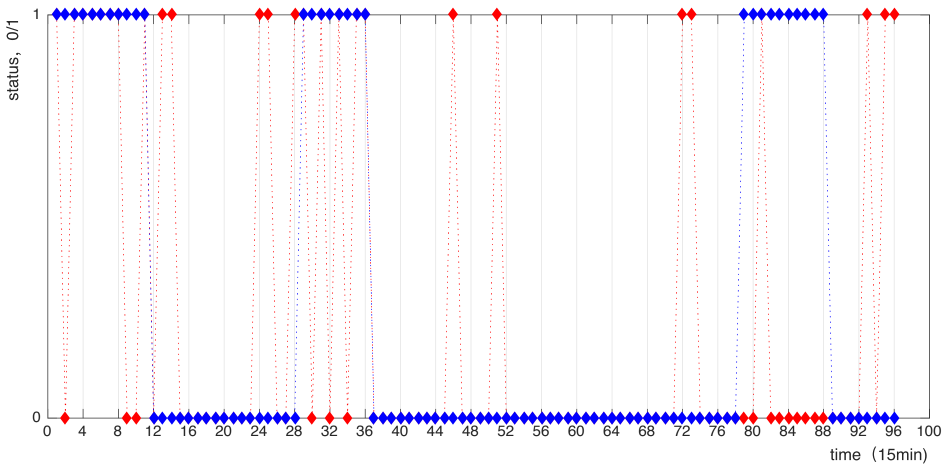
Figure 3.3 The Optimization Process of Single EWH using BPSO

Using the strategy proposed, the aim can be achieved efficiently. Some parameters referred to in Chapter 2 are used in simulation here, for example, the measurement is taken every 15 minutes over a 24-hour-period. To make sure the affect that BPSO working on EWH, a sensitivity study using different set point is proposed. Notice that set point here is for mixed hot water in tank. People can still adjust the water temperature they need, for example, when they take showers or wash dishes.

In the first scenario, the set point range is set to be [125,165], which presents a higher temperature preference customer. In the second scenario, the set point range is [105,150], which represents a lower temperature preference customer. The simulation results of the EWH working status in these 2 scenarios are shown in Figure 3.4 below.



(a)Temperature [105,150]



(b)Temperature [125,165]

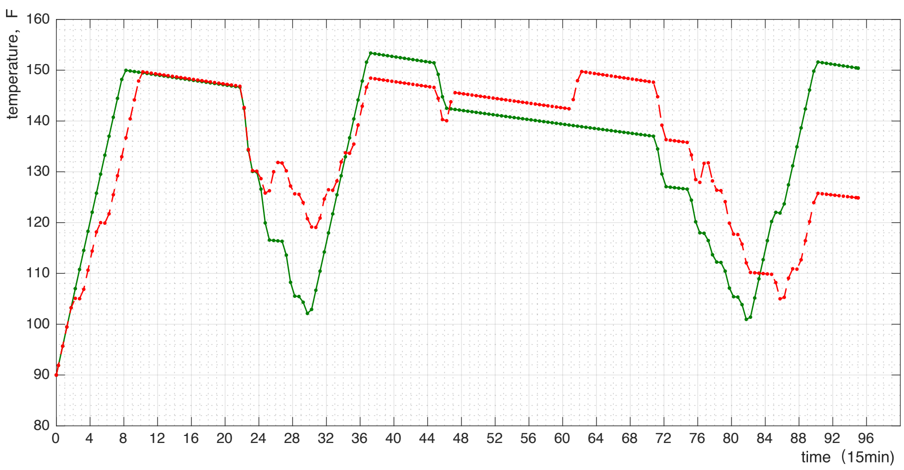
Figure 3.4 The Status Results of Different Set Point Range

Comparing the status queue with the EP curve, we could see the number of open status has been reduced during peak-hour after the proposed optimization process working on both scenarios. Although the frequency of working status changing is a little bit high, the money saved by re-operating is enough for replacing an old EWH. The total electricity cost of these two scenarios is compared in Table 3.1. Both electricity cost and total electricity consumption has been reduced by the optimization approach.

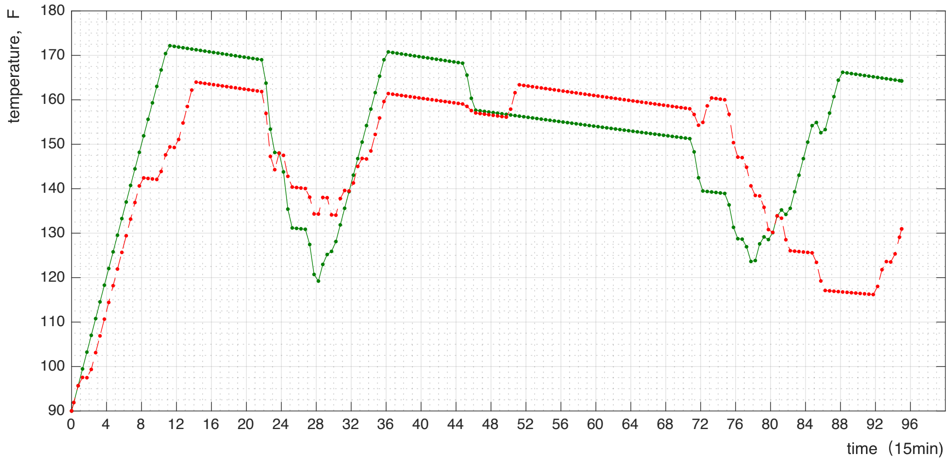
Table 3.1 The Comparison of Electricity Consumption and Cost

Number of scenario		**Electricity Consumption(KWh)**	**Electricity Cost (RMB:yuan)**
Scenario 1	Before	21.75	16.0026
	After	19.5	12.6084
Scenario 2	Before	17.25	11.9142
	After	16.5	11.4354

The water temperature curve was shown in Figure 3.5 considering different set point ranges. It turned out that the BPSO method is an effective way to keep the water temperature in a certain range in both scenarios.



(a)Temperature [105,150]



(b)Temperature [125,165]

Figure 3.5 The Temperature Results of Different Set Point Range

It was shown that the comfort limit of the mixed hot water temperature could be maintained. For further test, in this study, we define an index to represent the customers' comfort level considering the set point as follows [33]:

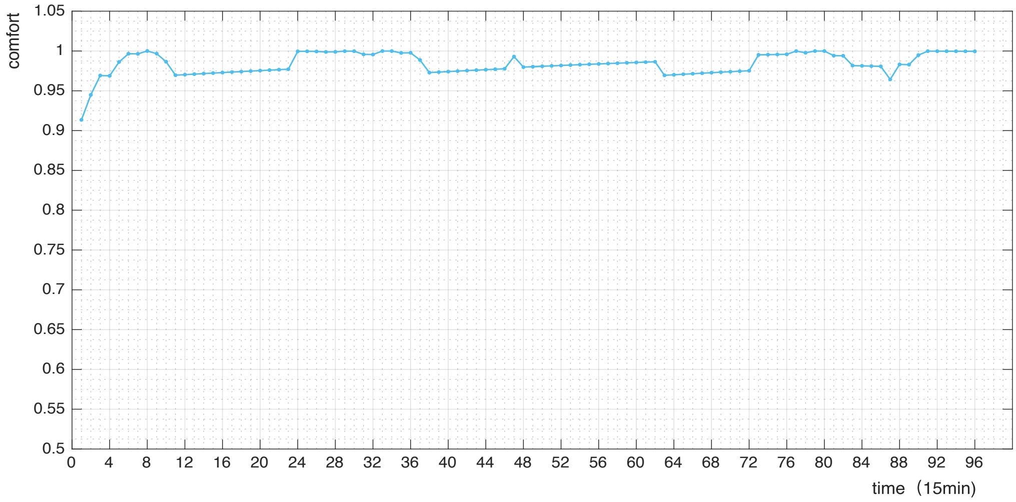
$$\mathrm{Comfort} = 1 - (\mathrm{e}/\mathrm{T_{set}})^2 \tag{3.10}$$

$\mathrm{Comfort}$ is the customer comfort limit index, which belongs to [0,1], the goal is to make the value much more close to 1;

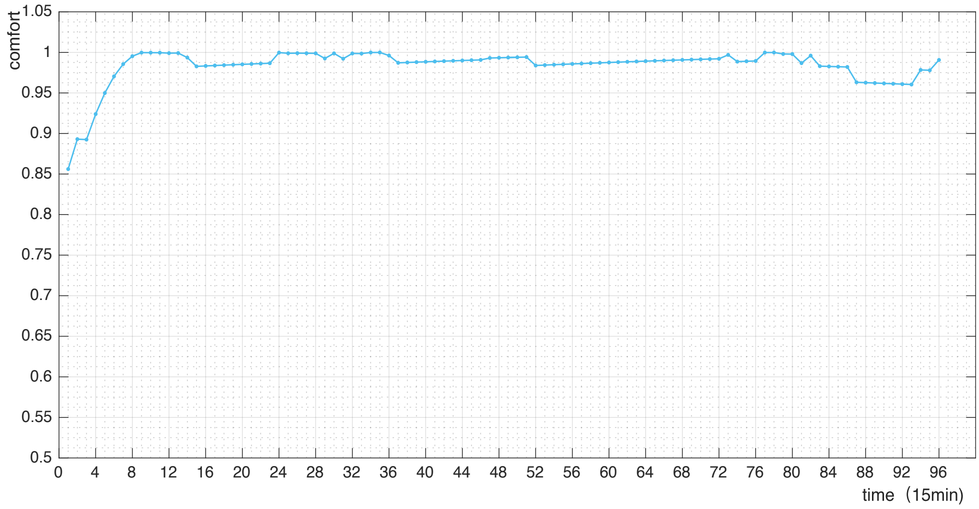
e represents the error between the customer's set point and the real value;

$\mathrm{T_{set}}$ represents the average value of upper set point and lower set point.

The simulation result of comfort limit is shown in Figure 3.6.



(a)Temperature [105,150]



(b)Temperature [125,165]

Figure 3.6 The Comfort Level of Different Set Point Range

Figure 3.6 shows that the value of comfort level index could be maintained above 0.95 during most time periods, and sometimes it could reach to 1. In other words, BPSO optimization strategy for EWH proposed in this study is proved to be effective.

To make the process of every iteration clear, the global best location value is shown in Figure 3.7.

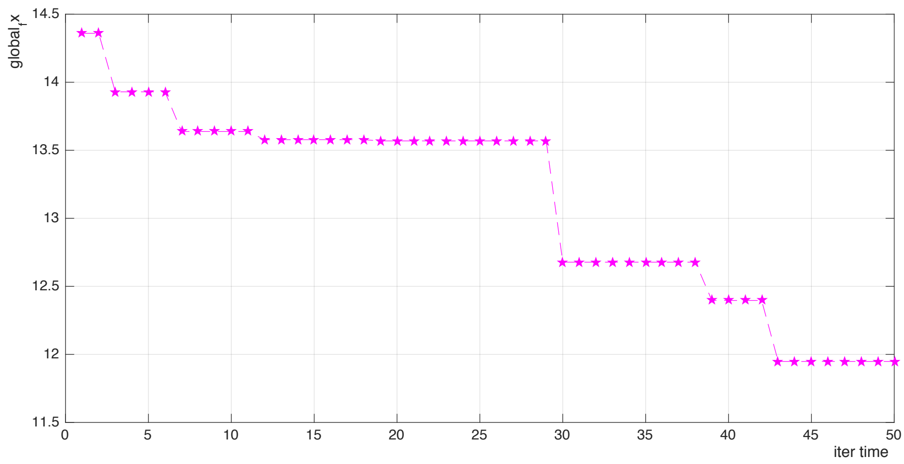


Figure 3.7 Example for the Iteration Situation of BPSO Optimization

3.4 Conclusion and Future Work

An optimization strategy for single EWH was proposed in this Chapter 3. The operating status queue and hot water temperature has been carried out. The electricity cost has been proved to be reduced by the strategy and the comfort level has been maintained.

In the BPSO algorithm, there are only two location values, 0 and 1, which matched the EWH operation status on and off. The location of traditional BPSO is initialized randomly. For the BPSO we proposed in this chapter, the initial location was the original operation status of EWH before optimization. This setting can help the BPSO to be more reasonable during a search process. It has been proved that the BPSO algorithm reduces total electricity cost and shifts the EWH load during peak hours in this study. When high load demand appears, the utility will increase the upcoming EP of the next few hours. Therefore, the EWH load could be suspended by the scheduler and the total electricity cost as well as the peak-hour load will be reduced by the strategy in this chapter.

As to future studies, the optimization strategy for EWH will be further improved. The Real-Time Price (RTP) should be involved because RTP better reflects the real-time load. In this thesis, the incentive is TOU price rather than Real-time price (RTP) considering the complex mixed water temperature calculation.

Chapter 4 Impact of Aggregated Electric Water Heaters on Power System Operational Reliability

4.1 Introduction of Electric Power System Reliability

The electric power system is not stable all the time because of many kinds of physical or geographical problems. The electricity could not be efficiently reserved on a huge scale so that sometimes uncertain situations may have bad influences on the power system. The fundamental task of the utility is to provide customers a reliable and economic electricity supply for power system, and the most important problem is to figure out how to evaluate and analyze the electric power system reliability.

Basically, there are two concepts, adequacy and security, in power system reliability. Adequacy relates to the existing equipment which need to be enough to meet the customers' demand. Security relates to the power system response capability to deal with some uncertainties. To guarantee the system supply (adequacy area), sufficient amount of generating capacity is needed. For security area, adequate operating capacity is required. Then the problems could be furthermore classified into two categories: the first one is static requirements and the second one is operating capacity requirements. The static requirement is related to the installed capacity that needs to be planned ahead of schedule considering system requirements in long-term evaluations. The operating capacity refers to the real capacity in short-term evaluations needed to ensure an existing load level.

The primary method to analyze the generation configuration adequacy is basically the same. The three parts are shown in Figure 4.1. A risk model can be obtained by combining the generation model and load model.

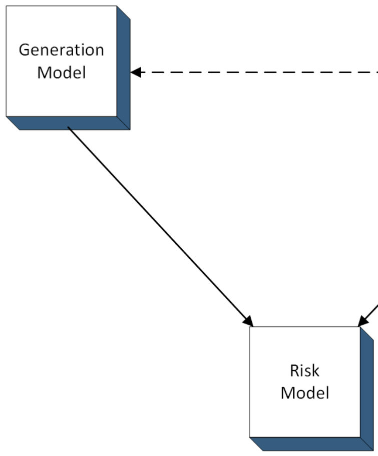


Figure 4.1 Conceptual task of Reliability

The probability consumers disconnect with electricity could be reduced by many methods, for example, increasing investment in the planning phase or operating phase. It's important to be adequate in investing because sometimes over-investment could lead to extra costs and under-investment could cause an opposite situation. To solve the problem between reliability and economy, some criteria and techniques have been applied over the past few years. There are two kinds of criteria and techniques, which is the deterministically based method and the probabilistic based method [38]. Usually, the probabilistic based method is much more reasonable than the deterministically based method.

In static capacity evaluation phase, the needed parameter for generating unit is the probability to find the on forced outage unit. This probability is the unit forced outage rate (FOR). The formulation used to calculate FOR is shown below:

$$\mathrm{Unavailability(FOR)} = \mathrm{U} = \frac{\lambda}{\lambda+\mu} = \frac{r}{r+m} = \frac{r}{T} = \frac{f}{u} = \frac{\sum \text{down time}}{\sum \text{down time}+\sum \text{up time}} \tag{4.1}$$

$$\mathrm{Availability} = \mathrm{A} = 1 - \mathrm{FOR} = \frac{\mu}{\lambda+\mu} = \frac{m}{r+m} = \frac{m}{T} = \frac{f}{\lambda} = \frac{\sum \text{up time}}{\sum \text{down time}+\sum \text{up time}} \tag{4.2}$$

Where,

λ represents the expected failure rate, while μ represents the expected repair rate;

m represents mean time to failure, m=MTTF=$\frac{1}{\lambda}$, while r represents mean time to repair, r=MTTR=$\frac{1}{\mu}$;

$m + r$ represents mean time between failures= MTBF=$\frac{1}{f}$

f represents cycling frequency, while T represents cycling period.

A capacity outage probability table (COPT) is used as the generation model in the long-term approach, which is also needed in the short-term approach in operating reserve evaluation.

4.2 Introduction of Operating Reserve and Calculation Method

The generation reserve capacity has a big influence on power system reliability. As shown in [12], the power system time period is usually divided into 2 phases, the first one is the planning phase and the second one is the operating phase. In case of some uncertainties of load prediction and power plant outages during operation period in power system, reserve generation must be planed appropriately. In the operation phase, both over-scheduling and under-scheduling are unreliable. A risk index based on the probabilistic approach is much more realistic for evaluation. Two risk indices can be evaluated generally, which are the unit commitment risk(UCR) and the response risk. UCR relates to the committed-unit-evaluation in the required period. Response risk relates to decisions for the unit dispatch which are in committed status so far. In the past, deterministic methods are used to evaluate operating reserve requirements. Nowadays, probabilistic methods are more useful in case of overscheduling. To calculate unit commitment, the PJM method and modified PJM method is proposed, which are required in this paper. Note that all the calculation methods based on PJM method and modified PJM method are summarized from book [12].

4.2.1PJM Method

The PJM method was came up in the year 1963 and is used to evaluate the Pennsylvania-New Jersey-Maryland interconnected system spinning requirements [39]. PJM method is a primary method to calculate UCR to evaluate the operating reserve requirements. PJM method is used to calculate the probability of the committed units satisfying or failing to satisfy the required demand when the failed unit could not be substituted. This period is defined as lead time. At the start of lead time, the operator must be in committing status considering other units cannot be replaced if there is an overload. Then, the risk index could refer to the risk that supplies or does not supply the demand in lead time. A two-state model, which are the operating state and failure to operate state, are shown in Figure 4.2. The repair probability when neglecting the lead time are used to describe each unit.

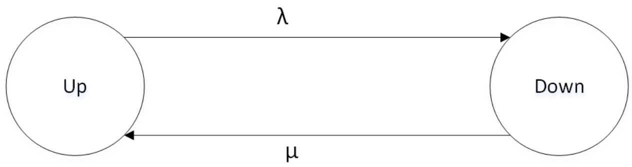


Figure 4.2 Two-state Model

In the Engineering System, usually repairs and failures are assumed exponentially distributed. A two-state model outage probability at time T, considering successful operating when beginning, is shown below

$$P(down) = \frac{\lambda}{\lambda+\mu} - \frac{\lambda}{\lambda+\mu} e^{-(\lambda+\mu)T} \tag{4.3}$$

If neglecting the repair process in time T, then it becomes

$$P(down) = 1 - e^{-\lambda T} \tag{4.4}$$

considering that if T<<1, then it changed to be

$$P(down) = \lambda T \tag{4.5}$$

Outage replacement rate (ORR) represents the failure probability of a unit in lead time, which is shown in equation (4.5). ORR is similar to FOR which is used in the planning phase. The generation model required for PJM method is also a COPT which used ORR instead of FOR. In the PJM method, the UCR can be gained from the outage replacement rate (ORR) table.

The UCR can be obtained from generation model afterwards assuming the load is constant during the calculated period. Usually, defining an acceptable risk at first to make sure a committed system can satisfy expected need is important. In practice, operators add units and commit them using PJM risk assessment method until the UCR meets acceptable risk.

4.2.2Modified PJM Method

The modified PJM method is basically analogous to the PJM method, the only difference is that modified PJM method includes additional rapid start unit or other generating unit with different parameters. In the modified PJM method, the risk at the beginning is whether 0 or unity is dependent on the difference between load and available generation [40]. The pictorial description of risk function (or density function) and area risk concept is shown in Figure 4.3.

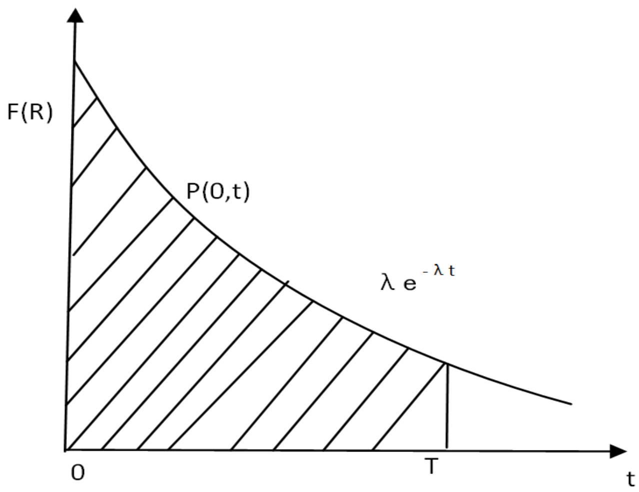


Figure 4.3 Pictorially Description Area Risk Concept

Considering a two-state model (Equation(4.4)), then the risk function becomes

$$f(R) = \frac{dp}{dt} = \lambda e^{-\lambda t} \tag{4.6}$$

The failure probability in time [0, T] becomes

$$P(0,T) = \int_0^T \lambda e^{-\lambda t} dt \tag{4.7}$$

The Figure 4.4 describes the system risk evaluation using an area risk curve. The unit failure probability is the area under curve. The Figure 4.4 (a) and (b) shows the system behavior considering reserve units using the PJM method and modified PJM method separately.

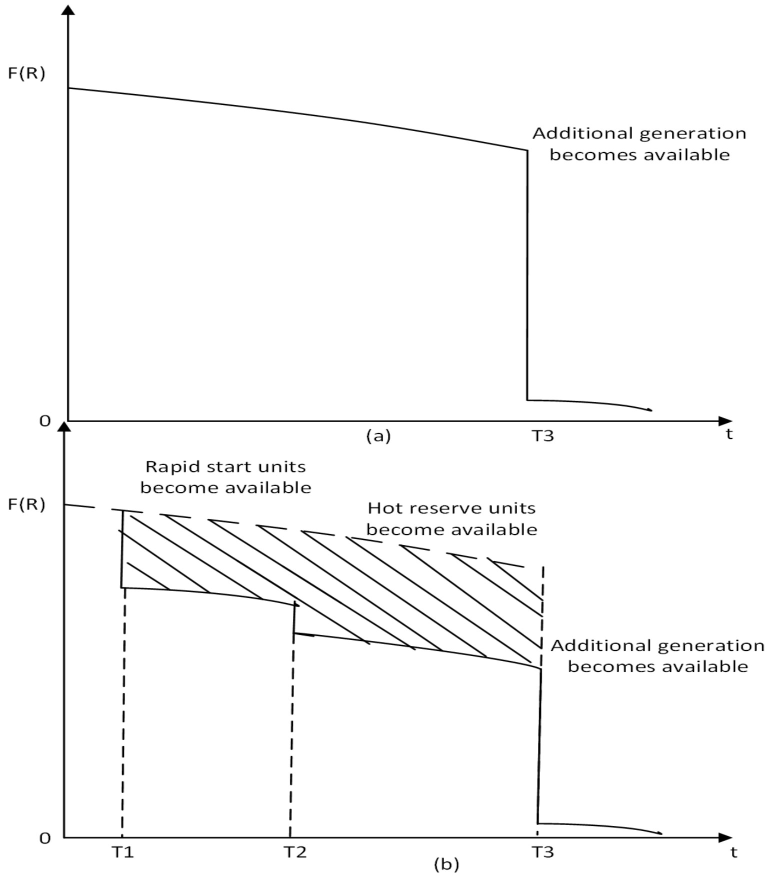


Figure 4.4 Approximate Area Risk Curve of $f(R)$

In Figure 4.4 (b), the rapid start units start to work after time T_1, and the hot reserve units start to work after time T_2. Therefore, the total risk is less than only accounting for additional generation shown in Figure 4.4 (a). The risk reduction is the shaded area in Figure 4.4 (b).

To calculate the risk, the individual risks are required during time interval $(0, T_1)$, (T_1, T_2) and (T_2, T_3), etc. Then the risk during $(0, T_3)$is the summation. The formulation used to calculate is shown below:

1) Risk in $(0, T_1)$

$$R_a = R_{T1-} \tag{4.8}$$

2) Risk in (T_1, T_2)

$$R_b = R_{T2-} - R_{T1+} \tag{4.9}$$

3) Risk in (T_2,T_3)

$$R_c = R_{T3-} - R_{T2+} \tag{4.10}$$

4) Total risk in $(0, T_3)$

$$R = R_a + R_b + R_c \tag{4.11}$$

4.3 Model of Rapid Start Unit

4.3.1 Unit Model

A four-state model is used here (Figure 4.5):

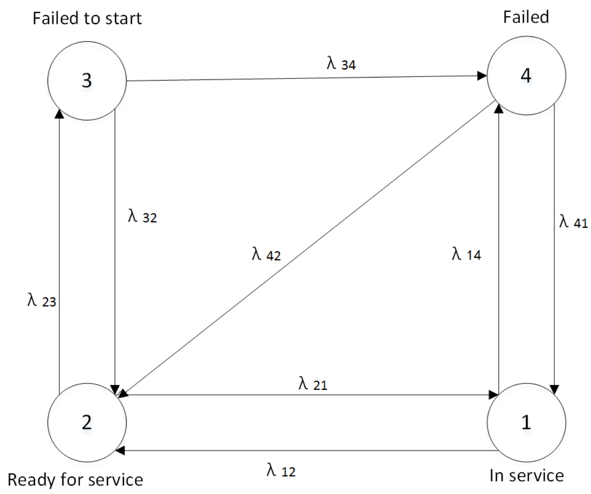


Figure 4.5 Four-state Model for EWHs load

The failure rate is

$$\lambda_{ij} = N_{ij}/T_i \tag{4.12}$$

Where,

λ_{ij} represents state transition rate from i to j

N_{ij} represents state transitions' number from i to j

T_i represents time spent in state i

4.3.2 Evaluating state probabilities

Markov techniques and the matrix multiplication techniques are used to calculate the probability of these states.

$$[P(t)] = [P(0)][P]^n \tag{4.13}$$

Where,

$[P(t)]$ represents the state probabilities vector;

$[P(0)]$ represents the initial probabilities vector;

$[P]$ represents the matrix of transitional probability;

n represents the number of time intervals.

The stochastic transitional probability matrix is

$$
P = \begin{bmatrix} 1-(\lambda_{12}+\lambda_{14})dt & \lambda_{12}dt & - & \lambda_{14}dt \\ \lambda_{21}dt & 1-(\lambda_{21}+\lambda_{23})dt & \lambda_{23}dt & - \\ - & \lambda_{32}dt & 1-(\lambda_{32}+\lambda_{34})dt & \lambda_{34}dt \\ \lambda_{41}dt & \lambda_{42}dt & - & 1-(\lambda_{41}+\lambda_{42})dt \end{bmatrix}
$$

(4.14)

It's noted that the value of dt should not be too small or too large, usually, 10 minutes is the acceptable value for most system.

The rapid start unit keeps in ready-for-service state with a united possibility instead of committing to the system in the lead time. The initial probabilities vector when the unit has probability to commit to system is as follows:

$$
[P(0)] = [P_{10} \ \ 0 \ \ 0 \ \ P_{40}] \tag{4.15}
$$

Where, P_{40} represents the failed probability (P_{fs})

$$
P_{fs} = \frac{number\ of\ frequencies\ that\ units\ failed\ to\ commit}{number\ of\ units\ start\ to\ commit} = \frac{N_{23}}{(N_{21+N_{23}})} = \frac{\lambda_{23}}{(\lambda_{21}+\lambda_{23})}
$$

(4.16)

$$
P_{10} = 1 - P_{fs} \tag{4.17}
$$

4.3.3 Evaluating State Probabilities

Combining the individual probabilities together is important to give the probability the unit failed to start. The index then becomes

$$
P_{down} = \frac{P_3(t)+P_4(t)}{P_1(t)+P_3(t)+P_4(t)} \tag{4.18}
$$

The numerator is the failed-state-unit probability and the denominator is the probability when there is a demand. So P_{up} is shown below

$$P_{up} = 1 - P_{down} = \frac{P_1(t)}{P_1(t)+P_3(t)+P_4(t)} \tag{4.19}$$

4.4 Calculation and Analysis

EWHs load can be chosen as the reserve because they can be interrupted as long as the temperature limit can be fulfilled sometime later. It's similar to the interruptible capacity of EVs. The EVs load could be interrupted on condition that the charging assignment could be achieved afterwards [41].

To analyze the reliability indices, the interruptible capacity should be considered first. For aggregated EWHs, the BPSO algorithm is still deployed to do the optimization. The group number of the EWHs set in this study is 5000. Then we can get the load curve of 5000 aggregated EWHs shown below. The difference between the red curve and the green curve here is the reserve capacity that aggregated EWHs could provide.

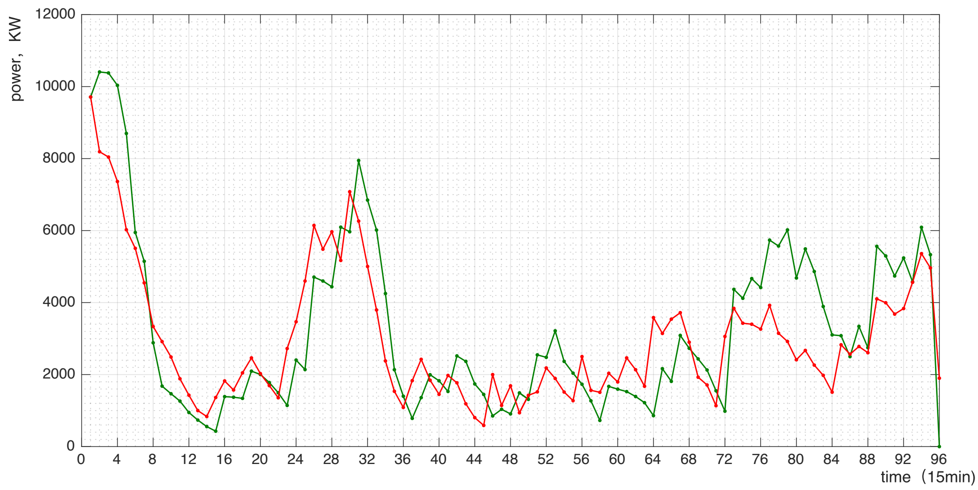


Figure 4.6 Aggregated EWHs Load Curve

The curves in Figure 4.6 show that the aggregated load has been shifted effectively during peak-hours which are from 8:00 to 14:00 and from 18:00 to 21:00 due to the optimization strategy. What's more, the electricity costs of each customer have also been reduced. The users' cost comparison statistics is collected in Figure 4.7, the blue one is the cost for each user before optimization, the red one is after optimization.

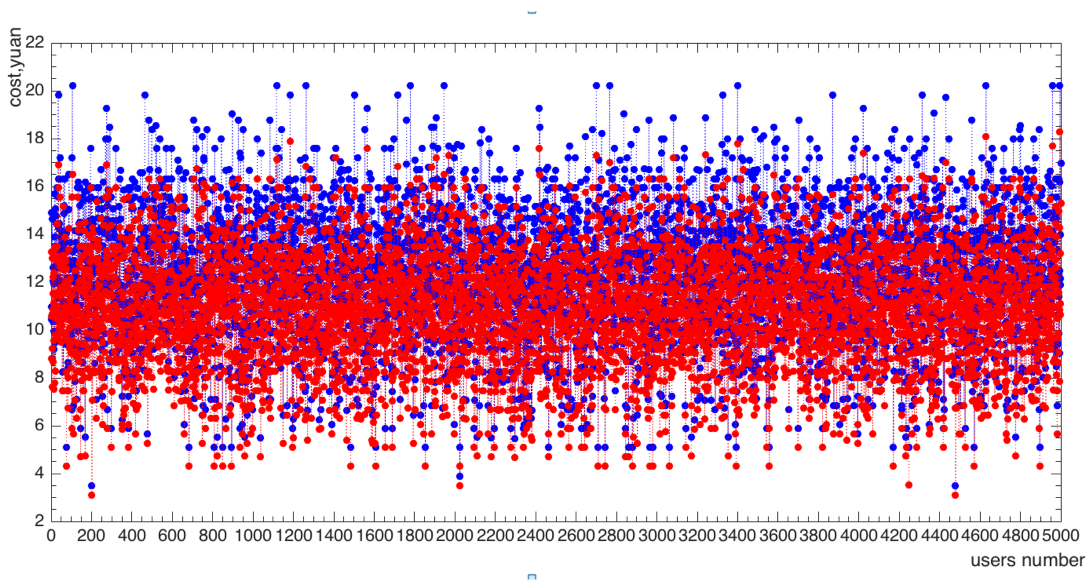


Figure 4.7 The Comparison of Each Users' Cost Statistics

The average cost comparison of these 5000 users is recorded in Table4.1. It proved that the optimization goal has been achieved.

Table 4.1 The Comparison of Average Electricity Cost

scenario	**Average cost**
before	12.2492
after	10.8962

Some units chosen from the given reliability test system in [42] composite the reliability test system in this thesis. These units can be combined together to system A using techniques referred in book [12], the RBTS is shown in Figure 4.8. The total installed generating capacity of the system is assumed to be 150 MW, the peak load is 110MW. A two-state model is used here to describe the generation unit , which is shown in Figure 4.2. PJM method is used to calculate the Outage Replacement Rate (ORR) [12] and lead time is assumed to be 1 hour, which is given in Table 4.2 as follows. It is important to define a reasonable risk that can be accepted in a real system to make sure the maximum demand of a committed system.

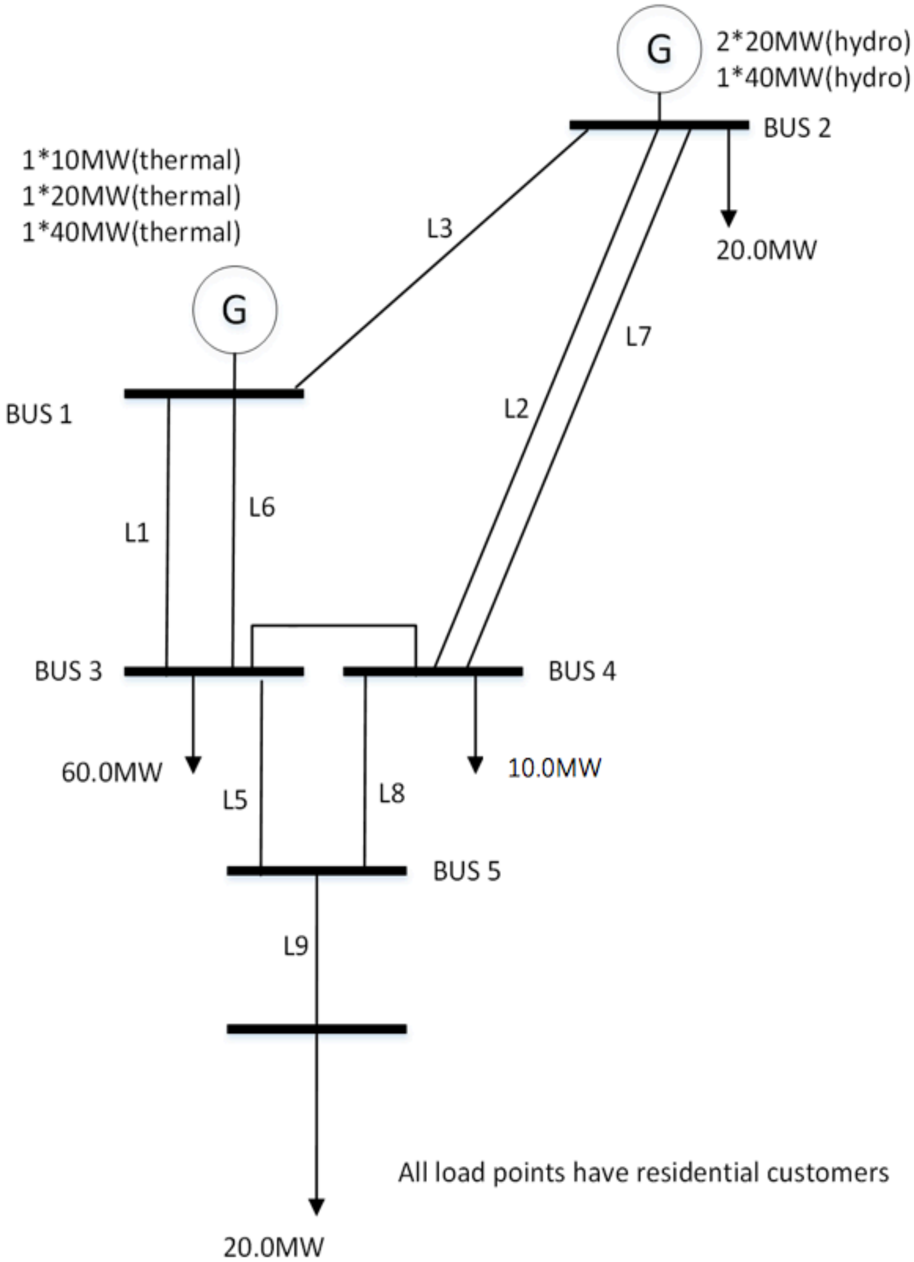


Figure 4.8 Single Line Diagram of RBTS

Before EWHs participate in operation reserve, the capacity they can provide should be known.

Table 4.2 Parameters of Original Generation System

Unit Size (MW)	**No. of units**	**Failure rate per year**	**ORR for lead time of 1 hour**
10 (thermal)	1	4.0	0.000457
20 (thermal)	1	5.0	0.000571
20 (hydro)	2	2.4	0.000274
40 (thermal)	1	6.0	0.000685
40 (hydro)	1	3.0	0.000342

The capacity outage probability table (COPT) of the test system is shown in Table 4.3.

Table 4.3 Capacity Outage Probability Table of Original Generation System

Capacity Out(KW)	**Capacity In(KW)**	**Cumulative Probability**
0	150	1.00000000000000000000
10	140	0.00260024932358005000
20	130	0.00214422923634106000
30	120	0.00102766373371734000
40	110	0.00102715322998244000
50	100	0.00000185138047061419
— —	— —	— —

The capacity of 5000 EWHs can be obtained from the simulation: approximately 0.5MW to 2 MW at each interval. To meet the load need, 10 communities with 5000 users are assumed to be combined together to provide operating reserves. The parameters to model the aggregated EWHs can be obtained from [12]. We chose the four-state model.

Then, an example of UCR calculation is shown as follows. The EWHs 10 MW capacity is assumed to start committing at t =0, with a 10-minute start-up time and some parameters of state transitions are shown in Table 4.4 [12]. The lead time is set as 1 hour and expected demand is set as 110 MW.

Table 4.4 Parameters of State Transition per Hour

state transitions (i,j)	(i,1)	(i,2)	(i,3)	(i,4)
(1,j)	--	λ_{12}=0.0050	--	λ_{14}=0.0300
(2,j)	λ_{21}= 0.0033	--	λ_{23}=0.0008	--
(3,j)	--	λ_{32}=0.0000	--	λ_{34}=0.0250
(4,j)	λ_{41}=0.0150	λ_{42}= 0.0250	--	--

There are two time intervals that need to be considered: the time interval before EWHs start committing (0, 10 minutes) and the time interval after EWHs start committing (10 minutes, 1 hour).

The ORR of each unit assuming 10-minute lead time is given in Table 4.6. The parameters are shown in Table 4.5. The risk during (0, 10 minutes) can be obtained from Table 4.5 that R_a =0.000171204369505394.

Table 4.5 Parameters of Generation Model at 10 min

Unit Size (MW)	**No. of units**	**Failure rate per year**	**ORR for lead time of 10 minutes**
10 (thermal)	1	4.0	0.0000762
20 (thermal)	1	5.0	0.0000962
20 (hydro)	2	2.4	0.0000457
40 (thermal)	1	6.0	0.0001142
40 (hydro)	1	3.0	0.000057

Table 4.6 Capacity Outage Probability Table of Original Generation System at 10 min

Capacity out(MW)	**Capacity in(MW)**	**Cumulative Probability**
0	150	1.00000000000000000000000000
10	140	0.00043492315880699900000000
20	130	0.00035875049559476300000000
30	120	0.00017121866052020200000000
40	110	0.00017120436950539400000000
50	100	0.00000005166524573506190000
— —	— —	— —

Aggregated EWHs load is equivalent to providing extra generating capacity by regarding the load as interruptible. The new generation model of combining the aggregated EWHs load with the generation units is shown in Table 4.6, then we can get the new generation model at 10 minutes as shown in Table 4.7.

Table 4.7 Outage Replacement Rate of New Generation System at 10 min

Capacity out(MW)	Capacity in(MW)	Cumulative Probability
0	160	1.00000000000000000000000000
10	150	0.19547206008221400000000000
20	140	0.00037361345798603300000000
30	130	0.00020781024724359200000000
40	120	0.00017120715799675700000000
50	110	0.00003344732320626030000000
60	100	0.00000004116735884031610000
— —	— —	— —

From the equation (4.12), the EWHs load has the value of $P_{fs} = \frac{0.0008}{0.0033+0.0008} = 0.195122$, so that $1 - P_{fs} = 0.804878$

$$P = \begin{bmatrix} 0.994167 & 0.000833 & - & 0.005000 \\ 0.000550 & 0.999317 & 0.000133 & - \\ - & 0.000000 & 0.995833 & 0.004167 \\ 0.002500 & 0.004167 & - & 0.993333 \end{bmatrix}$$

Using the values of P_{fs}, the initial probabilities vector (4.15) of the aggregated EWHs is $[P(0)] = [0.804878 \quad 0 \quad 0 \quad 0.195122]$.

The time period is divided into several time slots, each time slot is 10-minute. The stochastic transitional probability matrix using the transition rates can be obtained as follows:

$$[P(10min)] = [0.800670 \quad 0.001484 \quad 0.000000 \quad 0.197846]$$

$$[P(20min)] = [0.796496 \quad 0.002974 \quad 0.000000 \quad 0.200530]$$

$$[P(30min)] = [0.792353 \quad 0.004471 \quad 0.000000 \quad 0.203176]$$

$$[P(40min)] = [0.788241 \quad 0.005975 \quad 0.000001 \quad 0.205783]$$

$$[P(50min)] = [0.784161 \quad 0.007485 \quad 0.000002 \quad 0.208352]$$

The probability at 1 hour is $P(down) = 0.20995$ and $P(up) = 0.79075$ using the data of $P(50min)$.

A new generation model can be obtained from Table 4.8 combining the EWHs load and the generation model with 1-hour lead time. The UCR is the cumulative probability in Table 4.8 where the value of ‘capacity in’ is 110 MW.

Table 4.8 Outage Replacement Rate of New Generation System at 1 h

Capacity out(MW)	Capacity in(MW)	cumulative probability
0	160	1.0000000000000000000000000
10	150	0.2120043269780940000000000
20	140	0.0022399706536568600000000
30	130	0.0012620866609931700000000
40	120	0.0010272604102415500000000
50	110	0.0002171135037755950000000
60	100	0.0000014810230623751200000
——	——	——

From Table 4.7 and Table 4.8, the risk in (10 minutes, I hour) is R_b =0.000217113503775595-0.0000334473232062603=0.000183666180569335.

The total risk with a 1-hour period can be obtained eventually, which is $R = R_a + R_b$ =0.000171204369505394+0.000183666180569335=0.000354870550074729.

This value compares with the risk before optimization (0.00102715322998244) if no EWHs load is brought into service. Therefore, the UCR reduction can be 0.0006722826799.

Using the same method of calculating the UCR reduction shown above, the operating reserve capacity that aggregated EWHs could provide during other peak hours can be further calculated. The UCR reduction curve of EWHs in 24 hours is shown in Figure 4.9.

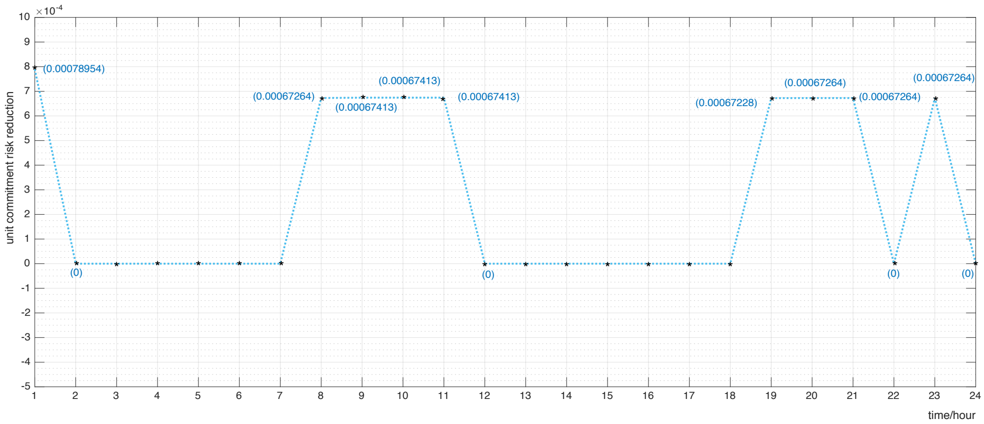


Figure 4.9 The UCR Reduction Curve

4.5 Conclusion and Future Work

This Chapter extends the generating system reliability analysis by treating EWHs load as interruptible and considering that they served as operating reserve to improve power system reliability. The aggregated EWHs load curve was proposed in this chapter based on the optimization strategy proposed in Chapter 3. The reliability index (unit commitment risk) was calculated, furthermore, the UCR reduction was analyzed.

The IEEE Reliability Test System proposed by Billinton, R. was used and modified to be the test system in this chapter. The 10MW operating reserve capacity of EWHs was proposed as an example of Unit Commitment Risk calculation and the results turned out that aggregated EWHs have good performance on reducing the Unit Commitment Risk. Then the total UCR reduction during other periods was calculated. The model used here is the rapid start unit model, which has similar characteristics with EWHs. From the numerical result, the EWHs load has been proved to be effective for reliability improvement. EWHs are able to provide operating reserve capacity to help the power system.

For future studies, the uncertainties of EWHs load should be taken into consideration when calculating the interruptible capacity the EWHs load could provide.

Chapter 5 Conclusion and Future Work

An optimization strategy was proposed in this thesis to reschedule EWHs to efficiently reduce customers' electricity bills and power system peak-hour loads. The optimization adopted a lightly modified BPSO algorithm considering the original EWHs operation status. As part of grid services, some basic information of EWHs should be known before optimization and scheduling. The thermal model and the customers' water usage profile were used to calculate the temperature and furthermore to calculate the optimization function within different temperature set point ranges. Some assumptions were made here to do the simulation of EWHs operations. Finally, using TOU price as DR incentive, the results show that BPSO has good performance on shifting peak load in different scenarios as well as reducing electricity cost for customers.

The comfort level index represents the comparison between water temperature after re-operation and the average temperature of set point range. The optimization process proved to be successful according to the value of comfort level index.

According to the interruptible capacity of aggregated EWHs which utilized the optimization strategy proposed in this thesis, the power system reliability will be improved. It's very important to use the proper model of aim appliances before taking them into account. The model of EWHs used to calculate the indices is the rapid start unit model because they have similar characteristics. Before calculating the UCR, the aggregated EWHs load has been simulated, so the capacity that EWHs load can provide can be obtained. Using the model and parameters known, the unit commitment risk has been carried out at last. Compare to the UCR before optimization, the risk has declined effectively. In other words, aggregated EWHs have good ability to provide operating reserve for enhancing power system reliability.

Residential users will be willing to participate in DR program if the strategy proposed in this thesis is utilized because of the visible economic benefits. Based on this optimization strategy, other home appliances that have the same characteristics with EWHs could also contribute themselves to power system reliability and help to shift the peak-hour loads.

For further study, real-time pricing (RTP) could be introduced into the optimization as DR incentive because RTP can reflect the load changes simultaneously. For the existing study in this thesis, the temperature changes are complex, so only TOU price is taken into account. As to the EWHs operational reliability, some uncertainties should be considered in the future research.

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