**International Conference on Applied Energy 2019**
**Aug 12-15, 2019, Västerås, Sweden**
**Paper ID: 155**

# SMART GRID PRIVACY PROTECTION STRATEGY BASED ON SOLAR ENERGY AND RECHARGEABLE BATTERY

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**ABSTRACT**

In smart grid, massive high-precision real-time electricity consumption data recorded in smart meter seriously threatens user privacy safety. In this paper, we propose an algorithm named DPRB (Data Precision Reduction Based) which can discretize smart grid energy supply into limited levels to control smart meter readings being several standard values rather than high-precision time-varying data, thus achieving the purpose of user privacy protection. We also consider time-sharing price and solar energy supply to reduce the total electricity cost. What's more, according to the different ways of selecting values of the power supply of smart grid, the DPRB algorithm is divided into the BCM-DPRB (Best-Cost-saving Method DPRB) algorithm and the RM-DPRB (Random Method DPRB) algorithm.

**Keywords:** smart grid, privacy protection, rechargeable battery, solar energy, GPRB algorithm

## 1. INTRODUCTION

Smart meter is the core component of smart grid. Compared with the monthly reading frequency of traditional meters, smart meters can achieve the reading frequency into minutes or even seconds getting massive high-precision real-time electric consumption data. It increases the risk of user privacy leakage. Once malicious attackers intercept data from smart meter through the eavesdropping technology, the specific electrical appliance usage can be mined by using the data mining technology such as NILM [1-3] and ED [4-5] which is used to infer the user's privacy information such as living habits, behavior patterns, and this information can be used to commit crimes such as burglary and kidnapping.

Therefore, it is necessary to study the privacy protection strategies in smart grid. At present, there are three main strategies including encryption, data tampering and battery-based load hiding (BLH). In encryption method, even if the encrypted power consumption data is intercepted, the attacker cannot decrypt the real data [6]. Data tampering method refers to injecting noise into the original power consumption data before the data is sent to the smart grid, which increases the uncertainty of power consumption data and achieves the effect of protecting user privacy. BLH method uses battery charging and discharging to change power consumption, so as to hide the situation of electrical appliances.

In this paper, we provide an algorithm using rechargeable batteries and solar energy together to make smart meter reading different from the real electric consumption of the user's appliances, achieving the purpose of user privacy protection. During this process, we also consider the time-sharing price to reduce the total electricity cost.

## 2. SYSTEM MODEL AND EVALUATION INDEX

### *2.1 System model*

Every user in smart grid owns a home microgrid. Based on this, we give a home microgrid model which consists of smart grid model, solar energy model, rechargeable battery model and household appliances model.

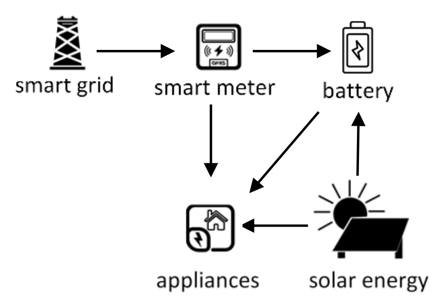


Fig 1 Electrical energy structur

Electrical energy structure is shown as Fig.1 and electrical energy circulation relationship is indicated by arrows. Electrical energy in home microgrid is continuously changing. The models of home microgrid in this paper discretize this process for the convenience of research.

2.1.1 Household appliances model

In $t$ time interval, the total amount of electricity used by household appliances is $X(t)$ where $t=\{1,2,\cdots,N\}$. $X_{\max}$ represents the state in which all household appliances work at maximum power in the $t$ time interval.

$$\mathrm{X}(t)\in\{\mathrm{X}(1),\mathrm{X}(2),...,\mathrm{X}(N)\} \tag{1}$$

$$\mathrm{X}(t)\le \mathrm{X}_{\max} \tag{2}$$

2.1.2 Smart grid model

The average electricity from smart grid in the $t$ time interval can be expressed as $Y(t)$. The electricity generated by solar energy cannot be delivered to smart grid in this paper, so the grid power supply must be non-negative, that is:

$$Y(t)\in\{Y(1),Y(2),...,Y(N)\} \tag{3}$$

$$0\le Y(t)\le X_{\max} \tag{4}$$

2.1.3 Solar energy model

The total amount of electricity generated by solar energy is $E(t)$ in $t$ time interval. But not all electricity generated by solar energy in the $t$ time interval can be effectively utilized. We write down the effective use as $E'(t)$, that is:

$$E(t)\in\{E(1),E(2),...,E(N)\} \tag{5}$$

$$0\le E'(t)\le E(t) \tag{6}$$

2.1.4 Rechargeable battery model

In $t$ time interval, $P(t)$ represents the charging and discharging power of rechargeable battery and $B(t)$ represents the amount of electricity in the battery. It is equal to the amount of electricity in the battery at last time interval plus battery charging or discharging electricity amount at the current time interval. $B_{\max}$ represents the maximum capacity of the battery.

$$B(t)=B(t-1)+P(t)t \tag{7}$$

$$0\le B(t)\le B_{\max} \tag{8}$$

Energy existence equality constraint in a home microgrid considered in this paper, that is, in every $t$ time interval, the electricity supplied by smart grid and solar energy should be equal to the sum of the electricity consumption of the household appliance and the charging or discharging of the battery.

$$Y(t)+E'(t)=X(t)+P(t)t \tag{9}$$

*2.2 Evaluation index*

To verify the effectiveness of DPRB algorithm, we define two evaluation indexes in this paper. $Plr$ (Privacy-leakage-rate) and $Csr$ (Cost-saving-rate). The definition of $Plr$ is based on the concept of self-information and mutual information.

Entropy function $H(X)$ is called the self-information of variable $X$. $I(X;Y)$ represents mutual-information.

$$Plr(X,Y)=\frac{I(X,Y)}{H(X)} \tag{10}$$

$Cost\_ref$ is the reference value of $\mathrm{Cos}t$ .It is calculated under the situation that there is neither adding rechargeable battery nor adopting any privacy protection strategy. $C(t)$ is the time-sharing price. In this case, smart grid power supply $Y_1(t)$ is equal to the household appliances electrical consumption minus solar energy supply.

$$\begin{gathered} Cost\_ref=\sum_{t=1}^{N}C(t)Y_1(t) \\ Y_1(t)=\left(X(t)-E'(t)\right) \end{gathered} \tag{11}$$

$\mathrm{Cos}t$ is the new electricity charges after using DPRB algorithm. The value of $Y(t)$ is calculated by the DPRB algorithm that will be introduced in Chapter 3.

$$Cost=\sum_{t=1}^{N}C(t)Y(t) \tag{12}$$

we define the $Csr$ as:

$$Csr=\frac{\mathrm{Cos}t-\mathrm{Cos}t\_ref}{\mathrm{Cos}t\_ref}\times 100\% \tag{13}$$

## 3. DPRB ALGORITHM PRINCIPLE

The principle of DPRB algorithm is to reduce smart meter reading precision. Based on BLH method, we suppose smart meter reading is equal to smart grid supply. Fig. 2 is an ideal case. From Fig.2, we can see, if we can make smart grid energy supply into limited levels to control smart meter readings being several standard values rather than high-precision time-varying data, the details will be blurred, and it is hard for attackers to know the specific usage of the household appliance and it is hard for attackers to know the specific usage of the household appliance.

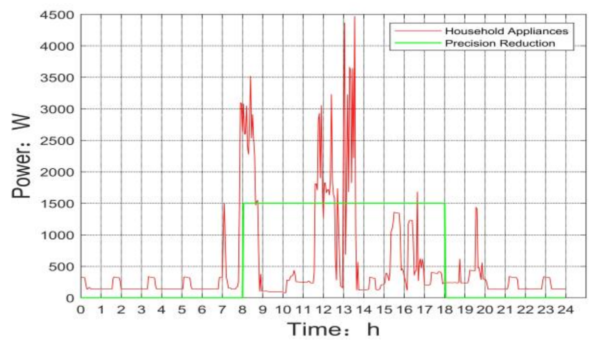

Fig.2 household appliances and household appliances after precision reduction

In order to reduce data precision, we hope that smart meter reading will remain unchanged value for a period of time instead of changing with the household appliances electrical consumption at all times. Considering (4) meanwhile, we define $Y(t)$ as following:

$$Y(t) = \varepsilon h(t) = h(t)\frac{X_{\max}}{h_{\max}} \tag{14}$$

where $h(t) \in \{0,1,2,...,h_{\max}\}$ .The value of $h(t)$ is the amplitudes of the smart grid power supply $Y(t)$. In this way, the smart meter reading will be discretized into multiples of $\varepsilon$ instead of household appliances electrical consumption data at all times, thereby achieving the purpose of protecting user privacy.

## 4. THE RANGE OF $h(t)$ IN DPRB ALGORITHM

To save electricity cost, we can consider two aspects. On the one hand, we need to reduce the amount of electricity obtained from smart grid, so the algorithm is designed to prioritize the electricity generated by solar energy. On the other hand, we can use time-of-use electricity price and let rechargeable battery store energy at low electricity prices, and release electricity at high electricity prices. Then, there are two situations based on DPRB algorithm.

**Situation 1:** when $E(t) > X(t)$, then set $Y(t) = 0$, that is , $h(t)$=0. The excess electricity $E(t) - X(t)$ is charging the battery.

**Situation 2:** when $E(t) \le X(t)$, the electricity generated by solar energy is totally used, that is, $E'(t) = E(t)$ . According to equation (9), under Situation 2, the charging and discharging of the battery is linked to smart grid. The method of confirming the range of $h(t)$ is given by time-sharing price to save cost in Situation 2.

- Low Price

In this case, battery should be in the state of charging, $P(t)t = E(t) + Y(t) - X(t) > 0$ ,consider (14),where, we get the following bounds hold on $h(t)$:

$$h(t) > \left\lceil \frac{X(t) - E'(t)}{E_{\max}} h_{\max} \right\rceil \tag{15}$$

Where function $\lceil a \rceil$ represents the smallest integer bigger or equal to $a$ .Then we get a new range of $h(t)$ at low price: $h(t) \in \{h_1(t), h_1(t)+1, ..., h_1^{\max}(t)\}$

Where $h_1(t) = \max\left\{0, \left\lceil \frac{X(t) - E'(t)}{E_{\max}} h_{\max} \right\rceil\right\}$ and $h_1^{\max}(t) = h_{\max}$ .

- High Price

In this case, battery should be in the state of discharging, $P(t)t = E'(t) + Y(t) - X(t) < 0$ , consider (14) , we get the following bounds hold on $h(t)$:

$$h(t) \le \left\lfloor \frac{X(t) - E'(t)}{X_{\max}} h_{\max} \right\rfloor \tag{16}$$

Where function $\lfloor a \rfloor$ represents the biggest integer smaller or equal to $a$ .Then we get a new range of $h(t)$ at high price: $h(t) \in \{h_1(t), h_1(t)+1, ..., h_1^{\max}(t)\}$

Where $\begin{cases} h_1(t) = 0 \\ h_1^{\max}(t) = \min\left\{h_{\max}, \left\lfloor \frac{C(t) - E'(t)}{C_{\max}} h_{\max} \right\rfloor\right\} \end{cases}$

## 5. THE SELSECTION OF $h(t)$ IN DPRB ALGORITHM

The key point of DPRB algorithm is the selection of $h(t)$ according to the description in the previous chapter. Chapter 4 give the rang of $h(t)$ . This chapter will give the method to select the specific value of $h(t)$ during its range. On the basis of different ways of selecting $h(t)$, DPRB algorithm is divided into BCM-DPRB method and the RM-DPRB method.

### *5.1 RM-DPRB Method*

In RM-DPRB algorithm, $h(t)$ is randomly selected according to uniform distribution within its optional range. Then, we have:

$$h(t) = randi([h_1(t), h_1^{\max}(t)]) \tag{18}$$

### *5.2 BCM-DPRB method*

In BCM-DPRB algorithm, at a low price, when the battery is in the state of low level, we choose the bigger $h(t)$ to accelerate the charging speed. At a high price, we choose the smaller $h(t)$ to slow down charging speed when the battery is in the state of high level. That is to say, there is an inverse proportional relationship between $h(t)$ and $B(t-1)$.

The mapping $f(g(B(t-1))): B(t-1) \to h(t)$ is given to realize the above idea: Mapping $g$ completes the mapping of battery power from continuous value $(0, B_{\max}]$ to discrete value $\{0, \ldots, h_1^{\max}(t) - h_1(t)\}$ as a percentage of capacity.

At low price:

$$h(t) = h_1^{\max}(t) - g(B(t-1)) \tag{19}$$

At high price:

$$h(t) = h_1^{\max}(t) + 1 - g(B(t-1)) \tag{20}$$

Where:

$$g(B(t-1)) = \begin{cases} \left\lfloor B(t-1) \dfrac{h_1^{\max}(t) - h_1(t)}{B_{\max}} \right\rfloor, & \textit{low price} \\ \left\lceil B(t-1) \dfrac{h_1^{\max}(t) - h_1(t)}{B_{\max}} \right\rceil, & \textit{high price} \end{cases}$$

## 6. SIMULATION RESULT

The simulation was performed using MATLAB. The original data of user household appliances data comes from REDD database [9] which published the actual data of residents in a Boston community. Radiation data is from NREL [10] (National renewable energy laboratory) website. Initial condition: battery capacity $B_{\max} = 13.5kWh$.

We set original $h_{\max} = 3$, then $h(t) \in \{0,1,2,3\}$, there are at most 4 states to be chosen. In Fig.3, they are 4469.47W, 2979.65W ,1489.82W and 0W. From Fig.3, we can see after applying BCM-DPRB or RM-DPRB, the smart reading is obviously different from the real household appliances electricity consumption. Both BCM-DPRB and BM algorithm can achieve the purpose of privacy protection. And at low price period (0:00-8:00&21:00-24:00), smart grid supplies more electricity than high price period (8:00-21:00) under BCM-DPRB and BM algorithm. They can also achieve the purpose of electricity cost saving.

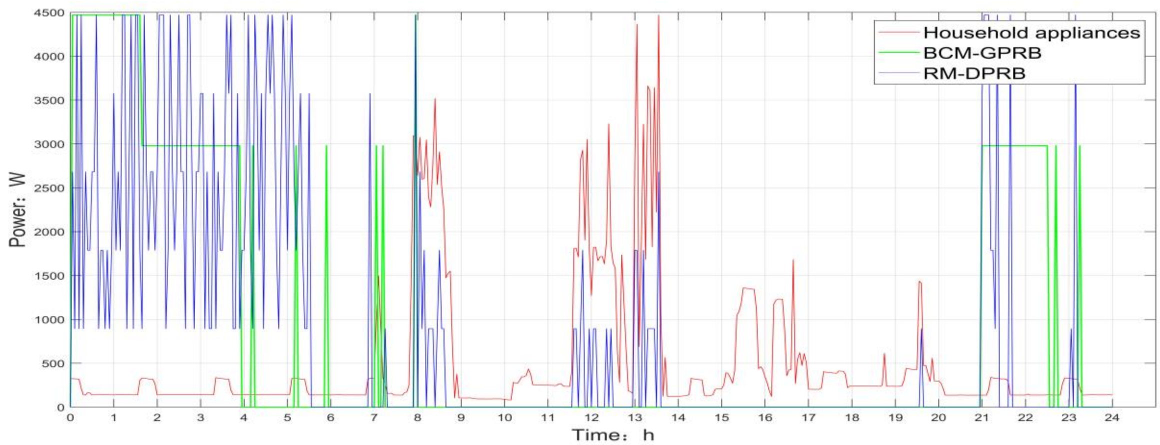

Fig.3 BCM and RM algorithm effect comparison chart

In Fig.4, under BCM-DPRB and BM algorithm, the value of $Plr$ is all small enough. From Fig.4, we can see, the bigger $h_{\max}$, the $Plr$ is higher. This is because the bigger value of $h_{\max}$ lead to the wider optional range of $Y(t)$ which can be more closer to the real household appliances electricity consumption.

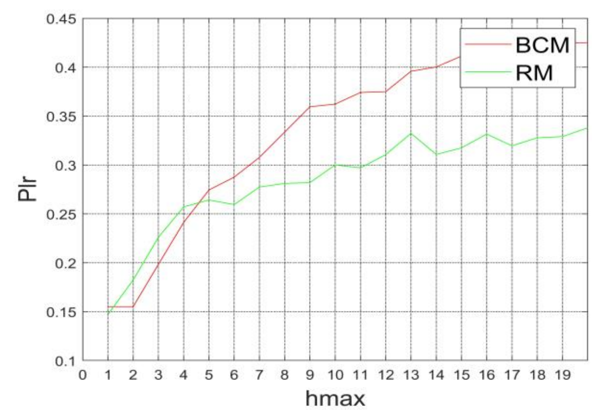

Fig.4 The effect of the value of $h_{\max}$ on $Plr$

In Fig.5, under BCM-DPRB and BM algorithm, the value of $Csr$ is all bigger than zero. It means they are all electricity cost saving algorithms.

Under same $h_{\max}$, BCM-DPRB method's cost-saving effect is better than RM-DPRB method. RM-DPRB method's privacy protection effect is better than BCM-DPRB method. This is because the choice of $h(t)$ value is more random in method RM-DPRB and BCM-DPRB algorithm can make sure the battery stores enough electricity near the end of the low-price situation, and releases enough electricity near the end of the high-price situation.

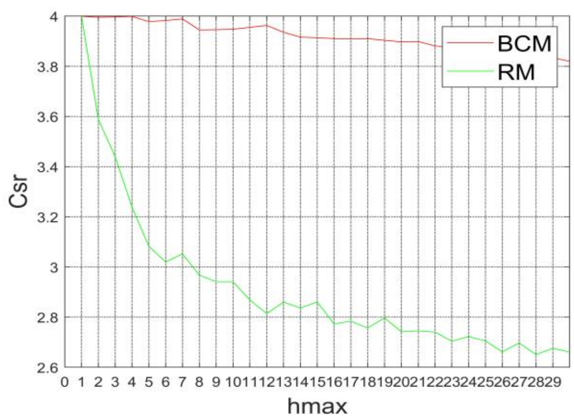


Fig.5 The effect of the value of $h_{\max}$ on $Csr$

**CONCLUSION**

In this paper, the DPRB algorithm is proposed in order to protect user privacy and save electricity cost. We hide the real user data by using solar energy and rechargeable battery. We successfully discretize the meter reading into the multiples of $\varepsilon$ by choosing appropriate $h(t)$. The simulation results show that the algorithm is effective.

This paper only considers using solar energy and rechargeable battery to protect electricity privacy. Consider adding more local energy devices to protect electricity privacy. Smart appliances, electric vehicles and other local energy devices still exist in the home microgrid. Making full use of these energy devices may achieve better privacy protection effect.

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