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# A Communication Performance Evaluation on Smoothing Power Fluctuations Based on Demand Response Control of Thermostatically-controlled Appliances

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## Abstract

Cyber security problem in energy system has been paid more and more attention recently. In this paper, impact of the packet loss and bit errors in the communication process on the performance of demand response was evaluated. Thermodynamic modelling mechanism of the typical electric heat pumps was first discussed. And, a novel heat pump demand response control strategy based on Optimal Temperature Regulation (OTR) was proposed. The control strategy was then applied to balance the power fluctuations caused by renewable energy. Packet loss and bit errors in the signal transmission were discussed, and their impact on the performance of the control strategy was analysed. Finally, case studies were used to validate the given method.

**Keywords:** Smart power consumption; Wind power; Distributed heat pumps; Demand response;

## 1. Introduction

Power supply has become one of the major economic and social life contradictions. The appearance of competition[1] in power market[2], the enhancement of the role of demand side resources playing in the electric market through price signals and incentive mechanism, and comprehensive planning and integration of the supply side and demand side resources, have become the inevitable requirement of development trend in the power market.

Wind power, solar energy and other renewable energy resources have the characteristics of randomness and intermittent, causing negative effects on power quality and reliability. Among most current solutions, setting the storage device for renewable energy to absorb injected power fluctuations are usually chosen, but due to its high cost, the use of residential thermostatically controlled appliances (TCAs)[3] to stabilize fluctuations of network node is more attractive.

As typical residential thermostatically-controlled appliances, heat pumps can be used as a kind of demand response resources providing auxiliary service of peak load shifting, virtual energy storage, load tracking and other variety of services[4] for power grid. To solve the problems like stabilizing the injected

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power fluctuations caused by distributed renewable energy, a variety of strategies to control demand response appliances can be applied.

Communication system is the base of demand response. In this paper, we want to evaluate the impact of packet loss and bit errors in the communication system on the control performance of demand response. A suitable model of demand response based on heat pumps was first derived, and its control strategy was proposed. And then, the influence of packet loss and bit errors in the signal transmission on the performance of the control strategy was analysed.

## 2. Modeling and control strategy of demand response based on heat pumps

### 2.1. Modeling of the heat pumps

An equivalent thermal parameters (ETP)[5][6] model of heat pump is used in this paper as follows.

$$\mathbf{A} = \begin{bmatrix} -\left(\frac{1}{R_m C_a} + \frac{1}{R_a C_a}\right) & \frac{1}{R_m C_a} \\ \frac{1}{R_m C_m} & -\frac{1}{R_m C_m} \end{bmatrix}, \mathbf{B} = \begin{bmatrix} \frac{1}{R_a C_a} & \frac{1}{C_a} \\ 0 & 0 \end{bmatrix}, \mathbf{T} = \begin{bmatrix} T_{a,k} \\ T_{m,k} \end{bmatrix}, \mathbf{C} = \begin{bmatrix} T_{o,k} \\ K_k \end{bmatrix} \tag{1}$$

$$\dot{\mathbf{T}} = \mathbf{AT} + \mathbf{BC} \tag{2}$$

Where  $C_a$  is the air heat capacity,  $C_m$  is the mass heat capacity,  $R_a$  is the air thermal resistant,  $R_m$  is the mass thermal resistant,  $T_o$  is the temperature outside,  $T_a$  and  $T_m$  are the air temperature and mass temperature inside,  $K$  is the electric operation rate.

The temperature and the power consumption have a one-to-one relationship. Thus, the model can be described as follows,

$$Q = CS \cdot Q_{op} = CS \cdot \frac{P_{rated}}{\eta_{AC}}, CS_k = \begin{cases} 1 & T_{k-1} \leq T_{-,k} = T_{s,k} - \frac{\delta}{2} \\ 0 & T_{k-1} \geq T_{+,k} = T_{s,k} + \frac{\delta}{2} \\ CS_{k-1} & \text{other wise} \end{cases} \tag{3}$$

where  $Q_{op}$  is the rating heat rate,  $CS$  is the off/on state,  $T_s, T_+, T_-$  represent the temperature set point, upper and down limits,  $\delta$  is the temperature range and  $T_a^{(0)}$  is the initial temperature inside.

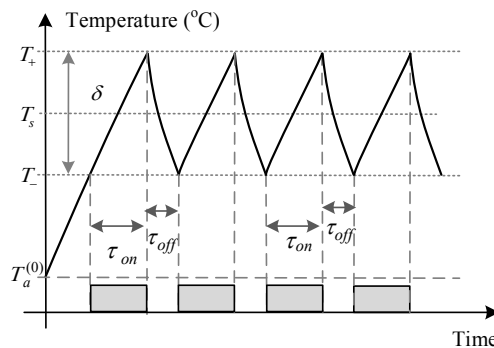


Fig.1. Operating characteristic of an individual heat pump

Fig.1 shows the operation characteristics of an individual heat pump.  $\tau_{on}$  is the time when the heat pump is on, while  $\tau_{off}$  is the time when the heat pump is off. Considering the difference on the regional distribution, model parameters, customer behaviour and so on, the parameters such as  $C_a, C_m, R_a, R_m$  have

randomized distributions. Normal distribution function  $N(a, \sigma)$  is used in this paper for different heat pump units to model typical load diversity[7]. The heat pump population with large majority can take part in demand response as a whole. With the increasing of the number of heat pumps, the power curve is going to be more stable and helping to achieve the goal.

2.2. Control strategy based on optimal temperature regulation (OTR)[8]-[10]

Heat pump is a typical TCA device, and temperature is its key operating and controlling parameter. In this paper, all heat pumps are grouped according to their temperature values. The heat pumps with the same temperature get together as a whole, represented by a square in Fig.2.(A). The heat pump population is distributed in the plane with the temperature as its vertical axis.

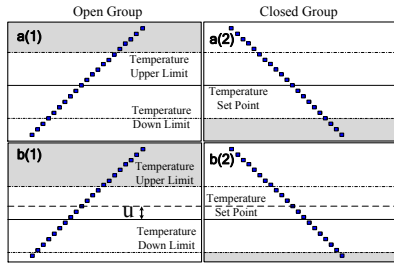


Fig.2. (A) Schematic diagram of load regulation

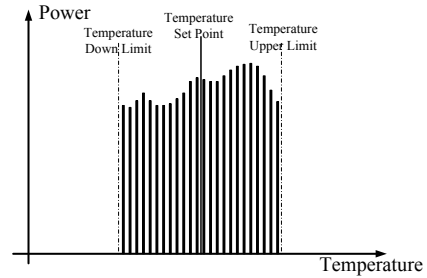


Fig.2. (B) Schematic diagram discrete temperature-power distribution

Sum of the power consumed by the heat pumps in on-state is the total power consumption of all heat pumps. And temperature regulated by heat pumps can be predicated when the next step is coming. Heat pumps near to the temperature upper limits in on-state are to be turned off, while those near to the temperature lower limits in off-state are to be turned on in the coming step. Thus the power change will be the difference of the power consumed by the heat pumps in the shadow of Fig2. (A) a(2) and Fig2. (A) a(1) in the next step. If the temperature set point is dropped, then its upper and lower limits are dropped. And, the number of switching heat pumps and their power consumption will also be changed accordingly. If the change of the power consumption can be controlled by the system operator, it can be used to balance the power fluctuation of the distributed renewable energy. Fig.2. (B) shows the relationship of temperature difference and power consumption changing. It can be used to the control strategy design.

To describe the power consumption of the heat pumps that have the same temperature state, two temperature-power factors are defined as follows:  $\varphi_{1,k}$  for the active and  $\varphi_{0,k}$  for inactive states.

$$\begin{aligned}
 \varphi_{1,k}(T_x) &= \sum_{i=1}^N y_{i,k} CS_{i,k} n(T_{a,i,k}, T_x), \\
 \varphi_{0,k}(T_x) &= \sum_{i=1}^N y_{i,k} (1 - CS_{i,k}) n(T_{a,i,k}, T_x), \\
 n(T_{a,i,k}, T_x) &= \begin{cases} 1, & (T_{a,i,k} = T_x) \\ 0, & (T_{a,i,k} \neq T_x) \end{cases}
 \end{aligned}
 \tag{4}$$

where  $T_x \in [-\infty, +\infty]$  is the temperature indoor,  $N$  is the number of heat pumps participating in the demand response.  $y_{i,k}$  is the active power of  $i$ -the device in step  $k$  and  $T_{a,i,k}$ ,  $T_{s,k}$  are its current temperature inside and temperature set point respectively.  $n(T_{a,i,k}, T_x)$  represents that only the devices in  $T_x$  will be calculated[10].

Eq.(4) describes the total power consumption of the whole heat pumps under a given temperature set point in step  $k$  and the potential power consumption when the devices in off-state are turned on. If the control signal (i.e. power change value) is known, power fluctuations caused by the renewable energy resources then can be smoothed by controlling the heat pumps through changing their temperature set point base on the so-called OTR algorithm [11].

Considering the distribution network with wind power generations and heat pump groups, we can use OTR control strategy to adjust the heat pumps to achieve the purpose of balancing power fluctuations on the tie line. We define three load types: nominal load  $P_N$ , heat pumps load  $P_H$  and wind power input  $P_W$ .

The idealized total net load is then:

$$P_L(k) = P_N(k) + P_H(k) - P_W(k) \tag{5}$$

In order to balance the wind power injection fluctuations, the power target of heat pumps can be calculated as follows:

$$P_{T,i}^*(k+1) = P_{W,i}(k+1) - P_{N,i}(k+1) + \frac{1}{2}[P_{L,i}(k) + P_{L,i}(k-1)] \tag{6}$$

where,  $i=1, 2, \dots, n$  for  $n$  individual heat pump groups.

Here, we assume that in step  $k+1$  the nominal load and wind power output are known. And then we set the heat-pump power target so as to minimize the deviations from the average total load over the last two sampling intervals. This control method is called 2-average control method given by [11].

### 2.3. Compensatory strategy of dealing with packet loss and bit errors

In customer sider, low cost communication techniques are usually used even in the stage of smart grid. Packet loss and bit errors often occur in the signal transmission. We assume that  $P_W$  will occur packet loss and bit errors in the process of signal transmission. If a packet loss occurs at current step, the control signal is maintained as the previous step; if a bit error occurs, the control signal is reversed then.

To weaken the influence of packet loss, we use the average value of  $P_W$  before the step  $k$  to replace  $P_W(k)$ . The target of heat pumps in step  $k$  can be expressed as:

$$P_{T,i}^*(k) = \frac{1}{k-1} \sum_{j=1}^{k-1} P_{W,i}(j) - P_{N,i}(k) + \frac{1}{2}[P_{L,i}(k-1) + P_{L,i}(k-2)] \tag{7}$$

Considering the wind power output  $P_W$  stays positive generally, we change the signal into absolute values. Then the Eq.(6) changes into:

$$P_{T,i}^*(k+1) = |P_{W,i}(k+1)| - P_{N,i}(k+1) + \frac{1}{2}[P_{L,i}(k) + P_{L,i}(k-1)] \tag{8}$$

Here, we call this control method as compensatory method.

## 3. Case study and discussion

In this section, IEEE 13 bus system and a scenario in [12] is employed to validate the proposed method. In the system, wind generator is integrated and the demand response is used to balance its output fluctuations.

### 3.1. Traditional control method

Fig.3 shows the output power flow change of node 671 with and without control under this strategy. Power variation rate can be used to probability density analysis and to evaluate the fluctuation condition.

In this paper, step of the simulation is 1 min. In the uncontrolled case, node 671 has large power fluctuations, which brings negative influence to power system operation. Under the control, it can be found the fluctuations are smoothed as shown by the red curve in Fig.3.

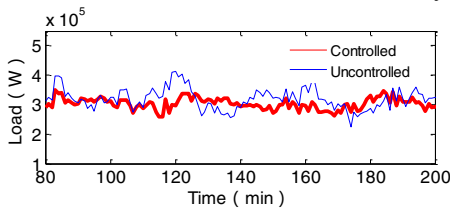


Fig.3. (a) Simulation results of power fluctuations

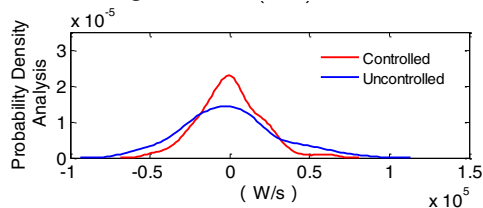


Fig.3. (b) Results of probability density analysis of power fluctuations

### 3.2. Influence of packet loss

In customer sider, packet loss often occurs in the signal transmission. Its influence on the control strategy of demand response will be discussed based on the method given in section 2.3. Degrees of packet loss defined in [13] will be used here. Fig.4.(a) gives the simulation results of the same node power fluctuations without packet loss and under the packet loss rate of 4%, 8%. And, the corresponding probability densities are shown in Fig.4. (b). It can be found that higher packet loss means larger power fluctuation. So, packet loss has a negative influence on the control obviously.

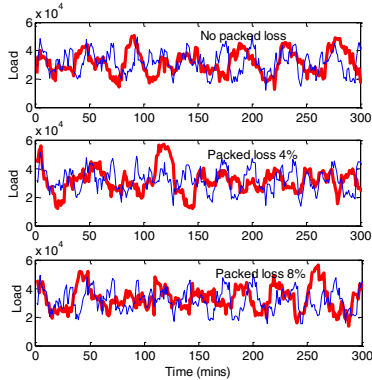


Fig.4. (a) Influence of different packet loss rate

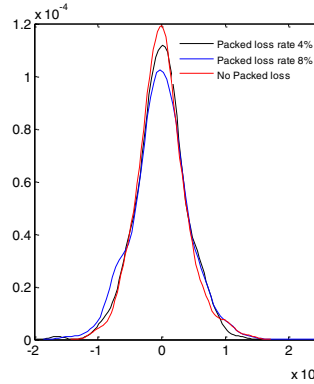


Fig.4. (b) Probability densities of different packet loss rate

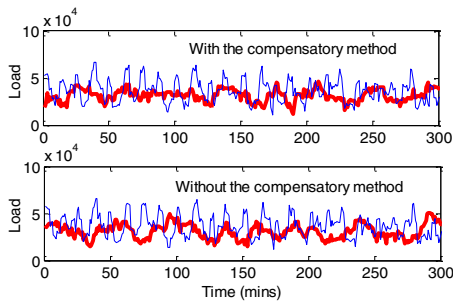


Fig.5. (a) Simulation results of power fluctuations

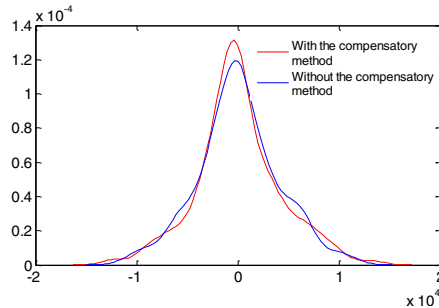


Fig.5. (b) Probability density analysis of compensatory method

Fig.5. (a) shows the simulation results of power fluctuation of node 671 with and without the compensatory method to deal with packet loss, and their probability densities are shown in Fig.5 (b). Under the control, it can be found the fluctuations are smoothed as shown by the red curve in Fig.5.

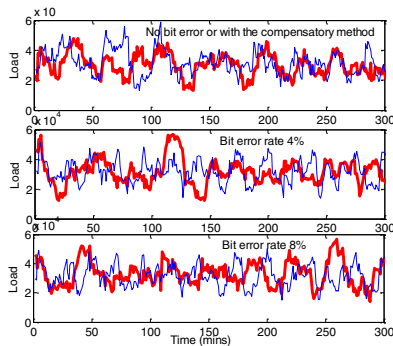


Fig.6. (a) Influence of different bit error rate

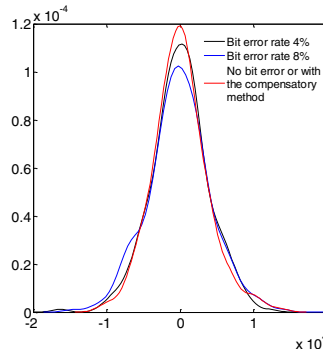


Fig.6. (b) Results of probability density analysis of differentbit error rate

### 3.3. Influence of bit error

Bit error is another common phenomenon in signal transmission. Its influence is discussed based on the method given in section 2.3. Fig.6. (b) shows the simulation results of the node fluctuations without bit error and under the bit error rate of 4%, 8% and Fig.6.(b) gives their probability densities. It can be found that higher bit error rate means larger fluctuations. Obviously, bit error also has a negative influence on the control.

When we use the compensatory method to deal with the bit error in the situation of bit errors occurring, the result will be the same as the case without bit errors.

## 4. Conclusion

Influence of packet loss and bit error in signal transmission on demand response based on heat pumps was evaluated in this paper. Models of single heat pump and demand response were first given. A control strategy based on optimal temperature regulation was then used to coordinate all heat pump devices. A simple power system with wind generator integration was selected to show the impact of packet loss and bit error on the control results. The simulations showed that such two phenomena both had negative influence to the demand response control strategy. So packet loss, bit error, signal attenuation, transmission delay, jitter problems and related problems should be carefully considered in the researches of demand response.

## 5. Acknowledgements

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## References

- [1] Tang Zhiwei, Sun Hanjing, Chen Qizhi. Interactive distribution grid under advanced metering infrastructure and demand response. *Proceedings of the CSU-EPSA*, 2011, 23(5): 31-34.
- [2] Zhang Qin, Wang Xifan, Wang Jian xue, et al. Survey of demand response research in deregulated electricity markets. *Automation of Electric Power Systems*, 2008, 32(3): 97-107.
- [3] Wang Dan, Parkinson S., Miao Weiwei, et al. Online voltage security assessment considering comfort-constrained demand response control of distributed heat pump systems. *Applied Energy*, 2012, 96: 104-114.
- [4] Callaway D.S., Hiskens I.A.. Achieving controllability of electric loads. *Proceedings of the IEEE*, 2011, 99(1): 184-199.
- [5] Li Yuyan, Chen Qian, Huang Wenying, et al. Dynamic characteristics and modeling of air conditioner loads. *High Voltage Engineering*, 2007, 33(1): 66-69.
- [6] Katipamula, Srinivas, and Ning Lu. Evaluation of residential hvac control strategies for demand response programs. *ASHRAE Transactions*, 2006, 112(1): 535-546.
- [7] Wang Dan, Ge Shaoyun, Jia Hongjie, et al. A demand response and battery storage coordination algorithm for providing microgrid tie-line smoothing services. *IEEE Transactions on Sustainable Energy*, 2014, 5(2): 476-486.
- [8] Parkinson S., Wang Dan, Crawford C., et al. Wind integration in self-regulating electric load distributions. *Energy Systems*, 2012, 3(4): 341-377.
- [9] Parkinson S., Wang Dan, Crawford C., et al. Comfort-constrained distributed heat pump management. *Energy Procedia*, 2011, 12: 849-855.
- [10] Miao Weiwei, Jia Hongjie, Wang Dan, et al. Active power regulation of wind power systems through demand response. *Science China Technological Sciences*, 2012, 55(6): 1667-1676.
- [11] Williams T., Wang Dan, Crawford C., et al. Integrating renewable energy using a smart distribution system: potential of self-regulating demand response. *Renewable Energy*, 2013, 52: 46-56.
- [12] Wang Dan, de Wit B., Parkinson S., et al. A test bed for self-regulating distribution systems: modeling integrated renewable energy and demand response in the GridLAB-D/MATLAB environment. *Proc. of 2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2012.1.16-1.20, Washington DC, US, pp.1-7.
- [13] Zheng Lei, Parkinson S., Wang Dan, et al. Energy efficient communication networks design for demand response in smart grid. *Proc. of 2011 International Conference on Wireless Communications and Signal Processing*, 2011.11.9.-11.11, Nan Jing, China, pp.1-6.