

Power Fluctuation Damping of Thermostatically Controlled Loads Based on State Estimation

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Abstract—As a kind of important demand side resource, the thermostatically controlled loads (TCLs) play an important role in the peak load shifting and load balancing programs. This paper establishes a state-queueing (SQ) model for the large-scale TCLs, and estimates the system states based on the Kalman-filtering. Based on state estimation, the control strategy, whose parameters are optimized by the genetic algorithm (GA), is designed to damp the power fluctuation of the TCLs. Finally, the effectiveness of the proposed method is verified.

Index Terms—Genetic algorithm, Kalman filter, state-queueing model, state estimation, thermostatically controlled loads.

I. INTRODUCTION

POWER demand side management refers to the management implemented by the power user. Demand side management has the potential to reduce the overall cost of generation, as the occurrences of the loads can be shifted at convenient times, thus making the load curve flat [1]. Direct load control (DLC) is a commonly used approach of demand side management [2]. Among all the electrical devices that participate in the DLC, the thermostatically controlled loads (TCLs) (such as air conditioners, refrigerators, and electric water heaters) have good heat/cold storage characteristics, causing less inconvenience for the users. The DLC of TCLs can be realized by temperature set-point control, on/off control, compressor frequency control, etc., aiming at reducing the peak load, saving the operation cost, and enhancing the stability of the power system [3], [4].

However, the large number of TCLs will impose heavy data processing burden on the control center. Long processing time may not meet the real-time requirements of power system scheduling and control. Furthermore, the curse of dimension may occur when the control center facing too many TCLs.

The state-queueing (SQ) model (or Markov model) is a TCLs modeling method. The SQ model characterizes the aggregated dynamics of TCLs through a state vector and a transition probability matrix, which not only saves the computation burden, but also reflects the temperature state information of aggregate TCLs [5]. The SQ model is not only suitable for the TCLs with homogeneous parameters [6], [7], but also for the TCLs with heterogeneous parameters, in which the transition probability matrix can be determined by Monte Carlo simulation [8], [9].

Although the SQ model provides an efficient way for modeling TCLs, it still faces more complicated problems in the actual control. Firstly, controlling the large number of TCLs may face data loss and out-of-sync problems. These uncertainties add difficulty in the control of the TCLs. Secondly, DLC may synchronize the states of the TCLs. The DLC signals are usually on/off control signals, which shifts the large number of TCLs into the same on/off states. Periodically switching these TCLs leads to fluctuation of the overall load. Damping control method is therefore needed. Focusing on the first problem [10], uses Kalman filtering to improve the performance of power-tracking control. However, the second problem is not concerned in [10].

To address this gap, this paper develops a power fluctuation damping control method for the TCLs, and uses Kalman filtering to estimate the states of the TCLs. The key parameters of the damping control are obtained by genetic algorithm (GA) to improve the overall control performance. The following of this paper can be summarized as follows: Section II describes the SQ modeling method for TCLs. Section III presents our TCLs' power fluctuation damping control method based on Kalman filtering. Testing results are analyzed in Section IV. Conclusions are provided in Section V.

II. SQ MODELING METHOD FOR THE TCLS

TCLs include electrical devices such as air conditioners, refrigerators, and electric water heaters, which have heat/cold storage capabilities. In order to maintain an approximately constant inside temperature, most TCLs need to periodically switch their on/off states during operation, as shown in Fig. 1. Given a temperature set-point T_{sp} and the dead-band ΔT , a minimum and maximum allowable variation range $[T_{min}, T_{max}]$ can be determined.

The temperature variation of an individual TCL can be de-

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$$C = C_1 = \underbrace{\begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}}_N \quad (6)$$

When the measured output $Y(k)$ is only the total power of the TCLs, C can take the following expression:

$$C = C_2 = P_{\text{ave}} \cdot n \cdot \underbrace{[0, \dots, 0]}_{\frac{N}{2}}, \underbrace{[1, \dots, 1]}_{\frac{N}{2}} \quad (7)$$

where n is the number of TCLs and P_{ave} is the average power of the TCLs in the “on” state. The approximate power of a large number of TCLs can be obtained by calculating $CX^T(k)$. When the observation includes both the elements of $X^T(k)$ and the total power of TCLs, C can be expressed as:

$$C = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} \quad (8)$$

In the following of this paper, C takes the form of (8).

III. TCLS POWER FLUCTUATION DAMPING CONTROL STRATEGY BASED ON STATE ESTIMATION USING KALMAN FILTER

The DLC of TCLs usually force a large number of TCLs to be “on” or “off” for a long time, in order to realize power-tracking control (track a reference load curve). However, the power-tracking control tends to synchronize the states of the TCLs. When the control is ended, the large number of TCLs probably switch “on” or “off” simultaneously, leading to aggregate power fluctuations [8]. In order to damp the power fluctuations of TCLs, the proper damping control strategy is needed at the end of power-tracking control.

The block diagram of the proposed TCLs power fluctuation damping control strategy is presented in Fig. 4. The states of a large number of TCLs are estimated by the Kalman filter, and the control signal is generated by the centralized damping control mechanism and sent to all the TCLs.

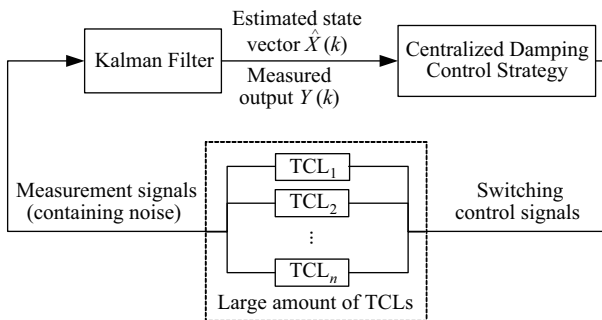


Fig. 4. Block diagram of the proposed damping control strategy.

A. State Estimation Using Kalman Filter

A large number of TCLs will face multiple uncertainties in actual control. On the one hand, the communication is faced with data loss problems during the control process. This uncertainty can be expressed as measurement noise. On the other hand, the DLC of TCLs is to some extent dependent on

the users' willingness of participation. This uncertainty can be expressed as system noise. In order to deal with these uncertainties, Kalman filtering method is used to estimate the state of a large number of TCLs.

After considering the uncertainties of mass TCLs, the state space equations of TCLs described in (3) and (4) can be modified to the following forms:

$$X^T(k+1) = AX^T(k) + BU(k) + W(k) \quad (9)$$

$$Y(k) = CX^T(k) + V(k) \quad (10)$$

where $W(k)$ and $V(k)$ are system noise and measurement noise, respectively, which reflect the uncertainties of TCLs in actual control. Assuming that Q and R are the covariance matrices of $W(k)$ and $V(k)$, the system state equations described in (9) and (10) can take the following steps to achieve Kalman filtering:

Step 1: Use the discrete state space model to calculate a priori estimate of the state vector at the next moment $\hat{X}_1(k+1)$:

$$\hat{X}_1(k+1) = A\hat{X}(k) + BU(k) \quad (11)$$

Step 2: Calculate a priori estimate of the covariance matrix $\hat{P}_1(k+1)$:

$$\hat{P}_1(k+1) = A\hat{P}(k)A^T + Q \quad (12)$$

Step 3: Calculate the Kalman gain:

$$H(k+1) = \hat{P}_1(k+1)C^T(C\hat{P}_1(k+1)C^T + R)^{-1} \quad (13)$$

Step 4: Correct the a priori estimate of the state vector $\hat{X}_1(k+1)$ to get the posterior estimate $\hat{X}(k+1)$:

$$\begin{aligned} \hat{X}(k+1) &= \hat{X}_1(k+1) \\ &+ H(k+1)(Y(k+1) - C\hat{X}_1(k+1)) \end{aligned} \quad (14)$$

Step 5: Update covariance matrix $\hat{P}(k+1)$:

$$\hat{P}(k+1) = (I - H(k+1)C)\hat{P}_1(k+1) \quad (15)$$

Repeat Steps 1–5 to achieve the best estimate of the state vector.

B. Control Strategy to Damp Power Fluctuation

The overall control strategy is shown in Fig. 5. Assume that the central controller obtains the states information of all TCLs through two-way communication. During power fluctuations, M is first initialized, and all TCLs are divided into M groups, and each group contains the same number of TCLs. Whenever time interval h is reached and at the same time the TCL's aggregate power is above a predefined threshold $P_{\text{agg}} > P_{\text{th}}$, the control is performed, and the value of M is increased by m . During control, one of the M groups of TCLs is selected and turned off (according to the predetermined priority order) until the power fluctuation is stabilized.

In the above definitions, h defines the minimum time-step-size for the damping control. Too small time-step-size is unnecessary and too large time-step-size would negatively affect the performance of the damping control. $P_{\text{agg}} > P_{\text{th}}$ defines the condition that switching-off signals are sent. Since

the control signals are switching-off signals, the control needs to be performed when majority of the TCLs are in the “on” state, which is judged by $P_{\text{agg}} > P_{\text{th}}$. Increasing M by m aims at reducing the number of switched TCLs whenever the damping control is performed. The larger M is, the intensity of the control reduces, until the power fluctuation of the TCLs is damped.

The damping control can be mathematically formulated as follows:

$$U(k) = \begin{cases} \begin{bmatrix} -\frac{x_N(k)}{M} \\ -\frac{x_{N-1}(k)}{M} \\ \vdots \\ -\frac{x_{N/2+1}(k)}{M} \end{bmatrix} & \text{Interval } h \text{ is reached} \\ & \text{and } P_{\text{agg}} > P_{\text{th}} \\ 0 & \text{Else} \end{cases} \quad (16)$$

Note that the control signal $U(k)$ is a mathematical description of the control signal, which is actually implemented by the strategy of Fig. 5. The element in $U(k)$ is the number of TCLs to be switched off in each state.

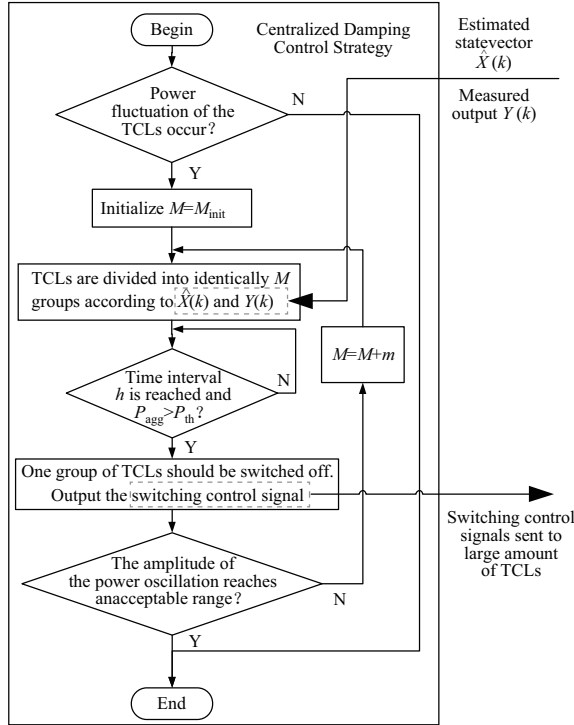


Fig. 5. Control method for stabilizing the fluctuation of the TCLs.

It can be seen that the control signal depends on the condition of time interval h , $P_{\text{agg}} > P_{\text{th}}$, as well as parameter M , which is dependent on the initial number of groups M_{init} , and the increasing value m . Proper determination of M_{init} , m and h is important for the control performance. However, since the control problem is discrete and time-variant (M varies with the time), traditional methods, such as linear quadratic regulator (LQR), is difficult to be applied. In this paper, the values of M_{init} , m and h are obtained by optimization.

The genetic algorithm (GA) is an optimization method based on the theory of biological evolution. Unlike the traditional methods, GA has no need for knowing the details of the system model, but only to calculate the objective function, and it is good at solving complex optimization problems. More details on genetic algorithms can be found in [11]–[13].

The steps for optimization using genetic algorithms are as follows:

- Step 1:* Randomly generate a number of candidate solutions;
- Step 2:* Calculate the fitness of each candidate based on the fitness function;
- Step 3:* Survive the fittest, select candidates with higher fitness, and eliminate candidates with lower fitness;
- Step 4:* Perform crossover operations. Randomly select two candidates and exchange their gene;
- Step 5:* Perform mutation operation. Randomly mutate the gene of the candidates;
- Step 6:* Repeat Steps 2–5 until the termination criterion or the maximum number of iterations is reached.

The fitness function of the optimization is defined as the integral of the absolute value of the power fluctuation amplitude of the aggregate TCLs:

$$\min \int_{t_1}^{t_2} |P_1(t) - P_{\text{mean}}| dt \quad (17)$$

where t_1 is the end time of the power fluctuation damping control, t_2 is the end time of calculation, $P_1(t)$ is the actual power of the aggregate TCLs from t_1 to t_2 , and P_{mean} is the average power of the aggregate TCLs from t_1 to t_2 . t_1 and t_2 should be sufficiently large values so that the power fluctuation is damped. The optimal values for M_{init} , m , and h can be obtained by using GA.

IV. TEST RESULTS

In the simulation, 10,000 air conditioners are considered. Assuming that they are operating in the cooling mode, the TCLs parameters are listed in the Appendix, which is the same as those in [9]. An SQ model for the 10,000 TCLs can be established by the Monte Carlo method. The state transition probability matrix is shown in Fig. 3.

A. State Estimation Based on Kalman Filter

Firstly, no additional control of TCLs is considered to test the performance of Kalman filtering. Consider the following four Cases:

Case 1: System noise and measurement noise are not considered (ideal case).

Case 2: System noise and measurement noise are considered without any noise filtering.

Case 3: System noise and measurement noise are considered, and a first-order Butterworth low-pass filter is used to filter the noise.

Case 4: System noise and measurement noise are considered, and Kalman filtering is used to estimate the status of a large number of TCLs.

In the four cases, the system noise and measurement noise are assumed to be normally distributed. The standard deviation

of the system noise is assumed to be 2% of the amplitude of the state vector, and the measurement noise is 20% of the maximum amplitude of the measurement.

Assuming that TCLs reach steady state at the initial time, the temperature of all TCLs is uniformly distributed. At $t = 0$ all TCLs are switched off. After that, no control is added to TCLs. The simulation time is set as 3 h. The simulation results are given in Fig. 6.

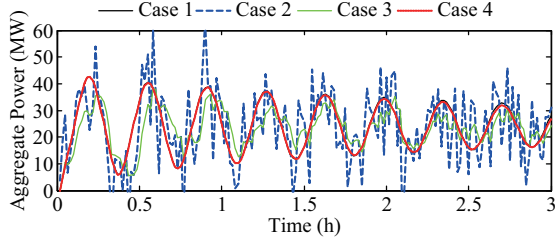


Fig. 6. Control method for stabilizing the fluctuation of the TCLs.

By comparison, we can see from Fig. 6 that when the system noise and measurement noise are considered (Case 2), the measured aggregate power of TCLs has large deviation from the ideal case (Case 1). The first-order Butterworth filtering (Case 3) can significantly filter the system noise and measurement noise, but there is still some deviation between the measurement results and Case 1; while the state estimation result of the Kalman filter (Case 4) is very similar to Case 1. It shows that the Kalman-filter-based state estimation can deal with the noise well and the result is close to the actual state.

For evaluating the performance of the state estimation based on Kalman filtering, the integrated square error (ISE) is used to calculate the accuracy of the state estimation, as shown in (18):

$$ISE = \int_0^T (P_{agg}(t) - P_{agg}^*(t))^2 dt \quad (18)$$

where P_{agg} is the actual measured total power of the TCLs, and P_{agg}^* is the total power of the TCLs in the ideal case (Case 1). The standard deviation of measurement noise (percentage account for the aggregate power magnitude) is increased from 5% to 30%. The curve of the relationship between ISE and noise's amplitude of Case 2–4 is shown in Fig. 7, reflecting that the ISE of the Kalman filtering state estimation (Case 4) is significantly lower than the other two cases when the measurement noise takes different amplitudes, indicating the accuracy of its state estimation.

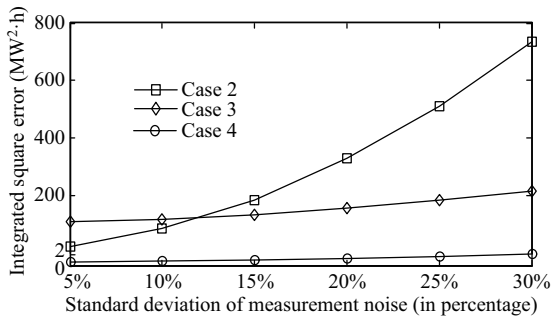


Fig. 7. The relationship between ISE and the noise's magnitude.

B. Power Fluctuation Damping Control in Complex Conditions

In the following examples, additional control is considered for 10,000 TCLs to study the entire control process of the TCLs. Assume that the TCLs are in steady state at the initial time. The entire control process includes three stages:

Stage 1: Power tracking control stage. Through the feedback control, the aggregate power of the TCLs keeps track of a reference load curve. The control strategy refers to [10].

Stage 2: Power fluctuation damping stage. Adopting the control strategy shown in Fig. 6, the aggregate power of TCLs is stabilized as soon as possible. By using GA, the optimal control parameters M_{init} , m , and h are obtained as $h = 2$ min, $M_{init} = 7$, $m = 1$.

Stage 3: The end stage. In this stage, no control is added to the TCLs, and its power curve is used to evaluate the degree of stability of the TCLs' aggregate power.

For contrast study, the following cases are considered:

Case 0: Ideal case, and the power fluctuation damping control is not considered in Stage 2.

Case 1: Ideal case, and the power fluctuation damping control is considered.

Case 2: Power fluctuation damping control is considered. System noise and measurement noise are considered without any noise filtering.

Case 3: Power fluctuation damping control is considered. System noise and measurement noise are considered, and a first-order Butterworth low-pass filter is used to filter the noise.

Case 4: Power fluctuation damping control is considered. System noise and measurement noise are considered, and Kalman filtering is used to estimate the status of many TCLs.

The simulation results are presented in Fig. 8. For further evaluating the control performance, ISE of actual aggregate TCLs' power curve and reference power of Stage 1 and Stage 3 are calculated. ISE of Stage 1 is used to evaluate the power tracking control performance, and ISE of Stage 3 is used to evaluate the control performance of power fluctuation stabilization. ISE of different cases are listed in Table I. From Fig. 8 and Table I, we can see that:

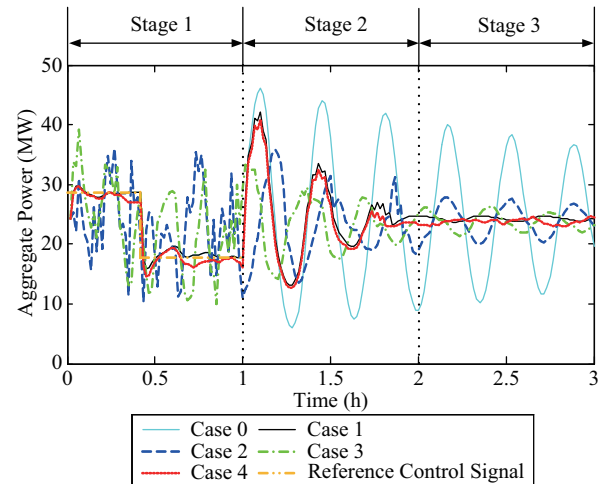


Fig. 8. Simulation results with stabilization control under three scenarios.

TABLE I
ISE OF THE TCLs' AGGREGATE POWER IN DIFFERENT SCENARIOS OF
STAGE 1 AND STAGE 3

	ISE (MW ² h)	
	Stage 1: Power tracking control stage	Stage 3: After control
Case 0	3.89	93.74
Case 1	3.89	0.11
Case 2	38.58	14.82
Case 3	80.80	2.86
Case 4	4.17	0.45

1) After the TCLs power tracking control (Stage 1) is completed, the aggregated power of TCLs fluctuates. Compared with the case that power fluctuation damping control is not adopted (Case 0), power fluctuations considering power fluctuation damping control are obviously suppressed (Case 1).

2) If system noise and measurement noise are considered (Case 2), the control results have large deviations from the ideal case (Case 1) both at the power tracking control stage and at end stage, and the aggregate load oscillates continually. The Butterworth low-pass filter (Case 3) can improve the control performance, but the effect is limited. By using the Kalman-filter-based state estimation (Case 4), the noise can be filtered and the control performance can be better and is very close to ideal case.

The effectiveness of the proposed power fluctuation damping method can be verified by the above results.

V. CONCLUSION

Based on the SQ model of TCLs, this paper designs a Kalman-filter-based TCLs state estimation method, which is applied to TCLs power fluctuation suppression. The simulation results verify the effectiveness of the method.

The main contributions of this paper are as follows:

1) The Kalman-filter-based state estimation algorithm is applied to power fluctuation damping control of the TCLs, which can significantly improve the control performances and improve the control robustness.

2) A power fluctuation damping control strategy is designed for TCLs and the genetic algorithm is used to optimize the key parameters so as to quickly stabilize the power fluctuation.

The future work may apply the proposed method to TCLs in a real power system and verify the effectiveness of the proposed method.

APPENDIX

The parameters of TCLs considered in the simulation are listed in Table A1.

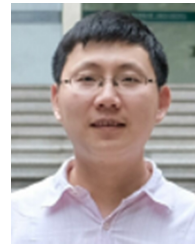
TABLE A1
TCLs PARAMETERS

Parameter	Mean value	Relative standard deviation (RSD)
T_{sp}	20 °C	0.1
ΔT	0.625 °C	0.1
T_0	32 °C	0
R	2 °C/kW	0.1
C	2 kWh/°C	0.1
Q	14 kW	0.1
η^*	2.5	0

* η is the transformation efficiency from electricity to heat (cold).

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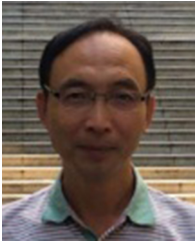
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