Control Parameters Optimization of Thermostatically Controlled Loads using Modified State-Queuing Model

Yu-Qing Bao, Pei-Pei Chen, Min-Qiang Hu, Xue-Mei Zhu

***Abstract*—Thermostatically controlled loads (TCLs) are one of the best candidates to participate in the direct load control (DLC). However, few attentions are given to the parameters optimization of the TCLs control system, due to the complexity of the TCLs' dynamics. In this paper, the parameters of the feedback control system based on the direct compressor control mechanism (DCCM) are optimized using the modified state-queuing (SQ) model, which can well characterize but greatly simplify the dynamics of the TCLs. The simulation results verify the effectiveness of the proposed method.**

***Index Terms*—Control parameters optimization, the direct compressor control mechanism, genetic algorithm.**

I. Introduction

RECENTLY, the direct load control (DLC), which is a kind of simple and practical way of load management, has received wide public concern. It is well known that the DLC is used mainly for reducing the demand of the peak load, shifting the load, or meeting the requirements of reliability [1]. With the development of the smart metering and high-speed communication technologies, the power consumption of the end-use appliances can be directly monitored and controlled through DLC and at the same time, the control means become more and more diversified.

Among all the end-use appliances which participate in the DLC, the most suitable appliances should be thermostatically controlled loads (TCLs), such as refrigerators, freezers, and water heaters. Because these loads can store thermal energy like batteries, and temporarily shutting down these loads would not cause much inconvenience to residents [2].

According to different mechanisms of TCLs participating in the DLC, the control methods can be mainly categorized into direct form [1], [3]-[5] and indirect form [2], [6]-[9]. The direct form means that the on/off states of the compressor in the TCLs are directly controlled to regulate the power. This form is also called the direct compressor control mechanism (DCCM) [10]. While in the indirect form, the parameters of the TCLs, such as the temperature set-points and the switch cycles of the TCLs, are indirectly controlled to regulate the power. If the parameters are the temperature set-points, this mechanism is also called thermostat set-point control mechanism (TSCM) [10]. The DCCM and TSCM can also be combined together to achieve better performance [10].

Though all sorts of methods are designed to control the TCLs, very few attentions have been given to the parameters optimization of the TCLs control system. One of the important reasons is that it takes a long time for simulation due to the complexity of the aggregate TCLs model.

So far there are some modeling approaches that can be applicable to the TCLs control system. The simplest one is the reduced-order linear time-invariant (LTI) model [11]-[13], which models the aggregate TCLs with a transfer function in order to simplify the TCL model. The LTI model can be used for the TCL controller parameters optimization. However, the LTI model is only a transfer function of the power and temperature. Thus it is only suitable for the TSCM, but is impossible for the DCCM. The recently proposed state-queuing (SQ) model is easier for extension compared with LTI model. It is used in characterizing the dynamics of large TCLs populations in many research works [7] [14]-[16]. However, to the best of our knowledge, the SQ modeling approach has not been used for parameters optimization of the TCLs control system. In addition, the traditional SQ model is not accurate enough according to the previous study [15].

To fill this gap, this paper puts forward a method for the controller parameters optimization of TCLs based on the modified SQ model. This paper is also an extension of our previous work [15]. This paper puts the modeling method [15], which proposes a modification method for improving the accuracy of the SQ model, into the application. Compared with [15], this paper makes the following progress: a) Considering close-loop control of TCLs based on DCCM, and b) Optimizing the control parameters based on genetic algorithm (GA).

The remaining of this paper is organized as follows: In Section II, the SQ modeling approach and the modified SQ model are presented. In Section III, the parameters optimization using the SQ model is provided. Testing results are analyzed in Section IV. Finally, conclusions are summarized in Section V.

II. THE STATE-QUEUING MODELING APPROACH

This section reviews the Equivalent Thermal Parameter (ETP) model of the individual TCLs, and further reviews the SQ modeling approach as well as the modified SQ modeling approach. Compared with the traditional SQ model, the modified SQ modeling approach can improve the accuracy of the SQ model.

A. Modeling of the Individual TCLs

Most TCLs should be periodically switched on and off with the purpose of maintaining the internal temperature in a predefined range, as shown in Fig. 1. The dynamics of individual TCLs can be represented by the ETP model. The discrete form of the ETP model for a single TCL can be written as [4]-[6], [10], [17]-[18]:

$$T_{\mathrm{i}}(t+1) = T_{\mathrm{i}}(t)\cdot e^{-\Delta t/RC} + (1-e^{-\Delta t/RC})\cdot(T_{\mathrm{a}}(t) - w(t)\cdot QR) \tag{1}$$

$$w(t+1) = \begin{cases} 0, & T_i(t+1) < T_- \\ 1\,, & T_i(t+1) > T_+ \\ w(t)\,, & \text{otherwise} \end{cases} \tag{2}$$

where t is the time step, T_{i} is the inside air temperature, T_{a} is the ambient temperature, Δt is the time step size, R is equivalent thermal resistance, C is equivalent heat capacity, Q is equivalent heat rate which is positive for the cooling mode and negative for the heating mode. w is a discrete variable which reflects the on/off states of the TCL (0 for off, and 1 for on). T_- and T_+ are the lower and upper limits of the inside temperature, and are usually determined by the temperature set-point and the dead-band ΔT (T_-=T_{set}–0.5ΔT and T_+= T_{set}+0.5ΔT) [5]. Note that though the accuracy and simplicity of the individual TCLs model, modeling the aggregate dynamics of large numbers of TCLs is not easy work due to the heavy computational burden.

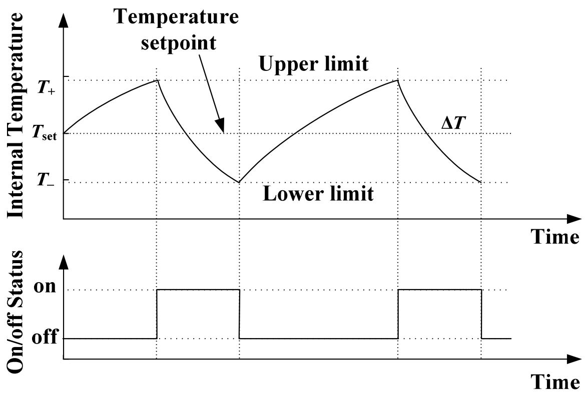

Fig. 1. The operating cycles of an individual TCL (in the cooling mode)

B. SQ Modeling Approach

To effectively model the aggregate dynamics of large numbers of numerous TCLs, SQ modeling approach is proposed [7], [16]. To implement the SQ modeling approach, the normalized temperature dead-band is divided into N_{off} and N_{on} intervals for both power-on and power-off states, as shown in Fig. 2. Let $x_i(k)$ denote the number of TCLs in state i at time step k. Then a state vector $\mathbf{X}(k)$=[$x_1(k)$, $x_2(k)$, …, $x_N(k)$] can be constructed to represent the aggregation of the TCLs. The time -depended variation of $\mathbf{X}(k)$ can be depicted by a state transition process, which can be represented by:

$$\mathbf{X}(k+1) = \mathbf{X}(k)\cdot\mathbf{P} \tag{3}$$

where $\mathbf{P}$ is a $N\times N$ transition matrix. The number of states N= N_{off}+N_{on} decides the size of the $\mathbf{P}$ matrix. According to the existing research works, we assume the N_{off} and N_{on} to be 20 [5] in the following examples if there is no special statement.

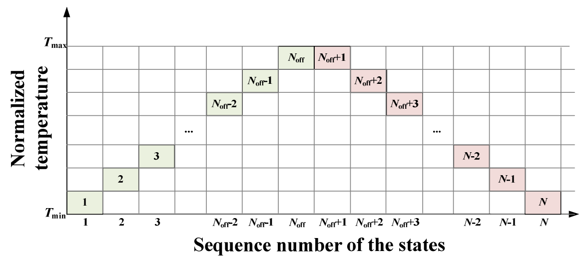

Fig. 2. The states of the SQ model (for the cooling devices)

For the TCLs with heterogeneous parameters, the $\mathbf{P}$ matrix can be derived by the Monte Carlo method [10]. The Monte Carlo method randomly creates a fleet of TCLs in a starting state. Based on the individual TCLs model, these TCLs' ending temperatures can be calculated, according to which the TCLs can be mapped into a number of ending states. Then the transition probabilities from the starting state to the ending states can be obtained.

To show an example of Monte Carlo method, we take State 1 as the starting state, and define uniformly distributed normalized temperatures for all the TCLs. At the next time step (one time step later), the ending temperatures of these TCLs can be calculated by (1). And the probability density is shown in Fig. 3. From Fig. 3(b) we can get the transition probabilities from State 1 to other states. Similar process can be taken to get transition probabilities from State 2-N to other states. Then the complete $\mathbf{P}$ matrix can be obtained.

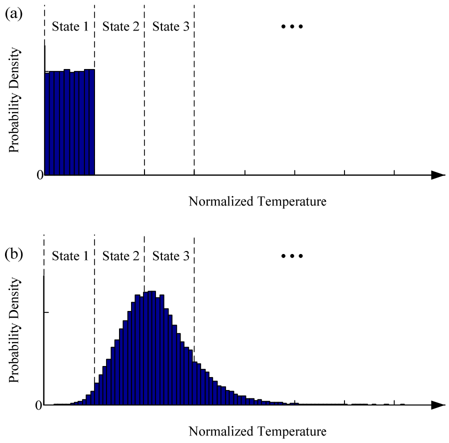

Fig. 3. An example of using the Monte Carlo method to get transition probabilities. (a) The probability density of the starting temperatures. (b) The probability density of the ending temperatures.

C. The Modified SQ Modeling Approach

Though the SQ modeling approach is computationally efficient, it is not accurate enough in characterizing the aggregate dynamics of TCLs.

The fundamental reason lies in that the aggregate TCLs do not exactly have the Markov property, which is the basic condition for the Markov-chain like modeling approach, such as the SQ modeling approach which is based on the transition matrix. Markov property requests that the future state $\mathbf{X}(k+1)$ depends only upon the present state $\mathbf{X}(k)$, and does not depend on the past (e.g. $X(k-1)$). However, the aggregate TCLs do not exactly have the Markov property according to [15]. More details about the Markov property analysis of the aggregate TCLs refer to [15].

To fill this gap, a modified SQ modeling approach is proposed in [15] to improve the accuracy of the SQ model. In the modified SQ modeling approach, the transition matrix is modified by

$$\mathbf{P}' = \mathbf{P} \cdot \mathbf{M} \tag{4}$$

$$\mathbf{M} = \begin{bmatrix} a & b & \cdots & b & b \\ b & a & & b & b \\ \vdots & & \ddots & & \vdots \\ b & b & & a & b \\ b & b & \cdots & b & a \end{bmatrix} \tag{5}$$

where $\mathbf{P}$ is the originally derived transition matrix and $\mathbf{M}$ is the modification matrix. To maintain the total number of TCLs consistency, the sum of the elements of each row of $\mathbf{M}$ should be 1, according to which the following relationship can be obtained:

$$a + (N-1)b = 1 \tag{6}$$

The parameter a can be determined by the optimization method [15]. After a is determined, the $\mathbf{M}$ matrix can be derived through (5) and (6). Then the transition of the states can be updated as following:

$$\mathbf{X}(k+1) = \mathbf{X}(k) \cdot \mathbf{P}' \tag{7}$$

To testify the effectiveness of the modified SQ model, we parameterize 25000 TCLs using the parameters in Table I. The $\mathbf{P}$ matrix can be obtained, and the values of a and b in the $\mathbf{M}$ matrix is calculated to be 0.9993 and 1.8×10^{-5}, respectively. For comparison, the individual TCLs model is taken as the benchmark to testify the accuracy of the other two SQ models (SQ model and modified SQ model). The simulation results are shown in the Fig.4. From Fig.4 it can be observed that the modified SQ model can more accurately characterize the aggregate dynamics of the TCLs.

TABLE I
THE PARAMETERS OF THE TCLS

Parameter	Mean value*	Relative standard deviation (RSD) of normal distributions
T_{set}	20°C	0.15
ΔT	0.625°C	0.15
T_a	32°C	0
R	2°C/kW	0.15
C	2 kWh/°C	0.15
Q	14kW	0.15
η	2.5	0

*The mean value of the TCLs' parameters refers [5]

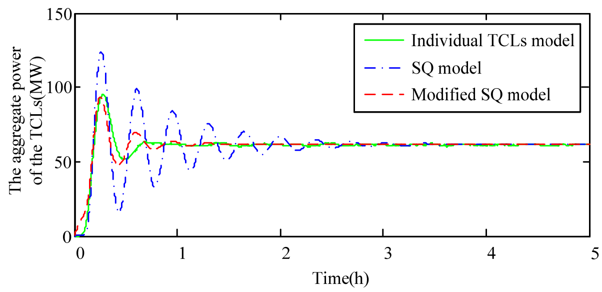

Fig. 4. The simulation results with different models

III. THE PARAMETERS OPTIMIZATION USING THE SQ MODEL

In this section, the feed-back control system of TCLs is developed and the SQ-model-based optimization technique is proposed to improve control performance of the TCLs.

A. The TCLs Control Method in the DLC

The overall structure of the TCLs control method is shown in Fig. 5(a). The overall control framework is a centralized architecture which is based on the two-way communications between the control center and the individual TCLs. The central controller meters all or a subset of the TCLs to estimate the states of TCLs in real time [5].

The DLC of the TCLs is to trace the aggregate power of the TCLs to a reference control signal, which is generated according to a desired load profile. The reference control signal can be co-optimized with other resources in the day-ahead scheduling, in order to minimize the operation costs and satisfy the temperatures limitations of the TCLs. Due to the page limits, this paper does not discuss much about the determination of the reference control signal. More details on determining the reference control signal can be found in [19].

To trace the reference control signal, the aggregate power of the TCLs is selected as the feedback signal and then is subtracted from the reference control signal, in order to get the error signal P_{error}. After computed by the controller, a control signal $u_{\text{controller}}$ is generated and sent to individual TCLs.

For different control mechanisms, the forms of the $u_{\text{controller}}$ are different. In the TSCM, the $u_{\text{controller}}$ is the temperature set-point of the TCLs. This paper is based on a DCCM namely broadcasting control mechanism [5], in which $u_{\text{controller}}$ is transformed into the switching probability of the TCLs.

The details of the broadcasting control mechanism is shown in Fig.5 (b). When the control signal $u_{\text{controller}}$ is computed, it is transformed into the switching probability s_{p} of TCLs according to the available TCLs. When $u_{\text{controller}}>0$, s_{p} is a switching-on probability, and s_{p} can be computed by $s_{\text{p}}=|u_{\text{controller}}/P_{\text{off}}|$. On the contrary, when $u_{\text{controller}}<0$, s_{p} is a switching-off probability, and s_{p} can be computed by $s_{\text{p}}=|u_{\text{controller}}/P_{\text{on}}|$. P_{off} and P_{on} are the total power of the available TCLs in the off state and the on state, respectively. After s_{p} is generated, it is broadcasted to all TCLs.

When each TCL receives s_{p}, it should firstly determine whether s_{p} is in accordance with its current state (switching on/off probability for on/off state). And then it generates a random number between 0 and 1 to determine whether it should be switched. If the random number is smaller than s_{p}, it is switched, and vice versa.

By this way, an approximate desired power of the aggregate TCLs can be obtained.

When modeled by the SQ model, the state vector $\mathbf{X}(k)$ is modified according to s_{p} at each time step. If $s_{\text{p}}>0$, the state vector can be modified by $\mathbf{X}'(k)=[(1-s_{\text{p}})x_1(k), (1-s_{\text{p}})x_2(k), \ldots, x_N(k)+s_{\text{p}}x_1(k)]$, and vice versa.

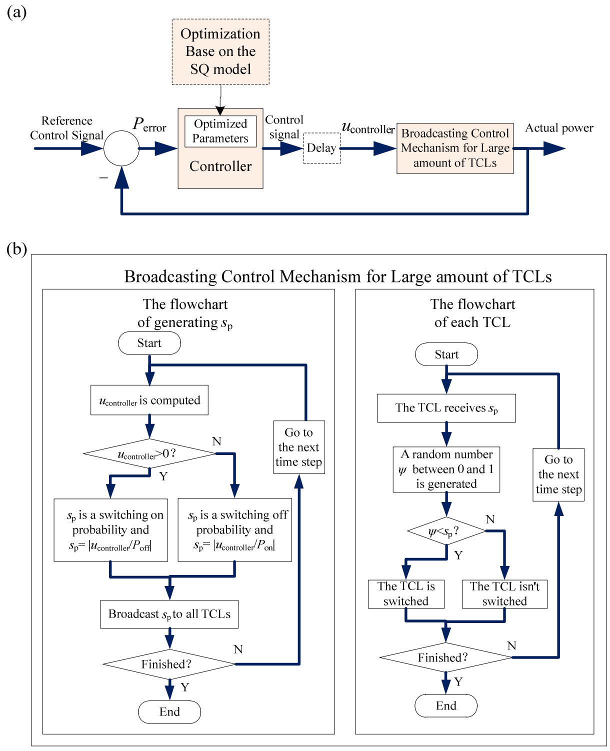

Fig. 5. The structure of the TCLs control method in the DLC

Besides the control mechanism, the central controller is also very important to the overall control performance. In most cases, the error signal is directly selected as the control signal of the TCLs [4]-[7], [10] since the error signal reflects the gap between the desired and actual power. Such method works well by simulation under ideal conditions. However, it faces problems when considering a comparatively large controller delay and a controller sampling period.

The aggregate dynamics of the TCLs is very close to a second order system [6] [13]. And the Proportional- Integral (PI) controller has a good performance to stabilize the second order delay system (a second order system with pure delay) [20]-[22]. So in this paper, the PI controller is adopted. The discrete time model of the PI controller can be expressed by:

$$u_{\text{controller}}(k) = K_{\text{P}}P_{\text{error}}(k) + K_{\text{I}}\sum_{i=0}^{k}P_{\text{error}}(i) \tag{8}$$

where P_{error} is the error signal, K_{p} and K_{I} are the parameters of the PI controller. In this paper, K_{p} and K_{I} are determined based on the optimization technique, which is introduced in the next subsection.

B. Parameters Optimization based on the Genetic Algorithm (GA)

The SQ model is used herein to optimize the control parameters of the TCLs control system.

For the tracing control system, the objective is to keep the tracing error as small as possible. Therefore, in our problem, the objective function can be formulated as the integrated square error (ISE) of the aggregate TCLs' power:

$$\text{Min} \quad \int_0^T \left(P_{\text{error}}(k)\right)^2 \mathrm{d}t \tag{9}$$

The optimization consider a steady-state initial condition of the TCLs suffering from a step change of the reference signal. Based on the objective function (9), the optimization can be implemented. In our problem, the task of the optimization is to find the best values of the parameters K_p and K_I, so that the objective function (9) is minimized. However, the objective function (9) is a nonlinear function which may make the optimization problem ill-conditioned and multimodal, and traditional optimization methods (e.g. Gradient-based methods) may have difficulties in achieving a satisfactory solution [23]. In this paper, GA is adopted to solve this optimization problem.

The GA is a modern robust optimization technique based on the principles of evolution. Different with traditional optimization methods, the GA has better global optimization ability regardless of the gradient information of the objective function. In most instances, the stability can be guaranteed with a properly defined objective function. These features enable GA to be used in various fields and solve different kinds of complicated problems [24].

The key idea of the GA-based optimization for determining the parameters can be summarized as following:

Step 1: Initialize the parameters. In a predefined range, generate a set of random values of the parameters.

Step 2: Calculate the objective function. Find the best values of the parameters in the set (these values of the parameters may lead to smaller value of the objective function).

Step 3: Generate new parameters. According to the best values of the parameters, a new set of random values of the parameters are generated by execute reproducing, crossover and mutation operation. Usually, the new set of values is better than the previous set. Return Step 2.

By implementing above three steps for dozens of times, the best values of the parameters can be found. More details about the GA-based optimization can be found in [25]-[27].

IV. Testing Results

In this section, case studies are performed and compared to testify the parameters optimization based on the SQ model.

A. Simulation Results under Step Change of the Reference Signal

The simulation considers large numbers of TCLs with the same condition as Subsection 2.3. For comparison, the following two control methods are considered in this simulation:

1) Un-optimized: When TCL feedback control is designed, control signal $u_{\text{controller}}$ is directly defined as P_{error} (K_P=1, K_I=0), which is the same as many existing methods ([4]-[5]).
2) Optimized: PI controller is adopted and the control parameters are obtained with the proposed method (optimized based on the modified SQ model).

Considering 1s controller sampling period and different communication delay, the optimization results are that: (a) 1s communication delay: K_P=0.5374, K_I=0.0022, and (b) 2s communication delay: K_P=0.3482, K_I=0.0013.

The time-domain simulation results are shown in Fig.6. It can be seen from Fig.6 that the optimized method based on the modified SQ model (the proposed method) performs better in tracing the reference signal than the un-optimized method, particularly under the situation with 2s communication delay.

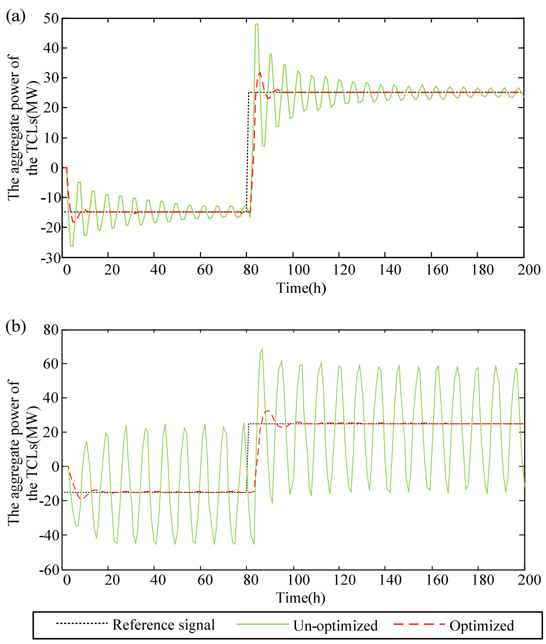

Fig. 6. The simulation results under step disturbance (with controller sampling period 1s. (a) 1s communication delay. (b) 2s communication delay.

Taking different controller sampling period, as well as different communication delay into account, the optimization results are shown in the Table II.

TABLE II
THE OPTIMIZATION RESULTS UNDER DIFFERENT COMMUNICATION DELAY AND DIFFERENT SAMPLING TIME OF THE TCLS CONTROLLER

		Under different communication delay			
		1s		2s	
		K_P	K_I	K_P	K_I
Under different sampling period of the TCLS controller	1s	0.5374	0.0022	0.3482	0.0013
	2s	1.0013	0.0076	0.5403	0.0022
	5s	1.0049	0.0118	1.0077	0.0099

From Table II it can be seen that different values of controller sampling period and communication delay can result in different optimal control parameters K_P and K_I. With larger values of the controller sampling period, the obtained optimal K_I tends to be larger.

B. Simulation Results under More Complicated Situation

In this subsection, the more complex situation is considered. In the following simulation, slightly varying ambient temperature is considered, and the reference control signal of the TCLs are obtained through reducing the unbalanced load data between 11:00 and 13:00 in reference [28] by 60% and then using the linear interpolation. The ambient temperature and the reference control signal are shown in Fig. 7(a) and Fig. 7(b), respectively. To develop the SQ model, T_a is assumed to be 32°C. The controller sampling period and the communication delay are both set to be 1s.

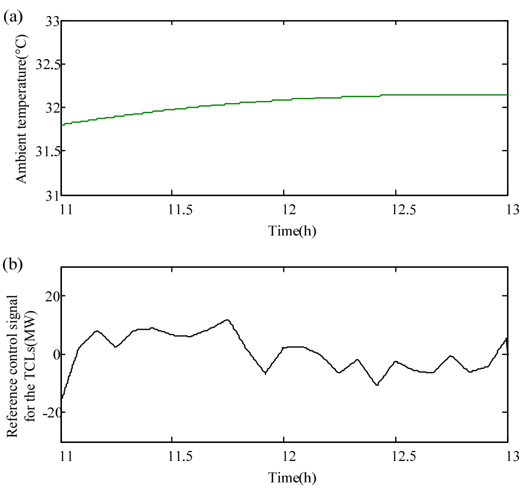

Fig. 7. The ambient temperature and reference control signal for simulation. (a) The ambient temperature. (b) The reference control signal for the TCLs

Three methods are taken into account:

1) Un-optimized: Control signal $u_{controller}$ is directly defined as P_{error} (K_P=1, K_I=0).

2) Optimized-SQ: PI controller is optimized based on the traditional SQ model. The optimized parameters are K_P=0.5366, K_I=0.0017.

3) Optimized-modified-SQ: PI controller is optimized based on the modified SQ model. The optimized parameters are listed in row 1, column 1 of Table II (K_P=0.5374, K_I=0.0022).

The simulation results are shown in Fig. 8. It can be seen that the optimized PI controller based on the SQ model can trace the reference signal more accurately than the un-optimized PI controller. Besides, the optimization results of the SQ model are very close to those of the modified SQ model, as well as the simulation results, which indicates that the SQ model and the modified SQ model are both applicable to the parameters optimization of the TCLs controller.

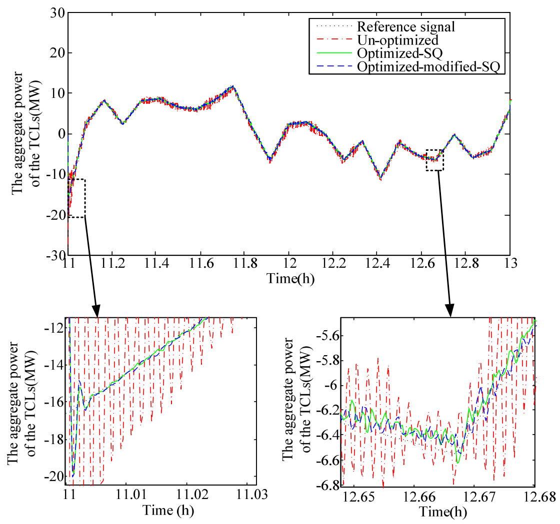

Fig. 8. The simulation results under more complicated situation (with controller sampling period 1s)

The above simulation results reveal that the parameters optimization based on the (modified) SQ model can significantly improve the performance of the TCLs controller. In addition, the modified SQ model can also be used to simulate the dynamics of the TCLs and therefore validate the control performance. In the following simulation, the reference signal is the same as Fig. 7 and Fig. 8, but the variation trend of the TCLs' aggregate power after the control is taken into account. The following three models are compared:

1) Individual TCLs model, as the benchmark verifying the next two models
2) SQ model
3) Modified SQ model

From Fig. 9 it can be seen that in the first 2 hours, when TCLs are in the power tracing control, the simulated curves of the TCLs' aggregate power based on the SQ model and the modified SQ model are both very close to that of the individual TCLs model. But after the control, the simulated curves of the TCLs' aggregate power exist rebound phenomenon. The rebound phenomenon of the modified SQ model is much closer to the individual TCLs model, which indicates that when the TCLs under the non-controlled conditions for a long time, the modified SQ model can characterize the variation trend of the aggregate power of the TCLs more accurately than the traditional SQ model. This advantage makes the modified SQ model able to precisely estimate the rebound of the TCLs after DLC, and enables the operators to take measures to restrain it.

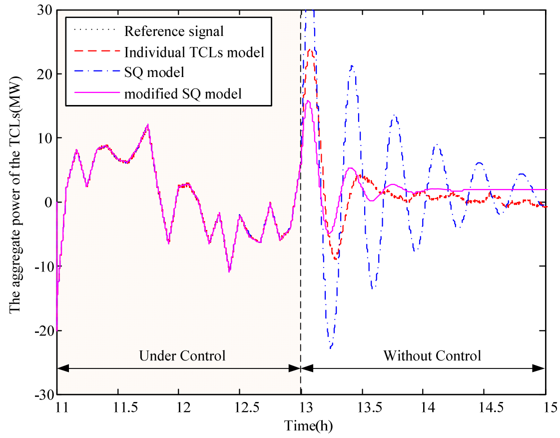

Fig. 9. The simulation results with different models

V. Conclusion

In this paper, a method for parameters optimization of the TCLs control system using the SQ model is proposed. The proposed method is based on the modified SQ model proposed in [15]. With the proposed method, the TCLs' aggregate power can better trace the reference signal and the modified SQ model can better characterize the aggregate dynamics of the TCLs. Compared with the existing works, the main contribution of this paper can be concluded as following:

1) A method for the parameters optimization of the TCLs control system is proposed, which is able to optimize the control parameters based on the DCCM.

2) This paper applies the method proposed in [15] in the parameters optimization of the TCLs control system. Compared with the traditional SQ model, the modified SQ model is able to characterize the dynamics of the TCLs more accurately.

The proposed method is suit for TCLs of which power are discretely adjusted (periodically change the on/off states). For those variable-frequency TCLs of which power can be continuously adjusted, the SQ model cannot be used. However, the control of these TCLs is much easier than managing the on/off states of the TCLs (such as DCCM).

In our future work, we will seek for opportunities to verify the effectiveness of the modified SQ model characterizing the aggregate the dynamics of TCLs when applied in a real system. Besides, we will consider some more special complicated control methods to cope with the uncertainties and the communication delay of the TCLs, and apply the proposed technique to optimize the control parameters.

Acknowledgments

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References

[1] N. Lu, Y. Zhang, "Design Considerations of a Centralized Load Controller Using Thermostatically Controlled Appliances for Continuous Regulation Reserves," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 914-921, 2013.

[2] Z. Xu, J. Østergaard, M. Togeby, "Demand as frequency controlled reserve," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1062-1071, 2011.

[3] S. Iacovella, F. Ruelens, P. Vingerhoets, B. Claessens and G. Deconinck, "Cluster Control of Heterogeneous Thermostatically Controlled Loads Using Tracer Devices," in IEEE Transactions on Smart Grid, vol. 8, no. 2, pp. 528-536, March 2017.

[4] N. Lu, "An evaluation of the HVAC load potential for providing load balancing service," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1263–1270, 2012.

[5] J. L. Mathieu, S. Koch, D.S. Callaway, "State Estimation and Control of Electric Loads to Manage Real-Time Energy Imbalance," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 430-440, 2013.

[6] C. Perfumo, E. Kofman, J. H. Braslavsky, J.K. Ward, "Load management: Model-based control of aggregate power for populations of thermostatically controlled loads," *Energy Conversion and Management*, vol. 55, no. 3, pp. 36-48, 2012.

[7] N. Lu and D. P. Chassin, "A state queuing model of thermostatically controlled appliances," *Proc. IEEE PES Power Syst. Conf. Expo.*, 2004, pp. 725–733.

[8] Aunedi M, Kountouriotis P-A, Calderon J E O, et al. Economic and Environmental Benefits of Dynamic Dem and in Providing Frequency Regulation [J]. IEEE Transactions on Smart Grid, 2013, 4(4): 2036-2047.

[9] S. H. Tindemans, V. Trovato and G. Strbac, "Decentralized Control of Thermostatic Loads for Flexible Demand Response," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 5, pp. 1685-1700, Sept. 2015.

[10] C. H. Wai, M. Beaudin, H. Zareipour, A. Schellenberg, N. Lu, "Cooling Devices in Demand Response: A Comparison of Control Methods," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 249-260, 2015.

[11] Cristian Perfumo, Julio H. Braslavsky, and John K. Ward, "Model-Based Estimation of Energy Savings in Load Control Events for Thermostatically Controlled Loads," IEEE

Transactions on Smart Grid, vol. 3, no. 5, pp. 1410-1420, 2014.

[12] N. Zemtsov, J. Hlava, "Aggregated Control of Electrical Heaters for Ancillary Services Provision," 19th International Conference on System Theory, Control and Computing, pp. 508-513, 2015.

[13] X. Hu, B. Wang, S. Yang, T. Short, L. Zhou. "A closed-loop control strategy for air conditioning loads to participate in demand response," *Energies*, vol. 8, no. 8, pp. 8650-8681, 2015.

[14] J. Hlava and N. Zemtsov, "Secondary control with thermostatically controlled loads using MPC based on extended bin state transition model," 2016 21st International Conference on Methods and Models in Automation and Robotics (MMAR), Miedzyzdroje, 2016, pp. 619-624.

[15] Y. Q. Bao, M. Hu, Y. Y. Hong, P. P. Chen, J. Q. Ju and G. Ma, "Accuracy analysis and improvement of the state-queuing model for the thermostatically controlled loads," *IET Generation, Transmission & Distribution*, vol. 11, no. 5, pp. 1303-1310, 2017.

[16] N. Lu, D. Chassin, and S. Widergen, "Modeling uncertainties in aggregated thermostatically controlled loads using a state queueing model," IEEE power engineering society general meeting, vol. 2. Jun. 2005, pp. 1336.

[17] U. C. Hinrichs and M. Sonnenschein, "Modelling and evaluation of desynchronization strategies for controllable cooling devices," *in Proc. 6th Vienna Int. Conf. Math. Model.* 2009, pp. 220–225.

[18] S. Koch, J. L. Mathieu, and D. S. Callaway, "Modeling and control of aggregated heterogeneous thermostatically controlled loads for ancillary services," *Proc. 17th Power Systems Computation Conf.*, 2011.

[19] J. L. Mathieu, , M. Kamgarpour, J. Lygeros, G. Andersson, , and D. S. Callaway, "Arbitraging Intraday Wholesale Energy Market Prices With Aggregations of Thermostatic Loads," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 763-772, 2015.

[20] R. Farkh, K. Laabidi, M. Ksouri, "Stabilizing Sets of PI/PID Controllers for Unstable Second Order Delay System," International Journal of Automation and Computing, vol. 11, no. 2, pp. 210-222, 2014.

[21] R. Farkh, K. Laabidi, M. Ksouri. "PI Control for Second Order Delay System with Tuning Parameter Optimization," *International Journal of Computer, Electrical, Automation, Control and Information Engineering*, vol. 3, no. 3, pp. 745-751, 2009.

[22] H. Wang, J. Liu, F. Yang, Y. Zhang, "Proportional-Integral Controller for Stabilization of Second-Order Delay Processes," International Journal of Control, Automation, and Systems, vol. 12, no. 6, pp. 1197-1206, 2014.

[23] C. G. Moles, P. Mendes, J. R. Banga. Parameter estimation in biochemical pathways: a comparison of global optimization methods. *Genome Research*, vol. 153, no. 4, pp. 2467-74, 2006.

[24] Y. -Q. Bao, Y. Li, Y. Y. Hong, B. Wang, "Design of a Hybrid Hierarchical Demand Response Control Scheme for the Frequency Control," *IET Generation, Transmission & Distribution*, vol. 9, no. 15, pp. 2303-2310, 2015.

[25] J. H. Holland, "Adaptation in natural and artificial systems: an introductory analysis with applications to biology," University of Michigan Press, 1975.

[26] B. Porter, A. H. Jones, "Genetic tuning of digital PID controllers," *Electronics letters*, vol. 28, no. 9, pp. 843-844, 1992.

[27] J. A. Vasconcelos, J. A. Ramirez, R. H. C. Takahashi, and R. R. Saldanha, "Improvements in genetic algorithms," IEEE Trans. Magnetics, vol. 37, no.5, pp. 3414-3417, 2001.

[28] Y. Bao, B. Wang, Y. Li, S. Yang, "Rolling Dispatch Model Considering Wind Penetration and Multi-scale Demand Response Resources," Proceedings of the CSEE, 2016, vol. 36, no. 17, pp. 4589-4599.

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