Control of Residential Air-conditioning Loads to Provide Regulation Services under Uncertainties

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***Abstract*—This paper presents a model-based approach for the collective control of residential air-conditioning loads to deliver robust and optimal demand management. The proposed approach performs an optimal trade-off between accurate tracking of system operator specified load-set points and minimisation of consumer discomfort, while ensuring robustness to parametric uncertainties and fluctuations in outdoor temperature. Benefiting from robustness to uncertainties, the proposed approach is reliant on minimal household specific information. The mathematical model of the population of residential air-conditioning loads is obtained through the aggregation of individual household specific thermal models. This is followed by the development of a robust model predictive control approach for aggregate demand management to deliver optimum regulation services to account for uncertainties in model mismatch and the prediction errors associated with outdoor temperature. The approach is consistent with the existing demand response standards and is validated using a reference signal from PJM.**

The results demonstrate that the developed control scheme is capable of precisely following the system-operator specified load set-points even under the worst-case uncertainties of thermal parameters. While achieving the target set-point, it is further observed that customer comfort is always preserved along with minimum compressor control action on air conditioners.

***Index Terms*—Ancillary services, uncertainties, robust model predictive control, aggregator, inverter-type air conditioners, demand response.**

I. Introduction

The rapid growth of renewable generation in the past decade has given rise to a highly demanding need for ancillary services. Although the provisions of ancillary services were limited to power-plants and large-scale facilities in the preliminary stages, the recent developments of the infrastructure at the consumer-end has paved the path to satisfactory utilisation of controllable loads in system related applications [1].

Due to the presence of high thermal inertia, Heating ventilation and Air Conditioning (HVAC) is considered to be an ideal candidate for demand-side control applications [2]. Based on the state-of-the-art, the demand response approaches for HVAC can be broadly categorised under rule-based control, optimisation-based control and advanced model-based control. In rule-based approaches [3], [4], heuristic algorithms are introduced to rank air conditioners based on their operating temperature for dispatch during a frequency regulation event. In optimisation-based approaches, an off-line optimisation problem is formulated based on multiple control objectives to determine the scheduling sequence of HVAC for optimal bidding in markets [5]. On the other hand, advanced model-based approaches utilise Model Predictive Control (MPC), where an on-line optimisation problem is solved at each time step to follow a reference signal or to minimise the energy consumption of HVAC.

Considering the literature on MPC in HVAC control applications, the authors in [6], [7] have implemented control strategies for maximising the energy efficiency in buildings whereas [5], [8], [9] develop control schemes for ancillary service provisions from individual houses and office buildings. A stochastic MPC scheme is proposed in [6] to meet the uncertainties in weather prediction and occupancy of individual buildings in order to minimise energy consumption. Vrettos *et.al* in [5] have proposed a robust MPC scheme to account for uncertainties in reserve capacity in commercial buildings providing frequency regulation services. Although some of the uncertainties are addressed to a certain extent in the aforementioned work, the uncertainties associated thermal model parameters are rarely discussed in the existing literature. For example, the authors in [8]–[10] have developed control schemes based on perfect models and further assumes that thermal parameters are perfectly known at the central dispatch utility. However, when a large population of residential units participate in such events, determining thermal parameters of each individual model is cumbersome. On the other hand, imperfect estimation of such parameters can lead to deviations from expected provision of demand in ancillary service events [11]. Hence, it is vital to develop a control scheme which is robust for parametric uncertainties in order for successful provision of ancillary services through demand management.

Beside uncertainties, it is important to develop control algorithms which are compliant with existing demand response standards. For example in Australia, inverter-type conditioners are only allowed to operate under pre-determined consumption levels identified as 'Demand Response Modes' (DRMs) [12] during a demand response event. Nevertheless the set-point control in [9], [13] and the fractional ON-OFF control approach in [14] are only applicable for regular ON-OFF type air conditioners, but not for inverter-type air conditioners operating under DRM standards. Hence, developing control algorithms complying with existing standards is equally important for practical implementation.

The specific contributions of this work are as follows:

- Developing a robust model predictive control approach

for inverter-type air conditioners operating under demand response modes to deliver ancillary services while ensuring robustness to uncertainties with minimal reliance on household specific information.
- Evaluating the effect of parametric uncertainties and outdoor temperature fluctuations at each household by means of a stochastic additive representation in individual thermal models and exploiting individual household models to develop the aggregate control scheme.

The rest of the paper is organised as follows. Section II describes the overall model of the system. Section III explains the robust MPC formulation for the provision of ancillary services. Section IV illustrates the performance of the developed control scheme under different scenarios and finally section V concludes the paper.

II. System Model

Since individual air conditioners do not meet the minimum capacity requirements to participate in electricity markets, a third-party utility or an aggregator accumulates the response from each air conditioner and participates in markets on behalf of them. The overall system model is presented in Fig. 1.

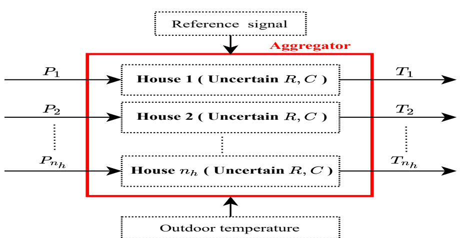


Fig. 1. Overall system model

A. Individual model

A discretised form of the Equivalent Thermal Parameter (ETP) model [14] is considered for each inverter air conditioner. Considering the cooling mode, the thermal model can be expressed as,

$$T_i(k+1) = a_i T_i(k) + (1-a_i)\left[T_i^{\text{out}}(k) - \eta_i R_i P_i(k)\right] \quad (1)$$

where i is the air conditioner index, $T_i(k)$ is the indoor temperature at time step k, $T_i^{\text{out}}(k)$ is the outdoor temperature, the parameter $a_i = e^{-h/R_i C_i}$, where R_i is the thermal resistance, C_i is the thermal capacitance and h is the simulation step. In addition to that, $P_i(k)$ is the power consumption at time step k and η_i is the coefficient of performance. Unlike a regular ON-OFF type air conditioner where $P_i(k) \in (P_i^{\text{min}}, P_i^{\text{rated}})$, an inverter-type air conditioner can operate at any power consumption level between P_i^{min} and P_i^{rated} where P_i^{min} is the minimum possible power consumption and P_i^{rated} is the rated power of the i^{th} air conditioner. Table I shows typical thermal parameters for air conditioners. However, if R_i and C_i information is imperfect, their uncertainties can be represented by,

$$R_i = R_{\text{nom},i} + \Delta R_i$$
$$C_i = C_{\text{nom},i} + \Delta C_i$$

TABLE I
Thermal parameters for air conditioners [14]

Parameter	Value
R	1.5 -2.5°C/kW
C	1.5 -2.5 kWh/°C
η	2.5

where $R_{\text{nom},i}$ and $C_{\text{nom},i}$ are the nominal values of R_i and C_i parameters, ΔR_i and ΔC_i represent the deviation from their nominal values. Hence the term a_i in (1) can be stated as,

$$\begin{aligned} a_i &= e^{-h/(R_i C_i)} = e^{-h/(R_{\text{nom},i}+\Delta R_i)(C_{\text{nom},i}+\Delta C_i)} \\ &= e^{-h/(R_{\text{nom},i}C_{\text{nom},i}+R_{\text{nom},i}\Delta C_i + C_{\text{nom},i}\Delta R_i + \Delta R_i \Delta C_i)} \end{aligned} \quad (2)$$

After assigning nominal values and possible deviations for R_i and C_i, (2) simplifies to,

$$a_i = a_{\text{nom},i} + \Delta a_i \quad (3)$$

where $a_{\text{nom},i} = e^{-h/(R_{\text{nom},i}C_{\text{nom},i})}$ is the nominal value of a_i and Δa_i is the deviation from the nominal value of a_i due to parametric uncertainties in the thermal model.

Let the error in predicting outdoor temperature at time k be $\Delta T_i^{\text{out}}(k)$, then substituting (3) in (1) yields,

$$\begin{aligned} T_i(k+1) &= \big(a_{\text{nom},i} + \Delta a_i\big) T_i(k) + \big(1 - (a_{\text{nom},i} + \Delta a_i)\big) \\ &\Big[\big(T_i^{\text{out}}(k) + \Delta T_i^{\text{out}}(k)\big) - \eta_i (R_{\text{nom},i} + \Delta R_i) P_i(k)\Big] \end{aligned} \quad (4)$$

Separating the certain terms and representing the uncertain terms with an additive stochastic term (w_i) leads to,

$$\begin{aligned} w_i(k) &= (1 - a_{\text{nom},i})\big(\Delta T_i^{\text{out}}(k) - \eta_i\, \Delta R_i\, P_i(k)\big) - \Delta a_i \cdot \\ &\Big(T_i^{\text{out}}(k) - \Delta T_i^{\text{out}}(k) - \eta_i (R_{\text{nom},i} + \Delta R_i) P_i(k)\Big) \end{aligned} \quad (5)$$

Hence (4) can be modified as,

$$\begin{aligned} T_i(k+1) &= a_{\text{nom},i} T_i(k) + (1 - a_{\text{nom},i}) \\ &\quad \big[T_i^{\text{out}}(k) - \eta_i R_{\text{nom},i} P_i(k)\big] + w_i(k) \end{aligned} \quad (6)$$

For brevity and ease of notation, 'nom' term is dropped and (6) is re-written as,

$$\begin{aligned} T_i(k+1) &= a_i T_i(k) + (1 - a_i) \\ &\quad \big[T_i^{\text{out}}(k) - \eta_i R_i P_i(k)\big] + w_i(k) \end{aligned} \quad (7)$$

Based on the derived thermal model in (7) , the state-space model for the i^{th} air conditioner can be expressed as,

$$x_i(k+1) = A_i x_i(k) + B_i u_i(k) + D_i v_i(k) + w_i(k) \quad (8)$$
$$y_i(k) = x_i(k) \quad (9)$$

where $x_i(k)$, $u_i(k)$, $v_i(k)$ and $y_i(k)$ represent the indoor temperature, power consumption, outdoor temperature and output at time step k respectively. Additionally, $A_i = e^{-h/R_{\text{nom},i}C_{\text{nom},i}}$, $B_i = -(1 - e^{-h/R_{\text{nom},i}C_{\text{nom},i}})\, R_{\text{nom},i}\, \eta_i\, P_i^{\text{rated}}$ and $D_i = 1 - e^{-h/R_{\text{nom},i}C_{\text{nom},i}}$. The term $w_i(k)$ accounts for the combined uncertainties in thermal parameters and outdoor temperature prediction.

B. Aggregate model

Let us consider a population of n_h houses under an aggregator. Hence, the state-space model of the aggregate system can be obtained by stacking the individual models described in section II-A and can be expressed as,

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{D}\mathbf{v}(k) + \mathbf{w}(k) \tag{10}$$

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \tag{11}$$

where $\mathbf{x}(k)=\left[x_1(k), x_2(k)\ldots, x_{n_h}(k)\right]^{\mathrm{T}}$, $\mathbf{u}(k)=\left[u_1(k), u_2(k), \ldots, u_{n_h}(k)\right]^{\mathrm{T}}$, $\mathbf{v}(k)=\left[v_1(k), v_2(k)\ldots, v_{n_h}(k)\right]^{\mathrm{T}}$ and $\mathbf{w}(k)=\left[w_1(k), w_2(k)\ldots, w_{n_h}(k)\right]^{\mathrm{T}}$ where $\mathbf{x}(k)$, $\mathbf{u}(k)$, $\mathbf{v}(k)$ and $\mathbf{w}(k) \in \mathbb{R}^{n_h}$. In addition to that, $\mathbf{A}=diag\{A_1, A_2, \ldots, A_{n_h}\}$, $\mathbf{B}=diag\{B_1, B_2, \ldots, B_{n_h}\}$, $\mathbf{C}=\mathbb{I}_{n_h}$ and $\mathbf{D}=diag\{D_1, D_2, \ldots, D_{n_h}\}$ such that $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D} \in \mathbb{R}^{n_h \times n_h}$ and $\mathbb{I}_{n_h}$ is the $n_h \times n_h$ identity matrix.

III. Proposed Methodology

Assuming the bids offered by the aggregator are accepted in day-ahead markets, the system operator sends a reference signal to the aggregator during an ancillary service event. After receiving the reference signal, the aggregator determines control actions on the population of air conditioners based on the robust MPC scheme implemented in this paper while taking account of household model parameter uncertainties and outdoor temperature prediction errors. The overall control scheme is depicted in Fig. 2.

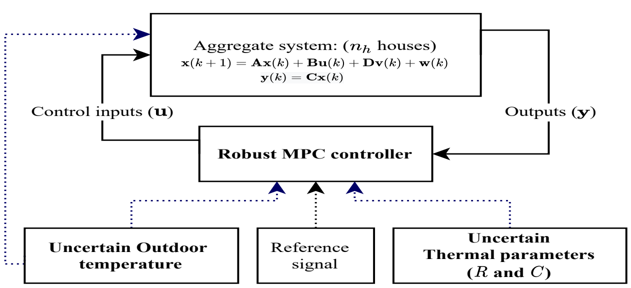


Fig. 2. The robust MPC implementation in the presence of parameter uncertainties and outdoor temperature prediction errors

A. Robust Model Predictive Control scheme

The control decisions on the population of air conditioners are based on a robust MPC scheme [15] implemented at the aggregator level. In this approach an on-line optimisation problem is solved at each step to determine the optimal control sequence for a certain prediction horizon under the worst-case uncertainties. Then only the first control input of the sequence is applied to the system and the procedure is repeated at the next step. Hence, at every sampling instant k, the control objective is to solve the following finite horizon robust optimal control problem:

$$\min_{\mathbf{u}} \max_{\mathbf{w}} \sum_{j=0}^{N-1} w_P \left\|(P_{\text{agg}}(k+j|k) - P_{\text{ref}}(k+j))\right\|_1 + w_x \left\|(\mathbf{x}(k+j|k) - \mathbf{x}_{\text{set}})\right\|_1 + w_{\Delta u} \left\|\mathbf{\Delta u}(k+j|k)\right\|_1 \tag{12}$$

subject to:

$$\begin{aligned}\mathbf{x}(k+j+1|k) = A\mathbf{x}(k+j|k) + B\mathbf{u}(k+j|k)\\ + D\mathbf{v}(k+j|k) + \mathbf{w}(k+j|k)\end{aligned} \tag{13}$$

$$P_{\text{agg}}(k+j|k) = {\mathbf{P}_{\text{rated}}}^{\mathrm{T}}\mathbf{u}(k+j|k) \tag{14}$$

$$\underline{\mathcal{X}} \leq \mathbf{x}(k+j|k) \leq \overline{\mathcal{X}} \tag{15}$$

$$\Delta\mathbf{u}(k+j|k) = \mathbf{u}(k+j+1|k) - \mathbf{u}(k+j|k) \tag{16}$$

$$\mathbf{u}(k+j|k) = \{0.5, 0.75, 1.0\} \tag{17}$$

$$\mathbf{w}(k+j|k) \in \mathbb{W} \tag{18}$$

$$\text{for } j = 0, 1, 2 \ldots N-1$$

where N is the prediction horizon, $\mathbf{u} = \mathbf{u}(k|k), \ldots, \mathbf{u}(k+N-1|k)$, $\mathbf{w} = \mathbf{w}(k|k), \ldots, \mathbf{w}(k+N-1|k)$, $P_{\text{agg}}(k)$ refers to the aggregate power of air conditioners at time step k, $P_{\text{ref}}(k)$ is the reference signal at time step k, $\mathbf{x}_{\text{set}} \in \mathbb{R}^{n_h}$ is the indoor temperature set-point, $\mathbf{\Delta u}(k)$ is the change in input computed at time step k, $\mathbf{P}_{\text{rated}} \in \mathbb{R}^{n_h}$ is the vector of rated power of air conditioners, $\underline{\mathcal{X}}, \overline{\mathcal{X}} \in \mathbb{R}^{n_h}$ are the sets corresponding to the lower and upper bounds of indoor temperature for air conditioners. $w_P, w_x, w_{\Delta u} \in \mathbb{R}$ are the penalty weights assigned for each of the objectives in the cost function. Please note that $(k+j|k)$ refers to the prediction at time $k+j$ based on the knowledge at time step k.

Minimising the cost function based on worst-case disturbance is given in (12). The first term in (12) corresponds to the error in tracking the reference signal sent by the system operator and the second term represents the error in tracking the set-point temperature. The final term expresses the change in control effort in achieving the other two objectives discussed above. The control effort is indirectly related to the life-time of the compressor of an air conditioner. It is important to mention that $\mathcal{L}$-1 norm ($\|.\|_1$) is considered for each objective to minimise the complexity of the resulting optimisation problem when a large population of air conditioners is considered in the aggregate model. The state update equation of the aggregate model is given in (13). The aggregated power of air conditioners is defined in (14). The constraints on state (indoor temperature) are given in (15). The change in control input is defined in (16). The constraint in (17) corresponds to the discrete power consumption levels (based on rated power) at which air conditioners can operate during an event and implies that the control algorithm is compliant with the existing demand response standards. Finally, (18) refers to the constraints on the stochastic additive uncertainty. The worst-case uncertainty set $\mathbb{W}$ is defined as,

$$\mathbb{W} = \{\mathbf{w} : \|\mathbf{w}\|_\infty \leq \mathbf{w}_0\} \tag{19}$$

where $\mathbf{w}_0$ is the worst case uncertainty associated with each household thermal model. Based on (5), an estimate of $\mathbf{w}_0$ can be obtained by setting $\Delta R_i = |\Delta R_i|_{\max}$, $\Delta C_i = |\Delta C_i|_{\max}$ and $\Delta T_i^{\text{out}}(k) = |\Delta T_i^{\text{out}}|_{\max}$ for all $i = 1, \ldots, n_h$.

B. Construction of the reference signal

In markets like PJM, the reference signal is usually given in the form of a normalised signal [16]. Hence, the signal should be reconstructed depending on the population in the study. Following the approach introduced in [4], the reference signal can be expressed as,

$$P_{\text{ref}}(k) = P_{\text{baseline}}(k) + B \cdot P_{\text{norm}}(k)$$

where, $P_{\text{baseline}}(k)$ is the baseline consumption of the population at time step k, B is the reserve capacity offered and accepted in markets and $P_{\text{norm}}(k) \in \{-1, 1\}$ is the normalised reference signal at time step k. The baseline consumption of the population of air conditioners can be found by averaging the consumption over a certain period of time. The power consumption of an individual air conditioner when operating at the set-point at time k can be found by determining $P_i(k)$ after setting $T_i(k+1) = T_i(k) = T_{\text{set}}$, where T_{set} is the set-point temperature, in (1). Hence, the baseline consumption for a duration of time T can be approximated as, $P_{\text{baseline}} = \frac{1}{T}\sum_{k=1}^{T}\sum_{i=1}^{n_h} P_i(k)$.

IV. Results

On a hot summer day in February, 03-02-2020, the system operator requests the aggregator to provide for ancillary services from 15:00 - 16:00. As discussed in section III-B, bids offered by the aggregator are accepted and the reserve capacity B is assumed to be 20% of P_{baseline}. The reference signal, P_{ref}, is obtained from PJM markets [16] and further considered that the aggregator has perfect information of the signal prior to the event. The outdoor temperature is obtained from [17]. The nominal parameters R_{nom} = 2 °C/kW and C_{nom} = 2 kWh/°C. In addition to that $|\Delta R|_{\max}$ = 0.5 °C/kW and $|\Delta C|_{\max}$ = 0.5 kWh/°C as in [14]. $P_{i,\text{rated}}$ = 2.5 kW for all $i = 1, \ldots, n_h$. Further, $\underline{\mathcal{X}} = \{22, 22, \ldots, 22\}^{\text{T}}$ and $\overline{\mathcal{X}} = \{24, 24, \ldots, 24\}^{\text{T}}$. Additionally, $\mathbf{x}_{\text{set}} = \{23, 23, \ldots, 23\}^{\text{T}}$ and all the air conditioners operate at their set-point before the event, i.e. $\mathbf{x}(0) = \mathbf{x}_{\text{set}}$.

The simulation time step h is chosen to be 1 min to match with the sampling time of the PJM reference signal. Consequently, the proposed control scheme is not susceptible to the effect of delays that are generally in the order of seconds [18]. Moreover, it is found that N= 3 delivers the best trade-off between computational tractability and perfect tracking performance. Although longer horizons lead to better outcomes in terms of performance, comparatively a short horizon is chosen to avoid a highly computationally demanding problem and to preserve the consistency with likely available forecasts of outdoor temperature and regulation signal. The penalty weights are w_P = 10, w_x = 1 and $w_{\Delta u}$ = 1. Furthermore, robust MPC scheme is developed in MATLAB with *YALMIP* toolbox [19] and *Gurobi 9.0.2* solver in a computing facility with 128 GB memory and 16 CPUs.

It is worth noting that the proposed implementation in section III leads to deploying control actions on the entire population and further requiring indoor temperature measurements from all units. This could be justified by the availability of real-time data as in [20] and local control using demand response enabling devices (DREDs) [12]. Following this, for a population of n_h = 1000, simulations are carried out for two scenarios: nominal case and under worst-case uncertainties.

A. Nominal system

In this scenario, it is assumed that perfect prediction of T^{out} is available and thermal parameters take their nominal values, i.e. $R_i = R_{\text{nom},i}$ = 2 °C/kW and $C_i = C_{\text{nom},i}$ = 2 kWh/°C for all $i = 1, \ldots, n_h$. As can be seen from Fig. 3(a) that with perfect knowledge on R_i and C_i parameters for all i and perfect outdoor temperature estimates, the developed control scheme is able to perfectly track the reference within a very narrow-band of deviation from temperature set-point. In addition to that, the majority of the air conditioners operate at 0.75$\cdot$ P_{rated} at each time step and avoid operating at either the lowest or highest possible level.

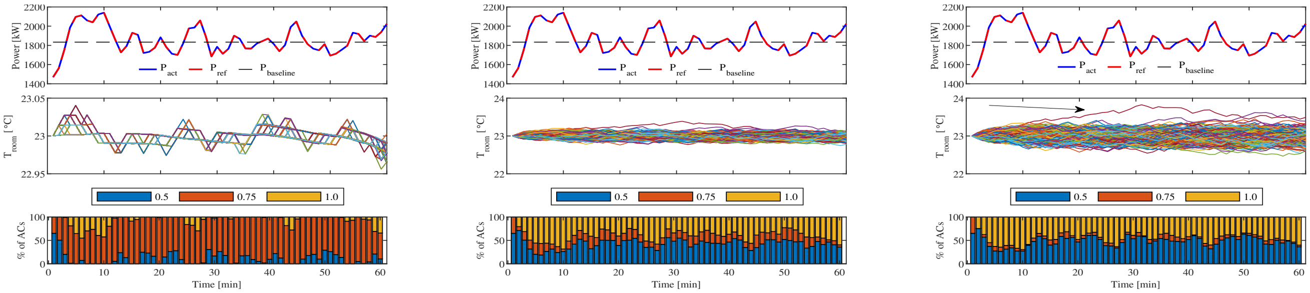
B. System under uncertainties

Considering the worst-case parametric uncertainties for all i, i.e., $\Delta R_i = |\Delta R|_{\max}$ = 0.5 °C/kW and $\Delta C_i = |\Delta C|_{\max}$ = 0.5 kWh/°C and outdoor temperature fluctuation, two worst-case uncertainty levels are determined for $w_i(k)$ in (5) such that: $\mathbf{w}_0$ = 0.050 °C and $\mathbf{w}_0$ = 0.075 °C. Further, $w_i(k)$ is assumed to be normally distributed between $(-\mathbf{w}_0, \mathbf{w}_0)$.

Looking at Fig. 3(b), it is apparent that accurate tracking can be achieved even under $\mathbf{w}_0$ = 0.050 °C. However, the corresponding indoor temperature for air conditioners tend to diverge more from their nominal set-point. On the other hand, when the population of air conditioners experience an uncertainty level of $\mathbf{w}_0$ = 0.075 °C as in Fig. 3(c), it is interesting that the aggregate consumption is still capable of accurately tracking the reference signal but with more dispersion of indoor temperature around the set-point compared to the case in Fig. 3(b). Further analysis on the corresponding control effort plots suggest that as the degree of uncertainty increases, more and more units tend to operate at either 50% of P_{rated} or P_{rated} compared to 75% of P_{rated}. Although this gives an intuition that air conditioners should operate at their extreme limits to mitigate thermal constraint violations, Fig. 3 in general does not provide a clear insight into the impact of uncertainties on the tracking performance.

The robustness of the tracking performance can be understood by thermal parameter heterogeneity of the aggregate population. When few air conditioners operate at their extreme limits to keep the indoor temperature within thermal limits, the compensation is provided by most of the other air conditioners who possess high thermal inertia. Hence, accurate tracking is achieved without any violation of temperature constraints. Comparatively, the effect of uncertainty on a homogeneous population of n_h = 100 air conditioners with R = 2 °C/kW, C = 2 kWh/°C and P_{rated} =2.5 kW is clearly depicted in Fig. 4.

As shown in Fig. 4, when the temperature constraints are further tightened to $[22.5, 23.5]$°C under $\mathbf{w}_0 = 0.02$°C and allowing $w_i(k)$ to be uniformly distributed between $(0, \mathbf{w}_0)$, the control scheme fails to provide desired regulation while maintaining indoor temperature within thermal limits. Thus,



(a) nominal scenario (b) with uncertainties: $\mathbf{w}_0$= 0.050 °C (c) with uncertainties: $\mathbf{w}_0$= 0.075 °C

Fig. 3. The performance of the developed control scheme in tracking the reference, tracking the temperature set-point and the percentage control action at each time step for three different scenarios (simulation time: scenario (a) = 103 mins, scenario (b) = 157 mins, scenario (c) = 283 mins)

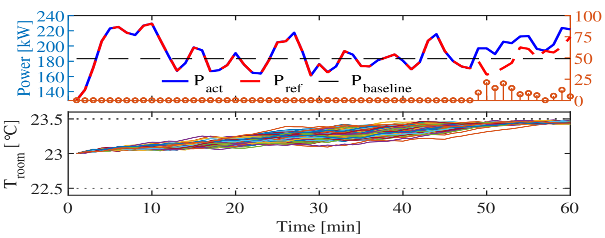


Fig. 4. The tracking performance and temperature variation for n_h=100 with R= 2 °C/kW, C= 2 kWh/°C, P_{rated}= 2.5 kW under $\mathbf{w}_0$=0.02°C (simulation time: 14 mins)

the trade-off between preserving temperature comfort and tracking the reference load set-point is clearly demonstrated.

V. Conclusion

In this paper, a robust model-based control scheme is proposed for the collective control of residential inverter-type air conditioners to provide ancillary services. The proposed discrete-level control approach is consistent with existing demand response standards and takes account of parametric uncertainties in the thermal model and outdoor temperature forecast errors. Furthermore, the proposed scheme requires minimal information of household parameters. The results demonstrate that accurate tracking of the reference signal can be achieved up to a certain degree of worst-case uncertainty while preserving customer comfort together with the lowest possible control action on air conditioners.

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