Abstract—In this paper, an resistance-capacitance network control-oriented model is developed, which is able to capture the thermal dynamics of different thermal zones in large open spaces. With this model, an agent-based distributed model predictive control (DMPC) strategy is implemented to minimize the HVAC operation cost. Experiment results demonstrate the effectiveness of the proposed method. In addition, a communication prototype for multi-agent optimization is established and tested. Results show the implementation advantage of the proposed parallel distributed optimization algorithm over its serial counterparts.

I. INTRODUCTION

Many office and commercial buildings consist of multiple thermal zones, with either coupled or decoupled dynamics. Each zone could be a small room, an area of an open space or even a corridor. These buildings are sometimes served by a central heating, ventilation and air-conditioning (HVAC) system, with multiple diffusers providing air to different zones. However, traditional feedback type control strategy is neither capable of recognizing the potential load imbalance between zones, nor able to provide flexibility of customized cooling/heating based on different occupancy preferences.

This study takes the Purdue Living Lab 3 (LL3) as a testbed, which is representative of a class of buildings with large open space and multiple thermal zones, and investigates the cost savings (in terms of electricity bill reduction) potential of utilizing building thermal mass for load shifting. The control strategy we adopt is the agent-based control approach, which not only explores the coordination between different pieces of equipment, but also has good scalability for large scale buildings with many thermal zones.

Many different advanced control or optimization methods have been utilized for building control and energy management problems. Among them, the model predictive control (MPC) approach [1] [2] has become increasingly popular due to its ability of incorporating weather and other disturbance information into the optimization of the operation of HVAC systems. Particularly, distributed model predictive control (DMPC) approach [3] [4] is more effective in dealing with large scale buildings compared to centralized MPC approach, due to the improved scalability.

In order to implement either MPC or DMPC approach on multi-zone buildings, the first step is to obtain a control-oriented multi-zone model that is able to capture the thermal behavior of the building and accommodate an efficient controller design. A second order multi-zone model was introduced in [5] for a room with six surfaces and a single air node. In this paper, we propose a new resistance-capacitance (RC) network multi-zone model that is suitable for large open spaces with multiple air nodes and asymmetric airflow exchange rates.

This paper is organized as follows. In section II, the current setup and features of LL3 are introduced. Section III first proposes the model structure for LL3, and then details the procedure of model identification (training + validation). Section IV outlines the distributed model predictive control approach on LL3 with the proposed multi-zone model using a parallel distributed optimization algorithm. Experiment results of the DMPC implementation in LL3 are given in section V. Section VI illustrates the multi-agent communication prototype based on TCP/IP protocol and demonstrates its scalability. Finally, some concluding remarks are given in section VII.

II. CASE STUDY BUILDING

LL3 is a large open-space student office, located in the Center for High Performance Buildings at West Lafayette, IN, USA. As shown in Fig. 1, the room is conditioned by a centralized air handling unit (AHU) through three VAV boxes with terminal units of one large rectangular diffuser and eight standard square ceiling diffusers.

![Double facade](image_url)

**Fig. 1.** Model structure of three-zone open space

For large open-plan office spaces similar to LL3, there are usually occupants with various schedules and different thermal comfort preferences. The typical static ceiling or
wall diffuser setup does not offer the flexibility of personalized local control and comfort delivery. In the case of LL3, there is further a significant load imbalance in the summer as the south-facing double facade accumulates much more solar radiation than the part of the room near the door. With this in mind, we retrofitted the HVAC system by replacing the eight traditional ceiling diffusers with eight VAV diffusers, which can be individually controlled to allow continuous and localized comfort control through the Building Automation System (BAS). The eight VAV diffusers are grouped into two clusters, each controlling one zone (Zone 2 and Zone 3 in Fig. 2), the zone controlled by the VAV box A through traditional rectangular diffuser is denoted as Zone 1.

This open-space multi-zone configuration is commonly encountered in many medium to large-sized office buildings. The VAV diffuser retrofit allows us to use LL3 as a testbed for investigating zone-level local comfort delivery as well as how different zones in an open space affect each other, and further evaluate the cost reduction potential when agent-based distributed control strategies are implemented in practice.

III. MODEL IDENTIFICATION

A. Model structure

Based on the description of LL3 in Section II, we propose the model structure in Fig. 2 to be used for its control in later sections.

In LL3, the double facade is separated from the three zones by glass windows while there are dynamic couplings between adjacent zones. Another feature of the room is that the return air duct is located on the back wall (bottom in Fig. 2) in Zone 3 near the door and thus there is significant air flow from Zone 1 to 3 but the airflow in the opposite direction is relatively small. Therefore, the coupling resistances connecting two adjacent zones have different values in different directions, as indicated by the two directional resistors in Fig. 2. Due to the airflow pattern of LL3, we have $R_{1,2} < R_{2,1}$ and $R_{3,2} < R_{3,1}$.

A continuous time state-space representation of the above model is formulated in (1),

$$\dot{x} = Ax + Bu + Fw,$$
$$y = Cx,$$

where the state variable $x \in \mathbb{R}^{10}$ consists of 10 temperatures, one for the double facade air and three for each zone ($T_1, T_{roof,i}, T_{wall,i}, i = 1, 2, 3$); the output $y \in \mathbb{R}^4$ represents the four measurable temperatures ($T_{exc, i}, T_1, i = 1, 2, 3$); the control input $u \in \mathbb{R}^3$ is a vector of the controllable sensible cooling/heating rates ($Q_{i, i}, i = 1, 2, 3$) into three zones provided by the air conditioning system ($T_{exc}$ is not controlled) while the disturbance $w \in \mathbb{R}^{12}$ consists of all uncontrollable disturbances, namely, ambient temperature, solar radiation, internal heat gains from lighting, plug load and occupants; $A, B, F, C$ are matrices with proper dimensions. Specifically, for model training and validation in III-B, all disturbances come from measurements while the heat gain of occupants is estimated based on the occupancy schedule of the room.

B. Model training and validation

Firstly, we briefly describe how to identify the RC values in Fig. 2. Since Zone 2 is affected by Zone 1 through the resistance $R_{1,2}$ and by Zone 3 through $R_{3,2}$, we can estimate the RC values of Zone 2 separately by treating the measured adjacent zones’ temperatures, $T_1$ and $T_3$, as boundary conditions. The same is also true for Zone 1 and Zone 3. Therefore, the RC values for each of the three zones can be estimated individually by treating adjacent zones’ measured temperatures as boundary conditions. The identification results of the three zones are then integrated together to form the overall system model in (1).

Next, we use Zone 2 as an example to demonstrate the identification of individual zones, of which the dynamics is

$$\dot{x}_2 = A_2x_2 + B_2w_2 + C_2w_2,$$
$$y_2 = C_2x_2,$$

where $A_2, B_2, F_2, C_2$ are constructed from the corresponding entries in $A, B, F$ and $C$, respectively. For $w_2$, besides the afore-mentioned uncontrollable disturbances in $w$, it also includes the air temperatures $T_1$ and $T_3$. Correspondingly, $F_2$ depends on the portion of $F$ relevant to Zone 2 and the coupling resistances $R_{1,2}$ and $R_{3,2}$. By discretization with a sampling time of 0.5 hour and concatenating all vectors over time $N$, we have

$$X_2 = \Omega_2 x_2(0) + \Phi_2 U_2 + \Psi_2 W_2,$$
$$Y_2 = \Gamma_2 X_2,$$

where $X_2 = (x_2(1), \ldots, x_2(N)), U_2 = (u_2(1), \ldots, u_2(N)), W_2 = (w_2(1), \ldots, w_2(N))$ and $Y_2 = (y_2(1), \ldots, y_2(N))$ is the estimation of Zone 2 temperature, which should be close to its real measurement $\tilde{Y}_2$, while $\Omega_2, \Phi_2, \Psi_2, \Gamma_2$ are just matrices built up from $A_2, B_2, F_2, C_2$. Then the objective is

Fig. 2. Model structure of three-zone open space
to minimize $\|Y_2 - \hat{Y}_2\|^2_2$ by optimizing the values of resistances/capacitances internal to Zone 2 as well as $R_{1,2}$ and $R_{3,2}$. This problem is solved with the function lsqnonlin in MATLAB, where initial guesses of parameters are derived based on rough estimation of construction parameters.

The data of 22 days collected from July 17, 2017 to August 8, 2017 is used for warm-up (8 days), model training (7 days) and validation (7 days). The validation result is shown in Fig. 3 and the root mean square deviation (RMSD) for each zone temperature is 0.46°C, 0.41°C, 0.39°C and 2.12°C respectively.

![Fig. 3. Model validation: blue lines represent estimated temperatures based on the identified model and green lines corresponds their measurements.](image)

**IV. AGENT-BASED DISTRIBUTED MPC**

To investigate the cost savings potential by optimizing and coordinating the operation of VAV diffusers, we formulate a receding horizon optimal control problem. An agent-based distributed optimization algorithm is adopted to solve the problem at each time instant. The effectiveness and the cost savings performance of the proposed distributed control strategy over a baseline localized controller is demonstrated with an actual implementation in an open-plan office space.

**A. Objective function**

In this case study, we assume that an air-cooled chiller is providing cold water to the central AHU system in LL3. An empirical model of a chiller from [6] is utilized

$$Pow = Chiller(T_{chs}, T_{chl}, m, T_{amb}),$$

where $T_{chs}$ and $T_{chl}$ are the entering and leaving chilled water temperatures, respectively; $m$ is the chilled water flow rate, and $T_{amb}$ is the ambient temperature; the output is the power consumption $Pow$. The chiller capacity $Q_c$ is calculated with a quadratic correlation to $T_{chl}$ and $T_{amb}$. An equivalent modified model [4] can be formulated as

$$Pow = Chiller(Q_{load}, T_{amb}),$$

where the cooling load $Q_{load}$ can be calculated as $Q_{load} = c_p m (T_{chl} - T_{chs})$. The modified model utilizes a quadratic correlation to scale power down based on the part load ratio $Q_{load}/Q_c$. All the model parameters were estimated with catalog data. We refer the interested readers to [6] for details.

The objective function for each centralized MPC problem is the total energy bill corresponding to the chiller operation in the prediction horizon,

$$\sum_{k=1}^{N} \left( P_{e}(k) \cdot Chiller \left( \sum_{i=1}^{3} Q_i(k), T_{amb}(k) \right) \right),$$

where $P_{e}(k)$ is the Time-of-Use (TOU) electricity price. From this objective function, we can make the observation that the cost savings potential come from coordinating and shifting the individual loads to a period that either has lower ambient temperature (leads to higher COP) or lower electricity price.

**B. Thermal dynamics constraint**

The discrete time state space model of LL3’s dynamics is obtained by discretization of (1) with a 0.5h sampling time. We can further concatenate the dynamics during an $N$ step prediction horizon as

$$X = \Omega x(0) + \Phi U + \Psi W,$$

where $X = (x(1), \ldots, x(N))$, $U = (u(1), \ldots, u(N))$, and $W = (w(1), \ldots, w(N))$. $\Omega$, $\Phi$, and $\Psi$ are constant matrices of proper dimensions.

**C. Optimization formulation**

The global objective function [5] can be written as $f(U) = f(U_1 + U_2 + U_3)$ because $P_e(k)$ and $T_{amb}(k)$ are predictable from utility service and weather forecast, respectively. Then, the centralized optimization problem can be represented as

$$\text{minimize}_{U,X} \ f(U),$$

subject to

$$X = \Omega x(0) + \Phi U + \Psi W,$$

$$Y_{i,min} \leq Y_i \leq Y_{i,max},$$

$$U_{i,min} \leq U_i \leq U_{i,max},$$

where $Y_i = (y_i(1), \ldots, y_i(N))$, $U_i = (u_i(1), \ldots, u_i(N))$, $[Y_{i,min}, Y_{i,max}]$ and $[U_{i,min}, U_{i,max}]$ specify the local comfort constraint on zone temperatures and the capacity constraint on the VAV diffusers, respectively; $Cap$ is a vector with elements denoting the chiller capacity for each $k$ during the prediction horizon (predictable from $T_{amb}(k)$). Because $X$ and $Y$ are affine transformations of $U$, we can eliminate them from the decision variables and obtain an equivalent formulation

$$\text{minimize}_{U_i} \ f(U_1 + U_2 + U_3),$$

subject to

$$\sum_{i=1}^{3} C_i U_i \leq c, \ U_{i,min} \leq U_i \leq U_{i,max},$$

where $C_i$ and $c$ are proper matrices and vector, respectively. Notice that the objective function [9] couples local variables $U_i$ together because all three zones are served by one central air-cooled chiller and the AHU system.
D. Distributed optimization solution

There are many existing distributed optimization methods designed for problems in the form (9), such as dual decomposition [7] and Gauss-Seidel Alternating Directions Method of Multipliers (serial ADMM) [8]. However, dual decomposition requires some stringent conditions for guaranteed convergence (such as strict convexity of the objective function). Gauss-Seidel ADMM has milder conditions than dual decomposition, but it is referred to as serial ADMM because it requires agents to take turns to update each block of the decision variables, which makes it not suitable or scalable to extend to cases with a large number of zones. In this study, we utilize the so called Proximal Jacobian ADMM (parallel ADMM) method, as discussed in [9].

First we introduce dummy variables $P_i$ for each agent and additional consensus constraints $P_i = \sum_{j \neq i} U_i$. By doing this, the objective function (9) can be decoupled into the summation of three local cost functions with respect to the local decision variables $Z_i = (U_i, P_i)$. Then, slack variables $Z_0$ are introduced to convert the shared inequality constraint in (9) to an shared equality constraint. The optimization problem (9) is equivalently cast as

$$\min_{Z_i} \frac{1}{3} \sum_{i=0}^{3} f_i(Z_i)$$

subject to

$$\sum_{i=0}^{3} D_i Z_i = d, \ Z_{i,min} \leq Z_i \leq Z_{i,max},$$

where $f_0(Z_0) = 0$, and $f_i(Z_i) = f(U_i + P_i)$ for $i = 1, 2, 3$. Notice that the new shared equality constraint $\sum_{i=0}^{3} D_i Z_i = d$ contains all the consensus constraints $P_i = \sum_{j \neq i} U_i$. The agent-based distributed optimization algorithm for solving (10) is summarized in Algorithm 1.

Algorithm 1 Agent-based Distributed Algorithm
1: Initialize $(Z_0^0, \lambda^0)$, set $v = 0$; 2: repeat 3: Update $Z_i$ (in parallel) according to

$$Z_i^{v+1} = \arg\min_{Z_i \in Z_i} \left( \mathcal{L}_i(Z_i, \lambda^v) + \frac{\phi_i}{2} \|Z_i - Z_i^v\|^2 \right.$$  
$$+ \phi(Z_i^v, Z_i, Z_{i+1}^v)),$$

4: Update $\lambda$ according to

$$\lambda^{v+1} = \lambda^v + \rho \left( \sum_{i=0}^{3} D_i Z_i^{v+1} - d \right).$$

5: $v \leftarrow v + 1$; 6: until some stopping criterion is satisfied.

In Algorithm 1, $\mathcal{L}_i(Z_i, \lambda) = f_i(Z_i) + \lambda^T D_i Z_i$ is part of the Lagrangian function of problem (10) dependent on $Z_i$; $\phi(Z) = \frac{\phi}{2} \|Z - Z_i^v\|^2$. In addition, $\sim i$ (resp. $i$) denotes indices smaller (resp. larger) than $i$. In Algorithm 1, each agent first updates their local decision variables $Z_i$ in parallel according to (11), then a central coordinator collect the updated $Z_i$ from all of the agents and use them to update the dual variable $\lambda$ according to (12), parameters $\varphi_i$ and $\rho$ need to satisfy certain conditions to ensure convergence of Algorithm 1. We refer the interested readers to [9] for more details.

V. EXPERIMENTAL RESULTS

The proposed agent-based DMPC algorithm is implemented in LL3. A 12-hour prediction horizon is chosen. It is assumed that the occupied hours are 10am-10pm (based on the real occupancy schedule). To demonstrate the potential of delivering local comfort using DMPC, different zone temperature intervals are set for the three zones (as summarized in TABLE I). Specifically, since there is no permanent occupants in Zone 1, it has a higher upperbound during the occupied hours. However, Zone 2 and Zone 3 are more heavily occupied, hence tighter comfort intervals need to be maintained during the occupied hours. The TOU price is assumed to have a peak value of 0.16/kWh from 12pm to 6pm, and an off-peak value of 0.067/kWh during other times. All local optimization problems are solved in MATLAB with CVX [10] [11].

<table>
<thead>
<tr>
<th>Zone</th>
<th>Occupied Hours</th>
<th>Unoccupied Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone 1</td>
<td>[21°C, 23.5°C]</td>
<td>[20°C, 24°C]</td>
</tr>
<tr>
<td>Zone 2</td>
<td>[21°C, 23°C]</td>
<td></td>
</tr>
<tr>
<td>Zone 3</td>
<td>[21°C, 22.5°C]</td>
<td></td>
</tr>
</tbody>
</table>

The DMPC implementation requires the prediction of disturbance information (ambient temperature, solar radiation, occupants, lighting and plug load). The ambient temperature prediction is obtained from National Oceanic and Atmospheric Administration (NOAA) website for the Purdue University Airport station. Solar radiation (GHI & GSI) is inferred from sky cover percentage prediction (also obtained from NOAA) using Zhang & Huang’s model [12]. Occupancy, lighting and plug load are predicted by averaging the corresponding history data for the same period in the previous three weeks. During the DMPC implementation, unmeasured state variables need to be estimated. Since the only coupling between adjacent zones are through their zone temperatures, a decentralized Kalman Filter was developed so that each zone can estimate local unmeasured states using standard Kalman Filter by treating adjacent zone temperatures as exogenous inputs.

To show the cost savings potential of the proposed DMPC method, we compare its performance against a baseline local PID controller, for which we modulate the damper position of VAV box A, openings of VAV diffusers 5-8, and openings of VAV diffusers 1-4 to maintain the individual temperatures in Zone 1-3, respectively. The setpoint temperatures for the three zones are always their current comfort upperbounds. If a zone temperature is lower than its setpoint, no cooling will be given and zone temperature is allowed to float freely inside comfort interval. The baseline controllers are run in simulation using the history disturbance information from the same days of the DMPC experiment.
After a 3 day warm-up period, the experiment and simulation are run for 3 days. The zone temperature trajectories as well as the optimal sensible cooling trajectories are given in Fig.4 (baseline) and Fig.5 (agent-based DMPC).

![Figure 4](image1.png)  
*Fig. 4. Simulation results of baseline local PID controller (dashed lines denote the comfort interval for Zone 2)*

![Figure 5](image2.png)  
*Fig. 5. Experiment results of agent-based DMPC (dashed lines denote the comfort interval for Zone 2)*

From the DMPC experiment result, we can observe that the proposed DMPC method is able to maintain zone temperatures inside their respective comfort intervals most of the time, which is a validation of its ability of delivering local comfort based on occupancy preferences. Different from the baseline controller, which always maintain zone temperature at its comfort upperbound, DMPC precool the room in the morning to a lower temperature before 12pm (when peak electricity price begins). In addition, one can observe that Zone 1 and Zone 3 are being pre-cooled at different time periods to avoid a peak load in the morning. This is one of the major benefits of implementing DMPC, i.e. taking advantage of the coordination among different zones. By providing extra cooling during the morning when ambient temperature and the electricity price are relatively low, and the chiller has higher efficiency, cooling load during the afternoon can be reduced, resulting in a lower total electricity bill. Specifically for our three-day experiment, the baseline controller consumes 208.24kWh sensible cooling, while the DMPC consumes slightly more at 216.63kWh. However, the total electricity bill of DMPC is $14.03, which is a 5.59% reduction from the bill of the baseline controller at $14.86.

VI. COMMUNICATION PROTOTYPE TESTING OF MULTI-AGENT OPTIMIZATION

The agent-based distributed optimization algorithm in Algorithm 1 requires three agents, representing each of the three zones, and a central coordinator. Three laptop computers are dispatched to the three zones, acting as the agents and are responsible for updating local decision variables as well as exchanging information with the central coordinator. The central coordinator is a server computer capable of communicating with the BAS by sending command signals (setpoints, cooling rates) and collecting sensor data.

A. Information flow

The MATLAB TCP/IP object and protocol was utilized for the communication between agents and coordinator, since the optimizations at local agents are run in MATLAB with CVX. At the beginning of each iteration, the coordinator sends to the agents: the updated Lagrange multiplier λ from the previous iteration, the TOU electricity price P(k) for the current prediction horizon and the predicted trajectories of other disturbances (solar, occupants, lighting, plug load, ambient temperature); and agents send their updated optimal local decision variables Z(k) back to the coordinator. One limitation of the MATLAB TCP/IP object is that it does not allow broadcasting, which means that the coordinator can only exchange information with one agent at each time.

B. Parallel ADMM v.s. Serial ADMM

One key advantage of the proposed agent-based distributed controller with parallel ADMM over other distributed algorithms with a serial updating structure such as the traditional multi-block Gauss-Seidel ADMM, is that it provides much better scalability when the number of agents or the prediction horizon increases.

The average decision times (including both the communication and computation times) for the convergence of each DMPC optimization problem with both serial and parallel ADMM methods under different prediction horizons are summarized in TABLE II (unit is second). As the prediction horizon doubles, the average decision time with the proposed parallel ADMM method only increases by 54% (from 47.06s to 72.25s). In comparison, the average decision time with the serial ADMM almost triples.

<table>
<thead>
<tr>
<th>Prediction Horizon</th>
<th>Average decision time for each DMPC problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>12h</td>
<td>47.06</td>
</tr>
<tr>
<td>24h</td>
<td>72.25</td>
</tr>
<tr>
<td></td>
<td>198.86</td>
</tr>
</tbody>
</table>
In addition, we can further break down the implementation time of each iteration of the parallel ADMM into communication, local optimization, dual update and idle times under 12h, 24h prediction horizons. The respective times are averaged over all iterations, and the results are given in TABLE III. A graphic visualization for two typical consecutive iterations is given in Fig. 6.

**TABLE III**

<table>
<thead>
<tr>
<th></th>
<th>Coordinator</th>
<th>Agent 1</th>
<th>Agent 2</th>
<th>Agent 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>2.35, 2.72</td>
<td>2.61, 2.76</td>
<td>2.62, 2.76</td>
<td>2.63, 2.77</td>
</tr>
<tr>
<td>Comm.</td>
<td>2.25, 2.27</td>
<td>2.57, 0.57</td>
<td>0.61, 0.62</td>
<td>0.59, 0.58</td>
</tr>
<tr>
<td>Local opt.</td>
<td>NA</td>
<td>1.12, 2.14</td>
<td>0.70, 1.22</td>
<td>0.48, 0.85</td>
</tr>
<tr>
<td>Dual update</td>
<td>0.30, 0.45</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Idle</td>
<td>NA</td>
<td>0.92, 0.05</td>
<td>1.32, 0.92</td>
<td>1.56, 1.34</td>
</tr>
</tbody>
</table>

Notice that the left and right values in each cell corresponds to 12h and 24h prediction horizons, respectively. Unit is second for all cells.

![Prediction horizon: 12h](Image)

![Prediction horizon: 24h](Image)

Fig. 6. Implementation time breakdown of two typical consecutive iterations of Parallel ADMM.

From the above table and figure, several observations can be made:

1) With the prediction horizon being doubled, the information to be exchanged between the coordinator and the agents also doubles, while the communication time barely increases. The reason is that most of the communication time comes from establishing the connection between two TCP/IP objects in MATLAB.

2) With a 12h prediction horizon, the communication time for an agent is comparable to its local optimization time. Due to the lack of broadcasting ability of the coordinator mentioned before, the parallel updating structure is not being taken full advantage of. The overlapping in local optimization time for different agents is small, while the idle time (especially for agent 3) is long.

3) With a 24h prediction horizon, although the local optimization time for each agent almost doubles, the total elapsed time for each iteration barely increases. This is because the ratio that the communication time takes in the total time decreases, leading to more overlapping in local optimization times for agents and less idle times.

4) A more advanced communication protocol that allows broadcasting from the coordinator to the agents will take better advantage of the parallel updating structure. This will be investigated in future studies.

**VII. CONCLUSION**

This paper focuses on the modeling and distributed control of a case study of the multi-zone open-space buildings. A multi-zone model structure is proposed and identified to capture the thermal couplings between adjacent zones. With the identified model, a DMPC algorithm is adopted and implemented in the Purdue Living Lab 3 to demonstrate the potential of energy bill reduction achieved via pre-cooling and agent coordination, and also zone-level local comfort delivery. A communication prototype especially suitable for the multi-agent distributed control in BAS is developed for the experiment. Testing results showed the superior scalability of the proposed parallel updating scheme against a serial updating scheme.

**REFERENCES**


