For review for publication in *ACC 2016*

Scalable Supervisory Control of Building Energy Systems using Generalized Gossip

Zhanhong Jiang
zhjiang@iastate.edu
Venkatesh Chinde
vchinde@iastate.edu
Adam Kohl
adamkohl@iastate.edu
Soumik Sarkar
soumiks@iastate.edu
Atul Kelkar
akelkar@iastate.edu

Department of Mechanical Engineering, Iowa State University, Ames, IA 50011, USA

***Abstract*— This paper presents a novel distributed optimization framework to achieve energy efficiency in large-scale buildings. The modular problem formulation presented in this paper decouples the supervisory optimization scheme from the data-driven micro-level modeling aspect leading to significant scalability and flexibility. Recently developed generalized gossip protocol is used as a robust distributed optimization technique. A supervisory control design problem for multi-zone temperature regulation and energy usage minimization is considered as a case study to describe the generic framework. Numerical simulation results, presented based on a physical testbed in the Iowa Energy Center, demonstrate the advantages of the distributed optimization methodology compared to a typical baseline strategy. The paper also outlines a software architecture based on the VOLTTRON platform, recently developed by the Pacific Northwest National Laboratory (PNNL), for real-life implementation of the proposed framework.**

1. Introduction

Today, approximately 40% of the total energy usage in the U.S. is consumed by the building sector (residential 22%, commercial 18%) [1]. Among various sub-systems, the performance of heating, ventilation, and air-conditioning (HVAC) systems significantly affects the amount of building energy consumed. Various control and optimization techniques have been developed by the community to minimize energy consumption while maintaining comfort requirements. For example, model predictive control (MPC) based approaches have been broadly used. While Bengea et al [2] demonstrated the effectiveness of centralized MPC for energy efficiency in large buildings, such schemes can be prohibitive due to modeling/computational complexity and commissioning cost. Various distributed control schemes have been proposed to alleviate some of these issues [3], [4]. Liang et al [5] presented an auto-regressive moving average exogenous model (ARMAX) and developed a MPC technique to minimize the energy consumption in air handling unit (AHU). Furthermore, various other policies were also proposed for building energy consumption optimization, such as cost-optimal analysis [6], event-based optimization [7], and metamodeling the heating and cooling energy needs and simultaneous building envelop optimization [8]. In order to achieve such self-learning and self-configuring schemes for building energy optimization, the community is increasingly focusing on data-driven, multi-agent networked systems based approaches [9]. For example, Cai [10] developed a hierarchical multi-agent framework to find the optimal operating points by using consensus-based distributed optimization algorithms.

The authors would like to thank Iowa Energy Center for supporting this work-Opportunity Grant No.OG-15-005.

This paper adopts a similar multi-agent hierarchical optimization framework for building energy efficiency. The supervisory optimization scheme is completely decoupled from the data-driven micro-level modeling aspect leading to a significantly scalable and flexible architecture. Moreover, a generalized gossip-based subgradient optimization algorithm [11] is applied to solve the energy-comfort optimization problem. This paper combines the generalized gossip algorithm with the subgradient approach to solve distributed optimization problems related to building energy efficiency. Finally, we also introduce a scalable implementation process for the proposed supervisory control scheme on an agent-based platform called VOLTTRON [12] that was recently developed by the Pacific Northwest National Laboratory (PNNL) for distributed control applications in energy systems such as buildings and power grid.

2. Problem Formulation

This section presents a formulation of the proposed methodology with regards to an illustrative example scenario for air-side heating, ventilation and air-conditioning (HVAC) system as presented in Fig. 1. In this energy supply-demand problem, individual zones become energy consumers that are served with conditioned air by an air handling unit (AHU).

A. Air-side HVAC (AHU-VAV) System

The general layout of a typical AHU-VAV HVAC system is shown in Fig. 1. While a central AHU provides conditioned

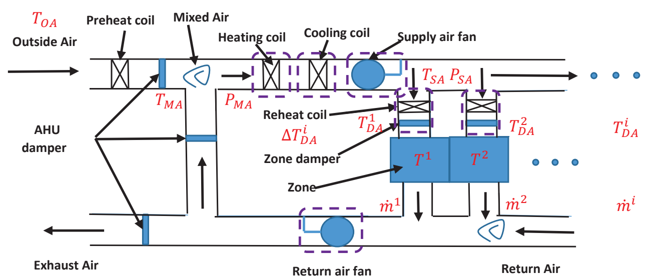

Fig. 1. *Typical layout of an AHU-VAV HVAC system*

air to each variable-air-volume (VAV) box, VAVs in turn supplies conditioned air to each zone. VAVs in this case have two types of actuators - a damper to control air flow rate and a reheat coil to heat up the air. Return air from zones circulates back to AHU (typically using a return air fan) and gets mixed with fresh outside air. Fractions of return and outside air get determined by the positions of AHU (outside, mixed and exhaust air) dampers. Mixed air then passes through both heating and cooling coils and eventually flows to VAVs (using a supply air fan) as supply air. Supply air temperature is controlled to a setpoint by controlling the cooling/heating coil. Supply and return fans aim to maintain a certain static pressure in the ducts. From a supervisory decision-making perspective, a few setpoints (e.g., supply air temperature (SAT) setpoint, mixed air temperature setpoint and duct static pressure setpoint) need to be determined for energy usage minimization while maintaining zone comfort levels. For simplicity, we consider SAT setpoint as the optimization variable to demonstrate the effectiveness of the proposed algorithm.

B. Optimization Problem Description

Consider a situation where every zone in a building has the same comfort requirement and the same external/internal loads. In that case, a common SAT setpoint can be determined that satisfies requirement of each zone. However, in reality due to the diversity among zones, AHU SAT is typically kept at a very low value (e.g., $55°F$) such that VAVs can reheat the supply air as needed before it enters the zones. Therefore, optimization can help decide a variable setpoint that reduces the excess energy use in this 'first cooling and then reheating' process. On the air-side HVAC, this paper considers the cooling and heating energy consumed in AHU, the reheat energy consumed in VAV boxes and the power consumptions by return air and supply air fans. Some relevant notations are provided in Table I before the problem formulation is presented mathematically.

Cooling/heating Energy: Between the cooling and heating modes in the AHU, we take the cooling mode to describe the formulation. The cooling energy consumed at the cooling coil in the AHU can be described as

$$E_C = \alpha_c \dot{m} c_p (T_{SA} - T_{MA}) = \alpha_c \sum_{i \in \mathcal{V}} \dot{m}^i c_p (T_{SA} - T_{MA}) \tag{1}$$

Variables	Definition
α	Ideal energy coefficient
α_c	Cooling coefficient
α_h	Heating coefficient
$\dot{m}$	Mass flow rate
T_{DA}^i	Discharge air temperature (for zone i)
T_{MA}	Mixed air temperature
T_{SA}	Supply air temperature
T_{RA}	Return air temperature
T_{OA}	Outside air temperature
T^i	Zone temperature (for zone i)
T_{HSP}	Heating set point
T_{CSP}	Cooling set point
c_p	Specific heat capacity
E_{Idl}	Ideal energy
E_{Act}	Actual energy
E_{Exs}	Excess energy
E_C	Cooling energy
E_H	Heating energy (including reheat energy)
E_F	Fan power

TABLE I

Table I: Variable nomenclature

In the heating mode, similar formula can be used with heating coefficient.

Reheat Energy: The reheat energy is consumed at the reheat coil of a VAV box and it can be described as

$$E_H = \alpha_h \sum_{i \in \mathcal{V}} \dot{m}^i c_p (T_{DA}^i - T_{SA}) \tag{2}$$

Fan Power: The fan power can be simplified as the function with respect to air flow rate and it can be given as a second order polynomial

$$E_F = a_0 + a_1 \dot{m} + a_2 \dot{m}^2 \tag{3}$$

where a_0, a_1 and a_2 are the polynomial coefficients.

Ideal Energy: According to the discussion above, we can obtain the expression of ideal energy as follows

$$E_{Idl} = \alpha \sum_{i \in \mathcal{V}} \dot{m}^i c_p (T_{DA}^i - T_{MA}) + E_F \tag{4}$$

Actual Energy: The total amount of actual energy can be written as

$$E_{Act} = E_C + E_H + E_F \tag{5}$$

Excess Energy: Finally, the excess energy is obtained as follows

$$\begin{aligned} E_{Exs} &= E_{Act} - E_{Idl} \\ &= \sum_{i \in \mathcal{V}} \dot{m}^i c_p [(\alpha - \alpha_c) T_{MA} \\ &+ (\alpha_c - \alpha_h) T_{SA} + (\alpha_h - \alpha) T_{DA}^i] \end{aligned} \tag{6}$$

As the mixed air consists of return air and outside air then the relation among these three variables, i.e., T_{MA}, T_{RA} and T_{OA} can be written as $T_{MA} = \delta T_{RA} + (1-\delta) T_{OA} = \delta \frac{\sum_{i \in \mathcal{V}} \dot{m}^i T^i}{\sum_{i \in \mathcal{V}} \dot{m}^i} + (1-\delta) T_{OA}$, where δ is fraction of return air in mixed air.

Moreover, the relation between T_{DA}^i and T_{SA} associated with a reheat coil in a VAV box can be correspondingly represented by $T_{DA}^i = T_{SA} + \Delta T_{DA}^i$, where ΔT_{DA}^i is the temperature difference between supply air and discharge air which is a function of VAV reheat coil parameters - inlet water temperature (T_{wi}), inlet hot water flow rate ($\dot{m}^i_w$), inlet air temperature (i.e., T_{SA}) and air flow rate ($\dot{m}^i$). Also, the zone thermal dynamics can be described as: $T^i = f(T_{SA}, \dot{m}^i, \Delta T^i_{DA}, T_{OA})$. The constraints related to actuators and comfort requirements are as follows: $\dot{m}^i \in [\dot{m}^i_{min}, \dot{m}^i_{max}]$: the air flow rate is bounded due to the VAV damper actuator; $T_{SA} \in [(T_{SA})_{min}, (T_{SA})_{max}]$: the supply air temperature is bounded due to the heating/cooling coil capacity; $T^i_{ref} \in [T_{HSP}, T_{CSP}]$: the zone temperature is in between a deadband of temperature setpoints; $\Delta T^i_{DA} \in [(\Delta T_{DA})_{min}, (\Delta T_{DA})_{max}]$: the discharge air temperature is bounded due to the reheat coil capacity.

The goal of the distributed optimization framework is to minimize the building energy consumption as well as to satisfy the zone comfort conditions. The cost function with the above constraints to determine optimal AHU supply air temperature can be obtained as follows

$$\begin{aligned} T^*_{SA} &= \underset{T_{SA}}{\text{argmin}}\, J, \quad \text{where,} \\ J &= \omega E^2_{Exs} + (1-\omega)\rho \sum_{i\in\mathcal{V}} \dot{m}^i \|T^i - T^i_{ref}\|^2_2 \end{aligned} \tag{7}$$

where, ω is the trade-off factor between the energy cost and zone comfort cost. To deal with the issue of scaling between energy and comfort cost values, a scalar parameter ρ is introduced. The corresponding distributed optimization formulation can be described as follows.

$$\begin{aligned} T^*_{SA} &= \underset{T_{SA}}{\text{argmin}} \sum_{i=1}^{N} J^i, \quad \text{where} \\ J^i &= \omega\{\dot{m}^i c_p[(\alpha-\alpha_c)[\delta \frac{\sum_{i\in\mathcal{V}} \dot{m}^i T^i}{\sum_{i\in\mathcal{V}} \dot{m}^i} + (1-\delta)T_{OA}] \\ &\quad +(\alpha_c - \alpha)T_{SA} + (\alpha_h - \alpha)\Delta T^i_{DA}]\}^2 \\ &\quad +(1-\omega)\rho\|T^i - T^i_{ref}\|^2_2 \end{aligned} \tag{8}$$

Note, during optimization every zone i needs to calculate return air temperature which in turn requires mass flow rate and zone temperature information from all other zones.

3. Generalized Gossip based Distributed optimization

In this section, a solution approach is presented for the distributed building energy optimization problem formulated above. The approach uses a recently proposed generalized gossip-based algorithm. The main results of the proposed algorithm is provided in the sequel. However, further details can be found in [11].

A. Background of Generalized Gossip protocol

Consider an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ consisting of N agents, where $\mathcal{V} = \{1, 2, ..., N\}$ and $\mathcal{A} \subseteq \mathcal{V} \times \mathcal{V}$. If $(i, j) \in \mathcal{A}$, then agent i can communicate with agent j. Let the distributed building energy optimization problem be defined on the network as follows:

$$\begin{aligned} &\text{minimize } , f(x) = \sum_{i=1}^{N} f^i(x) \\ &\text{subject to } , x \in \mathbb{X} \end{aligned} \tag{9}$$

where $f^i : \mathbb{R}^M \longrightarrow \mathbb{R}$ are agent level objective functions (possibly convex or non-convex), $\mathbb{X}$ is a nonempty, closed, and compact subset of $\mathbb{R}^M$. x is a vector whose i^{th} component is represented by x^i.

The basic definitions [13], [14] and assumptions used in this paper are:

Definition 1: A vector $g \in \mathbb{R}^M$ is a subgradient of a convex function $f : \mathbb{R}^M \longrightarrow \mathbb{R}$ at a point $z \in \mathbb{R}^M$ if $f(y) \geq f(z) + g^T(y - z), \forall y \in \mathbb{R}^M$.

Definition 2: The set of all subgradients of a convex function of f at $z \in \mathbb{R}^M$ is called the subdifferential of f at z, and is denoted by $\partial f(z)$: $\partial f(z) = \{g \in \mathbb{R}^M | f(y) \geq f(z) + g^T(y - z), \forall y \in \mathbb{R}^M\}$.

Assumption 1 (Subgradient boundedness): There exists a scalar G for all $i = 1, ..., N$ such that $\|g^i(x)\|_2 \leq G, \forall g^i(x) \in \partial f^i(x), \forall x \in \mathbb{X}$.

Assumption 2: The optimal solution set x^* is nonempty.

A vector notation of the update law for the proposed algorithm (derived from [15] and [16]) for the optimization variable is as follows:

$$x(k+1) = (1-\theta)\Pi(k)x(k) + \theta(x(k) - \nabla(k)). \tag{10}$$

where $\nabla(k)$ is the subgradient of f^i at $x^i(k)$ computed by agent i. $\Pi \in \mathbb{R}^N \times \mathbb{R}^N$ is the agent interaction matrix. θ is the user-defined control parameter.

For first moment analysis, ensemble average (over agents) of $x(k)$ and $\nabla(k)$ are denoted by $\bar{x}(k)$ and $\bar{\nabla}(k)$ respectively. They are defined as: $\bar{x}(k) = \frac{1}{N}\mathbf{1}x(k) = \frac{1}{N}\sum_{i=1}^{N} x^i(k)$; $\bar{\nabla}(k) = \frac{1}{N}\mathbf{1}\nabla(k) = \frac{1}{N}\sum_{i=1}^{N} \nabla^i(k)$, where $\mathbf{1}$ is a row vector with all elements being 1.

Note, multiplying the update rule described in eqn. 10 by $\frac{1}{N}\mathbf{1}$ yields the following relationship (as Π is doubly stochastic): $\bar{x}(k+1) = \bar{x}(k) - \theta\bar{\nabla}(k)$.

Next, optimal function values are denoted by f^*, that are assumed to be finite. Without loss of generality the optimal set is represented by x^*, i.e., $x^* = \{x \in \mathbb{R} | \sum_{i=1}^{N} f^i(x) = f^*\}$. Next we present the main results obtained in convergence analysis.

Theorem 1: If *Assumptions 1, 2* holds, then, for a sequence $\{x^i(k)\}$, $\forall k$ and $i = 1, \ldots, N$,

$$\begin{aligned} f^* \leq f(x^i(k))_{min} \leq f^* &+ \frac{N\|\bar{x}(1) - x^*\|^2_2}{2m\theta} \\ &+3NG\sigma + \frac{N\theta G^2}{2} \end{aligned} \tag{11}$$

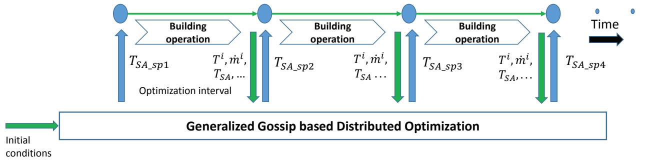

Fig. 2. *Workflow of the supervisory control framework*

where $f(x^i(k))_{min} = \min\{f(x^i(1)), \ldots, f(x^i(m))\}$, m is the number of iterations, G is the upper bound of subgradients, σ is the upper bound of Euclidean distance between $x^i(k)$ and $\bar{x}(k)$ and θ is the control parameter.

Next, the convergence characteristics can be analyzed as the control parameter approaches extreme values 0 or 1. Let a sequence $\{\theta_k\}$, $k = 1, 2, \ldots, m$ be defined as follows.

Definition 3:$\{\theta_k\}$ is a sequence that satisfies the following properties: (1): θ_k converges to 0; (2): $\{\theta_k\}$ is a nonsummable sequence. Hence, $\theta_k>0; \lim_{k\to\infty} \theta_k = 0; \quad \lim_{m\to\infty} \sum_{k=1}^{m} \theta_k = \infty$.

There exists an integer N_1, that satisfies $\theta_k \leq \frac{\delta}{NG^2}, \delta>0, \forall k>N_1$. Then there exists another integer N_2 such that $\sum_{k=1}^{m} \theta_k \geq \frac{1}{\delta}(N\|\bar{x}(1) - x^*\|_2^2 + NG^2 \sum_{k=1}^{N_1} \theta_k^2), \forall m>N_2$. This inequality holds because $\lim_{m\to\infty} \sum_{k=1}^{m} \theta_k = \infty$. Now, let $\mathfrak{N} = max\{N_1, N_2\}$, and the following *Theorem 2* can be stated.

Theorem 2: If *Assumptions 1, 2* holds, then, for a sequence $\{x^i(k)\}$, if θ_k satisfies *Definition 3*, $\forall k$, and $i = 1, \ldots, N$,

$$f(x^i(k))_{min} \leq f^* + \delta + 3NG\sigma, \forall m>\mathfrak{N}. \tag{12}$$

Now, the case where $\theta \to 1$ is analyzed by presenting the following theorem.

Theorem 3: If *Assumptions 1, 2* holds, then, for a sequence $\{x^i(k)\}$, with $\theta \to 1$, $\forall k$ and $i = 1, \ldots, N$,

$$f(x^i(k))_{min} \leq f^* + \frac{N\|\bar{x}(1) - x^*\|_2^2}{2m} + 3NG\sigma + \frac{NG^2}{2}. \tag{13}$$

B. Optimization algorithm overview

The proposed supervisory optimizer aims to determine optimal AHU supply air temperature based on information exchange among local zones. The crucial advantage of this framework is that local zones can use any local controllers and suitable modeling scheme. However, as long as they can compute subgradient for local cost function (J^i) for energy optimization and achieving comfort, the supervisory control layer can run the generalized gossip protocol for global energy optimization.

In this context, each local zone needs modeling of thermal dynamics in order to compute subgradients for their local cost functions (as outlined in Eqn. 8). Currently, simple PI controllers are used for these local controllers (which is common for most of the HVAC equipment in commercial buildings [2]). However, more sophisticated controllers can be used without any major change in the framework. The basic workflow of the supervisory control framework is illustrated in Fig. 2. In summary, the optimization framework is presented in an algorithmic format.

Algorithm: *Supervisory Control Algorithm*

initialize $\Delta, \theta, T_{SA}(1), \Pi(1)$
set $u = 1$
loop over u (until building operation schedule expires)
  set $k = 1$
  loop over k
   for $i = 1$ to N do
   calculate $J^i(k-1), J^i(k+1)$
   $g^i(k) \approxeq \frac{J^i(k+1) - J^i(k-1)}{2\Delta}$
   end for
   $T_{SA}(k+1) = (1-\theta)\Pi(k)T_{SA}(k) + \theta(T_{SA}(k) - g(k))$
   if (termination criterion met) **then**
    Break
   else
    $k = k + 1$
   end if
  end loop
  Run the building operation with $T_{SA_{sp}} = T_{SA}(k+1)$ over the span of one optimization interval
  $T_{SA}(1) = T_{SA_{act}}$ at the last time instant of building operation
  $u = u + 1$
end loop

$\Pi(k)$ here is set as a uniform stochastic matrix as defined in [11] to signify a complete collaboration among zones. u indicates the number of cycles; each cycle includes one optimization process and building operation over one optimization interval. k signifies the number of iterations in optimization. $T_{SA_{act}}$ is the actual supply air temperature while $T_{SA_{sp}}$ is the supply air temperature setpoint. Δ denotes the step size for the numerical differentiation.

4. Results and Discussion for a Case Study

The case study in this paper is performed on a simulation platform (one AHU, six zones) that is based on the physical Energy Resource Station testbed developed and maintained by the Iowa Energy Center [17]. Please find further details of the test bed in [18]. A typical baseline supply air temperature schedule is considered where the setpoint is kept constant at $55°F$ in order to explore the efficacies of the proposed algorithm. Furthermore, the zone thermal modeling was performed using actual historical data from the testbed during winter season and similarly, all the test days (i.e., outside air conditions) were taken from the winter season. A one month testing period is studied in order to validate the algorithm under different outside conditions. To maintain the reliability of the zone temperature predictions and supply air temperature setpoint optimality, the optimization interval is taken to be 15 minutes. As shown in Fig. 3, optimized supply air temperature setpoint turns out to be quite different from the constant baseline condition

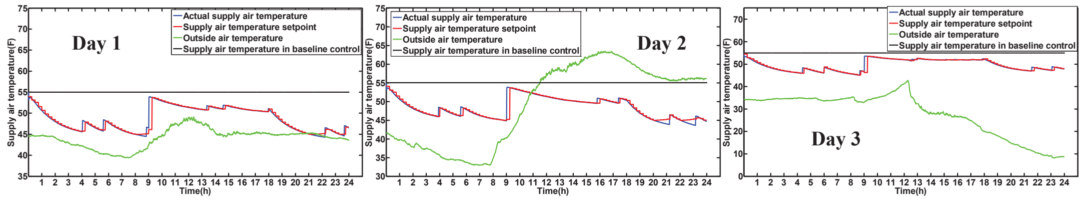

Fig. 3. *AHU supply air temperature under supervisory control and baseline control with different outside air temperatures*

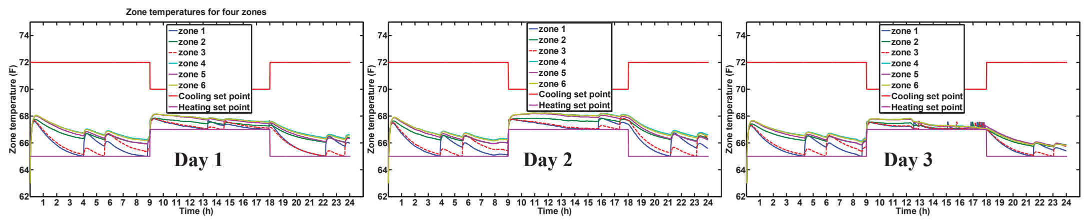

Fig. 4. *Zone temperature regulation during days with different outside air temperatures under supervisory control*

under different outside air conditions. Figure 4 shows zone temperature regulation performance for all 6 zones with different heating/cooling setpoints during unoccupied (wider temperature band) and occupied (narrower temperature band) hours. As the testing was performed in the winter season local zone temperature control aims at approaching heating setpoint as closely as possible in order to save energy under both baseline and optimized strategies. To study the supervisory control performance under heterogeneous disturbances, different outside air temperature patterns are used. By observing the AHU supply air temperatures and zone temperature regulation during different days, it can be concluded that the supervisory control scheme is robust to different external/internal disturbances while minimizing excess energy. For zone temperatures, it can also be seen that there were no violation of comfort setpoints. Figure 5 shows that in all 28 days, zone temperature regulation by the proposed supervisory control scheme consumes less energy compared to baseline control. Figure 6 shows the energy consumption during 6 representative days by AHU heating/cooling coils, VAV reheat coils and AHU fans under baseline and supervisory control. The results indicate that the difference in cooling/heating energy consumed in AHU and the fan energy to a certain extent causes the energy usage reduction in the supervisory framework. The energy savings and zone temperature regulation validate the effectiveness of both the proposed generalized gossip-based subgradient algorithm and the modular, distributed supervisory control framework for HVAC systems.

5. Architecture for Volttron based Implementation

A new open source language-agnostic agent platform called VOLTTRON™ has been recently developed by PNNL [12], [19] for smart city applications with built-in security and resource management. Customized applications can be built on this platform for efficiently managing energy usage

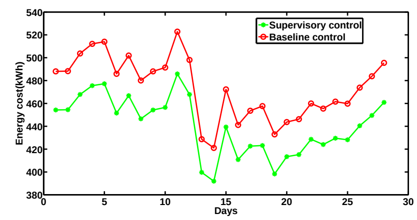

Fig. 5. *Energy cost in 28 test days in winter*

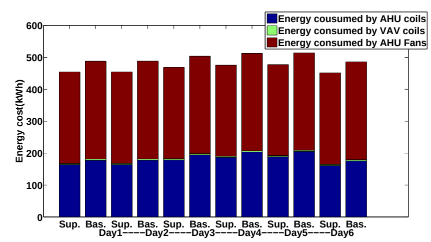

Fig. 6. *Within 6 days energy consumed in AHU, VAV and by fans by supervisory control and baseline control*

among appliances and devices, including HVAC systems, lighting and electric vehicles. Key features include: (i) real-time data processing, (ii) automatic adjustment of data resolution and sampling frequency, (iii) data correlation from multiple domains, and (iv) support for distributed sensing, optimization and control applications. A software architecture for VOLTTRON™ based implementation of the proposed application is shown in Fig. 7. While data being used by applications live on the message bus, historical data can be stored in a cloud service (with a RESTful web service called the simple Measuring and Actuation Profile (sMAP) or other processes) for future on- or off-line uses. Furthermore, it provides resource guarantees for agents in the platform, including memory and processor utilization, authentication and authorization services, directory services for agent and resource location. These capabilities make VOLTTRON™ an ideal candidate to implement our proposed modular, data-driven, hierarchical control scheme via deploying intelligent

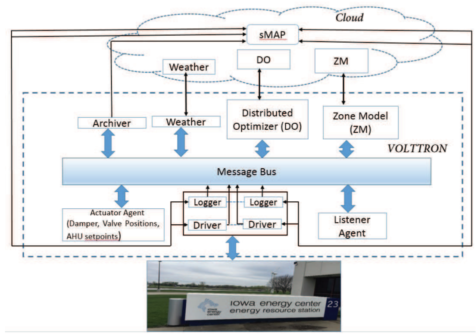

Fig. 7. *VOLTTRON^{TM} based implementation of the proposed framework for supervisory control of Building HVAC system; the Message Bus provides a common platform for sharing information between applications, e.g., actuator scheduler, weather forecast service and distributed optimizer; historical data can be stored in a cloud service built on sMAP or otherwise for future use*

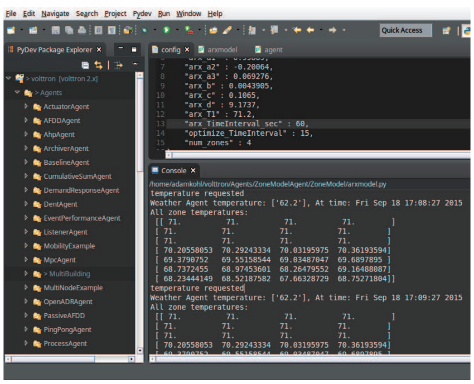

Fig. 8. *Zone Model Implementation in VOLTTRON*

agents for heterogeneous energy supply and demand entities to perform decentralized decision making. In this context, we have developed VOLTTRON agents related to zone model (which publishes the predicted temperature values onto the message bus by subscribing to the outside air temperature from the weather agent, given initial values of temperature) and distributed optimizer (which can compute subgradients and run generalized gossip algorithms). A sample template showing the predicted temperature values by the zone model agent in the output console is shown in Fig. 8. Note, due to the enormous flexibility of the agent based implementation framework, it will be extremely easy to plug or remove zone(s).

6. Conclusions and Future Works

This paper proposes a novel distributed optimization framework for building energy efficiency. A recently developed generalized gossip-based subgradient algorithm was used to solve this problem. A six-zone simulated usecase based on the physical testbed in Iowa Energy Center is used to validate the proposed framework. Simulation results show that the proposed supervisory control scheme is able to reduce the building energy consumption while maintaining zone comfort compared to a typical baseline strategy. The paper also presents an implementation scheme for the proposed framework on a recently developed agent-based data management platform, called VOLTTRON. A few other future research directions are: (1) the application of more advanced local controllers for guaranteeing the robustness of local zone temperature regulation, (2) inclusion of more optimization variables, such as mixed air temperature setpoint, static pressure setpoint (3) inclusion of chillers/boilers in the optimization loop.

References

[1] "Report on environment, final report epa/600/r-07/045f.," *Environmental Protection Agency*, 2008.

[2] S. Bengea, P. Li, S. Sarkar, S. Vichik, V. Adetola, K. Kang, T. Lovett, and F. Leonardi, "Fault-tolerant optimal control of a building heating, ventilation, and air conditioning system," *To appear in Science and Technology for the Built Environment*, 2015.

[3] H. Scherer, M. Pasamontes, J. Guzman, and J. Alvarez, "Efficient building energy management using distributed model predictive control," *Journal of Process Control*, vol. 24, pp. 740–749, 2014.

[4] M. Elliott and B. P. Rasmussen, "Optimal setpoints for hvac systems via iterative cooperative neighbor communication," *Journal of Dynamic Systems, Measurement and Control*, vol. 137, 2015.

[5] W. Liang, R. Quinte, X. Jia, and J.-Q. Sun, "Mpc control for improving energy efficiency of a building air handler for multi-zone vavs," *Building and Environment*, vol. 92, pp. 256–268, 2015.

[6] M. Ferrara, E. Fabrizio, J. Virgone, and M. Filippi, "A simulation-based optimization method for cost-optimal analysis of nearly zero energy buildings," *Energy and Buildings*, vol. 84, pp. 442–457, 2014.

[7] B. Sun, P. B. Luh, Q.-S. Jia, and B. Yan, "Event-based optimization with non-stationary uncertainties to save energy costs of hvac systems in buildings," *in Proceedings of 2013 IEEE International Conference on Automation Science and Engineering (CASE)*, pp. 436–441, 2013.

[8] Z. Ronami, A. Draoui, and F. Allard, "Metamodeling the heating and cooling energy needs and simultabeous building envelope optimization for low energy building design in morocco," *Energy and Buildings*, 2015.

[9] R. Yang and L. Wang, "Energy management of multi-zone buildings based on multi-agent control and particle swarm optimization," *in Proceedings of Systems, Man, and Cybernetics (SMC), 2011 IEEE Interanational Conference on, Anchorage, AK*, pp. 159–164, 2011.

[10] J. Cai, D. Kim, V. K. Putta, J. E. Braun, and J. Hu, "Multi-agent control for centralized air conditioning systems serving multi-zone buildings," *in Proceedings of American Control Conference, Chicago, IL*, 2015.

[11] Z. Jiang, S. Sarkar, and M. Kushal, "On distributed optimization using generalized gossip," *in Proceedings of 54th Conference on Decision and Control, IEEE, Osaka*, 2015.

[12] R. G. Lutes, J. Haack, S. Katipamula, K. Monson, B. Akyol, B. Carpenter, and N. Tenney, "Volttron: User guide," 2014.

[13] S. Boyd, L. Xiao, and A. Mutapcic, "Subgradient methods," 2003.

[14] B. Johansson, T. Keviczky, M. Johansson, and J. K. H., "Subgradient methods and consensus algorithms for solving convex optimization problems," *in Proceedings of the 47th IEEE Conference on Decision and Control, Caucun, Mexico*, pp. 4185–4190, December, 2008.

[15] A. Nedic and A. Ozdaglar, "Distributed subgradient methods for multi-agent optimization," *Automatic Control, IEEE Transactions on*, vol. 54, pp. 48–61, Janury, 2009.

[16] S. Sarkar, K. Mukherjee, and A. Ray, "Distributed decision propagation in proximity networks," *International Journal of Control*, vol. 86, no. 6, pp. 1118–1130, 2013.

[17] "Energy resource station (ers) technical description," *Iowa Energy Center Technical Report*, 2010.

[18] V. Chinde, J. C. Heylmun, A. Kohl, Z. Jiang, S. Sarkar, and A. Kelkar, "Comparative evaluation of control-oriented zone temperature prediction modeling strategies in buildings," *in Proceedings of DSCC, ASME, 2015, Columbus*.

[19] J. Haack, B. Akyol, B. Carpenter, C. Tews, and L. Foglesong, "Volttron: an agent platform for the smart grid," in *Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems*, pp. 1367–1368, International Foundation for Autonomous Agents and Multiagent Systems, 2013.