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A VOLTTRON[TM] based implementation of Supervisory Control using Generalized Gossip for Building Energy Systems

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ABSTRACT

Building energy systems comprising of many subsystems with local information and heterogenous preferences demand the need for coordination in order to perform optimally. The performance required by a typical airside HVAC system involving a large number of zones are multifaceted, involves attainment of various objectives (such as optimal supply air temperature) which requires coordination among zones. The use of traditional centralized optimization involving a large number of variables is very difficult to solve in near real time. This paper presents a novel distributed optimization framework to achieve energy efficiency in large-scale buildings. The primary goals are to achieve scalability, robustness, flexibility and low-cost commissioning. The results are presented using the proposed distributed optimization framework based on a physical testbed in the Iowa Energy Center and demonstrates the advantages of the proposed methodology compared to a typical baseline strategy. The paper outlines a real-life implementation of the proposed framework based on the VOLTTRON[TM] platform, recently developed by the Pacific Northwest National Laboratory (PNNL).

1. INTRODUCTION

Buildings are complex systems with a large variety of heterogeneous sub-systems involved in complex electro-mechanical interaction. Hence, energy usage optimization poses a difficult technical challenge that needs to be robust, scalable and easily deployable. In this context, a multi-agent based control strategy for optimal control of centralized air conditioning systems is proposed in (Cai, Kim, Putta, Braun, & Hu, 2015), where two distributed optimization algorithms have been formulated to minimize the energy consumption satisfying the constraints on the load. Recently, (Cai, Braun, Kim, & Hu, 2016) proposes a multi-agent control based demand response strategy for multi-zone buildings. In (Jiang, Chinde, Kohl, Sarkar, & Kelkar, 2016), authors have proposed a modular optimization framework using Generalized Gossip for building energy systems that naturally generalizes to the entire spectrum of "complete disagreement" to "complete agreement (consensus)" which will be useful for handling multiple energy resources and constraints. This paper implements and tests the effectiveness of the Generalized Gossip-based distributed optimization framework on the Iowa Energy Center's Energy Resource Station (ERS) testbed with the objective to reduce energy costs while maintaining zone comfort. These goals are accomplished by implementing the proposed framework within a multi-agent environment called VOLTTRON[TM].

VOLTTRON[TM] an open source multi-agent system platform, developed by PNNL (Akyol et al., 2012; Lutes et al., 2014) which has several built-in features such as security, resource management etc., and leaving the developers to write agents and control their behavior. The rationale (Weiss, 1999) behind multi-agent systems (MAS) is well suited for diverse applications ranging from the internet to the building sector. These applications are inherently distributed, complex and solutions to such problems using centralized architecture pose limitations to the hardware or software involved. Multi-agent systems, as distributed systems have succeeded in solving complex problems while offering several desirable features such as speed, efficiency, scalability, and flexibility etc., one such complex problem is the case of buildings which is discussed in this paper.

There are several agent development platforms which support the MAS conceptual design such as JADE, ZEUS, VOLTTRON[TM] etc. The description regarding these platforms and comparison studies in the context of microgrid

applications is provided in (Kantamneni, Brown, Parker, & Weaver, 2015). It is noted that VOLTTRON[TM] is best employed by facilities and building managers, since it efficiently utilizes sensor and instrumentation data. The use of VOLTTRON[TM] platform has been demonstrated in several applications (Haack, Akyol, Carpenter, Tews, & Foglesong, 2013; Haack, Akyol, Tenney, et al., 2013) such as achieving the power consumption goal in a building while charging Electric Vehicle within user schedule, control of an electric bus for a local transit company and coordinating commercial building energy usage. In (Khamphanchai et al., 2014; Khamphanchai, Pipattanasomporn, Kuzlu, & Rahman, 2015) a low-cost, user-friendly building energy management platform has been built on the top of VOLTTRON to facilitate improved sensing and control of equipment in small and medium-sized buildings. The platform is aimed at improving energy efficiency and participate in demand response by controlling the loads in buildings. Overall, VOLTTRON[TM] provides a natural way of designing and implementing distributed control algorithms.

The organization of the paper is as follows. In section 2, we discuss the problem setup. In section 3, we discuss the generalized gossip based distributed optimization framework. In section 4, the overview and implementation aspects of VOLTTRON[TM] are discussed followed by conclusions presented in section 5.

2. PROBLEM SETUP

Building are complex energy systems composed of multiple subsystems which have different mathematical structures and evolve in different scales either in time or space. These components are interconnected due to which there are inherent dependencies between the local and the system-wide events. The major issue that persists in the building systems research is to increase the energy efficiency in buildings, the reason for this is two folds: the percentage share in the total energy consumption and the greenhouse gas emissions. These key issues are of paramount importance to meet the national energy demands and the environment challenges. Building efficiency needs to be considered as a means to provide occupant comfort and safe indoor environment and also building systems, in particular, has distributed nature, which demands the need for distributed control architectures and optimization. There are several disadvantages associated with the centralized optimization such as handling large scale systems with given time complexity and scalability issues often lead to the path for distributed optimization. The computational complexity in the distributed setup is addressed primarily based on the modularity in the modeling and control design phases. Distributed optimization problems arise in various fields of engineering where the set of agents coordinate to perform the task optimally.

Multi-agent coordination and control framework is adopted and tested in diverse applications and in the context of building systems application (Cai et al., 2015) provides a multi-agent control methodology for optimal control of centralized air conditioning systems. We have proposed a modular optimization framework in (Jiang et al., 2016), where the supervisory optimization scheme is completely decoupled from the data-driven micro-level modeling aspect leading to a significantly scalable and flexible architecture. The primary goals of the proposed framework are to achieve scalability, robustness, flexibility and low-cost commissioning. We present 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).

2.1 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 air to each variable-air-volume (VAV) box, VAVs in turn supplies conditioned air to each zone. 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. 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 the requirement of each zone. However, in reality due to the diversity of 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. SAT setpoint can be further optimized based on the knowledge of outside air condition and zone thermal dynamics. For more details on the problem description and the assumptions refer to (Jiang et al., 2016).
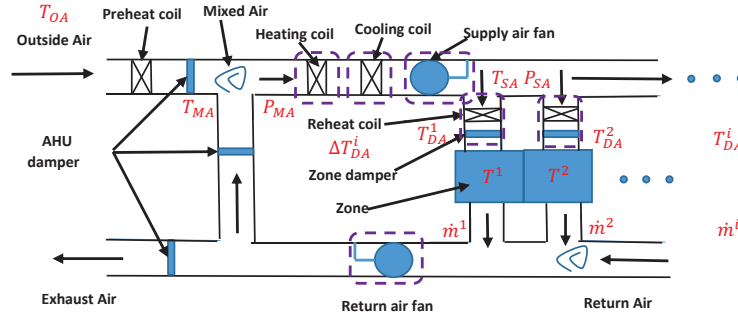
Figure 1: *Typical layout of an AHU-VAV HVAC system*

3. DISTRIBUTED OPTIMIZATION USING GENERALIZED GOSSIP

This section describes a solution approach for the distributed building energy optimization problem formulated above. Most of the material in this section is taken from (Jiang et al., 2016). The approach uses a recently proposed generalized gossip-based algorithm. Theoretical contributions to the proposed framework can be found in (Jiang, Sarkar, & Kushal, 2015).

3.1 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:

$$\text{minimize } f(x) = \sum_{i=1}^{N} f^i(x)$$

$$\text{subject to } x \in \mathbb{X} \tag{1}$$

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 (Boyd, Xiao, & Mutapcic, 2003; Johansson, Keviczky, Johansson, & H., December, 2008) 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

$$f(y) \geq f(z) + g^T(y - z), \forall y \in \mathbb{R}^M \tag{2}$$

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 $\partial f(z)$:

$$\partial f(z) = \{g \in \mathbb{R}^M | f(y) \geq f(z) + g^T(y - z), \forall y \in \mathbb{R}^M\} \tag{3}$$

Assumption 1 (Subgradient boundedness): There exists a scalar G for all $i = 1, ..., N$ such that

$$\|g^i(x)\|_2 \leq G, \forall g^i(x) \in \partial f^i(x), \forall x \in \mathbb{X} \tag{4}$$

Note, this assumption can be derived from the *Lipschitz continuity* relationship.

A vector notation of the update law for the proposed algorithm (derived from (Nedic & Ozdaglar, Janury, 2009) and (Sarkar, Mukherjee, & Ray, 2013)) for the optimization variable is as follows:

$$x(k + 1) = (1 - \theta)\Pi(k)x(k) + \theta(x(k) - \nabla(k)). \tag{5}$$

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.

3.2 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 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 (refer (Jiang et al., 2016)). In this paper, although we use a data-driven ARX modeling scheme for zones, any other technique with same input-output conditions can be seamlessly accommodated. However, the local cost functions may be nonlinear and nonconvex and therefore, subgradients can be found using numerical differentiation. The modeling and optimization scheme also consider the local controllers for heating/cooling coil in AHU and dampers, reheat coils in VAV boxes. Currently, simple PI controllers are used for these local controllers (which is common for most of the HVAC equipment in commercial buildings (Bengea et al., 2015).

The basic workflow of the supervisory control framework is illustrated in Fig. 2. In this framework, an optimization interval is considered within which it is assumed that predictions from zone thermal modeling would be reliable, as well as the optimized AHU supply air temperature setpoint, would be appropriate. The supervisory decision-making process begins with subgradient-based optimization depending on the initial conditions. The building operation starts with optimized AHU supply air temperature setpoint. After expiry of the optimization interval, the supply air temperature setpoint is re-optimized based on current conditions. For validating the proposed algorithms scheme, a case study in
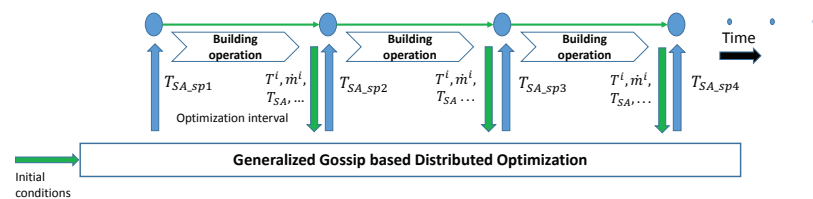

Figure 2: *Workflow of the supervisory control framework*
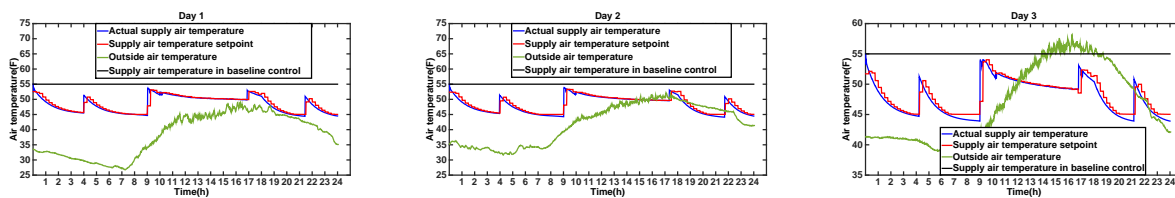

Figure 3: AHU supply air temperature under supervisory control and baseline control with different outside air temperatures.
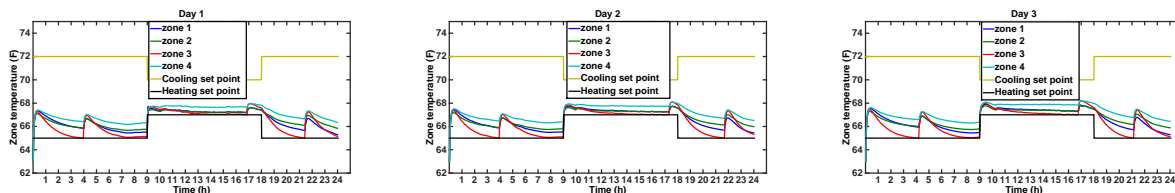

Figure 4: Zone temperature regulation during days with different outside air temperatures under supervisory control.

this paper is performed on a simulation (one AHU, four zones) based on the physical Energy Resource Station testbed in the Iowa Energy Center (Center, 2010). A typical baseline supply air temperature schedule is considered where the setpoint is kept constant at 55 °F. Moreover, the zone thermal modeling was performed using actual historical
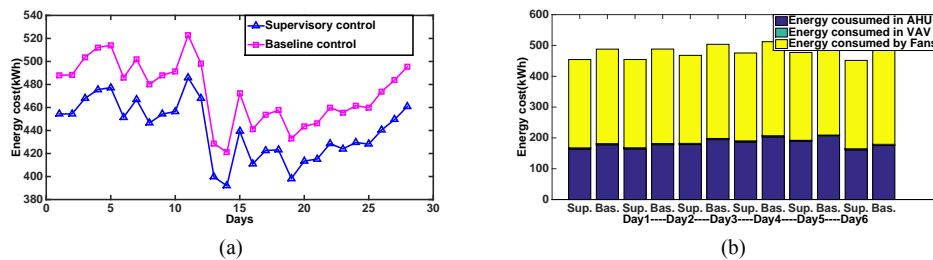
Figure 5: (a) Energy cost in 28 test days in winter; and (b) Within 6 days energy consumed in AHU, VAV and by fans by supervisory control and baseline control.

data collected from the testbed during winter season. For validating the algorithm under different ambient conditions, the testing period in this case study is one month. As shown in Fig. 3, optimized supply air temperature setpoint varies under different ambient conditions and is different from the constant baseline condition. Zone temperature regulation performance for all 4 zones with different heating/cooling setpoints during unoccupied and occupied hours is shown in Fig. 4. The reason why local zone temperature control aims at approaching heating setpoint is because the testing was performed in the winter season in order to save energy. Figure 5(a) shows that in all 28 days, zone temperature by the proposed supervisory control scheme consumes less energy compared to baseline control. The energy consumption during 6 representative days by AHU heating/cooling coils, VAV reheat coils and AHU fans under baseline and supervisory control is shown in Fig. 5(b). The results demonstrate that in the supervisory framework cooling/heating energy consumed in AHU and the fan energy is reduced compared to baseline control, which validates the effectiveness of the proposed algorithm and control framework for HVAC systems.

4. VOLTTRON$^{\text{TM}}$ PLATFORM: OVERVIEW & IMPLEMENTATION

A new open source language-agnostic agent platform called VOLTTRON$^{\text{TM}}$ has been recently developed by PNNL (Lutes et al., 2014; Haack, Akyol, Carpenter, et al., 2013) for smart city applications with built-in security and resource management. Customized applications can be built on this platform for efficiently managing energy usage 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$^{\text{TM}}$ based implementation of the proposed application is shown in Fig. 6(b). While data being used by applications live on the message bus, historical data can be stored in a cloud service and used for future on- or off-line uses. There are numerous database options of which, we consider SQLite as the VOLTTRON$^{\text{TM}}$ Historian which is very simple because of the automatic database creation during the launch. 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.

Fig. 6(a) shows the general layout of the ERS testbed. It consists of eight zones divided into two for each direction, East, South, West and North, respectively. The A test rooms (East-A,South-A, West-A, Interior-A) are served by air handling unit AHU-A, while B test rooms (East-B, South-B, West-B, Interior-B) are served by air handling unit AHU-B. The common and general service areas of the building are not typically used for research testing. All the test rooms within the ERS are intended to simulate a typical office space and each room has approximately 266 ft^2 of floor space. The building automation control system at the ERS is a modern commercial grade DDC system - Distech Controls' EC-Net AX^{TM} Web-based Multi-protocol Building Automation and Energy Management Platform(Center, 2010). The system at our facility is a fully native BACnet system. The DDC systems is fully equipped with instrumentation and senosrs required for various building energy efficiency related research. There are total 1200 monitoring and control points with 600 of them collect data every minute. For the implementation purpose, we have considered A-test rooms served by air handling unit AHU-A.
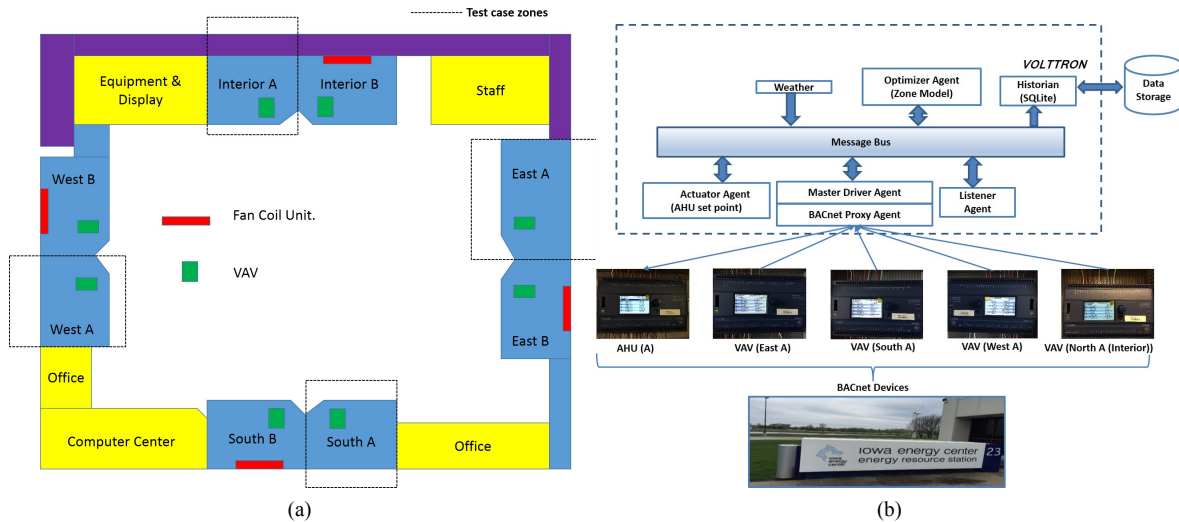
Figure 6: (a) *ERS Test bed*; **and (b)** *VOLTTRON^{TM} based implementation of the proposed framework for supervisory control of Building HVAC system; the Message Bus provides a common platform for sharing information between applications, e.g., actuator scheduler, weather forecast service and optimization agent; historical data can be stored in a cloud service built on VOLTTRON^{TM} Historian (SQLite) or otherwise for future use.*

4.1 VOLTTRON^{TM} Agents: Description

The VOLTTRON^{TM} user guide provides a systematic procedure, templates, and examples for developing agents and to install the VOLTTRON^{TM} platform, by which one can develop simple agents for their own purpose. In the proposed setup we have built optimization agent on the top of VOLTTRON^{TM} which avails the existing benefits. The agents in VOLTTRON^{TM} are given as follows: (1) BACnet Proxy agent (2) Master Driver Agent (3) Weather Agent (3) Optimization agent (4) Weather agent (5) Listener Agent (6) Actuator Agent. The functionalities of individual agents are described below:

1. BACnet Proxy Agent: Device communication on a network happens through the virtual BACnet device and this agent is specifically used for communicating with the BACnet devices and managing the virtual BACnet device.

2. Master Driver Agent: Coordination among the drivers of devices is accomplished using this agent.

3. Weather agent: This agent interacts with remote applications such as online weather services like Weather Underground (www.wunderground.com). The weather information is used by the Zone Model to calculate the temperatures needed for computing the subgradients.

4. Optimization Agent: This agent serves the purpose of predicting the temperatures given the weather information and the parameters of the zone model identified using the data from the ERS test bed. The algorithm described in (Jiang et al., 2016) is implemented in Python to calculate the subgradients based on which the optimal AHU supply air temperature (SAT) is calculated.

5. Listener Agent: It logs all the activity on the message bus and is useful in testing the agent functionality in terms of publishing the required data. It can be used as a starting point for developing other agents.

6. Actuator Agent: This agent has the capability to assert control over the devices by accepting commands from the agents and scheduling times to issue commands to devices.

Message Bus in VOLTTRON^{TM} is a common place where data from all the agents and the devices are collected. All agents use publish/subscribe mechanism to communicate with the other agents. All the data published onto the message bus either by the devices or the agents will be collected by the historian and stores for retrieval or analysis purpose such as plotting etc.

4.2 Implementation

A detailed description of the steps from installing to configuring devices and writing agents can be found in (Lutes et al., 2014). We briefly provide the implementation steps in our setting below:

- Install the VOLTTRON[TM] by following the steps given in user guide (Lutes et al., 2014) and move to the developer branch. ECLIPSE an integrated development environment (IDE) is used as a tool for agent development.

- The machine running the VOLTTRON[TM] is physically connected through Ethernet network to the DISTECH network manager (router) to which all the individual devices of interest are connected. For the sake of convenience, we have shown only the five devices (1AHU and 4 VAVs) in Fig. (6(b)).

- Since the Host machine is Windows, we installed Virtual Machine (VM) to run Linux and VOLTTRON[TM] and configured VM to use a bridged adapter to avoid problems with different IP address.

- The immediate step after installing VOLTTRON[TM] is to find and configure the BACnet devices. The scripts such as bacnet_scan and grab_bacnet_config files which are there in the VOLTTRON[TM] repository can be used to detect the devices and generates a registry configuration file in CSV format for the BACnet driver which consists of a list of point names. This points list can be changed based on user interest.

- Configure the BACnet Proxy Agent by filling the address field in the configuration file with the IP address of Linux machine and specify the subnet mask. Since the BACnet network is on a default port (47808) there is no need to mention the port number.

- Setup the Master Driver Agent which consists of list device configuration files. For each device, we need to create driver configuration file, CSV file and the entry in the Master Driver Agent configuration file.

- Import the VOLTTRON[TM] into ECLIPSE and launch VOLTTRON[TM], BACnet Proxy Agent, Master Driver Agent and Listener Agent using the steps given in (Lutes et al., 2014). The output console of Listener Agent displays the device topics and messages.

- Develop the Optimization Agent by subscribing to the data from the message bus and implementing the algorithm scheme provided in section (3).

- Launching the Optimization Agent similar to other agents and it publishes the Supply Air Temperature (SAT) setpoint to message bus. Launching Historian agent stores the data to the SQLite database.

- Launch the Actuator Agent and schedule the timing to override the SAT setpoint of the AHU device.

In this context, we have developed an Optimization agent and a screenshot showing the supply air temperature in the output console is shown in Fig. 7.

5. CONCLUSIONS

This paper presents the implementation aspects of the Generalized Gossip-based distributed optimization for building energy systems using VOLTTRON[TM]. Optimization agent has been developed in VOLTTRON[TM] to realize the proposed framework which generates the optimal supply air temperature setpoint. The future work is aimed at increasing the scope of the optimization framework to entire air-side as well as water-side HVAC system and comparison of the energy cost using the proposed framework with the existing framework at ERS testbed.

REFERENCES

Akyol, B., Haack, J., Carpenter, B., Ciraci, S., Vlachopoulou, M., & Tews, C. (2012). Volttron: An agent execution platform for the electric power system. In *Third international workshop on agent technologies for energy systems valencia, spain.*

Bengea, S. C., Li, P., Sarkar, S., Vichik, S., Adetola, V., Kang, K., … Kelman, A. D. (2015). Fault-tolerant optimal control of a building hvac system. *Science and Technology for the Built Environment*, *21*(6), 734–751.

Boyd, S., Xiao, L., & Mutapcic, A. (2003). Subgradient methods.

Cai, J., Braun, J. E., Kim, D., & Hu, J. (2016). A multi-agent control based demand response strategy for multi-zone buildings. In *American control conf.* (Accepted)

Figure 7: *Opitmization Agent implementation in VOLTTRON^{TM}*

Cai, J., Kim, D., Putta, V. K., Braun, J. E., & Hu, J. (2015). Multi-agent control for centralized air conditioning systems serving multi-zone buildings. In *American control conference (acc), 2015* (pp. 986–993).

Center, I. E. (2010). Ers technical description. *Iowa Energy Center. Ankeny, I A.*.

Haack, J., Akyol, B., Carpenter, B., Tews, C., & Foglesong, L. (2013). 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).

Haack, J., Akyol, B., Tenney, N., Carpenter, B., Pratt, R., & Carroll, T. (2013). Volttron: An agent platform for integrating electric vehicles and smart grid. In *Connected vehicles and expo (iccve), 2013 international conference on* (pp. 81–86).

Jiang, Z., Chinde, V., Kohl, A., Sarkar, S., & Kelkar, A. (2016). Scalable supervisory control of building energy systems using generalized gossip. In *American control conference (acc), 2016 to appear.*

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

Johansson, B., Keviczky, T., Johansson, M., & H., J. K. (December, 2008). Subgradient methods and consensus algorithms for solving convex optimization problems. *in Proceedings of the 47th IEEE Conference on Decision and Control, Caucun, Mexico*, 4185-4190.

Kantamneni, A., Brown, L. E., Parker, G., & Weaver, W. W. (2015). Survey of multi-agent systems for microgrid control. *Engineering Applications of Artificial Intelligence*, 45, 192–203.

Khamphanchai, W., Pipattanasomporn, M., Kuzlu, M., & Rahman, S. (2015). An agent-based open source platform for building energy management. In *Smart grid technologies-asia (isgt asia), 2015 ieee innovative* (pp. 1–6).

Khamphanchai, W., Saha, A., Rathinavel, K., Kuzlu, M., Pipattanasomporn, M., Rahman, S., … Haack, J. (2014). Conceptual architecture of building energy management open source software (bemoss). In *Innovative smart grid technologies conference europe (isgt-europe), 2014 ieee pes* (pp. 1–6).

Lutes, R. G., Haack, J., Katipamula, S., Monson, K., Akyol, B., Carpenter, B., & Tenney, N. (2014). *Volttron: User guide.* Report PNNL-23182. Richland, WA: Pacific Northwest National Laboratory.

Nedic, A., & Ozdaglar, A. (Janury, 2009). Distributed subgradient methods for multi-agent optimization. *Automatic Control, IEEE Transactions on*, 54, 48-61.

Sarkar, S., Mukherjee, K., & Ray, A. (2013). Distributed decision propagation in proximity networks. *International Journal of Control*, 86(6), 1118-1130.

Weiss, G. (1999). *Multiagent systems: a modern approach to distributed artificial intelligence.* MIT press.

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