An Open Source Smart Building Energy Management Platform through VOLTTRON

Amin Mirakhorli[1], Bing Dong[1]
[1] University of Texas at San Antonio, San Antonio, United States

Abstract

Buildings as one of the largest consumers of electricity in the grid have a large potential to participate in the grid operation. This paper represents a control and simulation test bed in VOLTTRON platform for building energy management. Several Control and simulation agents are designed for major consumers of electricity in buildings (Air conditioner, Electric Vehicle, Water Heater) considering grid signal, and occupant behavior. Simulator agents are capable of simulating multiple control scenarios simultaneously, and provide an estimation of different control performances using identified models in case of hardware implementation. Grid signal responsive controls, including model predictive control and transactional controls are implemented in control agents, and prediction from MPC is used to calculate future load of the building in a central management agent. Finally, performance and output of each controller, is visualized in a flexible graphical user interface.

Introduction

Increasing use of wireless enabled devices in buildings is bringing a need for development of building management systems and can be used for building to grid integration. However, this is not possible without a unique, secure, and reliable communication between the grid, building, and appliances. A reliable and secure communication between components of the grid can provide a platform to implement smart management of these components, which can bring more stability to a self-maintained, optimized, and controlled grid. VOLTTRON, as an open source, agent execution platform, is designed to provide this reliable and secure communication. This agent-based platform provides communication between applications, platforms, and hardware. Among software and hardware developed for building energy management, one can name BEMOSS as a scalable open source building energy management (Khamphanchai et al., 2014), GridLAB-D as an agent-based grid simulation and modelling (Chassin, Schneider, & Gerkensmeyer, 2008), and Dymola/Modelica as an object-oriented simulation and modelling software (He, Huang, Zuo, & Kaiser, 2016). This paper introduces software development in VOLTTRON platform to control major appliances of residential buildings for the purpose of building and grid integration.

Building to Grid integration

Buildings as one of the main consumers of the electricity in the U.S. (more than 70%) can reshape the current way of generating and distributing electricity. An integrated system of building and the grid can achieve a more stable system and reduce the cost of production and distribution of electricity. In this integrated system, buildings interact with the grid needs and change their consumption efficiently. This is a two-way communication and transmission of electricity, where buildings can operate as a consumer, producer, and energy storage (Marszal et al., 2011). This system works as an economic system, where building plays an interactive part in shaping demand, supply, and the price of electricity (Farhangi, 2010).

Related Studies

In (Goyal, Wang, & Brambley, 2016) an agent based test bed in VOLTTRON is introduced for decentralized and centralized control. This test bed is part of a larger test bed equipped with distributed generation, PV, batteries, and buildings. In this study decentralized and centralized controls for an AHU fan with VAV terminals is demonstrated.

In (Rangel, 2016) communication between GridLAB-D and VOLTTRON is tested and a communication agent in Volttron is used to transfer weather and power data between these two platforms.

VOLTTRON can be used as a test bed in commercial building. In (Chinde, Kohl, Jiang, Kelkar, & Sarkar, 2016) this software is used to identify each zone thermal model using ARX method and run decentralized model predictive control to optimally control each zone temperature. This test shows the capabilities of Volttron on running complex control algorithms in a small size computer board.

There are other studies using Volttron as a platform to control water heater (Williams, Kalsi, Elizondo, Marinovici, & Pratt, 2016), Electric vehicle (Haack et al., 2013), and smart home energy management

In this paper, different agents are designed and developed in the VOLTTRON platform to model, control, and monitor major consumers of electricity in residential buildings. Each agent communicates with other agents and VOLTTRON platform through VOLTTRON

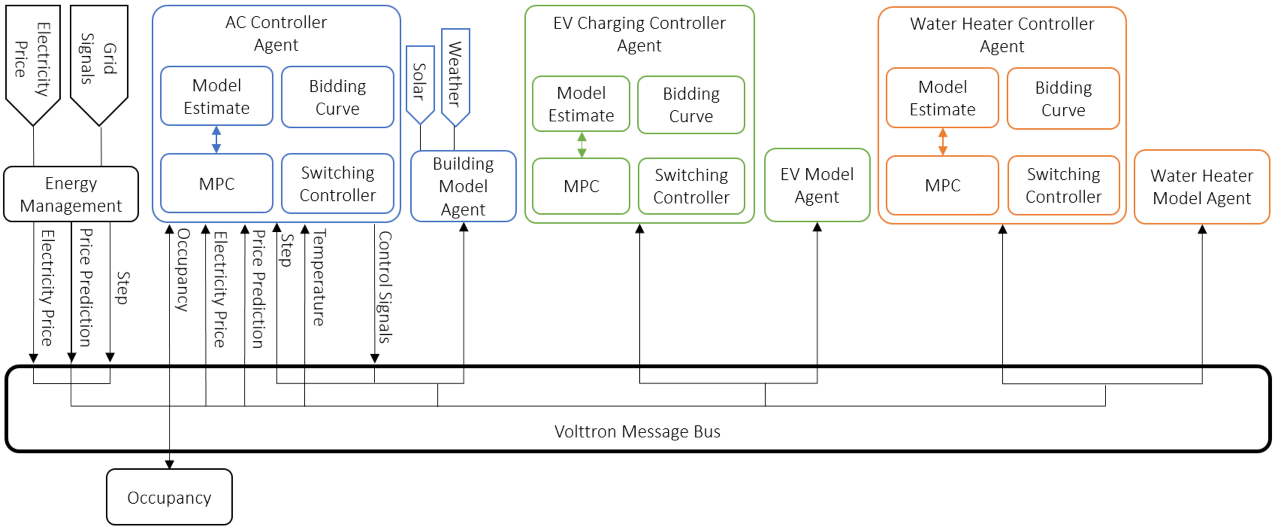

Figure 1: Overall Configuration of Building Energy Management System

message bus using ZeroMQ communication protocol. One central energy management agent synchronizes control and modelling agents and provide price and grid signals to others. Model Predictive Control (MPC), bidding curve, and traditional controllers are formulated in control agents for an Air Conditioning (AC) unit, Water Heater, and Electric Vehicle (EV) charger. The MPC uses total operation cost as objective, an estimated model, and occupants and actuation limits as constraint in a Linear Programming (LP) problem. All modelling agents can estimate multiple control scenarios simultaneously to compare total consumed energy, total cost of operation, efficiency of performed method, and comfort violation. Then they present building performance in a designed Graphic User Interface (GUI).

VOLTTRON

Two-way communication of a smart grid is a fundamental requirement for building to grid integration. This communication should be reliable, secure, and supports different communications protocols, hardware, and software. Data management is another important part of such platform, as there are numerous data points in a building and many more in a smart city. Such a platform should be capable of using distributed processing and centralized control at the same time for large scale implementations. The efficiency of such a platform for communication, processing, and data management is an important factor in dealing with large scale implementations.

VOLTTRON is an agent-based, open source software providing a secure and reliable communication between devices using different communication protocols and programming languages. Volttron uses ZeroMQ messaging library to provide this communication, which is a high-performance messaging library supported by a large community. There are some built-in driver agents in VOLTTRON supporting Modbus and BACnet, which is widely used in building automation, while other drives can be added to this platform. VOLTTRON does not restrict application development to any specific language, and agents can use any language to run their algorithms and talk to other agents in the VOLTTORN message bus. VOLTTRON does not consume large processing resources, and can run on a single board small computer, such as Raspberry PI. Supporting community and developers has produced different applications for this platform, including: HVAC fault diagnosis agents, Smart home appliances control agents, Electric vehicle charging station control, Power grid communication, and many more.

Building energy management system

To make building responsive to grid signals, a smart home energy management with intelligent appliance control shall be designed and developed. Thus, building and the grid interaction can happen through negotiations to exchanging electrical energy, or price and signal based control. In both ways, a price based control is needed to make the operation of in-building devices interactive. Among appliances in a building, air conditioner (AC) consumes the most in cooling dominated climate zones, which is about half of electricity consumption in buildings. Traditionally, building mass was utilized as a thermal energy storage to shift such energy consumption. However, this strategy normally does not consider occupant comfort, due to the unknown occupancy profile (Mirakhorli & Dong, 2016; Oldewurtel, Sturzenegger, & Morari, 2013). On the other hand, water heater consumes about 18% of electricity in a building. Larger temperature change window, and higher thermal efficiency make this device as capable as AC in shifting energy consumption in a building. Electric vehicles (EV) as one of the main consumers of electricity in future buildings are another important tool in shifting energy consumption in buildings. Arrival and departure time of electric vehicle plays an important factor in designing a smart controller for this device. In summary, occupant behavior in using these devices is a critical parameter to be considered in designing smarter controller.

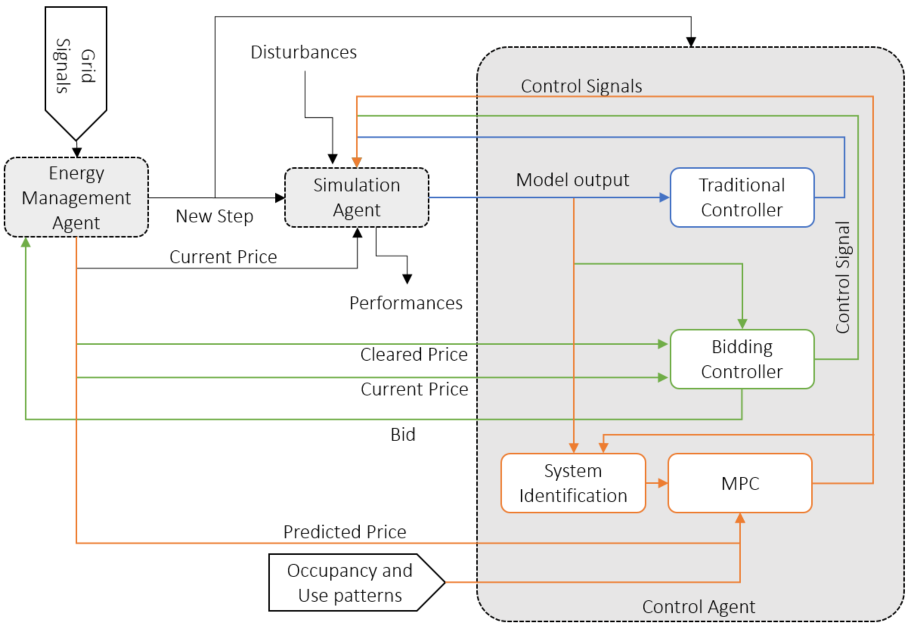

Figure 2: Control, simulator, and Central Management Agents communications

Overall Design

As shown in Figure 1, this software platform includes seven major components, for control and simulation. There are three controller agents to control AC, EV, and water heater, three simulator agents and one central management agent synchronizing, monitoring, and communication with these agents.

To design a home energy management system, each appliance should consider grid related signals in its control action. For this purpose, control agents are designed for major consumers of electricity in the building. To achieve a building scale control, all these controllers read signals from a central energy management system, and report to this agent. Central agent, read price and DR signals, combine them with other objectives in building, including upper limit on the total load and publish it as an electricity price signal for other agents to use. At every step of price changes, it sends a step signal to synchronize other agents to timing of the price change. Controllers, which are using bidding strategies for their control actions, place their bid to the central agent, and central agent place a bid to the grid or other buildings. Cleared price is published to the message bus, and bidding controllers take their control action based on this new price. Controllers report current and future energy consummation of each device to the central agent, and the central agent publishes current and future energy consumptions of the building for other agents to use. Finally, for visualization purpose, each agent is capable of reporting selected parameters to a central or local GUI, using a GUI class.

HVAC

A large portion of electricity in building is consumed in HVAC system, which is about half of building consummation. This is while thermal energy can be stored in the mass of the building, which can be utilized as a virtual energy storage for electricity. This storage can be used to shift energy consummation of this device. However, a smart signal based control considering occupants comfort and presence should be designed.

AC Controller Agent

AC control agent reads occupancy profile, solar radiation, outside temperature, electricity current and predicted price from weather, central management, and occupancy agents, and publish control actions. This agent estimates model of the controlled thermal zone using historical data for control actions, solar radiation, outdoor temperature and indoor temperature. The parameters of this linear model are estimated using linear regression.

$$\dot{T}_{\text{in}} = (Q_{AC})\times k_1 + (T_{\text{out}} - T_{\text{in}})\times k_2 + (Q_{\text{solar}})\times k_3 + k_4 \qquad (1)$$

k_1, k_2, k_3: Linearly online estimated coefficients relating control action, outdoor indoor temperature difference, and solar radiation to indoor temperature changes.

k_4: Estimated internal load effect on indoor temperature changes

This model can be used for model based controllers. Estimation errors and parameters can be viewed from the estimation window located in the graphic user interface, and can be reached from the message bus. This estimated model can be used in Simulator agent, if the control actions are implemented in a real hardware to compare the current performance to other approaches.

Three control methods are implemented in AC controller agent, including: Traditional ON/OFF controller, Bidding curve transactive controller, and Model Predictive Controller. ON/OFF controller is a simple thermostat with a defined deadband. Transactive bidding curve controller, use temperature difference from the set point to define a cost for turning on the AC, and place an offer for the amount of money it wishes to pay for electricity in the next five minutes, if the rate goes below the amount it offered, then the AC will turn on. It also calculates a new set point, in case the controller only has access to thermostat. By changing the set point on the thermostat, this controller can turn ON and OFF the AC if the bidding price meets the cleared price.

$$P_{bid} = P_{avg} + (T_{\text{in}} - T_{\text{set}})\frac{2k\sigma}{T_{\max} - T_{\min}}$$
$$T_{set}^{c} = T_{\text{set}} + \left(P_{cleared} - P_{avg}\right)\frac{T_{\max} - T_{\min}}{2k\sigma} \qquad (2)$$

P_{bid} : Bidding Price

$P_{cleared}$: Cleared Price

P_{avg} : Price Average

σ: Price standard deviation

$T_{\max}$, $T_{\min}$: Minimum and maximum acceptable Temperatures

T_{set} : Thermostat set-point

T_{set}^{c} : Controlled set-point

k: Design Variable

MPC controller considers the estimated model to predict future indoor temperature for designing control actions, and finds the best sequence of control actions to minimize total consumption cost, while maintaining comfort. MPC is formulated in linear format and mixed Integer Linear Programming is used to solve the problem. Control actions and predicted control action are published to the message bus on both AC controller agent and Central Energy management for load predictions. This prediction and awareness of central energy management of future control actions will bring an opportunity to monitor future load more precise and accurate. This can be useful in cases where the total load should stay below a designed limit, or battery management.

$$\min \sum_{i=1}^{m} p_i P_i + \omega s_i \qquad (3)$$

Subject to:

$$LB - s_i < X_{in}^{i+1} < UB + s_i$$
$$\mathrm{x}^{n+1} = \mathrm{A}\mathrm{x}^{n} + Bu$$
$$u_i \in U \quad s_i \in \mathbb{R}_{\geq 0}$$

p_i Price of Electricity at step i

P_i: Device electricity usage at step i

u_i System input (Heat gains)

m Prediction Horizon

In this MPC formulation the objective function is the cost of operation, which is calculated using electricity rate and electricity consumption of the AC. In order to avoid infeasibility of the problem a penalty free variable is introduced to the problem which can relax constraints of the problem with a large penalty weight on the objective function. As long as the rate of increasing the objective value due to relaxing the construing is greater than the rate of reducing cost of operation due to this relaxation, this free penalty variable tends to go to zero unless the system is physically unable to do so. Prediction horizon for the AC unit varies from one hour to 24 hours in literature. One method to find an optimal prediction horizon is to run many simulations with different prediction horizons and find a desired prediction horizon. A one hour prediction horizon is used in this paper corresponding to the time that it takes for the temperature to drop from the upper bound to the lower bound of the temperature in a summer day when the major savings are achieved. Higher cost savings can be achieved by increasing prediction horizon, however, it increases the computation effort due to a more complex optimization problem.

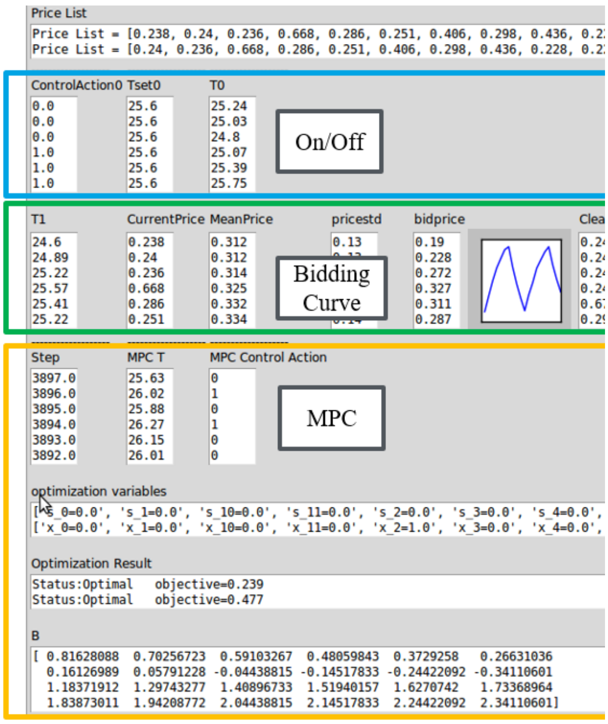

Figure 3: AC controller GUI

Figure 3 Shows a part of the controller GUI and its parameters, and how they are layout in the GUI. This GUI includes three windows for estimation, optimization and control parameters. The estimation window shows the online estimated parameters, their variation from the mean value, and error of the estimated indoor temperature from the actual simulated temperature using the previously estimated gains. The optimization window, shows the optimization problem, optimality status and the calculated control actions. The main control GUI shows related control parameters of each controller in different rows, which includes control actions, bidding price, cleared price, optimality status and decision variables.

AC and Building Simulator Agent

A residential building with a heat pump is modelled in this agent. This agent is capable of simulating multiple control scenarios simultaneously and report performance of each controller separately. Building thermal behavior can be modelled using the RC thermal network model. This model will end up in a linear model which can be represented using A and B matrices. For simulation purposes a residential building model has been used in this application as a default model (Dong, Li, Rahman, & Vega, 2016). Properties of the building are imported to the agent as a linear model, which can be modified editing A and B matrices in *settings.py*. This agent simulation step can be verified in the setting file. Simulation can be run in both real time and compressed time to use in both hardware demonstration and test scenarios. Run in compressed time can be verified in the *TimeScale* variable in *setings.py*. A unitary air to air single-speed heat pump common in residential building is used for simulation purposes. Thermal and electrical load of this system is fed into the problem using coefficient of performance (COP) model, which can be represented with the following formulation.

Building Model:

$$\mathrm{x}^{n+1} = \mathrm{A}\mathrm{x}^{n} + Bu \tag{4}$$

Performance Curve based HVAC model:

$$COP = a + b \times T_{out} + c \times T_{out}^{2} + d \times T_{in} + e \times T_{in}^{2} + f \times T_{out} \times T_{in} \tag{5}$$

x^{n}: System states (Inner and outer walls and roof temperatures, and indoor temperature)
A: System behavior metric relating different nodes temperature
B: Nodes temperature relation with heat gains (including internal heat gain, solar radiation, AC thermal load, and infiltration)
u: Thermal loads
a, b, c, d, e, f: Estimated coefficients to estimate COP of the modelled AC unit

This simulator agent reads control action from the input topic *'BuildingModel/InputN'* and generate a simulation threat for any number of inputs (N) published to this topic. Considering the current states as the initial condition for the generated simulation path. With the start of a new simulation, a new row is generated in the Building Model graphic user interface showing the output and the performance of the controller. This performance criteria include comfort violation, the total energy consumed, cost of operation, AC thermal load, Occupancy profile, and load predictions. Comfort violation and total operation cost formulation is as follow:

Comfort Violation:

$$\mathrm{CV} = \sum T_{difference} \times t_{duration} \tag{6}$$

$T_{difference}$: Temperature difference from the defined deadband
$t_{duration}$: Duration of temperature violation

AC Operation cost:

$$Total\ Cost = \sum p_i \times P_i \tag{7}$$

p_i: Electricity price at step i
P_i: AC electricity usage at step I (Wattage)

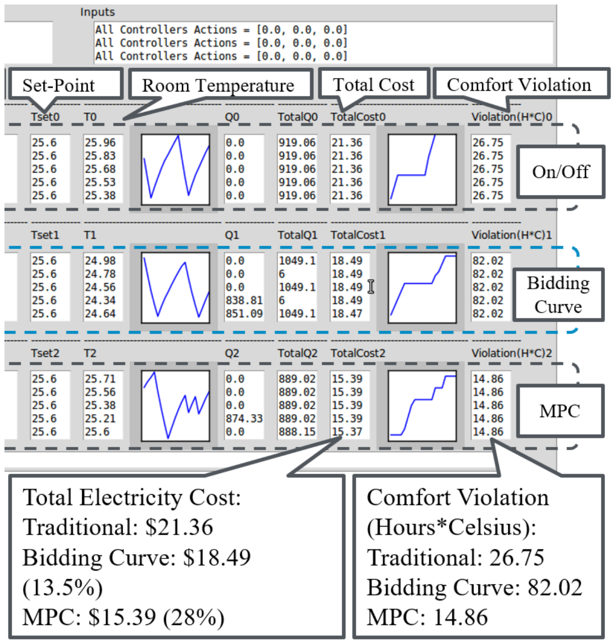

Figure 4: Building Thermal Simulator GUI

Figure 4 shows a part of the building simulator agent. This GUI has different rows for different control inputs generated by the control agent. Each row shows the indoor temperature, thermal load, electricity load, operation cost, comfort violation, and also outdoor temperature, solar radiation, occupancy presence, and temperature set-point. Running control and simulator agents for 13 days in compressed time resulted in 28% cost saving using MPC and 13.5% cost saving using bidding curve compared to traditional control methods. Occupancy presence data, were fed into the program using a CSV file measured from a small residential building.

Electric Vehicle

Electric Vehicle will be one of the main consumers of electricity in residential buildings in the future. EV batteries can be used to shift energy consumption of the building or its Charging (Wu, Hu, Moura, Yin, & Pickert, 2016). However, the cost of replacing EV battery after a limited number of charging cycles can reduce the amount of saving and gained profit from EV to Grid integration. This while, EV charging consumption can be shifted to a low peak period using a proper scheduling program. This scheduling can be as simple as shifting charging start time, to a complex problem of different charging sequence.

EV charging Controller Agent

This control agent is designed to schedule charging for a lower cost in dynamic and interactive pricing environments. For this purpose, model predictive and

Bidding controllers are implemented in this agent. The EV controller agent uses the same framework as the AC controller. However, estimation is not as useful as in AC. The EV charging model is as simple as one capacitor and resistance in series for scheduling problems. Effecting parameters, such as charging efficiency and total capacity of the battery can be introduced to this model in *setings.py*. This simple model can be used in model based controllers, such as MPC.

Model Predictive controller for electric vehicle uses a different configuration than AC. One important input of this controller is the departure time, which can be estimated using historical data of charging periods of used defined period. This departure time is used to define a lower limit on battery state of charge from the arrival time to the departure time, where the start time SOC lower limit is the starting SOC and departure time SOC lower bound is a full charge. This departure time should be estimated using historical departure time. However, for simulation purposes residential EV charger consumption data from smart meter data on Pecan Street Inc database is used to estimate the departure time. Figure 5 shows the probability of the EV charger uses electricity extracted from 104 residential building smart meter data in Pecan Street Inc database.

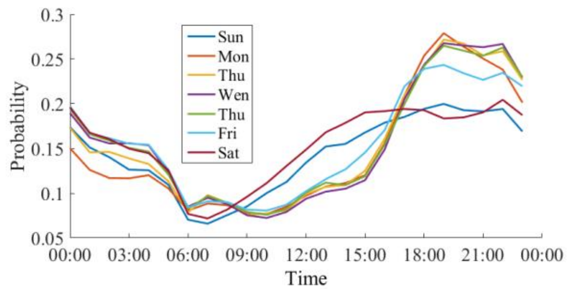

Figure 5: Probability of the EV charger use electricity form 104 residential building smart meter data(Pecan Street Inc, Dataport 2016)

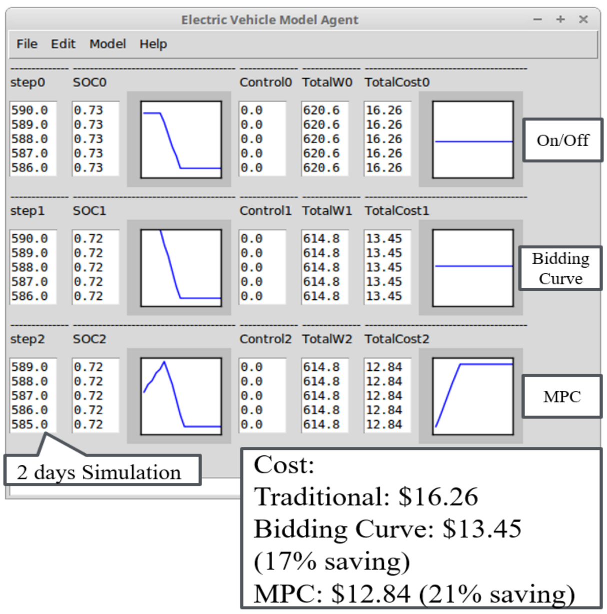

Figure 6: Electric Vehicle GUI

Figure 6 shows the designed GUI for EV charger. This GUI shows different controller performances, including: SOC, total charging energy, and charging cost in a dynamic price.

Running the proposed control and simulation application in a compressed time for two days resulted in 21% charging cost saving using MPC controller and 17% charging cost saving using bidding curve controller compared to traditional controller. For this simulation, electricity real time price was feed to the central energy management from a csv file and electric vehicle usage and presence data were extracted from a smart meter data in Pecan Street Inc database.

Water Heater Controller

Electric Water heaters are responsible for almost 18% of total building electricity consumption. This device storage tank can be used as a virtual energy storage to shift this device energy consumption. However, a responsive controller is required for this purpose.

Water heater control and simulations agents follow the same framework as the AC unit agent. Simulator agent simulate any number of control action simultaneously and report input, output and performance criteria. Controller agent, controls hot water temperature using three methods of control: ON/OFF, bidding curve, and MPC. MPC is formulated in a linear format and solved using MILP. MPC performance depends on the lower limit pf hot water, which is designed considering probability of the hot water being used and the amount needed in each hour. This data is extracted from the historical data of hot water use.

Central Energy Management Agent

Building energy management consist of individual appliance control, as each device has different behaviour and control requirement. However, from the grid perspective, the whole building is considered as one single load. This total load should be managed in a central energy management agent. This agent should reflect grid needs and signals to other controllers as a single signal, manage communication between buildings and the grid, receive and place negotiation price bids to different components inside the building and outside the building.

The main task of this agent is to provide electricity price signals to other agents. Demand Response events will be translated to price changes, and a prediction of future price is provided to other agents. This agent synchronizes other control agents by publishing a step signal to the message bus. The purpose of this step signal is to match the timing of control calculation to price changes. Currently this agent publishes a step signal every five minutes. The other task of this agent is to collect all controller agents control command predictions from MPC calculation, and sum up this prediction to come up with a total load prediction. Model Predictive control optimization solution for future control command represents a prediction of future consumption of the controlled device. The accuracy of this prediction depends on the accuracy of disturbances prediction price prediction and system model.

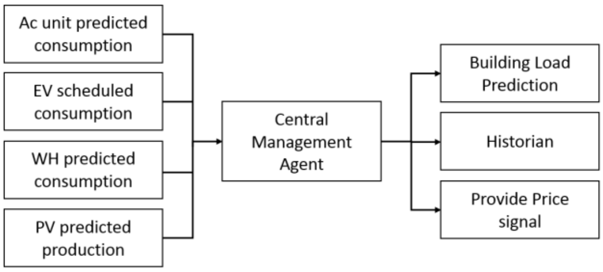

Figure 7: Central Energy Management Agent

Graphic user interface

A GUI class is designed for ease of creating GUI for different agents. Most used objects in control and simulation applications are modified to be used easily in agent creation. Each agent can get access to GUI in two ways: it can publish a message into the GUI agent and ask for an object to report a parameter, or it can run a GUI class and build up its own window. Each parameter can be reported in the GUI using one line command with options to add plot, change size, and position.

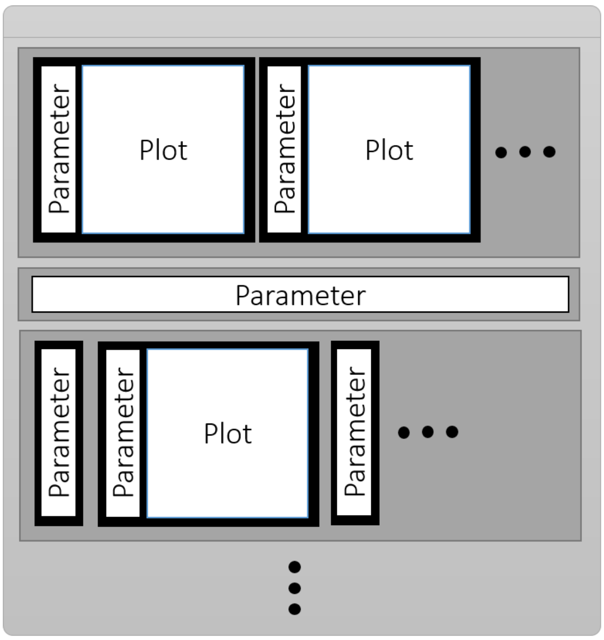

Figure 8: GUI configuration

Conclusion

In this paper, a residential building energy management system considering occupancy profile is designed and developed in VOLTTRON platform. This energy management is configured in different control agents for major appliances in building and synchronized in a central management agent. Simulator agents are designed for simulation, and testing purposes. The simulator agents can benefit from the device model in the control agent to run different control algorithms simultaneously for performance and baseline comparisons. The other feature of this application is the ease of designing GUI for different agents in a centralized and decentralized mode using the designed GUI class with simple commands.

VOLTTRON as an agent-based, open source, platform can provide a reliable grid and building communication to execute price and occupancy based controllers. Introduced application benefits from this reliable communication to connect the grid needs, building appliances, and occupancy behaviour for a better and smart control. This platform provides a distributed capability to this home energy management system, where each agent can run on a different computer and share information on a central message bus.

Acknowledgement

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