Optimization of Energy Efficient Operation of HVAC System as Demand Response with Distributed Energy Resource

ABSTRACT

In this paper, we describe a model predictive control (MPC) framework that optimally determines control profiles of the HVAC (Heating Ventilation and Air Conditioning) system as demand response in presence of on-site distributed energy resources such as energy storage system and energy generation system. The approach determines not only the optimal operations of HVAC system but also how to optimally source the energy needed to power the HVAC system from multiple sources of energy such as grid electricity and on-site stored electricity and on-site generated electricity. A Nonlinear Autoregressive Neural Network (NARNET) is used to model the thermal behavior of the building zone and to simulate various HVAC control strategies. The optimal control problem is formulated as a Mixed-Integer Non-Linear Programming (MINLP) problem and it is used to compute the optimal control profile. The MINLP is approximated as Mixed Integer Linear Programming (MILP), which is easier to solve by linearizing the transfer function of the neural network model.

KEYWORDS

HVAC, MPC, Demand Response, Optimization, Neural Network, Data-Driven Model

INTRODUCTION

The opportunity for energy reduction and energy cost savings for HVAC (Heating Ventilation and Air Conditioning) systems can come from both efficient operation of HVAC system and efficient sourcing of the energy required to power the HVAC system. Optimal operation of HVAC can achieve up to 45% of energy savings (Zavala et al. 2011). With emerging availability of distributed energy resources, such as renewables, energy storage system (ESS) and energy generation system (EGS), optimal sourcing of energy for the HVAC energy load can also achieve significant energy cost reduction. Advancement of Internet of Things (IoT), cognitive computing (e.g., machine learning and deep learning) and Big Data capability enable the data-driven, near real-time, simultaneous optimization of energy consuming operation and energy sourcing.

In this paper, we describe a Model Predictive Control (MPC) framework that optimally computes the control profiles of the HVAC system as well as how the power (load) needed by the HVAC system is optimally sourced through optimized combination of grid purchased energy with DR, on-site stored energy and on-site generated energy. The optimal control profile then can be communicated to the controller (i.e., Building Automation System) to control HVAC system.

Ever since DR became an important means to balance energy demand and supply, there have been new approaches to HVAC control, that compute optimal profiles while minimizing the total energy costs subject to DR signal (dynamic electricity price or pricing structure with local electricity providers). These approaches have been described by e.g. Zavala, Celinsky et al. (2011) and Zavala, Zimmerman et al. (2011). However, these approaches do not determine how the load of HVAC system resulting from the optimized control is optimally sourced through multiple energy supplies, e.g., grid electricity with DR, on-site stored electricity and on-site generated electricity. There has been prior research on management of energy generation, including the work by Kusiak and Guanglin (2012), who developed a MINLP for the optimal design and dispatch of distributed generation systems. The MINLP by Kusiak and Guanglin (2012) assumes that energy demand is given and does not integrate the energy demand control (e.g., HVAC control) with the energy storage decision: the authors focus on optimized dispatching (operational) decision on energy storage and generation. The approach described in this paper computes optimal HVAC control profile that minimizes the total energy costs and GHG emission, considering (1) DR signal, (2) on-site energy storage system (3) on-site energy generation system while satisfying thermal comfort (e.g., zone temperature), physical limitations of HVAC equipment, and physical limitation of energy storage system (ESS) and energy generation system (EGS). Our approach determines not only the optimal control profile but also how to power the HVAC system from the optimal combination of grid electricity, on-site stored electricity and on-site generated electricity.

A MPC problem of HVEC system consists of a predictive model of thermal behavior of building and an optimization model that optimizes a certain performance indicator (e.g. weighted sum of energy cost and thermal comfort of occupants) that obey the thermal dynamics described by the predictive model. The heat transfer involving HVAC system can be modeled by a physics model (usually in a reduced order form) which consists of a system of differential equations (Braun et al. 2001) (An et al. 2013). Developing a physics based predictive model through inverse modeling for a building may take significant effort, and adapting a model built for a building for other buildings can be quite challenging with respect to model accuracy. Another approach for developing a predictive model is a data-driven approach, which uses various machine learning models with data collected from sensors and building management system (BMS) of a building. Data-driven models can be easier to build and calibrate for different buildings. A data-driven modeling approach is used in this work.

In this MPC framework, the thermal behavior of the building zone described above is modeled by a NARNET and the optimal control problem is formulated as a MINLP model. We used a U.S. Department of Energy (DOE) reference building to simulate several HVAC control strategies and generated the data to be used for developing the thermal behavior model using EnergyPlus (EnergyPlus 2015). The reference building is a three story, medium office building in Baltimore MD, USA, Climate Zone 4A, and TMY (typical meteorological year) data (NREL 2008) was used. We simulated several different HVAC control strategies including night setup, demand limiting and pre-cooling strategy (Braun et al. 2001) (Lee and Braun 2004), with zone set point as the control variables. The data was simulated for one year with 10 minutes interval, and used for analysis and modeling.

MATHEMATICAL MODELING OF THERMAL BEHAVIOR

The thermal behavior in a building can be represented by:

$$x_t = f(x_{t-1}, x_{t-2}, \ldots, u_t, u_{t-1}, u_{t-2}, \ldots, e_t, e_{t-1}, e_{t-2}, \ldots) \qquad (1)$$

where x_t is the state variable at time t, u_t is the control variable at time t and e_t are the external inputs at time t. By Eq. 1, the state variable at current step depends on the state variables in previous steps, as well as control variables and external inputs at current and previous time steps. State, control and external inputs could be vectors that account for multiple components. Examples of state variables include the zone temperature of zone z at time t, $T_{t,z}^{zone}$. Examples of external inputs include the day of the week (DOW) indicator, the time of the day (TOD) indicator and the ambient temperature, T_t^{amb}. Examples of control variables include T_t^{sp}, the set point for zone z at time t, the supply temperature of AHU at zone z, and the supply flow of AHU at zone z. For the example of state variable $T_{t,z}^{zone}$ and control variable $T_{t,z}^{sp}$, the state variable equation (1) becomes:

$$T_{t,z}^{zone} = f(T_{t-1,z}^{zone}, T_{t-2}^{zone}, \ldots, \bar{x}_t, \bar{x}_{t-1}, \bar{x}_{t-2}, \ldots, T_{t,z}^{sp}, T_{t-1,z}^{sp}, T_{t-2,z}^{sp}, \ldots) \qquad (2)$$

where $\bar{x}$ are external inputs such as DOW, TOD and ambient temperature, T_t^{amb}. Eq. (1)-(2) are referred to as equations of system state.

The thermal phenomena of zones in a building can also be described by means of the system output. An example of system output variable is $P_{t,z}^{HVAC}$, power consumption of HVAC system for zone z at time t as shown in Eq. (3).

$$P_{t,z}^{HVAC} = h(P_{t-1,z}^{HVAC}, P_{t-2,z}^{HVAC}, \ldots,, T_{t,z}^{zone}, T_{t-1,z}^{zone}, T_{t-2,z}^{zone}, \ldots, \bar{x}_t, \bar{x}_{t-1}, \bar{x}_{t-2}, \ldots, T_{t,z}^{sp}, T_{t-1,z}^{sp}, T_{t-2,z}^{sp}, ..) \qquad (3)$$

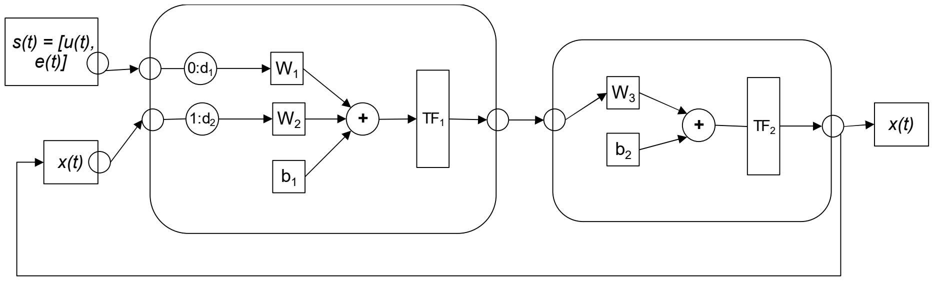

***Figure 1**. NARX model for thermal behavior of building*

Artificial neural networks (Anderson 1995) are a well-known method for modeling the thermal behavior (Eq. 2 and 3) of the building zone. As HVAC system behavior is usually dynamic and non-linear, one can employ a non-linear autoregressive data driven model with external input (NARX) in order to capture its properties and states. The neural network model is also called Nonlinear Autoregressive Neural Network (NARNET). NARX is a feed-forward time delay neural network, which maps input data to an output, using additional external input (see Fig. 1). The NARX network includes three layers: input layer, hidden layer and output layer (deep NARX networks with multiple hidden layers can also be considered).

The control problem is modeled by means of Mathematical Programming (MP), a formal language to describe optimization problems. The decision variables are control and state variables; the constraints describe system behavior, and the objective function minimizes costs. MP requires all functions appearing in constraints and objectives to be expressed in closed form, which is not the case for Eq. (1)-(3). However, ANN dynamics are essentially linear, followed by a usually nonlinear activation function. We therefore replace Eq. (1)-(3) by the closed form equations of the ANN dynamics, yielding, in general, a Mixed-Integer Nonlinear Program (MINLP). The choice of the activation function influences the extent to which this MINLP involves integer variables and nonlinear terms. Various types of activation functions such as hyperbolic tangent sigmoid transfer function (tansig), symmetric saturated liner transfer function (satlins) and hard-limit transfer function (hardlims) can be used. Choosing the discrete approximations satlins and hardlims results in a Mixed-Integer Linear Programming (MILP) problem, which is easier to solve. The ANN is trained on historic time-series data (e.g., few weeks' time series data). The entire dataset for neural network training may be randomly divided into three contiguous blocks: training, validation and testing.

This network described in Fig. 1 results in the following algebraic equation:

$$x(t) = TF_2[W_3 \cdot TF_1\{W_{1.} \cdot (s(t), s(t-1),..,s(t-d_1)) + W_2 \cdot (x(t-1),...,x(t-d_2)) + b_1\} + b_2] \tag{4}$$

where W_1, W, W_3 are weight matrices, b_1, b_2 are biases, d_1, d_2 are network time delays and TF_1, TF_2 are transfer functions, of which TF_2 is usually chosen to be linear. $s(t)$ is the network input (array of input that include both the control and external variables) at time *t* and $x(t)$ is the network output (e.g., zone temperature or power).

The NARX model predictions (with satlins transfer function) are compared with simulated data for a day in August, and the prediction accuracy is reasonably good. The zone temperature model (Eq. 2) prediction has mean absolute error (MAE) of 0.147 [ºC], mean squared error (MSE) of 0.038 [ºC^2], root mean squared error (RMSE) of 0.195 [ºC], coefficient of variation (CV) of RMSE of 0.007868 and mean bias error (MBE) of 0.00283 [ºC^2]. The power model (Eq. 3) prediction for the day is MAE of 1.017 [kW], MSE of 1.811 [kW^2], RMSE of 1.345 [kW], CV(RMSE) of 0.114 and MBE of 0.00758 [kW^2].

MODE PREDICTIVE CONTROL OF HVAC SYSTEM

The model predictive control of HVAC system is formulated as a MINLP with the following objective function (Eq. 5), and constraints (Eq. 6-9). Our solution is also subject to other physical constraints of the HVAC system, the energy storage system (ESS), and the energy generation system (EGS), not shown here for lack of space.

$$\min_{p_t, s_t^{in}, s_t^{out}, g_t, T_{t,z}^{sp}} \sum_{t \in \mathrm{T}} [\alpha_1 \{C_t^e (p_t + \frac{s_{in}}{\lambda^s}) + C^g \frac{g_t}{\lambda^g}\} + \alpha_2 \{G^e (p_t + \frac{s_{in}}{\lambda^s}) + G^g \frac{g_t}{\lambda^g}\} + \sum_{t \in T} \alpha_3 \left| T_t^{zone*} - T_t^{zone} \right| + \ldots] \tag{5}$$

The objective function is subject to the ANN closed form which approximates *f* and *h* in Eq. 6,7 and to Eq. 8,9 below:

$$T_{t,z}^{zone} = f(T_{t-1,z}^{zone}, T_{t-2,z}^{zone}, \ldots, \bar{x}_t, \bar{x}_{t-1}, \bar{x}_{t-2}, \ldots, T_{t,z}^{sp}, T_{t-1,z}^{sp}, T_{t-1,z}^{sp}, \ldots), \quad \forall t \in T, z \in Z \tag{6}$$

$$P_{t,z}^{HVAC} = h(P_{t-1,z}^{HVAC}, P_{t-2,z}^{HVAC}, \ldots, T_{t,z}^{zone}, T_{t-1,z}^{zone}, T_{t-2}^{zone}, \ldots, \bar{x}_t, \bar{x}_{t-1}, \bar{x}_{t-2}, \ldots, T_{t,z}^{sp}, T_{t-1,z}^{sp}, T_{t-1,z}^{sp}, \ldots), \forall t \in T, z \in Z \tag{7}$$

$$\sum_{z \in Z} P_{t,z}^{HVAC} = p_t + s_t^{out} \lambda^d + g_t, \quad \forall t \in T \tag{8}$$

$$T_{t,z}^{zone,L} \le T_{t,z}^{zone} \le T_{t,z}^{zone,H}, \quad \forall t \in \{t_L \le t \le t_H\} \tag{9}$$

The decision variables and input parameters are described in table 1.

***Table 1.** Decision variables and parameters*

Decision Variables	Description
p_t	Power (electricity) (for HVAC) purchased from grid at time *t* [kW]
g_t	Power of CHP generated by generator at time *t* [kW]
s_t^{in}	Power charged by ESS at time *t* [kW]

s_{in}^{out}	Power discharged from ESS at time t [kW]
$T_{t,z}^{sp}$	Zone set point at time t [°C]

Parameters	Description
C_t^e, C^g	Cost of grid purchased electricity, natural gas purchased [$/kWh]
G^e, G^g	Cost related to GHG emission rate of grid purchased electricity and natural gas purchased at time t [$/kWh]
$\lambda^s, \lambda^d, \lambda^g$	Efficiency of energy charges to ESS, discharged from ESS and on-site generation
$\alpha_1, \alpha_2, \alpha_3$	Weight of cost, GHG emission cost and occupant comfort deviation in objective function
T_t^{zone*}	Target temperature of zone
$T_{t,z}^{zone,L}, T_{t,z}^{zone,H}$	Lower and upper bounds for zone temperature at time t for zone z

Our optimal control method determines a profile of a control variable, e.g., set point of zone *z* and time *t* for a future time horizon (e.g., next 24 hours) that minimizes total energy costs of operating HVAC system subject to zone thermal behavior (Eq. 6 and 7) in a building, energy balance (Eq. 8) in a zone, comfort bounds for zone temperature (Eq. 9) and physical limitations of the equipment, i.e. HVAC system, ESS and EGS. Our optimization model takes into consideration demand response signal (dynamic pricing profile of grid electricity for next 24 hours), capacity and costs of on-site ESS, and on-site EGS, and attempts to satisfy the thermal comfort (e.g., zone temperature). The objective (Eq. 5) is to minimize the total cost. This includes (but is not limited to) the costs related to energy usage, greenhouse gas emission, and deviation from comfort temperature range for building occupants. The details of the physical constraints for ESS and EGS are omitted here. Our approach optimally computes how much electricity to purchase from grid, how much to generate on-site and how much to store on-site, and how much of the stored or generated electricity to use for the operations of HVAC system. The approach simultaneously computes the optimal control profile of HVAC system and the optimal way to power the HVAC system from the multiple sources.

In this paper, we simplify the MINLP by using linear transfer functions (hardlims or satlins), which results in MILP. This MILP can be solved using a variety of methods, depending on its size. One way to solve the MILP problem is with the IBM-ILOG CPLEX solver (2014).

INITIAL RESULTS AND DISCUSSION

Here we present a preliminary optimal solution for a zone for a day in August, shown in fig. 2, 4 and 5. We then compare the energy cost and savings of the optimal solution with two traditional HVAC control strategies: a night setup and demand limiting strategy (Braun and Montgomery et al. 2001) (Lee and Braun 2004). For the night setup strategy, the temperature set point profile is prescribed as 24°C during 5AM –

9PM and 26.7°C during 9PM – 5AM. For the demand limiting strategy, the set point profile is 22.5°C during 5AM – 1PM, 25.5°C during 1PM – 9PM, and 26.7°C during 9PM – 5PM. The CPLEX solver was stopped prior to termination for this scenario to save time: this means that we didn't wait until the global optimality was obtained. However, empirically this is a reasonably good, feasible solution. We are evaluating various formulations of the optimization problem and solution methods to obtain robust and good solution, this work is still in progress. For this scenario, we used satlins as the transfer function of NARX model, and 48 time steps for 24 hours period (i.e., 30 minutes interval).

The scenario is for a day in August; therefore, the energy consumption here is only for cooling.

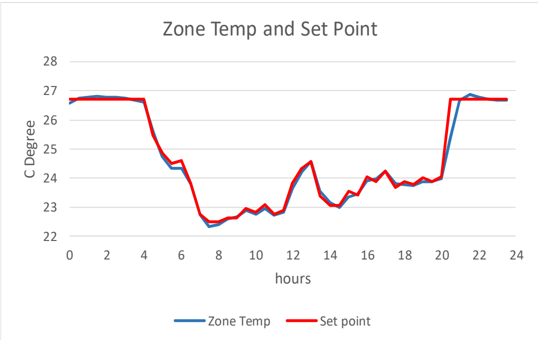

Figure 2. *Optimal of energy demand (operation)*

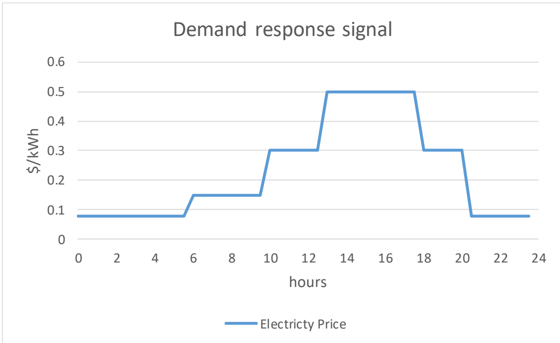

Figure. 3. *Demand response signal (grid electricity price)*

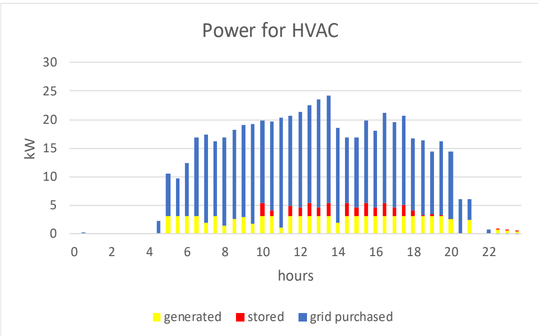

Figure 4. *Optimization of energy supply (sourcing)*

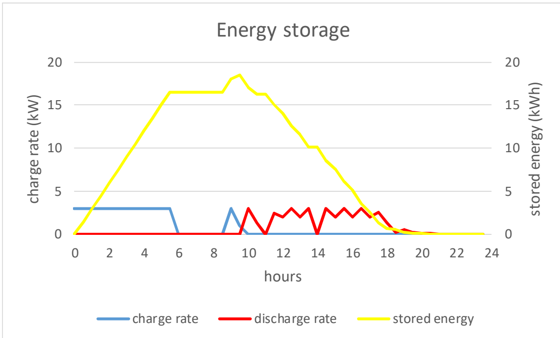

Figure 5. *Energy for powering HVAC*

Table 2. *Energy cost and savings for optimal control profile with respect to other control strategies*

	Night setup (base) (without ESS & EGS)	Demand limiting (without ESS & EGS)	Optimal solution (without ESS & EGS)	Optimal solution (with ESS & EGS)
Cost	$98.11	$83.14	$84.13	$75.49
Saving (w.r.t. base)	---	15.26%	6.36%	23.06%

Fig. 2 shows the optimal control profile (i.e. set point temperature of a zone) and corresponding zone temperature in 24 hours period in 30 minutes time intervals. The set point during the night period (9PM – 5AM) was kept at 26.7 °C by the model by assuming that free cooling can be obtained through ventilation during the night time. The DR signal, i.e. dynamic grid energy price is assumed to be available in hourly resolution for next 24 hours, and is updated in every hour. The demand response signal profile for this scenario is presented in fig. 3, where the price is ranged from \$0.08/kWh to \$0.5/kWh during a day. Fig. 2 illustrates that the set point is relatively low in morning hour when the electricity is price is low, and high when the price is higher. Fig. 4 shows the total electricity required to power the HVAC system (in this case, cooling) and sourcing of the total energy to the grid purchase electricity (blue line), on-site generated energy (yellow line) and on-site stored energy (red line). In this simplified scenario, it is assumed that the maximum generation rate for a zone is 3kW, maximum charge rate/discharge rate is 3kW, and the efficiency of charging and discharging are 85% and 80% respectively. The charge rate, discharge rate and the accumulated energy of ESS is shown in fig. 5. Note that electricity is charged to ESS when the electricity price is low and discharged when it is high.

The total cost for powering the HVAC system for the scenario is \$75.49, which is a saving of 23.06% with respect to the night setup (base case) control strategy (also simulated with the same NARX model). Even when it is assumed that all the electricity needed is sourced from grid purchased electricity (i.e. without ESS and EGS), the cost is \$84.13, which is 6.36% savings with respect to the base case and similar to the cost for demand limiting strategy (but with different zone temperature profiles) as summarized in table 2.

CONCLUSION AND IMPLICATIONS

We developed a data-driven method for computing the optimal control of HVAC operations as demand response tool by taking into consideration dynamic demand response signal, on-site energy storage system and on-site energy generation system using NARNET and MINLP. The MPC model can optimize both energy demand (energy efficient operation) and energy supply (cost effective sourcing including grid purchased electricity, ESS and EGS). The MINLP is hard to solve, and we are developing a novel approach to reduce the problem size and find the global optimal solution in reasonable computation time. We are working towards being able to compute the optimal HVAC control profile for multi-zones, for day ahead in 10 minutes intervals and communicate the control profile to building automation system (BAS) in real time.

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