
Building Energy Management System

Prabir Barooah

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Abstract This entry provides an overview of building energy management systems (BEMS). It includes a description of the communication and control architectures typically used for energy management, definition of the optimal supervisory control problem, and a description of current and future developments in optimal energy management.

Keywords Building energy management · HVAC · Indoor climate control · Model Predictive Control · Inverse modeling · Predictive control · Optimization

1 Introduction

A building automation system (BAS) enables building operators to manage the indoor environment control system, along with fire and safety system and other auxiliary functions such as Audio-Visual systems in a building. The phrase Building Energy Management System (BEMS) is sometimes used interchangeably with BAS, though energy management is only one aspect of a building's control system. Indoor environment control, which includes lighting and heating, ventilation, and air conditioning (HVAC), has a strong impact on energy use, and this may explain the meshing of the two terms. BEMS are typically used in large commercial buildings, though in recent times there is a trend toward smaller commercial buildings.

The number of possible types and configurations of HVAC systems in large buildings is enormous. In this section we will limit our discussion to single duct variable air volume (VAV), chilled water based HVAC systems. Figure 1 shows a schematic of such a system. Constant air volume systems, in which the volume of air supplied to the building interior is constant over time, are gradually being phased out. The system shown is a single duct system, since the conditioned air is supplied to the zones through a single duct. Some buildings employ a dual duct system, in which outdoor air (OA) is supplied through a separate, dedicated OA duct. The system shown in the figure is a hydronic system since it uses water to transfer energy: chilled water produced in a chiller is supplied to one or more air handling units (AHUs) that cools and dehumidifies the air supplied to the interior of the building. Chilled water based systems are common in large buildings, and even in some medium sized buildings if they are part of a campus. In case of a campus, chilled water is produced in a chiller plant with multiple chillers. In cold and dry climates that do not require cooling and dehumidification, there is no cooling/dehumidification coil in the AHUs. Only heating coils are used, which may use heating hot water (HHW) or electric heating elements. Many buildings use packaged rooftop units (RTUs) that use a vapor compression refrigeration cycle to directly cool and dehumidify air. These systems are referred to as "DX" (Direct eXpansion) systems. DX systems are common in small and medium buildings that typically do not have BEMS.

1.1 Control algorithms in current BEMS

There are many BEMS vendors, such as Siemens, Johnson Controls, and Automated Logic. Almost all of these BEMS vendors also offer their HVAC equipment and controller hardware. The larger vendors offers their BEMS not simply as products but also solutions that can integrate HVAC equipment from other

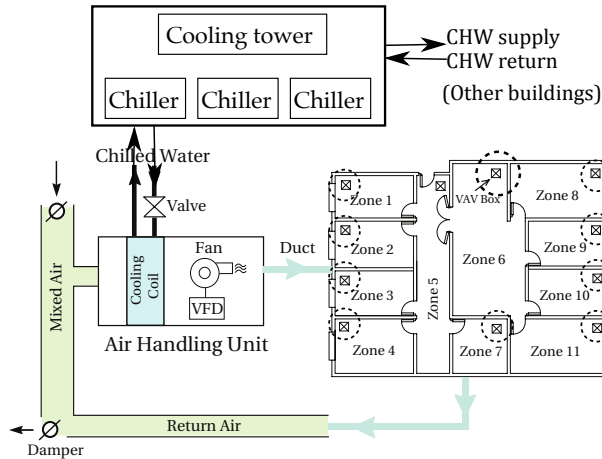


Fig. 1 A hydronic HVAC system with an Air Handling Unit (AHU) and multiple zones. A central chiller plant supplies chilled water (CHW) to multiple buildings.

manufacturers. The BEMS from smaller vendors are usually used to integrate HVAC equipment from the same vendor.

At present, commercially available BEMS are mostly used to perform setpoint tracking control. The setpoints are specified by human operators through a user interface. The default values of these setpoints are usually chosen during building commissioning. Some of these setpoints are informed by decades of engineering practice and field-studies. For instance, the conditioned air temperature (downstream of the cooling coil) is frequently chosen to be 55°F in hot humid climates [9].

Even the simplest setpoint control loops are hybrid controllers, employing a mix of logic loops and PI controllers. For example, a commonly used zone VAV box control algorithm is the so-called “single maximum control”. Depending on the current temperature of the zone and its past history, the controller switches to one of the three modes: cooling, heating, and deadband. In each mode, there is a distinct setpoint for the zone temperature, and a PI controller is used to manipulate the flow rate and the amount of reheating (except in the cooling mode in which reheating is turned off) to maintain that setpoint. These setpoint tracking control algorithms typically come pre-packaged in BEMS, and modifications to their programming are performed during installation and commissioning. A programming interface is offered as part of the BEMS that allows automatic changes to the setpoints. The degree of flexibility of these programming interfaces is typically limited, so usually only simple rule-based logics can be implemented. For instance, the Siemens offers a programming interface using a proprietary language called `ppcl`, which is reminiscent of BASIC, with features such as `GOTO` statements that are deprecated in modern programming languages.

1.2 Communication in BEMS

There are multiple levels of communication among devices and sub-networks in a BEMS. A simple classification employs three layers: floor level network layer, management layer and enterprise layer. BACnet is a communication protocol that runs on top of other existing electrical standards like RS-485 (serial communication), Ethernet, and MS/TP (Master slave/token passing). LonWorks was engineered to be both a data protocol and an electrical standard for digital communications. In the USA, BACnet is more widely used compared to Modbus and LON. In modern buildings, “BACnet/IP over Ethernet” is probably the most relevant. That essentially means that the BEMS uses BACnet/IP protocol for communication among devices, and BACnet packets are carried over Ethernet cables.

Interoperability is still an issue in BEMS even though BACnet was devised to resolve interoperability. A reason for this issue is that BACnet is a standard and not all vendors implement it the same way. To ensure the quality of BACnet implementation, one can apply for a BTL license, but most vendors do not. In recent years the NiagaraTM framework has provided a way to integrate multitude of devices from multiple manufacturers using a diverse protocols.

2 Optimization-based control of building energy systems

2.1 Opportunities

There is a large untapped opportunity to improve energy efficiency and indoor climate through advanced decision-making. This opportunity comes from gap between what the current BEMS are capable of and

what they are being used for. Modern buildings equipped with BEMS typically have sufficient actuation capabilities at many levels (chillers, AHUs and zone VAV boxes) that can be controlled to deliver high performance in terms of energy efficiency and indoor climate. Against this possibility, the reality at present is that BEMS are used to maintain constant set points which are designed based on steady-state considerations. Thus, the simplest way to improve HVAC operational performance is to change the set points in real time by solving an optimization problem that takes into account the difference between the design conditions and actual conditions. Lower level control algorithms that BEMS are already equipped with can then be tasked with maintaining these set points. This optimization problem has to be revisited periodically as new information - measurements and forecasts - becomes available. For this reason, there is an emerging consensus that model predictive control (MPC) - that repeatedly solves an optimization problem posed over a receding horizon - is appropriate for achieving high performance from existing BEMS. Another option is a model-free approach such as reinforcement learning, though little exploration has been performed into that frontier.

As in any control systems, sensing and actuation play as big a role as control algorithms. The control problem - whether one employs MPC or some other approach - can be made easier by adding more sensing and actuation. Additional actuation is quite expensive since that requires changing the building's physical structure. Adding sensors to a BEMS after it has been installed and commissioned is far more expensive than the cost of the sensors themselves due to the cost of integration and testing. Still, adding sensing is far less expensive than adding actuators. Adding advanced decision-making is perhaps the least expensive, especially if the computations are performed in the cloud, while the BEMS serves only to provide the sensor data and execute the decisions computed by the cloud-based algorithm through the building's actuators. This requires a middleware. BACnet, for instance, allows multiple commands to be sent to a controller board with different priorities, and the equipment controller implements the one with the highest priority. This mechanism can be used by the middleware to overwrite the default control commands computed by the BAS and replace them by the commands from the cloud-based algorithm.

We next discuss some of the opportunities of achieving high performance building operation using MPC, and the challenges therein. Although the right metric for performance will vary from one building to another depending on the preference of the building owner, operator, and its occupants, it is common in the research literature to take energy use (or energy cost) as the objective function to minimize, while indoor climate requirements are posed as constraints. The key energy consumers are the chillers that produce chilled water, reheat coils and supply air fans in air handling units (AHUs), and finally reheat coils in zone-level VAV boxes; see Figure 1. The control problem therefore has to consider decisions for these equipment, and the downstream effect of these decisions on the indoor climate. The energy consumed by pumps for chilled and hot water are ignored here.

2.2 “Air-side” optimal control

In the so-called air-side optimization problem, the control commands are set points of air handling units and perhaps zone-level VAV boxes. Chiller operation is outside the purview of the decision-making problem, and will be discussed in Section 2.3.

The optimization problem underlying an MPC controller will seek to minimize some objective function subject to the dynamic constraints and actuator limits. In a discrete-time setting, at time index k , the MPC controller computes the decisions $u_k, u_{k+1}, \dots, u_{k+N-1}$ over a planning horizon $\mathcal{K}_k = \{k, k+1, \dots, k+N-1\}$ of length N by solving an optimization problem of finite (N -length) horizon. The planning horizon depends on many factors. If the objective is to minimize energy cost, and monthly peak demand plays an important role in the energy cost, the planning horizon needs to span months. A day long planning horizon seems to be the shortest possible while keeping the problem practically relevant.

The single zone case We describe the problem in detail for a building in which an AHU is used to maintain the climate of one space, which we refer to as a “single-zone” building. In such a building, shown in Fig. 2, only four variables can be independently varied, which form the control command u : (i) \dot{m}^{SA} , the flow rate (kg/s) of *supply air*, (ii) r^{OA} , the *outdoor air ratio*, i.e., the ratio of outdoor air to supply air flow rates, $r^{\text{OA}} := \dot{m}^{\text{OA}} / (\dot{m}^{\text{OA}} + \dot{m}^{\text{RA}}) \in [0, 1]$, (iii) T^{CA} , the temperature of *conditioned air* and (iv) q^{rh} , the rate of reheating (kW). Thus, $u_t = [\dot{m}^{\text{SA}}, r^{\text{OA}}, T^{\text{CA}}, q^{\text{rh}}]_t^T \in \mathbb{R}^4$. Each of these four control commands are in fact setpoints of lower-level control loops that are common in existing building control systems.

There are many choices of control that can lead to similar indoor climate but distinct energy consumption. A small T^{CA} with small \dot{m}^{SA} can deliver the same “cooling” as a slightly larger T^{CA} and larger \dot{m}^{SA} . While lower \dot{m}^{SA} uses less energy consumption, lower T^{CA} causes more energy consumption since it removes more moisture, which requires removing the large latent heat of evaporation. It is important to emphasize that the conditioned air temperature and humidity $T^{\text{CA}}, W^{\text{CA}}$ cannot be decided independently,

only T^{CA} is a part of the control command since it can be maintained by a chilled water control loop. The humidity of the conditioned air is indirectly decided by T^{CA} due to the dynamics of the cooling coil. The relationship is highly complex and challenging to model for real-time optimization [7].

The relationship between the control command u and the disturbance d to indoor climate variables is best expressed as process (dynamic) models. They form the equality constraints in the optimization. Inequality constraints come from actuator limits and bounds on climate variables (state constraints). Apart from the dynamic constraints, there are two other types of constraints. The first set of constraints comes from thermal comfort and indoor air quality considerations. The second set comes from actuator limits.

For the purpose of exposition, we use the total HVAC energy (over a time interval N) as the objective function in the MPC optimizer: $J = E_{tot} = \sum_{t=k}^{k+N-1} (p_t^{cd} + p_t^{rh} + p_t^{fan}) \Delta t = \sum_{t \in \mathcal{T}_k} p_t^{tot} \Delta t$, though other choices are possible, such as the monthly energy cost that depends on total energy use and sometimes on a combination of energy use and peak demand during the month. In summary, the optimization problem within the MPC controller at time k is:

$$\mathbf{u}_k^* = \arg \min_{\mathbf{u}_k, \mathbf{x}_k} J(\mathbf{u}_k, \mathbf{x}_k, \hat{\mathbf{d}}_k), \text{ s. t. } \mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, \hat{\mathbf{d}}_k), \mathbf{x}_k \in \mathcal{X}_k, \mathbf{u}_k \in \mathcal{U}_k \quad (1)$$

where $\mathbf{u}_k := (u_k, \dots, u_{k+N-1})$ and $\mathbf{x}_k := (x_k, \dots, x_{k+N-1})$ are the inputs and states, and $\hat{\mathbf{d}}_k = (\hat{d}_k, \dots, \hat{d}_{k+N-1})$, in which \hat{d} is prediction of disturbance d , and $\mathcal{X}_k, \mathcal{U}_k$ are constraint sets for states and inputs.

Climate controllers currently used in buildings do not optimize; they err on the side of maintaining indoor climate since that is far more important than the energy bill [8]. Typically, T^{CA} is maintained by a PID loop at a setpoint that is decided based on decades of engineering experience. For instance, most hot and humid climates T^{CA} is set to 55°F [9]. The flow rate \dot{m}^{SA} and reheating rate q^{rh} are decided by feedback controllers to ensure space temperature is within predetermined bounds; the bounds are again decided based on decades of research on human comfort [3,2]. Finally, the outdoor air ventilation is usually maintained at a setpoint based on design occupancy, which fixes the fourth component of u , namely r^{OA} .

The disturbance and its predictions play a crucial role in predictive control. The disturbance d consists of 5 components: (i) weather variables: solar heat gain η^{sun} , OA temperature T^{OA} and OA humidity W^{OA} (ii) internal signals: sensible heat gain q^{int} (mostly from occupants and their actions, such as use of computers and lights), internal moisture generation rate \dot{m}_{H_2O} (from occupants' bodies, decorative plants, coffee machines, etc.), and the number of occupants o . At every instant k , the optimizer needs predictions of all the exogenous signals for the planning horizon. Except for weather related variables, obtaining forecasts of the remaining disturbance signals is a highly challenging problem.

Multi-zone case In most buildings an AHU is used to deliver air to multiple zones; see Figure 1. The problem described above can be expanded to the multiple-zone case in a straightforward manner. The state dynamics will involve the states of thermal dynamics from each zone, and the control command will now include not simple AHU-level variables but also the setpoints for each of the VAVs. The problem is considerably more challenging, and not simply due to the higher computational complexity caused by the higher state dimension. Additional challenges come from the higher degree of uncertainty in models.

2.3 The “water-side” optimal control

The so-called water-side control problem is to make decisions about the chiller and cooling towers. Most chillers at present are run by constant-speed motors, so the key decision is turn a chiller in a bank of chillers either on or off. Even in constant speed chillers, the load on the chiller can be changed by actuating the inlet

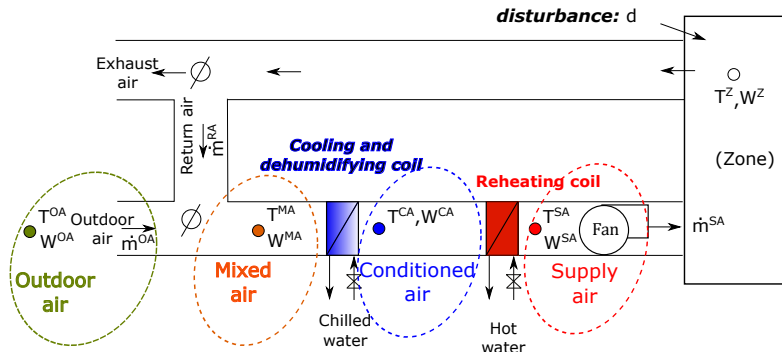


Fig. 2 A single zone VAV HVAC system

guide vanes. In some chiller plants, the supply water temperature can be manipulated and that becomes another decision variable. The water side problem is applicable only with buildings with chillers, which is more common in a campus or district setting [6].

3 Challenges

There are many challenges in successfully applying MPC to HVAC systems. One is the need for an accurate and yet computation friendly dynamic model. Although there is a long history of modeling HVAC systems and equipment, there are still unresolved issues. The underlying physical processes involve conductive, convective and radiative heat transfer as well as mixing and transport of several species such as moisture and CO₂. Thus, first principles based models can be arbitrarily complex. A popular class of models for modeling temperature evolution in a building is based on the resistance-capacitance networks, whose parameters are fitted to measured temperature data. There is a large unknown disturbance that comes from heat gains from occupants and their activities that makes system identification challenging [5]. Moreover, these models ignore humidity; work on identification of models that include both temperature and humidity is rare. Constructing control-oriented models for HVAC equipment, such as the cooling and dehumidification coil, is more challenging [7].

Another challenge for MPC-type control is the need for prediction of the disturbance signal over the planning horizon. Recall that there are many components in the disturbance signal, and while weather related disturbances can be reasonably forecasted, signals such as number of occupants and the moisture generation are difficult to predict.

Yet another challenge is addressing the high computational complexity due to the large number of decision variables, especially where there are a large number of zones and the planning horizon is long.

3.1 Building-specific requirements

There are many types of buildings and all have their own unique requirements on indoor climate which spill over to the constraints on the climate control system, MPC or not. Healthcare-related facilities in particular require special considerations and have distinct environmental constraints. The HVAC system described in detail in Section 2.2 is a hydronic (chilled water) system. The details of the control problem will differ in case of a DX cooling system, which are used widely in packaged rooftop units used in small commercial buildings.

The air-side control problem discussed in Section 2 involved continuously variable actuators and set points, and the optimization becomes a nonlinear program (NLP). However, in case of a DX system the decision variables may be integer valued if compressor stages need to be decided. In fact, many large HVAC equipment is ultimately on-off, such as compressors in chilled water plants, cooling towers with constant speed fans, etc. The optimization problem therefore becomes a mixed integer non-linear program (MINLP), which are considerably more challenging to solve than NLPs. Advances in solving MINLPs will thus benefit adoption of MPC in buildings.

Two other applications in which optimal control of BEMS can play an important role are demand side services and management of on-site renewable energy sources. More generally, in any building that moves away from the traditional role of being purely a consumer of energy that is supplied by someone else (power grid, gas grid, etc.) to one of a *prosumer* that uses on-site generation, and perhaps energy storage, can benefit significantly from more intelligent real-time decision making than the currently available rule-based control algorithms of existing BEMS.

4 Conclusion

BEMS augmented with advanced decision-making algorithms can improve both indoor climate and reduce energy use. In addition, they can help operate buildings with on-site generation and storage resources. There are many challenges in achieving this vision. Control-oriented models learned automatically from data, prediction of exogenous disturbances, and optimization algorithms all need advances. Another option is model-free (learning-based) control. No matter the approach, the resulting methods need to be inexpensive to deploy and maintain, which is challenging due to differences among buildings and changes that occur in a building over time. The systems and control community is well positioned to address many of these challenges.

References

1. American Society of Heating, Refrigerating and Air-Conditioning Engineers: The ASHRAE handbook fundamentals (SI Edition) (2017)
2. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.: ANSI/ASHRAE standard 55-2010, thermal environmental conditions for human occupancy (2010). URL www.ashrae.org
3. Baughman, A., Arens, E.A.: Indoor humidity and human health—Part I: Literature review of health effects of humidity-influenced indoor pollutants. *ASHRAE Transactions* **102 Part1**, 192–211 (1996)
4. Braun, J.: Reducing energy costs and peak electrical demand through optimal control of building thermal storage. *ASHRAE Transactions* **96**, 876 – 888 (1990.)
5. Coffman, A., Barooah, P.: Simultaneous identification of dynamic model and occupant-induced disturbance for commercial buildings. *Building and Environment* **128**(153-160) (2018)
6. Patel, N.R., Risbeck, M.J., Rawlings, J.B., Maravelias, C.T., Wenzel, M.J., Turney, R.D.: A case study of economic optimization of HVAC systems based on the Stanford University campus airside and waterside systems. In: 5th International High Performance Buildings Conference (2018)
7. Raman, N.S., Devaprasad, K., Barooah, P.: MPC-based building climate controller incorporating humidity. In: American Control Conference, pp. 253–260 (2019)
8. Tom, S.: Managing Energy and Comfort: Don't sacrifice comfort when managing energy. *ASHRAE journal* **50**(6), 18–26 (2008)
9. Williams, J.: Why is the supply air temperature 55F? <http://www.8760engineering.com/blog/why-is-the-supply-air-temperature-55f/> (2013). Last accessed: Oct, 02, 2017