Reducing greenhouse gas emissions by optimizing room temperature set-points

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Abstract

We design a learning and optimization framework to mitigate greenhouse gas emissions associated with heating and cooling buildings. The framework optimizes room temperature set-points based on forecasts of weather, occupancy, and the greenhouse gas intensity of electricity. We compare two approaches: the first one combines a linear load forecasting model with convex optimization that offers a globally optimal solution, whereas the second one combines a nonlinear load forecasting model with nonconvex optimization that offers a locally optimal solution. The project explores the two approaches with a simulation testbed in EnergyPlus and experiments in buildings on a university campus.

1. Introduction

Building energy consumption represents one-third of the United States' greenhouse gas (GHG) emissions, the largest of any sector (EPA, 2021). The Biden administration has set a target of a 50% reduction in 2005 GHG emissions by 2030 and net zero emissions by 2050 (White-House, 2021). Achieving these targets will require deep decarbonization across all sectors. This is particularly challenging in the building sector given that the existing building stock is large and there is relatively low turnover. Thus, to achieve such deep decarbonization targets the US must simultaneously create energy-efficient new buildings while lowering energy consumption in existing buildings.

A significant fraction of the GHG emissions in buildings is due to heating and air conditioning. In residential buildings they represent about one-third of energy consumption, which is the largest end-use type (EIA, 2021b). In commercial buildings they represent 17%, which is also the largest end-use type (EIA, 2021a). Many energy systems and building envelope technologies are being implemented to reduce heating and cooling demands. While these are important, they are also capital intensive.

An alternative approach is to adjust building temperature set-points to lower energy consumption and GHG emissions. The mechanism has two components. First, energy consumption can be reduced by limiting heating or cooling when a space is unoccupied, by learning behavioral patterns. Second, electricity-derived heating or cooling can be timed to coincide with low GHG emissions from the electrical grid and avoided during times of high emissions. Adjusting building temperature set-points requires little capital investment. Depending on the energy system being used, it may only require changes to software and/or thermostats, as opposed to changes in the much more expensive heating and cooling systems.

Numerous *smart thermostats* for residential buildings that rely on machine learning algorithms have been developed and are deployed in homes. Given that US residential and commercial GHG emissions are nearly the same (EPA, 2021), there is a significant opportunity to implement building temperature set-point machine learning algorithms for commercial buildings as well. This is a challenging task due to the scale and complexity of commercial buildings and the complicated management systems used to regulate temperatures.

The application of machine learning methods to commercial building heating and cooling systems is a well-studied field. In the review paper (Rolnick et al., 2019), these applications are broadly categorized as (a) building energy modeling and (b) optimizing energy use. The review paper (Esrafilian-Najafabadi & Haghighat, 2021) adds a further category (c), occupancy prediction. The project proposed here will eventually span all three categories, though this paper focuses on (a) and (b). Relative to existing research, the primary contribution of the project proposed here will be experimental validation in a real building, which we have instrumented with energy submeters, people counters, and other sensors. A secondary contribution will be optimizing

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for GHG emissions, rather than more common performance criteria such as energy consumption and operating costs. In (Esrafilian-Najafabadi & Haghighat, 2021), both experimental validation and new performance criteria are identified as important areas for future research.

2. Methods

Figure 2 illustrates the proposed GHG minimization framework. It involves two steps: (1) learning a model to predict energy consumption based on temperature set-points and other features, and (2) using the learned model and daily predictions of occupancy and the GHG intensity of electricity to decide set-point profiles that minimize GHG emissions. Specifically, we have developed an EnergyPlus model of the room we will control, then simulated operations under a wide variety of weather, occupancy, and temperature set-point conditions. This provided a larger and richer set of data than we could obtain from direct measurements of the room. We then applied linear and nonlinear machine learning algorithms to predict the load profile, using the simulated load as training and validation data. Finally, we are developing convex and nonconvex optimization algorithms that use the trained models to minimize GHG emissions. The resulting set-point profiles will be fed into EnergyPlus for validation. Once performance in the simulation test-bed is satisfactory, we will demonstrate the framework experimentally in the real building.

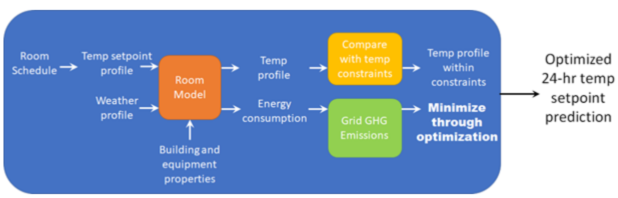

Figure 1. Information flow in the proposed framework.

2.1. EnergyPlus Simulation Testbed

EnergyPlus, a whole building energy simulation program developed by the U.S. Department of Energy, was used to model a medium-sized campus classroom in Cambridge, MA. EnergyPlus makes it possible to model new and complex building technologies which cannot be modeled by other whole building energy simulation programs and it can model a large number of zones and buildings that could be used to scale the results for the entire campus.

The current EnergyPlus model was designed to match the room's physical and geometric properties to the best of our knowledge. The corresponding modeled outputs provided information about the load behavior under steady-state and transient conditions. The methodology used in the project has the following steps: (1) data collection in the classroom, (2) preparation of schedules for occupancy and heating/cooling using actual data, (3) development of a detailed classroom energy simulation model in EnergyPlus, (4) modification of weather data file required for simulation using on-site measurements, and (5) comparison of results derived from the EnergyPlus simulation program with the utility data measured in the classroom, using the same time step and period for measured and simulated data.

2.2. Machine Learning Model Exploration

The problem of predicting energy consumption based on temperature set-points and other features is a time-series learning task. We have experimented with several model structures, such as ARIMA, the Prophet model developed by Facebook (Taylor & Letham, 2018), and multilayer perceptron.

2.2.1. Model Features and Target

The forecasting target is the hourly heating load. Although the simulation output includes a large number of modeling parameters that are important for load forecasting, we selected only the following, typically available features: the ambient dry-bulb temperature (T_{out}), the room temperature set-point (T_{set}), the time-difference of the temperature set-point ($dT_{set}(t) = T_{set}(t) - T_{set}(t-1)$), and functions of the time of day.

The temperatures T_{out} and T_{set} are scaled to standard normal distributions to ensure model convergence. Due to occupant behavior, building schedule, and seasonality, the building load demonstrates daily, weekly and seasonal trends. Consequently, we applied a sine and cosine embedding to all temporal information, as is discussed in (Gonzalez & Zamarreno, 2005). For example, to represent time of day, we used $[\sin(\pi(h)/12), \cos(\pi(h)/12)]$ to represent a 24 hour cyclic nature explicitly in the learning problem. In the case of the simulation dataset, we only encode time of day as a temporal feature.

2.2.2. Autoregressive with Exogenous Regressors (ARX)

Variations of the ARIMA model have been explored. Specifically, we compared AR, ARIMA, ARX, SARIMA (ARIMA with seasonality), and SARIMAX and found that including integration, moving average or seasonality only marginally improves model performance. Considering the trade-off between model complexity and performance, we selected ARX(6) as the preferred model. The autoregressive component includes the previous 6-hour load, and the exogenous regressors are the current T_{out}, T_{set}, dT_{set}, and time of day. The RMSE of ARX model forecast on the test set is 4.25 MJ.

Table 1. RMSE comparison in the test data, in units of MJ.

ARX	PROPHET	MLP
4.25	4.04	1.77

2.2.3. PROPHET MODEL

Although ARX models are interpretable and have strong forecasting performance when the lags parameters are trained well, they cannot capture the nonlinearities in the time-series trends. To address those challenges, we leverage the Prophet model (Taylor & Letham, 2018) to forecast the hourly heating load with T_{out} and T_{set} as regressors. The Prophet model is an adaptation of a decomposable time series model (Harvey & Peters, 1990) with three time-series components: trend, seasonality, and holidays. We found the model to be best trained when the change-point prior scale is tuned to 0.95. The model produces an RMSE of 4.04 MJ on the 24-hour forecast horizon, which is slightly better than the ARX model.

2.2.4. MULTILAYER PERCEPTRON (MLP)

To encode the time series properties embedded in the dataset, we decided to reuse the structure of an ARX model with nonlinear relations between each input by applying a ReLU activation function. The MLP takes in historical 24-hour load and current T_{out}, T_{set}, dT_{set}, and time of day as inputs and forecasts the load conditions for the next 12 hours. It is clear that the MLP nonlinear model outperforms the ARX and Prophet model by providing an RMSE of 1.77 MJ, which reduces approximately 60% RMSE.

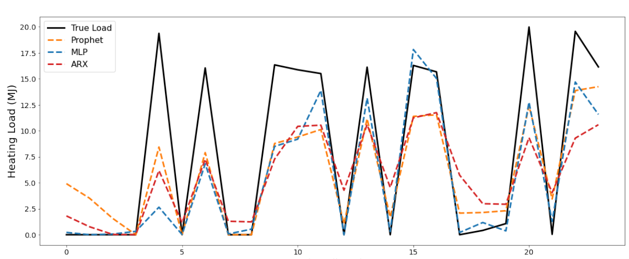

Figure 2. Model performance comparison on a 24-hour forecasting horizon from the test set. Black solid line represents true load, and the dashed orange, red and blue lines are from Prophet, ARX, and MLP models respectively. Compared to Prophet and ARX, MLP can better capture extreme load conditions such as peaks. Nonetheless, Prophet and ARX correctly forecast general load trend.

3. Options for Set-point Optimization

The project to date has focused on training an ensemble of models to predict energy use based on temperature set-points and other features. In the next phase, we plan to embed an energy prediction model in an optimization framework that will generate daily temperature set-point profiles that minimize GHG emissions.

The problem of minimizing cumulative GHG emissions takes the following general form:

$$\min_{x \in \mathcal{X}} \left\{ \mu^\top y \mid y = f(x) \right\}. \tag{1}$$

The decision variable $x \in \mathbf{R}^n$ (°C) contains the temperature set-points at each of the time n steps in the control horizon, $\mathcal{X} \subseteq \mathbf{R}^n$ is a convex set of feasible temperature set-point profiles, $\mu \in \mathbf{R}^n$ (kg/kWh) contains the predicted GHG intensity of electricity at each time step, $y \in \mathbf{R}^n$ (kWh) contains the predicted energy consumption at each time step, and $f : \mathbf{R}^n \to \mathbf{R}^n$ is the energy prediction model. In this representation, the structure of f includes the exogenous features and the trained model parameters. Similarly, the set $\mathcal{X}$ depends on the predicted occupancy, as temperature constraints are stricter when the space is occupied.

If the prediction model is linear in the temperature set-points, then the objective function in Problem (1) is linear in x. In this case, Problem (1) is convex, as the set $\mathcal{X}$ is convex by assumption. Therefore, the problem can be solved to global optimality in polynomial time using, *e.g.*, interior-point methods. In our applications, the set $\mathcal{X}$ can usually be described by a system of linear inequality constraints, in which case Problem (1) reduces to a linear program that can be solved efficiently and reliably by off-the-shelf software.

Unfortunately, our experience so far indicates that for our energy prediction applications, linear models are significantly less accurate than nonlinear alternatives. It is not clear that optimizing temperature set-points with a relatively inaccurate, linear energy prediction model will give acceptable performance. For this reason, we are considering a two-stage approach that uses both linear and nonlinear energy prediction models. The first stage of this approach involves solving a convex version of Problem (1) with a linear energy prediction model $f^{(\ell)}$ to generate a solution $x^{(\ell)} \in \mathcal{X}$. The second stage involves solving a nonconvex version of Problem (1), with the linear model $f^{(\ell)}$ replaced by a nonlinear model $f^{(n)}$, to generate a solution $x^{(n)} \in \mathcal{X}$.

While there are no guarantees that the second-stage problem can be solved to global optimality, it can be solved locally by various gradient descent algorithms. These algorithms can be warm-started with the first-stage solution $x^{(\ell)}$. Given that warm-start, running gradient descent on the second-stage problem should generate a solution $x^{(n)}$ that is at least as good as $x^{(\ell)}$, and possibly significantly better. In other words, we should find that $\mu^\top f^{(n)}(x^{(n)}) \leq \mu^\top f^{(n)}(x^{(\ell)})$. However, solving the second-stage problem will likely require coding our own local optimization routine and, in particular, computing derivatives of the nonlinear energy prediction model $f^{(n)}$. This is our next area of work, and we are currently exploring options for how to proceed.

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