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Bayesian evaluation of energy conservation measures: a case study with a model-predictive controller for space heating on a commercial building

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Abstract

We have developed a method, based on Bayesian statistics, to evaluate the efficacy of energy conservation measures on existing buildings. Unlike conventional methods, our method uses existing historic utility bills and climate data to establish a baseline. Comparing this baseline with the measured post-retrofit energy consumption yields the estimated energy savings, including their uncertainties.

We have applied this method after installing, in March 2016, a commercial model-predictive controller for space heating on a medium-sized office building in Switzerland. The baseline was established from historic oil tank refill records. 58 days after installing the controller, the energy efficiency of the building had improved by 33.1%, with 19.0 percentage points standard error.

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Keywords: Bayesian inference; heating degree days; base temperature; balance point temperature; total heat loss coefficient

1. Introduction

Many energy conservation measures can help reduce the energy consumption of buildings, but some are far more effective than others. Building owners want to know which measures will yield the highest return on investment, and how reliable they are. Moreover, once the measure has been applied, the owners want to verify that the measure delivers what it promised, an activity known as Measurement & Verification (M&V). But doing M&V correctly is hard. Many M&V projects ignore the uncertainties surrounding their models, and frequently report a point estimate for the energy savings, giving a false sense of accuracy.

Swisscom, a leading Swiss telecommunications company, owns, rents, and operates about 1 300 buildings in Switzerland. They have publicly committed themselves to “increase our own energy efficiency by a further 35% be-

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Fig. 1: Aerial (top left) and side views of the Altbau (bottom) and Neubau (right) parts of the Sargans building

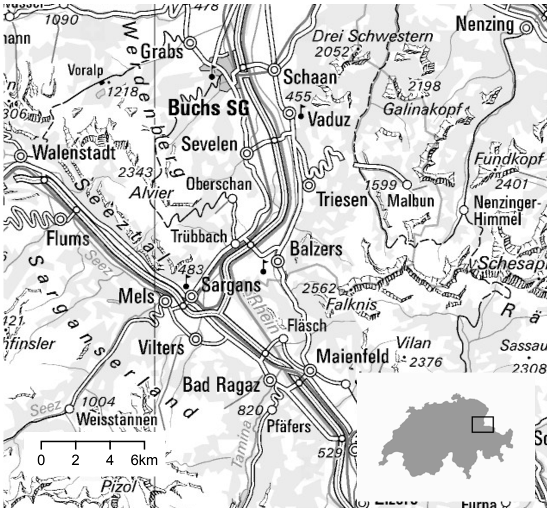

Fig. 2: Sargans region, including the Bad Ragaz and Vaduz weather stations

tween 2016 and 2020" [1]. Like many major Swiss companies, their building stock consists mainly in systems heated by non-renewable fuel that are frequently the object of retrofitting projects, provided the benefits can be demonstrated.

In late 2015, Swisscom designated a 2 700–2 800 m^2 building (Fig. 1 and 2) in Sargans, a Swiss locality in the canton of St Gall, to be fitted with a commercial adaptive model-predictive controller based on artificial neural networks called NOL[a] (Neurobat OnLine—analog) [2–6]. Comprising four heating circuits, with heating water provided by an oil-fired boiler, the energy efficiency of this building was not well understood and the project schedule did not allow for the measurement of the building's baseline. The pre-retrofit performance had to be established based on a history of oil tank refills, dating back to 2011. Because of such poor baseline data we had to develop new methods, based on Bayesian statistics, to estimate the improvement in energy performance.

2. Bayesian energy model

Under steady conditions, the daily heating demand of a building will balance the building's heat losses. We model the daily losses Q_d on a day d as a random variable drawn from a Gaussian distribution, whose mean is proportional to the positive difference between the building's base temperature and the average outdoor temperature:

$$Q_d = K \times (\theta_\mathrm{b} - \overline{\theta_{\mathrm{out}\,d}})^+ + \mathcal{N}(0, \sigma^2) \tag{1}$$

where the base temperature θ_b of a building is the outdoor temperature above which all heat losses are compensated by the sun and other free gains; it is equal to the indoor temperature, up to a constant offset that depends on the physics of the building. The building's total heat loss coefficient K is the quantity of extra heat required per day to maintain indoor comfort for each extra degree of cold.

Over a period p made up of n_p days, the total heating load will be

$$Q_p = \sum_{d \in p} Q_d = K \times DD_p + \mathcal{N}(0, n_p \sigma^2) \tag{2}$$

where $DD_p = \sum_{d \in p} (\theta_\mathrm{b} - \overline{\theta_{\mathrm{out}\,d}})^+$ is the number of degree days at base temperature θ_b during that period. Q_p is frequently available as utility bills or energy meter readouts, while DD_p must be calculated from historic weather data and the building's estimated base temperature.

Bayesian inference consists in finding the parameters of Eq. (2) that are the most consistent with the observed data, yielding probability distribution functions of these parameters [7]. We use the method proposed by one of the authors