FIELD TESTS OF AN ADAPTIVE MODEL-PREDICTIVE HEATING CONTROL SYSTEM

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ABSTRACT

Model-predictive control (MPC) has shown in the past great potential for optimising the operation of heating control systems in buildings, but the major drawback has always been the automatic identification of the system itself. In this work we report on field tests of a heating control system derived from previous research work at EPFL, implementing MPC with an adaptive model, i.e. a model that identifies automatically its parameters. These field tests involved 10 sites, most of them single-family houses. By alternating on a regular basis (typically every two weeks) between the original control system and the model-predictive one, we have derived estimates for the possible energy savings; these estimates range from 10% to 40%, with a marked improvement in the stability of the indoor temperature.

INTRODUCTION

Space heating is one of the largest consumers of energy in buildings, but even professional heating installers find it remarkably difficult to properly configure a central heating installation. Furthermore, there is little economic incentive for them to do so: few customers will be able to prove that a building could use less energy if it were better parameterised. This is especially true for smaller installations such as single-family dwellings. With little information at their disposal, most end-users are satisfied provided that the indoor comfort is maintained. Consequently, the energy demand of much of the existing building stock is significantly higher than needed, although there is little research on the subject.

A solution is the so-called *Model-Predictive Control* (MPC) class of algorithms, where a mathematical representation of the building, together with a model of the future climate conditions, let the system compute the flow temperature that minimises the consumed energy while preserving thermal comfort. MPC has attracted much interest because, provided the model is accurate and provided the prediction of future perturbations is correct, it is not possible to significantly outperform such a system. Furthermore, by choosing a suitable formulation of the objective function, it is possible to incorporate desirable attributes such as time-varying tariffs; future changes in setpoint; night-setback; constraints on control variables; and constraints on the rate of change of control variables. There is no significant additional computational cost for including such constraints.

The present work traces its roots to the Neurobat swiss research project [1, 2, 3, 4, 5], an early proposal for a so-called *adaptive model-predictive control* of heating systems. The algorithms enabled an efficient MPC for HVAC without requiring the user to provide an identified model; the model itself, being provided with sensor data, was capable of identifying its own parameters while running. However, computing costs at that time made its commercial implementation impractical.

In this paper we report on experimental tests carried out during the 2013–2014 heating season on ten test sites with a recently introduced commercial model-predictive heating controller that features a adaptive model. As will be seen, the controller achieved an average of 25% energy savings without requiring any major intervention on the building itself. A more complete description of the present work can be found in [6].

THE MODEL-PREDICTIVE HEATING CONTROLLER

Our building model is based on the adaptive model described in [1, 2, 3, 4, 5], and implemented in a commercial product called the NiQ. The NiQ samples its sensors always simultaneously and at regular intervals (every 900 s). The current and past sensor values are used by the model to predict the indoor temperature at the same instant. The actual, measured value of the indoor temperature is compared to the predicted value, resulting in some error. The self-learning algorithm uses this error to update the parameters of the building model. Thus, over time, the building model adjusts its internal parameters and reduces the prediction error. Similarly, a climate model is trained for the short-term prediction of local weather conditions.

The optimal control strategy consists in finding the sequence of hot water temperature values that results in the best trade-off between energy consumption and discomfort. We form a cost function that is to be minimised, taking as arguments the controlled values, as follows. Let t_{setpoint} be the normal indoor temperature setpoint (chosen by the user), t_{reduced} be the reduced indoor temperature setpoint (the minimum indoor temperature that must be maintained at all times), and t_{flowmax} the highest allowed flow temperature (detected by the NiQ from historic data). Furthermore, let $\sigma[i]$ be a vector of zeroes and ones, indicating whether normal or reduced comfort should apply at time i.

Then the problem can be stated as:

$$
\begin{array}{ll}
\text{minimize} & \displaystyle\sum_{i=1}^{N} \sigma[i](t_{\text{indoor}}[i] - t_{\text{setpoint}})^2 + \lambda \sum_{i=1}^{N} t_{\text{flow}}[i] \\
\text{subject to} & \begin{cases} t_{\text{indoor}}[i] \geq t_{\text{reduced}}, & i = 1, \dots, N \\ t_{\text{indoor}}[i] \leq t_{\text{flow}}[i] \leq t_{\text{flowmax}}, & i = 1, \dots, N \end{cases}
\end{array}
$$

Here it is understood that the $t_{\text{indoor}}[i]$ values are predicted by the building model from the future flow temperatures $t_{\text{flow}}[i]$, the future outdoor temperatures $t_{\text{out}}[i]$ and the future solar irradiance $e[i]$. The $t_{\text{flow}}[i]$ values are the N optimization variables of the problem; the control horizon being 24 hours at 900 s intervals, we have $N = 24 \times 3600/900 = 96$. The problem is a constrained minimization problem with 96 variables. λ is a parameter that controls the relative trade-off between discomfort and energy consumption.

When the problem is solved, $t_{\text{flow}}[1]$ is returned as the optimal flow temperature that is to be applied for the next 900 s, after which the process is repeated, in a classic receding horizon control strategy. The NiQ manipulates the outdoor temperature measured by the heating controller in order to keep the flow temperature close to this optimal value.

METHODOLOGY

We have tested the performance of this system during the 2013–2014 heating season on eight single-family houses and two appartments. The NiQ uses PT1000 temperature sensors to measure the forward and return flow temperatures, the indoor temperature, and the outdoor temperature. The solar irradiance is measured with a GBS01 irradiance sensor [7]. A laptop was connected to the NiQ, sampling the sensor values every 5 minutes through a serial port, and copied to a database every hour.

The NiQ features a mode where it merely copies the real outdoor temperature to the temperature "seen" by the heating controller. When in this so-called *bypass mode*, the original controller runs as if no NiQ had been installed. We alternated between the two modes (bypass and normal) at periodic intervals, letting each mode run for at least two weeks before switching again.

For each day of the experiment, we derive:

- The date;
- The mode, i.e. bypass or normal;
- The daily mean outdoor temperature;
- The daily mean indoor temperature;
- The daily mean temperature of the heating fluid;
- The daily mean solar irradiance;
- The energy consumption of the space heating.

RESULTS

The energy requirements for space heating in a residential building should be a linear function of the difference between the indoor and the outdoor temperature. If the indoor temperature is kept constant (as is usually the case in homes), then the energy requirement for space heating becomes an affine function of the outdoor temperature.

For each day of the field tests, and for each site, we plot in Fig. 1 the daily space heating energy against the mean daily outdoor temperature, together with a regression line. A separate regression is carried out for the NiQ and for the reference controller. The difference between the slopes of these regression lines yields the relative energy savings of one controller against another.

The estimated relative energy savings with their standard errors are given in Table 1 and shown graphically in Fig. 2.

From this sample of buildings, the mean energy savings can be estimated. We take into account the uncertainties surrounding the estimates for each site by forming a weighted average, taking as weights the inverse of the estimated variances (the squares of the estimated standard errors). We obtain a mean energy savings of 0.254 ± 0.034. In other words, installing the NiQ system on a large population of buildings can be expected to achieve about 25% heating energy savings.

We conclude by evaluating the resulting thermal comfort. We will use a metric commonly used by heating professionals: the proportion of daytime during which the indoor temper-

Site	$\alpha_{\text{Ref.}}$	$\Delta\alpha_{\text{NiQ}}$	Savings	Setpoint [°C]	$\text{RMSE}_{\text{Ref.}}$	RMSE_{NiQ}
Luedenscheid	-3.72 ± 0.69	1.88 ± 0.95	0.505 ± 0.20	22.00	1.86	1.73
Ruswil	-6.66 ± 0.31	2.71 ± 0.47	0.408 ± 0.06	21.00	4.00	2.12
Ihmert	-6.21 ± 4.97	2.24 ± 5.04	0.361 ± 0.53	23.00	1.49	0.76
Sprockhoevel	-11.1 ± 1.40	3.7 ± 1.62	0.332 ± 0.11	21.50	1.20	0.34
Brugg	-7.19 ± 0.23	2.23 ± 0.90	0.311 ± 0.12	22.00	1.24	0.38
Remscheid	-9.65 ± 0.48	1.59 ± 1.08	0.165 ± 0.11	21.00	0.48	0.30
Fey	-6.29 ± 1.64	0.715 ± 1.71	0.114 ± 0.24	23.00	1.32	0.25
Unterengstringen	-6.3 ± 0.55	0.711 ± 0.80	0.113 ± 0.12	21.00	0.87	0.21
Lausanne	-17.2 ± 0.76	1.04 ± 1.27	0.0603 ± 0.07	22.50	0.42	0.29
Hedingen	-4.62 ± 1.09	0.154 ± 1.20	0.0334 ± 0.25	23.50	0.29	0.17
Mean			$\mathbf{0.254 \pm 0.034}$			

Table 1: Slope of the regression line (α) for all test sites, mean energy savings, indoor temperature setpoint, and root mean square error between indoor temperature and setpoint. The sites are sorted by decreasing energy savings.

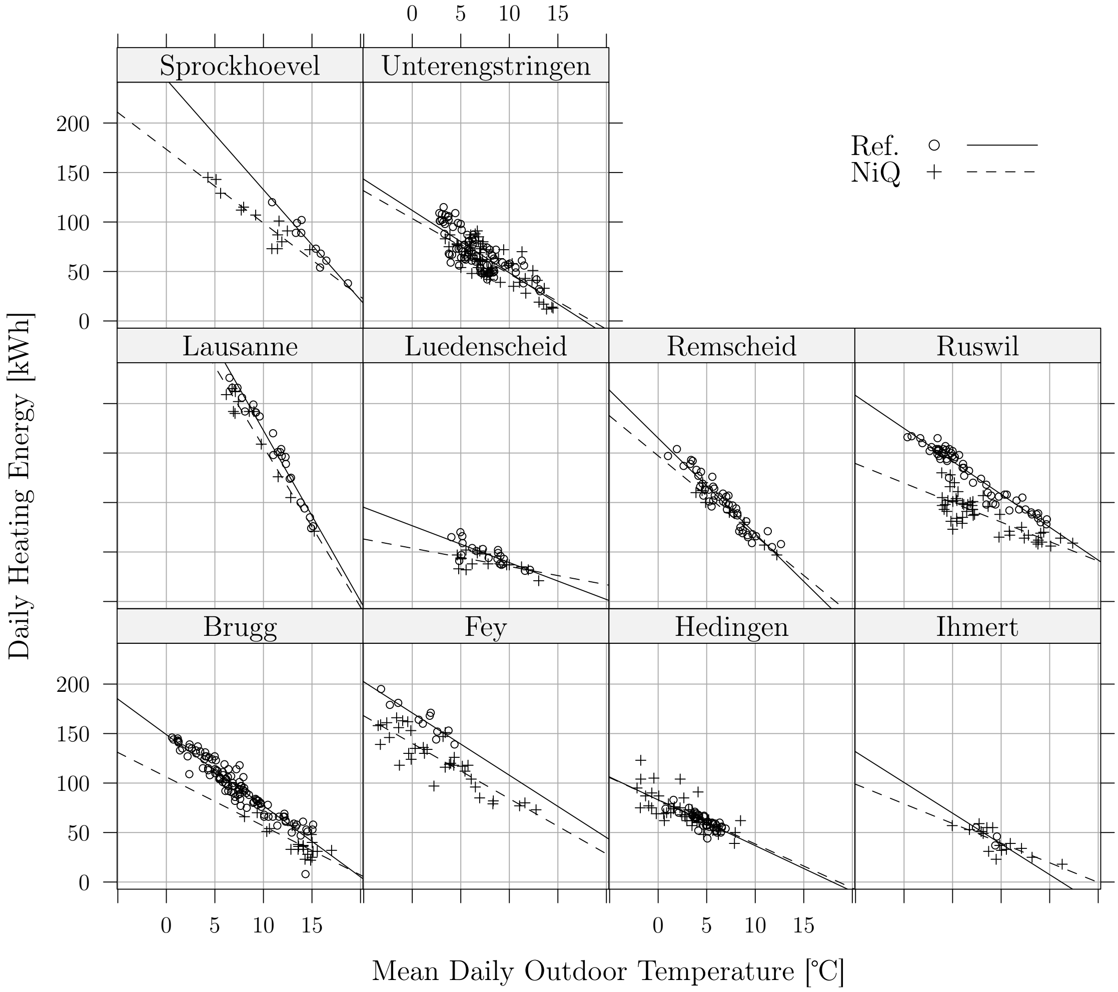

Figure 1: Energy signatures for all test sites, for both control systems.

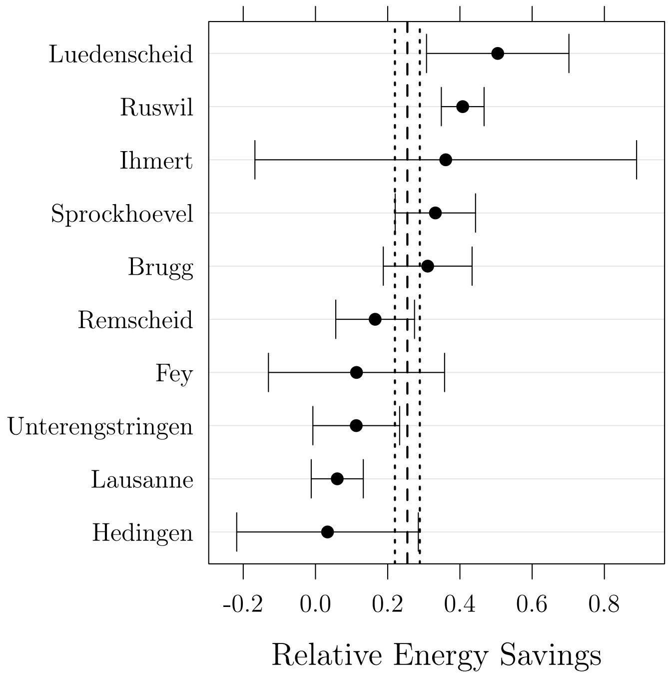

Figure 2: Estimated relative energy savings (with standard error) on all test sites. The dashed lines show the estimated average with its standard error.

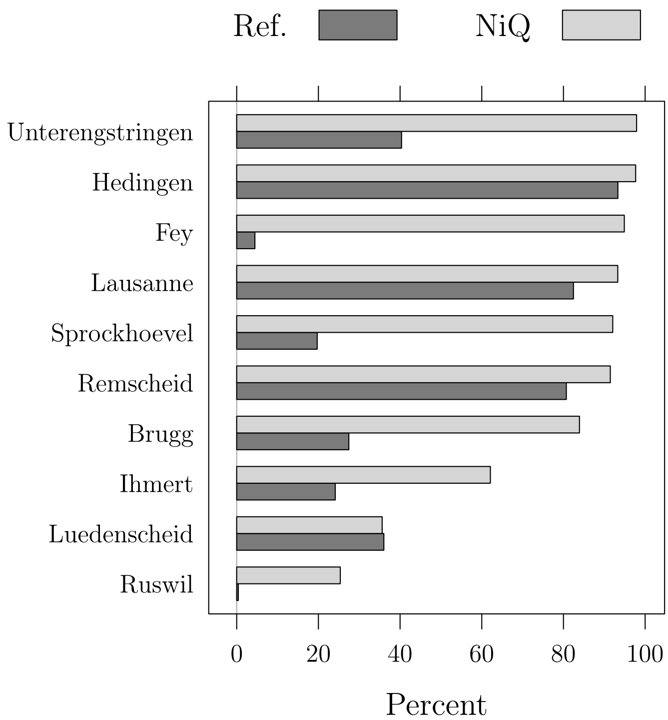

Figure 3: Percentage of time within half a degree of the indoor temperature setpoint, for both control systems. The sites are sorted by decreasing comfort with the NiQ.

ature is within half a degree of the desired setpoint. That fraction is shown, in percent, in Fig. 3 for all test sites and for both controllers. The comfort improvement with the NiQ is evident for all sites.

CONCLUSION

Conventional weather-compensated heating controllers are by nature open-loop controllers. Their efficiency depends on the correctness of their parameterization, and they are unable to take into account future climate conditions. This results in wasted energy and a less than optimal thermal comfort.

One solution to this problem is believed to be the adaptive model-predictive class of controllers. Such a controller has been proposed for the heating control of residential buildings by the NEUROBAT swiss research project, which we have implemented in an embedded controller.

We have tested this sytem against existing heating controllers during the 2013–2014 heating season on ten different test sites. All test sites have yielded positive relative energy savings, with a mean and standard error of 0.254 ± 0.034.

Adaptive model-predictive control has therefore been shown to be a viable solution to achieve significant energy savings on the heating of residential buildings, at a fraction of the cost usually required for more invasive procedures.

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