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Weather Forecast Control for Heating of Multi-Family Buildings in Comparison with Feedback and Feedforward Control

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Abstract: Our joint environmental and energy commitments mean we must reduce the building's energy use. Improved central heating control can play a role in how this is accomplished. There are three common control strategies: feedforward (traditional), feedback, and model predictive control (MPC). The latter two often work in parallel, where feedback uses indoor temperature sensors to adjust the supply water temperature. In contrast, the supply temperature setpoint is continuously calculated in MPC, fed with weather forecasts. The weather forecasts are often highlighted as essential ingredients in MPC, but at the same time, it is emphasized that temperature sensors are used to ensure a pleasant indoor temperature. To an outside observer, it is difficult to determine what is what in such combined control arrangements. Is energy saved because of the room sensors or because of the model? And what role do the weather forecasts play? This study quantifies the impact of the control strategy on energy use and indoor temperature. It concludes that PI-based feedback heating control saves approximately as much energy as MPC, and weather forecasts do not save significantly more energy than real-time weather data but are easier to obtain. The overall results for both control strategies align with the lower end of the result ranges of previous studies. The novelty is that the impact of weather forecasts has been studied separately and that different control strategies are compared against each other based on a model of a typical Swedish multi-family building.

Keywords: energy; muli-family building; heating control; model predictive control; digital twin; MPC

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1. Introduction

Buildings account for a large proportion of Europe's total energy use. It is therefore essential to make it more energy efficient. In multi-family buildings, heating often accounts for most energy use, especially in cold countries like Sweden. However, many measures are expensive and require extensive effort. In that context, improved heating control can be a simple and attractive supplement to implement quickly.

According to several studies, the average indoor temperature in Swedish multi-family buildings is about 22.0–22.5 °C [1–4] during the heating season. This can be compared with the Swedish Public Health Agency's (Folkhälsomyndigheten) guidelines of at least 20.0 °C [5]. The difference underlines a savings potential partly related to heat control.

But lowering indoor temperatures without it getting too cool is generally easier said than done. Poor adjustment of the radiator systems means there are often temperature differences between apartments (spatial variation), while poor heating control leads to temperature variations over the day (temporal variation).

This article focuses on improved central heating control of waterborne radiator systems. In principle, there are three strategies:

(1) Feedforward. This traditional strategy only considers outdoor temperatures.
(2) Feedback. This strategy is based on feedforward but also considers measured indoor temperatures.

(3) Model-based. This strategy processes various measurement data, such as indoor temperature (feedback) and weather, through algorithms in theoretical models of buildings. The technology can be adaptive so that it gradually learns to predict the required heating needs.

Feedback control considers internal heat gain and solar radiation indirectly through temperature sensors in the apartments. This is a reactive control strategy that, on the one hand, only reacts after the fact but, on the other hand, is completely adapted to the indoor environment experienced by the occupants. Model-based control is a proactive control strategy that considers various external inputs, either in the form of real-time measurement data or weather forecasts. It can also handle forecasts of daily patterns, etc. As a rule, however, the model-based control is supplemented with indoor temperature sensors. Model-based control in these contexts is thus, in practice, a combination of feedback and model-based control. One of the reasons for using weather forecasts instead of real-time weather data are that the heating control can react proactively and on several parallel weather components. Another reason is that weather forecasts are much more convenient to access compared to real-time measurement data from official weather stations or their own measurement arrangements for solar radiation, wind, temperature, etc.

In parallel with the central heating control providing the heating system with a supply water temperature, the hot water flow is also controlled locally by thermostats on radiators (see Figure 1).

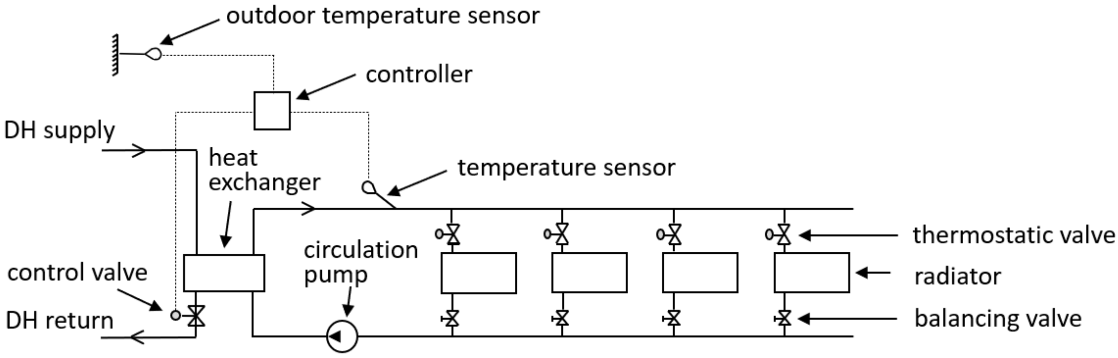


Figure 1. A radiator system and its connection with the local district heating system (DH) via a heat exchanger.

A survey from 2010 [6] found that an overwhelming majority of Swedish multi-family buildings have thermostatic radiator valves. Even though the survey did not investigate their status and function in practice, it is generally known that their function could be better. One reason is their large control range (often 2 °C), and they are relatively slow and easy to manipulate. Another common reason is that they often get stuck in the closed position after throttling the water flow during the summer. The need for advanced central heating control would probably decrease with better-functioning thermostats.

This article reports on a study whose purpose was to evaluate the energy-saving potential and impact on the indoor temperature of model-based control, with and without weather forecasts, and to compare it with feedforward and feedback control. This study's novelty lies in the fact that the impact of weather forecasts has been studied separately and that different control strategies are pitted against each other based on a typical Swedish multi-family building model. By using simulation models, the impact of the weather forecast could be studied separately. An alternative, based on actual measurements from several multi-family buildings, would have been disturbed by other influencing factors such as the residents' activities and, not least, other heating control components.

There has been a rapid growth in research about model predictive control (MPC) in buildings during the last decade. The reason for this is twofold. Firstly, the possibilities have seen tremendous growth due to increased computational power, more advanced simulation models, the availability of cheap, reliable, and easy-to-use sensors (temperature, carbon dioxide concentration, occupancy, light, etc.), and more controllable and connected energy systems (remotely controlled heat pumps, thermostats, etc.). Secondly, the need has also grown, primarily due to more use of both onsite and offsite renewable and intermittent energy sources, making energy prices more volatile and incentivizing the utilization and control of active energy storage systems such as hot water storage tanks and batteries.

Various review articles have summarized and analyzed different subsets of the vast amount of MPC research. A review article on MPC with weather forecasts in commercial buildings was presented by Lazos et al. [7]. The analysis also included energy pricing and electricity generation by wind and solar. It was concluded that taking weather forecasts into account could lead to energy savings of 15–30%. Serale et al. [8] reviewed and compiled energy savings from previous MPC research. Reported average energy savings were 15–20%, although substantially lower (<5%) and higher (>40%) were also reported. Pfeiffer et al. [9] also presented a review article comparing MPC with other strategies. Notable advantages were energy savings, cost efficiency, and robustness, while the disadvantages were the need to identify a suitable model and the cost of the installation, which may be high.

Mariano-Hernández et al. [10] reviewed various building energy management system strategies, one of which was MPC, and concluded that most of the available research on MPC is focused on non-residential buildings. This was contradicted by Taheri et al. [11], who also conducted a state-of-the-art review and found that 41% of the MPC research governed residential buildings. Yao & Shekhar [12] conducted a state-of-the-art review of MPC in the HVAC field. They concluded that MPC outperforms conventional control regarding energy-saving, minimizing cost, and maximizing thermal comfort. Similarly, Afram & Janabi-Sharifi [13] presented a review article, highlighted the advantages and disadvantages of different control strategies, and concluded that even the simplest MPC systems outperformed traditional non-predictive control. In contrast, Lomas et al. [14] concluded that, despite the vast amount of research, there is no high-quality evidence about the impact on energy demand. The authors called for well-founded, large-scale, multi-disciplinary, multi-year field trials. Focusing more on control of an active energy storage system in the building, Thieblemont [15] presented a state-of-the-art review and pointed out the work required to set up a helpful model as a potential drawback when implementing MPC in existing buildings.

Rocket et al. [16] presented a review article focusing on practical implementation rather than control-theoretic aspects, and Hilliard et al. [17] presented a review article focusing on commercial buildings. Afram et al. [18] conducted a comprehensive review article on an artificial neural network based on MPC. They concluded that minimizing energy costs is better than minimizing energy use and that an active thermal energy storage system can be beneficial. Also, Mirakhorli et al. [19] presented a review article and concluded that it is better to include the whole building in the model rather than only a heat pump or one single zone. It was also concluded that a one-hour timestep is insufficient to capture the dynamics of HVAC equipment; a 5- to 15 min timestep was recommended.

The most comprehensive and up-to-date MPC review article is by Drgoňa et al. [20]. The article, entitled *All You Need to Know About Model Predictive Control for Buildings*, gives an exhaustive overview of modeling approaches, performance assessment methodologies, methods for uncertainty mitigation, solution techniques, etc. It is also concluded that, despite the large amount of research in this area, practical applications are still in the early stages. Hence, the authors provided guidelines for practical implementation in real-world applications.

Privara et al. [21] implemented MPC with weather forecasts in a university building in Prague. Energy savings of 17–24% were achieved, and it was concluded that the mathematical model of the building was a crucial part of the implementation. Miezis et al. [22] proposed an algorithm for model predictive control of a heating system in a Latvian multi-family building. The heating system consisted of heat pumps, electric heaters, and water tanks. The algorithm, fed with weather forecasts and electricity tariffs, was tested by simulations for one month and reduced the electricity cost by 13% and carbon dioxide emissions by 9%.

Oldewuertel et al. [23] did a simulation-based study and investigated MPC with weather forecasts in different climates, HVAC systems, and types of buildings. The control was not restricted to heating but included control of blinds, lighting, cooling, ventilation, airflows, etc., and both perfect and inaccurate forecasts were analyzed. They concluded that MPC can offer significant energy savings, but the performance will vary with the quality of the model and the available input data.

While most, including the present, articles utilize conventional weather forecast services, Willegas-Mier et al. [24] studied a more innovative approach where a fisheye camera was used to track the movements of clouds to predict solar irradiance. In contrast to energy savings and improved thermal comfort, Hedegaard et al. [25] studied another advantage of MPC. Since MPC requires data from a weather forecast service, it were studied whether this data could also eliminate the need for onsite measured weather data. It was a simulation-based study on residential buildings in a Danish climate. It was concluded that onsite measurements could be eliminated with only a minor influence on performance. Energy savings decreased by 0.5%, and daily average comfort violations increased by less than 0.1-degree hours.

Cesari et al. [26] studied MPC while increasing the thermal storage capacity of a lightweight building by introducing a phase-changing material. The simulation-based study showed that, thanks to the weather forecast-based control, heating and cooling demand were reduced by 4% and 8%, respectively. It was also concluded that a prediction horizon of 12 h was preferred during heating, while a prediction horizon of 6 h was better during cooling conditions.

Cholewa et al. [27] studied a simple and low-cost system to improve heating control in one multi-family building and one office building in Poland. The system considered weather forecasts (temperature, wind speed, and solar insolation) and made it possible to set desirable night setback temperatures. Installation required less than 2 h and required no model. The energy savings were 15.2% in the residential building and 24.1% in the office building. A long-term field evaluation of the same system, this time in seven residential and three office buildings in Poland, was presented by Cholewa et al. [28]. The forecast control system decreased the heating demand by 10–19% (averaging 13.4%) in the residential buildings and by 8–14% (averaging 10.7%) in the office buildings. The average payback time for all buildings was 0.6 heating seasons. It was concluded that MPC was especially favorable in climates with a high daily amplitude of outdoor temperature, many hours of solar radiation, and long periods of transition between fall and winter as well as between winter and spring. Also, Pietrowska-Woroniak et al. [29] reported energy savings when installing weather forecast-based heating control in Polish buildings. Twenty-two residential multi-family buildings built between 1983 and 1996 were included in this study. Prior to the installation, the control system took only the current outdoor air temperature into account. The new control system used not only forecasted weather but also current wind speed, solar radiation, precipitation, indoor temperature, and humidity. The analysis included investigating differences between non-renovated buildings and buildings that had undergone major thermal modernization. It was shown that the heating demand decreased by 4.5–25.2% (averaging 13.2%) in the non-renovated buildings and by 2.4–29.5% (averaging 8.7%) in the modernized buildings. In addition, the heating demand increased in two of the modernized buildings.

While a lot of previous research on MPC governs active thermal energy storage systems and power generation [30], the present article is about a very typical Swedish residential building from the 1970s, with neither active thermal energy storage nor onsite power generation. Furthermore, while many previous articles focused on demand-side flexibility, aiming at enhancing the penetration of renewables [31], the focus of the present article is to minimize energy use.

2. Materials and Methods

By analyzing a building model in the simulation tool IDA ICE, the energy-saving potentials and impacts on indoor temperature of different control strategies were quantified. The weather data (climate file) consisted of data from Stockholm, Sweden, in 1977, since that year were considered metrologically representative for the area. Although climate change has driven up outdoor temperatures since then, the principle of this study remains the same. The building could be in a cooler location. Climate files in IDA ICE contain information on the outdoor dry bulb temperature, solar intensity (diffuse and direct), wind direction, and wind speed. In cases where the modeled building had weather forecast control, identical climate data were used, i.e., perfect weather forecasts. The control strategy cases are summarized in Table 1.

Table 1. Summary of the control strategies, Cases 1–4.

	I	II	III	IV	V	VI	VII	VIII	IX
1A			X						
1B	X		X						
1C		X	X						
2A	X		X	X					
2B	X		X		X				
3Aa	X					X			
3Ab	X						X		
3B	X						X	X	
4									X

I	50% thermostats	VI	Model (non-manipulatade weather data)
II	100% thermostats	VII	Model (manipulated weather data)
III	Outdoor temperarture (single weather parameter)		
IV	Indoor temperature (P)	VIII	Weather forecast
V	Indoor temperature (PI)	IX	Ideal

To apply the theoretical study to a typical Swedish multi-family building, calculation input corresponding to a classic multi-family building type from the 1970s was chosen. The building was primarily made of concrete and had, in total, 18 equal-sized apartments on three floors. The building had exhaust ventilation and district heating distributed with hot water radiators in all apartments. As in actual buildings, the model's radiators were oversized to avoid too low indoor temperatures.

According to experts contacted, the heating systems of the time were over-sized by approximately 30%, which was also assumed in this study's building model. That figure aligns well with a Swedish research report from 1978 [32], which concluded that older buildings were generally over-sized by approximately 30% for five main reasons:

- There are a limited number of radiator sizes on the market. The closest bigger size was chosen (this still applies).
- Key figures of that time for heat sizing were based on outside temperatures that were too cold. More accurate meteorological measurements later indicated warmer temperatures.
- A large thermal weight was not considered at that time. Heat demand calculations were only based on light construction (affected by short-term temperature drops).
- Old standard values regarding thermal insulation (U-value) were used even after building codes began to require more insulation.
- Old standard values regarding air leakage were used even when the windows, etc., became tighter.

Calculation inputs regarding typical envelope performance, internal heat gain from people, appliances, lighting, ventilation airflows, etc., were taken from various Swedish studies on the subject. The main input data for the building model, including user patterns, are summarized in Appendix A.

In addition to the three heating control strategies listed in the previous section, an ideal heating control was also analyzed to quantify the theoretical energy-saving potential through heating control alone.

During the simulation study, applying the different control strategies to heating systems with the representative/expected control performance of old radiator thermostats was essential. However, experts contacted claimed there is no apparent relationship between performance and age. Therefore, in this study, it was assumed that "normal operation" is best reflected by leaving 50% of the thermostats in the model in mint condition with a p-band (control range) of 2.0 °C, while the other 50% were out of order and fully open. This approach to mimicking standard local heating control was applied to all the models described in Sections 2.2 and 2.3.

To ensure relevant input and evaluation methods, a reference group was attached to this study. This consisted of four people from two different suppliers of MPC, six people with technical responsibility, etc., at different property companies, and one person from the company that develops the simulation tool. IDA ICE

2.1. Feedforward, Traditional Control (Case 1)

Three feedforward types were modeled to quantify the importance of traditional local heat control:

- Case 1A. Thermostats out of order, i.e., as in Figure 1, but without thermostats
- Case 1B. Thermostats in mint condition with a p-band of 2.0 °C, but every second thermostat erased.
- Case 1C. All thermostats are in mint condition, as in Figure 1.

2.2. Feedback Control (Case 2)

Each apartment in the model was equipped with a temperature sensor. The average temperature was supplied to the controller in Figure 1. The greater the difference between the apartments' average indoor temperature and a determined setpoint, the greater the correction of the supply temperature. Adjustment of supply temperature can be based on P-control or PI-control. Both were examined.

- Case 2A: P-controlled feedback.
- Case 2B: PI-controlled feedback.

This means that the supply temperature curve was adjusted with regard to the apartments' combined average temperature.

The building model had only one zone per apartment, meaning only one temperature per apartment.

2.3. Model-Based Control (Case 3)

Here, the supply temperature setpoint was continuously adjusted based on a calculated heat demand. Two model-based control strategies were used in this study, both controlling all the aspects that IDA ICE considers in its dynamic heat balance.

- Case 3A. Model-based control without a weather forecast.
- Case 3B. Model-based control with weather forecast.

The supply temperature was determined by Equations (1) and (2), initially presented by Kärkkäinen [33].

$$t_{supply} = t_{room,set} + \frac{e^{f^{(1-\frac{1}{n})}\cdot\frac{\Delta t_{w,r}}{\Delta t_{ln,r}}} \cdot f \cdot \Delta t_{w,r}}{e^{f^{(1-\frac{1}{n})}\cdot\frac{\Delta t_{w,r}}{\Delta t_{ln,r}}} - 1} \tag{1}$$

$$f = \frac{q_{demand}}{q_{demand,r}} \tag{2}$$

$t_{room,set}$	indoor temperature setpoint	[°C]
f	relative heat demand	[−]
n	radiator exponent	[−]
$\Delta t_{w,r}$	water temperature drop at reference case	[°C]
$\Delta t_{ln,r}$	logarithmic mean temperature difference, radiator—room	[°C]
q_{demand}	current heat demand	[W]
$q_{demand,r}$	heat demand at reference case	[W]

To simulate a central heat control system with a model-based feed-forward strategy based on weather forecasts, a setup with a digital twin was chosen where two building models were simulated simultaneously. See Figure 2.

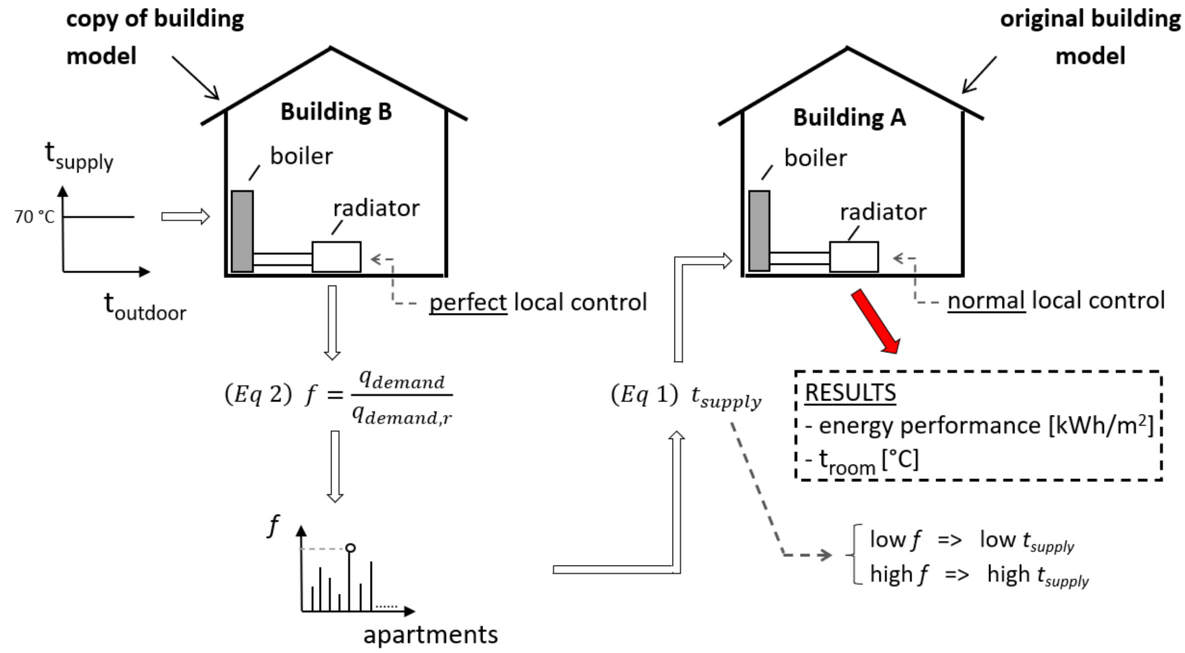


Figure 2. Principle sketch of "model-based control with a digital twin".

Building A: A model of a typical Swedish multi-family building from the 1970s, including typical internal heat loads and normally functioning local heat control (as in Case 1B). Building A delivered all the results.
Building B: A twin to Building A in all respects, including the use of it. The heat control was the only difference. Building B only provided input to Equation (2).

Building B had no central heating control in the true sense of the word. The boiler in that building constantly delivered a supply temperature of 70 °C to the heating system. Instead, all heat control took place locally in rooms with ideal thermostats that always maintained a constant indoor temperature as long as heat was needed. This was carried out by giving the radiators in Building B a p-band of 0.01 °C, which is a very small control range.

The heat demand at apartment level in Building B was continuously put in relation to its designed heat demand. A factor for the relative heat demand at apartment level was calculated in Equation (2) and constantly passed on to Equation (1) to calculate a suitable supply temperature for Building A. The supply temperature was thus calculated with respect to the apartment that currently had the highest relative heat demand. Hence, the control strategy could be called "model-based control with a digital twin".

In model predictive control systems, it is common for individual weather parameters to be amplified or reduced to better adapt to the character of the building. For example, solar radiation could be amplified and thus have a more significant impact than it would otherwise. In Case 3A, it was studied how that type of distortion affects indoor temperature and energy use by monthly testing the optimum amplification factors for a combination of weather data. Case 3A can thus be divided into two parts:

- Case 3Aa (without amplification/reduction)
- Case 3Ab (with amplification/reduction)

This was handled with a gain controller in the building model, where a gain factor (K) was multiplied by the difference between current weather data and a daily moving average of the same, which are exemplified by outdoor temperature in Equation (3).

$$t_{out,modified} = t_{out} + (t_{out} - t_{out,mean}) \times K \tag{3}$$

$t_{out,modified}$ modified outdoor temperature [°C]

t_{out} outdoor temperature [°C]

$t_{out,mean}$ outdoor temperature, daily moving average [°C]

K amplification factor [−]

For simulations with weather forecasts, i.e., Case 3B, the same principle was used as for Case 3Ab (see Figure 2), with the only difference that Building B received a time-shifted climate file. The result difference between Case 3Ab and Case 3B is thus the impact of the weather forecast. Here it can be noted that time-shifted weather information, without amplification, equals a perfect weather forecast. Since perfect weather forecasting does not exist, the approach yields results in favor of the weather forecast-driven control strategy. However, as will be shown shortly, this advantage for weather forecasting is not critical for energy performance but can affect the indoor temperature.

According to the project's reference group, the time steps forward should be adjusted individually depending on the weather parameter. In general, the optimization process for Case 3B involved trying to find the best monthly combination of time shifts and amplification for weather parameters. See Figure 3.

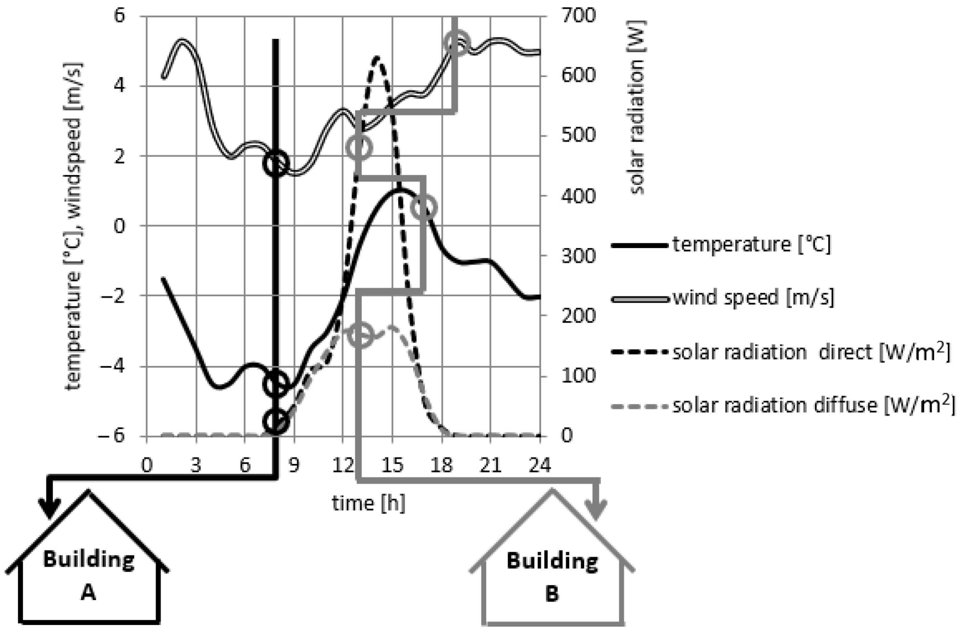


Figure 3. Model-based predictive control with a digital twin, where Building A (the original model) lives in the present while Building B (the copy) is exposed to time-shifted weather that has not yet occurred. The example is from March 1 in Stockholm. The time in Building A is 08:00, but the air temperature surrounding Building B is 17:00, wind speed is 19:00, and solar radiation is 13:00.

Finding a truly *optimal* combination of parameter settings can hardly be carried out manually. Yet, the optimization process was carried out without automatic optimization tools since the manual process was considered sufficiently optimized. One of the reasons was that wind speed was early on found to have no significant impact regardless of gain or time shift, allowing it to be kept unaffected during the optimization process. In fact, approximately 500 separate optimization simulations showed that small changes (time shift and gain) in outdoor temperature and solar radiation only had a small impact on energy use. It should also be mentioned here that all optimization alternatives leading to indoor temperatures below 20 °C were removed.

2.4. Theoretical Perfect Local Control (Case 4)

Finally, the reference building model was also simulated with perfect heating control at apartment level. This theoretical control strategy was better than anything that could ever be reproduced in reality. Still, the results are of interest as limits to be compared with simulation results from others and more realistic control strategies.

With this control, each room was always supplied (no delay) with the precise heating power required to maintain the desired indoor temperature (20 °C). This was achieved by using Case 1C, traditional control, but with thermostats in mint condition. The difference is that the p-bands were set to 0.01, which resulted in the indoor temperature constantly maintaining an even indoor temperature at the set point level when there was a need for heat.

2.5. Separate Sensitivity Analyses

This study also included some sensitivity analyses with the aim of quantifying how some different single parameters affect model-based control. One of the analyses concerned the influence of thermal mass; the other analyzed the impact on Case 3 when given a greater control range. In these two analyses, the same type of optimization procedure as previously described was required. For resource reasons, it was only possible to carry out the optimization process for three representative months during the heating season. January, April, and October were chosen. The results for those months were compared to previous simulations, whereupon an approximate result for the whole year could be calculated.

2.5.1. Impact of Thermal Mass

Providers of forecast-based control often highlight thermal mass as an essential aspect. In short, it is believed that forecast-based control is better suited to heavy buildings than light ones. To investigate this aspect, the models (both the reference building and its digital twin) were made very light and heavy, respectively. This was handled by changing the heat storage capacity of some of the building materials while keeping their thermal conduction abilities unchanged. In other words, the buildings were made heavier and lighter, respectively, but their thermal insulation capacity always remained the same. In the lightweight option, all load-bearing structural parts were adjusted to correspond to the thermal mass of wood and mineral wool. In the heavy option, they were given the same density as concrete. Please note that the original building already contained a lot of concrete and could thus be considered heavy.

2.5.2. Impact of Extended Margins for Forecasts and Modification of Weather Data

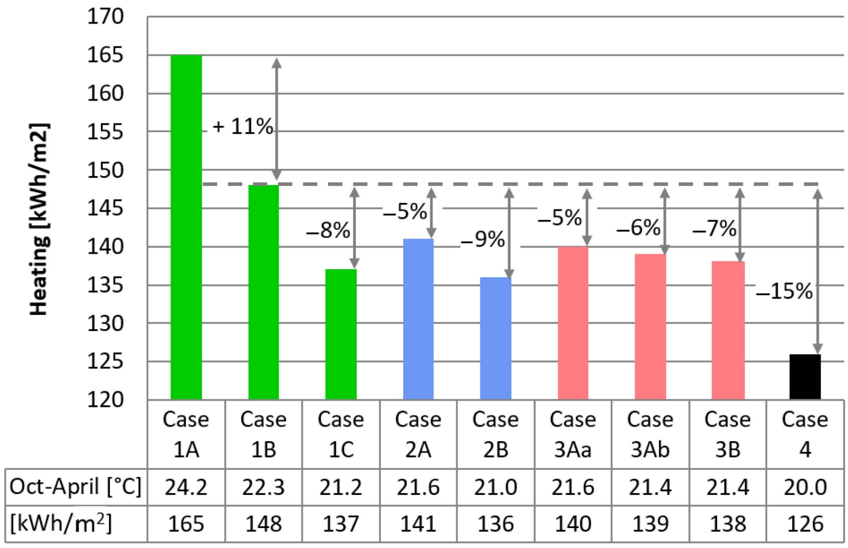
In its basic version, the heating control with a digital twin (Case 3Aa) resulted in indoor temperatures close to the lowest permitted level (t_{min} = 20 °C), leaving little space in Case 3Ab and Case 3B for further lowered indoor temperatures. To isolate the potential for modified and time-shifted weather parameters, the mean temperature in the reference building was increased. However, not by raising the building's set value (which would not have increased the control space), but by lowering the digital twin building's reference heating power demand (see Equation (2)), which was set for the coldest day. By doing so, heating power demands for all other occasions came closer to the maximum demand, resulting in higher supply temperatures and higher indoor temperatures. The reference power demand was adjusted until the indoor temperature was 22.3 °C on average during the heating season, i.e., the same as for Case 1B.

3. Results

A summary of the simulation results of the described control strategies is presented in Section 3.1, followed by further brief descriptions and results in Section 3.2, for some minor additional sensitivity analyses carried out during this work.

3.1. Main Results

Figure 4 shows the energy performance for Cases 1–4, where the results for the different control strategies are compared with Case 1B since that case can be considered the most representative for Swedish multi-family buildings from the 1970s.



Case 1A	Feedforward. Thermostats out of order
Case 1B	Feedforward. Thermostats with expected status
Case 1C	Feedforward. Thermostats in mint condition
Case 2A	Feedback. P-control
Case 2B	Feedback. PI-control
Case 3Aa	Model based. Without amplification
Case 3Ab	Model based. With amplification
Case 3B	Model based. With amplification and forecast
Case 4	Theoretical perfect local control

Figure 4. Energy performance and average indoor temperatures of the reference building for different control strategies. N.B. The vertical axis representing heating energy starts at 120 kWh/m^2 to clarify the differences.

By shifting the heat control in the building model, the impact of different control strategies could be determined. A pattern emerged showing a clear relationship between control strategy, average indoor temperature level, and energy performance. The better the control strategy manages to achieve indoor temperature levels close to the set point, the lower the energy use.

As shown in Figure 4, Case 1A results in the highest average indoor temperature, 24.2 °C, during the heating season. It is 4.2 °C higher than the theoretical optimum (20 °C) obtained in case 4. The high internal temperature was caused by the radiators' lack of thermostats, so there was no local heat regulation, and the heating system was oversized. When the traditional feed-forward control was instead equipped with new and well-functioning thermostats in Case 1C, the average indoor temperature dropped to 21.2 °C, which reduced the energy use. That level can be compared to Case 1B with normally functioning thermostats, resulting in a mean indoor temperature of 22.3 °C, which is in line with the Swedish studies mentioned [1–4].

In addition, the ideal heating control in Case 4, with thermostats that enabled an almost constant temperature level very close to the set point, the PI-based feedback control (Case 2B) resulted in the lowest mean temperature. That control strategy also resulted in stable indoor temperatures, i.e., small diurnal fluctuations. Not surprisingly, it was stated that Case 1A resulted in high diurnal variations. This, however, also appeared in Case 3Ab and Case 3B, which may seem strange since those strategies simultaneously resulted in relatively low average temperatures. Their instability was found to be mainly due to the amplification of weather parameters. The weather forecasts did not harm the daily fluctuations, but it should be noted that the weather forecasts were perfect all along. If Case 3B had instead been assigned weather forecasts with realistic accuracy, it would likely result in even more significant diurnal fluctuations.

3.2. Results from Sensitivity Analyses

The thermal mass analyses, described in Section 2.5.1, underlined that the building model in its basic version is thermally heavy. The energy performance of the heavy version was therefore similar to the original version, but the lightweight resulted in increased energy use, as shown in Table 2. In the light version, it was possible to quickly reduce the indoor temperature to lower levels by modifying and time-shifting the weather data. However, this control strategy was sensitive, often resulting in strong fluctuations. The lightweight alternative had poorer energy performance because it was less good at using stored free thermal heat from situations when the building had been overheated by solar radiation, etc.

Table 2. Energy performance for the reference building in three versions: "light", "heavy", and "original". The results for the latter are the same as previously reported.

Version	Case 3Aa [kWh/m^2]	Case 3Ab [kWh/m^2]	Case 3B [kWh/m^2]
Light	146	146	146
Heavy	140	137	137
Original	140	139	138

In Section 2.5.2, a sensitivity analysis was also described for evaluating the impact of extended control ranges for forecasting and other modifications to weather data. The analysis showed that increased control range resulted in a more significant effect (see Table 3), but still higher energy use than the original design. Therefore, it is better to let the primary control (Case 3Aa) lower the indoor temperature first and then allow Case 3Ab and Case 3B to adjust on the margin.

Table 3. Energy performance of the reference building in two designs: "extended control range" (average temperature: 22.3 °C for Case 3Aa) and "original" (average temperature: 21.6 °C for Case 3a). The results for the latter are the same as previously reported.

Version	Case 3Aa [kWh/m^2]	Case 3Ab [kWh/m^2]	Case 3B [kWh/m^2]
Extended margin	146	142	141
Original	140	139	138

4. Discussion

In this study, the outcome of different control strategies has been studied through simulations of a building model. When analyzing model-based control (Case 3), an exact copy of the original building model was used. Experience with that strategy shows that even relatively small changes in the digital twin could significantly affect control. In conclusion, digital twins should be accurate and calibrated to achieve the best results. However, creating an exact digital twin is very time-consuming and, in practice, cannot be justified for commercial use. Instead, today's model-based control strategies rest on simplified digital twins needing large safety margins. To partially compensate for this and to ensure that the heating control does not result in unwanted indoor temperatures, they are supplemented with temperature sensors in the apartments. Commercial model-based control is, in practice, therefore, a combination of model-based and feedback-heating control. Since this study shows that both control strategies can influence energy use to approximately the same extent (compare Case 2B with Case 3B), one can ask if model-based control is worth the investment or if feedback control is enough. The latter generally results in lower costs as it does not require software or weather forecasts from the supplier. In addition, temperature sensors can also be used for several other purposes, such as in dialogue with residents in the event of complaints or to determine whether there is a need for adjustment of the heating system and follow-up of a completed adjustment.

In measurement-based studies on several actual buildings, it would not be easy to distinguish between the impact of feedback control and model-based control since they are run in parallel. The different strategies would have to be alternately switched off for a long period of time.

Regarding the impact of weather forecasts as a separate aspect, this study showed that the additional benefit is very limited compared to if the model-based control are based on real-time weather data. The benefit of using weather data are, however, often highlighted when marketing such heating control services, but this should probably be seen as a way to make a virtue out of a necessity. Specifically, it is much easier to obtain detailed forecasts than real-time weather data, especially solar radiation. At the same time, it can be assumed that MPC, together with AI, might prove to be valuable in cases with very variable energy prices, intermittent energy sources, or active energy storage systems. In recent years, AI, with self-learning control technology, has started to be used in buildings. We are probably facing continued significant development; in fact, there are already AI techniques that can optimize heat control with regard to costs, power demand, etc., rather than energy and indoor temperature. In a study from 2023 [34], a model-based control with AI is described, where analysis of indoor temperature and the supply temperature led to an optimized supply temperature in a self-learning process. In parallel, however, their heat control still has feedback control to ensure that the inside temperature is acceptable. With this as a background, various types of advanced temperature control, including AI, will need to be studied further in the future.

In Sweden, heating is generally included in the rent, which reduces the personal incentive to save energy. Feedback heating control and other control strategies using indoor temperature could hence lead to increased heating demand caused by window airing. Such systems, therefore, usually have a function that sorts out the currently coldest and warmest apartments, respectively. However, if many apartments have open windows simultaneously, feedback control strategies would increase the supply temperature. One way to deal with this could be to install electronic thermostats on each radiator, which reduce the heat supply in the event of a rapid temperature drop (window airing, etc.). Many private houses have electronic thermostats, but only a few Swedish multi-family buildings do, even though they are more common in other countries. One reason is believed to be the Swedish form of housing, where the property owner (not the residents) is responsible for the installations. Another explanation is that the arrangement with heating included in the rent would lead to manipulation of the thermostats. However, the Swedish Energy Agency has recently initiated a mission where property owners and manufacturers of electronic thermostats jointly investigate the possibility of developing products adapted to the Swedish market. In the long term, this may mean that multi-family buildings in the future can have better heat control at room level than today. Whether such a development would affect the need for feedback or model-based heat control remains to be seen.

5. Conclusions

It hardly comes as a surprise that both central and local heat control turned out to be essential for energy performance and indoor temperature. Instead, this study's merit lies in the quantification of the savings potential for different aspects, which has been separately studied. However, one should be careful about making blanket statements about general energy-saving potentials in buildings, as all buildings are individual, with different numbers of residents, constructions, installations, indoor temperatures, etc. Similarly, one should be careful about relying too much on modeled results. Calculated values for both the indoor environment and energy use generally differ precariously from measured values [35], even if efforts are made to create a realistic building model. It could, however, be stated here that the calculated indoor temperature and energy use with traditional heat control (Case 1B) were utterly consistent with Swedish national statistics. Moreover, the calculated energy savings for feedback control (Case 2B) agreed fairly well with what was reported in study from 2023 [34], where energy savings for PI-based feedback control were summarized based on 107 Swedish multi-family buildings older than 25 years. Taken together, these findings indicate that this study's calculation model was credible and representative of that type of building. Having said that, since this study is about a comparison with the same building, the comparison itself is more interesting than the results matching reality in absolute terms (although that is also desirable).

As stated, this study showed that weather forecasts as a separate ingredient in model-based control did not lead to significant additional savings, not even if they were left with a large control range to work with. At the same time, weather forecasts significantly increased the risk of frequently ending up with too low indoor temperatures. The conclusion is that it is more important to adapt central control to the actual heating demand by considering some relevant parameters in real-time than to control it with weather forecasts. The better the central heat control, the smaller the margin for additional savings through forecasts. On the other hand, weather forecasts are a convenient way to obtain weather data. It is significantly easier than acquiring equipment for weather observations and continuously retrieving data from them.

Finally, although the purpose of this study was primarily to quantify the potential and impact of weather forecasting, it was also a step in developing a strategy for heating control in actual buildings through digital twins. In an ongoing research project, a pilot of such a technology solution is evaluated, which will be presented in the spring of 2024 in an article titled "Evaluation of the savings potential for model-based heating control with a digital twin—A measurement-based study in Swedish apartment buildings".

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Appendix A. Summary of the Building Model

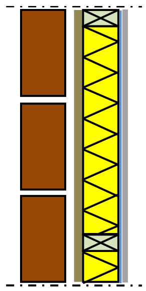
This appendix provides brief information about the reference building. Sources are indicated in connection with each task. In several cases, however, the sources had to be adapted. Size, geometry, and design were based on drawings from a typical building from the 1970s in a suburb outside Gothenburg. The drawings are referred to as [Gothenburg City 1968] in the description below.

General

3 floors, 45 m $\times$ 12 m, 540 m^2

18 apartments, 6 app./floor, 83.5 m^2/app. (90 m^2/app. incl. stairs)

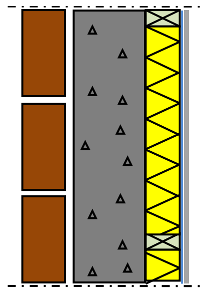
Internal ceiling height: 2.5 m
[36]
Walls



Outer wall—long side
(U = 0.41 W/m^{2}K)

- Brick 120 mm
- Air gap 30 mm
- Gypsum 3.5 mm
- Wood 95/45 mm
- Mineral wool 95 mm
- Gypsum 13 mm

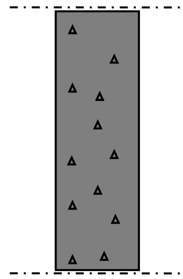
[36]



Outer wall—short side
(U = 0.41 W/m^{2}K)

- Brick 120 mm
- Air gap 30 mm
- Concrete 120 mm

[36] and
[Gothenburg City, 1968]

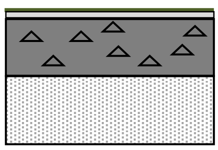


Partition wall
(Heat transmission ignored)

- Concrete 160 mm

[36]

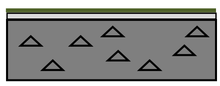
Joists



Base plate
(U = 0.7 W/m^{2}K)

- LW concrete 120 mm
- Concrete 150 mm
- Wooden board 20 mm
- Linoleum 5 mm

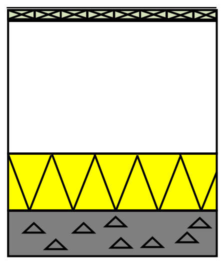
[36]



Intermediate floor
(Heat transmission ignored)

- Concrete 160 mm
- Wooden board 20 mm
- Linoleum 5 mm

[36]



Attic joist
(U = 0.22 W/m^{2}K)

- Concrete 120 mm
- Mineral wool 150 mm
- Air 350 mm
- Wood 23 mm
- Roofing felt 4 mm

[36]

Thermal Bridges

Factors for cold bridges made of various structural parts are specified below. Data were taken from course literature at Chalmers University of Technology [37], based on a Swedish standard [38], where suggested values for different aspects are given in ranges. The upper (inferior) part of the spans was chosen.

- Outer wall meets inner wall: 0.04 W/(m K)
- Outer wall meets outer wall: 0.06 W/(m K)
- Connections at windows: 0.05 W/(m K)
- Roof meets exterior wall 0.06 W/(m K)
- Basic construction meets outer wall: 0.87 W/(m K)
- External walls, general surcharge: 0.04 W/(m^2 K)
- Outer wall meets inner joists: 0.17 W/(m K) ^{A}

^{A} The value should be 0.05 W/(m K), but the stated value was increased to compensate for missing balconies.

Infiltration (air leakage)

The model was given a wind pressure-based infiltration corresponding to 0.8 l/(s·m^2) at a pressure difference of 50 Pa. A predefined "semi-exposed" wind pressure profile was chosen.

Windows

Coupled, 2-glass [36]

No external solar shading [City of Gothenburg 1968]

A number of living room windows were aired according to Table A1 [39]

A number of blinds in living rooms were used according to Table A2 [39]

- U = 2.2 W/m^{2}K (same for glass and frame) [1]
- SHGC (solar factor) = 0.76 (absolute value) [IDA ICE, default value]
- T (directly transmitted proportion) = 0.6764 (abs. value) [IDA ICE, default value]
- Blinds between glass [communication with retailer]
- Solar radiation factor with blinds closed = 0.24 (80°) [40]
- Sun shading factor with half-open blind = 0.38 (45°) [40]

The window area corresponded to 25% of the wall area, distributed as follows:

- Bedroom window 1.3 × 1.4 m × 2 pcs
- Kitchen window 1.8 × 1.4 m
- Living room window 1.4 × 1.4 m × 2 pcs.
- Balcony door 0.9 × 2.2 m (40% window, the rest frame)
- Toilet window (gable) 0.7 × 0.6 m

Heating system

- District heating [1]
- Radiators with waterborne heating [1]

Ventilation

- Constant airflow [1]
- Exhaust airflow [1]
- 0.39 l/sm^2 [41]
- Exhaust air from kitchen and bathroom [Gothenburg city, 1968]

Lighting

Design power: 151 W/apartment (see below) [42]

26% of max output daily at 23–07, 54% at 07–15, 100% at 15–23 [42]

By comparing a study on household electricity in Swedish multi-family buildings [42] with a study on the typical number of people (see under the section People), 790 kWh/household was obtained. This was then distributed as a loading curve in accordance with statistics from an end-use metering campaign based on 400 Swedish households [42].

Appliances

Maximum power excluding lighting and washing: 434 W/apartment [42]

Maximum power at 15–23. 65% of maximum at 07–15. 47% of maximum at 23–07.

People

A total of 2.2. persons/apartment [personal communication with SCB, responsible for official statistics and for other government statistics]

Attendance weekdays 15 h/day, weekends 18 h/day [43]

In this study, attendance was equated with:

During weekdays, 33% are gone at 07–19 and 50% are gone at 19–21 [assumption]

On weekends, 50% is gone at 09–21. [assumption]

Metabolism: 1.2 ± (sensible: 70 W/m^2 body) [44]

Clothing (CLO) during winter: 1.2, during summer: 0.5 [INNOVA, 1996]

Radiators

Under each window is a radiator with the same width as the window. [practice]

Each radiator has a height of 0.6 m [common]

Supply temp/return temp: 60/40 [own assumption] [common]

n (power curve exponent) = 1.28 [IDA ICE, default value]

P-band = 2 [practice]

Hot water circulation

Heating energy for domestic hot water: 30 kWh/m^2 [45]

Heating energy for hot water circulation: 350 kWh/apartment [45]

Heat losses (converted to internal heat): 25 W/apartment [communication with RISE, Swedish Research Institute]

Indoor temperature
Minimum allowed indoor temperature in any apartment: 20.0 °C. [5]
Average indoor temperature during heating season (Case 1B): 22.3 °C. [1–4]

Table A1. Solar screening.

Number of Living Room Windows Where	Living Room Windows in Different Directions			
	North	East	South	West
blinds are missing or completely drawn	18	7	9	8
blinds are fully drawn but angled up	0	10	7	9
blinds are fully drawn and closed	0	1	2	1

Table A2. Airing categories.

	Never/ Very Rarely	Rarely	Medium	Often	Very Often
Number of ventilated apartments	4	3	2	6	3
Clock	-	-	07.30–08.30 17.30–18.00	06.30–07.30 17.30–18.30	07.00–19.00
Area proportion of the opening	-	-	5.6%	4.6%	3.2%

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