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Impact of the weather forecast on a predictive controller performance: experimental studies with a residential heat pump for space cooling

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Abstract

Heat pumps represent ideal systems to exploit the energy flexibility potential of buildings and their embedded thermal storage possibilities, particularly when they are operated by intelligent management systems such as model predictive controllers (MPC). The present study proposes to evaluate in an experimental setup the performance of an MPC controller used to control an air-to-water, variable speed heat pump for a residential building. In particular, the impact of the forecast quality is investigated, since MPC relies on the access to forecasts of the disturbances (weather, price, occupancy…) to perform its optimization. Two experiments of three days were thus repeated, the first one with a real weather forecast retrieved periodically from a commercial service, while the second one considered a perfect forecast. In cooling mode, the case with imperfect forecast resulted in an increase of the electrical energy use of the heat pump of 5.8%, corresponding to a cost increase of 11.2%, compared to the case with perfect forecast. These experimental results highlight the importance of the forecast quality on the performance of model predictive controllers for heat pumps.

Keywords: model predictive control; weather forecast; experimental study; residential applications; space cooling.

1. Introduction

With the growing penetration of wind and solar plants in our energy mix, the need for demand-side flexibility is becoming more and more relevant to maintain a proper operation of the power grids. In particular, the heating and cooling loads of buildings can be regarded as flexible demand, since they can be shifted in time to a certain extent, by exploiting their embedded mass as thermal storage. Heat pump systems enable firstly to electrify this demand, and secondly to make it more flexible, if operated by smart controllers.

In this regard, model predictive controllers (MPC) have shown a growing interest in recent years to exploit the energy flexibility of buildings [1]. Such control strategies rely on an optimization problem solved periodically, making use of a forecast of the external disturbances and a model of the dynamic systems to project their behavior over a certain finite horizon in the future, and thus find the optimal control sequence. MPC usually provides greater benefits in terms of savings, comfort or energy flexibility (depending on the chosen objective), than simpler strategies such as rule-based controls, even though its development costs are higher. The performance of MPC depends highly on its formulation, the reliability of the model used, and the accuracy of the disturbances forecast, which most commonly consists of weather predictions. About this last point, little literature was found about the influence of the forecast quality on the performance of MPC used in building climate control. A summary of existing articles and their learnings is presented hereafter.

The literature on the subject often uses a "performance-bound MPC", sometimes also called "perfect MPC", "optimal MPC" or "optimal policy", as a benchmark for other control strategies [2]. It is an "idealized" MPC, which creates a perfect agreement between predictions and reality. Such studies are possible in computer simulations where the future evolution of the exogenous parameters can be known beforehand, but could not be applied to field tests. It enables to see the upper limit of the benefits that MPC could ideally provide, if it had a perfect knowledge of the future. Mendoza-Serrano et al. [3] compared for instance different configurations, with the MPC provided either with a perfect forecast (full future information), either with zero future information. The first case lead to savings of 31% compared to a standard reference case, while the second one lead to savings of only 27%. The authors highlighted the fact that the savings strongly depend upon the level of information provided to the MPC algorithm. Similarly, Allen et al. [4] reported savings of -13% on the total energy costs with a perfect forecast, and -11% with an imperfect forecast. Rolando et al. [5] developed a predictive rule-based control, and found that the system energy consumption was reduced of about 15% when the control logic utilized the information of the perfect solar radiation forecast, over the entire heating season. Lazos et al. [6] also commented that weather variables are significant components of the evolution of building energy systems and minimizing the uncertainty in predicting their evolution can lead to significant savings, usually in the range of 15–30% compared to a deterministic and non-weather sensitive control approach. Lohr et al. [7] compared a controller when fed with a perfect forecast, or with the data of the previous day used as predictions for the next day (yesterday-based predictions). They found that the performance decreased only slightly, if historical data is chosen as forecast for the upcoming day, but the proposed controller performed well in both cases.

Most of the reviewed literature agrees on a significant influence of the forecast quality over the MPC performance. However, it remains unclear how much better the MPC can perform with a perfect knowledge of the future, compared to other imperfect methods used to predict the future evolution of the disturbances. In fact, a complete absence of knowledge of the future is as unrealistic as a perfect knowledge: since weather parameters have a certain inertia, and repeat daily and seasonal patterns, a certain approximation of the next day weather can always be estimated. Furthermore, most of the reviewed articles resorted to simulation work, and did not consider the application on real systems like heat pumps operated in a realistic setup. The present work intends to fill this gap by proposing a comparative study which shows the performance of an MPC controller on a real heat pump operated in a semi-virtual laboratory setup. The experimental nature of the study considers all practical aspects related to applying MPC as a heat pump supervisory control, and enables to obtain more realistic results than previous simulation-only work. In this study, the MPC was run firstly in real time, using weather forecasts updated every hour from a commercial service, while the current weather was also measured in parallel. In a second experiment, the recorded weather conditions were reproduced in a climate chamber where the heat pump outdoor unit is placed, also providing this information as a perfect forecast to the MPC controller. In this way, the performance of the MPC with a perfect or with an imperfect, but real-life forecast could be compared with the same boundary conditions.

2. Methods

2.1. Experimental setup: semi-virtual environment and heat pump system

The tests were performed in a semi-virtual environment setup in a laboratory, according to the schematic of Figure 1. The real heat pump is an air-to-water, reversible model of 11 kW capacity, able to regulate the speed of its compressor (variable speed). Its outdoor unit is placed in a climate chamber where the air temperature and relative humidity can be accurately controlled to reproduce the desired climatic conditions in a dynamic manner. Two thermal benches emulate the thermal loads from the building according to the simulation made in real time with the TRNSYS software: the first thermal bench emulates the space cooling load, by controlling the return temperature from the emission system that goes back to the heat pump. The other thermal bench schedules the tapping of DHW from the storage tank, according to a fixed and predefined schedule.

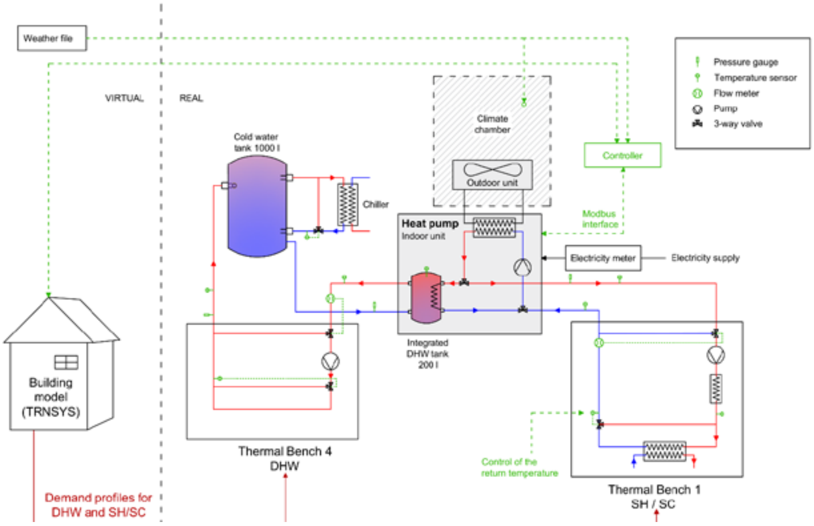

Figure 1. Schematic of the laboratory setup, applying the concepts of semi-virtual environment and hardware-in-the-loop.

2.2. Study case and utilized models

The control configurations have been tested on a building study case representative of the climate of the Catalonia region in Spain. It is a flat of 110 m^2 with 3 bedrooms, occupied by a family of 4 and conditioned by a circuit of eight Fan-Coil Units (FCU) supplied by the air-to-water heat pump. The flat is modelled in TRNSYS as a detailed white-box model. The occupation of the apartment is modelled stochastically, with a profile of the heat gains from people and equipment. The climate files used for the tests originate from a weather station situated in Tarragona (Spain), see also next section 2.4 about the forecasts on this matter.

In the present case, only a period of the cooling season was chosen for the tests. In this configuration, the heat pump functions in cooling mode to provide space cooling (SC), and in heating mode to produce Domestic Hot Water (DHW) stored in an integrated tank. Only one mode is allowed at any time, with DHW having priority over SC. The experiments carried out cover three days of September 2018, from the 13th to the 15th included, with a sufficiently high cooling load.

2.3. Model predictive controller

The controller tested in this study is a model predictive controller whose formulation is presented hereafter. The MPC formulation is summarized in this section; for any doubt or for further details, the reader is referred to previous publications [8], [9], and to the nomenclature at the end of this paper.

Objective: $\min_{u,\delta} J = [\alpha_\varepsilon J_\varepsilon + \alpha_{\Delta u} J_{\Delta u} + (1-\alpha_\varepsilon-\alpha_{\Delta u}) J_{cost}]$

Subject to, $\forall k \in [\![1, N]\!]$:

Model:

$$\begin{cases} \boldsymbol{x}(k+1) = \boldsymbol{A}\cdot\boldsymbol{x}(k) + \boldsymbol{B_u}\cdot\boldsymbol{u}(k) + \boldsymbol{B_e}\cdot\boldsymbol{e}(k) \\ \boldsymbol{y}(k+1) = \boldsymbol{C}\cdot\boldsymbol{x}(k) \end{cases}$$

Constraints on the inputs:

$$\begin{cases} \delta_{SC}(k)\cdot\underline{Q_{SC}} \leq Q_{SC}(k) \leq \delta_{SC}(k)\cdot\overline{Q_{SC}} \\ \delta_{TES}(k)\cdot\underline{Q_{TES}} \leq Q_{TES}(k) \leq \delta_{TES}(k)\cdot\overline{Q_{TES}} \\ \delta_{SC}(k) + \delta_{TES}(k) \leq 1 \end{cases}$$

Constraints on the outputs:

$$\begin{cases} T_{int}(k) \leq \overline{T_{int}}(k) + \varepsilon(k) \\ \underline{T_{TES}} - \varepsilon(k) \leq T_{TES}(k) \qquad (\varepsilon \geq 0) \end{cases}$$

The cost function is multi-objective: it combines a comfort objective J_ε, a smoothing objective $J_{\Delta u}$ (which aims at avoiding too frequent changes in the frequent actions), and a cost reduction objective J_{cost}. These conflicting objectives have been balanced by choosing appropriate values for the weighting coefficients α_ε and $\alpha_{\Delta u}$.

The MPC controller projects the behavior of the systems on a horizon of 24 hours in the future (denominated N), using a simplified model of the building. This model is a resistance-capacitance grey-box model which represents the building envelope and the capacity of the thermal mass of the building to store energy. The model is expressed here in a state-space format (matrices A, B_u, B_e and C), using two different kinds of inputs: the vector $u(k) = [Q_{SC} \;\; Q_{TES}]^T$ contains the thermal powers of the heat pump for either space cooling or DHW production operation. These are the decision variables of the MPC. The vector $e(k) = [T_{amb} \;\; I_H \;\; Q_{occ} \;\; Q_{DHW}]^T$ contains the exogenous, non-controllable variables (also called disturbances), that must be forecasted for the MPC to be able to make its projections in the future. The ambient temperature T_{amb} and the solar irradiation I_H represent the weather forecast: this is where different forecast strategies have been tested in the present work. The heat gains from occupants and equipment Q_{occ} and the DHW tapping profile Q_{DHW} represent the other disturbances.

The constraints on the inputs ensure that the thermal power chosen by the MPC stays within the operation limits of the chosen heat pump system, between the minimum $\underline{Q}$ and the maximum $\overline{Q}$. The binary variables δ_{SC} and δ_{TES} allow the MPC to decide whether to operate the heat pump in SC or in DHW mode, and the last input constraint guarantees that only one mode is activated at a time. The output constraints ensure the provision of comfortable conditions to the occupants. The indoor temperature T_{int} is thus limited below the limit of $\overline{T_{int}} = 25°C$ and the tank temperature T_{TES} above the limit of $\underline{T_{TES}} = 50°C$. These constraints are softened by the slack variable ε, which is included in the objective J_ε. In this way, the constraints can sometimes be violated, but at a certain cost reflected in the objective function.

Finally, the cost objective is formulated as shown in Equation (2). A simplified model of the heat pump enables to estimate its power consumption P_{el} in function of the thermal power Q, the ambient temperature T_{amb} and the supply temperature T_{sup}. This power consumption is then multiplied at every time step by the price of electricity c_{el} which varies hourly but still presents two distinct periods with high and low tariffs.

$$J_{cost} = P_{el}\left(Q, T_{amb}, T_{sup}\right) \cdot c_{el} \qquad (1)$$

The MPC controller is called every hour, and only the first control actions are sent to the real heat pump, before another instance of the MPC is formulated and solved.

2.4. Forecasts

In this study, the forecasts used within the MPC controller play an important role. Two configurations have been developed and tested: with perfect or imperfect forecast. During the days of September 13th to 16th of 2018, the outdoor temperature and solar irradiation were measured from a weather station situated in Tarragona (Spain). In parallel, every hour a forecast of these two weather parameters for the next 24 hours was retrieved from an external service and stored. It is a commercial service available online through an API [10], which enables the automatic download of the weather forecast periodically. This information was then used as input for the MPC.

The case with perfect forecast uses the actual measurements as forecasts, therefore it has a perfect knowledge of the future. It should be noted that the forecasts used are in fact a resampled version of the real measurements, to fit with the discretization time step of the MPC optimization problem (12 minutes). For this reason, the forecasts are slightly smoothed but have a very similar shape than the measurements.

The case with imperfect forecast uses the successive forecasts, as it would happen in a real operation on site with an actual building. The MPC runs its optimization every hour, therefore it updates with the best forecast information that it can have at the present moment.

The measurements and forecasts are presented in Figure 2. In the case of solar radiation, it appears that the forecasts did not take into account the cloud coverage, and only offered an estimation of the solar irradiation based on the location and hour of the day. This forecast matches well with the reality in the first day, as the sky was cloud-free, however it produces an important error on the third day, where the day was cloudier. The irradiation forecast does not actually change from one forecast to the next retrieved one hour later, for this reason all the curves are superposed. It should be noted that the weather forecast chosen was a free service, for this reason it is of poor quality, but it represents an actual service available on the market, for this reason it is interesting to investigate how the MPC would perform with such input.

In the case of the ambient temperature, the forecasts are shown on the bottom of Figure 2, and they provide a better estimation of the future evolution of the outdoor temperature, compared to the measurements carried out afterwards. The forecast is updated regularly, for this reason we observe a stack of curves. The forecast is relatively good although for instance in the third day it shows more uncertainty, probably due to the more irregular weather of that day.

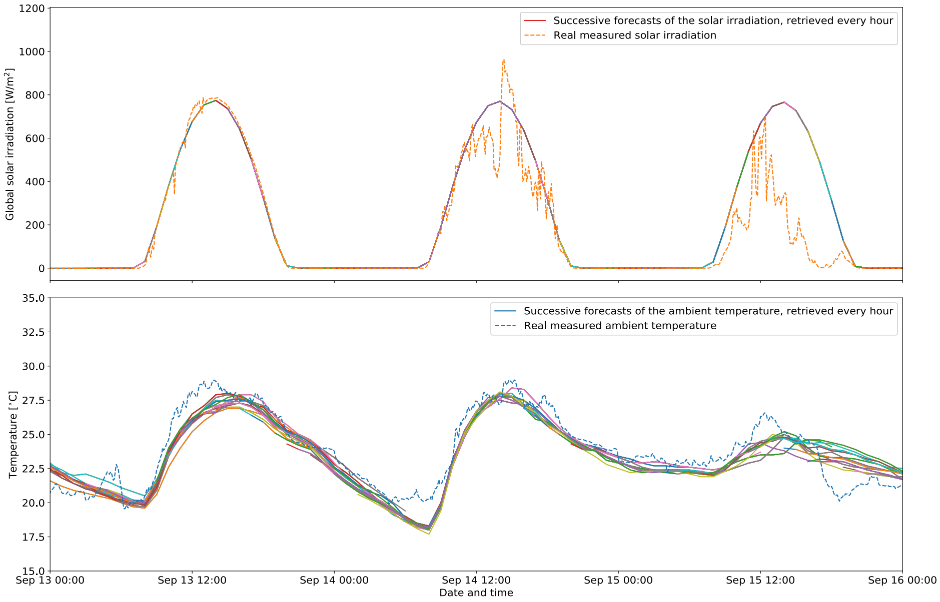

Figure 2. Measurements and successive forecasts of the solar irradiation and the ambient temperature in Tarragona (Spain) during three days of September 2018.

2.5. Performance indicators

The performed tests are analyzed in the view of different performance indicators. The summed energy values constitute the first series of indicators: the thermal energy produced by the heat pump, and the electrical energy that it used, over the three days of experiment. It should be noted that the thermal energy is always counted positive, whereas it is cooling energy like in space cooling operation, or heating energy like during DHW production (both of them are then summed to obtain the total thermal energy). The ratio of these two quantities (thermal and electrical energy) represents the efficiency of the heat pump, also called coefficient of performance (COP). Next, the costs incurred by the use of the heat pump are computed: the calculation consists in an integration of the electrical energy over the three days, weighted at each time step by the price of electricity in EUR/kWh at that time step, using for this purpose an hourly price profile available for small consumers in Spain (PVPC) [11]. This electricity tariff has a higher price period in the afternoon, therefore the economic MPC strategy tends to avoid the heat pump operation during these hours.

To evaluate the comfort conditions in the building, the average indoor temperature is calculated, as well as the percentage of time spent in Category I according to standard EN15251 [12], the category of highest comfort. Finally, an indicator able to estimate if the control strategy is able to shift the loads towards low-price periods is chosen. The flexibility factor is a performance indicator that reveals if the heat pump has used more energy during low price hours (up to a value of 1) or during high price hours (down to a value of -1) [13]. Its formula is indicated in Equation (2), where P_{el} represents the electrical power of the heat pump, and lp and hp the low and high price periods respectively.

$$FF = \frac{\int_{lp} P_{el} dt - \int_{hp} P_{el} dt}{\int_{lp} P_{el} dt + \int_{hp} P_{el} dt} \tag{2}$$

3. Results

The main results of the two experimental cases are presented in Table 1, in terms of summed energy values, average COP and comfort conditions, as well as with the chosen flexibility indicator.

Table 1. Summed or average values of several performance indicators over the three days of experiment in the two cases. The variation of the imperfect forecast case with respect to the perfect forecast case is indicated in absolute and/or relative terms.

Parameter	Unit	PERFECT	IMPERFECT
Thermal energy	**[kWh]**	**94.4**	**99.9**
Absolute variation	*[kWh]*		*+5.5*
Percentage variation	*[%]*		*+5.8%*
Electrical energy	**[kWh]**	**40.4**	**42.8**
Absolute variation	*[kWh]*		*+2.3*
Percentage variation	*[%]*		*+5.8%*
COP	**[-]**	**2.3**	**2.3**
Absolute variation	*[-]*		*+0.0*
Cost	**[EUR]**	**4.1**	**4.6**
Absolute variation	*[EUR]*		*+0.5*
Percentage variation	*[%]*		*+11.2%*
Average zone temperature	**[°C]**	**24.7**	**24.7**
Absolute variation	*[°C]*		*+0.0*
Time in Comfort Category I	**[%]**	**91.5%**	**95.0%**
Absolute variation	*[%]*		*+3.5%*
Flexibility factor cost FF	**[-]**	**0.5**	**0.3**
Absolute variation	*[-]*		*-0.2*

To evaluate the performance of the two configurations comparatively, the energy costs constitute the most interesting indicator, since this is the declared objective of the MPC controller. In this regard, the case with imperfect forecast performs worse than the case with perfect forecast, resulting in an increase of 11% of the costs. It thus appears that knowing an accurate forecast of the weather conditions in advance constitutes an important advantage for the controller. The thermal energy delivered and the electrical energy used by the heat pump both also increase when the forecast is imperfect, but in a less important manner, by 5.8%.

Next, the impact of the control configurations on the load shifting towards low price periods is investigated. Although the price forecast is equal in both cases, the case with perfect forecast managed to shift a greater proportion of the loads towards the periods of low price, reaching a value of $FF = 0.5$, while with imperfect forecast it stayed at a value of $FF = 0.3$.

The different strategies had little impact on the comfort of the occupants: the average temperature within the inhabitable zone is equal in both configurations, with a value 24.7°C. The percentage of time spent in comfort category I (i.e. with temperatures below 25.5°C in cooling mode for residential buildings) increased a little in the case of imperfect forecast, with 95%, while the case of perfect forecast only had 91.5% of the time in Cat. I, which is still entirely satisfactory, given that Cat. I represents the highest level of expectation. The extra energy spent thus enables to slightly improve the comfort conditions.

To understand better the dynamic behavior of the two configurations of the MPC controller, the time series of Figure 3 are plotted. The two versions of the controller behave in general similarly, for instance they tend to precool the building before the price increase happening every day, so as to limit the energy expenditure during the period of expensive electricity. However, some discrepancies are also observed, which explain the different results previously presented. For instance, on the third and last day, the imperfect forecast anticipated a large solar irradiation during the afternoon, while in fact the sky happened to be cloudy with low incoming solar radiation. Because of its overestimation, the MPC with imperfect forecast decided to cool the building in the early afternoon, anticipating an incoming solar radiation that never actually occurred, and so as to stay within the imposed comfort boundaries. On the other hand, the MPC with perfect forecast knew that the solar radiation would stay at a low level, and that active cooling would not be necessary to stay within the comfort zone. Since this difference in behavior occurred during a high price period, it had an important impact on the final energy costs, as can be seen in the end of the cumulative cost curves (third graph from the top). This illustrates perfectly the importance of an accurate forecast for an MPC controller, and explains why the MPC with perfect forecast performed significantly better.

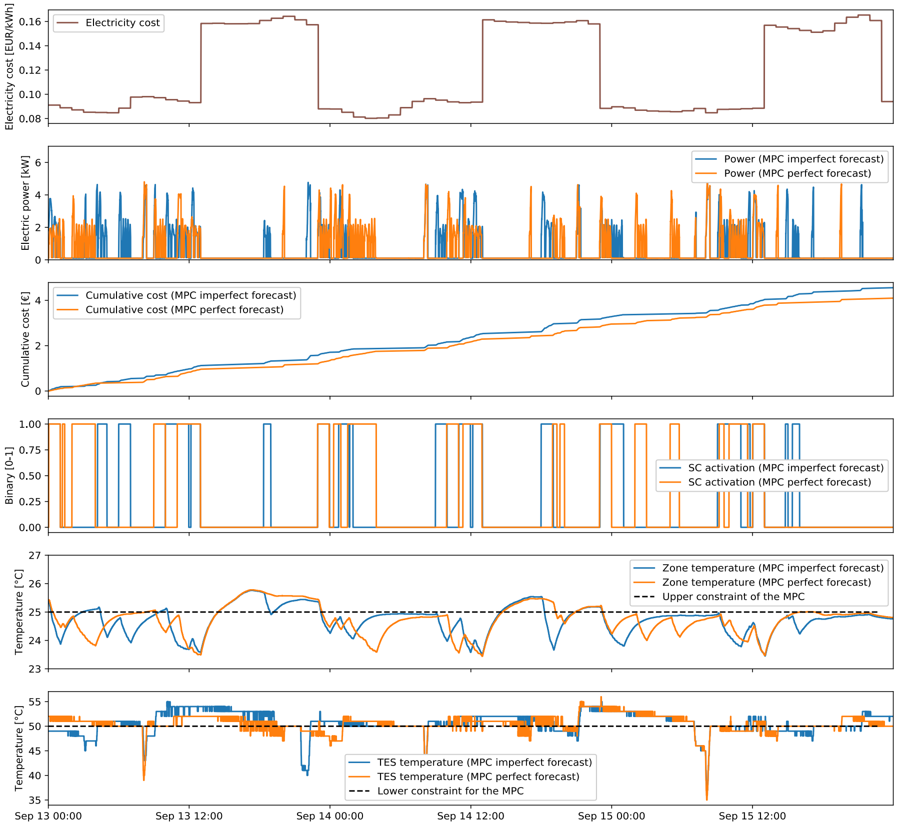

Figure 3. Time series comparing the dynamics of both studied configurations along the three days of the experiments.

4. Conclusions

In this study, an MPC controller was tested on a real heat pump system in an experimental laboratory setup, following the hardware-in-the-loop principles. Two experiments of three days duration were performed, one where the MPC controller was provided with a perfect forecast of the weather conditions for the next day, and the other where it used an imperfect forecast retrieved from an external service. When operated by the MPC with perfect forecast, the heat pump used 6% less electricity, which resulted in 11% savings on the energy costs, compared to the case with imperfect forecast. In the two experiments, the weather in the climate chamber where the heat pump is placed was identical, only the weather forecasts for the MPC was changed, which enabled to perform a thorough comparison on the MPC performance, when provided with a different forecast input. The results corroborate the learnings of the existing literature, highlighting the influence of the forecast accuracy on the savings achieved by the MPC. Additionally, the experimental nature of the work gives further reliability to the presented results, since few experimental studies on this topic had been carried out so far. From the obtained results, it can be concluded that a special care should be given to the choice of the weather forecast service when designing and implementing MPC in real buildings for climate control.

The weather forecasts used in this study originated from a commercial API available online, which gave a real-life example of service that could be connected to an MPC. However, it proved to be significantly inaccurate, especially regarding the solar irradiation. Better forecast service could have been used and would probably have reduced the difference with the perfect forecast case. Another idea for further research could be to study separately the influence of the forecast of the ambient temperature and the solar irradiation, to understand if there exists any difference in their impact, or if one of those parameters could be forecasted more loosely than the other without significant loss of performance. Finally, the presented study only presented real-life cases of three days duration in cooling mode: these results could be extrapolated by performing longer experiments or simulations, also considering heating mode to find out whether the impact of the disturbance forecast changes seasonally. For instance, it appears that it was particularly important to forecast well the solar irradiation in cooling mode, since it is responsible for important heat gains and thus of the cooling demand, but on the other hand in heating mode, the ambient temperature might be the most important parameter to forecast accurately. These constitute interesting topics for further research.

Nomenclature

$J, J_{\Delta u}, J_{\varepsilon}, J_{cost}$	Global objective function, and subobjective terms, respectively for smoothing, comfort and cost reduction.
$\alpha_{\varepsilon}, \alpha_{\Delta u}$	Weighting coefficients of the sub-objectives
A, B_u, B_e, C	Matrices of the state-space building model (parameterized with resistance and capacitance values)
x, y, u, e	Vectors of the states, outputs, controllable inputs, and exogenous inputs
$T_{amb}, I_H, Q_{occ}, Q_{DHW}$	Exogenous inputs: ambient temperature, solar irradiation, heat gains from occupants/equipment, heat losses from DHW tapping
$\delta_{SC}, \delta_{TES}$	Binary variables for the activation of SC or DHW
Q_{SC}, Q_{TES}	Thermal power for SC or DHW operation of the heat pump
$\underline{Q_{SC}}, \overline{Q_{SC}}, \underline{Q_{TES}}, \overline{Q_{TES}}$	Lower and upper limits of thermal power in SC or DHW modes respectively
$\overline{T_{int}}, \underline{T_{TES}}$	Comfort constraints (upper constraint for the room temperature and lower constraint for the DHW storage tank temperature)
ε	Slack variable to relax the comfort constraints
T_{sup}, T_{int}	Supply temperature of the heat pump, indoor temperature of the building
P_{el}	Electrical power use of the heat pump
FF	Flexibility factor

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References

[1] T. Péan, J. Salom, and R. Costa-Castelló, "Review of control strategies for improving the energy flexibility provided by heat pump systems in buildings," *J. Process Control*, vol. 74C, no. Special Issue on Efficient Energy Management, pp. 35–49, Apr. 2019.

[2] H. Thieblemont, F. Haghighat, R. Ooka, and A. Moreau, "Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the art," *Energy Build.*, vol. 153, pp. 485–500, 2017.

[3] D. I. Mendoza-Serrano and D. J. Chmielewski, "Smart grid coordination in building HVAC systems: EMPC and the impact of forecasting," *J. Process Control*, vol. 24, no. 8, pp. 1301–1310, 2014.

[4] J. Allen, A. Halberstadt, J. Powers, and N. H. El-Farra, "Supervisory Model Predictive Control of Flexible Building Loads with On-site Solar Generation," *Proc. Am. Control Conf.*, vol. 2018-June, pp. 4622–4627, 2018.

[5] D. Rolando, H. Madani, G. Braida, and R. Tomasetig, "Heat pump system control : the potential

improvement based on perfect prediction of weather forecast and user occupancy," in *12th IEA Heat Pump Conference 2017*, 2017, pp. 1–9.

[6] D. Lazos, A. B. Sproul, and M. Kay, "Optimisation of energy management in commercial buildings with weather forecasting inputs: A review," *Renew. Sustain. Energy Rev.*, vol. 39, pp. 587–603, 2014.

[7] Y. Lohr and M. Mönnigmann, "Receding horizon heat flow control in domestic buildings-Yesterday-based disturbance predictions," *2018 Eur. Control Conf. ECC 2018*, pp. 404–409, 2018.

[8] T. Péan, R. Costa-Castello, E. Fuentes, and J. Salom, "Experimental testing of variable speed heat pump control strategies for enhancing energy flexibility in buildings," *IEEE Access*, vol. 7, no. 1, pp. 37071–37087, 2019.

[9] T. Péan, R. Costa-Castelló, and J. Salom, "Price and carbon-based energy flexibility of residential heating and cooling loads using model predictive control," *Sustain. Cities Soc.*, vol. 50, Oct. 2019.

[10] Weatherbit, "Weatherbit API Documentation," 2019. [Online]. Available: https://www.weatherbit.io/api. [Accessed: 30-Oct-2019].

[11] Red Electrica de España, "ESIOS – Sistema de información del operador del sistema.," 2018. [Online]. Available: https://www.esios.ree.es/en (accessed 07/03/2018). [Accessed: 04-Apr-2017].

[12] CEN, "EN 15251: Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor quality, thermal environment, lighting and acoustic." European Committee for Standardization, Brussels, Belgium, 2007.

[13] J. Le Dréau and P. Heiselberg, "Energy flexibility of residential buildings using short term heat storage in the thermal mass," *Energy*, vol. 111, no. 1, pp. 1–5, 2016.