

A thermal control methodology based on a predictive model for indoor heating management

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Abstract. This paper presents a thermal control methodology based on an indoor temperature predictive model that regulates heating systems. Future indoor temperature is predicted from historical data of indoor temperature and other outside parameters. A control strategy is defined afterwards in order to retrieve the optimal parameters. The building simulation shows that the developed methodology provides satisfactory results by avoiding overheating and underheating periods and thus improving the thermal comfort and the energy consumption.

1. Introduction

1.1. Context

In France, the building domain is the most energy consuming sector. It dominates the total consumed energy share with 44% (compared to 33% per example for the transport sector) and a CO₂ emission that overpassed 123 million tonnes in 2015 (1).

In this context, France has established an energy policy for buildings with the aim of reducing both of the greenhouse gas emissions by a factor of four by 2050 and of at least 40% the energy consumption of government and public buildings by 2020 (1). This policy is called *Factor 4*. These commitments concern new and retrofitted buildings. Consequently, in order to reach these objectives, energy efficiency improvement is a must. This has been regulated in France under the Energy Performance Contract (EPC) law which guarantees the improvement of the buildings energy efficiency based on several standards after an energy renovation operation (1).

Generally, in the building life cycle, a significant difference is observed between the energy consumption predicted during the design phase and the real consumed energy during the operating phase. This difference is often called Energy Performance Gap (EPGAP) (2).

This EPGAP is due to several factors:

- During the design phase: incorrect sizing and unsuitable simulation tools,
- During the construction phase: poor quality of equipment and materials,
- During the verification phase: lack of systems verification and work execution,
- During the operation phase: occupant behaviour, weather and system control.

This paper presents a control methodology for indoor heating systems that optimizes indoor temperature and energy consumption in real time. It is organized as follows: Section 1 introduces the context of this work. Section 2 describes the proposed methodology. Section 3 presents an application case based on a simulated building. Finally, Section 4 concludes the paper and expresses some wayforwards of this work.

1.2. Building's Thermal modeling

Usually before each construction or renovation operation, the building is modelled in order to evaluate its performance and compare it with the requirements of current regulations. In the research and industry field, there are different methods for modeling building to study its energy efficiency. These methods can be classified as follows:

- White box: studies physical phenomena and can estimate them at a given time and in a given space, it is performed through a Dynamic Thermal Simulation (DTS) software (e.g. TRNSYS, EnergyPlus, etc.). It requires a good knowledge of the building (materials, geometry, Ventilation and Air Conditioning (HVAC) description, control strategies, occupancy, location, etc.). It can provide very detailed results but they can be very time-consuming (3),
- Black box: a model based on mathematical and statistical methods (Machine Learning, Markov Chain, etc.). It may require more or less important training time depending on the method used and the calculation time is generally low (3),
- Grey box: solution combining the two previous models requiring less learning data and less knowledge of physical phenomena (3). One of the most famous grey box models is the RxCy model (4).

As part of this work, the following criteria are set up to choose the suitable prediction model:

- Low calculation time: the model will be used to predict the indoor temperature and will also be used to evaluate a high number of control strategies,
- Adaptable: in the building, the year is composed of a heating period, a cooling period and an inter-season, the model must be efficient during these 3 periods,
- Generalizable: the model must be easily deployable on any type of building if the measurements are available.

Based on these criteria, it was decided to test Artificial Neural Networks (ANN) and multiple linear regression models. Indeed, many studies (5)(6)(7)(8) demonstrate the ability of ANNs to predict thermal data in the building sector. Nevertheless, the ANNs has shown a problem of robustness. Consequently it was decided to use the linear regression model. A comparison of the two methods will be discussed.

2. Control methodology

The porposed heating control methodology is based on a model insuring the predicting of the indoor temperature in order to avoid discomfort problems. The steps of the control methodology are presented in Figure 1.

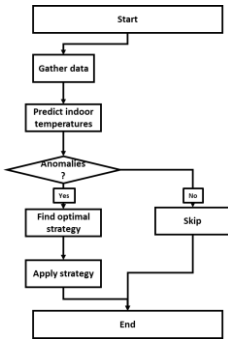


Figure 1: Proposed control heating methodology

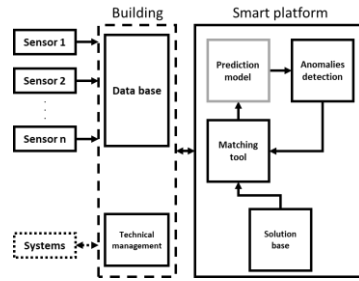


Figure 2: Functioning of the proposed platform

Based on this methodology, a platform was developed. The functioning of this platform is shown in Figure 2.

1.1. Step 1: Data gathering

In the first step, dynamic data (indoor measurements, HVAC and weather data) are gathered from sensors and Building Management System (BMS). Then collected data are structured and pre-processed (Normalization and Averaging).

1.2. Step 2: Predicting indoor temperature

A multiple linear regression model is implemented. To determine the model inputs, a correlation study was conducted. The most influencing inputs were selected. The data are normalized to be in the same scale. From the measured data, the averages of the last hour and the last two hours are calculated to take into account the inertia of the building. The final architecture (Figure 3) of the model is validated by varying the input parameters (adding or deleting one or more parameters). The prediction horizon is set to 3 hours which is sufficient to take into consideration the time response of the building while maintaining an acceptable model accuracy level (Figure 4). At each step, 12 data are predicted with a time step of 15 minutes.

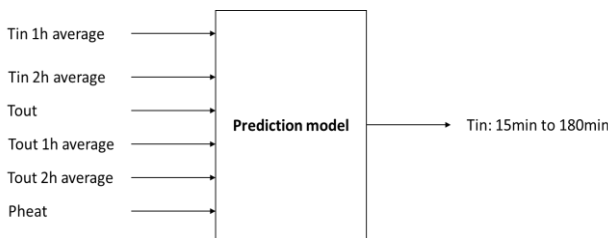


Figure 3: Prediction model of the indoor temperature

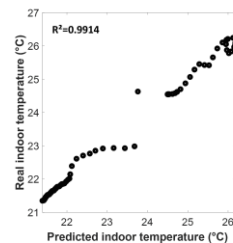


Figure 4: Results of the prediction model

1.3. Step 3: Detecting anomalies & finding optimal strategy

Using the predicted indoor temperature, the platform checks if the temperature is in the following comfort range during working hours (8am to 6pm): [18°C 25°C] (9) and during

unworking hours: 16°C, while reducing the heating consumption as much as possible. An anomaly is reported if the temperature is outside this range.

1.4. Step 4: Application of the new strategy

The selected control strategy is tested with the prediction model and then sent to the BMS.

3. Application

Tests were carried out on a simulated building. This building is composed of two thermal zones (Figure 6) and equipped with a power-controlled heating system. Between 8am and 6pm, the power is set to 100% and 0% for the rest of the day. This type of control is close to reality and can ensure the comfort criteria defined above. The control curve of the heating system is shown in the Figure 5. The building is described in Table 1.

Table 1: Building description

	Area (m ²)
Thermal zone 1	48.99
Thermal zone 2	11.86
Windows	North: 2 (1x2m), South: 1 (4x1.5), West: 1 (1x2m)
Door	East: 1 (1x2.5m)
Location	Lyon (France)

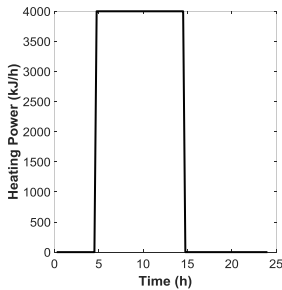


Figure 5: Heating setpoint power curve

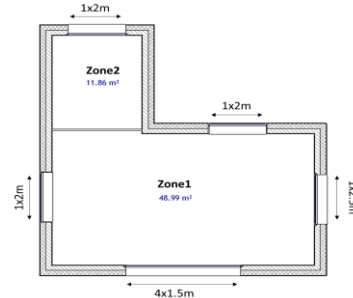


Figure 6: Plan of the fictitious building

Based on previous historical data (from simulation results) the prediction model is trained then the indoor temperature is predicted. At every time step, the prediction model is retrained using previous data (150), this method is called *sliding-window* (7). The size of the sliding-window (training data size) was determined by performing tests. Figure 7 shows that the temperature exceeds 25°C which is the comfort limit defined. As a consequence, the data analysis detects anomalies. To face this anomaly, the best heating control strategy is defined for the next 3 hours. Since the prediction model is fast, all possible strategies are tested. For this application case, the heating is controlled by an On/Off mode, then 4096 (corresponding to 2¹² with 12: nombre of time steps to predict, 2: ON/OFF state) possibilities were tested. At each time step (15 minutes), heating is switched ON or OFF. Figure 7 compares real indoor temperature to predicted indoor temperature and Figure 8 shows the result obtained by applying the new heating control strategy from the 152th until the 155th hour, with data from the 3rd to the 151th hour are used to train the prediction model.

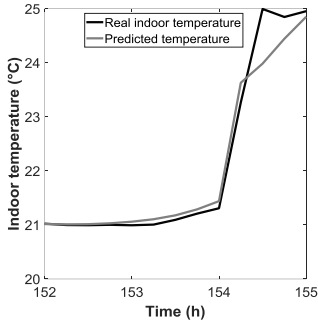


Figure 7: Initial simulation and prediction results

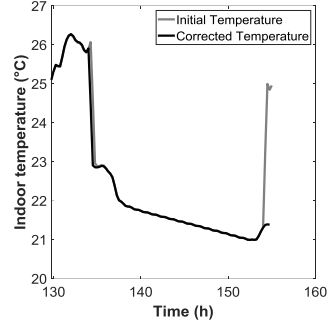


Figure 8: Corrected prediction results versus initial simulation results

This methodology is done in real time, obtaining the results shown in Figure 10. 30 hours of obtained result of the thermal zone 1 based on the simulated building is shown. Figure 9 shows the evolution of the indoor temperature and the heating power setpoints with the use of a standard control of the heating, while Figure 10 shows their evolution using the methodology proposed above. Comparing the data on the right of the two dotted lines representing the start time of the heating control correction, in Figure 10 the overheating zones are significantly reduced while respecting the comfort interval (here taken between 21 and 25°C for representativeness reasons) represented by the horizontal lines, which improves user’s comfort and reduces energy consumption.

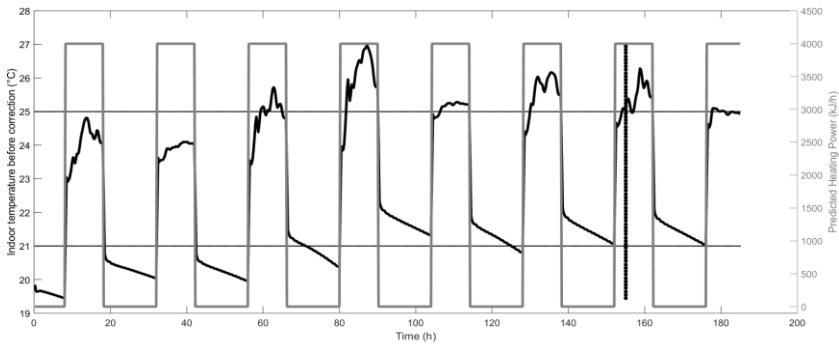


Figure 9: Simulation results with standard heating control

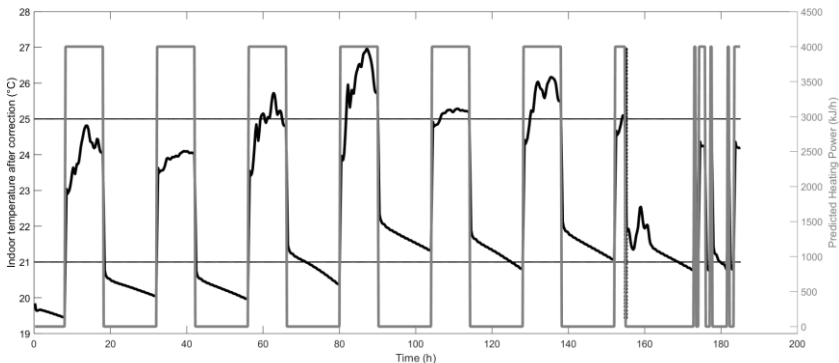


Figure 10: Simulation results with the proposed heating control methodology

4. Conclusion

This work aimed to develop thermal control methodology for reducing discomfort and energy consumption. In this context, a platform was developed based on a linear regression model to predict indoor temperature and to test possible control strategies. To validate this platform, a simulated building is studied using a BIM-based approach. Obtained results during heating period are promising. The heating control methodology allows the reduction of the heating energy consumption and improves the user comfort. In the next step, a real case-study will be examined. This study-case is a building located in Wasquehal (France) which has been equipped with a weather station and comfort sensors.

5. Acknowledgments

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6. References

1. Énergie dans les bâtiments [Internet]. 2016. p. 1–9. Available from: <https://www.ecologique-solidaire.gouv.fr/energie-dans-batiments>
2. Kallab L, Chbeir R, Bourreau P, Brassier P, Mrissa M. HIT2GAP: Towards a better building energy management. *Energy Procedia* [Internet]. 2017;122:895–900. Available from: <http://dx.doi.org/10.1016/j.egypro.2017.07.399>
3. Fouquier A, Robert S, Suard F, Stéphan L, Jay A. State of the art in building modelling and energy performances prediction: A review. *Renewable and Sustainable Energy Reviews*. 2013;23(January 2018):272–88.
4. Andriamamonjy A, Klein R, Saelens D. Automated grey box model implementation using BIM and Modelica. *Energy & Buildings* [Internet]. 2019; Available from: <https://doi.org/10.1016/j.enbuild.2019.01.046>
5. Zouak. A comparison of linear and neural network ARX models applied to a prediction of the indoor temperature of a building. 2004;32–7.
6. Moon JW, Lee JH, Kim S. Evaluation of artificial neural network-based temperature control for optimum operation of building envelopes. *Energies*. 2014;7(11):7245–65.
7. Moon JW, Yoon SH, Kim S. Development of an artificial neural network model based thermal control logic for double skin envelopes in winter. *Building and Environment* [Internet]. 2013;61:149–59. Available from: <http://dx.doi.org/10.1016/j.buildenv.2012.12.010>
8. Moon JW, Kim JJ. ANN-based thermal control models for residential buildings. *Building and Environment*. 2010;45(7):1612–25.
9. Réglementation officielle , mesures de prévention , droit d ’ alerte et de retrait [Internet]. 2018. Available from: <http://cgtdgfip75.org/spip.php?article3846>