A Sequential Modelling Approach For Indoor Temperature Prediction And Heating Control In Smart Buildings

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Introduction

A rising demand of ML in large scale, real-time applications such as:

- Internet of Things (IoT)
- Cyber-Physical Systems (CPS)
- Smart Building Networks (SBN).

Due to availability of data, efficient algorithms and computing power. In this case study, we focus on using statistical machine learning techniques in SBN to

- Optimize energy use
- Improve user comfort

Setting the Scene

The task is to simulate temperature trajectories in a target area, and achieve optimal control of heating in a residential building setting. An building management system (BMS) was built which integrates a sensor network and data processors.

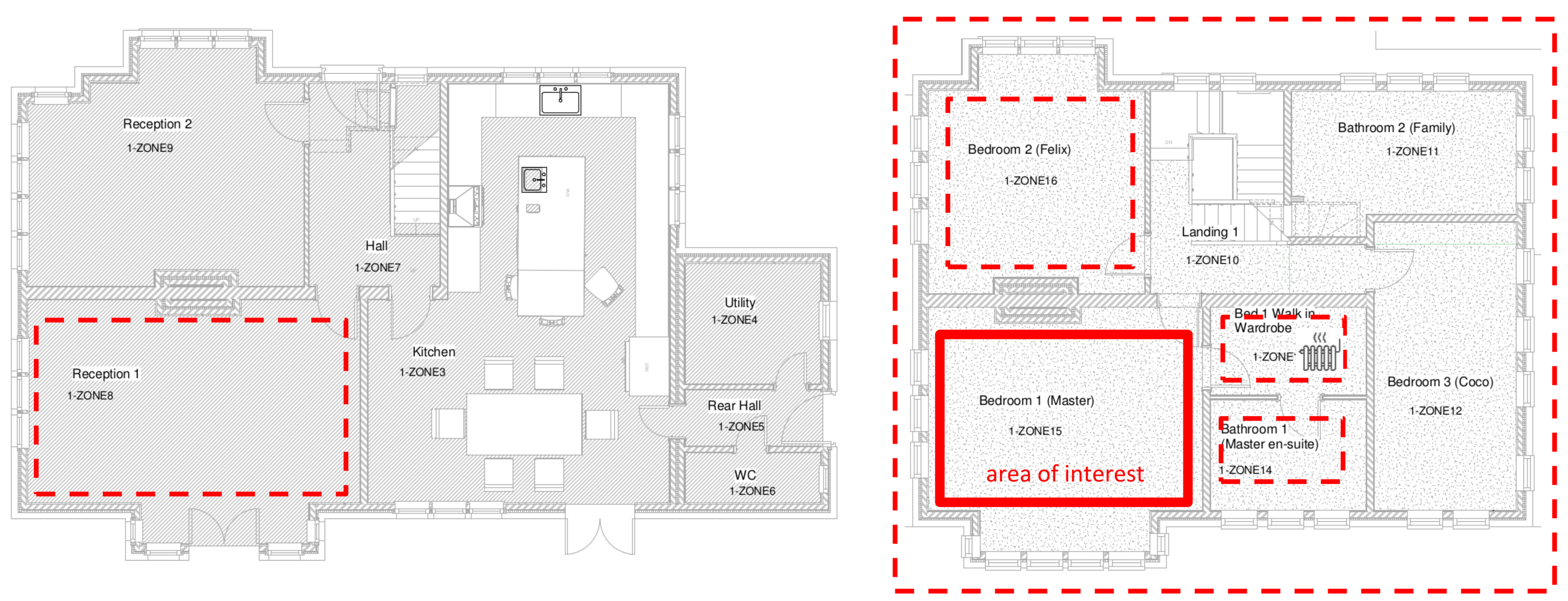

Fig. 1: Building topology

Approach

An mixed data-driven approach, *i.e.* statistical learning with input control, was proposed, and two sequential modelling phases, combining time series and ML models, were integrated to model the target room temperature trajectories:

- 1st stage: univariate AR-based ambient conditions modelling – temporal dependence
- 2nd stage: multivariate ML-based target room temperature modelling – spatial dependence

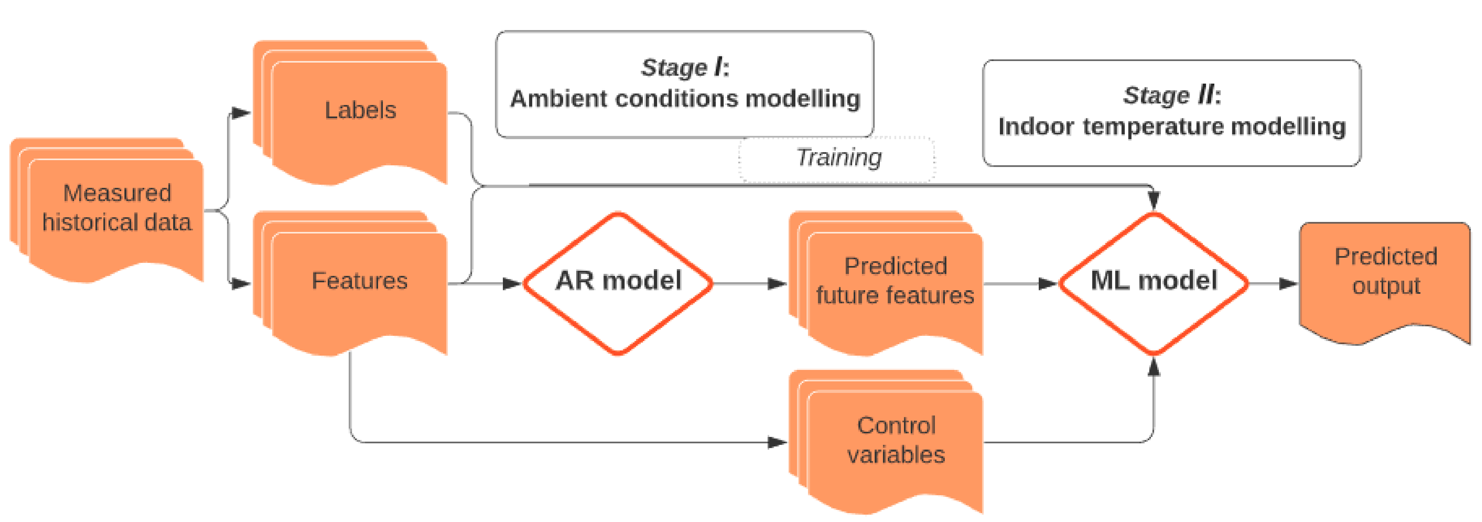

Fig. 2: A two-stage modelling framework

Data

Real world data was collected by the sensor network embedded in a two-floor residential building. Typical signals include:

- Fan status: *Boolean*
- Radiator status: *Boolean*
- Lighting: *Boolean / numeric*
- Passive Infrared motion (PIR): *numeric*
- Rain: *Boolean*
- Outside temperature: *numeric*
- Relative humidity (RH): *Boolean*
- Surrounding room temperatures: *numeric*

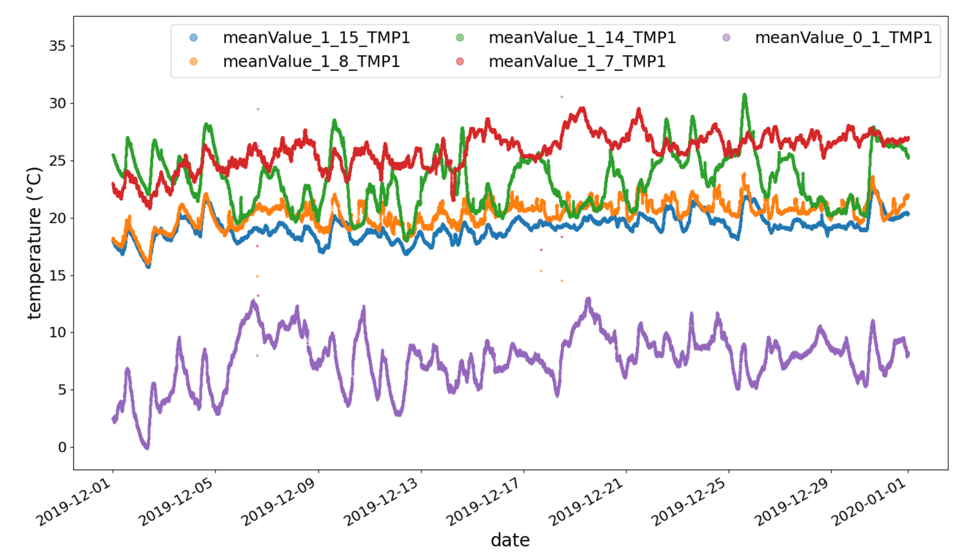

Fig. 3: Example of measured data

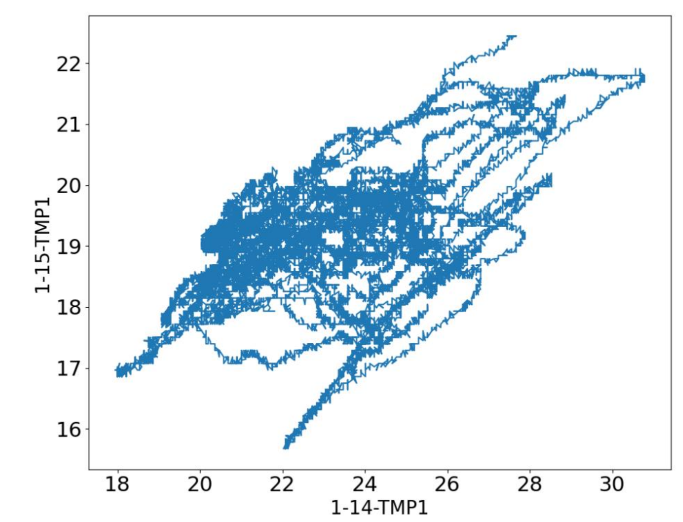

Fig. 4: Correlation between target room and bathroom temperatures

Stage I: Ambient Conditions Modelling

Each non-control variable such as RH, outside and surrounding room temperatures *etc*, are simulated using univariate autoregressive (AR) model. The number of lags used in each AR model was elected based on the partial autocorrelation function (*pacf*).

$$X_t = \mu + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \epsilon_t$$

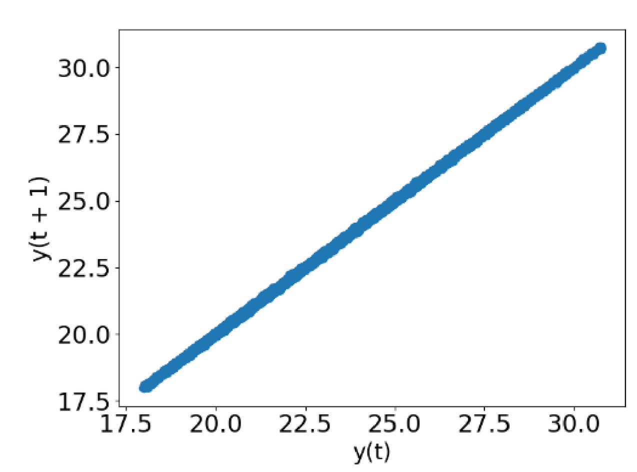

Fig. 5a: Correlation between two lag-1 sequences

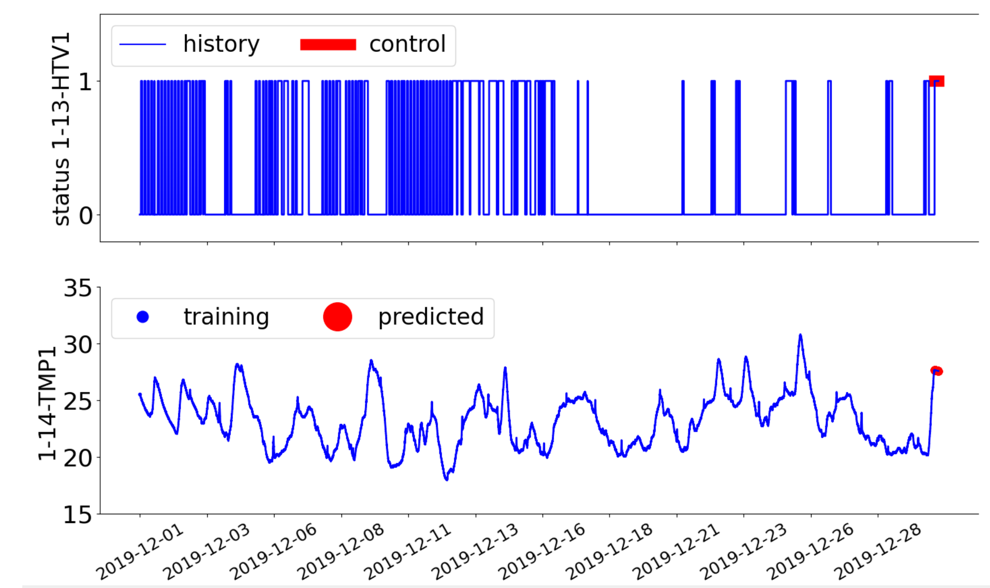

Fig. 6a: Historical and controlled/predicted values of radiator status (wardrobe) and surrounding temperature (bathroom)

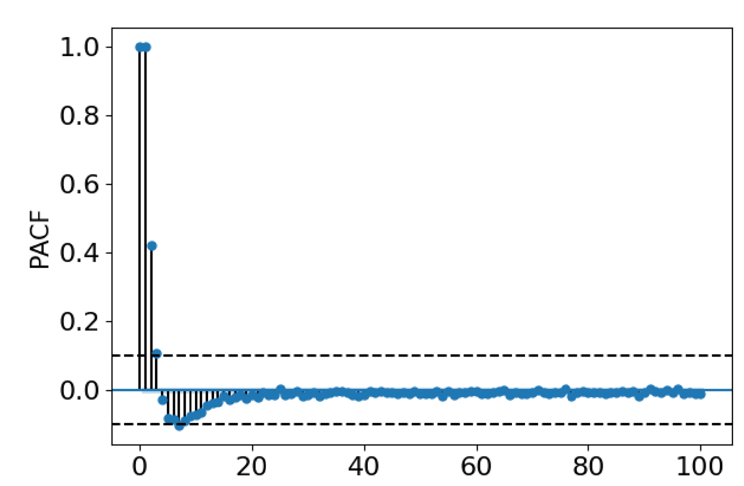

Fig. 5b: *pacf*-based lag selection

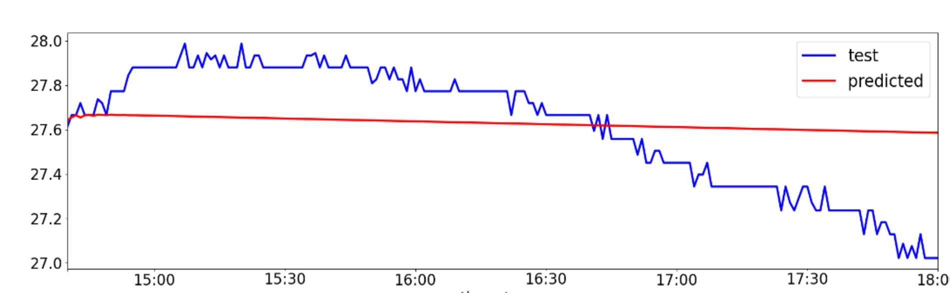

Fig. 6b: Bathroom temperature predictions (zoom-in of 6a on date 30/12/2019)

Stage II: Indoor Temperature Prediction and Control

In the second stage, the controlled and predicted features were input into an XGBoost model to yield predictions for the response variable, *i.e.* the target room temperature.

Non-control variables $x_1, x_2, x_3, \ldots, x_n$

Control variables $x'_1, x'_2, x'_3, \ldots, x'_n$

Statistical mapping: $y = f(x_1, x_2, x_3, \ldots, x_n, x'_1, x'_2, x'_3, \ldots, x'_n)$ $\longrightarrow$ *Response variable y:*

- *Target room temperature*

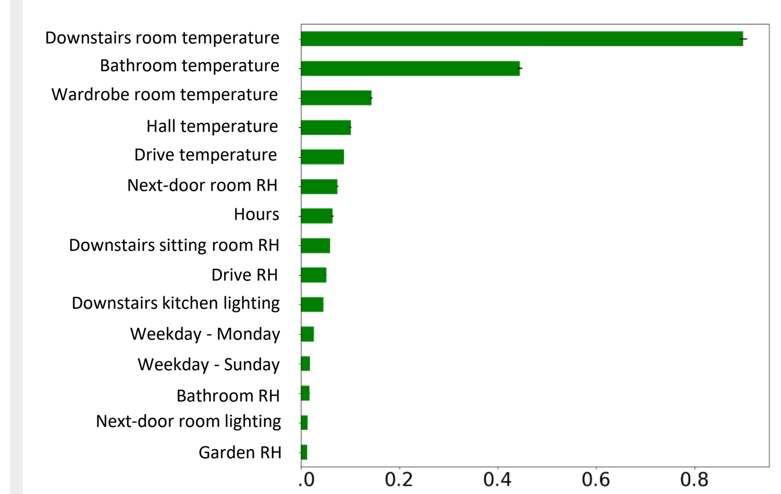

Fig. 7: Tree-based permutation feature importance

Ensemble learning: Extreme Gradient Boosting Tree [*T Chen et al*]

$$\hat{y}_i = \phi(\mathbf{x}_i) = \sum_{k=1}^{K} f_k(\mathbf{x}_i),$$

Where each f_k corresponds to an independent tree structure.

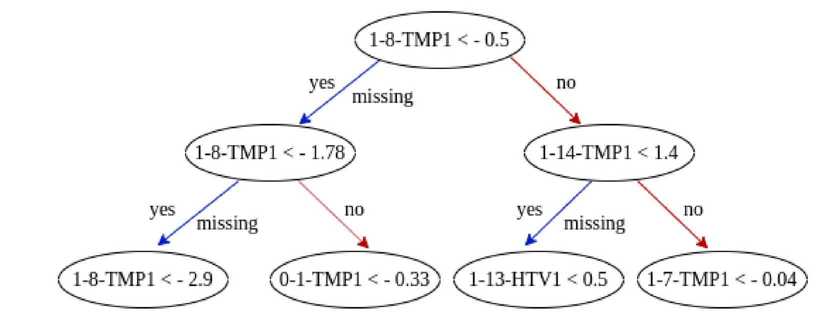

Fig. 8: A typical tree splitting example

Four scenarios, with different control strategies, were simulated:

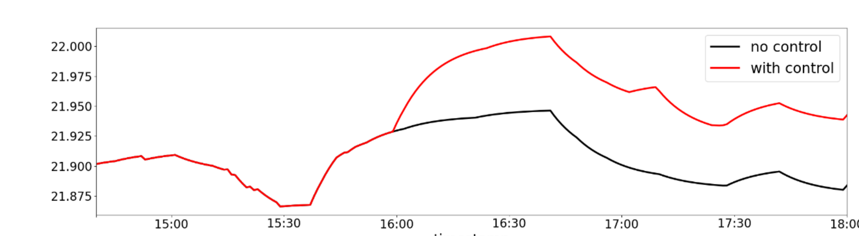

Fig. 9a: [case 1] Control of Wardrobe room radiator

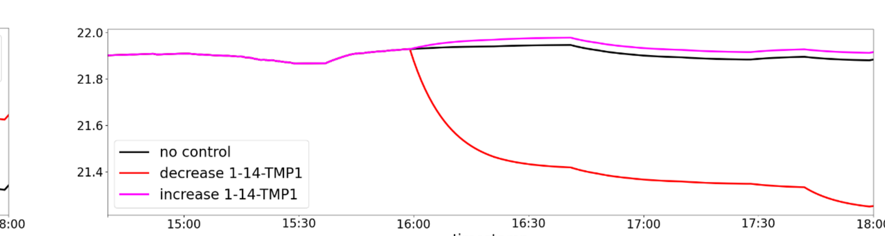

Fig. 9b: [case 2] Control of bathroom room temperature

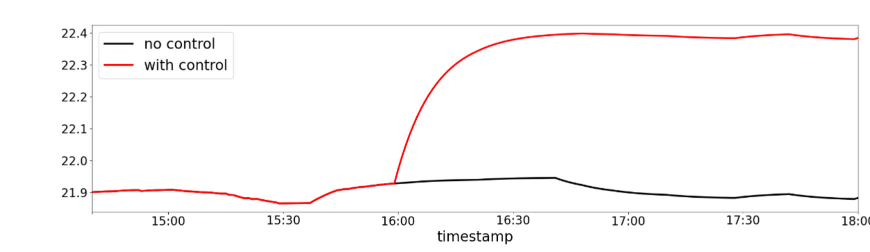

Fig. 9c: [case 3] Control of downstairs room temperature

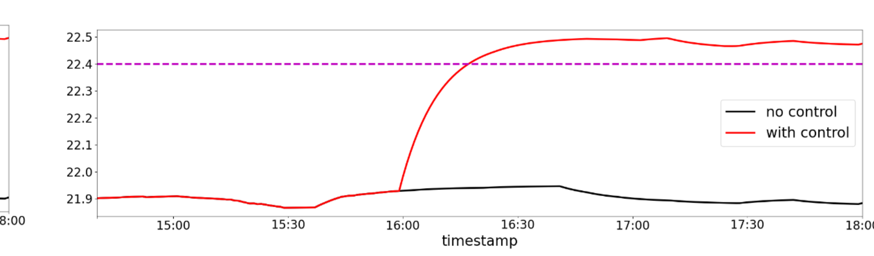

Fig. 9d: [case 4] Hybrid control of all three

Implementation and Summary

The combined learning and hybrid control strategy was implemented and the warm-up time was calculated in *Fig. 10*.

In summary,

- A mixed data-driven approach, *i.e.* sequential learning with input control, was demonstrated effective in modelling indoor temperature trajectories in buildings.
- ML can help turn sensory data into actionable decisions to achieve optimal control, maximize energy utilization, and improve human comfort.

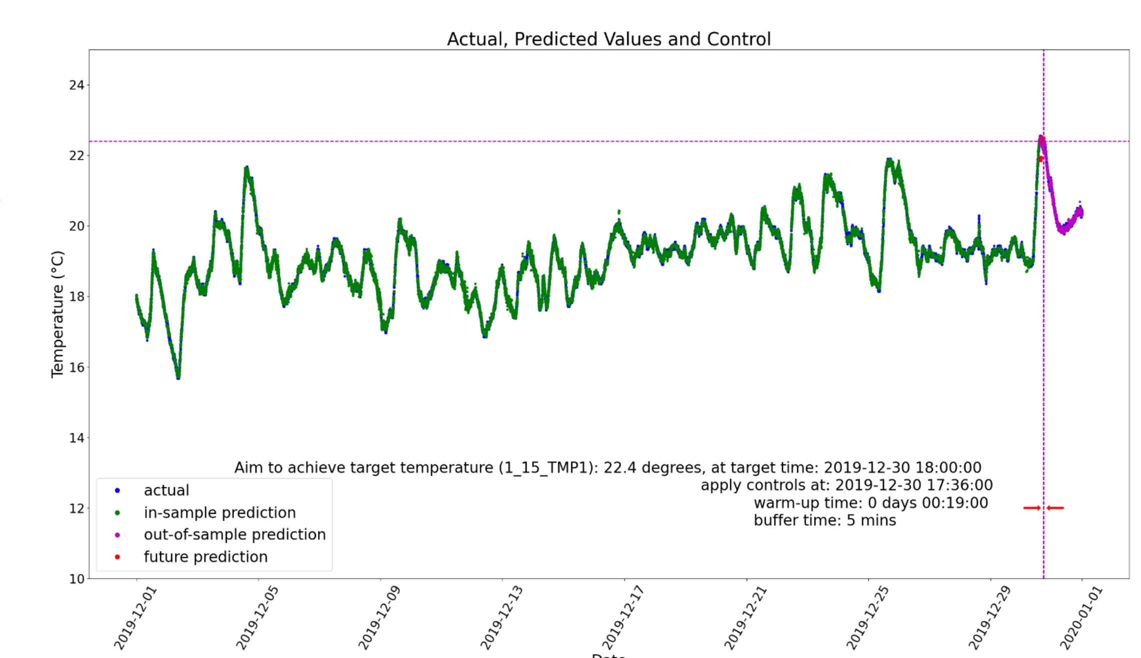

Fig. 10: A real world implementation example