

# Week 1: Weekly Report

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## Abstracts

*The abstracts and links to 3 articles which are similar in structure (not content) to the kind of paper you would like to write (not necessary to read all articles read abstract and figures)*

- Generate summaries for each with <https://www.explainpaper.com/>

|                        |   |
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| Article Name<br>[Link] | Generalized additive models: An efficient method for short-term energy prediction in office buildings [ <a href="https://doi.org/10.1016/j.energy.2020.118834">https://doi.org/10.1016/j.energy.2020.118834</a> ]   |
| Abstract               | In 2018, commercial buildings accounted for nearly 18.2% of the total energy consumption in the USA, making it a significant contributor to the greenhouse gases emissions (see, e.g. [1]). Specifically, office buildings accounted for 14% of the energy usage by the commercial sector. Hence, their energy performance has to be closely monitored and evaluated to address the critical issues of greenhouse gases emissions. Several data-driven statistical and machine learning models have been developed to assess the energy performance of office buildings based on historical data. While these methods often provide reliable prediction accuracy, they typically offer little interpretation of the relationships between variables and their impacts on energy consumption. Moreover, model interpretability is essential to understand, control and manage the variables affecting the energy consumption and therefore, such a feature is crucial and should be emphasized in the modeling procedure in order to obtain reliable and actionable results. For this reason, we use generalized additive models as a flexible, efficient and interpretable alternative to existing approaches in modeling and predicting the energy consumption in office buildings. To demonstrate the advantages of this approach, we consider an application to energy consumption data of HVAC systems in a mixed-use multi-tenant office building in Chicago, Illinois, USA. We present the building characteristics and various influential variables, based on which we construct a generalized additive model. We compare the prediction performance using various commonly used calibration metrics between the proposed model and existing methods, including support vector machine as well as classification and regression tree. We find that the proposed method outperforms the existing approaches, especially in terms of short term prediction. |
| Summary                | This paper discusses how office buildings in the USA consume a significant amount of energy, contributing to greenhouse gas emissions. The study uses a new statistical model to predict and understand energy consumption in office buildings more accurately than existing methods, with a focus on interpretability and performance improvement.   |

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| Article Name<br>[Link] | A Markov-Switching model for building occupant activity estimation [ <a href="https://doi.org/10.1016/j.enbuild.2018.11.041">https://doi.org/10.1016/j.enbuild.2018.11.041</a> ] |
| Abstract               | Heating and ventilation strategies in buildings can be improved significantly if information   |

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|         | <p>about the current presence and activity level of the occupants is taken into account. Therefore, there is a high demand for inexpensive sensor-based methods to detect the occupancy or occupant activity level. It is shown that the carbon dioxide (CO<sub>2</sub>) level in a room is dependent on the activity level rather than only on just the number of people. Therefore, this study suggests a new model based on the use of CO<sub>2</sub> trajectories to estimate the occupant activity level, trained on measurements both from a school classroom and from a Danish summerhouse. A hidden Markov-switching model was employed to identify the activity level. This modelling approach is a generalization of hidden Markov models, taking autocorrelation in the observations into account. This is done by an additional autoregressive part which models the persistence of the CO<sub>2</sub> concentration by relating the current value to past lags. The analysis of one-step prediction residuals shows that this method inherits the dynamics of the CO<sub>2</sub> curves much better than an ordinary hidden Markov model, and can therefore be considered a promising candidate for occupant activity estimation. Furthermore, it is shown that the presented model can be used for simulations of activity level and of the accompanying CO<sub>2</sub> levels.</p> |
| Summary | <p>This paper suggests a new model that uses carbon dioxide levels to estimate how active occupants are in a room, rather than just counting the number of people. By analyzing CO<sub>2</sub> trajectories, the model can predict occupant activity levels more accurately, making it a useful tool for improving heating and ventilation strategies in buildings.</p>   |

|                        |  |
|------------------------|--|
| Article Name<br>[Link] | Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization<br>[ <a href="https://doi.org/10.1016/j.apenergy.2020.115147">https://doi.org/10.1016/j.apenergy.2020.115147</a> ]   |
| Abstract               | <p>A model predictive control system with adaptive machine-learning-based building models for building automation and control applications is proposed. The system features an adaptive machine-learning-based building dynamics modelling scheme that updates the building model regularly using online building operation data through a dynamic artificial neural network with a nonlinear autoregressive exogenous structure. The system also employs a multi-objective function that could optimize both energy efficiency and indoor thermal comfort, two often contradicting demands. The proposed model predictive control system is implemented to control the air-conditioning and mechanical ventilation systems in two single-zone testbeds, an office and a lecture theatre, located in Singapore for experimental evaluation of its control performance. The model predictive control system is compared against the original reactive control system (thermostat in the office and building management system in the lecture theatre) in each testbed. The model predictive control system reduces 58.5% cooling thermal energy consumption in the office and 36.7% cooling electricity consumption in the lecture theatre, as compared to their respective original control. Meanwhile, the indoor thermal comfort in both testbeds is also greatly improved by the model predictive control system. Developing a model predictive control system using machine-learning-based building dynamics models could largely cut down the model construction time to days as compared to its counterpart using physics-based models, which usually take months to construct. However, the machine-learning-based modelling approach could be challenged by lack of building operational data necessary for model training in case of model predictive control development before the building has become operational.</p> |
| Summary                | <p>This paper introduces a smart control system for buildings that uses machine learning to adjust building models and optimize energy efficiency and comfort. The system was tested</p>   |

|  |   |
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|  | in two buildings in Singapore and showed significant energy savings and improved comfort compared to traditional control systems. |
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## Scripts and Code Blocks

-Names of scripts uploaded to git (as all scripts should be)

-brief description of function

-flowchart of function

-Status: Tested by higher ed team or untested

-data: what data does this run on (if applicable) where is it stored higher ed team should have access

Important codeblocks

- Explanations of function

[Add more as needed]

|   |  |
|---|--|
| Script Name                                   | N/A  |
| Description                                   | N/A  |
| Flowchart                                     | N/A  |
| Status  | <input type="checkbox"/> Tested by Higher Ed Team<br><input type="checkbox"/> Untested by Higher Ed Team<br><input type="checkbox"/> N/A |
| Data Source                                   | N/A  |
| Important Codeblocks and Function Explanation | N/A  |

## Documentation

List of steps you did as you would write them in your methods sections.

1. N/A

## Script Validation(optional)

If you have written a longer script which will take time to verify, such as model training etc.  
Please attach an unlisted youtube video link of you running the script to verify it works.

- Youtube Link:
- N/A

## Results Visualization

*Images with descriptions of results produced.*

| Image | Description |
|-------|-------------|
| N/A   | N/A         |

## Next Week's Proposal

*Propose what you will do next week*

- Experiment with a dataset using various algorithms reported in literature (ANN)
- Setup infrastructure for building application: CICD for testing
- If developing a mobile application, familiarize with Java applications