DELRAPPORT

Digitalization framework for energy optimization and smart maintenance of historic buildings

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1. Introduction and Background

Improving energy efficiency[1] and reducing energy consumption is on the agenda of every government in order to fight climate change. The building sector is responsible for around 40% of the energy consumption in Europe and US [1]. To improve energy efficiency new constructions in EU are subject of various regulations while funding programs have been developed to support retrofitting of older constructions. However, heritage buildings are often excluded from such initiatives as application of new techniques is not well studied and can potentially "do more harm than good" [2]. It is also commonly accepted that the preservation of the original state should be done with traditional materials and methods [2]. In buildings with cultural and historical value, apart from improving energy efficiency, the indoor climate needs to be maintained stable in terms of temperature and air humidity. This is needed to preserve interior decorations and collections and reduce sources of biological degradation (mould growth). This indoor climate control should be achieved while respecting the constraints imposed by the heritage site. Improvement of the indoor climate conditions could also benefit the conservation of the buildings and their structure [2]. However, measures applied to improve the indoor climate, could put additional demands on energy consumption.

In order to improve the energy efficiency, the energy demands and consumption patterns in each building should be studied. Two types of models are commonly used for modelling and estimating energy consumption: physical (white-box) models and data-driven (black-box) models. Physical models are developed in specialized, mostly proprietary, software applications which include simulation engines. These models require multiple input parameters regarding weather conditions, building structure and indoor climate control systems (e.g. HVAC). These data are then used by the simulation engine to simulate building's operations and calculate energy consumption. Such models have advantage to capture the detailed building operations but are time consuming to develop and require detailed knowledge of the building structure and installed equipment. These models allow also for simulating and selecting between various materials and systems and even layouts before the building has been built or retrofitted. This is in contrast with the data-driven models which can only be applied afterwards. Until recently, physical models have been mainly used due to the lack of data and insufficient development level of the data-driven models.

In the Big Data era, the data-driven models rely on statistical algorithms to capture possible correlations in a dataset. The most sophisticated of these models are known as machine learning (ML) and artificial intelligence (AI) models. The dataset consists of multiple measurements capturing the actual state of the building at different times obtained from multiple sensors. The sensors collecting the data can be installed when the building has been built or afterwards. With the proliferation of IoT technologies such datasets are getting more and more easy to obtain. And the electronic devices that is used for collecting the physical measurements are inexpensive.

Nowadays, several well-developed open-source software libraries are available for implementing such ML/AI models. However, data-driven models are very sensitive to the quality of the dataset in terms of completeness and correctness. Very important for a good and robust AI-model is that the coverage of most, if not all, possible combinations of states the system can be in is represented in

[1] Energy efficiency (instead of energy saving) is used in the report since it emphasizes reducing energy consumption while still performing necessary functions.

the dataset. So, in the case of buildings the collection of a good dataset will take a few years. The reason for that is one need to collect data from different seasons and weather conditions.

In the context of this project, it is envisioned that applying data-driven models will require reasonable data collection effort while still providing accurate predictions for the energy consumption of the three buildings.

Furthermore, data-driven models also provide opportunities for improved general maintenance of historical buildings. In the industrial sector the concepts of Smart Maintenance, Maintenance 4.0, Predictive Maintenance are already well known [3] and are now entering the facility management field. In the areas of facility management, they can be applied for fault detection and predictive maintenance of systems as well as improvement of the indoor climate. As mentioned earlier stable indoor climate is necessary to preserve interior decorations and collections and reduce sources of biological degradation. High levels of relative humidity contribute to mould growth as pointed out in [4].

We have investigated existing AI solutions for both heritage, preservation and energy savings, data cleaning of measurement values with edge device, data analysis and machine learning as well as change detection in digital twins.

2. Activities and Results

Literature review

We started by reviewing AI approaches most often used for energy prediction and which provide the basics of data-driven model development.

- Energy Efficiency Models: We compared physical (white-box) models and data-driven (black-box) models for estimating energy consumption. We suggest that data-driven models, powered by machine learning and AI, are becoming more feasible due to the availability of big data and IoT technologies. We provide a comprehensive overview of the steps involved in developing machine learning models and the various features used for energy consumption prediction.

- AI Approaches: We found out that Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees are the most commonly used AI-model approaches in the field. We detailed their applications, advantages, and limitations in the context of energy consumption prediction.

- Indoor Air Quality & Predictive Maintenance: Additionally, we explored the use of AI approaches in maintaining stable indoor climate conditions, crucial for preserving interior decorations and collections in historic buildings. We also discuss the potential of predictive maintenance to improve the conservation of these structures.

Data analysis and machine learning

Drawing from our literature review we started with implementation and adaptation of a more basic CNN (Convolutional Neural Network) solution to fit the data representation and to handle the multivariate signal. Since there were problems accessing the detailed indoor climate and control data from the Siemens ventilation system the goal of estimating the power consumption was selected after some discussion during one of the project meetings. The goal of this quicker implementation was to find a way to verify the data reduction algorithms and find out how it affects the accuracy of the predictions.

Next step was to look at the machine learning part of the task. The CNN-model proved to be an ok indicator of energy consumption for the building but to have something to compare it to the more advanced transformer model was also evaluated. The results from the transformer models however never surpassed the CNN-model. This is most likely because the energy consumption doesn't fluctuate that much in a given day and most parts of the building are still independent of how hard the air conditioning is working. Therefore, the model was relatively good at giving one or more steps ahead predictions. For the really hard cases none of the models had that great prediction capability. Transformer models should not be discarded though since they are proven to be powerful and LiU had more success implementing a transformer solution.

Data Cleaning with edge device

We have used the edge device from the Minerva platform to collect the data and explored data reduction methods to reduce the amount of data that needs to be transmitted and stored in the cloud as well as to improve the data quality by transmitting high-quality and relevant data only.

The data reduction method first used is simple removal of samples. The data was sampled with a high frequency 1Hz. The main things we are interested in such as temperature, CO_2 levels are rather slow in their fluctuations and take time to settle in. Therefore, those parameters could be sampled at a much lower rate that 1Hz. The only exception to this was vibrations that were not used anyway in the end. So, one simple approach was just to reduce the amount of data samples. Reducing it to the range of a measurement every 10th second had minimal impact however the more we went from there the AI training verification score lowered. In hindsight, the lowered result is mainly due to not re-training the CNN-model on the new timescale and having a sample per minute should more than well suffice for the slowly fluctuating parameters.

The other data reduction method is what is referred to as a statistics vector reduction containing the mean, max, min and standard deviation of the selected data size. The main advantage of this is that a lot of information regarding the data can be said with these four measurements and don't need to be inferred by the chosen model. The main drawback though was that we had no ML-model that utilized this to its full potential and was just standard multivariate time series models that expected multiple signals that might be correlated, not statistical descriptions of the measured signals.

Change detection AI digital twins

The last thing we looked at was change or anomaly detection. Change detection is often used in smart watches to automatically guess when a person is walking, running or biking. The idea came after a meeting with the group when discussing the moisture levels inside Lövstad Slott. An AI-model could monitor and warn when there is a drastic change in the indoor climate or give warnings when measurements exceed certain thresholds. The concept looked really promising, however, there was not enough time left in the project to properly test this especially since it would require annotations for the data and a bigger dataset that does not exist today. This is an area and concept that can be worth looking into for future work.

3. Discussion and Summary

Energy efficiency should be improved in both conventional and historical buildings as the building sector is one of the largest energy consumers in both EU and US. Historical buildings present additional challenges as they require stable indoor climate all year round which might impose conflicting energy consumption requirements. In this project we have investigated existing AI solutions for both heritage, preservation and energy savings, data cleaning with edge device, data analysis and machine learning as well as change detection in digital twins.

Here we discuss and summarize our findings:

1. The initial data reduction approach implemented with the edge device involved simple removal of samples, reducing the data sampled at 1Hz to a measurement every 10 seconds. This had minimal impact on the verification score, but further reduction without re-training the CNN model lowered the accuracy. The other method used was a statistics vector containing mean, max, min, and standard deviation, which provided significant information but wasn't fully utilized by the existing AI/ML model. This highlights the importance of balancing data reduction and accuracy to ensure efficient edge cleaning.
2. The CNN model for estimating power consumption proved to be an adequate indicator of energy consumption. Comparisons with a transformer model showed that the CNN was more effective. This was likely because energy consumption doesn't fluctuate much daily, making the CNN model more suitable for short-term predictions. Despite this, transformer models should not be discarded as they have shown potential in other implementations.
3. Change detection is often used in smart watches to guess when a person is walking, running, or biking. The idea was to use an AI-model to monitor and warn of drastic changes in indoor climate or when measurements exceed certain thresholds. Although promising, there was not enough time to test this idea properly, especially since it required annotated data does not exist. This area holds potential for future work, emphasizing the need for accurate change detection in AI digital twins to enhance monitoring and predictive capabilities.

4. References

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