The effects of artificial lights on comfort in the works space, A trade-off between Energy and Comfort: Case study LAB42 UvA

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1 INTRODUCTION

The energy consumed for lighting and the resulting emissions increased in 2021, following reduced commercial activity in 2020. However, with improving efficiency, lighting consumption is still expected to fall despite the growing amount of lighting being used in buildings [7]. Supported by the improvements in the carbon intensity of electricity and advancements in forecasting and machine learning can permit hands-free control of the production of artificial lighting in office buildings' common spaces. With the cost of energy increasing and the energy crisis being an imminent reality, the need to provide energy-efficient building designs becomes more important but doing so shouldn't come at the expense of human comfort. Our focus will be on visual comfort and more specifically on the illuminance of indoor spaces, other research on energy and comfort has shown that indoor environmental conditions may directly affect the performance of physical and mental work [5], theoretically an increase in the performance of postal workers was recorded after a lighting retrofit that improved light quality and also saved energy. For this research paper, an analysis of lighting sensors from the corresponding embedded sensors in sample office spaces in the Lab42 building on the campus of the University of Amsterdam plus a review of potential applications will be considered to tackle the following question: *To what extent can indoor artificial light affect the comfort users and is there a way to forecast discomfort levels in these areas to apply preventative measures?*

To answer that question we will break it down into the following sub-questions:

- How well do state-of-the-art forecast models perform for short-term prediction?
- Can the different collected data have an effect on each other?
- Does the quantity of historical data affect the accuracy of the predictions?
- Is there a noticeable energy efficiency improvement in the long term?
- How can we evaluate the different thresholds of comfort from the different sensors?

2 RELATED WORK

Time series forecasting can be divided into two different groups, statistical, and machine learning techniques, the literature made clear that the next steps for light forecasting are machine learning-based forecasting but still use the statistical methods to form a baseline [10], many surveys present state-of-the-art (SOTA) methods to be used or to consider their value for our research a couple of surveys that are going to be reviewed focus mostly either on comparison between statistical and machine learning performances [8] [6] or performances between SOTA approaches in machine learning generally [2] all of that under the focus of time series forecasting. Methods recommended from [3] not only tackle our issue of short-time series forecasting but also present methods for multivariate data handling in that regard, which will help us to see the relation between our different data sets and whether they affect each other. Other papers focus more on the comfort side of the project and how they were tackled in other or similar domains of comfort either in the form of forecasting approaches or social approaches [1] [11] [9]. These papers are going to be used for either methodology or mostly for how light comfort is interpreted in these office buildings. And lastly, some papers will help support the idea of integration of these models into the current embedded sensors to improve control and monitoring for the building energy management [4].

3 METHODOLOGY

In this section a presentation of the expected approaches to tackle the research question will be presented.

Data collection and preparation

The architects of the LAB42 building provided our data through CopperCube in the form of tables for each sensor and each room in the building and accessed through the university server. We have a total of 8171 tables out of these tables only 1287 tables or 429 rooms will be analyzed primarily. Each room has three types of light sensors, daylight sensors, room lighting sensors, and wall light sensors. The preparation of the data will depend highly on the amount and quality of the data. Another dataset will be prepared to include the relationship between the sensors to see if they affect the behavior of each other.

Forecasting methods

Statistical. The statistical methods that would be picked here will be decided on two factors, firstly on the simplicity of its usage and preparation to have a decent baseline to compare the other methods and the state-of-the-art methods. Secondly which common statistical methods were used in recent review papers on forecasting to have an idea of which methods are the most reliable for modern-day forecasting. Common recurrent models [6] [8] are ARIMA/SARIM (Seasonal - Autoregressive Integrated Moving Average),smooth-based, and moving average forecasting.

Machine learning methods. Similar to the statistical method literature [2] [6] [8] cross-review will be made to pick the state-of-the-art machine learning models that will be applied to the datasets. Examples of state-of-the-art models can be found either in these review papers or in competitions like the M4 and M5 forecasting competitions. Examples of recurrent models are Long Short Term-Memory (LSTM), FFORMA, XGBoost, Artificial Neural Networks (ANN), and many other hybrid and ensemble methods that look for boosting the models.

4 RISK ASSESSMENT

Limited Data and Data Quality

Depending on the room or the sensors observed there might be a limit to the amount of data for forecasting or for them to be full of outliers that lower the quality of the forecast. Plus since there are so many data tables and a high chance that many of the rooms will have corrupted or invalid data we will have a smaller sample size to test our theories. For this. many papers tackle the issue of data limitation for forecasting as well as tackling how to mitigate errors in the data for the benefit of the forecast.

Computation power/time

Many of the modern and state-of-the-art models require machine learning techniques and a lot of data to implement, also these models can become too complex that running them on a local machine might be not possible, so it is necessary to utilize some cloud computing and/or some kind of big data management tool to me make it accessible to work with that amount of data, especially since it is a comparison study between multiple models, time would be crucial.

Data privacy

All data collected by the sensors are linked to activities from unique users in the building and might link back to them which is a form of a data breach, so communication with the data officer of the university will be necessary to apply anonymizing steps to avoid any data breach or linking activities to some users.

5 PROJECT PLAN

Thought that writing and reading of research material will be happening parallel while work on the data and methodology will be done a Gantt chart is presented in this section to present the project plan with the milestones on the way to finish the paper.

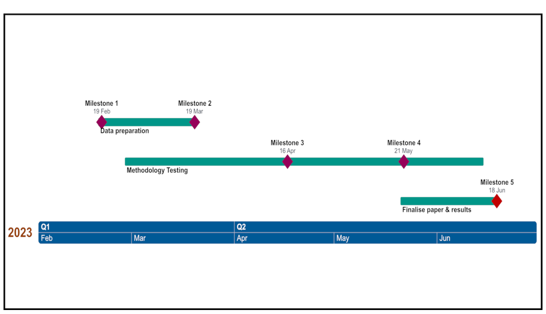

Figure 1: Gantt chart representation of project plan

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