A multitask learning approach for building energy optimization and comfort models

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Abstract

There has been an increase in the demand for building energy in the past decade for the purpose of supplying ventilation and air conditioning to achieve thermal comfort in buildings. However, despite these efforts, many occupants continue to report feeling thermally uncomfortable in the built environment. This discomfort has been found to have an impact on the productivity, emotions, and overall well-being of occupants. This project aims to create an optimization model that focuses on both energy optimization and individual thermal comfort. The results indicate that using deep learning can lead to more accurate predictions compared to baseline models, which suggests the potential for creating efficient models that can provide comfort to individuals while also reducing energy demand. All the code is accessible at https://github.com/jaimebw/cs541_finalproject

1. Introduction

The increasing demand for ventilation, heating, and air conditioning in buildings has contributed to the high levels of energy consumption in the building energy sector (Doe (2015), Mora & Bean (2018), Pérez-Lombard et al. (2008)). Despite efforts to provide optimal comfort for occupants, studies have shown that more than 42% of people still experience discomfort in the built environment (Huizenga et al., 2006). This discomfort can have a range of negative effects on occupants, including reduced productivity, increased stress levels, and decreased overall well-being (Amasuomo & Amasuomo (2016), Lan & Lian (2009), Yun (2018)).

One of the reasons for this discomfort may be the static nature of many buildings, which are designed to meet the average needs of occupants without considering individual preferences and needs. Additionally, the variability of individual preferences and needs can make it difficult to provide optimal comfort for everyone. To address this issue, it is important to develop efficient control methods that can adapt to the changing demands of occupants and provide better energy efficiency and thermal comfort.

Many studies have tackled this issue and provided solutions to answer occupants' needs while saving energy consumption. These methods include Personal Environment Systems (PES)(Arakawa Martins et al., 2022), which allow individuals to customize their own thermal environments, and advanced heating and cooling systems that can respond to real-time changes in temperature and occupancy (Qavidel Fard et al. (2022), Somu et al. (2021a)). Designing buildings with consideration for the specific needs and preferences of occupants can also enhance thermal comfort and energy efficiency.

This project aims to develop a multitask optimization model that simultaneously addresses the comfort of individuals and energy use for more efficient energy consumption. This model will integrate various control strategies and optimization techniques to strike a balance between occupant comfort and energy efficiency. It will consist of a thermal comfort prediction model, a time series energy load prediction model, an occupancy model, and a general optimization model. By implementing this model, we hope to offer a solution that enhances the thermal comfort of building occupants while also reducing energy consumption.

1.1. Research Contributions

There has been a great deal of research focused on developing smart and efficient models that can accurately predict the thermal comfort of building occupants, estimate plug load, and detect occupancy using artificial intelligence in order to reduce energy consumption. However, these studies have largely focused on individual aspects of building efficiency and comfort, rather than looking at how these factors can work together to create intelligent and efficient systems that can adapt to the changing needs of occupants.

Our proposed project aims to fill this gap by developing a

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machine learning model that can integrate all of these factors, allowing for better estimation and understanding of how to create comfortable and energy-efficient buildings that can adapt to the changing needs of occupants. By combining data on thermal comfort, plug load, and occupancy, our model will be able to provide a more complete picture of how buildings can be optimized for energy efficiency and comfort.

In addition to providing a more comprehensive view of building efficiency and comfort, our proposed model has the potential to yield better outcomes when applied in a variety of occupied spaces, such as residential buildings and offices. By taking into account the unique needs and preferences of occupants, our model will be able to provide more tailored and effective solutions for improving building efficiency and comfort.

2. Related Work

Several research studies have explored the use of control models with machine learning and deep learning to improve thermal comfort in buildings. Somu et al. (2021a) evaluated different machine learning models to increase the accuracy of thermal comfort prediction and found that transfer learning and LSTM models showed improved results. Qavidel Fard et al. (2022) discovered that using support vector machines (SVM) and ensemble learning could significantly improve the prediction of thermal comfort models. In the area of plug load prediction, Wang et al. (2019) found that incorporating exogenous input with an LSTM model could improve the accuracy of time series prediction and result in lower error rates compared to other methods. For occupancy modeling, there are numerous computer vision applications (Xu, 2021) that can accurately count and represent occupancy levels. The main limitation of these models is often the availability of suitable datasets.

3. Proposed Method

3.1. Model Architecture

The model architecture is illustrated in figure 1 below. It consists of four models: a thermal comfort model, an occupancy detection model, a plug load prediction model, and a deep reinforcement learning model to predict action space for the environment. The thermal comfort model functions as a classifier to predict thermal sensation for individuals based on various environmental, physiological, and general input information. The occupancy prediction model detects the number of occupants in the space. The plug load model operates as a time-series prediction of energy consumption using the energy load of previous time stamps. Finally, the DRL model acts as the final model that takes the previous predictions and detections as input and produces an action space of environmental factors that aim to provide comfort for individuals while also attempting to save energy

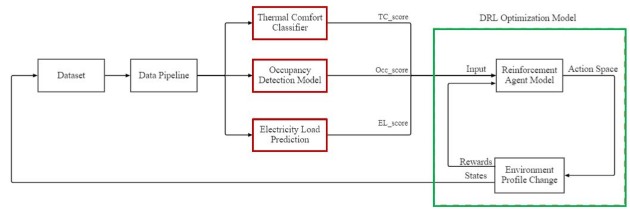

Figure 1. Proposed model architecture for the optimization model

3.2. Models

3.3. Thermal comfort model

In our literature review for thermal comfort models, we found some interesting results from Somu et al. (2021b). They were able to use deep neural nets to classify thermal comfort based on various parameters. In any case, we also learned about the implementation of LSTM.

The thermal comfort classifier will predict the thermal sensation of individuals based on environmental, physiological, and general inputs, as well as thermal preference and acceptability votes, which can influence the action to be taken, such as adjusting the air temperature, opening a window, or increasing air flow in the room. According to the literature, this prediction can provide a better understanding of individuals' thermal comfort profiles and thus improve the action space.

3.4. Energy Consumption

3.4.1. Occupancy model

As for the occupancy model, we thought about many different implementations. In our first attempts, we tried to reinvent the wheel and researched how to train our own computer vision model. This turned out to be unsuccessful due to the training times needed to achieve some kind of accuracy and the scarcity of our resources.

As a second attempt, we started reading some literature about crowd prediction and room counting using images. Moreover, we wanted to implement as well audio signals to improve the quality of our models, and we were able to find interesting resources based on transformers(Liang et al. (2022) and Hu et al. (2020)) and CNN architectures(Song et al., 2021).

Finally, we decided to use the proposed architecture by (Song et al., 2021) due to the good results that it yielded and its simplicity compared to other trained models.

3.4.2. P2P-Net

P2P-net(Song et al., 2021) is a framework that has been trained for counting people in crowds. The way it trained is by directly receiving point annotations as its learning targets and then providing the exact locations of individuals in a crowd, rather than simply counting the number of individuals within it. Then, the locations of individuals are typically indicated by the center points of heads, with optional confidence scores.

For our occupancy model, we use a transfer learning approach and we test how the model works with the dataset from Pardamean et al. (2021). More details on the evaluation can be found in subsequent sections.

3.5. Optimization Deep Reinforcement Learning Model

The optimization model we have chosen is a deep reinforcement learning (DRL) model, which allows for real-time learning from the environment. This is in contrast to traditional machine learning models, which are trained using pre-existing datasets. The specific DRL model we have chosen is an asynchronous actor-critic model, as illustrated in figure 2. This model consists of two main components: the environment module and the agent module.

The environment module represents the occupied space and receives inputs about the current state of the environment. It then outputs the current state of the environment (at time t) and a reward signal that reflects how well the environment is responding to the actions taken by the agent. The agent module, on the other hand, consists of two neural networks: an actor and a critic. The actor network receives inputs about the current state of the environment and outputs a set of actions that can be taken, such as adjusting the temperature, opening or closing windows, turning on or off the HVAC system, or adjusting the lighting. The critic network then evaluates the output of the actor network, taking into account the feedback from the environment, and helps the actor network improve its action selection over time.

This asynchronous actor-critic approach allows the agent to adapt to the varying preferences of occupants while also working towards optimizing energy use in the short and long term.

Given the complexity of training this model in real-life scenarios, or using human profile simulation modules, the training of this model was not covered in this paper and will be discussed in future work.

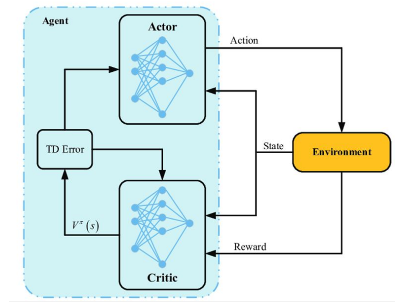

Figure 2. Actor Critic Reinforcement Learning Model Architecture.

3.6. Datasets

3.6.1. Occupancy dataset

We wanted to use a dataset that would contain images that would look like a real office. In an attempt to do this, the chosen dataset was based on CCTV images from an office with a standard-to-low-quality resolution from Pardamean et al. (2021). A sample of the chosen dataset can be shown in figure 3. To see the performance of the model with our chosen dataset, we test a couple of images before doing a full implementation. Figure 4 shows some results of these tests.

Figure 3. A sample from the dataset from Pardamean et al. (2021)

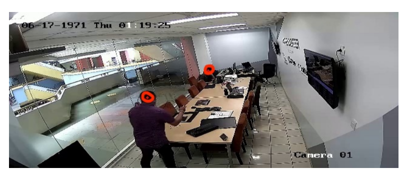

Figure 4. Transfer learning sample on the CCTV image dataset, the red point has been made bigger on purpose to show the results from the net.

3.6.2. Thermal comfort dataset

The dataset used for the thermal comfort classifier was the ASHRAE dataset Parkinson et al. (2022), which includes environmental, physiological, and general information about individuals and thermal comfort, thermal acceptability, thermal preference, and air movement as inputs. This dataset includes numerical and categorical data, which

Feature name
Age
Sex
Outdoor air temperature
Indoor air temperature
Indoor radiant temperature
Indoor relative humidity
Indoor air velocity
metabolic rate
clothing insulation
thermal comfort
thermal acceptability
thermal preference
thermal sensation

Table 1. Thermal comfort features

was normalized and encoded before feeding to the models. Furthermore, due to the lack of sufficient samples across all thermal conditions, we performed an oversampling technique called the Synthetic Minority Oversampling Technique (SMOTE)

A variety of thermal comfort models were tested. First, machine learning models were created as a baseline for comparison with the deep learning models developed and trained for this dataset. For the deep learning models, given the characteristics of the dataset, we considered two models: a Multi-Layer Perceptron (MLP) model and a Long-Short Term Memory (LSTM) model.

3.7. Energy Consumption dataset

3.7.1. PLUG LOAD DATASET

The plug load dataset was published by Hebrai & Berard (2017). Our main interest in training this model comes from being able to predict how the power consumption is For training our model, we are only interested in certain features, mostly the ones that deal with the total power consumption of the office every certain period of time. Some features of the dataset are shown in table 2. The main advantage when using this dataset is that we actually have a time series format that allows us to feed different kinds of models and try to search for trends.

4. Results

This section is going to be divided in two parts: the result from the intermediante models(Occupany, Thermal Comfort and Plug load) and the reinforced learning agent results.

Feature name
date
time
Global_active_power
Global_reactive_power
Voltage
Global_intensity
Sub_metering_2
Sub_metering_1
Sub_metering_3

Table 2. Features from the plug load dataset, these features are collected per timestamp every hour

4.1. Intermadiate model results

The table 3 exposes the thermal comfort results. As it can be observed, the best resuls were obtained from the Multi-layer Perceptron.

Model	Accuracy
Logistic Regression	50.25 %
KNN Classification	40.43 %
Random Forest Classifier	55.01 %
MLP	68.44%

Table 3. Results from the thermal comfort models

The plug load models regression results can be seen in table 4. It is possible to observe that the usage of more complex deep learning solutions yields similar results to the Machine Learning models.

Model	MSE	MAE	R^2
Linear model	0.0092	0.070	0.490
Polynomial model	0.0093	0.068	0.480
Random Forest model	0.0099	0.079	0.450
MLP	0.009	0.070	0.492
LSTM	0.0091	0.0653	0.492

Table 4. Results from the plug load model

Finally, the result from the occupancy model can be seen in the table 4.1.

4.2. Reinforced Learning model

We have not been able to train the reinforced learning. This has been due to multiple problems regarding the time constraint for this project and our lack of simulation software to be able to undertake results from the intermadiate models to a real scenario.

Model	MAE
P2P Crowd counting	1.83

Table 5. Results from the occupancy model

5. Conclusions and Future Work

As we have been able to show with this work, it is possible to train a wide variety of models that are capable of predicting comfort and energy usage. These models may be implemented with a Deep Reinforced Agent to create a system capable of optimizing all these variables and yielding the most favorable results.

The lack of a simulation environment makes the implementation of this framework impractical. Therefore, one of the lines for future works is creating a simulation framework in which the reinforced learning can learn and iterate.

As for the intermediate models, there are many possible lines of future actions. For the thermal comfort model, we haven't trained with all the features that we have. A future attempt could be based on using some kind of dimensionality reduction technique based on different types of embedding such as Isomaps or maybe training an autoencoder as input to the MLP. In any case, thermal comfort is something that is really subjective to the interviewed person. Therefore, it is quite difficult to train a model that has no bias.

For the occupancy models, the next steps would be based on using video and real-time recognizing models such as the ones proposed in Xu (2021). The main challenge of this model is obtaining access to a dataset and taking into consideration the ethical concerns that may result from using videos from people. As for the plug model, we obtained excellent results so for future works we will follow the same approach.

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