2_C28

Analysis and Optimisation of Building Efficiencies through Data Analytics and Machine Learning

Ryan Grammenos, EngD **Konstantinos Karagiannis** *Member ASHRAE* **Manuel Escalante Ruiz**

ABSTRACT

Productivity of workers is greatly affected by their comfort in the workplace. Research has shown that thermal comfort is one of the most influential parameters on worker productivity, and that the running costs of a Heating, Ventilation and Air Conditioning (HVAC) system could be up to ten times lower compared to productivity losses that would be incurred in a free-runing building. With the increased availability of Internet of Things (IoT) devices, it is now possible to continuously monitor multiple variables that influence a user's thermal comfort and to act pre-emptively to prevent discomfort situations. Smart buildings make use of technology that enable them to become more efficient, reduce costs and emissions and become more transparent in terms of operation. To this end, this work has the following two-fold aim; first, to develop a machine learning model to predict setpoint temperatures in an HVAC system towards the vision of making this system autonomous; second, to use exploratory data analysis techniques to evaluate the current operation and energy performance of an HVAC system in an office block by analyzing and comparing patterns and trends between building management system (BMS) parameters and thermal comfort standards. Results demonstrate that our machine learning model was able to predict the user's setpoint temperature with 94.14% accuracy using only environmental parameters, with this accuracy increasing to 97.68% when time-related features were added to the model. Subsequently, our exploratory data analysis revealed that over 50% of the room temperature readings in our sensor-acquired raw dataset lied outside the comfort zone for all seasons, while the setpoint deviation was equal to zero for only 4.31% of the cases, with an average value of 3.38°C (6.08°F).

INTRODUCTION

Research has shown that thermal comfort levels in the workplace has significant impact on the productivity of workers (Seppanen 2006). The running costs of a Heating, Ventilation and Air Conditioning (HVAC) system to maintain a productive temperature is ten times lower compared to the economic losses incurred as a result of lower worker productivity in a free-running building (Robertson 2016). Furthermore, studies have shown (Sarkar 2015) that buildings in the United States use 65% of all electricity produced, with HVAC and lighting systems accounting for 75% of this consumption. This work reports on the first steps taken towards implementing an autonomous HVAC system.

USER BEHAVIOUR SIMULATION

Achieving the vision of an autonomous HVAC system has a two-fold requirement; first, the system needs to self-configure and self-adapt itself to respond to the users' needs without intervention from the users themselves; second, the HVAC system should operate with a balanced trade-off between thermal comfort and energy efficiency.

Previous literature has considered the use of linear, ensemble, genetic and deep machine learning algorithms to predict the

Ryan Grammenos EngD, SFHEA, is an Associate Professor (Teaching) in the Department of Electronic and Electical Engineering, University College London, London, United Kingdom.
Konstantinos Karagiannis MBA, MSc, DIC, MEng, BEng is the managing director at General Technology Ltd, Athens, Greece.
Manuel Escalante Ruiz is an MEng student in the Department of Electronic and Electical Engineering, University College London, London, United Kingdom.

behavior of an indoor environment (Fayaz 2018, Jain 2017). Results from thermostat field studies using set point models have also shown that user behavior profiles can improve the interpretability of observed energy consumption (Urban 2013). In the context of our work and based on the raw sensor data available to us, we use the setpoint temperature (STP) as the feature of interest for emulating the users' behavior. This is due to the fact that the STP is the only feature that can be adjusted manually by the user with this intervention taking place by the user in an attempt to maximise their thermal comfort in the room they are occupying.

Data Preparation

The data considered in this work was acquired from individual sensors deployed in an 11-story commercial office building in Athens, Greece over 21 months between December 2017 and September 2019. The data comprises individual spreadsheets, one for each sensor, for three different rooms in this building. The building did not employ any other sensors except the ones provided in the dataset. It is worth highlighting that this is not a new build; it was constructed in the 1990's with some refurbishments in the HVAC system over the past decades.

For the purpose of this work, we considered Room 103 which was located on the fifth floor of this building with a southwest orientation, thus facing towards the sun and calling for a higher usage of air-conditioning. The variables available in the dataset include the following:

- RoomTemp (RT): Room temperature measured in °C (°F), with 0.5 °C (0.9 °F) precision.
- SetTemp (STP): Setpoint temperature measured in °C (°F), with 0.5 °C (0.9 °F) precision. The setpoint temperature is essentially the "thermostat temperature" which can be adjusted by the user (but can also return automatically to preconfigured values set for the HVAC system depending on the time of the day).
- OnOffState (OOS): Indicates whether the HVAC system is on or off, with one (1) representing On and zero (0) representing Off.
- OperationModeState (OMS): Operation mode of the HVAC system, which can take on one of four values; one (1) for Cooling, two (2) for Heating and three (3) for Ventilation.
- OUTAIRHUMD: Outdoor Air Humidity measured in % Relative Humidity with 0.005% resolution.
- OUTAIRTEMP: Outdoor Air Temperature measured in °C (°F), with 0.1 °C (0.18 °F) precision.
- AlarmState (AS): Returns a value of one (1) if there is a problem with the HVAC system, otherwise is zero (0).
- Timestamp: Given in string format as "Day.Month.Year Hour:Minute:Seconds".

As mentioned above, the raw data provided to us was in the form of a separate spreadsheet for each individual feature, that is to say, there were eight spreadsheets pertaining to each of the three rooms. The first step was to therefore combine these eight spreadsheets into a single structured table. In the interest of space, the reader is referred to Appendix 1 for an illustration of this merging process. Figure 1 shows the data preparation process for generating the final clean dataset for Room 103. Two key challenges had to be addressed during this process.

First, we had to account for the fact that recordings for the indoor features (OOS, OMS, RT, STP, AS) were acquired at fixed, periodic intervals (approximately every 10 minutes) while recordings for the outdoor features (outdoor air temperature and humidity) were acquired through state-change detection, that is to say, whenever the value of the feature changed beyond a predefined threshold (in this case, being the precision of the feature itself). The second challenge involved dealing with time mismatches across the different features which occurred as a result of sensor failures, time misalignment during the merging process or data losses. Initially we dealt with the indoor features and by using time slicing and synchronization techniques, we achieved in generating a first partial dataset comprising the five indoor features with a total of 89,082 observations. Subsequently, we had to expand this partial dataset to include the outdoor features. Due to the event-driven nature of the outdoor recordings, we had to "fill in" missing values amounting to 80.14% for the outdoor temperature and 55.11% for the outdoor humidity. While sophisticated techniques exist for filling in missing values in building sensor data (Chong 2016), it was determined that the best and simplest approach would be to hold previous values between time periods provided that a change had not been registered in that time period. If a change had been detected, then the outdoor recording closest (in terms of time) to the timestamp under consideration was used instead.

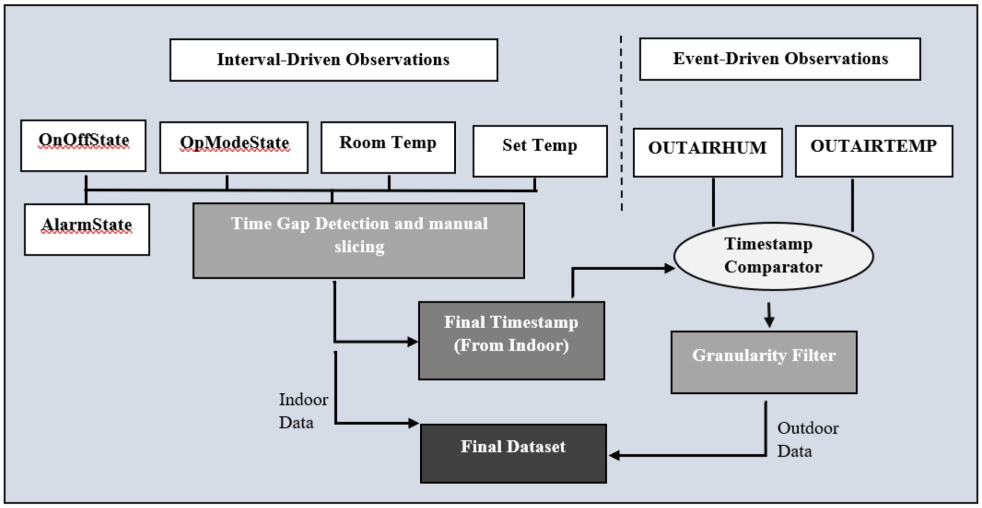

Figure 1 Data preparation process for generating the clean dataset.

Feature Engineering

Following the data preparation and cleaning process, the next step involved augmenting this dataset by removing unwanted features and adding new features that could improve the accuracy of our prediction model. After exploratory analysis, it was discovered that there was a single instance of the Alarm State having a value equal to one which upon close examination was found not to have an impact on the remaining features or the system itself. This feature was thus removed from the dataset. On the other hand, it was evident that the timestamp feature contained useful information around seasonality, yet the timestamp feature in its original format was not suitable for the model. Hence, the timestamp was extracted into four separate time-related features being the year, season, month of the year and hour of the day.

Machine Learning Model

Since we used the STP as the feature for emulating the users' behavior, we defined this variable to be the output response variable. The STP has quantitative values and hence at first glance it might seem that a regression algorithm is suitable for this application. Yet, the exploratory analysis revealed that the STP takes on 18 values in total, ranging from 19 ºC (66.2 °F) to 28 ºC (82.4 °F) in steps of 0.5 ºC (0.9 °F). Since the STP recordings within this dataset take on only these specific, 18 discrete values, it was determined that a classification approach would be best suited to this problem, whereby the STP values constitute "labels" for the possible outcomes.

While a comparison of all potential machine learning techniques for this scenario is beyond the scope of this work, previous studies have shown that black-box models are well-suited for simulation of indoor environments since they do not require complex calibration as white-box models and are more flexible in terms of inputs compared to grey-box models (Arendt 2018). For classification, ensemble models have been found to offer the best trade-off between accuracy and interpretability (Hall 2018). To this end, this work employs a Majority Voting Classifier (MVC) algorithm (Ruta 2005) which combines three classifiers namely a Random Forest Classifier (RFC), an Extreme Gradient Boosting Machine (XGBM), and a Support Vector Machine (SVM). Since all three underlying classifiers of the MVC algorithm are black boxes, that is to say, their inner working mechanisms are unknown, consequently the MVC algorithm itself also constitutes a black box.

The idea behind the MVC algorithm is to combine multiple machine learning classifiers in order to profit from the benefits provided by each classifier. Specifically, in this work, the RFC and XGBM are ensemble techniques which avoid model overfitting and improve the split regions in decision trees, respectively. The SVM is a kernel technique which optimizes decision boundaries between classes. When running the MVC algorithm, each classifier independently generates a prediction for each label with the MVC subsequently using a majority vote (hard voting in this case) to predict the corresponding class label. That is to say, the output label corresponds to the class that achieved the highest number of votes across the three classifiers.

Having selected our machine learning algorithm, the next step involved splitting our original, raw dataset into training and test sets. An initial trial of splitting the dataset randomly into a 70% training set and 30% test set yielded poor results and hence was abandoned quickly. In the second trial, the data was divided in an interleaved fashion taking the first three weeks of each month as the training set and the last week as the test set, thereby resulting in roughly a 75%-25% split between training and test sets. The accuracy of the model was obtained in terms of misclassification error with the aid of a confusion matrix. Specifically, the accuracy was measured by the ratio of the sum of class labels that were predicted correctly by the algorithm to the total number of estimated labels in the test set. Additional statistical metrics, such as F1 and R^2 scores (not included here for simplicity) were used during the evaluation of the models to corroborate the accuracy levels obtained.

The accuracy level obtained was 91.82%, which although seemed good, left room for further improvement. Examining the confusion matrix, it transpired that the cause of the errors was due to the fact that some labels were not present in the training set, yet appeared in the test set. To mitigate this problem, we adopted a more granular approach to the splitting of the dataset. Specifically, we first divided the dataset into daily subsets and split the observations for each day randomly into a 70% training subset and 30% test subset. We then consolidated the training and test subsets to yield the final training and test sets. In doing so, we achieved in increasing the model accuracy to 94.14%. It is worth noting that the 70%-30% split between training and test sets is in line with relevant work in this field (Chong 2016).

In the aforementioned models, the dataset used included only the environmental features (indoor and outdoor) excluding the Alarm State. We wanted to investigate the impact of including time-related features in the model's input variables and hence repeated the above process but this time including year, season, month of the year and hour of the day as additional model inputs. This increased the accuracy even further to 97.68%. The prediction accuracy of each component in the MVC algorithm for this final model is illustrated in Table 1. While this prediction accuracy might seem high, it is worth noting that accuracies ranging from 80% (Fayaz 2018) through to 99% (Jain 2017) have been reported in the literature.

Table 1. Prediction Accuracies for Majority Voting Classifier (MVC)

MVC Component	Prediction Accuracy
Random Forest Classifier	98.21%
XGBoost Classifier	84.69%
Support Vector Classifier	97.93%
Voting Classifier	97.68%

ANALYSIS OF THERMAL COMFORT AND ENERGY EFFICIENCY

Having developed our prediction model, we now turn our attention to evaluating the HVAC system in terms of thermal comfort and energy efficiency. Standards, such as CIBSE KS06 (2006), ASHRAE 55 (2017), CEN EN15251 (2006) and ISO 7730 (2005), all utilize Fanger's model (Charles 2003) to provide the most accurate measure of thermal comfort in buildings. The general formula for this model can be found in Appendix 2. This general formula makes certain assumptions about the physical specifications of the bulding, which were not available to us in this work. To overcome this issue, we employed Berkeley's CBE Comfort Tool (Hoyt 2019) instead, being a variant of Fanger's model which relies on environmental features and which uses the formula shown in Equation 1 to calculate the PMV:

$$PMV = Ts \times (MW - hl1 - hl2 - hl3 - hl4 - hl5 - hl6) \quad (1)$$

where Ts is the surface temperature, MW is the metabolic rate-outside work product, and hl1 to hl7 represent the heat losses through skin, sweating, latent respiration, dry respiration, radiation and convection, respectively. The reader is referred to Appendix 2 for a detailed breakdown of the parameters shown in Equation 1.

The next subsection presents the results and analysis obtained by using Fanger's adapted model shown in Equation 1. We only considered the recordings during which the HVAC system was turned on in Room 103, in order to evaluate its performance with respect to maintaining optimum thermal comfort levels while minimizing energy consumption. In absence of actual data recordings for the indoor room's relative humidity (RH), we set the interval to be from 30% to 70%, which is standard practice according to ASHRAE's handbook (2017) on moisture management in buildings.

Results and Analysis

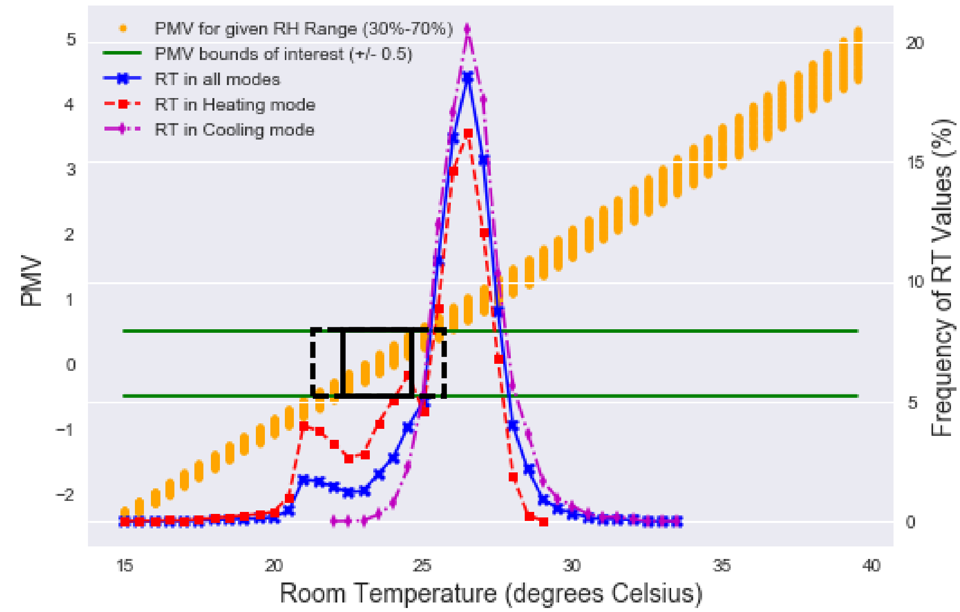

Figure 2 PMV versus room temperature (RT) for different modes when the HVAC is ON.

Figure 2 is dense but provides unique insights. The x-axis lists the range of room temperature (RT) values found in the dataset which are from 15 °C to 39.5 °C (irrespective of whether the HVAC is on or off). The green horizontal bars show the bounds of interest for the PMV being ±0.5. The orange vertical bars (which are essentially dots, as indicated in the legend) represent the PMV value for a given room temperature (RT) but with the relative humidity (RH) ranging between 30% and 70% for each RT value. The red, magenta and blue lines show the distribution of room temperature values when the HVAC is on and operating in heating mode, cooling mode, and across all operating modes, respectively. Finally, the black square (straight lines) shows the range of RT values that provide optimum thermal comfort (for the given RH range) being 22.5 °C (72.5 °F) to 24.5 °C (76.1 °F). The extended black rectangle (dashed lines) shows an extended thermal comfort range that can be achieved by imposing additional constraints on the RH range. Specifically, a RT of 21.5 °C (70.7 °F) with a RH > 57%, through to a RT of 25.5 °C (77.9 °F) with a RH < 43%, are considered to be in the ideal thermal comfort range given by PMV = ±0.5.

The first observation is that the RT values range from 15 °C (59 °F) to 33.5 °C (92.3 °F) and that as the RT increases, the range of PMV values also increases for the same fixed range of RH values. The second observation is that none of the three bell-shaped RT distributions lie completely within neither the black square or extended black rectangle. This affords greater discussion. Let us assume that the HVAC operation was configured to maintain optimum thermal comfort without considering energy efficiency. In this case, the ideal situation would be that all RT values were within the comfort range of 22.5 °C (72.5°F) to 24.5 °C (76.1°F). To put it differently, we would expect the peak and the tails of the bell-shape distribution to lie entirely within this RT range. Figure 2, however, shows that this is not the case. Instead, considering for example the RT distribution when the HVAC is operating in heating mode, we observe that only 21% of the RT values lie in the comfort range while approximately 59% of the values lie within 1 °C (1.8 °F) of the bell shape peak value being 26.5 °C (79.7 °F). Similar trends are shown for the cooling mode and indeed across all modes, that is to say, that the HVAC system has not been configured appropriately to optimize thermal comfort. It seems that a shift of the distribution towards the lower temperatures by 3 °C (5.4 °F) would ensure that the HVAC system would provide optimum thermal comfort for over 50% of the time. A more detailed design review, however, would be required to determine how to configure the HVAC system in such a way that would enable it to maintain the RT at a value of 23.5°C (74.3°F) and within 1°C (1.8°F) deviation from the RT distribution peak value.

The aforementioned analysis led us to consider the difference between the RT and the setpoint temperature (STP) throughout the period under consideration. The absolute difference between these two features is shown in Figure 3. Figure 3 shows that there is a notable fluctuation between the RT and STP values. Of course, some fluctuation is expected, which would occur when the HVAC system is initially turned on and therefore require some amount of time for the RT to reach the STP, especially in view of the fact that optimum start functionality is not present. Figure 3, however, shows that the average difference is 3.38 ºC (6.08 °F). Worse even, the data shows that the RT reached the SPT for only 4.31% of the total recordings in the aforementioned period while the HVAC system was on. Relaxing this constraint to an RT deviation of 0.5 ºC (0.9 °F) from the SPT increased the number of recordings in agreement to 13.3%, which is still very low.

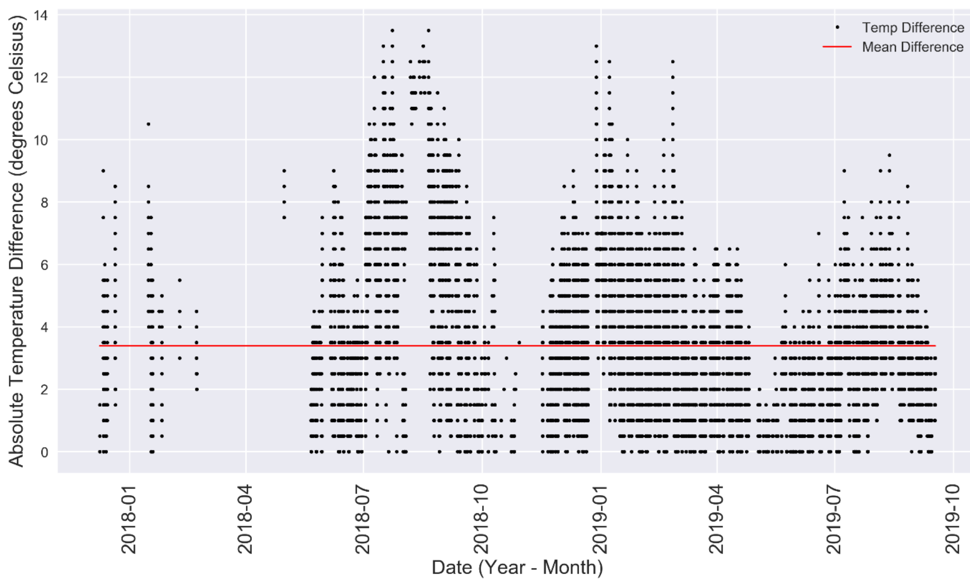

Figure 3 Difference between RT and SPT across all operation modes when the HVAC is ON.

The analysis thus far has only considered thermal comfort. Yet, a well-designed HVAC system would consider a balanced trade-off between thermal comfort and energy efficiency. Table 2 presents different approaches for configuring the setpoint temperature. The first row shows the STP values recommended by the CEN EN15251 standards (2006) for optimum energy efficiency without considering thermal comfort. The second and third rows present the STP values identified in this work for providing optimum thermal comfort based on insights obtained from Figure 2 without considering energy efficiency. The fourth row illustrates one example of recommended STP values to achieve a balanced trade-off between thermal comfort and energy efficiency. This recommendation is based on the thermal comfort and energy efficiency ranges identified in the previous rows and was put forward as an STP configuration that satisfies the two conditions as closely as possible.

Table 2. Comparison of different HVAC setpoint temperatures (STP) approaches

STP Approach	Heating Mode	Cooling Mode
STP for optimum energy efficiency	20.0ºC (68°F)	26.0ºC (78.8°F)
STP for optimum thermal comfort	22.5ºC (72.5°F) - 24.5ºC (76.1°F)	22.5ºC (72.5°F) - 24.5ºC (76.1°F)
STP for safe but slight thermal discomfort	21.5ºC (70.7°F) - 25.5ºC (77.9°F)	21.5ºC (70.7°F) - 25.5ºC (77.9°F)
Recommended STP for balanced trade-off	22ºC (71.6°F)	25ºC (77°F)

Having considered both thermal comfort and energy efficiency levels, our last task was to evaluate the performance of the HVAC system taking into account the optimum values identified previously. We considered the worst-case scenario that was present in the dataset, when the HVAC was operating in cooling mode. This date corresponded to the 12th August 2019, as illustrated in Figure 4. Figure 4 shows that the ideal STP value has been set to 25 ºC (77 °F) in line with Table 2. The horizontal black and red curve depict the SPT value set by the user on this date. The black section of this line corresponds to the time period during which the HVAC system was off, while the red section corresponds to the period the HVAC was on. First, we observe that the user-defined SPT is lower compared to the ideal SPT. This implies that the HVAC is operating inefficiently in terms of energy, since it will need to "work harder" in order to maintain the lower SPT that has been defined. The second point is that the RT does not reach the SPT at any point while the HVAC is on, which as can be seen from Figure 4, is for approximately 11 hours between 8 am and 7 pm. Herein lies a two-fold problem; first, the HVAC system is not able to maintain the RT at the desired STP – it is clear that there is an offset of 3 °C (5.4 °F) between the RT and the STP, which corroborates the statistics shown for Figure 3; second, as a result of this inability, the thermal levels in the room lie outside the optimum comfort range. Another unexpected observation is that the RT started to increase in the afternoon around 15:30 while the HVAC was still actively cooling the room until it was turned off more than three hours later. Finally, Figure 4 shows that the RT follows the same trend as the outdoor temperature when the HVAC system is off, accounting of course for a reasonable delay between the transient and steady-state periods. While it is not possible to determine the causes of the aforementioned discrepancies (since we do not have access to the system's full information), it is clear that the data analytics process has been successful in revealing hidden trends and providing useful insights that we would have otherwise been unable to extract.

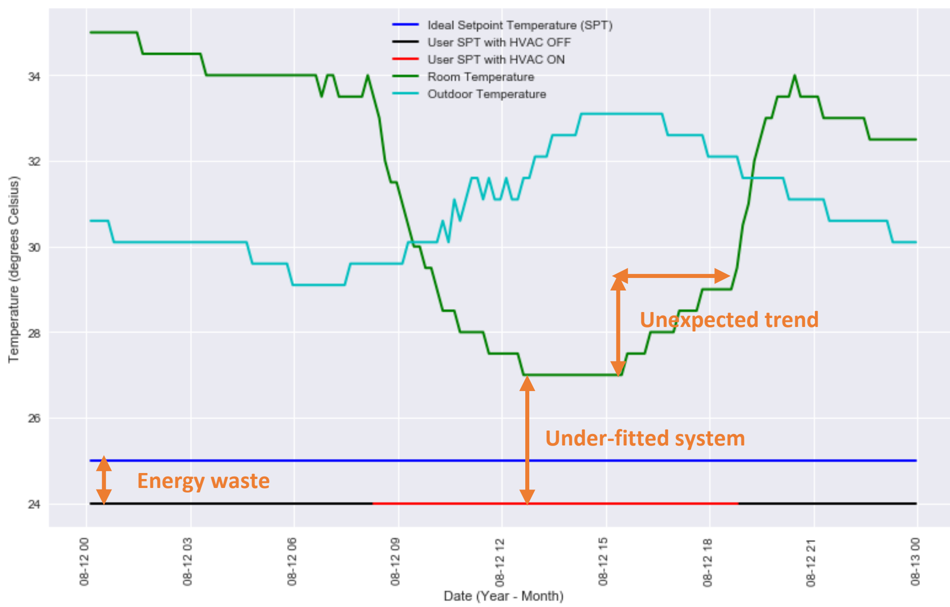

Figure 4 HVAC performance evaluation in terms of thermal comfort and energy efficiency.

Discussion

A close examination of the dataset revealed that there were no extreme values of RH, that is to say, having high humidity at large temperatures (too humid) or low humidity at low temperatures (too dry). Hence, this factor was not considered in any further detail. Figure 2 showed that in heating mode, only 1.22% of the RT values are below 20ºC (68°F) while in cooling mode, almost 62% of the RT values are above 26ºC (78.8°F) with most of these being recorded at values between 26.5ºC (79.7°F) and 29ºC (84.2°F). This would imply that the HVAC system operates better in heating mode (activated during winter) compared to cooling mode (activated during summer). In terms of STP, it was found that in heating mode, the STP was set at 24ºC (75.2°F) or higher for 99% of the recordings. While from a thermal comfort point of view, this setpoint is acceptable, the results analysed in the previous section came across as being contradictory. Specifically, even though the STP was set at 24ºC (75.2°F), we found that 59% of the RT values were recorded between 25.5ºC (77.9°F) and 27.5 ºC (81.5°F), that is to say, outside the comfort range meaning that the STP value did not give an accurate picture of the actual thermal comfort levels in the room. At the same time, this value of STP is 4ºC (7.2°F) higher than the level required to achieve optimum energy efficiency. Hence, this raises questions as to whether the HVAC system is indeed working better in heating mode or not. In cooling mode, it was found that for 66% of the recordings the STP value was set to be below 26ºC (78.8°F), yet almost 62% of the RT values were above this temperature threshold. We also found that the STP was varied more widely in cooling mode compared to heating mode.

CONCLUSION

Building data analytics and machine learning models can contribute significantly to the transparent operation and performance of smart buildings by identifying patterns of poor performance while eliminating occupants' intervention to the system. These self-adaptive systems can predict occupants' setpoint preference and balance the trade-off between thermal comfort and energy efficiency. In this study, we developed a machine learning model to predict setpoint temperatures of an HVAC system in an office building and used data analytics to assess the thermal comfort and energy performance to balance this trade-off. The results suggest that the implementation of a machine learning model will be able to predict the users' setpoint temperature, improve occupants' thermal comfort, and optimise the system's energy efficiency, thus providing benefits to both occupants and building owners. While the data analytics process identified hidden patterns that cause discomfort and energy waste, it did not explain the causes behind them due to lack of information regarding the whole system and building. Future work will look at further automating the process of identifying such unexpected patterns and trends and raising an alert for the end user. It would also be desirable to enable the algorithm to provide a reason for the cause of discrepancy encountered, however, to do so, would require access to additional features beyond the environmental and date/time parameters that were available to us in the given dataset.

ACKNOWLEDGEMENTS

This work was completed with the contribution of General Technology Ltd., Athens, Greece, and IntelliCasa Ltd., London, UK. General Technology Ltd. provided the data for this research work.

REFERENCES

Arendt, K. et al. (2018), "Comparative Analysis of White-, Gray- and Black-box Models for Thermal Simulation of Indoor Environment: Teaching Building Case Study", pp. 173-180, ASHRAE.

Charles, K.E. (2003), "Fanger's Thermal Comfort and Draught Models", National Research Council of Canada.

Chong, A. Poh Lam, K. Xu, W. et al. (2016), "Imputation of missing values in building sensor data", Center for Building Performance and Diagnostics, Carnegie Melon University.

Fayaz, M. & Kim, D. (2018), "Energy Consumption Optimization and User Comfort Management in Residential Buildings Using a Bat Algorithm and Fuzzy Logic" Energies, 11(1), p.161, MDPI.

Hall, P. Gill, N. (2018), "An Introduction to Machine Learning Interpretability", O'Reilly Media, Inc.

Han, J. Bae, J. Jang, J. Baek, J. Leigh, S.B. (2019) "The Derivation of Cooling Set-Point Temperature in an HVAC System, Considering Mean Radiant Temperature", Department of Architectural Engineering, Yonsei University Korea, Sustainability Symposium, MDPI.

Hoyt, T. Schiavon, S. Tartarini, F. Cheung, T. Steinfeld, K. Piccioli, A. and Moon, D. (2019), "CBE Thermal Comfort Tool", Center for the Built Environment, University of California Berkeley.

Jain, A. Behl, M. Mangharam, R. (2017), "Data Predictive Control for building energy management", University of Pennsylvania, School of Engineering, Real Time and Embedded Systems Lab (mLAB).

Robertson, C. Idziwoski Perez, I. (2016), "In control: Thermal Comfort and Productivity", CIBSE, AHMM, UCL.

Ruta, D. and Gabrys, B. (2005), "Classifier selection for majority voting", Information Fusion, vol 6, p. 63-81.

Sarkar, D. Datta, R. Mukherjee, A. and Hannigan, R. (2015), "An Integrated Approach to Environmental Management", Wiley.

Seppanen, O. Fisk, W. and Lei, QH. (2006), "Effect of temperature on task performance in office environment", Ernest Orlando Lawrence Berkeley National Laboratory.

Urban, B. and Gomez, C. (2013), "A case for thermostat user models", Proceedings of BS 2013: 13th Conference of the International Building Performance Simulation Association. 1483-1490.

Standards

ASHRAE (2017), "Standard 55 - Thermal Environmental Conditions for Human Occupancy".

ASHRAE Handbook-Fundamentals (2017), "Moisture Management in Buildings", Chapter 36, SI Edition.

CIBSE (2006), "KS06: Comfort (KS6)", Building Services Knowledge.

CEN (2006), "EN15251: Indoor environmental input parameters for design and assessment of energy performance of buildings-addressing indoor air quality, thermal environment, lighting and acoustics".

ISO (2005), "7730: Ergonomics of the thermal environment — Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria".