Clustering Heat Pump Efficiency: The role of urban building, demographic and operational factors

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ABSTRACT

Heat pumps (HP) are becoming increasingly popular due to their ability to heat and cool buildings efficiently. A comprehensive heat pump performance analysis is critical to ensure they are operating at peak efficiency, which is essential to optimise operational running costs and deliver comfort, longevity of the system, and other environmental benefits. The efficiency of Heat pumps is conventionally measured as the Coefficient of Performance (COP), which refers to the ratio of heat output to electrical energy input. This paper aims to understand the role of various operational factors (e.g. building, demographic, HP operations) in understanding the performance gap and classifying the efficiency of heat pumps. This is achieved by applying Self-Organising Map (SOM), one of the widely applied unsupervised Machine Learning (ML) classification approaches. The proposed methodology investigated 185 dwellings with Air Source Heat Pumps (ASHP) and utilises BEIS-measured datasets and metadata. For assessing the performance gap, the daily mean of heat pump COP, operational time, cycles and part load were included to derive quantitative features using the measured 185 dwellings dataset and then fed to the SOM machine learning model for clustering the HP efficiency and performance gap relative to their accredited position. The model performs reasonably well in clustering the 185 dwellings across the three specified categories for their performance under the given building, demographic and operational factors.

Keywords: Air Source Heat Pump, Machine Learning, Coefficient of Performance, Self-Organising Maps.

INTRODUCTION

Heat pumps (HP) are essential units in UK households that are widely used for efficiently heating and cooling buildings. HPs are also the core pathway for the decarbonisation of heat in the UK because of their environmental sustainability, low carbon and renewable sources of heat. The Electrification of Heat (EoH) Demonstration Project, funded by the Department for Business, Energy and Industrial Strategy (BEIS), evaluated the potential for large-scale adoption of heat pumps in the UK (Logue, 2021). The report provided real-world performance data to demonstrate the flexibility of heat pump installations across diverse residential settings, offering insights to guide future government policy (Williams, 2022). Recent studies on heat pumps have examined their adaptability across varying climates and housing types, as well as their real-world performance and policy implications (Monschauer, 2022). The suitability of heat pumps in cold climates has been widely explored (Jin, 2017; Mendes, 2020; Veilleux, 2024). The performance of geothermal or Ground Source Heat Pumps (GSHP) in various environments, particularly in commercial buildings, has been thoroughly studied (Kavanaugh, 2014). A critical evaluation of Air Source Heat Pumps (ASHP) compared to GSHPs in cold regions is also presented by (Jin, 2017). (Mendes, 2020) examined ASHP performance in low-temperature conditions and provided recommendations for technological improvements to enhance their

efficiency. Some studies indicate that while heat pumps are generally efficient, their performance can be limited in older, poorly insulated buildings, which may require supplementary heating systems (Love et al., 2017). Improving building enclosures and integrating heat pumps with the grid are essential for maximising efficiency in cold climates (Lowe et al., 2017). Reviews of heat pump performance in cold climates have identified issues such as reduced efficiency due to frost accumulation and suboptimal performance during extreme cold. Researchers suggest further development of multi-source heat pumps and better system integration to address these challenges (Konrad & MacDonald, 2023). In Europe, research similarly emphasises the importance of adapting both infrastructure and user behaviour to effectively integrate heat pumps (Toleikyte, 2023). Furthermore, challenges such as electrical grid capacity, energy storage solutions, and optimising system performance to align with seasonal electricity generation (e.g., higher solar output in summer) are recognised as crucial (Wan & Hwang, 2023). Heat pumps are highly dependent on proper installation and commissioning, as well as the conditions in which they operate. To lower their upfront operational costs and improve their efficiency, a thorough performance analysis is essential. This optimisation helps minimise running costs, enhance comfort, extend system lifespan, and provide additional environmental advantages (Gleeson et al., 2017). This paper primarily examines the potential of ASHP in the UK to contribute to the country's decarbonisation goals within the broader framework of the net zero agenda (*Net Zero Strategy: Build Back Greener. Presented to Parliament Pursuant to Section 14 of the Climate Change Act 2008: HM Government*, 2021). It will analyse the performance gap between the design expectations and the actual operation of heat pumps by conducting performance assessments, reporting findings, and providing feedback to occupants, installers, asset owners, and service partners. The central idea is that accurately predicting seasonal performance and identifying the factors contributing to performance gaps will enable timely interventions before warranty or retention periods expire, ultimately benefiting all stakeholders in the value chain. Within this context, this paper presents an unsupervised machine learning approach, the Self-Organising Map (SOM), to clustering various operational factors (e.g. building, demographic, HP operations) and aim to understand the performance gap and classify the efficiency of Heat pumps across three broad categories: a) well-perform, b) medium-perform, and c) worst-perform. The performance gap is explored as the difference between MCS-accredited performance (MCS Service Company Ltd, 2024) and the COP derived from the BEIS-measured dataset (Energy Systems Catapult, Electrification of Heat Demonstration Project, (UK Data Service, 2023).

Dataset

The BEIS dataset is available as part of the Electrification of Heat Demonstration Project and provides an open-access measured data set for 742 HP installations in existing homes across Great Britain between November 2020 and August 2022. Of these, 185 dwellings with Air Source Heat Pumps (ASHP) were selected for analysis based on completeness of operational and metadata. These were mainly located in 3 cities, London, Newcastle and Edinburgh, as shown in Figure 1. The datasets have approximately 12-24 months of 2-minute sensor readings recorded starting at different dates, varying from January 2021 to August 2021 and ending at approximately August 2022. The measured dataset includes 9 important features of heat pump activity, including external air temperature (Celsius), heat pump output energy (kWh), and system energy consumed (kWh). The metadata has 130 features, both quantitative and qualitative, including building parameters, i.e., (dwelling age, dwelling typology, floor area), demographic parameters, i.e., (occupant age, number of occupants, social class, HP awareness), and heat pump parameters, i.e., (model number, brand); 26 quantitative and 20 qualitative features were used in the model.

METHOD

The methodological pipeline involves the derivation of quantitative parameters for assessing the performance gap and performance attributes, as shown in Figure 2. This paper is developed in Python, and the ML model plots were implemented in Python using a free and open-source library, i.e., matplotlib (Hunter, 2007), SciPy

(Virtanen et al., 2020), scikit-learn (Pedregosa et al., 2011). Python is used because of its potential in advanced ML application, i.e., Deep Learning (DL), and its scalability for large-scale deployment and compatibility. The performance gap, the daily mean of the heat pump, COP, deployment time, cycles and part load were included to derive a total of 27 quantitative features using the measured dataset. A Hilbert transform and mean-pass filter is applied to de-noise the time-series of the COP gap and extract time-series features, i.e., maxima, minima, and area, are computed, resulting in an additional 53 quantitative features. Metadata was used to derive 20 categorical features encoded into 156 binary features for assessing performance attributes. After pre-processing and features computation, a data input matrix of 185[Dwellings] x 262[Features]: 185 dwellings dataset were randomly split into 3 sets: train set, test set and independent set, and then fed to the SOM machine learning model for clustering the HP efficiency and performance gap relative to their accredited position. An independent set is a dataset that has never been exposed to the ML model. Selected dwellings in the independent set are excluded at the split dataset procedure prior to model training and computing the model's standard scaler. The Independent set represents the blind test of the model, which indicates the true accuracy and performance of the trained model.

Figure 1: Geographic location of 185 dwellings in the BEIS dataset across the UK.

Pre-processing and features computation

Application of this handling procedure to a subsequent dataset is likely to vary depending on that dataset's characteristics and structures. The BEIS dataset has approximately 12 months of 2-minute sensor readings recorded. The 2-minute daily recording of 720 data points was computed to a daily data of 365 data points.

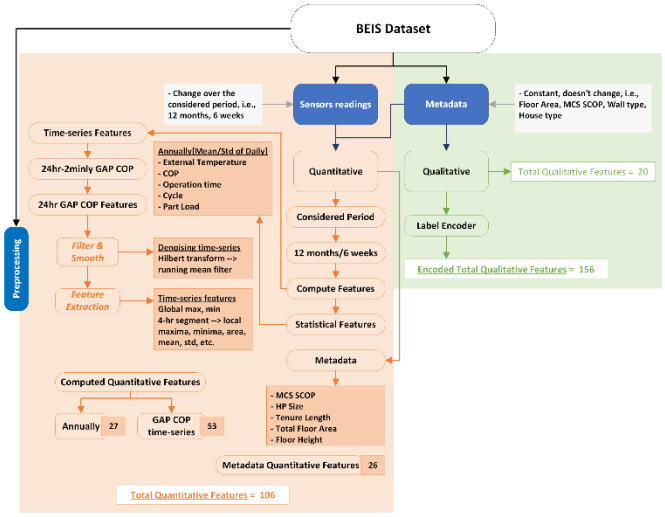

Figure 2: Flowchart of the data pre-processing method.

Statistical features

The statistical features were derived depending on the considered period. This case study considered 6-week and 12-month periods to compute statistical features, as shown in Table 1. Mean, maximum, minimum, standard deviation and summation of considered period data points were the statistical procedures used to compute annual features (12 months) and 6-week features, a total of 27 quantitative features. The mean daily COP of 185 dwellings across the UK can be illustrated in Figure 3. In contrast, bigger sizes and darker colours indicate higher COP. In this context, selected dwellings and considered period, dwellings in Edinburgh generally had higher COP than others.

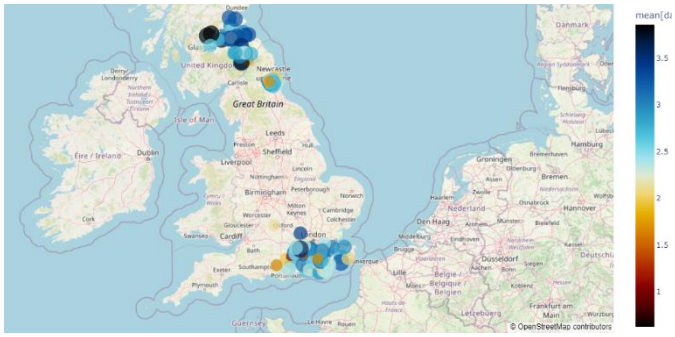

Figure 3: Annual mean COP in a geographic location of 185 dwellings.

Table 1: Summary of computed statistical features.

Computed statistical features
Mean of Daily Min External Temperature
Mean of Daily Max External Temperature
Mean of Daily Mean External Temperature
Max of Daily Min Heat Pump Heating Flow Temperature
Max of Daily Max Heat Pump Heating Flow Temperature
Max of Daily Mean Heat Pump Heating Flow Temperature
Max of Daily Cycle
Mean of Daily Cycle
Standard deviation of Daily Cycle
Summation of Daily Cycle
Mean of Daily Operation time
Mean of Daily Operation time
Mean of Daily Operation time
Mean of Daily Operation time
Min of Daily COP
Max of Daily COP
Mean of Daily COP
Standard deviation of Daily COP
Minimum of Daily COP of Space Heating
Maximum of Daily COP of Space Heating
Mean of Daily COP of Space Heating
Standard deviation of Daily COP of Space Heating
Min of Daily COP of Domestic Hot water
Max of Daily COP of Domestic Hot water
Mean of Daily COP of Domestic Hot water
Standard deviation of Daily COP of Domestic Hot water
Mean of Daily Part load

Time-series features

The 2-minute measured data was computed to 24-hour/2-minute gap cop. The cumulative heat pump energy output and cumulative whole system energy consumed were calculated to discrete differences with 2 minutely resolution. COP is computed as follows:

$$COP = HP_E/S_E \quad (1)$$

where HP_E is the summation of the discrete difference of heat pump energy output, and S_E is the summation of the energy use. The illustrative example of 2-minute summations over the considered period (12 months and 6 weeks) of the COP time-series can be illustrated as shown in Figure 4a, computed using the Property_ID: EOH1302 dataset.

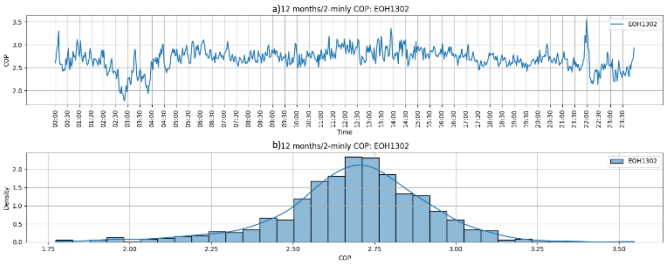

Figure 4: a) 12 months of 24-hour 2-minute COP time-series. b) a histogram of the density distribution of Figure 4a.

Figure 4b shows a histogram representing the density distribution (normalising the histogram's total area equals 1) of 2-minute COP over 12 months. The gap of the COP time-series was computed by:

$$GAP_COP = MCS - HP_E/S_E \quad (2)$$

where MCS is MCS-accredited performance according to (MCS Service Company Ltd, 2024). 53 time-series features, i.e., maxima, minima, and area, are computed from the gap COP time-series. Computed features and descriptions are summarised in Table 2. A Hilbert transform and mean-pass filter in the SciPy module (Virtanen et al., 2020) are applied to de-noise the time series of the COP gap, as shown in the illustrative example in Figure 5. In this case, the Hilbert transform performed well to capture the peak amplitude of the signal, while the low-pass filter performed fairly well just to smooth the signal. Time interval segmentation of time-series data was implemented to capture the behaviour of the heat pump usage in different periods in a day, i.e., every 4 hours. Then, time-series features were extracted to highlight the difference in the usage behaviour at different periods of the day for each dwelling. An example of the computation of time-series interval features can be seen in Figure 6.

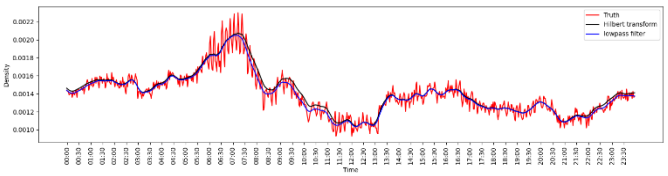

Figure 5: An illustrative example of the denoising time-series using the Hilbert transform.

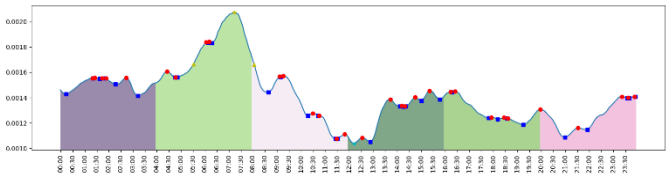

Figure 6: An illustrative example of the time-series features extraction, maxima minima and area.

Table 2: Summary of computed time-series features.

Name	Description
glob_min	Global minimum of COP.
time_gmin	Time of global min (in decimal from 0 to 24).
glob_max	Global maximum of COP.
time_gmax	Time of global min.
minima_count	Number of minima points appears in time-series.
minima_mean	Mean of COP of all minima points.
minima_std	Standard deviation of COP of all minima points.
time_minima_mean	Mean of time of all minima points.
time_minima_std	Standard deviation of time of all minima points.
maxima_count	Number of maxima points appears in time-series.
maxima_mean	Mean of COP of all maxima points.
maxima_std	Standard deviation of time of all maxima points.
time_maxima_mean	Mean of time of all maxima points.
time_maxima_std	Standard deviation of time of all maxima points.
maxima_factor	maxima_mean/glob_max
minima_factor	minima_mean/glob_min
glob_factor	glob_max/glob_min
local_factor	maxima_mean/minima_mean
GAP_COP_area	Area under the curve of gap COP time-series.
diff_percent_ MCS_SCOP_area	100*GAP_COP_area/MCS_SCOP_area where MCS_SCOP_area is the area under line of MCS_SCOP value.
hmax_area	Area under the curve of the global peak between 20% pre and post.
dist_den_min	Minimum distribution density value of the time-series.
dist_val_min	Corresponding value of the minimum distribution density.
dist_den_max	Maximum distribution density value of the time-series.
dist_val_max	Corresponding value of the maximum distribution density.
interv_dist_area_	Interval area under the curve of the distribution density. [0-33], [34-66], [67-100] %.
interv_maxima_count_	4 hrs interval of the maxima counts; ['0:01-4:00', '4:01-8:00', '8:01-12:00', '12:01_16:00', '12:01_16:00', '16:01_20:00', '20:01_0:00'].
interv_maxima_mean_	4 hrs interval of the maxima counts.
interv_maxima_std_	4 hrs interval of the mean of COP of all maxima points.
interv_GAP_COP_area_	4 hrs interval of the area under the curve of gap COP time-series.
interv_diff_percent_ MCS_SCOP_area_	4 hrs interval of the diff_percent_ MCS_SCOP_area.

A total of 80 computed quantitative features together with 26 selected metadata quantitative features, can be expressed in the correlation matrix of 106 features, as shown in Figure 7. The non-zero correlation value distribution, corresponding to the correlation matrix in Figure 5, can be illustrated in Figure 8.

Table 3: Summary of selected categorical features from BEIS metadata.

Name	Name
EmployStatus	Main_Fuel
EmployType	Heat_Primary_Source
HouseIncome	Heat_Secondary_Source
Social_Group	TS_Existing
House_Type	Name_Install
House_Form	HP_Brand
House_Env	HP_Model
House_Age	HP_Refrigerant
Wall_Type	HP_Awareness
Floor_Type	Delivery_Contractor

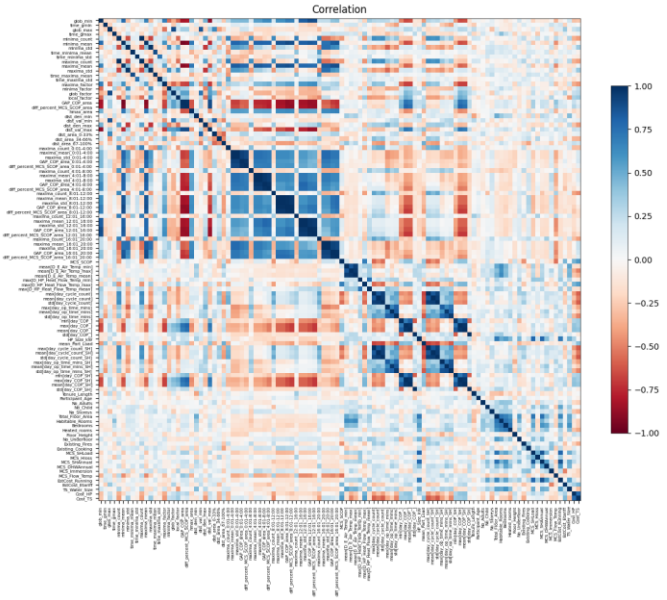

Figure 7: Heatmap of the correlation matrix of 106 features.

Categorical features

The BEIS metadata has 130 quantitative and qualitative features, but only 20 non-binary categorical features

were considered as the potential underlying performance gap factors, as shown in Table 3. 20 categorical features were encoded into binary values (0 or 1) to 156 binary categorical features using "OneHotEncoder" module from scikit-learn (Pedregosa et al., 2011).

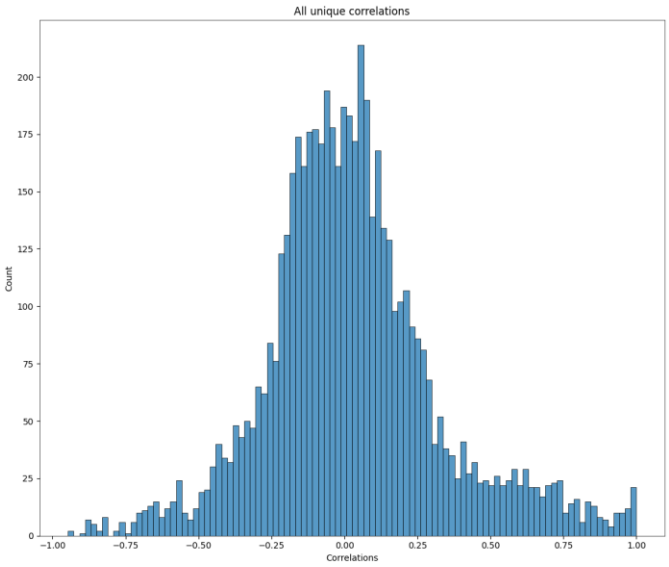

Figure 8: Histogram of the non-zero correlation values.

Self-organising map modelling

Self-organising map (SOM) is an unsupervised machine learning technique widely used to produce a simple low-dimensional representation of complex, nonlinear, high-dimensional dataset. MiniSOM (Vettigli, 2018) was used to implement the SOM model in this paper.

Splitting dataset

Annual COP for 185 dwellings calculated in the previous section; statistical features show that 41 dwellings have COP more than 3.0, around 100 dwellings, which account for more than 60 %, have COP ranging from 2.0 to 3.0, while only 18 dwellings have COP less than 2.0. This procedure is required to avoid overfitting issues and maintain the generalisation of the ML model performance in the training procedure; datasets were split into 4 groups based on the range of Annual COP, as shown in Table 4. Only 6-week period of BEIS-measured data were used in the test and independent set because the model was expected to utilise the least data to forecast and cluster the dwellings into the same categorical group in the train set. The underlying reason is that all occupants, installers, asset owners, and service partners can implement early intervention before warranty or retention periods expire. The 12 datasets from each group were randomly picked, as shown in the illustrative distribution density plot in Figure 9. An independent set is considered a dataset that has never been exposed to the ML model and is excluded at the beginning. Only train and test sets were used as a model standard scaler (Dataset standardisation).

Table 4: Datasets split into 4 groups based on annual COP.

Annual COP	Count-(%)	Train set-(%)	Test set-(%)	Indep set-(%)
< 2.0	18-(9.7)	12	5	1
2.0 – 2.5	61-(32.9)	12	39	10
2.5 – 3.0	65-(35.1)	12	43	10
> 3.0	41-(22.2)	12	24	5
Total	185-(100)	48-(25.9)	111-(60)	26-(14)
Start date		Aug 2011	Oct 2021	Oct 2021
End date		Aug 2022	Nov 2021	Nov 2021

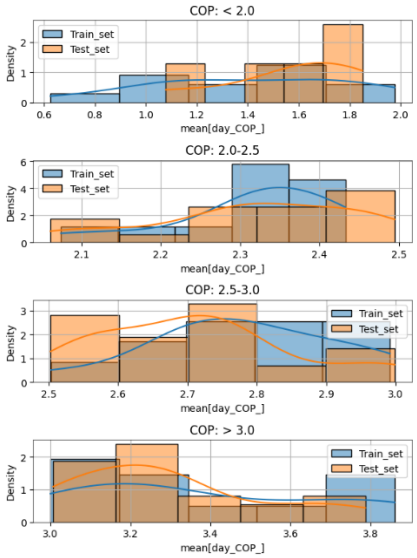

Figure 9: Distribution density plot of generated random pick for train and test set.

RESULTS AND DISCUSSION

Clustering

In this scenario, 3 cluster groups (Group 1, Group 2 and Group 3) were appropriate numbers for clustering using the SOM model together with a set of computed data, input matrix of 185[Dwellings] x 262[Features]. Group 1 is well-performed, Group 2 is medium-performed, and Group 3 is worst-performed. The SOM model performed well in the clustering test and independent set into the

same different percentages of MCS area, as shown in Figure 10. While Figure 10a shows clustering results between the train and test set, Figure 10b shows overlapping plots for the train, test, and independent set, indicating the SOM model can capture certain patterns and successfully cluster the COP gap dwellings together.

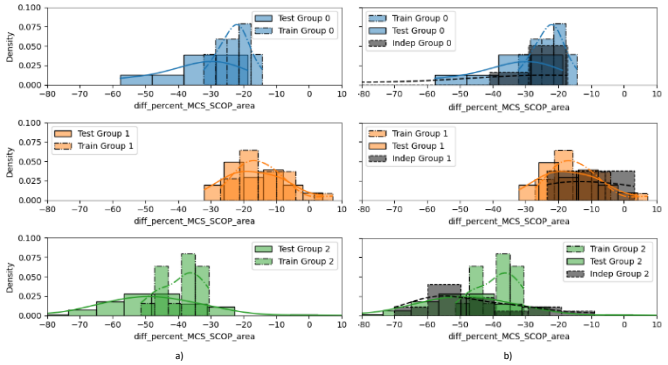

Figure 10: a) Distribution density plot of 3 clusters for train and test set. b) Overlapping distribution density plot of 3 clusters for train, test, and independent set.

Quantitative features

A coupled quantitative feature can be illustrated with a low-dimension plot. A 2-dimensional plot between the mean daily of the COP and the MCS percentage difference of COP can be plotted in Figure 11. The precise 3 clusters can be seen among well-performed, medium-performed, and the worst-performed clusters. The model performed well in clustering the test and independent set into the same cluster group from the train set. Figure 12 shows a low correlation between the estimated cost of HP and the MCS percentage difference of COP, and every range of estimated HP cost appeared all across the cluster groups. This indicates that the cost of HPs may not contribute to or have a minimal contribution to the heat pump's performance. The horizontal top and vertical left plots show the corresponding distribution density of each dataset and its cluster group by colour.

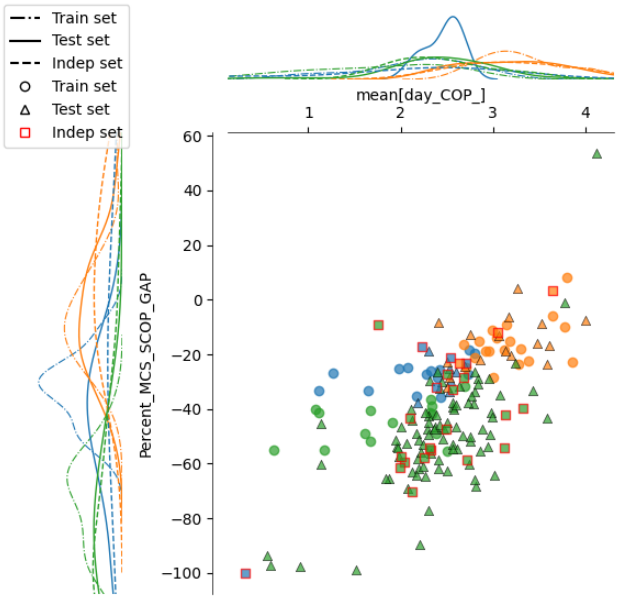

Figure 11: Scatter plot with distribution density between the annual daily mean COP and the area percentage different COP by cluster group.

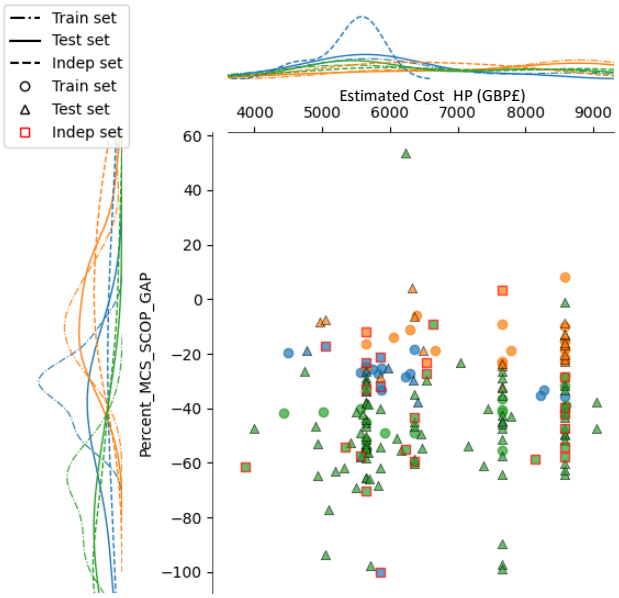

Figure 12: Scatter plot with distribution density between the area percentage different COP and the estimated cost of heat pumps by cluster group.

Qualitative features

Qualitative features are challenging to visualise; however, the number of counts and their mean can indicate the frequency and trends for each feature and cluster. The matrix histogram plot of the house environment from metadata and the MCS percentage

difference of COP by cluster group can be seen in Figure 13. The clustering result shows that houses in a suburban environment tend to perform better than other houses in different environments among the well-performed group (Group 1), while houses in an urban environment are obviously labelled in the worst-performed group (Group 3) compared to other clusters. The matrix histogram plot between the house type and the MCS percentage difference of COP, as shown in Figure 14, shows that most 185 dwellings in the BEIS datasets are detached and semi-detached house forms. In this scenario, it is appropriate to interpret a result accounting for only 2 major house forms, detached and semi-detached. The figure shows that the detached house form may perform better than the semi-detached house form, with a higher number of counts between Groups 1 and 2.

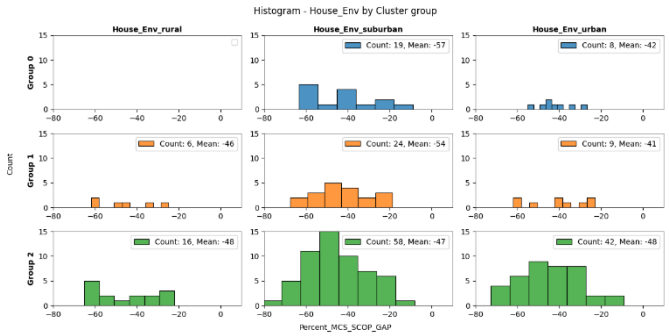

Figure 13: Matrix histogram plots between the house environment and the area percentage different COP by cluster group.

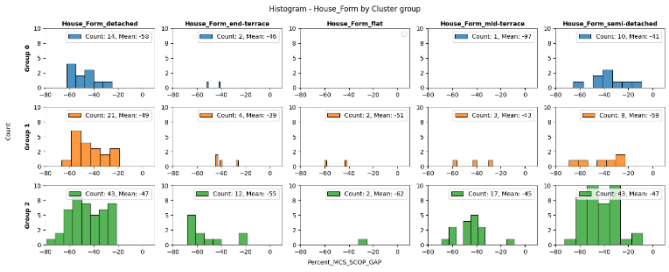

Figure 14: Matrix histogram plots between the house forms and the area percentage different COP by cluster group.

CONCLUSIONS

In this paper, the model performed well in this scenario, clustering the 185 dwellings across the three specified categories for their performance under the given building, demographic and operational factors. This proposed methodology, which has a computed set of features, works well for COP gap clustering. The model performs well in clustering the 6-week data from the test and independent set. The model can cluster independent datasets into expected groups with an accuracy of (25/26) 96%. The model can be further developed to be a reliable tool for predicting the performance of HPs based on the measured data and metadata. However, the performance may vary with another generated random pick of the dataset with another 6-week of data. Randomness is a part of constructing the model, resulting in variation in the model's performance. Many more simulations are needed to evaluate the model's performance and sensitivity.

ACKNOWLEDGEMENTS

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