



Occupancy level prediction based on a sensor-detected dataset in a co-working space

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ABSTRACT

Hybrid working has reshaped people's routines and working habits, while the workplace needs to evolve with the new working pattern. Co-working space is seen as an alternative work environment, for cost-effectiveness, the opportunity for flexible design and multi-use. This study investigates the occupancy patterns and occupants' behaviour using multiple occupancy sensor data with a twelve-months sample. Data-driven AutoRegressive Integrated Moving Average (ARIMA) time series model is applied to predict office occupancy in a co-working space in London. The results reveal some spatial-temporal variations in the number of occupants based on the detected locations. The spatial distribution of occupants around different working areas in the co-working space is plotted to demonstrate the seat preferences and its temporal occupancy density variation.

CCS CONCEPTS

• **Applied computing** → **Architecture (buildings); Engineering.**

KEYWORDS

hybrid working, occupancy prediction, co-working space, time series modelling

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1 INTRODUCTION

The workplace evolves with the change in information and communication technology, working pattern and human demand. While the pandemic has significantly influenced people's daily life and working routine, the local co-working hub is an alternative solution to traditional offices after the pandemic. It provides an environment

for different workers to network and collaborate with various usage options [12], while ensuring flexibility, diversity and dynamics at a lower cost [13, 17, 23]. Meanwhile, the improvement in the data available on quantifying the qualities and characteristics of space has enabled the search for generalised patterns in space and behaviour [14]. Collecting data-driven evidence about spaces, cultures, behaviours and space usage patterns helps form better design decisions [19]. The concept of data-driven and evidence-based design has immense potential for application to future office design to accommodate hybrid working.

There is a need to understand the change in working patterns and office use in the post-pandemic time. Sensor-tracked occupancy data could effectively reveal evidence of how people interact and use the office space. Furthermore, the analysis and prediction of occupancy level and occupants' preferences in offices could constructively be applied to inform and enhance the future designs and refurbishments of the offices. Therefore, this study explores the occupancy pattern in a co-working space in London with year-long high-resolution sensor-detected data. The sensors tracked occupancy from April 2021 to June 2022. A preliminary analysis of the occupancy data is presented in this paper. An AutoRegressive Integrated Moving Average (ARIMA) model is applied to predict occupancy. In this paper, Section 2 reviews the literature about office occupancy and the current research gap. Section 3 introduces the site information and key methods like exploratory analysis and prediction in time series modelling. Section 4 presents the preliminary results of the analysis and prediction model, and Section 5 includes the summary and future development of this study.

2 LITERATURE REVIEW

2.1 Occupancy analysis in offices

The analysis and prediction of occupancy in offices have long been a widely discussed topic, while most research focuses on predicting occupancy patterns for energy use [9, 20, 21]. Accurately determining occupancy detection contributes significantly to the efficient control of heating, ventilation and air conditioning. However, occupancy data is difficult to collect due to privacy concerns and the lack of infrastructure in buildings to sense people accurately [9]. The challenges are gradually solved by applying smart building and sensor technology. In current studies, the occupancy data are collected or detected in different methods, such as CO2 sensors [22], environmental sensors [5], real-time locating systems [21], surveillance video [26] and passive infrared motion sensors [9]. Various periods, approaches and scales are applied for the prediction. For example,



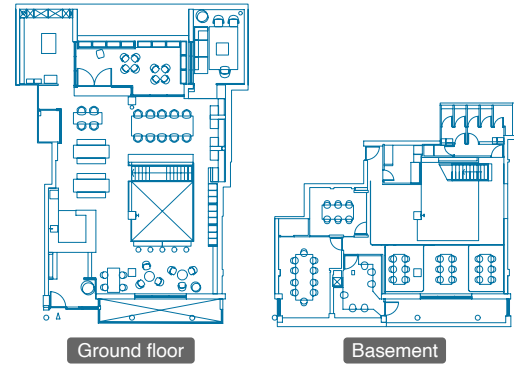
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Ref. [5] applies a classification model to predict occupancy based on environmental conditions like temperature, humidity, light and CO2 levels in a small office room. Ref. [25] generates the simulation of zone-level occupancy and occupants' location with the Markov chain method. Ref. [26] purposes a real-time head detection and occupancy measurement algorithm using the surveillance video in a university office. In addition to understanding the improvement of energy efficiency, the prediction of occupancy level in offices could have a further implication in the post-pandemic time to inform and utilise office design, which is discussed in the next section.

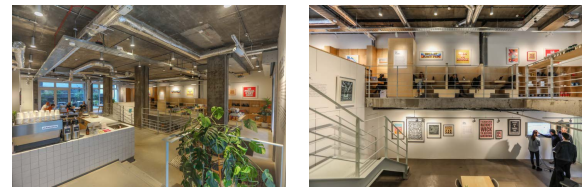
2.2 Hybrid workplace for future

The rise of hybrid working after the pandemic demands considerable freedom of choice in work seat location selection. A balanced hybrid mode is expected to be the dominant working mode globally, especially in the finance and technology sectors. In contrast, occupants are not expected to go into their workspaces five days a week [6]. Therefore, occupancy level in traditional offices is expected to decrease [3], while multiple new workplace options, such as home offices, co-working spaces and remote workspaces, have become popular alternatives. The role of the office is gradually shifting away from providing spaces for day-to-day work, and a fresh look at how the office space can be used to enhance collaboration, productivity, corporate culture, and work experience in the future is necessary [1, 6]. The design of the office could be more flexible and resilient by replacing the fixed seats and cubicles with flexible layouts and desk-sharing with multi-function areas, thus maximising the space efficiency and saving the rent, maintenance fee and operation costs [3]. Therefore, the variation of occupancy levels in offices after the pandemic is an essential topic to be explored. An accurate prediction of the number of occupants could contribute to the design decisions decision by answering the questions like how many employees are expected to come to the office and when they usually come in a hybrid working mode. Thus, the facilities, seats and design style can be reconsidered and redesigned accordingly.

Co-working space, with its concepts of flexible, dynamic and resilient design, is an alternative option to home offices and semi-public places [4] and an effective model for the future of the work environment [13]. However, the use, function and design of co-working spaces remain to be explored in research. Previous studies identify co-working space as a favourable workplace for start-ups, freelancers and creative industries [12]. Kwiatkowski and Buczynski [15] outline five core values for co-working space: collaboration, openness, community, accessibility and sustainability. The motivation for using co-working spaces comes from the desire to separate work and life and achieve a better balance and the willingness to meet and engage with similar professionals. Users' satisfaction is affected by the factors like the convenient location, open space layout, shared facilities, flexible leases and knowledge sharing [23]. In a questionnaire survey, occupants also indicate a preference for minimalist and industrial design styles [12]. However, there is a lack of literature focusing specifically on the design logistics of the co-working offices. With the aid of sensor-detected occupancy, the occupancy level and use of the co-working office can be explored further to inform data-oriented design, which has not been demonstrated in published research before.



(a) Site plans.



(b) Site photos.

Figure 1: Site information.

3 METHODS OF STUDY

3.1 Site information and data collection

The case study presented here is a co-working space located near Old Street in London. It started its operations in early 2020. While designed with concepts of multi-use, flexibility and creativity, it also functions as a local café, an event space and an exhibition space. The maximum occupancy capacity of the space is about 70 people. It runs from 9 am to 6 pm on weekdays. As Figure 1 shows, the case study site occupies the ground floor (left in Figure 1(a)) and basement (right in Figure 1(a)) of the building. The ground floor includes a café, a reception and multiple working areas. The basement is primarily used as the meeting area with two enclosed meeting rooms and several flexible tables for meeting and working. Site photos are presented in Figure 1(b).

The data is collected using about 30 PointGrab sensors installed on ceilings inside the case study space [18]. PointGrab sensors can be applied with a specific use case of space management and workplace optimisation in the hybrid working setting. The sensors detect the timestamped location of each occupant every second in an x-y coordination system. The data collection period is from the middle of April 2021 to early June 2022, which is about one year and a month (302 business days). The original data is stored in PostgreSQL [24] and analysed in Python 3 [24]. Firstly, the number of occupants is counted by adding up the number of coordinates recorded in the dataset. The frequency of this dataset is transformed from second to hour and business day. The maximum number of people per day is computed as the daily occupancy level.

Table 1: Model Information

Description	Value
Approach	Univariate
Original data shape	(302, 1)
Transformed data shape	(302, 1)
Transformed train set shape	(242, 1)
Transformed test set shape	(60, 1)
Rows with missing values	0%
Fold Generator	ExpandingWindowSplitter
Fold Number	3
Seasonal period tested	5
Seasonalities detected	5

3.2 Time series analysis of occupancy level

Time series is defined as a list of numbers and the time when those numbers are recorded [10]. Time series analysis is applied to extract meaningful statistics and characteristics of a time series dataset. In this analysis, the Python package PyCaret [2] is applied to perform most of the time series analysis and prediction. Table 1 shows the model setup information for exploratory analysis.

3.2.1 Autocorrelation and partial autocorrelation. Autocorrelation in time series exploration examines the linear relationship between lagged values of a time series [10]. The autocorrelation coefficients are plotted to present the autocorrelation function (ACF). Time series patterns like trend and seasonality can be observed in ACF. The trend implies the presence of a general trend of decreasing, increasing or stagnation over a period of time [11]. A seasonal pattern appears when a time series is influenced by seasonal factors with fixed and known frequency, such as the time of the year or the day of the week. Trend of time series is shown by a large and positive autocorrelation between small lags, while seasonality is observed from a larger autocorrelation in seasonal lags compared to other lags [10]. The partial autocorrelation function (PACF) is a supplement to ACF. It measures the correlation between two observed data after removing the effect of lags in between.

3.2.2 Stationarity test. The stationarity of time series data indicates whether the properties of data depend on the time at which the series is observed or not. A time series with trends or seasonality is not considered stationary, while a white noise series is a stationary series [10]. The stationarity tests help determine whether the differencing is required to process the data for the ARIMA model. An Augmented Dicky-Fuller (ADF) test examines the presence of unit roots. The null hypothesis is that there is a unit root, implying that the data series is not stationary [8]. The primary alternative hypothesis is that time series is stationary. The more negative test statistics indicate stronger evidence of rejection; subsequently, differencing is not needed. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is an alternative way to examine the stationarity of the dataset, with a null hypothesis that data are stationary [16]. In this case, a small p-value (normally less than 0.05) shows that differencing is required.

3.2.3 Time series decomposition. Time series decomposition splits the series into several components, while each component represents an underlying pattern category. There are three key components in the decomposition: a trend-cycle component, a seasonal component and a remainder component [10]. Both the classical decomposition and Seasonal and Trend decomposition using Loess (STL) decomposition are applied. Classical additive decomposition assumes the seasonal component is constant, while STL is a robust method that applies Loess smoother and handles any type of seasonality [7].

3.3 Time series modelling

Time series forecasting is the process of predicting future events based on past information and historical trends. In this study, ARIMA (AutoRegressive Integrated Moving Average) model is applied to predict the occupancy level of each business day. ARIMA is a classical univariate model for forecasting and describes the autocorrelations in the data. It refers to the combination of differencing with autoregressive (AR) model and a moving average (MA) model, represented in Eq (1).

$$y'_t = c + \phi_1 y'_{t-1} + \dots + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t, \quad (1)$$

where y'_t is the differenced series. The model is typically denoted as ARIMA (p, d, q), where p is the number of autoregressive lags; d is the order of differencing applied to make the data stationary; q is the number of moving average lags [10]. Seasonality can be added to ARIMA model while a seasonal pattern is detected in the dataset, to form a seasonal ARIMA (referred as 'SARIMA') with a seasonal order s . The values of p, d, q and s are determined in the exploratory analysis and by testing the combination to choose an optimal model. In this prediction, a period of 60 days is set as the prediction period, while the fold is set as three. The performance of the prediction model is evaluated by scale-dependent errors like mean absolute error (MAE) and root mean squared error (RMSE), percentage errors like mean absolute percentage error (MAPE) and 'symmetric' MAPE (sMAPE) and scaled error like mean absolute scaled error (MASE) [10].

3.4 Seasonal spatial analysis

A preliminary descriptive analysis of the spatial pattern is also presented. The coordinates of each occupant at every second are transformed to a grid structure and plotted as heatmaps by four seasons from June 2021 to May 2022. This part of the analysis aims to observe the spatial-temporal pattern of the occupancy and seat preferences around the study area, which could be developed into a location-based prediction model in the future.

4 PRELIMINARY RESULTS AND DISCUSSION

4.1 Descriptive data and exploratory analysis

The descriptive analysis of the collected sensor data is presented in Figures 2 to 4. The box plots show the variation of average occupancy level by hour (Figure 2), by business day (Figure 3) and by month (Figure 4). On a typical day, the occupancy level shows a steady increase from the beginning of the day and gradually reaches the peak at lunch time around 1 pm to 3 pm. Wednesday is the most popular day, with more people coming to work in a typical week,

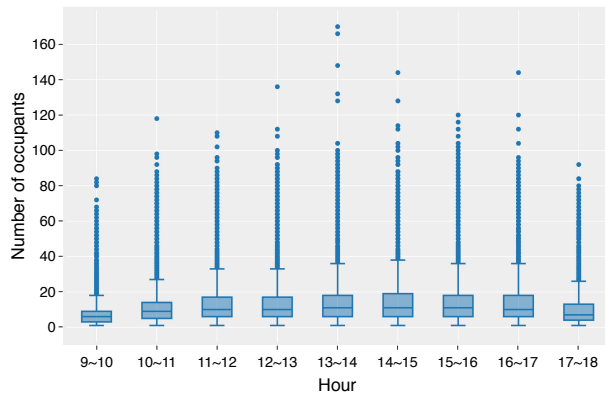


Figure 2: Average number of occupants by hour.

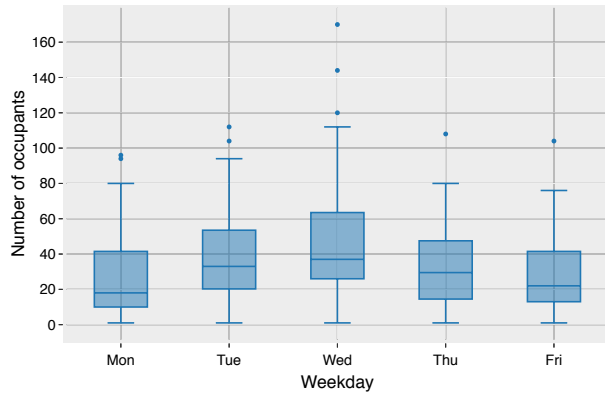


Figure 3: Average number of occupants by business day.

while Monday and Friday have a limited number of occupants. The daily number of occupants varied significantly across the months. An increase in occupancy level is observed in August, which is in line with the alleviation of COVID-19 social distancing restrictions in late July in England. The autumn months, like September, October and November in 2021, have a higher occupancy compared with other months. December features a substantial variation with an extremely high number and some relatively low, probably due to the Christmas event and the long holiday. The occupancy level shows a relatively stable trend with a slight increase since the year of 2022 starts.

Figure 5 is the time plot of the daily maximum occupancy series. The general trend agrees with the findings from the monthly occupancy plot, while the day-to-day fluctuating pattern potentially indicates the seasonal cycle of the data, which requires further exploration. Table 2 shows the basic statistics of the exploratory time series model. The mean daily occupancy is around 35 with a standard deviation of 27.18. The occupancy counts show a non-stationary trend according to the results of the ADF and KPSS tests, indicating differencing is required. A first-order differencing is applied to stabilise the data and make the series stationary. The differencing series is plotted in Figure 6. The result of stationary tests is presented in Table 3. Good stationarity is observed in this

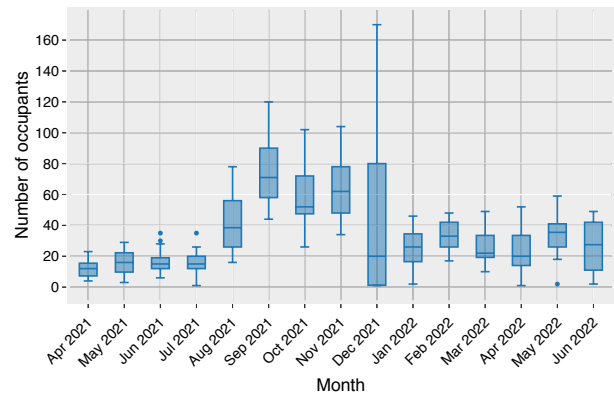


Figure 4: Average number of occupants by month.

Table 2: Model statistics test (occupancy count).

Test	Test name	Property	Setting	Value
Summary	Statistics	Mean	N/A	34.629
Summary	Statistics	Median	N/A	27
Summary	Statistics	Standard Deviation	N/A	27.182
Summary	Statistics	Variance	N/A	738.839
Stationarity	ADF	p -value	{alpha': 0.05}	0.278
Stationarity	ADF	Test Statistic	{alpha': 0.05}	-2.020
Stationarity	ADF	Critical Value 1%	{alpha': 0.05}	-3.453
Stationarity	ADF	Critical Value 5%	{alpha': 0.05}	-2.872
Stationarity	ADF	Critical Value 10%	{alpha': 0.05}	-2.572
Stationarity	KPSS	p -value	{alpha': 0.05}	0.010
Stationarity	KPSS	Test Statistic	{alpha': 0.05}	0.406
Stationarity	KPSS	Critical Value 10%	{alpha': 0.05}	0.119
Stationarity	KPSS	Critical Value 5%	{alpha': 0.05}	0.146
Stationarity	KPSS	Critical Value 2.5%	{alpha': 0.05}	0.176
Stationarity	KPSS	Critical Value 1%	{alpha': 0.05}	0.216

Table 3: Model statistics test (first-order differencing series).

Test	Test name	Property	Setting	Value
Summary	Statistics	Mean	N/A	0.149
Summary	Statistics	Median	N/A	0
Summary	Statistics	Standard Deviation	N/A	20.556
Summary	Statistics	Variance	N/A	422.533
Stationarity	ADF	p -value	{alpha': 0.05}	0.000
Stationarity	ADF	Test Statistic	{alpha': 0.05}	-6.599
Stationarity	ADF	Critical Value 1%	{alpha': 0.05}	-3.453
Stationarity	ADF	Critical Value 5%	{alpha': 0.05}	-2.872
Stationarity	ADF	Critical Value 10%	{alpha': 0.05}	-2.572
Stationarity	KPSS	p -value	{alpha': 0.05}	0.100
Stationarity	KPSS	Test Statistic	{alpha': 0.05}	0.066
Stationarity	KPSS	Critical Value 10%	{alpha': 0.05}	0.119
Stationarity	KPSS	Critical Value 5%	{alpha': 0.05}	0.146
Stationarity	KPSS	Critical Value 2.5%	{alpha': 0.05}	0.176
Stationarity	KPSS	Critical Value 1%	{alpha': 0.05}	0.216

transformed dataset, with a p -value of 0 for the ADF test that fully rejected the null hypothesis and a p -value of 0.1 for the KPSS test.

The ACF and PACF diagrams for the original data (Figure 7) and differencing data (Figure 8) validate the stationary tests. In the original series, the autocorrelation is the highest at the first and fifth day, and a seasonal lag of five can be identified from the ACF chart. The positive autocorrelation implies the presence of a trend. A similar fluctuation pattern is observed in ACF and PACF

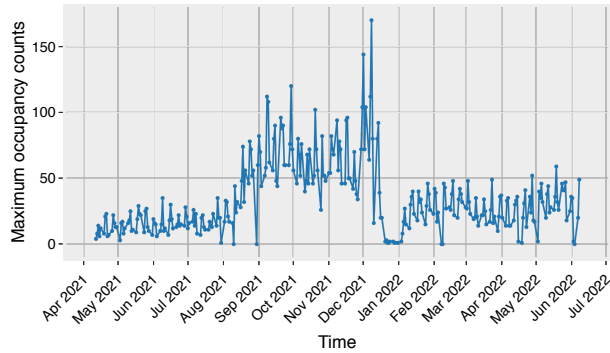


Figure 5: Maximum occupancy counts for each day (late April 2021 to early June 2022).

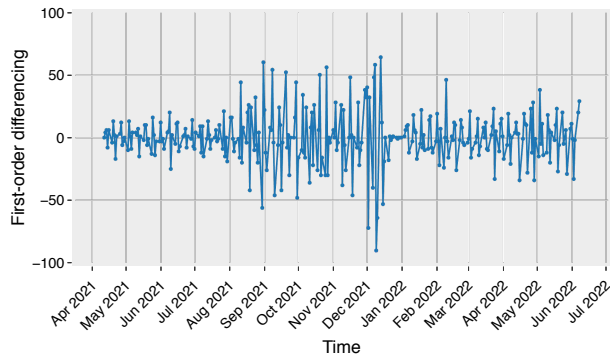


Figure 6: First-order differencing time plot.

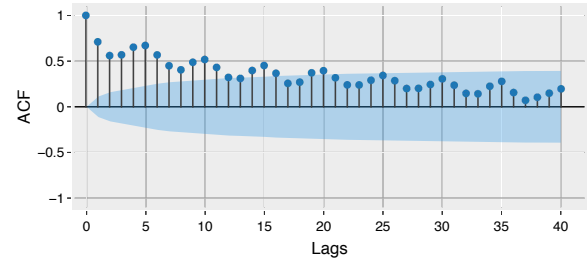
charts. For the series after differencing, the ACF value drops to zero quickly, which indicates the stationary characteristics.

The time series decomposition is plotted in Figures 9 and 10. The two decomposition charts generally look similar. STL decomposition reveals a stronger seasonal component with a larger violation during the autumn and winter of 2021. The value and variation of residuals are relatively large, indicating that the uncertain and random factors after removing trend-cycle and seasonal components probably require further exploration and interpretation.

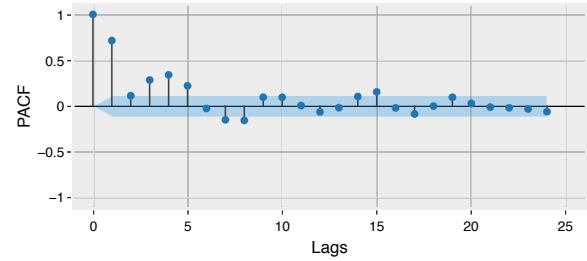
4.2 Time series forecasting

In the PyCaret model comparison function, the SARIMA (0, 1, 0, 5) model shows a better performance compared to other classical models like the exponential smoothing model, seasonal naïve forecaster and naïve forecaster, thus it is selected for the prediction in this case. Figure 11 shows the train-test split with a period of 60 days selected as the test set and a three-fold cross-validation.

The performance of the SARIMA (0, 1, 0, 5) model is shown in Table 4. The performance on cross-validation folds (in-sample results) is not very satisfying with a relatively large MASE at about 2.79, while the MASE for test set prediction is 0.6155, indicating a promising performance. Figure 12 visualises the prediction results of the ‘out of sample’ forecast. It could be observed that there are some deviations between the predicted value and the actual value in the zoom-in plot (Figure 12(b)). The largest gaps occur when



(a) Autocorrelation function (ACF).



(b) Partial autocorrelation function (PACF).

Figure 7: Autocorrelation plots for the occupancy count.

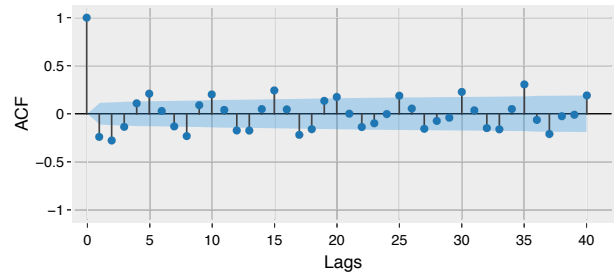


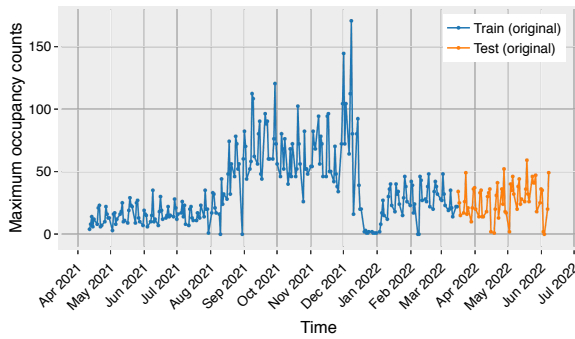
Figure 8: Autocorrelation function (ACF) plot for first-order differencing of the occupancy count.



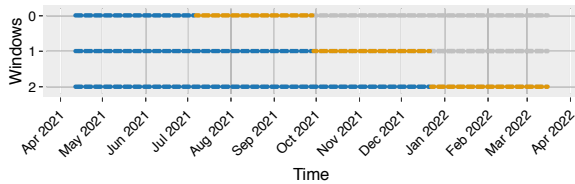
Figure 9: Classical time series decomposition (additive) for the occupancy count.



Figure 10: STL time series decomposition for the occupancy count.



(a) Time-series data.



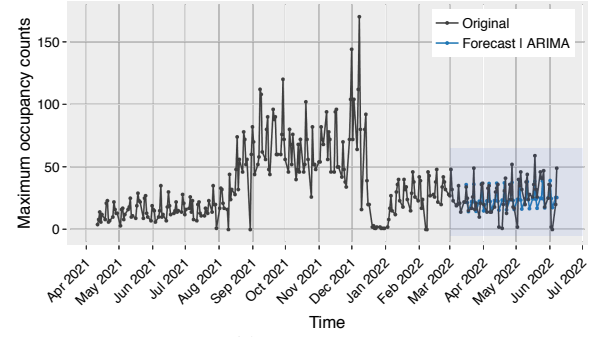
(b) Train cross-validation splits.

Figure 11: Train-test split for ARIMA modelling.

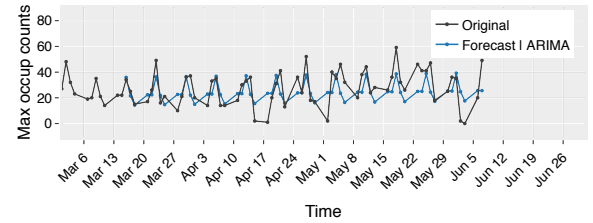
occupancy drops to zero on the easter holiday and bank holidays, which the model fails to consider in the prediction.

4.3 Spatial-temporal analysis by season

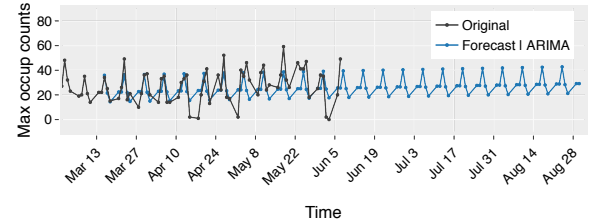
Four heatmaps of the cumulative occupancy level by season from June 2021 to May 2022 around the space are illustrated in Figure 13. The preliminary results indicate that the seasonal variation of occupants' seat preferences is relatively limited. In general, the table close to the window (upper side of the ground floor plan, Figure 14 (a)) and the semi-enclosed spaces (right side of the ground floor plan, Figure 14 (b) and (c)) are more popular. Occupants tend to use the small enclosed meeting room in the basement more compared to the larger one and the open meeting tables. It seems that less proportion of occupants choose the area close to the window during the summer, while the seats close to the central staircase with less direct natural lighting are preferable. In winter, even the sofa seats



(a) Full scale plot.



(b) Zoom-in plot (blue area in (a)).



(c) Zoom-in plot with a forecast period of 120 days.

Figure 12: ARIMA model forecasting plots.

facing the entrance street (lower side of the ground floor plan, Figure 14(d)) are more occupied than normal.

5 CONCLUSION

This study demonstrates the application of time series modelling in predicting occupancy levels in a co-working space in London. The sensor-detected occupancy data is transformed into time series to perform exploratory analysis and forecasting. A SARIMA (0, 1, 0, 5) model is used for time series forecasting, while the results shown in the performance of prediction is acceptable with some potential for improvement. The effective and accurate prediction of occupancy level help answer the questions like how many people will show up every day in a hybrid working context and how many fixed and flexible seats are required, subsequently helping designers figure out how to alter and utilise the current design according to the predicted occupancy. The heatmaps reveal the spatial pattern of the distribution of occupants, while the seats close to windows and the individual semi-enclosed spaces are more popular compared to other areas.

There are several limitations in this study. Firstly, the ARIMA model is a traditional time series forecasting model, while other

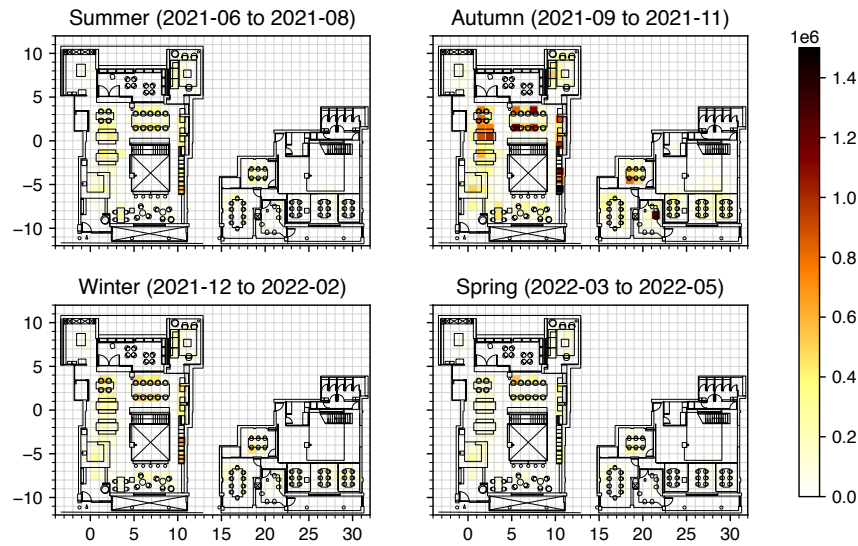


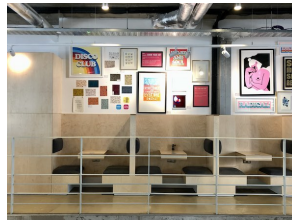
Figure 13: Heatmap of occupancy distribution by season 2021-2022.

Table 4: Model performance.

Cutoff	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
2021-07-06	4.6876	4.8485	24.3425	32.1610	4.0499×10^{15}	0.6625	-0.2418
2021-09-28	2.6031	2.2780	27.2768	35.5410	1.8898	0.4156	-0.3584
2021-12-21	1.0756	0.8018	17.4522	20.4717	3.0847×10^{14}	1.1557	-1.1151
Mean	2.7887	2.6427	23.0238	29.3913	1.4528×10^{15}	0.7446	-0.5718
Standard deviation	1.4804	1.6721	4.1178	6.4562	1.8407×10^{15}	0.3077	0.3871
Prediction model (period = 60)	0.6155	0.4992	9.0892	11.5501	1.3199×10^{15}	0.4098	0.2759



(a) Table close to the window.



(b) Semi-enclosed seat type 1.



(c) Semi-enclosed seat type 2



(d) Sofa seats near the entrance

Figure 14: Photos of the popular seats.

may have a better performance, which would require further exploration. The attempts on iteration, multiple train-test split and time scale alteration may also improve prediction performance. Additionally, the standard model fails to consider the holidays, which are found to have a significant impact on the occupancy level in an office. Secondly, the dataset is collected from only one case study site, while different data sources with various office layouts and capacities are required to reveal the general pattern. The preliminary analysis and results presented here are limited in providing insights to inform design decisions. However, they highlight the importance of understanding the spatial-temporal association of occupancy patterns in approaching future office design.

While the current time series forecasting is univariate, the future prediction could consider and build a multi-variate model to improve prediction accuracy. This study is being further developed to combine spatial analysis of the occupants' activities, seat preferences and environment preferences by coupling occupancy sensor data with multi-variate environmental sensors. These data-driven insights will visualise the changing demand and match the occupants' needs with the potential office design transformations.

models which combine the advanced machine learning methods

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