Do occupancy & environmental working conditions contribute to COVID-19 Outbreak risk in Meat Processing Plants (MMPs)?

Abstract: *This report investigated if occupancy and environmental factors contributed to COVID-19 outbreak risks within Meat Processing Plants (MPPs). Utilising analytical and visualisation techniques, the study analysed data from two primary sources: the WIBS (Wideband Integrated Bioaerosol Sensor) and Airvisual IQAir Pro. Data cleaning and processing were key, with the WIBS dataset undergoing consolidation and refinement to focus on biologically derived particles and temporal attributes. Similarly, the Airvisual IQAir Pro dataset was refined to highlight CO2 levels as occupancy indicators. The study's focus is its data visualisation in Tableau, featuring a dual-axis graph combining a line graph (CO2 levels) and a bar graph (bacterial bioaerosol particle counts), effectively demonstrating the correlation between these variables during work shifts. This visualisation employed contrasting colours for clarity and accessibility and included subtle annotations for work shift breaks. Additionally, an animation feature provided a dynamic view of data trends over a workday. The visualisation achieved its main goal in clearly illustrated the relationship between particle counts, CO2 levels, and working shifts, offering critical insights for mitigating COVID-19 risks in MPPs.*

1. INTRODUCTION

MPPs globally were deemed essential infrastructure due to their crucial role in the food supply chain, which allowed them to operate during COVID-19 lockdowns. However, the plants were especially susceptible to Covid outbreaks, which was likely due to the crowded indoor conditions and prolonged close contact among workers [8]. It has been noted in recent studies that there is a supposedly higher risk of airborne transmission of COVID-19 in indoor environments [7]. To determine if occupancy and environmental factors contributed to COVID-19 outbreak risks within MPPs, a pilot study was set to investigate the air quality in the boning hall and abattoir of various MMPs across Ireland. The study concluded that the spread of COVID-19 was more likely to happen in conditions with accumulated bioaerosols and carbon dioxide during a working shift [3]. However, there was a limited analysis conducted for the pilot study on a small set of the data for one or the various plants. This report will investigate and analyse the data from another one of the various plants to assess if occupancy and environmental working conditions contribute to COVID-19 Outbreak risk in MMPs by investigating the accumulation of bioaerosols and carbon dioxide during a working shift.

2. DATA COLLECTION

2.1. Dataset 1 - Wideband Integrated Bioaerosol Sensor (WIBS) data

The first set of data was collected using the WIBS is a real-time fluorescent spectrometer. This instrument is used to discern biological and non-biological aerosol particles. The differentiation is based on the detection of fluorescent concentrations in the particles. As a particle passes through the WIBS machine, the particle is excited by a laser, absorbing light and subsequently emitting fluorescence. The WIBS measures the particle's emission of fluorescent wavelengths providing insight into the particle's composition. Specifically, it can indicate if the particle contains Nicotinamide Adenine Dinucleotide (NADH) or tryptophan, biomolecules both prevalent in living cell proteins such as those in bacteria and viruses [4], [11].

Their presence can be used as a biomarker to indicate the presence of COVID-19 in the air. But they are not appropriate to use as official confirmation for the presence of COVID-19.

The structured raw data that was collected using the WIBS, was then stored and formatted into 1998 CSV files that ranged from 3 KB to 2.5 MB. The dataset consisted of quantitative data, with attributes being numeric measurements recorded by the WIBS and stored as real values (floats), suitable for mathematical analysis. The data is continuous, allowing each attribute to potentially assume any value based on the WIBS measurements. Once the files were aggregated into a data frame, the size of the dataset consisted of 8.7 GB of storage, with 21 columns and 53,125,456 rows of data.

<u>The attributes and their data types of the compiled data frame are as follows:</u>

- **Time:** This attribute is classified as temporal data, representing the milliseconds elapsed since initiation of the WIBS machine and the detection of a particle.
- **MeasT2, TotalT1, TotalT2:** These attributes are used for diagnosing the WIBS performance, such as power outages. They are categorised as interval data, as they contain negative numbers. This can be used to calculate the difference between individual readings.
- **Additional 15 attributes:** The rest of the attributes comprise of particle measurement and diagnosing the WIBS performance. These attributes are classified as ratio data, categorised by the absence of negative values and the significance of an absolute zero, which represents the non-detection of any entity within a given attribute [11].

2.2. Dataset 2 – Airvisual IQAir Pro data:

The second dataset was collected using the Airvisual IQAir Pro, a low-cost air quality sensor designed to capture environmental data such as temperature, humidity, and carbon dioxide (CO2) concentrations. The raw data from this sensor was stored into 6 text (.txt) files that ranged from 213 KB to 23 MB. Although text (.txt) files may initially be perceived as unstructured data, the format within these files was systematically organised, using semicolons to delineate each value, facilitating the easy conversion into a data frame. As there was a formatted orderly arrangement within the data, it should permit its classification as structured data. The structured data consisted of time series data and quantitative data, with attributes representing numerical measurements captured by the air sensor and stored as real values (floats). These data points are continuous, as each attribute can be ideally any value depending on how the sensor measures them. Once the files were aggregated into a data frame, the dataset size consisted of 142.5 MB of storage, with 18 columns and 910,905 rows of data.

<u>The attributes and their data types of the compiled data frame are as follows:</u>

- **Date, Time, Timestamp:** Are categorised temporal data.
- **SGPCO2(ppm), VOC(ppb), SGPCO2LTC(ppm), VOCLTC(ppb):** Are classified as interval data, these attributes include only negative numbers.
- **The remaining 11 attributes:** These are identified as ratio values; they are characterised by the absence of negative numbers. They include measurements such as temperature, CO2, and humidity levels.

The two datasets demonstrate key aspects of Big Data, specifically in terms of Volume and Variety. The WIBS dataset, with its extensive collection of over 53 million rows, illustrates the 'Volume' characteristic, whereas the air sensor dataset, comprising nearly 911 thousand rows, further supports this attribute. Additionally, the 'Variety' characteristic is highlighted through the analysis of data derived from two distinct types of sources, each gathered by specialised instruments. While the real-time data generation by both instruments could suggest the 'Velocity' aspect of Big Data, this study utilises static files from 2021, therefore it does not incorporate the 'Velocity' aspects of Big Data at this time.

3. DATA EXPLORATION, PROCESSING, CLEANING & INTEGRATION

In response to the research question, *"Do occupancy & environmental working conditions contribute to COVID-19 outbreak risks in MPPs"*, the primary goal was to investigate the potential correlation between bacterial bioaerosol particle counts, CO2 levels, and working shifts. Bacterial bioaerosol particle counts were utilised as biomarkers to indicate the presence of COVID-19. CO2 levels served as indicators of occupancy fluctuations within the plant, under the premise that increase in employee numbers would correspond to elevated CO2 levels. For the WIBS dataset, the key task involved extracting bacterial bioaerosol particle counts along with their associated temporal attributes. Similarly, for the Airvisual IQAir Pro dataset, the focus was on retrieving CO2 data and associated temporal attributes.

3.1. WIBS Dataset

	A	B	C	D	E	F
1	Filename: Friday_Restart_0004.csv					
2	SampleFlowRate = 5 ml/s					
3	Trigger Threshold 2 = 10					
4	Trigger Threshold 1 = 10					
5	Max Meas Per o/p File = 30000					
6	Auto Forced Trig Enabled = 0					
7	Auto Forced Trig Part Rate Thresh = 2 p/s					
8	Peak Offset FL2_SctPk = 0 (0x0)					
9	Integrator Offset FL2_SctInt = 69 (0x45)					
10	Integrator Offset FL1_280 = 0 (0x0)					
11	Integrator Offset FL2_280 = 0 (0x0)					
12	Integrator Offset FL2_370 = 0 (0x0)					
13	Peak Offset Pwr_280 = 0 (0x0)					
14	Peak Offset Pwr_370 = 0 (0x0)					
15	Peak Offset SCAT_EL1 = 0 (0x0)					
16	Peak Offset SCAT_EL2 = 0 (0x0)					
17	Peak Offset SCAT_EL3 = 0 (0x0)					
18	Peak Offset SCAT_EL4 = 0 (0x0)					
19	Scat El 2 gradient = 0.8704					
20	Scat El 2 offset = 1.6147					
21	Scat El 3 gradient = 1.2505					
22	Scat El 3 offset = 1.2597					
23	Scat El 4 gradient = 1.1150					
24	Scat El 4 offset = 5.5825					
25	Minimum Mean ScatEL = 20					
26	Glitch time = 30 (0.63us)					
27	Scat integrate pulse = 300 (6.25us)					
28	XE1 trigger delay = 471 (9.81us)					
29	XE1 integrate delay = 160 (3.33us)					
30	XE1 integrate pulse = 288 (6.00us)					
31	XE2 trigger delay = 551 (11.48us)					
32	XE2 integrate delay = 130 (2.71us)					
33	XE2 integrate pulse = 336 (7.00us)					
34	Recharge time = 18000 (6000us)					
35	FL1 280nm offset = 0					
36	FL2 280nm offset = 0					
37	FL2 370nm offset = 0					
38	Start Date/Time: 13/05/2021 14:02:43					
39	Time	FL2 SctInt	Scat_EL1	Scat_EL2	Scat_EL3	Scat_EL
40	38	514	22	20	34	
41	339	412	22	19	36	
42	561	346	20	18	28	
43	904	332	19	15	35	

Figure 1: CSV file layout

First Step: involved consolidating multiple CSV files into a single Pandas data frame. Fig.1 shows an example of file layout.

This process entailed using a loop function where each file underwent initial pre-processing and cleansing prior to being merged. The first 37 rows of each file, detailing the WIBS current configurations, were excluded from the analysis to focus solely on particle measurements and temporal attributes. The cell in row 38, column A, which documents the initiation timestamp of the WIBS machine, was initially set as the header for each file's data frame. After, the timestamp was indexed into the data frame. The index was then reset as a column and renamed 'Timestamp'. Each file's data frame was then created into a new data frame, starting from the second row, utilising the data in the second row as the new column headers. The iterative loop was applied to each file and then all the files were amalgamated into a single unified data frame.

Second Step: 'FL1_280', 'FL2_280' and 'FL2_370' are measures for the fluorescence intensity of particles, which allow for the categorisation of fluorescent particles into groups ranging from fungal spores, pollen, to bacteria. However, 'Size' which indicates the dimension, and 'AF', the asymmetry factor, are not essential for categorising fluorescent particles. 'Size' and 'AF' were not required for the analysis and therefore dropped from the data frame. The remaining attributes are secondary instrument data, used for diagnosing performance issues with the machine.

Third Step: entailed further refinement of the data frame. This involved exclusion of non-fluorescent particles, which means they are non-biological particles, as they hold no relevance to the study's primary objective of analysing biologically derived particles. Concurrently, a single column called 'fluorescent_class' is created to record and categorise all the fluorescent particles into seven distinct groups based on individual and possible combinations amongst the three fluorescence intensity channels (FL1_280, FL2_280, and FL2_370), as illustrated in Table 1. By removing non-fluorescent particles and categorising fluorescence intensity, the data more closely aligned with the specific aims of the study. This report predominantly focused on fluorescent category A, which are prominent bacterial bioaerosol, which were used as a biomarker to indicate the presence of COVID-19 in the air. This target approach allowed for a more in-depth exploration. The WIBS machine operated in two distinct operation modes.

Channel	Excitation (nm)	Emission (nm)
A	280	310-400
B	280	420-650
C	370	420-650
AB	280	310-400 420-650
AC	280 370	310-400 420-650
BC	280 370	420-650
ABC	280 370	310-400 420-650 420-650

Table 1: WIBS channel annotation matrix. Channels are matched with excitation wavelength and emission waveband [1]

<u>Normal Mode</u>: In this mode, particles are pumped into the machine's inlet, where the particle size, shape and fluorescent concentration are recorded.

<u>Force Trigger Mode</u>: In this mode, the pump is turned off, allowing the laser to fire on empty space. This enabled the WIBS to document the background noise of fluorescent values. Data collected under this mode has been recorded into a separate CSV file called 'Forced_Trigger_0000.csv', which mirrors the same format of the previously compiled WIBS data. This file was used to establish thresholds for fluorescent particles, which helped to identify non-fluorescent particles that were then filtered out from the main WIBS data frame.

The threshold was determined using the force trigger mode data. Both the mean & the standard deviation were obtained for the fluorescence intensity in each channel (FL1_280, FL2_280, and FL2_370). The threshold of each channel was calculated using; the mean plus 9 times the standard deviation of the fluorescence intensity. This method is grounded from research by N.J Savage, which observed that certain non-fluorescent particles may exhibit low-level fluorescence signals. By establishing a higher threshold, the accuracy in differentiating non-fluorescent particles from fluorescent ones was enhanced and significantly mitigated the likelihood of false positive identifications [13].

The thresholds were then applied to the WIBS data frame, categorising the data into their distinct classes within the 'fluorescent_class' column. Non-fluorescent data were then filtered out, further refining the dataset.

Fourth Step: Data manipulation and wrangling was used to enhance and produce additional temporal attributes. The existing 'Timestamp' column was transformed to include milliseconds. The 'Time' column was restructured to include milliseconds in timestamp format. Milliseconds as a timestamp. The two columns - 'Timestamp' and 'Time'- were amalgamated to create a new temporal attribute named 'Time_Series_Values'. This attribute accounted for the full timestamp event from the initiation time of the WIBS to the millisecond a particle was recorded. 'Time_Series_Values' was used to create additional temporal attributes such as date, day, and hour. The data relating to non-work shift days were filtered out from the data frame.

3.2. Airvisual IQAir Pro data

The data processing for the air sensor required a lower level of effort.

First Step: involved consolidating multiple .txt files into a single Pandas data frame. This process utilised a loop function where each file was created into a single data frame. The values within each file were delineated using the semicolon as the delimiter. After all the files were amalgamated into a single unified data frame.

Second Step: as CO2 and temporal attributes were the only required attributes for this analysis, all other data attributes were removed to refine the data frame.

Third Step: 'Timestamp' was utilised to create additional temporal attributes such as date, day, and hour. The data relating to non-work shift days were filtered out from the data frame.

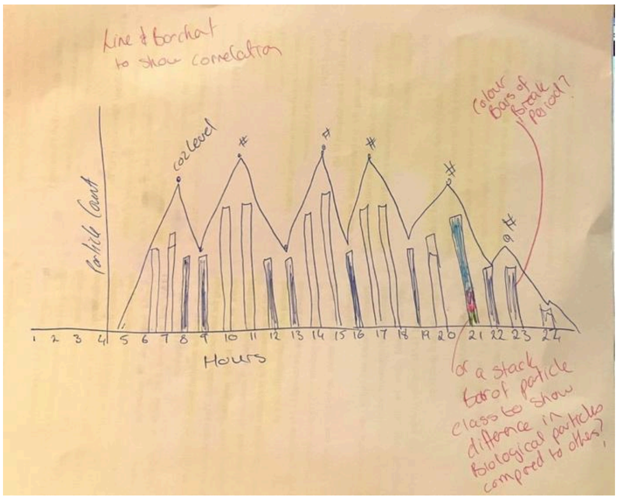
The final stage of the data processing involved merging the two data frames (WIBS & Airvisual IQAir Pro) to facilitate the exploration of possible correlation between biological particle counts and CO2 levels during working shifts. To achieve this, an inner join was employed, using the timestamps from both data frames as the key for merge. This aligned the data precisely for a comprehensive overview of the interrelationships of key attributes over a period of a month. The separate and merged data frames were all assessed for duplicate entries, missing or null values, and outliers in the CSV files. After this, the merged CSV file was used in Tableau to explore and create data visualisations.

4. DATA VISUALISATION

4.1. Audience and Consideration

To determine the most effective approach for the data visualisation design, it was important to first strategize the core message to be communicated through a data-driven lens. This core message focused on the role of occupancy and environmental working conditions contributed to COVID-19 Outbreaks within the MPPs. The visualisation needed to effectively illustrate a potential correlation between bacterial bioaerosol particle counts, as a biomarker for the virus, and CO2 levels that indicated occupancy fluctuations during working shifts. Identifying the primary audience for this visualisation was also crucial. Key considerations included what specific information the audience would comprehend, and the actions required by them upon understanding this information. This process also involved recognizing the advantages of successfully conveying the critical data to prompt action, and the potential risks associated with inaction.

The original pilot study, funded by the Ministry of Agriculture, aimed to explore causes of COVID-19 outbreaks in plants. The initial idea of showing particle counts and CO2 levels for each working day in a time-lapse format raised a concern about information overload. Including additional attributes like days with working hours risked cluttering the visualisation, although it could highlight variations in particle counts due to busier work shift days or the presence of more infected individuals on certain days. For this reason, it was decided that a compiled view of all the days, focusing solely on working shift hours, would offer a clearer and more streamlined message. This would give a more condensed graph, avoiding the complexity of scrolling through the data.



An effective visualisation would enable the audience to recognize the link between outbreak risks from the correlation of particle counts, CO2 levels and working shift hours. Prompting the audience to implement measures to mitigate risk of virus transmission. Such interventions might include reduced levels of occupancy, improved ventilation and ensuring employees practised social distancing. However, failing to clearly convey the core message clearly could lead to inaction, potentially increasing the risk of future outbreaks.

4.2. Design Process

For the data to effectively be displayed, it was important to understand the type of data being used, and the most suitable visual representation techniques. Given that the data was quantitative, and the aim was to explore potential correlations between attributes, a graph chart would be the most effective approach to display the progression and shape of the data over time, while also providing a comparative insight between the relationship of CO2 levels with particle counts. Figure 2 presents a sketch produced to conceptualise the visualisation strategy. Bar graphs were selected to depict particle counts due to their ability to show the levels of increasing and decreasing size in volume, particularly across spans of time. They are also advantageous for comparing different values. For CO2 levels, a line graph was considered more appropriate. While bar graphs are effective for showing volume changes, utilising bar types for two different attributes could potentially lead to confusion and hinder interpretation. A line graph was a better choice as it does well in representing time-series data, revealing trends and patterns over a period. The line graph also complements a bar chart well when used for comparison and correlation. From a personal standpoint, a line graph more aptly portrays the fluctuations of a gas like CO2 overtime than a bar chart. The combined use of bar and line graphs, each illustrating different attributes, provides a comprehensive interpretation of the data, facilitating clearer communication to the audience.

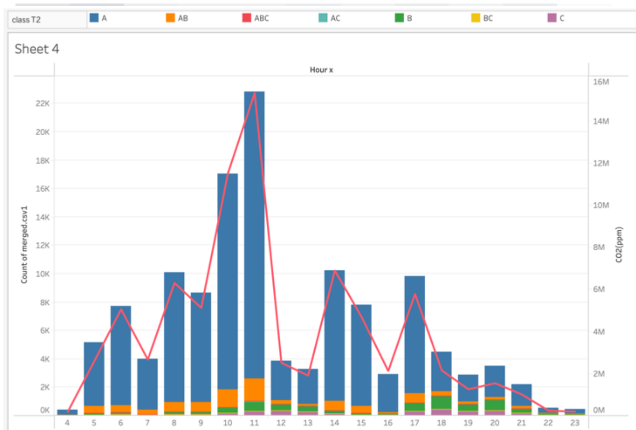


Figure SEQ Figure * ARABIC 3: Stacked Bar Chart for particle types.

During the design process and the creation of the initial sketch, different visualisation strategies were contemplated for the bar graph. One idea was to use distinct bars, or a column chart to display the different particle classes to compare their volumes. However, this approach risked overcrowding the graph, potentially obscuring the clarity of the data. Another idea, as displayed in the initial sketch, was the use of a stacked bar chart to represent the different particle type counts. This method was effective in highlighting the volume difference between bacterial bioaerosol particles and other categories, such as fungal spore particles, as demonstrated in Figure 3. While the stacked bar chart was valuable in highlighting the prominent volume of bacterial particles displayed as fluorescent category A, it obscured clarity for the core message that was central to the study and to the audience. Therefore, it was decided that the particle count would be filtered to exclusively represent fluorescent category A, the bacterial bioaerosol particles. Another alternative that was considered in the sketching phase included the use of a different colour for bars that would denote the work shift breaks and changes as noted in Table 2. However, there was a risk that this would have led to misinterpretation of the particle count data with work shift transitions. This ultimately would have affected the clarity of the core message and for this reason, the idea was not pursued.

Event	Time (24 hour)
First work shift commences:	06:45
20-minute work break between:	08:30 – 09:45
30-minute work break between:	12:15 – 13:30
First work shift ends:	16:15
Second work shift commences:	16:30
20-minute work break between:	19:00 – 20:00
30-minute work break between:	22:00 – 23:00
Second work shift ends:	00:00

*Table SEQ Table * ARABIC 2: Working shift events and start times.*

4.3. Final Visualisation

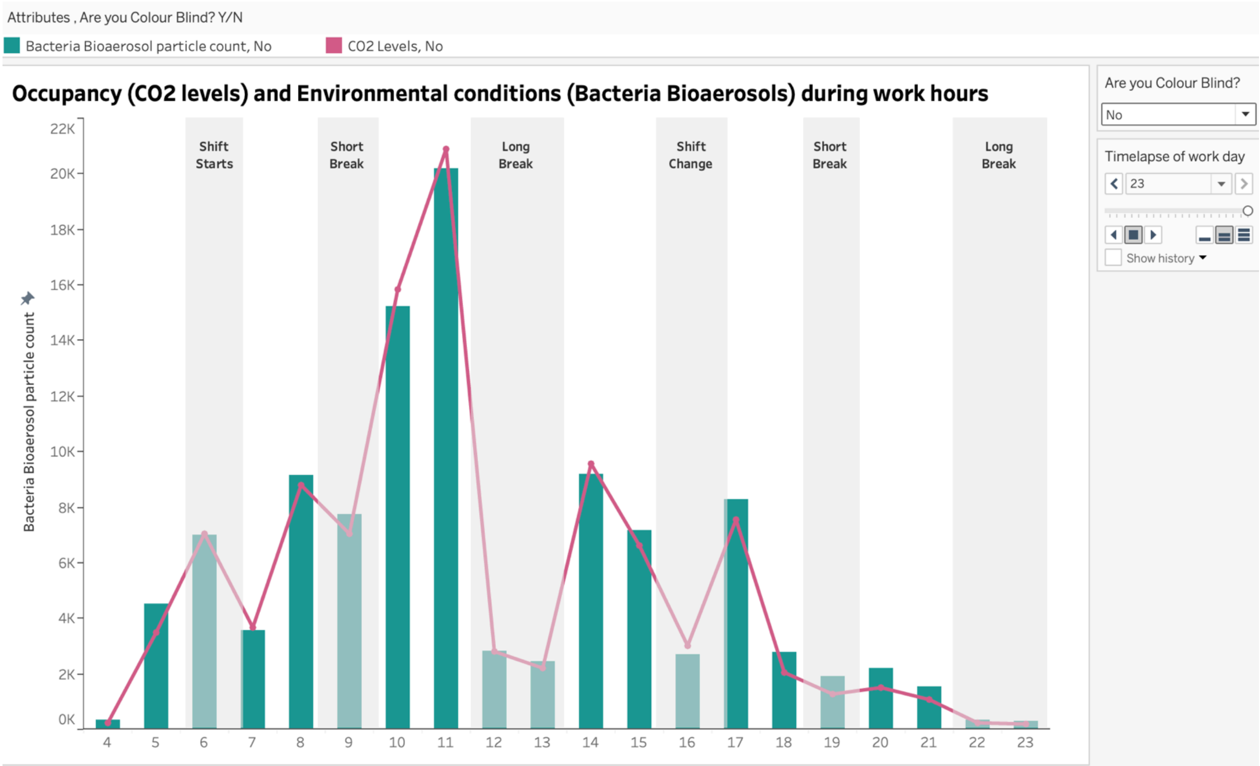


Figure 4: Final Visualisation.

Figure 4 showcases the finalised visualisation, created in Tableau. This visualisation combines a dual-axis format, overlaying a line graph, which represents CO2 levels, with a bar graph that depicts the count of bacterial bioaerosol particles. The dual graph is structured along an x-axis displaying the hours throughout the working shift. Annotation areas in light grey were incorporated to indicate work shift breaks and changes over the course of the day. These annotations used a reduced opacity of 50%, to ensure that they did not overly distract from the primary focus of the bar and line graphs.

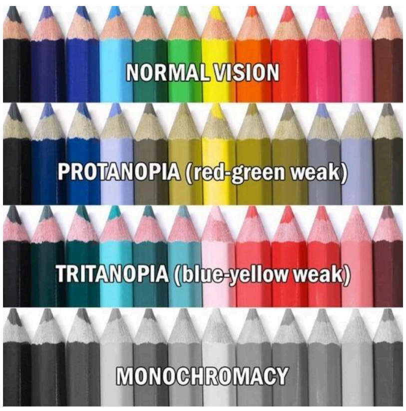


Figure 5: Colour blind vision chart.

The choice of the bright and robust colours for both the bar and line graphs was methodical, as it was intended to attract the audience's attention and emphasise the correlation between the two graphical elements. The use of the contrasting colours such as turquoise green and pale pink-purple, effectively distinguishes the two graphical elements in the visualisation, as each represents a different attribute. Personally, I find colour combination appealing both aesthetically and in terms of accessibility for those with colour blindness, as demonstrated in Figure 5. While the standard blue and orange default colours used in Tableau might be considered less engaging and can be often overused. However, to

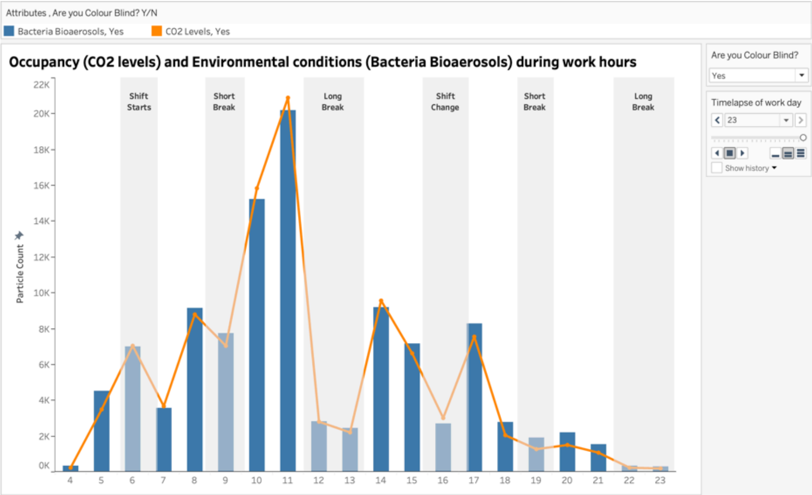


Figure 6: Final Visualisation filtered to colourblind friendly parameter.

accommodate a wider audience, including those with colour vision deficiencies, a parameter has been integrated into the graph, enabling users to switch to the default Tableau colours using blue and orange as displayed in Figure 6. This feature was inspired by a tutorial from Andy Kriebel on YouTube. An animated feature has been added to the graph, displaying a time-lapse view of the data over a workday. This animation serves as a dynamic presentation tool, allowing presenters to effectively illustrate and explain the graph's trends with work events throughout the working day. A demonstration of this animated feature is available for viewing here.

The y-axis in the visualisation presents the measurements for particle counts, providing users an indicator of particle volume throughout the workday. However, the inclusion of CO2 level measurements was excluded from the visualisation. This decision was made to maintain the clarity of the visualisation. The primary objective was to convey a correlation between particle count and CO2 levels to the audience. Introducing the CO2 measurement values, which are quantified on a significantly different scale (millions) compared to that used for particle count scale (thousands), might have introduced unnecessary complexity and potential confusion. Therefore, it was deemed more effective to focus solely on particle count measurement to preserve the visualisations clarity and effectiveness in communicating the core message.

5. CONCLUSION

This visualisation successfully addresses the research question, *"Do occupancy & environmental working conditions contribute to COVID-19 outbreak risks in MPPs?"* It proficiently demonstrates the correlation between bacterial bioaerosol particle counts and CO2 levels throughout the work shift in the plant. As elaborated earlier in this report, the CO2 levels signify occupancy fluctuations, while increasing bacterial bioaerosol particle counts, serving as a biomarker for the virus, collectively indicate that both occupancy and environmental conditions within the plant are factors that contribute to transmission risks. This evidence can be used to take actions to mitigate risk. Furthermore, the collection of additional data for similar analysis would be beneficial to evaluate the effectiveness of any interventions and action implemented. This approach would allow for a comparative analysis of before and after such interventions, providing insights into their impact and effectiveness in reducing transmission risks.

Reflecting on the visualisation, there are several areas where improvements could have enhanced its effectiveness and clarity.

One such area is the labelling of the x-axis. Ideally, there should have been an axis title "Hours of working day" positioned at the bottom of the x-axis for clarity. However, due to constraints in Tableau the only place it would appear was at the top of the visualisation. Placing it at the top appeared misplaced and potentially misleading, hence its removal from the visual.

Regarding the colour legend, its current format, which shows the attribute name alongside the status of the colour-blind filter (Yes or No), could be simplified by displaying the attribute names only and not the parameter status. I was unable to implement this in Tableau. Additionally, integrating the legend directly onto the graph would have looked nicer. Perhaps using a dashboard to display instead of a separate worksheet, might have been a more effective approach.

The presence of the pin symbol along the y-axis, which I was unable to remove, is another visual aspect that could potentially lead to confusion. Perhaps integrating the worksheet into a dashboard would remove the symbol which would be beneficial. Additionally, the y-axis could be simplified further by removing it entirely, contributing to a neater visualisation. Since the visualisation focuses more on demonstrating correlation that on the specific measurement values, the y-axis numbers are less critical. Implementing a tooltip feature in Tableau could provide users with measurement details without cluttering the visualisation.

Lastly, displaying the full 24-hour span on the x-axis would offer a more comprehensive view of the data. However, due to time constraints to investigate the future, the visualisation currently shows only the hours in which particles were detected. Future versions could explore ways to include the entire 24-hour cycle for a more complete representation of the data.

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