Building - Energy & Repair Data Insights

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Problem Statement

- BUENO generates insights on building data using analytics. These could be fault detection, (e.g. identifying a faulty temperature sensor) or optimisation opportunities (e.g. identifying when a piece of equipment could be run more efficiently). The insights are turned into work orders which a building technician can take action, such as replacing the temperature sensor. Completing work orders has benefits including reducing energy consumption, increasing equipment lifetime and improving tenant comfort. We would like you to quantify the value BUENO provides to its customers through the completion of these actions.
- Possible questions/ideas to explore - We welcome you to explore the data and come up with your own way to quantify the value. However here are some suggestions to consider:
  - What is the relationship between energy consumption and completed work orders?
  - Are there other relationships between energy consumption and problems, causes or remedies?
  - Are there any assets which appear to have a greater impact on energy consumption when they are not functioning correctly?

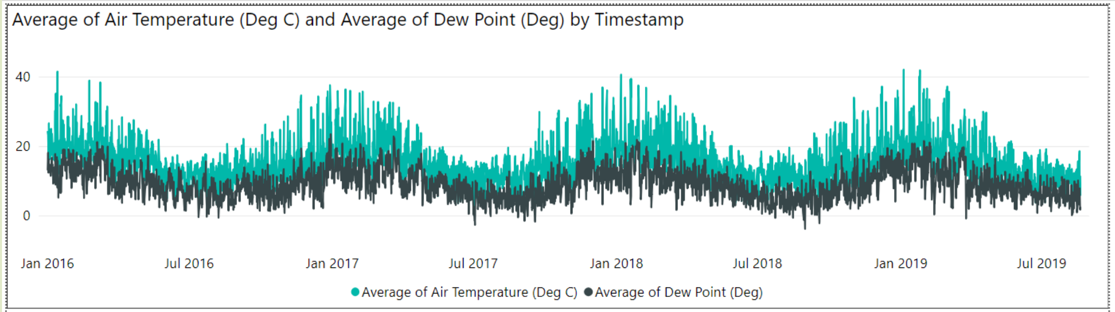
Hypothesis – Is there a correlation between energy consumption and completed repairs ?

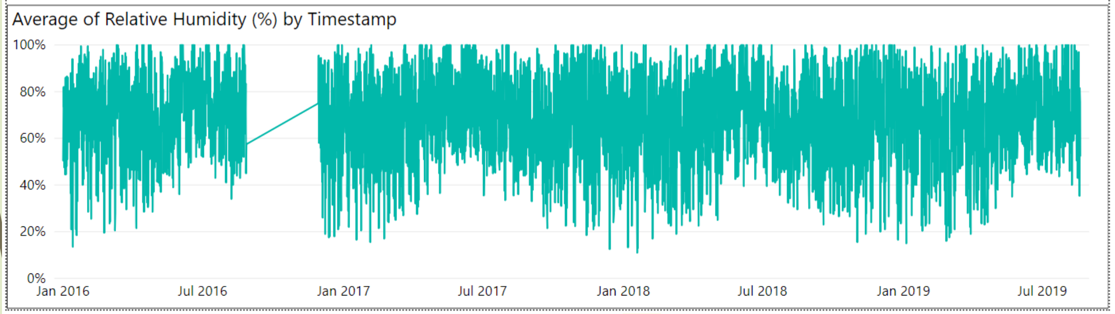
What are the key questions to answer to meet the objectives – Do the repairs reduce the energy bills ?

Analytics Level	Energy	Weather	Service Incidents
Descriptive Analytics What has happened ?	• Building energy consumption trend • How does it compare yearly, monthly, weekly, daily ?	• Trends of temperature, Humidity, Dew • How does it compare yearly, monthly, weekly and daily 24hr trend ?	• Pareto of repairs / failures, which failures drives 80% of the problem ? • What is the mean time between repair and time to resolve distribution ? • How do they compare between buildings and failure mode ?
Diagnostic Analytics Why it happened ?	• What are the factors driving the failures ? • Is there a correlation between failure vs. building energy consumption vs. weather ? • After each repair has the energy consumption reduced ? i.e. are the wear-out assets is consuming more energy ?		
Predictive Analytics What could happen next ?	• Do we have enough predictors in the given data-set to predict a future repair ? • Can we forecast, all the parts the maintains technician needs to carry when he goes for one repair?		

Descriptive Analytics

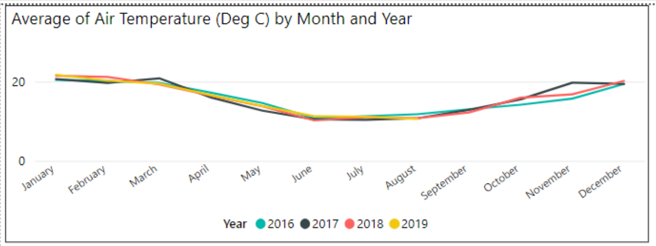
Weather Trend

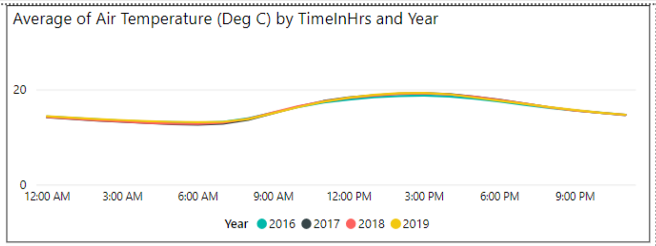


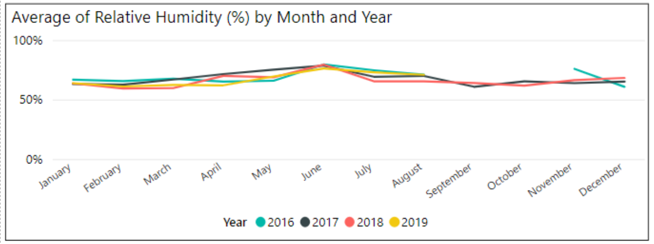


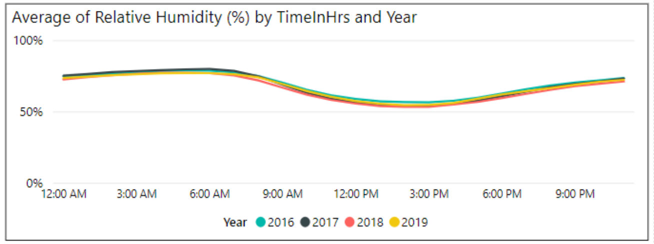
Observations

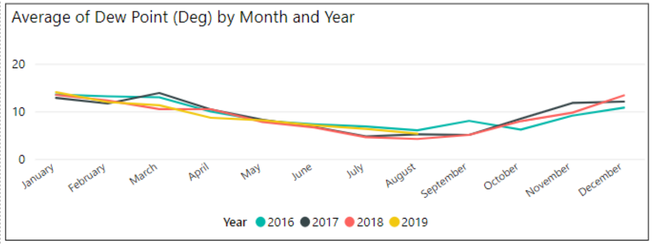
- At the location where all the 5 buildings exists, the weather condition seems normal as the dew point temperature is always below the air temperature
- Avg. relative humidity decreases as the temperature increases and vice-versa as observed in the below chart

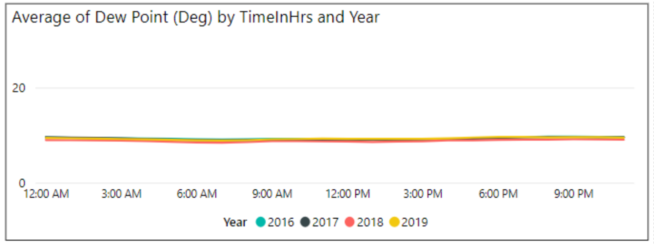












Inferences

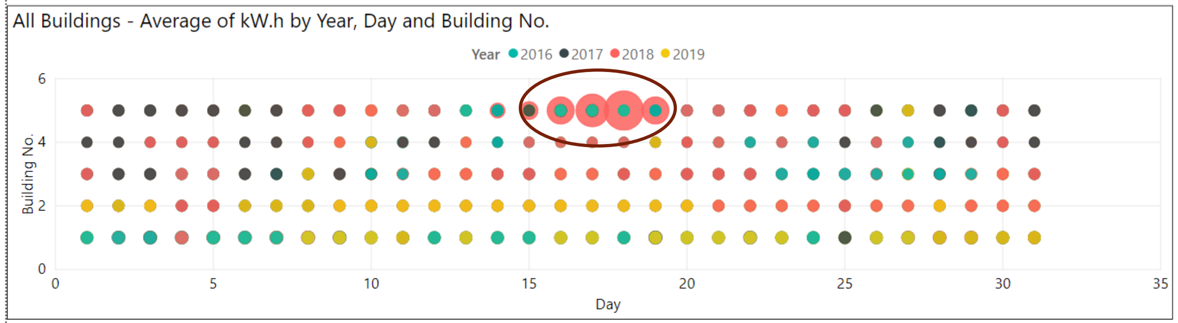
No major anomalies observed in the weather since Jan/2016

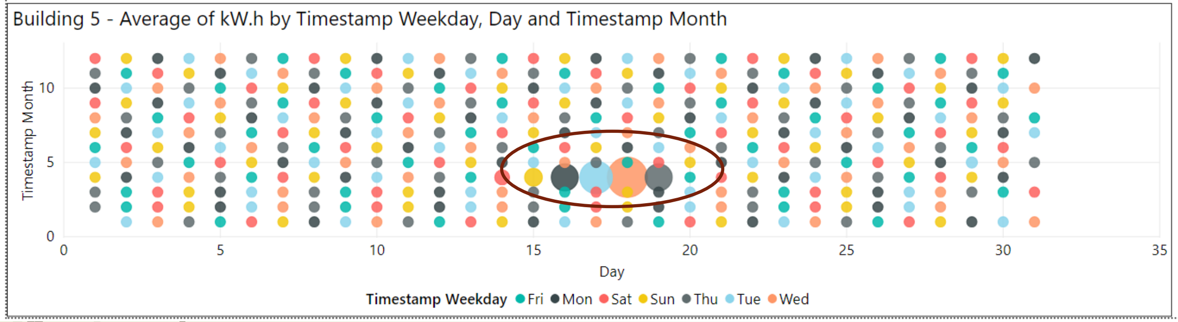
The avg. monthly and the hourly dew point is below 15°C, this shows that the weather does not provide any discomfort even to people in temperate climates like London and Chicago

References - https://en.wikipedia.org/wiki/Dew_point

Descriptive Analytics

Building energy consumption trend



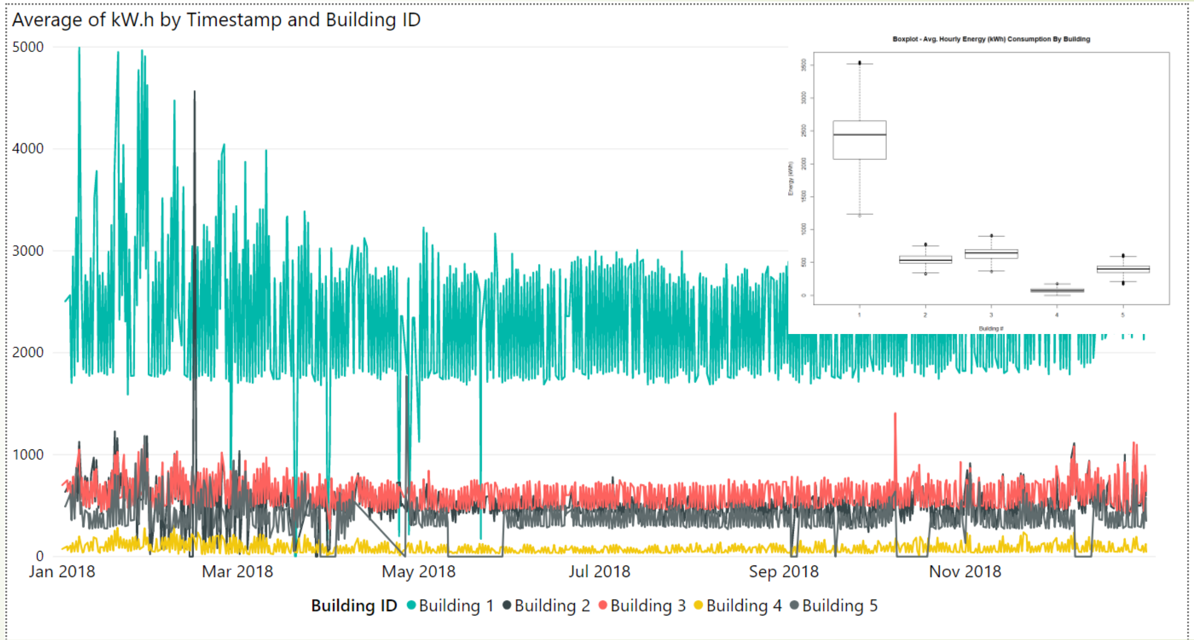


Inferences

Building 1 should have the highest failure occurrence rate followed by building 2, 3 & 5 and building 4 should have the least failure occurrence, provided the failure correlates to the hourly avg. energy consumption of each building

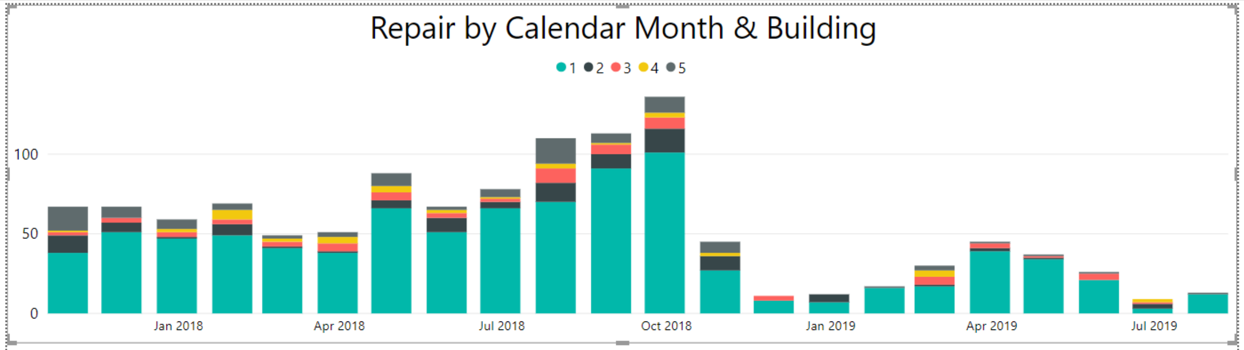
Observations / Assumptions

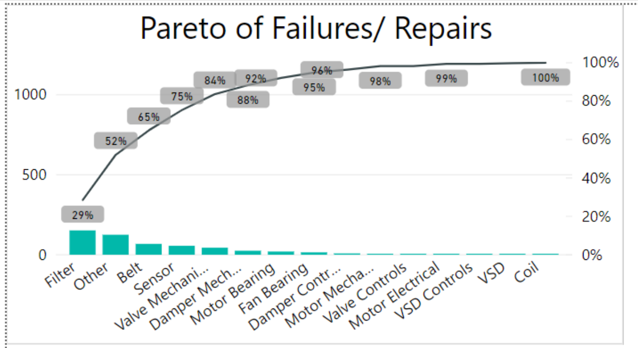
- Building 5 shows very high hourly avg. energy consumption during the 2nd & 3rd week of April-2018. These anomaly observations are excluded for further analysis
- Building 1 & 4 has the highest (~2500 kW.h) and lowest (~ 100kW.h) avg. energy consumption pattern, respectively
- Building 2, 3 & 5 has similar avg. energy consumption (~ 400 - 600 kW.h)

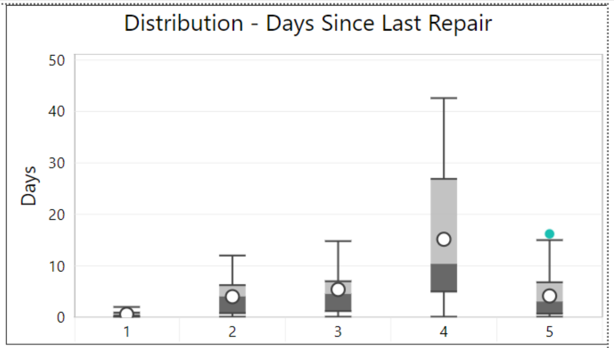


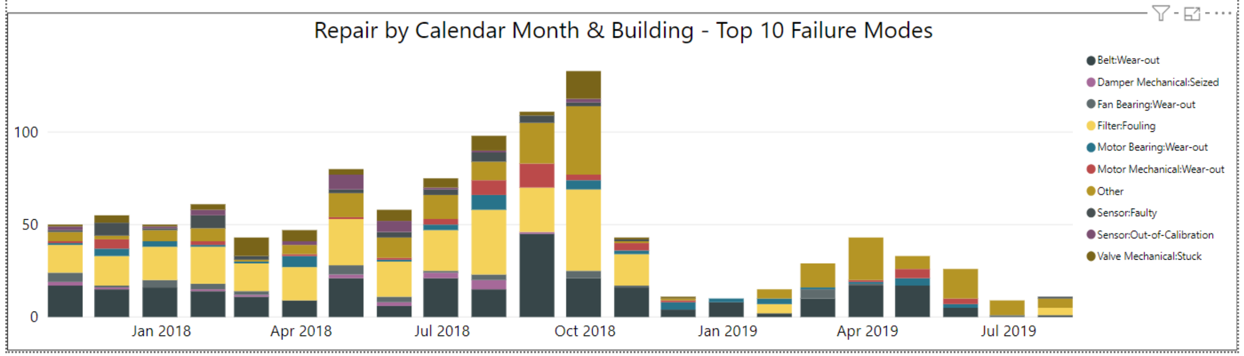
Descriptive Analytics

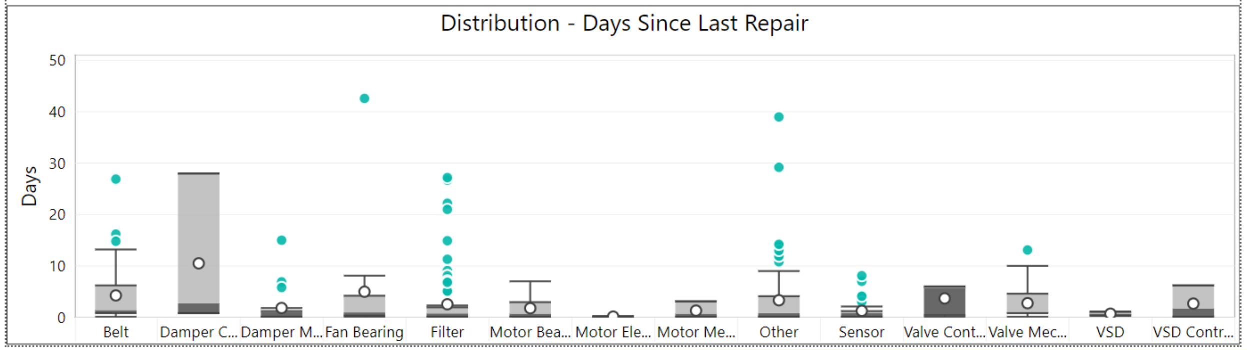
Repair trend , Pareto time between repair distribution











Inferences

- Majority of the failures are observed in building 1, the boxplot confirms, the median days between repairs, for building 1 < 2 days
- Days between repair distribution pattern is similar between building 2,3 & 5. Hypothesis testing (ANOVA) confirms the same
- Building 4 shows the highest time between repairs, can be observed from the median

- **There may be a correlation between kW.h and failure occurrences**
- **Filters, Sensors, Damper Mechanical & Belt may be replaced together**

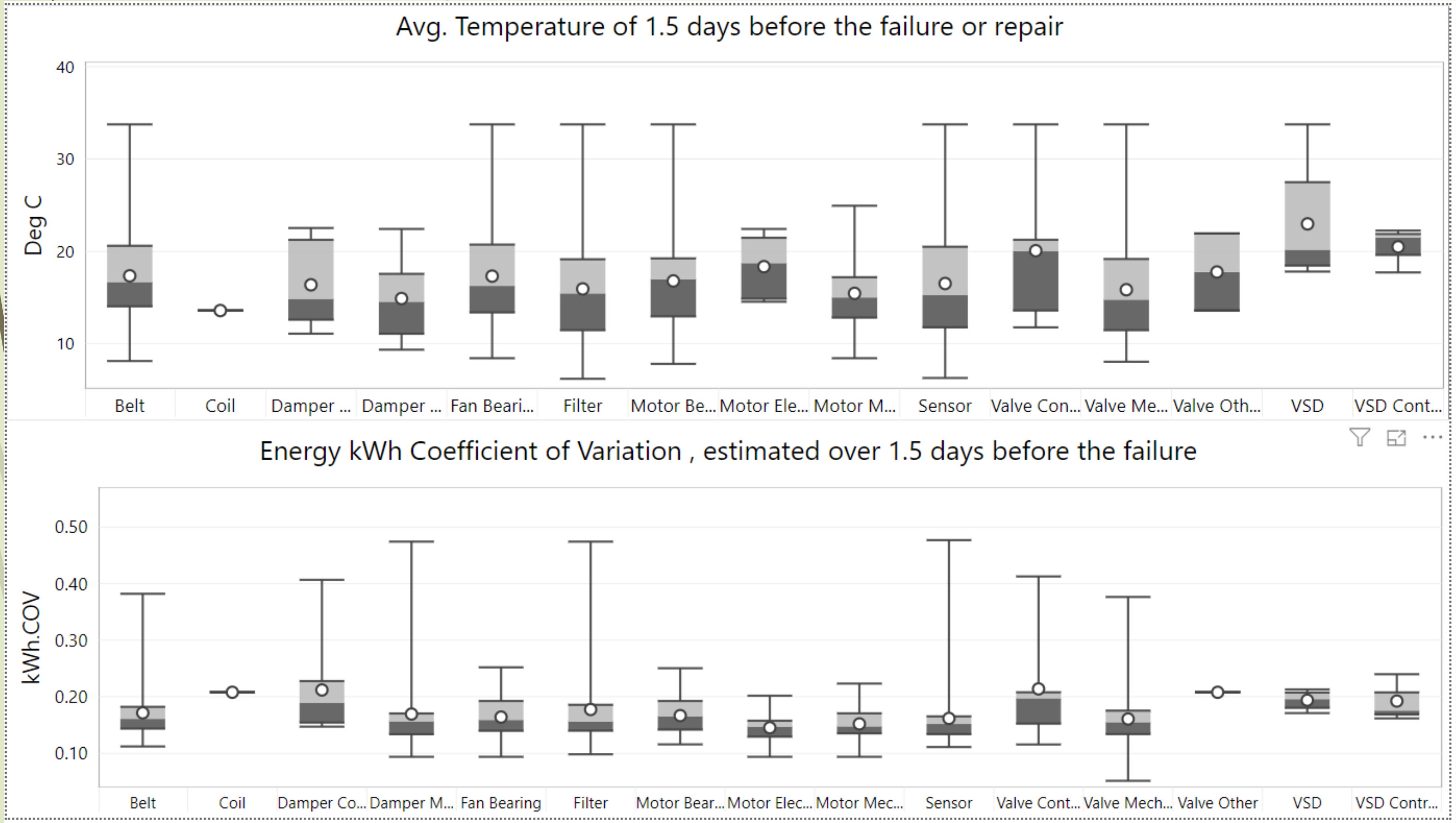
Diagnostic Analytics - After each repair has the energy consumption reduced ? Are the worn-out assets consuming more energy ?

Steps to analyze

- To understand there is change in energy consumption between each repair, we need to combine repairs which are within **"3"** days gap, forming failure groups which combines numerous work-order as one failure. Building 1 has the lowest avg. days since last repair i.e. 1.6 days, taking double of this as the minimum gap to say the failures or failure groups are different
- Once the groups are formed, identify the earliest and the latest repair date marks the boundary of before and after each failure
- Extract weather and energy snapshot for a duration of 1.5 days before and after the boundary for each repair group
- Compare the avg. energy and weather pattern before & after each failure repair group
- For energy use **Coefficient of Variation(COV)** measure to compare avg. hourly energy consumption between failure modes, as the energy levels for each building is different

Diagnostic Analytics

Does weather condition or power lead to a repair ?



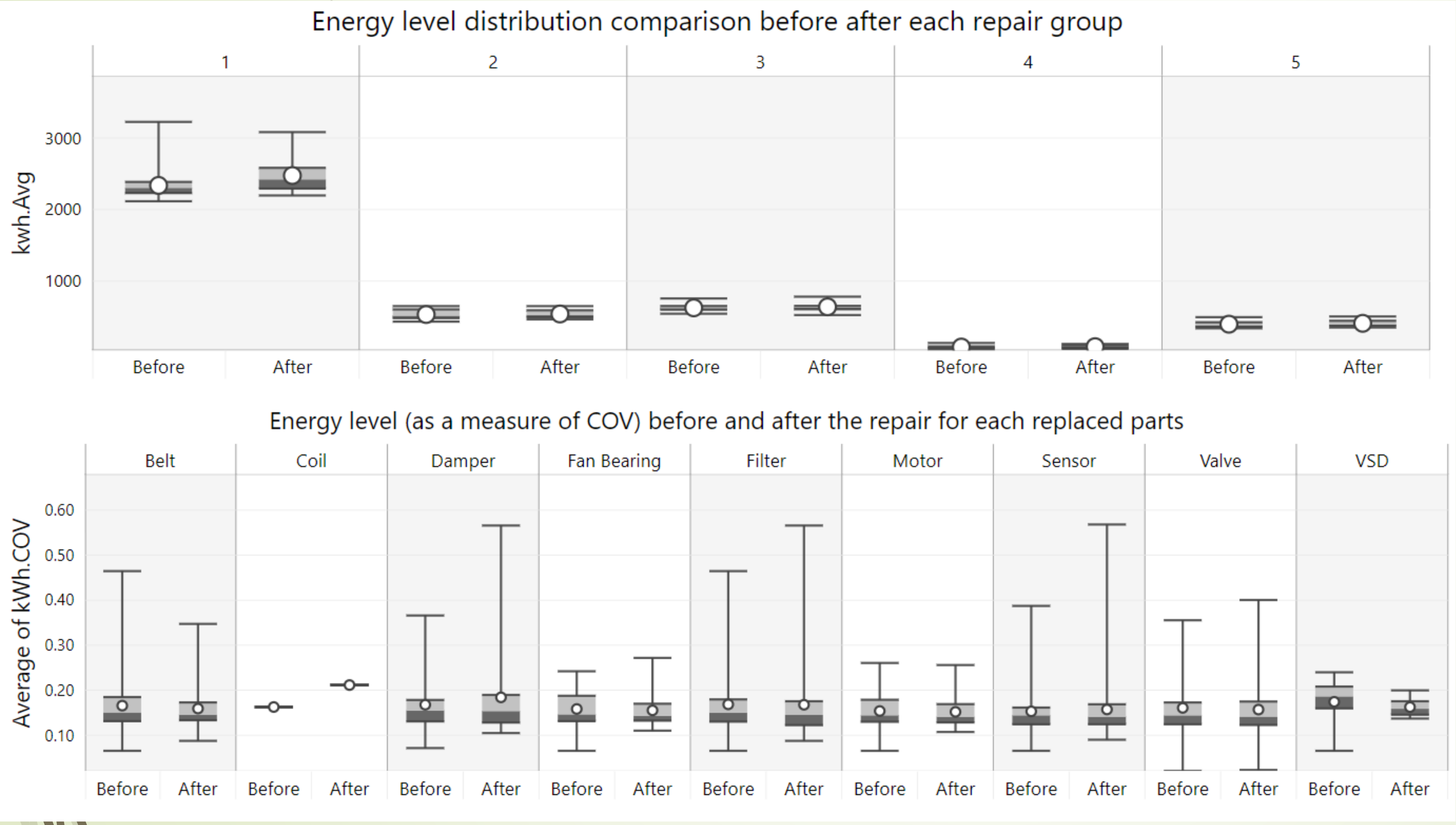
Inferences

Average temperature or energy (as a measure of COV) has a similar mean and dispersion for all failure areas

The VSD shows high temperature before the failure, may be a fact that all VSD failures are during summer.

Diagnostic Analytics

Has the energy levels reduced after each repair ?



Inferences

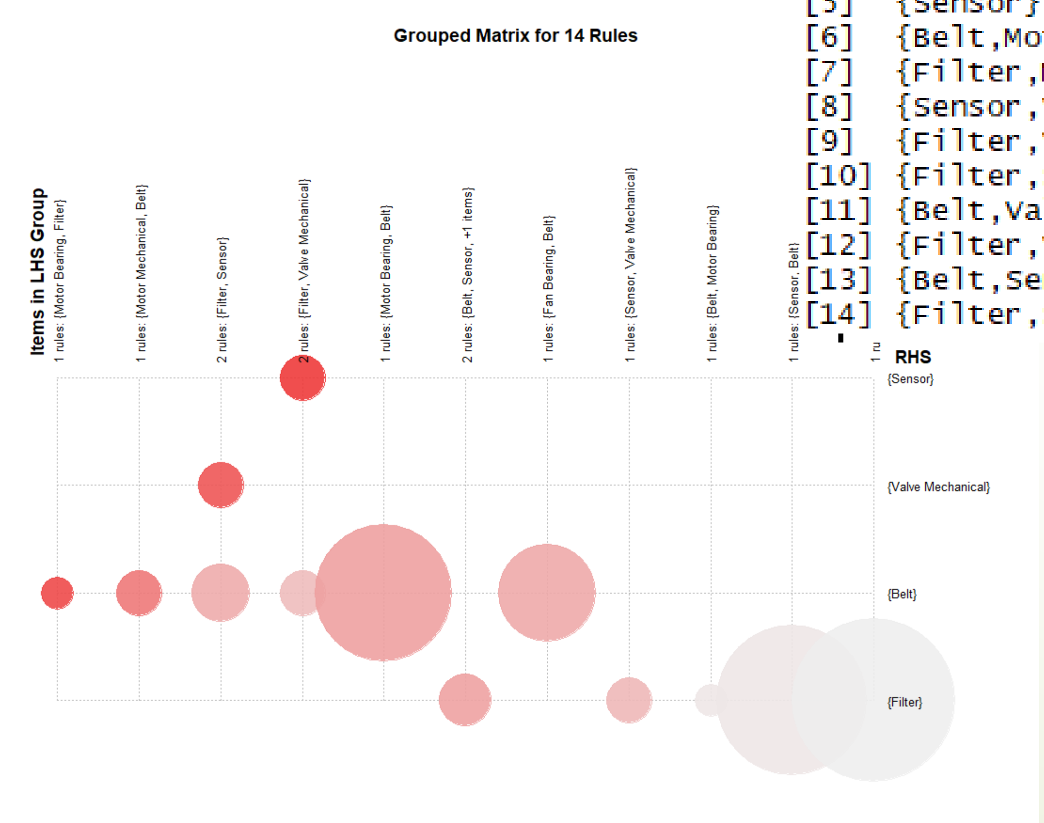
There is no change in Average energy levels before and after each repair for each building and also for each replaced part

The high energy levels of each building may drive different failure rate. However, there is no evidence to say that each worn-out or defective parts are consuming additional energy

Predictive Analytics

What additional parts the technician needs to carry if he goes for a particular repair ?

	lhs		rhs	support	confidence	lift	count
[1]	{Motor Mechanical}	=>	{Belt}	0.1073826	0.8421053	2.240602	16
[2]	{Fan Bearing}	=>	{Belt}	0.1342282	0.7142857	1.900510	20
[3]	{Motor Bearing}	=>	{Belt}	0.1543624	0.7419355	1.974078	23
[4]	{Valve Mechanical}	=>	{Filter}	0.1677852	0.6097561	1.195443	25
[5]	{Sensor}	=>	{Filter}	0.1610738	0.6486486	1.271693	24
[6]	{Belt,Motor Bearing}	=>	{Filter}	0.1006711	0.6521739	1.278604	15
[7]	{Filter,Motor Bearing}	=>	{Belt}	0.1006711	0.9375000	2.494420	15
[8]	{Sensor,Valve Mechanical}	=>	{Filter}	0.1073826	0.8888889	1.742690	16
[9]	{Filter,Valve Mechanical}	=>	{Sensor}	0.1073826	0.6400000	2.577297	16
[10]	{Filter,Sensor}	=>	{Valve Mechanical}	0.1073826	0.6666667	2.422764	16
[11]	{Belt,Valve Mechanical}	=>	{Filter}	0.1073826	1.0000000	1.960526	16
[12]	{Filter,Valve Mechanical}	=>	{Belt}	0.1073826	0.6400000	1.702857	16
[13]	{Belt,Sensor}	=>	{Filter}	0.1140940	1.0000000	1.960526	17
[14]	{Filter,Sensor}	=>	{Belt}	0.1140940	0.7083333	1.884673	17



Inferences

Association rule mining of the repair group parts (created per slide 7) clearly provides the frequent part set

For example rule 8 (strong association lift > 1.5) tells that whenever a technician goes for Sensor & Valve Mechanical Failure with 89% confidence it could be stated that he needs to carry a filter along

Overall Inferences & Recommendations

- There is no clear evidence in the data provided to show correlation between asset failure and energy consumption, however the high energy levels may drive high failure rate.
- There is a sudden drop in repairs after 2018, it may imply that by 2018 all age old assets in the building were replaced with new ones, will we see sample failure again may be not and also we may not be able to use the failure data from 2017 to 2018 to predict into the future
- To better understand the change in energy consumption before and after the asset is replaced, need to capture and investigate power closer to the asset. Hourly sampling rate may be insufficient to extract the right diagnostic features. Collecting sensors data close to the asset may help to extract the relevant signatures to predict
- Parts like filters may be replaced with the help of Preventive Maintenance strategy, if pressure and flow rate are already being captured closer to the filter the pressure drop estimate may provide some information to predict filter failures
- For assets where there is no sensors data we can follow Reliability Centered Maintenance (RCM) and plan inventory levels accordingly
- For assets with sensors data, condition based maintenance (CBM) can be established to predict or provide alert in advance so to convert unscheduled downtime to scheduled downtime