Clustering of Maintenance Work Data for Failure Mode Discrimination.

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Abstract

A fast and efficient method to discriminate failure modes from maintenance work orders will facilitate and motivate proactive maintenance development. This paper aims to propose a faster and as efficient clustering methodology that differs from previous text mining attempts. Text mining attempts are very dependent on correctly classifying text but the method proposed here is text independent. It is based on time to repair (TTR), time before failure (TBF) and other available identifiers. Using K-means as the clustering algorithm, the processing speed was greatly reduced. Singularity of discriminated failure modes were as good as previous text mining attempts.

Keywords
Failure mode, k-means, clustering, and data mining

1. Introduction
Buildings are complex systems encompassing many different systems including structural, electrical, mechanical, safety, security, information and communication systems. These systems are installed to facilitate the business and social functions that occurs in buildings (Bortolini and Forcada 2020**)**. To ensure that these building systems are always available for use, it is imperative that building systems are maintained.

In reality, (Labib et al. 1998) states that maintenance managers tend to be efficient before being effective. Efficient is reacting to failures with the least amount of waste in time and effort. Effectiveness is achieved by removing future failures. A failure is an unintended event where the unintended outcomes are known as failure modes (Parrott et al. 2011). Therefore, to eliminate failures, there is a need to identify the failure modes and assign appropriate proactive tasks. The expectation is that the failure modes and their corresponding preventative tasks are known by the designers and constructors of buildings. It is then expected that this information is made available to maintenance managers by the constructors. However, this transfer of information is not an industry mainstream activity (Abdullah et al. 2019).

Failing to have expected failure modes and preventative tasks, maintenance managers would have to plan preventative tasks based on experience and knowledge while monitoring for newly occurring failure modes that were not experienced before. These failure modes are recorded as work order descriptions in maintenance work orders whenever a failure event happens. The information recorded in work orders are shown in Table 1 (Yang et al. 2018).

Table 1: A work order sample (Yang et al. 2018)

Item	Meaning
Work Order ID	Unique identifier of work order (e.g. A1234)
Trade	Trade of work order (e.g. Electrical, Mechanical, Civil)
Location	Operation zone code
Description	AHU5 appears to be experiencing a return. AirLoeb AHU2, have Brian verify that the cold deck temperature on this unit is calibrated and in use.
Job Assignment	Person assigned for the work
Status	Work status (e.g. Open, Pending, Waiting, Close)
Priority	The work importance (e.g. Normal, Urgent, Emergency)
Created date and time	YYYY-MM-DD / HH:MM
Closed date and time	YYYY-MM-DD / HH:MM

Maintenance records such as maintenance work orders are mandated by quality standards organizations such as the International Standards Organization. Hence, maintenance work orders are readily available in most established asset maintaining organizations. Some are kept as paper copies, some are saved as digital copies on spreadsheets or computerized maintenance management systems (CMMS). Regardless of the type of work order storage, these work orders need to be data mined for failure modes before preventative measures can be assigned. However, the problem description data field is text based and has been proven to be complicated to data mine by various parties such as (Gunay et al. 2018, Sikorska et al. 2007 and Zhao et al. 2014). This is due to the non-standard text used (Steinberger 2010). Examples of text descriptions in a work order are shown in Table 2.

Table 2: Work Order "Description" Samples.

G-LAB-TRIP12
L1 - OKU - TOILET CLOGGED
L1 - DEW - LIGHTING FAULTY
L1 - DEW - ROOM 3 - AIRCOND LEAKING
L1 - O&G - BP SET FAULTY
L1 - O&G - DR THANEE - LIGHTING FAULTY
L1 - Surgical - dr sarina - roda kerusi rosak
L1 - SURGICAL CLUSTER - SINK LEAKING
L1 - Paeds Clinic - Weighting scale faulty
L5 - HDU - SPO2 ADULT REPLACE 2
Level 5 - HDU - Nurse Manager Room - Drawer faulty

In terms of data mining maintenance work orders, many text mining attempts have been performed. A sampling of these attempts is listed in Table 3. All these attempts focussed on clustering or classification of the work order description text. The text mining methodology used is summarized by (Salo et al 2018) as 1) Data Cleaning 2) Spelling & Vocabulary 3) Grouping Equivalent Tasks 4) Presenting Results. In general, all the attempts were successful in varying degrees. (Salo et al 2018) also mentions that there was a reduction from ten working days to one when text mining was performed as opposed to manual processing.

However, none of the literature surveyed, grouped work orders by time to repair (TTR) and time before failure (TBF). It is the intention of this paper to prove a "work order clustering by TTR and TBF" methodology that is viable and affords faster processing time. The reason for discriminating failure modes from work orders in this way, is to reduce dependency on "spelling and vocabulary" for which time-consuming ontology and almanacs need to be built. Text ontology building requires expertise and time that are often not readily available.

Table 3: Work Order Data Mining Attempts

Attempt	**Method**
Stenstrom et al, 2015	Natural Language Processing
Hodkiewicz & Tien-Wei Ho,2016	Word Rules
Arif-Uz-Zaman et al, 2017	Keyword Dictionary
Yang et al, 2018	Word Indexing
Salo et al, 2018	Word Clustering
Hastings et al, 2019	Word Tags
Blanco et al, 2019	Word Classification
Sexton & Fuge, 2020	Word Tags
Bortolini & Forcada, 2020	Word Indexing
Grabot, 2018	Association Rule

2. Methods

Figure 1 shows the relationship between time to repair (TTR) and time between failure (TBF) where TTR is defined as the time a failure occurs to the time it is fully restored. This includes administrative and logistical times that exists in the particular location and practice. In this paper, TTR will be taken from work orders as the time from when a work order was created to the time the work order was closed. TBF then is defined as the time from restoration to the next failure or the time between closed work order and the start of the next work order.

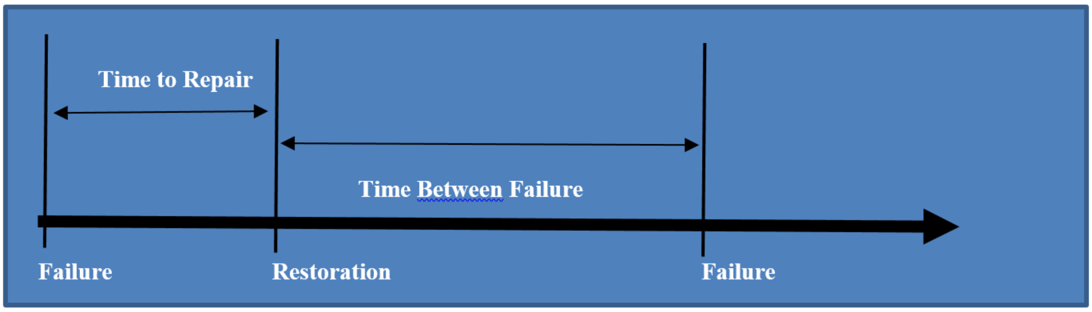

Figure 1: Repair Time and Time Between Failure

The method framework to cluster work orders using TTR and TBF is shown in Figure 2. Work orders are to be collected and the TTR and TBF of each work orders are to be determined from the work orders. These TTR and TBF are then to be clustered to presumably generate singular failure modes.

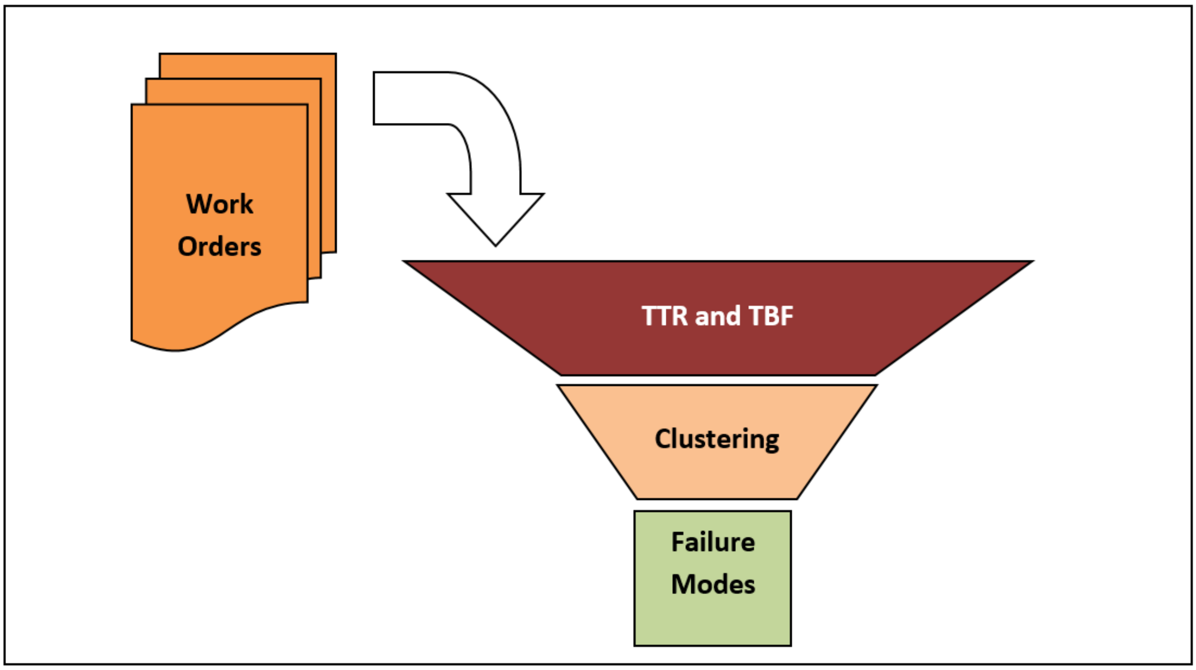

Figure 2: TTR-TBF based Clustering framework

For clustering, machine clustering was used. Machine clustering algorithms are unsupervised machine learning algorithms. The algorithms are used on a set of input data with no labels available. The algorithms learn the parameters and/or character of the clusters within the input set and outputs labels and members for each cluster (Siegenthaler 2020).

The objective is to discriminate failure modes from work orders by performing clustering of duration (TTR) and frequency (1/TBF) of work orders. Since inputs are in the form of hard integer values, not fuzzy and where density (frequency) is an output, not a cluster determinant, Euclidean distance-based machine clustering was proposed. Euclidean distance machine clustering methods mainly are of two types, agglomerative (hierarchical clustering) and k-means clustering (Arunajadai et al. 2004, Wang, Y and Moseley, B. 2020, Suwanda et al. 2020). They differ in clustering start points. Hierarchical starts with putting initial values in memory and then grouping by Euclidean distances. K-means instead, starts with random clusters. In terms of memory requirements, K-means is more conducive to large datasets. With hard integer in a sum squared error set to zero setting, randomness of starting centroids is irrelevant. Since the number of work orders to be analyzed is large (>'00), K-means is chosen as the machine clustering method.

Waikato Environment for Knowledge Analysis (Weka) version 3.8.4 machine learning software was chosen for clustering. WEKA was and is developed at the University of Waikato, New Zealand, under the GNU General Public License, and is the companion software to the book "Data Mining: Practical Machine Learning Tools and Techniques". This software was chosen as its k-means algorithms reports frequency of clusters which is a relevant failure mode discriminator to be studied. With K-means sum squared error set to zero, the clustering is only a sorting procedure similar to spreadsheet sorting but with instances reporting. Therefore, WEKA is deemed sufficient.

The steps taken to undertake the clustering are as in Figure 3. The indexes of duration and frequency were calculated and tabulated electronically without need for "text spelling or vocabulary" ontology and almanac. However, to refine the singularity of the resultant failure modes, the result output was further segregated by location and work trade identifiers.

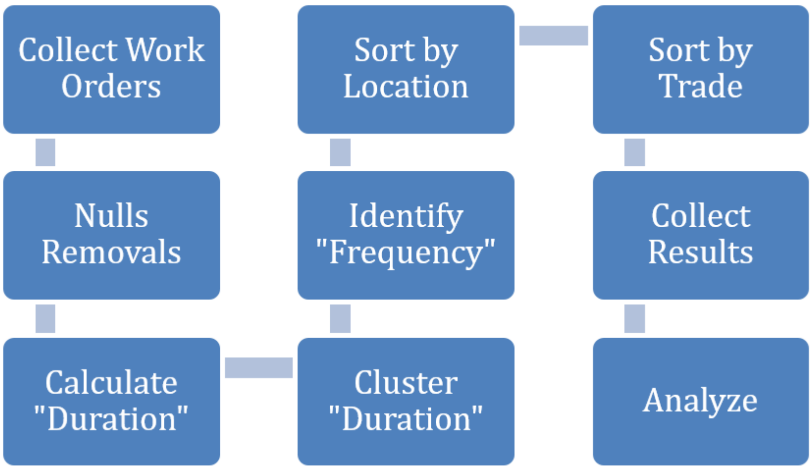

Figure 3: Data Sampling and Analysis

3. Data Processing

To test the approach of discriminating failure modes from work orders by clustering TTR and TBF, work order data from a full service, 20-year-old, 118 beds, 9-story hospital was acquired. A hospital was chosen for their extensive range of assets as compared to a typical office building. For this test study, 7438 work orders were collected. These work orders were from the years 2015 to 2019. From these work orders, 1097 of them had null fields and were removed using spreadsheet sorting and filtering software.

The same spreadsheet software was used to calculate duration for each work order. Duration here is defined by "work order closed time" minus "work order created time" as recorded in the work orders. These duration data were then clustered using K-means with the sum squared error set to zero. The sum of squared error is mathematically represented in Equation 1 (Patil 2018).

$$\mathrm{WCSS} = \sum_{P_i \text{ in Cluster } 1} \mathrm{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster } 2} \mathrm{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in Cluster } 3} \mathrm{distance}(P_i, C_3)^2$$

However only duration data in numeric form can be clustered, other identifiers with alphabetical notations such as descriptions, locations or trades cannot be clustered using K-means or any Euclidean based clustering method. To get sum squared error to zero, a number of K-means clustering passes were performed and the K number settled on for the final pass is 355 (refer to Table 4). Originally using spreadsheet sorting, 449 unique duration clusters were found but when K-means clustering using 355 as K value was conducted, the number of duration clusters found reduced to 355 clusters. Using K number of 355 on 6350 instances of attribute "duration", it took only 2 iterations in 0.25 seconds to perform the clustering from random initial starting points. From these 355 clusters, the number of instances per cluster were looked at and the most frequently occurring clusters are as shown in table 5 with the rest having instances at 1% or less:

Table 4: K number discovery passes

K number	**Sum Squared Error**	**No. of Clusters**
500	0	355
400	0	355
355	**0**	**355**
354	1.06E-11	354
300	7.81E-07	300

Table 5: Cluster Frequency

Cluster No.	**Instances**	**% of Instances**	**Duration in Minutes**
5	1440	23%	60
15	435	7%	10
13	333	5%	5
0	262	4%	20
16	251	4%	15
10	155	2%	30
24	128	2%	25
43	106	2%	8
14	104	2%	11
9	104	2%	12
25	102	2%	9
1	101	2%	7
20	99	2%	14
6	96	2%	13
2	96	2%	17

With the work orders clustered by duration and the number of instances per cluster known, the clusters were further refined by sorting them by location and work trade identifier. After sorting by locations and work trades, a sample result list for a single location (G-01-AE) with multiple trades is shown in Table 6.

4. Discussion

The intent of the paper was to reduce the dependency on text ontology and almanacs to discriminate failure modes from text-based work orders thus reduce the complexity and processing speed. In view of this, the proposed methodology was to attempt a work order discrimination using time data of TTR and TBF which every recurring failure event would have.

Processing 7438 work orders in 0.25 seconds, this automated process without an ontology development stage is much faster than the text mining time mentioned in (Salo et al, 2018). (Salo et al. 2018) processed 3400 records or about half of the 7438 records processed here. The 3400 records usually take 10 days to process manually and was processed in a day by text mining. However, TTR/TBF based clustering manages to process 7438 records in hours when data prepping time is added in.

Looking at Table 6, taking in all identifiers of duration, frequency, location and trade, the work order descriptions were clustered around similar failure mode themes. However, exceptions still exist. For instance, work trades 2, 4, 5 and 11 had singular, similar failure modes but the other work trades are split to 2 or 3 failure modes.

Table 6: A Sampling of Clustered and Sorted Work Order Description.

Description	**Location**	**Trade**	**Duration**	**Frequency**
G - A&E - BED FAULTY	G-01-AE	1	20	262
G - A&E - PATIENT MONITOR FAULTY	G-01-AE	1	20	262
G - A&E - SIDE RAIL FAULTY	G-01-AE	1	20	262
G - A&E - BED FAULTY - RUBBER BED	G-01-AE	1	20	262
G - A&E - ECG LEAD FAULTY	G-01-AE	1	20	262
G - A&E - ECG Machine faulty	G-01-AE	1	20	262
Level G - A&E - Side rail broken	G-01-AE	1	20	262
G - A&E - BULLET FAULTY	G-01-AE	2	20	262
G - A&E - PTS FAULTY	G-01-AE	2	20	262
G - A&E - PTS FAULTY	G-01-AE	2	20	262
G - A&E - PTS FAULTY	G-01-AE	2	20	262
G - A&E - PTS FAULTY	G-01-AE	2	20	262
G - A&E - PTS FAULTY	G-01-AE	2	20	262
G - A&E TOILET - LIGHTING FAULTY	G-01-AE	4	20	262
G- A&E - TOILET LADIES - LIGHTING FAULTY	G-01-AE	4	20	262
G - REGISTRATION - DOWNLIGHT FAULTY	G-01-AE	4	20	262
G - A&E - MYQ TV FAULTY	G-01-AE	5	20	262
G - A&E - WAITING TIME MONITOR FAULTY	G-01-AE	5	20	262
G-A&E-MYQ FAULTY-WAITING TIME	G-01-AE	5	20	262
G - A&E - MYQ DISPLAY FAULTY	G-01-AE	5	20	262
G - A&E - WAITING TIME FAULTY	G-01-AE	5	20	262
G - A&E - WAITING TIME FAULTY	G-01-AE	5	20	262
G - A&E - CHANGE WHEEL CHAIR	G-01-AE	6	20	262
G-A&E-MO3-RODA KERUSI TERCABUT	G-01-AE	6	20	262
G - A&E - LOCK LOCKER FAULTY	G-01-AE	6	20	262
G - A&E - SLIDING DOOR FAULTY	G-01-AE	6	20	262
G - A&E - WHEEL OF CHAIR FAULTY	G-01-AE	6	20	262
G - A&E - BIDET LOOSE	G-01-AE	9	20	262
G - A&E - PIPE HEAD FAULTY	G-01-AE	9	20	262
G - OKU - FLUSH LEAKING	G-01-AE	9	20	262
G - A&E - POSTER FALL	G-01-AE	11	20	262

The resultant discriminated information also adds a layer of risk ranking for prioritization. (Khan and Haddara 2003, Priyanta et al. 2021) states that:

Risk = probability of failure x consequence of failure

Extrapolating from this statement for historical work orders where failure probability is the frequency of occurrences (1/mean TBF) and the consequence is the mean time taken to repair (mean TTR) then we can see that risk is the product of mean TTR (duration) and 1/mean TBF (frequency). Figure 4 is a log-log scatter plot of frequency versus duration that shows the level of risk in terms of how frequent and how severe is the failure cluster. In Figure 4, the riskiest clusters are located to the right top of the plot. Plots like this helps in prioritizing failure prevention by both its frequency and severity (Knights, P.F. 2001 and Seecharan et al. 2018).

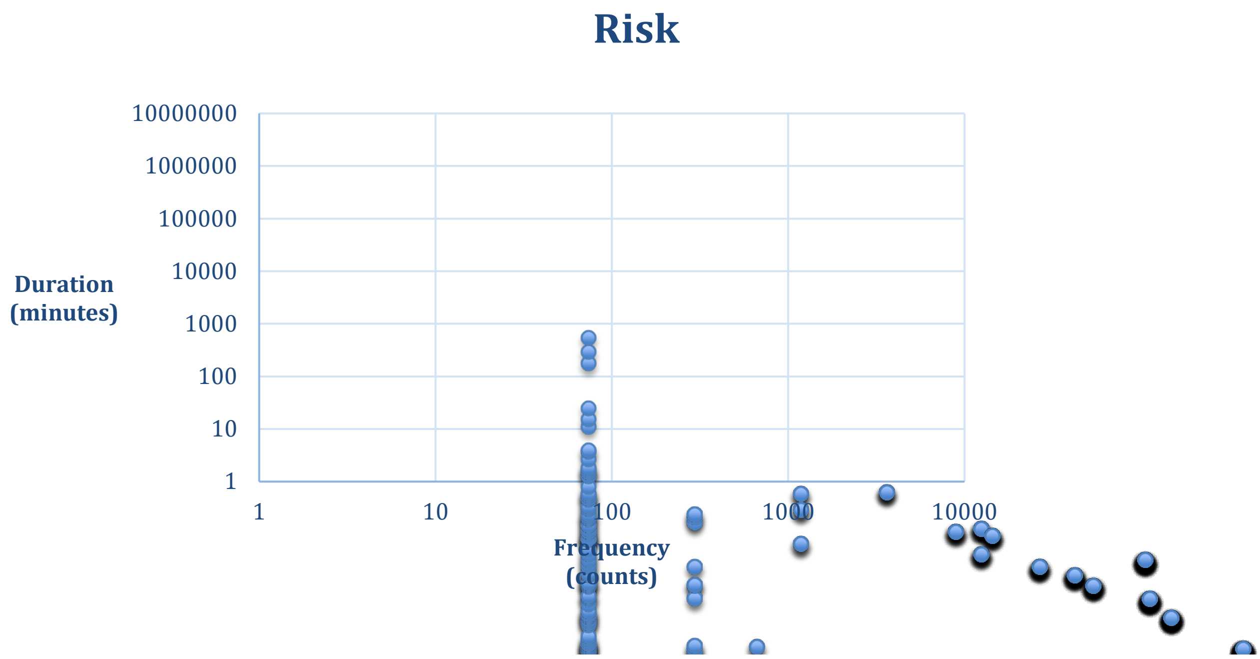

Figure 4: Risk is the product of duration and frequency

5. Conclusion

In terms of processing speed, the results show greatly higher speeds as compared to previous text mining processes (Salo et al. 2018). However, clustering of work orders by their TTR and TBF is not a perfect solution for discriminating failure modes from work orders. The results were not all singular and similar. Exceptions still exist as in other methods (Lin and Richi 2007). However, if for every cluster, results generally are not more than 3 different failure modes, as is seen in this clustering attempt, then the complexity of identifying failure modes have been simplified.

The results however could be more singular and finer if more identifiers were available. It is proposed that future attempts add more identifiers such as asset numbers, part numbers, asset categories and others if available. Location and trade labelling could also be more granular. Having these nouns as discriminators, will further individualize the failure modes. In future, these clusters could be coded as failure codes that can be used by maintenance departments to tag future work orders. This would aid in making proactive and priority decisions.

Added to this, is the recognition that each failure mode in a cluster have similar risks. Risks here being defined as the product of duration and frequency. Therefore, in terms of resource costs, discriminating by TTR and TBF has the added benefit of proactive task planning being prioritized by risks.

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