Determining Synonymy of Risk and Priority in Maintenance Prioritization.

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Abstract

For many decades, the industry has been using risk as to the basis for prioritization of maintenance activities in the form of Risk Priority Number (RPN) and risk matrices. The risk here is defined as the product of severity and frequency. However, priority is defined as the product of importance and urgency. This study is to determine whether risk and priority are synonymous. For the determination, maintenance data for various trades were collected from two Malaysian hospitals. These data were then clustered for risk and priority using the K-means clustering algorithm and statistical tools. The results were sorted, ranked, and compared. The resulting comparison shows that risk and priority are metrics of different properties. It was found that risk is a scalar magnitude while priority is a vector. Therefore, prioritization of maintenance by risk is a historical lagging indicator, while priority is a leading indicator and better predictor of future impact.

Keywords
Maintenance, Risk, Priority, Prioritization, and Urgency.

1. Introduction
For many decades, the main priority schema for failures in the industry has been the risk priority number (RPN) (Kim and Zuo, 2018). RPN is the product of the severity of impact, the likelihood of occurrence, and the likelihood of detection of failures as shown in Equation 1. The likelihood of detection is only used when there is a control system in place. However, RPN only defines failure risk. The industry has been taking risk ranking as the basis for failure priority ranking, where higher risk means higher priority and a lower risk means lower priority.

RPN = Severity x Occurrence x Detection. Equation 1

1.1 Objectives
The significance of priority ranking research lies mainly in budgets and the allocation of resources. When visibility to failure priority ranking is missing, then maintenance, repair, and overhaul (MRO) are budgeted but it is then up to operation managers to ascertain the allocation priority of these budgets. The study expects to prove that risk ranking is not synonymous with priority ranking. It is expected that this study will show that risk is a scalar magnitude and priority is a vector. There should be clear vector direction differences when risk and priority rankings are compared.

2. Literature Review
Industry activities in failure priority ranking have been using the severity and occurrence of RPN dimensions in risk matrixes to ascertain risk. For example, the Jack Knife Diagram shown in Figure 1, is a modified risk matrix that plots failures on a risk matrix of downtime and frequency. Failure priority ranking is then based on risk magnitude. The bottom right plotted failures are considered acute and chronic failures, thus, of high priority as compared to the left top bottom failures (Seecharan et al, 2018). For this paper, the risk is defined as a function of severity and occurrence where severity is represented by recorded failure downtime and occurrence by recorded failure frequency (Jianxing et al, 2021).

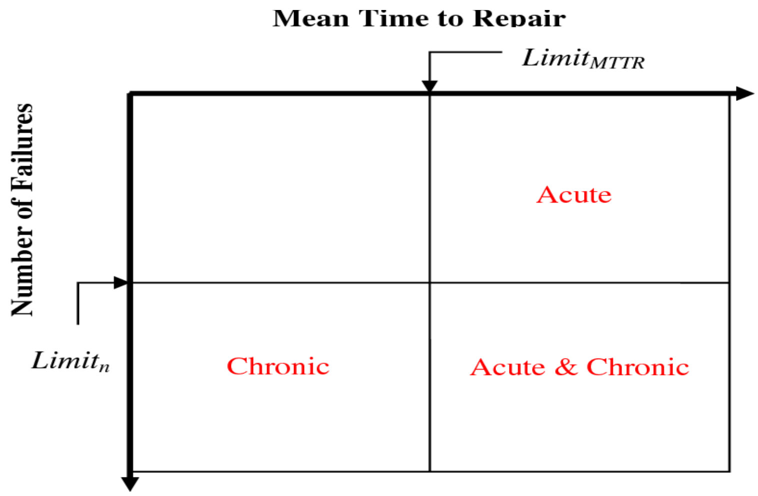

Figure 1: Jack Knife Diagram (Adapted from Seecharan et al, 2018)

However, a priority matrix or Eisenhower matrix prioritizes tasks based on the urgency and importance of tasks (Ngandam et al, 2019). The matrix is shown in Figure 2,

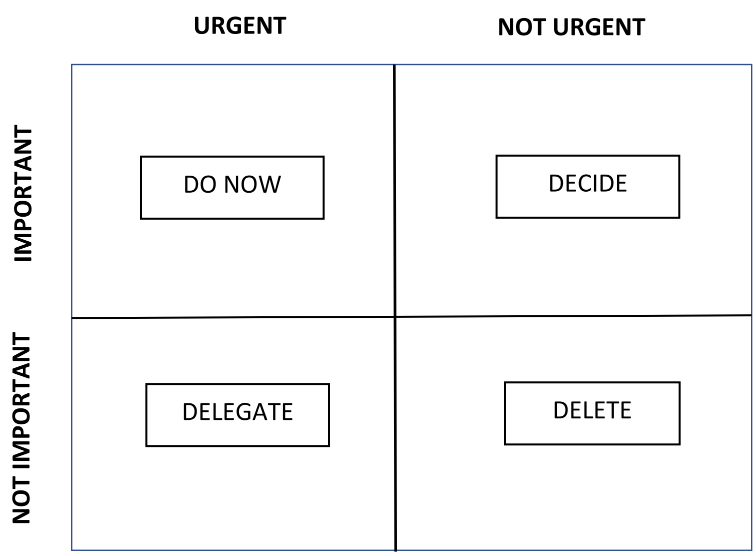

Figure 2: Eisenhower Priority Matrix - Adapted from (Besiktepe et al, 2021).

Consisting of four quadrants, the matrix is made up of a horizontal axis of urgency and a vertical axis of importance. The product of importance and urgency as in Equation 2, is then placed on the matrix and the product's relative position signifies the priority of the task. Where, importance is defined as "of great significance or value" and urgency as "promptly requiring attention" (Bratterud et al, 2020).

Priority = Importance x Urgency Equation 2

Comparing a risk matrix to a priority matrix, there is a misunderstanding of priority. If priority is the product of importance and urgency, then the risk is clearly seen as the "importance" in the equation but does risk also represent "urgency"? Risks of the same magnitude may not have the same urgency as some risks may be on a reducing rate and others increasing. The rate of risk or speed of risk to impact is mentioned by Ramamoorti et al. (2019) as risk velocity. Therefore, this study assumes that the rate of risk or risk velocity is the urgency or promptness requiring attention alluded to by risk matrices in prioritizing failures. How fast or slow risk is changing provides the urgency required for ranking failure priority. Hence, failure priority is assumed to be the product of risk and velocity. This assumption is illustrated in Equation 1.3.

Assumed Failure Priority = Risk x Risk Velocity Equation 3

The assumption of failure priority being the product of failure risk and risk velocity has a problem in that the assumption has no known reference. Bratterud et al. (2020) define urgency as promptly requiring attention, thus, it has an inherent time insistence factor and is, therefore, a vector that has magnitude and direction. Whether risk velocity is indeed the vector equivalent of urgency in the priority matrix, requires proving. In order to show the proof quantitatively, a case study based on actual failure data will be conducted. The case study will have the objective of comparing the resultant risk and priority rankings.

3. Methods

The study has to calculate the three equations of risk, risk velocity, and priority. The equations used in this research are shown in Equations 4, 5, and 6 respectively. For the purposes of this study, downtime was used to denote the severity and frequency of downtime as an occurrence where risk is the product of severity and occurrence (Jianxing et al, 2021). Equation 6 of priority was taken from the priority matrix where priority is the product of impact and urgency where urgency is taken as risk velocity (Ngandam et al, 2019).

Risk = Downtime x Frequency Equation 4

Risk Velocity = Change of Downtime / Change of Frequency Equation 5

Priority = Risk x Risk Velocity Equation 6

To begin the study, downtime records in the form of time to repair, and the difference between work end and work start time, was collected from selected site maintenance records. These downtime records were then machine clustered to acquire the frequency of each downtime cluster. From these data, the risk of each downtime cluster was calculated using Equation 4. Once risk was calculated for each downtime cluster, the risk values were then plotted on a risk matrix. Linear regression was then applied to find the rate of risk which is the slope of the regressed line. The calculated values of risk and rate of risk were then multiplied to get values of priority. Finally, risk and priority were ordered separately in the highest to the lowest ranking order, and a comparison analysis was applied.

4. Data Collection

To this study, failure data was collected from hospital facilities due to the range of failures that hospitals represent. This included not only the discipline mechanical and electrical type failures but also civil works. The data collection objective is to collect electrical, mechanical, and civil type failure data for comparisons of risk, risk velocity, and priority.

To provide further comparisons, two hospital facilities were chosen. Both hospitals chosen were active, multi-disciplinary hospitals. The first hospital chosen is a 20-year-old, 118 beds Malaysian hospital, and the other is a 10-year-old, 116-bed Malaysian Hospital. These hospitals were chosen because multiple-year failure data were available as digital records in their Computerized Maintenance Management System (CMMS). Availability of these digital records avails itself to quantitative analysis.

Once data was acquired, the data was then cleaned of null values and other inconsistencies. Using these cleaned data, the time to repair or downtime was calculated by subtracting the work start time from the work end time. These derived downtimes were then clustered using the K-means machine clustering algorithm. K-means was chosen because of its ability to cluster large data sets in the order of thousands. Due to downtime data being a “crisp” number of minutes, the sum squared error for this processing was set to zero. K-means was found to not only derive downtime clusters but also cluster instances for each cluster. These instance totals are then taken as the cluster frequency.

After downtime and frequency data are acquired then an examination of risk and priority began. Firstly, the data is divided by the trades of electrical, mechanical, and, civil to facilitate further analysis. Then the downtime and frequency data are multiplied to get risk values. The risk here is calculated as the product of downtime and frequency (Jianxing et al, 2021). The mean risk values of each trade were then derived. With these mean risk values by trade, the trades are ordered into a risk ranking table to find the order of trade by mean risk value. This risk ranking is then saved for comparison with priority rankings later.

Pursuant to the risk ranking phase, the frequencies and downtimes for each trade were then plotted on a risk plot. The risk plot used has a vertical axis of downtime and a horizontal axis of frequency. For this plot, a log-log plot was used because of the extreme variety of values and to facilitate linear regression (Seecharan et al. 2018). A linear regression using statistical software was then performed and the risk velocity was derived for each trade,

After the risk rate for each trade was derived, the rates were multiplied with trade mean risk values to derive the trade priority values. Here, priority was defined as the product of risk and risk velocity. The calculated priority values for each trade were then ordered in a priority ranking table. Finally, the risk ranking table and priority ranking table were displayed side by side. A comparison analysis that looks for differences was then performed.

In performing this study, a variety of software tools was used. The data from the hospital facilities came in the form of the Computerized Maintenance Management System (CMMS) format. The CMMS used was CWorks CMMS. The database was MySQL where SQL language was used to extract work order data, SQL language was also used to calculate downtime for each work order. For machine clustering, WEKA K-means software was used, and the Excel statistic package was used for statistical analysis, plotting, and linear regression.

5. Results and Discussion

As mentioned previously, the analysis methodology starts by clustering risk parameters of downtime and frequency from maintenance datasets of two selected hospitals. Clustering was by K-means machine clustering where the sum squared error was set to zero.

5.1 Numerical Results

Table 1 displays the passes that were attempted on the hospital 1 dataset to identify the K number that corresponds to the sum squared error of zero. The resultant K number, in this case, was identified as 355.

Table 1: K number sum squared error 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

Using this derived K-number, downtime was clustered and instances of frequency of each downtime cluster were identified. Clustering was conducted on both hospitals' datasets. A sample of the results is shown in Table 2. As can be seen from the table, the downtime in minutes is shown to be "crisp" integers thus justifying the setting of sum squared errors to zero. It is also seen that once the datasets are prepared for clustering, the clustering time was in minutes which shows clustering processing time advantage over spreadsheet sorting in counting the frequency of each downtime. Once clustering has been conducted, the statistical parameters of the clusters were identified using statistical software. This was done by the selected trades of mechanical, electrical, and civil to identify downtime and frequency means by trades for risk ranking later. The statistical parameters respectively are shown in Table 3 for hospital 1 and Table 4 for hospital 2.

Table 2: Cluster Frequency

Cluster No.	Frequency	% of Instances	Downtime 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

Table 3: Statistical Parameters by Trades (Hospital 1)

Trade	Mechanical		Electrical		Civil	
	Downtime	Frequency	Downtime	Frequency	Downtime	Frequency
Total	99.7	215972	425.68	64514	240.59	1495
Units	1013	1013	934	934	198	198
Mean	0.98	213.41	0.46	69.07	12.21	7.59
Mode	0.04	456	0.04	212	5	1
Max	669	456	194.9	212	906.9	16

Table 4: Statistical Parameters by Trades (Hospital 2)

Trade	Mechanical		Electrical		Civil	
	Downtime	Frequency	Downtime	Frequency	Downtime	Frequency
Total	7108.05	5176643	3390.94	8148636	2850.49	3140823
Units	7913	7913	8252	8252	5571	5571
Mean	0.9	654.19	0.41	987.47	0.51	563.78
Mode	0.02	1498	0.02	2287	0.02	1275
Max	736	1498	245.04	2287	209.38	1275

Mean values for all trades and hospitals were then tabled and the risk was ranked by hospital and trades. The risk ranking results can be seen in Table 5 below. For hospital 1, the risk ranking indicates that the mechanical trade has the highest risk of 209.8 followed by civil at 92.7 and electrical at 31.5. In comparison, hospital 2 also shows mechanical trades having the highest risk of 588.5 but civil at 287.5 has a lower risk rank than electrical at 404.6. As can be seen from the table, the two hospitals, mechanical ranks highest but differ in ranking when comparing electrical and civil trades. Therefore, risk is not dependent on the type of trade but on situational issues.

Table 5: Risk Ranking by Hospitals and Trades.

Site	Hospital 1		Hospital 2	
Trade	**Risk Values**	**Risk Rank**	**Risk Values**	**Risk Rank**
Mechanical	**209.8**	**1**	**588.8**	**1**
Civil	**92.7**	**2**	**287.5**	**3**
Electrical	**31.5**	**3**	**404.9**	**2**

5.2 Graphical Results

For priority to be compared to the derived risk rankings, risk velocity needs to be identified for each trade at the two hospitals. To solve for risk velocity, the slope of the best fit line for each is ascertained. This is because risk velocity is the rate or speed of risk. To find the slope of the best fit line, the downtime and frequency of each trade were plotted on a log-log graph. A log-log graph was used for easier linear line regression as the values have extreme order of differences. The log-log plots were plotted, and the results can be seen as Figure 3 for the trades of hospital 1 and Figure 4 for hospital 2 below.

From these plots, excel software was then used to derive the power trendline equation of $y = ax^b$ or log y=log(c)+blog(x) where b is the rate of the line. Among all the trendline types, for the data at hand, the power trendline regression visually fits the best linearly. The derived regression of each plot was then tabled for both hospitals and shown in Table 6. The regression equations were also included with their R-squared values. It is seen that hospital 2 has a better fit with single decimal place R-squared values. However, since this research is concerned only to prove differences based on relative direction and magnitude, outliers are not ignored for sake of brevity of the task.

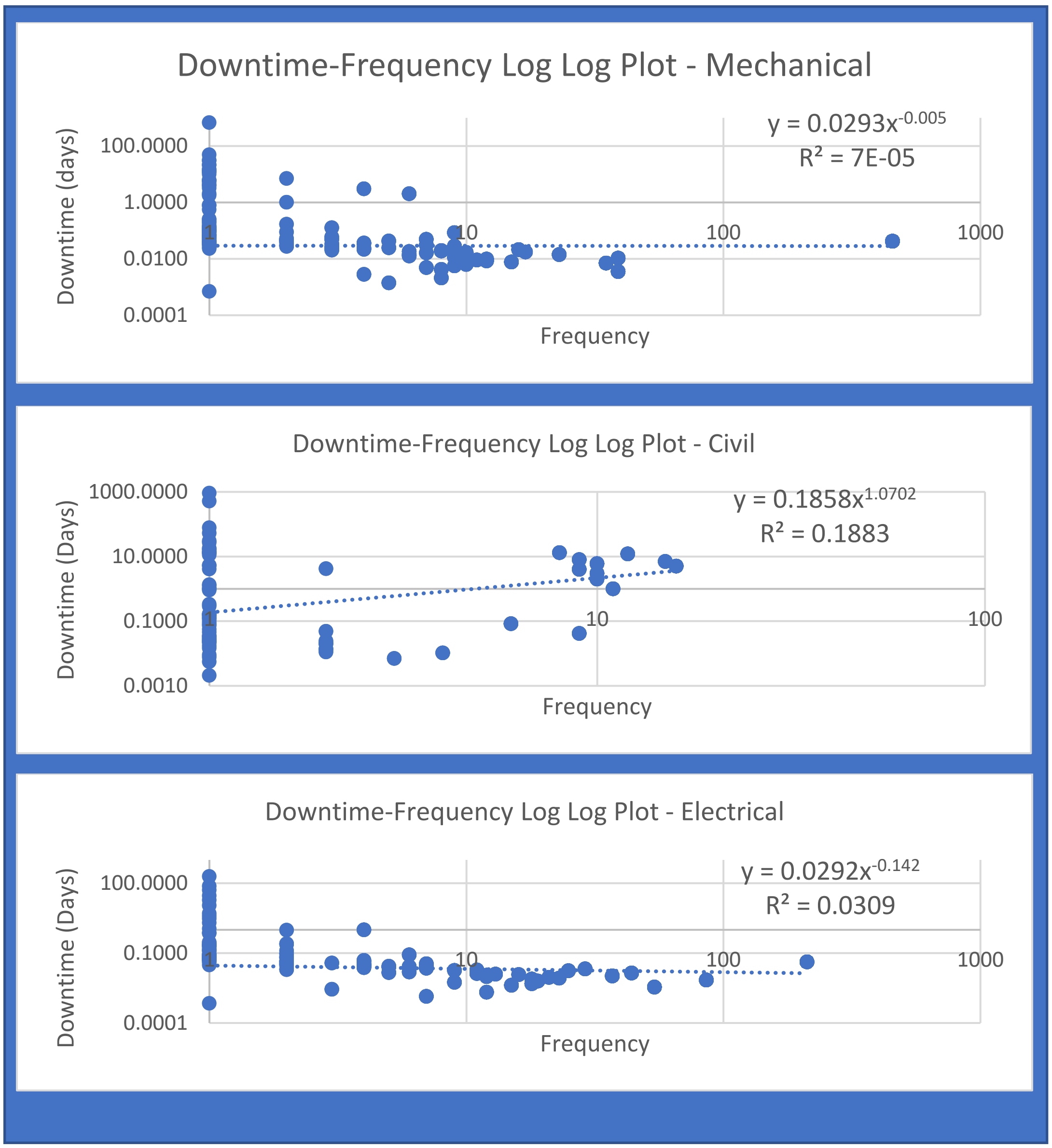

Figure 3: Log-Log Plots of Downtime and Frequency by Trades for Hospital 1

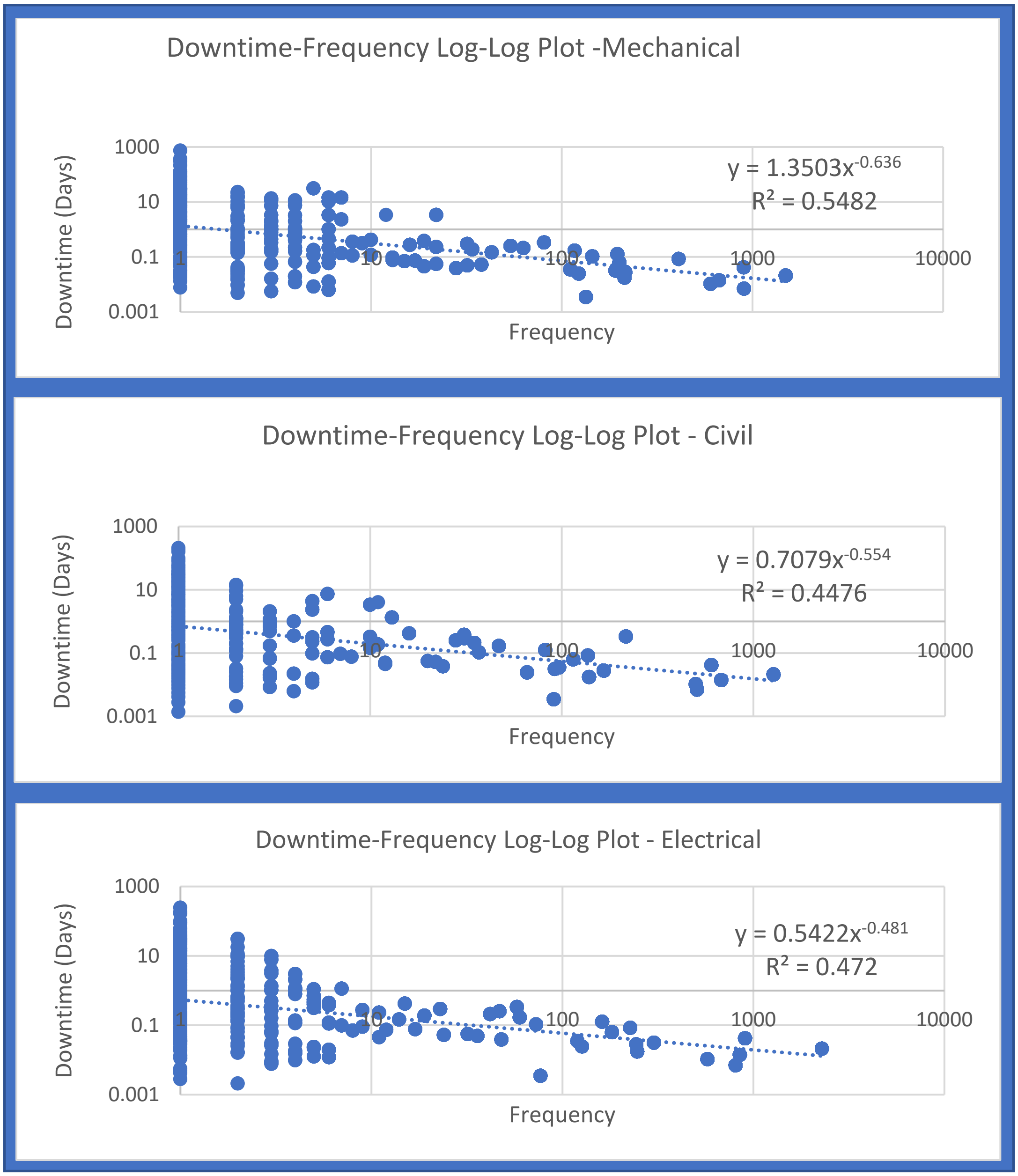

Figure 4: Log-Log Plots of Downtime and Frequency by Trades for Hospital 2

Table 6: List of Regression Equations by Hospital and Trade

	Hospital 1		**Hospital 2**	
Trade	**Equation**	**R-squared**	**Equation**	**R-squared**
Mechanical	$y = 0.0293x^{-0.005}$	$R^2 = 7E\text{-}05$	$y = 1.3503x^{-0.636}$	$R^2 = 0.5482$
Electrical	$y = 0.0292x^{-0.142}$	$R^2 = 0.0309$	$y = 0.5422x^{-0.481}$	$R^2 = 0.472$
Civil	$y = 0.1858x^{1.0702}$	$R^2 = 0.1883$	$y = 0.7079x^{-0.554}$	$R^2 = 0.4476$

5.3 Validation

The regressed line slopes for the plotted data at hand were taken as risk velocity. Priority was then calculated by multiplying risk values to velocity values. The resultant priority and ranking for each hospital and trade are tabled in Table 7 and Table 8 respectively. Risk values and their ranking were also tabled in the same tables for comparative analysis.

Table 7: Risk vs Priority (Hospital 1)

Trade	Risk	Risk Rank	Velocity	Priority	Priority Rank
Electrical	31.5	3	-0.142	-4.473	3
Mechanical	209.8	1	-0.005	-1.049	2
Civil	92.7	2	1.0702	99.207	1

Table 8: Risk vs Priority (Hospital 2)

Trade	Risk	Risk Rank	Velocity	Priority	Priority Rank
Electrical	404.9	2	-0.481	-194.757	2
Mechanical	588.8	1	-0.636	-374.477	3
Civil	287.5	3	-0.554	-159.275	1

For comparison between risk ranking against priority ranking, the site types and trades were kept similar. From the comparison, it was found that risk values remain positive, while priority values had different polarities. In this case, civil trade for hospital one has different polarity or vector polarity from the other priority. This indicates a vectorial property as compared to scalar risk values.

6. Conclusion

The results of the study show that a failure risk is not a failure priority. Priority has an element of rate of risk or risk velocity. As proven in the study, this risk velocity is a vector and not a scalar magnitude. This vector gives an indication of the speed of risk to the realization of the risk. The study shows that prioritizing by risks is prioritizing by the magnitude of risk. It does not prioritize by the speed to impact. This is shown by the difference in priority ranking by risk (severity-frequency) and by priority (magnitude-velocity). Prioritizing by risk is a scalar activity, whereas prioritizing by speed to impact is a vector with magnitude and direction. Incorporating speed to impact or risk velocity in maintenance prioritization schemas is a better leading predictor of future impact on budgets and resource allocations. Prioritizing purely on risk indicators such as risk priority number (RPN) is a lagging indicator that may or may not be a good future predictor. Further research in the usage of risk velocity in industrial maintenance prioritization is recommended.

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