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Analysis of Machine Breakdowns in a Cement Manufacturing Plant

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ABSTRACT

Machine breakdowns interrupt manufacturing processes and delay scheduled supplies. Proper analysis of machine breakdown data can provide insights about the breakdown patterns and vulnerable machines. We analyzed machine breakdown records of a cement manufacturing plant with the intension of understanding the patterns in the breakdown occurrences to predict future breakdowns. Data analysis revealed that 50% of all the breakdowns occurred in three machines while there were 47 machines which had at least one breakdown over a period of one year. More than 50% of the total breakdown time was also caused by these three critical machines. We calculated the time intervals between successive occurrences of breakdowns (inter-arrival times) and fitted probability distributions. The overall breakdown inter-arrival times of breakdowns follow a Weibull distribution and the machine breakdown times follow a Log-normal distribution. The estimated probability that another breakdown occurs within one day was 83% and within two days 94%. A simulation model was developed using the Arena simulation package to predict the breakdowns in near future. The model could identify the machines which are most likely to breakdown in the next month with 81% accuracy and both the total number of breakdowns and the total downtime for a month ahead with 92% accuracy.

1. Introduction

Machine breakdowns cause several direct and indirect losses to both manufacturers and their customers. They can delay production schedules, increase waste, underutilize resources. Though machine breakdowns are unavoidable in manufacturing environments, proper understanding of the temporal patterns of breakdowns and the susceptibility of various machines to breakdowns would help the management in efficiently managing machine maintenance thus reducing the adverse impacts of unexpected breakdowns. Analysis of past machine breakdown records leads to understand the patterns and probabilities of machine breakdowns. Such data can use in various statistical and mathematical models to generate foresights about future breakdowns [1-3].

Simulation is a widely used mathematical modelling technique to predict the occurrences and nature of machine breakdowns [2, 4]. Simulation models are also used to evaluate potential outcomes of different breakdown and maintenance scenarios [5, 6-7]. A taxonomy for modelling breakdowns in simulation models [8] and a method of grouping machines with similar probability distributions of breakdown times [2] have also been proposed to simplify the simulations. A simulation model has been developed to predict the probability of machine failure in a cement manufacturing plant [4].

In machine breakdown simulations, modelling of the arrival pattern of breakdowns is a key input. Advanced mathematical modelling approaches such as Bayesian network modelling [4], finite mixture distributions [2] and Bayesian hierarchical Weibull models [7] have been used to model the arrivals of breakdowns. However, the pattern of breakdowns in any given plant can be unique and should be independently analyzed to understand the breakdown behavior of machines and their causes.

In our study, we analyzed the machine breakdowns in a cement manufacturing plant in Sri Lanka. The objective of the study was to identify the patterns of breakdown occurrences and downtimes and to predict which machines would come down in near future. We performed classical descriptive analysis of the data set and then fitted probability distributions for the time intervals between successive occurrences of breakdowns (inter-arrival times) and for breakdown times. These probability distributions were then used to simulate the machine breakdowns over time to predict the expected breakdowns in the upcoming month.

2. Material and Methods

Data on Machine breakdowns for a period of one year from 1st December 2018 to 30th November 2019 were used for the analysis. Based on the fitted models, predictions on possible breakdowns were made for December 2019 and was compared with the actual breakdowns occurred in December 2019.

The original data set contained breakdowns reported from five processing areas in the cement manufacturing plant. We considered the breakdowns including feed-cuts occurred in the Roller Press Area (RP) and in the two packing plant areas (PM) where almost all the breakdowns have occurred. Altogether 481 breakdowns had occurred during the one year period out of which 231 had occurred in the RP area 250 had occurred in the two packing plant areas. The breakdown records consisted of the notification date, location (area) affected, machine, description of the breakdown, malfunction start date and time, malfunction end date and time, and breakdown time (downtime). There were 47 machines which had encountered at least one breakdown during the one-year period and 178 different breakdowns (descriptions) had occurred during the period. A snapshot of the dataset is given in Figure 1. We have slightly modified the location codes and machine codes for data security.

Notification Date	Notification Number	Area	Machine
20181201	2000266722	RP	RP-41-RP1
20181201	2000266752	RP	RP-41-BE1
20181204	2000267277	RP	RP-41-RP1
20181204	2000267294	RP	RP-41-RP1
20181205	2000267413	PM1	PM-91-LM1
20181206	2000267711	RP	RP-41-BE1
20181207	2000267912	PM1	PM-61-BD2

Breakdown Description
RP-41-MD1_MOTOR TRIP
FEED CUT DUE TO RP-41-BE1_HIGH AMP
RP-41-MD1_MOTOR TRIP
RP-41-MD2/M2_STOPPED DUE TO HIGH VIBRATION
PM-91-LM1_OPERATOR_PANEL_ISSUE
RP-41-BE1_BOOT CLOG
PM-61-BD2_GEARBOX_OIL_LEAKAGE

Malfunction Start Date	Malfunction Start Time	Malfunction End Date	Malfunction End Time	Breakdown Duration (h)
12/01/2018	03:20:00	12/01/2018	03:41:00	0.35
12/01/2018	10:15:00	12/01/2018	10:40:00	0.42
12/04/2018	07:47:00	12/04/2018	08:03:00	0.27
12/04/2018	12:41:00	12/04/2018	13:02:00	0.35
12/04/2018	19:30:00	12/04/2018	19:46:00	1.12
12/06/2018	03:10:00	12/06/2018	04:15:00	1.08
12/06/2018	21:26:00	12/06/2018	21:33:00	0.54

Figure 1: A snapshot of the breakdown data set

We first performed a numerical analysis to calculate the breakdown frequencies, probabilities and total downtimes for different machines and types of breakdowns using MS Excel. We calculated the inter-arrival times of breakdowns from the malfunction start dates and times. To model the pattern of the occurrences of breakdowns, we extracted the inter-arrival times and fitted probability distributions using the input analyzer in Arena simulation package[9]. We fitted distributions for the breakdown times also.

Using the estimated probabilities and fitted distributions, a simulation model was developed using Arena simulation package to predict the breakdowns for the next month. The simulation results were compared with actual breakdowns occurred in December 2019 to evaluate the performance of the simulation model as a tool for predicting machine breakdowns.

3. Results and Discussion

The primary descriptive analysis revealed significantly different breakdown behaviors among different machines. A summary of the machines which encountered breakdowns most frequently (contributing to 80% of the total number of breakdowns) is given in Table 1. There were three machines out of 47, which were critical. They were namely, PM-71-PA1, RP-41-RP1 and RP-41-BE1 which accounted for approximately 50% of the total number of breakdowns.

Table 1: Machines with most frequent breakdowns

Machine	No. of BDs	% of Total	Cum. %
PM-71-PA1	81	17%	17%
RP-41-RP1	80	17%	33%
RP-41-BE1	64	13%	47%
PM-92-LM2	45	9%	56%
PM-92-LM1	27	6%	62%
PM-61-PM1	22	5%	66%
RP-91-BE1	20	4%	70%
PM-61-CX1	14	3%	73%
RP-41-BC3	13	3%	76%
RP-41-3B5	11	2%	78%
RP-41-BF7	9	2%	80%

The machines which had highest total downtimes (contributing to 80% of the overall downtime) are summarized in Table 2. The same three machines identified above contributed to more than 50% of the overall downtimes.

Table 3 contains the types of breakdowns which have occurred more frequently than ten times during the one-year time period. The calculations indicated that though some breakdowns have frequently occurred, the average downtime is low while some other breakdowns which have occurred less frequently caused longer interruptions.

Table 2: Machines with highest total downtimes

Machine	Downtime (h)	% of Total	Cum. %
RP-41-RP1	160.81	24%	24%
PM-71-PA1	142.01	21%	44%
RP-41-BE1	62.95	9%	54%
PM-61-PM1	41.27	6%	60%
RP-91-BE1	29.12	4%	64%
PM-92-LM2	26.59	4%	68%
RP-41-3B5	22.23	3%	71%
RP-41-BC3	21.9	3%	74%
PM-62-PM1	13.53	2%	76%
PM-12-SC1	12.02	2%	78%
PM-92-LM1	11.5	2%	80%

Table 3: Most frequently occurring breakdowns

Machine	Breakdown Description	No.
PM-71-PA1	HOIST ISSUE	26
RP-41-BE1	FEED CUT DUE TO 41-BE1 HIGH AMP	24
RP-41-RP1	41-MD1 MOTOR TRIP	21
RP-41-BE1	41-BE1 BOOT CLOG	17
PM-92-LM2	92-M2 POWER SUPPLY FAULT	17
PM-92-LM1	92-LM1 CONTROL SUPPLY ISSUE	14
RP-91-BE1	91-BE1 SIDE DRIFT	11
PM-61-CX1	61-CX1 TRIPPED	11

We attempted to fit probability distributions separately for the inter-arrival times of roller-press area breakdowns, for packing area breakdowns, and for all breakdowns, considering the fact that grouping of machines can produce better results [2]. While roller-press breakdowns tended to follow a lognormal distribution, packing area breakdowns seemed to have no significant pattern of arrival. The fit for the distribution of overall breakdown inter-arrival times obtained for Weibull distribution (Figure 2). Both the Chi-square test (p=0.725) and the Kolmogorov-Smirnov test (p=0.063) indicated that the inter-arrival times follow a Weibull distribution (at 0.05 level of significance).

Distribution: Weibull

Expression: -0.001 + WEIB (9.88, 0.653)

Square Error: 0.000692

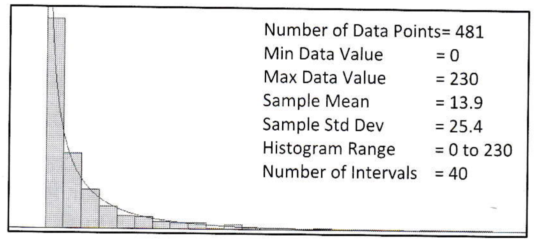

Figure 2: Distribution of Inter-arrival times

Useful information on the time between two breakdowns can be derived from the fitted distribution. The corresponding probabilities that the next breakdown occurs within 1 hour, 8 hours, 24 hours and within 2 days are 20%, 58%, 83% and 94%, respectively. Thus it is highly likely that another breakdown occurs within two days of a breakdown.

The best model fitted for the distribution of breakdown times was a Log-normal distribution (Figure 3). The model fit is not as good as the fit for the inter-arrival times. However, it can be accepted at 0.01 level of significance (Chi-square test: p=0.024 and Kolmogorov-Smirnov test:p=0.023).

Distribution: Lognormal

Expression: LOGN (1.4, 2.27)

Square Error: 0.001549

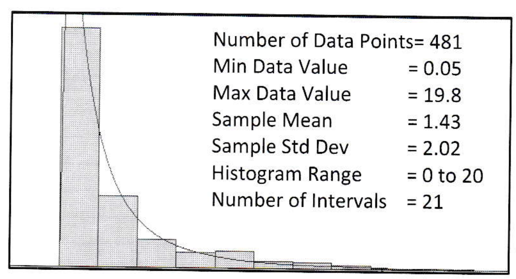

Figure 3: Distribution of breakdown times

We simulated the machine breakdowns for a period of one month using the inter-arrival times, probabilities of breakdowns associated with machines and different types of breakdowns, and the probability distribution of breakdown times. Results obtained from the simulation using 10 replications are given in Table 4.

The simulations estimated the total number of breakdowns in December 2019 as 48 and thus the prediction error was 8% compared to the actual number 52. The total estimated breakdown time was 45 hours whereas the actual was approximately 42 hours and thus the error in the predicted total downtime was 8%.

Table 4: The actual and simulated (predicted) numbers of breakdowns and breakdown times in December 2019

	No. of BDs		Downtime (h)	
Machine	Actual	Simul	Actual	Simul
PM-92-LM1	18	3	2.26	1.15
PM-71-PA1	11	10	15.17	15.78
RP-41-RP1	9	9	4.9	7.41
RP-41-BC3	3	2	3.43	3.04
RP-41-3B4	2	0	0.47	-
RP-41-BC1	2	1	2.1	0.41
RP-41-BE1	2	6	3.17	2.33
PM-71-BC7	2	0	3.4	-
RP-41-BF7	1	1	1.75	0.37
RP-41-VS1	1	1	1.2	1.77
PM-61-PM1	1	2	3.75	3.38
RP-41-3B5	0	2	-	1.80
RP-41-SR1	0	1	-	1.45
RP-91-BE1	0	2	-	0.23
PM-12-SC1	0	1	-	2.16
PM-61-CX1	0	1	-	0.62
PM-62-BD2	0	1	-	0.48
PM-92-LM2	0	5	-	2.66
Other 29 machines	0	0	-	-
Total	52	48	41.60	45.04

As shown in Table 4, the model predictions on whether a machine will breakdown in December were correct for 9 machines out of 11 which actually encountered breakdowns (error: 18%) and for 29 machines out of 36 which actually did not encounter breakdowns (error: 19%). Hence, for 38 machines out of 47 (81% of the machines), the model could correctly predict whether a breakdown would occur in December. The simulation also correctly identified the number of breakdowns to occur in two critical machines, PM-71-PA1 and RP-41-RP1. The series of consecutive breakdowns of PM-92-LM1 was an unusual event which hasn't occurred before. The mean absolute error (MAE) in the predicted number of breakdowns over all machines was 0.85~1. The MAE in the predicted machine downtimes over all machines was 0.48 hours = 29 minutes.

To predict which types of breakdowns would occur, we also simulated RP breakdowns considering both the machines and the probabilities of different types of breakdowns that can occur within each machine. Out of 10 different types of breakdowns which had actually occurred in 7 machines in RP area, the simulation could exactly predict only two types of breakdowns. Since only 20% of the actual types of breakdowns were correctly identified, the error is 80%. Therefore, the simulation model is not suitable for predicting what breakdowns would occur. However, it could predict which machines would encounter breakdowns in the upcoming month with approximately 81% accuracy. It could also predict the total number of breakdowns and the total time loss caused by machine breakdowns within 92% accuracy (i.e. with 8% error).

We also evaluated the possibility of modelling the breakdowns of an individual machine separately considering the machine PM-71-PA1 which has encountered the highest number of breakdowns. The best for the breakdown inter-arrival times of the particular machine was also a Weibull distribution (Figure 4) with the parameters given below (Chi-square test: p=0.007, Kolmogorov-Smirnov test: p=0.122). Only the Kolmogorov-Smirnov test indicated that the model fits the data at 0.05 level of significance. The poor fitting may be due to the fewer number of data points.

Distribution: Weibull

Expression: -0.001 + WEIB (21.5, 0.41)

Square Error: 0.007356

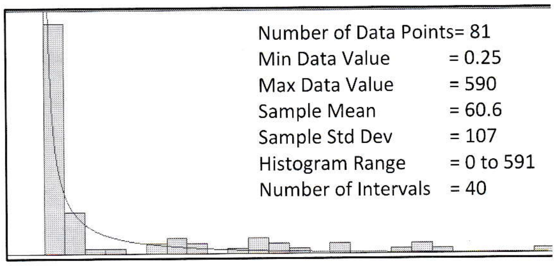

Figure 4: Distribution of breakdown times

Simulation of PM-71-PA1 breakdowns for a long period of time indicted that on average, 11.5 breakdowns can occur in a month, which is correct for the month of December 2019.

We analyzed machine breakdown records of a cement manufacturing plant for a period of one year to model and understand the breakdown patterns. Inter-arrival times of breakdowns were modeled using statistical probability distributions. Simulation experiments were carried out to generate useful insights about future breakdowns. Simulation outcomes were compared with the actual data for a month ahead.

Probability estimates indicated that there were three machines out of total 47 (i.e. 6% of the machines) which contribute to approximately 50% of both the total number of breakdowns and the total downtime. These machines were identified to be critical. We identified that the breakdown inter-arrival times tend to follow Weibull distributions while the breakdown times tend to follow log-normal distributions. The simulation model predicted the total number of breakdowns and the total downtime in the next month within 92% accuracy. The machines which would breakdown in the next month were also identified within 81% accuracy. However, the simulation model could correctly predict only 20% of the types of breakdowns occurred in the next month.

The accuracies of our results base on how well the probability distributions would model the actual breakdown process. Perhaps, data for a longer period of time would improve the performance of the model. However, both the breakdown inter-arrival times and the types of breakdowns can vary over time when the machines get older. Hence, most recent data, which readily incorporate the impacts of machine ages, more accurately represent the patterns of future breakdowns. To determine the optimal time period over which data should be used to build simulation models, we can test simulation models with data sets of different lengths (for example, 1 year, 2 years,..., 5 years) and compare the accuracy of predictions. Studying the causes of breakdowns, and incorporating such information into the simulation models can also improve the accuracy of the predictions. Simulation models for individual machines or for groups of similar machines may also generate more specific and reliable insights.

Our results provide useful information for machine maintenance. The identified critical machines can be given priority in preventive maintenance. The machines which are likely to breakdown in the next month should also receive more attention. For example, the required spare parts and equipment can be made available early. Production schedules can prepare to include the expected breakdown delays.

4. Conclusion

In conclusion, simulation experiments can predict the machines which are likely to breakdown, the number of breakdowns and the breakdown times with an acceptable level of accuracy. The predictions generated from the simulation models can support maintenance management and production scheduling.

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