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Stochastic Simulation of Machine Breakdowns

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Abstract

This paper explores the value of stochastic simulation as a tool for predicting current or future reliability of machinery, it helps to understand machine failures by using confidence levels developed through replications and exploring the changes that occur.

A stochastic simulation model has been constructed representing a crusher machine with in a cement manufacturing plant. The crusher machine has three parameters; namely those are drill head, dusting and lubrication. The consumption of these parameters results in the development of a probability of failure for the machine using Bayes theory.

Keywords: simulation; stochastic; reliability; manufacturing

1. Introduction

World class organisations invest vast amounts of capital into research and development to achieve a competitive edge over competitors. This competitive edge depending on industry can be on a number of different aspects [1]. For example, a new product, a new technology that helps the organisation reduce cost or even making certain business processes easier, new technology can mean the invention of a new product or feature etc. In the case of the cement manufacturing industry, to concentrate on how to increase capacity in order to cater for current and future predicted demand [2, 3]. Their research and development may include the consideration of machinery, the type of machinery, new machinery or new systems that enable a prolonged usage of machinery.

Often planned changes result in the implementation of new strategies or philosophies that enhance productivity via the means of quality maintenance management. Maintenance of machinery is integral to all industries in order to maintain lead times and produce consistent quality products that are free from faults. [4]

Hence, the ability to be able to predict the future reliability of machinery is pursued and encouraged by all industrial organisations in order to reach world class status i.e. to move from a '*fail and fix'* approach to a '*predict and prevent*' approach.

The following sections will highlight the development of the stochastic model and is really an attempt to fine tune the results extracted, because stochastic is based on numbers generated randomly. The results that are extracted i.e. failure probability, should be different for every replication made, every replication will use different number streams and hence there should be a variance in the probability of failure for each replication. This will help to understand the strength of the results and further enhance the validity.

2. Research Objectives

The objective of this research is to highlight the stochastic nature of the model, how the software is able to implement and generate random variables to enable an improvement in results by providing a more realistic approach.

3. Assumptions and Limitations

This paper uses a simulation model previously developed to work out the confidence levels of machine breakdowns i.e. Bayesian Model. The Bayesian model [5] constructed will have two scenarios i.e. 30 days (model running time of 43200 minutes, figure (1) and the running of the model until first breakdown occurs, figure 2.

These two scenarios will be replicated 50 times to achieve a strong result.

Model is based on a single machine with three parameters.

Model is based on the Bayesian Network Modelling, aided by the Hugin Software and further has the Chain Rule implemented to derive the probability.

Witness Scenario Manager has been used to run test replication and extract results.

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As mentioned previously above, the main concentration will be the '*failure probability'* of the machine, to understand how the model reaches or extracts this developed probability it is very important to highlight certain aspects of the process that add value to the results.

The parameters that represent component parts have life spans which are now eligible to change because of the stochastic approach, after their time is up, they need changing and hence inspections are now also eligible to change. This is the same for all three parameters; figure 1 and 2 shows screen shots of scenarios 1 and 2, all the key performance indicators show times and usage rates. This in turn has a direct affect on the amount of life or usage rate of the parameter i.e. the percentage 'Used' and 'Remaining'. This means that, all the parameters in terms of time and usage will change at different intervals within the systems that are interconnected in order to extrapolate a certain outcome i.e. failure probability.

Hence, instead of looking at parameters separately or their key performance indicators individually, the concentration will be the failure probability that takes into consideration all the changes that occur to develop the probability using the Chain Rule.

Figure 1 – Bayesian Model 43200 minutes/30 days

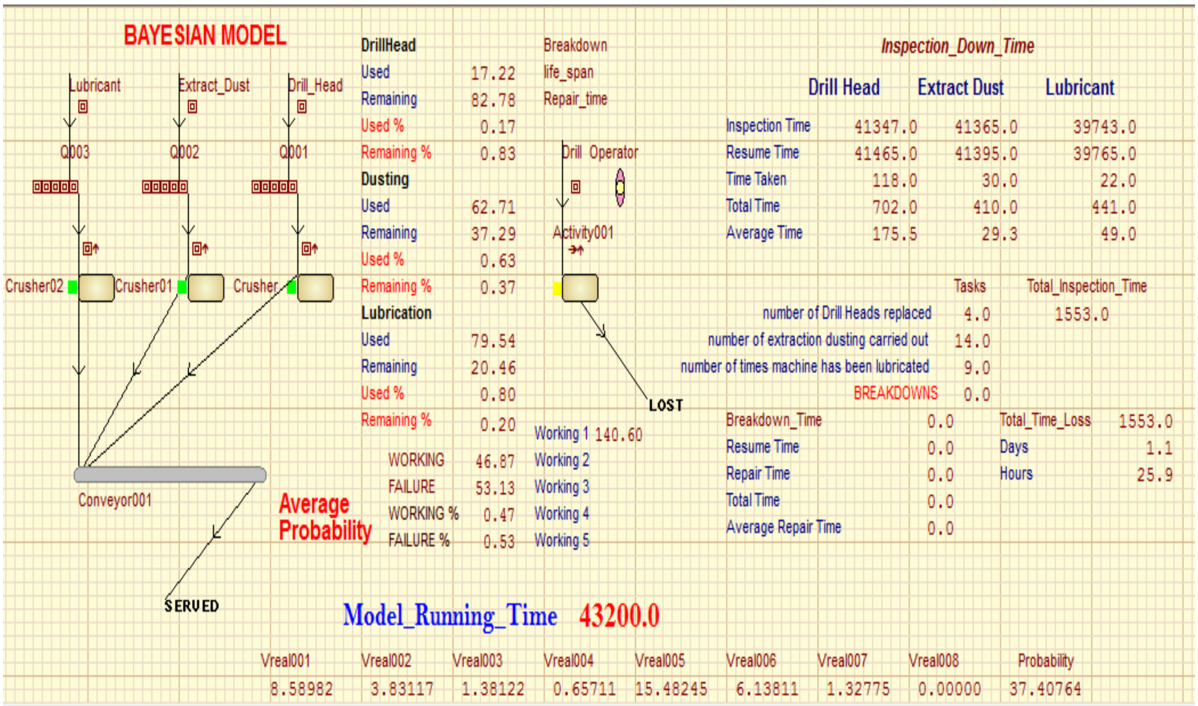
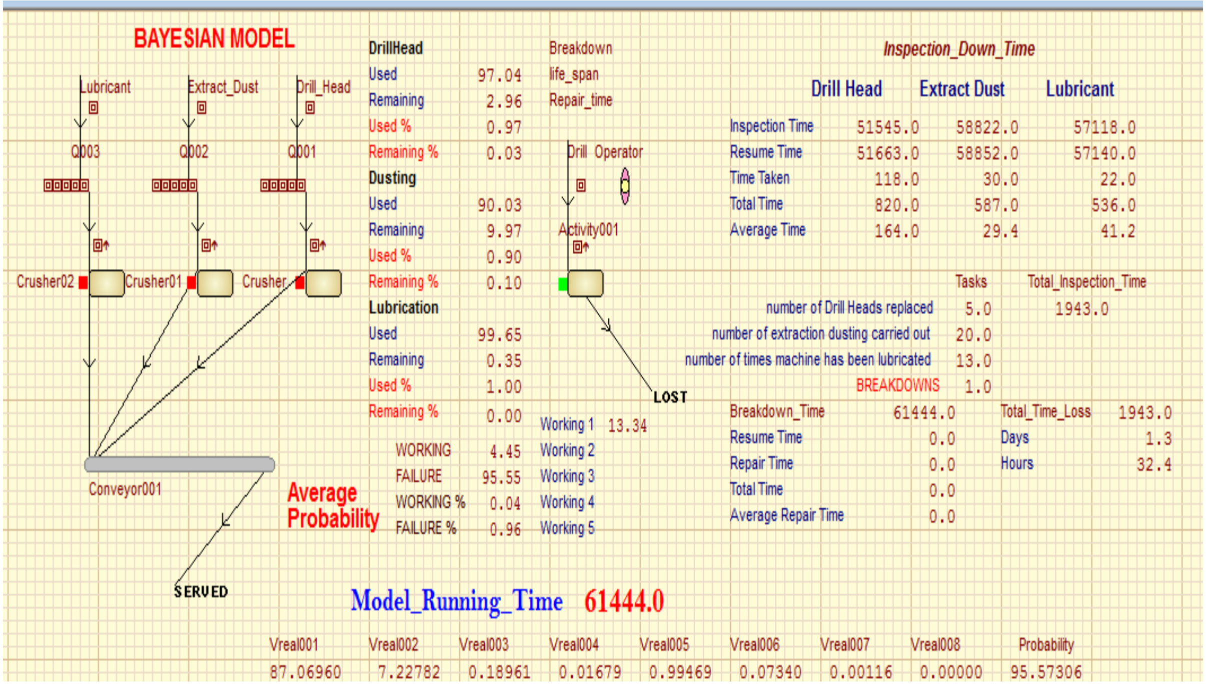


Figure 2 – Bayesian Model 61444 minutes/breakdown



4. Simulation Model

Witness simulation was used to create the Bayesian model in figure 1 and 2, the purpose of the model is to run reliability tests based on the information gathered and inputted into the system. The model is developed by the assembling of various elements and available modules that perform an array of different actions and calculations. As entities are created and travel through the model via other elements and modules, they interact with other elements that enable actions to be carried out and calculations to be made. The aim of the model is to simulate failures based on the existing parameters and their usage, hence as changes occur, the use and amount of time is recorded, and as time passes the usage allowance is noted. The consumption of the entire usage allowance of a single parameter does not result in the failure of the system according to historical and expert data, but rather an indication that the parameter has reached its full potential and needs changing or adhering to in other ways. However a combined effort of all three parameters reaching their close to the limit will result in a system failure.

5. Overview of Simulation Model

Entities are created at a random time within the lifespan given to the entities, the entities represent the three parameters that exist, after which they join the queue that represents the maintenance management. The three parameters i.e. Drill Head has a life span of 10080 minutes, Extract Dust has a life span of 2880 minutes and Lubrication has a life span of minutes 4320.

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Drill Head is the only parameter that has to be changed due to wear or tear and the other two parameters are tasks that need to be carried out on the machine. Once the entities are created they simply join the queue waiting to be consumed, after they are pulled from the queue i.e. needed, they are due for an inspection that has been demonstrated in figure 1 and figure 2 above i.e. inspection down time, this is represented by the variable repair time to indicate the time needed to carry out tasks.

After the inspection that is implemented within the activity setup as entities enter the activity, they simply spend the designated life spans as highlighted above after which they leave and the process restarts again. Within this process, variables have been implemented to take into account the different time allowances based on usage rates to develop calculations of probabilities. This can be seen in figure 1 and 2 via the use of counters that display an array of key performance indicators.

The simulation software generates pseudo random numbers according to an array of different probability distributions. This is used to generate the component repair times and breakdown times from the various available distributions.

As the model is running, the value of the parameters is taken under consideration based on the usage allowances of the parameters, these conditions that are represented by a variable when joined together produce the overall failure probability that can make the machine come to a halt or breakdown in effect. Further, fixed replacements based on timing and frequency can also raise aspects of concern i.e. does the component part need replacing or do the tasks need carrying out, hence the use of key performance indicators to show usage rate. So, if the machine does breakdown, the user can see how much of the usage allowances has been consumed and can also see if the component parts are responsible for the failure of the machine.

This simulation model will be replicated 50 times; a single replication of the model will produce one possible outcome based on the generation of pseudo random numbers. However, every replication after that should produce or generate a completely different outcome based on the development of pseudo random numbers. Therefore, it is very important to carry out many replications and use the MEAN of the results as the basis for the evaluation. The Witness Scenario Manager can execute multiple replications and the software calculates an array statistics based on the entire model and the number of replications.

After much testing, validation and calibration, the model was completed as needed to reproduce conditions based on historical data and expert knowledge of the actual plant, machinery, parameters and situations. Hence the life span given to the parameters is consistent with the actual tasks that need to be carried out.

6. Simulation Results and Analysis

The following tables and graphs have been selected which aid the understanding of the results. The results are based on two scenarios i.e. the running of the model for 30 days being scenario 1 and the running of the model until a breakdown occurs being scenario 2.

Scenario 1 consist of two main results as can be seen in table 1, this shows the variance in the total repair times consumed after 30 days, the 50 replications show the changes in time, this is a total time that is compiled by all the inspections gathered together that go through the stochastic process every single time an inspection is carried out and further are attached to the pseudo distributions. Every single replication produces a different result due to the stochastic nature of the model.

Table 1 - 30 day results for total inspection time

Mean		1553.44
Std. Dev		11.76
Confidence Level 95% Minimum		1549.27
Confidence Level 95% Maximum		1557.61

After the 50 replications have been carried out, the software shows the users chosen statistics as can be seen in table 1. Displayed is the mean result of all the replications, the standard deviation from all the replications and the minimum and maximum confidence level of 95%.

The results show how the values deviate and if they fall within the minimum and maximum confidence level of 95% and what the mean inspection times are after 30 days. This enables the user make certain decisions based on increased understanding and plan ahead, this can be used more as a tool for the management to move towards a predict and prevent approach.

The probability in table 2 is derived from a combination of variables as highlighted before from the life span of parameters as well as the table 1 where inspection times affect the usage rate and allowances of the existing parameters. Table 2 shows the probability of failure that is a variable developed by the chain rule and implemented via the use of mathematical formulae. The probability is the value seen within the tables; this value is the probability of failure after running the model for 30 days continuously.

Table 2 – 30 day results for probability

Mean		39.28
Std. Dev		1.89
Confidence Level 95% Minimum		38.61
Confidence Level 95% Maximum		39.95

From Table 2 it can be seen that the standard deviation is a very small 1.89, the minimum and maximum confidence levels only have a difference of 1.34%. These results firstly show the average or mean probability of failure from this set of replications falls within the minimum and maximum confidence level of 95%, this ensures strong validity in results achieved.

Table 3 of scenario 2 shows the same total inspection time taken but after running the model until a breakdown occurs, which happens to be approximately at 61444 minutes for a single simulation hence this figure has been used. Witness Scenario Manager does not allow replications to be run until a breakdown occurs or the user does not possess enough knowledge of the software in order to manipulate scenario manager to do so hence a set time has been appointed.

Table 3 – Breakdown results for Inspection Times

Mean		1947.30
Std. Dev		15.50
Confidence Level 95% Minimum		1941.81
Confidence Level 95% Maximum		1952.79

Scenario 2 produces the results for inspection times in table 3, a standard deviation of 15.50, the minimum confidence level being 1941.81 and the maximum being 1952.79, almost a difference on 1, however the mean or average of the 50 replications seem to be within the confidence intervals indicating very good results. Again, if looked at the replications individually, many seem to go slightly astray from the minimum and maximum intervals; however this is the reasons behind such replications to see what results a stochastic approach can have on a system.

Table 4 is the probability of failure when a breakdown occurs according to scenario 2 when the model is run for 61444 minutes. The results change according to replication, different replications produce different results due to the development of the probability that is based on different variables that change due to pseudo numbers being generated.

Table 4 – Breakdown results for probability

Mean		95.54
Std. Dev		0.13
Confidence Level 95% Minimum		95.49
Confidence Level 95% Maximum		95.59

Scenario 2 is of key importance as this highlights when a breakdown should actually occur, here the above statistics show very little variance in results, the standard deviation being a very small 0.13 and the confidence intervals having a difference 0.10, however with this is mind, the mean results seems to be at the very centre of the confidence intervals as can be seen. These graphs show how the results fluctuate although by a very small amount, further statistics results indicate the small change in the mean and confidence intervals. This shows a very strong result where the standard deviation is very small, the space between the confidence intervals is very small and the mean happens to be at the very centre.

Graph 1 is a visual comparison of the two probabilities derived from scenario 1 and scenario 2, this graph basically collates all the information together and allows a comparison. It can be seen as the probability of failure increases, the standard deviation is squeezed as is the confidence interval. This basically indicates as the crusher machine comes closer to its point of failure, the ratio of failure is squeezed by Witness scenario manager; this helps the user to understand and make sure that failures that do occur are within the given confidence intervals to be absolute.

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Graph 1 – Comparison of scenario 1 and 2

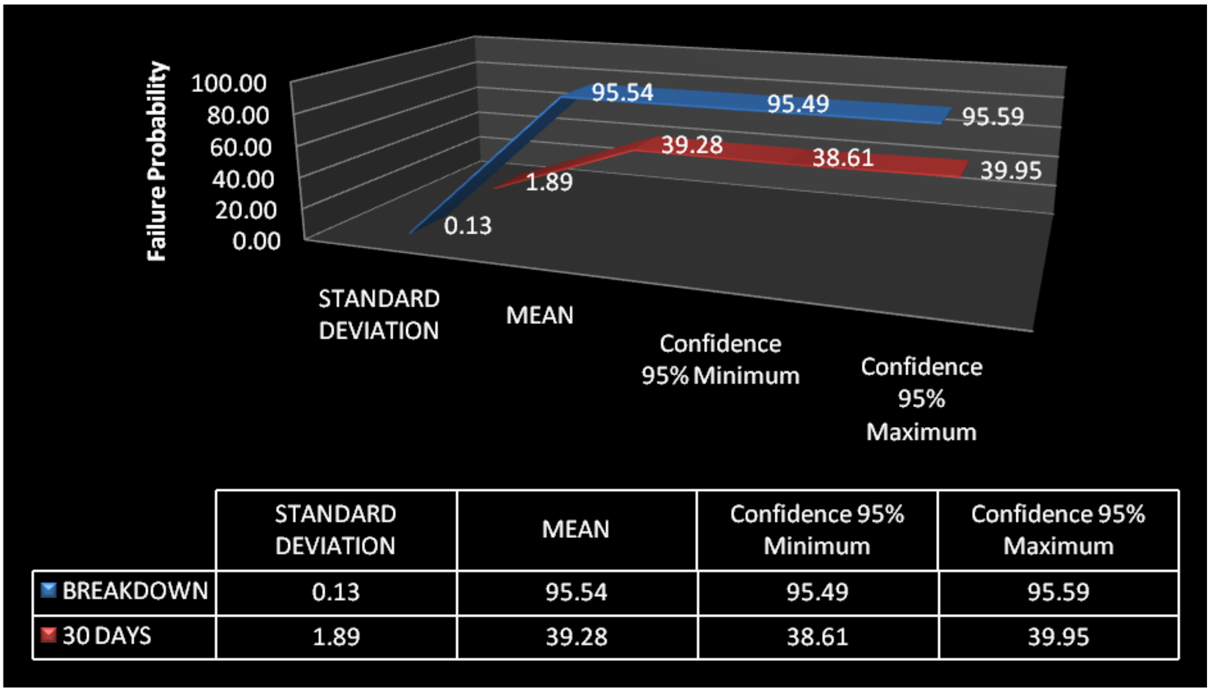

Table 5 shows the time breakdown occurs, the change in occurrences according to replications from one breakdown to another. The initial breakdown happens to be at 61444 minutes of simulation time hence, scenario 2 based on this figure as this is when the first breakdown occurs. However, by carrying out 50 replications shows how the time of break downs can change, and change significantly in many of the replications.

Table 5 – Breakdown occurrences

Mean		61335
Std. Dev		112
Confidence Level 95% Minimum		61295
Confidence Level 95% Maximum		61374

This shows how the stochastic nature of the model can develop significant changes to occur within the probability of the time of failure; the purpose in this paper has been on the probability of failure alone and not all the small transitions that take place within the system that enables the probability to be produced. This has been developed by a number of different variables that exist and working together within the system, this result shows a standard deviation of 112 minutes, almost 2 hours. The model has been run for 65000 minutes of which 50 replications were made, table 5 shows that the mean is between the confidence intervals although significant times changes occur, but when table 5 is taken under consideration it is a very small figure, hence the results show a strong confidence level as the time between them is only 79 minutes from minimum to maximum confidence level of 95%.

7. Conclusion

The purpose of this paper was to explore the importance of the stochastic nature and the role it can play in simulation models. The Bayesian modelling that takes into consideration the conditional and marginal probabilities, also that uses the chain rule theory and the simulation model that has these implemented within it. The stochastic nature of this model will most definitely change the outcome independent of the other analytical tools used.

This paper should help understand how a stochastic approach can develop better understanding of systems by showing how and where changes can take place, how change can occur knowingly and unknowingly in various different parts within a system. How a single change can lead to further development and change the overall outcome of a probability.

After carrying out the replications for breakdown occurrences it can be seen that the first breakdown that does occur at 61444 and upon which the rest of the scenarios are based on. Table 4 shows the probability of breakdown remaining very firm with a very small standard deviation, all in all the results extracted increase the confidence on the results and aid better understanding of the stochastic nature and the effects thereof.

The results of the simulation model have shown the feasibility of the current practices that are in place; where changes may need to be made in order to improve or simply test further to verify the strongest possible outcome. This has also shown how consideration of analysis and the valuation of outcomes can aid decision making.

8. Recommendation

By carrying out and testing scenario 1 and scenario 2 in a simple stochastic approach generated by the software, the importance is apparent. However, to carry out the analysis of the simulation output data thoroughly, the observations need to have a set of independent and identically distributed (IID).

In order for this to be accurate, the stochastic approach must be covariance-stationary and demonstrate no autocorrelations. A stochastic process beginning at zero minutes in time is unlikely to be covariance-stationery and can present autocorrelations [6].

Therefore, it is very important to research further to estimate the appropriate warm-up period for the machine to ensure that the output process of the simulation is in a steady state when gathering results. This will remove any initialisation bias in the simulation and enable the collating of results when it has reached a more stable state.

There are many discussions of initial transient and steady-state distributions and a list of relevant papers and books can be found in [7]. Hence, if the warm-up period is too short, the output stochastic process has not reached a steady-state, which can provide misleading data and on the other hand, if it is a very long warm-up period, it can be a waste of time and resources; therefore an appropriate warm-up period needs to be estimated accurately.

References

1-Gupta, S., Tewari, P. C., & Sharma, A. K. (2009). Availability simulation model and performance analysis of coal, handling unit a typical thermal power plant. *South African Journal of Industrial Engineering*, 20(1), 159-171.

2-Rausand, M., and Hoyland, A., (2004). *System Reliability Theory: Models, Statistical Methods, and Applications* (2nd ed.), Wiley, Hoboken.

3-Altuger, Gonca, and Chassapis, Constantin, (2009). Multi criteria preventive maintenance scheduling through Arena based simulation modelling, Proceedings of the Winter Simulation Conference, *IEEE*, 2123-2134.

4-Wang WB. (2009). An inspection model for a process with two types of inspections and repairs. *Reliability Engineering & System Safety*, 94(2), 526 – 33.

5-Jones BJ, Jenkins on I, Yang Z, Wang J. (2010). The use of Bayesian network modelling for maintenance planning in a manufacturing industry. *Reliability Engineering & System Safety*, 95, 267-277.

6 – Law, A. M. (2007). *Simulation Modelling and Analysis*. McGraw-Hill series in industrial engineering and management science. (4th ed.). McGraw-Hill (NY).

7- Glynn, P. W., (2005). Initial transient problem for steady-state output analysis. In *Proceedings of the Winter Simulation Conference*, 739–740