Application of the Bayesian Network to Machine breakdowns using Witness Simulation

Elbahlul M. Abogrean and Muhammad Latif

Abstract—**This paper explores the use of Bayesian network modeling of machine breakdowns within a cement manufacturing plant. The Bayesian network modeling is introduced using Hugin software and then implemented into a Witness Simulation model using historical data, expert knowledge and opinions. The models simulate 3 parameters of the machine based on life consumption and usage of each parameter, the developed Witness model produces a probability failure rate based on these parameter usages. The failure probability developed by Witness is implemented using the Chain Rule; this is compared with the probability for failure based on the Bayesian network model. This enables the user to see the probability of failure developed by the implementation of the chain rule and Witness based on the parameter usage, on a live streaming fashion as the model is running. This can be used as a decision making tool for management to consider machine maintenance affectively based on parameter usage.**

Index Terms—**Bayesian Network modeling, Conditional Probability Table (CPT), Witness Simulation, Chain Rule Theory, Directed Acyclic Graph (DAG).**

I. Introduction

Bayesian network modeling is a mathematical technique used to model uncertainty in a chosen area or a system, can help identify and highlight links between variables [1]. The recognition of important variables as well as consideration of other influencing factors that seem to exist within the system is integral to the Bayesian approach. The Bayesian network modeling is a mathematical formula that calculates conditional and marginal probabilities of a random event at any given time. Witness simulation has much to offer any organization, the role of simulation is to evaluate alternatives that either support strategic initiatives, or support better performance at operational and tactical levels. Simulation provides information needed to make these types of decisions. The simulation approach supports multiple analyses by allowing rapid changes to the models logic and data, and is capable of handling large, complex systems such as a manufacturing facility [2].This paper aims to model and reduce the effects of breakdowns that occur within a single crusher machine using the Bayesian network modeling approach and thereafter a simulation model that will replicate the machine and the parameters that exist. The development of these two models will result in different probabilities of failure or two different approaches in calculating the most likeliness of a failure occurrence.

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II. Methodology

A. Establishing relevant and accurate information.

B. Establishing nodes with dependencies.

One of the advantages of Bayesian network modeling is its flexibility in enabling new nodes to be added to an existing model. It allows existing information previously added to be updated as new information is gathered. [5] An example of Bayesian network is shown in figure 1 that represents the crusher machine and the parameters.

For the crusher machine three critical parameters that lead to machine failure are known to be drill head, dust level and lubrication. The drill head has to be changed once every 7 days due to the amount of time spent breaking and crushing raw materials that cause wear and tear, too much wear and tear of the drill head means the quality of crushed raw materials are affected and at times they take much longer to process. Due to the drill head breaking raw materials and crushing, much dust or small particles and fragments of rock gather in different areas of the machine and hence has to be cleaned in order to prevent failures i.e. dusting. Lastly, the machine must stay lubricated in order to work affectively because the lack thereof will cause failures to occur i.e. Lubrication. Figure 1 shows the three parameters with arrows pointing downwards to the crusher indicating they influence the crusher, further each node has two states i.e. 'Used' and 'Remaining' that can be seen in figures 2, 3 and 4. This example models the dependencies between the above parameters and the crusher.

C: Establishing of CPT (Conditional Probability Table)

A Bayesian network can visually represent the relationship between various nodes or events (qualitative representation), [5] or it can quantitatively represent each node through a conditional probability table (CPT) as can be seen below in figure 5. Further, each parameters states are given a probability i.e. figure 2 shows the drill head has 70% used and 30% remaining, the same system is followed for figure 3 and 4. The given probabilities can be based from historical data that has been gathered over time, research or expert knowledge/opinion.

Therefore the probability of the crusher machine failing or

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working is dependent or conditional on the existing parameters in figures 2, 3, 4. This can be seen in figure 5's conditional probability table for the crusher machine.

Figure 5 shows the probabilities of breakdown for the crusher machine based on the parameters, where at one end if all 3 parameters are 'remaining', the probability of 'working' can be 100%, whereas on the other side of the table if all 3 parameters are 'used' the probability of 'failure' can be 100%.

D. Normalise Probability

Probability values have to be between 0 and 100, all the values however is automatically normalized by using the Hugin Software that is used to develop the CPT tables and further probabilities as shown throughout the building of the model. [5]

E. Propagate Evidence

Fixing of nodes whilst other variables change accordingly enables propagation.[5] Based on a mixture of historical data and expert knowledge, three CPT Tables were created were the nodes life consumption and usage were fixed i.e. the failure of the Crusher was based on fixed dependency values that can be seen in figure 3.

F. Model Validation

In this example, the node crusher machine is dependent or conditional on the 3 parameters that exist and hence have influencing affects on the generated probability. In order to calculate the probability of the 'failure' of the crusher machine the chain rule (Equation 1) must be applied [6, 7]. The nodes Drill Head, Lubrication and Dusting can be termed 'A', 'B' and 'C' respectively, and the Crusher machine termed 'C'. The term 'CF' can represent the state Crusher Failure.

Equation 1 – Developed Chain Rule.

$$P\,(CF) = \sum_{I=1}^{3} \sum_{j=1}^{3} \sum_{k=1}^{3} P(CF/A_i\, B_j\, C_k)\, P(A_i)\, P(B_j)\, P(C_k)$$

Therefore,
P (Crusher Failure) =
P (Drill Head 'Used') x (Lubrication 'Used') x (Dusting 'Used') x P (Crusher 'Failure') +
P (Drill Head 'Used') x (Lubrication 'Used') x (Dusting 'Remaining') x P (Crusher 'Failure') +

P (Drill Head 'Used') x (Lubrication 'Remaining') x (Dusting 'Used') x P (Crusher 'Failure') +
P (Drill Head 'Used') x (Lubrication 'Remaining') x (Dusting 'Remaining') x P (Crusher 'Failure') +
P (Drill Head 'Remaining') x (Lubrication 'Used') x (Dusting 'Used') x P (Crusher 'Failure') +
P (Drill Head 'Remaining') x (Lubrication 'Used') x (Dusting 'Remaining') x P (Crusher 'Failure') +
P (Drill Head 'Remaining') x (Lubrication 'Remaining') x (Dusting 'Used') x P (Crusher 'Failure') +
P (Drill Head 'Remaining') x (Lubrication 'Remaining') x (Dusting 'Remaining') x P (Crusher 'Failure')
P (Crusher Failure) =

Probability = Variable1 + Variable2 + Variable3 + Variable4 + Variable5 + Variable6 + Variable7 + Variable8
(0.7 x 0.5 x 0.6 x 1) + (0.7 x 0.5 x 0.4 x 0.75) + (0.7 x 0.5 x 0.6 x 0.625) + (0.7 x 0.5 x 0.4 x 0.5) +
(0.3 x 0.5 x 0.6 x 0.375) + (0.3 x 0.5 x 0.4 x 0.25) + (0.3 x 0.5 x 0.6 x 0.125) + (0.3 x 0.5 x 0.4 x 0.0)
= 0.57625 or 57.625% probability.

Given the above, it can be seen when compared to the actual example model of the crusher machine nodes and dependencies, the outcome or probability is exactly the same. This data has been implemented and modeled using Hugin software with the above states, results are shown in figure 6. From this example it can be seen, given the above probabilities of the 3 parameters, the crusher machine has a 57.63% probability of failing. A crucial advantage of the Bayesian approach is it allows updated information to be considered in order to develop revised probabilities.

From this example, given the above probabilities of the 3 parameters, the crusher machine has a 57.63% probability of failing. A crucial advantage of the Bayesian approach is it allows updated information to be considered in order to develop revised probabilities.

Consider another example, the 'Drill Head' has now been fully used at 100%, this indicating maximum usage has been made and a change is required, this should increase the probabilities of failure for the Drill Head that should result in changes to the probability of failure for the crusher machine. This can be seen in figure 7 and 8, where drill head has been used 100% has resulted in a dramatic increase for the failure of the Crusher machine i.e. probability of failure is now 73.75%.

A single parameter being used 100% does not equal to a failure of the machine but rather an indication that the parameter needs attention however if all three parameters consumption is 100% this would without doubt lead to failure of the machine according to the Bayesian approach.

Similarly, as explained above, the chain rule that has been developed is to validate the failure probability. This same rule has also been implemented into the Witness Simulation i.e. Equation 1 has been applied to the simulation to work out a failure probability.

The Chain Rule (Equation 1) has now been implemented into a witness simulation by the use of variables, these variables represent the rules exactly as it is in the chain rule and similarly use the CPT's figures to work out a probability for failure as displayed within the witness simulation model. The expression in table 1 is the exact same as the rule explained earlier and shown , it consists of 8 segregated rules or equations [variables] that are added together to show the failure probability.

There are 8 different variables similar to that of the rule and the nodes and dependencies, one aspect that is apparent is the values from the CPT table have been used in order to attain the accurate results i.e. figure 5 shows the '*Failure*'

and '*Working'* rate that are dependent on parameter consumption, this can be seen below in the equation where the variable start at the failure rate of 100 and slowly starts to decrease in the same order as the CPT table in figure 5.
Finally all the 8 variables are added together to complete the probability, this can also be seen in figure 8, this is a screen shot of the model, figure 8 represents the same failure rate as figure 6, where the failure rate is 57.625, this failure rate has been validated by the chain rule as explained above and further can be seen.

However, we can consider the parameters further to certify the validity of the rule and the integration of the software and models developed. Figure 6 shows the used rate of each parameter in order to result in such a particular failure rate i.e. Drill head 70% Used, Dusting 60% Used and Lubrication 50% used.

Figure 10 shows when the model actually breaks down according to the Bayesian approach, this point of breakdown has been (decided according to historical data and expert opinions based on the parameters and the observation over many years). The initial breakdown point due to parameter consumption was chosen to occur when the failure rate surpasses the 90% consumption rate, with is an average probability for failure as can be seen in figure 10. However, further consultation highlighted areas of concern i.e. the average does not necessary mean that all parameters will reach above 90% threshold, only two parameters may increase the average resulting in a breakdown. Hence the implementation of further logic to allow machines to resume and carry on until all three parameters have surpassed the 90% threshold and the probability of failure according to the chain rule implementation is above the 95% threshold. This can be seen in figure 10, after running the model until a breakdown occurs, according to this approach a breakdown will occur approximately after 61444 minutes of continuous simulation. Figure 10 shows when the model actually breaks down according to the Bayesian approach, this point of breakdown has been (decided according to historical data and expert opinions based on the parameters and the observation over many years). The initial breakdown point due to parameter consumption was chosen to occur when the failure rate surpasses the 90% consumption rate, with is an average probability for failure as can be seen in figure 10.
However, further consultation-highlighted areas of concern i.e. the average does not necessary mean that all parameters will reach above 90% threshold, only two parameters may therefore, the above consumption rates have now been applied to the Hugin Software that can be seen in figure 9 and now the failure has slightly increased from 57.64 to 57.84, a very small deviation of 0.20%. This clearly shows that the Simulation Model developed is more than capable of developing a continuous probability for failure rate based the consumption of parameters.

Implementation of further logic to allow machines to resume and carry on until all three parameters have surpassed the 90% threshold and the probability of failure according to the chain rule implementation is above the 95% threshold. This can be seen in figure 10, after running the model until a breakdown occurs, according to this approach a breakdown will occur approximately after 61444 minutes of continuous simulation.

III. Experimentation

To validate the results of the simulation model further against the results of the Bayesian network modeling, 95 different values of the variables were considered and tested; table 2 shows some of the results. After the tests shown in table 2, it was clear that the results were correct with a very small change, however, the consumption of the parameter were different.
This is simply a result of how the Hugin software works i.e. Table 2 shows the usage rate of each parameter, this use rate is made up to test the system. In reality, these usage rates may not be correct as the consumption and usage of parameters identified in continuous and not a static rate or amount as inputted.
However, as highlighted above with the use of figure 8 and figure 9, when the probability of failure is shown in the witness model according to table 2. The usage of parameters are different to that which have been inputted, but if these new rates of usage are applied back to the Hugin Software, the results are the same as shown in figure 9.

IV. Discussion

The aim of the paper is to highlight the occurrence of breakdowns within the crusher machine. This was done firstly by implementing the Bayesian Network modeling that developed probabilities based on nodes and dependencies created from historical data that resulted in a probability of 'Failure' or 'Working' based on the parameters that were key influencing factors for breakdowns. This was all achieved via the gathering of historical data, expert opinions and statistical calculations/averages, this method could be adapted to ever changing influencing factors that are predominantly the cause of failures. The Bayesian Model enabled a greater understanding by allowing influencing aspects to be considered where needed resulting in a greater level of confidence overall. The influencing factors, 'Drill Head', 'Dusting' and 'Lubrication' has been used for this paper that are parameters for the failure of the Crusher machine. The Bayesian Network modeling demonstrates the probability of the crusher machine breaking down given the above parameters.

The Simulation Model on the other hand allows a development of the existing machine to be replicated, and the major influencing factors to be considered based on life expectancy and usage. This model allows the user to create and simulate live breakdowns, setups and other tasks that need to be carried out i.e. allows the model to carry out

Dusting and Lubrication when the machine requires based on life consumption and usage. This model allows the user to see exactly how much a parameter has been used and the amount of influence it can have on the machine based on

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life consumption and usage whether individually or as a group. The simulation model helps to identify the failure probability occur based on parameters, thereafter, if the breakdown is legitimate i.e. the implementation of the chain rule applied to the formula to check if the probability of failure is correct based on the consumption and usage rate of parameters. [8, 9] This enables deeper understanding of when breakdowns should occur based on the parameters that exist. Simulation enables the user to develop scenarios to see when the breakdowns actually occur in reality and apply appropriate measure thereafter.

The test results in table 2 validate this further as the probabilities developed by the Hugin software and witness simulation can be crossed referenced against each other. This shows how the tools can be applied and used to work with one another rather than against.

One has to remember that the Bayesian approach although takes influencing factors into consideration only produces instant results i.e. numbers or information have to be added and then calculation are made based solely on those figures, more results require implementation of further figures.
Whereas the witness simulation works on a continuous flow, as the consumption rates change so do the probability of failure. To validate the model results these consumption rates can be entered into the Hugin Software for comparison.

Figure 10 shows when the model actually breaks down according to the Bayesian approach, this point of breakdown has been (decided according to historical data and expert opinions based on the parameters and the observation over many years). The initial breakdown point due to parameter consumption was chosen to occur when the failure rate surpasses the 90% consumption rate, with is an average probability for failure as can be seen in figure 10. However, further consultation highlighted areas of concern i.e. the average does not necessary mean that all parameters will reach above 90% threshold, only two parameters may increase the average resulting in a breakdown. Hence the implementation of further logic to allow machines to resume and carry on until all three parameters have surpassed the 90% threshold and the probability of failure according to the chain rule implementation is above the 95% threshold. This can be seen in figure 10, after running the model until a breakdown occurs, according to this approach a breakdown will occur approximately after 61444 minutes of continuous simulation. Figure 10 shows when the model actually breaks down according to the Bayesian approach, this point of breakdown has been (decided according to historical data and expert opinions based on the parameters and the observation over many years). The initial breakdown point due to parameter consumption was chosen to occur when the failure rate surpasses the 90% consumption rate, with is an average probability for failure as can be seen in figure 10. However, further consultation-highlighted areas of concern i.e. the average does not necessary mean that all parameters will reach above 90% threshold, only two parameters may increase the average resulting in a breakdown. Hence the implementation of further logic to allow machines to resume and carry on until all three parameters have surpassed the 90% threshold and the probability of failure according to the chain rule implementation is above the 95% threshold. This can be seen in figure 10, after running the model until a breakdown occurs, according to this approach a breakdown will occur approximately after 61444 minutes of continuous simulation.

Understanding by allowing influencing aspects to be considered where needed resulting in a greater level of confidence overall. The influencing factors, ‘Drill Head’, ‘Dusting’ and ‘Lubrication’ has been used for this paper that are parameters for the failure of the Crusher machine. The Bayesian Network modeling demonstrates the probability of the crusher machine breaking down given the above parameters.
The Simulation Model on the other hand allows a development of the existing machine to be replicated, and the major influencing factors to be considered based on life expectancy and usage. This model allows the user to create and simulate live breakdowns, setups and other tasks that need to be carried out i.e. allows the model to carry out Dusting and Lubrication when the machine requires based on life consumption and usage. This model allows the user to see exactly how much a parameter has been used and the amount of influence it can have on the machine based on life consumption and usage whether individually or as a group. The simulation model helps to identify the failure probability occur based on parameters, thereafter, if the breakdown is legitimate i.e. the implementation of the chain rule applied to the formula to check if the probability of failure is correct based on the consumption and usage rate of parameters. [8, 9] This enables deeper understanding of when breakdowns should occur based on the parameters that exist. Simulation enables the user to develop scenarios to see when the breakdowns actually occur in reality and apply appropriate measure thereafter. The test results in table 2 validate this further as the probabilities developed by the Hugin software and witness simulation can be crossed referenced against each other. This shows how the tools can be applied and used to work with one another rather than against.

V. Conclusion

In this paper the Bayesian Network Modeling has been used to increase the confidence of the results of the Simulation Model i.e. probabilities that have been worked out according to the parameters that exist. The implementation of the *Chain Rule* from the Hugin software has enabled the increased validity of the results by using it as a guide for the failures that occur within the simulation model.

The Simulation Modeling and the Bayesian Network Modeling takes into account the influencing factors that increases the confidence as it is validated against one another. The Bayesian calculations produces a probability based on the dependencies and the simulation model has a dynamic display to see exactly how the three parameters are progressing every minute based on the chain rule

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implementation that the Hugin Software uses to extract results. This enables a true understanding of when breakdowns should actually occur i.e. when the majority of all three parameters life or usage has been consumed, rather than a random time based on the failure rate. This model has increased the confidence of when the crusher machine breaks down with the help of the Bayesian Network modeling and provided accurate insight into the parameters that exist and how they can affect the machine as a whole, further this model can be applied to all types of machinery with as many parameters as necessary.

FIGURES AND TABLES

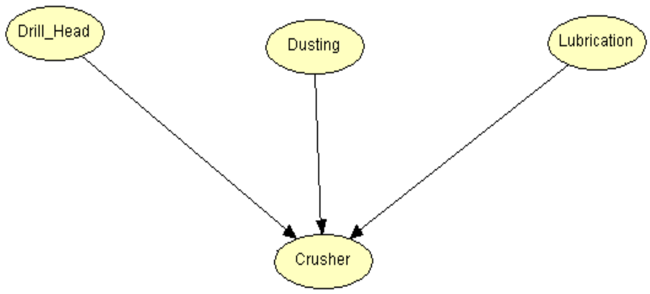


Fig. 1. Bayesian Network modeling of a Crusher Machine and Parameters

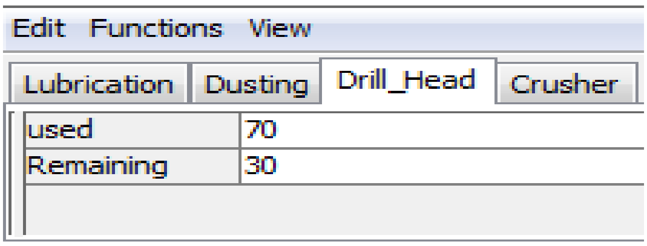


Fig. 2. Drill Head state.

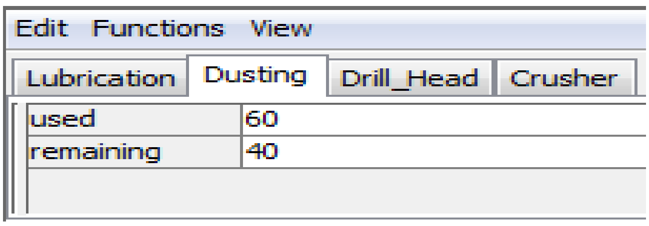


Fig. 3. Dusting state

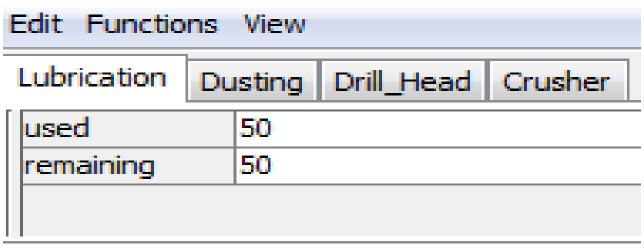
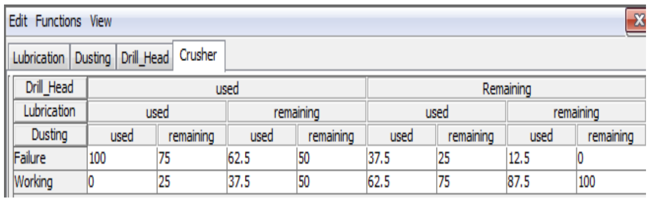


Fig. 4. Lubrication state



Drill_Head	used				Remaining			
Lubrication	used		remaining		used		remaining	
Dusting	used	remaining	used	remaining	used	remaining	used	remaining
Failure	100	75	62.5	50	37.5	25	12.5	0
Working	0	25	37.5	50	62.5	75	87.5	100

Fig. 5. Crusher Machine Parameter CPT

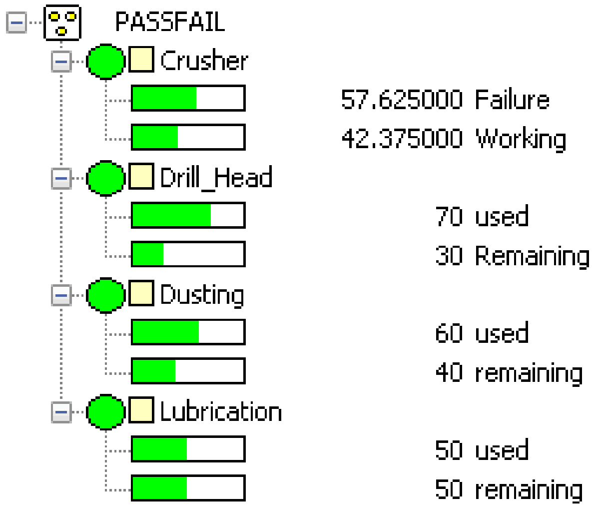


Fig. 6. CPT results for Drill Head, Dusting, Lubrication and Crusher.

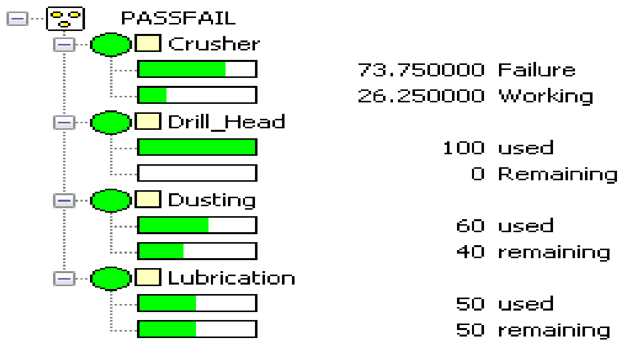


Fig. 7. Drill Head usage 100% results in increase in failure probability.

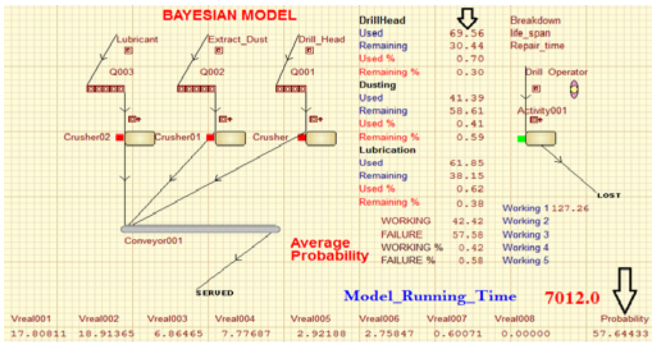


Fig. 8 . Failure Rate 57.64.

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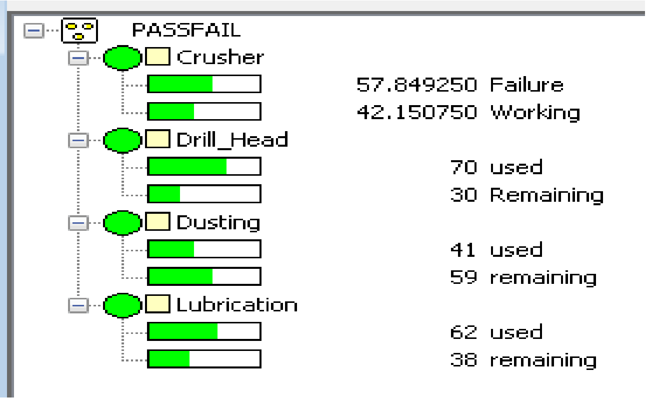

Fig. 9. Parameter Usage Rate Probability.

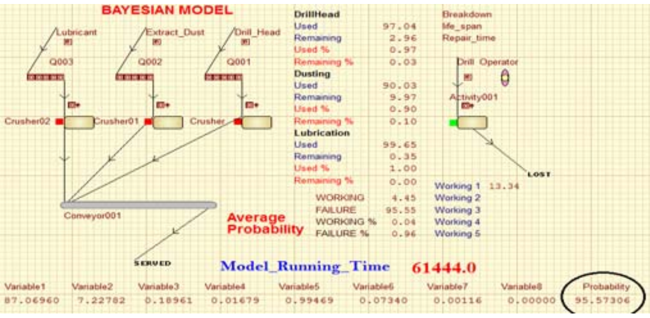

Fig. 10. Model Breakdown.

TABLE I
SEGARATED RULES OR QUESTION VARIABLE.

Variable1 = Drill Head (3) * Dusting (3) * Lubrication (3) * 100
Variable2 = Drill Head (3) * Dusting (4) * Lubrication (3) * 75
Variable3 = Drill Head (3) * Dusting (3) * Lubrication (4) * 62.5
Variable4 = Drill Head (3) * Dusting (4) * Lubrication (4) * 50
Variable5 = Drill Head (4) * Dusting (3) * Lubrication (3) * 37.5
Variable6 = Drill Head (4) * Dusting (4) * Lubrication (3) * 25
Variable7 = Drill Head (4) * Dusting (3) * Lubrication (4) * 12.5
Variable8 = Drill Head (4) * Dusting (4) * Lubrication (4) * 0.0
Probability =
Variable1 + Variable2 + Variable3 + Variable4 + Variable5 + Variable6 + Variable7 + Variable8

TABLE II
HUGIN SOFTWARE RESULT

	Failure Ratios	*Drill Head Usage*	*DUSTIN-G USAGE*	*Lubrication Usage*
Hugin Failure	*57.63*	*70*	*60*	*50*
Witnes Failure	*57.76*	*100*	*60*	*50*
Hugin Failure	*73.76*	*100*	*60*	*50*
Witnes Failure	*73.78*	*78*	*71*	*81*
Hugin Failure	*91.38*	*90*	*90*	*100*
Witnes Failure	*91.41*	*86*	*99*	*100*
Hugin Failure	*83.00*	*80*	*80*	*100*
Witnes Failure	*83.04*	*82*	*86*	*92*
Hugin Failure	*74.87*	*70*	*70*	*100*
Witness Failure	*74.91*	*79*	*73*	*83*

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