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Original Research Article

Predictable Maintenance: A Bayesian Network-based Model

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Abstract

Industries' increasing progress and complexity has made maintenance and repair tasks very challenging, complex, and time-consuming. Maintenance is one of the important sectors in several industries, and improvement in this sector can have excellent results. This paper develops a new maintenance prediction model based on Bayesian networks (BN) capabilities. The models include several variables that experts determine and their influence on each other's-called conditional probability tables-which are learned from historical data. The model is implemented in an automobile repair department case study to show its performance. The model is evaluated through a sensitivity analysis, and the results show the proficiency of the proposal mode.

Keywords: Maintenance; Prediction; Bayesian Networks; Conditional Probability.

1. Introduction

Maintenance is a series of procedures and operations which are being done for controlling, maintaining, and enhancing the efficient lifetime of equipment, machines, and facilities in optimal condition or at least in an accepted standard condition. So, this action requires establishing a maintenance system consisting of all overall industry strategies. Maintenance is an essential part of industries that can significantly lower costs & expenses; therefore, research on maintenance for enhancing and improving the service was always of interest to researchers. Over a half-century, since maintenance planning was introduced, it has demonstrated its usefulness in many industries. So nowadays, engineers and managers in the industry and services sectors are very interested in using this knowledge and tool. Paying attention to engineering and improvements to the maintenance and repair sector will significantly reduce repair costs by between 25% and 40% of the annual budget, which is a significant amount. Maintenance and repair policies aim to create an optimal system to increase reliability and productivity [1]. Maintenance and repair policies aim to create an optimal system to increase reliability and productivity Research in Canada. The US shows that labour productivity is 35 percent, not because of labour shortages but poor maintenance and planning, which wastes much time waiting and fixing crashing machines [2].

In comparison, a solid and efficient maintenance system can increase efficiency & productivity by about 70 to 80 percent. In follow, a review of research that has been carried out so far is given that was conducted in the field of maintenance and each of which has tried to take steps to improve the efficiency of this sector. Maintenance and reliability have been studied and evaluated from various perspectives over the last few decades, and various models have been proposed for these two issues [3-5]. This study aims to develop a predictive maintenance model based on the Bayesian network method so that the results of this prediction can be used in maintenance. The following sections show

how to create this model. Since maintenance is one of the important sectors in several industries and improvement in this sector can have excellent results, so in this study, we use the Bayesian network model, one of the most influential models. A predictable maintenance and repair model is presented to provide excellent problem analysis and prediction results. For example, this model can predict the type of failures created, the appropriate decisions when performing a stop-time operation, and the number of broken parts.

2. Literature Review

The current predictive maintenance (PdM) policy is implemented in various fields with exceptionally high reliability, such as power plants, infrastructure, transport systems, communications systems, and emergency services [1]. The (PdM) uses real-time system elements tracking and evaluation, processes, and supply chains [2]. The primary strategy is to respond whenever products or components exhibit such behaviours, which typically lead to system malfunction, depreciated results, or decreased product quality [4]. The early signs of fault or failure are primarily detected in a PdM system, and maintenance procedures start promptly. PdM data provide diagnostic and forecast information to explain the problem, why, whether it is a fault, and when a failure occurs [3]. Predictive maintenance has also been increasingly applied in recent years in (cyber) security problems, infrastructure management, energy manufacturing, power plants, marine systems, operations, and production chains or factories of the future [3].

One of the models that can be used to model predictive maintenance is the Bayesian network model. The modelling methods from artificial intelligence, such as Bayesian networks (BN), can provide effective support in PdM areas or risk reduction for industrial systems. BN has powerful modelling and analysis capabilities. They provide a formal framework for processing probabilistic events [5]. In particular, probabilistic graphic models and Bayesian belief networks have undoubtedly become a reference formalism in modelling and evaluating dependability. Together with the compact representation of the joint distribution of device variables of interest, the graphical structure provides the reliability engineer with a powerful tool at both the modelling and analytical level [5].

Also, Zhexue [6], a weighted data fusion approach, used the T-test and F- test for virtual simulation data and real-life test data based on a product's multistage immersive virtual maintenance simulation studies. In their research, the virtual and real fusion samples are then merged periodically by the multistage Bayesian iteration fusion method. Then, the multistage Bayesian iteration of the fusion method is fused with the simulated and actual fusion samples iteratively. In other research, Zhang [7] used Bayesian networks to address these challenges with real case studies. They applied the binary factorization technique to allow inference of multi-state condition prediction and further considered and developed it to predict the condition of an asset with multiple components.

Furthermore, Li [8] proposed a risk analysis and maintenance decision-making model for natural gas pipelines with external corrosion based on a Bayesian network. First, they used A fault tree model is first employed to identify the causes of external corrosion and then a Bayesian network for risk analysis is determined accordingly. After that, maintenance strategies are inserted into the Bayesian network to show a reduction of the risk. Also, they combined the costs of maintenance strategies and the reduced risk after the maintenance in an optimization function to build a decision-making model. Finally, a case study was carried out to verify the feasibility of the maintenance decision model.

3. Bayesian network model

Bayesian networks (BNs) refer to joint distributions of sets of random variables that conduct a graph by this random variable [9]. Bayesian networks use a directed acyclic diagram (DAG) to represent the joint probability distribution for multiple variables in the compact form [10]. Bayesian network inference algorithms promise to capture linear, non-linear, combinatorial relationships among variables across multiple levels of biological organization [11]. Bayesian theory is focused on the thought that we keep beliefs in certain events according to our prior knowledge of them [12]. Bayesian network (BN) combines graph theory and probability theory, which has unique advantages for solving problems with uncertainty and mining causality among variables [13]. Problem modelling based on the Bayesian network model is performed in two stages, creating the Bayesian network structure and learning the conditional distribution function. The Bayesian network structure is a non-loop direction graph between variables that represents the relationships between variables. In this non-loop-oriented graph, the relationships between the variables are represented by an arrow. Each arrow represents the effect of the parent node (the node from which the arrow exits) on the child node (the node to which the arrow enters). This effect is a conditional distribution function.

Consider a BN containing the n nodes, $X_1$to X_n, taken in that order. A particular value in the joint distribution is represented by $P(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n)$, or more compactly, $P(x_1, x_2, \ldots, x_n)$.

The chain rule of probability theory allows us to factorize joint probabilities so:

$$P(x_1, x_2, \ldots, x_n) = P(x_1) \times P(x_2|x_1) \ldots \times P(x_n|x_1, x_2, \ldots, x_{n-1}) = \prod_i P(x_i|x_1, x_2, \ldots, x_{i-1})$$

The structure of a BN implies that the value of a particular node is conditional only on the values of its parent nodes; this reduces to:

$$P(x_1, x_2, \ldots, x_n) = \prod_i P\big(x_i \big| Parents(x_i)\big)$$

Learning in the Bayesian network is based on two approaches, including expert-based learning and data-based learning [14-16]. Depending on the type and circumstances of the problem, each of these approaches can be used, but usually, data-based learning has more accurate results, so most researchers tend to learn based on data. Bayes theorem can be materialized and extended by a causal decision tree to represent chained causality in a system. The second half of the 20th century saw Bayesian processes return as an effective method to assist the decision-making process in an unpredictable world through the advancement of computer technology. They have provided solutions to problems such as predicting climate change or, more recently, spam detection in data communications [5].

4. Research Methodology

All steps and procedures of this study are illustrated in Figure (1).

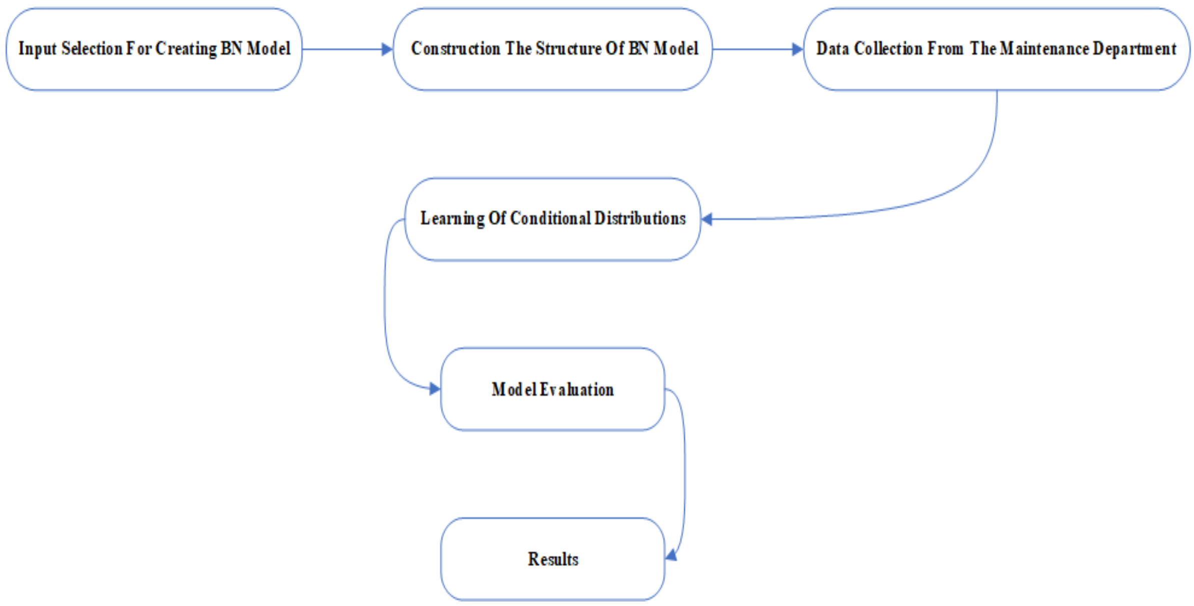

Figure 1: All steps and procedures of this study

5. Implementation and Results

5.1 Studied case

In this study, the maintenance department of a car company is studied.

Since the automotive industry is one of the most critical industries in any country, helping to improve productivity in this industry can have many results. Therefore, in this study, focusing on the maintenance and repair of the industry, which is one of the essential parts, a model is presented to improve the results in this sector.

The variables selected from the Maintenance and repair department for modelling with the Bayesian network are as follows.

- The relevant machine when a fault has occurred. (Machine), Machine names are given in Table (1).
- Operator associated with the machine, which operator worked with the machine when the crash occurred (Operator), the names of the operators are listed in Table (1).
- The type of failure that occurred or the reason for the stopping is considered three types of failures based on the data received: fragmentation of the production piece, breaking of the production piece, and the failure related to the machine itself.
- The relevant repairman, in previous machine repair, which maintenance specialists have repaired the machine. (Repairman), repairmen names have been given in Table (1).
- The type of repair performed, replacement, or repairs on the machine during a breakdown
- What type of operation was performed on the machine when the machine crashed? (Operations) Three types of operations are considered based on the received data, which are listed, respectively, with numbers 1, 2, and 3.
- The status of the mismatched piece, when the machine crashes, manufactured pieces on which the machine operates, will be crashed too. So related to these crashed pieces, there are two leading options. 1- The broken piece is reworked again. 2- The damaged part is considered a waste.

- The number of mismatched pieces, actually the number of mismatched pieces, is reworked or considered a waste.
- Stop time is the time that the device stops due to failure.

Below is information on each item listed in the table (1).

Table 1: Information about data received from the maintenance department

Variable	Type Of Variable	States
machine	Nominal	IA،IB،IC، ID، IE، MPA، MPB، MPC، MPD ، MPE
Operator	Nominal	A، AM، AS، AZ، B، GA، GH، HA، HF، K، KH، MA، R، RN، S، SE، SF، SH، VZ
Repairmen	Nominal	N، R، S، SA، SH، SHN، SHR، SZ
Operation	Nominal	1, 2, 3
Reason for stopping	Nominal	Pleated pieces(P), broken pieces(B) and damage related to the device(S)
Type of repair	Binary	Replacement(R) or repairing in the machine(M)
Damaged pieces status	Binary	Damages (WP) or Reworking the piece (RE)
Number of mismatched pieces	Number	Range 0 to 11811
Stop time	In hours	Range 0 to 1104

Two cases listed in Table (1) were separated, including the number of mismatched pieces and the stop time. The type of separation of the two cases is listed in Table (2).

Table 2: Discretization of the number of mismatched pieces and stop time

Variable			
Number Of Mismatched Pieces		**Stop Time**	
<=200	a	and <=8	a
200< and <=500	b		
500< and <=1000	c	8< and <=24	b
1000< and <=1500	d		
1500< and <=2000	e	24< and <=80	c
2000< and <=2500	f		
2500< and <=3000	h	80< and <=240	d
3000< and <=4000	j		

5.2 Bayesian network structure

In using the Bayesian network, one crucial section creates the graph's structure. We build a causal graphical model of BN based on eliciting expert opinion. This section uses three-car maintenance experts' opinions to create the Bayesian network, each with at least ten years of experience in this field. Thus, the network structure was facilitated by the assistance of three experts. For example, in the case of a stop reason node, which involves three levels of breakdown, Pleated, and device failure, in other words, these three types of stop reason have been identified and introduced when operating on the device. According to experts, multiple factors or nodes in the model can influence the stop reason; the relevant operator node can affect this node because the operator may not have the necessary training to operate the device and may have gaps in some of its training that may cause malfunctions and cause stoppages. The type of operation can be effective because the device needs to be adjusted when operating on the device. The lack of necessary settings can affect the failure and the type of failure. A repair that previously repaired the device may be affected because it may not have been adequately repaired or caused further damage during the repair. The structure of the Bayesian network is represented in Figure (2).

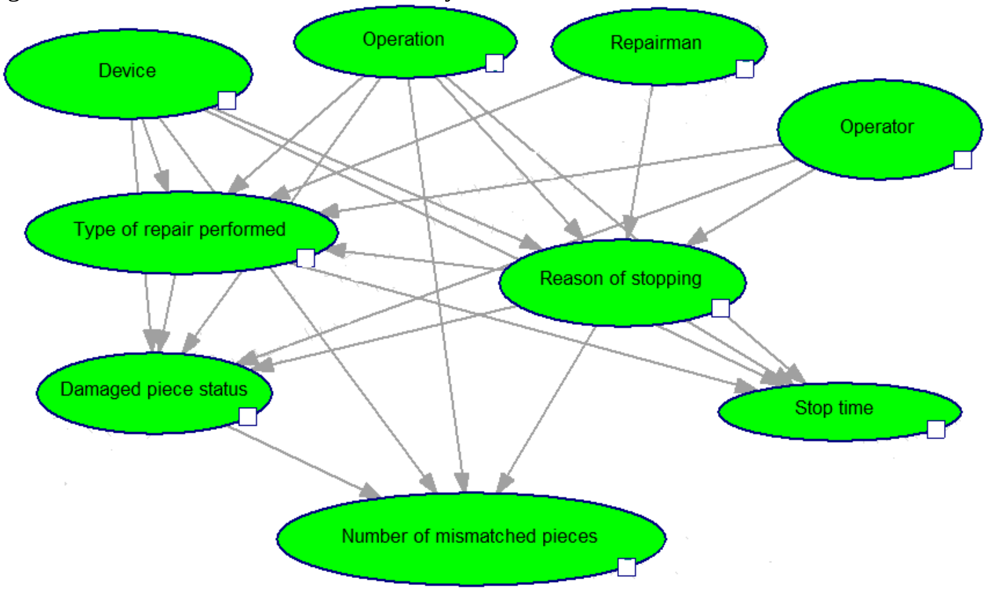

Figure 2: The structure of the Bayesian network

5.3 BN Conditions Probability Tables

As mentioned in the preceding sections, these two steps, constructing the network structure and learning the conditional distribution function, should be implemented to model problems with the Bayesian network method. In the previous section, we discussed how to build a structure, and in this section, how to use conditional distributions will be described. Since it was possible to obtain the data in the intended section of this study, learning the conditional distributions function in this study is based on the data. The data contained 1038 records received from the maintenance department, and based on them, the learning of conditional distributions was performed. The Pgmpy package in Python is used to learn the conditional distribution function. The package uses the Maximum Likelihood Estimator algorithm; the codes are available in the attachment. Also, the package uses the Maximum Likelihood Estimator algorithm. The codes are available in the attachment.

5.4 BN Model Evaluation

This section provides a sensitivity analysis to evaluate the BN model. The created model's primary sensitivity analysis was performed on two nodes, the number of mismatched parts and the stop time. The primary purpose of this sensitivity analysis is to find the best operating conditions to minimize the number of mismatched components and stop times. These two nodes, which are the end nodes of the network, and almost all other nodes, directly and indirectly affect the two cases, are selected as query nodes and with the change in the level of control nodes, including the type of operation performed, the operator, the previous repairer, and the intended device, which results in lowest level required in the nodes for the number of mismatched parts and the stop time.

5.5 Results

Considering the inferences and the different conditions concerning the printed nodes, we want to determine the maximum likelihood for each reason for stopping. In fact, we want to have a prediction of the reason for stopping during an operation. Figures (3) and figure (4) illustrate the states in which, placing the root nodes under different conditions, we could identify a state with a high probability that the reason for stopping is apparent.

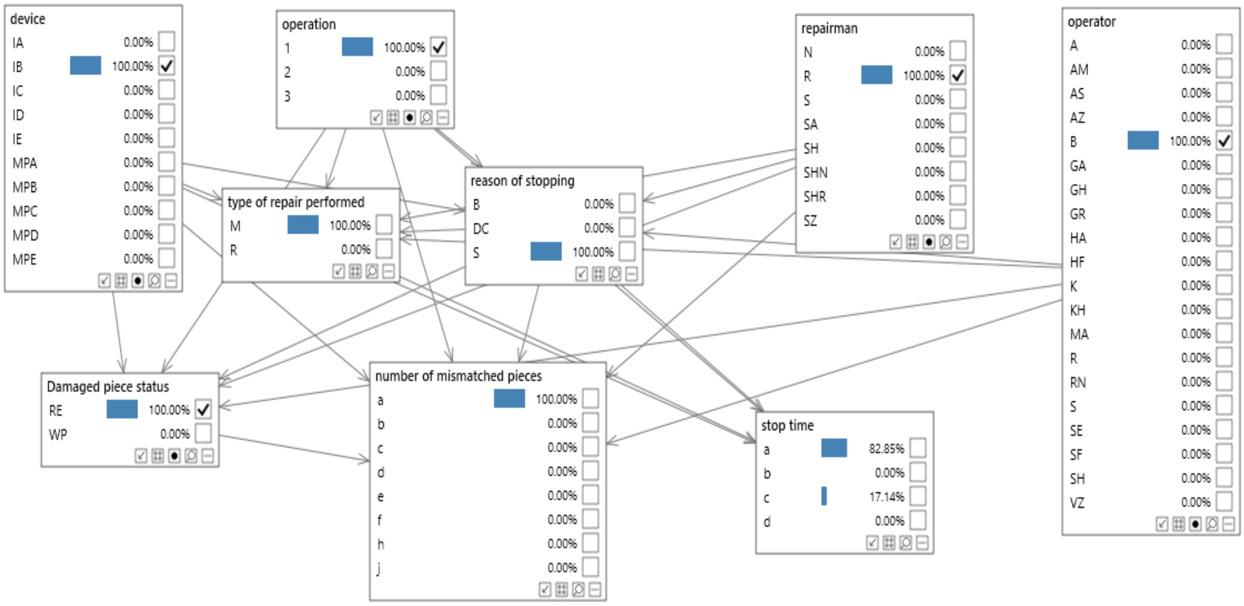

Figure 3: Show the inference performed in step one

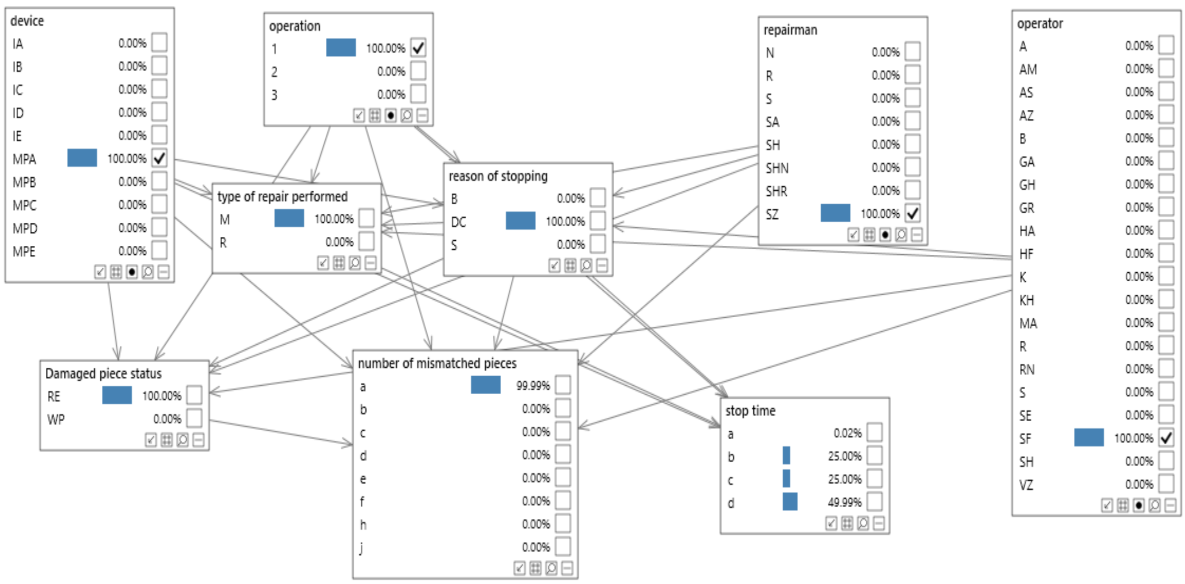

Figure 4: Show the inference performed in step two

Figure (3) and figure (4), respectively, show the conditions which by selecting root nodes as the control, machine, type of operation, operator, and repairers of the last machine failure, and accordingly, the most likely type of failure that equals to one are defined. Since, according to the precise circumstances of the operation, in case of the failure, with the probability of one, the cause of the failure and the stoppage are identified. Therefore, the maintenance team can take preventive maintenance measures to prevent the cause of the failure and ensure that if there is a breakdown, they are fully prepared to deal with the failure. The maintenance team can also better identify the reasons for stopping by examining the printed nodes about the node that caused problems. For example, in Figure (3), the Operator is B, the machine is IB, the last repairman of the machine is R, and the operation is 1. Therefore, due to the specificity of the control nodes, one can investigate why this stopping happens and take steps to reduce the reasons. According to the consultations with the Maintenance Team of the car company, another significant result of this study involves minimizing three cases, namely:

- Reducing the number of mismatched pieces
- Reducing stopping time
- In the event of failure, pieces should be reworked until they are considered waste.

Since there are also three types of operations with numbers 1,2, and 3, cases including the operator, the machine, and the repairman who repaired the machine at the last breakdown are specified. As noted earlier, these four are root nodes and have no prints.

In selecting Operation 1, we attempted to arrive at the conditions to reach the three listed.

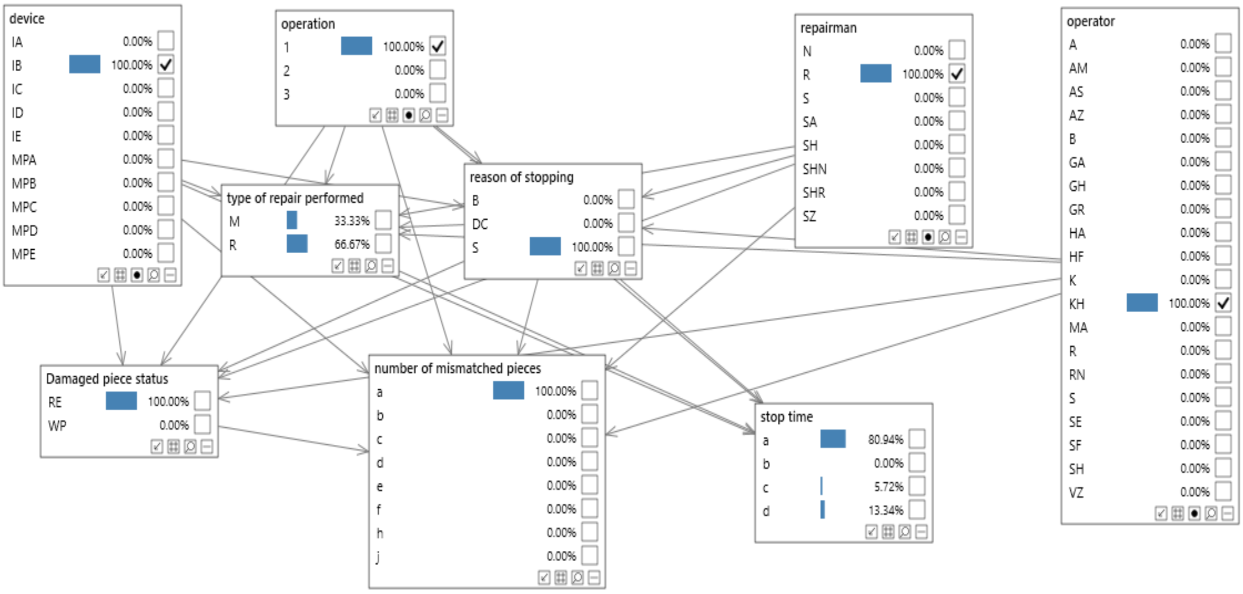

Figure 5: Show the inference performed in step three

Thus, according to Figure (5), it is clear that in Operation 1, it is best to have the relevant IB machine, the relevant KH operator, and the last R failure repairman to satisfy the above three requirements. By selecting the items listed according to operation 1, From the results of the figure (3), it is evident that with the probability of one, the number of mismatches is at minimum, the stop time with a probability of about 0.81 is at the minimum and with a probability of one broken piece need to be reworked.

Similarly, for Operations 1 and 2, optimum operating conditions are specified to achieve the highest satisfaction level for the three mentioned. These results are presented below. The other operation that exists is under the name of Operation 2. Similarly, with Operation 1, when performing this operation based on the network's conclusions, we achieved the conditions where the number of mismatched pieces and the stop time are at a minimum. If the malfunction occurred, pieces required more rework. These conditions are determined in Figure (6) too.

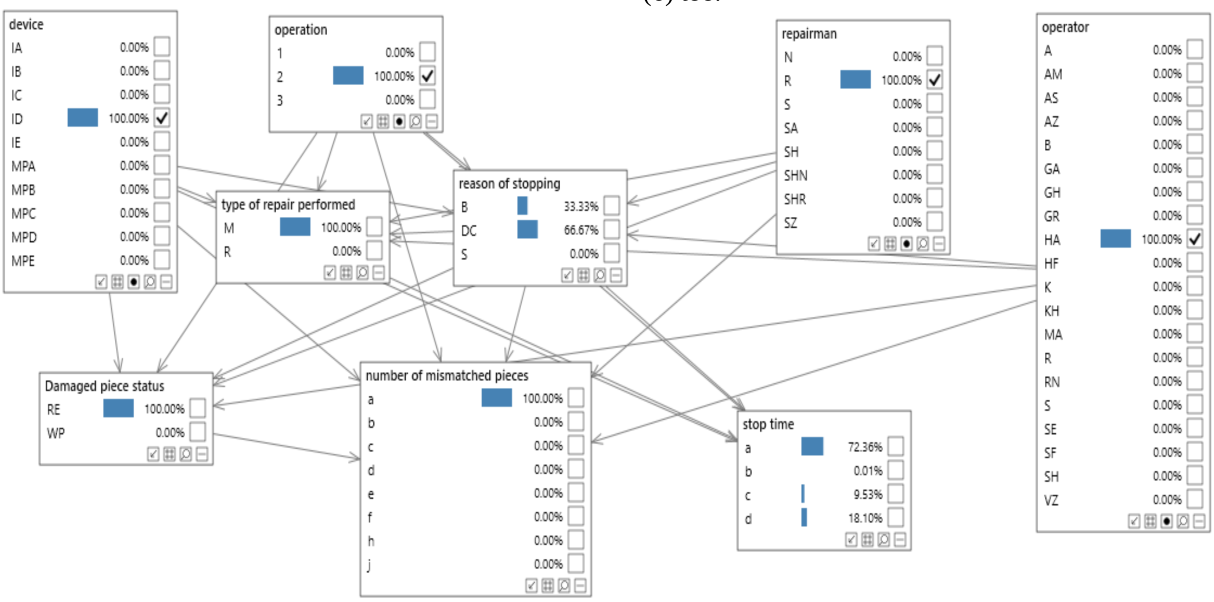

Figure 6: Show the inference performed in step four

According to the results of the figure (4), it can be concluded that during operation 2, if the machine is ID, operator HA, and the repairman of the last failure of the machine be R, then it can be expected that with a probability of one number of mismatches at their lowest level, level the stopping time with the probability of about 0.72 at their lowest level, level a, and mismatch pieces with the probability of one require rework. The last available operation is Operation 3. When performing this operation, the listed conditions required to satisfy the three objectives at their highest level are also presented in Figure (7).

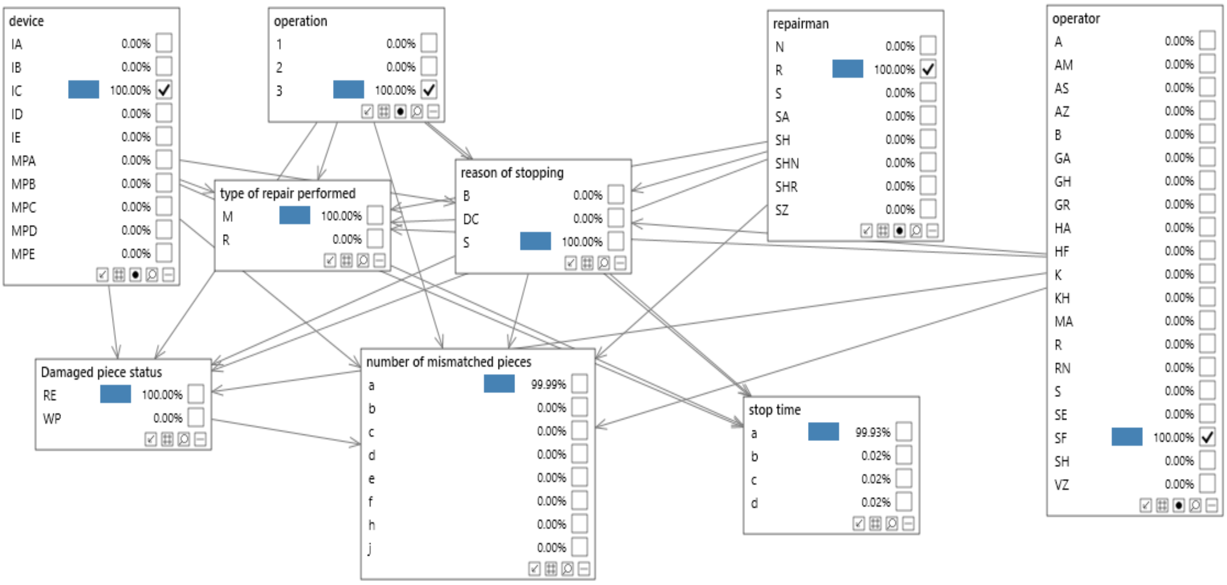

Figure 7: Show the inference performed in step five

According to the results of Figure (6), it can be concluded that during operation 3, if the device is IC, the operator is selected SF, and the repairman of the last machine is R, then one can expect the number of mismatches with the probability of one at its lowest level, and the stop time at its lowest level, level a; also the probability of pieces being reworked, if the components fail, is one.

6. Conclusion

In this paper, a predictable maintenance model was developed based on the Bayesian network method. In the first stage, according to the experts of the Maintenance Department, the necessary variables were selected from the Maintenance Department for modelling with the Bayesian network. In two stages of creating the Bayesian network structure and learning the conditional distributions function of the Bayesian model, results are obtained that can be very useful in the desired maintenance and repair by analysing the required sensitivities and the conclusions made in the network. The future suggestions for this article are mentioned in the following; better network models can be used in network structure, and the results of this model can be used to create an operator ranking system and by the use of other ranking models such as data envelopment analysis and compare the results of both models.

7. References

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