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Designing Expert System for Centrifugal using Vibration Signal and Bayesian Networks

Dedik Romahadi [a,*], Alief A. Luthfie [a], Wiwit Suprihatiningsih [a], Hui Xiong [b]

[a] *Department of Mechanical Engineering, Faculty of Engineering, Universitas Mercu Buana, Kembangan, Jakarta Barat, 11650, Indonesia*
[b] *Department of Manufacturing Engineering, Faculty of Engineering, Beijing Institute of Technology, Beijing, 100081, China*
*Corresponding author: *dedik.romahadi@mercubuana.ac.id*

Abstract*— Centrifugal machines are crucial in the process of making sugar. It requires proper centrifugal maintenance so that the production process runs smoothly. Efficiency and productivity are, therefore, critical factors in producing high-quality sugar. Centrifuge damages may occur, suddenly causing huge losses. Therefore, predictive treatment is essential. To achieve this, vibration analysis is a reliable and easy method to determine the vibration levels of spinning machines such as centrifuges. Simply by attaching the sensor to the outside of the engine, the engine condition will be read. Unfortunately, not all employees understand how to read vibration measurement data. Even experts need time to analyze the vibration signal. Therefore, the purpose of this study was to design an expert system that diagnoses centrifugal vibrations using the Bayesian Network. The vibration analysis process will be employed in the network using a series of complex nodes and trained according to the reference spectrum analysis. The presence or absence of spectral lines is evidence of Bayesian Network input in updating information regarding centrifugal damage. The result shows that the Bayesian network method was successfully applied to diagnose centrifuges based on vibration data. The inputs in the form of 1X and 2X produced an Unbalance probability value of 90%, Misalignment 93.2%, Looseness 57.38%, Bearing 33.79%, Pulley 50.3%, and produce a centrifugal damage probability of 7.86%. Therefore, these values were the actual conditions of the vibration data.

***Keywords*— Centrifuge; vibration analysis; vibration spectrum; Bayesian networks.**

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I. Introduction

The production of sugar with high-quality standards is the goal of every sugar factory. To achieve goals with minimal losses, it is important to maintain the good working conditions of machines involved in this process, thus accelerating productivity and profitability targets. One machine that plays an essential role in making sugar is centrifugal, shown in Figure 1. Good maintenance of centrifuges ensures good sugar quality and minimal losses [1], [2]. The centrifugal machine's primary function is to break up crystals in the massecuite from peripheral molasses by centrifugal force. Raw sugar is then sent to the drying or refining unit, matching its type and desired packing section [3]. To keep the centrifuge in good operating conditions, it is necessary to do predictive maintenance with proven reliability methods.

Vibration analysis has unique advantages associated with the monitoring and fault diagnosis of machinery. One of the vibration frequency characteristics is to show the types of damage that happen in a rotating machine. Vibration analysis is an effort to minimize damage to engine components that propagate to other engines [4]. This method also helps determine the engine structure and operating conditions using the latest technique used to analyze vibration signals and diagnose centrifuges according to standards taken from centrifugal casings [5]. This aims at detecting the location and nature of damage at an early stage. Furthermore, it includes the development and monitoring of its condition to estimate an engine's life span and prepare appropriate maintenance [6]. Fundamental frequencies and harmonics are the main components in the centrifugal frequency domain (spectrum) [7]–[9], and disturbances can be observed from an increase in amplitude as shown in the spectrum graph [10]–[12].

Unfortunately, not all employees understand how to analyze vibrations in industrial machinery, especially in centrifuges. The analysis of centrifugal vibrations requires time and experience. This is done with the use of standard software from the manufacturers. Sometimes, a company may have to pay dearly for this service. This may require them to employ external staffs to analyze data taken from centrifuges.

Furthermore, expert staff in vibration analysis also needs time to analyze spectrum data. Therefore, in solving this problem the research proposes to create a system that can read the spectrum of vibration data precisely to diagnose centrifuges. To perform operations, systems only require data and input spectrum specifications. Furthermore, the system provides important information about centrifugal conditions, including point of damage, what action is needed and damage level.

Fig. 1 Conical continuous centrifuges

The medical field has inspired the concept of diagnosis. At present, types of engine failure can be identified as the main cause of sophisticated diagnostic methodologies. However, the diagnosis is made after the damage has occurred, including in the reactive action. In fact, observing certain machine conditions has a problem fault diagnosis in detecting the characteristics of damage that might be hidden in the dataset. Also, signal processing and data acquisition are features of the vibration condition monitor, suitable for detecting damages in a spinning machine. Other ways of detecting damages are from historical data, expert insight, and physical formation, all of which are general frameworks for damage diagnosis systems [13]–[15]. Therefore, Bayesian Networks (BNs) can detect possible incidents that may occur. They are also able to handle uncertain causal relationships, update probabilities, multi-state variables, make two-way interpretations and handle data gaps [16]–[18].

The Bayesians Network and its application practices are widely used in various fields of science. The probabilistic graphic model has long been an exciting topic that supports computer science's rapid development, especially in data mining and machine learning [19]–[21]. Uncertainty arises and becomes the main component when designing knowledge-based reasoning and decision-makers methods [22], [23]. Regarding the expert systems in manufacturing, Barry R. Cobb and Linda Li emphasized that the Bayesians Network is most useful when dealing with uncertainty [24]. The Bayesian Network is a reliable tool for developing expert systems in the field of artificial intelligence. This is an advantage to reflecting and diagnosing complicated systems with incomplete, uncertain, and conflicting information. The BN is a probabilistic graphical model whose nodes are a set of random variables connected by a directed acyclic graph (DAG) to represent the conditional dependencies among those variables. Pearl was introduced in the early 1980s [25], [26], and states that probabilistic conclusions and fields of knowledge discovery were applied successfully [27], [28]. The BN was successfully applied to monitor engine conditions, especially in vibration analysis [29]–[31]. It is applicable as a decision-making tool. Furthermore, being supported by several journals on this similar topic, it was chosen as an effective method in designing expert systems for centrifugal diagnosis.

II. Materials and Methods

The implementation of this research was divided into several stages. This includes preparing centrifugal data, designing BNs according to vibration analysis principles, making programs in MATLAB, and testing systems that have been made. Data presentation in the form of centrifugal specifications and vibration values was shown in Table 1. This was prepared as input and training data when creating the system outlines and the vibration spectrum component so that the output data can be read as input for the BN obtained.

TABLE I
CENTRIFUGE SPECIFICATION

Machine Name	**Continuous Centrifugal III**
Power	90 kW
Motor Speed	1500 RPM
Rotor Speed	1800 RPM
Transmission System	Pulley Belt
Pitch Diameter of First Pulley	250 mm
Pitch Diameter of Second Pulley	208.34 mm
Pitch Diameter of Sheave	260 mm
Center Length between Pulleys	500 mm

The spectrum data entered was processed to determine each machine component's frequency, as shown in Figure 2. Centrifugal specification data was a reference for frequency calculation and will be adjusted to the spectrum.

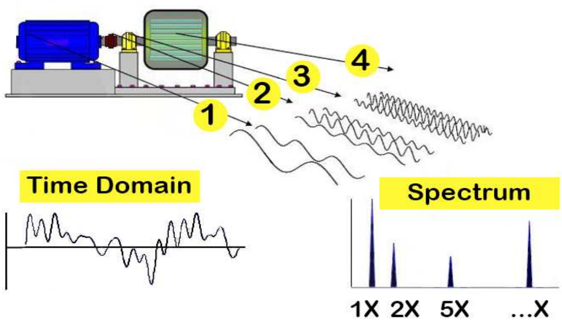

Fig. 2 Vibration frequency extraction

If the calculated frequency value is found in the spectrum, then it is input for the existence of evidence to the BN. Conversely, if the frequency value is not found in the spectrum, it becomes an input for the BN's absence of evidence. Furthermore, identification will be used as evidence to show whether there are frequencies associated with centrifugal damage. The frequency of centrifugal components can be seen in table 2.

Input data for BNs were grouped into 2 types. According to the frequency calculation, the frequency line that is proven to exist becomes input type 1 (true).

$$Approx.\ BPFI = \left(\frac{N_b}{2} + 1.2 \right) \times RPM \qquad (1)$$

$$Approx.\ BPFO = \left(\frac{N_b}{2} - 1.2 \right) \times RPM \qquad (2)$$

$$Approx.\ BSF = \frac{1}{2}\left(\frac{N_b}{2} - \frac{1.2}{N_b} \right) \times RPM \qquad (3)$$

$$Approx.\ FTF = \left(\frac{1}{2} - \frac{1.2}{N_b} \right) \times RPM \qquad (4)$$

where:

RPM : Revolutions Per Minute
FTF : Fundamental Train Frequency
BPFI : Ball Pass Frequency of Inner ring
BPFO : Ball Pass Frequency of Outer ring
BSF : Ball Spin Frequency
B_d : Ball or roller diameter
N_b : Number of balls or rollers
P_d : Pitch diameter

Calculate the belt length and belt frequency:

$$B_L = 2C + \pi\left(\frac{D_2 + D_1}{2} \right) + \left(\frac{D_2 + D_1}{4C} \right)^2 \qquad (5)$$

$$B_f = \frac{\pi \times D \times RPM}{B_L} \qquad (6)$$

where:

C : Center length between pulleys
D_2 : Pitch diameter of second pulley
D_1 : Pitch diameter of first pulley
D : Pitch diameter of sheave

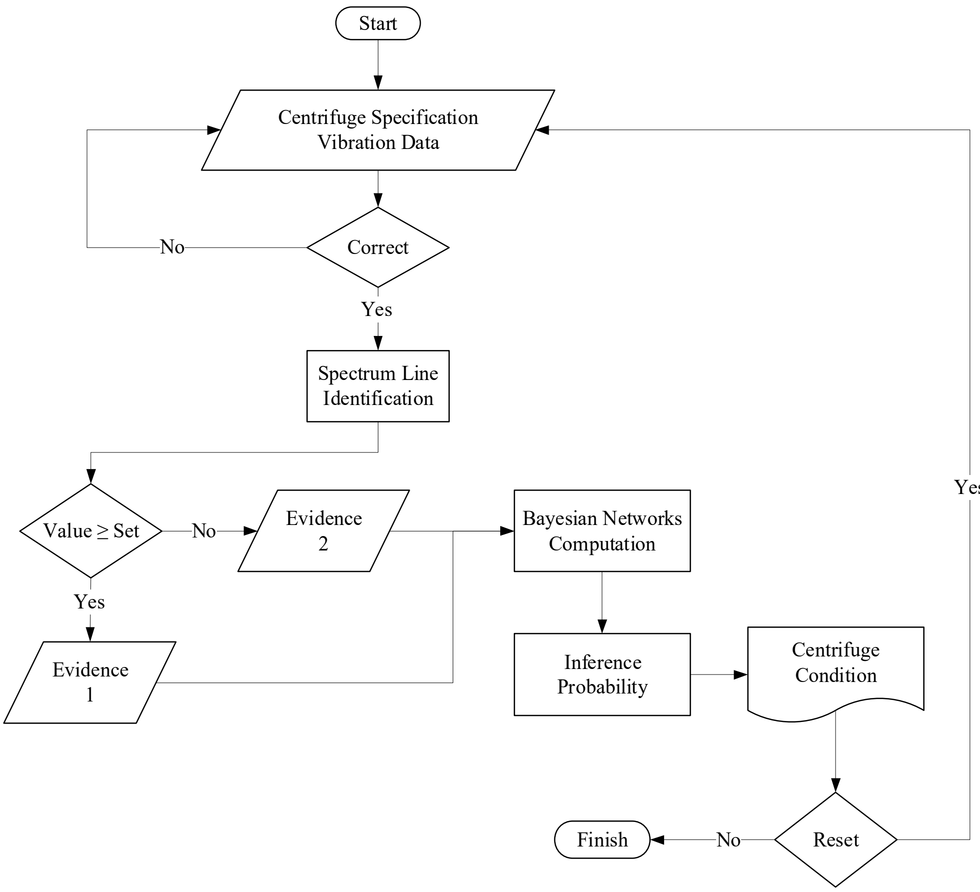

Fig. 3 System flowchart

This input has a large amplitude-frequency requirement of ≥ 2 mm/s RMS. Whereas for data that is not proven, there is a frequency line according to the calculation or the value of the frequency amplitude of < 2mm/s RMS. This becomes input type 2 (false). The machine specification data and process of grouping input types then enter the BN calculations to provide diagnosis results such as vibration status and damage location. Detailed research flow diagram can be seen in the Figure 3.

Based on the stages of vibration analysis in diagnosing centrifugal conditions, it is necessary to build a BN structure. The first process assumes the cause of the damage in the centrifuges is based on the spectrum lines that appear. Then BN is built to show the location of damages and the actions that the user should take. A BN structure model is shown in Figure 4.

Bayes Theorem:

$$P(B \mid A) = \frac{P(A \mid B) \times P(B)}{P(A)} \tag{7}$$

TABLE II
CENTRIFUGAL COMPONENT FREQUENCY

Component/Attribute		**Freq. 1 (Hz)**	**Freq. 2 (Hz)**
0.5X		13	15
1X		25	30
2X		50	60
3X		75	90
4X		100	120
5X		125	150
Bearing:	BPFI	23.5	268.25
	BPFO	176.75	211.75
	FTF	11	13.25
	BSF	209.75	251.5
Pulley		12	-

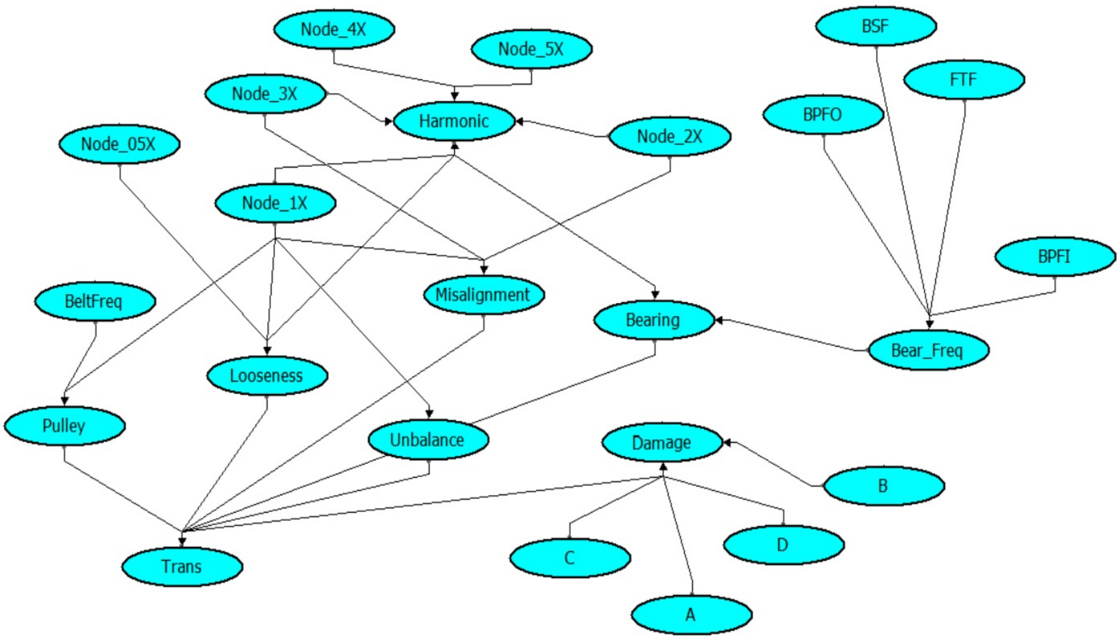

Fig. 4 Bayesian network structure

TABLE III
PRIOR PROBABILITY

Node Name	P (Yes)	P (No)
0.5X	0.1	0.9
1X	0.1	0.9
2X	0.1	0.9
3X	0.1	0.9
4X	0.1	0.9
5X	0.1	0.9
BPFI	0.05	0.95
BPFO	0.05	0.95
FTF	0.05	0.95
BSF	0.05	0.95
A	0.1	0.9
B	0.1	0.9
C	0.05	0.95
D	0.02	0.98

There are 24 nodes in the BN structure. The root of each node has a related Conditional Probability Table (CPT). Despite decreasing, it only contains a line that represents the prior probability. If a node has many parent nodes or if a parent can take many values, the CPT can be very large. The size of the CPT is exponential in the number of parent nodes. Thus, for Boolean networks a variable with n parents requires a CPT with 2^(n+1) probabilities. The nodes in this case include Harmonic, Trans, and Bear_Freq.

These nodes describe the source of centrifugal damage. In its design, they are directed to the Damage node to obtain the probability value of the centrifugal damage level. The Damage node also has CPT from nodes A, B, C, and D. The application of this will produce a probability of 1024, then by giving a Trans node, the number of probabilities at Damage node becomes 64.

Expert systems work with the acquisition of knowledge for the signs of centrifugal damage data, under the measurement of vibrations that have been converted into spectrum and processed using the BN method. The spectrum was used to analyze vibration amplitudes at various component frequencies. This identifies and tracks vibration occurring at specific frequencies. The information was used to diagnose the cause of excessive vibration (damage). Centrifugal damage is distinguished by the amplitude of the vibration that appears in the spectrum data. The prior probability values of each centrifugal symptom can be seen in Table 3.

TABLE IV
ISO STANDARD

No.	Machine Group	Machine Condition (mm/s RMS)			
	Rigid Foundation	**A**	**B**	**C**	**D**
1	Group 1	0 - 2.3	2.3 - 4.5	4.5 - 7.1	> 7.1
2	Group 2	0 - 1.4	1.4 - 2.8	2.8 - 4.5	> 4.5
3	Group 3	0 - 2.3	2.3 - 4.5	4.5 - 7.1	> 7.1
4	Group 4	0 - 1.4	1.4 - 2.8	2.8 - 4.5	> 4.5
	Flexible Foundation	**A**	**B**	**C**	**D**
5	Group 1	0 - 3.5	3.5 - 7.1	7.1 - 11	> 11
6	Group 2	0 - 2.3	2.3 - 4.5	4.5 - 7.1	> 7.1
7	Group 3	0 - 3.5	3.5 - 7.1	7.1 - 11	> 11
8	Group 4	0 - 2.3	2.3 - 4.5	4.5 - 7.1	> 7.1

Determined centrifugal conditions based on the amplitude of vibration at the frequency have been identified. The vibration value entered is then processed by the system and will be grouped into machine group 3 with a flexible foundation type. The level of damage detected will be compared with the vibration value that has been grouped in ISO standard. Therefore, conclusions on centrifugal action can be obtained. Table 4 shows the grouping of vibration values according to ISO 10816-3 Standard.

TABLE V
CPT FROM THE MISALIGNMENT NODE

Parent Node(s)			P(Misalignment | 1X, 2X, 3X)		
1X	**2X**	**3X**	Yes	No	Bar Charts
Yes	Yes	Yes	95%	5%	
		No	90%	10%	
	No	Yes	40%	60%	
		No	10%	90%	
No	Yes	Yes	45%	55%	
		No	25%	75%	
	No	Yes	45%	55%	
		No	0%	100%	

CPT shows the level of centrifugal damage. An expert was required to fill each table with a percentage of 0% - 100% (0-1). For example, the chance of misalignment if the evidence of X1, X2, and X3 was obtained is 95%. Determination of the value, 95%, is obtained from an expert. One of the most important advantages of BNs is its ability to calculate conditional probabilities between input and output nodes. It also performs more accurate probability inferences. Conditional probabilities will provide valuable advice for diagnosis of centrifugal damage. The CPT value for the Misalignment node can be seen in Table 5.

III. RESULTS AND DISCUSSION

This expert system uses probabilistic renewal beliefs in making decisions. The node with the largest percentage value will be determined as the highest trigger for damage in the centrifuges. As for other damages, it will be calculated according to the percentage level obtained from the system. Any value given to CPT will affect other nodes. Therefore, the CPT value is designed to determine appropriate results.

Each node in the system set has 2 states namely "Yes" and "No". The decision-making at focal point, 5 node location where the solution was broken were Unbalance, Misalignment, Looseness, Bearing and Pulley. At 1 node the conclusion is Damage. Figure 5 shows the information of no evidence of symptoms.

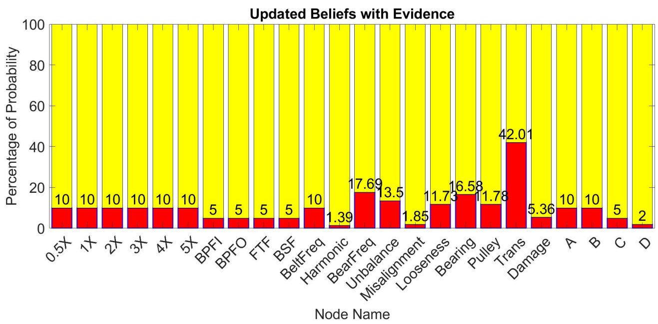

Fig. 5 Update on probability without evidence

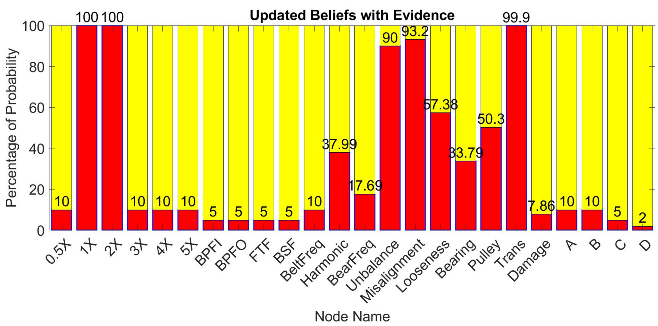

Fig. 6 Update on probability with evidence

Without evidence of the probability, value of Unbalance was 13.5%; Misalignment 1.85%; Looseness 11.73%; Bearing 16.58%; Pulley 11.78%; and results in the probability of centrifugal damage was 5.36%. All probability values were still less than 50%; this indicated no damage to the centrifuges.

Figure 6 shows the information with evidence of symptoms at 1X and 2X. It is important to know how a component will affect the whole system. The probability of Unbalance increased to 90%; Misalignment 93.2%;

Looseness 57.38%; Bearing 33.79%; Pulley 50.3%; and produce a centrifugal damage probability of 7.86%.

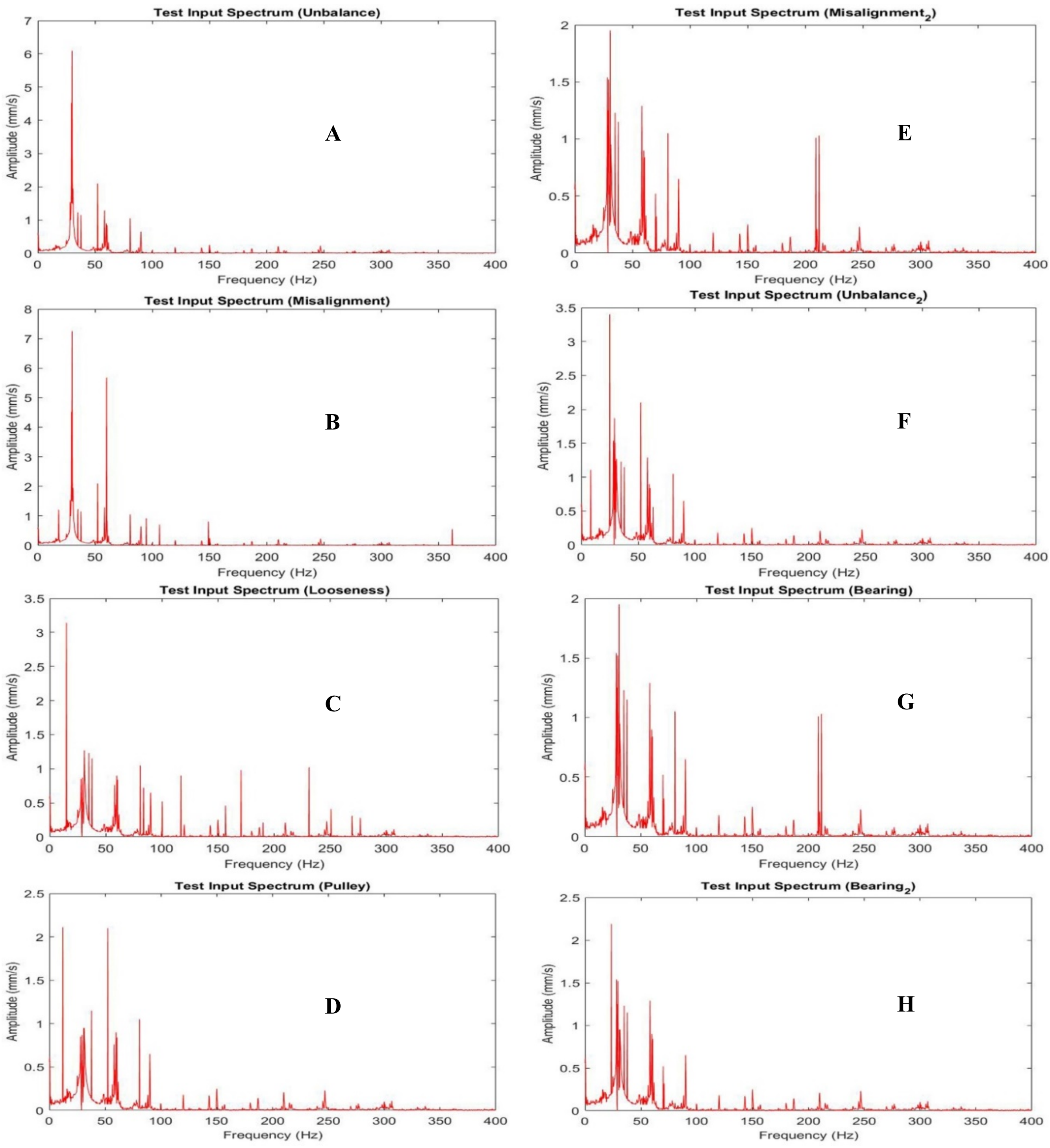

Fig. 7 Spectrum data

Through Figure 6 it can be concluded that the most damages occur due to unbalance and misalignment. Therefore, the corrective action on the Misalignment takes precedence because the percentage value of the probability is greater than Unbalance. The probability for Damage value is very little due to the absence of input in the form of vibration value. CPT node Damage has a small value or probability in case where there no evidence in the form of value for vibration.

The application is designed to be easy for users to understand the information generated by the system. Basic features were programmed to obtain important information from centrifugal conditions. The application created can display original spectrum data in graphic form, display BN results in bar graphs, and display important information about each centrifugal component's condition. Furthermore, the application is also programmed with facial expressions related to centrifugal conditions. If the centrifuges are in bad condition, facial expressions will adjust to sad facial expressions. Conversely, if the centrifugal conditions are in good condition, happy expressions will appear. Features like reset are also added so that users can restart the diagnosis easily.

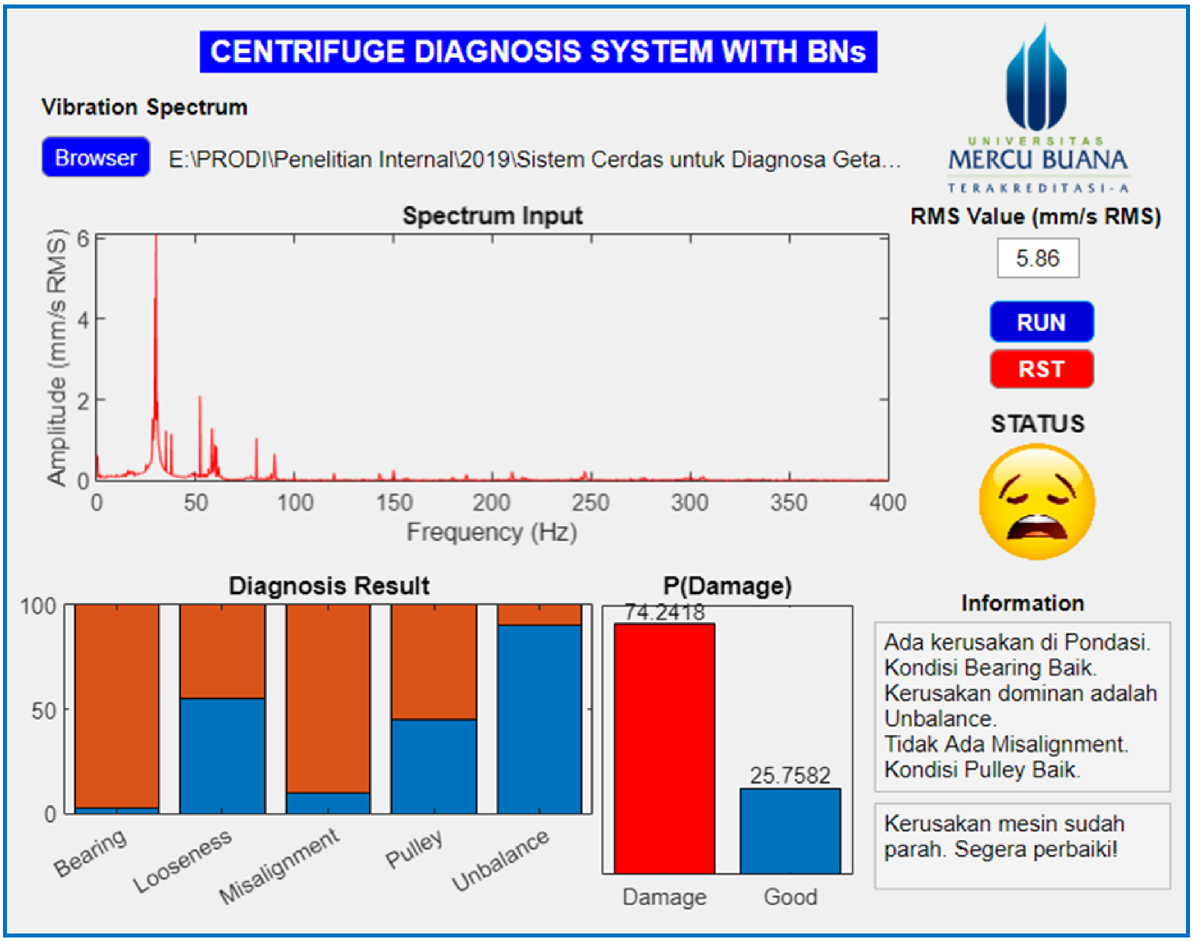

Fig. 8 System testing

TABLE VI
SYSTEM DIAGNOSIS RESULTS

No.	Spectrum	RMS Value (mm/s)	Actual Condition	System Diagnosis	Result
1	A	5.86	Unbalance	Unbalance	Correct
2	B	7.34	Misalignment	Misalignment	Correct
3	C	3.21	Looseness (good condition)	Looseness (good condition)	Correct
4	D	2.37	Pulley (good condition)	Pulley (good condition)	Correct
5	E	5.97	Misalignment	Misalignment	Correct
6	F	3.46	Unbalance (good condition)	Unbalance (good condition)	Correct
7	G	2.07	Bearing (good condition)	Bearing (good condition)	Correct
8	H	2.38	Bearing (good condition)	Bearing (good condition)	Correct

A system or software that has been designed and analyzed will undergo the stages of implementation, inspection and subsequently be released for running programs after been tested for eligibility. Therefore, the system is made in accordance with the desired goals and can be operated properly. The following will explain the implementation of an expert system, for diagnosing centrifugal damage-based analysis and design that has been done before. After the implementation phase is complete, it is followed by testing the implementation that has been carried out.

System testing was carried out to ensure the system is built in accordance with the results of analysis and design so that a final conclusion is made. Testing is done based on the results of the system's diagnosis with the same actual conditions, regarding the signs that have been obtained from the data that has been entered. Testing uses centrifugal vibration data whose measurements were obtained from the sugar factory of PT. Berkah Manis Makmur, where the data contains several types of measurements such as vibration and spectrum values. This data obtained was used for input to determine the conditions of the centrifuges. Search for sources of damage that occur in the centrifuge and actions to be taken by the user. Figure 7 shows the centrifugal spectrum diagnosis.

Figure 8 shows the calculation results of BNs that have been built, there are symptoms of possible indications of damage to the centrifuge. The diagnosis result states that the presence of unbalance causes the dominant damage. This characteristic is due to the appearance of 1X in the spectrum frequency. The system also states that the damage has been severe and recommends immediate repairs. Referring to table 4, the vibration level enters zone C. This means that short-term operation is still permitted. Table 6 shows the system's diagnosis results, which is the same as the actual conditions in the field. The system was able to predict the location of damage and centrifugal conditions accurately.

IV. CONCLUSIONS

Centrifuges can be diagnosed accurately and efficiently using vibration data in the form of vibration and their spectrum. Vibration values were used to determine centrifuge conditions. The spectrum was useful to find the source of damage. The vibration analysis method was successfully applied to the BN by making the signs of centrifugal damage into interconnected nodes. The BN method is advantageous because it does not need a lot of data to build a network so that it can recognize spectrum patterns. The network can also accurately diagnose centrifuges even though more than 1 symptom is found in the spectrum. Furthermore, prior actions can be adjusted by changing the CPT value. The results of the diagnosis by the system of 8 spectra showed the appropriate results. The predictions on centrifugal condition and location of damage were correct.

When building a BN, determining the prior probability and CPT should be done by an expert in this field. The accuracy of the results from the BN was determined by the values of the prior, CPT, and connections between nodes. The result obtained will not match if these processes were not carried out correctly. Many nodes may require tedious computer works and lots of time to fill the CPT. Therefore, minimizing the number of nodes when creating a network is advised. Each node does not have more than 5 parent nodes. Further research can be done using different machine methods, such as fuzzy logic, support vector machines, and others, to choose the best method for centrifugal diagnosis.

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REFERENCES

[1] Y. Fu, B. J. Gu, J. Wang, J. Gao, G. M. Ganjyal, and M. P. Wolcott, “Novel micronized woody biomass process for production of cost-effective clean fermentable sugars,” *Bioresour. Technol.*, vol. 260, pp. 311–320, Jul. 2018, doi: 10.1016/j.biortech.2018.03.096.

[2] I. Prasertsung, K. Aroonraj, K. Kamwilaisak, N. Saito, and S. Damrongsakkul, “Production of reducing sugar from cassava starch waste (CSW) using solution plasma process (SPP),” *Carbohydr. Polym.*, vol. 205, pp. 472–479, Feb. 2019, doi: 10.1016/j.carbpol.2018.10.090.

[3] J. Chen, X. Cai, E. Lale, J. Yang, and G. Cusatis, “Centrifuge modeling testing and multiscale analysis of cemented sand and gravel (CSG) dams,” *Constr. Build. Mater.*, vol. 223, pp. 605–615, Oct. 2019, doi: 10.1016/j.conbuildmat.2019.06.218.

[4] G. Chen, M. Liu, and J. Chen, “Frequency-temporal-logic-based bearing fault diagnosis and fault interpretation using Bayesian optimization with Bayesian neural networks,” *Mech. Syst. Signal Process.*, vol. 145, p. 106951, Nov. 2020, doi: 10.1016/j.ymssp.2020.106951.

[5] C. Zhou *et al.*, “Vibration singularity analysis for milling tool condition monitoring,” *Int. J. Mech. Sci.*, vol. 166, p. 105254, Jan. 2020, doi: 10.1016/j.ijmecsci.2019.105254.

[6] Y. Zhao, J. Pan, Z. Huang, Y. Miao, J. Jiang, and Z. Wang, “Analysis of vibration monitoring data of an onshore wind turbine under different operational conditions,” *Eng. Struct.*, vol. 205, p. 110071, Feb. 2020, doi: 10.1016/j.engstruct.2019.110071.

[7] D. Romahadi, A. A. Luthfie, and L. B. Desti Dorion, “Detecting classifier-coal mill damage using a signal vibration analysis,” *SINERGI*, vol. 23, no. 3, p. 175, Sep. 2019, doi: 10.22441/sinergi.2019.3.001.

[8] D. Romahadi, H. Xiong, and H. Pranoto, “Intelligent system for gearbox fault detection & diagnosis based on vibration analysis using Bayesian Networks,” in *IOP Conference Series: Materials Science and Engineering*, 2019, vol. 694, doi: 10.1088/1757-899X/694/1/012001.

[9] J. Jiang, H. Yang, G. Chen, and K. Wang, “Numerical and experimental analysis on the vibration and radiated noise of the cylinder washing machine,” *Appl. Acoust.*, p. 107747, Nov. 2020, doi: 10.1016/j.apacoust.2020.107747.

[10] T. Wang, Q. Han, F. Chu, and Z. Feng, “Vibration based condition monitoring and fault diagnosis of wind turbine planetary gearbox: A review,” *Mech. Syst. Signal Process*, vol. 126. Academic Press, pp. 662–685, Jul. 01, 2019, doi: 10.1016/j.ymssp.2019.02.051.

[11] L. Tian, T. Ye, and G. Jin, “Vibration analysis of combined conical-cylindrical shells based on the dynamic stiffness method,” *Thin-Walled Struct.*, p. 107260, Nov. 2020, doi: 10.1016/j.tws.2020.107260.

[12] X. Lu *et al.*, “Prediction and analysis of cold rolling mill vibration based on a data-driven method,” *Appl. Soft Comput. J.*, vol. 96, p. 106706, Nov. 2020, doi: 10.1016/j.asoc.2020.106706.

[13] M. Y. Asr, M. M. Ettefagh, R. Hassannejad, and S. N. Razavi, “Diagnosis of combined faults in Rotary Machinery by Non-Naive Bayesian approach,” *Mech. Syst. Signal Process.*, vol. 85, pp. 56–70, Feb. 2017, doi: 10.1016/j.ymssp.2016.08.005.

[14] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, “Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications,” *Mech. Syst. Signal Process.*, vol. 42, no. 1–2, pp. 314–334, Jan. 2014, doi: 10.1016/j.ymssp.2013.06.004.

[15] A. W. Biantoro, H. Maryanto, A. K. Hidayanto, and A. Hamid, “The investigation of end mill feeds on CNC router machine using vibration method,” *SINERGI*, vol. 24, no. 2, p. 117, Apr. 2020, doi: 10.22441/sinergi.2020.2.005.

[16] M. Hu *et al.*, “A machine learning bayesian network for refrigerant charge faults of variable refrigerant flow air conditioning system,” *Energy Build.*, vol. 158, pp. 668–676, Jan. 2018, doi: 10.1016/j.enbuild.2017.10.012.

[17] S. Kabir and Y. Papadopoulos, “Applications of bayesian networks and petri nets in safety, reliability, and risk assessments: A review,” *Safety Science*, vol. 115. Elsevier B.V., pp. 154–175, Jun. 01, 2019, doi: 10.1016/j.ssci.2019.02.009.

[18] T. Huang and K. U. Schröder, “Bayesian probabilistic damage characterization based on a perturbation model using responses at vibration nodes,” *Mech. Syst. Signal Process.*, vol. 139, p. 106444, May 2020, doi: 10.1016/j.ymssp.2019.106444.

[19] A. R. Sahu and S. K. Palei, "Real-time fault diagnosis of HEMM using Bayesian Network: A case study on drag system of dragline," *Eng. Fail. Anal.*, vol. 118, p. 104917, Dec. 2020, doi: 10.1016/j.engfailanal.2020.104917.

[20] G. Sharma and R. N. Rai, "Modeling and analysis of factors affecting repair effectiveness of repairable systems using Bayesian network," *Appl. Soft Comput. J.*, vol. 92, p. 106261, Jul. 2020, doi: 10.1016/j.asoc.2020.106261.

[21] B. Chen, L. Xie, Y. Li, and B. Gao, "Acoustical damage detection of wind turbine yaw system using Bayesian network," *Renew. Energy*, vol. 160, pp. 1364–1372, Nov. 2020, doi: 10.1016/j.renene.2020.07.062.

[22] T. Adedipe, M. Shafiee, and E. Zio, "Bayesian Network Modelling for the Wind Energy Industry: An Overview," *Reliability Engineering and System Safety*, vol. 202. Elsevier Ltd, p. 107053, Oct. 01, 2020, doi: 10.1016/j.ress.2020.107053.

[23] D. Lee and D. Choi, "Analysis of the reliability of a starter-generator using a dynamic Bayesian network," *Reliab. Eng. Syst. Saf.*, vol. 195, p. 106628, Mar. 2020, doi: 10.1016/j.ress.2019.106628.

[24] B. R. Cobb and L. Li, "Bayesian network model for quality control with categorical attribute data," *Appl. Soft Comput.*, vol. 84, p. 105746, Nov. 2019, doi: 10.1016/j.asoc.2019.105746.

[25] J. Pearl, *Bayesian networks: A model of self-activated: memory for evidential reasoning*. Los Angeles: UCLA, 1985.

[26] J. Pearl, "Fusion, propagation, and structuring in belief networks," *Artif. Intell.*, vol. 29, no. 3, pp. 241–288, 1986, doi: 10.1016/0004-3702(86)90072-X.

[27] D. Lee and R. Pan, "A nonparametric Bayesian network approach to assessing system reliability at early design stages," *Reliab. Eng. Syst. Saf.*, vol. 171, pp. 57–66, Mar. 2018, doi: 10.1016/j.ress.2017.11.009.

[28] X. Li, Y. Yang, L. Li, G. Zhao, and N. He, "Uncertainty quantification in machining deformation based on Bayesian network," *Reliab. Eng. Syst. Saf.*, vol. 203, p. 107113, Nov. 2020, doi: 10.1016/j.ress.2020.107113.

[29] W. Huang, Y. Zhang, X. Kou, D. Yin, R. Mi, and L. Li, "Railway dangerous goods transportation system risk analysis: An Interpretive Structural Modeling and Bayesian Network combining approach," *Reliab. Eng. Syst. Saf.*, vol. 204, p. 107220, Dec. 2020, doi: 10.1016/j.ress.2020.107220.

[30] S. Fan, J. Zhang, E. Blanco-Davis, Z. Yang, and X. Yan, "Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS," *Ocean Eng.*, vol. 210, p. 107544, Aug. 2020, doi: 10.1016/j.oceaneng.2020.107544.

[31] D. A. Quintanar-Gago, P. F. Nelson, Á. Díaz-Sánchez, and M. S. Boldrick, "Assessment of steam turbine blade failure and damage mechanisms using a Bayesian network," *Reliab. Eng. Syst. Saf.*, p. 107329, Nov. 2020, doi: 10.1016/j.ress.2020.107329.