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Applying Bayesian networks in making intelligent applications for static and dynamic unbalance diagnosis

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ABSTRACT

One of the problems often encountered in vibration analysis is unbalanced or imbalanced, namely the occurrence of a shift in the center of mass from the center of rotation to cause high vibrations. Unbalance itself is divided into two, namely static and dynamic unbalance. Identification of the right type of unbalance must be done because each type of unbalance requires different handling. Therefore, this study aims to design a system to identify the type of unbalance based on the required parameters. The system design determines the input and then builds an algorithm by combining vibration analysis methods and Bayesian networks (BN). Systems and applications are built using MATLAB. After the application is finished, testing is carried out using vibration measurement data obtained from a demo machine that has previously been conditioned for damage. The BN method has been successfully applied to the unbalance diagnosis system. When there is evidence of large amplitude in 1X the frequency spectrum and the value of the static phase range, the percentage of static unbalance from 26.8% increases to 75%. The system can predict all testing data quickly and precisely for the six experiments.

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1. INTRODUCTION

The vibration occurs due to damage to shafts, bearings, gears, lack of connection tightness, lack of smooth lubrication, and the imbalance of rotating machine elements or unbalance [1]–[5]. Vibration in a machine is very important to pay attention to because, from a vibration, many errors arise and damage the machine's components. In the past, vibration analysis required full-spectrum instruments to identify frequencies at which vibrations were dominant [6]–[8]. The operator then compares the peak frequency with the operating speed and converts it to a graph to determine the possible causes. One of the advantages of the method is that the operator can gradually learn how a piece of equipment vibrates and why certain problems occur at the same multiple rotational speeds [9].

The latest generation of vibration meters has more capabilities and automatic functions than its predecessors. Many units simultaneously display the full vibration spectrum of the three axes, providing an idea of what is happening with a particular machine [10]–[13]. Although today's vibration meters offer many automated features and capabilities, they still require a basic understanding of vibration analysis to use them effectively. Each parameter in the vibration data collection can indicate the type of damage in the machine. For this reason, proper analysis can produce appropriate recommendations for handling any engine failures that occur [14]–[16]. Many vibration measuring instruments do not have intelligent diagnostic features, especially for the type of unbalanced damage. Users must understand the basic concepts of vibration analysis for types of damage. An expert also still needs time in the process of diagnosing unbalanced damage, because most tools only provide unbalance damage parameters and users still need to carry out a series of data analysis processes until they can decide the unbalance damage that occurred [17].

A Bayesian network (BN) is a probability graphic structure that depicts a causal relationship between interrelated variables. There are four things that BN can offer as a method: first, BN can easily deal with incompleteness or problems with data [18]. Second, BN allows one to learn about causal relationships. The learning process becomes important when we try to understand the domain of the problem. Third, BN can facilitate the combination of domain knowledge and data. Lastly, BN offers an efficient and principled approach to avoiding overfitting the data [19]–[24]. Modeling in BN involves two steps, namely creating a network structure and estimating the probability value of each node. One of the programs that can be used to build the BN algorithm is to use matrix laboratory (MATLAB). Seeing the advantages that BN has as a decision-making tool and supported by several journals on the same topic, BN was chosen as a method for making intelligent applications for the diagnosis of static and dynamic unbalance [25]–[29].

Several studies have been conducted related to this research topic. Research to analyze unbalanced damage, as well as other damage that may arise when the motor is operating [30]. Research that aims to detect the location of damage that occurs in the classifier by using vibration signal analysis and measuring the magnitude of the vibration and presenting it in the form of a frequency domain (spectrum) using the fast Fourier transform or FFT [31]. The engine condition assessment refers to the ISO 10816-3 standard in velocity and acceleration modes. Based on the data spectrum analysis, the dominant damage lies in the unbalance rotor. Associated with expert systems in the field of vibration analysis, Cobb and Li [32], Li *et al.* [33]; Amrin *et al*. [19]; Sahu and Palei [34] emphasize that BN is highly reliable when dealing with uncertainty. BN is a suitable method for developing intelligent applications in the field of vibration diagnosis.

Based on some of the problems that mention on the second paragraph and the advantages of the BN method. The author assesses the importance of making an intelligent system to analyze a malfunction in a machine. For this reason, through this study, the author aims to create an intelligent system to analyze one of the common malfunctions that occur in a machine, namely unbalance using BN modeling which will be implemented in the MATLAB application.

2. METHOD

The implementation of this research can be divided into several stages. In general, the stages are preparing the concept of an algorithm scheme, modeling BN according to the concept of unbalance diagnosis, making a program in MATLAB, and testing the system that has been made. BNs are constructed using a statistical method known as Bayes' theorem. This theory employs conditional probability, which is the likelihood of an event A if it is known that event B has already occurred. The symbol for conditional probability is P(A|B). The conditional probability can be derived from (1). In addition, there is a joint probability, given by (P(A∩B)), which represents the likelihood that events A and B will occur. In (2) shows the joint probability.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A)+P(B|\bar{A})P(\bar{A})} \quad (1)$$

$$P(A \cap B) = P(A|B) \times P(B) \quad (2)$$

The network topology can be obtained by encoding the expert domain's subjective knowledge. One arrow can connect the greatest sequence of nodes to the lowest sequence of nodes if a condition is met. Each arrow is prevented from connecting the lowest node order to the highest node order by the algorithm. If the scheme is applied to other variables, the network topology may change. Many topologies are possible due to the fact that multiple arrows can connect various pairings of nodes. Instead, the variable may be subdivided into many causative variables, with arrows then connecting each cause variable to the corresponding effect variable.

The BNs network inference can be shown in (3). A basic example involving a three-node network, X → Y → Z. If we have a proof for the root node, X = x, updating in the same direction as the arc is a straightforward application of the chain rule based on the network's implied assumption of independence. Based on the input data obtained, the probability value will be calculated through several stages using the BN method, starting from determining the parameter value for each damage symptom, then determining the conditional probability value, after two values are obtained, the system will calculate the combined and posterior probability values for each type of damage. unbalance adjusted for the BN structure and the posterior probability value is used as a probability inference of the type of unbalance damage. BN generates relational information and conditional probabilities through bidirectional propagation between input and output nodes. Also, in real case implementations, it is common to use multistate nodes. So, from the consultation carried out by the user, then get the type of unbalance damage that occurred on the machine and the error percentage.

$$Bel(Z) = P(Z = X = x) = \sum_{Y=y} P(Z|Y)P(Y|X = x) \quad (3)$$

Data preparation in the form of machine specifications and vibration data. This data is prepared as input and training data when creating the system. Then describe the components of the vibration spectrum to obtain output data that can be read as input for BN. The entered spectrum data is then processed to find the frequency of each machine component. Machine specification data will be the reference for frequency calculations and will be adjusted to the spectrum. If the calculated frequency value is found in the spectrum, it will be input for evidence to BN, while if the frequency value is not found in the spectrum, it will be input for no evidence to BN. Then the input data for BN are grouped into 2 types. The frequency line that is proven to exist according to the frequency calculation becomes input type 1 (true). This input has the requirement that the frequency amplitude must be 2 mm/s in root mean square (RMS). Meanwhile, for data that is not proven to have a frequency line according to the calculation or the value of the frequency amplitude < 2 mm/s RMS, it becomes input type 2 (false). Furthermore, the engine specification data and the input type grouping process are then entered into the BN calculation so that it will provide information on the diagnosis results such as vibration status and type of unbalance.

2.1. Tools and materials

A vibration analyzer is a tool that serves to measure the amplitude and frequency of vibration of a machine (Rotating equipment). Vibration measurement tools as shown in Figure 1 also provide information about the spectrum data of the vibrations that occur, namely the amplitude data against the frequency, this data is very useful for analyzing the damage to a machine. The experiment setup as shown in Figures 2 and 3 can be conditioned to describe static and dynamic unbalance in the machine so that it can validate the diagnosis results. In addition, it also requires a computer that has Microsoft Belief Networks (MSBNx) and MATLAB applications installed.

Figure 1. Pruftechnic VibExpert II

Figure 2. Experiment setup

Vibration data was obtained from the measurement results of the demo machine. Measurements are made on the horizontal, vertical, and axial axes at the drive end and non-drive end bearing locations. When taking the overall vibration value and spectrum, the demo machine is conditioned to experience static and dynamic unbalance problems. The measurement and reference data will be used as a reference in building the BN system. The finished system will be tested using some random demo machine measurement data. Validate the results of the system diagnosis against the entered vibration data and look for the cause of an incorrect diagnostic result is found.

(a) (b)

Figure 3. Condition of unbalance setup, (a) static unbalance and (b) dynamic unbalance

2.2. Tools and materials

Before designing a program in the MATLAB application, it is necessary to determine the probability of the determinants of unbalance first. To reference the value of probability calculations, the author uses the MSBNx application. In building the BN structure, the steps are to diagnose engine damage using the vibration signal. In the first process, it is assumed that the parameters causing the damage are based on a predetermined probability value. Then build BN in such a way that it can show the type of unbalance damage that occurred and what actions must be taken to overcome it. The BN causality diagram model is shown in Figure 4 The parameters used to determine the probability of unbalance are a vibration at 1 time the motor frequency, the phase difference between horizontal and vertical, the phase difference between the drive end and non-drive end bearings, and the ratio of the thickness and diameter of the impeller. Prior probability values can be seen in Table 1.

Table 1. Prior probability

Node Name	Event	Percentage (%)
High 1X	Exist	20
	Not exist	80
T vs D	Thick < Diameter	60
	Thick > Diameter	40
Phase DE NDE	$20^{\circ} \geq$ Phase $\geq 340^{\circ}$	50
	$20^{\circ} \leq$ Phase $\leq 340^{\circ}$	50
Phase HV	$70^{\circ} \leq$ Phase $\leq 110^{\circ}$	50
	$70^{\circ} \geq$ Phase $\geq 110^{\circ}$	50

2.3. Prior and conditional probability

The BN structure consists of 6 nodes as shown in Figure 4, with 4 parameters specifying the type of unbalance. The first node is High_1X which is an event if a high amplitude is found that occurs at 1 time the engine revolutions per minute (RPM). The TvsD is the ratio of the thickness and diameter of the impeller. If the impeller thickness is equal to or greater than the impeller diameter, it will be one of the supporting factors for dynamic unbalance. While the Phase_DE_NDE and Phase_HV nodes represent the large difference in the vibration phase at the two measurement points. Phase_DE_NDE is the phase difference at two bearing locations, namely DE and NDE impeller, in which both measurement locations are the same, namely on the horizontal axis (DE H and NDE H) or vertically (DE V and NDE V). While the Phase_HV node is the phase difference at one bearing location which is carried out on the horizontal and vertical axes (DE H with DE V or

NDE H with NDE V). After finishing building the BN structure, the next step is to determine the probability value of each combination of event components that occur. The conditional probability table (CPT) for static unbalance and dynamic unbalance nodes can be seen in Table 2 and Table 3.

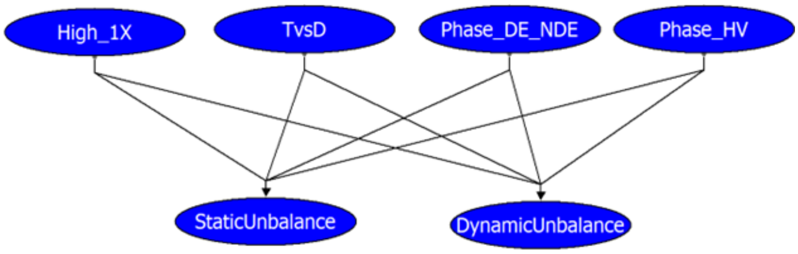

Figure 4. Bayesian network structure

Table 2. CPT of static unbalance

Parent Node (s)				P (Static Unbalance) (%)	
High 1X	T vs D	Phase DE NDE	Phase HV	Yes	No
Exist	T < D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	90	10
			$70^\circ \geq P \geq 110^\circ$	80	20
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	80	20
			$70^\circ \geq P \geq 110^\circ$	70	30
	T > D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	70	30
			$70^\circ \geq P \geq 110^\circ$	60	40
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	50	50
			$70^\circ \geq P \geq 110^\circ$	40	60
Not exist	T < D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	30	70
			$60^\circ \geq P \geq 110^\circ$	20	80
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	20	80
			$70^\circ \geq P \geq 110^\circ$	10	90
	T > D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	10	90
			$70^\circ \geq P \geq 110^\circ$	10	90
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	10	90
			$70^\circ \geq P \geq 110^\circ$	10	90

Table 3. CPT of dynamic unbalance

Parent Node (s)				P (Dynamic Unbalance) (%)	
High 1X	T vs D	Phase DE NDE	Phase HV	Yes	No
Exist	T < D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	30	70
			$70^\circ \geq P \geq 110^\circ$	40	60
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	40	60
			$70^\circ \geq P \geq 110^\circ$	60	40
	T > D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	30	70
			$70^\circ \geq P \geq 110^\circ$	70	30
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	70	30
			$70^\circ \geq P \geq 110^\circ$	90	10
Not exist	T < D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	10	90
			$70^\circ \geq P \geq 110^\circ$	10	90
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	10	90
			$70^\circ \geq P \geq 110^\circ$	20	80
	T > D	$20^\circ \geq P \geq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	10	90
			$70^\circ \geq P \geq 110^\circ$	20	80
		$20^\circ \leq P \leq 340^\circ$	$70^\circ \leq P \leq 110^\circ$	20	80
			$70^\circ \geq P \geq 110^\circ$	30	70

3. RESULTS AND DISCUSSION

3.1. Probability updates

Each piece of evidence received by the network will affect the percentage value of each node by the CPT value that has been applied. The highest percentage of the yield node, namely static unbalance and dynamic unbalance will be the basis for the system to determine the type of damage that occurs to the machine. Therefore, it is necessary to ensure that the CPT value is correct when building the BN so that the prediction results are correct in all conditions of the input data entered. Figure 5 is showing the updated probability of the computational result of the BN algorithm without any evidence provided. It can be seen without proof that the static unbalance probability value is 26.8% and produces a dynamic unbalance probability of 22.7%. All probability values are still less than 50%, this indicates that there is no damage to the centrifuge.

In ensuring that the prediction results are correct based on the concept of vibration analysis, a series of experiments are carried out and validate the results. Figure 6 shows the renewal of confidence because new information is provided with evidence of large amplitude symptoms at the 1X frequency and the phase on the horizontal-vertical axis is more than or equal to 70º and less than or equal to 110º. The probability value of static unbalances increases to 75% and dynamic unbalances to 41%. So, it can be concluded that the machine has a static unbalance problem because it has a larger percentage compared to the dynamic unbalance percentage value. If we review the results of the system from the inputs given, the results are same by theory and manual analysis. Probability updates due to the new information provided with evidence of large amplitude at 1X frequency, impeller thickness smaller than or equal to impeller diameter, and phase in DE-NDE bearings smaller than or equal to 20º and more than or equal to 340º as shown in Figure 7. It can be seen that the probability value of static unbalance increases to 80% and the percentage of dynamic unbalance becomes 40%. From these results, it can be concluded that the damage to the machine is static unbalance.

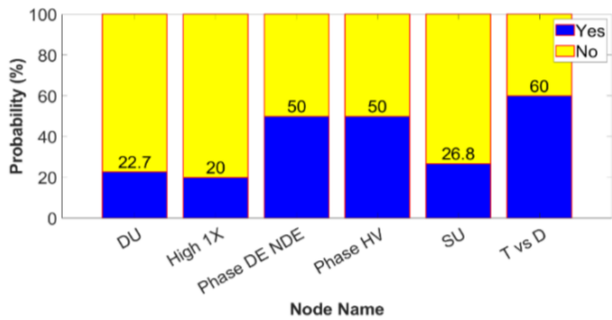

Figure 5. Probability updates without evidence

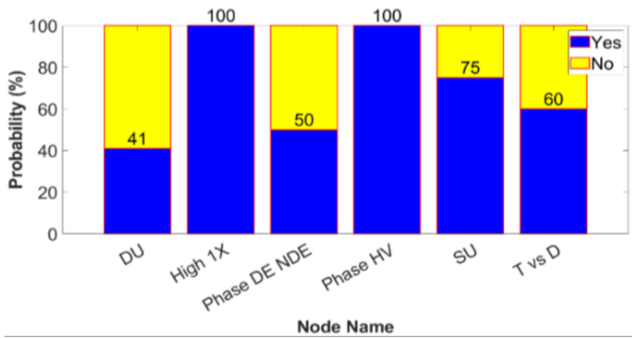

Figure 6. Probability updates with evidence of High 1X and Phase HV

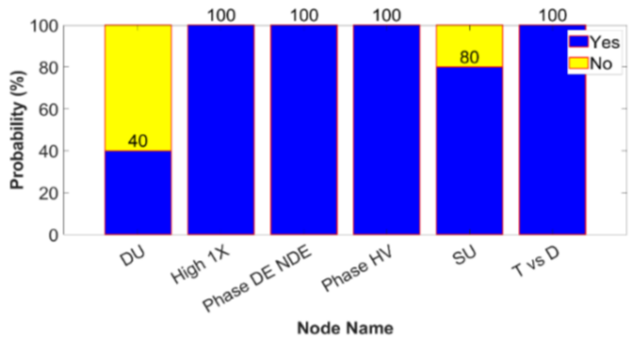

Figure 7. Probability updates with static unbalance spectrum

3.2. Designing of interface

The application interface design is shown in Figures 8-10. The application is made simple which aims to make it easy for users to enter data and understand the information generated by the system. Basic facilities are provided to obtain important information on the type of unbalanced damage to the machine. The application is designed to be able to display the original spectrum data in graphical form, display the results of the BN algorithm calculations for the prediction of the type of unbalance in the form of a bar graph and display important information about the diagnosis results. In addition, the application is equipped with a description of the image related to the type of damage that occurred. There are four conditions, if the data processed by BN produces static unbalance, the recommendation given by the system is to do balancing in single plane mode. Meanwhile, if the result of BN processing is dynamic unbalance, the system recommends balancing with two plane mode. If the spectrum data shows a large amplitude but the entered RMS value is small, then the system will recommend re-checking the input data and doing the analysis manually. This also applies if the RMS value is large, but no large amplitude is found in the spectrum. Facilities like reset are also added so that users can restart the diagnosis easily. The appearance of the application before running is shown in Figure 8.

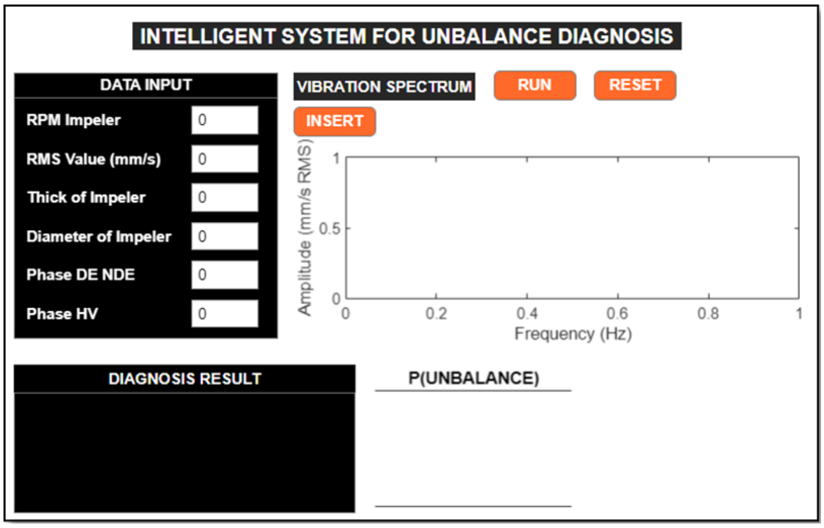

Figure 8. Application interface design

3.3. Software validation

Software feasibility testing by implementing and checking the system that has been designed in a series of validation processes. This is done to find out if the system can run well, and if all the features are as desired. This section will explain the implementation of an intelligent system for diagnosing machine failures based on the analysis and design that has been carried out previously.

3.4. Software validation

Software feasibility testing by implementing and checking the system that has been designed in a series of validation processes. This is done to find out if the system can run well, and if all the features are as desired. This section will explain the implementation of an intelligent system for diagnosing machine failures based on the analysis and design that has been carried out previously. After the implementation phase is complete, then proceed with the implementation testing that has been done. Software testing is carried out to ensure that the system built is by the results of the analysis and design so that a conclusion can be made. Validation is done by seeing whether the results of the system diagnosis with the actual conditions are the same, based on the symptoms that have been obtained from the data that has been entered.

The test uses vibration data whose measurements are taken from a balancing and alignment demo machine where the data contains several types of measurements such as vibration value, the phase between the horizontal-vertical axes, the phase between the two bearings, and the spectrum. This data will be used for input and to determine whether it is by the conditions of the demo machine. Read the results of the diagnosis in the form of the type of damage that occurred and what actions the user must take. Figure 9 is a trial operation of the application using data from the measurement results of the demo machine which is set to experience static unbalance. As seen in the input data column, the demo machine has a rotational speed of 1,482 RPM, a vibration value of 5 mm/s RMS, an impeller thickness of 20 mm, an impeller diameter of 100 mm, the phase between the two bearings on the same axis is 12º and the phase between the horizontal and vertical axes is 98º. The column of the spectrum graph shows a large amplitude at 1 time the impeller frequency. Then the system produces a diagnosis that the problem that occurs is static unbalance with a percentage value of 90%. The system recommends balancing using single plane mode.

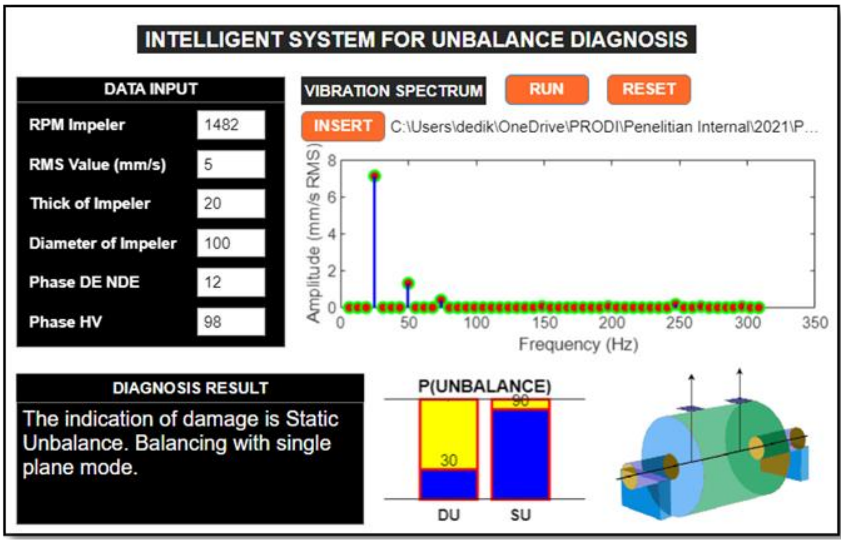

Figure 9. Test results with static unbalance

The application operation experiment using the data from the measurement results of the demo engine which is set to experience dynamic unbalance is shown in Figure 10. As seen in the input data column, the vibration value is 4.7 mm/s RMS, the impeller thickness is 120 mm, the impeller diameter is 100 mm, and the phase between the two bearings on the same axis is 45º and the phase between the horizontal and vertical axes is 15º. The column of the spectrum graph shows a large amplitude at 1 time the impeller frequency. The system produces a diagnosis that the problem that occurs is dynamic unbalance with a percentage value of 90%. The system recommends being balanced using the two-plane mode. The results of all experimental data in detail can be seen in Table 4.

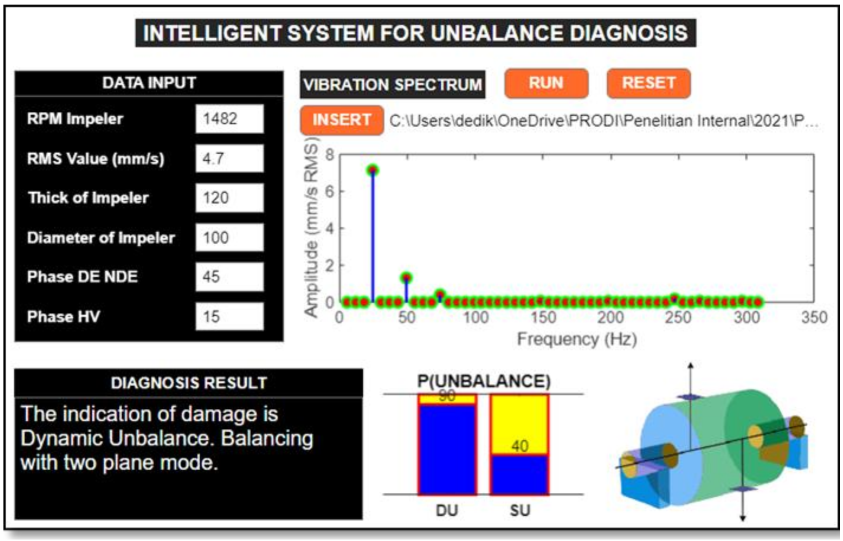

Figure 10. Test results with dynamic unbalance

Table 4. Summary of experimental results

No.	Data Input						Results	
	RMS (mm/s)	T	D	P2B	PHV	Spectrum	Actual	System
1.	5	20	100	12º	98º	1X	Static Unbalance	Static Unbalance
2.	4.7	120	100	45º	15º	1X	Dynamic Unbalance	Dynamic Unbalance
3.	1.8	50	100	12º	50º	None	Good	Good
4.	4.3	20	100	185º	95º	1X, 2X, 3X	Misalignment	Other Damage
5.	5.2	100	100	115º	132º	1X	Dynamic Unbalance	Dynamic Unbalance
6.	4.3	20	100	5º	100º	1X	Static Unbalance	Static Unbalance

The demo machine before a series of measurements is set up with several conditions and will be compared with the predicted problem results issued by the system, as shown in Table 4. The system diagnosis results are by the actual state of the demo machine. In the fourth experiment, the results of the system diagnosis are not the same as the actual conditions, this is because the system is only prepared to read the unbalance problem. Even so, the system can still recognize that misalignment damage is another type of damage. Therefore, it can be concluded that the system that has been designed can predict the state of the machine based on vibration data quickly and accurately.

4. CONCLUSION

BN-based software for the prediction of unbalance damage has been developed. The application of BNs in intelligent system design begins with making network modeling. Then the percentage of unbalance values is made based on the value of each parameter using the MSBNx software. The percentage results that have been collected will be used as a reference when creating the BN algorithm in the MATLAB application. In addition, a function is also made to enter data that will be used as the basis for calculating the percentage of unbalance in the system. Then an application was made with the AppDesigner menu in MATLAB so that the program that had been created could be installed on the computer and operated easily. BN Modeling was successfully built based on the concept of vibration analysis. Four nodes have been defined as input parameters and two nodes as output. The six nodes are connected according to their function so that it becomes a system that can predict the type of unbalanced damage to the machine. From six trials using different data, all data entered can be predicted by the system quickly and accurately. All software features also work properly.

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