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Bayesian networks approach on intelligent system design for the diagnosis of heat exchanger

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Abstract
The heat exchanger highly influences the series of cooling processes. Therefore, it is required to have maximum performance. Some of the factors causing a decrease in its performance are increased pressure drop in the Plate Heat Exchanger (PHE), decreased output flow, leakage, flow obstruction, and mixing of fluids. Furthermore, it takes a long time to conclude the diagnosis of the performance and locate the fault. Therefore, this study aims to design an intelligent system for the performance diagnosis of the PHE using the Bayesian Networks (BNs) method approach. BNs are applied to new problems that require a new BNs network model. The system was designed using MSBNX and MATLAB software, comprising several implementation stages. It starts by determining the related variables and categories in the network, making a causality diagram, determining the prior probability of the variable, filling in the conditional probability of each variable, and entering evidence to analyze the prediction results. This is followed by carrying out a case test on the maintenance history to display the probability inference that occurs during pressure drop on the PHE. The result showed that the BNs method was successfully applied in diagnosing the PHE. When there is evidence of input in the form of a pressure drop, the probability value of non-conforming pressure-flow becomes 61.12%, PHE clogged at 73.59%, and actions to clean pipes of 70.18%. In conclusion, the diagnosis carried out by the system showed accurate results.

Keywords:
Bayesian Networks;
Intelligent system;
Plate Heat Exchanger;
Pressure drops;

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INTRODUCTION

In the steel plate-making manufacturing industry, several types of machines are used to convert semi-finished steel into plates. Each machine has a hydraulic oil and lubrication system with several components: a tank, pump, filter, accumulator, water circulation, and heat exchanger. One of the extremely critical or important components is the Heat Exchanger (HE). This device is used to exchange heat from one fluid to another using temperature differences.

Furthermore, this heat exchange occurs through direct or indirect contact [1]. The fluid exchanged is either in the same phase, liquid to liquid or gas to gas, or in two different phases [2][3]. This tool is widely used in the industrial world due to its important function. There are many kinds of HEs based on their shape, including the Plate Heat Exchanger (PHE), which consists of a plate and frame, where the heat transfer process occurs between the two fluids on the side of the heat exchanger plate [4, 5, 6].

A HE is highly influential in the success of the whole series of processes because an operational failure has the ability to stop the system from operating. Therefore, an HE needs to have good performance to obtain maximum results and fully support an operating unit. Similar to other components or machines that generally have a service life applicable to HEs, problems are often encountered in operating conditions, such as decreased performance and operational failure at PHE. These are influenced by several factors such as increased pressure drop in PHE, decreased output flow, leakage, and inconsistency in fluid mixing [7, 8, 9]. Therefore, any form of a decrease in PHE performance needs to be immediately taken care of to avoid production losses [10].

When there is a problem with, HE, not everyone knows what the problem is. Only some people have experienced the HE system. The problems that exist in the HE are due to some factors that impact performance degradation and operational failure. Therefore, maintenance and maintenance are needed to maximize performance. Maintenance activities often carried out based on the history of inspection and maintenance need accurate data and take a long time to conclude the problem factors that arise in the HE, thereby making it less efficient. Therefore, a system that functions to diagnose the performance of the HE, thereby making it easier to conclude the problem factors, is needed [11]. One of the usable algorithms in Bayesian Networks (BNs) [12, 13, 14, 15].

The BNs itself is an uncertified method that presents a causality relationship and exploits conditional free relationships in building network structures. Therefore, it builds a more structured model and reduces the complexity of calculations in making inferences [16, 17, 18]. Generally, the structure and parameters of the BNs are learned from the data. In certain cases, its structures also rely on prior knowledge to realize non-data-type information fusion [19][20]. In addition, parallel computing frameworks have been introduced to accelerate the learning rate of the BNs model in cases related to big data environments [21][22]. BNs provide a complex description of interrelated risk and model uncertainty. In addition, even with limited data, conclusions still generate information using a Bayesian approach because it helps identify sensitive variables [23, 24, 25].

Therefore, using this BNs system makes it easier to diagnose the performance abnormality of the HE caused by its operational failure parameters. Hence a preventative solution is determined. On the other hand, in the absence of this system, it takes a prolonged period to determine the problem of operational failure on the HE, thereby making it less efficient. Therefore, this led to the research on the BNs approach for designing intelligent system performance diagnosis for PHE SH041H-1P-55.

METHOD AND MATERIAL

Bayesian Networks Algorithm

A basic equation description of Kim and Pearl's message-passing algorithm appears below as (1) [26][27]. It involves the repeated application of Bayes' Theorem and the use of the conditional independencies encoded in the network structure.

$$P(B_i \mid A) = \frac{P(A \cap B_i)}{P(A)} = \frac{P(A \mid B_i) \times P(B_i)}{\sum_{j=1}^{n} P(A \mid B_j) \times P(B_j)} \tag{1}$$

The probability of event A happening is mentioned by P(A), The probability of event B occurring is called P(B), The conditional probability of event B is called P(B|A), given the probability of a given event A, and P(A|B) is the conditional probability of event A occurring given event B occurring. For event B, P(B) is the prior probability and P(B|A) is the posterior probability, which is in terms of some pieces of evidence. P(A) and P(B) ≥ 0 and $P(B_i)$ is made up of mutually exclusive events.

The basic algorithm of each iteration, Bel(X) is updated locally using three types of parameters λ(X), π(X), and the Conditional Probability Tables (CPTs), as shown in (3). λ(X) and π(X) are computed using the π and λ messages received from X's parents and children respectively. Its neighbors need to perform updates so that π and λ messages are also sent out from X. Belief updating for a node X is activated by messages arriving from either children or parent nodes, indicating changes in their belief parameters. When node X is activated, inspecting $\pi_X(U_i)$ (messages from parents), and $\lambda_{Y_j}(X)$ (messages from children). Apply with (2) when node X is activated

$$Bel(x_i) = \alpha \lambda(x_i) \pi(x_i) \tag{2}$$

Where,

$$\lambda(x_i) = \begin{cases} 1 & \text{if evidence is } X = x_i \\ 0 & \text{if evidence is for another } x_j \\ \prod_j \lambda y_j(x_i) & \text{otherwise} \end{cases} \tag{3}$$

$$\pi(x_i) = \sum_{u_1,\ldots,u_n} P(x_i \mid u_1,\ldots,u_n) \prod_i \pi_X(u_i) \tag{4}$$

$$\sum_{x_i} Bel(X = x_i) = 1 \tag{5}$$

and α is a normalizing constant rendering (5).

Equations (2) and (3) show how to compute the $\lambda(x_i)$ parameter. Evidence is entered through this parameter, so it is 1 if x_i is the evidence value, 0 if the evidence is for some other value x_j, and is the product of all the λ messages received from its children if there is no evidence entered for X. The $\pi(x_i)$ parameter (4) is the product of the CPT and the π messages from parents. The combination between one parent and λ message (i) information that has been extracted from children via λ messages and been shortened in the $\lambda(X)$ parameter, (ii) the values in the CPT, and (iii) any π messages that have been received from any other parents. The $\pi_{Y_j}(x_i)$ message down to child Y_j is 1 if x_i is the evidence value and 0 if the evidence is for some other value x_j. If no evidence is entered for X, then it combines (i) information from children other than Y_j, (ii) the CPT, and (iii) the π messages it has received from its parents.

Heat Exchanger Specification

The HE used in the steel plate manufacturing industry discussed in this study is PHE SH041H-1P-55. This HE has material specifications A240-3040-NBR, a capacity of 21.1 Mcal/h, a surface area of 4.2 m^2, and an empty load divided by a fill weight of 100/110 kg. This heat exchanger works to transfer heat between two fluids, namely hot ISO VG 68 oil and cold water with the same flow rate and maximum working pressure of 9.0 m^3/h. Furthermore, it uses 10 bar, inlet oil temperature of ISO VG 68 50ºC with water 35ºC, and outlet oil temperature ISO VG 68 42.5ºC with water 38ºC. Therefore, this HE has hot and cold fluids entering the system at counter flow directions.

Table 1. Characteristics of ISO VG68 oil and water at PHE

Parameter	Hot Side	Cold Side
Fluid	Oil ISO VG68	Water
Manufacturer	Mobil DTE 26 Hydraulic Oil	-
Flow rate	9 m^3/h	9 m^3/h
Max. working pressure	10 bar	10 bar
Inlet temperature	50 ºC	35 ºC
Outlet temperature	42.5 ºC	38 ºC

Primary and secondary data were used by the authors to carry out this research. Primary data were obtained directly from the relevant companies where the research was conducted. In the HE installed, t water functions as a coolant and ISO VG 68 oil as the fluid to be cooled, as shown in Table 1.

Data Retrieval Process

The data collection technique in this research is used to perform a daily inspection on the PHE SH041H-1P-55 with the help of thermo and pressure gauges attached to the hydraulic oil cellar system, as shown in Figure 1. Furthermore, the data retrieval process from the HE is then inputted into the check sheet inspection and maintenance history of the replacement.

Identify Symptoms of Damage

HE plays an important function in the steel plate manufacturing industry. Therefore, it is necessary to carry out maintenance and prevention techniques that reduce performance. At this stage, problems that usually occur in the system are determined and solutions are applied to BNs.

Several problems occur within the PHE, such as increased pressure drop, decreased capacity, leakage, and mixing of the fluid. The occurrence of pressure drop is due to dirt in PHE. Therefore, it is necessary to clean the pipes before starting, and when it happens during the running process, then it is necessary to clean the plate, and the fluid that enters PHE needs to be given a filter. The solution to the viscosity problem is to check for appropriateness, and whether the temperature drops below the designed rate.

Figure 1. PHE SH041H-1P-55

Connection errors in the piping system are resolved by checking the connections and adjusting by drawing. If the flow quantity is too large, it is necessary to adjust it properly. PHE is clogged by external dirt or blocked flow, the plate needs to be cleaned and the media filtered. The excessive flow needs to be adjusted, while the connection error to the piping system requires inspection and adjustment to the drawing. When the pressure in HE exceeds the permitted value, it leads to leakage. Therefore, it is necessary to reduce the pressure according to the set point. It is essential to avoid sudden pressure by slowly opening and closing the system. Damage to the gaskets due to the impact of the medium attack is overcome by replacing the gaskets with better materials.

The final problem is associated with improper mixing of fluids, which causes inadequate fitting of plates, corrosion, and poor connections. Therefore, the action that needs to be conducted is to install the plate according to the guidelines, look for the cause of the corrosion, replace a new plate, replace the plate with a corrosion-resistant material, and adjust the drawing.

System Implementation

At this stage, a process is carried out in which the problem is translated into a software product through a series of activities according to the process model, methods, and tools to be used. A search was made to determine what, why, and how the problem decreased the performance of the PHE based on the results of the inspection and maintenance history, which was used as the basis for further analysis.

This intelligent system is designed in accordance with the concept used to solve the problem. The concept supports a description of knowledge, which explains each component and work procedures carried out according to the intelligent system flow diagram as shown in Figure 2. This is used to describe in detail the work system process flow.

In building the BNs structure, the stages are carried out by diagnosing the performance and damage to the heat exchanger. In the first process, it is assumed that the cause of the performance and damage diagnosis parameters is based on a predetermined probability value. Furthermore, the BNs are built in such a way as to show the causes of the decline in performance as well as the kind of damage and actions that need to be taken. The BNs causality diagram model is shown in Figure 2. Information on the object's history is useful in determining previous probability values. This type of information is also used as a reference in determining the HE's performance efficiency and component damage.

Therefore, BNs act as a knowledge base while the Bayesian inference rule is part of the control system. In addition, the MSBNX is used to facilitate the analysis of BNs data

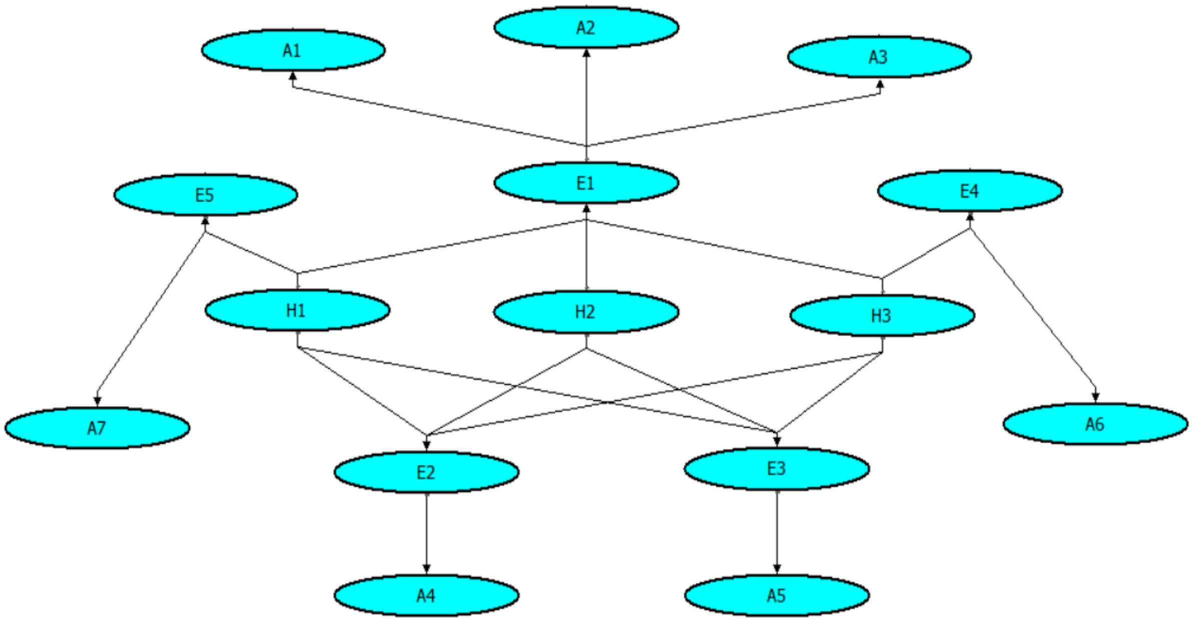

Figure 2. Bayesian Networks Structure

. There are five stages of data analysis with this software: determining variables and categories related to the network, creating a causality diagram, analyzing the prior probability of variables, filling in the conditional probability of each variable, and entering evidence to determine the prediction results.

The process of building the BNs structure by estimating the sequence of events enables the system to determine the decline in the performance of the PHE and network structure, as shown in Figure 2.

After the formation of the BNs structure, the next step is to determine the prior probability value of each cause of HE performance diagnosis. Prior probability is the degree of confidence of a symptom used when there is no other information capable of determining the likelihood of an event occurring. However, once new information is known, the probability is updated. The prior probability value is shown in Table 2.

CPT is the probability of events A and E after the occurrence of event H. Any table that contains the probability of each possible value of A and E is called the CPT. For example, Table 3 shows the CPT for node E1.

Table 2. Prior Probability

Node	Prior Probability		
	i = 1	**i = 2**	**i = 3**
$p(H_i)$	0.35	0.28	0.22

Table 3. Conditional Probability

Parent Node(s)			P(E1 | H1, H2, H3)		
H1	**H2**	**H3**	Yes	No	Bar Charts
Yes	Yes	Yes	95%	5%	
		No	85%	15%	
	No	Yes	80%	20%	
		No	65%	35%	
No	Yes	Yes	60%	40%	
		No	45%	55%	
	No	Yes	28%	72%	
		No	1%	99%	

In carrying out the probability inference based on the presence or absence of symptoms, after the rule table and the posterior value of each symptom are determined, the symptom probability of each disease is calculated from the BNs structure. The process of calculating this probability is intended to determine the estimated value of the symptoms that appear in HE for the easy determination of the probability problem and to provide suggestions.

RESULTS AND DISCUSSION

Bayesian Networks Computing Results

The posterior probability value is the result of designing an intelligent system to detect the performance of the HE based on the criteria for the problems that arise. BNs are used here because of the tendency that not all variables have evidence. However, one or more BNs are used in the design of intelligent systems for the diagnosis of performance and damage to HE with the help of data history inspection and maintenance.

The criterion in determining the diagnosis of performance and damage to HE is to produce a chance of error above 50%. In this study, several criteria were found that allowed opportunities to decrease the performance or damage to HE. Some of these are case-tested. Therefore, they have the ability to diagnose the symptoms that are present and make recommendations on the treatment that needs to be conducted.

This intelligent system uses probability update confidence to make decisions, as shown in Figure 3. The node with the largest percentage value is determined as the trigger for the biggest damage to HE. Meanwhile, other damages are determined according to the percentage level obtained from the system calculation process. Any value assigned to the CPT affects other nodes. Therefore, the CPT value is designed to obtain the right result. Each node in the system set has two states, namely "True" and "False".

When there is evidence of cases in HE, such as pressure drop (H1), then the system concludes that the cause of the problem comes from the clogged PHE variable (E1) with a percentage value of 65% and inappropriate pressure-flow (E3) of 52%. Then the system recommends maintenance by cleaning the pipe (A1) and plate (A2) with percentage values of 62.1% and 60.15%. Figure 4 shows the case of pressure drop on an HE. A system with true input at the pressure drop node (H1) produces conclusions on the causes of problems with blocked PHE (E1) and inappropriate pressure-flow (E3). It also provides maintenance recommendations for cleaning pipes (A1) and plates (A2).

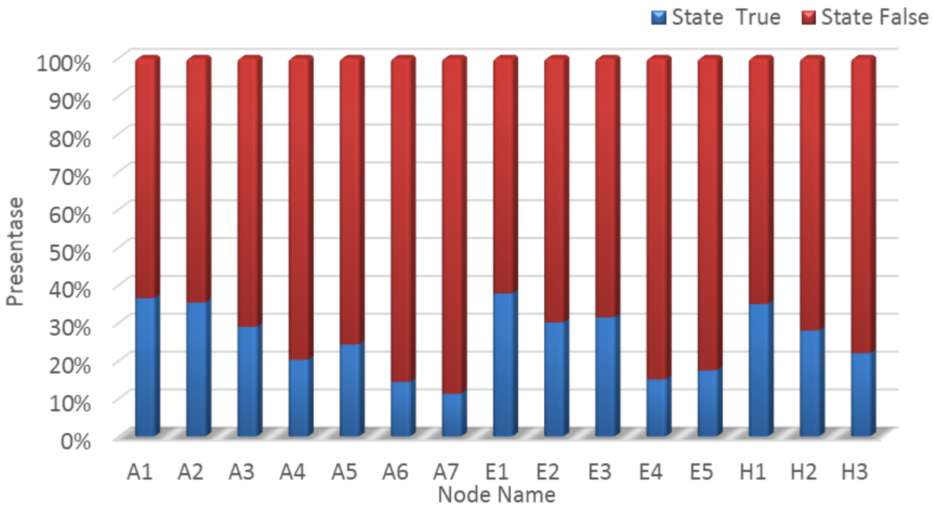

Figure 3. Probability Updates Without Evidence

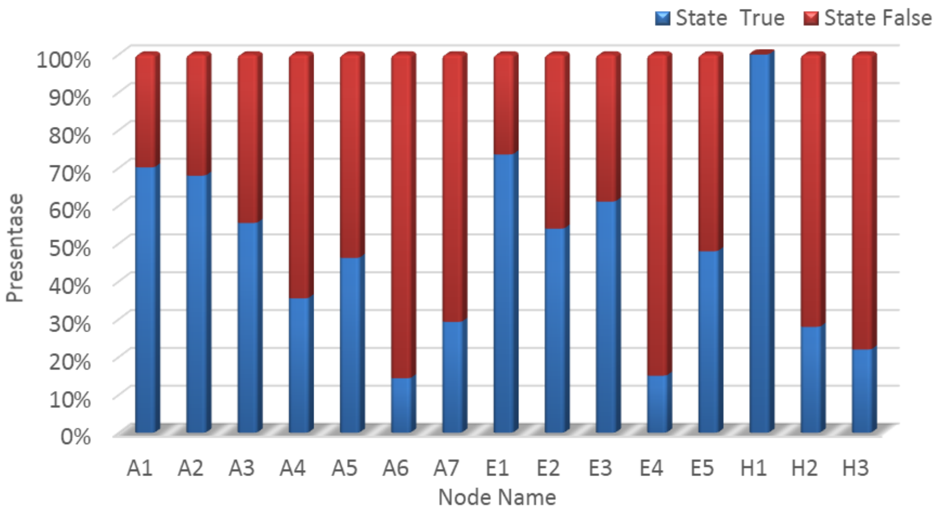

Figure 4. Probability Updates with Evidence

When the leak (H3) is true, the system concludes that the cause of the problem comes from the damaged gasket variable (E4) with a percentage value of 65%. Then the system recommends maintenance by replacing the gasket (A6) with a percentage value of 58.85%. Furthermore, a system with a true input value on the leak (H3) leads to a conclusion to the cause of the problem of gasket failure (E4) and inappropriate pressure-flow (E3), thereby providing maintenance recommendations for replacing gaskets (A6).

When the occurrence of 2 simultaneous cases on HE, such as pressure drop (H1) and the decrease in the output flow of HE (H2), is true, then the system concludes that the cause of the problem comes from the clogged PHE variable (E1) with a percentage value of 85%. Furthermore, the flow variable and pressure do not match (E3) with a percentage value of 75% and variable connection error (E2) of 55%. Therefore, the system recommends maintenance, by cleaning the pipe (A1) and plate (A2) with percentage values of 80.9%, and 78.35%, as well as replacing the filter (A3) and adjusting the flow and pressure (A5) with percentage values of 63.9%, and 56.5%. The results of case testing are pressure drop (H1) and leakage (H3), where a system with a true input value in the node leads to conclusions on the causes of problems with blocked PHE (E1), flow and pressure, incompatibility (E3), and connection errors (E2). It also provides maintenance recommendations to clean the pipe (A1), plate (A2), replace the filter (A3), as well as to adjust the flow and pressure (A5).

Interface Design

Figure 5 shows the menu interface that appears when the program is run. The interface contains an input menu of HE problem symptoms, BNs structures, solutions, problem probability graphs, and action probability.

The system is run by checking Yes or No on the input menu, which contains symptoms on HE. This is followed by clicking the start button, which enables the system interface to display a graph of the value of the problem, action probability, and provide solutions. The simulation of case testing is based on the results of the inspection check sheet and maintenance history on HE, which shows a decrease in pressure drop symptoms.

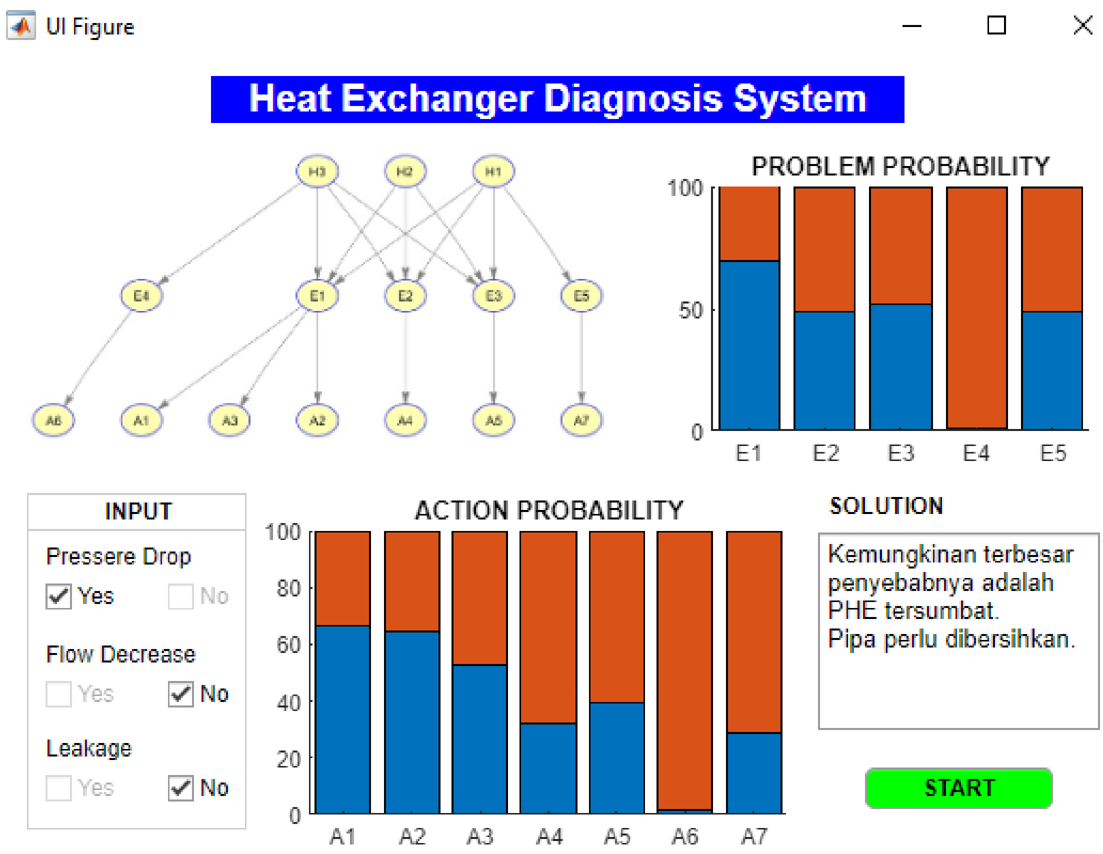

Figure 5. Interface Design

Therefore, there is a decrease in the performance of the HE. The interface system designed in this study makes it easier for user maintenance to determine the causes and the initial actions needed.

System Evaluation

The BNs method approach in this study is used to determine intelligent system design in terms of HE performance diagnosis. Evaluation of the system is done by entering eight different input variations. Determination of the number 8 because there are three input parameters, and each input has two possibilities. The results obtained show that all experiments can be guessed 100% correctly by the system.

This enables the accurate and precise conduction of the test in every case. There were symptoms of a blocked PHE in the pipe and plate components in the case history that occurred, such as a pressure drop. Therefore, the system recommends cleaning the two parts of the component. Table 4 shows a comparison of the results of manual diagnoses performed by experts and those carried out by the system.

Table 4. Evaluation of the Diagnosis Results

PHE Symptoms	Manual Diagnose	System Diagnose	Result
Pressure drops	PHE clogging, viscosity, piping connection error, flow quantity is too large.	PHE problem is clogged. Initial recommendation to clean pipe and plate.	Correct
Decreased HE output	PHE clogged, flow too high or fast, piping connection error.	PHE problem is clogged with the mismatch of flow and pressure. Initial recommendation to clean pipe and plate. Follows by adjusting flow and pressure	Correct
Leakage	Damage to the gasket, HE's pressure exceeds the allowable pressure, thereby blocking the flow in PHE.	Gasket failure problem. Gasket replacement recommendations.	Correct

By carrying out a series of test-related cases on HEs, the decline in performance and possible damages are easily diagnosed. The calculation results using different BNs methods in each trial case test are due to differences in the evidence obtained from each data based on the historical inspection and maintenance in HE. The results of the diagnosis show the suitability of the intelligent system design with the desired expectations.

CONCLUSION

The identification results concluded that there are three symptomatic parameter variables, namely increased pressure drop, decreased output flow, and leakage. Furthermore, five variables caused damage to the system: blocked PHE, connection errors, inappropriate flow and pressure, damaged gaskets, and viscosity on HE.

The design and implementation of an intelligent system for the diagnosis of HE performance and damage using the BNs method approach have been successfully implemented. The system can predict 100% correctly all input variations. Factors that need to be considered in this study are the input value of the prior probability and conditional probability parameters as well as the programming language carried out in the BNs software because it determines the results of the test cases on the created network.

The application of intelligent systems with the BNs method is carried out by testing cases or symptoms on an HE using the interface design. Users only need to check the symptom input obtained from the inspection results. Then the intelligent system concludes fully accurate diagnostic decisions for the source of the cause, speed, and location of the damage. Therefore, it tends to recommend treatments and how to deal with damage to HE. The diagnosis carried out by the system showed accurate results. When there is evidence of the input in the form of a pressure drop, the probability value of non-conforming pressure-flow becomes 61.12%, PHE clogged at 73.59%, and actions to clean pipes of 70.18%.

Currently, applications capable of processing general BNs from the tools are developed. The case testing results recommend that treatment decisions be carried out periodically to predict performance and damage. Further research is also needed to diagnose the performance of this system.

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