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Elicitation of Conditional Probability Table (CPT) for Risk Analysis of Biomass Boiler in Energy Plant

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ABSTRACT

The utilization of Empty fruit bunch (EFB) in energy production has increased in Malaysia over the last two decades. The EFB can be used as a solid fuel in a boiler system for heat and power generation. However, numerous safety and technical issues lead to a lower energy production rate. A holistic probabilistic risk analysis is developed using the Bayesian Belief Network (BBN) to reduce the risk in the boiler system. The Conditional Probability Table (CPT) indicates the influence strength between the parent node and child node in BBN. Due to scarcely available information on EFB boiler, elicitation from the expert's opinion is vital. The formulation for boiler failures likelihood prediction that relies on experts' perceptions was developed using the Weighted Sum Algorithm (WSA). A case study from BioPower Plant in Pahang was applied in this project. The model illustrates the relationship between the cause and the effect of the biomass boiler efficiency in a systematic way. Two types of analyses, prediction and diagnostic analysis, were performed. The results facilitated the decision-maker to predict and identify the influential underlying factors of the boiler efficiency, respectively. The result shows that the most important boiler failure factor is combustion stability. It agrees with experts' experience that most biomass boiler failure was caused by EFB, which contains high moisture content that affects flame stability. The proposed formulation for expert opinions and perceptions conversion

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can be utilized for risk analysis to benefit the boiler and other infrastructure that relies on experts' experience.

Keywords: Bayesian belief network, biomass boiler, biomass energy plant, conditional probability table, empty fruit bunch

INTRODUCTION

As one of the world's largest producers and exporters of palm oil, Malaysia has identified that at least 168 million tonnes of biomass have been produced annually. The extraction of oil from palm fruits has resulted in a tremendous amount of palm waste such as palm kernel shells, empty fruit bunch, and many others. The amount of waste keeps increasing each year, and the issue with the disposal of these wastes tends to burden the operators as it escalates the operating cost. This statistic proves that bioenergy is the most promising alternative for renewable energy (Hafyan et al., 2020).

However, many factors should be taken into account in biomass energy production. One of the most important factors that need to be considered in the bioenergy plant is the availability of technology to produce energy efficiently (Chala, 2019). Most technologies for efficient production of power and heat from major biomass resources are only available and are being used in the international market, such as catalytic liquefaction, pyrolysis, and carbonization (Basu, 2013). However, the most common method used in energy production is direct combustion. Therefore, there is a lack of local expertise for other methods of biomass energy conversion (Shafie et al., 2012). The combustion system is the most important part of any energy plant that needs extra attention. The combustion system, which mainly consists of the boiler, needs to be fully understood to set up an efficient production system. Many factors could contribute to the failure of the boiler. Therefore, it is necessary to construct a risk assessment for these factors to improve the combustion system for a better life of this equipment.

According to Sýkora et al. (2018), the design service life of the old power station is reaching its end, and an appropriate decision must be made based on the updated information of their equipment and component condition. In most risk assessment processes, any equipment or component is being focused on the possible failure. The key requirement of any operational risk analysis is that it should include the ability to consider the cumulative effect of many risk factors that might be minor to the system but collectively a cause for concern (Bolsover, 2015). It suggests that the risk analysis should be at least semi-quantified or fully quantified to assess the risks properly. There are some research for risk assessment of the biomass power plant that had been carried out, such as Failure Modes and Effects Analysis (FMEA) applied by Thievel et al. (2007), and Moreno and Cozzani (2015) introduced a fishbone diagram in the biomass risk analysis. However, FMEA is quite challenging for someone unfamiliar with this method since the FMEA worksheet is difficult to produce and understand. Meanwhile, the later method does not include a quantitative section for future prediction on risk analysis.

Over the recent years, the Bayesian network has been widely used in probability risk analysis. BN provides a useful tool because it represents the probabilistic relationship between causes and symptoms or between symptoms and faults. It can also represent multi-fault and multi-symptom models. Moreover, it could effectively analyze the complex causal relations among BN nodes with its inference and sensitivity methods. In addition, the structure of causal relationship networks could be flexibly adjusted by simply adding nodes and arcs into the existing BN model. Applications of the Bayesian network have been widely used in probability risk analysis in the past few years (Khan et al., 2018; Wang & Chen, 2017; Yazdi & Kabir, 2020). There are several adaptations of Bayesian network modeling in risk analysis depicting that Bayesian networks have demonstrated their capabilities and efficiencies as a practical engineering and problem-solving tool (Khakzad et al., 2017; Zerrouki et al., 2019).

A BN represents a graph with a set of probability tables. Each node in BN depicts an uncertain variable, and an arc demonstrates the causal relationship between two variables. A conditional probability table (CPT) provides the probabilities of each state of the variable considering each combination of parent states (Wang & Chen, 2017). The lack of detailed data on failure rates, inherent uncertainties in available data, imprecision, and vagueness of system phenomena may lead to uncertainty in outcomes that, in turn, produce and underestimate or overestimate risk levels. In this particular work, EFB as the boiler feedstock for commercial electricity generation is quite unpopular. Not much is reported, and the historical data is not widely available. Hence, it is difficult to establish conditional probability tables (CPTs). Such situations have for CPTs elicitation via expert knowledge only. Direct estimation from experts to generate conditional probabilities is typically applied. This approach, however, may unavoidably involve subjectivity and biases, which then leads to unreliability and inconsistencies (Chin et al., 2009).

The weighted sum algorithm (WSA) is incorporated in determining Bayesian Network CPTs to overcome the shortcoming of straightforward elicitation from the experts. Theoretically, the weighted sum algorithm is the common and the best for solving multi-criteria in decision-making. This method serves as a simple elicitation method. The weighted sum algorithm method will produce the number of assessments of a CPT linear instead of exponential (Das, 2004). The common issue involved in qualitative risk assessment is to convert the subjective data into quantifiable data. It is crucial to find the formulation in converting the experts' perceptions based on their experience into crisp and valuable information for the decision-making process. Thus, in this study, the WSA approach is introduced and incorporated into the Bayesian network in generating the conditional probabilities of the nodes with multi parents for risk assessment of boiler in the biomass energy plant.

MATERIALS AND METHODS

Identification of Causes and Consequences of Biomass Boiler Failure

The scope of risk analysis in this present paper is limited to boiler damage. The related factors and consequences of boiler failures were collected from existing literature, and interview sessions were conducted with the domain experts consisting of a steam engineer, boiler man, assistant manager, and plant manager to understand the process and factors contributing to boiler failure.

Constructing Bayesian Belief Network (BBN)

In this step, the structure of graphical representation was created. The association relationships between nodes were as well confirmed. A Bayesian node represented every variable. Then the network structure was developed by linking the directed edges from the nodes corresponding to cause to the node representing its effect or consequence. This illustration helps determine the network level of details and simplifies the cause-and-effect assumptions, which are not easily expressed in mathematical notation (Pearl, 2000). Once the graphical structure of the models had been developed, the quantitative parts of the model were formulated. Free software from BayesFusion that is GeNIe Modeler 2.4, was applied to construct the BBN based on the gathered data.

Conversion of Experts' Opinion by Weighted Sum Algorithm (WSA) Method

Probability estimation is the most crucial step in specifying the possible states and defining the CPTs value. Due to a lack of information regarding biomass boiler from existing literature, expert judgments were incorporated in a Bayesian network model as an alternative. This step entails the elicitation from engineers and technical teams for developing Conditional Probability Data (CPT) by preparing questionnaires and conducting interview sessions.

In the weighted sum algorithm (WSA) method, domain experts are needed to elicit the relative weight value for the parent nodes and the probability value between the child and parent node. Hence, two questionnaires were designed with proper questions that refer to the major factor and consequences of boiler failure. A probability scale was used to ease the industrial expert's decision-making process. The scale consists of five different ranges of value, and each of the ranges was provided with a description to assist the expert in judging according to the probability value, x_{pi}^{ji}. The qualitative, quantitative value, and description for probability scales used in the questionnaire for probability value are shown in Table 1.

Next, a set of questionnaires for weightage value, w_i, has carefully been made as the increased number of probabilities will eventually make the elicitation process difficult.

Table 1
Scale for probability data

Qualitative Value	Quantitative Value	Description
High	7–10	Expected to occur in most circumstances
Moderate	3–7	Would probably occur in most circumstances
Low	1–3	Might occur occasionally
Very Low	0.1–1	Could happen sometime
Rare	0	May happen only in exceptional circumstances

Table 2
Scale for estimation of weightage value

Weightage Value	Description
0	The stated event does not affect by the next event
0.1–0.29	The stated event is rarely affected by the next event
0.3–0.49	The stated event is slightly affected by the next event
0.5	The stated event is somewhat affected by the next event
0.51–0.69	The stated event is moderately affected by the next event
0.7–0.89	The stated event is highly affected by the next event
0.9–0.99	The stated event has a strong relationship to the next event
1.0	The stated event is totally affected by the next event

Table 2 is used as a scale for weightage value. In this work, 44 questions were developed for the probability value elicitation, and 19 were established to obtain the weightage values.

The experts' opinions were then converted to quantitative value using Weighted Sum Algorithm (WSA) approach as in Equation 1.

$$P\,(x_c^m|\, x_{p1}^{j1}\, x_{p2}^{j2}, \ldots \ldots x_{pn}^{jn}) = \sum_{i=1}^{N} P(\mathrm{xc}^{\mathrm{m}}|\, \{\mathrm{Comp}\ (\mathrm{X}_{\mathrm{pi}} = x_{pi}^{ji})\}). \qquad (1)$$

Where, $P\,(\mathrm{xc}^{\mathrm{m}}|\,\{\mathrm{Comp}\,(\mathrm{X}_{\mathrm{pi}} = x_{pi}^{ji})\})$ is the probabilities of compatible parental configuration for each state in parent nodes. Meanwhile, P $(x_c^m|\, x_{p1}^{j1}\, x_{p2}^{j2}, \ldots \ldots x_{pn}^{jn})$ is the conditional probability that populates the CPT. The factors contributing to the boiler failure were identified according to the probability of occurrence and the failure frequencies resulting from the calculation made.

BBN Model Analyses

All the parameters determined from the WSA method were used for Bayesian Belief Network (BBN) model in GeNIe 2.4. Two types of analyses were carried out: prediction analysis and diagnosis analysis. The model probabilities will be updated in the prediction analysis whenever new knowledge or evidence becomes available. Meanwhile, the accidental path will be discovered for the diagnostic analysis, and the posterior probability will be calculated. A real case study from a local biomass plant operator was adopted to come out with a performance predictions scheme as part of a validation process. Based on the results obtained, a countermeasure to reduce the risk of the important factors was suggested. The full validation of the proposed model, however, is impractical because it ideally requires the variables in the model to be monitored for some time. Thus, typically only partial validation was performed based on results from the analysis.

RESULTS AND DISCUSSIONS

Identification of Boiler Inefficiency Incident

Many hazards could occur in operating biomass boilers, such as ashes formation, scaling, and many more. The formation of ashes can lead to a serious problem in the boiler, which is clinker formation. This ash is made up of the incombustible mineral matter in the fuel. Clinker formation will eventually reduce the combustion area of the boiler, thus will affect the stability of the flame. It is happened due to the chemical reaction that relies on pressure and temperature. As the temperature and pressure increase, the ashes will melt and form a lump of clinker at the bottom of the boiler (Patel & Modi, 2016).

Another problem that can affect the boiler inefficiency is scaling in the tube. Scaling will cause tube clogging and localized heat that can finally lead to tube overheating. Scaling usually occurs due to untreated water, which contains high mineral content like calcium and magnesium, which will produce deposits or scale in the tube. A pinhole leak in the tube results from scaling. In addition, since the scale is known as a good insulator, the heat cannot transfer effectively to the water located in the tube; this will make the tube overheated (Ghosh et al., 2010). Overheating happens due to the buildup of heat, which eventually will raise the heat of the metal tube.

Moisture content in biomass generally decreases the heating value of biomass fuel. Moisture content lowers the boiler temperature and lowers the rate of combustion (Patel & Modi, 2016). Other than that, the fuel-air ratio in the boiler also plays an important role in the combustion system. Fuel to air ratio defines the amount of air needed to burn a specific fuel (Babatunde et al., 2021). Different types of air ratios will vary according to the type of fuel. However, enough oxygen is necessary to consume the fuel in all cases so that no combustibles are exhausted while minimizing the excess air to prevent energy loss.

It is also important to have a good boiler design to control the air draft balance. A viable boiler design is necessary to make full use of the forced convection heat transfer in the boiler (Snow, 1991). The air draft consists of two types of air; Induced Draft and Forced Draft. The forced air draft forces the outside air into the combustion system while the induced air draft draws the flue gases from the system out into the atmosphere. Both air drafts need to be balanced to ensure flame stability. The other consequence of the imbalance air draft is that it will cause incomplete burning. When this happens, the flue gas will contain a high amount of sulfuric acid gas, and this gas will cause corrosion to the chimney as it degrades the wall of the chimney before the gas is released into the atmosphere (Imran, 2014). Besides that, a good boiler system is also needed to prevent suspension burning in the system. If this happens, the combustion system will not produce enough heat, and the system will require more fuel consumption which is not cost-effective. Table 3 summarizes the causes and consequences of boiler inefficiency.

Table 3
Summary of causes and consequences of boiler inefficiency

Major Factor	Possible Causes	Consequences
Combustion Stability	• Suspension Burning • Reduced in the combustion area • Formation of ashes • Poor Boiler Design	• Explosion • Leakage • Low energy conversion
Corrosion	• H_2S contained in flue gas • Oxygen contained in RO water	
Tube Overheating	• Tube clogging • Localized Heating • Low water level in the tube	
Overpressure	• The failure of the pressure safety valve	
Superheater Thermal Shock	• Water carryover	

Proposed Bayesian Belief Network (BBN)

Based on the findings, the conditional relationships among failure factors were identified. Bayesian networks illustrating the influence factors and their relationships are shown in Figure 1. The graphical representations of the proposed Bayesian network models were constructed using the available software package GeNIe 2.4. The green nodes indicate marginal nodes or nodes without a parent. Meanwhile, the yellow nodes are the main threats directly affecting boiler efficiency.

Development of Conditional Probability Table (CPT) using Weighted Sum Algorithm (WSA)

WSA method is a simple elicitation method where it only consists of two main things: the relative weight value w_i for the parent nodes (marginal probability) and the probabilities of compatible parental configuration for each state in parent nodes x_i. The conditional probability table (CPT) was calculated using Equation 1, and it can be simplified into Equation 2.

$$y_i = \sum_{i=1}^{N} w_i x_i \tag{2}$$

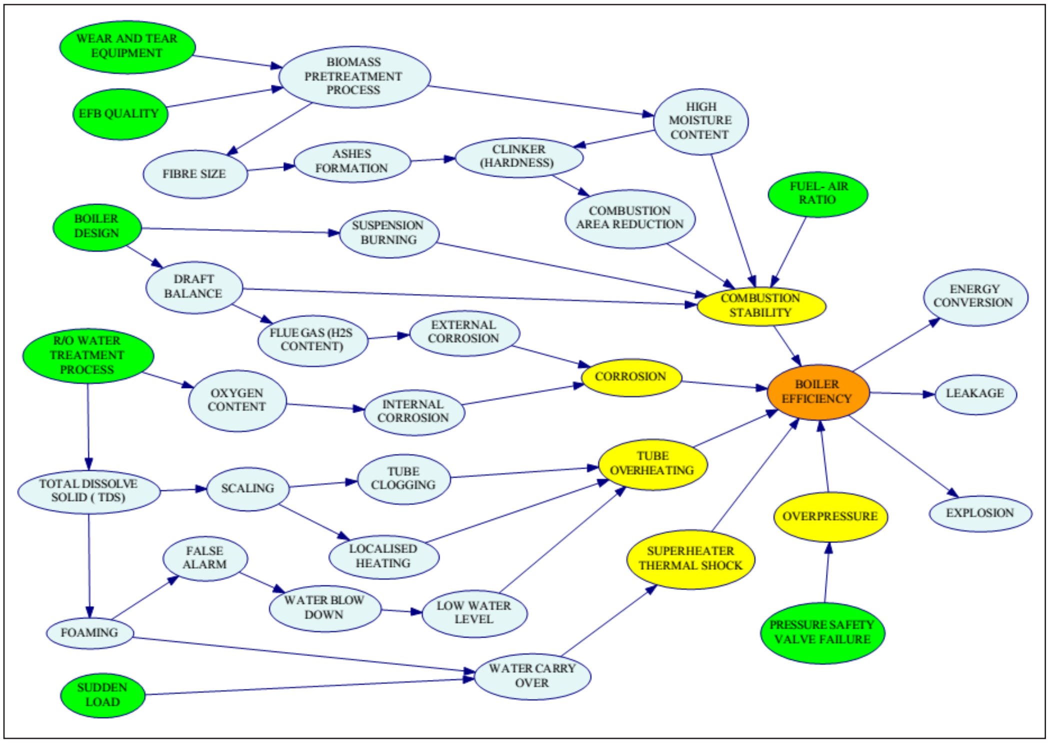

Figure 1. Proposed Bayesian Belief Network model of boiler efficiency

An example of CPT calculation on *Biomass Pretreatment Process* node connected with other two-parent nodes is shown in detail. Those parent nodes are *Wear and Tear Equipment* node and the *Empty Fruit Bunch (EFB) Quality* node, as in Figure 2. A general probability table for the nodes and their states is constructed, as shown in Table 4.

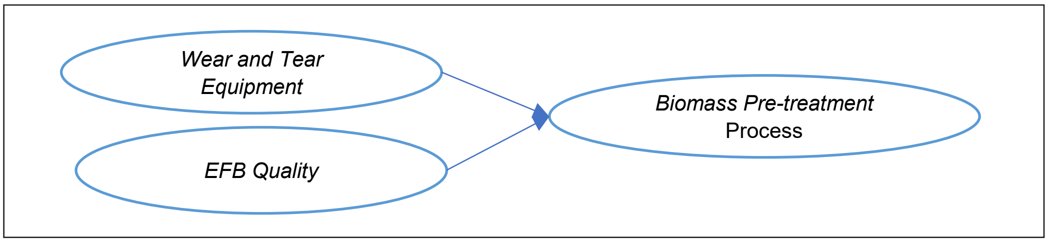

Figure 2. Parent nodes for *Biomass Pretreatment Process* node

Table 4
General probability table for Biomass Pretreatment Process node

Empty Fruit Bunches (EFB)Quality	**High**		**Low**	
Wear and Tear Equipment	**Yes**	**No**	**Yes**	**No**
Efficient	y_1	y_2	y_3	y_4
Inefficient	$(1- y_1)$	$(1- y_2)$	$(1- y_3)$	$(1\ y_4)$

By referring to Equation 1, the probability value, x_{pi}^{ji} the prepared questions for experts are 'What is the probability of *Wear and Tear Equipment* affects the efficiency of *Biomass Pretreatment Process?*' and 'What is the probability of *EFB Quality* affects the efficiency of *Biomass Pretreatment Process?*.' On the other hand, the appropriate questions for weightage value, wi would be "What is the weightage value for *Wear and Tear Equipment* to *Biomass Pretreatment Process* compared to *EFB Quality"* and "What is the weightage value of *EFB Quality* to *Biomass Pretreatment Process* compared to *Wear and Tear Equipment.*" The sum for the parents' weights should be equal to 1. For this set of questionnaires, a probability scale was implemented to ease the experts in giving the required weightage values, $w_{i.}$ The experts' judgment for nodes *Wear and Tear Equipment* and *EFB Quality* is shown in Table 5.

Table 5
Experts' judgment of Biomass Pretreatment Process node

Node Wear and Tear Equipment		**Node EFB Quality**	
	Scale		Scale
$w_{1,\ Yes}$	0.25	$w_{2,\ High}$	0.75
$w_{1,\ No}$	0.75	$w_{2,\ Low}$	0.25
P (Efficient biomass pretreatment process| yes wear and tear equipment)= $x_{1,\ Yes}$	0.7	P (Efficient biomass pretreatment process| High EFB Quality)= $x_{2,\ High}$	0.5

The example for CPT calculation for node biomass pre-treatment process in Figure 2 was calculated using Equations 1 and 2. The complete probability table for the Biomass Pretreatment Process is shown in Table 6.

$$y_1 = (w_{1,\ Yes} \times x_{1,\ Yes}) + (w_{2,\ High} \times x_{2,\ High}) = (0.25\times0.7) + (0.75\times0.5) = 0.55$$

$$y_2 = (w_{1,\ No} \times x_{1,\ Yes}) + (w_{2,\ High} \times x_{2,\ High}) = (0.75\times0.7) + (0.75 \times 0.5) = 0.9$$

$$y_3 = (w_{1,\ Yes} \times x_{1,\ Yes}) + (w_{2,\ Low} \times x_{2,\ High}) = (0.25 \times 0.7) + (0.25 \times0.5) = 0.3$$

$$y_4 = (w_{1,\ No} \times x_{1,\ Yes}) + (w_{2,\ Low} \times x_{2,\ High}) = (0.75 \times 0.7) + (0.25 \times 0.5) = 0.65$$

Table 6
Complete conditional probability table for Biomass Pretreatment Process

Empty Fruit Bunches (EFB)Quality	**High**		**Low**	
Wear and Tear Equipment	**Yes**	**No**	**Yes**	**No**
Efficient	0.55	0.9	0.3	0.65
Inefficient	0.45	0.1	0.7	0.35

BBN Model Analyses

By calculating the CPTs for all nodes and combining them in the GeNIe 2.4 software, the estimate on *Boiler Efficiency* and the prior probability for other nodes is depicted in Figure 3. From the result obtained, the probability of the boiler being in the state of efficiency is 47% which led to a 53% probability of energy conversion. The marginal parent nodes, *EFB Quality*, *Wear and Tear Equipment*, *Boiler Design*, *Fuel-air Ratio*, *R/O Water Treatment Process*, *Sudden Load,* and *Pressure Safety Valve Failure* are at uniform probability as elicited by the experts. Two analyses, for instance, predictive and diagnostic analyses, were conducted to evaluate the robustness of the proposed model.

Predictive analysis is defined as the statistical method to determine the likelihood of future consequences based on the probability distribution of causes (Carlsson et al., 2014). The main reason to conduct the predictive analysis is to predict the efficiency of the boiler and examine a combination of events taking place (i.e., 100% probability). In this work, three variables were considered: RO water treatment process fails, sudden load occurred, and pressure safety valve failure. It is observed in Figure 4 that the probability of boiler inefficiency escalates from 53% to 59%, and the energy conversion, leakage, and explosion

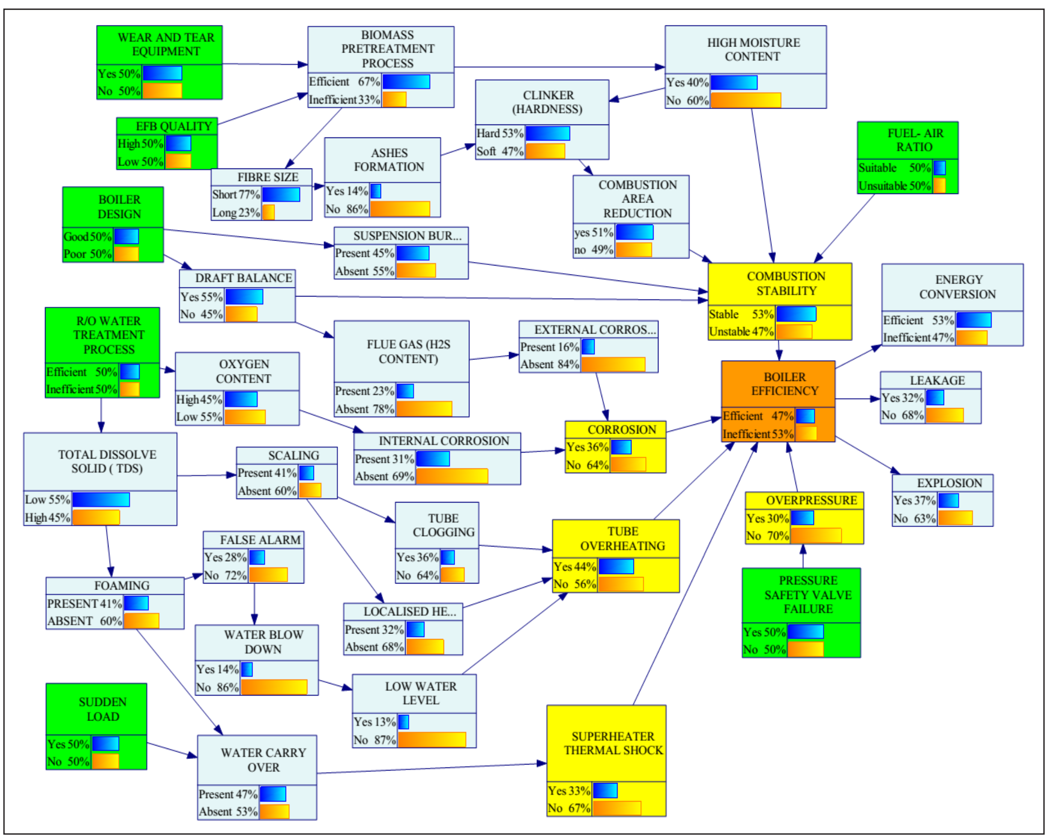

Figure 3. Simulated Bayesian Network Model

nodes were affected too. The efficiency of energy conversion decreases to 49% from 53%. The probability of the boiler exploding rises from 32% to 41%. Although some of the selected input variables were considered insignificant influences, it points out that they do possess an influence, even though a small one. This analysis perhaps demonstrates the strength of the Bayesian network in predicting a future event that may assist the operator in decision making and preparing any countermeasures or maintenance activities schedule.

For the diagnosis analysis, the probability of an event was calculated backward by specifying the probability of the particular event that contributes to the failure when the occurrence of the failure is known, i.e., 100% probability. This analysis is very helpful for the experts to identify and troubleshoot any possible problems from an incident (Cai et al., 2017; Lee et al., 2010). This work can discover the problems when the boiler is completely inefficient. Suppose it observed that *Boiler Efficiency* is in state *Inefficient* and P (*Boiler Efficiency* = *Inefficient*) =1 was entered into the model. It entered evidence to increase the belief in possible causes based on diagnostic inference. Figure 5 shows the results of boiler condition evidence to its parent nodes. The *Combustion Stability* changed from 54% of stable flame before the analysis to 52% of unstable flame. Compared to the previous

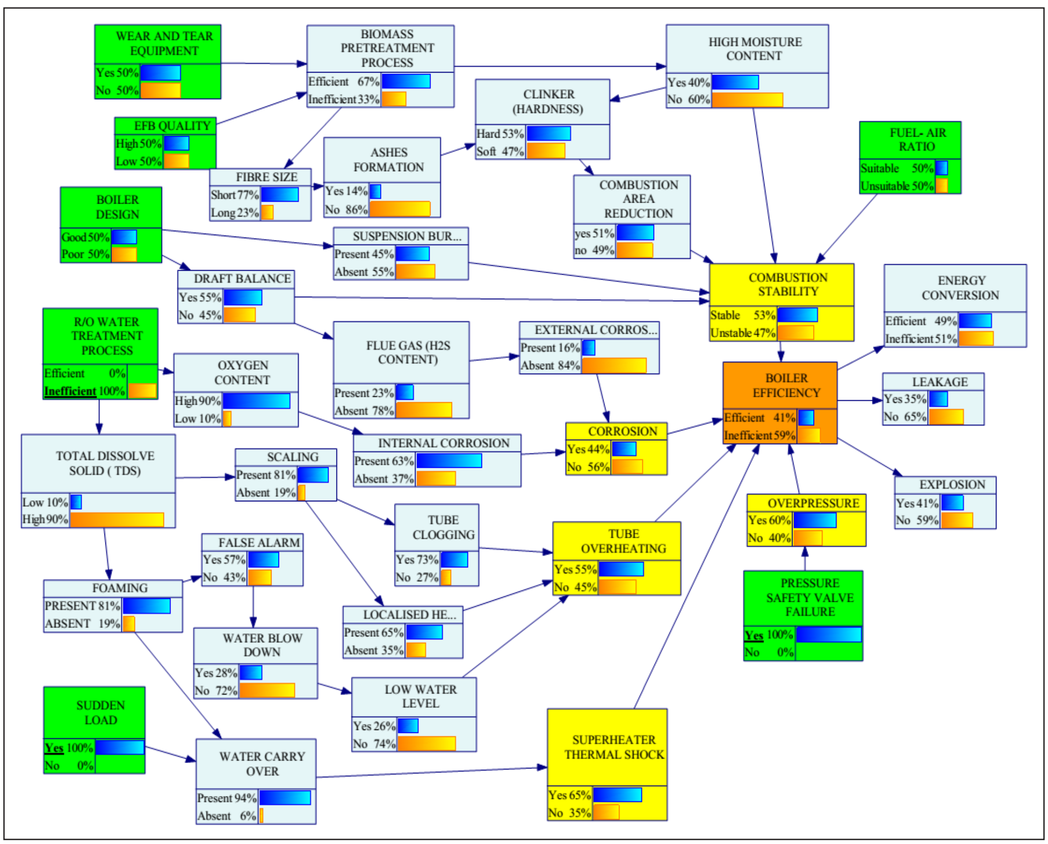

Figure 4. Predictive analysis for boiler failure

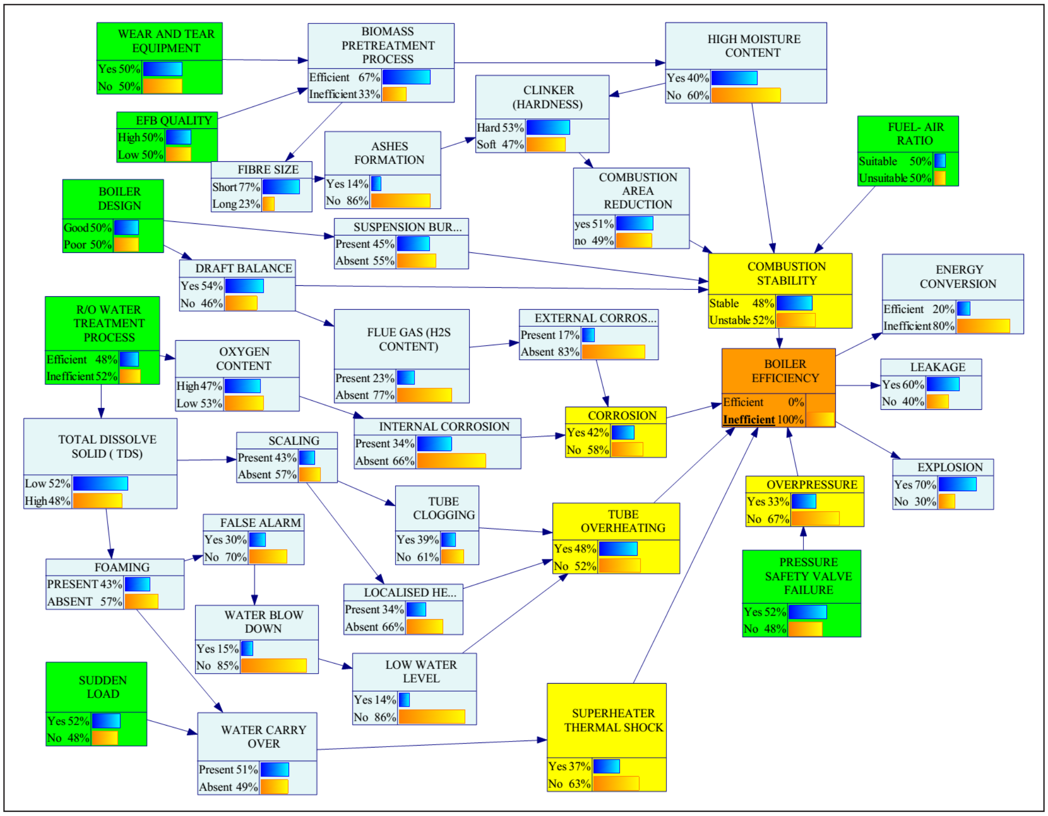

Figure 5. Diagnosis analysis for boiler failure

values (35% and 37% for leakage and explosion, respectively), the leakage and explosion are now likely to happen at high probability values of 60% and 70%, respectively.

From the analysis, unstable flame and corrosion are the ultimate contributors to the boiler inefficiency as both have the largest increment in probability value, which also indicates that they are the main sources of boiler failure. It is due to the clinker accumulating in the boiler due to incombustible mineral matter in the biomass fuel (Patel & Modi, 2016). Furthermore, it is also vital to treat the EFB so that its moisture content is less than 40wt.%. The moisture content could affect the flame stability and thus reduce the amount of steam generated (Barma et al., 2017). The typical moisture content for EFB is 67wt. %, thus a good EFB pretreatment process is necessary for EFB to be used as boiler feedstock (Hamzah et al., 2019).

The experts emphasize that reverse osmosis (R/O) water must reach a certain pH range to ensure the boiler operates efficiently. It indicates that the R/O water treatment process must be at the best effectiveness level. It agrees with Putra and Purba (2018) that suggested bad water quality results in boiler tube failure, thus reducing the energy conversion efficiency.

Model Validations

The validations of the model were carried out from the usability aspect and face validation aspect. The validation of the model usability aspect was performed to examine the sensitivities of variables by demonstrating the change of inputs data. As demonstrated in the predictive and diagnosis analyses, the probabilities of selected nodes were set to 1 in sequence, and the probability of *Boiler Efficiency* was kept constant. It is expected that the occurrence probability of the top event will gradually increase. The results obtained were verified with the three-axiom-based validation method suggested by Jones et al. (2010). Increasing the probabilities of each selected node after another satisfies the axiom and produces the required results, thus giving a partial validation to the proposed model.

Meanwhile, the face validation was carried out to evaluate the results generated from the proposed model by verification from experts. The results were verified by the case study with *Boiler Efficiency* in an inefficient state scenario. The results obtained are compared with the situation that occurred in the FTJ Bio Power Sdn. Bhd. The major reason affecting the boiler efficiency is that the stability of flame inside the boiler agrees with the experts' experience.

CONCLUSION

A BBN model was developed to determine the probability estimation value for boiler efficiency. The model aims to identify and evaluate the causes and effects of boiler conditions. This model also provides the means to examine how the underlying factors influence the pipeline condition probability. When constructing a BBN, conditional probability tables (CPTs) are not always solvable analytically. In this work, the probability of boiler efficiency was quantified by utilizing experts' judgment. The experts' judgments were converted into quantitative data using a simple approach, for instance, the WSA method, in a situation where there is a lack of historical data available. This work applied two assessments to the influence analysis: probability analysis and diagnosis analysis to attain a thorough description of the model variable influences on boiler efficiency probability. The analyses were conducted to examine the validity and robustness of the developed BBN model. The case study applied revealed that the path of accident occurrence with combustion instability is the most influential variable with the largest probability increment. In a nutshell, the model assists the industrial experts in detecting which factor they need to focus on in maintaining the boiler to avoid any catastrophic events. This method not only helps the boiler experts in risk analysis, but it can also assist them in decision-making on how to maximize the efficiency of the boiler as well as increase the electricity conversion efficiency.

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