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Techno-Press

Fault detection in industrial battery production using naive Bayes networks

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Abstract. This research presents a machine learning-based approach for monitoring an industrial battery production system using a Naive Bayesian Network, a probabilistic model widely recognized for its ability to handle uncertainty. The proposed framework infers system states from observed operational conditions and event data, providing predictive insights into machine behavior. Real-world production data were employed to train and validate the model, ensuring both accuracy and practical applicability. Through probabilistic inference, the model anticipates potential failures or abnormal behaviors, enabling timely maintenance interventions and minimizing downtime. Evaluation results demonstrate that the Naive Bayesian Network offers a robust and interpretable solution for industrial monitoring, with strong potential to enhance predictive maintenance strategies and improve the overall reliability and efficiency of battery manufacturing operations.

Keywords: Bayesian networks; failure analysis; machine learning; modelling; probability

1. Introduction

All equipment in an industrial installation is subject to degradation mechanisms due to operating or environmental conditions: wear, fatigue, and aging [1-3]. A failure is the cessation of an item's ability to perform a required function. A failure mode is the way the system can stop working or work abnormally. The cause of the failure of an element can be internal or external to it [4]. A mode of failure can correspond to several reciprocal causes Berg [5]. Detection is a phenomenon or physical parameter, anomaly or symptom that can be observed, detected or measured early and reflects the appearance of propagation or evolution of a failure mechanism [6].

An analytical model for battery manufacturing was proposed that integrates productivity and quality analysis, introducing decomposition-based methods and bottleneck indicators to optimize throughput and quality across inspection and repair stages [7]. Employs Fuzzy FMEA to evaluate

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risks in immersion-cooled battery packs for electric vehicles, identifying critical failure modes like sealing and thermal control, and recommends mitigation strategies to enhance safety, reliability, and efficiency during design, production, and testing [8]. A review on lithium-ion, lead-acid, and NiMH batteries was performed covering manufacturing, performance optimization, fault detection using AI/ML, and recycling methods. It highlights technological advancements and sustainability considerations shaping the future of battery systems in energy applications [9-12]. Introduces a random forest-based framework to classify electrode properties in lithium-ion battery manufacturing by effectively quantifying feature importance and correlations using multiple indicators, enabling improved sensitivity analysis and dimensionality reduction across key production stages [13]. A systematic investigative approach for lithium-ion battery failures, using disassembly, imaging, and electrical testing to determine root causes of overheating, rupture, or combustion in consumer electronics across various product categories, was carried out [14].

Several approaches are used to analyze or model maintenance systems for example: FMECA (Failure Mode, Effects & Criticality Analysis) is a method which involves quantitative failure analysis, involves creating a series of linkages between potential failures (Failure Modes), the impact on the mission (effects) and the causes of the failure (causes and mechanisms), Pareto chart Pareto's principle or law (80-20 law, or 20-80) is a theory that 20% of the causes are responsible for 80% of the effects [15-19]. Applicable to different fields and sectors, it is one of the most well-known maintenance methods in the industrial world. The A.B.C Method, an objective and effective method of choice based on knowledge of a previous period, presents the results in the form of a curve called -A.B.C Curve‖. That is to say classify in order of importance elements (products, machines, parts, operations) according to a value criterion retained (hours, etc.). The disadvantage of these methods is their limited field of application. To address this, the authors integrated a powerful tool to facilitate in-field maintenance analysis.

The recent evolution of methods and techniques of artificial intelligence, such as the method of naive Bayesian networks, which is based on probability, has been the subject of several studies in the industrial field. Bayesian networks are among the probabilistic analysis models. They offer a mathematical formalism and solid theoretical bases for the development of models for complex systems. A Bayesian network-based approach for fault detection and analysis in high-value equipment, enhancing condition-based maintenance through intelligent sensor data interpretation and case-based validation [20, 21]. Demonstrated through a practical maintenance case study by employing Bayesian network modeling to evaluate system failure rates by incorporating dynamic influencing factors and enabling real-time updates [22, 23]. A dynamic Bayesian network model with particle filtering to predict battery health and remaining life, using charging features for accurate, robust diagnostics, was utilized in electric vehicle batteries [24]. Integrates physics-informed and data-driven Bayesian networks to analyze lithium-ion battery risks, evaluates safety barriers, and offers strategies to reduce accident probability, particularly in air transportation scenarios [25]. Wang [26] developed collapse risk evaluation method on Bayesian network prediction model and engineering application.

Introduces a modular ensemble Bayesian network framework for robust, interpretable root cause analysis of product defects, combining multiple learning algorithms to enhance quality prediction using real-world manufacturing data [27].

BNs are increasingly used in areas such as risk analysis, operational safety, and maintenance [28]. They combine a representation of knowledge in graphical form (direct dependency relationships) and probabilistic (uncertainty about knowledge). Bayesian networks were initiated by [29]. BNs have been used to model and analyze the different types of behavior of complex components of a

Table 1. Type of failure

Failure	Probable cause
The alarm machine	The mold cooling water temperature may be high. The air pressure may be reduced. The ideal temperature of the lead present in the pot may be. The cooling water level may be low.

of a dynamic system [30]. Another interesting use of BNs is to assess the general reliability of a manufacturing process to optimize diagnosis and maintenance interventions. A review of how Bayesian networks are applied in Structural Health Monitoring, including damage prediction, uncertainty modeling, data fusion, and decision support [31].

In the context of optimization assistance in a doubly censored context, the work of Celeux [32] proposes to build a Bayesian model from expert opinions while integrating the interventions maintenance considered as model variables. The use of BNs has enabled to unify in the unification of several methods dedicated to the monitoring (detection and diagnosis) of multivariate processes [33]. Recently, work has been done to develop machine learning technology for data analysis, including [34] using artificial neural networks (ANN), he analyzed data and predicted the tribological properties of Al8090/TiB2/C composites, Sudha and Bolla [35] proposed an adaptive intrusion detection technique optimized for Big Data applications on social networks by the classification technique.

For this purpose, in this work, the capacity of this type of model to predict the real state of the industrial machine is analyzed. This machine is used for the purpose of the production of industrial batteries of direct current. The research is conducted along with the maintenance service in order to see the behaviour of this machine during a well-defined period.

2. Conception phase

The failure selected is presented in Table 1. We are interested in the causes that imply this failure, then we model our problem with the Bayesian network method. This method allowed us to calculate the probability of failure from these a priori causes.

In this phase of conception, authors used a naive Bayesian network of two levels; the first level is a node (random variable) which models the failure of the machine, whose values are [breakdown, no failure]. The second level presents the four causes (observations) that influence the failure. So the main objective of this study is to calculate the probability of failure P (Failure), knowing the four causes, Cause 1, Cause_2, Cause_3, and Cause_4.

$$P(Failure|Cause\_1, Cause\_2, Cause\_3, Cause\_4) = ? \tag{1}$$

With:

- Failure: presents the existence of the failure or not. These values take {alarm, no alarm}.
- Cause_1: Expresses the temperature of the mold cooling water. These values take {high, not high}.
- Cause_2: Expresses the air pressure. These values take {decreased, normal}.
- Cause_3: Expresses the ideal temperature of the lead present in the pot. These values take {increased, decreased}.

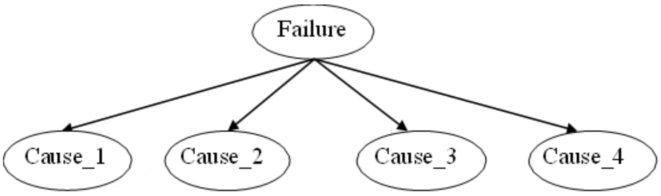

Figure 1. Naive Bayesian network design pattern

- Cause_4: Shows cooling water level. These values take {normal, decreased}.

Fig. 1 above illustrates the design model of our work.

3. Modeling by Bayesian networks

Bayesian networks made it possible to represent compactly the joint probability distribution of all the variables [29]:

$$P(X_1,\mathrm{X}_2,\ldots,\mathrm{X}_n) = \prod_{\mathrm{i}=1}^{n} P(X_i|\mathrm{Fa}(X_i)) \tag{2}$$

For statistical learning in the case where all the variables are observed. The simplest and most widely used method is statistical estimation, which consists of estimating the probability of an event by the frequency of occurrence of the event in the database. This approach called maximum likelihood (ML). Then gives us:

$$\hat{P}(X_i{=}\mathrm{x}_k \,\Big|\, \mathrm{Failure}(X_i){=}\mathrm{x}_j){=}\hat{\theta}^{\mathrm{MV}}_{\mathrm{j,j,k}} = \frac{N_{\mathrm{i,j,k}}}{\sum_k N_{\mathrm{i,j,k}}} \tag{3}$$

where $N_{i,j,k}$ is the number of events in the database for which the variable is in state and its parents are in configuration x_j.

3.1 Bayesian learning

Bayesian estimation follows a somewhat different principle. It consists in finding the parameters θ the most probable, knowing that the data have been observed. Using a priori on the parameters. Bayes' rule tells us that:

$$P(\theta|D) \propto P(D|\theta)P(\theta){=}\mathrm{L}(D|\theta)P(\theta) \tag{4}$$

when the sample distribution follows a multinomial distribution, the conjugate prior distribution is the Dirichlet distribution:

$$P(\theta) \propto \prod_{\mathrm{i}=1}^{n}\prod_{\mathrm{j}=1}^{q_i}\prod_{\mathrm{k}=1}^{r_i}\left(\theta_{\mathrm{i,j,k}}\right)^{\alpha_{\mathrm{i,j,k}}\text{-}1} \tag{5}$$

where $\theta_{i,j,k}$ are the coefficients of the Dirichlet distribution associated with the prior distribution

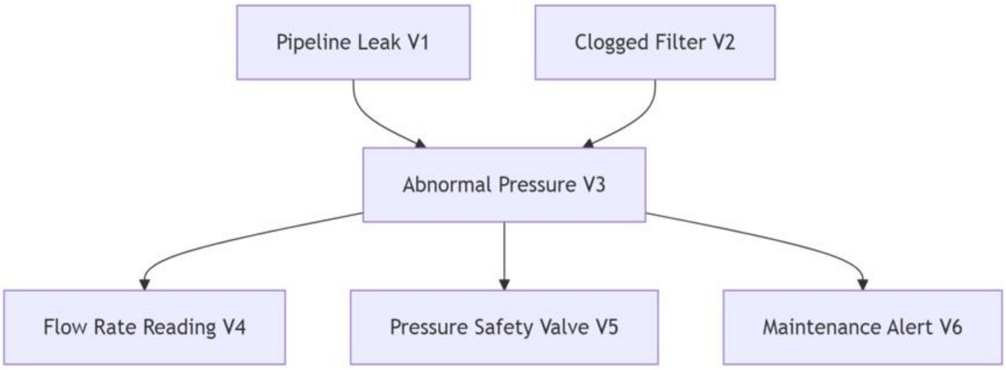

Figure 2. Example of a bayesian network

$P(X_i\text{=x}_k | \text{Failure}(X_i)\text{=x}_j)$. One of the advantages of exponential distributions like that of Dirichlet is that it makes it possible to easily express the posterior law of the parameters $P(\theta|D)$ [36].

$$P(\theta|D) \propto \prod_{i=1}^{n}\prod_{j=1}^{q_i}\prod_{k=1}^{r_i}(\theta_{\mathrm{i,j,k}})^{N_{\mathrm{i,j,k}}+\alpha_{\mathrm{i,j,k}}-1} \tag{6}$$

The maximum a posteriori (MAP) approach then gives us:

$$\hat{P}(X_i\text{=x}_k \left| \text{Failure}(X_i)\text{=x}_j\right.)\text{=}\hat{\theta}_{\mathrm{i,j,k}}^{\mathrm{MAP}} = \frac{N_{\mathrm{i,j,k}}+\alpha_{\mathrm{i,j,k}}-1}{\sum_k(N_{\mathrm{i,j,k}}+\alpha_{\mathrm{i,j,k}}-1)} \tag{7}$$

An example of a Bayesian network in the field of monitoring industrial systems is shown in Fig. 2. An abstract domain with six variables: V1 representing a leak in the hydraulic pipeline, V2 representing a clogged hydraulic filter, V3 representing the abnormal hydraulic pressure state, V4 representing the flow rate sensor reading, V5 representing the activation of the pressure safety valve, and V6 representing the triggering of the maintenance alert indicator.

4. Experimentation and validation

In this section, the authors calculated the probabilities (see Table of parameters) of our RBN. The learning database (corpus). See Table 2, which presents the experiments carried out that give the influence of the causes on the state of the failure. We have grouped together the 100 tests whose observed results are noted by the maintenance department during the year 2023-2024. This table allowed us to calculate the probability of failure in the two states (alarm or no alarm).

$$\begin{aligned}
&P(\text{Failure=x}) = \sum \frac{\text{Failure N}^{\text{ber}} \text{=x}}{\text{Total } N^{\text{ber}}} \\
&P(\text{Failure=alarme}) = \frac{55}{100}\text{=0.55} \\
&P(\text{Failure=no alarme}) = \frac{45}{100}\text{=0.45}
\end{aligned} \tag{8}$$

Table 1. Details of characteristics types

N^{bre}	Water Temperature C1	Air Pressure C2	Lead Temperature C3	Water Level C4	Machine Status
1	high	normal	decreased	normal	no alarm
2	high	normal	decreased	normal	no alarm
3	high	normal	decreased	normal	no alarm
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
51	not high	normal	decreased	decreased	no alarm
52	not high	normal	decreased	decreased	no alarm
53	not high	decreased	decreased	normal	alarm
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
98	not high	normal	increased	normal	no alarm
99	not high	normal	increased	normal	no alarm
100	not high	normal	increased	normal	alarm

We also calculate the probability of each cause knowing the state of the failure. From equation:

$$P(\text{Cause\_1}{=}\text{x}_k \big| \text{Failure}(\text{Cause\_1}){=}\text{x}_j) = \frac{N_{\text{i,j,k}}}{\sum_k (N_{\text{i,j,k}})} \quad (9)$$

For Cause 1:

$$P(\text{Cause\_1= not high}|\text{Failure=no alarme}) = \frac{29}{45}{=}0.64$$

$$P(\text{Cause\_1=high}|\text{Failure=no alarme}) = \frac{16}{45}{=}0.36$$

$$P(\text{Cause\_1=not high}|\text{Failure=alarme}) = \frac{37}{55}{=}0.67$$

$$P(\text{Cause\_1=high}|\text{Failure=alarme}) = \frac{18}{55}{=}0.33$$

For Cause 2:

$$P(\text{Cause\_2}{=}\mathit{decreased}|\text{Failure=no alarme}) = \frac{14}{45}{=}0.31$$

$$P(\text{Cause\_2=normal}|\text{Failure=no alarme}) = \frac{31}{45}{=}0.69$$

$$P(\text{Cause\_2}{=}\mathit{decreased}|\text{Failure=alarme}) = \frac{30}{55}{=}0.55$$

$$P(\text{Cause\_2=normal}|\text{Failure=alarme}) = \frac{25}{55}{=}0.45$$

For Cause 3:

$$P(\text{Cause\_3}{=}\mathit{decreased}|\text{Failure=no alarme}) = \frac{33}{45}{=}0.73$$

$$P(\text{Cause\_3=increased}|\text{Failure=no alarme}) = \frac{12}{45}=0.27$$

$$P(\text{Cause\_3=}decreased|\text{Failure=alarme}) = \frac{46}{55}=0.84$$

$$P(\text{Cause\_3=increased}|\text{Failure=alarme}) = \frac{9}{55}=0.16$$

For Cause 4:

$$P(\text{Cause\_4=}decreased|\text{Failure=no alarme}) = \frac{15}{45}=0.33$$

$$P(\text{Cause\_4=normal}|\text{Failure=no alarme}) = \frac{30}{45}=0.67$$

$$P(\text{Cause\_4=}decreased|\text{Failure=alarme}) = \frac{20}{55}=0.36$$

$$P(\text{Cause\_4=normal}|\text{Failure=alarme}) = \frac{35}{55}=0.64$$

Note that to facilitate writing and minimize the equations we set Fa=Failure, C1=Cause_1. C2=Cause_2. C3=Cause_3 and C4=Cause_4. Then the equations have to be written:

$$\begin{aligned}
&P(Fa|\text{C1,C2,C3,C4}) = P(\text{C1})P(\text{Fa,C2,C3,C4}|\text{C1}) \\
&= P(\text{C1})P(\text{C2}|\text{C1})P(\text{Fa,C3,C4}|\text{C1,C2}) \\
&= \text{P}(\text{C1})P(\text{C2}|\text{C1})P(\text{C3}|\text{C1,C2})P(\text{Fa,C4}|\text{C1,C2,C3}) \\
&= \text{P}(\text{C1})P(\text{C2}|\text{C1})P(\text{C3}|\text{C1,C2})P(\text{C4}|\text{C1,C2,C3})P(\text{Fa}|\text{C1,C2,C3,C4}) \\
&= \text{P}(\text{C1})P(\text{C2})P(\text{C3})P(\text{C4})P(\text{Fa}|\text{C1,C2,C3,C4})
\end{aligned}$$

$$\begin{aligned}
&P(\text{Fa}|\text{C1,C2,C3,C4,}) = \text{P}(\text{Fa})P(\text{C1,C2,C3,C4}|\text{Fa}) \\
&= \text{P}(\text{Fa})P(\text{C1}|\text{Fa})P(\text{C2,C3,C4}|\text{Fa,C1}) \\
&= \text{P}(\text{Fa})P(\text{C1}|\text{Fa})P(\text{C2}|\text{Fa,C1})P(\text{C3,C4}|\text{Fa,C1,C2}) \\
&= \text{P}(\text{Fa})P(\text{C1}|\text{Fa})P(\text{C2}|\text{Fa,C1})P(\text{C3}|\text{Fa,C1,C2})P(\text{C4}|\text{Fa,C1,C2,C3}) \\
&= \text{P}(\text{Fa})P(\text{C1}|\text{Fa})P(\text{C2}|\text{Fa})P(\text{C3}|\text{Fa})P(\text{C4}|\text{Fa})
\end{aligned}$$

$$\begin{aligned}
&P(\text{Fa}|C1, C2, C3, C4) = \frac{P(\text{Fa})P(C1|\text{Fa})P(C2|\text{Fa})P(C3|\text{Fa})P(C4|\text{Fa})}{P(C1)P(C2)P(C3)P(C4)} \\
&\simeq P(\text{Fa})P(C1|\text{Fa})P(C2|\text{Fa})P(C3|\text{Fa})P(C4|\text{Fa})
\end{aligned}$$

Whose factors of this equation are the (already calculated) parameters of our Bayesian network. So the solution of our model (equation 3) is given by the following relation:

$$P(\text{Fa}|\text{C1,C2,C3,C4}) = \text{P}(\text{Fa})P(\text{C1}|\text{Fa})P(\text{C2}|\text{Fa})P(\text{C3}|\text{Fa})P(\text{C4}|\text{Fa}) \tag{10}$$

Table 2 below presents a state of learning grouped during a period of one year and from this table we calculate the parameters mentioned in the Eq. (10). Table 2 summarizes the operational data of an industrial machine collected over a one-year period (2023–2024), focusing on how various environmental and process-related causes affect the machine's status. The table records 100 observations, each representing a distinct instance during machine operation. For every entry, four key input parameters are monitored: water temperature (C1), air pressure (C2), lead temperature (C3), and water level (C4). These parameters represent the primary conditions that may influence the machine's performance.

Table 3. The conditional probability table

N^{bre}	Status	$P(\mathrm{Fa})$	$P(\mathrm{C1}\|Fa)$	$P(\mathrm{C2}\|Fa)$	$P(\mathrm{C3}\|Fa)$	$P(\mathrm{C4}\|Fa)$	$P(\mathrm{Fa}\|\mathrm{C1,C2,C3,C4})$
1	no alarm	0.45	0.36	0.69	0.73	0.67	0.055
	alarm	0.55	0.33	0.45	0.84	0.64	0.044
2	no alarm	0.45	0.36	0.31	0.27	0.67	0.009
	alarm	0.55	0.33	0.55	0.16	0.64	0.010
3	no alarm	0.45	0.64	0.31	0.27	0.33	0.008
	alarm	0.55	0.67	0.55	0.16	0.36	0.012
4	no alarm	0.45	0.36	0.69	0.73	0.67	0.055
	alarm	0.55	0.33	0.45	0.84	0.64	0.044
5	no alarm	0.45	0.64	0.69	0.73	0.33	0.048
	alarm	0.55	0.67	0.45	0.84	0.36	0.050
6	no alarm	0.45	0.64	0.69	0.27	0.67	0.036
	alarm	0.55	0.67	0.45	0.16	0.64	0.017
7	no alarm	0.45	0.36	0.31	0.27	0.33	0.004
	alarm	0.55	0.33	0.55	0.16	0.36	0.006
8	no alarm	0.45	0.64	0.69	0.27	0.33	0.018
	alarm	0.55	0.67	0.45	0.16	0.36	0.010
9	no alarm	0.45	0.64	0.31	0.73	0.33	0.022
	alarm	0.55	0.67	0.55	0.84	0.64	0.109
10	no alarm	0.45	0.36	0.31	0.73	0.33	0.012
	alarm	0.55	0.33	0.55	0.84	0.36	0.030
11	no alarm	0.45	0.64	0.31	0.27	0.33	0.008
	alarm	0.55	0.67	0.55	0.16	0.36	0.012
12	no alarm	0.45	0.36	0.69	0.73	0.33	0.027
	alarm	0.55	0.33	0.45	0.84	0.36	0.025
13	no alarm	0.45	0.64	0.31	0.73	0.67	0.044
	alarm	0.55	0.67	0.55	0.84	0.64	0.109
14	no alarm	0.45	0.64	0.31	0.27	0.33	0.008
	alarm	0.55	0.67	0.55	0.16	0.64	0.021
15	no alarm	0.45	0.36	0.31	0.73	0.33	0.012
	alarm	0.55	0.33	0.45	0.84	0.64	0.044
16	no alarm	0.45	0.36	0.69	0.27	0.33	0.010
	alarm	0.55	0.33	0.45	0.16	0.36	0.005
17	no alarm	0.45	0.36	0.69	0.73	0.67	0.055
	alarm	0.55	0.33	0.45	0.84	0.64	0.044
18	no alarm	0.45	0.36	0.31	0.73	0.33	0.012
	alarm	0.55	0.33	0.55	0.16	0.36	0.006
19	no alarm	0.45	0.36	0.69	0.27	0.33	0.010
	alarm	0.55	0.33	0.45	0.16	0.36	0.005
20	no alarm	0.45	0.64	0.31	0.27	0.33	0.008
	alarm	0.45	0.36	0.31	0.73	0.33	0.012

Table 4. Causes with their failures

Test	Cause_1	Cause_2	Cause_3	Cause_4	Failure	Modele Failure
1	high	normal	increased	normal	no alarm	no alarm
2	high	decreased	normal	normal	alarm	alarm
3	not high	decreased	normal	decreased	alarm	alarm
4	high	normal	increased	normal	no alarm	no alarm
5	not high	normal	increased	decreased	alarm	alarm
6	not high	normal	normal	normal	no alarm	no alarm
7	high	decreased	normal	decreased	alarm	alarm
8	not high	normal	normal	decreased	no alarm	no alarm
9	not high	decreased	increased	normal	alarm	alarm
10	high	decreased	increased	decreased	alarm	alarm
11	not high	decreased	normal	decreased	no alarm	alarm
12	high	normal	increased	decreased	no alarm	no alarm
13	not high	decreased	increased	normal	alarm	alarm
14	not high	decreased	normal	decreased	alarm	alarm
15	high	decreased	increased	decreased	no alarm	alarm
16	high	normal	normal	decreased	no alarm	no alarm
17	high	normal	increased	normal	no alarm	no alarm
18	high	decreased	increased	decreased	alarm	alarm
19	high	normal	normal	decreased	no alarm	no alarm
20	not high	decreased	normal	normal	alarm	alarm

4.1 Parameter table

The Table 3 below shows the calculation of the probabilistic parameters of each cause knowing the failure. Then in this step we will calculate all the parameters in the two cases of the machine. That is to say the alarm or no alarm machine and do a comparison between the values. For this purpose, we will choose the greatest value of the probability to get to know the state of the machine.

4.2 Test and validation

In the test phase, authors studied the database of 20 tests with their failure states on the battery production machine, and then calculated the predicted failure state from our Bayesian model to compare this result with the state of the failure observed during the test. Table 4 below lists all the causes with their failures.

The Table 4 presents the outcomes of 20 individual tests conducted on a battery production machine, each characterized by four input conditions: Cause_1 through Cause_4, and their corresponding observed failure state. The final two columns represent the actual failure observed during the test and the failure predicted by the Bayesian model, respectively. Each test involved varying combinations of cause levels (e.g., -high, -decreased, -normal, -not high) that may influence machine behavior. These causes represent operational factors or sensor readings critical to the process. The model's objective was to predict whether a failure would occur under each test condition. A comparison of the actual outcomes and the model's predictions shows that, in 18 out of 20 cases, the Bayesian model correctly predicted the failure state. This results in a prediction accuracy of 92%, demonstrating a strong alignment between the model's inference and the real-world behavior of the machine.

The few discrepancies where the model predicted -no alarm but a failure occurred highlight areas for possible refinement. Nonetheless, the high accuracy confirms that the Bayesian model effectively captures the relationships between input causes and failure outcomes, making it a valuable tool for real-time monitoring and predictive maintenance in battery production systems.

5. Conclusions

In this work, our objective was the implementation of a monitoring tool for an industrial system; this tool must have the capacity to predict failure by observing the parameters of this industrial system. To achieve this objective, we have adopted the techniques of artificial intelligence, in particular artificial learning. This field offers us as many powerful techniques, of which we have chosen Bayesian networks. In a first step, we proceeded to the preparation of the learning database (corpus), and then we succeeded in designing the probabilistic model as well as its parameters. To validate our surveillance system, we used another database (test corpus), which gave relevant results (about 92% of cases predicted successfully).

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