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FAULT PREDICTION OF PHARMACEUTICAL AIR COMPRESSOR USING THE INTELLIGENT MODEL BASED ON THE BAYESIAN NETWORK

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Abstract: This paper presents a new approach of diagnosis and prognostic in real-time of strategic equipment of pharmaceutical industry. This approach is developed using Bayesian network (*BN*) which consider industrial data and feedback experience. The objective is to detect, locate and prevent any malfunction of the air compressor (oil-free) without air contamination, dedicated to pharmaceutical industry. The study is based on the functional analysis of the air compressor to obtain the fault tree (*FT*). This *FT* is transformed into *BN* to diagnose automatically the compressor and prevent any malfunctioning.

Key words: Pharmaceutical standard requirements, Air compressor (Oil free), Artificial intelligence, Bayesian network, Industrial diagnosis and prognostic, Fault tree.

1. Introduction

Nowadays, the economic stakes are more and more complex, in terms of production, quality, cost, security, reliability, etc. Pharmaceutical manufacturing processes are even more complex and rigorous in terms of rules. Considering these current standards and rules of air compressor oil-free, this is the principal organ of the pharmaceutical production line. A diagnostic strategy of the air compressor has been developed to optimize and make its operation more productive. The diagnostic approach is based on the fault tree remodeled in the form of Bayesian network to determine the most critical organs.

2. Application system description

Air compressor oil-free (standard: ISO 8573-1 Class 0) is the utility source in the pharmaceutical production line. Thus, any defects or incorrect parameters configuration of the compressor will cause the unavailability of all equipment in the process fabrication. The requirements fulfillment of the manufacturing process and quality criteria of the drugs are strictly rigorous in pharmaceutical industry. The physical parameterization (pressure, temperature ...) should be with normalized precision according to the standard requirements. The compressor air pressure should be as exact as possible with tolerance according to the norms and the international rules of drug manufacture. Compressor air Maintenance is one of the manufacturers concerns of health experts. In this study we propose a new approach to diagnose on-line the air compressor. [1, 2].

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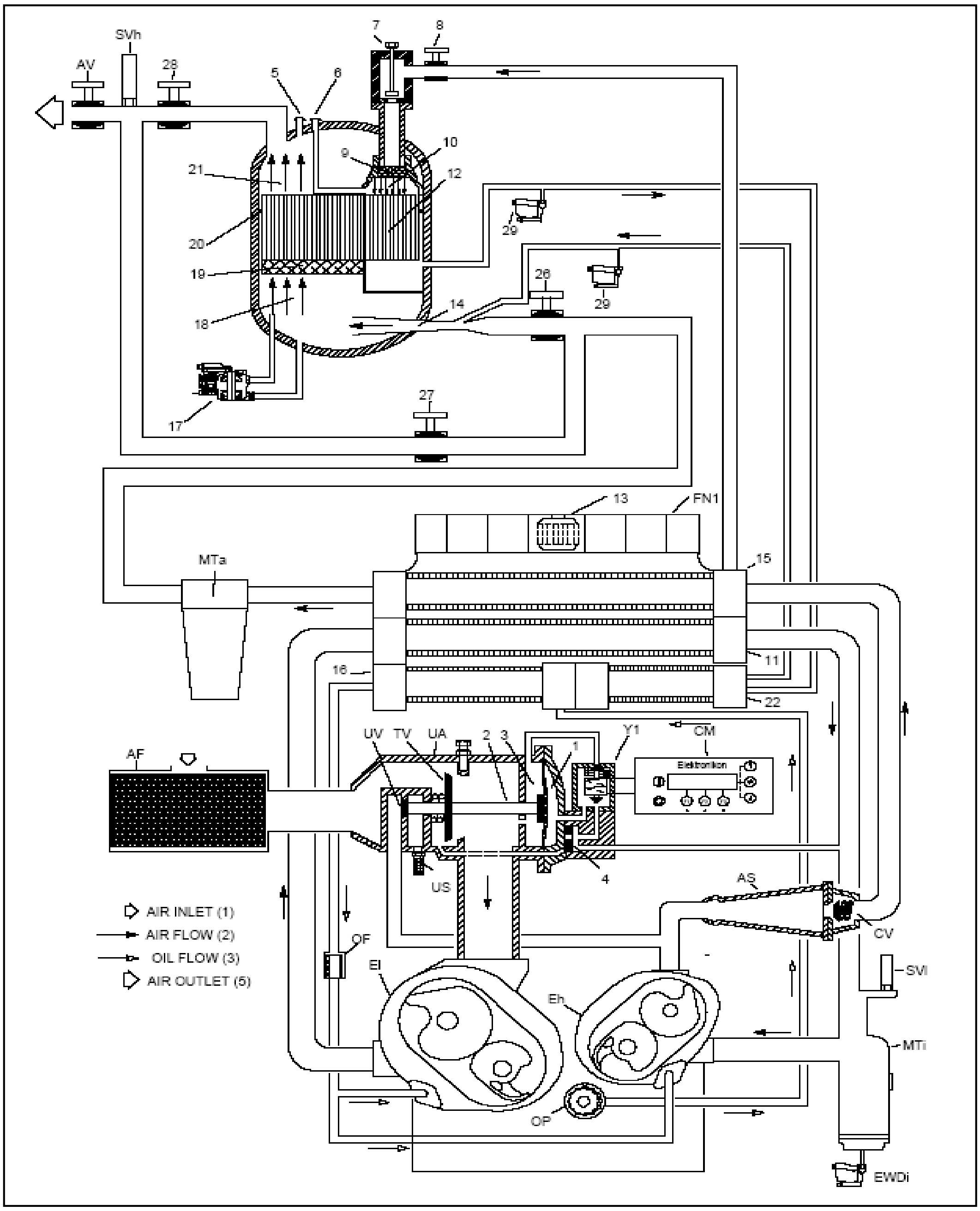

Fig.1. Mechanical schema of the air compressor [2]

3. Development of the new approach

The automated diagnosis [3], [4] of the air compressor is based on detailed functional analysis. This analysis is performed with the collaboration of maintenance engineer and feedback experiences. This is considered to consolidate the database. The fault tree construction (*FT*) is a crucial passage in modeling the normal functioning of the air compressor. However, the FT method gives the possibility to analyze and calculate the conditional probability of the default knowing that the results are offline. To make the default information essential on-line the conversion of the *FT* towards artificial intelligence tools are necessary. The proposed approach consists of developing and elaborating an automated diagnosis based on default prognostic.

3.1. Functional modeling of the compressor

The failure tree [5, 7, 8] is a deductive analysis method based on the construction of a tree structure which allows identifying the failure combinations or the leading causes of apprehended event (or undesirable event). To determine the apprehended events, we rely the manufacturer database, on the historical default events and the maintenance engineer experiences feedback. Based on these data, we have developed the functional decomposition model of the air compressor, oil-free.

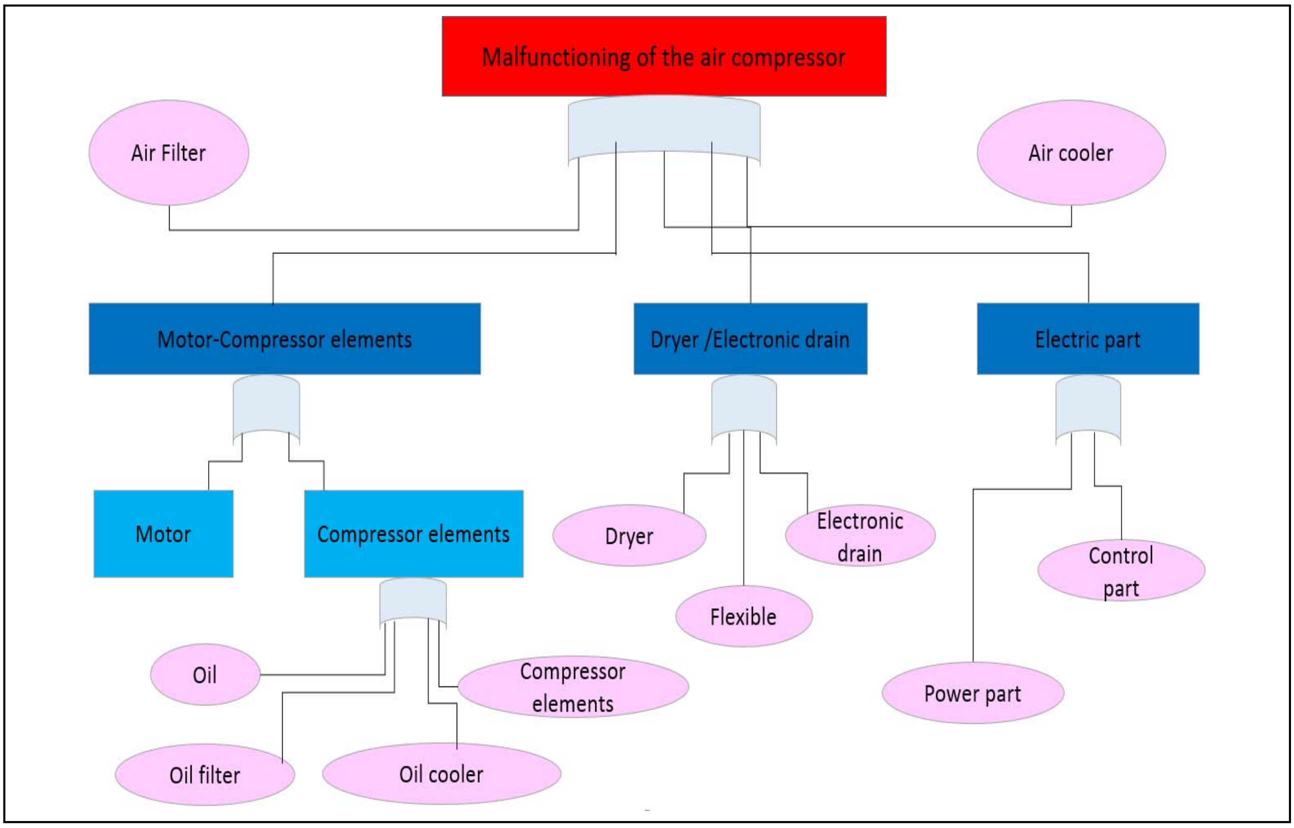

Fig.2. Failure Tree (*FT*) of Air-free compressor

This model is built by taking into account the most critical elements that cause the compressor defects. These critical elements are shown in Fig.2 (magenta color) and are connected by an OR gate appropriate to the functioning required. The detailed air compressor elements are shown in Fig.2 in blue lighted color. The first level functional decomposition is represented in darker blue of Fig.2. The red color area gives us the status of the diagnosed element. The *FT* of the air compressor is shown in Fig.2.

3.2. Functional Calculation of the failure probabilities of each element in the fault tree

Table 1 is filled according to the historical air compressor database. The total number of compressor failures is the sum of all failures of the *FT* elements. The total amount of compressor failures corresponds to a probability of 1. To find the probability of each element in the *FT*, we divide the number of each element by the total number of compressor failures. This allowed us to know the functioning status of each element in the FT. All these identified probabilities of each element of the air compressor will be considered as a reference in our analysis.

Table 1. Calculated failure probabilisties of each element in the *FT* [2]

Elements	Failure numbers	Failure Probability
Motor	1	0.0344
Compression element	3	0.1034
Oil	6	0.2068
Oil filter	6	0.2068
Oil cooler	4	0.1379
Dryer	1	0.0344
Electronic drain	2	0.0689
Flexible	1	0.0344
Air filter	2	0.0689
Control part	2	0.0689
Power part	1	0.0344
Total failure number	29	1

4. Development of the Bayesian network

Bayesian networks (*BN*) are models which allow presenting probabilistic reasoning situations based on uncertain knowledge. The Bayes theory is a formalism based on probability and graph theories. They are also known as the "causality network" for a single graphic probabilistic model.

4.1. Graphics

tool allowing visualizing and representing variables (attributes of a problem) and their dependencies for a system based on graph theory [9], where the variables are modeled by nodes. These nodes are related by oriented arcs to build an acyclic graph (without circuit). The fact of indicating an oriented arc between two nodes, it shows that there is a causal relation [10]. From this relation we can distinguish parent nodes which can influence the behavior of the child nodes and we have also root nodes (without parents).

4.2. Probabilistic events

A mathematical object relatively simple, allows describing quantitatively the functioning of a system by calculating the probabilities for each variable of the system based on Bayes theory. Suppose two events A and B, the conditional probability of B knowing A in a context C can be determined by the relation given by Eq.(4.1) [11-17].

$$P\left(\frac{B}{A,c}\right)=\frac{P\left(\frac{B}{c}\right)P\left(\frac{A}{B,c}\right)}{P\left(\frac{A}{c}\right)} \tag{4.1}$$

$P\left(\frac{B}{A,c}\right)$: Posteriori probability *B* knowing *A* in context *c*.

$P\left(\frac{B}{c}\right)$: Prior probability of *B* in context *c*.

$P\left(\dfrac{A}{B,c}\right)$: Likelihood function of *A* Knowing *B* in context *c*.

$P\left(\dfrac{A}{c}\right)$: Normalized probability.

Formally, a Bayesian network is defined by:

- Acyclic oriented graph without circuit $(AOG)G=(V,E)$, where V is the node sets of *G* and *E* the arc sets of *G*,
- The probabilistic space (Ω, Z, P), Ω a non-empty finite set, *Z* a set of subspaces of *Ω* and *P* a probability measure over Z with $P(\Omega)=1$,
- A set of random variables associated with nodes of the graph G defined on (Ω, Z, P) such that:

$$P(V1, V2, \ldots, Vn) = \sum_{i=1}^{i=n} P\left(\frac{Vi}{c(Vi)}\right) \tag{4.2}$$

Where $c(Vi)$ is the parents set (or causes) of Vi on graph G.

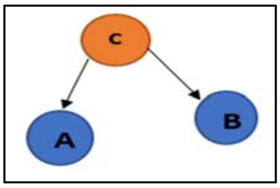

Fig.3. Bayesian graph representation.

4.3. Bayesian Network Construction

First step, we construct a database based on expert system and the study of functional analysis. This will allow us to build the fault tree of the air compressor. This *FT* constitutes the platform to an automatic triggering of an intelligent model based on Bayesian networks [11], [12].
Second step will concern the development of an offline basis, using *FT* functional method, to an online basis, using intelligent *BN* method. This passage is proceeded as follows:

4.4. Fault tree compressor codification

Fig. 4 shows the new representation of fault tree codification using numbers instead of organ element of the air compressor. This is done so, to facilitate the transformation of the FT in network form.

4.5. Conversion of the fault tree into Bayesian network

Figure 5 shows the transformation [6] of fault tree into Bayesian network. The first elements of the network are considered as 'parents' (magenta color). These elements are connected via oriented arcs to others elements considered as 'children' (blue and grey color). The same procedure is applied until we end up to the last element considered as the last 'child' of the Bayesian network. This last element is identified as the feared element (red color).

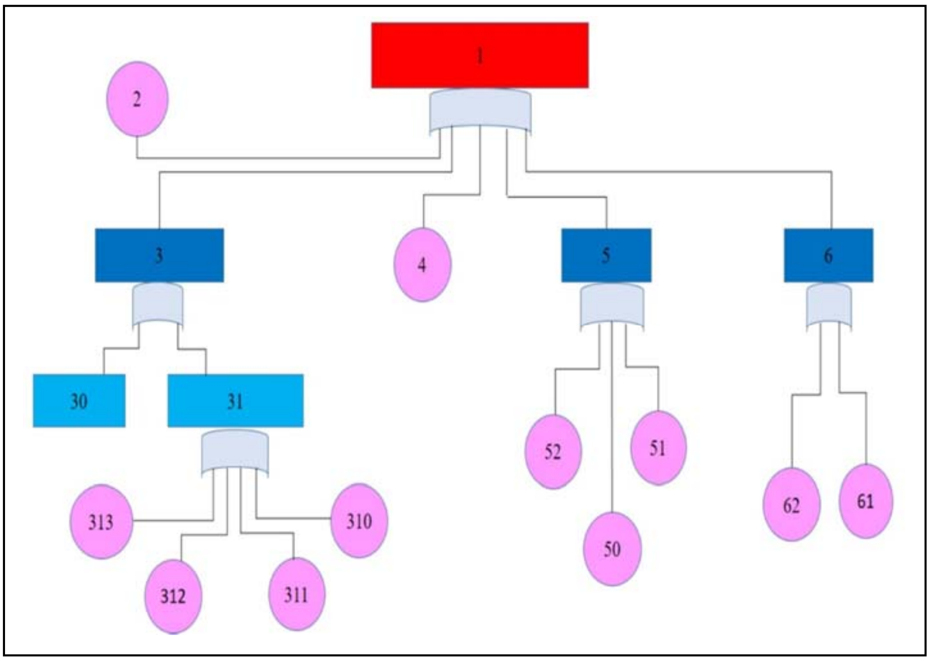

Fig.4. Fault Tree codification of the air compressor.

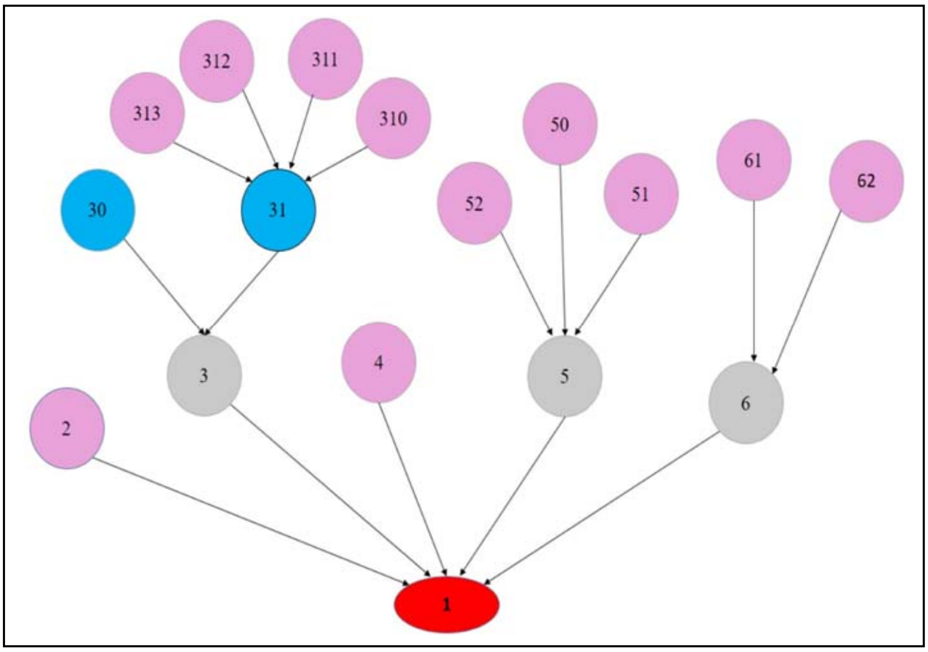

Fig.5. Developed Bayesian network based on *FT*.

4.6. Logical form conversion of the fault tree into a Bayesian network

After obtaining the developed Bayesian network based on the *FT* of the air compressor, we convert its representation into a graphical logic form. The fundamental graphic elements representations of the *FT* are events and logic gates type *OR/AND*. While the Bayesian network elements representations are nodes which represent the events and arcs model the dependencies. Then we calculate the probabilities of each element of the Bayesian network. It consists of performing the occurrence probabilities of the basic elements (primary) events of the *FT* to root nodes as priori probabilities. For the induced event (intermediate) cases and dreaded event (top of the *FT* or final event) their probabilities will be calculated based on the conditional probabilities calculations as explained in Fig. 6.

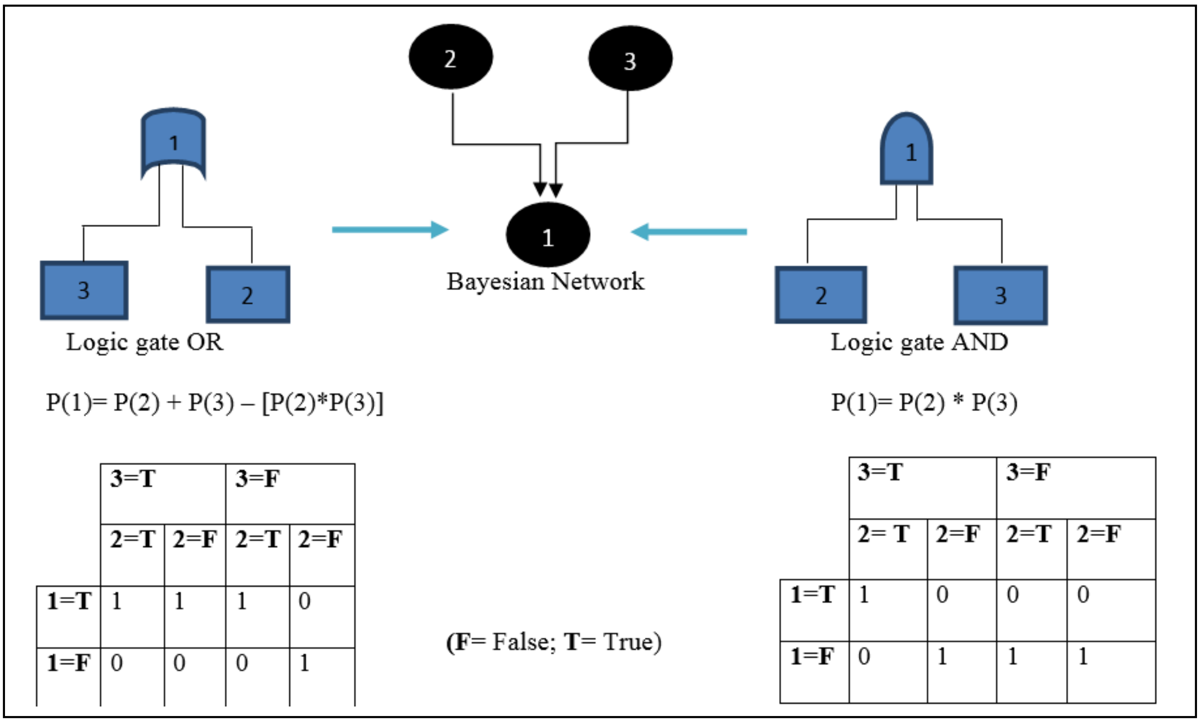

Fig.6. Logical form conversion of the *FT* into Bayesian network.

Table 2. Various events and their occurrence probabilities

	Events				**Code**	**Prior P( )**	**Posterior P( )**
01	Malfunctioning of the air compressor				1	Or Gate	0.9387
02	Or	Air Filter			2	0.1429	0.1429
03	Or	Motor-Compressor elements			3	Or Gate	0.82989
04			Motor		30	0.07143	0.07143
05		Or	Compressor elements		31	Or Gate	0.1832
06				Compressor elements	310	0.2143	0.2143
07			Or	Oil cooler	311	0.2857	0.2857
08			Or	Oil filter	312	0.4286	0.4286
09			Or	Oil	313	0.4286	0.4286
10	Or	Air cooler			4	0.2857	0.2857
11	Or	Dryer/ Electronic drain			5	Or Gate	0.2610
12			Flexible		50	0.07143	0.07143
13		Or	Electronic drain		51	0.1429	0.1429
14		Or	Dryer		52	0.07143	0.07143
15	Or	Electric part			6	Or Gate	0.20413
16			Power part		61	0.07143	0.07143
17		Or	Control part		62	0.1429	0.1429

Table 2 shows all the obtained occurrence probabilities of Bayesian network. The root event probabilities of Bayesian network are calculated from the failure's history, known as a priori probabilities. The intermediate events probabilities and the dreaded event probability are calculated using the conditional probabilities tables, known as posteriori probabilities (or occurrence probabilities).

5. Learning and Bayesian network

In this last step of our developed approach, we present in this section two important aspects of how to exploit the Bayesian Network with the obtained occurrence probabilities.

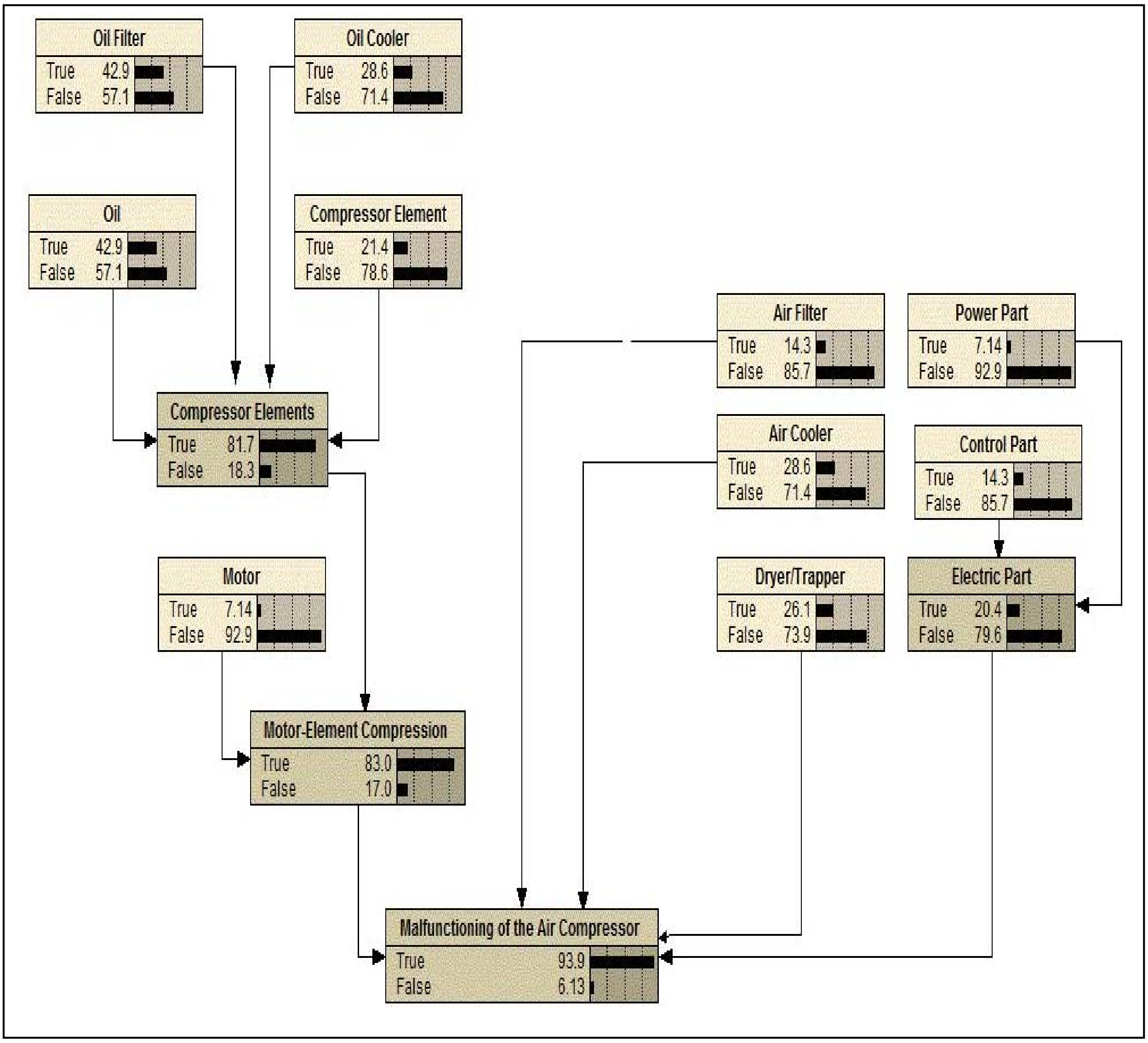

Fig.7. Obtained results of Bayesian network under NETICA software.

- **Network learning:** this step consists of learning the Bayesian network the good parameters in order to calculate the next probabilities (a posteriori) automatically by NETICA software as shown in Fig. 7.
- **Bayesian network test:** this step consists of testing the obtained results by the Bayesian network by comparing the theoretical calculation obtained in Table 7 and those obtained by NETICA Software.

6. Test and validation

The calculated results of the occurrence probabilities of Bayesian network, developed under the logical fault tree conversion are compared to those obtained by NETICA software. The comparison results are given in Table 2. Table 3; error evaluation of occurrence probabilities between calculated and simulated values Table 3. Error evaluation of occurrence probabilities between calculated and simulated values

Events	Calculated values in %	Simulation values in %	Error in %
Dreaded event			
Air compressor	93.87	93.9	0.03
Intermediate events			
Motor-compressor elements	82.989	83	0.011
Air Filter	14.29	14.3	0.01
Air cooler	28.57	28.6	0.03
Dryer / Traps	26.10	26.1	0.00
Electrical part	20.413	20.4	0.013
Average error is: 0.01			

According to Table 3 the probability of the dreaded event calculated theoretically is *93.87%* (see Table 2) which represents a good detection. The main cause of this defect is the Engine, element of compression which has the highest probability of failure in the Bayesian network which is *82.989%*, this represents a good localization.
From the obtained results given in Table III, we can deduce that:

- The choice of learning parameters of the network under NETICA software is adequate,
- The reliability of the results obtained by NETICA software is of high-quality sine the obtained average error value is *0.01%*,
- We obtain a good detection and a good localization of the defects with an average error of *0.01%.*
- The prevention of defects is automatic because all the Bayesian Network probabilities are quantifiable and the triggering of future probabilities is natural.

These obtained results allowed us to conclude that the diagnosis and prognostic of the compressor failures are automated.

7. Conclusion

In order to meet the quality requirements, reliability and availability of pharmaceutical facilities needed by the industrials, we propose a new approach which consider realistic parameters and fulfill the requirement of the industry. The expertise study and Fault Tree analysis show a perfect adequation between the theoretical and simulated results. The developed functional model of the air compressor by *FT* is the solution adopted in this work. The expertise analysis of the air compressor by the *FT* shows causal relationships between the elements constituting the system and their criticalities. This facilitates the diagnosis but the *FT* method gives offline results. Each time the *FT* method should restarted the expert analysis. This constitutes the major disadvantage of the method. To overcome this disadvantage, we have proposed a new approach. It consists of transforming the *FT* to Bayesian network. The objective of this transformation is to calculate automatically the default probabilities without restarting the analysis from the beginning. The probabilities are updated automatically and the threaded element is detected automatically. This will prevent any damaging of the air compressor.

Nomenclature

A – events
B – events
C – context
G – graph
V – set of modes of G
E – sets of arcs of G
Ω – non-empty finite set
Z – set of subspaces of Ω
P – probability measure on Z
ET – fault tree
BN – Bayesian network

References

[1] Benazzouz D., Amrani M. and Adjerid S. (2012): *Back-propagation algorithm used for tuning parameters of ANN to supervise a compressor in a pharmachemical industry*.– American Journal of Intelligent Systems, vol.2, No.4, pp.60-65.

[2] *Air compressor ZT45 operation and maintenance manual*.– Thechnical documentation of Laboratoires BEKER, Dar EL Beida, Alger, Algérie.

[3] Afia S.A., Rahmoune C., Benazzouz D. and Merainani B. (2019): *New gear fault diagnosis method based on MODWPT and neural network for feature extraction and classification*.– Journal of Testing and Evaluation, vol.49, No.2, pp.22.

[4] Zair M., Rahmoune C. and Benazzouz D. (2018): *Multi-fault diagnosis of rolling bearing using fuzzy entropy of empirical mode decomposition, principal component analysis, and SOM neural network*.– Journal of Mechanical Enginneering Science, vol.233, No.9, pp. 1-12, https://doi.org/10.1177/0954406218805510

[5] Chiremsel Z, Said R.N, and Chiremsel R. (2016): *Probabilistic fault diagnosis of safety instrumented systems based on fault tree analysis and Bayesian network*.– Journal of Failure Analysis and Prevention, vol.16, pp.747-760.

[6] Wang X., Wu K., and Xu Y. (2014): *Research on transformer fault diagnosis based on multi-source information fusion*.– International Journal of Control and Automation, vol.7, No.2, pp.197-208.

[7] Mahmood Y.A., Ahmadi A., Verma A.K., Srividya A. and Kumar U. (2013): *Fuzzy fault tree analysis: a review of concept and application*.– International Journal of System Assurance Engineering and Management, vol.4, pp.19-32.

[8] Steiner N. Y., Hissel D., Moçotéguy P., Candusso D., Marra D., Pianese C. and Sorrentino M. (2012): *Application of fault tree analysis to fuel cell diagnosis*.– Internationale Conference on Fundamentals and Developments of Fuel Cells in Grenoble, France.

[9] Zhe-wen Z., Yong W., Ding Y., Lei T. and Ying-Jian Z. (2019): *A transformer fault diagnosis method based on Bayesian network*.– Journal of Physics, Conference Series.

[10] Lakehal A., Chelli Z. and Djeghader Y. (2019): *A hybrid Bayesian network based method to assess and predict electrical power network reliability*.– 4th World Conference on Complex Systems (WCCS), Ouarzazate, Morocco.

[11] Lakehal A. and Ramdane A. (2017): *Fault prediction of induction motor using Bayesian network model*.– International Conference on Electrical and Information Technologies (ICEIT), Rabat, Morocco.

[12] Lakehal A., Ghemari Z. and Saad S. (2015): *Transformer fault diagnosis using dissolved gas analysis technology and Bayesian networks*.– International Conference on Systems and Control (ICSC), Sousse, Tunisia.

[13] Bacha A., Sabry A.H. and Benhra J. (2015): *An industrial fault diagnosis system based on Bayesian networks*.– International Journal of Computer Applications, vol.124, No.5, pp.1-7.

[14] Zhiqiang C., Weitao S., Shubin S. and Shudong S. (2014): *Modeling of failure prediction Bayesian network with divide-and-conquer principle*.– Hindawi Publishing Corporation Mathematical Problems in Engineering, vol.2014, pp.1-8.

[15] Carbery C.M., Woods R. and Marshall A.H. (2018): *A Bayesian network based learning system for modelling faults in large-scale manufacturing*.– IEEE International Conference on Industrial Technology, vol.2018, pp.1357-1362.

[16] Weitao S., Zhiqiang C., Shudong S. and Shubin S. (2014): *Integration of failure prediction Bayesian networks for complex equipment system.*– IEEE International Conference on Industrial Engineering and Engineering Management, Selangor, Malaysia.

[17] Soltanali H., Khojastehpour M., Farinha J.T. and Edmundo J. (2021): *An integrated fuzzy fault tree model with Bayesian network-based maintenance optimization of complex equipment in automotive manufacturing.*– Modeling and Optimization of Electrical Systems, vol.14, No.7758, pp.1-21.

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