Original Research

A probabilistic hybrid methodology for the management and control of risks related to the production system: Case of industrial textiles

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Abstract

A significant issue for businesses is the risks connected to the production system, which can be related to people and their expertise, the technology being utilized, or the environment, endangering their productivity, continuity, and development. Risk assessment procedures are necessary to determine the most likely source of an undetected hazardous event that prevents the system from performing its function. This paper proposes a probabilistic methodology to evaluate the risks associated with a combed spinning workshop factory inside a textile company. It is a hybrid strategy based on the BN and the MADS-MOSAR methodology. In this proposal, we employ the MADS model to pinpoint risk sources from both human and environmental sources. The MOSAR approach, however, has some quantitative drawbacks. To get past this issue, we also present the integration of BN. The results of the experiments show that the suggested technique is competitive and more effective for managing and reducing risks; all types of enterprises can use it.

Keywords - Risks management; MOSAR method; MAD model; Bayesian Network; Fault Tree

INTRODUCTION

The risks in a production system are a significant worry. In addition to potentially resulting in property damage and human life losses, they can degrade the performance system and prevent it from achieving its goals. Due to the wide range of products, identifying disruption risks in the manufacturing system takes frequent and intentional identification. The adherence to delivery dates will be severely hampered if a disruption becomes effective [1]. The goal of all the methodologies established by researchers over the past few years for dealing with system safety and risk analysis issues is to lower the catastrophic risk to an acceptable or tolerable level [2]. There are no "good" or "bad" risk analysis approaches among the sixty-two that Tixier et al. [3] found. These techniques are merely tools for directing reflection. Therefore, using the methods to help with the cases is wise. To get good outcomes, these approaches must be applied with experience. It may be a springboard for developing a novel approach [3]. The quantitative MADS/MOSAR method draws from these and incorporates deterministic and probabilistic methods. Considering technological, human, and environmental risk factors, plans and designs for the site, installations, and units are necessary for implementation. These factors make this approach suitable in our situation. "The analysis technique of dysfunctional systems" is called MADS, and "The organized and structured method of risk analysis" is called MOSAR [4]. On a methodological level, however, this methodology has certain drawbacks [5, 6, 7].

To tackle the challenge of simulating the domino effect, Smaiah et al. [7] suggested a method to enhance the MADS-MOSAR model framed by the SFT "Source-Flow-Target" triptych. The method presented by Hamzaoui et al. [6] uses the MOSAR method for risk analysis of building projects and integrates concepts from systems engineering and risk control with a multi-agent platform simulation. The UML-MOSAR methodology was created by Gallab et al. [5] and considers interactions between all maintenance activity components for assessing risk in maintenance. New risk assessment methods that can give the industry more data and flexibility for better risk management than the methods now in use must be developed. Many scholarly publications offer Bayesian Network (BN) based plans for risk analysis, system operational safety, diagnostics, or maintenance. BNs are probabilistic models that enable the description of complicated processes that are not amenable to analytical modeling. When attempting to solve a problem, including dependencies between uncertain variables, especially when these dependencies are also unclear, using the BN is advised [8]. We recommend incorporating the BN to develop and go over the limits of the MADS/MOSAR methodology because of this capability.

In a few recent academic papers on BN, Bobbioa et al. [9] contrasted BN with FT (Fault Tree) to examine the potential of BN formalism in analyzing reliable systems. Jones et al. [10] application of B N modeling provided an enhanced and accurate way of determining a system's parameter failure rate. An approach to transforming an FT into a BN was published by Khakzad et al. [11]. Additionally, Zheng et al. [12] contribution combines the strengths of two approaches—the F T and the B N—to boost the effectiveness of the subsequent fault analysis. At a hydrogen refueling station, Haugom and Friis-Hansen [13] constructed a BN of gas risks that considered gas leaks, jet fires, and human casualties. For geometric flaws of the tree with a discontinuous surface, Cao et al. approach of process evaluation and fusion control based on Bayesian theory was developed [14]. For handling uncertainty in the failure diagnosis of large CNC machines, Liu et al. [15] introduced an integrated method combining Bayesian theory with failure Tree Analysis (FTA). Smith et al. [16] compared the FT, BN, and Functional Resonance Analysis Method (FRAM) approaches to show the value of combining several analysis methodologies.

A dynamic BN and Fault tree-based operational risk assessment method for a chemical process system was presented by Barua et al. [17]. A grid-based risk mapping strategy designed for explosion events was put forth by Huang et al. [18]. This approach calculates each grid's outcomes and associated probabilities using a BN as a risk analysis tool. To identify crucial organizational and human elements in the escape, evacuation, and rescue systems, Norazahar et al. [19] established a method. They used BN to determine how crucial each factor was. Eickemeyer et al. [20] created forecasts to assess the workload in maintenance processes using data fusion in Bayesian networks. By identifying the causative parameters and the avoidable range of their values, Amit & Ravi [21] created a casting defect analysis method based on Bayesian inference to evaluate and prevent problems in investment castings. The benefits of B N over FT in reliability and safety analysis, as well as ways to enhance the safety system, were covered by Zerrouki & Smadi [2]. The risk treatment paths of the production system were developed and evaluated by Roth et al. [22] using the Bayesian technique. Dahia et al. [23], a dynamic B N, simulates and assesses multi-state degraded systems' upkeep and functional dependencies.

This study suggests a novel method for risk assessment that combines the Bayesian approach with the MADS/MOSAR method. These dangers may be caused by technology, the environment, or people and their knowledge. The technique was used at the textile company's combed spinning workshop. The remainder of the essay is organized as follows. The development of the approach is covered in Section 2, the case study is covered in Section 3, and the discussion in Section 4 is proven. The management plan proposed in Section 5. 6 provide summaries of the conclusion and viewpoint.

METHODOLOGY

The process is described in general in this section. By adding BN into MADS-MOSAR, a MADS-MOSAR-Bayes strategy is established in the current work to enhance the production process and manage the risks connected to the operation of a production system. In this instance, the suggested strategy to accomplish our research goal is focused on:

• Identification of risk sources.
• Recognizing potential scenarios for undesirable outcomes.
• Creating the risk analysis steps.
• Considering environmental, societal, and technological risk factors.
• Updates the data after each new piece of information.

The suggested method (Figure 1) progresses through various phases. When we apply the MADS approach to offer a general hazard model, the appropriate risk model chosen during this phase is the phase key of the risk analysis. After obtaining the model, the MOSAR method was utilized to determine the danger's origins and create scenarios for undesirable events. This method can provide a "restricted" description of the propagation of probabilities in a system for the risk assessment phase. Instead of calculating the likelihood that the events will occur, we have suggested integrating the BN to make the MOSAR more effective and specific. Finally, a list of safety barriers is offered based on the outcomes of the risk control.

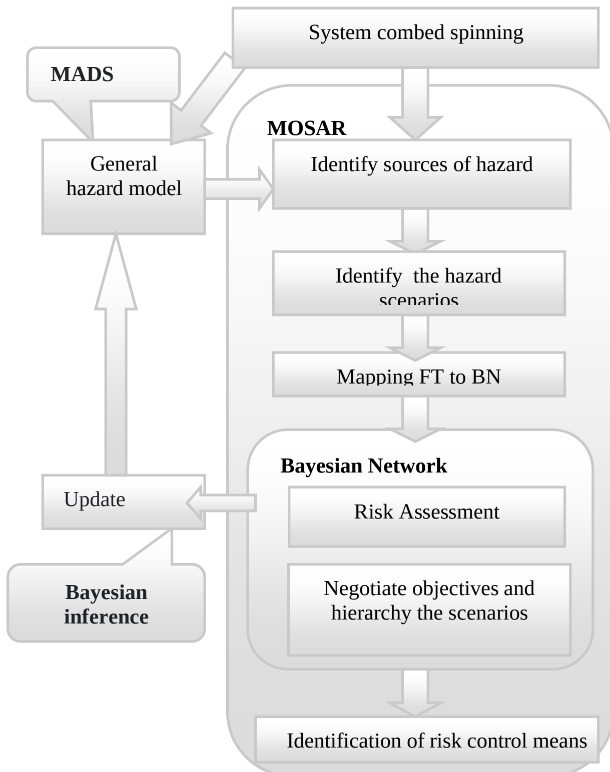


FIGURE 1
PROPOSED APPROACH

- *Presentation of the MADS / MOSAR methodology*

The strategy used is the "MADS-MOSAR" methodology that a team of experts from the CEA (French Atomic Energy Organization) developed [7]. The MADS model assesses the possible harm in certain areas and systematically unravels complicated systems. It enables the modeling and identification of the mechanisms that pose a risk between sources of hazard and targets (Figure 2) [4].

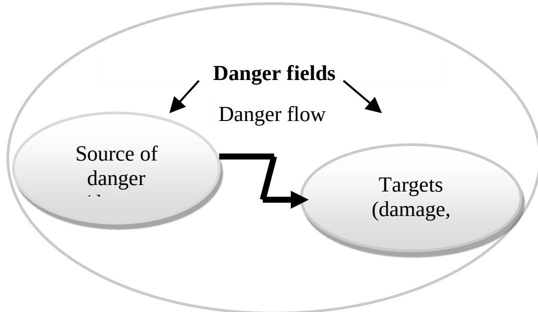


FIGURE 2
BASIC REPRESENTATION OF MADS [4]

On the MADS model, MOSAR is based. Its goal is to identify problems and control hazards in a complicated system. The MADS/ MOSAR methodology is a general strategy that analyzes the system's threats while defining the risk reduction strategies through protection, mitigation, and prevention [24]. The systemic modeling of the system is used by the MOSAR approach, which was primarily developed for industrial installations, to detect and assess the hazards. This approach's two modules, (A) and (B), are a system-wide macroscopic analysis and a system-wide microscopic research, respectively. It will be a matter of applying module (A) to the system of combed spinning shown in Figure 3 as part of this paper [4, 24].

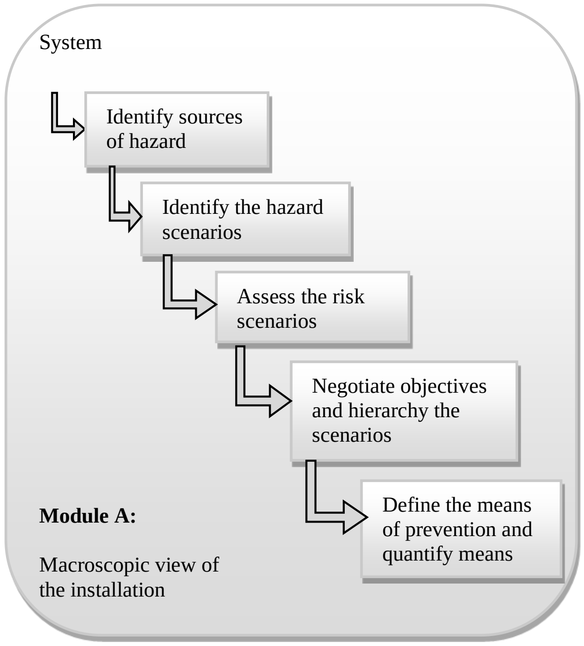


FIGURE 3
MODULE A OF THE MOSAR METHOD [24]

- *Bayesian Network (RN)*

An artificial intelligence technology, BNs, is used to model uncertainty in a system or domain [10]. Based on probabilistic and ambiguous knowledge, BNs are increasingly utilized to develop system reliability models, manage risk, and examine safety. Using a BN, you can view variables and their dependencies (or independences). The multiple probability calculations involving the system's variables also enable one to explain a system's operation quantitatively [25]. It is defined by:

- its graphic component represented by a directed acyclic graph *G* (DAG) comprising nodes *X* and arcs *E*, *G= (X, E),*
- its quantitative component μ represented by probability tables (PT) for parent nodes and conditional probability tables (CPT) for descendant nodes, $\mu = \{\mu i\} = \{P\ (Xi\ /\ Pa\text{-}rents\ (Xi))\}$,
- a set of random variables associated with the nodes, $X = \{X1, X2, X3\}$.

These variables can be discrete (PT, CPT) or continuous (distributions), observable or unobservable, and can take different states (true, false…). In the general case, $X = \{X1, X2,\ldots, Xn\}$, the distribution function joint *P (X)* breaks down in the following form:

$$P(X) = \prod_{i=1}^{n} P\big(Xi/\text{parents}(Xi)\big) \qquad (1)$$

The calculation in a BN based on Bayes' theorem (by T. Bayes), it is possible to obtain the updated (posterior) probability of events by observing new evidence (X1):

$$P(X2/X1) = \frac{P(X1/X2)\,P(X2)}{P(X1)} \qquad (2)$$

- *P (X1)* is the a priori (or marginal) probability of *X1*.
- *P (X2/ X1)* is the posterior probability of *X2* knowing *X1*. *P (X1 / X2)* is the likelihood function of *X1* knowing *X2*.

Probability updating is the primary use of BN. The purpose of inference in a BN is to compute (or update) all conditional probabilities of a model variable from the causal structure (tree of causes and effects) and the related probability distributions. The foundation of this computation is the Bayes theorem and the conditional probability laws [28]. Equation (2) can be used for probability updating or prediction. The conditional probabilities of type P (accident/event) are derived in the predictive analysis to show the likelihood of a specific accident occurring, given the existence or non-occurrence of a particular main event. On the other hand, those of form P (event/accident) are evaluated when updating the analysis, showing the likelihood that a specific event will occur given the occurrence of a particular accident [28].

APPLICATION OF THE METHODOLOGY; CASE STUDY

A combed spinning workshop within a Textile Company was selected as the case study for applying the MADS-MOSAR-Bayes. The primary function of this workshop is to remove the shortest fibres to obtain a more regular yarn and higher quality (more expensive but better). This system has additional steps compared to carded spinning (preparatory stretching, reuniting, combing, assembling, and twisting). The different stages of this process are presented in Figure 4.

1. Opener / Threshing: Opener and preliminary cleaning of cotton layers in small cotton flakes.

2. Carding: processing cotton in veils than in rolled-up ribbon in pots.

3. Preparatory stretching: ensure the regularity of the ribbons. Eight ribbons are joined to come out only one of the same size, and thus homogeneous.

4. Reuniting: the new ribbons are gathered in a 'sheet' to form rollers that feed the next step.

5. Combing: consists of eliminating the shortest fibers, essential to obtain a quality thread.

6. Stretching: it consists of three passes respectively on stretch machines in the purpose is to ensure the parallelism of ribbons.

7. High stretch: it aims to ensure the parallelism of ribbons from carding to make them more flexible.

8. Spinning: the Machines Continue to Filer (MCF) designed to transform the wick into a thread gauge (or a metric number of 60 and 20)

9. Winding: the thread spindles carried out by the MCFs are put under 2 kg conical winder shapes.

10. Assembly and Twisting:
Assembly: consists of assembling two simple yarns (60/1) to a determined length with some support.
Twisting: Sequence of twisting together the assembled yarns (60/2)

FIGURE 4
THE PROCESS STEPS OF THE COMBED SPINNING WORKSHOP

- *The MADS model*

The MADS model, which enables us to recognize and analyze the danger mechanism between sources of danger and targets in the combed spinning workshop (Figure 5), is an essential step in a risk study.

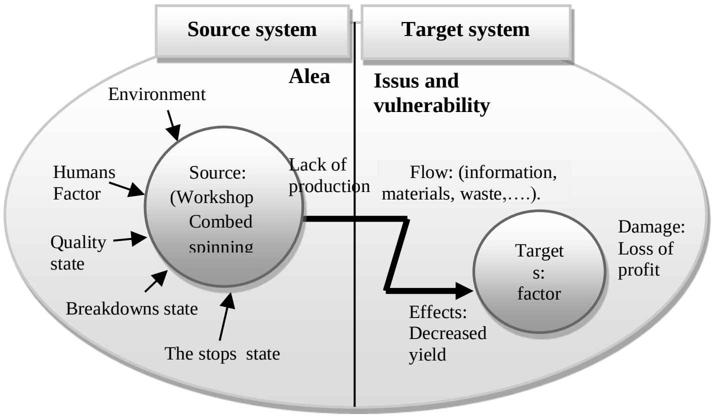


FIGURE 5
GENERAL HAZARD MODEL BY MADS

- *Identification of sources of hazard*

Modeling the combed spinning workplace utilizing a functional separation of the workshop into subsystems is the first step of the MADS/MOSAR method (Figure 6). We can identify three subsystems from the previous description of the combed spinning workshop:

1- SS1: The principal system consists of four groups: (a, b, c), and (d).

- a: Opener / Threshing, Carding, Preparatory stretching,
- b: Reuniting, Combing, Stretching.
- c: High stretch, Spinning.
- d: Winding, Assembly / Twisting.

2- SS2: Human factor.

3- SS3: Environment.

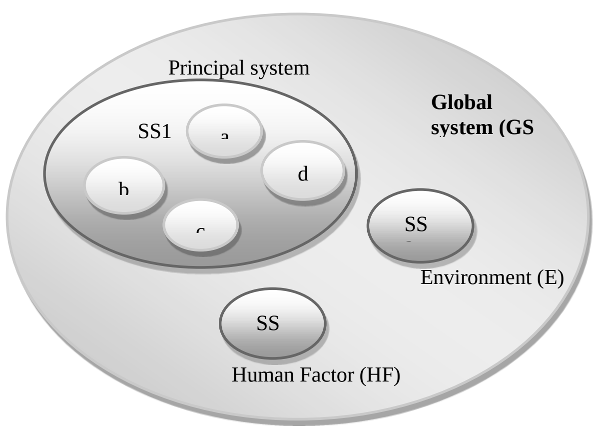


FIGURE 6
FUNCTIONAL DECOMPOSITION OF THE WORKSHOP

Table 1 of the MADS / MOSAR method used to define the possible initiating events (the risks associated with the combed spinning workshop) that may be the origin of the initial events (the effects on the system). Also, we determine the principal events (unwanted events) that have impacted the target company's performance decline.

TABLE 1
IDENTIFICATION OF THE SOURCES OF HAZARD FOR THE SUBSYSTEMS: THE 'A TABLE' OF THE MADS/MOSAR METHOD

Hazard sources	Initiating events	Initial events	Principal events
SS1: Principal system (a, b, c and d)	The stops state	- Decrease in production - Limited production	
	Breakdowns state	-Decreased profitability of the machine -Decrease in the production of the wick and blended ribbon (cotton + polyester)	
	Quality state	-Loss of yarn (poor quality: waste)	- Lack of production
SS3: Human factor	Responsibility	Influenced on the rate of production	
	Decisional process	Using the machines in the wrong place can damage them and make them of poor yarn quality	-Decreased profitability
	Group factor	- production disruption -Mismanagement -Product of non-quality	-Degraded of the global system (GS)
SS3: Environment	Sources of danger related to microorganisms (Virus-Covid-19)	-Plant shutdown -Disturbance of working conditions -Production disruption	

- *Identification of accident scenarios*

The brief accident scenarios that can be found for each subsystem Principal System (PS), Human Factor (HF), and Environment (E) are summarized in Figures 7, 8, and 9. Where element inputs are the causes of initiating events for each subsystem, the accident scenarios of the principal system make it possible to identify them. For example, we have the undesirable event of the shutdown of production (The stops state) that generates a drop in yield, perhaps because of the lack of raw material (C1), lack of spare parts (C2), fire (C3), machine failure (C4), lack of staff (C5), or power cut (C6). For breakdowns state, perhaps because of the mechanical failure (C7) or electrical failure (C8). For Quality state, perhaps because of the setting condition (C10), quality condition (C10), cleaning condition (C11), or condition of air conditioning (C12); and similarly for scenarios relating to human factors or the environment.

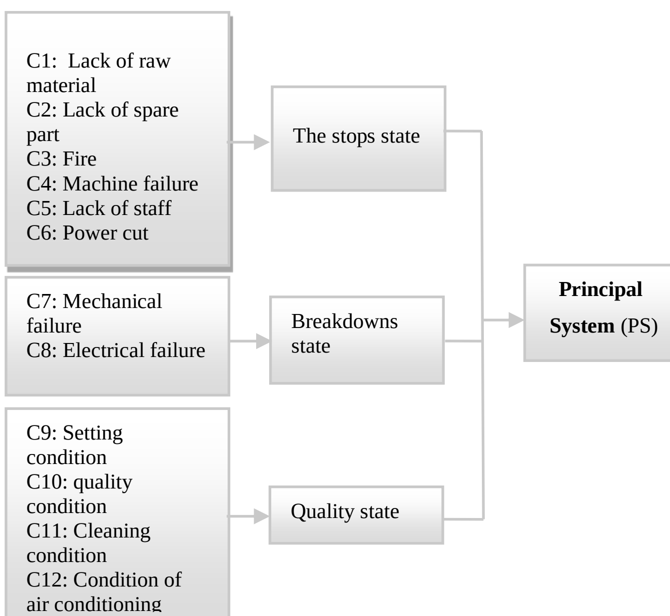


FIGURE 7
PS SCENARIOS

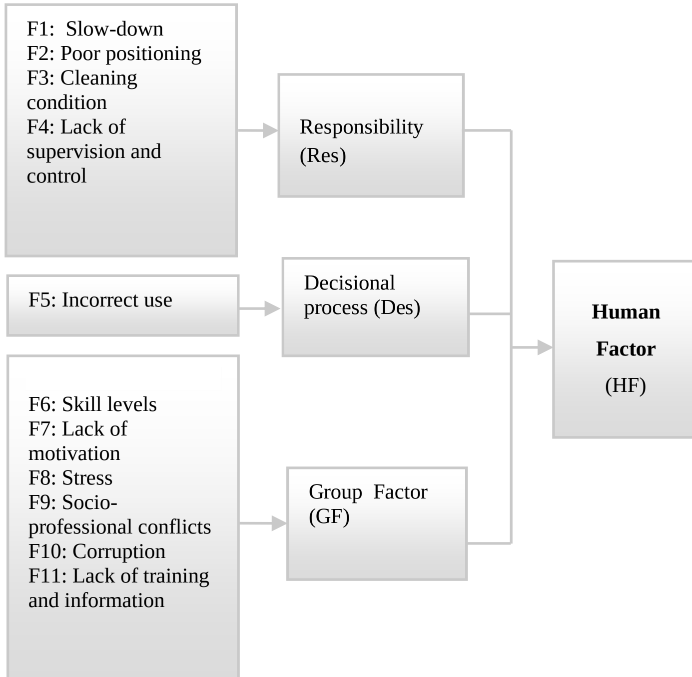


FIGURE 8
HF SCENARIOS

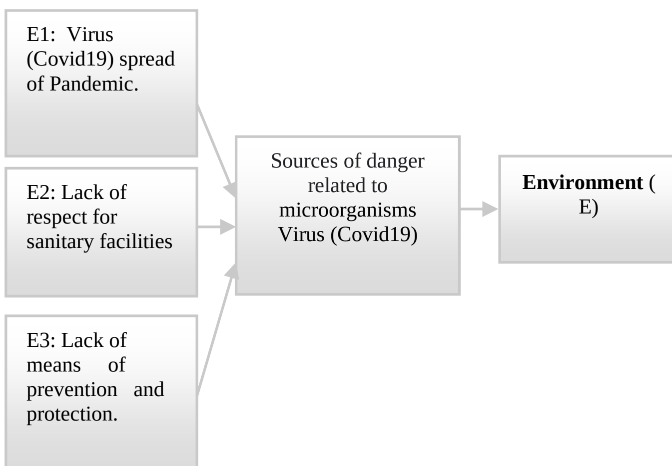


FIGURE 9
ENVIRONMENT SCENARIOS

Once the scenarios are identified, we go on to the structure step using the MOSAR method based on the FT. As a result, the development of these scenarios follows the architecture of the FT in a logical order (Figures 10, 11, 12).

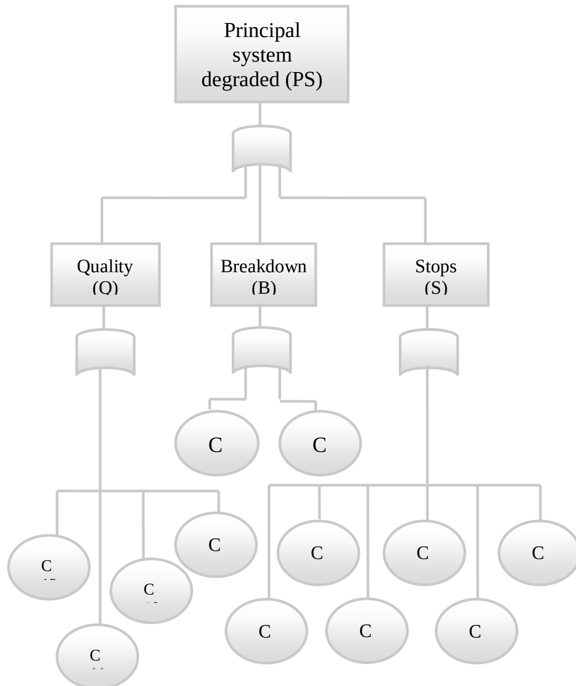


FIGURE 10
PS SCENARIOS IN THE FORM OF AN FT

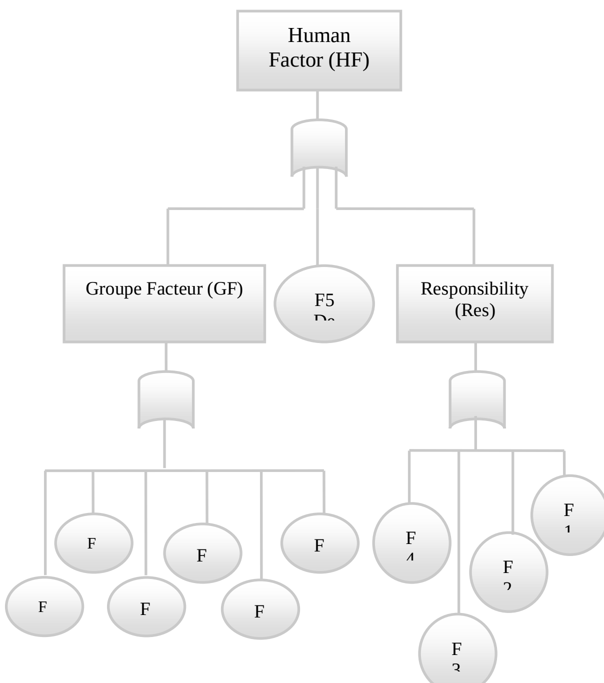


FIGURE 11
HF SCENARIOS IN THE FORM OF AN FT

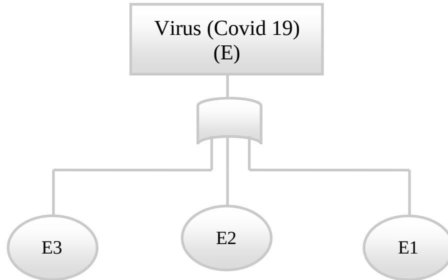


FIGURE 12
ENVIRONMENT SCENARIOS IN THE FORM OF AN FT

The assessment step for the MADS/MOSAR methodology based on FT can describe the propagation of the causes and the states of failure in a system but in a "restricted" way. As an example in our work, a faulty machine, represented by the event (C4) in the PS fault tree, does not make it possible to determine the various machine states (good operation, partial shutdown, total shutdown). We hybridized the BN to the MADS/MOSAR method to overcome this. The BN makes it possible to take several modalities; for example, the stop state has multiple states (good operation, partial shutdown, total shutdown, etc.). In addition, thanks to the modification of opinions by the method of Bayes. BN allows the system probabilities to be updated as soon as new data. In reliability and safety analysis, for instance, Zerrouki & Smadi [2] examine the benefits of BN over the fault tree. They also demonstrate how BN can update probabilities and represent multistate variables (dependent failures and failures with a common cause), which overcomes some limitations of FT.

- *Mapping FT to BN*

The BNs will be built based on the FT obtained by the MOSAR scenarios. We use fault tree mapping in BNs, an algorithm that includes graphical and numerical tasks. Figure 13 illustrates the simplified process of mapping FTs into BNs [11].

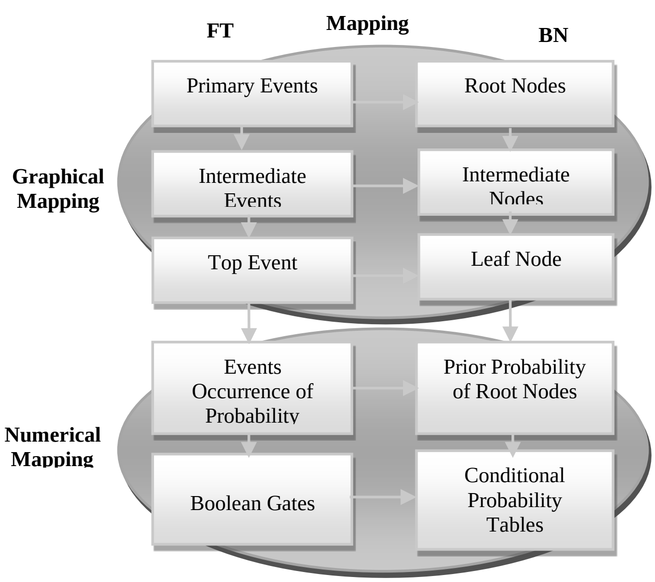


FIGURE 13
MAPPING FT TO BN [11]

We used the OpenMarkov software to construct the BN of each system (Figure 14, 15, 16) based on the FT of (Figure 10, 11, 12).

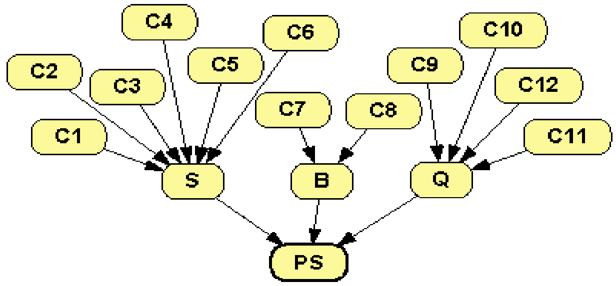


FIGURE 14
STRUCTURE OF THE BN BASED ON THE FT OF FIG 10 (BN FOR THE PRINCIPAL SYSTEM)

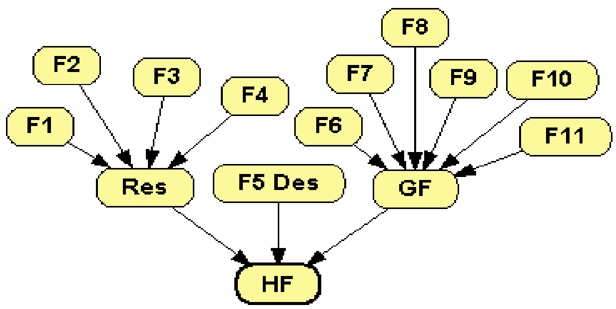


FIGURE 15
STRUCTURE OF THE BN BASED ON THE FT OF FIG11 (BN FOR THE HUMAN FACTOR)

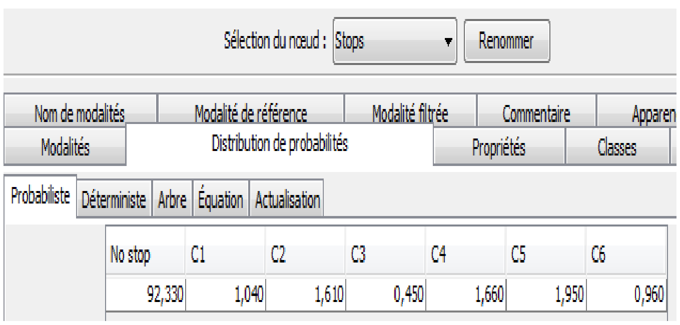


FIGURE 16
STRUCTURE OF THE BN BASED ON THE FT OF FIG 12 (BN FOR THE ENVIRONMENT)

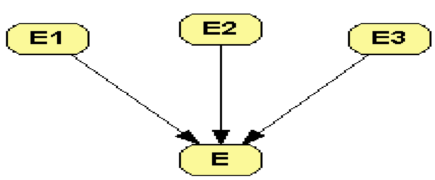
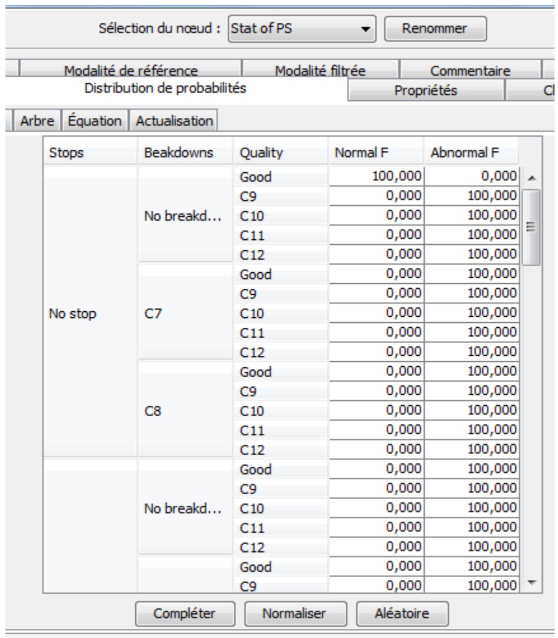


FIGURE 17
TABLE OF PRIOR PROBABILITIES, ON BAYÉSIALAB

We can now simplify and minimize the structure of the above subsystems by using the flexibility of BN to represent multiple state variables. For example, in our case, the node of the variable "The stops state" takes several modalities (No stop, C1: Lack of raw material, C2: Lack of spare part, C3: Fire, C4: Machine failure, C5: Lack of staff, C6: Power cut). For the a priori probability, calculate the failure rates of the subsystems defined in collaboration with the various managers of the company (example: Figure 17). To fill in the conditional probability tables, we use logical analysis (example: Figure 18), the probabilities of risks states calculated by the total probability law, which is also called the Bayes inversion property defined by:

$$p(A) = \sum_{i\in I} p(A|Bi)p(Bi) \qquad (3)$$

For the construction of the BN Global System (GS) (combed spinning production system), we used BayesiaLab software (Figure 19).



Sélection du nœud : Stat of PS | Renommer

Modalité de référence | Modalité filtrée | Commentaire | Distribution de probabilités | Propriétés

Arbre | Équation | Actualisation

Stops	Beakdowns	Quality	Normal F	Abnormal F
No stop	No breakd...	Good	100,000	0,000
		C9	0,000	100,000
		C10	0,000	100,000
		C11	0,000	100,000
		C12	0,000	100,000
	C7	Good	0,000	100,000
		C9	0,000	100,000
		C10	0,000	100,000
		C11	0,000	100,000
		C12	0,000	100,000
	C8	Good	0,000	100,000
		C9	0,000	100,000
		C10	0,000	100,000
		C11	0,000	100,000
		C12	0,000	100,000
	No breakd...	Good	0,000	100,000
		C9	0,000	100,000
		C10	0,000	100,000
		C11	0,000	100,000
		C12	0,000	100,000
		Good	0,000	100,000
		C9	0,000	100,000

Compléter | Normaliser | Aléatoire

FIGURE 18
TABLE OF CONDITIONAL PROBABILITIES, ON BAYÉSIALAB

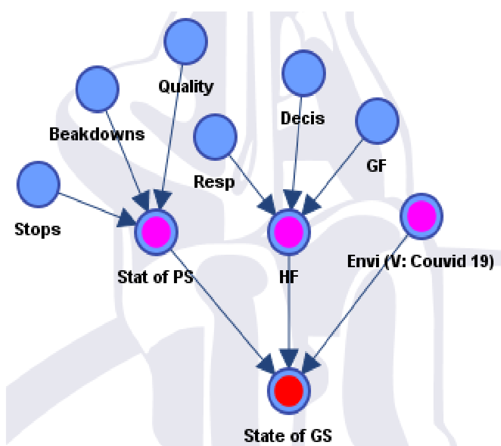


FIGURE 19
BN FOR THE GLOBAL SYSTEM (GS)

- *Risk Assessment*

With the quantitative aspect of the modeling completed, it is now possible to imagine several scenarios. It's about using the inference engines to interrogate the model, making it possible to propagate any probability a priori on the occurrence of the other nodes, obtaining a new table probability for each node. We then proceed to a first inference with the BayesiaLab software, which can present the current state of the global system (Combined spinning workshop) quickly and visually (Figure 20). After this first inference (Figure 20), we obtain the probability of the events recalculated by the Bayes theorem. The global system's functioning is evaluated directly on the node using normal functioning mode. In our case, it is 42,31%. The probability of normal functioning of the GS is very low. The most influencing this state are the states of the principal system, the human factor, and the environment (sources of danger related to the COVID-19 virus).

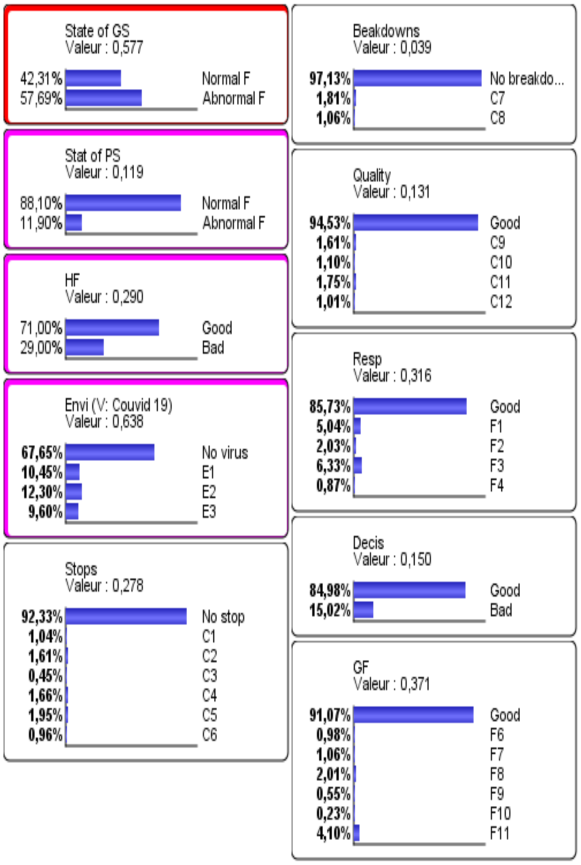


FIGURE 20
INFERENCE WITH BAYÉSIALAB, FOR THE CURRENT STATE OF THE GLOBAL SYSTEM **(GS)**

- *Negotiating objectives*

This phase prioritizes the accident scenarios and discusses their acceptability according to the predefined security objectives. It represented the risk by a two-dimensional quantity that characterizes an unwanted event by its level of Severity S (damage to personnel, damage to equipment, property, and the environment) and by its level of probability P, the level of risk results from the combination of the two which forming a grid (P, S), considered to eliminate or reduce the highest risks (high probability and significant consequence). Bayesian inference lets you prioritize risks (Figure 21) and negotiate the objectives.

	Moderate	Serieus	Important	Catastrophic	Desastrous
Material	No damage	Minor Damage	Damage with partial stop	Damage with stop	Totale destruction
Humain life	Not wonds	Light wonds	Insulated serieus wonds	1 Death	>1 Death

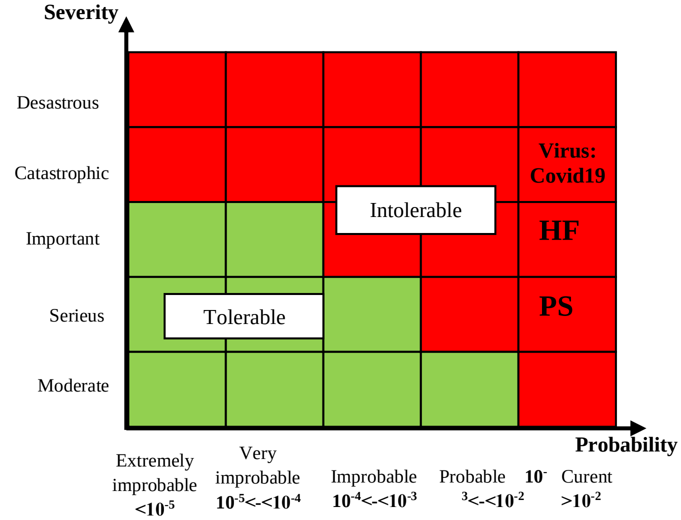


FIGURE 21
POSITIONING OF THE THREE SYSTEMS ON THE SEVERITY/PROBABILITY GRID [4]

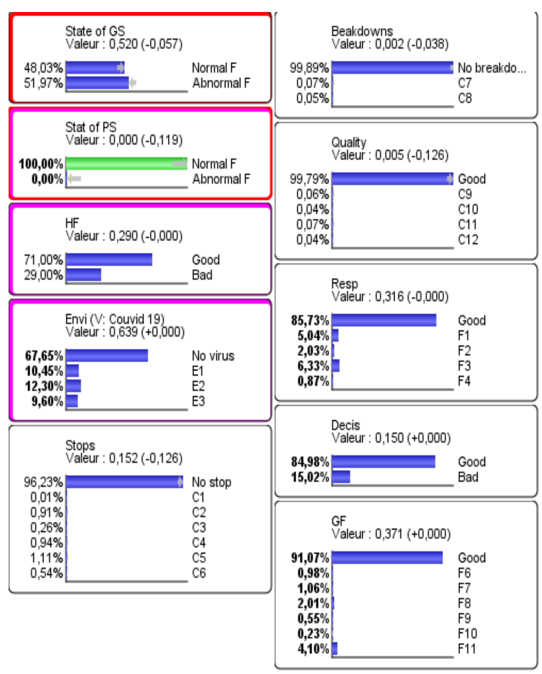


FIGURE 22
BAYESIAN INFERENCE FOR FUNCTIONING (GS) WITH THE GOOD FUNCTIONING OF PS

RESULTS AND DISCUSSION

From the Severity/Probability grid (Figure 21), we notice that all the subsystems are in the red zone and that the risks linked to these subsystems are intolerable. We have the degree of influence of each subsystem on the global system's functioning. It is a question of fixing the threshold productivity of the system, therefore a probability of good functioning for the corresponding node, then resending this given news in the Bayesian network. Assumed the PS is in the normal functioning of 100% (Figure 22). Notice that the GS changes from normal functioning 42,31% to 48,03%. To achieve this, we need to improve product quality, reduce the incidence of machine downtime, and monitor maintenance to avoid breakdowns and failures. Similarly, assuming that the subsystems (HF) usually are functioning at 100% (Figure 23), to achieve this, we must modify the tasks of the human factor, which includes responsibility with conscience and diligence and study before making decisions, taking into account the appropriate working conditions. In addition, it goes from 42,31% to 62,54% (Figure 24) if we set the subsystems environments (E) to the normal functioning of 100%; in this case, it is related to the COVID-19 virus, it may be a temporary state, so necessary measures should be taken to avoid damage as much as possible.

The elements with the most influence on the GS are the human factor and the environment, so it is necessary to eliminate or reduce the risk associated with these subsystems if possible. For the source of environmental hazard of the micro-organism type (COVID-19 virus), this is an exceptional case that disrupts production, leading to lower yields in the textile company as all companies, national and international. However, thanks to our methodology, we concluded that the human factor is the principal reason for the low profitability of this workshop. From these results, HF also has a significant influence on PS productivity. Therefore, better consideration of the risks associated with these two subsystems must be made.

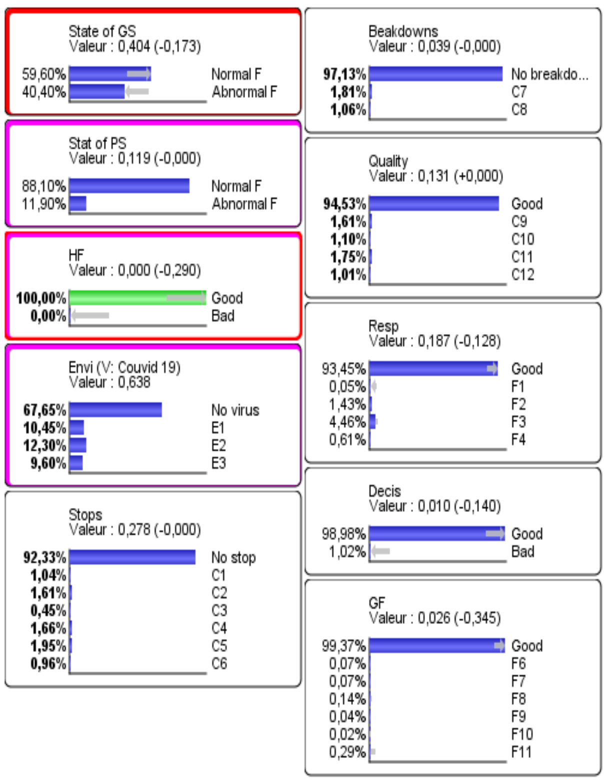


FIGURE 23
BAYESIAN INFERENCE FOR FUNCTIONING (GS) WITH THE GOOD FUNCTIONING OF HF

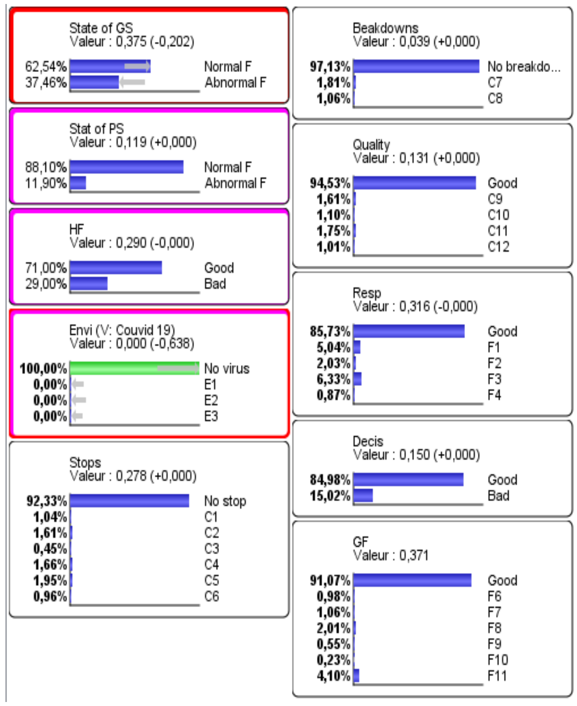


FIGURE 24
BAYESIAN INFERENCE FOR THE FUNCTIONING (GS), WITHOUT VIRUS (COVID 19)

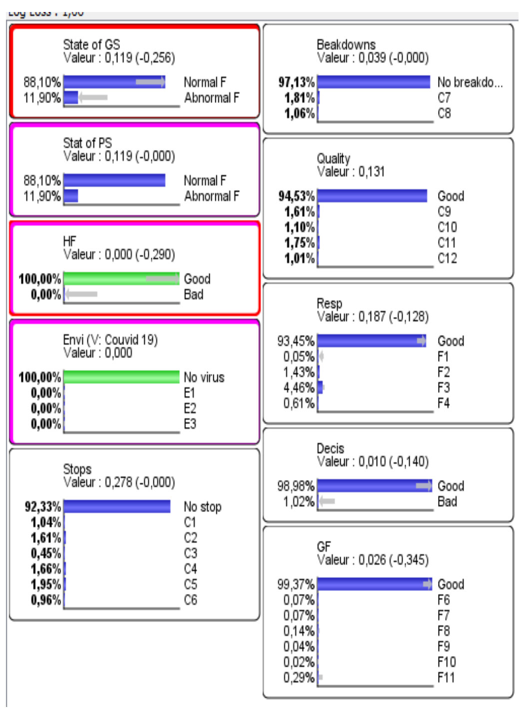


FIGURE 25
BAYESIAN INFERENCE FOR THE FUNCTIONING OF (GS) WITH A GOOD FUNCTIONING STATE OF HF AND WITHOUT VIRUS (COVID 19)

From the baseline research to the introduction [5, 6, 7] proposing approaches to improve and develop the MOSAR methodology, each has its improvement process; we cannot say that the evolution is good or bad; it is advisable to retain those which are best suited to the cases to be treated. The advantage of the proposed approach is that it is possible to predict the behaviour of the GS, either by good functioning of the sub-systems HF and without virus (COVID-19) presented in Figure 25 or by good functioning of three sub-systems (Figure 26). In this case, we cannot eliminate all the risks related to the production system since zero risk does not exist. So, we must minimize these risks to improve the productivity of GS and prevent losses in this system. Thus, we can update the information in our system using Bayesian inference.

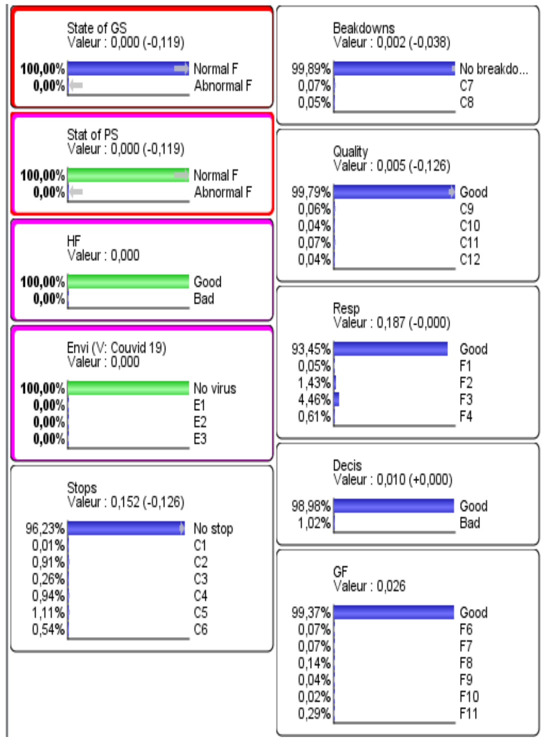


FIGURE 26
BAYESIAN INFERENCE FOR THE FUNCTIONING **(GS)** WITH THE GOOD FUNCTIONING OF THREE SUBSYSTEMS

IDENTIFICATION OF RISK CONTROL MEANS

This step consists of identifying the preventive and protective barriers necessary to reduce or remove the risk scenarios identified previously. In our case, the overall risk prevention approach consists of eliminating the causes of risks and putting in place protective and preventive measures to limit the importance of human and material consequences in the event of an accident. We suggest the means of risk control (Table 2), which can be determined from expert advice or brainstorming sessions.

This article proposes a new methodology for assessing the risks of operating a production system based on the MADS-MOSAR and BN hybridization methodology. Indeed, it is possible to identify the dependencies between the causes of the risks in the production system and update the probabilities of the system as soon as there is new data. In addition, the proposed methodology makes it possible to control the production system easily and more efficiently. With the same Bayesian model, it is possible to diagnose the state of the production system to propose the necessary interventions, predict to alert and suggest a preventive intervention.

TABLE 2
PROPOSAL FOR RISK CONTROL MEANS

Sub-system	Means of risk control
Principal system	- Check the machines after and before the operation, carry out preventive maintenance. - Well-defined management control. - The surveillance. - Improve working conditions. - Supply of spare parts and raw material with a well-defined deadline.
Human factor	- Renew the new "recruitment" contracts - Generalize training at textile company post level. - Make the right man in the right place. - Establish an information sheet for each the textile company station to improve the conditions of the job. - improve the circulation of important information. - Awareness of responsibility
Virus (Covid 19)	- Hazard awareness - Prevention and protection

CONCLUSION AND PERSPECTIVE

Our approach applied to a real case, namely the textile company. The system was composed of three sub-systems: The principal system (PS), the human factor (HF), and the environment (COVID-19). This work consists of assessing the functioning of the global system (GS) and considering several scenarios depending on the state of each sub-system for loss prevention in the production system; the results obtained are satisfactory, thanks to the proposal. We plan to add the analysis of human reliability and fuzzy logic to the proposed methodology to manage and prevent the potential for human error. To prevent unsatisfactory use and deteriorating profitability, we must be aware of system problems. I Yusuf and A Sanus [29] recommended taking a closer look at the performance models used to gauge the effectiveness and robustness of manufacturing systems. When combined with additional ideas and factors, our methodology makes it simple to address their study question. K Khalili-Damghani et al. [30] have written essential works that address problems with the manufacturing system. Their study is figuring out the best way to structure the confidence function, which directly affects how well a problem can be solved and how feasible it is. The same authors developed an approach in another study [31]; a proposed solution to the supply chain's stochastic production planning problem took into account financial risk, customer happiness, and training. A stochastic multi-objective mixed integer mathematical programming model was created by P Ghasemi et al. [32] to combine relief efforts throughout the pre-and post-disaster periods. I recommend working with the proposed methodology for diagnosis and prognosis in all areas since it allows us, with feedback, to offer solutions to avoid and reduce the risks that prevent companies from profiting and aid in making the right decisions, leading to good business management.

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