Université de Tunis
Institut Supérieur de Gestion

Université de Nantes
Polytech'Nantes

Mémoire de mastère

Spécialité

Informatique et Gestion de la Connaissance
(ISG Tunis)

Extraction des Connaissances à partir des Données
(Polytech'Nantes)

A NEW MULTI-OBJECTIVE APPROACH TO IMPLEMENT PREVENTIVE AND PROTECTIVE BARRIERS IN BOW TIE DIAGRAMS

Réalisé par

Aymen Haj Kacem

Encadré par

Pr. Nahla Ben Amor, ISG Tunis

Dr. Ahmed Badreddine, ISG Tunis

2012-2013

June 16, 2013

Abstract

Bow tie diagrams are known as an efficient tools for risk evaluation in industrial systems. However, their quantification is mainly base on expert knowledge in order to define the scenario of a given risk (i.e. causes and consequences), preventive and protective barriers to reduce respectively its frequency, and its severity. Recently, we have proposed the Bayesian approach based on learning from data to construct Bow tie. Indeed, this approach does not support the real behavior of the system while implementing barriers. Thus, our objective in this work is to extend the algorihom to construct Bow tie to propose a multi-objective approach based on mapping procedure form Bow tie structure to multi-objective influence diagram which is an appropriate graphical model to solve decision problems in order to generate optimal preventive and protective barriers.

Résumé

Les noeuds papillon sont des outils efficaces d'évaluation des risques industriels. En effet, leur construction se base principalement sur l'avis des experts pour définir le scénario (causes et conséquences) d'un risque donné et les barrières préventives et protectives permettant de réduire l'occurrence et la gravité du risque. Récemment, une approche probabiliste a été proposée pour construire des noeuds papillon en se basant sur des ensembles d'observation. Néanmoins, cette approche ne supporte pas l'aspect réel du système au moment d'implémentation des barrières. L'objectif de ce travail est d'étendre l'algorithme de construction de noeuds papillon pour développer une nouvelle approche multi-objectif d'implémentation des barrières qui se base principalement sur une transformation d'un noeud papillon à un diagramme d'influence multi-objective qui est un modèle graphique puissant pour la résolution des problèmes de décision.

Contents

List of Figures

List of Tables

General Introduction

In industrial system, the frequency of an accident is important to be assessed, since it may produce severe effects on the environment such as explosion, ignition, etc. Therefor, a methodology of risk analysis are proposed to identify the scenario of an accident, in order to reduce its risk. It is important to know what is the risk, and how asses it. From the standard ISO 14121 (1999), a risk is a combination of frequency and the severity of an undesired event. Whereas the risk assessment is defined as a process which encompasses a series of logical steps to examine the risk of an accident (Leger, Duval, Weber, Levrat, & Farret, 2006). This process consists of two steps: Analyzing risk and evaluating risk. The first step allows to identify the causes and consequence of an accident and estimate its frequency and its severity, while the second one focus on evaluate this latter.

In the literature, there is a several tools which have been developed in order to analyze the scenario of an accident, we cite, *barriers block diagrams* (Duijm, 2009), *fault and event trees* (Ferdous, Khan, Sadiq, Amyotte, & Vetich, 2009), *Bow tie* (Badreddine & Ben Amor, 2012) and *dynamic Bow tie* (Khakzada, Khana, & Amyotte, 2012). Among these techniques, we notify that the Bow tie is known as an efficient and reliable tool to represent the causes and the consequence of risk in the same model. Many researchers proposed to quantify Bow tie to estimate the risk of an accident. We note, the standard Bow tie diagrams (Cockshott, 2005) based on probability theory, which assume that the *likelihood* of events are available and precisely known, but in practice, these information's are uncertain and difficult to reach.

Thus, extensions of standard Bow tie diagrams are proposed to overcome this limit. These approaches can be classified into two main categories which are fuzzy and belief Bow tie. Fuzzy Bow tie (Markowski & Kotynia, 2011), (Markowski, Sam Mannan, & Bigiszewska, 2009) is employed to handle uncertainty due to vagueness and subjectivity, whereas belief Bow tie (Ferdous, Khan, Sadiq, Amyotte, & Vetich, 2011) is employed to handle uncertainty due to ignorance and inconsistency in expert knowledge. However, the quantification of these approaches presents a problem, which they are based on expert's knowledge, without any consideration of real and dynamic aspect of the system.

Recently, a Bayesian approach (Badreddine & Ben Amor, 2012) has been proposed to overcome this limit. This approach is based on learning Bow tie from data. This approach also improves Bow tie by including a numerical component which allows implementing preventive to reduce the frequency of an accident and protective barriers to limit its severity. However, the main drawback of this approach resides in the fact that it dos not consider the real aspect of existing system, for evaluating the barriers implementation while implementing them, which leads to a non realistic results. To overcome this weakness, we propose to extend the algorithm to construct Bow tie diagram to develop a new multi-objective approach to implement preventive and protective barriers in Bow tie diagram. We mention that the selection of barriers is constrained by four criteria namely, *effectiveness*, *reliability*, *availability*, *cost*. Thus, our idea is to propose a mapping procedure from Bow tie structure to multi-objective influence diagram which is an appropriate graphical model to solve this problem.

This report is organized in four chapters as follows:

Chapter 1: In the first part it presents an introduction to Bow tie diagrams, standard Bow tie and their extensions which are based on expert's knowledge. In the second part, is dedicated to introduce the Bayesian approach developed in (Badreddine & Ben Amor, 2012), which is the only approach based on learning from data to construct Bow tie diagrams.

Chapter 2: presents a new multi-objective approach to implement preventive and protective barriers in Bow tie diagram, based on mapping procedure from Bow tie structure into multi-objective influence diagrams (D. Michael, 2004).

Chapter 4: presents an example in TOTAL TUNISIA company in order to illustrate the proposed approach.

Chapter 1

Introduction to Bow tie diagrams

1.1 Introduction

In industrial process, the identification of possible accident scenario is a key point in risk assessment. We can distinguish several tools to evaluate the risk. This chapter focuses on one of these techniques, which are the Bow tie diagrams. The choice of this tool is argued by the fact that it is perfectly tool to represent both causes and consequence for identified risk called *the top event* TE via two parts: the first part corresponds to a *fault tree*(FT) to define all possible causes of the TE, the second corresponds to an *event tree*(TE) to define all possible consequences of TE.

Bow tie diagrams have the ability to define preventive barriers, to limit the occurrence of the TE and protective barriers, to reduce the severity of its consequences. However, most of approach (Ferdous et al., 2011), (Ferdous, Khan, Sadiq, Amyotte, & Vetich, 2009), (Markowski et al., 2009), (Markowski & Kotynia, 2011) propose to quantify Bow tie diagrams, whereas this quantification is based on expert's knowledge, without any consideration of real problems. Recently, a Bayesian approach has been proposed in (Badreddine & Ben Amor, 2012) to overcome this limit, which is the only approach based on learning from data to construct Bow tie. This approach also improves Bow tie structure by including a numerical component which allows to implement the preventive and protective barriers in a dynamic manner.

This chapter is organized as follows: Section 1.2 introduces basics of Bow tie diagrams. Section 1.2 presents the Bayesian approach to construct Bow tie.

1.2 Basics of Bow tie diagrams

Initially, Bow tie diagrams were developed by SHELL company in 1985, in order to represent the whole scenario of an accident for risk management. Many researches have developed a methods to represent the accident scenario of undesired event, we can mention *barriers block diagrams* (Duijm, 2009), *fault and event trees* (Ferdous, Khan, Sadiq, Amyotte, & Vetich, 2009), *Bow tie* (Badreddine & Ben Amor, 2012) and *dynamic Bow tie* (Khakzada et al., 2012), (Badreddine & Amor, 2010a). (Nivoliantou, Konstantinidou, & Leopoulos, 2006) and (Sklet, 2004) present an interesting comparison between these methods. Showing that the Bow tie diagrams are an efficent tool has to represent a complete accident scenario, starting from causes of an accident and ending with its consequences. Moreover, this tool is powerful and effective in several application domain such as accident risk assessment (Markowski & Kotynia, 2011), risk analysis (Markowski et al., 2009), safety barrier implementation (Badreddine & Amor, 2010b) and risk management of sea ports and offshore terminals (Mokhtarie, Ren, Roberts, & Wang, 2011).

Formally, Bow tie diagram can be defined as an assembly of a graphical and a quantitative component. The first one represents the possible events and emphasizes the relationships between them, while the second one, quantifies the occurrence of different events.

1.2.1 Graphical componet of Bow tie diagrams

For each identified risk R also named *the top event* TE, the Bow tie may be represented as a tree in order to identify both causes and consequences of TE. This tool is based on two parts, as shown in Figure 1.1:

- The first part associated to the left side of the model which represents a *fault tree*(FT) to define all possible causes of the TE. we can classify these causes on two types namely: *the initiator events IE* which defines the principal causes of TE, and *the undesired and critical events IndE and CE* which defines the causes of IE. The interaction between events and causes are described by logical **AND** and **OR** gates. The AND gate shows that the event requires the occurrence of all its related causes, whereas the OR gate shows that the event requires the occurrence of any its related causes.

- The second part associated to the right side of the model which represents an *event tree*(TE) to define all possible consequences of TE. We can classified these consequences into three types namely: *second events* (SE) which are the primary consequences of TE, *dangerous effects*(DE), which are the dangerous consequences of SE, and *major events*(ME) of each DE.

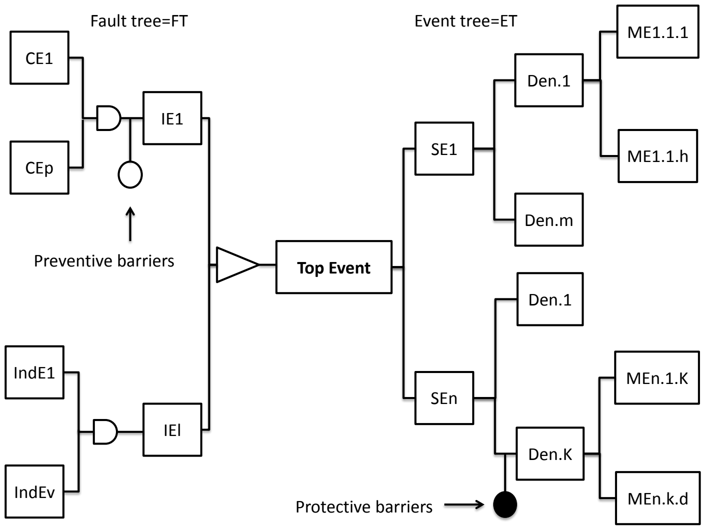

Figure 1.1: Bow tie diagrams model

Bow tie diagram enables us to identify preventive barriers to reduce the occurrence of TE and also protective barriers to limit the severity of its consequences. We can distinguish between two types of barriers, such as active means that this barrier requires a source of energy or a request (automatic or manual action) to fulfill its function (as safety valve, alarm etc.) and as passive means that it doesn't need a source of energy nor o request to fulfill its function (as procedure, retention dike, firewall)(Couronneau & Tripathi, 2003).

The construction of Bow tie diagram follows the same basic rules in development of FT and ET (Cockshott, 2005), as top down-manner, more precisely it starts with TE and diverges until the IndE and CE in the fault tree and begins form TE by following the sequences of events (i.e. consequences) to reach ME in the event tree.

Generally, the quantification of Bow tie is mainly based on expert's knowledge in order to evaluate the risk of an accident. We can distinguish in the literature, several techniques of quantification of Bow tie which can be summarized into two categories: standard Bow tie based on probability theory and extensions of standard Bow tie based on fuzzy (Zadeh, 1965) and belief function theory (Dempster, 1968), (Shafer, 1976).

Example 1.1. *Let us consider an example for risk management in sea ports. In this example we present a risk relative to pilot's related error when driving the ship. To build the corresponding Bow tie, we have defined six causes events of TE(Inappropriate command from pilot (ICP), Pilot unaware of ship' behavior (PU), Ship master make an error of judgment (SMM), Fail aids (FA), Command execution failure (CEF), Inappropriate passage plan (IPP), and seven events correspond to its consequences: (Grounding (G), Collision*

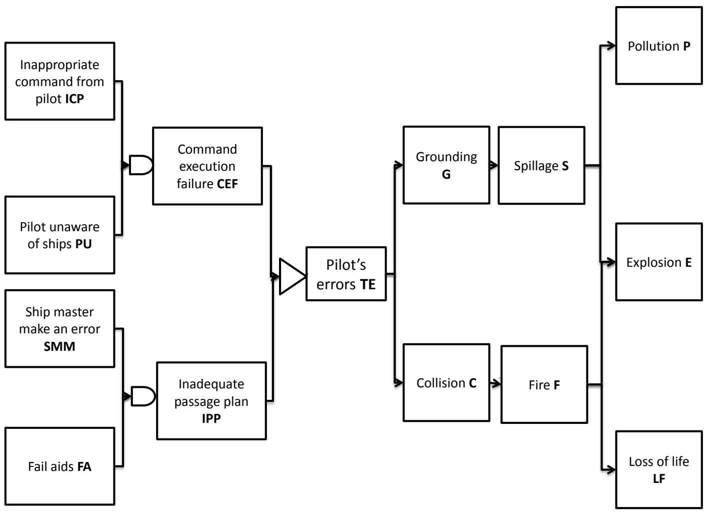

Figure 1.2: Bow tie diagram for risk management of sea ports

(C), Spillage (S), Fire (F), Pollution (P), Explosion (E), Loss of life (LF). The Bow tie diagram corresponding to the example, depicted by Figure 1.2.

1.2.2 Quantitative component of Bow tie diagram

Once the Bow tie structure defined, (Abrahamsson, 2002) and (Kurowicka, Cooke, Goossens, & Ale, 2008) propose to quantify it in the probabilistic framework using Equations (1.1) and (1.2) (resp. Equation (1.3)) in order to estimate *the likelihood* of the top event (resp. the major events).

- **For fault tree:**

$$P_{TE_{OR}} = 1 - \prod_{i=1}^{n}(1 - P_i) \tag{1.1}$$

$$P_{TE_{AND}} = \prod_{i=1}^{n} P_i \tag{1.2}$$

- **For event tree:**

$$P_{ME} = \prod_{n}^{i=1} P_i \tag{1.3}$$

Example 1.2. *Let us consider the Bow tie of Figure 1.2, the likelihood of events elicited by experts which are described by probability are given in table 1.1. The table 1.2 contains the likelihood of the top event (resp. the major events) estimated using Equations (1.1) and (1.2) (resp. equation (1.3)).*

Events	**Likelihood**
ICP	0.4
PU	0.5
SMM	0.3
FA	0.4
CEF	0.2
IPP	0.3
G	0.7
C	0.5
S	0.7
F	0.5

Table 1.1: Likelihood of events for Bow tie

Events	**Likelihood**
TE	0.4
P	0.5
E	0.3
LF	0.4

Table 1.2: Likelihood of top event(TE) and major events for Bow tie

(Delvosall, Fievez, Pipart, & Debray, 2006) and (Dianous & Fievez, 2006) proposed an approach to implement barriers in the standard Bow tie. The implementation of barriers is carried out by examining systemically the Bow tie structure, whereas it presents a problem that it doesn't reflect the real aspect of the system while implementing barriers.

1.2.3 Some extentions of Bow tie diagrams

The standard Bow tie assumes that the occurrence of events are precisely known, however these values are often missed and contain uncertainty. Moreover, the probability theory is appropriated only when all numerical information are available, in this way, it presents some weakness concerning the representation of total ignorance and impression in data. Thus, an extensions of standard Bow tie are proposed in (Ferdous et al., 2011) and (Markowski et al., 2009) which their quantification are based on fuzzy and belief function theory in order to overcome the limit of probability theory. These approaches will be detailed respectively in what follows.

Fuzzy Bow tie proposed in (Ferdous, Khan, Sadiq, & Veitch, 2009), based on expert's knowledge to quantify *the likelihood* of events, these information's are generally characterized by imprecision, thus fuzzy set theory (Zadeh, 1965) is employed to address this kind of uncertainty. Whereas this approach present a limits in regards to the representation of total ignorance and incompleteness. Thus, Belief Bow tie (Ferdous et al., 2011) are proposed in order to overcome this problem, by employing the belief function theory (Dempster, 1968), (Shafer, 1976) in order to handle this type of uncertainty.

However, these approach(Cockshott, 2005), (Ferdous et al., 2011) present a problem, wich are restricted to graphical without any consideration of real aspect of the system. Recently, a Bayesian approach (Badreddine & Ben Amor, 2012) based on learning Bow tie from data has been proposed in order to overcome this limit. In what follows, we introduce this approach.

1.3 A Bayesian approach to construct Bow tie

A Bayesian approach has been proposed in (Badreddine & Ben Amor, 2012) to overcome the limit of standard Bow tie, this approach is the only one based on learning Bow tie from data. Moreover, (Badreddine & Ben Amor, 2012) improves Bow tie structure by including a numerical component which allows to implement the preventive and protective barriers in a dynamic manner. Therefore, this approach s divided into two phases: Building phase and barriers implementation phase. We detail in what follows these two phases.

1.3.1 An algorithm to build Bow tie

The building method proposed in (Badreddine & Ben Amor, 2012), assumes that the Bow tie diagrams as Bayesian networks (Darwiche, 2009), (Pearl, 1988) which are a powerful tool to represent and analyze decision problems under uncertainty. Formally, Bayesian networks can be defined as an assembly of graphical and numerical components, the first one, outlines the different nodes of problems and represents the dependency/independency relationships between them in a DAG (Directed Acyclic Graph). While the second one, represents the conditional probability of each node in the context of its parents. In order to learn Bow tie, (Badreddine & Ben Amor, 2012) propose to apply the same learning algorithm of Bayesian networks, which can be submitted in two steps: learning Bow tie structure from training set and learning parameters. We note that the learning parameters phase is based, on one hand, to generate the set of conditional probability table of causes events, on other hand, to study the severity of the consequences events.

- **Learning Bow tie structure**

In order to learn the Bow tie structure, this approach considers this structure as tree, denoted by T, which is divided in two sub trees: the fault tree (FT) and the event tree(ET). These latters share a central node, denoted by TE. Le us consider V=$\{X_1, \ldots, X_n\}$ be the set of nodes of T, where X_i represents an event(i.e. IE, CE, ME, DE, SE), which take two states(i.e. T=present, F=absent). we note that, X_1 is considered as TE.

The learning structure can be submitted into two steps (Heckerman, 1999): Learning Bow tie skeleton and their orientation, we detail in what follows these two phases.

Learning Bow tie skeleton: (Badreddine & Ben Amor, 2012) propose to apply the *Maximal Weights Spanning Tree* (MWST) algorithm (Pearl, 1988) introduced by Chow and lieu (Chow & Liu, 1968) in order to learn Bow tie skeleton. Formally, given a training set TS, this algorithm generates a tree, denoted UT= $\{U, E$, where U is the set of nodes events and E is the set of arcs between events. This algorithm is based on computing the mutual information I_{ij} between each pair of variables events(X_i, X_j)in the training set defined as follows:

$$I_{ij} = \sum_{x_i x_j} P_{ij}(x_i, x_j) log(\frac{P_{ij}(x_i, x_j)}{P_i(x_i)P_j(x_j)}) \tag{1.4}$$

where $P_{ij}(x_i,x_j)$(resp. $P_i(x_i)$)represents the proportion of instances in the training TS, if X_i=x_i and X_j=x_j(resp. X_i=x_i). Seen that, the Bow tie structure is divided into two parts (i.e. FT and ET), this approach applies the algorithm of learning Bow tie skeleton twice, once for FT from training set, denoted by, TS_{FT} and other for ET from training set denoted, by TS_{ET}.

Let I_{ij} be the mutual-information between event i and j, M be the matrice which records the mutual-information and e be an event from V, then we define the algorithm of learning Bow structure as outlined in Algorithm 1.1.

Algorithm 1.1: Learning undirected tree structure

```
Data: V={X_1, ..., X_n}
Result: UT={U, E}
begin
    for i ∈ {1, ..., n − 1} do
        for j ∈ {2, ..., n} do
        Compute-mutual-information(I_ij)
        M [i] [j] ← I_ij
    U ← e
    E ← ∅
    while |U| ≤ n do
        X_i=e X_j=Find-heighest-mutual-information(M, X_i) U ← U ∪ X_j
        E ← E ∪ {X_i → X_i}
end
```

Where *Compute-mutual-information(I_{ij})* is a function which returns the mutual information between X_i and X_j which is computed by Equation 2.1, and *Find-heighest-mutual-information(M, X_i)* is a function which returns the variable of the heighest mutual information.

Orientation of Bow tie: From (Couronneau & Tripathi, 2003), the orientation of links in the Bow tie is made in top-down manner, means from the events of fault tree to the one of event tree. Thus, according to this recommendation the edges of fault tree (resp. event tree) of Bow skeleton which is produced form the previous phase, are oriented towards TE (resp. ME).

- **Learning Bow tie parameters**

Once learning structure Bow tie is performed, its quantification is realized by learning parameters. We note that this quantification differs between fault and event tree.

Quantification of fault tree: To quantify the fault tree, (Badreddine & Ben Amor, 2012) assign a conditional probability table (CPT) for each node X_i in the context of its parents $Pa(X_i)$. Then, a Bayesian approach used to estimate the $P(X_i = k|Pa(X_i) = j)$ which represents the probability that X_i is equal to k in the context of parents j. Thus, these values are obtained by using the *maximum a posterior* (MAP)()is defined as follows:

$$P(X_i = k|Pa(X_i) = j) = \frac{N_{ijk}}{\sum_k N_{ijk}} \tag{1.5}$$

Where: N_{ijk} represents the number of instance in the training set TS_{FT} in the case where X_i=k, and Pa(X_i=j).

Quantification of event tree: To quantify the event tree, (Badreddine & Ben Amor, 2012) assign a value of severity to each node X_i(expect ME) on its children node which is denoted, by Ch(X_i). In this way, these values examine the impact of the event X_i on its consequences events $X_j \in Ch(X_i)$. Thus, the severity degree S[j] of X_i on X_j is computed as follow:

$$S[j] = P(X_j = T|X_i = T) = \frac{N_{ij}}{N_i} \tag{1.6}$$

Where: N_{ij} represents the number of instances in TS_{ET} in the case where (X_i=T) and (X_j=T), and N_i represents the number of instances in TS_{ET} in the case where X_i=T.

- **Main learning program**

Algorithm 1.2 outlines the principal steps to construct Bow tie.

Algorithm 1.2: Learning Bow tie

Data: $\{TS_{FT}; TS_{ET}; TE\}$
Result: BT=$\{T, CPT, S\}$
begin
  % *Learning structure*
  $UT_{FT} \leftarrow Learning - undirected - tree - structure(TS_{FT}, TE)$
  $UT_{ET} \leftarrow Learning - undirected - tree - structure(TS_{ET}, TE)$
  $T_{FT} \leftarrow Orient - Fault - Tree(UT_{FT})$
  $T_{ET} \leftarrow Orient - Event - Tree(UT_{FT})$
  $T \leftarrow \{T_{FT,T_{ET}}\}$
  % *Learning parameters*
  foreach $X_i \in T_{FT}$ **do**
    $CPT[i] \leftarrow Compute - MAP(P(X_i|Pa(X_i)))$
  $S \leftarrow \oslash$
  foreach $X_i \in T_{ET}$ **do**
    foreach $X_j \in Ch(X_i)$ **do**
      $S_i\,[j] \leftarrow Compute - Degree - Severity(P(X_j = T|Pa(X_i = T)))$
    $S \leftarrow S \cup S_i$
end

Where:

- *Orient-Fault-Tree(UT_{FT})* is a function which orientates the fault tree.
- *Orient-Event-Tree(UT_{ET})* is a function which orientates the event tree.
- *Compute-MAP($P(X_i|Pa(X_i))$)* is a function which computes the occurrence of X_i in the context of its parents $Pa(X_i)$.
- *Compute-Degree-Severity($P(X_j = T|Pa(X_i = T))$)* is a function which computes the impact of X_j on X_i.

1.3.2 Barriers implementation

Once the Bow tie diagram is constructed, (Badreddine & Ben Amor, 2012) propose to implement barriers. The principal of the proposed approach, to examine the impact of events on the TE. We can mention that, the selection of barriers is constrained of specific criteria (Couronneau & Tripathi, 2003) namely: {*effectiveness*, *reliability*, *availability*, *cost*}. Formally, these criteria are defined by (Couronneau & Tripathi, 2003) as follows:

- *Effectiveness*: can be defined as ability of barrier to correctly achieve its necessary function.
- *Reliability*: can be defined as ability of barrier to correctly achieve its necessary function under given condition.
- *Availability*: can be defined as ability of barrier to correctly achieve its required function under given condition at a given moments.
- *Cost*: can be defined as the cost of barrier maintenance when implementing it.

Therefore, this problem of the barriers implementation is considered as a multi-criteria problem. Thus, (Badreddine & Ben Amor, 2012) propose to apply Analytical Hierarchical Process (AHP)(Saaty, 1980) as an appropriate method to solve the multi-criteria problem. In what follows, we will define the basics of the Analytical Hierarchical Process (AHP), and then we will present the implementation of preventive and protective barriers procedure of this approach.

- **Basics of the Analytical Hierarchical Process (AHP)**

AHP method introduced by (Saaty, 1980), which considers the structure of problem as multi-level hierarchical tree. This structure composed of three levels, the first level means the root, corresponds to the objective of problem, the second level presents the different criteria and their sub-criteria and the last one corresponds to the different alternatives which are the solutions of problem. For each level of this tree, assigning the decision matrices, denoted (DM), which provides a comparison between their elements.

The selection of preventive and protective barriers is performed by AHP method, which can be defined in three level hierarchical structures depicted in Figure 1.3 The first level presents the objective which is the selection of barriers, the second level presents four criteria called, {*effectiveness*, *reliability*, *availability*, *cost*}.The last one corresponds to the proposed barriers.

(Badreddine & Ben Amor, 2012) introduced a function AHP(B: a set of possible barriers, DM: a set of decision matrices) in order to implement the set of barriers sorted by their criteria weights. This method will be detailed in what follows.

- **Preventive barriers implementation**

This procedure is based on studying the impact of events on TE. First, the decision maker interact with the system to select the most critical event IE_s, since it represents the principal causes of TE. Second, the decision maker proposes a set of intervention of scenario.

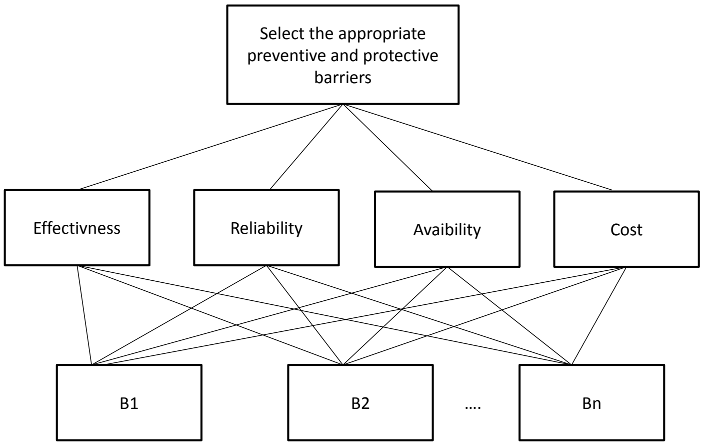

Figure 1.3: AHP method to implement preventive end protective barriers

By computing the impact of these interventions on the TE, this task can be performed on probabilistic inference algorithm proposed by (Peral, 1986) and (Kim & Peral, 1983) for polytrees, thus, the best interventions that reduces the occurrence of TE, is used to apply AHP in order to implement the appropriate preventive barriers.

Let I=$Ipre_i \ldots Ipre_n$ be the set interventions of scenario, $Ipre_i$=$\{Ipre_{i1} \ldots Ipre_{in}\}$ be the set of events intervening on the scenario, $Ipre_i^*$ be the best intervention of scenario, PB be the set of preventive barriers concerning $Ipre_i^*$ and DM be the set of the decision matrices concerning the different criteria and their alternatives. Then, Algorithm 1.3 outlines the procedure relative to the implementation of preventive barriers.

- **Protective barriers implementation**

To implement the protective barriers, first the decision maker proposes a set of protective interventions. Second, this approach computes their impact on each major event in similar way to preventive barriers. Then, the best intervention which reduces the severity of ME is used to apply AHP method in order to detect the appropriate protective barriers.

Let I=$\{Ipro_i \ldots Ipro_n\}$ be the set protective interventions of scenario, $Ipro_i$=$\{Ipro_{i1} \ldots Ipro_{in}\}$ be the set of events intervening on the scenario, $Ipro_i^*$ be the best intervention of scenario, PB be the set of protective barriers concerning $Ipro_i^*$ and DM be the set of the decision matrices concerning the different criteria and their alternatives. Then, Algorithm 1.4 outlines the procedure relative to the implementation of protective barriers.

Algorithm 1.3: Preventive barriers implementation

Data: TS_{FT}, CPT
Result: PB^*: The appropriate preventive barriers sorted by their criteria weights
begin
    foreach $IE_i \in IE$ **do**
        Compute $P(TE = T|IE_i = T)$
    $min \leftarrow 1$
    foreach $I_i \in I$ **do**
        $ComputeP(TE = T|I_{i1} = e_1, \ldots, I_{in} = e_n)$
        if $min \leq P(TE = T|I_{i1} = e_1, \ldots, I_{in} = e_n)$ **then**
            $I_i^* \leftarrow I_i$
    % *Select the appropriate barriers*
    $PB^* \leftarrow AHP(PB, DM)$
end

Algorithm 1.4: Protective barriers implementation

Data: TS_{ET}, S
Result: PB^*: the appropriate protective barriers sorted by their criteria weights
begin
    $min \leftarrow 1$
    foreach $I_{proi} \in I_{pro}$ **do**
        $P_{Me} \leftarrow 1$
        foreach $ME_{sj} \in ME_s$ **do**
            Compute $P(ME_{sj} = T|I_{proi1} = e_1, \ldots, I_{proin} = e_n)$
            $P_{Me} \leftarrow P_{Me} * P(ME_{sj} = T|I_{proi1} = e_1, \ldots, I_{proin} = e_n)$
        if $min \leq P_{Me}$ **then**
            $I_i^* \leftarrow I_i$
    % *Select the appropriate barriers*
    $PB^* \leftarrow AHP(PB, DM)$
end

1.3.3 Illustrative example

In this section we illustrate the Bayesian approach via an example in TOTAL TUNISIA company. For this example, we emphasize on a risk relative to a major fire and explosion on tanker truck carrying hydrocarbon (TE), in order to construct Bow tie concerning this risk, we can identify six causes events such as(hydrocarbon gas leak (HGL), source of ignition (SI), tank value failure (TVF), exhaust failure (EF), construction site close to the truck parking (CTP) and drilling a tank (DTA)) and nine consequences events such as(pool fire (PF), thermal effects (THE), toxic effects (TO), production process in stop (PPS), thermal damage to persons (TDP), damage to the other trucks (DT), toxic damage to persons (TODP), damage to environment (DE) and late delivery (LD)). For convenience, we consider two training sets TS_{FT} for fault tree (see in Table 1.5) and TS_{ET} for event tree (see in Table 1.6).

DTA	TE	EF	CTP	TVF	HGL	SI	LF
T	T	F	T	F	F	T	T
T	F	T	T	T	T	F	F
T	T	F	T	T	F	F	F
F	F	T	F	T	T	T	T
T	F	F	F	F	T	F	T
T	F	F	T	T	F	T	F
F	F	F	T	F	T	T	T
T	T	F	T	T	F	T	F
T	T	F	T	F	F	T	T
T	F	T	T	T	T	F	F
T	T	F	T	T	F	F	F
F	F	T	F	T	T	T	T
T	F	F	F	F	T	F	T
T	F	F	T	T	F	T	F
F	F	F	T	F	T	T	T
T	T	F	T	T	F	T	F

Table 1.3: Training set TS_{FT} associated to causes events for FT

- **Learning structure of Bow tie**: The first step is the structure learning of Bow tie by applying Algorithm 1.1. This step is based on computing the mutual information between events for fault tree (resp. event tree) which are illustrated in Table 1.7 (resp. Table 1.7). Figure 1.3 depicts the structure of this Bow tie diagram.

- **Learning parameters of Bow tie**: The second step has as target to identify the CPT tables for fault tree (shown in Table 1.7) and the severity degree for event tree (show in Table 1.8).

- **Preventive barriers implementation**: First, the impact of each $IE_i \in$ IE on TE $P(TE = T|IE_i = T)$ are illustrated in Table 1.9. Second, using these values, the decision maker defines three preventive interventions of scenarios as follows:

TE	LD	DE	TODP	DT	TDP	PPS	TOE	PF	THE
T	T	F	T	F	F	T	T	T	T
T	F	T	T	T	T	F	F	T	T
T	T	F	T	T	F	F	F	T	T
F	F	T	F	T	T	T	T	T	T
T	F	F	F	F	T	F	T	T	T
T	F	F	T	T	F	T	F	T	T
F	F	F	T	F	T	T	T	T	T
T	T	F	T	T	F	T	F	T	T
T	T	F	T	F	F	T	T	T	T
T	F	T	T	T	T	F	F	T	T
T	T	F	T	T	F	F	F	T	T
F	F	T	F	T	T	T	T	T	F
T	F	F	F	F	T	F	T	T	T
T	F	F	T	T	F	T	F	T	T
F	F	F	T	F	T	T	T	T	T
T	T	F	T	T	F	T	F	T	T

Table 1.4: Training set TS_{ET} associated to consequences events for ET

	TE	SI	HGL	TVF	CTP	EF	DTA
TE	-	0.0973	0.1096	0.0497	0.0143	0.0818	0.0102
SI	0.0973	-	0	0	0.0838	0.1147	0
HGL	0.0709	0	-	0.5149	0	0	0.0196
TVF	0.0497	0	0.6259	-	0	0	0
CTP	0.0143	0.0838	0	0	-	0	0
EF	0.0818	0.1147	0	0	0	-	0
DTA	0.0102	0	0.0196	0	0	0	-

Table 1.5: Mutual information values for FT

1. I_1=$\{I_{CP} = 0.9, I_{PU} = 0.6, I_{FA} = 0.8\}$.
2. I_2=$\{I_{SMM} = 0.7, I_{PU} = 0.3, I_{FA} = 0.2\}$.
3. I_3=$\{I_{CP} = 0.2, I_{IPP} = 0.4, I_{FA} = 0.3\}$.

Then, the propagation values of these interventions are presented in Table 1.9, we can deduce that I_3 is the most interesting intervention. Following this situation, the decision maker proposes four barriers which are illustrated in Table 1.10.

	TE	PF	THE	PPS	TOE	TDP	DT	LD	TODP	DE
TE	-	0.485	0.2173	0.1344	0.1461	0.0766	0.0191	0.113	0.085	0.1348
PF	0.485	-	0.3416	0.2395	0.2540	0.0766	0.0516	0.2125	0.085	0.1348
THE	0.2173	0.3416	-	0	0	0.2506	0.1677	0	0	0
PPS	0.1344	0.2395	0	-	0	0	0	0.3855	0	0
TOE	0.1461	0.254	0	0	-	0	0	0	0.3271	0.2948
TDP	0.0766	0.0766	0.2506	0	0	-	0	0	0	0
DT	0.0577	0.113	0.2599	0	0	0	-	0	0	0
LD	0.113	0.2125	0	0.3855	0	0	0	-	0	0
TODP	0.085	0.085	0	0	0.3271	0	0	0	-	0
DE	0.1348	0.1348	0	0	0.2948	0	0	0	0	0

Table 1.6: Mutual information values for ET

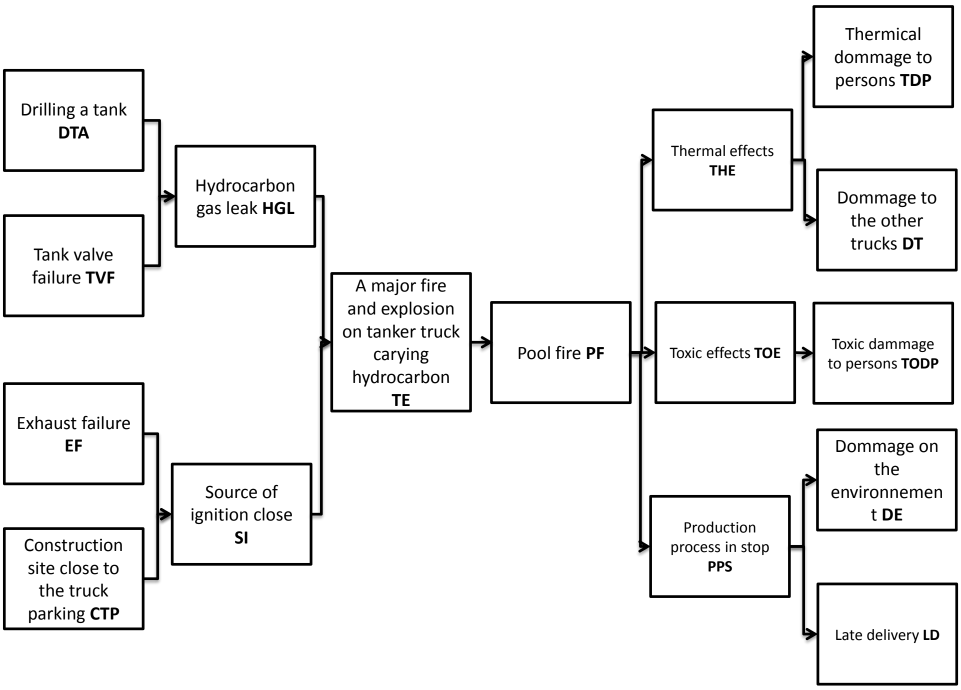

Figure 1.4: Structure of Bow tie diagram

Then, AHP method is applied in order to implement barriers. We can see the application AHP algorithm as process of three steps. First, a criteria weights are recorded, Second, a pairwise comparison between barriers and each criteria are performed, which are illustrated in Table 1.12, Finally, the weights of barrier's conforming to each criteria are

HGL	SI	TE	$P(TE\,\vert HGL, SI)$
T	T	T	0.7692
T	T	F	0.2308
T	F	T	0.7222
T	F	F	0.2778
F	T	T	0.7500
F	T	F	0.2500
F	F	T	0.1765
F	F	F	0.8235
EF	CTP	SI	$P(SI\,\vert EF, CTP)$
T	T	T	0.7143
T	T	F	0.2857
T	F	T	0.6250
T	F	F	0.3750
F	T	T	0.5882
F	T	F	0.4118
F	F	T	0.1786
F	F	F	0.8214
DTA	TFV	HGL	$P(HGL\,\vert DTA, TVF)$
T	T	T	0.9000
T	T	F	0.1000
T	F	T	0.8824
T	F	F	0.1176
F	T	T	0.4000
F	T	F	0.6000
F	F	T	0.0556
F	F	F	0.9444
DTA	P(DTA)	TVF	P(TVF)
T	0.4047	T	0.4444
F	0.5926	F	0.5556
EF	P(EF)	CPT	P(CPT)
T	0.3889	T	0.2222
F	0.6111	F	0.7778

Table 1.7: Numerical component

obtained, which are showed in Table 1.13, we can deduce that the most interesting barriers is PB_1 followed by PB_2.

	$P(THE = T\,\|PF = T)$	$P(TOE = T\,\|PF = T)$	$P(THE = T\,\|PF = T)$
S(PF)	1.000	1.000	1.000
	$P(TDP = T\,\|THE = T)$	$P(DT = T\,\|THE = T)$	
S(THE)	0.9474	0.5263	
	$P(TODP = T\,\|THE = T)$	$P(DE = T\,\|THE = T)$	
S(TOE)	0.9167	0.9853	
	$P(DE = T\,\|PSS = T)$	$P(LD = T\,\|PSS = T)$	
S(PSS)	0.9853	0.8820	
	$P(TE = T\,\|PF = T)$		
S(TE)	0.9000		

Table 1.8: Severity degree of events for ET

IE_i	P(TE=T|IE$_i$=T)
HGL	0.562
SI	0.487
I_i	P(TE=T|I$_i$=T)
I_1	0.2834
I_2	0.2958
I_3	0.3374

Table 1.9: Propagation values

Preventive barriers
Education and training task to deal with HGL (PB_1)
Fire simulation (PB_2)
Education and training task to deal with HGL (PB_3)
Periodic preventive to minimize TVF (PB_4)

Table 1.10: Preventive barriers

- **Protective barrier implementation**: To implement the appropriate protective barriers. First, the decision maker defines two protective interventions of scenario as follows:

1. I_1=(I_G=0.9, I_C=0.6, I_F=0.8).

2. I_2=(I_G=0.7, I_C=0.3, I_S=0.2).

The severity propagation values of these interventions are presented in Table 1.13. Using the results of propagation, we can deduce that I_2 is the most interesting intervention.

	Effectiveness DM				Reliability DM			
	PB_1	PB_2	PB_3	PB_4	PB_1	PB_2	PB_3	PB_4
PB_1	1	5	3	2	1	5	4	2
PB_2	0.2	1	0.33	0.25	0.2	1	0.5	0.33
PB_3	0.33	3	1	0.5	0.25	2	1	2
PB_4	0.5	4	2	1	0.5	3	0.5	1
	Availability DM				Cost DM			
	PB_1	PB_2	PB_3	PB_4	PB_1	PB_2	PB_3	PB_4
PB_1	1	4	7	2	1	3	0.33	1
PB_2	0.25	1	4	0.33	0.33	1	0.2	0.33
PB_3	0.142	0.25	1	2	3	5	1	3
PB_4	0.5	3	0.5	1	1	3	0.33	1

Table 1.11: Preventive barrier's criteria

PB_i	Effectiveness	Reliability	Availability	Cost	Weights
PB_1	0.47	0.502	0.487	0.2	0.465
PB_2	0.075	0.087	0.158	0.09	0.096
PB_1	0.171	0.212	0.14	0.51	0.206
PB_2	0.284	0.199	0.215	0.2	0.233

Table 1.12: Weights for preventive barriers

	P(TDP=T|I_i=T)	P(LD=T|I_i=T)	P(TODP=T|I_i=T)	$\prod P(\mathrm{ME}_j=\mathrm{T} \mid \mathrm{I}_i=\mathrm{T})$
I_1	0.2834	0.1547	0.1987	0.00032
I_2	0.2955	0.0898	0.3547	0.00061

Table 1.13: Severity propagation values

Thus, concerning this situation, four barriers are proposed which are illustrated in Table 1.14. Similar to preventive barriers, the implementation of protective barriers is performed

Protective barriers
Prevent incident of the site (PBr_2)
Blast protection window film to minimize PF (PBr_2)
Setting up equipment to limit TOE (PBr_3)
Setting up equipment to limit THE (PBr_4)

Table 1.14: Protectives barriers

by applying the (AHP) method. First, a criteria weights are recorded, Second, a pairwise comparison between barriers and each criteria are performed, which are illustrated in Table 1.15, Finally, the weights of barrier's conforming to each criteria are obtained, which are showed in Table 1.16, we can deduce that the most interesting barriers is PB_1 followed by PB_2.

	Effectiveness DM				Reliability DM			
	PB_1	PB_2	PB_3	PB_4	PB_1	PB_2	PB_3	PB_4
PB_1	1	5	0.5	2	1	4	5	5
PB_2	0.2	1	0.2	0.125	0.25	1	4	4
PB_3	2	5	1	5	0.2	0.25	1	1
PB_4	5	8	0.2	1	0.2	0.25	1	1
	Availability DM				Cost DM			
	PB_1	PB_2	PB_3	PB_4	PB_1	PB_2	PB_3	PB_4
PB_1	1	0.33	0.2	0.2	1	1	3	3
PB_2	3	1	0.33	0.33	1	1	2	2
PB_3	5	3	1	1	0.33	0.5	1	1
PB_4	5	3	1	1	0.33	0.5	1	1

Table 1.15: Protective barrier's criteria

PB_i	Effectiveness	Reliability	Availability	Cost	Weights
PB_1	0.169	0.56	0.068	0.3931	0.319
PB_2	0.050	0.253	0.156	0.319	0.165
PB_1	0.455	0.087	0.388	0.144	0.296
PB_2	0.326	0.1	0.388	0.144	0.22

Table 1.16: Weights for protective barriers

1.3.4 Limits of the Bayesian approach

We can mention that the procedure of barriers implementation of this approach presents many limits. First, this latter doesn't consider the real aspect of the system when implementing barriers. More precisely, (Badreddine & Ben Amor, 2012) assign the elements of decision matrices, when comparing the alternatives of barriers implementation with criteria, in a static way without any consideration of data.

Thus, we can notify that the transition, between the construction of Bow tie and its barriers implementation, is done manually. However, it seems unrealistic to use static information in a dynamic system.

Second, AHP presents a limit concerning the pairwise comparaisons between alternative of barriers and their criteria (Ishizaka & A.Labib, 2009). For instance, regarding the effectiveness criteria, the barrier PB1 is more interesting than PB2 by 5 as its intensity of importance, that implies the barrier PB2 is more interesting than PB1 by 1/5 as degree intensity of importance, we can deduce that isn't reasonable.

Finally, we can deduce that these shortcomings can lead to unrealistic results concerning the barriers implementation. So, in order to overcome these limits, we propose a new approach to implement barriers, taking into consideration the real aspect of our system.

1.4 Conclusion

In this chapter, we have presented a Bayesian approach (Badreddine & Ben Amor, 2012) to construct Bow tie which is the only approach based on learning by data. This approach is split into two phases: The first phase aims to construct Bow tie, to this end, a learning algorithm is proposed, which can be submitted in two steps: learning structure and learning parameters. The second phase aims to implement the preventive and protective barriers in a dynamic manner. The selection of barriers is performed by applying the AHP methods. However, this approach presents a limit while implementing the barriers. In the next chapter, we propose a new multi-approach to implement barriers.

Chapter 2

A new multi-objective approach to implement preventive and protective barriers in Bow tie diagrams

2.1 Introduction

As shown in the previous chapter, the Bayesian approach (Badreddine & Ben Amor, 2012) improves Bow tie by including a numerical component. However, the main drawback of this approach resides in the fact that it does not consider the real aspect for evaluating the barriers implementation while implementing them.

Our goal in this chapter is to extend this approach in order to implement the preventive and protective barriers in a dynamic way. In fact, the choice of barriers is constrained by several criteria namely, *effectiveness*, *reliability*, *availability* and *cost*. Thus, our idea is to model this problem by using an efficient graphical model which is a multi-objective influence diagram (D. Michael, 2004).

The remaining of this chapter is organised as follows: Section 2.2 presents a recal on multi-objective influence diagram. Section 2.3 presents a new muli-objective approach to implement preventive and protective barriers.

2.2 Recall on multi-objective influence diagrams

A multi-objective influence diagrams, denoted by MID, are an extension of classical influence diagrams in order to model the multi-objective decision problem (D. Michael, 2004). Formally, MID can be defined, similar to classical influence diagrams, as an assembly of graphical and numerical components.

The first component represents the different variables of problems and includes the dependency/independency links between them. While the second one, consisting in a quantification of different links.

2.2.1 Graphical component

The graphical component is devoted to consider influence diagrams as a directed acyclic graph (DAG), denoted by, G =(N,A), while N depicts the nodes and A represents the link between them. As indicated in Figure 2.1 the set nodes N includes three subsets C, D and V defined as follows:

- *Chance nodes*: $C_i \in C$, represents a set of random uncertain variable which is a elements relevant of decision problem. Chance nodes are usually drawn as circle.

- *Decision nodes*: $D_i \in D$, represents a set of decision that must be taken by the decision maker. They respect a total ordering among them. Decision nodes are usually drawn as rectangle.

- *Value nodes*: $V_i \in V$, represents a set of utility which are the objectives of problem must be maximized. In cases of multi-objective influence diagrams, the different objectives can be stored only in one value denoted a multi objective value node. Value nodes are usually drawn as lozenge.

The set arcs A include two types according to their target:

- *Conditional arcs*: which are connected toward chance nodes or value node, these links represent a probabilistic dependency.

- *Informational arcs*: which are connected toward a decision node, these links represent the time precedence between decision.

2.2.2 Numerical component

The numerical component quantifies the links between nodes. More precisely, each conditional arcs which represents chance node C_i as target, is assigned by conditional probability distribution of C_i in the context of its parents $\mathrm{Pa}(C_i)$. The conditional probability should respect the normalization of probability. In the case where $\mathrm{Pa}(C_i) \neq \emptyset, C_i$ as root node then a prior probability to C_i is assigned as follows:

$$\sum_{c_{ij} \in \psi_i} P(c_{ij}) = 1 \tag{2.1}$$

In the case where $Pa(C_i) = \emptyset$, then a conditional probability distribution of C_i in the context of its parents $Pa(C_i)$ is assigned as follow:

$$\sum_{c_{ij} \in \psi_i} P(c_{ij}|Pa(c_{ij})) = 1 \tag{2.2}$$

2.2.3 Properties of multi-objective influence diagrams

(Shachter, 1986) presents the properties of multi-objective influence diagrams, that they must be respected during the evaluation phase. Thus, the multi-objective influence diagrams should be regular, oriented means there is a value node in its structure.

Definition 2.1. *MID is considered as regular if its graphical component satisfies:*

I/ There is no cycles.

II/ The value node has not children.

III/ There is a directed path containing all decision nodes, known as the No forgetting propriety.

2.2.4 Evaluation of multi-objective influence diagrams

Once the structure of MID is obtained, we can evaluate it in order to generate the optimal decisions which satisfy the set of objectives. Thanks to an algorithm proposed in (D. Michael, 2004) that ensures a set of transformation in the structure of diagram aims to identify the optimal strategy with its expected utility. In the following, we will present the procedure of this transformation in order to evaluate MID.

1. Barren node removal: A barren node is identified as chance or decision node without children. They are characterized by the fact that they haven't effect while computing the optimal decisions, then they can be removed from the diagrams.

2. Chance node removal: A chance node C_i is removed when it has a unique children as value node, then this value node inherit the conditional parent of C_i. As mentioned in (D. Michael, 2004), for this situation, the modification of value table by applying operation expectation, is performed following two cases:

    - Case A: In this case, doesn't exist a decisions nodes which have been removed prior to the actual chance node, then for each unique combination of alternatives and outcome of the parent node which influence the value node, the expectation operation is performed on each outcome of this current chance node being removed. It should be noted that the expectation is performed on each objective.
    - Case B: In this case, one or more decisions nodes have been removed prior to the current chance node, then for each combination of outcome of this current chance node, they correspond a set of one or more non inferior decision rule. More simply, a decision rule is described as a particular alternative when a chance node is observed. We can mention that a decision rule is inferior, when there is another alternation which has better or equal values.

3. Decision node removal: In this procedure of transformation, the simple maximizing is replaced with an operation that can generate a set of non inferior alternative. A decision node D_i is removed when it has a children as value node and all parents of this value node must also be the parents of the current decision node.

4. Arc Reversal: When any removal operation have been carried, then there is two chance node C_i and C_j which are connected by unique arc (ij), then this arc (ij) can be reversed. Following this operation one of these chance nodes can be removed.

These operations proposed in (D. Michael, 2004) as outlined by Algorithm 2.1.

2.3 A multi-objective approach to implement preventive and protective barriers

As we have mentioned above that, the main drawback of the approach developed in (Badreddine & Ben Amor, 2012) resides in the fact that it does not consider the real aspect of existing system for evaluating the barriers implementation while implementing them.

In order to overcome this limit, we propose to solve the problem of barriers implementation by using a graphical model, namely the *influence diagrams*, which is known as extensions of Bayesian networks and powerful tool to represent and solve decision problems. Indeed, the selection of these barriers is constrained by different criteria especially:

Algorithm 2.1: Evaluation of multi-objective influence diagrams

```
Data: MID
Result: The optimal alternatives of the diagram and its optimal value
begin
    Make sure that the influence diagram is regular and oriented.
    Remove all barren nodes.
    while Par(V_i) ≠∅ do
        if ∃ chance node C_i ∈ Par(V_i) then
            Remove C_i
            Update the utility function of V_i
            else
                if ∃ decision node D_i∈ Par(V_i) then
                    Remove D_i
                    Update the utility function of V_i
                else
                    Find a chance node C_i where Ch(C_i) ∩ D ≠ ∅
                    while Ch(C_i) ≠∅ do
                        if ∃ C_j where C_i∈ Par(C_j) then
                            Reverse the arc between C_iandC_j.
                    Remove C_i.
end
```

effectiveness, *reliability*, *availability* and *cost*, in this way we can consider it as multi-criteria problem. Thus, we propose to use an extension of influence diagrams which are the multi-objective influence diagrams (D. Michael, 2004). Our idea is to develop a mapping procedure from Bow tie structure into MID. Then we propose to apply the algorithm of evaluation for MID, to define the appropriate preventive and protective barriers (shown in Figure 2.1).

Therefore, the proposed approach is divided into three phases: A qualitative phase in which we propose a mapping algorithm from Bow tie structure to multi-objective influence diagram, a quantitative phase in which we propose to quantify this MID based on the numerical component of Bow tie and an evaluation phase where we propose to apply Algorithm 2.1 in order to generate the optimal strategy of preventive and protective barriers implementation. We detail in what follows these three phases.

2.3.1 Qualitative phase

The implementation of barriers is constrained by criteria, thus we will consider these latters as four objectives that we will group them in a unique value node. We note that the main

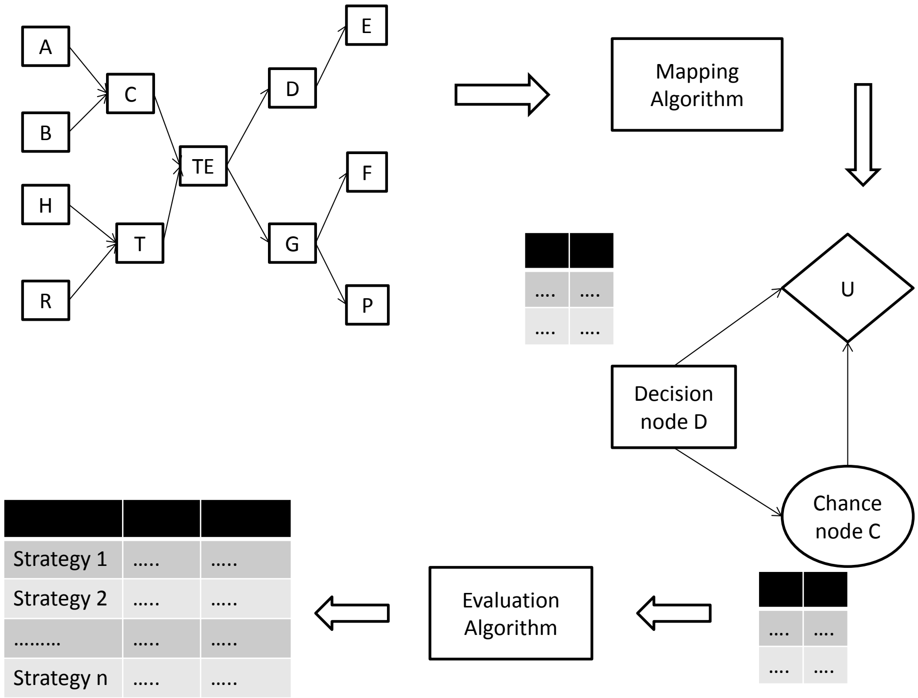

Figure 2.1: A multi-objective approach to implement barriers

objectives of this problem are to maximize effectiveness, reliability and availability and to minimize cost.

- Let BT be a Bow tie which is composed of:$\{IE, IndE, CE, SE, DE, PreB, ProB\}$ such that IE (resp. IndE, CE, SE, DE) is the set of initiator (resp. critical, undesired, second, dangerous) events, PreB (resp. ProB) is the set of preventive (resp. protective) barriers and ord be the order between these barriers.
- Let $O_1 \dots O_4$ be the objectives of barriers implementation.
- Let $R_1 \dots R_6$ be the set of rate nodes.

We describe in what follows the steps of qualitative phase.

First, we propose to incorporate a set of rate, we can represent them as chance node since they are random variable. These rates are used to obtain an information on the criteria of barriers. These variables are defined as follows:

- *Frequency reduction rate*, denoted by R_{redF}, represents the difference between the frequency of TE with implementation of preventive barriers and without them.

- *Severity reduction rate*, denoted by R_{redS}, represents the difference between the severity of ME with implementation of protective barriers and without them.
- *Frequency reduction rate under condition*, denoted by R_{redFuc}, represents the difference between the frequency of TE with implementation of preventive barriers under given condition and without them.
- *Severity reduction rate under condition*, denoted by R_{redSuc}, represents of the difference between the severity of ME with implementation of protective barriers under given condition and without them.
- *Response rate*, denoted by R_R, represents the response rate achieved during the implementation of barriers. We note that these values are assigned by experts.
- *Maintenance rate*, denoted by R_M, represents the rate of maintenance of barriers during their implementation.

The procedure of handling rate nodes in the MID is outlined in Algorithm 2.2.

Algorithm 2.2: Handel rate nodes

```
Data: R_1 ... R_6
Result: MID
begin
    for i ← 1...6 do
        % Create rate nodes
        MID.C ← R_i
        % Connect rate nodes with value node
        addLink(MID.C.R_i → MID.V)
end
```

Where *addLink(X, Y)* is a function which connects X node to Y node.

Then, each event form initiator event to dangerous event of Bow tie diagram, we will represent them as chance node since they are considered as random variable, we note that, all these variables are considered as binary(T=present, F=absent). Then, we propose to transfer all links between them to MID

It is important to pinpoint that, effectiveness and reliability criteria depend on R_{redF} and R_{redS}, we propose to incorporate these rates instead of representing TE and ME. Then, we propose to connect the initiator events to R_{redF} and R_{redFuc}, since they have an impact on the occurrence of TE. Then, we propose to connect R_{redF} and R_{redFuc} to seconder event SE, sine they have an impact on the occurrence of SE. After that, we propose to connect the dangerous events DE to R_{redS} and R_{redSuc}, since they have an impact on the gravity of ME. The procedure of handling events in MID is outlined in Algorithm 2.3.

Algorithm 2.3: Handel events

```
Data: MID; BT.IE; BT.IndE; BT.CE; BT.SE; BT.DE; I_1 ... I_6
Result: MID
begin
    % Create events
    MID.C ← MID.C ∪ BT.IE ∪ BT.IndE ∪ BT.CE ∪ BT.SE ∪ BT.DE
    copyLink(BT, MID.C)
    % Connect initiator events with R_redF and R_redFuc
    foreach IE_i ∈ BT.IE do
        if MID.C.R = R_redF ||MID.C.R = R_redFuc then
            addLink(IE_i → R_redF)
            addLink(IE_i → R_redFuc)
    % Connect R_redF and R_redFuc with seconder events
    foreach SE_i ∈ BT.SE do
        if MID.C.R = R_redF ||MID.C.R = R_redFuc then
            addLink(R_redF → SE_i)
            addLink(R_redFuc → SE_i)
    % Connect dangerous events with R_redS and R_redSuc
    foreach DE_i ∈ BT.DE do
        if MID.C.R = R_redS ||MID.C.R = R_redSuc then
            addLink(DE_i → R_redS)
            addLink(DE_i → R_redSuc)
end
```

Where *copyLink(BT, MID)* is a function which transfers all links between events from BT to MID.

Each barrier, we will represent it as decision node, since it is assumed as action. Then, we propose to connect these barriers with the concerned events. Next, each preventive barrier we will connect it to R_{redF} and R_{redFuc}, since they have an impact on the occurrence of TE. Then, we propose to connect each protective barrier to R_{redS} and R_{redSuc}, since they have an impact on the gravity of ME.

Then, we propose to connect each barrier to R_{RT} (resp. R_M) since these barriers have an effect on availability (resp. cost) criteria. Finally, we propose to connect together by respecting the order defined by experts. The procedure of handling barriers in MID is outlined in Algorithm 2.4.

Algorithm 2.4: Handel barriers

```
Data: MID; BT.Pre; BT.Pro; ord; R_1 ... R_6
Result: MID
begin
    MID.D ← BT.PreB ∪ BT.ProB
    % Connect preventive barriers with concerned events
    foreach PreB_i ∈ BT.PreB do
        foreach C_i ∈ InterBar(PreB_i) do addLink(PreB_i → C_i)
    % Connect preventive barriers with R_redF, R_redFuc, R_Rt, R_M
    foreach PreB_i ∈ BT.PreB do
        foreach R_i ∈ MID.C.R do
        if R_i ≠ R_redS ||MID.C.R ≠ R_redSuc then addLink(PreB_i → R_i)
    % Connect protective barriers with concerned events
    foreach ProB_i ∈ BT.ProB do
        foreach C_i ∈ InterBar(ProB_i) do addLink(ProB_i → C_i)
    % Connect protective barriers with R_redF, R_redFuc, R_Rt, R_M
    foreach ProB_i ∈ BT.ProB do
        foreach R_i ∈ MID.C.R do
        if R_i ≠ R_redF ||MID.C.R ≠ R_redFuc then addLink(ProB_i → R_i)
    % Connect protective barriers with R_redS, R_redSuc, R_Rt, R_M
    l=|MID.D|
    for t ← 1 ... (l − 1) do
        for t ← (t + 1) ... (l) do
        addLink(MID.D_ord → MID.D_ord+1)
end
```

Where *InterBar($PreB_{ij}$)* (resp. *InterBar($ProB_{ij}$)*) is a function which returns the event when $PreB_{ij}$ (resp. $ProB_{ij}$) intervenes.

It is important to pinpoint that, the structure of MID which is generated by the qualitative phase, satisfies the properties of MID.

2.3.2 Quantitative phase

When the structure of MID is constructed by the previous phase, we propose to quantify its numerical component, by taking into consideration the data.

- Let D_F be the difference computed the frequency of TE by implementing preventive barriers and without them.

- Let D_{Fuc} be the difference between the frequency of TE by implementing preventive barriers and without them, under given condition.
- Let D_S be the difference between the severity of ME by implementing protective barriers and without them.
- Let D_{Suc} be the difference between the severity of ME by implementing protective barriers and without them, under given condition.

Then, we present the details of quantification phase as follows:

- **Chance node**: For each event form initiator events to dangerous events of Bow tie diagram, we assign the tables of these nodes by using the CPT of Bow tie by taking into account the implementation and non implementation of barriers. The procedure of generating CPT of events nodes is outlined in Algorithm 2.5.

Algorithm 2.5: Generate CPT events

Data: MID; BT.CPT
Result: MID.CPT
begin
  foreach $IE_i \in BT.IE$ **do** $MID.C.IE_i.CPT \leftarrow BT.IE_i.CPT$
  foreach $Inde_i \in BT.Inde$ **do** $MID.C.Inde_i.CPT \leftarrow BT.Inde_i.CPT$
  foreach $CE_i \in BT.CE$ **do** $MID.C.CE_i.CPT \leftarrow BT.CE_i.CPT$
  foreach $SE_i \in BT.SE$ **do** $MID.C.SE_i.CPT \leftarrow BT.SE_i.CPT$
  foreach $DE_i \in BT.DE$ **do** $MID.C.DE_i.CPT \leftarrow BT.DE_i.CPT$
end

For rate nodes, we quantify them by using the different marginal, which are issued from the propagation phase. For example, the quantification of R_{redF} (resp. R_{redS}), is performed by computing the difference between the frequency of TE (resp. severity of ME) by implementing barriers and without them. We note that, R_R and R_M are assigned by experts.

The procedure of generating CPT of rate nodes is outlined in Algorithm 2.6.

Algorithm 2.6: Generate CPT rate

Data: MID; D_F; D_{Fuc}; D_S; D_{Suc}
Result: MID.CPT
begin
  for $i \leftarrow 1 \ldots 4$ **do**
    if $R_i = R_{redF}$ **then** $MID.C.R_i.CPT \leftarrow quantify - redF(D_F)$
    if $R_i = R_{redFuc}$ **then** $MID.C.R_i.CPT \leftarrow quantify - redFuc(D_{Fuc})$
    if $R_i = R_{redS}$ **then** $MID.C.R_i.CPT \leftarrow quantify - redS(D_S)$
    if $R_i = R_{redSuc}$ **then** $MID.C.R_i.CPT \leftarrow quantify - redSuc(D_{Suc})$
end

Where:

- *quantify-redF(D_F)* is a function which quantifies R_{redF}, taking into account D_F.
- *quantify-redFuc(D_{Fuc})* is a function which quantifies R_{redFuc}, taking into account D_{Fuc}.
- *quantify-redS(D_S)* is a function which quantifies R_{redS}, taking into account D_S.
- *quantify-redSuc(D_{Suc})* is a function which quantifies R_{redSuc}, taking into account D_{Suc}.

- **Decision node**: For barriers nodes, these values take two states which are, (T=implemented, F=Non implemented).

- **Value node**: This node contains four vectors namely, {*effectiveness*, *reliability*, *availability*, *cost*}, quantified as follows:

  - *Effectiveness*: According to its definition, this criteria depends on the rate of reduction frequency and the rate of reduction severity.
  - *Reliability*: According to its definition, this value depends on the rate of reduction frequency under condition and the rate of reduction severity under condition.
  - *Availability*: According to its definition, this value depends on the rate of reduction frequency under condition and the rate of reduction severity under condition and response time.
  - *Cost*: This value is assigned by experts, which is based on the rate of maintainability of barriers.

The procedure of generating utility function of value node is outlined in Algorithm 2.7.

Algorithm 2.7: Generate Utility function

```
Data: MID
Result: MID.UF
begin
    for O ← 1...4 do
        if O_i = Effectiveness then MID.O_i.UF ← measure − effectiveness(R_redF, R_redS)
        if O_i = Reliability then MID.O_i.UF ← measure − reliability(R_redFuc, R_redSuc)
        if O_i = Availability then MID.O_i.UF ← measure − avai(R_redFuc, R_redSuc, R_Rt)
        if O_i = Cost then MID.O_i.UF ← measure − cost(R_M)
end
```

Where:

- *quantify-effectiveness(R_{redF},R_{redS})* is a function which quantifies the effectiveness criteria, taking into account R_{redF} and R_{redS}.
- *quantify-reliability(R_{redFuc},R_{redSuc})* is a function which quantifies the reliability criteria, taking into account R_{redFuc} and R_{redSuc}.
- *quantify-availability(R_{redFuc},R_{redSuc},R_{Rt})* is a function which quantifies the availability criteria, taking into account R_{redFuc}, R_{redSuc} and R_{Rt}.
- *quantify-cost(R_M)* is a function which quantifies the cost criteria, taking into account R_M.

2.3.3 Evaluation phase

This phase consists to apply Algorithm 2.1 in order to generate the optimal strategy of barriers implementation, which satisfy $\{$*effectiveness*, *reliability*, *availability*, *cost*$\}$. In the remainng, the application of this algorithm is provided by calling generateoptimalStrategy() function.

Algorithm 2.8 outlines the proposed multi-objective approach to implement the preventive and protective barriers.

Algorithm 2.8: The appropriate preventive and protective barriers

Data: BT; BT.PreB; BT.ProB; ord; $I_1 \dots I_6$; $O_1 \dots O_4$
Result: Optimal strategy of barriers implementation
begin
  % *Qualitative phase*
  % *Collect the objectives in the same node V*
  $MID.V \leftarrow O_1 \cup O_2 \cup O_3 \cup O_4$
  Handel rate nodes()
  Handel events()
  Handel barriers()
  % *Quantitative phase*
  generateCPTevent()
  generateCPTratenodes()
  generateUtilityFunction()
  % *Evaluation phase*
  generateoptimalStrategy()
end

2.4 Conclusion

In this chapter we have presented a new multi-objective approach to implement preventive and protective barriers which reflect the real aspect of the existing system. To this end, we propose a mapping procedure from Bow tie structure into a multi-objective influence diagram. Then, we have applied algorithm of evaluation in order to define the appropriate preventive and protective barriers. Our choice to use this graphical model is argued by the fact that is an appropriate tool to solve the multi-criteria problem.

Chapter 3

Case of study

3.1 Introduction

The implementation mapping procedure from Bow tie structure to multi-objective influence diagram seems imperative since it allows us have an idea concerning automation of task of barriers implementation taking into consideration the real aspect of the system. Thus we have extended the algorithm to build Bow tie proposed in (Badreddine & Ben Amor, 2012), then we have implemented a mapping algorithm from Bow tie structure into MID in order to implement preventive and protective barriers. We illustrate our approach via an example in TOTAL TUNISIA company. Then, we propose to make comparison between our method and the one developed in (Badreddine & Ben Amor, 2012).

The remaining of this chapter is organized as follows, we will represent the different results obtained. Section 3.3 present the application of Algorithm 2.8 to implement preventive and protective barriers. Section 4.4 presents a comparison study between the both approaches.

3.2 Implementation

In order to illustrate the proposed approach, we have developed programs in Matlab V7, Obviously, we have implemented the MWST algorithm for structure learning, Peral algorithm in order to achieve the propagation task, the algorithm of evaluation of multi-objective influence diagrams aims to generate the optimal strategy of barriers implementation, and our proper algorithm of mapping from Bow tie structure to multi-objective influence diagram.

The outputs of the proposed approach are basically:

- The structure of Bow tie with its numerical component.
- The multi-objective diagram that is equivalent to the Bow tie.
- The optimal strategy of barriers implementation.

3.3 Preventive and protective barriers implementation

Once the Bow tie diagram is constructed by applying Algorithm 2.1, which is illustrated in Figure 1.3, then its numerical component for fault tree is generated (shown in Table 1.7) and its severity degrees for event tree are studied (shown in Table 1.8), we propose to implement the appropriate preventive and protective barriers. We assume that, the decision maker proposes a set of preventive and protective barriers which can be intervene on some branches of fault tree (resp. event tree) in order to reduce the frequency of TE (resp. the severity of major event). These barriers are illustrated in Table 3.9.

Preventive barriers
Periodic preventive to minimize TVF (PP)
Fire simulation to minimize EF (FS)
Education and training task to deal with HGL (ETT)
Protective barriers
Blast protection window film to minimize PF (BP)
Setting up equipment to limit THE (SUEH)
Setting up equipment to limit TOE (SUEO)

Table 3.1: Preventive and protectives barriers

3.3.1 Qualitative phase

As detailed in the previous section, we consider four creterias (O_1=effectiveness, O_2=reliability, O_3=availability, O_4=cost) in order to implement the appropriate barriers. As inputs of the proposed approach, we can define:

- BT, O_1, O_2, O_3, O_4.
- Prevetive barriers :PP, FS, ETT

- Protecetive barriers: BP, SUEH, SUEO

- Order (ord) between barriers in order to respect the propriety of No-forgetting, we consider it as (PP, FS, ETT, BP, SUEH, SUEO) means $\{1, 2, 3, 4, 5, 6\}$.

On the basis of these inputs, the qualitative phase is preformed as follows:

1. Collect objectives in the same value node V_C (shown in Figure 3.1.a).

2. Create the chance nodes R_{RedF}, R_{RedS}, R_{RedFuc}, R_{RedSuc}, R_{Rt}, R_M (shown in Figure 3.1.b).

3. Connect (R_{RedF} to V_C), (R_{RedS} to V_C), (R_{RedFuc} to V_C), (R_{RedSuc} to V_C), (R_{Rt} to V_C) and (R_M to V_C) (shown in Figure 3.1.c).

4. Create DTA, TVF, EF, CTP, HGL, SI, PF, THE, TOE, PPS, TDP (shown in Figure 3.1.d).

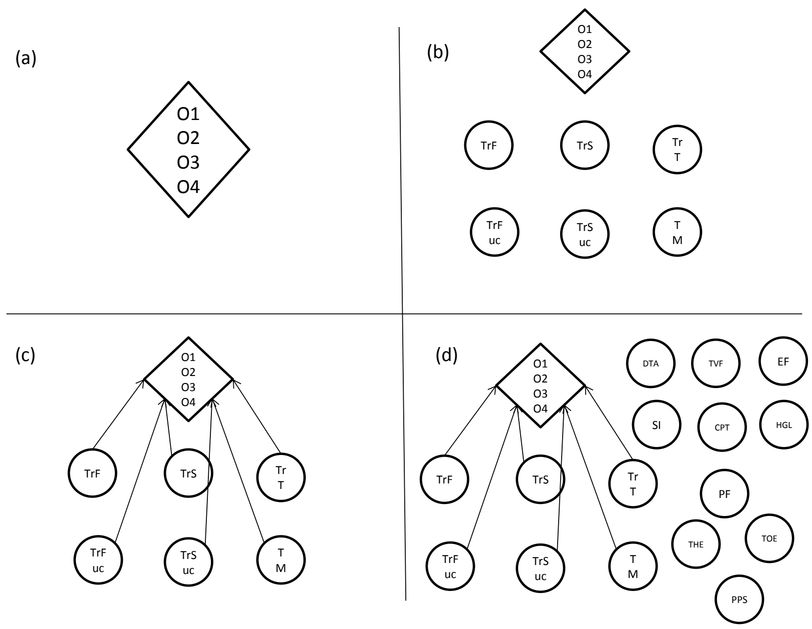

Figure 3.1: MID structure after steps 1, 2, 3, 4

5. Connect (DTA to HGL), (TVF to HGL), (EF to SI), (CPT to SI), (PF to THE), (PF to TOE), and (PF to PPS) (shown in Figure 3.2.a).

6. Connect (HGL to R_{RedF}), (HGL to R_{RedFuc}), (SI to R_{RedF}) and (SI to R_{RedFuc}), (THE to R_{RedS}), (THE to R_{RedSuc}), (TOE to R_{RedS}), (TOE to R_{RedSuc}), (PPS to R_{RedS}), (PPS to R_{RedSuc}) (shown in Figure 3.2.b).

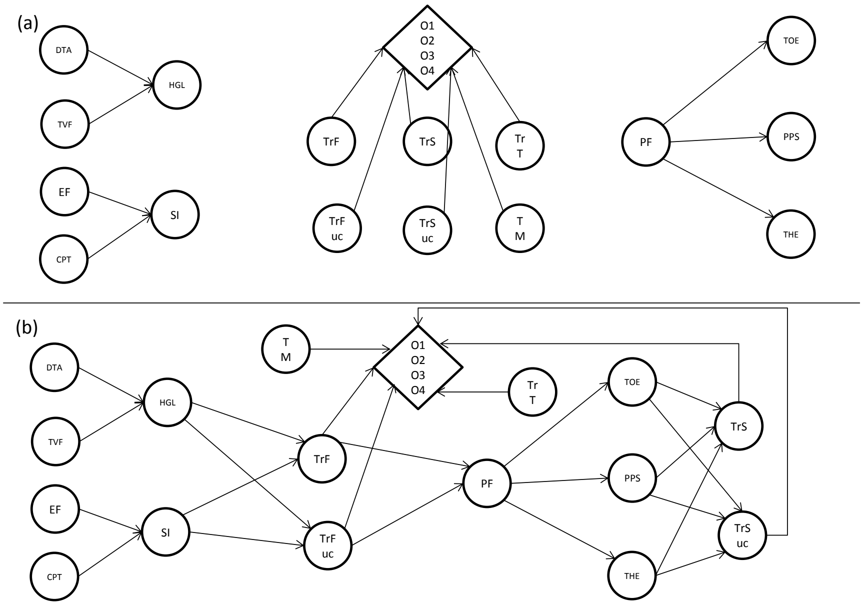

Figure 3.2: MID structure after steps 5, 6

7. Create the descion nodes PP, FS, ETT, BP, SUEH and SUOE (shown in Figure 3.4.a).

8. Connect (PP to TVF), (FS to EF), (ETT to HGL), (BP to PF), (SUEH to THE) and (SUEO to TOE) (shown in Figure 3.3.b).

9. Connect (PP to R_{RedF}), (FS to R_{RedF}), (ETT to R_{RedF}), (PP to R_{RedFuc}), (FS to R_{RedFuc}), (ETT to R_{RedFuc}), (BP to R_{RedS}), (SUEH to R_{RedS}), (SUEO to R_{RedS}), (BP to R_{RedSuc}), (SUEH to R_{RedSuc}), (SUEO to R_{RedSuc}) (shown in Figure 3.4).

10. Connect (PP to R_{Rt}), (FS to R_{Rt}), (ETT to R_{Rt}), (BP to R_{Rt}), (SUEH to R_{Rt}) and (SUEO to R_{Rt}) (shown in Figure 3.4).

11. Connect (PP to R_M), (FS to R_M), (ETT to R_M), (BP to R_M), (SUEH to R_M) and (SUEO to R_M) (shown in Figure 3.5).

12. Connect (PP to FS), (FS to ETT), (ETT to BP), (BP to SUEH)a nd (SUEH to SUEO)(shown in Figure 3.6).

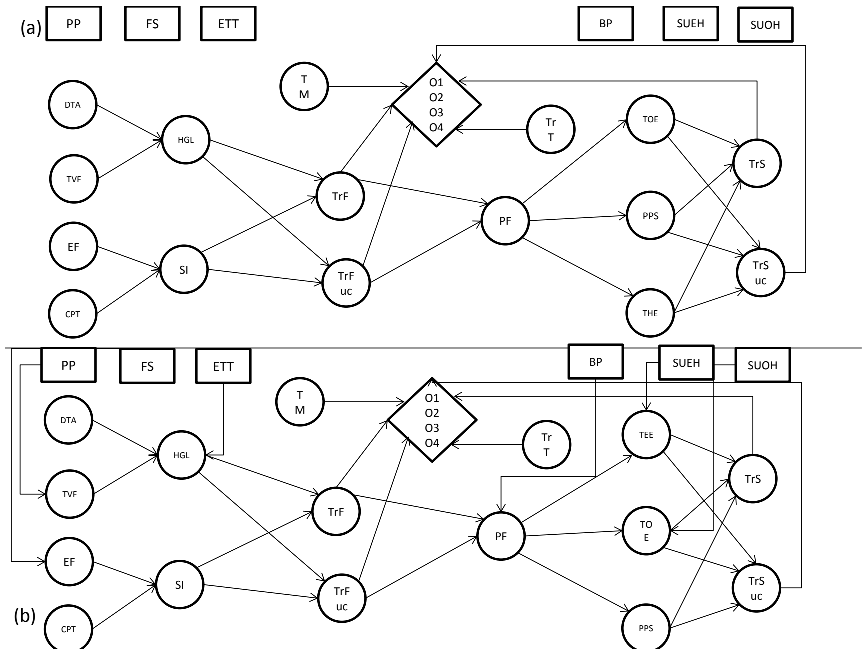

Figure 3.3: MID structure after steps 7, 8

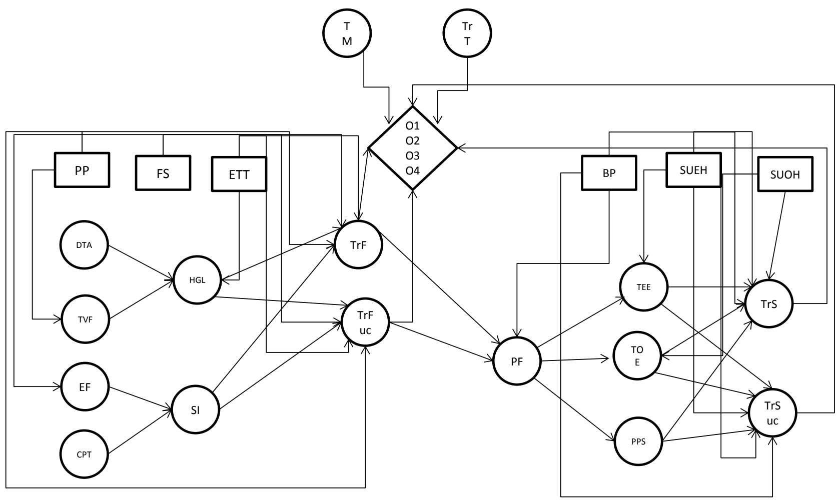

Figure 3.4: MID structure after steps 9, 10, 11

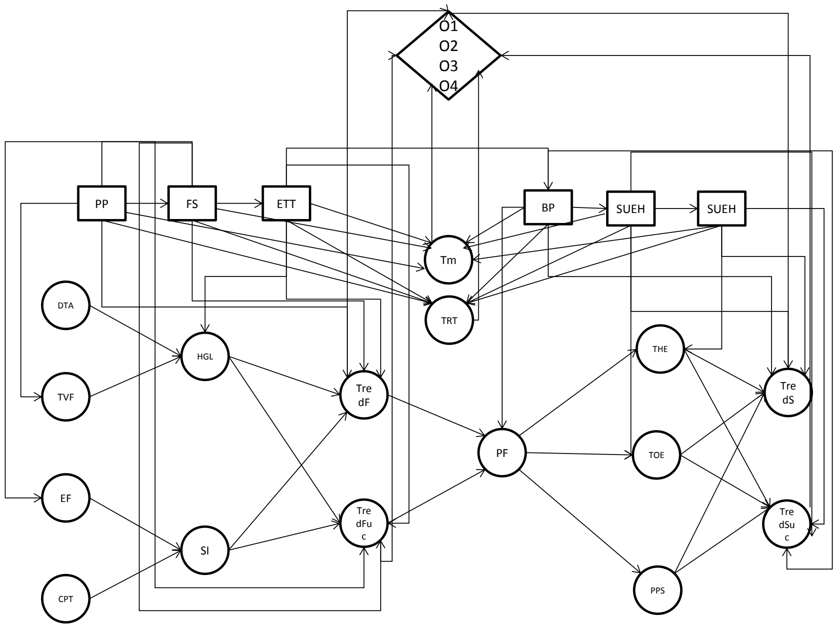

Figure 3.5: Resulted MID structure

The structure of this MID is illustrated in Figure 3.6, which is defined by:

- C=$\{R_{RedF}, R_{RedS}, R_{RedFuc}, R_{RedSuc}, DTA, TVF, EF, CTP, HGL, SI, PF, THE, TOE, PPS\}$.
  Where :
  - R_{RedF}, R_{RedS}, R_{RedFuc}, R_{RedSuc} have three states (i.e. H=High reduction, M=Moderate N=Non reduction).
  - R_R has three states (i.e. H=High response time, M=Moderate response time, L=Low response time).
  - R_M has three states (i.e. H=High maintenance, M=Moderate maintenance, L=Low maintenance).
- D=$\{PP, FS, ETT, BP, SUEH, SUEO\}$ such that, all decision nodes have two states (i.e. T=Implemented, F=Non implemented).
- V=$\{V_C\}$.

3.3.2 Quantitative phase

Once the MID structure is constructed, a quantification phase is performed in order to generate the numerical component of this structure. We first begin by copy the conditional probability table of events taking into a consideration the implementation of barriers, from Bow tie into MID, which can be summarized in Table 3.2…3.5.

FS	EF	$P(EF\|FS)$	CPT	P(CPT)
T	T	0.27	T	0.22
T	F	0.73	F	0.78
F	T	0.38		
F	F	0.62		
PP	TVF	$P(TVF\|PP)$	DTA	P(DTA)
T	T	0.35	T	0.4
T	F	0.65	F	0.6
F	T	0.44		
F	F	0.56		

Table 3.2: Conditional probability of CPT, DTA, EF, TVF

Then, we propose to generate the conditional probability of rates as outlined in Algorithm 2.6. Regarding R_{redF}, we first compute the difference between frequency of TE by implementing preventive barriers and without them. On the basis of D_F column in Table, we can quantify R_{redF}. Finally, we assign the utility function of V by applying the procedure outlined in Algorithm 2.7.

3.3.3 Evaluation phase

In order to define the optimal strategy of preventive and protective barriers, we apply Algorithm 2.1 which is performed as follows:

1. Remove R_{RedS}, R_{RedSuc}, since they have a unique multi objective value node as children node (shown in Figure 3.6).

2. Remove, THE, TOE, PPS same situation (shown in Figure 3.7).

3. Remove, PF same situation (shown in Figure 3.8).

4. Remove R_{RedF}, R_{RedFuc}, since they have a unique multi objective value node as children node (shown in Figure 3.10).

ETT	DTA	TFV	HGL	$P(HGL\,|ETT, DTA, TVF)$
T	T	T	T	0.65
T	T	T	F	0.35
T	T	F	T	0.29
T	T	F	F	0.71
T	F	T	T	0.9
T	F	T	F	0.1
T	F	F	T	0.4
T	F	F	F	0.6
F	T	T	T	0.73
F	T	T	F	0.27
F	T	F	T	0
F	T	F	F	1
F	F	T	T	0.8
F	F	T	F	0.1
F	F	F	T	0
F	F	F	F	1
EF	CTP	SI	$P(SI\,|EF, CTP)$	
T	T	T	0.71	
T	T	F	0.29	
T	F	T	0.62	
T	F	F	0.38	
F	T	T	0.58	
F	T	F	0.42	
F	F	T	0.17	
F	F	F	0.83	

Table 3.3: Conditional probability of HGL, SI

5. Remove HGL, SI same situation (shown in Figure 3.10).

6. Remove DTA, TVF, EF, CTP, same situation (shown in Figure 3.11.a).

7. Remove R_{TM}, R_{RT}, since they have a unique multi objective value node as children (shown in Figure 3.11.b).

8. Remove PP, FS, ETT, BP, SUEH, SUEO (shown in Figure 3.10.a, 3.11.b, 3.12.a, 3.13.b).

BP	R_{redF}	R_{redFuc}	PF	$P(PF\|BP, R_{redF}, R_{redFuc})$
T	H	H	T	0.34
T	H	H	F	0.66
T	H	N	T	0.47
T	H	N	F	0.53
T	N	H	T	0.35
T	N	H	F	0.65
T	N	N	T	0.39
T	N	N	F	0.61
F	H	H	T	0.66
F	H	H	F	0.34
F	H	N	T	0.7
F	H	N	F	0.3
F	N	H	T	0.55
F	N	H	F	0.45
F	N	N	T	0.57
F	N	H	F	0.43

Table 3.4: Conditional probability table of PF

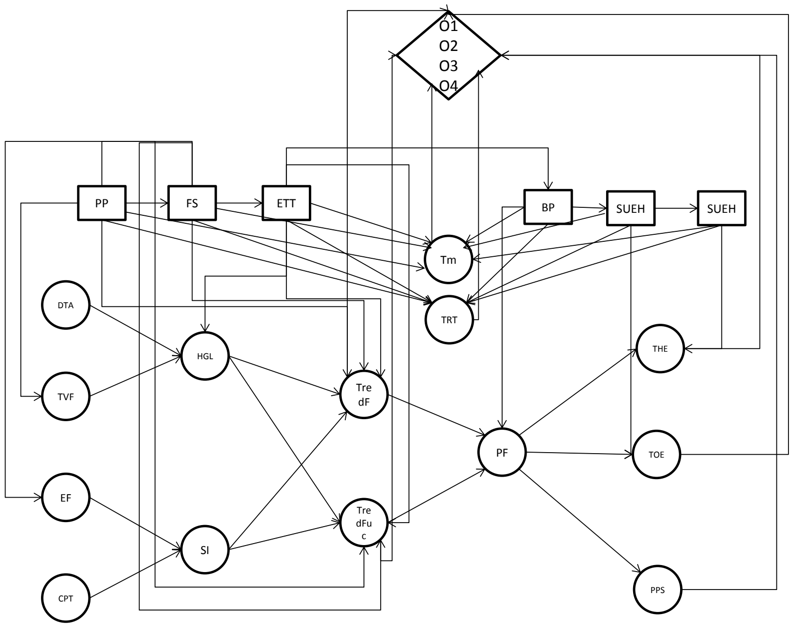

Figure 3.6: MID structure after removing R_{redS} and R_{redSuc}

SUEH	PF	THE	$P(THE\,\|SUEH, PF)$
T	T	T	0.63
T	T	F	0.37
T	F	T	0.22
T	F	F	0.78
F	T	T	1
F	T	F	0
F	F	T	0.21
F	F	F	0.79
SUOH	PF	TOE	$P(TOE\,\|SUOH, PF)$
T	T	T	0.59
T	T	F	0.41
T	F	T	0.23
T	F	F	0.77
F	T	T	1
F	T	F	0
F	F	T	0.3
F	F	F	0.7
PF	PPS	$P(PPS\,\|PF)$	
T	T	1	
T	F	0	
F	T	0.3	
F	F	0.7	

Table 3.5: Conditional probability table of THE, TOE, PPS

It is important to note that all operations of chance node removal follow case A, since there is not a removal decision node prior to chance node being removed. As output of this algorithm, the optimal strategy of preventive and protective barriers which satisfy {*effectiveness*, *reliability*, *availability*, *cost*}. For our example, the appropriate preventive and protective barriers are:

Strategy 1=$\{PP = T, FS = T, ETT = T, BP = F, SUEH = T, SUEO = T\}$.

Strategy 2=$\{PP = T, FS = T, ETT = T, BP = F, SUEH = F, SUEO = T\}$.

HGL	SI	PP	FS	ETT	D_F	$P(R_{redF} = H)$	$P(R_{redF} = M)$	$P(R_{redF} = N)$
T	T	T	T	T	0.02	0	1	0
T	T	T	T	F	0.03	0	1	0
T	T	T	F	T	0.02	0	1	0
T	T	T	F	F	0.02	0	1	0
T	T	F	T	T	0.02	0	1	0
T	T	F	T	F	0.03	0	1	0
T	T	F	F	T	0.03	0	1	0
T	T	F	F	F	0.02	0	1	0
T	F	T	T	T	0.27	1	0	0
T	F	T	T	F	0.35	1	0	0
T	F	T	F	T	0.33	1	0	0
T	F	T	F	F	0.28	1	0	0
T	F	F	T	T	0.28	1	0	0
T	F	F	T	F	0.29	1	0	0
T	F	F	F	T	0.29	1	0	0
T	F	F	F	F	0.27	1	0	0
F	T	T	T	T	0.05	0	1	0
F	T	T	T	F	0.04	0	1	0
F	T	T	F	T	0.02	0	1	0
F	T	T	F	F	0.03	0	1	0
F	T	F	T	T	0.04	0	1	0
F	T	F	T	F	0.04	0	1	0
F	T	F	F	T	0.03	0	1	0
F	T	F	F	F	0.04	1	1	1
F	F	T	T	T	0.25	1	0	0
F	F	T	T	F	0.05	0	1	0
F	F	T	F	T	0.03	0	1	0
F	F	T	F	F	0.02	0	1	0
F	F	F	T	T	0.02	0	1	0
F	F	F	T	F	0.03	0	1	0
F	F	F	F	T	0.03	0	0	1
F	F	F	F	F	0	0	0	1

Table 3.6: Conditional probability of R_{redF}

R_{redF}	R_{redFuc}	R_{redS}	R_{redSuc}	R_R	R_M	Eff	Rel	Avai	Cst
H	H	H	H	H	H	0.85	0.79	0.75	200
H	H	M	M	H	H	0.85	0.53	0.75	200
H	H	N	N	H	H	0.85	0.05	0.75	200
M	M	H	H	H	H	0.33	0.79	0.75	200
M	M	M	M	H	H	0.33	0.53	0.75	200
N	N	H	H	H	H	0.01	0.79	0.75	200
N	N	M	M	H	H	0.01	0.02	0.75	200
H	H	H	H	M	M	0.85	0.79	0.47	100
M	M	H	H	M	M	0.33	0.79	0.47	100
M	M	M	M	M	M	0.33	0.53	0.47	100
M	M	N	N	M	M	0.33	0.02	0.47	100
N	N	H	H	M	M	0.01	0.79	0.47	100
N	N	M	M	M	M	0.01	0.53	0.47	100
N	N	N	N	M	M	0.01	0.02	0.47	100
H	H	H	H	L	L	0.85	0.79	0.13	50
H	H	M	M	L	L	0.85	0.53	0.13	50
H	H	N	N	L	L	0.85	0.02	0.13	50
M	M	H	H	L	L	0.33	0.79	0.13	50
M	M	M	M	L	L	0.33	0.53	0.13	50
M	M	N	N	L	L	0.33	0.02	0.13	50
N	N	H	H	L	L	0.01	0.79	0.13	50
N	N	M	M	L	L	0.01	0.53	0.13	50
N	N	N	N	L	L	0.01	0.02	0.13	50
H	H	H	H	H	M	0.85	0.79	0.75	100
H	H	H	H	H	L	0.85	0.79	0.75	50
H	H	H	H	M	H	0.85	0.79	0.47	200
H	H	H	H	L	H	0.85	0.79	0.13	200
H	H	M	M	H	M	0.85	0.53	0.75	100
H	H	M	M	H	L	0.85	0.53	0.75	50
H	H	M	M	M	H	0.85	0.53	0.47	200
H	H	N	N	M	L	0.85	0.02	0.47	50
H	H	N	N	M	M	0.85	0.02	0.47	100

Table 3.7: Utility function of V

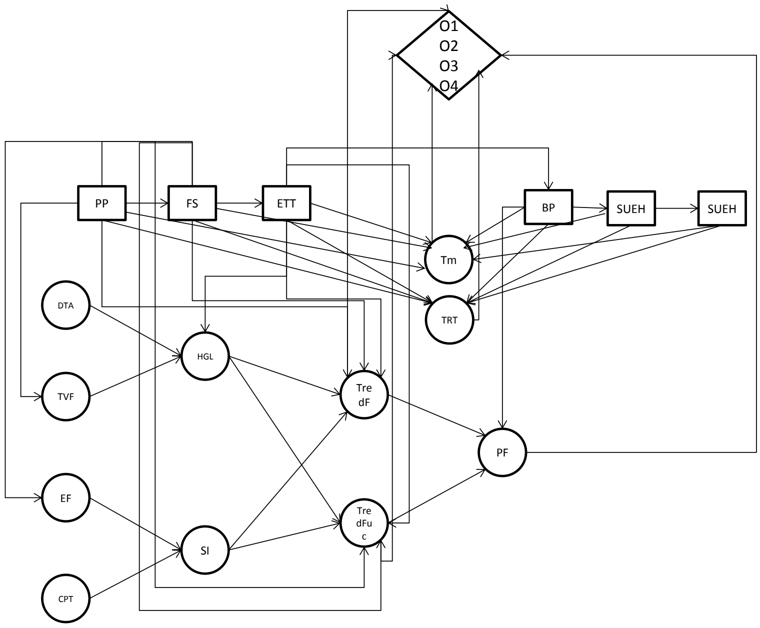

Figure 3.7: MID structure after removing THE, TOE and PPS

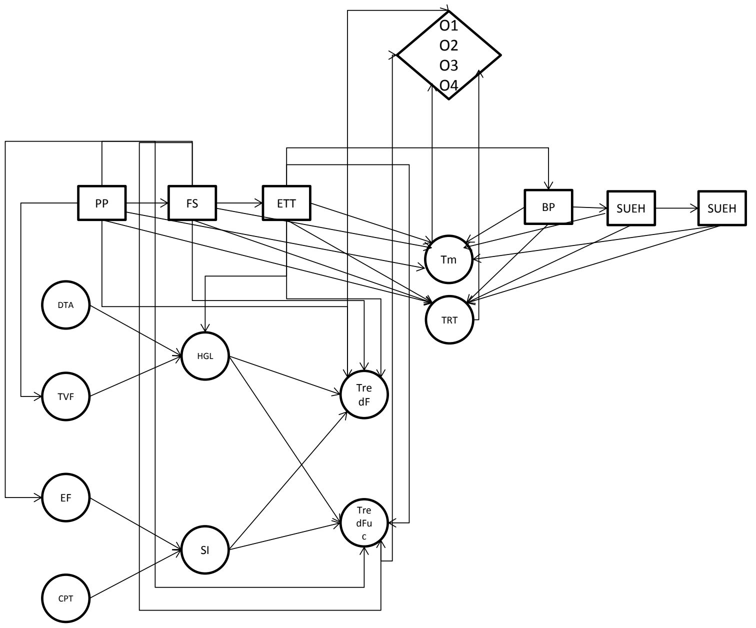

Figure 3.8: MID structure after removing PF

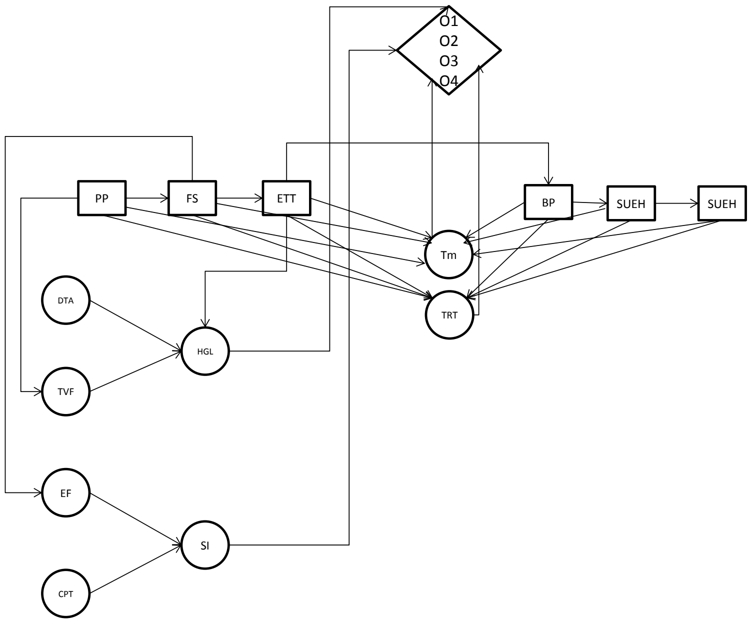

Figure 3.9: MID structure after removing R_{redF} and R_{redFuc}

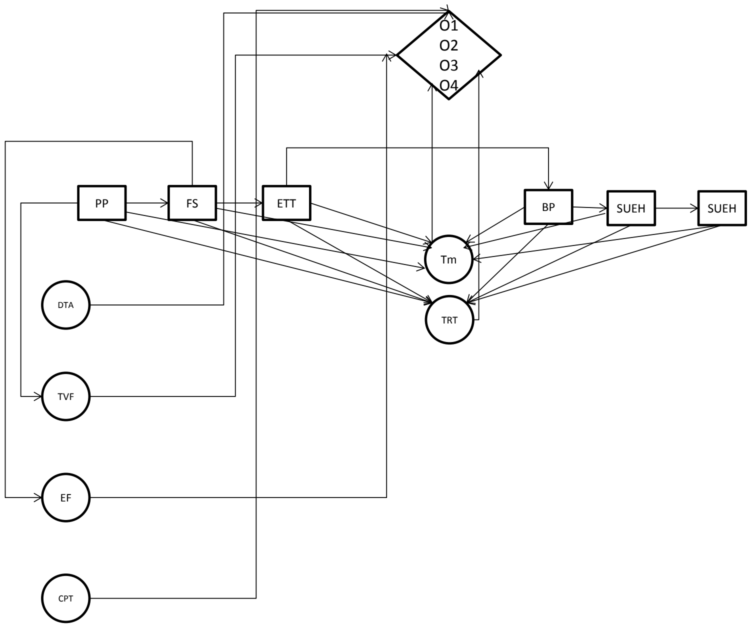

Figure 3.10: MID structure after removing HGL and SI

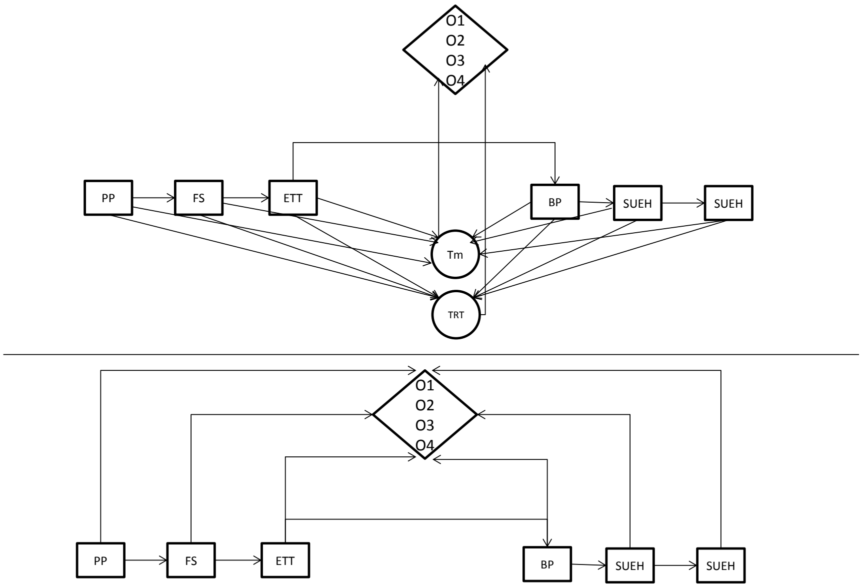

Figure 3.11: MID structure after removing R_{Rt} and R_M

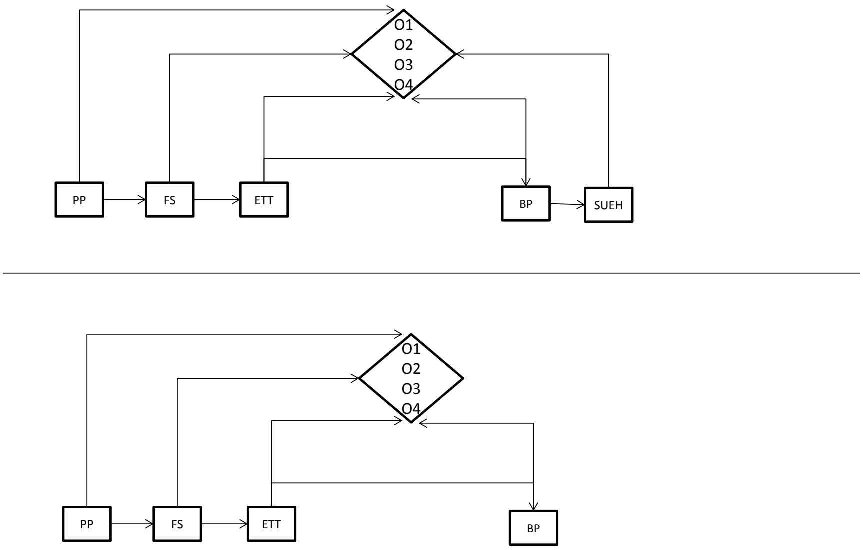

Figure 3.12: MID structure after removing PP, FS and ETT

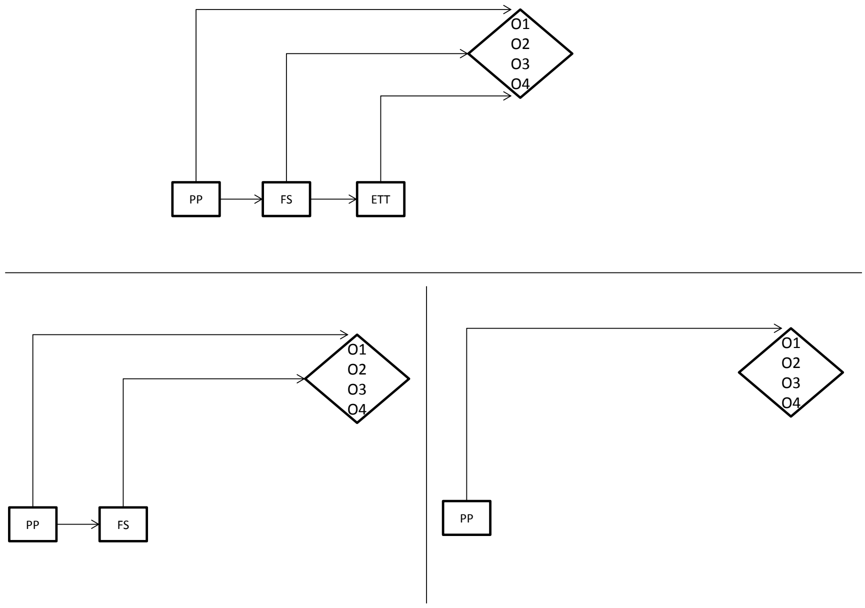

Figure 3.13: MID structure after removing BP, SUEH, SUOE

3.4 Comparative study

Interestingly enough, we establish a comparison between proposed approach and the one developed in (Badreddine & Ben Amor, 2012) for barriers implementation. When the appraoch of (Badreddine & Ben Amor, 2012) applyes AHP method in order to implement barriers, we chose to propose a mapping procedure form Bow tie structue to multi-objective influence diagram in order to solve this problem. It is important to pinpoint that, the proposed approach reflects the real behavior of the system, while the other apparch does not consider this latter while implementing the barriers. Thus, we can conclude that our method genearte a resuls more realistic than the one.

Principal steps to implement barriers for both approaches can be summarized in Figure 3.14. Table 3.6 illustrate a summary of comparison between the proposed approach, and the one is developed in (Badreddine & Ben Amor, 2012) for barriers implementation.

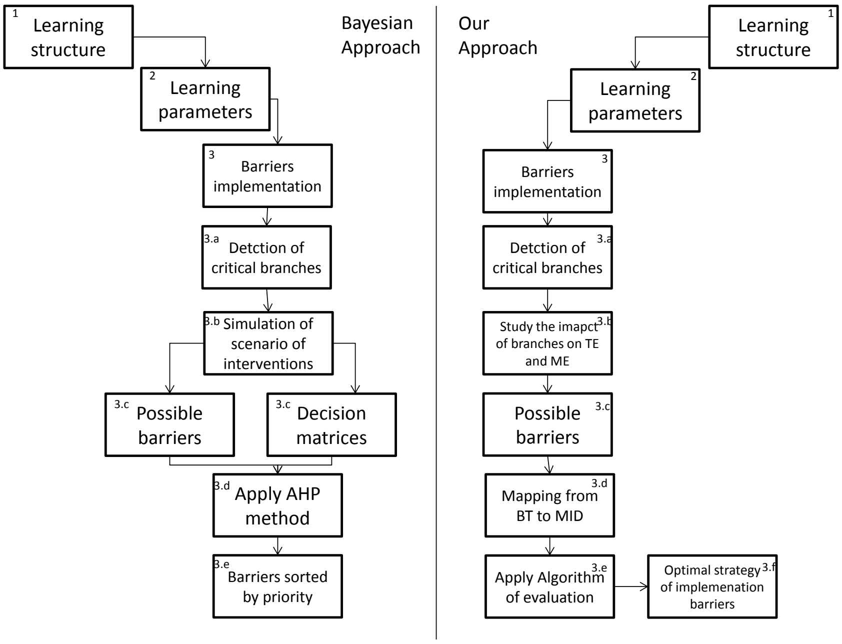

Figure 3.14: Principal steps of both approaches

Parameters	**The proposed approach**	**Approach of (Badreddine & Ben Amor, 2012)**
Inputs	Possible barriers	Possible barriers and decision matrices
Formulation problem	Multi-objective influence diagrams	Three-level hierarchical structure
Algorithm used	Algorithm of evaluation for MID	AHP method
Reflect a real aspect of the system	Yes	Non
Support an order between barriers	Yes	Non
Support a relationship between barriers	Yes	Non
Criteria	Same importance	Degree of importance
Output	Optimal strategy of barriers	Barrier sorted by their priority

Table 3.8: The proposed approach vs the Bayesian approach

3.5 Conclusion

In this chapter we have illustrated our approach via an example in TOTAL TUNISIA company. Then, we have established an interesting comparison between the proposed approach and the one developed in (Badreddine & Ben Amor, 2012). we conclude that, our approach produces a more realistic results, since it reflects the real behavior of the existing system while implementing the preventive and protective barriers.

General Conclusion

Bow tie diagrams remain effective tools to represent the scenario of an accident in the same model, however their quantification is mainly based on expert's knowledge to estimate the frequency and the severity of given risk. In order to overcome this weakness, the Bayesian approach was developed and it is based on learning Bow tie from data. Indeed, this approach presents drawbacks concerning the barrier implementation, which it does not supports the real behavior of the system while implementing them.

In our work, we have extended the algorithm to construct Bow tie proposed in (Badreddine & Ben Amor, 2012) to develop a new multi-objective approach in order to implement barriers, in which we have proposed a mapping procedure from Bow tie structure to multi-objective influence diagram. The choice of this graphical model is argued by the fact that it is an appropriate tool to solve the multi-criteria problem. Then, we have proposed to apply the algorithm of evaluation for multi-objective influence diagram (D. Michael, 2004) in order to generate the optimal strategy of barriers implementation.

We have illustrated an example in TOTAL company, Then, we have gave an interesting comparison between the proposed approach and Bayesian approach in which we have concluded that our approach generates a more realistic result than Bayesian approach.

Finally, regarding the interesting results obtained in this work, we could propose further works that may be done to improve our approach. Often, the training set presents a problem of uncertainty, thus, we propose an approach to overcome this weakness by learning Bow tie from possibilistic training set. Then, we can develop an algorithm that implements the appropriate barriers by using the possibilistic influence diagrams.

References

Abrahamsson, M. (2002). Uncertainty in quantitative risk analysisâcharacterization and methods of treatment.l. *Department of Fire Safety Engineering. Lund University, Sweden..*

Badreddine, A., & Ben Amor, N. (2012). A bayesian approach to construct bow tie diagrams for risk evaluation. *Process Saf. Environ. Protect.*

Badreddine, A., & Amor, N. B. (2010a). A dynamic barriers implementation in bayesian-based bow tie diagrams for risk analysis. *In: Proceedings of International Conference on Computer Systems and Applications*, 1â8.

Badreddine, A., & Amor, N. B. (2010b). A new approach to construct optimal bow tie diagrams for risk analysis. *International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE,*(23), 595â604.

Chow, C. K., & Liu, C. N. (1968). Approximating discrete probability distributions with dependence trees. *IEEE Transactions on Information Theory*(14(3)), 462-467.

Cockshott, J. (2005). Probability bow-ties as transparent risk management tool. *Process Saf. Environ. Protect.*(83)), 307-316.

Couronneau, J., & Tripathi, A. (2003). Implementaion of the new approach of risk analysis on france. *Proceedings of the 41st international Petroleum Conferance, Bratislava, Slovikia.*

Darwiche, A. (2009). Modeling and reasoning with bayesian networks. *Cambridge Univ. Press.*

Delvosall, C., Fievez, C., Pipart, A., & Debray, B. (2006). Aramis project: a comprehensive methodology for the identification of reference accident scenarios in process industries. *J. Hazard. Mater.*(130), 200-219.

Dempster, A. (1968). A generalisation of bayesian inference. *Journal of the Royal Statistical Society, Series B*(30), 205-247.

Dianous, V., & Fievez, C. (2006). Aramis project: a more explicit demonstration of risk control through the use of bow-tie diagrams and the evaluation of safety barrier performance. *J. Hazard. Mater.*(130), 220-233.

D. Michael, Y. H. (2004). Influence diagrams with multiple objectives and tradeoff analysis. *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICSâPART A: SYSTEMS AND HUMANS*(34).

Duijm, N. (2009). Safety-barrier diagrams as a safety management tool. *Reliab. Eng. Syst. Saf.*(94(2)), 332-341.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., & Vetich, B. (2009). Handling data uncertainties in event tree analysis. *Process Saf. Environ. Protect*(85), 283-292.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., & Vetich, B. (2011). Analyzing system safety and risks under uncertainty using a bow tie diagram: an innovative approach. *Process Saf. Environ. Protect, doi:10.1016/j.pesp.2011.08.10, in press.*

Ferdous, R., Khan, F., Sadiq, R., & Veitch, P. A. B. (2009). Methodology for computer aided fuzzy fault tree analysis. *Process Saf. Environ. Protect*(87), 217â226.

Heckerman, D. (1999). A tutorial on learning with bayesian networks. *In Learning in Graphical Models, M. Jordan, ed.. MIT Press.*

Ishizaka, A., & A.Labib. (2009). Analytic hierarchy process and expert choice: Benefits and limitationsl. *doi:10.1057/ori.2009.10*(22), 201â220.

Khakzada, N., Khana, F., & Amyotte, P. (2012). Dynamic safety analysis of process systems by mapping bow-tie into bayesian network. *Process Safety and Environmental Protection*(8).

Kim, J., & Peral, J. (1983). A computational model for causal and diagnostic reasoning in inference systems. *In Proceedings of the 8th International Joint Conference on Articial Intelligence*, 190-193.

Kurowicka, D., Cooke, R., Goossens, L., & Ale, B. (2008). Expert judgment study for placement ladder bowtie. *Saf. Sci*(46), 921â934.

Leger, A., Duval, C., Weber, P., Levrat, E., & Farret, R. (2006). Bayesian network modelling the risk analysis of complex socio technical systems. *4th Workshop on Advanced Control and Diagnosis, Nancy - France.*

Markowski, S., & Kotynia, A. (2011). Bow-tie model in layer of protection analysis. *Process Saf. Environ. Protect*(89), 205-213.

Markowski, S., Sam Mannan, M., & Bigiszewska, A. (2009). Fuzzy logic for process safety analysis. *J. Loss Prevent. Precess Ind.*(22(6)), 1-8.

Mokhtarie, K., Ren, J., Roberts, C., & Wang, J. (2011). Application of a generic bow-tie based risk analysis framework on risk management of sea ports and offshore terminals. *Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, School of Engineering, Technology and Maritime Operations, Liverpool John Moores University, Liverpool UK*(192), 465-475.

Nivoliantou, Z., Konstantinidou, M., & Leopoulos, V. (2006). Comparison of techniques for accident scenario analysis in hazardous systems. *J. Loss Prevent. Process Ind.*(17), 467-475.

Pearl, J. (1988). Probabilistic reasoning in intelligent systems: Networks of plausible inference. *Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.*

Peral, J. (1986). Fusion propagation and structuring in belief networks. *Artif. Intell*(29), 241-288.

Saaty, T. (1980). The analytic heriachy process. *McGraw-Hill New York.*

Shachter, R. D. (1986). Evaluating influence diagrams. *Operations Research*(34), 871-882.

Shafer, G. (1976). A matimatical theory of evidence. *Princeton Univ. Press. Princeton.*

Sklet, S. (2004). Comparaison of some selected methods for accident investigation. *J. Hazard. Mater*(111), 29-37.

Smets, P., & Kennes, R. (1990). The transferable belif model. *Artifcial Intelligence*(66)), 191-234.

Zadeh, L. (1965). Fuzzy sets. information and control. (8), 338â353.