# Occupational risks analysis metallurgy industry

### Bayesian inference

Nassima AISSANI, Islam Hadj Mohamed GUETARNI, Brahim BOUHADIBA

*Abstract*— The scrap metal factories are complex systems that play a crucial role in the transformation industry and construction. Since these factories face various safety issues in design, installation, operation, transportation and maintenance processes, there are many aspects open for improvement in Occupational Health and Safety risk assessment and it is required to deal with risks, reduce them to an acceptable level and control. To struggle with emerging risks and manage this process better, a risk assessment framework is proposed in this study. A case study is performed in an Algerian scrap metal company using the proposed framework. It is based on historical accident data exploitation using Bayesian Inference after a deep treatment. Results are recommendation which should improve the worker safety. (*Abstract*)

*Keywords*—Occupational risk, Bayesian approach, data treatment, metal industry, Risk assessment (*key words*)

### I. Introduction

Workers should be protected from occupational risks they could be exposed to. This could be achieved through a risk management process, which involves risk analysis, risk assessment and risk control practices. In order to carry out an effective risk management process, it is necessary to have a clear understanding of the legal context, concepts, risk analysis, assessment and control processes and the role played by all involved in the process. It is also desirable to base risk management on solid and tested methodologies. Quantitative approaches give right perception of risks and their causes and consequences they are based on formal design which could be understood, analysed and exploitable for many different cases.

Nassima AISSANI Institute of Maintenance and industrial Safety University Mohamed BenAhmed Oran 2 Algeria

Islam Hadj Mohamed GUETARNI University Mohamed BenAhmed Oran 2 Algeria line 4: e-mail address if desired

Brahim BOUHADIBA University Mohamed BenAhmed Oran 2 Algeria line 4: e-mail address if desired This paper is organized as follow, the first section is dedicated to an overview of the use of statistical data in occupational risk assessment, then the case of study is presented showing the availability of data and its pretreatment. In the third section the adopted Bayesian inference model is presented. Then experimentation and outcomes are presented, a predicting scenarios are developed, executed and analysed. Finally, recommendation and perspectives are given.

# II. Methods for occupational risk assessment

### A. Quantitative methods

Various methods and approaches have been developed for occupational risk assessment in many types of industries. [1] established an occupational health and safety and environment risk assessment index system by using Delphi method, and formulating a mathematical model by combining set pair analysis (SPA), trapezoidal fuzzy number (TPFN), and setvalued statistics (SVS) methods for determining the overall OHSE risk level for Nuclear Power Plant construction project.

The results showed that the approach helped reduce the risk level in those projects. Quantitative methods are also used in energy production industry, a method for estimating the individual occupational risk (IOR) level was upgraded in [2] by using new indexes working conditions, working experience of the employee in harmful and (or) hazardous working conditions, his age and health status) multiplied by the indicators of injury rate and morbidity in the workplace. Many time, statistical analysis were used to analyse occupational risks [3] analysed 152 fatal accidents in the Chinese metallurgical industry from 2001 to 2018 to predict the future characteristics of fatal accidents in the metallurgical industry and propose safety measures. In iron and steel industry in Ukraine [4], a research was made also on statistical data from 2012-2016 and use of known methods as HAZOP, This research motivated our study, because of area similarity and data availability. However, we target the use of Bayesian approach and its outcomes.



### B. Bayesian approach for occupational risk assessment

A number of generic screening tools are available for assessing occupational risks [5] [6] [7]. Screening tools provide conservative exposure estimates and are designed to filter out exposure scenarios of little concern from those that require further well-validated and However, whilst investigation. efficient screening tools may substantially reduce the pool of exposure scenarios to be investigated, a case-bycase assessment for every exposure scenario where a tier one tool is insufficient, based entirely upon exposure measurements, is impractical due to the time and expense of such assessments. Many authors [8] have proposed the use of Bayesian methods so that mathematical models of exposure can be combined with the limited data available from exposure measurements and utilized in risk assessments. Also in industrial area [9] used Bayesian approach for occupational accidents classification in petroleum industry and [10] used Bayesian approach in decisional process for risk assessment in cement factory based on 6 years accidents history. A Bayesian framework allows the various disparate sources of information that are relevant to an exposure scenario to be integrated within a statistically rigorous framework able to be analysed and exploited [11].

### ш. Case of Study

The scrap metal company is one of the most important companies in the metal industry.

It recovers and collects scrap metal, treats and transforms scrap metal, markets ferrous and non-ferrous materials, treats waste and supplies steelworks, and exports scrap metal. In addition, the company produces copper shot and PVC waste by shredding electric cables.





Figure 1. Pictures from the factory: Compression of ferrous scrap and ingot production

The company's activities are handled as follows:

#### a- Merger and Secondary Processing UFTS :

Recovery of mainly ferrous and non-ferrous metal scrap as well as non-metallic scrap, Treatment of this waste by sorting, oxy-cutting, shearing and bundling. Secondary melting to obtain ingots (lead, aluminium, brass). Shredding of all types of electrical cables under plastic for the production of copper shot and PVC waste. Demolition of industrial plants.

b- Industrial weighing and control UPCI :

Production of industrial weighing and control equipment:

- 18x3 & 16x3 mobile type weighbridges
- Digital Weighbridge
- On-board weighing system
- Radioactivity monitoring portal
- Belt conveyor belt scale

The company's staff is diversified (figure 2):

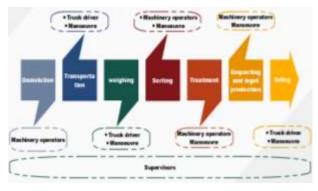


Figure 2. the process and staff involved

### A. Stored data relating to accidents

During these operations, the company's personnel suffer accidents or less serious ones, requiring more or less long stoppages. These accidents are recorded in a safety register of the company.

In addressed factory, from 2015 until now about 50 accidents, involving people with different levels of severity, were registered. The safety staff are responsible of reporting and identifying any type of accident. However, sometimes description is not clear and data are incomplete. That's why; any exploitation of these data needs use of complementary technics to deal with incompleteness and uncertainty.



2	<b>A</b> .	6	c	D.	8 F	G	
ċ	Qualification	Mois	PJ.	Duree	Cause_directCause_indiri Conseque		nc Filliere
£	Chauffeur	Fevrier	Matin	0	etourdissempresence_dctete		Transport
É	Ouvrier	Mars	Matin	8	Chute_de_matiere	pied	Tri
í,	Gardien	Septembre	Fin	F.	etourdissem Traveaux	or Bassin	Securite
ŝ	Chauffeur	Septembre	Mater	c	douteur manipula	r_cDos	Transport
Ē	Chauffeur	Juillet	Matin	D	presence_de_ferrail	Rate	Transport
Ē	Gardien	Octobre	Midi	F.	Chute_de_matiere	jambe	Securite
ŀ	Currier	Octobre	Matin	F	denudeur_e manque_	de Main	70
6	chef mainte	Octobre		C	transport_des_bors	pied	Maintenance
ą	Chauffeur	Novembre	Fits.	D	renveremen Deseguil	dire tete	Transport
3	Ouvrier	Fevrier	Matter	5	mausaise_manoeuvre	main	Tri
ź	Chalumiste	Fevrier	Matin	F	travail_en_hauteur	bres	Travail_au_chatum

Figure 3. Overview of safety register

Accident data are saved in data base according to a list of items like: date of accident, involved person, direct causes, material damage, injured body part... (figure. 3) and for each item a list of values are possible, for example, PLACE could be: "on the site", "Outside", "on road".

#### B. Data treatment

As per [9] data need to be treated cleaned to avoid textual description and determine possible value for each textual node:

```
//first step: identify key words for
each word{
   if (word not in word list) (
     word_list.addnewitem (word);
      word_indexlist.addnewitem(1); }
   else{
      index= word_list.find(word);
      word indexlist.at(index)++;
//second step: eliminate link words
link_word={"a", "the", "from", "to",...}
for each word in link_word{ index=
word_list.find(word);
word_list.delete(index);
word indexlist.delete(index);
   //third step: eliminate irrelevant words
   calculate average of apparition of each word
in word_list; calculate deviation for each word
in word_list;
  for each word in word list{
     if (word deviationlist.at(i)<0) {
     word_list.delete(i);
     word_indexlist.delete(i);
   //fourth step: eliminate all the words in the
database for that item if it doesn't exist in
word list
   for each word in database.item.value(
     index= word_list.find(word); if(index==0)
     database.item.value.delete (index);
   } end.
```

At this step, data are saved in orgnized in a file by "enregistrement" and items able to be used in knowledge extraction process.

### IV. Bayesian approach and inference

Bayesian statistics begins with a prior belief that has been being expressed as a prior distribution. So that the prior distribution is being viewed as an essential portion and it is based on the data from previous trials. This definition will be the guide line of our scheme [12]. In fact, the availability of experiments data which are historical accident data allow us to construct prior distribution. Now data are able to be used in a Bayesian network inference and the probability tables can be filled for each item the probability is elementary

$$p(e = value) = \frac{card(e = value)}{nbr of records}$$

Where *e* is the elementary event, *value* is one of its possible values or stats.

But for the deduced event, which are the e event and influenced by it, its probability depends on the parent's nodes e according to the Bayesian theorem it is given by the formula:

$$p(de = value / c_1 = value_1 \& \dots \& c_n = value_n)$$
$$= \frac{p(c_1 = value_1 \& \dots \& c_n = value_n / de = value)}{p(de = value)}$$

Where de is the sun event, ci are the parents' events and n is the number of parents. A Bayesian inference allows all events' probabilities update.

### v. Experiments and results

### A. Developed Bayesian network

In the Bayesian network The node is each item and the list of its possible values are the labels of that node. The dreaded event, which is the "consequence", is the node to predict in this network, so it is at the center of the network as shown in Fig 4. Some items are consequence of the dreaded event like: "potential gravity" describing the degree of damage and "injured body part" describing the level of body injury. These items are designed as cause nodes for the dreaded event. For each node a list of possible values is identified it is called node states.

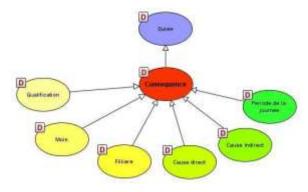


Figure 4. The developped network

### B. The network analysis

After the network is completed and data are loaded, the network (fig. 5) is ready for analysis and scenario generation.

According to this graph, some conclusions can be drawn:



- Drivers are the most involved in accidents. 21%
- It concerns mainly transport activities 40%
- These accidents mainly happen in the morning 68%
- The most common cause is falling material. 18%
- The most frequent accidents lead to long periods of downtime. 32%

In order to understand the influence of causes on the dreaded event three scenarios are developed. A scenario means the assumption of a truth and the observation of its consequences on the dreaded events as well as the other consequent events:

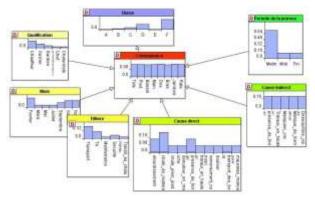


Figure 5. Distribution of each node

### c. Scenarios development

### 1) First scenarios: "Falling material"

It has been noticed that the cause most likely to occur is falling material. a scenario which assumes that the fall of matter is validated, in order to analyse its consequences. According to the graph obtained, falling material can cause any type of injury from head to toe, with a slight increase for the back due to the weight of the materials processed in this industry. That accidents mainly happen in the morning and this concerns all workers.

### 2) Second scenario: The longest "work stoppage"

An employer wishes to preserve its staff as much as possible, ensure continuity of work and thus avoid long stoppages. Therefore, we want to analyse what are the conditions of a long stoppage, in our network it is the stoppage with duration = F, by applying this condition we can notice that the drivers can be the most affected with affected limbs: leg or arm or even pelvis.

### *3)* Third scenario: "Worker" worker hit in the "Hand"

We then assume that the worker is hit in the hand in order to analyse the causes of these accidents. These are accidents that happen when the worker is "sorting" scrap metal. And that causes more or less long stoppages.

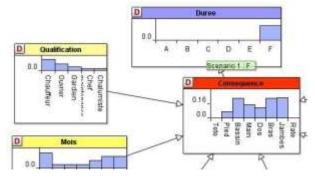


Figure 6. Scenario 3 application

## vi. Conclusion and recommendation

The study carried out in this paper focuses on the Bayes theorem in order to be able to estimate the posteriori probability of the occurrence of a dreaded event concerning occupational risks. This study was carried out on the statistics of accidents at work occurring within the scrap metal processing company.

Based on these statistics a data treatment method was used to prepare ad format data, then, a Bayesian network was made, of which "consequences" is the main event and the others are data describing the conditions in which the accident occurred and the consequences of this accident.

According to the results obtained on the network, the most probable accidents are transport accidents, with drivers being the most involved, with a long work stoppage.

As a result of this analysis and from what we have noticed, the following recommendations could be proposed to improve safety level and preserve worker's health:

- Train, raise awareness and inform workers, especially drivers, as they are the most affected according to our network;
- Respect the prevention and safety measures;
- Respect the legal working time;
- Convince the workers of the obligation to respect the company's internal regulations (work permits).
- The personal protective equipment door.

### References

[1] Y. Sui, R. Ding, et H. Wang, « A novel approach for occupational health and safety and environment risk assessment for nuclear



power plant construction project », *J. Clean. Prod.*, vol. 258, p. 120945, juin 2020, doi: 10.1016/j.jclepro.2020.120945.

- [2] N. Gorlenko et M. ν. Α. Murzin. « Comparative assessment of occupational risks at enterprises of oil production and coal industries in the Irkutsk region », IOP Conf. Ser. Earth Environ. Sci., vol. 408, p. 012022, janv. 2020, doi: 10.1088/1755-1315/408/1/012022.
- Q. Xu et K. Xu, « Statistical Analysis and Prediction of Fatal Accidents in the Metallurgical Industry in China », *Int. J. Environ. Res. Public. Health*, vol. 17, n° 11, Art. n° 11, janv. 2020, doi: 10.3390/ijerph17113790.
- [4] V. Kukhar, N. Yelistratova, V. Burko, Y. Nizhelska, et O. Aksionova, « Estimation of occupational safety risks at energetic sector of Iron and Steel Works », *Int. Journa Eng. Technol.*, vol. 7, p. 216-220, avr. 2018, doi: 10.14419/ijet.v7i2.23.11922.
- [5] E. Lundrigan, D. Hutchings, M. Mathews, A. Lynch, et J. Goosney, « A Risk Assessment Screening Tool for Community Health Care Workers », *Home Health Care Manag. Pract.*, vol. 22, n° 6, p. 403-407, oct. 2010, doi: 10.1177/1084822309348893.
- [6] « Chemical Risk Assessment Screening Tool of a Global Chemical Company », Saf. Health Work, vol. 9, n° 1, p. 84-94, mars 2018, doi: 10.1016/j.shaw.2017.06.012.
- [7] B. K. Vaughen, D. A. Hurban, K. First, et A. Ness, « The Risk Analysis Screening Tool: Part I, overview », *Process Saf. Prog.*, vol. 39, n° 2, p. e12142, 2020, doi: https://doi.org/10.1002/prs.12142.
- [8] K. Dean et J. Mitchell, « A dose response model for the inhalation route of exposure to P. aeruginosa », *Microb. Risk Anal.*, vol. 15, p.



Islam Hadj Mohamed Guetarni, is Ph. D. / M. Eng. in Process Safety and Environmental Engineering. His principal interests are Risk Analysis , Safety Management, Risk Modeling, Reliability Engineering



Brahim Bouhadiba, PhD in Environmental Engineering, he is the head of Institute of Maintenance and Industrial Safety 100115, août 2020, doi: 10.1016/j.mran.2020.100115.

- [9] Z. Naghavi-Konjin, S.-B. Mortazavi, H. Asilian-Mahabadi, et E. Hajizadeh, « Ranking the occupational incident contributory factors: A Bayesian network model for the petroleum industry », *Process Saf. Environ. Prot.*, vol. 137, p. 352-357, mai 2020, doi: 10.1016/j.psep.2020.01.038.
- [10] N. Aissani, I. H. M. Guitarni, et Z. Lounis, « Decision process for safety based on Bayesian approach », in 2018 3rd International Conference on Pattern Analysis and Intelligent Systems (PAIS), oct. 2018, p. 1-6, doi: 10.1109/PAIS.2018.8598533.
- [11] « Reliability analysis by mapping probabilistic importance factors into bayesian belief networks for making decision in water deluge system - Guetarni - 2019 - Process Safety Progress - Wiley Online Library ». https://aiche.onlinelibrary.wiley.com/doi/abs /10.1002/prs.12011 (consulté le févr. 10, 2021).
- [12] « Components Of Bayesian Approach | Genpro Life Sciences | Bayesian Theory | Bayesian Classification », Genpro Research | Clinical Research Organization | CRO. https://genproresearch.com/knowledge/com ponents-of-bayesian-approach/ (consulté le févr. 10, 2021).

About Author (s):



Aissani.N is a research faculty member in the Laboratory Of Safety Engineering and sustainable development (LISIDD) the Institute of Maintenance and Industrial Safety (IMSI) University of Oran2 Ahmed Benahmad. Over a 15-year career as a teacher in computer science and industrial safety.

