# Health, Safety, Environment and Ergonomic Improvement in Energy Sector Using an Integrated Fuzzy Cognitive Map-Bayesian Network Model

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## Abstract

Health, Safety, Environment and Ergonomics (HSEE) are important factors for any organization. In fact, organizations always have to assess their compliance in these factors to the required benchmarks and take proactive actions to improve them if required. In this paper[1], we propose a Fuzzy Cognitive Map-Bayesian Network (BN) model in order to assist organizations in undertaking this process. The Fuzzy Cognitive Map (FCM) method is used for constructing graphical models of BN to ascertain the relationships between the inputs and the impact which they will have on the quantified HSEE. Using the notion of Fuzzy logic assists us to work with humans and their linguistic inputs in the process of experts' opinion solicitation. The Noisy-OR method and the EM are used to ascertain the conditional probability between the inputs and quantifying the HSEE value. Using this, we find out that the most influential input factor on HSEE quantification which can then be managed for improving an organization's compliance to HSEE. Finding the same influential input factor in both BN models which are based on the Noisy-OR method and EM demonstrate how FCM is useful in constructing a reliable BN model. Leveraging the power of Bayesian Network in modelling HSEE and augmenting it with FCM is the main contribution of this research work which opens the new line of research in the area of HSE management.

**Keywords**: Power Plant; Health; Safety; Environment; Ergonomics; Bayesian Network (BN), Fuzzy Cognitive Map, Noisy-OR, Expectation-Maximization (EM)

[1] This work is the extension of our work entitled as "An Integrated Fuzzy Cognitive Map-Bayesian Network Model for Improving HSEE in Energy Sector" which was accepted in IEEE-FUZZ 2017 and to be published.

## 1. Introduction and Literature Review

In this section, we briefly present the significance and motivation of this study and then some related works. HSEE management is critically reviewed in Section 1.2 by presenting their main limitations. A related group of literature in BN and FCM are reviewed in sections 1.2 and 1.3.

### 1.1. Health, Safety, Environment and Ergonomic (HSEE)

HSEE management is a system for improving health, safety, environments and ergonomic indicators in organizations. In recent years, many structures and models have been proposed in order to improve HSEE systems. Many of these models do not reflect interrelationships between HSEE factors and the impact of these factors on each other. To overcome this issue, we use Bayesian Network (BN) which is a powerful tool for constructing a graphical model that shows the interrelationship between HSEE factors. By using them, we can discover these relationships by using a Fuzzy Cognitive Map (FCM) method. The capability of BN graphically present the nodes and the relationships between them with the possibility of updating this status after receiving the new evidence is the intuition behind using BN in modelling HSEE in organizations. The flexibility of BN in dealing with incomplete and noisy data makes it suitable for HSEE modelling. Moreover, the possibility of updating BN in the presence of new evidence makes it an intelligence model that facilitates a HSEE modelling base in unstable situations.

Accidents impose costs on companies. These costs are not only monetary but also lead to reduced worker satisfaction and productivity (Asadzadeh, Azadeh, Negahban, & Sotoudeh, 2013). Accidents and injuries maybe occur in any organization that has technological systems. Therefore, organization needs to consider a HSE program (Azadeh, Mokhtari, Sharahi, & Zarrin, 2015). The organizations that do not have any structure for improvement of health, safety and environment face many problems so, recently in many developing countries, concern for health, safety and environment are increasing (Azadeh et al., 2016). Safety management helps the manager improve performance for operational system design and assists them in prevention of accidents in the workplace. Safety management discipline consists of some factors like risk management, safety promotion and so forth that can help managers consider such factors to help an organization in continuous improvement (Azadeh, Fam, & Azadeh, 2009). For reducing environmental impacts a manager can use environmental management discipline that consist of: management leadership, commitment and accountability (Azadeh et al., 2009). HSEE systems can enhance worker productivity and in safety filed, help the employee that improve their physical and mental conditions (Azadeh, Fam, Khoshnoud, & Nikafrouz, 2008). Management and employees generally have different points of view on HSE management and culture. They have different rules for implementation of a HSE system in their organization but they are partners in a system, which is constructed for improving health, safety and environment of workplaces (Høivik, Moen, Mearns, & Haukelid, 2009). HSEE culture is one of the main courses in a HSE program for improving HSE in an organization. This culture can be considered a subcategory of overall organization culture (Bjerkan, 2010). In many organizations of Iran, employees do not care about health and safety of their workplace. HSE management and culture can encourage employees to learn and adopt the procedure that changes their working style and help them to have a healthy and safe workplace. By using HSEE in an organization, employees are encouraged to adopt a healthy and safe lifestyle. There is a strong relationship between HSE and ergonomics (Azadeh, Farmand, & Sharahi, 2012). Health and safety have more priority than other factors. By integrating HSEE and ergonomics in an organization, it can achieve more efficiency and this integration encourages employee motivation (Azadeh, Rouzbahman, Saberi, Valianpour, & Keramati, 2013).

### 1.2. Previous Studies in BN

As mentioned, BN is a powerful tool in constructing a graphical model (the model which illustrates interrelationship between some variables), which shows interrelationships between systems' various and diverse variables. There is abundant literature on Bayesian Networks and many researchers have used BN for constructing a graphical model for more convenient and easier analysing of complex systems (Korb & Nicholson, 2010). Akhtar & Utne (2014) used BN to decrease the risk of accidents in maritime ship transportation. Jones, Jenkinson, Yang, & Wang (2010) also utilized BN in maintenance planning which is one main component in any manufacturing industry. BN assists them to find influential factors in the failure rate of the system (Jones, et al., 2010). BN is also used in transportation filed. Zhao, Wang, and Qian (2012) leverage the power of BN to find factors that impact directly and indirectly on vehicle accidents which carry hazardous material. Another interesting application of BN was on the mobile game industry by Park and Kim (2013). They applied BN to the industry to find key success factors and also relationships between them.

Present study proposes a FCM-Bayesian network model for improvement of HSEE in a power plant. HSEE factors were defined by expert opinions and then a fuzzy BN model constructed. The Fuzzy cognitive map method was used for defining the relationship between factors utilzing expert opinions. The main objective of this study is to find factors that affect more on HSEE in a power plant which finally assist the HSE managers in enhancing HSEE planning by improving these factors. There are various ways to construct a BN model. However, all the previously mentioned studies suffer some drawbacks in constructing such BN models. Actually, the main limitation of the BN models is lack of an appropriate method for constructing them. In the next subsection, we propose a fuzzy cognitive map method, which is an appropriate task for constructing a BN model.

### 1.3. Fuzzy Cognitive Map

Fuzzy Cognitive Map (FCM) is a powerful tool which represents cause and effect relationships between factors and concepts in complex systems (Stylios, Georgopoulos, Malandraki, & Chouliara, 2008). A complex system (e.g. earth's global climate change) is a system which has many variables that influence each other. FCM can be used for simulation and analysis of the dynamic systems. FCM is a useful tool in many fields of science such as air transportation, robotics and so forth. Different kinds of tlearning methods are developed to allow it to work efficiently (Stach, Kurgan, Pedrycz, & Reformat, 2005); (Kang, Lee, & Choi, 2004); (Motlagh, Tang, Ismail, & Ramli, 2012). A new type of FCM is a dynamic fuzzy cognitive map which an impact of the concepts on each others are variable over the time, like pervious models, in addition to interrelationships between concepts which are also variable (Mendonça, Angelico, Arruda, & Neves, 2013).

One major issue in constructing a Bayesian Network model is the lack of a suitable method to determine relationships between BN factors. FCM is a powerful known method for representing cause and effect relationships between factors and concepts. Hence, in order to fill this gap, we used FCM method to construct BN model. According to our best of knowledge, this is the first research work of this type which uses FCM in conjunction with BN modelling. This puts FCM as one of main components of BN in a very handy way especially for applications like HSEE which need a flexible model base for its complex modelling procedure.

## 2. Materials and Method

### 2.1. Preparation of Case Study

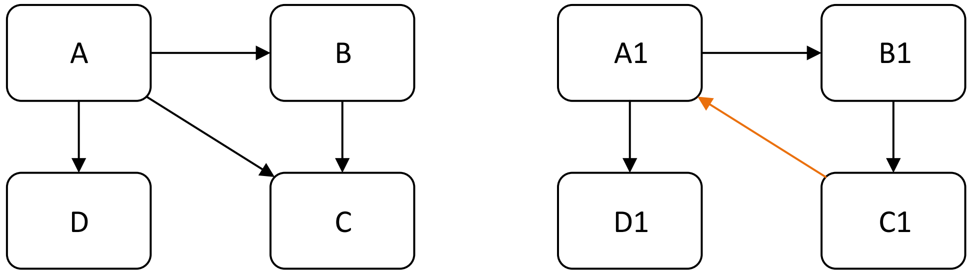
For data collection, a questionnaire developed by experts with extensive domain knowledge, (Azadeh, Rouzbahman, Saberi, Valianpour, & Keramati, 2013). comprising of 30 questions was utilized. This questionnaire covers four factors (concepts) namely, health, safety, environment, ergonomics. Questions 11, 4, 8, and 6 were allocated respectively in the questionnaire. Also, one question was designed for measuring the current situation of HSEE management. The final questionnaire has been distributed among forty operators in a power plant. As collected data should be prepared for using in FCM, the collected crisp data is fuzzified using several specified membership functions, to transform them to fuzzy linguistic variables.

Reliability of a questionnaire refers to accuracy and stability of collected data. Validity refers to the ability of questions to measure the factors which shape the problem (Sijtsma, 2009). For measuring the reliability of the questionnaire, Cronbach's Alpha (Cronbach, 1951) value has been used. Additionally, factor analysis has been applied in order to validate the questionnaire. In the results section, the validity of the questionnaire has been reported.

### 2.2. Algorithmic Mechanisms

*2.2.1 Bayesian Networks*

As discussed earlier, BN is a powerful and flexible tool for modelling complex systems with a graphical structure. A BN model displays the causal relationship between variables of a given complex system. A directed arc shows interrelationships between a given pair of factors. A BN model consists of two parts; quantitative and qualitative. The nodes and arcs make the qualitative part of BN. Nodes representing the variables that make model and arcs for representing causal relationships between these variables directed are used. BN is an acyclic graph; which means a BN graph does not have any cycle. For example, Figure 1 (Graph A) demonstrates a graphical model with no cycle while Graph B with a cycle (*A1, B1 and C1*) cannot represent any BN model.




graph (A) shows BN model  graph (B) cannot be BN model

**Fig.1.** graphical model of BN model

The quantitative part of Bayesian Network is composed of Conditional Probability Tables (CPTs) that signify the exact relationship between input variables. All the analysis on the model is achieved by using CPT. Figure 2 shows a BN model that consists of three nodes. Table 1 shows how CPT should be calculated for this BN with three states and two parents. This table shows variables A, B and C has 1, 2 and 3 states respectively. Equation (1) shows the formula for calculating joint probability in which $\{X_1, X_2, \dots, X_n\}$ is a set of nodes in BN model.

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Parent(X_i)) \qquad (1)$$

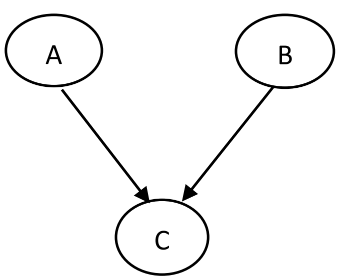



**Fig.2. BN model with 3 nodes**

**Table 1- Conditional probability table for node C considering three states**

| A | B | C1 | C2 | C3 |
|---|---|---|---|---|
| A1 | B1 | | | |
| A1 | B2 | | | |
| A2 | B1 | | | |
| A2 | B2 | | | |
| A3 | B1 | | | |
| A3 | B2 | | | |

There are two common reasoning types which can be used with the BN structure: diagnostic and predictive. In diagnostic reasoning, by observing some symptoms the cause of the symptom is determined. In predictive reasoning, direction of the reasoning is from cause to symptom. That is, to see what the output is based on the inputs (Korb & Nicholson, 2010). For example, based on an example of Korb & Nicholson 2010, in diagnostic reasoning a doctor observes a symptom such as "Dyspnoea" and then he updates his belief whether the patient has a cancer or the patient is a smoker.

*2.2.2 Fuzzy Cognitive Map*

A FCM was used for constructing the Bayesian Network model based on experts' opinions. FCM determines cause and effect variables which are reflected in the direction of BN's arcs.

In the first step, BN variables should be defined by using expert knowledge. It should be noted that the measurability of these variables is of importance. After defining the variables, for completing the model, interrelationships between variables should be defined. For this purpose some linguistic variables were specified for each node that are ready for use after development of their fuzzy membership function. These linguistic variables are used in order to determine relationships between nodes. Experts can define one or some rules for each arc between nodes but before this, they should determine the influence of a concept on another using linguistic notions like *negative*, *positive* and *no influence*. By using the rules which are developed by experts, linguistic weights were assigned on each arc. Using the sum aggregation method and fuzzy Mamdani inference system and centre of gravity method, linguistic variables were combined and then transformed to a crisp weight. A pseudo code of an FCM algorithm is presented in Figure 3. Figure 4 shows an example of a graphical model constructed using FCM method. This is a simple example of FCM in which we have four concepts (A, B, C, D) that have an influence on each other. To determine the initializing connection weight matrix (w), mentioned procedure is used. In this model concept C affected by concept A and the connection weight between these concepts is $W_{ac} = 0.43$. The flowchart of proposed algorithm has been shown in Figure 5.

$A_i$ is the value of the concept $C_i$ in range $[0,1]$, while the weight of the node $i$ and $j$ is $w_{ij}$, at each step of simulation the value of the $A_i$ is calculated by equation (1): $A_i^{(t+1)} = f\left(A_i^{(t)} + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(t)} w_{ij}\right)$ (1) Where $A_i^{(t+1)}$ is the value of the $A_i$ at the step $(t+1)$ and In the same way $A_i^{(t)}$ is the value of $A_i$ at simulation step $(t)$ and the transform function $f$ is used in this study that is showed in equation (2),Where $\lambda$ is a parameter defines the steepness. In this method the value of $\lambda$ =1 is used: $f = \frac{1}{1+e^{-\lambda}}$ (2).

begin

determining the concept of proposed problem by experts' opinions

determining the influence of each concept (variable) on another using linguistic variables

assigning linguistic weights to each arc by each expert

aggregating linguistic variables using sum method

defuzzification for obtaining a numerical value for each weight in range [-1,1] (W)

**While** $(A^t - A^{t+1} \leq 0.001)$ {

1. give the input vector $A^0$
2. Initializing connection weight matrix W
3. Calculate the concept vector at step $t$ by eq.1
4. applying the transform function to the output vector. $A_i^{t+1} = f(A_i^t)$

}

end

**Fig.3. Pseudo code of FCM algorithm**

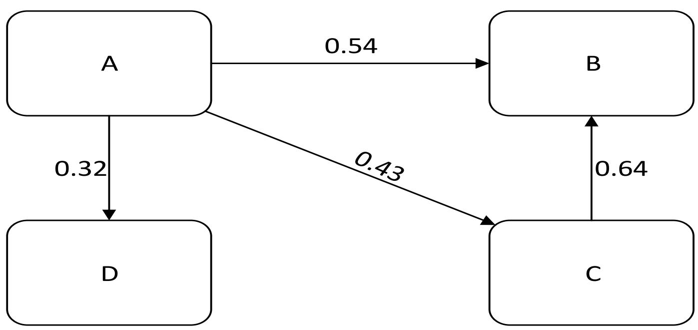



**Fig.4. graphical model which was constructed by using FCM**

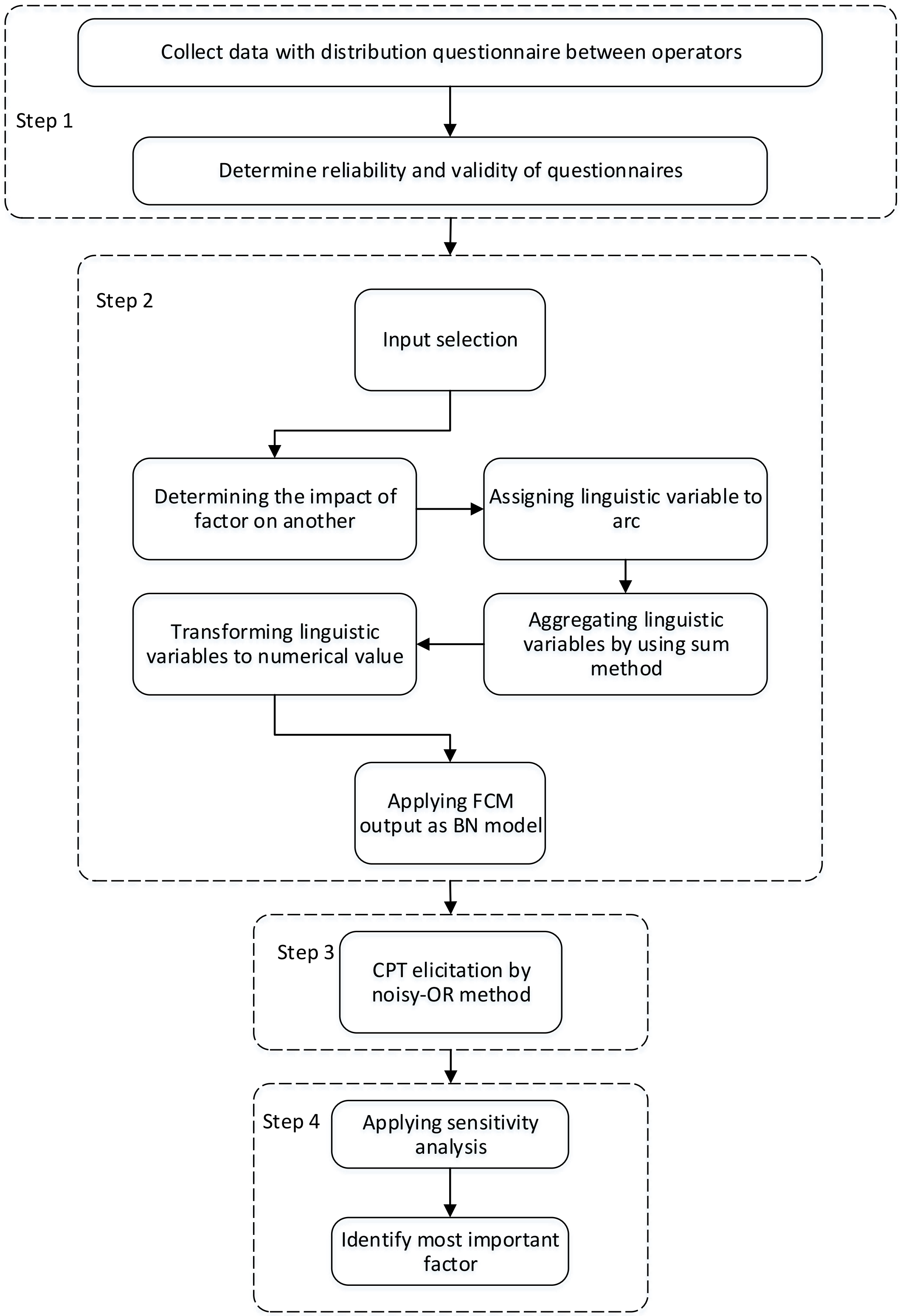



**Fig.5**. the structure of proposed algorithm

## 3. Results and Experiment

### 3.1. Preparation of Case Study (step 1)

Data were collected from a power plant which is the target of the proposed model to analyse its HSEE status. In this first step, questionnaires were distributed to 63 operators of which 40 questionnaires were returned. Operators were able to choose any real number between [1-20] to rate his/her answer.

In order to transform collected crisp data to linguistic variables, the specified range for each question were divided, using expert opinions, and two linguistic variables were defined for the divided range that is shown in Table 2. Linguistic variables "poor" and "good" are attributed to ranges [1-14] and [14-20] respectively. After collecting crisp data, by using the defined range, this crisp data is transformed to linguistic variables. These ranges are used to show the state of the nodes in the Bayesian Network model. Also data is fuzzified to calculate conditional probabilities by a learning algorithm that is described in Step 4.

**Table 2- Range of the linguistic variables**

| Range | Linguistic Variables |
|---|---|
| [1-14] | Poor |
| [14-20] | Good |

Cronbach's Alpha and factor analysis have been used to prove the reliability and validity of questionnaire. For each factor [health, safety, environment, ergonomic] Cronbach's Alpha has been calculated and reported in Table 3. Cronbach's Alpha value for the questionnaire is obtained as 0.924, which proves the reliability of the questionnaire.

**Table 3- Cronbach's Alpha for factors and questions factor loading**

| Factor | Reliability (Cronbach's Alpha) |
|---|---|
| Health | 0.831 |
| Safety | 0.642 |
| Environment | 0.876 |
| Ergonomic | 0.899 |

### 3.3. Constructing BN Model by FCM (step 2): Structure Elicitation

In the first step of constructing BN, the factors of the problem should be defined. Factors are defined by expert opinions and reviewing the literature in the field of HSEE. After factor definition, each expert can confirm current factors or reject and add new factors to the BN model. In this study, experts confirmed they added all factors and no factors to the BN model. Thus four factors, namely, health, safety, environment and ergonomic were confirmed and HSEE is considered as a response variable of the BN model. In the second step of constructing BN, the interrelationship between nodes should be defined. In this paper, a BN model for improving the HSEE status is constructed using FCM method. As mentioned before, FCM is a useful tool that determines cause and effect nodes.

Three experts who have knowledge in the HSEE field were selected for defining the interrelationships between factors. In the first step of FCM, each expert should determine the direction of the arc between variables. Then the impact of a factor on another is defined by using linguistic notion. Three linguistic notions were used for determining the direction of the influence of nodes on each other: *negative, positive, no influence*. If increasing one factor causes decrease in another factor, the negative notion must be assigned to the arc and if the factors have direct influence on each other the positive notion must be used. When two factors have no effect on each other "*no influence"* notion will be used.

However, there is an associated danger with the process of expert opinion elicitation by producing a cycle in the network. To mitigate this risk, if a condition happened that one direction cause makes a cycle between nodes, we can reject this direction before creation cycle. The experts should be aware that no cycle should create. As an example, Figure 6 shows a condition that may occur as a cycle between node A and C. In this situation, experts should be aware no cycle should be created.


**Fig.6. Prevention of creating cycle**

The variable "influence" announces the causal relationships between factors and is interpreted as a linguistic variable taking values in the range $[-1,1]$. For determining the impact rate of nodes on each other four states weak, medium, strong and very strong are considered for defined linguistic variables in direction of the influence, so overall, nine linguistic variables were defined which describe this variable: T(influence)={*negatively very strong, negatively strong, negatively medium, negatively weak, no influence, positively weak, positively medium, positively strong and positively very strong*}.Therefore, in addition to determining the direction of the influence, the impact rate of relationships should be determine by each expert. Membership functions for each variable have been shown in Figure 7.

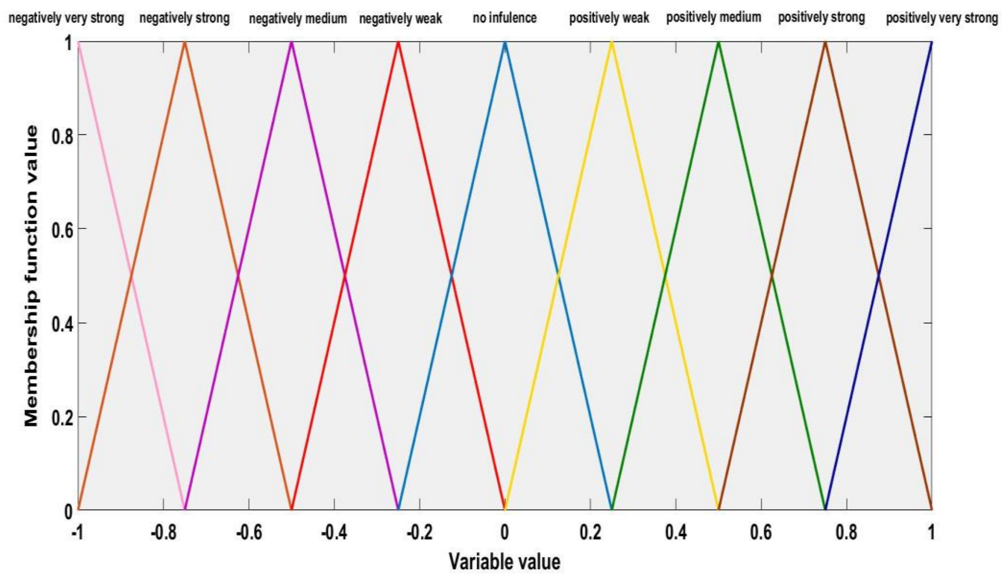



**Fig.7. Membership functions for each variable**

After assigning the linguistic variables to each arc, these variables should be aggregated and transformed to one weight. To this end, the aggregation sum method and Mamdani inference system were used to transform the aggregation linguistic variable to one crisp weight. After obtaining the initial matrix W, by using the FCM inference system, a simulation has been undertaken to calculate the final weight of the arcs. The arcs with weight lower than 0.4 were deleted from the model. The constructed BN model, by using FCM method, has been demonstrated in Figure 8.

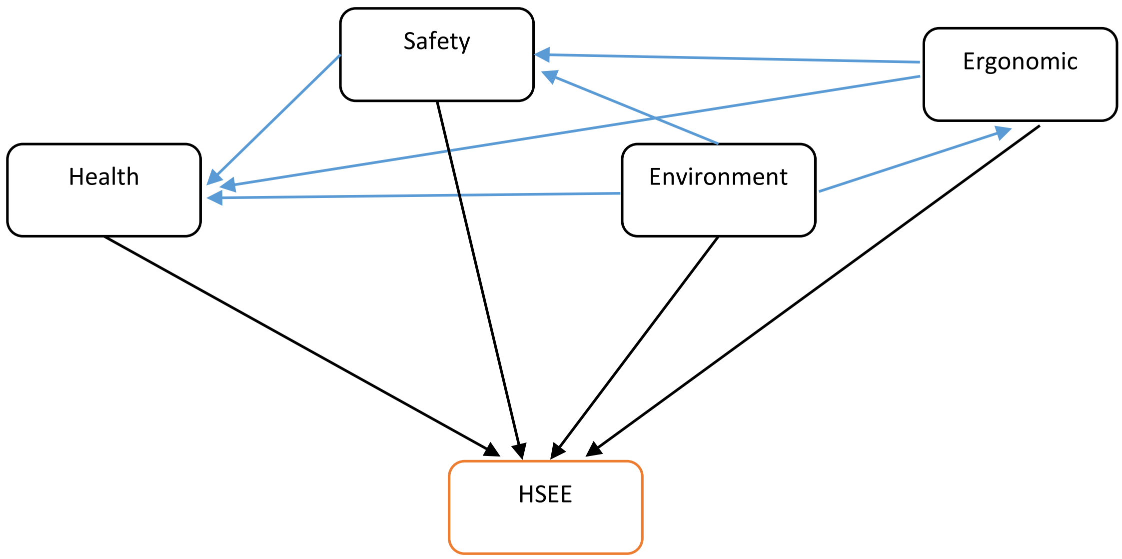



**Fig.8. Constructed BN model by FCM method**

### 3.4. CPT Elicitation by Noisy-OR Method (Step 3)

The last step of constructing BN model is CPT elicitation. We use the Noisy-OR method to do this (Li, Poupart, & van Beek, 2011). The common way for calculating CPT is leveraging the experts' knowledge. Experts were selected based on their extensive knowledge and experience of the current situation of the power plant. However, if we have $d$ states and $n$ parents for one child in the BN model, we should ask for $d^{n+1}$ probability values for completing the CPT which is a high number. This high number makes the expert based elicitation approach very costly and also hard to apply. To address this issue, we utilize the noisy-OR method which calculates the conditional probabilities by using less of the obtained probabilities via experts (Li, Poupart, & van Beek, 2011). For this purpose, HSEE nodes are selected in the first step and then, by considering HSEE parent nodes, four conditional probabilities were obtained via experts. The obtained probabilities are depicted in Table 4.

**Table 4- CPT elicitation by expert opinion**

| |
|---|
| C1=$P(HSEE = Poor \vert Health = Good, Safety = Poor, Environment = Poor, Ergonomic = Poor) = 0.9$ |
| C2=$P(HSEE = Poor \vert Health = Poor, Safety = Good, Environment = Poor, Ergonomic = Poor) = 0.8$ |
| C3=$P(HSEE = Poor \vert Health = Poor, Safety = Poor, Environment = Good, Ergonomic = Poor) = 0.4$ |
| C4=$P(HSEE = Poor \vert Health = Poor, Safety = Poor, Environment = Poor, Ergonomic = Good) = 0.6$ |

For using the noisy-OR method, some nodes should be considered as parent and one node is considered as output node. Noisy-OR formulas calculate a CPT using $n$ parameters, $s_1, \dots, s_n$, one for each parent, where $s_i$ represent the probability that $Y$ is false by considering that $X_i$ is true and all of the other parents are false (Li et al., 2011).

$$P(Y = 0 | X_i = 0, X_j) = s_i \qquad , \forall j, j \neq i \tag{3}$$

By calculating these parameters conditional probabilities can be generated using:

$$P(Y = 0 | X_1, \dots, X_n) = \prod_{i \in T_x} s_i \tag{4}$$

$$P(Y = 1 | X_1, \dots, X_n) = 1 - \prod_{i \in T_x} s_i \tag{5}$$

Where $T_x = \{i | X_i = 1\}$

Other conditional probabilities for CPT in HSEE are calculated by use of Table 5 and equation 3, 4, 5. Two states of conditional probabilities were calculated and are shown in Table 5.

**Table 5 -Noisy-OR method**

| Health | Safety | Environment | Ergonomic | HSEE=Good | HSEE=Poor |
|---|---|---|---|---|---|
| Good | Good | Poor | Poor | 0.9 * 0.8 | 1-(0.9 * 0.8) |
| Good | Good | Good | Good | 1 | 0 |

The BN model of noisy-OR method shown in Figure 6, was constructed by GeNIe software. As an example completed CPT for safety node is shown in Table 6. As can be seen, the probability of “poor” for the safety node equal to one when both parent nodes are in poor state. These values are obtained by using of Table 5 and equation 3, 4, 5.

**Table 6- CPT for safety node**

| Parent Nodes for Safety | | | |
|---|---|---|---|
| Ergonomic | Environment | Poor | Good |
| Poor | Poor | 1 | 0 |
| Poor | Good | 0.35 | 0.65 |
| Good | Poor | 0.55 | 0.45 |
| Good | Good | 0 | 1 |

We used GeNIe software for running the proposed and constructed BN. Obtained BN model is shown in Figure 9.

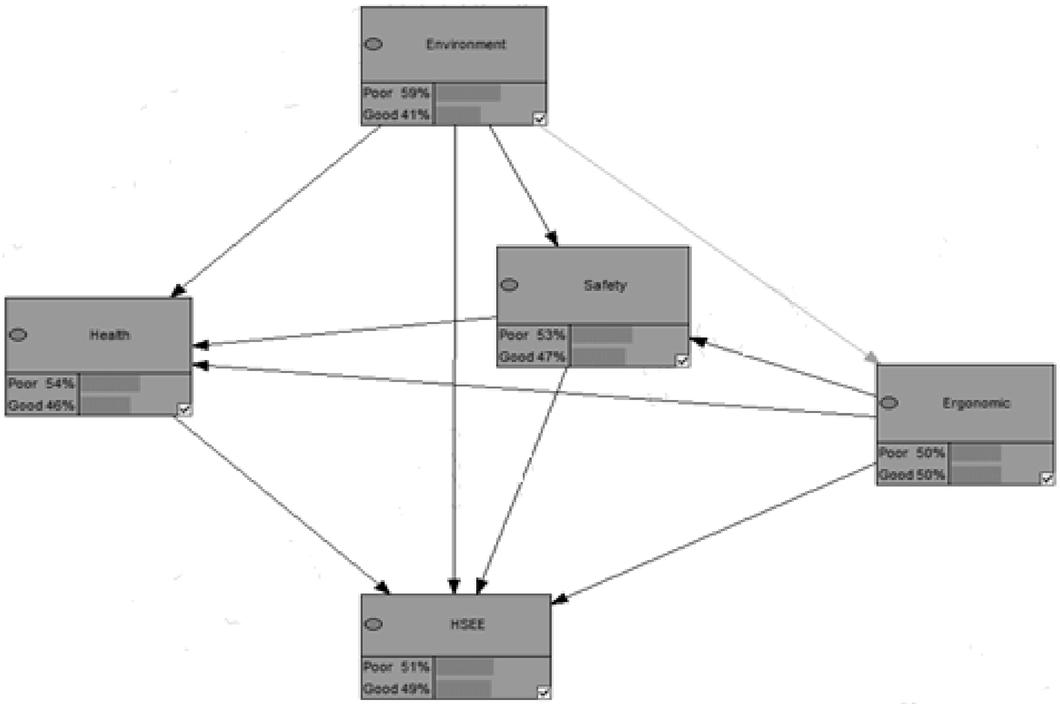



**Fig.9. Obtained BN model by noisy-OR method**

Figure 9 provides an outlook of the current situation of the company with respect to expert opinions. Thus, it can be deduced that with the possibility of 51% the HSEE management working poor in the power plant, which means the considering factors for HSEE management are not in a good situation and condition.

### 3.7. Identifying Most Effective Factor of BN Model (step 4)

In this step, by using various scenarios the most influential factor of the output is identified. It shows how the output of the BN model is changed when the input factors are changing (Kabir, Tesfamariam, Francisque, & Sadiq, 2015). For using scenarios, first a target node should be defined and then others are considered as parent nodes. In this paper, HSEE is considered a target node in which parent nodes should be changed in specified levels (Asadzadeh et al., 2013).

The first sixteen scenarios were defined. In each of them, one factor is completely in a good state on constructed BN models. By obtaining the rate of the HSEE node increasing good state, it can be deduced which factors have the most influence in HSEE management. The result is shown in Table 7.

**Table 7- Sensitivity analysis for obtained BN model of Noisy-OR**

| Health | | Safety | | Environment | | Ergonomic | | Rate of increasing HSEE |
|---|---|---|---|---|---|---|---|---|
| ***G*** | ***P*** | ***G*** | ***P*** | ***G*** | ***P*** | ***G*** | ***P*** | |
| 1 | 0 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 9% |
| 0.5 | 0.5 | 1 | 0 | 0.5 | 0.5 | 0.5 | 0.5 | 11% |
| 0.5 | 0.5 | 0.5 | 0.5 | **1** | **0** | 0.5 | 0.5 | **26%** |
| 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 1 | 0 | 18% |
| 0.8 | 0.2 | 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 7% |
| 0.6 | 0.4 | 0.8 | 0.2 | 0.6 | 0.4 | 0.6 | 0.4 | 10% |
| 0.6 | 0.4 | 0.6 | 0.4 | 0.8 | 0.2 | 0.6 | 0.4 | 15% |
| 0.6 | 0.4 | 0.6 | 0.4 | 0.6 | 0.4 | 0.8 | 0.2 | 17% |
| 0.1 | 0.9 | 0.3 | 0.7 | 0.3 | 0.7 | 0.3 | 0.7 | 8% |
| 0.3 | 0.7 | 0.1 | 0.9 | 0.3 | 0.7 | 0.3 | 0.7 | 12% |
| 0.3 | 0.9 | 0.3 | 0.7 | 0.1 | 0.9 | 0.3 | 0.7 | 14% |
| 0.3 | 0.7 | 0.3 | 0.7 | 0.3 | 0.7 | 0.1 | 0.9 | 10% |
| 0.2 | 0.8 | 0.5 | 0.5 | 0.6 | 0.4 | 0.3 | 0.7 | 11% |
| 0.5 | 0.5 | 0.2 | 0.8 | 0.3 | 0.7 | 0.6 | 0.4 | 11% |
| 0.6 | 0.4 | 0.3 | 0.7 | 0.2 | 0.8 | 0.5 | 0.5 | 16% |
| 0.3 | 0.7 | 0.4 | 0.6 | 0.5 | 0.5 | 0.2 | 0.8 | 15% |

The results of Table 7 show that scenario number 3 has most rate of increasing which means that *environment* is the most effective factor of BN model.

Also we used the mutual information (MI) method to assess the sensitivity of the BN factors. MI shows the amount of information that one factor shares with another factor. MI shows how much the level of one variable uncertainty is reduced when another variable receives some (Equation (6)). In fact, the higher value of MI between a pair of variables indicates a stronger dependence:

$$MI(X;Y) = G(X) - G(X|Y) \qquad (6)$$

Where:

$MI(X,Y)$: mutual information between variables $X$ and $Y$,

$G(X)$ : marginal entropy function of the variable $X$,

$G(X|Y)$ is conditional entropy of variable $X$ given $Y$.

MI is calculated as follows:

$$MI = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x).p(y)} \qquad (7)$$

Where:

$p(x,y)$ : joint probability density function of variables

$p(x)$ and $(y)$ : the marginal probability density functions of $X$ and $Y$, respectively.

The same procedure in identifying the most effective factor of BN is applied on Noisy-OR results which are reported in Table 8. Environment is the factor which has the highest effect on the HSEE. This is similar to the result obtained by previous analysis.

**Table 8- Sensitivity analysis using mutual information in Noisy-OR**

| Factors | Mutual Information(bits) | Percent |
|---|---|---|
| HSEE | 1.2743 | 100 |
| Health | 0.01134 | 3.7 |
| Safety | 0.02741 | 9.1 |
| Ergonomic | 0.04189 | 14 |
| Environment | 0.2183 | 18.4 |

Also analysis done by using the GeNIe software and results are shown in Figure 9.

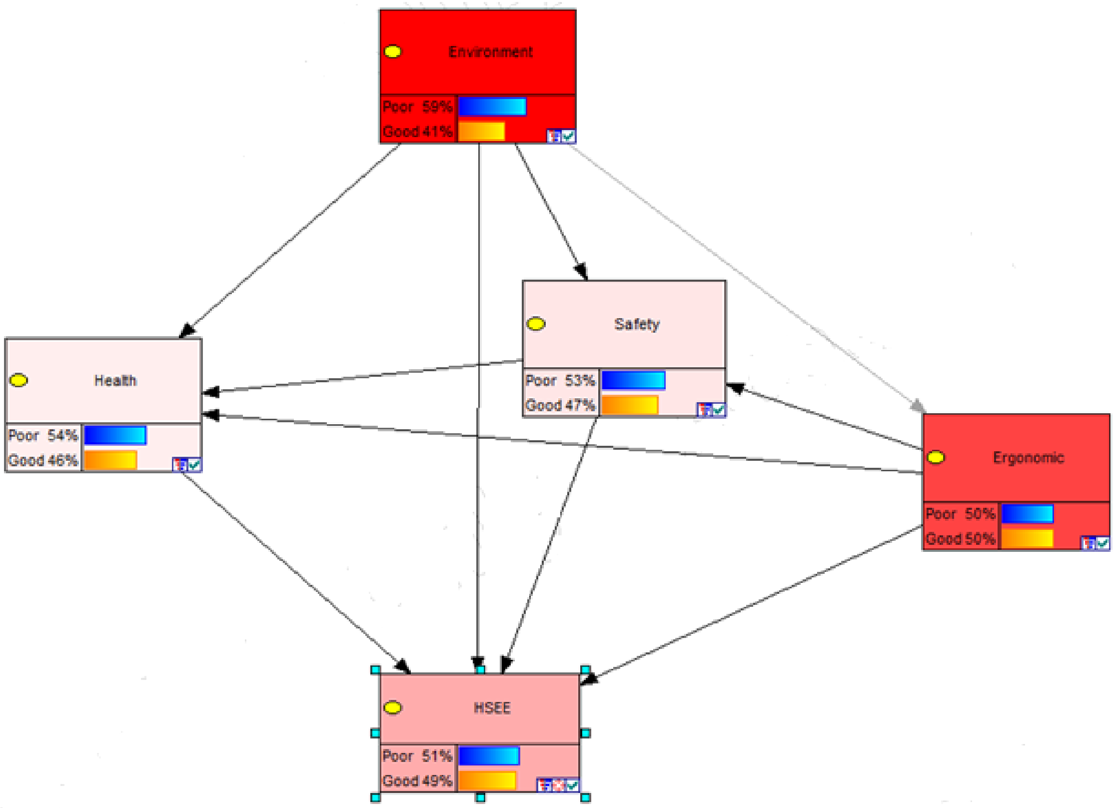



**Fig.9. The most effective factor of BN with noisy-OR based elicitation**

Nodes shown in red indicate the most effective factors of constructed BN model and whatever colour reduce the rate of the factor efficiency reduce so it can be deduced the most effective factor for both method is environment.

All designed analysis shows that 'Environment' is the most influential factor in HSEE management. According to this result, the company should concentrate on improving the environment.

## 4. Conclusion

A Bayesian Network model has been used for constructing a graphical model to improve HSEE in power plants. In the first step, the related data was collected from the power plant using a standard questionnaire. After validity and reliability of the questionnaire were confirmed, the variables of the model were confirmed by experts: Health, safety, environment and ergonomic. In the second step, a graphical model of BN was constructed by using the FCM method and CPT elicitation done using the noisy-OR (Step 2 and 3). Sensitivity analysis was used for finding the most influential factor in the model that finally identified environment as the most influential factor (Step 4). As future study, it would be interesting to consider more linguistic variables for network nodes and use of Noisy-max to calculate CPT. Dynamic Bayesian Network is a new concept which can used for future study. Also the proposed approach can be used in more complicated network.

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