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Health Risk Assessment in Lead Battery Smelter Factory: A Bayesian Belief Network Method

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***Abstract*—**This paper proposes the use of Bayesian belief networks (BBN) as a higher level of health risk assessment for a dumping site of lead battery smelter factory. On the basis of the epidemiological studies, the actual hospital attendance records and expert experiences, the BBN is capable of capturing the probabilistic relationships between the hazardous substances and their adverse health effects, and accordingly inferring the morbidity of the adverse health effects. The provision of the morbidity rates of the related diseases is more informative and can alleviate the drawbacks of conventional methods.

***Keywords*—**Bayesian belief networks, lead battery smelter factory, health risk assessment.

I. Introduction

A lead battery smelter factory located in Taichung, Taiwan disposed a large number of hazardous wastes in the nearby open field since 1991. Lead was found the major pollutant of metal in this dumping site and the concentrations of cadmium, copper and arsenic were also considerably high. This paper proposes the use of Bayesian belief networks (BBN) [1] as a higher level of health risk assessment (HRA), denoted as the BBN-HRA. The BBN is a directed acyclic graph with nodes denoting a set of random variables as nodes and arrows indicating their probabilistic cause-effect dependencies. Previous studies on the application of the BBN to environmental issues have dramatically increased. They can be roughly divided into four groups: prediction, evaluation, diagnosis and classification. For example of prediction cases, Liao et al. [2] used BBN to predict the rate of human neural tube defects by considering the number of doctors, the use of pesticides and fertilizer, the production of vegetable and fruit, per-capita net incomes, elevation, NDVI, road and fault buffer, influence of coal mines and distances to the nearest factory. An example study of evaluation was the work of Ticehurst et al. [3] who used the BBN to complement conventional analyses for exploring landholder management of native vegetation.

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Dawsey et al [4] proposed a diagnosis case, which used the BBN to integrate sensor data with other validating evidence of contamination scenarios and then to identify the most probable contamination release nodes in drinking water distribution systems. A classification example can be found in the study of Newton [5] who used the BBN to produce Red List classifications of threatened species for taxa in situations where the input data are uncertain.

On the basis of the epidemiological studies, the actual hospital attendance records and expert experiences, the BBN is capable of capturing the probabilistic relationships between the hazardous substances and their (critical and non-critical) adverse health effects, and accordingly inferring the morbidity of the adverse health effects if pollution concentrations are given. The provision of the morbidity rates of the related diseases is more informative and can alleviate the uncertainty in HRA.

II. Material and methods

A. Study Area

A lead battery smelter factory is located west of Hansi river (Taichung, Taiwan) about 50 to 100 meters where the groundwater level is about 4 to 4.5 meters, as shown in Fig. 1. From 1991, a large number of hazardous wastes produced by the factory were stacked or disposed in the nearby open field (about 1.3 hectares), and the problem of environmental pollution led the factory shut down in 2000. In 2001, the factory was investigated for environmental pollution and results showed that 0.7 hectares of area exceeded the soil control standard, as shown in Fig. 1. Lead was found the major pollutant of metal in this dumping site and the concentrations of cadmium, copper and arsenic were also considerably high. Since then the local environmental protection agency was continuously carrying out follow-up investigations to establish the background information of the area.

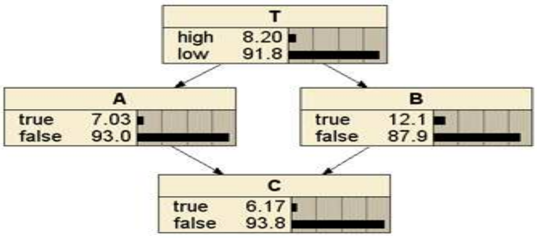
B. Brief Introduction of BBN.

A Bayesian belief network consists of a directed acyclic graph and an associated computational structure. In the graph, the nodes represent random variables (Xi) with several possible states while arrows connect pairs of nodes to display their probabilistic cause-effect relationships. Each node with parents has a conditional probability distribution table (CPT) that quantifies the uncertain effects the parents have on the node; and those nodes without parent has a probability distribution over all possible states. These probabilities are evaluated from historical data, expert judgment, or their combination. For example, a root node (T) can cause another nodes (A) and (B), and further leading to a node (C), as shown in Fig. 2(a). T has two possible states {high (h), low (l)} and its associated probability distribution is {8.2%, 91.8%}.

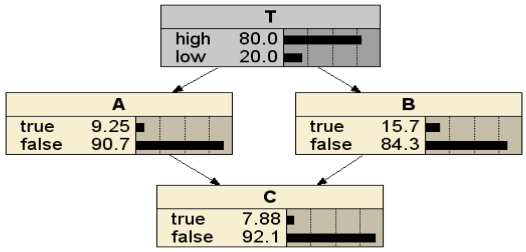
The possible states of the other three variables are true (t) or false (f) and their respective CPTs, as shown in Fig. 2(a).

The calculation complexity can be largely reduced if the conditional independence between some variables can be determined. In the graph theory, the conditional independence can be identified through the concept of "d-separation." Take again the example shown in Fig. 2(b). T and C are conditionally independent given {A, B}; A and B are conditionally independent given T. Assume that the probability distribution over {high, low} of T is predicted as {80%, 20%}; therefore $P(T = h, A = t, B = t, C = t)$ is computed by $P(C = t|A = t,B = t)\cdot P(B = t|T = h)\cdot P(A = t|T = h)\cdot P(T = h) = 0.91729 \cdot 0.1673 \cdot 0.09874 \cdot 0.8 = 0.01212 = 1.212\%$. Similarly, other JPDs can be calculated, as shown in Table 2. Finally, $P(A = t)$, $P(B = t)$ and $P(C = t)$ can be computed by Equation (4) as 9.25%, 15.73%, and 7.88%, respectively, as shown in Fig. 2(b).

Fig. 1 Area of case study



(a)



(b)

Fig. 2 (a) Example of BBN; (b) a given probability distribution {0.8, 0.2} over {high, low} of T and the associated inferred probabilities of other variables

C. Identification of Key Factors And Their Causal Relationships

The primary hazardous substances in a dumping site of lead battery smelter factor are lead (Pb), arsenic (As), cadmium (Cd) and copper (Cu). According to related research, the health effects of the hazardous substances are summarized in Table I. Lead can lead to kidney diseases, lung cancer, bladder cancer, skin cancer, prostate cancer and pulmonary edema; arsenic can cause lung cancer and stomach cancer; cadmium induces skin cancer, prostate cancer, stomach cancer and pulmonary edema; and exposure to copper can result in lung cancer. These hazardous substances and the induced diseases are the nodes in the BBN, as shown in Fig. 3.

TABLE I
HAZARDOUS SUBSTANCES IN DUMPING SITE OF LEAD BATTERY SMELTER FACTOR AND THEIR HEALTH EFFECTS

Hazardous substances	Adverse health effects
Lead (Pb)	Kidney diseases
	Lung cancer
	Bladder cancer
	Skin cancer
	Prostate cancer
	Pulmonary edema
Arsenic (As)	Lung cancer
	Stomach cancer
Cadmium (Cd)	Skin cancer
	Prostate cancer
	Stomach cancer
	Pulmonary edema
Copper (Cu)	Lung cancer

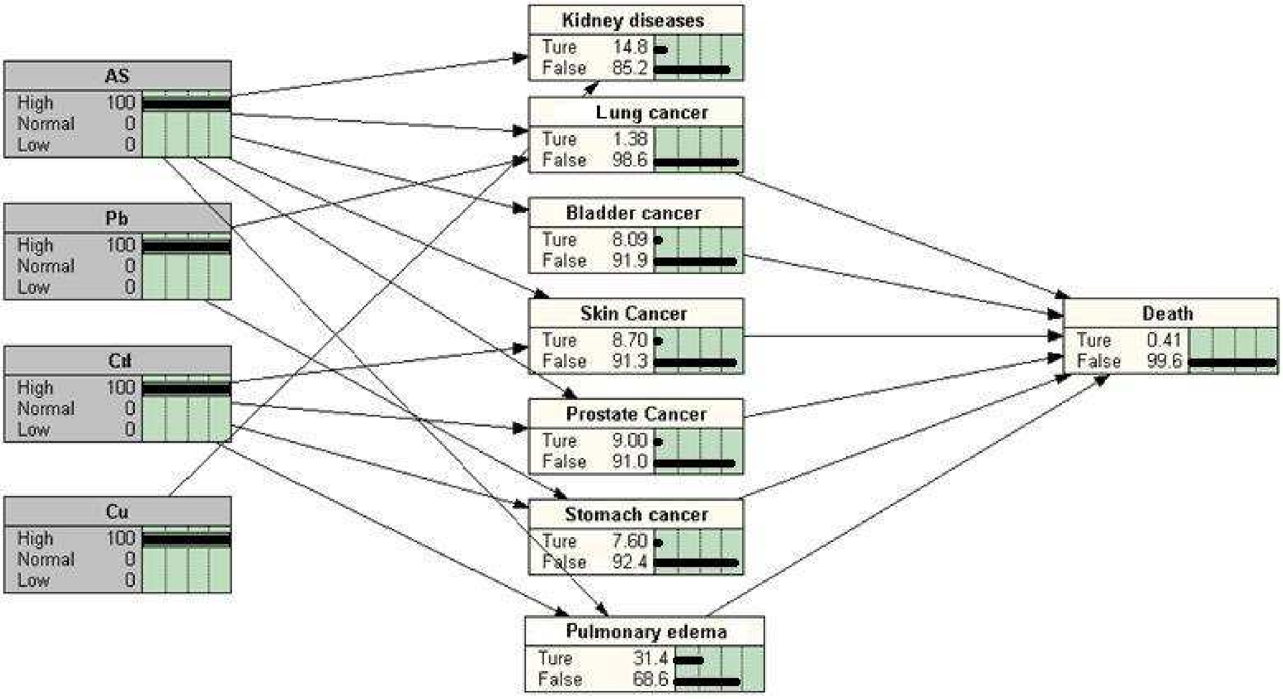


Fig. 3 BBN-HRA structure for hazardous substances in dumping site of lead battery smelter factor

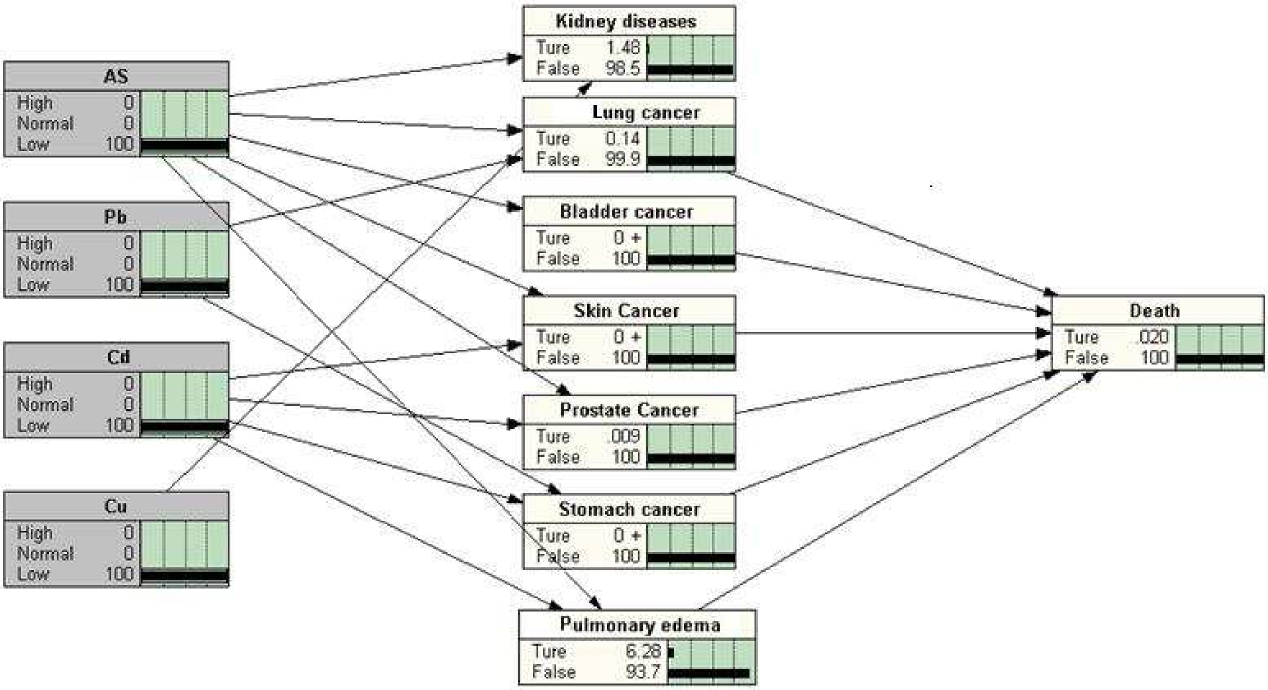


Fig. 4 BBN-HRA results after removing soil one meter below the surface and replacing with clean soil

C. Development of CPTs.

The four hazardous substances are essentially continuous variables. However, most BBN software cannot deal with continuous variables so that the solution is to discretize variables and build models over discrete domains. That is, the values for each node in the BBN should be categorized into the finite number of levels. How to discretize the variables is more difficult a question because the number and division points of the levels can make a notable difference in the complexity and precision of the resulting model. The bigger the number of levels, the more complex and precise the model is but more data are needed for it to construct probabilistic dependencies. In this research, the concentrations of the four hazardous substances are divided into three levels, as show in Fig. 3. The difficulty of defining conditional probabilities arises when the relevant literature on probabilistic relationships between causes and effects is insufficient. In such situation, experienced experts are usually able to use subjective judgment to assist in this task. In this paper, the determination of conditional probabilities suffers this difficulty due to the lack of sufficient information and therefore subjective judgment is exploited. In Taiwan, the morbidities of kidney diseases, lung cancer, bladder cancer, skin cancer, prostate cancer, stomach cancer and pulmonary edema are 1.482%, 0.138%, 0.008086%, 0.009439%, 0.009%, 0.076% and 6.2809%, respectively, which are baseline situations. Subsequently, experts use their expertise to determine the morbidities for the worst situations. Therefore, the conditional probabilities between baseline and worst situations are calculated assigned on an interpolative basis.

III. Results and discussion

The information of the sample points before and after remediation is inputted into the BBN-HRA model. Before remediation, the results are estimated as follows: the morbidities of kidney diseases, lung cancer, bladder cancer, skin cancer, prostate cancer, stomach cancer and pulmonary edema respectively are 14.80%, 1.38%, 8.09%, 8.70%, 9.00%, 7.60% and 31.40%, as demonstrated in Fig. 3. If the soil one meter below the surface is removed and replaced by clean soil then the morbidity rates will decrease to the baseline conditions; that is, the morbidities of kidney diseases, lung cancer, bladder cancer, skin cancer, prostate cancer, stomach cancer and pulmonary edema respectively are 1.48%, 0.14%, 0%, 0%, 0.009%, 0% and 6.28%, as demonstrated in Fig. 4.

IV. Conclusions

We suffered several difficulties in applying the BBN to HRA and they still need further endeavor to solve. The first one was to discretize appropriately the variables because the bigger the number of discretization, the more complex and precise the CPTs are but more data are needed. In this paper, three concentration levels of hazardous substances were adopted but they required more solid study in future research. The second difficulty was to gather sufficient epidemiological studies to avoid subjective judgments. The third difficulty came from insufficient studies on the joint effects of multiple pollutants, which compelled us to use expert experiences in aggregating conditional probabilities. Indeed, the last two difficulties are not due to the model itself, but for the lack of relevant epidemiological studies to support this model. If these difficulties can be overcome, the BBN will be very beneficial in HRA.

Acknowledgments

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