Using a Bayesian Network to Assess the Atmospheric Pollution Influence on Immunological Parameters

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Abstract. The paper proposes a methodology for using static Bayesian networks (BN) in the tasks of influence the surrounding environment pollution on immunity. The methods for constructing the BNs structure, their parametric learning, validation, sensitivity analysis and scenario analysis «What-if» are considered. The model was designed in collaboration with medical experts, as well as pharmacists, experts in the selection and quantification of input and output variables.

Keywords: Activation Markers, Pollution, Immunity, Monoclonal Antiboies, Immunoglobulins, Lysosomal Cationic Proteins, Bayesian Networks, Structural Learning, Sensitivity Analysis, Validation

1 Introduction

The problem of air pollution in cities is one of the most urgent environmental problems facing modern society worldwide. The connection between pollution and health is usually examined in an attempt to determine the dominant cause of pollution and its influence on health outcomes.

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This problem has a critical environmental situation allowing serious negative consequences for human health. In particular, this issue is relevant industrial regions, one of which is the Krivy Rig basin in Ukraine.

Modeling the influence of air pollution on health (taking into account all relevant variables) is quite complex from a theoretical point of view, because of the link between environment and health, as a rule, characterized by a complex structure of dependence. Computational problems are also evident, as the analysis of large database takes long processing time and can be handled only with adequate computing infrastructure. When resources are limited and studies are carried out mainly on the basis of open data, there is a need for models that may inherently identify, depending on the basis of the variability of functions and thus may further utilize the expertise to enhance the predictability of the models. To solve this problem the most appropriate computational tools are Bayesian networks.

It is known that the immune system responds to changes in the environment, in particular exposure to harmful substances, which affects the functional performance of the organism.

Accordingly, the immunological parameters are one of donosological health indicators. Therefore, to solve the problem of morbidity of the population of the city of Krivy Rig, along with the study of environmental factors in the region requires the development of probabilistic and deterministic models allow more locally to explore the effects of chemicals on the state of children's health.

In this paper we explore the use of Bayesian networks to determine the probability structure of the relationship between the environment and health. It consists of the exposure levels (the concentration of pollutants in the air) and the results for the children's health (indicators of the immune system).

In recent years, Bayesian methods have become the preferred method for reasoning with uncertainty due to their mathematical basis. Although Bayesian theory does not solve all the problems of probabilistic thinking, it gave scientists a solid basis for the submission and pragmatic analysis of uncertainty. Considering the system from the probabilistic point of view, the constructed models are clearly uncertainties in the basic system.

2 Problem Statement

Having a set of known data - chemical indicators of pollution and immunological parameters, we need to determine the effect of pollution on the performance characteristics of the immune population.

The main problem is the construction of a network structure of the Bayesian network and setting its parameters, taking into account the nature of the relationships between nodes and the predetermined conditional probabilities ancestral nodes network with the subsequent validation of the resulting model.

3 Review Of The Literature

Since Bayesian networks allow to identify the basis of variability depending on different functions, they are widely used in medicine [1], genetics [2] and Epidemiology [3].

In environmental science, Bayesian networks are an effective tool for structuring environmental research [4, 5].

There are two ways of applying them [6]. The first way is to assess the understanding of the functioning of the ecosystems studied, the second way is to use Bayesian networks when assessing the variables presented nodes. In the first case study focuses on Bayesian belief networks links and refers to a functional relationship in the ecosystem or in the "rules", used to build the conditional probabilities for the node and refers to mechanisms for describing the interaction of factors in determining the values of variables.

In the second case study focuses on the assessment, checking the model and provide empirical information that is quantitative, useful and relevant to the key environmental variables.

In [7] Bayesian belief networks are used to model and predict faults in the drinking water distribution system.

In [8] Bayesian belief networks are used to create a risk assessment model of soil threats. To determine the risk of soil compaction, or need information about the behavior of the soil, gather that is costly or expert data that are often subjective.

In [9] provides the use of events bush and Bayesian belief networks for assessing the environmental situation in the zone of potentially dangerous objects and chemically probability of certain situations related to its functioning.

In [10] investigated the use of Bayesian networks for determining probabilistic dependency structure the relationship between the environment and health. In the studied factors include environmental factors (relief and climate), the levels of exposure (the concentration of outdoor air pollutants) and implications for health (mortality rate). The results showed that the model has good predictive ability.

In general, studies have shown that the advantage of using Bayesian networks is their resistance to incomplete, inaccurate and noisy information. In these cases, the result will reflect the most likely outcome [11, 12].

4 Materials And Methods

A pair <***G***, *B*> called a **Bayesian network (BN)**, when the first part of G is a acyclic directed graph corresponding to random variables [13,14]. When each variable is autonomous of its parents in G, so a graph is written as a composition of autonomous conditions. The second part of the pair, B, is the composition of parameters defining the network. It composed of parameters $\mathrm{Q}_{x^i|pa(X^i)} = P(x^i \mid pa(\mathrm{X}^i))$ for each possible x^i value from X^i and $pa(X^i)$ from $Pa(X^i)$, where $Pa(X^i)$ means the variable X^i parents set in G . Each variable X^i in graph G is suggested as a vertex. If we consider more than only one graph, then we use the notation to identify the parents $Pa^G(X^i)$ in graph G[15-18].

The BN's cumulative probability B is determined by the equation $P_B(X^1,...,X^N) = \prod_{i=1}^{N} P_B(X^i \mid Pa(X^i))$.

The BN represents a model for getting probabilistic dependencies, as well as the absence of these dependencies. At the same time, the A→B relationship can be causal, when event A causes B to occur. So that is, at the time, when there is a mechanism whereby the value accepted by A affects the value adopted by B. When all BN's connections are causal, so BN is called causal.

The sensitivity analysis of the Bayesian network allows you to set for each of the network parameters a function expressing the output probability from the point of view of the parameter being studied.

To derive the probability, we will consider the posterior marginal probability of the form $y = p(a \mid e)$, where a is the value of the variable A and e means available evidence. Each of the network parameters has the form $x = p(b_i \mid \pi)$, where b_i is the value of the variable *B* and π is an arbitrary combination of the values of the set of parents $\Pi = pa(B)$ of *B*.

Denote $p(a \mid e)(x)$ as a function expressing the a posteriori marginal probability $p(a \mid e)$ in terms of the parameter *x*. In the future, we will assume that in a sensitivity analysis, as the parameter $x = p(b_i \mid \pi)$ changes, each of the probabilities $p(b_j \mid \pi)$ changes accordingly. The function *y(x),* obtained as a result of sensitivity analysis, is a quotient of two linear functions in *x* [19,20].

5 Experiments And Results

The purpose of modeling is to identify whether the impurities affect contained in the air on the human immune system. The initial data we have the results of laboratory tests and identified the following indicators of environmental pollution (dust, hydrogen sulfide, formaldehyde, metal impurities, etc.), which, in our opinion, could serve as criteria for our study.

The structural model of the influence of pollution on the immune system is presented in Figure 1.

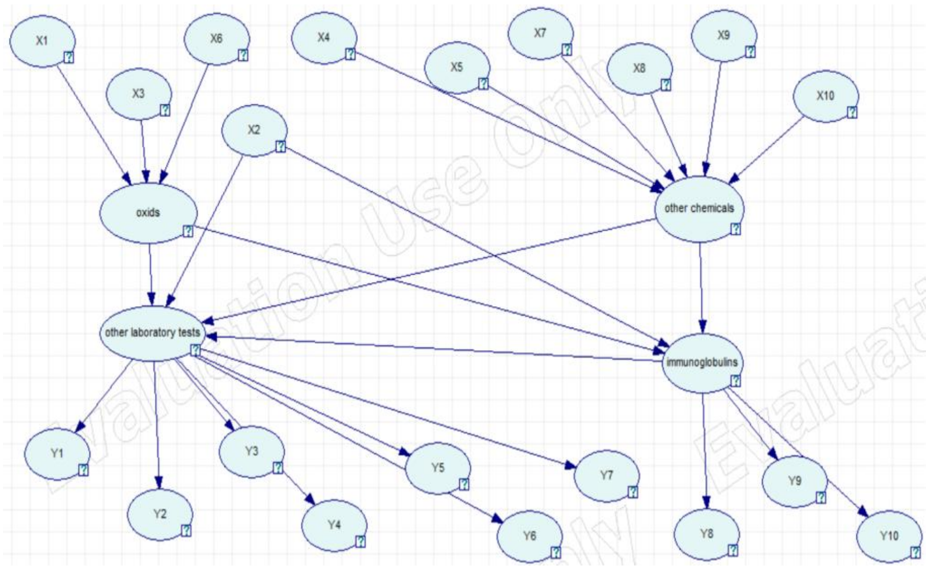

Fig. 1. The structural model of the influence of pollution on the immune system.

The proposed model is not limited to a rigid unidirectional action, and can be used to detect causative characteristics and predict the consequences. Arrows indicate the flow of information between the allocated blocks. All indicators X associated with Y (presence \ absence), also has a relationship of pollution data with laboratory tests: X2→Immunoglobulins, Oxids→Immunoglobulin, X2→Other laboratory tests.

5.1 Data

To determine the immunological criteria for assessing the factors of the environment on the human body have been conducting research lymphocyte subpopulations using monoclonal antibodies and immunoglobulin classes using basic enzyme immunoassay analyzers.

Studying the performance of the immune system conducted in different populations: the newborn (healthy) children aged 7-10 years.

In addition to the neonatal immune system has been studied in children aged 7-10 years and in adults. The choice contingent of children aged 7-10 years was due to the relatively stable performance of the immune system in children of this age, absence of bad habits and environmental factors.

The basic immunological parameters in children Krivy Rig industrial region are presented in Table 1.

Table 1. Initial data for the study.

Criteria	Designation of the node in the model	Symbol	Decryption
Environmental pollution indicators	X_1	NO_2	Nitric oxide
	X_2	Dust	Dust
	X_3	SO_2	Sulfur oxide
	X_4	Phenol	Phenol
	X_5	H_2S	Hydrogen sulfide
	X_6	CO	Carbon monoxide
	X_7	Formaldehyde	Formaldehyde
	X_8	Cd	Cadmium
	X_9	Zn	Zinc
	X_{10}	Fe	Iron
Lab test results	Y_1	CD_3	Multiprotein complex on the surface of T-lymphocytes, which is the main coreceptor of the T-cell receptor.
	Y_2	CD_4	CD is the monomeric transmembrane glycoprotein of the Ig superfamily. In humans, the CD4 gene is encoded
	Y_3	CD_8	CD8 (Differentiation Cluster 8) is a transmembrane glycoprotein that serves as a co-receptor for T-cell receptors (TCR).
	Y_4	CD_{16}	A cluster of a molecule of differentiation found on the surface of natural killer cells, neutrophils, monocytes and macrophages.
	Y_5	HCT	Phagocytic activity of neutrophils
	Y_6	LKB	The content of lysosomal cationic proteins
	Y_7	CIC	Circulating immune complexes
	Y_8	IgM	Immunoglobulin M
	Y_9	IgG	Immunoglobulin G
	Y_{10}	IgA	Immunoglobulin A

To determine the subpopulations of lymphocytes used monoclonal antibodies CD (T cells), CD4 (T-helper), CD (T-suppressor killers), CD (NK-cells). In addition to identifying the main populations and subpopulations of lymphocytes, the subjects were determined such indicators of activation markers as HCT test (hematocrit). To determine the non-enzymatic bactericidal activity of cells, the number of lysosomal-cationic granulocyte proteins (LCG) was determined.

As can be seen in Fig. 1, the network contains four key nodes:

- Oxides - summarizes the concentration of oxides present in the air,
- Other chemicals - summarizes the concentration of the remaining impurities, metals and chemical compounds present in the air,
- Immunoglobulins - summarizes the results of all tests for immunoglobulins,
- Other laboratory tests - summarizes the results of the remaining laboratory tests, which include:

It should be noted that due to the specifics of the Bayesian networks, all the conclusions of this model regarding the information sought are probabilistic in nature and are presented in the form of a ranked list (according to the values of the probability of fidelity of a particular conclusion). The final decision to confirm the effect between pollution data and test results, as well as the appointment of treatment, is made by the doctor.

The Bayesian network construction problem was solved using the GeNIe 2.3 Academic software environment. After sampling, the source data table acquired the form shown in Fig. 2.

immunoglobulins	other_chemicals	other_laboratory_tests	oxids	X1	X10	X2	X3	X4	X5	X6	X7	X8	X9	Y1	Y10	Y2	Y3	Y4	Y5	Y6	Y7	Y8
State2	State1	State1	State0	State1	State1	State0	State1	State0	State2	State1	State2	State0	State2	State2	State2	State0	State0	State1	State2	State2	State2	State2
State0	State1	State1	State2	State2	State2	State1	State1	State1	State2	State1	State0	State1	State1	State2	State0	State1	State2	State1	State1	State1	State0	State2
State0	State0	State2	State1	State2	State0	State2	State2	State2	State2	State2	State0	State1	State2	State2	State0	State0	State2	State1	State2	State2	State2	State0
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State2	State1	State0	State2	State1	State1	State1	State1	State1	State2	State1	State2	State1	State1	State0	State0	State1	State1	State1	State0	State1	State1	State1
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State2	State0	State0	State0	State1	State1	State1	State2	State2	State2	State1	State2	State1	State0	State1	State1	State0	State1	State2	State0	State1	State1	State1

Fig. 2**.** Sampled Data.

Let nodes X_1-X_{10} represent observational data (history). Nodes Y_1-Y_{10} - laboratory studies and the results of analyzes. All nodes have three states:

- state s0 - means the absence of this feature;
- state s0 - means uncertainty;
- state s2 - means the presence of this symptom in the clinical picture.

We have observations of air pollution indicators, supported by analyzes performed over the same time period.

A model of a static Bayesian network focused on solving the problem of determining the dependence of immunity on pollution is presented in Figure 3.

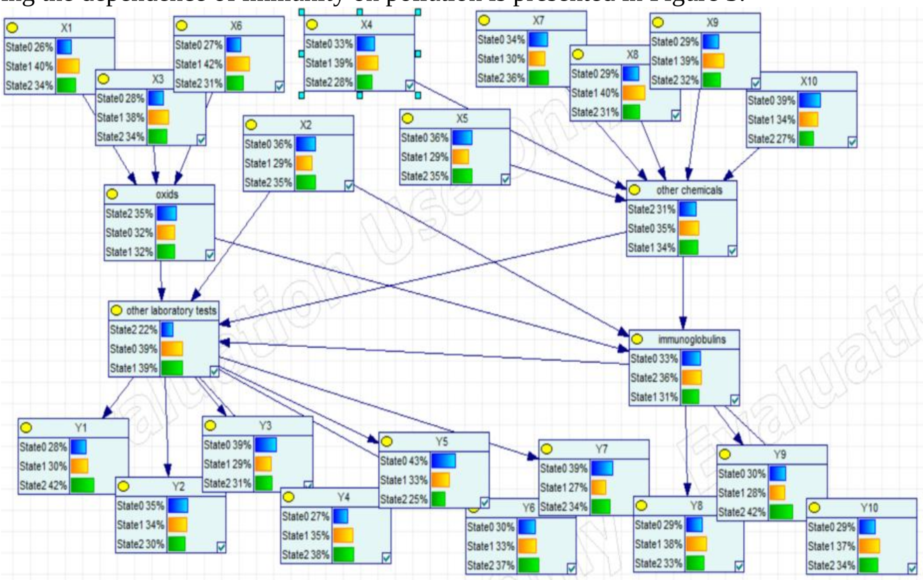

Fig. 3**.** A model of a static Bayesian network focused on solving the problem of determining the dependence of immunity on pollution.

6 Discussion

BNs are interesting for presenting knowledge because they allow both a top-down conclusion and a bottom-up conclusion, they easily capture expert opinions and can be trained on data, updated and personalized. During the sensitivity analysis, it was noted that:

- among all the parameters, node X_2 (dust) is not significant, the body easily gets rid of it (when coughing, dust comes out with phlegm);

- the presence of the X_5 unit (hydrogen sulfide) in the model is mandatory since the minimum concentration of hydrogen sulfide must be in the air.

General trends in the effect of pollution on human health were also identified:

1. At the maximum level of carbon monoxide (site X_6), the total content of oxides in the air increases by 46% (from 32% to 78%) compared to the initial concentration (Fig. 4).

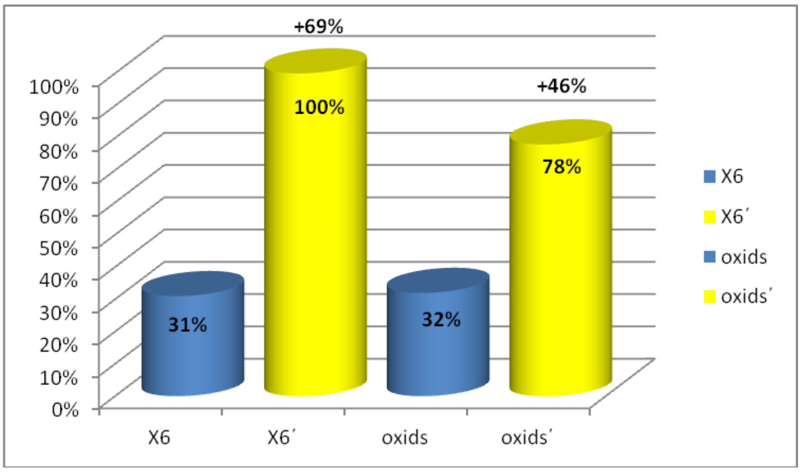

Fig. 4. Growth conditions for the total content of oxides in the air.

2. If it is possible to minimize the concentration of carbon monoxide, nitric oxide and sulfur oxide, the total content of oxides in the air will decrease by 27% (from 35% to 8%) compared with the initial concentration.
3. Immunoglobulins increase by 9% (from 33% to 42%) compared with the initial state if the concentration of phenol in the air reaches a maximum (Fig. 5).

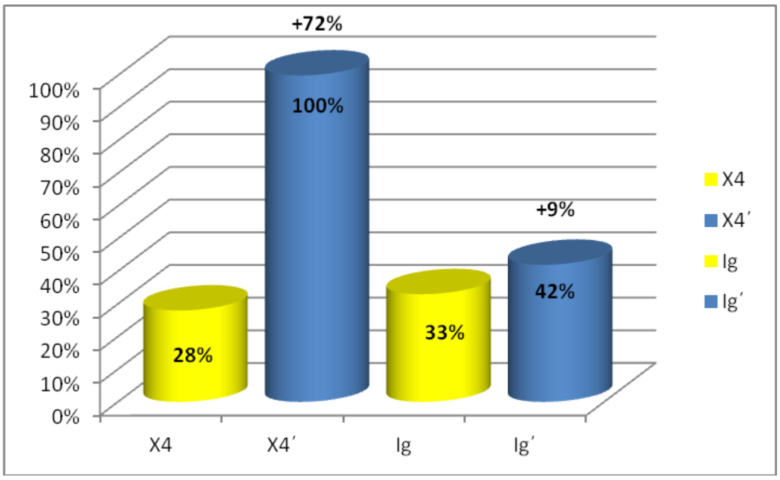

Fig. 5. Immunoglobulins growth conditions.

Other chemicals increases from 34% to 51% (17%) compared with the initial state at: X_4 maximum, X_5 maximum, X_7 minimum, X_8 maximum, X_9 minimum.

Provided that the air is polluted as much as possible (oxids = max, other chemicals = max), the results of laboratory tests, as well as immunoglobulin tests increase by

15% (from 39% to 54% and from 37% to 52%, respectively) compared with the initial state (Fig. 6).

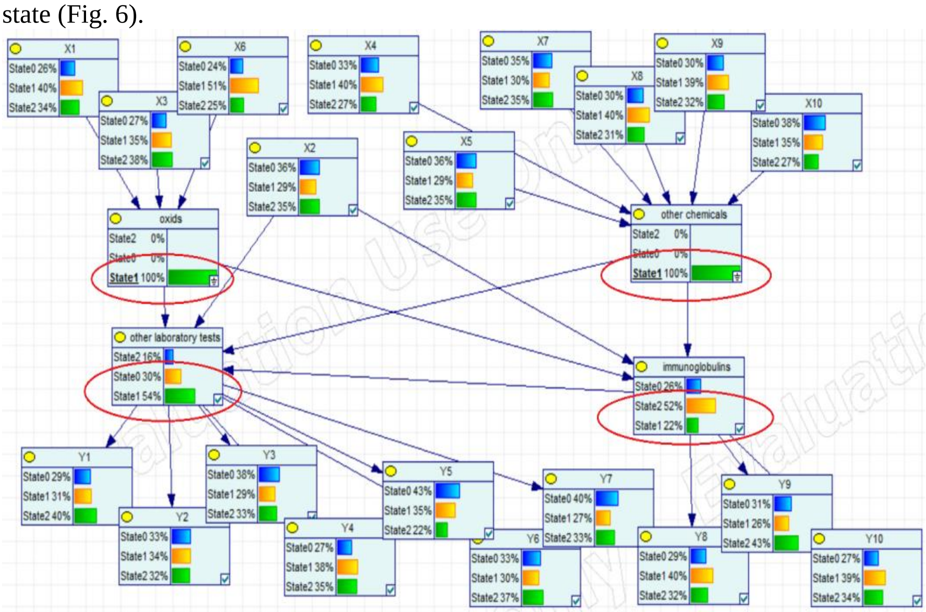

Fig. 6**.** Conditions for the influence of laboratory tests on the state of air pollution.

The resulting Bayesian model was tested on various data sets using various sampling methods. Given that a Bayesian network is a probabilistic approach in the presence of various types of uncertainty, the resulting model is adequate to the processes under study.

It is shown that validation with subsequent verification ensures the reliability of the model and also significantly increases the accuracy of the resulting model.
The proposed model allows researchers to find the optimal combination of key pollution factors that can significantly improve the value of immune indicators and, accordingly, improve children's health.

7 Conclusion

The developed BN model can contribute to the implementation of hygienic measures to improve the quality of the ecological state of the city and find its application in improving the mechanisms for managing hygienic measures by the city authorities of the city of Krivy Rig, which will affect the state of general morbidity in this region.

In future studies, it is planned to apply other structural learning algorithms, as well as to use the approach of dynamic Bayesian networks in order to trace the levels of the effect of pollution on the immunological parameters of the child population at different time slices.

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