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Control Action Demand for Major Cities Pollutants Using Bayesian Belief Networks

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ABSTRACT

Air pollutants in large cities are an overwhelming problem and have been responsible for many premature deaths all around the world. Risk perception maps how people evaluate a hazard in a subjective manner using different statistical tools. In this paper, we use of Bayesian belief network (BBN) to estimate the likelihood of control action demand from people towards authorities based on a proposed framework relating risk perception, risk judgment, and demand. The results showed that it is possible to model control action demand based on BBN structure, given an observed scenario for risk perception and judgment. Different pollutants were compared and the method distinguished the most feared from the lesser feared.

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Introduction

Outdoor air pollution is a major environmental health problem affecting everyone in developed and developing countries alike [1]. Environmental problems due to pollutants in large cities represent a major issue and people's perception of this risk is growing quickly [2].

Pollution and its effects on people's health were responsible for approximate 9 million premature deaths in 2015 [3]. In Brazil, it killed 101,739 people in 2015, which is equivalent to 7.49% of total deaths in the country in the same period. Air pollution represents the major concern, with 70,685 deaths [4].

In São Paulo State, The Environmental Sanitation Technology Company (*Companhia de Tecnologia Ambiental* - CETESB) classifies air pollutants in sulfur and nitrogen compounds, organic volatiles, carbon monoxide, halogen compounds, heavy metals, particulate matter, and photochemical oxidizing as major urban pollutants [5].

The ability to feel and avoid dangerous environmental conditions is necessary for the survival of human beings. Survival is also aided by the ability to cope and learn from past experiences. Humans still have a capacity to change the environment and adapt to it. This ability can both reduce and increase risks [6].

Risk perception is the subjective assessment of the likelihood of a specific type of accident occurring, and to what degree a person is worried about its consequences. Risk perception, however, goes far beyond the individual, and the result is a construct that reflects social and cultural values, symbols, history, and ideology. [7].

The study of risk perception has been developed since the initial work of Starr cited by [8]. Two theories currently prevail, one represented by the psychometric paradigm, based on psychology and decision sciences, and the other from cultural theory developed by sociologists and anthropologists [9].

The usual strategy to study risk perception employs the psychometric paradigm, which uses psychophysical scales and multivariate analysis techniques to produce quantitative representations, also known as cognitive maps of attitudes and perceptions. In the context of the psychometric paradigm, people make quantitative judgments about the current and desired risk of various hazards and desired level of regulation to control each of the risks. These judgments are then related to judgments about other properties, such as voluntariness, fear, knowledge, control, benefits to society, number of deaths in a year, number of deaths in a disastrous year [10].

Several authors have identified the behavioral factors that affect the perception of risk. That includes, whether the risk is natural or anthropogenic; voluntary or not; feared or not; familiar or new; chronic, in which the damages are small but constant in contrast to catastrophic effects (i.e. many deaths instantly); controllable or not by the individual; or memorable situations, due to personal or family experiences, or situations widely publicized in the media [8,11].

The literature contains several examples of risk perception studies that advocate the use of an indicator of risk perception among the stakeholders involved in a remote operation. The authors suggest measuring the impact of risk perception on safety and resilience when a task is distributed between onshore and offshore [12].

Comparison of safety perception among post-graduate students found that that oil and gas industries as well as aviation were considered safe industries; however, nuclear and mining industries are considered unsafe. The students relate risk perception with the severity of accidents rather than probability of occurring [13].

Perception of occupational risk in relation to safety training and injuries in a printing industry was studied by [14]. Using structural equation analysis, the authors confirmed a model of risk perception based on employee's evaluation of prevalence and lethalness of hazards as well as control over hazards that the employees gain through training.

Risk perception can be used to predict demand for risk mitigation, which is demand from the public towards governmental authorities [9]. The authors proposes that risk perception be understood as a cognitive construct that includes subjective assessment of probability and severity of negative consequences, as stated [14-16]. Risk judgment includes perceived risk and worry about risks. Risk perception can be a predictor of worry and both can be predictors of demand for risk mitigation [9].

Bayesian belief networks (BBNs) are increasingly being used in risk analysis applications to model the effect of multiple, diverse, inter-related influences on risk [17,18]. BBNs are useful to formalize, represent, and quantify subjective knowledge about uncertain events. [19]. As an example, recollection bias and risk perception was studied in terrorism risk assessments using BBNs [20].

Bayesian networks are graphical models that use Bayesian probability to model dependencies between knowledge domains. BBNs are used to determine or infer marginal probability and the posterior distributions for variables of interest given the observed information. The nodes of graphics represent the variables and the edges denote cause-effect relationship between pairs of nodes. The graphical model is represented by a directed acyclic graph (DAG).

The aim of this paper is to propose a framework to measure control action demand for major pollutants in large cities, using Bayesian Belief Networks to calculate likelihood of individuals demanding control actions from the authorities given that some evidence is observable. To achieve this basic framework, an exploratory study was undertaken with a small population of university students to verify the viability of the proposed framework.

The main contribution of this paper is to increase the possibilities of using statistical tools for the study of risk perception, in addition to the traditional factorial analysis (FA), multidimensional scaling (MDS), and structural equations modeling (SEM).

Method

A questionnaire was applied to assess risk perception; risk judgment, which is represented by risk perception and worry about a specific pollutant; and finally the demand for control actions from people towards governmental authorities.

Sample

The questionnaire was applied to 500 university students, who were attending classes in the sustainability course in the aeronautical sector. The response rate was of 20%, which was considered sufficient for the proposal of this paper.

Measures

The questionnaire evaluated eight pollutants: "CO" - carbon monoxide, "NOx" - nitrogen compounds, "SOx" - sulfur compounds, "VH" - volatile hydrocarbons, "O3" - photochemical oxidants, "Pb" - lead, "NS" - Noise, and "EMF" - electromagnetic fields. The last two are not classical air pollutants. For each of them, students should evaluate the perceived probability and consequence of a particular pollutant on a nine-point scale, ranging from 1-minimum level of probability/severity to 9-maximum level of probability/severity. Worry was assessed about their own health and quality of life and worry about other people's health and quality of life on a nine-point scale, ranging from 1-minimum level of worry, to 9-maximun level of worry. And finally control actions demand was evaluated on a five-point scale, ranging from 1-minimum level of demand, to 5-maximum level of demand.

All data collected was rescaled to a continuous 0-1 scale to dampen the effects of not using the entire scale, using the transformation (Eq.1):

$$var_{i,j} = \frac{obs_{i,j} - MIN\{obs_{i,j}\}}{MAX\{obs_{i,j}\} - MIN\{obs_{i,j}\}} \qquad \text{Eq 1}$$

Where,
Var: is the transformed variable (i for assessor; i=1, 2,…, n; j for columns; j=1, 2,…, 40 - 8 pollutants evaluated in 5 observational variables: severity, probability, worry about oneself, worry about others, and demand).
Obs: original scale assessed.

Analysis

A direct acyclic graph (DAG) was proposed in a Bayesian belief network (BBN). The network structure is represented in Figure 1. The basic relationship of the variables is that perceived severity of one pollutant influences perceived probability of the same pollutant. Both probability and severity represents a risk perception measure. The perception of risk influences the measurement of worry about other people and oneself. This level is called risk judgment about people when exposed to a particular pollutant. And, finally, the risk judgment influences the demands for control actions.

Figure 2 shows the entire proposed framework, highlighting "CO" pollutant perception using BBN.

The linear Gaussian model (Eq.2) was adjusted considering that Y has a linear Gaussian model (Figure 3) with continuous parents $X_1,\dots X_k$, with parameters $\beta_0,\dots,\beta_k$, and σ^2 such that

$$P(Y|\boldsymbol{X}_1, \dots \boldsymbol{X}_k) \sim N(\beta_0 + \beta_1 X_1 + \dots + \beta_k X_k; \sigma^2) \quad \text{Eq 2}$$

The estimate of parameters have a closed-form solution and were computed using R: A Language and Environment for Statistical Computing and "bnlearn" package [21,22].

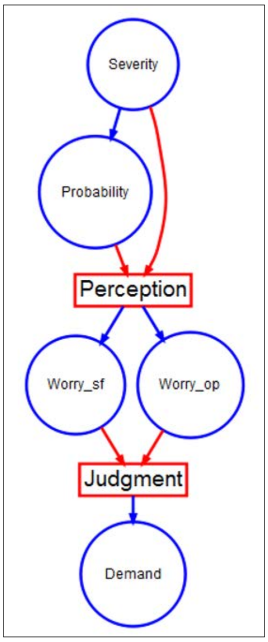

Figure 1: Framework proposed for risk perception, risk judgment, and control action demand.

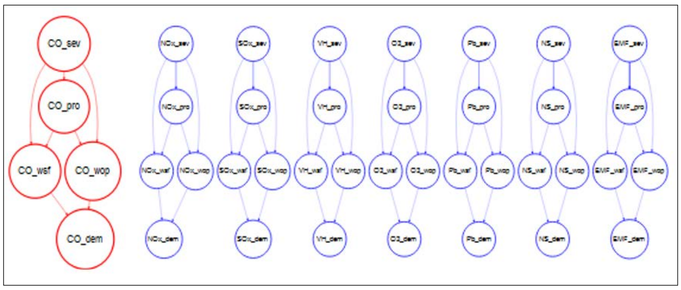

Figure 2: Network Structure, highlighting "CO" pollutant

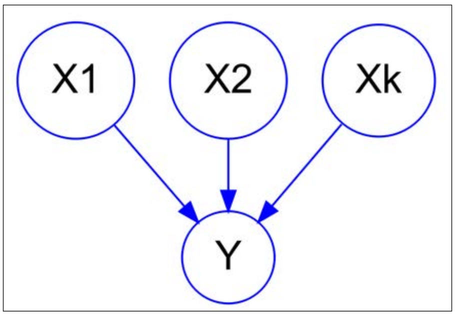

Figure 3: Example of linear Gaussian Adjustment

Results

A Pearson's correlation matrix for risk perception (severity and probability) was calculated and the results can be seen in Figure 4. The correlation between severity and probability is high for all severity-probability pairs for all pollutants. The maximum is 0.88 for "lead - Pb" and minimum for "electromagnetic fields - EMF" (0.24). These high correlations between severity and probability are explained by the fact that people express their perception of risk much more on outcome issues than frequency. Thus all events judged as having high consequence, reflect on the evaluation of probability. This fact justifies the adoption of the Bayesian network structure presented in Figure 1.

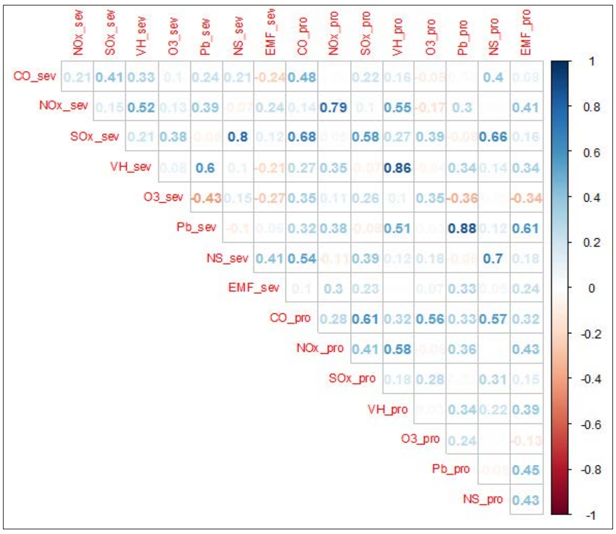

Figure 4: Correlation matrix for Risk Perception (severity and probability)

As a result of the BBN, a series of Gaussian relationships were constructed based on the network structure proposed in Figure 1.

An example of the linear Gaussian obtained for the node "CO_wsf" conditioned on "CO_sev" and "CO_pro" is presented in (Eq.3) (conditional density $CO_{wsf}|CO_{sev}+CO_{pro}$):

$$CO_{wsf} = 0.130 + 0.112CO_{sev} + 0.624CO_{pro} \quad \text{Eq 3}$$

With standard deviation, σ = 0.296.

Figure 5 shows the histograms of the residuals of Gaussian adjustment of all variables. As node variables are continuous, we must define intervals for evaluation of probability propagation in the network. An arbitrary interval was defined as follows: low level of risk perception (probability and severity) ranges in interval (0, 0.375], medium (0.375, 0.750], and finally high level (0.750, 1.000]. The same definition was used to evaluate risk judgment (worry about oneself and about other people) and control action demand. Figure 6 summarizes the procedure. Not all combinations were calculated, only equal ones, i.e. low level for probability and severity as well as Wop and Wsf and three combinations of control action demand (low, medium, and high). This procedure results in 9 output.

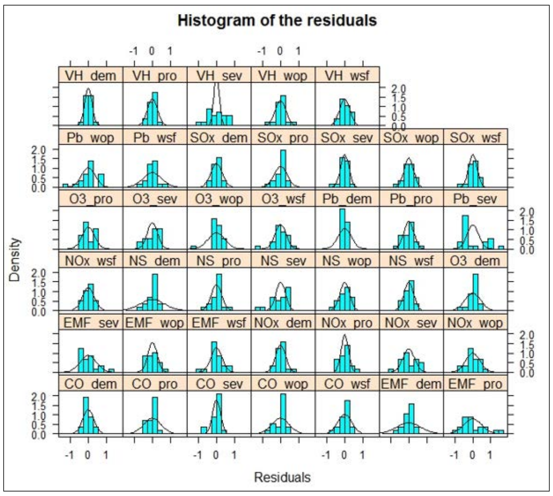

Figure 5: Histogram of the residuals of Gaussian adjustment of BBN

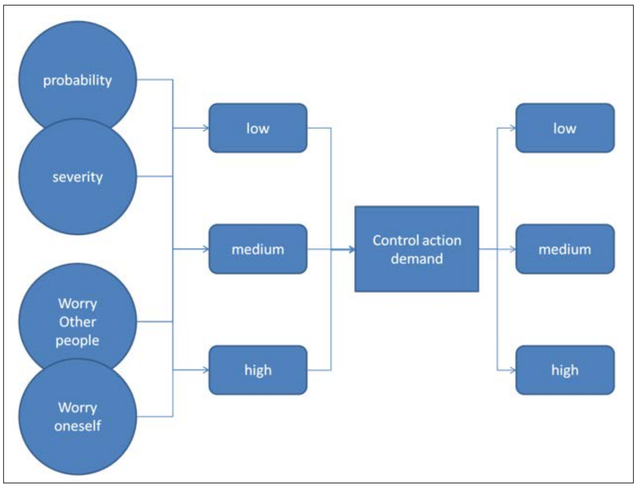

Figure 6: Instantiation structure for calculating low, medium, and high probability of control action demand

Figures 7 and 8 show the comparison between perception and judgment of low, medium, and high risk, as well as nodes in the DAG and the probability of low control action demand. Figure 7a shows the results grouped by pollutants, and Figure 7b grouped by instantiated levels.

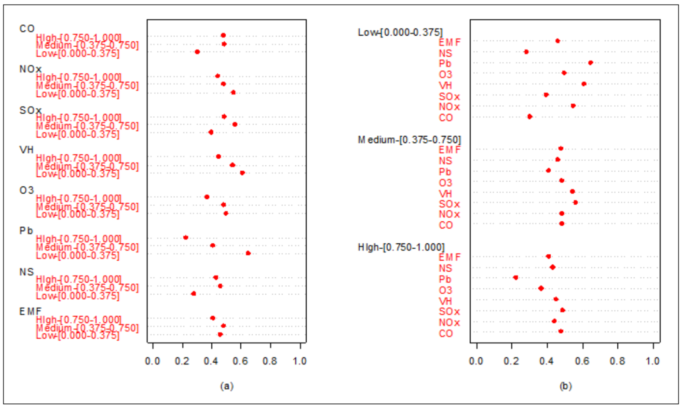

Figure 7: Probability of low control action demand for all pollutants, instantiated at low, medium and high level of risk perception and judgment. (a) Pollutants; (b) level

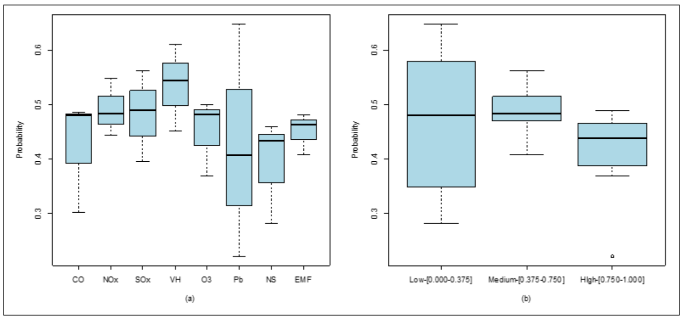

Figure 8: Box Plot of probability dispersion for low control action demand for all pollutants, instantiated at low, medium, and high level of risk perception and judgment. (a) Pollutants; (b) level

It can be inferred that probability of control action demand varies from 0.22 up to a maximum of 0.65, both values for "Lead - Pb". The data indicated that greater probability in control action demand were achieved when a low perceived risk and risk judgment were observed than when it was high for "NOx", "VH", "O3", "Pb", and the opposite for the others. Figure 8a shows that "Lead - Pb" has the major spread for probability of control action demand, and "electromagnetic fields -EMF" the minor one, with 0.41 to 0.48, which means in the last case that the difference among the three (low, medium, high) are almost imperceptible or people do not change behavior when facing this pollutant. Figure 8b shows that both mean probability and probability dispersion decreased from low to high risk perception and judgment.

Medium control action demand for all pollutant are shown in Figure 9 and 10. The range of probabilities varies from 0.04 for "SOx" to 0.76 for "Pb". Again, the last one presents the greatest spread of probability values (0.31 - 0.76), Figure 10a. All pollutants had greater probability values for high instantiated nodes (risk perception and judgment) than for low ones, which was expected.

Probability increases from low to high observational nodes instantiated in DAG, but the dispersion shrinks, with an exceptional outlier, "Lead - Pb", Figure 10b.

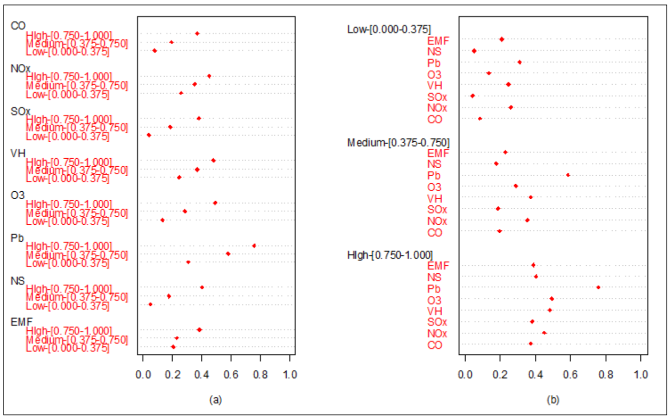

Figure 9: Probability for medium control action demand for all pollutants, instantiated at low, medium, and high level of risk perception and judgment. (a) Pollutants; (b) level

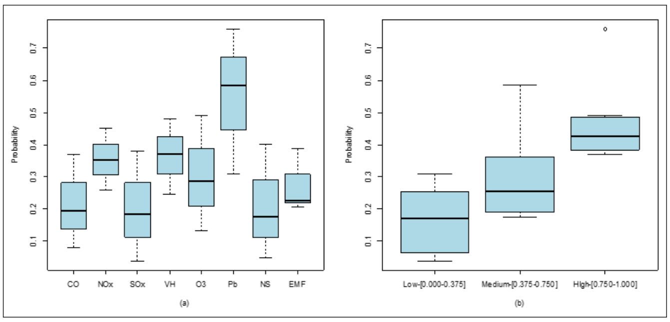

Figure 10: Box Plot of probability dispersion for medium control action demand for all pollutants, instantiated at low, medium, and high level of risk perception and judgment. (a) Pollutants; (b) level

Finally, Figure 11 shows probability for high control action demand, and surprisingly the probability ranges from 0 for "Pb" to 0.08 for "EMF", which is very low. The expectation here was to reveal large probabilities when high perception and judgment were instantiated; however, that was not confirmed; instead very low probabilities were found. The same behavior of medium control action demand was verified here, that is, probability is greater for high instantiated nodes (risk perception and judgment) than for low one. "EMF" presented the largest range of all, Figure 12a. The probability increases from low to high, Figure 12b, with an outlier, "EMF".

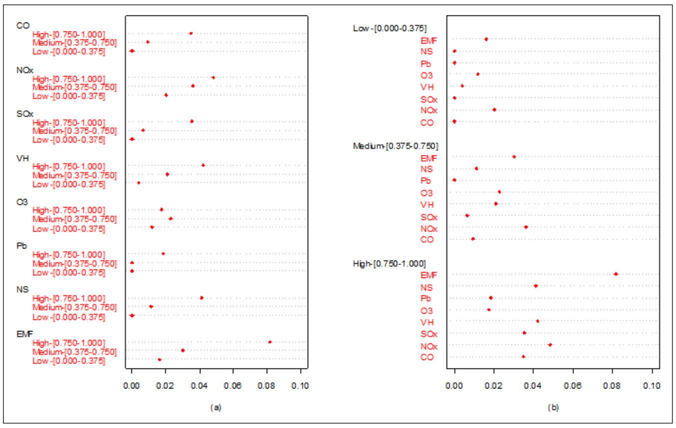

Figure 11: Probability for high control action demand for all pollutants, instantiated at low, medium, and high level of risk perception and judgment. (a) Pollutants; (b) level

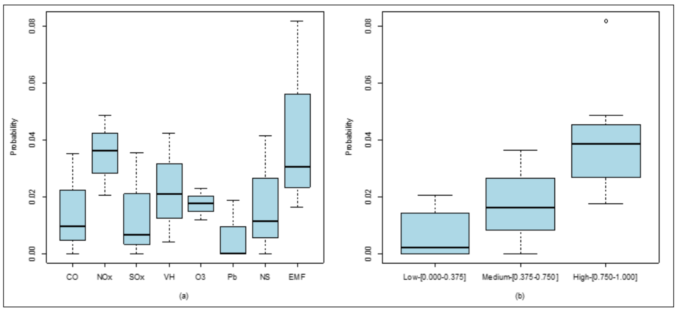

Figure 12: Box Plot of probability dispersion for high control action demand for all pollutants, instantiated at low, medium, and high level of risk perception and judgment. (a) Pollutants; (b) level

Up to now, it can be inferred that "Lead - Pb" is a pollutant that the analyzed group of students was greatly concern about, for high probabilities achieved in low and medium control action demand.

"Electromagnetic fields - EMF", which is an invisible pollutant, stands out in high control action demand.

In order to verify these two pollutants, a Monte Carlo simulation was performed.

Monte Carlo Simulation

In order to compare the 2 pollutants in demand probability, "Lead" and "electromagnetic fields", a Monte Carlo simulation was performed. The evidence nodes, "Pb_pro", "Pb_sev", "Pb_wsf", and "Pb_wop" were defined, as before, in high, medium, and low level to simulate control action demand distribution. Figure 13 presents data generated from Monte Carlo (n = 10.000 replications) for "Lead". The expected value observed for each level: 0.276 for low level in evidence nodes, 0.394 for medium, and 0.512 for high. The same procedure was undertaken with "EMF", and the results are in figure 14. The expected values obtained were 0.101 for low, 0.182 for medium, and 0.289 for high level of evidence nodes.

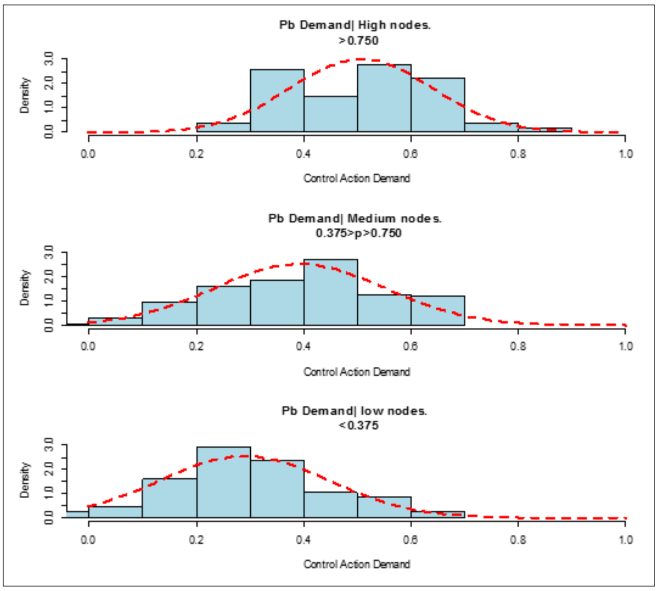

Figure 13: Monte Carlo simulation for control action demand for "Pb" with high, medium and low levels from evidence nodes

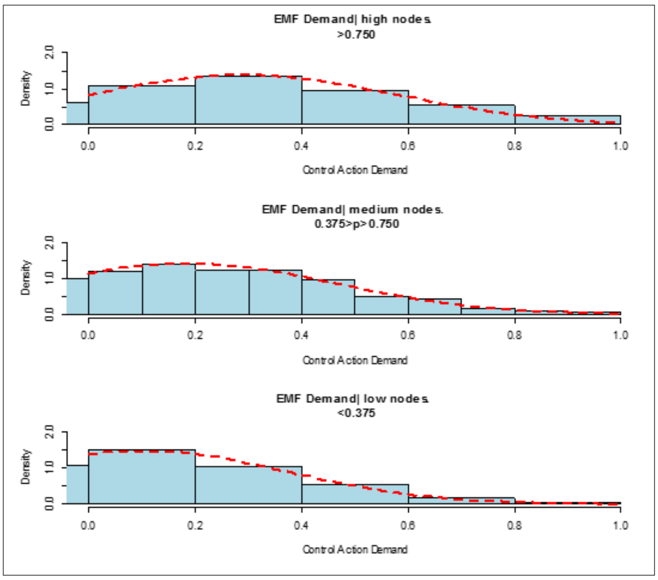

Figure 14: Monte Carlo simulation for control action demand for "EMF" with high, medium, and low levels from evidence nodes

Comparing both pollutants in high evidence nodes (>0.750), it is possible to conclude that Lead is expected, on average, to be in a medium control action demand ($0.375 \leq p < 0.750$), while "EMF" is in a low one ($p < 0.375$). We can infer that "Pb" is usually more feared than "EMF", as seen in all values obtained in the simulation.

A Monte Carlo simulation was also performed to verify the correlation among nodes "Pb_pro", "Pb_sev", "Pb_wsf", and "Pb_wop" with the instantiation or evidence node set to "Pb_dem" < 0.375. As a result, Figure 15 shows the correlation among variables. The probability and severity are high correlated, as well as severity and worry about oneself, and for a lesser extend with probability and worry about other people. The severity and probability are not well correlated with worry about other people. This fact suggests that severity greatly influences the worry about oneself and to smaller degree with worry about other people, which is a finding that deserves more investigation.

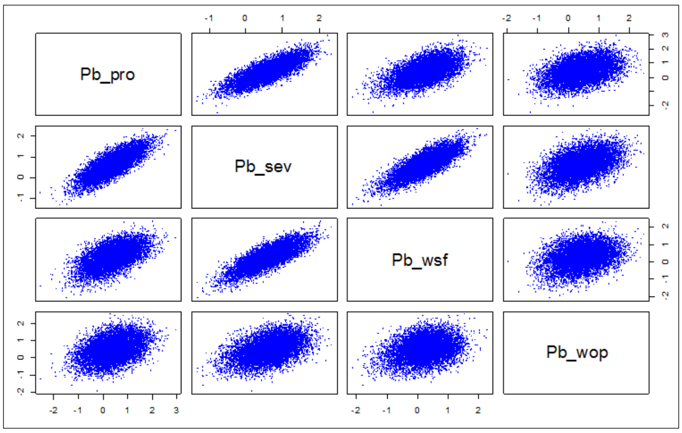

Figure 15: Correlation among probability, severity, worry about oneself and worry about other people

Final remarks

The main conclusion of this paper is that the proposed framework for measuring probability of control action demand based on a BBN structure is possible, although some surprising findings require further investigation. We emphasize the strange behavior for high control action demand. BBN showed that risk perception (probability and severity) and risk judgment (worry about health and quality of life) can be used to measure demand.

New research in this field should be done, varying pollutants and/or other environmental issues.

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