Verification of Kyoto Protocol - a fuzzy approach

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Abstract

The paper presents a new approach to the analysis of the greenhouse gases inventories. For the evaluation of the greenhouse gases emission we propose to use a fuzzy-random model. This model enables us to discriminate between different sources of uncertainty in estimates of emission inventories. The proposed model can be used for a more adequate verification of the commitments to the Kyoto Protocol.

Keywords: fuzzy-random model, greenhouse gases emission, Kyoto Protocol.

1 Introduction

The emission of greenhouse gases constitutes an important threat to the world's ecosystem. The Kyoto Protocol is an international agreement in which over one hundred countries agreed to mitigate the emission of greenhouse gases. The Parties who accept the Kyoto Protocol agreed to reduce the national emissions of greenhouse gases by specified percents given in the Annex I to this Protocol. In order to verify the compliance to agreed commitments it is necessary to evaluate the amount of greenhouse gases which are emitted by natural and non-natural (i.e. related to human's activities) sources. The results of these evaluations, known as greenhouse gas inventory estimates, are used by researchers and policy makers in a variety of ways. For example, researchers use these estimates in their investigations of possible ways for the mitigation of emissions. On the other hand, policy makers use them for the determination of the nation compliance with international commitments.

It is a well known and widely accepted fact that the estimates of greenhouse gases inventories are highly uncertain. Because of the importance of the problem, especially in policy making, scientists devoted considerable effort to understand the causes and magnitude of these uncertainties. An interesting review paper of this problem has been recently published by Gillenwater *et al.* [2]. According to these, and many other, authors estimates of uncertainties should be used to adjust emission inventories to make the compliance more credible and to establish more grounded rules of emissions trading in such situation. The latter problem was addressed in the paper by Nahorski *et al.* [6] who have proposed to link the number of permits in emission trading to the uncertainty in reported emission inventories. According to their proposal, a country whose inventory has higher uncertainty is alloted fewer permits than a country with the same inventory but smaller uncertainty.

Investigation of uncertainties related to the estimates of greenhouse gases inventories has attracted attention of many researchers. All of them agree that this is a very difficult problem, still not completely solved. The proposed nowadays solutions are outlined in the second section of the paper. We believe, that the cur-

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rently used probabilistic model does not reflect the complexity of all involved uncertainties. Therefore, we propose to distinguish between uncertainties of a random (stochastic) character, and uncertainties of a possibilistic (fuzzy) one. In the third section of the paper we propose a new model which combines the uncertainties of both considered types. According to our proposal, the estimated values of emission inventories should be described by fuzzy random variables. The consequences of this assumptions in the verification of the compliance to international commitments are discussed in the fourth section of the paper.

This paper presents first attempts to propose a new and more adequate mathematical model for the estimation of greenhouse gases emissions. Its further development should depend upon the opinions of the area specialists. It will not be an easy task because the majority of them are accustomed to purely probabilistic models of uncertainty. Therefore, other publications focused on the explanation of the random-fuzzy model are going to be published in the near future.

2 Assessment of national emissions of greenhouse gases

Let us consider the problem of the verification of commitments agreed in the Annex I to Kyoto Protocol. The Parties who accept the Kyoto Protocol agreed to reduce the national emissions of greenhouse gases by specified percents. The main problem with the verification of these commitments stems from a fact that these emissions cannot be directly measured. Therefore, the total emission X is estimated as a sum of emissions from every type of activity, evaluated indirectly using certain measures describing those activities. For example, the emission from electric coal power plants is evaluated using the knowledge about the amount of burned coal. A simple model recommended by IPCC [4] has a linear form

$$x_i = \sum_{j=1}^{m} x_{ij} = \sum_{j=1}^{m} c_{ij} a_{ij}, i = 0, 1, \ldots, \quad (1)$$

where a_{ij} is the j-th activity measure in the i-th year, and c_{ij} is the emission factor in the i-th year, which enables to calculate greenhouse gas emission knowing the activity measure for the j-th activity. At a national scale the values of activity measures a_{ij} are definitely uncertain, and the level of associated uncertainty strongly depends on the type of activity. For example, even simple activity like burning of fossil fuels, which may be known with quite good accuracy at the company level, not necessarily can be calculated sufficiently accurately at the country level, because of lack of exact data, for example for individually heated houses.

Analogously, the values of emission factors c_{ij} may be highly uncertain. This may be even the case for otherwise quite well known factors, when lack of detailed activity data requires aggregation of activities with different emission factors. As a consequence, an implied emission factor has to be used in such case corresponding, say, to the mix of different types of fuels. For other activities the emission factors may be confidential or simply not known due to the lack of precise knowledge of underlying emission processes. Thus, they can be only evaluated using experts opinions. That is why the IPCC document Guidelines [4] specifies that *Uncertainty range can be estimated using classical analysis or the Monte Carlo technique. Otherwise, the range will have to be assessed by national experts.*

In [5] the guidelines have been prescribed how to calculate the uncertainty ranges for national inventories. Two methods, called TIER1 and TIER2, are recommended. TIER1 uses simple error propagation equations, with assumptions of independent stochasticity of both activities and emission factors. TIER2 uses Monte Carlo analysis. It requires detailed knowledge of probability density functions of the above mentioned variables as well as their correlations. It is also much more resource intensive. Therefore, it has been performed only for few countries. Typically, even in those countries only TIER1 analysis is performed every year. TIER2 analysis is performed only then, when bigger methodological modifications in the inventory process are introduced.

More detailed information on this problem can be found in papers by Winiwarter [10], and by Rypdal and Winiwarter [9]. A detailed recent presentation of the calculation of inventory of greenhouse gases and its respective uncertainty can be found, for example, in [8].

3 Fuzzy-random model for the assessment of emissions

The existence of different types of uncertainty that influence the estimated value of total greenhouse gases emission is widely accepted by area specialists. There is no agreement, however, about mathematical models which are the most suitable for their description. In this paper we assume that all activity measures a_{ij} can be assessed with specific degrees of accuracy described in terms of probability distributions. Thus, we assume that uncertainties related to the assessments of a_{ij} are of random character. In fact they consist of two components: one related to measurement procedures and the other related to random variability of real (unobserved) values of all activity measures, known in the related literature as the trend uncertainty. Under certain rather strong assumptions this type of uncertainty may be estimated from time series consisted of point-wise assessments of the total emissions of considered types. However, for sake of simplicity, we assume that these two components are indistinguishable, and the total uncertainties related to the assessments of activity measures can be estimated from existing statistical data.

Suppose now, that for each activity we observe a time series consisted of $n+1$ yearly observations: $(a_{0j}, a_{1j}, \ldots, a_{nj}), j = 1, \ldots, m$. Nahorski and Jęda [7] considered different statistical methods for the analysis of time series describing the total greenhouse gases emissions. They investigated two models: one based on spline functions and the other of a regression type. In both cases it is assumed that the expected value of total emissions varies in time according to unknown deterministic function of time, and the randomness of observations is due to a random error component. We propose to apply the same methodology for the description of time series representing all activity measures.

The nature of uncertainty assigned to the associated emission factors $(c_{0j}, c_{1j}, \ldots, c_{nj}), j = 1, \ldots, m$ is hardly easy for precise evaluation. This uncertainty contains undoubtedly a random factor (for example, for an electric coal power plant the emission rate varies randomly with randomly varying quality of burned coal), but may also contain another factor, related to imprecise opinions of experts. The results of the assessment for Austria and Norway (see the papers Winiwarter [10] and Rypdal & Winiwarter [9]) show that imprecise expert opinions may contribute from 10% to 20% of total uncertainty of the total assessment. For this reason specialists assume that the values of emission factors, and more generally, the values of emissions from different activities, should be evaluated in terms of intervals of possible values. Moreover, in order to arrive at point-wise assessments of total emissions, calculated according to (1), they also provide decision makers with specific values for the emission factors $(c_{0j}, c_{1j}, \ldots, c_{nj}), j = 1, \ldots, m$. We claim, however, that even in case of very vague information about the values of c_{ij} using exclusively either interval values or precise values of emission factors is too restrictive. It seems to us that the representation of this information using possibility distributions is much more informative. Taking into account a double nature of uncertainty related to estimated values of the emision factors, we may assume that these quantities may be represented by fuzzy random variables. Therefore, each observed value of the emission factor should be given as a *fuzzy number* represented by a set of its α-cuts: $\left[c_{ij,L}^{\alpha}, c_{ij,R}^{\alpha}\right], \alpha \in (0, 1]$. The existing nowadays area-specific information usually does not allow us to build complicated possibility distributions representing the observed values of $(c_{0j}, c_{1j}, \dots, c_{nj})$, $j = 1, \dots, m$. In lack of specific information the possibility distribution of each emission factor may be approximated by the following triangular membership function:

$$\mu(c_{ij}) = \begin{cases} 0 & c_{ij} < c_{ij,min} \\ \frac{c_{ij} - c_{ij,min}}{c_{ij,sng} - c_{ij,min}} & c_{ij,min} \leq c_{ij} \leq c_{ij,sng} \\ \frac{c_{ij} - c_{ij,max}}{c_{ij,sng} - c_{ij,max}} & c_{ij,sng} \leq c_{ij} \leq c_{ij,max} \\ 0 & c_{ij} > c_{ij,max} \end{cases}, \quad (2)$$

where $(c_{ij,min}, c_{ij,max})$, $i = 0, \dots, n, j = 1, \dots, m$ are the intervals of possible values of emission factors c_{ij}, and $c_{ij,sng}, i = 0, \dots, n, j = 1, \dots, m$ are the singular values of these factors provided by experts for the point-wise assessment of the total emission. Therefore, the evaluated total yearly emission is a realization of a *fuzzy random variable* defined as

$$\tilde{X}_i = \sum_{j=1}^{m} \tilde{X}_{ij} = \sum_{j=1}^{m} \tilde{C}_{ij} A_{ij}, i = 0, 1, \dots, \quad (3)$$

where A_{ij} is the random variable of the j-th activity in the i-th year, and $\tilde{C}_{ij}$ is the fuzzy random variable of the j-th emission factor in the i-th year. We should note however, that in certain cases the representation of fuzzy variables using triangular membership functions may be inappropriate. Consider, for example, the case when the knowledge of physical and chemical mechanisms which link activities with emissions is known only partially. It happens, for example, when the specialist do not agree which mathematical model should be used for calculations. In such cases it is impossible to indicate a single value of the emission factor that has the highest measure of possibility. Thus, other possibility distributions such as e.g. trapezoidal may be more appropriate.

Probability distributions describing random variability of activities and emission factors are very difficult for precise estimation. First of all these random variables are usually correlated, and their probability density functions may have different shapes (not necessarily close to the bell-shaped normal distribution). Therefore, the exact shape of the probability distribution that governs the random variability of the total emission can be hardly evaluated. However, because of a usually large number m of considered activities we may assume that this probability distribution may be approximated by the normal distribution. This phenomenon has been already noticed by Winiwarter [10] who used Monte Carlo simulations for the evaluation of this probability distribution. The estimation of the expected fuzzy value of the total emission should be easier for calculation if we assume that the components of fuzzy random vectors $(A_{ij}, \tilde{C}_{ij})$ are mutually independent. When this assumption is true, the expected fuzzy value of the total emission may be calculated as the following linear combination of fuzzy numbers:

$$\tilde{x}_i^\star = \sum_{j=1}^{m} \tilde{x}_{ij}^\star = \sum_{j=1}^{m} \tilde{c}_{ij}^\star a_{ij}^\star, i = 0, 1, \dots, \quad (4)$$

where $a_{ij}^\star$ are the observed (estimated) values of activities, and $\tilde{c}_{ij}^\star$ are fuzzy numbers of triangular or trapezoidal shape that represents imprecisely evaluated emission factors. Unfortunately, the assumption of the mutual independence of the components of $(A_{ij}, \tilde{C}_{ij})$ is not sufficient for simple calculation of the variance of $\tilde{X}_i$. The main reason for this difficulty is the apparent dependence between the emission factors

Suppose now, that having the observed realizations of fuzzy random variables $\tilde{x}_{ij}, j = 1, \dots, m, i = 0, 1, \dots, n$ we want to predict the total emission for the commitment year $k > n$. Let $\left(a_{kj,L}^\gamma, a_{kj,R}^\gamma\right)$ be the prediction confidence interval on the confidence level γ for the amount of the j-th activity in the commitment year k. Note, that for $\gamma = 0$ this interval shrinks to the point-wise forecast for the value of x_{kj}. From the theory presented in the previous section we know that *fuzzy confidence interval* for $\tilde{X}_{kj}$ on the confidence level γ is represented by a set of α-cuts (nested α-level intervals): $\left(a_{kj,L}^\gamma * c_{ij,L}^\alpha, a_{kj,R}^\gamma * c_{ij,R}^\alpha\right)$. The construction of the fuzzy prediction interval for the total emission X_k in the commitment year k is a difficult task and, in general, may require the application of Monte Carlo methods. However, when the forecasts for a_{kj} are described by normal distributions this construction is straightforward.

4 Verification of Kyoto Protocol commitments

According to the Annex I to Kyoto Protocol a country fulfils its commitment if in the compliance year k its emission does not exceed the value $y_k = \rho x_0$, where x_0 is the emission in the base year, and ρ is a coefficient agreed upon in the Kyoto Protocol. In our analysis we begin from the simplest case when the value of y_k is given, and the activity measures in the commitment year $a_{kj}, j = 1, \ldots, m$ have been already established. Thus, we have to verify if $\tilde{x}_k \leq y_k$. From the theory of fuzzy sets we know that the unique method for the verification of this inequality does not exist. However, for this purpose we can use one of possibility and necessity measures proposed by Dubois and Prade [1], either the PD index or the NSD index. In the considered case the values of these indices should be calculated for the relation $y_k \succ \tilde{x}_k$.

The *Possibility of Dominance* index for two fuzzy sets $\tilde{A}$ and $\tilde{B}$ is defined as [1]

$$\begin{aligned} PD &= Poss\left(\tilde{A} \succeq \tilde{B}\right) = \\ &= \sup_{x,y;x\geq y} \min\left\{\mu_A(x), \mu_B(y)\right\} \end{aligned} \quad (5)$$

where $\mu_A(x)$ and $\mu_B(y)$ are the membership functions of $\tilde{A}$ and $\tilde{B}$, respectively. PD is the measure for a possibility that the set $\tilde{A}$ is not dominated by the set $\tilde{B}$.

The *Necessity of Strict Dominance* (NSD) for two fuzzy sets $\tilde{A}$ and $\tilde{B}$ is defined as [1]

$$\begin{aligned} NSD &= Ness\left(\tilde{A} \succ \tilde{B}\right) = \\ &= 1 - \sup_{x,y;x\leq y} \min\left\{\mu_A(x), \mu_B(y)\right\} = \\ &= 1 - Poss\left(\tilde{B} \succeq \tilde{A}\right) \end{aligned} \quad (6)$$

The value of the NSD index represents a measure of *necessity* that the set $\tilde{A}$ dominates the set $\tilde{B}$.

In the considered case by simple calculations we can show that the NSD measure is greater than zero if the α-cut of $\tilde{x}_k$ at the level $\alpha = 1$ is located to the left of y_k, i.e. if the inequality $x^1_{k,R} \leq y_k$ holds. Thus, we have

$$NSD = 1 - \alpha_\star \quad (7)$$

where

$$\alpha_\star : x^{\alpha_\star}_{k,R} = y_k. \quad (8)$$

From these equations we can also see that $NSD = 1$ if the whole support of $\tilde{x}_k$ is located to the left of y_k. In a more general case, when the the emission in the base year is given as a fuzzy number (due to the fuzziness of the emission factors), the commitment may be verified by the calculation of the NSD index for the relation $\tilde{y}_k \succ \tilde{x}_k$. In such a case, for the computation of NSD we use (7), but the value of $\alpha_\star$ is now calculated from the following expression:

$$\alpha_\star : x^{\alpha_\star}_{k,R} = y^{\alpha_\star}_{k,L}. \quad (9)$$

Decision on compliance can be now taken checking if $NSD \geq NSD_{crit}$, where NSD_{crit} is a preagreed value.

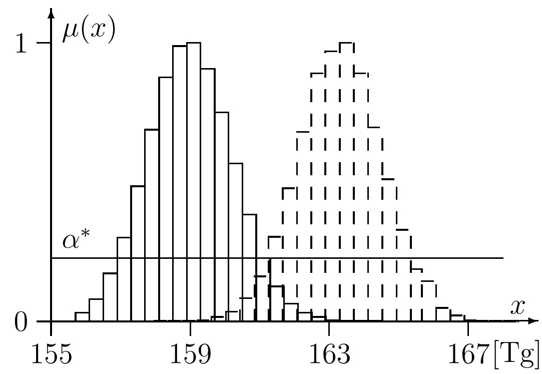

Figure 1: Uncertainty distributions of emissions inventory in the (shifted) base year (dashed lines) and compliance period (solid lines) with resulting value of α^*.

Let us consider an illustrative example. The data used are taken from [8] and represent the uncertainty distributions of CO_2 emissions inventories in the years 1990 and 2004 in the Netherlands, calculated using the Monte Carlo analysis. The situation discribed here is, however, ficticious. We assume that the higher emissions are from the base year, 1990, and the smaller from the compliance period, 2008-2012, as agreed in the Kyoto Protocol.

Further, we assume that the Netherlands obligation is to reduce 9% of the base year emissions. Then we get $\rho = 0.91$ and we can draw the shifted base year and compliance period emissions as in Fig. 1. The value found from the figure is $\alpha^* = 0.227$ and therefore we have $NCD = 0.773$. The final decision on compliance will now depend on choice of NCD_{crit}.

5 Further research

The value of the PD index, calculated according to (5), might be of practical interest only in case when the most plausible value of the estimated emission is greater than the most plausible required value. In this case the necessity of fulfillment is equal to zero, but the possibility of this may be positive. Both indices may be also used, if we want to know in advance, after the evaluations of emissions in years numbered from 0 (base year) to n have been observed, if the commitment in a year $k > n$ is likely to be fulfilled. We can solve this problem by the verification of a statistical hypothesis that the expected value of the predicted emission (estimated from fuzzy random data) is lower than a given fuzzy valued limit. Thus, we have the problem of constructing a statistical test for fuzzy data and fuzzy statistical hypothesis. This problem may be solved using, for example, a possibilistic approach proposed by Hryniewicz [3].

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