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Using Fuzzy Numbers to Model Uncertainty of Greenhouse Gases National Inventories

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Abstract

High uncertainty of greenhouse gases national inventories cause problems in credible fulfilment of the Kyoto Protocol obligations to decrease or limit emission of these gases, as well as in use of Kyoto flexible mechanisms, which include emission trading among Parties. In this paper it is proposed to model the uncertainty using the fuzzy set approach, and specifically using the fuzzy numbers to represent the uncertainty of the inventory values. This approach is a generalization of the earlier proposed interval approach to this problem.

Keywords: Greenhouse Gases, Inventory, Uncertainty, Fuzzy Numbers.

1 Introduction

Emissions of many pollutants can not be measured directly and must be estimated. This is the case of greenhouse gases, considered in this paper.

Estimates of emissions are calculated with sufficiently good accuracy only for some particular emission sources, for instance large electricity or power plants. Emissions for other sources are not known accurately enough. For example, uncertainty of emission of some gases may be as large as 50%, and for N_2O even more than 100%, [7].

In the Annex I to the Kyoto Protocol [13] the Parties agreed to reduce the national emissions by specified percents. The Protocol also specifies possibility of trading the emissions between the Parties. However, large uncertainties of emissions question credibility of checking fulfilment of the Kyoto targets, and of the emissions trade as well.

These problems have been already addressed in the literature, see [6] for a review of techniques, and specifically [3] and [11] for solutions closer in spirit to the present paper. The uncertainty in these papers has been modeled using either uncertainty intervals or stochastic normal distribution. Stochastic model has been discussed in [3] and in [11]. Regarding the emission commitments checking, practically same result has been derived in both papers. However, different prerequisites for the emissions trade have been used in these papers. Consequently, different formulas have been obtained. In [11] the principal idea was that during the trade the seller's uncertainty is appropriately transformed to the buyer and included in its commitment checking. In [3] the idea was to secure that the common for both Parties probability of exceeding emission commitments are the same before and after the trade. Within the framework presented in [11] and also in this paper, it was shown that the stochastic approach provides a complicated and practically useless formula for the emission trading rule.

In addition, recent findings from the Monte Carlo analysis, [12, 17], indicate that the distributions of uncertainty often do not resemble the stochastic normal distribution. They can be strongly nonsymetric.

In this paper a fuzzy approach is used. It can be considered as a generalization of the interval one. The fuzzy set calculus basically inherits the rules from the interval calculus, and this way provides linear dependencies in the derivations. At the same time, the fuzzy variables may be shaped appropriately to have more concentrated distributions than the interval ones and better approximate the real distributions. Moreover, the fuzzy variables may be easily shaped to be nonsymmetric, which corresponds to the Monte Carlo distributions presented in [12, 17]. Complications involved in using nonsymmetric fuzzy variables are much smaller in comparison to the stochastic non-Gaussian and nonsymmetric distributions. There is much less of underlying algebra. In this paper only symmetric fuzzy variables of a special class are considered. Application of nonsymmetric fuzzy variables will be published elsewhere.

It is perhaps worth to mention that the choice of distribution is not only of a theoretical question. It finally results in valuation of the uncertainty, and therefore influences the costs of emission reduction.

Using the fuzzy approach new rules for checking emission commitments and emission trading has been obtained. They generalize the rules presented in [9] and reduce to them when the fuzzy variables are equivalent to the uncertainty intervals. The results of application of these rules are compared to those obtained earlier, for the uncertainty intervals. The final conclusion is that a convenient interval uncertainty approach can be equivalently applied, but using much higher noncompliance risk.

The organization of the paper is as follows. In section 2 we formulate the problem and introduce some basic notation. Then, in section 3, we shortly review the interval type of uncertainty results and recall conditions for checking emission commitment and formulas for so called efficient emissions, which can be directly traded, without taking into account the emission uncertainty. In section 4 a family of fuzzy numbers is introduced. They are used to model the national inventory uncertainty and form the basis for derivations of generalized compliance and emission trading rules. These rules are compared to the interval approach rules. Section 5 concludes.

2 Notation and problem formulation

Basically, the total emission by a party is calculated by summing up emissions from every type of contributing activity and subtracting the gases absorbed by sinks. Yearly emissions $\hat{x}_i(t)$ of every type of activity, labelled here with the consecutive numbers i, are computed as the product

$$\hat{x}_i(t) = \hat{c}_i(t)\hat{a}_i(t)$$

where $\hat{a}_i(t)$ is the activity measure (e.g. in tons of material used) and $\hat{c}_i(t)$ is its emission factor, both in the year t. On the national scale both values on the right hand side are unsure, giving rise to uncertainty. The nature of the uncertainty is a complicated one. It originates from a lack of exact knowledge of some variables as well as from imperfect modeling of often poorly known processes. Table 1 gives uncertainty assessments for few countries. Full details can be found in [4, 5].

In the sequel by $x(t)$ we denote the real, unknown emission of a party in the year t and by $\hat{x}(t)$ its best available estimate. To simplify notation the time argument t will be dropped in the sequel.

The Kyoto Protocol declaration requires that each Party should reduce a prespecified percent of its basic year emission within the given period (around 20 years). However, some countries are granted a possibility of stabilizing the emission at the basic year level or even of a

Country	Kyoto reduction	Uncertainty
Austria	8	12
Holland	8	5
Norway	-1	21
Poland	6	6
Russia	0	17
U.K.	8	19

Table 1: Examples of Kyoto reduction commitments and published uncertainty estimates of national emissions, in per cents.

limited increase of its emission.

Let us denote by δ the fraction of the party emission that is to be reduced in the commitment period according to its obligation. The value of δ may be negative for parties, which were alloted limitation of the emission increase. Denoting by x_b and x_c the emissions in the basic and commitment year, respectively, the following inequality should be satisfied

$$x_c - (1 - \delta)x_b \leq 0 \tag{1}$$

As neither x_c nor x_b are known precisely enough, only the difference of estimates can be calculated

$$\hat{x}_c - (1 - \delta)\hat{x}_b \tag{2}$$

where both $\hat{x}_c$ and $\hat{x}_b$ are known with low accuracy.

3 Interval type uncertainty

Compliance. Assuming that the uncertainty intervals at the basic and the commitment years are $2d_b$ and $2d_c$, respectively, we have

$$x_b \in [\hat{x}_b - d_b, \hat{x}_b + d_b], \qquad x_c \in [\hat{x}_c - d_c, \hat{x}_c + d_c]$$

Using the interval calculus rules, we get

$$x_c - (1 - \delta)x_b \in [D\hat{x} - d_{bc}, D\hat{x} + d_{bc}]$$

where

$$D\hat{x} = \hat{x}_c - (1 - \delta)\hat{x}_b \tag{3}$$

and

$$d_{bc} = d_c + (1-\delta)d_b \tag{4}$$

However, the emission estimates in the basic, $\hat{x}_b$, and the commitment, $\hat{x}_c$, years are dependent on each other. Thus the values of d_{bc} are usually much smaller than those resulting from the above expression. In [11] it was proposed to modify (4) into

$$d_{bc} = (1-\zeta)(d_c + (1-\delta)d_b) \tag{5}$$

where $0 \le \zeta \le 1$ is an appropriately chosen variable. This case will be also considered in this paper.

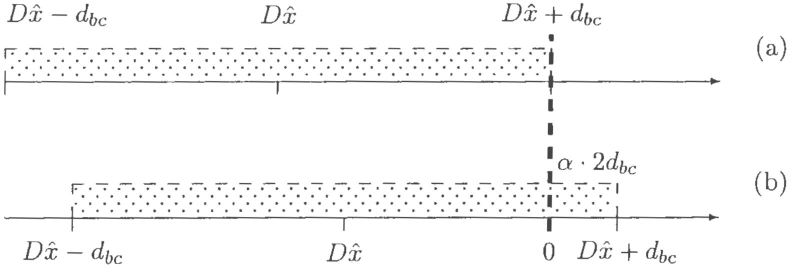

Figure 1: Full compliance, (a), and the compliance with risk α, (b), in the interval uncertainty approach.

To be fully credible, that is to be sure that (1) is satisfied, the party should prove $D\hat{x} + d_{bc} \le 0$. We say that the party is *compliant with risk* α, if $D\hat{x} + d_{bc} \le 2\alpha d_{bc}$, that is, not bigger part of its distribution than α lies above zero, see Fig. 1 for the geometrical interpretation. After simple algebraic manipulations this gives the condition

$$\hat{x}_c + (1-2\alpha)d_{bc} \le (1-\delta)\hat{x}_b \tag{6}$$

Thus, to prove the compliance with risk α, the party has to satisfy its obligation with the inventory emission estimate increased by the value $(1-2\alpha)d_{bc}$, dependent on its uncertainty measure expressed by d_{bc}. This value can be interpreted as emissions unreported due to uncertainty.

The condition (6) can be also rewritten as

$$\hat{r} = \hat{x}_c/\hat{x}_b \le 1 - \delta - (1-2\alpha)R_{bc}$$

where $\hat{r}$ is the estimated reduction factor and $R_{bc} = d_{bc}/\hat{x}_b$ is the half relative uncertainty interval. Thus, the compliance with risk α can be formally reduced to the form (2) by redefinition of the reduction factor

$$\delta \quad \longrightarrow \quad \delta_I = \delta + (1 - 2\alpha)R_{bc} \tag{7}$$

Emission trading. Admitting the above compliance proving policy it is possible to consider uncertainty in the emission trading. The main idea of this proposition consists in transferring the uncertainty to the buyer together with the traded quota of emission and then including it in the buyer's emission balance.

Let us denote by $R_c^S = d_c^S/\hat{x}_c^S$ the relative uncertainty of the seller and by $\hat{E}^S$ the traded amount of estimated emission. This emission amount is associated with uncertainty $\hat{E}^S R_c^S$. Before the trade the buying Party checks the following condition

$$\hat{x}_c^B + (1 - 2\alpha)d_{bc}^B \leq (1 - \delta)x_b^B$$

After the transaction the condition changes into

$$\hat{x}_c^B - \hat{E}^S + (1 - 2\alpha)[d_{bc}^B + \hat{E}^S R_c^S] \leq (1 - \delta)x_b^B$$

Due to the partial cancellation of the subtracted estimated emission and its uncertainty in the buyer's emission balance *the effective traded emission* is

$$E_{eff} = \hat{E}^S[1 - (1 - 2\alpha)R_c^S] \tag{8}$$

Thus, the bigger seller's uncertainty is, the less purchased unit is accounted for the buyer. Expression (8) reduces emissions estimated with an arbitrary precision to globally comparable values, which can be directly subtracted from country's estimated emission. This way it is possible to construct a market for the effective emissions, see [11].

4 A fuzzy type uncertainty

Although the interval approach provides a very simple and convenient solution, its criticism is sometimes aimed at low precision of defining the uncertainty intervals. Similarly to inventory calculation, also calculation of the uncertainty intervals is inexact and its accuracy is of the same order as that of the inventory calculation.

The uncertainty of the interval ends can be modeled using fuzzy set approach. A common way for this is to use so called fuzzy interval with the trapezoidal membership function, like that presented on Fig. 2. The uncertainty of the interval ends is modeled by linear change of the membership function from 0 to 1 at the interval ends.

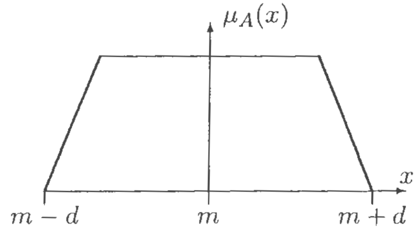

Figure 2: An example of a fuzzy interval.

However, in this paper the fuzzy numbers are used to model imperfect knowledge of the uncertainty. A fuzzy number is a particular case of a fuzzy interval and may be also considered as a straight generalization of an ordinary number, whose value is unsure. This is the situation, which we spot in the greenhouse gas inventories.

An usual problem with the fuzzy set approach is to determine the membership function. Here, we introduce a membership function dependent on a parameter. By fixing the parameter, a function which best fits the experimenter expectation can be obtained. Moreover, this function can well fit distributions obtained from the Monte Carlo simulations, as shown in the sequel.

Let us consider a family $\mathcal{F}$ of fuzzy numbers $A^\gamma = \{(x, \mu_A^\gamma(x)) | x \in \text{supp } A^\gamma\}$ indexed by a variable $\gamma \in C^+ = \{\gamma \in C | \gamma \geq 0\}$, with the support $\text{supp } A^\gamma = [d_A^l, d_A^r]$. Fig. 3 depicts examples of μ_A^γ representing a fuzzy number 0, for few values of γ. The membership function is chosen there as

$$\mu_A^\gamma(x) = \left(1 - \frac{|x|}{d_A}\right)^\gamma$$

with $d_A^l = -d_A$ and $d_A^r = d_A$. This is a special LR type fuzzy number as defined in [1], with $L = R$. As can be seen, the introduced family can model a wide arrays of fuzzy uncertainties. It can be generalized to nonsymmetric membership functions, if different values of γ and d_A are used for two branches, left and right.

For the symmetric case, it was suggested on the basis of Monte Carlo simulations [16] that distribution of the inventory error is close to the Gaussian one. Yet, as seen in Figs. 4 and 5, a membership function from

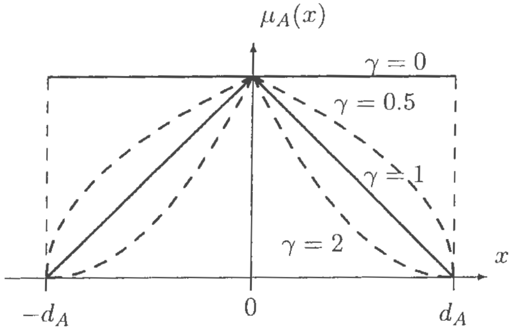

Figure 3: Membership functions for $\gamma = 0$, 0.5, 1 and 2.

the proposed family can also give good fit to Monte Carlo simulation data, presented originally in [15] and [16].

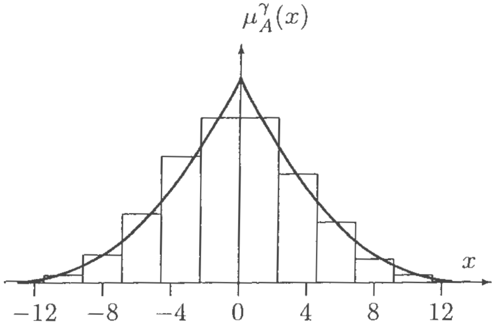

Figure 4: Fit of a membership function $\mu_A^\gamma(x)$ for $\gamma = 2.43$ and $d_A = 14.46$ to the histogram from [15], centered and normalized.

Compliance. Let us assume now that the uncertainty of $\hat{x}_b$ and $\hat{x}_c$ are of the fuzzy type with the membership functions from the family $\mathcal{F}$, that is they are fuzzy numbers $\hat{x}_b^\gamma$ and $\hat{x}_c^\gamma$ where

$$\hat{x}_b^\gamma = \{(x, \mu_{\hat{x}_b}^\gamma(x)) | x \in \text{supp } \hat{x}_b^\gamma\}$$

$$\text{supp } \hat{x}_b^\gamma = [\hat{x}_b - d_b, \hat{x}_b + d_b]$$

$$\mu_{\hat{x}_b}^\gamma(x) = \left(1 - \frac{|x - \hat{x}_b|}{d_b}\right)^\gamma$$

and similarly

$$\hat{x}_c^\gamma = \{(x, \mu_{\hat{x}_c}^\gamma(x)) | x \in \text{supp } \hat{x}_c^\gamma\}$$

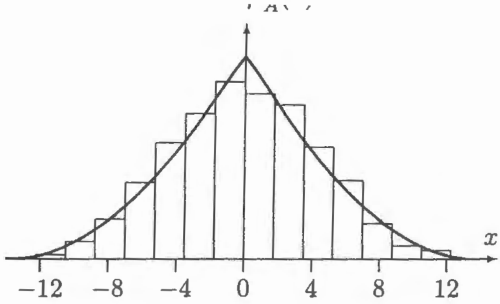

Figure 5: Fit of a membership function $\mu_A^\gamma(x)$ for $\gamma = 1.91$ and $d_A = 13.7$ to the histogram from [16], centered and normalized.

$$\text{supp } \hat{x}_c^\gamma = [\hat{x}_c - d_c, \hat{x}_c + d_c]$$

$$\mu_{\hat{x}_c}^\gamma(x) = \Big(1 - \frac{|x - \hat{x}_c|}{d_c}\Big)^\gamma$$

In the above, the membership functions have been normalized to take the value 1 in the core. This can be done by an appropriate calibration of the distribution data.

Then, calculating the difference in analogy to (2) a fuzzy number $D\hat{x}^\gamma$ is obtained

$$D\hat{x}^\gamma = \hat{x}_c^\gamma - (1 - \delta)\hat{x}_b^\gamma = \{(x, \mu_{D\hat{x}^\gamma}^\gamma(x)) | x \in \text{supp } D\hat{x}^\gamma\} \tag{9}$$

with the support

$$\text{supp } D\hat{x}^\gamma = [D\hat{x} - d_{bc}, D\hat{x} + d_{bc}] \tag{10}$$

and the membership function

$$\mu_{D\hat{x}^\gamma}^\gamma(x) = \Big(1 - \frac{|x - D\hat{x}_b|}{d_{bc}}\Big)^\gamma \tag{11}$$

where $D\hat{x}$ and d_{bc} are given by (3) and (5), respectively. The proof of expressions (9) to (11) may be done easily using slight generalization of the addition and multiplication rules on fuzzy numbers.

For this case we say that a party is *compliant with risk* α when not bigger than the αth part of the area under the membership function (11) lies above zero. Simple calculations show that this area is placed within the distance $y = (2\alpha)^{\frac{1}{\gamma+1}} d_{bc}$ from the right end of the interval $[D\hat{x} - d_{bc}, D\hat{x} + d_{bc}]$, see Fig. 6. Thus we get the following condition

$$D\hat{x} + d_{bc} \leq (2\alpha)^{\frac{1}{\gamma+1}} d_{bc}$$

or in a more explicit form

$$\hat{x}_c + [1 - (2\alpha)^{\frac{1}{\gamma+1}}] d_{bc} \leq (1 - \delta)\hat{x}_b \tag{12}$$

As before, it can be also transformed to the form

$$\hat{r} = \hat{x}_c/\hat{x}_b \leq 1 - \delta - [1 - (2\alpha)^{\frac{1}{\gamma+1}}] R_{bc}$$

giving rise to redefinition of the reduction factor

$$\delta \quad \longrightarrow \quad \delta_F = \delta + [1 - (2\alpha)^{\frac{1}{\gamma+1}}] R_{bc} \tag{13}$$

This formula can be interpreted as an extension of the formula (7), as it reduces to (7) when $\gamma = 0$.

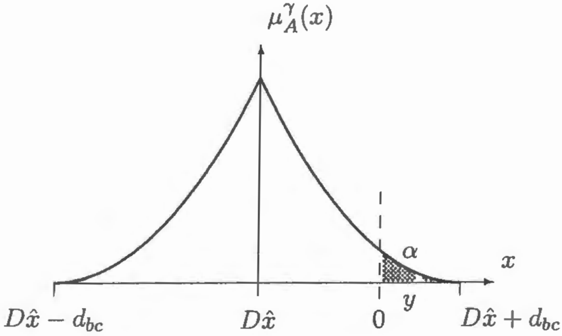

Figure 6: Graphical interpretation of the αth part of the area under the membership function.

Emission trading. After derivations analogous to the interval case we end with the effective reduction for the fuzzy type uncertainty

$$E_{eff} = \hat{E}^S\{1 - [1 - (2\alpha)^{\frac{1}{\gamma+1}}] R_c^S\} \tag{14}$$

It is again an extension of the formula (8) for the interval case. In comparison with the interval case it provides smaller differences between E_{eff} and $\hat{E}^S$, see Table 2.

Count.	Unc.	Interv.	Fuzzy				
	δ [%]	$\gamma = 0$	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 1.5$	$\gamma = 2$	$\gamma = 2.5$
AT	12	0.904	0.965	0.973	0.978	0.981	0.984
NL	5	0.960	0.986	0.989	0.991	0.992	0.993
NO	21	0.832	0.939	0.953	0.961	0.967	0.971
PL	6	0.952	0.983	0.986	0.989	0.991	0.992
RU	17	0.864	0.951	0.962	0.969	0.973	0.977
UK	19	0.848	0.945	0.957	0.965	0.970	0.974

Table 2: Comparison of the ratio $E_{eff}/\hat{E}^S$ for the interval and fuzzy approaches for $\alpha = 0.3$ and data from Table 1.

Equivalence of approaches. Let us notice that actually the fuzzy approach formulas (12) and (13) can be considered equivalent to the interval approach ones (7) and (8) provided the appropriate value of α is chosen. It can be easily noticed that this value is the same for both cases. Denoting by the subscript $_I$ the interval and by the subscript $_F$ the fuzzy case the equalities of the reduction factors or the effective reductions

$$\delta_I = \delta_F \quad \text{or} \quad E_{eff,I} = E_{eff,F}$$

after simple manipulations provide the same condition

$$(2\alpha_I)^{1+\gamma} = 2\alpha_F$$

For the adopted assumptions $0 \leq \alpha_I, \alpha_F \leq 0.5$ and $\gamma \geq 0$ we have

$$\alpha_I \geq \alpha_F$$

with strong inequality for internal points of the assumption set. Dependence of α_I on α_F and γ is shown in Table 3. The results show that α_I rises quickly with rise of γ. In two cases considered in our calculations estimates of γ close to 2 and 2.5 were obtained. Then practically it seems that $0.2 \leq \alpha_I \leq 0.3$ should be taken even for small values of α_F.

The interpretation of these results is quite straightforward. Ignorance of the uncertainty distribution introduces additional uncertainty, which adds to the uncertainty of the inventory itself. Thus, to obtain the same reduction factor or the same effective reductions a bigger risk should be taken in the interval approach. An important practical observation is that bigger values of α_I, like 0.2 to 0.3, should be used to compensate for ignorance of the exact knowledge of the uncertainty distribution, even if a smaller noncompliance risk is actually meant.

		γ					
		0.1	0.5	1	1.5	2	2.5
α_F	0	0	0	0	0	0	0
	0.05	0.06	0.11	0.16	0.20	0.23	0.26
	0.10	0.12	0.17	0.22	0.26	0.29	0.32
	0.15	0.17	0.22	0.27	0.31	0.33	0.35
	0.20	0.22	0.27	0.32	0.35	0.37	0.38
	0.25	0.27	0.32	0.35	0.38	0.40	0.41
	0.30	0.31	0.36	0.39	0.41	0.42	0.43
	0.35	0.36	0.39	0.42	0.43	0.44	0.45
	0.40	0.41	0.43	0.45	0.46	0.46	0.47
	0.45	0.45	0.47	0.47	0.48	0.48	0.49
	0.50	0.50	0.50	0.50	0.50	0.50	0.50

Table 3: Dependence of α_I on α_F and γ.

5 Conclusions

The paper deals with the problem of checking compliance of pollutant emission in case of a given limit, when the observed emission values are known with high uncertainty. This is the case of national inventories of greenhouse gases emissions. High uncertainty must influence trading in emission permits in the cap-and-trade system, which is frequently used to minimize the emission abatement cost [8].

However, not only the inventory itself, but also its uncertainty is calculated with relatively low accuracy. This should be taken into account when deriving the compliance and emission trading rules. The idea proposed in this paper lies in using the fuzzy set approach. A family of fuzzy numbers depending on a free parameter is introduced. This parameter can be chosen to appropriately shape the distribution of uncertainty. The approach provides the linear formulas, which can be used for designing a market for the efficient emission permits.

The results obtained are generalizations of the results derived for the interval type of uncertainty. It was shown that the rules for the interval case can be still used instead of the generalized ones, provided the appropriately higher value of the risk of noncompliance is used.

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