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ON UNCERTAINTY ESTIMATION IN ENERGY AND ENVIRONMENTAL STATISTICS

An anti-fragile approach

RT/2022/3/ENEA

ENEA
ITALIAN NATIONAL AGENCY FOR NEW TECHNOLOGIES, ENERGY AND SUSTAINABLE ECONOMIC DEVELOPMENT

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An anti-fragile approach

Marco Rao, Giancarlo Lutero

Abstract

Uncertainty in energy and environmental statistics is a major issue in decision support to policy making. The need for timely and reliable statistics boosts the search for methods that reduce error in estimation. In this work, a method for estimating the uncertainty of energy and environmental statistics coming from different statistical sources is outlined, using as a framework a discussion on nature of uncertainty and the Black Swan problem is also outlined. The proposed method is then applied to an environmental problem using the concept of anti-fragility, to improve the decision support systems in energy policy analysis.

Key words: *Official Statistics, Unpredictability, Black Swans, Anti-fragility.*

Riassunto

L'incertezza nelle statistiche energetiche e ambientali è un fattore critico nel supporto decisionale nelle politiche energetiche. In questo lavoro è proposto un metodo per la stima di dati provenienti da diverse fonti statistiche a partire da una discussione sul la natura dell'incertezza e il problema del cigno nero. Il metodo proposto viene poi applicato ad un problema ambientale utilizzando il concetto di anti-fragilità, per migliorare i sistemi di supporto alle decisioni nell'analisi di politica energetica.

Parole chiave: Statistiche ufficiali, Impredicibilità, Cigni neri, Anti-fragilità.

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1. Introduction

Economic growth, energy security, energy efficiency, and climate change, represents major global challenges in the agenda of the world's governments: these issues are related among them by strong correlations. For example, the dilemma between economic growth and climate change mitigation well shows [**1,2**], the increasing attention on social and economic costs of disasters due to extreme events from climate change [**3,4**]. In this work, we consider one of the crucial elements required to give decision support to policymaking: the statistics: furthermore, a special focus on the "making of" in data estimation is proposed.

The focus of this work is on energy and environmental statistics, one of the fundamental tools in energy policymaking [**5**]. The problem of the uncertainty of the statistics on emissions of PM2.5 is considered, using as a starting point of the analysis a previous work by one of the authors in this field [**6**]. The goal is to assess a particular concept of uncertainty, using as a case-study the estimation of residential wood combustion (RWC) in Italy from residential fireplaces and woodstoves, one of the main sources of PM2.5 emissions, a truly serious threat to human health [**7,14**].

About the statistic chosen, it can be recall that wood burning is a major contributor to the uncertainty in air quality forecasting [**15,16**], and it is featured by high uncertainty [**17,18**]; furthermore, RWC is underestimated [**19**]. This situation leads to an improvement in RWC estimation to reduce the gap between measured and predicted organic aerosol in CTMs (Chemical Transport Models) that will also influence source-receptor matrices and modeled source apportionment [**17**,**20**,**21,22**].

Starting from [**6**], the present work aims to show a new methodology, being the used method just the simplest case of a more general one. Subsequently, an anti-fragile approach to estimation is recommended as the optimal approach to implement the method.

2. Data and methods

2.1 The used methodology

After the review performed in the previous sections now we deal with a different kind of aggregation, moving from the concept of “reliability”. Indeed, here we focus on the same basic concepts of section 2.3: in particular, we try to address the key issues coming from the presence of the Black Swan, since we analyze the problem of reliability of different sets of available statistics, produced by any type of data collection (like a survey) or resulting from real or simulated experiment.

It is truly relevant to note that, since we deal, in the real world, with every type of unpredictability (intrinsic, black swans, extrinsic), we are forced to find an all-conditions answer, a methodology enough general and powerful to consider any type of problems that can occur.

The path to the answer is set starting with simple question: the answer led us to the concept of anti-fragility as the optimal case of an intuitive but reasonable methodology, entirely based on the information available at the time of prediction.

The question is: *how can we deal with different data sources to estimate the "real" or the “better” approximate value for an observed phenomenon*? For example, let us suppose that we have a set of N data about some variable, coming from two distinct statistical surveys. So, we will have a pair of values for each considered variable that we must estimate.

The first hypothesis here is to assume each value of such a pair, as the central moment of a certain probability distributions associated to the considered variable.

Each statistical survey produces data intrinsically subject to uncertainty. An in-depth analysis of the several types of uncertainty related to the data could be used to identify the most appropriate probability distribution model for the considered phenomena: for the sake of simplicity, here the Normal Distribution was used.

In the follows, a method to consider the resulted uncertainty is outlined by considering each of the N available values from the two different statistical sources as a certain moment of a probability distribution, assuming that the "true" value of the variables could be in a range between such reference values, and that any value between these extremes has a certain probability to occur.

Let us consider data coming from two distinct statistical surveys, A and B (we know that mean of A is equal to 70[1] and mean of B is equal to 110: we suppose that both A and B have the same variance, equal to 7). Now let us apply what we have said before to identify the new reference distribution, called E: see figure 1.

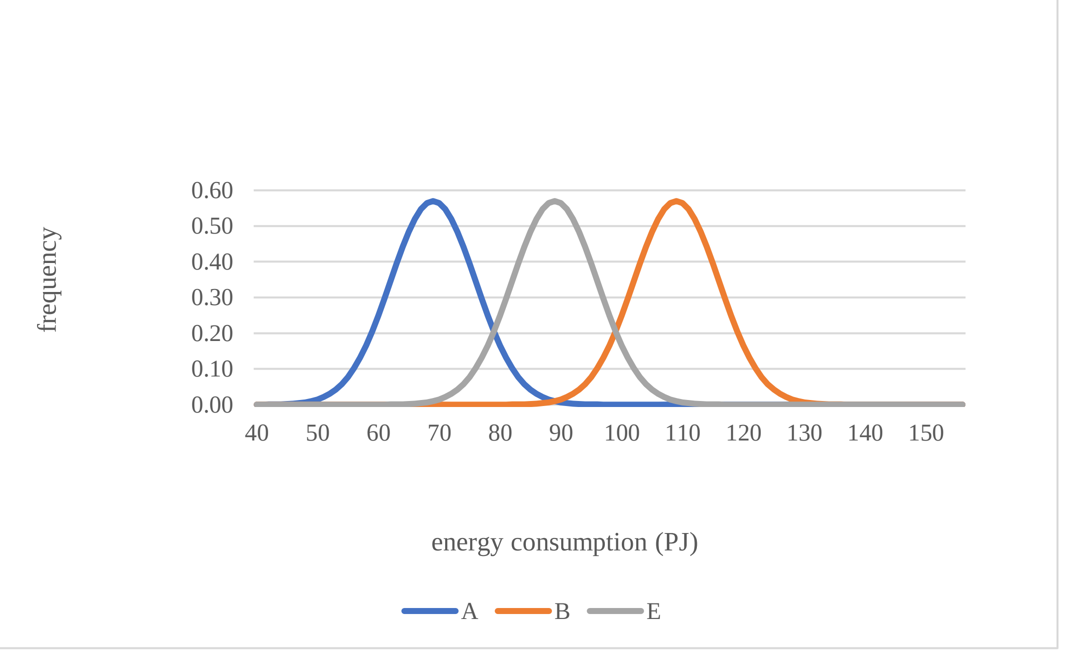

Figure 1 - Graphic representation of the proposed estimation method in a case of data coming from two statistical sources (hypothesis: Normal Distribution) – imaginary data

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[1] This is a pure arbitrary example, so let us suppose that the measure unit is PJ for energy consumption.

The mean of the new Distribution E is located exactly between the mean of the A and B distributions (this is just a possibility).

Why should we do this?

The experiment started from the results of two separate experiments (surveys, sample measurements, etc.). We have supposed the existence of a probability distribution model for the data (in fact, it could exist or not, or could be unknown, since we must deal with every kind of unpredictability). Subsequently, among the considered distributions, we hypothesize the existence of a further statistical distribution, which follows the same model of the existing ones. The key assumption is that the central moment of this last distribution is located among the existing ones.

Why the proposed approach should be interesting? It would be perfectly possible to believe that the results of one of the statistical sources considered is more reliable than the others. In the choice between various sources, several arguments could be leads to a certain one: for example, the statistical quality of the data, and so on. In such cases, it is possible to choose the “better” statistical source just basing on a thorough analysis of the available information, according to certain criteria.

The fact is, that it is also possible that we would prefer a certain source for some reasons, and another source for other reasons.

For example, a certain survey could be characterized by a high quality of data applied to the entire national territory of a given country; another, could present a higher quality than the previous about some specific region of the country itself. There are many examples in which there are good reasons to consider data from multiple sources, so a method to address such situations is required.

Let us start to define more specifically our approach.

Basically, basing on the initial information available about the investigated phenomena, and basing on the statistical methodology of data collection and/or estimation, as a first step, we *define a certain model of the probability distribution for data*. For example, in the survey on the household's wood consumption of a given territory, the data of physical consumption could be associated with a Normal model rather than a Continuous Uniform model, based on the knowledge of consumption patterns, of historical data and of any other relevant information known at the time of the survey.

So, it is possible to define a specification for available data, like in table 1:

Statistical Units	Source 1	Probability Distribution Model 1	Source 2	Probability Distribution model 2
Region 1	x1	Continuous Uniform	y1	Continuous Uniform
...	...	...	...	...
Region i	xi	Gaussian	yi	Gaussian
...	...	...	...	...
Region 12	xN	Continuous Uniform	yN	Continuous Uniform

Table 1 - Tabular representation of basic data of two statistical sources according to the proposed method (imaginary data from two statistical surveys about energy consumption in the regions of a country)

As a second step, each data is considered as the central moment of its distribution.

As already shown in an intuitively way in Figure 1, it is possible to build a new distribution E, in which its central moment is located between the central moments of A and B. The choice of a certain moment (like arithmetic mean) should be arbitrary.

This step sounds remarkably familiar with the Confucius Doctrine of the Mean, but here are required some further explanations by using an example.

Let us assume that a large-scale statistical survey on the national territory has estimated a certain level of firewood consumption x for each X region of the country. Furthermore, another specific survey carried out by some other statistical source in a certain number of regions has made a different estimate, indicated with y. The data x was obtained through a telephone interview: the data y, by physically reaching the households in their homes. To decide between the two statistical sources considered, many other structural and specific aspects could be important. For example, there may be differences in the statistical methodologies used; the samples analyzed could have been built using different methods; the investigations could refer to different moments in time, in which certain relevant events could occur, and so on. If, however, we start from the assumption that all the used methodologies are reliable, and that the investigations have been correctly performed, we could think that source A have a comparable data quality respect source B.

Let us recall the estimation performed in [**6**]: data from two separate statistical surveys were used as input to the analysis. The used surveys referred to the consumption of firewood by Italian households: consumption data were used to feed the model represented by equation 1.

1. $\mathrm{E_{i,p}} = \sum_{\mathrm{k}} \sum_{\mathrm{m}} \mathrm{Act_{i,k}}\, \mathrm{Ef_{i,k,m,p}} * \mathrm{x_{i,k,m,p}}$

Where, p and j represent the pollutant type and biomass burning type, respectively; E is annual emission of a particular type of pollutant (ton/year); m is the annual mass of dry matter burned (ton/year); finally, EF is the average emission factor (g/kg fuel). This model will be used in the follows for the results of a cost-effectiveness analysis reported at the end of this section.

So, we could use a simulation technique (like a bootstrap simulation [**23-25**] to estimate the parameters of the equation 1 and, subsequently, the emissions, expressed in PJ basing to reference survey's data [**26,27**]. In [**6**] the sample was built by generating 30 pseudo-random numbers distributed according to a uniform continuous variable between these extremes.

This kind of estimation can present some critical issues. In our example, it leads to consider as a reference value the mean of the central moments of two different surveys, which could lead to underestimation of consumption and the emissions (the exact opposite is also possible, but we consider only the adverse case).

The first consideration that can be made about it, is that such a problem can be compensated by modulating appropriately the variance of E distribution, as Figure 2 illustrates.

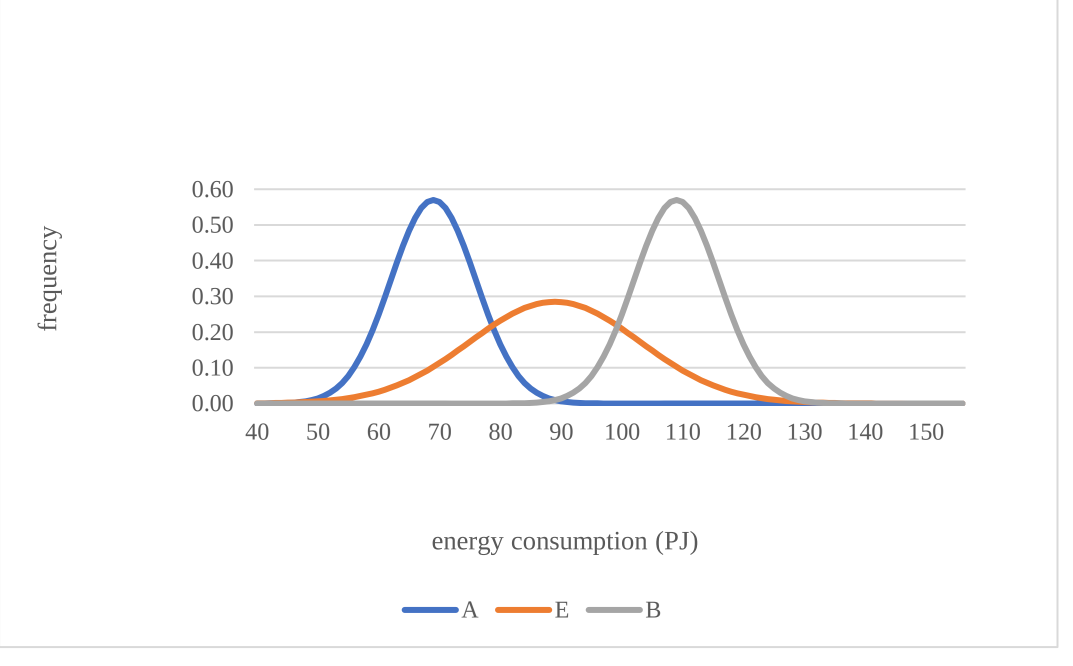

figure 2a

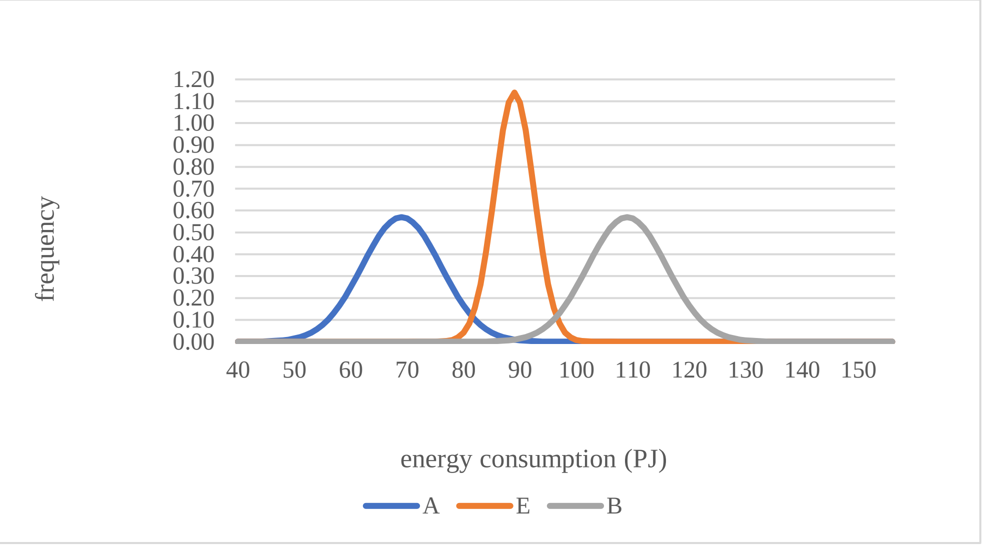

figure 2b

Figure 2a and 2b - Considering tails of distribution A and distribution B via variance modification of distribution E

This kind of procedure could be use different weights for each source, as shown in figure 3:

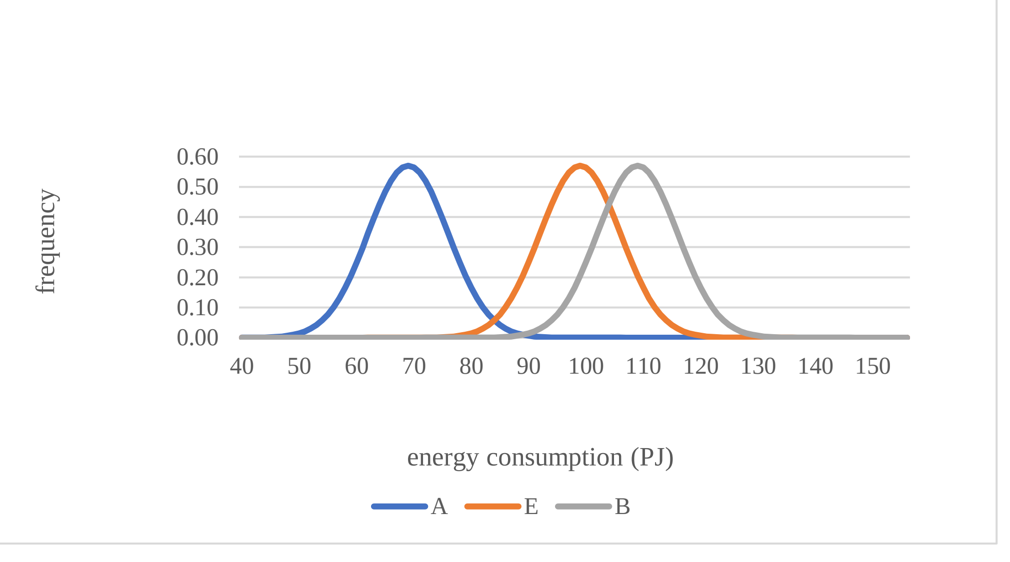

Figure 3 - Considering the tails of distribution A and distribution B via weighted mean modification of distribution E

What the main strengths by using this method?

First, let us remember that one of the basic assumptions is that the different statistical sources considered, all comply with a minimum level of data quality. So, we must search for methods that make it possible to exploit all available information, effectively (in terms of accuracy of estimates) and efficiently (in terms of computational and economic costs). In this context, the proposed approach is characterized by a certain caution (following the same distribution model estimated for the phenomenon, making the new estimates within the limits of the existent models and data), but, however, go beyond the results obtained by the surveys. Furthermore, the modularity of the approach is guaranteed by the possibility to choose the most appropriate models and parameters to manage the starting data.

Well, what is the connection between the proposed method and the concept of anti-fragility?

The first (and main) observation that can be made is that using an "interposed" distribution, among those of the statistical sources considered, is equivalent to not consider any of them as "true", and, moreover, "safe".

Searching a metaphor in Taleb's work, we could use the comparison between the two brothers, the employee and the taxi driver, whose gains seem respectively "safe" and "uncertain". In fact, we know that the safety of the first brother could quickly be eliminated by a sudden dismissal and that the taxi driver is less subject to uncertainty on income than it appears, being more robust to any sudden "black swan".

Let us look at a visual representation of some concepts to better understand.

Now we look at what Taleb says in Appendix 1 of **[28]**, about the graphics of the concepts above expressed.

We recall that, in this work, the focus is on PM2.5 emissions from firewood combustion by households: so, we must deal with some events (energy consumption by households) and with exposure to events dependent from the first ones (emissions).

We are talking about the barbell transformation, which can be quickly recall through Figure 4.

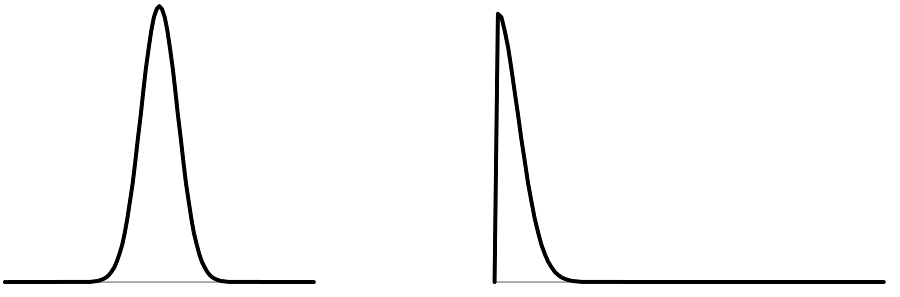

Figure 4 - Convex (or "barbell") transformation

The first consequence of adopting the anti-fragile approach implies the need to keep in mind the worst-case scenario: in this case, the distribution centered on the higher energy consumption value becomes the reference of any emission management policy and the distribution E of the previous figures changes as shown in figure 5.

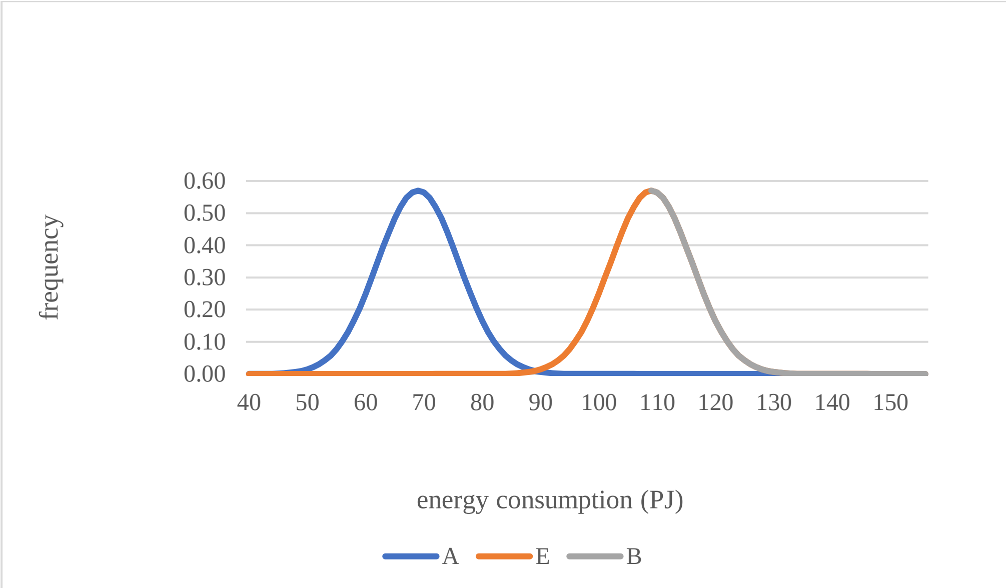

Figure 5 - Application of convex (or "barbell") transformation to the estimation of E distribution

The anti-fragile approach to estimation is revealed, in the context of this study, as one of the possible configurations of the proposed method. Furthermore, in fact, it is to be considered as the most effective and efficient configuration of estimation among the available options.

About the effectiveness, the proof is simple: just assuming that the worst possible case is (by definition) possible and you must be prepared accordingly: this means make energy policies according to the worst situation (in this case, the highest possible level of firewood consumption).

About efficiency, the problem is more complex, for two reasons. First, each policy has a cost: secondly, every policy has complex interactions with other different ones (energy policies are linked to economic and environmental policies, for example). To address such issues, we present the results of a simple simulation based on data and methodology of Rao et al [**20**] integrated by the presented method.

3 Results

At this point, further methodological development is introduced, using a Markov model [**29,30**] in a simple decision problem.

Let us assume we want to choose between two policies, A and B. In policy A, characterized as "fragile", we give equal weight to the data coming from the two surveys, the A, and the B. Its characteristic probability distribution is, therefore, the one reported in figure 1.

Policy B, defined as "anti-fragile", is, however, obviously associated with the distribution E of Figure 5.

Let us suppose now to consider the effects in terms of cost and effectiveness. The cost assigned to the two policies is an imaginary number, in this case, we hypothesize that the anti-fragile policy, the B, costs double than A (2000 USD per year versus 1000 USD per year).

The effectiveness of the two policies is expressed in terms of avoided PM2.5, calculated using equation 1 on the average consumption values of distributions A and distribution B. The average consumption values and the resulting particulate values are modeled as Normal distributions with an average of , respectively 70 and 110 with a same variance, 7 (arbitrary values according to the ones used in figure 1).

The calculation of emissions is restricted to a particular case, i.e., it is assumed to be equal to the consumption value multiplied by the emission factor of the wood burned in an open fireplace, in the absence of control technologies. Average consumption data are expressed in PJ.

At this point, we introduce two further hypotheses.

We assume that the situation is perfectly symmetric for the estimates coming from both the A and B surveys, each of them have a probability of 50% of being true.

Therefore, let us add another hypothesis: that there is a critical threshold not to be exceeded in emissions due to its environmental consequences on the health of households in the considered area. What follows reports data, decision tree and cost-effectiveness results of the simulation.

Name	Description	Definition
cost_A	Cost of Policy A	1000
cost_B	Cost of Policy B	2000
pEff_A	Probability of success for Policy A	0.5
pEff_B	Probability of success for Policy B	1
pCons_A	Probability of data consumption are from Distribution A	0.5
pCons_B	Probability of data consumption are from Distribution B	0.5
Eff_A	PM2.5 avoided	((70)*487*(69,23/100))/1000000
Eff_B	PM2.5 avoided	((110)*487*(69,23/100))/1000000

Table 2 - Variable properties of Markov model used in simulation

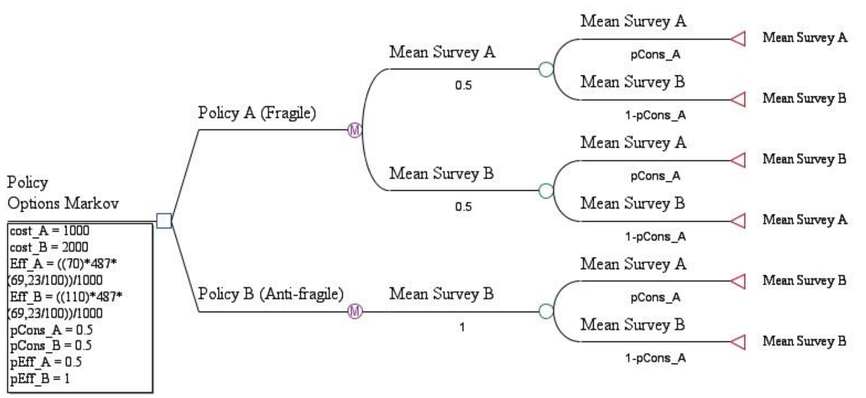

Figure 6 - Markov model decision tree

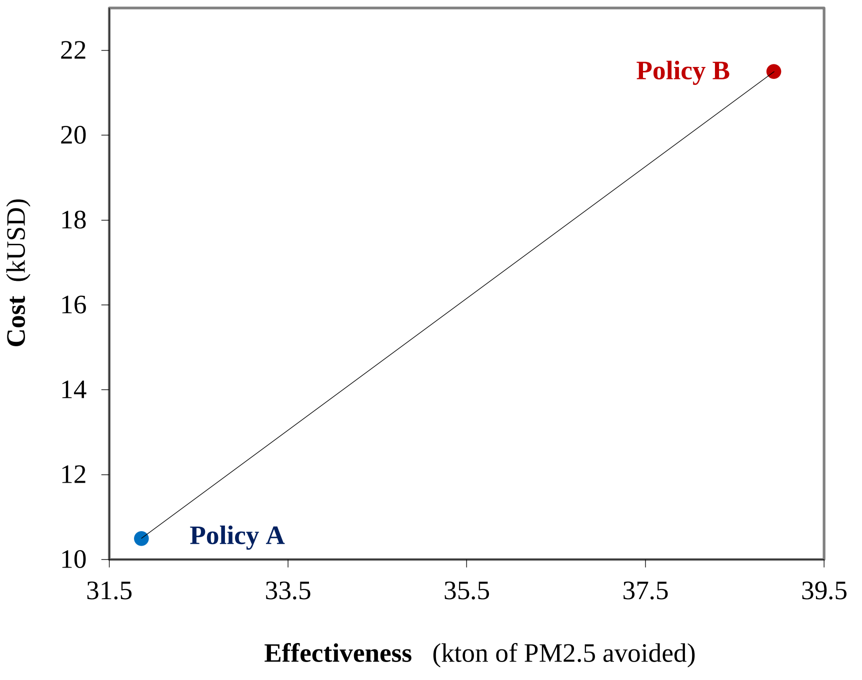

Figure 7 - Cost-effectiveness Analysis in comparison of Policy A and Policy B.

The cost of the policies (expressed in thousands of U.S. Dollars) is reported in the y-axis, while the x-axis reports the effectiveness, expressed in terms of thousands of tons of PM2.5 avoided.

Policy B, the "anti-fragile" one, confirms itself superior in terms of effectiveness, where its cost is higher: in C-E A, typically, this is the time to introduce further selection criteria to find a winner. For example, we could hypothesize that it could be mandatory to do not exceed a certain threshold of emissions. We observe that, in the simulation, we have assigned an equal likelihood to consumption data coming from distribution A and from distribution B. We can observe that the adoption of the anti-fragile concept makes risk evaluation useless, so we can just do not care about the probabilities of data. The simple fact of being able to avoid the maximum possible damage makes a difference. In this context, since the production of statistics resulting from overly complex surveys, this point is crucial, i.e., in the case in which a mandatory threshold for pollutants is settled. Furthermore, the cost formulas should be considering scenario-shift (if emissions exceed their critical levels, the cost data should also be updated to take account of the economic impact on human health).

Finally, we observe that in our hypothesis, we have made the anti-fragile policy as the most expensive one (twice the other policy): a strong hypothesis, which of course does not have to be intended, as necessary.

Conclusions and Discussions

The proposed methodology comes from considerations on the role of the unpredictability in the statistics production and on the use of such a statistic in decision support for energy policymaking. Our case study concerns the consumption of firewood by combustion from households and the consequent production of PM2.5. Estimating the emission uncertainty represents an ongoing area of research [**22**]: in an attempt of improving the methodology to better rely on available data and models, the proposed method uses the data and the related probability models (if known) to elaborate a new probability distribution of the same type, placed between the central moments of the starting distributions, according to the confidence in the likelihood of the data and models used.

In the proposed methodology, we do not focus on identifying the type of uncertainty related to the observed phenomenon. Instead, we use an anti-fragile approach to obtain the best possible answer to any type of unpredictability in a context of cost-effectiveness analysis.

Instead of focusing on the aspects of analysis that lead to the estimation of unpredictability, we set the worst case as the basis of the policy to be adopted. The cost-effectiveness analysis shows that even a single additional choice criterion can make this strategy successful, also in terms of economic costs.

The best possible configuration of the proposed method in terms of effectiveness is the so-called "barbell transformation" proposed by Taleb

[**28**], which can make a policy anti-fragile. The estimates obtained from the resulting model are in fact focused on the worst possible case, the event with the maximum negative impact on the system.

An anti-fragile policy like can involves increasing costs: so, as we said, this leads us to a cost-effectiveness analysis, here performed using a basic Markov model to compare a hypothetical anti-fragile policy with a fragile one.

The first simple case in which the superiority of the anti-fragile policy is clear is that in which there is an unacceptable (known) threshold of damage: in our case study, we hypothesized that there may exist a critical limit in PM2.5 particulate emissions not to be exceeded to protect human health.

About the cases in which emissions remain below the critical threshold, we can use the Incremental Cost-Effectiveness Ratio (ICER), with the possible addition of additional criteria, such as availability to pay (in this case, the willingness of the citizens to finance emission control policies by taxation, for example).

The proposed method starts with the use of the probability model related to the considered variables and move towards the decision theory to select the best policy option, increasing the quantity and quality of the data available in the decision-making process. Further in-depth could be dedicated to the analysis of the criteria to be used in the evaluation.

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Conflict of Interest

No conflict of interest to be declared.

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