

VALIDATION OF A FUZZY DECISION MAKING TECHNIQUE ON ENVIRONMENTAL QUALITY INDEXES MEASUREMENT

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Abstract – In this paper a Fuzzy Decision Making (FDM) technique is presented, making use of an original approach to uncertainty analysis, for the qualification of an environmental measurement process and its associated decision system. The proposed FDM technique leads to take a decision about the quality index overcoming of a warning or reference value; it is based on a model, which has statistical bases and offers an operative instrument that, in accordance with the initial conditions, allows to calculate the erroneous decision probability for settling the metrological characteristics of the measurement system. The strength of the proposed approach is to estimate the impact of measurement uncertainty onto the decision-making process, also modelling the vague features of the process itself by fuzzy logic.

Keywords: fuzzy decision-making, quality indexes monitoring, measurement uncertainty.

1. INTRODUCTION

Generally speaking, when quality indexes are used for process control, often the measured data are compared with a given reference value, and the overcoming of similar warning or threshold levels is index for an out-of-control situation. The inevitable measurement system uncertainty and the influence of human intervention sum with the natural process variability, so that it plays an important role in making a decision about the process. It's obvious that the cumulative effect of various causes to measurement uncertainty could lead measured data to be lower (higher) than the applicable limits, whereas the underlying process is below (beyond) the control levels. So, reliability of measurements cannot be guaranteed without an appropriate interpretation of data, which can be done resorting to appropriate decisional rules and minimizing risks and costs of the decision. In order to solve this problem, we propose a Fuzzy Decision Making technique. Experimentation of the FDM technique is made on a measurement system monitoring environmental quality indexes. In decision-making problems, it is needed to select or rank several, often colliding alternatives. Thus it seems appropriate to resort to probability theory to represent the stochastic nature of decision process and of measurement system, but it's likewise unsuitable to estimate the ‘uncertainty’ caused by human behaviour, which is far from being

stochastic. To face and model these types of vagueness, it's opportune to use fuzzy logic. This approach allows also to manage information of different characters, as human valuations in linguistic form. The fuzzy set theory solves the decision problems when an imprecise information is represented in ‘fuzzy’ terms, translating human knowledge in control actions. The design specifications are translated to perform the decision criteria using fuzzy sets, by defining fuzzy goals and constraints for the system under control. The proposed FDM technique allows to obtain a decision about the conformance or non-conformance of quality indexes with specifications or control limits [1], by observing a particular goal and a simultaneous constraint – reflecting the human preference information – in order to get the appropriate solution in a definite set of alternatives for the considered system. The proposed FDM technique is based on a statistical model that provides an original approach to uncertainty analysis, allowing a formal treating of decision-making stage for the given process under statistical control. The model allows the estimate of the erroneous decision probability, arising when the underlying process shows a different behaviour from measured data, depending on the statistical characteristics of the monitored process index and the measurement system uncertainty.

2. THE FUZZY DECISION MAKING TECHNIQUE

In decision problems the decision maker is faced with the task of selecting one alternative in a set $A = \{A_1, \dots, A_m\}$ that is the one that best satisfies simultaneously a set of associated goals and constraints $C = \{C_1, \dots, C_n\}$, with the highest satisfaction degree. The fuzzy membership functions are an effective tool to represent this satisfaction degree for goals and constraints of different priority, when vague and imprecise information are available. In order to justify the fuzzy approach, we can see fuzzy logic as an expansion to binary logic. An element can belong to a fuzzy set according to a membership degree in the real interval $[0,1]$: while the full belonging is represented by membership degree 1, the complete non-belonging by the value 0, in a reasonable way the ‘partial’ or fuzzy belonging of an element can be represented by the intermediate values.

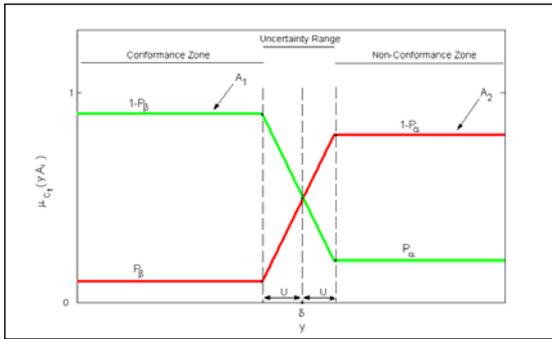


Fig. 1. Satisfaction degree for constraint C_1

The first step for the definition of the FDM technique is the choice of the possible alternatives, goals and constraints. In our case the available decision alternatives are two: conformance or non-conformance of the quality index with the specifications or control limits, respectively A_1 and A_2 , where A_1 asserts that the measured datum y (a single realization of quality index) is inside the reference limits, while by the alternative A_2 we affirm that y doesn't respect the specifications and so it's beyond the fixed limits. Now it's possible to single out a constraint C_1 or decision criterion; the starting-point is represented by European standards about conformance of indexes with specifications [1]. The standard indicates three zones for conformance, non-conformance and uncertainty range, they are delimited by an interval of amplitude equal to the expanded uncertainty U centred at the upper specification limits $USL = \delta$ (see Fig. 1). If a measured datum y falls in conformance or non-conformance zones, then the consistent decision is assumed. In a binary view it's possible to translate this matter saying that if datum y lies on conformance zone then it respects the fixed limits, so A_1 has a satisfaction degree equal to 1 and A_2 equal to 0. On the contrary, if y lies within the non-conformance zone then it doesn't respect the limits, and the satisfaction degree of the rule is 0 for A_1 and is 1 for A_2 . Unfortunately this 'rule of thumb' doesn't provide information about the decision confidence level, or indications about the choice when y lies in the uncertainty range. The original idea is to combine the decision rule of ISO 14253-1 with the erroneous decision probabilities of the statistical model in [2], [3] by a fuzzy approach. As a result, the proposed decision criterion C_1 utilizes a parametric fuzzy membership function $\mu_{C_1}(y, A_i)$ in Fig. 1, where y is the variable and A_i is the parameter; it expresses how the alternative A_i satisfies the constraint C_1 given a measured value y ; the green line refers to A_1 and the red one to A_2 .

The fuzzy approach is realized by combining the erroneous decision probabilities P_α and P_β with the previous binary satisfaction degrees of standard rule. P_α represents the erroneous decision probability that we face in stating that the process index is over the control limits (because of the measured data uncertainty) when instead it's within; while P_β represents the erroneous decision probability that we encounter



Fig. 2. Fuzzy triangular set for satisfaction level.

in stating that the process index is within the control limits (because of the measured data uncertainty), but instead it's over.

Consequently the value $\mu_{C_1}(y, A_i)$ provides for a given y the satisfaction degree of the constraint C_1 for alternative A_i in a scale 0 to 1; so it provides for y a plausibility criterion of the alternatives A_1 and A_2 . Each alternative, in a fuzzy meaning, is always plausible at a certain degree; and also it's noticeable that satisfaction degrees of A_1 and A_2 sum up to 1.

Moreover, since P_α and P_β "smooth" μ_{C_1} , the erroneous decision probabilities take part in conditioning the satisfaction degree of the decision criterion, also involving the statistical and metrological features of the examined process. It's interesting to notice that if $P_\alpha = P_\beta = 0$ (i.e., there is a zero probability of making an error, as in an ideal case), the function (outside the uncertainty range) is consistent with the standard acceptance/rejection rules in [1]. But the strength of this criterion is to provide a decision rule also valid in the uncertainty range, resolving a possible decision issue that the decision maker encounters when y lies in that interval.

Another observation is the consistence of the function in the pessimistic case $P_\alpha = P_\beta = 1$. Generally speaking goals and constraints are incommensurate, so it is necessary to normalize values to a common scale. Besides, since we are in a situation in which attributes, information, consequences and valuations are vague and not precisely known, in order to resolve these aspects it seems opportune to adopt fuzzy sets. In our case we can associate a fuzzy triangular set μ_{A_i, C_1} (Fig. 2) with the satisfaction degree μ_{C_1} , where the modal value $a_{mi} = \mu_{C_1}(y, A_i)$ (plausibility level of alternative A_i) is the satisfaction level with the largest 'reliability' degree (=1), while a_{li} and a_{ri} have a null reliability degree and represent the left and right base value. In this way a_{mi} represents the most plausible satisfaction degree, and at the same time the intermediate satisfaction degrees are also reasonable in a 'partial' or fuzzy manner.

We assume that if y is in conformance zone then $a_{li} = \mu_{C_1}(y, A_i) - P_\beta$ and $a_{ri} = \mu_{C_1}(y, A_i) + P_\beta$; while if y is in non-conformance zone then $a_{li} = \mu_{C_1}(y, A_i) - P_\alpha$ and $a_{ri} = \mu_{C_1}(y, A_i) + P_\alpha$. In these cases, generally, the fuzzy sets are very tight accord-

ing to the little vagueness for decision criterion. In uncertainty range, instead, we pose $a_{l1} = P_\alpha$, $a_{r1} = 1 - P_\beta$ and $a_{l2} = P_\beta$, $a_{r2} = 1 - P_\alpha$. The base of these triangular sets is wider according to the leaning trend of μ_{C1} and to the greater vagueness; in fact to put into account the vague information existing in the uncertainty range, triangle extremities coincide with the extreme values of uncertainty range. The fuzzy triangular set so obtained will represent the fuzzy satisfaction set of alternative A_i for C_j . Now it's possible to single out a goal C_2 or benefit criterion, that measures how less risky is the alternative A_i in terms of time and erroneous decision cost. This goal allows to make a decision between A_1 and A_2 when $\mu_{A_i, C_1} \approx \mu_{A_2, C_1}$ as in the uncertainty range, according to appropriate weights for C_1 and C_2 . A viable curve to represent the benefit criterion is a Gaussian fuzzy membership function normalized with $\mu = 0$ and $\sigma = 4$ (Fig. 3), which idealizes the pessimistic and optimistic cases in the best way [4].

The variable $z_i \in [0;9]$ represents the valuation of benefit for the alternative A_i , where $z_i = 0$ indicates an alternative with null risk and therefore with maximum benefit, while $z_i = 9$ indicates a very bad alternative in terms of time and erroneous decision cost, and so it has a very little benefit degree. The value $\mu_{C_2}(z_i)$ expresses how the alternative A_i satisfies the goal C_2 . Like above, we can associate a fuzzy triangular set μ_{A_i, C_2} to the satisfaction degree μ_{C_2} where $b_{li} = \mu_{C_2}(z_i + 1)$, $b_{mi} = \mu_{C_2}(z_i)$ and $b_{ri} = \mu_{C_2}(z_i - 1)$. Weights w_i of C_1 and C_2 can be obtained using the procedure in [5]. In our decision making process we can state that the decision criterion C_1 is strongly dominant over C_2 , and by imposing $w_1 + w_2 = 2$, from calculations we have $w_1 = 1,8$ and $w_2 = 0,2$. We are now able to estimate the total performance or satisfaction degree of the i -th alternative in terms of a global fuzzy triangular set, by the following weighted-sum method:

$$\mu_{p_i} = \sum_{i=1}^n w_i \cdot \mu_{A_i, C_i} = w_1 \cdot \mu_{A_i, C_1} + w_2 \cdot \mu_{A_i, C_2},$$

with $p_{li} = w_1 \cdot a_{li} + w_2 \cdot b_{li}$, $p_{mi} = w_1 \cdot a_{mi} + w_2 \cdot b_{mi}$, $p_{ri} = w_1 \cdot a_{ri} + w_2 \cdot b_{ri}$ with $\mu_{p_i}(p_{li}) = \mu_{p_i}(p_{ri}) = 0$ and $\mu_{p_i}(p_{mi}) = 1$.

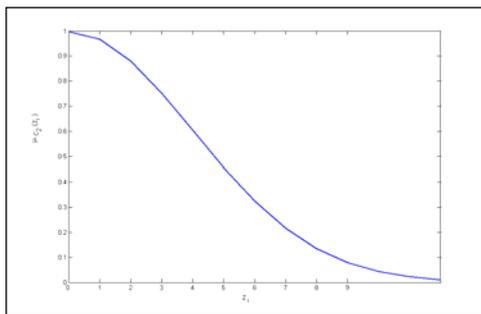


Fig. 3. Fuzzy membership function for C_2 satisfaction degree

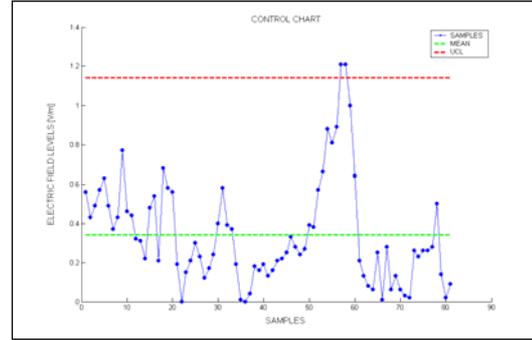


Fig. 4. Control Chart

If $\mu_{p1} > \mu_{p2}$ [6] then we assume A_1 as the best alternative and thus the index quality is within the specification control limits, differently it's over these limits.

Eventually, the best decision is the one that satisfies C_1 and C_2 with a higher satisfaction and reliability degree. The proposed FDM technique allows to choose also where the decision criterion C_1 alone doesn't provide a clear indication, thus exceeding the decision rules of ISO 14253-1; moreover the weighted-sum method allows for trade-off or compensation between criteria, translating the aggregation of the fuzzy sets as a simultaneous satisfaction of the fuzzy criteria, according to the weights.

3. EXPERIMENTAL VALIDATION AND RESULTS

The validation of the technique in Sect. 2 is performed on a distributed measurement system of mobile probes, for the monitoring of electromagnetic field in a urban area. Each acquisition system is equipped with a National Instrument Compact Field-Point module (c-FP2020) connected to a GPS device (GPS25HVS) and a PMM wideband electromagnetic field (EMF) probe (EP330), that sends position and EMF amplitude (i.e., the environmental quality index to be monitored) data to a remote server for analysis and storage [7]. According to manufacturer's specifications, EMF probe uncertainty on each measurement is $\sigma_x = 7,5\%$ with a Gaussian distribution of errors. Control chart in Fig. 4 shows the temporal evolution of electric field levels, in comparison with the average value μ and the Upper Specification (or Control) Limit $USL = \mu + 3\sigma = \delta = 1,1423$ V/m. Fig. 4 shows the presence of three values that lie around the control limit δ , so they need careful verification in order to assess their conformance or non-conformance to the limit, therefore evaluating if the overcoming is simply due to measurement uncertainty. The matter is to make the most suitable decision between the alternatives A_1 and A_2 as it has been described in Sect. 2.

Focusing on the electric field level $y = 1,21$ V/m, we notice that it exceeds δ and with lies in the uncertainty range when a coverage factor $K = 3$ is used to evaluate expanded uncertainty. Calculations of the

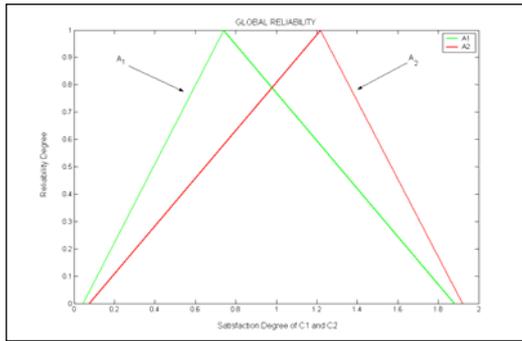


Fig. 5. Global Reliability of alternatives.

erroneous decision probabilities yield $P_\alpha = 7,97 \cdot 10^{-4}$ and $P_\beta = 0,0057$. For the goal C_2 the benefit values of the two alternatives have been fixed equal to $z_1 = 6$ and $z_2 = 5$, because the alternative A_2 is preferable in comparison with A_1 in terms of possible costs and consequences, in fact we could underestimate a possible risky situation for population in choosing the alternative A_1 as reliable. Proceeding with the construction of the global fuzzy triangular sets, the total performances of alternatives are illustrated in Fig. 5. From the triangles is it apparent that the best alternative is A_2 , which satisfies the constraint C_1 and the goal C_2 with the highest satisfaction and reliability degrees. That is, the level $y = 1,21$ V/m is to be considered non-conforming with δ , so it's beyond the control limit. In a similar manner, the remaining data resulted within the limit δ .

4. CONCLUSION

In the paper an innovative decision-making methodology for the qualification of an environmental measurement process and of its associated decision system has been proposed. The statistical model adopted allows to calculate the maximum measurement uncertainty that the system can be affected by according to the related effects on the decision-making process, therefore with information on the measurement system performances and on the level of measured data confidence.

The fuzzy decision-making procedure presents general hypotheses that make it applicable in process control field for a wide variety of measurement systems, where a generic quality index is put in comparison with a reference limit. It can be used as a support or in place of traditional process control tools, like control charts. In fact, the proposed technique allows also to have a quantitative information about the consistency of decision process, overcoming intrinsic limits of ISO 14253-1 standard.

It can be, also, used in synthesis phase to determine the metrological characteristics that the measurement system should have in order to assure prefixed levels of performance and of confidence for decision-making process [8-11].

A possible further development can be represented by the implementation of an algorithm that is able to

verify the measurement process on the fly in order to define the optimum calibration intervals, according to a fixed data confidence level to pursue for a reasonable decision consistency.

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