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A NEW APPROACH TO UNCERTAINTY REDUCTION IN ENVIRONMENTAL ELECTROMAGNETIC FIELD MEASUREMENTS THROUGH QUALITY ASSURANCE TECHNIQUES

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Abstract – Assessment of risks connected with exposure to electromagnetic fields at either low or radio frequencies requires appropriate evaluation of the value read on probe's display – whose variability depends on both EM field and measurement system – with respect to the actual value of the underlying monitored process. That can be accomplished through a statistical investigation about whether the overcome of reference limits which can possibly have happened is merely a transient effect of measurement uncertainty which sums up with random process variation, or rather a more serious stable condition which calls for countermeasures.

To that end, it is required that the probability distribution of the monitored process be obtained from the set of measured data, which can be done by taking out of them the fluctuation due to measurement itself. Such methodology falls under the generic name of deconvolution, after the operation used to separate the two contributions, and requires a preliminary measurement campaign for the evaluation of the statistical distribution of data. This paper presents the mentioned methodology and provides an example pertaining the evaluation of the electromagnetic field in urban area.

Keywords: uncertainty reduction; quality assurance; electromagnetic field.

1. INTRODUCTION

In the last years, exposure to electromagnetic (henceforth, EM) field has gained interest among researchers for its alleged connection with diseases, specifically when operating in conjunction with other physical agents. For this reasons, national, international and local authorities have paid higher attention to EM field radiation levels for both population and professionals, enforcing laws with exposure limits and promoting measurement campaigns to characterize sensitive locations such as residential areas, production plants, hospitals and highly populated areas in general.

Because of the nature of the process under investigation, results of environmental EM field amplitude measurements may be affected by high uncertainty. In fact, the field under observation is the resultant of a number of different uncorrelated contributions coming from different sources at different frequencies, possibly with different time-dependent behaviors, and therefore variations observed in the process are expected to be large. In addition, instruments commonly used for field monitoring (such as portable field probes) are themselves affected by large measurement uncertainty. This all sums up in a measured value characterized by a high standard deviation. In particular, it can be noticed that because of measurement uncertainty it may happen that a measurement exceeding the reference upper bound does not necessarily imply that the process under observation (in our case the EM field) is itself beyond the limit. Likewise, with opposite arguments, for a reading that is below the limits [1].

It is important therefore to assess to what degree measurement uncertainty affects measured values, in order to establish within a given confidence interval the significance of the results obtained from the measurement process. More so when reference values are fixed by national or international regulations and standards, as in the case of exposure of population and professionals to EM radiations.

Italian law for limiting exposure to EM fields [2] does not implicitly take measurement uncertainty into account, but somehow recalls it in the measurement procedure. The mentioned law in fact generally requires wide-band measurements to be performed within a certain frequency range in order to evaluate the *RMS* value over a six minute interval. If the obtained measure is over half the limit value, then narrow-band measurements are to be taken in order to estimate each different contribution along the frequency axis and determine it with higher precision. This additional requirement calls for a skilled technician, a costly equipment and mostly important an expense of time – and consequently money – for measurements to be carried out.

In authors' opinion, procedure implemented in the regulation may not be strictly correct because a single six-minute *RMS* value overcoming the law threshold does not imply that the underlying process is constantly over the limit. That is, it may only be an occurrence of a stochastic process from which no general information can be inferred about the process itself without any further analysis.

This led us to the conclusion that, because of the nature of the environmental EM field described above, a statistical approach could better suit the requirement of verifying whether the process complies with law limits or not. Obviously as in the deterministic approach, even a statistical one must necessarily take into account the presence of measurement uncertainty because both natural process variability and additional contribution given by instruments and measurement procedures play a role in determining the value read on probe's display.

More specifically, of the two causes of uncertainty mentioned, the former is intrinsic to the measured process, and therefore out of our direct control, whereas the latter poses the interesting problem of finding methodologies capable of assessing how much relevant the increase is, comparing it with the natural process variations, determining whether the contribution to the overall fluctuations is relevant, and finally providing a suitable algorithm to 'clean' measured results from uncertainty contribution given by the measurement if that is necessary.

This would eventually lead us to having a set of data in which only intrinsic process variability appears, so that observed data spread about the mean value is only affected by process intrinsic variance.

The methodology proposed can be referred to as deconvolution [1]. Leaving details to successive sections, we can briefly present its two constitutive steps. First, it is mandatory that a knowledge of probability distribution function (hereafter, *pdf*) of the measured data be gained. This can be done experimentally through repeated measurements in the area where investigation of the EM field is to be carried out. Then, with the information provided by probe manufacturers, we can claim how measurement uncertainty statistically affects the measured data. Using both measured data and 'noise' *pdf*'s we can assign a distribution to the process too, which otherwise would be masked by the filtering of the measurement device. This is the core of the proposed methodology: *deconvolving* measurement uncertainty from measured data so that information about the sole process shows up.

After process and measurement have been characterized in terms of average value and standard deviation, we have a complete knowledge of the scenario in which we play, and evaluation of the risk associated with stating that the EM is above the limits when indeed it is not (false alarm probability), or vice versa (missed target probability) can be made through use of plots referred to as "normalized diagrams". In that manner, we can state what probability we have that the measurement procedure is likely to move a measured data outside acceptable value intervals, or to bring it into that interval provided the underlying process is not.

In addition, having uncertainty separated into two different pieces of information gives us useful hints about how much relevant the influence of measurement noise is, thus allowing simple and immediate considerations about whether available countermeasures such as narrow-band analysis are appropriate for the case under investigation.

Finally, diagrams can also be applied when measured data spread is known and the accuracy of the measurement instruments is to be determined so that the false alarm (missed target) probability assumes a given value.

In this paper we present an application of the above mentioned techniques to the evaluation of the environmental EM field variations in complex scenarios such as cities. Presented results have been obtained through experiments carried out in the city of Naples, Italy during a specifically designed measurement campaign.

The paper is organized as follows. In the next section a brief review of the mathematical model for uncertainty deconvolution and expression of significant error probabilityies will be provided. Then, experimental setup will be outlined along with result of the analysis. They will be interpreted and some consideration about how they can be used will conclude the paper.

2. MATHEMATICAL MODEL

Before we start presenting and discussing result, a brief review of the mathematical model for the proposed deconvolution technique will be provided [1].

Suppose that a set of measured data $Y = \{y_1, \ldots y_n\}$ from a process x_m shows a variance σ_y. Such fluctuations around the mean value are due to both process intrinsic variations σ_m and measurement uncertainty σ_n. In fact, what we indeed see as the result of our measurement process is $y = x_m + n$, where x_m is the process under observation and n is the resultant of all the random processes that influence the outcomes of measurements. If n and x_m are independent, then the resultant process *pdf* is the convolution of the two source *pdf*'s and therefore

$$\mu_y = \mu_m + \mu_n \tag{1}$$

and

$$\sigma_y^2 = \sigma_m^2 + \sigma_n^2 \tag{2}$$

If n is centered around zero (i.e., $\mu_n = 0$), then the effect of poorly defined parameters resolves in a mere broadening of the measured data uncertainty.

Such broadening may pose interesting issues when readings must be compared to limits, as it is the case of the exposure to EM field which must be evaluated against a threshold to determine whether the environment is being significally polluted by EM radiation – according to the law definition – or not.

Particularly, it is relevant to assess the risk of declaring the measured value outside specification (in our case, regulation) interval when it is not, because of the effect of measurement uncertainty. Similarly, we may encounter situations where, for the same reasons, values appear within control limits because of measurement uncertainty, even if they're actually not.

We can therefore define a P_α (P_β) probability characterizing the error that we make in stating that the process is beyond (below) the limit. More specifically, the interval of acceptability for the process of our interest has only one bound in the upper position – i.e., the law limit – since every value below it is acceptable and we cannot have negative values for the EM field. Therefore, in order to estimate P_α, we must evaluate the probability that $x_m + n > \delta$, with δ being the reference limit, and $x_m < \delta$ at the same time. That is:

$$\begin{aligned} P_\alpha &= P\left(x_m + n > \delta,\ x_m < \delta\right) \\ &= \sum_i P\left(x_m + n > \delta,\ x_m \in \Delta_i\right) \end{aligned} \tag{3}$$

where the latter equality has been obtained by introducing a proper set of intervals $\{\Delta_i\}_{i=1,\dots,N}$, such that $\bigcup_{i=1}^{N}\Delta_i = [0,\delta]$ and $\bigcap_{i=1}^{N}\Delta_i = \varnothing$, and referring to the Total Probability Theorem. Following the definition of conditioned probability, (3) can be rewritten as:

$$\sum_i P\left(x_m + n > \delta \mid x_m \in \Delta_i\right)\cdot P\left(x_m \in \Delta_i\right) \tag{4}$$

We can now let $\Delta_i \to 0$, so that $x_m \in \Delta_i \Leftrightarrow x_m = x'$, which causes (4) to turn into

$$\begin{aligned} P_\alpha &= \int_0^\delta P\left(x_m + n > \delta \mid x_m = x'\right)\cdot f_{x_m}(x')\,dx' = \\ &= \int_0^\delta P\left(n > \delta - x'\right)\cdot f_{x_m}(x')\,dx' = \\ &= \int_0^\delta \left[1 - F_n\left(\delta - x'\right)\right]\cdot f_{x_m}(x')\,dx', \end{aligned} \tag{5}$$

where $F_n(x)$ and $f_{x_m}(x)$ are n's cumulative distribution function (*CDF*) and x_m's *pdf* respectively. Similarly, P_β can be evaluated recalling that

$$\begin{aligned} P_\beta &= P\left(x_m + n < \delta,\ x_m > \delta\right) \\ &= \sum_i P\left(x_m + n < \delta,\ x_m \in \hat{\Delta}_i\right), \end{aligned} \tag{6}$$

where $\bigcup_{i=1}^{\infty}\hat{\Delta}_i = [\delta, +\infty[$, and applying the same procedure as above we obtain:

$$P_\beta = \int_\delta^{+\infty} F_n\left(\delta - x'\right)\cdot f_{x_m}(x')\,dx' \tag{7}$$

Eq. (5) and (7) show that in the evaluation of error probabilities both x_m's and n's *pdf*'s are involved. While measurement uncertainty represented by n can be easily estimated and is usually provided by manufacturers, some issues may arise when evaluating x_m's distribution. Recalling that $y = x_m + n$, and that its distribution is the convolution of x_m's and n's *pdf*, we can evaluate x_m's one by deconvolving n from x_m.

The deconvolved *pdf* depends of course on the shape of the distributions involved, and in the following sections we will use experimental data to determine it.

3. EXPERIMENTAL SETUP

The measurement system we used, which is briefly sketched in fig.1, was made of two probes covering frequency bands 0.1~3000 MHz and 0.7~3 GHz, connected through a proprietary switch to a PC on which an acquisition software was installed. We stored field amplitude values from both probes, at a rate of one sample per second for three hours, for a grand total of 10800 values.

The set of data has been manipulated to obtain some quantities which we considered to be more significant. First, data were bunched into six-minute interval (i.e., all containing 360 elements), out of which an *RMS* values was been calculated as:

$$RMS = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N} x_i^2}\ , \tag{8}$$

where N = 360 in our case. This because, as already mentioned, the Italian exposure limits refer to the *RMS* values of the field amplitude averaged over six minutes, since that is the time interval after which the body is supposed to have reached a steady state for an electromagnetic wave impinging on it.

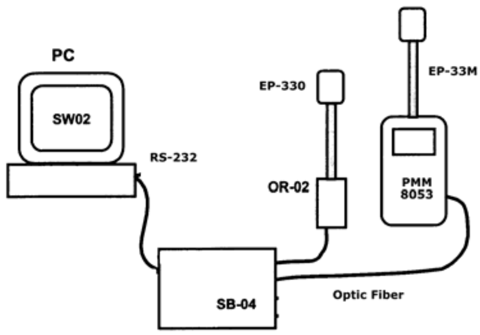

Fig. 1 – Measurement system

The set of the resulting 30 samples of *RMS* values were checked against a known distribution. To do that, the classical procedure of Chi-square test [3] was performed. Therefore, we first divided the set of *RMS* values into k different non-overlapping intervals (i.e., classes), and then computed the quantity:

$$\chi^2 = \sum_{i=1}^{k}\frac{\left(f_{e,i} - f_{t,i}\right)^2}{f_{t,i}} \tag{9}$$

where $f_{e,i}$ is the experimental absolute frequency of the i-th class and $f_{t,i}$ is the theoretical absolute frequency, i.e. the absolute frequency of the i-th class that we would see if data actually follow the expected distribution. We then checked the resulting χ^2 value against the theoretical value corresponding to k-3 degrees of freedom. Two of them are used to evaluate average and standard deviation for the expected distribution, the third is used in imposing:

$$\sum_{i=1}^{k} f_{e,i} = M\ , \tag{10}$$

where M = 30 is the total number of *RMS* values.

Results showed a good agreement with a normal distribution with mean and variance estimated from measured data.

This indeed deserves some comments, since what we found may not seem at first sight consistent with what we expect from a theoretical point of view. We know in fact that samples of the EM field amplitude in a complex environment such as a city, that is values obtained from a single signal being reflected and attenuated by buildings along the path between transmitter and receiver, is expected to exhibit a chi (χ) distribution with six degrees of freedom (*dof*) if measurements along the three axis (i.e., isotropic measurements) have been carried out, or with two *dof* if only one axis has been investigated. Such behavior derives from the fact that the field amplitude along each direction for a single signal is

$$\left|E_{\hat{u}}\right| = \sqrt{E_{\hat{u},r}^2 + E_{\hat{u},i}^2} \tag{11}$$

where $E_{\hat{u},r}$ and $E_{\hat{u},i}$ are the field's real and imaginary part. In a complex environment we usually assume both being normally distributed with zero mean so that the amplitude squared is chi-square distributed with two *dof*. If three axis are considered, each will contribute with two *dof* and therefore an isotropic set of data will show a total of six *dof*.

We also note that samples may show a non-central chi distribution if a direct path (also known as line-of-sight) propagation contribution exists between the transmitting and receiving stations.

Our scenario differs from those mentioned in one main aspect, that the object of our investigation is not the field amplitude of a single signal, but the *RMS* value obtained from $N = 360$ samples of a signal which is the sum of many uncorrelated signals, each traveling a different path to the receiving probe. Furthermore, we notice that (8) is a sample mean for the process observations x_i squared. Shouldn't there be the square operator, Central Limit Theorem would be sufficient to prove that the resulting *RMS* values are normally distributed. The square operation moves the output values to the positive portion of the real axis, in contrast with a gaussian distribution which does include negative values. That is an issue which we may deal with considering that if the (positive) mean of the distribution of the *RMS* values is much larger than its variance, the residual probability of the normal distribution associated with negative values has a very small weight in (9) compared to the contribution given by positive values. We considered this as the reason for the data passing the chi-square test with no apparent lack of validity.

4. ESTIMATION OF MEASUREMENT UNCERTAINTY

As already mentioned, measurement uncertainty sums up with the natural electromagnetic environment variations, resulting in a broadening of the measured data standard deviation σ_y. Thus what we see when estimating σ_y is indeed not the variance of the process under observation, but the sum of the variances of x_m and x, if the two processes are independent. Our objective is to obtain the variance of the EM field *RMS* value alone (i.e., σ_{x_m}), that is separated from the contribution given by measurement uncertainty, and therefore, in order to clean field probe accuracy off the observed data variability, we have to subtract σ_x^2 from σ_y^2. Next step is therefore to calculate an appropriate measurement accuracy value.

That requires some work, specifically in dealing with probe accuracy in the way it is usually assessed and declared by the manufacturer. In fact, uncertainty is expressed in probe's datasheet for each single measurement with two different values, according to the frequency content of the received signal:

$$\begin{cases} 2\sigma_{rdg} = 10\%\ V_{rdg} & \text{up to 150 MHz} \\ 2\sigma_{rdg} = 15\%\ V_{rdg} & \text{from 150 MHz to 3 GHz,} \end{cases} \tag{12}$$

for probe EP330 covering band 0.1~3000 MHz, and

$$\begin{cases} 2\sigma_{rdg} = 10\%\ V_{rdg} & \text{up to 300 MHz} \\ 2\sigma_{rdg} = 15\%\ V_{rdg} & \text{from 300 MHz to 3 GHz,} \end{cases} \tag{13}$$

for probe EP33M covering band 0.7~3 GHz[1].

We first notice that such definition inherently refers to a normal distribution of the instrumental contribution to read values, since if n's samples were uniformly distributed with zero mean and semi-amplitude a, then $2\sigma_n$ would be larger than a, which of course is nonsense. Secondly, since we don't know exactly the frequency location of the signal under analysis we can't rigorously tell which of the two expressions is more appropriate. But we do know that in a urban environment the largest contributions to EM field are by radio and TV broadcasting and cellular networks, which operate in the upper band. Upon this considerations, it seems more appropriate to calculate σ_n as 15% of the recorded value.

Furthermore, since the value of interest is not a single reading but an *RMS* value, i.e. a function of a certain number of different values, the associated measurement uncertainty has to be computed in some way that took such function into proper account. Thus, making use of the uncertainty propagation rule, we computed the uncertainty associated to each *RMS* value as:

$$\sigma_{RMS_i} = \sqrt{\sum_{j=1}^{360}\left(\frac{\delta RMS_i}{\delta x_j}\cdot\sigma_{x_j}\right)^2} \tag{14}$$

where σ_{x_j} refers to a single reading x_j and is calculated as in (12). Since each x_j is an observation from some distribution, so is RMS_i, and so n couldn't be characterized by a single value for the variance. After (14) is evaluated for each i = 1,..,30, the uncertainty of each *RMS* value can be averaged and the value we obtain be considered representative of the whole distribution of the σ_{RMS}. That is,

$$\sigma_n^2 = \overline{\sigma_{RMS_i}^2} = \frac{1}{30}\sum_{i=1}^{30}\sigma_{RMS_i}^2 \tag{15}$$

Therefore we will assume hereafter that the measurement procedure introduces a random contribution n which is normally distributed with variance given by the mean value of the accuracies obtained from the set of the thirty *RMS* values.

5. RESULTS

[1] Note that probe also reveals signals outside the operating band, but since they fall were response is very weak we can assume their contributions to the overall measured signal to be negligible.

So far we have achieved two results: first, we verified that both observed data y and measurement-related "noise" n are normally distributed. This results in an x_m being gaussian since its sum with a normally distributed random variable (r.v.) gives a normal r.v. [4]. We also have a value for σ_m^2 simply obtained subtracting σ_n^2 from σ_y^2. Summing up:

$$\begin{aligned} & n \sim N\left(0, \sigma_n^2\right) \\ & x_m \sim N(\mu_m, \sigma_y^2 - \sigma_n^2) \end{aligned} \tag{16}$$

The distributions in (16) can be now substituted into (5) and obtain:

$$P_\alpha = \frac{1}{2\sqrt{2\pi}\sigma_m} \int_0^\delta erfc\left(\frac{\delta - x}{\sqrt{2}\sigma_n}\right) e^{-1/2[(x-\mu_m)/\sigma_m]^2}\, dx \tag{17}$$

By posing $\gamma = (x - \mu_m)/\sqrt{2}\sigma_m$, $k_1 = \delta/\sigma_m$, $k_2 = \sigma_m/\sigma_n$, $k_3 = \mu_m/\sigma_m$ we have:

$$P_\alpha = \frac{1}{2\sqrt{\pi}} \int_{-K_3}^{K_{13}} erfc\left(k_2(K_{13} - \gamma)\right)\, e^{-\gamma^2}\, d\gamma\ , \tag{18}$$

where $K_3 = k_3/\sqrt{2}$ and $K_{13} = (k_1 - k_3)/\sqrt{2}$. Similarly, we can write (7) as:

$$P_\beta = \frac{1}{2\sqrt{\pi}} \int_{K_3}^{+\infty} erfc\left(k_2(\gamma - K_{13})\right)\, e^{-\gamma^2}\, d\gamma \tag{19}$$

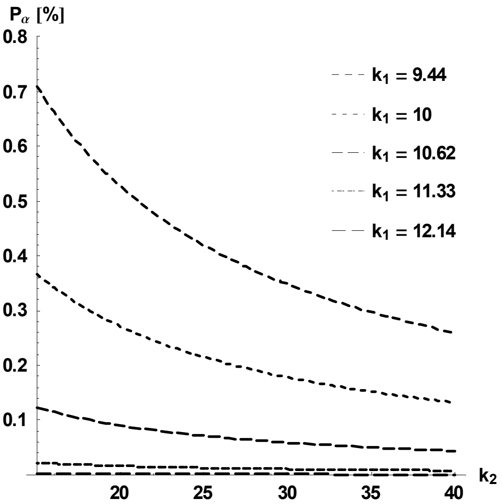

Fig. 2 – P_α versus k_2 with $k_3 = 8.50$

A graphical representation of both P_α and P_β can be given. Since they both depend on three variables (k_1, k_2, and k_3), we can either give 3-D parametric plots of probabilities for different values of k_3 – which is the only parameter that entirely depends on the process and therefore doesn't change once the process has been fixed, – or show cuts along the k_1 or k_2 axis keeping the other one and k_3 fixed.

Fig. 2 and 3 show P_α and P_β respectively for $k_3 = 8.50$, as resulting from measurement obtained with probe covering band 0.7~3 GHz.

Generally speaking, as expected both figures show higher curves for smaller values of k_1, since once the process has been identified (i.e., its mean and standard deviation are known) decreasing values of the reference limit δ make process average value closer to the limit itself, therefore resulting in a higher probability that measured value overcome the limit only as a result of measurement uncertainty. Referring to values obtained from our campaign, we have μ_m = 0,85 V/m, σ_m = 0,10 V/m, and we fixed δ = {0.94, 1.00, 1.06, 1.13, 1.21} V/m, so that μ_m corresponds respectively to 90%, 85%, 80%, 75% and 70% of the values chosen. Percentages have been calculated with respect to the average value because it is the most likely values to be read on display when only one single measurement is carried out.

Inclusion of plots with δ = 6 V/m or its 75% value δ = 4 V/m would have been immaterial indeed, since from plots it is apparent that with such values error probabilities would definitely be irrelevant, because the probability to observe a sample from the obtained distribution far from the average is very small because of the very small values of standard deviation of both process and measurement procedure.

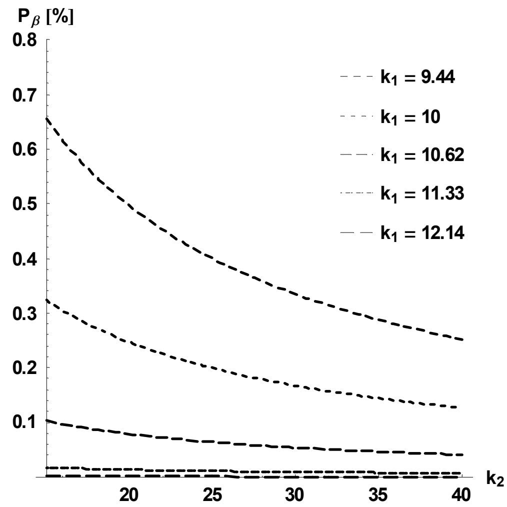

Fig. 3 – P_β versus k_2 with $k_3 = 8.50$

We also observe that both probabilities decrease with k_2. That is also expected since as process spread σ_m becomes more significant over measurement uncertainty σ_n, the probability P_α (P_β) that a measurement is above (below) control limits because of n when instead the process is in (out of) control is smaller.

Finally, we can calculate the error probabilities for the values obtained from measurements, assuming δ as the value for which μ_m corresponds to its 75%, and k_2 = 34.66. We obtain $P_\alpha = 5\cdot10^{-2}$ % and $P_\beta = 4\cdot10^{-2}$ %. Furthermore, if δ is chosen as the value corresponding to 85%, i.e., a value for which narrow-band measurements are required by law, we would still obtain P_α = 0.15 % and P_β = 0.14 %.

6. FURTHER REMARKS

One last interesting feature refers to the values of P_α and P_β for large values as opposed to small values of k_2. Intuitively the meaning of error probabilities is that we make an error α (β) if process realizations have a certain probability of falling in an interval whose upper (lower) limit is δ, and with an amplitude depending on σ_n.

If the latter is much smaller than σ_m than the x_m's *pdf* has almost the same value in both intervals. Therefore, false alarm and missed target probabilities have almost the same value, P_α being slightly larger (see Fig. 2 and 3). When σ_n increases up to values comparable to σ_m, probabilities assume different values because x_m's *pdf* over the intervals over which P_α and P_β are calculated are quite different (see Fig. 4). Again, P_α is much larger than P_β.

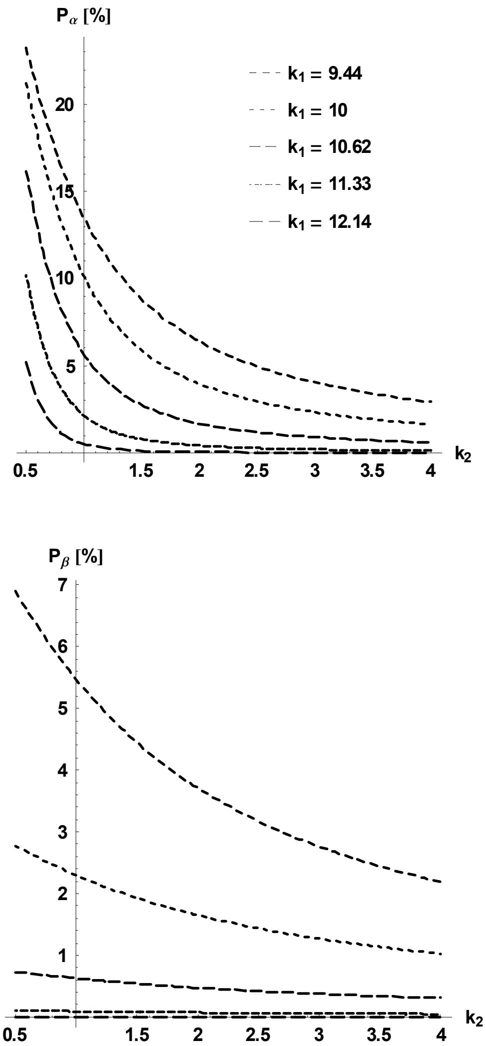

Fig. 4 – Comparison between P_α and P_β for small values of k_2

4. CONCLUSIONS

We addressed the issue of how to 'clear' the variations observed in a set of measurements of the environmental EM field from the contribution given by measurement accuracy, the aim being that of having only variations due to the natural process variability show in the data. Such procedure may prove very useful when measurements are to be compared with law or standard limits, since data devoid of any known measurement uncertainty will appear to be beyond (below) the reference values only when the underlying process, actually is, thus limiting the risk of 'false alarms' (missed target) which may lead to state a process is out of (in) control when indeed it is not.

Measurement campaign have also been carried out and from measured data we could obtain plots of P_α and P_β based on the observed process characteristics. Such values show quite low with reference to the limits considered and the values obtained from measurements.

In conclusion, we have show that a probabilistic approach seems to be more appropriate than a single measurement when it comes to determine whether a process is still in a safe condition. In fact, we have proved that even if the value which is most likely to be obtained from measurements is very close to the reference limit, because of the joint effect of natural variability and measurement accuracy, the probability that a single observation from that distribution is beyond the limit may still be very close.

Therefore it seems appropriate to change to a new philosophy in performing such measurements, consisting in the evaluation of the distribution of data and measurement uncertainty; then, after proper deconvolution in the sense explained before, we can evaluate the probability of making an error, upon which value we can then decide whether to proceed with exploitation of the necessary procedures for the case of limit overcome.

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