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A Wavelet Transform Based Study on the Representativeness of Preselected Frequency Points of the Insertion Loss Function in Fuzzy Performance Evaluation of Access Network Links

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Abstract: The performance evaluation of telecommunication networks and connections is a usual problem of telecommunications service providers and network owners. The performance evaluation in our previous approach is strongly (but not exclusively) based on the insertion loss values of the wire pairs measured at certain discrete frequency points. According to experimental results, the usage of these frequencies leads to correct evaluation, however, the theoretic verification of the correctness of the placement of these points seems to be necessary. The study was carried out using wavelet analysis, comparing the insertion loss values measured at the discrete frequency points with the wavelet transformed sections of the insertion loss functions corresponding to them. In this paper, using wavelet transform, we have studied whether the previously selected characteristic frequencies represent well the frequency domain around them also rules using wavelet transformed data are compared to the rules of the method based on characteristic frequencies.

Keywords: telecommunications, performance evaluation, access networks, fuzzy inference, wavelet analysis

1. Introduction

The examination of the correctness of the antecedent dimension selection for a telecommunications performance evaluation approach based on fuzzy models is presented in this paper. This new approach is appropriate for the classification of the telecommunications access networks' individual wire pairs for SHDSL (Symmetrical High Speed Digital Subscriber Line) [1] connections according to the possibly available data transfer rate (bit rate), however it can be generalized for any type of digital access network links. SHDSL is a symmetrical member of the DSL telecommunications transmission family which was evolved definitely for the copper wire pairs of the access networks. (According to recent studies, e.g., [2], copper wire pairs of access networks will be used for the installation of new telecommunication connections even beyond 2040, however, the replacement of the traditional metallic transmission medium by fibre optical ones has been recently announced in Hungary.)

Similarly to some other performance evaluation techniques in the field of telecommunications, our method uses observed electrical properties of the measured lines.[3] Differently from the currently used methods, our qualification is made according to mostly the measured values of insertion loss by fuzzy rule bases in our approach. [4]

In Fig. 1. insertion loss characteristics of the lines studied in this contribution can be seen. In accordance with the practice of telecommunication service providers, different ranges of bit rates were separated into different clusters. Typical examples of this classification can be seen in Fig. 2. Values of bit rates ascend from cluster 1 to cluster 5.

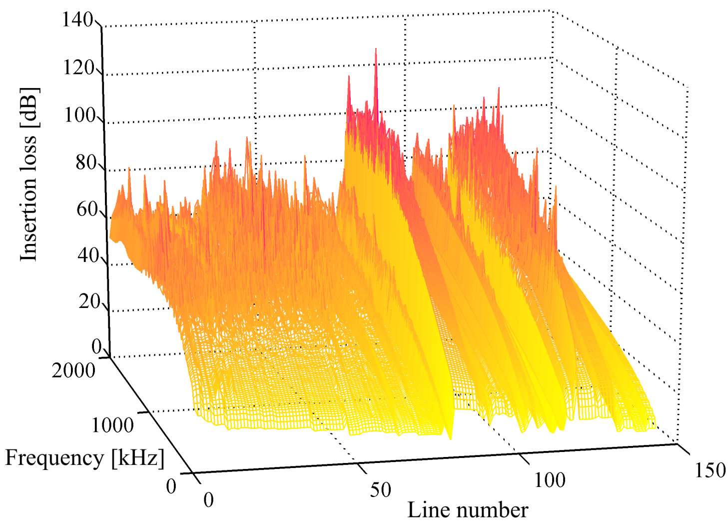


Fig. 1. Insertion loss characteristics of the observed lines.

Fig. 2. shows that the ranges defined by different bit rate clusters are overlapping, which makes the problem of wire pairs' performance evaluation nondescript and hardly classifiable by traditional methods. For such problems the fuzzy set theory was suggested by L. A. Zadeh in 1965 [5] and a widely used, successful application was introduced by E.

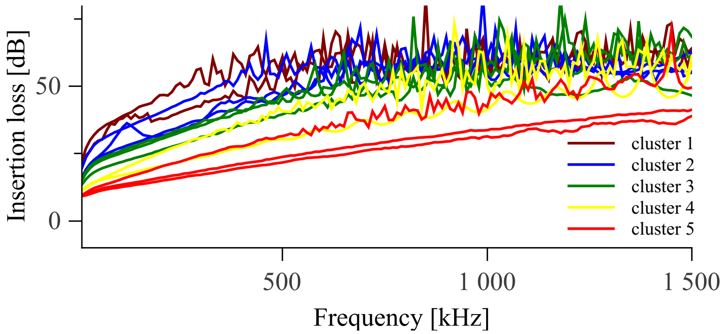


Fig. 2. Examples of the classification of insertion loss characteristics by bit rate clusters.

H. Mamdani [6] in 1975. In our approach Mamdani's fuzzy inference method has been applied.

Our approach is predominantly based on the insertion loss of the lines. Even though insertion loss values were measured only in 200 discrete points of the frequency in this study, this physical property of the wire pairs is continuous. In order to avoid the difficulty of handling continuous functions or too many values in the antecedent part of the evaluation, some of the frequencies were selected for the actual decision-making. Based on experimental results, these frequencies are 100 kHz, 500 kHz, 750 kHz, 1000 kHz, 1250 kHz and 1500 kHz. The distance between the characteristic frequencies is uniformly 250 kHz, the only difference is at 100 kHz. This irregularity of the position of the characteristic frequencies is explained by the stronger separation of the insertion loss functions around 100 kHz.

Measured insertion loss values at the 6 characteristic frequencies (see in Fig. 3.) were used in the construction of fuzzy rule bases. Based on these data, two types of rule bases were created, one type was made directly from the measured values (later referred to as D-type), and another by evolutionary algorithm [7] (E-type), where measured values were used as teaching samples. The D-type rule base has five rules – according to the five bit rate clusters – and six antecedent dimensions (the insertion loss values at the characteristic frequencies), and its fuzzy sets are triangular. One of the rules of the D-type rule base can be seen in Fig. 4 graphically, as an example.

The E-type rule base is not in direct connection with the five output clusters. It has 10 rules, however, also it has six antecedent dimensions. In this case the fuzzy sets are trapezoidal. See Fig. 5.

Both type of rule bases has been tested by evaluating previously unknown wire pairs. Comparing to the results of other, widely available and used pre-qualification methods, the

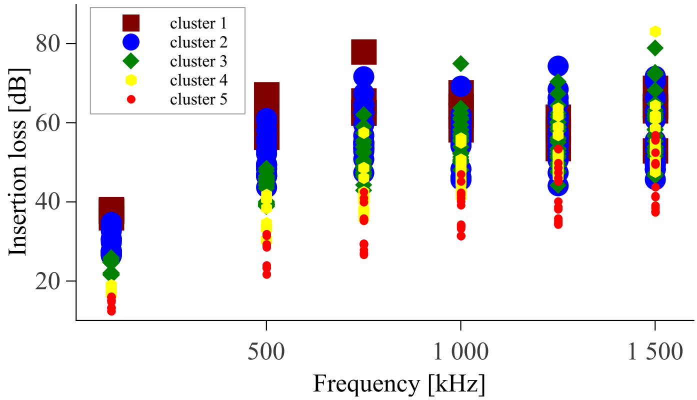


Fig. 3. Measured insertion loss values of the lines used for rule base construction at the characteristic frequencies.

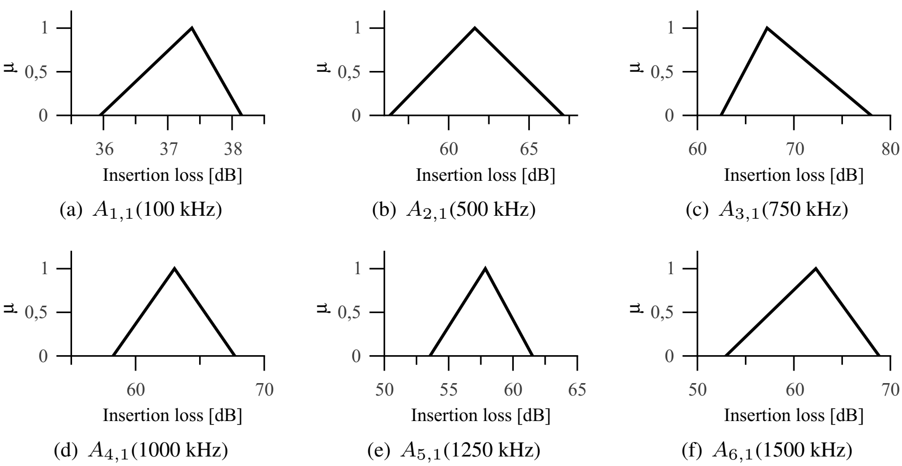
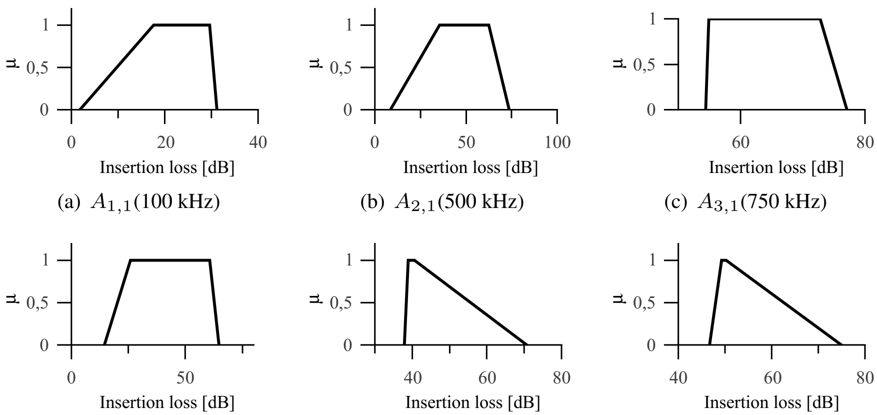


Fig. 4. Triangular antecedent sets of the 1st rule from the D-type rule base. The left axis shows the membership values and the bottom axis shows the insertion loss. The closures of the supports fo the membership functions were defined by the limits of the measured insertion loss values, whereas the core points were the mean values of the measured data. (In fuzzy set theory we study not only weather an element belongs to a set or not, but also how much it belongs to the set. The rate of this "belonging" is called membership value of the given element.)

success rate of our approach reached the success rate of the most accurate methods, and



(a) $A_{1,1}$(100 kHz) (b) $A_{2,1}$(500 kHz) (c) $A_{3,1}$(750 kHz)

(d) $A_{4,1}$(1000 kHz) (e) $A_{5,1}$(1250 kHz) (f) $A_{6,1}$(1500 kHz)

Fig. 5. Trapezoidal antecedent sets of the 1st rule from the E-type rule base. The left axis shows the membership values and the bottom axis shows the insertion loss.The measured data were grouped according to their performances and were used as teaching samples in the construction of the rule bas by the evolutionary algorithm defined in [7].

using different rule bases constructed from insertion loss values measured in areas with different line noise, the success rate was higher than in case of other methods [8].

Correctness of the frequency points used in rule bases is confirmed by the results of the tests, however, this verification is based on experiments carried out on finite number of wire pairs. Possibly there can be – and according to our expectations there are – wire pairs which have severe deviations in insertion loss exactly at the characteristic frequencies that provide the basis of our qualification method. In such cases the evaluation will be failed, the lines will be classified not into the correct, but its neighbouring cluster. The reason for this problem is that the insertion loss is studied not in the whole frequency range but only at discrete points of the frequency, therefore it seems to be important to examine how representative the insertion loss values at the selected frequency points are to the ranges around them. In this paper we apply wavelet analysis to determine, whether the large-scale behaviour of the insertion loss function can be represented well by the selected characteristic frequencies.

Wavelet theory – summarized e.g., in [9–11] – became one of the basic data procession methods in the past three decades. Even though the most successful branch of their application is the image compression – wavelets are used from fingerprint databases [12] to Mars rovers [13] and the JPEG2000 compressor [14] – one of the reasons wavelets arose was the analysis of one dimensional data, namely seismic echoes in oil research [15]. In the following considerations we also use wavelets for one dimensional data analysis: we gain information about the structure of the insertion loss-frequency function by wavelet analysis.

2. On wavelet analysis

Fourier analysis [18] of a signal can give information about the structure of the signal: it can tell the amount of slowly varying – low frequency – and rapidly varying – high frequency – components. The main problem with Fourier analysis from the practical applications point of view was that it requires infinite signal. In order to be able to gain information about the slowly and rapidly varying components of a real measured signal a short time Fourier transform or windowed Fourier transform was introduced. The basic idea behind the windowed fourier transform

$$\mathcal{F}_b\{f\}(\omega) = \int_{-\infty}^{\infty} w(t-b)\, f(t)\, e^{-i\omega t}\mathrm{d}t. \tag{1}$$

is to make a short snapshot of the studied function $f(t)$ with a short window function $w(t)$ at any point b and transform the thus arisen function. Of course, the integral of the resulting functions $\mathcal{F}_b\{f\}(\omega)$ along the variable b, we get the usual Fourier transform of the function,

$$\int_{-\infty}^{\infty} \mathcal{F}_b\{f\}(\omega) db = \mathcal{F}\{f\}(\omega).$$

The selection of the window function is a key for an effective transform. Dennis Gábor [17] suggested to use Gaussian type window

$$w_\alpha(t) = \frac{1}{2\sqrt{\pi\alpha}}\, e^{-\frac{t^2}{4\alpha}}$$

and the windowed Fourier transform with such window functions are still called Gabor transform.

However, if we look at (1) from another point of view, it can be seen as a transform with the windowed sinusoidal function

$$W_{b,\omega}(t) = e^{i\omega t}\, g(t-b),$$

thus

$$\mathcal{F}_b\{f\}(\omega) = \int_{-\infty}^{\infty} \left(W_{b,\omega}(t)\right)^*\, f(t)\mathrm{d}t, \tag{2}$$

with * meaning complex conjugation. The shape of the window function $W_{b,\omega}(t)$ for the Gabor transform is given in Fig. 6 with $b = 0$ and three values of ω.

The wavelet transform of a signal has the same approach as formula (2), only the window function has a different construction,

$$\psi_{b,a}(t) = |a|^{-1/2}\, \psi\left(\frac{t-b}{a}\right),$$

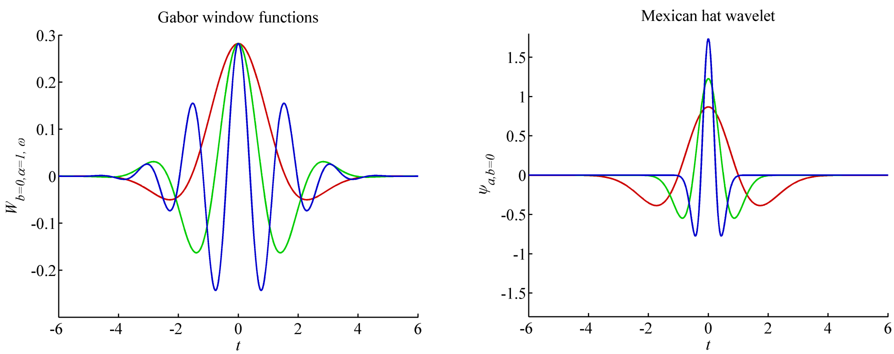


Fig. 6. The window function $W_{0,\omega}$ of the Gabor transform (left) with $\alpha = 1$, and the Mexican hat wavelet $\psi_{a,0}$ (right). Both function types are given for three resolutions, i.e., $\omega = 1$ (red), $\omega = 2$ (green), $\omega = 4$ (blue) for the Gabor transform function and $a = 1$ (red) $a = 2$ (green), $a = 4$ (blue) for the wavelet. All functions are centered to 0, i.e., the shift index $b = 0$. Arbitrary units.

resulting in the transform

$$\mathcal{W}_\psi\{f\}(b,a) = |a|^{-1/2} \int_{-\infty}^{\infty} \psi_{b,a}^*(t) f(t) \mathrm{d}t.$$

The wavelet function $\psi_{b,a}(t)$ is generated from the mother wavelet by simple shifting and shrinking/stretching, thus the window functions have the same shape for the fine scale and large-scale behaviours, only their widths varies, as it can be seen in Fig. 6. This shape is usually consisting of some waves in a short interval, hence the name little waves, or wavelets.

Generating the wavelet has lots of freedom, the only constraint that has to be fulfilled is

$$\int_{-\infty}^{\infty} \frac{1}{\omega} \, |\mathcal{F}\{\psi\}(\omega)|^2 \, d\omega < \infty.$$

The application of the wavelets is similar to that of the Fourier transform, besides data/signal analysis, they can be used for solving differential equations [19–21].

For our purposes the discrete version of the wavelet transform is more suitable as we have a series of insertion loss values measured at discrete frequencies. The realization of a discrete wavelet transform is relatively simple: one step consists of a filtering and a downsampling as it can be seen in Fig. 7. This step can be applied constitutively, as long as the number of the steps do not exceed the 2-based logarithm of the number of the points to be analysed. Both the high pass and the low pass convolution filter have the same coefficients during the transformation process, and means approximately halving the resolution (frequency) at each step.

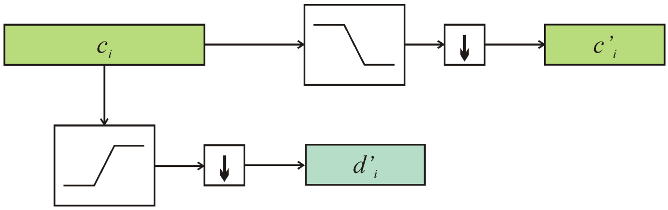


Fig. 7. One step of the discrete wavelet transform. After the high pass (direction down) and low pass (direction right) convolutional filters a downsampling by two unit is plotted by the downward arrow. The transformed vectors c'_i and d'_i are approximately half in the size compared to the original c_i.

The results will be the lowest resolution level (last) vector c'_i and all the vectors d'_i. The vectors d'_i carry the information about the fine-scale behaviour, whereas the vectors c'_i is a kind of weighted average, i.e., it describes the larger scale behaviour. Of course, the expressions "fine scale" and "large-scale" are roughening as the transformation steps carry on.

Theoretically the total number of the elements of the resulting vectors is approximately the same as that of the original vector c_i, so no information is lost in the process. In case of data compression, many of the vector components d'_i are omitted, as they are close to zero in the smooth parts of the functions, images, distributions that represented by the original c_i.

There exists a backward transform, which is the opposite of the one given in Fig. 7, from vectors d'_i and c'_i after an upsampling – filling in zeros between each of the vector elements – the inverse of the convolutional filters is applied and the results of the two branches are summarized. However, this step is not important for our purposes.

In the following considerations we do not study the fine scale components resulting from the analysis of the measured insertion loss data, only the rough scale coefficients. To be more precise, we are studying environments of the selected frequencies by two different wavelet families: Haar and the second Daubechies wavelet transform. As the Haar functions have only 2 filter coefficients (both 1), and due to the downsapmling there are no overlaps between the originals c_i of the neighbouring transformed points c'_i and d'_i, their low-pass components mean only an averaging. The low-pass transform with the 4-coefficient Daubechies filters means overlapped averaging with non-uniform coefficients. Both results gives information about the large-scale behaviour around the selected points, thus the representativeness of the frequency points to their environment.

3. Representativeness of the selected frequencies

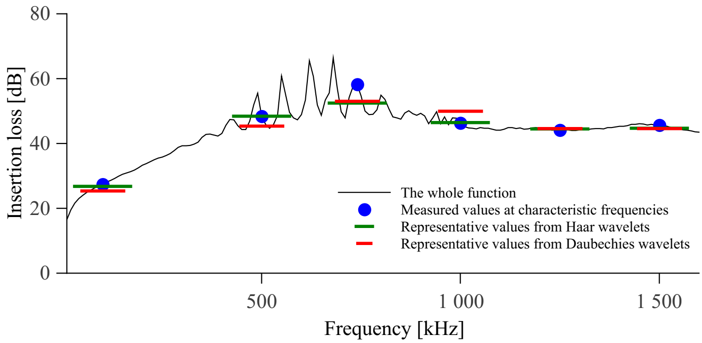
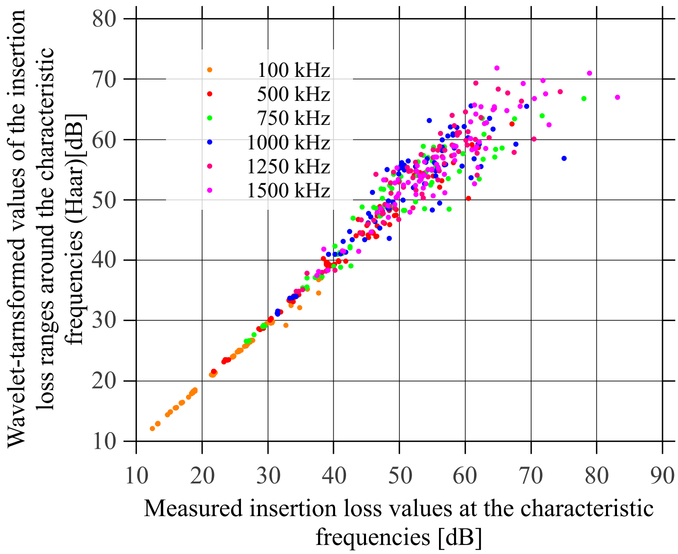


Fig. 8. Measured insertion loss and calculated levels by wavelet transformation.

One random wire pair's measured insertion loss function and its representative values resulting from the function's wavelet transforms can be seen in Fig. 8. Even though the insertion loss values measured at the six selected frequency points (indicated by blue ellipses) are close to the levels calculated by wavelet transformation (indicated by olive green lines) in the figure, in the case of a single line, the measured values at the characteristic frequencies have differences from the wavelet transformed values.

To check the deviations in case of all measured wire pairs, the wavelet transformed values versus the measured ones are plotted in Fig. 9. It can be seen that the dots are located very close to the ideal 45° line in case of higher insertion loss and higher frequencies, and follow the line in case of lower ones. It means, that although in case of some wire pairs the measured values and the levels calculated by wavelet transformation differ from each other – though this deviation is not too high –, statistically, the ranges of the insertion loss function are characterized well by the measured values at the six selected respective frequencies.

Though the whole insertion loss function is decently characterized by the values measured at the selected frequencies also in case of individual wire pairs, the alignment of the measured values with the ranges defined by the insertion loss values of the lines belonging to the corresponding bit rate clusters are much more important. The reason is that the antecedent fuzzy sets of the rule bases used in the performance evaluation represents a sort of model of the ranges disposed by the insertion loss values measured at the given frequency points. The selected discrete frequency points are appropriate if the wire pairs' physical properties measured at them fit to the ranges created from the insertion loss functions' wavelet transformed levels. Fig. 10 shows the results of this comparison. Corresponding areas derived from the wavelet transformed sections of the functions, denoted by red and blue lines, are followed by the ranges of measured values denoted by black lines in case of



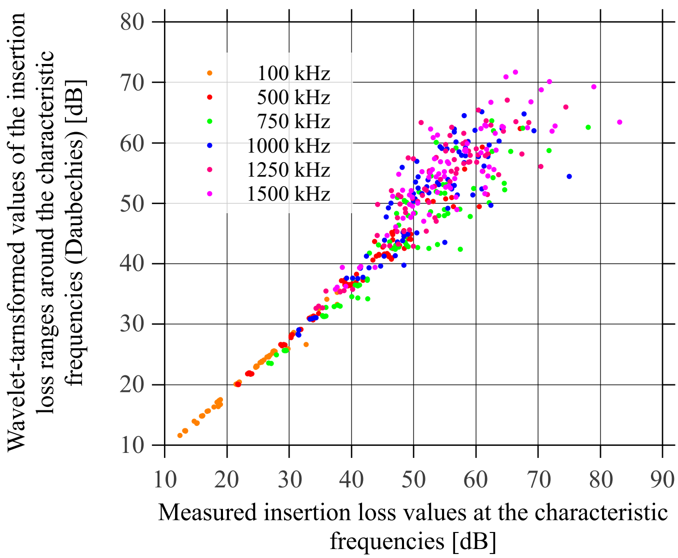


Fig. 9. Measured insertion loss and calculated levels by two different wavelet transformations of the lines used for deriving our rule bases. It can be seen that the selected frequency points of the measured functions represent quite well the large scale behaviour, however, the Haar wavelet transformed values lay significantly closer to the values measured than those of Daubechies transformed ones.

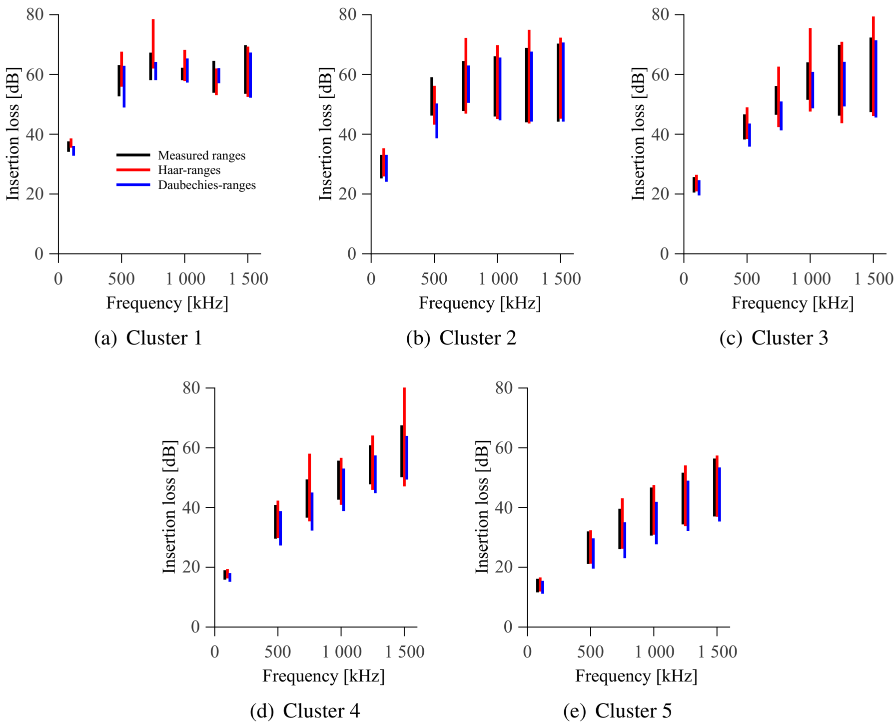


Fig. 10. Comparison of the insertion loss ranges measured at the characteristic frequencies with the ranges of wavelet transformed function environment around the characteristic frequencies by bit rate clusters.

all bit rate clusters. Minor deviations of the wavelet transformed ranges from the measured values can be noticed only in case of the cluster belonging to the lowest bit rates. As clear and strict mathematical formula does not exist for the connection between the physical properties of the wire pairs and the available maximal bit rates this kind of small deviation is acceptable in performance evaluation. The importance of the discrepancy is lessened by the fact that the deviations of all examined wire pars are depicted together in the same figure, but in the case of singular lines, generally, this degree of the deviation can be noticed only at one frequency point.

4. Conclusions, future work

The examination of characteristic frequencies of insertion loss in performance evaluation of access networks' wire pairs was presented. After the description of a novel approach for the performance evaluation and the problem with the used frequency points in the evaluation, the usage of the wavelet transformation as method of the examination was explained. Beside experimental observations, also theoretical results showed that the selected frequency points are appropriate for being used as characteristic frequencies in the measurement of the wire pair evaluation.

Using ranges of wavelet transformed sections of the functions of physical properties which are the basis of the evaluation showed that new type, wavelet based rule bases can help to reduce the number of the antecedent dimensions. In the future the reduction of the antecedent dimensions' number by wavelet analysis is planned.

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