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THE USE OF COMPLEX IMPEDANCE AS A PARAMETER FOR WOOD DIFFERENTIATION

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ABSTRACT

Electrical and dielectric wood properties are used in many applications. Wood parameters such as resistance, conductivity, complex impedance can be used e.g. for determination fungal decay, moisture content and density or for defects detection. In this work, the complex impedance of seven wood species was measured for frequency range 10 Hz - 1 MHz. The specimens were cut from sapwood and heartwood and measurements were conducted with parallel and perpendicular orientation of the electrical field with respect to the visible grain. The impedance of various wood types differs significantly for frequencies below 2 kHz. Therefore, for wood samples classification, the complex impedance values measured in frequency 1.1 kHz were used. Three different classification methods were used for clustering. Results show that the impedance can be a useful parameter for wood differentiation and membership of each group depends on number of clusters.

KEYWORDS: Complex impedance, clustering, wood classification.

INTRODUCTION

Wood is a material widely used for many purposes because of large number of its advantages in comparison with other materials. For example it's used in civil engineering as a building material, for furniture manufacturing, as a biomass in combustion process. Wood is a light material with low thermal conductivity and it can be easily treated. At the same time wood is non-humidity-resistant and can decay and deform. Wood consists of the cellulose, lignin and hemicellulose. It is an anisotropic porous substance with porosities ranging from 50 to 80 vol. %. The main cells in wood are parallel to the growth direction. There is significant difference between hardwoods and softwoods microstructure. The hardwood's cells are smaller and with large-diameter vessels transporting water. In the softwoods cells are larger and longer than in the hardwoods and microstructure has a more ordered arrangement. In both, hardwoods and softwoods, there are also smaller pores running in the radial direction. The open microstructure of softwoods generally results in its higher volume porosity than hardwoods (Duchow and Gerhardt 1996).

Electrical and dielectric wood properties depend on several factors such as wood species, temperature, moisture content, density, chemical properties, fiber direction, process of impregnation with preservatives and field frequency (Avramidis et al. 2006; Brischke and Lampen 2014; Brischke et al. 2014; Forrer and Funck 1998; Fredriksson et al. 2013; Husein et al. 2014; Kabir et al. 1998; Tiitta et al. 2003). The electrical and dielectric properties of wood are essential for its efficient use in many applications. In a prior literature one can find many reports describing the use of electrical and dielectric parameters for nondestructive and accurate measurements of wood features. Electrical resistance measurements provide information about wood moisture content (Brischke and Lampen 2014). Relationships between resistance and moisture content for different wood species and for the same species with different provenances have been investigated (Brischke et al. 2008; Forsen and Tarvainen 2000). The electrical resistivity tomography was used to determine the sapwood–heartwood boundary of *Pinus* trees (Guyot et al. 2013), to construct a spatial estimate of tree resistivity across the entire tree stem cross-section (al Hagrey 2007), to map changes in stem moisture content over time in *Populus* trees (Wu et al. 2009) and to determine fungal decay in tree stems (Bieker et al. 2010; Brazee et al. 2011). The THz time domain spectroscopy was used for wood moisture content and density determination (Inagaki et al. 2014), defect detection (Oyama et al. 2009) and dendrochronology (Jackson et al. 2009). The possibility of the detection of knot, defects and spiral grain (Kabir et al. 1998) as well as the differences in volume porosity and the arrangement of the longitudinal and radial pores (Duchow and Gerhardt 1996) by measuring dielectric properties was also reported. The dielectric properties of wood may be useful parameters for dielectric-based scanning of wood surfaces (Forrer and Funck 1998). It was reported that complex impedance was sufficient to distinguish between the samples from the brown-rot resistant and susceptible *Scots pine* trees (Tiitta et al. 2003).

Clustering is a fundamental method of data analysis. The aim of clustering is to divide a set of objects into groups (clusters) in a way that objects from the same group have a high degree of similarity. At the same time objects from various groups are different using the same criterion. Cluster analysis (CA) can be used only for discovering data structures without explanation of their nature. CA (segmentation analysis, taxonomy analysis) is the group of various algorithms and methods. It's widely used in many research fields like medicine, biology, food processing technology, agricultural engineering etc. (Andres-Agustin et al., 2006; Arciola et al. 2007; Medina et al. 2010; Rahman and Gamon 2004).

Except classical CA methods like hierarchical clustering or k-means clustering, also other methods are used. In this group of methods, artificial neural networks (ANN) can be found. The choice of certain clustering method depends on the nature of data and one should realize that different methods can provide different results.

MATERIAL AND METHODS

Wood samples

As summarized in Tab. 1, the seven native soft- and hardwoods were included in the tests.

Tab. 1: Wood species used for determination of complex impedance.

Wood species	Botanical name	Moisture content range (%)
Sweet cherry	*Prunus avium* L.	10.0 – 15.5
Roth birch	*Betula pendula* Roth	12.5 – 15.5
Oak	*Quercus robur* L.	13.5 – 18.0
Ash	*Fraxinus excelsior* L.	14.0 – 16.0
European larch	*Larix decidua* Mill.	10.5 – 15.5
Scotch Pine	*Pinus sylvestris* L.	9.5 – 15.0
Norway spruce	*Picea abies* L.	8.5 – 12.0

For each wood species four specimens cut from different parts of stem were prepared and labelled as wood species name with number from 1 to 4, e.g. oak1, oak2, oak3 and oak4. Afterwards, from each specimen, four rectangular specimens (60 x 60 x 15 mm, width x length x height) were cut - with the surfaces which have contact with electrodes during measurement oriented parallel and perpendicular with respect to the visible grain (each from sapwood and heartwood). Two surfaces of the specimen were smoothed with sand paper in order to ensure a good contact with electrodes. The moisture content was measured by means of Brookhuis Micro-Electronics FME moisture meter. The complex impedance measurements were carried out with a parallel plate electrodes at frequencies from 10 Hz to 1 MHz by using ATLAS 0441 HIA apparatus. In result of measurement procedure each wood species was described by complex impedance values measured for four specimens. For each specimen complex impedance was measured for four types of samples: from sapwood and heartwood and with parallel and perpendicular orientation of the electrical field with respect to the visible grain.

Cluster analysis

In this study three cluster analysis methods implemented in Statistica 10 software were used.

Joining (Tree clustering)

In this algorithm data are grouped into clusters iteratively. Objects are joined together into successively larger clusters of increasingly dissimilar elements on the basis of the metric of similarity. At the beginning, each object represents class by itself. In the last step of algorithm, all objects are joined together. A typical result of this type of clustering is the hierarchical tree (dendrogram). For tree clustering performance, two parameters have to be defined: a way to quantify the similarity of two objects (linkage distance) and linkage rule. The most intuitive metric for calculating distance between two points in Euclidean space is Euclidean distance (Eq.1).

$$d(x,y)=\sqrt{\sum_i (x_i-y_i)^2} \tag{1}$$

The other typical metrics used for distance calculation are Squared Euclidean distance, City-block (Manhattan) distance and Chebychev distance. When there is the significant difference in values range, the data standardization is recommended in order to avoid the unequal influence of variables describing objects in data set.

In tree clustering implemented in Statistica software, some linkage rules are available.

The most popular are as follows:

Single linkage (nearest neighbor) where the distance between two clusters is calculated as the distance of the two closest objects from these clusters.

Complete linkage (furthest neighbor) where the distance between two clusters is determined using the greatest distance between any two objects in these clusters.

Centroid linkage where the distance between two clusters is calculated as the distance between the centroids of these clusters. The centroid of a cluster is the average point in the multidimensional space defined by the dimensions.

Average linkage where the distance between two clusters is determined by the use of average distance between all pairs of objects in the two separate clusters (www.statsoft.com).

k-Means Clustering

This method of clustering is one of the well known clustering techniques. In k-means clustering the number of clusters has to be given a priori. The algorithm starts by choosing randomly k initial cluster centers. In the next step, the algorithm assigns every point from the data set to one of the clusters (the cluster having the closest center) (Wang 1983). Afterwards, the cluster memberships and the cluster centers are being changed during algorithm iterations until some stop criterion is met. When the different initial cluster centers are chosen in the first step of algorithm, the different results of clustering can be obtained and it may also affect the speed of convergence.

Kohonen neural networks

Artificial neural networks are very often used for solving classification tasks. ANN consists of many elements (neurons or nodes) linked by weighted connections and organized in layers. The very popular ANN type used as a classification tool is Kohonen neural network (KNN). It's the type of self-organizing maps (SOM) where the unsupervised algorithms are usually used in network training process. The KNN is used for mapping the high-dimensional data set onto a low-dimensional information describing how the data set can be divided into separate clusters. Typical KNN consists of two layers: an input layer and an SOM (competitive) layer (Fig. 1).

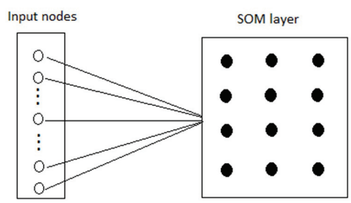

Fig. 1: The structure of Kohonen neural network.

The neurons (nodes) in input layer only transmit information to the neurons in competitive layer. Each neuron in SOM layer is connected to each input node but neurons in SOM layer are not connected to each other. In the first step of training algorithm, the weights of each neuron in SOM layer are set randomly. Afterwards, the Euclidian distance between input vector and the weight vectors is calculated (Eq. 2)

$$d(x, w_i) = \|x - w_i\| = \sqrt{\sum_{j=1}^{N} (x_j - w_{ij})^2} \qquad (2)$$

where: x - input vector,
w_i - weights vector of i-th neuron in competitive layer,
N - the number of weights.

The neuron in SOM layer that produces the smallest distance and its neighbors determined on the basis of the radius of the neighborhood (R) value change their weights in order to reduce the distance. Typically, R value is large in the first training cycle and is diminished with each time-step. The training process is stopped after a predefined number of training cycles. When the Euclidian distance is used for distance calculation, input vector elements and weights should be normalized to the same range, usually <0 – 1>. After learning process, neurons in competitive layer can „recognize" groups of input data. The theory of KNN has been described in several papers (Melssen et al. 2006; Ribeiro et al. 2014; Song and Hopke 1996).

In this work, the raw data used for classification task executed by each of methods described above were normalized to the range <0.1 – 1>. For Tree Clustering, as a linkage rule, the single linkage was used and for distance calculation, the Euclidean distance was implemented. For k-Means Clustering, the method of selection the initial cluster centers guarantees maximum distance between cluster centers in the first step of algorithm. The number of iterations was set as 30. During KNN training process, the epochs number was set as 2000, the learning rate was reduced from 0.1 to 0.02, the radius of the neighborhood was set as 1 and the initial value of weights vector was set randomly according to the Gaussian distribution. The data set was divided into training set (80 % of samples) and testing set (20 % of samples).

RESULTS AND DISCUSSION

The samples impedance was measured for frequency range from 10 Hz to 1 MHz.

In Figs. 2 and 3 the dependence between the real and imaginary part of impedance and frequency (in the range 10 Hz – 4 kHz) for selected wood samples is presented. The samples were taken from the heartwood and impedance was measured for parallel orientation of the electrical field with respect to the visible grain. The frequency range presented in figures was decreased and only three wood samples were chosen to show in order to make graphs more readable. For frequencies above 4 kHz, the differences between impedance of various wood samples are not noticeable. The data presented in Figs. 2 and 3 show that real part as well as imaginary part of impedance measured for samples of various wood types differ significantly only for lower frequencies (not exceeding 2 kHz). Therefore, for wood samples classification, the complex impedance values measured in frequency 1.1 kHz were used in this work. The eight parameters describing each sample were included into input vector: real and imaginary part taken separately and measured for parallel and perpendicular orientation of the electrical field with respect to the visible grain and for specimen taken from sapwood and heartwood.

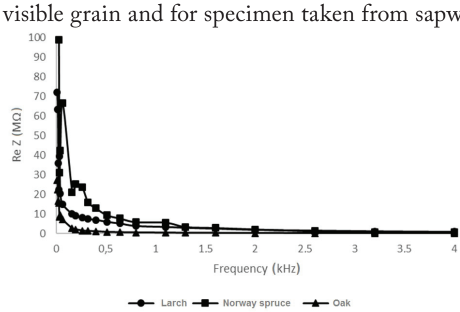

Fig. 2: The frequency dependence of the real part of impedance for larch, Norway spruce and oak.

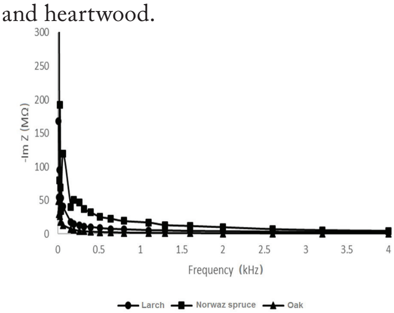

Fig. 3: The frequency dependence of the imaginary part of impedance for larch, Norway spruce and oak.

The very important wood parameter which significantly influences on electrical parameters is moisture content. Therefore, Pearson's correlation coefficients between moisture content and real as well as imaginary part of impedance were calculated. The results are presented in the Tab. 2 and they show that linear correlation between wood moisture content and complex impedance is not very high. In the publication Tiitta et al.(2005) the significant correlation between moisture content and complex impedance of Scots pine is reported. Authors were measured impedance for the frequency range of 5 kHz – 1 MHz, for only one wood species and they observed high correlation over the whole frequency range. Also Tomppo et al. (2011) and others reported high correlation between impedance and moisture content for the same wood species in frequency range 1 Hz – 10 MHz. The analysis of clustering results presented in this work with regard to samples moisture content indicate that samples of the same wood species with different moisture content were assigned to the same cluster. It means that in case of several wood species the parameters which characterize certain wood species influence on impedance measured for lower frequency (1.1 kHz) more than moisture content.

Likewise, the analysis of clustering results with regard to samples moisture content indicate that samples of the same wood species with different moisture content were assigned to the same cluster.

Tab. 2: Pearson's correlation coefficients between moisture content and complex impedance ($p<0.05$).

	Real part of impedance	Imaginary part of impedance
Moisture content	-0.60	-0.76

Three different classification methods were used because different methods used for clustering and even different parameters of these methods can cause dissimilarities in obtained results.

Joining (Tree Clustering)

The typical result of joining method is dendrogram. In Fig. 4 the horizontal dendrogram describing clustering results is presented.

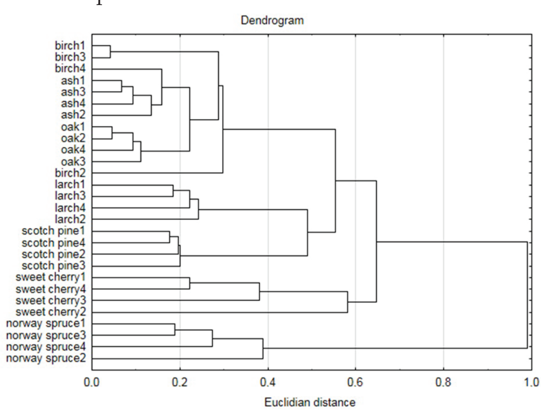

Fig. 4: Cluster dendrogram generated for wood samples.

The results presented in Fig. 4 show that samples of the same wood species are generally assigned to the same cluster with a low Euclidian distance. E.g. four oak samples are joined together with Euclidian distance not exceeding 0.15. Higher distance is observed for sweet cherry and Norway spruce samples. The graph shows a high similarity between birch, oak and ash samples (the distance not exceeding 0.3) as well as between larch and Scotch pine (the distance not exceeding 0.5). According to the dendrogram, Norway spruce samples are completely different from other wood species.

k-Means clustering

In this clustering method, the number of clusters must be given a priori. In the Tab. 3 the results of clustering obtained by k-means method with the different number of clusters are shown.

When k-Means Clustering method divides data set into two clusters, Norway spruce samples with one sample of sweet cherry are selected as one cluster and other samples are selected as the second cluster. For three clusters, sweet cherry and Norway spruce samples are recognized as two separate clusters and other samples are joined together as the third cluster. When the number of clusters is defined as four, the separate clusters membership is as follows: birch, oak and ash; sweet cherry; Norway spruce; larch and Scotch pine. When the number of clusters is the same as number of wood species, oak and ash are joined together into one cluster. Larch, Scotch pine and Norway spruce are assigned to separate clusters representing each species. In case of birch and sweet cherry, not all four samples of certain species are assigned to the same cluster. The results are similar to those obtained by means of Tree Clustering method and confirm the significant difference between Norway spruce and other wood species and similarity between larch and Scotch pine as well as between birch, oak and ash. When the data set has to be divided into more clusters, generally each cluster represents one wood species.

Tab. 3: Clusters membership and the distance from cluster center.

Sample	Two clusters		Three clusters		Four clusters		Seven clusters	
	Cluster	Distance	Cluster	Distance	Cluster	Distance		
birch1	1	0.12	1	0.13	4	0.08	2	0.04
birch2	1	0.17	1	0.19	4	0.17	2	0.07
birch3	1	0.11	1	0.12	4	0.08	2	0.04
birch4	1	0.16	1	0.15	4	0.07	1	0.06
sweet cherry1	1	0.27	3	0.00	2	0.00	7	0.04
sweet cherry2	2	0.29	3	0.21	2	0.21	6	0.00
sweet cherry3	1	0.25	3	0.15	2	0.15	7	0.00
sweet cherry4	1	0.27	3	0.08	2	0.08	7	0.04
oak1	1	0.17	1	0.15	4	0.09	1	0.06
oak2	1	0.17	1	0.15	4	0.09	1	0.06
oak3	1	0.17	1	0.16	4	0.07	1	0.05
oak4	1	0.18	1	0.16	4	0.11	1	0.09
ash1	1	0.11	1	0.12	4	0.05	1	0.06
ash2	1	0.09	1	0.10	4	0.07	1	0.08
ash3	1	0.13	1	0.14	4	0.06	1	0.07
ash4	1	0.13	1	0.13	4	0.05	1	0.05
larch1	1	0.26	1	0.25	1	0.12	4	0.00
larch2	1	0.23	1	0.23	1	0.09	4	0.09
larch3	1	0.27	1	0.26	1	0.16	4	0.07
larch4	1	0.31	1	0.29	1	0.17	4	0.08

scotch pine1	1	0.16	1	0.16	1	0.12	3	0.00
scotch pine2	1	0.20	1	0.21	1	0.16	3	0.07
scotch pine3	1	0.12	1	0.13	1	0.10	3	0.07
scotch pine4	1	0.19	1	0.18	1	0.15	3	0.06
norway spruce1	2	0.07	2	0.00	3	0.00	5	0.00
norway spruce2	2	0.16	2	0.14	3	0.14	5	0.14
norway spruce3	2	0.09	2	0.07	3	0.07	5	0.07
norway spruce4	2	0.12	2	0.10	3	0.10	5	0.10

Kohonen neural networks

When KNN are used for solving the clustering task, the number of nodes in input layer is adequate to the number of parameters describing samples. In this case, the number of input nodes was defined as eight. The number of neurons in SOM layer and the map structure must be defined by the user. In the Tab. 4 the results of clustering obtained by KNN for various structures of SOM layer are shown.

Tab. 4: Clusters membership presented as the position of "winning" neuron in SOM layer for each sample.

Sample	"Winning" neuron position			
	SOM layer structure			
	1x2	1x3	2x2	3x3
birch1	(1, 1)	(1, 3)	(1, 1)	(3, 2)
birch2	(1, 1)	(1, 3)	(1, 1)	(3, 2)
birch3	(1, 1)	(1, 3)	(1, 1)	(3, 2)
birch4	(1, 1)	(1, 3)	(1, 1)	(3, 1)
sweet cherry1	(1, 1)	(1, 2)	(1, 1)	(3, 3)
sweet cherry2	(1, 1)	(1, 1)	(1, 2)	(2, 3)
sweet cherry3	(1, 1)	(1, 3)	(1, 1)	(3, 3)
sweet cherry4	(1, 1)	(1, 2)	(1, 1)	(3, 3)
oak1	(1, 1)	(1, 3)	(1, 1)	(3, 1)
oak2	(1, 1)	(1, 3)	(1, 1)	(3, 1)
oak3	(1, 1)	(1, 3)	(1, 1)	(3, 1)
oak4	(1, 1)	(1, 3)	(1, 1)	(3, 1)
ash1	(1, 1)	(1, 3)	(1, 1)	(3, 1)
ash2	(1, 1)	(1, 3)	(1, 1)	(3, 1)
ash3	(1, 1)	(1, 3)	(1, 1)	(3, 1)
ash4	(1, 1)	(1, 3)	(1, 1)	(3, 1)
larch1	(1, 2)	(1, 2)	(2, 1)	(1, 1)
larch2	(1, 2)	(1, 2)	(2, 1)	(1, 1)
larch3	(1, 2)	(1, 2)	(2, 1)	(1, 1)
larch4	(1, 2)	(1, 2)	(2, 1)	(1, 1)
scotch pine1	(1, 2)	(1, 2)	(2, 2)	(1, 1)
scotch pine2	(1, 2)	(1, 2)	(2, 2)	(1, 1)
scotch pine3	(1, 2)	(1, 2)	(2, 2)	(1, 1)
scotch pine4	(1, 2)	(1, 2)	(2, 2)	(1, 1)
norway spruce1	(1, 2)	(1, 1)	(1, 2)	(1, 3)
norway spruce2	(1, 2)	(1, 1)	(1, 2)	(1, 3)
norway spruce3	(1, 2)	(1, 1)	(1, 2)	(1, 3)
norway spruce4	(1, 2)	(1, 1)	(1, 2)	(1, 3)

When in SOM layer only two neurons are defined, the network model divides the data set into cluster representing softwoods and cluster representing hardwoods. For SOM layer containing three neurons: Birch, oak and ash are joined together as well as larch with Scotch pine. Norway spruce samples form the separate group. Samples of sweet cherry are assigned to three different groups. For the map structure 2x2 the data set is divided as follows: three separate groups representing wood species: Larch, Scotch pine, Norway spruce and one big cluster representing hardwoods. When SOM layer contains nine neurons arranged as 3x3 map, three neurons don't "recognize" input vectors (dead neurons) and one neuron represents cluster containing only one sample – neuron (2,3) with sample sweet cherry 2. In case of bigger map structure, the neighborhood phenomena can be used for clusters similarity interpretation. In Fig. 5 the results obtained for 3x3 SOM layer structure are shown.

larch1 scotch pine1 larch2 scotch pine2 larch3 scotch pine3 larch4 scotch pine4		norway spruce1 norway spruce2 norway spruce3 norway spruce4
		sweet cherry2
oak1 ash1 oak2 ash2 oak3 birch4 ash3 oak4 ash4	birch1 birch2 birch3	sweet cherry1 sweet cherry3 sweet cherry4

Fig. 5: Clustering results presented in map form.

KNN with nine neurons in SOM layer divides wood samples into six clusters. Larch and Scotch pine as well as oak and ash are joined together. Norway spruce, sweet cherry and birch samples form separate clusters representing each wood species. Clusters containing larch and Scotch pine – neuron (1, 1) and Norway spruce – neuron (1, 3) are not similar to other clusters. Clusters represented by neuron (3, 1) – oak and ash, neuron (3, 2) – birch and neuron (3, 3) - sweet cherry are more similar to each other. Two samples are assigned to clusters representing different wood species – birch 4 and sweet cherry 2. But the clusters representing birch and sweet cherry are located beside clusters containing "lost" samples.

Generally, when the number of clusters given a priori is high enough or the clustering method fits the number of clusters to data set, the samples are divided into groups representing wood species. The research results reported in a prior literature show the strong correlation between wood density and impedance at high frequencies (about 1 Mhz) for sapwood specimens of Scots pine (Tiitta et al. 2005). In the report of Lis and Rapp (2005) the density of dry wood for some wood species is presented. The results presented in this work show, that wood samples classified as similar according to complex impedance are different according to density measured by Lis and co-authors. E.g. cluster analysis show high similarity between larch (the density equals 690 kg.m^{-3}) and Scotch pine (the density equals 520 kg.m^{-3}) and low similarity between Norway spruce (the density equals 470 kg.m^{-3}) and Scotch pine (the density equals 520 kg.m^{-3}) as well as low similarity between birch (the density equals 650 kg.m^{-3}) and larch (the density equals 690 kg.m^{-3}). Only oak and ash classified as similar species are described by similar density (the density equals 710 kg.m^{-3} and 750 kg.m^{-3} respectively). These results can lead to assumption that some other physical and chemical parameters which differentiate wood species influence significantly on electrical parameters. Tomppo et al. (2011) show significant correlations between impedance phase angle and contents of stilbenes and resin acids for Scots pine. More interesting results are reported by Gora and Yanoviak (2015) and prove that the resistivity differs among species and growth forms without respect to regional origin of wood. The results presented in this work as well as obtained by other authors suggest that impedance is the electrical parameter which can be potentially useful for wood species differentiation and provide a framework for studying the relationships between certain physical and chemical parameters which differentiate wood species and electrical parameters.

CONCLUSIONS

The analysis of results leads to the conclusion that complex impedance can be useful parameter for wood differentiation when impedance measurement is taken for samples cut from sapwood and heartwood, the electrical field is oriented parallel and perpendicular with respect to the visible grain and frequency doesn't exceed 2 kHz. The results obtained by three different methods prove that in case of methods where the number of clusters is given a priori, the results depend on this parameter. When the number of clusters defined for k-Means Clustering and the number of neurons in SOM layer of KNN is large enough, the results are similar to those obtained by Tree Clustering method. Generally, when the number of clusters equals two, the samples are divided into two groups representing softwoods and hardwoods. When the number of clusters is large enough, the samples are divided into groups representing wood species. The results obtained by Tree Clustering method and KNN with SOM layer with 3x3 topology prove high similarity between birch, ash and oak as well as between larch and Scotch pine. Moreover, the results show dissimilarity between Norway spruce as well as sweet cherry and other wood species.

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