

Research Article

Prototype of the Near-Infrared Spectroscopy Expert System for Particleboard Identification

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The overall goal of this work was to develop a prototype expert system assisting quality control and traceability of particleboard panels on the production floor. Four different types of particleboards manufactured at the laboratory scale and in industrial plants were evaluated. The material differed in terms of panel type, composition, and adhesive system. NIR spectroscopy was employed as a pioneer tool for the development of a two-level expert system suitable for classification and traceability of investigated samples. A portable, commercially available NIR spectrometer was used for nondestructive measurements of particleboard panels. Twenty-five batches of particleboards, each containing at least three independent replicas, was used for the original system development and assessment of its performance. Four alternative chemometric methods (PLS-DA, kNN, SIMCA, and SVM) were used for spectroscopic data classification. The models were developed for panel recognition at two levels differing in terms of their generality. In the first stage, four among twenty-four tested combinations resulted in 100% correct classification. Discrimination precision with PLS-DA and SVMC was high (>99%), even without any spectra preprocessing. SNV preprocessed spectra and SVMC algorithm were used at the second stage for panel batch classification. Panels manufactured by two producers were 100% correctly classified, industrial panels produced by different manufacturing plants were classified with 98.9% success, and the experimental panels manufactured in the laboratory were classified with 63.7% success. Implementation of NIR spectroscopy for wood-based product traceability and quality control may have a great impact due to the high versatility of the production and wide range of particleboards utilization.

1. Introduction

Particleboard is a panel product manufactured from lignocellulosic materials, combined with an adhesive system and bonded together under heat and pressure. Particleboards are easy to process and flexible in application. They are mainly used for furniture production, but in combination with other materials, they might be used for parquet, insulation materials, sheathing boards for timber framed walls, packaging, or “do-it-yourself products.” The major types of particles used to manufacture particleboard include wood shavings, flakes, wafers, chips, and sawdust [1].

A new strategy of EU aims at increasing the share of bioenergy in the EU's total energy production. It is expected that 20% of the energy produced in Europe after 2020 will be from renewable resources, where 80% of the above will be related to lignocellulosic feedstock. Simultaneously, a significant increase in the production volumes for other wood-based products (pulp, boards, and furniture) is expected. Therefore, even if supply and demand of wood on the market is balanced at present, it will most probably not be in equilibrium within the coming years [2]. As a consequence, several alternative resources, mainly agricultural and industrial residues, fast-growing shrubs and plantations, and

postconsumer wood, have received considerable attention in recent years [3]. Effective use of bagasse [4], oil palm waste [5], bark [6] paper sludge, [3], kenaf stalks [7] wheat straw [8], needle litter [9], vine pruning's [10] waste tissue paper, and corn peel [11] among others was previously reported. Such materials are ecological, functional, and environmental-friendly; therefore, they serve as sustainable raw materials for manufacturing particleboards. The type of raw resources used for panels manufacturing, its quality, size of particles, moisture content as well as type and amount of bonding system have significant effect on particleboard properties [12]. The most important quality assessment aspects of manufactured panels are emissions, which mainly depends on the type and amount of resin [1]. The recent trend to reduce the formaldehyde release from manufactured wood products has led to the substitution of urea-formaldehyde (UF) resin with several alternatives [12]. Liquefied wood was previously reported as an interesting replacement for commonly used adhesives [13–15]. The influence of liquefied wood on particleboard properties was previously investigated by the authors [16, 17]. However, alternative quality control tools with potential application for online process control are still desired.

Portable spectroscopic equipment operating in the NIR range is a highly interesting technology for the wood-based sector [18]. Meder et al. [19] reported successful implementation of FT-NIR spectroscopy for at-line measurement for quality control of melamine-urea-formaldehyde resin in composite wood-panel production. Taylor and Via [20] used visible and near-infrared spectroscopy to quantify phenol formaldehyde resin content in oriented strandboard. Campos et al. [21] used FT-NIR to evaluate composition of agro-based particleboards. Janiszewska et al. [22] reported the application of FT-NIR spectroscopy for clustering raw materials used for liquefaction and their transformation products. Even though several examples of NIR use for product and process quality monitoring have been reported, the majority of them rely on FT-NIR instruments that are relatively costly (both time and investment wise) and with limited applicability for inline measurement.

Numerous chemometric techniques for multivariate classification and discrimination were reported as suitable for processing of NIR spectra. These are usually divided into discriminant or class-modelling methods. In discriminant analysis, an unknown sample is always assigned and can be allocated only to one of the classes given in the training set. The class-modelling approach is more flexible. The sample can be accepted by more than one class model and therefore be recognized as confused. The most common classification methods are linear discriminant analysis (LDA), partial least-squares discriminant analysis (PLS-DA), k-nearest neighbours (kNN), SIMCA, and SVM [23].

LDA is a probabilistic method, which assumes that each sample belonging to a particular class follows a multivariate Gaussian distribution. It requires the explicit calculation of this probability for the formulation of the classification rule. The main disadvantage of this method is the fact that it requires a significantly higher number of training samples

than the number of variables, the variables themselves cannot be correlated, and all categories have the same within-class scatter, which is hard to assure in many experimental cases [23].

PLS-DA is a multivariate inverse least-squares analysis method used to classify samples. It decomposes the spectra as linear combinations of principal components (PCs) that express the majority of the information (variability) contained in the global dataset. The predictor variables or latent variables (LVs) are generated from the input variables to maximize the variance between sample classes in the model [24].

KNN is nonparametric and instance-based algorithm. This means that it does not make any assumption on the underlying data distribution and does not use the training data to do generalization. The kNN makes decision based on the entire training data set. The object is classified by a majority vote of neighbours. According to Adeniyi et al. [25], the main advantages of this method are capability of handling training data that are too large to fit in memory, use of simple Euclidean distance to measure the similarities between training and test data, providing a faster and more accurate recommendation as a result of straightforward application.

Soft independent modelling of class analogy (SIMCA) is the most common supervised modelling method, representing class-modelling approach. It requires a training data set of samples with a set of attributes and their class membership. In SIMCA, a principal component analysis (PCA) is performed on each class in the data set; thus, a principal component model is used to represent each class. In SIMCA, there is no restriction on the number of measurement variables, and few samples per class are enough to run the model.

Data classification is a common task in machine learning. The support vector machine (SVM) is a very flexible method that makes no assumption regarding data. It is a nonlinear classification method that constructs a set of hyperplanes in a high- or infinite-dimensional space. Good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class [24]. It works by obtaining the optimal boundary of two groups in a vector space independent of the probabilistic arrangements of vectors in training set. When the linear boundary in low-dimension input space is not enough to separate two classes, SVM can create a hyperplane that allows linear separation in the higher dimension feature space [26]. SVM has been successfully used for data mining, pattern recognition, and artificial intelligence fields [18].

Practical implementation of discrimination methods in the wood-based industry is a challenging task. Wood is a heterogeneous and anisotropic biological material. The correct implementation of NIR spectroscopy for bio-based materials requires a complex approach [27]. A two-level expert system is proposed here for identification of particleboard panels with a portable, commercially available NIR spectrometer. The overall goal of this work was to develop a prototype system that might assist quality control and traceability of particleboard panels on the production floor.

2. Materials and Methods

Four different types of particleboards manufactured in the laboratory and in industrial plants were evaluated. The materials differed in terms of panel type (single-layer or three-layer), composition (industrial particles, recycled wood, or alternative lignocellulosic materials including fast-growing species), and the adhesive system (urea-formaldehyde (UF) resin, UF resin modified with liquefied wood (LW), or UF resin modified with starch). A summary of investigated panels is presented in Table 1. In total, 170 samples representing 25 variants were investigated. A colour image of representative samples surface for each variant is presented in Figure 1.

2.1. Particleboards Manufactured with Recycled Wood (D). Industrial wood particles obtained from a local wood-processing sawmill, containing 25% recycled wood content, were used as a raw material for particleboard production. The particles were sorted using an Allgaier vibration screening machine with screens of mesh diameters 8, 2, 1, and 0.5 mm. Particle fractions ≤ 8 mm and ≥ 1 mm were selected for particleboard production.

The adhesive was prepared as a mixture of an industrial urea-formaldehyde resin and liquefied wood (10–20% relative to the dry weight of the resin). The liquefied wood was prepared from four types of wood-processing industry wastes: mixed hardwood-softwood powder (LWP), pine (LP), beech sawdust (LB), and bark (LB) [16].

The industrial urea-formaldehyde glue resin characteristics were as follows: gel time of 75 seconds, viscosity 336 mPa·s, total solids content 69.4%, and pH 7.3. Urea-ammonium nitrate solution (46%) was used as a curing agent, constituting 1% of the resin dry mass.

Single-layered particleboards of 12 mm thickness with 0, 10, 15, and 20% liquefied wood content in the adhesive resin were produced in the laboratory. The nominal density of the panels was $650 \text{ kg}\cdot\text{m}^{-3}$. All boards were conditioned after pressing at 20°C and 65% relative humidity. Nine types of single-layer panels were prepared with different adhesives system, as listed in Table 1. Each panel type was produced in two independent batches. Six replicates for each panel were analysed; in total, 108 samples were investigated.

2.2. Particleboards Manufactured with Fast-Growing Wood Species (S). Single- and three-layer particleboard panels were manufactured from Eastern red cedar (*Juniperus virginiana* L.) using 9% urea-formaldehyde, or a combination of 15% modified corn starch and 2% urea-formaldehyde adhesive. Three types of samples were prepared: type A: single-layer board with 9% UF; type B: three-layer board with 9% UF; and type C: three-layer board with a combination of 15% starch and 2% UF. All boards were produced in a laboratory press using a pressure of 5 MPa, at a temperature of 165°C for 5 and 10 minutes in the case of modified corn starch bonded samples [28]. Six independent replicates for each panel were analysed with an NIR spectrometer.

2.3. Particleboards Manufactured with Alternative to Wood Lignocellulosic Plants (G). Three-layer particleboards with the core made from different biomasses were produced, including Black locust (*Robinia pseudoacacia* L.), miscanth (*Miscanthus sinensis giganteus*), willow (*Salix viminalis*), and rapeseed (*Brassica napus*). The stalks of lignocellulosic materials were reduced in size with a Pallmann's chipper. Fractions smaller than 10 mm and bigger than 1 mm were used for the core of the panels. The chips were used for manufacturing four types of three-layer boards of 16 mm thickness, with the raw density of $680 \text{ kg}\cdot\text{m}^{-3}$ [29]. Six independent replicates for each panel were analysed with an NIR spectrometer.

2.4. Industrially Manufactured Particleboards (P). Three-layer urea-formaldehyde resin-bonded particleboards, type P2, suitable for non-load-bearing purposes in dry areas, manufactured by six diverse manufacturing plants of a corporation were used as reference industrial samples. In addition, panels with different thicknesses (38 mm, 28 mm, 18 mm, and 8 mm) prepared by a single producer were investigated. Three replicates for each panel type were analysed using NIR spectroscopy.

2.5. Spectroscopic Measurement and Data Mining. The MicroNIR 1700 compact sensor produced by Viavi Solutions (Santa Monica, CA, USA) was used for spectroscopic measurements. Each spectrum was measured as an average of 10 consecutive scans. The scanning frequency was 50 Hz, corresponding to 20 ms of integration time. The spectral range was from 950 to 1650 nm ($10526\text{--}6060 \text{ cm}^{-1}$). 128 spectral points were defined for each spectrum and corresponded to pixels of the CCD detector of the instrument. Ten independent measurements were done on each panel assuring measurements at different locations over its surface. Each set of 10 spectra was preprocessed with extended multiplicative scatter correction (EMSC) and after that averaged to homogenize the spectral fingerprint of heterogeneous surfaces of panel. The MicroNIR instrument has the proven potential for in-field and inline applications due to its rigid construction and integration of all optical, electronic, and mechanical components.

PLS_Toolbox 8.0 (Eigenvector Research, Manson, WA, USA) and LabView 13 (National Instruments, Austin TX, USA) were used for data processing and mining. Four discriminant analysis methods: PLS-DA, SVM, KNN, and SIMCA, were used for spectra classification. Models were calculated considering use of the raw spectra and spectra preprocessed with normalization, standard normal variate (SNV), EMSC, and 1st and 2nd derivatives (Savitzky–Golay algorithm, 2nd polynomial order, and 15 smoothing points). The order of data was randomized and then divided into calibration (66%) and independent validation (34%) data sets. The samples used for model validation were all different from those used for calibration.

TABLE 1: Manufactured panels investigated in this research.

Source	Sample code	Manufacturing	Panel type	Raw material	Adhesive system
Project LIDER	D1	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	0% LW + 100% UF1
	D2	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	10% LWP +90% UF1
	D3	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	15% LWP + 85% UF1
	D4	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	20% LWP + 80% UF1
	D5	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	20% LP + 80% UF1
	D6	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	20% LB + 80% UF1
	D7	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	20% LBK + 80% UF1
	D8	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	0% LW + 100% UF2
	D9	Laboratory	Single-layer	Industrial particles containing 25% of recycled wood	10% LWP + 90% UF2
OSU	S1	Laboratory	Single-layer	100% red cedar particles	9% UF
	S2	Laboratory	Three-layer	100% red cedar particles	9% UF
	S3	Laboratory	Three-layer	100% red cedar particles	15% starch and 2% UF
ITD	G1	Laboratory	Three-layer	Industrial pine particles (75%) + black locust particles (25%)	Core 8% UF, face layers 12%
	G2	Laboratory	Three-layer	Industrial pine particles (75%) + <i>Miscanthus</i> particles (25%)	Core 8% UF, face layers 12%
	G3	Laboratory	Three-layer	Industrial pine particles (75%) + willow particles (25%)	Core 8% UF, face layers 12%
	G4	Laboratory	Three-layer	Industrial pine particles (75%) + rapeseed particles (25%)	Core 8% UF, face layers 12%
Chipboard panel producer	P1	Industry	Three-layer	100% industrial particles	UF
	P2	Industry	Three-layer	100% industrial particles	UF
	P3	Industry	Three-layer	100% industrial particles	UF
	P4	Industry	Three-layer	100% industrial particles	UF
	P5	Industry	Three-layer	100% industrial particles	UF
	P6a	Industry	Three-layer	100% industrial particles	UF
	P6b	Industry	Three-layer	100% industrial particles	UF
	P6c	Industry	Three-layer	100% industrial particles	UF
P6d	Industry	Three-layer	100% industrial particles	UF	

3. Results and Discussion

3.1. General Concept of the Expert System Architecture.

Expert systems are innovative process tools that enhance the user's productivity in accomplishing a task or solving a problem. These vary in at least two important dimensions, including knowledge and technological complexities [30]. Knowledge complexity is mainly determined by the degree of depth and specialization of the internalized knowledge, the scope of the decision, and the level of expertise required to solve the problem. The technological complexity includes diversity of hardware and software, the complexity of the user's environment, the scale of the software design effort, the complexity of required database accesses, and special user interfaces among others [30].

The main goal of this work was to develop an expert system capable of detecting and tracing different particleboards. The general concept of such a system implemented in the furniture

factory is presented in Figure 2. The system relies on the spectroscopic measurements acquired during arrival of the new batch to the factory floor with the easy-to-handle and portable instrument. The particular characteristics of the instrument investigated within this project allow its direct implementation in the real-life applications. It is recommended to average several NIR spectra collected from the characterized sample in order to minimize the heterogeneity effect of the complex surfaces of particleboards. A spectrum acquired in that way is considered as a fingerprint of the distinct batch and is recorded in the database for further analysis. The usage of spectra is twofold. Firstly, it is applied for the further improvement of the chemometric models by providing new case data. Secondly, it is used for future tracking and identification of elements during production as well as in final products.

The NIR spectrum of an unknown sample is confronted at the first level of the expert system with broad classes representing different particleboard manufacturers or panel types.

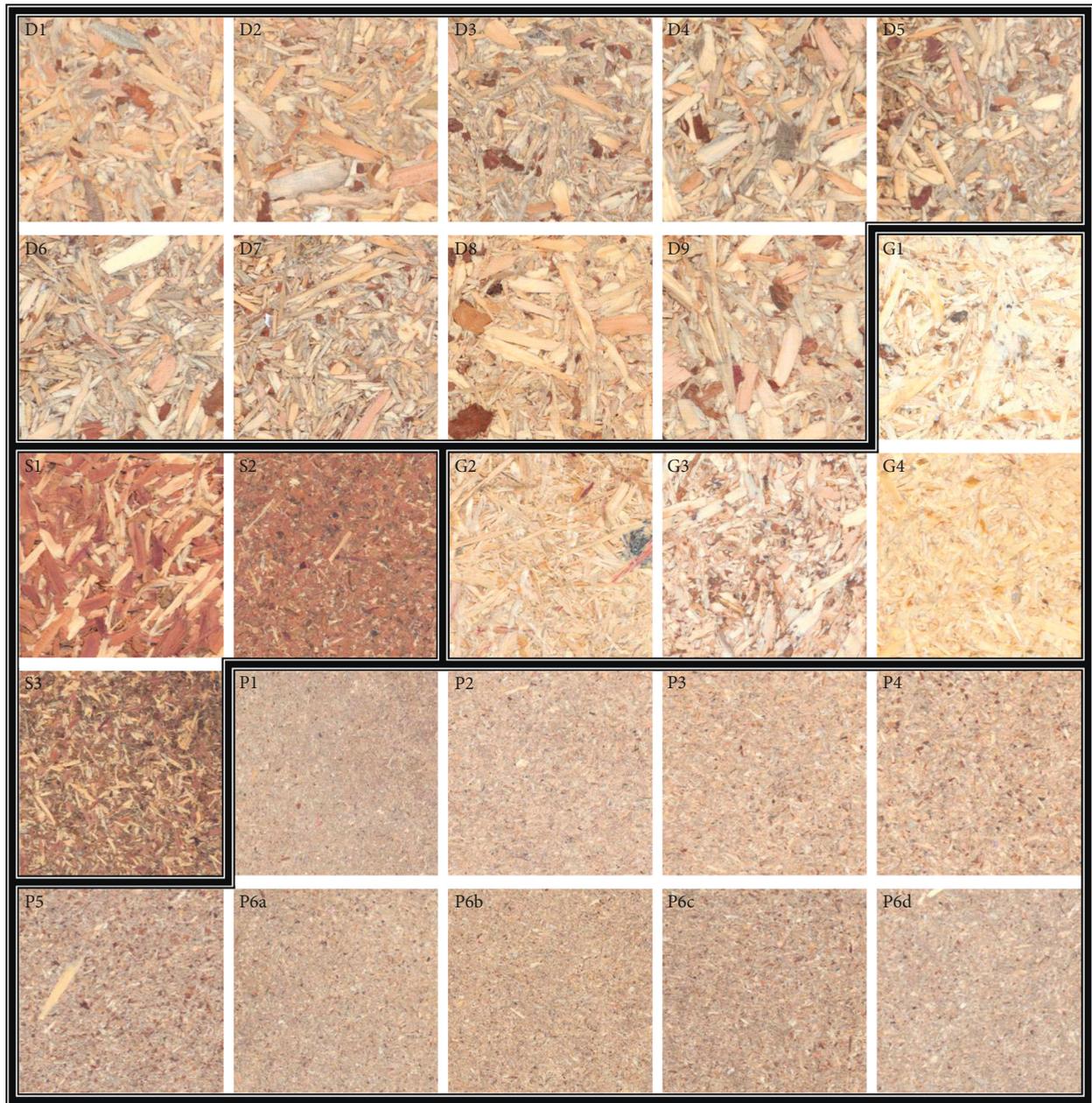


FIGURE 1: Appearance of particleboard surfaces representing 25 investigated categories.

In the case of successful identification, the same spectrum is an input for the second-level chemometric model, where affinity to the specific batches recorded previously is assessed. Such a numerical tool might be highly useful for the quality control of panels arriving to the production floor, as well as for authentication of their origin and composition. The demonstrative implementation of the proposed expert system was performed within this research project. The statistical evaluation of the discriminations success rate, performed at both system levels, is presented in the following section.

3.2. Prototype Expert System for Particleboard Identification. The concept of the abovementioned expert system implemented for demonstration of its feasibility is presented in

Figure 3. It consists of five chemometric models implemented at two discrimination levels. Model #1 is used to screen the unknown spectrum and determine the most probable class corresponding to the particleboard type. Four classes were therefore defined at the first level of the expert system corresponding to “sample sources” as summarized in the first column of Table 1. The second and more specific discrimination is executed afterward by implementing one of the second-level models (#2 to #5). The number of classes in each of these models corresponds to the number of previously defined batches. It has to be mentioned that it is critical to continuously feed the expert system with the most recent spectra of new batches in order to assure constant improvement of the discrimination

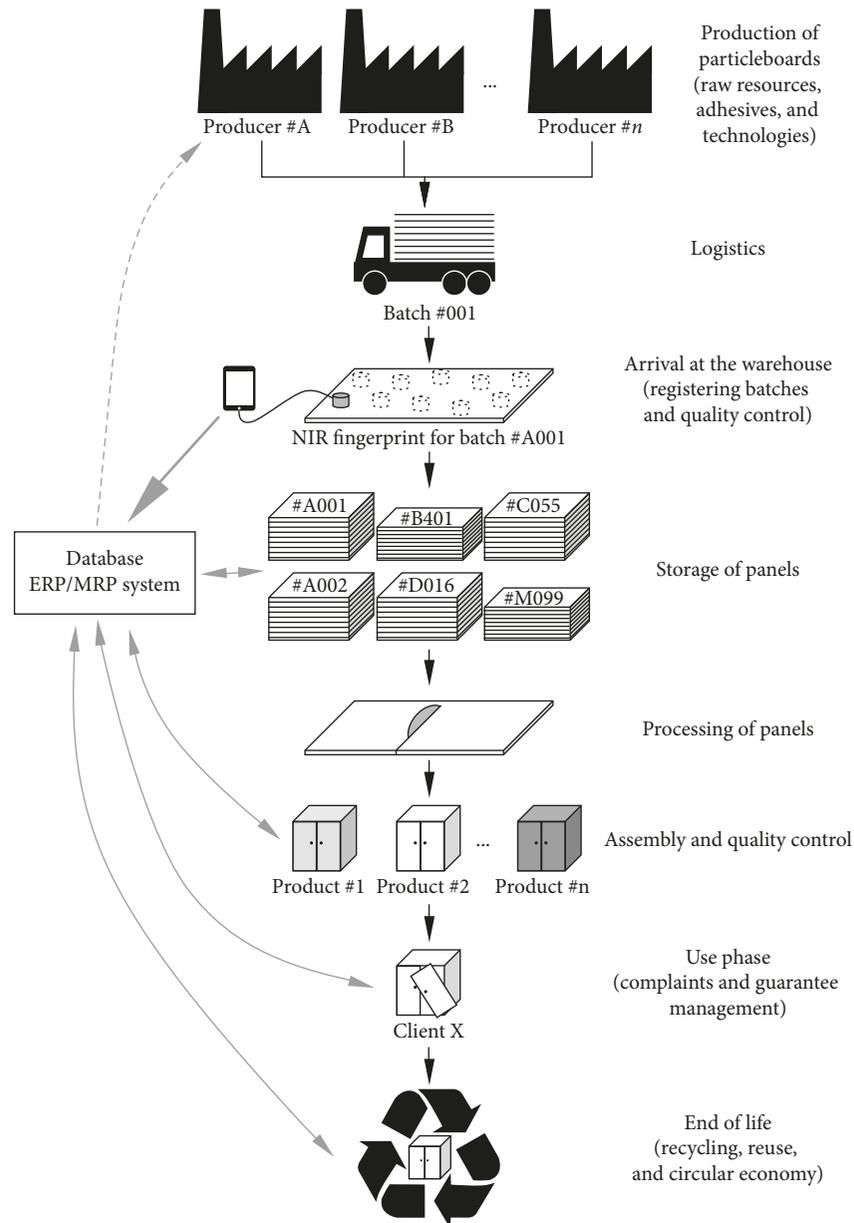


FIGURE 2: Concept for the traceability of particleboards in the furniture industry.

system and proper identification of all historically used particleboard batches.

An expert system approach to quality control at the industrial scale was proposed by Paladini [31]. He described three-step quality control approach that included precontrol activities, inspection, and a decision stage. Liukkonen et al. [32] described the intelligent optimization and modelling system for electronics production. They proposed three modules consisting of appropriate mathematical tools specifically tailored to each task: preprocessing, variable selection, and optimization. A data-driven approach was proposed to achieve proactive quality improvement of the production process. Hoballah et al. [33] proposed a casual map to show what variables should be included in the design optimization and how the components interact causally. This approach

was successfully used for the preliminary design of an insulating composite mat based on wood fibers.

3.3. Discriminant Analysis. Four alternative classification methods: KNN, PLS-DA, SVM, and SIMCA, were tested for the optimal NIR spectral data classification. All these methods are supervised techniques, as they use predefined information about the class membership for all samples selected for model calibration. In that way, the model can be tuned to classify new unknown samples in one of the known classes on the basis of its individual pattern [26]. Discriminating techniques usually build models based on all the categories concerned for the discrimination. Therefore, samples can be classified into one of the predefined categories, even if actually they do not belong to

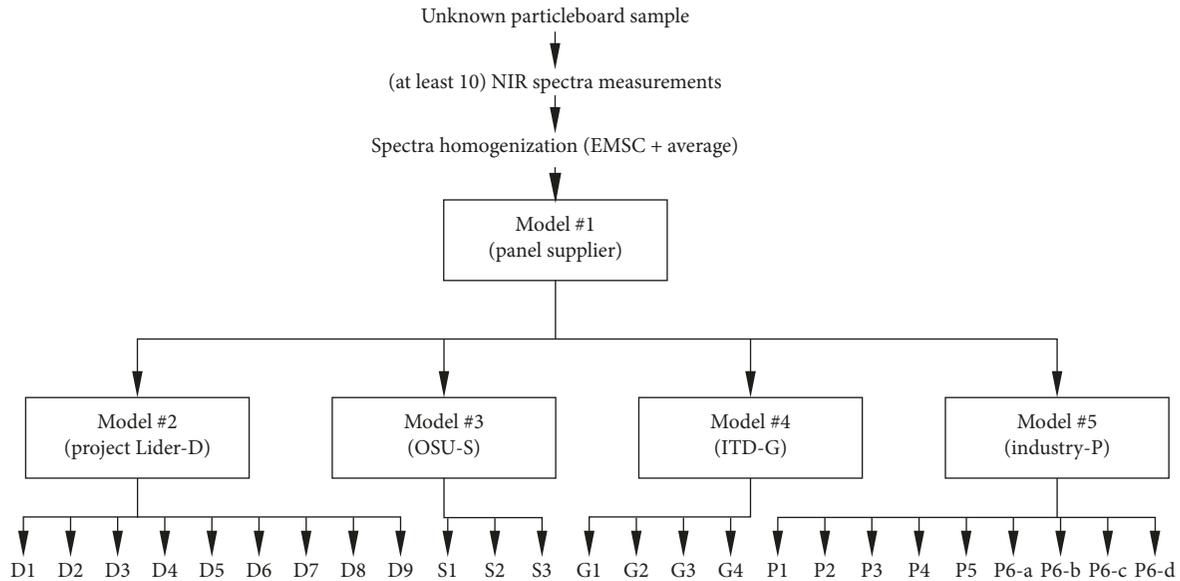


FIGURE 3: Prototype expert system's layout for the experimental set of particleboard samples.

any of these [26]. It is possible, however, to define a certain threshold for affinity to any of the classes. In that case, samples not passing the threshold may be classified as undefined.

Particleboard panel discrimination at the producer level (model #1) differentiated classes in terms of manufacturing conditions (laboratory or industrial scale), different resources used for panels manufacturing (industrial particles, addition of recycled wood, fast-growing wood species, agricultural wastes, etc.), or different adhesives used for panel production. The discrimination success scores between different panel providers are summarized in Table 2, where selected spectra preprocessing and diverse discrimination algorithms are presented. Four among twenty-four tested combinations resulted in 100% correct classification. The optimal combinations were PLS-DA and SIMCA with 2nd derivative spectra, and SVM with both SNV and EMSC preprocessing. Furthermore, discrimination precision with PLS-DA and SVM was high (>99%), even without any spectra preprocessing.

The second level of the expert system was designed to identify specific batches. Twenty-five lots of particleboards were modelled by four independent chemometric models (#2 to #5), developed for each panel provider separately. The SVM algorithm classifying SNV preprocessed NIR spectra was implemented. The summary of the model's performance is presented in Figure 4, where confusion tables indicate the ability of each model to properly classify (or misclassify) experimented samples from the validation set. All samples of panels manufactured by producer S and G were correctly classified. Industrial panels produced by different manufacturing plants of the producer P were classified with 98.9% success and the panels manufactured by producer D with 63.7% success. It is important to mention that, in the case of the producer D, the same substrate (industrial particles containing 25% of recycled

wood) was used for manufacturing all investigated panels. The only difference was the adhesive system, with 0, 10, 15, and 20% share of liquefied wood addition in the UF resin.

3.4. Implementation of the Prototype Expert System. The implementation of the expert system in real conditions is a challenging task. Qian et al. [34] proposed a four-step process that consists of the following:

- (i) Knowledge representation (including all variables characterizing production process)
- (ii) Database development (including all decision rules, functions, and metadata)
- (iii) Machine interface design (influencing the quality of the expert system for fault diagnosis and the real-time response of the system)
- (iv) Knowledge maintenance (including update, verification, and correction of the errors in knowledge base)

The experiences gained when developing chemometric models discriminating diverse particleboards stimulated extension of this research to a prototype expert system ready for testing in real-world applications. The hardware used for the prototype (portable NIR spectrometer and computer) was similar to the laboratory tests. The differences were in the software, where the original code was customised. It included integration of tools for the control of the sensor setup, data acquisition, spectra processing, and discriminant analysis. The required chemometric models (#1 to #5) were computed offline with PLS_toolbox and were exported as Matlab scripts to LabView. The algorithm of the prototype expert system for the batch identification is presented in Figure 5. The software allows acquisition of the new NIR

TABLE 2: The results of the discrimination success rate at the first level of expert system.

Discrimination algorithm	Spectra preprocessing					
	No preprocessing	Normalization	SNV	EMSC	1 st derivative	2 nd derivative
PLS-DA	99.1	99.1	98.2	98.2	98.2	100
SVM	99.1	63.2	100	100	93.9	63.2
KNN [3]	93.0	96.5	97.4	96.5	97.4	98.2
SIMCA	94.7	99.1	99.1	98.2	99.1	100

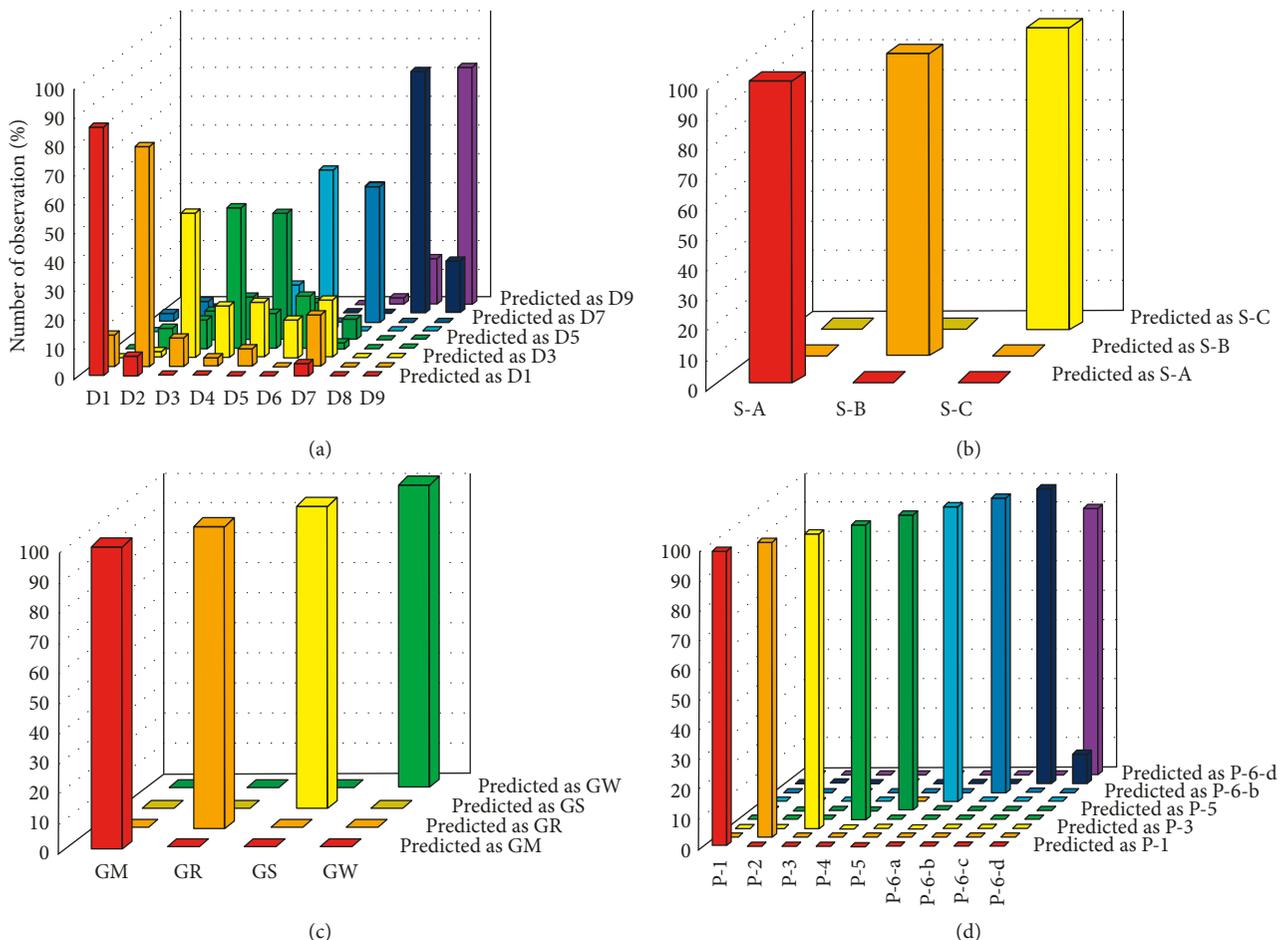


FIGURE 4: Confusion table of the particleboard batch prediction with the prototype NIR expert system: project LIDER-D (a), OSU-S (b), ITD-G (c), and industry-P (d).

spectra for feeding the database as well as assessment of the unknown spectrum in one of the predefined classes.

4. Conclusions

The traceability of particleboards is an important practical issue affecting economic performance of furniture producers and related industries. It allows control of material quality and ensures high standards of final products. NIR spectroscopy was employed here as a pioneer tool for development of the expert system suitable for assisting such a traceability. Twenty-five batches of particleboards, each containing at least three independent replicas, were used for the original system development and for its performance assessment. The hardware and software developed was

working properly, and it was implemented as a ready-to-use prototype system.

A two-stage expert system seems to be optimal for implementation of the particleboard discrimination as it allows a rough (in the first stage) and detailed (in the second stage) classification of particleboard samples to the level of a single batch. In two cases (two producers), 100% correct classification was achieved at the second stage.

It has to be mentioned that a drawback of the system presented is the necessity to condition samples before measurement. It includes both refreshing of the surface by gentle sanding and conditioning of samples at well-defined climatic conditions. It is due to the fact that NIR spectroscopy is extremely sensitive to the water molecules presented in the measured samples. Nevertheless,

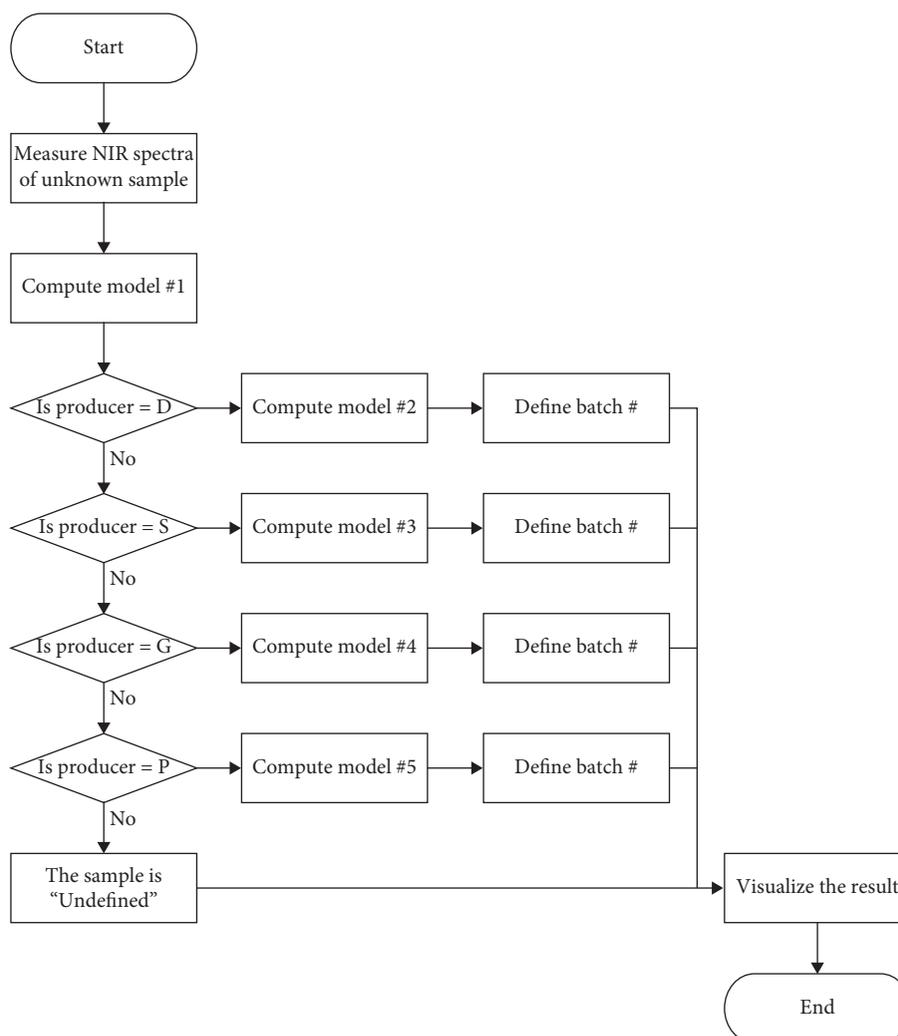


FIGURE 5: The algorithm of the prototype expert system.

implementation of NIR spectroscopy for product traceability and quality control may impact the industry due to the high versatility of the production and wide range of particleboard use.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

- [1] Compilation of Air Pollutant Emissions Factors, Chapter 10: Wood Products Industry Wood Products Industry, 2002, <https://www3.epa.gov/ttn/chief/ap42/ch10/index.html>, 2018.
- [2] The Bioenergy System Planners Handbook—BISY PLAN, <http://bisysplan.bioenarea.eu/>, 2018.

- [3] A. Taramian, K. Dooshoseini, S. A. Mirshokraii, and M. Faezipour, "Particleboard manufacturing: an innovative way to recycle paper sludge," *Waste Management*, vol. 27, no. 12, pp. 1739–1746, 2007.
- [4] J. Fiorelli, R. G. Galo, S. L. Castro Jr., U. L. Belini, P. R. O. Lasso, and H. Savastano Jr., "Multilayer particleboard produced with agroindustrial waste and amazonian vegetable fibres," *Waste and Biomass Valorization*, vol. 9, no. 7, pp. 1151–1161, 2017.
- [5] L. S. Hua, Z. Ashaari, L. W. Chen et al., "Properties of particleboard with oil palm trunk as core layer in comparison to three-layer rubber wood particleboard," *Journal of Oil Palm Research*, vol. 27, no. 1, pp. 67–74, 2015.
- [6] M. C. N. Yemele, P. Blanchet, A. Cloutier, and A. Koubaa, "Effects of bark content and particle geometry on the physical and mechanical properties of particleboard made from black spruce and trembling aspen bark," *Forest Product Journal*, vol. 58, no. 11, pp. 48–56, 2008.
- [7] H. Kalaycioglu and G. Nemli, "Producing composite particleboard from kenaf (*Hibiscus cannabinus* L.) stalks," *Industrial Crops and Products*, vol. 24, no. 2, pp. 177–180, 2006.
- [8] X. Mo, E. Cheng, D. Wang, and X. S. Sun, "Physical properties of medium-density wheat straw particleboard using different adhesives," *Industrial Crops and Products*, vol. 18, no. 1, pp. 47–53, 2003.
- [9] G. Nemli, S. Yildiz, and E. D. Gezer, "The potential for using the needle litter of Scotch pine (*Pinus sylvestris* L.) as a raw material for particleboard manufacturing," *Bioresource Technology*, vol. 99, no. 14, pp. 6054–6058, 2008.
- [10] G. A. Ntalos and A. H. Grigoriou, "Characterization and utilisation of vine prunings as a wood substitute for particleboard production," *Industrial Crops and Products*, vol. 16, no. 1, pp. 59–68, 2002.
- [11] P. Lertsutthiwong, S. Khunthon, K. Siralermukul, K. Noomun, and S. Chandkrachang, "New insulating particleboards prepared from mixture of solid wastes from tissues paper manufacturing and corn peel," *Bioresource Technology*, vol. 99, no. 11, pp. 4841–4845, 2008.
- [12] N. Čuk, M. Kunaver, and S. Medved, "Properties of particleboards made by using an adhesive with added liquefied wood," *Materials and technology*, vol. 45, no. 3, pp. 241–245, 2011.
- [13] B. Esteves, J. Martins, J. Martins, L. Cruz-Lopes, J. Vicente, and I. Domingos, "Liquefied wood as a partial substitute of melamine-urea-formaldehyde and urea-formaldehyde resins," *Maderas. Ciencia y tecnología*, vol. 17, no. 2, pp. 277–284, 2015.
- [14] A. Ugovsek, M. Kariz, and M. Sernek, "Bonding of wood with adhesive mixtures made of liquefied wood combined with tannin or phenolic resin," in *Future with Forests*, R. Ristić, M. Medarević, and Z. Popović, Eds., First Serbian Forestry congress, Beograd, Serbia, 2010.
- [15] M. Kunaver, S. Medved, N. Čuk, E. Jasiukaitytė, I. Poljanšek, and T. Strnad, "Application of liquefied wood as a new particle board adhesive system," *Bioresource Technology*, vol. 101, no. 4, pp. 1361–1368, 2010.
- [16] D. Janiszewska, I. Frąckowiak, and K. Mytko, "Exploitation of liquefied wood waste for binding recycled wood particleboards," *Holzforschung*, vol. 70, no. 12, pp. 1135–1138, 2016.
- [17] D. Janiszewska, I. Frąckowiak, and N. Bielejewska, "Application of selected agents for wood liquefaction and some properties of particleboards produced with the use of liquefied wood," *Drewno*, vol. 59, no. 197, pp. 223–230, 2016.
- [18] J. Sandak, A. Sandak, and R. Meder, "Assessing trees, wood and derived products with NIR spectroscopy: hints and tips," *Journal of Near Infrared Spectroscopy*, vol. 24, no. 6, pp. 485–505, 2016.
- [19] R. Meder, W. Stahl, P. Warburton et al., "At-line validation of a process analytical technology approach for quality control of melamine-urea-formaldehyde resin in composite wood-panel production using near infrared spectroscopy," *Analytical and Bioanalytical Chemistry*, vol. 409, no. 3, pp. 763–771, 2017.
- [20] A. Taylor and B. K. Via, "Potential of visible and near infrared spectroscopy to quantify phenol formaldehyde resin content in oriented strandboard," *European Journal of Wood and Wood Products*, vol. 67, no. 1, pp. 3–5, 2009.
- [21] A. C. M. Campos, P. R. G. Hein, R. F. Mendes, L. M. Mendes, and G. Chaix, "Near infrared spectroscopy to evaluate composition of agro-based particleboards," *Bioresources*, vol. 4, no. 3, pp. 1058–1069, 2009.
- [22] D. Janiszewska, A. Sandak, J. Sandak, I. Frąckowiak, and K. Mytko, "Influence of the raw material properties on the liquefied wood chemical composition," *Annals of WULS, Forestry and Wood Technology*, vol. 94, pp. 298–303, 2016.
- [23] M. Bevilacqua, R. Nescatelli, R. Bucci, A. D. Magri, A. L. Magri, and F. Marini, "Chemometric classification techniques as a tool for solving problems in analytical chemistry," *Journal of AOAC International*, vol. 97, no. 1, pp. 19–28, 2014.
- [24] Y. Tian, Z. Wang, X. Han, H. Hou, and R. Zheng, "Comparative investigation of partial least squares discriminant analysis and support vector machines for geological cuttings identification using laser-induced breakdown spectroscopy," *Spectrochimica Acta Part B: Atomic Spectroscopy*, vol. 102, pp. 52–57, 2014.
- [25] D. A. Adeniyi, Z. Wei, and Y. Yongquan, "Automated web usage data mining and recommendation system using K-nearest neighbor (KNN) classification method," *Applied Computing and Informatics*, vol. 12, no. 1, pp. 90–108, 2016.
- [26] L. A. Berrueta, R. M. Alonso-Salces, and K. Héberger, "Supervised pattern recognition in food analysis," *Journal of Chromatography A*, vol. 1158, no. 1–2, pp. 196–214, 2007.
- [27] J. Liu, T. J. Pan, and Z. Y. Zhang, "Incremental support vector machine combined with ultraviolet-visible spectroscopy for rapid discriminant analysis of red wine," *Journal of Spectroscopy*, vol. 2018, Article ID 4230681, 5 pages, 2018.
- [28] J. Sandak, A. Sandak, S. Hizirolu, and S. Bosak, "Surface characterization of particleboard panels manufactured from eastern redcedar using multi-sensor approach," in *Proceedings of International Panel Products Symposium*, pp. 27–37, Llandudno, North Wales, UK, October 2015.
- [29] I. Frąckowiak, D. Fuczek, and G. Kowaluk, "Impact of different lignocellulosic materials used in core of particleboard on modulus of elasticity and bending strength," *Drewno*, vol. 51, no. 180, pp. 5–14, 2008.
- [30] J. H. Bradley and R. D. Hauser, "A framework for expert system implementation," *Expert Systems with Applications*, vol. 8, no. 1, pp. 157–167, 1995.
- [31] E. P. Paladini, "An expert system approach to quality control," *Expert Systems with Applications*, vol. 18, no. 2, pp. 133–151, 2000.
- [32] M. Liukkonen, E. Havia, H. Leinonen, and Y. Hiltunen, "Expert system for analysis of quality in production of electronics," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8724–8729, 2011.
- [33] M. H. Hobballah, A. Ndiaye, F. Michaud, and M. Irle, "Formulating preliminary design optimization problems using expert knowledge: application to wood-based insulating

materials,” *Expert Systems with Applications*, vol. 92, pp. 95–105, 2018.

- [34] Y. Qian, L. Xu, X. Li, L. Lin, and A. Kraslawski, “LUBRES: an expert system development and implementation for real-time fault diagnosis of a lubricating oil refining process,” *Expert Systems with Applications*, vol. 35, no. 3, pp. 1252–1266, 2008.

