

FOOD WASTE MANAGEMENT USING STATISTICAL ANALYSIS TO OBTAIN NEW FUNCTIONAL PRODUCTS

Gjore NAKOV¹, Zlatin ZLATEV², Nastia IVANOVA¹, Ivan DIMOV²

¹“Angel Kanchev” University of Ruse, Razgrad Branch, Department of Chemistry, Food and Biotechnology, 47 Aprlosko vastanie Blvd., 7200 Razgrad, Bulgaria, Phone/Fax: +359882956044; Email: gnakov@uni-ruse.bg

²Trakia University, Faculty of Technics and technologies, 38 Graf Ignatiev str., 8602, Yambol, Bulgaria, Email: zlatin.zlatev@trakia-uni.bg

Corresponding author: gnakov@uni-ruse.bg

Abstract

A problem in food industry is the various types of waste that are produced during and after food preparation. In this article, mathematical studies have been implemented to obtain what amount of food waste is most appropriate for the enrichment of food and the production of new functional products. The subject of the study are cookies and the subject is the addition of Apple peel powder (APP). Physico-chemical, organoleptic characteristics and spectral indexes of biscuits were used as an input data. Vectors of the most informative features are selected, describing main indicators of the quality of cookies. Mathematical models have been developed to describe the relationship between the amount of APP and the weighting coefficients of the feature vectors. Using the partial least squares regression (PLS), principal component analysis (PCA), and factor analysis (FA) methods, it has been determined the optimum amount of APP for cookies preparation. The study found that using the Factor Analysis (FA) method performed better than using PCA and PLS. It has been found that the amount of apple residues in cookies is $APP=23,6\pm 1,3\%$, which can be considered as optimal. The proposed methods and tools have the potential to reduce food and waste losses. They are also one way to reduce production costs and improve food quality.

Key words: partial least squares, component analysis, factor analysis, equation models

INTRODUCTION

Reducing food and waste losses in recent years has been seen as a way of reducing production costs and improving food quality. This also leads to environmental sustainability [7].

The food industry produces a large amount of waste. The problem in this industry is the various types of waste that are generated during and after food preparation. According to the FAO, one-third of food produced worldwide for human consumption (1.3 billion tonnes) is estimated to be in the waste. Countries with a stable economy lose over 40% after harvest or during processing due to suboptimal storage and transportation conditions [6]. The waste from this industry can be used for the production of yeast, cellulose, vegetable oil [1]. This type of waste can also be a good source of biologically active substances. These biologically active

substances can be used to enrich a variety of bakery and confectionery products [10].

Figure 1 shows the possible products that can be obtained from food chain waste.

Apples (*Malus domestica*) are the fruits that are the most grown in the Republic of Bulgaria. After processing the apples in drinks, jams, dried apples and other products are obtained waste products. Based on their nutritional value, they can be used as a functional ingredient in food production. Apple waste products processed to a dry fine powder may be included in the composition of foods, most often in bakery products.

Apple waste products are discarded or used for animal feed. Recent advances in biotechnology make it possible to extract valuable substances from waste apple products: biologically active compounds, organic acids, aromatic compounds, bioethanol and enzymes. Apple peel is a waste product from the production of compotes, dried apples, apple puree and apple pie [16].

In our previous article, physicochemical and sensory parameters of biscuits enriched with 4%, 8%, 16%, 24% and 32% apple peel flour were published [12].

The purpose of this article is to predict, through mathematical studies, what amount of food waste is most appropriate for the enrichment of food and the production of new functional products.

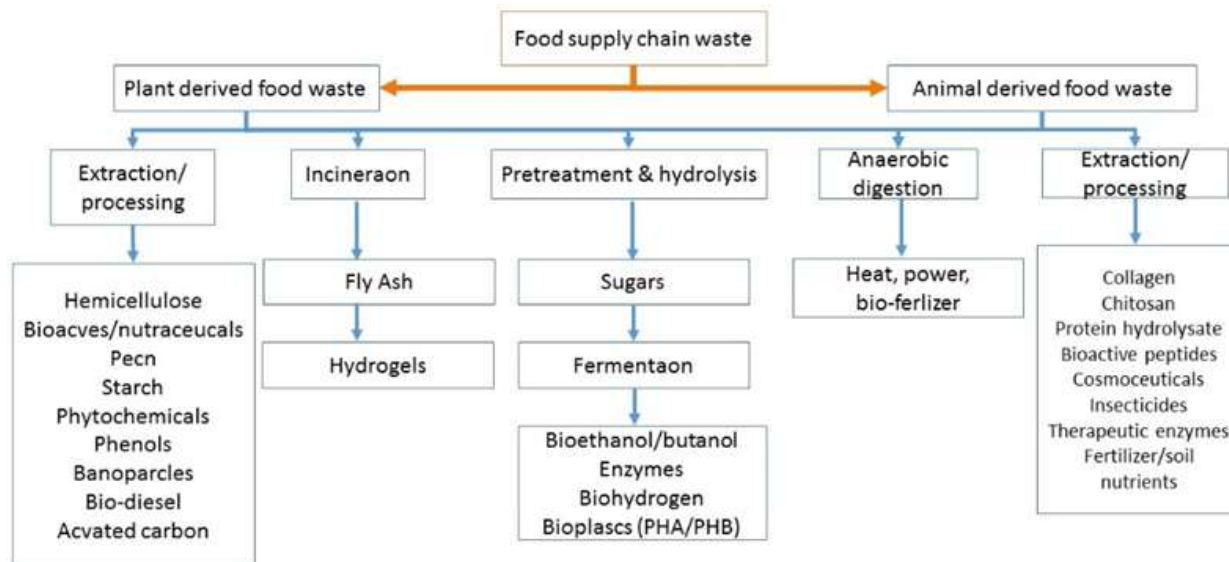


Fig. 1. Products derived from food chain waste
 Source: Ravindran and Jaiswal, 2016 [13].

MATERIALS AND METHODS

The methodology for obtaining cookies and determining their basic quality indicators is described in detail in [12].

Table 1 summarizes the indicators used to evaluate the quality of cookies with and without the addition of Apple peel powder (APP). The features used are:

- F1-F5 are the physicochemical characteristics of cookies;
- F6-F8 are geometric dimensions of cookies determined by a caliper, with accuracy 0,02 mm;
- The F9-F11 are the color components of the Lab color model. They were determined with a Minolta CR-400 colorimeter (Konica Minolta, Tokyo, Japan);
- F11-F20 are the physicochemical characteristics of cookies;
- F21-F27 are the organoleptic characteristics determined by the touch panel. It consists of 20 tasters;
- F28-F38 are spectral indices determined according to the methodology presented in [2, 4].

Figure 2 shows the principle of obtaining spectral indices. The determination of the Carotenoid Transmittance Index (CTI) has been demonstrated.

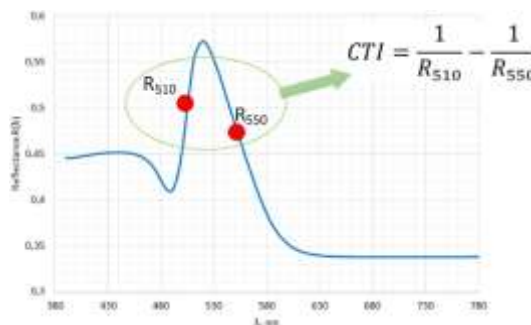


Fig. 2. Obtaining of Carotenoid Transmittance Index (CTI)
 Source: Own results.

The spectral reflectance characteristics are obtained by converting the values from the LMS model into reflection spectra in the VIS region, in the range 390-730nm, according to the mathematical dependencies presented in [15].

Table 1. Cookies quality assessment indicators (features)

№	Feature	№	Feature
F1	Peak Viscosity, BU	F20	FRAP, µgTE/g DM
F2	Breakdown, BU	F21	Appearance
F3	Setback, BU	F22	Internal structure
F4	Final viscosity, BU	F23	Texture
F5	Pasting temperatura, °C	F24	Odour
F6	Width, cm	F25	Taste
F7	Thickness, cm	F26	Aroma
F8	Volume, cm ³	F27	Overall quality
F9	L*	F28	REI
F10	a*	F29	PTI
F11	b*	F30	CTI
F11	Moisture, g/100g	F31	TVI
F13	Ash, g/100g DM	F32	G
F14	Lipids, g/100g	F33	NExG
F15	Proteins, g/100g	F34	NGRDI
F16	Fibre, g/100g DM	F35	RGBVI
F17	Carbohydrates, g/100g DM	F36	GLI
F18	TPC, mg GAE/100g DM	F37	VARI
F19	DPPH, µgTE/g DM	F38	ExG

Source: Own calculation.

The organization of the cookie output data is presented in Table 2. It consists of mxn rows and columns. In our case of n=38, the number of features used describes the basic quality of the cookies. The number of columns m=6 describing the amount of additive of apple peel powder (0%, 4%, 8%, 16%, 24% и 32% APP).

Table 2. Cookies input data

Feature \ %APP	P0	P1	P2	P3	...	Pm
F1	P0F1	P1F1	P2F1	P3F1	...	PmF1
F2	P0F2	P1F2	P2F2	P3F2	...	PmF2
F3	P0F3	P1F3	P2F3	P3F3	...	PmF3
...
Fn	P0Fn	P1Fn	P2Fn	P3Fn	...	PmFn

Source: Own calculation.

The selection of informative features is done by methods [8]:

-Correlation. Correlation dependence allows one to look for unknown links between the features describing basic indicators of cookie quality;

-ReliefF. This algorithm works well when evaluating the significance of characteristics for distance-based models;

-FSRNCA (Feature selection for regression using neighborhood component analysis). This algorithm also works well when evaluating the significance of characteristics for distance-based models.

The selected features are grouped into feature vectors, depending on the method used. The weight ratios of the amount of apple peel

powder added were obtained by the methods [3,11]:

-Factor Analysis (FA). It is a statistical technique in which a plurality of correlating data is transformed into a new set with non-correlating artificial variables or factors that explain as much of the total variation of the raw data as possible;

-Principal Component Analysis (PCA). The task with this method is to separate variables that are linear combinations of orthogonal variables and are not correlated;

-Partial least squares regression (PLSR). Data from feature vectors obtained describing product characteristics are not used directly, but new regression factors are created that concentrate information across the entire spectrum of data used.

The relationship between the amount of APP and its weight coefficients is described in four models. Their adequacy was estimated by coefficient of determination (R²), sum of squares of error (SSE), root of mean square errors (RMSE).

The following models are used:

Second order polynomial (poly2)
 Third order polynomial (poly3)
 Second order sinusoidal (sin2)
 First order Gaussian (gauss1)

$$y_1 = ax^2 + bx + c$$

$$y_2 = ax^3 + bx^2 + cx + d$$

$$y_3 = a \cdot \sin(bx + c) + d \cdot \sin(ex + f)$$

$$y_4 = a \cdot e^{-\left(\frac{x-b}{c}\right)^2}$$

The optimal value of% APP is determined by finding the minimum or maximum value in the model describing the relationship between% APP and their weight coefficients. The interval [x1, x2] in this case is [0,40] %APP. The way to find the optimal value depends on whether the model describes an increasing or decreasing function:

$$\min_x f(x) \text{ such that } x_1 < x < x_2$$

$$\max_x f(x) \text{ such that } x_1 < x < x_2$$

Matlab software (TheMathworks Inc.) and MS Excel (Microsof Corp.) were used. All data were processed at a level of significance α=0.05.

RESULTS AND DISCUSSIONS

Fig. 3 presents the results of a selection of main features describing the quality of the

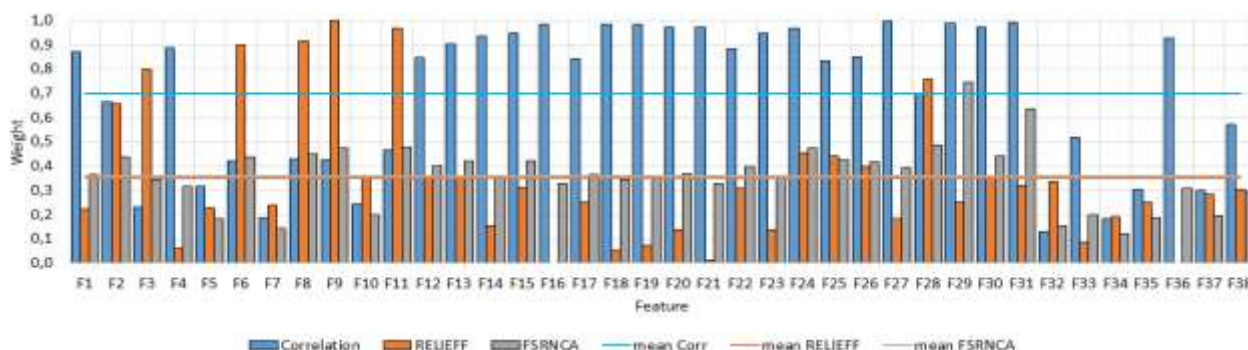


Fig. 3. Resu Source: Own results.

Its of feature selection

Table 3 shows the feature vectors obtained (FV), depending on the selection method used. FV1 contains a small part of the physicochemical and geometric features (2 features), the main part is the color components and organoleptic indicators of cookies (15 features) and part of the spectral indices (4 features). FV2 mainly contains the physicochemical, color and organoleptic characteristics of the product and only one spectral index. Like the first feature vector, FV3 contains most of the features but only 4 spectral indices.

Table 3. Selected feature vectors

Feature vector	Method	Selected features
FV1	Correlation	F1, F4, F12, F13, F14, F15, F16, F17, F18, F19, F20, F21, F22, F23, F24, F25, F26, F27, F29, F30, F31, F36
FV2	RELIEFF	F2, F3, F6, F8, F9, F11, F24, F25, F26, F29
FV3	FSRNCA	F1, F2, F6, F8, F9, F11, F12, F13, F15, F22, F24, F25, F26, F27, F28, F29, F30, F31

Source: Own calculation.

The feature vectors are used to determine the weights/loadings (according to the method used) for the different amount of APP additive in cookies. Four models were compared to describe the relationship between the amount of APP and its weight coefficients.

Fig. 4 shows the weight coefficients obtained for the amount of apple peel powder using feature vectors. Using PCA method, significant changes are shown by the weight

cookies containing apple peel powder. The features that have values above the average for the respective method are selected.

coefficients obtained from the feature vectors FV1 and FV3.

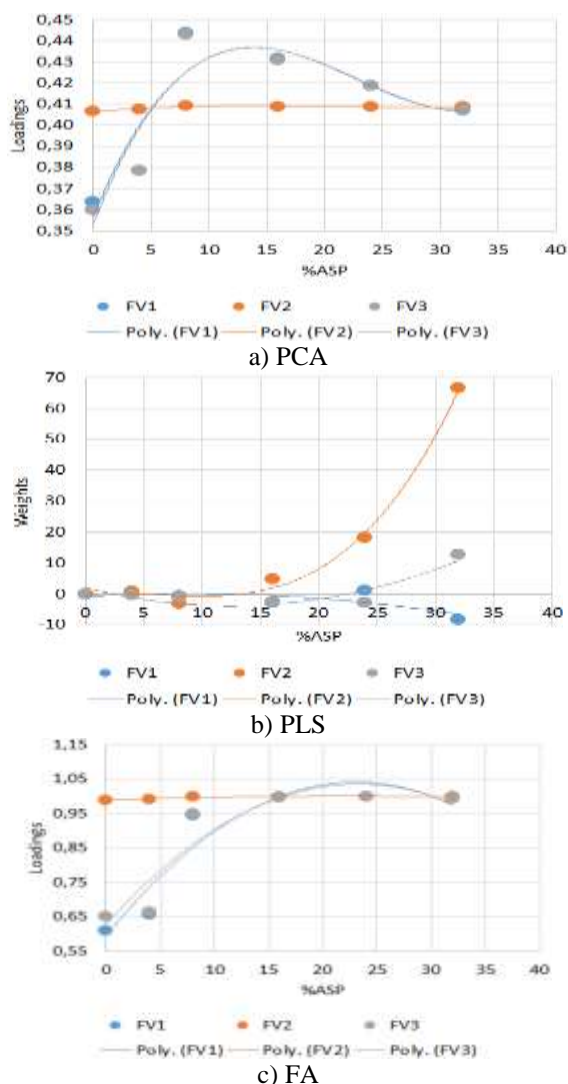


Fig. 4. Factor Loadings and weights of %APP Source: Own results.

For those obtained with the PLS method, only the FV2 feature vector showed a significantly greater variation than the other two vectors. Again in FA the vectors of signs FV1 and FV3 showed significantly changed values of the weight coefficients compared to FV1.

Table 4 shows the results of the comparative analysis of models representing the relationship between %APP and the factor

loadings obtained by the PCA method. With "Opt.", indicates the optimal amount of APP in cookies when using data from the appropriate model. SSE and RMSE error values are seen to be low (0-2%). The coefficient of determination is 0.71-0.86. This indicates that the models accurately describe the experimental data when PCA method is used.

Table 4. Model comparisons of %APP and PCA factor loadings

Feature vector Criteria Model	FV1				FV2				FV3			
	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.
y ₁	0.00	0.72	0.02	18.53	0.00	0.71	0.00	20.10	0.00	0.72	0.02	18.60
y ₂	0.00	0.81	0.02	13.90	0.00	0.86	0.00	27.86	0.00	0.81	0.02	21.97
y ₃	0.00	0.83	0.00	14.40	0.00	0.00	0.00	0.00	0.00	0.83	0.00	14.26
y ₄	0.00	0.85	0.00	12.00	0.00	0.00	0.00	0.00	0.00	0.84	0.00	12.00

Source: Own results.

Table 5 shows the results of the comparative analysis of models representing the relationship between %APP and the PLS weights. "Opt." Indicates the optimum amount of APP in cookies when using data from the model. In contrast to the PCA results, the SSE and RMSE error rates of up to 93% are

significantly higher using this method. Significantly lower are the values of the coefficient of determination R², which in some cases are 0. The highest values are this coefficient when using models y₃ and y₄, in combination with the reduced FV2 data, but at high error values up to 24%.

Table 5. Model comparisons for %APP and PLS weights

Feature vector Criteria Model	FV1				FV2				FV3			
	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.
y ₁	22.98	0.59	2.77	8.75	93.22	0.97	5.57	8.36	31.59	0.81	3.25	12.42
y ₂	11.01	0.80	2.35	19.74	19.99	0.99	3.16	9.94	3.17	0.98	1.26	18.64
y ₃	16.63	0.71	0.00	24.72	23.83	0.99	0.00	10.22	20.49	0.88	0.00	20.11
y ₄	19.59	0.65	2.56	35.98	10.52	0.99	0.00	39.99	6.01	0.97	0.00	24.01

Source: Own results.

Table 6 shows the results of the comparative analysis of models representing the relationship between %APP and the factor loadings obtained by the FA method. "Opt." Indicates the optimum amount of APP in cookies when using data from the model. This data processing has produced significantly

better results than the other two methods (PCA и PLS). SSE and RMSE error values are seen to be low (0-2%). The coefficient of determination is 0.71-0.86. This indicates that the models accurately describe the experimental data when analyzed using the factor loading from FA method.

Table 6. A comparative analysis of models for% APP and FA loadings

Feature vector Criteria Model	FV1				FV2				FV3			
	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.	SSE	R ²	RMSE	Opt.
y ₁	0,00	0,72	0,02	18,53	0,00	0,71	0,00	20,10	0,00	0,72	0,02	18,60
y ₂	0,00	0,81	0,02	13,90	0,00	0,86	0,00	27,86	0,00	0,81	0,02	21,97
y ₃	0,00	0,83	0,00	14,40	0,00	0,00	0,00	0,00	0,00	0,83	0,00	14,26
y ₄	0,00	0,85	0,00	12,00	0,00	0,00	0,00	0,00	0,00	0,84	0,00	12,00

Source: Own results.

The analysis made showed that the best results were obtained using the FA method compared to the other two (PCA and PLS).

The calculated values were used to determine the amount of APP in cookies to produce a product with optimum quality indicators. Only those optimal values that have been obtained from models describing with sufficient accuracy the relationship between the weight coefficients and % APP are taken into account. After averaging, an amount of apple residue was obtained, $\%APP=23.58\pm 1.27\%$, which may be considered as optimal.

The methodology proposed here improves the methods used so far by refining the way to determine the optimal amount of waste products in biscuits.

The methodology complements that of Sestrimaska, 2014 [14], with the option of determining the optimal amount of one-component cookies additive.

The addition of APP is over 20%, while reducing or completely discarding the use of white crystalline sugar in cookies.

Addition of other residues such as tomato peels is possible up to 7.5% [5]. This improves the functional properties of the cookies, but does not significantly reduce the amount of basic raw materials used.

A similar effect is obtained with the addition of apple seed powder [9]. Adding more than 10% of the total raw materials used decrease the quality of the cookies. This is due to the dilution of gluten-forming proteins caused by the incorporation of fibers.

The cited publications did not apply a precise methodology for determining the optimal amount of additional raw materials used.

CONCLUSIONS

A method and tools have been developed to determine the optimum amount of APP to use as a cookie additive. The method is based on the basic indicators of the quality of cookies, as well as on a certain set of ratios between them.

Mathematical studies have predicted what amount of food waste is most appropriate for

the enrichment of food and the production of new functional products.

A comparative study of different methods of successively improving assessments has been made, which substantially reduces the number of combinations of features obtained. Combining RELIEFF and FSRNCA with factor analysis (FA) results in the best results in determining the optimal amount of APP in cookies compared to the other methods used.

A comparative study was conducted to evaluate the impact of the methods used to reduce the volume of data on feature vectors and to determine their weight coefficients. The study found that using the Factor Analysis (FA) method performed better than using PCA and PLS.

The proposed methods and tools have the potential to reduce food and waste losses. They are also one way to reduce production costs and improve food quality.

Using the methods proposed would also improve the environmental sustainability.

REFERENCES

- [1]Arvanitoyannis, S, I., 2015, Waste Management for the Food Industries, Elsevier Academic Press, 2015: 1-19.
- [2]Atanassova, S., Nikolov, P., Valchev, N., Masheva, S., Yorgov, D., 2019, Early detection of powdery mildew (*Podosphaera xanthii*) on cucumber leaves based on visible and near-infrared spectroscopy, AIP Conference Proceedings 2075, 2019: 160014.
- [3]Bulut, E., Alma, O., 2011, Dimensionality reduction methods: PCR, PLSR, RRR and a health application, E-Journal of New World Sciences Academy, 2011, 6 (2): 36-47.
- [4]Cermakova, I., Komarkova, J., Sedlak, P., 2019, Calculation of Visible Spectral Indices from UAV-Based Data: Small Water Bodies Monitoring, 14th Iberian Conference on Information Systems and Technologies CISTI, 2019: 1-5.
- [5]Chouaibi, M., Rezig, L., Boussaid, A., Hamdi S., 2019, Insoluble tomato-fiber effect on wheat dough rheology and cookies' quality, Italian journal of food science, 2019, 31 (1): 1-18.
- [6]Coman, V., Teleky, B. E., Mítrea, L., Martău, G. A., Szabo, K., Călinoiu, L. F., Vodnar, D. C., 2020, Bioactive potential of fruit and vegetable wastes, Advances in Food and Nutrition Research, 2020: 157–225.
- [7]FAO, 2019, The State of Food and Agriculture 2019, Moving forward on food loss and waste reduction, Rome.

- [8]Jović, A., Brkić, K., Bogunović, N., 2015, A review of feature selection methods with applications, 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, 2015: 1200-12052015.
- [9]Kohajdová, Z., Karovičová, J., Magala, M., Kuchtová, V., 2014, Effect of apple pomace powder addition on farinographic properties of wheat dough and biscuits quality, *Chemical Papers*, 2014, 68: 1059-1065.
- [10]Martins, Z. E., Pinho, O., Ferreira, I. M. P. L. V. O., 2017, Food industry by-products used as functional ingredients of bakery products, *Trends in Food Science and Technology*, 2017, 67: 106–128.
- [11]Mladenov, M., Penchev, S., Deyanov, M., Mustafa, M., 2015, Automatic classification of grain sample elements based on color and shape properties, *University Politehnika of Bucharest, Scientific Bulletin, Series C*, 2015, 73 (4): 39-54.
- [12]Nakov, G., Brandolini, A., Hidalgo, A., Ivanova, N., Jukić, M., Komlenić, D. K., Lukinac, J., 2020, Influence of apple peel powder addition on the physico-chemical characteristics and nutritional quality of bread wheat cookies, *Food Science and Technology International*. 2020.
- [13]Ravindran, R., Jaiswal, A. K., 2016, Exploitation of Food Industry Waste for High-Value Products, *Trends in Biotechnology*, 2016 34(1): 58–69.
- [14]Sestrimska, M. 2015, Application of the statistical analysis in studying the properties of multi-component composition of biscuits, *University of Food technologies – Plovdiv, Bulgaria, Scientific works*, 2015, 62: 675-681.
- [15]Wyman, C, Sloan, P.P., Shirley, P. 2013, Simple Analytic Approximations to the CIE XYZ Color Matching Functions, *Journal of Computer Graphics Techniques JCGT*, 2013, 2(2): 1-11.
- [16]Zhou, Z., 2018, Effects of dried apple peel powder on the rheological and sensory properties of drinking yogurt, Guelph, Ontario, Canada, 2020.

