$O(\sqrt{nk}\cdot\log n/k)$, тобто при $k=\left(n^{2/3}:(\log n)^{1/3}\right)$ дає краще значення – $O(n^{1/6}(\log n)^{2/3})$. Крім того він не вимагає одночасного, постійного доступу процесорів до спільної пам'яті і не змінює закон оцінки складності і для $k<\left(n^{2/3}:(\log n)^{1/3}\right)$.

Перспективою продовження є комбінування цього методу з алгоритмом Поліга – Хелмана. Доцільно також розглянути модель пересилок на декілька комп'ютерів одночасно з одної ноди в дуплексному режимі з виконанням умови (1).

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МОДЕРНИЗИВАННЫЙ АЛГОРИТМ ПОЛИГА-ХЭЛМАНА, ШЕНКСА

Без сомнения многие криптоаналитические методы могут быть перевоплощены благодаря параллельным алгоритмам и применению алгебраического аппарата. Одним из них является метод Шэнкса решения ПДЛ. Целью работы является построение алгоритма позволяющего параллельно находить все значения из таблиц малого и большого шага, также сделать этот поиск более направленным и упорядочить все значения элементов таблиц, что позволит применить метод блочного поиска даст возможность разбиения на упорядоченные подблоки, ускорит применение метода индексации значений (или хэш от значений). Методом является параллельная оптимизация и блочная параллельная поразрядная сортировка. В данной работе предложен метод параллельного вычисления векторов, координатами которых являются значения таблицы BS. Также найдена оптимальная длина малого шага и как следствие и большого шага для метода. В работе предложено метод улучшения алгоритма Шэнкса путем его композиции с методом Полига-Хелмана.

Ключевые слова: *алгоритм, метод Шенкса, криптоанализ.*

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MODERN ALGORITHM OF POHLIG-HELLMAN AND SHANKS

There is no any doubts that most of cryptanalysis methods can be recreated owing to using parallel algorithms and algebraic apparatus in particular theory of groups. One of them is method of Shanks of solving discrete logarithms problem. The main goal of this article is to construct algorithm, which affording calculate all values of gigant and baby steps tables in parallel mode also allowing to do this search for values of table odered and oriented. It enables to apply method of blocs searching. It makes acxeleration in using of indexation of values method or calculating hex function. Method of solving problem is parallel optimization and blocs bitwise sorting. In given work method of parallel counting of vectors wich corresponds to tableaux are suggested. Also optimal length of baby and gigant steps were founded for this method. In given work method of improvement of Shanks algorithm via using algorithm of Pohlig-Hellman was suggested.

Key words: *algorithm, method of Shanks, cryptanalysis.*

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APPLICATION OF MODULAR NEURAL NETWORKS FOR ANALYSIS AND PREDICTION OF SOCIO-ECONOMICAL AND ECOLOGICAL INDICATORS OF THE REGION

The objective of this work is the use of modular neural networks for analysis and forecasting of environmental indicators and their impact on the socio-economic condition of the region, as well as the comparison of the results of the model used with the results of other methods of data analysis (methods of mathematical modeling and mathematical statistics).

Key words: artificial neural network (ANN), modular neural network, municipal solid waste (MSW), forecasting model

Introduction. Presently, the problem of analysis and forecasting of various environmental indicators for particular areas is extremely important. The solution to this problem provides an opportunity to plan efficiently and reasonably and to manage optimally and effectively the process of collecting, transporting and recycling or disposal of municipal solid waste (MSW). In particular, the relationship between socio-economic indicators and the composition and volume of MSW in a specific area is very important to research. Seasonal fluctuations in the values of parameters and a large number of factors affecting this is the feature that greatly complicates the construction and use of appropriate formal models for these processes.

Traditionally, the classical methods of mathematical statistics and systems analysis, expert systems, fuzzy models, etc. are used to solve this problem and similar ones [1–3]. Artificial neural networks are a powerful and effective tool for this analysis provided a small amount of training samples and the lack of a clear relationship between the input and output parameters. Application of an artificial neural network (ANN) to predict the characteristics of the waste according to the changing socio-economic factors described in the paper [4] cannot be called successful, as it uses a very simple small-sized ANN-model. Therefore, the resulting forecast differs little from the results of approximation of the input data by classical methods of mathematical statistics and numerical methods, as a result, the analyzed (extrapolated) data increase quickly and without bound outside the sample.

In this paper, the study of above-mentioned dependencies is done by means of the modular ANN [5, 6]. Modular neural networks are a new generation of artificial neural networks. Modular ANN is a very promising model, which allow during the training stage to combine different traditional architecture and algorithms for training neural networks in order to optimize and improve the effectiveness of the model, taking into account the adaptation of the model to a given situation. In particular, in this paper we have implemented a modular ANN using the following architectures: Hopfield network, Rosenblatt perceptron and neocognitron.

Various other methods of data analysis, such as regression and correlation analysis, interpolation, mathematical (analytical) modeling were tested for comparison and evaluation of the obtained results. Comparative analysis has shown that the classical methods are not effective in this concrete case: first, because of the small amount of time available data set provided a large variety of indicators. This fact makes it impossible to determine dependencies and sort data indicators on the degree of influence. Second, the training set for the proposed analysis is not sufficiently complete and representative.

Given the highly subjective and chaotic nature of the data provided by the environmental experts for the analysis pretreatment of the data was performed. This allowed a number of ways to divide the source data into the training and the control samples to verify the adequacy of the model. The studies clearly confirmed that the modular ANN-model showed the best results in the analysis and prediction of seasonal changes in the composition and volume of MSW.

1. Data analysis. At the first stage of the study regression and correlation analysis of input data was conducted to test the representativeness of the sample and the presence of the interdependence of these data. It was determined that the initial sample does not contain substantially interdependent data and it is well suited for the detection and prediction of seasonal fluctuations.

Training sample consists of data for the following regions (Table 1):

• Georgia, Kutaisi – 05.2010–04.2011;
• Lithuania, Kaunas – 01.2009–12.2010;
• Russia, Saint-Petersburg – 01.2010–12.2010;
• Ukraine, Boryspil – 01.2010–12.2010.

Statistical data used for prediction, were divided into the following categories:

• The composition of solid waste;
• Fullness of garbage bins;
• The total calorie;
• The result of recycling.

In this case, the results of recycling include a substance, energy and heat emitted directly during recycling, and after it.

In turn, MSW has been divided into separate categories in order to increase the efficiency of the system, since the studied parameters for these categories differ considerably among themselves and thus vary independently for each category.

Among these major categories were chosen:

• Paper and paperboard;
• Plastic;
• Black Metal;
• Other metals;
• Glass;
• TetraPack;
• Food waste;
• Garden waste;
• Other organic waste;
• Other inorganic waste.

We should also note the possible better efficiency of analysis by further separating these categories into sub-categories, namely: separate examination of paper and cardboard, the allocation of a separate category of packaging, office paper, etc. However, such an analysis requires a much more complete sample. In our case, such data were not available for most regions. Also, one should take into account that such an expansion will significantly increase the number of projected indicators and may reduce the accuracy of the forecast.

At the preliminary stage the version of analysis and prediction of deviations from the mean values for the year for each indicator has been considered since the sample does not show dynamics for long-term changes (Table 2). However, this approach was recognized as non-optimal, since it increases the amount of work during the preliminary exmination of the samples and the obtained results while the data obtained as the result of the analysis do not differ significantly.

When constructing a model we also took into account the results of previous studies, namely – the interdependence of the composition and volume of solid waste and socio-economic indicators [7]. As a result, for each indicator we actually allocated two modules for the prediction: the first – for prediction based on the values for the previous periods, the second – for prediction on the basis of the values of the socio-economic parameters for the current period.

2. Forecasting model. On the basis of the above and of the previous studies four main groups of indicators were suggested: 1) Composition of MSW; 2) Fullness of garbage bins; 3) The total calorie content; 4) The result of recycling.

Also we indicated three main areas of prediction:

1. Based on the value of indicators for the current period determining the value of the same indicators for the follow-up period;
2. Based on the socio-economic indicators for the next period of time, to determine the composition of MSW in the next period of time;
3. According to the composition of MSW for the next period of time to determine the results of their recycling in the next period of time.

Thus, for example, we have two values of the results of recycling: firstly, the values resulting from prediction based on the values of the previous periods, and secondly, "associated" values obtained from the composition of MSW for the predicted time taking into account the socio-economic and environmental situation in the region. The resulting value is taken as a kind of average value of these two values, and the corresponding coefficients are selected in the learning process.

Table 1

Input data for Kutaisi, Kaunas and St. Petersburg in 2009 and 2010

		2009											
		2009.01	2009.02	2009.03	2009.04	2009.05	2009.06	2009.07	2009.08	2009.09	2009.1	2009.11	2009.12
Lithuania, Kaunas	Population number, thousands	352285	352285	352285	352285	352285	352285	352285	352285	352285	352285	352285	352285
	GDP, EUR per capita	548	609	645	670	690	706	720	731	742	751	760	767
	GDP, USD per capita	726	807	854	888	914	935	953	969	983	995	1006	1016
	Average air relative humidity	81.02	84.49	80.74	70.03	73.51	71.47	70.24	74.18	78.49	78.68	85.75	86.00
	Average air temperature, oC	-11.46	-5.63	-1.65	5.43	11.36	14.02	18.69	17.65	9.68	2.83	1.84	-6.14
	Paper and cardboard	12.34	9.95	10.61	12.84	9.34	8.90	10.96	7.21	11.81	12.74	13.52	13.73
	Plastics	11.36	14.19	12.01	17.54	11.99	9.08	14.27	8.30	9.09	12.37	12.75	12.87
	Ferrous metals	2.48	2.20	2.24	1.95	1.85	1.44	1.70	0.49	0.76	0.90	0.92	0.94
	Other metals	0.26	1.94	0.80	0.42	0.78	0.83	1.11	0.28	0.57	0.32	0.34	0.34
	Glass	9.81	10.83	10.29	10.06	10.43	10.57	6.74	9.50	9.84	7.87	7.80	8.45
	Tetrapaks	0.82	0.63	1.22	0.72	1.69	0.40	0.95	0.71	0.45	0.54	0.81	0.41
	Food waste	40.71	37.72	32.53	29.44	29.92	31.20	32.84	49.00	40.96	36.45	37.37	37.39
	Yard waste	0.03	0.99	3.40	6.46	10.86	6.20	6.41	1.99	6.49	7.09	4.49	3.45
	Wood	2.01	0.10	0.32	2.97	0.96	0.02	0.51	1.68	2.28	1.61	1.66	1.66
	Other organic	11.42	12.81	9.07	8.51	17.29	22.34	18.58	19.62	13.27	12.72	12.78	13.19
	Other inorganic	8.73	8.62	17.49	9.06	4.89	9.01	5.94	1.22	4.47	7.35	7.54	7.54
	Hazardous	0.03	0.03	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.03
	Total:	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Table 1 *(continued)*

		2010											
		2010.01	2010.02	2010.03	2010.04	2010.05	2010.06	2010.07	2010.08	2010.09	2010.1	2010.11	2010.12
Georgia, Kutais	**Population number, thousands**					192.900	193.100	193.4	193.560	193.720	193.850	194.100	194.300
	GDP, EUR per capita					132	147	154	159	168	174	177	185
	GDP, USD per capita					189	211	221	228	242	250	255	266
	Average air relative humidity					70.00	73.00	74.00	65.00	67.00	80.00	62.00	58.00
	Average air temperature, oC					18.90	24.30	26.30	28.20	24.20	16.70	15.00	13.40
	Paper and cardboard					10.53	8.6	8.39	8.06	7.6	7.9	9.72	10.97
	Plastics					15.1	16.03	10.43	11.7	11.8	13.1	10.55	12.36
	Ferrous metals					0.48	0.22	1.3	0.73	0.64	0.5	1.05	1.82
	Other metals					0.19	0.2	0.24	0.19	0.2	0.5	0.16	0.58
	Glass					5.2	3.76	1.61	1.79	3.33	4.6	2.28	2.68
	Tetrapaks					0.34	0.5	0.4	0.54	0.23	0.34	0.52	0.43
	Food waste					43.52	51.1	52.47	53.13	50.9	51.2	52.3	45.7
	Yard waste					6.86	5.51	8.32	8.65	8.2	6.82	8.53	7.54
	Wood					2.79	2.89	4.4	3.91	4.8	2.6	2.14	1.14
	Other organic					7.07	5.83	4.56	2.98	4.1	5.4	5.86	6.18
	Other inorganic					7.74	5.27	7.25	7.66	7.85	6.8	6.21	10.3
	Hazardous					0.18	0.09	0.63	0.66	0.35	0.24	0.68	0.3
	Total:					**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Table 1 (end)

thuania, Kauna	**Population number, thousands**	348624	347728	346831	345935	345038	344142	343245	342349	341452	340556	339659	338763
	GDP, EUR per capita	548	609	645	670	690	706	720	731	742	751	760	767
	GDP, USD per capita	726	807	854	888	914	935	953	969	983	995	1006	1016
	Average air relative humidity	81.02	84.49	80.74	70.03	73.51	71.47	70.24	74.18	78.49	78.68	85.75	86.00
	Average air temperature, oC	-11.46	-5.63	-1.65	5.43	11.36	14.02	18.69	17.65	9.68	2.83	1.84	-6.14
	Paper and cardboard	13.70	11.86	17.42	8.76	11.79	10.12	11.10	21.84	15.20	15.61	13.48	10.63
	Plastics	13.84	15.28	12.19	6.42	18.10	9.87	9.83	10.61	14.91	14.78	16.60	12.27
	Ferrous metals	1.93	1.28	3.32	2.09	1.53	1.05	1.27	0.53	0.73	1.09	0.58	1.44
	Other metals	0.50	1.85	3.76	0.93	1.28	0.70	1.40	0.92	0.86	0.36	1.11	0.21
	Glass	10.01	12.55	10.54	7.39	12.58	13.21	11.54	9.21	6.90	5.95	7.40	10.36
	Tetrapaks	0.66	0.66	1.22	0.72	1.69	0.40	0.95	0.71	0.45	0.54	0.81	0.41
	Food waste	36.47	37.12	29.77	32.21	24.41	27.71	25.26	26.41	32.77	26.20	35.05	47.59
	Yard waste	0.90	0.00	0.25	9.68	7.49	5.19	8.58	10.11	13.44	15.31	9.38	0.00
	Wood	0.83	0.76	1.05	0.73	0.48	2.43	0.00	0.55	0.00	0.00	0.05	0.00
	Other organic	11.70	14.27	15.44	16.19	17.57	26.29	23.81	17.06	8.22	11.30	12.82	12.81
	Other inorganic	9.32	4.15	3.16	14.85	3.04	2.40	6.26	1.96	6.11	8.55	2.36	3.50
	Hazardous	0.15	0.22	1.87	0.04	0.05	0.62	0.01	0.08	0.40	0.31	0.35	0.79
	Total:	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

Table 2

Average values of the volume of MSW and garbage bins fullness

	Input				Landfill			
		2009.00	**2010.00**	**2011.00**		**2009.00**	**2010.00**	**2011.00**
Georgia, Kutaisi	**Population number, thousands**		193.62	194.99	**Population number, thousands**		193.62	194.99
	GDP, EUR per capita		162.00	199.75	**GDP, EUR per capita**		162.00	199.75
	GDP, USD per capita		232.75	266.50	**GDP, USD per capita**		232.75	266.50
	Average air relative humidity		68.63	73.75	**Average air relative humidity**		68.63	73.75
	Average air temperature, oC		20.88	7.95	**Average air temperature, oC**		20.88	7.95
	Paper and cardboard		8.97	14.23	**Paper and cardboard**		1.73	2.41
	Plastics		12.63	15.24	**Plastics**		2.46	2.58
	Ferrous metals		0.84	2.16	**Ferrous metals**		0.16	0.36
	Other metals		0.28	1.52	**Other metals**		0.05	0.26
	Glass		3.16	5.76	**Glass**		0.61	0.98
	Tetrapaks		0.41	0.31	**Tetrapaks**		0.08	0.05
	Food waste		50.04	31.02	**Food waste**		9.79	5.28
	Yard waste		7.55	5.26	**Yard waste**		1.48	0.88
	Wood		3.08	2.92	**Wood**		0.62	0.49
	Other organic		5.25	11.58	**Other organic**		1.01	1.95
	Other inorganic		7.39	9.72	**Other inorganic**		1.44	1.64
	Hazardous		0.39	0.30	**Hazardous**		0.08	0.05
	Average		100.00	100.00	**Total:**		19.51	16.93
Lithuania, Kaunas	**Population number, thousands**	352285.00	343693.25		**Population number, thousands**	352285.00	343693.25	
	GDP, EUR per capita	694.94	694.94		**GDP, EUR per capita**	694.94	694.94	
	GDP, USD per capita	920.46	920.46		**GDP, USD per capita**	920.46	920.46	
	Average air relative humidity	77.88	77.88		**Average air relative humidity**	77.88	77.88	
	Average air temperature, oC	4.72	4.72		**Average air temperature, oC**	4.72	4.72	
	Paper and cardboard	11.16	13.46		**Paper and cardboard**	4.03	4.25	
	Plastics	12.15	12.89		**Plastics**	4.41	4.61	
	Ferrous metals	1.49	1.40		**Ferrous metals**	0.53	0.50	
	Other metals	0.67	1.16		**Other metals**	0.24	0.41	
	Glass	9.35	9.80		**Glass**	3.42	3.14	
	Tetrapaks	0.78	0.77		**Tetrapaks**	0.29	0.29	
	Food waste	36.29	31.75		**Food waste**	13.23	11.68	
	Yard waste	4.82	6.69		**Yard waste**	1.83	1.11	
	Wood	1.32	0.57		**Wood**	0.48	0.21	
	Other organic	14.30	15.62		**Other organic**	5.27	5.82	
	Other inorganic	7.65	5.47		**Other inorganic**	2.78	2.09	
	Hazardous	0.02	0.41		**Hazardous**	0.01	0.15	
	Average	100.00	100.00		**Total:**	36.53	34.24	

Table 2 (end)

	Population number, thousands	4600.26		**Population number, thousands**	4600.26	
	GDP, EUR per capita	833.00		**GDP, EUR per capita**	833.00	
	GDP, USD per capita	1117.00		**GDP, USD per capita**	1117.00	
	Average air relative humidity	76.75		**Average air relative humidity**	76.75	
	Average air temperature, oC	5.83		**Average air temperature, oC**	5.83	
	Paper and cardboard	18.01		**Paper and cardboard**	4.56	
	Plastics	14.29		**Plastics**	3.62	
	Ferrous metals	2.17		**Ferrous metals**	0.54	
Russia, SPB	**Other metals**	0.67		**Other metals**	0.17	
	Glass	8.74		**Glass**	2.21	
	Tetrapaks	2.35		**Tetrapaks**	0.61	
	Food waste	6.12		**Food waste**	1.53	
	Yard waste	0.62		**Yard waste**	0.16	
	Wood	0.74		**Wood**	0.19	
	Other organic	22.61		**Other organic**	5.75	
	Other inorganic	22.92		**Other inorganic**	5.83	
	Hazardous	0.75		**Hazardous**	0.19	
	Average	100.00		**Total:**	25.35	
	Population number, thousands	58.12	58.49	**Population number, thousands**	58.12	58.49
	GDP, EUR per capita	662.32		**GDP, EUR per capita**	662.32	
	GDP, USD per capita	910.68		**GDP, USD per capita**	910.68	
	Average air relative humidity	72.65		**Average air relative humidity**	72.65	
	Average air temperature, oC	9.28		**Average air temperature, oC**	9.28	
	Paper and cardboard	8.34	11.31	**Paper and cardboard**	2.32	
	Plastics	12.49	14.47	**Plastics**	3.50	
	Ferrous metals	1.45	2.56	**Ferrous metals**	0.41	
Ukraine, Borispol	**Other metals**	0.25	0.53	**Other metals**	0.07	
	Glass	20.00	19.12	**Glass**	5.60	
	Tetrapaks	0.62	0.71	**Tetrapaks**	0.17	
	Food waste	22.95	20.26	**Food waste**	6.35	
	Yard waste	12.08	10.09	**Yard waste**	3.42	
	Wood	1.50	1.30	**Wood**	0.42	
	Other organic	11.46	10.66	**Other organic**	3.22	
	Other inorganic	8.79	8.76	**Other inorganic**	2.48	
	Hazardous	0.07	0.24	**Hazardous**	0.02	
	Average	100.00	100.00	**Total:**	27.99	

Table 3

Data on the composition of MSW obtained by prediction (2011)

		2010.01	2010.02	2010.03	2010.04	2010.05	2010.06	2010.07	2010.08	2010.09	2010.1	2010.11	2010.12
Lithuania, Kaunas	Population number, thousands	348624	347728	346831	345935	345038	344142	343245	342349	341452	340556	339659	338763
	GDP, EUR per capita	548	609	645	670	690	706	720	731	742	751	760	767
	GDP, USD per capita	726	807	854	888	914	935	953	969	983	995	1006	1016
	Average air relative humidity	81.02	84.49	80.74	70.03	73.51	71.47	70.24	74.18	78.49	78.68	85.75	86.00
	Average air temperature, oC	-11.46	-5.63	-1.65	5.43	11.36	14.02	18.69	17.65	9.68	2.83	1.84	-6.14
	Paper and cardboard	13.70	11.86	17.42	8.76	11.79	10.12	11.10	21.84	15.20	15.61	13.48	10.63
	Plastics	13.84	15.28	12.19	6.42	18.10	9.87	9.83	10.61	14.91	14.78	16.60	12.27
	Ferrous metals	1.93	1.28	3.32	2.09	1.53	1.05	1.27	0.53	0.73	1.09	0.58	1.44
	Other metals	0.50	1.85	3.76	0.93	1.28	0.70	1.40	0.92	0.86	0.36	1.11	0.21
	Glass	10.01	12.55	10.54	7.39	12.58	13.21	11.54	9.21	6.90	5.95	7.40	10.36
	Tetrapaks	0.66	0.66	1.22	0.72	1.69	0.40	0.95	0.71	0.45	0.54	0.81	0.41
	Food waste	36.47	37.12	29.77	32.21	24.41	27.71	25.26	26.41	32.77	26.20	35.05	47.59
	Yard waste	0.90	0.00	0.25	9.68	7.49	5.19	8.58	10.11	13.44	15.31	9.38	0.00
	Wood	0.83	0.76	1.05	0.73	0.48	2.43	0.00	0.55	0.00	0.00	0.05	0.00
	Other organic	11.70	14.27	15.44	16.19	17.57	26.29	23.81	17.06	8.22	11.30	12.82	12.81
	Other inorganic	9.32	4.15	3.16	14.85	3.04	2.40	6.26	1.96	6.11	8.55	2.36	3.50
	Hazardous	0.15	0.22	1.87	0.04	0.05	0.62	0.01	0.08	0.40	0.31	0.35	0.79
	Total:	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

		2011.01	2011.02	2011.03	2011.04	2011.05	2011.06	2011.07	2011.08	2011.09	2011.1	2011.11	2011.12
Lithuania, Kaunas	Population number, thousands	337866	336970	336073	335177	334280	333384	332487	331591	330694	###	328901	328005
	GDP, EUR per capita	547.90	609.09	644.89	670.28	689.98	706.08	719.68	731.47	741.87	751.17	759.59	767.27
	GDP, USD per capita	725.73	806.77	854.17	887.81	913.90	935.21	953.24	968.85	982.62	994.94	1006.08	1016.26
	Average air relative humidity	81.02	84.49	80.74	70.03	73.51	71.47	70.24	74.18	78.49	78.68	85.75	86.00
	Average air temperature, oC	-11.46	-5.63	-1.65	5.43	11.36	14.02	18.69	17.65	9.68	2.83	1.84	-6.14
	Paper and cardboard	17.74	14.87	20.68	10.56	14.10	12.43	16.34	10.91	17.22	18.57	20.01	20.28
	Plastics	15.59	17.34	13.48	6.97	19.05	10.34	15.71	9.09	9.91	13.95	14.64	14.43
	Ferrous metals	1.93	1.29	3.33	2.07	1.51	1.02	1.56	0.46	0.71	0.81	0.83	0.86
	Other metals	0.80	2.96	5.97	1.49	2.04	1.11	3.13	0.79	1.41	0.68	0.71	0.71
	Glass	9.94	12.26	10.45	7.47	12.89	13.46	7.13	10.00	10.27	8.31	8.26	8.78
	Tetrapaks	0.65	0.65	1.19	0.70	1.65	0.39	0.92	0.68	0.44	0.52	0.78	0.40
	Food waste	31.54	33.06	27.20	29.97	22.71	25.38	25.88	38.86	32.19	28.30	28.86	28.92
	Yard waste	2.32	1.07	1.37	11.31	8.43	6.19	10.03	3.92	10.68	11.65	7.87	6.59
	Wood	0.05	0.09	0.27	0.28	0.23	2.68	0.13	1.11	1.70	1.32	1.69	1.69
	Other organic	10.95	13.45	14.98	16.09	17.65	26.86	20.70	21.88	14.33	13.22	13.05	13.39
	Other inorganic	6.51	3.30	2.57	6.77	2.14	1.81	2.10	1.22	1.46	1.36	0.94	0.50
	Hazardous	0.11	0.16	1.17	0.04	0.05	0.35	0.02	0.03	0.03	0.06	0.06	0.06
	Total:	**98.13**	**100.48**	**102.67**	**93.72**	**102.45**	**102.04**	**103.66**	**98.97**	**100.36**	**98.76**	**97.70**	**96.61**

Thus, this approach allows to combine the main currently existing approaches for predicting the composition of MSW and the results of their recycling: namely – classical forecasting based on time series [1–3], and an approach that takes into account the interrelation between MSW and the socio-economic and environmental condition of the region. Implementation of the balance between these two approaches is performed automatically in the course of training the neural network. The result is a much more accurate forecast, as both of these approaches are not without drawbacks, and carried out balance allows to compensate for these shortcomings.

3. The obtained results. Modular neural network proposed in this paper, showed high efficiency and accuracy in comparison with traditional algorithms and approaches for solving this problem. Mainly as a result of the use of data dependency and the nature of changes in the composition of MSW and the results of their recycling.

Figure 1 shows a diagram of MSW for Lithuania (Kaunas), where the data for the year 2011 (the last third) display the values obtained from the prediction using the proposed modular neural network.

Numerical data for this diagram are shown in Table 3. As can be seen, for 2011, the values of which were predicted, the total amount of MSW obtained as the sum of the values for a particular month, ranges that can be interpreted as fluctuations in the amount MSW. Unfortunately, due to the fact that for the analysis were taken completely different data regions, the consideration of absolute values will strong error in assay results.

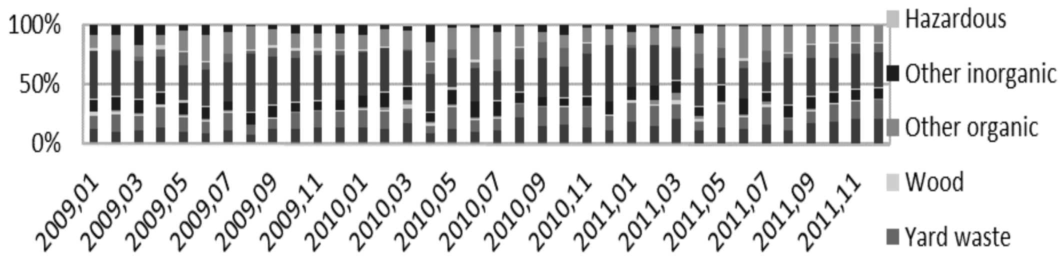

Figure 1: Diagram of oscillations the composition of MSW (Lithuania, Kaunas)

In Figure 2, we can see fluctuations in the area of waste bins for each category of waste.

As can be seen from the results shown in Figure 2 and Table 3, the proposed model takes into account the general downward trend in the amount of MSW and, accordingly, the territory occupied by them, which is observed in the region.

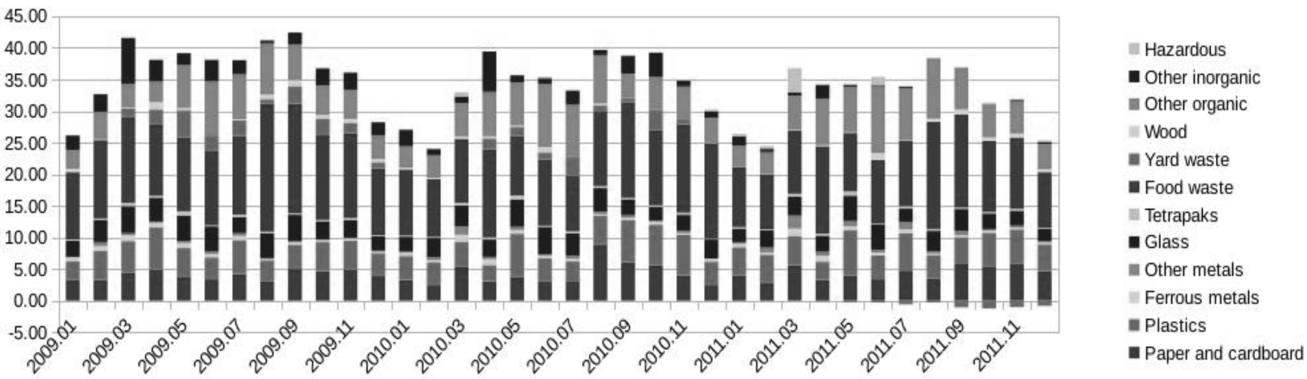

Figure 2: Diagram of fluctuations in the garbage bins fullness (Lithuania, Kaunas)

4. Conclusions. From these data it is evident that the modular neural network was able to accurately detect fluctuations and dependencies in the sample, and to reflect these fluctuations in the predicted data.

Analysis of the results also indicates that for long-term forecasting it is necessary to expand the sample so that the presented data displays information about the long-term fluctuations. This extension of the sample will not only get the forecast for the period of time sufficient to use the results in the optimization of storage and recycling MSW, but also will improve the accuracy of prediction of cyclical fluctuations (eg, seasonal).

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ВИКОРИСТАННЯ МОДУЛЬНИХ НЕЙРОННИХ МЕРЕЖ ДЛЯ АНАЛІЗУ ТА ПРОГНОЗУВАННЯ СОЦІАЛЬНО-ЕКОНОМІЧНИХ ТА ЕКОЛОГІЧНИХ ПОКАЗНИКІВ РЕГІОНУ

Метою даної роботи є використання модульних нейронних мереж для аналізу і прогнозування екологічних показників та їхнього впливу на соціально-економічний стан регіону, а також порівняння результатів використаної моделі з результатами інших методів аналізу даних (методи математичного моделювання та математичної статистики).

Ключові слова: *штучні нейронні мережі (ШНМ), модульні нейронні мережі, тверді побутові відходи (ТПВ), модель прогнозування.*

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ИСПОЛЬЗОВАНИЕ МОДУЛЬНЫХ НЕЙРОННЫХ СЕТЕЙ ДЛЯ АНАЛИЗА И ПРОГНОЗИРОВАНИЯ СОЦИАЛЬНО-ЭКОНОМИЧЕСКИХ И ЭКОЛОГИЧЕСКИХ ПОКАЗАТЕЛЕЙ РЕГИОНА

Целью данной работы является использование модульных нейронных сетей для анализа и прогнозирования экологических показателей и их влияния на социально-экономическое положение региона, а также сравнение результатов использованной модели с результатами других методов анализа данных (методы математического моделирования и математической статистики).

Ключевые слова: *искусственные нейронные сети (ИНС), модульные нейронные сети, твердые бытовые отходы (ТБО), модель прогнозирования.*