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NEUROCOMPUTING AND ITS APPLICATION IN THE SUGAR INDUSTRY

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Abstract:

The article is devoted to the development and adaptation of the tools of neuro-spectral analysis for the performance indicators of large agro-industrial holdings of the sugar sub-complex of the agro-industrial complex. Currently, neurocomputing is often used to analyze data, and therefore it is appropriate to compare it with old, well-developed statistical methods. In the authors' literature review on statistics (econometrics), it is often stated that the use of neurocomputing is an ineffective tool for analyzing the main components, regression and discriminant models. It is also noted that multilayer neural networks can actually solve problems such as regression and classification. However, firstly, the processing of data by neural networks is much more diverse, for example, the active classification by Hopfield networks or Kohonen feature maps, which have no statistical analogs. Secondly, many studies concerning the application of the combined approach in the form of neural networks and spectral analysis in the agricultural economy have revealed their advantages over classical statistical methods.

The necessity of a predictive assessment of the performance of large agro-industrial holdings of the sugar sub-complex of the agro-industrial complex is substantiated. Such forecast estimates can be obtained on the basis of the implementation of a neuro-spectral analysis describing the strategic management of large-scale enterprises of the sugar sub-complex along the optimal development trajectory. It is proved that the identified cycles make it possible to predict with a high probability the main trends in both regional and global data on the production of sugar and sugar beet (or cane).

The authors proposed the use of adapted tools in the form of neuro-spectral analysis in solving problems of predicting the performance of integrated production systems of the sugar sub-complex of the agro-industrial complex. Neuro-spectral analysis allows to improve the quality of the forecast for the development of complex dynamic processes to a greater extent than the classical spectral analysis in its pure form. This makes it possible to continue to develop strategically adjusted integrated management decisions. The results of the solution of the formulated problem were obtained and analyzed by the method of neuro-spectral analysis. The results of its application in the tasks of forecasting have demonstrated the possibility of solving them and confirmed their practical significance in the field of management of large industry enterprises of the sugar subcomplex. In parallel with this, the problem of forecasting high-frequency oscillations has been solved.

Key words: *neurocomputing, Fourier transform, neurospectral analysis, prediction, cycles, frequencies.*

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INTRODUCTION:

The hypothesis that the development of the sugar sub-complex of the agro-industrial complex occurs in accordance with certain unknown cycles is the biggest and unsolved problem of statistical and other types of analysis. This refers not to some astronomical cycles, but purely mathematical ones - for example, time cycles - a cycle with a period of 9 years or 12.4 years.

Thus, if this assumption is true, then we can try to determine this cyclicity, based on the assumption that this segment of the agro-industrial complex will continue to develop according to these cycles. Therefore, given their future dynamics, you can get an answer to a question that is interesting to any analyst (manager): how will this indicator of economic activity change in the future?

In this article we will consider the methods of classical spectral analysis of it from the point of view of modern concepts, in a hybrid form - using neural networks.

Neural networks are a relatively young, rapidly developing field of science. Most of the literature contains general descriptions of neural network models and theoretical substantiations of the possibility of using this method in analysis and forecasting. Thus, there is a significant “separation” of theoretical studies from the practice of their implementation (neurocomputing) [1].

MATERIAL AND METHODS:

In modern science, neural networks are a new word in the modeling of complex processes and phenomena. Their peculiarity lies in the fact that the sought dependence is not analytically found, but exists as some combination of weights in the computer's memory. Artificial neural networks (INS) are typical representatives of a structural approach to data processing. By inputting the predicted values of factors to the input of a trained INS, the values of the characteristic Y are obtained at the output. The INS, which differ in architecture, structure, and principles of operation, are widely used to predict various economic factors [1]. The process of implementing ANNs in practice is called neurocomputing (Figure 1).

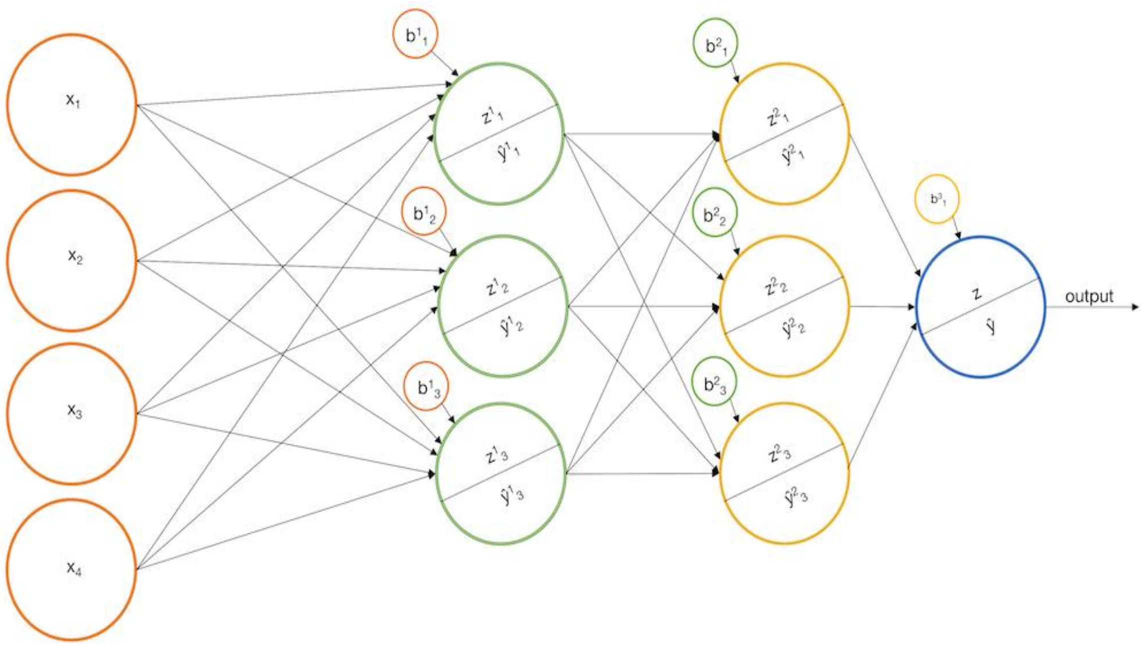

Figure 1: Schematic representation the deep learning with using three layers and more

Neurocomputing, or data processing using neural-like networks implemented on computers, either in the form of programs or in hardware, is now increasingly used to solve many poorly formalized problems. Neurocomputing refers to a relatively new area of information technology, called Machine Leaning (ML), that is, machine training.

RESULTS AND DISCUSSIONS:

Neurocomputing using spectral analysis models

Despite the fact that the Fourier transform (PF) is a classical algorithm in spectral analysis, its use in economics raises serious complaints.

Suppose that with the help of the FS, it is possible to identify cycles that have a high correlation with the quantity being studied. This information is very useful for analytics. She points out that these cycles are currently in effect (or not). We do not know this, because the PF does not provide information about the time coordinates of the detected cycles.

The transformation simply spreads the signal to the spectra, which cycles have completely "worked out" and have now subsided, which are only declining, and which, on the contrary, are gaining strength, nothing is known.
There is an objective explanation for this "indifference" of the PF with respect to time: this algorithm of spectral analysis was used initially in work with cycles that have high stability - sound waves, electromagnetic oscillations, radio waves, light flux, etc.

Among any indicators of the activities of enterprises of the sugar sub-complex of the agro-industrial complex, one can easily recognize cycles, which, however, will not be stable over time. Some of them appear at some point, "sound" at full power, and then quickly leave. Other cycles "work" in the time series all the time, but they do not show a pronounced correlation. As already mentioned, the application of the Fourie transform of this situation is ineffective.

Another problem with the use of PF in the analysis of the cycles of the sugar subcomplex of the APC is associated with differences in the nature of these cycles and those traditionally used for spectral decomposition. Both sound, and electromagnetic wave, and light are similar in that all these signals can be described by a static formula. Classic cycles are predictable: knowing the patterns of their development in the past, one can easily predict their future behavior.

Time cycles in the sugar market sector are quite different. They constantly change their characteristics (amplitude, phase, period), they are inadequately extrapolated to the future. For example, a cycle that demonstrates a very high correlation in the past can "fail" at any moment, because its predicative qualities are in no way connected with the level of correlation.

By virtue of these circumstances, it is not a statement of the correlation of cycles in the past (as evidenced by the FS), but the establishment of correspondences between past and future, has practical value for the analyst. In other words, the analyst needs to identify not cycles with a high magnitude of correlation in the past, but cycles that are effectively projected into the future, that is, those that are endowed with a high predicative ability. The classical spectral analysis based on the Fourier transform in this case is of little use.
Figure 2 presents an example of the identified frequencies of sugar beet yields in Russia.

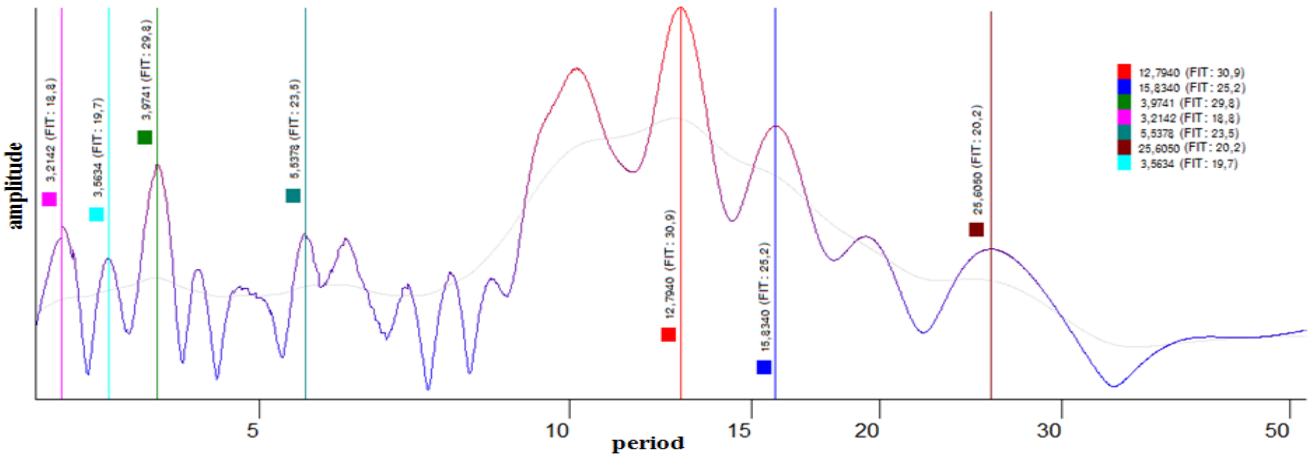

Figure 2: Spectral portrait of sugar beet yields

Using the Fourier transform, the time series is decomposed into many of its constituent cycles. These cycles are located along the X axis as their period increases (from 2 to 54 years). It is seen that the cycles differ in amplitude. The information obtained can be used by analogy with acoustic analysis. It is necessary to clear the value of "noise", retaining only the cycles that demonstrate the highest possible correlation (denoted as FIT, Figure 2).

After clearing the BP of "noise" (i.e., other cycles with weak correlation), combine the seven sinusoids obtained into one cumulative wave.

For a number of reasons, it is not recommended to use the cumulative wave in the "raw" form in forecasting, so it is much more productive to send the obtained cycles with high correlation first to the input nodes of the neural network, to conduct its training, and then use the signals issued by it at the output. It is this optimal algorithm of neurospectral analysis that will be followed in the prediction. The results are presented in Figure 3 and Table 1. Figure 3A shows the initial BP (sugar production in Russia is the black line) and its forecast (blue line is the neurospectral row), in Figure 3B the probabilistic development trajectory of BP is built, based on the spectral decomposition .

As can be seen, the prognostic line of magnitude in the future (pink background on the graph in the right part of the window) differs significantly from the projection line (Figure 3B), which is created by adding the seven cycles with the highest correlation. In particular, the cumulative wave (Figure 3B) indicates an unambiguous decline already in the near short term, while the forecast of the neuro-spectral network (Figure 3A is the blue line) turned out to be more restrained: instead of falling, growth in 2017 and a sharp drop in 2018–2020., ie, the forecast turns out better.

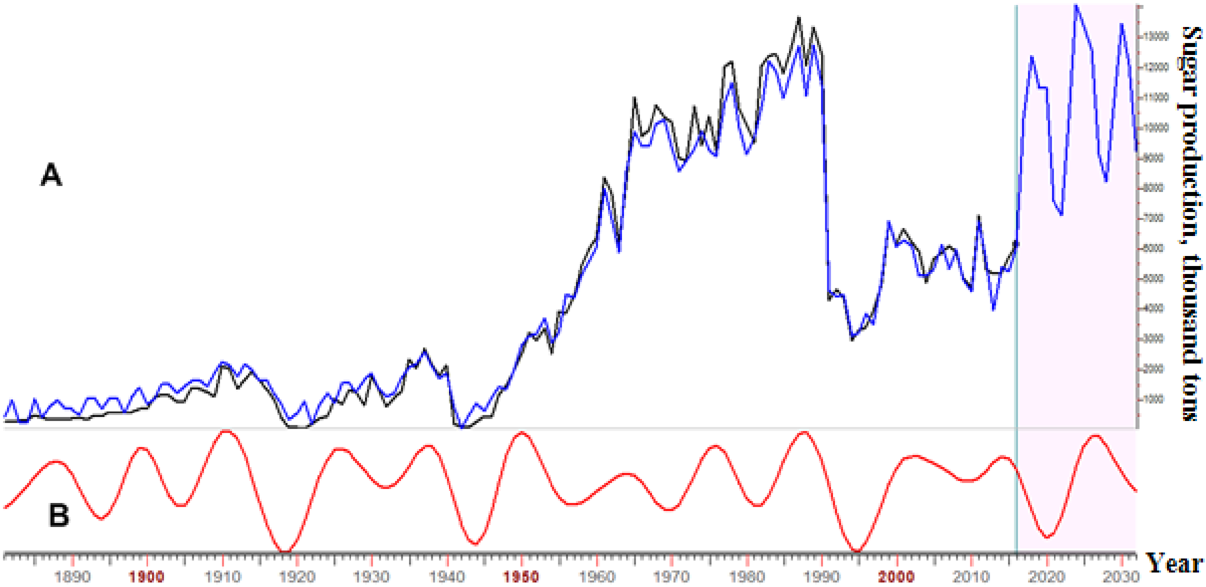

Figure 3: Total sugar production in Russia, and the neuro-spectral series (A); estimated forecast (spectral series) for the period up to 2030 (B); black graph - the original row; blue graph - neurospectral row; red graph - spectral range

Table 1: Forecast of the development trajectories the sugar industry, built by spectral analysis and neural network modeling, the Food Industry block

Sugar production	*Forecast Horizon (Years)*														
	2016	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	*2024*	*2025*	*2026*	*2027*	*2028*	*2029*	*2030*
World, 1864–2013.															
General, 1864–2016	1,6801	0,9404	0,2638	-0,0265	-0,085	-0,035	0,0915	0,2231	0,2896	0,3659	0,8789	1,2951	1,3103	1,2472	1,0811
Reed	-0,542	-0,383	-0,403	1,1035	0,2679	0,4493	-0,0541	-0,5208	-0,193	-0,204	-0,0163	-0,2053	0,3452	-0,076	-0,0918
Beetroot	2,5745	0,4403	3,4326	3,237	1,2855	1,3147	0,1251	1,5116	3,2691	4,1736	0,6831	3,9073	0,1289	0,2366	2,6406
In Russia (the Russian Empire, the USSR and the Russian Federation), 1881–2016															
General	5,9732	2,1416	5,876	7,5635	-0,145	-1,033	-4,134	-1,8975	4,1747	1,5856	8,805	6,51	8,8954	3,9005	4,8355
Beetroot, 1871–2016	0,575	0,6019	0,6458	0,536	0,6218	0,3092	0,1888	0,3749	0,4012	0,467	0,3556	-0,2201	-0,23	-0,137	-0,017
Reed, 1960–2016	0,1745	0,3493	0,3493	0,2487	0,2487	0,2487	0,2276	0,2276	0,443	0,2285	0,2285	0,4448	0,4448	0,3579	0,3579
In Russia (RSFSR and the Russian Federation), 1921–2016															
General	0,6026	0,5045	0,379	0,3233	0,2988	0,2825	0,465	0,6173	0,4862	0,1891	0,074	0,326	0,3475	0,4009	0,5545
Reed, 1960–2016	0,267	-0,728	-0,876	-0,438	-0,316	1,453	3,338	3,44	1,311	0,766	1,519	1,004	-0,27	-0,034	1,032
In the Kuban, 1921–2016															
General	1,495	0,97	0,606	0,422	-0,326	-0,422	0,512	1,055	1,169	0,958	0,13	-0,374	0,185	0,869	1,357
Reed, 1960–2015	0,5036	0,1864	0,053	-0,14	0,2359	0,5559	-0,374	0,5703	-0,272	-0,109	0,0329	0,5051	0,5284	0,2611	0,7536
In the USA,1832–2016гг.															
General	0,4148	0,3394	0,3443	0,3084	0,4054	0,4289	0,3148	0,2812	0,5143	0,6011	0,6415	0,6346	0,5894	0,6073	0,5132
Reed	0,3886	0,3253	0,166	-0,0532	-0,1	-0,064	-0,015	0,1053	0,0597	-0,023	-0,016	0,0343	0,062	0,0739	0,0959
Beetroot, 1873–2016	1,897	1,879	1,89	1,933	2,001	2,044	2,032	1,971	1,907	1,88	1,885	1,92	1,985	2,038	2,04
In individual countries															
Cuba (reed), 1849–2014.	-1,881	-2,607	-1,209	0,1506	0,9467	1,3635	1,0491	0,9082	0,5072	0,6725	0,7237	-0,1832	-0,973	-0,959	-0,4067
Germany (beet), 1910–2015.	1,6455	1,1247	1,3271	1,5394	1,2494	0,9286	1,1121	2,4552	1,1972	1,5537	0,4989	1,0628	1,2748	1,8605	1,2498
India (reed), 1949–2016	2,8413	1,5582	-0,156	-1,1177	-0,826	-0,165	0,0075	0,1033	0,3478	0,4589	0,293	-0,171	-0,758	-1,341	-1,096
Brazil (reed), 1949–2015	2,5190	2,5189	3,3412	3,3505	2,3938	0,9908	0,1602	0,1764	0,1778	0,045	0,7213	2,0625	2,4347	2,6553	2,9902

To improve the accuracy of the forecast, it is necessary to solve the problem of the temporal relevance of cycles, which can be removed using the so-called wavelet transform (wavelet neural networks). The problem with identifying cycles endowed with high predictability can be solved by replacing the classical spectrum with a wavelet or a quantum approach (in which the Fourier transform can be combined with forward analysis).

CONCLUSION:

The proposed methodology has been developed (adapted) to obtain a predictive estimate of successive data series of the sugar sub-complex of the agro-industrial complex.

1. The analysis was performed on the basis of modern information technologies used to solve forecasting problems. It is proved that the most promising technology is a combination of classical methods of spectral analysis and the theory of artificial neural networks, which are universal approximators.

2. Classical forecasting methods do not allow to solve the problem in full and with a given accuracy. Due to the non-adaptability of the applied procedures, the forecast adequacy period is significantly reduced, and therefore complex calculations are required to rebuild (resynthesis) the model when the external conditions of the object change [1, p. 23].

3. Studies have been conducted on many different BPs of the sugar subcomplex (with various combinations of cycles). The following recommendations (rules) have been developed:

a) do not use too many cycles, 1–7 is enough.

b) models that use too many cycles are good for explaining fluctuations in performance in the past and are not well suited for predicting future movements.

c) adding just one insignificant cycle to the cyclic model can completely distort it.

4. At the heart of any time series there are always some trends. Mathematically, it is necessary to use instead of real data indicators, “cleared” from the trend (i.e., implement the detrending procedure). In other words, to achieve this goal, when calculating the scheme of the spectra, it is not the value itself that is used, but the RPO without trend indicator.

5. Neuro-spectral analysis allows improving the quality of forecasting the development of complex dynamic processes to a greater extent than classical spectral analysis.

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