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Procedia - Social and Behavioral Sciences 166 (2015) 182 – 188

Procedia
Social and Behavioral Sciences

International Conference on Research Paradigms Transformation in Social Sciences 2014

# Neuro-fuzzy methods in cognitive systems of monitoring and forecasting of scientific and technological development of the country

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**Abstract**

On the basis of many national and international research a neural network model of the trajectory of and techno-economic development, which allows to calculate the level and rate of fuel and energy is developed and the method of evaluating the effectiveness of technological innovation projects on a range of qualitative and quantitative parameters based on the construction of the neuro-fuzzy solution tree is proposed. The developed model, in addition to the promising project choosing, explains the decision making process in an understandable way, in the structure of the neuro-diagnostic decision rules "If ... then." Thus, this technique allows to determine the significance of the indicators (trends) of the formation of new technological cycles and to identify the reference parameters of the social dimension of the economy. Data received as a result of the intellectual analysis can be used by experts to assess the efficiency of the automated calculation of the effectiveness of technology projects in order to predict the scientific and technological development of the country and make necessary recommendations to the political and socio-economic spheres. Research results can be used both by private and public companies and organizations. This will help to assess and predict future changes, give proper recommendations to scientific institutions in key areas: such as security and counter-terrorism; living systems; nanosystem and materials Industry, information and telecommunication systems, advanced weapons, military and special equipment, management natural resources, transport, aviation and space systems, energy and energy efficiency.


Peer-review under responsibility of Tomsk Polytechnic University.

*Keywords:* cognitive systems, neuro-fuzzy methods, forecasting, innovation;

## 1. Introduction

The present stage of scientific and technological progress is defined by the emergence of a new technological cycle, which refers to a certain set of adjacent industries, at the same level of technological development. An

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Peer-review under responsibility of Tomsk Polytechnic University.
doi:10.1016/j.sbspro.2014.12.507

economic system that can implement the process of self-reproduction by means of internal resources is being formed. Scientific progress in the long term prospect involves replacing the traditional technological cycle by an innovative one (Glazev S. Yu., 1992).
So far, national projects on choosing technology priorities require new approaches for obtaining objective assessments based on quantitative analysis of empirical data – patent statistics, citation information, bibliometric data etc (Ahmetzhanova S. B., et al.; Sokolov A.,2007; Ernst H.,1997; Karvonen M., 2013; Tseng F.-M., 2011; Cavaller V., 2009).

## 2. Research methods

In the framework of the study the results of expert seminars, as well as the remote expert evaluation (a special kind of research, in which experts do not get together, each of them is interviewed remotely, and the collective opinion is produced by special integration of opinions) have been used (Gorbachev S. V., 2012).
The participants of the expert interviews and workshops were asked questions regarding the indicators that could be significant in the analysis of the transition to the 6th technological cycle and development of the model of changing of technological cycles. As a result, the main groups of indicators of monitoring and analyzing trends that allow to assess the dynamics and directions shaping the new technological cycle (such as macroeconomic, geographical, natural and climatic, historical, innovative, including research and development) were identified (Syryamkin V. I., 2012).
For modeling of the trajectory of the engineering-and-economical development the group of investigated parameters was supplemented with the qualitative component of growth - productivity index of primary resources, which is measured as the ratio of GDP to the cost of consumed by the economy raw materials (Uzyakov M. N., 2004).
In order to improve the quality of the forecast, the simultaneous analysis of several available indicators (quantitative and qualitative) was conducted. Therefore macroeconomic indicators were supplemented with quality component of economic growth (the cost of primary raw materials), key factors of living standards, as well as innovation activities of countries (Ministry of Finance of the Russian Federation, 2011).

## 3. Display of the complex engineering-and-economical picture of the world by means of neural network clustering of countries

The problem of modeling the trajectory of the engineering-and-economical development is of considerable interest.On the one hand, there is a lot of statistical material on macroeconomic parameters, which can be formalized and evaluated (Ashimov A. A., 2010; Sadovnichij V. A., 2011). On the other hand the subject area is so difficult to study that traditional linear estimates are unlikely to reflect the real dynamics of the engineering-and-economical development. It is very important to choose the input parameters and indicators of the techno-economic development, and then put them in order according to their level of importance for solving the problem (Sitenko D. A., 2010).
Kohonen maps can be used for modeling, foresight, clustering, search for patterns in large volumes of data, for identification of independent features and data compression. Kohonen network training is done by means of successive approximations. The input is a pre-normalized data and the network is not adjusted for the reference output, but for pattern of the input data (Kohonen T., 1990).
Most generalized modeling result can be represented on two-dimensional and three-dimensional maps of countries distribution according to their level of technical and economic development:

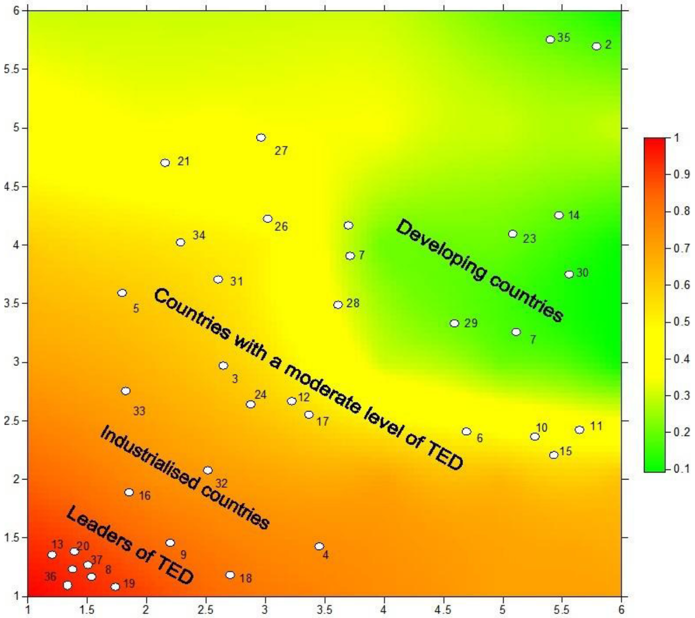
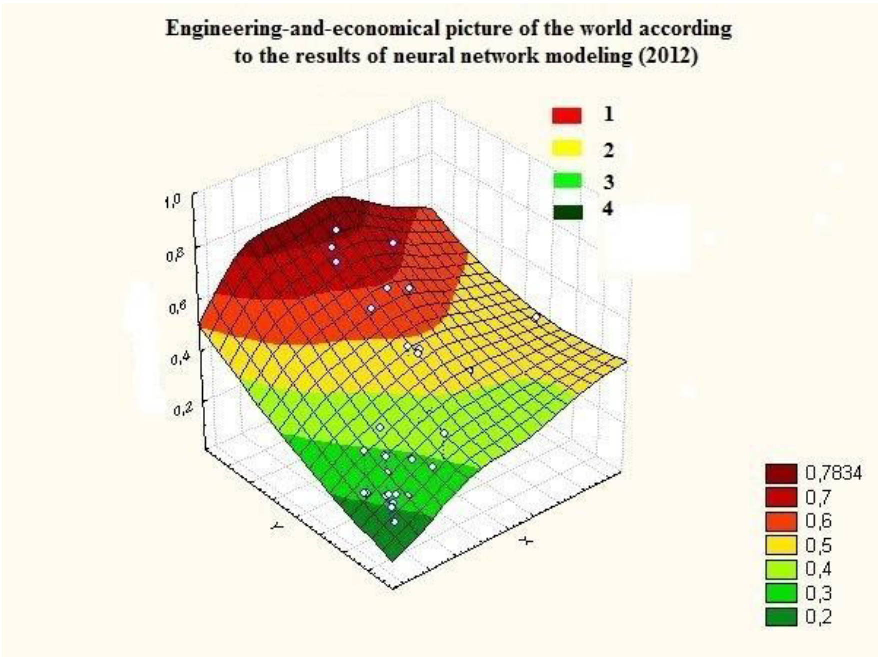



Figure 1. 2D engineering-and-economic picture of the world (Syryamkin V. I., 2012).




1 – Leaders of technical and economic development
2 – Industrialized countries
3 – Countries with a moderate level of technical and economic development
4 – Developing countries

Figure 2. 3D engineering-and-economic picture of the world (2012).

The trajectory model of techno-economic development as a dynamic range of trained neural Kohonen network shows hierarchy of the countries in the world engineering-and-economical picture - the degree of closeness to the level leader at the time of observation “t”. Thus, the model learns data structure by solving the problem of finding clusters in the space of input images. In this case, the trajectory of techno-economic development (fig. 3) can be represented as a time series of trained neural networks, each of which contains a model of the global techno-economic picture of the year of observation “t”:

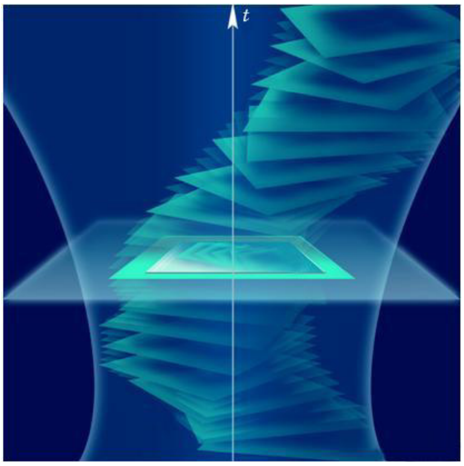



Figure 3. Techno-economic development trajectory model as a time series of the Kohonen trained neural network.

For each country, occupying its position according to the level of techno-economic development in the trained neural network, the following neural network parameters are calculated:

- the actual distance - the number of years passed from the moment when the reference level of the techno-economic development, matched the level of a country under study in a year of observation “t”;
- the upcoming distance - the number of years, needed by a country starting from the year “t”, in order to achieve the reference level of technological development in the year of observation “t”;
- the conditional distance - the number of years necessary for a country to enter the reference trajectory.

The importance of each input parameter in the observation year “t” can be calculated by trained neural network. Reducing the set of parameters and input data of neural network increases the speed of neural networks, reduces the price and simplifies the collection of data by discarding the least significant variables and facilitates the process of explicit verbal interpretation of data processing results.

## 4. Calculation of the level and pace of technological and economic development of countries according to the result of neural network modeling in the transition of the global economy from the dominant to the emerging technological cycle.

On the basis of the outputs of neurons in the year of observation the studied countries are divided into four main groups according to their engineering-and-economical development, which takes a value of 1 for the reference level to 0 for the minimum level of the development. The rate of technical and economic growth for the period of seven years was calculated for each country. For each five-year period the calculation is based on the output values of the trained neural network Kohonen, reflecting the change in the level of engineering-and-economical development in terms of absolute changes in macro-economic and innovative performance over this period (Kohonen T., 1990).

Table 1. Groups of countries divided according to their level of technical and economic development on the results of neural network modelling (2005-2012).

| Group | Leaders of the growth (more than 4 %) | Countries with a moderate level of growth (2–4 %) | Countries with a low level of growth (1–2 %) |
|---|---|---|---|
| Leaders of technical and economic development | Canada | USA, UK, Italy, France, Germany | Japan |
| Industrialized countries | Ireland, Denmark, Sweden, Switzerland | Iceland, Slovenia | Austria, Belgium, Luxembourg, Netherlands |
| Countries with a moderate level of technical and economic development | India, Brazil, China, Russia, Cyprus, Estonia | Hungary, Lithuania, Poland, Portugal, Finland, Slovakia | Norway, Spain, Greece, Malta |
| Developing countries | Turkey, Bulgaria, Romania | Greece, Latvia | Croatia, Serbia |

The received neuro-fuzzy model is adjustable. At the initial stage, it includes a set of chosen by experts quantitative and qualitative indicators. At the next stages the model can be modified depending on the socio-economic and political factors targeted. The automated system includes 2 levels, interconnected by means of analysis and forecast. This methodological approach contributes to the foresight studies (Gorbachev S. V., 2012).

## 5. Development of criteria and priorities for selecting effective scientific and technological trends

An additional question in the present study is the development of indicators for the experts to assess technological alternatives as well as the criteria of their selection.

In order to improve the foresight accuracy an algorithm for constructing neuro- fuzzy decision tree as a tool of an evolutionary methodology for solving classification problems, having such property as parameters adaptation and using neural network modeling, has been developed . In a direct cycle fuzzy decision trees are based on the algorithm of fuzzy ID3. In the feedback cycle the parameters of fuzzy decision trees are based on the gradient neural network algorithm by going from the «leaves to the root nodes» (Gorbachev S. V., 2012).

Thus, based on expert data a neuro-fuzzy decision tree was constructed that indentifies the list of the most promising technologies and scientific trends which can form the sixth technological order (fig. 4).

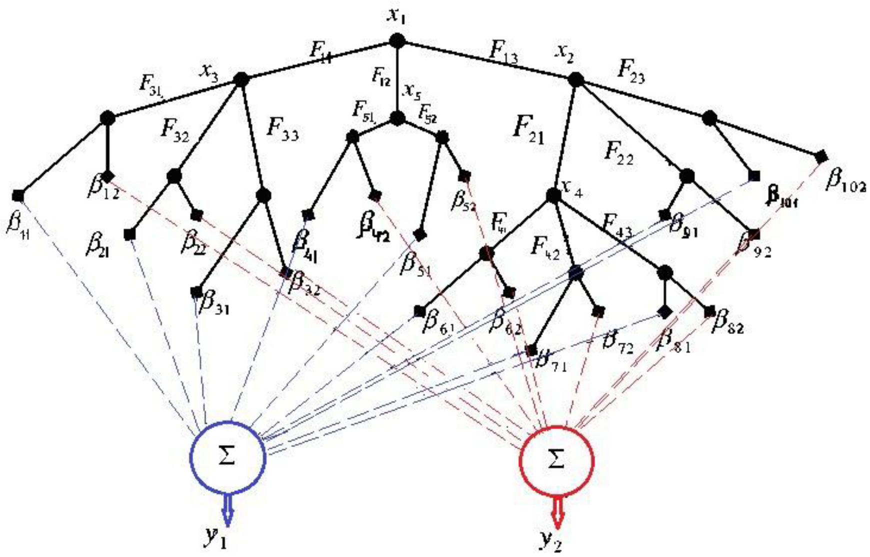


Figure 4. Neuro–fuzzy decision tree (Syryamkin V. I., 2012).

For a certain set of data the weight class *l* on *m-leaf node* is defined as follows:

$\mu^{i}_{path_m} * \beta_{ml}$,

where $\mu^{i}_{path_m}$ - degree of membership $path_m$ , which is calculated by the formula:

$\mu^{i}_{path_m} = \prod_{j=1,\dots,4} F_{jm}(s^{i}_{j})$,

where $F_{jm}$ – membership function of *j* variable, available on *m*-way.

Each *m*- way *(m = 1,...,9)* Is defined by the intersections of the input paths from the root node to the m- leaf node.

So far, $path_6$, can classify class 1 («Yes») with the degree of membership $\beta_{61}$ and classified Class 0 («no») with a degree of membership $\beta_{62}$.

The degrees of membership of all leaf nodes corresponding to the Class l, are summed to calculate foresight values of membership $y^{i}_{l}$ ($l$ = 1,2) of *i*- set while passing through the decision tree:

$y^{i}_{l} = \sum^{0}_{m=1} \mu^{i}_{path_m} * \beta_{ml}$,

Where $0 \le y^{i}_{l} \le 1$.

After completion of the classification classes with the highest degree of membership l0 are formed (Zadeh L. A., 1978):

$$l_0 = \arg\max_{l=1,2}\{y^{i}_{l}\}$$

Decision trees are a tool of decision support systems and data mining (data mining).

The effect of identifying consistent patterns in a neural network model provides comprehensive analysis of heterogeneous parameters which are not sufficient alone. The trained intelligent model calculates weighted coefficients and identifies diagnostic decision rules "If…, then…" in which certain figures are used in the problem solution. As a result, the forecasting presents multivariate time series, each element of which is the one of the system parameters. According to experts of the EU, "cognitive" science (or neuroscience) and "smart" systems (interdisciplinary research on a wide range of problems associated with mental activity) are a major challenge and the direction of development of fundamental science of the XXI century. They allow solving information processing tasks, in the face of uncertainty and low training time (Gan G., 2007; Avdeeva Z. K., 2006; Bashlykov A. A., 2013; Kuznecov O. P., 2009; Abdikeev N. M., 2010).

According to the experiments done, in most cases, the proposed procedure allows to increase the accuracy of classification.

The developed model, helps to explain the decision-making process in language understandable to decision makers, deriving diagnostic rules «if ... then» from the structure of a neuro-fuzzy decision tree. Thus, this it allows to identify the relevance of indicators (trends) of new technological cycles formation and to determine the reference parameters of the social dimension of the economy.

The particular data mining tools belong to hybrid computational intelligence systems that operate on the basis of principles that are significantly different from the data processing methods in traditional artificial neural networks and are related to the field of cognitive ("smart") technologies.

They allow to deal with complex information processing tasks, when the classes which are to be separated intersect with each other and are characterized by high accuracy and efficiency in the conditions of uncertainty, less training time and noise resistance.

Such hybrid neuro-fuzzy systems have a powerful cognitive potential (sensations and perceptions modeling). They find a significantly wider range of applications than other methods for the synthesis of fuzzy sets and neural networks. Such systems can make full use of «strong» sides of fuzzy systems (interpretability of accumulated knowledge) and neural networks (the ability to be trained on the data). Such systems are not only using a priori information, but also acquire new knowledge, being logically a «transparent». Therefore, they can be related to Data Mining - scientific field, studying methods and laws of extracting the subject area out of the data.

The main purpose of the new economic policy should be creation of the conditions under which the economic development will gradually move from raw materials to processing industries and the innovation sector will play the key role. The main goal of modern development of Russia is the implementation of self-dependent innovation policy, based on the competitive advantages of Russia instead of blind following the suggestions of foreign experts and copying foreign experience.

Thus, the developed models and tools are essential for science-based assessments and can be used by experts to evaluate the effectiveness of the automated calculation of technological projects in order to forecast the scientific and technological development of the country and make necessary recommendations in political and social and economic spheres.

**Acknowledgement**

The study was done within the framework of the competitive development program of Tomsk State University.

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