– location of an item in question (post-equatorial location, equatorial location, location within the disk of optic nerve, etc.);

– color (black, pigment-free, pink etc.);

– size (diameter, height).

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LOGIC-NEURAL NETWORK METHOD TO ANALYSIS OF AUDIT DATA

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Nowadays the scientific and technical issue of the modern information technologies in financial and economic sphere of Ukraine is forming of the methodology of planning and creation of the decision support systems (DSS) at the audit of enterprises in the conditions of application of IT and with the use of information technologies. Modern automated DSS audit are based on the automated analysis of the large volumes of data about financial and economic activity and states of enterprises with the multi-level hierarchical structure of heterogeneous, multivariable, multifunction connections, intercommunications and cooperation of objects of audit. The tasks automated DSS audit are expansion of functional possibilities, increase of efficiency and universality of IT-audit.

Currently, the analytical procedures used during the audit are based on data mining techniques [1, 2]. Automated DSS audit means the automatic forming of recommendable decisions, based on the results of the automated analysis of data, that improves quality process of audit. Unlike the traditional approach, computer technologies of analysis of data in the system of audit accelerate and promote the process accuracy of audit, that extremely critical in the conditions of plenty of associate tasks on lower and middle levels, and also amounts of indexes and supervisions in every task.

The development of methods of estimation and prediction [1], formation of generalized associative relationships [2] are described in the works of the authors of this article. The goals of creating these methods: reducing the computational complexity for simple tasks (a single mapping of elements or sub-elements of the audit subject area), automatic structural identification, increasing the accuracy for complex tasks (compositions of mappings of elements or sub-elements of the audit subject area) and the possibility of applying these methods for the generalized analysis of elements and sub-elements of the audit subject area (Table 1).

The choice of model in the audit DSS depends on:

1) characteristics of the audit data type (time series data, spatial data (as mappings));

2) audit level (upper middle, lower),

3) audit tasks (internal, external);

4) the type of analysis tasks (detection of anomalies, structural analysis, assessment of indicators);

5) the characteristics of the enterprise (large, medium, small) and the type of activity (industry) at the top level;

6) characteristics of sets and subsets of operations at lower levels (numerological, quantitative, semantic, logical).

This choice is schematically formalized in the form of a binary decision tree for choosing a neural network data audit model (Fig. 1)

At the first level, the choice of a model is carried out depending on data type. If map data is analyzed, therefore ANN with associative memory is used, otherwise ANN for forecasting.

When choosing models based on associative memory at the next stage, the choice depends on the type of production: with or without waste. If the production is waste-free, depending on the size of the enterprise and the specified accuracy of the decision maker, a model is selected that is the best in terms of the ratio of learning rate and accuracy. At the next levels, the choice depends on the type of analysis. In the case of structural analysis, models are selected in which the layers correspond to the stages of data transformation, in particular, production data. Also, the choice depends on the direction of analysis: direct or direct and reverse.

Table 1

Comparative analysis of intelligent analysis methods in audit tasks

The economic content of the display	**Model of processing elements of the subject area, Features of the model or method**	**Purpose of processing elements of the subject area**	**Advantages disadvantages of the model or method**
1	2	3	4
Payment – delivery of raw materials	Modified Liquid State Machine, one- dimensional hidden layer, parameter identification based on matrix pseudoreversion [1]	Evaluation and prediction of indicators of raw material supplies (by type) based on the values of payment indicators in a direct check of the display	Reducing computational complexity, improving the forecast accuracy
Settlements with suppliers-customer settlements	A neural network model based on a gateway recurrent unit. For parametric identification of this model, adaptive cross entropy (a combination of random and directional search) is faster to learn but less accurate than in [1] because the pseudoreversal is not paralleled	Evaluation of indicators of settlements with customers on the basis of values of indicators of settlements with suppliers in a direct verification of mapping	Reducing computational complexity, improving the forecast accuracy

Continued Table. 1

1	2	3	4
Settlements with suppliers – settlements with customers (a composition of mappings between a set of input and output data)	Forward-only counterpropagating neural network, which is a nonrecurrent static two-layer ANN [2], assumed that the audit indicators are noisy with Gaussian noise (learner model)	Construction of generalized associative relationships for generalized analysis tasks (in the forward direction)	Automating the formation of generalized features of audit sets and their mapping by means of a forward-only counterpropagating neural network the number of pairs (neurons in the hidden layer N1) is set manually
Release of raw materials - posting of finished products (a composition of mappings between a set of input and output data)	Bidirectional counterpropagating neural network, which is a nonrecurrent static two-layer ANN BCPNN (learner model)	Construction of generalized associative relationships for generalized analysis tasks (in the forward and reverse direction)	Automating the formation of generalized features of audit sets and their mapping by means of a bidirectional counterpropagating neural network the number of pairs (neurons in the hidden layer N1) is set manually

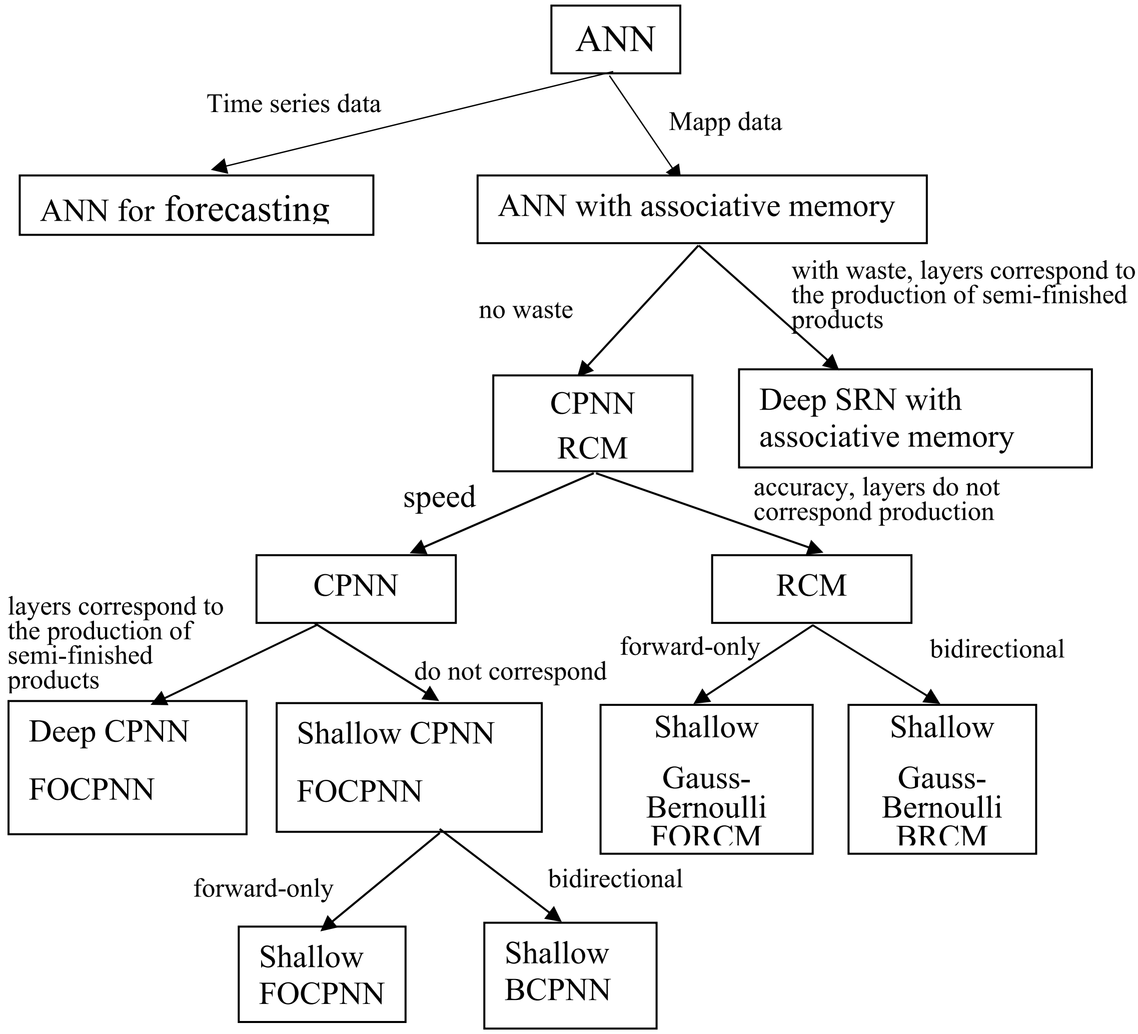

Fig. 1 Binary decision tree of neural network model selection for data analysis

Conclusion. The proposed logical-neural network method makes it possible to automate the process of data analysis in the audit DSS and optimize it depending on the characteristics of the audit process and the audit object.

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УДК 001.2

СТАТИСТИЧНА ОЦІНКА РІВНЯ МІЖДИСЦИПЛІНАРНОСТІ НАУКОВИХ ДОСЛІДЖЕНЬ З ВИКОРИСТАННЯМ ДАНИХ СИСТЕМИ DIMENSIONS

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Останнім часом велика увага прикута до міждисциплінарних досліджень, досліджень, які стосуються предметного поля кількох наукових спеціальностей. Найбільш поширеним способом кількісного оцінювання рівня міждисциплінарності наукових досліджень є аналіз цитувань. Для цього враховують, публікації з яких спеціальностей згадуються в списку літератури аналізованої статті. Зібравши такі дані за великою кількістю статей і провівши їх узагальнення, можна оцінити рівень взаємодії тих чи інших спеціальностей, визначити тенденції – зміни рівня взаємодії протягом деякого часу, виявити нові кластери кооперації тощо.

Зазначений вище підхід є досить трудомісткий, хоча збір початкових даних і автоматизується з використанням баз даних Wev of Science та Scopus. Ми пропонуємо інших підхід до оцінювання взаємодії між науковими спеціальностями. Для цього пропонується скористатися ресурсами інформаційної системи Dimensions, яка містить понад 110 млн категоризованих публікацій. В цій системі кожна публікація віднесена до однієї чи кількох наукових спеціальностей (рис. 1). На основі цих даних можна встановити рівень взаємодії між будь-якою парою спеціальностей протягом аналізованого часового інтервалу.

Dimensions використовує дворівневий варіант Австралійсько-Новозеландської системи класифікації наук – ANZSRC. Структурно він схожий на сучасний український перелік спеціальностей та галузей знань. ANZSRC містить 22 галузі (research divisions) та 157 спеціальностей (research groups). Наприклад, галузь *08 Information and Computing Sciences* включає такі спеціальності: *0801 Artificial Intelligence and Image Processing*; *0802 Computation Theory and Mathematics*; *0803 Computer Software*; *0804 Data Format*; *0805 Distributed Computing*; *0806 Information Systems*; *0807 Library and Information Studies*; *0899 Other Information and Computing Sciences*.