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FUZZY-NEURO SYSTEM FOR DECISION-MAKING IN MANAGEMENT

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This paper introduces a systematic approach for intelligent decision support system design based on a class of neural fuzzy networks built upon a general neuron model. The neural fuzzy networks can formally represent and process both the qualitative (linguistic) and quantitative information, which usually describe a complex, multi-dimensional systems or decision making processes. Presented the results of tests and a practical implementation of applications of fuzzy-neuro system for decision-making in strategic management and determination of product development strategy.

INTRODUCTION

Computer integrated manufacturing (CIM) provides manufacturing industry with the means to produce a variety of products efficiently. Effective planning, scheduling and control in the CIM environment depend largely on proper design of the decision support system (DSS). A manufacturing system is driven by input stimuli from the market in the form of direct product demand, market conditions and feedback on production with a variety of information perspectives. The activities of this system may be broadly classified as management (including strategic planning), design, production planning and production operation. Intelligent DSS have evolved as tools that attempt to support decision-making processes in problem contexts characterized by novelty and large search spaces. Problems with these characteristics are known as unstructured problems. The managerial problem domain is composed of dynamic, temporal relationships between variables. Solving many problems concerned with modern manufacturing management is connected with processing of incomplete, inexact information. First of all, these problems are mainly aspects of strategic management: market analysis, choice of product strategy and of manufacturing system development, choice of strategy for manufacturing arrangement, and others. To solve such tasks it is necessary to apply unstructured procedures for decision making, which use experimental data, skills and human intuition. To model and process fuzzy, linguistic or so called qualitative information fuzzy sets theory and mathematical apparatus of fuzzy logic are used [1, 2, 3, 4]. In such systems of decision making support, the process of obtaining explanations and inference engine operation during processing of fuzzy knowledge is highly complicated.

This paper aims at development of procedures and algorithms for application of artificial intelligence tools to acquire and process various types of knowledge (quantitative, qualitative, linguistic, fuzzy) and to solve selected unstructured problems and tasks in decision support systems. The proposed environment integrates techniques and methods of knowledge and decision process modeling such as artificial neural networks and fuzzy logic-based reasoning methods.

In this paper possibilities are presented of an approach which combines methods based on fuzzy logic and artificial neural networks, which results in creation of a structure called a fuzzy neural network. The structure of a fuzzy neural network combines the best properties of an artificial neural network, the ability to learn from examples, and fuzzy logic, i.e. conversion of fuzzy knowledge. Combination of these artificial intelligence technologies allows creation of comprehensive programming tools that can be used to solve complex decision problems when incomplete, uncertain or contradictory knowledge has to be processed or it is hard to formalize the knowledge. Fuzzy neural networks presented in this paper are a generalization and expansion of classical neural networks. These networks are able to process qualitative and linguistic information apart from quantitative information through the application of the fuzzy set theory and mechanisms of fuzzy decision making.

In this paper the results of the tests and a practical implementation of applications for decision support systems based on fuzzy neural networks used for strategic management and determination of product development strategy will be presented.

CLASSICAL ARTIFICIAL NEURAL NETWORK

The original source of fuzzy neural networks is a multilayer perceptron, which is a feedforward neural network characterized by transferring of information from the input level through K additional hidden layers to the output layer. Fig.1 presents the structure of a two-layer perceptron, i.e. a perceptron with one additional (hidden) layer. In the standard structure of a multilayer perceptron each i-th node in k-th layer is connected through synaptic weights W_{ij} with all the nodes of the previous layer $(k-1)$.

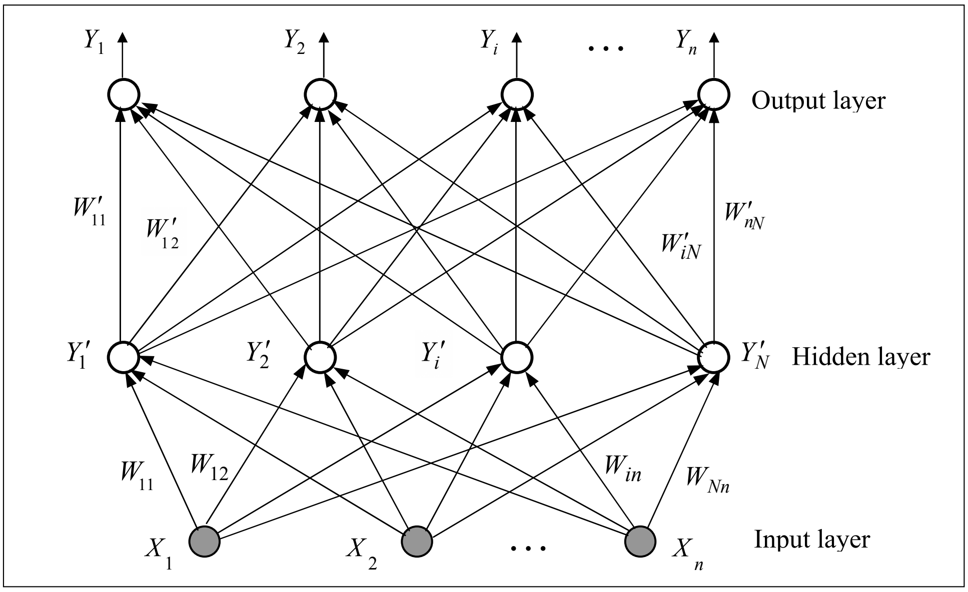

Fig. 1. Model of multilayer perceptron [2]

Output signals are calculated as follows:

$$Y_i' = f\left(\sum_{j=1}^{N} W_{ij}\, x_j - \theta_j\right) \text{ — for hidden layer neurons,} \tag{1}$$

$$Y_i = f\left(\sum_{j=1}^{N} W_{ij}'\, Y_j' - \theta_j'\right) \text{ — for output layer neurons,} \tag{2}$$

where W_{ij}, W_{ij}' — synaptic weights; $f\left(\sum_{j=1}^{N} W_{ij}\, x_j\right)$ — activation function; θ_j, θ_j' — shift values; x_j $(j = 1, 2, ..., N)$ — input signals.

In hidden perceptron layers transformation of nonlinear information takes place. For processing of non-linearity in the hidden layers sigmoid function is often used, which can be described as follows:

$$f(\alpha) = \frac{1}{1 + e^{-\alpha}}. \tag{3}$$

In practice, the main Back-Propagation algorithm, as well as its different modifications, is used for training neural networks of the multilayer perceptron type [4, 5]. Details of the network training process will be presented in the further part of this paper concerned with fuzzy neural networks, which is the object of the research.

MODEL OF A FUZZY NEURAL NETWORK

Let us consider a system with n inputs: $x_1, x_2, ..., x_n$ $(x_i \in X_i,\ i = 1, 2, ..., n)$ and m outputs: $y_1, y_2, ..., y_m$ $(y_j \in Y_j,\ j = 1, 2, ..., m)$, respectively, where $x = (x_1, x_2, ..., x_n)^{\mathrm{T}} \in X_1 \times X_2 \times ... \times X_n$ and $y_j \in Y_j$ are linguistic variables. Qualitative information, which describes the behavior of this system, is presented as a number of K fuzzy **IF – THEN** rules in the following form:

IF $(x_1$ is $A_{11}')$ and $(x_2$ is $A_{21}')$ and… and $(x_n$ is $A_{n1}')$
THEN $(y_1$ is $B_{11}')$ and $(y_2$ is $B_{21}')$ and… and $(y_m$ is $B_{m1}')$
and … and
IF $(x_1$ is $A_{1k}')$ and $(x_2$ is $A_{2k}')$ and… and $(x_n$ is $A_{nk}')$
THEN $(y_1$ is $B_{1k}')$ and $(y_2$ is $B_{2k}')$ and… and $(y_m$ is $B_{mk}')$ (4)

where A_{ik}', B_{jk}', $(i = 1, 2, ..., n)$, $(j = 1, 2, ..., m)$ and $(k = 1, 2, ..., K)$ are certain linguistic notions which describe appropriate system inputs and outputs. A_{ik}' and B_{jk}' are fuzzy sets, where $A_{ik}' \in R(X_i)$ and $B_{jk}' \in R(Y_j)$ and $R(X_i)$ and $R(Y_j)$ mean clusters of all fuzzy sets which are determined on the sets X_i and Y_j respectively.

Quantitative information that describes the behavior of the system may be presented as a number of L sets with numerical data of the following type: $(x'_{1l}, x'_{2l}, ..., x'_{nl},\ y'_{1l}, y'_{2l}, ..., y'_{ml})$, where $l = 1, 2, ..., L$, and $(x'_{il} \in X_i)$, $(y_{jl} \in Y_j)$ $(y'_{jl} \in Y_j)$. Quantitative information may also be presented as a system of L conditional rules in the following form:

$$\begin{aligned}&\textbf{IF} \quad (x_1 = x'_{11}) \ \text{ and… and } \ (x_n = x'_{n1}) \\ &\textbf{THEN} \quad (y_1 = y'_{11}) \ \text{ and… and } \ (y_n = y'_{n1}) \quad l = 1, 2, ..., L.\end{aligned} \tag{5}$$

The methodology of processing the above-presented information (i.e. qualitative, quantitative, and mixed) is based on the application of a fuzzy neural network. In accordance with the main idea the details of which are presented in papers [1, 3], all types of the input information are as if «built into» the structure of a fuzzy neural network during the process of network training. Another important task is development of the inference engine, which will be able to generate responses of the system to the types of input data determined above.

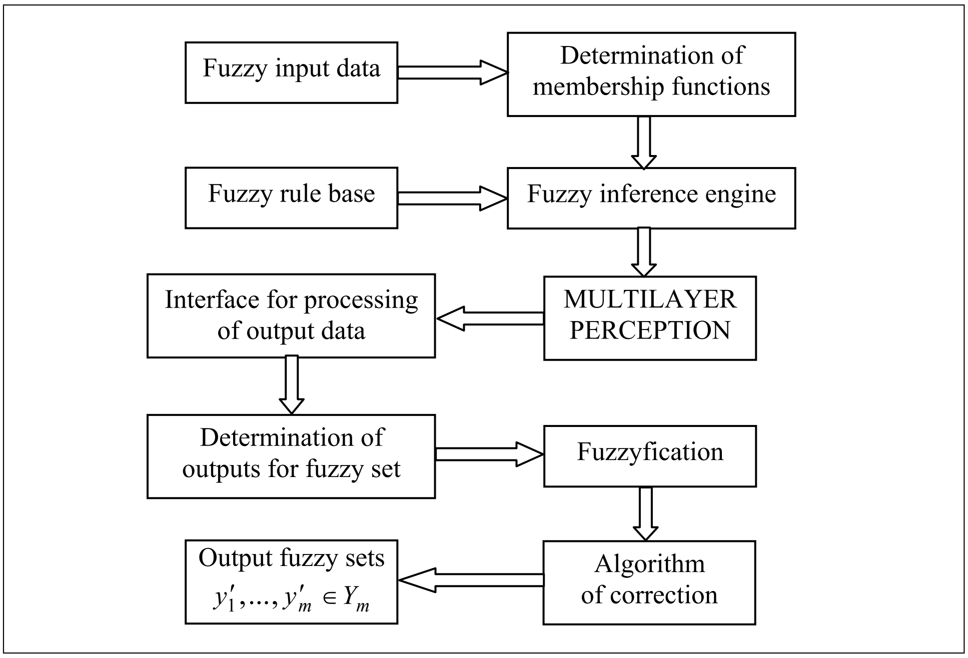

Fig. 2. Conception of fuzzy neural system

These problems according to the approach presented are solved in the following way: the input information and the corresponding output information is processed by means of two interfaces, which are developed on the basis of the fuzzy sets theory and fuzzy logic. These interfaces have the same structure. Main conception for processing of input and output fuzzy information may be presented by executing of such operations in the following sequence (Fig. 2).

The task of the interfaces is transformation of the input information to the form allowing for classical neural network processing. For performing this task, let us determine the following notions from the theory of fuzzy logic and fuzzy decision-making [4, 5].

- Membership function is a function which assigns a degree of membership (mostly, in the interval [0, 1]) to the fuzzy set: $\mu_{A_{ik}}(x_i)$, $\mu_{A'_i}(x_i)$.
- Assuming that $A'_{11} \times A'_{21} \times \ldots \times A'_{n1} \times \ldots \times A'_{1k} \times A'_{2k} \times \ldots \times A'_{nk} = A$ and $B'_{11} \times B'_{21} \times \ldots \times B'_{m1} \times \ldots \times B'_{1k} \times B'_{2k} \times \ldots \times B'_{mk} = B$, the fuzzy rules (4) and (5) can be interpreted by the product-operation rule of fuzzy implication:

$$\mu_{A \to B}(x_i, y_j) = \mu_A(x_i)\,\mu_A(y_j)\,. \tag{6}$$

- Each fuzzy set $A'_i \in R(x_i)$ can be described by means of primary fuzzy sets included in the set χ_i, and also with the use of compatibility measure of two fuzzy sets A'_i and A_{ik}:

$$\pi(A'_i, A_{ik}) = \sup_{x_i \in X_i} \left\{ \min\left[\mu'_{A_i}(x_i), \mu_{A_{ik}}(x_i)\right] \right\}, \quad k = 1, 2, \ldots, a_i\,. \tag{7}$$

- If the input data is quantitative $x'_i \in X_i$, then they are described by the membership function $\mu'_{x_i}(x_i) = 1$, if $x_i = x'_i$ and $\mu'_{x_i}(x_i) = 0$, if $x_i \neq x'_i$ (so called fuzzy singleton). Subsequently, the compatibility measure is used:

$$\pi(x'_i, A_{ik}) = \sup_{x_i \in X_i} \left\{ \min\left[\mu'_{x_i}(x_i), \mu_{A_{ik}}(x_i)\right] \right\} = \mu_{A_{ik}}(x'_i)\,. \tag{8}$$

Let us transform the output data in the same way too, by means of primary fuzzy sets, the membership function, and fuzzy logic.

- Let j be the number of output Y_j and, respectively, fuzzy sets $C_j^0 \in F(Y_j)$, which is determined by the composition «measure of activation» $\left(\{v_{jk}\}\ k = \overline{1, a_i}\right)$ and composition primary fuzzy sets in the following form:

$$\mu c_j^0(y_j) = \max \left\{ \min[\mu_{B_{j1}}(y_j), v_{j1}]\, \min[\mu_{B_{j2}}(y_j), v_{j2}] \ldots \right.$$

$$\left. \ldots \min[\mu_{B_{jk}}(y_j), v_{jk}] \right\}, \quad j = 1, 2, \ldots, m\,. \tag{9}$$

NEURAL NETWORK TRAINING

A multilayer perceptron is subjected to the process of training, i.e. a classical neural network, which is a component of the fuzzy neural network model described above.

For other research [2, 3, 5, 6], the Back Propagation algorithm and its modifications are used for training of this neural network. As it has been known, the above-presented algorithm for network training does not guarantee the obtaining of global minimum for quality evaluation (for error). Nevertheless, in research on solving a number of practical tasks, it is possible to obtain a very exact approximation of the training data, while the training process is taking place, by execution of calculations for various parameter values (η, α and, what is most important — the quantity of neurons in the hidden layer — N_1), after which the optimal variant is chosen. Consequently, a conclusion may be drawn that for solving of a number of practical tasks, the obtaining of global minimum for quality evaluation is not a necessary and indispensable condition of receiving satisfactory results. To avoid the problem referred to above, in this paper research on the use of genetic algorithms is carried out for solving the task of neural network training, and also for determination of the optimal topological network structure.

AN EXAMPLE OF A APPLICATION OF A INTELLIGENT DECISION SUPPORT SYSTEM

The fuzzy neural network presented above has been used for development of an intelligent decision support system. The decision support system has been applied to select a product strategy in the area of household equipment.

In this paper, the selection method of market-assortment-strategy has been applied for the choice of the product development strategy.

For development of the market-assortment-strategy basic notions of the Business Portfolio Models have been applied. Business Portfolio Models are tools for product classification used for determination of a competitive position of a business on the market, and assessment of the market possibilities. In this paper one of the most popular GE (General Electric) methods is applied, otherwise called the GE's Multifactor Portfolio Matrix. This approach has a variety of names, including the nine-cell GE matrix, GE's nine-cell business portfolio matrix, and the market attractiveness-business strength matrix [8]. The basic approach is shown in Fig. 3.

Industry Attractiveness		Business Strength		
		High	Medium	Low
		5 4	3 2	1
High	5 4	I	I	S
Medium	3 2	I	S	H
Low	1	S	H	H

Fig. 3. GE Multifactor Portfolio Matrix [8]

Each circle in this matrix represents the entire market and the shaded portion represents the organization's business market share. Each of an organization's businesses is plotted in the matrix on two dimensions, industry attractiveness and business strength. Each of these two major dimensions is a composite measure of a variety of factors. The two dimensions make good sense for strategy formulation, because a successful business is typically one that is an attractive industry and has a particular business strength required for succeeding in it. To use this approach, an organization must determine what factors are most critical for defining industry attractiveness and business strength. In this paper a list of the factors that are commonly used for placing businesses on the aforesaid dimensions has been used, which is presented in [8]. Depending on where businesses are plotted on the matrix, three basic strategies are formulated: **I** — invest/grow, **S** — Selective investment and **H** — Harvest/divest. The next step is to weigh each variable on the basis of its perceived importance relative to the other factors (hence the total of the weights must be 1,0). Subsequently, a fuzzy-neural system must indicate, on a scale of 1 to 5, how low or high the business scores on that factor. Table 1 presents this analysis for one business.

Table. Illustration of Industry Attractiveness and Business Strength Computations (source [8])

Industry Attractiveness	**Weight**	**Value**
Overall market size	0,20	0,8
Annual market growth rate	0,20	1,0
Historical profit margin	0,15	0,6
Competitive intensity	0,15	0,45
Technological requirements	0,15	0,45
Inflationary vulnerability	0,05	0,10
Energy requirements	0,05	0,15
Environmental impact	0,05	0,05
Social/political /legal	Must be acceptable	
	1,00	3,60

Business strength	**Weight**	**Value**
Market share	0,10	0,40
Share growth	0,15	0,60
Product quality	0,15	0,60
Brand reputation	0,10	0,50
Distribution network	0,05	0,20
Promotional effectiveness	0,05	0,25
Productive capasity	0,05	0,15
Productive efficiency	0,05	0,10
Unit costs	0,15	0,45
Material supplies	0,05	0,25
R&D performance	0,10	0,40
Managerial personel	0,05	0,20
$\sum$	1,00	4,30

Performance of a fuzzy neural expert system has been tested on the following input data:

- $N = 22$ — number neurons in input layer; $L = 68$ — rules.
- Fuzzyfication with 3 linguistic variables — $K = 3$ has been applied to the system (Fig. 3).

- Number neurons in hidden layer: 10, 15, 25, 30, 35 (Fig.5).
- Number neurons in output layer: 3.
- The fuzzy set defined in $R(X_i)$ is characterized by a membership function $\mu_{B_{jk}}(y_j): R \to [0,1]$, and is labeled by a linguistic term A_{ik}, such as «high», «medium», «low» (industry attractiveness and business strength). The membership function for the fuzzy set inputs, is shown in Fig. 4.

Fuzzy set conformity metrics (or activation levels in other words) are inputs to the neural network, according to (7)–(8) formulas. Next, they are processed by the neural network and compared to the required activation levels for outputs. A fuzzy neural network accepts both quantitative and qualitative information in the learning data set. Qualitative information is represented by the fuzzy set apparatus in the form of an appropriate set of membership functions for each linguistic variable. In the case of the generation of quantitative output data, defuzzyfication is carried out with the use of the center average method:

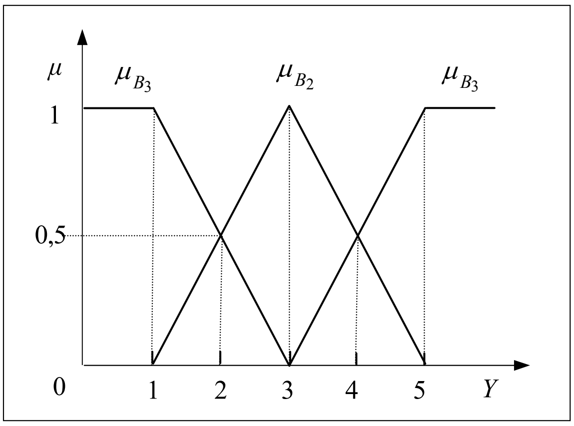

Fig. 4. Membership function for the inputs fuzzy set

$$y_j^0 = \frac{\sum_{j=1}^{m} \bar{y}\,\mu_{B_j}(\bar{y})}{\sum_{j=1}^{m} \mu_{B_j}(\bar{y})}. \tag{10}$$

During the system testing, mean absolute error was used as a criterion of quality evaluation and the assessment of the system, which for the training data assumes the form:

$$Q = \frac{1}{PM} \sum_{p=1}^{P} \sum_{l=1}^{M-1} (d_l^p - v_l^p)^2, \quad p = 1,2,...,P. \tag{11}$$

Another such criterion of system assessment with respect both to the training and testing data is the maximum system error $Q_{B_{\max}}$, defined as follows:

$$Q_{B_{\max}} = \max_{\substack{p=1,2,...,P \\ L=0,1,...,M-1}} \left| d_l^p - v_l^p \right|. \tag{12}$$

The structure of the neural network, namely the number of additional layers and quantity of neurons in an additional layer, has been chosen experimentally. The structures with one, two and three additional layers have been evaluated. A neural network with one additional layer and non-linear sigmoidal activation function returns as good results as does a network with two additional layers. A neural network with more additional layers requires large amount of training data in order to learn effectively. It is not necessary then to extend the network structure as it leads to increased quantity of data and learning time. That is why this paper presents the results for the neural network with one additional layer and with a layer with various quantities of neurons. All experiments have been run with various quantity of neurons in the additional layer ($N1$). The results of simulation researches are shown on Fig.5. This very important problem has been widely discussed in the literature. The present research just confirm the opinion that the neural network with one additional layer and with non-linear sigmoidal activation function is able to approximate any function, practically, with required accuracy.

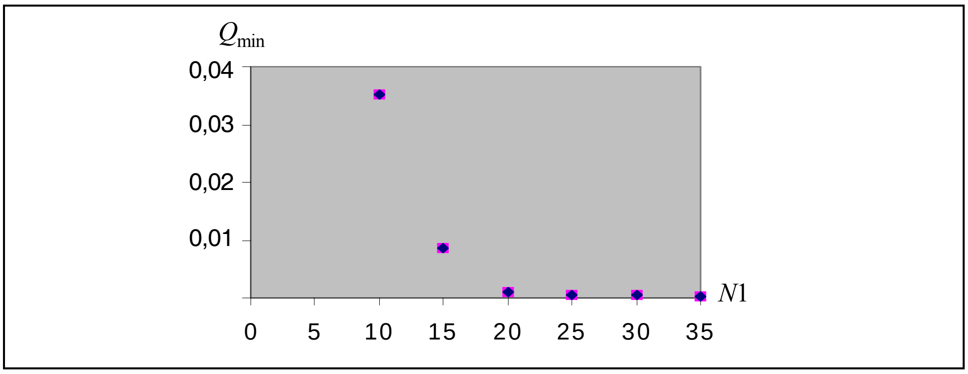

Fig. 5. Results of training phase for fuzzy neural network

The training data are prepared for a specific decision problem on the basis of data received from an expert (strategic management division). The data form a set of fuzzy rules for preparing a Multifactor Portfolio Matrix).

CONCLUSIONS

The paper uses fuzzy neural networks to model and process fuzzy, linguistic or mixed knowledge. The developed programming modules provide user interfaces that (based on fuzzy logic theories) allow conversion of the input information into numeric form and subsequent processing by a classic neural network.

On the basis of the results it may be supposed that fuzzy neural networks are a more universal theoretical instrument, which can be used for complex processes modeling and for developing intelligent decision support systems, characterized by the ability to process quantitative, as well as qualitative, and linguistic information, and thus to solve unstructured tasks in a fuzzy environment. Fuzzy neural network models show very good features for interpolation and extrapolation of training data used during the training process. The research conducted proves that fuzzy neural networks are a very effective and useful instrument of implementation of intelligent managerial systems.

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