S. SREMAC, J. TEPIĆ, I. TANACKOV, G. STOJIĆ, S. MLADENOVIĆ, B. MATIĆ

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PROCUREMENT MODEL FOR COPPER AND POLYMER ELECTRICAL PRODUCTS

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Procurement model for copper and polymer electrical products. Electrical cable structure (wire, insulation, filling and mantle) is in accordance with the technical specifications of individual cable components in terms of the incorporated materials. Materials used in cable manufacture are copper, aluminum, rubber and polyvinyl chloride. One of the key issues in managing the flow of goods pertains to the timing of procurement. The combination of the two concepts can take advantage of individual strengths of fuzzy logic and neural networks in hybrid systems of homogeneous structure. The model has high practical significance, as, with minor modifications, it can be applied in any enterprise responsible for managing the goods flows.

Key words: copper, polymers, electical product, neuro-fuzzy, goods flows

INTRODUCTION

Scientific and technological progress, in coordination with economic development, encompasses all areas of business operations and is used in the search for solutions for better goods flow organization and efficiency. Managing the flow of goods is an important part of logistics, dating back to the 600 BC, i.e. to the ancient times [1]. One of the main problems in any logistics process is optimal timing of the goods procurement.

Companies are increasingly facing extensive changes in all aspects of environmental issues and are challenged to find optimal ways of managing the flow of goods [2]. This issue was previously discussed in the pertinent literature by a number of authors, most of whom recommend that the decisions pertaining to the [3-5]. There is, however, paucity of cases where the goods flow control is based on the application of artificial intelligence methods.

PRODUCT CONSTRUCTION

For the development of the model presented here, we used data on the implementation of purchase of a group of electrical products, copper (Cu) and polymer – polyvinyl chloride (PVC) by the company specializing in electrical goods movement. More specifically, the products in question are electrical cables of PPY 3 × 1,5 type (EK). The EK cable structure is in accordance with the technical specifications of individually classified cable components in terms of materials used (Figure 1). EK consists of:

- Conductor – uniformly drawn, soft annealed copper wire of circular cross-section, uniform composition, without tears and cracks, used for conducting electricity. It is manufactured using electrolytic copper, according to IEC 60 028.
- Insulation – conductors are insulated using seamless layer of solid or foamed thermoplastic dielectrics that can have epidermis finish made of the same or different material. The most common materials used for conductor insulation are polyethylene (PE) and polypropylene (PP). The insulated conductors are commonly referred to as wires.
- Filling – pressed layer covering interwoven wires by filling the cavities between them.
- Sheath (mantle) – seamless tubular layer covering the wire bundles in order to protect them from mechanical damage, moisture penetration, chemical influences, etc. It is produced by extruding thermoplastic material, thus achieving uniform thickness and continuity of the mantle. The following thermoplastic materials are typically used in the sheathing production: PVC, Low Density Polyethylene (LDPE), high density PE and High Density Polyethylene (HDPE).

EK are conductors composed of soft annealed Cu insulated by PVC, with three interwoven wires. The wire core is covered by a layer of unvulcanized elastic or plastic filling, as well as PVC sheath, typically of gray color. This type of cable is used in dry and wet conditions for placing both over and under plaster or for electrical installations in buildings. Operating temperature ranges from -20 ÷ 70 °C.

PRODUCT MATERIALS

Materials used for EK production are: Cu, Al, rubber and PVC [6].

S. Sremac, J. Tepić, I. Tanackov, G. Stojić, B. Matić, Faculty of Technical Sciences, University of Novi Sad, Novi Sad, Serbia.
S. Mladenović, Faculty of Transport and Traffic Engineering, University of Belgrade, Belgrade, Serbia.

Figure 1 Product composition: 1 – Cu conductor, 2 – PVC insulation, 3 – unvulcanized tire filling and 4 – PVC sheath

For all types of cables, oxygen-free Cu is used as a conductor due to its high strength, and electrical conductivity of at least 58 Sm/mm^2 at 20 °C, the specific electrical resistance of 0,017241 Ω/mm^2 at 20 °C and the maximum tensile strength of 250 N/mm^2. Cu is very plastic material that can be processed by deformation, both hot and cold. Cu conductor wire is produced by drawing, annealing and tinning, when rubber insulation is applied. The density of copper is 8,9 g/cm^3. Raw Cu contains 97 % Cu and is not suitable for use, due to presence of steel, As, Au, etc., all of which are harmful and have to be removed, commonly by electrolysis.

In addition to Cu, Al is another suitable conductor material. Al conductor wire is also produced by drawing. It is characterized by density of 2,7 g/cm^3, electrical conductivity of 35,4 Sm/mm^2 at 20 °C and maximum tensile strength of 100 N/mm^2.

Vulcanized rubber (natural or synthetic) is one of the oldest materials used for conductor insulation. It is very flexible, irrespective of temperature, and is thus very suitable for usage in insulation and sheathing of insulated conductors. Its thermal reserve is very important in cases of excessive current overload or short-circuiting.

Due to its good electrical and mechanical properties, PVC is highly suitable for the production of insulation and sheathing of insulated wires. It is stable and resistant to weathering, moisture and oil. Its important features are that is self-extinguishing (which is of particular importance when cables are used in areas at high risk of fire) and does not absorb water. PVC compound softens at temperatures above 70 °C, and becomes rigid below 0 °C. Its key advantage in comparison to other materials is that it is compatible with plasticizers and other additives, is easily processed and is relatively inexpensive.

NEURO-FUZZY INTELLIGENT SYSTEMS

Many phenomena in nature, society and technological systems cannot be described or their behavior predicted using traditional approaches based on conventional mathematical methods. That is why, in solving practical complex problems, individual applied artificial intelligence methods, or their combination in the form of hybrid method, are used [7].

Fuzzy logic has emerged as a result of attempts to model human reasoning process, experience and intuition in decision-making based on imprecise data [8]. It is particularly suitable for expressing ambiguity and uncertainty. Fuzzy logic application has proved to be excellent in models in which intuition and assessment are the key elements [9]. Fuzzy models are typically represented in the form of neural networks when used in automatic determination of the fuzzy model parameters based on the available input-output data [10].

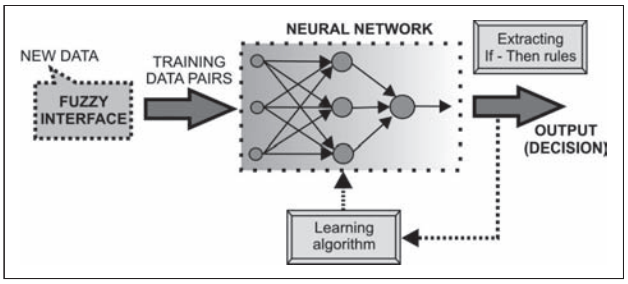

Figure 2 Hybrid artificial intelligence systems

Artificial neural networks are a concept of artificial intelligence based on the ideas and analogies that have arisen in the study of nervous systems of living organisms. Humans can easily perform a series of complex tasks that are very difficult to solve using computational techniques relying on the traditional algorithms.

Neuro-fuzzy systems are a modern class of hybrid artificial intelligence systems. They are also referred to as artificial neural networks characterized by fuzzy parameters [11, 12]. Parameters characterizing the corresponding membership functions are modified through the network training process.

The aim of combining the two concepts of artificial intelligence is to take advantage of individual advantages of fuzzy logic and artificial neural networks in hybrid systems of homogeneous structure known as hybrid artificial intelligence systems (Figure 2).

MODEL DEVELOPMENT

A model for the procurement implementation of electrical Cu and PVC product supply (PI model) was developed based on a hybrid neuro-fuzzy artificial intelligence system. For the model creation, real data on the procurement implementation in the EK company specializing in electrical product movement was used.

From the group of polymer and Cu electrical products, EK item was chosen, as it is most frequently used general-purpose product in the studied company. The basic EK packaging is in the form of 100 m – long cable coils supplied covered by a thermal "stretch" foil and arranged in cardboard boxes.

The model presented here was developed in the MATLAB version R2007b using ANFIS (Adaptive Neuro-Fuzzy Inference System) Editor, included in the Fuzzy Logic Toolbox. ANFIS editors only support Sugeno-type fuzzy systems. The course of the neuro-fuzzy model formation is presented in Figure 3.

PI model takes the form of a multilayer neural network that supports forward-propagating signal. The first

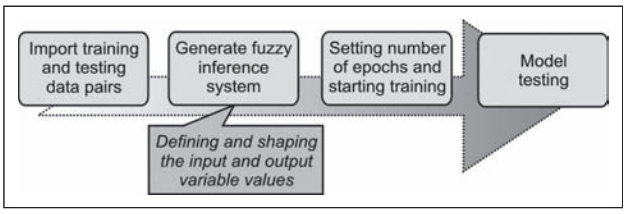

Figure 3 The model formation flowchart

layer consists of the input variables, hidden (middle) layer contains the fuzzy rules, with the output variable in the third layer. Fuzzy sets are defined in the form of weighted connections between the nodes. Model parameters are adjusted in the adaptive nodes in order to reduce errors at the network output. Error is defined as the difference between the known output values and those obtained at the network output. The signals carried across the network propagate forward, whereas the errors are transmitted backward. This ensures that the output numerical value gradually approaches optimal, i.e. required value.

Decision on implementation of procurement is based on the procurement preferences at a specific point in time. When the acquisition preferences are within 0 ÷ 0,4 range, acquisition is not implemented, and is realized when they range from 0,4 ÷ 1. When the preference is at the borderline value of 0,4, the decision is made in favor of the procurement implementation.

The procurement preference in the observed company is affected by the quantity of procured goods, the vehicle availability and the supply urgency. Although other factors can affect the decision to proceed with the procurement, according to the subjective evaluation of the logistics expert employed by the studied company, their influence on the final decision is negligible.

Input variables procurement quantity and vehicle availability are defined by five values (very small, small, medium, large, and very large), while the input variable procurement urgency can take three values (small, medium and large). This number of values yielded satisfactory accuracy of the model results. The input membership functions are of Gaussian shape. The neuro-fuzzy PI model structure of EK is shown in Figure 4.

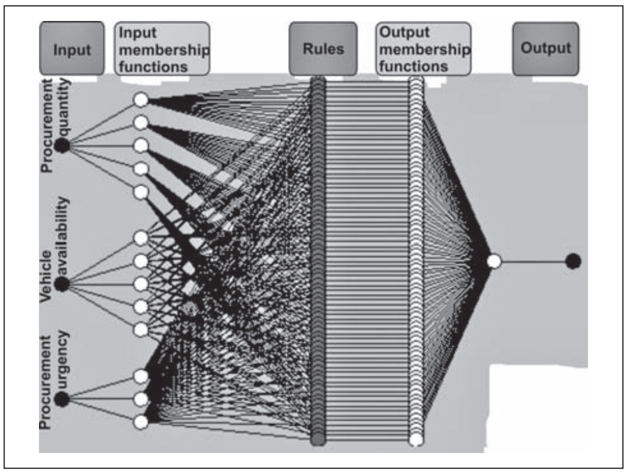

Figure 4 The neuro-fuzzy PI model structure

The key model characteristics are:

Number of nodes	182
Number of linear parameters	75
Number of nonlinear parameters	26
Total number of parameters	101
Number of training data pairs	100
Number of testing data pairs	20
Number of fuzzy rules	75

Network training and testing was performed using real data. During the network training process, hybrid optimization method was applied, comprising back-propagation and least-squares algorithms. For generating fuzzy inference system, network sharing (grid partition) technique was applied. The value of the output variable is a function of continuous membership type. The output variable of procurement implementation depending on the level of preference takes one of the two values, namely 1 – acquisition is not realized, or 2 – acquisition is implemented. Number of training cycles (epochs) is set to 500, even though during the network training, it was evident that, after only 15 epochs, minimum error is achieved. By training the neural network of the established model, the average error of 0,12252 was obtained (Figure 5).

Network training was performed using 100 input-output data pairs obtained from the studied company, based on which it was decided whether to proceed with the procurement. Neuro-fuzzy model training results are shown in Figure 6.

The model was tested using 20 input-output data pairs that were not used in the network training phase (Figure 7). The average error achieved during the model testing was 0,24212.

The size of both training and testing error is within the preset tolerance limits. Based on the model testing

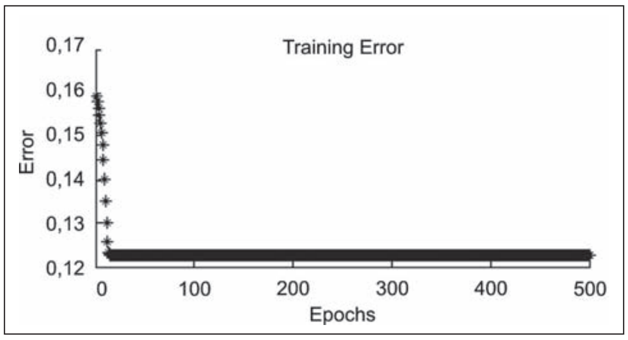

Figure 5 Training neuro-fuzzy PI model

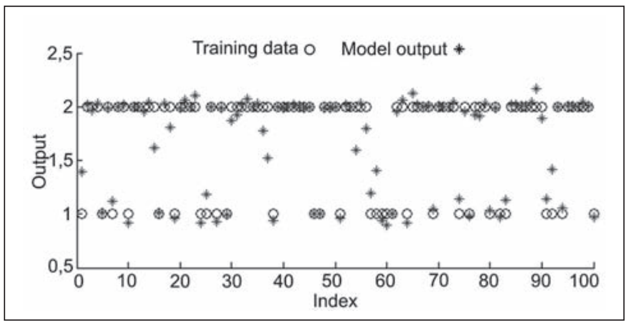

Figure 6 Neuro-fuzzy PI model training results

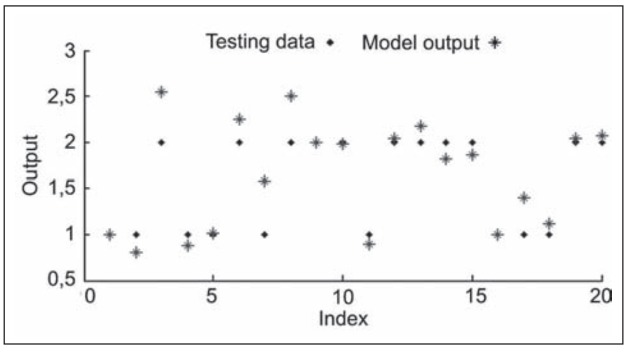

Figure 7 Neuro-fuzzy PI model testing results

results, it is evident that, in 95 % of cases, the model is capable of making the same decision as an expert working in the observed logistics company, i.e. there is a high degree of agreement between the expert decision-making and that of the model.

Sensitive analysis

Sensitive analysis of neuro-fuzzy PI model for EK was conducted by changing the shape of the input variable membership functions and the number of the allowed variable values (Table 1). More specifically, instead of the Gaussian curve, triangular, trapezoidal and bell-shaped membership functions were tested. Similarly, two variations in the number of input variable values were analyzed, whereby all the input variables were set to 3 and 5, respectively.

Table 1 **Sensitive analysis of model ***

Membership function	Number of the variable values	Training error	Testing error
Triangular	3-3-3	0,20	0,12
	5-5-5	0,03	0,77
Trapezoidal	3-3-3	0,22	0,12
	5-5-5	0,15	0,30
Bell	3-3-3	0,21	0,06
	5-5-5	0,02	0,41

* Number of epochs is set to 500.

For the defined test cases that assessed the neuro-fuzzy PI model sensitivity, the average errors obtained by training and testing the network had negligible differences, indicating that the proposed model is valid.

CONCLUSIONS

The hybrid artificial intelligence system was used to represent and implement human heuristic knowledge pertaining to the management of a particular process. Neuro-fuzzy concept is essentially based on fuzzy logic; thus, neural network has served to enhance the fuzzy model performance membership functions.

Neuro-fuzzy PI model decides whether EK procurement is realized at a specific point in time. The proposed model has been tested and its validity confirmed. Errors obtained during the model training and testing are within the tolerance limits. Some discrepancies in the results arose because of the relatively small number of data pairs used for network training and only two model output values (acquisition is either implemented or not implemented).

The model yielded good results and thus represents a successful tool for efficiently managing the flow of goods. With minor modifications and adjustments to a specific problem, the model can be applied in any company engaged in the realization of goods flows. Hence, the work represented here has both scientific and practical value.

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Note: The responsible translator for English language is N. Kozul, Novi Sad, Serbia