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ANFIS MODEL FOR DETERMINING THE ECONOMIC ORDER QUANTITY

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Abstract: *The determination of the economic order quantity is important for the rational realization of the logistics process of transport, manipulation and storage in the supply chain. In this paper an expert model for the determination of the economic order quantity has been developed. The model has been developed using the hybrid method of artificial intelligence Adaptive neuro-fuzzy inference systems - ANFIS. It has been used for modeling a complex logistics process in which it is difficult to determine the interdependence of the presented variables applying classical methods. The hybrid method has been applied to take advantages of the individual methods of artificial intelligence: fuzzy logic and neural networks. Experience of an experts and information on the operations of the company for a certain group of items have been used to form the model. Analysis of the validity of the model results was performed on the basis of the average relative error and it has showed that the model imitates the work of the expert in the observed company with great accuracy. Sensitivity analysis has been applied which indicates that the model gives valid results. The proposed model is flexible and can be applied to various types of goods in supply chain management.*

Key words: *Adaptive neuro-fuzzy inference systems, economic order quantity, supply chain management, logistics processes.*

1. Introduction

The economy is largely in the phase of intense globalization. This does not mean only increasing the interdependence of regional economies and levels of technological integration, but also significant structural changes in the field of science, highly developed technique and its way of functioning. Scientific and technological progress, in coordination with economic development, covers all areas

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of the economy and its possibilities are used in the search for solutions for better organization and efficiency of flow of goods (Sremac, 2013).

The determination of the economic order quantity (EOQ) is a logistics process that has a significant influence on the successful operation of a company (Melis Teksan & Geunes, 2016). From the logical aspect, the determination of the EOQ requires an adequate attention, since inadequate purchase can additionally burden the company's business (Abraham, 2001). On the other hand, in order to achieve a high level of service for the client, all purchase should be realized independently of their value (Maddah & Noueihed, 2017).

Many phenomena in nature, society and the economy cannot be described and it is not possible to predict their behavior by traditional mathematical methods (Griffis et al., 2012). Due to the lack of flexibility of this approach, the human factor compensates for the uncertainty of mathematical model using knowledge based on experience (Negnevitsky, 2005) and make decisions based on data that are difficult to enter into a mathematical model (Efendigil, 2014). A modern approach to determining EOQ is the application of Adaptive neuro-fuzzy inference systems (ANFIS), as one of the hybrid methods of artificial intelligence.

The basic hypothesis of this paper is that it is possible to design a model on hybrid neuro-fuzzy approach of artificial intelligence to determine EOQ. The next goal is to effectively use such a system in the observed company in a highly dynamic and changing business environment. One of the objectives is that the proposed system shall be flexible and applicable in other companies for other types of goods in supply chain management (SCM). The basic motive for the design of such a decision support system is the development of the tool for EOQ that will be able to perform complex and real processes of SCM using a hybrid artificial intelligence technique.

The rest of this paper is organized as follows. The relevant literature review is classified and reviewed in Section 2. Section 3 describes ANFIS used in the proposed methodology. Section 4 presents proposed models and a sensitive analysis for different membership functions. Conclusion remarks are drawn in Section 5.

2. Literature review

The problem often arising and being examined is determining the amount of goods needed to meet customers' demands (Lagodimos et al., 2018). A century ago, Harris (1913) introduced EOQ inventory model. Most of the companies apply EOQ model to determine the maximum level of inventory or ordering lot size (Abdel-Aleem et al., 2017).

The application of classical methods for EOQ is based on limited assumptions that cannot cover the nature of modern complex logistics processes such as - demand is constant in unit time, lead time is deterministic and stationary, constant price etc. (Maddah & Noueihed, 2017). But, making decisions in SCM takes place in an environment where objectives and constraints are not and cannot often be precisely defined (Latif et al., 2014; Taleizadeh et al., 2016). Therefore a certain approximation is required in order to obtain a high quality model of a real system where the application of artificial intelligence has an important role. Consequently, individual methods of artificial intelligence (Keshavarz Ghorabaee et al., 2016) or their combination in the form of hybrid method are increasingly used in solving real and complex problems (Teksan & Geunes, 2016, Zavadskas et al., 2016).

Some researchers (Davis-Sramek & Fugate, 2007) interviewed a few visionaries in the field of SCM and recognized the irresistible call of these individuals for modeling and simulation to be involved in the research (Wallin et al., 2006). Modeling of the

SCM seeks for the best possible system configurations to minimize costs and increase operational efficiency in order to meet customer expectations (Bowersox et al., 2010). Important issue in SCM is the need to make the right decision, despite the occurrence of significant ambiguity (Giannoccaro et al., 2003). In addition to fluctuations in demand and delivery times, vagueness is associated with the lack of information from the production and distribution processes in SCM (Chatfield et al., 2013). Some authors expressed uncertainty of market demand and inventory costs in the model theory of fuzzy sets (Azizi et al., 2015).

Hereinafter, there is a review of some works from the field of SCM based on neuro-fuzzy approach. Jang (1993) first introduced the ANFIS method by embedding the Fuzzy Inference System into the framework of adaptive networks. Demand uncertainty is considered in the optimization model of Gupta and Maranas (2003) in which by a two-stage stochastic programming model they consider all production decisions in the first stage and all the supply chain decisions in the second. Yazdani-Chamzini et al. (2012) used ANFIS and artificial neural network (ANN) model for modeling the gold price.

Guneri et al. (2011) developed a new method using ANFIS for the supplier selection problem. Vahdani et al. (2012) presented numerous quantitative methods for supplier selection and evaluation in the literature, where the most current technique is Hybrid approaches. Later Ozkan and Inal (2014) employed ANFIS in supplier selection and evaluation process.

Several methods for EOQ in SCM have appeared in literature, including approaches based on a neuro-fuzzy (Yazdani-Chamzini et al., 2017). Paul et al. (2015) presents the application of ANFIS and ANN in inventory management problem to determine optimum inventory level. Abdel-Aleem et al. (2017) study and analyze the optimal lot size in a real production system to obtain the optimal production quantity.

ANFIS has a wide application in the fields of finance, marketing, distribution, business planning, information systems, production, logistics etc. (Ambukege et al., 2017; Mardani et al., 2017; Rajab & Sharma, 2017). The route guidance system developed by Pamučar & Ćirović (2018) is an Adaptive Neuro Fuzzy Inference Guidance System that provides instructions to drivers based upon "optimum" route solutions.

3. Description adaptive neuro-fuzzy inference systems

ANFIS are the modern class of hybrid systems of artificial intelligence. They are described as artificial neural networks characterized by fuzzy parameters. By combining two different concepts of artificial intelligence it is tried to exploit the individual strengths of fuzzy logistics and artificial neural networks in hybrid systems of homogeneous structure (Figure 1). Such engineered systems are increasingly used to solve everyday complex problems and with assistance of logistics experts and historical data, this approach can be designed on the basis of computer aided systems.

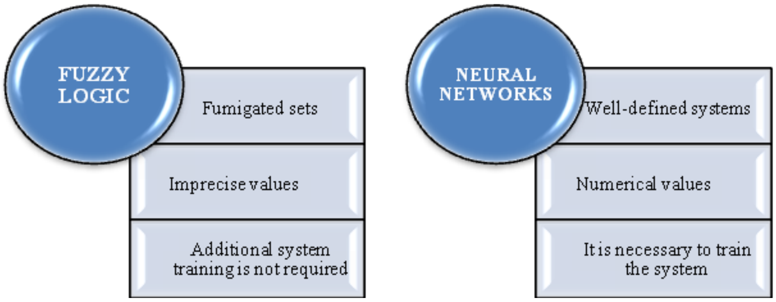

Figure 1. Basic characteristics of fuzzy logistics and neural networks

The possibility of displaying the fuzzy model in the form of a neural network is most often used in the methods of automatic determination of the parameters of the fuzzy model based on the available input-output data. The structure of Adaptive neuro-fuzzy inference systems is similar to the structure of neural networks. The membership functions of the input data are mapped to the input data of the neural networks and the input-output laws are defined through the output data of the neural networks (Figure 2).

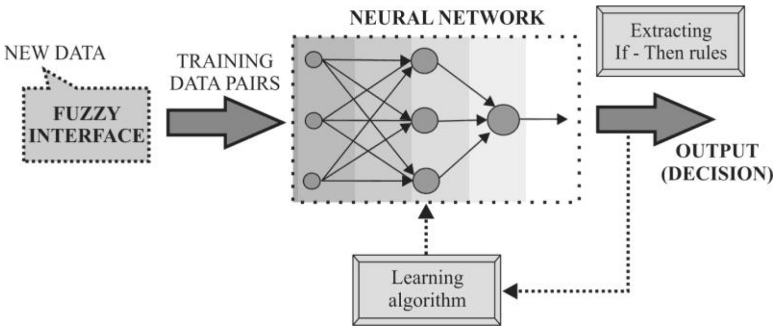

Figure 2. The basic structure of Adaptive Neuro-Fuzzy Inference Systems

Parameters characteristic of the corresponding membership functions change through the network learning process. Calculation of these parameters is usually done on the basis of the gradient of the vector, which is a measure of the accuracy of the transfer of the fuzzy inference system of the input set into the output set for the given set of verified parameters (Cetisli, 2010).

Basic idea of The Adaptive Neuro-Fuzzy Inference System is based on fuzzy modelling and learning methods according to the given dataset. Based on the input-output data set, an appropriate fuzzy inference system is formed and the parameters of the membership function are calculated. The parameters of the membership functions of the fuzzy system are set using the backpropagation algorithm or a combination of the algorithm and the method of least squares. This setting allows fuzzy systems to learn on the basis of input-output data set. This learning method is similar to the method of learning neural networks.

4. The development of ANFIS model for determining EOQ

4.1. Designing the model

This paper develops an adaptive neuro-fuzzy inference system model for determining the economic order quantity (ANFIS model EOQ) based on the input-output data in the observed company. The formation of the proposed model consists of the following steps:

- Determination of input-output data set in the form customized for training of the neuro-fuzzy inference system.
- The model structure with parameters is assumed, which by the rules reflects the input membership functions into output functions.

The model is trained on the training data. In doing so, the parameters of the membership functions are modified according to the selected error criterion in order to get the valid model results.

This way of modeling is appropriate if the training data are fully representative for all the properties that ANFIS model should have. In some cases, the data used to train the network contain measurement errors so they are not fully representative for all features that should be included in the model. Therefore, the model should be checked using the testing data. There are two ways of testing the model. The first way is to check the model when input data are those that are not used for training. This procedure shows how accurately the model predicts the output value set and it is implemented in the paper. Another way to test the model is a mathematical procedure when the data that were used for training are now used as a data set for testing and it is necessary to obtain the output with a minimal error.

The model presented here was developed in the MATLAB version R2007b using ANFIS Editor, included in the Fuzzy Logic Toolbox. ANFIS editors only support Sugeno-type fuzzy systems (Tahmasebi & Hezarkhani, 2010). Benefits of Sugeno type are that it is computationally more efficient, suitable for mathematical analysis, works well with linear, optimization and adaptive techniques. The course of the ANFIS model formation is presented in Figure 3.

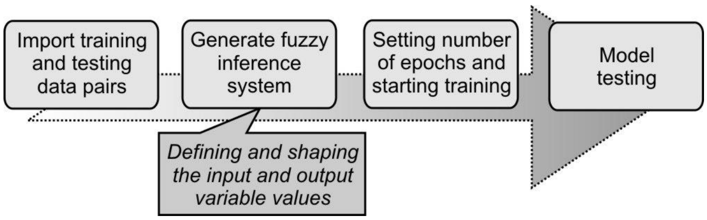

Figure 3. The model formation flowchart

The ANFIS model EOQ has the following structure. The input variables are: the size of demand, the level of inventory and price, while the output variable is EOQ. The number of membership functions of the input variables is three, except for the input variable the size of demand which has five values. Input membership functions are Gaussian. The structure of the neural network is shown in Figure 4.

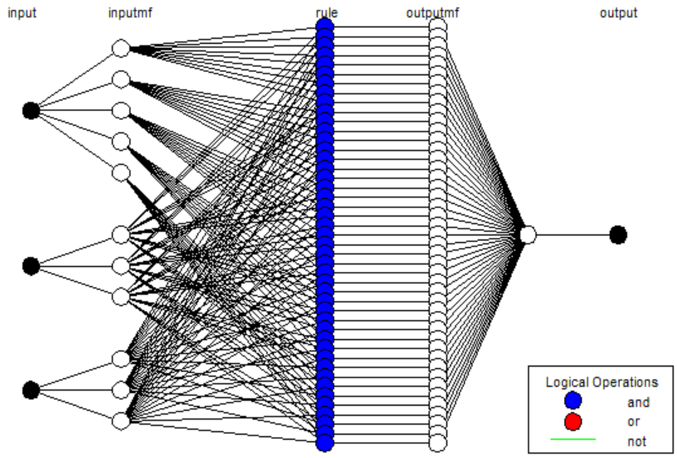

Figure 4. Fuzzy model mapped into a neural network

The developed model has the form of a multilayer neural network with the propagation of the signal forwards. The first layer represents the input variable, the hidden (middle) layer represents the fuzzy rule, and the third layer is the output variable. Fuzzy sets are defined in the form of link weights between nodes. Settings are performed in adaptive nodes to reduce the error that occurs at the exit of the model. The error is the difference between the known output values and the values obtained at the exit from the neuro-fuzzy network. The signals on the network are spreading forwards and the bugs are spreading backwards. Thus, the output numerical value approaches the optimal, i.e. the required value. The basic characteristics of the model are shown in Table 1.

Table 1. Basic characteristics of ANFIS model EOQ

The key model characteristics are:	
Number of nodes	118
Number of linear parameters	45
Number of nonlinear parameters	22
Total number of parameters	67
Number of training data pairs	50
Number of testing data pairs	10
Number of fuzzy rules	45

The data set for the training of the neural network was obtained on the basis of concrete data on business operations and the survey of the logistics expert in the observed company. For training (Figure 5), a hybrid optimization method was used consisting of:

- backpropagation algorithms, by which the errors of variables are determined recursively from the output layer to the input layers
- the methods of least squares for determining the optimal set of consequential parameters.

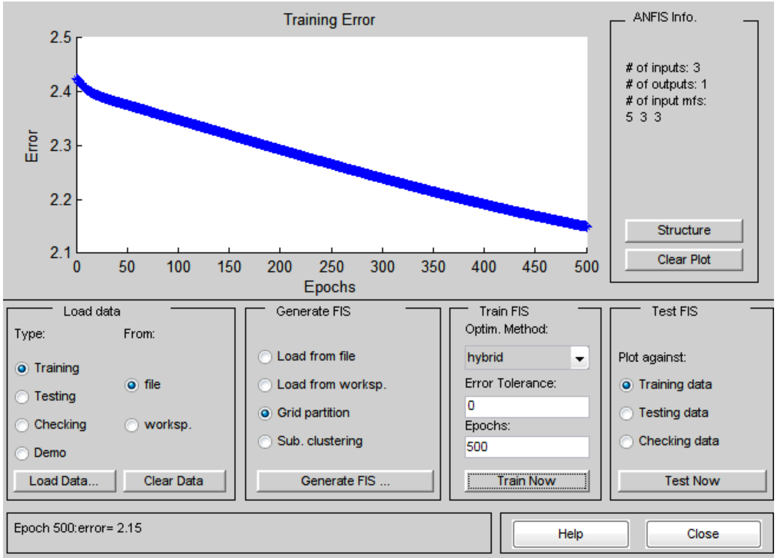

Figure 5. Training of the neural network

In order to train the network, 50 input-output procurement data sets were used in the observed company, while model testing was conducted on the basis of 10 input-output data sets. A grid partition technique was applied to generate one model output and a hybrid optimization method as well. It was assumed that the output membership functions are of a constant type.

The number of training cycles (epochs) is 500. At the output of the neural network, there is an error of 2.15 (Figure 6).

Figure 6. Results of training of ANFIS model EOQ

After the training phase, the ANFIS model EOQ was tested on the basis of 10 input-output datasets, which were not used in the training of the model. The average error in testing the model is 4.03 (Figure 7).

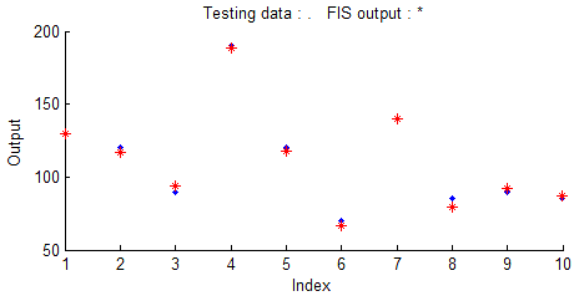

Figure 7. Results of testing of ANFIS model EOQ

Testing makes it possible to check the functioning of the model. Output data, generated by the network, are compared with known company data. The model is not expected to function without an error, but deviations must be within the limits of the predicted tolerance. If there are large deviations, a new training network needs to be done, or it is sometimes necessary to exclude problematic data.

The validity analysis of the model's results was carried out on the basis of the average relative error of the tested data (Figure 8). On the basis of the testing of 10 examples of EOQ determination, an average relative error of 3.28% was obtained. On the basis of this analysis it can be said that ANFIS model EOQ gives valid results.

Figure 8. Relative error of ANFIS model EOQ in %

4.2. Sensitive analysis

One of the basic requirements when modeling is to achieve a satisfactory sensitivity of the model. This means that with certain small changes in input variables, the output from the model must also have small changes in value.

The sensitive analysis of the ANFIS model EOQ was carried out by changing the shape of the membership functions of the input variables and the number of values of the input variables as well. Instead of the Gaussian curves applied in the basic model, triangular, trapezoidal and bell-shaped curves were tested (Table 2). In the analysis the "prod "(product of array elements) method was used for the operator "and" and "prob" (probably) method for the operator "or". Two cases were tested: first, where all input variables have three values, and the other one where the first input variable, size of demand, has five values, while the other two input variables, the level of inventory and price, have three values (Table 3).

Table 2. Sensitive analysis by changing the form of membership functions

	Membership function		
	Triangular	***Trapezoidal***	***Bell***
EOQ	120	124	125
	42	32	24
	220	225	228
	60	57	59
	132	133	135

Table 3. Sensitive analysis by changing the number of input values*

	Membership function					
	Triangular		***Trapezoidal***		***Bell***	
Number of the variable values	**3-3-3**	**5-3-3**	**3-3-3**	**5-3-3**	**3-3-3**	**5-3-3**
Training error	4,16	2,21	8,40	2,82	3,55	1,77
Testing error	7,02	6,58	8,56	6,99	6,36	2,83

** Number of epochs is set to 500.*

For defined cases of model sensitivity testing, the obtained results are the same or with negligible differences. This shows that the proposed ANFIS model EOQ gives valid results.

5. Conclusion

The applied concept of artificial intelligence is utilized for presenting, manipulating and implementing human knowledge on the efficient management for determining the economic order quantity. Adaptive neuro-fuzzy inference systems has proven to be a valuable artificial intelligence concept in determining EOQ that is designed using intuition and assessment of a logistics expert. Hybrid concept of artificial intelligence enabled the explanation of the system dynamics via a linguistic presentation of knowledge on a logistics process. It was used for modeling a complex linguistic system in which it is difficult to determine the interdependence of the presented variables applying other classical methods.

In the paper, ANFIS model EOQ for solving a concrete problem in a business practice was developed, following the tendency in contemporary scientific research. The model was tested and verified, and hence it can be practically applied. A sensational analysis was conducted and it gave the results of a model with negligible differences. The advantage of the proposed model is that with some minor modification, it can be applied in any company dealing with the flow of goods realization.

During the research it was observed that in addition to the advantages, the applied hybrid concept of artificial intelligence also had certain flaws, and that none of the tools was universally applicable. The observed flaws are that the selection and adjustment of the membership functions of the variables are very sensitive area that has a significant impact on the results of the model. Therefore, it is necessary to precisely and carefully form the logical base of the fuzzy rules. During development of the model, the neuro-fuzzy training time usually requires a large amount of data and can be very long, and therefore the need for frequent repetitions of training can make the application unusable. A small number of input parameters gives rough and inaccurate results, so the survey sample must be representative.

In further research, current methods of Multiple-criteria decision-making can be applied (Pamučar et al., 2018; Stević et al., 2017, Yazdani-Chamzini et al., 2017) and the flexibility of the proposed model can be used for determining the amount of procurement of other types of goods.

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