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# THE USE OF FUZZY MODELLING AND REVERSE INFERENCE TO ANALYZE THE EFFECTS OF ERP SYSTEM IMPLEMENTATION

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Abstract
The paper presents a concept for the use of fuzzy modelling and reverse inference to analyze the effects of planned implementation of an ERP system in a medium-sized manufacturing company. The proposed approach allows the possibility of achievement of the effects corresponding to the assumed enterprise targets to be evaluated, and is based on the assignation of sufficient conditions providing these effects defined in the form of selected indicators. The paper also includes a presentation of the results of computer experiments in the field of the determination of the influence of selected fuzzy modelling parameters on the obtained solutions. The suggested concept is dedicated to consultants of ERP software to support decision-making processes.

Keywords
ERP system implementation, planned effects, fuzzy modelling, Constraint Satisfaction Problem.

## Introduction

Strengthening the competitiveness of enterprises in the context of the challenges of globalization means there is a need for the implementation of innovation, including the newest information technologies and in particular ERP systems (Enterprise Resource Planning) to support business processes. These systems play an important role in integrating information and functions in all areas of an enterprise, as well as enabling a quick response to both new opportunities and threats appearing on the market [1–2].

The use of data collected in ERP, advanced mathematical algorithms and high-performance computer servers allows producers of ERP systems to meet the needs of manufacturing companies by offering APS (advanced planning and scheduling) functionality. APS modules enable optimization of production and logistics processes as well as the planning and scheduling of production orders in real time, taking into account the availability of all resources involved in their realization [3–5].

The implementation of an integrated ERP system is a very complex process, which consists of all the associated preparatory, organizational and execution activities and represents the largest information technology investment in an enterprise, with respect to the implementation cost, complexity and time [2, 5–8].

An important issue in ERP implementation projects is the failure of a successful realization. Some failure examples are: business goals not achieved, exceeding the planned budget or requirements for time or quality not being met. The most common reasons for ERP implementation failure are insufficient user preparation or unrealistic user expectations in respect of the time scale [9].

Therefore, new solutions are being sought to reduce the risk of failures occurring [10–12]. The previous study conducted by the author was focused on estimating the effects of a planned implementation of a given ERP system in a given enterprise and verifying that they met the preferences of the said enterprise [13].

The aim of this paper is to present a new concept for the assessment of the effects of the planned implementation of an ERP system with respect to enterprise requirements using fuzzy modelling and reverse inference. The proposed approach relies on the determination of sufficient conditions to guarantee the achievement of preferred values of the selected enterprise indexes in the assumed system exploitation period.

The suggested method is dedicated to consultants and vendors of ERP software and may be used to support decision-making processes.

In the next chapter the problem and the proposed model are described. In the next two chapters the procedure for assessment of the effects of the planned implementation of an ERP system using fuzzy modelling and reverse inference is presented and the detailed course of the proceedings according to the proposed procedure is illustrated by an example. The last chapter discusses the influence of fuzzy modelling parameters on obtained results.

## The model and the problem description

The problem is reduced to finding an answer to the following question:

Assuming a given ERP system with known experience from previous implementations and a given medium-sized enterprise the question is: Are there any sufficient conditions which, if satisfied, would guarantee achievement of enterprise requirements in terms of the values of selected indexes within the desired period of time after implementation?

The structure of the decision making model for the considered problem is as follows:

An ERP system with functionalities (modules) $F$=[$F_1$,...,$F_h$] serving business and production processes in the enterprise is given.

Furthermore, an enterprise, $P$, considering the implementation of a specified ERP system is given.

A vector of indexes

$$W(t) = [W_1(t), W_2(t), \ldots, W_k(t)],$$

determining ERP implementation effects in the $P$ enterprise prior to the commencement of planned implementation (for time moments $t = t_0$) and in subsequent periods of exploitation of the ERP system after the implementation ($t = t_1, t_2, \ldots, t_z$) is given.

A vector

$$WE = [WE_1, \ldots, WE_k]$$

(of target criteria) of values of indexes $W(t) = [W_1(t), W_2(t), \ldots, W_k(t)]$ (for $t = T$), preferred by the enterprise$P$, achieved after the implementation of specified ERP system within the system exploitation period $T$ is also given.

Furthermore, a vector

$$SF(t) = [SF_1(t), \ldots, SF_h(t)]$$

determining the current and planned implementation state of functionalities $F = [F_1, \ldots, F_h]$ of the ERP system in the enterprise $P$ in the time moments $t = t_0, t_1, \ldots, t_z$ is given, and its values before the commencement of the planned implementation of the specified ERP system are known.

Experience from previous implementations of the particular ERP system within selected enterprises of the same class, expressed by the values of $W(t)$ indexes and determining the effects of the considered implementation, is also given. A general representation of such data related to a single implementation realized in one enterprise is included in Table 1.

Table 1
Representation of implementation state of ERP system functionalities and indexes of given enterprise (Source: own work).

| Time | | $t_0$ | $t_1$ | ... | $t_z$ |
|---|---|---|---|---|---|
| Implementation state of ERP system functionalities | $SF_1$ | $SF_1(t_0)$ | $SF_1(t_1)$ | | $SF_1(t_z)$ |
| | $SF_2$ | $SF_2(t_0)$ | $SF_2(t_1)$ | | $SF_2(t_z)$ |
| | ... | | | | |
| | $SF_h$ | $SF_h(t_0)$ | $SF_h(t_1)$ | | $SF_h(t_z)$ |
| Enterprise indexes $W$ | $W_1$ | $W_1(t_0)$ | $W_1(t_1)$ | | $W_1(t_z)$ |
| | $W_2$ | $W_2(t_0)$ | $W_2(t_1)$ | | $W_2(t_z)$ |
| | ... | | | | |
| | $W_k$ | $W_k(t_0)$ | $W_k(t_1)$ | | $W_k(t_z)$ |

## The procedure for assessment of the effects of the planned implementation of an ERP system using fuzzy modelling and reverse inference

The proposal for the described problem solution for the assumed decision making model, presented below, constitutes the presented concept of the effects assessment of the planned implementation of an ERP system, in which fuzzy modelling (e.g. the mean fuzzy curve method and the geometric method of the maximum absolute error point described precisely in [14] and reverse inference (presented e.g. in [15–18]) are used. The process, according to the proposed idea, is divided into stages, included in Table 2.

Table 2

The concept of effects assessment of the planned implementation of an ERP system (Source: own work).

| | | |
|---|---|---|
| Stage 1. Formation of empirical knowledge base on the basis of experiences from previously completed implementations of the specified ERP system (in the form of fuzzy neutral network) | | |
| | 1.1) Filtration of measurement samples of the modelled system using the mean fuzzy curve method developed by Lin and Cunningham [14] | |
| | 1.2) The self-organization and tuning of fuzzy model parameters with the geometric method of maximum absolute error point (the MAEP method) [14] | |
| | | 1.2.1) Definition of a hyper-tetrahedral base model $M_0$ of the system with the method of extension of the universe of discourse of the model beyond the universe of discourse of the modelled system |
| | | 1.2.2) Tuning of the base model based on the measurement samples of the system using of neuro-fuzzy network |
| | | 1.2.3) Determination of the base model error $\mathrm{E}_0$ and checking of the precision of the base model. If its precision is adequate – termination of the modelling; otherwise – continuation of the modelling (step 1.2.4) |
| | | 1.2.4) Positioning 2 rules in the points of the maximum and minimum error of the base model $\mathrm{E}_0$ – the error model $\mathrm{E}_{0M}$ |
| | | 1.2.5) Tuning the membership function parameters of the error model $\mathrm{E}_{0M}$ on the basis of error samples of the base model $\mathrm{E}_0$ |
| | | 1.2.6) Creating a new model $\mathrm{M}_1$ with addition of the base model and the error model $\mathrm{E}_{0M}$ and checking the model precision. If it is adequate – termination of the modelling; otherwise – calculation of an error residuum $\mathrm{E}_1$ and continuation of the modelling until satisfactory precision is reached |
| Stage 2. Seeking parameters providing the assumed effects of the implementation of the specified ERP system with the use of reverse inference | | |

In stage 1, the empirical knowledge base is created. The purpose of this is to generalize information collected from previously completed implementations of the specified ERP systems. The identification of existing rules between the data from the previous period $t_i$ and the next period $t_{i+1}$, i.e. between the values of rates $W(t_i)$ and the values of indexes $W(t_{i+1})$ for $i = 1, \ldots, z$ is carried out on the basis of the collected measurement data. Once created, the knowledge base is recorded in the form of a fuzzy neural network, representing a fuzzy model of analyzed reality.

The first step in the procedure is the filtration of measurement samples. This filtering relies on the determination of significant and insignificant inputs of the modelled system using the mean fuzzy curve method developed by Lin and Cunningham [14].

Then, the fundamental elements of a fuzzy model structure (the rule base and the number of fuzzy sets assigned to the particular inputs and the output of the model) are determined using the geometric method of maximum absolute error point (MAEP) [14].

In the MAEP method, a global model is partitioned into a base model and error residuum models, so it is a set of parallel fuzzy models where each model has a simple structure and contains a small number of rules and fuzzy sets. A neuro-fuzzy network representing a model created with the MAEP method is trained in small fragments, one by one. Since only a fragment of the network is trained at a time, the training is simpler and easier than in the case of entire network training.

The empirical knowledge base obtained in this way constitutes the basis for the execution of Stage 2.

Stage 2 concerns seeking parameters providing the assumed effects of the implementation of the specified ERP system with the use of reverse inference based on the empirical knowledge base created in Stage 1.

The reverse inference related to the assessment of the effects of the planned implementation of the ERP system in the medium-sized company $P$, reduces to seeking initial parameters for the factors that provide these effects. This task is carried out with the use of constraint logic programming techniques (CLP). To this end, the problem of finding parameters which ensure achievement of the assumed values of indexes defining the effects of the planned implementation is presented in the form of a constraints satisfaction problem (CSP), which is defined as a triple [19–20]:

$$PSO = ((X, D), C) \tag{1}$$

where

– a set of decision variables:

$$X = \{x_1, x_2, ..., x_n\} \tag{2}$$

– a domain values of decision variables:

$$D = \{D_i/D_i = \{d_{i1}, ..., d_{im}\},\ i = 1...n\} \tag{3}$$

– a finite set of constraints:

$$C = \{C_i/i = 1...L\} \tag{4}$$

The language of recording a particular information knowledge base is adjusted to the requirements of this method implementation in the Mozart Oz environment [16, 18]).

The detailed course of the proceedings according to the various stages of the proposed concept is illustrated by an example shown below.

## An example of effects assessment of the planned implementation of an ERP system using fuzzy modelling and reverse inference

The considered integrated ERP system has the following functionalities $F$=[$F_1$, $F_2$, $F_3$, $F_4$, $F_5$, $F_6$]: $F_1$ – Basic data, $F_2$ – Sales and distribution, $F_3$ – Purchasing, $F_4$ – Material management, $F_5$ – Production, $F_6$ – APS. Furthermore, an enterprise $P$ considering an implementation of APS functionality of the given ERP system is given. The enterprise $P$ already uses other functionalities of the specified ERP system.

A $W_1$ indicator of delayed production orders (expressed as % of realized orders) is given. The value of this indicator in the company P before starting the planned implementation is $W_1(t_0) = 67\%$. The aim of company $P$ is to reduce the value of the index of delayed orders below 17% at the end of the second period of the system exploitation ($T = t_2$). Therefore, there is an intentional criterion of planned implementation for the values of the $W_1$ indicator $WE_1(t_2)$="up to 17%".

Furthermore, experience (in the form of values of $W_1$) from previous implementations of the specified ERP system in enterprises is given, as shown in Table 3. The functionality of APS in these enterprises was implemented, while the remaining functionalities had already been used.

The answer to the following question is sought:

Assuming a given ERP system and given enterprise, $P$, are there any sufficient conditions which, if satisfied, would guarantee achievement of $W_1$ index value at the $WE_1$ level required by the $P$ enterprise at the end of the second period of the ERP system exploitation ($T = t_2$)?

Table 3
Exemplified data from previous implementations of APS functionality of the ERP system – virtual data (Source: own work).

| | Enterprise 1 | | | Enterprise 2 | | |
|---|---|---|---|---|---|---|
| | $t_0$ | $t_1$ | $t_2$ | $t_0$ | $t_1$ | $t_2$ |
| $SF_6$ | 0 | 1 | 1 | 0 | 1 | 1 |
| $W_1$ | 86% | 62% | 27% | 78% | 42% | 24% |
| | Enterprise 3 | | | Enterprise 4 | | |
| | $t_0$ | $t_1$ | $t_2$ | $t_0$ | $t_1$ | $t_2$ |
| $SF_6$ | 0 | 1 | 1 | 0 | 1 | 1 |
| $W_1$ | 74% | 37% | 19% | 69% | 44% | 17% |
| | Enterprise 5 | | | Enterprise 6 | | |
| | $t_0$ | $t_1$ | $t_2$ | $t_0$ | $t_1$ | $t_2$ |
| $SF_6$ | 0 | 1 | 1 | 0 | 1 | 1 |
| $W_1$ | 96% | 72% | 46% | 91% | 58% | 35% |

Solution:

In order to find the answer to the question formulated above, following a course consistent with the successive stages of the proposed concept which are presented in Table 2 is proposed.

Stage 1. Formation of an empirical knowledge base on the basis of experiences from previously completed implementations of the specified ERP system.

The measurement data from previous implementations of the ERP system from Table 3 was prepared for modelling, the aim of which is to establish $W_1(t_i)$ index values for the next period based on the $W_1(t_{i-1})$ index values obtained during the previous one. The data, as prepared for modeling, is shown in Table 4.

Table 4
Measurement data prepared for modelling (Source: own work).

| | $W_1(t_{i-1})$ | $W_1(t_i)$ |
|---|---|---|
| Enterprise 1 | 0.86 | 0.62 |
| | 0.62 | 0.27 |
| Enterprise 2 | 0.78 | 0.42 |
| | 0.42 | 0.24 |
| Enterprise 3 | 0.74 | 0.37 |
| | 0.37 | 0.19 |
| Enterprise 4 | 0.69 | 0.44 |
| | 0.44 | 0.17 |
| Enterprise 5 | 0.96 | 0.72 |
| | 0.72 | 0.46 |
| Enterprise 6 | 0.91 | 0.58 |
| | 0.58 | 0.35 |
| Denotation | $x_1$ | $y_1$ |

On the basis of the data in Table 4, it can be seen there is only one input variable. In light of this, the filtration step 1.1 was omitted and modelling of the dependence sought was carried out with the use of the method of maximum absolute error point MAEP, according to step 1.2, in the following way:

1.2.1: Determination of the base model $M_0$ method beyond the space considerations.

In the case of $n$ input variables, a base model which constitutes the roughest generalization of modelled dependence takes the form of a hypertetrahedral model of $n+1$ rules. In the case of one input variable $x_1$, it is sufficient to place the rules in measurement points of minimum and maximum value of this input variable, i.e. in the example of the data from Table 4 at the points of $x_1 = 0.37$ and $x_1 = 0.96$.

The values of output variables are established at random at this stage, therefore the points for the initial rules of the example under consideration are: (0.37; 0.17) and (0.97; 0.72). These points determine the parameters of the membership function of input $x_1$, assumed in the base model, which are shown in Figure 1a: ($a_{11} = 0.37$, $a_{12} = 0.96$); and the parameters of membership function of output $y_1$, which are shown in Fig. 1b: ($yB_{11} = 0.17$, $yB_{21} = 0.72$).

It is assumed that the inference is performed using a PROD operator of implication, and defuzzification is performed by means of height method (using singletons placed on vertices of membership function) in the base model.

1.2.2: Tuning of the base model based on the measurement samples of the system using of neuro-fuzzy network.

The base model $M_0$ determined in step 1.2.1 is optimized. For this purpose, the model is converted into a neuro-fuzzy network and tuned on the basis of measurement samples. The subject of tuning is the parameters of membership function of the model outputs, therefore in the example under consideration these are the parameters $yB_{11}$ and $yB_{21}$. The parameter tuning is performed according to the principle of the method of error back-propagation and using the gradient methods. It relies on a gradual change of parameters tuned on the basis of measurement data such that leads to the minimization of a criterion which is an accumulated squared error.

A set of training samples and a set of test samples is separated from all measurement samples. The samples are divided randomly in a ratio of 2:1 (Table 5). The network is trained on the basis of the training data, then an average absolute error is determined for the test data, and following the execution of a series of experiments, those values of tuned parameters are selected with which the error on the test data is the least.

As a result of the experiments conducted with such an assumed division of measurement data, values of tuned parameters $yB_{11} = 0.1644$ and $yB_{21} = 0.06333$ with an average absolute error on the training data $avE_0u = 0.0599$, and on the test data $avE_0t = 0.0267$ are obtained.

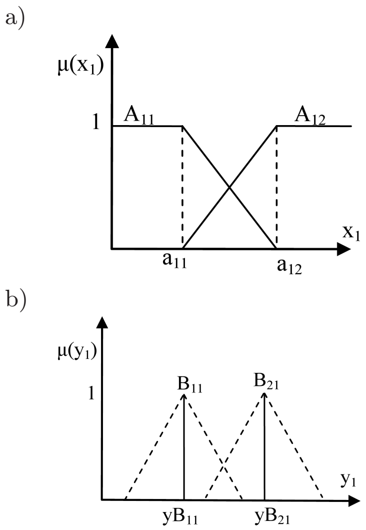


Fig. 1. Membership functions of fuzzy model (Source: own work based on [14]).

Table 5
Division of measurement data from Table 4 into training data ($x_1u$, $y_1u$) and test data ($x_1t$, $y_1t$) (Source: own work).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $x_1u$ | 0.86 | 0.62 | 0.78 | 0.42 | 0.74 | 0.69 | 0.96 | 0.72 |
| $y_1u$ | 0.62 | 0.27 | 0.42 | 0.24 | 0.37 | 0.44 | 0.72 | 0.46 |
| $x_1t$ | 0.37 | 0.44 | 0.91 | 0.58 | | | | |
| $y_1t$ | 0.19 | 0.17 | 0.58 | 0.35 | | | | |

1.2.3: Determination of the base model error $E_0$ and checking the precision of the base model. If the precision is adequate – termination of the modelling, otherwise – continuation of the modelling (step 1.2.4)

The precision of base model $M_0$ is controlled by comparing output values of the model and measurement data. The base model error:

$$E_0u = y_1u - y_{1M0}u \tag{5}$$

is shown in Table 6.

Table 6
Base model error (Source: own work).

| $x_1u$ | $y_1u$ | $y_{1M0}u$ | $E_0u$ |
|---|---|---|---|
| 0.86 | 0.62 | 0.5539 | 0.0661 |
| 0.62 | 0.27 | 0.3631 | −0.0931 |
| 0.78 | 0.42 | 0.4903 | −0.0703 |
| 0.42 | 0.24 | 0.2042 | 0.0358 |
| 0.74 | 0.37 | 0.4585 | −0.0885 |
| 0.69 | 0.44 | 0.4188 | 0.0212 |
| 0.96 | 0.72 | 0.6333 | 0.0867 |
| 0.72 | 0.46 | 0.4426 | 0.0174 |

The average absolute error:

$$avE_0u = \sum_{i=1}^{8} |E_0u_i|/8 = 0.0599. \qquad (6)$$

Because the precision of the model $M_1$, established in the example, was considered as sufficient, the modelling stage was completed. The obtained parameters of the fuzzy model are $a_{11} = 0.37$, $a_{12} = 0.96$, $yB_{11} = 0.1644$, $yB_{21} = 0.6333$. The output of the model is equal to:

$$y_1 = \frac{\mu_{A11} yB_{11} + \mu_{A12} yB_{21}}{\mu_{A11} + \mu_{A12}}, \qquad (7)$$

where

$$\mu_{A11}(x_1) = \begin{cases} 1 & x_1 < a_{11}, \\ 0 & x_1 > a_{12}, \\ \dfrac{a_{12} - x_1}{a_{12} - a_{11}} & a_{11} \le x_1 \le a_{12}, \end{cases} \qquad (8)$$

$$\mu_{A12}(x_1) = \begin{cases} 0 & x_1 < a_{11}, \\ 1 & x_1 > a_{12}, \\ \dfrac{x_1 - a_{11}}{a_{12} - a_{11}} & a_{11} \le x_1 \le a_{12} \end{cases} \qquad (9)$$

Stage 2 Seeking parameters providing the assumed effects of the implementation of the specified ERP system with the use of reverse inference.

The search parameters ensuring the effects of the implementation of the APS functionality of the ERP system in the company $P$ were based on the empirical knowledge base that was created in stage 1. The calculations were carried out using constraint logic programming techniques (CLP), which enable the propagation of constraints and the simple specification of the problem [15, 18, 21]. To this end, the problem was presented in the form of constraints in a constraint satisfaction problem (CSP), as follows:

$$PSO = ((XX, D), C \qquad (10)$$

where

– a set of decision variables:

$$XX = \{X, Y\} \qquad (11)$$

$$X = \{X_1, X_2\} = \{W_1(t_0), W_1(t_1)\} \qquad (12)$$

$$Y = \{Y_1, Y_2\} = \{W_1(t_1), W_1(t_2)\} \qquad (13)$$

– a domain of values of decision variables:

$$D = (DX, DY) \qquad (14)$$

$$DX = \{0, ..., 1000\} \qquad (15)$$

$$DY = \{0, ..., 1000\} \qquad (16)$$

– a finite set of constraints:

$$C = \{C_1, ..., C_9\} \qquad (17)$$

$$C_1 : Y_2 = X_1 \qquad (18)$$

$$C_{2-7} : Y_i = \frac{X_i(yB_{21} - yB_{11}) + (a_{12} yB_{11} - a_{11} yB_{21})1000}{a_{12} - a_{11}}$$

when

$$1000a_{11} \le X_i \le 1000a_{12} \qquad i = 1, 2 \qquad (19)$$

that is:

$$C_{2-7} : Y_i = X_i * 0,7947 - 0,1296 * 1000$$

when

$$370 \le X_i \le 960 \quad i = 1, 2 \qquad (20)$$

$$C_8 : Y_2 < 170. \qquad (21)$$

The language of recording particular information has been adapted to the requirements of the implementation of the Mozart Oz environment. In the calculations, accuracy to 0.1% was assumed. As a result of the calculations, 6 alternative solutions have been generated that meet the defined assumptions. They are presented below in Table 7.

Table 7
Forecasted indicator values $W_1(t_0)$ providing values $W_1(t_2) < 17\%$ (Source: own work).

| $W_1(t_0)$ | $W_1(t_1)$ | $W_1(t_2)$ |
|---|---|---|
| 62.9% | 37% | 16.4% |
| 63.1% | 37.1% | 16.5% |
| 63.3% | 37.3% | 16.6% |
| 63.5% | 37.5% | 16.8% |
| 63.7% | 37.6% | 16.9% |
| 63% | 37.1% | 16.5% |

The values of the $W_1(t_0)$ index in the first column of Table 7 allow $W_1(t_2)$ index values below 17% to be obtained. Thus, these are the conditions guaranteeing the achievement of the $W_1$ index value at the $WE_1$ level preferred by the company $P$ at the end of the second period of the ERP system exploitation ($T = t_2$). Therefore, it can be noted that the achievement of the assumed purpose of enterprise $P$ is possible when the values of the enterprise prior to the implementation of the APS functionality correspond to the values presented in Table 7.

## Analysis of the influence of fuzzy modelling parameters on obtained results

The use of the suggested concept creates the possibility to determine conditions providing a company with the achievement of the required effects of planned implementation of an ERP system, which is impossible in the case of traditionally applied methods.

Table 8
The influence of selected modelling parameters on the fuzzy model created in stage 1 (Source: own work).

| Number of epochs | Learning rate factor | Initial parameters of the member functions $[yB_{11},\ yB_{12}]$ | Obtained values of the member function parameters $[yB_{11},\ yB_{12}]$ | Average absolute error for the training data $avE_0u$ | Average absolute error for the test data $avE_0t$ |
|---|---|---|---|---|---|
| 300 | 0.6 | [0.17; 0.72] | [0.1279; 0.6685] | 0.0573 | 0.0391 |
| 300 | 0.2 | [0.17; 0.72] | [0.1210; 0.6617] | 0.0590 | 0.0392 |
| 300 | 0.1 | [0.17; 0.72] | [0.1196; 0.6603] | 0.0594 | 0.0391 |
| 300 | 0.01 | [0.17; 0.72] | [0.1213; 0.6576] | 0.0597 | 0.0384 |
| 1000 | 0.01 | [0.17; 0.72] | [0.1186; 0.6590] | 0.0597 | 0.0391 |
| 500 | 0.01 | [0.17; 0.72] | [0.1195; 0.6585] | 0.0597 | 0.0388 |
| 500 | 0.01 | [9.0899; 5.9625] | [0.4843; 0.4470] | 0.1293 | 0.2137 |
| 500 | 0.01 | [3.2896; 4.7819] | [0.1666; 0.6313] | 0.06 | 0.0263 |

Table 9
Exemplified comparison of forecasted results for various values of the parameters of the fuzzy model (Source: own work).

| Values of the member function parameters for the fuzzy model created in stage 1 $[yB_{11}, yB_{12}]$ | Number of solutions | $W_1(t_0)$ | $W_1(t_1)$ | $W_1(t_2)$ |
|---|---|---|---|---|
| [0.1644; 0.6333] | 9 | 62.9% | 37% | 16.4% |
| | | 63.1% | 37.1% | 16.5% |
| | | 63.3% | 37.3% | 16.6% |
| | | 63.5% | 37.5% | 16.8% |
| | | 63.7% | 37.6% | 16.9% |
| | | 63% | 37.1% | 16.5% |
| | | 63.2% | 37.2% | 16.6% |
| | | 63.4% | 37.4% | 16.7% |
| | | 63.6 | 37.5% | 16.8% |
| [0.1666;0.6313] | 6 | 62.9% | 37% | 16.6% |
| | | 63.1% | 37.2% | 16.8% |
| | | 63.3% | 37.3% | 16.8% |
| | | 63% | 37.1% | 16.7% |
| | | 63.2% | 37.2% | 16.8% |
| | | 63.4% | 37.4% | 16.9% |
| [0.1213; 0.6576] | 60 | 64.4% | 37% | 12.1% |

It should also be noted that the application of the suggested approach requires many experiments to be conducted in order to determine the fuzzy model sought. During the task of modelling with the use of a fuzzy neural network, the error function is optimized, which comes down to conducting numerous tests depending on various separations into testing and learning data as well as the value of the learning rate factor and the number of epochs. On each occasion, the obtained fuzzy model is only approximate to the modelled relation.

The results of the computer experiments conducted, showing the influence of various modelling parameters on the solutions obtained in the stage 1, are presented in Table 8.

The exemplified comparison of acquired solutions according to stage 2 for the various values of the fuzzy modelling parameters is shown in Table 9.

## Conclusions

This paper presents the concept of effects assessment of a planned implementation of an ERP system in a medium-sized enterprise based on fuzzy modelling and reverse inference techniques. The essence of the proposed approach is reduced to determining the values of parameters, which the company should fulfill prior to commencing implementation, in order to achieve the planned target defined in the form of preferred values of selected indicators. The resulting solution allows not only determination of whether the planned implementation will allow the enterprise to achieve the planned target, but also provides information as to the conditions that must be met in order to make the achievement of this goal possible.

The described concept is dedicated to the support of decision making processes related to the implementation of ERP systems and is the subject of further research.

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