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ORIGINAL PAPER

HYBRID MODEL OF AN EXPERT SYSTEM FOR ASSESSING THE STABILITY OF A PRODUCTION SYSTEM

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ABSTRACT. **Background:** The article presents the concept of control of the production system, which allows to maintain its stability, and thus to implement the established production plans. For this purpose, combinations of simulation models and artificial neural network (ANN) models of the production system have been suggested. The combination of both types of models was possible thanks to the development of a hybrid model of the expert system to assess the possibility of implementing the production plan (objective) depending on the risk size and the level of stability of the production system analysed. The analysed problem - the possibility of implementing production plans depending on the risk size and the level of stability of the production system - is difficult to mathematical modelling. However, based on the data analysis from the simulation model and the ANN model, we can obtain information on the dependences of the corresponding input and output values.

Methods: Based on the presented method of managing the production process using computer models, the possibilities of using simulation models and ANN models in assessing the stability and risk of production systems have been analysed. The analysis and comparison of both types of models have been performed due to the construction and the type of input and output data.

Results: The direct combination of simulation models and ANN models is not allowed by their different structure, specificity and other types of input and output data. Therefore, the concept of combination of both types of models presented in the article is conducted via a database of expertise and fuzzy inference.

Conclusions: For the purpose of controlling the production system, it was suggested to build a hybrid model of an expert system to assess the possibility of achieving the objective depending on the risk size and the level of stability of the production system.

Key words: production system, risk assessment, artificial neural networks, fuzzy logic, stability, variability.

INTRODUCTION

The development of modern enterprises is driven by innovations, diversified products and competition. Kjellberg, Azimont and Reid [2015] show in their work how innovations translate into the market of goods and services, which in turn forces the introduction of innovations in companies. The complexity of environment make necessary to create more and more effective production managing systems [Hadaś, Cyplik 2010]. The consequence is the need of continuous optimization and reorganization of production systems.

However, a problem with ensuring the stability of production appears here. Production of new, highly diversified products in small batches at low inventory levels is characterised by a much lower stability as compared with the large-batch manufacturing, which is presented, inter alia, in the works of Cheraghi and Dadashzadeh [2008]. Variability and fluctuations cause overloading of men and machinery; the consequence of this is low productivity and increased loss [Zwolińska,

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Grzybowska, Kubica 2017]. Additionally, the innovations introduced to products or processes result in disturbances in the current operations. Although these disturbances are usually temporary, they may lead to a loss of the functioning or manufacturing stability in a company, which in turn translates into financial losses as well as a loss of customers. Sustainable systems (supply chain system, production system, ergonomics system) operate on the basis of strictly defined principles and are capable of maintaining specific reliability and quality parameters [Grzybowska, Hoffa-Dąbrowska 2017; Sitek 2014].

The impact of single- or multi-criteria decisions on the production system can be verified very well on a simulation model that contains selected elements important in this context, their parameters and the relationships between them. Modelling and computer simulation have been widely used in the analysis and optimization of production systems and processes by scientists for almost 60 years [Taylor et al., 2009]. Matching an appropriate type of model to the type and character of the decision is a very important aspect here. Pawlewski [2014] presents in his work a multimodal approach as a new paradigm for modelling and simulation of production systems. Alexopoulos [2006] presents a comprehensive review of methods for the analysis of outputs from simulation modelling experimentation. Cheraghi and Dadashzadeh [2008] in their work use modelling and computer simulation to select an appropriate method of controlling a production system. They compare seven different production control methods and argue, inter alia, that the results of the computer simulation can be affected by an error, if too few input parameters are included in the model.

Artificial neural networks (ANN) are another very important group of models which is more and more commonly used when making decisions concerning the control or management of production processes. Some authors even indicate the advantage of ANN over modelling and computer simulation due to its higher efficiency and the ease of building the model [Can, Heavey 2012]. Some studies propose to combine the two methods for better control of a production system. For example, in the study by Bergmann, Stelzer and Strassburger [2014] it has been proposed that the decision was delegated to the neural network, which is connected to the simulation system at runtime. Training of the neural network is performed by observation of the real systems decision and based on the evaluation of data that can be gained through production data acquisition. Another such an example are the studies by Tasdemir, Saritas, Ciniviz and Allahverdi [2011] which shows that the ANN and Fuzzy Expert Systems (FES) approach has been applied comparatively to a gasoline engine for predicting engine power, torque, specific fuel consumption, and emission of hydrocarbon. The experimental data and the developed system analyses showed that ANN and FES reduce disadvantages such as time, material and economical losses to a minimum, thus saving both engineering effort and funds. In the literature there are many other studies on the possibility of using the data from ANN and simulation models in the operation of expert systems [Sahin, Tolun, Hassanpour 2012].

The results of these and many other studies show that from the point of view of the possibility of controlling a production process, the combination of simulation models with ANN models would be very beneficial. Therefore, a concept of merging the simulation models and ANN models will be proposed further in this paper. A simple connection of both models is not possible due to their different structure, specificity, different purposes, as well as different types of input and output data. Therefore the following concept of merging these two types of models was realized through an expert knowledge base and fuzzy inference. This resulted in building a hybrid model that allows assessing the possibility of achieving the goal set for the production system depending on the level of stability and the level of risk.

The paper is structured as follows. Section 2 presents the definition of the production system stability adopted for the needs of this study. In Section 3, advantages and disadvantages of simulation models and ANN models have been compared. In addition, both types of models were analysed in terms of the input and output data needed for their construction. Section 4 presents a concept of merging both types of models by building a hybrid model combining the simulation model with the ANN model by means of the expert knowledge base and fuzzy inference. Such a construction of the expert system model combines advantages of the simulation models and ANN models and allows assessing the possibility of achieving the goals set for the production system in the conditions of randomly occurring risk factors.

STABILITY OF A PRODUCTION SYSTEM

The stability, understood in a very broad sense, means the constancy (invariability over time) of any feature or a certain sequence of system states, or the level of resistance of the system to internal or external disturbances [Bijulal, Jayendran, Hemachandra, 2011]. In the literature, the features or parameters conditioning the correct operation of the system are analysed in the context of the proper operation, the achievement of the results assumed or the fulfilment of the standards established. The conditions for stability in terms of control parameters have been analysed in the literature [Venkateswaran, Son 2007]. The system response against an input can become stable, unstable or critically stable depending on the control parameter setting.

Each system is in a certain state, and because production systems are of dynamic character, a continuous transformation, which causes transition from one state to another, takes place in them. In other words, the parameters of a production process may have a different value at any moment. Taking into account any time interval, it can be said that there is a sequence of output or input states [Bijulal, Jayendran, Hemachandra 2011].

Therefore, the concept of standard is often introduced in relation to the desired course of processes. The standard describes the desired course of processes in the system. If there is a standard, the process control boils down to approximating the functioning of the process to the standard using feedbacks. Feedbacks allow comparing the actual states of the system with the desired states (standards), and then correcting the deviations found [Yu, Xi 2009].

In the case of production processes, the standard is typically a plan of production of final products with specified parameters or criteria and an appropriate time scale. However, the production practice is always accompanied by disturbances hereinafter referred to as risk factors (ri), which cause that the system becomes out of balance. Such disturbances constitute a permanent element of production system inputs and can be divided into internal ones, ones associated with the functioning of the elements forming the system, and the external ones coming from the environment of the system. Figure 1 shows the variability of any parameter ⟦P(t)⟧_i) caused by the impact of risk factors r_i.

If the value of the parameter ⟦P(t)⟧_i) in the instant t_i is within the defined range P_1≤⟦P(t)⟧_i)≤ P_2, it proves that the course of the process is correct. Otherwise, corrective measures should be taken. Corrective measures usually consist in changing the values of the control variables (inputs to the system X) in a way that will allow the values of the parameters characterizing the controlled variables (outputs from the system Y) to return to the process course standards established at the planning stage. A correct decision will cause that the system will return to the steady state.

In connection with the above, the stability of a production system at the assumed margin of variability will be understood in this paper as maintaining the steady state by the system for a certain assumed period of time. A production system is in the steady state, if values of the parameters characterizing the system are within the ranges defined in the planning function and recorded in a standard, i.e. a production plan.

Production systems are not only of technical nature, but also of economic character, and one of their purposes is to generate profit through a continuous increase of the market share. If the company's plans include the development and an increase in the market share, the stability of the production system can be understood as the ability to maintain or increase the values assumed in the plans of parameters.

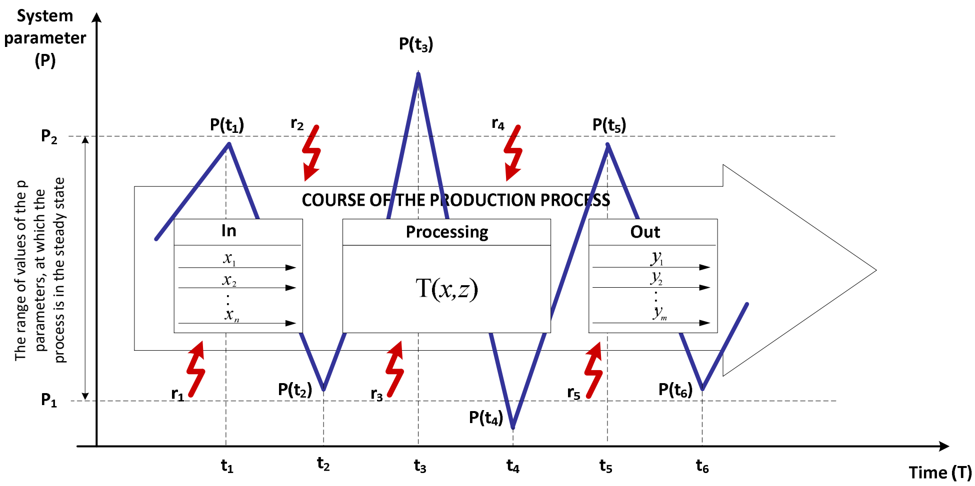

Fig. 1. The variability of the parameter P(ti) caused by the impact of disturbing factors (ri) on the production system

SIMULATION MODELS AND ANN MODELS OF PRODUCTION SYSTEMS

Treating a model as a duplicate of the actual system enables, inter alia, the transfer of the conclusions from the studies performed on the computer model to the actual production system. Both simulation models and ANN models are among the most important techniques supporting the production management and control, as they allow verifying solutions being introduced before their actual implementation, which is not possible in the case of conventional methods of conducting design work [Burduk 2010, Daaboul, Castagna, Da Cunha, Bernard 2014]. An additional advantage is a reduction in the costs of the changes made, based on the simulations carried out. Figure 2 presents a schematic overview of a method for managing a production system with the use of a computer model.

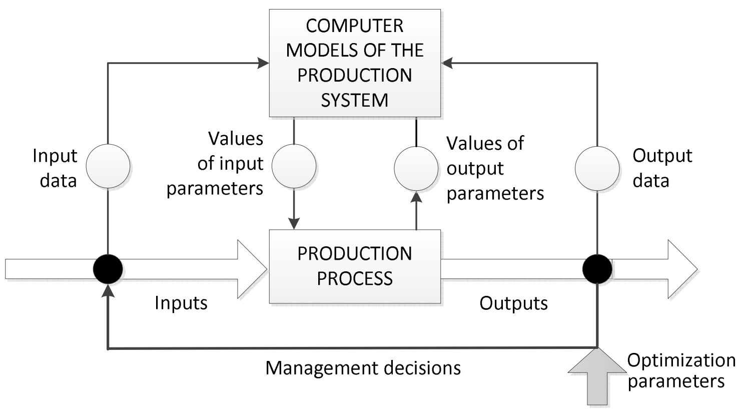

Fig. 2. Method for managing and optimizing a production process using a computer model

The purpose of modelling on the one hand is to formally describe a problem, while on the other hand to present the problem in such a way that will simplify its solution. When modelling production systems, regardless of the purpose of modelling and the optimization criteria adopted, generally six aspect of a company are taken into account:

management, structures, resources, production processes, basic manufacturing measures and tasks of the production system [Daaboul, et al., 2014, Cheraghi, Dadashzadeh 2008]. Figure 3 shows the aforementioned aspects along with the elements that are most commonly used in the manufacturing process modelling.

Modelling as a method of research and development is based on three main stages presented inter alia in the works of [Daaboul, et al. 2014; Cheraghi, Dadashzadeh 2008]: (1) Noticing the characteristics important from the point of view of the actual object being analysed; (2) Building a correct model which will accurately represent the system analysed in a specific but also simplified way; (3) Conducting experiments on the model and finding the best solutions for the criteria adopted.

Thanks to the use of IT systems, models can be populated with appropriate data from an actual system. Modern production systems are measured and monitored to a higher and higher degree. Many organizational, process-related, cost-related and other data are stored every day in databases of IT systems. The problem of the contemporary enterprises is not a lack of data, but rather their excess. This problem often boils down to adequate data acquisition, processing them, and generating a model [Delen and Pratt, 2006].

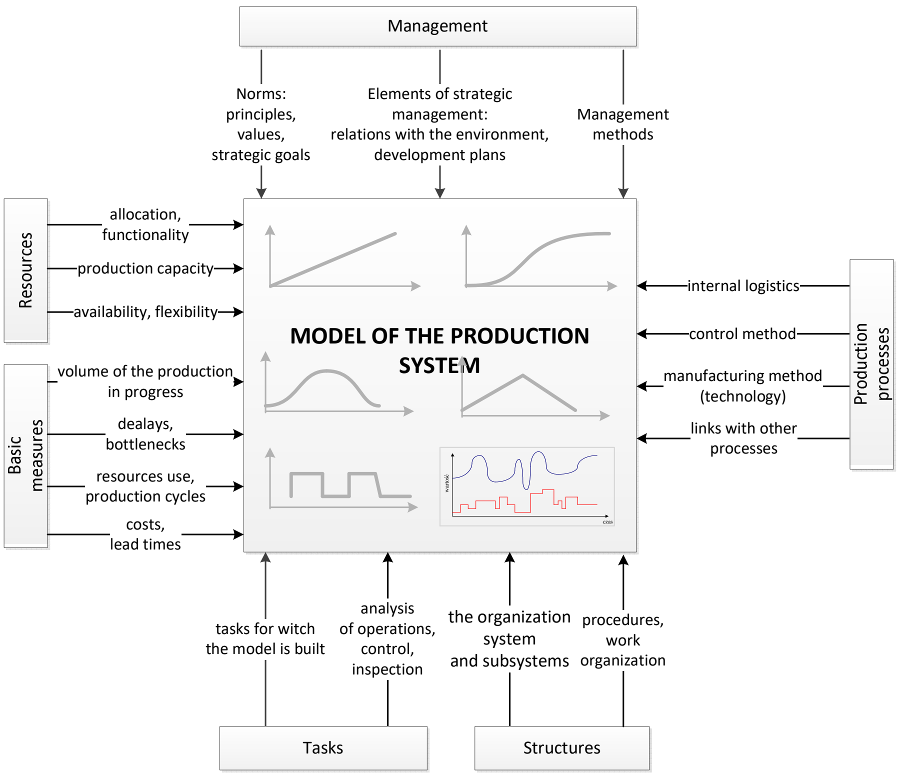

Fig. 3. Production system modelling usually takes account of parameters, as well as selected components

COMPARISON OF SIMULATION MODELS AND ANN MODELS

Simulation models allow solving these problems of the company management that are characterized by a high level of complexity, which means that there are many alternative ways of solving the problem. In turn, ANN can be used for representing complex relationships between input signals and selected output signals without the necessity of building complex mathematical models. Both types of models differ in their structure and in the manner of populating them with data as schematically shown in Figures 4 and 5.

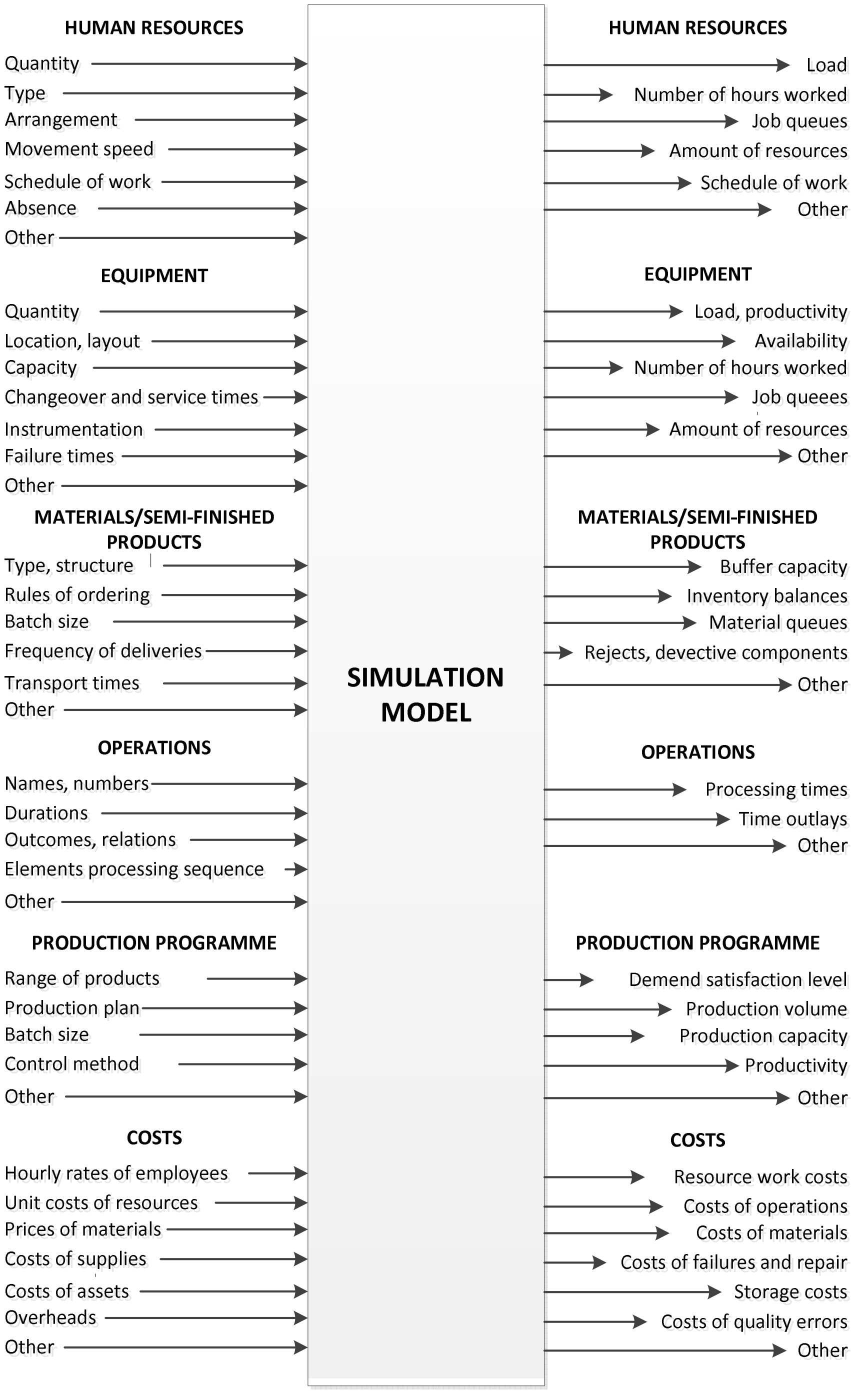

Fig. 4. Input and output data most commonly used in simulation models of production processes

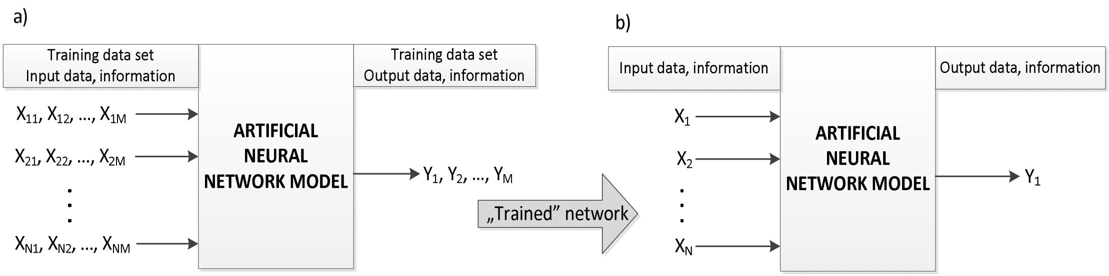

Fig. 5. Input and output data in ANN models a) network training, b) experiments

Despite many advantages and a widespread use of simulation and ANN models in the production management, their specific character and structure cause that the use of many simplifications is required, which translates into the need of simplifying the production reality or a decision problem. Other disadvantages of both types of models are presented in Table 1.

Table 1. Disadvantages of the simulation and ANN models in the context of management of a production system

Disadvantages of simulation models	Disadvantages of ANN models
– Lack of detailed rules regarding the construction of simulation models. The knowledge and experience of the model designer play an important role in the modelling process. – Building models takes a long time. In addition to collecting the data, a very good knowledge of the modelled system is needed to build such models. – Each simulation model is unique. The solutions used in such a model cannot be utilized to analyse other decision problems. – It allows preparing alternative decision solutions in next experiments, but these solutions are not the optimal for all conditions. – Simulation models generate answers to the questions relating to specific and variable conditions.	– Difficulties in extracting the knowledge from a trained neural network resulting from the fact that the networks are described by so-called "black box model". – The accuracy of calculations of the network depends on large amounts of data in the training set. – A lack of multi-stage reasoning, i.e. the conclusions are drawn based on the previous results. The multi-stage reasoning requires a use of several networks.

Source: Daaboul, et al 2014

From the point of view of ensuring the stability of production systems, a combination of both types of models would be beneficial. However, their different structure and different types of input and output data do not allow this, as shown in Figure 4 and Figure 5.

CONCEPT OF MERGING SIMULATION MODELS WITH ANN MODELS

The analysed problem, i.e. the possibility to execute production plans depending on the level of risk and the level of stability of the production system, is difficult to be modelled mathematically, but based on the analysis of data from the simulation and ANN models it is possible to get information concerning the relations between corresponding input and output values. The main elements of the proposed expert system will be a knowledge base and rules of inference. It is proposed here to use the fuzzy inference method, which is characterized by a knowledge system in the form of fuzzy rules "if ... then ..." and is utilized in modelling in situations where it is difficult to describe mathematically the relations between independent variables and dependent variables (input and output variables), while the corresponding values of inputs and outputs are known [Zadeh, 1975a,b]. The concept of building a model of a hybrid system is presented schematically in Figure 6.

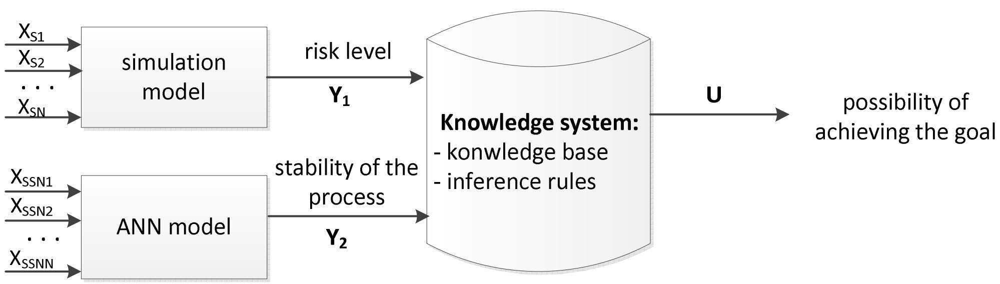

Fig. 6. Concept of building an expert system to assess the possibility to achieve a goal depending on the level of risk and the level of stability of the production system

The basic element of the fuzzy inference is the concept of linguistic variable (e.g. "the possibility to realize the plan") that takes linguistic values such as "high", "low". The values taken by linguistic variables are then represented by the so-called membership functions [Zadeh, 1975a,b]. Fuzzy conditional statements constitute one of the basic measures that allow presenting the relations between linguistic variables adopted. They allow describing cause-and-effect relationships. The most commonly used is the Mamdani architecture in which the base of rules is created on the basis of expert knowledge. Such statements are also called fuzzy inference rules of the following type [Mamdani, Assilian 1975]: If "fuzzy logical premise," then "fuzzy inference".

The Mamdani method is useful when the number of variables is low. Otherwise the following problems are encountered [Mamdani, Assilian 1975]: (1) the number of rules grows exponentially along with the number of variables in the premise; (2) the more rules, the more difficult to assess the degree of their matching to the problem; (3) if the number of variables in the premise is too high, it will be difficult to understand the relations between the premises and consequences.

Such rules are widely used in everyday natural language expressions. The most important task is to acquire them and solve the problem. Usually these tasks belong to an expert in a given field, who develops rules and selects membership functions for premises and conclusions in each case under consideration.

For the needs of building the model of the hybrid system, there was used a two-stage algorithm presented in Figure 7.

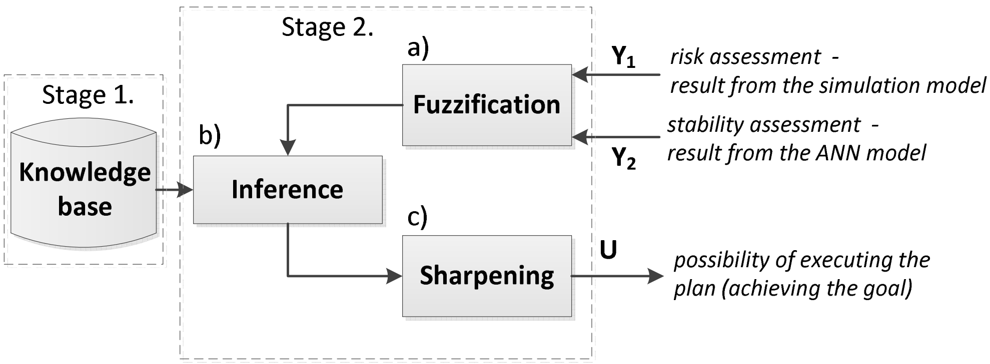

Fig. 7. Algorithm for building a fuzzy model of the hybrid system

Stage 1. Building a knowledge base that will store the set of IF-THEN rules provided by experts, i.e. the formalized knowledge of the problem being solved.

Stage 2. This stage consists of the following three steps: (1) Fuzzification consisting in the transformation of system inputs, i.e. sharp (numerical) values, to fuzzy values; (2) Selection and use of the interference mechanism that simulates human reasoning through the process of fuzzy inference at the inputs in accordance with the logic stored in the IF-THEN rules; (3) Defuzzification consisting in the transformation of the fuzzy set formed as a result of the inference on sharp values.

Knowledge base (Stage 1) is built individually and once for the production system, for which the possibility of executing the production plan will be assessed depending on the level of risk occurring in it and the level of stability. Stage 2 is responsible for the operation of the expert system and can be repeated several times. The values of the level of risk and the level of stability in the analysed production system are converted in steps a, b and c into an output value determining the possibility of executing the production plan assumed.

CONCLUSIVE REMARKS

The article presents the concept of building a hybrid model of an expert system to assess the stability of a production system. This model shows that the combination of simulation and ANN modelling would be of great benefit in analysing and ensuring the stability of production systems. The direct combination of both types of models is not allowed by their different structure, specificity, different construction goals of both models and other types of input and output data. Therefore, the concept of combination of both types of models was suggested via a database of expertise and fuzzy inference. The results from the simulation model and from the ANN model have been used to gain knowledge about the production system analysed. It was suggested that the information from the simulation model would provide knowledge about the risk size, while the information from the ANN model would provide knowledge about the process stability.

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HYBRYDOWY MODEL EKSPERCKIEGO SYSTEMU OCENY STABILNOŚCI SYSTEMU PRODUKCYJNEGO

STRESZCZENIE. **Wstęp:** W artykule przedstawiono koncepcję sterowania systemem produkcyjnym, pozwalającą na zachowanie jego stabilności, a tym samym na realizację założonych planów produkcyjnych. W tym celu zaproponowano połączenia modeli symulacyjnych i modeli sztucznych sieci neuronowych (SSN) systemu produkcyjnego. Połączenie obydwu typów modeli było możliwe dzięki opracowaniu hybrydowego modelu systemu ekspertowego do oceny możliwości realizacji planu produkcji (celu) w zależności od wielkości ryzyka i poziomu stabilności analizowanego systemu produkcyjnego. Analizowany problem – możliwość realizacji planów produkcyjnych w zależności od wielkości ryzyka i poziomu stabilności systemu produkcyjnego – jest trudny do zamodelowania matematycznego. Jednak na

podstawie analizy danych, pochodzących z modelu symulacyjnego i modelu ANN, można uzyskać informacje dotyczące zależności odpowiadających sobie wartości wejściowych i wyjściowych.
Metody: Na podstawie przedstawionego sposobu zarządzania procesu produkcyjnego z wykorzystaniem modeli komputerowych, przeanalizowano możliwości zastosowania modeli symulacyjnych i modeli ANN w ocenie stabilności i ryzyka systemów produkcyjnych. Dokonano analizy i porównania obydwu typów modeli ze względu na sposób budowy oraz rodzaj danych wejściowych i wyjściowych.
Wyniki: Na bezpośrednie połączenie modeli symulacyjnych i modeli SSN nie pozwala ich odmienna budowa, specyfika oraz inne rodzaje danych wejściowych i wyjściowych. Dlatego prezentowana w artykule koncepcja fuzji obydwu typów modeli odbywa się poprzez bazę wiedzy eksperckiej i wnioskowanie rozmyte.
Wnioski: Na potrzeby sterowania systemem produkcyjnym, zaproponowano budowę hybrydowego modelu systemu ekspertowego do oceny możliwości realizacji celu w zależności od wielkości ryzyka i poziomu stabilności systemu produkcyjnego.

Słowa kluczowe: system produkcji, ocena ryzyka, sztuczne sieci neuronowe, logika rozmyta, stabilność, zmienność

HYBRIDES MODELL EINES EXPERTEN-SYSTEMS FÜR DIE BEURTEILUNG VON STABILITÄT EINES PRODUKTIONSSYSTEMS

ZUSAMMENFASSUNG. Einleitung: Im vorliegenden Artikel wurde ein Konzept für die Steuerung eines Produktionssystems, das die Aufrechterhaltung dessen Stabilität und dadurch auch die Ausführung von angenommenen Produktionsplänen erlaubt, dargestellt. Zu diesem Zweck wurde eine Anbindung von Simulationsmodellen und Modellen künstlicher neuronaler Netze (KNN) des Produktionssystems vorgeschlagen. Die Verbindung der beiden Modell-Typen war dank des Konzeptes eines hybriden Modells vom Experten-System für die Zwecke einer Beurteilung von Möglichkeiten der Ausführung des Produktionsplans (Produktionsziels) in Abhängigkeit von der Risiko-Größe und dem Niveau von Stabilität des analysierten Produktionssystems möglich. Das analysierte Problem – also die Möglichkeit der Ausführung des Produktionsplans (Produktionsziels) in Abhängigkeit von der Risiko-Größe und dem Niveau von Stabilität des analysierten Produktionssystems – lässt sich kaum mathematisch modellieren. Allerdings auf Grund einer Analyse der Daten, die vom Simulationsmodell und vom KNN-Modell gewonnen werden, kann man die Informationen bezüglich der Abhängigkeiten von adäquaten Input- und Output-Werten erzielen.
Methoden: Anhand der projizierten Methode für das Management des Produktionsprozesses mit der Inanspruchnahme von Rechner-Modellen wurden für die Beurteilung der Stabilität und des Risikos von Produktionssystemen die Möglichkeiten der Anwendung der betreffenden Simulationsmodelle und der KNN-Modelle wahrgenommen und analysiert. Es wurden dabei eine Analyse und ein Vergleich der beiden Modell-Typen angesichts deren Aufbau und der Art von Input- und Output-Daten vorgenommen.
Ergebnisse: Eine direkte Verbindung der Simulationsmodelle und der KNN-Modelle lassen deren unterschiedlicher Aufbau, ihre Eigenart und verschiedenartige Input- und Output-Daten nicht zu. Daher kommt das im Artikel projizierte Konzept der Anbindung der beiden Modell-Typen über Datenbanken mit dem Experten-Wissen und mithilfe eines fuzzy-artigen Schlussfolgerns zustande.
Fazit: Für den Bedarf der Steuerung des Produktionssystems wurde der Aufbau eines hybriden Modells vom Experten-System für die Zwecke einer Beurteilung von Möglichkeiten der Ausführung des Produktionsziels in Abhängigkeit von der Risiko-Größe und dem Niveau der Stabilität des analysierten Produktionssystems vorgeschlagen.

Codewörter: Produktionsystem, Beurteilung des Risikos, künstliche neuronale Netze (KNN), Fuzzy-Logik, Stabilität, Variabilität

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