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SPECIAL SECTION
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# Intelligent system supporting technological process planning for machining and 3D printing

Izabela ROJEK[1*], Dariusz MIKOŁAJEWSKI[1], Piotr KOTLARZ[1], Marek MACKO[2], and Jakub KOPOWSKI[1,3]

[1] Institute of Computer Science, Kazimierz Wielki University, Chodkiewicza 30, 85-064 Bydgoszcz, Poland
[2] Faculty of Mechatronics, Kazimierz Wielki University, Chodkiewicza 30, 85-064 Bydgoszcz, Poland
[3] Faculty of Psychology, Kazimierz Wielki University, Chodkiewicza 30, 85-064 Bydgoszcz, Poland

**Abstract.** The study aimed to develop a system supporting technological process planning for machining and 3D printing. Such a system should function similarly to the way human experts act in their fields of expertise and should be capable of gathering the necessary knowledge, analysing data, and drawing conclusions to solve problems. This could be done by utilising artificial intelligence (AI) methods available within such systems. The study proved the usefulness of AI methods and their significant effectiveness in supporting technological process planning. The purpose of this article is to show an intelligent system that includes knowledge, models, and procedures supporting the company's employees as part of machining and 3D printing. Few works are combining these two types of processing. Nowadays, however, these two types of processing overlap each other into a common concept of hybrid processing. Therefore, in the opinion of the authors, such a comprehensive system is necessary. The system-embedded knowledge takes the form of neural networks, decision trees, and facts. The system is presented using the example of a real enterprise. The intelligent expert system is intended for process engineers who have not yet gathered sufficient experience in technological-process planning, or who have just begun their work in a given production enterprise and are not very familiar with its machinery and other means of production.

**Key words:** artificial intelligence; intelligent system; technological process; machining; 3D printing.

## 1. Introduction

The development and use of IT tools to support the planning of technological processes has been the subject of research all over the world for many years. While the potentially greater amount of data should facilitate task and problem solving, in practice this is rarely the case. The search for increasingly advanced IT tools for data analysis and exploration continues, as in the case of an intelligent expert system supporting the planning of technological processes for machining and 3D printing processes.

In machining, the technological process constitutes a core part of the production process, directly entailing changes to shapes, dimensions, and surface quality, as well as the physico-chemical properties of the processed item, or the arrangement of components or assemblies in relation to each other in a product. Starting with the preparation of the semi-finished product (input) in the technological process, certain technological operations need to be performed. The appropriate operations are selected by the process engineer. Technological-process planning is divided into several stages. The first stage involves selecting semi-finished products. This is followed by designing the technological process structure, i.e. the sequence of technological procedures and operations. Then, the workpiece instrumentation, machine tools, tooling, and machining parameters are selected for each technological procedure and operation.

Traditional manufacturing (Subtractive Manufacturing, Formative Manufacturing), long applied commercially with assured quality, often requires machining or other methods (drilling, grinding, etc.) to remove the surplus material (i.e. subtractive methods) or casting it into moulds, but there are novel alternative methods of production. In contrast, 3D printing is the industrial group of technologies which is characterised by a computer-controlled process which creates 3D products (objects) with precise geometric shapes by depositing material(s), usually in layers [1–4]. 3D printing allows for the creation of objects from:

- Digitalised physical objects of various dimensions (using 3D object scanners, with modifications made within the reverse engineering process) – mainly for the modification of existing objects; shapes, materials, physical and/or chemical properties
- Digital files using computer-aided design (CAD) – mainly for rapid prototyping or creating objects not achievable using other technologies
- A hybrid approach – e.g. for reconstruction and renovation purposes

3D printing provides:

- Easy customisation
- A low cost of the machines
- Increased material variability, including combined multiple materials (e.g. both hard plastics and elastomers)

*e-mail: izarojek@ukw.edu.pl

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- A higher level of design freedom
- The simplification of the supply chain
- A wide range of applications
- The ability to fabricate complex parts in one machine/process
- Both rapid prototyping and end-user product manufacturing techniques
- The integration of the technologies and materials
- Avoiding forging and joining processes by printing the complete product within one 3D printing process
- Rapid tooling developed towards Direct Manufacturing
- The development of high-value, low-volume manufacturing industries such as aviation or prosthetics
- Design optimisation using, e.g. computational intelligence.

However, the so-called Mass Customisation, i.e. the ability to provide individually designed products/services to every customer, is still limited by:

- Relatively low penetration into the commercial market
- A difference in surface smoothness across prints from the same digital file
- The unpredictability of the performance (e.g. random defects into the printed part)
- A lack of formalised guidelines for most 3D printing processes
- Few professionally trained specialists
- A lack of manufacturing design regulations, e.g. slow development of Quality Assurance (QA) and Quality Control (QC) strategies [1–3].

The idea of 3D printing began in the 1960s. The first 3D printing manufacturing equipment for two 3D printing methods for fabricating 3D models was invented by Hideo Kodama of the Nagoya Municipal Industrial Research Institute in 1980. What is more, most of the currently known 3D printing technologies were developed to the pre-commercial stage by 1991 but their rapid development and commercial use started in the 21st century. There is still a need for improvements concerning 3D printing techniques to lower the cost, energy consumption, and expand its capabilities, and recently – towards a broader use within the Industry 4.0 paradigm [5]. Many scientists, inventors, entrepreneurs, and companies aim at replacing or creating new manufacturing systems [1]. The co-incidence of various processes and materials has created a unique possibility of 3D printing objects made of polymer, metal, ceramic, or even composite/multi-material, which are hard or impossible to produce using conventional manufacturing technologies. Moreover, their mechanical, thermal, and/or dimensional properties can also be unique. This situation may create a very good foundation of Industry 4.0 processes.

This article is based on a paper that was prepared for the Machine Modelling and Simulations conference [6] and has been expanded to include 3D printing. An intelligent expert system is used for technological-process planning for machining and 3D printing based on neural networks and rules. The idea of this article is to show an intelligent system that includes knowledge, models, and procedures supporting the company's employees as part of machining and 3D printing. Few works are combining these two completely different types of processing. Nowadays, however, these two types of processing overlap each other into a common concept of hybrid processing. There is a rapid development of hybrid processes and devices that combine 3D printing and CNC machining [**7**]. Therefore, in the authors' opinion, such a comprehensive system is necessary.

The article consists of the following sections: introduction; literature review of artificial intelligence methods used in technological process planning for machining and 3D printing; the authors' case study – an intelligent system for technological-process planning for machining and 3D printing; conclusions and references.

## 2. Artificial intelligence methods used in technological process planning

**2.1. AI methods used in technological process planning for machining.** Attempts at increasing the use of artificial intelligence (AI) methods in computer-aided technological process planning systems have been made for many years. The use of data-mining methods to acquire the knowledge available in the databases of the existing technological processes facilitates the formalisation of the process, the engineer's inventiveness, and experience, taking the form of the knowledge included in knowledge databases, and the induction process similar to that which a human expert employs in technological process planning. The technological knowledge acquired with AI methods, coupled with an intelligent computer-aided process planning system (CAPP system), makes it possible to design technological processes that are better aligned with enterprise-specific needs. Expert systems have been widely used in technological process planning [8–10]. Neural networks facilitate the technological process planning by eliminating the need to search through numerous rules (as in the case of expert systems). The use of a neural network facilitates the simultaneous consideration of numerous limitations and is very popular in technical areas [11–13]. Random forests and decision trees represent a basic method of inductive machine learning due to their high effectiveness. This method is based on analysing examples and is characterised by exceptionally good classification properties. Rule generation based on decision trees makes it possible to formulate rules [14–16]. A large part of decision-making related to process planning can take place in an environment where objectives and limitations are fuzzy, i.e. not fully-known. Fuzzy logic can help to achieve this by transforming human knowledge into mathematical models and transposing that knowledge into engineering systems [17].

**2.2. AI methods used in technological process planning for 3D printing.** From a technological point of view, 3D printing can be broadly divided into three types:

- Sintering – the material is heated without being liquefied to create complex high-resolution objects.
- Melting – the material is fully melted.
- Stereolithography – using photopolymerisation, where an ultraviolet laser is fired into a vat of photopolymer resin to

create torque-resistant ceramic parts able to endure extreme temperatures.

The American Society for Testing and Materials (ASTM) has defined 7 categories of 3D printing technologies: vat photopolymerisation, material jetting, binder jetting, powder bed fusion, material extrusion, sheet lamination, and direct energy deposition [18].

Artificial intelligence is currently widely applied in 3D printing as part of an intelligent, efficient, high-quality, mass-customised, and service-oriented production process [19]. Many factors should be taken into consideration when selecting a manufacturing method, including cost, time, energy consumption, product complexity, material usage, material properties requirements, sustainability, and many more. Thus, automated, or semi-automated optimisation based on artificial intelligence is often used to meet these requirements [20–22]. Despite recent developments in automated and semi-automated AI-based optimisation of 3D printing processes, especially for Industry 4.0 purposes, they are still at the beginning of their development [23, 24]. The main applications were divided into parameter optimisation, and anomaly detection, and may be classified into different types of machine learning (ML) tasks, including regression, classification, and clustering [25]. They may significantly improve the efficiency in the prefabrication stage and defect detection. But the future aim is a real-time process control and built-in predictive maintenance.

There are many examples of the use of AI in additive manufacturing in the literature. Although fused deposition modelling (FDM) additive manufacturing technologies have advanced in the past decade, interlayer imperfections such as delamination and warping are still dominant when printing complex parts. Herein, a self-monitoring system based on real-time camera images and deep learning algorithms is developed to classify the various extents of delamination in a printed part. In addition, a novel method incorporating strain measurements is established to measure and predict the onset of warping [26]. At present, quality control in additive manufacturing is based on diligently controlling the temperature of the process zone or high resolution imaging. So far, no methods are known to monitor the quality of additive manufacturing in situ and in real-time. To achieve the goal of accurate real-time quality control, was proposed an approach that relies on acoustic emission, which is further analysed within the artificial intelligence framework [27]. Another article presents an AI-based algorithm for finding material deformations in 3D printed products in additive manufacturing [28]. In other research, an Artificial Neural Network was applied to build an optimisation system for finding optimal process parameters. The inputs of the system are the desirable properties of a product such as the relative density ratio, and surface roughness, while the outputs are laser power, laser velocity, hatch distance, and layer thickness. Applying the system not only requires less pre-manufacturing expenditure but also helps the printing users to choose approximate process parameters for printing a desirable product [29].

An analysis of the literature, the needs of enterprises from additive manufacturing, and the experience of the authors [30, 31], among others, allowed for the development of an intelligent planning system for technological processes towards additive processing.

## 3. Case study – an intelligent system for technological-process planning

**3.1. Data preparation.** Data were collected at a real enterprise providing a wide range of products. The company is engaged in the manufacture of injection moulds and plastic processing. Depending on the products being manufactured, the production involves unit, serial, or mass production. The company collects its knowledge, experience, and data in order to improve its processes and products. The data concerns machining and 3D printing processes. For machining, the data are collected on semi-finished products, technological process structures, conventional and CNC machine tools, cutting tools, workpiece instrumentation, and tooling. For 3D printing processes, the data are collected on process parameters: type of manufacturing, type of material, layer height [mm], shell thickness [mm], bottom thickness [mm], top thickness [mm], fill density [%], print speed [mm/s], bed temperature [°C], printing temperature [°C], second nozzle temperature [°C], build orientation [degree], no. of contours [no], and tensile strength [kN/mm$^2$]. For example, the surface roughness can be determined from the layer height, print speed, print temperature, and outer shell speed. The tensile strength can be determined from the material name, layer height, and temperature.

Technological knowledge is gathered in the form of technological processes which are developed. The exemplars of technological process elements comprise a significant amount of knowledge, experience, and intuition of the process engineers.

The majority of information obtained from databases is raw, incomplete, and noisy. For such data to become useful for mining purposes, they need to be cleaned and transformed [32, 33]. Data cleaning entails the unification of records, the supplementation of missing entries, or the identification of extreme points. In turn, data transformation involves normalisation or coding.

**3.2. An intelligent system schematic.** A schematic of an intelligent expert system for technological process planning is made up of (1) a user interface, and modules for (2) data management, (3) data normalisation using fuzzy logic, (4) a module of technological knowledge acquisition, and (5) a module of technological process planning (Fig. 1).

**3.3. Knowledge sources for the system for machining using the example of models of semi-finished product selection.** The type of task to be solved is considered to be the principal criterion for AI method selection. Fuzzy logic is used for the normalising and coding of facts in the expert system knowledge base, whereas neural networks and decision trees served the purpose of providing technical insights and assisting process engineers in the course of technological process planning. The underlying problem in technological process planning is related to the classification necessary for the proper selection of individual technological process elements. The results of

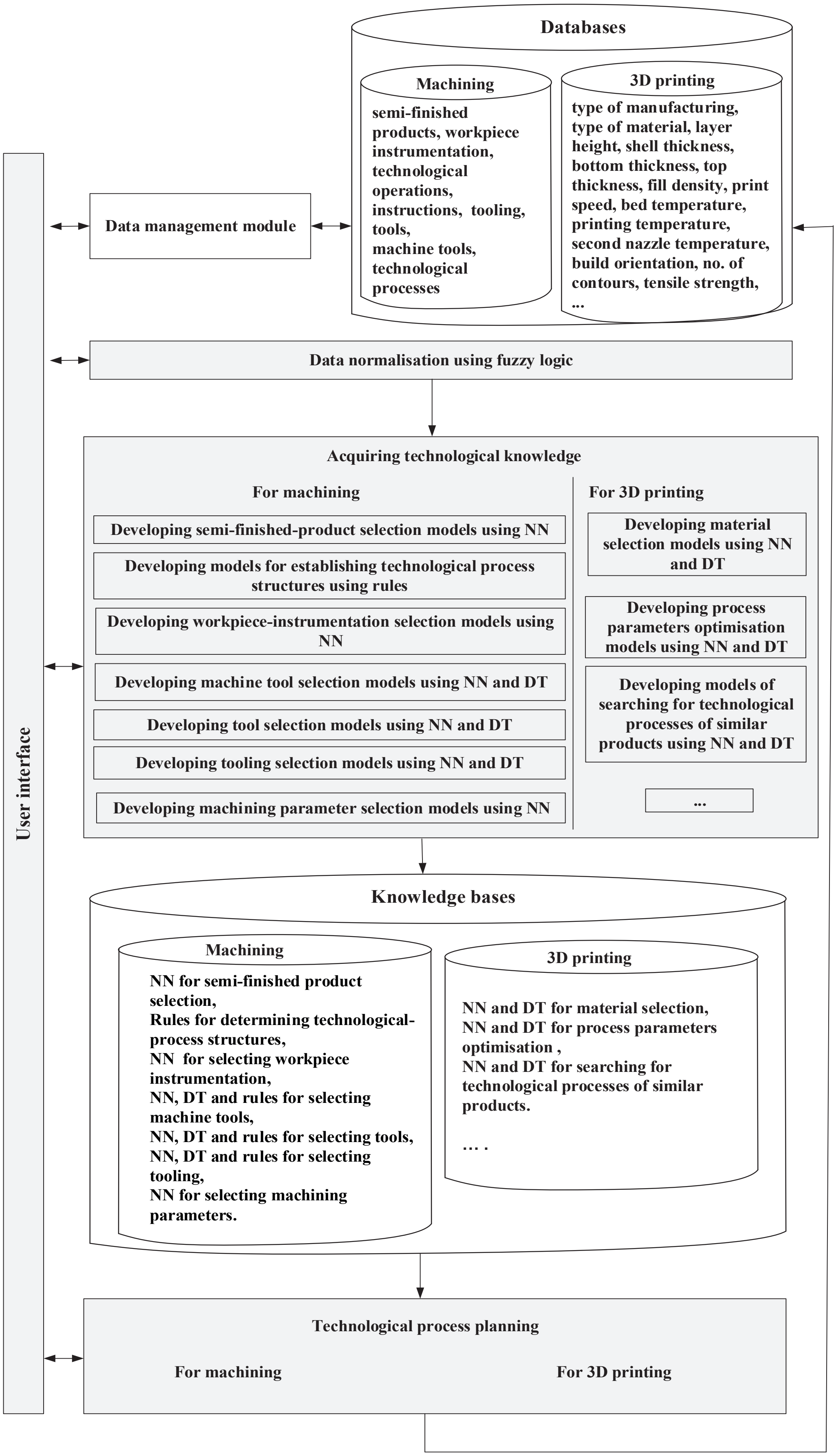


Fig. 1. Intelligent expert system for technological process planning for machining and 3D printing; NN – neural networks; DT – decision trees

the study presented in this article relate to identifying, analysing, and experimenting with various types of neural networks and decision trees. The following types of NN were selected: (1) unidirectional multi-layer perceptron (MLP) networks with backward propagation of errors; (2) radial basis function (RBS) networks; (3) self-organising Kohonen networks (KN); and (4) recurrent Hamming networks (HN). Certain types of decision trees, i.e. C4.5, C&RT, CHAID, boosted trees, and random forests, were also used in the analysis. Decision rules were developed based on expert trees, and then they were entered into the expert system, following which selected AI methods were analysed in terms of their application in specific tasks related to technological process planning. The combination of an expert system, neural networks, decision trees, and rules leads to an intelligent expert system for machining.

Semi-finished product selection was performed using unidirectional multi-layer perceptron (MLP) networks with backward propagation of errors, radial-basis function (RBS) networks, and Kohonen and Hamming networks. Figure 2 presents an exemplary structure of MLP and RBF neural networks for semi-finished product selection.

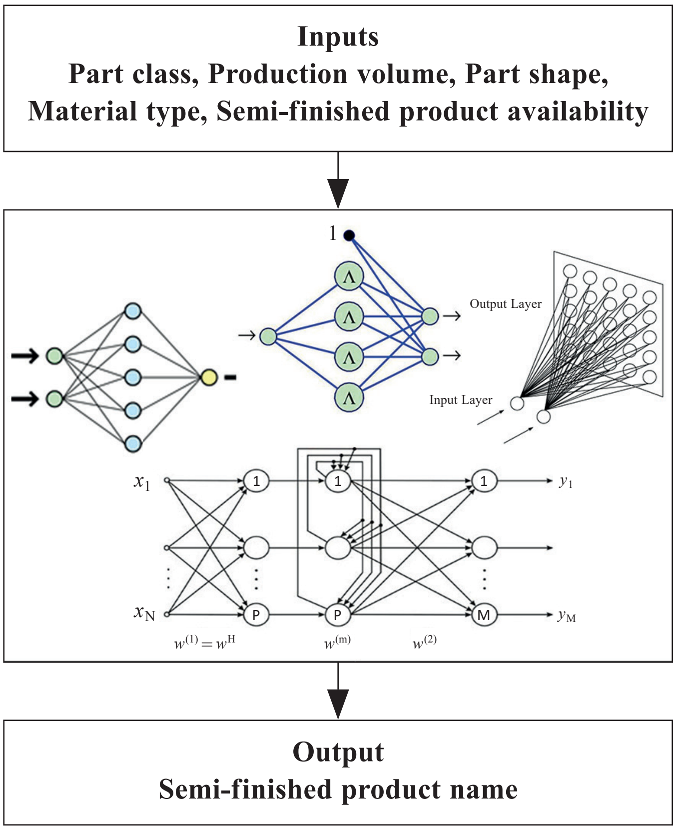


Fig. 2. Selection of semi-finished product by MLP, RBF, Kohonen, and Hamming neural-network structure [6]

Classification models were learned based on the example databases (the whole database contains about 1000 records). The learning database includes examples of a selection of semi-finished product (550 records). These examples are divided into files: training (75% of the records), testing (15%), and validation (10%). Neural network models were trained using a training file and tested with a test file, and their operation was checked with a validation file, which is a response to the model overfitting.

In the course of the analyses of the neural networks, their effectiveness was found to depend on the following parameters: in the case of MLP and RBF networks, on the number of neurons in the hidden layer, the number of training cycles according to a specific learning algorithm, the values of the error function and the function of activation in the hidden and output layer; and in the case of the Kohonen networks, on the network topology, the number of training cycles, and the error function. Neural-network outputs were also analysed. In the course of the analysis of all the neural network models developed, the MLP (5–15–1), Kohonen (6–100), and Hamming network models proved the most effective for semi-finished product selection (100.00% effectiveness). Therefore, the simplest network (MLP) could be used for their selection. The assessments also covered the operational network accuracy based on the new data, and the degree of certainty defining the relationship of the new input data with specific template classes. Both parameters influence neural network effectiveness, and the higher the accuracy and degree of certainty, the better the ability to classify the neural networks [6].

The same model-development method was used for establishing a neural network and decision tree models in the process of selecting the workpiece instrumentation, tool chucks, machine tools, tools, and tooling and machining parameters, while the framework of the technological process was created using the decision-making rules.

The use of the system for the selection of a semi-finished product is shown in Fig. 3. The process engineer first enters the relevant input data, including the product name and production volume, and then selects the appropriate semi-finished product. Before choosing a semi-finished product, you can choose the material. However, if you know the material, you provide it when choosing a semi-finished product. This way the selection process speeds up.

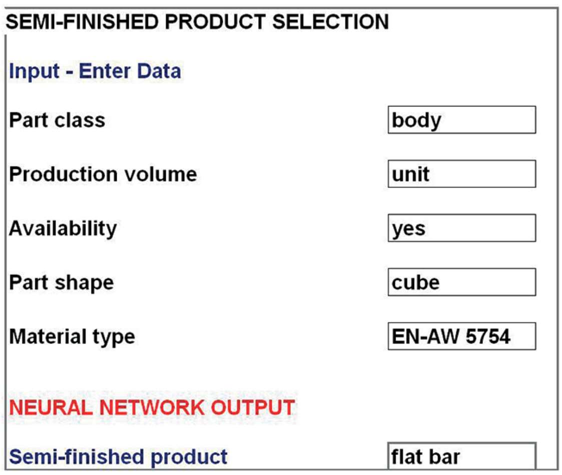


Fig. 3. Semi-finished product selection [6]

Next, the process engineer establishes further elements of the technological process. All the results obtained from the expert system were verified and recognised as correct by process engineers, which can be considered as confirming the usefulness of this kind of IT tool in industrial practice.

**3.4. Knowledge sources for the system for 3D printing using the example of material selection based on the tensile strength.** The intelligent system was expanded to include technological process planning for 3D printing in terms of the selection of appropriate materials for the production of specific products, optimisation of process parameters, and searching for technological processes of similar products.

Material development can probably create the most significant breakthrough in the area of 3D printing. The main 3D printing material features include the dimensional properties (accuracy and volumetric shrink), the production speed or (in smaller parts) the number of production cycles per minute, mechanical properties, thermal properties, chemical properties, and the ability to be used in direct contact with the human body. The pallet of materials which may be used in 3D printing processes cover almost all kinds of them (polymers, metals, ceramics, sand, glass, etc.), and this list is increasing each year, including the possibility of multi-material 3D printing. The creation of neural network models is shown using the example of material selection based on tensile strength. Classification models were learned based on example databases (the whole database contains about 500 records). The learning database includes examples of selection (150 records). These examples were divided into files: training (75% of the records), testing (15%), and validation (10%). The neural network models were trained using the training file, tested with the test file, and their operation was checked with the validation file, which is a response to the model overfitting.

The material selection based on the tensile strength was performed using unidirectional multi-layer perceptron (MLP) networks with backward propagation of errors. Figure 4 presents the structure of the MLP neural networks for the material selection based on the tensile strength. In the course of the analysis of the neural networks, their effectiveness was found to depend on the following parameters: the number of neurons in the hidden layer, the number of training cycles according to a specific learning algorithm, the values of the error function. and the function of activation in the hidden and output layers.

Table 1 features a comparison of MLP networks for the material selection based on the tensile strength, considering a correlation coefficient (r) that shows the fit of the model. The value of $r = 1$ gives the best fit of the model. The best model was the MLP network with a structure of 4–32–1, where 4–32–1 refers to the number of network inputs (4), the number of neurons in the hidden layer (32), and the number of network outputs (1).

Table 1
MLP networks for the material selection based on the tensile strength

| **MLP network** | MLP 4–18–1 | MLP 4–47–1 | MLP 4–32–1 | MLP 4–44–1 |
|---|---|---|---|---|
| Effectiveness [%] | 98 | 95 | 100 | 93 |
| Error function | SOS | SOS | SOS | SOS |
| Activation function in the hidden layer | Tanh | Sinus | Tanh | Logistic |
| Activation function in the output layer | Exponential | Exponential | Exponential | Logistic |
| Correlation coefficient | 0.908237 | 0.880434 | 1.000000 | 0.861899 |

The use of the system for the material selection based on the tensile strength is shown in Fig. 5. The process engineer first enters the relevant input data, including the material name, the layer height, the infill density and temperature, and the MLP network selects and returns the parameter of the tensile strength. If the tensile strength selected by the MLP network meets the requirements of the machine operator, he chooses this and the parameters for the technological process, which were provided to the neural network.

The intelligent system will be further developed towards the optimisation of the technological process parameters for

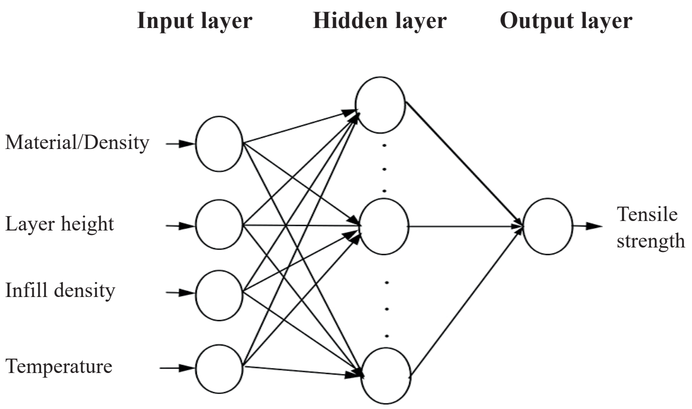


Fig. 4. MLP structure for the material selection based on tensile strength

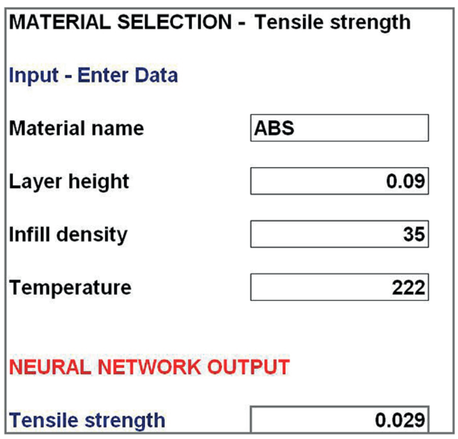


Fig.5. Material selection based on tensile strength

additive manufacturing and in terms of the selection of the appropriate materials for the production of specific products, as well as the search for technological processes of similar products.

## 4. Discussion

The study aimed to develop an intelligent expert system supporting technological process planning for machining and 3D printing, the functioning of which similarly the way human experts act in their fields of expertise, and should be capable of gathering the necessary knowledge, analysing the data, and drawing conclusions to solve problems. This can be achieved by employing AI methods. The study proved the usefulness of the AI methods (neural networks and decision trees) and their effectiveness in supporting the technological process design.

The advantages of the presented concept, especially compared to the solutions known and described in the literature, are the use of a real industry example, simplicity, real-time or close to real-time computation time, and high efficiency (even 100% achieved by the MLP 4–32–1). The advantages presented, in terms of the benefits resulting from the implementation of the presented concept, show the possibility of almost immediate application in 3D printing industrial processes, after the adaptation to the producers' assembly line or other manufacturing devices. Such adaptation may be performed even online, as part of the control module, if all of the features taken into consideration can be changed and controlled online. In some older 3D printers, such adaptation may be financially unprofitable or even not possible at all.

The intelligent expert system is intended for process engineers who have not yet gathered sufficient experience in technological process planning, or who have just begun their work in a given production enterprise and are not very familiar with its machinery and other means of production. It should be stressed that such a system plays an advisory role, and the final decision always belongs to the process engineer. The functioning of the expert system was described using the example of a real enterprise.

In future work, a general computational intelligence-aided design framework will be utilised in the smart design process. It can integrate not only the AI techniques (e.g. decision trees, ANNs, GA, fuzzy logic, and multifractal analysis) for technical optimisation and more accurate reasoning, but also a paradigm of design thinking, multi-scale performance simulations, and joint participation to better inform decision making [34]. Our further studies will focus on the systematic development and implementation of AI within Industry 4.0, i.e. the next generation of industrial systems, and the real impact of novel technologies such as 3D printing and the Internet of Things. The bigger complex systems aim at handling data, from material selection to semi-finished product selection, within the future AI-controlled multi-material 3D printers.

A limitation of the new solution is the necessity to continuously upgrade the datasets in a multifactorial database due to the relatively quick development of 3D printing technologies and materials, due to the emerging novel possibilities of the final products. Despite the quite well-established knowledge and experience within 3D printing, many various process variants and improvements still have to be taken into consideration, creating a lot of sub-technologies and possibilities to gain novel challenging product features. Additional factors are the accuracy and speed of production, which are often considered to pay particular attention to the quality of the final product. Further requirements for quicker development toward a wider commercial use within Industry 4.0 include the high stability of 3D printing processes and the database easing selection of the materials used in 3D printing, the formalised and widely accepted online quality control processes, and certification and provision of design rules [1].

## 5. Conclusions

The evaluation of the study results and their measurements showed that even a simple ANN can be effective in a really complicated task as presented in our case study. Compartmental studies showed that our results are similar to or better than the result of previous studies [19, 22–29]. We should be aware that the variability of 3D printing processes is so huge that each case may be hard to compare. The aforementioned feature makes 3D printing appropriate for customer-tailored products, but requires more advanced planning and control systems, and therefore more advanced AI support.

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