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MATERIAL SCIENCE AND NANOTECHNOLOGY

# Computational intelligence in the development of 3D printing and reverse engineering

Izabela ROJEK [1], Dariusz MIKOŁAJEWSKI [1]*, Joanna NOWAK [2], Zbigniew SZCZEPAŃSKI [2], and Marek MACKO [2]

[1] Institute of Computer Science, Kazimierz Wielki University, Bydgoszcz, Poland
[2] Faculty of Mechatronics, Kazimierz Wielki University, Bydgoszcz, Poland

**Abstract.** Computational intelligence (CI) can adopt/optimize important principles in the workflow of 3D printing. This article aims to examine to what extent the current possibilities for using CI in the development of 3D printing and reverse engineering are being used, and where there are still reserves in this area. Methodology: A literature review is followed by own research on CI-based solutions. Results: Two ANNs solving the most common problems are presented. Conclusions: CI can effectively support 3D printing and reverse engineering especially during the transition to Industry 4.0. Wider implementation of CI solutions can accelerate and integrate the development of innovative technologies based on 3D scanning, 3D printing, and reverse engineering. Analyzing data, gathering experience, and transforming it into knowledge can be done faster and more efficiently, but requires a conscious application and proper targeting.

**Key words:** additive manufacturing; three-dimensional printing; computational intelligence; optimization.

## 1. INTRODUCTION

We need additive manufacturing (three-dimensional printing, 3D printing) because it represents a transformational approach to industrial production that enables the creation of lighter, stronger parts and systems in an Industry 4.0 environment. When you create an object using traditional methods, it is often necessary to remove material by milling, machining, carving, shaping, or other means, whereas additive manufacturing adds material to the object being created. This is because 3D printing uses computer-aided design (CAD) software or 3D object scanners to guide the equipment for depositing material layer-by-layer in precise geometric shapes [1, 2].

Technological advances since the 1980s have been made possible by the transformation of processes from analogue to digital. Communication, imaging, architecture, and engineering have all undergone a digital revolution, making the next revolution possible: 3D printing brings digital flexibility and efficiency to manufacturing processes. Because of this, incremental manufacturing such as 3D printing requires a lot of expertise to produce parts. To further increase the efficiency of the manufacturing process, the abovementioned problems must be solved by computational intelligence (CI). CI can adopt/optimize important rules in 3D printing workflows. Faster and smarter algorithms will reduce the manual process performed by humans. CI will enable access to large datasets (big data) to better manage 3D technologies: 3D scanning, 3D printing, and reverse engineering. CI is therefore a natural solution to problems in the digital world [1, 2].

The key issues within 3D printing are as follows:

1. Advantages:
   - improved performance,
   - complex geometries,
   - simplified production,
   - rapid prototyping,
   - easy duplication.
2. Disadvantages:
   - complex process,
   - a vast amount of knowledge needed,
   - choice of technology and its rationale (need for multifactorial analysis),
   - slow individual production,
   - environmental issues.

The disadvantages of 3D printing are problems to be solved for CI applications. This is especially true for improving the main printing steps using knowledge from different disciplines: materials science, 3D printer technology, design engineering, and software engineering. To solve them creatively, the following are required above all: knowledge of material properties and behavior both during printing and within the object, selection of material and 3D printing technology for a specific application, design guidelines for a specific printed part, and optimization of parameters [1, 2]. Not only the geometrical accuracy and mechanical properties must be considered, but also the visual aspects, surface texture and color, repeatability, production time, and costs [3]. Sometimes factors that are difficult to predict are an obstacle, e.g. the proposed material complies with all requirements, but the delivery time is too long in the

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

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lean management model. Many technological issues should be considered in relation to 3D printing, which are related to the specificity of the application area, such as aviation, automotive, health care, product development, etc. First and foremost, there are many technologies:

- sintering,
- stereolithography (SLA),
- direct metal laser sintering (DMLS),
- direct metal laser melting (DMLM),
- electron beam melting (EBM)

related to many processes:

- powder bed fusion,
- binder jetting,
- directed energy deposition,
- material extrusion,
- material jetting,
- sheet lamination,
- vat polymerization

and materials:

- thermoplastics: acrylonitrile butadiene styrene – ABS, polylactic acid – PLA/PLA+, polycarbonate – PC, polyvinyl alcohol – PVA,
- metals: gold, silver, stainless steel, titanium, aluminum,
- ceramics: zirconia, alumina, tricalcium phosphate, powdered glass,
- biochemicals: bio-inks, silicon, calcium phosphate, and zinc.

This article aims to examine to what extent the current possibilities for using CI for the development of 3D printing and reverse engineering are being used, and where there are still reserves in this area.

## 2. METHODOLOGY

A literature review is followed by research on CI-based solutions applicable in the optimization of 3D printing decision-making.

The MATLAB 16.0 software was used for artificial neural network (ANN) training purposes. Input variables were scaled using the same maximum and minimum values from the data in the sample. The initial values of the network weights were estimated as equally random values from –1 to 1. To prevent deviations of the starting weight, randomly selected from the initialization weight, they were unified. Two different stopping points were considered in the learning process: after 1000 iterations and 5000 iterations. The targeted MSE level was monitored. The minimum number of inputs and outputs and the number of neurons in the hidden layer were each time experimentally investigated to find the minimum network load.

The results were stored in an MS Excel spreadsheet and analyzed using the Statistica 13 software.

## 3. RESULTS

According to the literature review, CI can help in this way: the machine itself can solve the problem without human intervention, based on previous data and experience. This is particularly interesting in combination with 3D printing technologies, as it may increase 3D printer performance by reducing the risk of error and facilitating automated production. Importantly, we do not have many years to develop and experiment slowly. We must do it quickly and precisely.

The main CI-based support areas are as follows:

- process analysis and control (e.g. for advanced functions),
- selection of materials,
- development of new materials,
- further parametric optimization,
- energy optimization,
- reduced number of errors due to technical inspection for the entire production cycle in Industry 4.0,
- automation of the entire 3D printing process: from the creation of the model in the form of a CAD file through its final printing, to preparation for printing in a cutting program,
- predicting quality,
- alarmed impurities from the material and air,
- removal of impurities from the material and air.

We considered four base cases: two of them are the result of our own research (Case 2, Case 3) and two are the result of literature review (Case 1, Case 4).

### 3.1. Case 1: Automating of the manual tasks

Artificial intelligence is widely used in the research, planning, optimization, and control of intelligent, efficient, high quality, mass production, service-oriented 3D printing processes [4].

CI can provide automation for some manual tasks, such as data collection, construction planning, and monitoring of costs [5, 6]. CI can be used to optimize production capacity by improving machine utilization, and scheduling production orders according to availability (but see the advantages and disadvantages of lean management such as delays and supply shortages in pandemic conditions) [7]. Material selection can also be automated with CI: depending on the requirements of the printed part, the software provides recommendations on the material to be used for the best result [8]. Depending on the task, we can reduce the average 3D print preparation process from 30 minutes to even 5–30 seconds. By reducing this time, we will increase the use of the printer, eliminate errors, and reduce the number of iterations [9, 10]. In this way, the use of CIs reduces the complexity of the traditionally manual process and provides better results. Previously, model molds were made by hand, hand-polished, epoxy resin cast or milled from wood. This was an arduous process which can take several working days depending on the complexity of the product. This procedure has changed radically in recent years thanks to digitization [11, 12]. Master forms are now designed using computer-aided design (CAD) and manufactured from polyurethane blocks on CNC milling machines.

To sum up, artificial intelligence is widely used in the research, planning, optimization, and control of intelligent, efficient, high quality, mass production, service-oriented 3D printing processes. The main research effort on AI applications here is focused on several main steps:

- checking the printability of 3D objects before starting the print job,

- selecting material/materials and parameters of the printing process, considering the durability, energy, or environmental impact through the amount of waste or emission of harmful particles into the atmosphere,
- optimizing and accelerating prefabrication slicing through parallel slicing algorithms,
- optimizing path planning,
- demand matching and resource allocation for providing on-demand 3D printing services to customers, and remote access to a collection of shared resources (including cloud computing),
- detecting product defects at every stage of production,
- increasing the security of the production cycle and the manufacturer's know-how by monitoring production and increasing its resistance to cyber attacks,
- a virtual twin makes it possible to predict future threats, both to the product itself and to the equipment running the production line,
- product lifecycle analysis, including recyclability, completes the picture.

The aforementioned approach enables artificially intelligent optimization of 3D printing while meeting multiple indicators/criteria, lowering the design and product complexity threshold, accelerating prefabrication, real-time control, increasing safety, and defect detection throughout the production cycle within the Industry 4.0 paradigm.

### 3.2. Case 2: Process analysis

The processing of new, high-performance materials is very complex and requires the tuning of all process parameters. In this way, we monitor the 3D printing process using various sensors. Using CI, we evaluate data flow and identify hidden relationships that are not recognizable to people. This is the advantage of CI: it can process very large amounts of data quickly, which is too burdensome for people. This work enables scientists to process complex alloys and predict the properties of materials. The printability of the facility can be analyzed before any process begins (and incurring production costs). We can also foresee the quality of parts and control the process to avoid printing errors and save time and material. This way, 3D printing departments will be able to effectively control their production processes and guarantee the precision and quality of manufactured parts. This is also becoming increasingly important as the industry moves into live finished parts. CI can analyze both the geometry and object color data, tracking the geometry and textures using a scanner, and color capture also makes it easier to, e.g., create photorealistic visuals at the design stage.

Takagishi and Umezu solved the problem of removing layer grooves in a 3D fused deposition modeling (FDM) printer using 3D-chemical melting finishing (3D-CMF), in which a pen-shaped device is filled with a chemical substance capable of dissolving the materials used to build structures printed in 3D. In this way, the convex parts of the layer grooves on the surface of the printed 3D structure are dissolved, which in turn fills the concave parts, ensuring safety, selectivity, and stability [13].

Modern stereolithographic devices use single-wavelength light to initiate in-plane polymerization. However, single wavelength irradiation causes a loss of polymerization limitation by the accumulation of exposure to non-target light. To overcome this disadvantage, three-color (UV, red and blue light) direct-recording photolithography was reported in which high conversion of blue light (without UV light), enhanced by pre-initial irradiation with red light, and UV light effectively reduced the limitation of thickness and for high printing speeds [14].

Thin shells that do not have a large volume to support or absorb the effects of differences in properties are particularly vulnerable to the mesostructure of 3D printing materials and natural cavities, which affects their structural stability. However, they are very useful, providing a good strength-to-weight ratio in many applications, particularly in aviation and structural design. Traditional finite element analysis (FEA) solutions for thin-walled buckling problems have assumed that the coating is uniform and free of defects, which is not true for 3D printing processes described in ordinary materials (acrylonitrile-butadiene-styrene (ABS) and polylactic acid) [15].

The influence of the thermal process called ironing on the surface, as well as on the mechanical and dimensional properties of ABS parts produced by the fused deposition modeling method (FDM) is based on the elimination of stress concentration factors after treatment (in the melting process), which can increase the deflection almost twofold at the break and maximum tensile strength of ABS parts produced by FDM. It can reduce the Ra factor of ABS parts up to 60% and the level of distortion by 33% [16].

Processing techniques used to recycle thermoplastic polymers with different types of reinforcement, especially in incremental (AM) applications, include primary (1°), secondary (2°), tertiary (3°), and quaternary (4°) processing of polymer materials from a recycling perspective, can raise the standards of industrial processing through inexpensive 3D printing technology [17].

Samples of the effect of the most common technological problems in 3D printing are shown in Figs. 1–11, including:

- stringing/oozing/whiskers, hairy prints – when small strips of plastic remain on the 3D printed model (Fig. 1, Fig. 2),
- over-/under-extrusion – when the printer is unable to supply the exact amount of the material (Fig. 3 and Fig. 4, respectively),
- weak infill – when the print speed is too high (Fig. 5),
- scars, scratches, or drips on the top surface of the printed object – due to, e.g., incorrect temperature, flow rate, or printing speed as well as incorrect slicer profile (Fig. 6),
- outer shell not sticking to inner shell – due to low adhesion of the materials (Fig. 7),
- too thin/high layers (Fig. 8 and Fig. 9, respectively),
- X or Y axis shift/layer shift – when the extruder or bed moves during printing and continues in another area of the build plate (Fig. 10),
- failure to feed filament or it stops mid-print (Fig. 11).

The above-mentioned wide spectrum of problems can be solved using more exact AI-controlled 3D printing procedures.

Automatic computational analysis of network data in real or near real time is a practical implementation of the IoT paradigm (layers: things-network-cloud) and Industry 4.0 (collection of

**Fig. 1.** Most common problems in 3D printing: stringing or oozing

**Fig. 2.** Most common problems in 3D printing: stringing or oozing

**Fig. 3.** Most common problems in 3D printing: over-extrusion

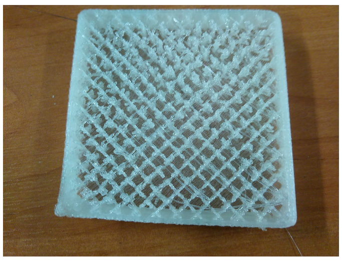

**Fig. 4.** Most common problems in 3D printing: under-extrusion

**Fig. 5.** Most common problems in 3D printing: weak infill

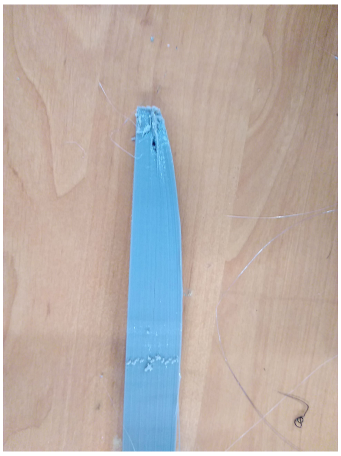

**Fig. 6.** Most common problems in 3D printing: scars or drips on the top surface

**Fig. 7.** Most common problems in 3D printing: outer shell not sticking to the inner shell

sensor data, construction of virtual twins of the production line and products, technical control at each stage). For the above-mentioned reasons, there is a need to reconcile an individual approach to the 3D printing of objects with simultaneous standardization of the procedures of design, manufacturing, monitoring of equipment operation, and life cycle control of 3D printed products.

ANNs, as an optimization and prediction system, provide optimal parameter selection while increasing the efficiency of the 3D printing planning process. In this context, ANNs are used to explore, model and predict the relationships between input and output datasets, reflecting non-linear relationships between

**Fig. 8.** Most common problems in 3D printing: too thin layers

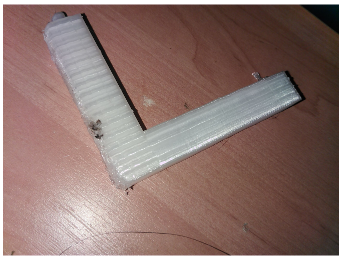

**Fig. 9.** Most common problems in 3D printing: too high first layers

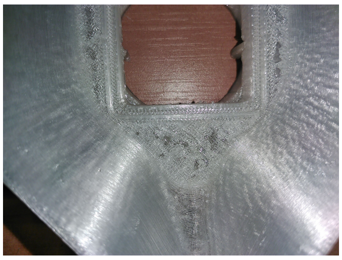

**Fig. 10.** Most common problems in 3D printing: X or Y axis shift

**Fig. 11.** Most common problems in 3D printing: failure to feed filament or stops mid-print

them that are difficult to capture using traditional analysis methods. Connections between neurons in successive ANN layers (input, hidden, output) are strengthened by similarities in the measured datasets, and complex, incomplete, or noisy datasets are not an obstacle. The aggregation of input data and the transfer function of the hidden layer are used to calculate a response (estimate), thanks to a learning process that is more accurate, sensitive, and specific than traditional statistical procedures. The new optimization decision rules are valid for the vast majority of 3D printing materials, technologies, and their features, and the networks are learned as new ones emerge. By inferring and predicting hidden causal relationships between large sets of properties, it is possible to find optimal and innovative ways to solve technological problems.

A relatively simple artificial neural network (ANN) based on multilayer perceptron, called MLP-5-17-9 (Fig. 12, Table 1) may solve similar problems, achieving (after 1000 epochs):

- MSE for the data in the training set: 0.02.
- Quality (learning): 0.8911.
- Quality (testing): 0.9134.

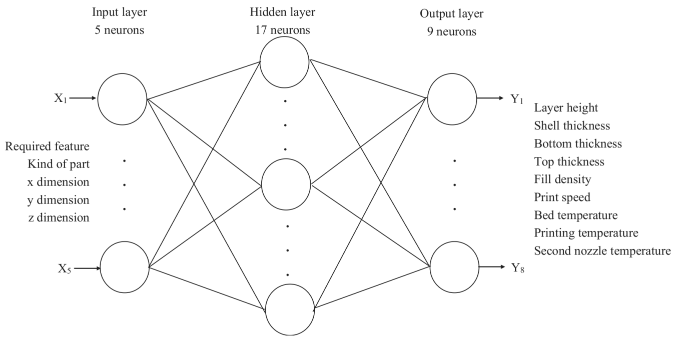


**Fig. 12.** Simple neural network optimized to solve problems with the choice of 3D printing process features

**Table 1**
Characteristics of used inputs and outputs

| Number and kind of input data | Number and kind of output data | Number of datasets and source of datasets (sensors used to collect them) |
|---|---|---|
| (5)<br>maximum tensile force<br>part no. 1<br>x dimension<br>y dimension<br>z dimension | (9)<br>layer height<br>shell thickness<br>bottom thickness<br>top thickness<br>fill density<br>print speed<br>bed temperature<br>printing temperature<br>second nozzle temperature | (110)<br>datasets taken directly from the software of the 3D printer |

Datasets from industrial and research practice with 3D printers were used to teach the neural networks. The datasets were initially divided into three groups: learning (70% of the dataset), testing (20% of the dataset), and validation (10% of the dataset).

In the preparation process, the input values were rescaled to values within ranges of the same maximum and minimum values. In addition, the initial values of the network weights were pre-estimated, normalized, and set between –1 and 1. This prevented bias in the weights when the network was started.

The MATLAB 16.0 (MathWorks) software, including the Statistics and Machine Learning Toolbox and the Deep Learning Toolbox, was used to develop, test, and optimize the proposed ANN-based solution. The structure of the ANN was optimized using a genetic algorithm (GA). More neurons were needed in the hidden layer of the network due to the complex connections to the output layer. Our experience shows that we can achieve similar results using MAXNET ANN.

Linking 3D printing technology with parameter selection support in the ANN model facilitates easier prediction and monitoring of energy consumption for different types of 3D printers and the integration of artificially intelligent analysis and prediction of energy consumption into Industry 4.0 processes using 3D printing. This is because the good quality (0.8911, 0.9134), low MSE (0.02) (Table 2), and short computation time facilitate the aforementioned optimization of the 3D printing process in real or near real time. The actual effects of the aforementioned optimization are observed from the first moments of using the improved process.

**Table 2**
Selected ANN quality assessment (bolded is the best)

| Network name | Quality (learning) | Quality (testing) | MSE |
|---|---|---|---|
| MLP-5-13-9 | 0.8832 | 0.8977 | 0.04 |
| MLP-5-15-9 | 0.8856 | 0.9011 | 0.03 |
| **MLP-5-17-9** | **0.8911** | **0.9134** | **0.02** |
| MLP-5-20-9 | 0.8901 | 0.9034 | 0.03 |
| MLP-5-25-9 | 0.8847 | 0.9001 | 0.03 |

### 3.3. Case 3: Material choice

The processing of new, high-performance materials is very complex and requires the tuning of all process parameters. In this way, we monitor the 3D printing process using various sensors. Using artificial intelligence, we assess the data flow and identify hidden relationships that are not recognizable to people. This is where the advantage of artificial intelligence lies: it can process very large amounts of data quickly, which is too burdensome for people. Thanks to this work, scientists can process complex alloys and preserve the properties of the materials. CI can combine many (up to 10) materials with a vision system that it uses in machine learning processes.

An innovative approach to the manufacture of flexible and expandable organic thermoelectrics includes printed thermoelectric polyurethane nanocomposites/multilayer carbon nanotubes. The 3D printing of such components using flexible, stretchable, and electrically conductive thermoplastic polyurethane (TPU) / multilayer carbon nanotubes (MWCNT) for 3D printing (TPU granules and two different types of MWCNT, namely NC-7000 MWCNT (NC-MWCNT) and Long MWCNT (L-MWCNT)) has been performed using melt deposition modelling (FDM). All samples printed in 3D showed anisotropic electrical conductivity and the same Seebeck factor in the print and cross-print directions. TPU/MWCNT can act as an excellent organic thermoelectric material for 3D printed thermoelectric generators (TEG) for potential large-scale energy storage applications [18].

Traditional methods of repairing bone defects have many disadvantages, and 3D bio-indication techniques offer new possibilities for designing and manufacturing bone implants for patients. The influence of composite materials, such as bioceramics, is important for resistance to polymer degradation of in vivo media. The new nano-architecture of hydroxyapatite (HA) in polymeric base material such as PLA can improve bone 3D printing properties [19].

A relatively simple artificial neural network (ANN) based on a multilayer perceptron, called MLP-8-24-1 (Fig. 13, Table 3), may solve similar problems, achieving (after 1000 epochs):

- MSE for the data in the training set: 0.01.
- Quality (learning): 0.9143.
- Quality (testing): 0.9303 (Table 2).

**Table 3**
Characteristics of used inputs and outputs

| Number and kind of input data | Number and kind of output data | Number of datasets and source of datasets (sensors used to collect them) |
|---|---|---|
| (8)<br>tensile strength<br>bending strength<br>modulus of elasticity in bending<br>part no. 7<br>x dimension<br>y dimension<br>z dimension<br>weight | (1)<br>suggested material type | (73)<br>datasets taken directly from the software of the 3D printer |

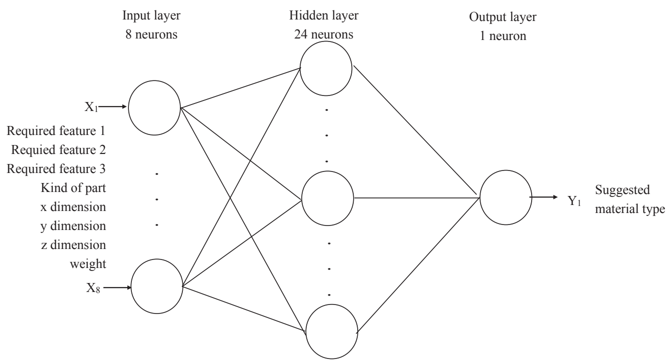


**Fig. 13.** Simple neural network optimized to solve problems with material (filament) choice

In our study, we used real datasets from industrial and research practice using 3D printers in normal operation (i.e. we did not develop sets of standardized tasks in the form of printing sample parts that might need to be introduced in subsequent stages of the research). The aforementioned sets were divided into three groups: 70% (teaching), 20% (testing) and 10% (validation). The input parameters were rescaled to the same maximum and minimum values, and the initial values of the network weights were estimated and randomly selected at initialization from –1 to 1 to prevent bias in the weights at network start-up.

The MATLAB 16.0 (MathWorks) software was used for the ANN work, including the Statistics and Machine Learning Toolbox and the Deep Learning Toolbox. The structure of the ANN was optimized using a genetic algorithm (GA). Our experience shows that we can achieve similar results using MAXNET ANN.

Even today, environmental pollution from plastic waste (both solid and fine air and water pollutants) which is the main material used for 3D printing, is already a major problem due to its lack of biodegradability and only partial recycling. It is reasonable to assume that the widespread use of 3D plastic printing technology should incorporate sustainability principles, including more economical use of materials (for printing and auxiliary materials, e.g. support materials and fluids for cleaning models), optimization of energy consumption, and safe collection and use of waste, and lifecycle monitoring and recycling of the 3D printed products themselves. Better matching of materials and properties of 3D printed products will allow them to be better suited to customers' needs, used longer, life cycle controlled, and recycled. The research results in easier prediction and evaluation of the selection of properties and material types, with short computation time, very good quality (0.9143, 0.9303), and low MSE (0.01), allowing optimization of the 3D printing process in the real world (Table 4). The above AI-based solutions can significantly contribute to the understanding of life cycle mechanisms and recycling of materials used in 3D printers as the beginning of the necessary research. The processes of control and optimization of 3D printing products are subject to multifactorial analysis and therefore require a systemic approach, urgent diagnosis, monitoring, and effective solutions.

**Table 4**

Selected ANN quality assessment (bolded is the best)

| Network name | Quality (learning) | Quality (testing) | MSE |
|---|---|---|---|
| MLP-8-16-1 | 0.8892 | 0.8997 | 0.02 |
| MLP-8-20-1 | 0.8947 | 0.9123 | 0.02 |
| **MLP-8-24-1** | **0.9143** | **0.9303** | **0.01** |
| MLP-8-34-1 | 0.9093 | 0.9212 | 0.01 |
| MLP-8-42-1 | 0.8912 | 0.9043 | 0.02 |

### 3.4. Case 4: Unidentified potential

Unidentified potential lies directly in troubleshooting and heuristic problem-solving. We aim to produce an automatic CI-based problem-solving guide for the most common problems with 3D printing (helpdesk bot). The further indirect, unidentified potential of the application of CI in 3D printing also lies in three main areas:

- medical applications of 3D printing [20, 21], both from polymeric materials (for educational purposes, testing (neuro) surgical access paths or implants and soft tissue strengthening with medical supplies), metal powders (prostheses), and bio-ink (printing of innervated and vascularized skin, parts of organs such as the heart [22, 23], muscles [24, 25]), as far as bioinspired labs-on-a-chip and associated systems [26–29]
- communications (including emerging IoT and Industry 4.0 abilities supported by AI) [30–32]
- safety of data and systems – even advanced technologies such as iris, facial, and finger vein recognition may not guarantee data security when faced with a 3D reconstruction of features based on medical imaging and 3D printing [33]

The sustainability of the 3D printing processes may be also supported by CI-based solutions – such solutions should be built into 3D printers in the future.

## 4. DISCUSSION

Examples from the literature and our own ANN-based approaches have shown that CI-based problem-solving in 3D printing is possible. Currently, it is not yet a common approach, but the development of 3D printing and the increase in complexity of these technologies and materials should significantly increase the popularity of CI-based decision support.

Even the proposed AI solutions with relatively simple structures (MLP-5-17-9 and MLP-8-24-1) are effective and can significantly contribute to the understanding of material and features selection in 3D printers, and their automatic or semi-automatic optimization. Incorporating the above-mentioned functionalities into Industry 4.0 systems involving 3D printing is essential to developing effective strategies for material properties optimization, life cycle control, and then environmental impact assessment and control, and prevention of environmental risks associated with industrial 3D printing and generated pollution.

The advantages of the proposed solutions are their simplicity, very short computation time allowing their use in real-time systems, good quality, and low MSE (0.01–0.02 for both). Their performance is progressing in the desired direction of better product personalization.

The proposed CI-based software is effective, but in the proposed scope of material and feature selection, it does not replace but only complements existing 3D printing software solutions. This involves not only the development of new 3D printing technologies, but also novel software, and new materials with improved properties and equipment operating conditions.

Written knowledge, experiences, and observations have become a structured process, with standardized procedures and methods for sharing with subsequent generations of scientists, practitioners, and new trainees. At the end of the 20th century, many innovative processes, analyses, as well as the exchange of knowledge and experience have become highly dependent on technology: electronic datasets, ICT for information exchange, 3D printing, sensors, effectors, CI algorithms, decision support systems, etc. Moreover, technology has started to influence decisions and the course of actions (within business intelligence and strategic planning). Advanced technologies, such as CI, will start a real era of expanded capabilities in many areas.

Directions for further research concerning support for 3D printing and reverse engineering based on CI should also include organizational, technical, and material problems.

Future developments may be hampered by the lack of specialists and the inconsistent pace of development in the various fields of advanced technology underlying 3D printing (materials science, nanotechnology, attotechnology) or based on 3D printing and reverse engineering (e.g. advanced diagnostic devices, neuro-prostheses, and brain-computer interfaces). Wider use of information technology, including more precise data analysis, inference, and prediction, can help overcome these limitations and contribute to the next breakthrough.

## 5. CONCLUSIONS

CI can effectively support 3D printing and reverse engineering especially during the transition to Industry 4.0. Wider implementation of CI solutions can accelerate and integrate the development of innovative technologies based on 3D scanning, 3D printing, and reverse engineering. Analyzing data, gathering experience, and transforming it into knowledge can be done faster and more efficiently, but requires a conscious application and proper targeting. This is demonstrated by the practical examples of process and material feature selection discussed in the paper. On the other hand, CI may mainly, but not only, support less experienced engineers, scientists, and clinicians, but the 'master-student' method will still not be fully replaced. The aforementioned solution may rather serve to supervise the quality of the work of teams without the support of advanced R&D departments.

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