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ASSESSMENT OF THE POSSIBILITY OF USING BAYESIAN NETS AND PETRI NETS IN THE PROCESS OF SELECTING ADDITIVE MANUFACTURING TECHNOLOGY IN A MANUFACTURING COMPANY

Abstract

The changes caused by Industry 4.0 determine the decisions taken by manufacturing companies. Their activities are aimed at adapting processes and products to dynamic market requirements. Additive manufacturing technologies (AM) are the answer to the needs of enterprises. The implementation of AM technology brings many benefits, although for most 3D printing techniques it is also relatively expensive. Therefore, the implementation process should be preceded by an appropriate analysis, in order, finally, to assess the solution. This article presents the concept of using the Bayesian network when planning the implementation of AM technology. The use of the presented model allows the level of the success of the implementation of selected AM technology, to be estimated under given environmental conditions.

1. INTRODUCTION

Additive manufacturing (AM) technologies are based on methods of manufacturing products from materials, e.g. metals, metal alloys, thermoplastics, ceramics or composites, mainly using their layering (Goole & Amighi, 2016). In contrast to subtractive methods, a number of benefits are seen in the use of AM technology, including maximum use of the material with a simultaneous reduction of post-production waste, the production of elements with a complex structure and shape that could not be achieved with traditional methods (Patalas-Maliszewska, Topczak & Kłos, 2020).

By characterising additive technologies, they can be divided into the following methods: layered extrusion of molten thermoplastic (*Fused Deposition Modelling, Fused Filament Fabrication*), curing of the applied material with UV (*PolyJet, ProJet*), lamination of material layers (*Laminated Object Manufacturing, Plastic Sheet Lamination*), curing photo-sensitive resin (*Stereo-lithography, Digital Light Processing*), sintering powders (*Selective Laser Melting, Direct Metal Laser Sintering)* and curing materials using a direct energy source (*Laser Engineering Net Shape, Electron Beam Additive Manufacturing*) (Patalas-Maliszewska, Topczak & Kłos, 2020).

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Additive technologies are used in modelling (Nagarajan, Hu, Song, Zhai & Wei, 2019), prototyping (Ahmed, 2019) and the repair and regeneration processes of machines and devices (Penaranda, Moralejo, Lamikiz & Figueras, 2017). According to the research conducted at the end of 2019, in western Poland, among 250 production companies, constituting 1% of production companies from the metal and automotive industries, it appears that approximately 44% of respondents declare the use of AM technology, of which approximately 46% are metal industry companies and approximately 42% are automotive industry companies. It was found that approximately 16% of metal industry companies are interested in implementing AM technology, while in the case of the automotive industry, about 36% of companies are interested in implementing AM technology (Patalas-Maliszewska, Topczak & Kłos, 2020).

It should be borne in mind that in order to achieve strategic goals, manufacturing companies are forced to make decisions in the area of their activity (Patalas-Maliszewska, 2012). The process of implementing AM technology in a production company is an investment that requires appropriate planning and forecasting. The analysis conducted on decision support models allows information and the appropriate planning of the project to be used effectively. In the literature (Biedermann & Taroni, 2006; Patalas-Maliszewska & Krebs, 2015; Constantinou, Fenton & Neil, 2016; Dahire, Tahir, Jiao & Liu, 2018; Fierro, Cano & García, 2020), one can find studies in which tools are presented that allow knowledge to be visualised in a qualitative and quantitative manner, using, *inter alia*, algorithms based on probability calculus. The emerging solutions and changes caused by the **Fourth Industrial Revolution**, *known as **Industry 4.0***, force manufacturing companies to analyse and evaluate potential implementations in the area of new manufacturing technologies. This article briefly describes AM additive manufacturing technology. Based on an analysis of the literature, the research gap in the area of the use of Bayes and Petri nets in the process of technology selection in manufacturing companies was identified and a comparative analysis of the network was carried out, taking into account the possibility of their implementation into the decision-making process in the field of the implementation of AM technology. The authors have presented the Bayes network model for the metal and automotive industries. On this basis, it is possible to determine the level of interest in AM technology and thus – to assess the possibility of its implementation in the enterprise.

2. CHARACTERISTICS OF PETRI NETS AND THE BAYESIAN NETWORK

2.1. Petri nets

Petri nets can be defined as a formalised model of processes enabling them to be accurately verified through analysis of basic network constructors (places, transitions, arcs and tokens). Petri network topology is a coherent, bipartite directed, graph with static features and dynamic, where places, transitions and arcs are used to model the static structure of processes and tokens, thus allowing their dynamics to be modelled (Kabir & Papadopoulos, 2019; Gao, Xu, Zhao, You & Guan, 2020; Giebas & Wojszczyk, 2018).

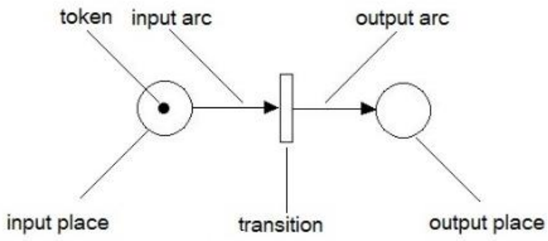

Fig. 1. Constructors of Petri nets

The structure of a classical Petri net is defined by an ordered four N = (P, T, I, O), where: P={p1 , p2 , p3 ,…, pn} is a finite set of places; T={t1, t2 , t3 ,…, tm} is a finite set of transitions (transitions); I: P × T → N is a function of the inputs, N is the number of edges between pit, O: T × P → N is a function of outputs, N is the number of edges between t and p. Petri net state, also called tagging, is a function representing a set of places into a set of natural numbers representing the number of tokens in a given place (Kabir & Papadopoulos, 2019; Gao, Xu, Zhao, You & Guan, 2020).

2.2. Bayesian network

The Bayesian Network (BN) algorithm is used in quantitative and/or qualitative modelling and forecasting. The functionality of the Bayes network enables the use of expert data where historical data is insufficient; this allows the collection and classification of knowledge through inference based on premises. The Bayesian network is based on two structures: directed and acyclic graph (1) and the probability table (2). The nodes included in the graph can be modified using logical functions, thus creating a network structure including a set of rules and facts (Wieleba, 2011; Aguilera, Fernandez, Fernandez, Rumi & Salmeron, 2011; Ramírez-Noriega, Juárez-Ramírez & Martínez-Ramírez, 2017; Karayuz & Bidyuk, 2015).

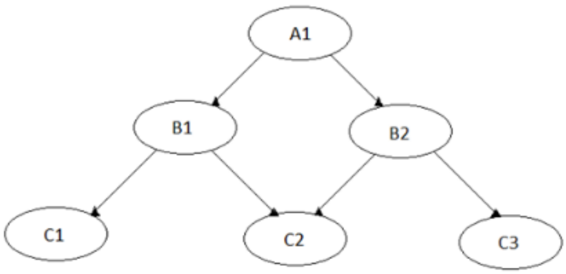

Fig. 2. Bayesian network structures over the set U = {A1, B1, B2, C1, C2, C3}, convergent connections

According to Bayes' theorem, if A and B are two random events and it is known that B has occurred, then the "a posteriori probability" of the occurrence of A, given that B has occurred, can be defined as:

$$P(A/B) = P(B/A)P(A)/P(B) \quad (1)$$

where P(A) and P(B) are the "a priori probability" of events A and B (Kabir & Papadopoulos, 2019).

2.3. Implications

Based on an analysis of the literature, a number of cases of the use of Petri nets and Bayes nets in modelling and evaluation of processes have been observed.

Examples of the application of the Bayes network have been described in the literature by Gran & Helminen (2001) – the authors used the BN model to assess the reliability of nuclear power plants. Models based on Bayesian networks have also been used to analyse the reliability of power systems and military machines (Yongli, Limin, Liguo & Yan, 2008; Daemi, Ebrahimi & Fotuhi-Firuzabad, 2012) as well as in modelling the mechanics of fracture (Nasiri, Khosravani & Weinberg, 2017). In the literature, there are also reports on the implementation of the Bayes network functionality in other areas, such as forensics (Biedermann & Taroni, 2006). Bayes' networks are used in risk assessment applications due to their flexible structure and the ability to include, *inter alia*, failure modes and states, components and systems, the uncertainty of system behaviour and data failure, during analysis. An additional advantage of BN is the ability to perform diagnostic analyses (Kabir & Papadopoulos, 2019). Bayes networks are used in the processes of estimating the optimal security threshold for complex industrial processes, where a dynamic risk assessment methodology, based on many process variables in real time, is proposed (Rebello, Yu & Ma, 2019). There have been attempts to prove the validity of the use of the probabilistic expert system as an industrial support tool, in preventing defects in the process and contributing to the increase in productivity (Rosário, Kipper, Frozza & Mariani, 2015). The work of Rosário, Kipper, Frozza & Mariani (2015) presents technical mapping and tacit knowledge acquisition in industry, with the participation of the Bayes network, modelling tacit knowledge in order to express it and present it in the form of rules to be used in production processes. In the work of Patalas-Maliszewska, Feldshtein, Devojno, Śliwa, Kardapolava & Lutsko (2020), the effectiveness of the data mining technique based on the Bayes algorithm was demonstrated for the analysis of trends in additive production processes and the practical application of knowledge, obtained using the Bayes algorithm. In the work of Shin, Kim & Lee (2015), an analysis of a production system with three volumes, *viz.*, ***planned production volume, quantity of delivered product*** and ***stock volume*** was performed, where it proved necessary to consider situations in which these three values would probably change due to various factors. For this purpose, a dynamic Bayesian network (DBN) was used, which is an extension of its basic form *and is also known as the belief network* for stochastic processes.

The Petri net, as a formalised graphical and mathematical tool enables modelling and analysis of the dynamic behaviour of systems, finding application in the case of visual representation of knowledge and inferential phenomena in expert systems (Yanrong, Hu, Yang, 2004; Louazani, & Sekhri, 2020). The possibility of using the network for the analysis and modelling of discrete events (Cassandras & Lafortune, 2008) is seen as a desirable phenomenon in the logical understanding of behaviour in the expert system (Liu, You, Li & Tian, 2017; Liu, Lin, Mao & Zhang, 2018). Their functionality is implemented, inter alia, in systems used to ensure safety, reliability and risk assessment. (Kabir & Papadopoulos, 2019). In the work of Lacheheub, Hameurlain & Maamri (2020), Petri nets have also found application in the analysis of business processes. The use of the functionality of the Petri nets assumed that consistency would be assured in the perspective of resources, by using the network to verify the correct execution of the business process with the resources initially allocated, based on some properties and choosing the path of similar low-consumption services. In the work of

Mansour, Wahab & Soliman (2013), Petri nets were used as a modelling tool for the construction of models for the diagnosis of faults in an element or section of a power plant, aimed at accurate fault diagnosis. The implementation of this type of solution aims to provide support and assistance in making decisions in critical situations and reducing the delay of recovery post-disaster. The development of the manufacturing sector has evolved supply chains into highly complex, dynamic and concurrent systems. Petri nets are characterised by formality and have been successfully tested in hierarchical modelling, analysis and in the control of distributed systems, which is desirable in the case of supply chain design (Fierro, Cano & García, 2020) and is a challenge for manufacturing companies in the area of the requirements of **Industry 4.0**.

In the case of the network model analysed, supporting the decision-making process in the implementation of AM technology, the authors decided to present the concept of using the Bayesian network as a tool that takes into account uncertain conditions based on the probability algorithm.

3. THE CONCEPT OF USING THE BAYESIAN NETWORK IN THE PROCES OF PLANNING THE IMPLEMENTATION OF AM TECHNOLOGY

At the end of 2019, research was carried out at 250 in metal and automotive industry production companies in western Poland, in order to recognise the needs and implementation status of additive manufacturing (AM). For this purpose, a dedicated questionnaire, consisting of closed and open questions was developed. 107 automotive industry companies and 125 metal industry companies were selected to build a tool supporting the process of selecting additive manufacturing technology. Two models of the Bayes network were designed in the study, for the metal and automotive industries, respectively. It was decided to use the research results containing answers regarding currently used AM technologies (1), the application of AM technology (2), used materials (3), interests in research on materials (4), factors determining the implementation of AM technology in the enterprise (5) and AM technologies that manufacturing companies are interested in (6). Based on selected questions present in the questionnaire, the nodes of the Bayesian network were designed. Where everyone had two alternatives suggesting the company's answer: YES – State 1 and NO – State 0, the results of the surveys regarding the question about the interest in the implementation of AM technology were aggregated and formed the basis for the result node in the Bayes network.

It is assumed that implementing the research results obtained *vis-à-vis* the designed Bayes networks and the network learning process carried out, will allow information to be obtained regarding the level of interest in implementing the selected AM technology in the manufacturing companies of a given industry.

The network modelling process included:

1. Designing a network for the metal and automotive industries, consisting of nodes corresponding to the following areas analysed:
   - AM technologies used by manufacturing enterprises (P9.1 nodes): FDM, EBM, laser technologies, processing technologies, welding, lamination and heat bonding technologies;
   - AM technology applications (P9.2 nodes): production, prototyping;

– materials used in production processes (P9.3 nodes): metals, other alloys, composites, polymers;
– materials on which the company wants to conduct research (P6 nodes): metals, other alloys, composites, ceramics, polymers;
– factors influencing the decision to implement AM technology (P10.2 nodes): Reduction of production costs (A), the effective use of material (B), freedom in product design (C), no assembly stage (D), personalisation of the product, according to specific, customer requirements (E), quick response to market needs (F), optimisation of product functions (G);
– AM technologies in which enterprises are interested (P10 node): metal industry – DMLS, SLS, welding; automotive industry – FDM, LOM, DLP, PolyJet, DMLS, SLS, SLA, EBM.

2. Analyzing the results of the questionnaire research and then selecting and preparing data corresponding to individual nodes.
3. Network learning (*each separately*) on the basis of the data prepared. The result was a graphical representation of the probability, determined in the network nodes, i.e. its initial state together with the strength of the relationship between the nodes.

The next step was to carry out network operation experiments and tests. The procedure included declaring the occurrence of selected states for individual network nodes and observing the probability obtained in the result node.

The GeNIe Modeler version 2.1 programme was used to build the Bayes network. The network for the metal and automotive industries was similar in design. Its result is the node P10_interest in AM. After science, for the metal industry network P(P10 = State1) = 31% (Fig. 3) and for the automotive industry P(P10 = State1) = 41%.

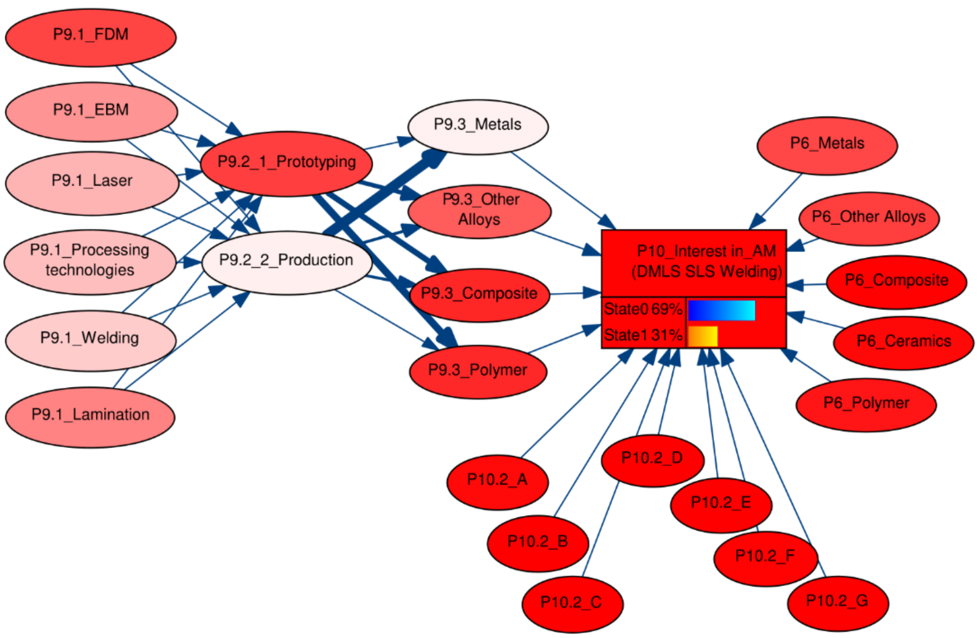

Fig. 3. Bayesian network for the metal industry

The models in Fig. 3 show the effect of the sensitivity analysis, i.e. the strength of the relationship between nodes. The bigger it is, the thicker the association. The intensity of the red nodes indicates the strength of the interaction with respect to the result node.

In order to verify the impact of the network vertices, in relation to P10 = state1, a "tornado analysis" was performed, based upon which, it is concluded that P10_2 A, *i.e. the factor determining the implementation of AM, that is to say,* ***cost reduction***, has the greatest impact on the increase in the probability of P(P10 = State 1). Nodes are in second place: P10_2 F – quick response to market needs and P10_2 G – optimisation of product functions. The P6_Ceramics node has the lowest impact, which corresponds to the company's interests in the field of material research on ceramics.

An analogous analysis was performed for automotive industry networks. The vertices: P10.2_A cost reduction and P10.2_C freedom in product design have the greatest positive impact on the level increase for State 1 in the result node P10_Zaintowanie_AM. The smallest change in probability was observed in the case of a set of nodes from analysis of interest in AM technologies, materials used and materials researched.

3.1. Research experiments

For the learned network, experiments were carried out based on the observation of its work under various conditions of uncertainty. Each time, the goal was to determine the probability of P10 = State1. In the case of the metal industry, tests were carried out that simulated the presence of State 1 at the following nodes: P9.1 Welding, P9.2 Production; P9.3 Metals; P10.2 A; P10.2 B; P10.2 C; P10.2 D; P10.2 E; P10.2 F; P10.2 G, P6 Metals, P6 Other alloys, P6 Ceramics, P6 Polymer, P6 Composite.

The experiment consisted of tests obtained by carrying out the following steps:

1. 1. Alternative State1 was declared for node group: P9.1 Welding; 9.2 Production; P9.3 Metals and P10.2 A, and then only for P10.2A vertex. In each case, the State 1 probability value determined, at result node P10, was recorded.
2. 2. It was examined whether the declared states in nodes (step 1) caused a difference in determining the probability of achieving State 1 for P10.
3. 3. The above steps were repeated for a group of nodes, taking into account, separately, the following vertices: P10.2 B; P10.2 C; P10.2 D; P10.2 E; P10.2 F; P10.2 G; P6 Metals; P6 Other alloys; P6 Ceramics; P6 Polymer; P6 Composite.

Selected results of the experiments dedicated to the metal industry are presented in Table 1.

Tab. 1. Experiments conducted on the Bayes network for the metal industry

Test No.	The alternatives observed in nodes	$P_{(P10 = State1)}$
0	Initial state after learning the network	0.31
1	(P9.1 Welding; 9.2 Production; P9.3 Metals; P10.2 A) = State 1	0.44
1a	P10.2 A = State 1	0.45
2	(P9.1 Welding; 9.2 Production; P9.3 Metals; P10.2 F) = State 1	0.44
2a	P10.2 F= State 1	0.48
3	(P9.1 Welding; 9.2 Production; P9.3 Metals; P10.2 E) = State 1	0.54
3a	(P10.2 E) = State 1	0.52
4	(P9.1 Welding; 9.2 Production; P9.3 Metals; P6 Metals) = State 1	0.38
4a	P6 Metals = State 1	0.37
5	(P9.1 Welding; 9.2 Production; P9.3 Metals; P6 Other Alloys) = State 1	0.49
5a	P6 Other Alloys = State 1	0.41
6	(P9.1 Welding; 9.2 Production; P9.3 Metals; P6 Ceramics) = State 1	0.50
6a	P6 Ceramics = State 1	0.47
7	(P9.1 Welding; 9.2 Production; P9.3 Metals; P6 Polymer) = State 1	0.50
7a	P6 Polymer = State 1	0.45

When analysing the obtained results, it can be noticed that the largest change in the result node P10, in relation to its initial state, was indicated for experiment 3, for the State1 declaration in: P9.1 Welding, 9.2 Production, P9.3 Metals and P10.2 E. The growth of probability, determined for State1, was also observed in test 3a, where the value of State 1 was set in the P10.2 E. This node corresponds to the factor that determines the implementation of AM technology, i.e. personalising a product to specific, customer requirements. A high level of P(P10 = State1) was also observed in the case of tests 6 and 7, where the determining variables were the materials on which the companies want to conduct research, namely ceramics and polymers. The lowest increase in the value of State1 was recorded for test 4, where the impact of the P6 Metals node, *as a material on which companies would like to conduct research*, was tested.

In the case of the automotive industry, experiments were carried out in order to observe alternatives at nodes: P9.1 EBM, 9.2 Production, P9.3 Other alloys, P10.2 A, P10.2 B, P10.2 C, P10.2 D, P10.2 E, P10.2 F, P10.2 G, P6 Metals, P6 Other alloys, P6 Ceramics, P6 Polymer, P6 Composite. The tests were carried out in three stages according to the procedure outlined for the metal industry network.

The results of the experiment have been collected and are presented in Table 2 which contains the tests for which changes in the result node P10 were observed.

Tab. 2. Experiments conducted on the Bayes network for the automotive industry

Test No.	The alternatives observed in nodes	$P_{(P10 = State1)}$
0	Initial state after learning the network	0.41
1	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P10.2 A) = State 1	0.50
1a	(P10.2 A) = State 1	0.44
2	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P6 Metals) = State 1	0.46
2a	P6 Metals = State 1	0.44
3	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P6 Ceramics) = State 1	0.50
3a	P6 Ceramics = State 1	0.49
4	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P6 Other Alloys) = State 1	0.48
4a	P6 Other Alloys = State 1	0.46
5	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P6 Composite) = State 1	0.50
5a	P6 Composite = State 1	0.49
6	(P9.1 EBM; 9.2 Production; P9.3 Other Alloys; P6 Polymer) = State 1	0.50
6a	P6 Polymer = State 1	0.48

Based on the results obtained in the experiment, it can be seen that the greatest change from the value of State1 for the P10 node in the initial state was noted in the case of tests 3, 5 and 6, where State1 was declared for the nodes: P9.1 EBM, 9.2 Production, P9.3 Other Alloys and in the following nodes: P6 Ceramics, P6 Composite and P6 Polymer. The peaks, examined in the P6 group, correspond to the materials on which enterprises want to conduct research. The lowest change in P (P10 = State1) was observed in test no. 2 for the declared choice of P6 Metals.

The analysis of the impact of individual nodes and the observation of the change in the probability value can be used to determine the implementation opportunities of AM technology in the metal and automotive industries. In addition, **it allows**, *among other things*, **the most important factors and areas** that affect a positive or negative change in the probability of success, in implementing additive technology, **to be identified**. The information obtained from the experiments can also be used in the strategic analysis of the company, where the strengths and weaknesses of the planned technology are considered.

4. CONCLUSIONS

Manufacturing companies consider changes in the production technologies they use. This is related to the growing competitiveness of enterprises and the requirements set by the **Fourth Industrial Revolution** (**Industry 4.0**), i.e. the digitisation of processes and automation. Considerations of production companies and actions taken towards the adaptation of new technologies are determined primarily by the desire to reduce production costs, tailor products to specific customer requirements and respond quickly to the needs of the market. According to the research carried out in western Poland, about 44% of respondents use AM technologies in manufacturing companies, while over 25% are interested in implementing AM technology in their enterprises. The article proposes an approach supporting decision-making in the implementation of AM technology. The authors proposed two Bayesian network models, *viz.*, one model for the metal industry and one for the automotive industry. The results of surveys selected and uploaded to the network and the appropriate learning of the network, allowed the level of interest in AM technologies to be determined for a specific industry, which can also be interpreted as the company's chances to implement AM technology. Research experiments were carried out on both networks to simulate the problems described by network nodes and their relationships. It has been observed that in the metal industry, in the case of welding metals for production purposes, the greatest impact on interest in implementing AM technology is the possibility of personalising a product to specific, customer requirements. Presumably, this is related to the possibilities offered by AM technologies, namely to produce elements with greater freedom of shape and complex geometry, which is not possible with conventional manufacturing methods. It is concluded that manufacturing companies see opportunities in gaining a competitive advantage, offering flexible production and adapting to the individual needs of customers. With regard to successes in implementing additive technology, the influence of the willingness to conduct material research on ceramics and polymers is important. This may indicate a desire to expand the range of manufactured products, search for hybrid solutions or cheaper alternatives. In the case of an experiment carried out on a network designed for the automotive industry, it was observed that material research carried out on composites, polymers and ceramics had the greatest impact. This may be related to the search for solutions, *vis-à-vis* new material. Additionally, it is important for the company to declare a vested interest in AM technology on account of a desire to reduce costs. The solution presented, based on the Bayesian network can help management to decide whether or not to implement AM technology. The article proves that the Bayesian network approach allows knowledge to be modelled under conditions of uncertainty regarding graphic presentation. The use of the algorithm makes it possible to test probabilities, with an indication of a decrease *vis-à-vis* an increase, in the chance of implementing AM technology under given environmental conditions.

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