ACTA METALLURGICA SLOVACA
2023, VOL. 29, NO. 2, 113-118

RESEARCH PAPER

SIMULATION TOOL FOR MATERIAL BEHAVIOUR PREDICTION IN ADDITIVE MANUFACTURING

Ľuboš Kaščák[1], Ján Varga[1], Jana Bidulská[2], Róbert Bidulský[3,4], Marco Actis Grande[5]

[1] Technical University of Košice, Faculty of Mechanical Engineering, Mäsiarska 74, 040 01 Košice, Slovakia
[2] Technical University of Košice, EPMA PM R&D Centre, Faculty of Materials, Metallurgy and Recycling, Park Komenskeho 10, 040 01 Kosice, Slovakia
[3] Bodva Industry and Innovation Cluster, Budulov 174, 045 01 Moldava nad Bodvou, Slovakia
[4] Asian Innovation Hub, Budulov 174, 045 01 Moldava nad Bodvou, Slovakia
[5] Politecnico di Torino, Department of Applied Science and Technology, Corso Duca degli Abruzzi 24, 10129 Torino, Italy

*Corresponding author: lubos.kascak@tuke.sk, Tel.: 055/6023508, Department of Technology, Materials and Computer Supported Production, Faculty of Mechanical Engineering, Technical University of Košice, Mäsiarska 74, 040 01 Košice, Slovakia

Received: 31.05.2023
Accepted: 09.06.2023

ABSTRACT

The application of simulation tools plays an important role not only in terms of understanding the processes taking place in the production and the possibility to prevent failures, but ultimately, and most importantly, to optimize the production process. Thus, simulation tools should be able to work with many input parameters and process them in such a way that the data obtained in the form of simulation outputs are as close as possible to the real conditions taking place in a production process. Metal Additive Manufacturing (AM) represents one of the processes in which many parameters influence the final quality of the part and its properties. Supports, traditionally used in Powder Bed Fusion (PBF) techniques, and their relative volumes are also of great importance, since their reduction plays an important role in terms of cost-effectiveness, which can be increased by minimizing the support structures. The aim of this paper is the numerical simulation in the Simufact Additive software, which can handle the input parameters of the metal AM process and, most importantly, to present an additive tool for support optimization. Two simulation analyses with the same input parameters were performed, comparing each other the support material distribution, volume fraction or shape deviation with respect to the conventional support generation method and the function allowing the support generation by means of the optimization mode. A lower variation in the shape of the part, in its volume fraction, in the density of the generated support structures as well as in the spacing of the generated support structure was achieved by using the support generation optimization mode.

Keywords: additive manufacturing; simulation;, simufact additive; distortions

INTRODUCTION

Metal additive manufacturing (AM) technology is mainly used in the aeronautical, aerospace and biomedical industries where parts' weight reduction plays a very important role [1]. However, residual stresses arising in the continuous transient melting and solidification process are still a significant obstacle to the AM of high-performance large-size metal parts, since they can lead to defects such as excessive deformation and cracking [2-4]. Therefore, additional operations are required to alleviate stresses during or after the fabrication process.
Several simulation tools solving design problems or analyzing material behavior in forming, joining, or injection molding processes are available in the market, as well as simulation programs specific to the field of AM [5-7]. One of the specific advantages of AM is the possibility of producing a part regardless of its geometry [8]. The metal AM process brings several advantages over conventional manufacturing technologies. The synergy/simultaneity achieved in AM, where the material in the form of powders and the geometry of the product are formed at the same time, equally requires the linking of the part design with the knowledge of the process. Since the entire manufacturing process, properties and factors entering metal AM are closely interrelated and interdependent, it is necessary to understand their influence on the part production. One way to achieve this is through the application of numerical simulation tools. Despite being a layer by layer technique, PBF processes are different from Fused Deposition Modeling (FDM), where molten plastic layers are deposited one onto the other [9]. The complexity of the geometry encountered in the production of metal parts represents the highest degree of complexity with respect to the size of the elements and their structure.
Nowadays, it is possible to come across various simulation tools for both design and process, but these are often only simple simulations. Increasing demands on the part geometry, the manufacturing process, or the chosen material require the use of a simulation tool containing computational modules that can not only predict the behaviour of the material but also provide process control and optimise the part functionality [10]. Therefore, the correct selection of the simulation tool is very important.
The possibility of applying simulation tools in the AM process, where it is possible to work with process input factors, allows controlling complex stress states as well as the microstructure

and geometry of the part. The control of the microstructure is done by the volume of the part, where process maps are used to define the extent of its control [11,12]. It also guarantees flexibility and agility, invaluable in product development. Furthermore, it allows for the generation and local control of the part geometry and material behaviour in each volume element - voxel in the part. Among other things, metal AM reduces the costs associated with producing moulds, tooling, or jigs on CNC machines. Its process efficiency also contributes to reducing material consumption in connection with the application of topological optimization. The combination of printed parts and post-machining likewise brings cost and time benefits [13].

One of the main requirements of the manufacturing process is dimensional accuracy, which is very difficult to predict. This is because it is ultimately the result of multiple interactions that are interconnected. These interactions include material type, machine process parameters (laser power, deposition strategy), physical properties, as well as part deformations caused by shrinkage and residual stresses in the material [14]. Therefore, it is important not only to understand the interactions taking place in the metal additive manufacturing process but equally to try to prevent negative phenomena from affecting the final quality and function of the part: it is the simulation of metal AM processes that plays an important role in the design of metal parts.

In Laser Powder Bed Fusion (L-PBF), the material in the form of metal powder is melted using a laser, which results in local heating that affects the mechanical properties as well as the dimensional accuracy of the part. It is therefore equally important to think about the thermal conductivity of the surrounding material and how much heat is dissipated due to the amount of heat concentrated by the laser to a certain point. In the L-PBF process [15-20], it is necessary to work with a larger number of input parameters as they affect the stability of the manufacturing process. The performance of the process can be influenced by factors such as settings, conditions, machine platform, powder material, or part geometry. During the process, negative features such as geometric deformations or residual stresses can be manifested, which have a significant effect on the strength of the future part [21]. These negative properties are closely related to the thermo-physical phenomena taking place in the manufacturing process, where rapid re-cooling cycles occur. These cycles may induce anisotropic properties of the future part, which affects its functionality and consequently leads to dimensional and geometrical changes in the accuracy of the final parts [22,23]; thermal gradients represent the main problem of the process. Deformation and damage to the part can result from residual stresses exceeding the yield strength and even the ultimate strength of the material [24]. The subsequent stress relaxation occurs during the removal of the part from the plate platform, and its final extent depends on the geometry of the part and its processing. Therefore, it is very important to recognize them early as well as to take them into account when planning the use of the part.

The point of using simulation tools is therefore not only to understand the manufacturing process but also to prevent unwanted influences. By using them, part deformations, residual stresses and other defects can be predicted and avoided before the actual production of the part, that is to say before the printing process takes place. Among other things, they can provide data on the behaviour of the material at the level of voxels appearing in a three-dimensional volume. This has implications not only for part production capabilities but also for the design, optimisation and control of the materials being designed. Ultimately, this is a costly process compared to conventional technologies, where in this case the goal is to achieve part production with minimal defects [25].

Thus, these are effective tools to achieve quality partly due to the correct setting of process input parameters and the ability to monitor the inter-behaviour of related parameters during production [26-27]. The application of simulation tools and the possibility of comparing the effect of changing parameters or using different materials is more advantageous in terms of time and economy. The simulation tools work with two FEA methods designed to evaluate the shape deformation and residual stresses of printed parts. It can be the possibility of applying the thermo-mechanical method or the inherent deformation method [28-30]. Simufact Additive software works with strain ($\varepsilon*$) values used for calculation, prediction of residual stress and partial distortion [31]. It also works with voxel elements, where a smaller voxel size means longer computation time [32].

In preparation for printing, laser parameters and parameters related to the scanning strategy can be relatively easily set. Spierings [33] compared 3 types of stainless steel powders with different particle size distributions. At maximum laser power, he determined the optimum scanning speed and then evaluated the surface texture for the fabricated samples. The smaller layer thickness may not necessarily mean higher surface quality, but the particle size distribution in the powder has a significant effect on the surface quality. Calignano [34] dealt with the optimization of the formation of support structures for AlSi10Mg aluminium alloy. The author evaluated the possibility of printing walls without support structures from an angle of 30° from the substrate. When the wall inclination angle was between 30° and 45°, the aluminium alloy samples showed higher surface roughness. This is confirmed by Wang [35], who measured surface roughness and strain on a structure with variable part overlap angle.

Yi et al. [36] researched the achievement of geometric accuracy in sample fabrication by considering the laser power and scanning speed used. As a result, the geometric accuracy of IN718 material samples was reduced due to the influence of lower speed and higher laser power. Huo et al. [37] applied the Simufact simulation tool to investigate the distortion of IN718 samples due to the influence of process parameters. The research concluded that each set of parameters chosen for the manufacturing process influenced the part quality. Increasing the laser power resulted in higher distortion effects, but conversely, increasing the scanning speed reduced the distortion effect. Some authors [38-39] investigated the effect of distortion and dimensional accuracy by analysing the change in part height size since this is the most affected dimension in the manufacturing process. The simulation tool in solving the effect of changing the scanning speed and laser power on the thermal behaviour of AlSi10Mg powder was applied by Yang [40]. The aim was to provide optimized solutions for the input parameters of the printing process without the need for extensive experiments. Cheng et al. [41] compared the experimental results with the Simufact simulation tool, where they used a multiscale approach method to analyse the part distortion. Some authors investigated the prediction of distortion, using a method incorporating a mathematical heat source model for thermo-mechanical finite element analysis - FEA [42]. This was a method where the powder is considered as the input material. Despite several papers dealing with the influence of parameters on various properties of the future product, there is still a lack of information on the accuracy and reliability of the simulation tools used for the additive manufacturing process of metals. One of the simulation tools that allow virtual simulation and optimization of factors such as parameter and material settings, removal of direction and support, and creation of support structure is Simufact Additive software. It is a simulation tool aimed at predicting and solving mistakes during the entire printing, heat treatment, cutting and HIP - Hot Isostatic Pressing process before sending the part to the machine. The present paper deals with the generation of part support depending on a defined critical surface angle, which has been set to 45°. Two simulation analyses were performed with the same input parameters, comparing each other the support material distribution, volume fraction, or shape deviation considering the conventional support generation method and the function allowing the support generation by means of an optimization mode.

MATERIAL AND METHODS

For simulation purposes, the component shown in **Fig. 1** and designed for the aerospace industry was chosen and assigned a specific material in the form of a powder. AlSi10Mg was selected as the alloy powder from the Simufact Additive software database.

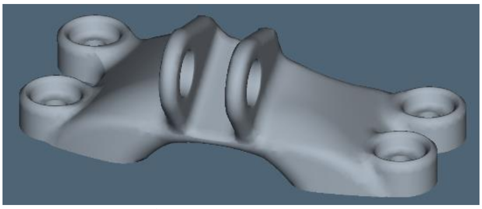

Fig. 1 Part selected for simulation

Aluminium components produced by laser melting are (almost) pore-free and have a homogeneous microstructure. Subsequent heat treatment can reduce the anisotropy that arises during the printing process and thus individually adjust the properties of the component. The heat treatment involves annealing to reduce the stress at 300 °C for 2 hours.
For simulation, the L-PBF was chosen, and a mechanical configuration was identified for the simulation process, which operates based on the eigenvalues of the deformations. A manufacturing type simulation was selected as the simulation type, to which three levels were assigned to represent the sequence of the process phases. The following levels were chosen: 1. Build, 2. Cutting, 3. Support removal.
An imported CAD model file is converted to the Parasolid format, and a surface mesh is created based on it. The surface mesh is thus always present from the import of the part and consists of triangular facets/elements. However, this mesh is not used for the analysis itself, since the Simufact Additive software works with voxel elements containing hexahedral elements for a so-called discrete part representation, which works in combination with the volume fraction of the element.
When defining the support formation, the value of the parameter defining the critical surface angle was chosen to be 45°. To better visualize the different areas where the support material will be needed, a function was used to display them based on a colour scale defining a specific angle on the surface of the part (**Fig. 2**).

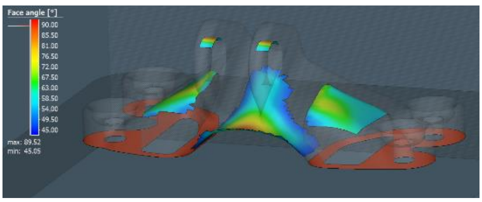

Fig. 2 Critical surface angle preview for support generation

For simulation purposes, the same input parameters were selected in both analyses based on the strain values (**Fig. 3**). Parameters defined as input data were powder layer thickness of 0.03 mm and laser power of 200 W. The support material distribution, volume fraction, or shape deviation considering the conventional method of support generation and the function allowing support generation using the optimization mode were compared with each other.

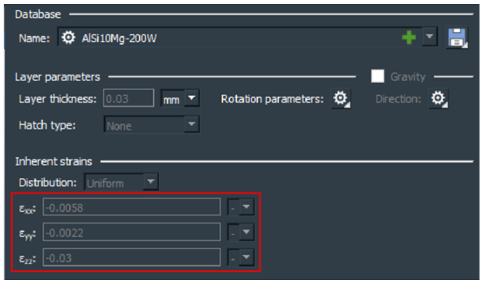

Fig. 3 Sample design in CAD

The creation of the part support based on the specified critical surface angle of 45° is shown in **Fig. 4** and **Fig. 5**. The conventional method of generating the support structure without using the optimization function represents in **Fig.4**. while **Fig. 5** demonstrates the generation of the support structure with the activation of the support optimization function. The geometry of cylindrical shape was used for both cases of support structure generation.

Fig. 4 The conventional method of generating support

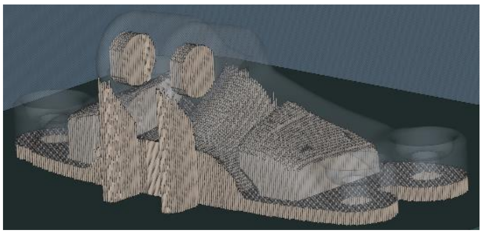

Fig. 5 Support generation using the optimization function

A closer comparison of the generated support structures without and with the use of the support generation optimization function is shown in detail in **Fig. 6**. In the comparison, it is possible to see the change not only in the density of the generated support structures but also in the spacing and size of the generated support. The difference lies in the recognition of important areas in the part construction where the size and spacing need to be maintained to maintain the necessary properties of the part after fabrication.
At the same time, the distribution of support structures has changed. More support structures have been created where the load is higher than in places with lower loads.

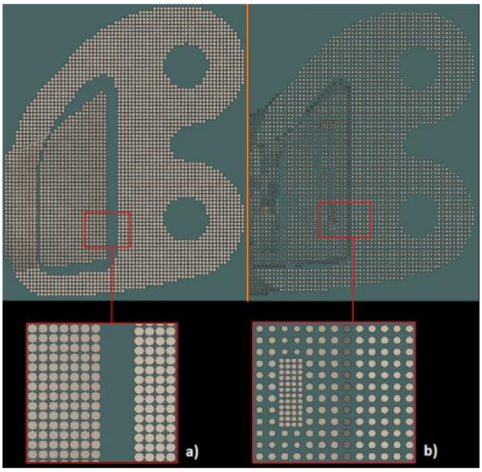

Fig. 6 Distribution of support structures: a) without optimization b) with optimization of support structure generation

It was necessary to define the size of an element known as a voxel to finish pre-processing of the simulation. A voxel defines a value on a consistent grid in a three-dimensional space, and thus the voxel itself refers to the volumetric structure of the grid. Its size thus represents the number of contained layers of the metal powder.

The surface mesh was set to a value of 2.42 mm for each analysis and the voxel element size was chosen to be 2 mm in all directions, i.e., voxel size X/Y/Z. The reason for selecting this value was to reduce the computation time. The purpose of the voxel grid is to analyse the deformations that will take place during the simulation process as well as the formation of the so-called volume decomposition of the particles. In general, however, more accurate solutions can be achieved by reducing the element size. This allows the software to display the volume fraction of the part, the value of which describes how much of the voxel volume is filled with geometry. A comparison of the volume fraction display without and with the use of support generation optimization is shown in **Fig. 7** and **Fig. 8**.

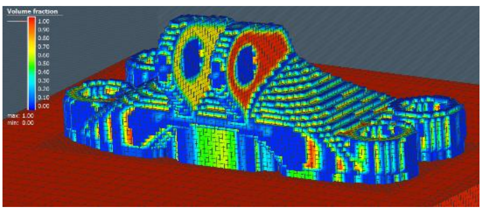

Fig. 7 Volume share without using support generation optimization

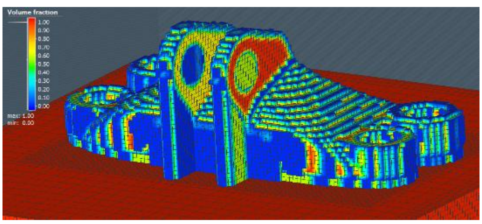

Fig. 8 Volume share using support generation optimization

The Simufact Additive software also can display the volume fraction in the cross-section (**Fig. 9** and **Fig. 10**), which can be used to determine the quality of the mesh. If the volume fraction parameter has a blue colour inside the part, in that case, this volume fraction is close to zero, which results in the mesh quality not being good. In that case, a smaller voxel element size should be used.

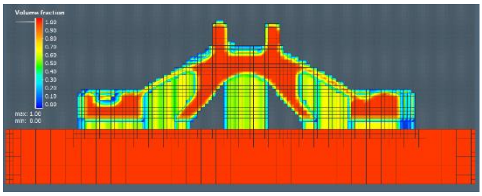

Fig. 9 Volume fraction in the cross-section without using support generation optimization

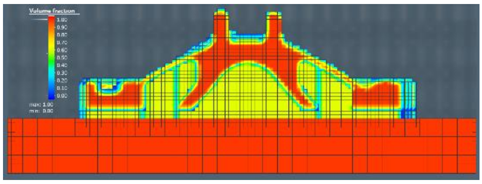

Fig. 10 Volume fraction in the cross-section using support generation optimization

A matrix solver called Iterative Sparse, designed for the mechanical configuration, was chosen for the computation. Simulation results such as total displacement, elastic strain, plastic strain, flow stress, relative density, temperature, shape deviations and others can be obtained.

The effect of generating the support structure without and with the use of the optimization function on the shape deviation was compared. Without using the support optimization function, the surface shape deviations were obtained in the range of min -0.52 mm and max 0.47 mm (see **Fig. 11**). With the use of the support optimization function, the surface shape deviations were achieved in the range: min -0.11 and max 0.06 mm (see **Fig. 12**). If positive values are reached, the calculated shape is outside the initial reference shape, and if negative values are reached, the calculated shape is inside the initial reference shape.

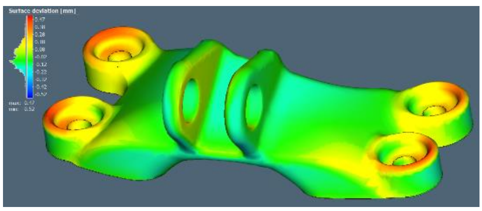

Fig. 11 Shape deviation without support optimization

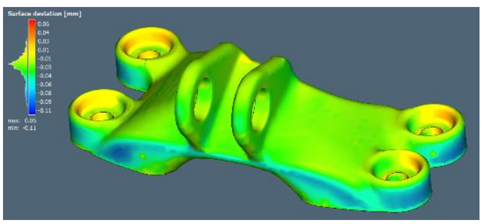

Fig. 12 Shape deviations with support optimization

The analyses without and with the use of the support generation optimization function (**Fig. 9**) led to results on the total support volume:
- support generation without optimization Σ Volume 71875.6 mm^3
- generating support with optimization Σ Volume 42693.7 mm^3

CONCLUSIONS

The paper dealt with the generation of part support depending on a defined critical surface angle, which was set to 45°. The support structure generation was compared between conventional generation and a function allowing the use of support optimization.
The use of a complementary tool designed to optimize support in Simufact Additive is important to achieve less deviation of part shape. Virtual acquisition of the results replaces time-consuming and costly testing and thus the visual presentation of the results based on the measurements allows the user to quickly assess whether the deviations are within the tolerances.
The simulation results show that by using the support optimization function, a reduction in the volume fraction of the part can be achieved. This reduction plays an important role in terms of cost-effectiveness, which can be further increased by minimizing the support structures. At the same time, by comparing the support structure formation without and with the optimization function, changes in the volume fraction values were found. The distribution of support structures was also changed. It can be concluded that more support structures were formed where the load is higher than in the locations with a lower load.

Acknowledgements: Authors are grateful for the support of experimental works by project KEGA 036TUKE-4/2021

REFERENCES

1. K. Riener, N. Albrecht, S. Ziegelmeier: Additive Manufacturing, 34, 2020, 101286. https://doi.org/10.1016/j.addma.2020.101286.
2. C. Li, Z.Y. Liu, X.Y. Fang, Y.B. Guo: Procedia CIRP – Manufacturing Technology, 71, 2018, 348-353. https://doi.org/10.1016/j.procir.2018.05.039.
3. M.K. Thompson, G. Moroni, T. Vaneker, G. Fadel, R.I. Campbell, I. Gibson: Procedia CIRP – Manufacturing Technology, 65(2), 737-760. https://doi.org/10.1016/j.cirp.2016.05.004.
4. B. Fotovvati, N. Namdari, A. Dehghanghadikolaei: Materials Research Express, 6(1), 2018, 1-15. https://doi.org/10.1088/2053-1591/aae10e.
5. B. Mueller: Assembly Automation, 32(2), 2012, 120-159. https://doi.org/10.1108/aa.2012.03332baa.010.
6. T. Ngo, A. Kashani, G. Imbalzano, K. Nguyen, D. Hui: Composites Part B: Engineering, 143, 2018, 172-196. https://doi.org/10.1016/j.compositesb.2018.02.012.
7. J. Kruth, P. Mercelis, J. Van Vaerenbergh, L. Froyen, M. Rombouts: Rapid Prototyping Journal, 11, 2005, 26-36. https://doi.org/10.1108/13552540510573365.
8. B. N. Turner, R. Strong, S. Gold: Rapid Prototyping Journal, 20(3), 2014, 192-204. https://doi.org/10.1108/RPJ-01-2013-0012.
9. D.D. Gu, W. Meiners, K. Wissenbach, R. Poprawe: International Materials Reviews, 57(3), 2012, 133-164. https://doi.org/10.1179/1743280411Y.0000000014.
10. P. Ninpetch, P. Kowitwarangkul, S. Mahathanabodee, P. Chalermkarnnon, P. Ratanadecho: AIP Conference Proceedings, 2279, 2020, 050002. https://doi.org/10.1063/5.0022974.
11. A. Vasinonta, J. L. Beuth, M. Griffin: Journal of Manufacturing Science and Engineering, 129 (1), 2007, 101-109. https://doi.org/10.1115/1.2335852.
12. J. Beuth, N. Klingbeil: JOM, 53(9), 2001, 36-39. https://doi.org/10.1007/s11837-001-0067-y.
13. M. Pagac, J. Hajnys, R. Halama, T. Aldabash, J. Mesicek, L. Jancar, J. Jansa: Applied Science, 11(4), 2021, 1656. https://doi.org/10.3390/app11041656.
14. B.H. Jared, H.D. Tran, D. Saiz, C.L. Boucher, J.E. Dinardo: The International Journal of Advanced Manufacturing Technology, 93(1), 2017, 2571-2598. https://doi.org/10.1007/s00170-017-0570-0.
15. D. Manfredi, R. Bidulský: Acta Metallurgica Slovaca, 23(3), 2017, 276–282. https://doi.org/10.12776/ams.v23i3.988.
16. R. Bidulsky, F. S. Gobber, J. Bidulska, M. Ceroni, T. Kvackaj, M. A. Grande: Metals, 11(11), 2021, 1831. https://doi.org/10.3390/met11111831.
17. B. Vicenzi, K. Boz, L. Aboussouan: Acta Metallurgica Slovaca, 26, 2020, 144-160. https://doi.org/10.36547/ams.26.4.656.
18. R. Bidulsky, J. Bidulska, F.S.Gobber, T. Kvackaj, P. Petrousek, M. Actis-Grande, K.P. Weiss, D. Manfredi: Materials, 2020, 13, 3328; https://doi.org/10.3390/ma13153328.
19. M.R. Ridolfi, P. Folgarait, A. Di Schino: Acta Metallurgica Slovaca, 26, 2020, 7-10. https://doi.org/10.36547/ams.26.1.525.
20. G. Stornelli, D. Gaggia, M. Rallini, A. Di Schino: Acta Metallurgica Slovaca, 27, 2021, 122-126. https://doi.org/10.36547/ams.27.3.973.
21. D. M. Nieto, D. M. Sánchez: Applied Science, 11(4), 2021, 1571. https://doi.org/10.3390/app11041571.
22. A. Alafaghani, A. Qattawi, M.S. Jaman, M.A. Ablat: The International Journal of Advanced Manufacturing Technology, 105, 2019, 3499–3520. https://doi.org/10.1007/s00170-019-04404-8.
23. X. Lu, M. Chiumenti, M. Cervera, H. Tan, X. Lin, S. Wang: Metals 2021, 11(5), 686; https://doi.org/10.3390/met11050686.
24. A.S. Wu, D.W. Brown, M. Kumar, G.F. Gallegos, W.E. King: Metallurgical and Materials Transactions, 45 (13), 2014, 6260-6270. https://doi.org/10.1007/s11661-014-2549-x.
25. F. Caiazzo, V. Alfieri, G. Corrado, P. Argenio: The International Journal of Advanced Manufacturing Technology, 93 (2), 2017, 4023–4031. https://doi.org/10.1007/s00170-017-0839-3.
26. B.B. Ravichander, A. Amerinatanzi, N.S. Moghaddam: Metals, 10(9), 2020, 1180. https://doi.org/10.3390/met10091180.
27. E.W. Hovig, A.S. Azar, F. Grytten, K. Sørby, E. Andreassen: Advances in Materials Science and Engineering, 2018(4), 2018, 1-20. https://doi.org/10.1155/2018/7650303.
28. X, Lu, X. Lin, M. Chiumenti, M. Cerverac, Y. Hu, X. Ji, L. Ma, H. Yang, W. Huang: Additive Manufacturing, 26, 2019, 166-179. https://doi.org/10.1016/j.addma.2019.02.001.,
29. B. Panda, S. Sahoo: Results in Physics, 12, 2019, 1372–1381. https://doi.org/10.1016/j.rinp.2019.01.002.
30. R.K. Ganeriwala, M. Strantza, W.E. King, B. Clausen, T.Q. Phan, L.E. Levine, D.W. Brown, N.E. Hogge: Additive Manufacturing, 27(2), 2019, 489–502. https://doi.org/10.1016/j.addma.2019.03.034.
31. H. Peng, M. Ghasri-Khouzani, S. Gong, R. Attardo, P. Ostiguy, R.B. Rogge, B.A. Gatrell, J. Budzinski, C. Tomonto, J. Neidig: Additive Manufacturing, 22, 2018, 869-882. https://doi.org/10.1016/j.addma.2018.05.001.
32. A. Çelebi, E.Z. Appavuravther: Düzce University Journal of Science & Technology, 6(4), 930-940, 2018. https://doi.org/10.29130/dubited.426063.
33. A.B. Spierings, N. Herres, G. Levy: Rapid Prototyping Journal, 17(3), 2011,195-202. https://doi.org/10.1108/13552541111124770.
34. F. Calignano: Materials and Design, 64, 2014, 203-213. https://doi.org/10.1016/j.matdes.2014.07.043.
35. D. Wang, M. Shuzhen, X. Dongming, Y. Yongqiang: The International Journal of Advanced Manufacturing Technology,

86(1-4), 2016, 781–792. https://doi.org/10.1007/s00170-015-8216-6.
36. J. Yi et al.: Journal of Alloys and Compounds, 786, 2019, 481–488. https://doi.org/10.1016/j.jallcom.2019.01.377.
37. Y. Huo, C. Hong, X. Li, P. Liu: Materials Research, 23(6), 2020, 1-7 https://doi.org/10.1590/1980-5373-MR-2020-0176.
38. C. Li, J.F. Liu, X.Y. Tesák, Y.B. Guo: Additive Manufacturing, 17, 2017, 157-168. https://doi.org/10.1016/j.addma.2017.08.014.
39. N.T. Nesma, N.M. Everitt, I. Ashcroft, Ch. Tuck: Additive Manufacturing. 1(4), 2014, 77-86. https://doi.org/10.1016/j.addma.2014.08.001.
40. D. Yang, Y. Xinyu, Q. Fengbin, G. Lijie, L. Zhengwu: Results in Physics, 12, 2018, 52-60. https://doi.org/10.1016/j.rinp.2018.11.031.
41. Q. Chen, X. Lianga, D. Haydukeb, J. Liua, L. Chenga, J. Oskina: Additive Manufacturing, 28, 2019, 406-418. https://doi.org/10.1016/j.addma.2019.05.021.
42. L. Xufei, M. Chiumenti, M. Cervera, M. Slimani, I. Gonzales: Journal of Manufacturing and Materials Processing. 7(2), 2023, 64. https://doi.org/10.3390/jmmp7020064.