**Solid Freeform Fabrication 2022: Proceedings of the 33rd Annual International
Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference
Reviewed Paper**

Boosting artificial intelligence in design processes by the use of additive manufacturing

M. Ott*, N. Meihöfener*, R. Koch*

*Direct Manufacturing Research Center (DMRC) and Group of Computer Application and Integration in Design and Planning (C.I.K.), Paderborn University, Germany

Abstract

Additive manufacturing offers the option of converting digital prototypes into real structures as quickly as possible by the special property of tool-free manufacturing. However, this process can only be used at optimum speed if bottlenecks can be effectively avoided. One of these constraints is the design process. Although modern CAD systems allow a significant increase in many areas, this always requires a person with specific skills (e.g. engineer). In the field of AM in particular, more and more powerful software solutions have recently been published which accelerate the Design for Additive Manufacturing, including most CAD-tasks. In many areas, therefore, attempts are already made to automate relevant design steps as much as possible, more and more using neural networks and artificial intelligence. This paper presents how and why such techniques can be used to generate three-dimensional structures quickly and efficiently in cases of deep generative design tasks.

Introduction

In today's product development process, technical solutions for data management and simplified geometry generation are receiving a great deal of attention, especially in the area of customization. Shorter product development cycles with a high number of variants and at the same time low unit costs are a primary goal demanded by the market. In the context of globalization, this already starts with the preparation of an offer, which is not possible without a conception of the product and therefore must be realized in a short time without much effort. Likewise knowledge generated in the enterprise is to be received and passed on. [BEEF+97, p. 65ff.] A high level of disertification requires very small quantities, which is why additive manufacturing is a very good choice for economical production due to its tool-free properties. However, processes must be optimized and automated in order to keep development costs as low as possible for unit numbers of 1.

Fundamentals in neural networks

One of the very important topics within this thesis will be the application of different neural networks. Therefore, in this section, the basic structure of such a network and its main tasks will be briefly discussed. Basically, the intention of a neural network is based on the fact that it can act like neurons located in the human body [MAY96]. In an input layer all processed data are transferred to the network. These are further processed there by different activation functions of different neurons and afterwards in an output layer again delivered to the environment (s. figure 1). In the two boundary layers the human has the possibility to interact with the network, whereas in the inner layer different hidden layers are not accessible [MAY96]. One main task of such superstructures is to classify data, for example. These can be based on different bases. Both 2D image data and thus an image recognition can be possible, often this is then realized over so-called Convolutional Neural Networks (CNN), and different semantic connections among other things in Natural Language Processing applications can be a focus of neural networks. For example, the mentioned CNNs try to generate a classification from an overall image (s. Figure 1) by iteratively extracting subregions of an image [SHNA15], whereas Graph Neural Networks (GNN) link information by the logical relation of points and edges between each other and thus draw corresponding conclusions [ZHCU20]. A special case are the so-called Generative Adversarial Networks (GAN), which generate data themselves. For this purpose, two competing networks operate simultaneously. One is the generator network and the other is the discriminator network. The generator network tries to generate real-looking data, whereas the discriminator tries to recognize it and declare it as fake. In this process, both networks learn from each other, so that after a large number of iterations, very real-looking data is produced. However, care should be taken to ensure a good balance between the two networks, as otherwise it favors a very unstable relationship [LULI21].

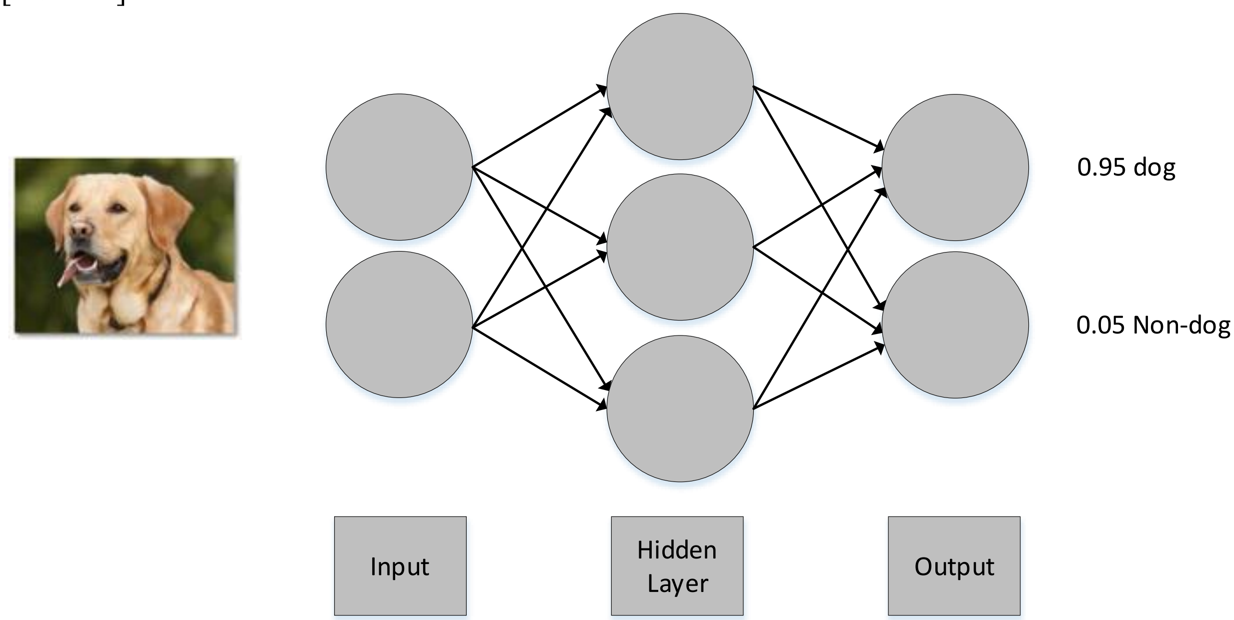

Figure 1: Schematic representation of a neural network for classification

Fundamentels in Product-Life-Cycle

Within the product life cycle, a product passes through various phases. A rough division can be made here as follows:

- Productdevelopment
- Production and
- After-Sales.

Product development is characterized by planning, design and production preparation before the component is finally physically manufactured. Subsequently, further support tasks arise, which appear more topical than ever, especially with regard to sustainability aspects. [SZBE07] Figure 2 shows the course of the product life cycle in simplified form.

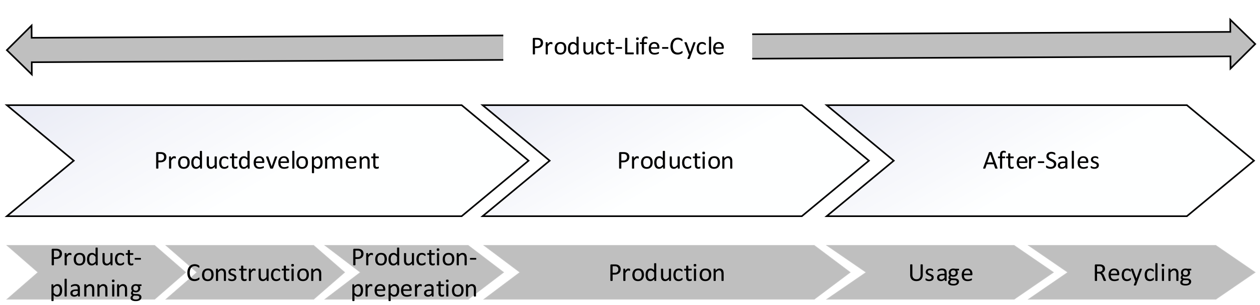

Figure 2: Course of the Product-Life-Cycle in simplified form [SZBE07]

In the context of this work the range of the product development stands above all in the foreground. Already in the product planning and construction a large part of the costs of a component are specified and the possibilities of influencing these for potential changes decrease with progress of the process. The well-known Rule-of-Ten shows this in Figure 3.

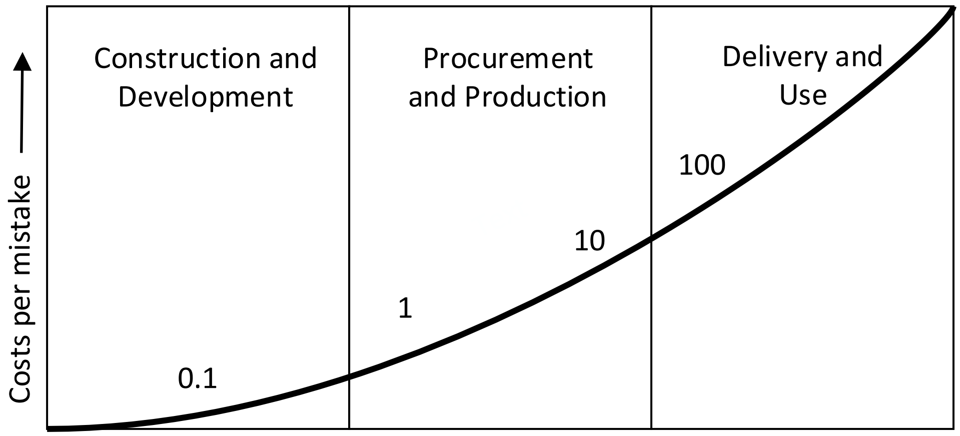

Figure 3: Rule of Ten [VDI2247]

In earlier processes, the first phases of product development in particular were characterized by a great deal of creative work. The use of Computer Aided Design (CAD) systems first appeared in later processes, the actual design, which is why the general use of software in product planning did not find much application. The following figure shows that the development effort has a relatively large margin in the transition area between the processing by design methodologies (the creative work in product planning and conception) and the elaboration in design (the resource-intensive work). Since a primary goal is to keep development times short and thus reduce the development costs incurred, it is advisable to make further use of this space [SKBL06].

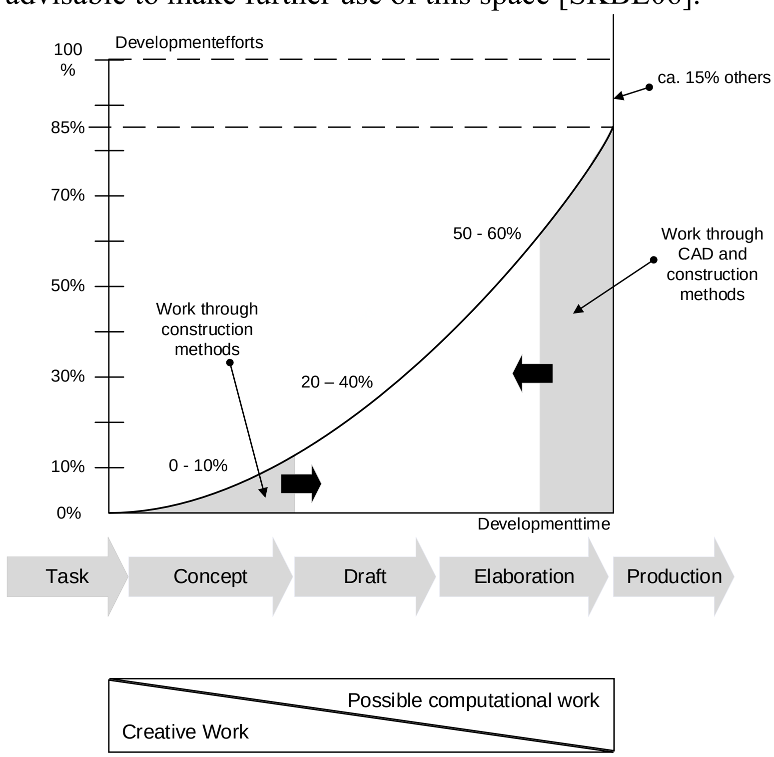

Figure 4: Developmentefforts and –time during the design process [SKBL06]

Automatization in design processes and modeling

Especially due to the design freedom of additive manufacturing, it is necessary to integrate and consider the corresponding knowledge about this at an early stage in the product development process. Modern automation of design processes is already attempting to enable "Design for X" in many areas, albeit with more or less success. One of the much-used software tools is Generative Design. In contrast to conventional topology optimization, here various input parameters of an optimization are varied in such a way that, subsequently, the user can select an optimum result from a number of design proposals on the basis of various criteria (construction time, amount of support material, thermal distortion, etc.). In addition to the topology optimization approach, there are also parameter and shape optimization approaches within structural optimization. These differ mainly with respect to three criteria. The detail quality, the computing power and the design freedom. From this field especially the parameter optimization is a much used possibility to generate semi-automated processes. Here the constructions are built up first parametrically, in order to interact then over suitable interfaces with the designer, in order to change these [BLFI05] [REI19]. Since parametric designs usually lead to conventional manufacturing methods due to their regular progressions, the greater focus here is placed on the possibilities of automated topology optimization or generative design methods. According to [REI19], there is a great need for action in the area of digital geometry processing, especially with regard to the benefits of geometries for additive manufacturing, where modern artificial intelligence systems can provide a remedy.

For this purpose, however, it is first important to know in which way geometries can be modeled and how to continue working with different methods. The following figure shows the basic classification of modeling processes according to [REI19]. In conventional CAD, the curve-based modeling processes specified there are primarily used. They make it possible to define analytically describable geometries, which the other two groups of polygons and digital sculpting cannot do. Points and surface meshes consisting of polygons can only approximate corresponding geometries [ZWE20]. The same applies to the group of voxel models. However, since each element of voxels as well as points stands for itself and neural networks exchange and calculate their information via

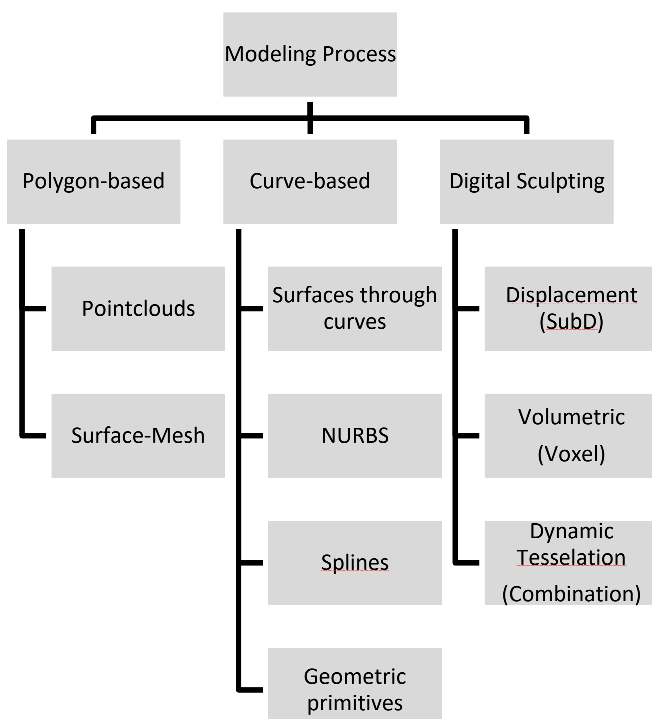

Figure 5: Modeling processes for geometries [REKO15]

vectors, tensors and matrices, these can be used very well to build corresponding arrays, which can function as input values. However, there are already first geometry recognition networks, which try to function on the known splines, but here the preparation of the data turns out to be much more complex [FELE18]. In the context of the paper a further intensification of the structure of the data contents within a file format can be renounced, since here the possibilities and application times are crucial.

Artificial intelligence in design processes

Artificial intelligence can be introduced at various points in the design process. For this purpose, it can be useful to link different neural networks in order to take over different tasks in the process. A very good example of how neural networks can work together to solve highly complex tasks with different characteristics is the topic of autonomous driving, for example at Tesla. There, 48 networks act simultaneously to perform all the tasks that enable driving without danger [KAR20]. In the design, different data types are present than in autonomous driving, however, depending on the time of application, a wide variety of activities are also to be performed by a neural network. In the following, the most important use cases will be shown in more detail, potential networks will be presented and a possible output will be shown.

Basically, it has been shown that the product development process can be uniformly divided into different phases and that especially mistakes made at the beginning are very expensive to fix. The initial situation in the design process is therefore always a problem, whether it is based on the market or on an existing product. This then raises the question of a new or variant design. Artificial intelligence can be used and supported at various points. In order to provide efficient support, the goal of the application must first be defined. By analyzing different scenarios, the inspiration for new designs can be defined as a clear goal in the area of new design. In variant or improvement design, on the other hand, problems that have already been identified must be eliminated or improved (s. Figure 6).

This paper is initially limited to the methods of the inspiration process and the prediction of mechanical behavior, which are based on the methods of polygons and digital sculpting. Therefore,

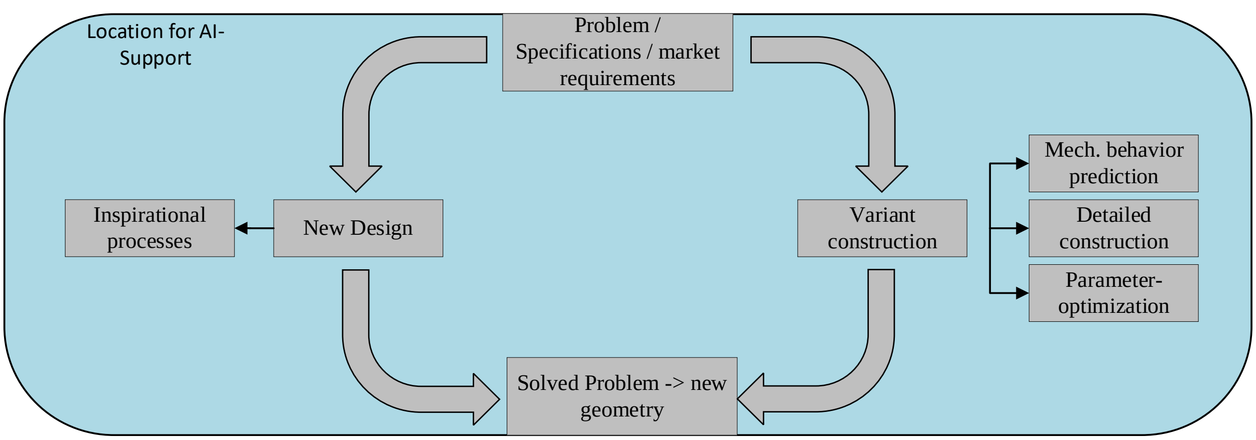

Figure 6: Possibilities on AI Support in design processes

the first step is to take a closer look at the inspiration process. Due to the early stage of development, data here often cannot be interpreted as finished volume models and a rather rudimentary form of representation is usually sufficient. In the context of this paper, therefore, a generative network is used, which initially has the task of generating different variants of one and the same product. This means that the rough framework is initially clearly defined, but can differ in fine features. An example is a chair, which initially consists of a seat, the backrest and the legs of the chair. The exact detailing of these features will then be varied. This is precisely the functionality offered by DECOR-GAN, which is therefore used for this application. However, since a generative network can only classify between real and non-real structures, an additional classification network is needed. Since the GAN is based on voxel data and was initially trained for the data set of the ModelNet10 , the VoxelNet was used for the classification of the resulting geometries, which offers a very good cost-benefit ratio.

1) Pure Inspiration Process

In the state of the art, the various phases in the product development process have already been addressed. Here in particular, it can be seen that the early phases are characterized by creative work, where the pure CAD benefit is rather low. In order to promote further ideas here and to search for possibilities for a potential design, supporting methods of artificial intelligence can be used here. Since it is not yet necessary to generate complete geometries that can be described analytically, it makes sense to use a polygon-based or voxel-based model. In the area of polygons, point clouds would be suitable here, since these cannot initially have any errors, since each point stands individually for itself. In the image processing area, we would be talking about pixels here. Voxel models offer the same properties here, but in three-dimensional space, and are therefore often referred to as 3D pixels. But here too, the absence of a single voxel exorbitantly disturbs the overall volume or representation. In the case of surface models, on the other hand, the absence of a surface leads to the fact that it is no longer possible to distinguish between inside and outside and thus no volume can be defined [REI19].

In the pure inspiration process, it is first important to differentiate which tasks the neural network should take over. It has already been shown that the VoxelNet (the network can be found at: https://github.com/dimatura/voxnet) provides a good tool to recognize geometries on a voxel basis. Training was done here with the ModelNet 10 / 40 dataset (https://modelnet.cs.princeton.edu), which is a freely available dataset with 10 and 40 classes, respectively. During the research, the network was used for two different types of classifications. This again depends on the data preparation which is exemplary shown in Figure 7. Since the training data requires a uniform input vector, the data must first be normalized for this purpose. Depending on the use case, two possibilities can be identified here. If only the geometries have to be recognized as such, for example that an airplane is an airplane, then it is sufficient to define a voxel space and to scale all geometries with their maximum dimension into it. However, for small classes of the data set, the details or features that precisely describe an object are omitted. If these are to be recognized

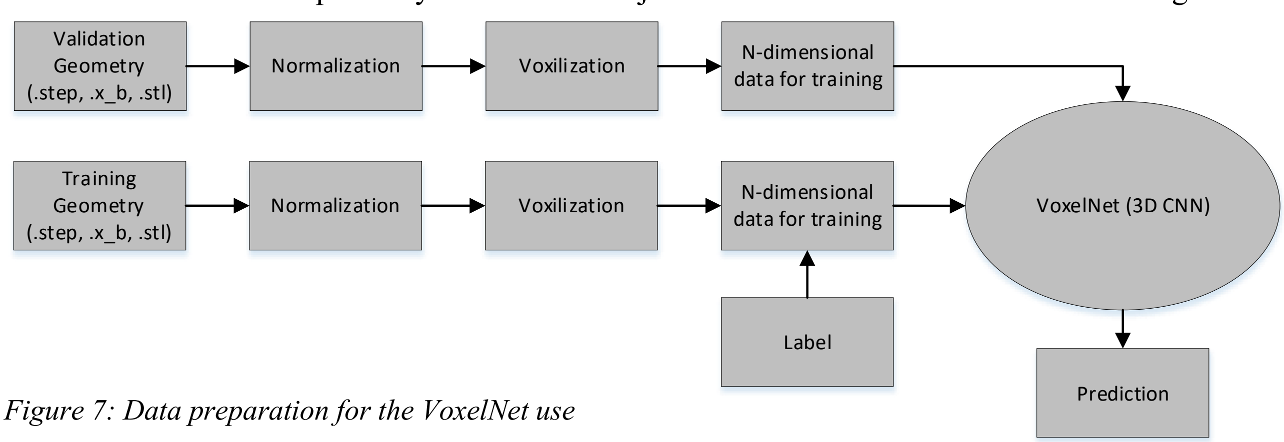

Figure 7: Data preparation for the VoxelNet use

however it offers itself to define the voxel space size in dependence of the geometry size. This makes it possible to recognize, for example, a two-engine or four-engine airplane or other features. Further input parameters are the labels of the individual data sets. Depending on the resolution of the voxel space, different sized batchsizes can then be chosen to train the mesh. We chose a 32x32x32 voxel space and a batch size of also 32. With this we achieved an accuracy in ModelNet 10 of 87% without any data augmentation, which is a very good reference value [MASC15].
In order to be able to use this principle for inspiration, further steps must be added. For this purpose, geometries must be generated automatically on the basis of certain properties or labels. This can be done very well with the "Generative Adversarial Networks (GAN)" explained in the basics. As already described above, these are able to generate geometries which are then classified as artificial or real by the network itself. Here, too, various networks have been selected within the scope of the work on the topic in order to be able to generate corresponding geometries automatically. Based on the classification of the modeling processes, care has been taken to include the two classes of polygon-based processes and digital sculpturing. The data preparation is to be equated here first with the procedure of the VoxelNet described before. Here it is to be paid attention only accordingly whether on voxel-basis or on point-basis one works. Accordingly, if necessary, the point of "voxilizing" must be replaced by "generating point clouds". In the voxel area, the DECOR-GAN (code available at: https://github.com/czq142857/DECOR-GAN) has been used here. This offers especially the possibility to generate exact features in geometrically similar elements. For example,

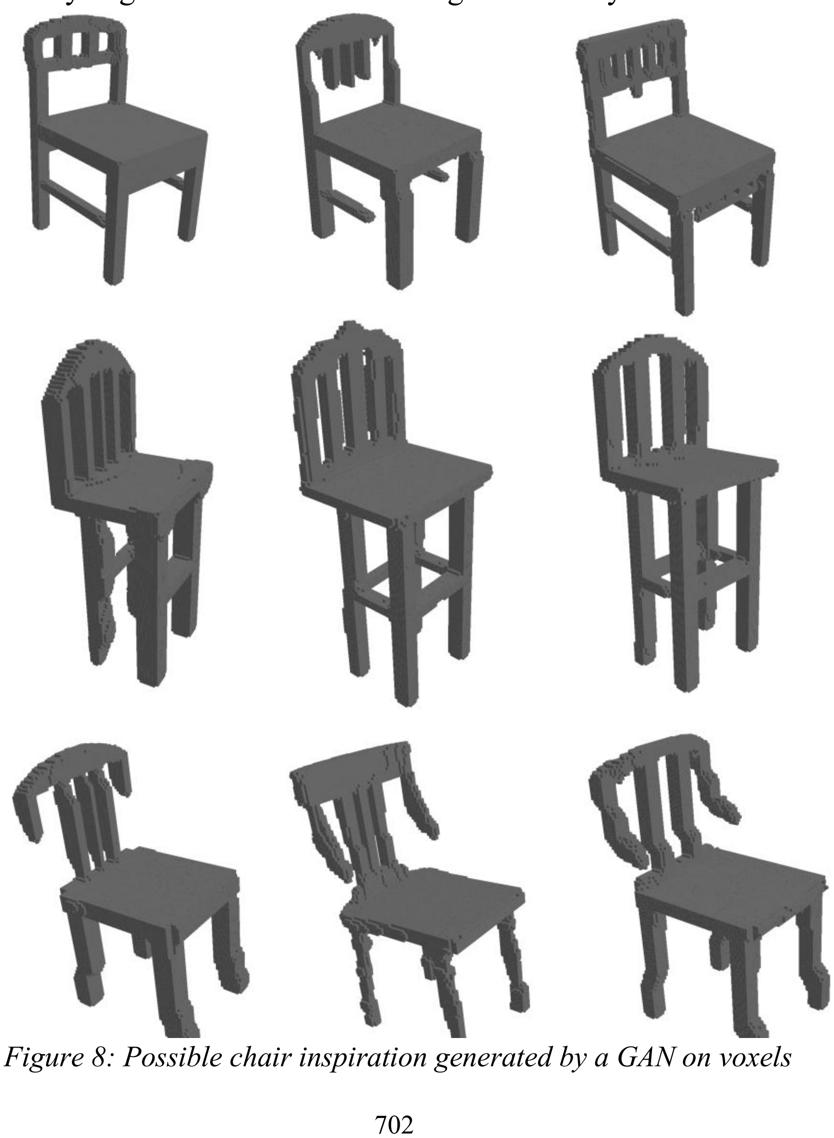

Figure 8: Possible chair inspiration generated by a GAN on voxels

if the class of the chair is considered from the dataset of the model net, a chair usually has some legs, a seat and a back. How exactly these are designed, however, is now to be determined in the design process. Various creativity methods can be used to remedy this situation. Alternatively, GANs can be used to accelerate these tasks. The figure 8 shows voxel-based chairs that have been classified as real objects by the network.

2) Prediction of mechanically stressed regions

A third neural network, which will be presented in this paper and has been applied in the work, is the DiffusionNet (code available at: https://github.com/nmwsharp/diffusion-net). It is based on the principle of natural distortion and manages to achieve extremely high accuracy in classification and segmentation independent of whether point clouds or polygon representations are used. Another positive aspect for the use of the network is the small number of samples needed to train because of its natural diffusion. In combination these two factors made the decision for using this network compared to others. In this paper, the segmentation was abstracted to generate stress predictions in components. For this purpose, the occurring stresses were first divided into classes and processed as a training set. With an accuracy of slightly over 93%, the stress predictions here are at a very good level for identifying any excess stresses. The training set here consisted of various simulations and stress values of a bracket optimized for additive manufacturing. In the figure, the left side shows the result from the simulation, while the right side shows the prediction of the mesh. In the prediction, even smaller edges can now be seen in the colored segmentation, which is due to the division of the stress values into certain classes (stress ranges). The more classes are defined here, the more exact the colored course becomes.

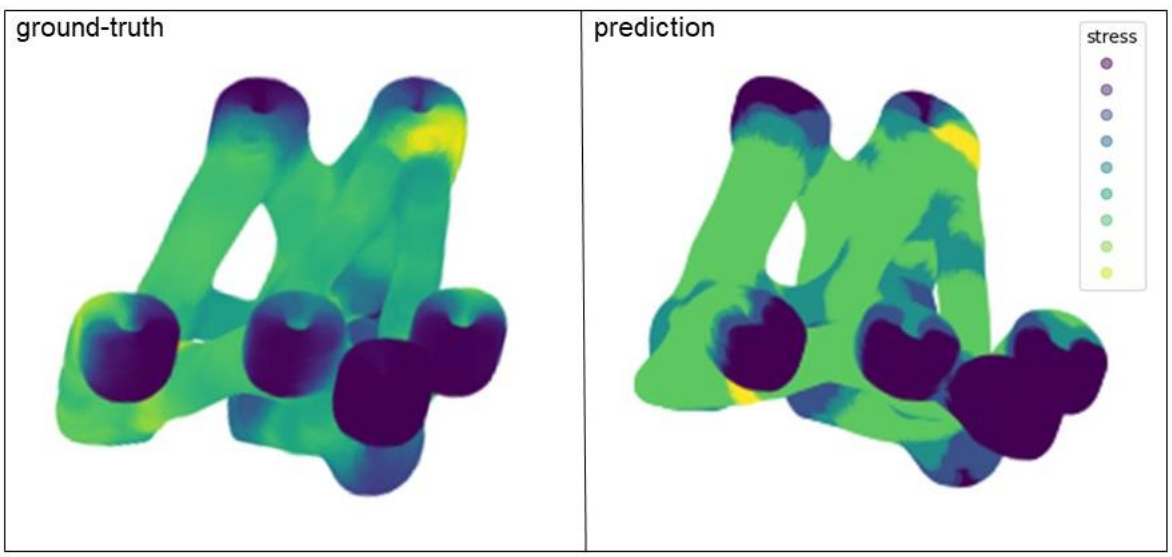

Figure 9: Left: Stress result from FEM ; Right: Stress Prediction from neural network

Impact and Summary

Along the elaboration, the main topics of additive manufacturing, time saving in development and the topics of artificial intelligence were addressed again and again. Especially the first partially automated possibilities of Generative Design try to make these goals usable with as little user experience as possible and extremely fast computational algorithms. However, similar to conventional topology optimizations, models must be built and calculated here as well, which in turn limits the time savings and thus the cost reduction per component. If the three neural networks presented and their functions highlighted in the paper are now considered in the context of the overall system, it is noticeable that there is a large overlap here if these functions can be coupled with each other. At this point it must be mentioned that this state is future work and right now just hypothetical.

In summary, the relationship described at the beginning of this paper between additive manufacturing and the benefits of artificial intelligence in the product development process can be assumed to be a direct causal relationship. It has been shown that the early phases of product development are characterized by work that has so far received little support from modern technologies, but which therefore requires a great deal of time, especially for small quantities, and this leads to high development costs. Individual solutions were shown, which can already be implemented with today's methods and that in combination of these possibilities there is a much greater potential, which must now be explored. Here, too, a potential solution approach for the further and profitable use of neural networks in the design process has been created, which should be used further, especially in combination with additive manufacturing. The production and development of a quantity of 1 is only possible efficiently if not only the production allows this, but also the costs for a product development can be reduced and this can be done by the increased computing power and excellent research work in the field of neural networks based on artificial intelligence.

References

[BEEF+97] Beitz, Wolfgang u. a.: „*Neue Wege zur Produktentwicklung*"; Stuttgart, Heidelberg: Raabe, 1997.

[BLFI05] Bletzinger, K.-U., Firl, M., Daoud, F.: "*Techniken der Formoptimierung*", Weimar: 2. Weimarer Optimierungs- und Statistiktage, 2005, http://www.dynardo.de/fileadmin/Material_Dynardo/bibliothek/WOST_2.0/WOST_2_Formoptimierung_De.pdf

[FELE18] Fey, Matthias; Lenssen, Jan Eric: *"SplineCNN: Fast Geometric Deep Learning with Continuous B-Spline Kernels"*, Salt Lake City: Conference on Computer Vision and Pattern Recognition, 2018

[KAR20] Karpathy, Andrej: *"AI for full-self-driving at Tesla";* California: Scaled Machine Learning Conference, 2020 https://www.youtube.com/watch?v=hx7BXih7zx8&feature=emb_logo

[LULI21] Luber, Stefan; Litzel, Nico: "Was ist ein Generative Adversarial Network (GAN)?", published 19.02.2021 on: https://www.bigdata-insider.de/was-ist-ein-generative-adversarial-network-gan-a-999817/

[MASC15] Maturana, Daniel; Scherer, Sebastian: *"VoxNet: A 3D Convolutional Neural Network for Real-Time Object Recognition"*, published in IROS, 2015.

[MAY96] May, Constantin: *"PPS mit neuronalen Netzen"*, Der deutsche Universitätsverlag, Gabler Verlag, Wiesbaden, 1996

[REI19] Reiher, Thomas: “*Intelligente Optimierung von Produktgeometrien für die additive Fertigung*”; Paderborn: Dissertation Universität Paderborn; Shaker Verlag GmbH, Düren, 2019

[REKO15] Reiher, Thomas; Koch, Rainer: *„FE-Optimization and data handling for Additive Manufacturing of structural parts”,* Austin: Solid Freeform Fabrication Symposium, 2015

[SHNA15] O’Shea, Keiron; Nash, Ryan :*“An Introduction to Convolutional Neural Networks”*, Salt Lake City: Conference on Computer Vision and Pattern Recognition, 2015

[SKBL06] Schmidt-Kretschmer, Michael; Gries, Bruno; Blessing, Lucienne: *“Bug or Feature? Möglichkeiten und Grenzen des Fehlermanagements in der Produktentwicklung”*; Neukirchen: 17. Symposium “Design for X”, 2006

[SZBE07] Szeghő, Krisztina; Bercsey, Tibor: *“Kosten- und Risikomanagement in der frühen Phase der Produktentwicklung”*; Neukirchen: 18. Symposium “Design for X”, 2007

[VDI2247] Verein Deutscher Ingenieure: *“Qualitätsmanagement in der Produktentwicklung”*, Beuth Verlag, 1994

[ZHCU20] Zhou, Jie; Cui, Ganqu: *“Graph neural networks: A review of methods and applications”*, published in AI Open 1 (2020) 57–81

[ZWE20] Zwettler, Monika: *“Was ist eigentlich das STL-Format?”*, Konstruktionspraxis 14.04.2020, https://www.konstruktionspraxis.vogel.de/was-ist-eigentlich-das-stl-format-a-921853/