Materials Research Proceedings 44 (2024) 511-518 https://doi.org/10.21741/9781644903254-55

A review of deep neuron network applications in extrusion die design

DING Jiangfeng[1,a *], CHEN Siyi[1,b], SHAO Zhutao[1,c], SHI Zhusheng[1,d] and LIN Jianguo[1,e]

[1]Imperial College London, Department of Mechanical Engineering, South Kensington, London SW7 2AZ, UK

[a]j.ding22@imperial.ac.uk, [b]siyi.chen18@imperial.ac.uk, [c]z.shao12@imperial.ac.uk, [d]zhusheng.shi@imperial.ac.uk, [e]jianguo.lin@imperial.ac.uk

Keywords: Metal Forming, Extrusion Die Design, Machine Learning, Neuron Network

Abstract. Ensuring the quality of extrusion product necessitates meticulous die design, typically achieved through simulation iterations and/or experimental trials. However, this process is not only time-consuming but also costly. Despite substantial research utilizing historical data and finite element analysis (FEA) to elucidate design guidelines and principles, and the existence of numerous empirical equations guiding die design, it remains more of an art reliant on the designer's experience. In contrast, Deep Neural Networks (DNNs) have the capability to capture design experience with appropriately defined inputs and outputs, transforming it into abstract features for further application. With the advancement of DNNs, the automatic generation of precise die designs has become achievable. Several research studies have been undertaken to enhance die design through the application of DNNs, particularly Convolutional Neural Networks (CNNs). CNNs, a machine learning method commonly applied to extract information from images, have been utilized due to the intricate nature of die design. Given the inherent characteristics of DNNs, a significant challenge in incorporating DNNs into die design lies in devising a scheme to abstract 3D die designs for defining inputs without loss of information. Various methods exist for handling 3D objects, such as point clouds or projecting 3D objects into 2D depth graphs. Nonetheless, most of these methods prove challenging to implement effectively in the realm of die design. Another challenge stems from the overall complexity of the extrusion die. While most research has focused on automatically designing specific features of the die, such as the location or shape of portholes, there have also been data-driven studies attempting to generate entire die designs using historical data. This paper aims to review the status of the application of DNNs in hot extrusion die design and explore the further potential in this field.

Introduction

Extrusion stands out as one of the most iconic metal forming techniques in modern industries, finding widespread applications in architecture, construction, display equipment, electrical systems, and various sectors of industrial and transportation fields [1]. This metal-forming process involves pushing a long cylindrical billet within a closed cavity through a die with the desired cross-section. The precision of the die is a critical factor influencing the quality of the final product. While other essential parameters like pressure and temperature play a role, die design emerges as the foremost consideration for ensuring product quality.

Currently, finite element analysis (FEA) remains the mainstream approach for die design. Once a die design is successfully simulated, experiments can be conducted, and adjustments to the die are made based on the results. However, this process involves several iterations, proving to be both time-consuming and costly. Despite extensive research leveraging historical data and FEA to establish design guidelines and principles, die design still relies heavily on the experience of the designer, making it more of an art than an analytical science.

In contrast, DNNs have shown promise in capturing design experience by translating it into abstract features for practical applications [2]. With advancements in DNNs, the automatic generation of precise die designs has become achievable. Numerous research studies have explored enhancing die design through the application of DNNs, with a particular focus on CNNs, a machine learning method commonly used for extracting information from images [3]. CNNs prove beneficial due to the intricate nature of die design.

Despite the potential advantages, incorporating DNNs into die design presents significant challenges. One major hurdle involves devising a scheme to abstract 3D die designs for defining inputs without losing information. While various methods exist for handling 3D objects, such as point clouds or projecting 3D objects into 2D depth graphs, effectively implementing them in the realm of die design has proven challenging. Additionally, the overall complexity of the extrusion die poses another challenge. Most research has concentrated on automatically designing specific features of the die, such as the location or shape of portholes [4]. Still, there have been data-driven studies attempting to generate entire die designs using historical data [5].

This article aims to review the current status of the application of DNNs in hot extrusion die design and explore their further potential in this field.

Die Design Challenges

The crux of a successful extrusion process lies in the intricacies of die design. While variables such as temperature and pressure also wield significant influence, these factors are often predetermined in practice. Achieving a straight final product or ensuring a uniform metal flow at a steady state necessitates the precision of die design.

Presently, the prevailing method for die design unfolds as follows: Designers begin by tailoring an initial design to the product's profile using empirical equations and expertise, sometimes adjusting from existing designs if applicable. They then employ FEA to test structural integrity, iterating if necessary. Validation through real-world experimentation follows, with any disparities prompting further refinement. Once the flow is achieved uniform at steady state, the design process concludes, readying the die for implementation.

The described method is notably laborious and time intensive, often stretching over months, particularly for inexperienced designers. Moreover, the execution of multiple sets of experiments adds to the overall costliness of this approach. The intricacies of die design give rise to a variety of guidelines and principles tailored to specific scenarios. However, many of these principles may conflict with each other, underscoring the experiential aspect of die design. Consequently, the quality of the final product is heavily reliant on the designer's experience and expertise.

The knowledge possessed by die designers is often subjective and lacks a systematic structure, leaning more towards intuition than analytical knowledge. For instance, study suggests that die designers commonly reduce the bearing length at the tip of a leg to between 50% and 75% of the bearing in the rest of the leg to account for the greater relative perimeter [6]. However, the exact percentage reduction is subjective and varies among designers. Designers often intuitively determine an optimal percentage based on their experiences with similar dies. Therefore, finding effective way to leverage this experiential knowledge to guide future designs would be invaluable.

Deep Neural Networks in Die Design

The continuous advancement of Deep Neural Networks (DNN) is shaping a significant shift in uncovering latent knowledge, while remaining grounded in academic principles. Essentially, DNN can be understood as a detailed approach using stochastic gradient descent (SGD) to minimize errors [7]. This method has earned DNN a reputation for its ability to uncover hidden features and simplify complex knowledge, leading to their widespread adoption across various industries. Particularly, it finds notable applications in areas like strain analysis and crack prediction [8].

Materials Research Proceedings 44 (2024) 511-518 https://doi.org/10.21741/9781644903254-55

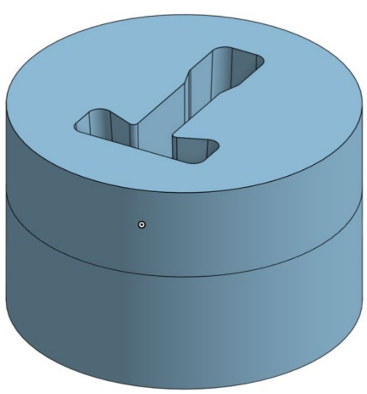
The burgeoning potential of DNN is especially conspicuous in the domain of metal forming. Pioneering contributions by Zhou et al. [9] in successfully developing a surrogate model for the hot stamping process and by Liu et al. [10] in effectively harnessing DNN in sheet metal forming, underscore the expanding utility and applicability of DNN methodologies across various facets of industrial practice.

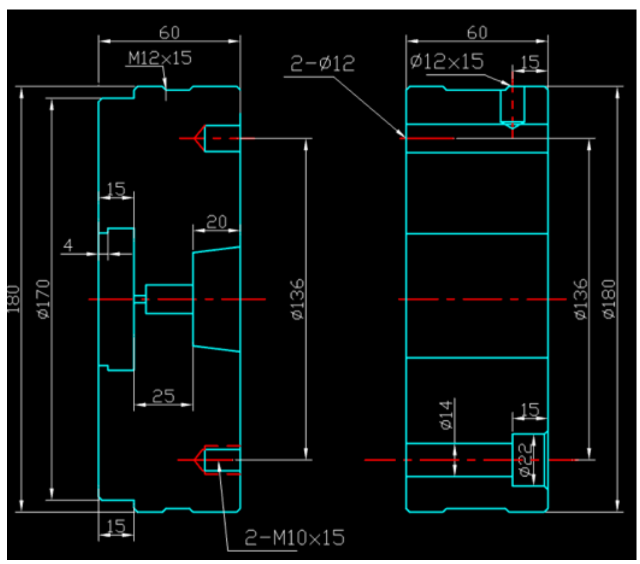
Considering the intrinsic nature of extrusion dies, where the product profile is represented as a 2D graph, the utilization of neural networks becomes imperative for handling graph-based data. Consequently, the CNN emerges as a pivotal player in contemporary automatic die design systems. Tailored for image processing, CNN employs filters and convolutional layers to autonomously learn hierarchical features, showcasing exceptional efficacy in tasks such as image recognition.

However, the integration of DNNs into the realm of extrusion die design introduces unique challenges. Unlike dies used for stamping or sheet metal forming, extrusion dies involve multiple parts, complicating efforts to simplify their intricate 3D properties into 2D or 1D representations. This intricacy necessitates further exploration and refinement in the seamless integration of DNN methodologies to address the distinct challenges posed by extrusion die design, a pivotal avenue for future research and advancement in the field.

Challenges in Incorporating DNNs into Die Design

Although DNNs hold significant potential in the field of extrusion die design, they face an inevitable challenge: digitization. To effectively utilize DNNs, all aspects of a die design must be captured and represented in a suitable format. Currently, there are two primary methods for extrusion die design: one method involves representing all information in a Multiview graph, while the other employs computer-aided design (CAD) techniques. Fig. 1a and 1b provide examples for both cases, respectively.





a) 3D representation of Die design b) Multiview representation of Die design

Fig. 1. Two different representations of die design.

There are two potential strategies for digitization 3D design emerge:

1. Finding an abstract representation of 3D design.
2. Finding a 3D representation that can capture most attributes.

While these strategies have been extensively studied, primarily not for the analysis of extrusion die design, they offer valuable insights into the digitization of CAD models.

Various methods exist to represent a 3D object as abstract vectors. For instance, Wu et al. [11] successfully translated CAD models into semi-natural language sequences (CAD sequences). They broke down the process of drawing a CAD model into step-by-step sequences, as illustrated in Fig. 2. This approach, based on the logic of the CAD platform Onshape, was first introduced by Willis et al. [12] in Fusion 360 Gallery. A CAD model is formed step by step through "sketch" followed by "extrude". By generating such sequences for a dataset, a transformer-based autoencoder is trained to capture the embedded abstract features of CAD designs, translating them into a 256*1 latent vector. Inspired by this work, Jobczyk and Homann [13] successfully created CAD models from multi-view images. The process involves generating CAD sequences, producing latent vectors using DeepCAD as ground truth, generating Multiview graphs from CAD models, and training a CNN-based DNN to return a 256*1 vector as output. This method has proven effective in generating CAD sequences (representing CAD models) from Multiview graphs.

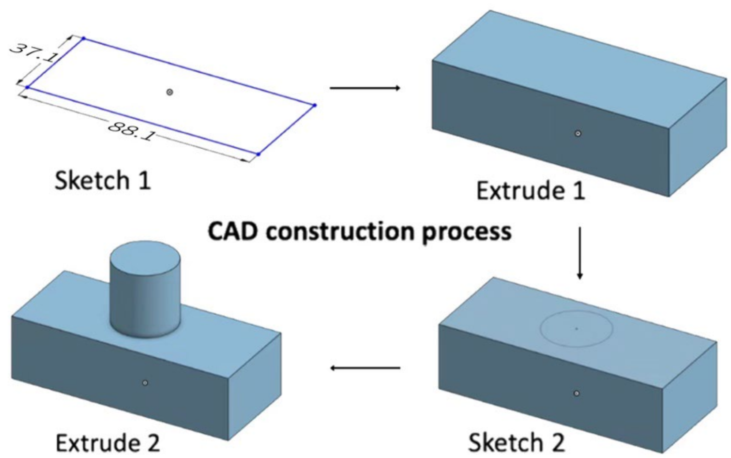


Fig. 2. The CAD construction process used in DeepCAD (unit: mm).

Medial axis transformation (MAT) is another technique employed in extrusion die design. The medial axis of an object refers to a set of points within the object, where each point serving as the center of a circle tangent to the object’s boundary at two nonadjacent points [14]. Prior to the emergence of DNN, MAT was applied in automatic extrusion die design, two representative product’s profiles are illustrated in Fig. 3. Lin [15] successfully utilized this method to analyze geometric aspects using MAT.

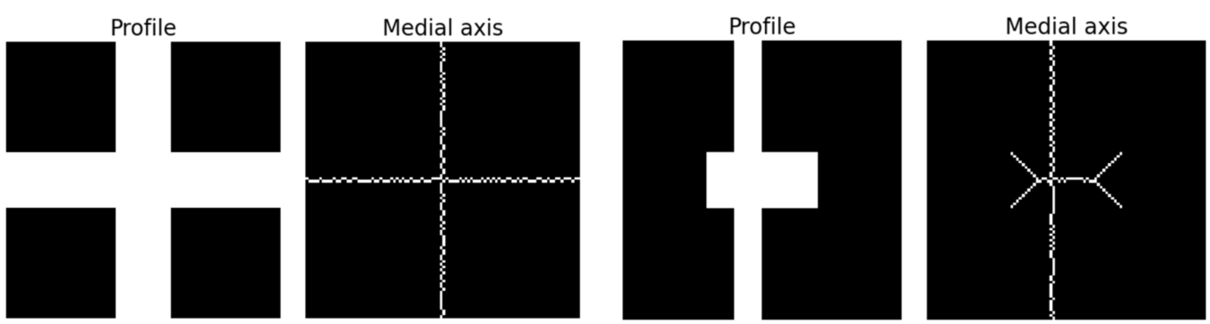


Fig. 3. MAT representation of different extrusion profile.

While MAT provides a valuable means of transforming the profile into a lower-dimensional representation, it does not offer a comprehensive solution for extrusion die design due to its limitation in addressing the entire 3D object. Despite this drawback, MAT has historically contributed to understanding and reasoning about certain geometric aspects relevant to extrusion die design.

An alternative widely employed approach involves sampling points across the entire 3D object, known as a point cloud. This method utilizes a collection of data points in a 3D coordinate system, where each point within the cloud signifies a specific spatial position, typically defined by its x, y, and z coordinates. In contrast to triangle meshes, point clouds do not necessitate the storage or maintenance of polygonal-mesh connectivity or topological consistency [16].

This method has demonstrated effectiveness in various studies; for instance, Lin et al. [17] utilized point clouds to represent 3D objects and train a surrogate model, a type of DNN designed to replace FEA in certain applications. Lin's approach proved capable of reconstructing 3D objects, however, achieving a more accurate representation often requires a substantial number of points, typically ranging from 2000 to 3000 for a solid representation. This quantity of points can be substantial as depicted in Fig. 4, leading to prolonged training times.

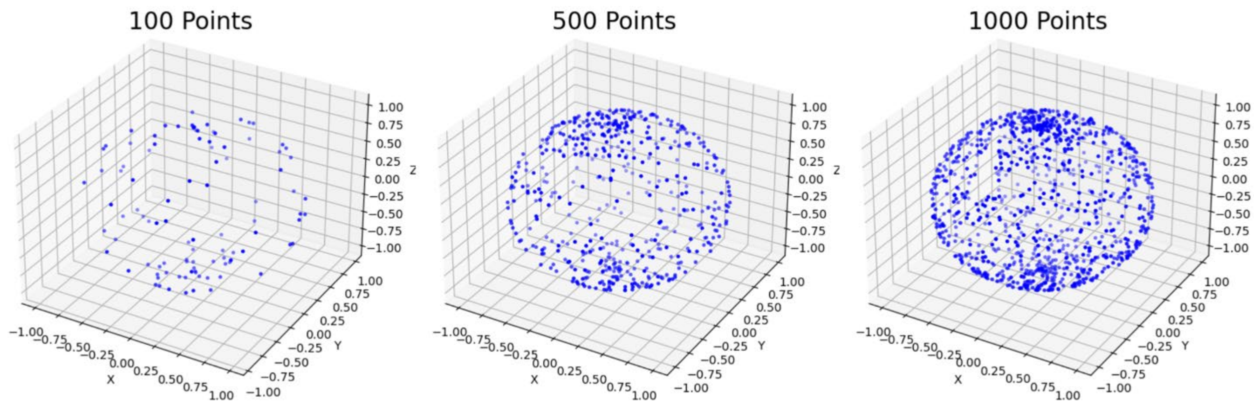


Fig. 4. Different number of points represent a same ball.

An alternative approach involves the use of 3D CNN to directly process 3D CAD data. Lee et al. [18] have employed this method to recognize features of 3D CAD models. While the results are promising in terms of feature recognition, it is noteworthy that existing literature predominantly focuses on classification and recognition tasks rather than generation using this method.

Status of DNNs in Hot Extrusion Die Design

Despite these aforementioned challenges, DNNs are beginning to make an impact in extrusion die design. However, owing to the regression-like attributes of DNNs, their current capability is primarily limited to providing predictions based on available data. Given the precision requirements of die design, existing literature offers guidance for specific parts of the die or provides a preliminary design for further refinement.

Llorca-Schenk et al. (2023) successfully analyzed the geometry of ports, including parameters such as port area, port perimeter, and die center to port center distance, utilizing various machine learning methods. Some variables they used to decompose a port is shown in Fig. 5. However, this analysis relied on a substantial amount of data from successfully designed porthole dies, specifically those made of H13 hot work steel with aluminum alloy 6063 billet material, which can be hard to collect.

Zangara et al. [19] decomposed critical attributes of extrusion die design into 12 parameters for digitization, e.g., Pocket width is called Rpc, Bridge length is called Hbr. The whole die is then parametrized with such decomposition and then can be used for training. Authors analyzed the correlations among these parameters using a support vector machine (SVM).

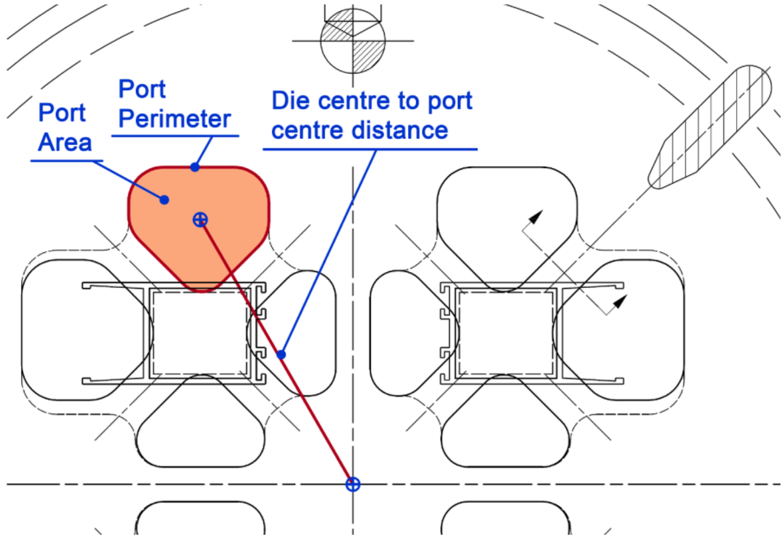


Fig. 5. Variables that been used to describe a porthole die [4].

In contrast to previous studies that focused predominantly on specific parts (ports) or aimed to assist in die design, Yu et al. (2023) successfully employed DNNs to design entire extrusion dies. By analyzing a large number of successful die designs and incorporating prior analytical studies on porthole die design, they identified porthole geometries and bearing length as the most crucial parameters. Porthole geometries were categorized based on shape and the number of portholes. For bearing length, an empirical equation with several constants was employed, with the values of these constants varying with changes in the profile's geometries. Different scenarios were categorized, and CNN was used to detect and locate them, reporting a set of constants. Bearing length was then calculated using these constants. Although numerous parameters require consideration, their results provide a robust outcome at steady state, demonstrating the effectiveness of their DNN-based approach in designing entire extrusion dies.

Potential of DNNs in Hot Extrusion Die Design

Incorporating DNNs into die design poses significant challenges, since emulating the expertise of experienced designers demands a substantial dataset of successful die designs for supervised learning. Yet, the intricacies of die design, considered a company's proprietary knowledge, hinder the collection of such data. Compounded by the messy nature of industrial data, primarily tailored for in-house understanding, the lack of a standardized approach across the industry further complicates the process. Consequently, the current study is constrained to specific die features or a narrow profile range due to these limitations.

The prospect of constructing a large-scale neural network akin to ChatGPT for die design becomes feasible if a standardization effort succeeds. However, establishing such a standard proves challenging. An alternative approach involves exploring semi-unsupervised learning, akin to control theory or reinforcement learning with feedback. While this method requires FEA to provide feedback, potentially time-consuming in practice, the application of surrogate models presents a viable solution to meet time constraints. Attar et al. [20] has successfully developed an automated platform for stamping die design. This approach acknowledges the intricate nature of die design while leveraging DNNs for improved automation and innovation.

Summary

Until now, extrusion die design has retained its status as more of an art form, relying heavily on designers' experience to create initial editions. Subsequent iterations involve the use of FEA and experiments to test design solidity, a process notorious for its time and cost intensiveness. Despite meeting analytical standards, designs frequently fall short of delivering robust results.

In efforts to mitigate design costs, DNNs are increasingly adapted in the realm of die design. Presently, studies predominantly concentrate on optimizing specific die components, such as porthole positioning or geometry, and bearing length design. Some endeavors even attempt to holistically design the entire die by segmenting it into models, selected based on product profiles.

However, integrating DNNs into extrusion die design encounters numerous challenges. The intricate nature of extrusion dies, comprising multiple complex parts, complicates the acquisition of concise parameterizations encompassing all geometric information for intricate 3D objects. Therefore, devising methods to digitize die designs for training purposes becomes imperative. Additionally, training DNNs necessitates vast quantities of consistent data, a hurdle exacerbated by the customized nature of die designs, often tailored for in-house comprehension. The establishment of a standard for extrusion die design could facilitate the creation of a comprehensive database for training purposes.

References

[1] Metal Extrusion - Engineering Ideas Clinic - Confluence. (n.d.). Uwaterloo.atlassian.net. Retrieved December 3, 2023, from https://uwaterloo.atlassian.net/wiki/spaces/EIC/pages/31727390596/Metal+Extrusion#handytip-7517022545358001

[2] J. Heaton, I. Goodfellow, Y. Bengio, A. Courville, Deep learning, Genet Program Evolvable Mach. 19 (2018) 305-307. https://doi.org/10.1007/s10710-017-9314-z

[3] Z. Li, F. Liu, W. Yang, S. Peng, J. Zhou, A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects, IEEE T. Neur. Net. Lear. 33 (2022) 6999-7019. https://doi.org/10.1109/TNNLS.2021.3084827

[4] J. Llorca-Schenk, J.R. Rico-Juan, M. Sanchez-Lozano, Designing porthole aluminium extrusion dies on the basis of eXplainable Artificial Intelligence, Expert Syst. Appl. 222 (2023) 119808. https://doi.org/10.1016/j.eswa.2023.119808

[5] Y.B. Yu, Y.R. Lai, Q.C. Hsu, T.T. Truong, Deep Convolutional Neural Network to Assist Die Design for Flow Balance of Aluminum Hollow Extrusion, in: K. Mocellin, P.O. Bouchard, R. Bigot, T. Balan (Eds.), Proceedings of the 14th International Conference on the Technology of Plasticity - Current Trends in the Technology of Plasticity, ICTP 2023, Lecture Notes in Mechanical Engineering (2024). https://doi.org/10.1007/978-3-031-42093-1_7

[6] N. Miles, G. Evans, A. Middleditch, Bearing lengths for extrusion dies: rationale, current practice and requirements for automation, J. Mater. Process. Tech. 72 (1997) 162-176. https://doi.org/10.1016/S0924-0136(97)00150-7

[7] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436-444. https://doi.org/10.1038/nature14539

[8] N.S. Gulgec, M. Takáč, S.N. Pakzad, Structural sensing with deep learning: Strain estimation from acceleration data for fatigue assessment, Comput.-Aided Civ. Infrastruct. Eng. 35 (2020) 1349-1364. https://doi.org/10.1111/mice.12565

[9] H. Zhou, Q. Xu, Z. Nie, N. Li, A study on using image-based machine learning methods to develop surrogate models of stamp forming simulations, J. Manuf. Sci. Eng. 144 (2022) 021012. https://doi.org/10.1115/1.4051604

[10] S. Liu, Z. Shi, J. Lin, Z. Li, Reinforcement learning in free-form stamping of sheet-metals, Procedia Manuf. 50 (2020) 444-449. https://doi.org/10.1016/j.promfg.2020.08.081

[11] R. Wu, C. Xiao, C. Zheng, DeepCAD: A deep generative network for computer-aided design models, in: Proceedings of the IEEE/CVF International Conference on Computer Vision (2021) 6772-6782. https://doi.org/10.48550/arXiv.2105.09492

[12] K.D.D. Willis, Y. Pu, J. Luo, H. Chu, T. Du, J.G. Lambourne, A. Solar-Lezama, W. Matusik, Fusion 360 gallery: A dataset and environment for programmatic CAD construction from human design sequences, ACM Transactions on Graphics 40 (2021) 1-24. https://doi.org/10.48550/arXiv.2010.02392

[13] H. Jobczyk, H. Homann, Automatic Reverse Engineering: Creating Computer-Aided Design (CAD) Models from Multi-view Images, in: U. Köthe, U., Rother, C. (eds.) Pattern Recognition, DAGM GCPR 2023, Lect. Notes Comput. Sc. 14264 (2024). https://doi.org/10.1007/978-3-031-54605-1_16

[14] H.I. Choi, S.W. Choi, H.P. Moon, Mathematical theory of medial axis transform, Pacific J. Math. 181 (1997) 57-88. https://msp.org/pjm/1997/181-1/p02.xhtml

[15] C. Lin, Optimal design of aluminium extrusion dies using a novel geometry based approach, Swansea University (2005). https://cronfa.swan.ac.uk/Record/cronfa42734

[16] X.F. Han, J.S. Jin, M.J. Wang, W. Jiang, L. Gao, L. Xiao, A review of algorithms for filtering the 3D point cloud, Signal Process. Image Commun. 57 (2017) 103-112. https://doi.org/10.1016/j.image.2017.05.009

[17] C.H. Lin, C. Kong, S. Lucey, Learning efficient point cloud generation for dense 3D object reconstruction, in: Proceedings of the AAAI Conference on Artificial Intelligence 32 (2018). https://doi.org/10.48550/arXiv.1706.07036

[18] J. Lee, H. Lee, D. Mun, 3D convolutional neural network for machining feature recognition with gradient-based visual explanations from 3D CAD models, Sci. Rep. 12 (2022) 14864. https://doi.org/10.1038/s41598-022-19212-6

[19] G. Zangara, F. Gagliardi, L. Filice, G. Ambrogio, A Coupled Approach Based on Statistical Methods and Machine Learning Techniques to Improve Porthole Die Design, in: K. Mocellin, P.O. Bouchard, R. Bigot, T. Balan (Eds.), Proceedings of the 14th International Conference on the Technology of Plasticity - Current Trends in the Technology of Plasticity, ICTP 2023, Lecture Notes in Mechanical Engineering (2024). https://doi.org/10.1007/978-3-031-42093-1_6

[20] H.R. Attar, H. Zhou, A. Foster, N. Li, Rapid feasibility assessment of components to be formed through hot stamping: A deep learning approach, J. Manuf. Process. 68 (2021) 1650-1671. https://doi.org/10.48550/arXiv.2104.13199