Application of Deep Learning for Design Optimization in Additive Manufacturing Process

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***Abstract*— Additive Manufacturing (AM) is an advanced fabrication technique that uses computerised three dimensional design information to construct components by accumulating textures chronologically. Due to " their achievement in constructing complex and difficult design concepts, rapid prototype testing, and reduced-volume or one-of-a-kind manufacturing throughout many industry sectors, AM methodologies are becoming much more popular comparison to traditional initiatives. Computational simulations are indeed an important part of AM design and optimization because they completely remove costly manufacturing process trial and error. This motivates the development of a predictive tool based on machine learning (ML) that can produce simulation results instantly rather than requiring expensive physics-based simulations.**

***Index Terms:* Additive Manufacturing, machine learning, Topology Optimization, Compliance, Density Distribution.**

I.INTRODUCTION

Information computer-aided design (CAD) technology or 3-Dimensional object screeners are used to guide hardware equipment to accumulate material in accurate geometric patterns, layer by layer. Additive manufacturing, as the names suggest, involves adding material to an entity to develop it. When creating an object using traditional methods, however, it is frequently required to eliminate material via milling, machine tools, carving, forming, or other methods.

Even though the concepts "3-Dimensional printing" as well as "quick prototyping" are often used interchangeably to refer to additive manufacturing, so every procedure is a subcategory of additive manufacturing. Whereas additive manufacturing may appear to be innovative to some, it has been there for decades. Additive manufacturing can distribute an excellent trifecta of enhanced quality, complex structures, and greatly simplified complete fabrication in the correct implementations. As a result, those who actively embrace additive manufacturing will have a plethora of opportunities.

Additive manufacturing enables the generation of items with accurate geometric patterns employing computer-aided design (CAD) or 3-Dimensional object scanners. In compared to conventional manufacturing, that also frequently necessitates material removal or other methodologies to eliminate surplus content, these would be constructed layer by layer, as in a 3-Dimensional printing procedure.

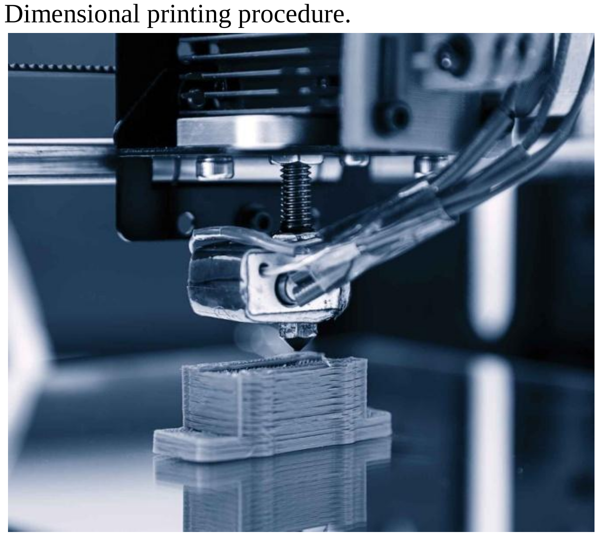

Figure 1 Additive Manufacturing

Three types of AM techniques can be distinguished. The initial is sintering, that also involves heating the material excluding liquifying it in order to generate complicated elevated objects. Selective laser sintering uses technology to stick thermoset powders together here, so although straightforward metal laser sintering utilises metal powder. The 2nd AM technique completely melts the materials, such as direct metal laser metal sintering, that also utilises a laser to melt layers of powder metallurgy, as well as electron beam melting, that also melts the powders using beam of electrons.Stereolithography is the 3rd broad sort of technological advances, that also employs a technique known as photopolymerization, wherein an ultraviolet laser is shot into a vat of photopolymer resin to generate torque-resistant ceramic components that can withstand temperature extremes.

Throughout additive manufacturing (AM) investigation, machine learning (ML), a subcategory of artificial intelligence (AI), is becoming incredibly common. Machine learning is characterized as programming language that uses instance data or previous experience to optimise a performance requirement. 3 Aside from the traditional implementation of making a prediction across data convenient, the scientific community is investigating novel approaches to incorporate Machine Learning and Artificial Intelligence methods into additive manufacturing. AM professionals are using machine learning algorithms, implementations, and systems to develop the product, optimise manufacturing techniques, and reduce spending.

The Machine Learning models information that can be provided from the training dataset and draw assumptions regarding the knowledge with a reliable training data. On the one side, trained machine learning techniques can quickly make a prediction and evaluate the best process conditions. On the other side, they can work with in-situ data for actual detecting defects. In current papers, several other Machine Learning implementations, including geometric deviation regulation, cost analysis, and assessment processes, have been revealed. In overall, machine learning implementations can be thought of as a form of manipulating data.

Additive Manufacturing has a significant benefit as the company moves forward into automated processes, interconnected information exchange, and robotics. No other manufacturing technique has indeed been built from the ground up to allow intercommunication; Additive Manufacturing machines already produce more constructed information than just about any other production technological advances. This information, if correctly was using, will lay the groundwork for the advancement of Machine Learning techniques that can enhance and modernise the Additive Manufacturing process at well almost every step of the process.

Because additive manufacturing was born with the world wide web, it always had access to connecting with people that its manufacturing counterparts did not. Because AM is a digital procedure, a construction can start generating terabytes of data. The value of additive manufacturing is found in the creation of performance-optimized elements that can only be produced using AM new tech. Additive Manufacturing contributes to the reduction of arrangement and, with it, touch labourers by allowing elements that would normally be made up of numerous sections to be generated in one piece.

This information or digital input could then be utilized to optimise the physical outcome using Artificial Intelligence (AI) as well as Machine Learning (ML). We believe that this equates to enhanced yields, better return, and the capacity to close the quality assurance loop rather than depending on expensive "afterwards the fact" investigation procedures.

MACHINE LEARNING

Machine learning is the process of machines learning from information, expertise, and communication. This is made possible by the able to manage huge quantities of information with advanced computing capabilities. Things get genuinely intriguing once we add the ability to utilize expertise and communication among sets of data or behaviour and implications. As we have transitioned from analog - to - digital processes, data is now all around us. This information could be health-related, weather-related, or, in our case, build achievement, verification, and dynamic mechanical information.

There are four broad types of learning :

Supervised Learning

Algorithms attempt to model the dependency relationships among the predicted source and destination combinations. The output value is matched with the labelled input (e.g., a vector) (e.g., a signal). The advantage is which we can anticipate an outcome with new information although we've built a relationship that allows us to forecast the outcome in previously unknown situations.

Unsupervised Learning

Trend identification and explanatory model - based algorithms are trained. Because the information has no labels, the model can only train on the original data. Constituent and cluster assessment, that what group unlabeled data and take a glance for similarity, are two methods that can be used in this methodology.

Semi-supervised Learning

Algorithms are a combination of the two. Occasionally, while not always, all of the data is labelled. Because extensive and comprehensive labelling of the data would be impossible, the model is constructed in this form, recognising that some interactions are recognised (labelled), but leaving others unknown. Even if the data isn't labelled, it still contains valuable information about just the collective.

Reinforcement Learning

Iteration allows techniques to learn from their surroundings. The computer becomes cleverer evey time it is presented with a risk vs reward proposal by employing observational data from interactions with nature. The algorithm applies generally to a game in this case, in which the aim is to win, however the environment induces the encounter to shift over time in an almost infinite amount pairings.

Although machine learning is already used in the advancement of AM products, the implementations have yet to be fully implemented. We're noticing data from conventional sources, as well as high - dimensional information, that recommends methodologies that can alert users to opportunities to improve. ML is now firmly a factor in the expansion of Additive Manufacturing, from powder feedstocks to advanced materials, through into the AM computer system in the form of variables, and finally with sections. Pictures, compounds, sensor data, mechanical characteristics data, and volumetric details, including such computerized tomography, could be used as data inputs for the types of learning (CT). Finally, we could indeed anticipate an output by combining volumetric data with characteristic qualitative statistics.

II.LITERATURE REVIEW

(Liu et al., 2021) [2] Introducing new metals The use of 3-Dimensional printers wants to introduce time and expense barriers to having to print parts of the same reliability as those produced by conventional printers. For property forecasting and process optimization, a significant number of trial-and-error experimentations or computation - intensive simulation models are usually needed. Machine learning (ML), on the other hand, has the potential to speed up the implementation of innovative printing machines. It should, in particular, allow prior knowledge built up from existing data to be transferred to the new printer, actually results in a data-informed starting place that is pretty close than it would be feasible. This research proposed a data-mining-assisted ML information sharing structure to allow the reusability of previous learning.Bayesian reputation as a leading support vector machine as well as logistic regression models in terms of modelling procedure relationships. Three "industry-use" situations for laser powder bed fusion of Ti-6Al-4V are used to validate this structure: 1) switching to a new setup printer from the very same manufacturing company that utilises technology similar, 2) switching to a new printer model from a different supplier that uses technology similar, and 3) switching to a new setup printer from a variety of manufacturers that uses different advanced technologies. Experimental studies with multi-property optimization show that cross-machine sharing knowledge can help accelerate the implementation of innovative metals AM printing machines.

(Xia et al., 2021) [3] WAAM has demonstrated to be an effective option for fabricating medium and large-scale metal components with an elevated deposition process rate and mechanization level. Moreover, because of the poor surface integrity of the substrate material, the production value may suffer. A surface morphology trying to measure methodology based on a laser sensor was established for WAAM in this manuscript. Various machine learning designs, such as ANFIS, ELM, and SVR, were proposed to predict surface quality to enhance the exterior authenticity of deposited films by WAAM. Moreover, GA as well as PSO algorithms were used to optimize the ANFIS prototype.To acquire the data for training, factorial design experiments were done, and the K-fold Cross-validation approach was used to train and test machine learning algorithm. The performance comparison show that GA–ANFIS is able to forecast surface quality. For GA–ANFIS, the RMSE, R2, MAE, and MAPE were 0.0694, 0.93516, 0.0574, and 14.15 percent, respectively. This research could also serve as a starting point and guidelines for multipass arc welding and cladding surface texture model construction.

(Q. Zhu et al., 2021) [4] This is the initial implementation of physics-informed deep learning to three-dimensional AM process modelling that the authors are aware of. Furthermore, we propose a Heaviside function-based hard-type approach for Dirichlet boundary conditions (BCs), that also can not only precisely implement the BCs but also speed up the training process. The 2018 NIST AM-Benchmark test match is used to apply the PINN structure to two typical metal manufacturing issues. Using a finite element relying finite difference multi-scale methodology method, researchers thoughtfully analyse the effectiveness of the PINN model and compare prognostications with available experimental data with high numerical simulations.The findings show that, thanks to the added physiological understanding, the PINN can effectively forecast thermal and melt pool dynamic behavior during metal AM procedures with only a small number of labelled data sets. The implementation of PINN to metal Additive Manufacturing demonstrates the vast potential of quantum theory deep learning in high tech manufacturing.

(Snow et al., 2021) [5] Process control in additive manufacturing could allow elements to be accredited more cheaply and quickly, as well as enable deficiencies to be repaired if they are discovered. Using labelled XCT data as an underlying data, neural networks (NNs) as well as convolutional neural networks (CNNs) are programmed to find weaknesses in layerwise pictures of a construction. With different lighting conditions, multiple images were captured it after every layer sometimes during powdercoating. For training and validation, categorization networks were provided a single image or picture elements of different lighting conditions. Among all tasks, CNNs outperformed NNs significantly. When CNNs trained on high-resolution layerwise images from one build were applied to data from another build, their performance deteriorated significantly, whereas the NNs' performance deteriorated substantially.

(R. Li et al., 2021) [6] This research suggested a technique for detecting geometric deficiencies in additively manufactured objects based on Machine Learning (ML) models. The machine learning models are given training with synthetic 3-dimensional point clouds containing defects before being used to detect defects in real-world production. Using synthesised 3-Dimensional point clouds instead of empirical studies can save a deal of time and resources in terms of training time and expense for every design. This arrangement uses a new concept known "patch" to encapsulate macro-level data regarding nearby points for ML implementation and execution, in relation to personal point range distinctions among source and target point clouds.The suggested methodology significantly outperforms the established Z-difference method in the literature in regarded in terms of model performance on exploratory data from different forms. Under variable circumstances, such as completely different angle cloud density values and defect sizes, five machine learning methods (Bagging of Trees, Gradient Boosting, Random Forest, K-nearest Neighbors, and Linear Supported Vector Machine) were especially in comparison. The best two models in terms of consistency were ended up finding to be Bagging and Random Forest, and the correct patch size was discovered to be 20. With the help of an appropriate 3D data acquisition system, the suggested Machine Learning -based arrangement can be used to detect in-situ defects during additive manufacturing.

(C. Wang et al., 2020) [7] Machine learning (ML) has gotten a lot of attention in the last few years because of its amazing performance in data tasks like categorization, stagnation, and clustering. This article provides a comprehensive overview of the state-of-the-art in machine learning applications across a wide range of AM domains. ML can be used to introduce additional elevated metamaterials and optimised topological design ideas in the DfAM. In AM computation, modern ML algorithms can aid in the optimization of process parameters, the investigation of powder spreading, and the able to monitor of in-process defects. ML can assist practitioners in pre-manufacturing planning, as well as merchandise quality evaluation and control, when it comes to AM manufacturing.

(Meng et al., 2020) [8] The most important advancements of machine learning (ML) in the additive manufacturing (AM) ground are evaluated in this review paper. These implementations, including such parameterization and outlier detection, are categorised as regression, categorization, and cluster analysis tasks, among others. In these kinds of AM tasks, the performance of different ML algorithms is assessed and compared. Eventually, several approaches and methods are suggested for the future.

(Qi et al., 2019) [9] Owing to the peculiar benefits it has over conventional subtractive manufacturing, additive manufacturing (AM), also recognised as three-dimensional printing, is drawing significant interest from academic and industrial. AM operating parameters, on the other hand, are difficult to optimize because they have such a significant impact on the printed microstructure and the effectiveness of successive products. Building a process–structure–property–performance (PSPP) connection for AM using conventional statistical and econometric models is a challenging task.Machine learning (ML) has been shown to be a valid process of performing complicated acknowledgement and regression assessment without the requirement to explicitly create and address the underlying computer model. Because of the huge dataset presently offered, strong computing capabilities, and advanced algorithm architectural style, the neural network (NN) is the most widespread utilised ML methodology. The advancement of implementing the NN algorithm to different aspects of the AM whole chain, which include model design, in situ measurement, and performance evaluation, is discussed in this paper. The number of challenges in implementing NNs to AM, as well as potential solutions, are then discussed.

(Baumann et al., 2018) [10] The impact and implementation of machine learning (ML) to the realm of Additive Manufacturing, also known as 3D printing, is examined in this paper. A literature search identifies available studies and groups it according to its application in 3D printing. Researchers discuss this research as well as the impact of machine learning (ML), deep learning, as well as other particularly affects learning techniques on additive manufacturing (AM) and its potential direction and incorporate, including such cloud industrialization 4.0. The use of machine learning to help solve a variety of Additive Manufacturing problems is mentioned, including process control, performance monitoring, and improving the quality of manufactured objects.

(Jiang et al., 2020) [11] Configuration for additive manufacturing (AM) has been considered as a means of enhancing work efficiency and reducing costs. The majority of contemporary AM approaches that rely on surrogacy arrangement models. Machine learning (ML) has been widely used in clinical diagnosis, image recognition, prediction, categorization, and having to learn connection, among other things, as a result of the increasing availability of data. Machine learning has also been used to find the optimum of AM with corresponding objectives in a number of studies. This paper proposes a machine learning (ML) integration framework for AM system that allows benefit of ML's ability to learn complicated relationships among implementation and quality spaces.

III.METHODOLOGY

In this research following problems are identified:

In design for additive manufacturing: Designing metamaterials manually is very challenging and exhaustive. This is due to the wide possibility of combinations. With the aid of the contemporary ML techniques, the discovery process of metamaterials can be significantly expedited.

In topology optimization: It is a systematic method that generates structures by optimizing the material distribution within a given design space subject to specific loads and constraints. Typically, conventional To process may require numerous iterations of design and prototyping and is thus computationally demanding particularly for large-scale, complicated structures.

In process parameter optimization: The design of experiment approach usually involves trial-and-error, which is time-consuming and costly.

The goal of this article is to suggest a machine learning technique for additive manufacturing design and optimization. Procedures would be as follows: Preparedness of the dataset: Trying to solve time-dependent heat equations as well as designed to simulate the manufacturing operations at the part scale would be used to create the training set. It calculates temperature and heat flux for each time step of the AM procedure for each component generated.

The steps of working would be as following:

Dataset preparation: The training dataset would be prepared by solving time-dependent equations and simulating the topology optimization of additive manufacturing process. It provides density and material distribution for every time step for every element that is created during the AM process.

Feature set preparation: There are many features that impact the material distributionof a given sample.

Learning Process: The feature set extracted in above step is used to train the deep learning model for design optimization of sample. After design optimization, the model also predicts its behaviour along with properties and also suggests that where this sample is suitable to implement.

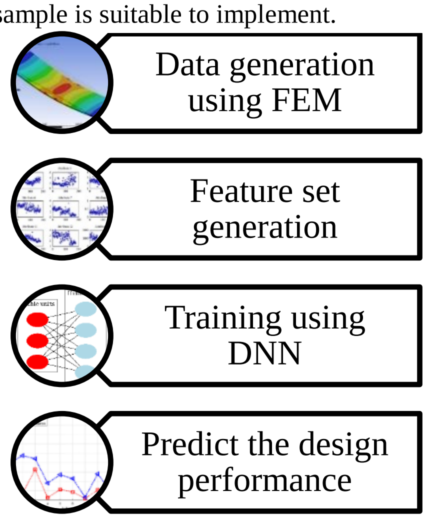

Figure 2: Deep Neural network model for topology optimization in AM

The simulation of 3D printing uses the finite element method where the complete simulation has two stages the printing and the subsequent stage. The printing is done on a base layer that activates the new layer of elements where distortions and thermal shrinkage are prescribed and calculated. The release stage releases suppressed degrees of freedom and the residual stresses cause additional distortions.

Additive manufacturing simulation by finite element method

The degree of freedom nodes connected to the base plate a0 are totally suppressed. At step i-1 the set of degree of freedom is given as.

$a(x-1) = (a^T{}_0, a^T{}_1, a^T{}_2, \ldots, a^T{}_{i-1})^T$

Where a is the displacement degrees of freedom. Now the newly activated row ai is added to the current set of degrees of freedom. The discretized finite element equation is given as.

$$L(i)\Delta a(i) = c(i)$$

Where Δa (i) is the displacement increment calculated for step i where

$$L(i) = \int_{zi} K^T BKyZ$$

$$M(i) = -\int_{zi} K^T \mathrm{B}\, \varepsilon_{inh} \mathrm{KyZ}$$

where Z (i) is the current deposited volume, B is the isotropic elastic material matrix, K evaluates strains from nodal displacements and ε_{inh} is the inherent strains vector. The value of inherent strains may either be assumed as

$$\varepsilon_{inh} = \delta\Delta t$$

Where δ is the thermal expansion tensor. Δt is the temperature change.

The freedom degree $\Delta a0$ is eliminated from the system. The set of freedom degree is divided into suppressed order $\Delta a0$ which can be determined as

$$\Delta a_m^{(i)} = [\Delta a_1^t, \ldots\ldots, \Delta a_i^t]t$$

$$\begin{bmatrix} L_{00} & L_{0m} \\ L_{m0} & L_{mm} \end{bmatrix}^{(i)} \begin{Bmatrix} 0 \\ \Delta a_m \end{Bmatrix}^{(i)} = \begin{Bmatrix} \Delta p_0 \\ M_m \end{Bmatrix}^{(i)}$$

Where p_0 is the react force which is required to track for which submatrix L_{m0}must be used which can be calculated as

$$p_0^{(i)} = p_0^{(i-1)} + L_{0m}^{(i)} \Delta a_m^{(i)}$$

Here $\Delta a_m^{(i)}$ has a different size for every step $(i) L_{0m}^{(i)}$ is the inspection matrix which sows it contains non zero terms connected with freedom degree of $\Delta a_m^{(i)}$and the size of $L_{0m}^{(i)}$ does not change per step. As resulting from the inherent strains in equation (4) that acts on suppressed degrees. The total displacements of nodes as in reduction of added sheets up to sheet $i(i \geq x)$

where x is the no. of rows that can be calculated as

$$a(i)x = \sum_{L=x}^{i} \Delta a_x^{(l)}$$

At each step a geometrically linear analysis is performed.

Distortion after release from the base plate

After the completion of this process the residual stress will cause reaction force P_m^0 in the suppressed freedom degree. The work should continue adequately maintained by a statically determinate set of freedom's degree. Towards the release step $(S+1)$ all degrees of freedom $a(S)$ are divided into the set of suppressed degrees of freedom $a(\mathrm{S}+1)$q and the remainder $a(\mathrm{S}+1)$m.The distortions can be calculated as

$$L_{mm}^{(S+1)} \Delta a_m^{(S+1)} = -p_m^{(S+1)} \quad (9)$$

Where $L_{mm}^{(S+1)}$ is the partition of the stiffness matrix and $p_m^{(S+1)}$ are the reaction forces and

$$p_m^{(S+1)} = Z_m p_0^S \quad (10)$$

The outcome of the selection is a vector as $\Delta a_m^{(S+1)}$ but the ones equivalent to p_0^Sequal to zero. The total vector$a(\mathrm{S}+1)$is same as to that of the last step $\Delta a_m^{(S)}$. The degrees of freedom $\Delta a_m^{(S+1)}$ pertaining to the release step differs from $\Delta a_m^{(S)}$for the last step. Therefore stiffness matrix division $L_{mm}^{(S+1)}$ differs from partition $L_{mm}^{(S)}$.

Topology optimization

In this optimize technique we calculate an optimal material distribution is calculated to optimize a desired performance. The compliance is most common objective to be minimized. The design variables are the element material densities $\delta(0 < \rho(x) \leq 1, x = 1, \dots, Qe)$ that describe the material distribution. Here $\delta = 0$ specifies invalid, while $\delta = 1$ signifies full attendance. The element contribution to the stiffness matrix can be calculated as

$L_x = \delta_x^p \int_{z0} \mathrm{K}^{\mathrm{T}}$ BKyZ $= \delta_x^p L_0$ x=1,….,Qe

A structure is desired, that minimizes compliance with a constraint on maximal allowable structure volume. Moreover, bounds on element density and the structure is required to be in balance with the practical loads. The optimization problem is mathematically formulated as:

$$\frac{min}{\delta} : c(\delta) = m_c^t a_t$$

$$s.t = \frac{1}{Q_e \sum_{e=1}^{Q_e} \delta_e} \leq Z$$

$$0 < \varepsilon \leq \rho \leq 1, e = 1\ Qe)$$

$\mathrm{L}\rho \leq 1, e = 1, \dots, Qe$ (12)

$L(\delta) a_c M_c$

Where $c(\delta)$ signifies compliance. $L(\delta)$ is the structural stiffness matrix, M_c and a_c are the load vector ε is a lower bound and Z is the maximum volume fraction.

IV.RESULT ANALYSIS

This section uses the MATLAB framework to demonstrate how to optimize the topography of any substance employing additive manufacturing. In this section, a sample plate with the arrangement seen below is presumed. The conformance convergence, mass convergence, and distributed energy resources are all optimized with this configuration. The goal is to investigate design method with a focus on three approximate solution: Given a set quantity of stuff, find the mass distribution on a plate that minimizes adherence (work of loads).

Table 1: Material Property

Material	Ti6Al4V
No of elements in x-axis	100
No of elements in y-axis	100
Material Young Modulus	110GPa
Material stress	0.3 MPa
Density	1 mg/mm³

"Compliance" is approximately the exact reverse of "stiffness" in mechanical systems. It is important to minimise strains in the system for improving topographic or relevant and essential, that also means minimizing compliance or maximizing stiffness, as rigidity is an important factor for the layout of additive manufacturing process sections.

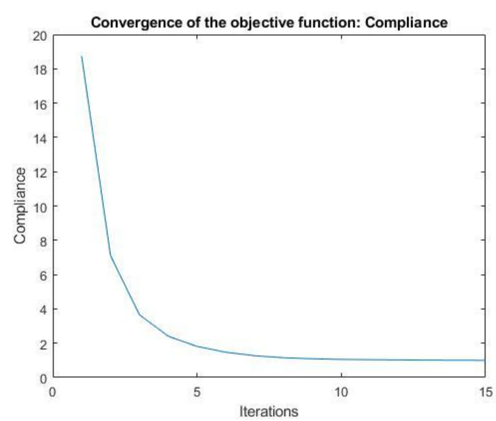

Figure 3: Convergence Curve of Compliance

AM's energy transfer in components has the power to impact not only of the process's long-term viability, but also the microstructure as well as structural characteristics of the manufactured elements. As a result, the graph below depicts the energy distribution obtained through an optimization method.

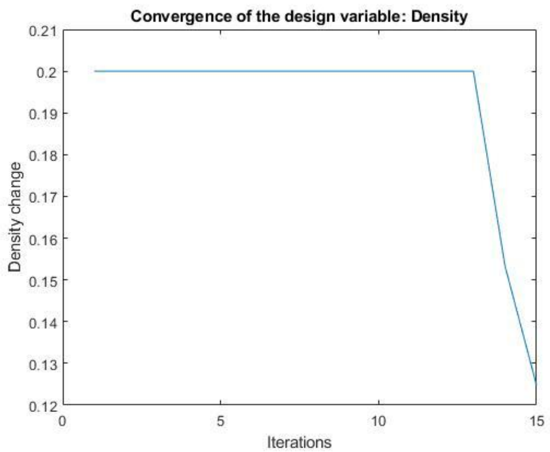

Figure 4: Convergence Curve of Density

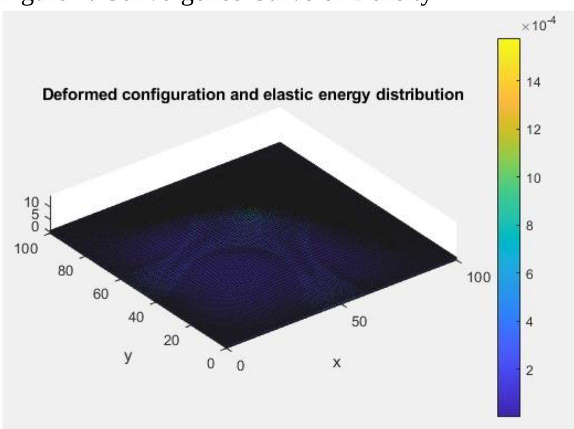

Figure 5: Energy Distribution in plate

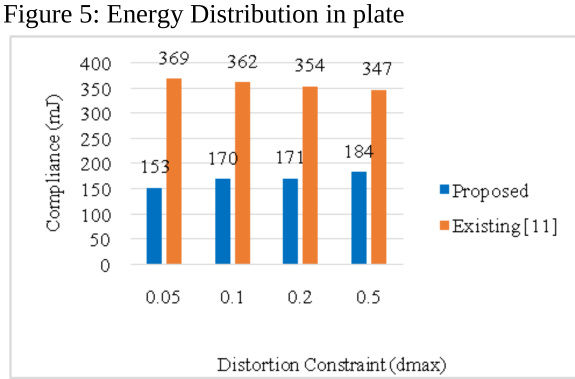

Figure 6: Comparison of Compliance

V.CONCLUSION

The term "additive manufacturing" refers to a group of 3D fabrication technologies. Furthermore, research on optimised topology and structures is still limited, preventing the use of machine learning in more complex designs. This paper would reduce the problem by applying machine learning for sample design and topology optimization to achieve a better performance. The desired configuration solution is obtained as a consequence of the assessment.

REFERENCES

[1] Liu, S., Stebner, A. P., Kappes, B. B., & Zhang, X. (2021). Machine learning for knowledge transfer across multiple metals additive manufacturing printers. Additive Manufacturing, 39(February), 101877. https://doi.org/10.1016/j.addma.2021.101877

[2] Xia, C., Pan, Z., Polden, J., Li, H., Xu, Y., & Chen, S. (2021). Modelling and prediction of surface roughness in wire arc additive manufacturing using machine learning. Journal of Intelligent Manufacturing. https://doi.org/10.1007/s10845-020-01725-4

[3] Jiang, J., Xiong, Y., Zhang, Z., & Rosen, D. W. (2020). Machine learning integrated design for additive manufacturing. Journal of Intelligent Manufacturing, 3. https://doi.org/10.1007/s10845-020-01715-6

[4] Baumann, F. W., Sekulla, A., Hassler, M., Himpel, B., &Pfeil, M. (2018). Trends of machine learning in additive manufacturing. International Journal of Rapid Manufacturing, 7(4), 310. https://doi.org/10.1504/ijrapidm.2018.10016883

[5] Qi, X., Chen, G., Li, Y., Cheng, X., & Li, C. (2019). Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives. Engineering, 5(4), 721–729. https://doi.org/10.1016/j.eng.2019.04.012

[6] Meng, L., McWilliams, B., Jarosinski, W., Park, H. Y., Jung, Y. G., Lee, J., & Zhang, J. (2020). Machine Learning in Additive Manufacturing: A Review. Jom, 72(6), 2363–2377. https://doi.org/10.1007/s11837-020-04155-y

[7] Wang, C., Tan, X. P., Tor, S. B., & Lim, C. S. (2020). Machine learning in additive manufacturing: State-of-the-art and perspectives. Additive Manufacturing, 36(January), 101538. https://doi.org/10.1016/j.addma.2020.101538

[8] Li, R., Jin, M., &Paquit, V. C. (2021). Geometrical defect detection for additive manufacturing with machine learning models. Materials and Design, 206, 109726. https://doi.org/10.1016/j.matdes.2021.109726

[9] Snow, Z., Diehl, B., Reutzel, E. W., & Nassar, A. (2021). Toward in-situ flaw detection in laser powder bed fusion additive manufacturing through layerwise imagery and machine learning. Journal of Manufacturing Systems, 59(February), 12–26. https://doi.org/10.1016/j.jmsy.2021.01.008

[10] Zhu, Q., Liu, Z., & Yan, J. (2021). Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks. Computational Mechanics, 67(2), 619–635. https://doi.org/10.1007/s00466-020-01952-9

[11] Grzegorz Misiun, Emiel van de Ven, Matthijs Langelaar, Hubert Geijselaers, Fred van Keulen, Ton van den Boogaard, Can Ayas, Topology Optimization for additive manufacturing with distortion constraints, Computer Methods in Applied Mechanics and Engineering, Volume 386, 2021.