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Topology Optimization using Nonlinear Finite Element Analysis

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Abstract:

Topology optimization is a structural-mechanical investigation that structures optimization function values in an optimization iteration. Topology optimization with nonlinear static behavior is difficult due to several design considerations. Due of significant integrate distortion, low-density finite elements provide significant numerical challenges in the prevailing element density focused topology planning taking nonlinear dynamics under factor. Iterative procedures are used in the Bi-directional Evolutionary Structural Optimization (BESO) technique for reducing waste from a structure while concurrently adding efficient material using a finite element-based topology optimization strategy. Integrating the fully-connected Deep Neural Network (DNN) with the norm-level-set techniques yields a powerful method for optimizing structural topology. Hence, BESO-DNN has been designed spatial optimization of material distribution inside a specified area is the focus of topology optimization is a mathematical approach for minimizing a certain cost function while meeting a set of predefined restrictions. Topology optimization of geometrically non-linear systems is advantageous because of the solutions' lack of intermediate-density components and their great processing efficiency of high-resolution barrier representation can be effective. As a result, topology optimization is ensuring effective and providing fresh and efficient designs, understanding that outcomes needs an integration of credible decision-making, domain knowledge, and numerical analytic skills. The outcome of finite element analysis has to understand and anticipate an object's performance under various physical conditions using mathematical models, and testing.

Keywords: Bi-directional Evolutionary Structural Optimization, Deep Neural Network, Topology, Nonlinear Finite Element Analysis.

1. Introduction:

Topology optimization strives to manage deformation at the system level despite minimizing entire volume, and can be interpreted a surrogate for structural system cost [1]. The layout design of structures and the components can be optimized using topology. The field of solid mechanics regards that method as an establish to across nonlinear elastic and small-displacement applications. [2]. Topology optimization is used to identify the ideal sensitive robotic structure for user-defined needs, unlike standard design approaches. Pressure-driven topology optimization and soft robotics has been to be combined [3]. Topology optimization is an approach for designing that can find the optimal arrangement of materials within a certain design domain and maintaining certain constraints and optimizing the effect on performance [4]. The topology optimization and finite element analysis to improve physical stability in the area of joint fixation and meet the requirements for behavior of minimally invasive distal radius fractures [5]. With analyzing nonlinear thermoelectricity using an extended perimeter technique, people focused emphasis on geometrical a nonlinear is the value pertains to topology optimization executing nonlinearity into issue [6]. Optimization and topology have been occupied prominent focus with several generations. The process has been regarded is the most adaptable due to that permits structural topology to be measured using merely loading and solving constraints [7]. The finite element analysis includes the advantage of gathered mathematical a nonlinear with utilizing difficulty; that can provide with evolving the structure's helps through bearings into relies, that outcomes in various suitable possibilities [8]. A geometrically nonlinear thermoelastic simulation is used to build a BESO method using sensitivity analysis. With predictable problems, the effect of altering the limitation of the quantity of the needed structure is analyzed [9]. Topology optimization utilizes the use of the DNN as a stand-in model, in the intended of generating a perfect flux intensity variation in the structure [10]. Truss structures, similar to measured girder structures, has been the focus of topology optimization analysis with contraction constraints. The constraints include important local buckling limits on the component to complicated overall contraction conditions [11]. As nonlinear structures interest greater developing that inverse structures, performance is essential in implementing topology optimization strategies [12]. Through merging density-based topology optimization with mixed rigid-plastic analysis, the suggested formulation minimizes volume and solves the optimization issue [13]. To develop optimum topologies of flexoelectric structures undergoing large displacement, a nonlinear structure evaluation tackle has devised. Optimizing the energy, the process efficiency generates the ideal important distribution [14]. Topology optimization has evolved in popularity is highly efficient method for mechanical design in more robust organizations and education, which accomplishes the necessary outcomes in the areas of structural mechanics at several scales, designing viscoelastic structures, compliance issues, and heat transfer [15].

The main objective of the paper:

- The formulation of minimal compliance topology optimization, that aims to reduce internal strain energy in a constant mass structure for a given strain scenario and collection of boundary conditions, is the problem that is the greatest often solved.
- BESO-DNN through minimizing a predefined cost function and satisfying predefined conditions, mathematically, topology optimization strives to optimize the distribution of materials inside a certain region.
- With satisfying and optimizing the previously defined cost function prior provided limitation, topology optimization develops the spatially effective distribution of material within a certain region.

The remainder of the research is structured as follows: Section 2 discusses the current method's work, while Section 3 discusses future plans introduces the BESO-DNN methodology, and section 4 analyzes the experiments. Section 5 wraps off by discussing the paper's influence.

2. Literature survey:

Miche Jansen et al. (2019) detailed using the Extended Finite Element Method (XFEM), a fixed mesh of the design domain is employed to model the non-conforming material interaction [16]. Geometric restrictions employed in density-based topology optimization with projection filters recently need a structure with a minimum length scale. The limits allow instabilities in level established XFEM topology optimization to be addressed computationally inexpensively. Both the density-based topology optimization and the level set optimization use the same geometric constraints to give an accurate comparison.

Yusuke Takahashi, et al. (2019) discussed the topology optimization approach using optimized network structure using a deep learning technique labeled a Convolutional Neural Network (CNN) challenges [17]. The addressing a verification case, a topology optimization issue targeted at maximizing strength, and demonstrate the usefulness of the provided topology optimization strategy. In the research, people observe a solution that differs from the prior topology optimization approach and an outcome of addressing the issue with a constrained design area of element. The result implies that structure stiffness information the density distribution utilizing CNNs in a picture, that can be used for structural design research.

Nicholas Napier et al. (2020) introduced the best structure on a rough grid prior to using an ANN to transform it into a refined mesh drastically cuts down on computing time [18]. Among the most important problems in element-based topology optimization. If a material interface that is well defined, that need a finite element mesh that has been fine-tuned. But solving this issue increases the computing cost. As an added bonus, unlike a fine-mesh optimization with minimal error, this one significantly reduces computing time while maintaining structural integrity. In addition to the time savings in computing, the method effectively refines the boundary edges, making the transition from solid to void sharper.

Mengcheng Huang et al. (2022) prepared the substrate provides a Problem-Independent Machine Learning (PIML) technique for reducing finite element analysis computation time, that is a significant obstacle to solving the problem [19]. Responding to earlier studies, the proposed mechanism is really issue-agnostic and applicable to any topology optimization problem during the minimal off-line training has been completed. The forecast is proved that the provided strategy greatly reduces the time required for finite element analysis.

Seungyeon Shin et al. (2023) examined the finite topology optimization, a Support Vector Machine (SVM) based structural boundary processing technique is used to transform the implicit rough boundary into the explicit smooth boundary [20]. Discrete topology optimization is widely used because of the large degree of flexibility and great efficacy in addressing problems. The penalization and discrete level-set techniques SVM are used to treat the boundaries of the solid isotropic material, respectively. The results indicate that perform in discrete topology optimization can provide unambiguous and smooth structural boundaries.

Jie Qiao et al. (2020) illustrated the develop a strategy for optimizing the electric truck frame's topology that takes use of orthogonal test designs and the Analytic Hierarchy Process (AHP) [21]. While there has been some systematic study on the frame's multi-objective topological design has been restricted in scope owing to the complexity of loads and competing incentives. As engineering issues become more complex, the hybrid approach is likely to provide valuable guidance. The process demonstrates that the suggested approach can be an effective technique for enhancing the electric truck frame's topology for several targets simultaneously with the goal of achieving both lightweight and comprehensive mechanical performance.

A few drawbacks Optimization of Topology with the use of nonlinear finite element procedures in the modern day. The numerical instability problem often arises in low-density element regions during nonlinear topology optimization, especially for cases of large deformation. The issue arises because of substantial element distortion. [16] overcomes the drawbacks of [17], [18], and compares to the suggested approach BESO-DNN.

3. Proposed method:

A topology optimization technique for composite structures that maximizes structure stiffness with including material element string into the BESO-DNN method of bidirectional evolutionary structural optimization. The provided solution can effectively optimize the topology of composite structure designs, like indicated in the illustrate and can provide shape designs with uniform stress distribution, resulting in decreasing the likelihood of structural failure due to excessive stress concentration. To identify the best solution, an average topology optimization model penalizes the intermediate density variables and uses models of solid isotropic materials with reasonable approximation of material abilities.

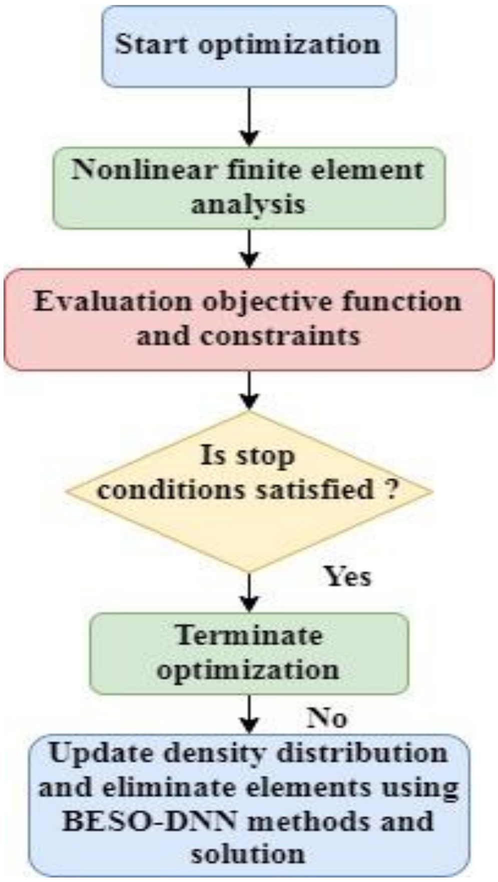

Figure 1 Flow chart of Topology optimization

Figure 1 shown in improve a structure's performance, topology optimization utilizes mathematics to identify the best material distribution within a given design area, grabbing into account a number of limitations. BESO-DNN has been find the issue with the design and state like reducing cost or increasing stiffness. Establish the limitations, like people pertaining to materials, production, and desired performance. Identify the boundary conditions and applied loads that the building can face in a operational lifetime. With the material's initial distribution, loads, and limitations, perform a finite element analysis to assess the structural reaction. Determine the sensitivity data that shows that the goal function and restrictions are affected by variations in material density. Access important details, including the optimized structure's final material configuration and performance data, and visualizing the organization. Utilize under effect multiple elements, including production procedures and pragmatic concerns. quite crucial to keep in mind that different optimization tools, algorithms, and design goals can be utilized for different procedures.

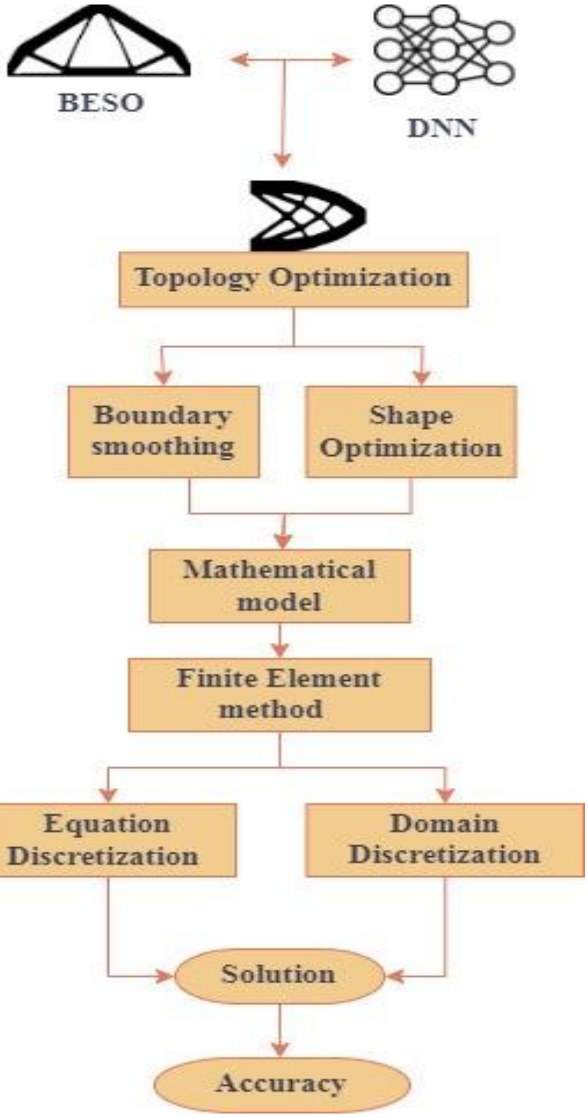

Figure 2 Overview of BESO-DNN

Figure 2 shown in optimization technique for topology optimization and structural engineering is BESO. The BESO is to maximize a certain objective function, like decreasing compliance and increasing stiffness, while taking into account a variety of limitations with repeatedly adding and removing material from a design area. In effect to help and improve the optimization process, that integration can include the use of a DNN, perhaps for tasks like material distribution prediction or topological optimization based on more complicated criteria that are difficult to explain analytically. topological optimization using nonlinear finite element analysis, particularly for deep neural network integration applications like as BESO-DNN. The material distribution can be optimized using the BESO algorithm repeatedly using this prediction model in accordance with the specified goals and limitations. BESO-DNN's efficacy would be determined by criteria like the difficulty concerned with the optimization problem, the surrogate model's quality, and the reliability of neural network predictions. One way to maximize efficiency in a given design space is by using topology optimization. The optimal material arrangement that minimizes material consumption while meeting certain performance goals. A single electronic method for studying how structures and materials react to different types of loads is nonlinear finite element analysis.

To represent the material's nonlinear properties, σ a generic relationship between effective stress and strain is established the equation (1)

$$\boldsymbol{\sigma_e = Kf(\varepsilon_e)} \qquad \textbf{(1)}$$

where K is a constant reference modulus of elasticity and function $\boldsymbol{f(\varepsilon_e)}$ is a generic function expressing the material properties can be linearized incremental analysis is introduced and the constitutive equation that incorporates material and geometric nonlinearities is examined. To explore surface wrinkling, material instability, and local buckling, the automated stabilization with the provided damping factor rule is applied. A constant damping factor is used in any nonlinear quasi-static approach based on the global equilibrium equation in the automated stabilization method.

$$\boldsymbol{F_v = \frac{P}{I}\; cM * v.v = \frac{\Delta u}{\Delta t}} \qquad \textbf{(2)}$$

where Δu and Δt are the displacement and time increments, M is a synthetic mass matrix with a density of a decision, v is the vector of nodal velocities, and c is a damping factor, F_v is viscous forces, and P and I are the exterior and internal forces. The structure is taken into account, the nonlinear assumptions employed can predict the structure's actual behavior in the case of minor deformation. The structure's Lagrange strain tensor is calculated using the whole Lagrange finite element approach.

$$\boldsymbol{E = \frac{1}{2}\;(F^T.F - I)} \qquad \textbf{(3)}$$

where $F^T$is the identity tensor, E, and different components comprise the deformation gradient tensor hyper elastic material model is useful for modeling materials with elastic responses are exposed to massive deformations, like rubber and resins. As The variables that compose to the design domain are the displacement within area and the factor is determined by interpolating between n nodal values.

$$\boldsymbol{F = \sum_{a=1}^{n} N^a\;(u_i^a)} \qquad \textbf{(4)}$$

Where n signifies an arbitrary point's coordinates of nearby elements the displacement vector at node u_i^a is denoted by F. In local element coordinates, the shape functions are represented by N^a counts the nodes that comprise form the element. The domain of design that is considered in the finite element approach is mesh-generated. A displacement vector, u, that satisfies the structural equilibrium is found using the Newton-Raphson method.

$$\boldsymbol{R(x,u) = P_{ext} - P_{int} = 0} \qquad \textbf{(5)}$$

In the moment though the residual vector $R(x,u)$ norm is less than a tiny positive number, static equilibrium has been achieved. In density-based topology optimization, P_{ext} is the residual force vector and P_{int} is the internal nodal force vector. The solid isotropic microstructure with penalty method is commonly employed because it offers an interpolation mechanism for determining the physical properties of the intermediate density element. A common method to describe an element's elastic modulus is in terms of the relative densities.

$$E_e = x_e^p E_0 \quad (6)$$

where E_0 denotes the solid element's elastic modulus the value of p is a reference to previous research that serves as a punishment for the element's density. If the elastic modulus is decreased, the empty element's impact on the behavior prediction of the structure overall can be mitigated. However, if such components occur early in the optimization process, that can cause severe distortion, causing the finite element analysis to fail. The displacement function used in the classic Finite element technique may be used with this formulation, and the integral in the element's void sub-domain can be removed. As a consequence, the Gauss quadrature, equation (7), can be used to numerically compute the integral.

$$K_e = \int B^T D_S B t d\delta \quad (7)$$

Here, DS stands for the solid material's elasticity matrix, B for the displacement differentiation matrix, and t for the element thickness matrix. After being chopped with a boundary region in the elements, the solid's form might be anything other than rectangular.

4. Experimental analysis:

Nonlinear finite element analysis has emerged as several of the greatest sophisticated methodologies to structural analysis. That analyzes numerous nonlinearity sources such as material, geometry, and boundary condition nonlinearities like contact. Due to several developing elements, optimization of topologies with nonlinear static behavior is an arduous undertaking. Numerical problems caused by low-density finite elements are substantial. Topology optimization using energy element densities exhibits nonlinear behavior. into account owing to high mesh distortion. For detecting the regions of the elements that can be eliminated to improve stiffness while minimizing weight and maintaining maximum stress below a specific value, topology optimization is a numerical approach that determines the best structure of structural components. Identifying the greatest potential structuring of the solid and hollow structural subsystems that generate across a structure is the essence of structural topology optimization. As a result of optimizing an established cost function and satisfying the preceding restrictions, topology optimization determines the best spatial distribution of stuff within a given location.

Dataset Description: The development, implementation, and demonstration of established a framework for functional grading of lattice structures based on topology optimization and triply periodic minimum surfaces. A compliance issue based on topology optimization is used to include the convex combinations; the lattices' volume fraction restrictions are represented by upper and lower density variable constraints. As a consequence of the optimization loop's usage of a sigmoid filter to handle the lower limit on the density variables, densities below the boundary approach zero. The implicit surfaces are then converted to a standard triangle language file through use of marching cubes. With combining the data with nonlinear finite element analysis, researchers can utilize data for future studies efficient ideal element method [22].

Table 1 Comparison of topology optimization and performance

Methods	f value	Time	Evaluations
XFEM	0.0118	6000s	2000 FEA
CNN	0.7446	5220s	1740 FEA
ANN	0.5167	600s	5000 FEA
BESO-DNN	0.0.224	400s	14000 FEA

Table 1 denotes the geometry due to the thorough Finite Element Analysis (FEA) method that was described. A lesser value, f = 0.517, was found using the BESO-DNN objective function than with the complete FEA optimization. With tens of thousands (50,000) function evaluations possible compared to a few hundred (1740) using complete FEA-based optimization, the BESO-DNN optimization technique allows for greater domain exploration at a lower time cost than full FEA-based optimization.

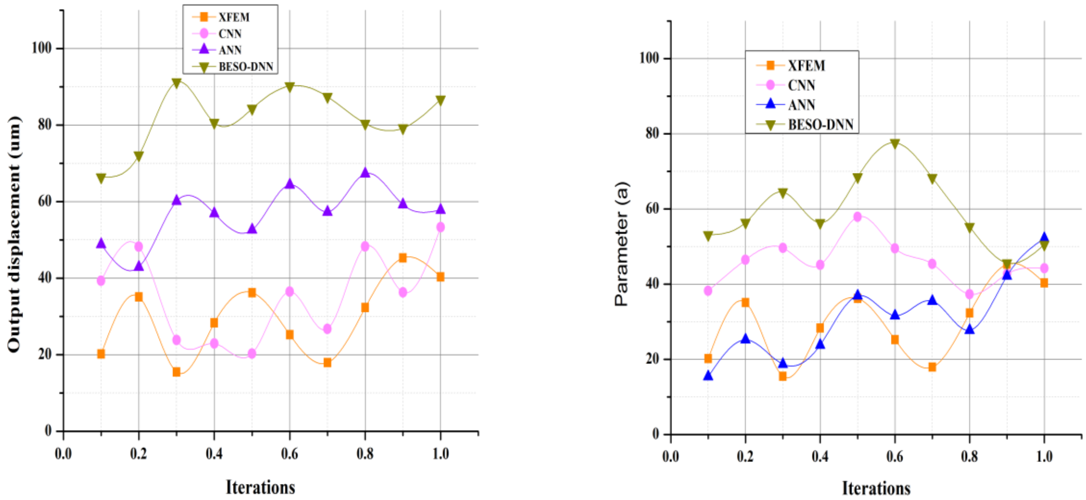

Figure 3 Comparison of optimal topologies under different stresses

Figure 3 shown in the optimization results, including the iteration numbers, output displacement before and after the void element is removed, and cetera. The value often increases as the input force increases in attempt to avoid extreme distortion, which occurs when the input force is increased and structural deformation increases. The design has been mentioned that the value may affect how accurate the finite element analysis is. To ensure that the optimization results operate similarly to the real behavior, the accuracy of the finite element analysis quickly drops and stays on a very low level with the suggested regulatory scheme.

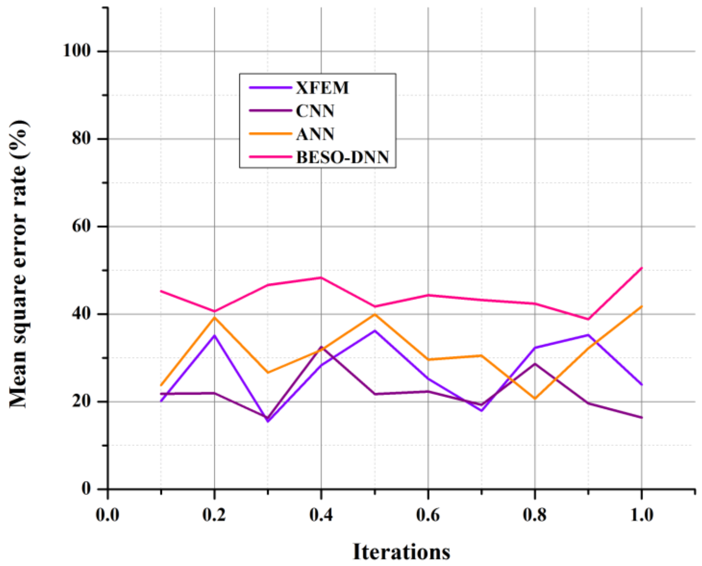

Figure 4 Mean square error rate in BESO-DNN

Figure 4 shown in the BESO technique is a finite element-based topology optimization approach that removes wasteful material from a structure while concurrently adding efficient material. The difference estimation error is the difference between the ideal network function and a network function that is estimated, and target function is the distance from this closest neural network function of a specific design. There is a more fundamental explanation incorporating statistical learning theory for the estimate error grows monotonically with increasing hypothesis class size.

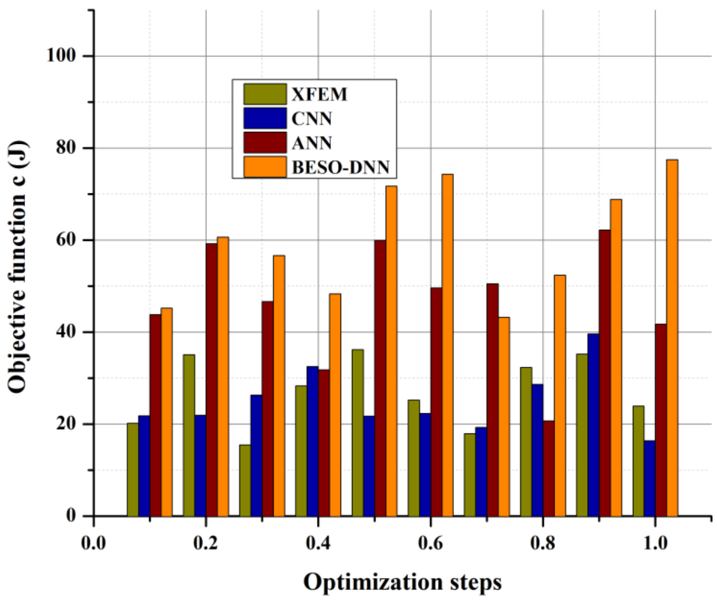

Figure 5 Impact of mesh resolution on c evolution during optimization

Figure 5 shown in geometries are mesh resolution-agnostic save for small changes like an additional horizontal element at low resolution. Solution quality is similar across structures. The Supplementary Information section shows that mesh fineness affects topologies and objective function values over the spectrum of meshes optimized for both the finite element technique and the constrained element method.

5. Conclusion:

Topology optimization mathematically enhances system performance and material arrangement in a design area for a given load, boundary condition, and constraint. The essential reason for that has due to low-density ingredients are softer and can efficiently distorted. Mechanical and structural engineers utilized topology optimization to save construction material and strain energy while maintaining mechanical strength. Topology optimization mathematically optimises system performance and composition inside a distinct design domain according to specified constraints, boundary conditions, and loads. Low-density finite elements can deform the mesh in nonlinear dynamic analysis due to BESO-DNN optimizes topology using density. Nonlinear dynamic analysis incorporates topological insights using transformation variables for unique iteration. Hence, geometrical nonlinearity is required to be considered in topology optimization finite element analyses. Due of unique component distortion, density interpolation-based topology optimization on the bigger palm frequently fails. Mixed-dimensional geometric modeling, tolerances, and physical behavior analysis use topology as a mathematical paradigm. Nonlinear static topology optimization is challenging due to the significant variety of design variables. Low-density finite elements generate major numerical issues addressing nonlinear behavior in visible element density-based topology optimization due to elevated grid distortion. Due to the impressive mathematical efficiency, avoidance of intermediate-density portions in the solutions, and maintained advantages of high-resolution limit representation, topology optimization of geometrically non-linear systems can be strongly efficient.

Reference:

[1] Changizi, N., & Warn, G. P. (2020). Topology optimization of structural systems based on a nonlinear beam finite element model. *Structural and Multidisciplinary Optimization*, *62*(5), 2669-2689.

[2] Paulino, D. M., & Leonel, E. D. (2021). Topology optimization and geometric nonlinear modeling using positional finite elements. *Optimization and Engineering*, 1-31.

[3] Wang, R., Zhang, X., Zhu, B., Zhang, H., Chen, B., & Wang, H. (2020). Topology optimization of a cable-driven soft robotic gripper. *Structural and Multidisciplinary Optimization*, *62*, 2749-2763.

[4] Rad, M. M., Habashneh, M., & Logo, J. (2021, December). Elasto-Plastic limit analysis of reliability based geometrically nonlinear bi-directional evolutionary topology optimization. In *Structures* (Vol. 34, pp. 1720-1733). Elsevier.

[5] Liu, H. C., Jiang, J. S., & Lin, C. L. (2020). Biomechanical investigation of a novel hybrid dorsal double plating for distal radius fractures by integrating topology optimization and finite element analysis. *Injury*, *51*(6), 1271-1280.

[6] Jie, H. O. U., Xiaojun, G. U., Jihong, Z. H. U., Jie, W. A. N. G., & Zhang, W. (2020). Topology optimization of joint load control with geometrical nonlinearity. *Chinese Journal of Aeronautics*, *33*(1), 372-382.

[7] Oliveira, H. L., e Andrade, H. D. C., & Leonel, E. D. (2020). An isogeometric boundary element approach for topology optimization using the level set method. *Applied Mathematical Modelling*, *84*, 536-553.

[8] O'Shaughnessy, C., Masoero, E., & Gosling, P. D. (2022). Topology optimization using the discrete element method. Part 1: Methodology, validation, and geometric nonlinearity. *Meccanica*, *57*(6), 1213-1231.

[9] Habashneh, M., & Rad, M. M. (2023). Reliability based topology optimization of thermoelastic structures using bi-directional evolutionary structural optimization method. *International Journal of Mechanics and Materials in Design*, 1-16.

[10] Barmada, S., Fontana, N., Formisano, A., Thomopulos, D., & Tucci, M. (2021). A deep learning surrogate model for topology optimization. *IEEE Transactions on Magnetics*, *57*(6), 1-4.

[11] Zhang, G., Khandelwal, K., & Guo, T. (2023). Finite strain topology optimization with nonlinear stability constraints. *Computer Methods in Applied Mechanics and Engineering*, *413*, 116119.

[12] Abdi, M., Ashcroft, I., & Wildman, R. (2018). Topology optimization of geometrically nonlinear structures using an evolutionary optimization method. *Engineering Optimization*, *50*(11), 1850-1870.

[13] Li, X., Zhang, X., & Zhang, Y. (2023). Three-dimensional plasticity-based topology optimization with smoothed finite element analysis. *Computational Mechanics*, 1-16.

[14] Zhuang, X., Thai, T. Q., & Rabczuk, T. (2023). Topology optimization of nonlinear flexoelectric structures. *Journal of the Mechanics and Physics of Solids*, *171*, 105117.

[15] Xie, W., Xia, Q., Yu, Q., & Li, Y. (2023). An effective phase field method for topology optimization without the curvature effects. *Computers & Mathematics with Applications*, *146*, 200-212.

[16] Jansen, M. (2019). Explicit level set and density methods for topology optimization with equivalent minimum length scale constraints. *Structural and Multidisciplinary Optimization*, *59*(5), 1775-1788.

[17] Takahashi, Y., Suzuki, Y., & Todoroki, A. (2019). Convolutional neural network-based topology optimization (cnn-to) by estimating sensitivity of compliance from material distribution. *arXiv preprint arXiv:2001.00635*.

[18] Napier, N., Sriraman, S. A., Tran, H. T., & James, K. A. (2020). An artificial neural network approach for generating high-resolution designs from low-resolution input in topology optimization. *Journal of mechanical design*, *142*(1), 011402.

[19] Huang, M., Du, Z., Liu, C., Zheng, Y., Cui, T., Mei, Y., ... & Guo, X. (2022). Problem-independent machine learning (PIML)-based topology optimization—A universal approach. *Extreme Mechanics Letters*, *56*, 101887.

[20] Shin, S., Shin, D., & Kang, N. (2023). Topology optimization via machine learning and deep learning: A review. *Journal of Computational Design and Engineering*, *10*(4), 1736-1766.

[21] Qiao, J., Xu, F., Wu, K., Zhang, S., & Liu, Y. (2020). Multi-objective topological optimization of an electric truck frame based on orthogonal design and analytic hierarchy process. *IEEE Access*, *8*, 140923-140935.

[22] https://datasetsearch.research.google.com/search?src=0&query=Topology%20Optimization%20using%20Nonlinear%20Finite%20Element%20Analysis&docid=L2cvMTFtaHJrczQ5Xw%3D%3D