Generative design method of machine tool conceptual configuration and its application

Yulong Yang[1], *Tianjian* Li [1*]

[1]School of Mechanical Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China

Abstract. This paper introduces a generative design framework for the conceptual configuration of machine tool structures, leveraging artificial intelligence (AI), topology optimization, and measurement-informed validation. The approach integrates a hybrid backpropagation neural network and genetic algorithm (BP-GA) with multi-objective topology optimization to identify structurally optimal configurations under varying force-flow conditions. A five-axis precision milling machine serves as a case study to demonstrate the method's effectiveness. Validation through finite element simulation and 3D digital image correlation confirms the accuracy and robustness of the proposed model. The results reveal significant improvements in stiffness, mass efficiency, and frequency performance, highlighting the method's potential in sustainable and intelligent manufacturing.

1 Introduction

Machine tools constitute the cornerstone of modern manufacturing systems, serving as critical enablers for precision production across strategic industries such as automotive, aerospace, and renewable energy [1]. These tools play a pivotal role in determining the accuracy, stability, and efficiency of modern manufacturing systems. Conventional design approaches, which typically focus on individual components, are inadequate in addressing global structural performance, primarily due to limited consideration of force transmission paths.

Pioneering work by Li et al. [2] demonstrated bio-inspired stiffener configurations derived from plant ramification patterns, while Shen et al. [3] achieved significant improvements in component stiffness through topology optimization. Li et al. [4] employed a neural-network algorithm and nondominated sorting genetic algorithm in the design of machine tool crossbeam, evaluating the influence of various parameters on the mass, deformation and frequency.

It is evident that the force-performance-structure lightweight design method of structural parts can be extended to the overall machine structure design. However, there are few methods available for the conceptual design of the overall structure of machine tools [5]. It is because that the optimization design of the entire machine structure is more complex than that of individual components due to the intricate structure, constraints, loads, and boundary conditions, making it difficult to implement using traditional topology optimization methods due to the large scale and computational complexity. And, now the advent of AI-driven design methods has made the optimization design of the entire machine structure possible. For example, Jiang et al. [6] developed an autonomous machine learning framework for topology optimization parameter tuning. This generative design methodology not only eliminates the dependency on manual parameter adjustments but also ensures the generation of feasible solutions across the entire design space. Among the generative design methodologies, topology optimization-based approaches have emerged as particularly powerful tools for discovering novel topological configurations that remain inaccessible to conventional parametric design techniques. These innovations facilitate the generation of high-performance solutions with superior mass efficiency and structural integrity compared to conventional methods [7]. Modern generative design systems demonstrate remarkable capabilities in producing diverse, high-performance design solutions that consistently outperform traditional design methods across multiple metrics, including significant mass reduction, enhanced structural strength, and minimized assembly complexity [8].

This paper proposes an AI-assisted generative design framework that integrates holistic optimization and measurement-informed validation for early-stage structural innovation. It is structured as follows: Section 2 presents the overall methodology, including AI-assisted optimization using neural networks and genetic algorithms and topology optimization. Section 3 describes the case study conducted on a five-axis vertical milling machine, detailing the implementation, BP-GA model validation, and optimization results under various loading conditions. Section 4 concludes the paper by summarizing key findings and outlining directions for future research.

* Corresponding author: litianjian99@163.com

2 Methodology

2.1 BP-GA hybrid optimization

The nonlinear relationship between input parameters and output performance metrics is modeled using a backpropagation (BP) neural network, which subsequently serves as the objective function for genetic algorithm (GA) optimization. Figure 1 illustrates the integrated BP-GA optimization workflow. To mitigate potential numerical inconsistencies arising from parameter scaling variations, all input and output variables are normalized according to Eq. (1) prior to network training.

$$y = \frac{(x - x_{min}) \times (x_{max} - x_{min})}{x_{max} - x_{min}} + x_{min} \tag{1}$$

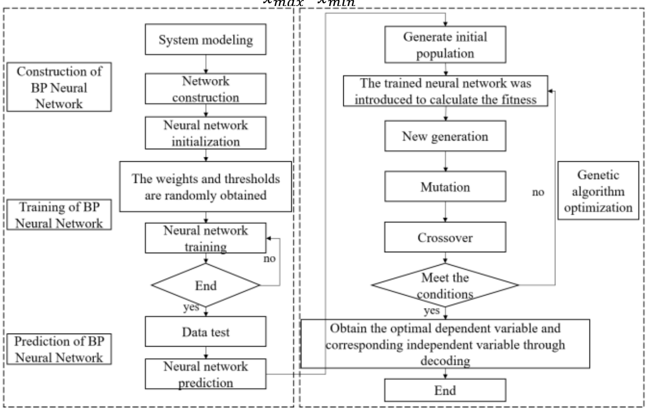


Fig. 1. BP neural network construction and GA optimization flow chart

The neural network adopts a three-layer architecture with 10 normalized inputs, an empirically optimized hidden layer, and 3 outputs—static deformation, natural frequency, and mass—effectively modeling nonlinear relationships in structural optimization.

2.2 Multi-objective topology optimization model

A multi-objective topology optimization model is developed by normalizing flexibility, natural frequency, and mass. A weighted objective function is used to explore Pareto-optimal configurations within the design space. The design domain is divided into machining and structural regions to balance lightweight and high-stiffness requirements. The model considers the effects of load conditions, volume ratios, and weight factors, with joint segmentation based on ISO standards and performance validated via simulation.

The compromise planning method and the average-frequency method are used to normalize and combine the three objective functions. The multi-objective optimization design model is as follows:

$$Find: \rho = \{\rho_1, \rho_2, \rho_i, \cdots, \rho_n\}^T$$

$$\min: F(\rho) = \left(\left(\omega_1 \frac{C(\rho) - C_{\min}}{C_{\max} - C_{\min}}\right)^2 + \left(\omega_2 \frac{\Lambda_{\max} - \Lambda(\rho)}{\Lambda_{\max} - \Lambda_{\min}}\right)^2 + \left(\omega_3 \frac{M(\rho) - M_{\min}}{M_{\max} - M_{\min}}\right)^2 \right)^{1/2} \tag{2}$$

where the M_{max} is set at 100% of the volume, while the M_{min} is set at 20% of the volume. For subsequent calculations, the mass determination relies on the maximum and minimum mass values corresponding to the optimal frequency and flexibility models within the model sets. The calculated mass reflects these specific values.

And C can be calculated by variable density method. It can be expressed as

$$Min: C = \boldsymbol{F}^T \boldsymbol{U} = \boldsymbol{U}^T \boldsymbol{K} \boldsymbol{U}$$
$$s.t. \begin{cases} V(\rho) = \Sigma v_i \eta_i \le f V_0 \\ \boldsymbol{KU} = \boldsymbol{F} \\ 0 < \rho_m \le \rho_e \le 1, e = 1,2,3,\cdots,n \end{cases} \tag{3}$$

Λ can be calculated by the modal optimization model. The formula is

$$\underset{\rho_1, \rho_2, \cdots, \rho_n}{Max} \ \Lambda_i = \lambda_0 + s\left(\sum_{i=1}^{m} \frac{\zeta_i}{\lambda_i - \lambda_0}\right)^{-1}$$
$$s.t. \begin{cases} (\boldsymbol{K} - \lambda_i \boldsymbol{M})\{\boldsymbol{\Phi}_i\} = 0, i = 1,2,\cdots,n \\ \sum_{i=1}^{n} V_i \rho_i - V(\rho) \le 0 \\ V(\rho) = f V_0 \\ 0 < \rho_m \le \rho_e \le 1, e = 1,2,3,\cdots,n \end{cases} \tag{4}$$

where the maximum of the first i-order natural frequency is taken as the optimization goal, and the volume fraction, stress, and deformation are used as constraints to construct the modal optimization model of the machine tool.

3 Case study: five-axis vertical milling machine

The proposed method was demonstrated using a five-axis vertical milling machine. A dataset comprising 420 design cases was created by varying the load direction and volume fraction. Finite element simulations, along with preliminary validation, were performed to verify the accuracy of the predictive model. Take a 5-axis precision milling machine as an example to illustrate the process and application of the generative design method.

3.1 Design domain definition

The connection between the tool and the fixed workpiece forms a crucial force transmission loop in the machine tools. On this basis, the generative design can be carried out on the whole machine structure.

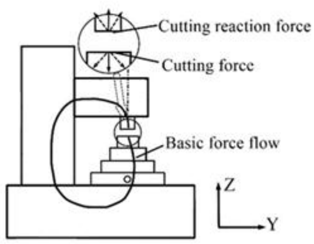
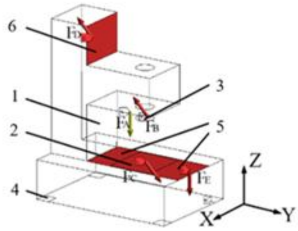


Fig. 2. Force flow

The machine tool shape as shown in Figure 3. The red area is the non-optimized area. FA is equal to the weight of the spindle. FB is the force on the lower end of the spindle. FC is the force on the worktable. FB and FC are the acting force and the reaction force. FD is the load from the tool magazine to the column. FE is the gravity load of the saddle and the workpiece. The main force flow transmission direction of the vertical machine tool is the closed-loop formed by the cutting force and the cutting reaction force, as shown in Figure 4. Therefore, the following analysis focuses on the influence of the direction and magnitude of F_B and F_C on the configuration. Other configurations of machine tools can be similarly defined.



1. Guide rail movement surface 2. Worktable mounting surfacec 3. Spindle cylindrical surface 4. Four hinge support surfaces 5. Slide rail surface of worktable 6. Tool bearing surface

Fig. 3. Design space, design domain, and load

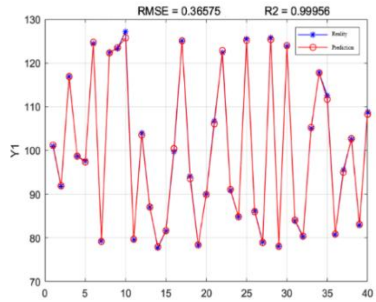
Accurate load modeling is critical for reliable topology optimization. In this study, machining loads on a vertical five-axis milling machine are evaluated in both magnitude and direction to reflect realistic conditions. Considering structural symmetry and open-loop force transmission, five representative force vectors (F1–F5) are defined to simulate typical cutting scenarios involving variations in spindle orientation and ±Y/±Z directional loads on key structural surfaces.

Table 1. Typical load

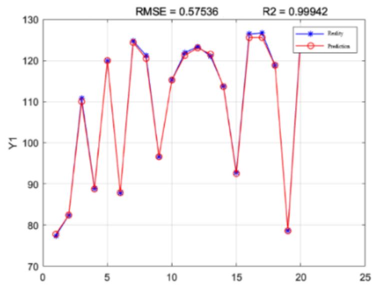
Load	Forced surface3	Forced surface2
F1	$[0\ 1\ 0]^T$	$[0\ {-1}\ 0]^T$
F2	$[0\ 1\ 1]^T$	$[0\ {-1}\ {-1}]^T$
F3	$[0\ 0\ 1]^T$	$[0\ 0\ {-1}]^T$
F4	$[0\ {-1}\ 1]^T$	$[0\ 1\ {-1}]^T$
F5	$[0\ {-1}\ 0]^T$	$[0\ 1\ 0]^T$

3.2 BP-GA model training and prediction

The experimental validation uses 60 samples, with 40 for training and 20 for testing. The model achieves high predictive accuracy ($R^2 > 0.98$) for both frequency and flexibility, as shown in Figures 4–6. These results confirm the BP neural network's effectiveness in capturing the complex nonlinear relationships between input parameters and structural performance.

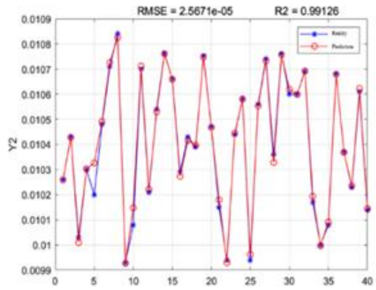


a)Training

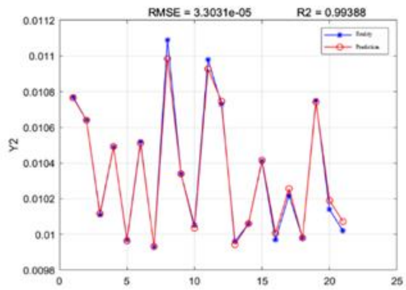


b)Testing

Fig. 4. BP neural network training diagram with frequency as the output



a)Training



b)Testing

Fig. 5. BP neural network testing diagram with flexibility as the output

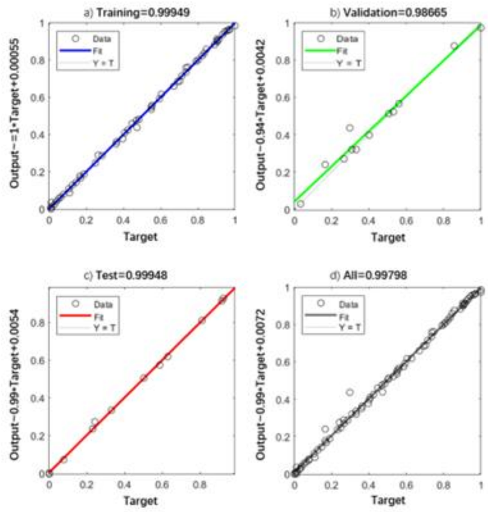
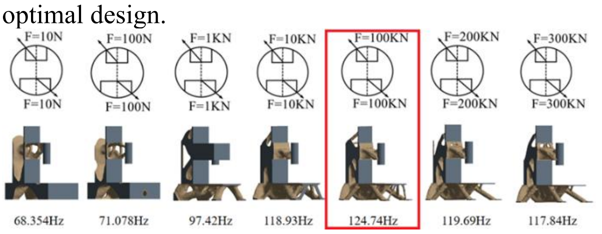


Fig. 6. Linear regression plot

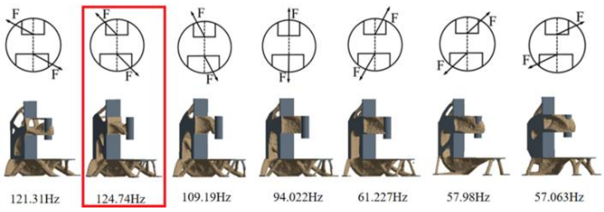
3.3 Load modeling and optimization settings

Different magnitude or direction of external loads form different structural configurations. Some typical configurations are shown in Figure 7. It can be seen from Figure 7(a) that the external force loaded should be much greater than the working load until the optimized configuration is obtained. Effects of external loads in different direction is shown in Figure 7(b).

The optimized structural configuration cannot be obtained directly by the design research under working load. Load analysis is a necessary prerequisite for optimal design.



(a) Different magnitude of external loads



(b) Different direction of external loads

Fig. 7. Optimized configurations under different loads

To explore structural performance under varying conditions, load magnitudes from 25 kN to 300 kN (in 25 kN increments) were combined with seven volume fractions (30%–50%), generating 420 design cases. This enabled Pareto-front analysis of flexibility versus natural frequency.

Optimal configurations consistently appeared under high loads (near 300 kN), especially for the diagonal load vector [0, -1, 1]^t, which yielded minimum flexibility and maximum frequency. These results highlight the significance of directional force flow in achieving global optimization.

Consequently, a design domain with volume fractions of 30%–50% and non-standard high-magnitude loading is recommended. The corresponding parameter ranges are listed in Table 2.

Table 2. Basic design analysis parameters

Parameter	Range	Vector
volume fraction (f)	[0.3,0.5]	/
External load (FB) (KN)	/	[0 -100 100]^T
External load (FC) (KN)	/	[0 100 -100]^T
Mass (M) (Kg)	[1541, 2567]	/
Flexibility (μm/N)	[0.00743,0.01197]	/
First-order natural frequency (Hz)	[116.1,125.8]	/

3.4 Simulation results and configuration analysis

Finite element simulations were conducted for all 420 configurations to assess their structural performance. The results reveal strong correlations between applied load conditions and the resulting configurations.

High-magnitude diagonal loads, particularly [0, -1, 1]^T, consistently produced structures with minimal flexibility and high natural frequencies. Optimized structures under extreme load conditions exhibited reinforced diagonal ribs and load paths that aligned with the direction of applied force vectors. Figure 7(a) illustrates structural differences under varying load magnitudes, while Figure 7(b) compares configurations across different load directions.

A Pareto-front analysis of frequency versus flexibility identified a cluster of optimal configurations within the 30–50% volume fraction range. These configurations represent effective trade-offs between structural stiffness, mass, and dynamic performance, reinforcing the value of multi-condition force analysis in early-stage machine design. As illustrated in Figures 7(a) and 7(b), a topology optimization model is first developed to determine the optimal load direction under various loading orientations. Based on the identified optimal direction, additional models with different load magnitudes are subsequently analyzed. Ultimately, a topology-optimized configuration is obtained with both the load magnitude and direction defined—specifically, a load of 100 kN applied at a 45° angle toward the upper left.

Overall, the simulation results validate the proposed generative design framework's ability to capture key structural behaviors and optimize performance under realistic manufacturing conditions.

4 Conclusions

This paper presents an AI-driven generative design method for machine tool structures, integrating measurement accuracy and sustainability considerations. The proposed framework enables early-stage global optimization, resulting in enhanced mechanical performance and reduced material usage.

(1) The structural design optimization should be implemented at the whole machine level and at the conceptual design stage.

(2) The load magnitude, load direction and structure volume fraction are solved through multi-condition force flow and load analysis, which ensures the global optimal of the structure configuration.

(3) The BP-GA algorithm achieved a coefficient of determination (R^2) close to 1 across the training, validation, and test datasets, demonstrating a high degree of predictive accuracy. The BP neural network's predicted values exhibited minimal deviation from the corresponding simulation results, indicating that the combined algorithm possesses robust fitting and optimization capabilities. These results offer strong theoretical and technical support for addressing similar structural optimization challenges.

(4) Structural configurations with volume fractions between 30-50% consistently demonstrate superior performance characteristics, establishing this range as the optimal design domain for machine tool structural optimization.

The generative design method of the conceptual configuration of the machine tool can determine the appropriate weight of the machine tool structure, improve the natural frequency and stiffness of the whole machine structure.

References

1. Y. Wang, D. Wang, S. Zhang et al, Design and development of a five-axis machine tool with high accuracy, stiffness and efficiency for aero-engine casing manufacturing. CJA. **35**, 485-496 (2022)
2. BT. Li, J. Hong, Z. Liu, Stiffness design of machine tool structures by a biologically inspired topology optimization method. IJMTM, **84**,33-44 (2014)
3. L. Shen, XH. Ding, TJ. Li, et al, Structural dynamic design optimization and experimental verification of a machine tool. IJAMT, **104**, 3773-3786 (2019)
4. XG. Li, CQ. Li, PH. Li, et al, Structural design and optimization of the crossbeam of a computer numerical controlled milling-machine tool using sensitivity theory and NSGA-II algorithm. INT J PRECIS ENG MAN, **22**, 287–300, (2021)
5. YL. Ma, JR. Tan, DL. Wang, et al, Light-weight design method for force-performance-structure of complex structural part based co-operative optimization[J]. CJME, **31**, 42 (2018)
6. X. Jiang, H. Wang, Y. Li, et al, Machine Learning based parameter tuning strategy for MMC based topology optimization. AES, 149, 102841 (2020)
7. JI. Saadi, MC. Yang, Generative Design: Reframing the Role of the Designer in Early-Stage Design Process. JMD, **145**, 041411 (2023)
8. A. Tkhenko, JC. Wang, Analysis of engineering structures and components created using the generative design. JPCS, **2762** (2024)

Nomenclature	
ρ	the density of element, Eqs. (2), (3), (4)
$F(\rho)$	the objective function, Eq. (2)
ω	the weight of the sub-goal, Eqs. (2)
C	the structural flexibility, Eqs. (2), (3)
$C(\rho)$	the flexibility of the current structural configuration, Eqs. (2)
C(max) C(min)	the maximum and minimum flexibility in all optional configurations (the different design configurations), Eqs. (2)
Λ	the first-order natural frequency
$\Lambda(\rho)$	the first-order natural frequency of the current structural configuration, Eqs. (2),
$\Lambda_{\max}$ $\Lambda_{\min}$	the maximum and minimum first-order natural frequency in all optional configurations, Eqs. (2), (4),
M	Mass, Eqs. (2)
$M(\rho)$	the mass of the current structural configuration, Eqs. (2),
$M_{\max}$ $M_{\min}$	the maximum and minimum mass in all optional configurations, Eqs. (2)
n	the number of elements in the structure, Eq. (3)
F	the load matrix at the nodes, Eq. (3)
U	the displacement vector, Eq. (3)
K	the total stiffness matrix of the structure, Eqs. (3), and (4)
$V(\rho)$	the reserved volume after optimization, Eqs. (3), and (4)
V_0	the initial volume of the machine tool, Eqs. (3), and (4)
V_i	the optimized removal volume, Eqs. (3), and (4)
f	the volume fraction before and after optimization, Eqs. (3), and (4)
ρ_m	the variable with the smallest relative density, Eqs. (3), and (4)
Λ_i	the corrected i-th order eigenvalue, Eq. (4)
λ_i	the i-th order eigenvalue, Eq. (4)
ξ_i	the weighted value corresponding to the i-th order, Eq. (4)
s, λ_0	the given parameter, Eq. (4)
$\boldsymbol{M}$	the total mass matrix, Eq. (4)
$\{\boldsymbol{\Phi}_i\}$	the i-th order characteristic Eigenvector corresponding to the value, Eq. (4)