Scientific Visualization, 2025, volume 17, number 4, pages 77 - 86, DOI: 10.26583/sv.17.4.08

This paper is an extended version of a contribution presented
at the Graphicon 2025 conference.

Integration of Generative Neural Networks in Mathematical and Three-Dimensional Modeling: Current State

N.A. Bondareva[1], A.E. Bondarev[2], S.V. Andreev[3], I.G. Ryzhova[4]

Keldysh Institute of Applied Mathematics RAS, Moscow, Russia

[1] ORCID: 0000-0002-7586-903X, nicibond9991@gmail.com
[2] ORCID: 0000-0003-3681-5212, bond@keldysh.ru
[3] ORCID: 0000-0001-8029-1124, esa@keldysh.ru
[4] ORCID: 0000-0003-1613-3038, ryzhova@gin.keldysh.ru

Abstract

This article provides a review of contemporary approaches to the application of generative neural networks in mathematical and three-dimensional modeling tasks. It examines the theoretical foundations of generative neural networks, their architectures, and training methodologies. Existing approaches to mathematical and three-dimensional modeling are analyzed, along with the potential for integration with generative neural networks. Particular emphasis is placed on hybrid approaches that combine the advantages of generative neural networks with traditional methods and expert knowledge, ensuring higher accuracy, reliability, and controllability of results. The article discusses the development prospects and socio-economic implications of implementing hybrid neural network technologies in engineering and scientific domains.

Keywords: generative neural networks, hybrid approach, mathematical modeling, three-dimensional modeling, artificial intelligence, automation, validation, machine learning.

1. Introduction

In the modern era of digital transformation, artificial intelligence technologies, and generative neural networks in particular, demonstrate impressive potential for solving a wide range of problems. However, despite obvious advances in content generation, data processing, and process automation, a number of critical limitations exist that hinder their full integration into production and research processes.

A key problem with modern neural network technologies is their "black box" nature, whereby results are generated without a transparent explanation of the decision-making logic. This significantly complicates the processes of validating the obtained results, identifying and correcting errors, and making targeted changes to the final solutions. This problem is particularly acute in areas requiring high accuracy and reliability of results, such as mathematical modeling and 3D design.

An analysis of existing approaches to integrating neural network technologies into production processes reveals a significant gap between the theoretical capabilities of artificial intelligence and the practical requirements of industry. Traditional implementation methods often focus either on fully automating processes using AI or on using neural networks as an auxiliary tool, which prevents these technologies from fully realizing their potential.

This study proposes a hybrid methodological approach designed to overcome these limitations. The approach is based on the synergy of natural language processing (NLP) technologies and verified software systems for mathematical and 3D modeling. The proposed methodology integrates the capabilities of artificial intelligence systems for natural language processing and the rapid generation of variable solutions with existing software algorithms.

The impact of generative neural networks on programming and software development deserves special attention. Modern language models demonstrate impressive capabilities in generating program code, automating routine programming tasks, and assisting with debugging. However, the "black box" problem also arises: generated code requires careful verification, as neural networks can create seemingly correct code that contains logical errors or vulnerabilities. This highlights the need to develop methodological approaches to verifying and validating generated software solutions.

The introduction of neural network technologies is significantly transforming the labor market structure in the technology sector. On the one hand, the barrier to entry into the profession has been significantly lowered: generative models provide budding specialists with powerful tools for learning and solving basic problems. This opens up new opportunities for professional development and allows for faster mastery of complex technological fields. On the other hand, the automation of routine operations reduces the need for low-skilled specialists performing standard tasks.

It's important to note that the role of highly qualified specialists not only remains but also grows. This is due to both the need for expert evaluation and validation of neural network results, as it is currently impossible to fully guarantee the quality and reliability of automatically generated solutions, and the need to develop and optimize methodologies for applying AI technologies.

2. Theoretical foundations and current state of the problem

Generative neural networks are one of the most dynamically developing areas in AI. Their evolution began with classic generative adversarial networks (GANs) in 2014 and continues to this day [1]. The current stage is characterized by a transition to more complex and controllable systems.

Diffusion models, a breakthrough in recent years, offer a new approach to content generation based on the gradual refinement of the result through sequential noise removal [2]. This method has demonstrated exceptional effectiveness in generating images, 3D models, and other types of data, delivering more stable and high-quality results than classical approaches. Diffusion models, a breakthrough in recent years, offered a new approach to content generation based on the gradual refinement of the result through sequential noise removal. Parallel to the development of diffusion models, a breakthrough occurred in the field of transformer architectures, originally developed for natural language processing but successfully adapted to work with various types of data, including program code and mathematical formulas. This opened up new possibilities for creating universal generative systems capable of simultaneously processing multiple data modalities.

In the context of training modern generative models, the example of Stable is illustrative. Diffusion XL, which uses a multi-stage training strategy. The model is first pre-trained on the massive LAION-5B image dataset, after which it is fine-tuned using specialized datasets for specific tasks. A similar approach is used in Meta 's CodeLlama-34b, where the base language model is further trained on specially prepared sets of program code, achieving high accuracy in generating specific programming constructs and working with various programming languages.

Self-supervised learning clearly demonstrates its effectiveness in the GPT-4V (Visual) architecture, where the model is capable of extracting semantic relationships between images and text without explicitly annotating these relationships in the training data. In the context of technical problems, a telling example is OpenAI 's Point -E, which can generate 3D models from text descriptions using an intermediate point cloud representation.

The practical application of generative models can be illustrated with specific examples from various industries. In industrial design, Autodesk uses generative design in Fusion 360 to create optimized designs. For example, when designing a bracket for the aerospace industry, the system generated multiple variants optimized for weight and strength, allowing for a 20-40% reduction in component weight while maintaining or improving mechanical performance.

Amazon Software Engineering CodeWhisperer and GitHub Copilot demonstrates the effectiveness of using generative models to automate development. According to GitHub research, developers using Copilot complete tasks on average 55% faster, while code quality, measured by the number of successfully passing tests, increases by 26% [3].

However, the implementation of such technologies is associated with specific technical challenges. For example, the use of Stable Diffusion XL for industrial design requires significant computing resources: at least 16 GB of video memory for basic operation and up to 24 GB for optimal performance. When integrating GitHub Copilot introduces security and code confidentiality issues into corporate systems, requiring the deployment of local versions of the system and additional control tools.

The choice of a specific architecture (Table 1) depends significantly on the specific problems being solved and the available computing resources. The current trend in the development of generative models is toward creating hybrid architectures that combine the advantages of various approaches while minimizing their drawbacks.

Table 1. Types of neural network architecture

Architecture	Advantages	Restrictions	Scope of application
Classic GANs	• High generation speed • Relative simplicity of architecture • Low requirements for computing resources	• Instability of learning • Mode problem collapse • Complexity of generation control	• Image generation • Data augmentation • Prototyping
Diffusion models	• High generation quality • Stability of results • Good process control	• High computational costs • Slow generation • Complexity of architecture	• Professional content generation • 3D modeling • Scientific research
Transformers	• Universality of application • Good scalability • Working with different types of data	• High memory requirements • Complexity of training • High development costs	• Code generation • Multimodal tasks • Complex automation
Hybrid architectures	• Combination of advantages of different approaches • Flexibility of configuration • Wide optimization possibilities	• Complexity of integration • Increased infrastructure requirements • Need for careful configuration	• Industrial applications • Complex production tasks • Research projects

Validation and verification of the obtained results play a key role in the development of generative technologies. While quality assessment in image or text generation tasks can be performed subjectively, technical tasks such as generating software code or 3D models require strict mathematical criteria and verification methods. This becomes especially relevant when integrating generative models into production processes, where the cost of error can be critically high.

In the context of training modern generative models, there has been a significant paradigm shift from classical methods to more comprehensive approaches. Traditional training methods based on direct minimization of the loss function have given way to multi-stage strategies that include pre-training on large datasets followed by specialized fine-tuning for specific tasks. The concept of transfer learning plays a special role in this process, enabling the efficient adaptation of pre-trained models to solve specific problems with significantly reduced requirements for computing resources and training data.

Modern approaches to training generative models also feature extensive use of supervised learning techniques. These methods enable models to extract useful features and patterns from unlabeled data, which is especially important in the context of technical problems where obtaining high-quality labels can be extremely expensive or practically impossible. Particular attention is paid to regularization and preventing overfitting, which is critical to ensuring the stability and reliability of the generated results.

3. Modern approaches to solving mathematical modeling problems

Mathematical modeling, a fundamental tool for scientific research and engineering development, is undergoing a significant transformation under the influence of AI. The integration of machine learning methods with classical approaches is creating a new paradigm in computational science. Traditional methods based on the numerical solution of differential equations face limitations when working with complex nonlinear systems.

According to a study [4] published in Nature Reviews In physics, the integration of machine learning methods with classical mathematical modeling approaches creates a new paradigm in computational science. Traditional mathematical modeling methods based on the numerical solution of differential equations face a number of significant limitations.

In this context, hybrid approaches that combine classical numerical methods with neural network models are of particular interest. For example, a study [5] demonstrates how the use of neural networks in hydrodynamics problems can reduce computation time by orders of magnitude while maintaining acceptable accuracy.

Mathematical modeling in the 2020s is characterized by the active implementation of high-performance computing systems and new methodological approaches. Leading research centers such as the US national laboratories (Argonne, Lawrence Berkeley and European research institutes are demonstrating a strong trend towards the use of hybrid computing architectures that combine classical approaches with elements of artificial intelligence.

The industrial sector is seeing active use of commercial mathematical modeling packages, with the following occupying leading positions:

1. ANSYS, which provides tools for:

- finite element analysis
- computational fluid dynamics
- electromagnetic modeling

2. COMSOL Multiphysics, which, according to the company's technical reports, has implemented machine learning support in its solvers, which has significantly accelerated the calculation of complex multiphysics problems.

3. MATLAB from MathWorks, which in recent versions has significantly expanded its integration capabilities with machine learning tools.

Supercomputer centers play a special role in scientific computing. According to the TOP500 (a ranking of the world's most powerful supercomputers), modern systems achieve performance in the hundreds of petaflops, opening up new possibilities for solving complex mathematical modeling problems [6].

Key trends in the development of mathematical modeling, confirmed by numerous publications in leading scientific journals and practical applications, are:

1. Development of multiscale modeling methods that allow taking into account processes on different spatial and temporal scales.

2. Implementation of machine learning methods for:

- acceleration of calculations;
- on optimization of computational grids;
- Predicting the behavior of complex systems.

3. Creation of digital twins, which is confirmed by successful implementations in the aerospace industry (Boeing, Airbus) and the energy sector (Siemens, General Electric)

4. Analysis of existing approaches to three-dimensional modeling

Modern 3D modeling is characterized by a variety of methodological approaches, each with its own advantages and applications. In industrial design, parametric, direct, and hybrid modeling, as well as generative design, are prominent. Cloud modeling and AI integration are also becoming increasingly popular. Various industries are developing their own approaches to 3D modeling, such as BIM modeling in architecture, surface modeling in industrial design, and polygonal modeling in animation and gaming. Current trends point to the automation of modeling processes, the integration of various approaches, and the increased availability of tools. and the implementation of AI.

In recent years, artificial intelligence technologies have been actively integrated into traditional 3D modeling tools. Autodesk, one of the industry leaders, has integrated neural network technologies into Fusion 360 to automate design and optimization processes. The system uses machine learning algorithms for generative design, enabling the creation of optimized designs based on specified parameters and constraints. According to the company, this approach reduces design time by 30-50% while simultaneously improving the performance of the final product.

Siemens NX is also actively developing artificial intelligence in its solutions. The latest software versions implement machine learning algorithms to predict potential design issues, automatically optimize topology, and assist in design decision-making. Neural networks have proven particularly effective in analyzing and optimizing assemblies, where algorithms can suggest more efficient layout options based on accumulated experience.

Blender, a popular open-source 3D modeling tool, has integrated support for various neural network plugins. Most notably, it introduced tools for automatic texture generation, model topology optimization, and machine learning-based animation. The developer community is actively pursuing these technologies, creating new tools for automating various aspects of 3D modeling.

In the context of neural network-based 3D modeling, several main approaches have emerged. Neural technology Radiance NeRF (Neural Network Fields), introduced by researchers at UC Berkeley, has revolutionized the creation of 3D models from photographs. This method enables the creation of detailed 3D reconstructions of objects using a set of 2D images. The main advantage of this approach is the high accuracy of reproducing the geometry and textures of real objects. However, a significant limitation remains the need for a large number of source images and significant computing resources for processing.

NVIDIA's GET3D represents a different approach to neural network modeling, enabling the generation of 3D models based on text descriptions or single images. The technology demonstrates impressive results in creating a variety of 3D objects, but its accuracy and detail are inferior to those of traditional modeling methods. Its main advantage is the speed of creating basic models and the ability to quickly prototype.

OpenAI 's Point -E offers an alternative approach based on generating point clouds and then processing them to create full-fledged 3D models. This method is characterized by high speed and lower computational requirements compared to other neural network approaches. However, the quality of the resulting models may be insufficient for industrial applications, limiting its use to rapid prototyping and conceptual design.

An important aspect of the development of neural network 3D modeling is the integration of various approaches and the creation of hybrid solutions. Current research aims to combine the advantages of various methods while minimizing their drawbacks. Particular attention is paid to the development of methods for validating and verifying the obtained results, which is critical for the industrial application of these technologies.

5. Methodological foundations of the hybrid approach

In modern practice, significant potential is being demonstrated for synergy between neural network technologies and traditional approaches in various fields of engineering and science. Experience in implementing such solutions at leading technology companies and research centers allows us to assess the real possibilities and limitations of this integration.

In the programming field, large-scale implementation of GitHub Copilot demonstrates the practical applicability of neural network technologies for automated software development. According to a 2023 GitHub study [7], the use of neural network assistants can significantly accelerate the coding process, especially in tasks related to creating standard software constructs and data processing. It is important to note that the programmer's role is being transformed: from writing routine code to higher-level architectural design and validation of generated solutions.

In mathematical modeling, the most promising direction is the creation of hybrid systems that combine classical numerical methods with neural network approaches. Research [4] demonstrates the possibility of significantly accelerating calculations while maintaining the physical correctness of the results. Such approaches are particularly effective in optimization and prediction tasks for complex systems, where traditional methods require significant computational resources.

3D modeling is being enriched by the ability to automatically generate and optimize models. NVIDIA, with its GET3D technology, has demonstrated the ability to create detailed 3D models based on text descriptions or images [8]. This opens up new possibilities for rapid prototyping and conceptual design. In industrial applications, the ability to automatically optimize existing models based on specified parameters and constraints is becoming especially important.

The integration of these technologies creates new opportunities for interdisciplinary collaboration. For example, the results of mathematical modeling can be automatically converted into 3D models, which are then optimized to accommodate technological constraints. Software code for controlling such systems can be automatically generated, taking into account the specifics of a particular task and performance requirements.

Verifying the results obtained using neural network technologies deserves special attention. In programming, this is achieved through automated testing and static code analysis. In mathematical modeling, comparison methods with classical solutions and experimental data are used. For 3D modeling, specialized methods are being developed to verify the geometric and topological correctness of the generated models.

Industrial implementation of such comprehensive solutions requires the creation of an appropriate infrastructure and methodology. The experience of companies that have successfully integrated neural network technologies into their processes demonstrates the need for a phased approach with thorough validation at each stage. The key to success is correctly defining the applicability limits of automated solutions and maintaining specialist oversight.

A promising development direction is the creation of unified platforms that integrate various aspects of design and modeling. Such systems enable a seamless process from conceptual design to the finished product, with neural network technologies acting as an intelligent assistant at every stage of the process. This is especially important in the context of the development of digital twins and smart manufacturing.

This study proposes a hybrid methodological approach [9] designed to overcome these limitations. The approach is based on the synergy of natural language processing (NLP) and verified engineering software systems. It is expected that the combination of these two approaches will minimize the likelihood of errors and inaccuracies in the design process, while ensuring the necessary level of oversight by specialists.

The proposed methodology is based on the integration of the capabilities of artificial intelligence systems in the field of natural language processing and the rapid generation of variable solutions with existing algorithms for constructing CAD models in domestic automated design systems, such as KOMPAS-3D [10] and TeFlex [11].

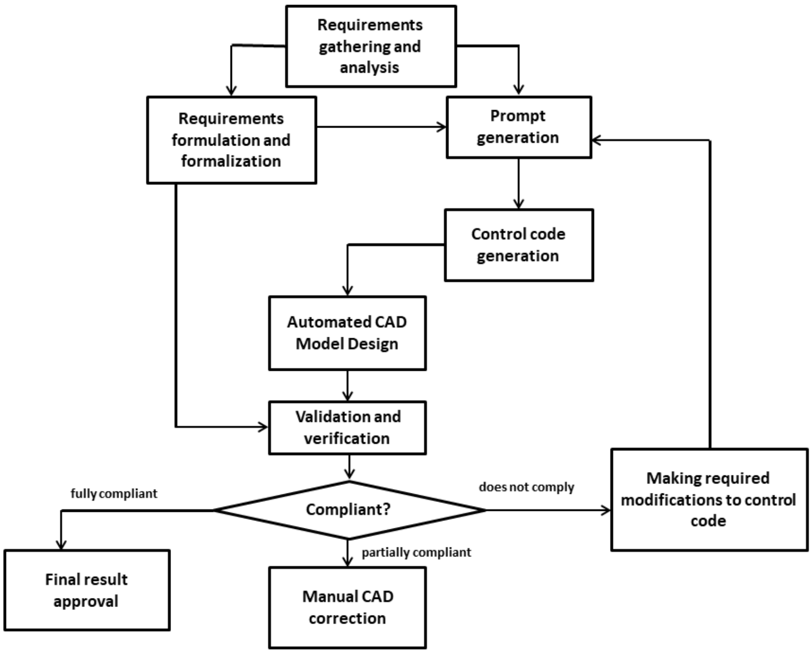

Fig. 1. Scheme of a hybrid methodological approach applied to CAD systems

The methodology is a hybrid approach to automated 3D modeling, combining natural language processing (NLP) with the use of proven engineering software packages (CAD), such as KOMPAS-3D or TeFlex. The so-called hybrid approach offers a compromise between automation and controllability of the 3D modeling process, combining the benefits of AI and proven engineering tools. This approach aims to minimize errors and improve the accuracy of the modeling process compared to using generative neural networks exclusively. The key advantage lies in the validation of the parameters of the AI-generated script, rather than the validation of the entire generated model.

Instead of directly using a neural network to generate a 3D model, which is prone to hidden errors, text-based AI is used to create a control script in a programming language compatible with the selected CAD system. This shifts the focus of control from checking the finished model to verifying the parameters specified in the script, ensuring earlier detection and correction of potential errors. The iterative nature of the process allows for prompt and script adjustments based on analysis of intermediate results, ensuring flexibility and high accuracy of the final 3D model.

The practical implementation of hybrid neural network solutions for engineering and scientific applications requires a comprehensive approach to ensuring process reliability, efficiency, and controllability. The experience of leading technology companies and research centers allows us to formulate key requirements for such systems.

6. Development prospects and socio-economic factors:

In the context of the rapid development of AI and its integration into industrial and scientific processes, an analysis of the development prospects and socio-economic consequences of the implementation of hybrid neural network technologies is particularly relevant.

McKinsey forecasts Global Institute [12], the introduction of neural network technologies into engineering and scientific fields will lead to a significant transformation of the labor market in the next 5-10 years. An interesting paradox is observed: despite the automation of many processes, the demand for highly qualified specialists is not only not decreasing but actually increasing. This is due to the need to develop, implement, and monitor new technological solutions.

The barrier to entry into programming has been significantly lowered thanks to tools like GitHub. Copilot and similar systems. However, as leading tech companies demonstrate, this doesn't reduce the skill requirements for experienced developers. Instead, their focus shifts toward more complex tasks such as architectural design, optimization, and code quality assurance.

Mathematical and engineering modeling is also undergoing significant changes. The introduction of hybrid approaches makes it possible to solve increasingly complex problems that were previously inaccessible due to computational limitations. At the same time, the role of specialists is transforming: from performing routine calculations to defining problems, selecting methodology, and validating results.

The ethical aspects of implementing neural network technologies deserve special attention. Questions of responsibility for decisions arise, especially in critical areas such as medical modeling or the design of critical engineering structures. Leading organizations, including IEEE and ACM, are actively working to develop ethical standards and guidelines for the application of AI technologies.

Prospects for further development revolve around several key areas. First, improving methods for ensuring the reliability and interpretability of neural network component output. Second, developing technologies for automatically adapting models to changing conditions and requirements. Third, creating more effective methods for integrating expert knowledge into the training and operation of neural networks.

Developing infrastructure to support hybrid solutions is also crucial. This includes both hardware improvements and the creation of specialized platforms for the development and implementation of such systems. Leading technology companies are actively investing in cloud services and tools that simplify the work with hybrid systems.

7. Conclusion:

A hybrid approach to using generative neural networks in mathematical and 3D modeling represents a promising direction, combining the benefits of AI with traditional methods, ensuring greater accuracy, reliability, and controllability of results. This approach not only opens up new opportunities for automating routine tasks and accelerating design processes, but also enables the solution of more complex and large-scale problems previously inaccessible due to computational limitations or the complexity of manual modeling.

Further development of this approach requires addressing a number of technological, methodological, and socioeconomic challenges. Key areas include developing new methods to ensure the reliability and interpretability of results, advancing technologies for automatically adapting models to changing conditions and requirements, and creating more effective methods for integrating expert knowledge into the training and operation of neural networks. Another important aspect is the development of infrastructure to support hybrid solutions, including hardware improvements and the creation of specialized platforms for the development and implementation of such systems.

The introduction of hybrid neural network technologies is having a significant impact on the labor market, requiring new competencies and skills from specialists. Educational institutions must adapt their programs to prepare specialists capable of effectively working with hybrid systems and critically evaluating AI-based results.

Overall, the hybrid approach to using generative neural networks opens up new prospects for the development of mathematical and 3D modeling, enabling the creation of more complex, accurate, and efficient models that can be used in various industries and sciences. Successful implementation of this approach requires a comprehensive approach that includes technological innovation, methodological developments, and socioeconomic transformation.

References

1. I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde -Farley, S. Ozair, A. Courville, Y. Bengio, Generative Adversarial Networks, 2014, https://doi.org/10.48550/arXiv.1406.2661
2. J. Ho, A. Jain, P. Abbeel, Denoising Diffusion Probabilistic Models, 2020, URL: https://doi.org/10.48550/arXiv.2006.11239 (date appeals of March 29, 2023)
3. Rodriguez M. Research: Quantifying GitHub Copilot's impact on code quality, GitHub Blog, 10.10.2023, URL: https://github.blog/news-insights/research/research-quantifying-github-copilots-impact-on-code-quality/
4. Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422-440.
5. Wang H., et al. Recent advances on machine learning for computational fluid dynamics: A survey, 2024 arXiv preprint arXiv:2408.12171
6. TOP500 List - June 2025, URL: https://top500.org/lists/top500/list/2025/06/?utm_source=Securitylab.ru
7. Daigle K. Octoverse : The state of open source and rise of AI in 2023, GitHub Blog, 11/08/2023, URL: https://github.blog/news-insights/research/the-state-of-open-source-and-ai/
8. Isha Salian, World-Class: NVIDIA Research Builds AI Model to Populate Virtual Worlds With 3D Objects, Characters, 2022, Blogs.nvidia, URL: https://blogs.nvidia.com/blog/3d-generative-ai-research-virtual-worlds/
9. NA Bondareva, AE Bondarev, SV Andreev, IG Ryzhova . Development of a Methodology for the Application of Generative Neural Networks in Creating 3d Models (2025). Scientific Visualization 17.3: 25 - 34, DOI: 10.26583/sv.17.3.034.
10. KOMPAS-3 D Russian import-independent system of three-dimensional design. URL: https://kompas.ru/ (date of access 04/29/2025)
11. T - FLEX CAD Russian engineering software for 3D design and development of design documentation URL: https://www.tflexcad.ru / (date of access 04/29/2025)
12. Ellingrud K., Sanghvi S., Dandona G., Madgavkar A., Chui M., White O., Hasebe P., Generative AI and the future of work in America, 2023, URL: https://www.mckinsey.com/mgi/our-research/generative-ai-and-the-future-of-work-in-america