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СОВРЕМЕННЫЕ ВЫЗОВЫ НА ПЕРЕСЕЧЕНИИ МАТЕМАТИЧЕСКОЙ МЕХАНИКИ И ИНФОРМАЦИОННЫХ ТЕХНОЛОГИЙ

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CONTEMPORARY CHALLENGES AT THE INTERSECTION OF MATHEMATICAL MECHANICS AND IT

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Аннотация. В данной статье рассматриваются три основные проблемы: вычислительные ограничения, накладываемые «проклятием размерности», и энергетические затраты на крупномасштабные симуляции. Изучая эти современные проблемы, статья стремится дать более четкое представление о текущем состоянии области и перспективных направлениях будущих исследований.

Ключевые слова: математическая механика, информационные технологии, сложные системы, проклятие размерности, искусственный интеллект, классическая механика

Abstract. This article examines three major issues: the computational limits imposed by the "curse of dimensionality" and the energy demands of large-scale simulations. By exploring these contemporary challenges, the article aims to provide a clearer picture of the current state of the field and promising directions for future research.

Keywords: mathematical mechanics, information technology, complex systems, curse of dimensionality, artificial intelligence, classical mechanics

In the 21st century the connections between mathematics, mechanics, and information technology have become tighter than ever before. These fields once worked mostly on their own, but now they depend on each other more and more. Mathematics provides the basic language, mechanics gives the physical rules, and information technology supplies the computing power needed to simulate and predict how complex systems behave. As M. Raissi showed for the first time, physics-informed neural networks offer a promising way to embed physical laws into deep learning architectures [1, p. 687]. From digital twins in aerospace engineering to AI-driven scientific discovery, bringing these fields together has become essential.

However, this integration does not come without serious problems. When we try to combine these areas, we run into fundamental difficulties. The computing power needed to simulate complex physical systems often pushes even the most advanced supercomputers to their limits. The rise of artificial intelligence can sometimes clash with the well-established principles of classical mechanics. And the growing demand for large-scale computing raises questions about energy use and fairness. This article looks at three major challenges at this intersection: first, the computational limits we face when dealing with complex systems; second, the conflict between AI's "black box" nature and the need for physical consistency;

and third, concerns about energy consumption, data security, and technological independence. By exploring these issues, we aim to paint a clearer picture of where the field stands today and where promising developments may lie ahead.

One of the toughest problems in mathematical mechanics is how to accurately simulate complex physical systems. Real-world situations like turbulent airflow around an airplane wing, how materials crack under stress, or a spacecraft re-entering Earth's atmosphere are governed by complicated equations that involve many variables and operate across many scales.

The mathematical difficulty here is what experts call the "curse of dimensionality". When the number of variables in a system increases, the computing power needed to solve it grows exponentially [2, p.14]. For example, to simulate turbulence inside a jet engine, you would need to capture all air movements from very large swirls down to tiny eddies a range of scales that challenges even the world's fastest supercomputers. For practical engineering purposes, the cost of such detailed simulations is often far too high.

From a mechanics perspective, the problem is equally tricky. Accurate simulations depend on good mathematical models of how materials behave. But under extreme conditions like very high temperatures, intense pressures, or rapid changes from solid to liquid many materials act in ways that our current models cannot describe accurately. There is a gap between what we can compute and what we can model well.

Information technology, while giving us more powerful computers, brings its own limitations. Most computers today separate memory from processing units, which creates a bottleneck when handling the massive amounts of data produced by detailed simulations. As computing demands grow, so does energy use. Running a large-scale simulation of a nuclear reactor or a climate model can consume as much electricity as a small town uses in a year. So the challenge is not just about better mathematics or better physics it also involves computer architecture and energy sustainability.

The second major challenge comes from combining machine learning and artificial intelligence with classical mechanics. In recent years, many people have been excited about replacing traditional physics-based solvers with data-driven AI models. These models promise speed, flexibility, and the ability to spot patterns that humans might miss. But there is a fundamental problem: pure data-driven AI models do not understand physics.

The core issue is that machine learning models are statistical they look for patterns in data while physical systems follow deterministic laws. An AI trained on data from a physical system might learn correlations that happened to appear in the training data, but that actually violate basic principles like conservation of energy or momentum. For example, if you train a neural network to predict the motion of a pendulum but give it only limited data, the network might produce predictions where the pendulum swings higher and higher, gaining energy out of nowhere something that could never happen in the real world.

This problem becomes especially serious in safety-critical applications. Think about self-driving cars, aircraft control systems, or structural health monitoring for bridges. In these fields, prediction reliability is crucial. Traditional physics-based models, though slower, give predictions that are grounded in actual physical laws. Pure neural networks cannot offer such guarantees. Because these networks are "black boxes" you cannot see exactly how they arrive at an answer engineers find it hard to trust them for critical decisions.

Researchers have been working on solutions, the most famous being physics-informed neural networks (PINNs). These models incorporate physical laws directly into the training process, penalizing the network when it makes predictions that violate conservation principles [3, p.3056]. That sounds promising, but PINNs come with their own problems. They struggle with complex boundary conditions, can be difficult to train, and often need careful tuning of many settings. More importantly, they do not fully solve the reliability issue predictions for situations not seen in the training data remain questionable. So, the fundamental challenge of making AI both flexible and physically reliable remains unsolved.

Beyond the technical problems, the combination of mathematical mechanics and information technology also raises important questions about sustainability, fairness, and security. These issues may seem less technical, but they are just as important for the future of the field.

The first issue is energy consumption. The computing power needed for modern AI models has grown extremely fast. According to E. Strubell and colleagues, training a single large language model produces as much carbon dioxide as several cars emit over their entire lifetimes [4, p.3645]. In mathematical mechanics, simulations often run for weeks on dedicated supercomputers, and the overall energy footprint is considerable. This raises an ethical question: how do we balance the desire for scientific and engineering progress with the responsibility to protect the environment? Developing more efficient algorithms and hardware is not just a technical goal it is also an ethical one.

The second issue concerns technological independence. The most advanced software for engineering design and simulation such as computer-aided design (CAD), computer-aided engineering (CAE), and finite element analysis programs is provided by only a handful of companies in just a few countries. For countries trying to develop advanced aerospace, defense, or semiconductor industries, relying on foreign software creates a strategic vulnerability. This problem sits right at the intersection we are discussing: we understand the underlying mathematics, but turning that mathematics into reliable, scalable software requires expertise in both mechanics and information technology expertise that is not evenly distributed around the world.

Finally, data privacy and security concerns make collaboration difficult. In areas like digital twins of critical infrastructure or collaborative aerospace design, organizations could build better models by sharing data. But much engineering data is proprietary or confidential, which prevents such sharing.

This article has explored three interconnected challenges at the intersection of mathematical mechanics and information technology: the computational limits of simulating complex systems, the conflict between AI's "black box" nature and the need for physical consistency, and the emerging issues of sustainability, independence, and security. While these challenges are significant, they also point toward promising future directions.

First, to address computational limits, we need not only better hardware but also smarter algorithms. Techniques such as reduced-order modeling, adaptive mesh refinement, and exploring quantum computing for solving physical equations represent exciting frontiers.

Second, to reconcile AI with physics, we need to move beyond simple combinations toward deeper integration. Developing "physics-aware" architectures where physical laws are built into the structure of AI models rather than just added afterward is an important direction. This will require close collaboration between computer scientists and mechanical engineers.

Third, to tackle sustainability and fairness issues, we need both technical solutions and institutional changes. Energy-efficient algorithms, specialized hardware, and open-source software can help reduce environmental impact while also making these powerful tools more accessible. At the same time, educational programs that train students in mathematics, mechanics, and computer science together are essential for building the cross-disciplinary expertise needed for future breakthroughs.

In summary, the integration of mathematical mechanics and information technology holds great promise, but realizing that promise means facing the challenges discussed in this article head-on. The way forward is not simply to throw more computing power at problems or to adopt the latest AI techniques without question. Instead, it requires thoughtful, cross-disciplinary approaches that respect the strengths of each field while seeking genuine integration. Only by acknowledging and addressing these challenges can we build a future where mathematics, mechanics, and information technology truly work together to solve the most important problems of our time.

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