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The Future of Scientific Modelling: Combining Physics with Artificial Intelligence: A Review

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Science Modelling is a traditional approach to analysing the complicated nature of physical events using mathematical equations, numerical methods, and empirical data. Despite the successful performance of the existing computational algorithms, there remain some problems related to the complexity of systems and data produced by modern scientific experiments, which cannot be solved easily using these methods. The recent development of AI technologies has made it possible to build sophisticated prediction algorithms based on data analysis, but these algorithms often yield results that contradict physical laws. The incorporation of physics in artificial intelligence has proven to be an innovative approach which blends the interpretability of physical theories with the flexibility of machine learning techniques. However, there are some drawbacks associated with such a technique including the high computational cost, optimization problems, non-interpretable nature of predictions, the need for uncertainty quantification, and scaling issues with real-world systems. This paper aims at reviewing the history of scientific modelling, exploring the concepts related to physics-integrated artificial intelligence, identifying the benefits and drawbacks associated with such a technique, and discussing the future research directions

Keywords: Artificial Intelligence, Scientific Modelling, Physics-Informed AI, Physics-Informed Neural Networks, Scientific Machine Learning, Computational Physics, Digital Twin, Hybrid Intelligence

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1. Introduction

Scientific modelling plays a central role in modern science and engineering by providing mathematical representations of natural phenomena. These models enable researchers to understand physical processes, predict system behaviour, optimize engineering designs, and support decision-making in numerous scientific disciplines. Traditionally, scientific modelling has relied on physical laws expressed through differential equations, conservation principles, numerical simulations, and laboratory experiments. Such approaches have successfully solved problems ranging from planetary motion and fluid flow to electromagnetic fields and quantum mechanics. The rapid growth of computational power has significantly expanded the capability of numerical modelling. Nevertheless, many modern scientific problems remain computationally demanding due to their nonlinear behaviour, high dimensionality, stochastic characteristics, and multi-scale interactions. Complex systems such as climate dynamics, plasma physics, turbulence, and biological processes often require enormous computational resources and extensive experimental data for accurate modelling.

Artificial Intelligence (AI), particularly machine learning and deep learning, has recently emerged as a powerful alternative for analysing large datasets and generating predictive models. AI algorithms excel at identifying hidden relationships within data and can often produce rapid predictions once trained. However, purely data-driven AI models suffer from an important limitation: they do not inherently obey the laws of physics. Consequently, AI-generated predictions may violate conservation of energy, momentum, mass, or fail to satisfy initial and boundary conditions, thereby reducing their scientific credibility.

To overcome these limitations, researchers have developed hybrid approaches that integrate established physical knowledge directly into artificial intelligence models. Rather than treating physics and AI as competing methodologies, this integration combines the strengths of both domains. Physics provides theoretical consistency and interpretability, while AI contributes flexibility, adaptability, and computational efficiency.

This paper examines how the integration of physics with artificial intelligence is reshaping scientific modelling. It discusses the underlying concepts, applications, benefits, current challenges, and future prospects of this emerging interdisciplinary field. By reviewing recent advances and identifying research gaps, the paper highlights the potential of hybrid intelligence to become the next generation of scientific computing.

2. The Role of Artificial Intelligence in Modern Physics

Nowadays, one of the key innovations in the realm of physics is Artificial Intelligence (AI). This innovation plays a vital role in the development of the science due to the possibility to apply advanced computing technologies to the study of physical processes. Conventional computational methods of investigation of physical phenomena presuppose solving of complicated mathematical equations as well as performing numerous numerical simulations, which usually take a lot of time. AI makes it possible to learn complicated relations between variables using data and make fast decisions. However, there are many other ways in which AI makes it possible to perform scientific research faster. Modern scientific equipment (such as particle accelerators, space telescopes, gravitational wave detectors, and synchrotron radiation sources) collects huge amounts of experimental and simulation data daily. It would be impossible to analyse such big amounts of data manually. Machine learning algorithms make it possible to identify hidden patterns, classify the events and detect anomalies extremely quickly. Therefore, researchers spend much less time analysing the data.

3. Physics-Informed Artificial Intelligence

Physics-Informed Artificial Intelligence (PIAI) is a novel discipline that combines physical laws with artificial intelligence's predictive power. Unlike traditional machine learning algorithms, which use big datasets to learn relationships from inputs to outputs, physics-informed AI directly incorporates scientific knowledge into the learning process. This approach guarantees that not only statistical accuracy but also physical consistency of the model predictions with known laws is ensured. Governing equations, conservation laws, initial and boundary conditions are embedded in the optimization process by means of PIAI.

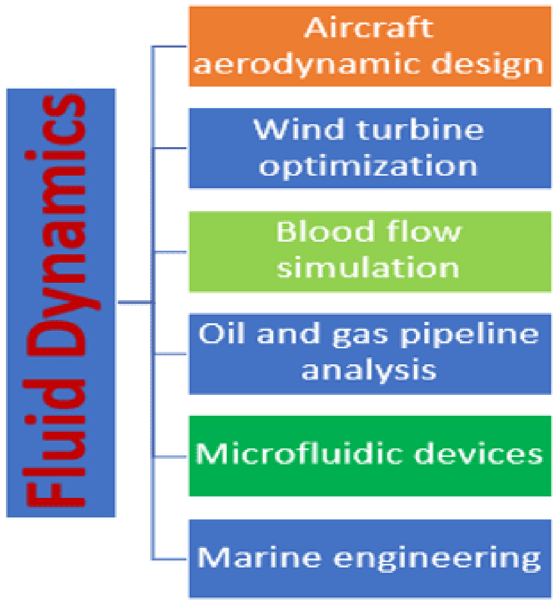
The advent of experimental and simulation data in scientific research has made artificial intelligence a powerful tool in many scientific disciplines. Data-driven models have some important limitations for scientific applications. They could predict results that would contradict the laws of conservation of mass, momentum or energy, be unrealistic when applied beyond the domain of training, and demand huge amounts of labelled data for learning.

4. Major Applications of Physics-Informed Artificial Intelligence

Physics-based artificial intelligence (PIAI) has emerged as an important computational approach in many different scientific and engineering fields. Through the use of physical laws in conjunction with machine learning, it can provide precise predictions despite lack of experimental data. The subsequent sections highlight some of the important applications of PIAI.

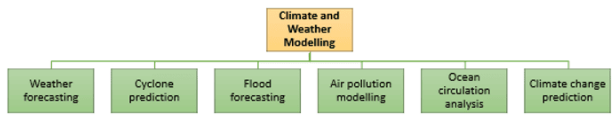
4.1 Fluid Dynamics

Fluid Dynamics is another of the oldest and most productive fields of application of Physics-Informed AI. Conventional methods of Computational Fluid Dynamics (CFD) use complex numerical calculations to solve the Navier-Stokes equations. These calculations become very costly if turbulent flow or multiphase fluids are considered.The main principle of Physics-Informed Neural Network is to incorporate the physical laws which govern the flow into the Neural Network itself. This allows for fast prediction of velocity fields, pressure fields, vortex formation, and heat transfer with much less computation cost compared to conventional CFD techniques.



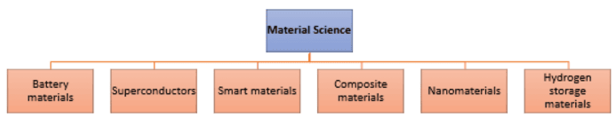
4.2 Climate and Weather Modelling

The relationship between various components such as the atmosphere, ocean, land surface, and ice sheets is highly nonlinear in climate systems. Conventional climate models demand massive computational power and time for simulations. Physics-guided AI integrates observed satellite data with equations that govern the atmosphere and oceans to enhance forecast accuracy. The inclusion of conservation principles makes it physically accurate climate forecasting.



4.3 Material Science

The process of identifying advanced materials usually requires expensive laboratory tests and extensive simulations. Physics-informed AI speeds up the discovery of advanced materials by learning the links between atomic structure, material composition, and physical properties.



4.4 Quantum Physics

Mathematical equations like the Schrodinger equation characterize quantum systems which are highly complicated in nature.

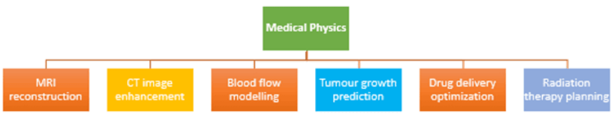
Physics-informed AI helps scientists in finding approximations to quantum wave functions, solving many body problems, estimation of quantum states, and design of quantum devices.

4.5 Astrophysics and Space Science

Current telescopes produce vast amounts of data which need intelligent processing. AI techniques enable researchers to detect galaxies, categorize stars, discover exoplanets, measure black holes, and analyse gravitational waves. Together with physics equations, predictions will be more accurate and scientifically valid.

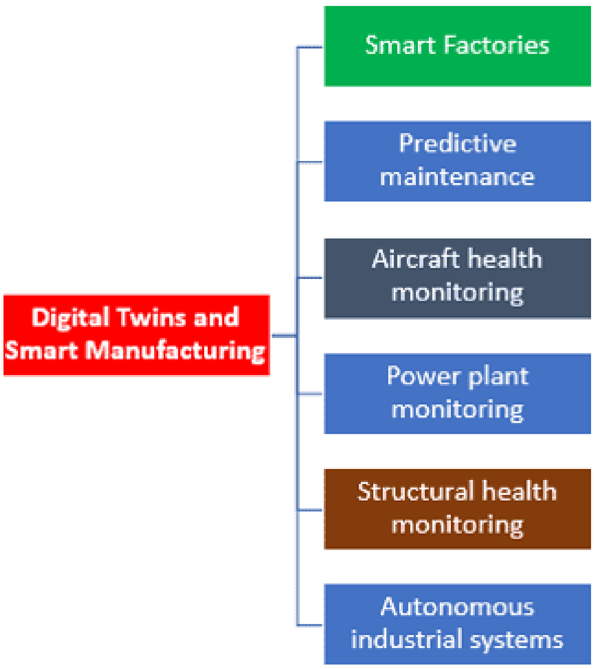
4.6 Biomedical Engineering and Medical Physics

Physics-informed AI plays an increasingly important role in healthcare by combining biological physics with machine learning.



4.7 Digital Twins and Smart Manufacturing

Digital twins are the digital models of physical systems updated continually using information from sensors. Physics-informed AI is used to enhance digital twins by adding engineering principles to the models.



5. Advantages of Integrating Physics with Artificial Intelligence

Physics and AI together in one system make use of the best aspects of both scientific modelling as well as machine learning, thus forming a highly capable computing method that is able to deal with scientific problems effectively. In contrast to data-based methods, which focus solely on statistical correlation, a physics-inspired AI approach uses physical principles in its learning process. The combination of physics with AI utilizes the best attributes of both the physical modelling approach and machine learning, leading to better models.

5.1 Improved Physical Consistency

Unlike traditional artificial intelligence models based only on statistics, Physics-Informed Artificial Intelligence guarantees that the outputs are consistent with the corresponding physical laws of conservation of mass, momentum, and energy. It allows one to avoid physically unrealistic results and gives a higher degree of scientific validity of the predictions.

5.2 Reduced Data Requirement

The main advantage of Physics-Informed Artificial Intelligence is the ability of the model to make accurate predictions in cases of small amounts of experimental data. Due to the guidance by physical equations, the model is able to predict the behavior of the system even in areas where the data are not sufficient.

5.3 Faster Computational Predictions

Classical numeric simulations usually take several hours or even days to simulate complicated physical systems. Once they are trained, Physics-Informed AI models become capable of predicting outcomes of those physical processes within just seconds or minutes, which makes them extremely useful for real-time applications.

5.4 Simultaneous Solution of Forward and Inverse Problems

Physics-informed AI can address both types of problems, namely forward and inverse. The ability to solve both forward and inverse problems is especially valuable in the field of engineering, medical imaging, geophysical prospecting, and parameter estimation.

5.5 Better Interpretability than Conventional AI

While deep neural networks are typically considered black-box models, the combination of physics helps increase their interpretability. Thus, it becomes possible to check whether the results comply with existing science principles.

6. Comparison with Traditional Computational Methods

The traditional computational approaches and Physics-Informed Artificial Intelligence vary greatly in respect to modelling approach, computing needs, flexibility and prediction capabilities. The former approach is based on physical laws and employs the direct solution of governing equations via FDM, FEM and FVM discretization methods. Despite the high interpretability of results provided by the traditional approach, it becomes costly in terms of computations when dealing with large scale or high-dimensional problems. Physics-Informed AI relies upon the combination of physical knowledge and machine learning to produce predictive models capable of producing approximations much faster once trained. While the initial training stage is computationally intensive, further predictions turn out to be faster than the consecutive run of traditional numerical methods. Moreover, Physics-Informed AI performs well even with a small amount of experimental data as the learning is guided by physical considerations. Nevertheless, the traditional computational approaches retain their superiority in interpretability and robust generalization for well-structured physical domains. In its turn, the performance of Physics-Informed AI becomes limited when used for extrapolation outside the range of training data. For this reason, the future belongs to the hybrid computational schemes combining traditional solvers with intelligent algorithms.

Table 1: Comparison between Traditional Computational Methods and Physics-Informed AI

Criterion	Traditional Computational Methods	Physics-Informed Artificial Intelligence
Physical Interpretability	Very High	High
Data Requirement	Very Low	Low to Moderate
Computational Cost	Moderate	High during training, Low during prediction
Prediction Speed	Moderate	Very High after training
Scalability	Good	Improving
Flexibility	Limited	High
Handling Sparse Data	Moderate	Excellent
Generalization	Strong within known models	Limited outside training domain
Real-Time Prediction	Difficult	Highly Suitable
Industrial Applications	Well Established	Rapidly Expanding

7. Conclusion

The integration of physics and artificial intelligence is one of the revolutionary developments in scientific modelling where machine learning models are incorporated with the reliable fundamentals of physics. Even though traditional numerical solutions are essential for solving well-stated physical problems, the evolving complexity of modern scientific systems requires flexible techniques that can save computational efforts. In this regard, physics-informed artificial intelligence integrates governing equations, conservation principles, and other physical restrictions within machine learning models to provide precise and physically coherent results with insufficient data samples.

There is a wide variety of scientific areas where physics-informed artificial intelligence shows its promising potential from fluid dynamics, climate science, quantum mechanics, materials science, astrophysics, biomedical engineering, and digital twin solutions. However, there are certain difficulties associated with physics-informed artificial intelligence, which include computational efficiency, scalability issues, optimization challenges, and lack of interpretability. Nevertheless, ongoing advancements in scientific machine learning, high-performance computations, and uncertainty quantification address those issues.

Physics-Informed Artificial Intelligence must not be considered as an alternative to the traditional computational approaches; instead, it should be regarded as an additional tool expanding the abilities of the classical scientific modelling approach. With the help of the combination of theory and data-based intelligence, future scientific models would be more precise, effective, explainable, and flexible enough to adapt to ever more complex reality. Hence, physics and AI integration would be considered the core of next-generation computational science.

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