Applications of Artificial Intelligence in Environmental Engineering

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Abstract

In recent years, issues such as environmental pollution, resource depletion, and ecological imbalance have become increasingly severe. Traditional environmental governance methods have shown limitations when dealing with the complexity of modern environmental systems. The rapid development of Artificial Intelligence (AI) offers a novel approach to addressing these challenges in environmental engineering. As a cutting-edge technology that integrates computer science, statistical modeling, and data-driven learning, AI has demonstrated strong capabilities in pattern recognition, adaptive modeling, and intelligent optimization, catalyzing a paradigm shift from traditional mechanistic modeling to data-centric approaches. It is now widely applied in key areas including environmental monitoring, pollution control, process optimization, resource allocation, and environmental decision-making. This paper systematically reviews the core application scenarios of AI in environmental engineering, analyzes its advantages and current challenges, and discusses future directions for integration and development.

Keywords

Artificial intelligence, environmental engineering, environmental monitoring, pollution control, intelligent decision-making.

1. Introduction

Environmental engineering is tasked with developing sustainable solutions for increasingly complex global challenges, from pollution abatement and resource management to ecological restoration. The field has traditionally relied on mechanistic models, such as computational fluid dynamics (CFD) or activated sludge models (ASMs), to simulate and understand environmental processes. These models are built upon fundamental scientific principles and provide valuable insights into system behavior. However, their practical application is often constrained by a reliance on simplifying assumptions, the need for extensive and costly parameter calibration, and inherent difficulties in capturing the high-dimensional, non-linear, and stochastic nature of real-world environmental systems. As a result, a gap often exists between theoretical predictions and observed realities.

In response to these limitations, the confluence of massive data availability from sensor networks, advances in computational power, and the maturation of sophisticated algorithms has positioned Artificial Intelligence (AI) as a powerful complementary tool. AI, particularly its subfields of machine learning, deep learning, and reinforcement learning, offers a data-centric approach to modeling complex systems. Instead of relying on pre-defined equations, these methods learn patterns and relationships directly from observational data. This capability allows AI to augment traditional methods by building highly accurate predictive models, optimizing operational controls in real-time, and extracting insights from vast, unstructured datasets. This is catalyzing a significant methodological evolution, encouraging a shift towards data-informed and hybrid approaches that integrate the strengths of both mechanistic understanding and data-driven learning [1][2].

This paper provides a structured overview of the growing role of AI in environmental engineering. It begins by systematically reviewing key application areas, including intelligent monitoring, environmental prediction, process control, and decision support. Following this, it examines the persistent challenges that may hinder its broader implementation, such as issues related to data quality, model interpretability, and generalizability. Finally, the paper discusses promising future research directions, aiming to offer a balanced perspective on how AI can be responsibly and effectively integrated to advance the goals of environmental sustainability.

2. Application Scenarios of Artificial Intelligence in Environmental Engineering

2.1. Intelligent Environmental Monitoring and Pollution Source Identification

Environmental monitoring is the foundation of environmental engineering. Traditional methods rely on manual sampling and point-based measurements, which are low in efficiency and slow to respond. AI enhances monitoring systems by integrating multisource data and image recognition algorithms, thereby increasing spatial coverage and temporal resolution. For instance, convolutional neural networks (CNNs) combined with remote sensing imagery can be used to classify land use, detect urban heat islands, and identify eutrophication in water bodies [3]. Support vector machines (SVMs) and clustering algorithms have also been applied for water quality classification and detection of heavy metal pollution.

Furthermore, AI enables real-time sensing of air, water, and soil conditions through the Internet of Things (IoT) and sensor networks. For example, machine learning models can be used to perform in-situ calibration of low-cost sensor networks, correcting for sensor drift and cross-sensitivity to environmental variables like temperature and humidity. This enhances data reliability, making widespread, high-density monitoring economically feasible. In pollution source identification, models based on spatiotemporal data analysis and Bayesian networks can effectively trace contamination pathways and support environmental law enforcement [4].

2.2. Environmental Quality Prediction and Process Modeling

Pollutant transport and dispersion are strongly time-dependent and spatially correlated. AI-based models have outperformed traditional physical models in environmental prediction tasks. Long short-term memory networks (LSTMs) are widely used to predict dynamic indicators such as AQI, PM2.5, O_3, and NO_2, achieving excellent results in urban atmospheric systems [1]. In water environments, random forest (RF) and gradient boosting trees (XGBoost) are often used to forecast key indicators like dissolved oxygen (DO) and biochemical oxygen demand (BOD).

Moreover, hybrid models that combine AI with physical mechanisms-known as physics-informed neural networks-are gaining popularity. These models embed physical laws, such as advection-diffusion equations, as a regularization term within the neural network's loss function. This approach ensures that the model's predictions are not only data-consistent but also physically plausible, which is particularly valuable in data-scarce scenarios [5]. For example, in river systems, combining hydrodynamic equations with neural networks yields more accurate simulations of water level and pollutant concentration.

2.3. Intelligent Optimization in Pollution Control Systems

Pollution control systems such as wastewater treatment and air purification are often nonlinear and involve multi-variable interactions. AI algorithms can autonomously learn system behaviors and adjust parameters accordingly. For instance, in activated sludge systems, deep reinforcement learning (DRL) can control aeration times and inflow rates to ensure effluent quality while minimizing energy consumption. In biological filtration systems, fuzzy logic combined with backpropagation neural networks allows precise control of flow rates and retention times, improving nitrogen removal efficiency [6].

In air pollution control, AI helps predict peak pollution periods based on meteorological, traffic, and emission data, and automatically adjusts equipment such as desulfurization and VOC removal systems. Optimization algorithms like genetic algorithms (GA) and particle swarm optimization (PSO) are also applied to reactor design, pipe network scheduling, and media selection.

2.4. Smart Sensing and Emergency Early Warning Systems

In response to sudden environmental events such as chemical spills, heavy pollution, or water contamination, AI can significantly improve emergency response speed and accuracy. By integrating drones, edge computing, and computer vision, AI-powered systems can rapidly collect site images and sensor data to analyze pollution spread and identify danger zones using CNNs.

Real-time data streams can be analyzed by sequential models to issue early warnings hours in advance, supporting timely government action. For example, the Beijing Municipal Ecology and Environment Bureau has deployed an AI-based air quality early warning system capable of forecasting pollution events 48 hours ahead and triggering coordinated responses [7].

2.5. Environmental Policy and Intelligent Decision Support Systems

Scientific decision-making is essential in environmental governance. AI contributes to decision support by integrating multisource information, conducting causal inference, and simulating scenarios. Knowledge graph and expert system integration can build causal chains among pollutants, emission sources, and health risks, providing a basis for policymaking. Multi-criteria decision-making models (e.g., AHP, TOPSIS integrated with ML) are used to evaluate trade-offs among economic, ecological, and social benefits, such as in the siting of wastewater treatment plants or air quality management strategies.

Some studies have also employed reinforcement learning to optimize urban traffic restrictions and building energy management policies, aiming for carbon neutrality while maintaining development goals. With the rise of digital twin technologies, AI will play an even deeper role in city-scale environmental governance and simulation.

3. Challenges and Future Directions

Despite the promising advancements of artificial intelligence in environmental engineering, its widespread and sustainable integration into the field still faces significant challenges. One of the foremost obstacles lies in the quality and heterogeneity of environmental data. Environmental systems often generate datasets that are incomplete, inconsistent in temporal or spatial resolution, and collected through diverse modalities. These characteristics complicate model training and reduce generalizability. Additionally, many AI models-especially deep learning architectures-suffer from limited interpretability. This "black-box" nature poses difficulties when such models are applied in high-stakes decision-making contexts, such as environmental policy formulation or public risk communication. Building models that are both accurate and explainable remains a critical research direction. Moreover, the ability of AI models to generalize across geographic regions or environmental conditions is often limited, as models trained in one locality may not perform well in another due to varying environmental drivers and system dynamics. Bridging this gap will require progress in transfer learning and domain adaptation. Another challenge is the lack of interdisciplinary integration between AI specialists and environmental scientists. Effective collaboration is often hindered by differing technical languages, conceptual frameworks, and training backgrounds. Thus, fostering interdisciplinary talent who can fluently operate at the intersection of environmental science and artificial intelligence is imperative. Looking ahead, future efforts should focus on developing hybrid models that integrate physical laws with data-driven learning, building AI-powered digital twins for environmental systems, expanding AI's role in carbon monitoring and management, and designing more energy-efficient algorithms that align with the principles of green computing and sustainability.

Future research should aim to deepen the integration of physical mechanisms with data-driven models, enabling AI systems to maintain both predictive accuracy and scientific interpretability. In particular, hybrid modeling approaches that embed environmental physics into neural network structures are expected to bridge the gap between mechanistic understanding and algorithmic efficiency. Moreover, the development of AI-driven digital twins for environmental systems will allow for real-time simulation and lifecycle management of infrastructure, offering unprecedented support for proactive governance. As concerns over climate change intensify, artificial intelligence is also anticipated to play a central role in regional carbon monitoring and emission trading systems, where timely, reliable data analysis is critical. To ensure the sustainability of AI applications, it is equally important to pursue research in green AI-designing algorithms and architectures that minimize computational overhead, reduce energy consumption, and align with broader ecological goals.

4. Conclusion

Artificial intelligence has become a transformative engine for shifting environmental engineering from experience-driven to data- and intelligence-driven decision-making. Its wide applications in monitoring, forecasting, control, and policymaking have enhanced environmental management efficiency and expanded the boundaries of engineering methods. In the future, deeper integration between AI and environmental engineering will be crucial for building intelligent, efficient, and sustainable environmental systems-empowering ecological civilization and green development with technological innovation. Ultimately, the successful and sustainable application of this technology will depend on fostering a synergistic collaboration between AI experts, environmental scientists, and policymakers to co-create solutions for a resilient and healthy planet.

References

[1] Li X, Li Y, Liu Y, et al. Deep air quality forecasting using hybrid deep learning framework\[J]. *IEEE Transactions on Industrial Informatics*, 2021, 17(7): 4818–4827.

[2] Rolnick D, Donti P L, Kaack L H, et al. Tackling climate change with machine learning\[J]. *ACM Computing Surveys*, 2019, 55(2): 1–96.

[3] Zhu X X, Tuia D, Mou L, et al. Deep learning in remote sensing: A comprehensive review and list of resources\[J]. *IEEE Geoscience and Remote Sensing Magazine*, 2017, 5(4): 8–36.

[4] Huang C, Li X, Zhang W, et al. Spatiotemporal modeling of air pollution based on deep learning: A review\[J]. *Environmental Research*, 2020, 191: 110139.

[5] Raissi, Maziar, Paris Perdikaris, and George E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations." Journal of Computational physics 378 (2019): 686-707.

[6] Zorita S, Martinez E, Lara A, et al. Machine learning to predict dissolved oxygen in wastewater treatment plant processes\[J]. *Journal of Environmental Management*, 2020, 267: 110644.

[7] Chen T, Xu W, Wu D, et al. Air pollution early warning system based on machine learning: A case study in Beijing, China\[J]. *Environmental Science and Pollution Research*, 2022, 29: 23481–23493.