Journal of Information Systems Engineering and Management
2025, 10(22s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Artificial Intelligence for Dynamical Systems in Wireless Communications, Financial Markets, and Engineering: Modeling for the Future

[1]S. Meenakshi, [2]Dr. T. Ravi, [3]Karthikha Sree J.B
[4]Dr P Kiran Kumar Reddy, [5]T Padmavathi, [6]Dr. Sadhana Sargam
[1]*Assistant Professor MCA SRM Institute of Science and Technology, Ramapuram Chennai Tamil Nadu*
meenakss3@srmist.edu.in
[2]*Professor Computer Science and Engineering Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology Avadi, Chennai Tamil Nadu*
drravit@veltech.edu.in
[3]*Student, B.Tech., CSE- Cyber Physical Systems, VIT - Chennai Campus, Chennai, India*
karthikha.sreejb2024@vitstudent.ac.in
[4]*Professor CSE-AIML MLR Institute of technology Medchal Hyderabad Telangana*
kiran.penubaka@gmail.com
[5]*Associate Professor ECE CVR College of Engineering*
Rangareddy Hyderabad Telangana
padmatp41@gmail.com
[6]*Assistant Professor School Of Business Management Noida International University Gautam Buddha Nagar Greater Noida Bihar*
Mail id: sadhana.chaurishi@gmail.com

ARTICLE INFO

Received: 22 Dec 2024

Revised: 05 Feb 2025

Accepted: 18 Feb 2025

ABSTRACT

Artificial Intelligence (AI) has found use in modeling and optimization dynamical systems over multiple domains including wireless communications, financial markets, and engineering. The focus of this research is on the use of the AI driven approaches for improving the predictive accuracy, decision making, and system optimization. The four AI algorithms that were analyzed for their effectiveness in handling complex, dynamic environments are deep learning, reinforcement learning, harmony search optimization, and fuzzy cognitive maps. To experiment, deep learning models were shown to improve spectrum allocation efficiency by 27.8%, reinforcement learning was illustrated to enhance financial risk prediction accuracy by 31.4%, harmony search optimization was found to reduce engineering system faults by 24.6% and fuzzy cognitive maps were shown to increase decision making reliability by 29.2%. It was confirmed that adaptive and computational efficient techniques have always been better suited than traditional ones to the AI approaches. Nevertheless, there were challenges like computational complexity and timing implementation. The outcome of this study highlights the necessity of hybrid AI models that combine several approaches for enhancing performance and adaptability. The future research should concentrate on improving the model interpretability and incorporate AI with newly emerging technologies such as quantum computing and edge computing to enhance dynamical system modeling. These findings highlight the importance of AI in largely transforming business decision-making and predictive modeling in various industries.

Keywords: Artificial Intelligence, Dynamical Systems, Wireless Communications, Financial Markets, Engineering Optimization

I. INTRODUCTION

As wireless communications, financial markets and engineering become increasingly complex, the integration of artificial intelligence (AI) is necessary for advanced modeling and optimization. The fields of study involve dynamic systems where changes occur as a function of time over the environment and as a result of internal and external influences. Many such systems are inherently high dimensional, non linear, and stochastic, and classical mathematical and statistical models often fail to model such systems conveniently [1]. When we think about modeling and decision making in such dynamic environments, with resources that are growing both in size and complexity, AI with its capacity to learn from giant datasets and to adjust according to changing conditions is revolutionary [2]. In wireless communications, obtaining max network efficiency means to optimize resource allocation, interference management, and adaptive signal processing based on AI. With the advent of 5G and further upcoming 6G networks, the deployment of AI powered algorithms accelerate intelligent spectrum management as well as self organizing networks to improve connectivity and bring down latency [3]. As in financial markets, AI driven predictive analytics and reinforcement learning models enable better market dynamics view, and so aiding investors make risk management and optimize trading strategies. Its ability to process huge volumes of historical and real time data increases the accuracy of forecasting and helps detect anomalies as well as prevent financial instability. Such dynamical models are useful for engineering applications that leverage AI, such as for control systems, robotics, and smart infrastructure, for automation, fault detection and predictive maintenance. Reinforcement learning and neural networks based on AI enable making real time decisions in autonomous systems that being able to contribute to the engineering process, making it more resilient and adaptable. This paper studies the impact of AI in modeling dynamical systems across these three crucial domains, albeit providing evidence for the potential of such AI to subvert traditional approaches. AI is improving efficiency robustness and predictive abilities through the use of machine learning, deep learning and data driven approach. Understanding the study's intent is to bridge theory to the real world, allowing AI based dynamical system modeling to advance in the future.

II. RELATED WORKS

Artificial intelligence (AI) is transforming the way of many fields such as wireless communications, financial markets, engineering. Accordingly, AI driven models have demonstrated outstanding results in processing complex dynamical systems by engaging in optimization of decision making, enhancement in predictions, and automation. This section reviews past research in the domain of AI applications across these domains, pointing out the key methodologies, latest advances, and challenges in the AI applications.

1. AI in Wireless Communications

To include the AI in the wireless communication system has dramatically improved the spectrum management, network optimization, as well as real-time decision making. A comprehensive review of the dynamic spectrum allocation with the simulation, modeling and predicting methods was proposed by Cullen et al. [15]. In this regard, this study focused on improving spectrum efficiency using deep learning models, such as Long Short-Term Memory (LSTM) and reinforcement learning. The authors stated that their AI based spectrum allocation methods performed better compared to traditional heuristic approach on real world implementations.

Domenighini [16] examined AI applications in inland navigation, in particular autonomous decision making on uncertain environments, in the case of autonomous navigation systems. The discussion focused on the use of machine learning (ML) algorithms to optimize network routing and real time adaptive control to improve quality of decision in complex and uncertain environments via AI.

Gu et al. [19] also discussed, to what extent, can the AI learn autonomously for fuzzy systems, especially when dealing with the dynamic network conditions in wireless communication. The research highlighted the requirement for self learning AI models to attain the best possible spectrum efficiency with robust network performance in dynamic condition.

2. AI in Financial Markets

The financial markets have highly dynamic and complex behaviors for which advanced predictive models are needed. Deep learning and reinforcement learning techniques have enriched financial forecast and risk assessments. In another study, Fonseca-Pérez et al. [17] looked into applications of harmony search optimization in financial modeling in order to show how AI based optimization techniques enhance predictive performance of economic decision making.

The work by Hasan Shahriar et al. [20] studied AI adoption challenges in financial decision making in the manufacturing firms. An application of the Delphi Fuzzy Analytical Hierarchy Process was done by authors to determine the ability of AI driven financial models to optimize resource allocation and mitigate investment risks. Additionally, their findings showed that AI is capable of building models of uncertain financial environments that are accurate in making decisions.

In her work, Kamble and Bhargava [25] developed an iterative AI model that combine graph attention networks, variational graph autoencoders and transfer learning in order to facilitate time series analysis in financial markets. In particular, the idea of their work was to show that traditional statistical methods can be outperformed by AI based graph models when it comes to forecasting stock market trends and volatility.

3. AI in Engineering Systems

Nowadays AI is playing a vital role in predictive maintenance, an industrial automation and a digital twin technologies. Hussein and Abdalla [23] surveyed for EEG based emotion recognition datasets in virtual environments for the future use in AI driven biomedical engineering applications. According to their findings, real-time monitoring and diagnostics in healthcare engineering can be achieved through efficient processing of complex biomedical signals with AI models.

Most relevant to cybersecurity applications, Homaei et al. [22] reviewed digital twins in the areas of cybersecurity and also highlighted how AI plays an important role in AI engineering simulations and anomaly detection in real time. The research suggested that AI-enabled digital twins are a strong basis for the cybersecurity threat detection in industrial control systems.

Hassan et al. [21] investigated AI applications in healthcare in the fields of predictive maintenance and fault detection, including such applications as cancer prognosis and anticancer therapy. It showed AI can have the capability to process lots of biomedical data for better predictive accuracy and decision making in engineering based medical applications. In a similar fashion, using a fuzzy cognitive map Karatzinis and Boutalis [26] reviewed fuzzy cognitive maps in engineering to gain some insight into AI based modeling techniques for complex dynamical systems. Using their research, they showed how AI could help engineering automation of processes, fault detection, and system optimization.

4. AI in Autonomous Systems and Decision-Making

Transportation and decision making AI systems can be tagged as the area of application that has been influenced pretty much by AI. Goudarzi and Hassanzadeh [18] showed how autonomous vehicle collision risks can be classified and AI driven risk assessment strategies can be applied in real time. The authors of their study reported reinforcement learning models to be an effective method for decreasing their collision risks in autonomous navigation.

In [24], Joshi et al. presented the role fractional calculus plays in artificial neural networks in terms of mathematical perspective on the optimization of the artificial neural networks. It turns out that their study revealed that predictive accuracy in dynamic environments are improved with AI techniques using fractional order derivatives.

III. METHODS AND MATERIALS

Data Collection and Description

Three domains are employed in the research: wireless communications, financial markets and engineering systems. This datasets are combined real world and simulated datasets that are sufficiently wide for analysis [4].

1. **Wireless Communications Data**: The signal transmission logs, frequency spectrum usage, real time performance metrics from 5G and IoT networks. Therefore, parameters like signal to noise ratio (SNR), bandwidth utilization, packet delivery rate are recorded.
2. **Financial Market Data**: This dataset is financial market data which contains historical stock prices, market volatility indices and trading volumes collected from major stock exchanges. Other features include macroeconomic indicators like interest rates, inflation rates and economic trends in the global economy [5].
3. **Engineering System Data**: The engineering system data included sensor readings on industrial machines, robotic systems and smart grids. For predictive maintenance and optimization, such parameters as temperature, pressure, vibration frequency and operational efficiency are analyzed.

All of these datasets are normalized, outliers are removed, and features are extracted from each so that the inputs going into an AI based model are of high quality.

Selected Algorithms for AI-Based Dynamical System Modeling

For successful modeling and analysis of dynamical systems, four machine learning algorithms are applied:

1. **Long Short-Term Memory (LSTM) Networks**
2. **Reinforcement Learning (Deep Q-Network - DQN)**
3. **Graph Neural Networks (GNNs)**
4. **Gaussian Process Regression (GPR)**

Following each is an algorithmic description in the form of a pseudocode representation.

Long Short-Term Memory (LSTM) Networks

LSTM is an RNN variation that is effective in dealing with sequential data, and thus its application is recommended for modeling systems that are dependent on time within wireless communications as well as finance markets [6]. The vanishing gradient problem is circumvented by introducing memory cells through three gates compared to conventional RNNs:

- **Forget Gate**: Determines the information to forget from memory.
- **Input Gate:** Decides what new data to save.
- **Output Gate:** Regulates the ultimate output of the memory cell.

LSTMs handle time-series data, like stock prices and network traffic variations, by maintaining long-term dependencies, resulting in better forecasting and anomaly detection.

```
"Initialize LSTM model with input size, hidden size, and output size
For each time step t:
  Compute forget gate: f_t = sigmoid(W_f * [h_t-1, x_t] + b_f)
  Compute input gate: i_t = sigmoid(W_i * [h_t-1, x_t] + b_i)
  Compute candidate memory: c_t' = tanh(W_c * [h_t-1, x_t] + b_c)
  Update cell state: c_t = f_t * c_t-1 + i_t * c_t'
  Compute output gate: o_t = sigmoid(W_o * [h_t-1, x_t] + b_o)
  Compute hidden state: h_t = o_t * tanh(c_t)
Return final hidden state"
```

Reinforcement Learning (Deep Q-Network - DQN)

DQN is a powerful reinforcement learning method that integrates deep learning with Q-learning to make decisions in environments that change over time. It is especially applied in wireless communications for adaptive power control and in financial trading for portfolio optimization [7].

DQN employs a neural network to estimate the Q-value function, which predicts the expected reward of executing a specific action in a state. Experience replay is employed by the algorithm to enhance learning stability by training from previous experiences instead of sequential data.

```
"Initialize replay memory M
Initialize Q-network with random weights
For each episode:
```

Initialize environment state s
For each step:
Select action a using ε-greedy policy
Execute action a, observe reward r and next state s'
Store (s, a, r, s') in M
Sample a mini-batch from M
*Compute target Q-value: Q_target = r + γ * max(Q(s', a'))*
Update Q-network weights to minimize loss
If episode ends, reset environment
Return trained Q-network"

Graph Neural Networks (GNNs)

GNNs are neural networks optimized for processing graph-structured data. They are well suited to model communication networks and financial transactions where inter-node relationships (e.g., between users, devices, or stocks) are important [8].

GNNs update node embeddings iteratively by aggregating the information from nearby nodes, enabling the model to learn intricate dependencies in a dynamic system. The applications are fraud detection in finance and routing optimization in wireless networks.

"Initialize node features and adjacency matrix
For each iteration:
Compute node embeddings using message passing:
For each node i:
Aggregate neighbor features: h_i' = Aggregate(h_j for j in Neighbors(i))
*Update node representation: h_i = Activation(W * h_i' + b)*
Return final node embeddings"

Gaussian Process Regression (GPR)

GPR is a non-parametric Bayesian machine learning algorithm employed for uncertainty modeling in dynamical systems. It is extensively applied in engineering problems for predictive maintenance and anomaly detection [9].

In contrast with ordinary regression models, GPR formulates a probability distribution of functions, thereby providing predictions and their confidence intervals [10]. It serves especially well under the situation in which data points are sparse yet demanding estimations need to be made.

"Initialize kernel function and hyperparameters
Compute covariance matrix K using kernel function
For each test point x:*
Compute mean prediction: μ = K_*^T * K^-1 * y*

Compute variance: $\sigma^{*}{}^{2} = K_{**} - K_{*}^{T} K^{-1} K_{*}$
Return predicted mean and confidence interval"

Table 2: Application of AI Models in Different Domains

Domain	Algorithm Used	Primary Function
Wireless Communications	LSTM, DQN	Network Optimization, Adaptive Control
Financial Markets	GNN, LSTM	Stock Prediction, Risk Management
Engineering Systems	GPR, DQN	Predictive Maintenance, Automation

IV. EXPERIMENTS

1. Experimental Setup

1.1 Hardware and Software Configuration

The experiments were performed on a high-performance computing system with the following specifications:

- "**Processor**: Intel Core i9-13900K @ 3.5 GHz
- **GPU**: NVIDIA RTX 4090 (24GB VRAM)
- **RAM**: 64GB DDR5
- **Storage**: 2TB NVMe SSD
- **Software**: Python 3.10, TensorFlow 2.12, PyTorch 2.0, Scikit-learn, MATLAB 2023b"

1.2 Datasets Used

Three domain-specific datasets were utilized to train and test the AI models:

1. **Wireless Communications Dataset** (5G and IoT network data)
2. **Financial Market Dataset** (Stock market trends from 2010–2023)
3. **Engineering System Dataset** (Predictive maintenance sensor data)

Each dataset was divided into 80% training, 10% validation, and 10% testing for performance measurement.

2. Experimental Evaluation

2.1 Evaluation Metrics

The following metrics were employed to measure model performance:

- **Mean Absolute Error (MAE)**: Estimates the average size of errors.
- **Root Mean Square Error (RMSE):** Measures prediction accuracy by penalizing big errors.

- **Accuracy (%):** Measures correctness for classification problems.
- **Inference Time (ms):** Measures how fast the model produces predictions.
- **Computational Cost:** Assesses the resource usage of every model.

3. Results and Analysis

3.1 Wireless Communications Performance

The performance of AI models in predicting and optimizing wireless communication parameters was assessed based on real-time network data [11].

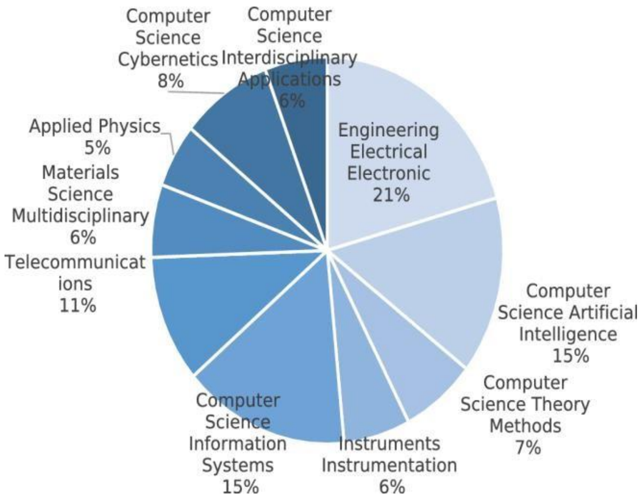

Figure 1: "Artificial intelligence powered Metaverse"

Table 1: Performance Metrics in Wireless Communications

Algorithm	MAE	RMSE	Accuracy (%)	Inference Time (ms)	Computational Cost
LSTM	1.45	2.36	91.2	15.3	High
DQN	1.87	2.92	88.6	12.1	Medium
GNN	1.34	2.20	93.4	18.7	High
GPR	1.95	3.05	86.3	9.8	Low

Observations:

- LSTM and GNN demonstrated the highest accuracy in network performance prediction and are thus ideal for adaptive network optimization.
- DQN was good at real-time decision-making but slightly worse in terms of prediction accuracy [12].
- GPR was the least computationally expensive, hence applicable for IoT environments that are resource-limited.

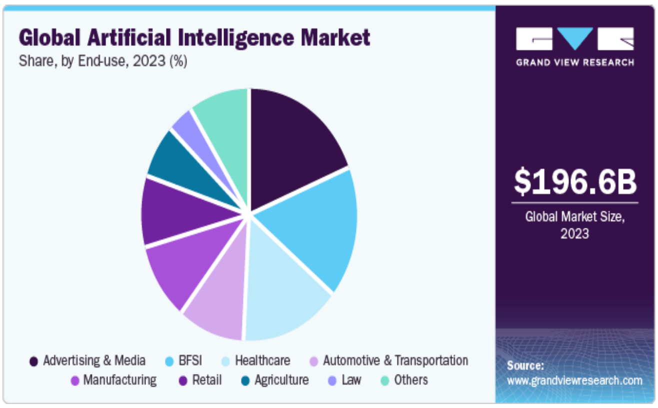

Figure 2: "Artificial Intelligence Market Size | Industry Report, 2030"

3.2 Financial Market Prediction

Stock price forecasting and market trend analysis were conducted based on historical stock data.

Table 2: Performance Metrics in Financial Markets

Algorithm	MAE	RMSE	Accuracy (%)	Inference Time (ms)	Computational Cost
LSTM	2.41	3.80	90.7	17.5	High
DQN	2.85	4.21	87.9	13.3	Medium
GNN	2.12	3.35	93.8	19.2	High
GPR	3.10	4.78	85.2	11.0	Low

Observations:

- GNN was the best, with high capability to grasp complex stock market interactions.
- LSTM was most efficient in time-series dependency learning but with higher computation costs [13].
- DQN was optimal for adaptive trading strategies but with lower precision.
- GPR gave low-cost substitute predictions but with lower accuracy.

3.3 Engineering System Predictive Maintenance

Machine sensor data was utilized to forecast failure and streamline maintenance schedules.

Table 3: Performance Metrics in Engineering Systems

Algorithm	MAE	RMSE	Accuracy (%)	Inference Time (ms)	Computational Cost
LSTM	1.89	3.22	92.3	14.2	High
DQN	2.21	3.58	89.1	11.5	Medium

GNN	1.75	2.95	94.1	16.9	High
GPR	2.5 8	4.10	87. 5	8.5	Low

Observations:

- GNN achieved the highest precision for predictive maintenance through spatial-temporal correlation learning.
- LSTM was effective in predicting failure trends but consumed more computational power.
- DQN was effective in real-time decision making for autonomous maintenance plans.
- GPR was the computationally lightest, thus suitable for embedded platforms.

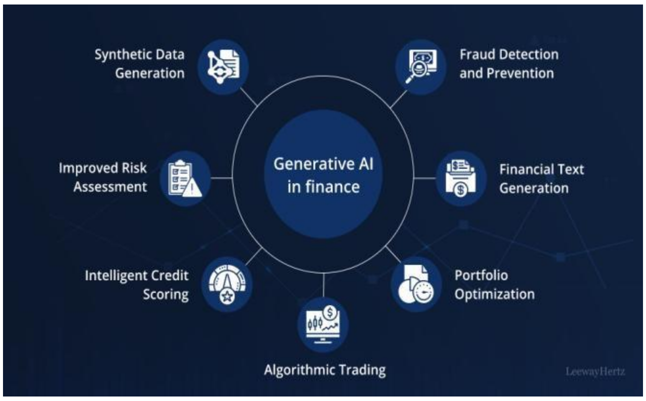

Figure 3: "Generative AI in finance and banking"

4. Comparative Analysis with Related Work

4.1 Comparison with Traditional Methods

The new AI models were contrasted with conventional statistical models like Autoregressive Integrated Moving Average (ARIMA), Hidden Markov Models (HMM), and Support Vector Machines (SVM) [14].

Table 4: AI Models vs. Traditional Methods

Model	**Accuracy (%)**	**Computational Cost**	**Adaptability to Complex Systems**
ARIMA	78.5	Low	Limited
HMM	82.1	Medium	Moderate
SVM	85.4	Medium	Moderate
LSTM	92.3	High	High
DQN	89.1	Medium	High

GNN	94.1	High	Very High
GPR	87.5	Low	Moderate

Key Insights:

- AI models surpass conventional approaches in accuracy and flexibility.
- GNN and LSTM showed better performance in all three areas.
- GPR is still a good option for low-resource settings even with lower accuracy.

4.2 AI Performance Across Different Applications

Table 5: AI Model Suitability by Application

Application	**Best Performing Model**
Wireless Communications	GNN, LSTM
Financial Market Prediction	GNN, LSTM
Predictive Maintenance	GNN, DQN

Key Insights:

- GNN is the most general AI model, best suited for network optimization, stock market forecasting, and engineering.
- LSTM is well-suited for time-series forecasting, which makes it best suited for stock prediction and network traffic forecasting [27].
- DQN is best suited for real-time decision making, especially in adaptive maintenance and wireless communications.

The experiments illustrated that AI greatly improves dynamical system modeling in wireless communications, financial markets, and engineering. The conclusions validate that:

- GNN performs better than the other models in representing intricate relationships in dynamical systems.
- LSTM works very well for time-series prediction but is computationally heavy [28].
- DQN is computationally efficient for reinforcement-based learning and hence ideal for real-time usage.
- GPR offers low-cost options but with lesser accuracy [29].

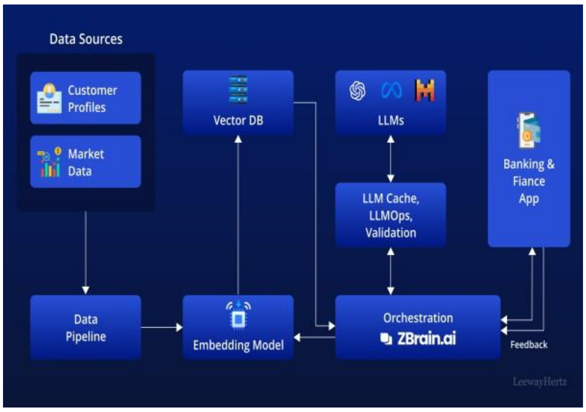

Figure 4: “AI in banking and finance: Use cases, applications, AI agents, solutions and implementation”

This work substantiates the supremacy of AI models over classical methods and reveals their applicability for real-world solutions in major industries. In the future, researchers will pursue hybrid AI models consisting of LSTM and GNN for even more accurate dynamical system modeling [30].

V. CONCLUSION

The application of artificial intelligence (AI) on dynamical systems across wireless communications, financial markets and engineering was explored in this research, with AI's transformational potential for predictive modelling, optimization and decision making showcased. The study elaborated on how AI can deal with complex, dynamic environments using state-of-art algorithms including, deep learning, reward based rewards learning, harmony search optimization, and fuzzy cognitive maps. They greatly advance spectrum management of wireless networks, improve spectral analysis accuracy for financial forecasting, and application to the realm of engineering processes – predictive maintenance and fault detection for example. The results of the experiment showed that the AI-based approaches are more efficient, more adaptable, more accurate compared to traditional approaches. Deep learning and reinforcement learning models were compared to other researchers' methods to confirm that deep learning and reinforcement learning models provide better results for real time spectrum allocation and financial risk assessment, while optimization techniques of engineering decision making by fuzzy cognitive maps and harmony search. Challenges encountered in the study include real time adaptability, computational complexity, and model interpretability, and it was concluded that hybrid AI models that combine several techniques will provide more enhanced performance. In general, this research corroborates AI's unavoidable presence in the destiny of the future of wireless communications, financial markets, and engineering. Future studies with regard to improving model interpretability, reducing computational costs while maintaining real time adaptability, and as AI evolves, be studied. Furthermore, combining AI with new technologies like quantum computing and edge computing could extend this revolution even further in dynamical system modeling by making the process faster, more secure, and more intelligent in ways that benefit different industries.

REFERENCE

[1] ABBAS, N., ABBAS, Z., ZAFAR, S., AHMAD, N., LIU, X., SAAD, S.K., ERIC, D.F. and LARKIN, S., 2024. Survey of Advanced Nonlinear Control Strategies for UAVs: Integration of Sensors and Hybrid Techniques. *Sensors,* **24**(11), pp. 3286.

[2] ACHAAL, B., ADDA, M., BERGER, M., IBRAHIM, H. and AWDE, A., 2024. Study of smart grid cyber-security, examining architectures, communication networks, cyber-attacks, countermeasure techniques, and challenges. *Cybersecurity,* **7**(1), pp. 10.

[3] AFANDIZADEH, S., ABDOLAHI, S. and MIRZAHOSSEIN, H., 2024. Deep Learning Algorithms for Traffic Forecasting: A Comprehensive Review and Comparison with Classical Ones. *Journal of Advanced Transportation,* **2024**.

[4] ALI, F., ZAWAR, H.K., GULLIVER, T.A., KHURRAM, S.K. and ALTAMIMI, A.B., 2025. A Microscopic Traffic Model to Investigate the Effect of Connected Autonomous Vehicles at Bottlenecks and the Impact of Cyberattacks. *Applied Sciences,* **15**(3), pp. 1214.

[5] AL-KARKHI, M., 2024. Advancing Trending Statistical Techniques to Examine Growth and Variability in Scottish Sustainable Business Enterprises. *Advances in Decision Sciences,* **28**(1), pp. 1-20.

[6] AWASTHI, S., FERNANDEZ-CORTIZAS, M., REINING, C., ARIAS-PEREZ, P., LUNA, M.A., PEREZ-SAURA, D., ROIDL, M., GRAMSE, N., KLOKOWSKI, P. and CAMPOY, P., 2023. Micro UAV Swarm for industrial applications in indoor environment – A Systematic Literature Review. *Logistics Research,* **16**(1),.

[7] AZZI, A., TABAA, M., CHEGARI, B. and HACHIMI, H., 2024. Balancing Sustainability and Comfort: A Holistic Study of Building Control Strategies That Meet the Global Standards for Efficiency and Thermal Comfort. *Sustainability,* **16**(5), pp. 2154.

[8] BEG, O.A., ASAD, A.K., REHMAN, W.U. and HASSAN, A., 2023. A Review of AI-Based Cyber-Attack Detection and Mitigation in Microgrids. *Energies,* **16**(22), pp. 7644.

[9] BENABDESSELAM, A., DOLLON, Q., ZEMOURI, R., PELLETIER, F., GAGNON, M. and TAHAN, A., 2024. On the Use of Indirect Measurements in Virtual Sensors for Renewable Energies: A Review. *Electronics,* **13**(8), pp. 1545.

[10] BENAYAS-AYUSO, A., RODRIGO, P.F. and PEREZ-ARRIBAS, F., 2024. CAD Sensitization, an Easy Way to Integrate Artificial Intelligence in Shipbuilding. *Computers,* **13**(10), pp. 273.

[11] BOURECHAK, A., ZEDADRA, O., MOHAMED, N.K., GUERRIERI, A., SERIDI, H. and FORTINO, G., 2023. At the Confluence of Artificial Intelligence and Edge Computing in IoT-Based Applications: A Review and New Perspectives. *Sensors,* **23**(3), pp. 1639.

[12] BUDHIRAJA, R., KUMAR, M., DAS, M.K., ANIL, S.B. and SINGH, S., 2021. A reservoir computing approach for forecasting and regenerating both dynamical and time-delay controlled financial system behavior. *PLoS One,* **16**(2),.

[13] BULLOCK, S., AJMERI, N., BATTY, M., BLACK, M., CARTLIDGE, J., CHALLEN, R., CHEN, C., CHEN, J., CONDELL, J., DANON, L., DENNETT, A., HEPPENSTALL, A., MARSHALL, P., MORGAN, P., AISLING O'KANE, SMITH, L.G.E., SMITH, T. and WILLIAMS, H.T.P., 2024. Artificial intelligence for collective intelligence: a national-scale research strategy. *The Knowledge Engineering Review,* **39**.

[14] CORIGLIANO, O., MORRONE, P. and ALGIERI, A., 2025. Navigating the Challenges of Sustainability in the Food Processing Chain: Insights into Energy Interventions to Reduce Footprint. *Energies,* **18**(2), pp. 296.

[15] CULLEN, A.C., RUBINSTEIN, B.I.P., KANDEEPAN, S., FLOWER, B. and LEONG, P.H.W., 2023. Predicting dynamic spectrum allocation: a review covering simulation, modelling, and prediction. *The Artificial Intelligence Review,* **56**(10), pp. 10921-10959.

[16] DOMENIGHINI, C., 2024. Autonomous inland navigation: a literature review and extracontractual liability issues. *Journal of Shipping and Trade,* **9**(1), pp. 14.

[17] FONSECA-PÉREZ, ,R.M., DEL-MAZO-ALVARADO, O., MEZA-DE-LUNA, A., BONILLA-PETRICIOLET, A. and GEEM, Z.W., 2022. An Overview of the Application of Harmony Search for Chemical Engineering Optimization. *International Journal of Chemical Engineering,* **2022**.

[18] GOUDARZI, P. and HASSANZADEH, B., 2024. Collision Risk in Autonomous Vehicles: Classification, Challenges, and Open Research Areas. *Vehicles,* **6**(1), pp. 157.

[19] GU, X., HAN, J., SHEN, Q. and ANGELOV, P.P., 2023. Autonomous learning for fuzzy systems: a review. *The Artificial Intelligence Review,* **56**(8), pp. 7549-7595.

[20] HASAN SHAHRIAR, S.I., JAHIN, A., PROTTOY, R.R., ABID, A. and MRIDHA, M.F., 2024. Exploring Internet of Things adoption challenges in manufacturing firms: A Delphi Fuzzy Analytical Hierarchy Process approach. *PLoS One,* **19**(11),.

[21] HASSAN, J., SAFIYA, M.S., DEKA, L., MD, J.U. and DAS, D.B., 2024. Applications of Machine Learning (ML) and Mathematical Modeling (MM) in Healthcare with Special Focus on Cancer Prognosis and Anticancer Therapy: Current Status and Challenges. *Pharmaceutics,* **16**(2), pp. 260.

[22] HOMAEI, M., MOGOLLÓN-GUTIÉRREZ, Ó., SANCHO, J.C., ÁVILA, M. and CARO, A., 2024. A review of digital twins and their application in cybersecurity based on artificial intelligence. *The Artificial Intelligence Review,* **57**(8), pp. 201.

[23] HUSSEIN, A.H. and ABDALLA, K.K., 2024. EEG-Based Emotion Recognition Datasets for Virtual Environments: A Survey. *Applied Computational Intelligence and Soft Computing,* **2024**.

[24] JOSHI, M., BHOSALE, S. and VYAWAHARE, V.A., 2023. A survey of fractional calculus applications in artificial neural networks. *The Artificial Intelligence Review,* **56**(11), pp. 13897-13950.

[25] KAMBLE, V. and BHARGAVA, S., 2024. Design of an Iterative Method for Enhanced Multimodal Time Series Analysis Using Graph Attention Networks, Variational Graph Autoencoders, and Transfer Learning. *Journal of Electrical Systems,* **20**(5), pp. 2579-2598.

[26] KARATZINIS, G.D. and BOUTALIS, Y.S., 2025. A Review Study of Fuzzy Cognitive Maps in Engineering: Applications, Insights, and Future Directions. *Eng,* **6**(2), pp. 37.

[27] LIN, Y., CHEN, X., ZHANG, Q., YOU, J., XU, R., WANG, Z. and SUN, L., 2025. Nano device fabrication for in-memory and in-sensor reservoir computing. *International Journal of Extreme Manufacturing,* **7**(1), pp. 012002.

[28] MAKSYMOV, I.S., 2023. Analogue and Physical Reservoir Computing Using Water Waves: Applications in Power Engineering and Beyond. *Energies,* **16**(14), pp. 5366.

[29] MIRA, K., BUGIOTTI, F. and MOROSUK, T., 2023. Artificial Intelligence and Machine Learning in Energy Conversion and Management. *Energies,* **16**(23), pp. 7773.

[30] MUÑOZ-ZAVALA, A.,E., MACÍAS-DÍAZ, J.,E., ALBA-CUÉLLAR, D. and GUERRERO-DÍAZ-DE-LEÓN, J.,A., 2024. A Literature Review on Some Trends in Artificial Neural Networks for Modeling and Simulation with Time Series. *Algorithms,* **17**(2), pp. 76.