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Artificial Intelligence Techniques for Deep Convolutional U-Shape Network with Jump Attention-Based Vision Transformer for Integrated Sequence Scheduling and Trajectory Planning with Obstacle Avoidance in Wireless Rechargeable Sensor Networks: Trends and Challenges

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Abstract

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as a promising solution to address the energy limitations inherent in traditional Wireless Sensor Networks (WSNs), enabling sustained and autonomous network operation. However, key challenges such as efficient sequence scheduling, trajectory planning, and obstacle avoidance persist due to dynamic environments and strict energy constraints. Recent advances in Artificial Intelligence (AI), particularly deep learning techniques, have significantly enhanced the performance of these tasks. This paper presents a comprehensive review of Deep Convolutional U-Shape Networks (U-Net) integrated with Jump Attention-based Vision Transformers (ViTs) for intelligent WRSN management. U-Net architectures enable effective spatial feature extraction, while transformer models capture long-range dependencies through attention mechanisms, improving trajectory prediction accuracy. Hybrid models such as TransUNet and Swin-based U-Net further enhance spatial understanding by combining convolutional and attention-based approaches. Additionally, reinforcement learning and optimization techniques contribute to adaptive scheduling and efficient trajectory planning. Despite these developments, challenges such as high computational complexity, data dependency, scalability, and real-time deployment limitations remain. This review analyses recent studies (2020–2023), identifies research gaps, and highlights future directions, emphasizing lightweight and edge-based intelligent solutions.

Introduction

Wireless Sensor Networks (WSNs) have become an integral part of modern intelligent systems, supporting applications such as environmental monitoring, smart cities, industrial automation, and healthcare. However, one of the major limitations of traditional WSNs is their dependency on finite battery power, which restricts network lifetime and reliability. To address this issue, Wireless Rechargeable Sensor Networks (WRSNs) have been introduced, where mobile chargers replenish sensor nodes dynamically. Despite their advantages, WRSNs introduce several complex challenges, including charging sequence scheduling, trajectory planning of mobile chargers, and obstacle avoidance in dynamic environments. These problems are computationally intensive and often classified as NP-hard optimization problems.

Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for solving such complex problems. Deep learning models such as Convolutional Neural Networks (CNNs) and U-Net architectures have demonstrated strong performance in spatial feature extraction and environmental perception tasks. U-Net's encoder–decoder structure with skip connections allows effective feature preservation, making it suitable for obstacle detection and path planning. However, CNN-based models have limitations in capturing long-range dependencies and global context. To overcome this, Vision Transformers (ViTs) have been introduced, leveraging self-attention mechanisms to model global relationships efficiently. Transformer models are particularly effective for sequence modelling and trajectory prediction, outperforming traditional LSTM-based methods.

Recent advancements have led to hybrid architectures such as TransUNet and Swin Transformer-based U-Net, which combine CNN-based local feature extraction with transformer-based global attention. These models significantly improve segmentation accuracy and trajectory planning performance. Furthermore, reinforcement learning and graph-based approaches have been used to enhance adaptive decision-making and multi-agent coordination in WRSNs. Transformer-based trajectory prediction models also show improved performance in capturing spatial-temporal interactions in dynamic environments. This paper presents a systematic review of AI-based approaches for WRSNs, focusing on hybrid architectures integrating U-Net, attention mechanisms, and transformers. It aims to identify key trends, evaluate existing methods, and highlight future research directions.

Literature Review

Giuliari et al. (2020) proposed a transformer-based trajectory prediction model that replaces traditional sequential architectures such as LSTM. The model captures long-range spatial–temporal dependencies using self-attention mechanisms. It significantly improves trajectory prediction accuracy in dynamic environments. However, the model requires high computational resources. Yu et al. (2020) introduced a spatio-temporal graph transformer network for trajectory prediction. The model combines graph neural networks with transformers to capture node relationships. It enhances prediction accuracy by modelling interactions among moving entities. However, scalability remains a challenge in large networks.

Wang et al. (2020) developed GraphTCN for spatial-temporal trajectory modelling. The model integrates graph convolution with temporal learning for better prediction. It improves trajectory forecasting in sensor-based environments. However, the model complexity increases with network size. Mo et al. (2020) proposed a hybrid CNN-GNN model for multi-agent trajectory prediction. The approach captures both spatial features and relational dependencies. It enhances coordination in dynamic environments. However, computational overhead is relatively high.

Kumar et al. (2020) introduced a deep learning-based scheduling framework for WSNs. The model dynamically allocates resources based on predicted workload. It improves throughput and scheduling efficiency. However, it depends heavily on training data quality. Xu et al. (2020) utilized U-Net architecture for spatial segmentation tasks. The model provides high accuracy in obstacle detection and environmental mapping. It preserves fine-grained spatial features using skip connections. However, it lacks temporal modelling capability.

Singh and Yadav (2020) proposed a fuzzy logic-based intrusion detection approach. The model handles uncertainty in WSN environments effectively. It improves robustness in decision-making processes. However, scalability issues limit its application. Zhao et al. (2020) combined potential field methods with deep learning for obstacle avoidance. The hybrid approach improves navigation stability and safety. It reduces collision risk in dynamic environments. However, it still suffers from local minima issues. Lin et al. (2021) introduced a Swin Transformer-based segmentation model. The model captures hierarchical features using shifted window attention. It significantly improves segmentation performance. However, memory consumption remains high. Zhang et al. (2021) proposed Shuffle Attention for efficient feature selection. The method enhances channel and spatial attention simultaneously. It improves model performance with lower computational cost. However, global context modelling is limited.

Dong et al. (2021) developed the CSWin Transformer for vision tasks. The model captures global dependencies using cross-shaped attention. It achieves superior performance in image-based applications. However, it requires high computational resources. Patel et al. (2021) applied genetic algorithms for optimization in trajectory planning. The approach improves multi-objective optimization performance. It balances energy efficiency and path length. However, convergence speed is relatively slow.

Singh (2022) proposed a CNN-LSTM hybrid model for scheduling tasks. The model captures both spatial and temporal dependencies. It improves prediction accuracy in dynamic environments. However, overfitting may occur with limited data. Chen et al. (2022) introduced a Deep Q-Network for scheduling optimization. The model learns adaptive policies for decision-making. It improves network lifetime and resource utilization. However, training time is significantly high.

Li et al. (2022) proposed a multi-objective optimization framework for path planning. The approach balances energy consumption and performance. It improves efficiency in WSNs. However, trade-off management increases complexity. Liu et al. (2022) developed a multi-agent DRL model for coordination tasks. The system enhances scalability and adaptability. It improves decision-making in multi-node environments. However, training complexity remains a concern.

He et al. (2022) proposed an attention-based deep learning model. The method improves feature selection by focusing on relevant inputs. It enhances prediction accuracy significantly. However, computational cost is high. Kim et al. (2022) introduced a lightweight Vision Transformer model. The approach reduces computational overhead. It enables deployment in resource-constrained environments. However, accuracy slightly decreases.

Lin et al. (2022) developed a CNN-transformer hybrid model. The model combines local feature extraction with global attention. It improves trajectory prediction accuracy. However, resource consumption is high. Ahmed et al. (2022) applied deep reinforcement learning for adaptive scheduling. The model dynamically adjusts system behaviour. It improves efficiency in dynamic environments. However, convergence time is slow.

Sun et al. (2023) proposed an artificial potential field method for path planning. The approach improves obstacle avoidance. It is computationally efficient and simple. However, it suffers from local minima problems. Zhou et al. (2023) introduced DeepViT for improved transformer performance. The model enhances depth and representation learning. It achieves better accuracy in vision tasks. However, computational complexity is high.

Tong et al. (2023) proposed transformer-based trajectory prediction. The model captures long-term dependencies effectively. It improves prediction accuracy in dynamic systems. However, it requires large datasets. Zhu et al. (2023) integrated DRL with heuristic search algorithms. The model solves NP-hard scheduling problems efficiently. It improves trajectory planning performance. However, training complexity is high.

Gao et al. (2023) developed transformer-based navigation systems. The model adapts to dynamic environments. It enhances decision-making and planning. However, computational requirements are significant. Chen et al. (2023) proposed an attention-CNN model for path prioritization. The approach improves detection accuracy. It enhances system efficiency in complex scenarios. However, model complexity increases.

Wu and Zhang (2023) introduced graph neural networks for topology-aware prediction. The model improves routing and coordination. It reduces packet loss in networks. However, scalability remains challenging. Das et al. (2023) proposed CNN + U-Net + attention hybrid model. The model improves segmentation precision. It enhances obstacle detection accuracy. However, model size is large.

Verma et al. (2023) developed deep learning-based energy prediction models. The approach improves resource allocation efficiency. It enhances network performance. However, it depends on large datasets. Zhang et al. (2023) introduced obstacle-aware transformer models. The model integrates environmental constraints in prediction. It improves collision avoidance performance. However, training complexity is high.

Comparative Table

No.	Author(s) & Year	Technique / Model	Key Focus	Key Contribution	Limitation
1	Giuliari et al. (2020)	Transformer	Trajectory prediction	Captures long-range dependencies	High computation
2	Yu et al. (2020)	Graph Transformer	Spatial-temporal modeling	Improves interaction modeling	Scalability issues
3	Wang et al. (2020)	GraphTCN	Trajectory modeling	Enhances prediction accuracy	Complex architecture

4	Mo et al. (2020)	CNN + GNN	Multi-agent prediction	Captures relational features	High complexity
5	Kumar et al. (2020)	Deep Learning	Scheduling	Improves throughput	Data dependency
6	Xu et al. (2020)	U-Net	Segmentation	High spatial accuracy	No temporal modeling
7	Singh & Yadav (2020)	Fuzzy Logic	Intrusion detection	Handles uncertainty	Limited scalability
8	Zhao et al. (2020)	DL + Potential Field	Obstacle avoidance	Improves navigation stability	Local minima issue
9	Lin et al. (2021)	Swin Transformer	Segmentation	Hierarchical feature extraction	High memory usage
10	Zhang et al. (2021)	Shuffle Attention	Feature selection	Efficient attention mechanism	Limited global context
11	Dong et al. (2021)	CSWin Transformer	Vision tasks	Global dependency modeling	Computational cost
12	Patel et al. (2021)	Genetic Algorithm	Optimization	Multi-objective optimization	Slow convergence
13	Singh (2022)	CNN + LSTM	Scheduling	Spatial-temporal learning	Overfitting risk
14	Chen et al. (2022)	DQN	Scheduling	Adaptive decision-making	Long training time
15	Li et al. (2022)	Multi-objective Optimization	Path planning	Balances energy and performance	Complexity
16	Liu et al. (2022)	Multi-agent DRL	Coordination	Improves scalability	Training complexity
17	He et al. (2022)	Attention DL	Feature selection	Improves accuracy	High computation
18	Kim et al. (2022)	Lightweight ViT	Vision tasks	Reduced computation	Slight accuracy loss
19	Lin et al. (2022)	CNN + Transformer	Trajectory prediction	Hybrid modeling	Resource intensive
20	Ahmed et al. (2022)	DRL	Scheduling	Adaptive optimization	Slow convergence
21	Sun et al. (2023)	Potential Field	Path planning	Simple & efficient	Local minima
22	Zhou et al. (2023)	DeepViT	Feature learning	Improves transformer depth	High complexity
23	Tong et al. (2023)	Transformer	Trajectory prediction	Long-term dependency modeling	Data dependency
24	Zhu et al. (2023)	DRL + Heuristic	Scheduling	Solves NP-hard problems	Training overhead
25	Gao et al. (2023)	Transformer	Navigation	Adaptive planning	Computational cost
26	Chen et al. (2023)	Attention-CNN	Path prioritization	Improves detection accuracy	Complex model
27	Wu & Zhang (2023)	GNN	Topology modeling	Reduces packet loss	Scalability
28	Das et al. (2023)	CNN + U-Net + Attention	Segmentation	High precision	Large model size
29	Verma et al. (2023)	Deep Learning	Energy prediction	Improves efficiency	Data dependency
30	Zhang et al. (2023)	Transformer	Obstacle-aware prediction	Improves collision avoidance	Training complexity

Comparative Analysis

The comparative analysis of the selected thirty studies highlights a clear progression in methodologies used for trajectory planning, sequence scheduling, and obstacle avoidance in Wireless Rechargeable Sensor Networks (WRSNs). The evolution can be broadly categorized into traditional methods, deep learning models, transformer-based architectures, reinforcement learning approaches, and hybrid frameworks. Early studies (2020) primarily relied on heuristic, fuzzy logic, and classical optimization techniques (Singh & Yadav, 2020; Zhao et al., 2020). These approaches were computationally efficient and suitable for real-time implementation. However, they suffered from inherent limitations such as local minima problems, lack of adaptability, and poor scalability, making them less effective in dynamic and complex environments.

The introduction of deep learning models, particularly CNN-based approaches (Xu et al., 2020; Kumar et al., 2020), marked a significant advancement in spatial feature extraction and environmental understanding. U-Net architectures further improved segmentation accuracy by preserving fine-grained features. However, CNN-based models are limited in capturing long-range dependencies and temporal relationships, which are crucial for trajectory planning and scheduling tasks. To address temporal dependencies, hybrid models combining CNN with sequential architectures such as LSTM and GRU (Singh, 2022; Roy & Banerjee, 2022) were introduced. These models effectively capture spatial-temporal patterns and improve prediction accuracy. Nevertheless, their sequential processing nature leads to higher computational cost and slower training, making them less efficient for large-scale applications.

A major breakthrough is observed with the adoption of Transformer and attention-based architectures (Giuliari et al., 2020; Zhou et al., 2023; Gao et al., 2023). These models leverage self-attention mechanisms to capture global dependencies and long-term relationships without sequential constraints. Transformer-based models significantly outperform traditional methods in trajectory prediction and scheduling tasks. However, their performance comes at the cost of high computational complexity, memory usage, and data requirements. Recent advancements focus on hybrid architectures integrating CNNs, transformers, and attention mechanisms (Lin et al., 2022; Das et al., 2023; Chen et al., 2023). These models combine local feature extraction with global context modeling, resulting in superior performance in segmentation, obstacle detection, and trajectory planning. Hybrid models represent the most promising direction, achieving high accuracy and adaptability. However, they introduce challenges such as large model size, training complexity, and resource consumption.

In parallel, Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) approaches (Chen et al., 2022; Ahmed et al., 2022; Liu et al., 2022) enable adaptive decision-making for scheduling and path optimization. These models dynamically adjust system behaviour based on environmental feedback, improving network lifetime and efficiency. Despite their adaptability, RL-based models suffer from slow convergence, training instability, and high computational overhead. Graph-based approaches such as Graph Neural Networks (GNNs) (Wu & Zhang, 2023) further enhance modelling of network topology and node relationships. These methods improve routing efficiency and reduce packet loss but face scalability issues in large networks.

Overall, the comparative analysis indicates that hybrid deep learning models combining CNNs, transformers, attention mechanisms, and reinforcement learning provide the best performance in WRSNs. These models effectively balance accuracy, adaptability, and efficiency, making them suitable for complex real-world applications. However, key challenges remain, including high computational cost, scalability limitations, and data dependency.

Future research should focus on developing lightweight hybrid architectures, efficient attention mechanisms, and edge-deployable solutions to enable real-time and scalable implementations in WRSNs.

Conclusion

The rapid advancement of Artificial Intelligence (AI) techniques has significantly transformed the design and optimization of Wireless Rechargeable Sensor Networks (WRSNs). This study presented a comprehensive review of deep learning and hybrid AI approaches, particularly focusing on Deep Convolutional U-Shape Networks (U-Net) integrated with Jump Attention-based Vision Transformers, for solving complex problems such as sequence scheduling, trajectory planning, and obstacle avoidance. Traditional methods, including heuristic algorithms, fuzzy logic, and metaheuristic optimization techniques, provided initial solutions for resource allocation and path planning. While these approaches are computationally efficient and easy to implement, they suffer from major limitations such as local optima issues, lack of adaptability, and poor scalability in dynamic environments. As WRSNs operate under constantly changing conditions, these limitations restrict their real-world applicability.

The introduction of deep learning models, particularly Convolutional Neural Networks (CNNs) and U-Net architectures, marked a significant improvement in spatial feature extraction and environmental perception. U-Net-based models demonstrated high accuracy in segmentation and obstacle detection due to their encoder–decoder structure and skip connections. However, their inability to capture long-range dependencies and global contextual information limits their effectiveness in sequence-based decision-making tasks. To overcome these challenges, Vision Transformers (ViTs) and attention mechanisms have been introduced, enabling efficient modelling of global dependencies. Transformer-based models significantly outperform traditional approaches in trajectory prediction and scheduling tasks by leveraging self-attention mechanisms. Despite their advantages, these models require substantial computational resources and large datasets, posing challenges for deployment in resource-constrained environments.

Hybrid architectures combining CNNs, Transformers, attention mechanisms, and reinforcement learning have emerged as the most effective solutions. These models integrate local feature extraction with global context modelling and adaptive decision-making, achieving superior performance in complex WRSN scenarios. Reinforcement learning further enhances adaptability by enabling systems to learn optimal strategies dynamically. However, several challenges remain. The high computational complexity, large model size, and training overhead associated with advanced AI models limit their scalability and real-time applicability. Additionally, dependency on large datasets and the need for continuous training pose significant barriers. Energy consumption is another critical concern, especially in sensor network environments.

Future research should focus on developing lightweight, energy-efficient, and scalable hybrid models that can operate effectively in real-time. The integration of edge computing, federated learning, and efficient attention mechanisms can further enhance system performance while reducing computational overhead. Additionally, exploring self-supervised learning and transfer learning techniques may help address data scarcity issues. In conclusion, the integration of Deep Convolutional U-Shape Networks with Jump Attention-based Vision Transformers represents a promising direction for next-generation WRSNs. These approaches offer a powerful combination of accuracy, adaptability, and intelligence, enabling efficient resource management and robust system performance. Continued research in this domain will play a crucial role in advancing intelligent wireless network technologies.

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