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# Recent Advances in 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: A Systematic Review

Leocadia Nasution
*Assistant Professor, Department of Electronics and Communication Engineering, Phnom Penh School of Management Sciences, Cambodia*
*Email: leocadia.nasution@ppsms-kh.net*

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**Abstract**

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as an advanced solution to extend the lifetime of traditional Wireless Sensor Networks by enabling energy replenishment through mobile chargers. However, challenges such as efficient sequence scheduling, trajectory planning, and obstacle avoidance persist due to dynamic environments, energy constraints, and real-time decision-making requirements. Recent advancements in deep learning, particularly Deep Convolutional U-Shape Networks (U-Net) and Vision Transformers (ViTs), have shown strong potential in addressing these issues. U-Net architectures excel in feature extraction through their encoder–decoder structure with skip connections, providing precise spatial and contextual representations. However, to overcome limitations in capturing long-range dependencies, attention-based transformer mechanisms are integrated, enhancing global context modelling. Hybrid models such as TransUNet and UNetFormer combine convolutional feature extraction with transformer-based attention, improving performance in path planning, obstacle detection, and scheduling optimization. Additionally, transformer-based models effectively handle temporal dependencies for trajectory prediction. The integration of deep reinforcement learning and attention-guided frameworks further enables adaptive and energy-efficient charging strategies, improving system responsiveness, network lifetime, and overall reliability in WRSNs.

## Introduction

Wireless Sensor Networks (WSNs) have become an essential component of modern intelligent systems, enabling applications such as environmental monitoring, smart cities, healthcare, and industrial automation. However, one of the primary limitations of traditional WSNs is the limited energy capacity of sensor nodes, which significantly restricts network lifetime. To address this issue, Wireless Rechargeable Sensor Networks (WRSNs) have been introduced, where mobile chargers are deployed to replenish sensor energy dynamically.

Despite their advantages, WRSNs introduce several complex optimization problems, including charging sequence scheduling, trajectory planning of mobile chargers, and obstacle avoidance in dynamic environments. These problems are inherently NP-hard and require efficient real-time solutions that can adapt to changing network conditions.

In recent years, deep learning techniques have revolutionized optimization and decision-making processes in wireless networks. Among them, Convolutional Neural Networks (CNNs), particularly U-Net architectures, have shown remarkable performance in extracting hierarchical spatial features. The U-Net model, with its encoder–decoder structure and skip connections, allows precise localization and feature preservation, making it suitable for tasks involving spatial mapping and path planning.

However, traditional CNN-based models face limitations in capturing long-range dependencies and global contextual relationships, which are crucial for sequence scheduling and trajectory optimization. To overcome this limitation, researchers have increasingly adopted Vision Transformers (ViTs), which leverage self-attention mechanisms to model global dependencies effectively. Transformer-based architectures have demonstrated superior performance in sequence modelling and trajectory prediction due to their ability to process entire sequences simultaneously rather than sequentially.

Hybrid architectures such as TransUNet and UNetFormer integrate the strengths of CNNs and Transformers, combining local feature extraction with global attention modelling. These models have achieved state-of-the-art performance in segmentation and planning tasks by effectively capturing both spatial and contextual information.

Additionally, the incorporation of jump attention mechanisms and deep reinforcement learning has further enhanced system adaptability. These approaches enable intelligent decision-making for optimal charging paths, obstacle avoidance, and efficient resource allocation in dynamic environments.

This paper presents a systematic review of recent advancements in deep learning-based solutions for WRSNs, focusing on hybrid U-Net and Vision Transformer architectures. It aims to provide a comprehensive understanding of current methodologies, highlight key contributions, and identify future research directions for improving efficiency, scalability, and robustness in WRSNs.

**Literature Review**

Giuliari et al. (2020) proposed a transformer-based architecture for trajectory forecasting, replacing traditional sequential models such as LSTMs. Their model effectively captures long-range spatial–temporal dependencies, demonstrating improved prediction accuracy. This work laid the foundation for applying attention mechanisms in trajectory planning within WRSNs. Ma et al. (2020) introduced a deep reinforcement learning (DRL)-based charging scheduling strategy for Wireless Rechargeable Sensor Networks. Their approach dynamically optimizes the movement of mobile chargers, significantly improving network lifetime. However, the model lacks spatial feature extraction capabilities. Nguyen et al. (2020) developed an energy-aware heuristic algorithm for trajectory planning in WRSNs. The study focused on minimizing travel distance while maintaining energy efficiency, though it lacked adaptability to dynamic environments. Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), demonstrating that transformer architectures can outperform CNNs in vision tasks. This work is critical for enabling global attention-based models in obstacle detection and trajectory planning.

Wang et al. (2021) proposed UNetFormer, a hybrid architecture combining CNN encoders with transformer-based decoders. Their model effectively captures both local and global features, improving segmentation and spatial decision-making. Fu et al. (2021) developed an attention-based sequence-to-sequence model for trajectory planning. The use of self-attention improved long-term dependency modelling and outperformed traditional RNN-based approaches. Zhang et al. (2021) introduced a CNN-based obstacle avoidance system for mobile chargers in WRSNs. While effective in local feature extraction, the model lacked global context awareness. Singh et al. (2021) proposed a deep Q-learning (DQN)-based scheduling mechanism. The model learns optimal charging policies through interaction, significantly enhancing energy utilization and reducing node failure.

Chen et al. (2021) developed a CNN-RNN hybrid model for trajectory prediction. The CNN extracts spatial features while RNN models temporal dependencies, although scalability remains an issue. Liu et al. (2021) introduced the Swin Transformer, a hierarchical vision transformer using shifted windows. This model improved computational efficiency and enhanced feature representation for vision-based tasks. Huang et al. (2022) proposed a multi-agent reinforcement learning (MARL) framework for cooperative charging in WRSNs. Their approach improves system efficiency but requires high computational resources.

Zhao et al. (2022) presented a graph neural network (GNN)-based scheduling model. By modeling network nodes as graphs, the approach improves scheduling accuracy and adaptability. Liu et al. (2022) developed a hybrid CNN-transformer architecture for spatial-temporal prediction. Their model significantly enhances trajectory forecasting accuracy. Tang et al. (2022) applied deep reinforcement learning to optimize mobile charger scheduling in WRSNs. The study demonstrated improved energy efficiency and reduced latency. Alshahrani et al. (2022) proposed an IoT-based machine learning framework for scheduling and routing optimization in WRSNs. The model improved network lifetime but introduced computational overhead.

Kumar et al. (2022) used Particle Swarm Optimization (PSO) for trajectory planning. While computationally efficient, the method lacks adaptability compared to learning-based approaches. Hatamizadeh et al. (2022) introduced UNETR, a transformer-based segmentation model that replaces CNN encoders. The model captures global context effectively, improving segmentation accuracy. Chen et al. (2022) conducted a survey on hybrid CNN-transformer architectures, highlighting their effectiveness in combining local feature extraction with global attention mechanisms.

Kim et al. (2023) proposed a Vision Transformer-based obstacle detection model, achieving superior performance in complex environments due to global attention capabilities. Sun et al. (2023) developed a U-Net-based spatial mapping model for environmental perception. The model provides high localization accuracy but lacks temporal modelling. Wang et al. (2023) introduced a jump attention mechanism integrated with CNNs. This approach improves feature propagation and enhances model performance in complex scenarios. Patel et al. (2023) proposed a hybrid DRL-transformer model for adaptive trajectory planning. Their model dynamically adjusts charging paths based on environmental conditions.

Roy et al. (2023) developed a CNN-based obstacle detection system integrated with IoT frameworks. The system improves navigation safety but lacks global context awareness. Ahmed et al. (2023) introduced a hybrid CNN-transformer model that improves trajectory prediction accuracy by combining local and global feature extraction. Lee et al. (2023) proposed a multi-head self-attention model for spatial-temporal prediction, enhancing decision-making in dynamic environments. Sharma et al. (2023) developed a DRL-based obstacle avoidance model that dynamically adapts to environmental conditions. Torres et al. (2023) introduced a graph attention network (GAT)-based routing framework, improving scheduling and communication efficiency.

Mehta et al. (2023) proposed an attention U-Net model for improved spatial feature extraction and obstacle detection accuracy. Ibrahim et al. (2023) developed a hybrid CNN-GNN model for network optimization, combining spatial and relational learning. Verma et al. (2023) introduced a transformer-enhanced DRL framework for trajectory planning and scheduling, achieving state-of-the-art performance.

**Comparative Table**

| Study | Year | Method | Technique | Key Contribution | Limitation |
|---|---|---|---|---|---|
| 1 | 2020 | Transformer | Attention | Trajectory prediction | High computation |
| 2 | 2021 | UNetFormer | CNN+Transformer | Spatial + global features | Complex model |
| 3 | 2023 | TransUNet | Hybrid | Improved segmentation | Heavy training |
| 4 | 2023 | Transformer Survey | Attention | Global dependency | Resource intensive |
| 5 | 2023 | DSTTN | Transformer | Spatial-temporal modelling | Dataset dependency |
| 6 | 2020 | DRL | RL | Adaptive scheduling | Slow convergence |
| 7 | 2021 | Seq2Seq | Attention | Long-term dependency | Data heavy |
| 8 | 2021 | CNN | Deep learning | Obstacle detection | No global context |
| 9 | 2022 | CNN+Transformer | Hybrid | Improved prediction | Complex |
| 10 | 2022 | MARL | RL | Cooperative charging | High cost |
| 11 | 2022 | GNN | Graph learning | Node relationship modelling | Scalability |
| 12 | 2023 | ViT | Transformer | Obstacle detection | Requires data |
| 13 | 2023 | U-Net | CNN | Spatial mapping | No temporal info |
| 14 | 2023 | Jump Attention | CNN+Attention | Feature enhancement | New technique |
| 15 | 2023 | DRL+Transformer | Hybrid | Adaptive trajectory | Complexity |

| | | | | | |
|---|---|---|---|---|---|
| 16 | 2020 | Heuristic | Optimization | Energy efficiency | Static |
| 17 | 2021 | DQN | RL | Scheduling optimization | Training cost |
| 18 | 2021 | CNN+RNN | Hybrid | Spatial-temporal | Sequential limits |
| 19 | 2022 | ML Framework | AI | IoT integration | Overhead |
| 20 | 2022 | PSO | Metaheuristic | Fast optimization | No learning |
| 21 | 2022 | Transformer | Attention | Sequence optimization | Resource heavy |
| 22 | 2023 | CNN | Deep learning | Obstacle detection | Limited context |
| 23 | 2023 | CNN+Transformer | Hybrid | Accuracy improvement | Complexity |
| 24 | 2023 | Self-Attention | Transformer | Global+local learning | Data intensive |
| 25 | 2023 | DRL | RL | Adaptive avoidance | Training time |
| 26 | 2023 | GAT | Graph attention | Routing optimization | Complexity |
| 27 | 2023 | Attention U-Net | CNN | Feature precision | Limited temporal |
| 28 | 2023 | CNN+GNN | Hybrid | Network optimization | High cost |
| 29 | 2023 | DL Model | AI | Predictive charging | Data dependency |
| 30 | 2023 | DRL+Transformer | Hybrid | Best performance | Complex |

**Comparative Analysis**

The comparative evaluation of the selected studies highlights a significant transition from traditional optimization and heuristic approaches toward hybrid deep learning and attention-based architectures for trajectory planning, scheduling, and obstacle avoidance in Wireless Rechargeable Sensor Networks (WRSNs). Early approaches, such as heuristic methods and metaheuristic optimization techniques, primarily focused on achieving energy efficiency and fast optimization. These methods are computationally lightweight and easy to implement; however, they lack adaptability and fail to handle dynamic environments effectively. Their static nature limits their applicability in real-time WRSN scenarios where network conditions frequently change.

The introduction of deep learning models, particularly Convolutional Neural Networks (CNNs), marked an important advancement in spatial feature extraction and obstacle detection. CNN-based models effectively capture local features and provide high accuracy in environmental mapping tasks. However, they suffer from a critical limitation: inability to capture long-range dependencies, which restricts their performance in sequence scheduling and trajectory optimization problems. To address these limitations, Recurrent Neural Networks (RNNs) and sequence-based models were introduced to model temporal dependencies. While these models improve sequential learning, they face issues such as high computational cost and sequential processing bottlenecks, making them less efficient for large-scale and real-time applications.

A major breakthrough is observed with the adoption of Transformer and attention-based architectures. These models leverage self-attention mechanisms to capture global dependencies without relying on sequential processing. As a result, they significantly improve trajectory prediction, sequence optimization, and obstacle detection. However, their effectiveness comes at the cost of high computational complexity and large data requirements, which pose challenges for deployment in resource-constrained environments. Further advancements are seen in hybrid architectures combining CNNs and Transformers Models such as UNetFormer and TransUNet integrate local feature extraction with global attention mechanisms, achieving superior performance in both spatial and temporal tasks. These hybrid models demonstrate improved accuracy in trajectory planning and scheduling, making them the most promising solutions. However, they are inherently complex and require extensive training resources.

The integration of Reinforcement Learning (RL) techniques, including DRL and MARL, enables adaptive and autonomous decision-making. These approaches dynamically optimize charging schedules and trajectories based on environmental feedback. While they offer high flexibility and adaptability, their performance is constrained by slow convergence, long training time, and computational overhead. Additionally, Graph-based models such as GNN and GAT provide an effective way to model relationships between sensor nodes, improving routing and scheduling decisions. However, these methods face scalability challenges when applied to large-scale networks.

Overall, the analysis reveals that hybrid deep learning models integrating CNNs, Transformers, attention mechanisms, and reinforcement learning provide the best performance in WRSNs. These models effectively balance spatial feature extraction, temporal modelling, and adaptive decision-making. However, key challenges remain, including high computational complexity, data dependency, and scalability issues.Future research should focus on developing lightweight hybrid architectures, efficient training strategies, and real-time deployment mechanisms to enhance practicality and scalability in real-world WRSN environments.

**Conclusion**

The rapid advancement of deep learning technologies has significantly transformed the design and optimization of Wireless Rechargeable Sensor Networks (WRSNs). This systematic review explored recent developments in Deep Convolutional U-Shape Networks integrated with jump attention mechanisms and Vision Transformer architectures, focusing on sequence scheduling, trajectory planning, and obstacle avoidance. Traditional approaches such as heuristic algorithms and metaheuristic optimization techniques, including Particle Swarm Optimization (PSO), provided initial solutions for trajectory planning and scheduling. However, these methods lack adaptability and fail to handle dynamic and complex environments effectively. The introduction of machine learning and deep learning techniques, particularly CNNs, marked a significant improvement in spatial feature extraction and obstacle detection.

U-Net architectures, with their encoder–decoder structure and skip connections, have demonstrated exceptional capability in capturing detailed spatial features. However, their inability to model long-range dependencies limits their performance in sequence-based decision-making tasks. This limitation has been effectively addressed through the integration of Vision Transformers and attention mechanisms, which enable global context modelling and improve decision-making accuracy. Hybrid models such as TransUNet, UNetFormer, and CNN-Transformer frameworks have emerged as state-of-the-art solutions, combining the strengths of convolutional and transformer-based architectures. These models achieve superior performance in trajectory prediction, obstacle avoidance, and scheduling optimization by leveraging both local feature extraction and global attention.

Furthermore, the incorporation of Deep Reinforcement Learning (DRL) and Multi-Agent Reinforcement Learning (MARL) has enabled adaptive and intelligent decision-making in WRSNs. These approaches allow systems to dynamically respond to environmental changes, optimize charging sequences, and enhance energy efficiency. The integration of transformers with DRL further enhances performance by improving policy learning and long-term dependency modelling. Despite these advancements, several challenges remain. High computational complexity, large data requirements, and model scalability are major concerns. Additionally, real-world deployment requires lightweight and energy-efficient models capable of operating under constrained resources.

Future research directions include the development of lightweight hybrid architectures, improved training strategies for limited data scenarios, and the integration of edge computing for real-time decision-making. Moreover, combining graph-based learning, attention mechanisms, and reinforcement learning holds significant potential for further enhancing WRSN performance. In conclusion, the integration of U-Net, jump attention mechanisms, and Vision Transformers represents a promising direction for achieving efficient, scalable, and intelligent WRSN systems. Continued research in this domain will play a crucial role in advancing next-generation wireless network technologies.

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