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A Survey of Methods and Architectures 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

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Abstract

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as a critical advancement in addressing the energy limitations of conventional Wireless Sensor Networks (WSNs). By incorporating mobile chargers and intelligent scheduling mechanisms, WRSNs enhance network longevity and operational efficiency. However, optimizing sequence scheduling, trajectory planning, and obstacle avoidance remains a complex challenge due to dynamic environments, energy constraints, and multi-objective optimization requirements. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), U-shaped architectures (U-Net), and Vision Transformers (ViTs), have demonstrated significant potential in addressing these challenges. CNN-based U-shaped architectures are highly effective in spatial feature extraction and segmentation tasks, while transformers provide superior capability in modelling long-range dependencies using self-attention mechanisms. Hybrid models such as TransUNet and Swin-Unet integrate convolutional and transformer architectures to capture both local and global contextual information, significantly improving decision-making performance in trajectory optimization tasks. This survey explores state-of-the-art deep learning approaches for integrated sequence scheduling and trajectory planning with obstacle avoidance in WRSNs. The study reviews recent literature from 2020–2023, categorizing methods based on CNN-based models, transformer-based models, hybrid architectures, and reinforcement learning techniques. Additionally, it analyses optimization strategies such as multi-objective algorithms and attention-based mechanisms for improving efficiency and adaptability. The survey identifies key challenges, including computational complexity, scalability, real-time deployment constraints, and data dependency. Finally, future research directions are outlined, focusing on lightweight architectures, edge computing integration, and hybrid intelligent optimization frameworks.

Introduction

Wireless Sensor Networks (WSNs) have become a cornerstone of modern intelligent systems, enabling applications such as environmental monitoring, healthcare, industrial automation, and smart city infrastructure. Despite their widespread adoption, WSNs suffer from a fundamental limitation—restricted battery life of sensor nodes. This limitation significantly reduces network lifetime and operational reliability. To address this issue, Wireless Rechargeable Sensor Networks (WRSNs) have been introduced, where mobile chargers replenish energy dynamically, ensuring continuous network operation. While WRSNs improve sustainability, they introduce new challenges in sequence scheduling and trajectory planning. Efficient scheduling determines the order in which nodes are charged, while trajectory planning defines the optimal path for mobile chargers. These problems are inherently complex and involve multiple constraints, including energy consumption, travel time, and environmental obstacles. Additionally, real-world environments introduce uncertainty and dynamic changes, making the problem even more challenging.

Traditional approaches such as heuristic algorithms, graph-based methods, and metaheuristic optimization techniques (e.g., Particle Swarm Optimization, Genetic Algorithms) have been widely used. However, these methods often struggle with scalability and adaptability in dynamic environments. Recent advancements in artificial intelligence, particularly deep learning, have opened new avenues for solving these complex optimization problems. Deep learning models such as Convolutional Neural Networks (CNNs) have shown remarkable performance in extracting spatial features from structured data. U-shaped architectures, such as U-Net, extend CNNs by incorporating encoder–decoder frameworks with skip connections, enabling precise localization and segmentation. These properties make U-Net highly suitable for environmental perception and obstacle detection in trajectory planning tasks.

However, CNN-based models have limitations in capturing long-range dependencies due to their local receptive fields. Vision Transformers (ViTs) address this limitation by using self-attention mechanisms to model global contextual relationships. Transformers have been successfully applied to trajectory prediction, scheduling, and navigation tasks due to their ability to process sequential data and capture temporal dependencies. Hybrid architectures such as TransUNet and UNetFormer combine CNN-based feature extraction with transformer-based global context modelling, significantly improving performance in segmentation and planning task. These models are particularly effective in complex environments where both local details and global relationships are essential.

Furthermore, deep learning approaches have been widely applied in trajectory prediction and navigation tasks. Studies show that CNNs, Graph Neural Networks (GNNs), and Transformers are capable of modelling complex spatial-temporal relationships, significantly outperforming traditional machine learning methods. Additionally, reinforcement learning techniques have been integrated with deep learning models to enable adaptive decision-making in dynamic environments. Recent research also explores hybrid frameworks combining CNNs, attention mechanisms, and transformers for sequence scheduling and trajectory optimization in WRSNs. For example, advanced architectures integrating spherical CNNs and adaptive transformer-based decision models have demonstrated significant improvements in energy efficiency, latency reduction, and trajectory accuracy.

Despite these advancements, several challenges remain. Deep learning models often require large datasets, high computational resources, and complex training procedures. Moreover, real-time deployment in resource-constrained WRSNs remains a significant challenge. This survey aims to provide a comprehensive overview of deep convolutional U-shape networks integrated with jump attention-based Vision Transformers for sequence scheduling and trajectory planning in WRSNs. By analysing recent literature from 2020–2023, the study identifies key trends, challenges, and future research directions.

Literature Review

Chen et al. (2021) proposed TransUNet, a hybrid architecture combining CNN-based U-Net with transformer encoders. The model effectively captures both local spatial features and global contextual dependencies, significantly improving segmentation accuracy. This architecture is highly relevant for obstacle detection and trajectory planning in WRSNs.Cao et al. (2021) introduced Swin-Unet, a pure transformer-based U-shaped architecture that uses hierarchical attention mechanisms for feature extraction. The model overcomes CNN limitations by capturing long-range dependencies and demonstrates superior performance in segmentation tasks.

Wang et al. (2021) proposed UNetFormer, which integrates transformer-based decoders with CNN encoders to achieve efficient real-time segmentation. The model effectively combines global attention with local feature extraction, making it suitable for dynamic navigation environments. Golroudbari and Sabour (2023) presented a comprehensive review of deep learning applications in autonomous navigation. The study highlights the importance of CNNs and transformers in obstacle detection, perception, and path planning, emphasizing their effectiveness in dynamic environments.

Jiang et al. (2025) analyzed deep learning-based trajectory prediction models, including CNNs, RNNs, GNNs, and transformers. The study identifies key challenges such as motion uncertainty and interaction modeling, providing insights into improving trajectory prediction systems. Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which applies transformer architectures directly to image patches, eliminating the need for convolutional layers. The model demonstrates strong performance in capturing global dependencies using self-attention mechanisms. This approach is highly relevant for trajectory planning and scheduling tasks where long-range dependencies are critical.

Liu et al. (2021) proposed the Swin Transformer, a hierarchical vision transformer using shifted windows for efficient computation. The model significantly reduces complexity while maintaining global context awareness, making it suitable for real-time applications such as obstacle detection and navigation Although originally proposed earlier, U-Net remains one of the most widely used architectures in recent research. It employs an encoder–decoder structure with skip connections for precise segmentation. Modern adaptations of U-Net are extensively used in obstacle detection and environmental perception in WRSNs.

Vaswani et al. (2017) introduced the transformer architecture based on self-attention mechanisms. Although foundational, it underpins most modern transformer-based models such as ViT and Swin Transformer. Its ability to capture long-range dependencies is critical for sequence scheduling and trajectory planning tasks. Zhang et al. (2022) proposed an attention-enhanced convolutional neural network for autonomous path planning and obstacle avoidance. The model integrates spatial attention mechanisms to focus on critical regions in the environment, improving navigation accuracy and efficiency in dynamic scenarios.

Chen et al. (2022) extended the TransUNet architecture by incorporating enhanced attention fusion mechanisms between CNN encoders and transformer layers. The improved model demonstrated better feature representation and segmentation accuracy, particularly in complex environments. This makes it highly suitable for obstacle-aware trajectory planning. Cao et al. (2022) further improved Swin Transformer for dense prediction tasks such as segmentation and path planning. The hierarchical attention structure allows efficient multi-scale feature extraction, improving performance in dynamic environments relevant to WRSNs.

Wu et al. (2021) proposed a CNN-based path planning framework for wireless sensor networks, focusing on energy-efficient routing and obstacle avoidance. The model demonstrated improved adaptability and reduced path cost compared to traditional heuristic methods. Liu et al. (2022) introduced a deep reinforcement learning framework for sequence scheduling in WRSNs. The model uses multi-agent learning to dynamically adjust charging priorities and trajectories, improving network lifetime and energy balance. Guo et al. (2021) proposed an attention-based CNN model that integrates spatial and channel attention mechanisms for navigation tasks. The model enhances important feature extraction and improves decision-making accuracy in obstacle-rich environments. Liu et al. (2021) extended the Swin Transformer framework for object detection and segmentation tasks. The hierarchical design and shifted window attention significantly improved performance while reducing computational complexity. This model is particularly effective for obstacle detection in dynamic WRSN environments.

Xu et al. (2021) proposed a deep reinforcement learning-based framework for scheduling mobile chargers in WRSNs. The approach uses policy optimization to dynamically adjust charging sequences and trajectories, resulting in improved network lifetime and reduced latency. Li et al. (2022) introduced a multi-objective optimization approach for trajectory planning in WRSNs. The model simultaneously optimizes energy consumption, travel distance, and charging delay, demonstrating superior performance compared to traditional optimization techniques.

Zhang et al. (2023) proposed a transformer-based trajectory prediction model that captures temporal and spatial dependencies using multi-head attention. The approach improves prediction accuracy and robustness in complex environments, making it suitable for dynamic path planning.

Wang et al. (2022) applied Graph Neural Networks (GNNs) to model spatial relationships in wireless sensor networks. The model captures node interactions effectively, improving routing decisions and trajectory planning accuracy. He et al. (2022) proposed Masked Autoencoders (MAE) as a scalable pretraining strategy for Vision Transformers. By reconstructing masked image patches, the model learns strong global representations with reduced computation. This approach benefits trajectory planning and obstacle perception by improving feature generalization.

Chen et al. (2021) developed a DRL-based framework to optimize mobile charger scheduling in WRSNs. The model dynamically adapts charging sequences based on node residual energy and spatial distribution, significantly extending network lifetime and reducing charging delay. Doshi et al. (2020) introduced a multi-agent reinforcement learning (MARL) approach for cooperative trajectory planning in dynamic environments. The method enables multiple agents to coordinate efficiently, improving scalability and collision avoidance—key requirements for WRSN mobile chargers.

Yang et al. (2022) proposed an attention-enhanced U-Net architecture that improves segmentation accuracy by focusing on relevant spatial features. The model is highly effective for obstacle detection and environmental perception in trajectory planning systems. Liu et al. (2023) introduced a transformer-based multi-agent scheduling framework for WRSNs. The model leverages self-attention to coordinate multiple mobile chargers, optimizing both scheduling and trajectory planning simultaneously. Results show improved scalability and reduced energy consumption.

Bao et al. (2021) introduced BEiT (Bidirectional Encoder representation from Image Transformers), a self-supervised pretraining approach for Vision Transformers. The model improves representation learning by predicting masked image tokens, enhancing performance in downstream tasks such as segmentation and trajectory planning. Khan et al. (2022) presented a comprehensive survey on transformer architectures in computer vision. The study highlights the advantages of transformers in capturing global dependencies and discusses their applications in segmentation, detection, and navigation systems relevant to WRSNs.

Zhang et al. (2022) proposed a deep learning-based obstacle avoidance framework combining CNNs and attention mechanisms. The model improves navigation safety and reduces collision risks in dynamic environments, making it suitable for trajectory planning in WRSNs.Wang et al. (2021) proposed a multi-agent deep reinforcement learning framework for cooperative path planning. The approach enables multiple agents to coordinate efficiently, improving trajectory optimization and scalability in complex environments such as WRSNs. Li et al. (2023) developed a lightweight transformer model optimized for edge computing environments. The architecture reduces computational overhead while maintaining high accuracy, making it suitable for real-time deployment in resource-constrained WRSNs.

Comparative Table

Study	Technique	Application	Key Contribution	Limitation
Chen et al. (2021)	TransUNet	Segmentation	CNN + Transformer hybrid	High complexity
Cao et al. (2021)	Swin-Unet	Segmentation	Hierarchical attention	Computation
Wang et al. (2021)	UNetFormer	Real-time segmentation	Efficient hybrid model	Limited scalability
Golroudbari (2023)	Review	Navigation	Comprehensive DL study	No implementation
Jiang et al.	DL models	Trajectory prediction	Multi-model comparison	Data dependency
Dosovitskiy (2021)	ViT	Vision tasks	Global attention	Large dataset needed
Liu et al. (2021)	Swin Transformer	Detection	Efficient attention	Complexity
Ronneberger	U-Net	Segmentation	Precise localization	Limited global context
Vaswani	Transformer	Sequence modelling	Self-attention	Computation heavy
Zhang et al. (2022)	Attention CNN	Path planning	Improved focus	Overhead
Chen et al. (2022)	TransUNet++	Segmentation	Enhanced fusion	Complexity

Cao et al. (2022)	Swin improvement	Dense tasks	Multi-scale modelling	Memory cost
Wu et al.	CNN	Routing	Energy efficiency	Local optima
Liu et al. (2022)	DRL	Scheduling	Adaptive learning	Training cost
Guo et al.	Attention CNN	Navigation	Feature selection	Complexity
Liu et al. (2021)	Swin detection	Vision	Efficient modelling	Heavy training
Xu et al.	DRL	Charging	Dynamic scheduling	Convergence
Li et al. (2022)	Optimization	Planning	Multi-objective	Trade-offs
Zhang et al. (2023)	Transformer	Prediction	Long dependency	Data heavy
Wang et al. (2022)	GNN	Networks	Spatial modelling	Scalability
He et al. (2022)	MAE	Pretraining	Efficient learning	Pretraining cost
Chen et al. (2021)	DRL	Charging	Adaptive scheduling	Stability
Doshi et al.	MARL	Planning	Multi-agent system	Complexity
Yang et al.	Attention U-Net	Segmentation	Improved accuracy	Data need
Liu et al. (2023)	Transformer	Scheduling	Multi-agent control	Complexity
Bao et al.	BEiT	Vision	Self-supervised learning	Pretraining
Khan et al.	Survey	Vision	Transformer overview	No experiment
Zhang et al.	CNN + Attention	Avoidance	Safer navigation	Overhead
Wang et al.	MARL	Planning	Coordination	Training time
Li et al.	Lightweight ViT	Edge	Low computation	Slight accuracy loss

Comparative Analysis

The comparative evaluation of the selected 30 studies published between 2020 and 2023 highlights a significant transition from traditional optimization techniques toward advanced deep learning and hybrid intelligent frameworks for sequence scheduling, trajectory planning, and obstacle avoidance in Wireless Rechargeable Sensor Networks (WRSNs). Among the analyzed approaches, Convolutional Neural Network (CNN) and U-Net-based architectures demonstrate strong capabilities in spatial feature extraction and environmental perception. These models, particularly TransUNet, Attention U-Net, and UNetFormer, effectively utilize encoder–decoder structures with skip connections to preserve spatial information and achieve high segmentation accuracy. As a result, they are highly suitable for obstacle detection and localization tasks. However, their inherent limitation lies in their restricted receptive field, which makes them less effective in capturing global dependencies required for long-range trajectory planning and scheduling optimization.

In contrast, transformer-based architectures such as Vision Transformer (ViT), Swin Transformer, and BEiT have shown superior performance in modeling global contextual relationships through self-attention mechanisms. These models excel in capturing long-range spatial and temporal dependencies, making them particularly effective for trajectory prediction and sequence scheduling tasks. Studies indicate that transformer-based models significantly outperform CNN-based methods in complex, dynamic environments due to their ability to process sequential data and maintain global awareness. Nevertheless, their high computational complexity, large memory requirements, and dependency on extensive training datasets limit their applicability in real-time and resource-constrained WRSN scenarios.

To address the limitations of standalone CNN and transformer models, hybrid architectures combining both approaches have emerged as the most effective solutions. Models such as TransUNet, Swin-Unet, and UNetFormer integrate CNN-based local feature extraction with transformer-based global attention mechanisms, resulting in enhanced performance across both perception and decision-making tasks. These hybrid models achieve a better balance between accuracy and contextual understanding, enabling efficient obstacle detection, trajectory optimization, and scheduling. However, the increased architectural complexity and computational overhead pose challenges for deployment in edge-based WRSN environments.

Reinforcement learning (RL), particularly Deep Reinforcement Learning (DRL) and Multi-Agent Reinforcement Learning (MARL), plays a crucial role in enabling adaptive and dynamic decision-making. RL-based approaches are highly effective in optimizing charging schedules and trajectory planning in uncertain and time-varying environments. They allow systems to learn optimal policies through interaction with the environment, thereby improving network lifetime, energy efficiency, and scalability. Despite these advantages, RL models often suffer from high training complexity, convergence instability, and significant computational requirements, which can hinder practical implementation.

Traditional and metaheuristic optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and multi-objective optimization frameworks continue to serve as baseline methods for trajectory planning and scheduling. These approaches are computationally efficient and relatively easy to implement; however, they lack adaptability and often struggle with scalability and dynamic environmental changes. Consequently, their performance is generally inferior to deep learning-based methods in complex WRSN scenarios. Additionally, Graph Neural Networks (GNNs) have been explored for modelling spatial relationships and node interactions within sensor networks. These models provide valuable insights into network topology and connectivity, enhancing routing and scheduling decisions. However, their computational overhead and limited real-time applicability restrict their widespread adoption.

Overall, the comparative analysis reveals that hybrid architectures integrating CNNs, Vision Transformers, and reinforcement learning techniques offer the most promising solutions for WRSNs. These models effectively combine local perception, global reasoning, and adaptive decision-making capabilities, leading to improved performance in sequence scheduling, trajectory planning, and obstacle avoidance. Nevertheless, challenges such as high computational cost, data dependency, scalability, and real-time deployment remain critical research issues. Future work should focus on developing lightweight, energy-efficient models and integrating edge computing solutions to enable practical implementation in real-world WRSN environments.

Conclusion

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as a transformative solution to overcome the energy limitations inherent in traditional wireless sensor networks. By integrating mobile charging mechanisms, WRSNs significantly enhance network lifetime and reliability. However, the effectiveness of WRSNs largely depends on efficient sequence scheduling, trajectory planning, and obstacle avoidance, which are complex and computationally intensive problems. This survey has explored the role of deep convolutional U-shape networks combined with jump attention-based Vision Transformer architectures in addressing these challenges. The analysis of 30 recent studies (2020–2023) reveals that deep learning techniques have significantly improved the performance of WRSN systems compared to traditional optimization approaches.

Convolutional Neural Networks (CNNs) and U-Net architectures have proven highly effective in spatial feature extraction and segmentation tasks, particularly for obstacle detection. Their encoder–decoder structures with skip connections enable precise localization, which is essential for safe navigation. However, CNNs are limited in capturing long-range dependencies, which are critical for trajectory planning and scheduling. Vision Transformers (ViTs) address this limitation by leveraging self-attention mechanisms to model global relationships. Transformer-based architectures such as Swin Transformer and BEiT have demonstrated superior performance in capturing spatial and temporal dependencies, making them highly suitable for trajectory prediction and sequence scheduling. Hybrid architectures like TransUNet further enhance performance by combining CNN-based local feature extraction with transformer-based global context modelling.

Reinforcement learning and multi-agent systems have also shown great potential in optimizing scheduling and trajectory planning in dynamic environments. These approaches enable adaptive decision-making and improve scalability in large-scale WRSNs. However, they often require extensive training and computational resources. Despite these advancements, several challenges remain. High computational complexity, data dependency, and real-time deployment constraints limit the practical applicability of these models. Additionally, ensuring scalability and robustness in dynamic environments remains a critical research challenge. Future research should focus on developing lightweight and energy-efficient models that can be deployed on edge devices. The integration of federated learning and distributed intelligence can further enhance scalability and privacy. Moreover, combining deep learning with advanced optimization techniques can lead to more robust and adaptive solutions. In conclusion, the integration of deep convolutional U-shape networks with attention-based Vision Transformers represents a promising direction for improving sequence scheduling and trajectory planning in WRSNs. Continued research in this area is expected to drive significant advancements in intelligent and autonomous sensor network systems.

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