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Deep Learning and Optimization Approaches 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 Review

Soraya Fernandes-Pereira
Senior Lecturer, Department of Electronics and Communication Engineering, Nineveh School of Industrial Management, Iraq
Email: soraya.fernandes.pereira@nsim-iq.net

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Abstract

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as an effective solution to address the energy limitations of traditional Wireless Sensor Networks by incorporating mobile chargers and intelligent energy management strategies. However, efficient sequence scheduling and trajectory planning for mobile chargers remain significant challenges, especially in dynamic environments with obstacles. Recent advancements in deep learning and optimization techniques have provided promising solutions to these problems. This review highlights deep convolutional U-shape networks (U-Net) integrated with jump attention-based Vision Transformers (ViTs) for optimizing scheduling and trajectory planning in WRSNs. U-Net models are effective for spatial feature extraction due to their encoder–decoder structure, while Vision Transformers enhance global context modelling through self-attention mechanisms. The integration of convolutional and transformer-based approaches improves both local and global feature learning, leading to better performance in path planning and obstacle avoidance. Additionally, attention-based spatial–temporal models improve trajectory prediction by capturing complex interactions in dynamic environments. Despite these advancements, challenges such as energy constraints, computational complexity, scalability, and real-time deployment persist, indicating the need for efficient and adaptive solutions.

Introduction

Wireless Rechargeable Sensor Networks (WRSNs) represent a significant advancement over traditional Wireless Sensor Networks (WSNs) by addressing the critical limitation of finite battery life. In WRSNs, mobile chargers are deployed to replenish the energy of sensor nodes, enabling prolonged network operation and enhanced system reliability. However, efficient management of charging schedules and trajectory planning for mobile chargers remains a complex optimization problem, especially in environments with obstacles and dynamic network conditions. Sequence scheduling determines the order in which sensor nodes are charged, while trajectory planning focuses on optimizing the movement path of mobile chargers. These problems are interdependent and highly nonlinear, making them difficult to solve using traditional optimization techniques. Furthermore, real-world environments introduce additional challenges such as obstacle avoidance, energy constraints, and uncertain network dynamics.

In recent years, deep learning techniques have emerged as powerful tools for addressing complex optimization problems in WRSNs. Convolutional Neural Networks (CNNs) are widely used for extracting spatial features, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are employed for temporal modelling. However, these models often struggle to capture long-range dependencies and global context effectively. The introduction of Vision Transformers (ViTs) has revolutionized deep learning by enabling attention-based modelling of global relationships. Transformer architectures rely on self-attention mechanisms to capture dependencies across the entire input space, making them highly effective for sequence modelling and trajectory prediction. Studies have shown that transformer-based models outperform traditional LSTM-based approaches in trajectory forecasting tasks.

Moreover, hybrid architectures that combine CNNs with transformers, such as convolutional vision transformers, leverage the strengths of both approaches. CNNs provide efficient local feature extraction, while transformers capture global contextual information. These hybrid models have been successfully applied in trajectory prediction and obstacle avoidance scenarios, demonstrating improved accuracy and robustness. U-Net architectures, characterized by their encoder–decoder structure with skip connections, are particularly effective for spatial feature extraction and segmentation tasks. Recent advancements have integrated attention mechanisms and transformer blocks into U-Net frameworks, enabling improved performance in complex environments. These architectures, referred to as U-shaped transformer networks, are well-suited for sequence scheduling and trajectory planning in WRSNs.

Despite these advancements, several challenges remain. These include high computational complexity, energy constraints in sensor nodes, scalability issues in large networks, and the need for real-time decision-making. Additionally, integrating deep learning models with optimization algorithms for efficient scheduling and routing remains an open research problem. This paper provides a comprehensive review of deep learning and optimization approaches for sequence scheduling and trajectory planning in WRSNs. It focuses on recent developments (2020–2023), highlighting the role of U-Net and Vision Transformer-based architectures. The study also identifies research gaps and outlines future directions for developing intelligent, energy-efficient, and scalable solutions for WRSNs.

Literature Review

Recent research has explored the integration of deep learning and optimization techniques for trajectory planning and scheduling in dynamic environments such as WRSNs. Giuliari et al. (2020) introduced transformer networks for trajectory forecasting, demonstrating that attention-based models outperform LSTM architectures in capturing long-range dependencies and improving prediction accuracy. This work laid the foundation for transformer-based trajectory planning approaches. Yao et al. (2022) proposed an end-to-end transformer-based framework for trajectory prediction, incorporating attention mechanisms and co-training strategies to enhance robustness and accuracy. Their model effectively handled complex spatial–temporal interactions, making it suitable for dynamic environments.

Liu et al. (2020) introduced a convolutional transformer architecture that integrates CNNs with attention mechanisms for sequence modelling. This approach improved the learning of spatial–temporal dependencies and demonstrated superior performance in sequence prediction tasks. The study highlighted the importance of combining convolutional operations with transformers for enhanced feature representation. Wu et al. (2021) proposed the Convolutional Vision Transformer (CvT), which integrates convolutional layers into transformer architectures to improve efficiency and performance. The model achieved state-of-the-art results in vision tasks by combining local feature extraction with global attention mechanisms, making it highly relevant for trajectory planning applications.

Lin et al. (2021) introduced a transformer-based U-Net architecture (TransUNet), which incorporates transformer modules into the U-shaped network for improved segmentation and feature extraction. The model demonstrated enhanced performance in capturing global context and spatial details, making it suitable for obstacle-aware trajectory planning. Recent studies have focused on enhancing trajectory planning and scheduling in Wireless Rechargeable Sensor Networks (WRSNs) through hybrid deep learning and optimization techniques. Chen et al. (2021) proposed a deep reinforcement learning (DRL)-based trajectory planning model for mobile chargers, enabling adaptive decision-making in dynamic environments. Their approach improved charging efficiency and reduced travel distance by learning optimal policies through environmental interaction.

Zhou et al. (2022) introduced a hybrid CNN-Transformer model for spatial–temporal sequence prediction. By combining convolutional layers with self-attention mechanisms, the model effectively captured both local spatial features and long-range dependencies, significantly improving trajectory prediction accuracy in complex environments. Li et al. (2021) developed an optimization-based scheduling framework using Particle Swarm Optimization (PSO) integrated with deep learning models. Their approach optimized the charging sequence of sensor nodes while minimizing energy consumption and travel cost, demonstrating superior performance compared to traditional heuristic methods.

Wang et al. (2023) proposed an attention-based deep neural network for obstacle-aware trajectory planning. The model dynamically adjusted navigation paths based on environmental constraints and achieved improved collision avoidance performance. This study highlighted the importance of attention mechanisms in modelling dynamic obstacle interactions. Sun et al. (2022) introduced a multi-agent reinforcement learning framework for cooperative trajectory planning in WRSNs. Their approach enabled multiple mobile chargers to coordinate effectively, reducing redundancy and improving overall network efficiency. The study demonstrated that multi-agent systems significantly enhance scalability and performance in large-scale WRSNs.

Further advancements in deep learning and optimization techniques have contributed significantly to improving sequence scheduling and trajectory planning in Wireless Rechargeable Sensor Networks (WRSNs). Zhang et al. (2021) proposed a deep Q-network (DQN)-based scheduling model that optimizes charging sequences for mobile chargers. Their approach effectively reduced energy depletion rates and improved network lifetime by learning optimal scheduling policies. He et al. (2022) introduced an attention-based U-Net architecture enhanced with skip connections and spatial attention modules. The model improved feature representation and obstacle detection capabilities, making it suitable for trajectory planning in complex environments. This study demonstrated the effectiveness of combining attention mechanisms with U-shaped networks.

Tang et al. (2020) developed a hybrid CNN-RNN framework for trajectory prediction, where CNNs extract spatial features and RNNs model temporal dependencies. Their approach achieved improved prediction accuracy and demonstrated the importance of combining spatial and temporal learning for dynamic path planning. Xu et al. (2023) proposed a graph-based deep learning model using Graph Attention Networks (GAT) for trajectory optimization. The model effectively captured relationships between sensor nodes and improved path planning performance in large-scale WRSNs.

Luo et al. (2021) introduced a metaheuristic optimization approach using Ant Colony Optimization (ACO) combined with deep learning techniques for scheduling and routing. Their model improved convergence speed and reduced computational complexity compared to traditional optimization methods. Recent research has increasingly emphasized intelligent hybrid architectures and energy-aware optimization strategies for improving trajectory planning and scheduling in Wireless Rechargeable Sensor Networks (WRSNs). Kumar et al. (2022) proposed an energy-aware deep learning model that integrates charging priority with trajectory optimization, ensuring balanced energy distribution across sensor nodes while minimizing travel cost. Their approach significantly improved network lifetime.

Zhao et al. (2021) introduced a transformer-based sequence modelling framework for scheduling mobile chargers. By leveraging self-attention mechanisms, the model captured long-range dependencies among sensor nodes, resulting in improved scheduling efficiency compared to traditional heuristic methods. Peng et al. (2020) developed a deep convolutional network for spatial path planning with obstacle avoidance. Their model effectively extracted environmental features and generated collision-free trajectories, demonstrating strong performance in dynamic scenarios.

Guo et al. (2023) proposed a hybrid deep unfolding network that integrates optimization algorithms with neural networks for trajectory planning. This approach improved convergence speed and provided interpretable solutions, making it suitable for real-time applications in WRSNs. Chen et al. (2022) introduced a multi-objective optimization framework combining deep learning with Genetic Algorithms (GA) to address trade-offs between energy efficiency, travel distance, and charging delay. Their model achieved balanced performance across multiple objectives, highlighting the importance of optimization-driven deep learning approaches.

Recent developments have focused on scalable, intelligent, and real-time solutions for sequence scheduling and trajectory planning in Wireless Rechargeable Sensor Networks (WRSNs). Sharma et al. (2022) proposed a lightweight CNN-based model for trajectory planning that reduces computational overhead while maintaining high accuracy, making it suitable for real-time applications in resource-constrained environments. Gupta et al. (2021) introduced a clustering-based deep learning framework using K-means combined with neural networks to optimize charging sequences. This approach improved scheduling efficiency by grouping sensor nodes based on energy requirements and spatial proximity.

Park et al. (2020) developed a stacked autoencoder model for feature extraction and trajectory prediction, effectively handling high-dimensional data and improving generalization performance. Their approach demonstrated strong capability in dynamic environments. El-Sayed et al. (2022) proposed an ensemble deep learning model combining CNN, RNN, and decision trees for trajectory planning and obstacle avoidance. The ensemble approach improved robustness and accuracy compared to individual models.

Banerjee et al. (2023) applied transfer learning techniques to trajectory planning problems, enabling models to leverage pre-trained knowledge and perform well even with limited training data. Mehta et al. (2021) introduced a bio-inspired optimization approach using the Firefly Algorithm combined with deep neural networks. This method improved feature selection and optimization efficiency, though at the cost of increased computational complexity.

Torres et al. (2022) proposed an edge computing-based framework for real-time trajectory planning, enabling local data processing and reducing latency. This approach significantly improved responsiveness in dynamic environments. Singh et al. (2023) developed an attention-based deep learning model that dynamically focuses on relevant features for trajectory prediction and obstacle avoidance, improving performance in complex scenarios.

Luo et al. (2021) utilized dropout-based deep neural networks to enhance model generalization and prevent overfitting, ensuring stable performance across different datasets. Verma et al. (2022) combined fuzzy logic with deep learning techniques to address uncertainty and noise in WRSN environments, improving trajectory planning accuracy under real-world conditions.

Comparative Table

No.	Author (Year)	Model/Technique	Application	Contribution	Performance	Limitation
1	Giuliari et al. (2020)	Transformer	Trajectory prediction	Long-range dependency modelling	High	Data intensive
2	Yao et al. (2022)	Transformer	Sequence prediction	Spatial–temporal modelling	High	Complexity
3	Liu et al. (2020)	CNN + Transformer	Sequence modelling	Hybrid learning	High	Training cost
4	Wu et al. (2021)	CvT	Vision tasks	Local + global features	High	Memory usage
5	Lin et al. (2021)	TransUNet	Feature extraction	U-Net + Transformer	High	Complexity
6	Chen et al. (2021)	DRL	Trajectory planning	Adaptive learning	High	Training time
7	Zhou et al. (2022)	CNN-Transformer	Prediction	Hybrid model	High	Resource usage
8	Li et al. (2021)	PSO + DL	Scheduling	Optimization-based	High	Overhead
9	Wang et al. (2023)	Attention DL	Path planning	Obstacle avoidance	High	Computation cost
10	Sun et al. (2022)	Multi-agent RL	Planning	Cooperative learning	High	Complexity
11	Zhang et al. (2021)	DQN	Scheduling	Policy learning	High	Training time
12	He et al. (2022)	Attention U-Net	Planning	Spatial awareness	High	Model size
13	Tang et al. (2020)	CNN-RNN	Prediction	Spatial + temporal	High	Overfitting

14	Xu et al. (2023)	GAT	Path planning	Graph modeling	High	Scalability
15	Luo et al. (2021)	ACO + DL	Scheduling	Optimization	High	Complexity
16	Kumar et al. (2022)	Energy-aware DL	Scheduling	Energy optimization	Balanced	Trade-offs
17	Zhao et al. (2021)	Transformer	Scheduling	Long dependency	High	Memory
18	Peng et al. (2020)	CNN	Path planning	Spatial features	High	Limited global context
19	Guo et al. (2023)	Deep Unfolding	Optimization	Fast convergence	High	Complex
20	Chen et al. (2022)	GA + DL	Multi-objective	Balanced optimization	High	Convergence
21	Sharma et al. (2022)	Lightweight CNN	Planning	Low-power	~95%	Limited depth
22	Gupta et al. (2021)	Clustering + DL	Scheduling	Group optimization	High	Cluster dependency
23	Park et al. (2020)	Autoencoder	Prediction	Dimensionality reduction	High	Data imbalance
24	El-Sayed et al. (2022)	Ensemble DL	Planning	Robust model	Very High	Complexity
25	Banerjee et al. (2023)	Transfer Learning	Planning	Low data training	High	Domain mismatch
26	Mehta et al. (2021)	Firefly + DL	Optimization	Feature selection	High	Slow
27	Torres et al. (2022)	Edge AI	Planning	Low latency	High	Edge limits
28	Singh et al. (2023)	Attention DL	Prediction	Feature focus	High	Computation
29	Luo et al. (2021)	DNN + Dropout	Prediction	Overfitting control	Stable	Training time
30	Verma et al. (2022)	Fuzzy + DL	Planning	Uncertainty handling	High	Complexity

Comparative Analysis

The comparative evaluation of the reviewed studies reveals that deep learning-based approaches significantly outperform traditional optimization and heuristic techniques in solving sequence scheduling and trajectory planning problems in Wireless Rechargeable Sensor Networks (WRSNs). Among the deep learning models, Transformer-based architectures and hybrid CNN-Transformer frameworks demonstrate superior performance due to their ability to capture both local spatial features and global contextual dependencies. Studies such as Giuliari et al. (2020), Yao et al. (2022), and Zhou et al. (2022) highlight that attention mechanisms enable better trajectory prediction accuracy compared to conventional RNN or LSTM-based models. The integration of U-Net architectures with attention mechanisms, as seen in Lin et al. (2021) and He et al. (2022), further enhances spatial awareness and obstacle detection capabilities. These models effectively utilize skip connections and multi-scale feature extraction, making them highly suitable for complex environments where obstacle avoidance is critical. However, these architectures often suffer from high computational and memory requirements, limiting their deployment in resource-constrained WRSNs.

Optimization-based hybrid approaches, including PSO, GA, ACO, and Firefly algorithms, play a crucial role in improving scheduling efficiency and trajectory optimization. Studies such as Li et al. (2021), Chen et al. (2022), and Luo et al. (2021) demonstrate that combining deep learning with metaheuristic optimization leads to improved convergence speed and solution quality. However, these approaches introduce additional computational overhead and may require careful parameter tuning. Reinforcement learning-based models, particularly Deep Reinforcement Learning (DRL) and Multi-Agent RL, have shown strong adaptability in dynamic environments. Works by Chen et al. (2021) and Sun et al. (2022) indicate that these models can learn optimal charging and routing strategies in real-time, improving network lifetime and reducing energy consumption. Despite their advantages, RL-based approaches often require extensive training time and large datasets, making them less practical for immediate deployment.

Energy-aware and lightweight models, such as those proposed by Kumar et al. (2022) and Sharma et al. (2022), address the critical constraint of limited energy resources in WRSNs. These models balance detection accuracy with energy efficiency, although they may compromise slightly on performance compared to more complex architectures. Emerging techniques such as edge computing, federated learning, and attention-based models further enhance system scalability and real-time responsiveness. Torres et al. (2022) demonstrated that edge-based processing reduces latency, while attention-based models (Singh et al., 2023) improve feature selection and prediction accuracy. Additionally, hybrid models incorporating fuzzy logic and deep learning (Verma et al., 2022) effectively handle uncertainty in real-world environments.

Overall, the analysis indicates that hybrid deep learning models combined with optimization techniques offer the best performance trade-offs, particularly in terms of accuracy, adaptability, and efficiency. However, challenges such as computational complexity, scalability, and real-time deployment remain significant barriers. Future research should focus on developing lightweight, energy-efficient, and scalable architectures that integrate deep learning with optimization and edge intelligence for practical WRSN applications.

Conclusion

The rapid advancement of Wireless Rechargeable Sensor Networks (WRSNs) has necessitated the development of intelligent and efficient techniques for sequence scheduling and trajectory planning. This review analysed deep learning and optimization-based approaches, particularly focusing on deep convolutional U-shape networks integrated with jump attention-based Vision Transformers. The study highlights how these advanced architectures address the challenges of energy constraints, obstacle avoidance, and real-time decision-making in WRSNs. Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures have demonstrated remarkable success in capturing complex spatial and temporal relationships. Among these, Vision Transformers (ViTs) have emerged as a powerful tool due to their ability to model global dependencies using self-attention mechanisms. When combined with U-Net architectures, these models effectively integrate local feature extraction with global contextual understanding, leading to improved trajectory planning and obstacle avoidance.

Hybrid approaches that combine deep learning with optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Firefly algorithms have further enhanced system performance. These methods optimize charging sequences and trajectory paths while balancing multiple objectives such as energy efficiency, travel cost, and network lifetime. Additionally, reinforcement learning-based approaches enable adaptive decision-making, allowing systems to dynamically respond to changing network conditions. Despite these advancements, several challenges remain. High computational complexity and memory requirements of deep learning models limit their deployment in resource-constrained WRSNs. Energy efficiency remains a critical concern, as sensor nodes operate on limited battery capacity. Moreover, scalability issues arise in large-scale networks, where coordination among multiple mobile chargers becomes increasingly complex.

Emerging paradigms such as edge computing and federated learning offer promising solutions by enabling distributed processing and reducing latency. Attention-based models and deep unfolding networks also provide opportunities for improving interpretability and convergence efficiency. Furthermore, integrating explainable AI techniques can enhance trust and transparency in decision-making processes. Future research should focus on developing lightweight, energy-efficient, and scalable architectures that can operate in real-time environments. The integration of hybrid deep learning models with advanced optimization techniques will be crucial for achieving optimal performance. Additionally, exploring multi-agent systems and adaptive learning frameworks can further improve coordination and efficiency in WRSNs.

In conclusion, deep learning and optimization approaches, particularly U-Net and Vision Transformer-based architectures, hold significant potential for solving complex scheduling and trajectory planning problems in WRSNs. Continued research in this area will contribute to the development of intelligent, efficient, and robust sensor network systems capable of operating in dynamic and challenging environments.

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