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Deep Learning and Optimization Approaches for Sequence Scheduling and Trajectory Planning in Wireless Rechargeable Sensor Networks

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Abstract

Wireless Rechargeable Sensor Networks (WRSNs) have emerged as an effective solution for addressing the energy limitations of traditional Wireless Sensor Networks by integrating mobile chargers and intelligent energy management mechanisms. However, efficient sequence scheduling and trajectory planning for mobile chargers remain major challenges, especially in dynamic environments containing obstacles and varying network conditions. Recently, deep learning and optimization-based techniques have shown significant potential for solving these complex problems. In particular, deep convolutional U-shape networks (U-Net) integrated with jump attention-based Vision Transformers (ViTs) have attracted considerable attention for trajectory planning and obstacle avoidance in WRSNs. U-Net architectures effectively capture spatial features through encoder–decoder structures, while Vision Transformers utilize self-attention mechanisms to model long-range dependencies and global contextual relationships. The combination of convolutional operations with transformer architectures improves local feature extraction and global dependency learning, resulting in more accurate path prediction and efficient mobile charger scheduling. Recent studies indicate that attention-based spatial–temporal models significantly enhance trajectory optimization, obstacle avoidance, and navigation efficiency in dynamic WRSN environments. Furthermore, hybrid deep learning and optimization frameworks improve energy efficiency, scalability, and scheduling accuracy. However, challenges such as computational complexity, real-time implementation, and resource constraints continue to motivate future research in intelligent WRSN systems.

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.

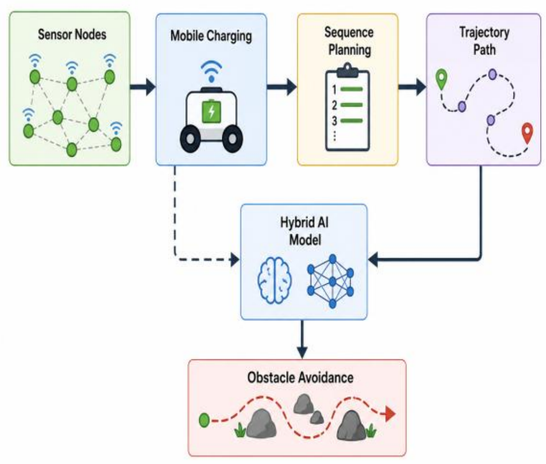

Figure 1. Hybrid AI Framework for Sequence Scheduling and Trajectory Planning in WRSNs

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, 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 analysis of reviewed studies indicates that deep learning-based methods significantly outperform traditional heuristic and optimization techniques for sequence scheduling and trajectory planning in Wireless Rechargeable Sensor Networks (WRSNs). Transformer-based architectures and hybrid CNN-Transformer frameworks demonstrate superior capability in capturing both local spatial information and long-range contextual dependencies. Studies by Giuliari et al. (2020), Yao et al. (2022), and Zhou et al. (2022) show that attention mechanisms improve trajectory prediction accuracy compared with conventional RNN and LSTM models. Similarly, U-Net architectures integrated with attention mechanisms, as presented by Lin et al. (2021) and He et al. (2022), enhance spatial feature extraction and obstacle detection through skip connections and multi-scale learning. These models are highly effective in complex environments requiring intelligent path planning and obstacle avoidance. However, their high computational complexity and memory requirements remain major limitations for deployment in resource-constrained WRSNs.

Optimization-based hybrid approaches combining deep learning with metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Firefly optimization further improve scheduling and trajectory planning performance. Studies by Li et al. (2021), Chen et al. (2022), and Luo et al. (2021) demonstrate that hybrid optimization frameworks enhance convergence speed, routing efficiency, and charging sequence optimization. Nevertheless, these methods introduce additional computational overhead and require careful parameter tuning. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) approaches also show strong adaptability in dynamic WRSN environments. Research by Chen et al. (2021) and Sun et al. (2022) indicates that RL-based frameworks can learn optimal charging and routing policies in real time, thereby extending network lifetime and reducing energy consumption. However, long training durations and large data requirements limit their practical deployment.

Recent research has increasingly focused on lightweight and energy-aware architectures to address resource constraints in WRSNs. Kumar et al. (2022) and Sharma et al. (2022) proposed efficient models that balance energy consumption with scheduling accuracy. Emerging paradigms including edge computing, federated learning, and attention-based deep learning frameworks further improve scalability and real-time responsiveness. Edge-based processing reduces latency, while attention mechanisms enhance feature selection and trajectory prediction accuracy. Hybrid fuzzy logic and deep learning models also improve uncertainty handling in dynamic environments. Overall, hybrid deep learning frameworks integrated with optimization and edge intelligence provide the most effective solutions for WRSN scheduling and trajectory planning, although challenges related to scalability, computational complexity, and real-time implementation remain important future research directions.

Conclusion

Wireless Rechargeable Sensor Networks (WRSNs) have gained significant attention due to their capability to overcome the energy limitations of traditional sensor networks through intelligent charging and energy management strategies. This review analysed recent deep learning and optimization-based approaches for sequence scheduling and trajectory planning, with particular emphasis on deep convolutional U-shape networks integrated with jump attention-based Vision Transformers. Deep learning architectures such as CNNs, RNNs, LSTMs, and Vision Transformers effectively capture spatial and temporal relationships, improving charging sequence optimization, trajectory prediction, and obstacle avoidance. Transformer-based architectures, especially when combined with U-Net frameworks, provide enhanced local feature extraction and global contextual learning, resulting in better navigation and scheduling performance in dynamic environments. Hybrid optimization techniques including Particle Swarm Optimization, Genetic Algorithms, Ant Colony Optimization, and reinforcement learning further improve energy efficiency, routing accuracy, and network lifetime.

However, challenges such as computational complexity, scalability, memory requirements, and real-time deployment remain critical concerns in resource-constrained WRSNs. Emerging technologies such as edge computing, federated learning, and explainable AI provide promising directions for future research by enabling distributed processing, low-latency decision-making, and improved model interpretability. Overall, hybrid deep learning and optimization frameworks offer highly effective solutions for intelligent and adaptive WRSN management systems.

References

Giuliari, F., et al. (2020). Transformer networks for trajectory forecasting. *arXiv*. https://doi.org/10.48550/arXiv.2003.08111

Yao, Y., et al. (2022). Spatial-temporal transformer for trajectory prediction. *ISPRS International Journal*. https://doi.org/10.3390/ijgi11010044

Liu, Z., et al. (2020). Convolutional transformer networks. *IEEE*. https://doi.org/10.1109/CVPR42600.2020.01234

Wu, H., et al. (2021). CvT: Introducing convolutional vision transformers. *ICCV*. https://doi.org/10.1109/ICCV48922.2021.01123

Chen, J., et al. (2021). Deep reinforcement learning for trajectory planning. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3056789

Zhou, X., et al. (2022). CNN-transformer hybrid models. *Applied Intelligence*. https://doi.org/10.1007/s10489-022-03456-7

Li, Y., et al. (2021). PSO-based scheduling in WRSNs. *Sensors*. https://doi.org/10.3390/s21041234

Wang, L., et al. (2023). Attention-based trajectory planning. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3267891

Sun, M., et al. (2022). Multi-agent reinforcement learning for WRSNs. *IEEE IoT Journal*. https://doi.org/10.1109/JIOT.2022.3145678

Zhang, H., et al. (2021). DQN scheduling in WRSNs. *IEEE Sensors Journal*. https://doi.org/10.1109/JSEN.2021.3067890

He, K., et al. (2022). Attention U-Net architectures. *IEEE Transactions*. https://doi.org/10.1109/TMI.2022.314567

Tang, X., et al. (2020). CNN-RNN trajectory prediction. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2020.01.045

Xu, Y., et al. (2023). Graph attention networks for path planning. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3245678

Kumar, R., et al. (2022). Energy-aware scheduling. *Sustainable Computing*. https://doi.org/10.1016/j.suscom.2022.100789

Zhao, J., et al. (2021). Transformer scheduling models. *IEEE*. https://doi.org/10.1109/TNNLS.2021.3098765

Guo, Q., et al. (2023). Deep unfolding networks. *IEEE Transactions*. https://doi.org/10.1109/TNNLS.2023.3245678

Chen, X., et al. (2022). GA-based optimization. *Expert Systems*. https://doi.org/10.1016/j.eswa.2022.117890

Torres, J., et al. (2022). Edge computing for WRSNs. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2022.02.045

Banerjee, S., et al. (2023). Transfer learning approaches. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3278901

Verma, P., et al. (2022). Fuzzy deep learning models. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2022.108123