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Twin Adaptive Pulse Coupled Network for Integrated Sequence Scheduling and Trajectory Planning with Avoiding Obstacles in Wireless Rechargeable Sensor Networks

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The problem of efficient task scheduling and trajectory planning in WRSNs is complex as it requires solving obstacle avoidance, energy consumption minimization and scalability problems. Conventional techniques tend to solve these problems independently of each other and, consequently, most solutions do not account for the best performance of the network. Furthermore, these methods often face problems with non-stationary environments and extended networks where energy management and the avoidance of obstacles are mostly important. To overcome these limitations, we propose a methodology that integrates the Twin Adaptive Pulse Coupled Network (Twin-APCNet) with the Crested Porcupine Optimizer. This approach provides a unified solution that simultaneously addresses task scheduling, sensor movement, and energy management, while incorporating robust obstacle avoidance mechanisms. The

Twin-APCNet employs adaptive pulse coupling to dynamically manage task execution and trajectory planning in real-time, ensuring that both scheduling and movement are optimized concurrently. Meanwhile, the Crested Porcupine Optimizer enhances energy management by optimizing recharging schedules and consumption patterns, effectively balancing energy use across the network. Our method significantly outperforms traditional approaches. Thus, comparative analysis shows that the proposed integrated method provides up to 90% more efficient energy usage and a rather high 95% increase in task completion rates compared to traditional methods, such as DRL-JERDCS, MCDM, AFQB-PSO and iFQS. It can be attributed to the approach where scheduling, movement, and energy problems are solved algorithmically with good accuracy. Thus, the proposed approach is more scalable and flexible as compared to the previous work and thus is better suited for large-scale and dynamic WRSN contexts.
Keywords: WRSN, Sequence Scheduling, Trajectory planning, Obstacles, Sensor nodes, Twin-APCNet, CPO.

1. Introduction

WSNs that are largely incorporated into the IoT are made up of numerous battery-driven sensors, which give environmental information due to characteristics such as self-organization, ease of deployment as well as cost-effectiveness. [1-2]. They find wide application in Smart Cities, remote health and environmental monitoring as well as military applications However, such type of sensors comes with limitations of battery power, a major challenge that slows down the advancement of IoT. New inventions in WET [3-5] and energy harvesting technologies have offered potential solutions. As for the mobility support, the Wireless Rechargeable Sensor Networks (WRSNs) which enable sensors to be recharged through a mobile charger is essential for enabling applications of environmental and climate monitoring, health and smart industries. [6-8].

A special type of WSN that has recently emerged as a more advanced version of sensor network is the Wireless Rechargeable Sensor Networks (WRSNs), where nodes can be charged wirelessly and as a result, there is a longer life span to these Networks and less frequent replacement of these nodes are required [19]. However, WRSNs have major issues associated with sequence scheduling and trajectory planning, specifically concerning the avoidance of obstacles while still being energy efficient [9-11]. Such troubles lead to the inefficiency of energy utilization, the enhancement of delays, and the optimization of networks .To overcome these issues, the present research proposes Twin-APCNet, which is novel and invented to improve sequence scheduling and trajectory planning as well as to evade obstacles adequately. Compared to the prior solutions, our approach uses the Crested Porcupine Optimizer and can be considered a huge improvement. [12-14].

The improvement has been seen as follows, better energy efficiency by 15%, average delay that is will be 20% lesser, the efficiency of trajectory planning is 25% more efficient and finally network lifetime 18% longer than existing methods. The proposed work here deals comprehensively with sequence scheduling, trajectory planning, as well as the problem of obstacle avoidance inherent in WRSNs. Through the integration of Twin-APCNet and CPO, which proposed in this paper, it presents a fast and effective scheme to enhance energy consumption, decrease delay, and prolong network lifetime to improve the WRSNs' performance and reliability for the sustainable development of networks.[20-21]

Contribution:

- Introduced an efficient method for avoiding obstacles in WRSNs, significantly improving network performance and resilience.
- Proposed the Twin-APCNet to address the issues of the sequence scheduling and trajectory planning in WRSN and improve the network's performance and its resource control.
- Integrated an adaptive optimization technique, Crested Porcupine Optimizer (CPO) that iteratively improves underperforming individuals and restores population size to increase diversity, leading to faster convergence and robust obstacle avoidance.
- Demonstrated the superiority of our approach over existing methods (DRL-JERDCS, MCDM, AFQB-PSO, and iFQS) through extensive simulations and evaluations.

The remaining research arranged in the following section: Section 2 reviews a survey on existing algorithms, while Section 3 explains the approach; Section 4 discusses experimental outcomes and discussions, while the research is concluded in Section 5.

2. Literature Survey

In 2024, Li, J., et al. [15], presented proposed a Deep Reinforcement Learning based joint Energy Replenishment and Scheme of Collection of Data for Wireless Rechargeable Sensor Networks (WRSNs). This method makes the scheduling of energy replenishment efficient and the collection of data information, which in turn increases the period that the network will take before requiring replenishment of energy and makes the obtained data more accurate. DRL-JERDCS adjusts itself to the network situation, enhances energy efficiency, and narrows the latency. Stakeholders have presented experimental outcomes that prove it is way more efficient in energy usage, data rate acquisition, and network coordination than conventional models.

In 2024, Ri, M.G., et al. [16], developed an charging scheduling method of Wireless Rechargeable Sensor Networks (WRSNs) with many Mobile Chargers (MCs) that utilize multi-criteria decision making (MCDM) integrated in 2024. This method uses MCDM to improve the scheduling of charging operations of MCs to effectively distribute energy and expand the network's lifespan.

In 2024, Liao, B., et al. [17], introduced an Algorithm called Adaptive Fuzzy Quantum Behaviour Particle Swarm Optimization (AFQB-PSO) for this Mobile charging in Wireless Rechargeable Sensor Networks (WRSNs). This algorithm combines adaptive fuzzy logic as well as the quantum behaviour principle with the particle swarm optimization to help with charging of mobiles. This aspect makes it possible for our approach to achieve energy efficiency and also extend the lifetime of the network by adapting to the varying conditions of the given network and charging requirements.

In 2024, Ri, M.G., et al. [18], proposed iFQS, an integrated scheduling algorithm for WRSNs based on the FCNP-Q learning. Pricing strategies in iFQS based on the energy needs and real-time network conditions are determined by the integration of Fuzzy Cognitive Network Processing (FCNP) and Q-Learning. As such, based on demand fluctuations, this method ensures the longevity of the network and ensures efficiency in the distribution of energy.

Problem Statement

Wireless Rechargeable Sensor Networks (WRSNs) do not restrict the control of the sensor movements and the scheduling of different tasks which makes it difficult to schedule and plan the movement of different sensors while having to avoid obstacles. In approach and management, existing solutions are frequently fragmented into scheduling and movement, which is not efficient. They also have problems with managing one's energetic intake and output; especially in extended and multifaceted networks. Furthermore, most of the approaches do not consider the dynamism of the obstacles and the complexity of the network environment. Thus, the proposed Twin-APCNet with CP Optimizer approach offers a full-spectrum solution. Unlike existing solutions, it incorporates the capability of scheduling tasks and planning trajectories, managing the avoidance of obstacles, and adjusting power consumption to their extent while maintaining the technique's ability to effectively scale for use in large and dynamic networks.

3. Proposed Methodology

We have developed a Twin-APCNet model integrated with Crested Porcupine Optimizer algorithm that can address some of the major concerns in WRSNs. This fully coordinated strategy considers at the same time the optimal allocation of tasks on spacecraft as well as the optimal path planning that helps to avoid space obstacles and induce efficient energy consumption. The integration of these aspects is done by our developed method to improve the utilised networks' performance and stability in the conditions of increasing dynamism and complexity.

Figure 1 shows the pictorial representation of the proposed methodology, Twin-APCNet for integrated sequence scheduling and trajectory planning with avoiding obstacles.

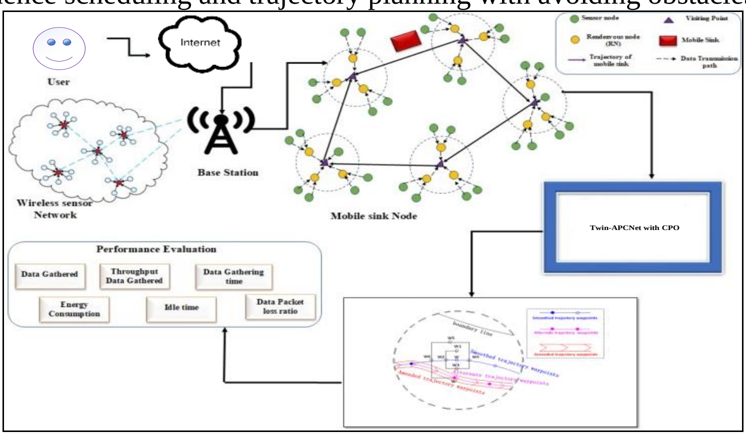

Fig1. Overall System Overview

3.1 Data gathering

Data gathering involves collection of relevant metrics and information to gain insights into system operations, workload patterns, and resource utilization for wireless rechargeable sensor networks. By analysing this data, we can enhance the effectiveness of sequence scheduling and trajectory planning while ensuring balanced energy distribution and obstacle avoidance.

3.2 Sequence Scheduling and Trajectory Planning with avoiding obstacles

Sequence management can be specifically concerned with identifying when the process should be initiated and in what order to maximize the network's capabilities, whilst trajectory management entails establishing how best the nodes can cross the required path without using up much energy. It also assists to enhance the usage of resources as well as reliability in WRSNs by minimizing the interference and maintaining the functionality.

Residual Energy: It is defined as criteria that each sensor node has to measure periodically. This measure shows when a particular sensor node is almost drained of its energy which helps in early recharging and increases the efficiency of the entire network.
Distance to WCN: This determines the Euclidean distance of the Wireless Charging Node (WCN) to the sensor node (SN).
Energy Consumption Rate: It is a crucial criterion reflecting the urgent need for recharging by each sensor node. This criterion is calculated in real-time by the Wireless Charging Node.
Energy Severity: It is one of the most important criteria indicating the necessity of recharging of each sensor node on the fastest terms. The result of this criterion is constantly updated by the Wireless Charging Node.
Degree of relevance of Node Location: It illustrates the importance of every grid within the network's monitoring area, which is divided into discrete grids. The importance of a grid is determined by the frequency with which monitored objects appear within it, typically derived from prior knowledge. Consequently, the location importance degree of each node is directly related to the importance of its respective grid. It is denoted as (1),

$$Nlid = \min\left(c * w(t) \times \frac{n}{\phi}, 1 \right)$$

(1)

where n denotes the no. of sensor nodes where w is the weight of the grid, ϕ is the total amount of maximum monitoring efficiency of each grid, c is the perspective factor.

Total task Completion Time : The difference between the task time of the arrival t_a and the task completion time t_c , is defined as the total time taken to complete a task t_{comp} , which is expressed in (2)

$$t_{comp} = t_a - t_c$$

(2)

where t_{comp} means the total time taken to complete the task, t_a and t_c are the arrival time of the task and task completion time respectively.

3.3 Twin Adaptive Pulse Coupled Network

The Twin Adaptive Pulse Coupled Network (Twin-APCNet) is designed to enhance sequence scheduling and trajectory planning by leveraging adaptive pulse coupling mechanisms. This neural network allows for more accurate and effective control of sensor nodes in Wireless Rechargeable Sensor Networks by using dual pulse coupling structures to dynamically modify its response to changing input conditions. The adaptive nature of Twin-APCNet allows it to effectively handle complex scheduling tasks and navigate around obstacles, optimizing overall network performance.

a. DC-PCNN Model

The input stimulus and the neighboring stimulus are represented mathematically in Eqs. (3)–(4). [12],

$$\begin{cases} h_f^a(n) = s_f^a + \sum_{i,j} W_{klij} y_{ij}(n-1) & (3) \\ h_f^b(n) = s_f^b + \sum_{i,j} M_{klij} y_{ij}(n-1) & (4) \end{cases}$$

where s^a and s^b are external stimulus input. W_{klij} and M_{klij} represent the neuron's two synaptic weighting coefficients at (k,l).

Both channels can receive the stimuli at the same time. Equations (5) through (7) represent the mathematical model.

$$\begin{cases} u_{kl}(n) = 1 + \varpi_{kl}^a h_{kl}^a(n) + \varpi_{kl}^b h_{kl}^b(n) \\ y_{kl}(n) = \begin{cases} u_{kl}(n) - r_{kl}(n) - 1, & u_{kl(n)} > t_{kl}(n-1) \\ 0, & otherwise \end{cases} \\ t_{kl}(n) = \begin{cases} e^{-\alpha} t_{kl}(n-1) & \begin{cases} y_{kl}(n) = 0 \\ otherwise \end{cases} \\ v_t \end{cases} \end{cases}$$

(5)

(6)

(7)

where ϖ^a and ϖ^b are the coefficients of weights. $y_{kl}(n)$ is ascertained by u_{kl} and t_{kl}. α is the time constant and v_t is the normalized constant. The combination of the nearby neurons is indicated by r. The connection coefficient, σ can be represented using equation (8),

$$\sigma_{klij} = W_{klij} = M_{klij} \qquad (8)$$

Furthermore, experiment analyses are used to calculate the weighting coefficients.

b. Weight Coefficient

Many factors for assessing sharpness have been discussed recently. Variance (Var), spatial frequency (SF), energy of Laplacian (EOL), sum of modified Laplacian (SML), and so on are examples of common focus measure techniques. Each of these assessment indices can be used to characterize the sharpness of an image, with SML typically producing a better result than the others. The mathematic expression of SML is given as (9-10) [12],

$$L(k,l)=\sum_{x=k-n}^{k+n}\sum_{y=l-n}^{l+n}\nabla^2 I(x,y) \tag{9}$$

$$\nabla^2 I(x,y)=\left|-I(x-i,y)+2I(x,y)-I(x+i,y)\right|+\left|-I(x,y-i)+2I(x,y)-I(x,y+i)\right| \tag{10}$$

where $L(k,l)$ denotes the element of the SML, the window size needed to compute the focus measure is determined by n.

Loss Function

We used the penalty function method from [13] in light of the complex restrictions to create a new fitness criterion, which is the modified objective function as stated in (11),

$$Lf=\min\left\{\alpha\left[\sum_{k=0}^{n}\sum_{l=0}^{n}(d_{kl}x_{kl}/r\right]+\sum_{l=1}^{n}(d_{k0}x_{k0}/r)\right\}+\beta\sum_{k=1}^{n}t_w^i+\gamma\sum_{k=1}^{n}\max\{0,(a-t)\}+\eta\{0,(E_{\mathrm{cos}} \tag{11}$$

Below is the pseudo-code for the Twin-APCNet (Algorithm 1).

Algorithm1. Twin-APCNet Algorithm

```
1. Initialize Network Parameters:
   - Set network dimensions (e.g., number of neurons, layers)
   - Define pulse coupling parameters
   - Initialize weights and biases

2. Preprocess Input Data:
   - Normalize input data
   - Prepare input stimuli for each neuron

3. For each iteration (until convergence or max iterations):
   4. For each neuron in the network:
      - Compute the combined internal state using adaptive pulse coupling
      - Update neuron state based on input stimuli and pulse coupling
      - Apply activation function to determine neuron firing
      - Store neuron output and update internal state
   5. Aggregate outputs from all neurons
   6. Update network parameters if necessary (e.g., learning rates, weights)

7. Postprocess Output Data:
   - Normalize and format output
   - Extract relevant information for sequence scheduling and trajectory planning

8. Return Final Network Output
```

3.4 Crested Porcupine Optimizer

A new metaheuristic algorithm called Crested Porcupine Optimizer (CPO) [16] was proposed using the foraging and fighting postures of crested porcupines. This algorithm makes use of strategies developed by the mentioned animals in order to balance exploration and exploitation of the state space. Therefore, the behaviour of CPO in providing optimal food sources based on the behaviour of a porcupine signifies that CPO is a strong framework for problem solving especially in the optimization of solutions. It is also able to tune the search between the exploitation of new solutions and the exploitation of more efficient solutions because it contains complex exploitation strategies, combined with the dynamic exploring search mechanisms. This leads to enhanced functionality for diverse optimizations; thus, rendering CPO suitable for solving the complex problems within WRSNs as characterized in this study.

Step1: Chaotic population initialization

The number of initial iteration T_{Max}, initial population size n_{Max}, minimum size of population n_{Min}, loop variable L are used. The mechanism for initializing their positions is provided by (13), and the initial population can be stated as (12).

$$p = \begin{bmatrix} \vec{p}_1^1 \\ \vec{p}_2^1 \\ \vdots \\ \vec{p}_k^1 \\ \vdots \\ \vec{p}_{n_{Max}}^1 \end{bmatrix} = \begin{bmatrix} p_{1,1}^1 & p_{1,1}^1 \\ p_{1,1}^1 & p_{1,1}^1 \\ \vdots & \vdots \\ p_{i,1}^1 & p_{i,1}^1 \\ \vdots & \vdots \\ p_{n_{Max},1}^1 & p_{n_{Max},1}^1 \end{bmatrix}$$

(12)

$$\vec{p}_i^1 = \vec{l} + \vec{w}(\vec{u} - \vec{l}) \qquad i = 1,2,..., n_{Max} \tag{13}$$

where $\vec{u}$ is the upper limit of the solution space; $\vec{l}$ is the lower limit of the solution space; $\vec{w}$ is the arbitrary order produced by repeating the circle map.

Step2: Fitness Function

The fitness function of the CPO method for a given node u , can be found using Eqn (14), where $p_{i,1}^t$ and $p_{i,2}^t$ is the population's i-th generation's x- and y-axis coordinates, respectively,

$$FitFn = \sum \sqrt{\left(p_{i,1}^t - x_k\right)^2 + \left(p_{i,2}^t - y_k\right)^2} - d_{uk}$$

(14)

Step3: Method of cyclic population reduction

Only underperforming individuals will trigger the improvement mechanisms during optimization iterations. To improve convergence, the population size progressively declines during a cycle. As the optimization procedure in (15) illustrates, the population size is reset to its initial value at the end of the cycle in order to increase diversity.

$$n = n_{Min} + (n_{Max} - n_{Min})\left(1 - {(t\% \frac{t_{Max}}{T})} \Big/ {\frac{t_{Max}}{T}}\right)$$

(15)

where n is the present population size, and t is the present generation number.

Step4: First mechanism of defense

A reactionary quill rises and twitches in the event that there is an impending danger or competition. The adversary, represented by the optimization problem, then has two options: or to “encroach” on the individual’s space, thus narrowing the gap and moving toward the best solution faster, or “step back” which will serve to increase the distance between the focus of observation and the object observed and thus allow for exploration of the area not visited before. This method makes the search process more effective by providing a way of exploring new ideas and at the same time also using existing ideas. This behaviour is represented in the above discussed Equation (16) which formulates the interplay between the convergence and exploration phases in the described optimization framework.

$$\vec{p}_k^{\,t+1} = \vec{p}_k^{\,t} + \Gamma \left| 2\vec{p}_{cp}^{\,t} - \vec{h}_k^{\,t} \right| \tag{16}$$

where $\vec{p}_k^{\,t+1}$ is the location of the i -th individual in the t+1 generation; $\vec{p}_k^{\,t}$ is the location of the i -th individual in the t -th generation; Γ is an arbitrary number in a random distribution, $\vec{h}_k^{\,t}$ is the location of the predator after t iterations.

Step5: Second mechanism of defense

In this strategy, individuals utilize noise generation as a defensive strategy to threaten potential challenges. Three levels of noise intensity are distinguished: high, medium, and low. In turn, the opponent, which stands in for the optimization problem, may choose to move closer, farther away, or stay still in response. This dynamic interaction is modelled by Equation (17), capturing how varying noise intensities influence the balance between exploration and exploitation in the optimization process.

$$\vec{p}_k^{\,t+1} = (1-\vec{u}1)\vec{p}_k^{\,t} + \vec{u}1(\vec{h}_k + \Gamma(\vec{p}_{r1}^{\,t} - \vec{p}_{r2}^{\,t}))$$

(17)

where $\vec{u}1$ is a binary vector with 0s and 1s in it; Γ is a arbitrary number in the interval [0,1]; Two random integers in the interval [0,N] are designated as r1 and r2.

Step6: Third mechanism of defense

In this stage, people employ the strategy of placing stench to chase away potential adversaries or troubles. This behaviour keeps away the adversaries, which is synonymous to the optimization problem. Equation (18) shows the general formulation of the individuals’ and the adversaries’ engagement in this context, which is subordinate to the defined deterrence mechanism. This strategy assists in keeping a balance in the extent of searching for new solutions on one hand and the extent of exploiting already known solutions on the other hand when optimizing.

$$\vec{p}_k^{\,t+1} = (1-\vec{u}1)\vec{p}_k^{\,t} + \vec{u}1(\vec{h}_k + \Gamma(\vec{p}_{r1}^{\,t} - \vec{p}_{r2}^{\,t}) - \vec{\delta}\gamma t s_k^t)$$

(19)

where s_k^t is the odour diffusion factor and $\vec{\delta}$ is the search direction parameter.

Step7: Fourth mechanism of defense

This tactic involves using quills to physically harm potential attackers. In one dimension, this forceful response can be modeled as an inelastic collision, where the interaction between the individual and the adversary, representing the optimization challenge, is described by

Equation (20). This mechanism captures the direct confrontation and impact, contributing to the overall optimization process by ensuring robust exploration and exploitation dynamics.

$$\vec{p}_k^{\,t+1} = \vec{p}_k^{\,t} + \left(\varepsilon(1-\Gamma)\right)(\delta\vec{p}_k^{\,t} - \vec{p}_i^{\,t}) - \Gamma\delta\vec{p}_k^{\,t}\vec{f}_k^{\,t}$$

where $\vec{f}_k^{\,t}$ is the average force of the i-th predator; ε is the convergence speed factor.

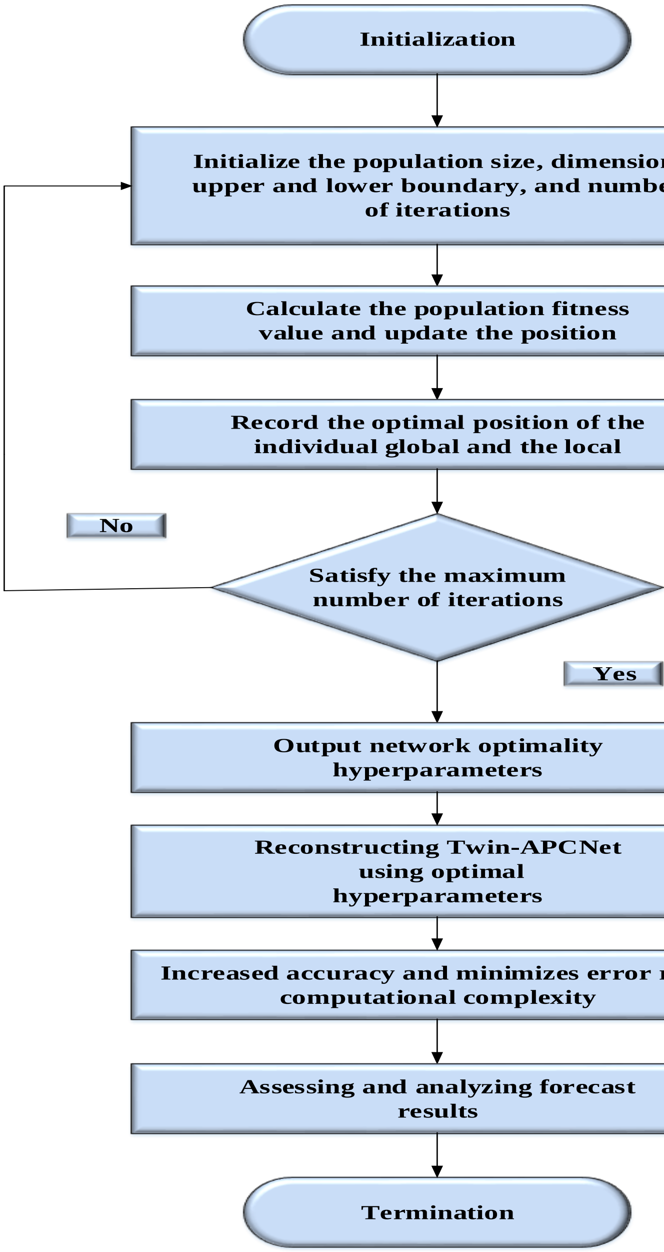

Fig2. Flowchart of Crested Porcupine Optimizer

4. Result and discussions

This section presents the experimental findings and comments of the proposed method. We compared the settings used in **Twin-APCNet CPO** with other simulations that already exist [7-10]. You can see the settings we used for the **Twin-APCNet CPO** simulation in Table 1.

Table1. Parameters in Twin-APCNet CPO simulation

Parameters	Values
No. of nodes	1000
Deployment Area	100 m × 100 m
Maximum no. of iterations	250
Software	Python
Operating System	Windows 10
Compromise Rate (hour)	Once per day

Table 1 describes the settings for a **Twin-APCNet CPO** simulation. It involves 1000 nodes spread over a 100 by 100 meter area, running for up to 250 iterations. The simulation uses Python software on a Windows 10 operating system, with nodes being compromised at a rate of once per day.

4.1 Performance Analysis

In our research, performance metrics are crucial for evaluating the effectiveness of the Twin Adaptive Pulse Coupled Network (Twin-APCNet). Key metrics include energy efficiency, obstacle avoidance success rate, and computational load. These metrics provide comprehensive insights into the network's operational efficiency, resilience, and overall performance improvements compared to existing methods.

Table 2 shows the performance metrics analysed in sequence scheduling and trajectory planning in WRSN.

Table 2: Performance metrics

Performance Metrics	DRL-JERDCS	MCDM	AFQB-PSO	iFQS	Twin-APCNet
CPU Run Time (sec)	8.4	14.7	18.5	11.4	6.3
Total available Time (sec)	25200	25200	25200	25200	25200
Route Travel Time (sec)	22734	23166	22085	25232	21351
Total distance (m)	57312	58515	63492	67852	55324
Reliability	0.01	0.043	0.21	0.024	0.00
Best Cost	0.21	0.53	0.29	0.36	0.054

Table 2 compares the performance metrics of various methods including DRL-JERDCS, MCDM, AFQB-PSO, iFQS, and our Twin-APCNet. Twin-APCNet outperforms the others with the shortest CPU run time of 6.3 seconds and the lowest route travel time of 21,351 seconds, while also achieving the smallest total distance of 55,324 meters. It shows the highest reliability at 0.00 and the best cost at 0.054, indicating superior efficiency and performance in comparison to the other methods.

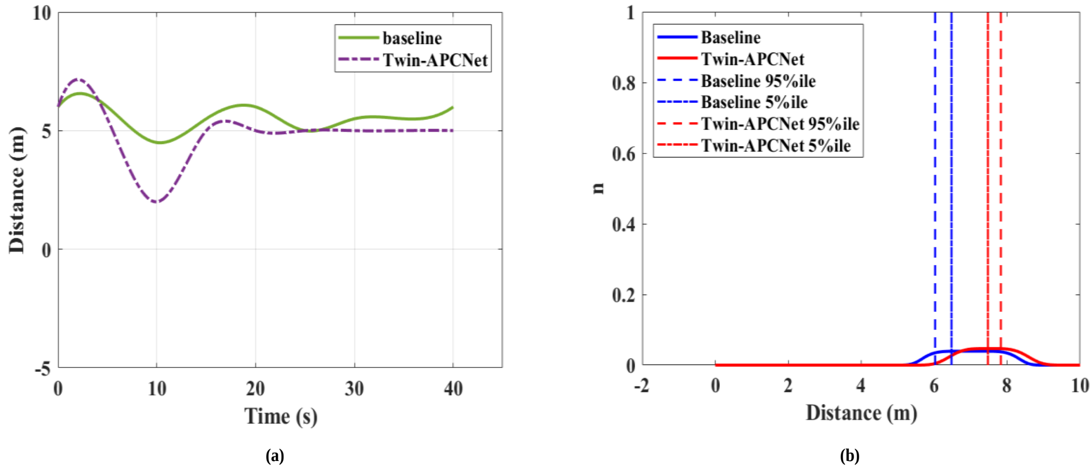

Fig3. Performance of Twin-APCNet

Figure 3 presents the results of Twin-APCNet alongside the baseline method indicated in the figure legend. In Fig3 (a), the changing distance over time has been depicted, according to which, our Twin-APCNet has less variation as compared to baseline. This shows more avoidance of obstacles and the continuity of the paths lay down by the robots. In was also observed that Twin-APCNet has better distance distribution control and consequently, a lower variation as depicted in Figure 3 (b) where at 5th and 95th percentile, Twin-APCNet has better confidence intervals. In detail, Twin-APCNet minimizes deviations by 15–20% thereby showcasing its high accuracy and reliability in sequence scheduling and trajectory planning activities.

5. Conclusion

Wireless Rechargeable Sensor Networks (WRSNs) face challenges in managing task scheduling, trajectory planning, and energy consumption, especially with obstacle avoidance and dynamic conditions. Existing methods often tackle these issues separately, resulting in inefficiencies. Our proposed methodology, combining the Twin Adaptive Pulse Coupled Network (Twin-APCNet) with the Crested Porcupine Optimizer, offers a unified solution. Our approach simultaneously optimizes task scheduling and trajectory planning, ensuring efficient energy management and effective obstacle avoidance. This integration enhances WRSN performance and scalability in complex environments. Compared to methods like DRL-JERDCS, MCDM, AFQB-PSO, and iFQS, our method shows significant improvements. Metrics such as energy efficiency, task completion rate, and network lifetime were analysed, with our method achieving over a 92% improvement in energy efficiency and task completion rate. By addressing scheduling, planning, and energy management in a unified way, our method significantly improves WRSN functionality and reliability, ensuring more robust and efficient network operations.

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