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A Routing Mechanism for Low-Power and Lossy Networks in Asymmetric Environments: Leveraging Digital Twin-Enabled Computing Power Networks

Yanan Cao *, Guang Zhang and Yuxin Shen

Tianjin Key Laboratory of Wireless Mobile Communications and Power Transmission, Tianjin Normal University, Tianjin 300387, China; 18185647570@163.com (G.Z.); yxshen@tjnu.edu.cn (Y.S.)

* Correspondence: caoyanan@tjnu.edu.cn

Abstract

Asymmetry is a prevalent phenomenon in low-power and lossy networks (LLNs) due to resource constraints and unstable links. The routing protocol for the low power and lossy network (RPL), standardized by the Internet Engineering Task Force (IETF), is specifically designed for LLNs with characteristics of resource constraints, lossy links, and complex communication environments. However, its performance is fundamentally limited by node capabilities and unstable links, a contradiction exacerbated by the stringent QoS demands of emerging applications like IIoT or precision agriculture. Consequently, new RPL routing technologies based on the digital twin-enabled computing power network, called RPL-DTCP, were designed to improve network QoS and support practical applications. First, a low-power and lossy network architecture based on twin-enabled computing network was proposed, considering LLN requirements and computing twin services. Second, in response to the requirements of the digital twin, computing power network and LLNs for low synchronization latency, high data accuracy, efficient computing resource utilization, and energy conservation, several routing metrics were designed, including the data processing model, model deployment rate, end-to-end delay, node remaining energy, and ETX. Then an initial matrix and a comprehensive objective function were formulated to comprehensively evaluate these metrics. Third, to solve the multi-objective optimization problem, an enhanced whale optimization algorithm (E-WOA) was developed. E-WOA improved upon the standard version by using improved Tent chaotic mapping for population initialization, nonlinear adaptive convergence factor, and Cauchy variation mutation operator for solution perturbation, thereby enhancing its global search capability and convergence speed, enabling it to effectively identify the optimal routing path. Simulations confirmed that RPL-DTCP outperforms benchmark algorithms, achieving significant reductions in end-to-end delay, higher packet delivery ratios, extended network lifetime, etc. These findings demonstrate that RPL-DTCP effectively addresses the resource-performance contradiction in LLNs, providing a reliable and efficient routing framework for emerging compute-intensive IoT applications.

Keywords: LLN; RPL; digital twin; computing power network; whale optimization algorithm

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Academic Editor: George Karabatsos

Received: 9 April 2026
Revised: 11 May 2026
Accepted: 12 May 2026
Published: 14 May 2026

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1. Introduction

Low-power and lossy networks (LLNs) [1] serve as a fundamental networking technology for the Internet of Things (IoT), enabling ubiquitous connectivity. A primary challenge

in LLNs stems from the inherent asymmetry of their constraints, as nodes typically possess limited computing and storage capabilities, unstable link quality, and scarce energy supplies. Consequently, the core of LLN routing lies in effectively balancing energy consumption, reliability, and cost under these stringent resource limitations. Digital twin [2] technology offers a promising avenue to enhance routing decisions by constructing high-fidelity models and synchronizing real-time states, enabling comprehensive sensing and simulation of the network. This capability can significantly reduce the service interruptions caused by path failures or erroneous decisions, thereby improving the reliability and intelligence of LLNs. However, as LLN scales expand and applications grow more complex, the computational demands of digital twin—for processing high-frequency data and running intelligent models—escalate dramatically, creating a severe bottleneck that exceeds the local capabilities of typical LLN infrastructures.

The Computing power network [3] emerges as a potential architectural solution to this computational bottleneck. By embedding service state information—such as computational load and network cost—within the network protocol, a CPN controller can dynamically assess and collaboratively schedule distributed computing resources. Nevertheless, current research predominantly focuses on isolated aspects: optimizing the Routing Protocol for LLNs (RPL), managing network resource constraints, or performing multi-objective routing. This fragmented approach overlooks the deep technical complementarity among digital twin, computing power network, and RPL. Specifically, existing works often either focus on leveraging DT to enhance the perceptual capability of routing decisions while neglecting its substantial overhead on local resources or attempt to utilize CPN for distributed computing support without co-designing it with the dynamic routing mechanisms of LLNs. This disconnection hinders the system's ability to achieve global optimization of computing and communication resources while ensuring QoS.

Although symmetry represents an ideal state of balance, real-world LLNs are predominantly characterized by asymmetry. The inherent heterogeneity of node capabilities and the stochastic nature of lossy links create fundamental imbalances between available resources and application demands. To address these challenges, this paper proposes a novel RPL routing algorithm based on digital twin-enabled computing power network (RPL-DTCP). RPL-DTCP constructs LLN architecture that deeply integrates digital twin and computing power network, aiming to achieve efficient collaboration between perception, computation, and routing. Based on the characteristics and application requirements of LLNs, the algorithm formulates a unified model incorporating multiple routing metrics: the data processing model, model deployment rate, end-to-end delay, node residual energy, and ETX. A comprehensive objective function was subsequently constructed. To solve this complex multi-objective optimization problem efficiently, a tailored enhanced whale optimization algorithm (E-WOA) was developed. E-WOA incorporates mechanisms such as optimized Tent chaotic mapping initialization, nonlinear convergence factor, and weighted Cauchy mutation operator to improve the balance between global exploration and local exploitation, as well as convergence speed.

Given the inherent asymmetry discussed above, this work aimed to mitigate these asymmetries within LLNs by leveraging digital twin-enabled computing power networks, ultimately striving to restore balanced performance in such asymmetric environments. The main contributions of this paper are summarized as follows:

1. A new RPL routing algorithm based on digital twin-enabled computing power network (RPL-DTCP) is proposed.
2. LLNs based on digital twin-enabled computing power network are proposed. The routing metrics including the data processing model, model deployment rate, end-to-end delay, node remaining energy, and ETX are established.

3. New comprehensive objective function and multi-objective optimization are established which can jointly consider the computational and network state.
4. A tailored enhanced whale optimization algorithm (E-WOA) is developed. With mechanisms of optimized Tent chaotic mapping initialization, nonlinear convergence factor, and weighted Cauchy variation operator perturbation, it can obtain the optimal path, achieve the balance between global search and local search, and attain rapid convergence.
5. A series of simulation experiments was carried out and simulation results show that RPL-DTCP can not only reduce the computing resources required by the data processing model but also improve the network performance. Furthermore, compared with different schemes, RPL-DTCP demonstrates superiority in terms of packet loss rate, latency, and network lifetime, etc.

The remainder of this paper is scheduled as follows: Section 2 introduces the related works including LLN, digital twin, computer power network, RPL, and relevant research problems analysis. Section 3 details the newly designed RPL routing algorithm based on the digital twin-enabled computing power network (RPL-DTCP). Section 4 presents the simulation results and analysis of RPL-DTCP and RPL optimizations. Finally, Section 5 concludes the paper.

2. Related Works

2.1. LLN, Digital Twin, and Computing Power Network

2.1.1. LLN

LLN [4,5], the important distributed subnet of 6G network architecture, is a special type of distributed network architecture for future IoT and edge computing scenarios, aiming to solve the matter of efficient and reliable communication in resource constrained situations. Nodes and links in LLN are resource limited and suitable for a complex and harsh scenario. The key features of LLN are low power consumption, high lossy transmission tolerance, and low processing and storage capabilities of nodes. It can be widely used in industry 5.0, disaster rescue, smart agriculture, etc. Compared with IoT, LoRa, or Sigfox [6], LLN has significant improvements in energy efficiency, intelligence, reliability, and effectiveness, while being particularly suitable for sustainable communication in a complex and harsh scenario.

Figure 1 shows an instance of LLN architecture [7], which can be composed of tree-type and hybrid-type structures. DODAG, the directed graph wherein all edges are oriented in such a way that no cycles exist, is constructed according to control messages and objective function. Nodes and links are limited by computing, storage, bandwidth, etc. Consequently, to ensure the reliability and effectiveness of data transmission, designing green, efficient and reliable routing algorithms and communication mechanisms are crucial. The routing protocol for the low power and lossy network (RPL) [8], standardized by the Internet Engineering Task Force (IETF), is specially designed for LLN and can supply theoretical and technical support for LLN to realize green, efficient, and reliable communication. Nevertheless, this traditional RPL algorithm is no longer capable of meeting the development needs of new-generation information technology, and it cannot meet the requirements of the multi-dimensional network QoS, high energy consumption efficiency, etc. Hence, this paper designed a new RPL algorithm based on the digital twin-enabled computing power network (RPL-DTCP) for LLN, which can utilize the characteristics of LLN, digital twin, and the computing power network comprehensively to ensure a green, high energy efficient, and multi-dimension network QoS.

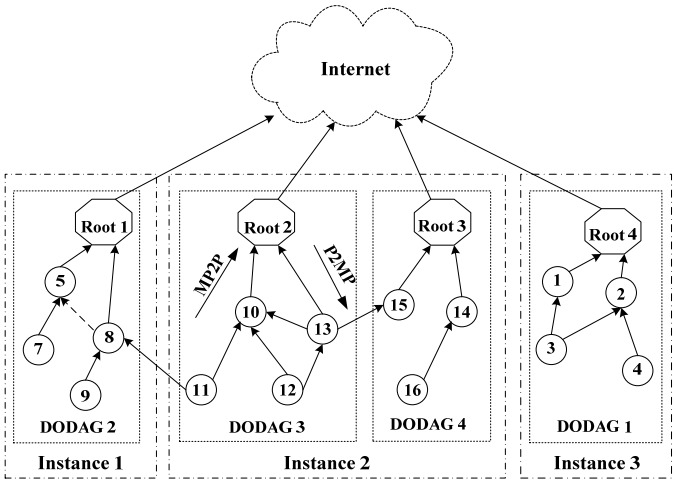


Figure 1. LLN architecture.

2.1.2. Digital Twin

Digital twin [9] is a network system that features both physical entities and their virtual counterparts, and these two can interact and map in real time. Various network management and application systems can utilize the network virtual twins constructed by digital twin technology to conduct efficient analysis, diagnosis, simulation, and control of the physical network. Meanwhile, digital twin technology can accelerate the innovation of mobile networks, reduce the research and development costs of the telecommunications industry, and shorten the research and development cycle. It enables real-time data exchange between the physical network and the digital twin network, influencing each other. In this way, a more secure, intelligent, efficient, and visualized smart LLN can be achieved.

At present, several studies have been conducted on the digital twin routing technologies. In [10], authors proposed a detour routing reconfiguration method based on digital twin to analyze link parameters and communication devices and enable real-time network monitoring and automatic fault detection to ensure the accuracy and efficiency of detour path selection. In [11], authors proposed a novel routing algorithm designed for direct-to-cell satellite constellations in satellite networks by incorporating large-scale digital twin constellations to offer agents with high precision state data inputs and feedback for training and application support. In [12], authors proposed a novel load balancing routing algorithm based on digital twin by establishing a directed acyclic graph model, deriving the average load of hierarchy, and proposing a hierarchical load balancing strategy based on the black-winged kite algorithm to evaluate the superiority of the proposed algorithm. In [13], authors addressed the challenge of optimizing multi-hop routing in IoT based on digital twin by proposing two corresponding evolution-based metaheuristics that utilize well-designed solution representations and genetic operators to obtain near-optimal solutions to reduce energy consumption and improve net-work stability. It can be seen that the digital twin technology, through virtual and real integration and closed-loop control, can achieve a safer, smarter, and more efficient intelligent network. It can serve as an important foundation for realizing data perception, intelligent control, routing calculation, data transmission, and autonomous security lifetime management of LLN. Therefore, this paper proposed the LLN architecture based on digital twin to ensure an improved performance.

2.1.3. Computing Power Network

The computing power network [14] is centered around a computing, fundamental network. It integrates network, cloud, data, intelligence, security, edge, end, and chain, providing a comprehensive service-oriented new type of information infra-structure. As

shown in Figure 2, the computing power network should be equipped with computing power service functions, computing power routing functions, and computing network orchestration management functions. It needs to integrate computing network resources; that is the actual situation and application efficiency of computing processing capabilities and network forwarding capabilities in the network, to achieve high-quality transmission and flow of various computing and storage resources. It accomplishes this by deeply integrating computing power and networks to enhance the utilization of computing resources and improve user experience for network services.

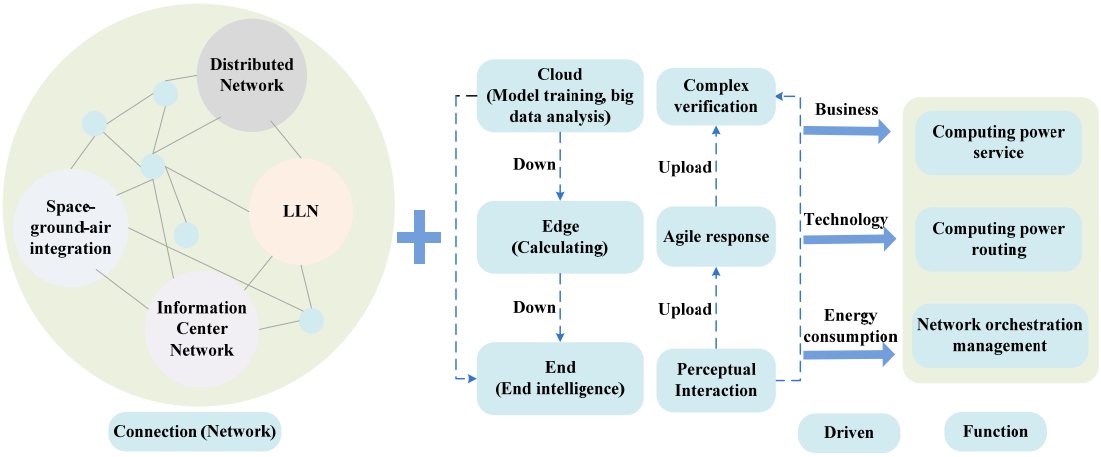


Figure 2. Computing power network function requirement architecture.

Here, the computing power routing function is equipped with abilities to achieve functions such as association, distribution, addressing, allocation, and optimization of computing power information resources within the network through the network control plane. According to the discovery of abstracted computing and networking resources, the network control can take into account the network status and computing resource status and can flexibly schedule services to different computing resource nodes as needed, to realize the computing power routing function. At present, several studies have been conducted on the computing power network routing technology. In [15], the authors proposed a novel computing power network architecture to support routing and scheduling for stateless computing services to enhance differentiated QoS. New insights for evolving the computing power network from "resource provisioning" to "service inter-connection" were provided. In [16], the authors designed a novel multi-path ant colony algorithm for deterministic computing power networks, which introduces dynamic pheromone updating and heterogeneous resource-aware path selection, enables reliable task transmission under node/link failures, and optimizes computing resource utilization. In [17], the authors developed a dynamic control policy for routing to determine both paths and computing nodes in the distributed computing power network. Meanwhile, according to multi-attribute decision and fuzzy logic theory, the fuzzy logic-based routing (FLBR) algorithm and low-complexity pairwise multi-attribute decision-making (lPMADM) algorithm were proposed to achieve better performance. In [18], the authors presented a novel routing planning method based on multi-objective optimization for computing power networks to improve the performance and efficiency of routing by considering multiple objectives. It is observed that through the collaboration of network and computing power resources, the network can perceive computing power resources and guide the routing of the entire network. Therefore, low-power and lossy network routing technologies for LLN can be combined with the digital twin and computing power network to further optimize user

experience for network services. Hence, low-power and lossy network routing technologies based on the digital twin-enabled computing power network were designed in this paper.

2.2. RPL Introduction

RPL [19], designed by the ROLL working group, is a kind of distance-vector routing protocol specifically for LLN. It can effectively combine objective function and routing metrics according to the specific application scenario requirements, thereby constructing the corresponding network topology. Therefore, RPL has strong interoperability and flexibility and is suitable for different scale interconnected network scenarios, such as environmental monitoring, smart grids, and smart agriculture.

RPL constructs network topology and data transmission mainly based on DODAG (Destination Oriented Directed Acyclic Graph), OF (Objective Function), Rank, and control messages. DODAG is a destination oriented directed acyclic graph, and its edges are oriented in such a way that no loops exist. It is the basic unit for constructing network topology. OF stipulates how routing metrics, optimization objectives, and other related functions are utilized to calculate Rank. Rank, calculated according to OF, represents the node's position relative to others with respect to the Root. Meanwhile, Rank can dictate the node's parent selecting and network formation. Control messages mainly used in RPL are DIO (DODAG Information Object, DIO), DAO (Destination Advertisement Object, DAO), DIS (DODAG Information Solicitation, DIS), and DAO-ACK (Destination Advertisement Object Acknowledgement). DIO, broadcast by the parent, carries information that makes the node discovering network, obtaining configuration parameters, selecting parent, and maintaining the network. DAO delivers upward destination in-formation and constructs uplink route. DIS can be used to request DIO from its neighbors to join the nearby network. DAO-ACK is sent by the DAO recipient to acknowledge the DAO message. Then, the simplified network construction process can be illustrated as in Figure 3. Its explanation steps are as follows.

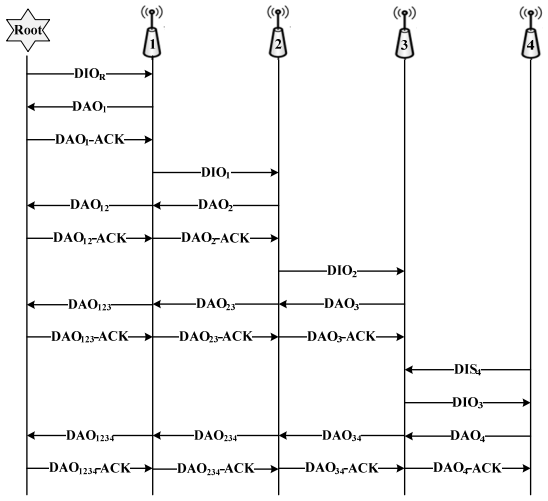


Figure 3. Simplified network construction process.

Step 1: Root broadcasts DIO which includes elementary information to enable its neighbors to join this current network.

Step 2: If node 1 (neighbor of Root) receives DIO_R, it decides whether to choose Root as its parent based on information included in DIO_R. If so, node 1 should unicast DAO_1 to Root to construct upward routing. If not, node 1 does not perform any operation.

Step 3: After receiving DAO_1, Root adds node 1 into its child node list and unicast DAO_1-ACK to node 1. After receiving DAO_1-ACK, node 1 has completed the downward routing construction from Root to node 1.

Step 4: Node 1 has completed updating its routing information and then broadcasts DIO_1 periodically.

Step 5: If node 2 (neighbor of node 1) receives DIO_1, it decides whether to choose node 1 as its parent based on information included in DIO_1. If so, node 2 should unicast DAO_2 to node 1 to construct upward routing. If not, node 2 does not perform any operation.

Step 6: After receiving DAO_2, node 1 adds node 2 into its child node list and forwards DAO_{12} to Root.

Step 7: After receiving DAO_{12}, Root uni-casts DAO_{12}-ACK to node 1 and node 1 uni-casts DAO_2-ACK to node 2. Then, the downward routing from Root to node 2 has been established.

Step 8: Other nodes, such as node 3, perform the same operation to establish their upward and downward routing.

Step 9: If node 4 has not received any DIO from other nodes within a period of time, it will broadcast DIS_4 to solicit DIO from its neighbors to join the network.

Step 10: If node 3 (neighbor of node 4) receives DIS_4 and agrees that node 4 joins in this network, then it uni-casts DIO_3 to node 4.

Step 11: After receiving DIO_3, node 4 adds node 3 into its parent node list and uni-casts DAO_4 to node 3. Thus, the upward routing from node 4 to node 3 has been completed.

Step 12: After receiving DAO_4, node 3 adds node 4 into its child node list and forwards DAO_{34} to node 2. Then, node 2 forwards DAO_{234} to node 1 and node 1 forwards DAO_{1234} to Root.

Step 13: After receiving DAO_{1234}, Root adds relevant information of node 4 into its routing table and uni-casts DAO_{1234}-ACK to node 1. Then, node 1 uni-casts DAO_{234}-ACK to node 2. Node 2 uni-casts DAO_{34}-ACK to node 3. And node 3 uni-casts DAO_4-ACK to node 4. Thus, the downward routing from Root to node 4 has been established.

The above steps are repeated until the network covers all nodes.

In RFC 6550, the transmission of DAO-ACK is optional, controlled by the "K" flag within the DAO message. Figure 3 depicts a scenario where the DAO-ACK is requested. When a node sends DAO with the "K" flag set, a retransmission timer is initiated. If the corresponding DAO-ACK cannot be received from the parent before the timer expires, the node will retransmit the DAO message. The maximum retransmission number and the retransmission interval are implementation-specific and may be adapted to network conditions. If the acknowledgment is still absent after exhausting the permitted retries, the node will declare the current path invalid and initiate the parent switch mechanism to select a new parent.

2.3. Relevant Research Problems Analysis

This section primarily focuses on analyzing the current research status and existing problems in network architecture, resource-constrained routing technologies, construction of OF, multi-routing metrics measurement theories, and the optimal route selection regulation.

2.3.1. Network Architecture

The current research studies are mostly based on the network topology construction process shown in Figure 3, and the established network architecture is similar to that shown in Figure 1, with almost no fundamental optimization. The network construction process and network architecture have not undergone significant improvements. The original network construction and maintenance mechanisms may encounter high control

overhead, low construction efficiency, high energy consumption, and high maintenance costs. Moreover, any node can become the preferred parent through broadcast DIO, but its quality may be too poor to delivery packets, which will further squander energy, cache resources, and affect network reliability. Meanwhile, the constructed network architecture has unstable links, poor resilience, limited computing and storage resources for nodes, and lacks load balancing and energy balancing mechanisms, etc. Hence, it seriously affects information transmission and fails to guarantee network QoS.

Therefore, this paper proposed LLN architecture based on the digital twin-enabled computing power network which effectively integrates digital twin, the computing power network, and LLN together. In this way, the computing resources, storage resources, and network resources demands can be effectively alleviated. Meanwhile, the overall scalability and reliability of the system can be enhanced fundamentally.

2.3.2. Resource-Constrained Routing Technologies

In LLN, the bandwidth is limited, links are lossy, and the computing power, processing capacity, energy, and cache of nodes are limited. Thus, its routing technologies, oriented resource-constrained, should be researched to guarantee network QoS. Meanwhile, it is necessary to improve the processing capabilities and energy consumption efficiency, avoid the resource limitation obstacle, and provide differentiated services according to different application scenario requirements. As a result, RPL based on energy awareness, load balancing, and multi-attribute decision optimization technologies have been researched. For instance, in [20], the authors proposed the RT-Ranked (Resiliency TSCH/RPL Ranked, RT-Ranked) algorithm to save the control message number and load, support unforeseen traffic bursts, and significantly improve the network reliability. In [21], the authors designed the TLR (Traffic aware Load-Balancing Routing, TLR) algorithm. TLR fully considered buffer limitations and adopted the active path selection strategy to achieve efficient load balancing and high throughput. In [22], the authors combined residual energy and several other routing metrics to determine whether the candidate parent could be selected as the preferred parent. The weighting coefficient was used to confirm the importance of each routing metric. In [23], the authors combined the Energy Efficient Multipath Routing Protocol (EM-RPL) with the Load-Based Energy Efficient RPL (LBEE-RPL) to handle energy bottlenecks and prolong network lifetime. In [24], the authors enacted the QFS-RPL (Q-learning and Fish eye State RPL, QFS-RPL) algorithm, which predigests the data delivery process to reduce energy consumption and balance load. In [25], the authors designed the RARL (RPL routing optimization Algorithm based on deep Reinforcement Learning, RARL) algorithm based on deep reinforcement learning. It adopts centralized training and decentralized execution architecture to provide intelligent parent selection strategies for all nodes and to improve the training efficiency of the reinforcement learning model. RARL can effectively solve the problems of the node buffer and energy limitation. The comparative analysis of them is listed in Table 1. However, the existing studies either fail to detect the node's remaining energy in real time, or only focus on load balancing and energy consumption without evaluating other key routing metrics, or lack scientific multi-routing metric assessment theory, thus being unable to meet multi-objective optimization requirements for the network QoS. Additionally, routing technologies with limited resource capabilities may lead to compromises in network performance, reliability, security, and flexibility. These routing technologies should also seek new and better balance points amid the contradictions.

Table 1. Comparison of some routing technologies for resource-constrained environments.

Algorithm	Constrained Resource	Technical Scheme		Optimization Objectives	Limitation(s)	Publication Year
		Solution	Other Method			
RT-Ranked [20]	Network topology information	RPL control message option extension	Traffic burst prediction	Unexpected traffic surge, delay bandwidth/slot allocation	Stale information risk, non-storing mode Limitation	2024
TLR [21]	Channel/slot resources	Traffic-aware Load-balance Routing	Integrate multi-dimensional traffic perception metrics	Load balance, low delay, high energy efficiency	State maintenance, Protocol complexity	2024
IP-RPL [22]	Energy	Environmental perception power prediction method	Enhance OF, Dynamic power level selection	Energy, delay, reliability	Model training dependency, Parameter sensitivity	2025
EM-RPL [23]	Energy	Energy efficient multi-path RPL, load-based energy efficient RPL	Child node switch mechanism, improved trickle	Network lifetime, load balance	Control overhead, Parameter tuning	2025
QFS-RPL [24]	Energy	Q-learning, fish eye state routing algorithm	Support mobility	Energy efficiency, load balance, delay, control overhead, etc.	Parameter sensitivity, Memory consumption	2024
RARL [25]	Buffer, energy	Deep reinforcement learning	optimized trickle timer	Energy, load balance, network efficiency and reliability	High complexity/overhead	2024

Therefore, this paper designed a new RPL routing algorithm based on the digital twin-enabled computing power network (RPL-DTCP) to be better applied to LLN. In RPL-DTCP, key routing metrics such as the data processing model, model deployment rate, end-to-end delay, node remaining energy, and link quality are established based on the digital twin-enabled computing power network architecture of LLN. Moreover, it also attempts to minimize the data processing, model deployment rate, and end-to-end delay while maximizing the remaining energy of the nodes and link quality; thereby network performance and QoS can be guaranteed.

2.3.3. Objective Function Construction

Objective function (OF), contained in DIO, can be used for regulating how nodes select and optimize routes within the network. It regulates how nodes translate one or more routing metrics into Rank, which is similar to the distance between nodes and Root. OF also stipulates how the nodes select parents. The corresponding OFs can be designed according to different application environments. For instance, OF0, designed as the default OF, selects parents based on hop. ETXOF makes RPL select the minimum ETX route from nodes to Root. In [26], the authors proposed cross-layer energy-efficient objective function (CL-RPL-OF). CL-RPL-OF evaluates ETX and energy per packet needed by the fuzzy logic method both in routing and in MAC layers. In [27], the authors designed OF based on multi-objective like trust, delay, energy, link quality, and distance. Then, a novel hybrid optimization method called Dwarf Mongoose aided Shuffle Shepherd Optimization (DM-SSO) was proposed to select the path. In [28,29], the authors proposed to design the objective function by combining multiple routing metrics in a lexical or additive manner. Usually, the network performance in the additive manner is better than that of the lexical manner. Nonetheless, it is difficult to scientifically determine the importance of each routing metric in the additive method. Most of them are based on the expert's personal subjective experience or experimental experience accumulation.

Currently, the construction basis of OF mainly includes two categories: single routing metric and multiple routing metrics. In the single routing metric, OF is largely constructed based on ETX, hop, energy, delay, etc. In the multiple routing metrics, several of node state and attribute (NSA), energy, hop, throughput, delay, ETX and other new proposed routing metrics are considered as the basis to construct OF. It has been shown that OF constructed based on multiple routing metrics performs significantly better than that of OF constructed based on single routing metric in network construction efficiency and network QoS. Meanwhile, the constructing and solving methods for OF based on multiple routing metrics mainly include the linear weighting method, the weighted product method, the fuzzy comprehensive evaluation method, the Pareto optimal method, the fuzzy logic method, the fuzzy analytic hierarchy process, the swarm intelligence algorithm, the rough set method, etc.

Therefore, this paper proposed the construction of OF by using multiple new routing metrics to optimize the network performance. Based on the digital twin-enabled computing power network, the data processing model, model deployment rate, end-to-end delay, node remaining energy, and link quality were established to construct OF. Moreover, an enhanced WOA algorithm (E-WOA) was proposed to solve this proposed optimization problem (OF). In this way, network performance could be optimized and guaranteed.

2.3.4. Multi-Routing Metrics Assessment Theories

Multi-routing metrics assessment is the theory in the network routing decision-making process, where multiple indicators such as delay, bandwidth, reliability, etc. are comprehensively considered to evaluate and select the optimal path. Compared with the traditional single routing metric assessment such as that based solely on hop or the shortest path, it has more comprehensive perception of network status, supports differentiated QoS requirements, optimizes resource utilization and load balancing, supports multi-objective optimization and Pareto optimal solutions, enhances the flexibility and scalability of routing decisions, and adapts to the future network's evolving requirements, presenting significant advantages. Therefore, through systematic modeling and optimization, multi-routing metrics assessment theory can achieve comprehensive optimization of network performance, reliability, efficiency, and adaptability. It enhances the scientificity of routing decisions and provides a theoretical basis for the next generation intelligent network construction. Thus, it is imperative to establish scientific multi-routing metrics evaluation theories. In [30], the authors proposed an entropy-based weighted approach to assign the weights of the routing metrics in the objective function. In [31], the authors proposed a novel objective function which integrates network load and congestion conditions by a fuzzy multi-criteria decision-making approach. In [32], the authors selected the Takagi–Sugeno fuzzy method to construct objective function through several routing metrics to improve network performances. In [33], the authors introduced an objective function that considers expected life time, delay, and energy aware-expected transmission count. PSO was used to optimize the parent selection process and the trickle timer mechanism. In [34], the authors designed OF function based on CVSS (Common Vulnerability Scoring System, CVSS) values, vulnerability severity, and network topology. Then, they integrated risk assessment mechanisms into the routing process. In this way, routes with lower security risks can be selected as the optimized one. In [35], the authors introduced a secured swarm intelligence-based path selection framework and secure ant colony objective function (S-ACOF) to enhance reliability and security. S-ACOF evaluated energy consumption and control overhead, based on ACO to compute globally the optimal and trustworthy paths.

It can be seen that multi-routing metrics assessment theory has significant advantages and has made certain progress in research. But there still exist some issues that need to be

addressed. For instance, when taking into account the correlation and conflict between routing metrics, how can a universal model for routing metrics be established? There is a dilemma in selecting Pareto optimal solutions in multi-objective optimization. The importance of each routing metric cannot be adjusted in real time according to the network actual operation. Meanwhile, intelligent adaptive adjustment, distributed autonomy, and network QoS cannot be assured. Therefore, constructing intelligent, adaptable, effective, and reliable multiple routing metrics assessment theories can effectively guarantee network QoS and achieve resource optimization and intelligent collaboration.

2.3.5. The Optimal Route Selection Criteria

Currently, there is relatively little research on the optimal route selection criteria. Most research studies maintain the route that is the best with regard to the following rules: The node with the maximum or minimum Rank value computed according to OF will be chosen as the next hop. If there are multiple neighbors with the maximum or minimum Rank values, different routing metric criteria can be used to choose among these neighbors or randomly choose one as the next hop. For example, in [36], the authors proposed RSOF (Reliable and Secure Objective Function) which employs an adaptive parent selection mechanism that incorporates multiple metrics, including residual energy, ETX, extended RPL node trustworthiness and node failure rate (NFR). Also, nodes with high NFR are excluded from the parent selection process to guarantee network reliability and stability. In [37], the authors proposed a mobility-aware secure trust-based routing protocol for RPL-based IoT (MSecTrust) to prevent routing attacks. MSecTrust calculates the trust values based on Dempster–Shafer theory and mobility-related characteristics for secure routing selection. Thus, rough route selection strategy cannot be used, and routing protocols intelligently select the optimal routes from multiple routes based on routing metrics or policy rules, and must take into account factors such as efficiency, reliability, and controllability, etc. Therefore, it is necessary to conduct in-depth research on the optimal route selection criteria. Hence, this paper proposed optimal route selection criteria based on stability, effectiveness, reliability, and controllability of the new designed RPL-DTCP.

To sum up, RPL and its relevant research studies used in LLN, IoT, or other application scenarios encounter inefficient and unreliable construction and maintenance strategies of network architecture, poorly take into account resource-constrained features of LLN, have inappropriate OF construction, unintelligent and low adaptability multi-routing metric assessment theories, and rough optimal route selection criteria as before. Hence this paper designed a new RPL routing algorithm based on the digital twin-enabled computing power network (RPL-DTCP). RPL-DTCP proposed LLN architecture based on the digital twin-enabled computing power network and established the data processing model, model deployment rate, end-to-end delay, node remaining energy, and link quality indicators. Then, based on the above indicators, the new comprehensive OF could be constructed. RPL-DTCP also proposed an enhanced WOA (E-WOA) algorithm to solve the proposed optimization problem (the new comprehensive OF). Through mechanisms such as chaotic mapping initialization, nonlinear convergence factor, and Cauchy variation operator perturbation, it achieves the optimal solution (the optimal path), balance between global search and local search, and rapid convergence. That is, the intelligent, adaptive, and appropriate multi-routing metric assessment theories were designed in this paper which can minimize data processing, model deployment rate, and end-to-end delay while maximizing the remaining energy of nodes and link quality, thereby optimizing network performance and ensuring the network QoS. Meanwhile, RPL-DTCP establishes the optimal route selection criteria based on stability, effectiveness, reliability, and controllability of network performance. Finally, simulation results show that RPL-DTCP can not only reduce computing

resources required by data processing model but also improve network performance. Furthermore, in the comparison of different schemes, RPL-DTCP demonstrates superiority over the existing ones in terms of packet loss rate, control overhead, and network lifetime, etc. Consequently, RPL-DTCP fully takes into account network resource-constrained features and takes the multi-dimensional network QoS as the goal orientation, providing certain theoretical support for LLN routing technologies.

3. RPL-DTCP

In this paper, an enhanced algorithm of RPL based on digital twin-enabled computing power network and E-WOA called RPL-DTCP is proposed, which enhances network architecture and the packet delivery ratio while reducing delay and energy consumption. The main innovations of RPL-DTCP are as follows:

1. Network architecture based on digital twin-enabled computing power network is proposed.
2. Data processing model, model deployment rate, end-to-end delay, remaining energy, and link quality (ETX) are designed according to this new network architecture.
3. New comprehensive OF is established to expediently solve the contradictory multi-objective optimization routing metrics problem.
4. An enhanced whale optimization algorithm (E-WOA) is proposed to effectively solve this proposed optimization problem (comprehensive OF). Through mechanisms such as optimized Tent chaotic mapping initialization, nonlinear convergence factor and weighted Cauchy variation operator perturbation, it achieves the optimal solution (the optimal path), better balance between global search and local search, and rapid convergence.
5. A new Rank calculating manner is designed and the optimal route selection criteria are formulated according to the network actual situation and the aforementioned intelligent algorithm.

In the following, RPL-DTCP will be explained in detail based on the aforementioned outlines.

3.1. LLNs Based on Digital Twin-Enabled Computing Power Network

The resources of LLN are limited in terms of computing, storage, energy, bandwidth, etc. Its link reliability is poor. It also lacks global perspective and collaborative capabilities, has weak data processing capabilities, and easily makes data islands, while the application of the digital twin-enabled computing power network in LLN can effectively solve these problems. Specifically, the computing power network achieves the coordinated arrangement of ubiquitous and heterogeneous computing resources through unified management, and dynamically and flexibly schedules computing resources based on demand, thereby improving the utilization rate of the computing resources and providing computing resource support for LLN. Digital twin achieves accurate mapping from the physical world to the digital world by establishing precise twin models and collecting and updating real-time network status data. This enables the optimization of the entire cycle of LLN operation, maintenance, routing calculation, etc. Then, it realizes simulation verification of routing decisions and data transmission, thereby improving the construction and maintenance efficiency of LLN, enhancing data transmission reliability, and reducing the trial-and-error costs of network operation, maintenance, and data transmission. The digital twin-enabled computing power network overcomes fundamental limitations of LLN in terms of capabilities, energy efficiency, reliability, and intelligence level, making it possible for large scale, intelligent and highly reliable IoT applications such as industry 5.0, smart cities, and precision agriculture, etc.

The digital twin-enabled computing power network for LLNs was designed and is shown in Figure 4. It consists of a physical layer and digital twin layer. The physical layer consists of cloud central nodes, network nodes, edge nodes, and terminals, while the cloud central nodes, network nodes, and edge nodes jointly form the computing power network, promoting collaborative use of distributed computing resources. The digital twin layer tracks the states and behavior of each physical entity, establishes corresponding digital twin models, forms a global digital twin, and uses the intelligent models for state analysis, resource management, and simulation, while providing functions such as route fault detection, route search, and packet delivery optimization.

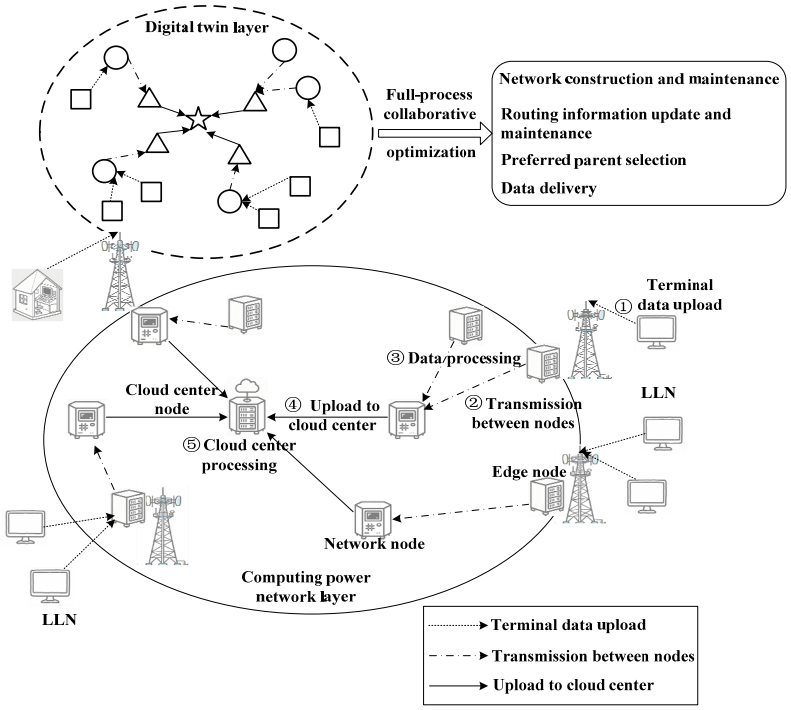


Figure 4. Digital twin-enabled computing power network for LLN.

As illustrated in Figure 4, the edge node and digital twin layer handles latency sensitive tasks, whereas the cloud center is primarily used for non-real-time tasks. The cloud central node responds to routing calculations and collaborative optimization requests based on real-time data. If uploading all data to the cloud central node to process, it may cause cloud central node overload, wasting bandwidth resources, and resulting in longer data processing and integration response time, thereby failing to ensure real-time synchronization update of data in the digital twin-enabled computing power system. Therefore, the proposed digital twin-enabled computing power network architecture for LLN deploys data processing models on the network nodes. Data must be pre-processed and then uploaded to the cloud central node to support the establishment and operation of the digital twin-enabled computing power. Compared with edge nodes, network nodes are farther from terminals but closer to the cloud central node. Thus, they can provide more abundant computing resources and storage resources for data processing. Then, data pre-processing mainly includes data duplication checking, outlier detection, and data standardization, which is conducive to subsequent updates and efficient processing.

1. Mitigating energy and overheads

To mitigate the resource overheads inherent in integrating the twin-enabled computing power network, the proposed architecture is founded on a hierarchical offloading principle. The core rationale is to decouple the computationally intensive digi-

tal twin processes—including network simulation, global optimization, and predictive maintenance—from the resource-constrained LLN devices. These processes are instead hosted on cloud or edge nodes. Consequently, the terminal nodes retain only their fundamental roles of data sensing and packet forwarding. This design fundamentally addresses the "size" concern: the memory and processing footprint on the end devices is virtually unchanged, as the complex virtual layer is not co-located with the physical hardware.

From an energy perspective, the architecture introduces a strategic trade-off. A modest overhead of periodic state reporting to the digital twin layer is incurred to enable a significant advantage: predictive, optimized routing. In conventional RPL, a dominant source of energy waste is reactive packet retransmission and route discovery triggered by unstable links. By leveraging the digital twin's global view and predictive capability, the proposed system can proactively avoid such unstable paths, thereby drastically reducing these energy-intensive recovery operations. The resulting net energy balance is positive, as the energy saved from avoiding inefficient data transmissions far exceeds the marginal cost of the control signaling.

2. Hierarchical execution of optimization

For optimization execution, E-WOA is deployed in a hierarchical manner across the network stack. Local optimization (e.g., route and parent selection) is executed directly at the edge and network nodes to minimize latency and adapt to dynamic link conditions. Conversely, global optimization (e.g., model training, topology maintenance, and resource scheduling) is offloaded to the cloud center, where comprehensive computational resources enable large-scale coordination. This hybrid strategy ensures that the algorithm operates efficiently at the network periphery while maintaining system-wide optimality.

3. Synchronization mechanism and state consistency

The interaction between the physical LLN and its digital twin is governed by a well-defined synchronization protocol. This protocol balances the imperative for up-to-date network awareness against the constraints of LLN nodes.

Synchronization frequency: State updates are not continuous but follow a hybrid push–pull model. The cloud-based digital twin controller issues periodic synchronization requests at a configurable interval T_{sync}. T_{sync} is a tunable parameter, typically set in the order of seconds to minutes, allowing a trade-off between control overhead and state freshness. Crucially, nodes are mandated to push immediate, event-driven updates upon detecting critical state transitions, such as a parent node failure or a precipitous drop in ETX. This design ensures that the global view remains sufficiently current for routing optimization without imposing prohibitive communication costs on the constrained devices.

Consistency model: In the distributed, hierarchical system where central digital twin coordinates multiple edge instances, enforcing strong consistency is neither feasible nor necessary for routing decisions. The proposed architecture adopts a timed, causal consistency model. Local routing decisions at edge nodes are made based on the most recent state snapshot received from the digital twin. During the interval between synchronizations (T_{sync}), the physical network state may diverge from the digital twin model. The system is designed to be tolerant of such transient inconsistencies. The digital twin optimization algorithms account for this by incorporating staleness bounds into their models; for instance, a path calculated by digital twin is considered valid for a duration $T_{valid} \leq T_{sync}$, after which it must be re-evaluated. This model guarantees that all nodes will converge to a consistent network-wide routing strategy within a bounded time after the last state change, ensuring system stability and loop-free operation despite asynchronous updates.

4. Network topology model description

Suppose in the computing power network for LLN, there is one cloud center node, M network nodes $S = \{s_1, s_2, \ldots, s_M\}$, and I edge nodes $V = \{v_1, v_2, \ldots, v_I\}$, the amount of data that each edge node v_i needs to update to digital twin layer regularly is d_i. The computing resource size of each network node s_m is f_m, and its storage resource size is c_m. The amount of computing resources required to deploy one data processing model is f_0. There are K terminals $U = \{u_1, u_2, \ldots, u_K\}$, and the amount of data that each terminal u_k needs to update regularly is d_k. Then, the digital twin layer can abstract the entire network architecture into an undirected connected graph $G = (V, \zeta)$, where V is the set of edge nodes, network nodes, and cloud center nodes, and $\zeta = [L] \subseteq v \times v$ represents the network link set. Furthermore, $l \in \zeta$ indicates that there is a direct link between nodes, and each link has non-negative weight. The weight matrix $D = (w_l) \in \mathbf{R}^{v \times v}$ represents the physical distance of transmission between nodes. If $l \in \zeta$, then w_l is finite positive real number. Otherwise, $w_l = \infty$. Meanwhile, the matrix $B = (b_m) \in \mathbf{R}^M$ represents the available bandwidth for transmission between network node s_m and cloud center node.

3.2. New Routing Metric Indicators

For the characteristics of LLN based on digital twin-enabled computing power network architecture, several new routing metric indicators are designed. This mainly includes the data processing model, model deployment rate, end-to-end delay, node residual energy ratio, and ETX. Furthermore, it is pointed out that the data processing, model deployment rate and end-to-end delay should be minimized, while the node energy remaining ratio and link quality should be maximized as well. In the following, the routing metric indicators proposed in RPL-DTCP are elaborated, supposing node b has M candidate parents (neighbors).

3.2.1. Data Processing Model

In LLN based on the digital twin-enabled computing power network architecture, data processing refers to the cleaning of data related to routing decisions and fault detection. Data cleaning involves removing duplicates, handling outliers, and converting data formats, which can enhance data accuracy and reliability, further improve the precision of data analysis and twin modeling, and save network bandwidth resources.

Data deduplication: eliminating duplicate records from the data set. The hash deduplication strategy based on the sliding window cache is adopted in this paper. First, the unique identifier should be extracted from the received data. Then the identifier information within the recent period can be stored by maintaining a sliding time window cache. When new data arrive, whether the identifier is already in the cache will be checked. If it is, this data will be determined as duplicate data and discarded. Otherwise, this data can be regarded as new data, stored in the cache, and added to buffer for upload. Additionally, to ensure the cache usage within the controllable range, the expired identifiers must be cleaned regularly. Thus, by this deduplication strategy, redundant data can be reduced, and the streamlined and high-quality data input for the cloud center for data analysis and simulation verification can be provided—the waste of communication resources can be reduced.

Outlier handling: detecting and handle outliers in the data set. Outliers should be directly removed or replaced with acceptable values. For LLN, the lightweight outlier detection method should be used to economize network resources. Therefore, the threshold-based outlier detection method was used in this paper. Then, the corresponding thresholds are set for ETX, delay, and the remaining energy of the nodes. For instance, if the ETX value exceeds the set threshold, it indicates that the current link quality is poor and should not be used. The same also applies to the detection of delay and the nodes' remaining energy.

This outlier detection method is relatively simple and almost does not consume resources, making it suitable for LLN.

Data standardization: For the different types of data collected, standardization is the key step to achieve data consistency and compatibility. The standardization process includes field alignment and unit conversion. Field alignment is mapping field names of the original device data to a unified standard format. Unit conversion can be achieved through predefined rules to standardize the measurement units of various data. This can provide high-quality, consistent, and easily interpretable input for the subsequent analysis and simulation of the cloud center.

3.2.2. Model Deployment Rate

The decision on deploying data processing models at network nodes can be represented by vector $\boldsymbol{X} = [x_m]$, $x_m \in \{0, 1\}$. If $x_m = 1$, it indicates that a data processing model is deployed at network node s_m; if $x_m = 0$, it means no deployment. Based on this placement decision X, the deployment rate of the data processing model can be formulated as Equation (1):

$$\phi_1(m) = F(\mathbf{X}) = \sum_{m=1}^{M} \frac{c_m x_m}{M} \tag{1}$$

Here, c_m is the node-specific computational cost factor. In practical heterogeneous network scenarios (as illustrated in Figure 4), nodes are often equipped with diverse computational capabilities and energy constraints. Simply averaging the deployment rate (as in Equation (1) without c_m) without considering these disparities may lead to suboptimal resource allocation, where high-cost nodes might be over-utilized while powerful nodes remain underutilized. To tackle this issue, c_m is incorporated into Equation (1). The resource occupation is re-evaluated by weighting the deployment status with the corresponding node's processing cost, effectively transforming the metric from a simple average to a weighted resource efficiency calculation. This adaptation ensures that the optimization process favors placing models on nodes with higher computational efficiency (i.e., lower cost per unit of processing power), thereby eliminating resource waste caused by ignoring hardware heterogeneity and achieving truly optimized network resource utilization in complex multi-tiered architectures.

Since the amount of computing resources and storage resources required for deploying the data processing model is linearly related to the deployment number. RPL-DTCP proposed using the model deployment rate to measure the resources occupied amount by the model. Through this resource optimization strategy, the wasting of resources caused by duplication or incorrect processing can be eliminated. Then, efficient data processing and optimized network resources utilization rate can be achieved.

3.2.3. End-to-End Delay

End-to-end delay refers to the total time required for packets to travel from source to destination in their entirety, including transmission delay, propagation delay, processing delay, queuing delay, and protocol interaction delay, etc. It is an accumulated routing metric and represents the sum of the links delay. The path with the minimum end-to-end delay can be selected to deliver packets. End-to-end delay can be calculated by adding two sections: (1) end-to-end delay of the link from node to its neighbor, (2) end-to-end delay included in DIO sent by this neighbor. As illustrated in Equation (2), D(m) and D_{max} are the end-to-end delay from node b through m to Root and the maximum end-to-end delay among all paths from node b through its neighbors to Root, respectively. It can be seen that

end-to-end delay is not a single value but rather the cumulative result of multiple links. It needs special attention:

$$\phi_2(m) = \frac{D(m)}{D_{\max}},\ m = 1, 2, \ldots, M \tag{2}$$

3.2.4. Node Residual Energy Ratio

Energy is clearly a critical resource in most scenarios and can be used to avoid selecting a neighbor with low residual energy as the next hop. Thus, node residual energy ratio, formulated as Equation (3), is designed to measure how much energy remains in the node. $E_i(m)$ and $E_c(m)$ are the initial and current energy of neighbor m. m_p is the preferred parent of m. μ_1 = 0.21, and is the adjustment parameter, used for reducing the energy influence of parents, so that the energy consumption effect does not go farther than some degree. $E(m)$ evaluates the nodes' residual energy in a recursive manner and can reflect the residual energy situation of neighbor m and preferred parent m_p. Then, the influence of the parent remaining energy is lower when it gets farther down the path. Therefore, $E(m)$ can be used to avoid selecting routes with low residual energy to delivery packets, thereby extending the network lifetime:

$$\phi_3(m) = E(m) = \begin{cases} \frac{E_i(m)-E_c(m)}{E_i(m)}, & m = root \\ Max(\frac{E_i(m)-E_c(m)}{E_i(m)}, & \phi_3(m_p) \times \mu_1), \quad m = 1, 2, \ldots, M \end{cases} \tag{3}$$

3.2.5. Link Quality (ETX)

Link quality is a key metric for evaluating the reliability and performance of the link between two nodes. LQL (Link Quality Level, LQL) or ETX is a commonly used assessment method. LQL is used to quantify the link reliability using a discrete value, from 0 to 7, where 0 represents that the link quality level is unknown and 1 indicates the highest link quality level. However, the discretization of LQL leads to information granularity loss, strong dependence on thresholds and lagging performance, and rigid decision-making. Therefore, ETX is employed to evaluate the link quality, and LQL can be used as a constraint for link quality screening. ETX, calculated based on Equation (4), is the number of transmissions required to successfully deliver and acknowledge a packet. D_f is the probability that a packet is received by a neighbor and Dr is the probability that the acknowledgment packet is successfully received. Then, the link quality evaluation method used in RPL-DTCP can be designed as Equation (5) where ETX(m) is the path ETX from node b through neighbor m to Root and ETX_{max} is the maximum ETX among all paths from node b through its neighbors to Root. Then the path with the minimum ETX will be selected as the optimal route. Thus, network reliability can be ensured:

$$ETX = \frac{1}{D_f \times D_r} \tag{4}$$

$$\phi_4(m) = ETX(m) = \frac{ETX(m)}{ETX_{\max}},\ m = 1, 2, \ldots, M \tag{5}$$

3.3. New Comprehensive Objective Function (OF)

In RPL-DTCP, the optimization objective is to find the optimal placement decision $\boldsymbol{X}$ for the data processing model of the network-simulated system, while minimizing the model deployment rate, end-to-end delay, and maximizing network lifetime, reliability, and efficiency. Thus, its mathematical expression is as follows:

Supposing that node b has M candidate parents, a_{mj} is the value of the j-th routing metric for the m-th candidate parent. The sample set of each routing metric value at every candidate parent is the following and can be designed as initial matrix **A**:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1J} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2J} \\ \dots & \dots & \dots & a_{mj} & \dots \\ a_{M1} & a_{M2} & a_{M3} & \dots & a_{MJ} \end{bmatrix}$$

According to the newly proposed routing metric indicators (Section 3.2) and the initial matrix A, the new comprehensive objective function can be expressed as Equation (6):

$$\begin{gathered} F(m) = w_1\phi_1(m) + w_2 \sum_{m=1}^{M} \frac{\phi_2(m) \times X}{M} + w_3 \sum_{m=1}^{M} \frac{\phi_3(m) \times X}{M} + w_4 \sum_{m=1}^{M} \frac{\phi_4(m) \times X}{M} \\ OF = \min F(m) \\ s.t. \;\; 0 \le w_1,\, w_2,\, w_3,\, w_4 \le 1,\; m = 1, 2, \dots, M \end{gathered} \tag{6}$$

Table 2 illustrates the comparison between several traditional OFs and the new proposed comprehensive OF in routing metrics, mathematical form, and solution methodology, etc. It shows the advantages of the newly proposed comprehensive OF: (1) The routing metrics system is more complete. It covers link, node, computing power, etc. enabling a more comprehensive depiction of "resource-performance" contradiction relationship in LLNs. (2) The problem formulation is more precise. It formalizes the routing decision as a constrained multi-objective optimization problem. This transformation not only more accurately reflects the multiple constraints and trade-off requirements in actual networks but also provides a natural mathematical framework for applying efficient meta-heuristic solving algorithms. (3) The solution methodology is highly compatible with E-WOA. The constrained optimization problem can be dynamically and adaptively efficiently solved by the E-WOA algorithm, effectively approximating the Pareto optimal solutions under different network states. Eventually, an optimal balance can be achieved between resource constraints and performance requirements.

Table 2. Comparison analysis of RPL objective functions.

Aspects	Several Traditional OFs	New Comprehensive OF	Analysis
Routing metrics	ELT, delay, EA-ETX [33] ETX, hop [38] ETX, RSSI [39] Hop [40]	ETX, delay, residual energy, data processing model, model deployment rate	Routing metrics span network, node, links and computing resource layer
Mathematical form	OF = f(ELT, delay, EA-ETX) [33] OF = αETX + βHop [38]	Equation (6)	Transforms OF to constrained optimization problem, which is conducive to solving by metaheuristic-E-WOA
Solution methodology	Offline PSO [33] Empirically set constants [38] Fixed [39,40]	Dynamic Metaheuristic: E-WOA	E-WOA enables self-adaptive trade-off between resource and performance

It is clear to see that the newly designed comprehensive objective function investigates model deployment rate, end-to-end delay, ETX, and node remaining energy. The weight parameters (w_1, w_2, w_3, and w_4) are used to adjust the importance of each routing metric to obtain different experiment results. Thus, the scientific and efficient multiple routing

metrics investigation method is the key section for obtaining the optimal experimental results. Therefore, this paper proposed the enhanced whale optimization algorithm (E-WOA) to comprehensively investigate the newly designed routing metrics in a scientific and efficient manner. WOA has strong generalization ability for handling various optimization problems. Moreover, it uses few parameters, it is a simple model, and it has an easy implementation method, making it particularly suitable for RPL-DTCP. Then, the most suitable next hop can be selected based on the network actual situation. Therefore, the network reliability and effectiveness can be significantly optimized.

3.4. Enhanced Whale Optimization Algorithm (E-WOA)

3.4.1. Whale Optimization Algorithm

The whale optimization algorithm (WOA) [41], proposed by Mirjalili et al., is a kind of swarm intelligence optimization algorithm. Its operation mechanism simulates the hunting behavior of humpback whales. WOA regards the optimization problems as prey and searches for the optimal solution by simulating the process of whales' encirclement and pursuit. Due to its strong generalization ability, its simple parameters, strong robustness, convenient operation, and excellent solution performance, WOA—the emerging population intelligence optimization algorithm—has received particular attention. It is widely applied in lightweight path planning such as optimization of RPL, parameter optimization, power system dispatching, etc.

WOA, inspired by the social behaviors of whales, simulates the unique search methods and hunting mechanisms of humpback whales, mainly including three important stages: encircling prey, spiral bubble net attack, and searching for prey. The position of each humpback whale represents a potential feasible solution, and the global optimal solution is the prey's position. By continuously updating the whales' positions in the solution space, the global optimal solution is ultimately obtained. Then, the mathematical model of WOA can be described as follows:

Humpback whales form a spiral bubble net around their prey and dive underwater to catch it. WOA simulated this behavior by employing three main strategies: encircling prey, spiral bubble net attack, and searching prey.

(1) Encircling prey

Humpback whales possess the ability to detect and encircle prey. Thus, in WOA, the optimal solution is regarded as the target prey or a position close to prey within the search space. During the process of encircling prey, other whales attempt to approach the optimal solution and update their positions based on Equation (7):

$$X_i(t+1) = X^*(t) - A \cdot D \tag{7}$$

$$D = \left| C \cdot X^*(t) - X_i^t \right| \tag{8}$$

Here, t represents the current iteration number, Xi(t + 1) is the position of the *i*-th whale at iteration t, and $X^*(t)$ is the position vector of the current optimal solution, which is updated in each iteration based on a better solution. D indicates the distances between the prey $X^*(t)$ and the whale, which is calculated by Equation (8). A and C are coefficient vectors, whose calculation formulas are given in Equations (9) and (10):

$$A = 2a \cdot r - a \tag{9}$$

$$C = 2 \cdot r \tag{10}$$

$$a = 2 - t \cdot \left(\frac{2}{T_{\max}}\right) \tag{11}$$

Here, r is a random value within [0, 1], a is the convergence factor in WOA, which is calculated according to Equation (11). t and T_{max} are the current iteration number and the maximum iteration number, respectively.

(2) Spiral bubble net attack

The feeding behavior of humpback whales is illustrated in Figure 5. Humpback whales create bubble nets and approach their prey in a spiral manner to encircle and capture them. This strategy can be mathematically modeled into two stages: shrinking encircling stage and spiral updating stage.

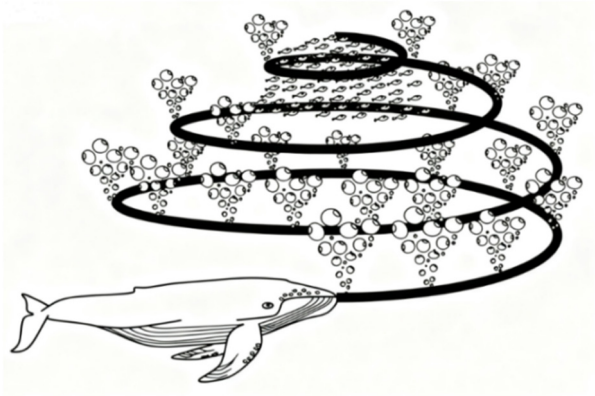


Figure 5. Schematic diagram of humpback whale hunting behavior.

Shrinking encircling stage: in Equation (9), the parameter a decreases from 2 to 0 during the iterative process, while A is a random value within $[-a, a]$. When $|A| \leq 1$, humpback whale shrinking the encirclement occurs by moving from its original position toward the target location.

Spiral updating stage: the distance D′ between the optimal solution X*(t) and whale can be calculated by Equation (12). Then, Equation (13) defines how the humpback whale moves from its current position along spiral path toward the optimal solution:

$$D' = |X^*(t) - X_i(t)| \tag{12}$$

$$X_i(t+1) = D' e^{bl} \cdot \cos(2\pi l) + X^*(t) \tag{13}$$

Here, b is a constant parameter that determines the spiral shape, and l is random number within $[-1, 1]$.

Suppose each humpback whale selects one of the two search manners with equal probability, then the mathematical expression is given in Equation (14). Here, p is a random number within [0, 1]:

$$X_i(t+1) = \begin{cases} X^*(t) - A \cdot D, & p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t), & p \geq 0.5 \end{cases} \tag{14}$$

(3) Searching prey

When $|A| > 1$, humpback whales enter the searching prey stage, where they no longer update their positions based on the current optimal solution. Instead, they randomly select an individual to update the optimal solution position, aiming to avoid being trapped in local optima. The mathematical expression is Equation (15). Here, X_{rand} is the position vector of a randomly selected whale:

$$X_i(t+1) = X_{rand} - A \cdot D \tag{15}$$

$$D = \left| C \cdot X_{rand} - X_i^t \right| \tag{16}$$

3.4.2. Enhanced Whale Optimization Algorithm (E-WOA)

WOA has been widely applied to complex optimization problems due to its simple structure and low computational cost. However, WOA still has the following limitations in practical applications, which affect its optimization performance:

1. WOA usually uses pseudo-random numbers to initialize the population positions. This method easily leads to uneven population distribution, reducing the search space coverage and affecting the algorithm's traversal and search efficiency.
2. The convergence factor a in WOA is implemented in a linearly decaying manner, gradually decreasing from 2 to 0. This fixed decay strategy may lead to insufficient exploration in the early stage and limit the convergence speed in the later stage. It also fails to effectively balance the global and local search of the algorithm, resulting in both reduced search accuracy and slower convergence speed.
3. In the later optimization stage, WOA's search strategy mainly relies on the spiral encircling mechanism around the optimal solution, causing population individuals to tend to converge to a local area. It lacks an effective escape mechanism, thereby increasing the risk of getting trapped in local optimum.

Therefore, E-WOA with global optimization performance was designed, which includes improvement strategies: the improved Tent chaotic mapping, nonlinear convergence factor, and Cauchy variation operator perturbation. This algorithm provides a powerful tool for solving the multiple routing metrics evaluation optimization problem. The specific improvement mechanisms of E-WOA are as follows:

1. Generate an initial population based on the improved Tent chaotic mapping

Chaos appears to be irregular and similar to random, but it has a delicate internal structure. The chaos optimization algorithm has the characteristics of avoiding local optimization, randomness, and ergodicity in the search processes. Also, Tent chaotic mapping can initial individuals to be distributed as evenly as possible within the search area, enhance diversity and adaptability of the initial population, and accelerate the population evolution process. In this way, the uneven distribution of the initial population in WOA can be solved.

The expression of Tent chaotic mapping is shown in Equation (17). Since the chaotic sequences generated by the Tent chaotic mapping may contain small periodicities and unstable periodic points, it is prone to cause the algorithm to fail to escape from the local optimum. Therefore, a small random variable is introduced for perturbation, which enhances the randomness, ergodicity, and uniformity of the chaotic initialization population of the Tent chaotic mapping, thereby improving the robustness and accuracy of the optimal solution. The optimized Tent chaotic mapping operator is shown in Equation (18). Here, β is the control parameter, rand() is a random number in [0, 1], and N is the total number of individual particles within the Tent mapping range (the population size):

$$\omega(t+1) = \begin{cases} \frac{\omega(t)}{\beta}, & 0 \le \omega(t) < \beta \\ \frac{1-\omega(t)}{1-\beta}, & \beta \le \omega(t) < 1 \end{cases} \tag{17}$$

$$\omega(t+1) = \begin{cases} \frac{\omega(t)}{\beta} + rand() \times \frac{1}{N}, & 0 \le \omega(t) < \beta \\ \frac{1-\omega(t)}{1-\beta} + rand() \times \frac{1}{N}, & \beta \le \omega(t) < 1 \end{cases} \tag{18}$$

The simulation results of pseudo-random numbers, Tent chaotic mapping, and the optimized Tent chaotic mapping method for generating the initial population are shown in Figure 6. It can be seen that the initial population generated by optimized Tent chaotic mapping is more diverse and well-distributed which can effectively improve the candidate solutions' quality.

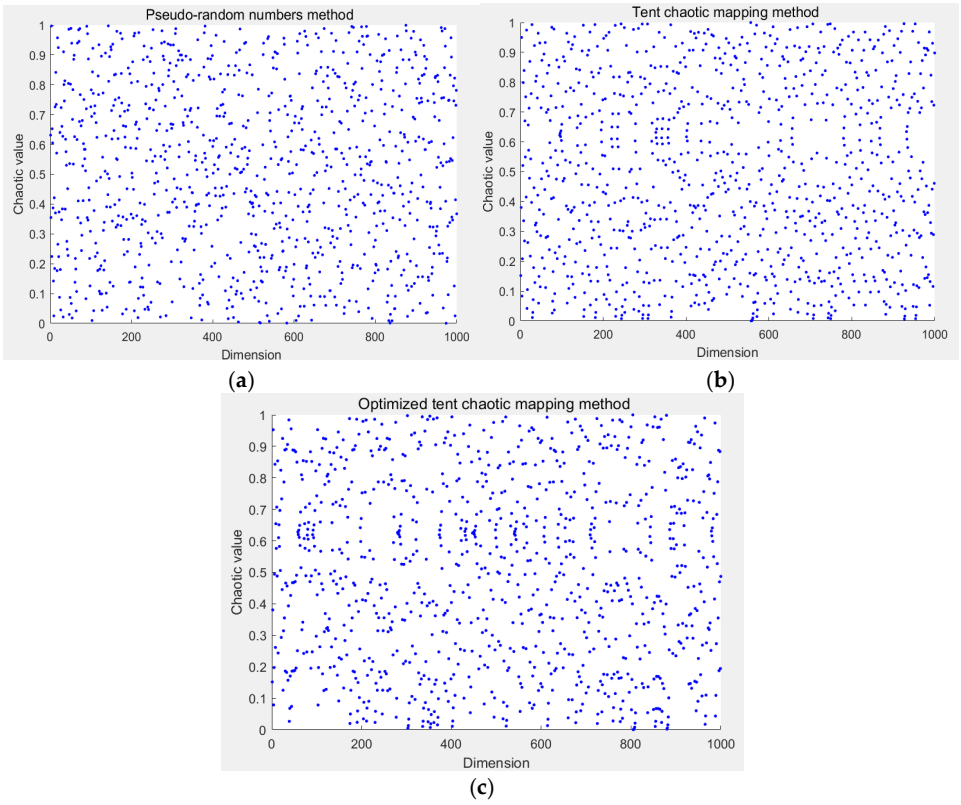


Figure 6. Generating initial population through pseudo-random numbers, Tent chaotic mapping, and optimized Tent chaotic mapping method. (**a**) Pseudo-random numbers method, (**b**) Tent chaotic mapping method, (**c**) Optimized Tent chaotic mapping method.

Thus, the improved location update formula of E-WOA can be constructed as Equation (19):

$$X_i(t+1) = \omega(t) \cdot X_{rand} - A \cdot D \tag{19}$$

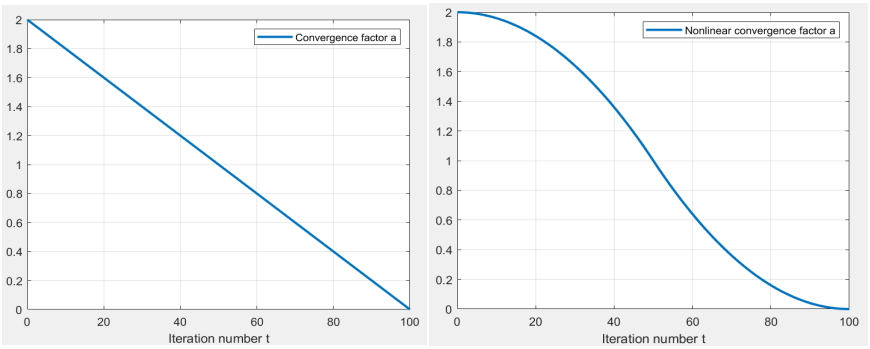
2. Nonlinear convergence factor

Balancing global search and local exploitation is the key to enhancing optimization accuracy and convergence speed. Excessive search may reduce optimization precision and slow down convergence speed, while excessive exploitation may cause the algorithm to prematurely fall into local optima, hindering further progress towards the global optimum. In WOA, the balance between global and local search is mainly controlled by the convergence factor a (Equation (11)). This way may lead to insufficient exploration of the solution space in the early stage and slow convergence in the later stage, thereby affecting the overall optimization efficiency. Therefore, the piecewise nonlinear convergence factor is designed as shown in Equation (20). It can better balance the relationship between local development and global search while maintaining the original equilibrium point unchanged:

$$a = \begin{cases} 2 - \left(\frac{t}{T_{\max}/2}\right)^2, \ t \le T_{\max}/2 \\ \left(1 - \frac{t - T_{\max}/2}{T_{\max}/2}\right)^2, \ t > T_{\max}/2 \end{cases} \tag{20}$$

The simulation results of convergence factor a according to Equations (11) and (20), respectively, are shown in Figure 7. From Figure 7b, it can be seen that in the early stage of the optimization process, using a smaller deceleration rate can ensure that the algorithm conducts extensive exploration within a larger search space, avoiding premature convergence to the local optimal solution. The enhancement of the global search capability enables the algorithm to discover potentially better solutions. As the convergence factor

gradually decreases, the optimization enters the local search stage in the later stage. Then, the smaller convergence factor allows the algorithm to conduct the local search with fine-grained fluctuations, further improving the solution accuracy. Through appropriate randomness, the premature convergence can be avoided and can accelerate convergence to the global optimal solution. This gradually reducing convergence factor strategy ensures global search while effectively improving local search stability and solution quality.



(**a**) (**b**)

Figure 7. Variation of convergence factor a over iterations for WOA (Equation (11)) and proposed E-WOA (Equation (20)). (**a**) Convergence factor based on Equation (11), (**b**) Convergence factor based on Equation (20).

3. Weighted Cauchy variation operator perturbation

Since WOA is prone to becoming stuck in local optimal solutions in the later stage, the Cauchy variation operator is proposed to appropriate the perturbation to escape from the local optimum. The probability density function of the Cauchy distribution is shown in Equation (21). When an individual falls into the local optimum, Cauchy mutation operator searches for the original position changes. Since the mathematical expectation of the Cauchy distribution does not exist and its variance tends to infinity, it has strong jumpiness, thereby increasing the diversity of the new solution, inhibiting premature convergence of the individual, and enhancing the ability to escape from the local optimum. The optimized position formula incorporating the Cauchy mutation operator is shown in Equation (22). Here, X^*_{new} is the new position after disturbance, $X^*(t)$ is the current optimal solution, $\rho \in [0,\ 1]$ is the parameter used to regulate the importance of $X^*(t)$ and $cauchy(0,\ 1)\cdot X^*(t)$, and $cauchy(0, 1)$ refers to the standard Cauchy distribution:

$$f(x) = \frac{1}{\pi \times (x^2 + 1)},\ x \in (-\infty,\ +\infty) \tag{21}$$

$$X^*_{new}(t) = \rho X^*(t) + (1 - \rho)\cdot cauchy(0,\ 1)\cdot X^*(t) \tag{22}$$

$$f(m) = \frac{1}{F(m) + 1} \tag{23}$$

The designed fitness function f(m) in RPL-DTCP is illustrated in Equation (23). Then, the optimization steps of E-WOA are as follows.

Step 1: input basic network parameters—node number, network size, node communication distance, initial nodes' energy, packet size, energy consumption formula, node death determination conditions, etc.

Step 2: E-WOA parameters initialization—the whale population size N (solution number), problem space dimension D (evaluated routing metrics number), the maximum iteration number T_{max},, determining the upper and lower limits of optimization variables. Based on the solution range, the initial population positions are generated through Tent chaotic mapping.

Step 3: calculate fitness values—calculating fitness value for each whale by Equation (6), and recording the optimal whale's position $X^*(t)$ in the current population as well as the corresponding optimal fitness value.

Step 4: update parameters—updating nonlinear convergence factor according to Equation (20), updating control parameters A, C, l, p, and starting iteration.

Step 5: specific operations—

When $p < 0.5$:

If $|A| \leq 1$—updating the current individual position according to Equation (7), which simulates the behavior of whales surrounding their prey.

If $|A| > 1$—randomly selecting an individual X_{rand} and updating the current individual position according to Equation (15) to increase diversity.

When $p \geq 0.5$:

Updating the current individual position according to Equation (13) to perform global search.

Step 6: Boundary checking—performing boundary checking and recalculating fitness value for each whale. Updating the current optimal position and the optimal fitness value.

Step 7: Cauchy variation operation—according to Equation (22), performing the Cauchy mutation operation on the current optimal whale position.

Step 8: Checking iteration number—checking whether the current iteration number t exceeds the maximum iteration number T_{max}. If it does, terminate the loop. Otherwise, t = t + 1 and return to Step 4 to continue the iteration.

Step 9: Output the optimal solution $X^*(t)$.

Through E-WOA, the optimal solution can be obtained. Then, the fitness value of each candidate parent can be obtained. Thus, the one with the maximum fitness value will be selected as preferred parent. This scientific multiple routing metrics evaluation theory synthesizes the advantages of the subjective and objective weighting method, and can be updated in real time according to the actual network situation. Therefore, E-WOA can significantly optimize network performances. Moreover, it provides theoretical basis for multi-domain network QoS requirements.

3.5. Computational Complexity Analysis

Suppose the search space dimension of the optimization problem is D, whose value is determined by the number of effective parameters in the routing solution and is generally related to the network scale. The algorithm employs E-WOA for solving. Then, the core computational overhead C_{total} can be expressed as follows:

$$C_{total} = T_{max} \times (N \times C_f \times C_u) \tag{24}$$

where

T_{max}: The maximum number of iterations, a predefined constant.

N: The population size, i.e., the number of candidate solutions per generation.

C_f: The computational cost of a single objective function evaluation.

C_u: The overhead of the population update operations per iteration.

The objective function overhead complexity can be calculated as $C_f = O(V \cdot J)$, where V is the network node number and J is the evaluated routing metric number. The population update overhead complexity is $C_u = O(N \cdot D)$. Then, the total time complexity is $C_{total} = O(T \cdot N \cdot V \cdot J)$.

This complexity is polynomial with respect to the network size V, ensuring the algorithm is theoretically tractable and can converge within an acceptable timeframe by controlling T and N. Additionally, all complex computations are confined to the digital twin layer. The LLN nodes in the physical network do not participate in the optimization

process; they only perform forwarding based on the disseminated routing table, an operation with $O(1)$ complexity. This computation offloading mechanism completely decouples the algorithm's computational complexity from the operational overhead of the underlying resource-constrained devices.

3.6. The Optimal Path Selection Strategies

Based on the aforementioned improvements, the scientific optimal path selection strategies proposed by RPL-DTCP are as follows:

1. If the fitness value of a candidate parent is greater than or equal to that of a current preferred parent, and the difference between them is lower than the threshold for replacing the preferred parent, then the current preferred parent remains unchanged. This strategy can balance both network QoS and topology stability.
2. If the fitness value of a candidate parent, calculated based on Equation (23), is an anomaly, then this candidate parent should be removed from candidate parent set. Since its quality is too poor to be a candidate parent or its fitness value is wrongly calculated. It can rejoin the network by sending DIS. In this way, candidate parents' quality and the correctness of the fitness calculation can be ensured.
3. If multiple candidate parents have the same maximum fitness value, the one with the minimum hops can be chosen as preferred parent. This strategy can further guarantee network performance and avoid difficult choices in this situation simultaneously.
4. RPL-DTCP will be executed only when the candidate parent number is greater than or equal to 2. If node c has only one candidate parent, then c directly selects it as its preferred parent and will not execute RPL-DTCP. In this way, the resources utilization rate and efficiency can be improved.
5. Except for the aforementioned special cases, RPL-DTCP will operate normally and select the optimal path based on the maximum fitness value

4. Experiment Results and Analysis

4.1. Simulation Parameters and Statistical Performance Indicators

To verify the performance of RPL-DTCP based on E-WOA proposed in this paper, a series of simulation experiments were conducted by MATLAB2024b. Some of the key simulation parameters are illustrated in Table 3, and the statistical experimental result indicators are shown in Table 4.

Table 3. Simulation parameters.

Parameters	Value
Network area	$500 \times 500\ m^2$
Number of nodes	200
Node distribution	Random distribution
Packets' arrival	Poisson distribution
Initial energy of node (J)	0.8–1.8
Node death determination condition	Node's remaining energy is less than 5% of its initial energy
Energy consumption of relaying v bit message	$E(v,d) = \begin{cases} 2E_{elec} \times v + \varepsilon_{amp} \times v \times d^2, d < d_0 \\ 2E_{elec} \times v + \varepsilon_{fs} \times v \times d^4, d > d_0 \end{cases}$
E_{elec} (Energy consumption of relaying 1 bit message)	50 nJ/bit
ε_{amp} (Energy consumption of transmission amplifier sending 1 bit message ($d < d_0$))	10 pJ/bit/m^2
ε_{fs} (Energy consumption of transmission amplifier sending 1 bit message ($d > d_0$))	0.0013 pJ/bit/m^4
d_0 (Threshold value)	87 m
d	Communication distance between nodes
Simulation time (s)	1000
Packet format	IPv6
Physical and data link layer	IEEE 802.15.4 g
Size of packet (kbits)	0.2
Maximum buffer size (packet number)	20
Minimum buffer size (packet number)	0
Queue type	FIFO

Table 4. The statistical performance indicators.

Statistical Indicators	Explanations	Calculation Formula
Control overhead	The total control message number.	$C = \frac{\sum DIO + \sum DAO + \sum DIS}{simulation\ time}$
Packet delivery ratio	The ratio of successfully received packet number and total sent packet number.	$P(\%) = \frac{\sum received\ packet}{\sum send\ packet}$
End-to-end delay	The average time needed for a packet being sent to its destination.	$D = \frac{\sum (received_{time} - send_{time})}{\sum received\ packet}$
Throughput	The amount of effective data actually successfully transmitted over the network within a unit of time.	$T = \frac{\sum effective\ payload}{tranmit\ time}$

4.2. Experiment Results and Comparative Analysis

A series of simulation comparisons of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA were conducted in this paper. Here RPL-GWO and RPL-WOA are the improved RPL routing technologies based on the grey wolf optimization algorithm and the whale optimization algorithm. ETXOF is the technology in RPL that selects the next hop based on ETX. In this way, RPL-DTCP is compared not only with traditional routing technologies (ETXOF) but also with routing technologies based on swarm intelligence strategies (RPL-GWO and RPL-WOA), which can fully demonstrate the effectiveness and reliability of RPL-DTCP.

4.2.1. Control Overhead

Control overhead, non-data communication traffic, is necessary for managing and maintaining network normal operation. It is an inevitable management cost in network communication, and its design and optimization directly affect the overall network performances. Therefore, in the design of routing technology, attention should be paid to balancing the control overhead and throughput. Then, Figure 8 illustrates the control overhead of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA. It is observed that in the initial network construction stage, the control overhead of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA are all relatively high. At approximately 600 s, the network operation gradually enters a stable state and so does the control overhead of the other algorithms. However, during the entire network construction and operation period, the control overhead of RPL-DTCP is obviously lower than that of others since RPL-DTCP optimizes the network construction process and reduces the quantity of the control overhead used. In this way, the network construction efficiency and control overhead can be significantly optimized.

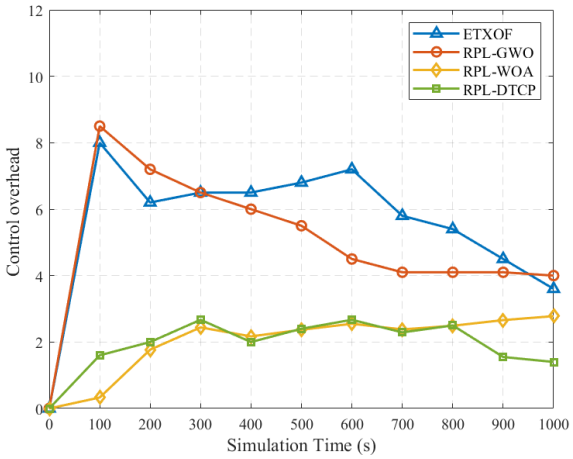


Figure 8. Control overhead.

4.2.2. Packet Delivery Ratio

Packet delivery ratio is the ratio of the data packet numbers successfully transmitted from source to destination to the total sent packet numbers. It is one of the basic indicators for measuring network reliability. Figure 9 illustrates the average packet delivery ratio of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA. It shows that in the initial network construction stage, the packet delivery ratio of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA fluctuate. It gradually reaches a stable state around 300 s. Moreover, the average packet delivery ratio of RPL-DTCP is distinctly superior to that of ETXOF, RPL-GWO and RPL-WOA. Since the RPL-DTCP designed network architecture is based on the digital twin-enabled computing power network, appropriate routing metrics, and the comprehensive objective function model, scientific multiple routing metrics evaluation theories (E-WOA), etc., then the optimal path can be selected to transmit data packets. Therefore, the packet delivery ratio of RPL-DTCP is significantly superior to that of others.

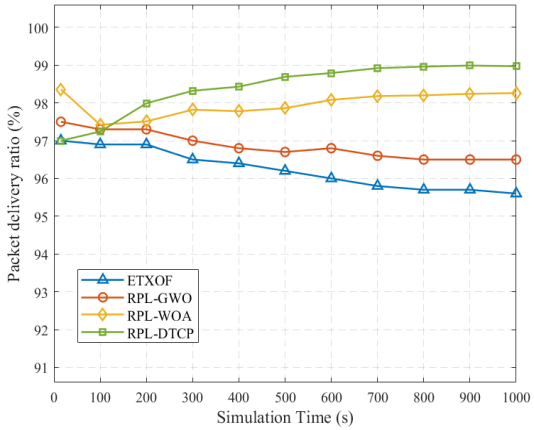


Figure 9. Average packet delivery ratio.

4.2.3. End-to-End Delay

End-to-end delay refers to the total time it takes for the data packet to be transmitted from source to destination. It is one of the key indicators for measuring network performances, especially in scenarios with high real-time requirements. Figure 10 gives the average end-to-end delay of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA. It serves to show that the end-to-end delay of RPL-DTCP is significantly lower than that of ETXOF, RPL-GWO, and RPL-WOA, since the RPL-DTCP optimized network architecture based on the digital twin-enabled computing power network to improve the network construction efficiency and delay routing metric was evaluated. Therefore, RPL-DTCP can significantly optimize network real-time performance.

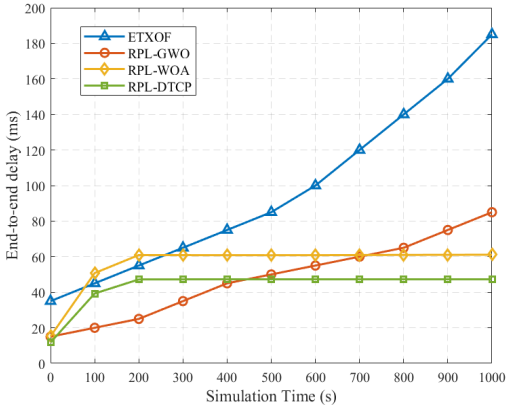


Figure 10. Average end-to-end delay.

4.2.4. Network Lifetime

Network lifetime refers to the duration in which the network can maintain its basic function or meet the performance requirements under specific conditions. It can be measured through the dead node number or the average residual energy of the nodes. Essentially, both revolve around "maintaining the expected service duration". Figures 11 and 12 illustrate RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA of these two indicators. It can be seen that these two indicators of RPL-DTCP are superior to those of ETXOF, RPL-GWO, and RPL-WOA, since RPL-DTCP can reduce the control overhead by the optimized network construction process, propose energy consideration routing metrics, and design the E-WOA algorithm to scientifically evaluate the multiple routing metrics to improve energy consumption efficiency. Therefore, RPL-DTCP can obviously reduce the energy consumption and prolong network lifetime.

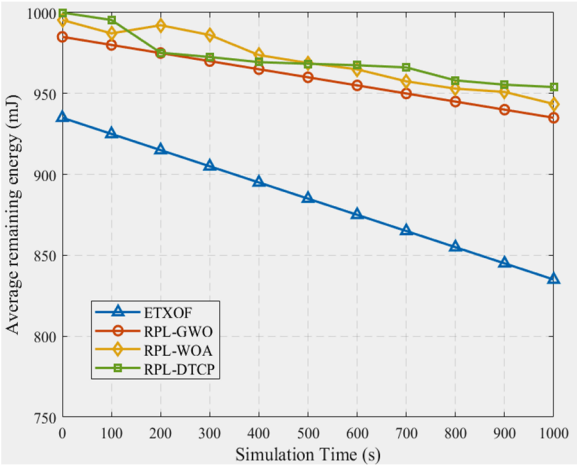


Figure 11. Average remaining energy.

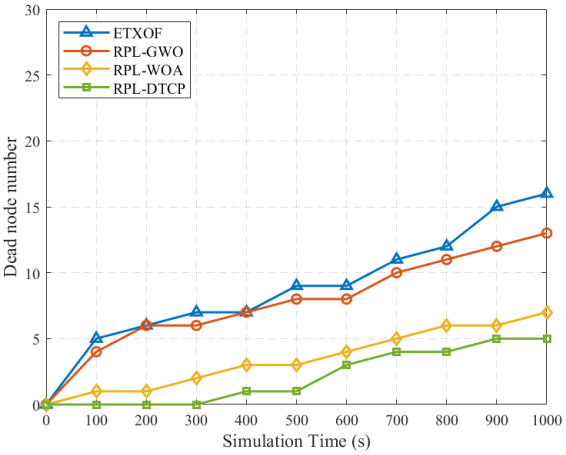


Figure 12. Average dead node number.

4.2.5. Throughput

Throughput refers to the amount of effective data successfully transmitted by the network within a unit of time, which measures the actual data transmission capacity of the network. Figure 13 shows the throughput of RPL-DTCP, ETXOF, RPL-GWO, and RPL-WOA. It is observed that the throughput of RPL-DTCP is higher than that of ETXOF, RPL-GWO, and RPL-WOA, since RPL-DTCP can select the optimal path to delivery packets through the E-WOA algorithm.

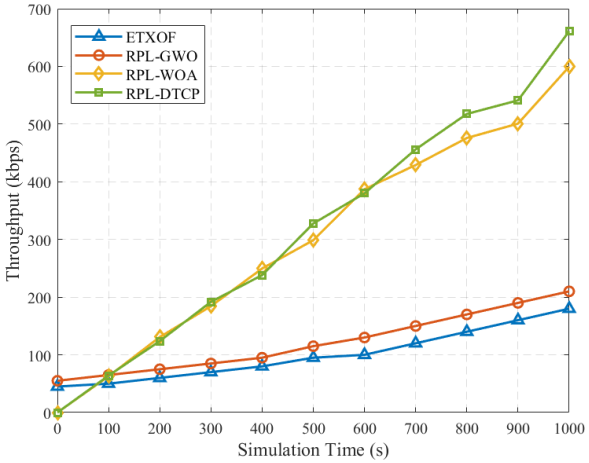


Figure 13. Average throughput.

5. Conclusions

This paper introduced RPL-DTCP, a novel routing algorithm designed to address the inherent conflict between the stringent QoS requirements of IoT applications and the resource-constrained, unreliable nature of LLNs. First, LLNs based on the twin-enabled computing power network were designed to bridge physical LLN operations with the virtual digital twin layer enabling intelligent computing aware network management. Second, a comprehensive multi-objective function was formulated, incorporating both traditional network metrics (e.g., end-to-end delay, node remaining energy, ETX) and computing-resource metrics (e.g., data processing model, model deployment rate). Third, to solve this complex optimization problem efficiently, an E-WOA was developed, featuring the improved Tent chaotic mapping for initialization, a nonlinear adaptive convergence factor, and a weighted Cauchy mutation operator, which collectively enhance the global search capability and convergence speed. Overall, simulation results show that RPL-DTCP significantly outperforms ETXOF, RPL-GWO, and RPL-WOA, delivering improved network QoS. Specifically, compared with ETXOF, RPL-DTCP reduced the average end-to-end delay by approximately 65%, the number of dead nodes by approximately 68%, the control overhead by approximately 54%, while improving the packet delivery ratio by approximately 3% compared with ETXOF. These results validate that RPL-DTCP effectively mitigates the inherent asymmetry between the resource constraints and performance requirements in LLNs, restoring a balanced operational state. The orchestration of multiple resource dimensions enhances the routing efficiency, thereby improving the suitability of RPL for complex, latency-sensitive IoT application scenarios.

For future work, we will continue to conduct further research on the computing power network, digital twin, and LLN routing technologies with segment routing technologies.

Author Contributions: Y.C.: Conceptualization, Methodology, Writing—Original draft preparation, Writing—Reviewing and Editing. G.Z.: Software, Data curation, Writing—Reviewing and Editing. Y.S.: Investigation, Supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This document is funded by the National Natural Science Foundation of China (62401392).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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