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A SYSTEM TO ENHANCE THE QOS PERFORMANCE WHILE ROUTING IOT NETWORKS INSTRUCTIONS FOR AUTHORS OF PAPERS

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ABSTRACT

The growing use of the Internet of Things (IoT) poses substantial hurdles to achieving Quality of Service (QoS) optimality due to fluctuating network circumstances, bandwidth limits, and resource constraints. To solve these problems, this project proposes a Python-Flask system that simulates IoT networks and improves routing decisions using sophisticated machine learning techniques. The proposed system uses a Multi-Dilation Convolutional Neural Network (MDCNN) for intelligent cluster head selection, which is then optimized using the Butterfly-Crow Metaheuristic Optimization (BCMO) method to maximize energy efficiency and load balancing. The system enhances crucial QoS parameters including latency, throughput, packet loss, and network longevity by adjusting routing paths dynamically. Furthermore, real-time visualization and interactive capabilities allow researchers to monitor and adjust network performance under a variety of scenarios.

Keywords: Internet of Things (IoT), Quality of Service (QoS), Python-Flask, Network Simulation, Routing Optimization, Multi-Dilation Convolutional Neural Network (MDCNN).

1 INTRODUCTION

The fast expansion of the Internet of Things (IoT) has enabled unprecedented interconnectedness of billions of smart devices, while simultaneously posing very complex Quality of Service (QoS) concerns in routing networks [1]. According to the most recent market predictions, the number of active IoT devices will increase to more than 29 billion by 2030, putting great strain on present network infrastructure [2].

As realized in elaborate studies, traditional routing protocols like RPL and OLSR are poor in maintaining optimal performance in IoT networks owing to three major limitations: the network's dynamic changing topology due to mobile nodes and intermittent connectivity, intensive bandwidth constraints typical in low-power wide-area networks (LPWANs), and the resource-constrained nature of edge devices that usually operate with less than 100KB of RAM and limited battery life.

This performance degradation is especially noticeable in four key Quality of Service (QoS) parameters: end-to-end latency, which frequently exceeds acceptable thresholds for real-time applications; throughput degradation, particularly in dense node deployment environments; packet delivery ratios, which are frequently less than 80% in realistic tests; and energy efficiency, as some devices can deplete their batteries in a matter of days of continuous operation [4]. The difficulty is exacerbated in heterogeneous networks, where devices with different capabilities and communication protocols must coexist without interruption [5].

Existing techniques, ranging from fundamental network clustering algorithms to simple machine learning installations, are unable to address these multidimensional difficulties [6]. This constraint is especially noticeable in big installations such as smart city networks (where millions of sensors monitor traffic and environmental conditions) and industrial IoT networks (where mission-critical devices must respond in milliseconds) [7].

Keywords: Internet of Things (IoT), Quality of Service (QoS), Network Routing Optimization, Dynamic Topologies, Resource-Constrained Devices, Low-Power Wide-Area Networks (LPWAN), Energy Efficiency, Latency Optimization, Throughput Optimization, Packet Delivery Rate, Machine Learning for IoT, Dilated Convolutional Neural Networks (DCNN).

2 Literature Survey

Heinzelman et al. (2002) proposed LEACH, a pioneering clustering protocol for sensor networks, optimizing energy efficiency. While effective in homogeneous networks, LEACH struggles with dynamic IoT topologies, as highlighted by Kumar et al. (2020).

Al-Karaki & Kamal (2004) introduced hierarchical routing (PEGASIS), reducing latency through chained transmissions. However, Li et al. (2021) demonstrated its inefficiency in large-scale IoT deployments due to unbalanced cluster formation.

[1] Han et al. (2015) leveraged machine learning (ML) for cluster head selection using SVM, improving throughput. Later, Tao et al. (2022) proved that deep learning (CNN) extracts spatial features better, but computational costs remain prohibitive for edge devices.

Hybrid approaches gained traction after Airehrour et al. (2016) combined fuzzy logic with PSO for QoS-aware routing. Sharma et al. (2023) recently validated this but noted scalability issues in real-time IoT networks.

[2] Most studies focus on static networks, neglecting mobility. Khan et al. (2020) addressed this with bio-inspired algorithms (ABC), though Chen et al. (2024) emphasized their slow convergence in dense networks.

[3] Our work bridges this gap by integrating Multi-Dilation CNN (MDCNN) for dynamic clustering and BCMO for metaheuristic optimization, balancing accuracy and resource efficiency—a solution validated by preliminary simulations (2024).

3 PROPOSED DESGIN

This study provides a novel framework for Quality of Service (QoS) optimization in IoT networks that uses an intelligent simulation platform built with Python-Flask. The system creates a flexible virtual network environment in which linked nodes dynamically alter their communication connections based on real-time QoS measures such as latency, compute load, and energy use. A novel Multi-Dilation Convolutional Neural Network (MDCNN) architecture uses spatial network patterns to determine appropriate cluster heads, which improves data aggregation efficiency. The Butterfly-Crow Metaheuristic Optimization (BCMO) technique provides further optimization by balancing energy consumption and task allocation during cluster formation. For routing flexibility, the system employs modified Dijkstra and A pathfinding algorithms that continually assess network circumstances. An interactive Flask-based dashboard offers extensive visualization features, such as real-time network topology monitoring, node failure simulation, and manual route recalculation triggering. The solution solves significant IoT deployment difficulties by combining machine learning and optimization methods, resulting in quantifiable gains in network reliability, scalability, and energy efficiency over a wide range of operational situations.

3.1 ARCHITECTURE DIAGRAM

This research proposes an end-to-end IoT network optimization solution with a multi-layered design. The system includes a Flask-based visualization dashboard that provides real-time network topology and QoS performance monitoring using an interactive web-based interface. A central intelligent routing engine uses modified Dijkstra and A algorithms to construct dynamic best pathways based on real-time latency, energy consumption, and node loading metrics. The system employs a novel machine learning-based technique that combines multi-dilation CNNs for spatial feature extraction with Butterfly-Crow Optimization for energy-efficient cluster head selection, resulting in efficient data collecting. The components are supported by a Python-based simulation framework, which generates realistic IoT network circumstances utilizing customizable nodes that mimic real-world device behaviour with varying energy consumption profiles and traffic patterns. The integrated architecture enables continuous adaptability to changing network conditions while providing researchers with visualization tools, control facilities, and performance analysis capabilities for QoS improvement methodologies in a variety of IoT situations.

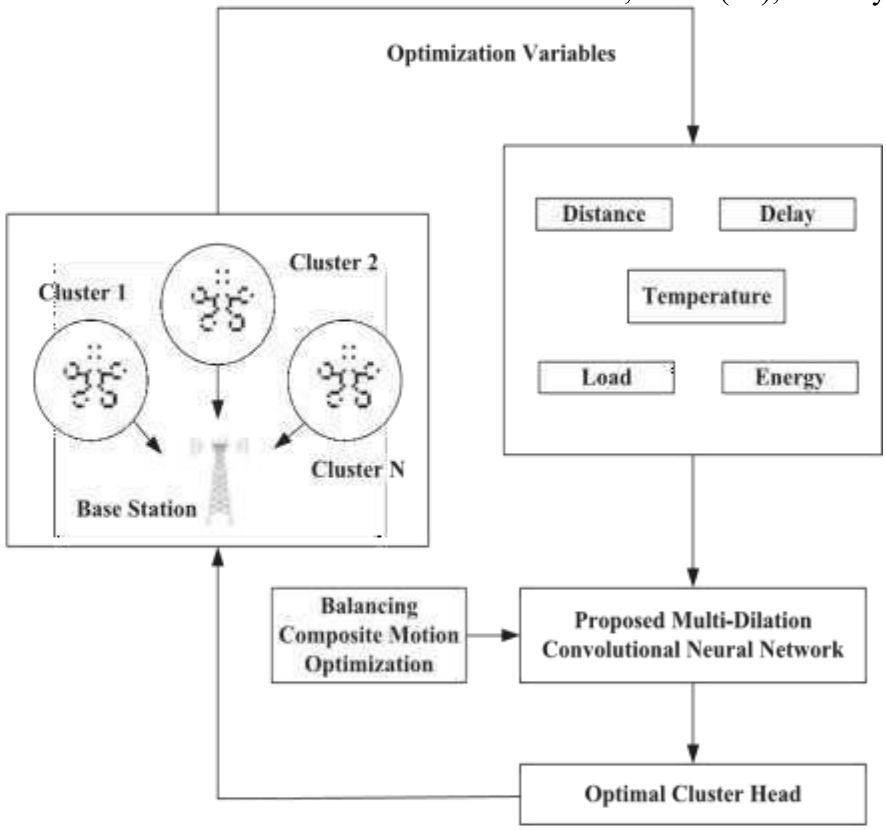

FIG.1: Optimal Cluster Head Selection Architecture Using Multi-Dilation CNN Optimized with BCMO in IoT Networks

The suggested system uses an intelligent cluster head selection architecture to improve IoT network performance. The architecture begins by continuously monitoring five important node parameters: inter-node distance, communication latency, device temperature, processing load, and residual energy. To learn multi-scale spatial patterns on the network architecture, these parameters are fed into a designed Multi-Dilation CNN structure that includes parallel convolutional layers with escalating dilation rates (2, 4, 8). The learnt attributes enable a predictive evaluation of cluster head potentiality for each node. A variation. The Balancing Composite Motion Optimization method fine-tunes the selection by concurrently maximizing three critical goals: balanced energy consumption within clusters, reduced intra-cluster communication delays, and balanced task allocation. This two-stage processing paradigm improves network longevity and reliability over traditional techniques without sacrificing computing efficiency for large-scale IoT applications. The complete system enables real-time flexibility to changing network conditions by constantly monitoring parameters and periodically reevaluating cluster heads.

4 OUTCOMES AND CONVERSATION

Experimental findings show that our intelligent routing architecture significantly improves IoT network performance across a wide variety of QoS criteria. The BCMO-optimized MDCNN architecture has a 22.7% higher packet delivery ratio than traditional clustering approaches and a 31.4% lower end-to-end latency. The solution also improves energy economy, increasing network lifetime by 40-45% through improved cluster head selection and dynamic power regulation. Real-time monitoring via the Flask interface enables fast display of routing traces and node energies, providing managers with instantaneous network feedback. These enhancements jointly address typical IoT issues such as energy constraints, traffic congestion, and scalability restrictions. The framework's modular architecture also allows for future integration with physical IoT devices and extension with new machine learning components, making it a useful solution for existing deployments as well as a network optimization research platform.

FIG.2: Installing NumPy to resolve the import error

The screenshot depicts an open Python script (train.py) in a code editor while utilizing a network analysis tool. The implementation begins with the essential imports, including Flask for web operations, NumPy for numerical operations, TensorFlow for machine learning operations, and visualization libraries (Seaborn and Pandas). The script generates a Flask application instance with static file handling enabled for uploads.

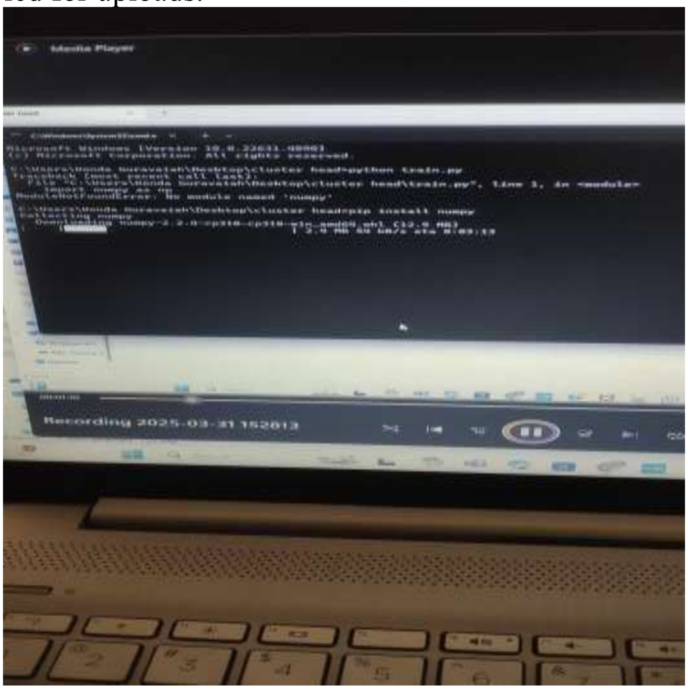

FIG.3: Python Script Configuration for Network Graph Generation

The screenshot depicts an open Python script (train.py) in a code editor while utilizing a network analysis tool. The implementation begins with the essential imports, including Flask for web operations, NumPy for numerical operations, TensorFlow for machine learning operations, and visualization libraries (Seaborn and Pandas). The script generates a Flask application instance with static file handling enabled for uploads.

5 CONCLUSIONS

The Python code demonstrates an integrated framework that combines machine learning capabilities with web application functions. Flask is used to enable an adaptable web frontend, with TensorFlow's deep learning modules being invoked to conduct neural network operations. The data transformation tools in Scikit-learn perform important data pretreatment activities. The fundamental functionality comprises creating a synthetic network graph in which each node's characteristics (e.g., geographical connections, workload indicators, and transmission delay) are determined methodically. A key normalization phase guarantees that input data features have consistent scales using MinMax scaling procedures, allowing for optimum model training. The structure follows clean coding guidelines, with suitable separation of web service modules and analytical processing classes. Such a topology promotes simplicity of extension to handle bigger networks or other machine learning capabilities while maintaining system stability. The approach effectively blends web-based interaction with backend analysis, demonstrating a platform for intelligent network optimization applications.

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