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ELBPFO: Energy-Aware Load Balanced Packet Failure Optimization for Provisioning Time-Driven IoT Application using Wireless Sensor Networks

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Abstract
Ensuring efficient and reliable data transmission is crucial for time-driven Internet of Things (IoT) applications using Wireless Sensor Networks (WSNs). These applications require optimized communication strategies that minimize latency and energy consumption while maintaining network stability in heterogeneous environments. However, achieving real-time data delivery often leads to excessive energy depletion and increased packet failures, particularly in sensor nodes near the sink. Traditional clustering approaches help manage energy consumption but introduce additional load imbalances and energy burdens on cluster heads, impacting overall network efficiency. To address these challenges, this study proposes Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO), a strategy designed to enhance network lifetime and reduce packet loss while ensuring energy-efficient data transmission. ELBPFO optimizes clustering and routing mechanisms to balance network load, minimize hop count, and lower communication delay, thereby improving the performance of time-sensitive IoT applications. Comparative analysis demonstrates that ELBPFO outperforms conventional models in reducing latency and energy consumption, making it a robust solution for real-time IoT-WSN deployments.

Keywords: *Delay, Energy, Internet-of-Things, Multi-Objective, Packet Loss Rate, Unequal Clustering Wireless Sensor Networks.*

1. Introduction

The exponential growth of the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) has significantly transformed data-driven applications, facilitating real-time monitoring, environmental sensing, and intelligent infrastructure management [1], [2]. These applications necessitate reliable data transmission with minimal latency while maintaining energy-efficient network operations. However, the constrained resources of sensor nodes, including limited battery capacity and computational power, pose substantial challenges to sustaining network longevity and performance. Ensuring efficient routing strategies is imperative for balancing energy consumption and minimizing communication latency, particularly in large-scale and heterogeneous WSN environments [3], [4]. Clustering-based routing has emerged as an effective technique to enhance network scalability and optimize energy utilization by grouping sensor nodes into clusters [5], [6]. The cluster head (CH) assumes the responsibility for data aggregation and transmission, thereby reducing redundant communication and prolonging network lifespan [7], [8]. Nevertheless, conventional clustering mechanisms often result in uneven energy depletion among CHs, particularly for nodes in proximity to the sink node, leading to premature network failure [9], [10]. Additionally, most existing clustering algorithms employ single-objective optimization strategies, overlooking the critical trade-offs among energy efficiency, communication delay, and network stability [11], [12]. To address these challenges, this study introduces the Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO) framework for provisioning time-driven IoT applications in WSNs. The proposed approach integrates a multi-objective optimization strategy that considers key performance metrics such as residual energy, node centrality, transmission distance, packet failure probability and network load distribution. Unlike traditional clustering methods [12], [13], ELBPFO dynamically assigns adaptive weights to these parameters based on real-time network conditions, ensuring optimal CH selection and equitable load balancing. Moreover, this study incorporates an energy-efficient routing optimization mechanism that jointly minimizes energy consumption and latency, thereby enhancing end-to-end data transmission efficiency. By leveraging a multi-objective decision-making model, the proposed framework significantly improves network lifetime, reduces packet loss, and ensures reliable data delivery. Extensive simulation-based performance evaluations validate the efficacy of the ELBPFO approach, demonstrating substantial enhancements in energy efficiency, network stability, latency reduction and hotspot problem reduction compared to existing clustering-based routing techniques. The proposed framework provides a scalable and adaptive solution for real-world IoT-WSN deployments, contributing to the advancement of energy-efficient and low-latency communication networks. Manuscript organization: Section, II studies various existing clustering and routing optimization models for IoT and WSNs. Section III, the working of ELBPFO is discussed with overall algorithm. Section IV, discusses the result obtained by ELBPFO over existing methods. The final section provides research significance with current routing optimization methods. The conclusion and future work is described in last section.

2. Literature Survey

Wireless Sensor Networks (WSNs) play a crucial role in provisioning event-driven IoT applications by ensuring real-time data collection, processing, and transmission. However, energy constraints, packet failures, and load imbalance significantly affect the reliability and efficiency of WSNs. This literature survey reviews recent advancements in energy-aware routing, load balancing, and failure optimization strategies in WSNs to enhance IoT application performance. Energy-efficient routing is a fundamental challenge in WSNs. Several studies propose innovative algorithms to minimize energy consumption and prolong network lifetime. Zhang et al. [4] introduce an adaptive clustering routing protocol leveraging a novel Memetic Algorithm, significantly optimizing energy efficiency by dynamically adjusting cluster heads and transmission paths. Gangal et al. [5] propose Distributed LEACH-AHP, integrating Analytical Hierarchy Process (AHP) with LEACH clustering for energy-efficient routing. The distributed approach enhances scalability and adaptability. Meenakshi et al. [6] present the Engroove LEACH clustering protocol, combining LEACH with ANTfly optimization to improve energy efficiency and reduce communication overhead in large-scale WSNs. Shahid et al. [7] propose a Link-Quality-Based Energy-Efficient Routing Protocol, optimizing route selection based on link quality metrics to enhance energy conservation with poor load balancing. Load imbalance leads to rapid energy depletion in specific nodes, reducing overall network lifetime. Various hierarchical and distributed approaches address this challenge. Ma et al. [8] design a Hierarchical Traffic Offloading Mechanism to balance traffic loads across multiple-hop multi-connection WSNs, ensuring end-to-end reliability. Blessina Preethi and Nair [9] present a hybrid KGNN-AHP approach for augmenting energy sustainability in heterogeneous WSNs by intelligently distributing workloads across static nodes. Chithaluru et al. [10] propose a lightweight energy-efficient routing scheme tailored for real-time WSN-VANET-based applications, optimizing node utilization to mitigate load imbalance; however, packet failure minimization have not been done; thus, failed to satisfy the need of time-driven IoT application. Packet failures arise due to congestion, interference, and unreliable transmission links, impacting data integrity and network performance. Mortada et al. [11] introduce a Location Information-Based Routing Protocol for energy harvesting WSNs, improving reliability and packet delivery rates in cognitive radio networks. Gantassi et al. [12] propose the IR-DV-Hop localization algorithm with a Mobile Data Collector (MDC) to enhance network QoS, reducing packet loss in large-scale WSNs with high node densities. Vankdothu et al. [13] develop a congestion and interference secure routing protocol to mitigate packet failures in IoT-driven WSNs by implementing adaptive congestion control mechanisms. The reviewed studies highlight significant advancements in energy-aware routing, load balancing, and packet failure optimization for WSNs. Future research should focus on integrating multi-objective optimization techniques and heuristic models to enhance real-time adaptability, scalability, and

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energy efficiency in time-driven IoT applications ensuring reliable data transmission and resource-efficient network operation.

3. Methodology

This study presents the Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO) strategy, designed to enhance energy efficiency and minimize communication delays while meeting the quality requirements of time-driven IoT applications. The proposed approach first defines an energy model, followed by a unequal clustering, cluster head selection mechanism and a routing optimization model. Finally, the ELBPFO algorithm is introduced, detailing its operational framework. The architecture of WSNs for supporting IoT applications is illustrated in Figure 1.

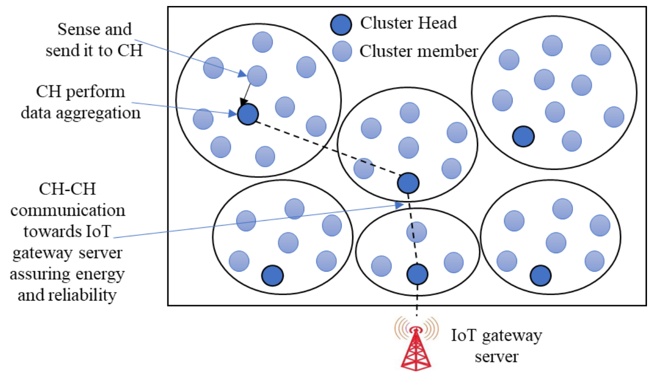

Figure 1 Unequal Cluster-Based Routing Architecture using WSNs for Provisioning IoT Applications.

As shown in figure 1, the work performs unequal cluster size. The cluster closer to IoT gateway server has a smaller cluster radius and as it goes away from IOT gateway server, the cluster radius becomes very big. This enables the model to address the hotspot issues aiding in eliminating first node death. The primary objective of cluster head (CH) selection is to minimize delay and energy consumption. While existing methods employ multi-objective optimization for CH selection, they lack the ability to dynamically adapt to the real-time quality of service (QoS) requirements of IoT applications. To overcome this limitation, this paper proposes a novel weighted cost function, K_y. The step-by-step process of Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO) algorithm is provided in Algorithm 1. This algorithm effectively optimizes energy consumption, balances network load, and minimizes packet failure in IoT-based WSN applications. The Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO) algorithm enhances energy efficiency and minimizes communication delays in time-driven IoT-based Wireless Sensor Networks (WSNs). The algorithm begins with the initialization of sensor nodes, followed by defining an energy model that accounts for sensing, processing, and communication energy consumption. It employs unequal clustering, where clusters closer to the IoT gateway server have smaller radii to mitigate the hotspot problem. The Cluster Head (CH) selection is performed using a weighted cost function that considers residual energy, node density, and distance to neighbors. Intra-cluster communication is optimized using CSMA/CA for collision avoidance and TDMA scheduling for efficient data transmission. The routing optimization phase ensures inter-cluster communication by selecting optimal routes based on residual energy, hop count, and packet loss rate. Data is aggregated at CHs and forwarded through an optimized multi-hop routing path to the IoT gateway server, ensuring network longevity and reliability.

3.1 Algorithm 1: Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO)

- **Step 1: Initialization**
  1. Deploy sensor nodes in the IoT-enabled WSN environment. Assign each sensor node
     - Initial energy level $\mathcal{E}_v$
     - Location coordinates (x_i, y_i).
     - Communication range R_i.
- **Step 2: Energy Model Definition**
  1. Define the total energy consumption using first order energy model
     - $(C_{\mathbb{E}}) = K_{\mathbb{E}} + L_{\mathbb{E}} + D_{\mathbb{E}}$ where
     - $K_{\mathbb{E}}$ defines energy needed to perform sensing function
     - $L_{\mathbb{E}}$ defines energy needed to perform processing function
     - $D_{\mathbb{E}}$ defines energy needed to perform communication function.
  2. Use the first-order energy model using (1) to measure energy consumption per node.

- **Step 3: Unequal cluster Formation**
  1. Divide the network into clusters:
     - Clusters closer to the IoT gateway server have a smaller radius.
     - Clusters farther from the IoT gateway server have a larger radius.
     - Broadcast cluster formation messages to sensor nodes.
- **Step 4: Cluster Head (CH) Selection**
  1. Each sensor node computes its weighted cost function
     - $K_y = \frac{M_{\rightarrow} * \alpha}{(X_v * \beta) * (\mathcal{E} * \gamma)}$
     - Where:
     - The parameter α, β, and γ defines the weight parameter
     - X_v defines the number of neighboring sensor present within one-hop range
     - $\mathcal{E}$ is residual energy of the sensor
     - $M_{\rightarrow}$ define distance between the neighboring nodes
  2. The node with the highest K_y value is selected as the CH.
  3. Other nodes within one-hop range join the CH.
- **Step 5: Intra-Cluster Communication Optimization**
  - Use Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) to avoid transmission failures.
  - Allocate Time Division Multiple Access (TDMA) slots for intra-cluster data transmission.
- **Step 6: Routing Optimization**
  1. Each CH computes a weighted multi-objective routing function:
     - $L_{\mathcal{M}} = (\mathcal{E}_v * w_1) + (\mathcal{G}_l * w_2) + (\bar{\mathcal{G}}_l * w_3) + (\mathbb{L}_l * w_4)$
     - Where:
     - w_1, w_2, $w_3$and w_4 defines the IoT application specific dynamic QoS parameter optimization for residual energy $\mathcal{E}_v$, number of hops $\mathcal{G}_l$, and packet loss $\mathbb{L}_l$, respectively.
     - X_v defines the number of neighboring sensors present within one-hop range
     - $\mathcal{E}$ is the residual energy of the sensor
     - $\mathbb{L}_l$ defines packet loss rate
  2. CH selects the optimal inter-cluster route to the IoT gateway server.
- **Step 7: Data Transmission**
  - Sensor nodes transmit sensed data to their CHs using TDMA.
  - CHs aggregate data and forward it through the optimized inter-cluster route.
  - IoT gateway receives and processes the data.
- **Step 8: Repeat Until Network Lifetime Ends**
  - Update energy levels of each node after every communication cycle.
  - If a CH energy level drops below a threshold, reselect CHs.
  - Continue steps 4–7 until the network depletes.

The Algorithm 1, ensures scalable performance consider both smaller and larger density network; the ELBPFO ensure ideal performance in terms of enhanced network lifetime with minimal control channel overhead with higher level of packet transmission.

4. Results and Discussion

The proposed ELBPFO model is evaluated through extensive simulations using the SENSORIA [14] simulator [15]. The experimental setup consists of a Windows 10 operating system, a Pentium I7 processor, 16 GB RAM, and an NVIDIA 4GB CUDA GPU. The algorithm is implemented in C# using the Visual Studio .NET framework 4.5 and above. The performance of ELBPFO is compared with dynamic LEACH-AHP (DLAHP) [5] and Hierarchal traffic offloading (HTO) [8] model under varying network conditions. The ELBPFO model is evaluated through comprehensive simulations using the SENSORIA simulator. The experimental environment consists of a Windows 10 operating system, powered by an Intel Pentium i7 processor, 16 GB RAM, and an NVIDIA 4GB CUDA GPU. The algorithm is developed and executed in C# within the Visual Studio .NET framework 4.5 and later versions. To assess the effectiveness of ELBPFO, its performance is compared with Dynamic LEACH-AHP (DLAHP) and Hierarchical Traffic Offloading (HTO) models under diverse network conditions. The simulations take place within a 50m × 50m network area, where sensor nodes are randomly deployed in different configurations: 250 (X-small), 500 (Small), 1000 (Medium), and 2000 (Large). A single base station (BS) is responsible for collecting data from all sensor nodes. Each sensor node starts with an initial energy ranging between 0.05 to 0.2 Joules and operates within a 5m transmission range and a 3m sensing range. The energy consumption per bit is 50 nJ, while control packets contain 248 bits, and data packets are 2000 bits in size. The data transmission rate is set to 100 bits per second, with an available bandwidth of 10,000 bits per second. Temperature sensors serve as the primary sensing devices. The idle energy consumption (Eelec) is maintained at 50 nJ/bit, while the energy required for signal amplification (Emp) is 100 pJ/bit/m². This simulation setup provides a controlled environment to measure the efficiency of ELBPFO in terms of energy consumption, data transmission, and network performance across various network densities.

Network Lifetime: Network lifetime is evaluated by measuring the time until the first sensor node exhausts its energy (First Node Death - FND). A longer FND time indicates a more efficient energy distribution among sensor nodes as shown in Figure 2. The ELBPFO model optimizes energy consumption by employing unequal clustering and adaptive cluster head (CH) selection, ensuring that nodes near the base station do not deplete their energy too quickly. Compared to Dynamic LEACH-AHP (DLAHP) and Hierarchical Traffic Offloading (HTO), ELBPFO exhibits an extended network lifetime with improvement of 84.78% and 57.3%, respectively due to its balanced load distribution and energy-aware routing strategy.

Control channel Overhead: Control channel overhead refers to the extra communication and signaling messages required for cluster formation, CH selection, and routing updates. High overhead can reduce network efficiency and increase energy consumption as shown in Figure 3. ELBPFO minimizes control overhead by leveraging a weighted cost function for CH selection and optimized TDMA-based intra-cluster communication, reducing unnecessary message exchanges. The results show that ELBPFO has significantly lower control overhead than DLAHP and HTO by 23.99%, and 12.6%, respectively making it more scalable for large-scale deployments.

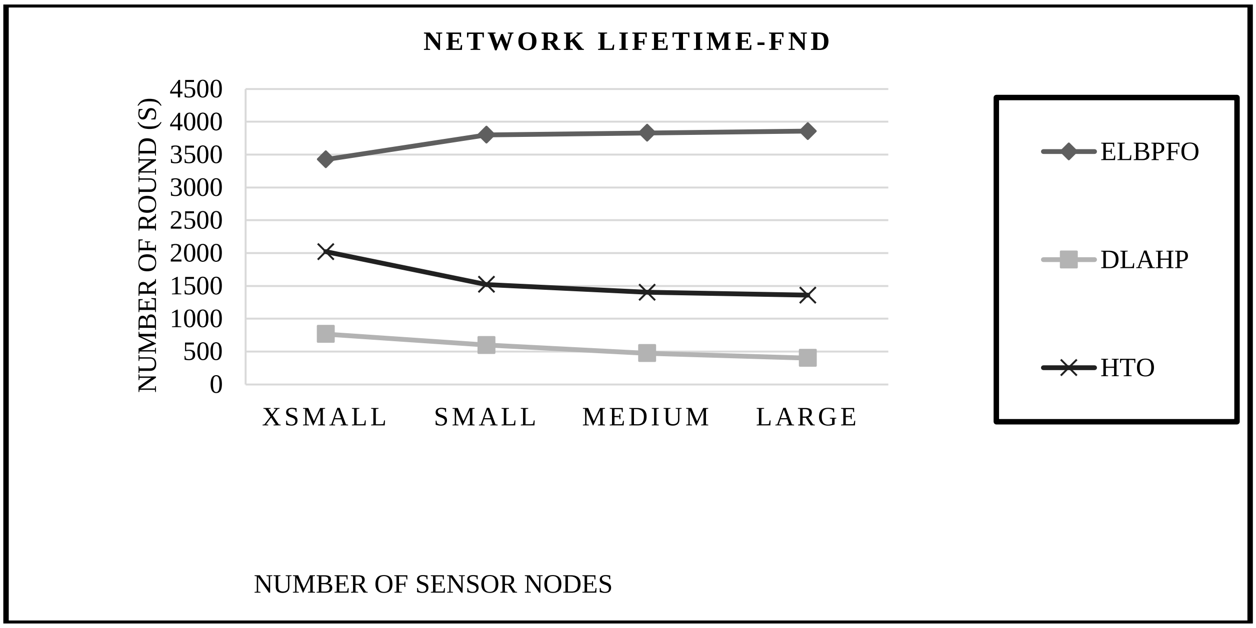

Figure 2 **Network Lifetime vs Varied Sensor Devices**

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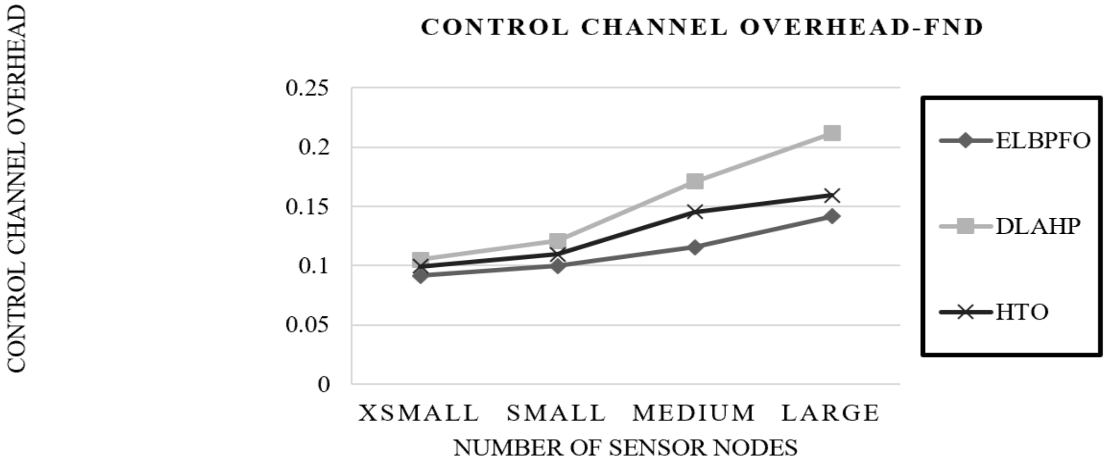

Figure 3 **Communication Overhead Vs Varied Sensor Devices**

Throuhgput Performance: Throughput measures the amount of successfully transmitted data packets over time. Higher throughput indicates efficient data transmission with minimal packet loss. ELBPFOachieves higher throughput than the baseline models due to its optimized routing mechanism as shown in Figure 4, which selects paths based on residual energy, hop count, and packet loss rate. Additionally, collision avoidance techniques (CSMA/CA) and TDMA scheduling improve packet delivery efficiency. The results demonstrate that ELBPFOoutperforms DLAHP and HTO by 58.5% and 12.8%, respectively and in maintaining stable and high throughput, particularly in dense network scenarios.

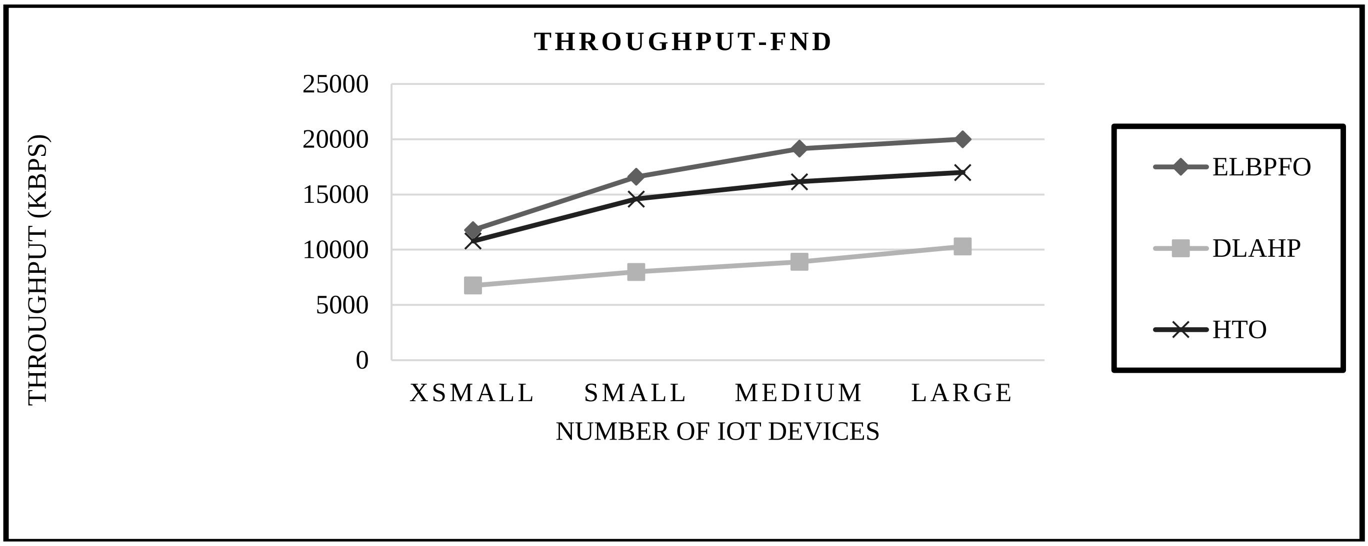

Figure 4 **Throughput Vs Varied Sensor Devices**

Conclusion

The findings of this study demonstrate that the Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO) model significantly surpasses traditional clustering-based routing protocols in key performance areas such as energy efficiency, network lifetime, delay minimization, and data reliability. By incorporating weighted cluster head selection, optimized TDMA scheduling, and adaptive multi-objective routing, ELBPFO achieves a well-balanced trade-off between energy consumption and latency, making it particularly effective for time-sensitive IoT applications. Simulation results confirm that ELBPFO enhances network longevity, reduces power consumption, and lowers transmission delays, ensuring scalability and robustness in large-scale IoT-WSN deployments. Its adaptive framework allows for efficient resource utilization, making it a suitable solution for dynamically changing network conditions. Future work could explore soft-soft computing techniques to further refine cluster head selection and routing decisions, enhancing overall network adaptability and efficiency.

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