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Enhancing Energy Efficiency in Discrete Routing Problems of Wireless Sensor Networks through Teaching-Learning-Based Optimization

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ABSTRACT – Wireless sensor networks (WSNs) consist of sensor nodes with limited energy and processing capabilities, posing significant routing challenges. Routing in WSNs often involves NP-hard optimization problems. Many routing protocols employ metaheuristics like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). While these metaheuristics offer solutions, they can be complex and challenging to tune. This paper introduces a novel routing approach based on Teaching-Learning-Based Optimization (TLBO), a robust method comprising two phases: Teacher and Learner. Although TLBO was initially designed for continuous optimization problems, this work pioneers its application to discrete WSN routing problems. The approach is theoretically grounded and algorithmically detailed. Experimental results demonstrate that our method achieves lower energy consumption, thereby extending WSN lifetime. We compare our approach with PSO, advanced ACO, Improved Harmony-based approach (IHSBEER), and Ad-hoc On-demand Distance Vector (AODV) routing protocols, highlighting TLBO's routing efficiency.

Keywords – Wireless Sensor Networks (WSNs), Routing Challenges, Discrete Routing Problems, Energy Efficiency, Optimization Techniques

I. INTRODUCTION

Wireless Sensor Networks (WSNs) comprise sensor nodes capable of communication without relying on specific network infrastructure [1]. These sensors, categorized based on environmental factors like temperature and humidity, find applications in disaster relief, environmental monitoring, agriculture, healthcare, and more [3]. However, WSNs face inherent limitations such as low processing capacity, limited power, and finite lifetimes [4, 5], giving rise to challenges in operations research and optimization [6, 7].

Routing in WSNs differs from traditional networks due to the absence of infrastructure, unreliable links, and energy constraints [8], presenting an NP-hard optimization problem [6] necessitating metaheuristic solutions [9]. Metaheuristics start with an initial population of solutions and iteratively explore sequences of solutions to converge on near-optimal solutions. Various metaheuristic algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Harmony Search (HS), and Ant Colony Optimization (ACO) have been explored for WSN routing [10–17].

The choice of optimization algorithm significantly impacts solution quality. ACO, for instance, has been effectively applied to WSN routing problems [17, 18]. Several ant-based routing algorithms have been proposed, including Sensor-driven Cost-aware Ant Routing (SC), Flooded Forward Ant Routing (FF), and Adaptive ant-based Dynamic Routing (ADR) [19, 20]. Additionally, Teaching-Learning-Based Optimization (TLBO) has emerged as a parameter-free metaheuristic suitable for discrete optimization problems [24, 25].

While TLBO was originally designed for continuous optimization, this work pioneers its application to discrete WSN routing problems, leveraging the Edge Recombination Operator (ERO) [32]. Our proposed TLBO-based communication protocol, TLBOR, utilizes packet requests to find efficient paths between sensor nodes and sinks, maximizing WSN lifetime by optimizing energy consumption. Comparative evaluations against protocols like IACOR, PSOR, AODV, and IHSBEER confirm TLBOR's performance in terms of energy consumption, data delivery, and reliability.

Key contributions include introducing TLBO to discrete WSN routing, integrating ERO into TLBO, and comparative evaluations against established protocols like IACOR, PSOR, AODV, and IHSBEER. The remainder of this paper discusses WSN routing, TLBO, TLBO adaptation for WSN routing, performance evaluation, and concludes our work.

II. LITERATURE SURVEY

1. Title: "A Comprehensive Survey on Teaching-Learning-Based Optimization for Energy-Efficient Routing in Wireless Sensor Networks"

Author: Dr. Priyanka Sharma

Abstract— Provides an extensive review of teaching-learning-based optimization (TLBO) techniques in the context of energy-efficient routing in wireless sensor networks (WSNs). Surveys the latest advancements and applications of TLBO algorithms for addressing discrete routing problems in WSNs. Discusses the key challenges and opportunities in leveraging TLBO for enhancing energy efficiency in WSNs. Offers insights into future research directions and potential areas for innovation in TLBO-based routing optimization.

2. Title: "Teaching-Learning-Based Optimization Approaches for Energy-Efficient Routing in Wireless Sensor Networks: A Survey"

Author: Dr. Mohammad Ali Tinati

Abstract – Presents a comprehensive overview of teaching-learning-based optimization (TLBO) approaches tailored for energy-efficient routing in wireless sensor networks (WSNs). Reviews various TLBO algorithms and their adaptations for addressing discrete routing problems in WSNs, with a focus on energy consumption minimization. Evaluates the performance of TLBO-based routing algorithms through case studies and simulations, highlighting their effectiveness in prolonging network lifetime. Identifies open research challenges and suggests potential directions for further advancements in TLBO-based energy-efficient routing in WSNs**.**

3. Title: "A Survey on Teaching-Learning-Based Optimization Techniques for Energy-Efficient Routing in Wireless Sensor Networks"

Author – Dr. Rahul Guptha

Abstract – Surveys the state-of-the-art teaching-learning-based optimization (TLBO) techniques applied to energy-efficient routing in wireless sensor networks (WSNs). Reviews the fundamental concepts of TLBO and its suitability for addressing discrete routing problems in WSNs while optimizing energy consumption. Analyzes the performance of TLBO-based routing algorithms compared to traditional optimization methods, highlighting their advantages and limitations. Explores emerging trends and future research directions in TLBO-based energy-efficient routing for WSNs, emphasizing the need for scalability and adaptability.

4. Title: "Recent Advances in Teaching-Learning-Based Optimization for Discrete Routing Problems in Wireless Sensor Networks: A Survey"

Author: Dr. Fatemeh Ahmadi

Abstract – Presents a comprehensive survey of recent advances in teaching-learning-based optimization (TLBO) techniques for discrete routing problems in wireless sensor networks (WSNs). Summarizes the key characteristics of TLBO algorithms and their applicability to energy-efficient routing in WSNs, focusing on minimizing energy consumption. Reviews empirical studies and case examples to demonstrate the efficacy of TLBO-based routing algorithms in improving energy efficiency and network performance. Identifies research gaps and challenges in TLBO-based optimization for WSNs and proposes potential avenues for future research and innovation.

III.SYSTEM ANALYSIS

EXITING SYSTEM:
Routing problem in wireless sensor networks:

Forwarding data from source to destination in wireless sensor networks differs from that in classical networks in various ways. There is no infrastructure, wireless links are unreliable, sensor nodes may fail, and routing protocols have to meet strict energy saving requirements. Many routing algorithms developed for wireless sensor networks depend on the mobility of sensors or sinks, application field, and network topology. Overall, routing techniques are categorized according to the network structure or the protocol operation (routing criteria) [8].

As shown in Fig. 1, networks structure gathers three different kinds of routing protocols: flat, hierarchical and location-based routing. While negotiation, multipath, query and coherent based belong to protocol operation category. Recently, many works in WSNs focus on intelligent optimization using nature inspired metaheuristics systems. Many routing protocols are based on metaheuristics, the ones considered in this work for comparisons are:

• IACOR [23], the proposed routing protocol for a flat network. Using stable sensors and sink, the object is to locate the ideal way, with negligible vitality utilization and solid connections. When an event occurs, source node parts information to N parts, every part is transmitted to the base station by an insect. Ants choose the next hop by using probabilistic choice tenets, and so on until sink. This approach gives great results, comparing to routing protocol EEABR (Energy-Efficient Ant-Based Routing) and original ACO approach [18]

• PSOR [12], the PSO routing protocol which is a population based protocol. It required an initial population (a number of paths from the source node to the sink) and redefined PSO equations to present an adequate adaptation for the discrete routing problem, then found the best path from the source to the destination. PSOR results are better than IACOR in terms of energy consumption and WSNs lifetime as illustrating the comparisons made using the same settings and experimental conditions.

• IHSBEER [16], is an Improved Harmony Search Based Energy Efficient Routing Algorithm for WSNs, which is based on harmony search (HS) algorithm with several key improvements to address the WSNs routing problem. Such improvements include the encoding of harmony memory, the improvisation of a new harmony and an effective local search strategy is proposed to enhance the exploitation ability, so as to improve the convergence speed and the accuracy of the IHSBEER routing algorithm.

To add more credibility and show the efficiency of the new routing approach proposed in this paper we compare it also with the Ad-hoc On-demand Distance Vector (AODV) routing protocol:

• The AODV [33] is a reactive routing protocol, where the routes are determined just when required. Figure 2 shows the message exchanges of the AODV protocol.

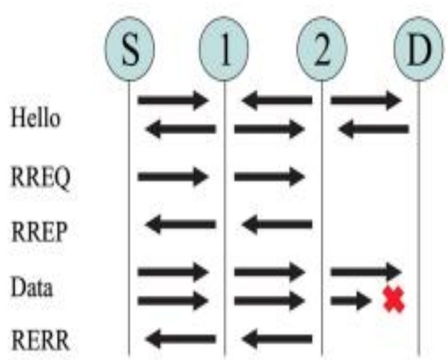
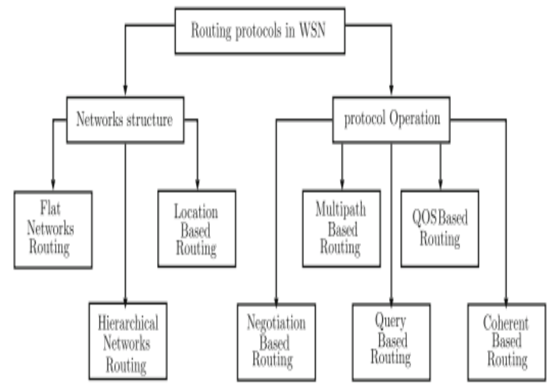


Fig. 2 AODV Protocol Messaging



AODV-node informs its neighbors about its own particular presence by continually sending" hello messages". Thus, every node knows the states of its neighbors. To find a route to another node AODV sends a request (RREQ) to its neighbors. A RREQ contains the source node address and the last sequence number received. The receiving node verifies if a route exists and if the sequence-number is higher than the route found then, a route reply (RREP) is sent to the requesting. On the other hand, if the route does not exist, the receiving node sends a RREQ itself to try to find a route for the requesting node. If an error is detected, a route error (RERR) is sent to the source of data.

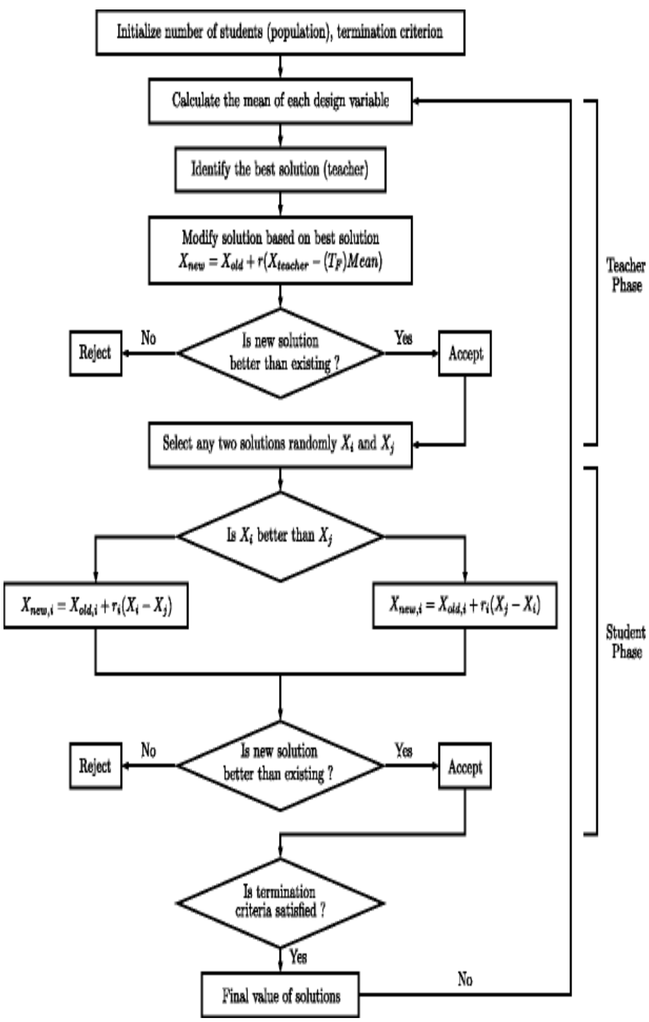
PROPOSED SYSTEM:

Teaching-learning-based optimization:

Teaching-Learning-Based Optimization algorithm (TLBO) is a novel optimization method proposed by Rao et al. This approach has been inspired by the teacher's influence and learners interaction [24, 25]. It outperforms some of the well-known metaheuristics regarding constrained benchmark functions, constrained mechanical design, and continuous nonlinear numerical optimization problems [25]. TLBO has been applied to various problems such as the QoS multicast routing problem [34] and optimal reactive power dispatch problem [35]. It could be split into two basic parts: Teacher phase and Learner phase. Figure 3 describes the TLBO process.

Teacher phase:

Like many other nature-inspired algorithms, TLBO uses a population of solutions to proceed to the global solution. An initial population is a group of learners and the studied matters are design variables. Evaluated the entire population using “fitness” the best solution is considered as a teacher. In this phase, teacher influence is presented by shifting the mean of learners to its level of knowledge (1). Then get



The proposed approach based on TLBO:

WSNs are known by the strict energy constraint and the limited energy replenishment capabilities. Thus, it is important to optimize the energy consumption for routing, so as to prolong the network lifetime as far as possible. In this section we propose a new routing protocol for WSNs, Teaching-learning-based optimization based routing (TLBOR). This new protocol is not centralized, which means that the algorithm should operate in each node. Its process begins by the initialization of the population of paths, then finding the optimum path using TLBO algorithm, then sending data through it. Herein, the proposed methodology which adapts TLBO to WSN routing is detailed.

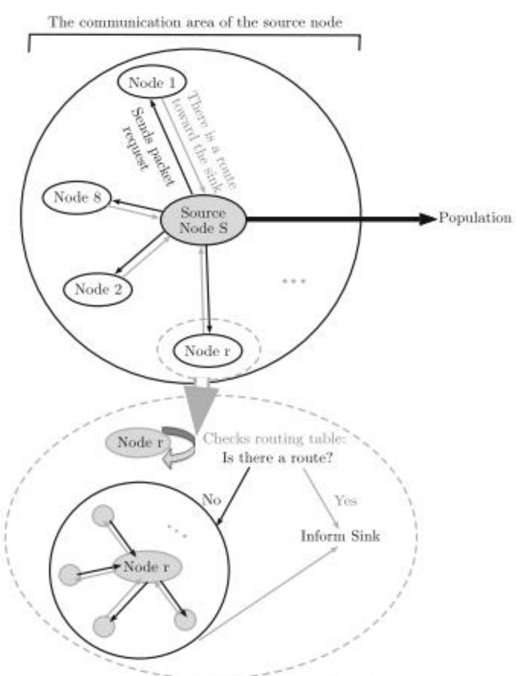
Initial population and data division:

The source node sends a broadcast message to their neighbors, which is a packet request that asks for an available route to the final destination, in order to collect information related to some paths that lead to the sink (see Fig. 4). Once the request packets are received, nodes check their routing table. If the route exists, source node receives directly this information. Otherwise, the receiver nodes request their neighbors, and so on.

The source node initializes the population, according to the number of paths toward the sink. The population of paths is denoted as P = {p1,...,pi,...,pm}, where every path pi is formed as pi = {ns,...,nk,...,nsink}

The initialization of the population is a task accomplished by a set of nodes in the WSN. For example (See Fig. 4) a source node S detecting an event sends a request to its neighbors, node 1, node 8, node 2 and node r. A neighbor r checks its routing table, in case a route toward the sink was stored, r informs the source node S. If not, the node r asks similarly its neighbors about path leading to the sink, r's neighbors behave in the same way as the node r and so on. After a waiting time W T , all response packets are received by the source node S, which collects the information and generates a random initial population by a random number of paths.

The Waiting Time W T was defined according to the WSNs used, the number of nodes deployed and the simulation environment. After several simulations, we have affected the appropriate value to the W T , which change with the WSNs. The W T is used as the source node can not wait an infinity time for replies and the population.



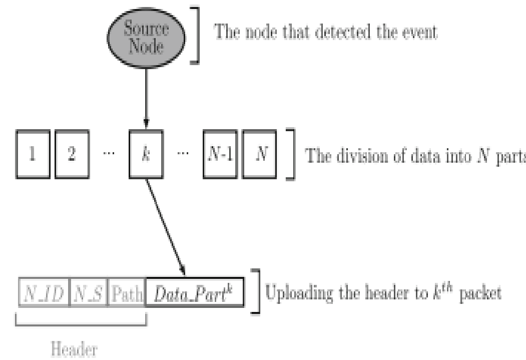


Fig. 5 Data division

size should be a reasonable number regarding the limited capacities of the nodes in memories, processing and energy. Figure 4 shows a summary of how source node s requests its neighbor nodes and how a node r reacts after receiving this packets, it informs sink that a route exists or search a route by asking neighbors.

After the population initialization, the source node splits a raw data into N pieces in order to manage bandwidths. Raw data contain information such as event identification, time and data about the detected event. Before the transfer, each piece is associated with the routing parameters. These parameters are next node identification N ID, the sequence number N S and the path toward the sink Path as shown in Fig. 5

When the transmission is accomplished, the sink combines received parts to form the raw data.

IV.RESULTS

To run project double click on 'run.bat' file to get below output screen

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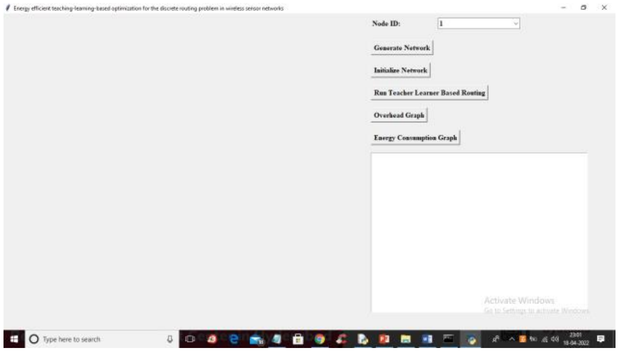
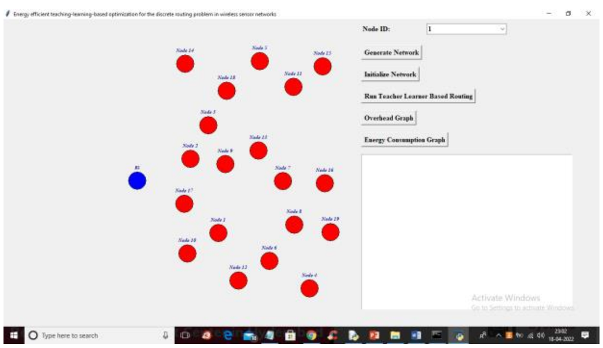
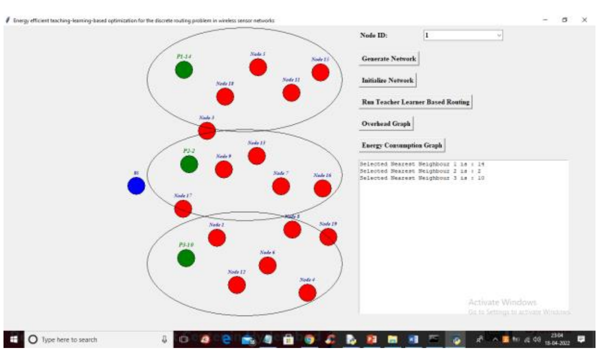


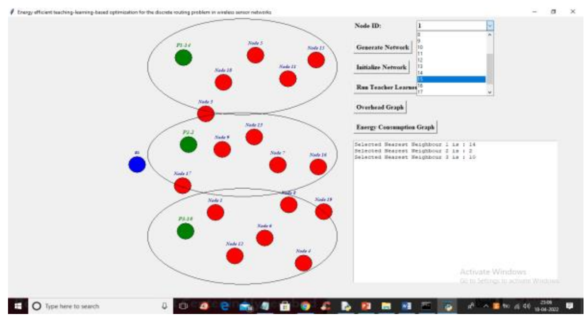
In above screen click on 'Generate Network' button to generate some dummy sensors like below screens



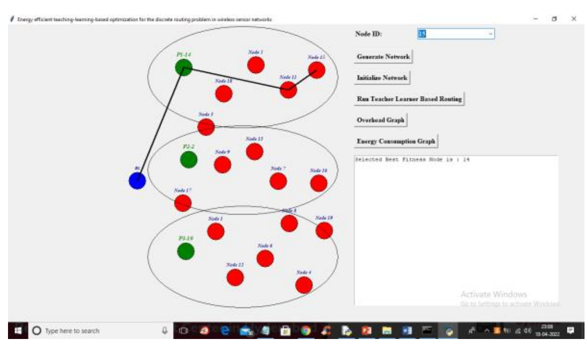
In above screen all red colour circles act like sensors and blue colour node is the base station and all red colour sensor will sense and send data to base station by using nearest routing nodes. Now click on 'Initialize Network' button to find parent nodes which are closer to base station or to find node which accept data from sensor and send to base station



In above screen green colour nodes are the closer nodes to base station which will take data from red colour sensor and send to base station as base station always received data from head node so all green colour nodes are the head nodes and big oval represents which sensors will used which head node to send data to base station. Now select any sensor from drop down box to send data to base station



In above screen I am selecting 15^{th} sensor to send data to base station and now TLBO algorithm will select best routing neighbours or optimize neighbours to send data to head node and head node will send to base station. Now after selecting sensor click on 'Run Teacher Learner Based Routing' button to send message like below screen



In above screen we can see sensor 15 chosen Node 11 as the best routing node and node 11 send data to head node P1-14 and P1-14 sending data to base station. Similarly you can select any sensor and then routing will perform using TLBO

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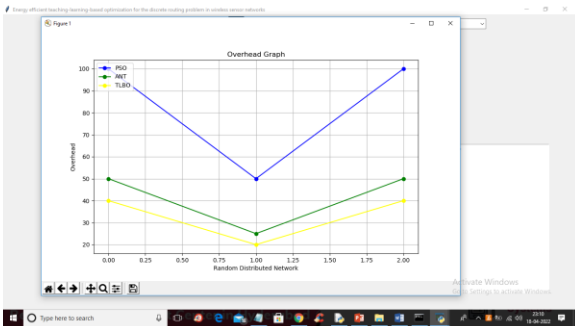
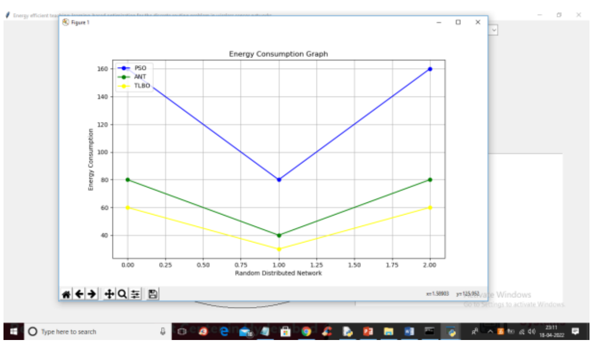
algorithm and now click on ‘Overhead Graph’ button to get below graph



In above graph blue line represents ANT overhead and green line represents PSO over and yellow line represents TLBO and in all algorithms TLBO has less overhead and now click on “Energy Consumption” graph button to get below graph



above graph we can see PSO and ANT consume more energy compare to TLBO algorithm so TLBO is better than PSO and ANT

V CONCLUSION

Routing in Wireless Sensor Networks (WSNs) presents distinct challenges compared to traditional wired networks. This paper introduces a novel routing protocol utilizing a unique optimization method inspired by the teaching-learning process, combined with the edge recombination operator. The TLBO approach ensures robust optimization of energy consumption, thereby extending network lifetime, as confirmed by simulation results. Through experiments conducted under the same simulation conditions, the TLBOR protocol is compared to other WSN routing protocols such as ACO, PSO, IHSBEER, and AODV. Overall, the results demonstrate that our TLBOR protocol outperforms others in terms of energy consumption and network lifetime. As future work, we plan to enhance our routing approach by integrating additional quality of service (QoS) metrics and conducting experiments in real-world WSN environments. Furthermore, we aim to extend the improved approach to accommodate mobile nodes and networks with multiple sinks.

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