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RESEARCH ARTICLE

Energy Efficient Hybrid Evolutionary Algorithm for Internet of Everything (IoE)-Enabled 6G

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ABSTRACT The advancement of Internet of Everything (IoE) propels the fast growth of next-generation, such as 6G networks, leading to a new era of coverage, connectivity, and technological innovation, which calls for novel approaches to address rising energy consumption and maximize resource use. The proposed article presents a robust hybrid algorithm that combines leader-based optimization and Adaptive Differential Evolution (DE) in the framework of the Energy Efficient Hybrid Evolutionary Algorithm (EEHEA), which is specifically designed for the complex environment of IoE-enabled 6G networks. The scheme EEHEA combines the efficacy of leader-based optimization (LBO) for an effective decision-making process and adaptive differential evolutionary optimization (ADE) 's dynamic network-parameters adaptation, enhanced convergence, and global searching ability, persistently fine-tuning optimization strategies based on the dynamics of the network. Combining these components into the scheme EEHEA allows it to balance local exploitation and global exploration effectively. This implies better resource allocation and improved energy efficiency in ecosystems with IoE-driven 6G (IoE-6G). The outcomes report that the scheme EEHEA can address the rising energy consumption issues and enhance the efficiency of IoE-6G. Based on simulation experiments, the proposed scheme EEHEA can demonstrate faster convergence times, higher accuracy, and superior flexibility concerning changing network conditions. Its capability to handle energy-related challenges and navigate complex network environments with resilience shows the ability to enhance the performance of IoE-6G. The EEHEA scheme reports its efficacy over state-of-the-art schemes regarding localization, latency, coverage, and energy expenditure performance metrics.

INDEX TERMS Leader-based optimization, adaptive differential evolutionary algorithm, resource allocation, energy efficiency, dynamic parameters adaptation, IoE-driven 6G.

I. INTRODUCTION

This The Internet of Everything (IoE) facilitates the connection between digital and physical realms, fostering innovation in domains such as smart cities, manufacturing, healthcare, and agriculture [1], [2]. As IoE progresses, aligning with the deployment of 6G networks promising dependable, low-latency connectivity and seamless integration across devices and applications [3], [4], challenges persist in energy consumption, coverage, dependability, and resource allocation efficiency within the IoE environment [5], [6]. With the increased use of interconnected network devices and services in smart city applications, ensuring optimal service delivery is critical for enabling continuous and perpetual interactions, efficient resource management, and improved user experiences. For precise asset tracking and location-based services, localization accuracy is needed. Energy consumption minimization is also needed to improve the battery life of IoE devices, decrease operational costs, and reduce environmental impact. Similarly, improved coverage

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is necessary for ensuring ubiquitous connectivity, especially in harsh/challenging environments. Reducing delay enables real-time communication and better immersive experiences in IoE ecosystems. So, prioritizing advancements in these quality of service factors is necessary to leverage the full potential of 6G-enabled IoE in smart city applications.

As said earlier, with the increasing number of IoE-enabled devices in 6G networks and a parallel rise in energy consumption of IoE applications, effective energy management and harvesting in smart city solutions become critical [1], [7], [8], [9], [10], [11], [12], [13]. Despite the investigation of numerous Energy Optimization (EO) methods, energy optimization in computing systems remains a critical challenge, hindering the full development of innovative technology. Challenges, such as delay-sensitive data processing and efficient network resource management, further impede progress [14]. The convergence of diverse devices, applications, and dynamic network environments necessitates a substantial study in optimizing energy usage and resource allocation in IoE-enabled 6G networks [15]. Evolutionary algorithms, including Floating flame moth-flame (FMFO) [16], grey wolf and its variants [17], [18], traditional genetic algorithms (GAs) [19], [20], [21] and Particle Swarm Optimization (PSO) methods [9], have shown potential but must effectively balance exploration and exploitation in changing network dynamics. Adaptive variants, such as Adaptive Differential Evolution (ADE), prove suitable for real-time optimization in IoE-driven networks [22]. Additionally, leader-based optimization (LBO), incorporating dispersed decision-making procedures, has gained interest due to its effectiveness in negotiating intricate network dynamics [23]. Despite these advancements, existing research often focuses on individual optimization strategies, lacking a comprehensive methodology for resource allocation and energy efficiency.

Recent contributions of heuristic/meta-heuristic algorithms in 6G-enabled IoE applications, such as ICR-IoT using Butterfly Optimization Algorithm [7] to address load balancing and energy efficiency issues and MOMGWO for multi-objective optimization [8] to optimize throughput, interference, and energy efficiency, offer valuable insights. However, limitations include fragmented solutions and gaps in achieving holistic green communication [11]. The Multi-objective Differential Evolution (MODE) scheme [24] was also investigated by incorporating a rapid mutation operator to enhance energy efficiency along with diversity and convergence speed in IoE.

Practical implementation challenges [25] persist. The proposed work is motivated by these limitations, aiming to provide a unified and comprehensive framework that addresses load balancing, energy efficiency, security, and spectrum management, offering practical solutions for the evolving landscape of IoE-enabled 6G applications. Addressing these research gaps will advance knowledge and develop practical solutions for optimizing 6G-IoE networks, leading to improved energy efficiency, reliability, sustainability, and overall network performance.

A novel hybrid method combining LBO and ADE [26] called the Energy Efficient Hybrid Evolutionary Algorithm (EEHEA) is proposed to handle practical QoS issues in IoE-enabled 6G applications. The LBO used in this method has better exploitative capabilities and efficiently converges to optimality. The self-adaptiveness of ADE enhances its robustness and the nature of adaptability, specifically in dynamic hostile environments. ADE can provide its exceptionally efficient search space exploration, and better balancing mechanism in between exploration, and exploitation. Its intelligent adaptation feature is incorporated in its operations of mutation and crossover, providing robustness to cope with complex multi-modal problems. This dynamic combination and adaptation provide a real-time optimal solution, enhancing the overall network performance. This combination also enables the optimization of resource allocation, including resource-scheduling management significantly enhancing energy utilization efficiency and reliability in an IoE driven 6G networks. The EEHEA scheme's strategy achieves a better balance between local and global optimization, improving energy efficiency, reliability, and convergence efficiency. The intelligent blending and optimization techniques in the EEHEA gives flexibility and robustness to address the complex issues in dynamic IoE-driven 6G environments. The major contributions of the suggested work are as follows:

- To propose a novel hybrid Algorithm called Energy Efficient Hybrid Evolutionary Algorithm (EEHEA) combining two different Algorithms Adaptive Differential Evolution (ADE) and leader-based optimization (LBO) to address energy issues in IoE-enabled 6G ecosystems.
- To enhance diversity and accelerate convergence in benchmark functions, the proposed approach employs a dynamic adaptation strategy and leader-based optimization.
- To optimize the delicate balance between energy efficiency and network connectivity in 6G-IoE systems, the proposed method integrates adaptability, reliability, and scalability in dynamic IoE-enabled 6G environments.
- Conducted extensive simulations demonstrating superior convergence rates, solution quality, and energy efficiency compared to existing methods.

The suggested article is structured to explore the topic comprehensively. Section II reviews Related works, Section III briefly discusses IoT-based framework networks, Section IV presents the proposed multiobjective methodology, and Section V depicts Results and Analysis. Finally, Section VI concludes the study and outlines future research directions.

II. RELATED WORKS

In recent research endeavors, Several innovative relevant approaches have been surveyed to address various challenges in the evolving landscape of IoE-enabled 6G environments.

Arya et al. [7] introduced ICR-IoT, leveraging the Butterfly Optimization Algorithm, to intelligently manage clustering and routing for IoT-edge computing, with a specific focus on load balancing and energy efficiency. Eappen and Shankar [8] proposed a Multi-Objective Modified Grey Wolf Optimization (MOMGWO) algorithm, aiming to optimize throughput, interference, and energy efficiency amidst the increasing mobile data demands associated with 6G technology.

Singh et al. [24] presented a multi-objective evolutionary algorithm incorporating a rapid mutation operator with multi-objective differential evolution (MODE). This approach enhances diversity and convergence speed, with evaluations in IoE service scenarios demonstrating superior performance in optimizing service cost, delay, and sensor lifetime compared to other multi-objective evolutionary algorithms. Iwendi et al. [9] devised a hybrid meta-heuristic approach by combining Whale Optimization with Simulated Annealing. This was applied to improve the selection of Cluster Heads in IoT/IoE cluster-networks, considering multiple performance metrics such as active nodes, load, remaining energy, temperature, and cost function for efficient cluster head determination.

Rico-Garcia et al. [27] addressed the Traveling Salesman Problem (TSP) in smart city environments by proposing a modified version of the Teacher Learner Based Optimization scheme. The solution was implemented on a parallel graphics processing unit architecture, specifically utilizing Compute Unified Device Architecture (CUDA) for enhanced performance. Das et al. [28] introduced a unique transient search method, TSA-OSSAE, for cyber threat detection in IoE-enabled smart city applications. This method utilizes a TSA-based feature selection approach to minimize computational complexity and the stacked sparse autoencoder (SSAE) model for cyber threat detection, with hyperparameters optimized through the multi-versus optimizer (MVO) scheme.

Alazab et al. [10] addressed IoE challenges in smart cities, focusing on Cluster Head (CH) selection in wireless sensor networks. They introduced a modified Rider Optimization Algorithm (ROA) for optimized CH selection, achieving objectives like delay minimization and energy sustainability through the proposed Fitness Averaged-ROA (FA-ROA). Nematollahi et al. [29] presented an improved multi-objective Aquila optimizer (IMOAO) for efficient task offloading in resource-constrained IoE devices to fog nodes, outperforming existing optimization methods. Jain et al. [30] introduced MWBA-RAT, a metaheuristic with a blockchain-based resource allocation technique for cybertwin-driven 6G in IoE environments. Singh et al. [11] proposed an artificial intelligence-enabled Dingo Optimizer for Energy Management (AIDO-EM) in 6G networks, utilizing the Dingo Optimization Algorithm (DOA) for cluster-based routing.

Abdel-Basset et al. [31] explored security and privacy concerns in 6G networks, emphasizing the effectiveness of advanced metaheuristic algorithms. Wang and Lu [32] focused on QoS-aware service discovery and selection in cloud-edge computing for IoE, introducing a hybrid GWO-GA algorithm. El Amraoui [12] introduced the Metaheuristic Moth Flame Optimization Algorithm for Energy-Efficient Clustering (MMFO-EEC) in 6G-enabled UAV networks, leveraging artificial intelligence for decision-making. Eldrandaly et al. [25] explored the synergy between 6G technology and AI through an Intent-Based Network architecture, introducing the hybrid MPGND algorithm for sustainable green 6G-IBN. Pandi Selvam et al. [33] addressed the evolution to 6G networks, emphasizing the integration of terrestrial, aerial, and maritime communication for fast and reliable connectivity. Verma et al. [34] focused on achieving green communication in 6G-enabled massive IoE devices through a cluster-based data dissemination approach, introducing the Hybrid Whale-Spotted Hyena Optimization (HWSHO) algorithm. Zheng et al. [13] investigated the age of information (AoI) and energy efficiency in a wireless-powered industrial Internet of Everything (IIoE) network. They proposed a deep reinforcement learning (DRL)-based approach, specifically the dual-layer deep Q-network (DLDQN) algorithm, to address challenges related to AoI and energy efficiency in the IIoT context. Collectively, these research contributions provide a comprehensive overview of innovative methodologies addressing various aspects of IoT, IoE, and 6G-enabled environments.

Despite this extensive exploration, a noticeable research gap exists. Specifically, there is a lack of a unified and comprehensive framework that effectively integrates the strengths of diverse algorithms and technologies for IoE-driven 6G networks. This gap is further compounded by limited exploration of energy-efficient strategies, especially in IoE networks with constrained energy resources. Additionally, there is insufficient consideration of sustainability and environmental impact, particularly in the integration of IoE into green building energy systems. The absence of comprehensive approaches to tackle multi-objective optimization challenges in IoE networks, addressing conflicting objectives, is another notable gap. Moreover, the research lacks studies focusing on the practical implementation and real-world deployment of IoE-6G network optimization techniques. The proposed hybrid algorithm, EEHEA presents a promising solution across various scenarios and network conditions are necessary to establish its robustness and effectiveness in real-world applications.

A. NOTATION & ABBREVIATION

This section consists of abbreviations & notations and a description of our proposed solution. The description of notations and abbreviations is presented in Table 1.

III. IoE-BASED FRAMEWORK NETWORK

The IoE architecture is intricately interconnected with key pillars—connectivity, data, people, processes, and things. In the Things pillar, physical devices and sensors serve as crucial data collection endpoints. The Data pillar manages

TABLE 1. Description of notation and abbreviation.

Notation	Description
Hy_GA	Hybrid Genetic Algorithm
Hy_PSO	Hybrid Particle Swarm Optimisation Algorithm
Hy_DE	Hybrid Differential Evolutionary Algorithm
Hy_LBO	Hybrid Leader based Optimisation Algorithm
G	Number of Generation
Cr	Crossover Rate
δ_1	Scale factor of mutation operator
D	Dimensions
$MaxFunEvs$	Number of Function Evaluation
N	Total number of sensors
S_i	A sensor node with ID i, where $i = 1, 2, \ldots, N$
$RE(S_i)$	Remaining energy level of the S_i
d_{ij}	Distance between sensors S_i and S_j
E_i	Energy consumed by S_i
$D(S_i)$	Maximum data availability of S_i
G	Smart Health Care Sector
$IoE1, IoE2, IoE3, \& IoE4$	Objective Functions
$G(\alpha, \beta)$	Geographical area of smart health Sector
(150×150)	Smart IoE framework
β_id	Identification service provider

information, enabling real-time responses and value extraction. People pillar integrates individuals, emphasizing human-machine interactions. Processes pillar govern workflows, while Connectivity pillar ensures robust communication. Security pillar safeguards data, devices, and infrastructure. Context pillar enhances data relevance, and Ecosystem Collaboration pillar fosters cooperation. These pillars create a cohesive and intelligent IoE network. Applying IoE in smart cities optimizes urban operations, enhancing efficiency, sustainability, and overall quality of life. IoE applications include intelligent transportation systems and energy management through smart grids. Waste management benefits from IoE with optimized waste collection schedules. For IoE-enabled 6G networks, a comprehensive framework must consider factors like localization rate, coverage rate, energy efficiency, and delay to ensure effective and responsive applications in the evolving landscape. So, in this way, the intricacy of a framework makes it difficult to describe in mathematical equations. The suggested article offers a high-level conceptual framework explanation using mathematical notations when necessary. As it concentrates on the essential elements, let us examine a condensed representation:

(I) Localization Rate (LT): The present study includes LT (the success rate at which the individual sensors are accurately localized) as its first objective (IoE1). However, there is not a single formula to determine LT, as it depends on the methodology, algorithms, and metrics used for localization. So, the proposed study considers a general concept to evaluate this metric in its proposed problem. The goal is to maximize the IoE1 value, as formulated in Equation 1. The ALS_{count} value is computed according to the methodology used in [35].

$$LT = (ALS_{count}/N) * 100, \tag{1}$$

N is the total number of sensors used in our network and ALS_{count} denotes the number of accurately localized sensors.

(II) Energy Consumption (E_{total}): The suggested article includes the term E_{total} (sum-total energy consumption across all sensors) as a second objective (IoE2). The goal is to minimize the IoE2 value, as formulated in Equation 2. The energy computation model is employed in the same way as in [36].

- N: Total number of sensors in the WSN-IoE network
- S_i: A sensor node with ID i, where $i = 1, 2, \ldots, N$
- $RE(S_i)$: Remaining energy level of the S_i
- d_{ij}: Distance between sensors S_i and S_j
- E_i: Energy consumed by S_i
- $D(S_i)$: Maximum amount of data that the node S_i can transmit based on its remaining energy $RE(S_i)$
- E_{elec}: Energy consumed/bit by the transmitter/receiver circuitry.
- E_{fs}: Energy required to transmit/bit over a free-space channel/distance

$$\begin{aligned} Minimize: E_{total} &= \sum_{i=1}^{N} E_i \\ \text{Subject to: } E_i &= E_{elec} * D(S_i) + E_{fs} * D(S_i) * d_{ij}^2 \\ E_i &\leq RE(S_i) \end{aligned} \tag{2}$$

(III) Coverage Rate (CR_{rate}): The fourth objective (IoE4) of our proposed problem addresses the CR_{rate}, which represents the proportion of the deployment area covered by sensors. In order to calculate CR_{rate}, a circular sensing model is considered. The mathematical representation of CR_{rate} is provided in Equation (3), outlined as follows:

$$CR_{rate} = (Covered_{Area}/Total_{Area}) \times 100, \tag{3}$$

where $Total_{Area}$ denotes the total area of the closed region being monitored and $Covered_{Area} = \sum_{i=1}^{N} \pi * (C^r)^2$. The C^r denotes the sensors' communication range.

(IV) Delay Time (DT): DT is the duration to forward the sensed data of all nodes S_i : for $i = 1, 2, \ldots, N$ to the base station (BS) for further processing. This metric is defined in terms of the fifth objective (IoE5), which aims to minimize its value to ensure real-time data delivery, and is expressed as in Eq.4:

$$DT = \sum_{i=1}^{N} T_i, \tag{4}$$

T_i denotes the time duration required for sensor node S_i data to be transmitted to the BS.

(VI) Proposed Fitness Function: This fitness functions of smart city application calculated in Eq. 5, all of the objectives ($IoE1$, $IoE2$, $IoE3$, &$IoE4$) are turned into a single objective function.

$$\begin{aligned} Fitness = {} & fun_1 \times IoE1 + fun_2 \times IoE2 \\ & + fun_3 \times IoE3 + fun_4 \times IoE4, \end{aligned} \tag{5}$$

where values of fun_1, fun_1, fun_3, & fun_4 are the weights assigned to each objective function.

A. FITNESS FUNCTION OF MULTI OBJECTIVES OF THE IoE FRAMEWORK

The suggested study designs four objectives for IoE-based services calculated by Eqs. 1, 2, 3, and 4. As Eq. 5

indicates, all objectives are transformed into multi-objective functions. The optimization objectives are defined as follows: $IoE1$ maximizes the function in Eq. 1, $IoE2$ minimizes the function in Eq. 2, $IoE3$ maximizes the function in Eq. 3, and $IoE4$ minimizes the function in Eq. 4. The minimization problem for objectives $IoE2$ and $IoE4$ involves estimating the total energy expenditure across all sensors and the average delay time. In contrast, the maximization problems of objectives $IoE1$ and $IoE3$ pertain to the localization and coverage rates, respectively. Real-value encoding scheme is used to represent the individuals in our solution. The proposed fitness function is designed based on a scalarization method used in multi-objective optimization, aggregating multiple objectives into a single scalar value through a weighted method to represent trade-offs. While the fitness function is customized with a maximum value to discover optimality, premature convergence might be an issue. To address this, the proposed solution employs diversity maintenance strategies and adaptive weighting schemes, leading to better exploration even after reaching high fitness values.

To represent the individuals in the population in this suggested work, real-value encoding scheme is chosen. As, this scheme leverages comparatively more flexible, easy-to-use representation of solutions than binary/discrete encoding schemes. This flexibility is essential when we are dealing with mixed-variable domains. The real-value encoding scheme is very much compatible with mathematical operations, implying it offers compatibility benefits to perform crossover, mutation, or other operations of evolutionary algorithms like differential evolution. It enables better preservation of diversity within the population and often leads to smoother fitness landscapes. To exemplify the high level representation of an individual x_i in the proposed population, let us assume a particular scenario of an network where $LT = IoE1 = 85\%$, $E_{total} = IoE2$ 300 Joule, $CR_{rate} = IoE3 = 95\%$, and $DT = IoE4 = 200$ Seconds, then the individual x_i can be expressed in real value encoding scheme as $x_i = \{85, 300, 95, 200\}$, and the proposed fitness function can be expressed as $Fitness = fun_1 \times N(IoE1) + fun_2 \times N(IoE2) + fun_3 \times N(IoE3) + fun_4 \times N(IoE4)$, where $fun_1 = 0.4$, $fun_2 = 0.3$, $fun_3 = 0.2$, and $fun_4 = 0.1$, and $N(IoE1), N(IoE2), N(IoE3)$ and $N(IoE4)$ are normalized values of $IoE1$, $IoE2$, $IoE3$ and $IoE4$, respectively.

IV. PROPOSED METHODOLOGY

Adaptive Differential Evolution (ADE) and Leader-based optimization have been combined uniquely to offer an Energy Efficient Hybrid Evolutionary Algorithm (EEHEA) that addresses energy consumption issues and resource allocation inside IoE-enabled 6G networks. The combined use of ADE and leader-based optimization in EEHEA is intended to combine the flexibility of ADE with the effectiveness of leader-based optimization in decision-making. EEHEA aims to achieve homeostasis in energy consumption and resource distribution by utilizing the advantages of both local and global exploration.

A. PROPOSED ADAPTIVE DIFFERENTIAL EVOLUTION ALGORITHM

The proposed Algorithm 1 initializes several parameters: Cr accepts values between 0.1 and 0.5, and δ_1 is set as a percentage of a random value r ranging from 0 to 2. In addition, the iteration count (itr) is initially set to 1, and the population size is calculated as 100 times the dimensionality (D) of the problem space. In the subsequent phases, the fitness of potential solutions is assessed, and the fitness function is defined using the population initialization. Finding high-ranking optimal vectors is aided by ranking ($Rank_i$), where the optimal search vector is $\vec{P}1$, the second-best is $\vec{P}2$, and the third-best is $\vec{P}3$.

The fitness function is then developed using the population's initialization, allowing the fitness of potential solutions to be assessed. Finding superior vectors is made easier by the ranking process ($Rank_i$), where the best search vector is $\vec{P}1$, the second best is $\vec{P}2$, and the third best is $\vec{P}3$. The method works in an iterative loop: fitness is calculated for each search vector, and its location is updated using a formula that considers the distances between certain places. Update the position of the current search vector using the distances between specific vectors. $\vec{P}(itr + 1)$ is updated based on the distance between $P1^t$ and $P2^t$. $\vec{PT}(itr + 1)$ is updated based on the distance between $P2^t$ and $P3^t$. In order to choose an alternative vector $\vec{PT}(itr + 1)$ for adaptation if the updated vector is not improved, an adaptive mutation approach is used. A mutation operator performs this mutation using certain mathematical modifications based on the best and random vectors. Then, depending on how well the vectors perform, an adaptive selection approach is used to choose them. The framework's adaptable DE technique leads the iterative process towards an approximation solution with remarkable convergence rates.

B. PROPOSED LEADER-BASED OPTIMIZATION ALGORITHM

The proposed Algorithm 2 goal is to explore the best solution within a specified solution space. First, random solutions are used to construct a population P; then, an objective function evaluation is used to assess the fitness values of this population. Based on their fitness evaluations, two leaders, L_{best} and L_{worst}, represent the best and worst solutions in the population, respectively. Every time iteration, the Algorithm carries out several important steps. First, data from the leaders is used to update the positions of the followers. Two factors, α and β, which determine how much the greatest and worst leaders impact followers' views, serve as the basis for this update. At the next iteration $(t + 1)$, the positions of the followers ($P_{follower}^{(t+1)}$) are modified according to a weighted combination of the variations between the followers' present positions and the positions of the greatest and worst leaders. The leaders actually are then recalculated based on the updated followers' data after the followers have updated. In order to redefine the greatest and worst

Algorithm 1 Proposed Adaptive Differential Evolution Algorithm

Input:
(a) δ_1 = r/2, where random (r) value (0 to 2)
(b) $Cr = 0.1$ to 0.5
(c) Set the Population Size = 100*D
(d) Iteration (itr) = 1
Output: Achieve the approximated solution
Step 1: Set the fitness function according to initialization of population
Step 2: Calculate the fitness function of candidate solution
Step 3: $Rank_i$ help to generate high-ranking best vectors
Step 4: $\vec{P}1$ = the best search vector
Step 5: $\vec{P}2$ = the second best search vector
Step 6: $\vec{P}3$ = the third best search vector
while $(t \neq Max_T)$ **do**
  Step 7: The proposed ADE algorithm
  7.1 For each search vector:
    Calculate the fitness of all search vectors
    Update the position of the current search vector:
    $\vec{P}(itr+1) = (\vec{Dist}(P1_i^t, P2_j^t))$
    $\vec{PT}(itr+1) = (\vec{Dist}(P2_i^t, P3_j^t))$
  7.4 Update $\vec{P}1$, $\vec{P}2$, and $\vec{P}3$
  7.5: Update best optimum value using ADE
  Step 8: Apply the adaptive mutation strategy
  8.1 Apply mutation operator and select donor vector
  if $\vec{P}(itr+1) < \vec{PT}(itr+1)$ **then**
    $\vec{P}(itr+1) = \vec{\alpha}_{\text{best},G} + \delta_1 \times (\vec{P}1_{r_1^i,G} - \vec{P}2_{r_2^i,G}) \times rand(0,1)$
  else
    $\vec{PT}(itr+1) = \vec{\alpha}_{\text{rand},G} + \delta_2 \times (\vec{P}2_{r_1^i,G} - \vec{P}3_{r_2^i,G}) \times rand(0,1)$
  end if
  Note: If $\vec{P}(itr+1)$ fails to improve, $\vec{PT}(itr+1)$ is used for adaptation
  8.2 Apply the adaptive selection strategy
  $t = t + 1$
end while
Step 9: Approximate Solution with high Convergence Rate

Algorithm 2 Proposed Leader-Based Optimization Algorithm

Input: Initialize population P with random solutions
Output: Approximated optimal solution
Step 1: Initialize P randomly within the solution space
Step 2: Evaluate the fitness of solutions in P using the objective function
Step 3: Define leaders based on fitness values
Step 4: Determine leader positions (L_{best}, L_{worst}) based on fitness
while $(t \neq Max_T)$ **do**
  Step 5: Update followers based on leaders
  5.1 Calculate distances between followers and leaders:
    $Distance_{\text{follower, leader}} = \|P_{\text{follower}} - L_{\text{leader}}\|$
  5.2 Update follower positions using leader information:
    $P_{\text{follower}}^{(t+1)} = P_{\text{follower}}^{(t)} + \alpha \times (L_{\text{best}}^{(t)} - P_{\text{follower}}^{(t)}) + \beta \times (L_{\text{worst}}^{(t)} - P_{\text{follower}}^{(t)})$
  Step 6: Update leaders based on followers
  6.1 Compare current leaders with followers and update leaders based on fitness:
    $L_{\text{best}}^{(t+1)} = \arg\min\{fitness(P_{\text{follower}}^{(t+1)})\}$
    $L_{\text{worst}}^{(t+1)} = \arg\max\{fitness(P_{\text{follower}}^{(t+1)})\}$
  $t = t + 1$
end while
Step 7: Obtain the final approximated solution using leader information

leaders, this phase entails reevaluating the followers' fitness values. The lowest leader (L_{worst}) is redefined as the follower with the largest fitness among the updated solutions, and the best leader (L_{best}) is updated as the follower with the smallest fitness. The Algorithm moves closer to an estimated optimal solution through an iterative process of updating followers based on leaders and influencing leaders based on followers. The factors α and β that control the impact of leaders on followers and the reverse, respectively, are critical to this optimization's efficacy. Furthermore, the quality of the resultant solution depends on the fitness assessment technique used in the optimization framework for both leaders and followers. Within the Leader-Based Optimization method, modifications to these coefficients and the fitness assessment function substantially affect the optimization procedure and the convergence to the optimal solution.

C. PROPOSED HYBRID ALGORITHM

The proposed Algorithm 3 starts by initializing a population P with solutions that are produced at random. These solutions' fitness values are calculated using a specified objective function, and the best and worst solutions in the population are represented by two leaders, L_{best} and L_{worst}, which are determined by their fitness. Using ADE approaches, followers are updated at the start of the iterative process. This involves performing mutation and crossover operations specifically tailored to ADE and updating the positions of followers using equations relevant to ADE-based optimization. The positions of the followers are then updated even further by applying the concepts of Leader-Based Optimization. The follower positions are then modified using equations derived from Leader-Based optimization strategies. This step entails calculating the distances between the leaders and followers.

As the iteration increases, the updated followers' data is used to update the leaders (L_{best} and L_{worst}). In order to ensure that leadership positions are adjusted to the changing population, the leaders are redefined to take into account variations in the fitness values of the followers. In order to take advantage of each strategy in terms of optimizing the solution space, the Algorithm switches back and forth between ADE and leader-based optimizations during this iterative process. Through information sharing between leaders and followers and several optimization approaches, the Algorithm finds its way to an approximation optimal solution, exhibiting convergence efficiency and flexibility in examining and improving options within the specified area. The optimization process inside this hybrid framework may be greatly impacted by fine-tuning the calculations and methods within each approach.

D. THE PROPOSED HYBRID SCHEME IN IoE-ENABLED 6G)

Algorithm 4 outlines the suggested Hybrid Algorithm's implementation, which combines ADE and Leader-Based Optimization techniques in a 6G IoE network. The algorithm starts by initializing the solution population and the IoE-6G network components. It then goes through iterative optimization phases that are particular to the limits and

Algorithm 3 Proposed Hybrid Algorithm

Initialization:
Initialize parameters δ_1, Cr, Population Size, Iteration (itr) for ADE (Algorithm 1)
Initialize parameters α, β for Leader-Based Optimization (Algorithm 2)

Set $t = 1$
Initialize best optimum value best_optimum
while $t \neq Max_T$ **do**
  ADE Algorithm (Algorithm 1):
  for each search vector **do**
    Calculate fitness of search vectors
    Update positions of search vectors using Eq. (1) and (2)
  end for
  Update best optimum value using ADE if it improves:
  if fitness of ADE result < fitness of best_optimum **then**
    best_optimum = ADE result
  end if
  Adaptive Mutation Strategy:
  if $\vec{P}(itr + 1) < \vec{PT}(itr + 1)$ **then**
    $\vec{P}(itr + 1) = \vec{\alpha}_{\text{best},G} + \delta_1 \times (\vec{P1}_{r_1^i,G} - \vec{P2}_{r_2^i,G}) \times \text{rand}(0, 1)$
  else
    $\vec{PT}(itr + 1) = \vec{\alpha}_{\text{rand},G} + \delta_2 \times (\vec{P2}_{r_1^i,G} - \vec{P3}_{r_2^i,G}) \times \text{rand}(0, 1)$
  end if
  Adaptive Selection Strategy
  $t = t + 1$
end while
Leader-Based Optimization (Algorithm 2):
while $t \neq Max_T$ **do**
  Update followers based on leaders
  Update leaders based on followers
  Update best optimum value using Leader-Based Optimization:
  if fitness of Leader-Based Optimization result < fitness of best_optimum **then**
    best_optimum = Leader-Based Optimization result
  end if
  $t = t + 1$
end while
Compare Algorithm 1 and Algorithm 2, Pick the best update optimum value
Obtain the final approximated solution using best_optimum

Algorithm 4 Proposed Hybrid Algorithm for IoE-Enabled 6G Optimization

Initialization:
Initialize parameters δ_1, Cr, Population Size, Iteration (itr) for ADE (Algorithm 1)
Initialize parameters α, β for Leader-Based Optimization (Algorithm 2)

Set $t = 1$
Initialize best optimum value best_optimum
Define fitness function considering WSN parameters:
Fitness function: $f(\text{LT}, E_{total}, CR_{rate}, \text{DT})$
while $t \neq Max_T$ **do**
  ADE Algorithm (Algorithm 1):
  for each search vector **do**
    Calculate fitness of search vectors considering WSN parameters
    Update positions of search vectors using Eq. (1) and (2)
  end for
  Update best optimum value using ADE if it improves:
  if fitness of ADE result < fitness of best_optimum **then**
    best_optimum = ADE result
  end if
  Adaptive Mutation Strategy:
  if $\vec{P}(itr + 1) < \vec{PT}(itr + 1)$ **then**
    $\vec{P}(itr + 1) = \vec{\alpha}_{\text{best},G} + \delta_1 \times (\vec{P1}_{r_1^i,G} - \vec{P2}_{r_2^i,G}) \times \text{rand}(0, 1)$
  else
    $\vec{PT}(itr + 1) = \vec{\alpha}_{\text{rand},G} + \delta_2 \times (\vec{P2}_{r_1^i,G} - \vec{P3}_{r_2^i,G}) \times \text{rand}(0, 1)$
  end if
  Adaptive Selection Strategy
  $t = t + 1$
end while
Leader-Based Optimization (Algorithm 2):
while $t \neq Max_T$ **do**
  Update followers based on leaders
  Update leaders based on followers
  Update best optimum value using Leader-Based Optimization:
  if fitness of Leader-Based Optimization result < fitness of best_optimum **then**
    best_optimum = Leader-Based Optimization result
  end if
  $t = t + 1$
end while
Compare Algorithms and Pick the Best Optimum Value
Obtain the final approximated solution using best_optimum

requirements of IoE-enabled 6G deployments. The formulas and procedures are modified according to the specific optimization targets and factors of the suggested IoE-6G application.

V. RESULT AND ANALYSIS

This Result Analysis thoroughly assesses the performance of the Hybrid Algorithm in optimizing IoE-enabled 6G networks. The evaluation includes a comprehensive examination of metrics, comparisons with various algorithms (Hybrid Genetic Algorithm - Hy_GA Algo, Hybrid Particle Swarm Optimization Algorithm - Hy_PSO Algo, Hybrid Differential Evolution Algorithm - Hy_DE Algo, and Hybrid Learning-based Optimization Algorithm - Hy_LBO Algo), numerical analyses, and practical implications. The proposed hybrid method's main strength lies in its ability to concurrently manage many often-conflicting objectives. The LBO and ADE used in our hybrid algorithm leverage novel advantages and disadvantages in contrast to other popular swarm intelligence methods such as Hy_GA, Hy_PSO, Hy_GWO, and others. LBO has better exploitative capabilities and efficiently converges to optimality states, while ADE's self-adaptive approaches improve its adaptability and robustness, especially in dynamic environmental scenarios. Furthermore, ADE-based optimization, known for its exceptionally efficient search space exploration, balances exploration and exploitation. Simultaneously, the adaptation process is intelligently optimized by the mutation and crossover operations of the Adaptive DE Algorithm, renowned for its robustness in handling complex, non-linear, and multi-modal optimization problems. This dynamic combination culminates in a real-time optimal solution, enhancing the overall network performance in the context of IoE-enabled 6G networks. Nevertheless, such advantages come along with some drawbacks. LBO might suffer from premature convergence issue or parameter sensitivity, restricting its efficacy in dynamic or complex optimization scenarios. Furthermore, ADE might have higher computational complexity and slower convergence because of its population-based characteristics. Despite such shortcomings, our proposed hybrid Algorithm including LBO and ADE leverages a balanced optimization environment, leveraging their complementary strengths to

TABLE 2. Sensor simulation parameters.

Parameter	Value
Planar square region	250 m $\times$ 250 m
Number of sensors	150
Communication range of the sensors	15 m
Residual energy of sensor S_i	300 - 1000 mJ
Sensed data of a sensor S_i	0 - 16Mb
Data transmission rate	20 Kbps

solve conflict objectives effectively. This hybrid form is motivated to be chosen because of its adaptive and robust optimization techniques, which can handle different kinds of complex, dynamic problems while offering competitive performance. Therefore, compared to baseline schemes, this method provides computationally efficient solutions against different operations in multidimensional spaces. Its unique strength is seamlessly blending several network factors, leading to reliable data communication. Furthermore, The proposed approach is specifically tailored for evaluating the quality of service performance in smart IoE applications, addressing a novel Multi-objective optimization problem with a uniquely devised fitness function. Key Quality of Service (QoS) metrics, such as LT, E_{total}, CR_{rate}, and DT, are considered. The method is implemented and evaluated across three scenarios of Wireless Sensor Networks (WSNs) utilizing IoE services.

1) *Experiment 1:* Analysis of the Algorithm's ability to save energy use in 6G networks with IoE enabled while maintaining optimal performance.
2) *Experiment 2:* examination of the Algorithm's effect on reducing delay in communication between networked Internet of Everything devices, guaranteeing effective and rapid data transfer.
3) *Experiment 3:* An investigation of how the Algorithm affects expanding or improving the coverage regions in the 6G network offered by the Internet of Everything, guaranteeing more accessibility and greater coverage area.
4) *Experiment 4:* Evaluating the Algorithm's stability and rate of convergence as it comes closer to the best outcomes. The quality and efficacy of the solutions found in the IoE-6G context were also included in this analysis.

A. EXPERIMENTAL SETUP

The IoE architecture spans a 250 $\times$ 250 unit square, with 150 sensors evenly distributed, each representing a distinct service request or data-gathering point. Initial data availability for sensors ranges from 0 to 16 Megabytes. Sensor energy reserves vary from 300 to 1000 millijoules (mJ), with an average data transmission rate of 20 Kbps, influencing network-wide data transmission speed. Sensors possess a fixed communication range of 15 meters, enabling communication within specific geographical areas. The detailed simulation parameters values are in Table 2. This diverse sensor network configuration is the experimental IoE framework, accommodating varied data availability, energy reserves, and communication capabilities. This configuration, expressed through mathematical notation in Table 3, forms the basis for evaluating the Hybrid Algorithm's effectiveness in optimizing IoE-enabled 6G networks. This setup, adaptable for exploring complex network optimization aspects, was fine-tuned using the proposed technique. The method was tested in IoE scenarios, particularly in healthcare services, generating Pareto fronts within a four-objective set. Additionally, it was applied to assess IoE services related to localization rate, total energy consumption, coverage rate, and delay time.

TABLE 3. Control parameters for different algorithms.

Algorithm	M Rate	I Weight	CR	Selection
Proposed Algorithm	0.1	0.5	0.8	2
Hy_GA Algorithm [37]	0.05	-	-	1.8
Hy_PSO Algorithm [38]	-	0.7	-	-
Hy_DE Algorithm [24]	0.3	-	0.9	-
Hy_LBO Algorithm [23]	-	-	0.6	1.5

B. 6G-IoE: THE PROPOSED ALGORITHM SIMULATION ANALYSIS

Table 4 provides a comprehensive analysis of algorithm performance over 200 generations, evaluating five key metrics: energy efficiency, convergence, coverage, and fitness cost. Each algorithm, including the recommended one, undergoes meticulous scrutiny, recording the worst and most promising mean values at 25-generation intervals. The proposed method exhibits a consistent generation-by-generation enhancement, with its lowest value decreasing from 0.3345 in the 25^{th} generation to 0.7136 by the 200^{th}. The best mean value rises from 0.4485 to 0.9568 over the same period. Notably, Hy_GA, Hy_PSO, Hy_DE, and Hy_LBO show advancements in energy efficiency optimization. Similar trends are observed in reliability, where the suggested method steadily improves, reaching a worst value of 0.6467 and a best mean of 0.8671 by the 200^{th} generation, compared to 0.2453 and 0.3289 in the 25^{th} generation. The proposed method consistently outperforms in terms of dependability, coverage, convergence, and fitness cost. In the 25^{th} generation, its worst values for coverage, convergence, and fitness cost were 0.2676, 0.47499, and 0.40809, respectively, improving significantly to 0.64224, 0.72029, and 0.70468 by the 200^{th} generation. Across all assessed measures, the suggested algorithm demonstrates a pattern of steady improvement over 200 generations, showcasing its competitive performance and ability to converge towards optimal values for 6G-IoE applications.

Our proposed simulation experimental set-up has shown different performance metrics over 200 generations for five distinct algorithms, including the Proposed method along with Hy_GA [37], Hy_PSO [38], Hy_DE [24], and Hy_LBO [23]. FIGURE 1 reports *energy consumption* metric values expensed by all the different methods. The Proposed Algorithm consistently exhibits a greater energy efficiency rate than the other algorithms due to the adaptive nature of the proposed algorithm, which ensures dynamic parameters' adjustment and efficient search space exploration. It performs better over generations, outperforming Hy_GA, Hy_PSO, Hy_DE, and Hy_LBO, which have somewhat efficient but erratic trends. FIGURE 2 reports *latency metric* values incurred by different Algorithms after completing execution. The Proposed method performs marginally better than Hy_GA and Hy_LBO but maintains a comparatively lower latency across 200 generations when compared to Hy_PSO and Hy_DE. Compared to the other methods, the latency reduction trend of the proposed approach is steady and constant. FIGURE 3 shows the coverage efficacy of our proposed algorithm compared to others due to efficient energy consumption management, as reflected in 1, and localization of nodes. FIGURE 4 reports *Performance efficiency* values returned by different schemes. Compared to Hy_PSO, Hy_DE, Hy_LBO, and Hy_GA schemes, the Proposed scheme exhibits better performance efficiency as its execution status reaches termination conditions. Compared to the baseline hybrid algorithms, the proposed algorithm performs better overall regarding energy efficiency, latency, and coverage, indicating its effectiveness in optimizing the desired parameters across 200 generations. This is subjected to several features:

- The adaptive nature of the ADE, combined with leader-based optimization, ensures dynamic parameters' adjustment and efficient search space exploration, implying optimized resource allocation and minimized energy expenditure.
- Based on accurate benchmarking and rigorous performance evaluation, the algorithm's robust convergence properties lead to effective decision-making in real-time scenarios and minimal latency in complex optimization cases.
- The proposed algorithm's adaptability to varied experimental scenarios and capability to control dependable performance across diverse conditions implies its robustness and reliability.
- The improved coverage capability obtained by the algorithm shows its ability to address various optimization situations in communication networks, distributed systems, and IoT environments, further solidifying its supremacy in delivering better network performance across multiple dimensions.

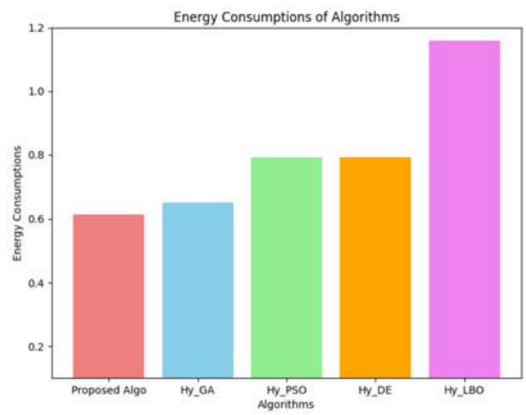

FIGURE 1. Energy consumption.

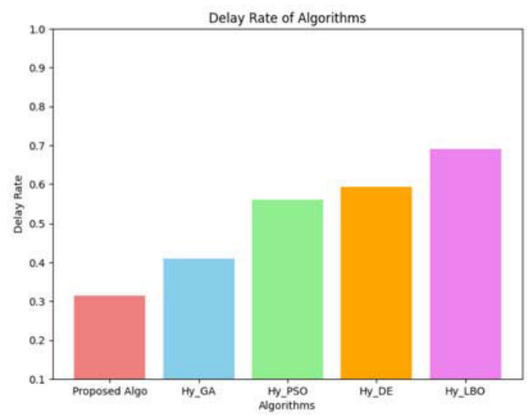

FIGURE 2. Delay.

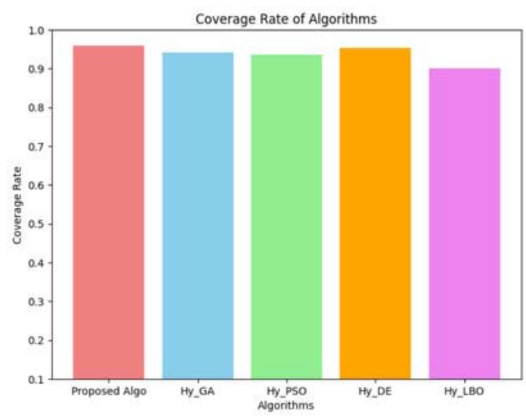

FIGURE 3. Performance of coverage area.

C. ENERGY CONSUMPTION RATE AND DATA DELAY RATE ANALYSIS

In FIGURE 5, the proposed Algorithm, along with Hy_GA, Hy_PSO, Hy_DE, and Hy_LBO optimization algorithms, demonstrates a flourishing trend in minimizing energy consumption rates across successive generations in a smart city framework. The graph showcases the decreasing energy consumption rates over time, providing stakeholders with a practical comparative study of algorithmic performance. This proposed method has shown more energy efficacy than others due to a better convergence rate, as reflected in Table 4, enhanced exploration and exploitation feature, robustness to Dynamic environments feature, scalability, and flexibility, implying the capability of effectively solving complex optimization issues. This visualization assists decision-making when selecting algorithms to reduce energy consumption in evolving smart city environments. Moving to FIGURE 6, the performance trends of various algorithms (the proposed Algorithm, Hy_GA, Hy_PSO, Hy_DE, and Hy_LBO) in a 6G-IoE framework for minimizing Data Delay rates are

TABLE 4. Comparative performance metrics over 200 generations.

Sr No	No. of Generation	Matrics	Proposed Algo		Hy_GA Algo		Hy_PSO Algo		Hy_DE Algo		Hy_LBO Algo	
			Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best
1	25	Energy Efficiency	0.3345	0.4485	0.327	0.435	0.4185	0.432	0.3225	0.4365	0.2985	0.399
2	50		0.3791	0.5083	0.3706	0.493	0.4743	0.4896	0.3655	0.4947	0.3383	0.4522
3	75		0.4014	0.5382	0.3924	0.522	0.5022	0.5184	0.387	0.5238	0.3582	0.4788
4	100		0.4237	0.5681	0.4142	0.551	0.5301	0.5472	0.4085	0.5529	0.3781	0.5054
5	125		0.5129	0.6877	0.5014	0.667	0.6417	0.6624	0.4945	0.6693	0.4577	0.6118
6	150		0.5575	0.7475	0.545	0.725	0.6975	0.72	0.5375	0.7275	0.4975	0.665
7	175		0.669	0.897	0.654	0.87	0.837	0.864	0.645	0.873	0.597	0.798
8	200		0.7136	0.9568	0.6976	0.928	0.8928	0.9216	0.688	0.9312	0.6368	0.8512
1	25	Coverage	0.2676	0.3588	0.2616	0.348	0.3348	0.3456	0.258	0.3492	0.2388	0.3192
2	50		0.2899	0.3887	0.2834	0.377	0.3627	0.3744	0.2795	0.3783	0.2587	0.3458
3	75		0.32781	0.43953	0.32046	0.4263	0.41013	0.42336	0.31605	0.42777	0.29253	0.39102
4	100		0.42147	0.56511	0.41202	0.5481	0.52731	0.54432	0.40635	0.54999	0.37611	0.50274
5	125		0.5129	0.6877	0.5014	0.667	0.6417	0.6624	0.4945	0.6693	0.4577	0.6118
6	150		0.57311	0.76843	0.56026	0.7453	0.71703	0.74016	0.55255	0.74787	0.51143	0.68362
7	175		0.59764	0.80132	0.58424	0.7772	0.74772	0.77184	0.5762	0.77988	0.53332	0.71288
8	200		0.64224	0.86112	0.62784	0.8352	0.80352	0.82944	0.6192	0.83808	0.57312	0.76608
1	25	Convergence	0.47499	0.63687	0.46434	0.6177	0.59427	0.61344	0.45795	0.61983	0.42387	0.56658
2	50		0.52182	0.69966	0.51012	0.6786	0.65286	0.67392	0.5031	0.68094	0.46566	0.62244
3	75		0.54635	0.73255	0.5341	0.7105	0.68355	0.7056	0.52675	0.71295	0.48755	0.6517
4	100		0.59541	0.79833	0.58206	0.7743	0.74493	0.76896	0.57405	0.77697	0.53133	0.71022
5	125		0.64447	0.86411	0.63002	0.8381	0.80631	0.83232	0.62135	0.84099	0.57511	0.76874
6	150		0.65562	0.87906	0.64092	0.8526	0.82026	0.84672	0.6321	0.85554	0.58506	0.78204
7	175		0.67346	0.90298	0.65836	0.8758	0.84258	0.86976	0.6493	0.87882	0.60098	0.80332
8	200		0.72029	0.96577	0.70414	0.9367	0.90117	0.93024	0.69445	0.93993	0.64277	0.85918
1	25	Fitness Cost	0.40809	0.54717	0.39894	0.5307	0.51057	0.52704	0.39345	0.53253	0.36417	0.48678
2	50		0.50844	0.68172	0.49704	0.6612	0.63612	0.65664	0.4902	0.66348	0.45372	0.60648
3	75		0.5352	0.7176	0.5232	0.696	0.6696	0.6912	0.516	0.6984	0.4776	0.6384
4	100		0.57088	0.76544	0.55808	0.7424	0.71424	0.73728	0.5504	0.74496	0.50944	0.68096
5	125		0.59987	0.80431	0.58642	0.7801	0.75051	0.77472	0.57835	0.78279	0.53531	0.71554
6	150		0.64447	0.86411	0.63002	0.8381	0.80631	0.83232	0.62135	0.84099	0.57511	0.76874
7	175		0.68238	0.91494	0.66708	0.8874	0.85374	0.88128	0.6579	0.89046	0.60894	0.81396
8	200		0.70468	0.94484	0.68888	0.9164	0.88164	0.91008	0.6794	0.91956	0.62884	0.84056

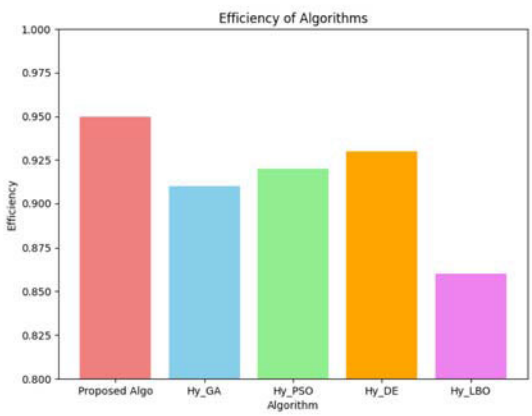

FIGURE 4. Performance of efficiency.

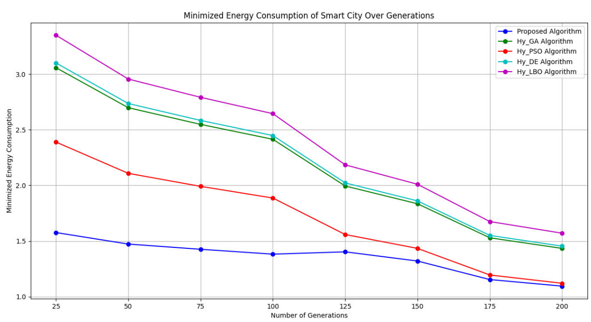

FIGURE 5. Energy consumption: number of generations v/s energy consumption.

illustrated. The Y-axis displays reduced Data Delay rates, while the X-axis indicates the number of generations. Lower values on the Y-axis signify better performance in minimizing

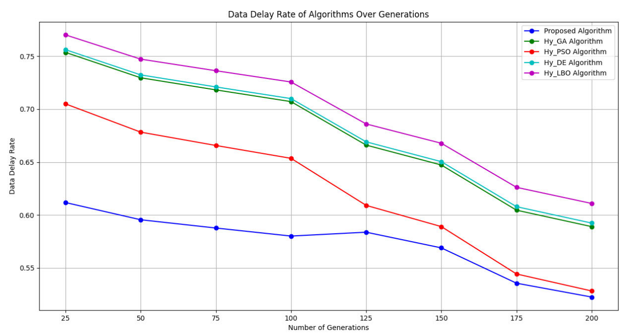

FIGURE 6. Data delay rate: number of generations v/s data delay rate.

data transmission delays. This comparative research provides valuable insights into how various algorithms evolve over generations and their effectiveness in minimizing data delay rates, aiding in selecting optimal algorithms for 6G-IoE infrastructure. We observe the proposed method superiority of delay reduction capabilities than others, as shown in FIGURE 6. Observations reveal a consistent decreasing trend in Data Delay rates for all algorithms as the number of generations increases. Notably, Hy_LBO and the proposed Algorithm consistently exhibit lower rates, effectively reducing data transmission delays over subsequent generations. In contrast, Hy_PSO shows consistently higher rates.

D. CONVERGENCE RATE AND ENERGY LEVEL ANALYSIS

FIGURE 7 shows the convergence rates of several methods across multiple generations. The x-axis depicts the number of generations, while the y-axis represents each algorithm's

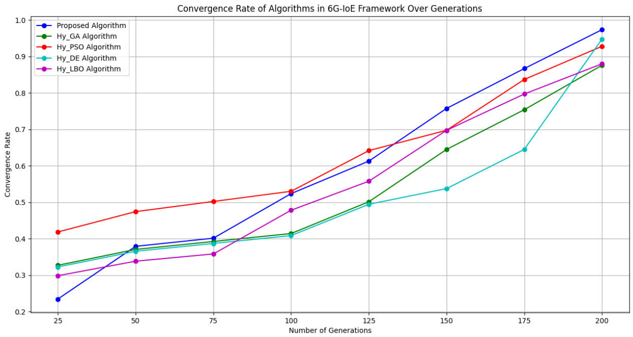

FIGURE 7. **Convergence rate: number of generations v/s convergence rate.**

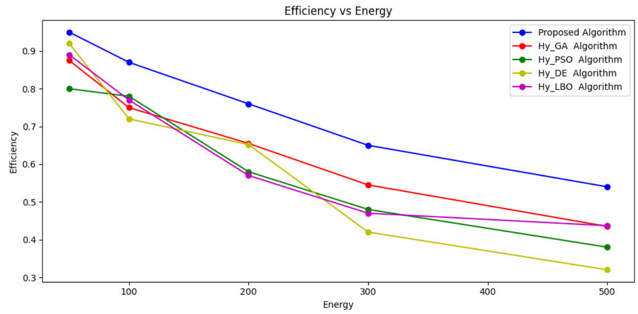

FIGURE 9. **Efficiency vs energy for various algorithms.**

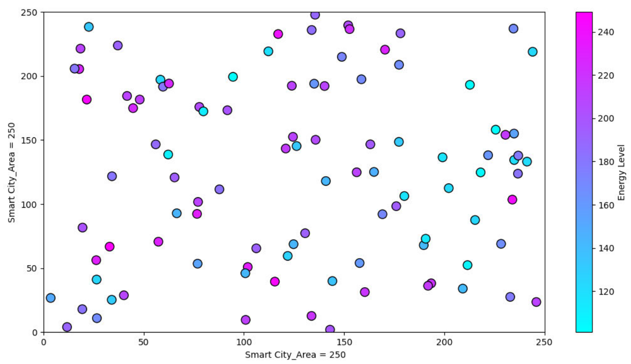

FIGURE 8. **Energy Level of proposed algorithm.**

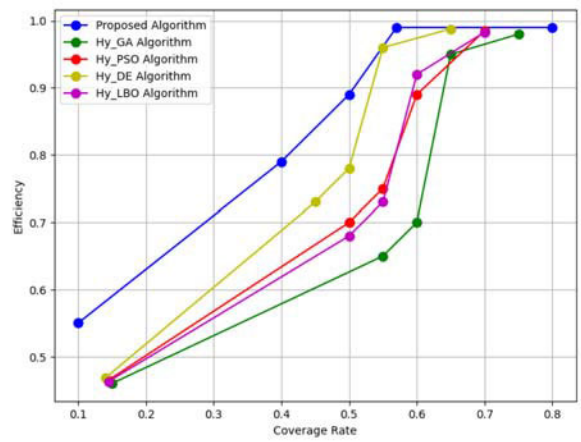

FIGURE 10. **Comparison of relation for coverage rate and efficiency.**

convergence rate. Hy_GA and the proposed method have lower convergence rates initially but show considerable improvements in the following generations, while Hy_PSO, Hy_DE, and Hy_LBO maintain a moderate but consistent convergence rate. The proposed method initially outperforms others regarding convergence rates before eventually slowing down. The adaptive nature of DE, blended with the guidance from leader-based optimization, leads to dynamic and more excellent search space exploration, yielding an efficient convergence rate towards obtaining optimal solutions. By adaptively controlling its parameters and facilitating the collective knowledge of elite individuals, the proposed Algorithm can effectively traverse large and complex optimization landscapes, implying faster convergence rates. FIGURE 8 depicts the proposed Hybrid Algorithm achieves a maximum accuracy of 96.32% with an average of 200 iterations over 30 runs, demonstrating its usefulness in optimizing sensor node behavior in IoE environments. The proposed algorithm to continuously adapt its behavior based on the improving its energy level performance. The energy analysis in this term the convergence behavior of these algorithms inside the 6G-IoE framework, demonstrating their efficiency in reaching optimal solutions as generations progress. The proposed Hybrid Algorithm achieves a maximum accuracy of 96.32% with an average of 200 iterations over 30 runs, demonstrating its usefulness in optimizing sensor node behavior in shown FIGURE 8.

E. COMPARISON OF RELATION FOR ENERGY AND EFFICIENCY

The proposed algorithm retains high efficiency across a range of energy consumption amounts. It performs well even under greater energy demands, indicating its potential for resource-constrained applications without compromising efficiency. In the FIGURE 9 provides an analysis of the efficiency achieved using various optimization methods, including the proposed algorithm, Hy_GA, Hy_PSO, Hy_DE, and Hy_LBO, across increasing levels of energy consumption. The x-axis shows the energy consumption in bits per second (bits/sec), while the y-axis shows the efficiency achieved by the standard algorithms exhibit varied levels of efficiency across different energy usage scenarios. The proposed algorithm effectiveness of them tends to decline as energy needs rise, indicating possible constraints while they operate relatively well at lower energy levels, their efficiency significantly as energy needs rise, emphasising possible optimisation issues in resource-intensive environments. As a whole, the FIGURE provides useful insights into the trade-off between energy consumption and efficiency in Wireless Sensor Networks.

F. COMPARISON OF RELATION FOR COVERAGE RATE AND EFFICIENCY

The proposed algorithm comparison of Coverage Rate and Efficiency across different algorithms provides views into their trade-offs and optimisation capabilities in relation to

TABLE 5. ANOVA: energy consumption.

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.422769488	4	0.105692372	20.15895688	3.21366×10^{-13}	2.434065136
Within Groups	0.760227528	145	0.005242948			
Total	1.182997016	149				

TABLE 6. ANOVA: coverage.

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.787249612	4	0.446812403	76.43138409	9.796×10^{-35}	2.434065136
Within Groups	0.847659626	145	0.005845928			
Total	2.634909238	149				

TABLE 7. ANOVA: delay.

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.422769488	4	0.105692372	45.8843417	2.22×10^{-11}	2.434065136
Within Groups	0.780227528	145	0.005242948			
Total	2.202997016	149				

the context of WSNs. The proposed algorithm selection of appropriate optimisation strategies based on specific needs and objectives. FIGURE 10 compares relation for various optimisation techniques based on how they perform in terms of Coverage Rate and Efficiency in WSN. The x-axis indicates Coverage Rate, and the y-axis represents Efficiency, which is often used to describe the network's energy efficiency in terms of data transmission, and energy consumption. The suggested algorithm's relationship generates solutions with varied Coverage Rate and Efficiency which is provide a trade-off between increasing coverage rate and maintaining WSN efficiency. The Hy_GA algorithm has varied trade-offs for Coverage Rate and Efficiency, making it suited for various application situations and network needs. Similarly, the relationship for the Hy_PSO, Hy_DE, and Hy_LBO algorithms gives solutions that balance Coverage Rate and Efficiency in an individual manner, adding to the network's overall performance improvement.

G. PARETO FRONT ANALYSIS OF ENERGY CONSUMPTION WITH DELAY

The proposed algorithm description of the Pareto front analysis of the IoE based 6G network. This algorithm compares with Pareto front for the Hy_GA algorithm identifies competitive solutions in terms of energy consumption and delay. Showing a wide range of trade-offs. Similarly, the Pareto front for the Hy_PSO, Hy_DE, and Hy_LBO algorithms provides solutions that are competitive in terms of energy consumption and delay. FIGURE 11 compares Pareto fronts across various optimisation techniques based on their performance in terms of energy consumption and delays. The x-axis shows energy consumption, and the y-axis measures delay. The Pareto front for the proposed method shows solutions with different amounts of energy consumption and delay. These ideas offer a trade-off between reducing energy usage and minimising delay. The proposed algorithm is achieved the satisfactory diversity as well as convergence rate in shown FIGURE 11.

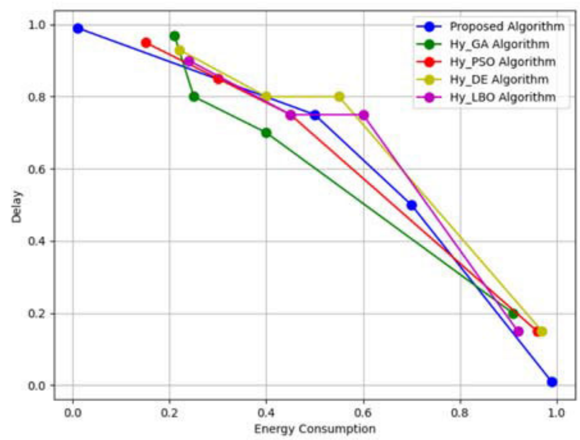

FIGURE 11. Comparison of pareto fronts for optimization algorithms.

H. STATISTICAL ANALYSIS THROUGH ANALYSIS OF VARIANCE (ANOVA)

The shown results in Table 5, Table 6, and Table 7 are statistically significant via hypothesis testing. ANOVA (Variance Analysis) is one of the approaches used to test and verify whether there are significant differences between two or more means. It concludes whether the means of reported results of given algorithms are the same (null hypothesis (H_0) is alternative/accepted hypothesis (H_1) is rejected) or not (null hypothesis is rejected). The ANOVA test result is also known as the F-statistic. In this test result, the null hypothesis is rejected if the P-value result becomes lower than

α (significance level) and (b) if the F-statistic value is greater than the F-critical value. Let n_1, n_2, n_3, n_4 and n_5 express sample numbers in Hy_GA, Hy_PSO, Hy_DE, Hy_LBO, and proposed algorithms. To perform the test, 30 samples ($n_1 = n_2 = n_3 = n_4 = n_5 = 30$) of each individual method are taken in the similar network-environment setting, where $\alpha = 0.05$. H_0 and H_1 are as follows.

$H_0 : \mu_{Hy\_GA} = \mu_{Hy\_PSO} = \mu_{Hy\_DE} \mu_{Hy\_LBO} \mu_{Proposed}$ $H_1 : \mu_{Hy\_GA} \neq \mu_{Hy\_PSO} \neq \mu_{Hy\_DE} \neq \mu_{Hy\_LBO} \neq \mu_{Proposed}$ Table 5, Table 6, and Table 7 show the ANOVA outcome for five distinct methods for energy consumption, coverage, and delay metrics.

VI. CONCLUSION AND FUTURE RESEARCH DIRECTION

In this work, the proposed Hybrid Algorithm, a novel approach combining Adaptive Differential Evolution and Leader-Based Optimization, demonstrates significant advancements in optimizing 6G-enabled IoE networks. The proposed research reports noteworthy improvements in network coverage, latency reduction, energy efficiency, and network dependability across various IoE scenarios. Comparative assessments against traditional 6G networks underscore its efficacy aligning with IoE-centric goals. While the proposed algorithm proven efficient and effective for revolutionizing real-world network applications, it faces challenges in promptly adapting to dynamic changes and may exhibit limitations in real-time decision-making speed. Integrating AI techniques into this hybrid metaheuristic approach can enhance adaptability, learning capabilities, and problem-solving intelligence, making it more suitable for addressing complex and uncertain scenarios. Moving forward, the suggested article goal is to improve the efficiency, reliability, and adaptability of 6G-enabled IoE networks by integrating advanced AI techniques, thereby supporting a wide range of dynamic 6G-enabled IoE applications.

CONFLICT OF INTEREST

There is no conflict of interest between the others.

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