# A Hybrid Multi-Objective Optimisation for 6G-enabled Internet of Things (IoT)

Shailendra Pratap Singh, Naween Kumar, Gyanendra Kumar, Balamurugan Balusamy, Ali Kashif Bashir, and Yasser D. Al-Otaibi

***Abstract*—The advent of 6G-enabled networks marks a transformative era in the Internet of Things (IoT), promising unparalleled connectivity and innovation. These networks are set to revolutionize the IoT landscape by offering remarkable capabilities, including ultra-high data speeds, ultra-low latency, and extensive network coverage and connectivity. However, optimizing such networks' is a complex challenge, mainly when dealing with numerous conflicting objectives. So far, existing works have employed heuristic or meta-heuristic algorithms to address this issue. This research introduces a novel approach, 'Hybrid Multi-Objective Optimization,' which combines Multi-Objective forms of Red fox (RFOX) optimization with Differential Evolution (DE) to address this issue. This hybrid framework is designed to solve the complexity of Multi-Objective optimization within the context of 6G-enabled IoT networks. It leverages the flexibility and search capabilities of RFOX, along with the population-based search techniques of DE. The primary objective of this research paper is to identify the Pareto-optimal front, which encapsulates the complex trade-offs among various conflict objectives in Multi-Objective optimization. Extensive simulation outcomes demonstrate the significant efficacy of the proposed Algorithm for its adaptability, diversity, and multi-objective optimization capabilities compared to existing ones in terms of data throughput, delay, energy efficiency, and packet loss ratio in 6G-enabled IoT applications.**

***Index Terms*—Adaptation, Red fox Optimization, Differential Evolution, Multi-Objective Evolutionary Algorithms, Internet of Things**

## I. Introduction

The ongoing evolution of wireless networks, leading to the anticipated sixth generation (6G), holds the promise of significant advancements in network capabilities and applications, shaping our digital interactions. The IoT is at the forefront of this transformation, a paradigm shift connecting an ever-expanding array of devices and sensors. The IoT paves the way for defence [1], health-care [2], [3], motion tracking [4], and more [5]. Crucially, 6G-enabled networks are expected to underpin this IoT-driven future.

Shailendra Pratap Singh is with SCSET, Bennett University, Greater Noida, India (e-mail: shail2007singh@gmail.com)

Naween Kumar is with SCSET, Bennett University, Greater Noida, India (e-mail: kr.naween@gmail.com)

Gyanendra Kumar is with the Department IoT and Intelligent Systems, Manipal University Jaipur, Jaipur, India (e-mail: gyanendra.kumar@jaipur.manipal.edu)

Balamurugan Balusamy is with Shiv Nadar Institution of Eminence, Delhi-National Capital Region (NCR), India (e-mail: balamurugan.balusamy@snu.edu.in)

Ali Kashif Bashir is with Networks and Security, Manchester Metropolitan University, UK (e-mail: a.bashir@mmu.ac.uk)

Yasser D. Al-Otaibi is with Department of Information Systems, Faculty of Computing and Information Technology in Rabigh, King Abdulaziz University, Jeddah 21589, Saudi Arabia (e-mail: yalotaibi@kau.edu.sa)

6G networks are projected to deliver terabit-per-second data speeds, ultra-low microsecond latency, and support for numerous devices in confined spaces. However, optimizing integrated 6G-enabled WSN-IoT poses multifaceted challenges with conflicting objectives [6]. These objectives include maximizing data throughput, enhancing energy efficiency, reducing packet loss, improving packet delivery ratio, and minimizing latency for optimal efficiency, dependability, and responsiveness. Maximized data throughput ensures network connectivity, efficient resource utilization, and a seamless user experience for high-bandwidth applications and critical scenarios. Energy efficiency extends the network's operational lifespan. Reducing packet loss, enhancing packet delivery ratio, and minimizing latency ensure reliable data communication and responsiveness, which is crucial in critical scenarios like remote surgery. Balancing these goals is essential to exploit the network's potential fully. The dynamic 6G-enabled IoT ecosystem demands adaptable optimization strategies to meet evolving user demands and network dynamics.

Traditional optimization methods often face limitations when confronted with the complexities of multi-objective challenges involving the simultaneous optimization of diverse network parameters, such as data throughput, packet loss ratio, energy efficiency, packet delivery ratio, and sustainability [7]. While some attempts have been made to balance various network parameters [8], [9], these methods often fall short of achieving a significant mathematical balance between exploration and exploitation. Notably, existing approaches like NSGA-III [10], MOPSO [11], and MOFOX (derived from [12]) algorithms have succeeded in striking a balance between exploration and exploitation but lack the robustness required for managing complex and multi-modal optimization problems, similar to those posed in our study.

Many studies have investigated ensuring Quality of Service (QoS) in communication and network optimization, defining communication index dimensions corresponding to QoS factors like data throughput, delay, energy efficiency, data gathering time, and packet loss ratio. Intelligent capabilities become crucial, introducing considerations beyond communication performance, including end-to-end delay, data throughput, data loss, energy efficiency, traffic congestion [13], and other relevant factors [9]. This shift underscores the inadequacy of single-objective approaches and traditional multi-objective methods in addressing the complexities of emerging network optimization challenges in 6G-enabled IoT systems. To address the concurrent optimisation of multiple network factors in the 6G-enabled IoT communication ecosystem, the Contributions of this article are as follows:

- To introduce two different Multi-Objective algorithms, namely MOFOX and MODE, which are derived by adapting the RFOX [12] and DE [14] algorithms, respectively, to address the proposed optimization problem, while maintaining the network performance requirements of 6G-enabled IoT networks.
- To introduce a flexible, robust, and adaptive hybrid of MOFOX and MODE algorithms, leveraging MOFOX's adept exploration of diverse solution spaces and MODE's efficient exploitation of discovered solutions, the algorithm is tailored to address the proposed problem effectively. This hybrid approach enhances network performance and adaptability.
- To propose Pareto-optimal front solutions for Multi-Objective problems of various conflicting 2-objective and 3-objective scenarios, capturing valuable trade-offs among conflicting objectives. This empowers network operators to navigate complex optimization environments and make better-informed decisions.
- To perform experimental evaluation of proposed hybrid algorithm and compare and validate with the state-of-the-art approaches NSGA-III [10], MOPSO [11], MOFOX [12], and MODE [8] algorithms to prove the proposed method efficacy in achieving data throughput, packet loss ratio, energy consumption, packet delivery ratio, delay, and data transfer time.

The subsequent sections of this research paper are structured as follows: Section II briefly surveys the related work on utilizing multi-objective evolutionary solutions in the 6G-enabled IoT domain and basic preliminaries. Section III describes the proposed Hybrid-based Multi-Objective technique designed around IoT services. The experimental results and analysis are presented in Section IV. Finally, Section V concludes the study and highlights potential directions for future research.

## II. Literature Review

In this section, we briefly survey a few existing multi-objective optimisation methods relevant to this work. Zhang et al. [15] devised an evolutionary method with Penalty strategy to address the constrained multi-objective optimization of cost and QoS. Shrestha et al. [16] have shown the adaptability of 6G-enabled networks to improve coverage of Industrial IoT devices. Barakabitze et al. [17] exploited network orchestration and management to improve QoS using pervasive artificial intelligence, machine learning, and big data analytics. Chaudhry et al. [18] devised an improved-multi-objective PSO method called MOPSO scheme with improved running time to handle multicast routing issues, including different metrics such as energy consumption, latency, and packet loss. Qi et al. [19] introduced two innovative multi-objective-based joint beamforming schemes to maximize the network's overall performance while concurrently minimizing the total transmit power while adhering to stringent performance requirements. Jain et al. [20] introduced a novel metaheuristic approach intricately combined with a blockchain-based resource allocation technique for effectively managing and sharing network resources. Sheena et al. [21] devised an improved, energy-efficient seagull-based multi-objective-optimisation scheme for clustering and load-balancing for IoT-enabled Disastrous Management Scenarios with minimal overhead and better convergence. Salimian et al. [22] used the MOPSO Algorithm to optimize IoT service placement. Their goal was to enhance the utilization of fog resources and improve the QoS in IoT. Khosroabadi et al. [23] introduced the SCATTER algorithm for delay-sensitive applications in integrated fog-cloud environments and addressed the service placement problem with the primary objective of enhancing QoS. Natesha et al. [24] devised a two-level resource provisioning fog framework using a containerization approach and formulated the service placement problem in a fog computing environment as a multi-objective optimization problem for minimizing the cost, energy depletion, service time and thus ensuring the QoS of IoT applications.

Despite extensive research on 6G-enabled IoT networks, there's a need for deeper exploration of conflicting goals, such as data throughput and energy efficiency improvement, requiring further refinement of multi-objective optimization techniques in real and dynamic environments. Additionally, the integration of emerging technologies like machine learning and artificial intelligence remains insufficiently explored, demanding a thorough examination of their applications and limitations. Closing these gaps is crucial for advancing the field for deploying efficient 6G-enabled IoT.

The limitations mentioned above emphasize the need for a comprehensive, efficient, multi-objective solution with the following features: (1) exploiting a multi-objective Algorithm to balance multiple IoT parameters simultaneously, (2) an efficient computational algorithm that works effectively in multi-dimensional space, (3) combining various network attributes to ensure reliable data communication and responsiveness, (4) exploiting a hybrid multi-objective variant where MOFOX having exceptional mathematical ability to balance exploration and exploitation, controls population optimization and adaptation and robustness are controlled by mutation and crossover of MODE for finding a real-time optimal solution to enhance the network performance in adaptable 6G-enabled IoT. Table I compares existing and proposed work across five essential parameters: energy, delay, throughput, packet loss ratio, and data gathering time. In this Table I, a cross mark ($\times$) indicates the parameter's absence, and a tick mark ($\checkmark$) signifies its presence in a specific research study.

### A. *Problem Statement*

In the context of a 6G-enabled Healthcare IoT ecosystem, the goal is to optimise the QoS for a given set $\mathbb{SN}$ of IoT devices $(s_1, s_2, \ldots, s_N)$ along with their respective data-availability set $\mathbb{DAA}$ and initial remaining energy distribution set $\mathbb{IRE}$ across a random 2-D plane. The objective is to jointly optimise various conflicting objectives [8], [10], [25] expressed as:

- Data Throughput Enhancement: Balancing the diverse goals involves improving the overall data throughput in the network.
- Data Loss Minimization: Simultaneously, minimizing the packet loss ratio is crucial to ensure the reliability of the IoT ecosystem.

TABLE I. Comparative analysis of relevant related works

| Authors | Multiple Network Parameters | | | | |
|---|---|---|---|---|---|
| | Energy | Delay | Throughput | Packet Loss Ratio | Data Gathering Time |
| Sheena (2023) | × | ✓ | × | × | × |
| Shrestha (2023) | × | ✓ | × | × | × |
| El-Shorbagy (2019) | ✓ | × | ✓ | ✓ | × |
| Qinyin (2022) | × | × | ✓ | × | × |
| Liang (2021) | × | ✓ | × | × | × |
| Zaborski (2022) | ✓ | ✓ | × | × | × |
| Chaudhry (2019) | ✓ | ✓ | × | ✓ | × |
| Reffad (2023) | ✓ | ✓ | × | × | × |
| Urgelles (2022) | ✓ | × | × | × | ✓ |
| Natesha (2021) | ✓ | × | × | ✓ | ✓ |
| Khosroabadi (2021) | ✓ | × | × | ✓ | × |
| Salimian (2022) | × | ✓ | × | × | × |
| Our Scheme | ✓ | ✓ | ✓ | ✓ | ✓ |

- Packet delivery ratio maximization: Maximizing packet delivery ratio is crucial to ensure the data quality transferred in the IoT ecosystem.
- Energy Efficiency Improvement: The optimization framework aims to enhance energy efficiency, maximizing the utilization of available energy resources.
- Ultra-Low Latency Achievement: Achieving ultra-low latency is a key objective, ensuring swift response times in the dynamic environment.

### B. *Proposed 6G-enabled IoT Framework*

This section introduces a 6G-enabled IoT optimization framework comprising several vital components. Subsection A defines a taxonomy for categorizing services within this 6G-enabled IoT framework. Following that, in Subsection B, the paper provides a detailed explanation of the architecture and intricacies characterizing an IoT-based smart healthcare system. The subsequent Section C introduces a comprehensive framework for an IoT-based healthcare system, setting the stage for the study's subsequent analysis and exploration.

*1) Taxonomy of service placement for 6G-enabled IoT:* This sub-section presents a taxonomy of IoT service-based applications within IoT service placement, as illustrated in Fig. 1 [26], [27]. The taxonomy helps to identify the use of different services, architectures, resources, problem-solving approaches, and applications in the context of the 6G-enabled IoT landscape. This taxonomy highlights the inherent challenges of ensuring QoS and uninterrupted service delivery. To address this issue, a conceptual optimization solution to effectively and efficiently select optimal resources to fulfil service requests across various layers of service processing. This study proposes the problem as a multi-objective optimization problem, considering the heterogeneity intrinsic to IoT-based healthcare applications, the resources at hand, and the distinctive service requirements.

*2) Architecture of IoT based smart healthcare system :* The architecture of an IoT-based smart healthcare system [28] is structured around four fundamental layers: Perception, Decision/Optimization, Cloud/Middle, and Application/Business. The Perception layer consists of sensors that capture various health-related data, including temperature, blood pressure, position, heartbeat, vibration, pulse oximetry, and respiratory rate. These sensors utilize various communication technologies such as Wi-Fi, Infrared, ZigBee, Bluetooth, 5G, and 6G, among others, to transmit this data for further processing. Notably, the optimization technique employed here is agnostic to specific communication technology setups, ensuring compatibility with 5G and 6G and adaptability to other communication technologies. Processed data is then forwarded to the following processing stage. The Decision/Optimization layer is crucial in selecting the most appropriate sensor source using optimization techniques considering IoT's core objectives. This layer dynamically adapts to maximize various objectives, encompassing parameters like service cost, energy efficiency, service load, delay, and other fitness functions. The selected source transfers the data to the upper layers for additional processing. Energy and delay optimization are the primary focus areas within the Optimization layer. In the Middle layer, the primary goal is to enhance QoS by minimizing service costs within the IoT healthcare framework. This layer is dedicated to refining the system's efficiency and performance, ensuring that healthcare services are delivered with the highest possible quality while optimizing operational costs. To evaluate the performance of 6G-enabled IoT systems, we introduce several key metrics, which are explained in detail below:

*3) Proposed 6G-enabled IoT Framework Overview:* The architecture enables seamless information exchange, encompassing patient health records, blood or tissue samples, imaging data, and other related information among the IoT interface devices or nodes. However, it's essential to recognize that the continuous and real-time exchange of multi-sensory information within this IoT ecosystem significantly emphasizes real-time data quality, energy efficiency, and system latency. Furthermore, the energy-intensive operations within this system can potentially lead to rapid energy depletion and the emergence of non-functional or 'dead' IoT nodes [29]. To evaluate the performance of this system, six key objective metrics are used as follows:

1) **Data Throughput ($DT$) - Maximizing**
   It is defined mathematically as follows [30]:

$$Obj1 = (DT) = \frac{Tot_{Data_{received}}}{Tot_{DGT}}, \tag{1}$$

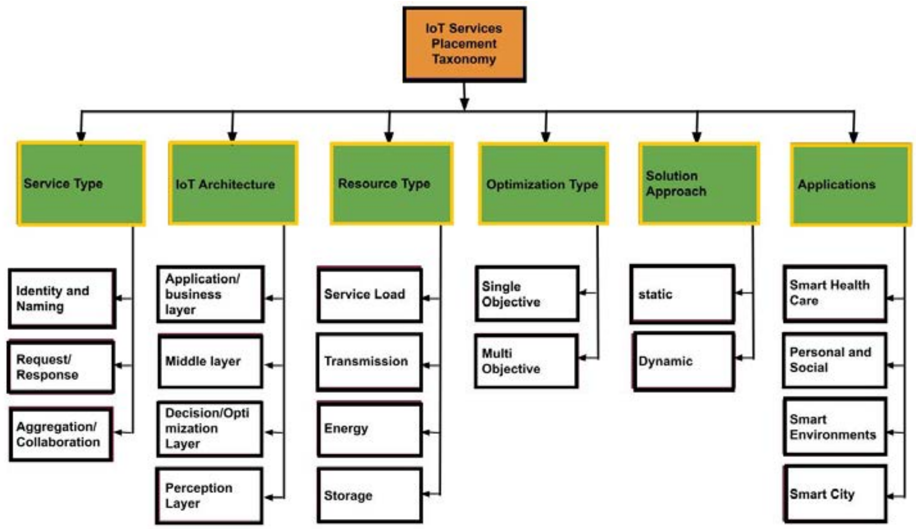


Fig. 1. Various taxonomy of the service placement for 6G-enabled IoT [26], [27]

where $Tot_{Data_{received}}$ denotes total amount of data collected, and $Tot_{DGT}$ denotes total amount of time taken to receive $Tot_{Data_{received}}$ unit data.

2) **Packet Loss Ratio ($PL_{Ratio}$) - Minimizing**
It is exprssed as follows [31]:

$$Obj2 = (PL_{Ratio}) = \frac{Tot_{Data_{sent}} - Tot_{Data_{received}}}{Tot_{Data_{sent}}} \tag{2}$$

3) **Energy Consumption ($TEcon$) - Minimizing**
Energy consumption ($TEcon$) is the total energy all the sensors consume to transfer their all-sensed data to destinations [32]. Its unit of measurement is KiloJoules (KJ).

$$Obj3 = (TEcon) = \frac{Tot_{Data_{sent}}}{E_T}, \tag{3}$$

where $E_t = \frac{E_t}{\mu}$ is a constant and denotes the effective energy consumption for transmission of one unit of data.

4) **Packet Delivery Ratio ($PD_{Ratio}$) - Maximizing**
The packet delivery ratio $PD_{Ratio}$ presents the ratio of the number of received packets and the amount of sent packets [31].

$$Obj4 = PD_{Ratio} = \frac{Tot_{Data_{received}}}{Tot_{Data_{sent}}} \tag{4}$$

5) **Delay - (Minimizing)**
Delay is the time duration to transfer the packet from source to destination than the actual time [32]. Its unit of measurement is in microseconds ($\mu$Sec).

$$Obj5 = D = \frac{Tot_{Data_{sent}} - Tot_{Data_{received}}}{dtr}, \tag{5}$$

where $D$ denotes delay.

6) **Data Transfer Time ($DT$) - Minimizing**
It is the total time for Transferring the total data from all senders to all receivers [33], expressed as follows:

$$Obj6 = DT = \frac{Tot_{Data_{sent}}}{dtr}, \tag{6}$$

where $dtr$ is measured in terms of $Mbps$.

*a) Fitness function of IoT-framework::* The fitness function in an IoT framework refers to a mathematical representation that evaluates the quality or performance of a particular solution or configuration within the framework. It helps guide the optimization process by quantifying the fitness or suitability of different settings, configurations, or decisions. The fitness function in an IoT framework can incorporate various factors and metrics relevant to the specific application and optimization problem, as expressed in Eq. 7.

$$\begin{aligned} Fitness(x, y) = Min(&-Obj1(x, y), Obj2(x, y), Obj3(x, y), \\ &-Obj4(x, y), Obj5(x, y), Obj6(x, y)), \end{aligned} \tag{7}$$

where $x$ denotes $Tot_{Data_{sent}}$ and $y$ denotes $Tot_{Data_{received}}$.

*b) Formulation of 2-objective of IoT service framework:* We created 2-objective functions based on IoT service estimation that conflict with each other during this procedure. As stated in Eq. 8, all objectives are turned into MOP utilizing IoT service settings.

$$F(x, y) = Min(-Obj1(x, y), Obj5(x, y)) \tag{8}$$

The maximization problem of $Obj1(x, y)$ involves calculating the data throughput for the IoT framework when sending data between sensors and receiver, and the term $Obj5(x, y)$ represents the measurement of calculating the delay.

*c) Formulation of 3-objective of IoT service framework:* We designed 3-objective-based IoT-based service estimations that conflict during this procedure. As demonstrated in Eq. 9, all objectives are turned into multi-objective functions utilizing IoT-based service parameters.

$$F(x, y) = Min(Obj3(x, y), -Obj4(x, y), Obj5(x, y)) \tag{9}$$

The minimization problem of $Obj3(x, y)$ involves calculating the energy consumption for sensors in IoT services. Similarly, the maximization problem of $Obj4(x, y)$ pertains to calculating the packet delivery ratio for IoT services based on data transmission from sensor nodes, and $Obj5(x, y)$ represents the objective of minimizing the delay between sensor nodes. The Table II includes the relevant terminology considered in this work.

## III. Proposed Methodology: Hybrid Multi-Objective Optimisation Algorithm

The key strength of the proposed approach lies in its ability to handle a multitude of often conflicting objectives simultaneously. Within the realm of 6G-enabled IoT networks, it handles the need to optimize various aspects such as data throughput, packet loss reduction, energy efficiency, packet delivery ratio, minimizing delays, and optimizing data transfer times. The proposed hybrid methodology employs Red Fox and DE, a comprehensive Multi-Objective optimization framework to generate solutions that balance these diverse objectives.

The Red Fox algorithm demonstrates a high capability to find the best optimal solution by leveraging its foraging-inspired exploration strategies. On the other hand, DE excels in generating a diverse population, contributing to a more robust exploration of the solution space. Combining the strengths of these algorithms in our proposed approach aims to achieve a balance between exploration and exploitation, enhancing the overall efficiency of optimization in the context of 6G-enabled IoT networks.

### A. Proposed MOFOX Optimization

Red FOX Optimisation is the leading exploration and exploitation approach, and Red foxes' adaptability inspires it. Each " Red fox" in the population represents a different optimisation strategy. These Red foxes dynamically modify their tactics according to how well they achieve the various objectives, enabling them to navigate the challenging optimisation environment efficiently. The 6G-enabled IoT networks provide complicated optimisation issues, where various and sometimes competing objectives must be considered simultaneously. The suggested MOFOX Algorithm for Many Objectives has been developed to address these challenges. This technique aims to find a collection of Pareto-optimal solutions, which reflect trade-offs between several goals, including increasing data throughput, minimising packet loss, conserving energy, improving packet delivery ratio, lowering latency, and speeding up data transmission.

The Proposed MOFOX algorithm begins by initializing a population of Red foxes randomly. These "Red foxes" represent individual optimization strategies and dynamically adapt their exploration and exploitation behaviours based on their success in improving the objectives. Key parameters, including the maximum number of generations ($MaxGenerations$), mutation rate ($MutationRate$), and crossover rate ($CrossoverRate$), are initialized. The objectives to be optimized, denoted as $f_1, f_2, \ldots, f_k$, are defined for the 6G-enabled IoT network scenario. The fitness of each Red fox in the population is evaluated by considering these objectives. The Algorithm employs a generation counter, $t$, initialized to zero, to keep track of the optimization process. In the main loop, the Algorithm iteratively selects parent

**Algorithm 1:** Proposed MOFOX Algorithm

**Require:** Initialize population of Red foxes $P$ randomly, parameters: $MaxGenerations$, $MutationRate$, $CrossoverRate$, objectives $f_1, f_2, \ldots, f_k$
**Ensure:** Pareto-optimal solutions and corresponding trade-offs

```
Set t ← 0 {Initialize generation counter}
for t < MaxGenerations do
    Select parent Red foxes for reproduction based on fitness
    Generate offspring using crossover and mutation operators
    Evaluate the fitness of offspring using objectives
    Select the best offspring based on Pareto dominance
    Update the population P with the best offspring
    Apply dynamic adaptation mechanisms to adjust parameters
    t ← t + 1
end for
Identify the Pareto-optimal solutions in P
```

Red foxes for reproduction based on their fitness, generating offspring using crossover and mutation operators. The fitness of the offspring is evaluated concerning the defined objectives. The best offspring, determined through Pareto dominance, is selected to update the population $P$. Furthermore, dynamic adaptation mechanisms are applied to adjust algorithm parameters, allowing it to adapt to changing network conditions and objectives. This iterative process continues until the maximum number of generations specified by $MaxGenerations$ is reached. Subsequently, the Algorithm identifies the Pareto-optimal solutions within the population $P$, representing the trade-offs between the multiple objectives.

TABLE II. Terminologies & Notations

| Symbol | Description |
|---|---|
| $Fitness$ | Fitness function |
| $MOP$ | multi-Objective Optimization Problem |
| $MOA$ | multi-Objective Optimization Algorithm |
| $MaxGenerations$ | Maximum number of generations of Algorithm |
| $PopulationSize$ | Size of population of solution |
| $MutationRate$ | Mutation method |
| $CrossoverRate$ | Crossover method |
| $DV_1$ | Dynamic-based vectors in search area |
| $D$ | Dimensions of search space |
| $IoT$ | Internet of Things |
| $Obj1, Obj2, Obj3, Obj4, Obj5, \&Obj6$ | Objectives functions of IoT service framework |
| $fit_{Rank}$ | Candidate solution select to high fitness value |
| $\vec{\alpha}_{\text{rand},G}$ | Random vector of search area |
| $\alpha_{r_1^i,G}, \alpha_{r_2^i,G}$ | Target vector1 and vector2 of search area |
| $\gamma_{i,G}$ | Standard donor vector of DE algorithm |
| $P$ | Set of Pareto optimal solution |
| $Rank_i$ | First rank Pareto front solutions |

### B. Modified Multi-Objective-based DE Optimisation (MODE)

The proposed MODE algorithm begins by randomly initializing a population of candidate solutions, denoted as $P$. These candidate solutions are potential solutions to the optimization problem. Essential parameters, including the maximum number of generations ($MaxGenerations$), population size ($PopulationSize$), mutation rate ($MutationRate$), and crossover rate ($CrossoverRate$), are set to govern the Algorithm's behaviour. Additionally, the specific objectives to be optimized, labelled as $f_1, f_2, \ldots, f_k$, are defined based on the characteristics of the problem. Each candidate solution in the population is evaluated for its fitness concerning the defined objectives. The Algorithm initializes a generation counter, $t$, to zero, tracking its progress. Within the main loop, the Algorithm iteratively conducts the optimization process. It selects

**Algorithm 2:** Proposed MODE Algorithm

**Require:** Initialize population of candidate solutions $P$ randomly, parameters: $MaxGenerations$, $PopulationSize$, $MutationRate$, $CrossoverRate$, objectives $f_1, f_2, \ldots, f_k$
**Ensure:** Pareto-optimal solutions and corresponding trade-offs
Set $t \leftarrow 0$ {Initialize generation counter}
**for** $t < MaxGenerations$ **do**
    Select parent solutions for reproduction based on fitness and diversity
    Generate offspring using mutation and crossover operators
    Evaluate the fitness of offspring using objectives
    Apply nondominated sorting to create Pareto fronts
    Select solutions for the next generation based on Pareto dominance and diversity
    Apply dynamic adaptation mechanisms to adjust parameters
    $t \leftarrow t + 1$
**end for**
Identify the Pareto-optimal solutions in the final generation

parent solutions for reproduction based on their fitness and diversity, generating offspring through mutation and crossover operators. These offspring are subsequently evaluated based on the defined objectives. The Algorithm then employs non-dominated sorting to create Pareto fronts, identifying solutions not dominated by others regarding objectives. Solutions for the next generation are selected based on Pareto dominance and diversity criteria. Dynamic adaptation mechanisms are applied to fine-tune the Algorithm's parameters, allowing it to adapt effectively to changing optimization landscapes and objectives. This adaptability ensures that the Algorithm can respond to evolving problem characteristics during optimization. The Algorithm continues to iterate until the maximum number of generations specified by $MaxGenerations$ is reached. At this point, the Algorithm identifies the Pareto-optimal solutions within the final generation. These solutions represent a set of trade-off solutions, providing decision-makers with a range of options that balance the multiple and often conflicting objectives of the optimization problem.

### *C. Proposed Hybrid Scheme including MOFOX and MODE*

The hybrid multi-objective optimization algorithm is a powerful approach for resolving complicated optimization issues with several competing objectives, as shown in Algorithm 3. It tries to obtain Pareto-optimal solutions that provide trade-offs between these goals. The Algorithm runs through several generations, each of which improves the quality of the results. The MOFOX Algorithm, a reliable optimization method, is used by the hybrid Algorithm to initialize a population of potential solutions. The fitness of each potential solution is then assessed across all objectives. The primary loop, spanning numerous generations, includes applying MODE-based mutation and crossover operations to parent solutions to produce offspring solutions. After being introduced to the offspring population, these offspring solutions are assessed for their fitness concerning all objectives. The Algorithm then combines the populations of the parents and offspring, applies non-dominated sorting, and generates Pareto fronts. To find attractive trade-offs, Pareto fronts group solutions independent of others. By choosing solutions based on Pareto fronts and diversity preservation techniques, a new population for the following generation is created. In order to improve flexibility in various optimisation settings, the Algorithm also incorporates dynamic adaptation mechanisms to modify the parameters of both the MODE and MOFOX Optimisation algorithms. The Algorithm repeats this step for a predetermined number of generations. The last generation, based on Pareto dominance, identifies Pareto-optimal solutions. These options show the optimal compromises between the many competing agendas.

**Algorithm 3:** Proposed Hybrid Multi-Objective Algorithm including MOFOX and MODE

**Require:** Number of objectives $k$, Population size $PopulationSize$, Maximum generations $MaxGenerations$, DE mutation rate $MutationRate$, DE crossover rate $CrossoverRate$, Red fox Optimization parameters
**Ensure:** Set of Pareto-optimal solutions
Initialize a population of candidate solutions using Red Fox Optimization:
$P \leftarrow$ InitializePopulationUsingRed fox($populationsize$, Red fox Parameters)
Evaluate the fitness of each candidate solution for all $k$ objectives:
$P \leftarrow$ EvaluateFitness($P$)
**for** $generation = 1$ to $MaxGenerations$ **do**
    Create an empty offspring population $O$
    **for** each parent solution $x$ in population $P$ **do**
        Select a random subset of parent solutions for DE-based mutation
        Apply DE mutation operator to generate a trial solution $y$
        Apply crossover with a selected parent to produce an offspring solution $z$
        Evaluate the fitness of the offspring solution $z$ for all $k$ objectives
        Add the offspring solution $z$ to the offspring population $O$
    **end for**
    Combine the parent population $P$ and offspring population $O$ to create a combined population $Q$
    Perform non-dominated sorting on $Q$ to create Pareto fronts
    Create a new empty population $P_{next}$
    Select solutions for the next generation based on Pareto fronts, crowding distance, and diversity preservation strategies:
    $P_{next} \leftarrow$ SelectNextGeneration($Q$, Pareto Fronts, Diversity Preservation)
    Apply dynamic adaptation mechanisms to adjust DE and Red Fox optimization parameters
**end for**
Identify the Pareto-optimal solutions in the final generation:
$ParetoOptimalSolutions \leftarrow$ IdentifyParetoOptimal($P_{next}$)
**return** ParetoOptimalSolutions representing trade-offs among $k$ objectives

### *D. The Proposed Algorithm applied in the application of IoT*

The challenging job of optimizing 6G-enabled IoT networks, characterized by many and sometimes competing objectives, is addressed by the Algorithm being given. The proposed technique blends MOFOX Optimization and MODE optimization to develop solutions that balance the various aims. The MOFOX Algorithm creates an initial population of potential solutions to start optimisation. These solutions show possible setups for enhancing IoT network performance. The Algorithm then assesses each candidate solution's fitness, considering both general multi-objective optimisation goals and particular goals relevant to 6G-enabled IoT in addition to the general goals. These goals include data speed, packet loss, energy use, and other crucial performance indicators. The method applies MODE mutation and crossover operations on parent solutions to produce offspring solutions within each generation. All objectives, including those particular to IoT, are rigorously evaluated to determine the fitness of these offspring solutions. This guarantees that the Algorithm can successfully negotiate these objectives' complex interconnections and trade-offs. These fronts are produced using group solutions that other groups and non-dominated sorting do not dominate. Notably, the sorting procedure considers IoT-specific goals, improving the ability to find solutions that match the needs of 6G-enabled IoT. Then, while considering IoT-specific goals, solutions for the following generation are chosen using Pareto fronts and diversity preservation methodologies. This algorithm method considerably aids the design and operation of reliable and effective 6G-enabled IoT networks that can accommodate the demands of new applications and services.

**Algorithm 4:** Multi-Objective Optimization for 6G-enabled IoT Networks

**Require:** Number of objectives: $k$, Population size: $PopulationSize$, Maximum generations: $MaxGenerations$, DE mutation rate: $MutationRate$, DE crossover rate: $CrossoverRate$, Red fox Optimization parameters, Set of IoT network-specific objectives: $IoTObjectives$ (e.g., data throughput, packet loss, energy consumption)
**Ensure:** Set of Pareto-optimal solutions: $ParetoOptimalSolutions$

```
Initialization:
P ← InitializePopulationUsingRedfox(PopulationSize,
Red fox Parameters)
P ← EvaluateFitness(P, IoTObjectives)
for generation = 1 to MaxGenerations do
    Create an empty offspring population O
    for each parent solution x in population P do
        Select a random subset of parent solutions for DE-based mutation
        y ← Apply the DE mutation operator to generate a trial solution
        z ← Apply crossover with a selected parent to produce an
        offspring solution
        Evaluate the fitness of offspring solution z for all k objectives,
        including IoTObjectives
        Add offspring solution z to offspring population O
    end for
    Combine parent population P and offspring population O to create
    a combined population Q
    Perform non-dominated sorting on Q to create Pareto fronts,
    considering IoTObjectives
    Create a new empty population P_next
    P_next ← SelectNextGeneration(Q, Pareto Fronts, Crowding
    Distance, Diversity Preservation, IoTObjectives)
    Apply dynamic adaptation mechanisms to adjust DE and Red Fox
    optimization parameters
end for
Identify Pareto-optimal solutions in the final generation:
ParetoOptimalSolutions ← IdentifyParetoOptimal(P_next)
return ParetoOptimalSolutions representing trade-offs among k
objectives, including IoTObjectives
```

## IV. Result Analysis and Discussions

The proposed work is assessed using benchmark functions in the 6G-enabled IoT framework. In a series of tests within 6G-enabled IoT-based QoS services, our technique is thoroughly evaluated. We focus on real 6G-enabled IoT application scenarios from the IoT services sphere, each defined as a multi-objective optimization problem with three goals. Scenarios represent diverse service models based on service requests and sensor-generated solutions. Our innovative methodology, integrating Hybrid adaptation-based approaches for optimization, successfully handles the complexity of these multi-objective scenarios, considering natural trade-offs. We conducted studies on a Windows 11 platform using MATLAB 2023a, utilizing a Core-i7 CPU running at 3.6GHz and 8GB of RAM. This comprehensive assessment reveals insights into the effectiveness and potential of our technique in addressing 6G-enabled IoT-based service challenges. Scenarios from IoT-based services [10], [25], [29] are used to test our proposed method, covering various QoS parameters.

- Diversity measures the spread of solutions across the Pareto front, including those relevant to 6G-enabled IoT. An expansive and diverse set of solutions signifies the algorithm's ability to traverse diverse areas within the search space and capture a wide array of trade-off solutions, particularly in the context of 6G-enabled IoT applications.
- The proposed system relies on simulating the six DTLZ (3-objective) scenarios, as illustrated in Table III.
- Data throughput, packet delivery ratio, energy consumption, and latency are performance evaluation requirements for 6G-enabled IoT. These metrics evaluate the algorithm's ability to cover the whole Pareto front. The algorithm's results should ideally be distributed uniformly throughout the front, covering a variety of solutions from different parts of the search space. This strategy ensures that it supports a wide range of tastes and needs within the fluid environment of 6G-enabled IoT applications.
- The proposed method determines how quickly the algorithm could reach the Pareto front. A faster convergence speed indicates higher effectiveness in finding the best solutions.

TABLE III. Framework scenario of the IoT services

| Problem Variant | Control Parameters and Characteristics |
|---|---|
| DTLZ1 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Convex Pareto Front - Uniformly Distributed Solutions |
| DTLZ2 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Concave Pareto Front - Non-Uniformly Distributed Solutions |
| DTLZ3 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Concave Pareto Front - Uniformly Distributed Solutions |
| DTLZ4 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Convex Pareto Front - Non-Uniformly Distributed Solutions |
| DTLZ5 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Mix of Convex and Concave Pareto Front - Uniformly Distributed Solutions |
| DTLZ6 | - Number of Objectives (M) - Number of Variables (n) - Number of Constraints (k) - Problem Dimension (k + M - 1) - Scaling Factor (λ) - Mix of Convex and Concave Pareto Front - Non-Uniformly Distributed Solutions |

*1) Experimental setup:* In our IoT framework's experimental setup, 150 sensors are deployed in uniform distribution across a 2-D dimensional area. Within the 6G-enabled IoT system, these sensors serve as service request agents. Additionally, we have included 150 active sensors that work as service providers and are responsible for producing response data in response to incoming requests from various entities, such as processes, people, and linked devices inside the system. We developed an area for testing as a $15 \times 15$ matrix to focus our attention and preserve a particular location within the IoT framework. We conducted studies using the development of 15 service requests within this matrix, all independently produced and unaffected by the three different service methodologies [25], [34].

In Table III, we explored six service strategies (scenarios) within the 6G-enabled IoT framework, each subjected to sensor availability. These scenarios, reflected in three dimensions, represented various configurations of the IoT service framework. We aimed to evaluate their effectiveness by calculating critical performance parameters—service traffic, energy loss, load, and latency. The proposed algorithm was run 30 times, ensuring statistically meaningful results and considering variability. We assessed performance indicators through iterative processes, including packet delivery ratio, energy expenditure, packet loss ratio, and delays. This approach allowed us to capture performance variation comprehensively, evaluating the method's consistency and robustness in the 6G-enabled IoT framework. We focused on understanding trade-offs and Pareto front representation related to packet loss, packet delivery ratio, energy utilization, and delay—critical factors in optimizing IoT services for the 6G-enabled future.

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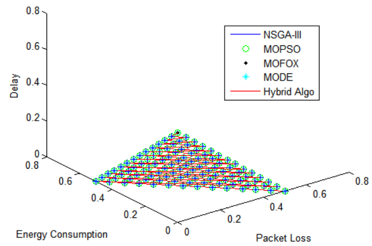
*2) 6G-IoT Framework: Fitness Cost Performance Comparison of Optimization Algorithms:* Table IV presents valuable insights into the performance of the proposed Hybrid algorithm in contrast to many established optimisation algorithms, notably NSGA-III [10], MOPSO [11], MOFOX [12], and MODE [8]. These comparisons were carried out under various experimental circumstances, including varying numbers of generations, number of runs (30), and aims. To begin, it is clear that as the number of generations grows, all algorithms provide improved fitness cost values, as expected, given the extensive exploration of the search area. Across the generations evaluated, the Hybrid algorithm consistently demonstrates competitive or better performance than its alternatives. Table IV reveals the algorithms' performance under multi-objective optimization scenarios with 3, 5, 8, and 10 objectives. The Hybrid algorithm adapts to increasing complexity, consistently achieving high-quality results and demonstrating flexibility in diverse multi-objective settings. Employing 30 runs per configuration underscores the algorithm's resilience and reliability, which are critical for real-world applications. The Hybrid algorithm consistently outperforms others in fitness cost values, excelling in identifying high-quality solutions ("Best" fitness cost values) while avoiding low-quality solutions ("Worst" fitness cost values). The Hybrid algorithm maintains its competitive and consistent performance regardless of experimental settings, positioning it as a strong candidate for handling complex multi-objective optimization challenges, particularly in the 6G-enabled IoT framework. It achieves better results due to its leveraging hybridization of techniques and an optimal balance between exploration and exploitation, making it adaptable to diverse problem characteristics.

*3) 6G-enabled-IoT Framework Analysis of the Pareto Front in 3-Objectives: Packet Loss, Energy Consumption, and Delay:* The proposed method has demonstrated superior performance to other algorithms, particularly in achieving optimal values using a non-dominating sorting algorithm for energy, delay, and load. Across various scenarios, it consistently attains higher Pareto ranks, as evidenced in Figs. 2(a), 2(b), 2(c), 2(d), 2(e), and 2(f). In Fig. 2, we visualize the results, where the X-axis represents energy, the Y-axis represents delay, and the Z-axis represents load, based on the multi-objective problem defined in Eq. 9. The proposed approach significantly enhances both the diversity and rate of convergence for scenario-based services. The well-spread Pareto fronts showcased in the figures signify the algorithm's remarkable ability to provide diverse optimal solutions, empowering decision-makers with various choices across scenario-based services. It is important to note that the method we propose regularly achieves superior optimal values than conventional algorithms like NSGA-III [10], MOPSO [11], MOFOX [12], and MODE [8]. This performance advantage underlines our strategy's success in minimising packet loss, maximising energy efficiency, and minimising latency inside the 6G-enabled IoT context. These outcomes confirm the algorithm's applicability for improving performance and service quality in 6G-enabled IoT applications.

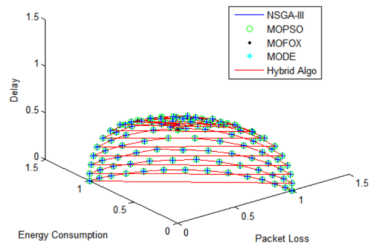
*4) Pareto Front: Multi-Objective-Based 6G-enabled-IoT Framework:* We have examined the complex interplay between data throughput and packet delivery ratio, two crucial performance indicators for reliable and effective communication networks, inside the 6G-enabled IoT architecture. Our research's generation of a Pareto front offers a thorough analysis of trade-offs and ideal solutions in the context of 6G-enabled IoT applications. The main conclusions and result analysis are as follows:

1. Data Throughput and Packet Delivery Ratio in a Multi-Objective-Based 6G-enabled-IoT Framework as evidenced in Figs. 3(a) and 3(b): We analyze the complex interaction between communication network criteria, specifically packet delivery ratio and data throughput. Our investigation reports key findings showcased in the Pareto front order. It highlights the necessity of optimization to balance these aspects, illuminating the trade-off dynamics between Data Throughput and Packet Delivery Ratio. The Pareto front supports benchmarking performance and finding effective methods. Additionally, it permits dynamic adaptability to changing network circumstances or application demands. Our study highlights how crucial it is to make well-informed judgments in order to satisfy various IoT demands in the evolving 6G-enabled environment.

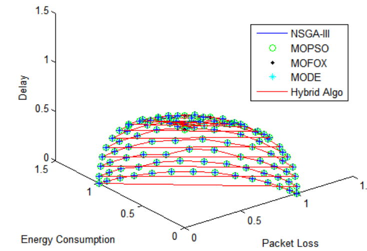
2. Energy Consumption and Packet Delivery Ratio in a Multi-Objective-Based 6G-enabled-IoT Framework as evidenced in Fig. 4: The fundamental trade-off dynamics between Energy Consumption and Packet Delivery Ratio in diverse 6G-enabled-IoT situations are vividly shown by the Pareto front, emphasizing the necessity for strategic optimization to attain an ideal balance. Improving the Packet Delivery Ratio at the expense of energy efficiency can result in higher energy consumption and vice versa. The Pareto front offers a broad set of solutions, each representing a different equilibrium point between these two important measures. This variety gives network operators the freedom to choose solutions that perfectly match the requirements and limits of their IoT applications, enabling personalized optimization to



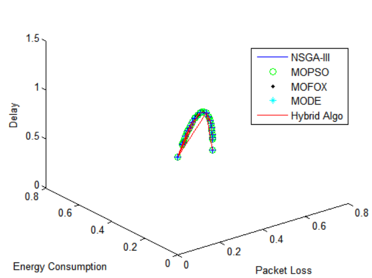

(a) 3-objectives variant 1



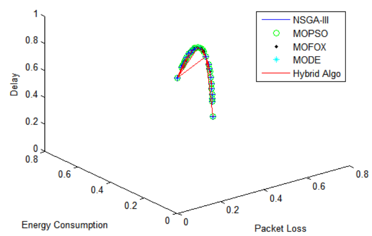

(b) 3-objectives variant 2



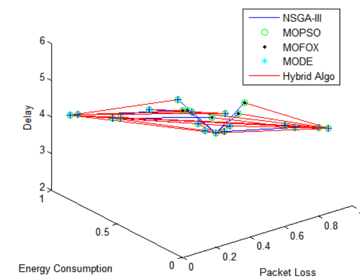

(c) 3-objectives variant 3




(d) 3-objectives variant 4

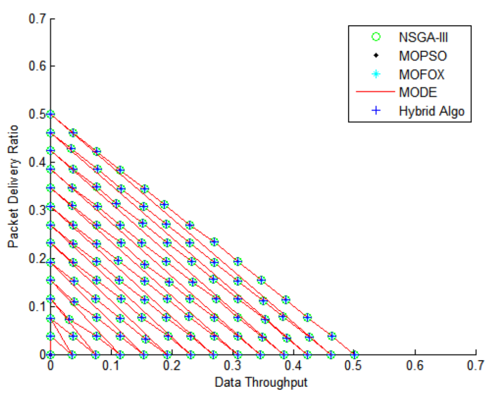



(e) 3-objectives variant 5

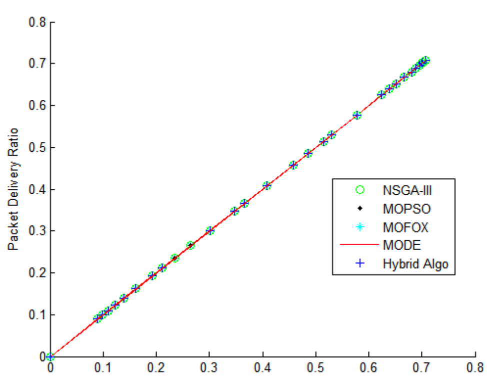



(f) 3-objectives variant 6

Fig. 2. Pareto front: Packet loss, energy, v/s Delay on 3-objectives functions




(a) DTLZ1: Data Throughput and Packet Delivery Ratio




(b) DTLZ5: Data Throughput and Packet Delivery Ratio

Fig. 3. Data Throughput and Packet Delivery Ratio in a Multi-Objective-Based 6G-IoT Framework

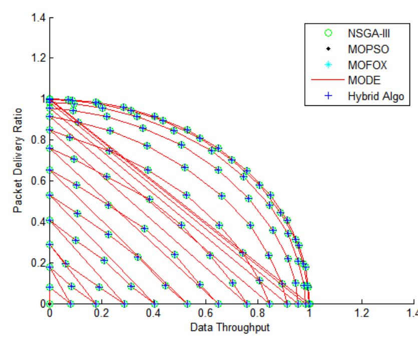



Fig. 4. Energy Consumption and Packet Delivery Ratio in a Multi-Objective-Based 6G-IoT Framework

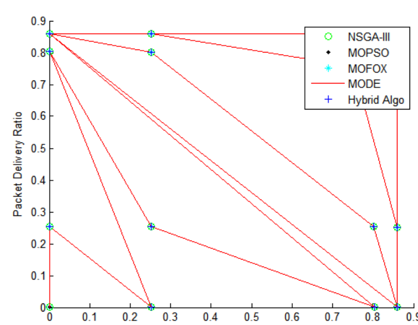



Fig. 5. Packet Transfer Rate and Packet Delivery Ratio in a Multi-Objective-Based 6G-IoT Framework

TABLE IV. 6G-IoT Framework: Fitness Cost Performance Comparison of Optimization Algorithms

| No. of Gen. | No. of Obj. | NSGA-III Algo [10] | | MOPSO Algo [11] | | MOFOX Algo [12] | | MODE Algo [8] | | Hybrid Algo | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Best | Worse | Best | Worse | Best | Worse | Best | Worse | Best | Worse |
| 20 | 3 | 5.523 | 7.101 | 4.734 | 6.7065 | 6.312 | 7.6533 | 4.3395 | 6.6276 | 3.945 | 6.0753 |
| 40 | 3 | 3.746 | 5.102 | 4.068 | 5.763 | 5.424 | 6.5766 | 3.729 | 5.6952 | 3.39 | 5.2206 |
| 60 | 3 | 4.62 | 5.94 | 3.96 | 5.61 | 5.28 | 6.402 | 3.63 | 5.544 | 3.3 | 5.082 |
| 80 | 3 | 3.969 | 5.103 | 3.402 | 4.8195 | 4.536 | 5.4999 | 3.1185 | 4.7628 | 2.835 | 4.3659 |
| 100 | 3 | 3.192 | 4.104 | 2.736 | 3.876 | 3.648 | 4.4232 | 2.508 | 3.8304 | 2.28 | 3.5112 |
| 120 | 3 | 2.947 | 3.789 | 2.526 | 3.5785 | 3.368 | 4.0837 | 2.3155 | 3.5364 | 2.105 | 3.2417 |
| 140 | 3 | 2.457 | 3.159 | 2.106 | 2.9835 | 2.808 | 3.4047 | 1.9305 | 2.9484 | 1.755 | 2.7027 |
| 160 | 3 | 2.268 | 2.916 | 1.944 | 2.754 | 2.592 | 3.1428 | 1.482 | 2.7216 | 1.62 | 2.4948 |
| 180 | 3 | 1.477 | 1.899 | 1.266 | 1.7935 | 1.688 | 2.0467 | 1.1605 | 1.7724 | 1.055 | 1.6247 |
| 200 | 3 | 1.169 | 1.503 | 1.002 | 1.4195 | 1.336 | 1.6199 | 0.9185 | 1.4028 | 0.835 | 1.2859 |
| 20 | 5 | 6.216 | 7.992 | 5.328 | 7.548 | 7.104 | 8.6136 | 4.884 | 7.4592 | 4.44 | 6.8376 |
| 40 | 5 | 6.132 | 7.884 | 4.256 | 6.446 | 7.008 | 8.4972 | 4.818 | 7.3584 | 4.38 | 6.7452 |
| 60 | 5 | 5.516 | 7.092 | 4.728 | 6.698 | 6.304 | 7.6436 | 4.334 | 6.6192 | 3.94 | 6.0676 |
| 80 | 5 | 5.355 | 6.885 | 4.59 | 6.5025 | 6.12 | 7.4205 | 4.2075 | 6.426 | 3.825 | 5.8905 |
| 100 | 5 | 5.201 | 6.687 | 4.458 | 6.3155 | 5.944 | 7.2071 | 3.865 | 5.2412 | 3.715 | 5.7211 |
| 120 | 5 | 4.823 | 6.201 | 4.134 | 5.8565 | 5.512 | 6.6833 | 3.7895 | 5.7876 | 3.445 | 5.3053 |
| 140 | 5 | 3.724 | 4.788 | 3.192 | 4.522 | 4.256 | 5.1604 | 2.926 | 4.4688 | 2.66 | 4.0964 |
| 160 | 5 | 3.169 | 4.203 | 2.802 | 3.9695 | 3.736 | 4.5299 | 2.5685 | 3.9228 | 2.335 | 3.5959 |
| 180 | 5 | 2.513 | 3.231 | 2.154 | 3.0515 | 2.872 | 3.4823 | 1.9745 | 3.0156 | 1.795 | 2.7643 |
| 200 | 5 | 2.254 | 2.898 | 1.932 | 2.737 | 2.576 | 3.1234 | 1.771 | 2.7048 | 1.61 | 2.4794 |
| 20 | 8 | 6.293 | 8.091 | 5.394 | 7.6415 | 7.192 | 8.7203 | 4.9445 | 7.5516 | 4.495 | 6.9223 |
| 40 | 8 | 6.237 | 8.019 | 5.346 | 7.5735 | 7.128 | 8.6427 | 4.9005 | 7.4844 | 4.455 | 6.8607 |
| 60 | 8 | 6.146 | 7.902 | 5.268 | 7.463 | 7.024 | 8.5166 | 4.829 | 7.3752 | 4.39 | 6.7606 |
| 80 | 8 | 5.901 | 7.587 | 5.058 | 7.1655 | 6.744 | 8.1771 | 4.6365 | 7.0812 | 4.215 | 6.4911 |
| 100 | 8 | 3.361 | 5.007 | 3.738 | 5.2955 | 4.984 | 6.0431 | 3.4265 | 5.2332 | 3.115 | 4.7971 |
| 120 | 8 | 3.997 | 5.139 | 3.426 | 4.8535 | 4.568 | 5.5387 | 2.7405 | 4.0964 | 2.855 | 4.3967 |
| 140 | 8 | 3.521 | 4.527 | 3.018 | 4.2755 | 4.024 | 4.8791 | 2.7665 | 4.2252 | 2.515 | 3.8731 |
| 160 | 8 | 2.842 | 3.654 | 2.436 | 3.451 | 3.248 | 3.9382 | 2.233 | 3.4104 | 2.03 | 3.1262 |
| 180 | 8 | 2.583 | 3.321 | 2.214 | 3.1365 | 2.952 | 3.5793 | 2.0295 | 3.0996 | 1.845 | 2.8413 |
| 200 | 8 | 2.114 | 2.718 | 1.812 | 2.567 | 2.416 | 2.9294 | 1.661 | 2.5368 | 1.51 | 2.3254 |
| 20 | 10 | 6.916 | 8.892 | 5.928 | 8.398 | 7.904 | 9.5836 | 5.434 | 8.2992 | 4.94 | 7.6076 |
| 40 | 10 | 6.832 | 8.784 | 5.856 | 8.296 | 7.808 | 9.4672 | 5.368 | 8.1984 | 4.88 | 7.5152 |
| 60 | 10 | 6.601 | 8.487 | 4.658 | 7.0155 | 7.544 | 9.1471 | 5.1865 | 7.9212 | 4.715 | 7.2611 |
| 80 | 10 | 6.447 | 8.289 | 5.526 | 7.8285 | 7.368 | 8.9337 | 5.0655 | 7.7364 | 4.605 | 7.0917 |
| 100 | 10 | 4.816 | 6.192 | 4.128 | 5.848 | 5.504 | 6.6736 | 3.784 | 5.7792 | 3.44 | 5.2976 |
| 120 | 10 | 4.032 | 5.184 | 2.756 | 4.396 | 4.608 | 5.5872 | 3.168 | 4.8384 | 2.88 | 4.4352 |
| 140 | 10 | 3.549 | 4.563 | 3.042 | 4.3095 | 4.056 | 4.9179 | 2.7885 | 4.2588 | 2.535 | 3.9039 |
| 160 | 10 | 3.409 | 4.383 | 2.922 | 4.1395 | 3.896 | 4.7239 | 2.6785 | 4.0908 | 2.435 | 3.7499 |
| 180 | 10 | 3.122 | 4.014 | 2.676 | 3.791 | 3.568 | 4.3262 | 2.453 | 3.7464 | 2.23 | 3.4342 |
| 200 | 10 | 3.031 | 3.897 | 2.598 | 3.6805 | 3.464 | 4.2001 | 2.3815 | 3.6372 | 2.165 | 3.3341 |

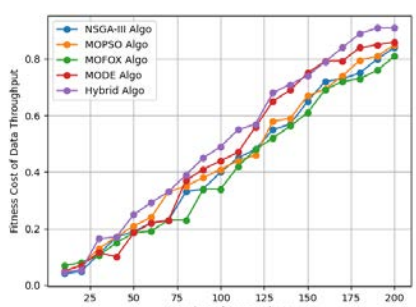



Fig. 6. Data Throughput of 6G-IoT Service

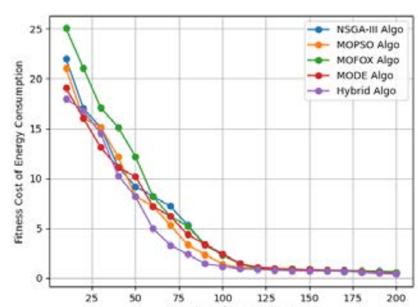



Fig. 7. Energy Consumption of 6G-IoT Service

make decisions that correspond with their goals and get the best results.

3. Packet Transfer Rate and Packet Delivery Ratio in a Multi-Objective-Based 6G-enabled-IoT Framework as evidenced in Fig. 5: In our investigation, the dynamics of the trade-off between packet transfer rate and packet delivery ratio are strongly highlighted. The packet delivery ratio frequently decreases when the packet transfer rate rises and vice versa. This trade-off highlights how important it is for network optimisation to find the right balance between these two crucial indicators. The Pareto front that our study produced is distinguished by its variety, exhibiting a wide range of options. Each point along this front denotes a different point at which the Packet Transfer Rate and Packet Delivery Ratio have reached equilibrium. This variety allows network operators to choose products that closely match the demands and limitations of particular IoT applications, enabling specialized optimisation.

*5) Multi-Objective-Based 6G-enabled-IoT Framework:* In Figure 6, we conducted a performance comparison between our Hybrid algorithm and joint optimization approaches, including NSGA-III [10], MOPSO [11], MOFOX [12], and

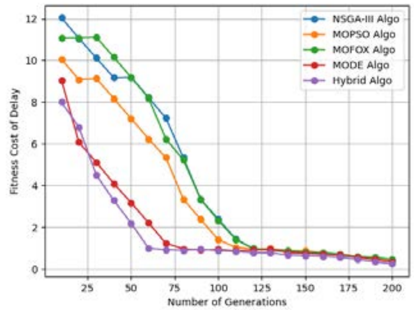



Fig. 8. Delay of 6G-IoT Service

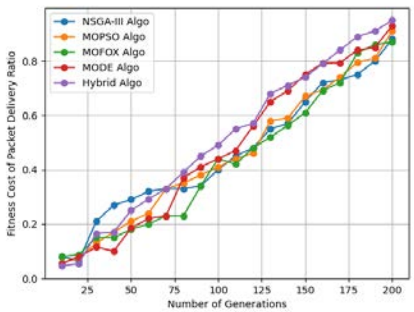



Fig. 9. Packet Delivery of 6G-IoT Service

MODE [8], across 200 generations within the 6G-enabled IoT framework, with a focus on Data Throughput. The Hybrid algorithm consistently outperformed its competitors, achieving higher Data Throughput over generations. Its reliability and consistency ensured steady data transfer rates for IoT applications. In contrast to conventional methods, our Hybrid algorithm's multi-objective optimization capabilities struck a fine balance between objectives, resulting in improved Data Throughput without compromising other critical metrics. This performance enhancement is significant, promising faster and more efficient data transfer, reduced latency, and improved network performance in the 6G-enabled IoT landscape.

*6) Energy Consumption and Delay Over 200 Generations in the 6G-enabled-IoT Framework:* In Figures 7 and 8, we carried out a performance evaluation, comparing our novel Hybrid algorithm with conventional optimization methods, including NSGA-III [10], MOPSO [11], MOFOX [12], and MODE [8]. This assessment spanned 200 generations within the framework of 6G-enabled IoT, with a particular focus on two critical metrics: energy consumption and delay. The results were quite surprising. The Hybrid algorithm consistently outperformed the others, achieving lower energy consumption and reduced delay, showcasing its effectiveness in optimizing energy efficiency and communication speed in the context of 6G-enabled IoT. The algorithm's reliability and steady maintenance of these low values underscore its suitability for maintaining low-latency, energy-efficient IoT connections. In contrast to standard methods, our Hybrid algorithm excelled in simultaneously reducing energy consumption and delay thanks to its multi-objective optimization capabilities.

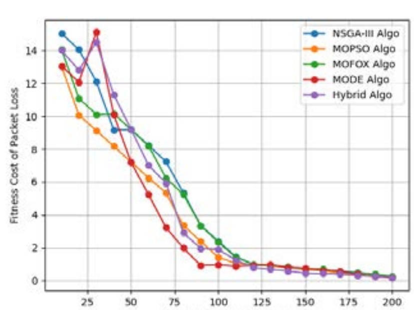



Fig. 10. Packet Loss Ratio of 6G-IoT Service

*7) Packet loss Over 200 Generations in the 6G-enabled-IoT Framework:* In Figure 10, we rigorously compared the performance of our proposed Hybrid algorithm to existing optimisation strategies such as NSGA-III [10], MOPSO [11], MOFOX [12], and MODE [8] across 200 generations inside the 6G-enabled-IoT environment. The critical statistic of Packet Loss was the core focus of this examination. The outcomes were both positive and eye-opening. The Hybrid algorithm consistently performed better than typical approaches, delivering reduced Packet Loss. This proven performance highlights the algorithm's effectiveness in preventing data loss and delivering the strong and trustworthy connectivity necessary in the dynamic 6G-enabled IoT Scenario. Furthermore, as demonstrated by its ability to retain decreased Packet Loss values across generations, the algorithm's consistency and dependability are critical for ensuring dependable data transmission in IoT applications. In direct contrast to the traditional approaches, our Hybrid algorithm regularly outperformed them by attaining reduced Packet Loss. This validates its robustness and efficiency in optimising Packet Loss while considering various IoT application demands. In practice, the Hybrid algorithm's effectiveness in minimising Packet Loss is crucial for 6G-enabled IoT applications, as it opens up the possibility of increased data dependability, decreased retransmission cost, and improved QoS in the 6G-enabled era.

## V. Conclusion

This article proposed a new Hybrid Algorithm to address the conflicting objectives, including data throughput, energy efficiency, packet loss, packet delivery ratio, and latency for optimal efficiency, dependability, and responsiveness in 6G-enabled IoT networks. The proposed algorithm combines the robustness of the MOFOX algorithm with the diverse exploration of the MODE algorithm, allowing us to find Pareto-optimal solutions. Through rigorous experimentation and assessment, we have shown the algorithm's efficacy in handling the several optimisation needs of 6G-enabled IoT networks. It has regularly delivered sets of Pareto-optimal solutions that suit a wide range of application scenarios, from increasing data throughput and reducing packet loss to reducing energy usage and improving packet delivery ratios. Our approach is a step forward in optimising 6G-enabled

IoT networks. However, the proposed hybrid algorithm, being metaheuristic, may face challenges in promptly adapting to dynamic changes, discovering patterns, and adjusting strategies in evolving conditions. It might exhibit limitations in real-time decision-making speed and require more problem-solving intelligence for complex and uncertain scenarios. Integrating AI into this algorithm can enhance its adaptability, learning capabilities, and problem-solving intelligence, making it more suitable for addressing similar problems. In the future, the aim is to improve the efficiency, reliability, and adaptability of 6G-enabled IoT networks by integrating AI techniques, enabling them to support a wide range of dynamic 6G-enabled IoT applications.

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