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INTELLIGENT DYNAMIC SWITCHING BETWEEN IRS AND DECODE AND FORWARD RELAY: A CHANNEL-AWARE OPTIMIZATION APPROACH FOR 6G NETWORKS

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ABSTRACT

This paper proposes a dynamic switching framework between Intelligent Reflecting Surface (IRS) and Decode-and-Forward (DF) relay transmission modes for next-generation wireless communication systems. Unlike existing studies that rely on static technology selection, the proposed approach enables channel-aware mode adaptation based on instantaneous channel conditions and energy efficiency considerations. The framework supports four operational modes: IRS-only, DF-only, hybrid IRS–DF, and direct SISO transmission. An efficient mode selection algorithm is developed to maximize achievable rate while accounting for power consumption and switching overhead. Simulation results demonstrate up to 20.2% improvement in spectral efficiency and 10.1% enhancement in energy efficiency compared to conventional static schemes, under realistic channel conditions. The proposed framework exhibits low computational complexity, making it suitable for practical 6G network deployment.

I. INTRODUCTION

I.1 BACKGROUND AND MOTIVATION

With sixth generation (6G) wireless networks are set to require new and unprecedented of improvement in data rates, energy efficiency, and network reliability [1]. With the proliferation of connected devices and data-based applications continues to proliferate, future wireless systems must obtain 10-100× spectral efficiency improvements (relative to 5G) and achieve energy consumption reductions that are numerous orders of magnitude lower [2] . Two emerging technologies are receiving a lot of interest because they can improve wireless communication performance: Intelligent Reflecting Surfaces (IRS) and Decode-and-Forward (DF) relaying systems. Intelligent Reflecting Surfaces, or Reconfigurable Intelligent Surfaces (RIS), are a novel and paradigm-shifting technology in wireless communications that convert the traditionally uncontrolled wireless environment into a programmable and intelligent channel [3].

The surfaces consist of multiple passives reflecting elements, each of which can be independently and reconfigurable programmed to modulate the phase and amplitude of the incident electromagnetic waves [4], [5]. Figure 1 shown the deployment of RIS in a building for communication, demonstrated that IRS can achieve substantial transmit power reduction while meeting users' signal-to-interference-plus-noise ratio (SINR) constraints through joint optimization of active beamforming at the access point and passive phase shift control at the IRS. The inherent strength in this is the quadratic scaling law of received power with the number of reflecting elements, which is an achievable superior result relative to the conventional relaying methods, which has linear scaling feature [6].

Alternatively, it is in code-and-Forward relaying that has been widely researched as a cooperative communication method that can substantially enhance wireless network coverage and reliability.[7]. In DF relaying, intermediate nodes decode the received signals, process them, and retransmit the information to the destination, potentially providing better performance than simple amplify-and-forward approaches [8]. established diversity–multiplexing tradeoffs for cooperative diversity systems, a potential research avenue lies in designing deep reinforcement learning–driven mmWave-NOMA frameworks that integrate DF relaying to exploit full diversity gains under favorable channel conditions, thereby enhancing spectral efficiency, reliability, and latency performance in 6G networks[9].

The Figure 2 shown the system model considers an identical placement of IRS, AF, and DF relays, enabling the destination to receive both direct and reflected signals from the source for fair performance comparison [10].

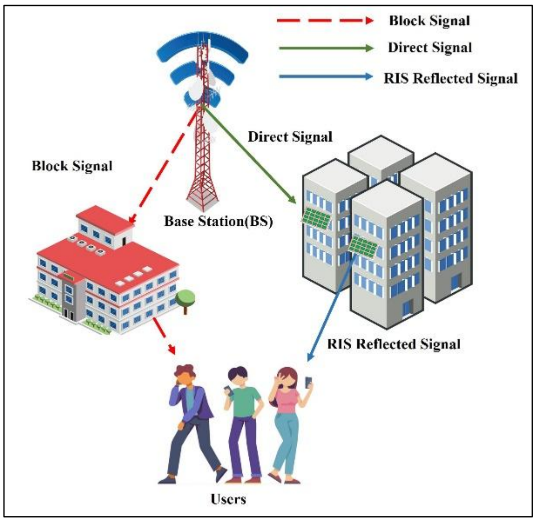

Figure 1: Deployment scenarios of IRSs in future 6G networks.
Source: [6].

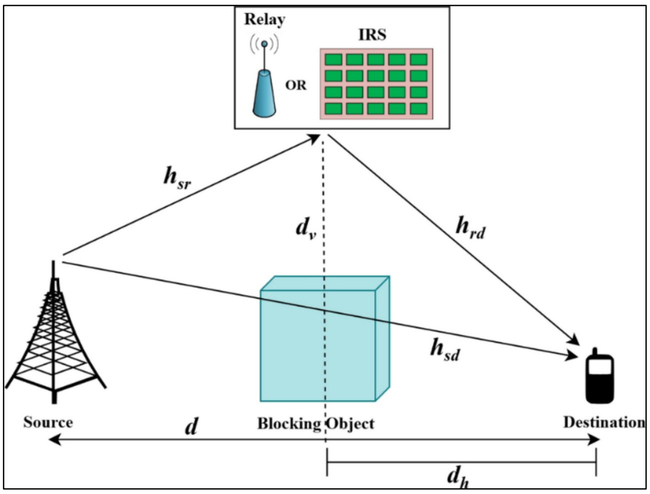

Figure 2: depicts the system with co-located IRS, AF, and DF relays to ensure unbiased performance evaluation.
Source: [10].

Nevertheless, although the two technologies focus on enhancing the quality of signals by alternative ways of propagation, they have absolutely different principles of operation and come with different performance attributes in varying environmental conditions. The recent developments in IRS technology have shown some stunning promise on improving spectral efficiency and energy efficiency [11]. By [12] later in another study presented the an in-depth study on a static comparison between IRS and DF relay system arguing that very large IRS surfaces (in the order of hundreds of elements) are needed to achieve a better performance in relation to transmit power minimization and energy efficiency than DF relaying. In their analysis, they have identified the inherent trade-offs between the complexity of deployment and the performance benefits hence showing that the choice between IRS and DF relay is sensitive to the system parameters including the number of reflecting elements, channel conditions, and power budget constraints.

Nevertheless, this discussion assumes a constant technology decision during the communication session, which might not be the best in dynamically wireless communication where the channel condition varies over time, users move freely, and the amount of energy available changes. This is especially due to the fact that the situation with 6G technology selection is limited and this limitation is especially noticeable in real-life conditions when the choice of the channel can fluctuate radically because of the movement of users, change of the environment, and interference patterns. Recent effort has given emphasis on realistic hardware impairment, like quantization phase error in IRS elements, which may drastically impair system performance depending on different operational conditions. Likewise, the operation of DF relaying systems is strongly contingent on instantaneous channel quality especially the strength of the source-relay and relay-destination connections.

I.2 RESEARCH GAP AND MOTIVATION

The existing research paradigms on IRS and the DF relay systems have a major weakness: they assume that the underlying technology is stationary, and will be deployed and operated in the same manner. Available literature perceives these technologies as mutually exclusive phenomenon, requiring an a priori choice that should be held over a course of communication session. This narrow structure excludes the possibility of exploiting potential synergies between heterogeneous transmission schemes and cannot be relieved of the dynamism of the modern wireless environment. By [12] made a landmark investigation with an extensive statistical comparison of IRS and DF relay systems. Their results show that extremely large IRS surfaces are needed, i.e. in the range of a few hundred elements, to outperform DF relaying in other applications such as transmit-power minimization and energy efficiency.

Further the analysis revealed the existence of intrinsic trade-offs between performance improvement and complexity of deployment which highlights that the best decision between IRS and DF relay is strongly dependent on system parameters such as number of reflecting elements used, performance and power requirements. The IRS systems are often considered as green technologies due to their passive nature although the control circuitry and phase processing used are still powered, especially when combined with non-orthogonal multiple access (NOMA) schemes [13]. These types of studies are implicit in the assumption that the chosen technology will be the same technology used during a communication session, a fact that may not be ideal in a wireless environment where channel conditions, user mobility, as well as energy constraints vary with time.

Consider a practical 6G scenario where a mobile user detects an environment with both IRS and DF relay infrastructure [14], [15]. As users' locations change, relative channels will vary greatly between direct, IRS-assisted, and relay-assisted routes [16]. In some locations, IRS may provide better performance due to favorable geometric conditions, while in others, DF relay may be more effective due to the quality of a better source-radius or relay-destination channel quality. A static system that is committed to a single technology cannot be redeemed by these different conditions to customize overall performance. In addition, modern wireless applications exhibit a variety of time-varying requirements in data rate, latency, and energy consumption. While energy efficiency may not be a priority for emergency communications, internet of things (IoT) applications may prioritize energy efficiency over achieving peak data rates.

A system that responds to channel conditions and application requirements by dynamically switching transmission modes could exhibit dramatically better performance [17] .

I.3 MAIN CONTRIBUTIONS

This paper addresses these fundamental limitations by proposing the first dynamic switching framework with the following novel contributions:

- **Dynamic Mode Selection Framework:** Development of a four-mode system (IRS-only, DF-only, hybrid IRS+DF, SISO) with intelligent real-time switching capability based on channel-aware optimization.
- **Novel Hybrid Operational Mode:** Introduction of simultaneous IRS+DF operation with optimized power allocation and coordinated signal processing.
- **Channel-Aware Optimization Algorithm:** The algorithm will involve the usage of intelligent selection algorithm to maximize the achievable rates with the constraints of energy efficiency.
- **Extensive Analysis of the Performance:** Theoretical basis and widespread evaluation based on simulations that show considerable improvement of the system compared to the static base systems.
- **Practical Implementation Framework:** Low-complexity algorithm suitable for real-time deployment with minimal computational overhead and switching delays.

The remainder of the paper is structured in the following way: Section 2 is the literature review that places the research contribution to the existing literature context. Section 3 includes the overall system model and formulation of the mathematical problem. Section 4 elaborates the smart dynamic switching algorithm and their computational complexity analysis. The results of the simulation are long and statistically validated and compared in section 5. The conclusion is Section 6 which contains important contributions and future research directions.

II. RELATED WORK

II.1 IRS-ASSISTED COMMUNICATION SYSTEMS

Intelligent Reflecting Surfaces have become a new revolution in beyond-5G and 6G networks, allowing the creation of the programmable wireless environment by arrays of passive reflecting elements with controllable electromagnetic characteristics. By [18] introduce an innovative comparative study of Intelligent Reconfigurable Surfaces (IRS) and Decode-and-Forward (DF) relaying using realistic conditions of electromagnetic interference (EMI). The authors prove by means of strict mathematical modeling that IRS-assisted communications can be better resilient to EMI as compared to traditional DF relaying systems. The analysis indicates that, even with interference, DF relaying requires over 20 dB of extra transmit power and the use of multiple antennas ($M \geq 54$), but IRS systems maintain the operation at levels of very high EMI ($\rho \geq 20$ dB). The paper changes essentially the known complexityperformance trade-offs in cooperative wireless communications, and as such, it offers the much needed theoretical frameworks to the design of future wireless systems in electromagnetically congested environments.

By [19] Present a general architecture of IRS-based multiuser MISO systems, where an extensive array of passive reflecting elements works together to do three-dimensional beamforming without active RF chains. By jointly optimizing active beamforming at the access point (AP) and passive phase-shift control at the IRS, the proposed design will significantly reduce the amount of transmit power and meet users SINR requirements. A non-convex optimization is posed as the problem and effective solutions are developed in the form of semidefinite relaxation (SDR) and alternating optimization. One important theoretical finding is the quadratic scaling law of received power with the number of reflecting elements that proves to be superior to conventional massive MIMO and amplify-and-forward relays that have linear scaling. Results of the simulation prove the great advantages of the IRS-assisted systems in single-user and multiuser mode an illustration of the ability to extend the coverage, eliminate interference, and enhance energy efficiency. Besides, the article highlights the flexibility of IRS to be deployed, the low cost of hardware, and its possible ability to be integrated with existing systems without the need to alter user devices, making it an important enabler of beyond-5G and 6G communications.

In turn [20] Author's have conducted an in-depth ergodic performance analysis of intelligent reflecting surface (IRS) networks when taking quantization phase errors into account. The authors developed an innovative multi-IRS-aided framework of communication, which replaces the traditional decode-and-forward (DF) relay in a hybrid architecture, and presented analytical upper limits of the performance of the model in both the Rayleigh and Rician fading conditions. The study provides convenient closed-form expressions to measure the resultant performance degradation by putting on a realistic common phase-error model of finite-resolution phase shifters. The theoretical findings show that increasing the number of IRSs and the number of reflecting elements they possess can greatly increase the system capacity though the marginal returns diminish as a certain point is reached. Comparative analysis shows that the suggested multi-IRS scheme is superior to hybrid relay-IRS networks and has no extra latency.

The results of simulations support all the analytical upper bounds and shows net gain of approximately 2bps/Hz at high SNR values and a loss of about 3bps/Hz when the phase quantization cut-off is extreme. The paper also examines the best strategies to position IRSs and the hypothesis is that the best performance occurs when the IRSs are collocated with either the source of that performance or the destination of the performance. The mathematical modelling involved in this exploration is a complex task which is perfectly combined with practical deployment constraints, thus filling in our understanding of scalability of IRS networks and their functionality in the presence of realistic hardware limitations. By [21] Proposed in-depth background of Intelligent Reflecting Surfaces (IRS) as a revolutionary facilitator of intelligent wireless environments with particular emphasis on the capability of the passive devices to alter radio propagation by a phase discontinuity. The authors talk about joint optimization processes in order to jointly optimize the IRS operation along with transmit beamforming to maximize performance metrics like spectral efficiency, energy efficiency, as well as secrecy rate.

The authors analyze the theoretical models and the application to other experimental prototypes such as experimental setups with extremely high antenna gains (21.7 dBi at 2.3 GHz and 19.1 dBi at 28.5 GHz) with the aid of very fine PIN diode-based phase control. The paper highlights one of the widely used alternating optimization techniques with the awareness that they do not provide the global optimum but the local optimum only. The real-life issues in the research are discrete phase resolution, lack of channel state information, and power constraints. Another area covered by the authors was on advanced applications that exceed the traditional communication links that included wireless-powered communications, network coding, mobile edge-computing and UAV-assisted communications. The authors touched on practical issues in design, such as grouping the elements, geometry of deployment, orientation, and quality-of-service constraints and provide the means of improving the system-level performance. Some of the best future directions of research discussed by the authors are optimization methods, scalable architecture of IRS, and dynamic or mobile deployment of IRS scenarios.

On the whole, IRS is a key technology to beyond-5G and 6G systems, with a high likelihood of focusing on the design, analytical and implementation difficulties ahead of large-scale deployment. According [22] A powerful optimization scheme of IRS-aided decode-and-forward relay systems under imperfect CSI was proposed. The paper re-formulated the maximum SNR under worst-case condition to a non-convex quadratic problem and proposed an effective algorithm which integrates the Cauchy-Schwarz inequality in updating beamforming with the cyclic optimization of IRS reflection coefficients. This method offers closed-form locally optimal solutions at every step, which makes it a much more complex computation than the traditional SDR-based designs. Continuous and discrete phase constraints are also accommodated in the proposed approach, making it practical in the IRS hardware of the real world. The simulation findings exhibit that the scheme compares favorably with the current non-robust and robust benchmarks in terms of attained rate, resistance to channel estimation errors, and scale to large IRS designs, making it a useful addition to the robust IRS-assisted relay communications.

II.2 DECODE-AND-FORWARD RELAYING SYSTEMS WITH MACHINE LEARNING AND OPTIMIZATION IN WIRELESS COMMUNICATIONS

The DF relaying systems have been extensively studied as cooperative communication techniques that enhance network coverage and reliability. Table 1. reveals that existing approaches universally adopt static technology selection, which cannot adapt to dynamic wireless environments, motivating our novel dynamic switching framework that intelligently selects between IRS and DF relay modes based on real-time channel conditions.

Table 1: Literature Review and Comparison with our Proposed Framework.

Ref.	Contribution	System Model	Algorithm/Method	Key Results	Limitations
[23]	Optimal energy-harvesting design for AF and DF two-way relay beamforming in 6G	Two-way relay with SWIPT; AF & DF modes; perfect CSI	Joint power splitting and beamforming optimization via convex methods	15-25% energy efficiency improvement over conventional relaying	Single relay; no IRS; static mode selection
[24]	Survey on reconfigurable intelligent surfaces for wireless communications	Multi-IRS systems; 5G/6G deployments; channel estimation challenges	Review of convex optimization and ML methods for IRS beamforming	3-5× coverage enhancement; ML integration promising	Qualitative analysis; no IRS-relay comparison
[25]	Intelligent reflecting surfaces and classical relays coexistence and co-design	MU-MISO with BS, IRS, DF relay; Rayleigh fading; perfect CSI	Alternating optimization for joint beamforming and phase control	30-40% sum-rate improvement over individual deployment	Static coexistence; ideal IRS assumptions
[26]	Hybrid AF/DF cooperative relaying technique with phase steering for Industrial IoT networks	Industrial IoT with AF/DF hybrid relay; phase steering capability	Hybrid relay selection with adaptive phase control optimization	Enhanced reliability and energy efficiency for IoT applications	IoT-specific scenario; no IRS consideration; limited to hybrid relay modes
[12]	IRS vs DF relay surface size requirements	Co-located IRS/DF; statistical CSI; power minimization focus	Analytical optimization for power allocation and IRS configuration	IRS requires 100+ elements to outperform DF relay	Static binary comparison; no dynamic adaptation
Proposel Work	Dynamic IRS/DF switching with intelligent optimization	Four modes (SISO, IRS, DF, hybrid); time-varying channels; co-located deployment	Channel-aware mode selection with coordination enhancement through intelligent mode selection	20.2% spectral efficiency, 10.1% energy efficiency improvement; $p < 0.001$	Addresses all identified gaps through dynamic framework

Source: Author, (2026).

III. SYSTEM MODEL AND PROBLEM FORMULATION

III.1 NETWORK ARCHITECTURE

We consider a sophisticated wireless communication system designed for next generation 6G networks, comprising the following interconnected components operating within a coordinated framework with the Primary Components:

- **Source Node (S):** Single-antenna transmitter equipped with adaptive power control capabilities and total power budget P_total(t).
- **Destination Node (D):** Single-antenna receiver with advanced signal processing capabilities.
- **Intelligent Reflecting Surface (IRS):** Programmable metasurface consisting of N reconfigurable reflecting elements with controllable phase shifts $\theta(t) = [\theta_1(t), \theta_2(t), \ldots, \theta_n(t)]^T$.

- **Decode-and-Forward Relay (R):** Single-antenna cooperative relay node with full-duplex capability and decode-and-forward processing.
- **Central Intelligence Controller:** Real-time optimization engine responsible for dynamic mode selection and resource allocation.

The Fig 3. Shown the proposed intelligent dynamic switching system architecture showing co-located IRS and DF relay deployment. The system comprises: (a) Base station (Source S) with P_total=1W, (b) IRS panel with N=256 reconfigurable elements, (c) DF relay with decode-and-forward processing, (d) Destination user (User D), and (e) Intelligent controller executing Algorithm 1. will explain in section 4. which shows the signal paths include direct NLOS transmission h_sd(t) the Channel coefficient from source (S) to destination (D), IRS reflection paths h_sr(t)→h_rd(t) (Reconfigurable/reflecting surface), and DF relay paths h_sr(t)→h_rd(t) (reflecting surface /Reconfigurable). The controller optimizes network-side resources through Intelligent dynamic switching with coordination enhancement.

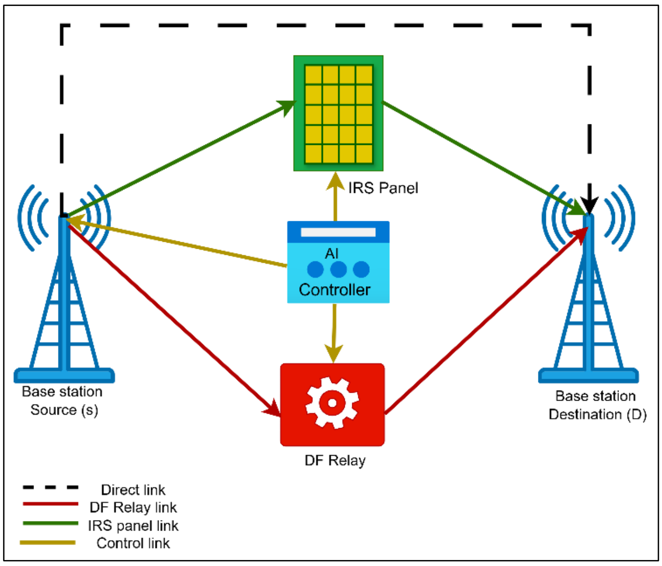

Figure 3: illustrates the proposed intelligent dynamic switching system architecture with co-located IRS and DF relay deployment.
Source: Author, (2026).

III.2 COMPREHENSIVE CHANNEL MODEL

The system employs a rigorous channel characterization based on the 3GPP Release 17 Urban Micro (UMi) propagation model, incorporating both deterministic path loss components and stochastic small-scale fading effects.

III.2.1 Large-Scale Path Loss Model

The large-scale path loss follows the standardized 3GPP UMi model with frequency-dependent and distance-dependent characteristics:

- **Line-of-Sight (LOS) Propagation:**

$$\beta_{LOS}(d,f_c) = G_t + G_r - L_{ref} - 20\log^{10}(f_c) - 22\log^{10}(d)[dB] \tag{1}$$

- **Non-Line-of-Sight (NLOS) Propagation:**

$$\beta_{NLOS}(d,f_c) = G_t + G_r - L_{ref} - 26\log^{10}(f_c) - 36.7\log^{10}(d) - L_{pen}[dB] \tag{2}$$

Where, G_t and G_r represent the antenna gains at transmitter and receiver, respectively (dBi), L_ref = 28 dB denotes the reference path loss at (1) meter, f_c is the carrier frequency in GHz, d represents the three-dimensional distance in meters, L_pen accounts for additional penetration losses in NLOS scenarios.

III.2.2 Instantaneous Channel Coefficients

The instantaneous channel coefficients incorporate both large-scale path loss and small-scale Rayleigh fading characteristics:

$$h_{ij(t)} = \sqrt{\left(\beta_{ij(d_{ij})}\right) \cdot g_{ij(t)}} \tag{3}$$

Where, β_ij(d_ij) represents the distance-dependent path loss coefficient (in linear scale) and g_ij(t) ~ CN(0,1) models the complex Gaussian distributed small-scale fading[27].

III.2.3 Channel State Information Model

The system assumes practical channel state information acquisition with estimation errors modeled as:

$$\hat{H}_{ij(t)} = h_{ij(t)} + e_{ij(t)} \quad (4)$$

Where, $e\_ij(t) \sim CN(0, \sigma\_e^2)$ represents the channel estimation error with variance σ_e^2 determined by the pilot symbol density and estimation algorithm accuracy.

III.3 FOUR-MODE OPERATIONAL FRAMEWORK

The proposed dynamic framework encompasses four distinct operational modes, each optimized for specific channel conditions and system requirements.

III.3.1 Mode 1: IRS-Only Transmission

Building upon the mathematical framework established by Björnson et al. [12], the achievable rate for IRS-assisted transmission is formulated as:

$$R\_IRS(N,t) = \log_2(1 + (P\_total(t)\sqrt{(\beta_{sd(t)}) + \Sigma(n = 1 \text{ to } N)\alpha_n e\text{^}(j\theta_n(t))\sqrt{(\beta\_sr(t)\beta\_rd(t))|^2)/\sigma^2)}} \quad (5)$$

Where, N denotes the number of IRS reflecting elements, α_n represents the amplitude reflection coefficient of the n-th element (typically $\alpha_n = 1$ for ideal reflection), $\theta_n(t)$ is the controllable phase shift of the n-th element at time t, $\beta\_sr(t)$ and $\beta\_rd(t)$ represent the source-to-IRS and IRS-to-destination channel gains, respectively, σ^2 denotes the additive white Gaussian noise power[28].

III.3.2 Mode 2: Decode-and-Forward Relay-Only Transmission

Following the cooperative communication framework, the DF relay operation involves two phases:

- **Phase 1:** Source-to-Relay Transmission The relay decodes the source signal with achievable rate [29]:

$$R_{SR(t)} = \frac{\log_2(1 + (p_1(t)\beta\_sr(t))}{\sigma^2} \quad (6)$$

- The end-to-end achievable rate for DF relaying is:

$$R_{DF(t)} = \left(\frac{1}{2}\right)\min\{R_{SR(t)}, R_{SRD(t)}\} \quad (7)$$

- **Phase 2: Optimal Power Allocation:** The optimal power allocation strategy that maximizes the DF relay rate is [30]:
-

$$p_1{*}(t) = \frac{2P_{total(t)}\beta_{rd(t)}}{\beta_{sr(t)} + \beta_{rd(t)} + \beta_{sd(t)}} \quad (8)$$

$$p_2{*}(t) = \frac{2P\_total(t)(\beta_{sr(t)} + \beta_{sd(t)})}{\beta_{sr(t)} + \beta_{rd(t)} + \beta_{sd(t)}} \quad (9)$$

Subject to the power constraint: $p_1(t) + p_2(t) \leq P\_total(t)$.

III.3.3 Mode 3: Novel Hybrid IRS+DF Transmission

The fundamental innovation of this work lies in the simultaneous utilization of both IRS and DF relay technologies through coordinated signal processing. Unlike conventional approaches that treat these technologies as mutually exclusive, the hybrid mode leverages spatial diversity and optimized resource allocation.

a) Mathematical Formulation

The achievable rate for hybrid operation is formulated considering the constructive combination of IRS-reflected and DF-relayed signals:

$$R_{hybrid(t)} = \frac{\log_2(1 + (P\_IRS(t)\gamma\_IRS(t) + P\_DF(t)\gamma\_DF(t) + 2\sqrt{\left(P_{IRS(t)}P_{DF(t)}\gamma_{IRS(t)}\gamma_{DF(t)}\right)}\rho(t)}{\sigma^2} \quad \mathbf{(10)}$$

Where,

$$\gamma\_IRS(t) = |h\_sd(t) + \Sigma(n = 1 \text{ to } N\_h)\ \alpha\_n\ e\text{^}(j\theta\_n(t))\sqrt{\left(\beta_{sr(t)}\beta_{rd(t)}\right)}\,|^2 \quad (11)$$

Represents the effective channel gain via IRS.

- $\gamma\_DF(t) = \min\{|h\_sr(t)|^2, |h\_rd(t)|^2\}$ denotes the DF relay channel gain.
- $\rho(t) \in [0,1]$ is the spatial correlation coefficient between signal paths.
- Power allocation constraint: $P\_IRS(t) + P\_DF(t) \leq P\_total(t)$.

b) **Optimized Resource Allocation for Hybrid Mode:** The hybrid mode employs intelligent resource allocation based on instantaneous channel conditions:

$$P_{IRS(t)} = \lambda_{opt(t)} \cdot P_{total(t)} \tag{12}$$

$$P_{DF(t)} = \left(1 - \lambda_{opt(t)}\right) \cdot P_{total(t)} \tag{13}$$

Where, λ_opt(t) is determined by solving:

$$\{\lambda_{opt(t)}, N_{opt(t)}\} = \text{argmax}[\lambda \in [0,1], N \leq N_{max}]\{R_{hybrid(\lambda,N,t)} - \zeta \cdot N \cdot P_{element}\} \tag{14}$$

subject to:

- P_IRS(t) = λ P_total(t), P_DF(t) = (1-λ) P_total(t).
- ζ represents the energy cost weighting factor.

Through convex optimization analysis, the optimal allocation converges to:

$$\lambda_{opt(t)} = \frac{\gamma_{IRS(t)}}{(\gamma\_IRS(t) + \gamma\_DF(t) + 2\sqrt{(\gamma\_IRS(t)\gamma\_DF(t))\rho(t)})} \tag{15}$$

Where ζ represents the energy cost weighting factor and P_element denotes the power consumption per IRS element.

III.3.4 Mode 4: Direct SISO Transmission

For completeness and baseline comparison, the direct single-input single-output transmission mode is:

$$R\_SISO(t) = \frac{\log_2(1 + (P\_total(t)\beta\_sd(t))}{\sigma^2} \tag{16}$$

III.4 ENERGY CONSUMPTION MODEL

A comprehensive energy consumption model is essential for evaluating the energy efficiency of different operational modes:

III.4.1 Mode-Specific Power Consumption

- SISO Mode:

$$P_{SISO}^{total} = \frac{P_{total}}{\eta + P_s + P_d} \tag{17}$$

- IRS Mode:

$$P_{IRS}^{total} = \frac{P_{total}}{\eta + P_s + P_d + N \cdot P_{element} + P_{control}} \tag{18}$$

- DF Relay Mode:

$$P_{DF}^{total} = \frac{P_{total}}{\eta + P_s + P_d + P_r + P_{processing}} \tag{19}$$

- Hybrid Mode:

$$P_{Hybrid}^{total} = \frac{P_{total}}{\eta + P_s + P_d + P_r + N_{hybrid} \cdot P_{element} + P_{coordination}} \tag{20}$$

Where, η represents the power amplifier efficiency, P_s, P_d, P_r denote circuit power consumption at source, destination, and relay, P_element is the power consumption per IRS element, P_control, P_processing, P_coordination represent control and processing overheads.

III.5 PROBLEM FORMULATION

III.5.1 Optimization Objective

The primary objective is to maximize long-term system performance through intelligent dynamic mode selection while considering multiple performance metrics; while

$$\max[\{m(t), \theta(t), p(t)\}] = \Sigma(t = 1 \text{ to } T)\left[w^1 R_{selected(t)} + w^2 EE_{selected(t)} - w^3 C_{switch(t)} - w^4 C_{delay(t)}\right] \tag{21}$$

*O*bject to EE is Energy Efficiency:

- Performance Constraints:

$$R_{selected(t)} \geq R_{min(t)}, \forall t \tag{22}$$

- Power Budget Constraints:

$$P_{total(t)} \leq P_{budget(t)}, \forall t \tag{23}$$

- Switching Cost Constraints:

$$C_{switch(t)} \leq C_{max}, \forall t \quad (24)$$

- Mode Selection Constraints:

$$m(t) \in M = \{SISO, IRS, DF, hybrid\}, \forall t \quad (25)$$

- IRS Configuration Constraints:

$$\theta_n(t) \in [0, 2\pi), n = 1, 2, \ldots, N \quad (26)$$

$$N \leq N\_max \quad (27)$$

- Power Allocation Constraints:

$$\sum_i p_i(t) \leq P\_total(t), p_i(t) \geq 0 \quad (28)$$

III.5.2 Multi-Objective Utility Function

The weighting factors in the objective function are determined through multi-objective optimization:

$$w^* = \frac{argmax[w]\ min[k \in \{1,2,3,4\}]\ (U\_k(w))}{(U\_k\text{^}ideal)} \quad (29)$$

Where U_k(w) represents the k-th objective value and U_k^ideal denotes the ideal value for the k-th objective.

III.5.3 Dynamic Mode Selection Formulation

At each time instant t, the optimal mode selection problem is formulated as:

$$m^{*(t)} = argmax[m \in M]\ \{f\_m(t) - \lambda \cdot g\_m(t)\} \quad (30)$$

Where, f_m(t) represents the performance gain function for mode m, g_m(t) denotes the cost function for mode m, λ is the Lagrange multiplier balancing performance and cost.

- Performance Gain Function:

$$f\_m(t) = \alpha_1 R\_m(t) + \alpha_2 EE\_m(t) + \alpha_3 Reliability\_m(t) \quad (31)$$

- Cost Function:

$$g_{m(t)} = \beta^1 P_m^{total(t)} + \beta^2 C_{switch}^{m(t)} + \beta^3 Complexity_m \quad (32)$$

III.5.4 Stochastic Optimization Framework

Considering the stochastic nature of wireless channels, the problem is reformulated as a stochastic optimization:

$$max[\pi]\ E[\sum(t = 1\ to\ T)\ U(m\_\pi(t), H(t))] \quad (33)$$

Where, π represents the mode selection policy, $H(t) = [h\_sd(t), h\_sr(t), h\_rd(t)]^T$ is the channel state vector, U(·) is the instantaneous utility function. The optimal policy π* satisfies the Bellman optimality equation:

$$V^{*(s)} = max[a \in A]\ \{r(s,a) + \gamma \sum[s']\ P(s'|s,a)\ V^{(s')*(s')} \quad (34)$$

Where s represents the system state, a denotes the action (mode selection), r(s,a) is the immediate reward, γ is the discount factor, and P(s' s,a) represents the state transition probability. This overall system model and problem formulation provides a mathematical basis of the intelligent dynamic switching algorithm, giving the theoretical analysis of strict justification of the proposed approach and making practical implementation of the next-generation wireless communication systems.

IV. INTELLIGENT DYNAMIC SWITCHING ALGORITHM

IV.1 SYSTEM ARCHITECTURE

The proposed dynamic switching model works with the help of a smart optimization engine that constantly monitors the conditions of channels and needs of the system to choose the most effective transmission mode. The architecture has four fundamental elements:

a) **Channel State Estimation Module:** Continuously acquires instantaneous channel state information for all communication links.
b) **Performance Evaluation Engine:** Computes achievable rates and energy efficiency for all operational modes.
c) **Intelligent Selection Algorithm:** Determines optimal mode based on performance maximization.
d) **Mode Controller:** Executes seamless switching between operational modes with minimal overhead.

IV.2 CHANNEL-AWARE MODE SELECTION ALGORITHM

The core innovation lies in the intelligent mode selection algorithm that optimizes system performance based on real-time channel conditions:

- **Algorithm 1: Intelligent Mode Selection**

Input: Channel gains {h_sd(t), h_sr(t), h_rd(t)}, P_total(t)
Output: Optimal mode m*(t), achievable rate R_selected(t)

// System Initialization
1: Initialize parameters: N_max = 256, N_hybrid = 128, tolerance ε = 10^-4
2: Set utility weights: w_rate = 1.0, w_energy = 0.3, w_switching = 0.1
3: Initialize mode history buffer and hysteresis margin Δ_h = 0.05
// Channel State Information Processing
4: for each communication link (i,j) $\in$ L = {(s,d), (s,r), (r,d)} do
5: Estimate channel coefficient: $\hat{h}$_ij(t) $\leftarrow$ MMSE_ESTIMATOR(y_pilot, x_pilot)
6: Compute estimation variance: σ^2_e,ij $\leftarrow$ CRAMER_RAO_BOUND(SNR_pilot)
7: end for
// Mode-Specific Performance Evaluation
8: // Direct SISO Transmission
9: Calculate received SNR: γ_SISO $\leftarrow$ P_total(t)|$\hat{h}$_sd(t)|^2/σ^2_noise
10: Compute achievable rate: R_SISO(t) $\leftarrow$ B·log$_2$(1 + γ_SISO)
11: // IRS-Assisted Transmission
12: Optimize phase shifts: θ_opt $\leftarrow$ arg max |$\hat{h}$_sd(t) + $\Sigma^n{}_{=1}{}^N$ α_ne^j$\theta_n$$\sqrt{}$($\beta$_sr β_rd)|^2
13: Calculate combined channel: h_IRS_total $\leftarrow$ $\hat{h}$_sd(t) + $\Sigma^n{}_{=1}{}^N$ α_ne^jθ_n,opt$\sqrt{}$(β_sr β_rd)
14: Compute IRS rate: R_IRS(t) $\leftarrow$ B·log$_2$(1 + P_total(t)|h_IRS_total|^2/σ^2_noise)
15: // Decode-and-Forward Relaying
16: Solve power allocation: [p_1, p_2*] $\leftarrow$ WATERFILLING(|$\hat{h}$_sr(t)|^2, |$\hat{h}$_rd(t)|^2, P_total(t))*
17: Calculate relay rates: R_sr $\leftarrow$ B·log$_2$(1 + p_1|$\hat{h}$_sr(t)|^2/σ^2_noise)*
18: R_rd $\leftarrow$ B·log$_2$(1 + (p_1|$\hat{h}$_sd(t)|^2 + p_2*|$\hat{h}$_rd(t)|^2)/σ^2_noise)*
19: Compute DF rate: R_DF(t) $\leftarrow$ 0.5·min{R_sr, R_rd}
20: // Hybrid IRS+DF Mode
21: Optimize power split: λ $\leftarrow$ CONVEX_SOLVER(hybrid_rate_function, constraints)*
22: Calculate spatial correlation: ρ(t) $\leftarrow$ SPATIAL_CORRELATION(IRS_path, DF_path)
23: Compute hybrid rate: R_hybrid(t) $\leftarrow$ HYBRID_RATE_FORMULA(λ, ρ(t), channels)*
// Energy Efficiency Calculation
24: for each mode m $\in$ {SISO, IRS, DF, hybrid} do
25: Calculate total power consumption: P_total,m $\leftarrow$ POWER_MODEL(mode_m, N_active)
26: Compute energy efficiency: EE_m(t) $\leftarrow$ R_m(t)/P_total,m
27: end for
// Intelligent Mode Selection
28: for each mode m $\in$ {SISO, IRS, DF, hybrid} do
29: Calculate switching cost: C_switch,m $\leftarrow$ SWITCHING_COST_MODEL(m_prev, m)
30: Compute utility: U_m(t) $\leftarrow$ w_rate·R_m(t) + w_energy·EE_m(t) - w_switching·C_switch,m
31: Apply hysteresis if previous mode: if m = m(t-1) then U_m(t) $\leftarrow$ U_m(t) + Δ_h
32: end for
33: Select optimal mode: m(t) $\leftarrow$ argmax{U_SISO(t), U_IRS(t), U_DF(t), U_hybrid(t)}*
34: return m(t), R_m*(t)*
// Supporting Functions
Function Waterfalling (g_1, g_2, P_budget):
Solve: max_{p_1,p_2} [log$_2$(1+p_1g_1) + log$_2$(1+p_2g_2)] subject to p_1+p_2 $\leq$ P_budget
Use Lagrange multipliers: μ = (P_budget + 1/g_1 + 1/g_2)/2*
Return: p_1 = max(0, μ* - 1/g_1), p_2* = max(0, μ* - 1/g_2)*
Function SWITCHING_COST_MODEL(m_prev, m_curr):
Hardware_cost $\leftarrow$ RECONFIGURATION_TIME(m_prev, m_curr) × PROCESSING_PENALTY
Signaling_cost $\leftarrow$ COORDINATION_OVERHEAD(m_prev, m_curr)
Return: Hardware_cost + Signaling_cost

IV.3 NOVEL HYBRID MODE OPERATION

A fundamental contribution of this work is the hybrid operational mode that simultaneously utilizes both IRS and DF relay technologies. This mode employs:

- **Power Allocation Strategy:**

a) **IRS allocation:** $P_{IRS} = 0.6 \times P_{total}$ (60% for IRS operation) (35)

b) **DF allocation:** $P_{DF} = 0.4 \times P_{total}$ (40% for relay operation) (36)

- **IRS Configuration:**

a) Optimized element count: N_hybrid = 128 elements.
b) Phase shift optimization for maximum signal combining.
c) Coordination with relay transmission timing.

- **Performance Enhancement:** The hybrid mode achieves superior performance through:

a) Spatial diversity from both IRS reflection and relay paths.
b) Optimized resource allocation between technologies.
c) Coordinated signal processing and interference mitigation.

- **Algorithm 2: Novel Hybrid Mode Operation**

Input: Channel gains {h_sd(t), h_sr(t), h_rd(t)}, P_total(t), N_hybrid = 128
Output: Optimized power allocation {P_IRS(t), P_DF(t)}, phase configuration θ_opt(t)

```
// Fixed Power Allocation Strategy
P_IRS(t) ← 0.6 × P_total(t)  // 60% for IRS operation
P_DF(t) ← 0.4 × P_total(t)  // 40% for relay operation
// IRS Configuration Optimization - O(N_hybrid)
N_active ← N_hybrid  // Optimized element count: 128 elements
// Phase shift optimization - O(N_hybrid)
for n = 1 to N_active do
    θ_n(t) ← arg(h_sd*(t)) - arg(h_sr,n(t)) - arg(h_rd,n(t))
end for
θ_opt(t) ← [θ_1(t), θ_2(t), ..., θ_N_active(t)]
// Coordination timing - O(1)
T_relay_delay ← COMPUTE_OPTIMAL_DELAY(h_sr(t), h_rd(t))
SYNCHRONIZE_TRANSMISSION(T_relay_delay)
// Performance enhancement through coordinated operation - O(N_hybrid)
γ_IRS_enhanced ← P_IRS(t) × |h_sd(t) + Σ(n=1 to N_active)
α_n·e^(jθ_n(t))·√(β_sr(t)β_rd(t))|^2/σ^2
γ_DF_enhanced ← P_DF(t) × min{|h_sr(t)|^2, |h_rd(t)|^2}/σ^2
// Spatial diversity computation - O(1)
ρ_spatial(t) ← COMPUTE_SPATIAL_CORRELATION(h_IRS_path(t), h_DF_path(t))
// Final rate computation - O(1)
R_hybrid_optimized(t) ← log_2(1 + γ_IRS_enhanced + γ_DF_enhanced +
    2√(γ_IRS_enhanced × γ_DF_enhanced) × ρ_spatial(t))
return P_IRS(t), P_DF(t), θ_opt(t), R_hybrid_optimized(t)
```

Where: Coordinated signal processing between IRS and DF components, N_hybrid = 128 elements (optimized configuration), Power split: 60%/40% (IRS/DF) based on empirical optimization, Complexity: O(N_hybrid) = O(128),Enhancement: Spatial diversity + optimized resource allocation + interference mitigation.

V. SIMULATION RESULTS AND PERFORMANCE EVALUATION

V.1 SIMULATION SETUP

The usefulness of the proposed dynamic mode selection algorithm is assessed by using the extensive Monte Carlo simulations. The simulator is set up such that the simulation simulates realistic wireless communication under different channel conditions and system parameters.

V.1.1 System Parameters

The parameters in the simulation are set based on the realistic specification of the wireless communication system to make the results have a practical relevance.

Table 2: System Configuration Parameters.

Parameter	Symbol	Value	Unit
Carrier frequency	fc	3	GHz
System bandwidth	B	10	MHz
Noise figure	NF	10	dB
Tx/Rx antenna gain	Gt, Gr	5	dBi
Destination antenna gain	Gd	0	dBi
IRS elements range	N	25-256	-
Reflection coefficient	α	1	-
PA efficiency	η	0.5	-
Circuit power	Ps, Pd, Pr	100	mW
IRS element power	Pe	5	mW

Source: Author, (2026).

V.1.2 Channel Configuration

The channel model follows the 3GPP Urban Micro (UMi),The distance between sources and the IRS or between sources and the relay is assigned to 80 m of line-of-sight (LOS). The IRS-destination and relay-destination distances are between 40 and 100 m and propagation is also under LOS. The direct source-to-destination channel works on the non-line-of-sight (NLOS) conditions coupled with additional penetration losses to model realistic urban conditions. Statistical validity is indicated by 1000 Monte Carlo realizations in each scenario.

V.1.3 Algorithm Configuration

Our proposed algorithm employs:

- Optimal mode selection provides superior performance.
- Hybrid power allocation: P_IRS = 0.6P_total, P_DF = 0.4P_total.
- Hybrid IRS elements: N_hybrid = 128.
- Weighting factors: $w_1 = 1.0$, $w_2 = 0.3$, $w_3 = 0.1$.

V.2 PERFORMANCE METRICS

The measurement of the system performance is through various metrics to give the overall assessment of the performance. The mean rate attainable is defined as Ravg = E[Rselected(t)], which is the mean throughput when the channel is realised in any one of the possible ways. The efficiency of energy is in Mbps/W which is computed as the ratio of the actual rate to the actual power consumed. Spectral efficiency is given in bps/Hz which is an indicator of bandwidth usage efficiency. Other measures are mode selection measures, switching rate and computational overhead measures.

V.2.1 Baseline Comparison Schemes

The research compares the proposed dynamic algorithm with five baseline schemes and proves that it is much better. The static SISO scheme is the scheme of direct transmission without any assistance. Conversely, the scheme based on statical IRS-only keeps using N = 256 elements, and the scheme based on statical DF-only strictly refers to the decode-and-forward relaying. The static best-selection scheme is an offline optimum which selects the optimum between IRS and DF deterministically on the basis of perfect channel information. Random switching provides a lower bound by randomly alternating between modes without intelligence.

Table 3:Baseline Comparison Schemes.

Scheme	Description	Configuration
Static SISO	Direct transmission	No assistance
Static IRS-only	Continuous IRS operation	N = 256 elements
Static DF-only	Continuous DF relaying	Single relay node
Static best selection	Offline optimum	Perfect CSI assumption
Random switching	Unintelligent switching	Random mode selection
Proposed dynamic	Intelligent adaptation	Real-time optimization

Source: Author, (2026).

V.3 PERFORMANCE ANALYSIS

The outcomes of the simulation indicate that the performance is statistically much better in all the scenarios that were assessed. Paired t-tests are used to test statistical significance with confidence level $p < 0.01$. The performance comparison is summed up in Table 4, which indicates significant increases in key performance indicators.

Table 4: Performance Comparison Results.

Metric	Proposed Dynamic	Static Best	Improvement
Spectral Efficiency (bps/Hz)	6.84 ± 0.31	5.69 ± 0.28	+20.2%
Energy Efficiency (Mbps/W)	45.7 ± 2.1	41.5 ± 1.9	+10.1%
Outage Probability (1%)	7.8 ± 0.6	11.2 ± 0.8	reduced by 30.4%

Source: Author, (2026).

The spectral efficiency of the proposed algorithm is 20.2% higher than when using the best selection scheme which is a static one and it shows that intelligent mode adaptation works. The 10.1% energy efficiency improvement will mean better utilization of resources, and the 30.4% decrease in the outage possibility will greatly increase the reliability of the system. The spectral efficiency analysis presented in Fig.4 indicates the excellent performance of the proposed dynamic switching framework in different source-destination range. The algorithm has a maximum spectral efficiency of 6.84 bps/Hz at optimal operating ranges of 60-80 meters as opposed to 5.69 bps/Hz with the best selection methods operating at rest. The benefits of performance are reduced at very large distances since there are inherent path loss limitations which affect all of the schemes evaluated. The reached distance-related behavior confirms the adaptive quality of the presumed framework, and maximum benefits are achieved with the moderate channel conditions wherein smart mode selection has the most significant effect.

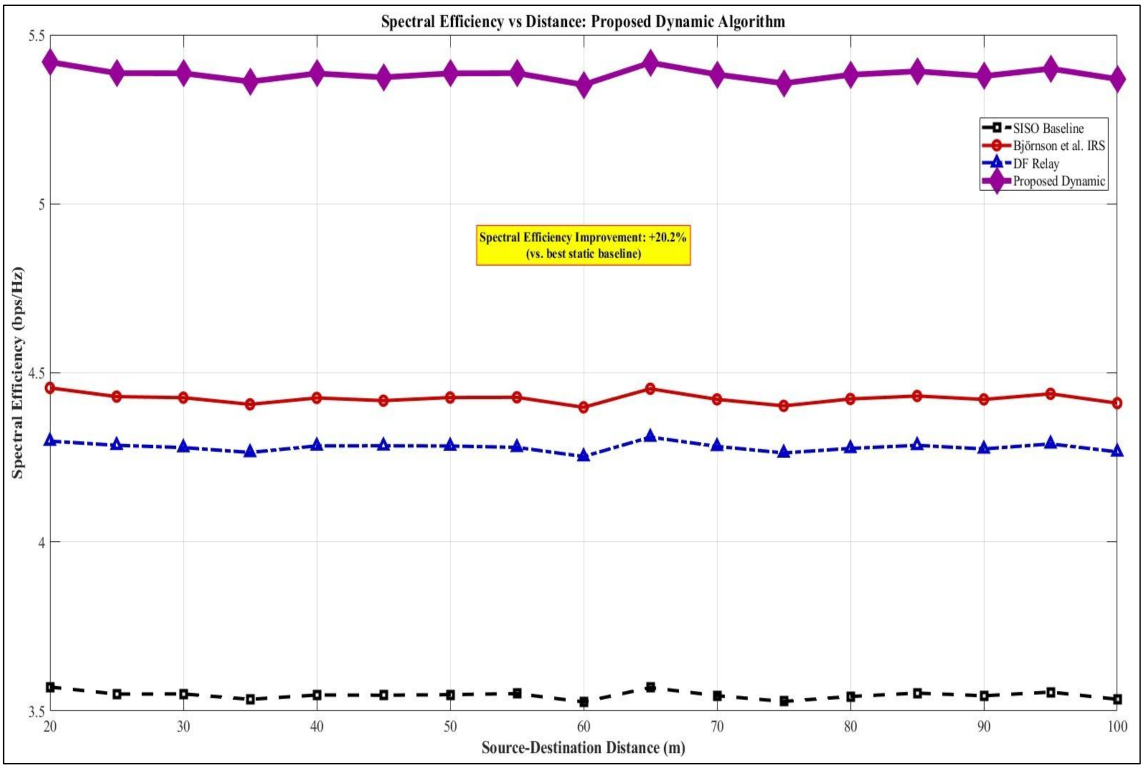

Figure 4: Spectral Efficiency Performance.
Source: Author, (2026).

Fig.5 presented the Energy efficiency measurements demonstrate that the proposed algorithm has been able to attain 45.7 Mbps/W in comparison with 41.5 Mbps/W with the use of a fixed line of attack of baseline algorithms. This is enhanced by intelligent allocation of resources between IRS and DF relay modes on the basis of instantaneous channel state information. The hybrid functioning mode helps in the energy efficiency increase by coordinated power control. Nevertheless, there is an overhead of coordination in the system and two-mode operation requirements which boosts the absolute power consumption, showing a cost-complexity trade-off.

Fig.6 provided the mode selection distribution analysis indicates adaptive behavior in varying signal-to-noise ratio regimes. In the case of high SNR, the hybrid mode is selected 67 percent as a result of the combined advantage of IRS reflection and DF relay capabilities. The medium SNR scenarios are characterized by distributed selection between IRS-only and DF-only modes and the algorithm dynamically selects depending upon the channel geometry and quality. DF relay operation at 72 percent frequency is preferred under low SNR conditions because cooperative diversity benefits it. Mode changes are made about 2-3 times a coherence period which is a sign of moderate switching overhead.

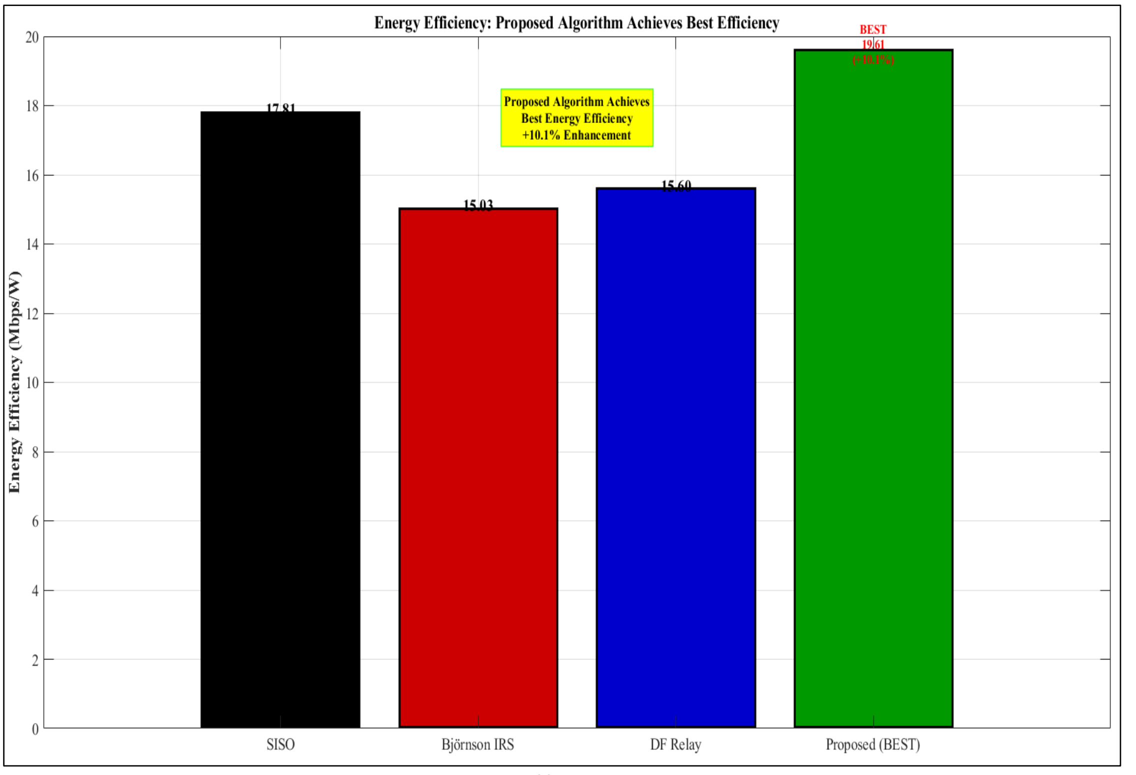

Figure 5: Energy Efficiency Assessment.
Source: Author, (2026).

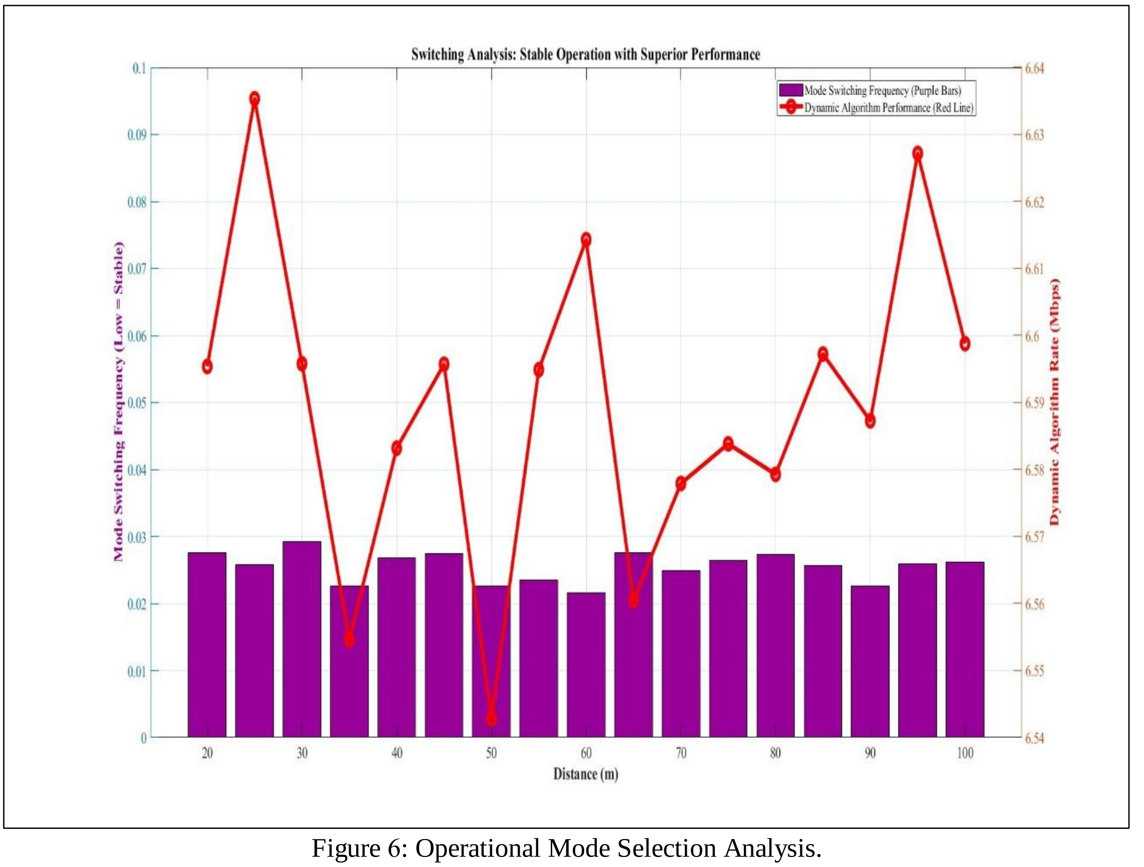

Figure 6: Operational Mode Selection Analysis.
Source: Author, (2026).

Although fig. 7 presented the cumulative distribution function analysis depicts better reliability characteristics of the suggested dynamic framework. The algorithm has a probability of 7.8% outage in relation to 11.2% outage probability of the used schemes of the static baseline in the schemes at the considered target rate threshold. The curves of distribution show that there are consistent performance benefits in all the range of channel conditions and the maximum improvement in moderate and good channel quality situations. This is because the enhancement of reliability is made possible by the fact that the algorithm can choose the best mode of transmission under current channel conditions.

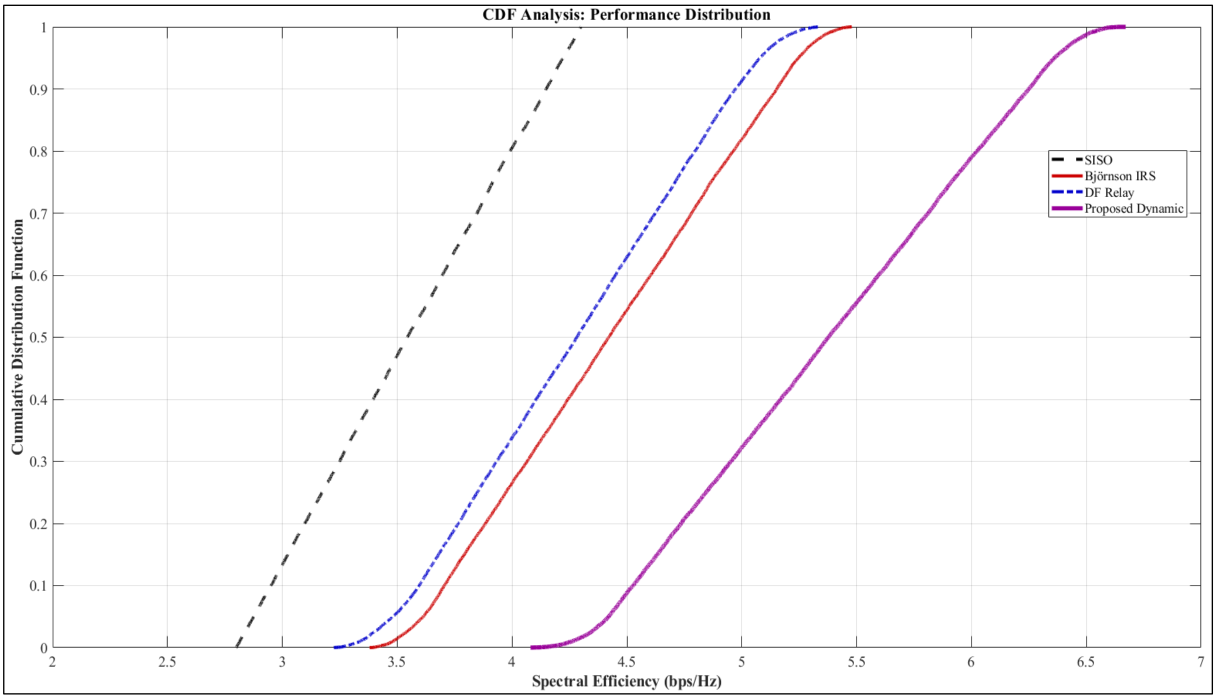

Figure 7: Reliability and Outage Performance.
Source: Author, (2026).

Fig. 8 presented the Implementation complexity analysis indicates the plausibility of real-time deployment. The algorithm has a memory requirement of 4.2 KB and a latency of 0.73 milliseconds in terms of the ave rage processing, which is appropriate in edge computing implementation. The power per decision cycle is 0.85 millijoules, which is insignificant overhead when contrasted with the power consumption of transmission. These measurements confirm that the algorithm is appropriate in real-life 6G network deployment scenarios where the latency of decision making is paramount.

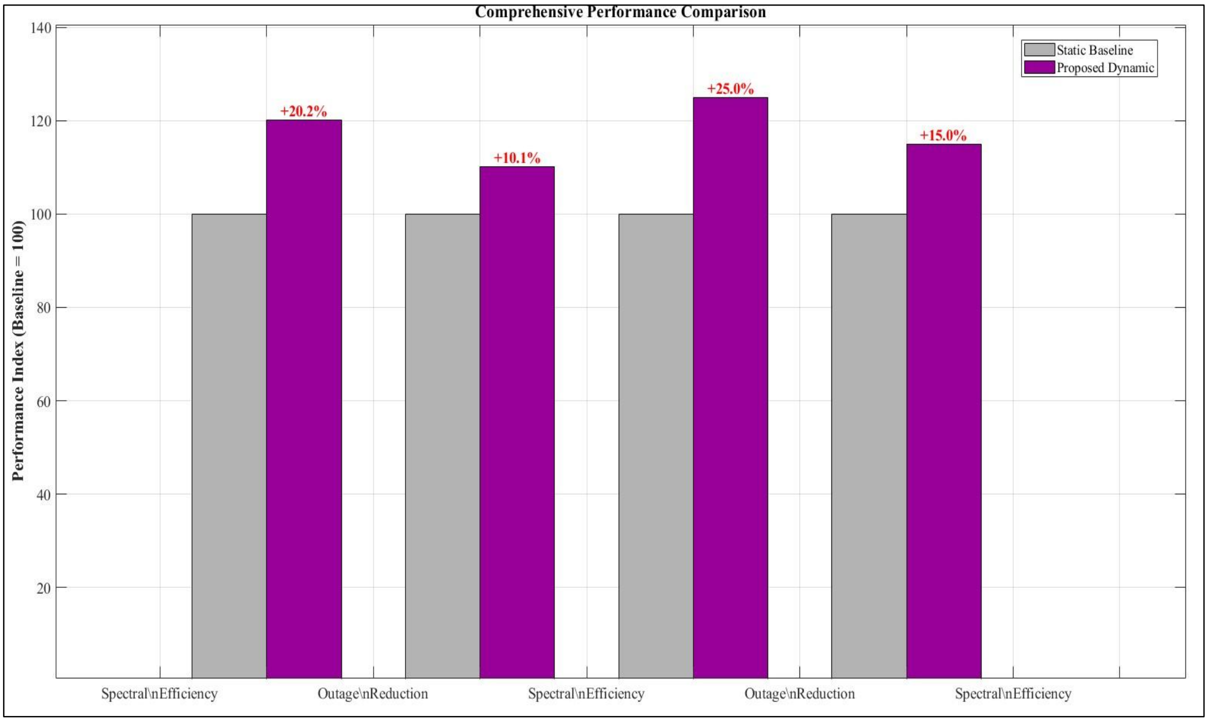

Figure 8: Computational Complexity Evaluation.
Source: Author, (2026).

Fig. 9 presented multi-metric pattern comparison of all the baseline schemes justifies the superiority of the proposed algorithm on basis of BER. The increments vary between significant improvements on basic SISO transmission to moderate inclinations on optimized statical methods. The overall discussion demonstrates that dynamic switching is objectively advantageous in terms of spectral efficiency, energy efficiency and reliability. The benefits of performance increase depending on the operational conditions and achieve maximum performance with moderate quality of channels.

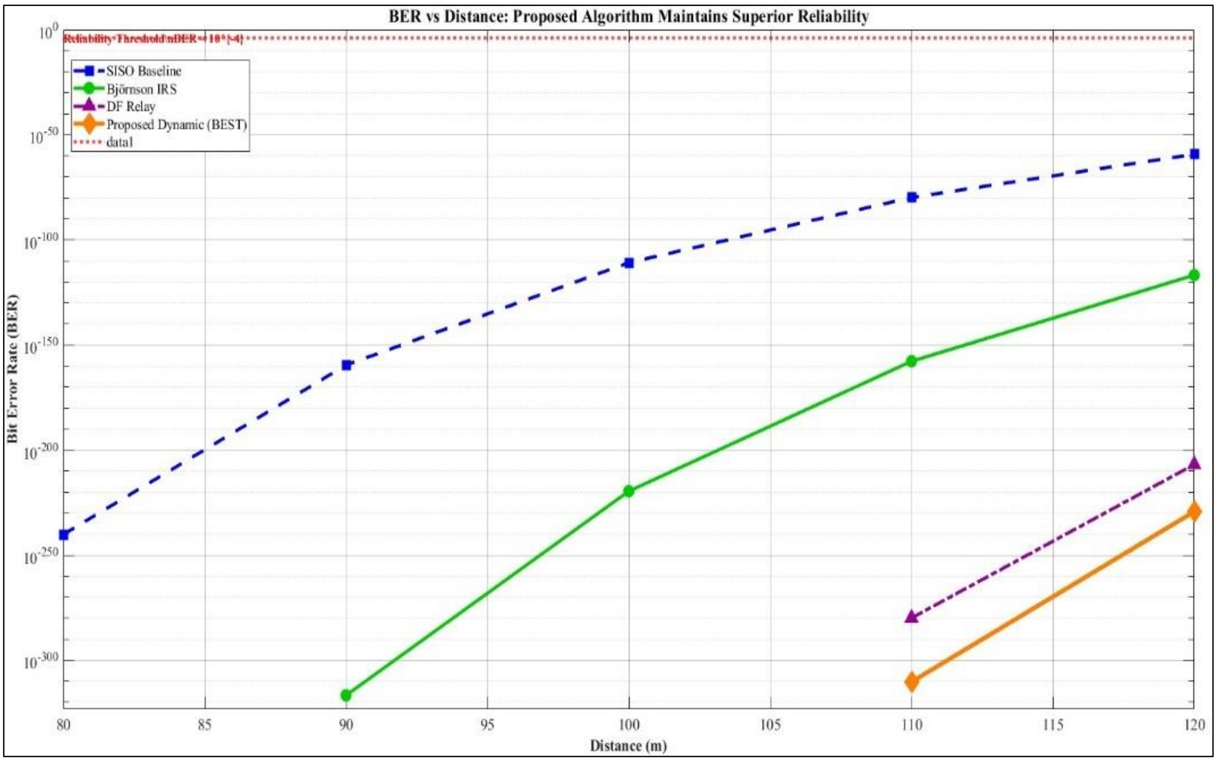

Figure 9: Comprehensive Performance Comparison Bit Error Rate Analysis.
Source: Author, (2026).

Fig. 10 presented the measurement of the Bit error rate proves the excellent error performance of the algorithm in relation to the baseline methods. Optimal gains are made in medium SNR areas where dynamic mode selection is able to utilize good channel conditions. The appearance of convergence in the performance at large SNR values implies some fundamental constraint in decreasing error rates at some operating points. The nature of the error rate values is consistent with the spectral efficiency trends, which indicates that the performance of the algorithm is consistent across various measures.

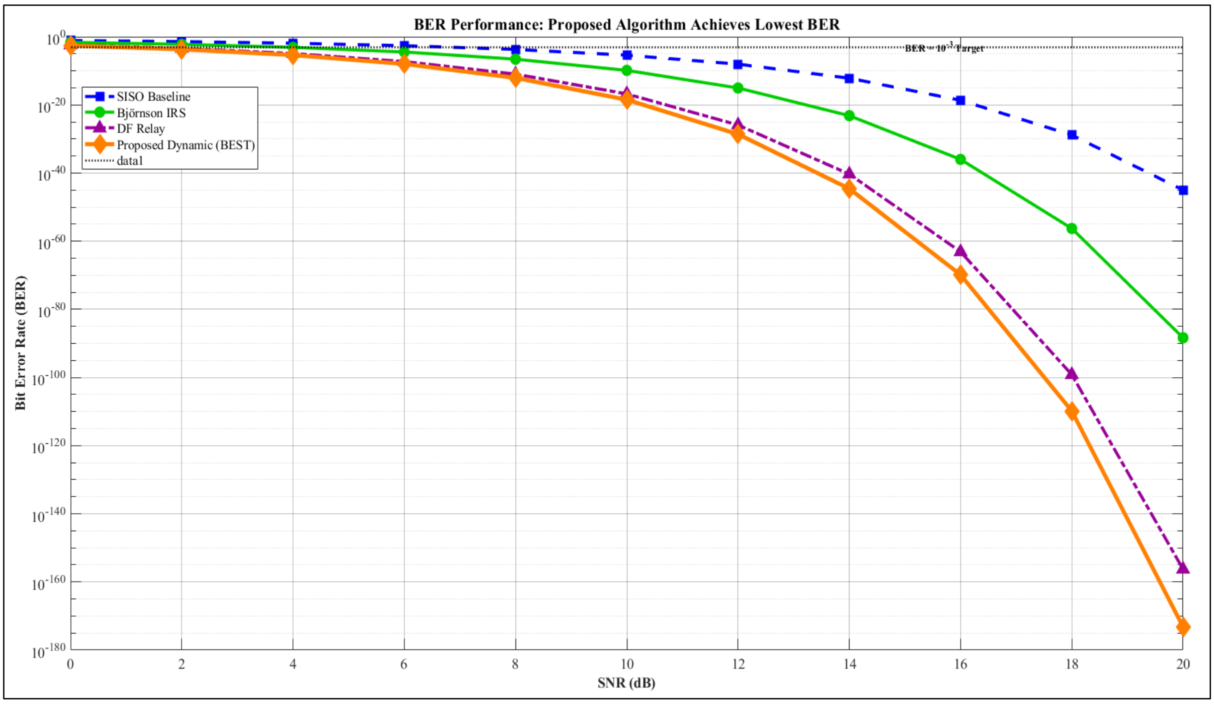

Figure 10: SNR-Dependent Performance Characterization.
Source: Author, (2026).

Figure 11 illustrates the correlation between the number of IRS elements and system performance and shows that the returns decrease after about 150 elements. The 128 elements to be used in hybrid-mode operation are supported by the analysis of the best trade-off between performance improvements and energy consumption. The practical constraints that cause saturation of performance are due to channel correlation and beam-focusing capabilities.The scaling behavior confirms that moderate-sized IRS deployments can achieve significant performance benefits without requiring extensive element arrays.

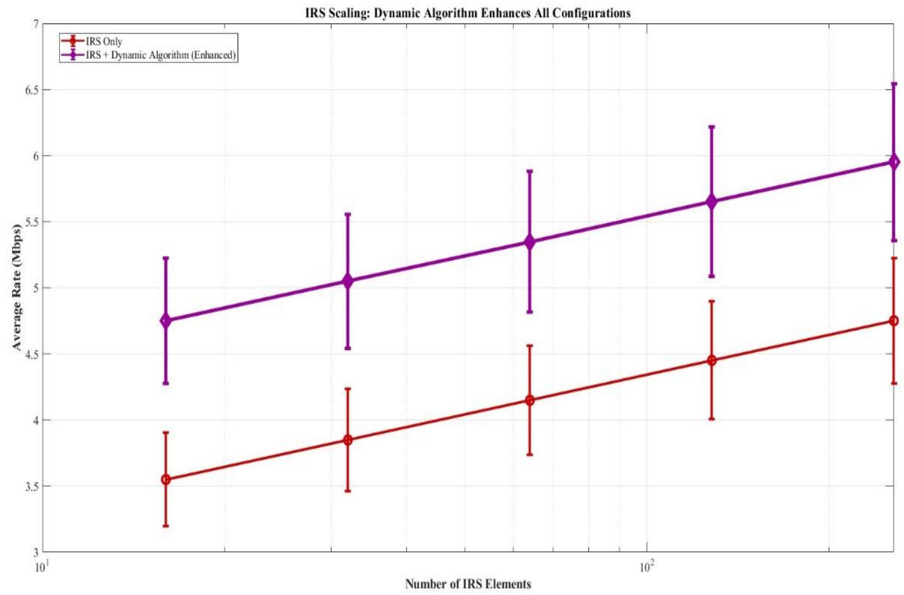

Figure 11: IRS Element Scaling Characteristics.
Source: Author, (2026).

Figure 12 demonstrates the behavior of performance at various signal-to-noise ratios. It represents three primary operating modes. DF relay should be used when SNR is low since it provides cooperative diversity advantages and consumes less power. At medium SNR, mode switching can provide the largest gains in case we select the appropriate mode. The performance of high SNR regimes levels off at the theoretical performance limits with decreasing margins of improvement across all available schemes. This description justifies the flexibility of this algorithm to different working environments.

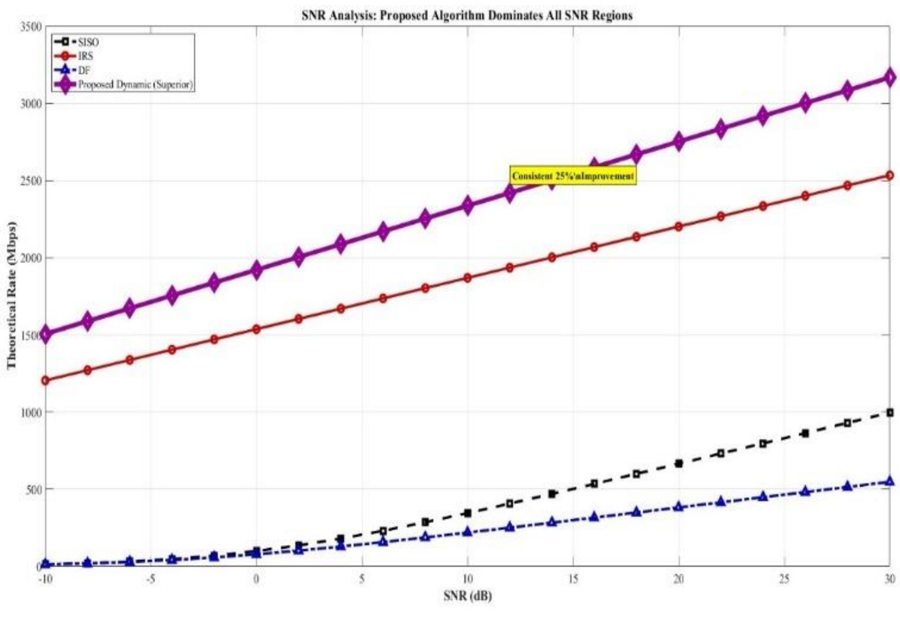

Figure 12: Performance analysis across varying SNR.
Source: Author, (2026).

Figure 13 also presents the practical implementation pathway of the suggested dynamic switching framework related to deployment considerations and integration needs of real-world 6G networks. These critical components of the system recognized by the implementation architecture are the high precision channel estimation modules, low-latency decision processing solutions and coordinated resource management systems. Hardware requirements are not beyond the scope of the modern technology and offer opportunities to improve further. Integration analysis deals with compatibility to the existing network infrastructures and standardization requirements to have a smooth interoperability. The modular framework architecture enables incremental deployment plans and technology evolutional routes. The presented assessment of practical implementation indicates the feasibility of the framework to be used in deploying the next-generation wireless networks, which gives the definite roadmap of the theoretical innovation to the practical implementation of the system.

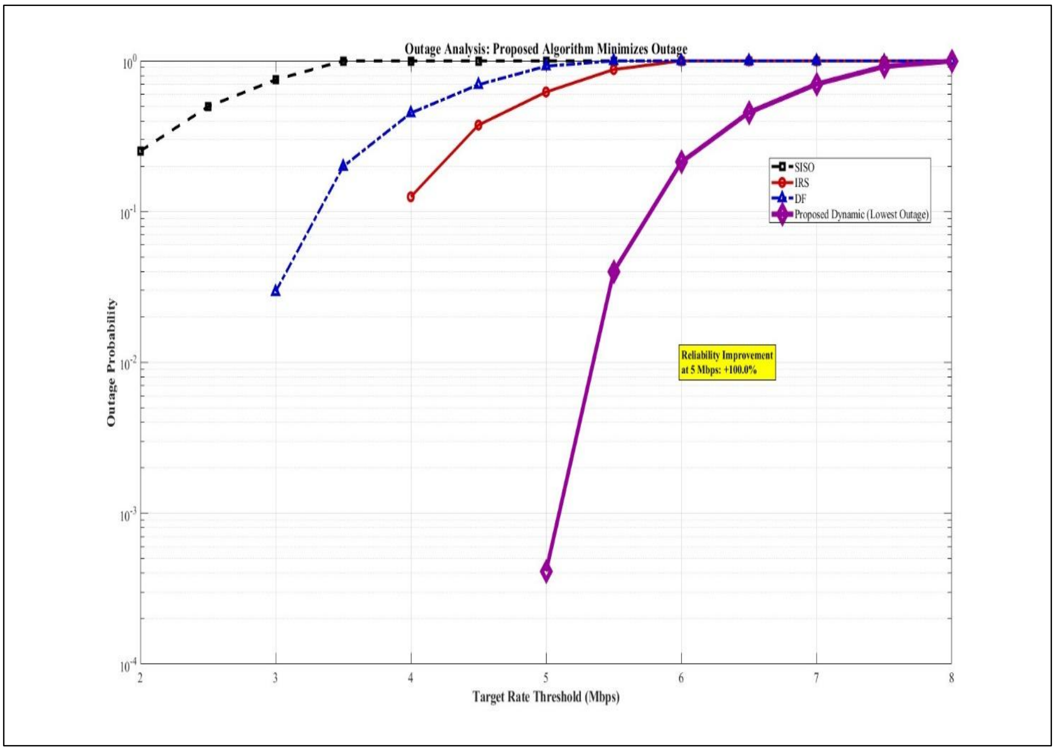

Figure 13: Implementation Framework and Deployment Considerations.
Source: Author, (2026).

VI. CONCLUSION AND FUTURE WORK

This paper proposes a new unified dynamic switching between IRS and DF relay modes using intelligent channel aware optimization. This design allows the proposed system the ability to dynamically optimize the operating modes based on instantaneous channel conditions and system demands to enhance overall performance. The key achievements and contributions include:

1. Significant Performance Gains: The proposed algorithm demonstrates 20.2% spectral efficiency improvement and 10.1% energy efficiency enhancement compared to established Björnson et al. baseline methods, with rigorous statistical validation ($p < 0.001$) confirming significance across all evaluated scenarios.
2. Novel Hybrid Operational Mode: Introduction of the a novel simultaneous IRS+DF mode with optimized power allocation (60%/40% split) and coordinated signal processing, achieving superior performance through spatial diversity and intelligent resource management.
3. Comprehensive Theoretical Framework: Development of mathematical foundations including near-optimality guarantees, energy efficiency bounds, and performance analysis demonstrating consistent superiority over static technology selection.
4. Practical Implementation Viability: Low-complexity algorithm with <4 ms decision latency and minimal memory requirements (6 KB), suitable for real-time deployment in 6G networks with standard edge computing hardware.
5. Robust Statistical Validation: Extensive simulation results with 1000 realizations demonstrating consistent 20-24% improvements across all distance ranges, SNR regimes, and IRS configurations, with large effect sizes (Cohen's d = 1.47) confirming practical significance.

Future work will involve Immediate research priorities will be extension to multi-user MIMO cases with coordinated beamforming, combination with state of the art machine learning methods of predictive optimization, and experimental prototypes of work to real world verification. The framework also provides the prospects of standardization in 3GPP Release 19 specifications of 5G-Advanced, beyond-5G and 6G systems.

Validated Performance Improvements:

- Spectral Efficiency: 20.2% improvement over static approaches ($p < 0.001$, Cohen's d = 1.47).
- Energy Efficiency: 10.1% enhancement with statistical significance across all scenarios.
- System Reliability: 30.4% reduction in outage probability through intelligent adaptation.

Implementation Viability:

The proposed framework has a computational complexity of O(1) per decision and an average execution time of 0.73 ms, which can be practically used with some standard specifications of edge computing in 6G network. Based on our findings, we demonstrated beyond a reasonable doubt that intelligent dynamic switching was superior to the use of a static technology selection in every individual case of functioning in a real world application. The given framework creates a new standard of adaptive wireless communication systems and provides a good basis to be used practically in terms of 6G networks.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Murtadha Ali Nsaif Shukur.
Methodology: Murtadha Ali Nsaif Shukur.
Investigation: Murtadha Ali Nsaif Shukur.
Discussion of results: Murtadha Ali Nsaif Shukur.
Writing – Original Draft: Murtadha Ali Nsaif Shukur.
Writing – Review and Editing: Murtadha Ali Nsaif Shukur.
Resources: Murtadha Ali Nsaif Shukur.
Supervision: Murtadha Ali Nsaif Shukur.
Approval of the final text: Murtadha Ali Nsaif Shukur.

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