

Relay Placement Optimization in In-Band Full-Duplex Relay Systems for 6G Industrial Automation

Nann Win Moe Thet and Kenichi Takizawa

Resilient ICT Research Center

National Institute of Information and Communications Technology (NICT)

Miyagi, 9800812, Japan

Email: {nann, takizawa}@nict.go.jp

Abstract—Industrial automation requires ultra-reliable low-latency communication (URLLC) for mission-critical operations. In-band full-duplex (IBFD) relay systems offer a promising solution by enabling simultaneous transmission and reception, improving spectral efficiency and latency. However, in industrial environments, performance is limited by severe blockages and residual self-interference (RSI) at the relay. This paper investigates relay placement optimization for IBFD-enabled URLLC systems with RSI. Under finite blocklength and RSI, a data rate maximization problem is formulated, which is non-convex due to the SINR structure. To solve it, Lagrangian Dual Transform (LDT) and Quadratic Transform (QT) are applied, and an efficient iterative algorithm is developed for relay optimization. Simulation results show that the optimal relay location varies with the RSI level and transmit power, while the proposed scheme achieves performance comparable to grid search with lower computational complexity, demonstrating its practicality for industrial 6G deployments.

Keywords: In-band full-duplex (IBFD), ultra-reliable low-latency communication (URLLC), relay placement, residual self-interference (RSI), 6G, industrial automation.

I. INTRODUCTION

Wireless industrial automation is a key application of future sixth-generation (6G) networks, requiring ultra-reliable and low-latency communications (URLLC) with stringent latency and reliability requirements [1]. Due to severe blockage in industrial environments, relay-assisted communication is widely adopted to improve coverage and reliability [2]–[4]. Among relay technologies, in-band full-duplex (IBFD) relaying enables simultaneous transmission and reception, improving spectral efficiency and latency, and is regarded as a key technology for IMT-2030 [5]–[8]. However, residual self-interference (RSI) even after self-interference cancellation (SIC) degrades the effective signal-to-interference-plus-noise ratio (SINR) [9], making relay placement crucial in blockage-prone industrial environments.

Existing studies have investigated relay placement in IBFD networks for outage probability and symbol error rate (SER) minimization under RSI [10]–[12]. Meanwhile, URLLC research has focused on power allocation, blocklength optimization, and learning-based relay adaptation to meet reliability

and latency requirements [2], [4], [13]–[16]. However, the impact of relay placement on finite-blocklength URLLC performance in IBFD systems in the presence of RSI remains largely unexplored. Moreover, most prior works consider outage or error-rate metrics, whereas finite-blocklength rate maximization is more challenging due to the resulting non-convex SINR structure.

To address these limitations, this paper investigates an IBFD relay-assisted URLLC system with RSI in non-line-of-sight (NLOS) industrial environments. We formulate a finite-blocklength data rate maximization problem that explicitly depends on relay placement under RSI. To solve the resulting non-convex problem, we develop an efficient iterative framework based on Lagrangian dual transform (LDT), quadratic transform (QT), and successive convex approximation (SCA), yielding the optimal relay position. Finally, simulation results reveal the impact of RSI, transmit power, and URLLC requirements on the optimal relay location and system performance.

II. SYSTEM MODEL

We consider an amplify and forward (AF)-IBFD relay system in Fig. 1 to reduce processing delay from decoding or filtering. AF-IBFD relays enable simultaneous transmission and reception, improving reliability in obstructed industrial URLLC environments. The relay uses one transmit and one receive antenna, while the source (S) and destination (D) employ single antennas to focus on relay placement under residual self-interference. A blockage-dominant industrial scenario is considered where the direct line-of-sight (LOS) S – D link is unavailable due to severe obstruction, making relay-assisted transmission necessary. For notation, h_{SR} , h_{RD} , and h_{SD} denote the channels with distances d_{SR} , d_{RD} , and d_{SD} . The relay moves on an ellipse with foci at S and D , satisfying $d = d_{SR} + d_{RD}$, which captures practical factory constraints (e.g., corridors, obstacles, safety zones) while ensuring a bounded end-to-end propagation distance. Due to simultaneous transmission and reception at the IBFD

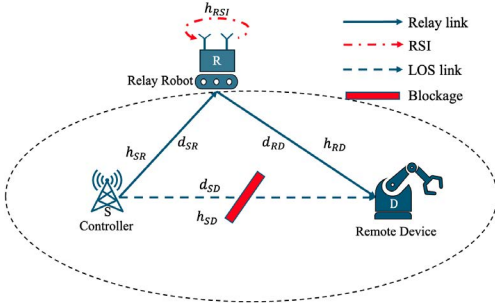


Fig. 1. AF-IBFD relay system in a factory automation environment.

relay, RSI persists even after applying SIC. The received signal at the relay is given by

$$y_R(k) = h_{SR}\sqrt{P_S}s(k) + h_{RSI}\sqrt{P_R}x_R(k) + w_R(k), \quad (1)$$

where h_{SR} is the source-relay channel, $h_{RSI} \sim \mathcal{CN}(0, \epsilon)$ models RSI with variance ϵ , P_S and P_R are transmit powers, and $w_R(k) \sim \mathcal{CN}(0, N_0)$ is additive white Gaussian noise (AWGN). The transmit signal satisfies $\mathbb{E}[|s(k)|^2] = 1$. The relay operates in amplify-and-forward mode with one-slot delay, $x_R(k) = Ay_R(k-1)$, where the gain is chosen to ensure unit relay power, i.e., $A = \sqrt{\frac{1}{\mathbb{E}[|h_{SR}|^2]P_S + \epsilon P_R + N_0}}$.

The received signal at the destination is expressed as

$$y_D(k) = h_{RD}\sqrt{P_R}x_R(k) + w_D(k), \quad (2)$$

where h_{RD} is the relay-to-destination channel coefficient, and $w_D(k) \sim \mathcal{CN}(0, N_0)$ is the AWGN at the destination. Substituting $x_R(k)$ into the above equation yields

$$y_D(k) = Ah_{RD}(h_{SR}\sqrt{P_R P_S}s(k-1) + h_{RSI}P_R x_R(k-1) + \sqrt{P_R}w_R(k-1)) + w_D(k). \quad (3)$$

Due to the recursive dependence of $x_R(k)$, higher-order self-interference terms arise. For tractability, we use a first-order approximation and neglect higher-order RSI components, which is valid under effective SI suppression ($\epsilon \ll 1$). In this regime, higher-order terms scale with powers of ϵ and are therefore negligible.

The SINR at the destination is then written as

$$\Gamma = \frac{A^2|h_{SR}|^2|h_{RD}|^2P_R P_S}{A^2|h_{RD}|^2P_R(|h_{RSI}|^2P_R + N_0) + N_0}. \quad (4)$$

Substituting A^2 , the RSI level $|h_{RSI}|^2 = \epsilon$, and letting $\gamma_s = P_S/N_0$, $\gamma_r = P_R/N_0$, we have

$$\Gamma = \frac{|h_{SR}|^2|h_{RD}|^2\gamma_s\gamma_r}{|h_{RD}|^2(\epsilon\gamma_r^2 + \gamma_r) + \gamma_s|h_{SR}|^2 + \epsilon\gamma_r + 1}. \quad (5)$$

Quasi-static fading is assumed, where channels remain constant during each packet transmission period and vary independently across different periods. For each link $m \in \{SR, RD\}$, the channel coefficients $h_m \sim \mathcal{CN}(0, \sigma_{h_m}^2)$ are modeled as zero-mean complex Gaussian random variables with variance $\sigma_{h_m}^2$. The average channel gain is $\sigma_{h_m}^2 = \mathbb{E}[|h_m|^2] = Kd_m^{-v}$, where K is the path loss at reference distance d_0 and v is the path loss exponent (typically 2–8) [17].

III. OPTIMIZATION FRAMEWORK

A. Problem Formulation

This work focuses on relay position optimization in IBFD-enabled URLLC systems under residual self-interference, where the objective is to maximize the achievable rate by optimizing the relay distance ratio. The relay placement problem is formulated using the SINR. Due to the NLOS condition, the relay cannot lie on the direct $S \rightarrow D$ path, leading to $d_{SR} + d_{RD} = d > d_{SD}$. The normalized relay position is defined as $\rho_d = \frac{d_{SR}}{d}$ with $0 < \rho_d < 1$, and $1 - \rho_d = \frac{d_{RD}}{d}$. The resulting SINR is expressed as

$$\Gamma = \frac{\gamma_s\gamma_r K^2 d^{-2v} \rho_d^{-v} (1 - \rho_d)^{-v}}{K d^{-v} (\epsilon\gamma_r^2 + \gamma_r)(1 - \rho_d)^{-v} + \gamma_s K d^{-v} \rho_d^{-v} + \epsilon\gamma_r + 1}. \quad (6)$$

Due to the short packet transmission, the maximum achievable data rate for URLLC is lower than the Shannon capacity and can be expressed as [18]

$$R = \log_2(1 + \Gamma) - \sqrt{\frac{V(\Gamma)}{M}} \log_2(e) Q^{-1}(\epsilon), \quad (7)$$

where $V(\Gamma) = 1 - (1 + \Gamma)^{-2}$ is the channel dispersion, $Q^{-1}(\cdot)$ is the inverse of Gaussian Q-function $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$, ϵ is transmission error probability, and M is a sufficiently large effective blocklength (e.g., $M \geq 100$). The data rate maximization problem is formulated as

$$\mathbf{P1}: \underset{\rho_d}{\text{maximize}} R, \quad (8a)$$

$$\text{subject to: } 0 < \rho_d < 1. \quad (8b)$$

Although **P1** represents a standard rate maximization problem, obtaining the optimal solution is challenging due to the non-convex nature of the objective function.

B. Proposed Algorithm

We propose an iterative algorithm to sub-optimally solve **P1** using fractional programming with LDT and QT methods [19]. Specifically, LDT decouples non-convex logarithmic terms via dual variables, while QT introduces auxiliary variables to handle fractional SINR expressions, resulting in an equivalent reformulation that facilitates iterative optimization. We begin by reformulating the (8) into a convex optimization problem based on the first term of (7), $\log_2(1 + \Gamma)$. The SINR term Γ can be expressed in fractional form as $\Gamma = \frac{A(\rho_d)}{B(\rho_d)}$, where $A(\rho_d) = G_1 \rho_d^{-v} (1 - \rho_d)^{-v}$ and $B(\rho_d) = G_2 (1 - \rho_d)^{-v} + G_3 \rho_d^{-v} + \sigma_1$. The coefficients are denoted as $G_1 = \gamma_s \gamma_r K^2 d^{-2v}$, $G_2 = K d^{-v} (\epsilon\gamma_r^2 + \gamma_r)$, $G_3 = \gamma_s K d^{-v}$, and $\sigma_1 = \epsilon\gamma_r + 1$.

Using the LDT introduced in [19], $\log_2(1 + \Gamma)$ can be equivalently rewritten as

$$f_{LD}(\gamma, \rho_d) = \log_2(1 + \gamma) - \gamma + \frac{(1 + \gamma)A(\rho_d)}{A(\rho_d) + B(\rho_d)}, \quad (9)$$

where γ is an auxiliary variable for the SINR. Given the initial fixed value ρ_d , the optimal value for the auxiliary variable γ can be obtained by solving $\frac{df_{LD}(\gamma)}{d\gamma} = 0$, yielding

$$\gamma^* = \frac{A(\rho_d)}{B(\rho_d)}. \quad (10)$$

Given that the updated $\gamma = \gamma^*$ is constant, substituting it into the LDT function in (9) makes $\log_2(1 + \gamma) - \gamma$ constant. Consequently, the new objective function is simplified, and the problem can be reformulated as

$$\mathbf{P1a}: \underset{\rho_d}{\text{maximize}} \quad f_1(\rho_d) = \frac{(1 + \gamma)A(\rho_d)}{A(\rho_d) + B(\rho_d)} \quad (11a)$$

$$\text{subject to: } 0 < \rho_d < 1. \quad (11b)$$

Since $f_1(\rho_d)$ in (11a) remains non-convex, and **P1a** is still a fractional programming problem, QT introduced in [19] is subsequently applied to (11a), transforming $f_1(\rho_d)$ into

$$f_Q(\rho_d, \alpha) = 2\alpha\sqrt{(1 + \gamma)A(\rho_d)} - \alpha^2(A(\rho_d) + B(\rho_d)), \quad (12)$$

where α is the fractional programming auxiliary variable. Now, with the fixed ρ_d and γ , the auxiliary variable α can be obtained by solving $\frac{df_Q(\alpha)}{d\alpha} = 0$, yielding the following expression for the solution α^* as

$$\alpha^* = \frac{\sqrt{(1 + \gamma)A(\rho_d)}}{A(\rho_d) + B(\rho_d)}. \quad (13)$$

By applying the QT function in (12) with the updated $\alpha = \alpha^*$ and γ and substituting back the finite blocklength code rate term from (7), the problem **P1** in (8) is transformed into

$$\mathbf{P1b}: \underset{\rho_d}{\text{maximize}} \quad 2\alpha\sqrt{(1 + \gamma)A(\rho_d)} - \alpha^2(A(\rho_d) + B(\rho_d)) \\ - \sqrt{\frac{V(\Gamma)}{M}} \log_2(e)Q^{-1}(\varepsilon), \quad (14a)$$

$$\text{subject to: } 0 < \rho_d < 1. \quad (14b)$$

It is evident that $A(\rho_d)$ and $B(\rho_d)$ remain non-convex due to the terms ρ_d^{-v} and $(1 - \rho_d)^{-v}$. Moreover, $\sqrt{V(\Gamma)}$ is also non-convex, making the overall problem non-convex. To address this, we apply first-order Taylor expansions to approximate these functions. For a given function $f(x)$, the first-order Taylor series expansion around the previous iterate is given by $f(x) \approx f(x^{(l)}) + f'(x^{(l)})(x - x^{(l)})$, where $l = i - 1$ denotes the index of the previous iteration. Thus, ρ_d^{-v} and $(1 - \rho_d)^{-v}$ in $B(\rho_d)$ are approximated as follows:

$$\rho_d^{-v} \approx \rho_d^{(i-1)-v} - v\rho_d^{(i-1)-v-1}(\rho_d - \rho_d^{(i-1)}). \quad (15)$$

$$(1 - \rho_d)^{-v} \approx (1 - \rho_d^{(i-1)})^{-v} + v(1 - \rho_d^{(i-1)})^{-v-1}(\rho_d - \rho_d^{(i-1)}). \quad (16)$$

Similarly, a multiplicative function $f(x)f(y)$ can also be approximated using the first-order Taylor series expansion as

Algorithm 1 Proposed Relay Location Optimization

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1: Initialize: Set feasible  $\rho_d^{(0)} \in (0, 1)$ ,  $i = 1$ 
2: while  $\frac{|R(\rho_d^{(i)}) - R(\rho_d^{(i-1)})|}{|R(\rho_d^{(i-1)})|} \geq \delta$  and  $i \leq I^{\max}$  do
3:   Set  $l = i - 1$ ;
4:   Update  $\gamma^{(i)}$  using previous  $\rho_d^{(l)}$  via (10);
5:   Update  $\alpha^{(i)}$  using previous  $\rho_d^{(l)}$  via (13);
6:   Linearize  $Y(\rho_d)$  via (18);
7:   Solve P1b in (14) using CVX to obtain  $\rho_d^{(i)}$ ;
8:    $i \leftarrow i + 1$ ;
9: end while

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$f(x)f(y) \approx f(x^{(l)}) + f'(x^{(l)})(x - x^{(l)}) + f'(y^{(l)})(y - y^{(l)})$. Thus, the multiplicative term in $A(\rho_d)$ is approximated as

$$\rho_d^{-v}(1 - \rho_d)^{-v} \approx \rho_d^{(l)-v}(1 - \rho_d^{(l)})^{-v} \\ + v\rho_d^{(l)-v}(1 - \rho_d^{(l)})^{-v-1}(\rho_d - \rho_d^{(l)}) \\ - v(1 - \rho_d^{(l)})^{-v}\rho_d^{(l)-v-1}(\rho_d - \rho_d^{(l)}). \quad (17)$$

Let $Y(\rho_d) = \sqrt{V(\Gamma)}$ with respect to ρ_d , then the first-order Taylor approximation $Y(\rho_d)$ can also be written as

$$Y(\rho_d) \approx Y(\rho_d^{(l)}) + Y'(\rho_d^{(l)})(\rho_d - \rho_d^{(l)}). \quad (18)$$

where $Y'(\rho_d) = \frac{(1+\Gamma)^{-3}}{\sqrt{V(\Gamma)}} \frac{d\Gamma}{d\rho_d}$, and $\frac{d\Gamma}{d\rho_d} = -v\Gamma\left(\frac{1}{\rho_d} - \frac{1}{1-\rho_d}\right) - \frac{v\Gamma K d^{-v}}{B} \left[(\epsilon\gamma_r^2 + \gamma_r)(1 - \rho_d)^{-v-1} - \gamma_s\rho_d^{-v-1} \right]$.

After incorporating the approximations (15)-(18) into the objective function of **P1b**, the original non-convex problem is converted into a sequence of convex surrogate subproblems under the SCA framework, which are efficiently solved using standard convex optimization solvers such as MATLAB CVX [20]. In this work, the transmit powers at the controller and relay are fixed to isolate the impact of relay placement.

The proposed algorithm, summarized in Algorithm 1, is an iterative SCA-based method initialized with a feasible $\rho_d^{(0)} \in (0, 1)$. At each iteration i , $\gamma^{(i)}$ and $\alpha^{(i)}$ are updated from the previous iterate $\rho_d^{(i-1)}$ via (10) and (13), and $Y(\rho_d)$ is linearized via (18). The resulting surrogate problem **P1b** is solved via CVX [20] to obtain an updated $\rho_d^{(i)}$. The procedure repeats until convergence under a predefined relative rate tolerance δ or $i > I^{\max}$. Each surrogate satisfies standard SCA conditions (first-order consistency and continuous differentiability), ensuring a locally tight approximation and convergence to a stationary point under standard assumptions [21]. The framework can be extended to multi-relay multi-antenna systems by jointly optimizing relay locations and beamforming via SCA-based alternating optimization under inter-relay interference and RSI.

C. Complexity Analysis

We focus on the complexity of problem **P1b**, as solving the convex optimization problem has a higher time complexity compared to solving the QT equation in (12). CVX solves the

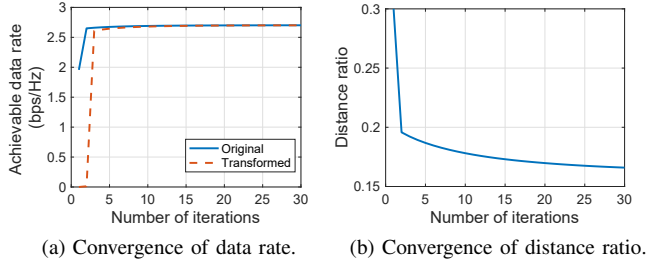


Fig. 2. Convergence of the proposed algorithm.

convex subproblem via interior-point methods with complexity $\mathcal{O}(n^3C)$, where n is the number of variables and C the number of constraints [22]. In Algorithm 1, with $n = 1$ and $C = 1$, the total complexity over $I^{\max}$ iterations is $\mathcal{O}(I^{\max})$. In contrast, grid search has exponential complexity $\mathcal{O}(p^n)$, where p is the number of samples per parameter. For $n = 1$, this reduces to $\mathcal{O}(p)$, growing with the number of search steps. Thus, the proposed algorithm is more efficient and does not require exhaustive evaluation.

IV. SIMULATION RESULTS

This section presents simulation results for the proposed IBFD relay positioning algorithm under finite-blocklength URLLC constraints. Performance is compared with non-optimized and grid search baselines, as well as full-duplex (FD) and reconfigurable intelligent surface (RIS) schemes. A sub-6 GHz industrial scenario is considered with $f_c = 4.9$ GHz, $W = 20$ MHz, and $d = 50$ m, assuming equal power allocation ($\rho_p = \frac{P_S}{P} = 0.5$) and total transmit power $P = 10$ dBm. The channel follows the 3GPP TR 38.901 dense indoor model, $PL(\text{dB}) = 18.6 + 35.7 \log_{10}(d) + 20 \log_{10}(f_c)$, with shadowing standard deviation $\sigma = 4.3$ [23], noise figure 10 dB, and noise power spectral density is $N_0 = -174$ dBm/Hz. Antenna gains are 5 dBi (transmitter/relay) and 0 dBi (destination). The target error probability is $\varepsilon = 10^{-5}$ with blocklength $M = 500$ [2], and results are averaged over 10^5 channel realizations.

Figure 2 shows the convergence of the proposed algorithm from $\rho_d^{(0)} = 0.3$. In Fig. 2a, the data rate converges within fewer than 10 iterations, confirming the effectiveness of the LDT and QT-based reformulation and the resulting SCA procedure. Fig. 2b shows that the distance ratio quickly stabilizes after a short initial adjustment phase, demonstrating the practicality of the proposed method in dynamic environments.

Figure 3 presents the achievable rate versus distance ratio under different RSI levels, compared with grid search. The “ $\varepsilon = 0$ ” curve is the ideal case without RSI. The proposed algorithm (star markers) closely matches the grid search (diamond markers) across all RSI levels, confirming its accuracy, while higher RSI significantly degrades performance and shifts the optimal relay position toward the source to mitigate self-interference. This highlights the need for adaptive relay placement to ensure reliable, high data rates.

Figure 4 illustrates the impact of RSI on system performance. In Fig. 4a, the achievable rate increases with

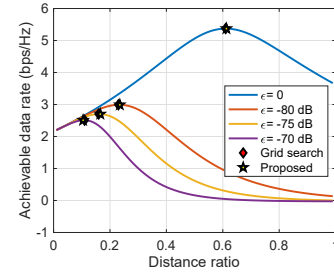


Fig. 3. Comparison of data rates versus relay location for the proposed algorithm and the grid search method, at $\rho_p = 0.5$.

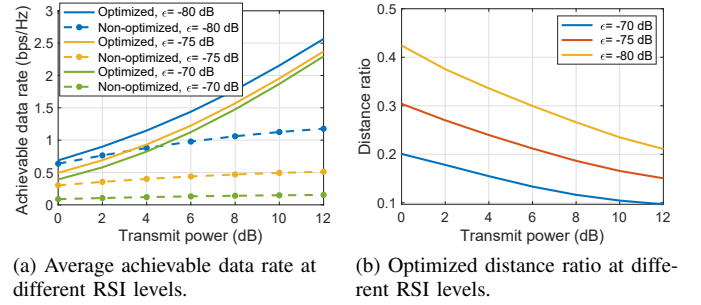


Fig. 4. Performance of the proposed algorithm across different RSI levels.

transmit power and decreases with higher RSI, while the optimized scheme consistently outperforms the non-optimized one, with larger gains at higher transmit powers. In Fig. 4b, the optimal relay position shifts toward the source as the transmit power increases and the RSI becomes stronger. These results highlight the trade-off between link quality and SI, emphasizing the need for adaptive relay placement under RSI.

Figure 5 evaluates the proposed algorithm under different power allocation ratios ρ_p . Fig. 5a shows that increasing ρ_p shifts the relay toward the destination, with a stronger effect under lower RSI due to reduced interference constraints and improved $R \rightarrow D$ link quality. Fig. 5b shows that the optimized scheme consistently outperforms the non-optimized case across all ρ_p , with larger gains at low ρ_p where relay placement becomes more critical due to a weaker $S \rightarrow R$ link, highlighting the benefit of joint power and relay optimization.

Figure 6 shows the achievable rate versus blocklength M for different error probabilities ε . The optimized scheme outperforms the baselines across all M and ε . Increasing M improves the rate due to reduced finite-blocklength penalties but increases latency, while stricter reliability (smaller ε) reduces the rate. Overall, the results highlight the URLLC trade-off among blocklength, channel dispersion, and reliability, and confirm the effectiveness of the proposed optimization.

Figure 7 compares the proposed IBFD scheme with the baseline methods. The optimized scheme outperforms the non-optimized and HD schemes, particularly at high transmit power. It also achieves competitive performance against RIS with moderate size ($N = 16$) while requiring lower hardware complexity; however, large RIS ($N = 128$) provides higher rates at the cost of greater deployment and hardware overhead. These results demonstrate the effectiveness of the proposed IBFD relay optimization under practical industrial constraints.

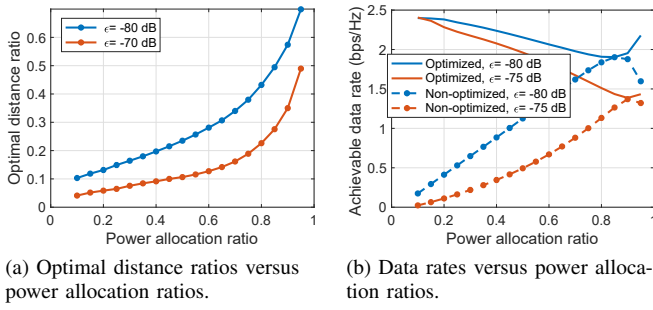


Fig. 5. Performance of the proposed algorithm across different power allocation ratios.

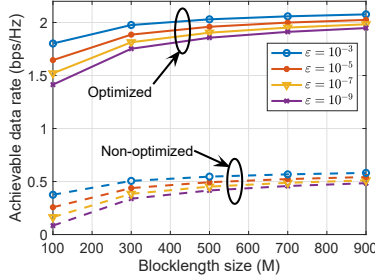


Fig. 6. Average achievable data rate versus blocklength under different error probabilities.

V. CONCLUSION

This paper proposes a relay location optimization algorithm for IBFD systems in industrial automation under residual self-interference. By reformulating the non-convex problem as a convex surrogate, the algorithm provides an efficient solution. Simulations demonstrate that it closely approximates grid search while reducing computational complexity. The optimal relay position shifts closer to the source with increasing transmit power and stronger RSI. Optimizing relay positions under RSI improves data rates and ensures transmission reliability, enhancing IBFD performance in URLLC-enabled industrial settings. Future work will consider joint power allocation and relay placement in multi-relay networks.

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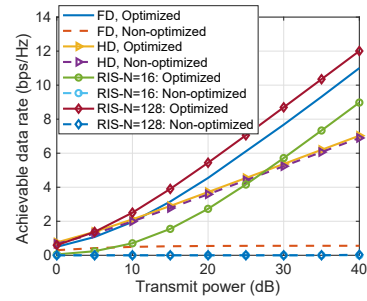


Fig. 7. Comparison of average achievable data rate for baseline schemes with the proposed algorithms ($\epsilon = -75$ dB).

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