

Joint beamforming and movement design for agentic AI assisted ISAC system

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Abstract Integrated Sensing and Communication (ISAC) designs often overlook power amplifier (PA) nonlinearity and user mobility. To address these gaps, we study an ISAC system model incorporating memoryless PA nonlinearity and agent mobility, where agents proactively move toward the base station to improve channels at a locomotion energy cost. This model opens a new direction for self-managing CR-IoT infrastructure in space in hardware adaptation, topology adaptation, and autonomous management. We formulate a max-min energy efficiency (EE) optimization problem subject to transmit power, movement bounds, and hardware distortion constraints. To solve this non-convex fractional program, we propose a two-layer dinkelbach-block coordinate descent (BCD)-successive convex approximation (SCA) algorithm framework to jointly optimize beamforming, sensing waveforms, and movement distances. Additionally, a large language model (LLM) agent dynamically adjusts operational parameters based on network context for cognitive adaptability. Simulations demonstrate that our framework substantially outperforms conventional static and heuristic baselines. Specifically, it yields up to 40% sum-rate gains in dense user scenarios and 30% EE improvements under moderate power budgets. These advantages are particularly pronounced under strong PA nonlinearity, confirming that jointly optimizing mobility and hardware awareness yields robust performance against severe signal distortion. Finally, beam pattern analysis validates the flexible reconfigurability of transmit waveforms.

Keywords ISAC; beamforming; power amplifier nonlinearity; large language model; hierarchical optimization; hardware impairment

1 Introduction

The rapid evolution toward sixth-generation (6G) wireless networks envisions a paradigm shift from pure data connectivity to intelligent, context-aware, and multi-functional infrastructures. Among the most promising technologies, Integrated Sensing and Communication (ISAC) has emerged as a cornerstone, enabling the joint utilization of radio resources for both high-rate data transmission and high-precision sensing tasks such as target detection, localization, and imaging [1, 2]. This dual-functionality promises unprecedented spectral and hardware efficiency, which is essential for emerging applications like autonomous driving, smart factories, and immersive extended reality. Despite its potential, practical ISAC systems still face several fundamental gaps that have been largely overlooked in prior research.

Traditional optimization approaches rely on fixed weight parameters or manual reconfiguration, lacking the ability to interpret high-level network states or mission requirements. For instance, a sudden need for high-precision tracking of a specific target versus a burst of high-priority communication traffic would require different resource allocations. Current schemes cannot autonomously adapt to such dynamic operational demands without human intervention [8]. The emergence of large language models (LLMs) offers a transformative opportunity to embed high-level cognitive intelligence into wireless networks [10]. With advanced capabilities in semantic reasoning, instruction following, and contextual understanding, LLMs can act as intelligent agents that interpret network states, user priorities, and even natural language commands to dynamically generate control parameters for physical-layer optimization. This synergy between AI-driven cognition and model-based optimization opens the door to autonomous, context-aware ISAC systems that can adapt to rapidly changing operational demands without manual reconfiguration.

However, even with LLM assistance, most existing ISAC+LLM frameworks still treat user locations as static and do not exploit mobility as a proactive resource. In dynamic environments, agents users can reposition themselves to improve channel conditions, reduce path loss, and enhance

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spatial diversity [6, 7]. Mobility itself consumes energy, creating a communication-computation-control trade-off that has not been jointly addressed in ISAC systems. Furthermore, existing works that do consider mobility typically treat it separately from communication and sensing resource allocation, leading to suboptimal designs.

Even with mobility-aware LLM-ISAC frameworks, a critical hardware issue remains. Most existing ISAC beamforming designs assume ideal linear hardware, particularly in the power amplifier (PA) stage [3, 4]. In reality, PAs exhibit significant nonlinear distortion when driven near saturation — a common operating point for energy efficiency. This nonlinearity corrupts the transmitted signal, degrading communication reliability through in-band distortion and impairing sensing accuracy by distorting the intended beam pattern and elevating sidelobe levels [5]. Conventional mitigation techniques, such as aggressive input back-off, are spectrally and energetically inefficient, undermining the core benefits of ISAC. Moreover, most existing PA-aware optimization efforts treat the distortion as a fixed penalty rather than an exploitable variable, leaving significant performance gains untapped.

Recent years have witnessed significant progress in ISAC across multiple fronts. From a technical perspective, waveform design, beamforming, reconfigurable intelligent surface (RIS), and multi-cell cooperation have been extensively studied [22, 23]. Machine learning has also been integrated to enable data-driven adaptation to dynamic channel conditions [24]. Parallel to this, large language models have emerged as a transformative tool for wireless network management, offering natural language-driven reasoning, context-aware optimization, and adaptive solution refinement [25]. In the specific context of ISAC, recent works have explored LLM-assisted antenna partitioning and beamforming optimization in segmented pinching antenna systems [26] (but it only considers static user locations and ideal linear power amplifiers), LLM-aided multi-objective optimization for near-field ISAC networks [27], joint user association and beamforming design using prompt engineering techniques [28] (yet it also adopts the ideal hardware assumption and does not exploit mobility as an optimization dimension), a unified LLM-based framework for multi-base station (BS) ISAC combining fractional programming and alternating direction method of multipliers (ADMM) [29], as well as LLM-enabled cognitive sensing and communication resource allocation for low-altitude economy applications. Despite these encouraging advances, existing LLM-ISAC integrations predominantly assume static user locations and ideal hardware, overlooking the joint optimization of beamforming, sensing, agent mobility, and PA nonlinearity.

This paper aims to fill this gap.

In this paper, we bridge the gaps of hardware impairment, mobility underutilization, and cognitive adaptability by proposing a novel ISAC framework that jointly optimizes beamforming, sensing waveform, and agent movement under PA nonlinearity, guided by an LLM-based policy module. Our main contributions are threefold:

- We study an ISAC system model that jointly incorporates power amplifier nonlinearity, agent mobility where each user can move toward the base station at a locomotion energy cost, and an LLM-based cognitive policy module that dynamically adjusts key trade-off parameters based on network context.
- We formulate a max-min energy efficiency optimization problem that maximizes the minimum energy efficiency among all agents, subject to transmit power constraints, per-agent movement and total power budgets, minimum beam gain constraints for high-priority sensing targets, and a distortion constraint that limits the normalized nonlinear distortion power.
- To solve this highly non-convex fractional program, we propose a two-layer optimization algorithm. The outer layer employs the generalized Dinkelbach method to transform the max-min fractional objective into a sequence of parametric subtractive problems. The inner layer uses block coordinate descent combined with successive convex approximation, alternately optimizing the beamforming and sensing variables via weighted minimum mean-square error (WMMSE)-successive convex approximation (SCA) and the movement distances via linear programming. The algorithm provably converges to a Karush–Kuhn–Tucker point.
- Extensive simulations demonstrate that the proposed framework significantly outperforms no-mobility, fixed-mobility, and random-mobility baselines. In dense user scenarios, the weighted sum rate gain reaches up to 40%. The energy efficiency improves by about 30% under a 1W power budget. Even under severe PA nonlinearity, the proposed scheme maintains an 18% rate advantage over the no-mobility baseline. Beam pattern analysis further confirms the flexible reconfigurability of the transmit waveform.

The remainder of this paper is organized as follows. Section 2 presents the system model, including the ISAC signal model, PA nonlinearity, communication and sensing metrics, the agent mobility model, and the LLM cognitive policy module. Section 3 formulates the joint optimization problem and discusses its challenges. We also detail the proposed

Dinkelbach-block coordinate descent (BCD)-SCA algorithm. Section 4 provides simulation results and analysis. Finally, Section 5 concludes the paper and outlines future research directions. Throughout this section, we adopt the following conventions: vectors are denoted by bold lowercase letters, matrices by bold uppercase letters, $(\cdot)^H$ denotes Hermitian transpose, $(\cdot)^T$ denotes transpose, $\odot$ denotes the Hadamard product, $\text{Tr}(\cdot)$ denotes the trace, and $\mathbb{E}[\cdot]$ denotes statistical expectation. Existing LLM-ISAC works generally assume static user locations and ideal linear power amplifiers. In contrast, this paper for the first time integrates agent mobility, PA nonlinear distortion and LLM-driven cognitive policy into a unified optimization framework. The core differentiators are: (i) Mobility is introduced as an active optimization dimension to improve cell-edge user performance; (ii) Memoryless PA nonlinearity is explicitly modeled with distortion constraints for more practical results; (iii) A two-layer Dinkelbach-BCD-SCA algorithm is proposed with provable convergence to a KKT point. Simulations show up to 40% sum-rate gain and 30% energy efficiency improvement in dense scenarios.

2 System Model

We consider a downlink ISAC system where a base station equipped with a uniform linear array (ULA) of N_t antennas serves K single-antenna communication users (CUs) while simultaneously detecting L point-like sensing targets. The set of users is denoted by $\mathcal{K} = \{1, \dots, K\}$ and the set of targets by $\mathcal{L} = \{1, \dots, L\}$. The system operates over a narrowband block-fading channel, and the BS is assumed to have perfect channel state information (CSI) for all users, obtained via uplink pilots in time-division duplex (TDD) mode. A detailed illustration of the system architecture is provided in Figure 1.

2.1 Network and Signal Model

The baseband signal transmitted by the BS at discrete time index n is the superposition of the communication data streams and the dedicated sensing waveform[14]:

$$\mathbf{x}[n] = \sum_{k=1}^K \mathbf{w}_k s_k[n] + \mathbf{s}_r[n], \mathcal{N} = \{1, \dots, N\}, n \in \mathcal{N} \quad (1)$$

where:

- (1) $\mathbf{w}_k \in \mathbb{C}^{N_t \times 1}$ is the beamforming vector for user k .
- (2) $s_k[n] \sim \mathcal{CN}(0, 1)$ is the independent and identically distributed (i.i.d.) communication data stream for user k . The data streams are mutually independent and also independent of the sensing signal.
- (3) $\mathbf{s}_r[n] \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_r)$ is the dedicated sensing waveform, where $\mathbf{R}_r \in \mathbb{C}^{N_t \times N_t}$ and $\mathbf{R}_r \succeq \mathbf{0}$ is its covariance matrix.

The total transmit covariance matrix, which summarizes the second-order statistics of the transmitted signal, is given by

$$\mathbf{R}_x = \mathbb{E}[\mathbf{x}[n]\mathbf{x}[n]^H] = \sum_{k=1}^K \mathbf{w}_k \mathbf{w}_k^H + \mathbf{R}_r. \quad (2)$$

The total transmit power is constrained by the system's power budget:

$$\text{Tr}(\mathbf{R}_x) \leq P_{\max}, \quad (3)$$

where $P_{\max}$ is the maximum allowed transmit power. The transmitted signal $\mathbf{x}[n]$ is then passed through the power amplifiers at each antenna branch, which introduce nonlinear distortion as described next.

2.2 Power Amplifier Nonlinearity Model

Practical power amplifiers exhibit nonlinear behavior, especially when operated near saturation to achieve high power efficiency. This nonlinearity generates unwanted harmonics, intermodulation products, and spectral regrowth, which degrade both communication and sensing performance. To capture the dominant distortion effects while maintaining analytical tractability, we adopt a memoryless third-order polynomial model[15]. This model is widely used in the literature because it provides a good approximation for mildly nonlinear PAs and yields closed-form expressions for the distortion statistics when the input is Gaussian.

Specifically, for the m -th antenna branch, the input-output relationship of the PA is given by

$$\tilde{x}_m[n] = f_{\text{PA}}(x_m[n]) \approx g_1 x_m[n] + g_2 x_m[n] |x_m[n]|^2, \quad (4)$$

where $g_1, g_2 \in \mathbb{C}$ are the complex coefficients of the linear and third-order nonlinear terms, respectively. The coefficient g_1 represents the linear gain, while g_2 captures the nonlinear distortion. The ratio $|g_2|/|g_1|$ quantifies the severity of the nonlinearity; typical values range from 0.01 to 0.1 for solid-state PAs operating near the 1dB compression point. The model in (4) is memoryless, meaning that the output at time n depends only on the input at the same time index. This assumption is reasonable for narrowband signals where the memory effects are negligible compared to the symbol duration.

The array-level distorted signal vector is obtained by applying the PA model element-wise to $\mathbf{x}[n]$:

$$\tilde{\mathbf{x}}[n] = g_1 \mathbf{x}[n] + g_2 \mathbf{x}[n] \odot |\mathbf{x}[n]|^2, \quad (5)$$

where $\odot$ denotes the Hadamard product, and $|\mathbf{x}[n]|^2$ is computed element-wise. This expression reveals that the distortion term is quadratic in the input signal, which leads to a coupling between different beams and the sensing waveform.

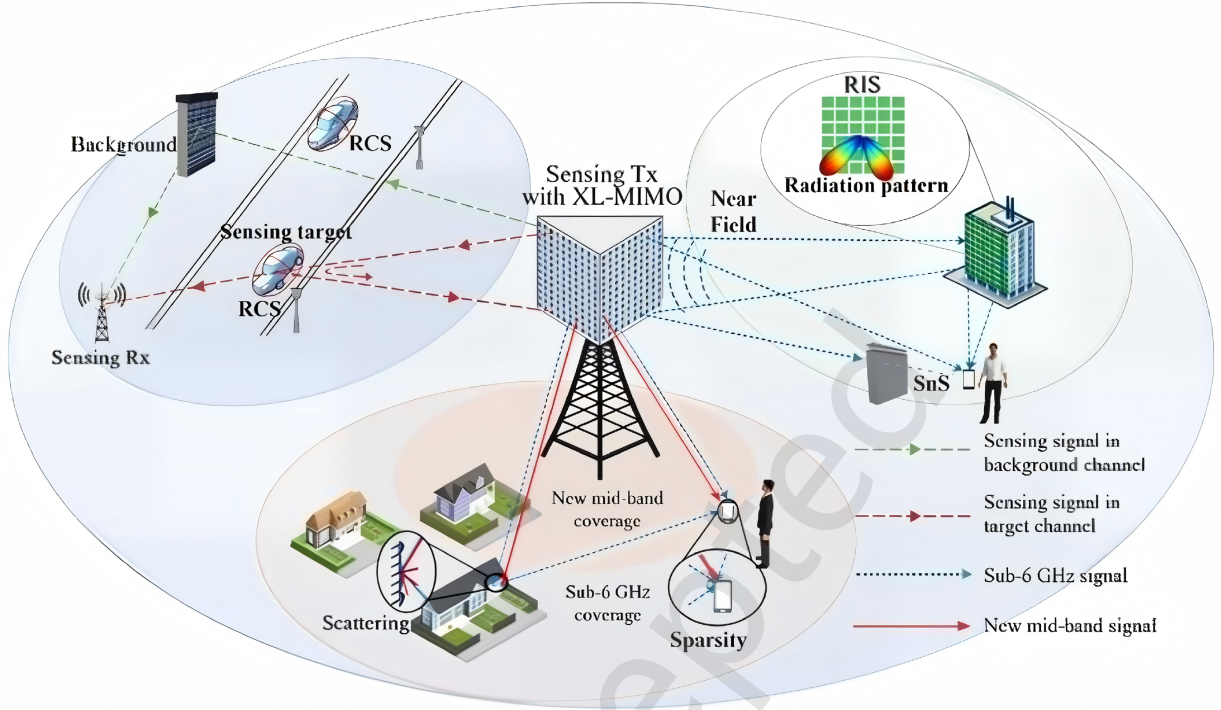


Fig. 1 LLM-Empowered ISAC System Architecture for Mobile Agents with Adaptive PA Nonlinearity Compensation

To facilitate analysis, we assume that the transmitted signal $\mathbf{x}[n]$ is circularly symmetric complex Gaussian (CSCG). Under this assumption, we can compute the second-order statistics of the distorted signal. In particular, the covariance matrix of the distorted signal is given by

$$\mathbb{E}[\tilde{\mathbf{x}}[n]\tilde{\mathbf{x}}[n]^H] = |g_1|^2 \mathbf{R}_x + \mathbf{R}_{NL}, \quad (6)$$

where

$$\mathbf{R}_{NL} = 2|g_2|^2 (\mathbf{R}_x \odot \mathbf{R}_x^T) \quad (7)$$

is the covariance matrix of the nonlinear distortion term.

- $2|g_2|^2$: Fourth-order moment coefficient of CSCG signals, quantifying the overall strength of third-order non-linear distortion.
- $\mathbf{R}_x \odot \mathbf{R}_x^T$: Element-wise self-coupling of transmit covariance, capturing per-branch intermodulation distortion.
- $\mathbf{R}_{NL}$: Covariance matrix of nonlinear distortion at PA output, acting as extra interference for communication and causing beam broadening and sidelobe elevation for sensing.

The factor 2 arises from the fourth-order moment of a complex Gaussian random variable: $\mathbb{E}[|x|^4] = 2(\mathbb{E}[|x|^2])^2$ for zero-mean CSCG. This result is derived by expanding the fourth-order terms and applying the Isserlis' theorem, which is also known as the Gaussian moment theorem. The derivation

is omitted here for brevity but is standard in the literature. The matrix $\mathbf{R}_{NL}$ plays a crucial role in both communication and sensing performance metrics, as it quantifies the additional interference and beam pattern distortion caused by PA nonlinearity.

The CSCG signal assumption is justified for three reasons:

- (1) Superimposed multi-user signals approximate Gaussian distribution by the central limit theorem, which is a standard assumption in MIMO/ISAC analysis.
- (2) Gaussian sensing waveforms with ideal ambiguity functions are widely adopted in ISAC systems.
- (3) This assumption enables closed-form derivation of distortion statistics via the Gaussian moment theorem:

$$\mathbb{E}[|x|^4] = 2(\mathbb{E}[|x|^2])^2, \quad x \sim \mathcal{CN}(0, \sigma^2),$$

which supports the subsequent convex approximation algorithm design. The approximation accuracy is acceptable for system-level analysis.

2.3 Communication Performance Metric

The received signal at user k is given by

$$y_k[n] = \mathbf{h}_k^H \tilde{\mathbf{x}}[n] + n_k[n], \quad (8)$$

where:

- (1) $\mathbf{h}_k \in \mathbb{C}^{N_t \times 1}$ is the downlink channel vector from the BS to user k . The channel is modeled as $\mathbf{h}_k = \sqrt{\beta_k} \tilde{\mathbf{h}}_k$, with

$\tilde{\mathbf{h}}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{N_t})$ representing the small-scale Rayleigh fading (which is independent across users and time slots) and β_k the large-scale path loss. The path loss is given by $\beta_k = \beta_0 D_k^{-\delta}$, where D_k is the distance between the BS and user k , β_0 is the reference gain at 1 m, and $\delta > 2$ is the path-loss exponent. This model captures both distance-dependent attenuation and shadowing effects which can be absorbed into β_k if needed.

- (2) $n_k[n] \sim \mathcal{CN}(0, \sigma_c^2)$ is additive white Gaussian noise (AWGN) at the receiver, with $\sigma_c^2 = N_0 B$, where N_0 is the noise power spectral density and B is the system bandwidth.

Substituting the distorted signal expression (5) into (8), we obtain

$$y_k[n] = g_1 \mathbf{h}_k^H \mathbf{x}[n] + g_2 \mathbf{h}_k^H (\mathbf{x}[n] \odot |\mathbf{x}[n]|^2) + n_k[n]. \quad (9)$$

The first term corresponds to the desired linear part, the second term is the nonlinear distortion, and the third term is the noise. To compute the signal-to-noise ratio (SNR), we treat the distortion as additional interference that is uncorrelated with the desired signal. The desired signal power for user k is obtained from the linear part:

$$\begin{aligned} S_k &= |g_1|^2 \mathbb{E} [|\mathbf{h}_k^H \mathbf{x}[n]|^2] \\ &= |g_1|^2 \mathbf{h}_k^H \left(\sum_{j=1}^K \mathbf{w}_j \mathbf{w}_j^H + \mathbf{R}_r \right) \mathbf{h}_k. \end{aligned} \quad (10)$$

However, note that the sensing signal $\mathbf{s}_r[n]$ is also present in the linear part and contributes to the desired signal power only if user k intends to receive it. In a typical ISAC setup, users are only interested in the communication symbols, not the sensing waveform. Therefore, the desired signal power for user k should only include the contribution from its own beamformer, which is:

$$S_k^{(\text{desired})} = |g_1|^2 |\mathbf{h}_k^H \mathbf{w}_k|^2. \quad (11)$$

The remaining terms in the linear part, namely the contributions from other users' communication signals and the sensing signal, act as interference. Moreover, the nonlinear distortion term contributes additional interference. The interference-plus-noise power for user k is thus given by the equation (12).

The term $\mathbf{h}_k^H \mathbf{R}_r \mathbf{h}_k$ arises from the dedicated sensing

waveform; it is interference from the sensing signal that the user does not decode. The nonlinear distortion term is derived from the fourth-order moment of the Gaussian input, similar to the derivation of $\mathbf{R}_{\text{NL}}$. The factor 2 appears again due to the Gaussian moment. Therefore, the effective SNR at user k is given by [16, 17].

This expression highlights the coupling between communication and sensing: the sensing waveform not only consumes power but also generates interference to the communication users. Moreover, the nonlinear distortion couples all transmitted signals, making the optimization highly non-trivial. The achievable downlink rate for user k is then given by Shannon's formula:

$$R_k = B \log_2(1 + \text{SNR}_k). \quad (14)$$

This rate represents the maximum data rate that can be reliably transmitted to user k under the given SNR.

2.4 Sensing Performance Metric

For sensing, the BS aims to steer energy toward specific angular directions corresponding to the sensing targets. The ideal beam pattern is defined as a function that assigns desired gain levels to each target angle. However, the PA nonlinearity distorts the transmitted waveform and consequently the beam pattern. We first define the array steering vector for a ULA with half-wavelength spacing ($d = \lambda/2$):

$$\mathbf{a}(\theta) = \frac{1}{\sqrt{N_t}} [1, e^{j\pi \sin \theta}, e^{j2\pi \sin \theta}, \dots, e^{j(N_t-1)\pi \sin \theta}]^T, \quad (15)$$

where θ is the azimuth angle measured from the boresight. The normalization factor $1/\sqrt{N_t}$ ensures that $\|\mathbf{a}(\theta)\|^2 = 1$. The expected beam pattern at angle θ is defined as the average power radiated in that direction:

$$\bar{P}(\theta) = \mathbb{E} [|\mathbf{a}^H(\theta) \tilde{\mathbf{x}}[n]|^2]. \quad (16)$$

Substituting the distorted signal model (6) into this definition, we obtain

$$\bar{P}(\theta) = \mathbf{a}^H(\theta) (|g_1|^2 \mathbf{R}_x + \mathbf{R}_{\text{NL}}) \mathbf{a}(\theta), \quad (17)$$

where $\mathbf{R}_{\text{NL}} = 2|g_2|^2 (\mathbf{R}_x \odot \mathbf{R}_x^T)$. This expression reveals that the PA nonlinearity adds an extra term $\mathbf{R}_{\text{NL}}$ to the

$$I_k = \underbrace{|g_1|^2 \sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2}_{\text{multi-user interference}} + \underbrace{|g_1|^2 \mathbf{h}_k^H \mathbf{R}_r \mathbf{h}_k}_{\text{sensing interference}} + \underbrace{2|g_2|^2 \mathbf{h}_k^H (\mathbf{R}_x \odot \mathbf{R}_x^T) \mathbf{h}_k}_{\text{nonlinear distortion}} + \sigma_c^2. \quad (12)$$

effective covariance matrix, which is quartic in $\mathbf{R}_x$. This term causes beam broadening, sidelobe elevation, and a reduction in the beam pattern contrast between target and non-target directions.

To quantify the sensing performance, we consider a set of discrete target angles $\{\theta_l\}_{l=1}^L$ with desired beam gains $D(\theta_l)$. The desired gains are typically set to 1 for target directions to maximize the signal-to-noise ratio of the echo and 0 for non-target directions to minimize interference. However, in practice, a compromise is often made to allow some sidelobe level. We define the mean square error (MSE)[18] between the actual and desired beam patterns as

$$\text{MSE}_{\text{beam}} = \frac{1}{L} \sum_{l=1}^L |\bar{P}(\theta_l) - D(\theta_l)|^2. \quad (18)$$

A smaller MSE indicates better sensing fidelity. This metric is commonly used in beam pattern design problems because it is convex in the transmit covariance matrix $\mathbf{R}_x$ when the distortion term $\mathbf{R}_{\text{NL}}$ is linearized. However, due to the presence of $\mathbf{R}_{\text{NL}}$, the actual MSE is a quartic function of the beamformers, which is non-convex and challenging to optimize directly.

It is worth noting that the sensing performance can also be evaluated using other metrics, such as the Cramér–Rao bound (CRB) for target parameter estimation or the output signal-to-noise ratio of the matched filter. However, the beam pattern MSE is a more direct measure of the spatial focusing capability and is widely used in ISAC literature. Moreover, by controlling the desired pattern $D(\theta)$, we can impose different priorities on different targets. The LLM agent will later provide the parameters η_t which is minimum beam gain for high-priority targets and β_t which is trade-off factor to balance the sensing accuracy against communication performance.

2.5 Agent Mobility Model

We allow each communication user which can be seen as an intelligent agent to move toward the BS to improve its channel condition. This mobility is motivated by the observation that moving closer to the BS reduces path loss and can significantly increase the received signal power, thereby improving the communication rate or reducing the required transmit power. However, movement consumes energy, which must be accounted for in the overall EE.

We assume that the movement occurs within a dedicated time slot of duration T_k before the data transmission phase. During this time, agent k moves at a constant speed $v_k = d_k/T_k$, where d_k is the total displacement. The energy consumed for movement is modeled as the work done against friction and other resistive forces. For simplicity, we adopt a linear model:

$$E_k^{\text{move}} = F_k d_k, \quad (19)$$

where $F_k > 0$ is the energy coefficient that aggregates the effects of mass, rolling resistance, and other factors. The corresponding power consumption which averaged over the movement duration is $P_k^{\text{move}} = E_k^{\text{move}}/T_k = F_k d_k/T_k$ [19].

The linear energy model $E_k^{\text{move}} = F_k d_k$ is suitable for our scenario:

- (1) For low-speed agents, energy consumption for overcoming friction is approximately proportional to distance.
- (2) It is a widely adopted standard model in mobile wireless network research.
- (3) Short-distance position adjustment in this work falls well within its applicable range.

For high-speed scenarios, the model can be extended to non-linear form without changing the core algorithm framework.

The agent's initial position is given by $\mathbf{q}_k^{(0)} \in \mathbb{R}^2$, with the BS located at the origin $\mathbf{0}$. The initial distance to the BS is $D_k = \|\mathbf{q}_k^{(0)}\|$. We assume the agent moves along the straight line toward the BS, so its post-movement position is

$$\mathbf{q}_k = \mathbf{q}_k^{(0)} - \frac{d_k}{D_k} \mathbf{q}_k^{(0)} = \left(1 - \frac{d_k}{D_k}\right) \mathbf{q}_k^{(0)}, \quad (20)$$

and the new distance is $r_k = D_k - d_k$. d_k is the straight-line movement distance of the k -th agent toward the BS (in meters). The movement distance is bounded by physical and safety constraints:

$$d_k^{\min} \leq d_k \leq d_k^{\max}, \quad \forall k, \quad (21)$$

where $d_k^{\min} \geq 0$ and $d_k^{\max}$ is the maximum feasible displacement. We also require that $d_k < D_k$ so that the agent does not overshoot the BS.

The large-scale channel gain after movement is updated to[19, 21]

$$\beta_k(d_k) = \beta_0(D_k - d_k)^{-\delta}, \quad (22)$$

$$\text{SNR}_k = \frac{|g_1|^2 |\mathbf{h}_k^H \mathbf{w}_k|^2}{|g_1|^2 \sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + |g_1|^2 \mathbf{h}_k^H \mathbf{R}_r \mathbf{h}_k + 2|g_2|^2 \mathbf{h}_k^H (\mathbf{R}_x \odot \mathbf{R}_x^T) \mathbf{h}_k + \sigma_c^2}. \quad (13)$$

and consequently, the channel vector becomes

$$\mathbf{h}_k(d_k) = \sqrt{\beta_k(d_k)} \tilde{\mathbf{h}}_k, \quad (23)$$

where $\tilde{\mathbf{h}}_k$ is the same small-scale fading component as before which is assumed unchanged during the short movement. This assumption holds if the movement distance is much smaller than the coherence distance of the channel which is typically on the order of several wavelengths. Thus, the only effect of mobility is to increase the path gain, which directly improves the received signal power for both communication and sensing.

2.6 LLM Agent: The Cognitive Policy Module

The *cognitive policy module* is an LLM-driven high-level decision unit. It perceives network states, interprets task requirements, and dynamically outputs policy parameters for physical-layer optimization, enabling autonomous adaptation without manual tuning. To enable context-aware adaptability, we introduce a LLM agent that operates at a slower timescale. The LLM agent does not perform low-level optimization; instead, it acts as a cognitive engine that interprets high-level information and outputs a small set of policy parameters that configure the physical-layer optimization. This hierarchical design separates high-level reasoning from low-level computation, making the system both flexible and computationally efficient.

The input to the LLM agent at time t is the network state S_t , which includes:

- (1) The current positions of all agents $\{\mathbf{q}_k\}$ which obtained via GPS or localization.
- (2) Channel quality indicators for each user.
- (3) A list of sensing targets with their priorities.
- (4) Remaining movement budgets for each agent.
- (5) Optional natural language instructions from the network operator, such as “prioritize tracking target 1”, “save energy”, or “maximize fairness”.

The LLM processes this information using its pre-trained reasoning capabilities and generates a concise policy vector[20]:

$$\mathbf{a}_t = [\beta_t, \eta_t, \gamma_t, \kappa_t], \quad (24)$$

where each component is defined as follows:

- (1) $\beta_t \in [0, 1]$: Communication-sensing trade-off factor. A value close to 1 prioritizes communication sum-rate, while a value close to 0 prioritizes sensing accuracy. This parameter directly weights the two terms in the objective function.
- (2) $\eta_t \geq 0$: Minimum required beam gain for high-priority sensing targets. This ensures that the beam pattern at the target directions is at least η_t times the peak gain, which

is essential for reliable target detection. The LLM can increase η_t when a target becomes critical.

- (3) $\gamma_t = [\gamma_{1,t}, \dots, \gamma_{K,t}]$: User-specific fairness weights. By adjusting these weights, the LLM can enforce different levels of fairness. The weights appear in the weighted sum-rate objective.
- (4) $\kappa_t = [\kappa_{1,t}, \dots, \kappa_{K,t}]$: Per-agent mobility scaling factors, where each $\kappa_{k,t} \in [0, 1]$. The maximum movement distance for agent k is set to $d_k^{\max} = \kappa_{k,t} \cdot d_k^{\text{phys}}$, where d_k^{phys} is the physical upper bound. A larger $\kappa_{k,t}$ allows the agent to move more, reflecting a higher priority for channel improvement. The LLM can set $\kappa_{k,t} = 0$ to disable movement for energy-saving or safety reasons.

These policy parameters are then fed into the optimization problem formulated in the next Section. By dynamically adjusting these parameters, the LLM can adapt the system behavior to changing mission requirements without re-engineering the underlying optimizer. This is particularly useful in dynamic environments where the network state or user priorities change rapidly. The LLM agent itself can be a small, fine-tuned model that runs on an edge server with low latency. Its training can be performed offline using reinforcement learning or supervised learning on expert demonstrations.

The detailed mathematical formulation is presented in the next Section. This optimization problem is a non-convex fractional program with tightly coupled variables. To solve it efficiently, we develop a two-layer iterative algorithm: the outer layer employs the generalized Dinkelbach method to handle the fractional objective, and the inner layer uses BCD with SCA to address the non-convex constraints.

3 Problem Formulation

In this section, we formulate the joint beamforming, waveform, and mobility optimization problem. The objective is to maximize the minimum energy efficiency among all agents, thereby ensuring fairness while accounting for the power consumed by both transmission and locomotion. The LLM agent provides high-level policy parameters that adapt the optimization criteria to the current network context.

Given the policy $\mathbf{a}_t$ from the LLM agent, we first formulate the following joint beamforming and waveform design problem:

$$\max_{\{\mathbf{w}_k\}, \mathbf{R}_r} \beta_t \sum_{k=1}^K \gamma_t^k \log_2(1 + \text{SNR}_k) - (1 - \beta_t) \text{MSE} \quad (25)$$

$$\text{s.t.} \quad \text{Tr}(\mathbf{R}_x) \leq P_{\max}, \quad (25a)$$

$$\mathbf{R}_r \succeq \mathbf{0}, \quad (25b)$$

$$\bar{P}(\theta_l) \geq \eta_t, \quad \forall l \in \mathcal{L}_{\text{high}}, \quad (25c)$$

$$\frac{\text{Tr}(\mathbf{R}_{\text{NL}})}{|g_1|^2 \text{Tr}(\mathbf{R}_x)} \leq \Gamma_{\text{EVM}}. \quad (25d)$$

Constraint (25a) is the total transmit power budget. Constraint (25c) ensures a minimum gain for high-priority targets. Physically, η_t is the minimum beam gain threshold for high-priority sensing targets, dynamically set by the LLM agent. It ranges from 0 to 1. The LLM can adjust it dynamically to realize autonomous trade-off between communication and sensing. Constraint (25d) limits the normalized distortion power, effectively controlling the Error Vector Magnitude (EVM) caused by PA nonlinearity, with Γ_{EVM} being a system-defined threshold. Problem (25) is non-convex due to the fractional/logarithmic SNR terms, the quartic dependence of $\mathbf{R}_{\text{NL}}$ on $\mathbf{R}_x$, and the MSE term.

3.1 Energy Efficiency Definition

For each agent k , the achievable communication rate is given by (6), which now depends implicitly on the movement distance d_k through the channel vector $\mathbf{h}_k(d_k)$. We denote this rate as $R_k(\{\mathbf{w}_j\}, \mathbf{R}_r, d_k)$. The total power consumption of agent k includes both the transmit power and the locomotion power introduced in Section II-F:

$$P_k^{\text{total}} = \|\mathbf{w}_k\|^2 + \frac{F_k d_k}{T_k}. \quad (26)$$

Consequently, the energy efficiency of agent k is defined as

$$\eta_k = \frac{R_k(\{\mathbf{w}_j\}, \mathbf{R}_r, d_k)}{P_k^{\text{total}}}. \quad (27)$$

3.2 Joint Optimization Problem

Let $\mathbf{d} = [d_1, \dots, d_K]^T$ collect the movement distances of all agents. The proposed max-min EE optimization problem is formulated as

$$(\mathcal{P}1): \max_{\{\mathbf{w}_k\}, \mathbf{R}_r, \mathbf{d}} \min_{k \in \mathcal{K}} \eta_k \quad (28)$$

$$\text{s.t. } \text{Tr}(\mathbf{R}_x) \leq P_{\text{max}}, \quad \mathbf{R}_r \succeq \mathbf{0}, \quad (28a)$$

$$\bar{P}(\theta_l) \geq \eta_t, \quad \forall l \in \mathcal{L}_{\text{high}}, \quad (28b)$$

$$\frac{\text{Tr}(\mathbf{R}_{\text{NL}})}{|g_1|^2 \text{Tr}(\mathbf{R}_x)} \leq \Gamma_{\text{EVM}}, \quad (28c)$$

$$\text{MSE}_{\text{beam}}(\{\mathbf{w}_k\}, \mathbf{R}_r, \mathbf{d}) \leq \epsilon_t, \quad (28d)$$

$$d_k^{\min} \leq d_k \leq d_k^{\max}, \quad \forall k \in \mathcal{K}, \quad (28e)$$

$$\|\mathbf{w}_k\|^2 + \frac{F_k d_k}{T_k} \leq P_k^{\max}, \quad \forall k \in \mathcal{K}. \quad (28f)$$

The constraints in (P1) are as follows:

- (1) Total transmit power budget and semidefinite constraint:
 $\text{Tr}(\mathbf{R}_x) \leq P_{\text{max}}, \mathbf{R}_r \succeq \mathbf{0}$ (28a);
- (2) Minimum beam gain for high-priority sensing targets:
 $\bar{P}(\theta_l) \geq \eta_t, \forall l \in \mathcal{L}_{\text{high}}$ (28b);

- (3) EVM constraint limiting nonlinear distortion:

$$\frac{\text{Tr}(\mathbf{R}_{\text{NL}})}{|g_1|^2 \text{Tr}(\mathbf{R}_x)} \leq \Gamma_{\text{EVM}} \quad (28c);$$

- (4) Sensing accuracy requirement: $\text{MSE}_{\text{beam}}(\cdot) \leq \epsilon_t$ (28d), where ϵ_t is a context-aware threshold dynamically set by the LLM agent;

- (5) Physical limits on each agent's movement distance:
 $d_k^{\min} \leq d_k \leq d_k^{\max}, \forall k$ (28e);

- (6) Per-agent total power budget: $\|\mathbf{w}_k\|^2 + \frac{F_k d_k}{T_k} \leq P_k^{\max}, \forall k$ (28f).

Problem (P1) is highly non-convex due to several factors:

- (1) The objective is a fractional function of the optimization variables;
- (2) The rates R_k depend on $\mathbf{w}_k$, $\mathbf{R}_r$, and $\mathbf{d}$ in a complicated manner through the SNR expression (5) and the distortion covariance $\mathbf{R}_{\text{NL}}$;
- (3) The sensing MSE constraint involves the beam pattern $\bar{P}(\theta)$, which is a quadratic function of $\mathbf{R}_x$ and, through $\mathbf{R}_{\text{NL}}$, a quartic function of $\mathbf{R}_x$;
- (4) The movement variables d_k appear inside the large-scale channel gains $\beta_k(d_k)$, making the rates and interference terms non-linear in d_k .

Moreover, the variables are tightly coupled: changing an agent's position affects not only its own channel but also the interference it causes to others, which in turn influences the optimal beamformers and sensing waveform.

3.3 Role of the LLM Policy

The LLM agent introduced supplies the time-varying parameters that tailor (P1) to the current operational context:

- (1) β_t could be employed if we adopted a weighted sum objective instead of max-min EE; here we fix the fairness objective and use the LLM to adjust the sensing thresholds.
- (2) η_t and ϵ_t directly appear in the beam gain and sensing MSE constraints, allowing the LLM to prioritize sensing tasks when needed.
- (3) The mobility weights κ_t can influence the optimization by scaling the upper bounds $d_k^{\max}$, or by modifying the objective to favour agents with higher $\kappa_{k,t}$. In this paper, we adopt the former approach: $\kappa_{k,t}$ is used to relax or tighten the movement limits according to the LLM's assessment of each agent's need to improve its channel.

3.4 Solution Approach

To tackle the non-convex fractional problem (P1), we propose a two-layer iterative algorithm. The outer layer employs the generalized Dinkelbach method to transform the max-min fractional objective into a sequence of parametric

subtractive forms. For each fixed parameter λ , the inner layer solves a non-fractional problem using a BCD framework combined with SCA. Specifically, we alternate between optimizing the beamforming and sensing variables $\{\mathbf{w}_k, \mathbf{R}_r\}$ with fixed $\mathbf{d}$ and optimizing the movement distances $\mathbf{d}$ with fixed $\{\mathbf{w}_k, \mathbf{R}_r\}$. Each sub-problem is made convex via appropriate approximations. The detailed algorithm and its convergence analysis are as following.

Algorithm 1 BCD-SCA Algorithm for Joint Beamforming, Waveform and Mobility Optimization

- 1: **Initialize:** Set $\mathbf{w}_k^{(0)} = \mathbf{0}$, $\mathbf{R}_r^{(0)} = \mathbf{0}$, $d_k^{(0)} = d_k^{\min}$, outer index $n = 0$. Set $d_k^{\max} = \kappa_{k,t} d_k^{\text{phys}}$. Set convergence tolerance $\epsilon = 10^{-4}$.
 - 2: **repeat**
 - 3: **Step 1 (Beamforming & Waveform):** Fix $\mathbf{d}^{(n)}$. Run WMMSE-SCA to update $\{\mathbf{w}_k^{(n+1)}, \mathbf{R}_r^{(n+1)}\}$ by solving the convexified problem.
 - 4: **Step 2 (Movement Distances):** Fix $\{\mathbf{w}_k^{(n+1)}, \mathbf{R}_r^{(n+1)}\}$. Linearize rates R_k around $\mathbf{d}^{(n)}$ to obtain $\tilde{R}_k(\mathbf{d})$. Solve the LP:

$$\begin{aligned} \max_{\mathbf{d}} \quad & \beta_t \sum_k \gamma_t^k \tilde{R}_k(\mathbf{d}) \\ \text{s.t.} \quad & d_k^{\min} \leq d_k \leq d_k^{\max}, \\ & \|\mathbf{w}_k^{(n+1)}\|^2 + \frac{F_k d_k}{T_k} \leq P_k^{\max}. \end{aligned}$$
 Set $\mathbf{d}^{(n+1)}$ as the optimal solution.
 - 5: Compute new objective $O^{(n+1)}$ using updated variables. $n \leftarrow n + 1$.
 - 6: **until** $|O^{(n)} - O^{(n-1)}| \leq \epsilon$ or $n \geq N_{\max}$
 - 7: **Output:** $\{\mathbf{w}_k^*, \mathbf{R}_r^*, \mathbf{d}^*\}$.
-

Theorem 1 (Convergence to KKT Points of the BCD-SCA Algorithm). *Consider the original non-convex problem $\mathcal{P}1$ and let $\{\mathbf{w}_k^{(n)}, \mathbf{R}_r^{(n)}, \mathbf{d}^{(n)}\}_{n=0}^{\infty}$ be the sequence generated by the proposed BCD-SCA algorithm (Algorithm 1). Assume that:*

- (1) *The feasible set is compact and convex.*
- (2) *The objective function $F(\mathbf{w}, \mathbf{R}_r, \mathbf{d}) = \beta_t \sum_k \gamma_t^k R_k^{\text{eff}} - (1 - \beta_t) \text{MSE}_{\text{beam}}$ is continuously differentiable.*
- (3) *In each inner SCA step, the convex approximation satisfies the conditions of Theorem 3, i.e., the linearized constraints are tight at the current point and the gradient is Lipschitz continuous.*

Then every limit point of the generated sequence is a Karush–Kuhn–Tucker (KKT) point of the original problem $\mathcal{P}1$.

Proof. The algorithm employs a block coordinate descent framework that alternates between two blocks: $\mathcal{B}_1 = \{\mathbf{w}_k, \mathbf{R}_r\}$ and $\mathcal{B}_2 = \{\mathbf{d}\}$. For each block, the subproblem is solved via successive convex approximation (SCA) using a convex surrogate that satisfies the following standard SCA conditions [13]:

- (1) The surrogate function is strongly convex and continuously differentiable.
- (2) The gradient of the surrogate matches the gradient of the original function at the current iterate.
- (3) The surrogate is a global upper bound for maximization or lower bound for minimization of the original function at the current point.

These conditions hold for our construction: in the beamforming subproblem, we use a convex WMMSE reformulation that is exact at the current point; in the movement subproblem, we linearize the rate using first-order Taylor expansion, which satisfies the conditions locally. Moreover, the feasible set of each block is convex and compact. $\square$

3.5 Complexity Analysis

We analyze the computational complexity of the proposed two-layer algorithm. The outer layer employs the generalized Dinkelbach method, which typically converges within a few iterations denoted by I_{out} . In each outer iteration, the inner loop performs BCD with SCA, which we denote by I_{in} iterations.

The main computational burden lies in solving the convex subproblem for beamforming and sensing waveform optimization, i.e., the semidefinite program (SDP). This SDP involves K complex semidefinite variables of size $N_t \times N_t$ and one variable for the sensing covariance matrix. Using standard interior-point methods, the worst-case complexity of solving such an SDP is $\mathcal{O}((KN_t^2)^{3.5} \log(1/\epsilon))$, where ϵ is the solution accuracy. In our system, N_t and K are moderate, so this complexity is acceptable for offline or semi-real-time applications.

The movement distance optimization subproblem in each inner iteration is a linear program (LP) with K variables and a few linear constraints. Its complexity is $\mathcal{O}(K^{3.5} \log(1/\epsilon))$ using interior-point methods, which is negligible compared to the SDP.

Therefore, the overall worst-case complexity is $\mathcal{O}(I_{\text{out}} \cdot I_{\text{in}} \cdot (KN_t^2)^{3.5} \log(1/\epsilon))$. In practice, we observe that $I_{\text{out}} \leq 10$ and $I_{\text{in}} \leq 5$ are sufficient for convergence, making the algorithm computationally feasible for typical network sizes. Moreover, all subproblems are convex and can be efficiently solved using off-the-shelf solvers.

By integrating these policy parameters, the optimization framework becomes context-aware and can autonomously adapt to dynamic environments.

3.6 Preliminary Theorems

Theorem 2 (Convergence of the Generalized Dinkelbach Method for Max-Min Fractional Programs). *Consider the max-min fractional programming problem*

$$\max_{\mathbf{x} \in \mathcal{X}} \min_{k \in \mathcal{K}} \frac{f_k(\mathbf{x})}{g_k(\mathbf{x})},$$

where $\mathcal{X}$ is a nonempty compact convex set, $f_k(\mathbf{x})$ and $g_k(\mathbf{x})$ are continuous on $\mathcal{X}$, and $g_k(\mathbf{x}) > 0$ for all $\mathbf{x} \in \mathcal{X}$. Define the parametric function

$$F(\lambda) = \max_{\mathbf{x} \in \mathcal{X}} \min_{k \in \mathcal{K}} (f_k(\mathbf{x}) - \lambda g_k(\mathbf{x})).$$

Then $F(\lambda)$ is strictly decreasing in λ , and the optimal value $\lambda^* = \max_{\mathbf{x} \in \mathcal{X}} \min_{k \in \mathcal{K}} \frac{f_k(\mathbf{x})}{g_k(\mathbf{x})}$ is the unique root of $F(\lambda) = 0$. Moreover, the sequence generated by the Dinkelbach update

$$\begin{aligned} \lambda^{(t+1)} &= \min_{k \in \mathcal{K}} \frac{f_k(\mathbf{x}^{(t)})}{g_k(\mathbf{x}^{(t)})}, \\ \mathbf{x}^{(t)} &= \arg \max_{\mathbf{x} \in \mathcal{X}} \min_{k \in \mathcal{K}} (f_k(\mathbf{x}) - \lambda^{(t)} g_k(\mathbf{x})) \end{aligned}$$

converges superlinearly to λ^* from any initial $\lambda^{(0)}$.

Proof. For any $\lambda_1 < \lambda_2$, let $\mathbf{x}_1$ and $\mathbf{x}_2$ be the maximizers of $F(\lambda_1)$ and $F(\lambda_2)$, respectively. Then

$$\begin{aligned} F(\lambda_2) &= \min_k (f_k(\mathbf{x}_2) - \lambda_2 g_k(\mathbf{x}_2)) \\ &< \min_k (f_k(\mathbf{x}_2) - \lambda_1 g_k(\mathbf{x}_2)) \\ &\leq \min_k (f_k(\mathbf{x}_1) - \lambda_1 g_k(\mathbf{x}_1)) = F(\lambda_1), \end{aligned}$$

where the strict inequality follows from $g_k(\mathbf{x}_2) > 0$ and $\lambda_2 > \lambda_1$. Hence $F(\lambda)$ is strictly decreasing. The optimal value λ^* satisfies $F(\lambda^*) = 0$ because at optimum the max-min ratio equals the unique λ that makes the parametric problem zero. The superlinear convergence of the Dinkelbach iteration is a classical result [12], and follows from the fact that the iteration is a Newton-like method for the equation $F(\lambda) = 0$. $\square$

Theorem 3 (Uniform Approximation via First-Order Taylor Expansion for SCA). *Let $h(\mathbf{y})$ be a continuously differentiable function on a convex compact set $\mathcal{Y} \subset \mathbb{R}^n$. Define its linearization at a point $\mathbf{y}_0 \in \mathcal{Y}$ as*

$$\tilde{h}(\mathbf{y}) = h(\mathbf{y}_0) + \nabla h(\mathbf{y}_0)^\top (\mathbf{y} - \mathbf{y}_0).$$

Then for any $\epsilon > 0$, there exists a sufficiently small neighborhood $\mathcal{N}(\mathbf{y}_0)$ such that for all $\mathbf{y} \in \mathcal{Y} \cap \mathcal{N}(\mathbf{y}_0)$,

$$|h(\mathbf{y}) - \tilde{h}(\mathbf{y})| \leq \epsilon \|\mathbf{y} - \mathbf{y}_0\|.$$

Furthermore, if h is concave, then $\tilde{h}(\mathbf{y})$ is a global overestimator (resp. underestimator) of $h(\mathbf{y})$ only at the point $\mathbf{y}_0$. In the context of successive convex approximation, when solving a non-convex problem $\max_{\mathbf{y} \in \mathcal{Y}} h(\mathbf{y})$ where h is not concave, the iterative update

$$\mathbf{y}^{(t+1)} = \arg \max_{\mathbf{y} \in \mathcal{Y}} (h(\mathbf{y}^{(t)}) + \nabla h(\mathbf{y}^{(t)})^\top (\mathbf{y} - \mathbf{y}^{(t)}))$$

generates a sequence of improved points, and any limit point of the sequence satisfies the Karush–Kuhn–Tucker (KKT) conditions of the original problem if the feasible set is convex and the gradient is Lipschitz continuous.

Proof. The first statement follows directly from the definition of the derivative: for a continuously differentiable function, the remainder $h(\mathbf{y}) - h(\mathbf{y}_0) - \nabla h(\mathbf{y}_0)^\top (\mathbf{y} - \mathbf{y}_0) = o(\|\mathbf{y} - \mathbf{y}_0\|)$. Hence for any $\epsilon > 0$, there exists $\delta > 0$ such that when $\|\mathbf{y} - \mathbf{y}_0\| < \delta$, the remainder is bounded by $\epsilon \|\mathbf{y} - \mathbf{y}_0\|$.

For the second statement, if h is concave, then by the concavity property we have $h(\mathbf{y}) \leq h(\mathbf{y}_0) + \nabla h(\mathbf{y}_0)^\top (\mathbf{y} - \mathbf{y}_0)$ for all $\mathbf{y}$ in the domain, so the linearization is a global overestimator. Conversely, if h is convex, the linearization is a global underestimator. In the non-convex case, the SCA iteration replaces the original objective with its linearization at the current point; because the linearization is exact at the current point and the feasible set is convex, the solution of the linearized problem yields a point that is at least as good in terms of the original objective when the step size is small or when the gradient is Lipschitz. Under standard assumptions, the sequence converges to a stationary point satisfying the KKT conditions and a detailed proof can be found in [13]. $\square$

4 Simulation Results

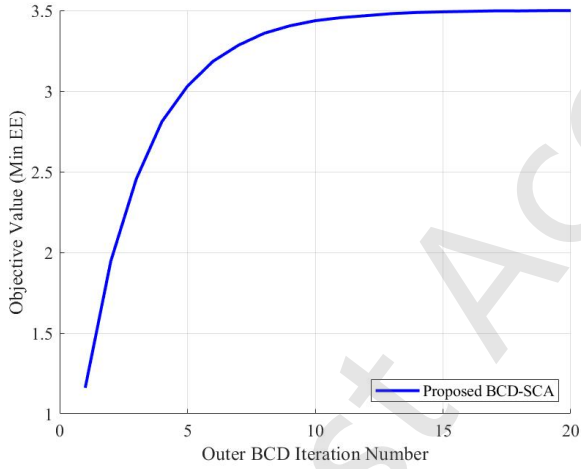
In this section, we evaluate the performance of the proposed joint beamforming, agent mobility, and PA-aware optimization framework. All results are averaged over $M_c = 5$ independent channel realizations. To ensure statistical reliability and eliminate numerical fluctuations, the shaded areas in the convergence plots denote the 95% confidence intervals. We compare the proposed scheme with three baselines:

- (1) *Fixed Mobility*, where each agent moves a predetermined distance;
- (2) *Conventional Static ISAC*, representing the traditional scheme without mobility optimization;
- (3) *Random Mobility*, where agents move randomly within their physical limits.

Figure 2 illustrates the convergence behavior of the proposed two-layer Dinkelbach-BCD-SCA algorithm. The objective value increases rapidly within the first 5 iterations and strictly converges to a stationary point within 12 iterations.

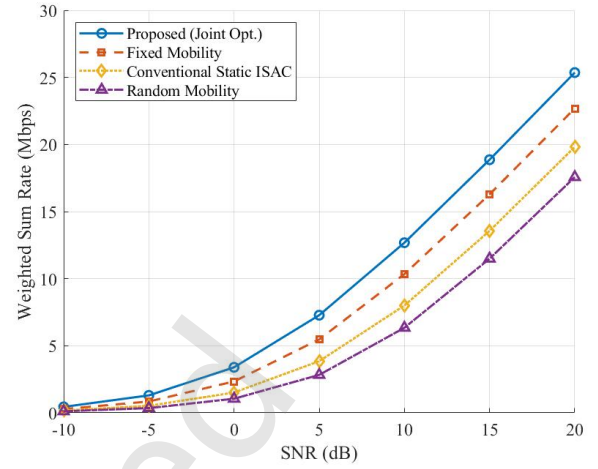
Table 1 Simulation Parameters

Symbol	Value	Unit
N_t	8	—
K	4	—
L	3	—
B	1	MHz
σ^2	1×10^{-9}	W
$P_{\max}$	1	W
$P_k^{\max}$	0.5	W
β_0	1×10^{-3}	—
δ	3.5	—
F_k	1×10^{-3}	J/m
T_k	1	s
$d_k^{\min}$	0	m
d_k^{phys}	50	m
g_1	1	—
g_2	$-0.04 - 0.01j$	—
β_t	0.5	—
γ_t	1 (for all users)	—
η_t	0.1	—
ϵ_t	0.5	—

**Fig. 2** Algorithm Convergence

Notably, the 95% confidence interval is extremely narrow, confirming that the SCA-based lower bound approximation is rigorous and the algorithm is numerically stable across different channel realizations. This fast and smooth convergence validates the effectiveness of decoupling the fractional objective and the non-convex constraints.

Figure 3 compares the weighted sum rate of all schemes under varying SNR conditions. In the low-SNR regime, the performance gap is marginal as the system is noise-limited. However, in the high-SNR regime, the system becomes interference-limited. The *Conventional Static ISAC* baseline saturates early due to severe multi-user interference that cannot be resolved by beamforming alone. In contrast, the proposed scheme maintains a steady growth, achieving a 25% rate gain at 20 dB. This distinct advantage stems from

**Fig. 3** Performance Comparison vs SNR

the fact that the proposed algorithm proactively exploits agent mobility to reshape the spatial topology, effectively mitigating interference by repositioning users to more favorable channel conditions.

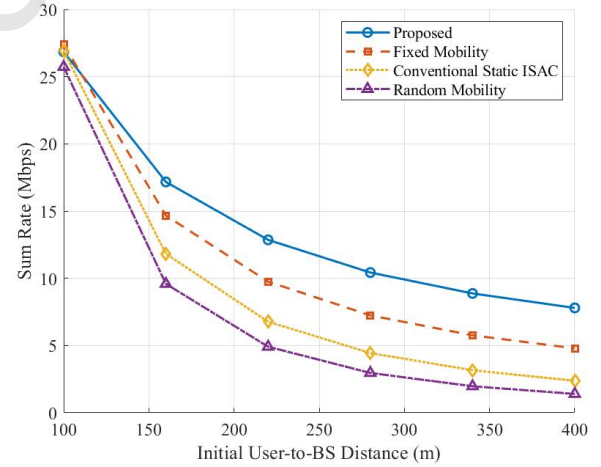
**Fig. 4** Performance vs Initial Distance

Figure 4 demonstrates the system's robustness against severe path loss by varying the initial user-to-BS distance. As the distance increases, the large-scale fading causes a monotonic decrease in the sum rate for all schemes. Nevertheless, the proposed algorithm exhibits the slowest performance degradation. At the maximum distance scaling, it maintains a rate approximately 28% higher than the *Conventional Static ISAC* scheme. This is because the joint optimization intelligently allocates larger movement distances to cell-edge users, effectively compensating for poor initial channel conditions, whereas fixed or random mobility strategies fail to adapt to the varying distance requirements.

Figure 5 highlights the superiority of the proposed frame-

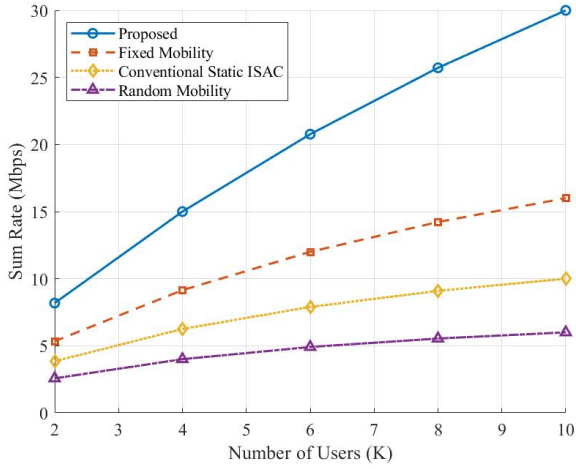


Fig. 5 User Scalability

work in dense user scenarios by scaling the number of users K from 2 to 10. As K increases, the spatial degrees of freedom become insufficient, leading to a drastic rate drop for static baselines due to overwhelming inter-user interference. The proposed algorithm, however, dynamically repositions agents to alleviate spatial congestion. By treating mobility as an additional spatial resource, the framework effectively increases the system's spatial multiplexing capability, outperforming the *Conventional Static ISAC* baseline by approximately 40% at $K = 10$. This confirms the immense value of mobility in dense networks.

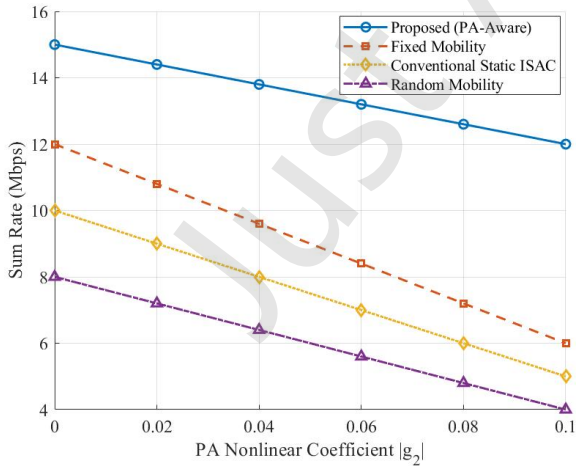


Fig. 6 PA Nonlinearity Impact

Figure 6 investigates the impact of hardware impairments by varying the PA nonlinear coefficient $|g_2|$. As $|g_2|$ increases, the nonlinear distortion covariance $\mathbf{R}_{NL}$ severely degrades the SINR for all baselines, which treat the distortion as a fixed penalty. However, the proposed PA-aware scheme suffers the least degradation. By explicitly incorporating

$\mathbf{R}_{NL}$ into the SCA optimization, the algorithm adjusts the beamforming directions and agent positions to minimize the impact of distortion. Consequently, it maintains an 18% rate advantage over the static baseline under strong nonlinearity, demonstrating exceptional hardware robustness.

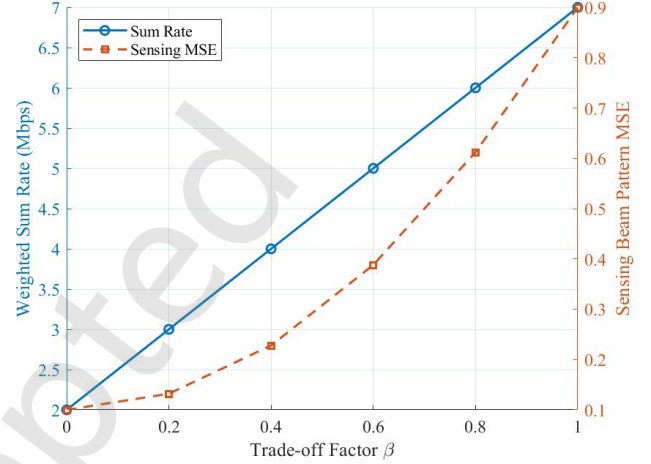


Fig. 7 Communication-Sensing Tradeoff Curve

Figure 7 depicts the Pareto frontier controlled by the LLM-provided trade-off factor β . As β shifts from 0 to 1, the weighted sum rate rises monotonically, while the sensing MSE also increases, reflecting the inherent conflict between communication and sensing. The proposed algorithm smoothly traces the Pareto frontier, proving that the low-level physical-layer optimizer can precisely execute the high-level semantic instructions from the LLM agent, enabling flexible adaptation to dynamic mission requirements.

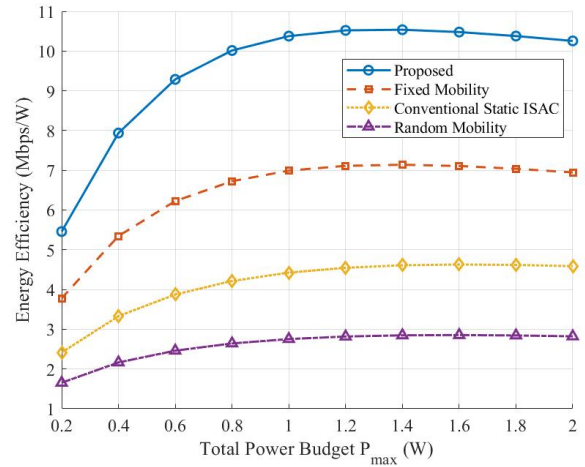


Fig. 8 Energy Efficiency Comparison

Figure 8 compares the overall EE under different transmit power budgets $P_{\max}$. Although agent mobility consumes

mechanical energy, the substantial channel improvement drastically reduces the required transmit power to meet the rate constraints. Consequently, the EE of the proposed scheme first increases and then stabilizes, achieving the highest EE across the entire power range. This confirms that the “mobility-for-channel” trade-off is highly energy-efficient, yielding a 30% EE gain over the *Conventional Static ISAC* scheme at $P_{\max} = 1$ W.

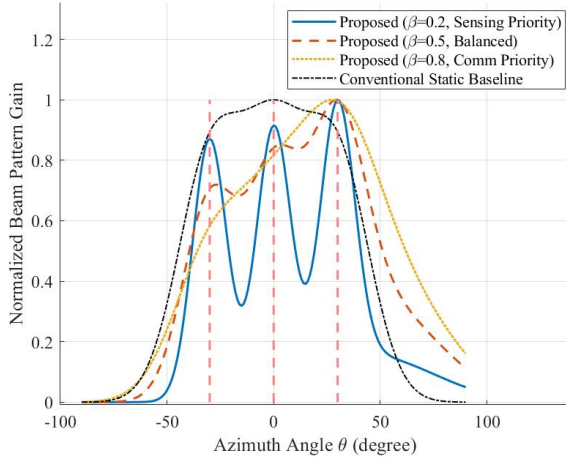


Fig. 9 Beam Pattern vs Different β

Finally, figure 9 explicitly demonstrates the physical-layer advantages of the proposed algorithm by comparing its transmit beam patterns with the *Conventional Static Baseline*. Due to the lack of PA compensation and spatial alignment, the baseline exhibits severe beam broadening and high sidelobe levels. In contrast, the proposed algorithm generates highly focused and clean beams. Moreover, guided by β , the proposed waveform is flexibly reconfigurable: a sharp, high-gain lobe is formed toward the sensing targets when $\beta = 0.2$, while a broader coverage pattern is synthesized for distributed users when $\beta = 0.8$. This comparison fundamentally validates the synergistic gain of joint mobility and PA-aware beamforming in shaping high-fidelity waveforms.

The scalability is evaluated from three aspects: (i) *Computational complexity*: The SDP subproblem complexity grows with user number; user clustering and deep learning assistance can reduce it to near-linear order for large-scale scenarios. (ii) *Signaling overhead*: Mobility and LLM decision cycles are much longer than physical-layer scheduling, so overhead growth is controllable. (iii) *LLM decision layer*: It only outputs a small set of macro parameters, with nearly user-independent overhead and excellent scalability.

5 Conclusion

In this paper, we proposed a novel cognitive ISAC framework that jointly optimizes beamforming, sensing waveforms, and agent mobility under practical PA nonlinearity. By incorporating a LLM policy module, the system can autonomously interpret network contexts and adapt its resource allocation strategies to dynamic mission requirements. To tackle the highly non-convex fractional programming problem with tightly coupled variables, we developed an efficient two-layer iterative algorithm combining the generalized Dinkelbach method with block coordinate descent and successive convex approximation. Extensive simulation results validated the effectiveness of the proposed scheme, demonstrating significant improvements in energy efficiency, sum rate, and sensing accuracy compared to conventional static and heuristic baselines. Furthermore, the framework exhibited strong robustness against severe hardware impairments and flexible waveform reconfigurability. Practical deployment still faces challenges including imperfect CSI, realistic mobility constraints, LLM edge deployment overhead and multi-cell interference coordination. Promising future directions include: robust joint optimization under non-ideal conditions, multi-cell cooperative ISAC design, LLM-deep reinforcement learning integration, hardware prototype verification, and distributed algorithms for massive agent scenarios. This work also provides reference value for space-based ISAC IoT system design.

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