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Energy Optimization and Coverage in 6G Wireless Communications Using Intelligent Reflecting Surfaces Under Dynamic Channel Conditions

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Abstract
Energy efficiency and coverage optimization are key challenges in the development of sixth-generation (6G) wireless networks, particularly with the integration of Intelligent Reflecting Surfaces (IRS). Leveraging IRS technology can significantly enhance signal propagation and network performance, but optimizing their deployment under dynamic channel conditions remains a complex problem. This paper conducts an in-depth analysis of energy efficiency and coverage optimization in 6G networks utilizing IRS-assisted communication. We develop a novel mathematical framework that captures the intricate relationship between energy consumption and coverage enhancement in IRS-based systems operating under fluctuating channel conditions. Using stochastic geometry, we model the spatial distribution of IRS units and user equipment, while a tensor-based representation is employed to characterize the multi-dimensional channel state information. To adapt to time-varying wireless environments, we propose an adaptive phase-shift configuration protocol that dynamically adjusts IRS elements, resulting in a 43% improvement in energy efficiency compared to static configurations. Additionally, a deep reinforcement learning approach is integrated into our framework to optimize the balance between coverage extension and power consumption, considering both direct and IRS-reflected transmission paths. Extensive numerical simulations validate our theoretical insights, showing that the strategic deployment of IRS units based on our optimization model can expand coverage by 68% in urban environments while maintaining quality of service constraints. Moreover, we derive closed-form expressions for the probability of coverage under Rician fading conditions, incorporating the effects of hardware impairments and phase noise in IRS elements. These findings offer critical insights into the practical implementation of energy-efficient IRS deployments, laying the groundwork for future advancements in 6G cellular networks.

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1. Introduction

The imminent deployment of sixth-generation (6G) wireless communication networks promises unprecedented data rates, ultra-low latency, and massive connectivity to support emerging applications such as holographic communications, extended reality, and autonomous systems [1]. These ambitious performance metrics, however, come at the cost of significantly increased energy consumption, posing substantial challenges to the sustainability and operational costs of future wireless networks. The energy efficiency problem is further exacerbated by the anticipated use of higher frequency bands in 6G, which suffer from severe path loss and blockage effects, necessitating denser network deployments and higher transmission powers [2, 3].

Intelligent Reflecting Surfaces (IRS) have emerged as a promising technology to enhance wireless communication systems by manipulating electromagnetic waves through passive reflection [4]. An IRS consists of a large number of low-cost, passive reflecting elements, each capable of independently adjusting the phase shift of the impinging electromagnetic waves, thereby enabling constructive combining of reflected signals at intended receivers. This passive nature of IRS presents a compelling advantage in terms of energy efficiency compared to traditional active relaying technologies, as IRS units operate without power-hungry radio frequency chains for signal processing and amplification.

The fundamental principle behind IRS operation lies in the reconfiguration of the wireless propagation environment itself, rather than adapting to it as in conventional wireless systems. By intelligently controlling the phase shifts of the reflecting elements, IRS can create favorable channel conditions for wireless communication, effectively extending coverage to areas previously considered challenging due to blockages or excessive path loss. This paradigm shift in wireless system design offers new degrees of freedom for optimizing network performance, particularly in terms of energy efficiency and coverage extension. [5]

The potential benefits of IRS-assisted communication in 6G networks extend beyond mere energy savings and coverage enhancement. By providing additional signal propagation paths, IRS can improve communication reliability, increase spectral efficiency through spatial multiplexing gains, and enhance physical layer security. Moreover, the passive nature of IRS allows for environmentally friendly and visually unobtrusive deployments, addressing both ecological concerns and aesthetic considerations in dense urban environments.

Despite these promising attributes, the integration of IRS into future wireless networks presents several technical challenges that require careful consideration. The optimization of IRS configurations involves complex mathematical formulations to determine the optimal phase shifts for a large number of reflecting elements, often under dynamic channel conditions and multiple users with potentially conflicting requirements. Additionally, accurate channel state information (CSI) acquisition becomes particularly challenging in IRS-assisted systems due to the passive nature of the reflecting elements, which cannot perform channel estimation independently.

Previous research in IRS-assisted communication has primarily focused on maximizing spectral efficiency or signal-to-noise ratio under perfect CSI assumptions and static channel conditions. While these studies provide valuable insights into the fundamental performance limits of IRS technology, they often overlook the practical constraints related to energy efficiency, imperfect CSI, and dynamic wireless environments that characterize real-world deployments. Furthermore, the existing literature typically addresses the design of IRS configurations for single-cell scenarios with a limited number of users, leaving the analysis of large-scale multi-cell networks with IRS largely unexplored. [6]

In this paper, we address these limitations by developing a comprehensive mathematical framework for analyzing and optimizing energy efficiency and coverage in IRS-assisted 6G networks under realistic deployment scenarios. We consider dynamic channel conditions, imperfect CSI, hardware impairments, and large-scale network deployments to provide insights that are both theoretically sound and practically relevant. Our approach combines tools from stochastic geometry, tensor analysis, and deep reinforcement learning to formulate and solve the complex optimization problems associated with IRS deployment and configuration.

The key contributions of this paper can be summarized as follows. First, we develop a stochastic geometry-based framework to model the spatial distribution of IRS units, base stations, and user equipment in a large-scale network, enabling the analysis of coverage probability and energy efficiency from a system-level perspective. Second, we propose a tensor-based representation of the multidimensional channel state information in IRS-assisted systems, facilitating efficient processing and optimization of IRS configurations. Third, we design an adaptive phase-shift configuration protocol that dynamically adjusts to time-varying channel conditions, significantly improving energy efficiency compared to static configurations. Fourth, we formulate a deep reinforcement learning approach to optimize the trade-off between coverage extension and power consumption, considering both direct and IRS-reflected transmission paths [7]. Finally, we derive closed-form expressions for the probability of coverage under Rician fading channels, accounting for hardware impairments and phase noise at the IRS elements.

The remainder of this paper is organized as follows. In Section 2, we present the system model and problem formulation. Section 3 introduces our stochastic geometry framework for analyzing large-scale IRS deployments. In Section 4, we develop the tensor-based channel representation and adaptive phase-shift configuration protocol. Section 5 presents the deep reinforcement learning approach for joint optimization of coverage and energy efficiency. Numerical results and performance evaluation are provided in Section 6, followed by concluding remarks in Section 7.

2. System Model and Problem Formulation

We consider a downlink wireless communication system operating in a 6G network environment, where multiple base stations (BSs) serve numerous user equipment (UEs) with the assistance of strategically deployed IRS units. The spatial distribution of network elements is modeled as a heterogeneous Poisson point process (PPP), with BSs, IRS units, and UEs following independent PPPs with intensities λ_B, λ_I, and λ_U, respectively [8]. Each IRS consists of N passive reflecting elements arranged in a uniform planar array configuration, capable of independently adjusting the phase shift of the incident electromagnetic waves.

The propagation environment is characterized by a combination of line-of-sight (LoS) and non-line-of-sight (NLoS) paths, with the probability of LoS connectivity decreasing exponentially with distance according to $P_{LoS}(d) = e^{-\beta d}$, where β is an environment-dependent parameter and d represents the distance between the transmitter and receiver. The channel coefficients for LoS and NLoS paths follow Rician and Rayleigh fading distributions, respectively, with appropriate path loss exponents α_{LoS} and α_{NLoS}.

For a typical UE located at position $\mathbf{x}_u$, the received signal can be expressed as the superposition of the direct signal from the serving BS located at $\mathbf{x}_b$ and the reflected signals from all IRS units in the vicinity. Mathematically, the received signal at the UE can be written as:

$$y_u = \sqrt{P_t}\left(\mathbf{h}_{bu}^H s + \sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \blacksquare_i \mathbf{h}_{bi} s\right) + n_u$$

where P_t represents the transmit power of the BS, s denotes the transmitted symbol with unit power, $\mathbf{h}_{bu} \in \mathbb{C}^{M\times 1}$ is the channel vector from the BS to the UE, $\mathbf{h}_{bi} \in \mathbb{C}^{M\times N}$ is the channel matrix from the BS to the i-th IRS, $\mathbf{h}_{iu} \in \mathbb{C}^{N\times 1}$ is the channel vector from the i-th IRS to the UE, $\blacksquare_i = \mathrm{diag}(e^{j\theta_{i1}}, e^{j\theta_{i2}}, \ldots, e^{j\theta_{iN}})$ represents the phase-shift matrix of the i-th IRS with θ_{in} denoting the phase shift introduced by the n-th element of the i-th IRS, and $n_u \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN) at the UE.

To account for hardware impairments and phase noise at the IRS elements, we model the actual phase shift implemented by the n-th element of the i-th IRS as $\tilde{\theta}_{in} = \theta_{in} + \Delta\theta_{in}$, where $\Delta\theta_{in} \sim \mathcal{N}(0, \sigma_\theta^2)$ represents the phase noise following a Gaussian distribution with variance σ_θ^2. The imperfect phase shift implementation modifies the phase-shift matrix to $\tilde{\blacksquare}_i = \mathrm{diag}(e^{j\tilde{\theta}_{i1}}, e^{j\tilde{\theta}_{i2}}, \ldots, e^{j\tilde{\theta}_{iN}})$.

The signal-to-interference-plus-noise ratio (SINR) at the typical UE can be expressed as:

$$\gamma_u = \frac{P_t\left|\mathbf{h}_{bu}^H + \sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{bi}\right|^2}{\sum_{j\in\Phi_B\setminus\{b\}} P_t\left|\mathbf{h}_{ju}^H + \sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{ji}\right|^2 + \sigma^2}$$

where $\Phi_B \setminus \{b\}$ represents the set of interfering BSs.

The coverage probability for a given SINR threshold γ_{th} is defined as:

$$P_{cov}(\gamma_{th}) = \mathbb{P}(\gamma_u > \gamma_{th})$$

which represents the probability that the SINR at the typical UE exceeds the threshold γ_{th}.

The energy efficiency of the system, measured in bits per Joule, is defined as the ratio of the achievable data rate to the total power consumption:

$$\eta_{EE} = \frac{B\log_2(1+\gamma_u)}{P_{total}}$$

where B is the system bandwidth, and P_{total} represents the total power consumption, which includes the transmit power of the BS, the circuit power consumption of the BS, and the power consumed by the IRS controller for phase shift adjustments. Specifically, P_{total} can be expressed as:

$$P_{total} = \frac{P_t}{\eta_{PA}} + P_{BS,0} + \sum_{i=1}^{N_I}(P_{IRS,0} + N \cdot P_{ele})$$

where η_{PA} is the efficiency of the power amplifier at the BS, $P_{BS,0}$ is the fixed circuit power consumption of the BS, $P_{IRS,0}$ is the fixed power consumption of the IRS controller, and P_{ele} is the power consumption per reflecting element for phase shift adjustment.

Under dynamic channel conditions, the channel coefficients $\mathbf{h}_{bu}$, $\mathbf{h}_{bi}$, and $\mathbf{h}_{iu}$ evolve over time according to a first-order Markov process:

$$\mathbf{h}(t+1) = \rho\mathbf{h}(t) + \sqrt{1-\rho^2}\mathbf{w}(t)$$

where $\rho = J_0(2\pi f_d T_s)$ is the temporal correlation coefficient, $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, f_d is the maximum Doppler frequency, T_s is the sampling period, and $\mathbf{w}(t) \sim \mathcal{CN}(0, \mathbf{I})$ is a complex Gaussian random vector.

Given this system model, our objective is to jointly optimize the deployment of IRS units and their phase-shift configurations to maximize the energy efficiency while ensuring adequate coverage throughout the network. The optimization problem can be formulated as:

$$\max_{\lambda_I, \{\tilde{\blacksquare}_i\}} \eta_{EE} \ \text{s.t.} \quad P_{cov}(\gamma_{th}) \geq P_{target} \qquad \tilde{\theta}_{in} \in [0, 2\pi), \forall i, n \quad \lambda_I \leq \lambda_{I,max}$$

where P_{target} is the target coverage probability, and $\lambda_{I,max}$ is the maximum allowable deployment density of IRS units due to practical constraints.

This optimization problem is challenging due to several factors: (1) the complex expression of the SINR involving multiple IRS units and interfering BSs, (2) the large number of optimization variables corresponding to the phase shifts of all reflecting elements across all IRS units, (3) the stochastic nature of the network topology and channel conditions, and (4) the dynamic evolution of the channel coefficients over time. In the following sections, we develop novel methodologies to address these challenges and solve the optimization problem efficiently. [9]

3. Stochastic Geometry Analysis for Large-Scale IRS Deployments

To analyze the performance of large-scale IRS deployments in 6G networks, we employ tools from stochastic geometry to characterize the distribution of network elements and derive analytical expressions for coverage probability and energy efficiency. The key advantage of this approach is its ability to capture the spatial randomness of wireless networks while providing tractable mathematical expressions for system performance metrics.

We begin by deriving the distribution of the equivalent channel gain between a typical BS-UE pair with the assistance of IRS units. Let $g_{eq} = |\mathbf{h}_{bu}^H + \sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{bi}|^2$ denote the equivalent channel gain. Under the assumptions of our system model, the exact distribution of g_{eq} is challenging to obtain due to the complex interactions between multiple signal paths. However, we can approximate it using a gamma distribution based on moment matching:

$$g_{eq} \sim \mathrm{Gamma}(k_{eq}, \theta_{eq})$$

where the shape parameter k_{eq} and scale parameter θ_{eq} are determined by matching the first and second moments of the equivalent channel gain:

$$k_{eq} = \frac{(\mathbb{E}[g_{eq}])^2}{\mathbb{V}ar[g_{eq}]}$$

$$\theta_{eq} = \frac{\mathbb{V}ar[g_{eq}]}{\mathbb{E}[g_{eq}]}$$

The expected value of the equivalent channel gain can be expressed as:

$$\mathbb{E}[g_{eq}] = \mathbb{E}\left[|\mathbf{h}_{bu}^H|^2\right] + \mathbb{E}\left[\left|\sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{bi}\right|^2\right]$$
$$+ 2\mathbb{E}\left[\mathrm{Re}\left\{\mathbf{h}_{bu}^H \sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{bi}\right\}\right]$$

For a BS equipped with M antennas, the expected value of the direct channel gain is $\mathbb{E}[|\mathbf{h}_{bu}^H|^2] = M \cdot L(d_{bu})$, where $L(d_{bu})$ is the path loss at distance d_{bu} between the BS and UE. The expected value of the reflected channel gain depends on the spatial distribution of IRS units and their configurations. Using Campbell's theorem from point process theory, we can express it as:

$$\mathbb{E}\left[\left|\sum_{i=1}^{N_I} \mathbf{h}_{iu}^H \tilde{\blacksquare}_i \mathbf{h}_{bi}\right|^2\right] = \lambda_I \int_{R^2} \mathbb{E}[|\mathbf{h}_{xu}^H \tilde{\blacksquare}_x \mathbf{h}_{bx}|^2] dx$$

where the integration is performed over the two-dimensional space R^2, and $\mathbb{E}[|\mathbf{h}_{xu}^H \tilde{\blacksquare}_x \mathbf{h}_{bx}|^2]$ represents the expected reflected channel gain from an IRS located at position x. For optimal phase shift configurations that maximize the constructive combination of reflected signals, this term can be approximated as $N^2 \cdot L(d_{bx}) \cdot L(d_{xu}) \cdot e^{-\sigma_\theta^2}$, where $L(d_{bx})$ and $L(d_{xu})$ are the path losses for the BS-IRS and IRS-UE links, respectively, and the exponential term accounts for the impact of phase noise.

The third term in the expression for $\mathbb{E}[g_{eq}]$ represents the correlation between the direct and reflected paths. Under the assumption of independent Rayleigh fading for different paths, this term vanishes for random phase shift configurations. However, for optimized phase shifts that align the phases of the reflected signals with the direct signal, this term becomes positive and can be approximated as $2M\sqrt{N} \cdot \sqrt{L(d_{bu}) \cdot L(d_{bx}) \cdot L(d_{xu})} \cdot e^{-\sigma_\theta^2/2}$.

Using similar techniques, we can derive the variance of the equivalent channel gain, which completes the characterization of its distribution. [10]

With the distribution of the equivalent channel gain established, we can derive the coverage probability by analyzing the distribution of the SINR. The SINR at the typical UE can be rewritten as:

$$\gamma_u = \frac{P_t g_{eq}}{\sum_{j \in \Phi_B \setminus \{b\}} P_t g_j + \sigma^2}$$

where g_j represents the equivalent channel gain from the j-th interfering BS to the typical UE, including both direct and IRS-reflected paths.

The coverage probability can then be expressed as:

$$P_{cov}(\gamma_{th}) = \mathbb{P}(SINR > \gamma_{th}) = \mathbb{E}\left[e^{-\frac{\gamma_{th}\sigma^2}{P_t g_{eq}}} \cdot \mathscr{L}_I\left(\frac{\gamma_{th}}{g_{eq}}\right)\right]$$

where $\mathscr{L}_I(s)$ is the Laplace transform of the interference power distribution evaluated at s. Using the properties of PPP and the gamma approximation for the equivalent channel gain, we can derive a closed-form expression for the coverage probability:

$$P_{cov}(\gamma_{th}) =$$
$$\int_0^\infty e^{-\frac{\gamma_{th}\sigma^2}{P_t x}} \exp\left(-2\pi\lambda_B \int_{R_0}^\infty \left(1 - \mathbb{E}_{g_j}\left[e^{-\frac{\gamma_{th} P_t g_j}{P_t x}}\right]\right) r dr\right) f_{g_{eq}}(x) dx$$

where R_0 is the minimum distance between the typical UE and interfering BSs, and $f_{g_{eq}}(x)$ is the probability density function (PDF) of the equivalent channel gain g_{eq}.

To evaluate this integral, we approximate the interference as a shot noise process and leverage the moment-generating function of the gamma distribution. After mathematical manipulations, the coverage probability can be approximated as:

$$P_{cov}(\gamma_{th}) \approx$$
$$\left(1 + \frac{\gamma_{th}\sigma^2}{P_t k_{eq}\theta_{eq}}\right)^{-k_{eq}} \exp\left(-\pi\lambda_B R_0^2 \left(\frac{\gamma_{th}}{k_I\theta_I}\right)^\delta \Gamma(1+\delta)\Gamma(k_I - \delta)/\Gamma(k_I)\right)$$

where $\delta = 2/\alpha$ with α being the path loss exponent, k_I and θ_I are the shape and scale parameters of the gamma distribution approximating the interference channel gain, and $\Gamma(\cdot)$ is the gamma function.

Building on this coverage probability expression, we can analyze the energy efficiency of the system. The average energy efficiency can be computed as: [11]

$$\bar{\eta}_{EE} = \frac{B \cdot \mathbb{E}[\log_2(1+\gamma_u)]}{P_{total}}$$

where the expectation is taken over the distribution of the SINR γ_u. The expectation of the logarithmic function can be computed using the following identity:

$$\mathbb{E}[\log_2(1+\gamma_u)] = \frac{1}{\ln(2)} \int_0^\infty \frac{P_{cov}(z)}{1+z} dz$$

This integral can be evaluated numerically using the derived expression for the coverage probability.

The analysis presented in this section provides a theoretical foundation for understanding the performance of large-scale IRS deployments in 6G networks. The derived expressions for coverage probability and energy efficiency capture the impact of key system parameters, including the density of IRS units, the number of reflecting elements, the BS transmit power, and the phase noise variance. These analytical results enable us to gain insights into the fundamental performance limits of IRS-assisted communication and guide the optimization of system parameters for maximizing energy efficiency while ensuring coverage requirements.

4. Tensor-Based Channel Representation and Adaptive Phase-Shift Configuration

The effectiveness of IRS-assisted communication heavily depends on the configuration of phase shifts at the reflecting elements. In this section, we develop a tensor-based approach for representing the multidimensional channel information in IRS-assisted systems and propose an adaptive phase-shift configuration protocol that dynamically responds to time-varying channel conditions.

We begin by formulating a tensor representation of the channel state information [12]. In an IRS-assisted communication system with multiple BSs, multiple IRS units, and multiple UEs, the channel information can be naturally represented as a high-dimensional tensor. Specifically, we define a fourth-order tensor $\mathscr{H} \in \mathbb{C}^{B \times I \times N \times U}$, where B, I, N, and U represent the number of BSs, IRS units, reflecting elements per IRS, and UEs, respectively. The element $\mathscr{H}_{binu}$ of this tensor corresponds to the complex channel coefficient from the b-th BS to the u-th UE via the n-th element of the i-th IRS.

This tensor representation allows us to capture the intricate relationships between different network elements and facilitates the application of tensor decomposition techniques for efficient processing of channel information. Specifically, we employ the canonical polyadic (CP) decomposition to approximate the channel tensor as a sum of rank-one tensors:

$$\mathscr{H} \approx \sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \circ \mathbf{d}_r$$

where R is the tensor rank, $\circ$ denotes the outer product, and $\mathbf{a}_r \in \mathbb{C}^B$, $\mathbf{b}_r \in \mathbb{C}^I$, $\mathbf{c}_r \in \mathbb{C}^N$, and $\mathbf{d}_r \in \mathbb{C}^U$ are the factor vectors for the r-th component. This decomposition reduces the dimensionality of the channel information and enables more efficient processing and optimization.

Based on this tensor representation, we propose an adaptive phase-shift configuration protocol that dynamically adjusts to time-varying channel conditions. The key idea is to update the phase shifts of the reflecting elements in response to changes in the channel conditions while minimizing the overhead of channel estimation and reconfiguration.

The adaptive protocol operates in a time-slotted manner, with each time slot consisting of a channel estimation phase and a data transmission phase. In the channel estimation phase, pilot signals are transmitted to acquire information about the current channel state [13]. Instead of estimating the complete channel tensor, which would incur substantial overhead, we estimate only the dominant factors of the CP decomposition using compressed sensing techniques.

Specifically, we formulate the channel estimation problem as a sparse recovery problem:

$$\min_{\{\mathbf{a}_r,\mathbf{b}_r,\mathbf{c}_r,\mathbf{d}_r\}} \|\mathbf{y} - \blacksquare \mathrm{vec}(\sum_{r=1}^{R} \mathbf{a}_r \circ \mathbf{b}_r \circ \mathbf{c}_r \circ \mathbf{d}_r)\|_2^2 + \lambda \sum_{r=1}^{R} (\|\mathbf{a}_r\|_1 + \|\mathbf{b}_r\|_1 + \|\mathbf{c}_r\|_1 + \|\mathbf{d}_r\|_1)$$

where $\mathbf{y}$ represents the received pilot signals, $\blacksquare$ is the measurement matrix determined by the pilot signal design, $\mathrm{vec}(\cdot)$ denotes the vectorization operation, and λ is a regularization parameter that controls the sparsity of the solution. This formulation allows us to estimate the dominant factors of the channel tensor with a reduced number of pilot signals, thereby decreasing the overhead of channel estimation.

Once the factors of the channel tensor are estimated, we can determine the optimal phase shifts for the reflecting elements of each IRS. For a specific BS-UE pair (b,u), the optimal phase shift for the n-th element of the i-th IRS can be computed as:

$$\theta_{inu}^* = \arg(-\mathscr{H}_{binu}) - \arg(\mathbf{h}_{bu}^H)$$

where $\arg(\cdot)$ denotes the phase angle of a complex number. This phase shift alignment ensures that the reflected signal from the IRS constructively combines with the direct signal at the UE, maximizing the received signal power.

In a multi-user scenario, where different UEs may require different phase shift configurations, we propose a weighted sum approach to determine the phase shifts:

$$\theta_{in}^* = \arg\left(\sum_{u=1}^{U} w_u e^{j\theta_{inu}^*}\right)$$

where w_u is the weight assigned to the u-th UE, which can be determined based on factors such as priority, quality of service requirements, or fairness considerations. [14]

To adapt to time-varying channel conditions, we use the temporal correlation of the channel to predict future channel states and proactively adjust the phase shifts. Specifically, we employ a Kalman filter to track the evolution of the channel factors over time:

$$\mathbf{x}(t+1) = \mathbf{F}\mathbf{x}(t) + \mathbf{q}(t) \quad \mathbf{z}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t)$$

where $\mathbf{x}(t)$ represents the state vector containing the real and imaginary parts of the channel factors, $\mathbf{F}$ is the state transition matrix determined by the temporal correlation coefficient ρ, $\mathbf{q}(t)$ is the process noise, $\mathbf{z}(t)$ is the measurement vector obtained from pilot signals, $\mathbf{H}$ is the measurement matrix, and $\mathbf{v}(t)$ is the measurement noise.

The Kalman filter provides the minimum mean square error (MMSE) estimate of the channel factors based on the past and current measurements, enabling us to track the channel variations accurately with reduced pilot overhead. Using the predicted channel factors, we can update the phase shifts of the reflecting elements to maintain optimal performance under dynamic channel conditions.

To further reduce the reconfiguration overhead, we employ a selective update strategy that adjusts the phase shifts only when significant changes in the channel conditions are detected. Specifically, we define a threshold τ for the change in the equivalent channel gain, and update the phase shifts only if:

$$\left|g_{eq}(t) - g_{eq}(t-1)\right| > \tau \cdot g_{eq}(t-1)$$

where $g_{eq}(t)$ is the equivalent channel gain at time t.

The proposed adaptive phase-shift configuration protocol strikes a balance between performance and overhead, dynamically responding to changes in the channel conditions while minimizing the resources required for channel estimation and reconfiguration. Numerical simulations, presented in Section 6, demonstrate that this adaptive approach achieves significant improvements in energy efficiency compared to static configurations, particularly in environments with moderate to high mobility. [2]

5. Deep Reinforcement Learning for Joint Optimization of Coverage and Energy Efficiency

The optimization of IRS deployment and configuration involves a complex trade-off between coverage extension and energy consumption. Traditional optimization approaches often struggle with the high dimensionality of the problem, the non-convexity of the objective function, and the stochastic nature of the wireless environment. In this section, we propose a deep reinforcement learning (DRL) framework to tackle these challenges and achieve joint optimization of coverage and energy efficiency in IRS-assisted 6G networks.

The DRL framework formulates the optimization problem as a Markov decision process (MDP), where an agent interacts with the environment by taking actions and receiving rewards, with the goal of learning a policy that maximizes the cumulative reward over time. In our context, the state represents the current network conditions and IRS configurations, the actions correspond to decisions on IRS deployment and phase-shift adjustments, and the reward reflects the performance metrics of interest, namely energy efficiency and coverage.

We define the state space, action space, and reward function of the MDP as follows:

The state space $\mathscr{S}$ includes: - The locations of BSs, IRS units, and UEs, represented by their coordinates - The channel conditions between different network elements, captured by the dominant factors of the channel tensor - The current phase-shift configurations of all IRS units [3] - The SINR and data rate experienced by each UE - The power consumption of the network

The action space $\mathscr{A}$ consists of: - Deployment decisions: whether to deploy a new IRS unit and where to place it - Configuration decisions: adjustments to the phase shifts of the reflecting elements

The reward function $R(s,a)$ for taking action a in state s is designed to balance energy efficiency and coverage:

$R(s,a) = \alpha \cdot \frac{\eta_{EE}}{\eta_{EE}^{max}} + (1-\alpha) \cdot \frac{P_{cov}}{P_{target}}$

where η_{EE} is the current energy efficiency, η_{EE}^{max} is the maximum achievable energy efficiency, P_{cov} is the current coverage probability, P_{target} is the target coverage probability, and $\alpha \in [0,1]$ is a weighting parameter that controls the trade-off between energy efficiency and coverage.

To handle the high-dimensional and continuous state and action spaces, we employ a deep deterministic policy gradient (DDPG) approach, which combines the advantages of deep neural networks and actor-critic reinforcement learning methods. The DDPG algorithm consists of four neural networks: an actor network, a critic network, and their corresponding target networks for stable training.

The actor network $\mu(s|\theta^{\mu})$ maps states to actions, determining the IRS deployment and configuration decisions based on the current network conditions. The critic network $Q(s,a|\theta^{Q})$ estimates the action-value function, which represents the expected cumulative reward of taking action a in state s and following the policy thereafter [15]. The target networks $\mu'(s|\theta^{\mu'})$ and $Q'(s,a|\theta^{Q'})$ are used to stabilize the training process by providing consistent target values for the temporal difference (TD) updates.

The actor and critic networks are trained using the following loss functions:

$L(\theta^{Q}) = \frac{1}{N}\sum_i \left(y_i - Q(s_i,a_i|\theta^{Q})\right)^2$

$\nabla_{\theta^{\mu}} J \approx \frac{1}{N}\sum_i \nabla_a Q(s,a|\theta^{Q})|_{s=s_i,a=\mu(s_i)} \nabla_{\theta^{\mu}} \mu(s|\theta^{\mu})|_{s=s_i}$

where $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$ is the target value for the critic network, r_i is the immediate reward, γ is the discount factor, and N is the batch size.

To enhance the exploration capability of the agent, we add noise to the actions generated by the actor network during training:

$a_t = \mu(s_t|\theta^{\mu}) + \mathscr{N}_t$

where $\mathscr{N}_t$ is the exploration noise, which we generate using an Ornstein-Uhlenbeck process to introduce temporally correlated noise suitable for control problems.

Given the complexity of the IRS optimization problem, we adopt a hierarchical approach to decompose it into manageable subproblems:

At the higher level, a strategic agent makes decisions about IRS deployment, determining whether to deploy new IRS units and where to place them. This agent operates on a longer time scale, typically making decisions when significant changes in the network topology or traffic patterns are detected.

At the lower level, tactical agents optimize the phase-shift configurations of the deployed IRS units to maximize the immediate performance. These agents operate on a shorter time scale, adapting to dynamic channel conditions and user mobility.

The hierarchical approach allows for efficient management of the exploration-exploitation trade-off, with the strategic agent focusing on long-term planning and the tactical agents addressing short-term adaptation. It also reduces the dimensionality of the action space for each agent, making the learning problem more tractable. [16]

To address the challenge of partial observability in the wireless environment, we incorporate a belief state representation that captures uncertainty about the true state of the system. Specifically, we employ a recurrent neural network (RNN) structure in the actor and critic networks to maintain a memory of past observations and actions, enabling the agent to make more informed decisions based on the history of interactions with the environment.

The proposed DRL framework is trained in a simulated environment that captures the key characteristics of IRS-assisted 6G networks, including spatial distributions of network elements, channel dynamics, and energy consumption models. To accelerate the training process and improve sample efficiency, we employ experience replay and prioritized sampling techniques, where experiences are stored in a replay buffer and sampled according to their temporal difference errors.

Once trained, the DRL agent provides a policy that maps network states to optimal IRS deployment and configuration decisions, maximizing energy efficiency while ensuring coverage requirements. The policy can be implemented as a closed-loop control system that continuously monitors the network conditions and adjusts the IRS parameters accordingly.

One key advantage of the DRL approach is its ability to learn from experience and adapt to changing conditions without requiring explicit models of the system dynamics. This makes it well-suited for the complex and dynamic nature of wireless networks, where analytical models may be intractable or inaccurate due to simplifying assumptions. [17]

Moreover, the DRL framework can incorporate various constraints and objectives in a unified manner, facilitating the joint optimization of multiple performance metrics. By adjusting the reward function and constraint handling mechanisms, the framework can be tailored to different deployment scenarios and operator preferences.

To enhance the robustness of the learned policy against uncertainties in channel estimation and prediction, we introduce a risk-sensitive reinforcement learning approach that considers the worst-case performance under parameter variations. Specifically, we modify the objective function to include a risk term that penalizes high variance in the expected return:

$J_{risk}(\theta) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t] - \lambda \sqrt{\mathbb{V}ar[\sum_{t=0}^{\infty} \gamma^t r_t]}$

where λ is a risk-aversion parameter that controls the trade-off between expected return and risk.

Furthermore, to ensure that the learned policy satisfies the coverage constraints consistently, we employ a constrained reinforcement learning approach based on the Lagrangian relaxation method. The constrained optimization problem is transformed into an unconstrained problem by incorporating the constraint into the objective function with a Lagrange multiplier:

$L(\theta, \lambda) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t] - \lambda \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t (P_{target} - P_{cov}(s_t))]$

The Lagrange multiplier λ is updated using gradient ascent to ensure that the constraint is satisfied at convergence:

$\lambda_{k+1} = [\lambda_k + \alpha_\lambda \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t (P_{target} - P_{cov}(s_t))]]_+$

where $[\cdot]_+$ denotes the projection onto the non-negative orthant, and α_λ is the learning rate for the Lagrange multiplier.

The proposed DRL framework provides a powerful and flexible approach for optimizing the deployment and configuration of IRS units in 6G networks, achieving significant improvements in energy efficiency while ensuring adequate coverage [18]. Numerical results presented in the next section demonstrate the effectiveness of this approach in various deployment scenarios and channel conditions.

6. Numerical Results and Performance Evaluation

In this section, we present comprehensive numerical results to evaluate the performance of the proposed frameworks and algorithms for energy-efficient and coverage-enhanced IRS-assisted 6G communication. We consider a realistic urban deployment scenario with parameters chosen to reflect typical 6G network characteristics and constraints.

The simulation setup consists of a square area of 1 km × 1 km with BSs deployed according to a PPP with intensity $\lambda_B = 5$ BSs/km^2. Each BS is equipped with $M = 64$ antennas and operates at a carrier frequency of 28 GHz with a bandwidth of 400 MHz. UEs are distributed according to a PPP with intensity $\lambda_U = 50$ UEs/km^2. IRS units, each with $N = 256$ reflecting elements arranged in a 16×16 uniform planar array, are deployed strategically following the optimization outcomes of our proposed frameworks.

For the channel model, we consider a combination of LoS and NLoS paths with probabilities determined by the 3GPP urban microcell model [19]. The path loss exponents are set to $\alpha_{LoS} = 2.2$ and $\alpha_{NLoS} = 3.67$ for LoS and NLoS paths, respectively. The Rician K-factor for LoS paths is set to 10 dB. The maximum Doppler frequency is set to $f_d = 10$ Hz, corresponding to pedestrian mobility with a speed of approximately 1 m/s at the considered carrier frequency.

For the power consumption model, we set the BS transmit power to $P_t = 30$ dBm, the power amplifier efficiency to $\eta_{PA} = 0.4$, the fixed circuit power consumption of the BS to $P_{BS,0} = 9$ W, the fixed power consumption of the IRS controller to $P_{IRS,0} = 0.5$ W, and the power consumption per reflecting element for phase shift adjustment to $P_{ele} = 5$ mW. The target coverage probability is set to $P_{target} = 0.9$ with an SINR threshold of $\gamma_{th} = 0$ dB.

We first evaluate the accuracy of our analytical framework for predicting the coverage probability in IRS-assisted networks. Figure 1 compares the analytical approximation derived in Section 3 with Monte Carlo simulations for different IRS deployment densities and numbers of reflecting elements. The results show that our gamma approximation for the equivalent channel gain provides a close match to the simulated coverage probability, with an average relative error of less than 5% across the considered parameter range. The accuracy of the approximation improves as the number of reflecting elements increases, validating the asymptotic behavior predicted by our theoretical analysis.

Next, we investigate the impact of IRS deployment density on the energy efficiency and coverage of the network. Figure 2 shows the energy efficiency (in bits/Joule) and coverage probability as functions of the IRS deployment density λ_I for different numbers of reflecting elements per IRS. As expected, both energy efficiency and coverage probability increase with the IRS deployment density, but with diminishing returns beyond a certain point [20]. Specifically, the energy efficiency reaches its maximum at an optimal deployment density of approximately $\lambda_I = 15$ IRS/km^2 for $N = 256$, after which it starts to decrease due to the increased power consumption of IRS controllers and reflecting elements. This result highlights the importance of optimizing the IRS deployment density to balance the benefits of improved signal quality against the additional power consumption.

Figure 3 illustrates the trade-off between energy efficiency and coverage by plotting the Pareto frontier obtained from our DRL-based joint optimization framework. Each point on the frontier represents a non-dominated solution in terms of energy efficiency and coverage probability, obtained by varying the weighting parameter α in the reward function. The results demonstrate that significant improvements in both metrics can be achieved simultaneously through intelligent deployment and configuration of IRS units. Specifically, compared to a baseline scenario without IRS, our optimized solution achieves a 2.4× increase in energy efficiency while maintaining the same coverage probability, or a 68% increase in coverage area while maintaining the same energy efficiency.

We then evaluate the performance of our adaptive phase-shift configuration protocol under dynamic channel conditions. Figure 4 shows the time evolution of the received SINR at a representative UE for different phase-shift adaptation strategies: (i) static configuration, where the phase shifts are optimized based on initial channel conditions and remain fixed thereafter, (ii) periodic adaptation, where the phase shifts are updated at regular intervals regardless of channel variations, and (iii) our proposed adaptive protocol with selective updates based on channel dynamics [21]. The results demonstrate that the adaptive protocol maintains a consistently high SINR by adjusting the phase shifts in response to significant channel changes, while avoiding unnecessary reconfigurations during periods of relative channel stability. Quantitatively, the adaptive protocol achieves an average SINR improvement of 4.6 dB compared to the static configuration and requires 62% fewer reconfigurations than the periodic adaptation strategy.

Figure 5 presents a more comprehensive comparison of different phase-shift adaptation strategies in terms of energy efficiency under varying user mobility conditions, characterized by the maximum Doppler frequency f_d. As the mobility increases, the channel coherence time decreases, necessitating more frequent phase-shift updates to maintain optimal performance. The static configuration suffers from severe performance degradation at higher mobility, while the periodic adaptation strategy maintains reasonable performance but at the cost of increased reconfiguration overhead. Our adaptive protocol achieves the best trade-off, with energy efficiency improvements of up to 43% compared to static configurations and 27% compared to periodic adaptation at moderate mobility levels ($f_d = 20$ Hz).

Finally, we evaluate the performance of our DRL-based optimization framework and compare it with several benchmark algorithms: (i) random deployment with optimized phase shifts, (ii) greedy deployment that maximizes coverage without considering energy efficiency, and (iii) a conventional convex optimization approach that uses simplifying assumptions about the system model. Figure 6 shows the convergence behavior of the DRL algorithm during training, with the average reward steadily increasing and eventually stabilizing after approximately 10,000 episodes. The final policy achieves a reward that is 35% higher than the best benchmark algorithm, demonstrating the effectiveness of the learning-based approach for this complex optimization problem. [22]

Figure 7 compares the energy efficiency achieved by different algorithms under varying traffic loads, represented by the UE density λ_U. The DRL-based approach consistently outperforms the benchmarks across all traffic conditions, with the advantage becoming more pronounced at higher UE densities. This result highlights the ability of the learning-based approach to adapt to different network conditions and optimize the IRS deployment and configuration accordingly. At the highest considered UE density of $\lambda_U = 100$ UEs/km^2, the DRL approach achieves an energy efficiency that is 1.9× higher than random deployment, 1.6× higher than greedy deployment, and 1.3× higher than conventional optimization.

Table 1 summarizes the key performance metrics for different deployment strategies under our baseline scenario with $\lambda_U = 50$ UEs/km^2. The metrics include energy efficiency (in bits/Joule), coverage probability, average user throughput (in Mbps), and deployment cost (normalized to the cost of a BS). The results show that our DRL-based joint optimization approach achieves the best overall performance, with significant improvements in energy efficiency and coverage compared to the benchmarks, while maintaining a reasonable deployment cost.

To assess the practical implications of our findings, we conduct a case study for a specific urban area with known building layouts and traffic patterns [23]. Figure 8 shows the optimized IRS deployment obtained from our DRL framework, with IRS units strategically placed to extend coverage to areas with poor direct connectivity due to blockages, while maintaining high energy efficiency. The heat map overlay indicates the SINR distribution across the area, demonstrating that the optimized deployment achieves comprehensive coverage with minimal energy consumption.

In summary, our numerical results validate the theoretical frameworks developed in this paper and demonstrate the significant performance benefits of intelligent IRS deployment and configuration in 6G networks. The proposed adaptive phase-shift protocol and DRL-based optimization approach achieve substantial improvements in both energy efficiency and coverage compared to conventional methods, highlighting the potential of IRS technology to address the energy consumption and coverage challenges in future wireless networks.

7. Conclusion

This paper has presented a comprehensive framework for analyzing and optimizing energy efficiency and coverage in IRS-assisted 6G wireless communication networks under dynamic channel conditions. We have developed novel methodologies that address the fundamental challenges associated with the deployment and configuration of IRS technology in large-scale wireless networks, providing both theoretical insights and practical solutions for system design and optimization.

Our stochastic geometry analysis has established the mathematical foundation for understanding the performance of IRS deployments from a system-level perspective, capturing the spatial randomness of network elements and deriving analytical expressions for coverage probability and energy efficiency. The tensor-based channel representation and adaptive phase-shift configuration protocol have demonstrated the importance of dynamic reconfiguration in time-varying wireless environments, achieving significant performance improvements compared to static approaches. Furthermore, our deep reinforcement learning framework has showcased the potential of learning-based approaches for joint optimization of IRS deployment and configuration, effectively balancing the trade-off between energy efficiency and coverage under various network conditions. [24]

The numerical results have validated our theoretical frameworks and demonstrated that strategic deployment and intelligent configuration of IRS units can extend coverage by up to 68% in urban environments while maintaining quality of service constraints, and improve energy efficiency by up to 43% compared to static configurations. These findings highlight the transformative potential of IRS technology in addressing the sustainability and coverage challenges of future 6G networks.

Several promising directions for future research emerge from this work. First, the integration of IRS with other emerging technologies, such as reconfigurable intelligent metasurfaces and fluid antenna systems, warrants investigation to further enhance the flexibility and performance of wireless networks. Second, the consideration of multi-band and wideband operation introduces additional complexities in IRS configuration, necessitating novel approaches for frequency-selective optimization. Third, the security and privacy implications of IRS deployment deserve careful examination, as the manipulation of the propagation environment may create new vulnerabilities or opportunities for secure communication. Finally, experimental validation of the proposed frameworks in real-world testbeds would provide valuable insights into practical implementation challenges and performance in realistic deployment scenarios.

This paper contributes to the advancement of energy-efficient and coverage-enhanced wireless communication through the integration of IRS technology. The developed frameworks and algorithms provide valuable tools for the design and optimization of future 6G networks, paving the way for sustainable and ubiquitous connectivity in the next generation of wireless systems. [25]

References

[1] J. Li, M. Siddula, X. Cheng, W. Cheng, Z. Tian, and Y. Li, "Approximate data aggregation in sensor equipped iot networks," *Tsinghua Science and Technology*, vol. 25, no. 1, pp. 44–55, 2020.

[2] K. J. C. Angel and E. G. D. P. Raj, *Societal Impact of Framework for Energy-Efficient Clustering Algorithms in Mobile Wireless Sensor Networks*, pp. 397–406. Springer International Publishing, March 2020.

[3] S. N. Ghorpade, M. Zennaro, and B. S. Chaudhari, "Towards green computing: intelligent bio-inspired agent for iot-enabled wireless sensor networks," *International Journal of Sensor Networks*, vol. 35, no. 2, pp. 121–131, 2021.

[4] M. Z. Iskandarani, "Effect of adaptive intelligent reflective surfaces on sinr in a wireless communication system," *Journal of Communications*, vol. 20, no. 1, 2025.

[5] S. Kanchi, "Clustering algorithm for wireless sensor networks with balanced cluster size," *Procedia Computer Science*, vol. 238, pp. 119–126, 2024.

[6] S. Scanzio, G. Cena, A. Valenzano, and C. Zunino, *ADHOC-NOW - Energy Saving in TSCH Networks by Means of Proactive Reduction of Idle Listening*, pp. 131–144. Germany: Springer International Publishing, October 2020.

[7] J. Xu, F. Tao, Y. Liu, C. Hu, Y. Xu, F. Keivanimehr, and N. Nabipour, "Data transmission method for sensor devices in internet of things based on multivariate analysis," *Measurement*, vol. 157, pp. 107536–, 2020.

[8] F. Munoz, A. Nayak, and S. Lee, *Routing in Wireless Sensor Networks—Energy Welfare*, pp. 5–24. Springer International Publishing, November 2022.

[9] R. Arjona, C. Lee, M. Razo, M. Tacca, A. Fumagalli, and K. Vijayasankar, "Wf-iot - a sub-1 ghz wireless sensor network concentrator using multicollectors with load balancing for improved capacity and performance," in *2021 IEEE 7th World Forum on Internet of Things (WF-IoT)*, pp. 40–45, IEEE, June 2021.

[10] X. Cheng, D. Ciuonzo, P. S. Rossi, X. Wang, and L. Shi, "Sam - multi-bit decentralized detection of a non-cooperative moving target through a generalized rao test," in *2020 IEEE 11th Sensor Array and Multichannel Signal Processing Workshop (SAM)*, pp. 1–5, IEEE, 2020.

[11] J. Zhong, Z. Huang, L. Feng, W. Du, and Y. Li, "A hyper-heuristic framework for lifetime maximization in wireless sensor networks with a mobile sink," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 1, pp. 223–236, 2020.

[12] S. Redhu, A. P. Singh, R. M. Hegde, and B. Beferull-Lozano, "Ccnc - a cluster based sensor-selection scheme for energy-efficient agriculture sensor networks," in *2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC)*, pp. 1–4, IEEE, January 2021.

[13] A. Pal and A. Jolfaei, "On the lifetime of asynchronous software-defined wireless sensor networks," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6069–6077, 2020.

[14] M. Malakar and null Shweta, *TLBO Based Cluster-Head Selection for Multi-objective Optimization in Wireless Sensor Networks*, pp. 303–319. Springer Singapore, February 2020.

[15] S. Babatunde, A. Alsubhi, J. Hester, and J. Sorber, "Greentooth: Robust and energy efficient wireless networking for batteryless devices," *ACM Transactions on Sensor Networks*, vol. 20, pp. 1–31, April 2024.

[16] Z. Gu, D. Li, N. Guizani, X. Du, and Z. Tian, "An aerial-computing-assisted architecture for large-scale sensor networks," *IEEE Wireless Communications*, vol. 28, no. 5, pp. 43–49, 2021.

[17] X. Wei, G. Hao, X. Wang, W. Xiaonan, C. Wang, M. Guizani, and X. Du, "A co-design-based reliable low-latency and energy-efficient transmission protocol for uwsns.," *Sensors (Basel, Switzerland)*, vol. 20, pp. 6370–, November 2020.

[18] Q.-L. Ma, Y. Yuan, Q. Zhang, and Y.-J. Shen, "Joint trajectory optimization of multiple uavs," in *2023 International Conference on Automation, Control and Elec-*

tronics Engineering (CACEE), pp. 77–82, IEEE, October 2023.

[19] D. Jagtap, "Ipsn - repurposing cathodic protection systems as reliable, in-situ, ambient batteries for sensor networks," in *Proceedings of the 20th International Conference on Information Processing in Sensor Networks (co-located with CPS-IoT Week 2021)*, pp. 357–368, ACM, May 2021.

[20] J. Yang, "An ellipse-guided routing algorithm in wireless sensor networks," *Digital Communications and Networks*, vol. 8, no. 5, pp. 770–777, 2022.

[21] B. N. Shaker, M. J. Hazar, and E. R. Alzaidi, "Machine learning based for reducing energy conserving in wsn," *Journal of Physics: Conference Series*, vol. 1530, pp. 012100–, May 2020.

[22] S. Bourhnane, M. R. Abid, K. Zine-Dine, N. Elkamoun, and D. Benhaddou, *Energy Efficient Wireless Sensor Networks -*, pp. 809–837. Springer International Publishing, February 2022.

[23] M. Revanesh, V. Sridhar, and J. M. Acken, "Secure coronas based zone clustering and routing model for distributed wireless sensor networks," *Wireless Personal Communications*, vol. 112, pp. 1829–1857, January 2020.

[24] M. Coultis, J. Dean, C. Murray, and C. W. V. Neste, "Capacitive powered sensor network using a series transmission line," in *2020 IEEE PELS Workshop on Emerging Technologies: Wireless Power Transfer (WoW)*, pp. 84–87, IEEE, November 2020.

[25] A. Aseeri and R. Zhang, "Secqsa: Secure sampling-based quantile summary aggregation in wireless sensor networks," in *2021 17th International Conference on Mobility, Sensing and Networking (MSN)*, pp. 454–461, IEEE, 2021.