DEER: Simultaneous Multi-Modal Decentralized Energy Efficient Covert Routing

Khandaker Foysal Haque*, Justin Kong†, Terrence J. Moore†, Francesco Restuccia*, Fikadu T. Dagefu†
*Institute for the Wireless Internet of Things, Northeastern University, United States
†U.S. Army DEVCOM Army Research Laboratory Adelphi, Maryland, USA
{haque.k, f.restuccia}@northeastern.edu*, {justin.s.kong.civ, terrence.j.moore.civ, fikadu.t.dagefu.civ}@army.mil†

2025 IEEE Wireless Communications and Networking Conference (WCNC) | 979-8-3503-6836-9/25/$31.00 ©2025 IEEE | DOI: 10.1109/WCNC61545.2025.10978544

***Abstract*—A fundamental challenge in covert routing is that meeting both covertness and throughput requirements often leads to increased transmit power, which can significantly elevate the overall energy consumption of the network. Therefore, it is important to achieve higher throughput and better energy efficiency while maintaining the required covertness. To this end, we propose a novel simultaneous multi-modal Decentralized Energy- Efficient covert Routing approach – DEER for a multi-hop heterogeneous network (HetNet). Unlike the prevailing single-modal approaches, DEER leverages the diversity of the available wireless communication technologies for simultaneous multi-modal routing. DEER aims to minimize the end-to-end total transmit power of the whole route in a decentralized fashion while maintaining the constraints on required throughput and covertness. DEER stems into two main steps: node-level optimization followed by network-level optimization using the proposed custom-tailored Dijkstra's based link state routing protocol to meet the constraints while minimizing the end-to-end total transmit power. We demonstrate by numerical analysis that DEER improves the energy efficiency by 23.5x and 2.9x times in comparison to the baseline single-modal and naive simultaneous multi-modal approaches respectively.**

I. Introduction

The study of covert communication aiming to conceal wireless signals from potential adversaries has garnered much attention for various civilian and military applications [1]. Recently, extensive research has been conducted in point-to-point [2], [3] and multi-hop [4], [5] covert communication approaches. Kong et al. in [4] introduced algorithms for optimizing covert routing communication in a heterogeneous network (HetNet), focusing on three key problems: maximizing detection error probability (DEP), maximizing throughput, and minimizing latency with various constraints. They also designed a reinforcement learning-based covert routing algorithm for HetNets [5]. Lv et al. proposed an intelligent reflecting surface (IRS)-assisted non-orthogonal multiple access (NOMA) scheme for covert communication, optimizing transmit power and IRS beamforming [6]. Aggarwal et al. presented a joint detection threshold and transmit power optimization approach to enhance covertness in multi-modal wireless communication [3]. However, this work only considers the single-hop scenario. Moreover, most of these approaches are inadequate to meet the requirements of the next-generation applications pertaining to digital twins, augmented reality, and virtual reality due to their (i) higher latency and lower throughput, (ii) higher energy consumption, and (iii) lower covertness. Firstly, the lower throughput of the prevailing approaches [4], [6] is due to bandwidth scarcity and allocation of limited transmit power required to maintain covertness. On the other hand, if the covertness requirement does not limit the allocated transmit power, wireless networks might end up using higher

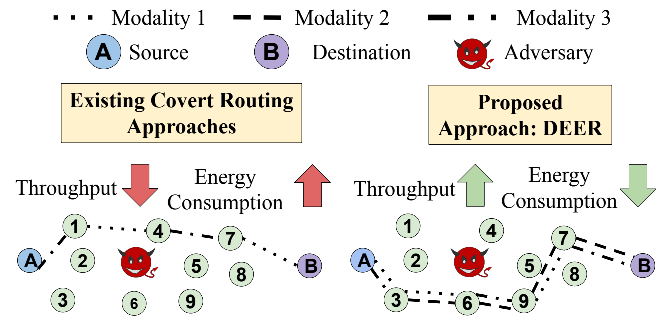


Fig. 1: Existing single modal approaches (left) vs the proposed simultaneous multi-modal scheme – DEER (right) for HetNets covert routing.

transmit power to achieve the required throughput, hampering the energy efficiency of the whole system [7]. To further complicate matters, higher covertness necessitates the network to meet conflicting requirements of lower transmit power while achieving higher network performances i.e., higher throughput and lower latency [4].

Thus to address the challenge of conflicting requirements of higher throughput and strict covertness requirement while having lower energy consumption, we propose a novel approach, *simultaneous multi-modal decentralized energy-efficient covert routing (DEER)*. As presented in Figure 1, unlike the existing approaches, DEER exploits multiple modalities (i.e., different wireless communication technologies) simultaneously in a multi-hop HetNet to improve end-to-end throughput and energy efficiency. It is based on the intuition that, as the throughput of any modality depends on the instantaneous channel condition and has a non-linear relationship with transmit power, higher throughput is achievable with comparatively lower energy consumption by optimally exploiting multiple modalities simultaneously.

Preliminarily, we prove our intuition through numerical analysis for a single-hop scenario where we have three modalities at 400 MHz, 900 MHz, and 2.4 GHz of center frequencies with a bandwidth of 3 MHz each. Figure 2 demonstrates, that by using two of the modalities simultaneously, we can improve the energy efficiency by up to 7.4x times in comparison to the single modality cases while ensuring requirements on the throughput and the level of communication covertness.

Thus, the proposed covert routing method, termed DEER, is designed to exploit multiple modalities simultaneously and efficiently to minimize the total end-to-end transmit power across the entire communication route in a decentralized manner while adhering to user-defined throughput and covertness

979-8-3503-6836-9/25/$31.00 ©2025 IEEE
Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.

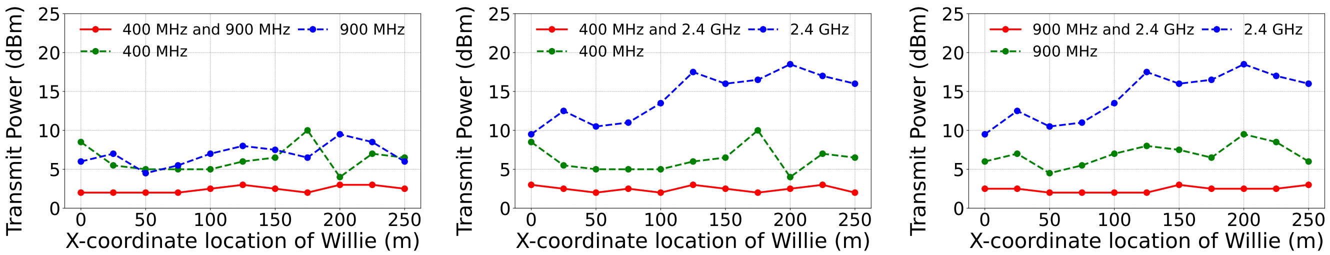


Fig. 2: Transmit power consumption of single modal vs simultaneous multi-modal transmissions with user-required throughput and covertness level for a single hop scenario.

constraints. The approach is divided into two key phases. **Node-level optimization:** for all the possible combinations of modalities, the sum transmit power of all probable next hops is minimized while adhering to user-defined throughput and covertness constraints. Then, each node independently selects the optimal combination of communication modalities that minimizes the per-hop sum transmit power of all probable next-hops. **Network-level optimization:** the network employs a custom Dijkstra's based link state routing protocol (D-LSRP) algorithm to maintain these constraints while minimizing the end-to-end total transmit power. This dual-phase approach ensures efficient covert routing with minimal power usage.

Summary of Novel Contributions

• We present `DEER`, a novel decentralized energy-efficient covert routing approach that leverages simultaneous multi-modal transmissions to improve the energy efficiency of the network while maintaining the user-required constraints on throughput and covertness.

• `DEER` includes the formulation of an optimization problem for simultaneous multi-modal decentralized covert routing, aiming to minimize the end-to-end total transmit power across the entire route through **node-level** and **network-level** optimization strategies.

• We introduce D-LSRP, a novel routing approach that combines link state routing protocol (LSRP) and Dijkstra's algorithm, prioritizing decentralized, energy-efficient routing by minimizing total transmit power based on local information.

• Through numerical analysis, we demonstrate that `DEER` significantly enhances network energy efficiency by up to 23.5x.

II. Network Model and Problem Formulation

A. Network Model

We consider a HetNet consisting of a source (Alice), a destination (Bob), multiple relay nodes, and an adversary (Willie) as presented in Figure 1. All the nodes in the considered network are equipped with M modalities each having different operating frequencies and channel characteristics. The adversary Willie is also equipped with a radiometer that spans the frequency bands of all M modalities and tries to detect the existence of the communication in all the defined M modalities simultaneously at all times. The aim is to transmit data from Alice to Bob via multiple modalities and hops, undetected by Willie while minimizing total transmit power and maintaining throughput requirements. Note that in the proposed `DEER` algorithm, the best two out of M available modalities are selected for every hop of the transmission where the multiple modalities for each hop are on the same node, not allowing split hops with multiple modalities.

Let us assume that the set of all possible routes from Alice to Bob is denoted by Ψ. Every multi-hop link is defined by $\psi = (h_i, ...h_{N_\psi}) \in \Psi$ where $h_i = (T_{h_i}, R_{h_i})$ presents the single hop link between the transmitter and receiver pair of T_{h_i} and R_{h_i} respectively. The total number of required hops in the route ψ is defined by N_ψ. Now, each of the `DEER` nodes adaptively chooses two modalities m^a and m^b from the pool of M modalities based on constraint requirement and per-hop combined transmit power. Any single-hop communication between two nodes consists of L channel uses whereas the transmitter decides whether to transmit the data to the next hop receiver with an equal a priori probability. Thus, for a single-hop link h between T_h and R_h with the modality $m \in \{m^{(a)}, m^{(b)}\}$ for the transmission of the data symbol $x_h[l] \sim \mathbb{C}(0,1)$ in the l-th channel use, the received signals at receiver R_h and Willie W are respectively defined by

$$y^{(m)}_{T_h,R_h}[l] = \sqrt{P^{(m)}_h} g^{(m)}_{T_h,R_h} x_h[l] + n^{(m)}_{T_h,R_h}[l], \tag{1}$$

$$y^{(m)}_{T_h,W}[l] = \sqrt{P^{(m)}_h} g^{(m)}_{T_h,W} x_h[l] + n^{(m)}_{T_h,W}[l]. \tag{2}$$

Here, $l = 1, \ldots, L$, where $P^{(m)}_h \in \{P^{(m^{(a)})}, P^{(m^{(b)})}\}$ is the transmit power of the selected modalities m^a and m^b for the hop h. $g^{(m)}_{T_h,R_h}$ and $g^{(m)}_{T_h,W}$ represents the channels from transmitter T_h to receiver R_h and Willie W respectively for modality $m \in \{m^{(a)}, m^{(b)}\}$. $n^{(m)}_{T_h,R_h}[l] \sim \mathcal{CN}(0, \Omega^{(m)} N_{0,B})$ and $n^{(m)}_{T_h,W}[l] \sim \mathcal{CN}(0, \Omega^{(m)} N_{0,W})$ respectively specify the additive white Gaussian noise (AWGN) at receiver R_h and Willie W for modality m. $\Omega^{(m)} \in \{\Omega^{(m^{(a)})}, \Omega^{(m^{(b)})}\}$ accounts for the bandwidth for modality m. N_{0,R_h} and $N_{0,W}$ specify the spectral density of AWGN at receiver R_h and Willie W respectively.

For a route $\psi = (h_i, ...h_{N_\psi}) \in \Psi$ from a source to a destination, the single-hop link having the lowest throughput becomes the bottleneck of the entire route Ψ. Thus, we write the end-to-end throughput of modality m for the route ψ as

$$U^{(m)}(\psi) = \min_{h \in \psi} U^{(m)}_h, \tag{3}$$

Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.

where $U_h^{(m)}$ is the throughput of a single-hop link h for the modality m, which is expressed as

$$U_h^{(m)} = \Omega^{(m)} \log_2 \left(1 + \frac{P_h^{(m)} \left| g_{T_h,R_h}^{(m)} \right|^2}{\Omega^{(m)} N_{0,R_h}} \right). \quad (4)$$

Therefore, the per-hop sum throughput is expressed as $U_h = U_h^{(m^{(a)})} + U_h^{(m^{(b)})}$, whereas the total end-to-end throughput is the sum throughput of the selected two modalities and expressed as $U(\psi) = U^{(m^{(a)})}(\psi) + U^{(m^{(b)})}(\psi)$.

B. Detection at Willie

We assume that Willie has the knowledge of the channel $g_{T_h,R_h}^{(m)}$, the transmit power $P_h^{(m)}$, and the bandwidth $\Omega^{(m)}$ of all the modalities (based on the feedback from neighboring nodes) for hop $h \in \Psi$. Note that this is the worst-case scenario from the transmitter's point of view who is trying to evade the detection from Willie for the complete route Ψ. Since the channels change independently from one transmission slot to the next and remains constant in a single slot, Willie can make use of a single transmission slot for detection. Each transmission slot consists of a block of $l = 1, 2, \ldots, L$ channel uses.

To detect communication between transmitter T_h and receiver R_h for the hop h, Willie performs a separate hypothesis test for each modality and combines the result from each modality and each hop $h \in \psi$. The individual hypothesis tests for any hop h are denoted by

$$\begin{aligned} \mathcal{H}_0^{(m)} &: y_{T_h,W}^{(m)}[l] = n_{T_h,W}^{(m)}[l], \\ \mathcal{H}_1^{(m)} &: y_{T_h,W}^{(m)}[l] = \sqrt{P_h^{(m)}} g_{T_h,W}^{(m)} x_h[l] + n_{T_h,W}^{(m)}[l], \end{aligned} \quad (5)$$

where $\mathcal{H}_0^{(m)}$ and $\mathcal{H}_1^{(m)}$ are the null and alternative hypotheses respectively denoting no transmission and existence of transmission for the hop $h \in \Psi$ and modality m.

Using the average received signal strength $\bar{y}_{T_h,W}^{(m)} = \frac{1}{L} \sum_{l=1}^{L} \left| y_{T_h,W}^{(m)}[l] \right|^2$, to make a binary decision about whether there is communication over link h [3], [8]–[10], Willie performs a threshold test as

$$\bar{y}_{T_h,W}^{(m)} \underset{\mathcal{D}_0^{(m)}}{\overset{\mathcal{D}_1^{(m)}}{\gtrless}} \delta. \quad (6)$$

Here, $\delta \in \{\delta_h^{(a)}, \delta_h^{(b)}\}$ denotes the detection threshold for modality m and hop h where $\mathcal{D}_0^{(m)}$ and $\mathcal{D}_1^{(m)}$ denote decisions in favor of $\mathcal{H}_0^{(m)}$ and $\mathcal{H}_1^{(m)}$, respectively. The probability of missed detection $\mathrm{P}_{\mathrm{MD},h}^{(m)}$ and the probability of false alarm $\mathrm{P}_{\mathrm{FA},h}^{(m)}$ of each threshold test for hop h and modality m are defined as

$$\mathrm{P}_{\mathrm{MD},h}^{(m)} \triangleq \mathbb{P}\left(\mathcal{D}_0^{(m)} \mid \mathcal{H}_1^{(m)}\right), \quad \mathrm{P}_{\mathrm{FA},h}^{(m)} \triangleq \mathbb{P}\left(\mathcal{D}_1^{(m)} \mid \mathcal{H}_0^{(m)}\right). \quad (7)$$

We leverage the probability distribution of the detection statistic– $\bar{y}_{T_h,W}^{(m)}$ and the threshold test defined in equation 6 to illustrate the $\mathrm{P}_{\mathrm{MD},h}^{(m)}$ and $\mathrm{P}_{\mathrm{FA},h}^{(m)}$ using equation 8.

$$\begin{aligned} \mathrm{P}_{\mathrm{FA},h}^{(m)} &= 1 - \frac{\gamma\left(L, \frac{L\delta}{\Omega^{(m)} N_{0,W}}\right)}{\Gamma(L)}, \\ \mathrm{P}_{\mathrm{MD},h}^{(m)} &= \frac{\gamma\left(L, \frac{L\delta}{P_h^{(m)} \left| g_{T_h,W}^{(m)} \right|^2 + \Omega^{(m)} N_{0,W}}\right)}{\Gamma(L)}. \end{aligned} \quad (8)$$

After performing a threshold test for each of the chosen modalities, Willie then combines the decision obtained for each modality to form an overall decision for hop h as follows:

$$\mathcal{D}_0 = \{\mathcal{D}_0^{m^{(a)}} \cap \mathcal{D}_0^{m^{(b)}}\}, \quad \mathcal{D}_1 = \{\mathcal{D}_1^{m^{(a)}} \cup \mathcal{D}_1^{m^{(b)}}\}, \quad (9)$$

where $\mathcal{D}_0$ represents Willie's overall decision that no communication occurs on hop h, specifically between transmitter T_h and receiver R_h. Conversely, $\mathcal{D}_1$ signifies Willie's decision in favor of the existence of the transmission. Thus, the probability of missed detection $\mathrm{P}_{\mathrm{MD},h}$ and the probability of false alarm $\mathrm{P}_{\mathrm{FA},h}$ for the hop h based on the overall decision made by Willie are respectively presented as

$$\mathrm{P}_{\mathrm{MD},h} \triangleq \mathbb{P}(\mathcal{D}_0 \mid \mathcal{H}_1), \quad \mathrm{P}_{\mathrm{FA},h} \triangleq \mathbb{P}(\mathcal{D}_1 \mid \mathcal{H}_0). \quad (10)$$

The decision made for one modality is independent of the decision made for the other modality. Further, since the two modalities are being used simultaneously, we have $\mathcal{H}_1^{(m^{(a)})} = \mathcal{H}_1^{(m^{(b)})} \triangleq \mathcal{H}_1$ and (b) $\mathcal{H}_0^{(m^{(a)})} = \mathcal{H}_0^{(m^{(b)})} \triangleq \mathcal{H}_0$. Using these facts, we can simplify $\mathrm{P}_{\mathrm{MD},h}$ and $\mathrm{P}_{\mathrm{FA},h}$ in (10) as

$$\mathrm{P}_{\mathrm{MD},h} = \mathbb{P}(\mathcal{D}_0^{(m^{(a)})} | \mathcal{H}_1) \mathbb{P}(\mathcal{D}_0^{(m^{(b)})} | \mathcal{H}_1) = \mathrm{P}_{\mathrm{MD},h}^{(m^{(a)})} \mathrm{P}_{\mathrm{MD},h}^{(m^{(b)})}, \quad (11)$$

$$\begin{aligned} \mathrm{P}_{\mathrm{FA},h} &= \mathbb{P}(\mathcal{D}_1^{(m^{(a)})} \cup \mathcal{D}_1^{(m^{(b)})} \mid \mathcal{H}_0) \\ &= \mathrm{P}_{\mathrm{FA},h}^{(m^{(a)})} + \mathrm{P}_{\mathrm{FA},h}^{(m^{(b)})} - \mathrm{P}_{\mathrm{FA},h}^{(m^{(a)})} \mathrm{P}_{\mathrm{FA},h}^{(m^{(b)})}, \end{aligned} \quad (12)$$

Since every node tosses an unbiased coin to decide whether to transmit or not, transmitter T_h transmits with an equal priori probability of 1/2. Hence, the overall DEP at Willie with simultaneous multiple modalities for hop $h \in \psi$ is presented by

$$\begin{aligned} \mathrm{P}_{\mathrm{DEP},h} &= \frac{1}{2} \mathrm{P}_{\mathrm{MD},h} + \frac{1}{2} \mathrm{P}_{\mathrm{FA},h} \\ &= \frac{1}{2} \left(\mathrm{P}_{\mathrm{MD},h}^{(m^{(a)})} \mathrm{P}_{\mathrm{MD},h}^{(m^{(b)})} \right) \\ &\quad + \frac{1}{2} \left(\mathrm{P}_{\mathrm{FA},h}^{(m^{(a)})} + \mathrm{P}_{\mathrm{FA},h}^{(m^{(b)})} - \mathrm{P}_{\mathrm{FA},h}^{(m^{(a)})} \mathrm{P}_{\mathrm{FA},h}^{(m^{(b)})} \right). \end{aligned} \quad (13)$$

Willie fails to detect the communication in a route ψ if Willie makes wrong decisions for all hops in the route. Therefore, the end-to-end DEP of route ψ is defined by $\mathrm{P}_{\mathrm{DEP}}(\psi) = \prod_{h \in \psi} \mathrm{P}_{\mathrm{DEP},h}$.

C. Problem Formulation

DEER aims to optimally choose two simultaneous modalities out of M available modalities for each of the hops in route ψ. It also needs to minimize the end-to-end total transmit power while satisfying the user-defined end-to-end

Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.

throughput, U_{req}, and per-hop DEP, $\mathrm{P}_{\text{req DEP},h}$. We denote the sum transmit power of both the selected modalities $m^{(a)}$ and $m^{(b)}$ for hop h as $P_h = P^{(m^{(a)})} + P^{(m^{(b)})}$. The total transmit power for the entire route is then defined by

$$P(\psi) = \sum_{h \in \psi} P_h. \tag{14}$$

Thus, we can formulate the end-to-end transmit power minimization problem with constraints on the end-to-end throughput, $U(\psi)$ and per-hop DEP, $\mathrm{P}_{\text{DEP},h}$ as

$$\begin{aligned} \min_{\psi \in \Psi, h \in \psi} \quad & P(\psi) \\ \text{s.t.} \quad & \mathrm{P}_{\text{DEP},h} \geq \mathrm{P}_{\text{req DEP},h} \\ & U(\psi) \geq U_{req}, \end{aligned} \tag{15}$$

where U_{req} and $\mathrm{P}_{\text{req DEP},h}$ denote the user-defined end-to-end throughput and per-hop DEP constraints, respectively. In this work, we focus on the development of an algorithm to solve the problem in (15) in a distributed fashion.

III. Proposed Decentralized Energy Efficient Covert Routing

The proposed DEER algorithm jointly optimizes the route and transmit power at all nodes along the route with the aim of minimizing end-to-end total transmit power while maintaining the user-defined constraints on the throughput and the DEP.

A. Node-level Optimization of Power and Modality

Let us first focus on the power optimization at a transmitter in route ψ. To maintain the end-to-end throughput constraint of U_{req}, all the hops h in route Ψ also need to meet this requirement from (3). Thus, we can simplify the end-to-end throughput requirement to per-hop throughput requirement as $U_h \geq U_{req}, \forall h \in \psi$. The data throughput for any hop h with the transmission modality m is an increasing function of the corresponding transmit power of the modality as in (4). Hence, the sum throughput of multiple modalities for any given hop is also an increasing function of the sum transmit power of the corresponding modalities. Contrarily, the DEP is a decreasing function of transmit power [3] where the higher DEP indicates better covertness. This indicates that the problem in (15) has conflicting requirements of minimizing transmit power while maintaining the constraints on throughput and DEP.

Algorithm 1: Node-level optimization

1) Find the optimum $P^{(m^{(a)})}$ and $P^{(m^{(b)})}$ to minimize $P_h = P^{(m^{(a)})} + P^{(m^{(b)})}$ while maintaining $U_h \geq U_{req}$ and $\mathrm{P}_{\text{DEP},h} \geq \mathrm{P}_{\text{req DEP},h}$ for each neighboring node across all modality combinations.
2) Find the best modality combination ($m^{(a)}$ & $m^{(b)}$) for all neighboring nodes based on minimum P_h.

Through the two-step process outlined in Algorithm 1, we minimize the sum transmit power for each node by finding the optimal combination of modalities that satisfies the required sum throughput and DEP constraints. For all the possible combinations of the available modalities for link h, we determine the optimal transmit powers, $P^{(m^{(a)})}$ and $P^{(m^{(b)})}$ such that the sum power $P_h = P^{(m^{(a)})} + P^{(m^{(b)})}$ is minimized. This optimization is subject to the constraints $U_h \geq U_{req}$ and $\mathrm{P}_{\text{req DEP},h} \geq \mathrm{P}_{\text{req DEP},h}$. To achieve this, we leverage the sequential least squares programming (SLSQP) algorithm, which effectively handles the necessary equality and inequality constraints [11]. SLSQP operates by iteratively adjusting the transmit powers while ensuring the constraints are respected at each step. It does so by utilizing gradient-based methods to navigate the solution space, ensuring convergence towards the minimum sum power P_h while maintaining the required throughput and DEP thresholds. In the second step, the algorithm selects the best combination of modalities for all neighboring nodes based on the minimized sum transmit power P_h.

B. Network Level Optimization with D-LSRP

We employ a custom-tailored D-LSRP algorithm to find an optimal route for the network that minimizes the end-to-end sum transmit power $P(\psi)$, considering the selected modalities and power optimizations at each node through Algorithm 1.

For routing in DEER, we introduce D-LSRP, a novel approach that significantly deviates from conventional methods by integrating key features of the LSRP [12] and Dijkstra's algorithm [13]. Unlike the traditional LSRP, which is typically concerned with finding the shortest path based on distance or hop count, D-LSRP prioritizes minimizing the total transmit power required to route data between two nodes. Moreover, while Dijkstra's algorithm is traditionally a centralized approach where a single node or controller with complete knowledge of the network topology calculates the shortest paths, the D-LSRP algorithm operates in a decentralized manner. This means that each node independently participates in the routing process, making decisions based on local information and the link state advertisements (LSAs) it receives from other nodes. Algorithm 2 presents the proposed D-LSRP for optimizing the route from Alice (A) to Bob (B) to minimize the total transmit power of the whole route. The process begins with each node broadcasting an LSA, which not only includes information about the network topology, as in traditional LSRP but also the optimum transmit power combination obtained from Algorithm 1 for each outgoing link. These LSAs are then collected by all nodes to construct a link state database (LSDB) that captures a global view of the network, enriched with power consumption data. However, unlike the centralized Dijkstra's algorithm, where a central node or controller would compute the optimal paths, the D-LSRP allows each node to independently compute the most energy-efficient route to the destination using the LSDB. Thus, each node determines the optimal route from itself to the destination, ensuring that the route selection is decentralized and tailored to minimize the end-to-end total transmit power. In the optimization phase, each node utilizes the LSDB to adapt Dijkstra's method for power optimization. The process starts with each node initializing

Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.

Algorithm 2: Route Optimization with D-LSRP

```
Input: Nodes N, Links L, Starting node A ∈ N, Target node B ∈ N
Output: Route from node A to node B with minimized transmit power
Step 1: Execute Algorithm 1
Find the best combination of modalities m^(a) and m^(b) and corresponding transmit powers tx_power(l) for each l ∈ L.
Step 2: Initialize D-LSRP
for each node n ∈ N do
    Broadcast Link State Advertisement LSA(n) with outgoing links and transmission powers.
end for
Step 3: Construct Link State Database (LSDB)
for each node n ∈ N do
    Collect LSAs from all nodes to build the LSDB and network topology.
end for
Step 4: Optimize Transmit Power using Dijkstra's Algorithm
Initialize p(A) = 0, p(n) = ∞ for n ≠ A, and an empty set S for visited nodes.
Use a priority queue Q to process nodes based on p(n).
while Q is not empty do
    Extract node u with smallest p(u) from Q and & to S.
    for each neighbor v of u do
        if v ∉ S and (u, v) ∈ L then
            Update p(v) if p(u) + tx_power(u, v) < p(v) and adjust Q.
        end if
    end for
end while
Store the minimum power route from A to B.
Return route with minimized transmit power from A to B.
```

itself with a transmission power value of zero. In contrast, all other nodes are initially assigned infinite power values. Nodes are then processed using a priority queue, which prioritizes nodes based on the minimum cumulative transmission power required to reach them. This approach ensures that nodes with lower cumulative power costs are processed first, facilitating efficient power optimization throughout the network. For each node, the algorithm evaluates all unvisited neighbors updating their power values if a more energy-efficient path is found. Each node maintains its own list of visited and unvisited nodes locally, based on information from the LSDB. This updating process is conducted independently by each node, without the need for a centralized controller, ensuring that each node estimates the optimized routing path independently. In this way, the network can adapt dynamically to changes, such as node failures or varying transmission power conditions.

IV. Numerical Evaluation

A. Simulation Environment and Baselines

As illustrated in Figure 3, we consider a 3D simulation environment of dimension $250 \times 250 \times 9.5$ m^3 with multiple concrete buildings (green cuboids) and 36 transceiver nodes. The nodes are represented by small red cones and

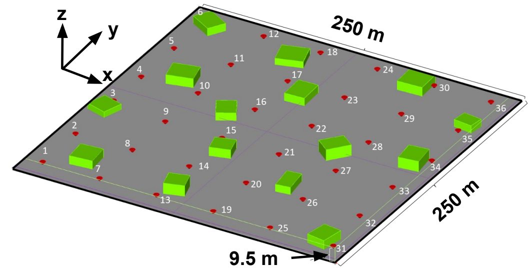


Fig. 3: Simulation environment of DEER

equipped with vertically polarized short dipole antennas at a height of 3 m above ground. Each node is equipped with three communication modalities with center frequencies at 400 MHz, 900 MHz, and 2.4 GHz whose channel information is estimated using the ray tracing module of the EM.CUBE commercial software [14]. For the numerical analysis, we set L = 100, $N_{0,B} \in [-110\,\text{dBm}, -105\,\text{dBm}]$, $N_{0,W} \in [-110\,\text{dBm}, -105\,\text{dBm}]$, $\Omega^{(m)}$ = 3 MHz and Y-coordinate of Willie at 125 m unless specified otherwise.

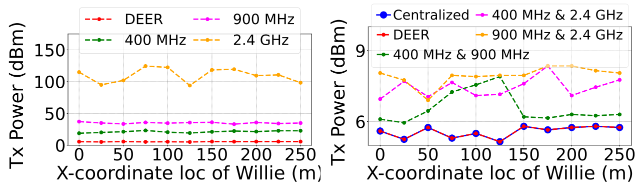
We compare the proposed routing approach DEER with different single-modal, and simultaneous multi-modal approaches including Dijktra's based centralized routing approach [13]. Firstly, we compare DEER with the traditional single-modal approach for modalities at center frequencies of 400 MHz, 900 MHz, and 2.4 GHz. We also compare the proposed approach with different simultaneous multi-modal approaches with modalities 400 MHz & 900 MHz, 400 MHz & 2.4 GHz, and 900 MHz & 2.4 GHz. These simultaneous multi-modal approaches keep the same set of modalities for all hops in the route. On the contrary, in DEER, each hop optimizes the combination of modalities based on the channel condition, transmit power, and DEP, and hence the selected modalities may vary over hops.

B. Performance Analysis

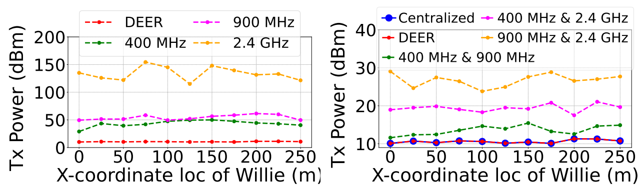
1) Transmit power as a function of Adversary location: Figure 4 provides a comparative analysis of the end-to-end transmit power of DEER as a function of the X-coordinate location of the adversary, Willie under a DEP constraint of 0.5 and throughput constraints of 20 Mbps and 30 Mbps, respectively. Each of the modalities has 3 MHz of bandwidth and the data has been averaged over 10 different randomly chosen transmitter and receiver node locations. The results indicate that for the 20 Mbps throughput requirement, DEER improves energy consumption by up to 23.5x and 1.5x compared to the single-modal and the naive simultaneous multi-modal approaches, respectively. For the 30 Mbps throughput, the improvements are 14.4x and 2.9x, respectively, clearly demonstrating DEER's superior performance, particularly under higher throughput constraints compared to other multi-modal approaches.

Next, we analyze DEER's performance when different modalities have varying bandwidths. Figure 5 presents the end-to-end transmit power analysis of DEER as a function of the X-coordinate location while the bandwidth of the modality

Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.

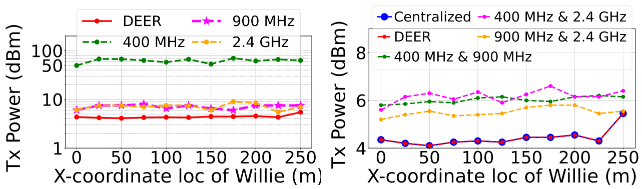


(a) DEER vs single modality (b) DEER vs multi-modalities



(c) DEER vs single modality (d) DEER vs multi-modalities

Fig. 4: End-to-end total transmit power as a function of Willie's X coordinates with $\mathrm{P}_{\text{req DEP},h} = 0.5$ and $U_{req} = 20$ Mbps (a & b) and 30 Mbps (c & d). Each modality has 3 MHz of bandwidth.



(a) DEER vs single modality (b) DEER vs multi-modalities

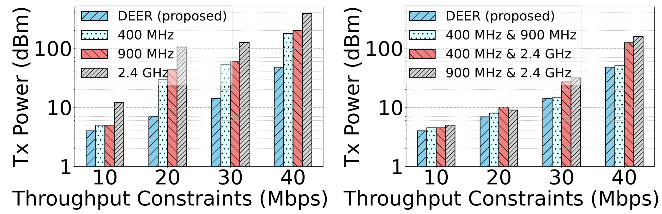
Fig. 5: End-to-end sum transmit power as a function of Willie's X coordinates with $\mathrm{P}_{\text{req DEP},h} = 0.5$ and $U_{req} = 20$ Mbps. The bandwidth of each modality is 1% of its center frequency.

with center frequency 400 MHz, 900 MHz, and 2.4 GHz are 4 MHz, 9 MHz and 24 MHz respectively. In this scenario, DEER still shows significant energy efficiency improvements of up to 16x and 1.5x compared to single-modal and multi-modal approaches, respectively. However, unlike the equal bandwidth scenario in Figure 4, the modality centered at 400 MHz performs worst.

2) Transmit power as a function of Throughput Constraint: We now analyze the transmit power consumption of DEER as a function of the throughput constraint, with a DEP requirement of 0.5 and a bandwidth of 3 MHz per modality, as presented in Figure 6. The results indicate a clear monotonic relationship between transmit power and the throughput constraint across both single and multi-modal scenarios. Notably, DEER consistently achieves the lowest end-to-end transmit power, highlighting its superior energy efficiency. The most significant improvement is observed at a throughput constraint of 40 Mbps, where DEER reduces power consumption by up to 15x.

V. Conclusion

In this paper, we introduce DEER, a decentralized energy-efficient covert routing strategy that leverages multiple wireless modalities simultaneously to enhance network energy efficiency. We begin by formulating an optimization problem focused on minimizing the total transmit power in a multi-modal decentralized covert routing scenario, while still meeting user-specified throughput and covertness. To achieve this, we employ both node-level and network-level optimization in a decentralized framework. Our numerical analysis reveals that DEER significantly boosts energy efficiency, achieving improvements of 23.5x and 2.9x compared to baseline single-modal and non-optimized multi-modal approaches, respectively.



(a) DEER vs single modality (b) DEER vs multi-modality

Fig. 6: End-to-end total transmit power as a function of different throughput constraints U_{req} when $\mathrm{P}_{\text{req DEP},h} = 0.5$.

Acknowledgments

This work is funded in part by the National Science Foundation (NSF) grant CNS-2134973, ECCS-2229472, and ECCS-2329013, by the Air Force Office of Scientific Research under contract number FA9550-23-1-0261, by the Office of Naval Research under award number N00014-23-1-2221.

References

[1] X. Chen, J. An, Z. Xiong, C. Xing, N. Zhao, F. R. Yu, and A. Nallanathan, "Covert Communications: A Comprehensive Survey," *IEEE Communications Surveys & Tutorials*, vol. 25, no. 2, pp. 1173–1198, 2023.

[2] K.-W. Huang, H.-M. Wang, and H. V. Poor, "On Covert Communication Against Sequential Change-point Detection," *IEEE Transactions on Information Theory*, vol. 67, no. 11, pp. 7285–7303, 2021.

[3] R. Aggarwal, J. S. Kong, T. J. Moore, J. Choi, P. Spasojevic, and F. T. Dagefu, "Covert Communications with Simultaneous Multi-Modal Transmission," in *Proceedings of the 17th ACM Conference on Security and Privacy in Wireless and Mobile Networks*, 2024, pp. 1–7.

[4] J. Kong, F. T. Dagefu, and T. J. Moore, "Covert Routing in Heterogeneous Networks," *IEEE Transactions on Information Forensics and Security*, vol. 19, pp. 7047–7059, 2024.

[5] J. Kong, T. J. Moore, and F. T. Dagefu, "Decentralized Covert Routing in Heterogeneous Networks Using Reinforcement Learning," *IEEE Commun. Lett.*, 2024, DOI: 10.1109/LCOMM.2024.3430828.

[6] L. Lv, Q. Wu, Z. Li, Z. Ding, N. Al-Dhahir, and J. Chen, "Covert Communication in Intelligent Reflecting Surface-Assisted NOMA Systems: Design, Analysis, and Optimization," *IEEE Transactions on Wireless Communications*, vol. 21, no. 3, pp. 1735–1750, 2021.

[7] T. Kim and D. Qiao, "Energy-efficient Data Collection for IoT Networks via Cooperative Multi-hop UAV Networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 13 796–13 811, 2020.

[8] B. A. Bash, D. Goeckel, and D. Towsley, "Limits of Reliable Communication with Low Probability of Detection on AWGN Channels," *IEEE journal on selected areas in communications*, vol. 31, no. 9, pp. 1921–1930, 2013.

[9] J. Kong, F. T. Dagefus, J. Choi, and P. Spasojevic, "Intelligent Reflecting Surface Assisted Covert Communication with Transmission Probability Optimization," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1825–1829, 2021.

[10] R. Ma, X. Yang, G. Pan, X. Guan, Y. Zhang, and W. Yang, "Covert Communications with Channel Inversion Power Control in the Finite Blocklength Regime," *IEEE Wireless Communications Letters*, vol. 10, no. 4, pp. 835–839, 2020.

[11] Y. Ma, X. Gao, C. Liu, and J. Li, "Improved SQP and SLSQP Algorithms for Feasible Path-based Process Optimisation," *Computers & Chemical Engineering*, p. 108751, 2024.

[12] P. Jacquet, P. Muhlethaler, T. Clausen, A. Laouiti, A. Qayyum, and L. Viennot, "Optimized Link State Routing Protocol for Ad-Hoc Networks," in *Proceedings. of IEEE INMIC 2001.* IEEE, 2001, pp. 62–68.

[13] E. Dijkstra, "Dijkstra's algorithm," *nd http://en. org/wiki/Dijkstra_ algorithm (accessed 2007/10/12)*, 1959.

[14] EMAG Technologies Inc., "Em-cube," https://emagtech.com/product/em-cube/, 2024, accessed: 2024-08-20.

Authorized licensed use limited to: Northeastern University. Downloaded on September 22,2025 at 07:34:37 UTC from IEEE Xplore. Restrictions apply.