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Energy Efficient Routing for Wireless Mesh Networks with Directional Antennas: when Q-learning meets Ant Systems

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***Abstract*—Energy Efficiency (EE) is a key performance metric to design future wireless networks. Since Directional Antennas (DAs) focus the transmission energy towards the destination, it has been shown as a cost-effective solution when used in a backhaul network. In this paper we propose a new joint optimization framework of energy consumption and throughput in backhaul Wireless Mesh Networks (WMNs) equipped with DAs. We first formulate the joint optimization problem as a Mixed Integer Linear Problem (MILP) using a weighted objective function of both the consumed energy and the throughput. Then, we propose to use the Ant-Q algorithm, a Reinforcement Learning (RL) based approach, to reduce the solution complexity and enhance its convergence. Considering a discrete power control scheme, we define a new routing scheme based on the Ant-Q heuristic to select jointly the transmission beam and the transmission power. Using ILOG Cplex to find the optimal solution and NS-3 to conduct extensive simulations, we show the effectiveness and the accuracy of the proposed routing algorithm. Moreover, we analyze the optimization tradeoff depending on the beamwidth, the network topology, the gateway position and the optimization weight factor.**

keywords: Energy Efficiency, Wireless Mesh Network, Directive Antennas, Ant-Q algorithm, Reinforcement learning.

I. Introduction

As green computing and networking is a primary environmental issue, future wireless networks are expected to increase their energy-efficiency (EE) while transmitting massive data traffic up to tens of Exabytes per month [1] with different QoS parameters. However, within the requirements of 5G systems to be deployed in the coming years, it is recommended that *the 1000 times capacity increase must be achieved at similar or lower power consumption as today's networks* [2]. However, on the other hand, some of today's networks already require energy savings, especially when there is an inherent power supply deficit, like in rural and poorly developed areas. Consequently, the design of energy-efficient networks are of great interest in both industrial and academic research.

Several advanced solutions in communication techniques are proposed in the 5G-PPP initiative to address the EE challenge such as Cloud-RAN, massive MIMO, Base Stations (BSs) cooperation, heterogeneous and hierarchical cellular networks, etc. In [3], an investigation of the EE in Cloud-RANs is proposed by minimizing the total network power consumption by taking into account both the BSs and the backhaul network power consumption. In [4] and [5] innovative models are proposed to optimize the EE for 5G networks while taking advantage of the emerging techniques of OFDMA, MIMO, sleeping strategies of BSs, Coordination MultiPoint (CoMP), and relay transmission. However, most of these related work on EE mainly focuses on urban environments where dense network infrastructure is deployed. In this paper, we tackle the problem of EE in poorly-covered areas as: suburban, rural, and desert region. Their characteristics are different from urban ones, and many challenges have to be addressed at both the economic and the energetic sides. Indeed, many blocking factors exist, such as a poor communication infrastructure for Internet penetration in suburban and rural areas. The problem is even more severe in desert environments due to the lack of energy suppliers. Furthermore, the lack of infrastructure requires higher costs for network planning, deployment, and maintenance. In such conditions, the goal of ensuring a highly energy-efficient network is hardly achievable.

An innovative and low-cost solution to deal with these issues is to use self-configured Wireless Mesh Networks (WMNs) [6] to connect outdoor multi-mode access points to a remote macro base station. A multi-mode access point is a Low Power Node (LPN) embedding cellular (4G/LTE) and WiFi mesh technologies. The WiFi mesh nodes form a local backhaul network to gather and relay cellular terminals' data to the macro base station through a few gateways. Therefore, optimizing the wireless backhaul network's energy consumption is an essential task in poorly-covered regions with limited energy sources and infrastructure.

In this paper, we tackle the problem of EE in poorly-covered areas as their characteristics are different from urban ones, and where many challenges have to be addressed at both the economic and the energetic sides. However, many blocking factors exist, such as a poor communication infrastructure for Internet penetration in suburban and rural areas. The problem is even more severe in desert environments due to the lack

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of energy suppliers. Furthermore, the lack of infrastructure requires higher costs for network planning, deployment, and maintenance. In such conditions, the goal of ensuring a highly energy-efficient network is hardly achievable.

Directional Antennas (DAs[1]) have proved their efficiency in terms of improving the network throughput and reducing the consumed energy [7]. DAs can focus the transmission power toward the desired receiver without radiating in all directions as Omni-directional Antennas (OAs). DAs provide many advantages for WMNs, where multi-hop communications are generally used. Indeed farthest nodes can be reached through the shortest paths because of the high antenna gain that improves the transmission range. By following this, spatial reuse is improved, and concurrent transmissions can occur without collisions. In [7], the relationship between the antenna beams number, and the number of links in a WMN used to relay data from a source to a destination has been defined for chain and grid topologies. It is shown that the more antennas are directive, the less is the number of links on the communication path. In other words, directive antennas shorten the routes. Hence, packets are forwarded through fewer intermediate hops to the destination by enhancing the transmission service.

To the best of our knowledge, no previous work except [8] addressed the problem of joint energy consumption and throughput optimization in WMNs equipped with DAs. Some related work were limited to OAs-based WMNs [9]–[11] and some others considered only the throughput optimization in case of DAs WMNs [12]. In [8], the optimization problem is presented, and the optimal solution using CPLEX solver is computed for small size networks. The obtained results showed an energy-saving gain of 30% and up to 20% of throughput while using DAs.

This work aims to develop a routing scheme that takes advantage of spatial diversity offered by DAs by selecting the beamwidth and the transmission power level intelligently and adaptively.

To achieve this goal, several main contributions are presented here as follow :

- we provide an optimization framework with a weighted objective function to capture the energy consumption and the throughput tradeoff.
- we develop a heuristic based on Ant Colony and Q-learning algorithms to resolve the optimization problem and reduce its complexity. The problem is formulated as a Mixed Integer Linear Program (MILP).
- we design a routing scheme based on two algorithms: the Directional Neighbors Discovery algorithm (DNDa) and the Ant-Q for Energy Efficient Routing over Beams (AQ-EERoB). The first algorithm is used to set up the network, mainly the possible neighbors and links (power levels and beams direction) for a given network topology. The second one is used to define the routing scheme over the underlying links by selecting the appropriate beam and transmission power to optimize the throughput and energy consumption.
- we implement this routing approach on the NS-3 simulator. We conduct an extensive simulation to evaluate the routing benefits regarding OAs, considering different network topologies and traffic loads while varying the gateway position in the WMN.

[1]We will use this acronym through the paper, not to be confused with DAS which means Distributed Antennas Systems

In this paper, and regarding the previous description and the framework assumptions, we answer the following questions which are common to those of most papers on optimal routing through a network:

- What is the optimal tradeoff between the energy and the throughput considering all previously cited parameters?
- What is the gain in terms of throughput and energy consumption when using DAs in WMNs compared to OAs?
- What is the adequate routing strategy in order to forward traffic over less hops with high energy or over more hops with less energy?
- What are the AQ-EEoB algorithm convergence speed, accuracy, and effectiveness?

The rest of the paper is organized as follows. In section II, some related work are presented and classified into two types: *(i)* these focusing on energy-throughput optimization for OAs WMNs and *(ii)* these targeting throughput optimization for DAs networks. In section III, the system model is described, and the weighted objective function of the energy-throughput tradeoff is derived, as well as the related constraints. The discussion of the AQ-EEoB heuristic is detailed in section IV. Finally, simulation results are highlighted in section V. Conclusions and perspectives of this work are given in section VI.

II. Related Work

Several studies have been conducted on WMNs equipped with either OAs or DAs. Most of these work considered optimization tools to derive and improve WMNs performance either by using software solvers such as ILOG Cplex optimizer [13] or by proposing heuristics to solve the considered optimization problem, which is NP-Hard.

This section focuses on some recent optimization-based studies for both OAs and DAs WMNs by presenting the proposed heuristics and approaches. The network performance commonly studied in literature are throughput, energy consumption or efficiency, and end-to-end delay. In order to summarize previous work, we use the following optimization model for which the throughput, the energy consumption, and the deployment costs (Capex and Opex) of a WMN are jointly considered as follows:

$$\begin{cases} \text{Minimize} \quad \alpha.\mathcal{E} + \beta.\mathcal{IR} + \gamma.\mathcal{C} \\ \text{s.t.} \quad \text{Link capacity constraints,} \\ \qquad \text{Flow conservation constraints,} \\ \qquad \text{QoS constraints} \end{cases} \tag{1}$$

Here, $\mathcal{E}$, $\mathcal{IR}$ and $\mathcal{C}$ represent the consumed energy, the inverse of throughput and the deployment related cost respectively. α, β and γ are real values $\in$ [0,1] representing weighting coefficients such that $\alpha+\beta+\gamma \leq 1$. The constraints of the outlined optimization problem are: *(i)* the *link capacity constraints* to ensure that the traffic transiting through a link does not exceed the link capacity, *(ii)* the *flow conservation constraints* to ensure that all input flows at a node coming either from its attached users or from its neighbors nodes are forwarded, and *(iii)* the *QoS constraints* related to fulfill flows requirements.

A. *Optimization over OAs-based Networks*

Deployment costs and the energy consumption of a WMN are jointly minimized in [14], [15] such as β = 0 in the *general* optimization problem (1). Three network sizes (small, medium, and large) and two traffic types (standard and busy) are investigated. Simulation results showed that the optimal solution obtained using ILOG Cplex could save up to 30% of energy and the standard traffic scenario consumes less energy.

Two Master optimization Linear Problems (MLP) are proposed in [16], one to Maximize the Capacity (MPMC), and the other to Minimize the Energy consumption (MPME). The energy consumption model comprises a fixed energy cost for the idle state and a linear variable cost related to the node activity: transmitting or receiving. A column generation algorithm is used to solve the optimization problem. The authors showed that a solution could be obtained reasonably for a network size of 30 nodes.

Furthermore, for a fixed Modulation and Coding Scheme (MCS), the simulation results showed that: *(i)* higher capacity can be reached with the same energy consumption while increasing the maximum transmission power (P_{max}), *(ii)* power control reduces the consumed energy. It improves the network capacity compared to fixed transmission power, and *(iii)* the uplink-only, downlink-only, or mixed traffics have no impact either on energy consumption or capacity.

A joint optimization of the energy consumption and the end-to-end delay modeled as a MILP is developed in [11] and solved using GLPK [2]. The cost function is a weighted sum of delay and energy consumption, corresponding to γ = 0, in the general optimization problem (1). The minimization problem's output is the set of active APs, and their transmission power, which depends on the number and locations of attached users. Considering only OAs, simulation results showed an enhancement of 16%, compared to a fixed transmission power strategy.

Within another MILP, the authors in [9] models an optimal routing and a scheduling framework to optimize energy consumption and throughput jointly. A heuristic based on the Ant-Colony (AC) algorithm is used to solve the optimization problem. Simulations are performed for different CBR traffic loads. A multi-channel network is considered where each node can choose one among many channels to communicate. The authors showed that the proposed algorithm improves the average throughput, energy consumption, and average path length. However, the node activity is limited to transmission and reception with the same power level. Nevertheless, it is not a strong assumption since the transmission power is much higher than the power needed for reception [17].

[2]GNU Linear Programming Kit

The authors of [10] outlined an optimization framework and provided guidelines for network design based on the obtained results. A continuous power control, and a multi-rate transmission are considered to optimize the energy-capacity tradeoff (γ = 0 in (1)).

An energy-saving approach for WMNs in a time-variable context is addressed in [18]. The problem is formulated as a MILP, with an objective function minimizing the APs number while satisfying the traffic demand (corresponding to β=0 and γ = 0 in (1)). The limitation of this approach is that it does not take into account the interference between APs.

The authors of [19] proposed a throughput and energy-aware routing scheme aiming at switching off as many APs as possible while satisfying the throughput guarantees of the admitted flows (γ = 0 in (1)).

SpeeD-IoT [20] is a spectrum-aware energy-efficient routing approach for D2D communications in IoT mesh networks. The highlighted multi-hop routing scheme allows IoT device energy preservation and-end-to end rate optimization. To reduce the overhead, a power control-based selective flooding technique is considered. Additionally, a dynamic learning algorithm is proposed to optimally assign routes to interfering source-destination pairs (γ = 0 in (1)).

The Dynamic Energy Efficient Routing (DEER) protocol for wireless sensor networks was proposed in [21] to improve average network lifetime. In DEER, routes are selected based on the energy levels of neighboring nodes to maximize the session time between source and destination, and to maximize the network lifetime of source-destination pairs. The paper [21] focuses on the energy consumed and lifetime, and hence corresponding to β=0 and γ = 0 in (1). However, this paper was limited to OA and did not consider the throughput optimization into account in routing.

The HELPER framework [22] is an end-to-end solution able to connect self-sufficient ad-hoc networks that can be set up rapidly in case of natural or made-man disasters. The framework requires SEEK, *diStributed Energy Efficiency bacKpressure* algorithm. SEEK is a cross-layer optimized routing algorithm enabling each node to find the next hop based on location available information such as the geographic information of nodes, the queue backlog, and the residential battery energy. This algorithm allows improving the network lifetime by 53% compared to a greedy geographical routing approach. This problem is equivalent to γ = 0 in (1).

The Energy Efficiency based on Adaptive Threshold (ATEER) scheme [23] is a clustering cross-layer routing protocol for wireless sensor networks. When sensor nodes are grouped into clusters, it reduces energy consumption since the number of long-distance transmitted nodes is minimized. The cluster head is responsible for aggregating data and sending it to the base station.

The Energy-efficient and Robust Multipath Routing (ERMR) protocol for ad-hoc networks [24] provides an alternative and more robust pathfinding approach. It consists of route discovery, route reply, data transmission, and route maintenance phases. ERMR builds efficient primary and backup paths to counteract route failures for a source-destination pair. This makes the proposed algorithm robust and leads towards performance enhancement.

The work in [25] presents a demonstration setup based on a switch On/Off mechanism for small-cell networks in a 5G scenario equipped with omnidirectional antennas. The main idea is to turn off small cells during low-traffic periods. The proposed strategy reduces the energy consumption of small cells.

B. Optimization over DAs-based Networks

More recently, DAs have been used in WMNs to improve their performance. DAs increase the radio range and reduce the interference by concentrating the transmitted signal. However, only a few works addressed the optimization issues on DAs WMNs scenarios. For example, in [17] which is an extension of [12], an Iterative Local Search (ILS) is used to solve the proposed MILP for the congestion minimization problem. The optimization problem is equivalent to the *general* problem in (1) with α=0 and γ=0. Compared to the OAs model in [12], the proposed DAs scheme reduces the end-to-end delay and improves the packet delivery ratio. However, the impact of DAs on energy consumption is not studied.

The authors of [26] considered two MILP problems to model the reliability over WMNs. The first one is the Max-Min optimization problem to maximize the minimum flow. The minimum flow is defined as the difference between the link capacity and the traffic amount transiting over that link at a given time. As DAs generate a further cost, the second problem is minimizing antenna directions or beams. The optimal value of the first problem is used in the second problem. Optimal solutions obtained by using ILOG Cplex for different random topology sizes are presented. The beams are given for each scenario and for different values of $\alpha \in [0, 1]$ in the *general* problem (1) to indicate the expected service quality after a failure.

The topology control and the routing assignment problems are jointly solved in [27]. This study showed that the formulated problem could be reduced to the *NP-hard partition problem*, and it proposes TORA (Topology and Routing Assignment) based on the Ant Colony algorithm. Two types of traffic are considered for simulations: (i) normal distributed UDP traffic to analyze the end-to-end delay and the loss ratio, and (ii) CBR TCP traffic to analyze the throughput. Compared to the shortest path algorithm, TORA achieves both a lower packet loss ratio and higher TCP throughput.

A joint channel assignment, link scheduling, routing, and rate control problem for the WMNs with multiple orthogonal channels and directional antennas equipped APs is tackled in [28]. The problem is formulated as a mixed-integer nonlinear problem, and the authors develop an algorithm to solve the problem using the generalized Benders decomposition approach. This scheme corresponds to α=0 and γ=0 in (1). The work in [29] introduces a novel Multi-Pipe High-Throughput Routing Protocol with Hole Avoidance for Multi-Beam Directional Mesh Networks. The proposed protocol comprises two main phases, a primary path search phase using a hierarchical score system to find optimal main paths and a Volcano establishment phase, where multi-beam traffic is scheduled.

In [30], a new version of AODV is highlighted with directional antennas and multiple network interfaces. Simulations are conducted using NS-2 for random and grid topologies. Results showed that the proposed approach improves the throughput, reduces the end-to-end delay, and that directional antennas' network performances are not affected by increasing the communication distances, and connection numbers. However, in this paper, the impact of beams on performance metrics is not studied, and no interference model is considered.

For real-time data processing requirements in industrial applications, [31] presents a new directional routing and scheduling algorithm. The proposed directional routing approach is formulated as a Maximum Weight Independent Set (MWIS) problem and solved to maximize the number of independent sets and assign time slots to the links with maximum traffic loads. It calculates sub-optimal link scheduling results and reduces the end-to-end delay by ensuring transmission fairness and throughput among the directional links.

In [32], the authors discuss a multipath enhanced OLSR Optimized link state routing (OLSR) exploiting the benefit of multi-beam directional antennas, and allowing simultaneous antennas delivery. The paper proposes a social network-inspired algorithm for Multi-Point relays (MPR) selection which chooses the nodes with higher connectivity level with other routing nodes as MPR to reach all nodes using a limited broadcast. Additionally, a short-cut algorithm is proposed to reduce the redundancy of the hops in the auxiliary path. However, the number of beams and the impact of the proposed algorithm on energy consumption are not studied.

Table I summarizes the related work and classifies them depending on the considered antenna type and the optimized metrics. From this summary and to the best of our knowledge, no previous study has addressed the joint problem of energy consumption and throughput optimization in DAs-based networks using an optimization and learning approach. Our objective is to tackle this joint optimization problem considering a transmission power control scheme and different beams in this work. Furthermore, we examine various network topologies, traffic loads, and gateway positions in the WMN. Indeed, all the works cited above consider several gateways in their optimization problem, allowing a tremendous spatial diversity. On the other hand, we claim that when the number of gateways is reduced, the impact on the network performance needs to be evaluated. It is more worthwhile and even challenging to investigate the energy/throughput trade-off in this case. Moreover, the gateway positions cannot be neglected since they can lead to bottlenecks or variable congestion levels in massive traffic, and hence the more energy consumption due to retransmissions.

III. System Model

In this section, we present the interference, the power control, and the energy models followed by the joint optimization problem.

Paper	Paper objective and Resolution approach	Antennas		Optimized metrics		
		OA	DA	Energy	Throughput	Capex
[14], [15]	ILOG Cplex to solve the joint optimization of the deployment cost and the energy consumption	✓		✓		✓
[16]	Column generation algorithm to solve the capacity maximization and Energy minimization problems	✓		✓	✓	
[11]	GLPK to solve a joint optimization of the energy consumption and the end-to-end delay modeled as a MILP	✓		✓		
[9]	A heuristic based on the Ant-Colony (AC) algorithm to solve the joint routing and scheduling optimization problem	✓		✓	✓	
[10]	An optimization framework is proposed for network design	✓		✓	✓	
[17]	Iterative Local Search (ILS) to maximize the packet delivery ratio and reduce the end to end delay		✓		✓	
[26]	ILOG Cplex to maximize the minimum flow and to minimize the number of antenna directions or beams		✓		✓	
[27]	Inspired by Ant Colony system, a topology control and routing assignment joint optimization problem (TORA) is proposed		✓		✓	
[29]	Volcano: Multi-Pipe High-Throughput Routing Protocol with Hole Avoidance for Multi-Beam Directional Mesh Networks		✓		✓	
[28]	Using the generalized Benders decomposition approach, a Channel Assignment, Link DAs algorithm proposed to solve a mixed integer nonlinear problem (MINLP)		✓		✓	
[33]	The exact method branch-and-priceFair is used for flow rate optimization by effective placement of directional antennas in wireless mesh networks		✓		✓	
[19]	Throughput and energy-aware routing for 802.11 based mesh networks by switching off as many APs as possible	✓		✓	✓	
[18]	Energy Savings in Wireless Mesh Networks in a Time-Variable Context problem is formulated and solved as a MILP	✓		✓		
[20]	SpeeD-IoT, a multi-hop routing scheme allowing IoT device energy preservation and end to end rate optimization.	✓		✓	✓	
[21]	DEER, a protocol for wireless sensor networks improving average network lifetime	✓		✓		
[22]	SEEK, a distributed cross layer optimized routing algorithm based on location available information	✓		✓	✓	
[23]	ATEER, a clustering cross layer routing protocol for wireless sensor networks proposing to group sensor nodes into clusters	✓		✓		
[24]	Efficient primary and backup paths are built to counteract route failures for a source-destination pair	✓		✓	✓	
[30]	A new version of AODV is highlighted with Directional antennas with multiple network interface		✓		✓	
[31]	A directional routing and scheduling algorithm to calculate sub-optimal link scheduling results and to reduce the end-to-end delay		✓		✓	
[32]	A social network inspired algorithm for MPR selection		✓		✓	
[25]	A demo based on a switch On/Off mechanism for small cell networks	✓		✓		

TABLE I: Related Work Summary

A. Interference Model

Various interference models have been used in OAs WMNs, considering either the node's location or the received power as metrics to characterize the interference. However, these models are not valid in DAs scenarios since *(i)* some directions are interference-free because DAs radiate only towards the destination, and *(ii)* DAs can reach farther nodes since the directional range is extended.

In this work, we consider a new interference model by combining the ones used in [34] to compute the overlap count representing the number of overlaps between beams, and those in [35], [36] to ensure that a minimum distance between the nodes is maintained. The obtained model considers the distance between nodes depending on their positions, and the angles formed by the beams overlap. Let $\mathcal{I}$, the set of mesh nodes, and (i, j) and (p, q) two pairs of transmitting-receiving nodes. Fig. 1 illustrates the position of nodes and the used variables. Communication between pairs (i, j) and (p, q) can occur simultaneously without generating interference, if and only if

$$\begin{Bmatrix} \mid\mid p-j \mid\mid_2 \geq (1+\sigma) \mid\mid i-j \mid\mid_2 \\ (\widehat{i-j, i-p}) \geq \theta_T \quad \text{and} \quad (\widehat{p-q, p-i}) \geq \theta_T, \end{Bmatrix} \tag{2}$$

where $\mid\mid . \mid\mid_2$ is the $\mathcal{L}_2$ norm, θ_T is a threshold angle and σ represents a guard zone. In fact, a transmission link (i,j) is successful if *(i)* the distance, $d_{p,j}$, between the receiver j and the source of another simultaneous transmission (p,q) is greater than its distance from the intended source i, $d_{i,j}$, by a factor of σ, and *(ii)* the angles $\theta_{ij,ip}$ and $\theta_{pq,pi}$ are greater than the threshold angle θ_T to avoid collisions. Hence, the set of interferers to the communication between nodes i and j is defined as follows:

$$\mathbb{I}_{(i,j)}^{(p,q)} = \{(p, q) \in \mathcal{I}^2 \text{ s.t. eq. (2) is not verified } \} \tag{3}$$

Please note that we only consider main lobe interference in this work and do not consider side lobe interference for simplicity.

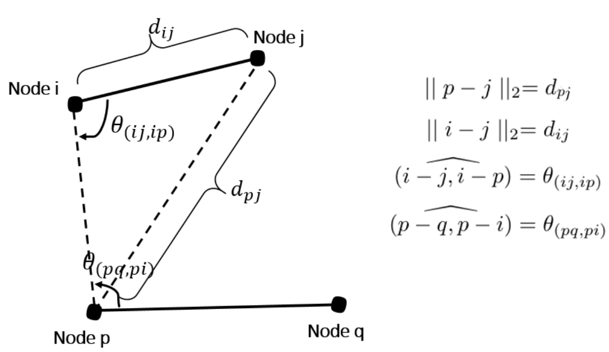


Fig. 1: Illustration of the interference model

B. Energy Model

We consider that each node can have four states; either (i) transmitting, (ii) receiving, (iii) idle, or (iv) Off. A node in an ON state can be either in an active state (i.e., transmitting or receiving) if it has some packets to send, forward, receive, or idle. Otherwise, it is Off.

C. Power Control Scheme

In this work, we consider a discrete power control scheme, where each node has many transmission levels $\mathcal{L} = \{1, ..., \mid \mathcal{L} \mid\}$ available to be used depending on the next-hop location. For example, a node with three power levels either transmits at full power (P_{max}), at $\frac{P_{max}}{2}$ or does not transmit at all (0). If the next hop is too close and can be reached using $\frac{P_{max}}{2}$ of transmission power, then the remaining $\frac{P_{max}}{2}$ of power is saved.

D. Optimization Problem Formulation

In this subsection, we define the joint optimization problem of energy consumption and throughput. Firstly, we present the set of variables and parameters we used to describe the issue. Then we introduce the objective function followed by the optimization constraints. Note that we use the terms mesh node or node interchangeably.

1) Sets, Variables and Parameters:

- *Sets*: we consider the following sets:

- $\mathcal{I} = \{1, ..., \mid \mathcal{I} \mid\}$: the set of mesh nodes including the gateways.
- $\mathcal{G} = \{g_1, ..., g_n\}$: the set of mesh gateways in the WMN.
- $\mathcal{U} = \{1, ..., \mid \mathcal{U} \mid\}$: the set of users generating the traffic, per node. Note that for simplicity reasons the number of users is the same for all mesh nodes in the network.
- $\mathcal{L} = \{1, ..., \mid \mathcal{L} \mid\}$: set of possible power levels that can be used by a node.
- $\mathcal{B}_i = \{1, ..., \mid \mathcal{B}_i \mid\}$: set of beams that can be used by a mesh node i.
- $\mathcal{T} = \{1, ..., T\}$: set of time intervals with $\mid \mathcal{T} \mid$ = T.

- *Parameters & Input*:

- c_{ij}: the link capacity between mesh nodes i and j.
- $d_{u,t}$: the amount of traffic to send by user u at time t.

Additionally, we suppose that each user is connected to the nearest mesh node.

- *Binary variables*:

- $x_{u,ij,t}^{l,v}$ is used to express the link between two nodes and the beams used for communication at time t:

$$x_{u,ij,t}^{l,v} = \begin{cases} 1 & \text{if} \quad \begin{array}{c} \text{nodes } i \text{ and } j \text{ are connected with beam } l \\ \text{using a transmission power level } v \text{ at time } t \\ \text{to forward traffic of user } u \end{array} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

- $a_{i,t}^{l,v}$ describes node i transmission activity at time t using beam l at power level v:
$\forall i \in \mathcal{I}, \quad t \in [1, T], \quad l \in \mathcal{B}_i, \quad v \in \mathcal{L}$

$$a_{i,t}^{l,v} = \begin{cases} 0 & \text{if} \quad \sum_{j=1}^{|\mathcal{I}|} \sum_{u=1}^{|\mathcal{U}|} x_{u,ij,t}^{l,v} = 0 \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

- $b_{i,t}$ indicates if node i is receiving at time t:

$\forall i \in \mathcal{I}, \quad t \in [1,T]$

$$b_{i,t} = \begin{cases} 0 & \text{if} \quad \sum_{u=1}^{|\mathcal{U}|}\sum_{k=1}^{|\mathcal{I}|}\sum_{l=1}^{|\mathcal{B}_i|}\sum_{v=1}^{|\mathcal{L}|} x_{u,ki,t}^{l,v} = 0 \\ 1 & \text{otherwise} \end{cases} \tag{6}$$

- $c_{i,t}$ indicates that node i is on the idle state at time t:

$$c_{i,t} = \begin{cases} 1 & \text{if} \quad \text{node } i \text{ is at } \textit{idle} \text{ state at time t} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

This variable is introduced to differentiate the idle and Off states. The aim is to take into account the non-zero power consumed during the idle state regarding the Off one.

- $w_{ui,t}$ indicates the user association:

$$w_{ui,t} = \begin{cases} 1 & \text{if} \quad \text{user } u \text{ is attached to node } i \text{ at time slot t} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Note that we consider that reception is omnidirectional to reduce the complexity of the neighbor discovery process and the optimization problem.

2) Objective Function: We consider a weighted objective function capturing the consumed energy and the throughput. The general problem we define serves to optimize both the throughput and energy consumption by selecting the beams and transmission powers.

The total energy consumed by a mesh node i during the time interval $[1,T]$ depends on its state: transmission, reception, or idle. Thus, it can be written as :

$$\begin{aligned} \mathcal{E}_{i,t} = & \underbrace{\sum_{l=1}^{|\mathcal{B}_i|}\sum_{v=1}^{|\mathcal{L}|} a_{i,t}^{l,v}\mathcal{E}_{\text{TX},v}}_{\substack{\text{Energy consumed when node } i \\ \text{is transmitting at power level } v}} + \underbrace{b_{i,t}\mathcal{E}_{\text{RX}}}_{\substack{\text{Energy consumed} \\ \text{if node } i \text{ is receiving}}} \\ & + \underbrace{\left(1 - \sum_{l=1}^{|\mathcal{B}_i|}\sum_{v=1}^{|\mathcal{L}|} a_{i,t}^{l,v}\right).(1-b_{i,t}).c_{i,t}\mathcal{E}_{\text{idle}}}_{\substack{\text{Energy consumed} \\ \text{if node } i \text{ is idle}}} \end{aligned} \tag{9}$$

where $\mathcal{E}_{\text{TX},v}$ is the energy consumed by a mesh node when it is transmitting with one beam at level v. $\mathcal{E}_{\text{RX}}$ is the energy consumed by a mesh node when it is receiving in the omnidirectional mode and $\mathcal{E}_{\text{idle}}$ when it is idle.

The total energy consumed in the network is:

$$\mathcal{E} = \sum_{t=1}^{T}\sum_{i=1}^{|\mathcal{I}|} \mathcal{E}_{i,t}. \tag{10}$$

An inverse throughput quantity can be defined as:

$$\mathcal{IR} = \sum_{t=1}^{T}\sum_{i=1}^{|\mathcal{I}|}\sum_{v=1}^{|\mathcal{L}|}\sum_{l=1}^{|\mathcal{B}_i|} a_{i,t}^{l,v}, \tag{11}$$

Where $\mathcal{IR}$ stands for Inverse Rate. For a given amount of traffic to transmit, minimizing the time when mesh nodes are transmitting and receiving (i.e., minimizing the number of active links and minimizing the transmission time to send the traffic) is equivalent to maximizing the bit rate.

Eq. (12) represents the objective function to be minimized, and it consists of minimizing the energy consumed by the network during the considered period T while maximizing the network throughput. We recall that our objective is to design a new routing protocol to find routes over a WMN while taking into account the energy consumption and throughput tradeoff such as:

$$min \; \frac{\alpha\mathcal{E} + (1-\alpha)\mathcal{IR}}{T} \tag{12}$$

where $\alpha \in \{0,1\}$ is a weighting coefficient used to balance the energy consumed and the rate. If $\alpha = 0$, we mainly maximize the achievable rate, and if $\alpha = 1$, we minimize the energy. For the comparison purpose, we consider the normalized throughput and consumed energy.

In the following, we outline the constraints of the joint energy consumption and throughput optimization problem.

3) Optimization Constraints: The following equations (13)-(23) represent the optimization problem constraints.

- Link capacity constraint (13) controls the traffic on links between nodes i and j not to exceed the total link capacity.
  $\forall (i,j) \in \mathcal{I}\times\mathcal{I},\ \forall u \in \mathcal{U},\ v \in \mathcal{L},\ t \in [1,T], m \in \mathcal{B}_i$

$$\sum_{u=1}^{|\mathcal{U}|} x_{u,ij,t}^{m,v} \times d_{u,t} \leq c_{i,j} \qquad . \tag{13}$$

- Flow conservation: at node i, all the entering flows are forwarded. The left side of Eq. (14) corresponds to the number of flows going from node i, while the right side of the equation is the number of both flows coming from neighbors of node i and flows generated by the attached users:

$$\begin{aligned} \sum_{u=1}^{|\mathcal{U}|}\sum_{t=1}^{T}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{h=1}^{|\mathcal{B}_i|} x_{u,ij,t}^{h,v} = \sum_{u=1}^{|\mathcal{U}|}\sum_{t=1}^{T}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_j|} x_{u,ji,t}^{m,v} \\ + \sum_{s=1}^{|\mathcal{U}|}\sum_{t=1}^{T} w_{ui}, t \sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_i|} x_{s,ij,t}^{m,v} \qquad \forall i \in \mathcal{I}\backslash\{G\}. \end{aligned} \tag{14}$$

- Flow conservation at the gateway: (15) ensures that all the flows must arrive to the gateway ($\mid \mathcal{I} \mid +1$)

$$\sum_{t=1}^{T}\sum_{v=1}^{|\mathcal{L}|}\sum_{i=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_i|} x_{u,ij,t}^{m,v} = 1, \quad \forall u \in \mathcal{U} \text{ and } \; j = \mid \mathcal{I} \mid +1. \tag{15}$$

- Interference constraint: at a given time-slot t, two pair nodes (i,j) and (p,q) are not allowed to transmit simultaneously if they interfere with each other.

$$\forall (i,j),(p,q) \in \mathcal{I}^2,\ (v,v') \in \mathcal{L}^2,\ t \in [1,T]; (u,u') \in \mathcal{U}^2,$$

$$(m,l) \in \mathcal{B}_i \times \mathcal{B}_p, \qquad x_{u,ij,t}^{m,v} + x_{u',pq,t}^{l,v'}\mathbb{I}_{(i,j)}^{(p,q)} \leq 1, \tag{16}$$

  where $\mathbb{I}_{(i,j)}^{(p,q)}$ is the set of interferers defined in Eq. (3).
- One direction and one power level constraints: (17) and

(18) are stated to ensure that a mesh node can transmit only at one power level and in one direction in a given time:

$$\sum_{l=1}^{|\mathcal{B}_i|} x_{u,ij,t}^{l,v} \leq 1 \qquad \forall (i,j) \in \mathcal{I}^2, \forall u \in \mathcal{U}, v \in \mathcal{L}, t \in [1,T], \tag{17}$$

$$\sum_{v=1}^{|\mathcal{L}|} x_{u,ij,t}^{l,v} \leq 1 \qquad \forall (i,j) \in \mathcal{I}^2, \forall u \in \mathcal{U}, l \in \mathcal{B}_i, t \in [1,T]. \tag{18}$$

- Simultaneous transmissions and receptions constraints: they prevent that a node from transmits and receives at the same time slot:

$$\sum_{u=1}^{|\mathcal{U}|}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_i|} x_{u,ij,t}^{m,v} + \sum_{u=1}^{|\mathcal{U}|}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_i|} x_{u,ji,t}^{m,v} \leq 1 \tag{19}$$

$\forall i \in \mathcal{I}$ and $t \in [1,T]$.

- Loops avoidance constraints: (20) and (21) force the traffic of a given user to go through a given node only once to prevent loops:

$$\sum_{t=1}^{T}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_i|} x_{u,ij,t}^{m,v} \leq 1, \text{ and} \tag{20}$$

$$\sum_{t=1}^{T}\sum_{v=1}^{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{I}|}\sum_{m=1}^{|\mathcal{B}_j|}\sum_{n=1}^{|\mathcal{B}_i|} x_{u,ji,t}^{m,v} \leq 1, \tag{21}$$

$\forall i \in \mathcal{I},\ \forall u \in \mathcal{U}$.

- Uplink transmission constraint: it ensures that the traffic is not forwarded back to nodes after reaching the gateway:

$$x_{u,ij,t}^{m,v} = 0 \tag{22}$$

$\forall j \in \mathcal{I}$ and $t \in [1,T],\ i = \mid \mathcal{I} \mid +1,\ \forall v \in \mathcal{L},\ \forall m \in \mathcal{B}_{N+1}$.

- Binary variables constraints:

$$x_{u,ij,t}^{m,v}, \quad a_{i,t}^{m,v}, \quad b_{i,t}, \quad c_{i,t}, \quad u_{li,t} \in \{0,1\}, \tag{23}$$

$\forall (i,j) \in \mathcal{I}^2, \quad m \in \mathcal{B}_i, \quad v \in \mathcal{L}, \quad u \in \mathcal{U}$.

Solving the previously defined optimization problem involves selecting the beams and transmission power levels to establish the network links and defining a routing scheme. The remaining beams can be disabled to save energy. In the following, we describe the developed solution framework and highlight the optimization gain of DAs on both throughput and energy consumption. In practice, this framework can be integrated into the control plan of a WMN for network management.

IV. Joint Energy Consumption and Throughput Optimization Solution Framework

The contribution of this section is twofold. Firstly, we propose a Directive Neighbors Discovery algorithm (DNDa) for network establishment. Each mesh node senses the network's overall beams and using all possible transmission powers. As a result, it determines the set of its neighbors and the corresponding transmit power needed to reach them. This step is important since it sets up the physical network and defines the connectivity matrix. The physical network is used in the second step to finding routes from any mesh node to gateways while optimizing the objective function defined earlier. Additionally, as the optimization problem in Eq. (12) is known to be NP-Hard [37] [38], we propose a Ant-Q heuristic, based on Q-learning and Ant Colony systems, to reduce the solution complexity.

A. Directive Neighbors Discovery Algorithm (DNDa)

Based on beam directions, each mesh node uses DNDa to discover the network and defines the physical links with the associated beam and the power levels to reach its neighbors.

DNDa (Algorithm 1) is presented as follows: After the initialization phase, where all neighbor sets ($\mathcal{NS}$s) are initialized to be empty, the nodes probe the network on all beams directions using all power levels. For each node, this discovery phase is done sequentially so that a node i sends a HELLO message in a given direction with a given power level l, waits for a REPLY message during a period of t_{wait} sec., and repeats this procedure for all power levels for the current beam (m), then switches to the next beam ($m+1$). The output of this step is the set of neighbours $\mathcal{NS}_i$ of node (i), such that $\mathcal{NS}_i = \{(m,v,j), \quad m \in \mathcal{B}_i,\ v \in \mathcal{L}$ and $j \in \mathcal{I}\}$.

Algorithm 1: Directional Neighbors Discovery Algorithm (DNDa)

Initialization: $\mathcal{NS}_i = \varnothing$;
for *each node* i **do**
  for *each beam* $m \in \mathcal{B}_i$ **do**
    for *each power level* $v \in \mathcal{L}$ **do**
      Send a HELLO message into this direction using power level v ;
      Wait for t_{wait} seconds ;
      if node i receives a REPLY from a node j **then**
        $\mathcal{NS}_i \leftarrow \mathcal{NS}_i \cup (m,v,j)$;
        /* update the node's i neighbours set */ ;
      end
      $v \leftarrow v+1$ /* Switch to next power level */ ;
    end
    $m \leftarrow m+1$ /* Switch to next beam */ ;
  end
end
Result: $\mathcal{NS}_i$ $(\forall i \in \mathcal{I})$

Once all links are defined, each node should set up the optimal routes to transmit traffic flows toward destinations or gateways. This task is performed using another algorithm, Ant-Q for Energy Efficiency Routing over Beams (AQ-EERoB), presented in the next paragraph and based on the Ant-Q heuristic. AQ-EERoB **Algorithm 2** aims at finding routes on a WMN while optimizing the energy consumption and the throughput trade-off. More precisely, the proposed heuristic aims to select the beam direction and the transmission power level to satisfy the trade-off between throughput and energy consumption.

B. AQ-EERoB: Ant-Q for Energy Efficiency Routing over Beams

Ant-Q heuristic [39] is a combination of Ant colony algorithm [40], [41], known to be efficient in solving path-finding problems, with a reinforcement learning approach, Q-learning, widely used in solving optimization problems. Ant-Q is a distributed algorithm where the agents (ants) cooperate by exchanging information in Ant-Q values, denoted as AQ-values. The learning feature is the crucial difference between the Ant-Q algorithm and the Ant Colony algorithm adopted in [9] for a WMN equipped with OAs.

In Ant-Q, agents cooperate to learn AQ-values. For our routing problem, the learning environment can be modeled as:

- States are the set of nodes in the network. Being at a given state i means being at node i.
- Actions: are the set of possible actions/moves that an agent can perform. Moving from node i to node j is an action in this set.
- Reward is scalar feedback measuring the success or failure of an agent acting in a given state. The reward function is a function of the path length (L).

The proposed AQ-EERoB algorithm consists of four major steps: *(i)* an initialization phase, *(ii)* a tour building and local pheromone updating, *(iii)* a global pheromone updating, and finally *(iv)* a condition check.

Let T_u be the tour set of ant u, which is also called an agent. The ant u visits all nodes and returns to the starting node to define its tour.

1) AQ-Values and Heuristic Information (HE): We recall that our objective is to reduce the consumed energy while improving network throughput. Therefore, we need to define HE w.r.t the optimization problem presented earlier. Naturally, the heuristic function (HE) should closely depend on the considered performance metrics.

a) Heuristic information: $HE_{i,j}$ indicates how useful for an agent to move to node j from node i, and it is defined as:

$$HE_{i,j} = \frac{1}{\alpha \mathcal{E}_i + (1-\alpha)\frac{1}{\mathcal{R}_j}}, \tag{24}$$

where $\mathcal{R}_j$ is the energy consumed by node i, $\mathcal{R}_j$ is the rate at node j and α is a weighting factor. $\mathcal{R}_j$ and $\mathcal{R}_j$ can be shown as;

$$\mathcal{R}_j = \frac{\text{Number of received packets}}{\Delta t} \tag{25}$$

and

$$\mathcal{E}_i = \sum_{p \in \mathcal{P}_i} \mathcal{E}_{p,i}, \tag{26}$$

where $\mathcal{E}_{p,i}$ the energy consumed when node i sends a packet $p \in \mathcal{P}_i$ and $\mathcal{P}_i$ is the set of packets sent by node i.

b) Pheromone Laid: $AQ_{i,j}$ is a positive real value associated with the link (i,j) to represent how the link connecting nodes i and j is evaluated in the previous iterations by all ants. The AQ-value is updated locally and globally at each cycle (steps *(ii)* and *(iii)*).

Algorithm 2: AQ-EERoB Algorithm

1 initialization;
2 For each link(i,j), let AQ_0, the initial quantity of pheromone;
3 Each ant initializes the set of not yet visited nodes (J_u);
4 **for** *Each cycle* **do**
5   **for** *Each ant* u **do**
6   **repeat**
7   Each ant applies the state transition rule (27) to choose the next hop (node j);
8   j is applied on the best solution of the set T_u;
9       $T_u \leftarrow T_u + j$;
10   Locally update the AQ value: $AQ_{i,j} = (1-\nu)AQ_{i,j} + \nu(\lambda. \max_{k \in \mathcal{NS}_i} AQ_{i,k})$
11   **until** *fixed number of tours*;
12   Compute L_{best}.
13   **end**
14 **end**
15 **for** *each link(i,j) belonging to best solutions* **do**
16   Compute the delayed reinforcement $\Delta AQ_{i,j}$;
17   Globally update AQ values according to: $AQ_{i,j} = (1-\nu)AQ_{i,j} + \nu.\Delta AQ_{i,j}$
18 **end**
19 **if** $end-condition$==*true* **then**
20   Print sol_{best} and the appropriate heuristic_sequence_best ;
21 **else**
22   go to ligne 4 (step (*ii*));
23 **end**

2) AQ-EERoB Algorithm:

Step (1) - The Initialization Phase

In the initialization phase, lines 1-3 of **Algorithm 2** can be explained as: *(i)* the quantity of pheromone (AQ-value) of all links (i,j) found by using DNDa is initialized to the same value ($AQ_{i,j} = AQ_0$) [line 2], and *(ii)* the set of not yet visited nodes is initialized to $J_u = \{1, ..., \mid \mathcal{I} \mid\} - r_u$, where r_u is the starting node of agent u [line 3].

Step (2): Tour Building and Local Pheromone Updating

After the initialization phase, a loop allows each agent u to build a tour T_u (lines 4-14). A tour is composed of a total of m transitions. At each transition t where ($t \leq m$), agent u:

(*1*) chooses the next node to visit according to Eq. (27) and Eq. (28) [line 7]. The next node j is selected as follows:

$$j = \begin{cases} \underset{k \in \mathcal{NS}_i}{argmax} \left\{ [AQ_{i,k}]^{\delta} [HE_{i,k}]^{\beta} \right\} & \text{if} \quad q < q_0 \\ S \quad \text{otherwise,} & \end{cases} \tag{27}$$

where δ and β weight the relative importance of $AQ_{i,j}$ and $HE_{i,j}$, respectively. q is a random value chosen uniformly in [0,1], and q_0 is a parameter such that the higher q_0 is, the smaller the probability is to make a random choice. S is a random node selected according to a given probability distribution as in Eq. (28) and gives the probability for an ant u in node i to move to node j:

$$p_u(i,j) = \frac{[AQ_{i,j}]^{\delta}[HE_{i,j}]^{\beta}}{\sum_{k \in \mathcal{NS}_i}[AQ_{i,k}]^{\delta}[HE_{i,j}]^{\beta}} \tag{28}$$

(*2*) updates J_u and T_u [line 9],

(*3*) updates the pheromone of the corresponding link ($AQ_{i,j}$) according to Eq. (29):

$$AQ_{i,j} = (1-\nu)AQ_{i,j} + \nu(\lambda . \max_{k \in \mathcal{NS}_i} AQ_{i,k}) \tag{29}$$

The locally update term is respectively composed of the discounted old value ($AQ_{i,j}$), which refers to the pheromone evaporation, and the discounted evaluation of the following state, which takes into account the importance of the future rewards. ν and λ are the pheromone evaporation and the discount factor parameters [line 10].

(*4*) updates the actual node.

Step (3): Global Pheromone Updating

In the third phase, which covers lines (15-18) in **Algorithm 2**, when all agents complete their tours, each agent u computes the length of its tour (T_u) [line 15]. The AQ-values of links belonging to the best tour (T_{best}) [line 17] are then updated according to Eq. (30):

$$AQ_{i,j} = (1-\nu)AQ_{i,j} + \nu\Delta AQ_{i,j}. \tag{30}$$

In this global update phase, the update terms are respectively composed of the discounted old value ($AQ_{i,j}$), and the reinforcement term ($\Delta AQ_{i,j}$), namely delayed reinforcement reward, which adjusts the new information learned towards the old one.

The tour length of the best ant, i.e., the ant with the shortest tour length L_{best}, is used to compute the global Ant-Q value according to Eq. (31):

$$\Delta AQ_{i,k} = \begin{cases} \dfrac{W}{L_{best}} & \text{if} \quad \text{(i,k) belong to the best ant tour } T_{best} \\ 0 & \text{otherwise,} \end{cases} \tag{31}$$

where W is a parameter used to adjust L_{best} values as showed in [39].

Step (4) - End Condition Check

Finally, the last step checks the termination condition [line 19]. If not verified, the algorithm returns to step *(2)* and starts a new cycle (from line 4) [line 22].

In the next section, we explain how simulations are conducted through different network scenarios, parameters, and software tools to show both the effectiveness and accuracy of the proposed algorithms.

V. Performance Evaluation

This section is structured as follows:

- We introduce the simulation methodology and parameters.
- We present the optimal results of the joint optimization problem using the ILOG Cplex solver at the first step of the analysis.
- We tackle the convergence analysis of the AQ-EEoB algorithm for various network topologies, sizes, and traffic loads.

Afterward, we highlight the AQ-EEoB algorithm's performance and compare it with state-of-the-art algorithms such as the Ant Colony and shortest path algorithms through extensive simulation experiments using the NS-3 simulator.

Parameters	Signification	Default Values
$\mathcal{E}_{\text{Tx}}$	Energy consumed by a mesh node in a transmission state using one beam at level v	1 (Joules)
$\mathcal{E}_{\text{RX}}$	Energy consumed by a mesh node at the reception state in the omnidirectional mode	0.5 (Joules)
$\mathcal{E}_{\text{idle}}$	Energy consumed by a mesh node in the idle state	0.1 (Joules)
$\mid \mathcal{I} \mid$	Mesh node number	[9, 16, ..., 49]
$\mid \mathcal{U} \mid$	Total number of agents per node	1 agent per node
$\mid \mathcal{G} \mid$	Number of mesh gateways	1
$\mathcal{L}$	Set of power levels	1,2, and 3
α	Optimization weight	[0,1]
$\mid \mathcal{B} \mid$	Number of beams	[1,..,12]
$d_{u,t}$	CBR traffic rate of user u at time t	300 Kbps
$c_{i,j}$	Link capacity	5 Mbps
σ	Interference model guard zone	0.1
θ_T	Interference model threshold angle	$\frac{\pi}{3}$
t_{wait}	Waiting time for a REPLY message	1 sec
ν	Pheromone evaporation parameter	0.1
λ	Discount factor	0.3
q_0	Parameter for action selection	0.9
δ	Weigh the relative importance of pheromone laid (AQ)	1
β	Weigh the relative importance of Heuristic information (HE)	2
W	Parameter to adjust the tour length L_{best} values	10
AQ_0	Initial pheromone evaporation value	0

TABLE II: A Summary of Simulation Parameters and Default Values

A. Evaluation Methodology & Simulation Parameters

First, we use the ILOG Cplex solver [13] to find the optimal solution of the joint optimization problem defined in Eq. (12). ILOG Cplex, based on the branch-and-cut algorithm [13], is one of the most efficient optimization problems solvers in terms of the resolution delay, and the number of handled variables as compared in [42]. Due to the space constraint, we do not present here the linearization steps of the optimization model, but they are available in [8].

Since the number of variables increases exponentially with the network size, we consider relatively small-sized networks with few beams. The optimization problem solutions are the routes set defined using variables ($x^{l,v}_{u,i,j,t}$) indicating which beam l, and power level v are active in a given time slot t to carry the user traffic u, from node i to node j to reach the destination (gateway). We show the impact of the optimization weight α, and the beamwidth on the energy-throughput trade-off, considering three possible power levels ($|\mathcal{L}|$=3).

For NS-3 simulations, we consider a wireless mesh network with a regular topology, a grid in particular, except when indicated differently. Nodes are deployed in an area of $1km^2$ and spaced by $200m$ in the x- and y-axis. All nodes are equipped with DAs with beamwidths varying from $\frac{\pi}{6}$ to 2π. Moreover, we consider a Constant Bit Rate (CBR) traffic of $300Kbps$ generated by each node toward the gateway. Note that each node can either transmit or receive at a given time.

Figure 2 illustrates two network topologies: grid topology with a center placed gateway and random topology with a randomly placed gateway.

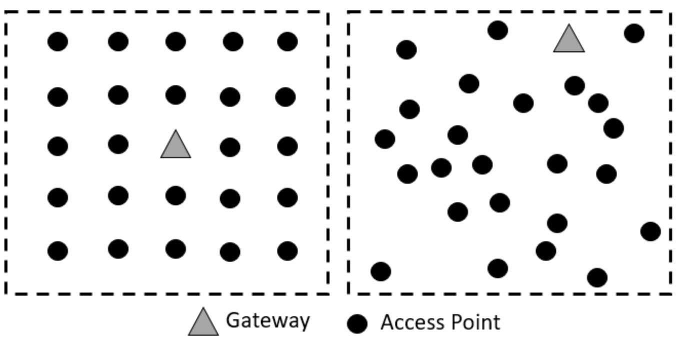


Fig. 2: Illustration of a Grid with a Gateway placed at the Center and a Random Topology

AQ-EERoB algorithm default parameters are set to δ=1, β=2; ν=0,1; λ=0,3; q_0=0,9 and W=10. These values were optimized using a grid search in early experiments [39]. Simulation parameters are summarized in Table II.

B. Joint Optimization Problem Solution using the Cplex Solver

1) Impact of Antenna Beamwidth: In this part, we investigate the impact of antenna beamwidth on the performance results. We consider the two extreme cases: (i) α=1, where we focus only the energy consumption optimization, (ii) α= 0, to only maximize the throughput, and (iii) two intermediate cases, $\alpha = 0.5$ and $\alpha = 0.7$.

Figure (3a) illustrates the energy consumed versus the beamwidth for different values of α. The beamwidth is varied from $\frac{\pi}{6}$ to 2π. Note that using antennas of 2π beamwidth is equivalent to an OAs based WMN. We observe that the energy consumption increases when the beamwidth gets larger, and the maximum consumed energy is observed when the beamwidth is 2π (OA). Figure (3b) shows that the throughput decreases with beamwidth for the optimal solution. For a given beamwidth, the closer α is to 1, the worse the throughput, and conversely, α being close to 0 improves the throughput. In Table III, we give some numerical values of the throughput and the energy-saving gains, considering the four cases cited above depending on the value of α. Please note that for the energy consumption, the highlighted gains are concerning the case of α=0 (no energy optimization) and are for the case of α=1 for the throughput (no throughput optimization). For instance, when $\alpha \neq 0$, the energy saving is always better than the throughput enhancement thanks to the antenna gain. Moreover, retransmissions do not severely affect the energy consumption since the nodes are in the idle state in case of saturation, waiting to access the network. If a packet fails to leave a node, it stays at this node. The node will not consume transmitting power. However, the throughput is affected since the packet is not delivered.

α	Throughput	Energy Saving
0	34%	0%
0.5	12%	34%
0.7	25%	29%
1	0%	93%

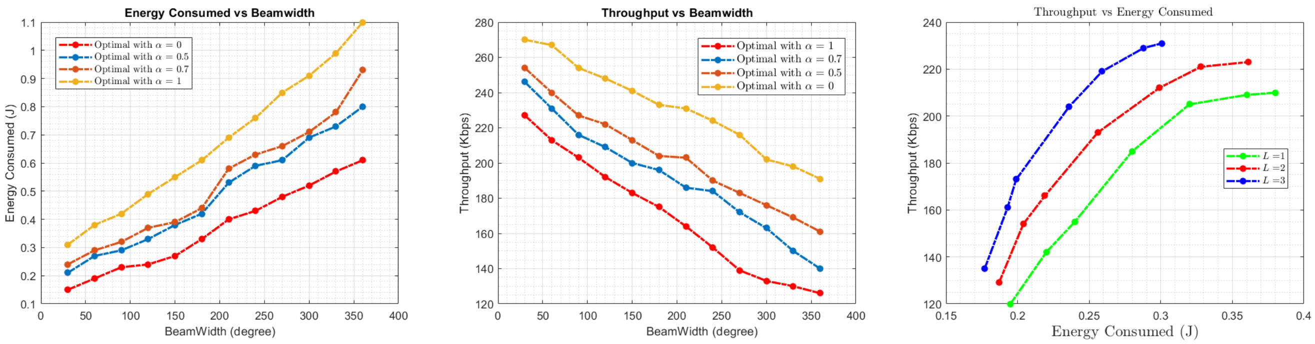
TABLE III: Throughput and Energy Saving Gains vs α

2) Energy consumption & Throughput Trade-off : Figure (3c) shows the energy consumption and the throughput trade-off for various values of L, the number of power levels. For each value of α, we show the corresponding consumed energy and throughput. The results here are obtained using ILOG Cplex over a network of 25 nodes equipped with 4-beam antennas. The two extreme points $P_0(E_{min}, \mathcal{R}_{min})$ and $P_1(E_{max}, \mathcal{R}_{max})$ correspond to values of α=1 to minimize the energy consumption and α=0 to maximize the throughput, respectively. The curve between these two points represents the *Pareto-front*. Each front point is derived for a given value of α as shown in the figure. Power control improves the trade-off between energy consumption and throughput. For example, in the 2-levels power control, the throughput gain is about $15,5\%$, and the energy-saving is about $17,8\%$. On the other hand, with 3-levels power control, the enhancement reaches $29,2\%$ and $34,5\%$ for the throughput and the energy saving, respectively.

C. AQ-EERoB Convergence

Before going further in the analysis of simulation results on energy consumption and throughput, we focus on the convergence and optimization parameters of the AQ-EERoB algorithm. We consider a WMN equipped with four beams antennas. Simulation results are averaged over 500 runs.

In Figure (4a), we highlight the convergence of the AQ-EERoB algorithm. We plot the averaged path length (L) depending on the iteration number for three different grid networks of 9, 16, and 25 nodes and with one gateway placed at the grid's top right. The average tour length converges first. It decreases exponentially for small-sized networks and takes

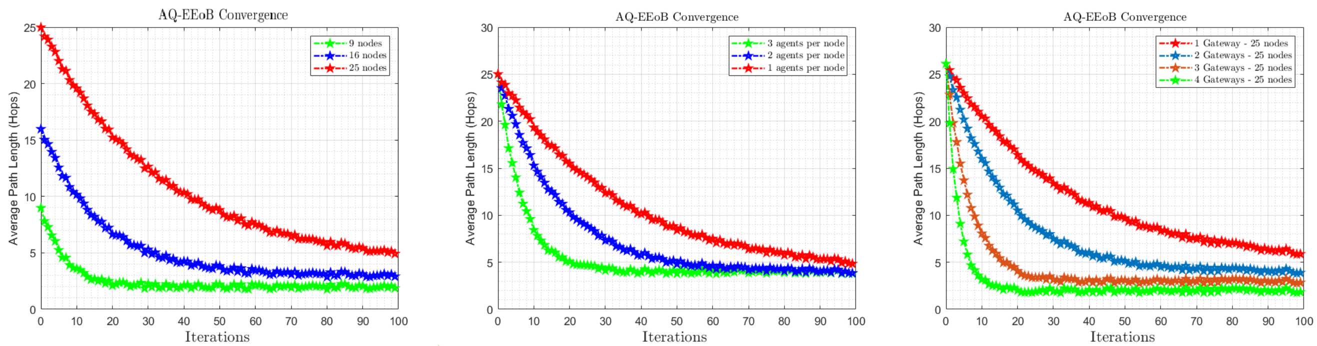


(a) Energy Consumed vs Beamwidth for Different Values of α and for v=1

(b) Throughput vs Beamwidth for Different Values of α and for v=1

(c) Throughput vs Energy Consumed for Different Values of L

Fig. 3: Joint Optimization Problem Optimal Results



(a) Convergence for Various Network Sizes

(b) Convergence for Different Number of Ants per Node

(c) Convergence for Different Number of Gateways in the Network

Fig. 4: AQ-EERoB convergence

more time for larger ones. Agents have more paths to explore in larger networks and take more time to find the gateway's optimal path. The optimal tour lengths are 2, 3, and 5 nodes (hops) for networks of 9, 16, and 25 nodes, respectively.

Next, we investigate the impact of the number of agents per node. In Figure (4b), we vary the number of agents per node in a 25 nodes grid topology network with one gateway placed at the top right of the grid. It can be seen that the more agents per node for fixed network size, the faster the algorithm convergence is. Note that an iteration corresponds to a cycle in the AQ-EEoB algorithm. Having more agents per node increases the spatial exploration rate, where agents take different paths and different directions around the source node simultaneously and update the AQ values. The average path length converges to the optimal length, five hops for the 25 nodes grid topology network.

In Figure (4c), we focus on the scenario with one agent per node, and we study the impact of the number of gateways on the algorithm convergence. We vary the number of gateways while keeping the same network size (25 mesh nodes). It can be seen that with a few gateways in the network, the convergence of AQ-EERoB is slower than in the case where more gateways are available. Having more gateways on the network makes it easier for the agents to reach one of the gateways.

Generally, the AQ-EEoB convergence shape is exponentially decreasing and converges to the optimal number of hops. The convergence is reached after 30 iterations on average.

Once the AQ-EERoB algorithm converges and routes to reach the gateway are known, we tackle the performance analysis on a particular and extreme case where only one gateway is considered and located either at the edge or the network center. This case is challenging since all routes must converge to the same gateway reducing. As a result, the spatial diversity increases the convergence of the AQ-EERoB algorithm, as shown just before. Besides, this case is relevant for poor/rural deployment scenarios or desert areas where reducing the network infrastructure as the gateways mitigate the lack of power suppliers and reduce the deployment-related cost.

D. AQ-EEoB Algorithm Effectiveness

1) Impact of Network Topology: This section analyzes the impact of the nodes' spatial distribution on energy consumption and throughput. We consider three different scenarios: (i) a grid topology with a gateway placed at the top right corner with the grid size varying from 2×2 to 7×7; (ii) a grid topology with a gateway placed at the center, where the considered sizes are 3×3, 5×5 and 7×7, since the other sizes cannot have a node at the center; and (iii) a random topology of $n \in \{6, 8, ..., 49\}$ wireless mesh nodes, generated randomly inside the considered area, and the gateway is selected randomly among these nodes. All nodes transmit at the full power ($v = 1$), and α is set to 0.5. Results are obtained using NS-3 simulations and presented in Figure 5, via the curves denoted x-Grid-TR (top right), x-Grid-Center, and x-Random, where x is the number of the beams.

Simulations results in Figure 5 show that in random topologies with a few numbers of nodes, the nodes fail to reach the gateway. Moreover, most of the nodes are out of the communication range and, the connectivity between nodes is not ensured. Beyond 12 nodes, the network can be formed, and flows are routed to reach the gateway. Furthermore, the confidence intervals are significant for a topology with fewer nodes and smaller ones while increasing the nodes' number. The energy consumption increases with the number of nodes in the network. Moreover, it is interesting to observe that energy consumption is reduced when 4-beams are used, considering the network topology and the gateway location. On the contrary, the throughput is higher with a 4-beams antenna than with 2-beams one due to the enhanced spatial diversity of the network, which allows concurrent transmissions. The more directional the antennas are, the better the trade-off between power consumption and throughput.

Furthermore, considering the same number of beams, less energy is used in a network with the gateway placed at the center. However, the scenario with a central gateway provides better throughput. Indeed, fewer nodes are used to relay the traffic compared to the edge gateway topology. However, the traffic load is higher around the gateway as the same nodes are constantly solicited, thus reducing their throughput. On the other hand, when the gateway is at the network edge, the throughput is enhanced since more nodes are used to relay data traffic, despite almost the same traffic load rate.

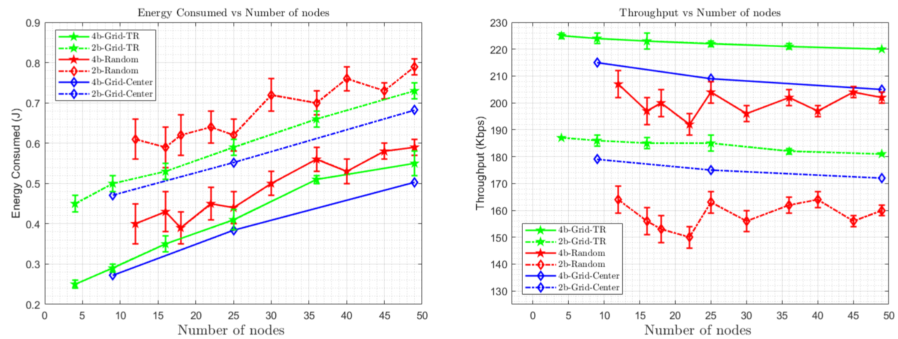
2) Impact of the Number of Gateways: In this section, we study the impact of the number of gateways on network performance. We vary the number of gateways and analyze the impact on energy consumption and throughput for a grid topology 6. The energy consumption is decreasing against the number of nodes in the network. Additionally, the more gateways in the network, the less energy consumed is. The inverse trend can be observed for the throughput, which is improved for many gateways in the networks. Having one or a few gateways in the network causes congestion and collisions that induce additional retransmissions. Moreover, for networks with a few nodes, the gap between 1, 2, and 4 gateways is high, but it is lowered for a larger network size. When the network size gets more significant with a few gateways, the gateways cannot absorb the traffic as in the small-size network.

3) The AQ-EERoB Algorithm Effectiveness: In this paragraph, we investigate the effectiveness of the proposed AQ-EERoB scheme. In Figure 7, we compare the average consumed energy and the average throughput obtained using the AQ-EEoB, Ant-Colony algorithms, and the optimal solution while changing the number of nodes in the network. The average consumed energy increases with the network size, whereas the throughput decreases when the network gets larger. Furthermore, we observe only a slight difference in the consumed energy between the optimal solution and the AQ-EERoB heuristic. Neglecting this difference, we can conclude that the AQ-EERoB algorithm outperforms the other two algorithms. It provides the best performance, i.e., lower consumed energy and higher throughput, for both 2- and 4-beams scenarios, whatever the network size. Therefore, the AQ-EERoB scheme finds routes with a maximum bit rate and minimum energy.

4) Impact of Power Control: This paragraph investigates the trade-off between energy consumption and throughput, considering a discrete power control scheme. The impact of power control is considered in Figure 8a where we show the consumed energy versus the beamwidth for different values of $\mid \mathcal{L} \mid$, the number of power levels for a network of 25 nodes. We consider the case of $\mid \mathcal{L} \mid= 3$ where each node selects its transmit power from the set $\{0, \frac{P_{max}}{2}, P_{max}\}$. As observed previously, energy consumption grows with the increase of beamwidths. Moreover, the Ant-Q-based heuristic is close to the optimal one and provides the best performance. As stated before for $\alpha = 0.5$ in Figure 7, AQ-EERoB algorithm gives a good approximation of the optimal solution. Furthermore, regardless of the considered algorithm, the power control scheme with several levels considerably decreases the energy consumption, mainly for DAs with larger beams. In narrow beams, a small improvement is observed for the consumed energy using only one power level (P_{max}) compared to 3 levels of power control. However, this improvement is greater when the DA's beamwidth is larger.

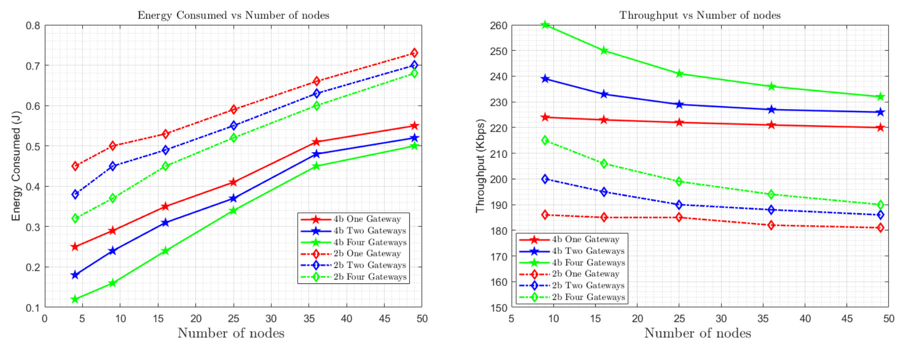
5) Impact of the Weight Factor (α): Figure 9 highlights the variation of the consumed energy, the throughput, and the route length versus the optimization weight factor α. As in the previous setting, a 4-beams DAs equipped WMN of 25 nodes is considered. The shortest path algorithm provides invariant and the worst results since it is independent of α. For α=0, the consumed energy is not considered in the Heuristic information (HE) (Eq. 24) used to build the routing path; hence, it corresponds to the highest value of consumed energy. Increasing α gives more importance to the consumed energy. The consumed energy decreases smoothly for α below 0.7, then decreases roughly above 0.7, as shown in Figure 9a. As expected, in Figure 9b, the throughput is maximal for α=0 and decreases until reaching its minimal value for α=1. Fig. 9c compares the average route length obtained using AQ-EERoB and shortest path algorithms when OAs and 4-beams DAs are used. In omnidirectional antennas, the AQ-EERoB algorithm selects routes composed of several hops to reduce energy consumption when $\alpha \rightarrow 1$, using fewer transmission powers at each node, while the shortest path algorithm aims at finding the shortest path by default. On the other hand, when maximizing the throughput ($\alpha = 0$), the path length is fixed to 4, as same as the shortest path algorithm. Fortunately, the AQ-EERoB algorithm is beneficial for the 4-beams network since the route length is significantly reduced. Therefore, we can deduce from the three figures that the optimal value of α is 0.7 since the throughput and energy consumption trade-off are satisfied. Moreover, the number of relay nodes is lower.

Results show that the AQ-EERoB algorithm outperforms both Ant-colony and shortest path algorithms. Using Ant-Q heuristic traffic routing over backhaul WMN with direc-



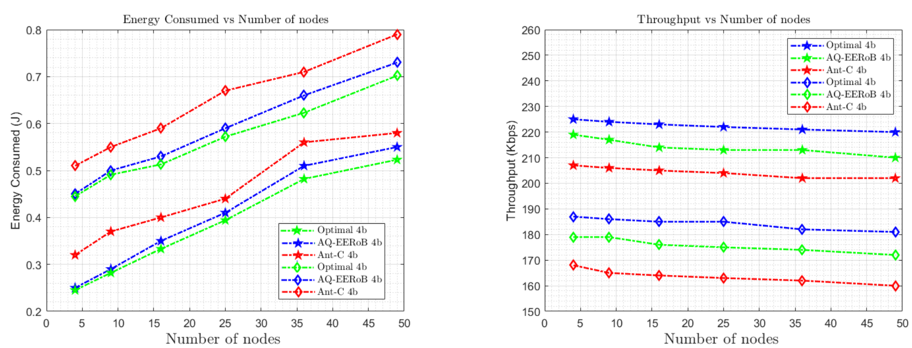
(a) Energy Consumed (b) Throughput

Fig. 5: Impact of Network Topology on Performance.



(a) Energy Consumed (b) Throughput

Fig. 6: Impact of the Number of Gateways on Network Performance.



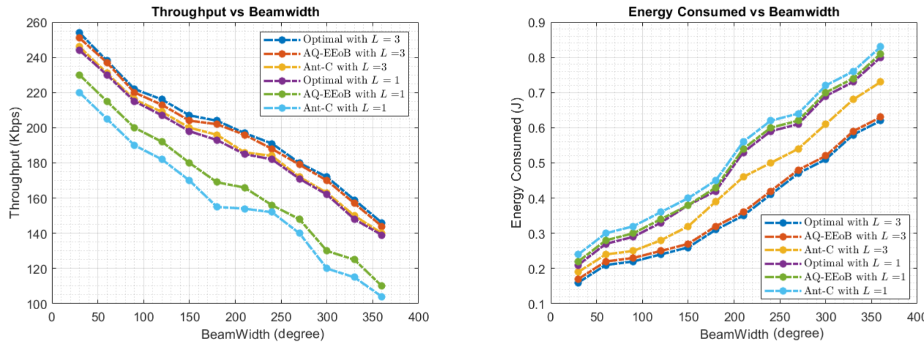
(a) Energy Consumed (b) Throughput

Fig. 7: Network Size Impact: Comparison between AQ-EERoB Heuristic, Ant-C and Optimal Solution for α=0.5.

tive antennas can reduce energy consumption and improve throughput.

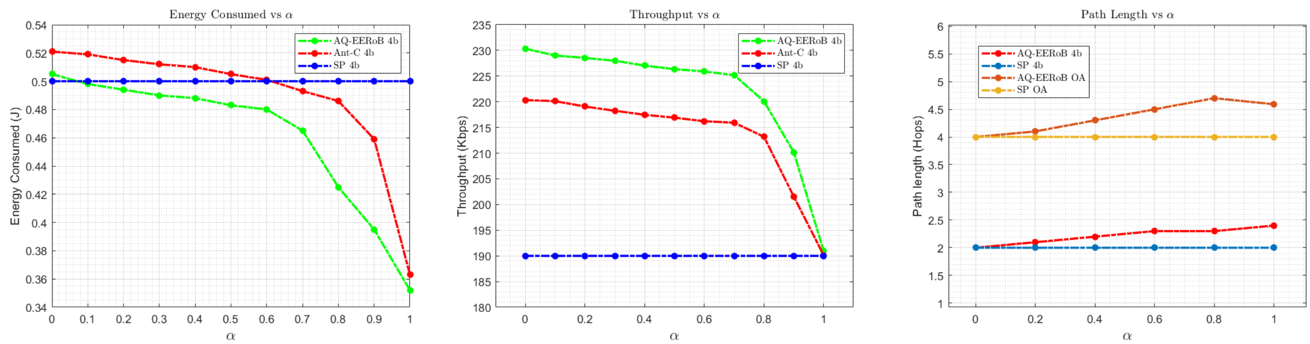
E. AQ-EEoB vs Baseline Algorithms

In this subsection, we compare the performance of the proposed AQ-EEoB algorithm with two algorithms optimizing either the throughput: Backhaul Link Scheduling algorithm (BLSa) [31] for directional antennas, or both energy and throughput: Energy-efficient and Robust Multipath Routing (ERMR) protocol [24]. For a fair comparison, we consider the same network for all algorithms. We implement the two approaches using NS-3. Figure 10 shows the energy and throughput depending on the number of nodes for the different benchmark algorithms and various values of α. For the throughput, it can be seen in Figure 10a that the more α of the AQ-EEoB algorithm is close to 0, the better the throughput is, and that the case of α=0 outperforms both considered benchmark approaches. The BLSa approach optimizing the throughput shows better performance than the ERMR, optimizing the throughput and energy consumption, and to AQ-EEoB for values $\alpha > 0.7$. However, BLSa is less efficient than the case of AQ-EEoB $\alpha = 0$ (which is equivalent to optimize only the throughput). The ERMR approach has slightly less performant in throughput than the case of AQ-



(a) Impact of Beamwidth on Consumed Energy. (b) Impact of Beamwidth on Throughput.

Fig. 8: Impact of Beamwidth on Consumed Energy and Throughput for different Values of L and for $\alpha = 0.7$.



(a) Energy consumed (b) Throughput (c) Length (number of hops)

Fig. 9: Routing Scheme Performance versus α: AQ-EERoB, Ant-C and Shortest Path algorithms

EEoB $\alpha = 0.7$ On the other hand, Figure 10b highlights the energy consumption depending on the network size for the benchmark algorithms and different values of α. It can be seen that the more α is close to 1, the lower the energy consumed is. The BLSa approach induces a higher energy consumption since it is designed to maximize the throughput and does not consider the energy issue. The ERMR approach, jointly optimizing the throughput and energy, has similar energy consumption as α=0.7.

F. AQ-EEOB Computation Time

In this subsection, we evaluate the computation time of the proposed AQ-EEoB algorithm. Table IV presents the average computation time, the time needed to run the algorithm and to find possible routes for each source flow. We reported computation time for three different network sizes: small (25 nodes), medium (50 nodes), and large (100 nodes) network sizes, equipped with four beam antennas and one gateway.

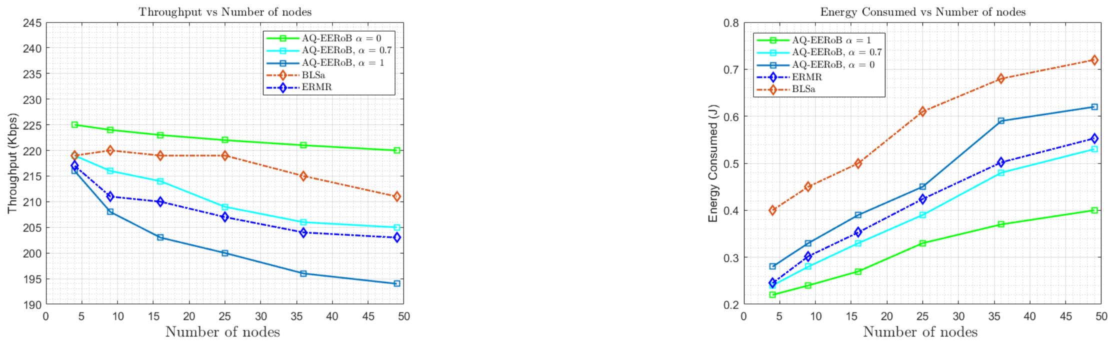
Simulation is performed using a standard PC with a 3,1 GHz Dual-Core Intel processor and 8 GB of RAM. Results show that the AQ-EEoB algorithm takes a shorter time to solve the problem compared to the optimal solution. Furthermore, AQ-EEoB has a computing time comparable to that of Ant-Colony. Additionally, the computation time of the proposed algorithm is scalable with the network size. An increase in the number of nodes in the network leads to a stable linear increase in the computation time. Furthermore, the BLSa algorithm has comparable computation time to the AQ-EERoB and Ant-Colony approaches. However, the ERMR algorithm is more time-computationally complex.

	Small Network	Medium Network	Large Network
Optimal	349.00 ± 26.27	721.00 ± 21.91	-
AQ-EEoB	2.56 ± 0.11	4.96 ± 0.35	9.22 ± 0.73
Ant-Colony	2.41 ± 0.14	4.83 ± 0.12	9.18 ± 0.23
BLSa	4.01 ± 0.10	5.07 ± 0.29	10.56 ± 0.45
ERMR	34.14 ± 1.10	40.91 ± 2.31	87.22 ± 5.10

TABLE IV: Computation Time (in seconds).

VI. Conclusion & Perspectives

This paper addressed joint energy consumption minimization and throughput maximization in WMN using DAs to advantage of spatial diversity. As a resolution approach, we developed a routing scheme based on beam and transmission power selection while guaranteeing a trade-off between energy consumption and throughput. First, we formulated the joint energy consumption and throughput optimization problem as a Mixed Integer Linear Program (MILP). Secondly, we proposed an algorithm based on the AQ-EERoB heuristic to reduce the resolution complexity. The routing scheme we proposed allows us to jointly select optimal beams and transmission power levels, using two algorithms: DNDa (Directional Neighbors Discovery Algorithm) and AQ-EERoB (Ant-Q for Energy



(a) Throughput (b) Energy Consumed

Fig. 10: AQ-EEoB Algorithm vs Benchmark Algorithms

Efficient Routing over Beams). We used both the ILOG Cplex solver and NS-3 network simulator to evaluate and discuss the optimization results depending on the network parameters and the optimization weight factor.

The obtained results are very promising and demonstrate our approach efficiency. Overall, the more antennas are directive, the greater the tradeoff between throughput and energy consumption, regardless of the network topology, gateway position, and weight factor α. Additionally, introducing power control improves the obtained results. This enhancement remains significant even in the case of antennas with larger beams, mainly omnidirectional antennas. Moreover, paths are shorter, which reduces consumption and increases throughput. Our results show that the AQ-EERoB algorithm is effective and provides a good approximation of the optimal solution compared to the Ant colony and the shortest path algorithms. Finally, setting the scenario using the 3-level power control and an optimization weight factor α of $0,7$ provides the optimal throughput and energy consumption tradeoff.

This work limited our analysis and evaluation of the AQ-EEoB algorithm to WMNs where nodes communicate using a single frequency channel. It would be interesting to extend the optimization model to study the impact of using multi-channel on network performance. Moreover, the AQ-EEoB algorithm is based on the Q-learning algorithm. In future work, Deep Q Learning, a neural network version of Q-learning, and other reinforcement learning algorithms such as value iteration and Sarsa [43] can be used to improve the solution's performance. The neural network approach can apprehend the complexity of large-sized networks and help to adapt the routing scheme to topology changes. Additionally, considering the channel quality through a cross-layer approach to improve the routing strategies and investigates the network lifetime for a limited battery-powered network are interesting perspectives of this work.

References

[1] (2015) Why the eu is betting big on 5g.

[2] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What will 5g be?" *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065–1082, 2014.

[3] D. Pompili, H. Abolfazl, and T. X. Tran, "Elastic resource utilization framework for high capacity and energy efficiency in cloud ran," *IEEE Communications Magazine*, pp. 26–32, 2016.

[4] E. S. L. Derrick Wing Kwan Ng and R. Schober, "Energy-efficient resource allocation in ofdma systems with large numbers of base station antennas," *IEEE Transactions on Wireless Communications*, vol. 11, no. 9, pp. 3292–3304, July 2012.

[5] T. E. K. Stefano Buzzi, Chih-Lin and all, "A survey of energy-efficient techniques for 5g networks and challenges ahead," *IEEE Journal on Selected Areas in Communications*, pp. 697–709, 2016.

[6] I. Akyildiz and X. Wang, "A survey on wireless mesh networks," *Communications Magazine, IEEE*, vol. 43, no. 9, pp. 23–30, Sept 2005.

[7] I. Lahsen Cherif, L. Zitoune, and V. Veque, "Joint optimization of energy consumption and throughput of directional wmns," in *IEEE WiMob*, New York City, New York, USA, 2016.

[8] I. L. Cherif, L. Zitoune, and V. Vèque, "Joint optimization of energy consumption and throughput of directional wmns," in *IEEE ICC*, Paris, France, May 2017.

[9] A. Amokrane, R. Langar, R. Boutaba, and G. Pujolle, "Energy efficient management framework for multihop tdma-based wireless networks," *Computer Networks*, vol. 62, pp. 29 – 42, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S138912861400005X

[10] A. Ouni, H. Rivano, F. Valois, and C. Rosenberg, "Energy and throughput optimization of wireless mesh networks with continuous power control," *IEEE Transactions on Wireless Communications*, vol. 14, no. 2, pp. 1131–1142, Feb 2015.

[11] F. Moety, S. Lahoud, K. Khawam, and B. Cousin, "Joint power-delay minimization in green wireless access networks," in *IEEE PIMRC*, Sept 2013, pp. 2819–2824.

[12] A. H. Mohsenian-rad and V. W. S. Wong, "Joint logical topology design, interface assignment, channel allocation, and routing for multi-channel wireless mesh networks," *IEEE Transactions on Wireless Communications*, vol. 6, no. 12, pp. 4432–4440, December 2007.

[13] I. I. CPLEX, "V12. 1: Users manual for cplex," *International Business Machines Corporation*, vol. 46, no. 53, p. 157, 2009.

[14] S. Boiardi, A. Capone, and B. Sansó, "Joint design and management of energy-aware mesh networks," *Ad Hoc Networks*, vol. 10, no. 7, pp. 1482–1496, 2012.

[15] A. Capone, F. Malandra, and B. Sansò, "Energy savings in wireless mesh networks in a time-variable context," *Mobile Networks and Applications*, vol. 17, no. 2, pp. 298–311, 2012.

[16] M. Imran, E. Katranaras, G. Auer, O. Blume, V. Giannini, I. Godor, Y. Jading, M. Olsson, D. Sabella, P. Skillermark *et al.*, "Energy efficiency analysis of the reference systems, areas of improvements and target breakdown," Tech. Rep. ICT-EARTH deliverable, Tech. Rep., 2011.

[17] N. Sadeghianpour, T. C. Chuah, and S. W. Tan, "Joint channel assignment and routing in multiradio multichannel wireless mesh networks with directional antennas," *International Journal of Communication Systems*, vol. 28, no. 9, pp. 1521–1536, 2015. [Online]. Available: http://dx.doi.org/10.1002/dac.2731

[18] A. Capone, F. Malandra, and B. Sansò, "Energy savings in wireless mesh networks in a time-variable context," *Mobile Networks and Applications*, vol. 17, no. 2, pp. 298–311, 2012.

[19] A. de la Oliva, A. Banchs, and P. Serrano, "Throughput and energy-aware routing for 802.11 based mesh networks," *Computer Communications*, vol. 35, no. 12, pp. 1433–1446, July 2012.

[20] S. Debroy, P. Samanta, A. Bashir, and M. Chatterjee, "Speed-iot: Spectrum aware energy efficient routing for device-to-device iot communication," *Future Generation Computer Systems*, vol. 93, pp.

833–848, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X17307148
[21] M. E. Haque and U. Baroudi, “Dynamic energy efficient routing protocol in wireless sensor networks,” *Wireless Networks*, pp. 1–19, 2020.
[22] J. Jagannath, S. Furman, A. Jagannath, L. Ling, A. Burger, and A. Drozd, “Helper: Heterogeneous efficient low power radio for enabling ad hoc emergency public safety networks,” *Ad Hoc Networks*, vol. 89, pp. 218–235, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1570870518309168
[23] R. Singh and A. K. Verma, “Energy efficient cross layer based adaptive threshold routing protocol for wsn,” *AEU-International Journal of Electronics and Communications*, vol. 72, pp. 166–173, 2017.
[24] K. Singh and S. Moh, “An energy-efficient and robust multipath routing protocol for cognitive radio ad hoc networks,” *Sensors*, vol. 17, no. 9, p. 2027, 2017.
[25] I. Allal, B. Mongazon-Cazavet, K. Al Agha, S.-M. Senouci, and Y. Gourhant, “A green small cells deployment in 5gâswitch on/off via iot networks & energy efficient mesh backhauling,” in *2017 IFIP Networking Conference (IFIP Networking) and Workshops*. IEEE, 2017, pp. 1–2.
[26] M. Żotkiewicz and M. Pióro, “Exact approach to reliability of wireless mesh networks with directional antennas,” *Telecommunication Systems*, vol. 56, no. 1, pp. 201–211, 2013. [Online]. Available: http://dx.doi.org/10.1007/s11235-013-9829-4
[27] W. Wong, X. Chen, F. Long, and S. H. G. Chan, “Joint topology control and routing assignment for wireless mesh with directional antennas,” in *Global Communications Conference (GLOBECOM), 2012 IEEE*, Dec 2012, pp. 5699–5704.
[28] H. Roh and J. Lee, “Channel assignment, link scheduling, routing, and rate control for multi-channel wireless mesh networks with directional antennas,” *Journal of Communications and Networks*, vol. 18, no. 6, pp. 884–891, Dec 2016.
[29] N. Toorchi, F. Hu, S. Pudlewski, E. Bentley, and S. Kumar, “Volcano routing: A multi-pipe high-throughput routing protocol with hole avoidance for multi-beam directional mesh networks,” *IEEE Transactions on Mobile Computing*, vol. 19, no. 12, pp. 2981–2996, Dec 2020.
[30] M. F. Bedasa, A. S. Bedada, and W. B. Mulatu, “Adaptation of smart antenna with aodv routing protocol for ad hoc wireless networks,” *Open Access Library Journal*, vol. 7, no. 7, pp. 1–21, 2020.
[31] W. Na, Y. Lee, N. Dao, D. N. Vu, A. Masood, and S. Cho, “Directional link scheduling for real-time data processing in smart manufacturing system,” *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3661–3671, 2018.
[32] L. Zhang, L. Hu, F. Hu, Z. Ye, X. Li, and S. Kumar, “Enhanced olsr routing for airborne networks with multi-beam directional antennas,” *Ad Hoc Networks*, vol. 102, p. 102116, 2020.
[33] Y. Li, M. Pioro, and B. Landfeldt, “Fair flow rate optimization by effective placement of directional antennas in wireless mesh networks,” *Performance Evaluation*, vol. 87, pp. 92 – 106, 2015, special Issue: Recent Advances in Modeling and Performance Evaluation in Wireless and Mobile Systems. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0166531615000085
[34] B. Hu and H. Gharavi, “Directional routing protocols for ad-hoc networks,” *Communications, IET*, vol. 2, no. 5, pp. 650–657, 2008.
[35] V. Ramamurthi, A. Reaz, S. Dixit, and B. Mukherjee, “Link scheduling and power control in wireless mesh networks with directional antennas,” in *Communications, 2008. ICC ’08. IEEE International Conference on*, May 2008, pp. 4835–4839.
[36] P. Gupta and P. Kumar, “The capacity of wireless networks,” *IEEE Transactions on Information Theory*, vol. 46, no. 2, pp. 388–404, Mar 2000.
[37] S. Ramanathan and E. L. Lloyd, “Scheduling algorithms for multihop radio networks,” *IEEE/ACM Transactions on Networking*, vol. 1, no. 2, pp. 166–177, Apr 1993.
[38] M. Kodialam and T. Nandagopal, “Characterizing achievable rates in multi-hop wireless mesh networks with orthogonal channels,” *IEEE/ACM Trans. Netw.*, vol. 13, no. 4, pp. 868–880, Aug. 2005. [Online]. Available: http://dx.doi.org/10.1109/TNET.2005.852873
[39] L. M. Gambardella and M. Dorigo, “Ant-q: A reinforcement learning approach to the traveling salesman problem,” in *12th International Conference on Machine Learning*. Morgan Kaufmann, 1995, pp. 252–260.
[40] M. Dorigo and L. M. Gambardella, “Ant colonies for the travelling salesman problem,” *biosystems*, vol. 43, no. 2, pp. 73–81, 1997.
[41] ——, “Ant colony system: a cooperative learning approach to the traveling salesman problem,” *IEEE Transactions on evolutionary computation*, vol. 1, no. 1, pp. 53–66, 1997.
[42] B. Meindl and M. Templ, “Analysis of commercial and free and open source solvers for linear optimization problems,” 2012.
[43] S. Zou, T. Xu, and Y. Liang, “Finite-sample analysis for sarsa with linear function approximation,” *arXiv preprint arXiv:1902.02234*, 2019.