Joint optimization of transmission and propulsion in aerial communication networks

Omar J. Faqir, Eric C. Kerrigan, and Deniz Gündüz

Abstract—Communication energy in a wireless network of mobile autonomous agents should be considered as the sum of transmission energy and propulsion energy used to facilitate the transfer of information. Accordingly, communication-theoretic and Newtonian dynamic models are developed to model the communication and locomotion expenditures of each node. These are subsequently used to formulate a novel nonlinear optimal control problem (OCP) over a network of autonomous nodes. It is then shown that, under certain conditions, the OCP can be transformed into an equivalent convex form. Numerical results for a single link between a node and access point allow for comparison with known solutions before the framework is applied to a multiple-node UAV network, for which previous results are not readily extended. Simulations show that transmission energy can be of the same order of magnitude as propulsion energy allowing for possible savings, whilst also exemplifying how speed adaptations together with power control may increase the network throughput.

I. INTRODUCTION

We aim to derive a control strategy to minimize communication energy in robotic networks. In particular, uninhabited aerial vehicle (UAV) networks are considered, with results being generalizable to broader classes of autonomous networks. A dynamic transmission model, based on physical layer communication-theoretic bounds, and a mobility model for each node is considered alongside a possible network topology. As a cost function, we employ the underused interpretation of communication energy as the sum of transmission energy and propulsion energy used for transmission, i.e. when a node changes position to achieve a better channel.

For simulation purposes we consider the two wireless network setups shown in Figure 1. We first present the most basic scenario consisting of a single agent $U_1$ moving along a predefined linear path while offloading its data to a stationary access point (AP). We compare results for variable and fixed speeds, before studying a two-agent single-hop network.

For UAV networks, research efforts largely break down into two streams: the use of UAVs in objective based missions (e.g. search and pursuit [1], information gathering/mobile sensor networks [2], [3]), and use as supplementary network links [4]. Optimal completion of these macro goals has been addressed in the literature, but there is no necessary equivalence between optimal task-based and energy-efficient operations.

Efforts concerning mobility focus on mobile (in which node mobility models are random) or vehicular (where mobility is determined by higher level objectives and infrastructure) ad-hoc networks [5]. Since neither are fully autonomous networks, mobility is not available as a decision variable. The work in [6] introduced the concept of proactive networks, where certain nodes are available as mobile relays. However, the focus is on relay trajectory design and a simplistic transmission model is assumed, inherently prohibiting energy efficiency. The related problem of router formation is investigated in [7] using realistic models of communication environments.

We assume hard path constraints, possibly due to the existence of higher level macro objectives, but allow changes in trajectory along the path by optimizing their speed (as in [8], we define a trajectory as being a time-parameterized path). Use of fixed paths does not restrict our results as most UAV path planning algorithms operate over longer time horizons and are generally restricted to linear or circular loiter trajectories [8]. A linear program (LP) is used in [9] to determine how close a rolling-robot should move before transmission in order to minimize total energy. However, the linear motion dynamics used restricts applicability of the model. Similarly to our current work, [10] uses a single mobile UAV relay to maximize data throughput between a stationary source-destination pair. An optimal trajectory for an a priori transmission scheme is iteratively found. Similarly, for a given trajectory, the optimal relaying scheme

\[ U_1 \]

\[ U_2 \]

\[ a_1 \sqrt{a_2^2 + \delta_2^2} \]

\[ (0, 0) \]

Fig. 1: Geometric configuration for simulation setups featuring $N = 1$ (black) and $N = 2$ (green) nodes. Speeds along these paths may be variable or fixed. The altitudes and lateral displacements of $U_1, U_2$ are $a_1 = a_2 = 1000 \text{ m}$ and $\delta_1 = 0, \delta_2 = 1000 \text{ m}$, respectively.

The support of the EPSRC Centre for Doctoral Training in High Performance Embedded and Distributed Systems (HiPEDS, Grant Reference EP/L016796/1) is gratefully acknowledged.

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may be obtained through water-filling over the source-to-
relay and relay-to-receiver channels.

Our contribution differs from the above works in terms of
the formulation of a more general nonlinear convex OCP for
finding joint transmission and mobility strategies to minimize
communication energy. We solve this problem, exemplifying
possible savings for even just a single node. As a final
point, we show analytically and numerically that, even at
fixed speeds, the optimal transmission scheme for a two-
user multiple-access channel (MAC) is counter-intuitive and
not captured by naive transmission policies.

II. PROBLEM DESCRIPTION

Consider \( N \) homogeneous mobile nodes \( U_n, n \in \mathcal{N} \triangleq \{1, \ldots, N\} \), traveling along linear non-intersecting trajec-
tories at constant altitudes \( a_n \) and lateral displacements \( \delta_n \) over
a time interval \( T \triangleq [0, T] \). The trajectory of node \( U_n \) is
denoted by \( t \mapsto (q_n(t), \delta_n, a_n) \), relative to a single stationary
AP \( U_0 \) at position \((0, 0, 0)\) in a three dimensional space. At
\( t = 0 \), \( U_n \) is initialized with a data load of \( D_n \) bits, which
must all be offloaded to \( U_0 \) by time \( t = T \). We consider a
cooperative network model, in which all nodes cooperate to
offload all the data in the network to the AP by relaying each
other’s data. Each node has a data buffer of capacity \( M \) bits, which
limits the amount of data it can store and relay.

A. Communication Model

We employ scalar additive white Gaussian noise (AWGN)
channels. For UAV applications, we assume all links are
dominated by line-of-sight (LoS) components, resulting in
flat fading channels, meaning all signal components undergo
similar amplitude gains [11]. All nodes have perfect infor-
mation regarding link status, which in practice may be
achieved through feedback of channel measurements, while
the overhead due to channel state feedback is ignored.

Similar to [12], for a given link from source node \( U_n \) to
receiver node \( U_m \), the channel gain \( \eta_{nm}(\cdot) \) is expressed as

\[
\eta_{nm}( q_{nm} ) \triangleq \frac{G}{\sqrt{q_{nm}^2 + \delta_{nm}^2 + q_{nm}^2}} ,
\]

where \( q_{nm} \triangleq q_n - q_m \), constant \( G \) represents transmit and
receive antenna gains and \( \alpha \geq 1 \) the path loss exponent. We
define \( a_{nm} \) and \( \delta_{nm} \) in a similar fashion. The channel gain
is inversely related to the Euclidean distance between nodes.

Each node has a single omnidirectional antenna of maxi-
mum transmit power of \( P_{\text{max}} \) Watts. We consider half duplex
radios; each node transmits and receives over orthogonal
frequency bands. Accordingly, a different frequency band is
assigned for each node’s reception, and all messages
destined for this node are transmitted over this band, forming
a MAC. We do not allow any coding (e.g. network coding) or
combining of different data packets at the nodes, and instead
consider a decode-and-forward-based routing protocol at the
relay nodes [13]. The resulting network is a composition of
Gaussian MACs, for each of which the set of achievable
rate tuples defines a polymatroid capacity region [14]. If \( N \)
nodes simultaneously transmit independent information to
the same receiver, the received signal is a superposition of
the transmitted signals scaled by their respective channel
gains, plus an AWGN term. We model the achievable data
rates using Shannon capacity, which is a commonly used
upper bound on the practically achievable data rates subject
to average power constraints. Due to the convexity of the
capacity region, throughput maximization does not require
time-sharing between nodes [14], but may be achieved
through successive interference cancellation (SIC).

Consider a single MAC consisting of \( N \) users \( U_n, n \in \mathcal{N} \),
transmitting to a receiver \( U_m, m \not\in \mathcal{N} \). The capacity region
\( \mathcal{C}_N(\cdot, \cdot) \), which denotes the set of all achievable rate tuples \( r \),
is defined as

\[
\mathcal{C}_N(q, p) \triangleq \{ r \geq 0 \mid f_m(q, p, r, S) \leq 0, \forall S \subseteq \mathcal{N} \} ,
\]

where \( q \) is the tuple of the differences \( q_{nm} \) in positions
between the \( N \) users and the receiver, \( p \in \mathcal{P}^N \) is the
tuple of transmission powers allocated by the \( N \) users on
this channel, and \( \mathcal{P} \triangleq [0, P_{\text{max}}] \) is the range of possible
transmission powers for each user. \( f_m(\cdot) \) is a nonlinear
function bounding \( \mathcal{C}_N(q, p) \), given by

\[
f_m(q, p, r, S) \triangleq \sum_{n \in S} r_n - \frac{B_m \log_2 \left( 1 + \sum_{n \in S} \eta_{nm}( q_{nm} ) p_n / \sigma^2 \right)} ,
\]

where \( r_n \) is the \( n\text{th} \) component of \( r \), \( B_m \) is the bandwidth
allocated to \( U_m \), and \( \sigma^2 \) is the receiver noise power. Consider
the example (Section IV-B) where we do not allow relaying.
This gives rise to a MAC with \( N = 2 \) transmitters \( U_1, U_2 \)
and the AP \( U_0 \). The capacity region \( \mathcal{C}_2(q, p) \) is the set of
non-negative tuples \((r_1, r_2)\) that satisfy

\[
r_1 \leq B_0 \log_2 \left( 1 + \frac{\eta_{10}(q_{10}) p_1}{\sigma^2} \right)
\]

\[
r_2 \leq B_0 \log_2 \left( 1 + \frac{\eta_{20}(q_{20}) p_2}{\sigma^2} \right)
\]

\[
r_1 + r_2 \leq B_0 \log_2 \left( 1 + \frac{\eta_{10}(q_{10}) p_1 + \eta_{20}(q_{20}) p_2}{\sigma^2} \right)
\]

for all \((p_1, p_2) \in \mathcal{P}^2\). The first two bounds restrict individual
user rates to the single-user Shannon capacity. Dependence
between \( U_1 \) and \( U_2 \) leads to the final constraint, that the sum
rate may not exceed the point-to-point capacity with full
cooperation. For transmit powers \((p_1, p_2)\) these constraints
trace out the pentagon shown in Figure 2. The sum rate
is maximized at any point on the segment \( L_3 \). Referring
to SIC, the rate pair at boundary point \( R^{(1)} \) is achieved
if the signal from source \( U_2 \) is decoded entirely before
source \( U_1 \), resulting in the signal from \( U_2 \) being decoded at
a higher interference rate than the signal from \( U_1 \). At \( R^{(2)} \)
the opposite occurs.

B. Propulsion Energy Model

The electrical energy used for propulsion in rolling robots
has been modeled as a linear or polynomial function of speed
in [9], [15] respectively. We take a more general approach, restricting the fixed wing UAV to moving at strictly positive speeds and using Newtonian laws as a basis, as in [16]. The function $\Omega(\cdot)$ models the resistive forces acting on node $U_n$ in accordance with the following assumption.

**Assumption 1:** The resistive forces acting on each node $U_n$ may be modeled by the function $x \mapsto \Omega(x)$ such that $x \mapsto x\Omega(x)$ is convex on $x \in [0, \infty)$ and infinite on $x \in (-\infty, 0)$.

Comparatively, in the fixed wing model proposed in [17], the drag force of a UAV traveling at constant altitude at subsonic speed $v$ is

\[ \Omega(v) = \frac{\rho C_D v^2}{2} + \frac{2L^2}{(\pi \epsilon_0 A_R) \rho S v^2} \quad (5) \]

where the first term represents parasitic drift and the second term lift-induced drag. Parasitic drag is proportional to $v^2$, where $\rho$ is air density, $C_D$ is the base drag coefficient, and $S$ is the wing area. Lift induced drag is proportional to $v^{-2}$, where $\epsilon_0$ is the Oswald efficiency, $A_R$ the wing aspect ratio and $L$ the induced lift [17]. For fixed-altitude flight, $L$ must be equal to the weight of the craft $W = mg$. The power required to combat drag is the product of speed and force.

The propulsion force $F_n(\cdot)$ must satisfy the force balance equation

\[ F_n(t) - \Omega(v_n(t)) = m_n v_n(t), \quad (6) \]

where $m_n$ is the node mass, $v_n(t)$ is the speed and $\dot{v}_n(t)$ is the acceleration. The instantaneous power used for propulsion is the product $v_n(t) F_n(t)$, with the total propulsion energy taken as the integral of this power over $T$. We assume $v_n(t) \geq 0, \forall t \in T$, which is valid for fixed wing aircrafts. Thrust is restricted to the range $[F_{\text{min}}, F_{\text{max}}]$.

### C. General Continuous-Time Problem Formulation

We formulate the problem in continuous-time. At time $t$, node $U_n, n \in \mathcal{N}$ can transmit to any node $U_m, m \in \{\mathcal{N}, \mathcal{N}+1\}\setminus\{n\}$ at a non-negative data rate $r_{nm}(t)$ using transmission power $p_{nm}(t)$. The sum power used in all outgoing transmissions from $U_n$ is denoted by $p_n(t)$. From this, the set of achievable data rates is bounded above by a set of $2^{\mathcal{N}} - 1$ nonlinear submodular functions $f_m(\cdot, \cdot, \cdot)$, where $|\cdot|$ applied to a set denotes the cardinality operator. Exponential growth in the number of nodes is a computational intractability. Hence, results are limited to small or structured networks where only a subset of nodes use each MAC.

The trajectory of node $U_n$ is denoted by the tuple

\[ Y_n \triangleq (p_n, r_n, s_n, q_n, v_n, \dot{v}_n, F_n), \quad (7) \]

where $q_n(t)$ is the node’s position at time $t$ and $s_n(t)$ the state of its storage buffer subject to maximum memory of $M$ bits. The optimal control problem that we want to solve is

\[ \min_{p, r, s, q, v, F} \sum_{n=1}^{N} \int_{0}^{T} p_n(t) + v_n(t)F_n(t)dt \quad (8a) \]

s.t. $\forall n \in \mathcal{N}, m \in \{\mathcal{N}, \mathcal{N}+1\}, t \in T, S \subseteq \mathcal{N}$

\[ f_m(q(t), p(t), r(t), S \setminus \{m\}) \leq 0 \quad (8b) \]

\[ \dot{s}_n(t) = \sum_{m \neq n}^{N} r_{mn}(t) - \sum_{m \neq n}^{N} r_{nm}(t) \quad (8c) \]

\[ s_n(0) = D_n, \quad s_n(T) = 0 \quad (8d) \]

\[ q_n(0) = Q_{n,\text{init}}, \quad q_n(T) = Q_{n,\text{final}} \quad (8e) \]

\[ v_n(0) = v_{n,\text{init}} \quad (8f) \]

\[ F_n(t) = m_n \dot{v}_n(t) + \Omega(v_n(t)) \quad (8g) \]

\[ Y_{n,\text{min}} \leq Y_n(t) \leq Y_{n,\text{max}} \quad (8i) \]

The cost function (8a) is the sum of nodal transmission and propulsion energies. Constraint (8b) bounds the achievable data rate to within the receiving nodes’ capacity region, and (8c) updates the storage buffers with sent/received data. Constraints (8d) act as initial and final constraints on the buffers, while (8e)–(8h) ensure all nodes travel from their initial to final destinations without violating a Newtonian force-acceleration constraint; $\zeta_n \in \{-1, 1\}$ depending on whether the position $q_n(t)$ decreases or increases, respectively, if the speed $v_n(t) \geq 0$. The final constraint (8i) places simple bounds on the decision variables, given by

\[ Y_{n,\text{min}} \triangleq (0, 0, 0, -\infty, V_{\text{min}}, -\infty, F_{\text{min}}), \quad (9a) \]

\[ Y_{n,\text{max}} \triangleq (P_{\text{max}}, \infty, M, \infty, V_{\text{max}}, \infty, F_{\text{max}}), \quad (9b) \]

where $0 \leq V_{\text{min}} \leq V_{\text{max}}$ and $F_{\text{min}} \leq F_{\text{max}}$. The above optimal control problem may then be fully discretized using optimal control solvers, such as ICLOCS [18]. Before simulation results are presented we prove that this problem admits an equivalent convex form under certain conditions.

### III. Convexity Analysis

Efficient convex programming methods exist, which may be used in real-time applications. We first show that the nonlinear data rate constraints (8b) are convex in both positions and transmission power. We then show that the non-linear equality constraint (8g) may be substituted into the
cost function, convexifying the cost function. This, however, turns the previously simple thrust bound \( F_{\min} \leq F_n(t) \) into a concave constraint, resulting in a convex OCP if thrust bounds are relaxed. The absence of thrust bounds arises when considering a fixed trajectory, or is a reasonable assumption if the speed range is sufficiently small.

**Lemma 1:** The rate constraints (8b) are convex in powers and positions for all path loss exponents \( \alpha \geq 1 \).

**Proof:** By writing the channel gains as an explicit function of node positions, for receiver \( U_m \) each of the capacity region constraints is of the form

\[
\sum_{n \in S} r_n(t) - B_m \log_2 \left( 1 + \frac{G \sum_{n \in S} \left( a_{nm}^2 + p_n(t) + q_n(t)^2 \right)}{\sigma^2} \right) \leq 0.
\]

(10)

Since the non-negative weighted sum of functions preserves convexity properties, without loss of generality we take \( S \) to be a singleton, and drop subscripts. We also drop time dependencies. The above function is the composition of two non-positive sub-determinants. Therefore, \( \phi \) turns the previously simple thrust bound cost function, convexifying the cost function. This, however, is no coupling between nodes or between propulsion and transmission. By noting that there is no coupling between nodes or between propulsion and transmission powers in this cost, the transformation used in the general problem (8) admits an equivalent convex form. Therefore, the total cost function \( \phi(\cdot) \) is also convex.

**Removal of thrust \( F \) as a decision variable results in the set**

\[
\mathcal{V}_F \triangleq \{ v_n \mid F_{\min} \leq \Omega(v_n(t)) + m_n v_n(t) \leq F_{\max} \}.
\]

(18)

Even if \( \Omega(\cdot) \) is convex on the admissible range of speeds, the lower bound represents a concave constraint not admissible within a convex optimization framework. Therefore, dropping constraints on thrust results in a final convex formulation of

\[
\min_{v_n} \int_0^T v_n(t) \Omega(v_n(t)) dt + \frac{m_n}{2} \left( v_n^2(T) - v_n^2(0) \right)
\]

(19a)

s.t. \( \forall t \in \mathcal{T} \)

\[
V_{\min} \leq v_n \leq V_{\max}
\]

(19b)

\[
v_n(0) = v_n^{\text{init}}.
\]

(19c)

Addition of bounds \( v_n \in \mathcal{V}_F \) naturally results in a difference of convex (DC) problem [20] that may be solved through exhaustive or heuristic procedures.

**Theorem 1:** In the absence of constraints on thrust, the general problem (8) admits an equivalent convex form.

**Proof:** Non-convexities in this formulation arise from the posynomial function of speed \( v(t) \) and thrust \( F_m(t) \) in the cost function (8a), the nonlinear force balance equality (8g), and the capacity region data rate constraints (8b). The cost function is a superposition of the energies used by each node for propulsion and transmission. By noting that there is no coupling between nodes or between propulsion and transmission powers in this cost, the transformation used in Lemma 2 may be used to eliminate the nonlinear equality. We eliminate \( F_n(t) \) and \( \dot{v}_n(t) \) and move the nonlinear equality
into the objective function, simultaneously convexifying the objective to get
\[
\min_{p_n \in \mathbb{R}^N} \sum_{n=1}^N \int_0^T \left( p_n(t) + v_n(t) \Omega(v_n(t)) \right) dt + \frac{m_n}{2} v_n^2(T)
\]
\[\text{s.t. } \forall n \in N, m \in \{N, N+1\}, t \in T, v \in V^N, S \subseteq N\]
(8b)–(8f), (8h), \( Y_{n,\min} \leq Y_n(t) \leq Y_{n,\max} \)

where \( Y_n(t) \triangleq (p_n(t), r_n(t), s_n(t), q_n(t), v_n(t)) \), and the bounds \( Y_{n,\min} \) and \( Y_{n,\max} \) are similarly changed. It follows from Lemma 1 that all data rate constraints in (8b) are also convex, therefore the whole problem is convex.

IV. SIMULATION RESULTS

The open source primal dual Interior Point solver Ipopt v.3.12.4 has been used through the MATLAB interface. Table I contains parameters common to the following experiments. Force constraints are relaxed in all experiments. From [5], the speed of a typical UAV is in the range 30 to 460 km/h. All nodes are initialized to their average speeds \( v_{n,\text{init}} = (V_{\text{max}} + V_{\text{min}})/2 \). We assume all nodes move in symmetric trajectories around the AP such that \( Q_{n,\text{final}} = -Q_{n,\text{init}} = (T/2)v_{n,\text{init}} \).

A. Single Node

A single mobile node \( U_1 \) of mass 3 kg traveling at fixed altitude \( a = 1000 \text{m} \) and lateral displacement \( \delta = 0 \text{m} \), depicted in Figure 1, is considered first. In this section, simulation results are presented for the problem of minimizing the total communication energy to offload all data to \( U_0 \). This is compared to a water-filling solution [21] for minimizing the transmission energy. Subscripts denoting different nodes have been dropped in the remainder of this section. Specifically, we use \( \Omega(\cdot) \) of the form
\[
\Omega(x) \triangleq \begin{cases} 
\infty, & \forall x \in (-\infty, 0) \\
C_{D1} x^2 + C_{D2} x^{-2}, & \forall x \in [0, \infty),
\end{cases}
\]
where \( C_{D1} = 9.26 \times 10^{-4} \) is the parasitic drag coefficient and \( C_{D2} = 2250 \) is the lift induced drag coefficient [17].

Simulation results are shown in Figure 3 for a storage buffer initialized to \( D = 75 \text{MB} \) and speeds restricted in the range \( [V_{\text{min}}, V_{\text{max}}] = [30, 100] \text{km/h} \). This results in a total energy expenditure of 309.50 kJ, where 105.05 kJ is due to transmission and 204.51 kJ is due to propulsion. Of this, only 48.01 kJ of extra propulsion energy is used to vary speed on top of the base energy required to traverse the distance at a constant speed. Furthermore, the problem would have been infeasible if the node was restricted to a constant speed of 65 km/h. We note that, with the given parameterization, it is possible to transmit up to 78 MB of data in the defined time interval.

| \( \sigma^a \) [W] | \( B \) [Hz] | \( M \) [GB] | \( P_{\text{max}} \) [W] | \( \alpha \) | \( T \) [min] |
|---|---|---|---|---|---|
| \( 10^{-10} \) | \( 10^2 \) | 1 | 100 | 1.5 | 20 |

**TABLE I:** Dynamic model parameters that have been used across all simulation results.

In comparison, if the speed of \( U_1 \) is fixed, then the maximum transmittable data is approximately 56 MB, using 120.00 kJ of transmission energy. Although considerably more energy is used, the optimal power policy for a fixed trajectory is characterized by a water-filling solution, an equivalent proof of which may be found in [21]. This problem results in a one dimensional search space, easily solved through such algorithms as binary search.

B. Multiple Nodes

We now investigate the transmission energy problem for two nodes, traveling in parallel trajectories at fixed speeds such that \( V_{\text{max}} = V_{\text{min}} = 65 \text{km/h} \), as depicted by the green lines in Figure 1. Relaying is not allowed, as may be the case if no bandwidth is allocated to \( U_1 \) and \( U_2 \) to receive each other’s transmissions, equivalently turning them into pure source nodes. Simulation results are presented in Figure 4. \( U_1 \) is closer to the AP at all times, and therefore is advantaged in that it experiences more favorable channel conditions. The disadvantaged node \( U_2 \) transmits for a longer duration due to the smaller relative change in its channel gain. The interior point algorithm converged after 42 iterations to a minimum energy of 52.707 kJ and 26.77 kJ for \( U_1 \) and \( U_2 \), respectively, for a starting data load of \( D_1 = D_2 = 25 \text{MB} \).

It is notable that the advantaged node uses considerably more transmission energy than the disadvantaged node. Referring to [22], which derives two-user optimal power allocations that achieve arbitrary rate tuples on the boundary of \( C \) we explain this as follows. From Figure 2, the optimal rate pairs for given transmit powers \( p_1 \) and \( p_2 \) lie on the
We may interpret \( \varrho = 1 \) means that data from \( U_1 \) is being decoded second, subject to a lower noise rate, while \( \varrho = 0 \) means the opposite decoding order. We may think of the mapping \( \varrho \) as being the priority assigned to each transmitting node by the \( U_0 \) when SIC is being carried out. \( \varrho = 1 \) means data from \( U_1 \) is being decoded second, while \( \varrho = 0 \) means the opposite decoding order. We may think of the mapping \( t \mapsto \varrho(t) \) as a time-varying priority. However, by calculating \( \varrho(t) \) from the optimum powers and rates seen in Figure 4, we find that \( \varrho(t) = 0, \forall t \in \mathcal{T} \) such that \( p_1(t) > 0, p_2(t) > 0 \). In other words, the disadvantaged node is always given priority, which is why it uses less energy at the optimum, even though it always experiences a worse channel gain.

V. CONCLUSIONS

We have presented a general optimization framework for joint control of propulsion and transmission energy for single/multi-hop communication links in robotic networks. The relaxation of transmission constraints to theoretic capacity bounds, with relatively mild assumptions on the mobility model, results in a nonlinear but convex OCP. We showed that optimizing over a fixed path, as opposed to a fixed trajectory, increases the feasible starting data by at least 30% for just a single node. For the fixed-trajectory two-node MAC simulation, the optimal solution has been presented and analyzed. Immediate extensions of this work include higher fidelity models, and analysis of the relay network encompassed in problem (8). Considering the overarching goal of real-time control, further developments will be closed-loop analysis of the control strategy, and consideration of the computational burden and energy expenditure [3], [23] in the network.

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