A Novel Flocking Inspired Algorithm for Self-Organization and Control in Heterogeneous Wireless Networks

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Abstract—**This paper presents a new model and algorithm for slef-organization and control of a class of next generation communication networks: hierarchical heterogeneous wireless networks (HHWNs), under real world physical constraints. A nature inspired flocking algorithm (FA) is investigated in this context. Our model is based on the control framework at the physical layer presented previously by the authors, where network robustness is characterized in terms of the system's potential energy, and control mechanisms are designed to minimize potential energy for optimized network performance. We first focus on the modeling of HHWNs under real world physical constraints. Second, we propose a new FA for self-organization and control of the backbone nodes in an HHWN by collecting local information from end users. Our algorithm is examined in our built simulation platform that supports various dynamic scenarios. Experimental results demonstrate that FA outperforms current algorithms for the self-organization and optimization of HHWN under real world physical constraints.**

Index Terms —**Heterogeneous wireless networks, directional wireless communication, self-organization, flocking algorithm.**

I. INTRODUCTION

Recent advances in directional wireless communications for providing broadband wireless solutions are making next generation communication networks increasingly complex. These networks are characterized by hierarchical architectures, with heterogeneous properties and dynamic behavior. The need for ubiquitous broadband connectivity and the capacity limitation of homogeneous wireless networks is driving communication networks to adopt hierarchical architectures with diverse communication technologies and node capabilities at different layers that provide end-to-end broadband connectivity in a wide range of scenarios [1-3]. In particular, HHWNs use a wireless backbone network consisting of a set of base station or backbone nodes that use directional wireless communications to provide end-to-end broadband connectivity to capacity-limited ad hoc networks and/or end hosts. As an example, backbone-based wireless networks use a two-tiered network infrastructure, which consists of a set of flat ad-hoc wireless networks and a broadband wireless mesh backbone network of higher capability nodes. In this architecture, backbone nodes use directional wireless communications, either free space optical (FSO) or directional radio frequency (RF), to aggregate and transport traffic from hosts at lower layers. The advantages of directional wireless communications can be well exploited at the upper layer, where line of sight constraints are less restrictive and interference-free, point-to-point communication links can provide extremely high data rates [1-3].

The most important concern in HHWNs is to assure network coverage and backbone connectivity in dynamic wireless environments. Llorca et al. [4] first proposed a quadratic optimization method to jointly control network coverage and backbone connectivity. They defined a quadratic energy function to characterize the robustness of HHWNs and designed a force-driven algorithm that dynamically drives the network topology to minimum energy configurations based on local forces exerted on network nodes. A quadratic model of the energy function was then extended to an exponential model that takes into account the effects of atmospheric attenuation on the propagation of electromagnetic energy in directional wireless links [5]. The convex energy model was used by the authors to develop an Attraction Force Driven (AFD) algorithm, where the net force used to relocate the backbone nodes is computed as the negative gradient of the energy function at the backbone nodes locations. By considering practical power limitation constraints at the network nodes, recently Llorca et al. [1] further extended the energy model using the Morse potential [6], i.e. Morse Force Driven (MFD) algorithm, such that the convex energy function [5] was transformed into a non-convex function where communication energy saturates with distance emulating the effects of link breaking due to power limitation constraints. Based on this non convex energy model, the authors developed a hybrid control model where communication links are retained or released autonomously based on their cost within the network architecture [1]. Although these models take into account some constraints on communication links such as transmitted power limitations, a comprehensive model with real world physical constraints such as taboo areas has not yet been developed.

In this work, we show that when adding real world constraints into the problem, such as power limitations, capacity of the base stations and blockage from terrain, the problem can no longer be formulated as a convex optimization problem. This research thus focuses on the modeling of HHWNs under real world physical constraints at the physical layer, and the development of effective biology-inspired algorithms for topology control in dynamic scenarios.

II. Network Control Model

The topology control problem in HHWNs can be effectively formulated as a potential energy minimization problem [4, 5]. Llorca et al. defined the potential energy of a communications network as the total communications energy stored in the wireless links forming the network, as follows:

$$\begin{array}{l} U(b_{ij}, h_{ik}, B_1, B_2, ..., B_N) = \\ \alpha \cdot \sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u(B_i, B_j) + \sum_{i=1}^{N} \sum_{k=1}^{M} h_{ik} u(B_i, T_k) \end{array}, \quad (1)$$

where B_i is the location of backbone node i, T_k is the location of terminal node k, N is the number of backbone nodes, M is the number of terminal nodes, α ($\alpha \geq 0$) is a weighting parameter to balance the energy used for forming the mesh backbone network and covering end hosts, b_{ij} and h_{ik} are the binary variables, which are given by

$$b_{ij} = \begin{cases} 1 & if(i,j) \in \Lambda_B \;\; is \quad connected \\ 0 & otherwise \end{cases}, \quad (2)$$

where Λ_B refers to the backbone topology, and

$$h_{ik} = \begin{cases} 1 & if(i,k) \in \Lambda_T \;\; is \quad connected \\ 0 & otherwise \end{cases}, \quad (3)$$

where Λ_T refers to the coverage topology, i.e. $h_{ik} = 1$ indicates that backbone node i covers terminal node k. The measurement of communication cost $u(B_i, B_j)$ is usually associated with the Euclidean distance between link ends (i, j) and is precisely defined as the communications energy per unit time required to send information from node i and node j at the specified BER (bit error rate) [2, 5]

$$u_{ij} = P_{R0}^{j} \frac{4\pi}{D_T^i A_R^j} (\exp(\gamma ||B_i - B_j||))(||B_i - B_j||^2), \quad (4)$$

where P_{R0}^{j} is the minimum received power, D_T^i is the directivity of the transmitter antenna, A_R^j represents the effective receiver area and γ is the scattering coefficient [7].

Note that the first term in the cost function in Eq. (1), denoted by U_{BB}, represents the total energy stored in the directional wireless links forming the mesh backbone network, and the second term in Eq. (1), denoted by U_{BT}, represents the total energy stored in the wireless links covering the end hosts. Thus, U_{BB} measures the cost for the backbone connectivity, and U_{BT} measures the cost for network coverage [4].

The topology control problem in HHWNs is then formulated as an energy minimization problem of the following form:

$$\min\{U(b_{ij}, h_{ik}, B_1, B_2, ..., B_N)\}(B_i = (x_i^b, y_i^b, z_i^b), B_i \in {}^3), \quad (5)$$

which is subject to Eqs. (2) and (3). Note that the optimization problem formulated in Eq. (5) is performed over: b_{ij}, the assignment of directional wireless links between backbone nodes; h_{ik}, the assignment of wireless links between backbone nodes and covered end users; $(B_1, B_2, ..., B_N)$, the location of the N backbone nodes. But the link assignments b_{ij} and h_{ik}, and the location of backbone nodes $(B_1, B_2, ..., B_N)$ must be subject to real world physical constraints, which include:

- **Power limitation**: refers to the maximum power at a transmitter. In practice, the increase in transmitted power needed to maintain a given link BER is limited by the maximum power at the transmitter. Both backbone nodes and terminal nodes have power limitations because either of them might be a transmitter or a receiver.
- **Traffic capacity**: refers to the maximum traffic that a backbone node can receive and transfer. In this paper, the capacity of a backbone node is defined as the maximum number of terminal nodes a base station can handle.
- **Distance threshold**: is defined as the minimum distance for a backbone node to avoid collisions with another backbone node or a terminal node.
- **Taboo areas**: refers to constraints imposed by the physical world such as geographic obstacles (e.g. mountains and high-rise buildings), undesired weather events (e.g. heavy clouds or regions of precipitation), and security areas (e.g. signals are fully blocked due to security requirements). It is worth noting that these taboo areas are dynamic. Note that the taboo area, for a particular backbone node changes dynamically with the movement of the end user (here, we assume total blockage if there is no direct line of sight between end user and backbone node; in fact, the signal attenuation due to blockage can be incorporated into the link energy function in Eq. (4)).

Let Θ represent the set of physical constraints, which includes power limitation C_p, traffic capacity of backbone nodes C_c, minimum physical distance C_d, and taboo areas C_t, i.e. $\Theta = \{C_p, C_c, C_d, C_t\}$, then the optimization problem described in Eq. (5) is transformed into

$$\begin{array}{l} \min\{U(b_{ij}, h_{ik}, B_1, B_2, ..., B_N)\} \\ s.t. \quad \Theta = \{C_p, C_c, C_d, C_t\} \end{array}. \quad (6)$$

The energy based models such as AFD model [4] and MFD model [1], while leading to efficient, scalable and physically accurate control methods for self-organization in HHWNs, are parameter-sensitive and require knowledge of the dynamics of the channel as well as explicit formulations, which can be difficult to obtain when considering dynamic taboo areas such as atmospheric agents and terrain. Furthermore, the presence of taboo areas makes gradient-based methods not able to guarantee convergence to global optimal solutions. Therefore, in this research, we propose to use a novel approach for the self-organization and optimization of HHWNS, which do not require explicit knowledge of the channel nor rely on gradient methods: FA, which uses heuristic forces based on local information for the system's self-organization.

III. Flocking Algorithm

The earliest works on flocking are derived from the animation of flocking dynamics of birds. Reynolds et al. [8] developed a basic flocking model using three simple steering rules to control individual agents in the flock. These steering rules [8] include

- **Alignment**: steer to move toward the average heading of neighboring flock mates,
- **Separation**: steer to avoid collision with other local flock mates,
- **Cohesion**: steer to move toward the average position of neighboring flock mates.

The size of a neighborhood is determined by the sensor range of a flocking agent. Since the movement of an agent is only based on local information, the computational time complexity is significantly reduced. These three rules in Reynolds's model [8] are sufficient to emulate the group behavior in nature.

Recall that the objective in HHWNs is to optimize the total energy cost of the system while guaranteeing end-to-end communications with physical constraints. We indicate that the use of energy functions makes it challenging to obtain the objective when considering physical constraints that we include in this research. In this section, we develop a new flocking algorithm that uses heuristic forces to straightforwardly model the effects of various constraints on the network, while preserving the distributed nature and low time complexity of the entire system.

A. Flocking Rules

In this paper, each backbone node represents an agent in a flock. A terminal node $T_k(s)$ is assumed to be stationary during the movement of backbone nodes due to the time delay, which is consistent with practical situations. Here s represents the time series of terminal node dynamics. Thus time $t \in [0, t_{\max}]$ (t_{max} is the stopping time point) with respect to backbone nodes is a sub-interval of $[s-1, s]$ with respect to terminal nodes. A backbone node i at time t is characterized by its location $B_i(t)$ associated with the real coordinates $(x_i^b(t), y_i^b(t), z_i^b(t))$ and its force vector (or velocity vector) $\upsilon_i(t)$. Let $b_{ij}(t)$ and $h_{ik}(t)$ be the link assignment variables for backbone-to-backbone links and backbone-to-terminal links at time t, respectively. The forces acting on backbone node i include

- **Survival force**: makes a backbone node to try to maintain connection to those terminal nodes it had covered at the last time period $s-1$. This force enables the effective reduction in the loss of the closest terminal nodes to backbone node i due to the existence of taboo areas such as geographic constraints. The force is given by

$$\upsilon_{agn}^{i} = \frac{\sum_k^M \delta(h_{ik}(s-1)=1)(T_k(s-1) - B_i(t))}{\sum_k^M \delta(h_{ik}(s-1)=1)}, \tag{7}$$

where $\delta(\cdot)$ is an indicator function (its value is 1 if the statement within its argument is true, and 0 otherwise).

- **Repulsion force**: is produced by three sources: terminal nodes covered by the backbone node i at the bottom layer in HHWNs, neighbor backbone nodes connected to backbone node i at the upper layer, and the terrain. The whole repulsion force is determined by

$$\upsilon_{pul}^{i} = \upsilon_{pul}^{i,BT} + \upsilon_{pul}^{i,BB} + \upsilon_{pul}^{i,ter}, \tag{8}$$

$$\upsilon_{pul}^{i,BT} = -\frac{\sum_k^M \delta(H_{sta})\delta(D_{sta}^{pul,BT})(T_k(s) - B_i(t))}{\sum_k^M \delta(H_{sta})\delta(D_{sta}^{pul,BT})}, \tag{9}$$

$$\upsilon_{pul}^{i,BB} = -\frac{\sum_j^N \delta(b_{sta})\delta(D_{sta}^{pul,BB})(B_j(t) - B_i(t))}{\sum_j^N \delta(b_{sta})\delta(D_{sta}^{pul,BB})}, \tag{10}$$

$$\upsilon_{pul}^{i,ter} = \delta(Z_{sta})((0,0,z_i^{b,pro}(t)) - B_i(t)), \tag{11}$$

where, H_{sta} denotes the statement $(h_{ik}(t)=1)$, $D_{sta}^{pul,BT}$ denotes the statement $(d_{BT}(T_k(s), B_i(t)) \leq d_{th,pul}^{BT})$, b_{sta} denotes the statement $(b_{ij}(t)=1)$, $D_{sta}^{pul,BB}$ denotes the statement $(d_{BB}(B_j(t), B_i(t)) \leq d_{th}^{BB})$, Z_{sta} denotes the statement $(z_i^b(t) - z_i^{b,pro}(t) \leq d_{th}^{ter})$, $d_{B\cdot}(\cdot) = ||\cdot||$ is a distance function, $d_{th,pul}^{BT}$ is the distance threshold between backbone nodes and terminal nodes, d_{th}^{BB} is the distance threshold between backbone nodes, d_{th}^{ter} is the minimum distance between a backbone node and the ground, which is measured by the height difference in the z coordinate, i.e. $z_i^b(t) - z_i^{b,pro}(t)$. Note that the exerted repulsion force $\upsilon_{pul}^{i,ter}$ avoids collision with mountains or other obstacles on the ground. The repulsion force also contributes to the balance between network coverage and backbone connectivity and reduces the risk of solutions getting stuck in local minima, which it can be observed from the experiments presented in section 4.3.

- **Retention force**: is produced by two sources and it is calculated according to

$$\upsilon_{ten}^{i} = \upsilon_{ten}^{i,BT} + \upsilon_{ten}^{i,BB}, \tag{12}$$

$$\upsilon_{ten}^{i,BT} = \frac{\sum_k^M \delta(H_{sta})\delta(D_{sta}^{ten,BT})(T_k(s) - B_i(t))}{\sum_k^M \delta(H_{sta})\delta(D_{sta}^{ten,BT})}, \tag{13}$$

$$\upsilon_{ten}^{i,BB} = \frac{\sum_j^N \kappa_{ij}\delta(b_{sta})\delta(D_{sta}^{ten,BB})(B_j(t) - B_i(t))}{\sum_j^N \delta(b_{sta})\delta(D_{sta}^{ten,BB})}, \tag{14}$$

where, $D_{sta}^{ten,BT}$ denotes the statement $(d_{th,pul}^{BT} \leq d_{BT}(T_k(s), B_i(t)) \leq d_{th,lea}^{BT})$, $D_{sta}^{ten,BB}$ denotes the statement $(d_{th}^{BB} \leq d_{BB}(B_j(t), B_i(t)))$, $d_{th,lea}^{BT}$ is another distance threshold between backbone nodes and terminal nodes (we explain it in the following section), and κ_{ij} is a coefficient that considers the effect of sharing the load between backbone nodes, which is defined by

$$\kappa_{ij} = \exp\left(\frac{R_j - \sum_k^M \delta(H_{sta}) + \sum_k^M \delta(H_{sta})}{R_j}\right), \tag{15}$$

where R_j is the capacity of the backbone node j.

- **Release force**: is used to consider the effect of power limitation, which is controlled by a distance threshold $d^{BT}_{th,lea}$. Here, we only consider the release force between backbone nodes and terminal nodes because a large power between backbone nodes is usually available in practice to assure the connectivity at the upper layer. The release force is given by

$$\upsilon^i_{lea} = \frac{\sum_{k=1}^M \gamma_{ik}\delta(H_{sta})\delta(D^{lea,BT}_{sta})(T_k(s) - B_i(t))}{\delta(H_{sta})\delta(D^{lea,BT}_{sta})}, \tag{16}$$

where, $D^{lea,BT}_{sta}$ denotes the statement $(d^{BT}_{th,lea} \leq d_{BT}(T_k(s), B_i(t)))$, and γ_{ik} is a release coefficient determined by

$$\gamma_{ik} = \exp\left(-\varepsilon\left(d_{BT}\left(T_k(s), B_i\left(t\right)\right) - d^{BT}_{th,lea}\right)\right), \tag{17}$$

in which ε is a positive constant with small value, in this paper we set $\varepsilon = 0.001$.

In order to achieve comprehensive flocking behavior, we sum up all the forces described above to obtain a net velocity for the backbone node i as follows

$$\upsilon_i(t) = \upsilon^i_{ten}(t) + w_p\upsilon^i_{pul}(t) + w_l\upsilon^i_{lea}(t) + w_a\upsilon^i_{agn}(t), \tag{18}$$

where w_p, w_l, w_a are positive weighting parameters to balance the effects of the different forces. Then the location of backbone node i is updated according to the following

$$B_i(t+1) = B_i(t) + \rho \cdot \upsilon_i(t). \tag{19}$$

Based on this flocking model, we are capable of straightforwardly addressing constraints such as power limitation with the use of the release force υ^i_{lea}, capacity with the use of the sharing function κ_{ij}, distance threshold with the use of the repulsion force υ^i_{pul}, and taboo areas with the use of the survival force.

B. Algorithm and Implementation

Our FA algorithm is developed using the above flocking rules and based on discrete time. Suppose all the terminal nodes update their positions synchronously at every time interval $[s, s+1]$ (e.g. every minute), and all the backbone nodes move synchronously to update their positions and velocities at every time step t until the movement of each backbone node is smaller than a pre-defined resolution μ, i.e. $||B_i(t) - B_i(t-1)|| \leq \mu$, or the maximum number of iterations t_{max} is satisfied. Given a new input of coordinates of all the terminal nodes $\{T_k(s)\}$ $(k = 1, 2, ..., M)$, the initial locations (i.e. the old locations at last time interval) of the backbone nodes $\{B_i(0)\}$ $(i, j = 1, 2, ..., N)$, we first calculate the coverage topology $h_{ik}(0)$ $(i = 1, 2, ..., N$; $k = 1, 2, ..., M)$ while satisfying physical constraints. In the current implementation, the constraints with respect to taboo areas only include mountains in a 3-D space with full terrain information. A large number of mountains with different heights are randomly generated. In the simulation environment, we partition the x-y plane with a fixed grid size, which is fine enough to produce satisfactory resolution, corresponding to a terrain matrix $A_{terrain} = [a_{pq}]_{m\times m}$, where each component represents the altitude of a point in the x-y plane. Given a terminal node with location $T_k = (x^t_k, y^t_k, z^t_k)$ and a backbone node located at $B_i = (x^b_i, y^b_i, z^b_i)$, we have developed an effective approximation algorithm to evaluate if there is direct line of sight between the terminal node T_k and the backbone node B_i bearing in mind the location of mountains. In this research we only consider blockage between terminal nodes and backbone nodes, as the backbone nodes are usually located at fixed high altitudes. It is easy to extend our approach to include blockage between backbone nodes in military applications. The terrain checking algorithm is aided by the interpolation function 'interp1' from the MATLAB toolbox (we used MATLAB as our simulation environment).

Forming the coverage topology, we first check the constraints from the terrain. The basic idea is that each terminal node will first connect to its closest backbone node. If there is no line of sight between them, we put the backbone node into a taboo archive and connect to the second closest backbone node. The process stops when a connection is achieved that satisfies the geographic constraints. If there is no line of sight for all the backbone nodes, the terminal node is considered isolated. We then consider the capacity constraint R_i $(i = (1, 2, ..., N))$, i.e. the maximum number of terminals that can be connected to each backbone node. In other words, if the number of terminals n_i connecting to backbone node i exceeds the capacity R_i, we reconnect $(n_i - R_i)$ terminals to other backbone nodes. The selection of terminal nodes that need to be reconnected is based on the minimum-energy-cost-first principle. The capacity checking process is similar to the geography checking algorithm, but the reconnection to other backbone nodes is required to first satisfy the geographic algorithm, i.e. the geography checking algorithm is embedded in this process. Finally, the overall implementation for the flocking algorithm is summarized as follows

1) Given the initial positions of terminal nodes $\{T_k(0)\}$, the physical constraints $\Theta = \{C_p, C_c, C_d, C_t\}$, set time $s = 0$ for the dynamics of terminal nodes.
2) Given the initial positions of backbone nodes $\{B_i(0)\}$, set time $t = 0$ for the dynamics of backbone nodes.
3) Set time $t \leftarrow t + 1$, use the topology configuration algorithm [9] to determine $\{b_{ij}\}$, then check the geographic constraints and the capacity constraints for all the terminal nodes to determine the coverage topology $\{h_{ik}\}$.
4) Calculate the force or velocity $\upsilon_i(t)$ for the backbone node i according to Eq. (18).
5) Update the positions of backbone nodes $\{B_i(t)\}$ ac-

cording to Eq. (19).

6) Evaluate $||B_i(t)-B_i(t-1)||$ for each backbone node, if $||B_i(t)-B_i(t-1)|| \leq \mu$, then fix the current position of backbone node i. If the maximum number of iterations $t_m ax$ is satisfied, go to Step 7); otherwise, go to step 3).
7) Set time $s \leftarrow s+1$, terminal nodes move to new positions $\{T_k(s)\}$, i.e. the new dynamics from terminal nodes. Set $B_i(0) \leftarrow B_i(t)$ for each backbone node, and go to step 2) until simulation is over.

Note that the FA can be executed in a distributed manner because each backbone node only uses local information from neighbor backbone nodes and the terminal nodes in its coverage range. It is difficult to provide an explicit form with respect to the computational time complexity of the whole system due to the heterogeneous dynamics of the end users. In each time step t, the computational time complexity approximates to $O(NM)$, where we do not take into account the computation time required for the geography and capacity checking algorithms. In practice, geographic information can be directly obtained by the system almost in real time. The computational time with respect to the capacity checking algorithm is closely related to the dynamics of the end users and backbone nodes. Thus, FA is able to maintain the distributed nature and low time complexity of the entire system, while significantly improving the system's performance over existing algorithms (as will be shown in the next section).

IV. Experiments

A. Experimental Setup

In order to verify the performance of our proposed self-organization and optimization algorithm for HHWNs, we conducted experimental studies and present the corresponding results for the dynamic scenario in which the HHWN includes 100 terminal nodes and 10 backbone nodes, i.e. $M = 100$, $N = 10$. In all simulations, M terminal nodes are distributed over a $50\mathrm{km} \times 50\mathrm{km}$ plane and organized in clusters using the Minimum Spanning Tree algorithm [10]. N_m mountains are randomly generated in this plane with a maximum height of 1.6km (we set $N_m = 80$ in this research). The altitudes of terminal nodes are updated according to the terrain. The backbone network in the upper layer is constructed using N backbone nodes forming a ring topology. We use ring topologies for the backbone network to assure resilience through bi-connectivity. Terminal nodes move according to the RPGM model [11]. We place the backbone nodes at an altitude of 2 km, which indicates the backbone nodes move in 2D space (i.e. x-y plane), and compare FA to the AFD model [4] and the MFD model [1]. FA, AFD and MFD are used to make backbone nodes adjust their locations until convergence to the best possible backbone configuration.

In our experiments, FSO links with 2 mrad half beam divergence are used for the backbone-to-backbone links and RF links with $\pi/4$rad half beam divergence for the backbone-to-terminal links. The minimum required received power used

TABLE I
COMPARATIVE RESULTS OF ENERGY COST

Time		0	1	2	3	4	5	6	7	8	9	10
FA	Initial	3100.7	650.2	813.6	617.1	621.2	537.7	534.5	511.4	510.8	634.8	674.5
	Optimized	654.5	798.5	565.6	564.3	511.8	507.1	466.2	442.5	555.3	598.4	631.2
MFD	Initial	3100.7	1623.1	1061.8	767.8	700.1	633.7	568.5	585.3	641.8	757.5	936.0
	Optimized	1749.6	1545.1	799.7	747.7	671.8	584.4	537.3	541.4	606.9	815.2	837.1
AFD	Initial	3100.7	680.4	816.5	724.1	632.7	583.8	517.1	496.9	548.5	634.9	956.5
	Optimized	663.3	815.7	692.2	644.3	573.7	501.2	458.7	492.6	560.5	916.6	727.5

TABLE II
NUMBER OF LOSS OF CONNECTIONS

Time		0	1	2	3	4	5	6	7	8	9	10
FA	Initial	4	1	1	0	0	0	0	0	0	0	0
	Optimized	1	1	1	0	0	0	0	0	0	0	0
MFD	Initial	4	2	1	0	0	0	0	0	0	0	0
	Optimized	3	1	1	0	0	0	0	0	0	0	0
AFD	Initial	4	1	1	0	0	0	0	0	0	0	0
	Optimized	1	1	1	0	0	0	0	0	0	0	0

was -45 dBm (31.6 nW) for all network nodes. The scattering coefficient γ is set to zero. We set the power limitation for both backbone nodes and terminal nodes at $P_{\mathrm{Tmax}} = 5\mathrm{W}$. The configuration of parameter settings for FA is: the distance threshold for the backbone-to-terminal links $d_{th,pul}^{BT} = 2\mathrm{km}$, the distance threshold for the backbone-to-backbone links $d_{th}^{BB} = 10\mathrm{km}$, the threshold to control the release force $d_{th,lea}^{BT} = 10\mathrm{km}$, all the weighting parameters used in Eq. (18) $w_p = 1$, $w_l = 1$ and $w_a = 1$, the step size used in Eq. (19) $\rho = 0.01$, the resolution $\mu = 0.1$, capacity of each backbone node $R_i = 40$, and maximum number of iterations for FA $t_{max} = 2000$. The basic parameter settings for the AFD model [4] and MFD model [1] follow the FA setting. All the scenarios were run continuously for 10 minutes in simulated clear atmosphere conditions.

B. Performance Metrics

We use three metrics, which are energy cost, loss of connections (LC), source-to-destination (SD) and standard deviation of communication load in backbone nodes, to evaluate the performance of the different algorithms including FA, AFD [4] and MFD [1]. The metrics are specified as follows

- **Energy cost** U: the total communication energy stored in the wireless links as defined in Eq. (1) (here, $\alpha = 1$), i.e.

$$\begin{aligned} U = &\textstyle\sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u(B_i, B_j) \\ &+ \textstyle\sum_{i=1}^{N} \sum_{k=1}^{M} h_{ik} u(B_i, T_k) \end{aligned} . \quad (20)$$

- **Loss of connections** U_{LOS}: the number of isolated end users (terminal nodes) that are not able to connect to any backbone node due to physical constraints. Its definition is described as

$$U_{LOS} = (M - \sum_{i=1}^{N} \sum_{k=1}^{M} h_{ik}). \quad (21)$$

- **Source-to-destination** U_{SD}: note that wireless links will not always be available with respect to power constraints. Exceeding link distances and atmospheric obscuration

TABLE III
PERFORMANCE OF AVERAGE ENERGY COST

Algorithm	Initial	Optimized	Energy Save
FA	836.95	572.31	31.62%
MFD	1034.20	857.84	17.05%
AFD	881.10	640.57	27.30%

TABLE IV
COMPARATIVE RESULTS OF SOURCE-TO-DESTINATION

	Time	0	1	2	3	4	5	6	7	8	9	10
FA	Initial	1122	3080	2352	3306	3422	4556	4032	4290	4032	3906	3782
	Optimized	3442	3660	4160	4160	4556	4422	4556	5122	4692	4422	4556
MFD	Initial	1122	1560	3660	4160	4160	4830	5112	5852	5550	4556	4970
	Optimized	2652	4032	4160	4422	4692	5256	5402	5550	5256	4970	5112
AFD	Initial	1122	3422	3422	3422	3306	3782	3906	4290	4160	3906	3906
	Optimized	3660	3660	3540	3540	4160	4556	4692	4970	4422	4290	3906

will cause link breaks that will terminate SD connections in the network [1]. Here, SD refers to the number of SD pairs for which a path exists between them, which is defined as

$$U_{SD} = \sum_{i=1}^{N_s} n_{s_i}(n_{s_i} - 1), \qquad (22)$$

where N_s represents the number of clusters or connected components at the backbone network and n_{s_i} represents the number of terminal nodes connected to a backbone node in cluster s_i.

C. Results and comparison

In this section, we compare the performance of our proposed algorithm, i.e. FA, to AFD [4] and MFD [1] based on the above defined metrics. Table I lists the energy costs of the system at the starting point and at the end of each time interval during 10 minutes. For each interval, we list the results based on the initial configuration of the HHWN and the results after the optimization by the algorithms. On the other hand, we summarize the results associated with LC in Table II. We clarify that a large value of LC brings low the energy cost, but results in bad quality of service. Based on the similar results for LC, it is observed that FA delivers better results compared to AFD and MFD in overall simulation time. Table III shows the average energy cost for the different algorithms according to Table I. FA saves 31.62% energy, which significantly outperforms AFD and MFD. Another observation is that the value of the energy cost produced by FA during minutes 4, 7, 9 and 10 oscillates, which is caused by the pre-defined resolution μ. In terms of the SD metric, we compare the results in Table IV for every time interval and also summarize the average SD in Table V. From minute 3 to minute 7, MFD produces a larger number of SD connections than FA and AFD, but FA delivers a more significant improvement based on average SD connections as shown in Table V. It is noted that although MFD achieves a large number of average SD connections, the improvement it delivers is relatively small due to the large initial number of SD connections.

TABLE V
PERFORMANCE OF AVERAGE SOURCE-TO-DESTINATION

Algorithm	Initial	Optimized	Energy Save
FA	3443.6	4340.7	26.05%
MFD	4139.3	4682.2	13.12%
AFD	3513.1	4126.9	17.47%

V. CONCLUSIONS AND FUTURE WORK

This paper presents a new framework to model and optimize HHWNs under real world physical constraints. First, we propose a mathematical modeling method for the self-organization and optimization of HHWNs by taking into account physical constraints. Second, using only local information, we develop new flocking rules and a corresponding algorithm to autonomously assure and optimize network performance in a practical way. Experimental results confirm that FA outperforms current algorithms. FA is capable of maintaining the distributed nature and low complexity of the system while achieving improved performance associated with the dynamic configuration of an HHWN under real world physical constraints. Furthermore, with the use of FA, the backbone nodes can move flexibly in 3D space by taking into account the repulsion force from physical constraints (e.g. mountains). In future work, we plan to investigate our algorithms in more complex dynamic environments. We also note that the stability analysis of dynamic HHWNs is still an open problem. We plan to conduct a theoretical analysis of the stability of an HHWN in the context of self-organization and control.

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