ABSTRACT

In our attempts to model, characterize and control increasingly complex network systems we introduced a novel physics framework in which communication networks are modeled as physical systems that react to local forces exerted on network nodes. We showed that under clear atmosphere conditions the network communication energy can be modeled as the potential energy of an analogous spring system, which led to the development of distributed mobility control algorithms where nodes react to local forces exerted by neighbor nodes driving the network to energy minimizing configurations. This paper extends our previous work by including the effects of atmospheric attenuation in the channel. We show how our new formulation still results in a convex energy minimization problem. Accordingly, an updated force-driven mobility control algorithm is presented. Exponential forces are shown to appear on backbone nodes when atmospheric attenuation is present, which make them stay closer to each other to optimize backbone connectivity and reduce the network power usage. We present results in terms of power usage, network coverage and backbone connectivity and show how our updated mobility control algorithm allows the network to react to the effects of changing channel conditions.

MOTIVATION

In a flat network architecture, all wireless nodes are homogeneous in terms of their communication capabilities. It is well known that the throughput capacity of a flat wireless network architecture without an infrastructure support is not scalable as the number of nodes becomes large [1]. Consequently, in order to meet the increasing communication demands of wireless users, it is necessary to supplement the wireless network with a higher layer of communication mode. This new communication mode enables a small group of nodes to communicate with each other over longer distances and at higher bit rates than the ordinary wireless nodes. We refer to these nodes as base station or backbone nodes. Such nodes are equipped with a hybrid communication mode that enables them to communicate with both the terminal wireless nodes and the other base station nodes. Base station nodes form a backbone for the network, through the use of point-to-point communication technologies such as free space optical communication, fiber optic communication, directional antennas, etc.

Fig. 1 illustrates this 2-tiered network architecture. The lower tier consists of a set of flat ad-hoc networks based on standard diffused RF technology, while the higher tier forms a mesh backbone network consisting of base station nodes connected using directional wireless communication technologies [2]. We refer to the higher tier as the directional wireless backbone (DWB). The advantages of directional wireless communications, which combine the high capacity of point-to-point interference-free communication systems with the flexibility of wireless communication technologies, are used at the backbone layer to provide end-to-end wireless broadband connectivity.

In a backbone-based wireless network architecture, a communication between two terminal wireless nodes takes place by a multi-hop transmission scheme over the wireless nodes until the traffic of the source reaches one of the backbone nodes, then it travels over the backbone network until it reaches a backbone node which is close enough to the intended destination, and finally it travels over a few wireless nodes until it reaches its destination. From a networking point of view, some of the most important design aspects of this architecture are: the required number of backbone nodes for a certain target performance, and the efficient placement of the backbone nodes in the network.

Moreover, DWB networks must provide robust end-to-end broadband connectivity in a dynamic wireless environment, where the state of wireless links is constantly changing due to node mobility and atmospheric obscuration [3]. The DWB topology, as defined by the location of the backbone nodes and the connections between them, needs to adjust to the changing environment. Thus, it is important to provide the DWB with the capability of autonomous reconfiguration. The
locations of the backbone nodes need to be updated in order to dynamically meet the wireless users’ demands.

This paper focuses on the design of an adaptive mobility control scheme for providing robust end-to-end connectivity in dynamic backbone-based wireless networks. Network robustness is addressed in terms of the following two main objectives: network coverage and backbone connectivity. The DWB must provide coverage to as many wireless nodes as possible and maintain robust backbone connectivity. These are typically competing objectives. That is, maximizing network coverage involves backbone configurations where nodes are spread in regions where wireless users are deployed, whereas assuring robust backbone connectivity involves bringing backbone nodes together to increase connectivity and/or strength of connectivity. This paper presents a novel approach to jointly optimize these two objectives in dynamic environments.

![Network architecture](Image)

Fig. 1: Network architecture.

We propose to solve the joint coverage-connectivity optimization problem by formulating it as an energy minimization problem. Convex energy functions for both coverage and connectivity are defined in terms of the distance between each terminal and its assigned backbone node (for network coverage) and between neighbor backbone nodes (for backbone connectivity). We then compute forces on every node as the negative energy gradient and show how backbone nodes achieve optimal topology configurations when reacting to local forces exerted by neighbor nodes.

Similar problems have been considered in the past which can be related to the coverage-connectivity optimization problem for DWB networks.

In facility location problems (FLPs), a set of client locations are to be serviced by facilities. If a client at location $j$ is assigned to a facility at location $i$, a cost of $c_{ij}$ is incurred that is proportional to the distance between $i$ and $j$. The objective is to find the optimal placement of facilities so as to minimize the total assignment costs. In DWB-based networks, terminal nodes are considered as clients and backbone nodes as facilities. The main difference between facility location problems and our problem is that in FLPs the connectivity between facilities (backbone nodes) is not considered, which is of critical importance in DWB-based networks, as terminal nodes cannot communicate with each other if the backbone is not connected. Also, in facility location problems, the locations of the facilities take discrete integer values. FLPs are thus usually formulated as integer programming problems and are shown to be NP-Complete. Approximation algorithms have been developed that give constant approximation guarantees [4].

On the other hand, the problem of optimizing backbone connectivity given the location of the backbone nodes has been considered in the past. In this case, the location of the backbone nodes is given and the optimization is done over the assignment of links between them so as to minimize to total communication cost. This problem can also be formulated as an integer programming problem and is shown to be NP-Complete. We have developed approximation algorithms that find close-to-optimal solutions in polynomial time [5].

In this paper, we propose to jointly optimize coverage and connectivity by minimizing a cost function which takes into account both objectives and it is related to the actual energy usage of the network system. We show desirable properties such continuity and convexity for the cost function defined, and design a mobility control scheme to achieve optimal network topology configurations in dynamic scenarios.

Unlike algorithms for FLPs and backbone optimization problems, which generally require centralized global information, our mobility control scheme is shown to be completely distributed and self-organized. That is, nodes can react locally based on neighbors’ position information only, and yet the network achieves optimal topology configurations.

**COVERAGE AND CONNECTIVITY OPTIMIZATION**

Assume we have a network of $N$ backbone nodes and $M$ end terminals or hosts located in a geographical space $A \in \mathbb{R}^3$. The end hosts are at locations $r_1, r_2, ..., r_M$ in the network, in which $r_i = (x_i, y_i, z_i)$ represents the location of the $i^{th}$ end host in $A$. Similarly, the backbone
nodes are at locations $R_1, R_2, ..., R_N$ in the network, in which $R_j = (X_j, Y_j, Z_j)$ denotes location of the $j$th backbone node in $A$. Each backbone node provides coverage to a group of end hosts in its proximity. In this scheme, a host $s$ communicates with another host $d$ in the following way: host $s$ transmits its information to the closest backbone node; then the traffic traverses through the backbone network until it reaches the backbone node that is closest to the destination. Finally, the backbone node that is closest to the destination transports the traffic to the host $d$. As it can be observed, this scheme is based on two properties: first, the end hosts need to be well covered by the backbone nodes, and second, the backbone nodes must have good connectivity among themselves. We describe both aspects in our model in terms of the following two cost metrics:

- **Coverage cost**: takes into consideration the cost of covering the end hosts by the backbone network. This component of cost is defined as a function of the communications energy needed in order for the end hosts to communicate with their closest backbone node. The more the energy required, the higher the coverage cost. Assume that $h(i)$ represents the index of the backbone node that provides coverage to the end host node $i$. Apparently, we have $1 \leq h(i) \leq M$. Now, we define the following form of coverage cost:

$$G = \sum_{i=1}^{M} u(R_{h(i)}, r_i),$$  \hspace{1cm} (1)

where $G$ represents the coverage cost and it is computed as the summation of the energy stored in the wireless links connecting each end host to its closest backbone node.

- **Connectivity cost**: considers the cost of maintaining the backbone nodes connected. In the simplest form, backbone nodes may be connected forming a chain topology, which implies that a chain of links starts from a backbone node and passes through all the other backbone nodes. In many practical applications such a simple graph is vulnerable to link failures; if a single link fails the network becomes disconnected. In practice, it is desirable to achieve some degree of fault tolerance by superimposing a redundant connectivity graph among the backbone nodes. Samples of such connectivity patterns include ring topologies, or $k$-connected graphs (the graphs for which there are $k$ disjoint paths between every arbitrary pair of backbone nodes). For a given connected topology, the connectivity term of the cost function models the energy used by the backbone network to keep its nodes connected. Similar to the coverage cost, we define the connectivity cost as follows:

$$F = \sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u(R_i, R_j),$$  \hspace{1cm} (2)

where $b_{ij} = \begin{cases} 1 & \text{if } (i,j) \in T \\ 0 & \text{o.w.} \end{cases}$, and $T$ refers to the backbone topology. $F$ thus represents the connectivity cost and it is computed as the summation of the energy stored in the links forming the backbone topology.

Based on the above cost components, we define the following composite cost function as:

$$U = \eta \cdot F + G =$$

$$= \eta \left( \sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u(R_i, R_j) \right) + \left( \sum_{i=1}^{M} u(R_{h(i)}, r_i) \right).$$  \hspace{1cm} (3)

Note that the cost function above $U$ integrates both coverage and connectivity cost terms and represents the total energy usage in the network system.

Thus, in this work, the mobility control problem is formulated as an energy minimization problem, as follows:

$$\min U(X_1, ..., X_N) =$$

$$= \eta \left( \sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u(R_i, R_j) \right) + \left( \sum_{i=1}^{M} u(R_{h(i)}, r_i) \right).$$  \hspace{1cm} (4)

s.t. $b_{ij} = \begin{cases} 1 & \text{if } (i,j) \in T \\ 0 & \text{o.w.} \end{cases}$

Note that in this case the backbone topology $T$ ($b_{ij}$ variables) is given and the optimization is performed over the location of the backbone nodes ($R_1, ..., R_N$). Changing the location of the backbone nodes changes the link cost function $u_{ij}$ for both backbone-to-backbone and backbone-to-terminal links. The objective is to find the location of the backbone nodes that jointly optimizes network coverage and backbone connectivity by minimizing the total energy of the network system.
The form of the above energy function depends on the communication cost model, which is presented in the next section.

**COMMUNICATION COST MODEL**

The cost of a wireless link \((i,j)\) is defined as the communications energy per unit time used to send information at a specified BER between node \(i\) and node \(j\), and it is described in terms of three main components: the link margin \(P_{R0}^j\), the atmospheric attenuation \(\tau_{\text{obs}}\) and the free space path loss \(\tau_{fs}\):

\[
u_{ij} = \begin{pmatrix} P_{R0}^j \end{pmatrix} \left( e^{\alpha_{ij} R_{ij}^{-1} R_j^{-1} 1} \right) \left( \frac{4 \pi}{D_i A_R^j} \| R_i - R_j \|^2 \right) \tau_{fs}, \tag{5}\]

where \(P_{R0}^j\) is the minimum received power needed at node \(j\) in order to guarantee the specified BER, \(\alpha_{ij}\) is the atmospheric attenuation factor, \(D_i\) the directivity of the transmitter and \(A_R^j\) the effective receiver area [6].

Note that the term \(\frac{4 \pi}{D_i A_R^j}\) is what determines the directionality of link \((i,j)\) and depends on the wireless technology used (FSO or RF) [7]. Thus, it is a constant that will not change with the location of the backbone nodes. The minimum received power required \(P_{R0}^j\) is a function of the receiver sensitivity and the fading margin and will also be a constant independent of the backbone nodes’ location [7]. Thus, the link cost function \(u_{ij}\) can be written as:

\[
u_{ij} = k_{ij} \left( e^{\alpha_{ij} R_{ij}^{-1} R_j^{-1} 1} \right) \| R_i - R_j \|^2, \tag{6}\]

which is the product of a polynomial and an exponential function of the link distance \(L = \| R_i - R_j \|\), and thus, convex.

The atmospheric attenuation coefficient \(\alpha_{ij}\) is defined as the attenuation in dB/km undergone by the electromagnetic radiation in going from node \(i\) to node \(j\) [8, 9]. In this work, we assume uniform atmospheric conditions throughout the deployment area and thus define \(\alpha_{ij} = \alpha\) for all \((i,j)\).

In [7] we showed that under clear atmospheric conditions \((\alpha_{ij} = 0)\) the link cost function \(u_{ij}\) is a quadratic function of the link distance, analogous to the potential energy of a spring with spring constant \(k_{ij}\) and displacement the link distance \(L\). We also showed that the network system can be modeled as a spring system where network nodes react to Hooke-type forces exerted by neighbor nodes driving the network topology to the energy minimizing configuration [7].

In this work, we extend the link cost model in order to include the effects of atmospheric attenuation in the channel. We show that by preserving the convexity of the energy function an updated force-driven mobility control algorithm can still be used to drive the network topology to energy minimizing configurations and optimize coverage and connectivity in the presence of atmospheric obscurcation.

In the following section, we present the updated force-driven mobility control algorithm.

**FORCE-DRIVEN MOBILITY CONTROL**

Our approach to solve the optimization problem described in Eq. 4 is to use iterations on the placement of the backbone nodes. In each iteration, forces are computed at each backbone node that determine the backbone nodes’ relocation directions. We define force acting on backbone node \(i\) as the negative energy gradient with respect to its location \(R_i\) as:

\[
F_i = -\nabla U_i = \eta \sum_{j=1}^{N} b_j \left( -\frac{\partial u_{ij}}{\partial X_j} \right) + \eta \sum_{j=1}^{m} l(h_{ij}) = i \left( -\frac{\partial u_{M_{ij}}}{\partial Y_j} \right) + \eta \sum_{j=1}^{N} b_j \left( -\frac{\partial u_{ij}}{\partial Z_j} \right)
\tag{7}
\]

in which \(l(.)\) is the indicator function; it takes value one if the statement within its argument is true, and it is zero otherwise.

Note that the net force on node \(i\) is a three dimensional vector pointing in the direction of the steepest descent of the energy function \(U\) at the location of backbone node \(i\).
Thus, relocating a backbone node in the direction of the force results in the steepest decrease of the cost function.

Eq. 7 can be restated in terms of the link energy gradient $\nabla u_{ij}$ as:

$$F_i = \eta \sum_{j=1}^{N} b_{ij} \begin{bmatrix} \frac{\partial u_{ij}}{\partial X_i} \\ \frac{\partial u_{ij}}{\partial Y_i} \\ \frac{\partial u_{ij}}{\partial Z_i} \end{bmatrix} + \sum_{j=1}^{M} l(h_{(j)}) \begin{bmatrix} \frac{\partial u_{h(j)j}}{\partial X_i} \\ \frac{\partial u_{h(j)j}}{\partial Y_i} \\ \frac{\partial u_{h(j)j}}{\partial Z_i} \end{bmatrix},$$

where the vector $\nabla u_{ij}$ represents the gradient of the link cost function $u_{ij}$ with respect to the location $R_i$. Now, we can introduce the notion of the force acting at location $R_i$ due to the interaction of node $i$ with its neighbor node $j$, as the negative gradient of the potential energy stored at link $(i,j)$. $u_{ij}$, with respect to the location $R$, as:

$$f_{ij} = -\nabla' u_{ij}. \quad (9)$$

Using Eq. 9, we can compute the net force acting at location $R_i$ as the aggregation of the forces resulting from the interaction of node $i$ with all its neighbor nodes as:

$$F_i = \eta \sum_{j=1}^{N} b_{ij} f_{ij} + l(h_{(j)}) = \sum_{j=1}^{M} f_{h_{(j)}j}, \quad (10)$$

which in parametric form becomes:

$$\begin{bmatrix} F_{i,x} \\ F_{i,y} \\ F_{i,z} \end{bmatrix} = \eta \sum_{j=1}^{N} b_{ij} \begin{bmatrix} f_{ij,x} \\ f_{ij,y} \\ f_{ij,z} \end{bmatrix} + \sum_{j=1}^{M} l(h_{(j)}) \begin{bmatrix} f_{h_{(j)}j,x} \\ f_{h_{(j)}j,y} \\ f_{h_{(j)}j,z} \end{bmatrix}. \quad (11)$$

Using the general link cost model $u_{ij}$ in Eq. 6, the $x$ component of the force $f_{ij}$ that results at node $i$ due to its interaction with node $j$, can be computed as:

$$f_{ij,x} = -\frac{\partial u_{ij}}{\partial X_i} = -k_{ij} \begin{bmatrix} \alpha_j e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \right\|^2 \left( X_i - X_j \right) \\ 2 e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \left( X_i - X_j \right) \end{bmatrix} \right].$$

(12)

Combing the three components of the vector force, $f_{ij}$ can be expressed as:

$$f_{ij} = \begin{bmatrix} f_{ij,x} \\ f_{ij,y} \\ f_{ij,z} \end{bmatrix} = -k_{ij} \begin{bmatrix} \alpha_j e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \right\|^2 \left( X_i - X_j \right) \\ 2 e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \left( X_i - X_j \right) \end{bmatrix} \right].$$

(13)

Using the notion of the displacement vector $R_{ji}$, defined as:

$$R_{ji} = \begin{bmatrix} X_i - X_j \\ Y_i - Y_j \\ Z_i - Z_j \end{bmatrix}, \quad (14)$$

Eq. 13 becomes:

$$f_{ij} = -k_{ij} \left( \alpha_j e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \right) |R_{ji}| \begin{bmatrix} X_i - X_j \\ Y_i - Y_j \\ Z_i - Z_j \end{bmatrix}.$$

(15)

Finally, noting that $R_{ji} = -R_{ij}$, we have that the vector force acting on node $i$ from its interaction with node $j$ is described as:

$$f_{ij} = k_{ij} \left( \alpha_j e^{d_{R_i-R_j}} \left\| R_i - R_j \right\| \right) R_{ji}, \quad (16)$$

where now $R_{ji}$ is the displacement vector starting at the location of node $i$ and ending at the location of node $j$. 
From Eq. 16, it can be observed that the net force acting on a given backbone node \( i \) can be computed using local information only, that is, information about node \( i \) itself and its neighbors. Thus, distributed solutions to the mobility control problem can be developed in which each backbone node reacts locally based on forces exerted by neighbor nodes. No centralized global information is needed. Each backbone node can make movement decisions by itself informed by purely local information. The distributed nature of our force-driven mobility control approach is of key importance in our attempt to provide a scalable and self-organized control system for network performance optimization in dynamic scenarios.

Note that the vector force \( f_{ij} \) has the direction of \( R_{ij} \) and the amplitude is given by a function of the link distance
\[
L = \| R_i - R_j \| \quad \text{and the atmospheric attenuation factor} \quad \alpha_{ij}.
\]
Thus, the interaction of a given node \( i \) with its neighbors results in attraction forces acting at the location of node \( i \), \( R_i \), which pull node \( i \) towards the location of its neighbors for improved communications performance.

In the next section we present an algorithm for relocating the backbone nodes based on the value of the net force at the backbone nodes’ locations. This algorithm also gives a method that assigns each end host to one of the backbone nodes.

**OPTIMIZATION ALGORITHM**

The mathematical formulation of the previous section gives us a method for relocating each backbone node in the direction of the net force such that the cost function shows the steepest descent. In this method, we use a set of iterations that both relocate the backbone nodes iteratively, and reassign the end hosts to the backbone nodes in each iteration.

We use two operations in each iteration: in the first operation we use the values of the forces to relocate the backbone nodes; in the second operation, we use the new locations of the backbone nodes to reassign the end hosts to the backbone nodes. These operations can be stated in a more accurate way as follows:

- **Relocation**: this operation uses the value of the force on each backbone node to find the backbone node’s new location. Such a relocation process can be done as follows:
  \[
  R_i^{n+1} = R_i^n + \delta F_i
  \]  
  in which \( R_i^n \) denotes the location of the backbone node \( j \) at iteration \( n \), \( F_i \) is the net force on backbone node \( i \) as define in Eq. 10 and \( \delta \) is a small step size, and we have \( \delta > 0 \).

- **Reassignment**: this operation assigns each end host node \( i \) to the backbone node \( j \) that minimizes the link cost function \( u_{ij} \) for all \( 1 \leq j \leq N \). For this purpose, we find the following value for each end host node \( i \):
  \[
  h^n(i) = \arg \min_j u(R_j, r_i), \quad 1 \leq j \leq N
  \]  
  in which \( h^n(i) \) represents the backbone node that provides coverage to the end host node \( i \) at iteration \( n \), and \( \arg \min_j \) represents the index \( j \) that corresponds to the minimum of \( u(R_j, r_i) \) for all \( 1 \leq j \leq N \).

Our main conjecture regarding the above iterations is that in each step of each type of the above iterations, the cost function remains constant or decreases. Note that the first operation decreases the cost function because it relocates a backbone node in the direction of the force, which is the opposite direction of the gradient of the cost function. The second operation further reduces the cost because it reassigns a node \( i \) from a backbone node \( j \) to another backbone node \( j' \) only if \( u(R_j, r_i) \geq u(R_{j'}, r_i) \), and such an operation either reduces the cost function or does not change its current value.

Also note that if we form the a sequence \( U_1, U_2, \ldots, U_{(n)}, \ldots \) with \( U_{(n)} \) representing the values of cost function during the above iterations, then the above sequence is non-increasing and lower bounded (because \( U_{(n)} > 0 \)). Therefore, this sequence has to converge to a value as \( n \) increases. Thus, the convergence criterion is stated as follows:

\[
U_{(n+1)} - U_{(n)} < \varepsilon, \quad (19)
\]

in which \( \varepsilon \) is a small positive constant.

Note from Eq. 19 that convergence is met when the variation of the energy function \( U \) is negligible, which implies that the overall net force acting on the system is also negligible. In analogy with physical systems, we refer to this condition as the equilibrium condition of the
network system. In equilibrium, the net forces acting on the backbone nodes must converge to zero. Thus, an algorithm based on relocating backbone nodes in the direction of the net forces at each node stops when the amplitude of the force at all backbone nodes is small enough. We use the following criterion to stop the algorithm iterations:

$$\|F_i\| < \varsigma$$  \hspace{1cm} for 1 \leq i \leq N \hspace{1cm} (20)$$

where $\varsigma$ is a small positive constant.

**SIMULATION RESULTS**

In order to verify the performance of our optimization algorithm, we present results from simulation studies with different design parameters. In all simulations, $N$ terminal nodes are distributed in a 50km x 50km plane. Terminal nodes are organized in clusters. The first terminal node is placed in the plane according to a uniform random distribution. Each other terminal is placed within $\text{clusterRange}$ of the previous terminal node with probability $p_{\text{cluster}}$, and uniformly in the 50km x 50km plane with probability 1-$p_{\text{cluster}}$ (in the results presented in this section we used $\text{clusterRange} = 1 \text{ km}$ and $p_{\text{cluster}} = 0.1$). Next, $M$ backbone nodes are placed forming an initial non-optimal ring topology. Then, our mobility control algorithm is executed to make backbone nodes adjust their position until convergence to the optimal backbone configuration. In these results we use a balancing factor $\eta = 1$.

Fig. 2 shows different network configurations obtained using the spring algorithm presented in [7] (Figs. 2a, 2c, 2e, 2g) and using the extended version presented in this paper (Figs. 2b, 2d, 2f, 2h). Links from each terminal node to its closest backbone node are shown in red and links between backbone nodes are shown in blue. In Figs. 2a and 2b the average atmospheric attenuation is $\alpha = 0 \text{ dB/km}$. In this case, both algorithms obtain the same solution. The network is able to stretch to cover the terminal nodes and in the final equilibrium configuration, the total energy per unit time used is 270.6 Watts. Note that in clear atmospheric conditions the connectivity cost ($F=0.1W$) is relatively low compared to the coverage cost ($G=270.5W$). In Figs. 2c and 2d the average atmospheric attenuation is increased to $\alpha = 0.5 \text{ dB/km}$. As expected, the spring algorithm obtains the same solution as in clear atmospheric conditions, but the total power used increases due to the effect of the atmospheric attenuation on the directional wireless links forming the backbone network ($U=321.4W$). Note that the coverage cost remains $G=270.5W$ and the connectivity cost increases from 2mW to 50.9W. On the other hand, using the extended algorithm presented here, additional exponential forces appear between backbone nodes the make them stay closer to each other and reduce the total energy of the system ($U=315.4W$). As we increase the value of $\alpha$, the improvement in power usage increases. Note how in Figs. 2e and 2f, where $\alpha = 0.75 \text{ dB/km}$, the total power usage of the network goes from 1557.3W to 575W when including the effects of atmospheric attenuation in the mathematical model. Finally, when $\alpha = 1 \text{ dB/km}$ (Figs. 2g and 2h), the power usage improvement is from 34413W to 773.7W.

**CONCLUSIONS**

In this paper, we considered the problem of dynamically optimizing network coverage and backbone connectivity in dynamic DWB-based wireless networks by adjusting the location of the backbone nodes. We proposed a novel approach to solve the joint coverage-connectivity optimization problem that uses analogies from physical systems that react to external forces in order to minimize potential energy. We extended our previous work [7] by including the effects of atmospheric attenuation in the channel. Our new mathematical formulation models the joint coverage-connectivity optimization problem as a convex minimization problem. We define convex cost functions for both coverage and connectivity in terms of power needed to transmit information among the nodes in the network. Our link cost model includes an exponential function of the link distance modeling the effects of atmospheric attenuation. We developed a completely distributed mobility control algorithm that computes local forces on network nodes to find the relocation directions. The net force on a backbone node is defined as the energy gradient at the location of the backbone node, and only depends on neighbors’ locations and atmospheric attenuation information. We provided simulation results that show the effectiveness of our extended force-based mobility control algorithm to provide network configurations that optimize both network coverage and backbone connectivity in different atmospheric conditions.
Fig. 2: Comparison of optimal network configurations obtained using the spring algorithm (a, b, c, d) and using the extended version (e, f, g, h) under different atmospheric attenuation conditions.