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Research Article

Molecular System Dynamics for Self-Organization in Heterogeneous Wireless Networks

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We have been looking at the properties of physical configurations that occur in nature in order to characterize, predict, and control network robustness in dynamic communication networks. Our framework is based on the definition of a potential energy function to characterize robustness in communication networks and the study of first- and second-order variations of the potential energy to provide prediction and control strategies for network-performance optimization. This paper describes novel investigations within this framework that draw from molecular system dynamics. The Morse potential, which governs the energy stored in bonds within molecules, is considered for the characterization of the potential energy of communication links in the presence of physical constraints such as the power available at the transmitters in a network. The inclusion of the Morse potential translates into improved control strategies, where forces on network nodes drive the release, retention, or reconfiguration of communication links based on their role within the network architecture. The performance of the proposed approach is measured in terms of the number of source-to-destination connections that have an end-to-end communications path. Simulation results show the effectiveness of our control mechanism, where the physical topology reorganizes to maximize the number of source-to-destination communicating pairs. The algorithms developed are completely distributed, show constant time complexity and produce optimal solutions from local interactions, thus preserving the system's self-organizing capability.

1. Introduction

Next-generation communication networks are becoming increasingly complex systems due to their heterogeneous architecture and dynamic behavior. The need for ubiquitous broadband connectivity and the capacity limitation of homogeneous wireless networks [1] are 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 [2–5].

As an example, backbone-based wireless networks use a two-tiered network architecture, where a set of flat ad hoc wireless networks are interconnected through a broadband wireless backbone network of higher capability nodes that use directional wireless communications, either free space optical (FSO) or directional radiofrequency (RF), to aggregate and transport traffic from hosts at lower layers (see Figure 1). The advantages of directional wireless communications can be well exploited at the backbone layer, where line of sight constraints are less restrictive and interference-free, point-to-point communication links can provide extremely high data rates [2–5].

The main challenge in the design of directional wireless backbone (DWB) networks is to assure robust network performance in a highly dynamic wireless environment. As opposed to wireline backbone networks, DWB-based networks are subject to changing platform (node mobility, addition, and deletion) and link-state (atmospheric turbulence, atmospheric attenuation, and path loss) conditions. Thus, topology control mechanisms need to provide the self-organizing capability that enables the network to adapt to the changing environment in order to maintain network performance.

In such a complex and dynamic environment, our work has focused on physical layer guarantees. Communication

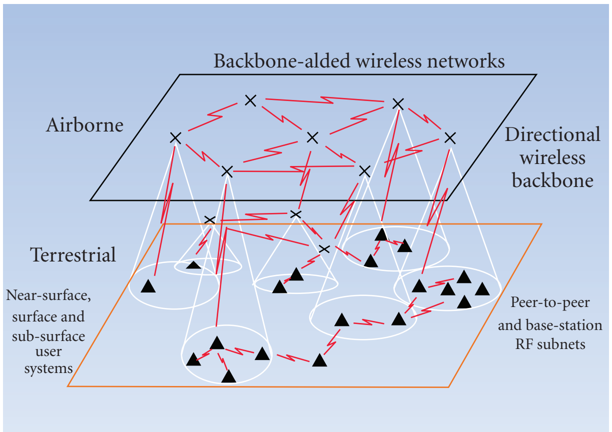


Figure 1: Hierarchical wireless network architecture.

links need to be available for nodes to communicate. For that purpose, we have developed a mathematical framework in which communication networks are modeled as physical systems, where their entities exchange electromagnetic energy. The spatial distribution of the electromagnetic energy used for communications and its temporal variations are used to characterize, predict, and control the robustness of the network system. A potential energy function is defined for the network system and, topology-control mechanisms are developed to mimic the self-organizing reaction of physical systems in nature, and to minimize potential energy for improved robustness.

In DWB networks, topology control is defined as the autonomous network capability to dynamically reconfigure its physical topology through (1) the redirection of point-to-point links and/or (2) the reposition of backbone nodes. Our work is aimed at designing scalable, self-organized DWB networks that can autonomously adjust their physical topology in order to dynamically optimize network performance [6–8].

In our previous work [6–8], we have addressed network performance in terms of two main objectives: network coverage and backbone connectivity. The DWB must provide coverage to as many users 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.

Previous work, mostly in the area of Facility Location Problems (FLPs) [9], has considered optimal base station placement for coverage optimization, which is typically addressed as a design problem and shown to be NP-complete. Centralized approximation algorithms have been developed that achieve close-to-optimal solutions in a relatively fixed scenario, but the need for global network information makes them unsuitable for coping with the heterogeneous and dynamic nature of next-generation wireless networks. Also, backbone connectivity is usually assumed to be guaranteed by a fixed backbone infrastructure, a very limiting assumption in a dynamic wireless scenario.

New mathematical models and optimization methods that can address the increasing heterogeneity and dynamic behavior of next generation complex network systems are required. Specifically, new methodologies need to provide: (1) accurate link physics models to precisely model and characterize the heterogeneous set of link states in the network, (2) distributed low complexity algorithms for dynamically optimizing network performance by providing the network with the required self-organizing capability, and (3) joint coverage-connectivity optimization.

In our previous work, we formulated a convex optimization method for joint coverage and connectivity control [7, 8]. In [7, 8], convex functions for the actual communications energy used in the network were defined. Uncontrolled network dynamics (such as users' mobility and changing atmospheric conditions) are modeled as external excitations changing the energy of the system, and topology control mechanisms are developed as internal system reactions that minimize its potential energy. The uncontrolled network dynamics are modeled as an excitation changing the energy of the system and topology control mechanisms are developed as the system reacts to minimize its potential energy. Results showed how the use of control strategies that minimize the energy of the network system can ensure desirable network properties such as coverage, connectivity, and power efficiency [7, 8].

In this paper, we introduce a nonconvex energy model for the characterization of communication links with physical constraints, such as the available power at the transmitters. This new link energy function is founded on molecular models used to characterize the potential energy stored in bonds forming molecules, which include the effects of bond breakage [10, 11].

In the following section, we describe the relationship between potential energy and network robustness, and introduce the molecular model analogy. In Section 3, we briefly describe the optimization problem for topology control presented in [7, 8] formulated as an energy minimization problem. In Section 4, we introduce a nonconvex energy function within the link characterization model. In Section 5, we describe the control strategies arising from this improved energy model, and in Section 6, simulation results are presented to show the effectiveness of our approach.

2. Molecular Dynamics for Topology Control in Hierarchical Networks

In nature, physical systems have developed robust self-organizing capabilities in order to adapt to the changing environment. We have investigated the use of topology control mechanisms for complex dynamic wireless networks that mimic the natural and self-organizing behavior of analogous physical systems whose topologies are adaptive and robust as a result of internal physical interactions among the nodes forming the network.

Robustness in physical systems is related to the system's potential energy, which is defined as the energy a system has due to its physical configuration in space. A wireless network is, in essence, electromagnetic energy being propagated among a set of nodes in space. The location of the network nodes and the choice of communication links between them define the network topology, which determines the total energy usage for the network system. Thus, we have defined the potential energy of a communications network as the total communications energy needed to maintain network performance given its physical configuration.

Uncontrolled parameters such as the mobility of terminal nodes (whose motion is determined by their respective missions, tasks, or applications) and the presence of atmospheric obscuration change the energy of the network system. Physical systems naturally react to minimize their potential energy and thereby increase their robustness. Internal forces are responsible for bringing the network to an equilibrium condition where the total energy is minimized. Our approach models network control strategies as internal forces minimizing the energy of the network system.

We have presented algorithms and protocols for mobility control that dynamically adjust the location of backbone nodes by computing internal forces at the backbone nodes' locations as negative energy gradients and have showed how the network can autonomously achieve energy minimizing configurations driven by local forces exerted on network nodes. Results suggest our optimization framework to be very promising for the modeling, characterization, and control of next-generation complex wireless networks. Force-based mobility control methods that arise from our energy minimization framework are shown to be scalable and self-organized, they are able to track the network dynamics, retain physical accuracy, and provide joint coverage-connectivity optimization [7, 8].

Even greater insight about the behavior of heterogeneous communication networks can be obtained by modeling the network as nodes interconnected with non-convex springs. This is analogous to representing the network as a giant molecule, where the nodes correspond to atoms and internode link connectivity to bond strengths. In Section 4, we precisely describe this new energy model.

3. Network Control Framework

In [7, 8], we introduced the formulation of the topology control problem in DWB-based networks as an energy minimization problem. The potential energy function for the network system is defined as the total communications energy stored in the wireless links forming the network topology, as follows:

$$U = \underbrace{\sum_{i=1}^{N}\sum_{j=1}^{N} b_{ij} u(R_i, R_j)}_{F} + \underbrace{\sum_{k=1}^{M} u(R_{h(k)}, r_k)}_{G}, \qquad (1)$$

where R_i is the location of backbone node i, r_k the location of terminal node k, N the number of backbone nodes, M the number of terminal nodes, $h(k)$ the index of the backbone node covering terminal node k, and b_{ij} the integer variables that determine the backbone topology

$$b_{ij} = \begin{cases} 1, & \text{if } (i,j) \in T, \\ 0, & \text{o.w.,} \end{cases} \qquad (2)$$

where T refers to the backbone topology. The link cost function $u(R_i, R_j)$ represents the potential energy of link (i, j) and will be precisely defined in the following section as the communications energy per unit time needed to send information from node i to node j at the specified BER.

Note that the first term in of the cost function, denoted by F, represents the total energy stored in the directional wireless links forming the backbone network, and the second term G represents the total energy stored in the wireless links covering the end users. Thus, F is a measure of cost for the backbone connectivity; that is, a higher value of F indicates a backbone topology, where higher communications energy needs to be provided in order to maintain backbone nodes connected. On the other hand, a higher value of G indicates a higher demand for communications energy in order to maintain end users covered at the specified QoS (BER).

Thus, the joint coverage-connectivity optimization problem is formulated as a weighted multi-objective optimization problem of the following form:

$$\begin{aligned} \min \quad & \Bigg\{ U\Big(b_{ij}, R_1, \ldots, R_N\Big) = \eta \cdot F + G \\ & = \eta \cdot \left(\sum_{i=1}^{N}\sum_{j=1}^{N} b_{ij} u\Big(R_i, R_j\Big) \right) \\ & + \left(\sum_{k=1}^{M} u(R_{h(k)}, r_k) \right) \Bigg\}, \\ \text{s.t.} \quad & b_{ij} = \begin{cases} 1, & \text{if } (i,j) \in T, \\ 0, & \text{o.w.} \end{cases} \end{aligned} \qquad (3)$$

Note that in the above formulation, the optimization is performed over (1) the assignment of directional wireless links between backbone nodes b_{ij} and (2) the location of the N backbone nodes $(R_1, \ldots, R_N)$. These are the controllable parameters from the topology control perspective. Topology Reconfiguration (TR) mechanisms determine the link assignments b_{ij} and Mobility-Control (MC) mechanisms determine the locations $(R_1, \ldots, R_N)$.

The cost function U represents the potential energy of the communications network, that is, the communications energy needed to guarantee the communications functionality of the network system given its physical configuration in space. It can also be thought of as the communications energy stored in the network system; that is, the potential energy of an analogous physical system where communications links define forces of interaction between network nodes.

Of key importance in the optimization problem stated in (3) is the definition of the link cost functions u_{ij} that will determine the form of the overall cost function U. In Section 4, we present link cost models that take into account the spatial distribution of electromagnetic energy for the different wireless technologies used in DWB-based networks.

3.1. Topology Reconfiguration. Topology-reconfiguration algorithms try to find the optimal link assignments between backbone nodes in order to minimize the overall network-cost function. The topology-reconfiguration problem can be formulated as

$$\begin{aligned} \min \quad & U\left(b_{ij}\right) = \sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u\left(R_i, R_j\right), \\ \text{s.t.} \quad & b_{ij} = \begin{cases} 1, & \text{if } (i, j) \in T, \\ 0, & \text{o.w.} \end{cases} \end{aligned} \tag{4}$$

Note that in the case of topology reconfiguration, the location of the backbone nodes $(R_1, \ldots, R_N)$ is fixed, and the optimization is performed over the link assignment variables b_{ij}.

The problem becomes that of finding subgraphs with minimum total cost while satisfying connectivity constraints. Typically, at least biconnectivity is imposed on the network topology, which assures the existence of at least two disjoint paths between any pair of nodes in the network. These problems are typically formulated as integer programming problems and shown to be NP-complete. We have presented various approximation algorithms that obtain close-to-optimal solutions in polynomial time [12]. We will not describe these algorithms as it is beyond the scope of this paper.

3.2. Mobility Management. Mobility management in DWB networks allows adjustment of the backbone topology without breaking point-to-point links and thus avoiding temporary loss of data.

The mobility control problem is formulated using (3) as

$$\begin{aligned} \min \quad & U(R_1, \ldots, R_N) = \eta \cdot F + G \\ & = \eta \cdot \left(\sum_{i=1}^{N} \sum_{j=1}^{N} b_{ij} u\left(R_i, R_j\right) \right) \\ & \quad + \left(\sum_{k=1}^{M} u\left(R_{h(k)}, r_k\right) \right), \\ \text{s.t.} \quad & b_{ij} = \begin{cases} 1, & \text{if } (i, j) \in T, \\ 0, & \text{o.w.,} \end{cases} \end{aligned} \tag{5}$$

where now the link assignment variables b_{ij} are fixed and the optimization is performed over the location of the backbone nodes $(R_1, \ldots, R_N)$.

An iterative approach to solve the optimization problem described in (5) has been presented [7, 8]. In each iteration, the net force acting on each backbone node is computed, which determines the backbone node's relocation direction. We define the net force acting on backbone node i as the negative energy gradient with respect to its location R_i

$$F_i = -\nabla^i U = \eta \sum_{j=1}^{N} b_{ij} \left(-\nabla^i u_{ij}\right) + \sum_{k=1}^{M} 1\left(h_{(k)} = i\right) \left(-\nabla^i u_{ik}\right), \tag{6}$$

in which $1(\cdot)$ is the indicator function (it takes value one if the statement within its argument is true, and it is zero otherwise) and $\nabla^i u_{ij}$ is the link energy gradient.

The notion of the force acting at location R_i due to the interaction of node i with its neighbor node j, is defined as the negative gradient of the potential energy stored at link (i, j), u_{ij}, with respect to the location R_i, as

$$f_{ij} = -\nabla^i u_{ij} = \begin{bmatrix} -\dfrac{\partial u_{ij}}{\partial X_i} \\ -\dfrac{\partial u_{ij}}{\partial Y_i} \\ -\dfrac{\partial u_{ij}}{\partial Z_i} \end{bmatrix}. \tag{7}$$

Using (7), 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

$$F_i = \eta \sum_{j=1}^{N} b_{ij} f_{ij} + \sum_{k=1}^{M} 1\left(h_{(k)} = i\right) f_{ik}. \tag{8}$$

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 from (14) that the net force acting on backbone node i is computed as the sum of two sets of attraction forces: one coming from its neighbor backbone nodes, for backbone connectivity optimization, and the other one coming from the terminal nodes assigned to backbone node i, for coverage optimization (see Figure 2).

In [7, 8], results were presented showing the effectiveness of our force-driven control approach to morph a directional wireless backbone so as to optimize end-to-end connectivity in dynamic heterogeneous networks. Figure 3 shows an example of a simulation where a 10 node FSO backbone network (blue lines) morphs by relocating backbone nodes in the direction of the net force (green lines), driving the network topology to a minimum energy configuration that optimizes end-to-end connectivity.

The magnitudes of the forces depend on the variation of the link energy function with respect to the location of the

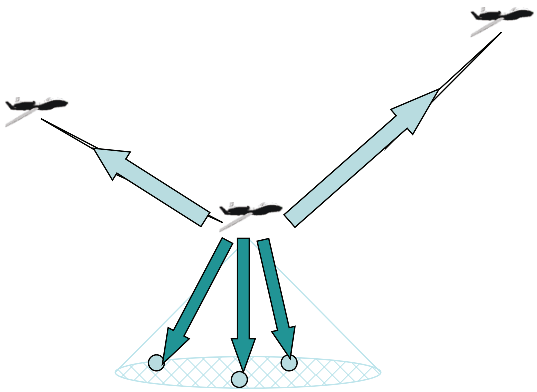


Figure 2: Illustration of the two sets of attraction forces acting on each backbone node: backbone-terminal for network coverage optimization and backbone-backbone for backbone connectivity optimization.

backbone nodes. To date, convex energy functions have been used to characterize the potential energy of communication links, taking into account the different communication technologies used in hierarchical wireless networks. These convex energy functions translate into convex forces that increase with increasing signal attenuation and compete for improved connectivity, as shown in Figures 2 and 3. In practical situations, the optimal configuration of backbone nodes may involve transmitted power requirements exceeding physical constraints. Thus, backbone nodes need to be able to compromise and reduce the force on certain links in order to minimize the loss of end-to-end connections.

In the next section, we introduce the Morse potential as an energy function that allows the relaxation of forces between nodes when reaching power limitation constraints.

4. The Morse Potential

In next-generation hierarchical wireless networks, a heterogeneous set of communication technologies is used to provide end-to-end broadband connectivity to a diverse group of end users or hosts. Thus, it is necessary to define a comprehensive link cost function for a wireless link (i, j) that takes into account the behavior of the diverse wireless technologies used in next-generation wireless networks, including FSO, directional RF, and omnidirectional RF.

In the harmonic model we have used to date, the cost of a wireless link or its potential energy is a convex function of the link distance [7, 8], as

$$u_{ij} = k_{ij}\left(e^{\alpha\|R_i - R_j\|}\right)\left(\left\|R_j - R_i\right\|^2\right), \quad k_{ij} = P^j_{R0}\frac{4\pi}{D^i_T A^j_R}, \tag{9}$$

where P_{R0} is the minimum received power, D_T the directivity of the transmitter antenna, and A_{efR} the effective receiver area [13]. The scattering coefficient α measures the attenuation electromagnetic radiation undergoes as it travels through the atmosphere due to the scattering effects caused by the presence of atmospheric agents in the form of suspended water particles such as fog, clouds, rain, or snow. Note that k_{ij} and α_{ij} vary from RF to FSO links. The high energy confinement of FSO links, used at the backbone layer, allow for long-distance links, while omnidirectional RF links used to communicate between backbone and terminal nodes produce stronger forces to maintain short link distances and low energy cost [6].

A non-convex extension of this model, which we propose, is to use the Morse potential, where the potential energy of the connection is

$$U(q) = D_e\left(1 - e^{-\beta q}\right)^2, \tag{10}$$

where D_e is the "dissociation energy," at which point the bond breaks, q is bond distance, and β is related to the force constant [14].

In practical situations, the increase in transmitted power needed to maintain a given link BER is limited by the maximum power at the transmitter. Thus, the "Morse potential" is a convenient model for the potential energy of a communications link with power limitation constraints as it explicitly includes the effects of bond breaking. In the context of communication networks, (5) is used for the potential energy of wireless link (i, j) as

$$u_{ij} = D_{ij}\left(1 - e^{-\beta_{ij}\|R_j - R_i\|}\right)^2. \tag{11}$$

Recall that our control strategies dynamically morph the network topology based on local forces exerted on network nodes, and the force is computed as the gradient of the potential energy. Thus, note that using the harmonic potential model, the force increases quadratically (or exponentially in the presence of atmospheric obscuration) as the link distance increases. The idea is that the longer the distance, the stronger the force in order to maintain the connection. We refer to this control process as the "retention" of a connection. On the other hand, under the Morse potential model, the force increases up to a point and then starts decreasing and converges to zero as the link distance increases. We refer to this control process as the "release" or relaxation of a connection. Figure 4 illustrates the potential energy (Figure 4(a)) and the force (Figure 4(b)) for both the harmonic and Morse potentials. Note that for small link distances, both models behave analogously, and after a given link distance (in this case around 10 km), the harmonic potential models the increase in both energy and force to retain the connection, the Morse potential, the saturation of the energy, and the decrease of the force to relax the given connection.

In the next section, we describe the improved force-driven topology-control approach for dynamic heterogeneous networks with physical constraints, which includes different type of forces for releasing or retaining connections depending on their effect on the communications functionality.

5. Retain, Release, and Reconfigure, a Hybrid Topology-Control Approach

Results presented in [7, 8] show the efficiency of our self-organized mobility control system in terms of jointly

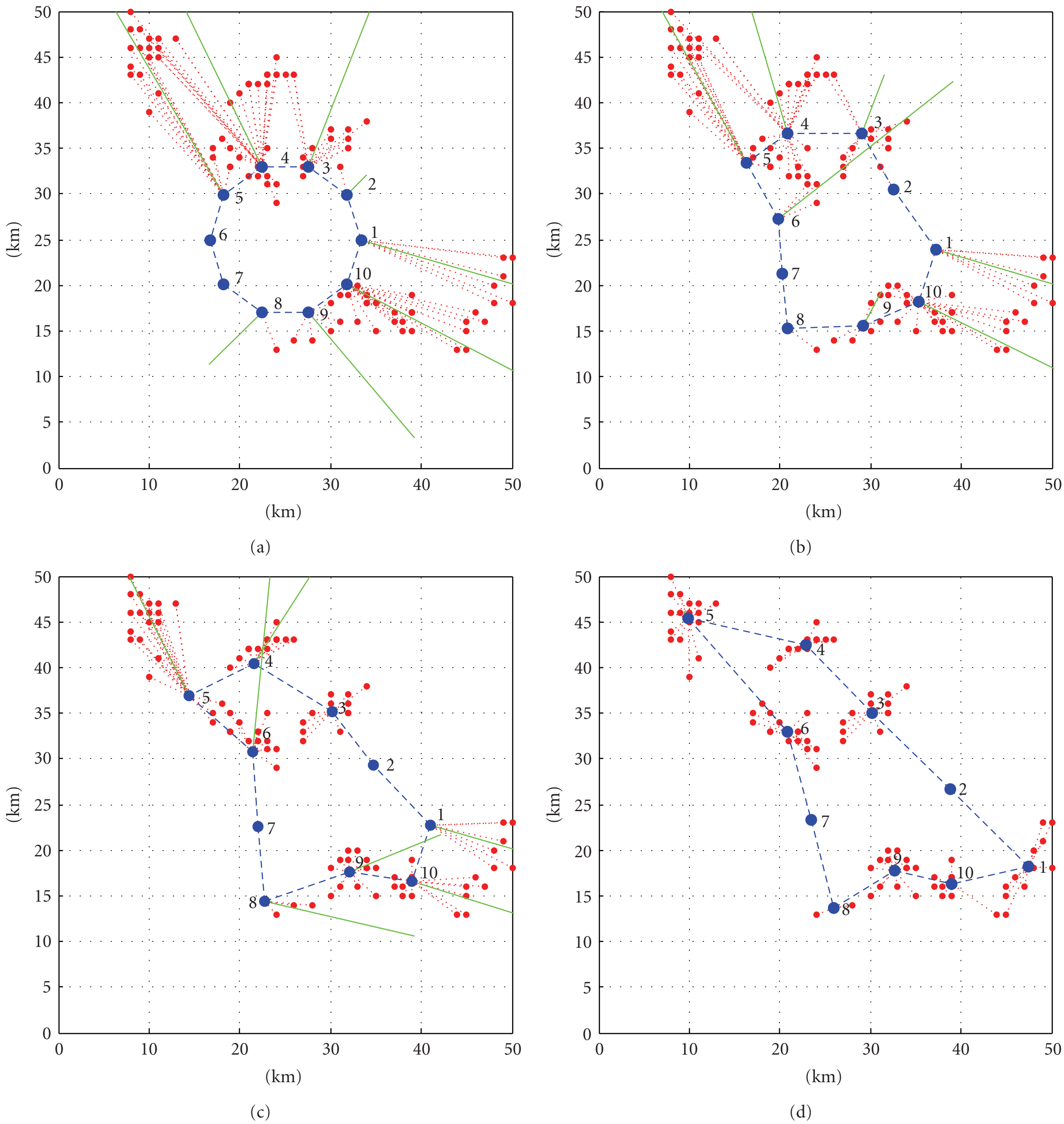


Figure 3: Snapshots of the evolution of a 10 node FSO backbone network morphing from an initial non optimal configuration to an equilibrium configuration that minimizes communications energy and optimizes end-to-end connectivity. Green lines show the direction and amplitude of the forces acting on the backbone nodes.

optimizing coverage and connectivity in dynamic scenarios by driving the network to energy-minimizing configurations. In our simulations, we measured the cost of coverage and connectivity in terms of the energy metrics F and G defined earlier. In practical situations, the energy available at the network nodes will be limited. In this section, we include power-limitation constraints in the optimization problem.

Note that with power constraints, wireless links will not always be available. Exceeding link distances and atmospheric obscuration will cause link breaks that will terminate source-to-destination (SD) connections in the network. To take into account this effect, we introduce the following metric of interest: SD connections. We refer to SD connections as the number of SD pairs connected in the network; that is, the number of SD pairs for which a path exists between them. This metric will be used as a measure of network performance under power limitation constraints.

5.1. Exponential Retention. We include power limitation constraints as an additional exponential force that avoids

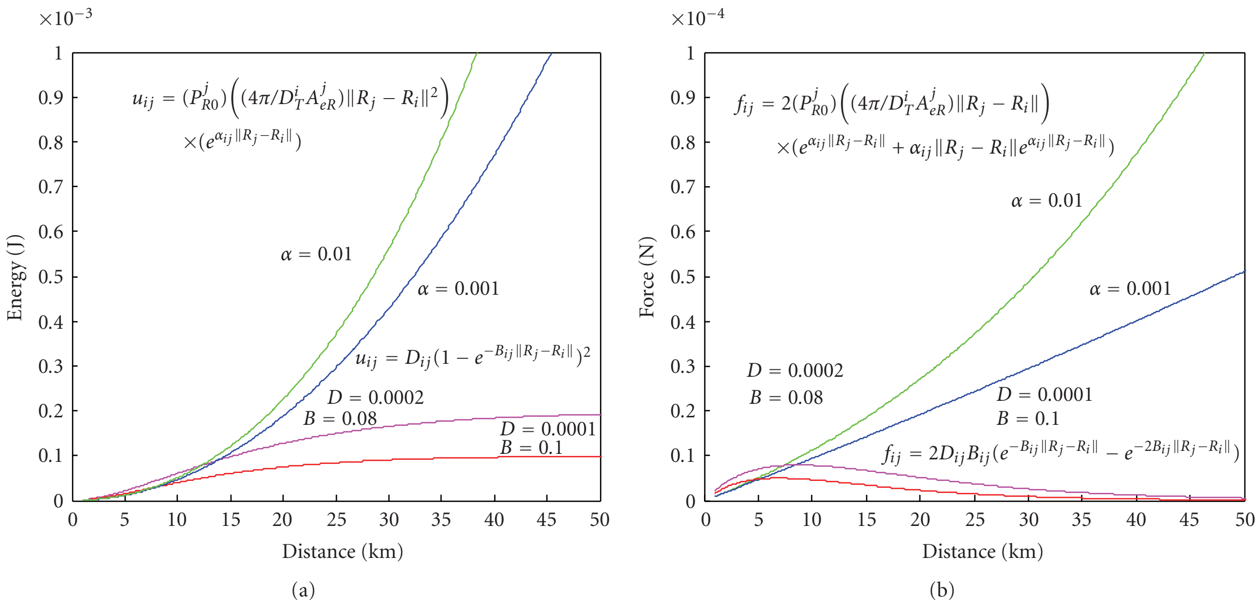


Figure 4: Potential energy (a) and force (b) for harmonic and Morse energy models.

nodes moving further apart from the maximum distance allowed by the maximum transmitted power available at the network nodes. We define the exponential constraint force at the location of node i due to its interaction with node j as

$$f_{ij}^c = e^{m(\|R_i - R_j\| - (d_{ij}^{\max} - \delta))}, \tag{12}$$

where m is the constraint force exponent and $d_{ij}^{\max}$ is the maximum distance allowed between node i and node j in order to maintain the specified link BER when node i transmits with maximum transmit power $P_{Ti}^{\max}$, and δ is a positive distance value.

From (12), note that

$$f_{ij}^c \begin{cases} \leq 1 & L \leq d_{ij}^{\max} - \delta, \\ \geq 1 & L \geq d_{ij}^{\max} - \delta. \end{cases} \tag{13}$$

Thus, the values for m and δ are chosen to make f_{ij}^c negligible for values of $L \leq d_{ij}^{\max}$ and large enough to compensate other forces and avoid link breaks for values of $L \geq d_{ij}^{\max}$.

In order to define the total force acting on node i due to its interaction with node j under power limitation constraints, we now refer to the unconstrained force f_{ij} defined in (7) as f_{ij}^u. The total force acting on backbone node i due to its interaction with node j is then defined as

$$\begin{aligned} f_{ij} &= f_{ij}^u + f_{ij}^c, \\ f_{ij} &= \left(P_{R0}^j \frac{4\pi}{D_T^j A_{eR}^j} \right) \\ &\quad \times \begin{pmatrix} n\left\|R_i - R_j\right\|^{n-2} e^{\alpha_{ij}\|R_i - R_j\|} \\ +\alpha_{ij}\left\|R_i - R_j\right\|^{n-1} e^{\alpha_{ij}\|R_i - R_j\|} \end{pmatrix} R_{ij} \\ &\quad + e^{m(\|R_i - R_j\| - (d_{ij}^{max} - \delta))}. \end{aligned} \tag{14}$$

Thus, when power limitations are imposed on network nodes, the force-driven mobility control algorithm is updated with f_{ij} computed using (14).

The constraint force involves a sharp increase in the magnitude of the force when the link distance reaches its maximum. In a heterogeneous network such as in DWB-based networks with terminal nodes connected through a directional backbone, the use of the constraint force on all wireless links will have instability effects as a number of links could very rapidly produce very strong attraction forces in different parts of the network, leading to oscillations around an equilibrium configuration. Thus, initially, we use the constraint force for backbone links only, as they are the most essential links for maximizing end-to-end communications.

Table 2 shows results for the average number of SD connections maintained using the FORCE mobility-control algorithm with and without the additional exponential constraint force. For this simulation, we use the atmospheric obscuration pattern shown in Table 1 and a maximum transmitted power of 5, 10, and 15 Watts for all network nodes.

We use 10 different 1-hour dynamic scenarios changing the placement of the terminal nodes and the mobility patterns (always using the RPGM model [15]). We use the FORCE mobility-control algorithm to update the backbone topology and compare the average number of SD connections with and without the exponential constraint force. Table 2 shows the results obtained. When the maximum transmitted power is 5 W, the average percentage improvement in SD connections is 30%. As expected, the improvement is still significant, but decreases with higher values of the maximum transmitted power. As the maximum transmitted power increases, the constraints are less restrictive, and backbone links have larger margins to elongate before the constraint force appears to avoid exceeding

Table 1: Atmospheric attenuation pattern.

Time (minutes)	α (km^{-1})
1	0.1
2	0.2
3	0.3
4	0.4
5	0.5
6	0.6
7	0.7
8	0.8
9	0.9
10	1.0
11	1.0
12	0.9
13	0.8
14	0.7
15	0.6
16	0.5
17	0.4
18	0.3
19	0.2
20	0.1

distances. As seen in Table 2, the average improvement goes down to 29% and 25% when the maximum transmitted power increases to 10 W and 15 W, respectively.

5.2. Morse Release. As introduced in Section 4, the Morse potential models the saturation of link cost/energy when reaching physical constraints (see Figure 4).

Thus, we can use the Morse potential model to allow backbone nodes to relax the force on certain connections that are causing excessive stress on the network and are not essential for communications.

For example, in the case of DWB-networks, it is clear that backbone links are of most importance for communications. The loss of a single backbone-backbone link may cause multiple end-to-end disruptions, while the loss of a single backbone-terminal link causes at most one end-to-end disruption.

5.3. Control Methodology. In this paper, we propose a hybrid network control method based on the following dynamic reaction under a possible network degradation/partition event.

(a) *Release connection:* nonessential links are modeled using the Morse potential so that if the cost to maintain the connection is too high the link is relaxed or released.

(b) *Retain connection:* essential links are modeled using the harmonic potential so that the network will always make the effort to retain such connections.

(c) *Reconfigure topology:* if there is a better topology or an essential link has been lost, the network topology should go into a reconfiguration phase to try to regain/improve connectivity (low-complexity algorithms for dynamic topology optimization have been developed [14]).

The essentiality of communication links will depend on the application or network objectives. Typically, essential links will involve links with critical high-priority traffic or carrying a high number of end-to-end flows. Also, within this control framework, a given link could be treated as essential or nonessential at different points in time. It is the traffic being carried and the importance of the link within the global network, at the moment, that will determine its essentiality label.

In this paper, we label backbone-backbone links as essential or priority links and backbone-terminal links as nonessential or nonpriority links.

6. Simulation Results

In order to verify the performance of our force-driven mobility control approach, we present results from simulation studies with different design parameters. In all simulations, M terminal nodes are distributed over a 50 km $\times$ 50 km plane, organized in clusters. The backbone network is formed by N backbone nodes forming a ring topology. We use ring topologies for the backbone network to assure resilience through biconnectivity. The backbone nodes are placed at an altitude of 1 km. Terminal nodes move according to the RPGM model, and our force-driven control method is used to make backbone nodes adjust their locations until convergence to the optimal backbone configuration.

In this first simulation, the convex model is used for all links, with the additional exponential constraint force for the backbone-to-backbone links. Thus, only a retain/reconfigure control method is used. Also, FSO links with 2 mrad half-beam divergence [9] 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 was -45 dBm (31.6 nW) for all network nodes.

Figure 5 shows the evolution of a network with 100 terminal nodes (red), and 10 backbone nodes (blue) during 30 minutes of network dynamics. Each plot in Figure 5 has 5 subplots showing: the 3D network scenario (yellow lines indicate links with excessive transmission power requirements), the 2D projection with the forces (green) acting on each backbone node, the network cost metric U (blue), F (red) and G (green), the scattering coefficient α for both FSO and RF, the number of SD connections available and the distribution of terminals assigned to each base station (in blue the number of terminals within range of the base station and in red the number of terminals out of range of the assigned base station). In this simulation, the scattering coefficient is set to zero throughout the 30 minutes, simulating clear atmosphere conditions.

Figure 5(a) shows the initial network configuration. The simulation time is 1 minute, and the total number of SD connections is 156 out of the 9900 possible. Figure 5(b)

Table 2: Average percentage improvement in SD connections using the additional constraint force for networks using the FORCE mobility-control algorithm with maximum transmitted power of 5 W, 10 W, and 15 W.

	SD conns $P_{T\max} = 5\,\mathrm{W}$	SD conns $P_{T\max} = 10\,\mathrm{W}$	SD conns $P_{T\max} = 15\,\mathrm{W}$
FORCE (unconstrained)	3112.1	4874.2	5915.3
FORCE (constrained)	4107.8	6325.0	7388.9
Average percentage improvement	32%	29%	25%

corresponds to the minute 5 of the simulation. Forces are stretching the backbone network for improved network coverage. Note how the total network cost U (communications energy) has decreased considerably due to the reduced distances from terminal nodes to their assigned base stations, and the number of SD connections has increased to 3782. Figure 5(c) shows the network at an equilibrium configuration, in which no significant forces act on the backbone nodes. The network cost has reached a minimum for the given network conditions (terminal nodes layout and atmospheric conditions), and there are 4556 SD pairs connected.

At minute 8, terminal nodes start moving according to the RPGM model causing an excitation to the system in the form of an increase in network coverage cost (G). The DWB reacts to this excitation by moving backbone nodes in the direction of the net force acting at the backbone nodes' locations, thus minimizing the overall communications energy. Figures 5(d) and 5(e) show the network configuration at minutes 17 and 26, respectively. Note the evolution of the network cost U at the lower left graph. The oscillations show the excitation-reaction process that undergoes as terminal nodes move and the DWB reacts.

After illustrating the dynamic and self-organizing network control process, we are interested in comparing the performance of the network control methodology when we include the Morse potential for the characterization of the backbone-to-terminal links. For these results, we again used 10 different one-hour dynamic scenarios changing the placement of the terminal nodes and the mobility patterns. We measured the average number of SD connections for each of the simulations using the convex energy model for backbone-to-terminal links versus the Morse potential model. For the backbone-to-backbone links the convex energy model with exponential constraint was always used.

Table 3 shows the results obtained. As expected, using the Morse potential, the network is able to increase the average number of SD connections. Forces on terminal nodes causing excessive network cost are relaxed to avoid excessive loss of SD connections. Note how the impact of the use of the Morse potential is more significant the more restrictive the constraints are. The lower the maximum transmitted power, the more significant the improvements in SD connections.

The Morse potential allows the network to release high-cost links that have an effect on the overall assurance of end-to-end connectivity.

Also, we would expect that the higher the network dynamics, that is, the higher the mobility, number, and sparsity of the terminal nodes and the higher the atmospheric attenuation, the more significant the improvements in SD connections would be.

Table 3: Average percentage improvement in SD connections using the Morse potential for backbone-to-terminal links, with maximum transmitted power of 3 W, 5 W, and 7 W.

	SD cons $P_{T\max} = 3\,\mathrm{W}$	SD cons $P_{T\max} = 5\,\mathrm{W}$	SD conns $P_{T\max} = 7\,\mathrm{W}$
Convex potential	3077	4843	6166
Morse potential	3606	5368	6441
Average percentage improvement	17.2%	10.8%	4.5%

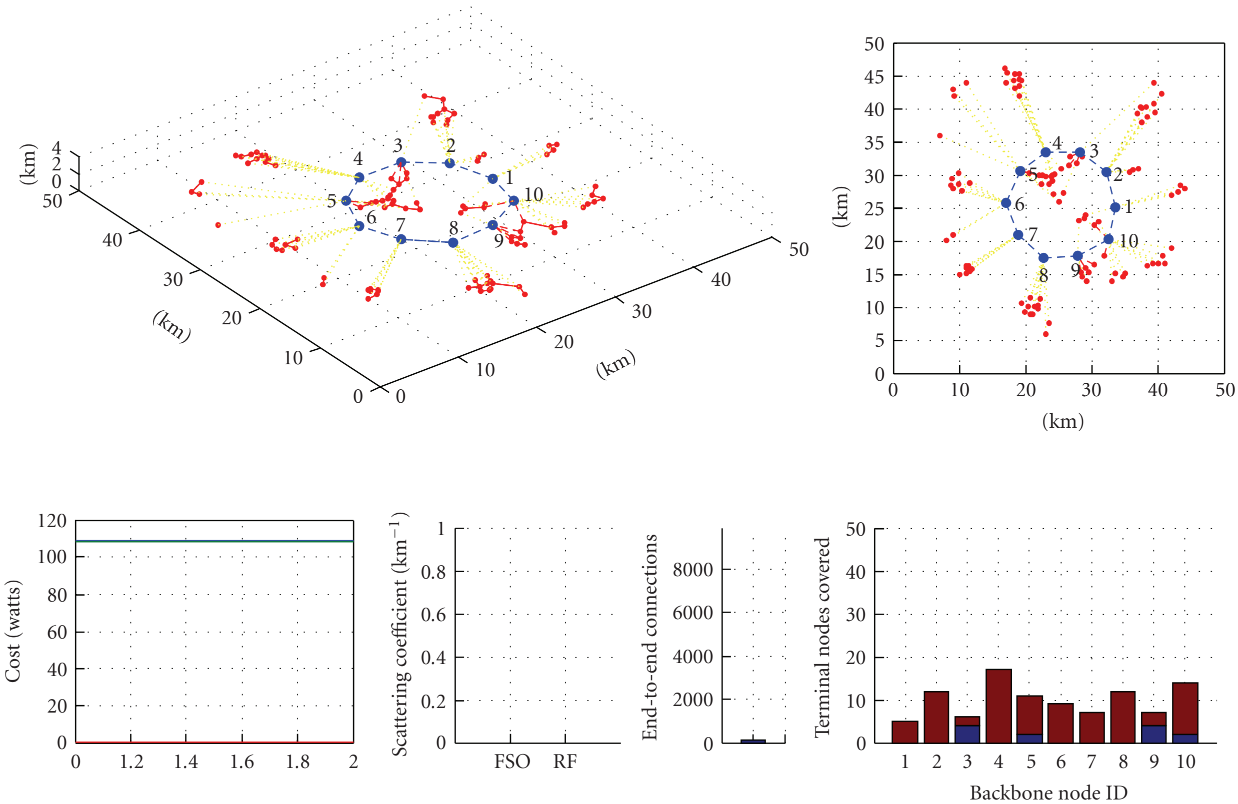
Current investigations include extensive simulation analysis to better assess the impact of varying network dynamics parameters.

7. Conclusions

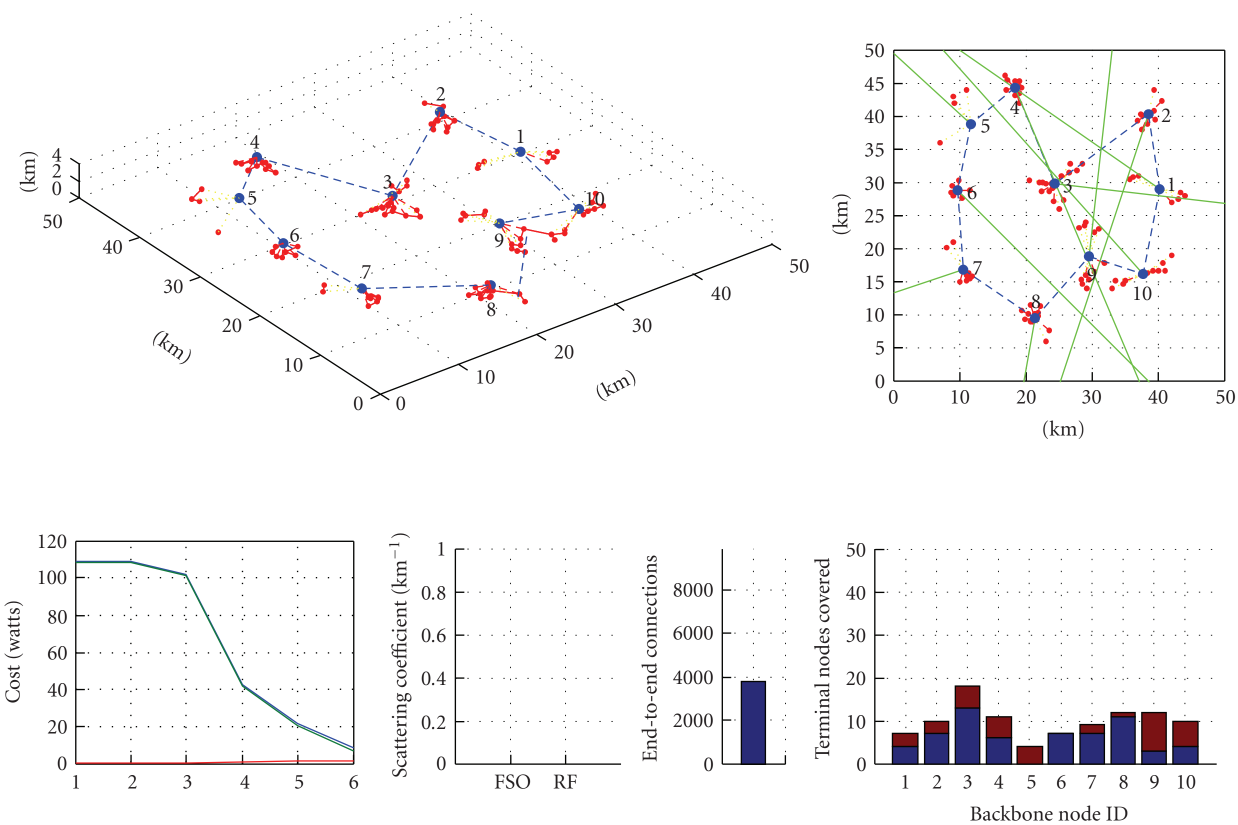
In this paper, we have presented a novel dynamic topology control approach for next-generation wireless networks, which are becoming increasingly complex systems due to their heterogeneity (hierarchical architectures with diverse communication technologies) and dynamic behavior (high node mobility and changing atmospheric conditions).

The network control framework is based on the work described in [7, 8] which models heterogeneous and dynamic communication networks as physical systems, where network robustness is characterized in terms of the system's potential energy and forces on network nodes drive the network topology for network performance optimization. The potential energy of a communications network is defined as the electromagnetic energy stored in the wireless links forming the network, and the topology control problem is formulated as an energy minimization problem whose solution is shown to jointly optimize coverage and connectivity in highly dynamic scenarios.

This paper extends the model in [7, 8] by introducing the Morse potential as an alternative link energy function that leads to a hybrid topology-control methodology, where communication links are retained, released, or reconfigured based on their communications role within the network architecture. A convex energy function with exponential

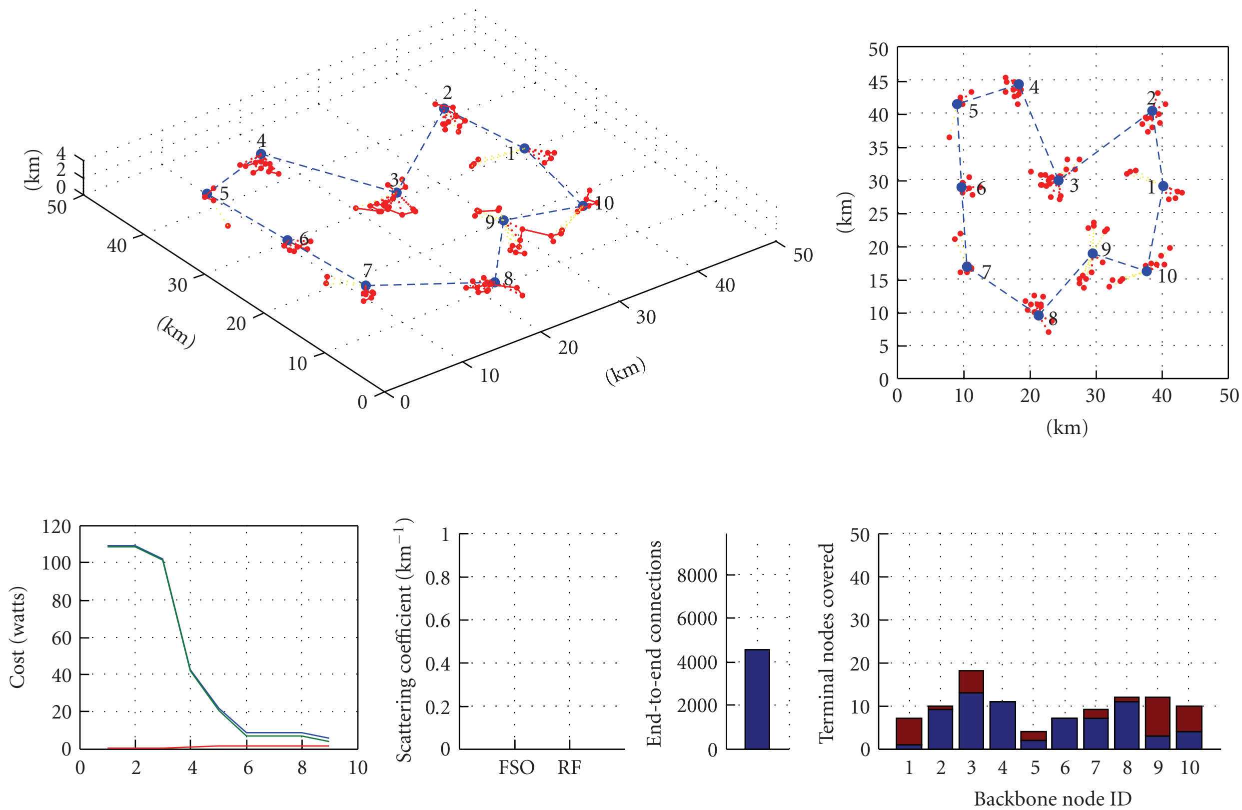


(a) T = 1 min; SD connections = 156

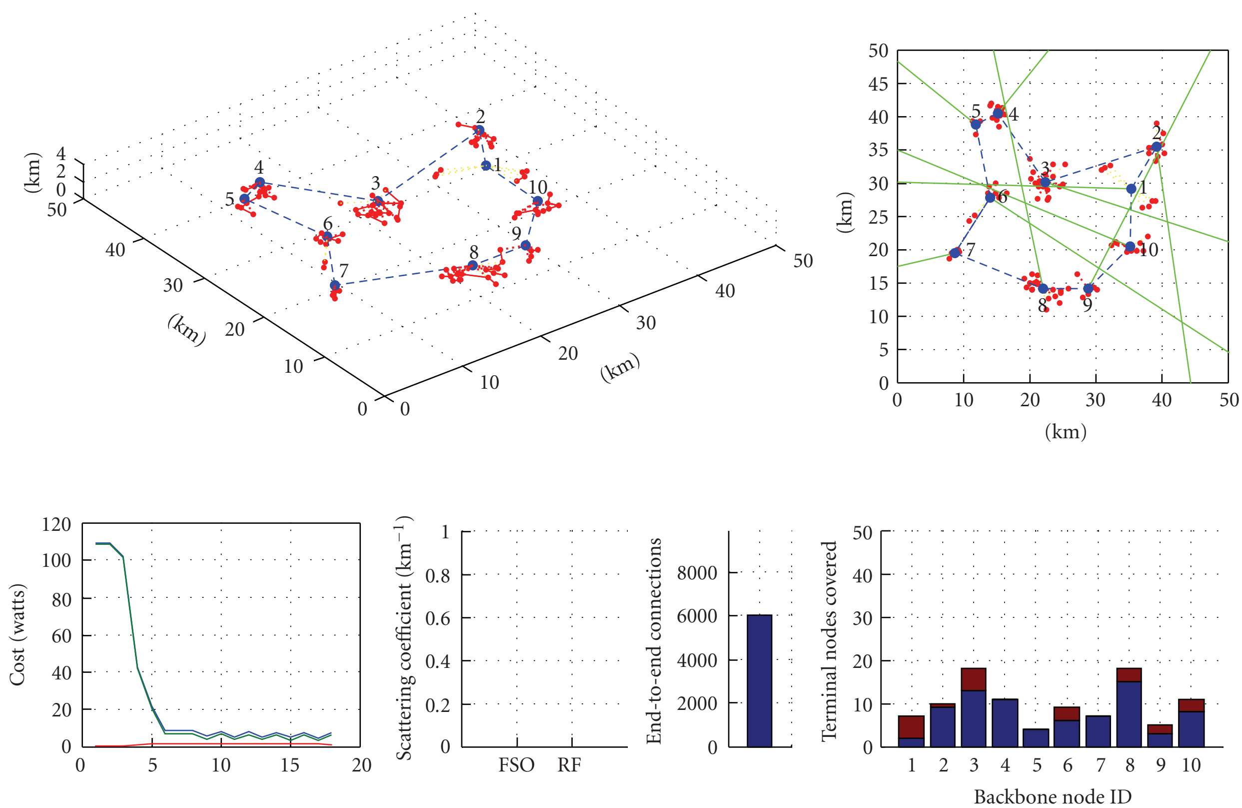


(b) T = 5 min; SD connections = 3782

Figure 5: Continued.

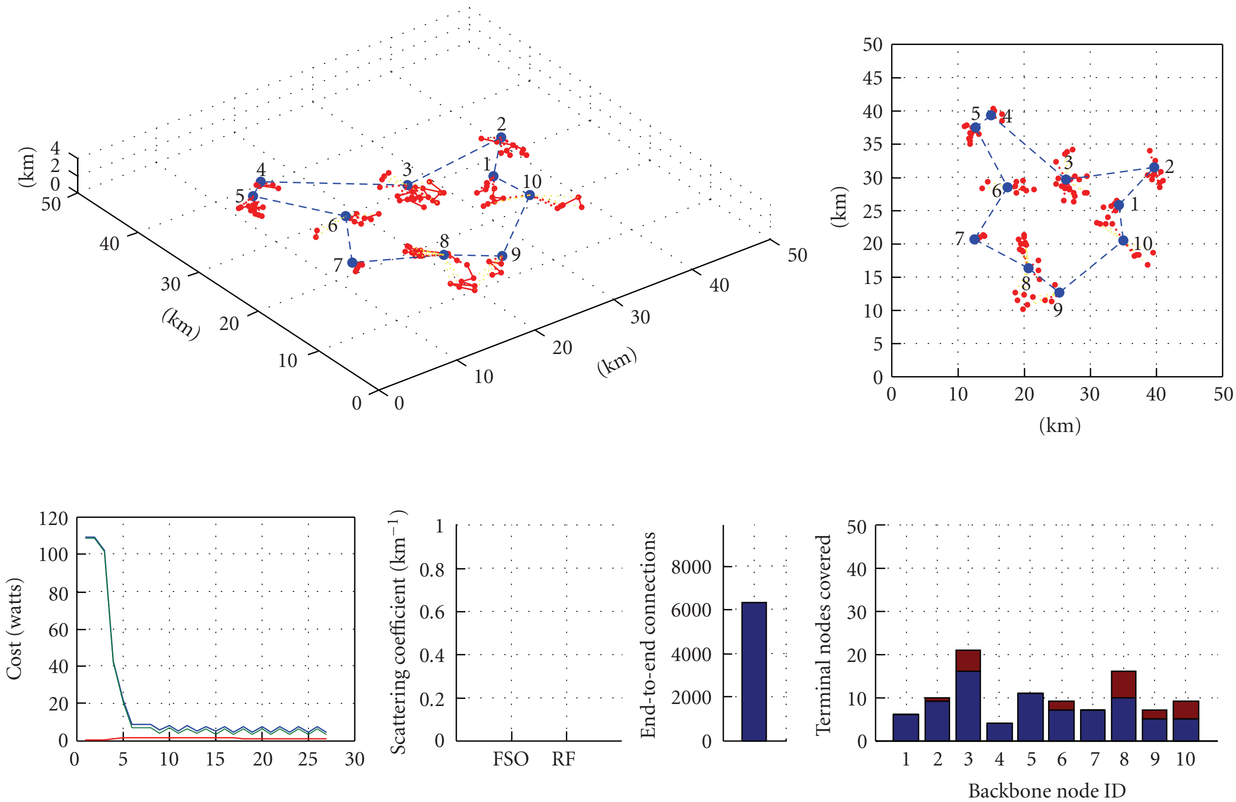


(c) T = 8 min; SD connections = 4556



(d) T = 17 min; SD connections = 6006

Figure 5: Continued.



(e) T = 26 min; SD connections = 6320

Figure 5: Network evolution with terminal nodes moving according to the RPGM model and backbone reacting using the FORCE algorithm.

constraint is used to model the link retention process, where attraction forces drastically increase their magnitude when reaching physical constraints. The Morse potential, on the other hand, which models the energy saturation leading to bond breaks in molecular systems, is used to model the link release process, in which attraction forces reduce their magnitude when reaching physical constraints.

In our simulations, backbone-to-backbone links, of critical importance in the network architecture, are modeled using the convex model with exponential constraint, while the backbone-to-terminal links are modeled using the Morse potential. We measured the average number of SD connections maintained and showed a significant improvement when using the hybrid energy model. The use of the Morse potential at the backbone-to-terminal links allows the network to release high-cost links that have an effect on the overall assurance of end-to-end connectivity. Results suggest a more significant improvement the more restrictive the physical constraints, such as the maximum transmission power and the mobility of terminal nodes.

Of key importance is the analysis of the convergence and robustness of molecular-based optimization methods, including the characterization of the multiple equilibrium configurations that might arise from the adoption of non-convex potentials.

Ongoing work also includes extensive simulation analysis with varying network parameters and the evaluation of Normal Mode Analysis (NMA) [14] for prediction of anomalous network behavior leading to partitions and/or degradation.

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