

CONTROL AND PREDICTION IN HIERARCHICAL WIRELESS NETWORKS

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Abstract

Directional wireless networks (DWNs) using free space optical (FSO) and RF transmissions provide wireless backbone support for mobile communications in dynamic environments. The heterogeneous and dynamic nature of such networks challenges their robustness and requires self-organization mechanisms to assure end-to-end broadband connectivity. We have developed a framework to provide prediction and control strategies for assured network operation. We draw an analogy between a set of interconnected communication nodes and a molecule in which the bonds between atoms are representative of the links in the equivalent network. The dynamics of the network, and its optimization, can be analyzed by the methods of molecular dynamics. Links are modeled as bonds described by potential energy functions, such as the Morse potential, and a global description of the stability of the network can be obtained by a normal mode analysis (NMA). Effective “forces” act on nodes, which include the effects of power control, link length, and channel characteristics. A molecular re-arrangement or fragmentation occurs because this reduces the potential energy. In the same way a network can undergo topological reconfiguration, and an adaptive control strategy can be used to release, retain or reconfigure communication links for network performance optimization. Simulation results show the effectiveness of our self-organized control mechanism, where the physical topology reorganizes to maximize the number of source to destination communicating pairs. NMA of a network suffering degradation shows a correlation between anomalous eigenvalue behavior of the Hessian matrix describing the network and the improvement of network performance that can be achieved by topology change.

Keywords: FSO communications, heterogeneous wireless networks, self-organization, mobility control, network robustness, molecular dynamics.

1. INTRODUCTION AND CONTEXT

Next generation communication networks are becoming increasingly complex due to their heterogeneous nature and dynamic behavior. The need for ubiquitous broadband connectivity and the capacity and scalability limitations of homogeneous wireless networks [1] are fostering the adoption of 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, 3].

We consider backbone-based wireless networks, which use a two-tiered architecture, where a set of flat ad-hoc wireless networks with limited communication capabilities (tier 1) are interconnected through a broadband wireless mesh backbone network (tier 2) of higher capability nodes that use directional wireless communications (FSO and/or directional RF) to aggregate and transport traffic from end users or hosts (Fig. 1). Examples of research projects in Tier 2 architectures can be found in [2, 3, 17,18]. Our research has uniquely focused on prediction and control of such mobile wireless Tier 2 backbones in order to provide assured connectivity and coverage.

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, 3]. We refer to these networks as directional wireless backbone networks (DWBNs), whose platforms can be airborne, terrestrial and/or sea-based. Such networks provide adaptive infrastructure support for users or networks such as mobile ad hoc networks (MANETs). In this sense, the DWBN becomes the substrate that provides the scalable end-to-end assured transmissions that omnidirectional MANETs (O-MANETs) were not designed to provide [1, 2]. We refer to these as Directional Mobile Ad Hoc Networks (D-MANETs).

In this architecture, end users are not controllable; their actions are guided by their respective applications and they rely on the seamless availability and assured quality of service of the backbone. The backbone network, on the other hand, must be controlled to provide assured end-to-end communications.

Our work considers the use of topology control to assure robust end-to-end broadband connectivity in heterogeneous and dynamic environments. Topology control is defined as the autonomous network capability to dynamically reconfigure its physical topology. In the case of directional wireless backbone networks, the physical topology can be reconfigured through:

- 1) **Topology Reconfiguration:** dynamic redirection of directional wireless point-to-point links using algorithms for creating new topologies and pointing, acquisition and tracking of links [14, 15].

2) **Mobility Control:** dynamic reposition of backbone nodes for joint coverage-connectivity optimization [10, 11, 12].

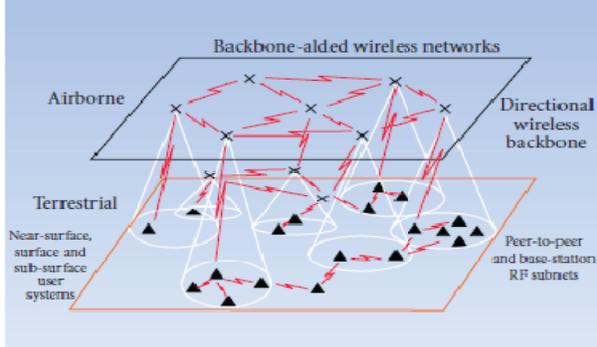


Fig. 1: Hierarchical wireless network architecture

Topology control in broadcast ad hoc networks has been extensively studied in terms of power control and node placement, where the transmitted power and the location of movable nodes are adjusted to avoid excessive interference [4-8]. In DWBNs directional links avoid the mutual interference problems of omnidirectional broadcast wireless networks and provide physical reconfiguration, with the added complexity of the pointing, acquisition, and tracking (PAT) of the links [9]. Moreover, physical constraints such as terrain blockage and channel loss gain importance. Thus, topology and mobility control in DWBNs is a fundamental new problem area.

DWBNs can autonomously adapt their physical topology to maximize coverage to terminals or hosts while maintaining robust backbone connectivity. Our paradigm includes an interface between IP and the topology reconfiguration processes (Fig.2). The reconfiguration algorithms and heuristics show low complexity and by presenting a new topology to the IP layer, significantly reduce the routing convergence time needed to discover new interfaces [12].

The most important concern in a hierarchical wireless networks is to assure network coverage and backbone connectivity in dynamic wireless environments. In our previous work, we have formulated a physics-inspired convex optimization method for joint coverage and connectivity control [11, 12]. The uncontrolled network dynamics are modeled as external forces changing the energy of the system and topology control mechanisms are developed as internal forces driving the system to minimum energy configurations. Results have shown 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 [11, 12]. However, in the presence of physical constraints such as the power available at the network nodes, non-convex potentials provide a more accurate characterization of the behavior of wireless

links by inherently including the effects of link breakage [12, 13].

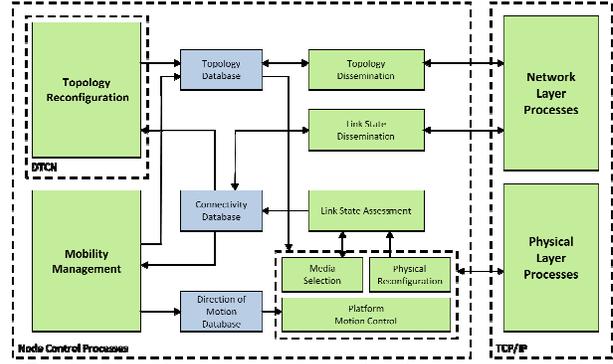


Fig. 2: Control processes integrated with internet protocols

In recent work we have developed molecular inspired network models in which links are analogous to bonds, and the topology is the molecular structure. Non-convex molecular potentials, allow the use of adaptive control strategies where forces on network nodes drive the release, retention or reconfiguration of links based on their role within the network architecture, and can incorporate the effect of transmitter power constraints.

In this paper we present architecture and models as well as results from our molecular inspired control methodology for dynamic hierarchical wireless networks, as well as molecular dynamics techniques for the prediction of network robustness that relate failures in communication networks to bond breaks or partitions in the analogous molecular structure.

2. APPROACH

Our topology control mechanisms are designed to mimic physical systems' reactions to external excitations that drive the network topology to minimum energy configurations for increased robustness and improved performance. We have developed and evaluated algorithms and protocols for mobility control by computing internal forces at each backbone node as negative energy gradients and showed how the network can autonomously achieve an energy minimizing configuration.

2.1 Joint coverage-connectivity optimization by reaction to physical forces

Network robustness in DWBNs is addressed in terms of the following two main objectives: network coverage and backbone connectivity. In backbone-based wireless networks, communication between two terminal 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 terminal nodes until it reaches its destination.

Clearly, in this type of architecture, the end hosts need to be well covered by the backbone nodes and the backbone nodes must have good connectivity. Thus, the objective is to find the optimal backbone topology configuration to jointly maximize network coverage and backbone connectivity.

In [11, 12] we introduced a convex optimization framework for topology control in DWB-based networks. 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:

$$U = \sum_{i=1}^N \sum_{j=1}^N b_{ij} u(\mathbf{R}_i, \mathbf{R}_j) + \sum_{k=1}^M u(\mathbf{R}_{h(k)}, \mathbf{r}_k), b_{ij} = \begin{cases} 1 & \text{if } (i,j) \in T \\ 0 & \text{o.w.} \end{cases} \quad (1)$$

where \mathbf{R}_i is the location of backbone node i , \mathbf{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 link assignment variables that determine the backbone topology T . The link cost function $u(\mathbf{R}_i, \mathbf{R}_j)$ represents the potential energy of link (i,j) and it is defined as the communications energy per unit time needed to send information from node i to node j at the specified BER,

$$u(\mathbf{R}_i, \mathbf{R}_j) = k_{ij} \left(e^{d \|\mathbf{r}_i - \mathbf{r}_j\|} \right) \left(\|\mathbf{R}_i - \mathbf{R}_j\|^2 \right), \quad k_{ij} = P_{R0}^j \frac{4\pi}{D_T^i A_R^j} \quad (2)$$

where P_{R0} is the minimum required received power, D_T the directivity of the transmitter and A_R the effective receiver area.

Note that the first term in the cost function U represents the total energy stored in the directional wireless links forming the backbone network and thus is a measure of backbone connectivity; while the second term represents the total energy stored in the wireless links covering the end users and is therefore a measure of network coverage.

In [11, 12] we developed force-driven mobility control algorithms that autonomously relocate each backbone node in the direction of the net force, computed as the negative energy gradient at the backbone node's location, achieving global optimality from local interactions. The net force acting on a given backbone node can be computed using local information only; no centralized global information is needed. 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 [10,18].

2.2 Modeling directional wireless networks as molecular systems

A wireless network is analogous to a giant molecule, where the nodes correspond to atoms and the links to

bonds. In a harmonic energy model, the cost of a wireless link or its potential energy is a convex function of the link distance. One non-convex extension of this model that we use is the *Morse potential*, defined as

$$U(x) = D_e (1 - e^{-\beta x})^2, \quad (3)$$

where D_e is the "dissociation energy," at which point a link fails, and β is related to the force constant.

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 convex energy model, the "force" increases quadratically (or exponentially in the presence of channel loss) as the link distance increases: the longer the distance, the stronger the "force" needed to maintain the connection. We refer to this control process as the "retention" of a connection. On the other hand, under the Morse energy 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" of a connection.

2.2.1 Adaptive control

The use of non-convex potential energy models to characterize the behavior of wireless links in DWB-based networks under power limitation constraints leads to more effective control strategies where communication links are retained, released or reconfigured based on their role in the network architecture. Along with molecular inspired prediction methods, which are presented in section 2.3, a novel adaptive control mechanism can be developed based on the following scheme:

1. Network health prediction: link degradation, network partition or node failures should be predicted and assessed before occurrence. Section 2.3 describes our approach to predicting network degradation using normal mode analysis in molecular systems.

2. Dynamic force-driven reaction: under a possible degradation/failure event, three main control processes can be executed:

a) **Retain connection:** essential links (e.g. links carrying priority data traffic) are modeled using the convex potential so that the network will always make the effort to retain such connections.

b) **Release connection:** non-essential links (e.g. links carrying non-priority traffic) are modeled using the Morse potential so that if the cost to maintain the connection is too high the link is relaxed or released.

c) **Reconfigure topology:** if there is a better topology or an essential link has been lost, the network topology goes into a reconfiguration phase in order to re-gain/improve connectivity. We have developed low

complexity algorithms for dynamic topology optimization [14, 15].

In our initial simulations, the performance of the proposed approach is measured in terms of the number of source to destination (SD) connections that have an end-to-end communications path. Results show the effectiveness of our adaptive control mechanism, where the physical topology reorganizes to maximize the number of source to destination communicating pairs (see section 3).

2.2.2 A hybrid energy model:

In this work, we introduce a new continuous energy function that considers power limitations as well as distance threshold constraints, as an extension to the Morse energy model. The basic idea with respect to considering a distance threshold between a backbone node and a terminal node (or another backbone node) is that the network nodes should repel each other when the distance between them decreases to a certain point.

We define the force \mathbf{f}_{ik} that terminal node (or another backbone node) k exerts on backbone node i , as

$$\mathbf{f}_{ik} = q(\mathbf{R}_k - \mathbf{R}_i). \quad (4)$$

The direction of the force \mathbf{f}_{ik} is given by the link distance vector $(\mathbf{R}_k - \mathbf{R}_i)$ and its amplitude by the function of repulsion/retention/release $q(\cdot)$, which can be defined as

$$q(x) = -x \left(a - b \left(\exp(-\|x\|^2/c) \right) + r \left(\exp(-\xi \|x\|^2) - \exp(-v \|x\|^2) \right) \right) \quad (5)$$

where $x = (X_k - X_i)$ is the one dimensional link distance vector and a, b, c, r, ξ and v are positive constants such that $a < b$ and $\xi < v$. For the case with $a = 0.005, b = 8, c = 0.8, r = 0.002, \xi = 0.001$ and $v = 0.03$, the function is shown in Fig. 3.

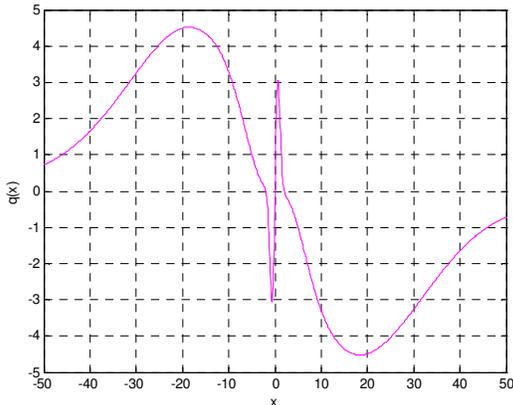


Fig. 3: One dimensional repulsion/retention/release function $q(x)$ with respect to the link distance vector x

Note that when the link distance is smaller than 2, the repulsion force is the one acting on the nodes, while the release force acts after the distance increases to around

18. Note that the parameter a represents the retention of the connection, the item $b \left(\exp(-\|x\|^2/c) \right)$ represents the repulsion at small distances, and the item $r \left(\exp(-\xi \|x\|^2) - \exp(-v \|x\|^2) \right)$ represents the release of a connection for long distances.

2.2.3 Analysis and results

We have developed a software tool in Matlab that allows the modeling and simulation of dynamic heterogeneous wireless networks with different design parameters. Terminal nodes move according to the RPGM [16] model and our force-driven control method is used to make backbone nodes adjust their locations until convergence to the optimal backbone configuration.

In table 1, we compare 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 used 10 different one hour dynamic scenarios changing the placement of the terminal nodes and the mobility patterns. We measured the average number of source to destination (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 was always used. 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. 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 adversely affect QoS. Also, we expect the more complex the network dynamics in terms of number and sparsity of the terminal nodes and the greater the channel loss, the more significant the improvements in SD connections will be.

Table 1: Average percentage improvement in SD connections using the Morse Potential for backbone-to-terminal links, with maximum transmitted power $P_{Tmax} = 3, 5$ and $7W$.

	$P_{Tmax} = 3W$	$P_{Tmax} = 5W$	$P_{Tmax} = 7W$
CONVEX POTENTIAL	3077	4843	6166
MORSE POTENTIAL	3606	5368	6441
Average Percentage Improvement	17.2%	10.8%	4.5%

2.3 Normal mode softening in molecular systems for network health prediction

We are extending our analysis of a network as a giant molecule, to not only optimize the network configuration, but to also predict the likelihood of link failures. A molecular structure has an equilibrium arrangement that minimizes its potential energy. The overall potential energy of the structure is

$$V = V_0 + \sum_{i=1}^N \left(\left(\frac{\partial V}{\partial x_i} \right) x_i + \left(\frac{\partial V}{\partial y_i} \right) y_i + \left(\frac{\partial V}{\partial z_i} \right) z_i \right) + \sum_{i=1}^N \left(\left(\frac{\partial^2 V}{\partial x_i^2} \right) x_i^2 + \left(\frac{\partial^2 V}{\partial y_i^2} \right) y_i^2 + \left(\frac{\partial^2 V}{\partial z_i^2} \right) z_i^2 \right) + \sum_{i,j=1}^N \left(\left(\frac{\partial^2 V}{\partial x_i \partial y_j} \right) x_i y_j + \left(\frac{\partial^2 V}{\partial y_i \partial z_j} \right) y_i z_j + \left(\frac{\partial^2 V}{\partial z_i \partial x_j} \right) z_i x_j \right) \quad (6)$$

In our equivalent network model, the (x_i, y_i, z_i) are the spatial coordinates if the i th node. If the structure is in equilibrium the first derivatives are zero, so the behavior of the network under perturbation depends primarily on the second derivatives. By analogy with the corresponding molecular model we write: $\frac{\partial^2 V}{\partial x_i^2} = k_{xx}^{ii}$

, which is the x -directed “force” on node i (and analogously the y and z -directed forces). In the molecular model these force constants are mass-weighted so that if atom i has mass m_i and atom j has mass m_j , the mass weighted k 's are of the form $\tilde{k}_{xx}^{ij} = \frac{k_{xx}^{ij}}{\sqrt{m_i m_j}}$. The matrix of mass weighted force

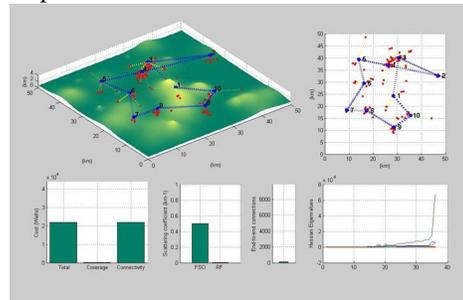
constants is called the Hessian matrix, which for an N -node network is a $3N \times 3N$ matrix. In our molecular analogue of a network the node “masses” can be assigned to describe the degree of mobility of a node. An immobile node has very large (infinite) mass, while a highly mobile node has very small mass. The eigenvalues of the Hessian matrix give the normal mode frequencies of the network. A “normal mode” is an overall movement of the network, where all nodes move at the same frequency about their equilibrium positions.

In the molecular model, mode softening is the process by which a normal mode frequency approaches zero, which is an indicator of an impending conformational change. A good example is provided by the “unzipping” of DNA, where the two backbones of the molecule separate when replication is about to occur [13]. In the network context, if the normal mode frequencies are tracked as the nodes of the network move, then a normal mode tending towards zero should suggest a potential network disruption and the need for topology re-configuration. This will allow a prediction of the onset of link failure and allow a topology re-configuration to be adopted before this happens.

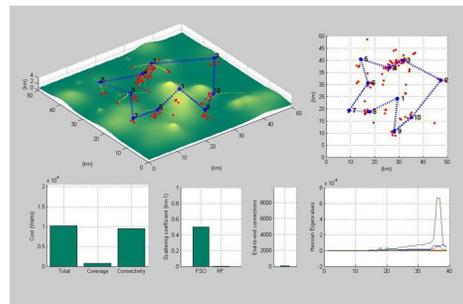
We have extended our network modeling tool in Matlab to include the computation of the network Hessian matrix at any point in the dynamic simulation.

In our simulation, we track the eigenvalues of the Hessian matrix as the network system evolves. Fig. 4 shows an example of a simulation where the network undergoes a topology re-configuration when reaching an anomalous non optimal configuration. As shown in Fig. 4, the largest eigenvalue of the Hessian matrix is able to track the network anomaly. Note the peak in the value of the largest eigenvalue of the Hessian Matrix at the point where the network undergoes re-configuration.

Initial results such as those presented here are encouraging and show the potential of molecular normal mode analysis techniques for prediction and network health monitoring, and the ability to trigger more effective network reactions prior to degradation. Our preliminary results are intriguing in the molecular analogy context. Our mode eigenvalues approach large values (increasing slope) when network failure is imminent, in contrast to molecular systems where normal mode frequencies “soften” (approach zero) when re-configuration approaches. The difference arises because of the way we characterize communication links. In a molecule a strong bond holds two atoms together strongly, and it is the weaker bonds that break. In our network model, a requirement of increasing transmitter power to maintain link connectivity presages link failure because operational constraints limit available powers.



(a) Network before reconfiguration. Eigenvalue peak correlates with anomalous configuration.



(b) Network after reconfiguration. Eigenvalue goes down as network goes back to a minimum energy configuration.

Fig. 4: Illustration of the correlation between the evolution of network dynamics and the Hessian Eigenvalues.

3. CONCLUSIONS

We have developed a new paradigm for prediction and control in heterogeneous and dynamic wireless networks. Communication networks are modeled as physical systems where network robustness is characterized in terms of the system's potential energy, and mobility control mechanisms as internal forces that the network system uses to react to external excitations by driving the network topology to energy minimizing configurations, based on local forces exerted on network nodes.

We have introduced non convex molecular potentials such as the Morse potential, used to describe the potential energy of bonds within molecules, for the characterization of communication links in the presence of power limitation constraints at the network nodes. The inclusion of the Morse potential leads to an adaptive topology control methodology where communication links are retained, released or reconfigured based on their communications role within the network architecture. Our results show how molecular-based control strategies are able to increase the average number of available source to destination connections over existing methods. Also, initial correlations have been observed between dramatic changes in the eigenvalues of the network Hessian matrix and network topology anomalies.

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