Scalability Analysis of Tactical Mobility Patterns

Ertugrul Necdet Ciftcioglu† Ram Ramanathan‡ Thomas F. La Porta†
† Dept. of Computer Science and Engineering, The Pennsylvania State University, University Park, PA 16802
‡ BBN Technologies, Cambridge, MA, 02138
Email: enc118@psu.edu, ramanath@bbn.com, tlp@cse.psu.edu

***Abstract*—Military networks are characterized by varying degrees and patterns of mobility. In this work, we consider the scalability of real-world mobile tactical networks, including the effects of protocols and bottlenecks, from a non-asymptotic viewpoint. Such analysis has been previously done for static networks [1], where the scalability of static scenarios was characterized by identifying the signature, which depends on the topology and traffic properties.**

We analyze the signature and scalability of a network consisting of two convoy groups moving according to the *repeated traversal* tactical mobility model. We observe that tactical mobility significantly reduces network scalability. Furthermore, we identify the instances in time where nodes of the network are loaded the most, preventing the network to scale to larger number of nodes. We demonstrate that this bottleneck instant depends on the routing algorithm considered. Finally, we demonstrate how the scalability is affected by the variation of network resources and traffic characteristics, and uncover significantly different trends compared with the static case.

I. Introduction

The increasing proliferation of mobile wireless devices has lead to a significant increase in network size for many commercial, civilian and military applications. Hence, a fundamental question is how large a network can be sustained for a given user behavior, topology, protocol and routing algorithm. The use of simulations to answer this question is not efficient or flexible because a small change in any parameter or algorithm configuration requires re-running the simulation. Further, for scalability (maximum network size) estimation, one needs to run simulations of different size networks to find the point at which it "breaks". This is likely to be prohibitively expensive especially for large network sizes.

On the other hand, the natural alternative, which is analytical modeling, has traditionally been performed in an asymptotic manner [2], [3]. While these works provide fundamental theoretical bounds, they represent the limiting case where network size goes to infinity (i.e, *asymptotic bounds*). This does not address real-world scenarios with large but still finite network sizes, as well as MAC layer issues, control protocol, and bottleneck phenomena.

This problem was addressed in [1] which examines to how many nodes may a given network scales. Specifically, expressions for network scalability were presented for three different structured topologies, namely line, mesh and clique networks. Unlike asymptotic analysis, this analysis is non-asymptotic and presents closed form expressions that apply to finite-sized real-world networks and hence has been termed *symptotic scalability*. Whereas this work provides a fundamental framework for network scalability analysis, the main study and analysis in [1] focused on static network scenarios where the topology does not change over time. On the other hand, for many realistic scenarios, including tactical networks, it is necessary to address the impact of mobility. For instance, squads of surveillance and attack forces form a mobile tactical network [4]–[6] to accomplish military operation missions.

In this paper, we present the first symptotic scalability analysis of mobile scenarios, in particular the scalability of convoy groups that move in accordance with the *repeated traversal* military mobility pattern [6]. While repeated traversal is a tactical mobility model designed to maximize the security of troops, it is also applicable to commercial applications such as disaster recovery where robot or delivery convoys are deployed. Additionally, repeated traversal also captures the phenomenon of group mobility, which is very common in tactical networks [7], [8].

We observe that the overall effect of mobility on symptotic scalability is twofold: (i) Different stages of connectivity throughout the movement result in different topologies; (ii) Link breakages and creations necessitate exchange of Link State Updates (LSU), increasing control overhead. We demonstrate analytically that mobility significantly reduces the scalable network size. We consider two different routing algorithms for multihop scenarios, one solely minimizing hop count and the other also being energy-efficient[1]. We demonstrate that scalability, and the instant when the network is loaded the most depends on the routing algorithm used. We observe that incorporating objectives such as reducing energy may further reduce scalability for certain scenarios, including cases with lightly loaded data traffic for each user. Our work can be applied to designing the maximum size of a convoy network, or given the size to adequately provision the bandwidth and control the traffic load.

II. Symptotic Network Scalability

The crux of the symptotic scalability framework is governed by the following parameters [1]:

For any given node m of the network at hand,

Research was sponsored by the U.S. Army Research Laboratory under the Network Science Collaborative Technology Alliance, Agreement Number W911NF-09-2-0053.

[1]Accordingly, this is also the first paper to investigate symptotic analysis of advanced routing algorithms as energy-minimizing routing algorithms.

$W(m)$: *Available capacity*, the amount of data that can be supported by node m.

$D(m)$: *Demanded capacity*, amount of data load at m required to transport a given set of flows.

$B(m)$: *Blocked capacity*, capacity unusable by node (e.g. due to contention)

$R(m)$: *Residual capacity*, $R(m) = W(m) - D(m) - B(m)$

$B(m)$ and $D(m)$ depend on input traffic load L_j at each node for traffic j as well as the following parameters:

$\Gamma_j(m)$: *Contention factor*, Number of nodes in the contention neighborhood of m for traffic j (nodes that either cause interference or can cause m to defer when they are active).

$\Upsilon(m)$: *Transit factor*, The traffic from other sources relayed by node m for traffic j.

ν: Inefficiency factor due to medium access scheme accounting for effective rate and the actual capacity.

$\Psi(m)$: Blocked capacity for all sessions for reasons other than contention (e.g. due to sensing time)

The remaining capacity at node m is then given as:

$$R(m) = \eta W(m) - \Psi(m) - \sum_j (1+\Gamma_j(m)) L_j (1+\Upsilon_j(m)). \quad (1)$$

Denote remaining capacity of a network with N nodes by $R_N(m)$. Then, we have the following definition:

Definition 1: [1] Symptotic scalability of a network is the number of nodes X such that for all $N \leq X$, and for all m, $R_N(m) \geq 0$ and for all $N > X$, there exists a node m_b such that $R_N(m_b) < 0$.

The node m_b is called the bottleneck node. A network might have multiple bottlenecks.

The most prominent factors which depend on the network are the contention and transit factors of the bottleneck node of a network, referred to as the *signature* of the network. The main interest of scalability analysis then boils down to the determination of the (Γ_j, Υ_j) pair for the network.

Expanding factors due to multiple traffic types,

$$\eta W = (1+\Gamma_d)L_d(1+\Upsilon_d) + (1+\Gamma_l)L_l(1+\Upsilon_l) + (1+\Gamma_h)L_h(1+\Upsilon_h) \quad (2)$$

provides the expression to determine the critical value to which the network scales, where subscript d denotes data, l denotes link state update (LSU) and h denotes hello packets.

Expressions for the signatures (Γ_j, Υ_j) were provided in [1] for line, mesh and clique networks for TDMA and CSMA medium access schemes, and traffic consisting of data and control components, e.g. link state updates and hello packets for the latter. The analysis carried out assumed static networks. The accuracy of the framework was also confirmed by ns-2 simulations. In this work, we extend this analysis to mobile scenarios. Specifically, we are interested in tactical mobility models. Next, we present a prominent tactical mobility model, namely repeated traversal [6].

III. Repeated Traversal

In this section, we present the Repeated Traversal tactical mobility model [6]. In repeated traversal, while moving through unknown, highly hostile terrain, troops traverse along same paths one squad after another in order to increase security. The squads are called leading squad and following squad. The sequential movement pattern is as follows: Leading squad takes initiative and moves first. If the terrain is cleared of threats, the leading squad communicates to the following squad. The leading squad rests and waits for the following squad. In case an unfriendly event occurs, the leading squad communicates this outcome and the following squad avoids that path. Fig. 1 depicts an example of repeated traversal.

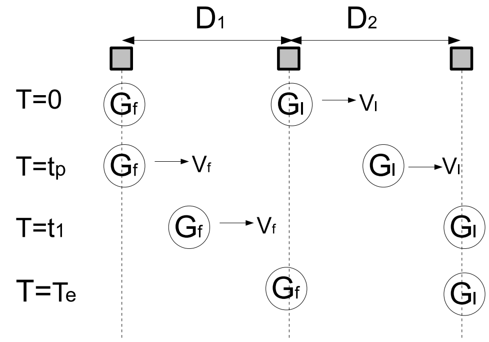

Fig. 1. Stages and connectivity of Repeated Traversal of convoy groups. G_f, G_l represent the following and leading groups respectively. G_l starts moving at time T=0, G_f at time T= t_p, G_l stops moving at time T = t_1.

This strategy results in a structured and regular movement. The movement is based on an epoch-based model. Inter-group communication is necessary for coordination. Consequently, even though contact might be lost at some stage of the maneuver, the groups should come back in contact towards the end of each epoch.

In this simplified diagram, where nodes from each group are assumed to be co-located, inter-group distance D_g is given by the following set of equations:

V_l, V_f: Velocity of leading (l) and following (f) groups

(i) $0 \leq t \leq t_p$:

$$D_g(t) = D_1 + V_l t \quad (3)$$

(ii) $t_p \leq t \leq t_1$:

$$D_g(t) = D_1 + V_l t_p + (V_l - V_f)(t - t_p) \quad (4)$$

(iii) $t_1 \leq t \leq t_e$:

$$D_g(t) = D_2 + V_l t_p + (V_l - V_f)(D_2/V_l - t_p) - V_f(t - D_2/V_l), \quad (5)$$

where t_p is the pause time for the following squad. Due to the movement of the leading group, when $D_g(t)$ exceeds a threshold distance $D_{threshold}$, the groups are disconnected for some portion of the movement. However, reduction of $D_g(t)$ after t_1 ultimately enables groups to come in contact again.

IV. Scalability of Repeated Traversal

We study a specific case of the repeated traversal depicted in Fig.1 in which each group is arranged in a line. We assume that the two groups are identical in terms of group size and node density. Specifically, distances between consecutive nodes are identical throughout each group. Moreover, we also assume that inter-group distances are significantly larger than intra-group distances, and the communication range of each node is such that it can reach all nodes in its group in one hop. Note that the while the connectivity is a "clique network", the fact that the nodes are in a line means that inter-group connectivity changes happen in a step-by-step manner than all at once.

Figures 2 and 3 demonstrate the specific stages of different connectivity for the case when the leading group moves away from the following group, resulting in link breakages. The second part when the following group recovers the distance and links are created involves exactly the same intermediate topologies, so is not depicted due to space constraints. The time scale in which stages increment depend on both group velocities and the physical layer model through path loss. Each group is a clique network, and when both groups are in full communication range at the beginning of the movement, the overall network is a giant clique. As the leading group moves, eventually, some pairs of nodes from separate groups start to lose direct contact, leading to a different topology. Ultimately, when the groups are completely isolated, the network consists of two disjoint cliques.

The overall effect of mobility on symptotic scalability is twofold:

(i) Different stages of connectivity throughout movement results in different signatures $(\Gamma_j(t), \Upsilon_j(t))$.

(ii) Link breakages and creations necessitate exchange of Link State Updates (LSU), increasing control overhead. The amount of LSU packets required depend on the number of link breakages or creations, hence potentially vary with the specific stage. Moreover, $(\Gamma_l(t), \Upsilon_l(t))$ also potentially depend on the stage number, since relaying options are changed.

The goal in this work is to characterize the signatures for repeated traversal of convoy groups and eventually analyze the scalability of such a scenario. In the rest of this work, for convenience, we call a member of a group or a squad a *node*. Similar to the static case, this study necessitates the identification of bottleneck nodes.

Bottleneck Node: For the static case and disconnected case, since the graph is composed of either a giant clique or two separate cliques for each group, there is no relaying and the network is symmetric, leading to the fact that every node is equally loaded. Hence, each node is a bottleneck node.

For intermediate stages, it is readily seen that contention factor is largest for nodes with maximum number of neighbors. Specifically, nodes which are closer to the other group have a larger contention factor. Additionally, these nodes are also associated with a large transit factor, since they provide relaying for the farther nodes. As a result, at each intermediate stage, the two nodes from each group which are closest to the other node are the bottlenecks.

One subtle difference from the static case is that in addition to the bottleneck node m_b, we are also interested in the *bottleneck instant/bottleneck stage* t_b which is the first stage of the tactical movement where the bottleneck condition occurs.

Since the repeated traversal mobility pattern results in instances with broken links between node pairs from different groups, relaying and multi-hop communication is necessary for communication between such node pairs. We consider two different routing algorithms for multi-hop communication:

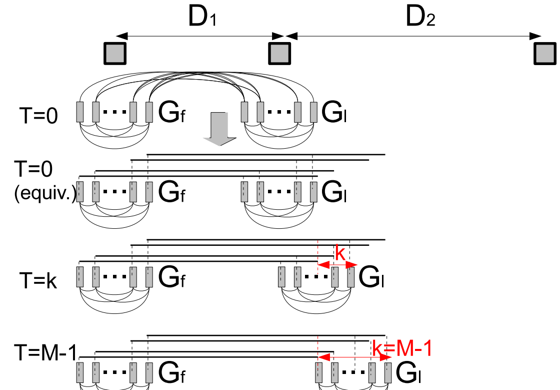

Fig. 2. Stages and connectivity of Repeated Traversal of convoy groups, leading group moving, stages 0 to M-1

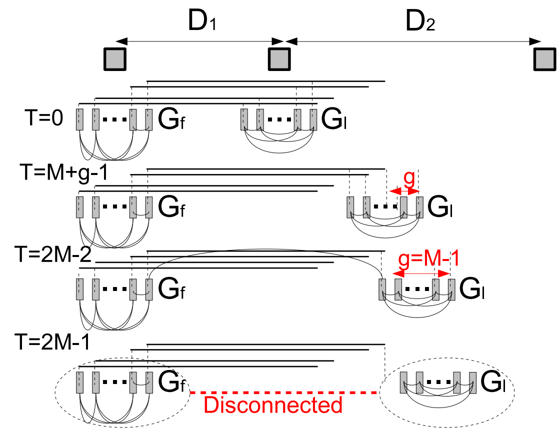

Fig. 3. Stages and connectivity of Repeated Traversal of convoy groups, leading group moving, stages M to 2M-1

Algorithm 1 (Min. Hop Count-Random): Communication between each pair is done with the minimum number of hops. If there exists more than one route which results in the minimum number of hops possible, the algorithm chooses one of these routes with equal probability.

Algorithm 2 (Min. Hop Count-Energy Aware): Communication between each pair is done with the minimum number of hops. If there exists more than one route which results in the minimum number of hops possible, the algorithm chooses a route which minimizes the total power consumption.

Consider a typical wireless channel with path loss exponent $2 \leq \alpha \leq 4$. In order to support communication, transmitting nodes adjust power levels to meet a Signal-to-Noise ratio (SNR) requirement at the receiving node. In other words, transmit SNR at transmitting node i is greater than or equal to: $P_t^i(P_{req}, d_{ij}) = P_{req} d_{ij}^{\alpha}$, which is a convex function of d_{ij}. Now consider a case where there exists multiple two hop routes between nodes s and t. The total power expended using a relay node r is lower bounded by:

$$P_{tot} = P_{req} d_{sr}^{\alpha} + P_{req} d_{rt}^{\alpha}. \quad (6)$$

Since the total distance between s and t is equal to d_{st} for any choice of r ($d_{sr} + d_{rt} = d_{st}$), from Jensen's inequality [9] it can be easily shown that the energy-minimizing relaying choice attempts to equalize individual hop distances as much as possible. In essence, Algorithm 2 attempts to equalize hop lengths among the choices of routes with equal hop count.

A. Signatures of Repeated Traversal

For convenience of notation, let us recall the following expression for the Harmonic number $H(m)$:

$$H(m) := \sum_{i=1}^{m} \frac{1}{i}. \tag{7}$$

We next present the signatures of the network for the k^{th} stage number, where stages increment with change of topology. We assume unicast data traffic with each node equally likely to select one of the other nodes in the network as the destination of a newly generated packet, and TDMA for the medium access scheme.

At $k = 0$ (Every node connected-whole clique of size $2M$):
$\Gamma_d(k) = \Gamma_l(k) = \Gamma_h(k) = 2M - 1$,
$\Upsilon_d(k) = \Upsilon_l(k) = \Upsilon_h(k) = 0$.

We note that these signatures for $k = 0$ are equivalent to those of the static case.

For $1 \le k \le M - 1$: (There exists $2(M - k)$ nodes which are still connected to every other node), while the furthermost nodes lost connection with k of the nodes from the other group. Either one- or two- hop connections exist.
$\Gamma_d(k) = \Gamma_l(k) = \Gamma_h(k) = 2M - 1$,
$\Upsilon_l(k) = 2k$, $\Upsilon_h(k) = 0$
$\Upsilon_d(k) = \frac{1}{2M-1}\{2kH(2M-k-1) - 2\sum_{z=1}^{k-1} H(2M-2k+z-1)\}$.

Algorithm 2 differs by $\Upsilon_d(k) = \frac{k(k+1)}{4M-2}$.

For $M \le k \le 2M - 1$: (No node is connected to all of the other nodes, the innermost nodes m_b have lost connection with l nodes of the other group). Some connections require 3 hops. Define $g := k - M$;
$\Gamma_d(k) = \Gamma_l(k) = \Gamma_h(k) = 3M - k - 1$,
$\Upsilon_l(k) = 2(M - g) - 1$, $\Upsilon_h(k) = 0$,
$\Upsilon_d(k) = \frac{1}{2M-1}\{\frac{4g^2}{M-g+1} + gH(M-g) + 2(M-g)H(M-g-1) - 2\sum_{i=1}^{M-g-1} H(i) + gH(M-g)\}$.

Algorithm 2 differs by
$\Upsilon_d(k) = \frac{1}{2M-1}\{2g^2 + 2g(M-g) + \frac{(M-g-1)(M-g)}{2}\}$.

For $k = 2M-1$ (Groups disconnected, two separate cliques of size M each):
$\Gamma_d(k) = \Gamma_l(k) = \Gamma_h(k) = M-1$, $\Upsilon_d(k) = \Upsilon_l(k) = \Upsilon_h(k) = 0$.

The signatures of the stages where the following group recovers the distance and connects again with the leading group are identical, only as a reverse sequence of the above.

While we omit the details of the derivation of these signatures due to lack of space and refer the interested reader to [10], we obtain the expressions by rigorously enumerating the expected number of paths that the bottleneck node relays for each algorithm and traffic type.

B. Characterizing Symptotic Scalability

In this section, we attempt to characterize how the scalability changes for a given network when specific network parameters (e.g. resources, traffic) are varied.

Different from the scalability equation (2) for the static case, since here signatures are a function of both the group size M and the stage k, the scalability equation is expressed as follows:

$$\eta W = (1 + \Gamma_d(M,k))L_d(1 + \Upsilon_d(M,k)) + (1 + \Gamma_l(M,k))L_l \times (1 + \Upsilon_l(M,k)) + (1 + \Gamma_h(M,k))L_h(1 + \Upsilon_h(M,k)), \tag{8}$$

for $\forall k$ such that $0 \le k \le 2M - 1$, resulting in $2M$ equations for a given group size M.

The ultimate goal is to identify the minimum M where any of the stages results in the RHS of (8) to exceed ηW. Scalable network size is then given by $2M$. To that end, we first fix M and investigate which stage k maximizes the RHS of (8).

We ignore the static cases since it is apparent that the residual capacity is lower for intermediate stages (transit factors increase compared with the static case for a range of stages where the contention factor is not reduced). We point out that the signatures are piecewise functions which have one form for stages $1 \le k \le M - 1$ and another form for stages $M \le k \le 2M - 1$.

First consider stages $1 \le k \le M - 1$. Note that the contention factor is fixed for these stages, so which stage the residual capacity is minimized depends on the transit factors. For simplicity, let us make the assumption that the data packets are significantly larger than LSU and hello packets, hence dominate the demand from the bottleneck. Accordingly, we can focus on simply the transit factor:

$$\Upsilon(M,k) = \frac{1}{2M-1}\{2kH(2M-k-1) - \sum_{z=1}^{k-1} H(2M-2k-z-1)\} \tag{9}$$

Even though this is actually a staircase function, let us assume that stages can take non-integer values and we have a continuous function. We seek for any monotonic properties of (9). To that end, let us use Euler's formula to closely approximate the Harmonic numbers:

$$H(n) \approx \ln n + 0.577 - \frac{1}{2n}. \tag{10}$$

We take the derivative of the approximation of (9) $\tilde{\Upsilon}(M,k)$ with respect to k, and observe that the transit factor is a monotonic increasing function and takes its maximum value at $k = M - 1$ for $0 < k \le M - 1$.

For algorithm 2, the expressions are much simpler and it is readily apparent that the only factors depending on k, which are $k(k+1)$ is monotonically increasing and is maximized for stage $M - 1$ in $[0, M - 1]$.

Next, we focus on stages M to $2M-1$. Here, the contention factor is not constant with stage number so we also have to consider its impact. Note that the transit factor expressions are much more complicated for this scenario, leading to a more cumbersome analysis. Hence, we take the following approach:

Lemma 1: $\Upsilon_d(M,k)$ of resulting from Algorithm 2 is at least as big as the $\Upsilon_d(M,k)$ resulting from Algorithm 1 $\forall k \in [M, 2M-1]$.

Proof: We prove this lemma by a term-by-term comparison, and omit details due to lack of space. Please see [10] for full details. ■

Next, let us establish the following structural result:

Lemma 2: Recall that we have defined $g = k - M + 1$ for stages $M-1 < k < 2M-1$. $(1+\Gamma_d(M,k))L_d(1+\Upsilon_d(M,k)))$ is concave increasing for Algorithm 2 in g.

Proof: Define $B_{d,2}(M,g) := (1 + \Gamma_d(M,k))L_d(1 + \Upsilon_d(M,k)))$ as a function of g for Algorithm 2. Its the first- and second- order derivatives with respect to g result in:

$$\frac{\partial B_{d,2}}{\partial g} = \frac{L_d}{2M-1}(-1.5g^2 - g + (1.5M^2 - 0.5M + 1)) > 0, \quad (11)$$

$$\frac{\partial^2 B_{d,2}}{\partial g^2} = \frac{L_d}{2M-1}(-3g-1) < 0. \quad (12)$$

This implies the concavity stated in the lemma. ■

As a result, $B_{d,2}$ is maximized at $g = M-1$, with the resulting value of $\frac{2M^3+2M^2-M-1}{2M-1}$, which can be approximated by $M^2 + 1.5M + 0.75$.

Next, we compare this with the value at $k = M-1$, where:

$$B_{d,2}(M, M-1) = \frac{M^3 - 3M^2 - 2M}{2M-1}, \quad (13)$$

which is roughly the half of the value at $k = 2M-2$. Hence, we conclude that the largest amount of capacity required due to data traffic from the bottleneck occurs at stage $2M-2$.

Next, let us re-consider Algorithm 1. While the contention factors are identical for both algorithms at each stage, from Lemma 1, the transit factor is larger for Algorithm 2 at each stage except $k = 2M-2$, where they are equal. This implies that the largest loading for Algorithm 1 also occurs at stage $2M-2$ for stages $[M, 2M-2]$. For stage $k = M-1$, which was shown to result in the largest loading between stages $[0, M-1]$, we have

$$\begin{aligned} B_{d,1}(M, M-1) &< (2M)\frac{(2(M-1)H(M) + 2M - 1)}{2M-1} \\ &\leq (2M)(H(M)+1) \end{aligned} \quad (14)$$

For $M > 4$, $H(M) < 0.457M$, hence we have that $B_{d,1}(M, M-1) < 0.914M^2 + 2M$, and the loose upper bound for $B_{d,1}(M, M-1)$ is less than the case for $B_{d,1}(M, 2M-2)$ for practical values of M. Hence, for Algorithm 1, stage $2M-2$ results in the largest loading for the bottleneck node.

Remark 1: While the loading due to data traffic is maximized for both algorithms at stage $2M-2$, we can also demonstrate that the loading due to LSU traffic is maximum at stage $M-1$. Since the increase in transit factor is smoother than with stage for Algorithm 2 from signatures and Lemma 1, for cases such as lightly loaded data traffic where the impact of LSU traffic is not negligible compared with data traffic, the overall bottleneck instant when LSU traffic is considered may occur in an earlier stage. However, for Algorithm 1, the loading at intermediate stages is lower, hence LSU traffic might not effect the bottleneck instant unless extreme circumstances. These facts result in the following lemma:

Lemma 3: The scalable group size of Algorithm 1 is greater or equal than the scalable group size of Algorithm 2.

Next, having found approximate expressions for B_d for the bottleneck stage, we have the following approximation to (2):

$$\eta W = (M^2 + 1.5M + 0.75)L_d \quad (15)$$

The scalable group size can hence be expressed as

$$M = \frac{\sqrt{4\eta W - 0.75} - 1.5}{2\sqrt{L_d}}, \quad (16)$$

revealing roughly the dependence of scalability to bandwidth, which can be approximated as follows for large enough M

$$M \approx \sqrt{\frac{\eta W}{L_d}}. \quad (17)$$

On the other hand, for the static case the (2) is approximately

$$\eta W = 2ML_d, \quad (18)$$

($M \approx \frac{\eta W}{2L_d}$) implying a linear increase in scalable group size with bandwidth, while we rather have a square root dependence for repeated traversal. In other words, to double the supported number of nodes, roughly the bandwidth must be increased four times. Equation (16) also reveals that scalable network size is roughly proportional to $L_d^{-0.5}$, i.e. doubling the load only reduces scalable group size by about 30 percent rather than halving it.

V. Numerical Results

We next present numerical results for the following set of parameters: LSU packet size: 52 bytes, Hello packet size: 48 bytes, Net Header: 20 bytes, Data packet size: 1000 bytes. Unless specified other wise, we have λ_d=1 pps, λ_l=1 pps, λ_h=1 pps, and bandwidth $W = 10Mbps$.

We vary bandwidth in Fig. 4-5, and observe the scalable group size M. Total scalable network size is simply $2M$. First, we observe that mobility significantly reduces scalability as shown in Fig. 4. Since contention factor for the static case is equal to $2M-1$, it is apparent that this decrease is due to the increase in transit factors Υ_d and Υ_l. Moreover, while the scalable group size increases linearly for the static case, it is nonlinear and concave increasing for the mobile case. Specifically, we observe that indeed the scalable group size is roughly proportional to the square root of the bandwidth. This results from the non-trivial dependence of transit factors on M. We compare the scalability of the two algorithms for varying bandwidth in Fig. 5. We observe that both algorithms have identical scalable group size for this scenario.

Finally, for fixed bandwidth $W = 10Mbps$ we vary data traffic load λ_d. This allows us to observe the effect of LSU traffic on scalability more explicitly for scenarios with light data load. We immediately observe from Fig. 6 that scalable group sizes of both algorithms differ when λ_d is small, and in line with Lemma 3, Algorithm 1 scales to a higher number of nodes. This is due to the fact that the due to the prominent

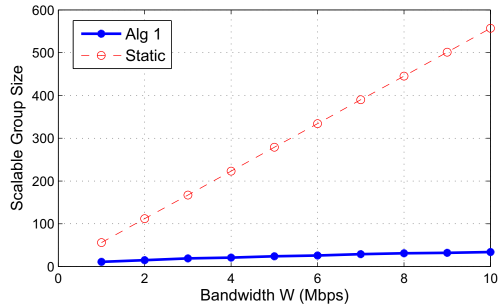

Fig. 4. Scalable groups sizes for varying bandwidth

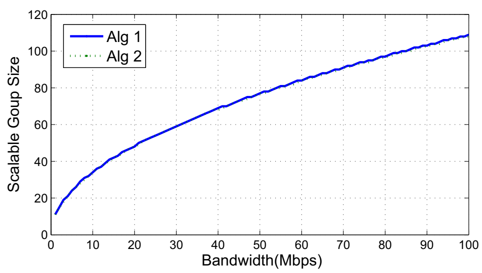

Fig. 5. Scalable groups sizes for varying bandwidth

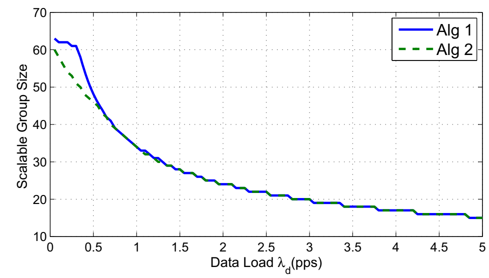

Fig. 6. Scalable groups sizes for varying data load

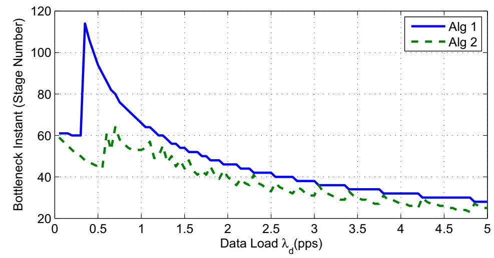

Fig. 7. Bottleneck instances for varying data load

effect of LSU-related terms, the bottleneck instant is shifted to an earlier stage than $2M-2$, where Υ_d is strictly larger for Algorithm 2, resulting in a lower scalable group size.

Another notable difference between the two algorithms is observed in Fig. 7, where we demonstrate the stage when the residual capacity reduces below 0. Considering Fig. 6 and 7, for Algorithm 1, the bottleneck instant occurs at stage $2M-2$ unless data load is very small, which is the stage when there is only one node from each group that can reach the other group, e.g. there are only two bridge nodes in the network. The subtle increase in Υ_d for that stage results in highest loading to the network, dominating over the reduced values of both Γ_d and Υ_l at that stage. On the other hand, the increase of transit factor Υ_d for Algorithm is considerably smoother, causing the instant to occur earlier than $2M-2$ in many cases. For such stages, even though the transit factor is less compared with the subsequent stages, the fact that it has larger Γ_d and Υ_l takes into effect and results in the most loading for the bottleneck nodes. We observe that the effect of increased LSU traffic results in the bottleneck instant to occur in an earlier stage.

VI. Conclusions

In this work, we provide the first non-asymptotic analysis of scalability for real-world mobile networks. We provide expressions for the signatures for different stages for repeated traversal. These contention factors and transit factors depend on group size, the stage of movement, and traffic type and the routing algorithm used. Leveraging the signature expressions, we find approximate values for scalable network size. We demonstrate that mobility significantly reduces scalable network size. For instance, we observe that the scalable group size is roughly proportional to the square root of available bandwidth with mobility in contrast to the previously studied static case where there was a linear relationship. The main reason for the reduction in scalable network size is the change in topology, and increased traffic in some specific nodes, which are the bottleneck nodes. While the effect of LSU traffic is not as significant as the actual change in topology, the marginal effect depends on the routing algorithm. We observe that LSU traffic can have a higher impact on scalability and the stage when the network is maximally loaded for the energy-aware routing algorithm.

While we have presented fundamental outcomes for scalability of mobile scenarios, future work incudes incorporating for other mobility models, as well as other medium access schemes and topologies.

References

[1] R. Ramanathan, A. Samanta, and T. F. La Porta. Symptotics: A framework for analyzing the scalability of real-world wireless networks. In *9th ACM International Symposium on Performance Evaluation of Wireless Ad Hoc, Sen- sor, and Ubiquitous Networks (PE-WASUN 2012)*, 2012.

[2] P. Gupta and P. R. Kumar. The capacity of wireless networks. *IEEE Transactions on Information Theory*, 46(2):388–404, 2000.

[3] M. Grossglauser and D. Tse. Mobility increases the capacity of ad-hoc wireless networks. *IEEE/ACM Transactions on Networking*, 10:477–486, 2002.

[4] M. Rollo and A. Komenda. Mobility model for tactical networks. In *HoloMAS '09*, 2009.

[5] T. Camp, J. Boleng, and V. Davies. A survey of mobility models for ad hoc network research. *Wireless Comm. and Mobile Comp. (WCMC)*, 2:483–502, 2002.

[6] S. Ray Y. Zhang, G. Cao, T. F. La Porta, and P. Basu. Data replication in mobile tactical networks. In *MILCOM 2011*, Baltimore, November 2011.

[7] S. Kumar, S. C. Sharma, and B. Suman. Mobility metrics based classification and analysis of mobility model for tactical network. In *International Journal of Next Generation Networks*, 2010.

[8] J. P. Macker, J. E. Klinker, and M. S. Corson. Reliable multicast data delivery for military networking. In *Proc. IEEE MILCOM 96*, pages 399–403, 1996.

[9] T. M. Cover and J. A. Thomas. Elements of Information Theory. *John Wiley and Sons, New York, NY*, 1991.

[10] E. N. Ciftcioglu, R. Ramanathan, and T. F. La Porta. Technical Report: Scalability Analaysis of Tactical Mobility. *http://www.personal.psu.edu/enc118/TRscalmob.pdf.*