# On the Fundamental Performance Limits of Peer-to-Peer Data Replication in Wireless Ad hoc Networks

Szu-Chi Wang, Member, IEEE, Hong-Zu Chou, David S. L. Wei, Member, IEEE, and Sy-Yen Kuo, Fellow, IEEE

Abstract-Wireless ad hoc networks are drawing increasing attention from the research community because of their potential applications. However, the fundamental capacity limits of these networks pose various technological challenges to designers of network protocols. In this paper, we attempt to capture the inherent constraints on information dissemination in a mobile wireless environment, with the emphasis on peer-to-peer (P2P) communications. More specifically, we introduce the notion of "replication-induced gain" to quantify the impact of data replication under the paradigm of P2P query-response mechanisms. Our major contribution lies in presenting several preliminary results with respect to the complexities and trade-offs involved in enhancing data availability. To the best of our knowledge, the data replication problems that arise because of scarce system resources in wireless ad hoc networks have not been investigated from this perspective. We believe that our results could provide additional insights and practical implications for P2P system designers.

*Index Terms*—Ad hoc networks, peer-to-peer system, scaling laws, wireless communications.

#### I. INTRODUCTION

Wireless ad hoc network is an autonomous system that consists of mobile nodes capable of wireless communication. These networks are drawing increasing attention from the research community because of their potential applications, such as rescue missions and battlefield deployments (see e.g., [1]–[3]). Nonetheless, the networks' fundamental capacity limits pose various technological challenges to the design of large-scale applications. In this paper, we address the inherent constraints on information dissemination multi-hop wireless relaying, with the emphasis on peer-to-peer (P2P) computing. More specifically, we focus on the fundamental limits and scaling laws of data replication under the paradigm of P2P query-response mechanisms. Our work is motivated by the pressing need for effective and efficient information exchange in a wireless environment, where each node has a number of its own objects and issues queries to search for objects of interest. In the real world, objects are diverse in type, e.g., an

S.-Y. Kuo is with the Electrical Engineering Department, National Taiwan University, Taipei 106, Taiwan, and also with Department of Comupter Science and Information Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan (e-mail: sykuo@cc.ee.ntu.edu.tw).

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object may be a numerical dataset, a certain phenomenon, or a duplicable service code. Likewise, queries may consist of file names, serial numbers, or an elaborate Boolean predicate [3]. In recent years, a great deal of effort has been devoted to searching for and replicating data in the context of P2P applications over the Internet (see e.g., [4]–[6]). Unfortunately, P2P applications in wireless ad hoc networks are rather disparate in nature (see [2] [7] [8] and the references therein). For example, the impact of interference and channel assignment is crucial to the efficiency of the network; moreover, most communications between source-destination pairs are carried out via multi-hop relays. In addition, a network's traffic pattern depends on the purpose of the application (e.g., monitoring, data gathering, etc.). In view of these limitations, the abovementioned techniques cannot be adopted directly.

For communication functionality, a fundamental question is how much information a wireless network can transport. The seminal work of Gupta and Kumar [7] proposed the concept of transport capacity. Informally, it correlates to the sum of the products of bits and the distances covered by message transmissions; the unit of measurement is bit-meters per timeslot. The finite queue lengths of the network nodes restrict the maximum throughput that can be achieved by each mobile node. Note that, as shown in [7]–[9], the transport capacity is a hard constraint on the amount of data a wireless ad hoc network can deliver. The studies of Grossglauser, Tse, and Diggavi [25] [26] showed that if mobility is allowed, the throughput capacity grows linearly with the number of users, which represents a very substantial increase. The tradeoff between throughput and delay in wireless ad hoc networks has been studied extensively in recent years (see e.g., [27]-[29]). We are particularly interested in the work of Herdtner and Chong [29], who explored the scaling law of throughput capacity with constraints on the buffer size. In addition, based on the theory of continuum percolation, Dousse et al. [21] noted that full connectivity would be compromised if the whole network is operating at a given rate. Capacity degradation and interface switching delay in multi-channel networks have also been addressed in [31].

The prime objective of this paper is to explore several fundamental bounds on the gain of data availability induced by replication, rather than propose new replication strategies or a new P2P overlay design for multi-hop networks. Our main contribution lies in presenting several preliminary results with respect to wireless ad hoc networks. To the best of our

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S.-C. Wang, and H.-Z. Chou are with the Electrical Engineering Depart-

ment, National Taiwan University, Taipei 106, Taiwan.

D. S. L. Wei is with the Department of Computer and Information Science, Fordham University, Bronx, NY 10458 USA.

knowledge, the problems that arise due to the scarce resources of P2P applications in wireless ad hoc networks (e.g., transport capacity, memory, and energy) have not been investigated, particularly in the form of theoretical expressions. We believe that the results could provide additional insights and practical implications for P2P system designers.

The remainder of the paper is organized as follows. The system model, terminology, and problem formulation are presented in Section II. In Section III, we make some basic observations about the trade-off between communication costs and query responsiveness. Then, in Section IV, we explore the intrinsic difficulties of several replication-related performance issues, particularly in the context of stochastic analysis. Finally, we present our conclusions and discuss the direction of our future work in Section V.

#### **II. PRELIMINARIES**

## A. System Model

We assume that the whole network is synchronized in rounds,<sup>1</sup> each of which is expressed by successive, discrete time-slots; and an integer number of rounds comprises a communication session. The *Physical model* [28], [31] is used to describe the interference scheme, i.e., the relation between packet transmission and the combination of available channel(s) and the time-slot arrangement. We assume that node *i* can transmit a packet to node *j* if the signal received by *j* is strong enough. Formally, the emitting power of node *i* (denoted as  $P_i$ ) is within the range [0,  $P_{max}$ ]; note that  $P_{max}$  determines the maximum transmission radius (denoted as  $r_m$ ). Let  $\Gamma_i$  denote the set of other nodes transmitting in the same time-slot, and let the signal to interference and noise ratio (SINR) at *j* be sufficient for successful decoding, i.e., the following inequality holds:

$$SINR_{i} \equiv \frac{P_{i}G(i,j)}{N_{0} + \varphi \sum_{k \in \Gamma_{i}} P_{k}G(k,j)} \ge \beta,$$

where  $G(\cdot)$  is the attenuation function associated with the wireless medium; and  $N_0$  is the power of the thermal background noise, which is assumed to be the same for all nodes. The coefficient  $\varphi$ , which indicates the effect of interference, is dependent on the orthogonality between the codes adopted during simultaneous transmissions [30].

The limited power and signal loss during propagation over the wireless medium impose fundamental constraints on the capacity of data transmissions. Specifically, each node is capable of transmitting at most W bits per second through a wireless channel.<sup>2</sup> Half-duplex transmission is assumed, i.e., nodes cannot transmit and receive simultaneously. Based on one of the most widely-used radio models, the energy costs of packet transmission over the Euclidean distance dis:  $E(d) = c_1 + c_2 d^{\alpha}$ , where  $c_1$  and  $c_2$  are constant model parameters, and  $\alpha$  is the path loss exponent determined by the specific propagation environment [34]. For simplicity, we

<sup>2</sup>Note that this capability still holds in the case where a channel can be split into several subchannels [7].

do not consider the effect of wireless fading channels in this paper.

#### B. Terminology

Throughout the paper we adopt the following notations. For two functions f, g defined on natural numbers: (i) If  $\lim_{n\to\infty} \inf f(n)/g(n) < \infty$ , we have f(n) = O(g(n)); (ii) if  $\lim_{n\to\infty} \inf f(n)/g(n) > 0$ , we have  $f(n) = \Omega(g(n))$ ; (iii) if  $\lim_{n\to\infty} \inf f(n)/g(n) = 0$ , we have f(n) = o(g(n)); and (iv) if f(n) = O(g(n)) and  $f(n) = \Omega(g(n))$ , we have  $f(n) = \Theta(g(n))$ . All logarithms, unless otherwise specified, are to the base 2. In addition, the expression *w.h.p.* (with high probability) is used to qualify an event whose probability approaches 1 when *n* approaches infinity. We use the terms link and edge, as well as data and object, interchangeably.

Generally, nodes in a wireless ad hoc network have restricted memory. Let the memory capacity  $\Phi(u)$  for each node u be quantified by the maximum amount of memory available for data replication. The considered scenario assumes that each node possesses some exclusive objects and requests extra objects from other nodes in a communication session. The former are called the *innate objects* of u, and denoted as INNATE(u). In the sequel, we assume that the content to be replicated can be divided into small packets of the same size; thus,  $\Phi(u)$  can be defined by an integer.<sup>3</sup> The replicated objects in u's memory are denoted as REP(u). When a node u starts searching for an object o, a query q(u, o) is issued by u within the current time-slot. Note that we do not assume any a priori knowledge about objects, such as data types and their correlation characteristics. Since the content of objects may change over time, asynchronous updates of object replicas can cause data consistency problems. Furthermore, incorporating distributed data synchronization is very challenging and could be the subject of research in itself. For the sake of clarity, we assume that the packet size is small enough so that the packet delay is essentially equal to the number of hops taken by the packet. Moreover, as assumed in most previous works, each peer can only serve an object after it has been fully downloaded. However, as the issue of data coherence is beyond the scope of this paper, we assume that all objects remain valid for a "sufficiently long" period.<sup>4</sup> We discuss this point further in Section V.

#### **III. PROBLEM DESCRIPTION**

#### A. Basic Observations

In this section, we use a simplified model for clarity. Specifically, the network topology is represented by a graph G = (V, E), where V denotes a set of nodes. We assume that all nodes have equal transmission radius  $r_m$  and, for each edge  $(u, v) \in E$ , the Euclidean distance between u and v ||u, v|| is no larger than  $r_m$ . Let |u, v| denote the hop

<sup>&</sup>lt;sup>1</sup>As noted in the literature, rational synchronization can be achieved via extra facilities; e.g., with the assistance of GPS signals or other types of beacon. In addition, some works (e.g., [10]) propose ways to design and analyze round-based protocols for wireless ad hoc networks.

<sup>&</sup>lt;sup>3</sup>The assumption of equal-sized objects, albeit very idealistic, can serve as a basis for understanding the intrinsic tradeoffs involved in this multi-objective optimization framework. Moreover, in this work we address the problem from the viewpoint of the finest granularity, i.e., the bit-wise information transfer.

<sup>&</sup>lt;sup>4</sup>Perfect data consistency in large wireless ad hoc networks is extremely expensive, if not impossible [37]. Thus, modified evaluation metrics and sophisticated treatments for the relevant issues are required.

distance between nodes u and v in G. We assume that a maximum of one packet can be transmitted over an edge in either direction. Given an integer h,  $N^{h}(u)$  is defined as  $\{v: v \in V, |u, v| \le h\}$ ; and the nodes in  $N^h(u)$  are called hhop neighbors of u. Similarly, for a given node set  $S \subseteq V$ , we denote  $\bigcup_{u \in S} \{v : v \in V, |u, v| \le h\}$  as  $N^h(S)$ . We disregard the notation for a round to keep the formulation simple. A query q(u, o) is said to be *resolved* if at least one route to the target has been transferred to u. Consequently, a query resolution r for q(u, o) is derived (denoted as  $r \Rightarrow q(u, o)$ ). Note that r includes the path information  $v_0v_1 \dots v_{h-1}$ , where  $v_0 = u$  and  $o \in INNATE(v_{h-1}) \cup REP(v_{h-1})$ . The hopdistance between  $v_0$  and  $v_{h-1}$  in G is denoted as |r,q|. In principle, efficient object replication can best be defined by the following properties: (i) replicas are relayed in a powerefficient manner; and (ii) nodes in the vicinity try to cooperate in order to share replicas and reduce memory consumption. However, there is a trade-off between the communication cost and query responsiveness. An elementary observation is shown in Fig. 1, in which for each node  $u_i$ ,  $INNATE(u_i) = o_i$ . The innate objects are black, while the replicated ones are white. The dashed lines indicate that the objects are replicated via wireless transmissions. Consider an extreme case in which: (i) all combinations of a query and an object are equally probable (i.e., uniformly distributed); and (ii)  $\forall u, o, r \Rightarrow q(u, o)$  exists iff |r, q| = 1.

To outline the basic concepts, we show that, by replicating objects efficiently, more queries can be resolved within the one-hop neighborhood. Consider a simplified case in which data packages are relayed via the shortest paths (in terms of the hop-count) and no re-transmissions occur. The performance of query processing can be evaluated as follows. In Fig. 1(a), we achieve 8 query resolutions at a cost of 8 wireless transmissions (per data package); in Fig. 1(b), the numbers are 14 and 12, respectively. The matrices in the figure show object availability over G after replication. Since communications are the main cause of power depletion in wireless ad hoc networks [11], the replication strategy in Fig. 1(b) is regarded as "more efficient" in the sense of more query resolutions per joule. We call the improved efficiency *replication-induced gain*. Further details are given in Section IV.

## B. Hardness Result

Initially, we consider a very simple case — each node u in G possesses exactly one innate object. Then, for  $\forall$  query set  $Q' \subseteq Q$ , if there exits a resolution set R' such that  $q(u, o) \in Q'$ ,  $\exists r \in R', r \Rightarrow q(u, o)$ , and  $|r, q| \leq \kappa$ , we call  $Q' \kappa$ -coverable and R' a  $\kappa$ -covering resolution set of Q' (denoted as  $R' \Rightarrow^{\kappa} Q'$ ). Given a query set  $Q' \subseteq Q$ , the question arises: How can we replicate objects so that some  $R' \Rightarrow^{\kappa} Q'$  with a small  $\kappa$  can be formed? In a sense, the concept of confining communications to local regions is similar to existing "zone-based protocols" [38].<sup>5</sup> For brevity, the memory consumption of different replication schemes is quantified by the number of replicated objects located by R'.

Definitition 1: The Efficient Memory Conservation (EMC) problem: Given a unit-disk graph G = (V, E) and a query set Q'.  $\forall u \in V$ ,  $\Phi(u) = c$ , does there exist a resolution set R' such that Q' is  $\kappa$ -coverable with memory consumption less than d, and  $(\kappa, c, d) \in \mathbb{N}^3$ ?

Proposition 1: EMC is NP-complete.

Due to space limitations, only sketched proofs are presented in the Appendix. Clearly, the EMC problem is easier to solve than the problem of finding a  $\kappa$ -covering resolution set for Q' with minimal memory consumption. Note that the EMC problem can be generalized as a probabilistic version, i.e., the values of  $\kappa$  and c can be adjusted adaptively, based on measurements of the relevant network parameters. Because of the intractability of this problem, we cannot solve it with a priori knowledge. In fact, global knowledge about a network's topology is normally unavailable and, in most cases, a node cannot recognize other nodes that might best resolve its queries. As a consequence, we must extend our investigations to an online setting. Informally, an online algorithm receives and services a sequence of requests without prior information of their order. The cost of online algorithms should be compared with that of an optimal offline algorithm that has full knowledge of the request sequence. Nevertheless, how to design online object-replication algorithms and how to perform the associated competitive analysis are left as open problems. Such extensions are beyond the scope of this paper; however, we will address them in our future work.

#### **IV. STOCHASTIC ANALYSIS**

In the following, we examine replication-induced gain from various perspectives.<sup>6</sup> First, we investigate the bounds on such a gain, taking into account the communication cost subject to several fundamental limitations of wireless relay networks (see [7]–[9], [22]–[29] and the references therein). Then, we consider a wireless ad hoc network in which the nodes are uniformly and independently distributed in a disk area A. In the literature, the presence of nodes is typically modeled by a *spatial Poisson point process*. Let  $\lambda$  denote the spatial density. The probability of finding ne nodes in area  $A_e$  is given by

$$\Pr\{n_e = k\} = \frac{(\lambda A_e)^k}{k!} e^{-\lambda A_e}, k \ge 0.$$
(1)

#### A. From the Perspective of Network Capacity

Initially, we ignore the issues of energy and memory constraints.<sup>7</sup> Assume that all relay nodes make their best efforts to cooperate in transmitting information. Consider an arbitrary source-destination pair of nodes  $(v_s, v_t)$  and a replicated object  $o_i$  transmitted by node  $v_s$ , where  $o_i \in INNATE(v_s)$ . As mentioned in Section III,  $\kappa$ -covering resolutions for most queries are preferable (i.e.,  $\kappa$  is a "small-enoug" integer), as shown by the example in Fig. 2(a). Note that: (i)  $r_s \leq r_m$ ; and (ii) the replicated object is delivered via multi-hop relays. Let  $l_s = ||v_s, v_t||$  such that we have  $l_s \geq r_m$ . If full connectivity is a prerequisite, it has been shown that there is an inherent

<sup>&</sup>lt;sup>5</sup>Furthermore, as noted in previous studies, localized communications are vital in wireless ad hoc networks (e.g., [12], [13] argue that the scalability of a network depends on whether network traffic can be localized). Thus,  $\kappa$  is a small integer determined primarily by the application layer.

<sup>&</sup>lt;sup>6</sup>Specifically, we focus on information transfer under the P2P queryresponse paradigm.

<sup>&</sup>lt;sup>7</sup>In a sense, we discuss the instances where the ratio of energy/memory resources to network capacity is high.



Fig. 1. A simple example to demonstrate that different replication scenarios influence the communication cost and time of query resolution (in terms of the number of hops).

lower bound on  $r_m$  [7], [14]. Hence, a loose lower bound on  $l_s$  can be directly deduced by  $l_s \ge \sqrt{A \log n / \pi n}$ . It is not hard to validate that the maximum area to benefit from replication-induced gain (denoted as  $A_g^*$ ) is the gray region in Fig. 2(b).<sup>8</sup> The observations in Section III imply that the ratio of the involved communication cost to the area  $A_g^*$  should be minimized. Consequently, several bounds on can be derived. First, from Fig. 2(b) we obtain the following:

$$\pi(\kappa^2 - \kappa)r_m^2 < A_q^* \le \pi \kappa^2 r_m^2. \tag{2}$$

Information theoretic limits of data transmission in wireless networks have been investigated intensively in recent years. Specifically, the work of Gupta and Kumar [7] was the first to identify the scaling law of transport capacity for static multi-hop radio networks in which the nodes are randomly located. As noted in [9], *transport capacity* serves as an instinctive quantity of network-layer capacity, since it summarizes the information a network can deliver via a single number. Informally, transport capacity correlates to the sum of the products of bits and the distances covered by message transmissions; the unit of measurement is bit-meters per second, or bit-meters per time-slot. Note that we consider

<sup>8</sup>Consider a node at the intersection of two circles, e.g.,  $v_r$  in Fig. 2(a), where the hop-distance between the node and v)s may be larger than  $\kappa$ . In this case, an extra query resolution of  $v_r$  may be derived by the replication, i.e., each white node in Fig. 2(a) is a probable candidate to benefit from replication-induced gain.

a more realistic situation than most previous studies, in which the ratio of channels to interfaces (denoted as  $\gamma_c$ ) may be greater than one [31]. Although an interface can transmit or receive data on any channel at a given time, that capacity might be lost if the number of interfaces is insufficient. In contrast, since we focus on a fixed region A and the geometry of A affects the constants, but not the scaling behavior, no explicit path loss model is necessary. The commonly used *Protocol model* (see e.g., [28], [30], [31]) is described as follows. The transmission from a node *i* to a node *j* on a channel is deemed successful if the following condition holds for every other node *k* simultaneously transmitting on that channel:

$$\parallel k, j \parallel \ge (1 + \Delta) \cdot \parallel i, j \parallel \Delta > 0,$$

where  $\triangle$  is a parameter that ensures the concurrently transmitting nodes are sufficiently distant from the receiver to prevent excessive interference. Note that if  $\alpha$  is greater than 2 and each transmitter adopts the same power, the *Physical* model is equivalent to the *Protocol* model [7].

Consider a fixed placement of nodes and assume that the constraint on per-node throughput is  $\eta$ (bits/sec). Moreover, during a communication session, the replicated objects are delivered with the cooperation of participating nodes in the network. If the mean transmission rate of the optimal object replicating strategy is  $R^*$  (bits/sec), then, by definition we have  $R^* \leq n\eta$ . Denote  $L_s$  as the sum of the Euclidean distances between all source-destination pairs involved in transferring the replicated objects. Similarly, the sum of the



(b)

Fig. 2. The maximum area that may benefit from replication-induced gain.



Fig. 3. Illustration of the process addressed by Lemma 1 and Lemma 2. This is a simplified instance consisting of three source-destination pairs only. We present the difference between  $l_s$  (the solid line) and  $l_h$  (the dashed line) by labels in the 1<sup>st</sup> node pair, assuming every bit of the replicated object is routed via the same relay path.

Euclidean-distances between all corresponding relay nodes of the replicated objects is denoted by  $L_h$ . Note that the values of  $L_s$  and  $L_h$  for a source-destination pair can be different under multi-hop relaying (see Fig. 3 for an illustration). Let the means of  $L_s$  and  $L_h$  be  $\overline{l}_s$  and  $\overline{l}_h$ , respectively. The scaling behavior of  $R^*$  can then <u>be bound</u>ed as follows.

Lemma 1:  $R^* \leq \Theta\left(\sqrt{An/\gamma_c \overline{l}_h^2}\right)$ 

*Proof:* We slightly rewrite the proofs presented in some previous works (e.g., [7], [28]). First, a source node (denoted as  $v_s$ ) is chosen arbitrarily. Note that in the process of data

dissemination, a packet may traverse one or more hops before arriving at its destination, depending on the underlying node placement. Additionally, there must exist a long enough time period  $\sigma$  such that the total number of transmitted bits is limited to  $\sigma n\eta$ . We denote hc(b) as the number of hops taken by bit b, which is bounded by  $[1, \sigma n\eta]$ . Let the Euclidean distance of the hth relaying hop of bit b be  $r_h(b)$  and the mean of the sum of  $r_h(b)$  during  $\sigma$  be  $\overline{l}_{\sigma}$ . Since data replication does not necessarily comprise the total traffic during  $\sigma$ ,  $\overline{l}_h \leq \overline{l}_{\sigma}$ . Consider all the data transmitted over the whole area in this time period. Then, we have:

$$\sum_{p=1}^{\sigma n\eta} \sum_{h=1}^{hc(b)} r_h(b) \ge \sigma n\eta \overline{l}_{\sigma}.$$
(3)

The total number of hops taken by all the transmitted data packets is denoted by  $H_r = \sum_{b=1}^{\sigma n\eta} h_c(b)$  Hence, by convexity and Jensen's inequality, the following expression holds:

$$\left(\sum_{b=1}^{\sigma n\eta} \sum_{h=1}^{hc(b)} \frac{1}{H_r} r_h(b)\right)^2 \le \sum_{b=1}^{\sigma n\eta} \sum_{h=1}^{hc(b)} \frac{1}{H_r} r_h^2(b).$$
(4)

Summing all channels, we obtain the following inequality according to the transport capacity of the entire network:

$$\sum_{b=1}^{\sigma n\eta} \sum_{h=1}^{hc(b)} r_h^2(b) \le \sigma \cdot \left(\frac{4WA}{\pi \Delta^2}\right).$$
(5)

Then, substituting (4) into (5), we derive the following inequality:

$$\sum_{b=1}^{\sigma n\eta} \sum_{h=1}^{hc(b)} r_h(b) \le \sqrt{\frac{4\sigma W A H_r}{\pi \ \Delta^2}}.$$

Unlike the proofs in most previous works, we exploit a modification of  $H_r$  in [31], which addresses the impact of an odd number of channels and interfaces. More precisely,

$$H_r \le \sigma n W / 2\gamma_c. \tag{6}$$

Combining (3)-(6) gives the inequality  $n\eta \bar{l}_{\sigma} \leq W \sqrt{\frac{2An}{\pi\Delta^2 \gamma_c}}$ ; thus, we have

$$n\eta \overline{l}_{\sigma} \leq W\sqrt{An/\Delta^2 \gamma_c}$$

Since  $R^* \leq n\eta$  in our scenario, we obtain the optimal bitmeters/sec in A:

$$R^* \overline{l}_h \le R^* \overline{l}_\sigma \le n \eta \overline{l}_\sigma \le W \sqrt{\frac{An}{\Delta^2 \gamma_c}}.$$
(7)

Recall that  $\Delta$  is a constant that is independent of A, n, and W. This is consistent with the results in [31], namely, the network capacity is  $\Theta\left(W\sqrt{An/\gamma_c}\right)$ . The formulation can be concluded as:

$$R^* \leq \Theta\left(\sqrt{An/\gamma_c \overline{l}_h^2}\right)$$

Provided that the number of channels is not too large, i.e.,  $\gamma_c = O(n)$ , we have  $R^* \overline{l}_h \leq \Theta(\sqrt{A})$ . Below, we address the problem of bounding  $l_s$  from a different perspective: Given the number of hops traversed by the transmitted data, can we characterize its relationship with the corresponding Euclidean distance? In [35] Vural and Ekici provided an insightful stochastic study of relating Euclidean distances to hop distances in a uniformly distributed sensor network. More specifically, the Euclidean distance of a hop (i.e., the single-hop-distance) is regarded as a random variable r. The maximum possible distance covered in multiple hops (i.e., the *multi-hop-distance*), is of particular interest. A statistical measure, kurtosis, is used to verify the Gaussianity of the multihop-distance. Although most given theoretical expressions are nested integrals, several approximations are presented for computational efficiency. Let  $\overline{r}$  be the expected single-hopdistance traversed over A. The value of  $\overline{r}$  in our model can be obtained numerically as follows (Further details about the numerical results can be found in [35]):

$$\lambda \overline{r} = \ln\left(1 - \frac{\lambda \overline{r}}{\lambda r_m - \lambda \overline{r} - 1}\right).$$
(8)

The results in [35] show that, as the number of hops is not too small, the distribution of the multi-hop-distance will approximate a Gaussian distribution. In other words, its value can be totally specified by its mean and variance. Consider the replication scenario described above, where  $R^*$  is the optimal average transmission rate of all replicated objects. We denote the mean number of hops over these  $\sigma R^*$  bits by  $\overline{h}_g^*$ . Then, by the linearity of expectation,  $\overline{l}_s$  can be derived as follows:

$$\overline{l}_s = E[h_g^*] \cdot \overline{r} = \overline{h}_g^* \cdot \overline{r}.$$
(9)

Lemma 2: Let  $\delta_s^2$  be the variance of  $l_s$ ; then,  $(\overline{h}_g^*)^2 \geq \left(\frac{l_s - \delta_s \sqrt{2 \ln n}}{\overline{\tau}}\right)^2$  w.h.p.

*Proof:* Given a normalized Gaussian random variable  $n_s$  with zero mean and unit variance, it follows that

$$l_s = \delta_s n_s + \overline{l}_s. \tag{10}$$

Let  $X \in \mathbb{R}^+$  be a random variable, and recall that the general form of Chernoff's bound with the cumulant-generating function  $\log(E[e^{\lambda X}])$  [33] states that:

$$\log \Pr\{X \ge u\} \le \inf_{\lambda \ge 0} \left\{ -\lambda u + \log\left(E[e^{\lambda X}]\right) \right\}.$$
(11)

Note that exploring this bound is a convex optimization problem. Because of the Gaussianity of  $l_s$ , the inequality below can be derived directly from the Chernoff's bounds:

$$\forall u_0 \ge 0, u_0 \ge \sqrt{2 \ln n}, \Pr\{n_s \ge u_0\} \le e^{-u_0^2/2} \le 1/n.$$
(12)

Accordingly,  $Pr\{n_s \le u_0\} = 1 - o(n)$ . That is, with high probability we have:

$$l_s \le \delta_s \sqrt{2\ln n} + \overline{l}_s. \tag{13}$$

Moreover, it is obvious that  $\overline{l}_s \leq \overline{l}_h$ ; thus, by rearranging (31) in [35] we obtain:

$$E\left[\left(\sum_{i=1}^{h_g^*} \overline{r}_i\right)\right] = E\left[(h_g^* \cdot \overline{r})^2\right] = E\left[(h_g^*)^2\right] \cdot \overline{r}^2 \ge (\overline{h}_g^* \cdot \overline{r})^2 = \overline{l}_s^2.$$
(14)

The proof can be completed by combining (13) and (14), i.e.,

$$(\overline{h}_g^* \cdot \overline{r})^2 \ge (l_s - \delta_s \sqrt{2 \ln n})^2$$

Furthermore, let the optimal number of nodes that benefit from data replication be a random number  $n_g^*$ . The expectations of  $l_s$  and  $A_g^*$  can be expressed as  $E[A_g^*] \leq E[\pi \cdot l_s^2]$ , which means that

$$E[A_g^*] \le \pi (\delta_s \sqrt{2\ln n} + \overline{l}_s)^2 \text{ w.h.p.}$$
(15)

Since the expectation of nodes in  $A_g^*$  is  $\lambda A_g^*$ , we have  $E[n_g^*] \leq \lambda \pi \left( \delta_s \sqrt{2 \ln n} + \overline{l}_s \right)^2$  w.h.p..

Note that  $\overline{r}$  and  $\delta_s$  only depend on  $\lambda$ . Clearly, more sophisticated expressions of these upper-bounds can be obtained numerically in certain instances. Due to space limitations, we omit the detailed analytical calculations in [35]. For clarity, however, we demonstrate the Big-O notation to grasp the scaling behavior.

We now consider nontrivial instances that are restricted by the limitations of data replication. More specifically, the scenario illustrated in Fig. 2 is augmented with (i) multidirectional transfer of replicated objects; and (ii) a more constrained network capacity. We denote the area correlated with such replication-induced gain as  $A_g$ . An illustration of the shape of a potential region is shown in Fig. 4, where the transmission radii of the relay nodes are depicted by dotted circles. The white nodes are those that benefit from the replication-induced gain derived from the black nodes. As mentioned earlier, due to the finite transport capacity of



Fig. 4. An example of a potential region that correlates with the replicationinduced gain derived from multiple objects. The arrows indicate that the white nodes can acquire the desired objects from the black nodes in their vicinity.

a wireless ad hoc network, the value of  $A_g$  might be further constrained if the amount of traffic induced by delivering these replicated objects is too large within a given communication session. Let  $m_g$  be the random variable representing the total number of nodes inside  $A_g$  according to the mentioned spatial Poisson process (i.e., with intensity  $\lambda$ ). Clearly  $A_g < A$ . Let  $m_g^*$  denote the number of nodes that benefit from replicationinduced gain via the optimal object replication strategy. Using the Chernoff's bounds again, we obtain the following result (see, e.g., [33]).

 $\begin{array}{l} \textit{Lemma 3:} \ \Pr\{m_g \geq m_g^*\} \leq \exp\{\lambda \cdot (e^{A_g} - 1) - m_g^* \cdot A_g\}.\\ \textit{Lemma 4:} \ \forall m_g^* \ \text{such that if} \ m_g^* \cdot (\ln m_g^* - 1) + 1 \geq \ln n \\ \text{holds, we have} \ m_g^* > m_g \ \text{w.h.p.} \end{array}$ 

**Proof:** Based on the argument in [33], to minimize the right-hand side of Lemma 3, we have to minimize  $\lambda \cdot (e^{A_g} - 1) - m_g^* \cdot A_g$ . In other words,  $m_g^*$  and  $\lambda$  should satisfy  $m_g^* = \lambda \cdot e^{A_g}$ . We rescale the graph such that A = n (with the constraint on  $m_g \geq \lambda$ ); consequently,  $\lambda = 1$ . In this case, even under the network capacity constraint, the probability that more than  $m_g^*$  nodes exist inside  $A_g$  is minimized, since the optimal object replicating strategy implies that nodes not in need of this object-replication gain are rarely found inside  $A_g$ .

It is not hard to validate that, with the proper choice of value for  $m_g^*$  that satisfies  $m_g^* \cdot (\ln m_g^* - \ln \lambda) \ge \ln n + (m_g^* - \lambda)$ , we can obtain the minimized probability expression below. Note that under our rescaling,  $m_g^* \cdot (\ln m_g^* - 1) + 1 \ge \ln n$ . Therefore,

$$\Pr\{m_g \ge m_g^*\} \le \frac{e^{-\lambda} (\lambda e)^{m_g^*}}{(m_g^*)^{m_g^*}} \le \frac{1}{n},$$

i.e., we have

$$\Pr\{m_g \ge m_g^*\} \ge 1 - \frac{1}{n} = 1 - o(n)$$
 w.h.p.

Proposition 2: Provided that  $m_g^* \cdot (\ln m_g^* - \ln \lambda) \ge \ln n + (m_g^* - \lambda)$ , and given the network diameter  $dr_m, d \in \mathbb{R}^+$ , we have  $\kappa/d = \Theta(\sqrt{\ln \ln n/n})$  w.h.p.

*Proof:* From Lemma 3 and Lemma 4 we obtain the relations between  $m_g^*$ ,  $m_g$ , and  $\lambda$  under the optimal scheme of node placement and object replication. Implicitly, nodes that do not issue any query for replicated objects in this time period are outside  $A_g$  w.h.p. It is not hard to validate that  $\exists u_1 \in \mathbb{R}^+$  such that  $A_g \cdot e^{A_g} = (1 + u_1) \ln n$ 

Moreover, the following result can be derived:

$$\frac{\pi\kappa^2 r_m^2}{A} \ge \frac{\ln\ln n + \ln(1+u_1) - \ln A_g}{n}.$$
 (16)

Therefore,  $\exists u_2 \in \mathbb{R}^+$  such that

$$\frac{\kappa}{\sqrt{A}} = (1+u_2) \cdot \sqrt{\frac{\ln \ln n - \ln A_g}{n\pi r_m^2}}$$

Since  $\lim_{n\to\infty} \left(\frac{\ln A_g}{n\pi r_m^2}\right)$  and  $A = \pi (dr_m/2)^2$ , with large enough n we obtain:

$$\frac{\kappa}{d} = \Theta\left(\sqrt{\frac{\ln \ln n}{n}}\right)$$
 w.h.p.

*Remark 1:* Although the derived bounds are not tight, we have established a preliminary relation between  $\kappa$  and A. The scaling laws are events that almost certainly occur asymptotically. Moreover, under the inherent energy constraint, new problems emerge when optimizing the balance between conflicting requirements. For instance, in the illustration in Fig. 3, if most optimal relay paths pass through the same region (i.e., the shadowed rectangle), some tradeoff between replication efficiency and network lifetime is inevitable. Network lifetime will be addressed further in a future study.

## B. From the Perspective of Resource Management

In real-life applications, because of the inherent constraints on the memory and energy resources of mobile nodes, requested objects are not usually replicated and delivered with maximum efficiency. From the recent work in [29], it can be deduced that the buffer size should be scaled in order to sustain a certain throughput capacity. Here, we present some preliminary observations and an analysis of inter-node resource management. For example, as objects are replicated and transmitted in the application-layer, consider the events illustrated in Fig. 5. Once an object  $o_i$  has been replicated in node u during a communication session, there is a (perhaps high) probability that more than one query for  $o_i$  will be issued before the communication session ends. The available memory of u is reduced by one object if another query for object  $o_i$ ,  $o_i \neq o_i$ , is issued after the observation point and before object  $o_i$  is removed from the memory. We denote such a case as a event induced by the incoming request for object j (or  $\Downarrow_j$  in brief). However, the memory capacity of u may be insufficient if  $\Downarrow$  events occur frequently and only a few objects can be removed from its memory in subsequent time-slots.

the observed communication session



Fig. 5. Illustration of an object *j*-induced  $\Downarrow$  event, where (i) the dotted vertical lines indicate the time-slots; and (ii)  $r_i$ ,  $r_j$  indicate the data traffic generated by replicating object  $o_i$  and  $o_j$ , respectively.

Accordingly, the following question arises: Given the object request pattern<sup>9</sup>, what would be a "suitable" time period to keep the replicated object in the memory to address further queries in this communication session? First, consider an observation point (chosen at random) and examine the subsequent  $\tau$  time-slots. We assume the memory of node uis insufficient after k successive objects (namely  $\{o_s : 1 \leq i\}$  $s \leq k$ ) arrive within t time-slots after the observation point. Note that not all k objects are unique (i.e., one or more may be duplicates). Let m denote the minimum number of different requested objects subsequent to  $o_i$  that causes the memory of u to overflow; note that m correlates directly with  $\Phi(u)$ . In addition, let the permutation of these objects be  $s_1, \ldots, s_m$ . For simplicity, we assume that the time between successive arrivals of queries for each object is an independent, exponential random variable with constant mean  $\rho$ . Below, we show that even with full knowledge of an object's request pattern, some trade-off must be made.

Proposition 3: Given m,  $\exists \tau \in \mathbb{R}^+$ , and  $\tau = \rho \ln m$  such that if node u holds some object for more than  $\tau$  time-slots in the above scenario, the memory of u will overflow w.h.p.

*Proof:* First, for each of the subsequent objects, the probability that no queries will arrive in later t time-slots is:

$$e^{-t/\rho} \cdot (t/\rho)/0! = e^{-t/\rho}$$

For any set of object indices  $\{s_1, \ldots, s_{m-1}\}$ , the independent property of the Poisson distribution infers that within t time-slots, the probability that the  $s_m$ th object will arrive is:

$$\Pr\{\bigcup_{s_m}^t |\cap_{j=1}^{m-1} \bigcup_{s_j}^t\} = \Pr\{\bigcup_{s_m}^t\} = (1 - e^{-t/\rho}).$$
(17)

Using the well-established Poisson distribution-based techniques, the probability that the memory of u will become insufficient within t time-slots can be approximated as follows:

$$\Pr\{\neg(\cup_{j=1}^{m}\neg \Downarrow_{j}^{t})\} = \Pr\{\bigcap_{j=1}^{m}\Downarrow_{j}^{t}\}$$
$$= (1 - e^{-t/\rho})^{m} \approx e^{-m \cdot e^{-t/\rho}}.$$
(18)

Furthermore, given that  $d \in \mathbb{R}$  and  $\tau = \rho \ln m$ , let  $T_o$  be a random variable that indicates the interval between the

<sup>9</sup>We use the term "object request pattern" loosely, to describe all query terms during a communication session.

observation point and the event of memory overflow. The following formulation is derived based largely on the results given in [15]:

$$\Pr\{T_0 > \rho(\ln m + d)\} = \Pr\{\bigcup_{j=1}^m \neg \bigcup_j^{\tau}\} \\ = 1 - \Pr\{\bigcap_{j=1}^m \bigcup_j^{\tau}\}$$
(19)

$$\approx 1 - e^{-e^{-d}}.\tag{20}$$

As shown in [15], the probability that all m different requested objects will arrive within  $\tau$  time-slots changes abruptly from nearly 0 to almost 1 in a small interval c centered around  $\tau$ . (See [15] for more rigorous arguments and relevant details.)

Remark 2: Proposition 3 implies a "deterministic-like" (i.e., very high probability) result that can provide application designers with some constructive insights into conserving memory resources. More specifically, in the above scenario, since m different subsequent objects overflow the memory of node u within  $\rho$  time-slots, the following inequality can be given:  $m/\rho \geq \Phi(u)/\tau$ . Hence, u may find an eligible node (one with sufficient memory before the communication session ends) in its vicinity to take over  $o_i$  if the remaining memory  $\Phi'(u)$  is not enough, i.e.,  $\Phi'(u)/m \leq \tau/\rho \leq \ln m$ . Furthermore, if object sizes are determined by some random distribution with a constant mean, how should a node decide to remove the inside objects? We assume that, for each node, a cyclic index indicating the available memory exists. The index advances with time; if it encounters the position of an object  $o_i$ , then  $o_i$  is removed. On the other hand, if the index moves too slowly, the available memory might be insufficient if a large object is received. Intuitively, the speed of the index should be the median of the buffer I/O rates. We are working towards more sophisticated formulas and algorithms based on Stochastic Process theory, especially from an information theoretical point of view.

Finally, one of the most important challenges in the design of ad hoc network applications is to reduce the energy consumption of the network. Nodes are typically batterypowered and, hence, have a limited lifetime. The energy used in communicating a bit from a source to a destination has two components — one due to transmission, which depends on the number of hops and the distance and power used at each hop, and the other due to transceiver circuit energy, which is proportional to the number of hops. The number of hops determines the amount of power required for optimal energy scaling [36]. In fact, the trade-off between throughput and delay in wireless ad hoc networks has also been addressed in recent years (see [8], [27], [28] and the references therein). Note that the effect of node mobility is considered in most related work.

We complete our analysis by proposing the following expression based on the results of several recent works. Let T(n) and D(n) denote the scaling behavior of network throughput and packet delay, respectively. Under the timedivision multiplexing (TDM) policy, the scaling quantity of dissipated energy E(n) with the optimal throughput-delayenergy notion has been shown to be as follows [36]:

$$E(n) = \Omega(D(n) + A^{\alpha/2} \cdot D(n)^{1-\alpha}), D(n) = \Theta(n(T(n))).$$
(21)

*Remark 3:* From the above discussion, we can suggest some practical implications: (i) To keep D(n) scaling as  $\Theta(1)$ , the minimum energy-per-bit result shows that:  $E(n) = \Omega(A^{\alpha/2})$ . (ii) Alternatively, if the scaling quantity of packet delay is enlarged to be proportional to  $\sqrt{A}$ , it follows that  $E(n) = \Omega(\sqrt{A})$ , i.e., data transfer can be achieved in a more energy efficient manner.

*Remark 4:* In practice, power consumption during packet transmission depends on the number of relay nodes and the number of trials required to successfully transmit a packet in one hop. Let  $P_{lb}$  denote the probability of successful transmission determined by the MAC protocol. If we consider a CSMA/CA scheme with RTS and CTS frames (i.e., an IEEE 802.11-like protocol), the expected number of one-hop packet transmissions is proportional to  $1/P_{lb}$ . Readers can find a detailed analysis of  $P_{lb}$  in [32].

# V. CONCLUDING REMARKS AND FUTURE RESEARCH DIRECTIONS

The characteristics of wireless ad hoc networks pose particular challenges to P2P applications. This paper represents a step toward developing a better understanding of the fundamental performance limits of these networks, with special emphasis on data replication. More specifically, we highlight some of the intrinsic difficulties in computing and communications. We also introduce the concept of replication-induced gain and derive several preliminary results in a resourceconstrained environment. To clarify the whole approach, we have made manifold assumptions in our argument; however, we believe the analysis adequately captures the intrinsic characteristics of P2P data replication in wireless ad hoc networks. Furthermore, we suggest some ways in which the results could shed new light on handling the various complexities and tradeoffs in wireless ad hoc networks. The results have several implications that P2P system designers may wish to consider.

Further approximations could be derived with more realistic scenarios of the underlying replication-and-query process. In addition, the constructive forms that can generate algorithms from the above proofs are of particular interest, e.g., devising a replicating strategy that minimizes the expected memory consumption. We have not studied approximation algorithms in this paper because the traditional means of analyzing and evaluating online algorithms, namely, competitive analysis, has been criticized as being unrealistic in many real-life instances [16]. This problem tends to be exacerbated in our model due to the complications that follow from applying various constraints in practice (e.g., the dynamics of mobility, limited bandwidth, and frequent link failure). We are trying to refine competitive analysis in order to address the above concerns. As mentioned earlier, communication and computation overheads can contribute to a loss of data fidelity, and replication-induced gain also relies on the rate at which nodes lose interest in searching for certain objects. Techniques to optimize the balance between replication-induced gain and data fidelity have yet to be investigated.

Finally, the dynamics of user request traffic is an important subject that has not been fully investigated. As noted in [17], the intuitive solution of simply re-applying placement from scratch may cause several problems (e.g., sluggish reaction to system changes and substantial reconfiguration costs). Moreover, a new approach for dealing with dynamic queries, such as the use of flooding techniques in unstructured P2P networks, has been proposed by Jiang and Jin [18]. Nonetheless, the optimization of search latency and search costs often conflict with each other; hence, another interesting aspect would be to adaptively balance query execution against the routing overhead to facilitate higher data availability. Note that, in multihop wireless communication networks, it is usually necessary to support an evolving set of applications; therefore, resourceadaptive protocols are needed to improve throughput and other performance factors. Obviously, numerous technological challenges must still be resolved in the development of practical and efficient strategies that use fewer system resources and are more robust against network failures and delays.

## Appendix

## **PROOF OF PROPOSITION 1**

Proof: For ease of reduction, we introduce the maximal independent set (**MIS**) problem. Briefly, an independent set Sof G = (V, E) is a subset of V such that  $\forall u, v \in S, (u, v) \notin$ E. S is called a maximal independent set (MIS) if any node v not in S is adjacent to some node in S. The problem of deciding whether there exists an independent set of cardinality larger than an integer s is NP-complete (see [19] for more details). The MIS problem is obviously NP-complete, since by randomly taking a resolution set R', one can easily check whether  $R' \Rightarrow^{\kappa} Q'$  with memory consumption less than d in polynomial time. To prove the NP-completeness of EMC, we prove that MIS can be reduced to EMC in polynomial time. For brevity, we consider a special case of  $\kappa = 1 \wedge$ c = n (denoted as the EMC' problem). A reduction to EMC' can thus be performed as follows. First we construct G' =(V', E') via the following s: (i) we duplicate V and mark the copies with a prime, thus  $\forall u \in V, \exists a \text{ copy } u' \in V'$ ; and (ii) we add an extra node s' to V', thus |V'| = |V'| + 1. A corresponding **EMC**' problem can be derived for G': (i)  $\forall u'_i \in$  $V', u'_i$  possesses an innate object  $o'_i$  (the innate object of s' is denoted as  $o'_{s}$ ); and (ii) the query set is  $\{q(u'_{i}, o'_{s}) : u_{i} \in V\}$ . A polynomial time node clustering algorithm is then exploited on G.<sup>10</sup>

We adopt the terms "cluster-head" and "border-node" used in [20]. Let  $E' = \{(u'_i, u'_j) : (u_i, u_j) \in E\}$ . Finally, we choose an arbitrary node  $u \in V$  and add an edge (s', u')to E. An example is given in Fig. 6, where nodes a and d are the cluster-heads; and nodes b and e are the bordernodes. Now we consider the above case with  $\kappa = 1$ . Note that all cluster-heads are separated by at least one border-node. Hence, it is easy to verify that: (i) the minimal number of

<sup>&</sup>lt;sup>10</sup>Considering the approaches proposed in [19], after construction of the dominating set, the resulting graph consists of two types of nodes: cluster-heads and border-nodes. Note that the cluster-heads induce an independent set (i.e., a dominating set, where each node pair is not adjacent). A node is a border-node if it is not a cluster-head and there is more than one cluster-head in its two-hop neighborhood.



Fig. 6. Graphs that facilitate the proof of NP-completeness.

object replications that satisfies the 1-coverable requirement is h, where h denotes the number of cluster-heads in G; and (ii) h is also equivalent to the cardinality of an independent set S over G, where S is approximated by the node clustering algorithm mentioned above. As a result, any answer to this 1-coverable **EMC**' problem with memory consumption d = hcan be associated with an answer MIS with the same number over G. Note that all data structures and computations involved can be carried out in polynomial time. Since a general problem cannot be easier than its special cases, we can conclude that EMC is NP-complete.

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Szu-Chi Wang received the B.S. degree in Computer Science and Information Engineering and the Ph.D. degree in Electrical Engineering from National Taiwan University in 1995 and 2005, respectively. His research interests lie in the areas of computer networks and telecommunication systems, with focuses on wireless ad hoc networks, wireless sensor networks, and wireless access networks. He is a member of the IEEE.



**Hong-Zu Chou** received the B.S. degree in computer science and information engineering from National Central University in 2003. He is a Ph.D. candidate in the Department of Electrical Engineering at the National Taiwan University. His research interests lie in the areas of the design, implementation and analysis of distributed algorithms for wireless ad hoc networks, with emphasis on energy efficient and dependable mobile communication.



**David S. L. Wei** received his Ph.D. degree in Computer and Information Science from the University of Pennsylvania in 1991. He is currently a Professor of Computer and Information Science Department at Fordham University. From May 1993 to August 1997 he was on the Faculty of Computer Science and Engineering at the University of Aizu, Japan (as an Associate Professor and then a Professor). Dr. Wei has authored and co-authored more than 70 technical papers in the areas of distributed and parallel processing, wireless networks and mobile

computing, optical networks, and peer-to-peer communications in various archival journals and conference proceedings. He served on the program committee and was a session chair for several reputed international conferences. He served as a co-chair of Power Aware Communication and Software, Minitrack in the Software Track at the 34th Hawaii International Conference on Systems Sciences (HICSS-34). He was a lead guest editor of IEEE Journal on Selected Areas in Communications for the special issue on Mobile Computing and Networking, and is a guest editor of IEEE Journal on Selected Areas in Communications for the special issue on Peerto-Peer Communications and Applications. Currently, Dr. Wei focuses his research effort on wireless networks, mobile computing, and peer-to-peer communications.



**Sy-Yen Kuo** is Dean of the College of Electrical and Computer Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan. He is also a Professor at the Department of Electrical Engineering, National Taiwan University where he is currently on leave and was the Chairman at the same department from 2001 to 2004. He received the BS (1979) in Electrical Engineering from National Taiwan University, the MS (1982) in Electrical & Computer Engineering from the University of California at Santa Barbara, and the PhD (1987) in

Computer Science from the University of Illinois at Urbana-Champaign. He spent his sabbatical years as a Visiting Professor at the Computer Science and Engineering Department, the Chinese University of Hong Kong from 2004-2005 and as a visiting researcher at AT&T Labs-Research, New Jersey from 1999 to 2000, respectively. He was the Chairman of the Department of Computer Science and Information Engineering, National Dong Hwa University, Taiwan from 1995 to 1998, a faculty member in the Department of Electrical and Computer Engineering at the University of Arizona from 1988 to 1991, and an engineer at Fairchild Semiconductor and Silvar-Lisco, both in California, from 1982 to 1984. In 1989, he also worked as a summer faculty fellow at Jet Propulsion Laboratory of California Institute of Technology. His current research interests include dependable systems and networks, software reliability engineering, mobile computing, and reliable sensor networks.

Professor Kuo is an IEEE Fellow. He has published more than 250 papers in journals and conferences. He received the distinguished research award between 1997 and 2005 consecutively from the National Science Council in Taiwan and is now a Research Fellow there. He was also a recipient of the Best Paper Award in the 1996 International Symposium on Software Reliability Engineering, the Best Paper Award in the simulation and test category at the 1986 IEEE/ACM Design Automation Conference(DAC), the National Science Foundation's Research Initiation Award in 1989, and the IEEE/ACM Design Automation Scholarship in 1990 and 1991.