

# MOBIX: System for managing MOBility using Information eXchange

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## ABSTRACT

We propose a different approach to determining network availability of mobile nodes which leverages on the fact that nodes on the move will meet other nodes who will be able to share conditions of networks they have recently encountered. This paper presents MOBIX, a system where nodes exchange information about network conditions using short-range communication such as Bluetooth. Our simulation results show that the required number of nodes needed for 100% success is not unrealistic of densely populated metropolitan areas. Even with relatively low population densities, we can expect a data store hit more than 50% of the time. Although our evaluation used WiFi, our scheme can easily be extended for other technologies such as GSM and WiMax.

## 1. INTRODUCTION AND MOTIVATION

In the future mobile world, users will be carrying devices with multiple radio interfaces. These interfaces will have varying energy profiles and network characteristics, ranging from low power, low transmission range Bluetooth to relatively high power, longer range interfaces such as WiFi or WiMax. Despite rapid progress in battery technology, small, mobile devices of the future will still be energy constrained. Thus, turning on all wireless interfaces all the time even for the purpose of detecting available network points of attachments to decide which interface to use will significantly shorten the battery life of most portable devices.

Current methods rely mostly on the radio interfaces itself for detecting network availability, or attempts at predicting future networks by learning from user history. In our work, we explore a different approach altogether by having mobile users exchange reports of network conditions with other nodes they encounter using a short-range, low-power communication channel, such as Bluetooth.

Although it may seem counter-intuitive, we argue that there are benefits to such a system. Firstly, as previously mentioned, to turn on all of the multiple radio interfaces to monitor for current condi-

tions will be an extreme drain on battery power. For instance, the WiFi interface can consume more than 60% of total system power, even when idle [6]. The Bluetooth interface on the other hand consumes very little power even when active. Secondly, only RSSI can be measured by relying on the radio layer. Throughput and delay can only be estimated based on inherent properties of the interface such as maximum theoretical bandwidth. On the other hand, in our proposed system we can share information such as actual throughput and delay experienced by other users on their connected networks. Finally, we can make better decisions as our information hinges not just on a single measurement but on multiple measurements gathered by other devices nearby.

## 2. RELATED WORK

The problem of determining network availability has been the subject of much research. [8] used semi-Markov models to predict WLAN availability from user context such as time of day, GSM location area, available WLANs, and number of Bluetooth devices found. Similarly, [7] estimated WiFi network conditions using past WiFi and Cellular ID information and acceleration approximations.

The work by [7] showed that network availability is very high in urban areas, but the energy cost of network interfaces is a significant problem. They thus proposed to leverage the complementary energy profiles of GSM and WiFi by developing policies for choosing between the two interfaces with the goal of extending battery life. Other works that seek to conserve energy of portable devices by switching between radio interfaces include [6] and [1].

Another approach to network availability involves the use of network maps or QoS maps. In [2], network coverage was modeled as a two dimensional map of the geographic coverage of each network. This network map was used in determining whether the node is in a transition zone and a vertical hand-over is warranted. A more sophisticated map was proposed in [3], where two dimensional representations of VoIP QoS metrics are made available to mobile VoIP users.

Our techniques for information dissemination is closely related to similar work on vehicular ad-hoc networks (VANET). [5] examined selective data dissemination by estimating the novelty probability of reports from a spatio-temporal perspective. Similarly, [12] used a ranking method based on perceived supply and demand of reports, with supply estimated using a machine learning algorithm. Our work can be classified under mobile encounter networks, discussed in [4], a form of mobile peer to peer networks created by mobile devices.

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### 3. SYSTEM OVERVIEW

In brief, our system works as follows: Nodes generate *reports* on network conditions at certain points in time and keep these reports in a data store. When a node meets or *encounters* another node, they exchange information by sending a portion of reports from their data stores. The node then calculates the relevance of each report and keeps the top  $N$  reports in the data store. When a packet has to be sent to the Internet, the node retrieves reports generated within a maximum radius from its current location and determines the integrity of each report by calculating its trustworthiness value. It then combines these reports to make a decision on which interface and network point of attachment to use for data transfer.

Nodes in MOBIX can operate in two modes, either as a *generator* or as a *forwarder* node. A generator node is a node that has other interfaces aside from Bluetooth which are active, or are at least in a mode that allows it to gather relevant network data. A generator node generates reports and stores and forward reports it receives from other nodes. A forwarder node on the other hand only has its Bluetooth interface actively turned on for receiving and forwarding reports.

Fundamental to the success of our system are the proper management of reports for optimum information dissemination and estimating the integrity of received reports, which we discuss next.

#### 3.1 Report Management

A report is the basic piece of information exchanged between nodes and is generated periodically using a timer on the mobile node. Each report includes a timestamp and the node's geographical location when the report was created, and the network parameter of interest for all available interfaces and all possible points of attachment. In our evaluation, Received Signal Strength Indicator (RSSI) was used as a baseline parameter as it is a basic indicator for all wireless interfaces.

The data store is where generated and received reports are stored and from which data is retrieved when a decision needs to be made. The data store has a finite buffer size and can hold at most  $B$  reports. Reports are transmitted periodically as long as another node is within transmission range. Although flooding the network leads to the highest bandwidth consumption as opposed to epidemic or proximity-based information dissemination, we argue that the size of the reports are small enough (about 170 bytes/report in our simulation) that bandwidth is not an issue. Additionally communication is essentially free using Bluetooth so there are no financial costs involved for transmitting reports.

Reports are arranged in the data store according to relevance factor, which is an indication of how new and how useful this report will be to the node. Intuitively, we know that younger reports will most likely bring fresher information while reports generated within the node's current vicinity will be more pertinent than those generated farther away. Thus we compute the relevance factor of report  $R$  to be

$$Relevance_R = W_{age} * age + W_{dist} * dist$$

where  $W_{age}$  and  $W_{dist}$  are the weighting factors of age and distance, respectively, ranging between 0 and 1.0.

When a MOBIX node encounters another node, it exchanges reports in its data store. It first sorts the data store from highest to lowest relevance factor. It then transmits the top  $N$  reports. For each report it receives, the node checks that the report does not yet exist in its data store. If the report is a duplicate, it is dropped and the drop count for that report is incremented. Otherwise, the relevance factor is computed and the report is inserted in the data store.

#### 3.2 Data Integrity

Data trust in traditional schemes is essentially dependent on trusting the entity where the information came from. Such entity-centric trust is usually based on a priori relationships and hinges on a single source of trust, eg certification authorities. Even in reputation-based systems, trust is formed over lengthy interactions as nodes build up their reputations over time. Due to the highly mobile and ephemeral nature of node encounters in our system, trusting the data by verifying the source will not be appropriate, almost impossible. Instead we propose to use a *data-centric* approach to evaluating the trustworthiness of reports, similar to that adopted in [9].

The trustworthiness of each report is evaluated as a function of its static and dynamic properties and expressed as

$$w_{R,k} = F(k, R) = F(s(k), d(R), t(R))$$

where  $w_{R,k}$  is the trust level of report  $R$  generated by node of type  $k$ . This function returns a value in the interval  $[0,1]$  and is a measure of the over-all trustworthiness of the report. The higher the value, the more trustworthy a report is.

The *static trustworthiness*,  $s(k)$ , depends on the attributes of the node  $k$  which generated the report. Nodes can either be *mobile* or *fixed* and owned *publicly* or *privately*. Privately owned nodes have relatively low default settings as there is no a-priori means of establishing their integrity. Publicly owned fixed nodes, such as those set up by government agencies, have higher trust settings as they are assumed to have no biases towards specific networks or operators and will generate reports faithfully.

The *dynamic trustworthiness*,  $d(R)$  and  $t(R)$ , are a function of the distance and age of report  $R$ , respectively. As the strength of radio signals vary according to distance and multi-path interference, reports generated farther away would not be as reliable as those produced closer to where the node currently is. This is especially true in boundary conditions experienced near the edges of network coverage. Similarly, reports which are introduced more recently would likely reflect current conditions more accurately than older reports. Cryptographic means can be used so that these geotimestamps cannot be tampered with by other nodes.

#### 3.3 Decision Engine

When a node has a packet to send to the Internet, it needs to make a decision on which interface and network point of attachment to use for this transaction. To do so, the node retrieves all the reports from the data store generated within a maximum radius of its current location. It determines the integrity of each report by calculating the trustworthiness value and uses this to combine the reports into a single RSSI measure for each possible network found. The decision engine then chooses which point of attachment to use by matching application requirements and user preferences with the combined RSSI measures that meet a minimum trust level.

The combined RSSI for point of attachment  $n$  at time  $t$ , denoted by  $RSSI(PoA_{t,n})$ , can be evaluated using a variety of techniques. The most straightforward, and the method used in our evaluation, is to calculate the average of the RSSI with the trust level of each report treated as weights, as in

$$RSSI(PoA_{t,n}) = \frac{\sum w_{R,k} \cdot RSSI_{R,n}}{\sum w_{R,k}}, \forall R : dist < d_{max}$$

. The trust level of the combined RSSI can be evaluated as

$$w(PoA_n, t) = \frac{1}{K} \sum_{k=1}^K w_{R,k}$$

where  $K$  is the total number of reports which contributed to the combined RSSI measurement.

We are currently investigating the use of Bayesian Inference and Dempster-Shafer Theory for data fusion using trustworthiness values as weights in our calculations.

## 4. INITIAL RESULTS

We evaluated our system through simulation in NS2 using two well-known mobility models, random waypoint and Manhattan grid. Mobile nodes were set to move at an average walking speed around a 500m x 500m simulation area, with four access points placed at equidistant locations. We varied the number of mobile nodes to determine the effect of population density. We also varied the percentage of generator nodes, the data store size, and the percentage of data store sent per transmission. Reports are sorted according to age ( $W_{age}=1.0$  and  $W_{dist}=0.0$ ) or distance ( $W_{age}=0.0$  and  $W_{dist}=1.0$ ) to determine which factor is a better indicator of relevance.

To determine how effective our system is, we let a mobile forwarder node attempt a file transfer and make a decision on which base station to connect to based on reports alone. If no reports within the vicinity are found, the packet is dropped and no connection attempt is made. The file transfer is deemed successful if the node receives a FIN packet within a specified interval. The percentage of total number of successful file transfer attempts is thus used as an indicator of our system's performance, as a FIN packet will only be received if relevant reports were found in the data store and a successful WiFi connection was established.

Our results showed that as the number of mobile nodes increases the success ratio also increases. This is not surprising, since the probability of encountering a node carrying useful information increases as the number of mobile nodes increases. At 250 nodes, the success ratio is approximately 50% for the Manhattan grid model. Considering that the baseline value is around 78%, more than half the time the node needs to make a decision at least one relevant report can be found in its data store. By extrapolating our results, we approximated that the number of mobile nodes needed in order to have a data store hit 100% of the time is  $\sim 780$  nodes for Manhattan grid and  $\sim 520$  nodes for Random Waypoint. This translates to a population density of 3,120 nodes/km<sup>2</sup> and 2,080 nodes/km<sup>2</sup>, respectively. As a point of comparison, Sydney's Waverly district has a population density of 6,900 people/km<sup>2</sup> [10] while Tokyo metropolitan area has 11,526 people /km<sup>2</sup> [11]. Thus even if only half of the population is mobile at any given time and assuming all of them carry a mobile device, the calculated population density is not unrealistic of current highly urbanized cities.

Our results also showed that the mobility model has a significant impact on the success ratio. The system consistently performed better using the Manhattan grid model, even in other experiments where we vary the number of generators and change the relevance factor.

The success ratio increased as the number of generators increases. In particular, there was a significant increase in success ratio going from 1% to 10% generators. However, adding more generator nodes after 25% did not improve performance as dramatically.

We conclude that age is a better indicator of relevance than distance as it allowed reports to propagate further and refreshed the data store much quicker. It is also much easier to manage the data store since we did not have to constantly sort the reports as the node moves around.

We gained significant improvement in system performance by increasing the data store size. On the other hand, sending more reports per transmission may not significantly improve performance. Thus for low population densities, it is paramount for nodes to have larger data store capacities and to send about 10% to 20% of the data store contents per transmission to make up for the lesser prob-

ability of node encounters.

We additionally compared the decisions on which access point to connect based solely on reports and if the node made its own measurements. Our simulations showed that the same decisions were reached 97% of the time. False conclusions occurred at the edges of network coverage where the RSSI value approaches the minimum threshold (-70dBm).

Finally, we calculated the theoretical energy savings of our scheme using power measurements reported in [6]. Even if the Bluetooth interface is active 100% of the time, it will still be drawing more than 50% less power than the WiFi interface at idle state. Thus, even at very high population densities where nodes have a lot of neighbors within transmit range and the Bluetooth device is busy all the time, it is still more energy-efficient to use Bluetooth rather than powering on the WiFi interface. The approximate energy consumed by Bluetooth in our simulation scenario, wherein the interface was active at most 5% of the time, was around 12% of the energy consumed by the WiFi card.

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