From Parallel to Emergent Computing: Book Chapter Proposal
Vol. 00, No. 00, Month 2011, 1–24

RESEARCH ARTICLE

Towards an Opportunistic Software-Defined Networking Solution

Lefteris Mamatas[a]*, Alexandra Papadopoulou[b] and Vassilis Tsaoussidis[c]

[a]*University of Macedonia, Department of Applied Informatics, 156 Egnatia Street, 546 36 Thessaloniki, Greece*; [b]*Aristotle University of Thessaloniki, Department of Mathematics, 541 24 Thessaloniki, Greece*; [c]*Democritus University of Thrace, Department of Electrical and Computer Engineering, Building A, Panepistimioupoli Xanthis, Kimmeria, 67100 Xanthi, Greece*

(*v1.0 released May 2017*)

In the recent years, there is a major architectural shift in the Internet infrastructure, where network control is being gradually decoupled from the data plane. The Software-Defined Networking (SDN) paradigm is a prominent relevant technology that offers logically-centralized control based on the global picture of the network environment. This strategy allows a better understanding of the context environment while offers improved levels of adaptability and flexibility towards diverse application requirements and resource constraints.

In another research front, opportunistic networks attempt to exploit even the slightest communication opportunity in challenging network conditions, associated with both fixed and mobile resources. For example, in disaster areas where a major part of the infrastructure may not be in place, the mobile devices may bridge the communication gaps by adopting opportunistic routing strategies.

Along these lines, we attempt to borrow ideas from the SDN paradigm and apply them in such challenging environments, including investigating a logically-centralized networking solution manifesting mobility prediction. In our case, a significant part of the network control resides at centralized components in the infrastructure network that surrounds the mobile devices. We present a reference Semi-Markov based mobility model and an opportunistic routing protocol implementation demonstrating the potential of our solution.

Keywords: Software-Defined Networks; Opportunistic Networks; Infrastructure-supported Mobile Communication; Mobility Prediction

1. Introduction

Internet is gradually being extended to areas that was not present before, including those with challenging network conditions. Examples are the space missions, disaster environments and places with limited population. Such deployments may be characterized with intermittent network connectivity and/or other problematic network conditions, such as erroneous communication channels. In the past, opportunistic communication solutions have been proposed to exploit the scarce resources in the most efficient way, by adopting store-carry-and forward communication strategies among the surrounding mobile devices. However, the mobile devices that may be present in the area usually have limited resources, in terms of available energy, processing power or memory. The complexity of this task increases more, if we consider application, device and protocol diversity. The need to

This work is an extension of our conference paper [1].
*Corresponding author. Email: emamatas@uom.edu.gr

ISSN: 1744-5760 print/ISSN 1744-5779 online
© 2011 Taylor & Francis
DOI: 10.1080/17445760.YYYY.CATSid
http://www.informaworld.com

increase the available resources and utilize them in the best possible way, highlights the requirement to exploit available fixed infrastructure as well; either those that may be available or be added on-demand (e.g., through bringing communication vans or balloons in a disaster area).

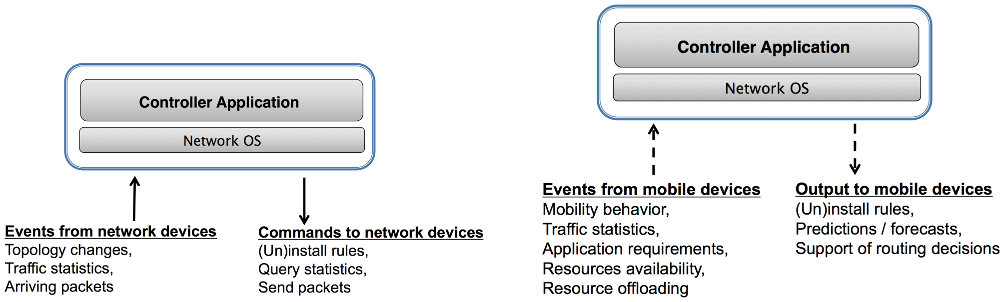
Since it is difficult to design communication protocols that work in every condition, the research communities focus in particular context-sensitive solutions. A next evolution step is to generalize based on the specialized results, handle and hide the present heterogeneity using abstractions. A similar process happens in the area of infrastructure networks, where Software-Defined Networks (SDN) and the most prominent relevant proposal so far, OpenFlow [2], decouples network control from the data plane. This introduces a common control space that works on top of diverse and multi-vendor equipment, as long as the latter supports the same open standards in terms of protocols and interfaces.

However, the common control space assumes common management decisions for the deployed infrastructure that may be difficult to take in parts of the Internet that are owned by multiple competing operators. So, SDNs work well and are very efficient when they match a relevant economic demand, i.e., so far in medium- or large-scale networks that belong to the same organization or industry. In other words, logically-centralized control is a very efficient way to manage resources, as long as everybody is happy with the direction it takes. This may not be an issue in challenging wireless environments, since a single mobile operator or a centralized authority may be present (e.g., after a disaster).

Here, we argue that in an opportunistic context the core ideas of SDNs are valid. In this chapter, we propose an experimental networking solution as a first step towards: (i) Decoupling network control functionality from data plane in the mobile devices and integrate it in fixed infrastructure components; and (ii) Selecting, deploying and evaluating alternative protocol and mobility forecasting solutions using a common infrastructure with its associated design abstractions. The main idea is to offload expensive operations from the mobile devices to the resourceful fixed resources and to maintain a global-picture for the network environment. The latter enables better forecasting for the communication opportunities and harmonized network control towards common performance goals in the system. For example, in a disaster environment all available resources should be operating with a common goal to increase the network lifetime as much as possible.

A main issue to tackle in opportunistic networks is the prediction of future contacts, i.e., poor prediction means waste of available resources and communication opportunities. Furthermore, a network designer should always consider the cost of prediction, in terms of communication overhead, processing load and memory utilization. Here, we suggest that maintaining a global-picture for the network environment improves the accuracy of predictions, since it allows significantly more input data for the associated prediction mechanisms. The forecasting overhead is being offloaded in the infrastructure nodes, so there is insignificant cost for the mobile devices as well. Although the above vision is being demonstrated here with a reference Semi-Markov mobility prediction model, we plan to generalize the platform to support alternative prediction approaches in parallel, for the different coexisting mobility patterns.

In figure 1, we compare the different approaches to control plane separation between the traditional SDNs and our proposed paradigm. In the former solutions, a software controller responds to events from network devices (i.e., topology changes, traffic statistics or arriving packets) with commands to network switches or routers (i.e., manipulates rules, queries statistics or sends packets). In the studied framework, an equivalent controller application collects statistics from mobile devices



(a) Infrastructure Networks (b) Mobile Networks

Figure 1. Approaches to Control Plane Separation for infrastructure and mobile networks

regarding mobility behavior, traffic characteristics, application requirements and resource availability. Based on this input, sophisticated decision mechanisms may decide to install a new forwarding rule in the mobile devices or communicate particular forecasts to the nodes, e.g., probabilities to contact other nodes or the fixed infrastructure. In this case, we do not have a complete separation between control and data plane, rather than a different balance between them. The mobile nodes may still take network control decisions, but using inputs from the fixed infrastructure for a better accuracy and resource utilization, i.e., communicated at times there is a fixed infrastructure connection.

In the proposed platform, the fixed nodes residing around areas with poor or intermittent connectivity are collectively building and, based on historical data, training a stochastic model that predicts future contacts. Practically, each infrastructure node traces the coordinates of mobile devices passing by along with their corresponding connectivity times. Such data are being communicated within the platform and constitute valuable input for the mobility model, which produces node-level (i.e., detect mobility patterns of certain nodes) or system-level estimations (e.g., number of nodes at a certain area after some time). The mobiles nodes may query the platform for information on their future contact opportunities through communicating with their neighboring fixed nodes. The latter responds with potential suggestions, such as a probability value or coefficients of a known distribution representing the inter-contact time PDF between the mobile devices, classes of devices with common characteristics or Internet access nodes, depending on the context.

So, the moving device can calculate the cost functions associated with potential tactics - from holding data further, to forwarding to another node and also to which particular direction - and make a decision with respect the delivery time of the data or, perhaps, the certainty to reach the destination within some required timeframe. It is obvious that storing the data in the source mobile node until a new hotspot appears is a conservative strategy that misses communication opportunities. Furthermore, 3G networks are often expensive and unavailable. In experiments documented in [3], in places 3G is not available there is WiFi availability roughly half of the time. In our experience, forwarding decisions can be taken with a level of accuracy that can be occasionally high (when the scenario allows) although communication and processing overhead could be low. Other approaches to location-prediction using historical information are based on the limited contact history of a single node (e.g., [4]), group contact-time information of a certain number of users (e.g., based on their social ties [5]) or use offline network traces to evaluate the accuracy of Markov or semi-Markov based approaches (e.g., [6], [7]).

In this chapter, we employ a semi-Markov model for the prediction of contact opportunities. Semi-Markov models [8] were introduced as stochastic tools with capacity to accommodate a variety of applied probability models: they may provide more generality to describe the semantics of complex models - which, in turn, increases the complexity of analysis. However, the extra-added variables improve the modeling expressiveness of real-life problems. We also note that the increased complexity is assigned to the resource-capable fixed nodes, improving prediction accuracy without damaging the sensitive performance of mobile, battery-powered devices. It is documented (e.g., in [7], [9]) that Markov-based location predictors perform very well in practice, but require more complex and expensive mobility data for sophisticated forecasts such as the time and location of the next user movement or duration of stay in an area.

Our approach is characterized by two main advantages: (i) the fixed infrastructure allows for a global view of the system and improved predictions of connectivity opportunities; (ii) the mobile devices delegate resource-expensive operations to the infrastructure nodes in order to exploit their capabilities in terms of energy availability, processing power and memory allocation. Therefore, the performance of mobile devices is preserved without trading prediction accuracy and hence communication efficiency. Decoupling (but also improving) the forecasting capability from the routing strategy enables a number of new efficient protocols to be introduced. Furthermore, the forecasting connectivity opportunities can be a basis for an efficient energy-saving strategy also; the mobile devices could be switching off their communication subsystems at times the probability to meet other nodes is low.

To demonstrate the potential of our solution, we consider an urban scenario where mobile users are interested into getting Internet access. Different hotspots are scattered in a city center (i.e., around 60 km^2 in Thessaloniki, Greece), covering with Internet connectivity some percentage of that area (i.e., less than 40%). The hotspots are deployed in real points of interest (central squares, museums and other places attracting people) and are collectively building a communication model. The mobile nodes can request information on neighboring nodes: how often or with what probability they do contact the available hotspots. Such information is passed from the closest hotspot to the mobile device. So, a moving user can easily make decisions on whether a neighboring node is more suitable to forward its own data towards the Internet.

This chapter is an extension of our prior work presented in [1]. Compared to the latter, we consider the infrastructure supporting such estimations as important as the proposed model and study both aspects in parallel. Here, we describe a first architectural version of the discussed platform and its core features. Along with an extended version of our Semi-Markov mobility prediction model (i.e., initially appeared in [10]), we propose a reference opportunistic routing implementation validating our main arguments. Our experimental results confirm the potential of our solution.

The chapter is structured as follows. In Section 2 we review the state of the art that is relevant to the present work. In Section 3 we describe a relevant scenario, a first architectural description of the studied platform along with the proposed semi-Markov stochastic model. In Section 4 we evaluate the above model in four experimental scenarios. Finally, in Section 5 we conclude the chapter.

2. Related Works

Internet complexity has been increased rapidly since new communication paradigms, other than Infrastructure - based networking, have been incorporated into the internetworking model (e.g., ad-hoc, mesh or space networking). In this context, the network becomes also a storage device - not just a communication vehicle. This new property of the Internet alone challenges all known models and evaluation standards for internetworked systems. Furthermore, approaches such as Delay - and Disruption - Tolerant Networks (DTNs) [11] undergo major standardization efforts that target a unification perspective for the various pieces of the global network jigsaw puzzle. An example work that brings closer different types of networks (i.e., wireless and mobile) is [12], attempting to define a continuum between the different networks. We note that protocols originally designed for a homogeneous network environment are not expected to work optimally in such a hybrid setting.

A number of approaches support mobile communication using the surrounding infrastructure. In the area of VANETs, proposals either exploit infrastructure to support car-to-car communication (e.g., through roadside access points) or the opposite (e.g., [13]). Recent papers consider clouds as a dynamic infrastructure that improves mobile communication through offloading resources from the mobile users (e.g., [14]). DTN throw-boxes have been introduced as stationary, battery-powered nodes, embedded with storage and processing capabilities, being able to enhance the capacity of DTNs [15]. Mobile infostation networks use the infostation nodes to support mobile communications for this specific context (e.g., to keep information close to the mobile users [16]). Other proposals move a portion of the mobile data traffic to WiFi networks, exploiting the significantly lower cost of WiFi technology and existing backhaul infrastructure [17].

Our proposal, inspired from the Software-Defined Networking paradigm, focuses on how the infrastructure can support mobile communication through taking over the contact forecasting operations from the mobile devices. This allows for more accurate but resource - efficient estimations. We attempt to offer much better environmental conditions for the forecasting capabilities and leave the routing strategies to the opportunistic network protocol. This allows both aspects to evolve in parallel, allowing clearer evaluations as well, i.e., their interrelation makes difficult a justification for the potential performance gains or losses. In our understanding, this is the first SDN-inspired opportunistic networking proposal, employing mobility prediction. Other wireless SDN approaches cover aspects such as Software-defined wireless mesh and sensor networks [18], [19], software-defined cellular networks [20] or home networks [21]. Our solution does not depend to OpenFlow [2], although it can inspire its future evolution, i.e., to support mobility prediction features.

Another important aspect in mobile communication is the study of the inter-contact time distributions (e.g., [22]). The inter-contact time distribution is related to the potential existing mobility patterns and allows for an estimation of the contact opportunities. This essentially determines the strategy of network protocols (e.g., the routing decisions). The inter-contact time distribution type may change under certain conditions. For example, in [23] the distribution change is associated with the examined time-scale and in [24] with the geometry of the topology. In our experience, there is a range of typical distributions that may match the inter-contact time distributions for particular network settings. Theoretical models ending up in analytical expressions (e.g., [24]) may cover the typical general models but are often inefficient in practice. Here, the proposed infrastructure supports a number of typical distributions and performs curve-fitting whenever is possible (for a certain time-period or set of nodes). Beyond that, an on-line estimation of upcoming probability values is way more appropriate since our ultimate goal is to exploit all opportunities to turn a temporarily-incapable to a soon-capable communication system.

Along these lines, we model user mobility with a semi-Markov process with heterogeneous properties, allowing for flexible definition of different distributions for inter-contact times, under different conditions. Such conditions and other relevant patterns are extensively explored and associated with practical constraints (e.g., resource availability). Other relevant approaches using semi-Markov processes are [25, 26]. Both approaches model routing behavior rather than mobility patterns. Other works attempting to predict node mobility using semi-Markov processes in wireless environments are [27–29]. Another work but in a different scientific area is [30] (i.e., mobility tracking for elderly people).

At this stage, we evaluate the proposed infrastructure and model in the context of an urban scenario, where mobile devices require Internet connectivity even at times they are not covered from deployed hotspots. For methodological reasons, we focus on the particular environment and the study of next-place or WiFi connectivity forecasts in order to devise strategies for extended and efficient Internet access. In the near future, we plan to move on to more complicated scenarios, predicting device-to-device connectivity opportunities in heterogeneous deployments (i.e., mixing networked vehicles with pocket switched networks).

In the literature, approaches to mobile connectivity forecasting have been proposed in different contexts, such as resource reservation in cellular networks or handoff planning (e.g., [31, 32]). The BreadCrumbs [33] proposal maintains a personalized mobility model on the user's device that tracks Access Points (APs) using RF fingerprinting and combines the predictions with an AP quality database to produce connectivity forecasts. MobiSteer [34] uses specialized hardware (i.e., a directional antenna) to detect connectivity opportunities and to maximize the duration and quality of connectivity between a moving vehicle and stationary access points. Song et al [35] studies the efficiency of different mobility prediction models in the context of improved bandwidth reservation and smoother handoffs for VoIP communications. In this work, they assume a centralized collection of mobility information. Regarding the algorithms used for next-place or WiFi connectivity forecasts, they range from Markov approaches (e.g., second- or higher-order Markov models [4, 33], Gauss-Markov models [36], semi-Markov [6, 10, 37] and hybrid Markov approaches [38]), raw and semantic trajectories (e.g., [39]) and models predicting human mobility to solutions exploiting sociological aspects (e.g., [40]).

Compared to the related works, our SDN-inspired solution decouples network control features (i.e., the mobility model aspects) from the routing protocol and offloads them to the surrounding infrastructure (e.g., the prediction operations). This allows a larger number of samples to be considered (i.e., due to the more complete view) and more complicated calculations to be performed, improving the forecasting accuracy in a resource friendly way for the mobile devices. The semi-Markov model extends the modeling complexity through introducing extra parameters, matching better the details of networking scenarios. For example, it can relax the basic assumptions of Markov models that durations of states follow geometric / exponential distributions and can represent non-homogeneous distributions or heterogeneity in time for waiting times. Its hybrid properties can match well the hybrid characteristics of the Internet (i.e., heterogeneity in many aspects, including topologies mixing fixed with mobile nodes).

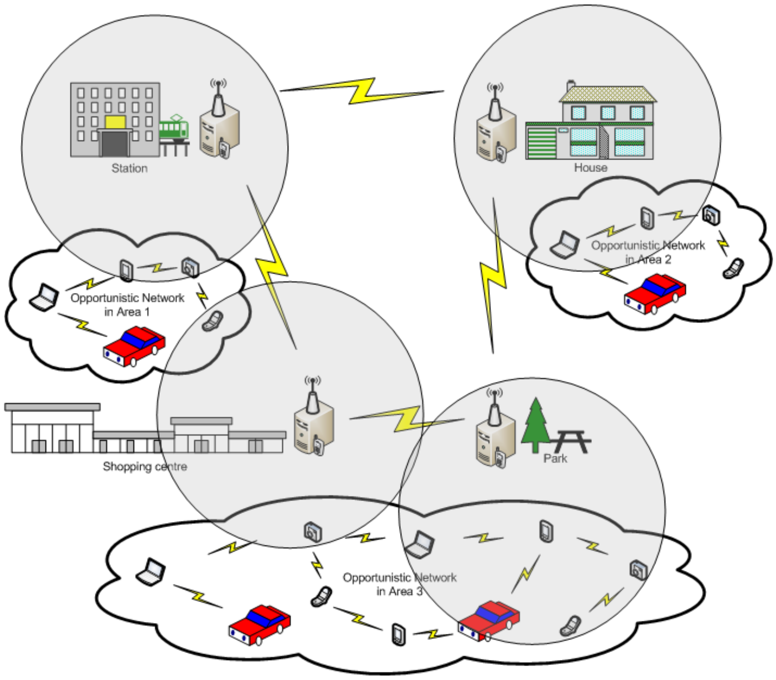


Figure 2. The studied environment

3. Case Study and Modeling Considerations

3.1 Studied Environment

In this chapter, we consider a heterogeneous network scenario consisting of both mobile and infrastructure nodes. Along these lines, we assume a communication system that integrates deployed infrastructure (e.g., a network of hotspots) with opportunistic networks, therefore allowing for additional communication opportunities even for uncovered city areas. The infrastructure nodes have been delegated the responsibility of tracking the position of mobile nodes as well as the potential estimation of their future positions.

As we show in figure 2, the studied city scenario includes a number of hotspots covering with connectivity only a percentage of the area (e.g., 30-40 %). There is a wide-range of mobile device types moving around the hotspots. Each mobile node may need to access the Internet or to interact with any other node. To address this demand, a dynamic path should be established between the communicating nodes, carrying the data to be transmitted. This is not trivial, since all nodes may be constantly moving and all participating node positions are not known in advance.

In figure 3, we give an initial architectural version of the investigated Opportunistic SDN solution. We plan to further design and complete its implementation in the near future. The main idea is as follows:

- A network monitoring system collects measurements regarding the mobility behavior of mobile nodes (e.g., locations, contact times and durations).
- Classifiers group users according their mobility behavior. Each user group can be assigned a particular trained mobility model (e.g., the proposed semi-Markov model).
- The coordination component is the "heart" of our infrastructure and is responsible to control all other components, evaluate and add or remove new mobility models, corresponding user groups or classification algorithms.
- A management interface allows an administrator to parameterize the coordina-

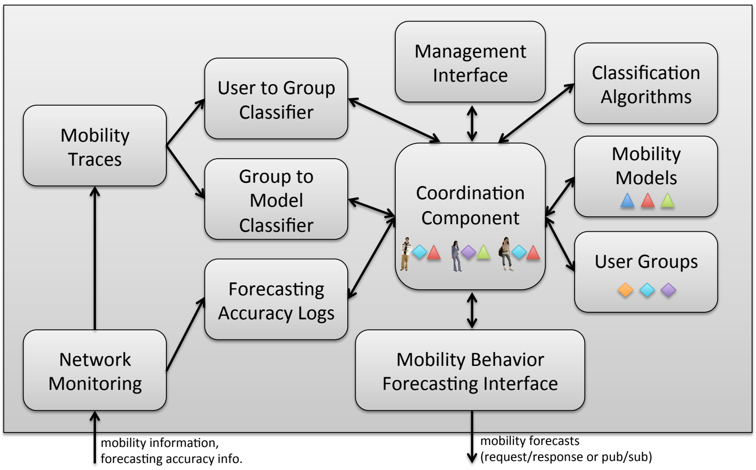


Figure 3. An initial architecture of the investigated infrastructure

tion component.

- The mobility behavior forecasting interface communicates the appropriate predictions to the mobile nodes requesting them.
- The monitoring system collects prediction accuracy information from the mobile nodes, implementing a close-loop that assists the selection of the appropriate classifier and mobility model each time.

Of course the above solution is associated with a number of research challenges that are beyond the focus of this chapter. For example, privacy issues could be addressed with an approach that periodically refreshes the device id's assigned to each user, at time-scales there is minor impact to the forecasting accuracy. After the collection of the data, there is no use to keep the mobile users identity, since new users will be classified to the previously detected mobility patterns. We consider a similar solution and its associated trade-offs as a subject of a future work. The issue of trust or other privacy matters (e.g., whether you can trust strangers to forward your data) can be handled in the same way with most other solutions in the area of DTNs (an example solution is [41]).

3.2 Semi-Markov Model and Basic Equations

In this subsection, we detail the proposed stochastic model and its basic equations reflecting different aspects of users' mobility behavior. The stationary nodes implement collectively the model and communicate the output of the equations to the interested mobile nodes. An efficient routing decision may require one or more calculations, based on its own criteria. We present usage examples along with the model description, in the context of our proposed infrastructure. We highlight that all equations can be used as contact predictors for communication between the mobile nodes as well.

We model the users' mobility behavior using a Discrete - Time Semi - Markov System (DTSMS). A semi-Markov chain is a generalized Markov model and can be considered as a process whose successive state occupancies are governed by a Markov chain (i.e., embedded Markov chain), although state duration is described by a random double variable which associates with the present but also with the next transition state. A relevant model discussion focused on theoretical aspects can be found in [10].

At the beginning of our analysis, we assume a population of users moving around a city center (i.e., in this chapter we considered the city of Thessaloniki) and pass through a number of scattered hotspots in real points of interests in the area (e.g., central squares, museums etc). The users can be stratified into a set of areas $S = 1, 2, ..., N$. We assume that a number of areas have network coverage (e.g., 1 to K) while other areas do not (e.g., K to N). These areas are assumed to be exclusive and exhaustive, so that each user is located at exactly one area at any given time. The state of the system at any given time is described by the following vector:

$$N(n) = [N_1(n), N_2(n), ..., N_N(n)] \tag{1}$$

The $N_i(n)$ represents the expected number of users located at an area i, after n time slots. We consider a closed system with constant total population of users denoted with T. Also, we assume that individual transitions between states occur according to a homogeneous semi-Markov chain (i.e., embedded semi-Markov chain). In this respect, let us denote by P the stochastic matrix whose $(i, j)th$ element equals to the probability of a user in the system which entered an area i to make its next transition to area j. Thus, whenever a user enters area i selects area j for its next transition, according to the probabilities $p_{i,j}$.

A mobile node may request a specific probability value in the form of $p_{i,j}$ from the infrastructure system. This expresses the probability of a node to reach an area j after being at an area i, in the next transition. This value could be used from a mobile node in order to check if there is a chance for a user to pass by area i and reach area j straightaway. For example, the mobile node could perform a quick check if two areas are adjacent.

In our model, the mobile user remains for sometime within area i, prior to entering area j. Holding times are described by the holding time mass function $h_{i,j}(n)$, which equals to the probability that a user entered area i at its last transition holds for n time slots in i before its next transition, given that node moves to area j.

The holding time mass function $h_{i,j}(n)$ could be used by a mobile node in order to check the possibility of a direct transition from area i to area j at a given time. Occasionally, the destination area may not matter, but instead, the transition is important: for example, a transition from a non-covered to a network-covered area. A node, therefore, at an isolated area may evaluate the cumulative probability to move to any area with connectivity, independently of which area it is.

By the same token, we discuss the following variation of the holding time mass function:

$$h_i(n) = \sum_{j=1,2,...N(j \neq i)} p_{i,j} h_{i,j}(n) \tag{2}$$

The $h_i(n)$ function captures the probability of a mobile node at state i to make a transition at time n (the particular destination area is irrelevant). Along the same lines, we introduce the probabilities:

$$h_i^{con}(n) = \sum_{j=1,2,...K} p_{i,j} h_{i,j}(n) \tag{3}$$

$$h_i^{disc}(n) = \sum_{j=K,K+1,\dots N} p_{i,j} h_{i,j}(n) \tag{4}$$

The functions $h_i^{con}(n)$ and $h_i^{disc}(n)$ capture the probabilities of a mobile node to move from area i to any area with connectivity or not at time n, respectively. For example, a forwarding decision could be made based on the possibility of the forwarding node to carry data to an Internet access network.

We also detail equation ${}^{>}w_i(n)$ which expresses the probability of a user who made a transition to area i to reach the next area in longer than n time slots:

$${}^{>}w_i(n) = \sum_{m=n+1}^{\infty} \sum_{k=1}^{N} p_{i,k} h_{i,k}(m) \tag{5}$$

The initial condition is ${}^{>}w_i(0) = 1$.

Similarly, variations like ${}^{>}w_i^{con}(n)$ and ${}^{>}w_i^{disc}(n)$ could be introduced.

The ${}^{>}w_i$ equations can support the forwarding decisions of the opportunistic routing protocol inline with data transmission deadlines, e.g., delay constraints for real-time or other time-critical applications.

A main aspect of the proposed model is related to the interval transition probabilities which correspond to the multistep transition probabilities of a Markov process. So, let us define as $q_{i,j}(n)$ the probability of a user from area i to be at an area j after n time slots, independently of the required intermediate state changes. This metric allows multi-path contact predictions, i.e., captures the probability of a node to be at an area after some time (or two mobile nodes to contact each other, in a general setting), independently of the required steps.

The basic recursive equation for calculating the interval transition probabilities is the following [42], [43]:

$$q_{i,j}(n) = \delta_{i,j} \cdot {}^{>}w_i(n)$$

$$+ \sum_{k=1}^{N} \sum_{m=0}^{n} p_{i,k} h_{i,k}(m) q_{k,j}(n-m) \tag{6}$$

The initial condition is $q_{i,j}(0) = \delta_{i,j}$, where $\delta_{i,j}$ is defined:

$$\delta_{i,j} = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ elsewhere} \end{cases} \tag{7}$$

Also, since our semi-Markov model allows for a distinction between the number of time slots passed and the number of transitions occurred, a mobile node can request separately the probability distribution of the number of areas that a user has crossed starting from area i and ending at area j at time n. In this respect, we define as $\phi_{i,j}(x/n)$ the probability of a user who has made a transition to area i to be in area j after n time slots and having crossed x areas.

Using probabilistic arguments, it is proved (i.e., in [42], [44]) that the basic recursive equation for calculating the above probabilities is as follows:

$$\phi_{i,j}(x/n) = \delta_{i,j}\delta(x) \cdot {}^{>}w_i(n)$$

$$+\sum_{k=1}^{N}\sum_{m=0}^{N} p_{i,k}h_{i,k}(m)q_{k,j}(x-1/n-m) \tag{8}$$

with initial condition $\phi_{i,j}(0/n) = \delta_{i,j} \cdot {}^{>}w_i(n)$.

The expected number of areas that a user passes by, starting from area i and moving to area j after n time slots can be calculated by [42]:

$$d_{i,j}(n) = \frac{g_{i,j}(n)}{q_{i,j}(n)} \tag{9}$$

where:

$$g_{i,j}(n) = \sum_{k=1}^{N}\sum_{m=0}^{n} p_{i,k}h_{i,k}(m)[2g_{k,j}(n-m) -$$

$$\sum_{r=1}^{N}\sum_{u=0}^{n-m} p_{k,r}h_{k,r}(u)g_{r,j}(n-m-u) + \delta_{k,j} \cdot {}^{>}w_j(n-m)] \tag{10}$$

Equations $\phi_{i,j}(x/n)$ and $d_{i,j}(n)$ can be considered from routing decisions involving the number of steps required to reach an area. An example is to check the distance in steps between a user and a particular area. This maybe translated to more chances to reach a hotspot or even extra overhead to reach to the target area, i.e., it depends on the context.

We define the entrance probabilities $e_{i,j}(n)$ as the probabilities of a user which made a transition to area i to reach area j after n time slots.

According [42], [44] the entrance probabilities can be calculated from the following equation:

$$e_{i,j}(n) = \delta_{i,j}\delta(n) + \sum_{k=1}^{N}\sum_{m=0}^{n} p_{i,k}h_{i,k}(m)e_{k,j}(n-m) \tag{11}$$

with initial condition $e_{i,j}(0) = \delta_{i,j}$, where $\delta(n)$ is:

$$\delta(n) = \begin{cases} 1 \text{ if } n = 0 \\ 0 \text{ elsewhere} \end{cases} \tag{12}$$

Equation $e_{i,j}(n)$ is considering entrance of node at a particular area. This can be used as a way to decouple contact duration with a hotspot from exact contact time.

Also, if we define as $\nu_{i,j}(x/n)$ the probability that a user will pass through area j, on x occasions during an interval of length n, given that the user started at area i, then we can derive the following result [42]:

$$\nu_{i,j}(x/n) = \delta(x)^{>} w_i(n) + \sum_{m=0}^{n} \sum_{k=1,k\neq j}^{N} p_{i,k} h_{i,k}(m) \cdot$$

$$\nu_{k,j}(x/n-m) + \sum_{m=0}^{n} p_{i,j} h_{i,j}(m) \nu_{j,j}(x-1/n-m) \tag{13}$$

A usage example for the $\nu_{i,j}(x/n)$ equation follows. Taking into consideration the number of times a user passes through an area (i.e., the value x), is useful for cases we request some data through a forwarding node and expect that node to return. We can check with the equation $\nu_{i,j}(x/n)$ the possibility of a node at a particular area to leave the area and come back again (e.g., for $x = 1$).

For closed semi-Markov systems, such as the one we assume here, the expected user population structure is calculated by the equation [43]:

$$N_j(n) = \sum_{i=1}^{N} N_i(0) q_{i,j}(n) \tag{14}$$

where $N_i(0)$ is the initial population of users at an area i.

Using equation $N_j(n)$, we can make estimations regarding the node density at each area and at any given time. This result could be combined with the probabilities of a node to be at some particular area, and exploit its forwarding opportunities beyond the traditional restrictive models.

4. Evaluation

4.1 Evaluation Methodology

Here, we detail our evaluation methodology and the experimental scenarios we carried out. We extracted a large area of the city center of Thessaloniki, Greece from the OpenStreetMap website [45]. The area's dimensions are 6.2km x 10.1km, including 397 streets and 1884 landmarks. We selected twelve representative points of interest, assuming they offer Internet connectivity as well. Their locations were extracted from the same information source and selected based on their popularity (e.g., the Aristotles Square, the railway station, the St. Sophia Church, well-known museums etc). We conduct simulations with real parameters using the opportunistic networks simulator *theone* [46]. A map screenshot that includes some of the selected points of interest is shown in figure 4. The mobile users walk around the city, following one of the identified streets each time and directing towards an area based on a mobility pattern detailed in the corresponding scenario. The users stay in each area from few minutes to hours and their walking speed ranges between 0.5 and 1.5 m/sec. Our next step is to use alternative mobility traces from the CRAWDAD database [47] in order to validate the general applicability of our proposal. A real deployment is in our plans as well.

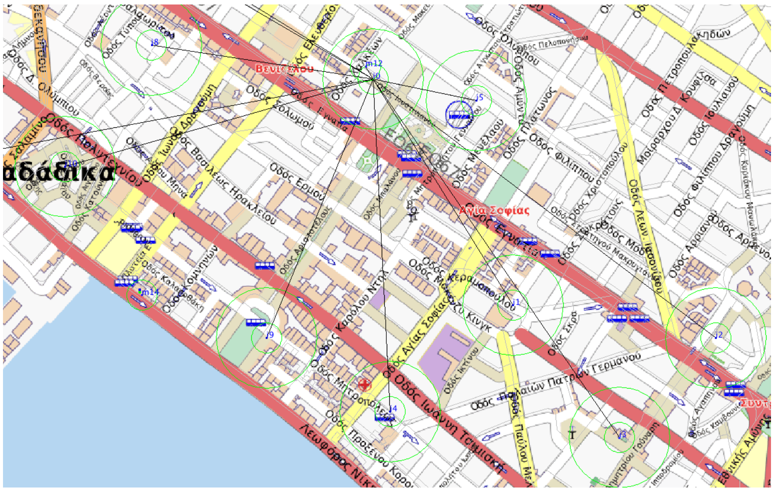


Figure 4. The experimental scenario

We grouped our experiments into four distinct scenarios, focusing on different aspects of our proposal. The first three scenarios demonstrate the efficiency of the proposed semi-Markov model, assuming corresponding user mobility behavior in the city center:

- A "Home-to-work" scenario, where a mobile node walks occasionally between home, work and the main city square. There is 33% probability of the user to be in one of these three areas.
- A "Walking around the city" scenario, where the mobile node occasionally selects one of twelve different areas in the city center as the next visiting area, with equal probability.
- A "Going out" scenario, where the mobile node has a high probability (33%) to be in the main square (assuming it as a meeting point) and an equal probability for each of the other eleven areas.

For the above three scenarios, we show how the proposed equations can be used as prediction mechanisms for a number of different mobility aspects and how different mobility patterns can be detected and exploited by a communication protocol.

In the fourth scenario, we implement a particular example of a routing protocol using the proposed infrastructure and model. In this scenario, mobile users walk around the city according to one of the three example mobility patterns demonstrated in the first three scenarios. Here, we ultimately target Internet access. The twelve areas in the city are Internet access points (i.e., hotspots). The purpose of each mobile user is to route data sooner and with minimum overhead to one of these hotspots.

The routing decisions use the h_i variations of equations, since the destination area does not matter, as long as it is a hotspot. For simplicity, we assume one area without Internet connection (i.e., area 13). Each mobile user looks up from the infrastructure the h_i calculated predictions assigned for the corresponding model. The predictions are in the form of tabular data with the upcoming forecasts or distribution parameters, in case of a successful curve fitting. The matching of mobile users with the mobility models is handled by the infrastructure using a simple heuristic algorithm (i.e., using predefined matching rules). The model matching methodology is an important aspect in its own right; due to space limitations, we do not extend this discussion here. Although the heuristic algorithm we used is rather simple, the results are very promising. An improved version of the user classification algorithm with an associated comparative analysis with relevant solutions (such as

[38]) is a subject of a future work. A mobile node attempting to transmit data follows a simple forwarding strategy, according to which the node either keeps data further until a window of opportunity occurs or forwards it immediately in case the neighboring mobile node has a higher h_i value from the source mobile node, at the given time. More details on the SemiMarkov protocol implementation can be found in Pseudocode 1.

4.2 Evaluation Results

4.2.1 Scenario 1: "Home-to-Work"

In figures 5, 6 we show the equations h_i and $h_{i,j}$, respectively. Both metrics reflect the probabilities of a mobile node to move to the next area, at some particular time slots. In the case of figure 6, the destination area does not matter, as long as we have a state change. It takes some time (i.e., more than 50 secs) for the mobile node to change state, a value that is a factor of the movement speed and the distance between the three areas. In figure 5, we show the probability of a mobile node to move to one of the three areas (i.e., home, work or main square), when it is located at an area without connectivity (i.e., area 13). The three h probabilities (i.e., $h_{13,1}$, $h_{13,3}$ and $h_{13,9}$) have often similar values, something not surprising given the experimental setup parameters. This behavior leads to reduced communication overhead of the forecasting request interactions between mobile nodes and infrastructure: an average value suffices.

The w metric (figure 7) reflects the probability of a user who made a transition to an area, to reach to the next area after at least n time slots. In this case, there is a very low probability for a state change, if the mobile node stays at a particular area for more than 600 secs. The $w_{13}(n)$ value is indeed interesting, since it represents the probability of a mobile node being at an area without connectivity, to move to an area with connectivity in less than n minutes. In this example, there is an insignificant chance of a connectivity time that exceeds 200 secs. Of course, this result is guided by the experimental setup parameters.

Equation q, shown in figure 8, reflects the probability of a node being at an area without connectivity to move to an area with connectivity at some given time, but without considering the number of areas crossed. We see that after some time, i.e., 200-300 secs, the probabilities to move to one of the three areas with connectivity, tend to converge to fixed values. Curve $q_{13,13}(n)$ shows the probability of a mobile node being at an area without Internet connectivity to visit an area covered by a hotspot, stay for a while and then leave the hotspot again.

In figure 9, we trace the behavior of metric $\phi_{i,j}$ for this particular scenario. In the same figure, we note that the number of areas crossed increases by time, but is typically no more than 2-3 areas. Higher values are justified because of a ping-pong movement between two areas. Metric $\phi_{i,j}$ is useful, in case a routing decision incorporate the number of hops data should transverse. For example, a node crossing a number of areas with connectivity, may appear more attractive due to its increased connectivity opportunities. Of course, in case delay is a crucial parameter, more areas crossed means also more resources used and more time to reach to the destination.

4.2.2 Scenario 2: "Walking Around the City"

Compared with scenario 1, the h values have a similar behavior (see figures 10, 11) because the transition probabilities of state changes in the two scenarios are similar. The main difference lies in the number of states (i.e., 12 areas for scenario two and 3 areas for scenario one). In figures 10, 11, we depict three states only, for

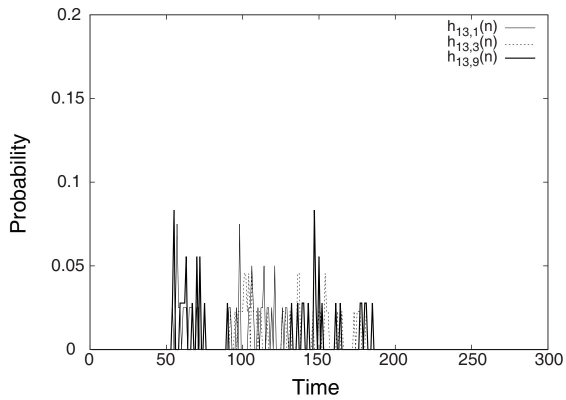


Figure 5. Probability of a user to remain for time n within area i, prior to entering area j - $h_{i,j}(n)$

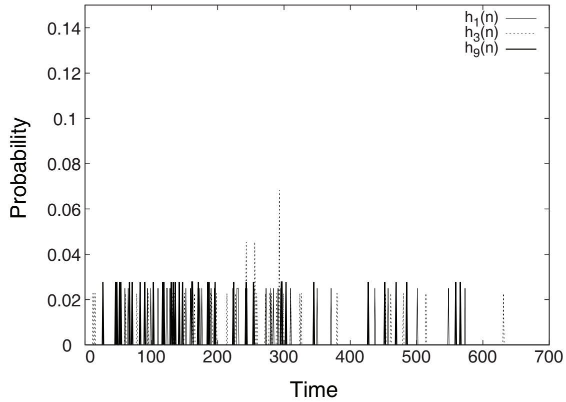


Figure 6. Probability of a user to remain for time n within area i, prior to entering any other area - $h_i(n)$

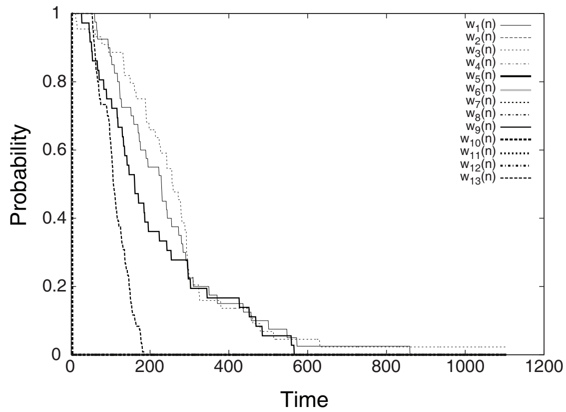


Figure 7. Probability of a user who made a transition to area i to reach the next area in longer than n time slots - $w_i(n)$

clarity and comparison purposes (i.e., between the first three scenarios). We note that the h values reflect changes between state 13 (i.e., area without connectivity) and any other available state. This happens because we assume that available hotspots do not have overlaps but instead have gaps between them. State changes are associated with the parameters of our system (i.e., waiting time at each state). In our case, this is a random value picked from a uniform distribution in the range of [0, 120] seconds.

Of course, the topological properties of the system (i.e., locations and distances between the hotspots) do matter and impact the state change probabilities between the different areas within the same scenario. This is reflected on the w values (i.e.,

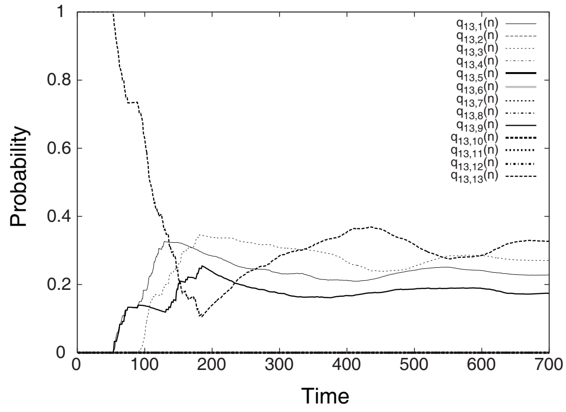


Figure 8. Probability of a user to leave area i and reach area j with multiple steps, after n time slots - $q_{i,j}(n)$

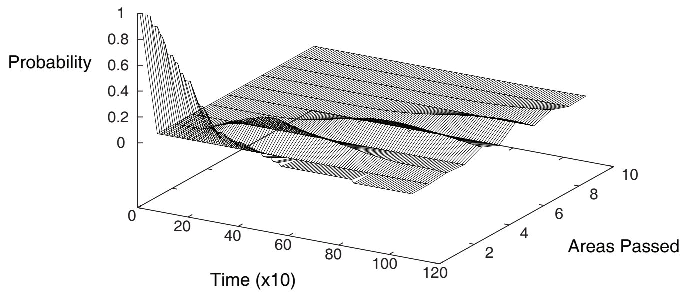


Figure 9. Probability of a user leaving area i to be in area j after n time slots and having crossed x areas - $\phi_{1,1}(x/n)$

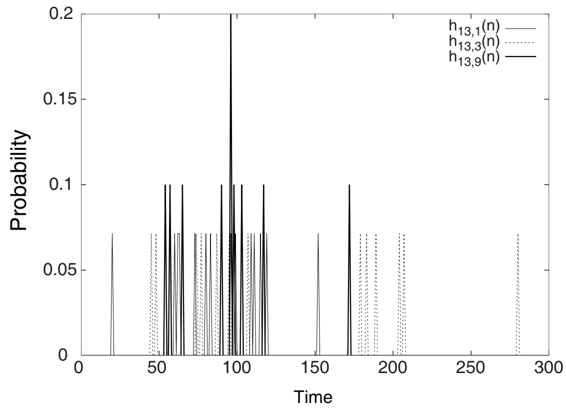


Figure 10. Probability of a user to remain for time n within area i, prior to entering area j - $h_{i,j}(n)$

figure 12) and the q values (i.e., figure 13). After some time, the different q values converge to fixed values.

4.2.3 Scenario 3: "Going out"

Through the h metrics (i.e., figures 14, 15), we see a notable difference compared with the previous two scenarios. The h values for area 1 (the main square of the city, the Aristotle Square) are significantly lower. In this scenario, state 1 has been chosen with a probability 0.33. So, there is a high probability for a node to remain at the main square (i.e., same destination state to the source state). This is a

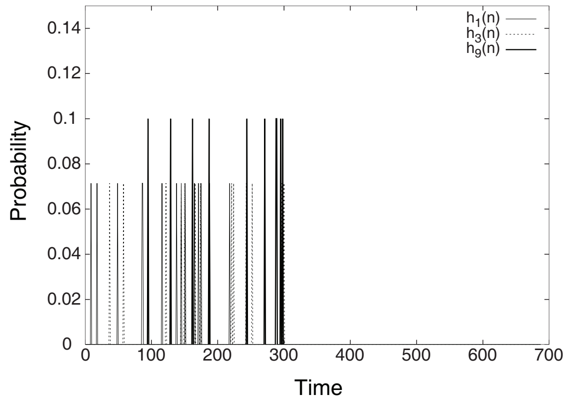


Figure 11. Probability of a user to remain for time n within area i, prior to entering any other area - $h_i(n)$

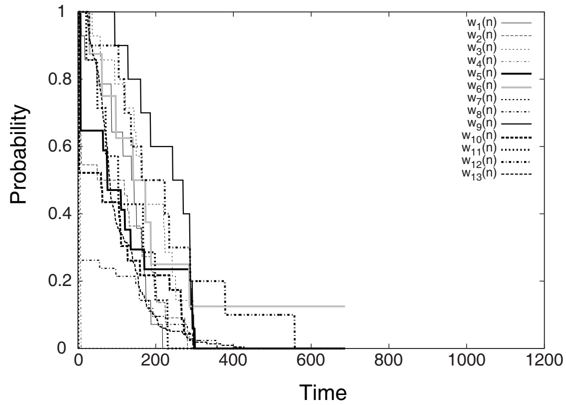


Figure 12. Probability of a user who made a transition to area i to reach the next area in longer than n time slots - $w_i(n)$

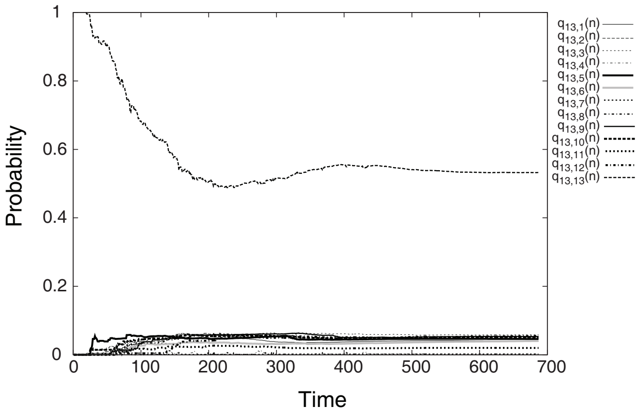


Figure 13. Probability of a user to leave area i and reach area j with multiple steps, after n time slots - $q_{i,j}(n)$

pattern that could be detected (i.e., hotspots that have a high probability to host mobile users). The same is reflected in a number of other metrics. For example, the $w_1(n)$, $q_{13,1}(n)$ values are significantly higher than other q, w values, respectively (see figures 16, 17). In figure 18, we observe that, as time passes, a mobile user may return back to the main square, but the number of areas crossed increases.

To summarize, the proposed model detects certain patterns regarding the spatial behavior of the users. Some examples are:

- How probable is a state change between two particular states in a single step

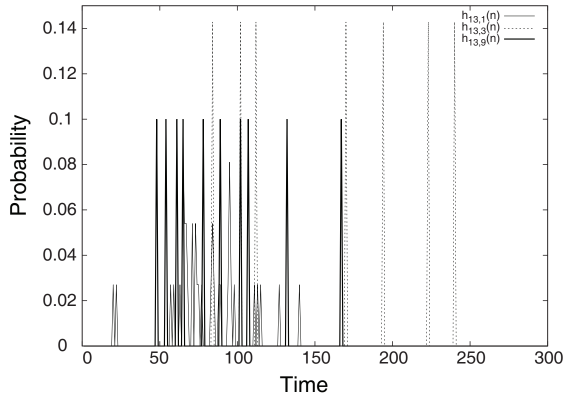


Figure 14. Probability of a user to remain for time n within area i, prior to entering area j - $h_{i,j}(n)$

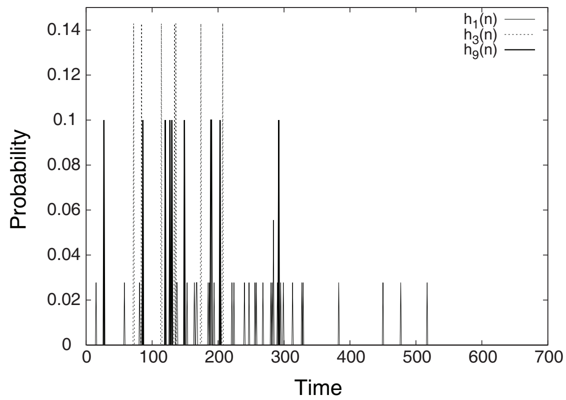


Figure 15. Probability of a user to remain for time n within area i, prior to entering any other area - $h_i(n)$

(i.e., $h_{i,k}$ values) or in many steps (i.e., $q_{i,k}$ values).
- What is the probability of a state transition from some given state to any other target state (i.e., h_i and w_i values).
- Whether some states have a significantly higher probability to be reached (i.e., $q_{i,k}$, or w_i or h values).
- What is the number of areas that need to be crossed by a mobile user walking across two predetermined areas (i.e., $\phi_{i,j}$ values).

In the following scenario, we present results from our sample protocol implementation in order to demonstrate the potential of the proposed model and infrastructure.

4.2.4 Scenario 4: The SemiMarkov Protocol

Here, we present indicative results from a comparative analysis between three different routing protocols:

- The simple *FirstContact* protocol that forwards data to the first contacted node. We use it as a reference, because our protocol is based on a similar implementation.
- The *SemiMarkov* protocol that uses h_i type of equations and a simple model matching technique for the mobile nodes, in order to forward data from the source nodes to other nodes with higher chance to reach one available hotspot.
- The *MaxProp* protocol, as a representative opportunistic routing protocol. Certainly, this is a sophisticated protocol, having many of its mechanisms optimized and well-tuned.

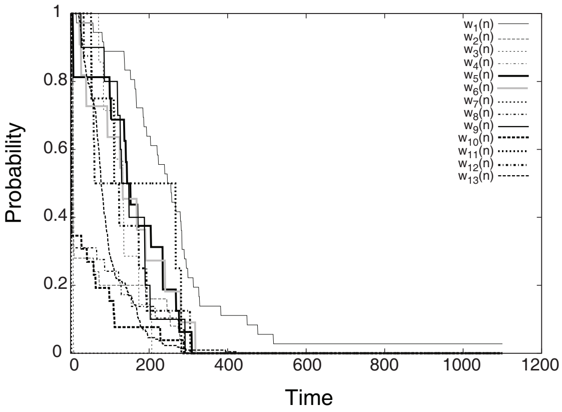


Figure 16. Probability of a user who made a transition to area i to reach the next area in longer than n time slots - $w_i(n)$

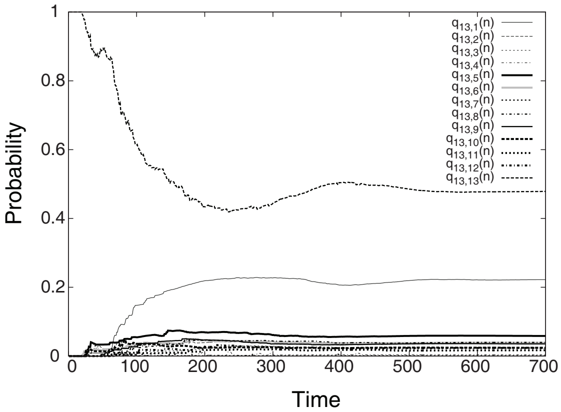


Figure 17. Probability of a user to leave area i and reach area j with multiple steps, after n time slots - $q_{i,j}(n)$

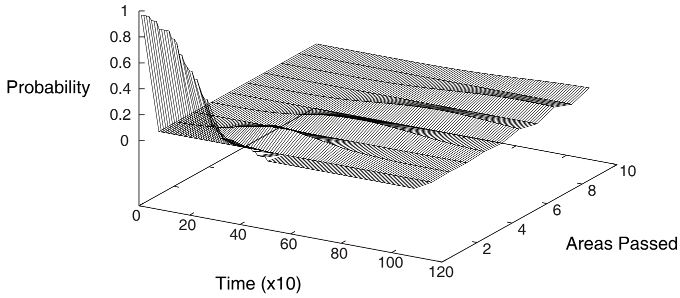


Figure 18. Probability of a user leaving area i to be in area j after n time slots and having crossed x areas - $\phi_{1,1}(x/n)$

We range the number of mobile nodes that follow the selected mobility patterns and measure three representative metrics, namely, average time the data are buffered (i.e., average buffertime), average latency for the data to reach to the Internet and overhead ratio.

The *SemiMarkov* protocol performs significantly better in terms of average latency compared with the two other protocols (see figure 20). Furthermore, it requires slightly lower buffering capacity compared with the *FirstContact* and significantly lower compared with the *MaxProp* protocol (see figure 19). The overhead

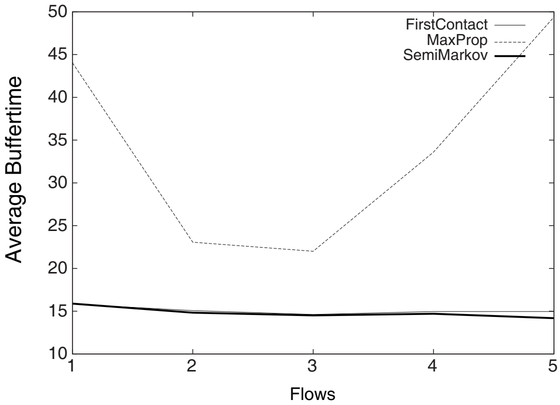


Figure 19. Average time the data are buffered

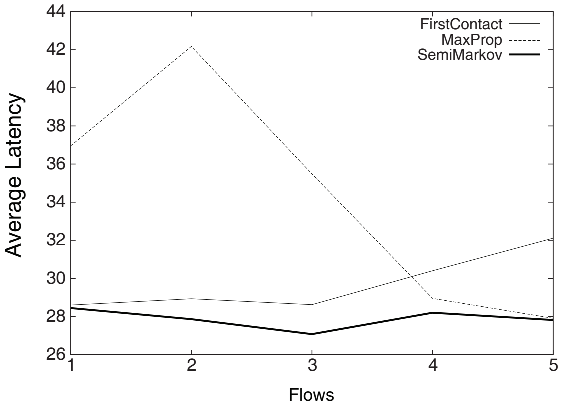


Figure 20. Average latency for the data to reach to the Internet

ratio is comparable with that of the *FirstContact* protocol but significantly lower than the one of the *MaxProp* protocol (see figure 21). The reduced latency and overhead demonstrate that a gentle forwarding scheme that relies on accurate estimation of user mobility behavior is indeed possible, in a number of conditions. This result is interesting, since it shows that sophisticated calculations may lead, based on the context, to simple actions rather than sophisticated actions that may make the protocol inefficient in terms of network overhead and delay.

Although our sample protocol uses fractions of the proposed model (i.e., h_i type of equations only) and is based on a protocol implementation that could be tuned further in many aspects (e.g., using redundancy or other novel opportunistic routing techniques), the potential of our approach was clearly demonstrated.

5. Conclusions

In this chapter, we investigated an SDN-inspired communication paradigm where infrastructure and opportunistic networks can efficiently interoperate. We argue that:

- Opportunistic networks can bridge distant infrastructure networks (i.e., in areas without connectivity) using sophisticated routing protocols capable of detecting and exploiting user mobility patterns.
- Centralized infrastructure nodes can support opportunistic communication with mechanisms that: (i) detect system - wide mobility patterns; and (ii) perform resource - expensive estimation calculations for the benefit of the mobile devices.

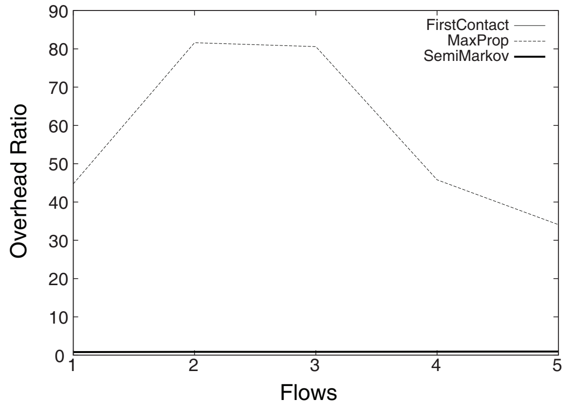


Figure 21. Overhead ratio

We introduced a semi-Markov model and detailed a number of equations suitable to predict different aspects of user mobility behavior, including detection of mobility patterns. Through a reference protocol we have developed, we demonstrated that routing does not require high latency, costly buffering and prohibitive overhead. This work focuses on the infrastructure being able to support a variety of network protocols exploiting communication opportunities using a number of accurate user- and system-level forecasts. Our approach allows for more complete and complex mobility models that would be difficult to integrate in the resource-constrained mobile devices. A more sophisticated protocol contrasted experimentally with the related solutions is in our short-term plans, together with a further design and implementation of the fixed infrastructure side of the platform.

Acknowledgement

The research leading to these results has received funding from the European Community's Seventh Framework Programme ([FP7/2007-2013, FP7-REGPOT-2010-1, SP4 Capacities, Coordination and Support Actions) under grant agreement number 264226 (project title: Space Internetworking Center-SPICE).

References

[1] L. Mamatas, A. Papadopoulou, and V. Tsaoussidis, *Exploiting Communication Opportunities in Disrupted Network Environments*, in *Proceedings of the 13th international conference on Wired/Wireless Internet Communication (WWIC 2015)*, Malaga, Spain, May 25-27, 2015.

[2] N. McKeown, T. Anderson, H. Balakrishnan, G. Parulkar, L. Peterson, J. Rexford, S. Shenker, and J. Turner, *Openflow: enabling innovation in campus networks*, ACM SIGCOMM Computer Communication Review 38 (2008), pp. 69–74.

[3] A. Balasubramanian, R. Mahajan, and A. Venkataramani, *Augmenting mobile 3G using WiFi*, in *Proceedings of the 8th international conference on Mobile systems, applications, and services*, MobiSys '10, San Francisco, California, USA, New York, NY, USA, 2010, pp. 209–222.

[4] S. Gambs, M. Killijian, and M. Prado Cortezdel , *Next place prediction using mobility Markov chains*, in *Proceedings of the First Workshop on Measurement, Privacy, and Mobility*, 2012, p. 3.

[5] M. De Domenico, A. Lima, and M. Musolesi, *Interdependence and Predictability of Human Mobility and Social Interactions*, in *Proceedings of the Pervasive 2012, Newcastle, UK*, 2012.

[6] J.K. Lee and J. Hou, *Modeling steady-state and transient behaviors of user mobility: formulation, analysis, and application*, in *Proceedings of the 7th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, 2006, pp. 85–96.

[7] Y. Chon, H. Shin, E. Talipov, and H. Cha, *Evaluating mobility models for temporal prediction with high-granularity mobility data*, in *International Conference on Pervasive Computing and Communications (PerCom 2012)*, 2012, pp. 206–212.

[8] A. Iosifescu Manu, *Non homogeneous semi-markov processes*, Studii si Cercetuari Matematice 24 (1972), pp. 529–533.

[9] L. Song, U. Deshpande, U.C. Kozat, D. Kotz, and R. Jain, *Predictability of wlan mobility and its effects on bandwidth provisioning*, in *Proceedings of the 25th IEEE International Conference on Computer Communications (INFOCOM)*, 2006, pp. 1–13.

[10] A. Papadopoulou, L. Mamatas, and V. Tsaoussidis, *Semi Markov modeling for User Mobility in Urban Areas*, in *Proceedings of the 2nd Stochastic Modeling Techniques and Data Analysis International Conference (SMTDA 2012)*, Chania, Greece, June 5-8, 2012.

[11] K. Fall, *A delay-tolerant network architecture for challenged internets*, in *Proceedings of the 2003 conference on Applications, Technologies, Architectures, and Protocols for Computer Communications*, 2003, pp. 27–34.

[12] Y. Chen, V. Borrel, M. Ammar, and E. Zegura, *A framework for characterizing the wireless and mobile network continuum*, ACM SIGCOMM Computer Communication Review 41 (2011), pp. 5–13.

[13] B. Petit, M. Ammar, and R. Fujimoto, *Protocols for roadside-to-roadside data relaying over vehicular networks*, in *Wireless Communications and Networking Conference (WCNC 2006)*, Vol. 1, 2006, pp. 294–299.

[14] K. Kumar and Y. Lu, *Cloud computing for mobile users: can offloading computation save energy?*, Computer 43 (2010), pp. 51–56.

[15] N. Banerjee, M. Corner, and B. Levine, *An energy-efficient architecture for DTN throwboxes*, in *26th IEEE International Conference on Computer Communications (INFOCOM 2007)*, 2007, pp. 776–784.

[16] U. Kubach and K. Rothermel, *Exploiting location information for infostation-based hoarding*, in *Proceedings of the 7th annual international conference on Mobile computing and networking*, MobiCom '01, Rome, Italy, ACM, New York, NY, USA, 2001, pp. 15–27.

[17] V.A. Siris and D. Kalyvas, *Enhancing mobile data offloading with mobility prediction and prefetching*, in *Proceedings of the seventh ACM international workshop on Mobility in the evolving internet architecture*, MobiArch '12, Istanbul, Turkey, ACM, New York, NY, USA, 2012, pp. 17–22.

[18] F. Hu, Q. Hao, and K. Bao, *A survey on software-defined network and openflow: From concept to implementation*, IEEE Communications Surveys & Tutorials 16 (2014), pp. 2181–2206.

[19] A. Hakiri, A. Gokhale, P. Berthou, D.C. Schmidt, and T. Gayraud, *Software-defined networking: Challenges and research opportunities for future internet*, Computer Networks 75 (2014), pp. 453–471.

[20] N.A. Jagadeesan and B. Krishnamachari, *Software-defined networking paradigms in wireless networks: a survey*, ACM Computing Surveys (CSUR) 47 (2015), p. 27.

[21] I.T. Haque and N. Abu-Ghazaleh, *Wireless software defined networking: A survey and taxonomy*, IEEE Communications Surveys & Tutorials 18 (2016), pp. 2713–2737.

[22] T. Karagiannis, J. Le Boudec, and M. Vojnovic, *Power law and exponential decay of intercontact times between mobile devices*, IEEE Transactions on Mobile Computing 9 (2010), pp. 1377–1390.

[23] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, *Impact of human mobility on opportunistic forwarding algorithms*, IEEE Transactions on Mobile Computing 6 (2007), pp. 606–620.

[24] H. Cai and D. Eun, *Toward stochastic anatomy of inter-meeting time distribution under general mobility models*, in *Proceedings of the 9th ACM international symposium on Mobile Ad hoc Networking and Computing*, 2008, pp. 273–282.

[25] C. Boldrini, M. Conti, and A. Passarella, *Modelling Social-aware Forwarding in Opportunistic Networks*, in *IFIP Performance Evaluation of Computer and Communication Systems (PERFORM 2010)*, 2010, pp. 1–12.

[26] Q. Yuan, I. Cardei, and J. Wu, *Predict and relay: an efficient routing in disruption-tolerant networks*, in *Proceedings of the tenth ACM international symposium on Mobile Ad hoc Networking and Computing*, 2009, pp. 95–104.

[27] G. Xue, Z. Li, H. Zhu, and Y. Liu, *Traffic-Known Urban Vehicular Route Prediction Based on Partial Mobility Patterns*, in *15th International Conference on Parallel and Distributed Systems (ICPADS 2009)*, 2009, pp. 369–375.

[28] S.A.W. F. Meucci and N.R. Prasad, *Data Mules Networks Analysis with Semi-Markov-Process for Challenging Internets and Developing Regions*, in *Proceedings of the 4th Africa ICT Conference*, Kampala, Uganda.

[29] S.Z. Yu, B.L. Mark, and H. Kobayashi, *Multiaccess, mobility and teletraffic for wireless communications*, chap. Mobility tracking and traffic characterization for efficient wireless internet access, Kluwer Academic Publishers, Norwell, MA, USA, 2000, pp. 279–290, URL `http://dl.acm.org/citation.cfm?id=371391.371438`.

[30] M. Pavel, T. Hayes, A. Adami, H. Jimison, and J. Kaye, *Unobtrusive assessment of mobility*, in *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS 2006)*, 2006, pp. 6277–6280.

[31] A. Bhattacharya and S.K. Das, *LeZi-update: an information-theoretic approach to track mobile users in PCS networks*, in *Proceedings of the 5th annual ACM/IEEE international conference on Mobile Computing and Networking*, MobiCom '99, Seattle, Washington, United States, ACM, New York, NY, USA, 1999, pp. 1–12.

[32] F. Yu and V. Leung, *Mobility-based predictive call admission control and bandwidth reservation in wireless cellular networks*, Computer Networks 38 (2002), pp. 577–589.

[33] A.J. Nicholson and B.D. Noble, *BreadCrumbs: forecasting mobile connectivity*, in *Proceedings of the 14th ACM international conference on Mobile Computing and Networking*, MobiCom '08, San Francisco, California, USA, ACM, New York, NY, USA, 2008, pp. 46–57.

[34] V. Navda, A.P. Subramanian, K. Dhanasekaran, A. Timm-Giel, and S. Das, *MobiSteer: using steerable beam directional antenna for vehicular network access*, in *Proceedings of the 5th International Conference on Mobile Systems, Applications and Services*, MobiSys '07, San Juan, Puerto Rico, ACM, New York, NY, USA, 2007, pp. 192–205.

[35] L. Song, D. Kotz, R. Jain, and X. He, *Evaluating location predictors with*

extensive wi-fi mobility data, SIGMOBILE Mobile Computing and Communications Review 7 (2003), pp. 64–65.

[36] B. Liang and Z.J. Haas, *Predictive distance-based mobility management for multidimensional pcs networks*, IEEE/ACM Transactions on Networking 11 (2003), pp. 718–732.

[37] Q. Yuan, I. Cardei, and J. Wu, *An efficient prediction-based routing in disruption-tolerant networks*, IEEE Transactions on Parallel and Distributed Systems 23 (2012), pp. 19–31.

[38] A. Asahara, K. Maruyama, A. Sato, and K. Seto, *Pedestrian-movement prediction based on mixed Markov-chain model*, in *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, GIS '11, Chicago, Illinois, ACM, New York, NY, USA, 2011, pp. 25–33.

[39] J. Krumm and E. Horvitz, *Predestination: inferring destinations from partial trajectories*, in *Proceedings of the 8th international conference on Ubiquitous Computing*, UbiComp'06, Orange County, CA, Springer-Verlag, Berlin, Heidelberg, 2006, pp. 243–260.

[40] J. Su, J. Scott, P. Hui, J. Crowcroft, E. De Lara, C. Diot, A. Goel, M. Lim, and E. Upton, *Haggle: Seamless networking for mobile applications*, Ubiquitous Computing (UbiComp 2007) (2007), pp. 391–408.

[41] A. Kate, G. Zaverucha, and U. Hengartner, *Anonymity and security in delay tolerant networks*, in *Third International Conference on Security and Privacy in Communication Networks (SecureComm 2007)*, 2007, pp. 504–513.

[42] R. Howard, *Dynamic Probabilistic Systems: Vol.: 2.: Semi-Markov and Decision Processes*, John Wiley and Sons, 1971.

[43] P. Vassiliou and A. Papadopoulou, *Non homogeneous semi markov systems and maintainability of the state sizes*, Journal of Applied Probability 29 (1992), pp. 519–534.

[44] A. Papadopoulou, *Counting transitions - entrance probabilities in non homogeneous semi markov systems*, Applied Stochastic Models & Data Analysis 13 (1997), pp. 199–206.

[45] *OpenStreetMap - The Free Wiki World Map, http://www.openstreetmap.org* .

[46] A. Keränen, J. Ott, and T. Kärkkäinen, *The ONE Simulator for DTN Protocol Evaluation*, in *SIMUTools '09: Proceedings of the 2nd International Conference on Simulation Tools and Techniques*, Rome, Italy, ICST, New York, NY, USA, 2009.

[47] *CRAWDAD, A Community Resource for Archiving Wireless Data At Dartmouth, http://crawdad.cs.dartmouth.edu* .

Pseudocode 1 The SemiMarkov Protocol

```
' This function is executed every time the mobile node
(e.g., node A) contacts any other node (e.g., node B)
function NewContact (node B):
    ' Updates the local contact history of node A
    UpdateContactHistory (node B)
    if (B is an infrastructure node):
        ' Node A communicates its local contact
        history with the infrastructure
        CommunicateContactHistory ()
        ' Retrieves fresh predictors from the
        infrastructure (can be tabular data with the
        upcoming predicted values or distribution
        parameters after curve fitting)
        RetrieveHiConValues ()
        ' Forwards the pending data to the Internet
        ForwardDataToInternet ()
    end if
    if (B is a mobile node):
        ' Retrieves the last time node B was
        connected to the infrastructure
        lasttimeBconnected = RetrieveLastTimeConnected
        (node B)
        ' Calculate how much time passed since
        node B reached the infrastructure
        timepassedforB=currenttime() - lasttimeBconnected
        ' Calculate how much time passed since
        node A reached the infrastructure
        timepassedforA=currenttime() - lasttimeAconnected
        ' Calculate the latest hicon values
        for nodes A, B
        hAcon = hicon (node A, timepassedforA)
        hBcon = hicon (node B, timepassedforB)
        if (hAcon>=hBcon):
            ' Keep the pending data to node A
            KeepData ()
        else
            ' Forward the pending data to node B
            ForwardData (node B)
        end if
    end if
end function
```