PaFiR: Particle Filter Routing – A Predictive Relaying Scheme for UAV-assisted IoT Communications in Future Innovated Networks

Baohua Shao [a,b] and Mark S. Leeson [a]

a School of Engineering, The University of Warwick, Coventry CV4 7AL, UK

b Warwick Institute for the Science of Cities, The University of Warwick, Coventry CV4 7AL, UK

Abstract

Increasing urbanization, smart cities and other cutting-edge technologies offer the prospect of providing more functions to benefit citizens by relying on the substantial data processing and exchange capabilities now possible. This can generate significant unpredictable and unbalanced data loads for the bearing IoT network to support its application and service demands. We thus propose a wireless routing scheme designed to use the Particle Filter algorithm to empower portable smart devices with intelligent capacities for the radio communication system. This facilitates the offloading of traffic from traditional wireless networks and enables the IoT system to adopt unmanned aerial vehicles, thus also offering further innovation to flying network platforms. The proposed PaFiR routing protocol offers the network more scalability, tolerance and resilience, to achieve the goal of smart relaying. Simulation results that demonstrate the routing algorithm designed offers excellent performance when compared with existing wireless relaying schemes. It provides delivery ratios that are improved by up to 40% without unmanageable increases in latency or overheads.

Keywords:

IoT (Internet of Things); Particle Filter; Flying network platform; ONE (Opportunistic Network Environment) simulator.

Nomenclature

5G	Fifth Generation of Cellular Networks
DARPA	Defense Advanced Research Projects Agency
DTN	Delay Tolerant Network
FSO	Free Space Optics
HetNet	Heterogeneous Network
IoT	Internet of Things
MANET	Mobile Ad Hoc Network
MC	Monte Carlo
NoF	Network of the Future
ONE	Opportunistic Network Environment
PaFiR	Particle Filter Routing
PF	Particle Filter

PRNET	Packet Radio Network
PRoPHET	Probabilistic Routing Protocol using History of Encounters and Transitivity
RF	Radio Frequency
SIS	Sequential Importance Sampling
SMC	Sequential Monte Carlo
SURAN	Survivable Packet Radio Network
TTL	Time to live
UAV	Unmanned Aerial Vehicle
VANET	Vehicular Ad-hoc Network
VDTN	Vehicular Delay Tolerant Network

1. Introduction

1.1. Background

Increasing urbanization means that smart cities can provide more and more functions to benefit their citizens by relying on the substantial data processing and exchange capabilities now possible. City sizes are constantly increasing so that the population living in urban territories is anticipated to double by 2050 [1]. In consequence, the number of IoT devices in smart cities will grow significantly. Although it is difficult to predict the numbers precisely, the total sum of Internet-connected things is most likely to be between 25 billion to 50 billion by 2020. The issues of security and interoperability can now be solved by multiple state-of-the-art solutions [2]. All of these provide substantial opportunities for applications of IoT techniques that can generate significant unpredictable and unbalanced data loads for the bearing IoT network to support the consequent application and service demands. Therefore, for the citizens to enjoy the benefits of ubiquitous networking, the traffic-bearing infrastructure of smart cities will face more and more challenges on its resources in high density smart cities. In particular: limited radio frequency (RF) spectrum; radio signal coverage and blind spots; extremely high density of wireless network subscribers; network congestion caused by unbalanced or bursty data; mobile site acquisition; electromagnetic interference. Furthermore, natural disasters (hurricanes, thunderstorms, earthquakes and tsunamis) or unpredictable incidents (power cuts, system failures, fire accidents, hacker or terrorist attacks and sabotage) are potential risks that make the communication system vulnerable and ubiquitous access extremely challenging. A backup solution could alleviate these problems; however, the degree and scale of the solution is complex, and even a small-scale solution could result in an extremely high cost for some complex cases in such a super smart city. Here, we present a sophisticated algorithm to provide an enhanced solution to adapt to these changes but offer easy deployment.

1.2. Challenges

The flexibility of Unmanned Aerial Vehicles (UAVs) permits the rapid implementation of Delay Tolerant Network (DTN) systems leading to the proposal of a low altitude UAV-based solution for IoT services that can be applied to assist data packet relaying by Motlagh et al. [3].

Considering the expansion of mobile IoT systems in smart cities, a large population of portable devices will attach to the network in the air and on the ground. The motions of UAVs and ground moving elements are thus dramatically diversified, bringing numerous uncertainties into the wireless network. For instance, the movement direction of the message carrying node is uncertain, meaning that data packets could suffer unpredictable long delays; the best next hop changes every moment based on different criteria; the individual mobile radio signal patterns change caused by different ambient environments as the location changes. This puts the RF (Radio Frequency) channel in an unpredictable condition and the radio coverage of the whole wireless network is different at every moment.

2. Related work

As the interest in smart cities applications and IoT technologies joined with 5G has grown substantially, there has been significant research work undertaken regarding different aspects of the various issues, applications and services.

Al-Turjman et al. provided an overview of the deployment of femtocells in 5G/IoT environments [4]. Ozera et al. presented a detailed review on the IoT architecture and protocols, followed by the introduction of a fuzzy-based control approach for cluster management for Vehicular Ad-hoc Networks (VANETs) [5]. With respect to the difference between DTN and ad-hoc systems, Rahman and Frater proposed vehicular communication based on a DTN system, referred to as a Vehicular Delay Tolerant Network (VDTN) [6]. Given the limited energy of each network terminal within the DTN scenario, Pino et al. proposed dominating set algorithms for decentralized wireless networks [7].

The idea of DTN systems was first introduced by Intel Corporation’s Kevin Fall at the beginning of 21st century [8] and this paper defines the network architecture and application interface of wireless DTNs. Mobile Ad Hoc Networks (MANETs) have a much longer history than DTNs. The Packet Radio Network (PRNET) [9] can be seen as their first generation, which was sponsored by the Defense Advanced Research Projects Agency (DARPA) [10]. It can be traced back to 1972 and evolved into the Survivable Packet Radio Network (SURAN) program in the early 1980s [11].

Early DTN routing protocols operated under simple relaying strategies, such as the epidemic routing scheme that floods messages without network knowledge to maximize delivery probability [12]. However, this strategy can waste a large volume of network resources in the transfer of redundant data packages. This method was made more sophisticated by Spray-and-Wait, which limits the number of message duplicates using a duplication control design [13]. The Probabilistic Routing Protocol using History of Encounters and Transitivity (PRoPHET) is a classical network protocol that introduced a prediction mechanism into the forwarding determination by using the number of meetings between pairs of mobile nodes to estimate the future encounter probability [14].

The development of the big data era has resulted in information systems and intelligent knowledge processing playing an increasingly essential role in everyday life [14]. Moreover, machine learning coupled with the big data revolution is changing ways of living, working, studying and thinking [16]. Smart digital devices are increasingly everywhere to keep collecting various pieces of information, but these are commonly only in the form of raw and rough digital symbols, digits, graphs or images. The information cannot mean anything without subsequent processing, such as machine learning, data mining, pattern recognition, data analysis and knowledge discovery. All these applications give rise to significant demands on data transmission and processing that cause exponentially increasing requirements for data communication networks and affiliated technologies.

The flexibility of the UAV can assist more applications into the system in difference scenarios. The applications of UAVs in some critical scenarios have been developed by Al-Turjman [17], and Al-Turjman and Alturjman [18] adapt UAVs into the applications of multimedia and video streaming services in the 5G/IoT system. The idea of the network of the future (NoF) is a technology fusion of the future network design that includes the multi-layer network structure and hybrid system. Flying network platforms are an essential part of the different communication systems [19].

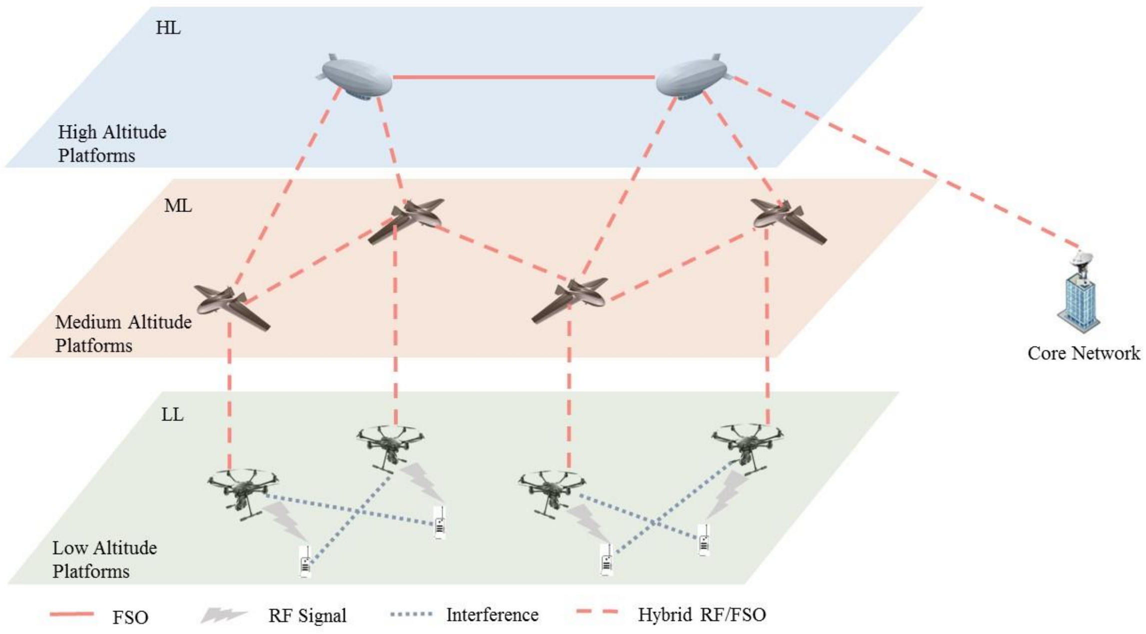


Fig. 1. Multi-layer UAV assisted network flying platform.

The application of UAV technology allows mobile networks to easily acquire the characteristics of flexibility, energy-efficiency and adaptability for multiple applications. The UAV aided mobile IoT system could be a part of the multi-layer network flying platform in the NoF, since both wireless systems can share flying intermediate nodes to relay the data packets. Figure 1 shows a UAV-assisted network flying platform with a multi-layer structure that forms a substantial complex system for movement analysis [20], as network flying elements need to catch the motion of cruising nodes and find out the best intermediate relaying hop, then transfer data packets cross aerial platforms.

In this work, a Particle Filter (PF) based DTN routing strategy is proposed to assist complex mobile networking structures with multiple aerial platforms. To the best of our knowledge this work is one of the first studies on adopting filtering technologies for use in movement tracking to assist the DTN routing determination process.

3. Routing algorithm design

3.1. Relay hop selection

Here, we introduce a case study that is Vertical FSO-based Front haul for Ultra-dense HetNets in an NoF mobile system with a single-layer network flying platform as shown in Figure 2 [21]. The scenario considered assumes that the UAVs fly horizontally at a constant altitude and the movement of each for the flying platform can be projected onto a two-dimensional ground trajectory. In the mathematical and statistical model, the motion of the UAV can thus be mapped onto the ground and processed as a ground moving node. Given the freedom of movement of each element involved in the NoF system, the movement of each node is random meaning that UAVs and ground mobile devices establish a stochastic system, which can be represented by a stochastic process. This random motion (or movement state) is measurable for other mobile users as long as they are in bi-directional radio connection range. The state of surrounding nodes is collected by the observers at every instant, and the collected data (locations, velocities and accelerations or decelerations) are the samples to be used to track and predict the motion of targeted objects in a future moment. If there are obstacles in unknown real states that make the scheduled pass unavailable, the nodes will generate an instant message to indicate the disconnection of bi-directional air links. The data package carrying nodes then needs to discover an alternate route.

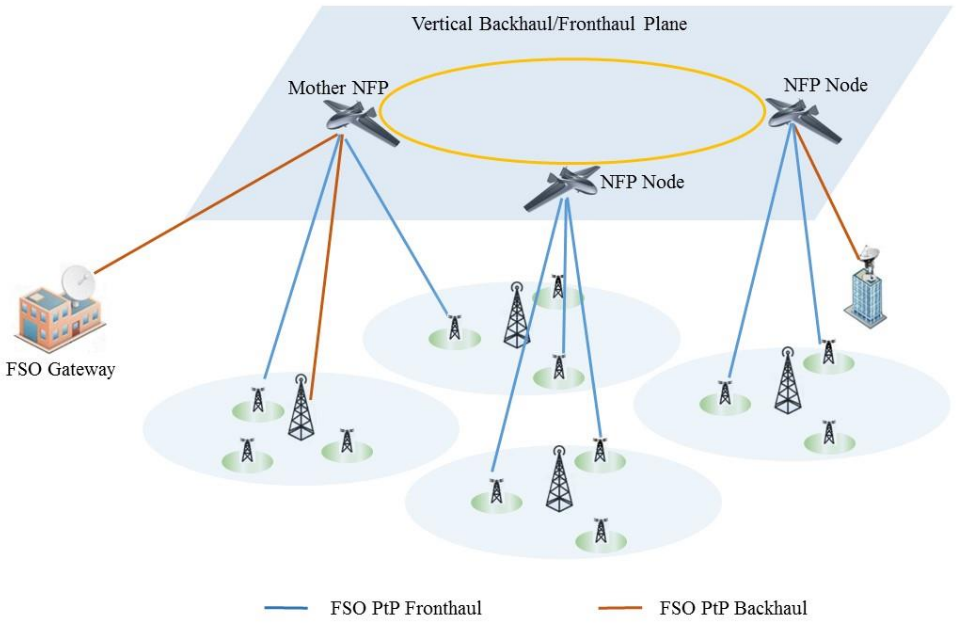


Fig. 2. Vertical FSO-based Fronthaul for Ultra-dense HetNets [21].

However, the real states of the observed targets could be different from the observations at a certain instant so two different data categories are defined: (a) the unknown real state of the observed portable device which is denoted by X; (b) the observed data of a targeted node which are denoted by Y. Based on the mathematical and statistical model, the unknown data comprising X can be computed using the observed data Y by reasoning or tracking that includes a series of filtering, prediction and smoothing operations relying on the Bayesian statistical approach [22]. Here, we adopt the PF algorithm discussed in detail in Section 3.3 below to undertake the prediction.

When a message is generated by a source device or stored and carried by an intermediate node, an observation takes place to gather the movement state of neighboring network elements with the ability to create a bi-directional radio connection to relay the message. The observed data give the input as the prior probability distribution for the PF algorithm to predict the movement state of portable nodes in the next moment, which implies the transmission probability of the observed device moving towards the destination to deliver the message, for example, when one moving node has the highest likelihood to move towards the destination node then this node will have the highest transmission probability to fulfil the relaying task. After the packet holding smart device replicates the observation and prediction procedure for each surrounding bi-directional connected mobile node, it will have a comprehensive list of transmission probabilities for all adjacent portable terminals. Following the exchange of transmission probabilities among the serving nodes, each message holding intelligent device will have knowledge of the transmission probabilities of every potential hop along the forwarding path toward the message destination. The node with the highest transmission probability will then be selected to relay the packets. If the next hop is not present, the intermediate node will store and carry the packets until the appropriate node appears.

When only low transmission probability nodes are available for relaying packets, to avoid inappropriate relaying actions taking place, an optional predefined threshold n may be utilized. The predefined n will only allow the data transfer through a bi-directional connection that happens when the transmission probability between two adjacent mobile nodes is greater than the threshold. Thus, if the transmission probabilities of all surrounding smart devices are lower than *n*, the relaying process will pause and the message will be buffered by the carrying node. The transmission threshold is designed to help the NoF mobile system planner design a parallel DTN system to balance the traffic load or make a backup solution in emergency cases. This permits the satisfaction of different system performance criteria in various scenarios regarding delivery probability, average latency, message hop count and energy consumption. For some instances, a higher value of transmission threshold ensures that the message is relayed to a more reliable forwarding device. This does, however, cause the message to suffer a longer delay waiting for an appropriate relaying node, potentially increasing the overall average latency. The strength and purpose for the transmission threshold is to save the message hop count and transmission energy consumption. As high transmission probability intermediate nodes rarely appear in some scenarios, the predefined transmission threshold cannot be very high, and the application circumstance needs careful consideration.

3.2. Forwarding Strategies

There are advantages and disadvantages of established forwarding strategies for different DTN routing protocols. Thus, the proposed PaFiR DTN routing protocol uses the current status of network nodes to forecast the future pattern of the network topology. This is especially pertinent to the movement trajectory pattern of UAVs with high mobility since even using energy efficient routing they present a very different behavior to ground-based portable nodes [23]. Conventional forwarding strategies are not applicable to cope with the complex scenarios exhibiting highly diversified behavioral instances but the nature of the PF algorithm makes it easy to track and predict different mobile patterns of ground smart terminals and UAVs.

3.3. Particle Filter (PF)

The PF, also known as the Sequential Monte Carlo (SMC) method [24], is a statistical filtering method based on Monte Carlo (MC) simulation and recursive Bayesian estimation [25]. It uses MC to solve the integral operation of Bayesian estimation based on the Bernoulli Law of large numbers and the central limit theorem in probability theory. When a problem is repeated infinitely many times, the suboptimal solution that is closest to the correct result, and the frequency of occurrence of time is used to replace the probability of occurrence of an event [26].

The idea of Monte Carlo sampling is to use the empirical mean value to substitute for the integral operation:

$$E(f(x)) \approx \frac{f(x_1) + \cdots + f(x_N)}{N} \tag{1}$$

This is based on the Law of large numbers, so if the number of samples N is large enough, the above formula approximates the expected value. The method of estimating the probability is to achieve the expected probability by the MC method. Assuming that N samples can be acquired from the posterior probability, the calculation of this can be expressed as:

$$\hat{p}(x_k|y_{1:k}) \approx \frac{1}{N}\sum_{i=1}^{N} \delta\left(x_k - x_k^{(i)}\right) \approx p(x_k|y_{1:k}) \tag{2}$$

where, $f(x) = \delta(x_k - x_k^{(i)})$ is the Dirac delta function [27].

For object tracking, it is necessary to acquire the expected value of the movement current state that is the meaning of filtering:

$$E\big(f(x_k)\big) \approx \int f(x_k)\hat{p}(x_k|y_{1:k})dx_k$$

$$\frac{1}{N}\sum_{i=1}^{N}\int f(x_k)\delta(x_k - x_k^{(i)})dx_k$$

$$= \frac{1}{N}\sum_{i=1}^{N} f(x_k^{(i)}) \quad (3)$$

The PF algorithm generates a set of random samples in the state space according to the empirical condition distribution of the system state vector, and then continuously adjusts the weight and position of the particles to correct the initial empirical condition distribution by adjusting the information of the particles. When the sample size is large, MC can formulate a distribution that is similar to the real posterior probability density function of the state variable. Here, samples are the particles that can be understood as estimators. The PF is applicable to any non-Gaussian and nonlinear stochastic system that can be represented by a state space model. [28]

Thus, the PF enhances the traditional filtering theory framework and has no restrictions on the process noise and measurement noise of the system. It can be applied to any nonlinear system and the accuracy can approximate the optimal estimation, which is a very effective nonlinear filtering technology. With the increasing capability of portable terminals and improvements in algorithm optimization, the PF can be widely applied in smart devices.

4. PaFiR Routing Protocol

As stated in Section 3.3, the PF algorithm is very appropriate for tracking objects in complex scenarios that contain various states of moving objects. This is particularly true when UAVs are introduced into the system as intermediate relaying nodes to assist data packet forwarding. Here the proposed DTN routing strategy is termed as the Particle Filter Routing (PaFiR) protocol. Another strength of the PF algorithm is that the number, *m*, of particles applied for processing can be adjusted to cut down the algorithm's computational complexity. This is useful as the numerous smart terminals attached to the wireless DTN system differ greatly in their available processing resources such as, processing capacity, memory size and battery capacity and this is easily accommodated by adjusting the number of particles in the PaFiR routing algorithm.

4.1. Principles of Design

One of design purposes of the PaFiR routing protocol is to accommodate a hierarchical wireless relaying network that consists of the ground layer with one or multiple layers in the air. The applied scenario assumes that all intelligent devices deployed on the ground are completely free to move within the radio coverage area. The assisted UAVs cruise at a constant altitude dedicated for each aerial layer, and their cruising area can cover the ground network radio coverage or the lower aerial layer. All of network elements can be either maneuvering objects or non-maneuvering objects. In this article, the proposed routing strategy will address the single aerial layer network.

The air links between ground nodes or between UAVs and ground devices are taken to be bi-directional connections and the movement of ground portable devices and UAVs is observable when they are in the bi-directional radio connection range.

The PaFiR routing scheme can be a solution for offloading traffic from the conventional traffic bearing system voluntarily to balance the network data traffic load or for use as an emergency connection with tolerable propagation delays when the traditional mobile communication system is not available.

4.2. PF Inferencing

As all the network elements in a DTN system are autonomous, the movement states of portable devices and different types of UAVs could be extremely diversified, for example stable with zero speed and acceleration, steady speed with zero acceleration, small speed change with low acceleration (or deceleration) and significant speed change with high acceleration (or deceleration). Thus, in addition to maneuvering objects there are thus slow-moving or stationary objects classified as non-maneuvering. In the mathematical and statistical model, these different states are classified into two categories: a non-maneuvering model and a maneuvering model. For wireless systems with complex multi-layer relaying networking in smart cities or other applications, there are many network elements that are required to have high mobility; this is particularly true as UAVs are deployed into the NoF precisely because of their movement flexibility. The strength of the PF lies in its application of the SMC method to form particle sets that express probabilities in a way that can be used in any form of state space model to achieve online tracking.

To express the probability distribution, the algorithm extracts posterior probabilities through random state particles, which is referred to as the Sequential Importance Sampling (SIS) method. The PF algorithm refers to the process of obtaining a state minimum variance distribution by finding a set of random samples in the state space to approximate the probability density function instead of the integral operation with the sample mean. For example, it is not possible to acquire the exact distribution information of moving targets directly, however, the approximation process can be operated from a known distribution that is sampled with weight coefficients and each sample particle has its own corresponding weight that reflects the importance of the particle. If the weight of a particle is significant, it means it is reliable in approaching the true distribution.

If more samples are given to describe the posterior probability distribution, the algorithm can approximate a more complex probability density function, and outcomes will be presented more accurately. However, the complexity of the algorithm will become higher in consequence hence costing more in terms of individual smart terminal processing capability and other resources to process it.

The design of the routing protocol for decentralized wireless networks must consider various embedded resources on different portable devices and minimize impacts on client applications and customer experience. It is necessary to estimate the appropriate value for the number of particles employed in the routing algorithm based on the various capabilities of the terminals deployed in the multi-layer wireless relaying network applications and the scenario in which devices are required to work. As an option, the design of the routing protocol may introduce this estimation process as an adaptive function, after the air connected nodes exchange information, the protocol self-adjusts the number of particles to balance the algorithm complexity and prediction accuracy. The proposed protocol routing process is shown in Fig. 3.

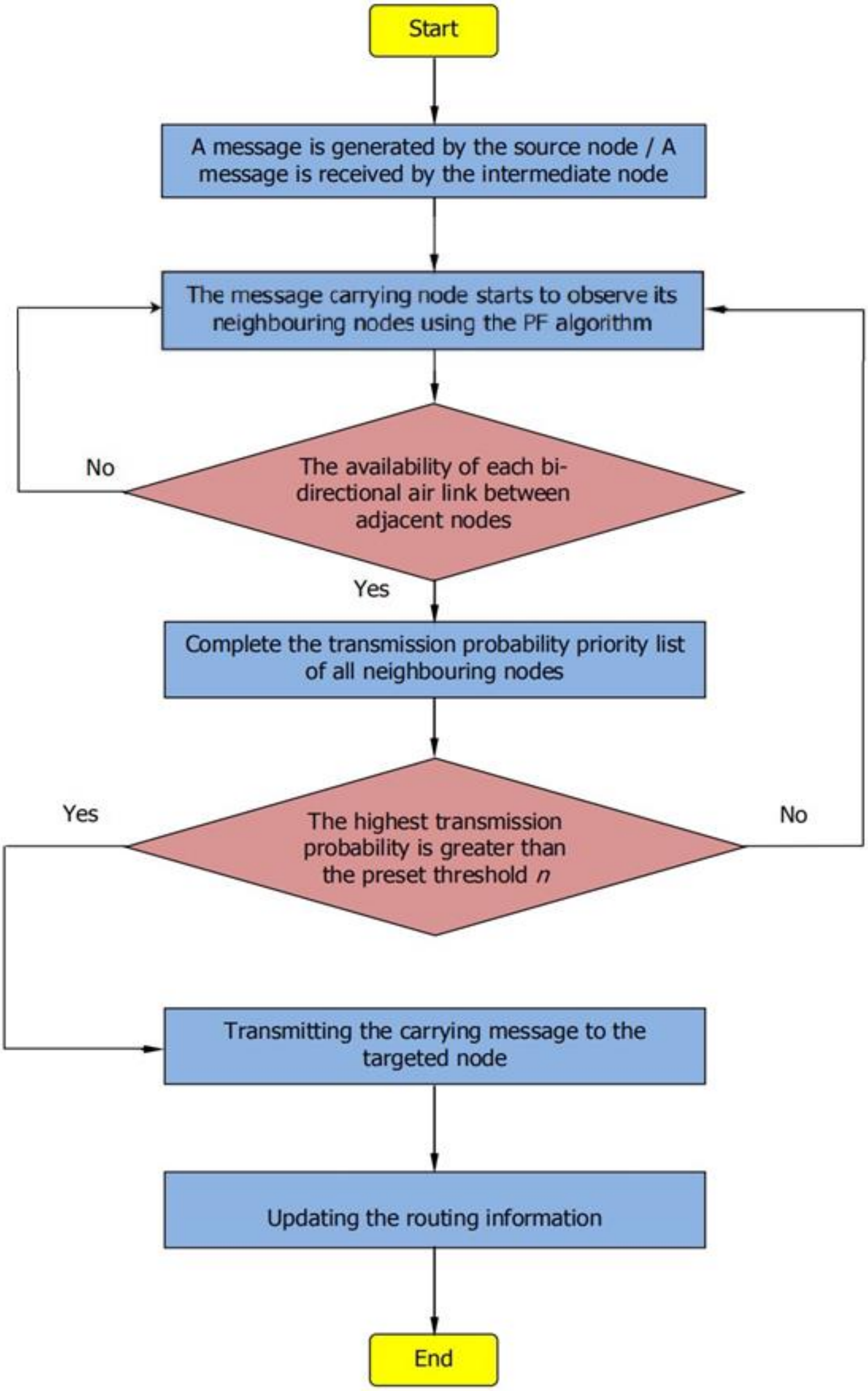


Fig. 3. Flowchart of the protocol routing process.

5. Routing protocol simulation

5.1 Introduction

The current version of the Opportunistic Network Environment (ONE) simulator [29] does not support three-dimensional trace data, and there are no three-dimensional object movement trace data available for public use. All proposed applications and scenarios were thus mapped into a two-dimensional model, and the mapping approach of the single-layer network flying platform. If the multi-layer network flying platform in the NoF had more than one aerial layer, the UAV flying trace of the upper layer was mapped to the lower layer, and then aerial layers were projected onto a two-dimensional trajectory on the ground.

The entire simulation process will be presented in two parts. The first was designed evaluate the individual performance of the PaFiR message forwarding protocol produced and test it with various parameters to simulate different application scenarios. The second, compared the PaFiR relaying strategy to some existing routing methods to find the best solution for the multi-layer network flying platform in the NoF.

5.2 Performance Evaluation

This section presents the evaluation of the performance in terms of resilience and tolerance of the proposed PaFiR DTN protocol. The sample dataset was generated by the ONE simulator event generator utilized to simulate a complex wireless network condition, and the map data set was the downtown area of Helsinki city including road and pedestrian walk paths. The connectivity traces for the real time location data of various moving objects in the defined region carrying portable smart devices, such as pedestrians, cars and trams, were generated by the ONE simulator. Parameters for the simulation configurations were as specified in Table 1. These were chosen to be of the same order as the parameters in [30] with the buffer size large enough that it did not impact performance.

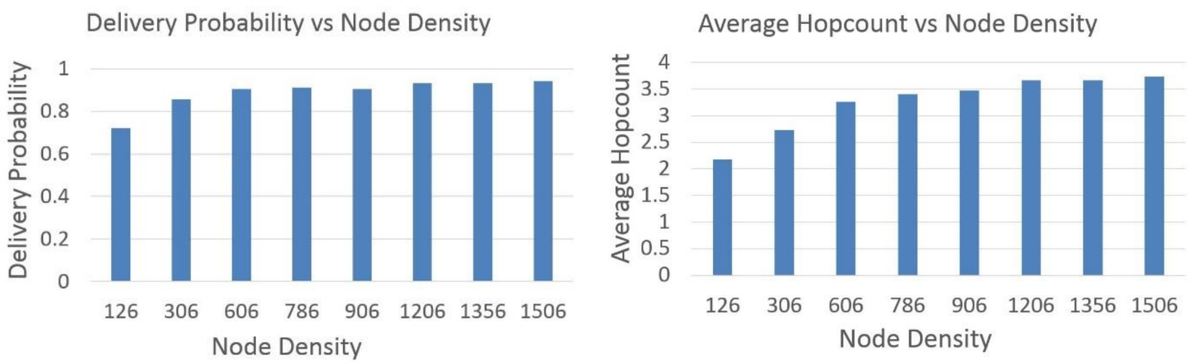
Table 1
Parameters of Simulation Configurations.

Parameters	Value of parameters
Simulation Time (second)	86400
Buffer Size (MB)	10, 20, 50, 75, 100, 200, 500
Packet Lifetime (TTL) (minutes)	60, 120, 180, 240, 300, 360, 420
Message Interval (second)	3, 5, 10, 20, 30, 60
Message Size (MB)	0.3-0.5, 0.5-1, 1-2, 2-3, 3-4, 4-5, 5-6, 6-7
Number of Nodes	126, 306, 606, 786, 906, 1206, 1356, 1506

The message interval simulated the information rate of the sender. The parameters for this category tested the circumstances from a low packet generation rate of 1 packet per minute (67 kbps) to a high packet generation rate of 20 packets per minute (1.33 Mbps). The number of nodes varied the density of the wireless system from a low-density (126 nodes) mobile network to an extremely high-density (1506 nodes) system.

In this part of work, there are four key factors of wireless system that are addressed to evaluate the overall performance of proposed mobile routing strategy, which are: Delivery Probability, Overhead Ratio, Average Latency and Average number of hops. The variety of simulation parameter against different performance metrics are given as follows:

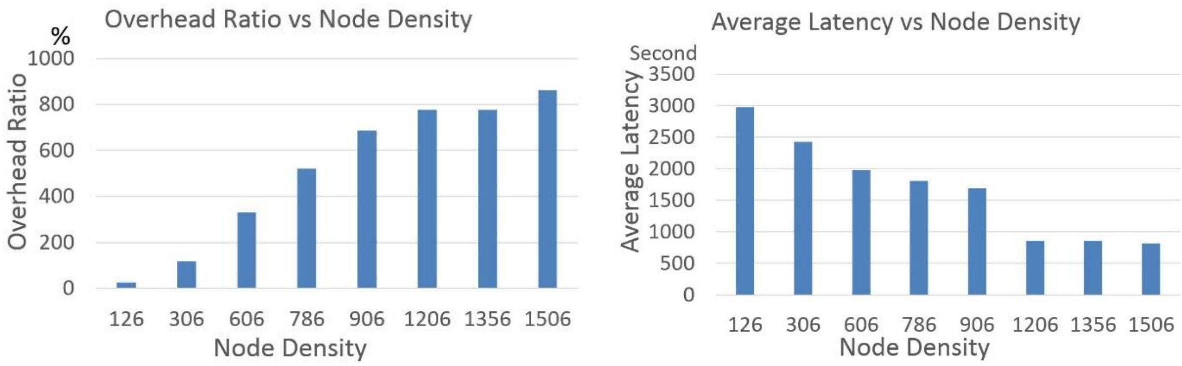
5.2.1 Node Density



(a) (b)

Fig. 4. (a) Delivery probability; (b) average hop count for different network densities.

Fig. 4 shows that the delivery probability and average hop count reach an approximately steady state when the total node number exceeds 606. The delivery ratio remains above 0.9 with a highest point of 0.941 when the node population is 1506. This means that the PaFiR protocol can handle a high-density network and keep improving its performance with the increase in the number of nodes. At the same time, the average hop count only slightly increases from 3.3 to 3.7, even if the node population almost triples.

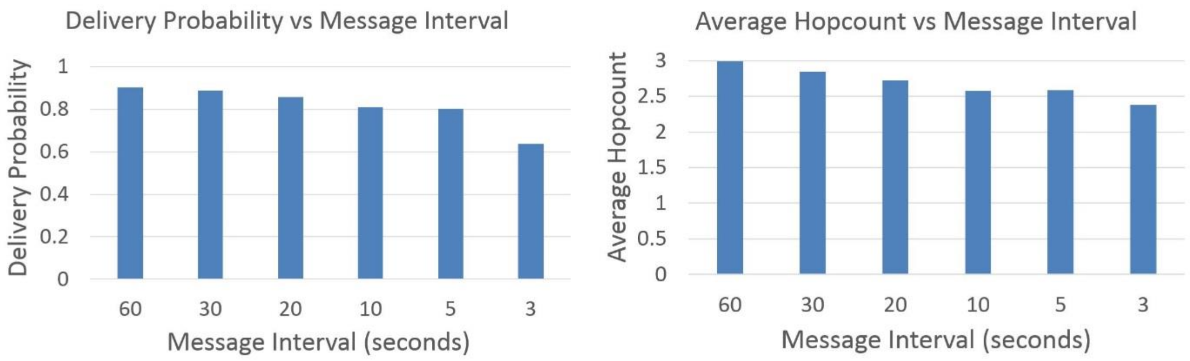


(a) (b)

Fig. 5. (a) overhead ratio; (b) average latency for different network densities.

Fig. 5 indicates that the changes of overhead ratio and average latency are almost in step. The increase of the overhead ratio slows down when the node density is over 1000. Meanwhile, the average delay time drops from 2974 seconds to 819 because more candidate nodes participate into the message relaying process and PaFiR can manage to find the better or best intermediate nodes to forward data packets.

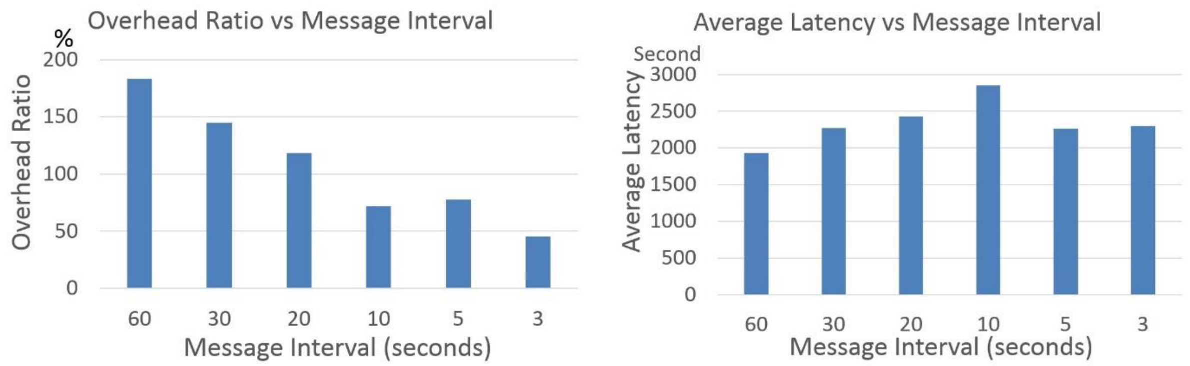
5.2.2 Message Interval



(a) (b)

Fig. 6. (a) Delivery probability; (b) average hop count for different message generation intervals.

Fig. 6 presents that the delivery probability decreases when the message generation rate increases, however, the delivery ratio only has 10% drop from 0.91 to 0.81 when the generation interval changes from 60 seconds per message to 5 seconds per message. A larger decrease occurs when the message interval changes from 5 seconds to 3 seconds but such high message generation rates are rare in DTN systems. The constant decrease in average hop count improves the system performance since smaller hop counts consume less transmission energy to relay the data packets.



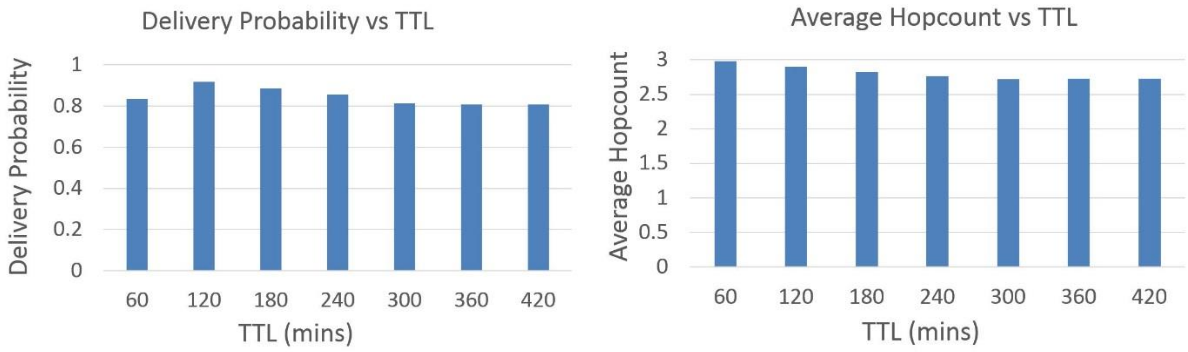
(a) (b)

Fig. 7. (a) overhead ratio; (b) average latency for different message generation intervals.

Fig. 7 reveals that the overhead ratio becomes only a quarter as the data rate increases from 67 kbps to 1333 kbps. The average latency has a drop after increasing from 1929 seconds to 2851 seconds and stays at 2263 seconds and 2299 seconds when the message interval is 5 seconds and 3 seconds respectively.

The PaFiR routing scheme exhibits a good overall performance, in particular with respect to tackling the heavy data traffic between nodes, PaFiR does not show a substantially degraded overall result.

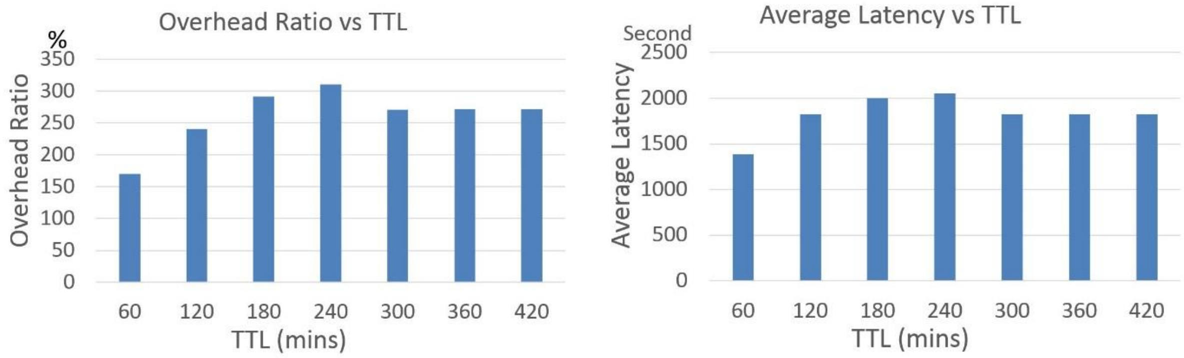
5.2.3 Time To Live



(a) (b)

Fig. 8. (a) Delivery probability; (b) average hop count for different TTL in mins.

In Fig. 8, the diagrams indicate that the delivery probability only fluctuates between 0.81 and 0.92, and it gets steady after message lifetime is larger than 240 mins. The average hop count drops from 2.98 to 2.76 as the TTL increases from 60 mins to 240 mins, then slows down and remains the same from 360 mins to 420 mins.



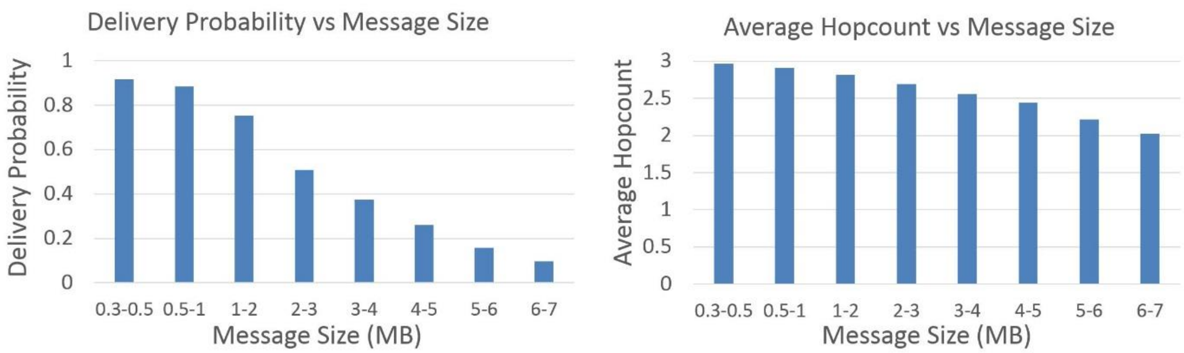
(a) (b)

Fig. 9. (a) overhead ratio; (b) average latency for different TTL in mins.

The changes of the overhead ratio and average latency display the same pattern in Fig. 9. A substantial increase happens as message lifetime rises from 60 mins to 240 mins, then there is a 20% drop and to a level that remains unchanged for the rest of the parameter changes.

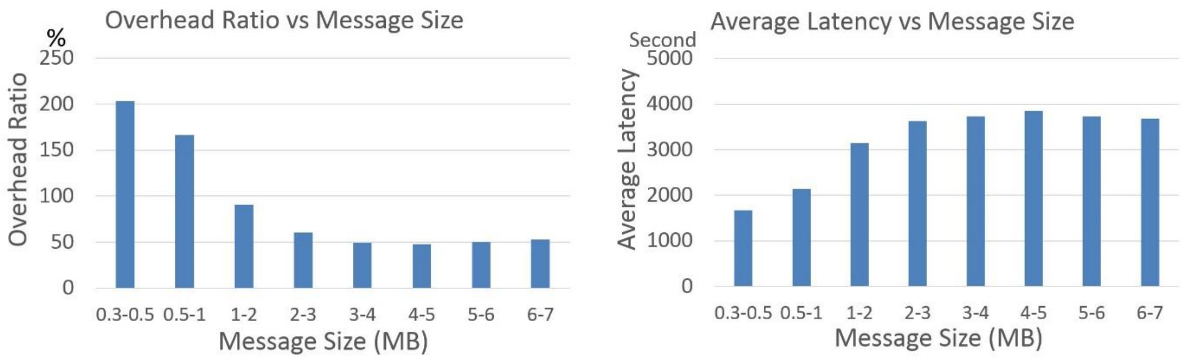
5.2.4 Message Size

Fig. 10 shows that increasing the message size affects the delivery probability significantly. The delivery probability is acceptable for the majority of DTN services while the data packet size extends from 0.3-0.5 MB to 1-2 MB; the delivery ratio decreases from 0.92 to 0.75, however, when the size exceeds 2MB, there is a rapid reduction. The ratio is only 0.097 by 6-7 MB that makes most of the nodes unreachable as most of messages are dropped during the relaying process. The average hop count only has one hop reduced when packets become 20 times larger so is less affected.



(a) (b)

Fig. 10. (a) Delivery probability; (b) average hop count for different message sizes.



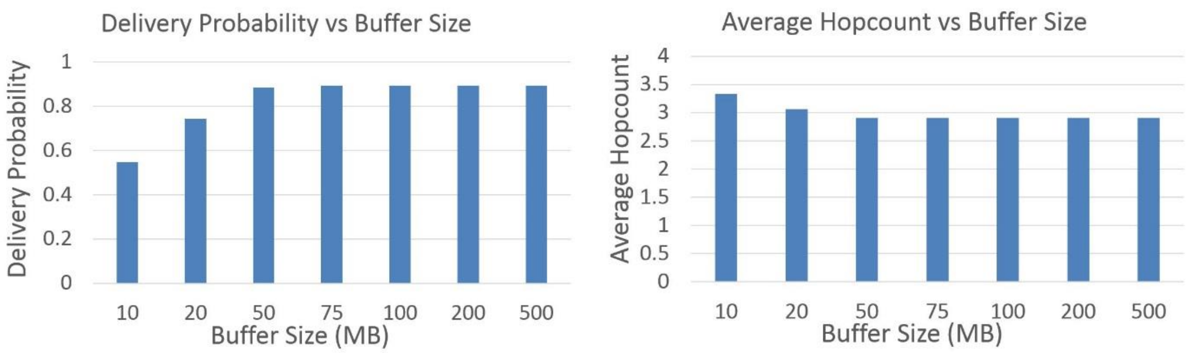
(a) (b)

Fig. 11. (a) overhead ratio; (b) average latency for different message sizes.

By a ten times expansion of message size from 0.3-0.5 MB to 3-4 MB, the overhead ratio shows a more than four times improvement from 203% to 50%, meanwhile, the average time delay grows from 1673 seconds to 3733 seconds.

These test results imply that the PaFiR routing protocol is more appropriate for services that generate small messages or applications that encapsulate data in to small packets -it is better to keep the size smaller than 1MB.

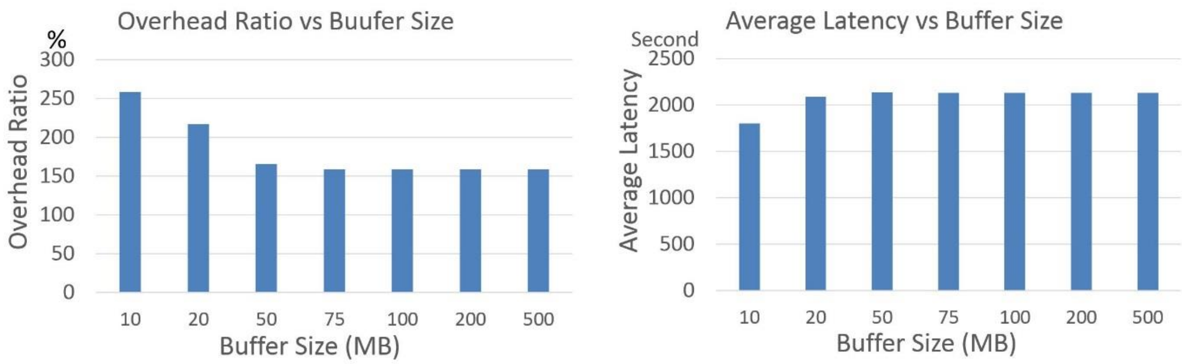
5.2.5. Buffer Size



(a) (b)

Fig. 12. (a) Delivery probability; (b) average hop count for different buffer sizes.

Fig. 12 presents that when the capacity of the buffer on smart terminals reaches 50 MB, the expansion of buffer size will not help to improve the system performance. For the delivery probability, it rises from 0.55 to 0.88 and then remains at 0.89 when the buffer size is bigger than 50 MB. The average hop count reduces slightly from 3.33 to 2.91 and stays at the same value when more cache is given.



(a) (b)

Fig. 13. (a) overhead ratio; (b) average latency for different buffer sizes.

As can be seen in Fig. 13, the overhead ratio drops by almost a half when the buffer extends its size from 10 MB to 75 MB. At the same time, only 18% of extra time delay is added to the entire packet forwarding process.

5.3. Performance Comparison with Other DTN Routing Protocols

In the last section, the overall performance of the proposed PaFiR DTN routing protocol has been tested comprehensively, and the results have indicated that PaFiR can deliver a good overall result in complex wireless network conditions. In this section, the simulation process was used to investigate how PaFiR performed in comparison to established DTN routing strategies under the same mobile system conditions, in particular when the population of portable smart devices expands from a sparse network to high dense system.

Parameters for the simulation configurations in this part are specified in Table 2.

Table 2
Parameters of Simulation Configurations.

Parameters	Value of parameters
Simulation Time (second)	18000
Buffer Size (MB)	15
Packet Lifetime (TTL) (minutes)	60
Message Interval (second)	25-35
Message Size (MB)	0.5-1
Number of Nodes	126, 156, 186, 306, 606, 906, 1056

The simulation outcomes reveal that the PaFiR routing protocol delivers an excellent performance compared with the existing DTN forwarding methods. In Fig. 14, the delivery probability of the PaFiR protocol exhibits a constant improvement as the density of the wireless network increases, which means that as more mobile subscribers join the network it becomes more reliable. For instance, when more than 1000 IoT devices are involved in the network, the delivery probability can reach 0.9 which is 40% increased when the population grows by almost one order of magnitude. The Epidemic protocol performs well in lower density DTN networks but when the number of smart nodes exceeds 186, the delivery rate decays fast. PRoPHET shows good performance only when the portable device population is less than 606. After the number of smart terminals in the system exceeds 909, the delivery probability starts to drop more quickly. The delivery rate of Spray and Wait only fluctuates between 0.55 and 0.69 and most of parts are the worst among the tested protocols, and the trend shows that it will have a further decrease when the number of portable nodes is over 1000.

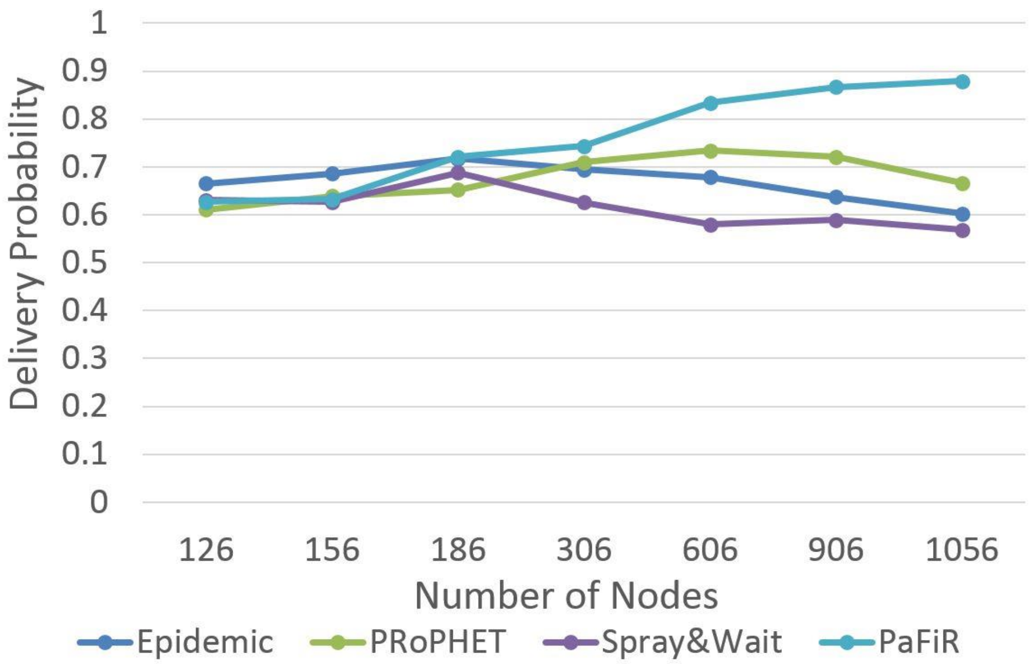


Fig. 14. Delivery Probability vs. Number of Nodes.

In Fig. 15, the average latency of the different forwarding schemes, except Spray and Wait, follows the same downward trend as the number of smart nodes increases but PaFiR has the strongest performance as the overall time delay drops much faster than any of the other schemes. When the system population is greater than 550, PaFiR presents the smallest of delay by up to 27% over Spray and Wait. As the node number grows from 126 to 1056, the average latency is reduced by 40%. Spray and Wait performs well only when the device population is small and does not benefit from the growth in the number of nodes.

In Fig. 16, Spray and Wait keeps the overhead ratio at a very low level all the time, meanwhile, Epidemic and PRoPHET begin to increase rapidly after number of nodes exceeds 306. PaFiR shows a slight increasing trend when the node population is greater than 306, which is 71% to 81% less than Epidemic and 54% to 74% less than PRoPHET respectively.

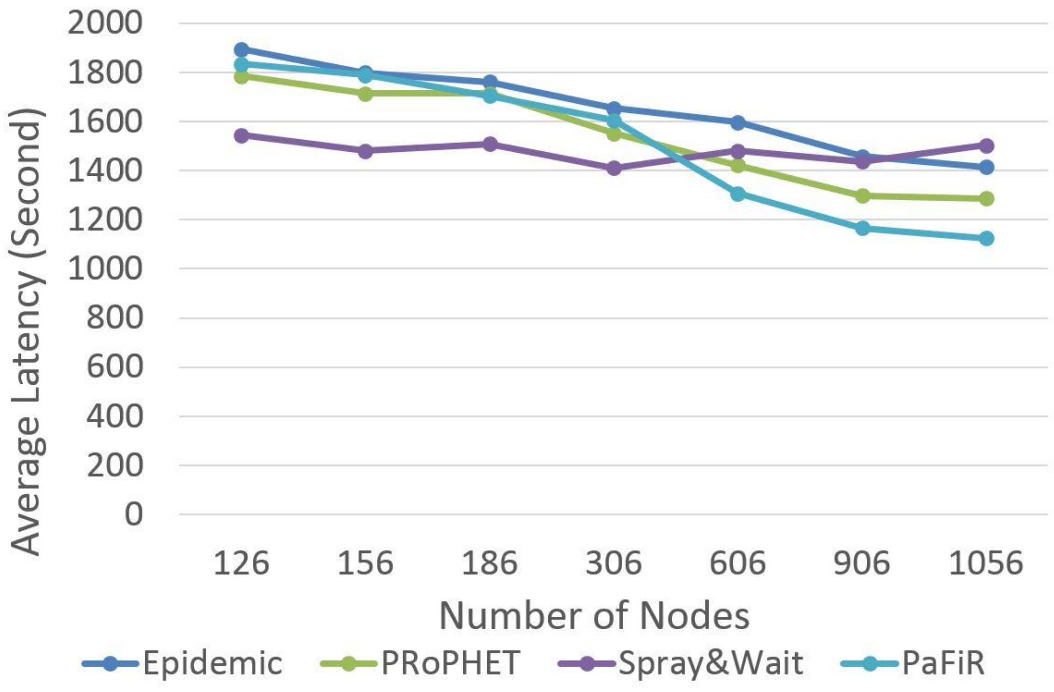


Fig. 15. Average Latency vs. Number of Nodes.

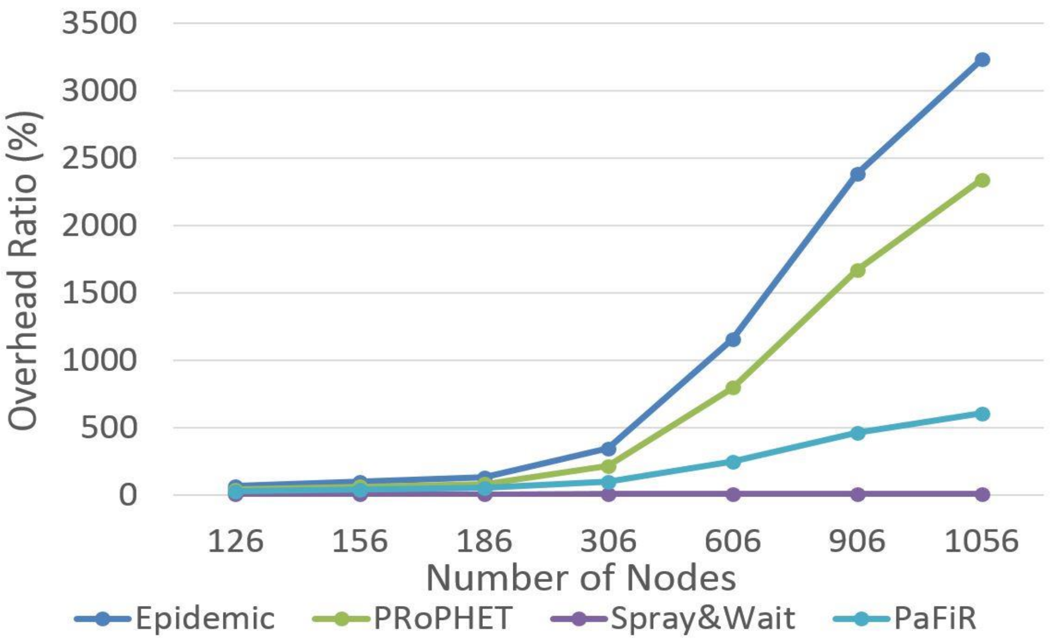


Fig. 16. Overhead Ratio vs. Number of Nodes.

In Fig. 17, Spray and Wait has a very stable average number of hop count, in contrast, Epidemic and PRoPHET have a significant growth after the node population exceeds 306. PaFiR keeps an almost constant level of average hop count, and only one hop is added when the node population grows almost ten times. This means that even in a dense network, the PaFiR protocol can manage the number of relaying events as well as in a sparse system without many more intermediate nodes being required.

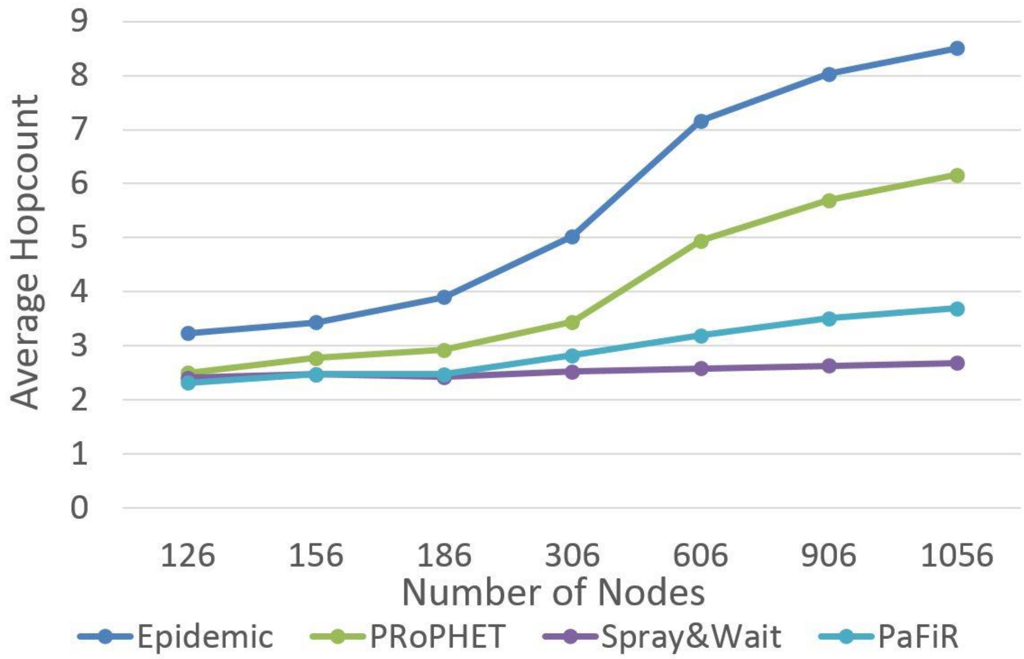


Fig. 17. Average Hopcount vs. Number of Nodes.

Although Spray and Wait has the best performance on overhead ratio and average hopcount, the poor performance on the more important aspects of delivery probability and average latency indicates that Spray and Wait has less ability with respect to resilience, tolerance and scalability.

All the results show that the PF prediction algorithm assists the protocol in tracking and inferring the movement of ground intelligent gadgets and associated UAVs. Hence, the proposed PaFiR routing protocol offers an extremely competitive performance with respect to all key assessment metrics when the mobile network becomes more complex.

6. Conclusions and Future Work

With the flexibility of IoT portable devices and assisted UAVs deployed in mobile IoT Smart Cities, and the variety of application and service demands, a routing protocol needs to cope with extremely complex scenarios. The characteristics of the PF algorithm endow the PaFiR routing protocol with more tolerance, resilience and scalability than other current relaying schemes. It offers delivery ratios that are up to 40% better than existing methods and latency gains of up to 27%. Its hop count is closer to Spray and Wait but for a much smaller overhead and reduced latency compared to PRoPHET. The movement prediction capability of the PaFiR routing protocol potentially enables the IoT system to provide more functionalities and applications, such as positioning services, behavior analysis and object tracking.

In future research work, the movement prediction can cooperate with UAV trajectory optimization to improve the accuracy of prediction and to optimize the packet relaying path. Also, by consideration of the optimization of relaying path, balancing of the data traffic flow to increase the overall IoT system performance can be achieved.

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