Smart Relaying for Decentralized Wireless Networks

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***Abstract*—This research paper presents a new relaying strategy for decentralized wireless networks that target mobile node motion recognition and prediction, using statistical reasoning to give portable devices more intelligence, which we term the Smart Relaying scheme. The aim of the proposed protocol is to enable intelligent terminals to observe the movement of adjacent wireless nodes so as to analyze the measured data and infer the targeted mobile subscriber motion strategies in different scenarios. This ability is of use within the Store-Carry and Forward Relaying scheme to create opportunities for the system to increase its overall performance. The motion data are processed by the Kalman Filter (KF) algorithm that can be seen as a series of prediction, tracking and smoothing calculations of the movement of mobile subscribers. The protocol is tested using the Opportunistic Network Environment (ONE) simulator. Compared with other DTN routing protocols in simple networks, the KF algorithm offers a well-controlled on hop count and overhead ratio with same delivery rate. In complex scenarios, the results show the KF routing protocol balances the delay, the times of relay and overhead ratio very well, which means the designed routing scheme delivers outstanding performance with good tolerance and resilience.**

***Keywords*— Store-Carry and Forward; Decentralized Wireless Networks; Kalman Filter; Opportunistic Network Environment (ONE) simulator**

I. INTRODUCTION

Lack of resources is always a potential issue for communication networks, however, well designed in terms of a wired or wireless backup system. In the case of natural disasters, such as hurricane, earthquake, landslide and so on, portable devices can only work under an ad hoc model to achieve the transmission of information, forming a type of decentralized wireless system.

In a decentralized wireless network, each of the mobile nodes is allowed to have its own determination of how to assist other mobile nodes or the attached wireless network. In this case, the wireless node can be designed to simply forward or flood the relayed message as required, however, this will cause the mobile system to be less controlled or to lack management. Providing the portable node with intelligence to analyze the ambient situation and provide input to the routing decision process helps the system improve its overall performance. The widespread use of smart devices makes this easy to implement and provides an advantageous network feature [1].

Delay Tolerant Networks (DTNs) [2] are typical of decentralized wireless networks, and FANETs (Flying Ad Hoc Networks) [3] constitute a very modern DTN application, in which end-to-end connectivity is provided between a pair of nodes despite intermittent link connectivity and long delays thus providing more network flexibility and resilience [4]. As the network needs to use the limited connectivity to forward segments of the payload, the packets can be randomly forwarded to any neighboring nodes depending on the relaying strategy. This results in reduced system efficiency, overall delay and considerable energy wastage. The Store-Carry and Forward (SCF) relaying scheme [5] is a well-designed DTN wireless system based on random segment forwarding capabilities. The mechanisms used to determine the forwarding will critically influence the wireless network performance, including factors such as network efficiency, transmission delay, Quality of Service (QoS), energy efficiency and network load distribution [6].

The mobility of wireless subscribers is one of the benefits of mobile networks, providing more flexibility to mobile users. Moreover, it also allows portable device vendors to offer advanced functionality comparable to wired networks but in a much more adaptable and reconfigurable way. The SCF relaying scheme may use this mobility to achieve its relay work, whilst the nature of the uncertainty of the wireless nodes causes uncontrollable DTN performance. However, if the overall motion of wireless subscribers can be observed and the future movement can be foreseen, then the relay route can be well managed and optimized.

The rest of the paper of the paper is organized as follows. In Section II, the context for the work is provided by a short overview of the literature. Section III gives a review of a list of existing related DTN routing protocols. In Section IV, detailed information is provided on the proposed Kalman Filter (KF) routing protocol regarding its mathematical model. Section V shows the simulation results and comprehensive comparisons with other relaying strategies. The last section presents the conclusions and suggestions for future work.

II. RELATED WORK

To deal with the motion of the nodes within a DTN, it has been common to form routing paths between nodes that are in each other's direct communication range [7]. Thus, the network needs to maintain an end-to-end structure whilst its intermediate structure varies with node movement. This is difficult because the variations in node positions constantly change the underlying communication graph and mean that nodes must quickly adapt to the new configurations. One of the methods for solving this problem is link reversal [8], which models the problem as a directed graph, reversing the link directions when needed as a result of motion induced connection loss. Unfortunately, as shown in [8], the time to produce a stable link for communication grows as the square of the number of nodes in the network, limiting the scalability of such algorithms. As a result, the SCF approach [5] was developed, in which intermediate mobile nodes store messages in their local memories if they do not encounter a suitable relay node. The messages are then carried whilst the nodes move until they find an appropriate node to which they can forward their data towards the destination.

With particular reference to uncertainty in wireless subscriber movement prediction, it is known that given knowledge of a large population, accuracies approaching 90% can be achieved [9]. However, here we need real-time estimation based on limited information. Sometimes, the DTN in question will have movement restrictions such as that considered by Ahmed and Kanhere [10]. They considered operation where public transport networks or street patterns reduced the range of subscriber movement choices to simplify the prediction work. In general, we need to allow the network nodes more freedom and the approach taken can be reactive or proactive [11]. In the former, nodes report their location to a central network authority such as a base station. However, in the latter, prediction is used and this has the potential to reduce the inevitable latency whilst waiting for location updates. The uncertainty arises from the mobility model extending into the future based on known mobility history data. The success of a mobility model depends on how well it can learn and predict future node locations based on the available scenario history [11]. User movements are to a large degree predictable [12] so the problem becomes one of designing an efficient location prediction algorithm using past data.

Similarly, the idea of using prior probability and Bayesian inference to properly drive a search process in ad hoc delay tolerant networks has been exploited [13]. This use of a generic computable inference mechanism to increase the performance of DTNs has gained popularity in the last few years, culminating in a recent study employing a weighted feature Bayesian predictor that outperforms a naïve Bayesian approach [14]. However, there is no comprehensive and systematic research study on the entire system to improve the network performance by using rigorous prediction and analysis methods. Although Kalman filtering has been used to update connection probabilities [15], the work in [13] was the first adoption of Bayesian inference in the context of DTN routing. However, the main focus of the paper is on gradient routing in which the message tends to follow a gradient of increasing utility function values towards the destination. Another paradigm has been employed by Talipov et al. [16], who utilize a hidden Markov model to predict the future location of individuals. The inspiration for the scheme is the same as ours and based on the observations of Gonzalez et al. [17] that human trajectories show a high degree of temporal and spatial regularity, and in social environments individuals move subject to a deterministic schedule with only a few random deviations.

III. ROUTING PROTOCOLS

There are many existing routing protocols that could be applied in the DTN system. In this work, the following routing strategies will be reviewed and compared with the proposed Smart Relaying algorithm to present its performance for various network scenarios.

Direct Delivery routing protocol [18] also known as the Direct Transmission protocol, in which the sender only delivers the message to the final receiver directly as soon as an encounter happens. There are no other intermediate nodes involved in the packet relaying offering advantages when there are no reliable intermediate nodes available. The protocol is able to securely deliver the information with minimum overhead ratio and transmission energy consumption. However, the delivery probability relies on the likelihood of node encounters, which determines that this routing scheme is only appropriate for some particular scenarios or requests.

Epidemic routing protocol [19] is based on a simple flooding mechanism to relay the data packets. As its name implies the relaying strategy is to maximize the delivery probability by spreading messages as an epidemic disease to any mobile nodes it encounters that has not already stored them in its buffered message list. This mechanism causes a substantial waste of buffer capacity, air interface bandwidth and transmission energy to flood the packets. If the network is experiencing a high traffic volume, this protocol could affect the normal usage of mobile subscribers or the efficiency of the wireless system.

Spray and Wait routing protocol [20] has two versions: Binary and Vanilla. In this work, we consider only the widely applied Binary version for comparison with the proposed routing protocol and other candidate protocols. As indicated by its name, Spray and Wait consists of two phases: a Spray phase and a Wait phase. In the former, a source node transfers half of a replicated message to the first node it encounters, then the relay node forwards half of replicated packets to future nodes encountered, until a node has only a single copy of message; the latter phase is entered at this point and a direct delivery strategy is used to deliver the data packet to the final receiver.

Spray and Focus routing protocol [21] is the upgraded relaying strategy of the Spray and Wait protocol, to tackle some problems with that scheme by introducing a new second phase, called the Focus phase, instead of the Wait phase. When a node only has one forwarding token left for a message, Spray and Focus routing no longer waits for the direct delivery opportunities but rather each relay can forward its copy to a potentially more appropriate node, using a sophisticatedly designed utility-based scheme.

Location Prediction-based Forwarding for Routing using Markov Chain (LPFR-MC) routing protocol [22] uses a Markov Chain to predict the probability of a targeted mobile node moving towards the destination location or region of a relayed packet. The computation is based on the present location of a portable node and the angle between itself and its intended destination, to determine the next hop forwarding the message segments.

Game Theoretic Approach for Context Based Routing (GT-ACR) protocol [23] relying on a non-zero sum cooperative game of two players assisting with the context information, encounter index, and distance of the corresponding node from the destination as vital attributes in framing the game, to select the best possible relaying node.

Some of the above reviewed routing strategies fully depend on the dissemination of data packets that can cause a big waste of network resources and some problems or risks in the wireless network, such as radio bandwidth, buffer and battery life of terminals, and furthermore network congestion. Some prediction-based relaying protocols are highly reliant on history records that require a large memory capacity to store the history data. Even though modern smart devices embed substantial memories, batteries and processor power, massive hardware usage requests can still cause substantial impacts on the normal function operation of terminal users. The ideal routing scheme needs to provide an optimized relaying path for the message to obtain network service and maintain a high performance of the wireless system, whilst meanwhile keeping the occupation of resources on the working terminals as low as possible.

IV. The KF Routing Protocol

The DTN system benefits from the mobility and flexibility of mobile subscribers, however, it brings many uncertainties into the wireless network. The routing schemes mentioned before attempt to minimize the nature of DTN uncertainty using different strategies. Study of movement prediction of the mobile users is a method to control these uncertainties comprising a series of estimations of moving targets. For each particular moment or interval, every individual mobile node will have its own set of state data to indicate its state space information in a state space model. This set of data will be denoted as a vector of the state space identification [24]. A series of state vectors is used to record the trajectory of a particular mobile subscriber or a predetermined mobile user group within the network.

All mobile nodes have the ability to move around the radio frequency coverage area freely, and this random motion is a category of stochastic system. In particular, this is in mathematical or statistical terms a random walk of subscribers described via a stochastic process. The unknown state of the targeted wireless subscriber (denoted by X) is computable by the appropriate mathematical and statistical theories based on the observation or measurement data of behavior of the particular mobile subscriber (denoted by Y). For further movement, mathematical and statistical methods can also assist the production of an inference result using historical measurements [25].

Here, established Bayesian statistical methods are used to accomplish the moving object motion prediction operation [26]. According to the overall behavior of mobile subscribers, the nodes will be classified into different categories by utilizing different criteria, for instance, non-maneuvering objects and maneuvering objects. If the objects are maintaining a constant velocity so that they may be classified as the non-maneuvering type, then the system can be defined as a Linear Quadratic Gaussian (LQG) one [25]. Such a system belongs to a framework of circumstances which contains the fundamental tools of stochastic optimal control, and the tracking, filtering, smoothing and prediction operations can be solved using linear system models. The motion of maneuvering objects is normally more dynamic with different accelerations and the trajectory is non-linear so the solution will be found under more complicated circumstances which could be such that only sub-optimal solutions are achievable [27]. Each mobile node only needs to track and predict the nodes with which it is able to establish a direct bi-directional radio connection and the prediction information is only exchanged among these neighboring mobile nodes. To achieve this prediction, each mobile node needs to track and obtain the state information for all of its neighboring nodes by observing and tracking their movement.

A. *Tracking Strategies*

The tracking problem is actually to estimate the state of moving targets based on the observation data via statistical algorithms. The state of the targets can thus be seen as belonging to a dynamical system [28] and the states are independent of the time, forming an autonomous system. The motions (or trajectories) of targeted mobile subscribers are normally continuous, but the observers take the observation data in each constant time interval or according to a preset fixed sampling frequency, making the observations discrete. This mathematical statistics mode is called the continuous – discrete filtering mode [24], and the observation results are in the discrete mode that will be the state space information input. The movement of mobile users cannot remain at a constant velocity or absolute steady state. In practice, small changes in the velocity or state close to the mean value may be treated as Gaussian noise.

The classical Bayesian approach provides us with a method to deduce the further states of observed moving objects. Bayes' theorem [26] implies that the mobile node states can be predicted from the observation data, which is the joint probability of the state of event x and the observation of event y divided by the unconditional probability of the observation of event y, which is the normalization factor.

The movement of a mobile subscriber is a random walk [25] obeying the Markov property [29], so the stochastic motion of each mobile node can be treated as a series of Markov process individually. A first order Markov chain can be used for predicting the state space identification of each mobile subscriber step by step. The recursive Bayesian solution is [28]:

$$p(\boldsymbol{x}^k|\boldsymbol{y}^k) = \frac{p(\boldsymbol{y}_k|\boldsymbol{x}_k)}{p(\boldsymbol{y}_k|\boldsymbol{y}^{k-1})} p(\boldsymbol{x}_k|\boldsymbol{x}_{k-1}) p(\boldsymbol{x}^{k-1}|\boldsymbol{y}^{k-1}) \quad (1)$$

Leading to a state conditional density:

$$p(\boldsymbol{x}_k|\boldsymbol{y}^k) = \int_{x_{k-1}} p(\boldsymbol{x}^k|\boldsymbol{y}^k) d\boldsymbol{x}_{k-1} \qquad (2)$$

In these equations, the superscripts refer to vectors of all *x* or *y* values from one to *k* or *k*-1 whereas the subscripts denote single instances of *x* or *y*.

B. Simulation Model

The targeted system and observation methods are based on linear system models with quadratic system optimization. The wireless system and observation are subject to Gaussian noise so they obey the basic LQG regulator equations [25]. Hence, the object tracking and movement prediction problem can be solved by a KF [25]. Equation (2) is the recursive estimation of the state conditional density function and the term $p(\boldsymbol{x}^{k-1}|\boldsymbol{y}^{k-1})$ gives the prior probability density function. In the Bayesian recursive solution, $p(\boldsymbol{x}_k|\boldsymbol{y}^k)$ is a conditional density of the targeted mobile subscriber state $\boldsymbol{x}_k = (x_{k1}, x_{k2}, \dots, x_{kn}) \in \mathbb{R}^n$ at the moment k given all the observed data $\boldsymbol{y}^k = (\boldsymbol{y}_1, \boldsymbol{y}_2, \dots, \boldsymbol{y}_k)$ with $\boldsymbol{y}_k = (y_{k1}, y_{k2}, \dots, y_{km}) \in \mathbb{R}^m$.

The moving object tracking algorithm with noise is:

$$\boldsymbol{x}_k = \mathrm{f}(\boldsymbol{x}_{k-1}) + \boldsymbol{v}_k \qquad (3)$$

where $\mathrm{f}(\boldsymbol{x})$ is some function of $\boldsymbol{x}$ and $\boldsymbol{v}_k$ is a vector of Gaussian noise.

In practice, the movement of mobile users cannot remain at a constant velocity or absolute steady state but the relatively small perturbations occur that can be regarded as Gaussian noise. Given that only a small portion of wireless users will exhibit high mobility [17], such a model is of some utility.

In the decentralized wireless networks designed to date, to implement the SCF relaying scheme, each mobile node has to observe the movement of other nodes which are nearby, and try to estimate the state. In this work the estimated state is only limited to the position of mobile subscriber nodes. The observation cannot be ideal, and there is always some noise that enters the system. Generally, the KF algorithm is able to deal with two kinds of noise, one is the measurement noise (Gaussian sampling noise) or sensor noise, and the other is transition noise or process noise [30]. Both of these two kinds of noise are zero mean Gaussian noise, and the dynamic and observation models are linear Gaussian. The filtering model presented above acts as a basic LQG regulator as mentioned before, so the filtering equations can be expressed as [31]:

$$\boldsymbol{x}_k = \mathbf{A}\boldsymbol{x}_{k-1} + \boldsymbol{q}_{k-1} \qquad (4)$$

$$\boldsymbol{y}_k = \mathbf{H}\boldsymbol{x}_{k-1} + \boldsymbol{r}_k \qquad (5)$$

where $\boldsymbol{x}_k \in \mathbb{R}^n$ is the hidden state vector at time k, $\boldsymbol{y}_k \in \mathbb{R}^m$ is the observation vector at time k, respectively; $\boldsymbol{q}_{k-1} \sim N(0, Q)$ is the transition noise; $\boldsymbol{r}_k \sim N(0, R)$ is the sensor noise.

The movement of the mobile subscriber is described by two-dimensional Cartesian coordinates, so the hidden state vector has four dimensions $\boldsymbol{x}_k = (x_{k1}, x_{k2}, x_{k3}, x_{k4})$. The first two elements, (x_1, x_2), capture the position of the mobile node and the second two, (x_3, x_4), represent its corresponding velocity. The observation vector is a two-dimensional column vector that only has two elements and so is $\boldsymbol{y}_k = (y_{k1}, y_{k2})$.

The matrices within the dynamic model are:

$$\mathbf{A} = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\mathbf{Q} = \begin{pmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0.1 \end{pmatrix}$$

where Δt is one second in the simulations and $\boldsymbol{Q}(i,j)$ is the transition covariance [30].

The matrices in the observation model are:

$$\mathbf{H} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$\mathbf{R} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

where $\boldsymbol{R}(i,j)$ is the observation covariance [30].

Here, the KF equations can be described as two steps, which are a prediction step and an update step [3]:

(i) prediction:

$$\boldsymbol{m}_k^- = \mathbf{A}_{k-1}\boldsymbol{m}_{k-1} \qquad (6)$$

$$\boldsymbol{P}_k^- = \mathbf{A}_{k-1}\boldsymbol{P}_{k-1}\mathbf{A}_{k-1}^T + \boldsymbol{Q}_{k-1} \qquad (7)$$

(ii) update:

$$\mathbf{S}_k = \mathbf{H}.\mathbf{P}_k^-.\mathbf{H}^T + \mathbf{R} \qquad (8)$$

$$\mathbf{K}_k = \mathbf{P}_k^-.\mathbf{H}^T.\mathbf{S}_k^{-1} \qquad (9)$$

$$\mathbf{m}_k = \mathbf{m}_k^- + \mathbf{K}_k.\{\boldsymbol{y}_k - \mathbf{H}.\mathbf{m}_k^-\} \qquad (10)$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k.\mathbf{S}_k.\mathbf{K}_k^T \qquad (11)$$

In which

$\boldsymbol{y}_k$ is the measurement at the time step k;

$\mathbf{P}_k$ is the covariance of a Kalman/Gaussian filter at the time step k;

$\mathbf{P}_k^-$ is the predicted covariance of a Kalman/Gaussian filter at the time step k just before the measurement $\boldsymbol{y}_k$;

$\boldsymbol{S}_k$ is the innovation covariance of a Kalman/ Gaussian filter at step k;

$\mathbf{K}_k$ is the gain matrix of a Kalman/Gaussian filter;

$\mathbf{m}_k$ is the mean of a Kalman/Gaussian filter at the time step k;

$\mathbf{m}_k^-$ is the predicted mean of a Kalman/Gaussian filter at the time step k just before the measurement $\boldsymbol{y}_k$.

Before the filtering process starts, both the state vector **initial_state** (which is a column vector) and the state covariance vector **initial_V** have to be initialized thus:

$$\textbf{initial\_state} = \begin{pmatrix} 10 \\ 10 \\ 0 \\ 0 \end{pmatrix}$$

$$\textbf{initial\_V} = \begin{pmatrix} 10 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 10 \end{pmatrix}$$

C. Algorithm Simulation

To simulate the scenario studied, the true mobile user locations are generated by MATLAB, producing a stochastic linear dynamical system, which is a type of hidden state [30]. This is because the mobile node states cannot be directly measured by neighboring mobile subscribers and KF algorithms are used for estimation. Figure 1 illustrates the results of simulated KF algorithms using 50 individual states in each time step. These are the true states that simulate the real locations of the mobile subscriber during a continuous period of time, and that are represented by the black squares. The trajectory shown by the black line linking the black squares is the 'real path' of the motion of a certain mobile node. The blue stars indicate the observed location of the mobile device which simulates the measurements from another neighboring mobile terminal. The red crosses show the KF outcomes, processed by the neighboring mobile smart device with the estimated path represented by the red dotted line.

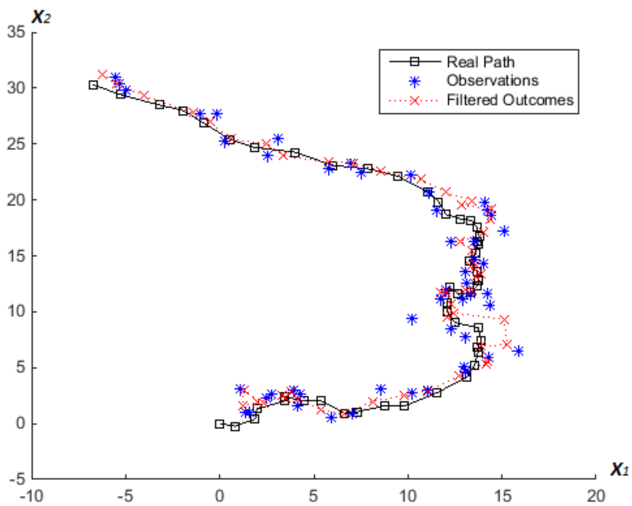


Fig. 1. Results of the prediction simulation for the filtering model.

It may be seen in Figure 1 that for most of the time, the filtered trace represents the true path well. Only when the mobile user's movement is more dynamic (close to the maneuvering model) [32], particularly the right hand side of Figure 1, does the algorithm have difficulty following the true path. Nevertheless, when the motion of the object exhibits behavior that is close to the non-maneuvering scenario, the outcomes still reflect the real motion of the target very well as in the top and bottom parts of the trajectory, and the mismatched portion is relatively small.

D. Protocol Simulation

The simulation testbed for this part used the Opportunistic Network Environment (ONE) simulator and a JAVA based protocol for the KF routing scheme was developed. For testing the performance, resilience and tolerance of the protocol designed, the sample dataset that comes with the ONE simulator package (collected from the downtown Helsinki area) was utilized to simulate a complex wireless network condition. The parameters for the simulation configurations are specified in Table I. These are chosen to be of the same order as the parameters in [2] with the buffer size large enough that it does not impact performance [2].

TABLE I. PARAMETERS OF SIMULATION CONFIGURATIONS

Simulation Time (s)	86400
Buffer Size (MB)	50
Packet Lifetime	100 minutes
Message Interval (s)	3, 5, 10, 20, 30, 60
Message Size (kB)	500
Number of Nodes	40, 100, 200, 300, 400, 500

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 (40 nodes) mobile network to an extremely high-density (500 nodes) system.

In this work, there are four key factors of wireless systems 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 [33].

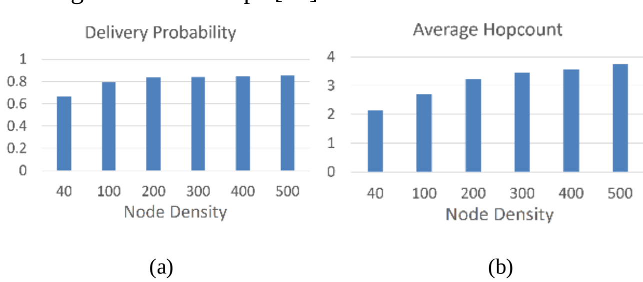
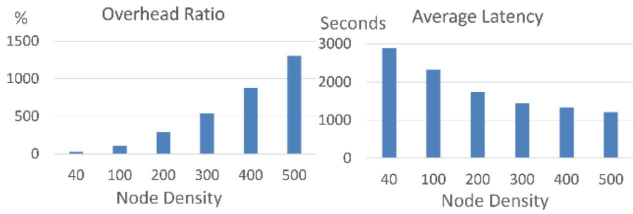


Fig. 2. (a) Delivery probability; (b) average hop count for different network densities.

Figure 2 shows the performance of the proposed protocol at the maximum bit rate considered. It provides good resilience for different network densities and maintains a delivery probability in excess of 0.7 for all circumstances. Moreover, as the algorithm is able to predict the movement of portable nodes, the protocol delivers an average hop count of between 2.1 and 3.7, leading to the involvement of fewer intermediate nodes in the relaying path saving retransmission energy and improving efficiently.

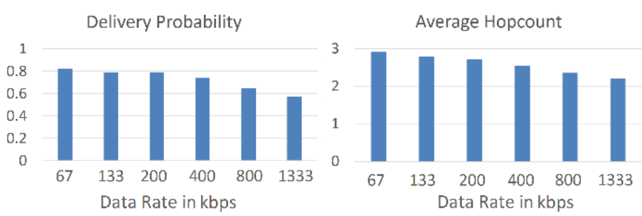
Figure 3 shows the increase in overhead ratio with the number of nodes resulting from more possible packet relay candidates. However, there is a corresponding decrease in the average latency since more nodes can complete delivery. The balance of these two factors maintains useful protocol performance when the network setup changes.



(a) (b)

Fig. 3. (a) overhead ratio; (b) average latency for different network densities.

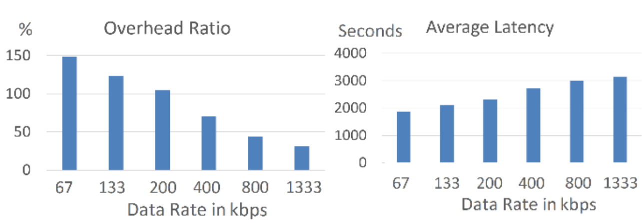
To test the capability of the protocol to deal with various traffic volumes, the packet generation rate in a network comprising 40 nodes was varied. Figure 4 illustrates the variation in delivery probability and hop count as the data rate increases. The former drops with increasing traffic volumes but the KF protocol still maintains a probability of approximately 0.6 whilst the hop count falls from almost three to a little over two with increasing bit rate.



(a) (b)

Fig. 4. (a) Delivery probability; (b) average hop count as a funcion of data rate for low node density.

Figure 5 shows that the overhead ratio decreases from 148% to 31% as the bit rate increases but this is accompanied by an increase in average Latency from 1875 seconds to 3153 seconds.



(a) (b)

Fig. 5. (a) Overhead ratio; (b) average hop count as a funcion of data rate for low node density.

The KF relaying scheme exhibits a good overall performance which benefits from the portable device movement predication ability allowing more packets to arrive successfully at the receiver or be relayed to the correct intermediate nodes. This feature maintains the delivery probability at a high value whilst keeping the average hop count at a low level.

V. SIMULATION RESULTS

To obtain the comprehensive performance of the protocol designed, the algorithm was tested in two kinds of networks: a simple wireless network and a complex wireless network. The dataset of the simple wireless network was the real trace of mobile users downloaded from CRAWDAD (A Community Resource for Archiving Wireless Data At Dartmouth) datasets [34]. This dataset contains mobility and connectivity traces extracted from GPS traces collected from the regional Fire Department of Asturias, Spain. The original data source is one year of GPS traces extracted from a Geographical Information System (GIS). The traces were generated by GPS devices embedded mainly in cars and trucks, but also in a helicopter and a few personal radios. A total of 229 devices reported 19,462,339 locations. A new location is reported with an interval of approximately 30 seconds when the GPS device detects movement. To convert GPS traces into ONE connectivity traces, the circular communication range was been assumed be 200 meters. The complex wireless network dataset is the same ONE simulator dataset used for the protocol simulation in Section IV.

Parameters for the simulation configurations are specified in Table II.

TABLE II. PARAMETERS OF SIMULATION CONFIGURATIONS

	Label on the graphs	Value of parameters
Buffer Size	B	10, 20 MB
Message TTL	T	30 minutes
Message Interval	I	1, 5 seconds
Message Size	M	10, 20, 200 kB
Number of Nodes	H	50, 75, 100, 160, 200(only for simple network)
Simulation Time		86400 Seconds
Protocol		The KF, Epidemic, Direct Delivery, Spray and Wait (Binary version), Spray and Focus

A. *Simple Network*

Figure 6 shows that in a simple mobile network, when it is sparse, the KF relaying scheme and other routing plans give approximately the same delivery probability around 0.03 in various scenarios. For the Spray and Focus scheme, when the message interval is high, delivery probability is higher than 0.08, however, when the message rate is high, delivery probability is at most 0.05.

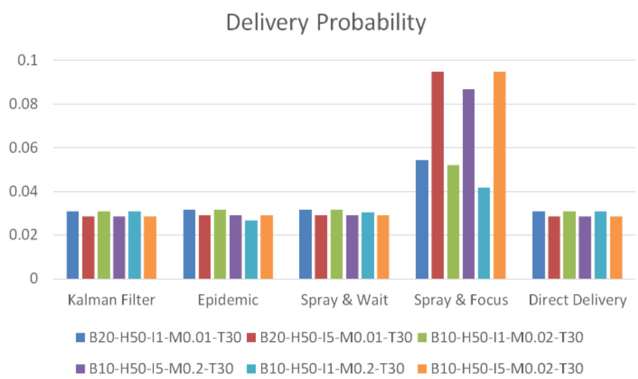


Fig. 6. Delivery Probability for Sparse (50 nodes) Simple Network

In Figure 7 and Figure 8, it is shown that the delivery probabilities of different wireless routing strategies do not change significantly from Low Density to High Density networks, which indicates for the simple network, when the network density reaches a certain level, the growth of number of mobile nodes cannot help to increase the delivery probability, as the opportunities for node encounters relatively low and this limits the chance for messages to be received by the destination nodes.

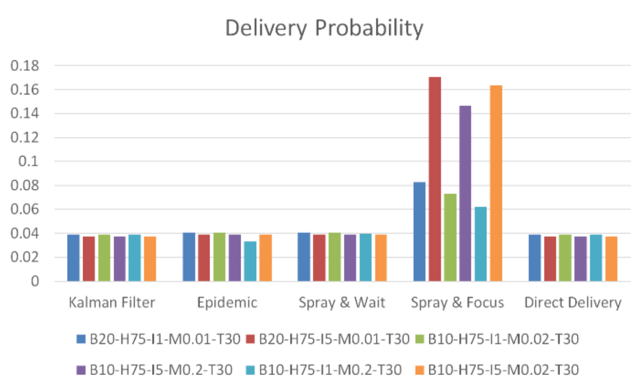


Fig. 7. Delivery Probability for Low Dense (75 nodes) Simple Network

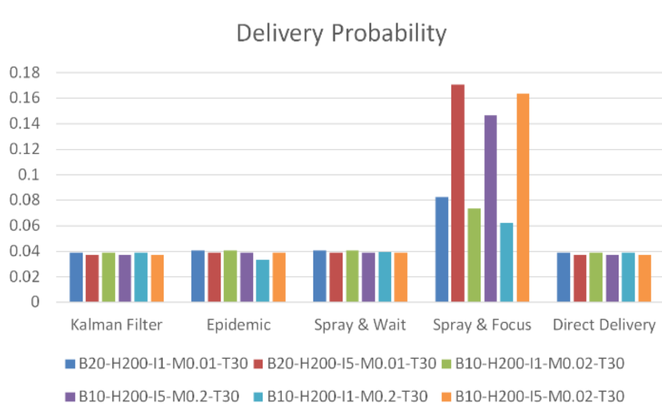


Fig. 8. Delivery Probability for High Dense (200 nodes) Simple Network

The KF routing protocol uses statistical methods to determine the next hop selection. For the simple system, it is easy for a source node to learn whether it will encounter the destination by statistical inference. The protocol can keep its Overhead Ratio close to zero, which close to the Direct Delivery relaying scheme.

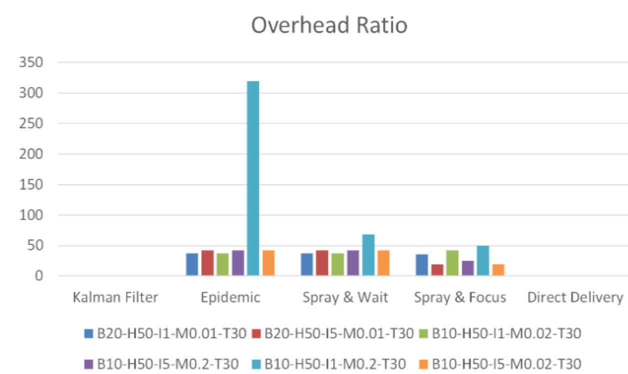


Fig. 9. Overhead Ratio for Sparse (50 nodes) Simple Network

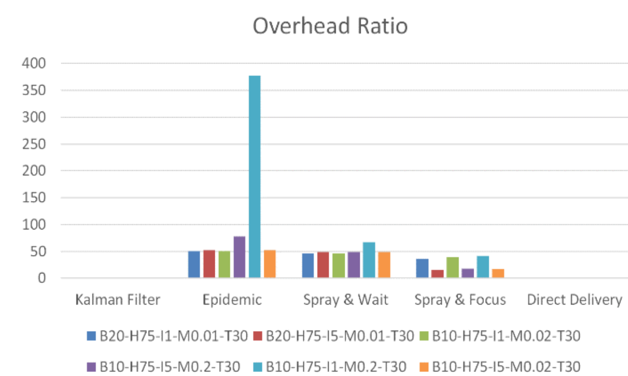


Fig. 10. Overhead Ratio for Low Dense (75 nodes) Simple Network

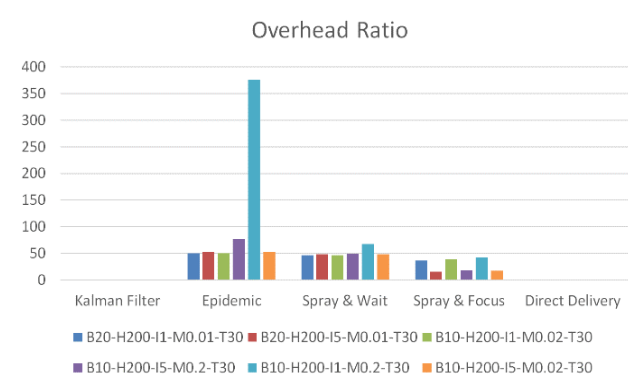


Fig. 11. Overhead Ratio for High Dense (200 nodes) Simple Network

In Figure 9, Figure 10 and Figure 11, the overall Overhead Ratio of the sparse network is a little lower than other dense networks. After the population of nodes reaches 75, then the Overhead Ratio becomes steady.

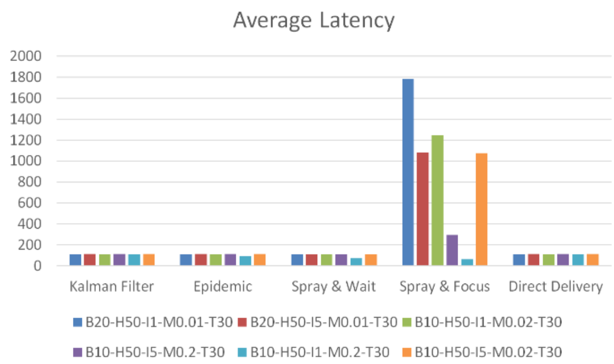


Fig. 12. Average Latency for Sparse (50 nodes) Simple Network

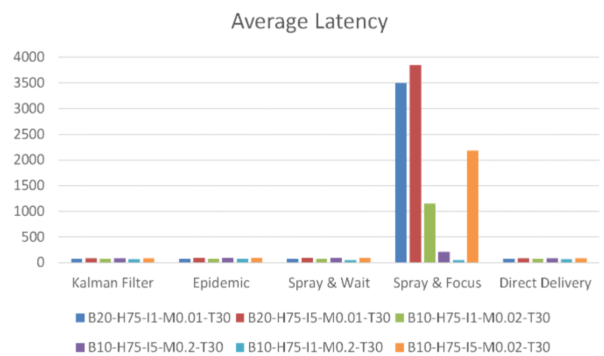


Fig. 13. Average Latency for Low Dense (75 nodes) Simple Network

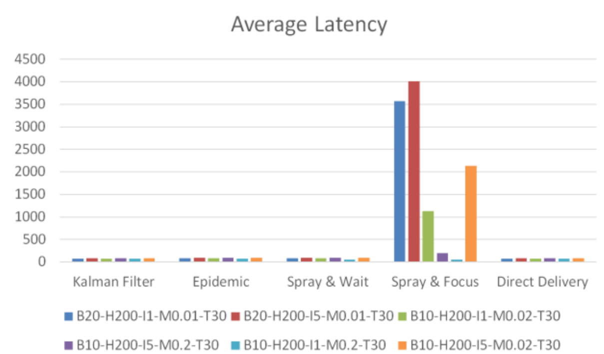


Fig. 14. Average Latency for High Dense (200 nodes) Simple Network

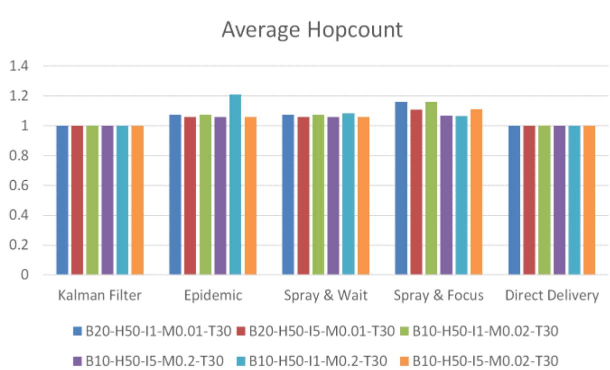


Fig. 15. Average Hopcount for Sparse (50 nodes) Simple Network

In Figure 12, Figure 13 and Figure 14, all protocols, except the Spray and Focus scheme, deliver low degrees of average latency avoiding long packet delivery delays.

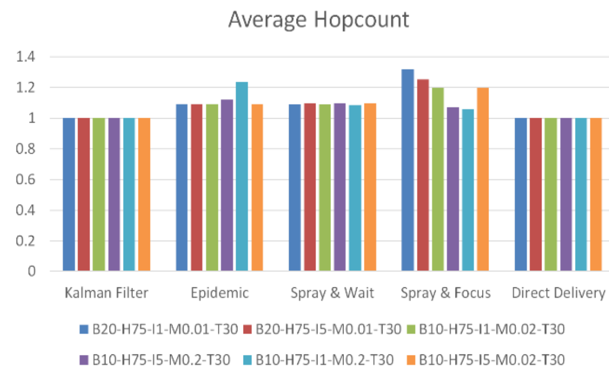


Fig. 16. Average Hopcount for Low Dense (75 nodes) Simple Network

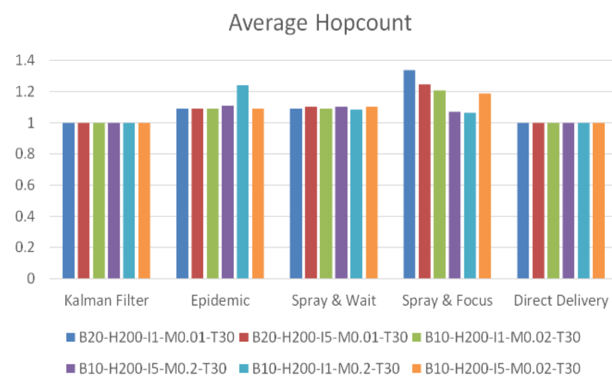


Fig. 17. Average Hopcount for High Dense (200 nodes) Simple Network

As the KF protocol tends to use the Direct Delivery method, these two protocols keep the average hop count at one hop. Figure 15, Figure 16 and Figure 17 indicate that there is no significant difference between various network densities for simple networks but for some scenarios, Spray and Focus presents a slightly higher average hop count than other protocols.

B. Complex Network

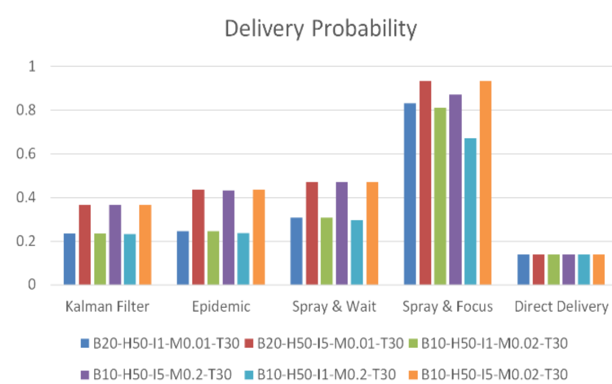


Fig. 18. Delivery Probability for Sparse (50 nodes) Complex Network

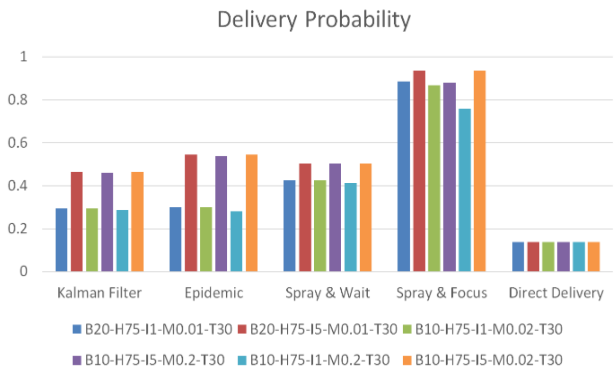


Fig. 19. Delivery Probability for Low Dense (75 nodes) Complex Network

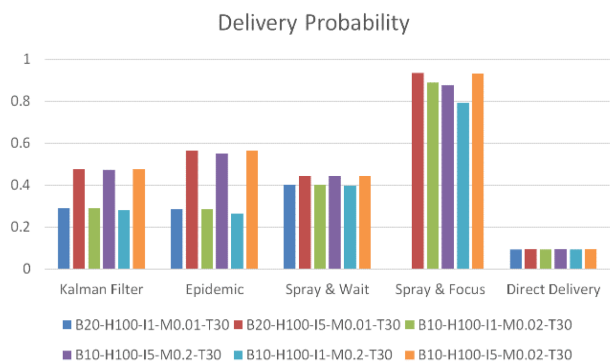


Fig. 20. Delivery Probability for MidLow Dense (100 nodes) Complex Network

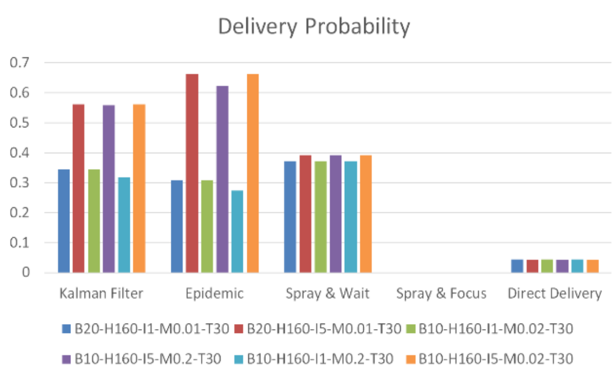


Fig. 21. Delivery Probability for Dense (160 nodes) Complex Network

From Figure 18 to Figure 21, the delivery probabilities of the KF and Epidemic routing plans show a stable increase and tolerance when the number of wireless nodes increases, especially, in a dense network, they are the best two relaying schemes as long as the message rate is low. In contrast, the delivery probabilities of Spray and Wait and Direct Delivery drop slightly when the network density grows. Spray and Focus provides a significantly higher delivery probability than other protocols and also benefits from the increasing number of portable nodes, however, Spray and Focus is unable to work well in the dense network.

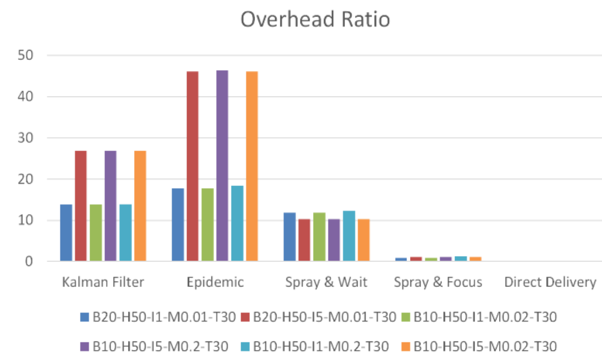


Fig. 22. Overhead Ratio for Sparse (50 nodes) Complex Network

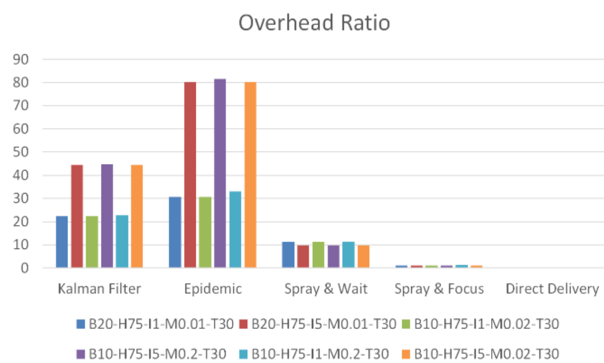


Fig. 23. Overhead Ratio for Low Dense (75 nodes) Complex Network

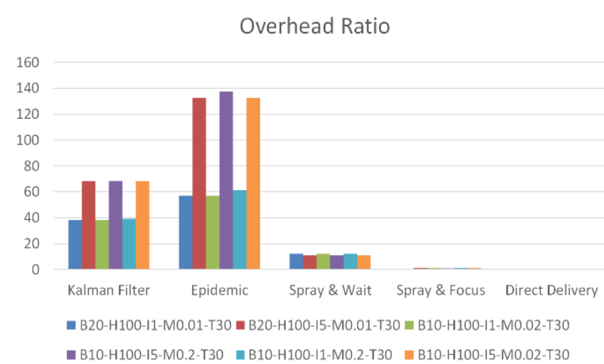


Fig. 24. Overhead Ratio for MidLow Dense (100 nodes) Complex Network

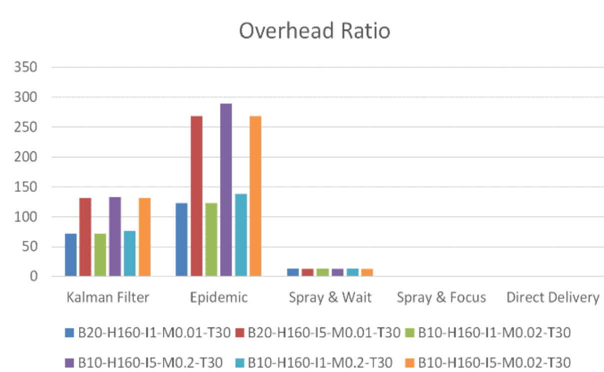


Fig. 25. Overhead Ratio for Dense (160 nodes) Complex Network

From Figure 22 to Figure 25, we see that in a complex network, the KF protocol does not rely mainly on a Direct Delivery strategy. Instead, it predicts the movement of neighboring nodes to find the best relaying node, so the overhead ratio does not remain at zero since prediction of the probability of a source node encounter with a destination node becomes increasing difficult with the number of nodes. As the outcomes show from Figure 26 to Figure 29, the average hop count for the KF scheme also does not remain at zero as in the simple network but rather grows with the network scale.

In contrast, Spray and Focus keeps the overhead ratio at a low level, and it reduces with the growth in the number of mobile nodes, reflecting into the average hop count, which shows the strategy needs very close to one hop for the entire message route. The overhead ratio and average hop count for Spray and Wait stay in narrow ranges of 9 to 14 for the overhead ratio, and 2 to 3 for the average hop count.

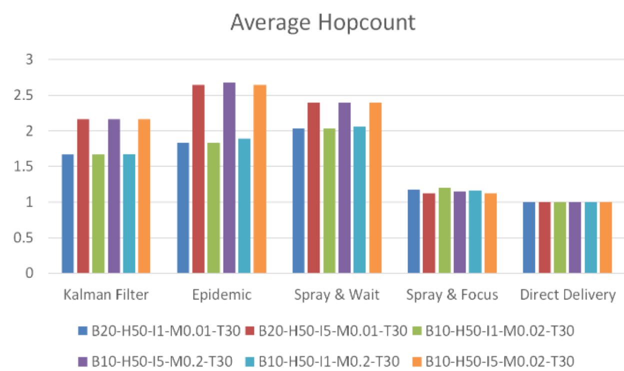


Fig. 26. Average Hopcount for Sparse (50 nodes) Complex Network

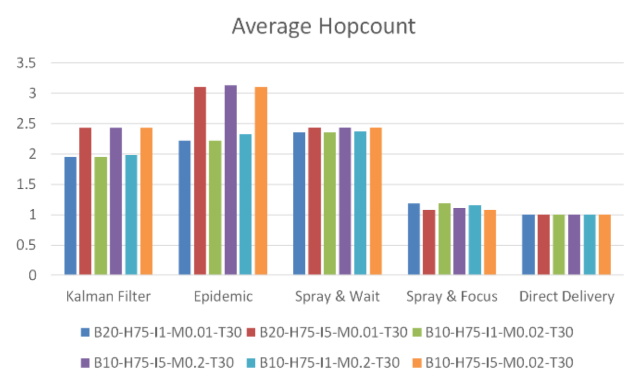


Fig. 27. Average Hopcount for Low Dense (75 nodes) Complex Network

From Figure 30 to Figure 32, the graphs indicate that the average latency of Spray and Focus is significantly higher than the other protocols in some scenarios, and it goes down when nodes number goes up. The average latency for rest of the protocols stays at about the same level for all the tests.

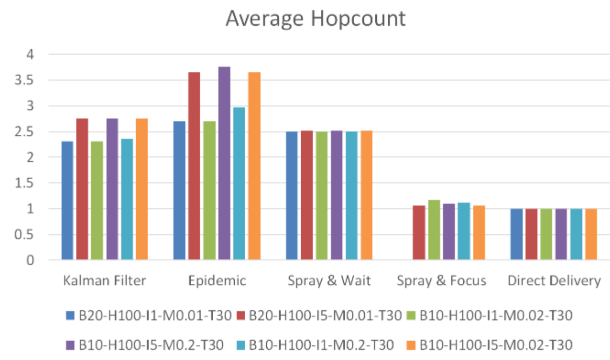


Fig. 28. Average Hopcount for MidLow Dense (100 nodes) Complex Network

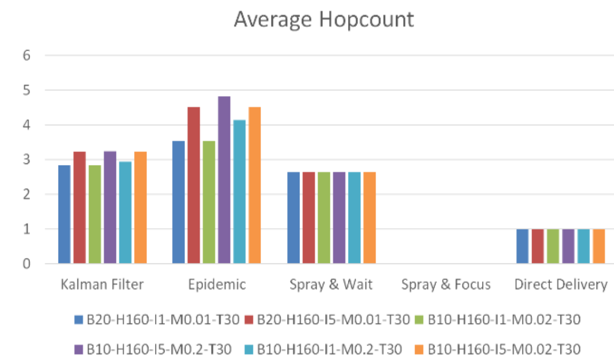


Fig. 29. Average Hopcount for Dense (160 nodes) Complex Network

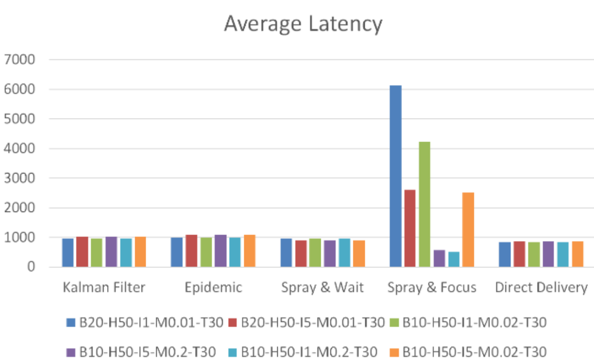


Fig. 30. Average Latency for Sparse (50 nodes) Complex Network

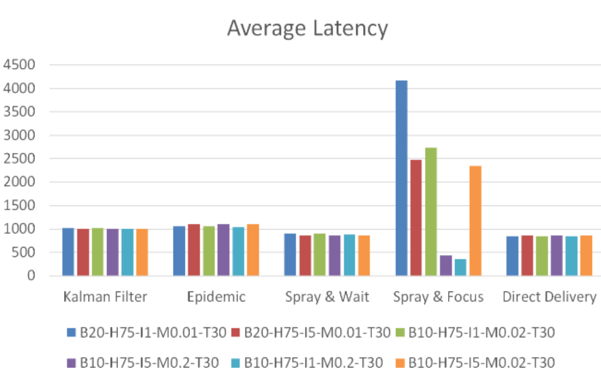


Fig. 31. Average Latency for Low Dense (75 nodes) Complex Network

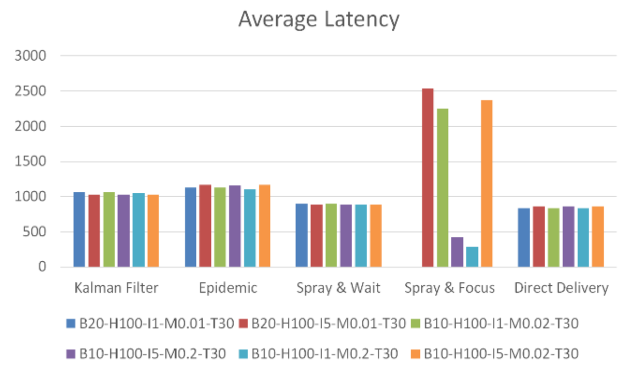


Fig. 32. Average Latency for MidLow Dense (100 nodes) Complex Network

C. *Comparison with recent DTN protocol research*

DTN is a significant emerging paradigm in the wireless communication domain, and there has been much research concerning routing algorithms and relaying strategies to improve the system performance. Game Theoretic Approach for Context Based Routing (GT-ACR) is one of the latest DTN routing protocols. In [23], GT-ACR has been tested in delivery probability, average hop count, overhead ratio, average latency and number of messages dropped against various time to live, number of nodes and message interval. Here, the KF relaying scheme is tested in the same series of metrics to compare its overall performance to this latest routing protocol with the results in Figure 33 to Figure 35 respectively, and the comparisons for each factor are listed in Table III.

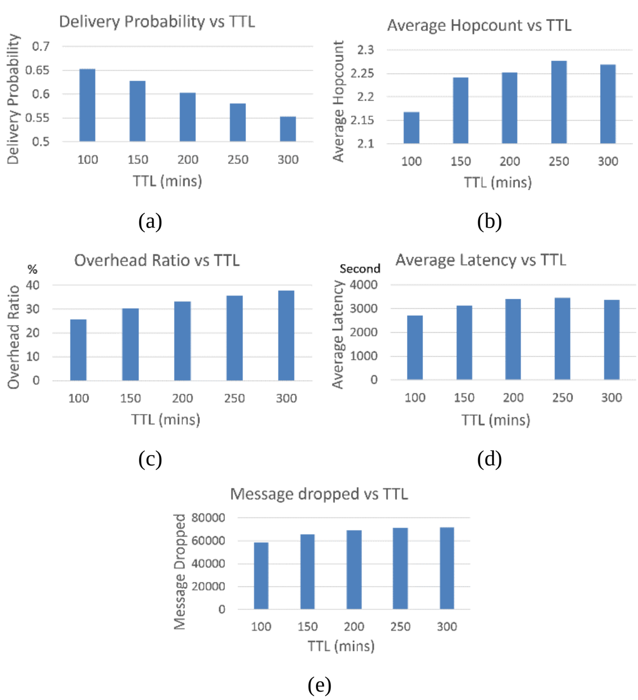


Fig. 33. (a) Delivery probability; (b) average hop count; (c) overhead ratio; (d) average latency; (e) number of messages dropped for different TTL.

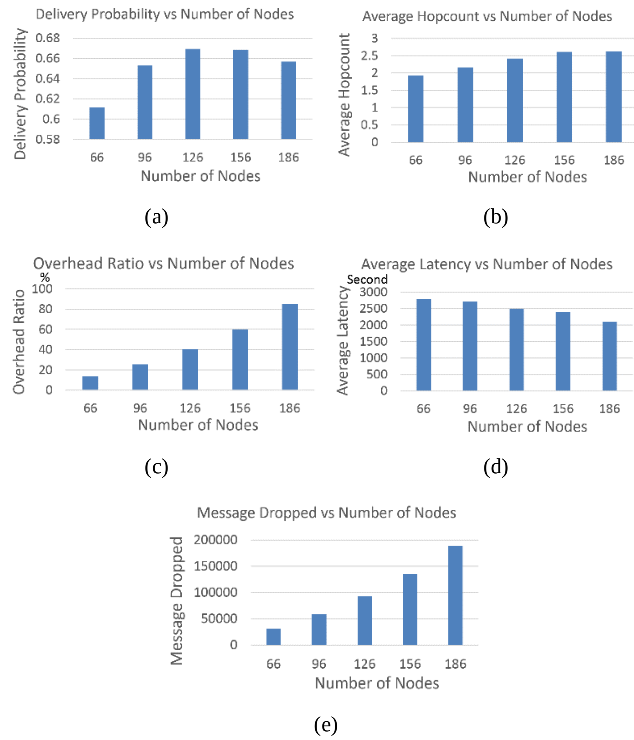


Fig. 34. (a) Delivery probability; (b) average hop count; (c) overhead ratio; (d) average latency; (e) number of messages dropped for different number of nodes.

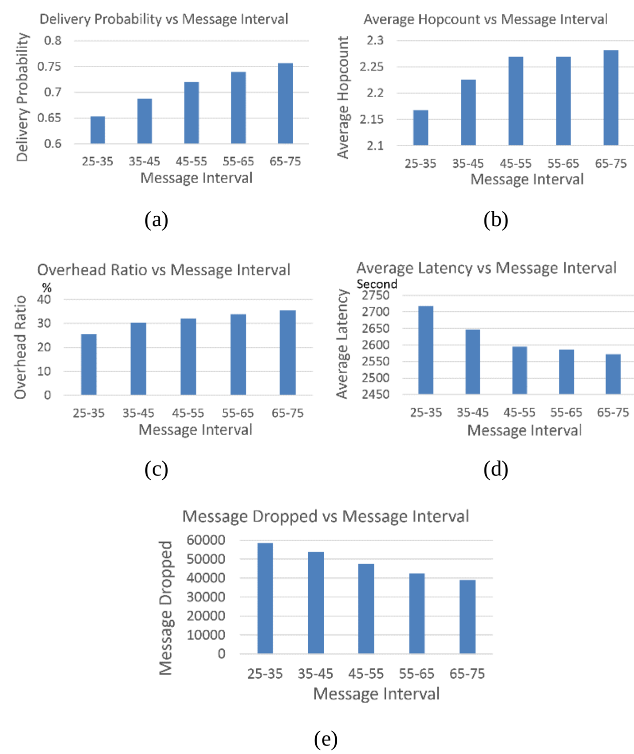


Fig. 35. (a) Delivery probability; (b) average hop count; (c) overhead ratio; (d) average latency; (e) number of messages dropped for different message interval.

TABLE III. COMPARISON BETWEEN KF AND GT-ACR ROUTING PROTOCOLS

	Performance factor	Mean of each factor	
		KF	GT-ACR
TTL (Time To Live)	Delivery Probability	0.60	0.54
	Average Hopcount	2.24	2.42
	Overhead Ratio	32.5	52.1
	Average Latency	3216.2	2513.2
	Messages Dropped	67381.4	91041.4
Number of Nodes	Delivery Probability	0.65	0.53
	Average Hopcount	2.35	2.54
	Overhead Ratio	44.9	66.5
	Average Latency	2501.6	2200.4
	Messages Dropped	101447	152661
Message Interval	Delivery Probability	0.71	0.69
	Average Hopcount	2.24	2.42
	Overhead Ratio	31.5	42.5
	Average Latency	2623.5	2361.3
	Messages Dropped	48233.6	66969.0

In comparisons above between the KF routing scheme and GT-ACR routing protocol with various of Time To Live, number of nodes and message intervals, Table IV gives the various values for the test parameters. The KF routing protocol delivers an outstanding performance for almost all of the factors, particular in number of messages dropped and overhead ratio, the KF performs 35% to 50% and 35% to 60% better than GT-ACR respectively. For data packet delivery probability, the KF presents 3% to 22% better performance. Regarding average hop count, the proposed algorithm offers an average of 8% better. Only on average latency, is the KF 11% to 28% behind GT-ACR.

TABLE IV. PARAMETERS FOR COMPARISON

Parameter	Value	Unit
Time To Live (TTL)	100, 150, 200, 250, 300	Minute
Number of nodes	66, 96, 126, 156, 186	Node
Message intervals	25-35, 35-45, 45-55, 55-65, 65- 75	Second

The comparison results show that the KF has a significant performance among the latest DTN routing protocols, it only make a small sacrifice in the message delay to get outstanding improvements on others wireless system performance metrics.

D. Summary

In simple mobile networks, the performance for all relaying schemes is very stable as there is little difference for various network densities. In comparison to other routing plans, the KF strategy delivers the same performance apart from Spray and Focus, with fewer hops, which can save transmission energy for the entire relaying process and help to improve network security. Spray and Focus offers a higher delivery probability but this comes at the cost of an extremely high average latency. Such a long delay might not be applicable for some applications, even in a DTN system.

For complex wireless networks, the routing strategies test results show a significantly different performance in the various setups and network conditions, but the overall delivery probability gets substantially improved compared to that in simple networks. The delivery probabilities of Spray and Focus are much better than other methods with improved overhead ratio and average hop count but at the price of even greater latency; for some scenarios, this will be unacceptably high. Furthermore, as the node density increases further, this protocol is unable to achieve its function, which pulls down its overall performance. Comparing all key factors, the KF routing scheme shows a good overall performance, and it balances different factors for various scenarios, which presents a good resilience and tolerance.

In comparison with the latest DTN routing techniques, the significant improvements for most factors of wireless system performance indicate that mobile subscribers take advantage of the prediction capability of the KF.

VI. CONCLUSIONS AND FUTURE WORK

The KF routing protocol shows itself to be a versatile and useful one that offers wide ranging good resilience and tolerance when compared to the other existing protocols tested, and even to the latest techniques. Thus, it is a general purpose paradigm that offers steady outcomes in a broad range of system conditions without significant changes to key network factors. This is a significant advantage since it is desirable in DTN networks for protocols to deliver near equal performance under unpredictable conditions.

The KF algorithm enables smart devices to predict and track the motion of targeted mobile nodes and assist them to find the next hop as a better or best option for a message relaying route. In simple networks, it takes the most advantage of Direct Delivery routing to maintain the overhead ratio at zero and the number of hops as one. This means that the KF protocol offers efficiency without wasting any resource to transfer unnecessary packets. Meanwhile, employing fewer hops saves packet forwarding energy and avoids surplus intervention by intermediaries since portable devices have limited power and buffering space, which minimizes the negative effort to other mobile subscribers and the whole wireless system. For complex networks, the KF scheme benefits from the growing number of host nodes as there are more candidates in the prediction pool for the relay selection, so the delivery probability can steadily rise without affecting other key factors.

The strength of the KF method is that the algorithm is rather small and simple and thus a wide range of smart portable gadgets are able to process the program easily. Moreover, the algorithm does not require substantial memory resources to store the movement history of targeted mobile nodes. With growing numbers of subscribers and more smart terminals offering connectivity in the mobile system, routing strategies that rely on the encounter history could face an unprecedented challenge due to the exponential increase in processing load and memory requests, despite the fast growing capability of smart devices. The KF routing algorithm will be of yet further utility in mobile networks.

As a classical optimal prediction and tracking algorithm, the KF is suitable for many scenarios, since only small portion of wireless users will exhibit high mobility [12]. The introduction of users who move rapidly according to a random walker model as described by Shang [35] would lead to significant prediction errors. Hence, to broaden the application of this smart relaying scheme to include such very mobile users, other algorithms that can improve the prediction and tracking performance for the manoeuvring model, such as the Extended KF (EKF) [36], Unscented KF (UKF), Particle Filter and other potential filtering schemes [29], and more applications in DTN will be examined in the future.

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