Received: 26 March 2020 | Revised: 8 December 2020 | Accepted: 12 December 2020

IET Networks

DOI: 10.1049/ntw2.12008

ORIGINAL RESEARCH PAPER

Innovative mutual information-based weighting scheme in stateless opportunistic networks

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Abstract

Recently, opportunistic networks (OppNets) are considered as one of the most attractive developments of mobile ad hoc networks that have emerged, thanks to the development of intelligent devices. Owing to the harsh and dynamic topology of these networks, attaining high delivery ratio is a challenging issue. Hence, it is imperative to select which node's attribute must be adjusted to achieve a higher performance in such unpredictable networks. A mutual information-based weighting scheme (MIWS) that exploits the entropy concept to assess the impact of the nodes' attributes on the network performance was proposed. The weighting procedure aims to figure out the correlative relations between different attributes and delivery ratio performance of the network. The high weight of certain attributes implies a correspondingly high impact in achieving efficient data forwarding. The proposed scheme is proofed conceptually and simulated using the Opportunistic Network Environment simulator. In contrast to previous studies conducted in the context of weight resolution, the proposed approach allows us to address this issue in real-time stateless non-social OppNets. Regardless of the deployed routing protocol, experiments show that adjusting nodes' attributes based on the proposed MIWS can improve the performance up to encouraging delivery ratios.

1 | INTRODUCTION

Opportunistic networks (OppNets) are challenging networks in which contacts are irregular and the performance of links varies widely. The mobility of nodes results in instability of the paths between sources and destinations. In such networks, the store-carry-and-forward (SCF) paradigm has become the traditional data forwarding mechanism [1, 2]. In the SCF mechanism, each node stores data packets in the buffer. When the node encounters another node, it forwards the duplicated data packets. However, as each node forwards the duplicated data packets to all nodes it encounters, network resources such as bandwidth (BW) and packet buffer of all nodes are consumed significantly.

Many research studies have been devoted to improve the performance of the OppNets by means of proper routing algorithms able to find routes according to some optimization criteria and network metrics [3–6]. Delivery ratio, transmission latency, BW and packet buffer are considered as the most important metrics in the OppNets. The maintaining of high delivery ratio with minimizing the end to end delay is becoming a major challenge in OppNets. The basic methodology to address this issue is to flood the network with message copies in the hope that an error free message will reach the destination. However, this approach will overwhelm the network with redundant copies of messages and drain network resources. A more sophisticated approach is to codify messages by forwarding them only to nodes who are more likely to meet destination. This can be achieved through the exchange of messages between the nodes when they meet with each other. Currently, many researches endeavours to maximize the probability of message delivery while minimizing the end to end delay by means of involving node's attributes in the forwarding metric's expression. Node's attributes represent various characteristics of a node, such as available buffer space, mobility speed (MobSp), BW, information about node's community. The impact of a node's attribute is generally quantified by a specific weight.

Motivated by the above considerations, we propose a mutual information-based weighting scheme (MIWS).

The proposed weighting method is achieved by using the concept of mutual information between random variables which allows estimating the amount of information that knowing either variable provides about the other. The weights are calculated by measuring the amount of information obtained about the nodes' relaying effectiveness through observing the nodes' attributes. Certain attributes are more significant than others, or they are more semantically important than others. We emphasize that the weight of an attribute is an indicator of an efficient data forwarding achievement, that is, the larger the attribute's weight is, the higher the impact of the attribute to the forwarding efficiency is. The resulting scheme is referred to as MIWS. To the best of our knowledge, there is no previous work dealing with the estimation of weights using mutual information between attributes of nodes and network effectiveness. We also emphasize that the proposed weighting approach makes it possible to recognize the most impactful attribute in stateless, non-social OppNets in real time where the environment is characterized by a high degree of randomness and it is difficult to reveal a meaningful statement about the attributes that must be met in the routing protocols to achieve high performance. This is indeed an important contribution to this paper. Most of the previous research and existing schemes, if not all, illustrate knowledge about weight calculation of attributes by focusing only on stateful or social OppNets in non-real time. It is worth to note that stateful OppNets require an entity to preserve and manage details for communication partners, however, in stateless OppNets, there is no requirement for a central entity to save and manage status for communications among devices that are appointed to a network. In addition, and in contrast to the forwarding in social OppNets, no specific characteristics or user behaviours are required to conduct the proposed weighting approach.

The proposed scheme is proofed conceptually and simulated using the well-known Opportunistic Network Environment (ONE) simulator [7]. Regardless of the applied routing protocol, experiments show that adjusting attributes of nodes based on the proposed MIWS can improve the performance up to encouraging delivery ratios. This approach is very promising for the recognition of the most impactful attribute in OppNets where attaining high delivery ratio is a challenging issue due to their harsh and dynamic topologies. On top of that, the proposed scheme could be integrated as a plug-in in routing protocols so as to involve the estimated weights in the message forwarding decisions.

The remainder of this paper is organised as follows: Section 2 presents related works. Section 3 describes the proposed MIWS. Performance evaluation is presented in Section 4. At last we give a conclusion and point out some perspectives for future researches.

2 | RELATED WORKS

In this section, we describe some of the existing opportunistic forwarding methods. Furthermore, we list some routing approaches based on attributes of nodes in OppNets. Several machine learning based approaches exploiting the attributes of nodes are also presented. Finally, some approaches are presented that incorporate the concept of entropy into the forwarding process in OppNets.

In OppNets, mobile nodes are not supposed to possess or acquire any knowledge about the network topology. Routes from the sender to the destination of a message are dynamically created, and any possible node can opportunistically be used as the next hop if the message is more likely to be brought closer or faster to its final destination. For these reasons, relaying data in OppNets is a challenge.

Some routers for OppNets, like the Epidemic router [8] and the Spray and Wait (SaW) router [9], use a flooding-based principle of spreading copies of the messages to newly discovered contacts. In the Epidemic routing protocol, a node forwards a packet to all of its neighbours, and each node receiving the packet also forwards it to its neighbours. It has been shown that in Epidemic schemes an optimal delivery ratio and a lower average delay could be achieved if the buffer size is infinite. Epidemic Routing incurs significant demand on both BW and buffer. In respect to this issue, there are many studies to make Epidemic routing consume fewer resources such as [9, 10]. Spyropoulos et al. [9] proposed the so called SaW technique to control the level of flooding. SaW has two phases; in the first phase, the source node 'sprays' a predefined number of copies to the network, and then in the 'wait' phase the nodes do direct delivery to the destination. In ref. [10], the authors proposed control flooding by restricting it to certain areas, known as cells. They used a special node to forward messages to another cell and the passed messages are dropped from the current cell. The authors in ref. [11], have recently proposed an approach establishing a message duplicate adaptive allocation and spray routing strategy algorithm. The model allows to develop a self-adaptive control replication transmission mode.

A lot of research has suggested controlling the flood scheme based on utility functions. These utility functions depend on the history of the previous contacts and the transitive calculation. MaxProp [12] is one of the first routers proposed in this category. The MaxProp router uses an estimated delivery likelihood for each node in the network according to historical data. So, a node schedules packets transmission to its peers based on the path likelihoods and determines which packets should be deleted when buffer space is almost full. PRoPHET is also an example of a routing protocol based on utility functions [13]. PRoPHET estimates a probabilistic metric called delivery predictability which characterizes the probability of successfully delivering a message to the destination from the local node. If two nodes are often encountered, they have high delivery predictability to each other. However, the forwarding metric of PRoPHET doesn't take into account the nodes' attributes, which undoubtedly play an important role. Later, many researchers built their forwarding metrics on PRoPHET to improve it. For instance, in ref. [14], the authors proposed a DEEP scheme to improve the original version of PRoPHET by including energy in their considerations. In ref. [15], the authors proposed the PRoPHET + routing protocol, which shaped its forwarding metric based on the attributes of a weighted node. They inherit nodes' attributes, namely buffer size, BW, popularity, and predictability. However, the weights of the nodes' attributes are estimated based on work experience. The authors confirmed that users need to adjust weight values according to the actual scenario. In ref. [16], the authors combined PRoPHET routing protocol with an acumen buffer management scheme. They take into consideration two issues, namely limiting the maximum number of message copies and deleting the node cache in time.

Some special connections between users are reflected by social attributes of humans, which can be a strong basis for forwarding messages. Therefore, opportunistic social networks are becoming a new trend that recently emerged through the use of human behaviours and social relationships to build more efficient and trustworthy message dissemination schemes. For instance, but not limited, the authors in ref. [17] established a fuzzy routing-forwarding algorithm exploiting node similarity, namely the mobile and social similarities between nodes and the destination. The authors in ref. [18] propose a transmission strategy based on node socialization, which divides nodes in the network into several different communities. The scheme involves a community reduction method that removes some inefficient nodes according to the attributes of optimal relay nodes. In ref. [19], the authors propose an energy-efficient altruism-based message forwarding protocol for opportunistic networks, where social matrices are exploited to establish the reliability of a node in participating in the message forwarding procedure. Nguyen et al. [20] recommended a social context-based routing algorithm based on context information prediction. This algorithm essays to predict the context information related to the node via historical communication statistics of nodes. Meanwhile, the authors in ref. [21] proposed the Predict and Forward algorithm, which is an efficient routing-delivery scheme based on node profile in OppNets. The node profile effectively characterizes nodes by analysing and comparing their attributes rather than network addresses such as physical characteristics, places of residence, workplaces, occupations or hobbies.

Recently many researches incorporate machine learning as a tool to investigate the impact of nodes' attributes. For instance, in ref. [22], authors proposed the cognitive routing protocol for OppNets (CRPO), a neural networks machine learning scheme, to make acumen forwarding decisions. CRPO scheme depends on buffers, speed difference, normalized distance and destination contacts history. However, due to the method of calculating the normalized distance, this approach is applied to stateful OppNets. The authors in ref. [23] proposed a kROp routing scheme. This scheme uses the k-means machine learning tool to group neighbouring nodes into k clusters based on the buffer size, number of successfully delivered messages, distance from target and number of contacts with the target. The kROp node forwards messages to the most optimal cluster members. Although this approach is valid in stateless OppNets, it does not specify the number of clusters k to be formed. In addition, other attributes of nodes, such as degree of mobility, which plays a significant role in the performance of OppNets, are not involved [24]. The MOTOR approach, proposed in ref. [25], is based on the optimization of a weighted function for formulating the message forwarding decision. However, since knowledge of the distances between all nodes in the network is required, this scheme is only used for stateful OppNets. In ref. [26], authors used a machine learning scheme to learn the weights of some attributes of nodes such as buffer, remaining energy, MobSp, popularity. In fact, they calculate the likelihood of message delivery success to their destination based on two machine learning models, namely neural networks and decision tree. Both models only work after they have been created from a training data set. Therefore, they are only suitable for the scenarios for which they were designed. In a recent publication [27], the authors proposed a link prediction approach for opportunistic networks based on random walk and a deep belief network. A predictive model is established based on a deep belief network which draw out the time-domain characteristics in the process of dynamic evolution of the opportunistic network.

In addition, many recent researches benefit from revisiting the information theoretical concept of the entropy in OppNets. For example, authors in ref. [28] suggest using the entropy concept to estimate the freedom of node movement directions. The nodes that are most likely to move to more locations are selected. It is very likely that these nodes will reach the destinations of the messages. However, because this approach relies on global position information, it cannot be used in stateless OppNets because global information is not available on these networks. The authors in ref. [29] used the concept of entropy to calculate the metrics of centrality and similarity. Despite the impressive results of this approach, however, it is only suitable for social OppNets where node membership information is available. Authors in refs. [30, 31] suggest employing the concept of hesitant fuzzy entropy to reduce energy consumption in the network. Although the proposed approaches succeeded in saving energy and increasing the network lifetime, they were tailored for the system model for which they were designed.

3 | MUTUAL INFORMATION-BASED WEIGHTING SCHEME

The use of entropy to measure attribute's weights is inspired from the ability of mutual information to measure the degree of dependency between random variables. Mutual information of two random variables allows to estimate the amount of information that knowing either variable provides about the other. This section aims to present a weighting procedure based on the mutual information between nodes effectiveness and attributes of nodes so as to figure out the correlative relations between different attributes and delivery ratio performance of the network. Let $\mathbf{Y}$ be a random variable that takes two values, effective and ineffective, denoted by eff and ineff, respectively. Effective and ineffective indicates whether a node in the vicinity of a certain node, that is, within its communication range, is effective or ineffective. A node is characterized as effective or ineffective based on its successful number of forwarding messages compared to the average successful forwarding messages of all neighbouring nodes. The set of the neighbouring nodes inside a node's communication range is denoted by $\mathbf{N}$. The following subsection illustrates an example to explain this issue. Let p_{eff} and p_{ineff} denotes the probabilities of effective and ineffective nodes in the neighbourhood of a given node, respectively. Thus $p_{\text{eff}} = n_{\text{eff}}/W$, where n_{eff} is the number of effective nodes and W is the size of $\mathbf{N}$ and is referred to as window size. It is noteworthy that the window size is constant, but the contained nodes could be altered, that is, whenever a new node enters the communication range, the oldest one is removed from the set $\mathbf{N}$. Hence, a dynamic window concept is adopted. Let $\mathbf{F} = \{f_1, \ldots, f_{n_\mathbf{F}}\}$ be the set of attributes, where $n_\mathbf{F}$ is the number of attributes included in the weights estimation process, and let $\mathbf{V}_{f_i}$ be the set of values that f_i can take, $i = 1, \ldots, n_\mathbf{F}$. V_{f_i} can be considered as a random variable where its probability density function is characterized by the frequency of use of the attribute value, normalized by the total number of nodes. The Entropy of the random variable $\mathbf{Y}$ is given by the following expression [32]:

$$H(\mathbf{Y}) = -\sum_{y=\text{eff},\text{ineff}} p_y \log_2\left(p_y\right). \tag{1}$$

The entropy of $\mathbf{Y}$ given a certain attribute value v from the set $V_{f_i}, i = 1, \ldots, n_\mathbf{F}$, is expressed as follows:

$$H(\mathbf{Y}/\mathbf{V}_{f_i} = v) = -\sum_{y=\text{eff},\text{ineff}} p_{y/v} \log_2\left(p_{y/v}\right), \tag{2}$$

where $p_{y/v}$ is the conditional probability that $\mathbf{Y} = y$, given that $\mathbf{V}_{f_i} = v$. Hence, the entropy of $\mathbf{Y}$ given that the set of attributes $\mathbf{V}_{f_i}$ occurs, could be calculated by averaging the expression above and is given as follows:

$$\begin{aligned} H(\mathbf{Y}/\mathbf{V}_{f_i}) &= -\sum_{v\in\mathbf{V}_{f_i}} p_v \sum_{y=\text{eff},\text{ineff}} p_{y/v} \log_2\left(p_{y/v}\right) \\ &= -\sum_{v\in\mathbf{V}_{f_i}} \sum_{y=\text{eff},\text{ineff}} p_{y,v} \log_2\left(p_{y/v}\right). \end{aligned} \tag{3}$$

The basic idea behind the proposed weighting approach is to assign each attribute a weight corresponding to the amount of mutual information between nodes' effectiveness and the attribute. Certain attributes are more significant than others, or they are more semantically important than others. The mutual information between the effectiveness random variable $\mathbf{Y}$ and the attribute set $\mathbf{V}_{f_i}$ quantifies the amount of information obtained about $\mathbf{Y}$ through observing $\mathbf{V}_{f_i}$ and is given by the following expression:

$$I(\mathbf{Y}, \mathbf{V}_{f_i}) = H(\mathbf{Y}) - H(\mathbf{Y}/\mathbf{V}_{f_i}). \tag{4}$$

Assuming that the knowledge of $\mathbf{V}_{f_i}$ reduces dramatically the randomness of $\mathbf{Y}$. This reflects the impact of $\mathbf{V}_{f_i}$ on the neighbouring node's forwarding efficiency. Hence, the reduction of the randomness when knowing the distribution of a certain attribute, could be considered as the weight of the corresponding attribute. For this reason, the weight of the attribute f_i, $i = 1, \ldots, n_\mathbf{F}$, will be calculated as follows:

$$\begin{aligned} w(f_i) &= \frac{I(\mathbf{Y}, \mathbf{V}_{f_i})}{H(\mathbf{Y})}, \\ &= 1 - \frac{H(\mathbf{Y}/\mathbf{V}_{f_i})}{H(\mathbf{Y})}. \end{aligned} \tag{5}$$

The proposed attributes' weighting method is referred to as Mutual Information based Weighting scheme (MIWS).

The most impactful attribute is then determined by

$$\hat{f} = \arg\left(\max_{f_i\in\mathbf{F}}\{w(f_i)\}\right). \tag{6}$$

Lemma: The weight of a given attribute resulting from the MIWS is always positive.

Proof: Please refer to appendix.

The algorithm of the proposed MIWS is resumed below.

Algorithm: Mutual information-based weighting scheme

Input:

- **N** ← **set of the neighbouring nodes**
- **F** ← $\{f_1, \ldots, f_{n_\mathbf{F}}\}$
- **Y** ← $\{y_1, \ldots, y_W\}$
- $\mathbf{V}_{f_i}$ ← $\{v_1, \ldots, v_{n_{f_i}}\}, i = 1, \ldots, n_\mathbf{F}$

Output: $w(f_i)$, $i = 1, \ldots, n_\mathrm{F}$

---

begin

  for each attribute $f_i \in \mathrm{F}$

  do

    $H(\mathbf{Y})$ ← Entropy of **Y**

    $H(\mathbf{Y}/\mathbf{V}_{f_i})$ ← Entropy of **Y** given $\mathbf{V}_{f_i}$

    $w(f_i) = 1 - H(\mathbf{Y}/\mathbf{V}_{f_i})/H(\mathbf{Y})$

  end for

  $\hat{f} = \arg(\max_{f_i\in\mathbf{F}}\{w(f_i)\})$ ← most impactful attribute

end

3.1 | Case study

Figure 1 shows the scenario corresponding to the studied case, where six nodes encounter the node n and enter within its communication range.

The information obtained by the node n from its neighbouring nodes are listed in Table 1. Each node should broadcast the attributes to the neighbouring nodes. The attributes' weights are propagated as a broadcast message and will be received by all neighbouring nodes which are within the communication range. Security and privacy management protocol should authenticate the message exchange between the nodes in the networks. In ref. [33] security and privacy issue in opportunistic networks are highlighted. Based on the received attributes' messages, the MIWS estimates the weights of the attributes BW, buffer size and MobSp, which are denoted by BW, BS and MobSp, respectively, that is, the set of attributes is $\mathbf{F} = \{\text{BW, BS, MobSp}\}$. The number of successful relayed messages is used as a metric for the node's effectiveness. The window size is equal the number of neighbouring nodes and hence equal to 6 as mentioned before. In order to characterize whether the node is effective or ineffective, the number of successful relaying is compared to the average. In this case study the average is equal to 7.3. This means that, if the number of successful relaying is larger than the average then the node is characterized as effective, otherwise the node is characterized as ineffective.

If we apply Equation (1) to the last field in Table 1, we get a value of one because the probabilities of effective and ineffective are the same. It is worth noting that in the case that all values in $\mathbf{Y}$ are eff or ineff, the entropy of $\mathbf{Y}$ becomes zero and therefore cannot be used to estimate the weight of attributes. As explained above, the attribute's weight is measured as the decreasing amount of $\mathbf{Y}$'s entropy when the distribution of the attribute is known. Using the MIWS to evaluate the weight of an attribute, we have to apply Equation (5). As stipulated in Table 1, the buffers provide only two distinct sizes 4 and 32 MB, that is, $\mathbf{V}_{\text{BS}} = \{4, 32\}$, where $p(\mathbf{V}_{\text{BS}} = 4) = 4/6$ as shown in Table 1.

Table 2 shows an example to calculate the conditional probability $p_{y/v}$ of the neighbouring nodes' effectiveness (y) given the buffer size (v) from the set $\mathbf{V}_{\text{BS}}$. The presented example relies on the events presented in Table 1. Hence, the conditioned entropy of $\mathbf{Y}$ when knowing the distribution of $\mathbf{V}_{\text{BS}}$ is calculated by applying Equation (3) and is given as follows:

$$H(\mathbf{Y}/\mathbf{V}_{\text{BS}}) = -\sum_{v=4,32}\sum_{y=\text{eff,ineff}} p_{y,v}\log_2\left(p_{y/v}\right) = 0.54 \quad \text{bit.}$$

Applying Equation (5), we can calculate the weight of the buffer size attribute which is given by:

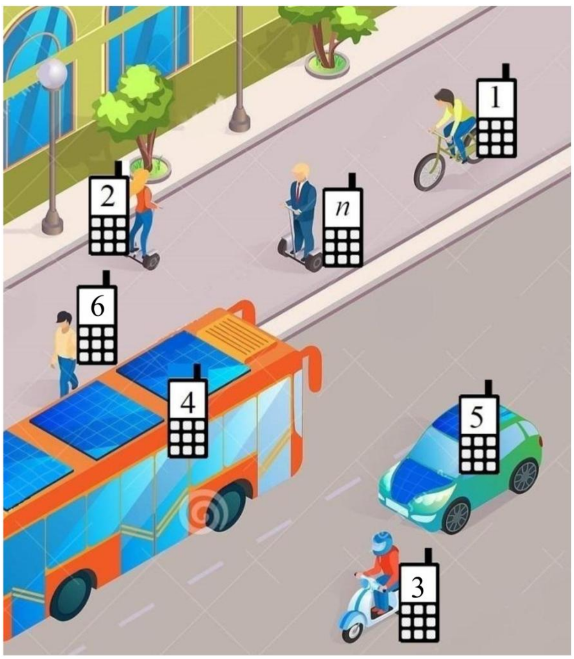

FIGURE 1 case study scenario

TABLE 2 Example of conditional probability calculation of the neighbouring nodes' effectiveness given the buffer size from Table 1 for the calculation of the buffer size attribute's weight

Effectiveness (y)	BS (v)	p_v	$p_{y,v}$	$p_{y/v}$
eff	4	4/6	1/2	3/4
ineff	4	4/6	1/6	1/4
eff	32	2/6	0	0
ineff	32	2/6	1/3	1

TABLE 1 Data obtained by node n from its neighbouring nodes

Node ID	Bandwidth (BW) [kB/s]	Buffer size (BS) [MB]	Mobility speed (MobSp) [m/s]	Number of successful relays	eff or ineff
1	250	4	0.5	15	eff
2	1	4	0.5	10	eff
3	250	32	13	2	ineff
4	1	32	13	1	ineff
5	250	4	13	3	ineff
6	1	4	0.5	13	eff

$$
\begin{aligned}
w(\mathrm{BS}) &= 1 - \frac{H(\mathbf{Y}/\mathbf{V}_{\mathrm{BS}})}{H(\mathbf{Y})} \\
&= 1 - 0.54 \\
&= 0.46
\end{aligned}
$$

The same steps are carried out for the calculation of the MobSp and BW attributes, where we obtain:

$$
\begin{aligned}
w(\mathrm{MobSp}) &= 1 \\
w(\mathrm{BW}) &= 0.08
\end{aligned}
$$

Obviously the MobSp shows the highest weight, followed by the buffer size and the bandwidth weights. As given in Equation (6), we conclude that the MobSp is the most impactful attribute among the attributes in the studied scenario on the performance in terms of the relayed messages.

4 | PERFORMANCE EVALUATION

In this section, we apply the proposed MIWS in conjunction with some routing algorithms to evaluate its performance in terms of delivery ratio, overhead ratio, average delay and efficiency.

We consider an opportunistic network with 50 nodes classified in five groups, where each group is defined by a speed range. This division into speed ranges was used to obtain reduced values for this attribute, which makes calculation easier when reducing the attribute set's alphabet size. In addition, the range size is so chosen that all the MobSps of all possible mobile groups (Pedestrian, Bicycle, Bike, Car, Train) are covered. Helsinki city centre is chosen as environment for the experiments. Bluetooth is used as communication medium between nodes. Two different scenarios are analysed. The attributes of both scenarios, regarding each group, are listed in Tables 3 and 4 (columns $2-4$) and implemented using the well-known ONE simulator. The ONE simulator has a set of pre-made features like movement models and protocols for routing. The generated messages have size range of 64 to 500 kB. The surface of the experimentation area is $4500 \times 3400\ \mathrm{m}^2$. No assignment of any special routes or maps to any group is considered. We assume that all nodes are energy-recharged.

TABLE 4 Simulation settings of the five groups in scenario 2

Group ID	BW (MB/s)	BS (MB)	MobSp (m/s)
1	1	8	65–120
2	1	1	33–65
3	1	2	0.5–1.5
4	1	4	4–10
5	1	16	16–32

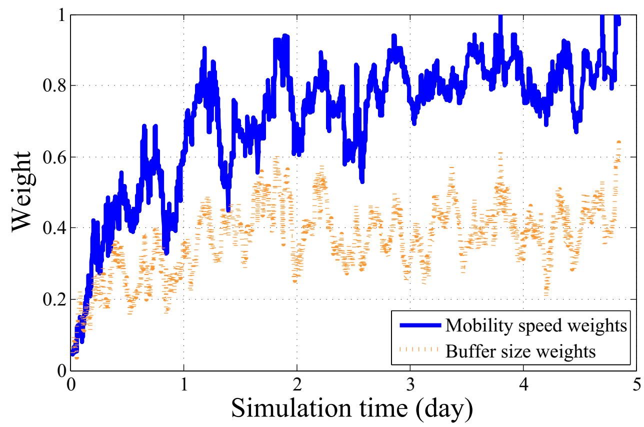

FIGURE 2 Mobility speed and buffer size weight evolution for window size $W = 100$

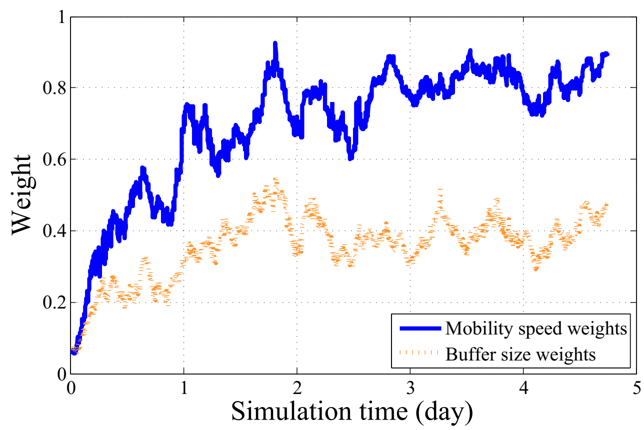

FIGURE 3 Mobility speed and buffer size weight evolution for window size $W = 200$

TABLE 3 Simulation settings of the five groups in scenario 1

Group ID	BW (MB/s)	BS (MB)	MobSp (m/s)	Number of relayed messages
1	0.1	1	65–120	598
2	0.1	2	33–65	764
3	0.1	64	0.5–1.5	1203
4	0.1	16	4–10	1517
5	0.1	8	16–32	745

We evaluate the proposed MIWS to estimate the weights of the attributes in both scenarios. We emphasize that the two scenarios mainly differ in buffer size and bandwidth. The bandwidth in scenario 2 is ten times than that in scenario 1. In both scenarios, the groups are assigned the same MobSp ranges.

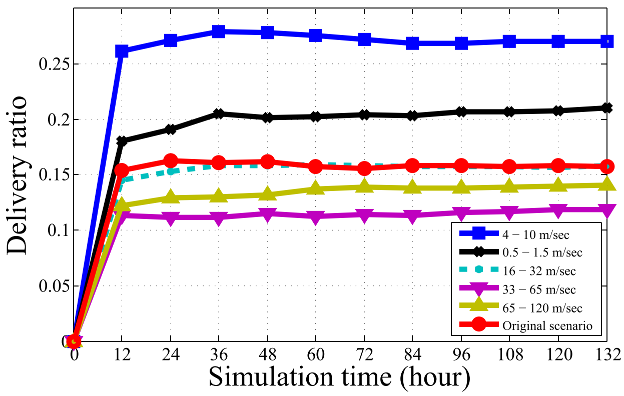

FIGURE 4 Performance of the MIWS in terms of delivery ratio when varying the mobility speed attribute. MIWS, mutual information-based weighting scheme

4.1 | Weights estimation of scenario 1

Figure 2 shows the weight variation of buffer size and MobSp attributes over time for a window size of 100 nodes, while Figure 3 shows the weight variation of the same attributes for a window size of 200 nodes. All estimated weights gradually increase with increasing simulation time. The fact that the weights initially take small values can be explained that initially the effectiveness of the nodes is minted by no attribute. This means that in the first trial steps, the knowledge of the attribute does not lead to an important decline in the effectiveness information. With increasing time, active nodes are distinguished in favour of other nodes, and the effect of distributing a particular attribute will gradually shape the effectiveness of nodes. Hence, the conditional effectiveness information given that a certain attribute's distribution is realized, is reduced and hence the weight possibly increase. In other words, the attribute's distribution of nodes will mint the nodes' effectiveness and therefore reduces their randomness. In case that the node's attribute don't infer the effectiveness, the conditional effectiveness entropy given the attribute set will be very close to the effectiveness entropy itself and hence the weight remains small. The observed fluctuations in Figure 3 are finer than those in

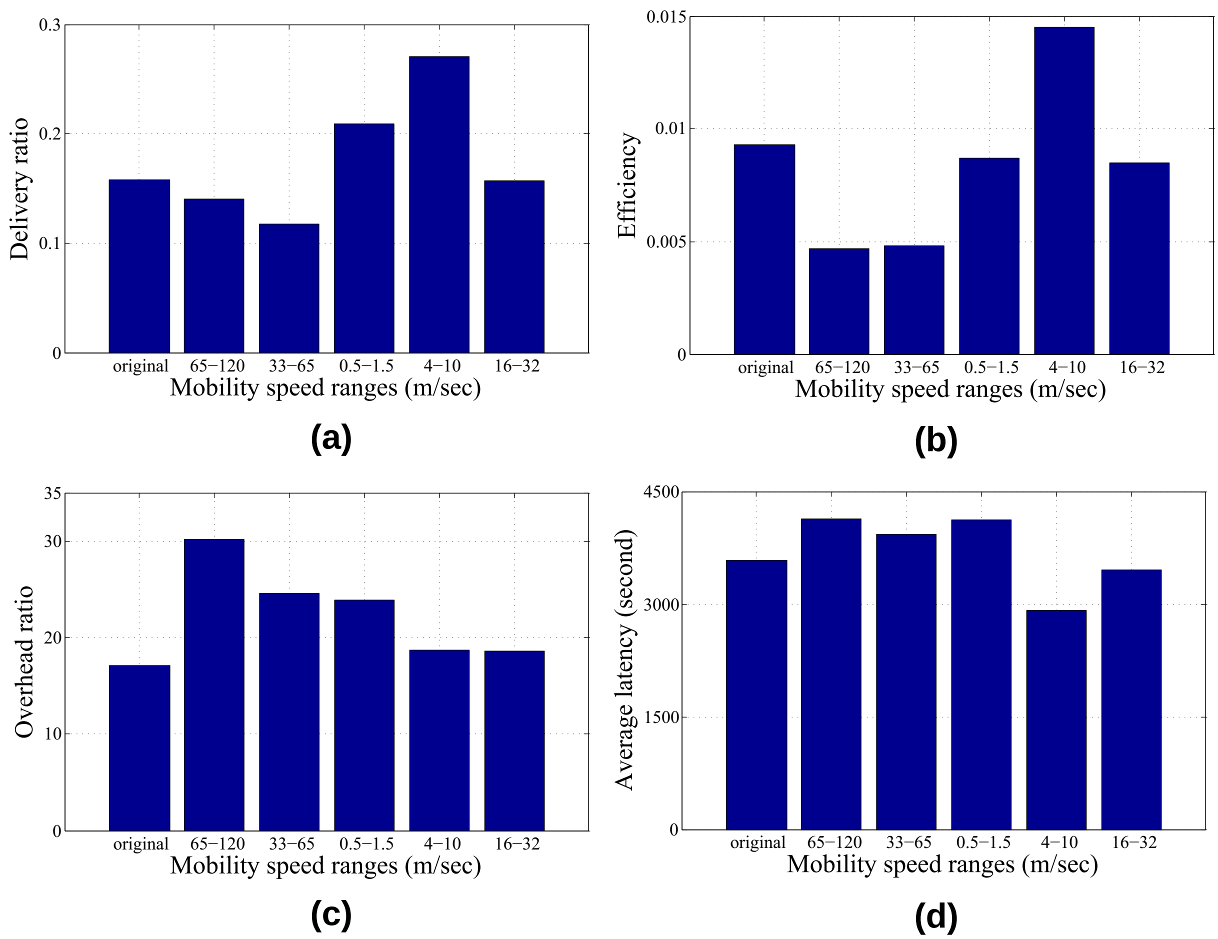

FIGURE 5 Performance evaluation of the proposed MIWS in terms of different metrics, namely, delivery ratio (a), efficiency (b), overhead ratio (c) and average latency (d), when varying the mobility speed attribute. MIWS, mutual information-based weighting scheme

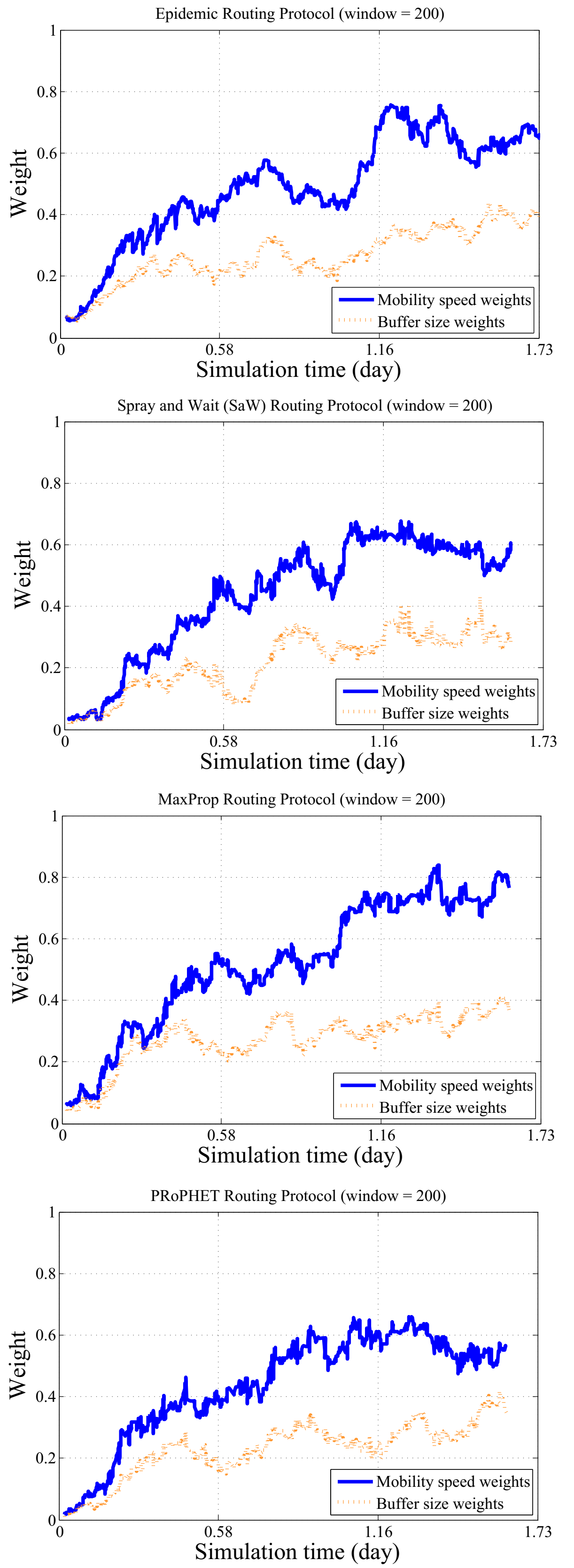

FIGURE 6 Time evolution of mobility speed and buffer size weights for different routing protocols applied to the nodes of scenario 1

Figure 2. Thus, the proposed model becomes more precise with larger window sizes. It is noteworthy that the transmission speed weights are zero as the bandwidth values are identical for all nodes.

4.2 | Impact of the optimal attribute on network performance

As shown in Figures 2 and 3, the MobSp attribute has greater weight, and hence, it has larger impact on the forwarding performance. The number of the relayed messages of the five groups are listed in the fifth column of Table 3. By referring to these later, we observe that group 4 has the highest number of successful relayed messages. Since the MobSp attribute provides the highest weight, we can deduce that group 4 has the optimal MobSp for this scenario. In order to confirm this inference, we repeat the same experiment for all groups, keeping the same setting except for the MobSp, which is set to 4–10 m/s for all groups as in group 4.

Figure 4 shows a comparison between the performance of the original scenario where the nodes of each group move with their own speeds that are stipulated in Table 3 and that of the optimal scenario where all nodes in all groups move with the optimal speed (4–10 m/s). The simulation results show that the delivery ratio raised to 70% after adjusting the nodes to move at optimal speed. To consolidate this finding, five further experiments are conducted. In each experiment, all nodes have the same MobSp range. Figure 4 shows that the network achieves the best performance when the MobSp of 4–10 m/s is used.

Figure 5 illustrates the performance of the proposed MIWS in terms of delivery ratio, overhead ratio, efficiency, and average delay for the original setting, as well as five further settings, each with a single speed range for all applied nodes. The speed ranges are those listed in Table 3. In addition, Figure 5a,d shows that the highest delivery ratio and the lowest average delay are achieved when all nodes move with the optimal speed. In addition, Figure 5c shows that the produced overhead ratio of the scenario with optimal speed is about 5% higher than that of the original scenario, which provides the lowest overhead ratio. We emphasize that this difference is negligible and could be explained by the fact that the number of redundant messages when using the optimal speed is slightly larger than that of the original one. The scenario with the optimal MobSp clearly outperforms all other scenarios in terms of efficiency, as shown in Figure 5b.

In all previous experiments, we used the Epidemic routing protocol [8] which is optimal in terms of delivery ratio and latency. Epidemic algorithm is flooding-based in nature, as nodes continuously replicate and transmit messages to newly discovered nodes that do not already holds a copy of the message. In fact, both nodes exchange the so-called summary vector, which contains their respective message IDs. The messages remain in buffers until they are delivered to their

TABLE 5 Comparision of percentage improvement of different routing protocols when using the optimal attributes

Routing protocol	Average delivery ratio of original attributes	Average delivery ratio of optimal attributes	Improvement percentage
Epidemic	0.1610	0.2717	70%
PRoPHET	0.1360	0.2717	100%
MaxProp	0.1580	0.2932	86%
SaW	0.1665	0.3154	89%

destination or dropped due to their expired lifetime. Figure 6 shows the results of the estimated attributes' weights for scenario 1 when using different routing protocols, namely:

- Spray and Wait routing protocol [9]: It has two phases; in the first phase, the source node sprays a predefined number of copies to the network, and then in the wait phase all nodes that received a copy of the message wait to meet the destination node directly to deliver data to it
- MaxProp routing protocol [12]: Each node in the network maintains a vector list which contains the estimation of encountering of all other nodes in the network. Message forwarding decisions are performed based on this vector.
- PRoPHET routing protocol [13]: Messages are routed based on the destination's encounter probability which is termed as delivery predictability.

A detailed explanation of the aforementioned routing mechanisms in OppNets has been included in ref. [5].

Figure 6 shows that the weights of the MobSp attribute for all deployed routing protocols are larger than the weights of the buffer size attribute. From this finding, we can conclude that the proposed MIWS can calculate and differentiate weights regardless of the provided routing protocol. This underlines the robustness of the proposed weighting scheme. Furthermore, Table 5 shows a comparison of the performance improvement percentage in terms of delivery ratio between the deployed routing protocols when using the proposed weighting scheme. The proposed weighting scheme shows promising results in conjunction with all protocols. We note that the percentage of improvement differs significantly from one protocol to another. This is due to the way each routing protocol works. This leads us to conclude that the proposed MIWS could be integrated as a plug-in in routing protocols to involve these estimated weights in the message forwarding decisions.

4.3 | Weights estimation of scenario 2

As shown in Tables 3 and 4, the bandwidth (transmission speed) of scenario 2 is ten times larger than that of scenario 1 and the buffer sizes of scenario 2 are smaller than those of scenario 1. Figure 7 shows the estimated attributes' weights of the scenario 2 under different routing protocols as performed for scenario 1 and reveals that, in contrast to scenario 1, in which MobSp plays the most important role in the characterization of the network performance, the buffer size has the greatest influence on the forwarding rate in scenario 2. This can be explained by the fact that transmission speed in scenario 2 is much larger than that of scenario 1, and hence, MobSps of nodes are no longer as important. In turn, buffer sizes play a greater role in determining the network performance in scenario 2 as they have become very restricted. Under other circumstances, this could result other attributes that provide the highest impact on the network performance. Therefore, we could not commit ourselves to a specific attribute value, be it MobSp, buffer size or other attributes.

5 | CONCLUSION AND PERSPECTIVES

We proposed the MIWS which aims to measure the correlative relations between the nodes' attributes and the delivery ratio performance in OppNets. We have proofed conceptually that the proposed scheme can identify the node attribute that has the greatest impact on the forwarding efficiency. In contrast to previous studies, the proposed approach is conducted in the context of stateless non-social OppNets, where the environment is characterized by a high degree of randomness and it is difficult to reveal a meaningful statement about the characteristics that must be met in the routing protocols to achieve high performance. Through extensive simulations, we have shown that, regardless of the routing algorithms used, adjusting the nodes' attributes based on the proposed scheme can improve the performance up to encouraging delivery ratios. To this end, the MIWS provides an innovative way to explore the depths of these networks, so that it becomes possible to determine the importance of the role played by every attribute of the nodes. This opens the door wide to address the aforementioned statement. The estimated weights can be used to control nodes' attributes and can be included in the work flow of the routing process and forwarding decision. For example, by knowing the buffer size's weight, the routing protocol can control buffer consumption in the network. This is the future challenge that will open new horizons in dealing with OppNets with limited resources.

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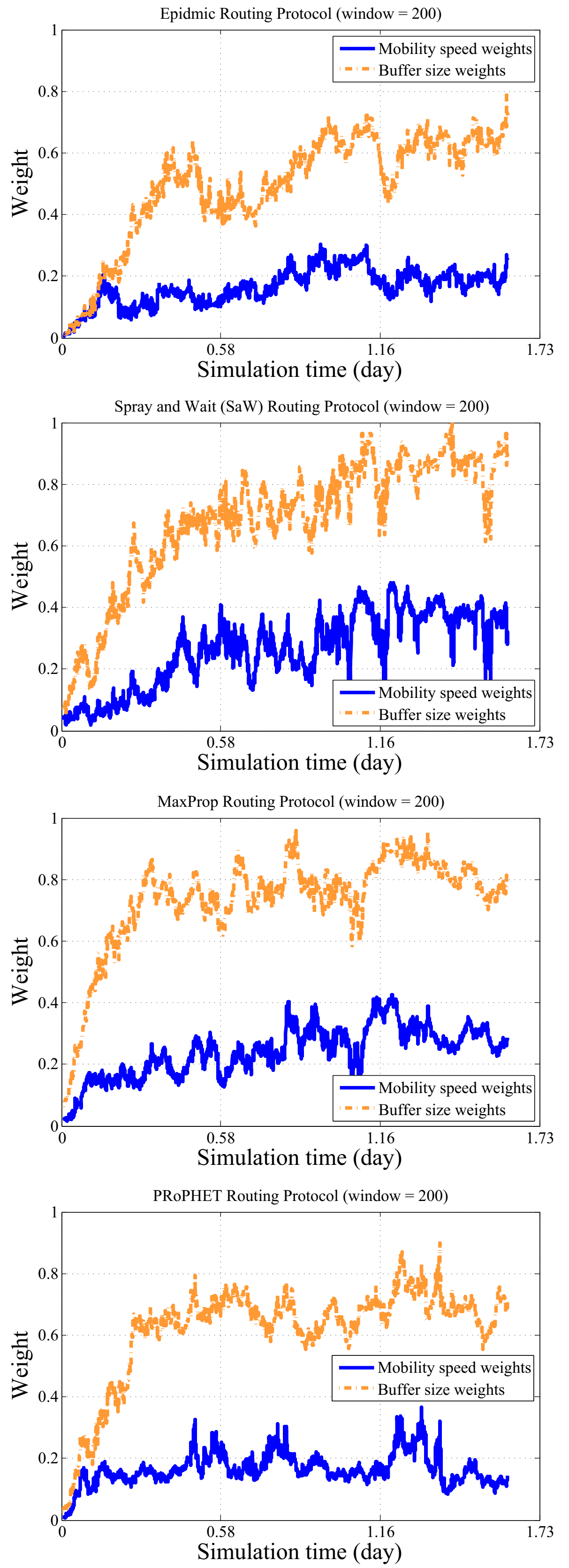

FIGURE 7 Time evolution of mobility speed and buffer size weights for different routing protocols applied to the nodes of scenario 2

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Lenando H, Kurd Ali AH, Chaoui S, Alrfaay M. Innovative mutual information-based weighting scheme in stateless opportunistic networks. *IET Netw*. 2021;10:162–172. https://doi.org/10.1049/ntw2.12008