

# Social mobility and geo-context aware macroscopic routing scheme for mobile opportunistic network

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## ABSTRACT

Mobile opportunistic networks (MONs) are deliberated as important aspect to proliferate the wireless communications. These networks pose several challenges such as network lifetime, storage capacity, and forwarding capacity. End-to-End routing schemes are considered as promising technique solution to deal with these issues. In this domain, opportunistic routing has gained huge attention because it follows the broadcasting nature of wireless communication and focus on selection of relay node for packet transmission to ensure the better quality of service (QoS) and energy efficiency. This work focuses on optimizing the next hop selection process and introduced reinforcement learning approach which considers distance, energy and link connectivity to assign the reward for different actions to identify the suitable relay node. Moreover, geo-context and social behaviour based opportunistic routing models are used to increase the reliability of next hop selection. Similarly, social model considers social profiling, social connectivity, and social interaction model to identify the relay node. The outcome of proposed approach is compared with several existing approaches such as prophet, spray and wait, and epidemic routing in terms of packet delivery, and network overhead. The relative study shows that the proposed approach achieves the average packet delivery as 47.22% and minimizes the network overhead.

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## 1. INTRODUCTION

During last two decades, the communication industry has noticed tremendous advancements in wireless communication technology. This technological growth has led to exponential growth of adoption of wireless mobile devices for several applications [1]. Opportunistic networks (ONs) [2], [3] are a type of ad-hoc network, in which there is no end-to-end path between source and destination. Also, a type of delay tolerant network [4] that can deliver messages with a reasonable delay. In advanced delay-tolerant communication scenarios such as underwater communication, deep space exploration, and smart transportation ONs have been highlighted [5]–[7]. Li *et al.* [8] introduced transmission probability for candidate node selection. Kandhoul and Dhurandher [9], the next-hop choice was made based on the node's estimated message delivery probability and current energy. Zhang *et al.* [10] used reinforcement learning to update node weights and choose candidate sets based on transmission probability, energy, and the number of neighbour nodes within a hop range. Ge and Jiang [11] created a novel hybrid fitness function based on variables including energy, trust, quality of service (QoS), connection, distance, hop count, and network traffic [11]. Fu *et al.* [12] presented a wireless sensor network (WSN) assisted opportunistic network model for disaster management and introduced a novel messaging forwarding NetSpray for efficient communication. Byeon *et al.* [13] presented flooding routing in

multihop wireless network. Guong and Yoon [14] utilized probabilistic routing approach to limit the replication of messages. Adaptive data transmission scheme is applied in social opportunistic network [15]. Ying *et al.* [16] presented a combination of geo-social parameters to design the routing protocol. Kim and Gerla [17] reported the advantage of opportunistic routing in delay tolerant networks (DTNs). Yang *et al.* [18] used the concept of social relationship to improve the communication among opportunistic network members. Wang *et al.* [19] proposed including physical contact social activity-based approach for mobile opportunistic network (MON).

Zhou *et al.* [20] focused on underwater communication strategy as these models have different configuration than the traditional sensor networks. To obtain an efficient path, a Q-learning based model is used to expand the network lifetime, decrease the delay via minimizing the energy consumption. Alghamdi [21] focused on increasing the network lifetime and presented a novel approach for optimized cluster formation and selection of cluster head. The cluster head (CH) selection is carried out based on the energy, distance, and security parameters. Later, dragon fly and firefly optimization methods are combined to formulate the hybrid optimization strategy. Unfortunately, none of the aforementioned protocols fully account for end-to-end performance and the unique aspects of the dynamic environment, making them unsuitable for WSNs that operate in highly dynamic environments. In contrast to these traditional algorithms, opportunistic routing has gained attention which can reduce the packet retransmission caused due to link failure due to its nature to dynamically select the forwarder from neighbouring node. Opportunistic routing can more easily handle to the erratic and changing networks. In order to describe the nodes selection procedure as a supervised multiclass non-linear separable problem, Bangotra *et al.* [22] employed Bayesian machine learning.

Traditional routing methods suffer from various challenges such as random CH selection, use of single-hop in CHs to communicate with sink nodes which is not suitable for large scale networks. Moreover, these networks are dependent on cluster head thus inappropriate selection of cluster head can lead to deteriorate the performance of network. Similarly, unstable cluster head selection leads to frequent variations in CH therefore it increases overall energy consumption. Therefore, the energy consumption, network lifetime and QoS are the important factors to be considered while developing any routing algorithm for WSNs. Aforementioned traditional routing algorithms focus on identifying the best sequence of node from source to destination for packet forwarding. However, the wireless communication follows the broadcast nature where a node can hear the transmission of another node which is in its transmission range. In order to focus on this broadcasting scenario of these networks, opportunistic routing has gained huge attention which takes the advantage of broadcast nature of wireless networks. Several schemes have adopted the opportunistic methodology which are mainly focused on increasing the link reliability and throughput of the system. However, these networks pose several challenges and have special requirements such as reduced power consumption, storage limitations which characterize their different nature of traditional multi-hop mesh networks. Therefore, the challenges have motivated us to develop an opportunistic routing approach considering the various factors to increase the overall performance of the system.

## 2. PROPOSED MODEL

This section presents the proposed macroscopic routing approach for MON, which extracts the social information based on the social behaviour model. Moreover, geolocation information also incorporated to increase the packet delivery. The proposed approach considers three main phases: presenting geo-context aware routing for opportunistic network, development of social behaviour-based model for routing and Q-learning based model for finalizing the forwarder node.

### 2.1. Network architecture and system model

The MON architecture adopted in this work is depicted in Figure 1. According to the social based routing model, the network is divided into three components as social graph, network graph and social parameters for networks. The social graph is denoted as  $G = (V, E)$  as an undirected and unweighted graph representation of community. This work considers that there are  $N$  number of nodes and  $M$  links in the graph. This graph represents a mobile user which has same transmission range as other nodes. Similarly, the link between nodes represents the social relation between nodes where each node can have multiple relations but it can be connected with two nodes only. The connectivity of link depends on the mobility and location of nodes. Figure 2 depicts the logical social relation graph. Similarly, Figure 3 demonstrates the network graph model which shows the change in connectivity at different given time stamps.

This shows the communication status at time  $t$  and change in the communication status at time  $t + 1$ . To deliver the data packets the social community  $C(t)$  and its related parameters can be expressed as follows:

- Social graph: as discussed before  $G$  is the undirected graph of entire social community which is called as social graph where  $V$  denotes the vertices and  $E$  denotes the edges in the network.

- Similarly, to facilitate the routing task, this model considers a collection of disjoint social communities as  $C(t) = \{C(t)_1, C(t)_2, \dots, C(t)_k\}$  where  $C(t)_\epsilon \in C(t), \epsilon \in [1, k]$  belong the community of graph  $G$ . Any node  $n$  present in community  $C(t)$  has set of neighbouring nodes denoted as  $L_n^C = \{m \in C(t)_\epsilon | (n, m) \in E\}$ . Moreover, the  $C(t)_k$  depends on the time instance  $t$  to analyze the node movement.

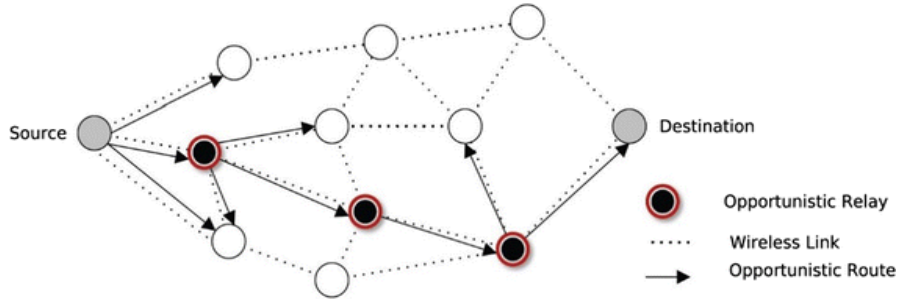


Figure 1. Packet forwarding process in MON

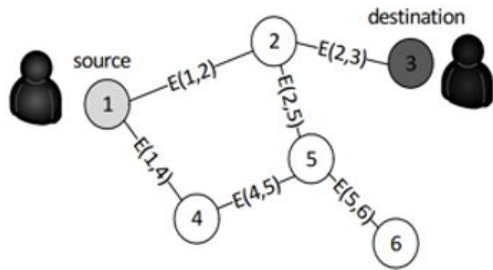


Figure 2. Social graph

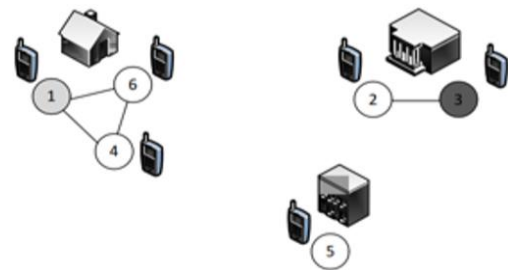


Figure 3. Network graph

The packet exchange consumes most of the energy resources. The energy consumed by the mobile node to transmit the  $b_i$  bit data over a distance  $d$  is given as shown in (1):

$$E_{TX}(b_i, d) = \begin{cases} b_i \times E_{elec} + b_i \times \epsilon_{mp} \times d^4, & d > d_0 \\ b_i \times E_{elec} + b_i \times \epsilon_{fs} \times d^2, & d < d_0 \end{cases} \tag{1}$$

where  $E_{elec}$  denotes the energy consumption for each bit transmission by circuit,  $\epsilon_{fs}$  and  $\epsilon_{mp}$  denote the free-space and multipath energy consumption of amplifier, and  $d_0 = \left(\frac{\epsilon_{fs}}{\epsilon_{mp}}\right)^{\frac{1}{2}}$ . Similarly, the energy consumption in receiving the  $b$  bits is expressed as:  $E_{RX}(n_i) = b_i \times E_{elec}$ .

**2.2. Social mobility and location information model**

The social behaviour model shows that if two entities share the same profile then they will have high probability to be connected for long duration in future. Let  $C(t)$  represents the community as Markov chain model where the probability of node moving from one community to another community is independent to the probability of node being in the previous community. This process of node movement can be defined as Markovian chain as shown in (2):

$$\begin{aligned} \pi_{ij}^n &= P(X_{c+1}^n = j | X_c^n, X_{c-1}^n, X_{c-2}^n, \dots, X_0^n, t_c, t_{c-1}, \dots, t_0) \\ &= P(X_{c+1}^n = j | X_c^n = i, t_c) \end{aligned} \tag{2}$$

where  $C_c^n$  shows that node  $n$  remains in the community  $c$  at time  $t_c$ ,  $\pi_{ij}^n$  is the transition probability of node  $n$  to switch from community  $i$  to community  $j$ . It is assumed that the nodes are allowed to switch their position in discrete time slots, thus the transition probability matrix can be given as  $\Pi_n = \{\pi_{ij}^n: i, j = 1, 2, \dots, |C(t)|\}$  which can be expressed in the form of matrix as shown in (3):

$$\Pi_n = \begin{pmatrix} \pi_{11}^n & \pi_{12}^n & \dots & \pi_{|C(t)|1}^n \\ \pi_{21}^n & \dots & \dots & \pi_{2|C(t)|}^n \\ \dots & \dots & \dots & \dots \\ \pi_{|C(t)|1}^n & \dots & \dots & \pi_{|C(t)||C(t)|}^n \end{pmatrix} \tag{3}$$

where  $C(t)$  denotes the community at time  $t$ . Theoretically, if  $\Pi_n$  is able to cover all transition of each node then the cumulative probability can be denoted as:  $\sum_{j=1}^{C(t)} \pi_{ij}^n = 1$ , however, some transitional probabilities are hard to achieve. Let's consider that node  $n$  keeps record of node's community visit then the probability of node  $n$  can be expressed as shown in (4):

$$\pi_{ij}^n = \frac{H_{ij}}{H_i} \tag{4}$$

where  $H_{ij}$  represents the total visits from community  $i$  to community  $j$  and  $H_i$  is the transition from  $i$  to any other community present at a given certain period of time.

**2.2.1. Social profiling**

Social profiling plays an important role in this field of wireless communication. Let  $R_n$  is the social meta information which is stored in the node. Here, it is assumed that the node and its neighbouring nodes are in the same category as  $|R_n| = |R_n|$  and  $\forall_k \in [1, |R_m|]$  and  $r_m^k \in R_m$ . Thus, the social information of all nodes can be denoted as  $R = \{R_1, R_2, \dots, R_N\}$ . At this stage, when any two nodes encounter in the current community then they can exchange the information or profile without discriminating the community and selfishness. However, this work considers greedy mechanism to select the forwarding node by increasing the profile matching as shown in (5).

$$\arg \max_m \{r_n^k = r_m^k: \forall_k, k \in [1, |R_m|]\} \tag{5}$$

**2.3. Geo-context aware routing in mobile opportunistic network**

This section presents the proposed model for geo-context aware based opportunistic routing. The geo-context-based routing considers location of packet delivery and finding the next hop to reach to the destination. The proposed model computes the delivery probability for location based opportunistic routing. The complete probability is calculated based on geographic progress made by node  $p_i(m)$ , node's probability to have contact to transmit the packets to its destination  $p_i(c)$ . So, geo-context routing has two main location parameters: node's capacity upto which it can transmit the packet, and location of another node which can be considered as next hop for data transmission. Figure 4 depicts the geo-context aware routing model.

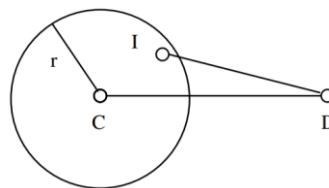


Figure 4. Capacity of node to transmit the packet to specific location

In order to compute the  $p_i(m)$ , this model considers a representation of node  $N$  whose current location is  $I$  in the current community and  $D$  is the destination of node and  $C$  is the center of cell. This probability is computed based on the euclidean distance between current location and destination. This can be expressed as shown in (6):

$$p_i(m) = \frac{\|C,D\|_2 - \|I,D\|_2}{\|C,D\|_2} \tag{6}$$

where  $\|C,D\|_2$  is the distance between current location and destination which is given as  $\sqrt{(x_C - x_D)^2 + (y_C - y_D)^2}$ , similarly, the  $\|I,D\|_2$  can be represented as  $\sqrt{(x_I - x_D)^2 + (y_I - y_D)^2}$ .

Similarly, when the packet is delivered to the closer location to the destination node by node  $N$ , neighbour should be available which can act as next hop to transmit the packet to destination node. In this work, this is determined by the contact availability per visiting to cell. Let us consider if any node  $N$  has one time visited cell  $i$  then its contact availability rate is  $X_i(c) = 1$  otherwise if node has not visited the cell the contact availability is  $X_i(c) = 0$ . Based on these connectivity and packet delivery location, the probability of node connection  $p_i(c)$  can be computed as shown in (7):

$$\begin{aligned} p_i(c) &= P\{X_i(c) \geq 1\} \\ &= P\{X_i(c) - \mu_c \geq 1 - \mu_c\} \end{aligned} \quad (7)$$

where  $\mu_c$  is the mean obtained by average historical contact availability per visiting of the cell  $i$ .

#### 2.4. Reinforcement learning model

Reinforcement learning approach consists of the main components as  $\langle a_t, s_t, r_t \rangle$  where  $a_t$  denotes the action taken at  $t$ ,  $s_t$  is the state at  $t$  and  $r_t$  denotes the reward for the action taken in the considered environment. This method focusses on selecting the new actions and update the Q values to maximize the performance of the system. The overall process of this approach is depicted in Figure 5 where agent, action environment, states and reward/punishment are presented. The agent detects the environment's reinforcement signals that correlate to the current state before acting. The following stage and rewards are influenced by the quality of the action choices. The tendency of the agent to choose this action will be reinforced if the environment generates favourable incentives as a result of the activity. The agent will eventually discover the best course of action to take in order to maximise rewards. The terminologies of this method are defined:

- Agents: according to this model, each node of network is considered as an agent it is not dependent on other nodes. These agents are responsible for data collection, and transmit those packets to the next hop or relay. These nodes are denoted as  $N = \{n_1, n_2, \dots, n_j, \dots, n_m\}$  where  $n_j$  is the  $j^{\text{th}}$  sensor node out of total  $m$  nodes.
- States: State represents the different phases of network operations. This is denoted as  $S = \{s_1, s_2, s_3, \dots, s_j, \dots, s_m\}$  which denotes the set of state. The state includes the overall packet transmission.
- Actions: actions are represented as  $A = \{a_1, a_2, \dots, a_j\}$  which represents the set of actions. In this set,  $a_j$  characterizes action of  $j^{\text{th}}$  node which designated as the next hop node.
- Reward: this represents the response to the actions taken for each state. The reward can be negative or positive. This is denoted as  $R_{s_i s_j}^{a_j}$  which shows an immediate reward for an action  $a_j$  taken by agent to transfer the state from  $s_i$  to  $s_j$ . The reward mechanism is based on several parameters such as energy consumption, delay, and residual energy.

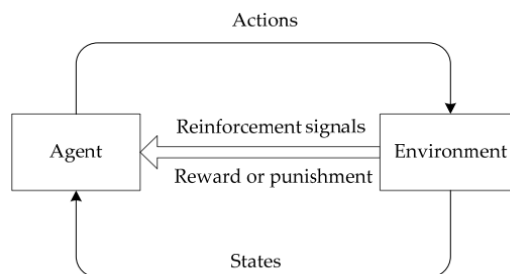


Figure 5. Reinforcement learning process

According to the Q-learning, the any action's Q-value in the considered state can be expressed as shown in (8):

$$Q(s_i, a_j) = r_i(a_j) + \gamma \sum_{s_j \in S} P_{s_i s_j} \max_a Q(s_j, a) \quad (8)$$

where  $\gamma (0 \leq \gamma < 1)$  represents the discount factor, this discount factor helps to characterize the weightage or importance of the reward received by the agent node i.e. if the value of  $\gamma$  is small then it receives more attention by agent to give immediate reward. In contrast to this, for higher  $\gamma$  values, the nodes become eligible for future rewards. Here,  $r_i(a_j)$  represents the direct reward function. It plays an important role because it helps to determine the behaviour of the action  $a_j$  at the state  $s_i$  which can be expressed as shown in (9).

$$r_i(a_j) = \sum_{s_j \in S} P_{s_i s_j}^{a_j} R_{s_i s_j}^{a_j} \tag{9}$$

Further, the maximum Q-value can help to achieve optimal policy. The optimum action  $a_i^*$  for given state  $s_i$  can be expressed as shown in (10):

$$a_i^* = \arg \max_{a_i \in A(s_i)} Q(s_i, a_i) \tag{10}$$

where  $a_i$  denotes the action from the set of action  $A(s_i)$ . Generally, the greedy Q based method selects the action with highest Q value which helps to select the best path from source to sink for successful packet forwarding.

**2.5. Candidate node selection matrices**

To select the candidate nodes, this model uses link reliability, and residual energy distribution as the important parameters. The link connectivity between these nodes remains a challenging task therefore a link reliability prediction matrix is considered. It uses broadcasting of ‘‘Hello’’ packets to examine the reliability of link between nodes. For this broadcast, the received power can be given as shown in (11):

$$P_R(d) = P_t - PL(d_0) - 10\alpha \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma \tag{11}$$

where  $P_t$  represents the transmit power,  $PL(d_0)$  denotes the loss of signal strength,  $d_0$  is the reference distance  $d_0 = 1m$  which is used to measure the path loss,  $\alpha$  represents the exponent of path-loss attenuation and  $X_\sigma$  is the shadowing factor on the propagation path.

Let  $r$  be the communication radius of node present in the network, we assume that the nodes are placed at average distance of  $0.9r$ , then, the received signal threshold for the node can be expressed as shown in (12):

$$P_{RTh} = P_t - PL(d_0) - 10\alpha \log_{10} \left( \frac{0.9r}{d_0} \right) \tag{12}$$

here,  $P_{RTh}$  is the minimum signal strength, with this signal strength the node is capable to receive message of its neighbour node. Based on this threshold, the link connectivity can be defined as shown in (13):

$$LC_{ij} = \begin{cases} 0, & \text{if } P_r(d) \leq P_{RTh} \\ 1 - e^{-\frac{P_{RTh}}{P_r(d)}}, & \text{if } P_r(d) > P_{RTh} \end{cases} \tag{13}$$

where  $LC_{ij}$  denotes the link connection probability between two nodes  $i$  and  $j$ . Larger value of  $LC$  denotes the more stable link,  $LC = 0$  denotes the interruption in the link. Residual energy is also considered to prioritize the candidate nodes based on their remaining energy. The energy probability distribution is denoted as  $\bar{\zeta}_i = (\bar{\zeta}_{i_1}, \bar{\zeta}_{i_2}, \dots, \bar{\zeta}_{i_j})$ . The node with high residual energy is considered, eligible for candidate node. Finally, these parameters are used to find the priority of forwarding node to maximize the QoS by ensuring the packet delivery for the given distance, better link connectivity, and minimize the energy consumption. Therefore, the priority of candidate node  $j$  at time  $t$  can be calculated:

$$P_{ij}(t) = \ln \left( 1 + \frac{LC_{ij}(t) \cdot \bar{\zeta}_{ij}(t)}{d_{j-sink}(t)} \right) \tag{14}$$

based on this, the optimal next hop can be obtained as shown in (15):

$$j^* = \arg \max P_{ij}(t) \tag{15}$$

the probability  $P_{ij}(t)$  can be used to determine the priority list of all obtained candidate nodes. Further, the packet forwarding is performed based on timer coordination approach. The node which have the high priority is used to forward the data packet, in contrast to this, other nodes in the candidate forwarding node list remain dormant or inactive for packet forwarding. Furthermore, Q-learning approach is incorporated to improve the candidate optimization which is based on the reward mechanism process as discussed in previous section. Let  $n_i$  is the current forwarder node and  $n_j$  is the candidate node of the current forwarder node. To avoid the inappropriate forwarder node, Q-learning based reward mechanism is adopted. The immediate reward function  $R_{s_i s_j}^{a_j}$  for action  $a_i$  at  $s_j$  state can be expressed as shown in (16).

$$R_{s_i s_j}^{\alpha_j} = (2 + \alpha \rho_j)^{\delta_{ij}[\beta E_j + (1-\beta)D_{ij}]} \quad (16)$$

Here,  $\delta_{ij}$  is the binary value decision function,  $\delta_{ij} = 1$  if the node  $n_j$  forwards the packet successfully otherwise its value is -1. Here,  $\rho_j \geq 0$  is the node discarding factor, the node with smaller value of  $\rho_j$  is discarded for candidate selection process,  $\alpha$  value ranges as  $0 < \alpha \leq 1$  denoted as adjustment coefficient of  $\rho_j$ . To ensure the positive value of above exponential function,  $E_{ij}$  is the factor used for energy value representation and  $D_{ij}$  denotes the distance between nodes and  $\beta \in (0,1)$  characterize the weight factor used for harmonizing the effect of energy and distance values. The energy and distance values are represented as shown in (17):

$$E_{ij} = \frac{e_j^r}{e_j^i}, \text{ and } D_{ij} = \frac{d_i - d_j}{R_{max}} \quad (17)$$

where  $e_j^r$  and  $e_j^i$  represents the residual energy and initial energy respectively. According to this, higher residual energy leads to generate more rewards,  $d_i$  and  $d_j$  are the distance of node  $i$  and  $j$ , respectively and  $R_{max}$  represents the maximum range of communication between two nodes.

Q-learning based model considered link connectivity distance and energy values to identify the next hop. The social model-based routing model includes social profile matching, connectivity matching, and social interaction analysis. As the algorithm initiates, it triggers the need to best candidate to transfer the packet. The main rationale behind this approach is that node which are having similar interests have more probability to interact more frequently with each other. When a direct route cannot be established at once, this social phenomenon has shown that there is a high expectation that the packet may be effectively delivered in a multihop fashion. This task is accomplished in three phases:

### 2.5.1. Phase 1: social profile matching

The main aim of this process is to identify the intermediate nodes which have most common social profiles. This method is applied recursively tracking backward to the source node and produces the set of nodes which can be considered as forwarding node. This process is presented in Algorithm 1.

Algorithm 1: Profile matching for forward node selection

**Input:**  $G, R, m, \Phi, C(t)_\epsilon$  **Output:** Set of forwarding node

Step 1: for all  $\psi \in C(t)_\epsilon$  do

Step 2: search for a node whose conditions meet with the social profile parameters

$$\arg \max_{\psi \in \text{forward node set}} \{r_n^k = r_m^k, \forall k, k \in [1, |R_m|\}}\}$$

Step 3: assign  $\Phi = \Phi \cup \psi$

Step 4: if *source node*  $\in \Phi$  then

Step 5: apply social profile matching operation

Step 6: else

Step 7: Stop

Step 8: End if

Step 9: End for

Step 10: Return  $\Phi$

### 2.5.2. Phase 2: social connectivity matching

The previous step provides the set of forwarding node. However, some of these nodes may fall out of communication range which shows disconnection from the node of current community. Therefore, it is important to discard these nodes. This is done by applying social connectivity matching. This process of selecting the node based on social connectivity is presented in Algorithm 2.

Algorithm 2: Social connectivity matching to refine the list of forwarder nodes

**Input:**  $\Phi, L_n^c$  **Output:**  $\Phi$

Step 1:  $\Phi = \Phi \cap L_n^c$

Step 2: return  $\Phi$

### 2.5.3. Phase 3: social interaction model

Initially, it considers all nodes from the list of forwarding nodes and find the node  $n$  to meet the data transmission requirement. This task is performed based on the transition matrix which keeps the node's location and traverse history in each community. According to the proposed model, if the node has higher residual energy, link connectivity and it successfully transfers the packets then it receives rewards otherwise it receives penalty. The reward function for node  $n_i$  for its action  $a_j$  can be expressed as shown in (18):

$$r_i(a_j) = P_{s_i s_j}^{a_j} R_{s_i s_j}^{a_j} - P_{s_i s_i}^{a_j} R_{s_i s_i}^{a_j} + Profile + connectivity + interaction + Geo Location Probability \tag{18}$$

where  $P_{s_i s_j}^{a_j}$  denotes the transition probability for successful packet forwarding and  $P_{s_i s_i}^{a_j}$  is the probability for failed. Therefore, the Q-value of node  $n_j$  can be updated as shown in (19).

$$Q(s_i, a_j) = r_i(a_j) + \gamma \sum_{s_j \in S} P_{s_i s_j}^{a_j} \max_a Q(s_j, a) \tag{19}$$

Therefore, the complete process of routing in mobile opportunistic network can be described as in Algorithm 3. According to the proposed approach, after receiving a data packet, the node decides whether it is eligible to participate in packet forwarding. In order to plan packet forwarding, it first determines the Q-value, which is an anticipated reward received for an action, distance, and residual energy information. The node will maintain the continuous relaying of the packet to carry out the continuous routing process by following greedy packet forwarding until it receives the packet delivery information until its holding period expires.

**Algorithm 3: Social relation based opportunistic routing**

- Input 1:  $G, R, L_n^c, \Pi_n, m$       Output: list of forwarder node and best forwarder node  
 Step 1: Initialize the communication process where node  $n$  attempts to transmit the packet to node  $m$   
 Step 2: Apply social profile matching ( $G, R, m, \Phi$ ) as per algorithm 1  
 Step 3: Return *list of forward node set*  
 Step 4: Apply social connectivity matching ( $\Phi, L_n^c$ ) as per algorithm 2  
 Step 5: Return refined *list of forward node set*  
 Step 6: Apply interaction matching ( $\Phi, \Pi_n$ )  
 Step 7: Return forward node list by discarding the disconnected and out of communicate range nodes  
 Step 8: Apply packet delivery probability computation as function of Q-learning  
 Step 9: Compute the final reward as  $r_i(a_j) = P_{s_i s_j}^{a_j} R_{s_i s_j}^{a_j} - P_{s_i s_i}^{a_j} R_{s_i s_i}^{a_j} + Profile + connectivity + interaction + Geo Location probability$   
 Step 10: Send (Forward node)  
 Step 11: Repeat until  $t_{TTL} \geq 0$ .

**3. RESULTS AND DISCUSSION**

The proposed model considered a network setup which has varied number of nodes as 10, 20, 30, 40 and 50 nodes in the given 2D region. Conducted 10 simulation tests and each simulation has 500 rounds of simulations. Each link is assigned a bandwidth of 10 Mb/s. During the packet generation process, 10 packets are generated per second and each packet has size of 1,000 bytes. Simulation parameters for this experiment are described as shown in Table 1.

Table 1. Simulation parameters

Parameter	Considered value
Number of nodes	10, 20, 30, 40, 50
Packet size	1,000 bytes
Initial energy	1
Buffer size	500

The proposed model is evaluated for different number of nodes starting from 10 to 50 increasing with a step size of 10 nodes. The nodes are capable to transmit and receive the packet size of 1,000 bytes with an initial energy of 1J. This energy is further updated based on its usage for receiving and transmitting the packets. Table 2 shows the hyper parameters used in Q-learning model where learning rate of Q-learning is set as 0.12 with a discount factor of 0.9 in reinforcement learning.

Table 2. Hyperparameters of Q-learning

Parameter	Considered value
Learning rate	0.12
Discount factor	0.9



Figure 6 shows the comparative analysis for packet delivery ratio vs buffer size. The obtained performance is compared with the existing fuzzy-based check-and-spray routing (FCSG) [23], reinforcement learning-based fuzzy geocast routing protocol (RLFGRP) [24] and fuzzy logic-based Q-learning routing (FQLRP) [25]. The average packet delivery ratio is obtained as 20.25%, 18.75%, 17.25%, and 21.5% by using RLFGRP, FQLRP, FCSG and proposed approach, respectively. The performance of proposed is improved by 6.17%, 14.66%, and 24.63% when compared with RLFGRP, FQLRP, and FCSG, respectively.

Figure 7 shows the comparative analysis of network overhead for varied buffer size. As the buffer size is increasing, the model is able to handle more traffic resulting in decreasing the network overhead. The average overhead is obtained as 38.375, 40.125, 44, and 31.875 by using RLFGRP, FQLRP, FCSG, and proposed approach, respectively. This study shows that the average overhead of proposed approach is reduced by 16.93%, 20.56%, and 27.55% when compared with RLFGR, FQLRP, and FCSG, respectively. The performance of proposed approach is measured with other existing schemes such as prophet, epidemic, and spray and wait routing protocols. The result shows that the delivery ratio of these algorithms increases as the node density increases because it becomes easier to select the forwarding node. In comparison to Epidemic's [26] blind forwarding, prophet's [27] relay selection process and spray and wait's [28] partial flooding may both significantly lower the amount of created packets and increase packet delivery ratios.

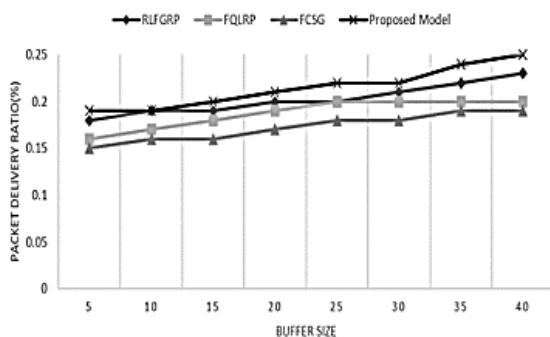


Figure 6. Packet delivery ratio vs buffer size

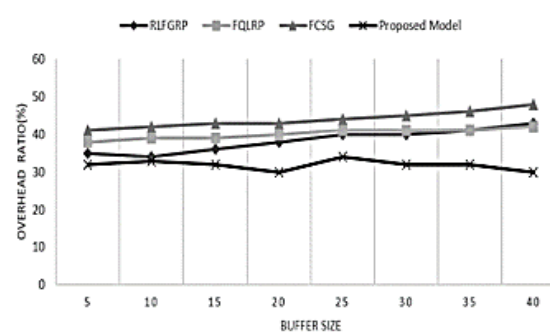


Figure 7. Overhead ratio vs buffer size

According to this experiment, the number of nodes are increased and packet delivery performance is measured. The increased number of nodes leads to increase the density which facilitate faster CH selection and data forwarding without consuming extra energy. Therefore, the packet delivery is improved. The average packet delivery ratio is obtained as 41%, 35.33%, 43.33%, and 47.22% by using prophet, epidemic, spray and wait, and proposed model, respectively as presented in Figure 8. Figure 9 depicts the network overhead performance. Epidemic has the largest overhead, as is to be expected. Prophet has a high overhead because as the number of nodes grows, there are more chances to select a suitable relay with a better delivery probability. In spray and wait, the overhead is steady as the node density rises, since each message has a fixed length. The suggested technique, however, has a lower overhead than the other three methods because it may choose an effective forwarder based on node properties during message relaying.

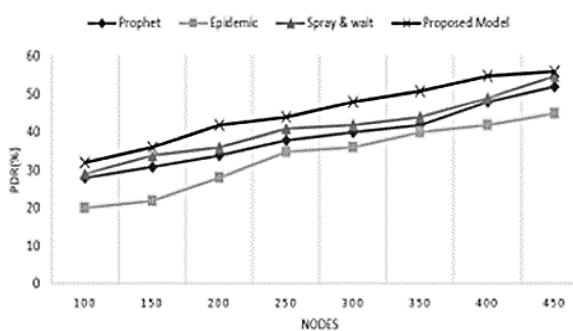


Figure 8. Packet delivery vs nodes

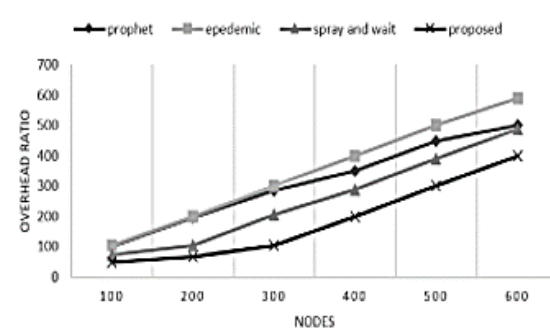


Figure 9. Network overhead vs nodes

#### 4. CONCLUSION

Wireless communication plays an important role in daily life. Mobile opportunistic networks are widely adopted in various real-time applications. These networks are equipped with limited resources such as storage, energy and generally deployed randomly in harsh environment where providing the extra resource is not feasible. Due to these issues network lifetime and QoS management becomes tedious task. Routing algorithms are well-known solution for these problems but traditional routing also suffers from various challenges. Therefore, the opportunistic routing is adopted and focus on improving the performance of OR protocols. In order to achieve this, the proposed model introduces Q-learning based model which uses several parameters to identify the best node from candidate node. The comparative analysis shows that proposed approach achieves average packet delivery ratio as 47.22%, and faces the average network overhead which is low when compared with the other opportunistic routing protocol. In future work, security and reliability management can be considered as an important aspect of these routing protocols.




#### REFERENCES

- [1] M. Shafiq, H. Ashraf, A. Ullah, and S. Tahira, "Systematic literature review on energy efficient routing schemes in WSN – a survey," *Mobile Networks and Applications*, vol. 25, no. 3, pp. 882–895, Feb. 2020, doi: 10.1007/s11036-020-01523-5.
- [2] S. Trifunovic, S. T. Kouyoumdjieva, B. Distl, L. Pajevic, G. Karlsson, and B. Plattner, "A decade of research in opportunistic networks: challenges, relevance, and future directions," *IEEE Communications Magazine*, vol. 55, no. 1, pp. 168–173, Jan. 2017, doi: 10.1109/MCOM.2017.1500527CM.
- [3] C. M. Huang, K. C. Lan, and C. Z. Tsai, "A survey of opportunistic networks," in *Proceedings - International Conference on Advanced Information Networking and Applications, AINA*, 2008, pp. 1672–1677, doi: 10.1109/WAINA.2008.292.
- [4] T. Abdelkader, K. Naik, A. Nayak, N. Goel, and V. Srivastava, "A performance comparison of delay-tolerant network routing protocols," *IEEE Network*, vol. 30, no. 2, pp. 46–53, Mar. 2016, doi: 10.1109/MNET.2016.7437024.
- [5] H. Zhou, T. Wu, X. Chen, S. He, and J. Wu, "RAIM: a reverse auction-based incentive mechanism for mobile data offloading through opportunistic mobile networks," *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 6, pp. 3909–3921, Nov. 2022, doi: 10.1109/TNSE.2021.3126367.
- [6] G. Goudar and S. Batabyal, "Optimizing bulk transfer size and scheduling for efficient buffer management in mobile opportunistic networks," *IEEE Transactions on Mobile Computing*, vol. 21, no. 12, pp. 4471–4487, Dec. 2022, doi: 10.1109/TMC.2021.3075993.
- [7] G. Goudar and S. Batabyal, "Estimating buffer occupancy sans message exchange in mobile opportunistic networks," *IEEE Networking Letters*, vol. 4, no. 2, pp. 73–77, Jun. 2022, doi: 10.1109/lnet.2022.3151363.
- [8] N. Li, X. Yuan, J. F. Martinez-Ortega, and V. H. Diaz, "The network-based candidate forwarding set optimization for opportunistic routing," *IEEE Sensors Journal*, vol. 21, no. 20, pp. 23626–23644, Oct. 2021, doi: 10.1109/JSEN.2021.3105535.
- [9] N. Kandhoul and S. K. Dhurandher, "An Efficient and secure data forwarding mechanism for opportunistic IoT," *Wireless Personal Communications*, vol. 118, no. 1, pp. 217–237, Jan. 2021, doi: 10.1007/s11277-020-08010-w.
- [10] Y. Zhang, Z. Zhang, L. Chen, and X. Wang, "Reinforcement learning-based opportunistic routing protocol for underwater acoustic sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 3, pp. 2756–2770, Mar. 2021, doi: 10.1109/TVT.2021.3058282.
- [11] L. Ge and S. Jiang, "An efficient routing scheme based on node attributes for opportunistic networks in oceans," *Entropy*, vol. 24, no. 5, p. 607, Apr. 2022, doi: 10.3390/e24050607.
- [12] X. Fu, H. Yao, O. Postolache, and Y. Yang, "Message forwarding for WSN-assisted opportunistic network in disaster scenarios," *Journal of Network and Computer Applications*, vol. 137, pp. 11–24, Jul. 2019, doi: 10.1016/j.jnca.2019.04.005.
- [13] S. Byeon, S. Park, H. Y. Seo, and J. D. Kim, "CLOF: contribution-level-based opportunistic flooding for multihop wireless networks," *International Journal of Distributed Sensor Networks*, vol. 14, no. 5, p. 155014771877820, May 2018, doi: 10.1177/1550147718778200.
- [14] D. V. A. Duong and S. Yoon, "An efficient probabilistic routing algorithm based on limiting the number of replications," in *ICTC 2019 - 10<sup>th</sup> International Conference on ICT Convergence: ICT Convergence Leading the Autonomous Future*, Oct. 2019, pp. 562–564, doi: 10.1109/ICTC46691.2019.8939947.
- [15] Y. Lu, L. Chang, J. Luo, and J. Wu, "Routing algorithm based on user adaptive data transmission scheme in opportunistic social networks," *Electronics (Switzerland)*, vol. 10, no. 10, p. 1138, May 2021, doi: 10.3390/electronics10101138.
- [16] Z. Ying, C. Zhang, F. Li, and Y. Wang, "Geo-social: routing with location and social metrics in mobile opportunistic networks," in *IEEE International Conference on Communications*, Jun. 2015, vol. 2015-Sept, pp. 3405–3410, doi: 10.1109/ICC.2015.7248851.
- [17] S. Kim and M. Gerla, "Socio-geo: social network routing protocol in delay tolerant networks," in *2016 International Conference on Computing, Networking and Communications, ICNC 2016*, Feb. 2016, vol. 2016-March, pp. 1–6, doi: 10.1109/ICNC.2016.7923427.
- [18] Y. Yang, H. Zhao, J. Ma, and X. Han, "Social-aware data dissemination in opportunistic mobile social networks," *International Journal of Modern Physics C*, vol. 28, no. 9, p. 1750115, Sep. 2017, doi: 10.1142/S0129183117501157.
- [19] X. Wang, Y. Lin, S. Zhang, and Z. Cai, "A social activity and physical contact-based routing algorithm in mobile opportunistic networks for emergency response to sudden disasters," *Enterprise Information Systems*, vol. 11, no. 5, pp. 597–626, Jul. 2017, doi: 10.1080/17517575.2015.1067840.
- [20] Y. Zhou, T. Cao, and W. Xiang, "Anypath routing protocol design via Q-learning for underwater sensor networks," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 8173–8190, May 2021, doi: 10.1109/JIOT.2020.3042901.
- [21] T. A. Alghamdi, "Energy efficient protocol in wireless sensor network: optimized cluster head selection model," *Telecommunication Systems*, vol. 74, no. 3, pp. 331–345, Mar. 2020, doi: 10.1007/s11235-020-00659-9.
- [22] D. K. Bangotra, Y. Singh, A. Selwal, N. Kumar, P. K. Singh, and W. C. Hong, "An intelligent opportunistic routing algorithm for wireless sensor networks and its application towards e-healthcare," *Sensors (Switzerland)*, vol. 20, no. 14, pp. 1–23, Jul. 2020, doi: 10.3390/s20143887.
- [23] K. Khalid, I. Woungang, S. K. Dhurandher, J. Singh, and L. Barolli, "A fuzzy-based check-and-spray geocast routing protocol for opportunistic networks," *Journal of High Speed Networks*, vol. 27, no. 1, pp. 1–12, Mar. 2021, doi: 10.3233/JHS-210648.
- [24] K. Khalid, I. Woungang, S. K. Dhurandher, and J. Singh, "Reinforcement learning-based fuzzy geocast routing protocol for opportunistic networks," *Internet of Things (Netherlands)*, vol. 14, p. 100384, Jun. 2021, doi: 10.1016/j.iot.2021.100384.




- [25] A. M. Rahmani *et al.*, "A Q-learning and fuzzy logic-based hierarchical routing scheme in the intelligent transportation system for smart cities," *Mathematics*, vol. 10, no. 22, p. 4192, Nov. 2022, doi: 10.3390/math10224192.
- [26] M. Alajeely, R. Doss, and A. Ahmad, "Routing protocols in opportunistic networks—a survey," *IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India)*, vol. 35, no. 4, pp. 369–387, Apr. 2018, doi: 10.1080/02564602.2017.1304834.
- [27] A. Lindgren, A. Doria, and O. Schelén, "Probabilistic routing in intermittently connected networks," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 7, no. 3, pp. 19–20, Jul. 2003, doi: 10.1145/961268.961272.
- [28] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Spray and wait: An efficient routing scheme for intermittently connected mobile networks," in *Proceedings of the ACM SIGCOMM 2005 Workshop on Delay-Tolerant Networking, WDTN 2005*, 2005, pp. 252–259, doi: 10.1145/1080139.1080143.

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