# A Comprehensive Cellular Learning Automata Based Routing Algorithm in Opportunistic Networks

Feng Zhang(✉)

School of Computer and Information Technology, Shanxi University, Shanxi 030006, China
zhangfeng@sxu.edu.cn

**Abstract.** A distinctive cellular learning automata based routing algorithm is proposed which exploits the ambient nodes feature to polish up the performance of opportunistic networks. The factors of each phase in the routing procedure of store-carry-forward are taken into account. Messages would be dropped on the basis of the dropping probability when congestion occurs during the store phase. Energy consumption would be balanced according to the threshold set by the node itself which is used to accept messages in the carry phase. Connection duration between nodes has been estimated to reduce the energy waste caused by fragment messages transmission during the forwarding process. To evaluate the validity of our proposed algorithm, we conduct comprehensive simulation experiments on the ONE platform. The results show that the proposed routing algorithm achieves higher delivery ratio and less overhead ratio. In addition, it gains a balance of energy consumption and an enhancement of the whole network performances.

**Keywords:** Opportunistic networks · Routing algorithm · Energy efficient · Cellular learning automata · Ambient intelligence

## 1 Introduction

With the rise of smart mobile devices, the mobile Internet has achieved great success in recent years. This brings huge data volumes that can be generated and propagated. Although the cellular network has been improved rapidly, there are still some limitations in specific scenarios such as sparsely populated areas, large gatherings and disasters. In these circumstances, the communication infrastructure of cellular network might not be economically beneficial or increasingly costly or almost to be infeasible [1, 2].

These restricts boost the blossom of the opportunistic networks, which are a special type of mobile ad-hoc networks (MANETs). When nodes in the opportunistic networks are moving within wireless transmission range, they can directly communicate with each other via the equipped short-range wireless technology such as Wi-Fi or Bluetooth. This

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is very essential when the infrastructure collapses during natural or man-made disasters. Opportunistic networks are usually composed of spatially distributed human carried mobile devices with short range wireless communication modules. There may never be an end-to-end transmission path available between a source and a destination node in opportunistic networks [3]. The traditional routing protocols in MANETs would not work well due to the sparse restrict resource and the mobility of nodes in opportunistic networks. Compared with the traditional infrastructure-based cellular networks, opportunistic networks adopt a new routing paradigm which is store-carry-forward. Once this pattern is defined, the architect can focus on more specific details of the routing algorithm. In this way, intermediate nodes typically relay messages through random contacts [4]. Nodes usually store messages first and then carry them as they move around in the networks. If an appropriate opportunity arises, messages will be forwarded or replicated to the destination or other relay nodes. Due to the limited buffer capacity of nodes, the unfair load distribution and the unrestricted volumes of traffic will lead to capacity saturation in a buffer, resulting in congestion, and the severely degraded network performance accordingly [5]. On the other hand, as the devices people carried are always powered by batteries and it is very difficult to charge the batteries during the movement. So the energy consumption is a fatal element influencing the network lifetime in opportunistic networks. Nodes that have run out or severely low on battery power will not be able to participate in messages relay in the future [6].

Generally, the resources of nodes in the opportunistic network are limited, and they act as relay stations for other nodes when routing messages. To increase delivery ratio of messages, replication-based policies are applied to allow multiple messages to exist. But this may increases a risk of congestion and excessive energy consumption [7, 8]. Therefore, how to make the best use of finite resource of local and ambient nodes to achieve good routing performance including message delivery ratio, overhead ratio and energy utilization is a great challenge topic and study hotspot in opportunistic networks. All the factors should be devised carefully throughout the whole store-carry-forward procedure. In this paper, a comprehensive routing algorithm based on the cellular learning automata is proposed. In this scheme, nodes in opportunistic networks are considered as cellular, and each element is updated by the automata assigned to the node. Nodes update their own internal state on discrete cycles periodically according to the same regulation. Then efficient routing algorithm including congestion control and energy balance are addressed based on the local state and ambient state of nodes.

The remainder of this paper is organized as follows. Section 2 gives an overview of some existing related work and the concept of cellular learning automata. Section 3 presents the proposed comprehensive routing algorithm. Simulation results and analysis are shown and discussed in Sect. 4. At last, we conclude this paper in Sect. 5.

## 2 Related Work

In this section, we firstly introduce the concept and mathematical model of DICLA which is the fundamental model used in this paper. Then we address the key area of routing protocols in the opportunistic networks. Some recently researches in opportunistic networks are followed.

### 2.1 Dynamic Irregular Cellular Learning Automata

CLA (Cellular Learning Automata) is a useful mathematical model for many discrete problems and phenomena, and the characteristics of CA and LA [9] are combined together. The abstract environment of LA is replaced by the cells around LA, and the rule of CA is evolved according to the reinforcement signal. The states of cells mean different actions. On the basis of CLA, the Irregular Cellular Learning Automata (ICLA) and Dynamic Irregular Cellular Learning Automata (DICLA) are developed [10, 11]. An ICLA is a CLA which the restriction of rectangular grid structure in traditional CLA is removed. A DICLA is an ICLA with the variable structure according to the given principle. In other words, the adjacency matrix of the underlying graph of the ICLA can be changed over time in DICLA. This dynamic feature and universality are necessary for the applications that cannot be totally modeled with rectangular grids such as Mobile Ad hoc Networks and Wireless Sensor Networks, Opportunistic Networks, web mining, grid computing and data aggregation [12].

### 2.2 Routing Issue

Routing messages in opportunistic networks present challenges (such as constantly moving and intermittent connectivity). This is because that the absence of the steady and stable connections between source and destination which are exist in other traditional network. Also the limited resource of nodes such as energy and storage are other factors that must be carefully considered. Routing schemes must implement techniques that are efficient and ingenious to increase the performance benefit of opportunistic networks.

To address temporary connection, random moving and limited resource challenges, the distinctive routing strategies are determined and separate the routing phase into three steps, store, carry and forward. Routing strategy in opportunistic networks always involves appropriate forwarding scheme, efficient buffer management and balanced energy utilization. Multiple copies forwarding scheme is the most common and widely used strategy [13, 14]. The representative algorithm is the Epidemic [15]. Messages will be replicated to any other nodes while nodes roam in the network. Obviously there are maximum replications of messages in opportunistic networks for Epidemic and high messages delivery probability in an ideal environment.

However, there is no energy and storage considered in the above mentioned routing protocols [13–15]. Because of the finite storage constraint of mobile nodes in practice, the congestion phenomenon arises as the time goes on when node buffer is full in Epidemic fashion. So the criterion of selecting messages to drop is very important if congestion occurs. The simplest selection method is according to the time feature of messages [16]. These congestion control strategies do not take the copies number of message into account and are local view of node itself. In order to overcome this shortcoming, GLCCS (game of life based congestion control strategy) [17] scheme is proposed. CLACCS (cellular learning automata based congestion control strategy) [18] is an improvement of GLCCS. Different from GLCCS, messages drop probability is defined in this strategy. It describes the dropping probability of message using the distribution of messages around current neighbor nodes under the rule of learning automata automatically. With the help of this probability, it is very easy to pick up which message to drop when congestion situation.

An optimization in terms of energy consumption based on Epidemic is proposed in [15]. In this scheme, messages will not be transmitted if the number of neighbors less than the threshold n. The classic routing protocol in this type is named n-Epidemic. A novel adaptive adjustment strategy of n-Epidemic routing (ANER) is proposed in [19], which employs the cellular learning automata model to depict the dynamic characteristics of opportunistic networks, and local rule is defined to tune the parameter n of n-Epidemic dynamically according to the energy level of nodes and their neighbors'. EACC [20] is a congestion control scheme under the consideration of energy consumption in Epidemic paradigm. The cellular learning automata model is used in EACC to update the energy level of node and its neighbors. Furthermore, fragmental messages are wholly unused in the opportunistic networks. This is very easy to be prevented in a stable link network environment. As long as the message follows a run-to-completion model on a per-message basis, the message will be received totally. However, messages may be transferred partially in opportunistic networks for the wireless links between nodes are temporary. This may be caused when link connections break down as with the nodes moving. Messages will not be scheduled to forwarding if the left connection duration time is shorter than the messages transfer time.

These above schemes only take partial factor (energy or congestion) into account. However, a complete routing protocol should consider feasibility as many as possible. Our proposal focuses on the fragmental message, congestion and energy consumption in Epidemic paradigm. We introduce CLA to opportunistic networks to deal with the TTL value of messages like EACC when they were replicated. Also the message dropping probability is updated periodically according to the messages stored in the neighbors using the principle of CLA as CLACCS. In the forward phase, fragment message will be cancelled avoiding energy consumption. The proposed algorithm is to balance the delivery and energy concerns associated with Cellular Learning Automata. Our contributions of this paper are the following:

- We take all the factors of the process of store-carry-forward routing paradigm into account.
- We update the message dropping probability and energy level of nodes at the same time using the principles of cellular learning automata in the store and carry phases.
- Connection durations between nodes are calculated according to the historical records in the forward phase.
- The simulation results are implemented comparing with the existing routing algorithms to show the efficient of proposed algorithm.

## 3 Proposed Routing Algorithm

In opportunistic networks scenario, nodes have distinct levels of remaining energy and messages information of themselves, and can get these information of their current neighbors through the inquiring method. Hence a detrimental replicating decision for adjacent nodes can be canceled ahead of schedule according to the messages dropping probability and nodes' energy status. In the scheme, each node is described as a cellular equipped with multiple number LAs in each cellular. These multiple LAs assigned to a cellular act different roles. We will use two kinds of LAs to describe the message dropping probability and threshold of receiving message associated with energy level respectively in the following scheme. The reinforcement signals of each LAs are independent, and calculated according to the different information from ambient neighbors.

The proposed scheme is based on the original Epidemic routing protocol. Furthermore, it takes the message dropping probability and energy consumption of nodes into account in the following aspects: a) message distribution situation of ambient nodes within nodes' communicate range. b) message dropping probability of each message stored in nodes. c) current energy level of individual node. d) time to live (TTL) of messages before they want to be flooded to the neighbors. e) residual connection duration time between neighbors. The main idea of this paper is that there is a dynamic process to update message dropping probability and adjust ratio criterion on the basis of the remainder energy level of node and its neighbors. Nodes with the more energy retained can receive the wide range of TTL of messages. And message with higher dropping probability will be removed firstly when buffer is full. Furthermore the fragment message transmission can be avoided in advance for energy considerations. This is more energy efficient and much more transmission for the energetic nodes. It is superior for the prime Epidemic routing for receiving any messages from its neighbors without considering energy level of nodes.

In the rest part, we firstly describe message dropping probability, threshold of receiving message and connection duration respectively. Then the detailed description of proposed cellular learning automata based routing algorithm is followed.

### 3.1 Message Dropping Probability

The message dropping probabilities are updated according to the Ref. [18] using the principle of dynamic irregular cellular multiple learning automata. We think a node as a cellular, and each message buffered in this node equipped with a learning automata. Connections between nodes establish and break can be described as the dynamic process of the DICLA. The variables $a_0$ and $a_1$ mean the actions that DICLA can take which indicate discard or keep this message respectively. The probability of each action is $p_r$ or $p_d$ accordingly and the initial value of $p_r$ and $p_d$ is assigned as 0.5. The status of each cellular should be updated periodicity as the fixed interval. At the begining of each interval, every node inquires messages distribution from its neighbors. The reinforcement signal $\beta(n)$ of each learning automata corresponding to a message is given according to the number of neighbors who hold the same message variety.

$$\beta_i(n) = \begin{cases} 1, & \sum_{j=1}^{SUM_i(n)} a_j(n) - \sum_{j=1}^{SUM_i(n-1)} a_j(n-1) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The $n$ is the identifier of current interval. $SUM_i(n)$ is the number of neighbors of node $i$ and $a_i(n)$ is the action of node $i$ which keeps the message at this interval. The message dropping probability is updated according to the $\beta(n)$ and show as Eq. (2) and Eq. (3).

$$p_d(n+1) = p_d(n) + a(n) * (1 - p_d(n)) \tag{2}$$

$$p_d(n+1) = (1 - b(n)) * p_d(n) \tag{3}$$

The $a(n)$ and $b(n)$ are the simulate and punishment parameters. $0 < a(n) < 1$, $0 < b(n) < 1$, And they are calculated as Eq. (4) and Eq. (5). $\varphi$, $\rho$ are the factors and range in [0,1] in Eq. (4) and Eq. (5). $R_i^m(n)$ is the number of neighbors who store the message m at the $n$th intervals.

$$a(n) = \phi * R_i^m(n)/SUM_i(n) \tag{4}$$

$$b(n) = \rho * R_i^m(n)/SUM_i(n) \tag{5}$$

If the number of nodes which store a message is increasing relative to the previous time interval, the dropping probability of this message should be increased. That is to say, there is much more nodes store this message. The impact of dropping this message is smaller than other messages at this time. So if the buffer of this node is not enough to store other message from neighbors, it should delete the messages with higher dropping probability to free space to receive the new messages.

### 3.2 Threshold of Receiving Message

In traditional Epidemic routing strategies, any node accepts any message from its peers randomly. If the buffer is full, the node will remove message with the given criterion from its buffer until there is enough room to store the new coming message. For activity nodes, especially in terms of energy, the efficiency is very low, because activity nodes have more opportunities to meet other nodes. This also accelerates the energy consumption of activity node because there are much more transmissions for activity nodes. It is easy to cause the disproportion energy consumed among nodes.

Some criteria of receiving message have been adopted in EACC [20] to insure energy conservation trade-off among nodes. These criteria neither ignores energy constraints of the nodes themselves, nor neglect the current energy state information of local ambient when making replicate decisions. Some definitions associated with energy have been introduced in EACC.

### 3.3 Connection Duration Estimation

Because of the indeterminate wireless connection among mobile nodes in the opportunistic networks, many sudden abort of message transmissions caused by unpredictable connection interrupted between nodes will waste the limited resource including buffer and energy. If we can estimate the connection duration time before a transmission, we will decide whether or not to start this transmission so as to avoiding resource wasted.

For this purpose, each node records the begin time and end time for every connection. Then the connection duration time of this connection can be accurately obtained by subtracting the begin time from end time. Also each node records every connection duration time with the other nodes to a historical information database while moving in the network. We consider the connection duration as a discrete random variable $X$, and the $E(X)$ denotes the expectation of this random variable $X$. The expectation $E(X)$ of this random variable $X$ can be gained as follows:

$$E(X) = \sum_{k=1}^{\infty} x_k p_k \tag{6}$$

where $p_k$ represents the distributing of random variable $X = x_k$.

Based on this prediction, nodes can make a wise decision whether to start a transmission according to current message size, transmission rate and the expected left time of this connection duration.

### 3.4 Proposed Routing Algorithm

The flow chat of proposed forwarding algorithm is shown in Fig. 2, and it is explained as follows:

1. Whenever two nodes encounter, and a wireless connection is established between them, they will exchange the message summary information buffered on their storage. Acknowledgments of delivered messages are flooded in the whole network to remove the redundant copies of messages.
2. At the beginning each interval, they update and calculate the *AEL* and *REL* respectively. The *LTL* value can be computed on the basis of current neighbors. This process is identical with the Ref. [20].
3. Each message updates its own dropping probability accordingly to the proportion of its neighbors. This is borrowed from Ref. [18].
4. Nodes record the connect time as the begin time of this connection.
5. Message transmission sequence is made based on the dropping probability. That is message with largest dropping probability will be sent first.
6. If the buffer of peer is full, message replicated to the peer must be check whether the *RTL* of messages is large than the peer's current *LTL* product the initial TTL value when message created.
7. The node will reject any messages from its neighbors if the current value of it *LTL* is less than a fix threshold (THD), which is very useful for balancing the energy consumption among nodes. This means that the remaining energy level between current nodes and its neighbors is very different. Therefore will refuse to receive any messages to reduce energy consumption until the difference exceeds the threshold.
8. Message m transfer time $\mathrm{t_m}$ is defined as Eq. (7).

$$t_m = s_m / w \tag{7}$$

where $s_m$ is the size of message m and w is the speed of wireless communication.

9. If the message transfer time is longer than the left connection duration time between peers, this transmission should be canceled. All messages in the buffer are processed in this way in turns.
10. When the connection broken down, each node of this connection records this time. The detailed flow chat of this algorithm is showed in Fig. 1.

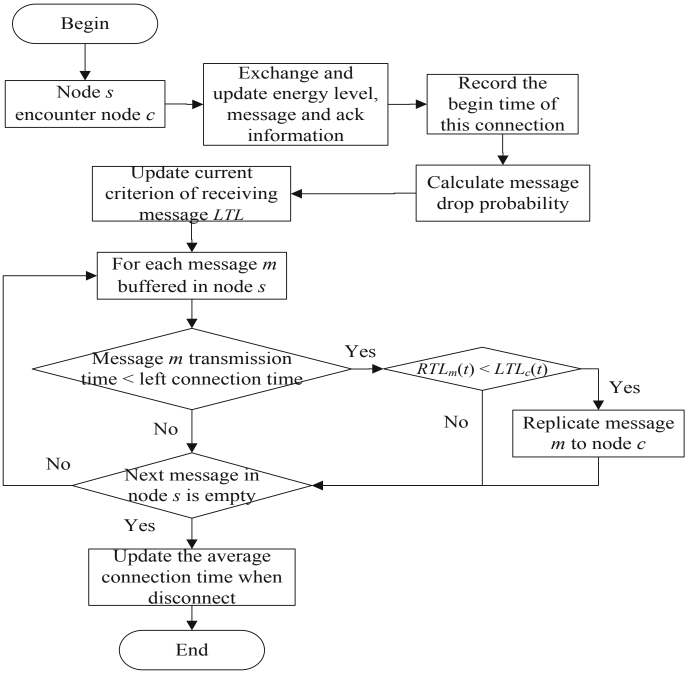


**Fig. 1.** Flow chat of proposed algorithm

## 4 Performance Evaluation

In this section, we use the java-based ONE (Opportunistic Network Environment) simulator [21] to evaluate the performance of our routing algorithm and other two other proposed routing algorithms CLACCS [18] and EACC [20] under the Levy Walk mobility model. The proposed scheme named Cellular Learning Automata based Routing Algorithm (CLARA) and routing and energy performances are compared among these three policies. The base routing protocol used in all simulations is Epidemic routing protocol.

### 4.1 Simulation Parameter Setting

The scenario of our simulation is limited to a region of 800 m x 400 m. Nodes deployed randomly in the range. The number of nodes ranges from 50 to 110 and they are all the same with the initial energy, movement speed and buffer size. The detailed simulation and energy parameter are shown in Table 1.

**Table 1.** Simulation parameters settings

| | |
|---|---|
| Map size | $800 \times 400$ m$^2$ |
| Transmit speed | 2 Mbps |
| Transmit range | 25 m |
| Nodes speed | 0.5–1.5 m/s |
| Buffer size | 70 MB |
| Time to live (TTL) | 300 m |
| Nodes movement | Levy walk |
| Message size | 500 kB – 700 KB |
| Initial energy | 5000 units |
| Scan energy | 0.1 units |
| Transmit energy | 0.2 units |
| Scan response energy | 0.1 units |
| Simulation time | 10 h |

Especially, the routing performance named delivery ratio, overhead ratio and energy performance named average residual energy, standard deviation of residual energy metrics in our experiments are compared to show the efficiency of proposed CLARA.

## 4.2 Performance Under Different Node Number

Figure 2 and Fig. 3 show the routing and energy performance respectively. As can be seen from Fig. 2(a) and Fig. 2(b), in these compared strategies, the delivery ratio and overhead ratio of our CLARA are almost the best. With the increase in the number of nodes, the delivery ratio of CLACCS and EACC increases. This is because that as the number of nodes increases, the encounter probability of nodes increases. Messages replication between nodes becomes more frequent and there are more message copies in the network. Therefore, messages are more likely to reach their destinations. At the same time, the overhead ratio is also increased.

Although CLACCS policy don't consider energy consumer, it uses the message dropping probability to choose message to remove when buffer is full. This is superior to the in EACC schemes. So CLACCS can obtain a higher delivery ratio. Our CLARA incorporates the two features of EACC and CLACCS. Hence the consequence of delivery ratio is clearly achieved better than the two schemes mentioned above. On the other hand, the goal of these policies is only to increase the delivery ratio by copying as many as possible messages to intermediate nodes. The overhead ratio is arising as the number of node increasing. For there are much more opportunities to exchange messages among

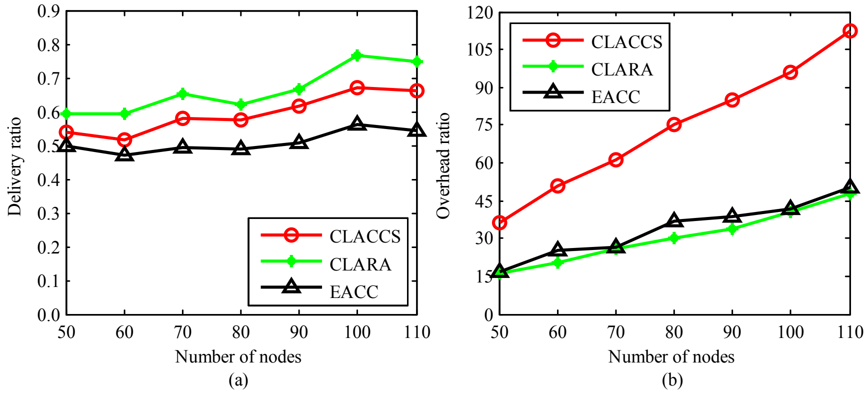


**Fig. 2.** (a) message delivery ratio and (b) overhead ratio under different number of nodes

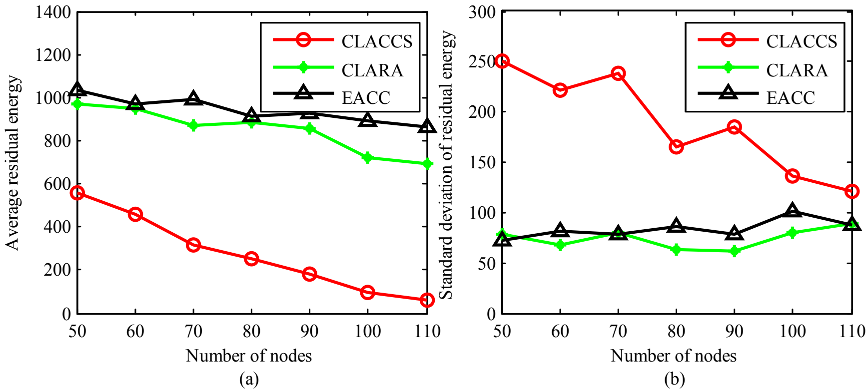


**Fig. 3.** (a) average residual energy (b) standard deviation of residual energy under different number of nodes

nodes while node moving in the network. Our CLARA gets almost the comparative performance of overhead ratio with EACC. And they are much better than CLACCS does. This is because that EACC and CLARA only receive specific messages rather than arbitrarily accept any message from their peers. This will reduce the copying of some messages that are about to expire between nodes. In addition, these two algorithms periodically adjust the TTL proportion of receiving messages based on the energy level of neighbors. This is of great help to the ping-pong effect of message exchange. Furthermore, EACC and CLARA will propagate the messages with larger TTL to much more intermediate nodes. When the buffer is full, these messages can not be replaced by other messages with smaller TTL values. So the overhead ratio is decline.

It can be clearly seen in Fig. 3(a), the average residual energy of nodes decreases as the nodes number increases. This is due to that as the number of nodes increases, nodes contact with each other more frequently. There are much more messages exchange between pairs and energy consumption. When buffer is full, the CLACCS will continuously discard messages to receive new messages from neighbors. This is especially energy consuming under the Epidemic routing pattern. This is because all messages will be exchanged between nodes even through it may exceed the life time of the message. However, the CLARA and EACC can utilize the energy level of current environment before starting the transfer. Some replications for neighbors with energy levels lower than the launch node will be canceled. The messages with the life time will expire in proportion of the initial TTL according to the energy level will be canceled to avoid wasting energy. So it can get better energy performance compared with CLACCS. Under the same conditions, CLARA and EACC perform a longer network life time than compared others.

As can be seen from Fig. 3(b), with the number of nodes increases, the standard deviation of residual energy among nodes of CLARA and EACC is increases slightly. This is because the energy level is dynamically updated according to the LA rules in these schemes. This will avoid difference latitude changing vibrational among nodes. Nodes with low energy levels still reduce replication times to save energy. In addition, this is an efficient method to prevent the energy from excessively wasting for the given node with conclusive energy left. It is of great significance significant for nodes which are powered by battery and energy consumption unbalance among nodes in the opportunistic networks.

In summary, CLARA can get better performance than EACC and CLACCS policies during the congestion condition in the opportunistic networks. Also it reduces the energy consumed and overhead ratio for messages replicated. It discriminates messages and nodes according to TTL and energy level. Moreover the message dropping probability is calculated according to the status of messages stored in the ambient nodes. This reduces the possibility of dropping the less copies messages. Therefore the messages delivery ratio is enhanced.

## 5 Conclusions

How to select the appropriate messages to transmit to intermediate node in terms of limited storage capacity and energy resource to improve the message delivery ratio is an eternal topic in the opportunistic networks. If nodes can make intelligent decisions according to the circumstances of current environment, this is an advisable scheme to existing routing algorithms. A novel intelligent approach based on the ambient nodes using DICLA model which is a dynamical system model widely used in the ambient intelligence situations is proposed in this paper. Message density and node energy status are updated dynamically to compute the message dropping probability and criterion of receiving message of each node. Furthermore the connection duration time between nodes is used to choose proper size message to avoid the incomplete message transfer. The simulation results showed that the proposed CLARA scheme can efficiently improve the message delivery ratio and get the balance of congestion and energy consumption. The life time of network is also prolongs accordingly.

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