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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 6 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i06.42021

PAPER

Improving Data Delivery in Unreliable Networks Using Network Coding and Ant-Colony Optimization

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ABSTRACT

Wireless Sensor Networks (WSNs) comprise interconnected wireless nodes that receive and transmit data across applications and platforms. This paper addressed the problem of link failures in WSNs that potentially could lead to the loss of data packets while still in transit. This was achieved through the use of network coding which is known to address capacity bottleneck problems in WSNs. In particular, a technique called Ant Agent-Assisted Network Coding (AAANC) is proposed that employs the ant colony optimization technique in addition to network coding operations. The main aim of AAANC is to facilitate the successful delivery and decoding of coded data packets in the presence of link failures. AAANC employs a packet route selection technique that is inspired by the social behavior of natural ants. For natural ants, a strong pheromone trail along a path indicates a promising route to a food source, and this is analogous to a reliable communication link for routing data packets in this paper. Through simulations, AAANC was compared to diagonal pseudorandom network coding (DNC) and triangular pseudorandom network coding (TNC), and it proved to have a superior performance in terms of packet delivery ratio and number of decoded packets. Significant performance gain can be achieved if AAANC algorithm is made to dynamically adapt the ant colony and network coding parameters in response to traffic changes.

KEYWORDS

ant colony optimization, network coding, graph, routing, wireless sensor network

1 INTRODUCTION

Network coding, which involves nodes storing data packets and forwarding their linear combinations to the next-hop node, has proven to be highly invaluable in communication networks [1, 2, 3]. Normally, information in standard communication networks is usually only stored and sent according to a routing mechanism. However, network coding diverges from this norm by combining routing and coding functions together, while ensuring that intermediate nodes in a network linearly combine received messages to increase the capacity of a multicast network; it can

Afolabi, A.S., Umar, M.O., Akinola, O.A. (2024). Improving Data Delivery in Unreliable Networks Using Network Coding and Ant-Colony Optimization. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(6), pp. 97–111. https://doi.org/10.3991/ijim.v18i06.42021

Article submitted 2023-06-05. Revision uploaded 2023-12-05. Final acceptance 2023-12-05.

encode received information and send the resulting compressed information to the next nodes; and finally, sink nodes can decode it. Network coding maximizes the utilization of transmission channel resources while improving network speed and reliability [4]. As a result of the immense usefulness of network coding, it has been applied in wireless mesh networks [5], star-of-star networks (LoRa) [6], cognitive radio networks [7], satellite networks [8], vehicle-to-everything networks (V2X) [9], P2P networks [10], and interplanetary file system (IPFS) networks [11], just to mention a few.

In network coding, coding is done on the fly at individual nodes, and this is one of the features that makes network coding different from the end-to-end approach of channel and source coding [12, 13]. In network coding, a transmitter breaks a block of data into *n* original packets and puts them into a group known as a generation. It then creates random linear combinations of those *n* packets, while the receiver(s) gathers coded packets until the whole generation can be decoded. This decoding operation happens when the receiver receives *n* linearly independent coded packets [14]. The concept of network coding is illustrated in Figure 1. In the figure, destination node 5 receives symbol "A" directly from source node 1, while destination node 6 receives symbol "B" directly from source node 2. Assuming the links can only send one symbol at a time, the central link between nodes 3 and 4 can only send either symbol "A" or symbol "B", but not both at the same time. Alternatively, node 3 can combine symbols "A" and "B" into a single symbol "A + B" (where the addition is a logical exclusive OR operation) through network coding.

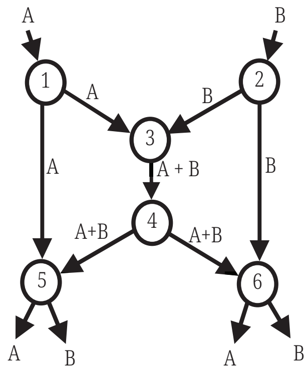

Fig. 1. Butterfly network [15]

Hence, node 5 can receive symbol "A" from node 1 and symbol "A + B" from node 4. It can then decode symbol "B" by computing $A + (A + B) = (A + A) + B = 0 + B = B$. Likewise, node 6 can receive symbol "B" from node 2 and symbol "A + B" from node 4. It can then decode symbol "A" by computing $(A + B) + B = A + (B + B) = A + 0 = A$. Therefore, both nodes 5 and 6 receive both symbols "A" and "B" despite the capacity bottleneck between nodes 3 and 4, thanks to network coding.

Several network coding techniques are in existence which include random linear network coding, deterministic linear network coding, triangular network coding, diagonal network coding, and opportunistic network coding, just to mention a few.

2 RELATED WORKS

The concept of network coding was first demonstrated in Ref. [16] where it was reported that bandwidth efficiency can be improved through network coding when compared to simply routing or replicating information in a network. The work introduced a novel approach to performing unicasting (or multicasting) operation in which information is considered to diffuse from source to sink, which is an important foundation upon which many later works on network coding was built. Network coding design involves the determination of what linear combinations each node in a network transmits while ensuring that message diversity is preserved. One common approach to realizing the linear combination involves independently and randomly selecting coefficients from a finite field based on a uniform probability distribution [15].

Network coding has found immense relevance in sparse networks [17, 18], where the end-to-end path from source to destination may be absent or difficult to form; for example, in Ref. [17], due to their high design and manufacturing costs, sensor nodes in underwater wireless sensor networks (UWSNs) are sparingly dispersed throughout a broad sea region. The authors developed a sliding window-based coding technique to realize effective coding gains while minimizing coding costs. Then, to decrease decoding overhead, they used a sliding window-based decoding method.

Reference [19] solved the low transmission efficiency problem at data centers resulting from massive data transmission caused by the use of multiple codecs and inefficient decoding processes. In particular, they proposed a network coding technique that jointly considers wireless sensor network coding strategies and redundant data storage at data centers to achieve fast data delivery.

Khalily-Dermany *et al.* [20] formulated an extended optimization problem based on two vectors of variables (transmission range and network traffic). They showed, in particular, that there is a coding solution if and only if the extended optimization problem has at least one optimum solution. This theorem provides a new goal function that is more practical for extending the lifespan of wireless sensor networks (WSNs). The simulation results show that the proposed model can effectively increase transmission range to achieve a longer lifespan for network-coding-based WSNs.

Vanitha et al. [21] presented EPRCDA-FBA, a technique that aggregates data in WSNs by using network coding to reduce data transmission latencies and power consumption while enhancing network throughput. Network coding increases channel utilization and decreases packet redundancy in the network by combining data for transmission to the next hop. When there is congestion, an adaptive technique is used in which the packet-dropping rate is raised and the node delivers packets by aggregating them using network coding. When compared to competing methods, EPRCDA-FBA achieved 25% less packet loss and 67% lower energy use, according to simulations. However, if subjected to a substantial connection failure, EPRCDA-FBA may suffer performance deterioration.

To provide reliable data transmission in a WSN, Laurindo et al. [22] introduced the ORST (Optimized Relay Selection approach) approach, which they integrated with network coding. The ORST technique selects a small number of relay nodes in the network for data transmission. Each selected relay node creates a fresh encoded packet with a huge number of received messages, which results in a limited number of linear system equations and, as a result, the coordinator finds it difficult to decode incoming signals. The decoding difficulty arises due to a crucial requirement that a node using the linear network coding approach must receive a number of coded messages that is greater than or equal to the number of original messages. This is why the ORST method showed poor performance when combined with network coding. To remedy the poor performance of ORST, we propose combining network coding with the ant colony algorithm. This will ensure that optimum routes are selected for data transmission to facilitate the delivery of as many data packets as possible to the destination node. The advantage of our proposed approach is that the coefficient of the decoding matrix of the received data packets will be fully ranked before the decoding operation is performed, and this enhances the probability of a successful decoding operation.

The proposed ant colony optimization [23] [24] has been studied extensively in the literature. It is a subclass of swarm intelligence methods that searches for the best solution in discrete optimization problems. In ant colony optimization, artificial ants serve as agents that deposit pheromones on the ground to indicate the most rewarding path that should be plied by other members of the colony [25, 26].

The ant colony optimization algorithm has been applied in diverse contexts [27, 28]. For example, to provide quick, accurate, real-time interactive, and high-quality learning path recommendations, Li et al. [29] developed the online personalized learning path recommendation model (OPLPRM), which was based on the saltatory evolution ant colony optimization (SEACO) algorithm. The model tackles the delayed convergence and low accuracy difficulties that occur when online learning route recommendation problems are solved using the conventional ant colony optimization (ACO) technique. It was shown that the SEACO algorithm achieved a 12.3% performance improvement compared to the traditional ACO method.

An adaptive ant colony optimization for large-scale traveling salesman problem (AACO-LST) was proposed by Tang et al. [30] First, AACO-LST improved the state transfer rule so that it can adapt to population evolution, hence accelerating convergence speed; then, a 2-opt operator was used to locally optimize the part of better ant paths to further improve the AACO-LST algorithm's solution quality. Simulation of 45 traveling salesman problem instances showed that AACO-LST was able to improve solution quality by 79% when compared to the traditional ant colony system (ACS). However, it is unclear how AACO-LST can be applied to optimization problems in continuous spaces as it was specifically modeled to solve the traveling salesman problem. Considering the attractive performances of ant colony optimization, it promises to be beneficial when combined with network coding for route selection in WSNs.

The first network protocol that was based on ant colony optimization was introduced by [31], and it was named AntNet [32]. AntNet was implemented for the first time in live routers in [33] and was observed to outstandingly outperform the widely used OSPF (open shortest path first) routing protocol [34]. In particular, AntNet successfully forwarded surplus packets to their destinations, whereas these packets were lost by the OSPF protocol [33]. The tremendous success of ant colony optimization for packet routing has therefore inspired its selection in this paper to aid the delivery of network-coded data packets.

The main contributions of this article are as follows.

1. First, we proposed a framework for setting up edges between the nodes that make up a wireless sensor network
2. Then we formulated a network coding scheme for forwarding data packets through optimum routes and these routes are determined by the ant colony algorithm (AAANC).
3. Finally, we demonstrated through simulation that when a WSN is exposed to link failure, AAANC achieves a higher data packet delivery ratio when compared to other comparative schemes

3 MATERIALS AND METHODS

We consider the problem of implementing random linear network coding in an acyclic multi-hop sensor network $Q = (V, E)$, where V denotes the set of vertices, and

E is the set of edges in the multi-hop network. It is assumed that in the network, a unique source node $s \in V$ has the capability of generating data packets of size W denoted by d_1, d_2, d_3, …, d_W, which it encodes and forwards to the next-hop node. We also assume that source s has no input channel and there is no directed cycle in the sensor network. Apart from the source node, two other categories of nodes in the network include the intermediate node and the destination node. All the nodes in the network, except the sink node, perform random linear coding by mapping input packets to output packets based on coding coefficients drawn from a finite field of size q denoted as GF(q) (where GF denotes Galois Field).

An intermediate node has both input and output channels, while a destination node has only input channel(s) but no output channel. It should be noted that, in this paper, the notion of channel and edge are used interchangeably. The forwarding end of an edge is the head while the receiving end is the tail. Both the source node and the intermediate nodes must discover all the next-hop nodes in their vicinity to facilitate the relaying of coded data. Relaying of coded data is repeated over multiple hops until arrival at the destination node.

3.1 Neighbor node discovery

Neighbor node discovery must be performed by the source node as well as by all intermediate nodes. It is a process whereby nodes in the network become aware of other nodes within their communication range. Consider nodes v, $u_a \in V$ (where $a = 1, 2, 3, \ldots, n$ is the index of the next-hop node(s) with which node v is presumed to share an edge); a link or edge from node v to node u_a is denoted as e(v, u_a). If e(v, u_a) exists, then e(u_a,v) can not exist because a signal is considered to flow in only one direction from the head to the tail of an edge (directed graph). Let Ψ_{v,u_a} denote the set of candidate nodes u_a that share an edge with node v, where v is the head and each $u_a \in \Psi_{v,u_a}$ is the tail. This is represented as:

$$\Psi_{v,u_a} = \{u_1, u_2, u_3, \ldots, u_n\}, \tag{1}$$

where

$$n = |V| - 1, \tag{2a}$$

and

$$u_a \neq v. \tag{2b}$$

Equations (2a) and (2b) indicate that n is the total number of nodes in the network excluding node v, while Eq. (1) suggests that node v has an edge to every other node in the wireless sensor network; but in reality, it is unlikely that node v has a communication link to all the other nodes due to constraints, such as separation distance, and so on. Therefore, to determine the set of nodes that node v shares an edge with, let $B_{v,u_a} \in \{0,1\}$ denote a binary variable that indicates whether or not a link exists from node v to u_a. If B_{v,u_a} is 1, then a link exists from node v to u_a; conversely, a value of 0 indicates otherwise. Consider the set

$$\{B_{v,u_a}\} : B_{v,u_a} \in \{0,1\},\ v, u_a \in V, \tag{3}$$

for any two adjacent nodes v and u_a, the value of B_{v,u_a} is determined as:

$$B_{v,u_a} = \begin{cases} 1;\text{if } d(v,u_a) \le d_T,\ v \notin \Psi_{u_a,v}, \text{ and } v \ne u_a, \\ 0;\text{otherwise} \end{cases} \quad \forall a \in \{1,2,\cdots,n\} \tag{4}$$

Equation (4) ensures that B_{v,u_a} has a value of 1 if all of the following conditions are simultaneously true:

i) The distance $d(v, u_a)$ between nodes v and u_a is less than or equal to the maximum communication range d_T, i.e.; $0 \le d(v, u_a) \le d_T$
ii) There is no link from node u_a back to node v i.e., $v \notin \Psi_{u_a,v}$ (this ensures that edges in the graph are unidirectional)
iii) There is no link from node v back to itself, i.e., $v \ne u_a$

On the other hand, B_{v,u_a} has a value of 0 if any of the listed conditions is violated. Let Ψ_v denote the set of all the nodes that share edges with node v in which node v is the head of the edge, such that Eq. (4) resolves to 1. Then, Ψ_v can be represented by

$$\Psi_v = \bigcup_{u_a \in V, B_{v,u_a}=1} u_a \tag{5}$$

Equation (5) gives the set of all nodes that node v can directly communicate with as a next-hop node in the wireless sensor network. Note that

$$\Psi_v \subseteq \Psi_{v,u_a}, \tag{6}$$

The neighbor node discovery algorithm is illustrated in Algorithm 1.

Algorithm 1: Neighbor Node Discovery

```
begin
  for each v ∈ V do
    Ψ_v = ϕ //initialize the set of next hop nodes
    for each ua ∈ V do
      if v ≠ u_a and v ∉ Ψ_{u_a} //no existing edge between v
                                 // and u_a from a previous iteration
        if d(v, u_a) ≤ d_T then
          Ψ_v ← Ψ_v ∪ u_a //add node ua to the set
        end if
      end if
    end for
  end for
end
```

3.2 Network coding

As mentioned in the preceding discussion, the nodes in the network are classified as the source node, intermediate nodes, and destination nodes. It is assumed that the source node generates the data that is to be sent over the network. Let the message data to be sent in generation x be denoted as D_x, which is divided into W parts, and each part is referred to as a packet. The dimension of D_x is $1 \times W$ and it is represented as

$$D_x = [d_{1,x}, d_{2,x}, d_{3,x}, \ldots, d_{W,x}]. \tag{7}$$

The packets are encoded at the source node using coding coefficients drawn from a Galois Field GF(q) of finite size. Each coding coefficient, α, drawn from the field, is selected randomly according to a uniform probability distribution function, and the packets are linearly combined as

$$M_x = \sum_{w=1}^{W} \alpha_{w,x} d_{w,x} \qquad \forall x \in X \tag{8}$$

Note that only packets belonging to the same generation can be combined together. The vector of coding coefficients $[\alpha_x]$, is appended to the packet header and is referred to as the local encoding coefficient vector. $M_{1,x}$, $M_{2,x}$, $M_{3,x}$, …, $M_{R,x}$, which are linear independent combinations of the original data packets, arrive at the next-hop node. If the next-hop node is not a destination node, but an intermediate node, the node draws a re-coding coefficient β from the Galois field according to a uniform probability distribution function which is used to re-encode R received coded packets as

$$N_x = \sum_{r=1}^{R} \beta_{r,x} M_{r,x} \forall x \in X \tag{9}$$

Re-coding operation is repeated at each intermediate node, such that, the received packets are linearly combined and forwarded to the next-hop node, and each time, the vector of re-coding coefficients $[\beta_{r,x}]$ is appended to the packet header.

At the destination node, the original packet generated at the source is recovered with the aid of the global encoding coefficient matrix available in the packet header. The decoding operation makes use of not only the global encoding coefficient matrix but also the linearly combined copies of the original packets, both of which are available to the destination node.

The decoding process can be implemented by using Gaussian elimination if the number of packets R received at the destination node is not less than the number of packets W sent from the source. Each received coded packet represents a linear equation, where unknown variables are the W source packets. The values of the unknown variables can be obtained by solving a system of linear equations. This is only possible when at least W packets have been received, so that the rank of the decoding matrix is W. If the rank of the decoding matrix is less than W, linear dependence will exist among the received packets, and it will be necessary for more packets to be received before the decoding operation can be successful. Let the coding coefficient at the source node and intermediate node be denoted by vectors G_x and H_x, respectively. Then, the original data packets vector D_x can be recovered by solving Eqs. (10) and (11):

$$M_x = H_x^{-1} N_x. \tag{10}$$

$$D_x = G_x^{-1} M_x. \tag{11}$$

3.3 Packet routing

In this paper, the routing of coded packets from node v to node $u_a \in \Psi_v$ is achieved by using artificial ants as agents. Natural ants are endowed with the ability to build trails made up of pheromones along the path they tread from their nest to a food source. A pheromone is a chemical substance secreted by ants as they transverse a path. By using a pheromone trail, a colony of ants is able to follow the shortest path to a food source without each ant having a global vision of the path [25]. The ants that follow the shortest path arrive at the destination first, thus making the pheromone deposited along the path they followed stronger than other paths.

A path with a higher concentration of pheromone is more attractive to other ants that are embarking on a journey to the food source; hence, they follow that path with a high probability, and, in the process, deposit additional pheromone along the path, which makes the path even more appealing to other ants that are coming behind. Based on this background, this paper employed a stochastic process to determine $P(v, u_a)$, which is the probability that an artificial ant at node v moves to the next-hop node $u_a \in \Psi_v$ computed as:

$$P(v,u_a) = \begin{cases} \dfrac{\tau(v,u_a)^{\gamma}\,\eta(v,u_a)^{\delta}}{\sum_{u_a \in \Psi_v} \tau(v,u_a)^{\gamma}\,\eta(v,u_a)^{\delta}}; & \text{if } u_a \in \Psi_v, \\ 0; & \text{otherwise} \end{cases} \tag{12}$$

In Eq. (12), γ and δ are weight parameters that indicate the importance of the size of deposited pheromone and visibility, respectively. The visibility, $\eta(v, u_a)$, is computed as:

$$\eta(v,u_a) = \frac{1}{d(v,u_a)}, \tag{13}$$

while $\tau(v, u_a)$ is the size of pheromone deposited along edge $e(v, u_a)$. In this paper, ants and packets are analogous. This means that if an ant successfully arrives at a food location, it directly translates to a data packet successfully arriving at a destination node. Each time an ant transverses a path, it deposits pheromone on the path. Let $\Delta\tau_{d_w}$ be the size of the pheromone deposited by ant d_w; then the size of the pheromone deposited by a single ant d_w along edge $e(v, u_a)$ is computed as

$$\Delta\tau_{d_w}(v,u_a) = \begin{cases} \dfrac{Q}{L_{d_w}}; & \text{if } e(v,u_a) \in T_{d_w}, \\ 0; & \text{otherwise} \end{cases} \tag{14}$$

where T_{d_w} is the set of edges traversed by ant d_w, and L_{d_w} is the length of the tour taken by the ant, while Q is a constant. If a set of $D' \subseteq \{d_1, d_2, d_3, \ldots, d_W\}$ ants follow a particular edge $e(v, u_a)$, the total pheromone they deposit on the edge is

$$\Delta\tau(v,u_a) = \sum_{d_w \in D'} \Delta\tau_{d_w}(v,u_a). \tag{15}$$

Whenever an ant traverses a path, the size of the pheromone along that path increases due to the deposition by the ant; conversely, it reduces through evaporation if the ant does not traverse the path. The amount of pheromone on the path is updated periodically depending on the utilization of the path, and this update can increase or decrease the amount of pheromone along the path. The amount of pheromone, depending on the utilization of the path, is computed as

$$\tau(v,u_a) = (1-\rho)\cdot\tau(v,u_a) + \rho\Delta\tau(v,u_a) \tag{16}$$

where $\rho \in (0,1]$ is the pheromone evaporation coefficient and $\Delta\tau(v, u_a)$ is the size of pheromone that ants $\{d_w\} \subseteq D$ deposit on edge $e(v, u_a)$. Algorithm 2 describes the ant agent-assisted packet routing algorithm.

Algorithm 2: Ant-Colony Based Packet Routing Algorithm

- **i)** Deploy ants on nodes of the network
- **ii)** Determine the path to be followed by each ant using Eq. (12)
- **iii)** Compute the pheromone deposited by each ant on the path it followed using Eq. (14)
- **iv)** Compute the total pheromone deposited by all ants that followed a path using Eq. (15)
- **v)** Update the size of pheromone on paths using Eq. (16)
- **vi)** Repeat (ii) to (v) until ants get to the destination
- **vii)** All ants die and new ants are born
- **viii)** End of the current run
- **ix)** Repeat steps (i) to (viii) T number of times

The flowchart of the proposed ant agent-assisted network coding (AAANC) is illustrated in Figure 2.

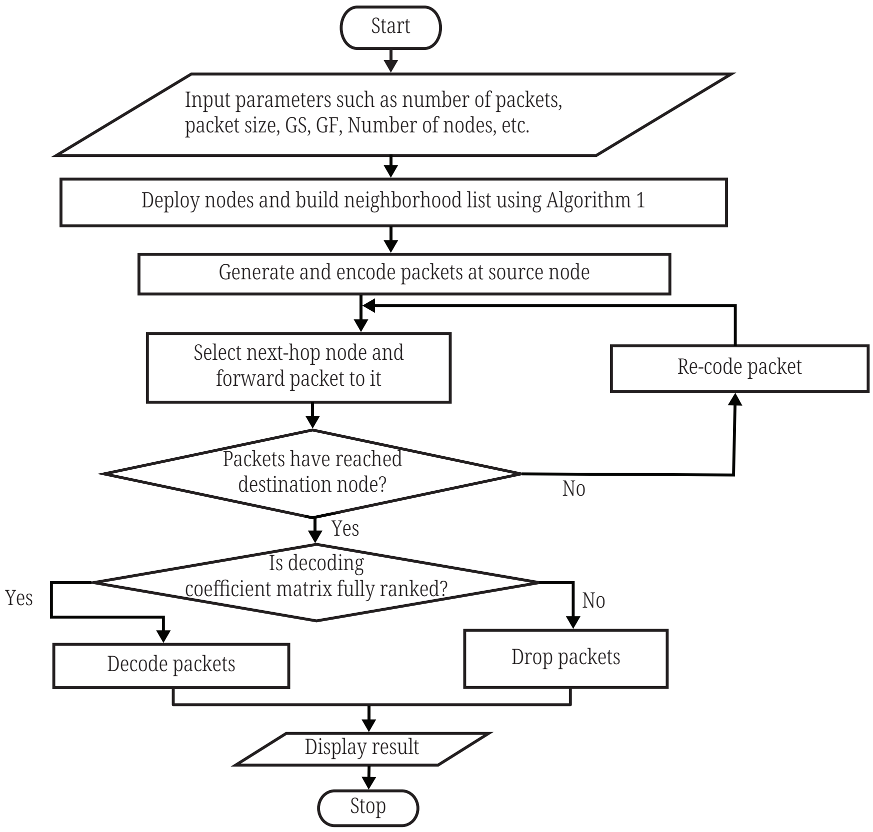

Fig. 2. Flowchart of ant agent-assisted network coding (AAANC)

4 RESULTS AND DISCUSSION

Through simulations, we compare the performance of our proposed AAANC scheme with diagonal pseudorandom network coding (DNC) and triangular pseudorandom network coding (TNC) [35]. The simulator was developed using MATLAB and the values of parameters shown in Table 1 were selected.

Table 1. Simulation settings

Parameter	Value
Galois Field Size (GF)	8
Link Error Pattern	Gilbert Elliot Model (Probability = 0.025 – 0.25)
Generation Size (GS)	5 – 100
Number of Nodes	6 – 14
Pheromone Trail Control (δ, γ)	1,4
Evaporation Coefficient (ρ)	0.01
Initial Pheromone (τ)	0.15
Constant (Q)	20

Figure 3 shows the fraction of total packets lost as a function of generation size. It can be noticed that packet loss increases with an increase in generation size. The figure also shows that by using AAANC, enhanced performance is achieved compared to DNC and TNC; that is, there was a reduction in the number of packets lost when AAANC scheme was used. This is because ant colony-based routing makes an effort to route data packets through reliable paths, hence reducing the probability of data packets not arriving at the destination due to link failure. It should, however, be noted that not all packets that arrive at the sink node are decodable. A coded packet belonging to a message (i.e., a generation) is decodable based on the condition that $R \geq W$, where R is the number of linearly independent coded packets that arrive at the sink node, while W is the number of native packets sent from the source node s.

Hence, Figure 3 gives a picture of the fraction of the packets sent from s that never arrived at the sink node but it does not account for the packets that arrived at the sink node but were not decodable as a result of not satisfying the condition $R \geq W$. It can be observed in the figure that the fraction of packet lost increases with an increase in generation size for all the schemes; this is because the number of nodes is held constant, which means that the overall capacity of the network is not changed. The injection of more packets into the network without a corresponding increase in the capacity of the network culminates in more packets getting lost.

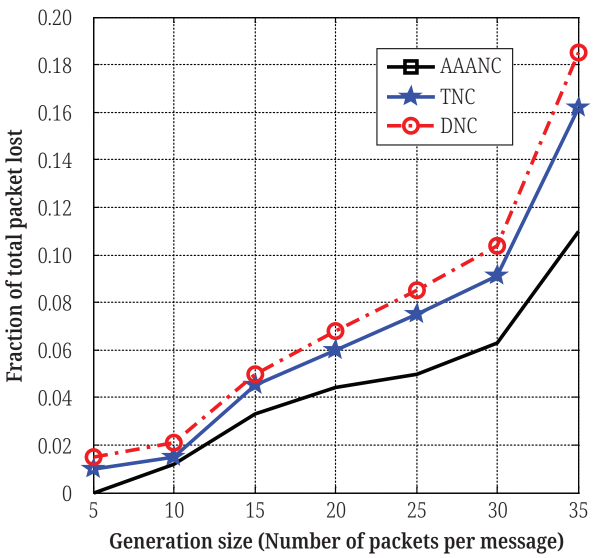

Fig. 3. Fraction of total packet lost VS generation size (Number of packets per message)

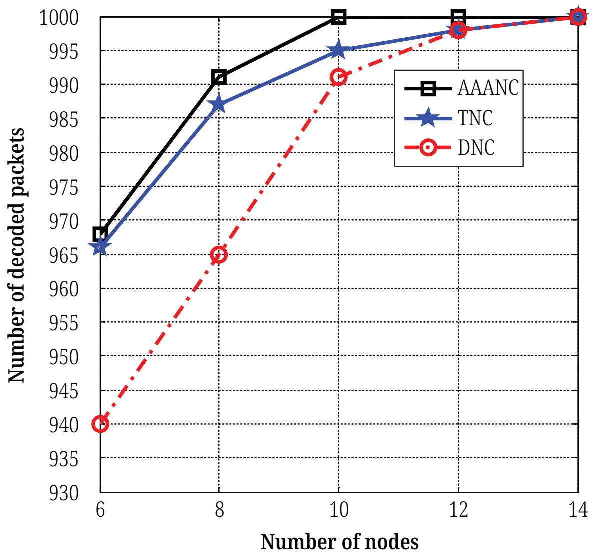

Fig. 4. Number of packets decoded VS number of nodes

Figure 4 compares AAANC with the other schemes based on the number of decoded packets when the number of nodes is increased from 6 to 14 and the probability of link error is held at 0.075. It can be observed that all the schemes successfully decoded all the packets when the number of nodes in the network was 14. However, only our proposed AAANC scheme could decode all the packets when the number of nodes in the network was 10. The number of packets decoded by DNC dropped sharply when the number of nodes was reduced further from 10 to 6, whereas, the drop was more gentle for AAANC and TNC. Hence, AAANC outperforms DNC and TNC in terms of the number of packets decoded, especially when only a few nodes are in the network. This is because, in AAANC, the ant agents help to increase the probability of routing data packets through links that are void of link failure, and hence, increases the chances of successfully delivering coded packets to the destination node.

Next, we compared the performances of the 3 schemes when link failure was deliberately introduced into the network based on Gilbert Elliot's model. The corresponding result is shown in Figure 5. The number of nodes was set to 10, the generation size was set to 20 and the probability of link failure was increased from 0 to 0.25. As can be observed in Figure 5, our proposed AAANC scheme and TNC scheme were able to decode all packets when the link error probability was 0.075. It can be observed that at a link error probability of 0.25, the poor performance of the DNC scheme is significant compared to AAANC and TNC because it lost approximately 25% of the original packets that were sent and was only able to decode the remaining 75%. Therefore, it can be inferred that link failure has a significant impact on the number of decodable packets, hence the need for the adoption of techniques that could ameliorate its impact, such as our proposed AAANC scheme.

The results of packet overhead for TNC, DNC, and AAANC are shown in Figure 6. The figure shows that our proposed AAANC has the worst packet overhead performance.

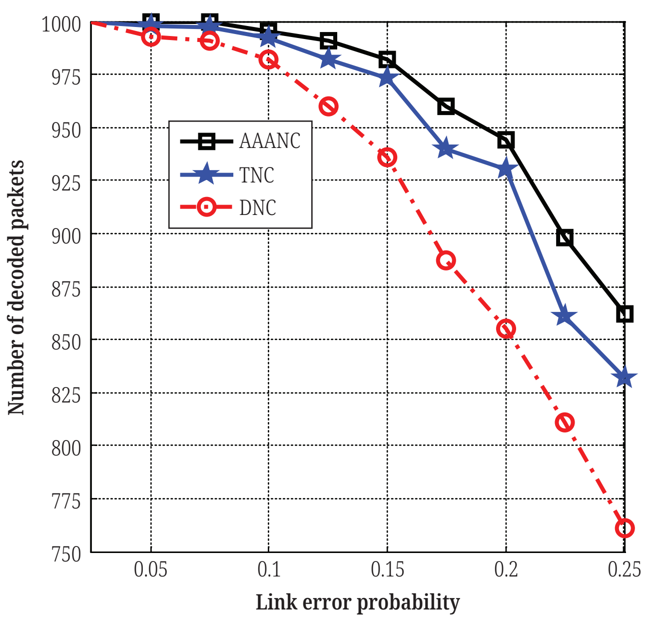

Fig. 5. Number of packets decoded VS link error probability (GS = 20, 10 nodes)

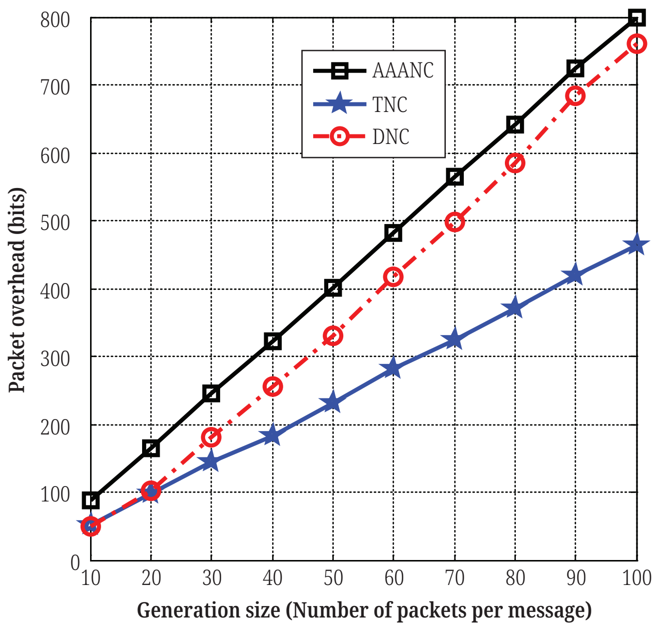

Fig. 6. Packet overhead VS generation size

This is because, in TNC and DNC, the source node *s* puts an index of the coding coefficient vector drawn from a codebook into the packet header, whereas our scheme on the other hand puts the full coding coefficient vector in the packet header, which made our scheme perform poorly in terms of packet overhead. Therefore, the incorporation of an overhead reduction method into AAANC is the subject of our future work.

5 CONCLUSION

In this paper, we proposed the application of the ant colony optimization method in the development of a routing strategy for delivering data packets that have been linearly combined using network coding and we called our proposed scheme ant agent-assisted network coding (AAANC). Although, network coding has the attractive feature of achieving a higher throughput efficiency when compared to other widely used routing protocols such as OSPF (open shortest path first) that only store and forward data packets, its performance could, however, depreciate when a minimum number of packets fail to arrive at the destination node, hence making packet decoding impossible, and, therefore, rendering the already received packets useless. Our proposed scheme emulates the social behavior of ants and inherits the success inherent in the strategies that ants employ for survival, which involves searching for food. In particular, AAANC uses simulated ants to route data packets from a source node to a destination node through routes that have low probabilities of failure. Extensive simulations showed that AAANC outperformed other network coding techniques in terms of packet delivery ratio and number of decoded packets.

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