Abstract— At present, the field of wireless sensor networks (WSNs) is an important and challenging research area. Advancements in sensor networks enable a wide range of environmental monitoring and object tracking applications. Moreover, multihop routing in WSN is interrupt by new nodes constantly entering/leaving the system. Therefore, biologically inspired algorithms are reviewed and enhanced to tackle problems arise in WSN. Ant routing has shown an excellent performance for sensor networks. In this paper, the design and work on ant based autonomous routing method for wireless sensor network are presented. Certain parameters like energy level, link quality and velocity are considered while making the decision. These decisions will come up with the optimal route to forward data towards destination. The given bio-inspired self-optimized mechanism will maximize traffic throughput while reducing the end to end delay over the network.

Keywords—ANT Colony, Multihop, Routing, Self-Optimization, Wireless Sensor Network

I. INTRODUCTION

Wireless communication plays an important role these days in the sector of telecommunication and has huge importance for future research. Wireless medium is making the world’s life easier with the development of sensing and monitoring systems. In these sensing and monitoring systems new gadgets and software advancement are very frequently available to the end-user. The fast growth makes wireless communication more and more complex. Also some of infrastructure less wireless sensor networks deployment area is out of human reach. The above mentioned challenges like growing complexity, unreachable maintenance and unsecure communication need new mechanisms. The new mechanism can maintain the features of wireless sensor networks (WSNs) such as multihop routing and dynamically environmental changes in a complete autonomous mode. In order to address autonomous capability for multihop WSNs, it has been visualize that self-organized network application can understand the network operational objectives. Additionally, probabilistic methods that provide scalability and preventability can be found in nature and adapted to technology. Towards this vision, it is observed that various biological principles are capable to overcome the above adaptability issue. The area of bio-inspired network engineering has the most well known approaches which are swarm intelligence (ANT Colony, Particle swarm), AIS and intercellular information exchange (Molecular biology)[1-4]. WSN routing algorithms based on ACO have been presented in last few years, such as [5], Sensor-driven Cost-aware Ant Routing (SC), the Flooded Forward Ant Routing (FF) algorithm, and the Flooded Piggybacked Ant Routing (FP) algorithm [6], Adaptive ant-based Dynamic Routing (ADR) [7], Adaptive Routing (AR) algorithm and Improved Adaptive Routing (IAR) algorithm [8], E&D ANTS [9].

This paper propose an architecture by implementing the most well known and successful approaches. ANT Colony Optimization (ACO) method is utilized for the optimum route discovery in multihop WSN. This technique will be accomplished by assigning each procedure to the group of agents. The agents will work in a decentralized way to collect data and/or detect an event on individual nodes and carry data to the require destination through multihop communication. The next section reviews the related research for optimum route discovery through ACO. Section 3 shows the methodology of our mechanism. Section 4 describes the implementation and results obtained through network simulation. The conclusion and future work are stated under section 5.

II. RELATED RESEARCH

A. Overview of AntRouting in WSN

Ant colony algorithms were first proposed by Dorigo et al [5] as a multi-agent approach to difficult combinatorial optimization problems like the travelling salesman problem (TSP) and the quadratic assignment problem (QAP), and later introduced the ACO meta-heuristic.

There are two types of ants applied in the algorithms, forward ants and backward ants. Forward ants, whose main actions are exploring the path and collecting the information from the source nodes to destination node, have the same number as the source nodes. The paths that forward ants travel will construct a tree when they merge into each other or reach the destination and data is transmitted along the tree paths. There are two key factors that conduct the movement of the forward ants: one is pheromone trails that are deposited along the edges, and the other is the nodes potential which provides an estimate of how far an ant will have to travel from any the node to either reach the destination or to aggregate data with another node. While the backward ants, travelling back from destination node to source nodes contrary to the forward ants,
perform their uppermost function of updating the information of their pass-by nodes.

ACO algorithms are a class of constructive meta-heuristic algorithms that mimic the cooperative behaviour of real ants to achieve complex computations and have been proven to be very efficient to many different discrete optimization problems. Many theoretical analyses related to ACO show that this optimization can converge to the global optima with non-zero probability in the solution space [10] and their performance have greatly matched many well-studied stochastic optimization algorithms, for example, genetic algorithm, pattern search, GPASP, and annealing simulations [5].

Sanjoy Das et al have given an on-line ACO algorithm using AntNet techniques for MSDC [11] which has been formalized to be a typically Minimum Steiner Tree problems. They also have proposed an improved algorithm by adding another type of ants, random ants, just like the newspaper deliverer, whose main task is to dissipate information gathered at the nodes among other neighbouring nodes. Practically, simulation results also show that their algorithms are significantly better than address-centric routing. In these proposed algorithms the forward ants normally spend a long time. There is a bug of dead lock in their algorithms. In their improved algorithm, a large amount of random ants are needed.

In [5] the authors propose a new idea of keeping the information by all sensor nodes of their own. By this even in the absence of global processing the nodes still can work on their own information. In this research still have a drawback of broadcasting while initialization phase which consumes lot of energy at the beginning of the network deployment.

Zhang et al. [6] proposed three ant-routing algorithms for sensor networks. The SC algorithm is energy efficient but suffers from a low success rate. The FF algorithm has shorter time delays; however, the algorithm creates a significant amount of traffic. Despite high success rate shown by the FP algorithm that it is not energy efficient.

An Adaptive ant-based Dynamic Routing (ADR) algorithm using a novel variation of reinforcement learning was proposed by Lu et al. [7]. The authors used a delay parameter in the queues to estimate reinforcement learning factor.

In [12] proposed a novel approach for WSN routing operations. Through this approach the network life time is maintained in maximum while discovering the shortest paths from the source nodes to the base node using an evolutionary optimization technique. The research has also been implemented on microchip PIC® series hardware, called Pic12F683.

In [8] propose two adaptive routing algorithms based on ant colony algorithm, the Adaptive Routing (AR) algorithm and the Improved Adaptive Routing (IAR) algorithm. To check the suitability of ADR algorithm in the case of sensor networks, they modified the ADR algorithm (removing the queue parameters) and used their reinforcement learning concept and named it the AR algorithm. The AR algorithm did not result in optimum solution. In IAR algorithm by adding a coefficient, the cost between the neighbour node and the destination node, they further improve the AR algorithm.

[9] proposed a dynamic adaptive ant algorithm (E&D ANTS) based on Energy*Delay metrics for routing operations. Their main goal is to maintain network lifetime in maximum and propagation delay in minimum by using a novel variation of reinforcement learning (RL). E&D ANTS results was evaluated with AntNet and AntChain schemes.

**B. Comparison of the most recent ANT routing algorithms**

SC and [12] depends on the energy metric while FF based on delay. IA and IAR is the modification of ADR which used a delay parameter in the queues to estimate reinforcement learning factor. In FP they combine the forward ant and data ant to enhance the success rate. E&D ANT based on energy*delay metrics for routing operations. In our proposed algorithm, the best values of velocity, PRR and remaining power mechanism [13] are used to select forwarding node because velocity alone does not provide the information about link quality. The best link quality usually provides low packet loss and energy efficient [14]. Another novel feature of proposed algorithm is, it utilizes the remaining power parameter to select the forwarding candidate node. The remaining power assists the source node or intermediate node to distribute the forwarding load to all available forwarding candidates and hence avoid the routing holes problem.

**III. METHODOLOGY**

System design deals mainly with the development of state machine diagram which contains the routing management, neighborhood management and energy management as shown in Fig. 1. Routing management will be dependent mostly on forwarding metrics calculation. The routing management will look for the next best node towards the destination through the routing table, available at every node. By acquiring the optimal route the forwarding process will take place. Otherwise, routing management will call the process of neighbor discovery under neighborhood management as shown in Fig. 1.

The neighbourhood management then search for the best neighbouring node by broadcasting hello massages. By broadcast the node receive replies from the neighbouring nodes along with their characteristics. On the base of these replays it provides the solution back to the routing management state.

The key role of power management state is to check the remaining power to the higher state. The power management state can adjust the power for the transceiver. Under this state the energy parameter is imported from the physical layer into the network layer. In wireless sensor node there are 5 levels of power transmission. At the time of forwarding the first level is utilized, but if node is out of reach then the power level is increased in stages. Helping neighborhood management state in the energy aware route discovery and power level management is controlled by the power management state.

Inside routing management the forwarding metrics calculation as given in Table 1 takes place as shown is Fig. 2. If the error occurred while processing this state, it will be
control by routing problem handler as elaborated in Fig. 2.
The error can be like required neighbour not present or the best neighbouring node is lost or the required parameter is not there. Otherwise, if there is no error while forwarding calculation then the anycast state will be called to forward the required packets.

Common functions under neighbor management state are neighbor table maintenance, neighbor discovery, insert new neighbor, neighbor replacement, etc as exposed in Fig. 3. Main and most important thing the routing table is maintained via this state. If the best node towards the destination could not be found, the child state neighbor discovery is initiated.

Our proposed self-organized system mainly based on routing section. The optimal route discovery is tackled by ant colony optimization. Routing decision will achieved through probabilistic decision rule as shown in (1) [12].

The probabilistic decision rule can be expressed mathematically by (1). The decision depends on velocity, PRR and remaining power mechanism as given in Table 1.

\[
p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{h\in I}[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}
\]

- \(p_{ij}^k(t)\) overall desirability for ant \(k\) located in city \(i\) to choose to move to city \(j\).
- \(\tau_{ij}\) is a value stored in a pheromone table.
- \(\eta_{ij}\) is an heuristic evaluation of edge \((i,j)\).
- \(\alpha\) and \(\beta\) control the relative weight.

The decision will depend on the used metrics as, velocity, PRR and remaining power mechanism as given in Table 1.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>ROUTING METRICS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy</strong></td>
<td><strong>Link Quality</strong> (Packet Receiving Rate)</td>
</tr>
<tr>
<td>Node 1</td>
<td>(\alpha^1)</td>
</tr>
<tr>
<td>Node 2</td>
<td>(\alpha^2)</td>
</tr>
<tr>
<td>.</td>
<td></td>
</tr>
<tr>
<td>.</td>
<td></td>
</tr>
<tr>
<td>Node n</td>
<td>(\alpha^n)</td>
</tr>
</tbody>
</table>

The algorithm for each component in the designed system has been written and relations between the system models are
established. Energy management is evolved to maintain the energy consumption of every sensor node in WSN. The system is also capable of avoiding permanent loops which promotes deadlock problem in the running wireless sensor network. The dead lock is cured by assigning unique sequence ID to every forward ANT and also to the search ANT.

IV. LOGICAL IMPLEMENTATION

To evaluate the above system, we use network simulator 2 (NS2) to construct the network topology graph as given in Fig. 4. The topology is described as a randomly deployed 25-sensor nodes were deployed onto 50 x 50 m² grid.

![Network Topology](image)

For the Bio-inspired routing protocol implementation, the program is written in C++ and OTcl programming languages. In Fig. 4, each link is bidirectional and the weighting value of the link depends on the power consumption (nJ/bit) and ant’s moving time delay (ms). After the source nodes produce a quantity of artificial ants or packets conforming to the Poisson distribution, the destination nodes are randomly chosen by average probability. When one packet passes through a node by a certain speed, the node takes the first step to gather all the ant agents into buffer storage and then selects the optimal path from its routing table to transfer packets. In this way all the ants disperse in as many paths as possible to achieve the balance of the load.

A fixed size of one packet is considered in our simulation. During the animation produced by nam we can examine the output of network. The cbr traffic is produced first from node 2 to node 6, then the Poisson traffic from node 8 to node 23. The experimental parameters used to configure the system according to WSN are listed in Table 2.

In order to avoid cycles and the routing table’s freezing, we need to initialize $\tau_0$ as in [15]. In this case, ant agents can adjust to the more efficient path when the network traffic loads change and the congestion fades away. Simulation methods for the AntNet were attempted in [16] where the parameters $(c, a, a', \epsilon, h, t)$ were set to $(2, 10, 9, 0.25, 0.04, 0.5)$.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>SYSTEM PROPERTIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>Values</td>
</tr>
<tr>
<td>Reinforcement factor</td>
<td>0.05</td>
</tr>
<tr>
<td>Propagation Model</td>
<td>Shadowing</td>
</tr>
<tr>
<td>path loss exponent</td>
<td>2.5</td>
</tr>
<tr>
<td>shadowing deviation (dB)</td>
<td>4.0</td>
</tr>
<tr>
<td>reference distance (m)</td>
<td>1.0</td>
</tr>
<tr>
<td>phyType</td>
<td>Phy/WirelessPhy/802_15_4</td>
</tr>
<tr>
<td>macType</td>
<td>Mac/802_15_4</td>
</tr>
<tr>
<td>CSThresh</td>
<td>1.10765e-11</td>
</tr>
<tr>
<td>RXThresh</td>
<td>1.10765e-11</td>
</tr>
<tr>
<td>frequency</td>
<td>2.4e+9</td>
</tr>
<tr>
<td>Traffic</td>
<td>CBR, Poisson</td>
</tr>
</tbody>
</table>

The result through this implementation is pheromone table on each node. As an example pheromone table at node 24 is shown in Table 3. Table at each node contains the pheromone value for the next node towards the required destination. While the network is online, the routing table is directly built up through pheromone table exponential transformation.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>PHERMONE TABLE AT NODE 24</th>
</tr>
</thead>
<tbody>
<tr>
<td>dest</td>
<td>next</td>
</tr>
<tr>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

The graph is generated by the Trace graph 2.05[17]. This graph depends on the result extracted from trace file produced under NS2. In Fig. 5 the throughput of generated traffic at node 8 against the simulation time is exposed. With the help of these results we can monitor different states on the certain node, like
sleep and wake states. By examining these states we can improve our parameters to minimize the energy consumption.

**V. CONCLUSION**

Here, we proposed biological inspired self-optimized routing mechanism for Wireless Sensor Networks. This mechanism is based on delay, energy and velocity model. This model introduces a great energy efficient solution while keeping velocity also under consideration. This velocity parameter will maintain performance for the real time applications as well. The optimal decision also depends on an addition factor which is reinforcement learning (RL) technique. Finally, this autonomic routing mechanism will come up with better throughput rate.

Our immediate future work will involve the comparison with the most recent and famous routing protocols. Onwards, other ant colony variants will also be considered. The stated architecture as described in this paper will then be implemented on the WSN hardware. Furthermore, the security module will be integrated to tackle most well know attacks occur on WSNs.

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**REFERENCES**


