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Article

Energy Enhancement in Multipath Routing Protocol Based Antnet and Artificial Intelligent Model in Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) are characterized by severe energy constraints, dynamic topology, and limited computational resources, making routing design a critical challenge. Traditional single-path and static routing protocols often lead to uneven energy consumption and premature node failures, thereby reducing network lifetime. To address these limitations, this paper proposes an energy-aware multipath routing protocol that integrates AntNet with a lightweight Multilayer Perceptron (MLP) model. Unlike existing artificial neural network-ant colony optimization (ANN-ACO) or deep learning based routing approaches, the proposed method does not embed complex learning mechanisms into the routing core. Instead, the MLP model is used as an auxiliary decision-support component to assist AntNet in selecting energy-efficient and reliable paths while preserving low computational overhead. The routing decision process considers residual energy, end-to-end delay, packet delivery ratio, and routing overhead, enabling a balanced trade-off between energy efficiency and communication performance. The proposed protocol is evaluated using the NS2.35 simulator under different network densities and traffic conditions. Simulation results demonstrate that the proposed approach reduces energy consumption by up to 32% and routing overhead by 28%, while improving packet delivery ratio by 40% and network lifetime by 22% compared to conventional Ad hoc On-Demand Distance Vector (AODV) and AntNet-based routing protocols. These results confirm that combining AntNet with a lightweight MLP yields an effective and scalable solution for energy-efficient multipath routing in WSNs, without the complexity of deep learning-based schemes.

Keywords: Wireless Sensor Networks; Energy Consumption; Multilayer Perceptron; Ant Colony Optimization; Intelligent Multi-Path Routing Protocol

1. Introduction

Wireless Sensor Networks (WSNs) have become a fundamental component of many modern applications, like environmental monitoring, industrial automation, and smart infrastructure [1,2]. Despite their wide applicability, WSNs are inherently constrained by limited battery capacity, restricted computational resources, and dynamic wireless conditions. As a result, routing protocols must be carefully designed to minimize energy consumption while maintaining reliable data delivery and network stability.

Traditional routing protocols such as the Ad hoc On-Demand Distance Vector (AODV) protocol were originally developed for mobile ad hoc networks and do not explicitly consider the energy constraints of sensor nodes. Consequently, their direct application in WSN environments often leads to premature node depletion, frequent route failures, and reduced network lifetime. To overcome these limitations, numerous energy-aware and adaptive routing strategies have been proposed [3].

Swarm intelligence-based routing, particularly Ant Colony Optimization (ACO), has garnered significant attention due to its distributed nature and ability to discover dynamically multiple paths [4]. Ant-based routing protocols can effectively balance traffic and adapt to topology changes [5]; however, they often suffer from slow convergence and increased control overhead when deployed in dense or large-scale WSNs. To mitigate these issues, several studies have incorporated heuristic metrics such as residual energy, hop count, and link quality into the pheromone update process.

In parallel, machine learning techniques have been increasingly explored for intelligent routing in WSNs. Artificial Neural Networks (ANNs), reinforcement learning, and deep learning models have been employed to predict link quality, node failures, or optimal next-hop selection. While these approaches demonstrate improved adaptability and prediction accuracy, many of them rely on complex models and extensive training processes, which may not be well-suited for resource-constrained sensor nodes.

More recently, hybrid routing schemes combining swarm intelligence and machine learning have been proposed to leverage the strengths of both paradigms. Existing ANN-ACO and deep-learning-assisted routing protocols generally focus on improving routing decisions by embedding learning mechanisms into the path-discovery process. However, many of these solutions introduce significant computational and communication overhead, limiting their practical applicability in large-scale or energy-constrained WSNs.

Motivated by these limitations, this work designs an energy-aware multipath routing protocol that improves routing efficiency and network lifetime while maintaining low computational and communication overhead.

This paper proposes a hybrid routing protocol that combines AntNet with a lightweight MLP model in a complementary manner rather than embedding learning into the routing core. Unlike existing hybrid approaches that employ complex neural architectures, the proposed method uses a simple MLP structure to predict path quality based on a limited set of features, namely residual energy and link reliability. In the proposed approach, AntNet is responsible for multipath exploration and pheromone-based route reinforcement, while the MLP model acts as an auxiliary decision-support component to evaluate candidate paths based on residual energy and performance metrics. This separation allows the protocol to benefit from learning-assisted decision making without compromising scalability or increasing routing complexity.

The proposed protocol is evaluated through extensive simulations using the NS2 network simulator. Performance is assessed in terms of energy consumption, end-to-end delay, routing overhead, and network lifetime, and compared against the conventional AODV protocol. The results demonstrate that the proposed hybrid routing strategy achieves notable performance improvements while maintaining a lightweight design suitable for WSN environments.

The main contributions of this work can be summarized as follows:

- A lightweight hybrid routing protocol that combines AntNet-based multipath exploration with MLP-assisted route selection.
- An energy-aware path prediction mechanism that improves routing efficiency without relying on complex learning models.
- A comprehensive simulation-based evaluation demonstrating improvements in energy consumption, delay, routing overhead, and network lifetime.

The remainder of this paper is organized as follows. Section 2 reviews related work on energy-aware and intelligent routing in WSNs. Sections 3 and 4 describe the proposed routing protocol and its underlying algorithms. Section 5 presents the simulation setup and performance evaluation. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Related Works

2.1. Literature

Routing in Wireless Sensor Networks (WSNs) has been extensively studied due to the stringent energy constraints that affect network longevity and reliability. Classical routing protocols such as AODV and DSR laid the foundation for dynamic routing but lack mechanisms to cope with energy depletion and congestion in large-scale WSNs.

To address these limitations, several energy-aware and intelligent routing approaches have been proposed in recent years. Among them, bio-inspired and learning-based routing approaches have been widely investigated [6,7] and give remarkable results in WSNs.

Ant Colony Optimization (ACO)-based routing has attracted attention for its distributed nature and adaptability. Early ACO routing algorithms improved path discovery. In the research by Baran and Sosa [8], the authors develop the AntNet algorithm, which implements ACO to find the optimal path for WSNs. It is based on traveling ants called forward ants (FANT) that collect features of running networks, and backward ants (BANT) that analyze the database and update the routing parameters. However, the nature of WSNs leads to low convergence of such routing protocols. In addition, ARA (Ant Routing Algorithm) [9] is a multi-hop routing protocol composed of three steps. Firstly, route discovery where forward and backward ants cooperate to establish the path from the source node to the destination node and vice versa. Secondly, routing maintenance is where the transmission of data packets is relayed. Finally, a routing failure is generated by the mobility of nodes in the network. AntHocNet [10] is another version of the ACO algorithms that is implemented for wireless networks. Multiple routing protocols were presented to address energy issues in the WSNs. The algorithm uses balanced loading to limit energy consumption during the routing process and dynamically selects the path that efficiently increases network lifetime. In addition, the optimization of load balance with ACO improves the performance of the AODV [11] routing protocol. However, they suffered from excessive control overhead and slow convergence under dense deployments [12,13]. New mechanisms were proposed for maximizing the network lifetime and minimizing the usage of the power [14–19], which constitutes the main issue in WSNs, and the ACO method were the best to find the shortest paths in WSNs and lead to different constraints related to the dynamic, the resource, the convergence, and more studies have focused on hybrid ACO mechanisms that integrate heuristic metrics such as residual energy, link reliability, and queue length to guide ant movement more efficiently. These approaches demonstrated improvements in energy balancing and route stability [20,21]. However, these approaches often rely solely on heuristic-based decision processes, which limit their adaptability under rapidly changing network conditions.

Furthermore, machine learning techniques have been increasingly applied to WSN routing. Artificial Neural Networks (ANNs) and Deep Learning predictors have been used to estimate link quality, detect node failures, and assist in intelligent next-hop selection.

Several recent works [22–26] explored Multilayer Perceptron (MLP) models to predict high-quality routes using features such as residual energy and RSSI, resulting in more stable and energy-efficient paths [27].

Hybrid schemes that combine swarm intelligence with machine learning have also emerged. For example, some studies integrated ACO with ANN-based predictors to reduce the number of route repairs and improve energy distribution. These works demonstrated significant improvements in lifetime extension, delay reduction, and packet delivery reliability. However, many of these hybrid solutions rely on complex training processes or require extensive real-time feedback, limiting their applicability in resource-constrained sensor nodes [28].

More recently, energy-aware multipath routing has been a major research direction. Approaches that incorporate dynamic multipath selection, energy heterogeneity, and reinforcement learning have shown strong potential for improving resilience and adaptability in highly mobile or harsh environments [29].

Recently, artificial intelligence has been incorporated into many IoT-based applications. Moreover, with the rapid progress of WSNs based on IoT applications, many works are interested in analysis issues revealed, and despite the advancements, existing methods still suffer from limitations such as high control overhead, insufficient prediction accuracy, or a lack of integration between learning-based prediction and swarm-based exploration. Therefore, there remains a strong need for an efficient hybrid routing strategy that combines the rapid exploration capability of ACO with the predictive intelligence of MLP models to achieve energy-balanced and stable routing in WSNs [30,31].

2.2. Motivation

The sensor capabilities are limited in the wireless network. Moreover, it affects the routing process [32,33]. Discovering an optimal route in WSN is one of the designed solutions to deal with those issues. In this paper, we propose an intelligent routing protocol based on the MLP model that extracts input values from artificial ants. In addition, we modified the traditional Ant Colony Optimization algorithm in order to combine it with MLP to overcome path discovery and energy efficiency issues. Unlike existing ANN–ACO and deep learning–based routing schemes, the approach proposed in this paper adopts a lightweight MLP model as an auxiliary decision-support mechanism rather than embedding learning into the routing core. The MLP assists AntNet by evaluating candidate paths based on energy and performance metrics, while AntNet maintains routing exploration and path reinforcement. This separation reduces computational overhead, preserves protocol scalability, and enhances energy efficiency, making the proposed method more suitable for large-scale and resource-constrained WSNs.

3. Theoretical Background

3.1. ACO

3.1.1. Real Ant Mechanism

The idea behind the ACO technique is inspired by an ant society in the natural environment. Initially, worker ants randomly wander around the nest searching for food to feed their queen. During their discovery process of the route, they deposited a trail of a chemical substance named pheromone. When the food is reached, they take it back to the colony and leave more pheromones on the route. Other ants can sense the pheromone intensities and prefer to follow directions with higher pheromone concentration. Since shorter paths can be traversed faster, they will eventually outweigh the less optimal routes in terms of pheromone density. Pheromones evaporate over time, so ants are less likely to follow an older path, which makes them search for newer paths simultaneously. In a case where an obstacle appears in their path, ants initiate the route discovery operation by randomly selecting the next hop until the ants converge on the paths with a relatively higher density of pheromones.

3.1.2. Artificial Ant Mechanism

Generally, ACO algorithms have mainly three procedures. Firstly, the ants find the solution to the construction of the graph. Secondly, ants update their pheromone levels, and finally, ants can execute additional actions. In a computer implementation, the pheromone is extracted from the routing tables. Artificial ants were used to mimic real ants to calculate and adjust the probabilities. There exist forward and backward artificial ants with the structure. The agents jump every time one hop to the adjacent node through the current links. The communication is indirect between them by reading and writing simultaneously on the routing table while they move on their route.

3.1.3. Notation

Table 1 below illustrates the useful ACO parameters used in this manuscript.

Table 1. ACO parameters.

Notation	Description
$P_{i,j}$	Probability to take the route i to j
k	Current ant
d	Final destination
t	Over time
$\tau_{i,j}$	Pheromone value of the route i -> j
α	intensity
η	link between 2 nodes
β	Constant of control visibility
N_i	Set of candidate neighbor of node i

3.1.4. AntNet

It is a variation of ACO, and it is closer to the real behavior of the ant that inspired the development of the ACO meta-heuristic algorithms. AntNet is widely used as an adaptation of ACO for WSN [34,35]. AntNet is appropriately defined in terms of forward and backward ants (FANT/BANT). In spite of their similar structure, they are divided disparately in the network. In addition, they sense various input data and provide autonomous outputs. The communication between ants is indirect and belongs to the stigmergy factor, through the information received concurrently from the nodes they visit. In the AntNet algorithm, each node s initiates a forward ant that searches an optimal path to a destination node d. Moreover, they have identical queues, and they experience the same traffic load. The steps of a path construction are as follows:

1. Every forward ant selects through its neighbors, either visited or not. Probability $P_{i,j}$ depends on the function of $\tau_{i,j}$ and always follows the higher pheromone concentration finding.

$$P_{i,j}(t) = f(\tau_{i,j}(t)) \tag{1}$$

The expression of the probability of selecting the next hop could be presented as:

$$P_{k,n}^{d} = \frac{\tau_{k,n}^{d} + \omega * \eta_{k,n}}{C} \tag{2}$$

with

$$\eta_{k,n} = 1 - \frac{q_n}{\sum_{i=1}^{N_k} q_i}, \omega \in [0,1] \tag{3}$$

where $P_{k,n}^{d}$ is the probability that node k chooses node n as the next hop for destination d for each neighbor node (N_k).

Another multiplicative function is used to select the neighbor j with a probability $P_{i,j}$ computed as the normalized sum of the pheromone $\tau_{i,j}$ with a heuristic value $\eta_{i,j}$ taking into account the state (the length) of the j^{th} rank link queue of the current node i:

$$P_{i,j}(t) = \begin{cases} \frac{\tau_{i,j}^{\alpha}(t) * \eta_{i,j}^{\beta}(t)}{\sum_{l}^{N_i} \tau_{i,l}^{\alpha}(t) * \eta_{i,l}^{\beta}(t)} \text{ if } j \in N_i \text{at time } t, \\ \alpha, \beta \in R^{+} \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

The heuristic value $\eta_{i,j}$ is a [0, 1] normalized value function of the length $q_{i,j}$ (in bits waiting to be sent) of the queue on the link connecting the node i with its neighbor j. The value of α weighs the importance of the heuristic value concerning the pheromone values stored in the pheromone matrix T. β is a heuristic algorithm in formation and could seriously affect the quality of the link between ants. The value $\tau_{i,j}$ reflects the instantaneous state of the node's queues and, assuming that the queue's consuming process is almost stationary or slowly varying, $\tau_{i,j}$ gives a quantitative measure associated with the queue waiting time.

2. Bant, a backward ant, is created after achieving the destination d, and the FANT is deleted.
3. The backward ant follows the inverse route of the forward ant. Furthermore, they use higher-priority queues to rapidly send the data received from Fant. In this paper, the transition states between ants can also be represented by a transition matrix based on their power level. After the routing process and the next-hop selection, ants update their pheromone routing table by using the following equations.

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \rho\Delta\tau_{i,j}(t) \tag{5}$$

and

$$\Delta\tau_{i,j} = \begin{cases} r(1+\tau_{i,j}), & \text{if link } i \to j \text{ is on the selected path} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where $\tau_{i,j}(t)$ is the pheromone concentration that ants deposit during their navigation at t on the link support among ants (i and j). ρ defines the probability of the evaporation of pheromone during the time. Its value is between [0, 1]. The residual pheromone value is given by $1-\rho$. $\Delta\tau_{i,j}$ is the reinforcement.

4. The pheromone routing table is updated after the ant link visits. The parameter r is computed by dividing the time that an ant took to travel toward a node i by the time taken by all ants to that node i, where r is higher than 0 and lower than 1. It is predetermined in the algorithm, and the pheromone entries change in the routing table according to the normalization or the evaporation heuristic parameters, as shown in the previous equations.

The Antnet process is described in **Figure 1**. At a constant interval, each node launches a forward ant to a random destination and stores its routes in a table. This table stores forward-ant and neighboring information to take the next hop. If the node in the neighboring list was not initially visited, the forward ants select the next hop among these neighbors. Alternatively, if all nearest nodes were visited earlier, the next hop is preferred with lower probabilities compared to other neighbors. The selection process generates a cycle in which the ants can return to a neighbor already visited. At the destination, the node creates a backward ant that takes the same path as the equivalent forward ant, but in the reverse direction, and updates the routing table used for all entries.

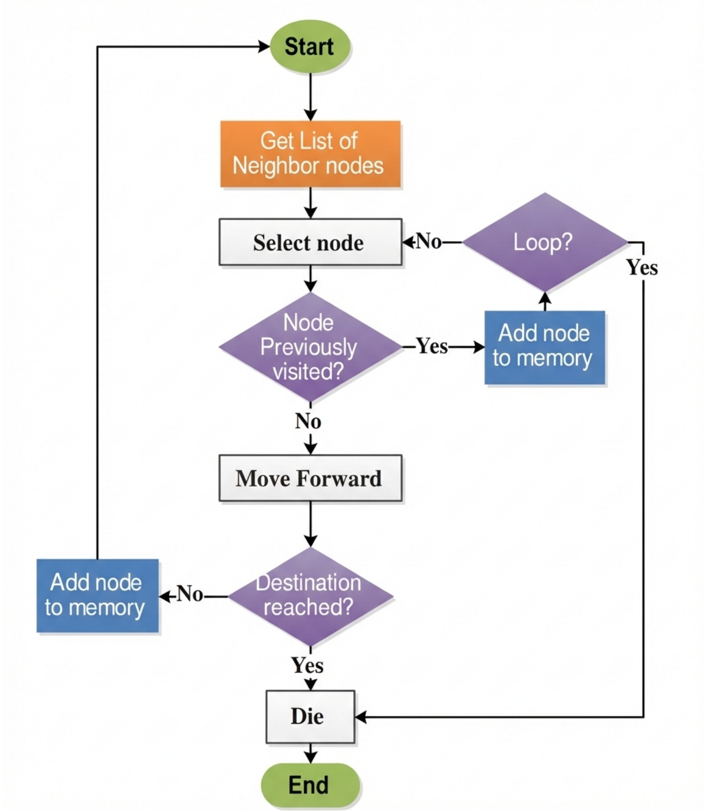

Figure 1. Antnet process.

3.2. Multilayer Perceptron Description

An MLP is a subset of neural network learning algorithms that has demonstrated its effectiveness in different fields like pattern recognition, fault detection, intrusion detection, image processing, etc. In **Figure 2**, the main idea behind this type of model is detailed. It is an iterative algorithm that gets the relationship between the input values and their output values and minimizes the error by updating the parameters in each iteration until the condition is reached.

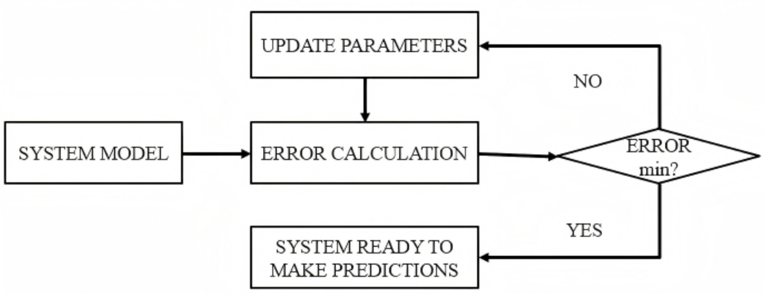

Figure 2. Multilayer Perceptron Process.

In our case, MLP, giving remarkable results in sub-mention domains, is adjusted to implement a new intelligent routing protocol. To the best of our knowledge, this is the first time MLP combined with ACO has been used in routing techniques. The main idea is to obtain the assumption of the paths by exploiting the classification Multilayer

Perceptron algorithm. This method allows learning from running WSN features, less computational power, and predicting the optimal path to send data.

In the next section, we present the proposed methodology. The flowchart of the model and the proposed implementation are explained.

4. Methodology and Material

The research paper aims to increase the lifetime of the network. In this paper, we propose an intelligent learning-based approach integrated with an MLP to enhance the availability period of the network. MLPyields remarkable results in various disciplines, including prediction, clustering, pattern recognition, and classification [36–40]. The proposed algorithm enhances the selection of the shortest path by incorporating AntNet algorithms and neural artificial intelligence behavior based on energy levelsy level.

An overview of the whole system is illustrated in **Figure 3**. The process starts by discovering the paths by using the AntNet algorithm, which permits us to compute the cost of each path-based energy criterion and then forward the result to the MLP model, which predicts the best path with efficient energy and gets an optimal routing process.

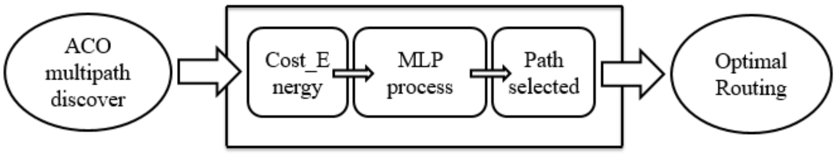

Figure 3. Topology of Proposed MLP.

The multilayer perceptron model proposed in that work implements the empirical MLP version by combining FeedForward and Backpropagation algorithms. All of the proposed processes are presented in detail in the following sections.

4.1. MLP Prediction Model

In our work, network training is performed by the backpropagation algorithm [41,42]. It is the most powerful algorithm of Neural Networks (NNs), which involves a backward pass for adjusting the weights to minimize the error. The algorithm is repeated until some specific conditions are satisfied: the minimal error obtained, the end of the dataset, or both. In the scope of this paper, the training is concluded when the error RMSE reaches 10^3, where the system can make predictions for each new input **Figure 4**.

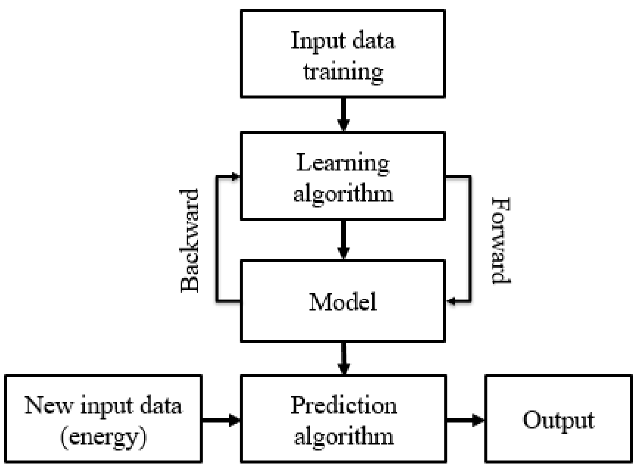

Figure 4. MLP Prediction Algorithm.

The whole process is delineated in **Figure 4**. The labeled data are transmitted to achieve the output through the hidden layer. After all necessary calculations, the model can decide if the result is satisfactory or use a backward propagation for another training phase.

4.2. MLP Prediction Algorithm

The entire operation of the proposed model and the computations of the factors in each node of the different layers, including the error and weights, is illustrated in **Algorithm 1**.

Algorithm 1 Prediction Model

Require: Initialization:
Random weight initialization $w(i,j) \in [-0.5, 0.5]$
Learning rate $\alpha = 0.01$
Training epochs = 500
Threshold = 10^{-3}
Dataset size = number of discovered paths
Ensure: Model Trained
Repeat
for each example (x, d) in Dataset **do**
  forward propagation(x)
  for each node i in input layer **do**
    $p(i) \leftarrow x(i)$
  end for
  for $l = 2$ to N **do**
    for each node j in layer l **do**
      $h(j) \leftarrow \sum_i w_{i,j} \cdot p(i)$
      $p(j) \leftarrow f(h(j))$
    end for
  end for
  backward propagation $p(j)$
  for each node j in output layer **do**
    $RMSE(j) \leftarrow \sqrt{\frac{\sum(p_j - d_j)^2}{\text{datasize}}}$
  end for
  for $l = N - 1$ down to 1 **do**
    for each node i in layer l **do**
      $RMSE(i) \leftarrow f(h(i))\,(1 - f(h(i))) \sum_j w(i,j) \cdot RMSE(j)$
    end for
  end for
  update every weight in the network using $RMSE$
  for each weight $w(i,j)$ in network **do**
    $w(i,j) \leftarrow w(i,j) + \alpha \cdot p(i) \cdot RMSE(j)$
  end for
end for
until $RMSE <$ Threshold

where: $p(i)$ present the input layer activation of neuron i, $h(j)$is the weighted sum at neuron j and $RMSE$ refer to the root mean square error.

4.3. Flowchart Overview

The proposed routing protocol combines AntNet-based multipath exploration with a Multilayer Perceptron (MLP) model to enhance energy-aware route selection in Wireless Sensor Networks.

Unlike classical AntNet routing, where pheromone updates alone determine path preference, the proposed approach separates the exploration and decision phases. AntNet is responsible for discovering and maintaining multiple candidate paths, while the MLP model assists in selecting the most energy-efficient path based on current network conditions.

This separation allows the routing process to benefit from swarm-based adaptability while avoiding the integration of complex learning mechanisms directly into the routing core, thereby reducing computational overhead.

The flowchart concerns the representation of the entire process and its execution by the proposed shortest path selection algorithm. It illustrates the overall workflow of the proposed routing protocol. The flowchart explicitly distinguishes between the AntNet exploration phase, MLP based evaluation phase, and the final routing decision phase. Directional arrows indicate the sequence of operations and data flow between modules.

Our proposed flowchart in **Figure 5** clarifies when ants are generated, how routing metrics are collected, and at which stage the MLP model is invoked. It describes the whole process of selecting the best route by the combination of AntNet and MLP. The paths are discovered in the first block using the AntNet algorithm. Then, the features of MLP are processed to make assumptions about the different paths given. Finally, the best path selected will be used to forward the information through it.

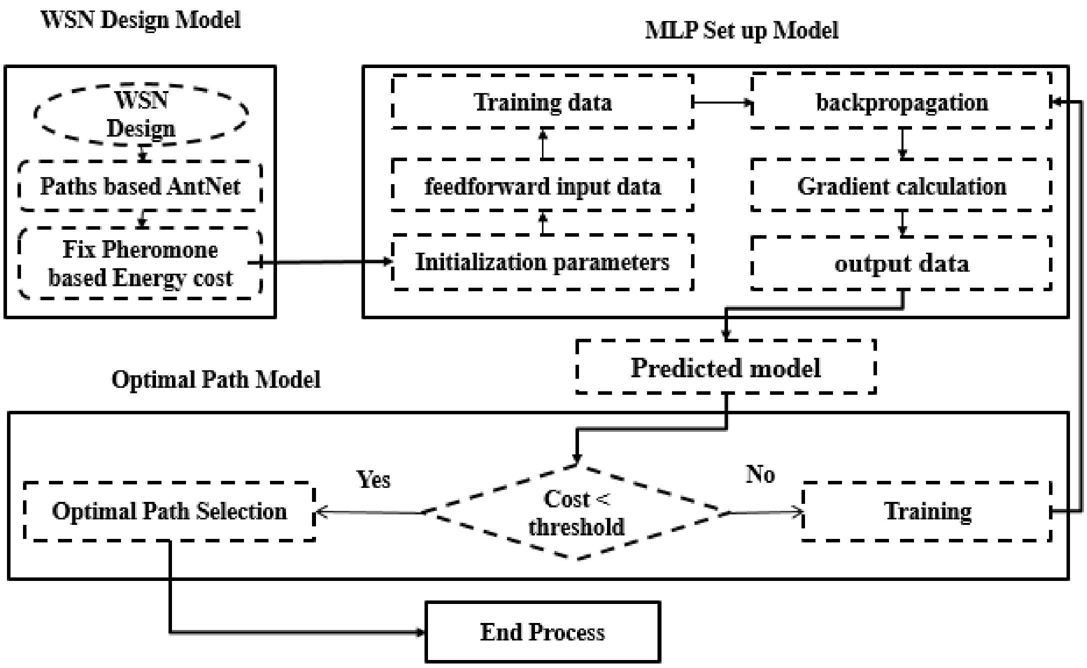

Figure 5. Overview system of the shortest path selection based on MLP and AntNet.

The primary objective of our proposed algorithm is to enhance the performance of selecting the shortest path by combining a Multilayer Perceptron and AntNet to determine the optimal route based on the remaining energy of each node. Our proposed algorithm optimizes the choice of the route with the highest energy level, which allows nodes' availability to be saved along the routing operation and increases the lifetime of the network. In that approach, the algorithm of feedforward networks for the multilayer perceptron is trained in two phases. Firstly, the process starts with a random initialization process of the weights and the biases, and then forwards input data from the data preposition to compute the predicted output. Secondly, the model computes the gradient between the calculated and the desired output. If the obtained result is minimal, the training step is finished. At the end of the training, the model could make decisions about new values. In that work, the new input data belonging to the current energy of the node in the running step was exploited. The route selection starts by assuming each data point to predict the output related to the energy. This value helps to evaluate the probability of choosing the optimal path in terms of energy to forward data through it.

4.3.1. AntNet-Based Multipath Discovery

In the proposed protocol, forward ants (FANTs) are periodically generated at source nodes and traverse the network toward destination nodes using probabilistic next-hop selection based on pheromone intensity and heuristic information. Upon reaching the destination, backward ants (BANTs) retrace the discovered path to update routing tables and pheromone values.

Each ant maintains a record of the traversed path, hop count, and cumulative energy metrics, which are later used as input features for the MLP-assisted decision process.

The pheromone update mechanism follows a reinforcement strategy that favors paths with higher residual energy and stable links, while evaporation is applied to prevent premature convergence. The pheromone value $\tau_{i,j}$ associated with the link(i,j) is updated according to Equation (5), where ρ denotes the pheromone evaporation rate (0< ρ <1), and $\Delta\tau_{i,j}$ represents the pheromone reinforcement proportional to path quality.

The pheromone evaporation rate is set to ρ = 0.1 to ensure a balance between exploration and exploitation. This value is widely adopted in AntNet-based routing literature and was empirically found to provide stable routing behavior in dynamic WSN environments by preventing premature convergence while preserving historical routing information.

4.3.2. Path Selection Probability

The probability $P_{i,j}$ of selecting the next hop j from node i is computed using Equation (4), where: $\tau_{i,j}$ is the pheromone intensity on link (i,j) $\eta_{i,j}$ is the heuristic value associated with link quality and residual energy, α and β are weighting parameters controlling the influence of pheromone and heuristic information, respectively N_i denotes the set of neighboring nodes of node i.

All parameters are kept constant during simulation to ensure fair comparison with baseline routing protocols.

4.3.3. MLP-Assisted Path Quality Prediction

The MLP model is employed to predict the quality of candidate paths discovered by AntNet. The input layer consists of features derived from the ant exploration phase, including residual energy and link reliability. The hidden layer contains four neurons, and the output layer produces a scalar value representing the predicted path quality.

The choice of a lightweight MLP architecture is motivated by the limited computational capabilities of sensor nodes and aims to achieve a balance between prediction accuracy and processing overhead.

The MLP is trained offline using representative routing data and is used online only for inference, thereby minimizing runtime computational cost.

4.3.4. Integration of AntNet and MLP Decision Process

After AntNet identifies a set of candidate paths between a source and destination, the corresponding path features are provided to the MLP model. The MLP evaluates each path and assigns a quality score, which is then used to rank the available routes.

The path with the highest predicted quality is selected for data transmission, while alternative paths are retained for fault tolerance and load balancing.

This integration enables intelligent path selection without altering the fundamental operation of the AntNet routing mechanism.

4.4. Proposed Algorithm

A step-by-step procedure is presented in the pseudo-code as shown in **Algorithm 2**. The algorithm shows the whole process of the shortest path discovery with the dynamic routing algorithm based on the MLP-AntNet model. Before execution, the following parameters are initialized:

— α (pheromone influence) = 1
— β (visibility influence) = 2
— Evaporation rate $\rho = 0.1$
— Maximum ant population = 20
— MLP weights initialized as in **Algorithm 1**

$G = (V, E)$ is the network graph; K is the number of candidate paths discovered by AntNet; $W(i, j)$ is the MLP weight matrix.

Algorithm 2 Proposed Routing Model Decision

Require: $G = (V, E)$
Ensure: Find K-shortest paths based on AntNet-MLP
Compute consumed energy for each path
Compute the cost for each path-based pheromone
Set up initial parameters $W(i, j)$
Present input datasets
Forward-Backward algorithm
if system reached Threshold **then**
  Prediction Routing Decision
else
  Back-propagation
  Repeat Forward-Backward algorithm
end if

5. Simulations and Analysis

We have simulated our model and compared it with the results of the classical AODV version. For a fair comparison, the performance of all algorithms was compared in the same environmental conditions.

5.1. Simulation Setup

The proposed routing protocol is evaluated using the NS-2 network simulator (version 2.35). A set of sensor nodes is randomly deployed in a two-dimensional area, and data packets are generated periodically from source nodes toward a sink node. NS-2.35 was selected due to its widespread adoption in WSN routing research, stable support for energy models, availability of Ant-based and AODV routing implementations, which facilitate fair comparison with existing protocols, and suitability for packet-level analysis. Compared to more complex simulators, NS-2 enables controlled evaluation of routing behavior and energy consumption under reproducible conditions, making it appropriate for comparative performance studies in WSN environments. All simulations were conducted on an Ubuntu 14.04 platform to ensure compatibility with the selected NS-2 version. The main simulation parameters are summarized in **Table 2**. The number of sensor nodes, transmission range, packet size, and simulation duration are selected to reflect typical WSN deployment scenarios. The packet size and transmission interval were chosen to balance traffic load and energy consumption, avoiding congestion while ensuring sufficient data generation for performance evaluation. Each simulation scenario was executed multiple times with different random seeds, and the reported results correspond to the average values to reduce statistical bias.

Table 2. Simulation Parameters.

Parameter	Value
Network size	250 m × 250 m
Transmission range	50 m
Number of nodes	100
Initial energy per node	40 J
Packet length	6400 bits
MAC type	802.11
Simulation time	600 s
Routing protocols compared	AODV, ANT-AODV

The energy consumption model used in this work follows the first-order radio energy model, which is commonly adopted in WSN studies.

$$E_{tx}(k,d) = kE_{elec} + \begin{cases} kE_{fs}d^2, & d < d_0 \\ kE_{mp}d^4, & d \geq d_0 \end{cases} \tag{7}$$

$$E_{rx}(k) = kE_{elec} \tag{8}$$

where

$$d_0 = \sqrt{E_{fs}/E_{mp}} \tag{9}$$

The energy consumed for transmitting and receiving a packet depends on the packet size and the communication distance.

Although this model does not explicitly account for idle listening, sleep scheduling, or CPU processing energy, it provides a widely accepted abstraction for evaluating routing-level energy efficiency.

In this manuscript, the training dataset consists of two input entries, four nodes in the hidden layer, and one output entry. Moreover, Tanh is used as the Transfer function. The model is trained for 500 epochs with a learning rate of 0.01, and the stopping criterion is defined by a threshold of RMSE < 10^{-3}. The MLP model employed in the proposed protocol uses a learning rate of 0.01 (a higher learning rate was avoided to prevent unstable convergence, while a lower learning rate significantly increased training time without noticeable performance gains), a hidden layer with four neurons, and a maximum of 500 training epochs. The training process is terminated when the root mean square error (RMSE) reaches a predefined threshold.

These parameters were selected to achieve a trade-off between training convergence and computational simplicity, ensuring that the model remains lightweight and suitable for resource-constrained WSN environments.

To ensure result reliability, each simulation scenario was executed multiple times with different random seeds, and the reported results represent averaged values. Variations observed across runs were limited, indicating stable routing behavior. Although detailed confidence intervals are not explicitly reported, the consistent performance trends across scenarios validate the robustness of the proposed routing protocol.

Although comparisons with other energy-aware or intelligent routing protocols could further strengthen the evaluation, the current comparison focuses on AODV to establish a clear baseline and highlight the improvements introduced by the proposed hybrid approach. Additional benchmarks are considered as future work. The performances are analyzed in terms of Energy, Delay, and Normalized Overhead to discuss the experimentation results of our proposed algorithm. Network lifetime is assessed in terms of the time until the first node depletes its energy, which provides insight into the protocol's ability to balance energy consumption across the network.

5.2. Comparison Results

The variation of the overall power usage during simulation time is illustrated in **Figure 6**. Consumed energy is lower in the proposed routing protocol compared to the ad hoc routing protocol AODV. Moreover, the average energy consumption of the entire network during simulation is depicted in **Figure 7**. On average, the proposed protocol reduces total energy consumption by approximately 32% compared to AODV. This improvement is primarily attributed to the MLP-assisted path selection, which avoids routing through nodes with low residual energy and unstable links. The final result of the system demonstrates that energy is used efficiently and significantly reduced. Moreover, **Figure 8** illustrates the evaluation of the delay during the simulation time. ANT-AODV takes less time compared to AODV. The proposed method selects the path that minimizes the time required to send and receive packets between nodes during the routing process. The reduction in delay, measured at approximately 28%, is due to the availability of multiple candidate paths and the intelligent selection of routes with higher predicted quality, which reduces route discovery latency and packet retransmissions. **Figure 9** shows the evolution of routing overhead during simulation time and the number of nodes. The routing overhead is the ratio of the total number of packets sent divided by the total number of packets delivered. The routing overhead is reduced by about 40% relative to AODV because the proposed protocol minimizes frequent route rediscoveries by maintaining stable multipath routes and leveraging MLP predictions to select reliable paths. The results of the comparison between ANT-AODV and AODV show that ANT-AODV has the best performance.

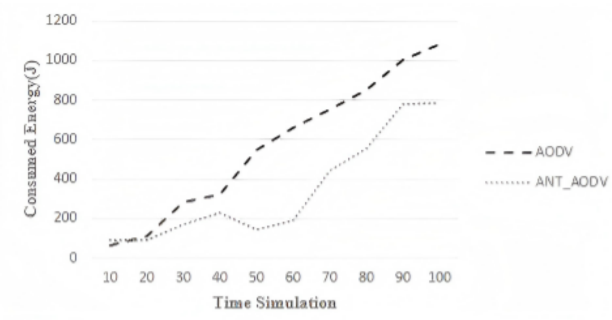

Figure 6. Total Energy Consumption Comparison.

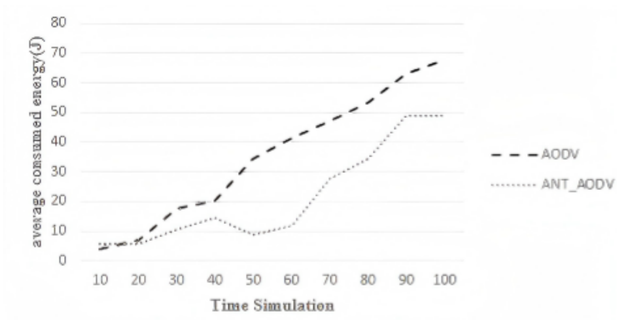

Figure 7. Average Energy Consumption vs time.

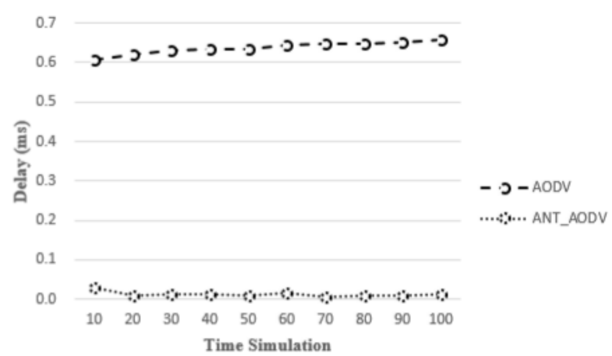

Figure 8. Delay Comparison.

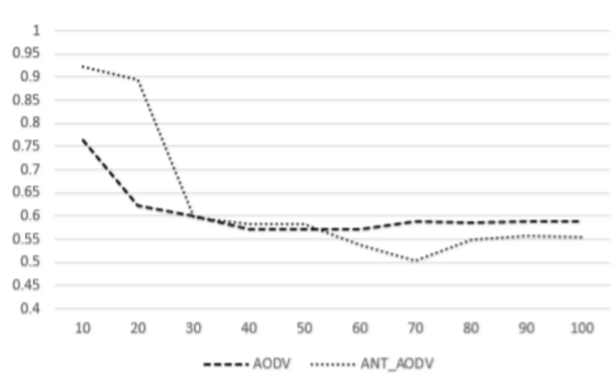

Figure 9. Routing Overhead comparison.

5.3. Discussion

This paper evaluates a new intelligent routing model based on a combined AntNet and MLP algorithm. Thus, permit the use of power resources in the network effectively. The results were promising, and the system uses less energy since the selection of the shortest paths is based on the energy factor in the calculation of the pheromone used in the AntNet multipath routing algorithm. Also, the MLP model gives an assumption of the best route by optimizing the results that consider the energy cost of the path. At the beginning, energy consumption is higher due to the high probability of choosing a route with more nodes. After adjustment of the power resource using the proposed system, the energy is decreased and optimized, which increases the network lifespan and saves energy consumption, as shown clearly in the results. As delineated in **Figures 6** and **7**, the remaining power after the simulation is greater up to 32% for our proposed routing protocol compared to AODV. As a consequence, the lifespan of the network is increased due to the consideration of the remaining energy level in the shortest path selection, which focuses on the energy node side, extending the network's availability and improving its scalability. As mentioned in **Figures 8** and **9**, which present the delay and the routing overhead results, our proposed routing protocol outperforms the classical AODV. The overhead was 28% lower, and the delay was improved by approximately 40% compared to AODV. In the proposed system, a route with a higher energy level is selected for data transmission, which increases the proportion of transmission and reception packets during execution time and enhances the network's reliability. The reduction in delay is achieved because the MLP prediction guides AntNet toward routes with higher residual energy and lower congestion probability. This reduces path breakages, queue buildup, and retransmissions. Similarly, the reduction in routing overhead results from fewer route repairs, since energy-aware path selection stabilizes the topology.

The results demonstrate that combining AntNet-based multipath exploration with a lightweight MLP model yields significant performance gains without introducing excessive computational overhead. To assess scalability, simulations were conducted under different node densities. Although the number of control packets increases with network size, the routing overhead remains comparatively lower than baseline protocols due to adaptive path reinforcement. These results indicate that the proposed protocol scales effectively to larger WSN deployments without incurring excessive computational or communication overhead. While the proposed protocol shows clear advantages, the evaluation is limited to simulation-based analysis and comparison with AODV. Factors such as node mobility, heterogeneous energy models, and real-time training overhead are not explicitly considered and represent directions for future research.

6. Conclusion

Wireless Sensor Networks face persistent challenges related to limited energy resources, routing instability, and scalability. In this paper, an energy-aware multipath routing protocol integrating AntNet with a lightweight Multilayer Perceptron (MLP) model has been proposed to address these challenges.

Unlike conventional ANN–ACO or deep learning-based routing approaches, the proposed protocol adopts a lightweight MLP architecture that assists AntNet in selecting energy-efficient routes without introducing significant computational or communication overhead. This design choice makes the approach suitable for resource-constrained WSN environments.

Simulation results demonstrate that the proposed protocol achieves a reduction in total energy consumption of approximately 32%, decreases end-to-end delay by 28%, and lowers routing overhead by 40% compared to AODV. In addition, the network lifetime is extended by about 22%, indicating improved energy balancing across sensor nodes.

Furthermore, scalability analysis indicates that the proposed protocol maintains stable performance under increasing node density, and statistical observations across multiple simulation runs demonstrate robust and consistent behavior. These findings suggest that the proposed AntNet–MLP routing protocol is suitable for large-scale WSN deployments.

The integration of swarm intelligence for multipath exploration and machine learning for path quality prediction enables more stable routing decisions and reduces the frequency of route failures and rediscoveries.

Although the proposed protocol shows promising performance, the evaluation is limited to simulation-based analysis and a simplified energy consumption model. Factors such as idle listening, sleep scheduling, node heterogeneity, and real-world deployment constraints were not explicitly considered.

Future work will focus on extending the proposed approach to heterogeneous and dynamic WSN scenarios, incorporating additional benchmark routing protocols, and validating the model under more realistic energy and traffic conditions.

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Data sharing does not apply to this article as no datasets were generated or analyzed during the current study.

Conficts of Interest

The authors declare that they do not have any commercial or associative interest that represents a conflict of interest in connection with the manuscript entitled "Energy Enhancement in Multipath Routing Protocol Based Antnet and Artificial Intelligent Model in Wireless Sensor Networks".

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