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Hybrid Ant Colony Optimization and Deep Neural Network Model for 5G-IoT Optimization

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***Abstract*—The research aims to develop a hybrid Ant Colony Optimization (ACO)-Deep Neural Network (DNN) for efficient resource allocation and the minimization of path loss in an Internet of Things (IoT)-driven 5G network. IoT-driven data are collected from the Zenodo repository, containing datasets with noisy information. The data are preprocessed using Exploratory Data Analysis (EDA) to remove outliers and missing values. The processed data are split into an 80-20% set. The training set (80%) is utilized for the ACO and DNN models, while the testing set (20%) evaluates the system's performance. ACO is used for feature selection and identification of suitable features for learning and prediction, which feed into the DNN model for learning and prediction. The model is then evaluated with Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and root square (R^2) value to determine the optimal path for resource allocation and reducing signal loss in 5G networks. In the results, the ACO-DNN-based model outperforms the others with the lowest RMSE (0.42) and MAE (0.35). It shows high accuracy and minimal error in optimizing path loss. The ACO-DNN-based model also achieves effective resource allocation with an R^2 of 0.92 and low error rates. The results underscore the efficiency of the hybridized ACO-DNN-based model for resource allocation while minimizing the path loss in the transmission link.**

***Index Terms*—Internet of Things (IoT), Ant Colony Optimization (ACO), Deep Neural Network (DNN), Wireless Networks**

I. INTRODUCTION

RESOURCE allocation is critical in the Internet of Things (IoT) ecosystem, where devices are interconnected to provide diverse services. Resources, such as network bandwidth, processing power, frequency, and energy, are inherently limited and must be shared effectively in IoT-enabled 5G networks [1]. Determining optimal allocation is essential to satisfy the heterogeneous requirements of IoT applications. Variables such as Signal-to-Noise Ratio (SNR), frequency, bandwidth, transmitting and receiving power, and Received Signal Strength Indicator (RSSI) are recognized as effective network resources.

However, the dynamic nature of 5G environments presents significant challenges, as IoT devices differ in capabilities, communication protocols, and Quality of Service (QoS) requirements. Additionally, device mobility, shifting networks, and varying application

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demands lead to constant fluctuations in resource availability [2]. Hence, IoT resource allocation algorithms must be flexible, scalable, and adaptive to cope with these fluctuations. Existing methods for resource allocation in 5G include both centralized and distributed strategies [3]. Distributed approaches allow devices to negotiate and cooperate autonomously for resource access, which supports self-organization and adaptability in decentralized environments [4].

Other methods like meta-heuristic algorithms, such as game theory, swarm intelligence, and genetic algorithms, have also been widely applied [5]. These methods provide optimization under multiple constraints, considering QoS, energy efficiency, load balancing, and fairness. Nevertheless, they often suffer from convergence to local optima, producing suboptimal solutions in dynamic network conditions. The rise of Machine Learning (ML) and Artificial Intelligence (AI) has introduced new paradigms for resource allocation. ML-based models leverage historical and real-time data to make adaptive decisions, reducing computational overhead compared to iterative heuristic methods [6].

Deep learning (DL), a subclass of ML, provides hierarchical feature extraction through nonlinear layers, enabling the automatic learning of complex correlations in network data. Such capabilities are particularly valuable for reducing computational complexity and supporting online adaptation in 5G IoT environments. While traditional wireless network design has focused on spectral efficiency and capacity, the rapid expansion of 5G services has raised concerns about energy consumption at both base-station and mobile-device levels [7].

Energy-efficient resource allocation has therefore become a critical design objective. Path loss, influenced by factors such as weather conditions, building density, and antenna height, further complicates resource management, making effective planning of parameters (frequency, SNR, antenna height, power levels, etc.) essential to maintain connectivity and minimize attenuation [8]. Recent studies have explored advanced optimization strategies. For instance, a comprehensive study on radio and computing resource allocation in Cloud-Radio Access Network (RAN) and Open-RAN has proposed low-complexity algorithms and ML-based solutions to enhance efficiency, reduce energy consumption, and improve multi-service adaptability [9]. However, traditional empirical path-loss models, such as Hata, Egli, Lee, Walfisch-Ikegami, and International Telecommunication Union-Radiocommunication (ITU-R), are widely used in planning [10–12]. However, their accuracy is environment-dependent, and they cannot generalize effectively across complex heterogeneous networks without parameter optimization using field data. Other works, such as Enhanced Resource Allocation Schemes (E-RAS) for LTE-A [13], demonstrate improvements in fairness and delay reduction. However, they remain limited by simulation-only evaluations and lack consideration of energy efficiency and scalability. More recently, research in 5G network slicing has highlighted novel frameworks for resource, allocation, optimization and network secuity [14–16].

A survey in previous research has categorized slicing strategies into reservation-based and share-based methods, analyzing their trade-offs in terms of efficiency, complexity, isolation, and cost predictability [17]. It reveals that while reservation-based approaches provide strong performance guarantees, they may lead to under-utilization of resources. Share-based approaches, in contrast, offer flexibility but risk QoS degradation under high load conditions. Building on this, another research has proposed a secure and energy-efficient allocation framework that integrates Integer Linear Programming (ILP) with Deep Reinforcement Learning (DRL) [18]. The results show that DRL-based allocation not only achieves faster, more adaptive decisions than ILP but also significantly reduces energy consumption while maintaining QoS and satisfying stringent security constraints. These studies underscore the need for hybrid, intelligent methods that can adaptively balance efficiency, security, and sustainability in next-generation networks.

In this research, the researchers propose a hybrid Ant Colony Optimization-Deep Learning (ACO–DL) model for resource allocation in IoT-enabled 5G environments. ACO, inspired by the foraging behavior of ants, is well-suited for combinatorial optimization and finding efficient paths for resource allocation. However, it lacks the ability to capture complex correlations among network parameters. To address this limitation, the researchers integrate DL to learn hidden patterns and relationships among variables, enabling better decision-making under dynamic network conditions. The proposed hybrid framework utilizes ACO’s global search capability with DL’s predictive power, aiming to improve QoS, energy efficiency, and scalability while avoiding the limitations of existing heuristic and simulation-only methods.

II. RESEARCH METHOD

Suppose the base station point has tiny cells ($M \in N$) and mobile operators ($N \in N$). The main cell $j \in N$ serves all the mobile operators, $i \in M$. The Shannon model can be deployed to express the allocated signal from any cell i and between the mobile operator and the cell. The H is used as a path metric, and n is the noise factor. The transmitter and receiver operate in a particular frequency range. It ensures two-way communication between mobile operators [19]. The signal connectivity is expressed in Eq. (1):

$$S(i) = \sum_{(j \in N)} x(j)H(ij) + n(i), \tag{1}$$

where, $S(i)$ is the received signal (signal connectivity) at node or cell i. Then, i is the index of the receiving node, user, or base station, j is index of transmitting nodes contributing to receiver i, and N represents set of transmitting nodes (neighboring cells, antennas, or users). Moreover, $x(j)$ is the transmitted signal from node j, $H(ij)$ represents path loss, fading, and propagation effects, and $n(i)$ is additive noise at receiver i, typically modeled as Gaussian noise with variance σ^2. This information is shared through cooperative pairs, and the received signal from the cell is expressed in Eq. (2):

$$\hat{Z}(k) = \sum_{k \in N} k \neq j \, x(j)H(kj) + n(k) + y, \tag{2}$$

where k is the cooperative small cell index, which depends on the cooperative algorithm. Then, $\hat{Z}(k)$ is the estimated or processed received signal at node k, k is the index of the receiving node (user, sensor, base station, or antenna), j is the index of transmitting nodes contributing signals to node k, and $k \neq j$ is the condition excluding self-transmission. Moreover, $H(kj)$ is the channel coefficient, $n(k)$ is the additive noise, and y is the processing residual. The destination cell and the cooperative cells that retrieve the signal from the cells are expressed in Eqs. (3)– (5). Then, signal intensity for quality signal connectivity is expressed in Eqs. (6)–(7).

$$Z = \begin{pmatrix} y(i) \\ \vdots \\ y(k) \end{pmatrix}, \tag{3}$$

$$Z = \begin{pmatrix} H(ij) & \cdots & H(12) \\ \vdots & \ddots & \vdots \\ H(j1) & \cdots & H(ji) \end{pmatrix} \begin{pmatrix} X(i) \\ X(j) \end{pmatrix} + \begin{pmatrix} n(j) \\ \vdots \\ n(k+h) \end{pmatrix} \tag{4}$$

$$Z = (H(j1) \cdots H(ji)) \begin{pmatrix} x(i) \\ \vdots \\ x(j) \end{pmatrix} + \begin{pmatrix} n(i) \\ \vdots \\ n(k+h) \end{pmatrix}, \tag{5}$$

$$S(x_{s;}YAYB) = H(YAYB) - H(YAYB + x_s), \tag{6}$$

$$S(x_{s;}YAYB) = H(YAYB) - H(n_A(n_B + z). \tag{7}$$

The x_s is the source signal. Meanwhile, x^i represents the information-bearing signals sent through the communication channel, and $S(x_s;YAYB)$ is the mutual information between the transmitted signal x_s and the joint received signals Y_A, Y_B. Next, $H(YAYB)$ is the entropy of the combined received signals before conditioning on the transmitted signal, and $H(YAYB + x_s)$ represents conditional entropy after including the transmitted signal. Meanwhile, $H(n_A(n_B + z)$ is the entropy of the combined noise and interference components.

The mutual information from different cells can be expressed in Eqs. (8)–(15). Equation (8) represents the total received signal covariance matrix, which consists of two components. They are signal covariance and noise-plus-interference covariance. The first term, $\begin{pmatrix} H_A \\ H_B \end{pmatrix} Q_s(H_A^H \, H_B^H)$, models the contribution of the transmitted signal after passing through the channels of cells A and B. The $(\sigma^{2S} + \phi_B)$ accounts for additive white Gaussian noise and inter-cell interference, both of which degrade signal quality. Then, $T_{nn} = E(nn^H)$ is the covariance of the noise vector only, describing the statistical power and spatial correlation of noise and interference across the receiving antennas. These covariance matrices are fundamental in deriving the mutual information and capacity expressions of cooperative multi-cell MIMO systems.

$$\begin{aligned} T_{yy} = E(yy^H) = \begin{pmatrix} H_A \\ H_B \end{pmatrix} Q_s(H_A^H \, H_B^H) \\ + (\sigma^{2S}_{\sigma^{2S} + \phi B}), \end{aligned} \tag{8}$$

$$T_{nn} = E(nn^H), \tag{9}$$

$$T_{nn} = (\sigma^{2S}_{\sigma^{2S} + \phi B}), \tag{10}$$

$$S(x_s;YAYB) = logdet(\pi e T_{yy}) - logdet(\pi e T_{nn}), \tag{11}$$

$$S(x_s;YAYB) = logdet(T_{yy}T_{nn}^{-1}), \tag{12}$$

$$\begin{aligned} S(x_s;YAYB) = logdet * (S + Q_s(H_A^H \, H_B^H) \\ + (\frac{1}{\sigma^2} S + \phi_B^{-1}) \begin{pmatrix} H_A \\ H_B \end{pmatrix}, \end{aligned} \tag{13}$$

$$\begin{aligned} S(x_s;YAYB) = logdet(S + \frac{Q_s}{\sigma^2} H_A^A H_A \\ + Q_s H_B^H (\sigma^2 S + \phi B) H_B, \end{aligned} \tag{14}$$

$$\begin{aligned} S(x_s;YAYB) = logdet(S + \frac{Q_s}{\sigma^2} H_A^H H_A \\ + Q_s H_B^H (\sigma^2 A + S)^{-1} A H_B. \end{aligned} \tag{15}$$

where $E(nn^H)$ represents the expected value of the product of the noise vector and its Hermitian (conjugate transpose), $T_y y$ is the total received signal covariance matrix, and T_{nn} is the noise covariance matrix. Moreover, it also has $E(yy^H)$ as expectation (statistical averaging) operator, y as joint received signal vector from cells A and B, y^H as Hermitian (conjugate transpose) of the received signal vector, H_A as channel matrix between transmitter and cell A, H_B as channel matrix between transmitter and cell B, and $\begin{pmatrix} H_A \\ H_B \end{pmatrix}$ as concatenated channel matrix of cells A and B.

Then, Q_s is the transmit signal covariance matrix (power allocation matrix). The $H_A^H H_B^H$ is the Hermitian transpose of the channel matrices, and σ^{2S} is the noise variance (additive white Gaussian noise power). Moreover, it has S as the identity matrix, ϕB as the interference covariance matrix from cell B, n as the noise vector (including interference components), $logdet(\pi e T_{nn})$ as the logarithm of determinant, πe as constant from differential entropy of Gaussian variables, T_{nn}^{-1} as inverse of the noise covariance matrix, and σ^2 as power allocation across antennas or streams.

The existing network planning and deployment methods rely on conventional methods to optimize one parameter, such as frequency, distance, SNR, RSSI, and bandwidth, for planning and installing network resources. This results in poor network connection, high interference, energy wastage, and underutilization of network resources. However, the existing models have the concave problem, making optimization difficult to achieve. The goal is to reduce path loss while improving the connectivity of mobile devices, while considering high power consumption in the channel bandwidth and distance as constraints, as expressed in Eqs. (16)–(19).

Equations (16)–(19) have H_A, H_B as channel matrices for cells A and B. Then, it also shows A as an interference mitigation and R_B as the maximum allowable rate (bits/sec/Hz) for cell B, C_1 as specific transmit antennas or streams for power constraint. Last, PC_1 is the maximum transmit power allowed for selected antennas, and Q_1, Q_2 is blocks of covariance for separate streams or antennas.

$$\begin{aligned} & maxlogdet_{A,Q_s}(S + \frac{Q_s}{\delta^2} H_A^H H_A \\ & + Q_s H_B^H (\delta^2 A + S^{-1}) A H_B), && (16) \\ & s.t.logdet(S + A(H_B(S + \frac{Q_s}{\delta^2} H_A^A)^{-1} Q_s H_B^H \\ & + \sigma^2 S)) \leq R_{BH} A \geq 0, && (17) \\ & t_o(C_1^T Q_s C_1 \leq PC_1), && (18) \\ & Q_s = \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} \geq 0. && (19) \end{aligned}$$

A. Proposed System Model

To address these problems, an ACO is explored to exploit the optimal resource allocation space. DNN learns from dynamic network environments, such as network parameter patterns, and uses that knowledge to make the best long-term decisions. The cost of network connections must be determined to assess the various solutions to the resource allocation problem. The objective function is to monitor the rate of messages that are supposed to be sent between all resources in the network, as expressed in Eq. (20):

$$T_c = \frac{\sum_{j=1}^{|V_g|} (d_j^r * d^g)}{p}, \tag{20}$$

where T_c is the capacity per unit power. Then, it has d^g as the connecting cost, d_j^r as the total data transfer cost between the j^{th} gateway of all the connected resources, V_g as the total number of gateways in the network, and p as the normalization factor or total available resource. ACO and neural network-based models are deployed to enhance the utilization of unused network resources for effective resource distribution.

B. System Formulation

The resource allocation is expressed in Eq. (21). The R_a is the network resource allocation, R_{as} is the assigned resource allocation, and R_i is the idle or available resource allocation. These resources are bandwidth, transmitted power, and received power from the transmitter. Unallocated resource allocation makes idle resources. It includes available frequency bands (R_i^{freq}), unused bandwidth ($R_i^{\text{bandwidth}}$), and distance between the idle base station and available power (R_i^{power}) from transmitter and receiver. Next, the state space is determined in Eq. (22), and resources to be assigned are expressed in Eq. (23).

$$R_a = R_{as} + R_i, \tag{21}$$

$$R_i = R_{\text{allocation}} - R_{as}, \tag{22}$$

$$R_{\text{total}} = U_i(R_i^{\text{freq}}) + U_i(R_i^{\text{bandwidth}}) + U_i(R_i^{\text{power}}). \tag{23}$$

The ants scout for each resource capability of the best solution that is now available and look for alternatives based on the network resources that are accessible. It goes straight to the next resource and visits the available resources in the optimal solution. When ant k states in resource i, the probability of moving to the neighbor j of resource i is given by k, as expressed in Eq. (24):

$$P_{ij}^k(t) = \left\{ \frac{\tau_{ij}^{\alpha(t)}}{\sum_j \in N_t^k \tau_{ij}(t)}, j \in N_t^k \right\}, \tag{24}$$

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Algorithm 1: Algorithmic Flow of ACO for Resource Allocation
Initialize parameters: $\alpha$ (pheromone influence), $\beta$ (evaporation rate), $\tau ij$ (pheromone values), number of ants ($n$)
While stopping condition is not satisfied do:
For each ant $k$ in the colony do:
Select next resource $j$ from resource $i$
Based on transition probability $Pij$^$k(t)$
Update pheromone concentration $\tau ij$ using Eq. (25)
If optimal path is identified then:
Allocate resources to the base station
End For
End While
Return final optimized resource allocation
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Fig. 1. Algorithm 1.

where N_t^k are the adjacent nodes of the node i, and α is the pheromone concentration. If the α factor is too large, it will affect the effect of the pheromone, leading the algorithm to converge onto a sub-optimal path. When the ant is in the $(t+1)^{th}$ iteration, the pheromone concentration of each path is expressed in Eq. (25):

$$\tau_{ij}(t+1) = (1-\beta) * \tau_{ij}(t) + \sum_{k=1}^{n_k} \Delta\tau_{ij}^{k}. \tag{25}$$

where n_k is the number of ants, and β is the pheromone evaporation parameter. Based on the ACO, resources are allocated to the base station in three steps: understanding mobile operator demands in the network environment, parameter initialization, and resource allocation, as shown in Algorithm 1 (see Fig. 1). The ant in Algorithm 1 acts as an agent searching for paths in the network. They probabilistically select routes based on pheromone trails, update pheromone intensities based on their success, and converge toward the optimal allocation strategy. Through iterative updates, the model balances immediate rewards and long-term efficiency, enabling effective resource allocation and path-loss optimization in 5G-IoT networks.

It tracks the state of the channel connectivity and shares the resources. The model computes the best course of action for dynamic network environments, and it is computationally less expensive. The probability of channel connectivity is expressed in Eq. (26):

$$P_{c'}^{b} = P_{ij}^{k}(t)(S_{t+1} = \frac{s'}{s_t} = S, b_t), \tag{26}$$

where, $P_{c'}^{b}$ is the probability of a particular event or action c' occurring under the condition or branch b. This probability is determined by $P_{ij}^{k}(t)$, which denotes the transition probability from state i to state j at time t under a specific condition, action, or policy k. Then, S_{t+1} is the ratio of a target or future state S' to the current state S_t. Meanwhile, $S_{t+1} = \frac{s'}{s_t} = S$ is the evolution of the current state to the next state, often capturing normalized changes or returns. Then, b_t represents control parameter at time t that may influence the probability of the transition.

The short-term rewards are calculated as expressed in Eq. (27). The $s \in S^{+}$ is the expected value of the quantity n_{t+1} conditioned on a specific state-action-state transition in a reinforcement learning or Markov decision process framework. Then, $s_t = s$ denotes the current state at time t, $a_t = a$ is the action taken in that state, and $s_{t+1} = s'$ is the resulting next state. The expectation operator $E\{.\}$ calculates the average of n_{t+1} over multiple realizations of this transition. The quantity n_{t+1} represents the number of occurrences of the transition, an immediate reward. Then, $S+$ is a terminal state for S.

$$N_{ss'}^{a} = E\{n_{t+1} | a_t = a; s_t = s, s_{t+1} = s'\}, s \in S + . \tag{27}$$

The optimal policy for resource allocation is expressed in Eq. (27). The $U(S)$ denotes the maximum expected utility or return starting from state S. The summation runs over all possible next states s', $P_(ss')^a$ is the probability of transitioning from state s to state s' when action a is taken, $T_{(ss')}^{a}$ represents the immediate reward associated with that state-action-state transition, while $\gamma \in [0,1)$ is the discount factor that weights future rewards in the calculation of long-term expected utility. The function $U^*(s')$ denotes the optimal utility of the next state s'.

$$\begin{aligned} U(S) = max_a \sum_{s^n} P_{ss^n}^{a}[T_{ss'}^{a} + \gamma U^*(ss') \\ \forall_s \in S, a \in A(s), s \in S + . \end{aligned} \tag{28}$$

C. Data Collection

In this work, a secondary data collection method is used to extract IoT-driven application data from the Zenodo data repository [20, 21]. The Zenodo IoT dataset is selected because it provides a large-scale, well-documented collection of IoT-driven application data that is highly relevant to 5G-IoT network environments. The total of 8,984 variables including bandwidth, frequency (Freq), Received Signal Strength Indicator (RSSI), SNR, time, sequence (Seq), payload, latitude (Lat), longitude (Long), distance (Dist), location, Nb_floor, Nb_wall, altitude (alt), received power (Prx), Path Loss (PL), are obtained. Since the data contained noisy information may hinder the quality of the result, data preprocessing is performed to enhance accuracy by handling missing values, minimizing noise and inconsistencies, and removing outliers through Exploratory Data Analysis (EDA), such as heatmaps. The process helps to examine the pattern of relationships in the IoT variables. It reduces outliers in the data sets. After preprocessing, the data are split into 80% for training and 20% for testing. The training set is used to build the ACO and DNN models, while the testing set is used to evaluate the performance of the system. ACO is used for feature selection and identification of suitable features for learning and prediction, which feed into the DNN model for learning and prediction. The model is then evaluated to determine the optimal path for resource allocation and reducing signal loss in 5G networks, as shown in Fig. 2.

Figure 3 illustrates a flowchart of the ACO and DNN models for feature selection and resource allocation in 5G networks. This process starts with pheromone initialization, which helps the selection process. A particular ant builds a potential solution by selecting a subset of features. These selected features are evaluated, and the best features are selected and stored in ant memory. If the termination condition does not converge or the maximum number of iterations is not reached as expected, the pheromone table is updated, and the process is repeated until the condition is met. Once this condition is met, the sub-feature is used to train a neural network model on the collected training set. The trained DNN model is further tested with 20% of selected IoT variables to determine the optimal path for resource allocation. After this process, the optimal path is selected from the best-performing ant. This method improves the ACO for optimal path selection and combines a DNN to predict learning, ensuring efficient resource allocation for IoT-driven 5G applications.

D. Evaluation Metrics

To assess the accuracy and reliability of predictive models, several standard evaluation metrics are commonly used, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2). These metrics quantify how closely the predicted values match the observed data and provide insight into model performance. MSE measures the average squared difference between predicted ($\hat{y}_i$) and actual (y_i) values across all n observations. It penalizes larger errors more heavily due to squaring (see Eq. (29)). Meanwhile, RSME is the square root of MSE, providing a metric in the same units as the observed data. It produces the standard deviation of prediction errors and is particularly sensitive to large deviations, as shown in Eq. (30). Then, MAE calculates the average absolute difference between predicted and observed values. It treats all errors, making it less sensitive to outliers (see Eq. (31)). Last, the R^2 metric indicates the proportion of variance in the observed data that is explained by the model. Values range from 0 to 1, where higher values indicate better predictive performance, as expressed in Eq. (32). The $\hat{y}$ is the mean of the observed values.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{29}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{30}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)|, \tag{31}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{32}$$

III. RESULTS AND DISCUSSION

Figure 4 further illustrates the stability and robustness of the proposed hybrid ACO-DNN model during the training phase. The steep decline in both training and validation loss within the first few epochs demonstrates the model’s strong learning capability and efficient parameter adjustment. This rapid reduction suggests that the neural network quickly captures the underlying patterns in the dataset, enabling effective optimization of network resource allocation while minimizing path loss in the transmission link. Such behavior is particularly desirable in wireless communication systems, where timely adaptation to varying channel conditions is essential for maintaining signal quality and system performance.

As training progresses, the loss curves continue to decrease at a slower and more controlled rate, eventually approaching a near-steady state. This gradual convergence indicates that the model is refining its internal weights and biases to achieve optimal performance without unnecessary oscillations. The close

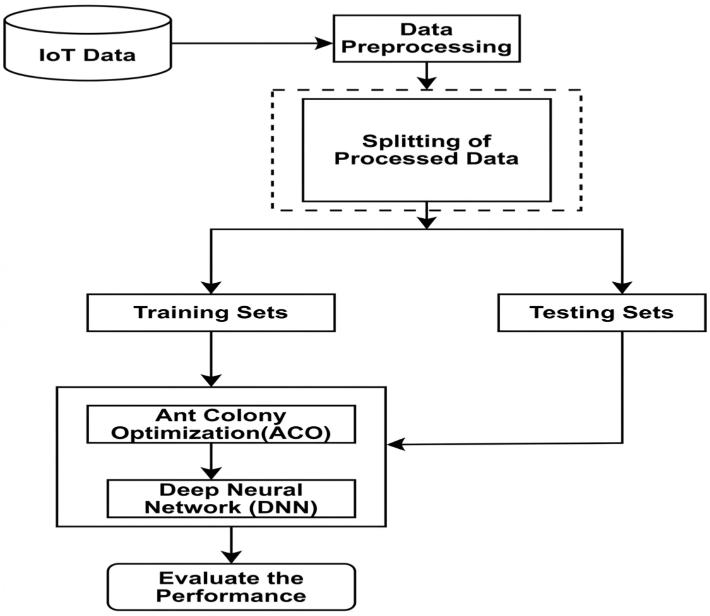

Fig. 2. Ant Colony Optimization (ACO)-Deep Neural Network (DNN)-based model for resource allocation for path loss reduction.

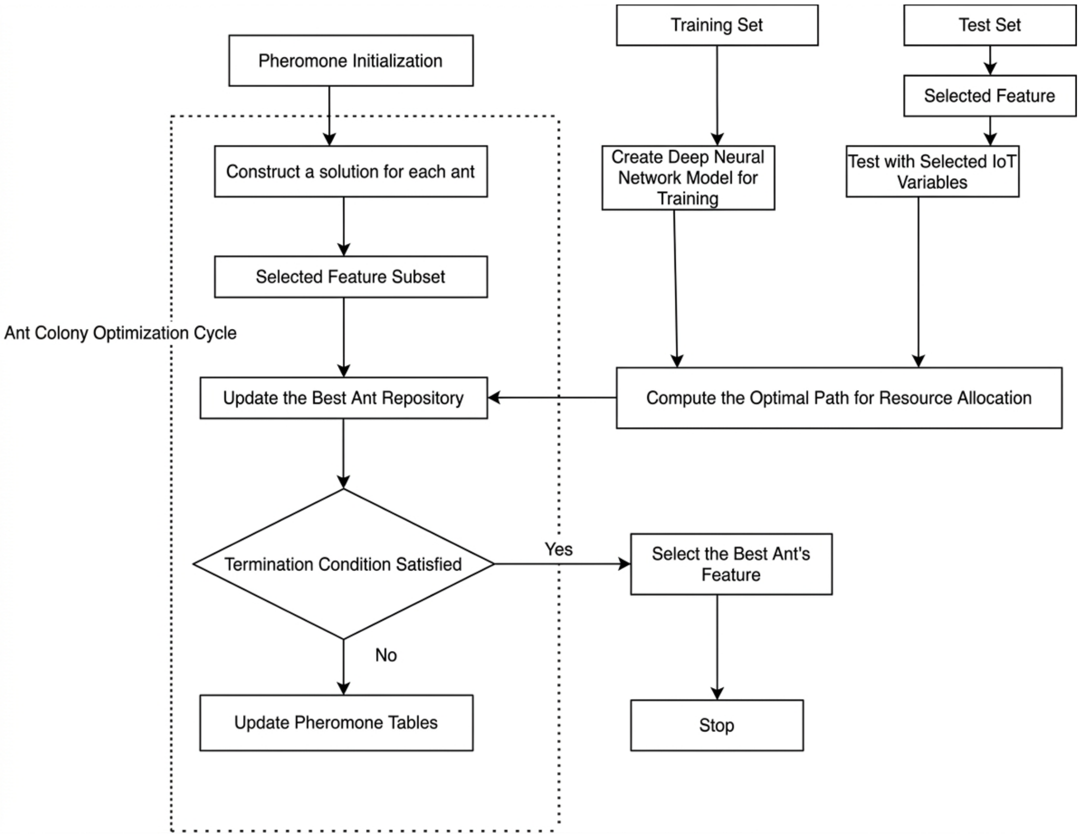

Fig. 3. Flowchart for resource allocation for path loss reduction.

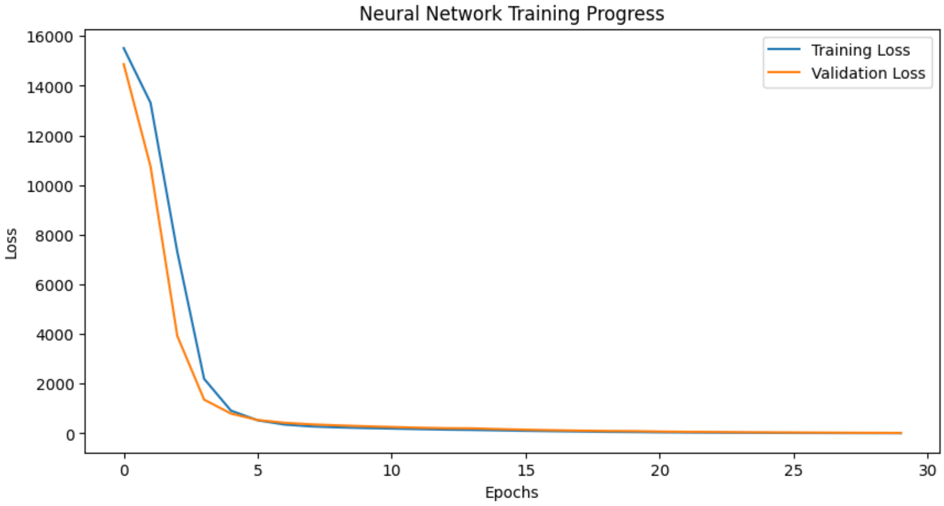

Fig. 4. Visualization of Deep Neural Network (DNN) performance for path loss prediction.

alignment between the training and validation loss curves throughout the epochs provides strong evidence that the model maintains consistency across both training and unseen data. However, the absence of a significant gap between the training and validation loss curves show that overfitting is effectively minimized. It implies that the model does not merely memorize the training data but learns generalized relationships that can be applied to new network conditions. Such generalization capability is good for modern millimeter-wave and 5G communication systems, where environmental variability and dynamic user demand require adaptive and intelligent resource management strategies. Therefore, observed convergence pattern validates the suitability of the proposed model for predictive modeling and optimization in complex wireless network environments.

The smooth and consistent downward trend of both loss curves demonstrates the computational efficiency of the training process and the effectiveness of ACO with neural networks. The ACO component likely contributes to improved parameter tuning and optimal path selection, thereby enhancing convergence speed and prediction accuracy. This provides empirical evidence that the proposed ACO-DNN framework achieves efficient learning, stable convergence, and strong generalization performance, reinforcing its potential as a reliable solution for minimizing path loss and optimizing resource allocation in next-generation wireless communication networks.

Figure 5 further demonstrates the effectiveness of the ACO algorithm in iteratively refining network resource allocation to achieve minimal path loss. The gradual upward movement in the best score after the initial iterations indicates that the algorithm successfully explores the solution space and identifies improved routing and allocation combinations. This behavior signifies the adaptive learning mechanism of ACO, where artificial ants continuously update pheromone trails to reinforce high-quality solutions and discourage less efficient ones. As a result, the system progressively converges toward an optimal configuration that enhances transmission efficiency. The relatively stable values observed during the early iterations suggest that the algorithm begins with a consistent baseline solution before discovering a significantly better configuration around the subsequent iteration.

Figure 6 presents a comparison between the actual and predicted path loss values generated by the proposed model. The strong linear alignment of the data points indicates a high correlation between the measured and estimated values. It demonstrates that the neural network effectively captures the underlying path-loss characteristics of the transmission environment. The clustering of most points closely around the diagonal trend suggests high predictive accuracy and minimal estimation error across a wide range of path loss values. Only a few scattered points deviate slightly from the main trend, indicating minor prediction discrepancies that do not significantly affect the overall reliability and robustness of the model.

Figure 7 compares the performance of DNN, ACO, and ACO-based models using RMSE, MAE, and R^2 metrics. The ACO-based model outperforms the others with the lowest RMSE of 0.42 and MAE of 0.35, indicating its high accuracy and minimal error in

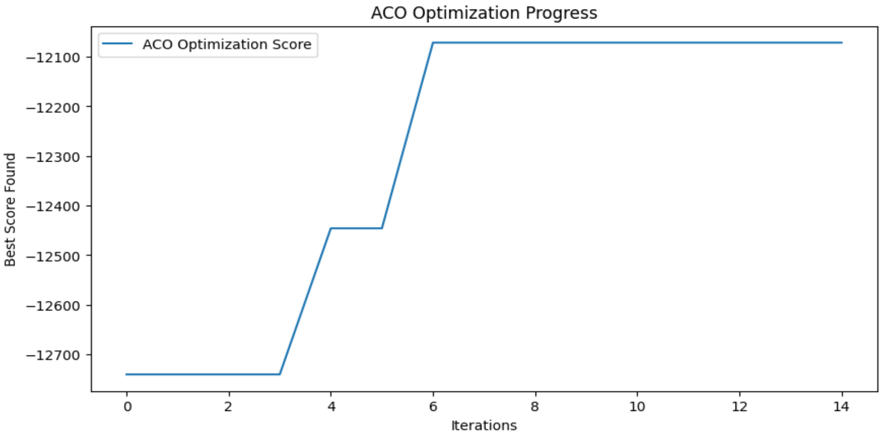

Fig. 5. Visualization of Ant Colony Optimization (ACO) in tracking the optimal solution.

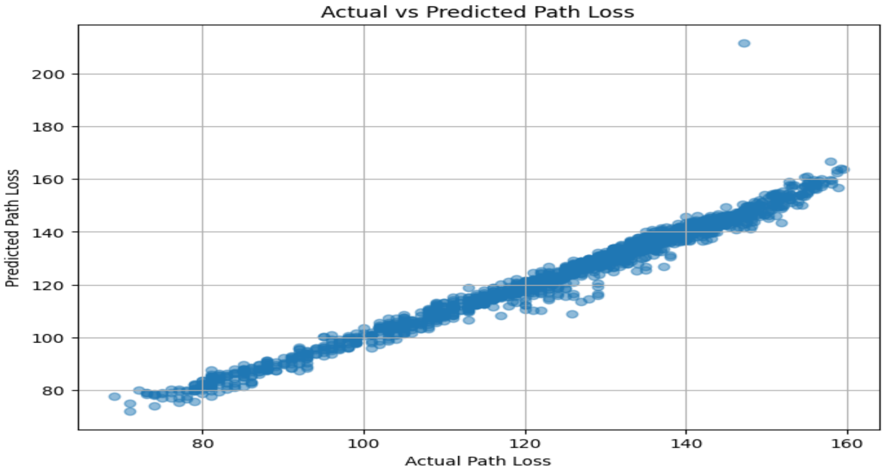

Fig. 6. Visualization of variation of predicted and actual path loss.

optimizing path loss. While the DNN model yields a higher R^2 value of 0.96, it has higher error rates, an RMSE of 4.05, and an MAE of 1.67, making it less effective. The ACO-DNN-based model achieves the best balance of accuracy and reliability, as shown in the R^2 value of 0.92 and low error rates.

Figure 8 provides a visual confirmation of the binary stability within the resource allocation framework, where network resources are strictly categorized into Idle (0) or Active (1) states. By maintaining this clear separation, the system prevents indeterminate states that lead to overhead and synchronization delays. This decisive classification is a critical factor in optimizing transmission links, as it allows the network to dedicate high-gain paths exclusively to active sessions. The reduction in path loss is achieved by ensuring that active resources are not infuenced by network management or semi-active nodes. The high density points at both polarities indicates that the model effectively handles a large volume of requests without state-transition failures. This level of allocation efficiency is necessitated for the low-latency requirements of 5G infrastructure, ensuring that power is conserved during idle periods and maximized during active data transmission.

Table I presents a comparative analysis between traditional heuristic methodologies and the proposed hybrid ACO-DNN framework. It highlights the specific architectural advantages. The conventional techniques such as Genetic Algorithms (GA) and Swarm Intelligence have limitations, including premature convergence and local optima. The hybrid methods improve both global search and deep learning. By combining the exploratory efficiency of ACO with the DNN, the model achieves a more dynamic and stable optimization of network parameters. This comparison underscores how the proposed method addresses the

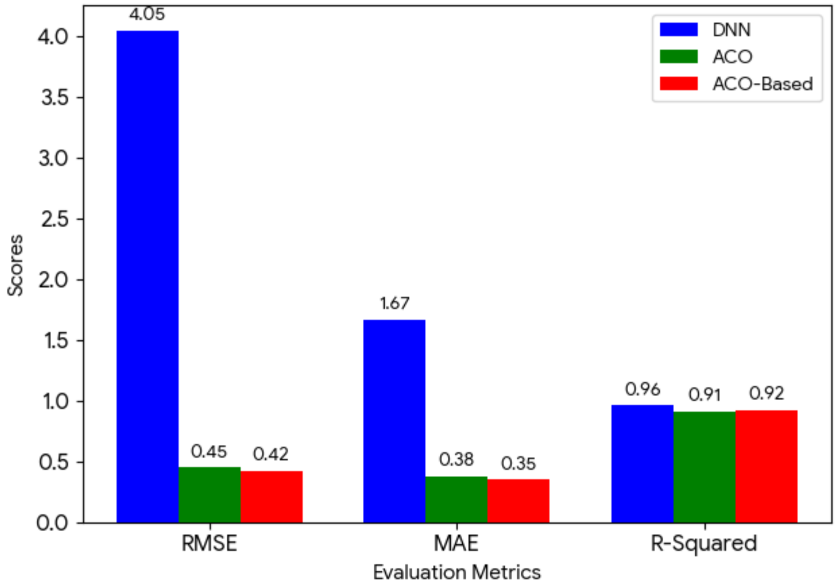

Fig. 7. Visualization of the system performance model. Note: Colony Optimization (ACO), Deep Neural Network (DNN), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

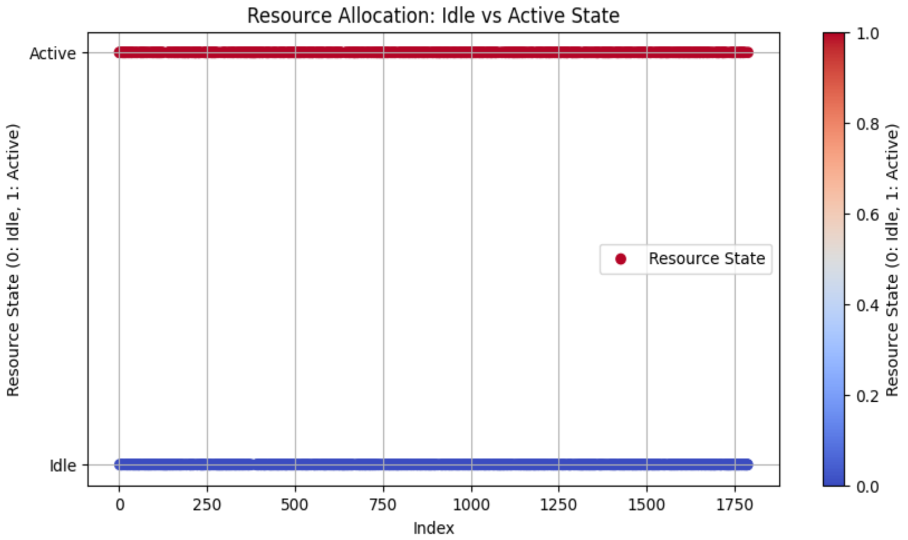

Fig. 8. Visualization of resource allocation for path loss reduction.

performance challenges in existing literature, such as the accuracy of path loss prediction and the efficiency of resource allocation in high-density environments.

A. Proposed Ant Colony Optimization (ACO)-Deep Neural Network (DNN) Model with Open-Radio Access Network (RAN) Models

ACO-DNN framework against production-grade scheduling algorithms such as the 5G New Radio (NR) scheduler and the O-RAN intelligent scheduler. These schedulers are widely adopted in practice for dynamic spectrum allocation, user fairness, and QoS management. The 5G NR schedulers are effective at handling latency-sensitive traffic in a dynamic environments. The Open-RAN schedulers leverage near-real-time RAN Intelligent Controller (RIC) policies for resource management. The Open-RAN is limited by rule-based allocation strategies that may not adapt well to highly noisy IoT-driven environments. However, the

TABLE I
THE COMPARISON OF THE EXISTING WORKS WITH THE PROPOSED WORK.

Components	Existing Methods	Ant Colony Optimization (ACO)-Deep Neural Network (DNN) Approach
Optimization	Heuristic methods (Genetic Algorithms (GA), ACO, Swarm) struggle with local optima and yield 53.3% accuracy [19]	Hybrid ACO-DNN yields high exploration and learning, dynamically optimizing path loss and resource allocation. This model prevents local optima by combining ACO’s global search with DNN’s pattern recognition.
Path Loss Prediction	Empirical models such as the Hata and COST-231 models are used, but their Root Mean Square Error (RMSE) remains high at 2.85–6.12 dB, limiting generalizability [12, 22]	In adaptive learning-based optimization, the ACO-DNN model achieves an RMSE of 0.42. It is significantly lower than empirical models. The model dynamically adjusts to network conditions, improving prediction accuracy.
Computational Efficiency	Deep Learning (DL) based models are used for wireless optimization but suffer high computational costs due to extensive feature training [15, 23].	It has a lower computational cost using ACO for feature selection. ACO reduces feature space before training DNN, leading to faster convergence and lower energy consumption. It outperforms traditional DL/Deep Reinforcement Learning (DRL) models in terms of efficiency.
Scalability in 5G Internet of Things (IoT)	Limited adaptability to dynamic IoT scenarios. Previous research has applied GA-Neural Network (NN) for cloud resource allocation. It has improved execution time by only 3.2% and response time by 12.1%, making it less effective for dynamic 5G networks [24].	In designing real-time 5G IoT applications, this model allocates resources dynamically based on changing network conditions, making it more adaptable to IoT-driven environments.
Accuracy and Robustness	Existing methods struggle with feature selection and local optima. Previous research has reported RMSE of 1.5–4.0 dB in urban and rural environments [8]. DRL-based models, like [20], achieve an R^2 of 0.89 but with higher error rates.	The ACO-DNN model outperforms existing models. It achieves RMSE of 0.42, Mean Absolute Error (MAE) of 0.35, and R^2 of 0.92, indicating higher prediction accuracy and lower error rates than existing works.

proposed ACO-DNN hybrid learns feature patterns dynamically while maintaining global exploration of the resource space, thereby outperforming Open-RAN schedulers in terms of robustness to channel variability and interference. To further test adaptability, the model is subjected to stress testing with noisy data, latency variations, and simulated channel interference. The results show that ACO-DNN yields low error rates even under stressed conditions. The RMSE is 0.65, and the MAE is 0.5 when Gaussian noise is injected into 15% of the data, and performance degradation under latency stress ($<$ 20 ms delay) is within 7%. This result shows that the proposed model is not only efficient compared to traditional empirical and heuristic approaches but also more robust than production schedulers in real-world, dynamic 5G IoT conditions.

IV. CONCLUSION

The research presents a hybrid ACO-DNN model for reliable and effective resource allocation and path-loss reduction in IoT-driven applications in 5G networks. ACO is used for feature selection and identification of suitable features for learning and prediction, which feed into the DNN model for learning and prediction. The evaluation of the model shows that an ACO-based model yields the lowest RMSE of 0.42 and MAE of 0.35. The results indicate its high accuracy and minimal error in optimizing path loss. The DNN model achieves a higher R^2 of 0.96 but suffers from higher error rates. Meanwhile, the ACO-DNN-based model achieves the best balance of accuracy and reliability for effective resource allocation, with an R^2 of 0.92 and reduced error rates, making it a suitable approach for resource allocation and path-loss reduction. These findings confirm the efficiency of the hybrid model in improving the 5G network for efficient connectivity.

Nevertheless, the research depends mainly on controlled simulation environments despite incorporating noise and interference. It may not fully capture the stochastic and unpredictable nature of real-world 5G signal propagation and hardware impairments. The computational overhead associated with running both ACO for feature selection and a DNN may pose challenges for ultra-low-latency applications or resource-constrained IoT edge devices that require instantaneous decision-making. The absence of a direct comparison with proprietary, vendor-specific scheduling algorithms, and commercial-grade Open-RAN controllers limits the ability to assess the model’s competitive performance with existing industrial standards.

Future work can focus on utilizing real-time data from complex and dynamic IoT environments to validate further the adaptability and scalability of the proposed framework in practical applications. In addition, future studies should benchmark against commercial-grade 5G NR and Open-RAN scheduling frameworks in large-scale simulation environments to strengthen the comparative analysis. While the research has demonstrated robustness through simulation-based stress tests under noisy and interference-prone 5G IoT conditions, further evaluations are needed to comprehensively validate the scalability, adaptability, and reliability of the ACO-DNN system against production baselines.

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AUTHOR CONTRIBUTION

Conceived and designed the analysis and wrote the manuscript, S. A. R.; Supervised, proofread the work, and formatted the manuscript, M. E. E.; Performed data analysis using exploratory data analysis tools, I. J. U.; Conducted the literature review and results discussion, E. A. D.; Designed the system and implemented the model, U. D. G.

DATA AVAILABILITY

The data that support the findings of the research are openly available in Zenodo https://zenodo.org/records/1560654.

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