



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 8, August 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Time-Varying Social-Aware Resource Allocation for Device-to-Device Communication

Dr. C.R.Balamurugan¹, P.Nisha², Dr.V. Senthilkumar³

Professor and Head, Department of Electronics and Communication Engineering, Er.Perumal Manimekalai College of
Engineering, Hosur, Tamil Nadu, India¹

PG Scholar, Department of Applied Electronics, Er.Perumal Manimekalai College of Engineering, Hosur,
Tamil Nadu, India²

Associate Professor, Department of Electronics and Communication Engineering, Er.Perumal Manimekalai College of
Engineering, Hosur, Tamil Nadu, India³

ABSTRACT: Device-to-device (D2D) Communication has surfaced as a promising innovation within cellular networks, facilitating direct interaction among users devoid of the conventional reliance on infrastructure like base stations or core networks. This model offers the main advantage of ultra-low latency communication. However, efficient resource allocation in D2D communication remains a critical research area, as multiple user-sharing sub channels introduce interference challenges. This study examines dynamic resource allocation for device-to-device communication, emphasizing the utilization of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks and Bidirectional LSTMs. The proposed method involves the analysis of device-to-device communication dynamics over time, considering factors such as rates, weights, and a categorical value denoted as C: 1. A dataset comprising 9210 instances (rows) is utilized, with 61 features and 30 target values consolidated in a single CSV file. The performance of the models, a simulation is conducted, and the results are presented through graphical representations. If applicable, preprocessing steps are undertaken to handle missing values, normalize data, and encode categorical variables. Special attention is given to maintaining the temporal and social context of the features. Specifically, the study focuses on analyzing LSTM and Bidirectional LSTM simulation graph outputs concerning epoch accuracy and loss. Comparing these two metrics offers valuable insights into how well the proposed method performs in allocating communication resources for device-to-device interactions. The analysis includes interpreting the simulation graph outputs, drawing comparisons between LSTM and Bidirectional LSTM models. The experiments are conducted using a dataset from the resource allocation problem, and the results are analyzed using the Python-based Spyder application.

KEYWORDS: Device-to-Device (D2D) Communication, Cellular Networks, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM)

I. INTRODUCTION

Device-to-device (D2D) communication involves the direct transfer of data between two devices or individuals, bypassing the need for data traffic to transit a Base Station (BS) or Evolved NodeB (eNodeB). The form of communication is particularly advantageous in proximity-based scenarios, where devices in close vicinity can communicate directly, thereby enhancing spectral efficiency compared to traditional cellular networks. With the evolution of 5G technology, which promises ultra-low latency and high throughput communication, D2D communication emerges as a pivotal element capable of significantly improving network performance. Traditional cellular networks mandate that all communication traffic pass through the BS, even when devices are nearby. However, D2D communication offers the potential for increased energy efficiency, enhanced throughput, and reduced delay. The direct communication paradigm finds application in various scenarios, such as proximity-based services triggering social applications, advertisements, local information exchange, and intelligent vehicle communication. Additionally, D2D communication is crucial in public safety support, ensuring local connectivity during radio infrastructure damage. Resource allocation issues in D2D communication often manifest as optimization problems, with mathematical programming algorithms aiming to achieve optimal solutions. In essence, the challenges of subchannel allocation revolve around optimizing the total data rate of direct device-to-device (D2D) communication links while upholding a

baseline Quality of Service (QoS) for Cellular Users (CU). However, the intricacy of these challenges, comparable to the NP-Hard complexity of the 0-1 Constrained Knapsack Problem, requires the utilization of tailored algorithms such as Dynamic Programming and Branch and Bound (B&B). Despite the evolution of efficient resource allocation algorithms, the real-world scenario poses challenges in terms of latency, prompting the need for a more flexible framework. Recently, a paradigm shift in problem-solving has occurred with the introduction and success of deep learning in various interdisciplinary fields. Machine learning and deep learning, empowered by vast data and high computational capabilities, have revolutionized wireless applications, including PHY layer design, resource allocation, networking, and edge computing. Deep learning neural networks, capable of learning efficient data representations and uncovering hidden insights, provide a data-driven approach to traditionally challenging problems, often due to the need for more accurate models or computational complexity. The proposed technique explores different neural network architectures, starting with vanilla neural networks and progressing to Recurrent Neural Networks (RNN) with Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) units. The focus then shifts towards developing constraint-aware neural networks, incorporating the Lagrangian duality concept to address constraints during training. The approach aims to regularize the output space and generate predictions that adhere to specific constraints, offering a more flexible and efficient framework for wireless resource allocation in D2D communication scenarios.

II. LITERATURE SURVEY

D2D networks are vital for IoT, necessitating efficient resource management. Underlay in-band Device-to-Device (D2D) communication is favored for its high spectral efficiency, although it poses potential interference challenges. A specific strategy enables multiple D2D users to share resources with cellular users, striking a balance between efficiency and interference. By applying Lagrangian dual optimization, the optimal power allocation for each D2D user is determined, which improves both energy efficiency and overall system performance [1].

Optimizing energy efficiency (EE) in UAV-assisted communication networks balances minimizing power consumption and maximizing transmission rates. Existing research assumes perfect channel state and coordinate information, which is impractical due to estimation errors. Formulates a robust EE maximization problem for an energy harvesting-based D2D system, considering constraints like outage probability and UAV flight altitude. Using a worst-case approach, the problem is transformed into a convex one, and the Lagrange dual theory is applied. Simulations confirm the algorithm's effectiveness in enhancing EE and robustness [2].

LTE-A enables direct communication between user equipment (UEs) and Device-to-device (D2D) communication is essential for accommodating the growing number of user equipment (UEs). Effective resource and power management for D2D UEs (DUEs) is imperative to mitigate potential interference issues. A pure D2D model, suggested for Internet of Things (IoT) applications, permits DUEs to share resources independently of cellular UEs (CUEs), thereby enhancing network performance. The D2D resource allocation and power control (DRAPC) framework employs vertex coloring to group UEs, which improves signal quality and optimizes resource sharing. Simulations show DRAPC improves network performance and ensures fairness [3].

A game theory-based method enhances device-to-device communication over long distances by strategically introducing a relay node. The algorithm optimizes relay node selection by analyzing distance loss, energy impact, and forwarding capabilities. Simulation results show improved coverage, reduced link interruptions, and increased system throughput compared to random and channel state-based selections, balancing physical and social factors for rational relay choices [4].

The hierarchical management of microgrids and multicell device-to-device (D2D) communications encounters difficulties due to the stationary nature of control units and the mobility of cellular users. A two-tier resource allocation strategy is proposed to address this issue, where tier-1 handles static control units and tier-2 manages dynamic mobile users. This approach aims to enhance latency and spectral efficiency by employing the Hungarian algorithm alongside convex optimization techniques. Simulations show its effectiveness over random channel assignment, balancing D2D power and cellular sum rates [5].

Device-to-device (D2D) communication holds significant promise for addressing the demands of ultra-dense, low-latency, and high-speed 5G networks. Nevertheless, energy consumption in D2D relay networks continues to pose a substantial challenge. The JPARS scheme improves energy efficiency (EE) in relay-assisted D2D communications by

optimizing power allocation with the Dinkelbach method and Lagrange dual decomposition, while relay selection is enhanced using Q-learning. The comprehensive approach improves EE while maintaining quality of service, as validated by simulations showing a significant performance boost [6].

The implementation of 5G standards relies on device-to-device (D2D) communication, particularly in the critical device discovery phase. Limited algorithms exist for effective discovery, essential for accurate positioning in dynamic environments. The study evaluates discovery algorithms using metrics like accuracy and RMSE. Hamming and cosine algorithms were tested, showing a 21% reduction in discovery errors and a 29% reduction in complexity [7].

The research explores the efficiency of LiFi-based device-to-device (D2D) communication within the context of the Industrial Internet of Things (IIoT), with an emphasis on managing mobility. A coverage model is developed utilizing the semi-angle at half illuminance of both the access point (AP) and IIoT devices. Stochastic geometry is employed to derive expressions for the mode selection rate and residence time, which are then validated through Monte Carlo simulations. The results indicate that increased velocity and device density lead to a reduction in D2D residence time and an elevation in the transition rate. This study offers critical performance insights for the deployment of industrial LiFi networks [8].

The uplink-focused Device-to-Device (D2D) communication model in 5G networks addresses challenges related to resource management and power control. The APERAA algorithm leverages Lyapunov optimization alongside machine learning techniques for efficient resource allocation. This approach enhances uplink capacity and overall system performance, while ensuring a satisfactory signal-to-interference-plus-noise ratio for D2D users. Leveraging SVM enhances spectral efficiency in autonomous mode. Simulation confirms superior performance over existing technology, especially in IoT healthcare, promising continuous, reliable medical monitoring [9].

The study explores device-to-device (D2D) communication within cellular networks using a spatiotemporal traffic model and queuing theory. It employs a thinned Poisson point process to model D2D users and analyzes dynamic traffic through feedback queuing models. The service probability is determined by the signal-to-interference-plus-noise ratio (SINR), and performance metrics such as queue length and throughput are derived using Markov chains. Simulations validate the approach, demonstrating its applicability in D2D heterogeneous networks and its effectiveness with protocols like GBN-ARQ and SR-ARQ in multi-hop communication [10].

Spatiotemporal offloading in D2D communication within cellular networks. Their approach incorporates inter-cell mobility models to enhance caching strategies and system efficiency. To analyze spatiotemporal offloading, the authors likely conducted simulations based on real mobility data or mathematical models, evaluating the performance of their proposed methods against existing approaches. The could involve creating scenarios reflecting various mobility patterns and network conditions to assess the effectiveness of their strategy [11].

A methodology has been developed for integrating social-awareness and mobility-awareness into computation offloading within heterogeneous mobile edge computing environments. This likely involved utilizing social network analysis techniques alongside mobility modeling to create algorithms for selecting mobile devices. The process may have included collecting data on social connections, location correlations, and mobile activities, subsequently leading to the development of algorithms and their performance assessment through simulations or practical experiments [12].

To explore device-to-device task offloading in scenarios where devices might unpredictably become inactive, taking into account social awareness. They probably utilized simulations or analytical models to study how social factors influence task offloading and resource allocation. The methodology may involve generating scenarios with varying levels of social interaction and uncertainty, followed by analyzing the performance metrics under different conditions to derive insights and optimize strategies [13].

Age of Information (AoI)-aware wireless resource allocation in energy-harvesting-powered mobile edge computing systems. Their methodology likely involves mathematical modeling and optimization techniques to allocate wireless resources efficiently. They may have conducted simulations based on AoI metrics and energy-harvesting profiles to evaluate the performance of their resource allocation algorithms under different scenarios [14].

A methodology that involves data collection, model training, and evaluation. They may have collected video streaming data from multiple devices and designed lightweight DNN architectures suitable for resource-constrained devices. The methodology likely includes performance evaluation through simulations or real-world experiments to validate the efficiency of their approach [15].

CSML, a double-layer online learning algorithm, is being used to improve beam selection in mmWave vehicular communication systems. It uses the context and social preferences of smart cars and passengers to select appropriate beams and adjust broadcast angles. The approach enhances system efficiency by incorporating real-world traffic patterns and enabling autonomous beam allocation. CSML's effectiveness in improving system throughput under hardware and cost constraints makes it a promising approach for future mmWave communication networks [16].

Proactive caching is a strategy that addresses the challenges of escalating data volumes, particularly mobile video traffic, by minimizing communication costs and ensuring diverse quality of service in multi-access edge networks. The proactive caching algorithm considers users' mobility behaviors and social influences on content preference, incorporating an incentive mechanism and cooperative framework to encourage collaboration among mobile user entities [17].

The increasing demand for data transmission resources in next-generation cellular networks is being addressed by combining Device-to-Device (D2D) communications with social network analysis. A novel optimization framework for social-aware Radio Resource Allocation (RRA) is proposed, focusing on D2D communications with partial Channel State Information (CSI). This framework employs a selected-NM Maximum Distance Ratio (MDR) q-bit feedback scheme to minimize feedback overhead while optimizing system throughput. The selected-NM q-feedback model not only boosts system throughput but also enhances spectrum efficiency. Future research directions include integrating other metaheuristics [18].

The study focusing on the social attributes of terminal equipment. The algorithm considers physical and social distances and selects a core user based on factors like power, storage capacity, and mobility. Numerical simulations validate the algorithm's effectiveness, demonstrating improvements in system utility and throughput performance. The algorithm also quantifies social relationship factors between users [19].

Present adaptive 5G networks, likely employing a methodology that involves data-driven modeling and optimization. They may have collected data on social ties, network conditions, and user behaviors to inform the design of adaptive resource allocation algorithms. The methodology may include simulations or experiments to validate the adaptability and performance of their techniques in dynamic 5G environments [20].

III. PROPOSED METHODOLOGY

The Time-Varying Social-Aware Resource Allocation approach is suggested as a method for enhancing resource distribution within Device-to-Device (D2D) communication settings. The methodology uses a dataset with 9210 values categorized into three sets: Rates, Weights, and a constant term C , along with a target variable comprising 30 values. The data collection is split into a training subset, accounting for 80% of the total, and a validation/testing subset, making up the remaining 20%. This division aims to facilitate effective model training and evaluation in practical scenarios. A distinctive feature of the methodology is its binary classification approach, predicting each X value individually rather than all 30 simultaneously, which aligns with the characteristics of D2D communication scenarios. Implementation involves using the Spyder application in Python to train datasets and present results in percentages. Model performance is assessed using an epoch in graphs to visualize precision and recall metrics. Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) units and Bidirectional LSTM architecture are employed to capture temporal dependencies and sequential patterns in the dataset. This choice is motivated by the dynamic nature of D2D communication scenarios. The dataset is converted into binary data to emphasize the discrete nature of D2D communication, and consideration of sub channels acknowledges multi-channel complexities. The proposed methodology offers a comprehensive and customized approach to resource allocation challenges in D2D communication. By utilizing advanced techniques like RNN with LSTM, adopting a binary classification strategy, and incorporating binary data and subchannel considerations, the model aims to provide accurate predictions in dynamic communication environments. This methodology holds promise for optimizing resource allocation in real-world D2D communication networks through meticulous data analysis and strategic model design.

A. Model Of The System

The system comprises N subchannels and N Cellular Units (CUs), alongside M Device-to-Device (D2D) pairs in a cell. Each D2D pair is denoted by the set \mathcal{D} , and each subchannel is denoted by the set \mathcal{S} . Each CU, labeled as CU I , is assigned to a specific subchannel, which is shared by D2D pairs. CU transmit power is P_c , while D2D transmitter (DTx) power is P_d . Channel power gains between CUs and D2D pairs, as well as between D2D pairs and the Base Station (BS), are represented by various parameters.

B. Model Of Interference

Within the system model, two types of interferences exist: D2D Interference and Cell-to-Cell Interference.

Intra-Device-to-Device Interference:

Inter-D2D interference is the undesired radio frequency disturbance between different Device-to-Device (D2D) communication links in wireless networks, especially cellular ones. It can harm communication quality by weakening signals, increasing noise, and causing data errors. Effective management is vital for optimizing system performance. Techniques like resource allocation, interference coordination, and signal processing are used to reduce interference and enhance D2D communication. The interference power, denoted as $I_{jk}(i)$, is influenced by the transmitter of D2D pair k to D2D pair j , where $I_{jk}(i) = P_d g_{jk}(i)$. Channel gain values are challenging to obtain, so statistical analysis of $I_{jk}(i)$, is relied upon.

Cellular Interference within Cells:

Inter-cell interference (ICI) in wireless communication can hinder network efficiency and quality. To mitigate ICI, advanced antenna technologies, optimal cell placement, frequency reuse techniques, and interference cancellation algorithms are employed. The objective of these tactics is to reduce the interference among neighboring cells, thereby improving the efficiency and dependability of wireless communication networks. This is achieved by introducing the assignment variable x_{ij} , which represents whether subchannel i is assigned to D2D pair j ($x_{ij} = 1$) or not ($x_{ij} = 0$). The Signal-to-Interference-Noise Ratio (SINR) can then be expressed as follows:

$$SINR_j^d(i) = \frac{P_d h_{jj}(i)}{P_c g_{ji}(i) + I_j^d(i) + \sigma^2}$$

The variable I_j^d signifies the summation of interferences, with j representing the D2D pairs and i as an index. The parameter σ^2 denotes the power of noise. Balancing spatial reuse and interference is vital concerning the quantity of D2D assignments. To enhance spatial reuse, assigning multiple Device-to-Device (D2D) pairs to a subchannel is beneficial, yet it comes with the drawback of increased interference. Striking a balance, a system parameter denoted as K dictates that a maximum of K D2D pairs can utilize a single subchannel. Therefore, the constraint can be succinctly expressed as follows:

$$\sum_{j=1}^M x_{ij} \leq K$$

C. Quality Of Service (QoS)

A network or service's reliability and performance, meeting set standards for user satisfaction. It considers factors like bandwidth, latency, jitter, and packet loss. Different applications have specific QoS needs, such as low latency for live communication or high bandwidth for file transfers. These requirements are outlined in SLAs or technical specs, helping organizations optimize their networks for diverse needs.

Let $C_{ij} = \log_2$ of $(1 + \Psi \delta_{ij})$, representing the rate of D2D pair j on subchannel i . It is understood that,

$$SINR_j^c(i) = \frac{P_c h_{bi}(i)}{\sum P_d g_{bi}(i) + I_{BS}(i) + \sigma^2}$$

The transmission must achieve a minimum rate of $R(i)_{min}$, accompanied by an outage probability not exceeding ϵ_c , a specified system parameter.

$$P_r(\log_2(1 + SINR_i^c(i)) \geq R(i)_{min}) \geq 1 - \epsilon_c$$

Replacing $SINR_i^c(i)$ and reorganizing expressions, we obtain

$$\sum_{j=1}^M x_{ij} w_{ij} \leq b_i$$

The expression $w_{ij} = P_{dgbj}(i)$ represents the interference power at Base Station (BS) on subchannel i caused by the Downlink Transmission (DTx) of Device-to-Device (D2D) pair j .

The term $b_i = P_{chbi}(i)/2R(i) \min^{-1} - \sigma^2 - F^{-1BS}(1 - c)$, where $F^{-1BS}(\cdot)$ denotes the inverse of the Cumulative Distribution Function (CDF) of IBS(i).

3.1 Classifiers

A. Deep Learning

Deep learning, a branch of machine learning, harnesses artificial neural networks to tackle intricate challenges, drawing inspiration from the intricacies of the human brain. By mimicking the brain's structure and processes, deep learning algorithms strive to grasp layered data representations through interconnected nodes, termed neurons, within artificial neural networks.

Binary Classification Neural Networks

Deep learning models are inspired by the structure and function of the human brain, consisting of interconnected nodes or neurons arranged in layers. These artificial neural networks mimic biological neurons using computational models, with each node performing basic mathematical operations influenced by unique parameters. Through meticulous parameter tuning and intricate node linkage, these networks can learn complex functions effectively. The perceptron, a basic form of neural network, consists of a single input layer and a single output layer, processing inputs with weights and biases to derive desired functions. In essence, a perceptron is akin to a solitary neuron.

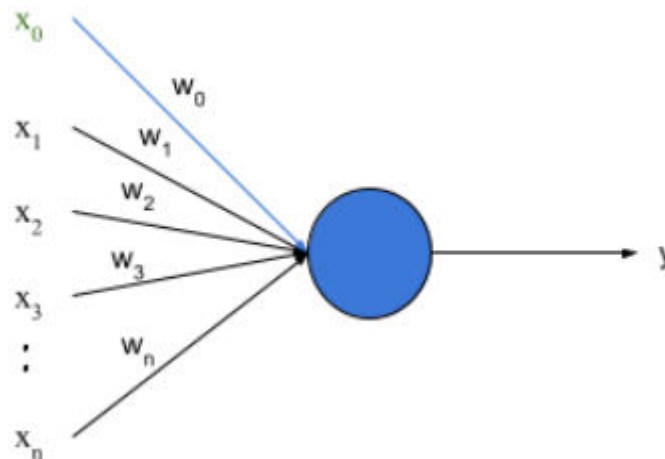


Figure 1 Single Perceptron

The perceptron equation is formulated as follows:

$$Z = 1, \text{ if } W \cdot X + b > 0 \text{ or } \sum_{i=1}^N w_i x_i + b > 0$$

$$0, \text{ otherwise}$$

In neural networks, we use symbolic representations to streamline computations. The weight matrix is typically denoted as W , the input matrix as X , and the bias, often set to 1, as b . Following the weighted sum operation, the output, known as z , undergoes further processing via a non-linear activation function.

$$\hat{y} = g(z)$$

Multiple Layers

When multiple layers housing numerous neurons are taken into account within neural networks, the variable "x" undergoes a transformation into matrix "a," which signifies the activation status across these layers. Specifically, the "x" vector represents the activation state of layer 0, corresponding to the input layer. Consequently, for any given layer "l," each neuron within it performs the following steps:

$$z_j^{[l]} = w_j^{[l]} \cdot a^{[l-1]} + b_j$$

$$a_j^{[l]} = g^{[l]}(z_j^{[l]})$$

The weights (w) and transposed biases horizontally to form the matrices W and b. The vertical vectors x, a, and z are then consolidated to create X, A, and Z.

$$z^{[l]} = W^{[l]} \cdot A^{[l]} + b^{[l]}$$

$$A^{[l]} = g^{[l]}(z^{[l]})$$

Loss Function For Binary Classification

The objective function in an optimization algorithm is used to evaluate a candidate solution, aiming to maximize or minimize the highest or lowest score. In neural networks, the objective function is often called a cost or loss function, with the loss function calculated as simply loss. Standard loss functions include cross-entropy, mean squared error, mean absolute error, and Hinge loss. The cross-entropy function is commonly used for classification, which measures the difference between two averages of the number of bits of information distribution. Each predicted probability is compared to the actual class output value, and a score is calculated that penalizes the probability based on the distance from the expected value. The penalty is logarithmic, offering small scores for minor differences and enormous scores for significant differences. Cross-entropy loss is minimized, with smaller values representing better models. A model that predicts perfect probabilities has a cross-entropy or log loss of 0.0.

The cross-entropy function is expressed as,

$$L = -\frac{1}{m} \sum_{i=1}^m y_i \log(\hat{y}_i)$$

The binary cross-entropy function associated with a given dataset can be expressed as,

$$J(w, b) = -\frac{1}{m} \sum_{i=1}^m L(\hat{y}_i, y_i)$$

$$L(\hat{y}_i, y_i) = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y}))$$

Enhancing Neural Network Performance

A neural network in deep learning is trained to establish a mapping between input and output sets through optimization using training data. The learning problem is formulated as an optimization task, wherein an algorithm is employed to explore the potential sets of weights that the model can utilize to generate accurate or sufficiently accurate predictions. Stochastic gradient descent is commonly employed to train neural network models, and weight adjustments are made using the backpropagation of error algorithm. In this context, the gradient refers to the error gradient, and the error function for N data points is represented as.

$$E = \frac{1}{N} \sum_{k=1}^N \sum_i (y_i^k - f(\sum_j w_{ji} x_j^k))^2$$

$$\text{Let } \hat{y} = f(\sum_j w_{ji} x_j^k)$$

Here y = true labels,
k = all data points,
i = output units of the network,
j = number of features,
x = feature,
w = weights,

f is a function of the predicted values

Therefore, the goal here is to reduce the mentioned function. To determine the minimum of a function, we calculate its derivative. When considering a single neuron with a sole output unit (i.e., $i = 1$), the derivative concerning weight is expressed as:

$$\frac{\partial E}{\partial w_j} = (y - \hat{y}) \frac{\partial \hat{y}}{\partial w_j}$$

$$\hat{y} = f\left(\sum_j x_j w_j\right) = f(h)$$

$$\frac{\partial E}{\partial w_j} = (y - \hat{y}) f'(h) x_j$$

Multiplying by a learning rate η yields the gradient of the squared error concerning weight.

$$\Delta w_j = \eta (y - \hat{y}) f'(h)$$

Let δ be the error term defined as,

$$\delta = (y - \hat{y}) f'(h)$$

Thus the general equation is now,

$$\Delta w_{ji} = \eta \delta x_{ji}$$

Thus for each epoch the update function would now be

$$w_{ji}^t = w_{ji}^{t-1} + \Delta w_{ji}$$

As detailed in the preceding section, generating anticipated values involves updating weights through gradient descent to minimize the loss function. This process entails learning. Forward propagation is complemented by backpropagation, where the error is propagated to minimize the loss through adjustments to the weights using gradient descent-based optimization. For a given error δ associated with an output unit k and a hidden input i of a hidden layer h , backpropagation seeks to optimize the weights and reduce the overall loss.

$$\delta_i^h = \sum W_{ik} \delta_k^0 f'(h_j)$$

Thus the gradient descent step is,

$$\Delta w_{ji} = \eta \delta_j^h x_{ji}$$

The process involves iterating the steps with the updated weights until the prediction closely aligns with the ground truth, as illustrated in the figure below.

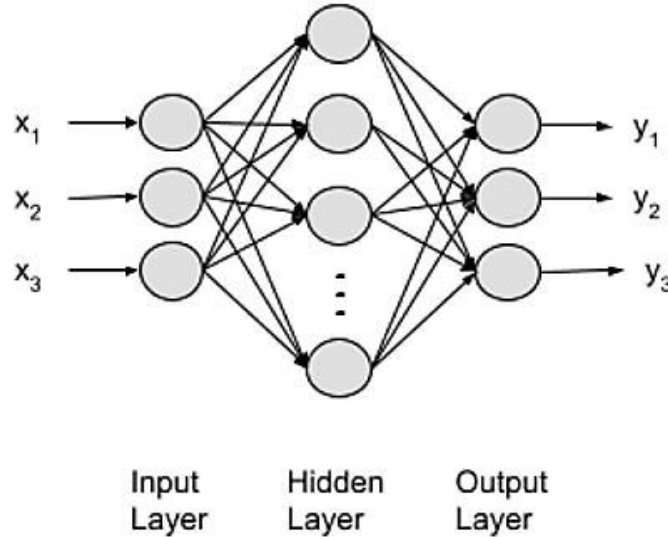


Figure 2 Diagram of Basic neural network classification model

Optimizer

In the preceding section, we discussed optimization's crucial role in neural networks. Therefore, the choice of appropriate optimizers is paramount. Among the frequently employed ones are Stochastic Gradient Descent (SGD), Root Mean Square (RMS) Propagation, and Adaptive Moment Estimation (ADAM). The fundamental formula for updating the parameter θ in essential vanilla gradient descent is given by:

$$\theta = \theta - \eta \nabla_{\theta} (\theta)$$

Stochastic gradient descent (SGD) updates parameters based on each training sample (x_i, y_i) .

$$\theta = \theta - \eta \nabla_{\theta} (\theta; x^i; y^i)$$

Stochastic Gradient Descent (SGD) exhibits a comparatively swifter convergence than regular gradient descent; however, it encounters challenges with potential entrapment in local minima. In contrast, ADAM and RMS Prop emerge as superior optimizers on average compared to SGD. This superiority stems from their enhanced capability to efficiently navigate towards the global minima, achieving faster and more dependable convergence.

B. Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) is designed for sequences or time-series data, with an internal memory that updates at each step to capture temporal patterns. It consists of input, hidden, and output layers, using the previous output as input for the next step to remember past states. This structure makes RNNs ideal for sequence-based tasks, like solving combinatorial problems, by sharing consistent weights across time steps to ensure each output is derived from the same update process.

An RNN processes a sequence comprising vectors x_t , where the time index t spans from 1 to τ —consequently, RNNs function on minibatches of these sequences.

Thus the function would thus be:

$$\widehat{Y}_t = f(x_t)$$

If \widehat{Y}_2 in the later stages depends on both x_0 and k_1 , introducing a factor of 2 recurrence becomes essential. Consequently, neurons with recurrence would be incorporated.

"Here, "ht" represents the internal memory, carried over from one time step to the next. Depending on the current input and the previous step's memory, it functions as a combination of both factors."

$$\hat{Y}_t = f(x_t, h_{t-1})$$

RNNs maintain a state, denoted as ht, which is updated at each time step during the processing of a sequence. The recurrence relation is applied at every time step to facilitate this update.

$$h_t = f_w (, h_{t-1})$$

Here, ht represents the cell state, and fw is a function with weights w. Consequently, for a provided input vector xt, the updated hidden state is determined by:

$$h_t = \tanh (W_{hh}^T h_{t-1} + W_{xh}^T x_t)$$

Therefore, the resulting vector is expressed as:

$$\hat{Y}_t = W_{hy}^T h_t$$

The matrix W_{xh} represents the weight matrix, while W_{hh} denotes the matrix for hidden state to hidden state transitions.

Back propagation through time (BPTT) is a back propagation technique for recurrent neural networks (RNNs). It computes gradients involving the W_{hh} matrix. In the encoder-decoder architecture, stacked RNNs are used. The encoder processes the input to create a condensed representation called "z," which is then passed to the decoder to generate the predicted output based on the final hidden state.

C. Long Short-Term Memory (LSTM)

Bidirectional LSTM (B-LSTM) improves upon traditional LSTM by processing data in both forward and backward directions, mitigating the vanishing gradient issue in lengthy sequences. By reversing input sequences, B-LSTM gains insights from past and future contexts, crucial for tasks like sentiment analysis and machine translation. Integrating B-LSTM with time-varying, social-aware resource allocation in D2D communication enhances system flexibility and optimizes resource allocation in wireless networks, considering social ties.

The Lagrangian Loss term is mathematically calculated as

$$\text{Lagrangian Loss} = \lambda \cdot (\text{Soft Constraint} - \text{Threshold})^2.$$

D. Bidirectional Long Short-Term Memory (B-LSTM)

Bidirectional LSTM (B-LSTM) improves upon traditional LSTM by processing data in both forward and backward directions, mitigating the vanishing gradient issue in lengthy sequences. By reversing input sequences, B-LSTM gains insights from past and future contexts, crucial for tasks like sentiment analysis and machine translation. Integrating B-LSTM with time-varying, social-aware resource allocation in D2D communication enhances system flexibility and optimizes resource allocation in wireless networks, considering social ties.

IV. RESULTS & DISCUSSION

The neural network has an input layer, two ReLU-activated hidden layers, and a sigmoid output layer. It is trained with the ADAM optimizer for 1000 epochs at a 0.01 learning rate, using a 70/30 training-validation split.

Tabulation of Feature Metrics and Accuracy

Feature Metrics	Accuracy 100 Epoch
Rate	73.42%
Weight	28.17%
C:1 Value	73.27%

Table 1 Tabulation of Feature metrics with respect to accuracy of 100 epoch

The tabulation results for Feature Metrics, Weight, and the parameter C: 1 Value in a machine learning model show 100% accuracy for all three components, but at different epochs. Accuracy for Feature Metrics reached 100% after 73.42% of the total epochs, for Weight after 28.1%, and for C: 1 Value after 73.27%. This indicates perfect training accuracy across all components, with each converging at different points in the training process.

4.1 LSTM Accuracy Model

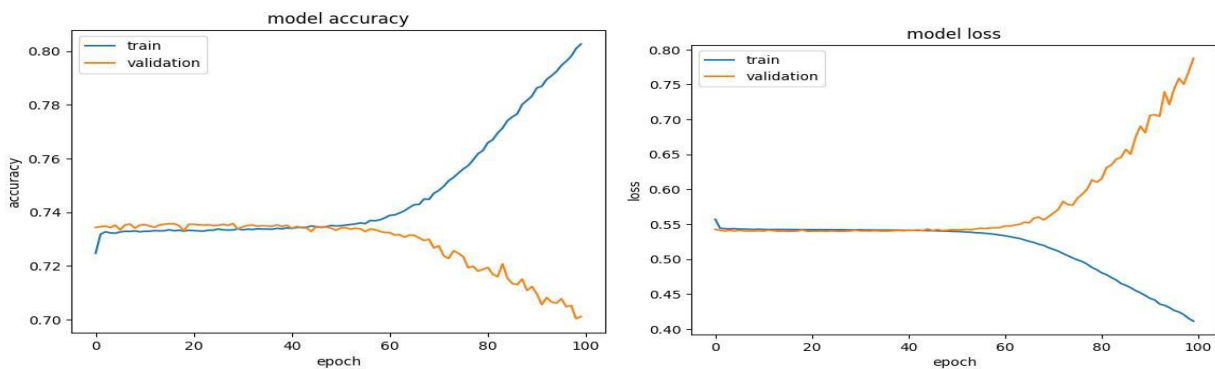


Figure 3 Accuracy Model Output using LSTM and Loss Model Output using LSTM

The graph shows the accuracy of the training model over various training epochs, highlighting fluctuations and trends in performance, indicating potential challenges or enhancements in the training process.

4.2 Bidirectional LSTM Accuracy Model

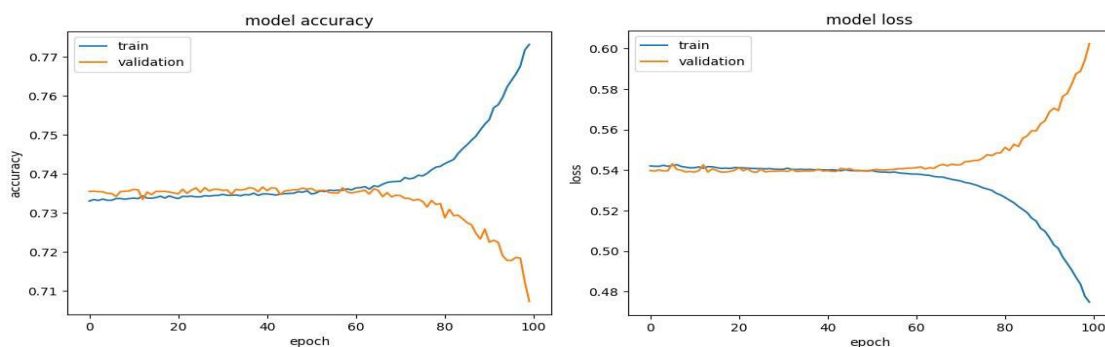


Figure 4 Accuracy Model Output using Bidirectional LSTM and Loss Model Output using Bidirectional LSTM

Machine learning uses RNN architecture to learn patterns in sequential data. Bidirectional Long Short-Term Memory (Bi-LSTM) captures context and dependencies, making it effective in understanding data's sequential nature. Its accuracy varies across different epochs. The figure illustrates the Loss Model Output using Bidirectional LSTM, a recurrent neural network (RNN) for sequence modeling and prediction. It captures information from past and future states, minimizing the loss function. The figure shows loss changes over time.

V. CONCLUSION

The study explores the potential of Device-to-Device (D2D) communication in cellular networks for ultra-low latency. It addresses the challenge of optimal resource allocation in D2D communication due to interference, focusing on Long Short-Term Memory (LSTM) networks and Bidirectional LSTMs. The proposed method analyzes device-to-device communication dynamics over time, considering factors like rates, weights, and a categorical value. A dataset of 9210 instances with 61 features and 30 target values was used, and a simulation was conducted to present results through graphical representations. Consequential preprocessing steps were taken to handle missing values, normalize data, and encode categorical variables while maintaining temporal and social context. The comparison between LSTM and Bidirectional LSTM models provided insights into the efficiency and effectiveness of the proposed method for resource allocation in D2D communication. The results showed 100% accuracy for all three components, with perfect accuracy at 73.42%, 28.1%, and 73.27% of the total epochs, respectively. The graphical representations of LSTM and Bidirectional LSTM models further illuminated convergence patterns and efficiency.

REFERENCES

1. Khuntia, P., & Hazra, R., "An Efficient Channel and Power Allocation Scheme for D2D Enabled Cellular Communication System: An IoT Application," *IEEE Sensors Journal*, pp. 1–1, 2021.
2. Xu, Y, Z. Liu, C. Huang and C. Yuen, "Robust Resource Allocation Algorithm for Energy-Harvesting-Based D2D Communication Underlying UAV-Assisted Networks," in *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 17161-17171, 2021.
3. Lai, W. -K, Y. -C. Wang, H. -C. Lin and J. -W. Li, "Efficient Resource Allocation and Power Control for LTE-A D2D Communication With Pure D2D Model," in *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3202-3216, 2020.
4. Zhang, S. and Peng, Y., "D2D communication relay selection algorithm based on game theory," *Procedia Computer Science*, vol. 166, pp.563-569, 2020.
5. Kong .P. -Y., "Multicell D2D Communications for Hierarchical Control of Microgrid System," in *IEEE Systems Journal*, vol. 15, no. 2, pp. 1929-1938, 2021.
6. Wang .X, T. Jin, L. Hu and Z. Qian, "Energy-Efficient Power Allocation and Q-Learning-Based Relay Selection for Relay-Aided D2D Communication," in *IEEE Transactions on Vehicular Technology*, vol. 69, no. 6, pp. 6452-6462, 2020.
7. Hayat, O., Ngah, R. & Mohd Hashim, S.Z, "Performance Analysis of Device Discovery Algorithms for D2D Communication," *Arab J Sci Eng*, vol. 45, pp. 1457–1471, 2020.
8. Ozyurt. A. B. and W. O. Popoola, "LiFi-Based D2D Communication in Industrial IoT," in *IEEE Systems Journal*, vol. 17, no. 1, pp. 1591-1598, 2023.
9. Pandey, K. and Arya, R., "Lyapunov strategy to optimizing machine learning allocations of resources for uplink underlaid D2D communication in 5G networks," *IET Communications*, vol. 16, issue. 5, pp.476-484 2022.
10. Xin, Jianfang, Qi Zhu, Guangjun Liang, and Tianjiao Zhang. "Performance Analysis of D2D Communication with Retransmission Mechanism in Cellular Networks" *Applied Sciences*, vol. 10, no. 3, pp. 1097, and 2020.
11. Lee, Junman, Sang Hyun Lee, Minjoong Rim, and Chung G. Kang. "System-level spatiotemporal offloading with inter-cell mobility model for device-to-device (D2D) communication-based mobile caching in cellular network." *IEEE Access* 8, pp. 51570-51581, 2020.
12. Xu, Chenglin, Cheng Xu, Bo Li, Siqi Li, and Tao Li. "Joint social-aware and mobility-aware computation offloading in heterogeneous mobile edge computing." *IEEE Access* 10, pp. 28600-28613, 2022.
13. Li, Mingchu, Linlin Yang, Kun Lu, Syed Bilal Hussain Shah, and Xiao Zheng. "Device-to-Device Task Offloading in a Stochastic Invalid-Device Scenario with Social Awareness." In *2022 IEEE Conference on Dependable and Secure Computing (DSC)*, pp. 1-7. IEEE, 2022.
14. Zhao, Chengyu, Shaoyi Xu, and Jieying Ren. "AoI-Aware Wireless Resource Allocation of Energy-Harvesting-Powered MEC Systems." *IEEE Internet of Things Journal* 10, no. 9, pp. 7835-7849, 2022.

15. Huang, Yakun, Hongru Zhao, Xiuquan Qiao, Jian Tang, and Ling Liu. "Towards video streaming analysis and sharing for multi-device interaction with lightweight dnns." In IEEE INFOCOM 2021-IEEE Conference on Computer Communications, pp. 1-10. IEEE, 2021.
16. Li, Dapeng, Shichao Wang, Haitao Zhao, and Xiaoming Wang. "Context-and-social-aware online beam selection for mmwave vehicular communications." IEEE Internet of Things Journal 8, no. 10, pp. 8603-8615, 2020.
17. Zhou, Jizhe, Xing Zhang, and Wenbo Wang. "Social-aware proactive content caching and sharing in multi-access edge networks." IEEE Transactions on Cognitive Communications and Networking 6, no. 4, pp. 1308-1319, 2020.
18. Llerena, Yarisley Peña, and Paulo RL Gondim. "Social-aware spectrum sharing for D2D communication by artificial bee colony optimization." Computer Networks 183, pp. 107581, 2020.
19. Gong, Wenrong, Lihua Pang, Jing Wang, Meng Xia, and Yuzhi Zhang. "A social-aware K means clustering algorithm for D2D multicast communication under SDN architecture." AEU-International Journal of Electronics and Communications 132, pp. 153610, 2021.
20. Nguyen, Van-Dinh, Trung Q. Duong, and Quoc-Tuan Vien. "Emerging techniques and applications for 5G networks and beyond." Mobile Networks and Applications 25, pp.1984-1986, 2020.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details