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Enhancing V2I and V2V Communication in Vehicular Networks through GSA-BPSO Optimized Neural Network

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Abstract: In vehicular networks, efficient communication between vehicles and infrastructure relies on the ergodic capacities of V2I links. Meanwhile, the crucial transmission of urgent information, collision avoidance, and improved safety hinges on the ergodic capacities of V2V links. Within this context, the present research endeavors to optimize fundamental parameters within a communication system. The ultimate goal is to achieve peak performance by employing the GSA-BPSO (Gravitational Search Algorithm and Binary Particle Swarm Optimization) optimized neural network approach. The primary objective entails maximizing a weighted sum encompassing three critical components. These components encompass the ergodic capacities of Vehicle-to-Infrastructure (V2I) links, Vehicle-to-Vehicle (V2V) links, and the latency requirements tied to V2V links. The study introduces a time delay threshold for V2V data transmission and leverages the GSA-BPSO optimized neural network to optimize key parameters. This enhances system capacity without compromising link communication. Result analysis, specifically for varying time intervals (0.2 ms to 1.2 ms), reveals insights. The Kuhn-Munkres model exhibits the lowest throughput consistently, implying limitations in handling power variations efficiently. The NN model surpasses Kuhn-Munkres but lags behind the GSA-BPSO optimized NN model. Longer time intervals lead to decreased throughput for all models, indicating interference and channel variations. The optimized NN model maintains consistent performance across time intervals, achieving superior throughput under fixed power. The GSA-BPSO optimized NN model outperforms both NN and Kuhn-Munkres models, highlighting its potential for enhancing system throughput with fixed power settings. This research underscores the efficacy of the optimization technique in wireless communication scenarios.

Keywords: BPSO, GSA, Neural network, QoS, V2I, V2V.

1. Introduction

Vehicles communicate with each other wirelessly through vehicle-to-vehicle (V2V) communications, fostering improved road safety, traffic efficiency, and facilitating various cooperative driving applications. The significance of V2V communication extends to the advancement of connected and autonomous vehicles (CAVs) and intelligent transportation systems (ITS).

A prominent challenge in V2V communications arises from effectively utilizing radio resources, especially when V2V links share the same resources as vehicle-to-infrastructure (V2I) uplinks. This scenario introduces intracell interference, necessitating efficient management for ensuring reliable communication. To tackle this concern, resource allocation strategies have been proposed, aiming to maximize V2I link throughput while guaranteeing a minimum quality-of-service (QoS) for V2V links.

Resource allocation in vehicular communication systems involves the adept distribution of limited network resources among vehicles, enabling reliable and efficient communication. These communication systems serve the purpose of facilitating seamless communication between vehicles and infrastructure, as well as inter-vehicle communication, with the goal of enhancing road safety, traffic management, and providing diverse services to drivers and passengers [1].

The design and challenges of vehicular-to-vehicle (V2V) communications in the context of sharing radio resources with vehicle-to-infrastructure (V2I) uplinks. The focus here is on improving spectral efficiency and managing intracell interference between the two types of links in vehicular communication systems.

Researchers have presented various resource allocation strategies, as cited in references [2, 3, 4], to attain the desired objectives. These strategies have a dual focus: maximizing V2I link throughput while ensuring a minimum quality-of-service (QoS) guarantee. Achieving effective coordination and management of radio resource allocation for both V2V and V2I links entails employing spectrum sharing and power allocation techniques.

The overall goal is to optimize the use of available radio resources, minimize interference between V2V and V2I communications, and enhance the performance and efficiency of vehicular communication systems. By doing so, these strategies can contribute to more reliable and efficient communication between vehicles and infrastructure, ultimately supporting safer and more intelligent transportation systems.

As we look ahead to future 5G and beyond systems, the demand for ultra-reliable and low-latency communications (URLLC) becomes paramount, particularly concerning V2V connections. Numerous studies have endeavored to establish low-latency V2V communications. However, an aspect often overlooked is the preservation of QoS requirements for V2I links, which constrains their applicability in coexisting V2V and V2I scenarios.

In recent research efforts exploring hybrid V2V and V2I communication settings, the primary aim has been to optimize the information rate of V2I links. To achieve this, approaches leveraging techniques like Lagrange dual decomposition and binary search have been employed. Nonetheless, these methods come with a substantial computational complexity.

To surmount the computational burden associated with iterative optimization-based resource allocation schemes, the application of deep learning techniques has garnered significant attention. Leveraging the prowess of neural networks (NN), they present a solution to intricate nonlinear and non-convex problems, bypassing the need for explicit mathematical models. The successful implementation of NN spans diverse domains, such as image and voice processing. In the realm of wireless communications, researchers have been exploring NN's potential to approximate traditional iterative algorithms, thus enabling real-time wireless resource management.

By harnessing the power of machine learning, it becomes possible to develop efficient and real-time resource allocation solutions for V2V and V2I communications. Unlike traditional iterative algorithms, which require numerous iterations to converge, NN-based approaches offer the potential for faster and more practical implementation.

The central aim of this study revolves around optimizing specific parameters to achieve peak performance for the entire communication system. Specifically, they aim to maximize a weighted sum that includes three key components:

- Ergodic capacities of V2I links: This refers to the average data rates of Vehicle-to-Infrastructure (V2I) links, which represent the communication performance between vehicles and the infrastructure (e.g., base stations).
- Ergodic capacities of V2V links: This represents the average data rates of Vehicle-to-Vehicle (V2V) links, which play a crucial role in transmitting urgent information between vehicles to avoid collisions.
- Latency requirement of V2V links: As mentioned earlier, this represents the acceptable maximum time delay for the transmission of data packets in V2V communication [5].

By making optimal decisions on certain parameters, the paper aims to maximize the combined performance of these three components in a weighted manner. The weights represent the relative importance of each component in achieving the overall system performance. This optimization process helps design resource allocation strategies that efficiently utilize radio resources, manage interference, and prioritize latency-sensitive V2V communications while ensuring a minimum QoS for C-UEs.

The study seeks to strike a balance between maximizing the data rates for V2I and V2V communications, meeting V2V link latency requirements, and ensuring a minimum level of service quality for C-UEs. This is achieved through careful resource allocation and decision-making processes in the communication system.

1.1 Problem definition

The proliferation of vehicle-to-vehicle (V2V) communications has emerged as a pivotal factor in enhancing road safety, traffic efficiency, and enabling cooperative driving applications. These advancements also underpin the development of connected and autonomous vehicles (CAVs) and intelligent transportation systems (ITS). Despite these promising prospects, the coexistence of V2V links with vehicle-to-infrastructure (V2I) uplinks presents a formidable challenge in effectively utilizing limited radio resources. The resulting intracell interference necessitates a robust management framework to ensure reliable communication. This study delves into the critical task of resource allocation in vehicular communication systems, aiming to optimize spectral efficiency and manage intracell interference between V2V and V2I links. The overarching objective is to distribute network resources efficiently among vehicles to facilitate reliable and efficient communication. The challenge lies in maximizing the throughput of V2I links while upholding a minimum quality-of-service (QoS) standard for V2V links. The complexity of this task requires sophisticated coordination mechanisms, including spectrum sharing and power allocation techniques.

The primary research focus centers on the utilization of resource allocation strategies to optimize V2V and V2I communications. These strategies must address the intricate interplay between radio resources, interference, and communication efficiency. The root of the matter involves devising mechanisms to mitigate interference between V2V and V2I links while concurrently maximizing their respective data rates. Achieving this balance necessitates the careful allocation of resources and strategic decision-making within the communication system.

A distinctive aspect of this study involves harnessing the power of neural networks (NN) to tackle the inherent complexities of resource allocation. Traditional iterative algorithms often prove computationally demanding, prompting researchers to explore NN's ability to approximate these algorithms efficiently. NN-based approaches present the potential for real-time wireless resource management, offering speedier convergence and implementation. The application of NN in resource allocation holds significant promise, particularly in addressing the challenges of V2V and V2I communication scenarios.

To this end, the core objective of this research is to optimize specific parameters that collectively define the communication system's performance. The study strives to maximize a weighted aggregate encompassing the ergodic capacities of V2I links, V2V links, and the latency requirements of V2V communication. The intrinsic significance of each component is encapsulated within their respective weights, dictating their influence on the overall system performance. By making astute decisions on these parameters, the research aims to strike a balance between optimizing data rates, meeting latency requirements, and ensuring a baseline quality of service for cellular user equipment (C-UE)

The study commences with an extensive literature review in section 2, highlighting pertinent research within the field. Section 3 expounds on the intricacies of the proposed methods. Subsequently, section 4 showcases the results derived from the MATLAB-based simulation, followed by a meticulous analysis. Eventually, the paper concludes in section 5 by summarizing the findings and presenting concluding remarks.

2. Literature review

Over the past few years, vehicular Ad-Hoc networks (VANETs) have garnered substantial interest owing to their capacity to transform transportation systems by enhancing V2I and V2V communication. Several researchers have explored the challenges in VANETs and proposed solutions to enhance communication efficiency. The authors of [6] highlighted the advantages of V2I communication in reducing accidents and optimizing traffic signal control, while the authors of [7] focused on V2V communication for collision avoidance and cooperative driving applications. However, the dynamic nature of VANETs, with high vehicle mobility and varying network conditions, poses significant challenges. The authors of [8] emphasized the impact of intermittent connectivity on data dissemination, leading to increased latency and packet loss. To address these issues, researchers have turned to artificial neural networks (ANNs) due to their ability to handle complex data patterns. The authors of [9] demonstrated the effectiveness of neural networks in vehicular traffic prediction, while The authors of [10] proposed an ANN-based approach for improving V2V communication. To optimize the performance of neural networks, various optimization techniques have been explored. The authors of [11] utilized particle swarm optimization (PSO) for traffic flow prediction, but traditional PSO suffers from premature convergence and limited global exploration. To overcome these limitations, the authors of [12] proposed binary particle swarm

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optimization (BPSO) for binary optimization problems. Additionally, the authors of [13] applied the gravitational search algorithm (GSA) to optimize routing paths in VANETs. The authors of [14] showcased the integration of V2V communication using neural networks to enhance cooperative collision warning systems, thereby minimizing accidents. Resource allocation in V2I and V2V communication was addressed by the authors of [15, 16], indicating reduced latency and enhanced data delivery. Security issues were tackled by the authors of [17], who proposed neural networks to safeguard V2I and V2V communication against malicious attacks. The role of GSA in improving quality of service was explored by the authors of [18]. Artificial intelligence and machine learning integration in V2I and V2V communication was investigated by the authors of [19], resulting in promising outcomes. The authors of [20] investigated resource allocation in D2D-based vehicular networks, where V2I links share spectrum with multiple V2V links, excluding those terminating at the BS. Graph partitioning splits V2V links into distinct spectrum-sharing clusters, minimizing interference. However, a limitation of the approach lies in its reliance on randomized algorithms for resource allocation, potentially leading to unpredictable outcomes and reduced control over resource distribution. The authors of [21] investigated a joint approach to cluster formation and robust power control in D2D-based vehicular networks. To mitigate inherent trade-offs, an optimal price C approach with delayed CSI feedback is suggested. However, a drawback of this approach is that it heavily depends on the effectiveness of the delayed CSI feedback. Delays in acquiring accurate CSI information could lead to suboptimal power control decisions, potentially compromising the overall system performance, especially in scenarios with rapidly changing channel conditions or high mobility environments.

The authors of [22] introduced an optimized method for allocating resources to intra-cluster D2D users. The approach comprises two stages. Initially, a bipartite graph is constructed to depict concurrent D2D and cellular user associations within the same resource pool. The resource allocation quandary is reformulated as a maximal weighted matching (MWM) problem, subsequently addressed through the Kuhn-Munkres algorithm, optimizing transmission capacity. The drawback of this method is its focus solely on intra-cluster D2D users. It does not explicitly address inter-cluster interference between different D2D clusters or potential interactions with cellular users outside the designated cluster. This could result in suboptimal resource allocation decisions in scenarios where the influence of neighboring clusters or other cellular users is significant, impacting the overall network performance and efficiency.

Following are the drawbacks of each conventional technique:

Particle swarm optimization (PSO):

- Drawback: PSO can suffer from premature convergence and limited global exploration, leading to suboptimal solutions.
- Differentiation: The proposed work combines BPSO and GSA, enhancing the optimization process by leveraging both algorithms to address the limitations of traditional PSO.

Binary particle swarm optimization (BPSO):

- Drawback: BPSO is designed for binary optimization problems, limiting its applicability to more complex optimization scenarios.
- Differentiation: This research introduces a novel approach by combining BPSO with GSA to optimize neural network parameters, offering a versatile solution beyond binary optimization.

Gravitational search algorithm (GSA):

- Drawback: GSA's performance might degrade in high-dimensional spaces or when facing intricate optimization landscapes.
- Differentiation: The proposed methodology employs a hybrid approach that merges GSA and BPSO, capitalizing on their respective strengths while mitigating the individual weaknesses of these algorithms.

Artificial neural networks (ANNs):

- Drawback: Training neural networks can be computationally intensive, requiring large datasets and substantial computational resources.
- Differentiation: The study presents a unique framework that optimizes neural network parameters using the combined GSA-BPSO approach, aiming to enhance the performance and efficiency of V2I and V2V communications.

This study differentiates itself by ingeniously merging the BPSO and GSA optimization techniques to fine-tune neural network parameters, thereby advancing the performance, robustness, security, and scalability of both V2I and V2V communication in dynamic vehicular environments. This holistic approach holds the promise of fostering more efficient and intelligent transportation systems in the future.

Scalable and efficient V2I and V2V communication protocols were emphasized, highlighting neural network as a viable solution. Overall, the reviewed literature collectively supports the effectiveness of neural network in enhancing V2I and V2V communication in vehicular networks, offering improved performance, robustness, security, and scalability in a dynamic and challenging environment. Building upon these foundations, the research paper presents a novel approach that combines BPSO and GSA to optimize neural network parameters, leading to improved V2I and V2V communication in VANETs. The experimental results demonstrate that the GSA-BPSO optimized neural network outperforms traditional non-optimized neural networks in terms of communication reliability and efficiency, contributing significantly to the field of intelligent transportation systems and paving the way for more efficient vehicular communication in the future.

3. Proposed methodology

3.1 System model

Intelligent spectrum reuse and power allocation play pivotal roles in contemporary intelligent transportation systems, facilitating the coexistence of hybrid vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. By enabling simultaneous communication between vehicles and infrastructure, this approach enhances the vehicular network's safety, efficiency, and overall performance. To achieve efficient spectrum utilization and optimize power allocation, artificial neural networks (ANNs) is be employed, taking into account the optimal transmit power according to channel gain.

Problem Statement: The primary objective revolves around devising an intelligent mechanism for spectrum reuse and power allocation, specifically tailored to cater to hybrid V2V and V2I communications. Given the dynamic nature of vehicular environments and varying channel conditions, the challenge is to allocate available spectrum and transmit power optimally to maximize the communication efficiency, minimize interference, and enhance overall network capacity.

This approach is particularly important in the context of the rapidly growing automotive industry, where V2V and V2I communications play a critical role in enabling various advanced driving applications, such as cooperative collision avoidance, traffic management, and autonomous driving.

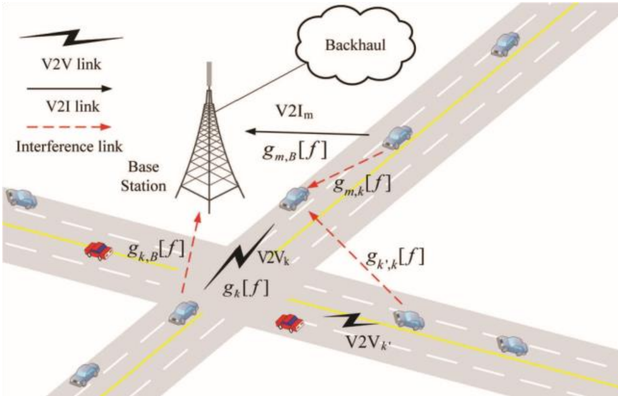

Figure. 1 Vehicle communication in highway scenario [20]

In this exposition, we explore a vehicle networking communication scenario characterized by a singular cellular span, wherein the central hub is represented by the base station. The radius of this coverage is symbolized as R_c. The stretch of road encompassed in this setup is denoted as L, and the distance between the base station's core and the road's center is designated as D. A fundamental relationship binds these parameters, given by $D^2 + (L/2)^2 = R_c^2$.

The V2I link set finds its representation in the form of $M = \{1,2,\dots,M\}$, while the V2V link set is expressed as $K = \{1,2,\dots,K\}$. Moreover, the comprehensive bandwidth is identified by $F = \{1,2,\dots,F\}$ resource blocks (RB).

This article delves into the concept of resource allocation in the context of V2V (Vehicle-to-Vehicle) and V2I (Vehicle-to-Infrastructure) communication. To enhance the system's immunity against interference, the approach taken here involves utilizing V2V direct link multiplexing while sharing V2I uplink spectrum resources. When V2V direct link operates using the V2I uplink spectrum resources, the channel power gain between the transmitter of the m^{th} V2I link and the base station through the f^{th} RB is denoted as $g_{m,I}(f) = \alpha_{m,I}\left|h_{m,I}(f)\right|^2$, where $h_{m,I}$ represents the small-scale fading components, and $\alpha_{m,I}$ accounts for the large-scale fading effects like path loss and shadowing.

Similarly, the link gain g_k for the k^{th} V2V channel and the interference gain $g_{k'k}$ between the k^{th} V2V vehicle and the k'^{th} V2V vehicle are characterized. These gains are associated with the transmission from the m^{th} V2I transmitter to the k^{th} V2V vehicle through the f^{th} RB. Moreover, the interference channel $g_{m,k}$ from the first V2V receiver, routed to the base station via the k^{th} V2V receiver's interference channel, is taken into consideration [20, 21].

This paper is focusing on the communication latency requirement for vehicular-to-vehicular (V2V) links. V2V links are crucial for transmitting urgent information between vehicles to avoid collisions and ensure road safety.

The paper uses two key parameters to describe the latency requirement:

B : Average packet size - This parameter represents the size of data packets that need to be transmitted between vehicles.

L : Tolerable transmission latency - This parameter denotes the maximum acceptable time delay or latency for the transmission of data packets. In other words, it represents the time limit within which the information must be successfully transmitted to serve its purpose of avoiding collisions effectively.

To address the latency requirement, this paper introduces the concept of the target transmit rate (R) for V-UEs (vehicular user equipment), which is given by the ratio of average packet size (B) to the tolerable transmission latency (L): $R = B/L$. This target transmit rate is used as a performance metric to assess how effectively the V2V links are meeting the late. In this scenario, we introduce a minimum capacity constraint for the C-UEs (cellular user equipment) to ensure a minimum predetermined quality of service (QoS). This requirement aims to maintain a certain level of service quality for the C-UEs in the cellular communication system.

$$\xi = P_L\{C_{ss}(k) \geq R\}, \;\; k = 1,2, \tag{1}$$

To quantify the latency requirement further, the paper calculates the smallest ergodic capacity (C_{ss}) among V-UEs, considering fast fading conditions. Ergodic capacity refers to the average data rate over multiple fading realizations. Subsequently, we perform computations to determine the likelihood of the V-UE's capacity (C_{ss}) surpassing the designated transmit rate (R) under fast fading conditions. This probability provides a measure of how often the V2V link can meet the latency requirement based on the given target transmit rate.

The primary goal of this study is to explore methods for optimizing spectrum utilization in a highly populated vehicular setting, with a particular focus on multiplexing V2I uplink resources for V2V users. To achieve this objective, we intend to devise a resource allocation strategy that specifically aims to improve V2I channel capacity. This allocation plan will take into account various factors such as diverse services, reliable V2V users, vehicle speed, and communication overhead. The problem at hand is mathematically formulated using a specific equation, which has been introduced and defined in a prior reference [20].

Where γ_0 denote the minimum SINR (Signal-to-Interference-plus-Noise Ratio) required for establishing a dependable V2V (Vehicle-to-Vehicle) link, and let p_0 represent the outage threshold. The maximum transmission power for V2I and V2V transmitters is denoted as P_{max}^i and P_{max}^v , respectively. Constraint $\boldsymbol{C_2}$ is formulated to meet the V2V link's reliability criterion, with the probability calculated as a function of the random fast fading in the mobile channel. Constraint $\boldsymbol{C_3}$ governs the allocation of orthogonal spectrum for V2I connections. As for $\boldsymbol{C_4}$ and $\boldsymbol{C_5}$, they model the aforementioned capability of V2I and V2V systems to access multiple RBs (Resource Blocks). To ensure that the maximum power limit for V2I and V2V links is not violated, we introduce Constraints $\boldsymbol{C_6}$ and $\boldsymbol{C_7}$, respectively.

The objective of this paper is to assess and articulate the latency prerequisite for V2V links. This entails examining the interplay between average packet size, permissible transmission latency, and achievable capacity amid fast-fading conditions. This analysis helps in designing and optimizing V2V communication systems to meet the stringent latency demands of safety-critical applications in vehicular environments.

$$\begin{aligned}
&\boldsymbol{C_1}: && \max_{\substack{\{\mu_{m,f}^i,\mu_{k,f}^v\} \\ \{P_{m,f}^i,P_{k,f}^v\}}} \sum_m \sum_f \mu_{m,f}^i \log_2\left(1+\gamma_{m,f}^i\right) \\
&\boldsymbol{C_2}: && s.t.\;\; \mu_{k,f}^v P_r\{\gamma_{k,f}^v \leq \gamma_0^v\} \leq p_0, \;\; \forall k,f \\
&\boldsymbol{C_3}: && \sum_m \mu_{m,f}^i = 1, \quad \forall f \\
&\boldsymbol{C_4}: && \sum_f \mu_{m,f}^i \leq F, \sum_f \mu_{k,f}^v \leq F, \forall m,f \\
&\boldsymbol{C_5}: && \mu_{m,f}^i, \mu_{k,f}^v \in \{0,1\}, \quad \forall m,k,f \\
&\boldsymbol{C_6}: && \sum_f \mu_{m,f}^i, P_{m,f}^i \leq P_{max}^i, \sum_f \mu_{k,f}^v, P_{k,f}^v \leq P_{max}^v \;, \forall m,k \\
&\boldsymbol{C_7}: && P_{m,f}^i \geq 0, P_{k,f}^v \geq 0, \quad \forall m,k,f
\end{aligned} \tag{2}$$

3.2 Data Generation for neural network

The passage describes the data generation process for training a neural network (NN) in a hybrid Vehicular-to-Infrastructure (V2I) and Vehicular-to-Vehicular (V2V) transmission network. This data generation process involves generating training data using pre-generated channel gains and predetermined parameters.

Here are the steps involved in the data generation process:

Channel gains: The channel gains are pre-generated and denoted as $h = \{h_{m,B}, h_{md}, h_{s,d}, h_{s,B}, \forall\, m, d, s\}$. These channel gains represent the wireless channel characteristics between different entities in the communication system, including between vehicles (V2V) and between vehicles and infrastructure (V2I).

In this scenario, multiple vehicles in proximity (V2V) and infrastructure elements (V2I) share the same spectrum for communication purposes. The objective is to maximize the overall system capacity while minimizing interference among different links. The optimization problem includes finding the optimal allocation of available spectrum bands and transmission power levels for each vehicle and infrastructure node.

Mathematical model

Let's define the key variables and constraints involved in the optimization problem:

Variables:

- P_{ij}: Transmission power of vehicle i for communicating with vehicle/infrastructure j.
- x_{ij}: Binary variable indicating whether vehicle i communicates with vehicle/infrastructure j (x_{ij} =1 if communication happens; otherwise, x_{ij}=0).
- h_{ij}: Channel gain between vehicle i and vehicle/infrastructure j.

Constraints:

- Power constraint: The total power transmitted by each vehicle should not exceed a predefined maximum value

$$P_{max} = \sum_{j=1}^{N} x_{ij}.P_{ij} \le P_{max}, \quad \forall i \tag{3}$$

- Interference constraint: In order to control interference within an acceptable range, it is imperative that the signal-to-interference-plus-noise ratio (SINR) at each receiver surpasses a specific threshold value (denoted as γ):

$$SINR_{ij} = \frac{x_{ij} \cdot P_{ij} \cdot h_{ij}}{\sum_{k \ne i} x_{kj} \cdot P_{kj} \cdot h_{kj} + \sigma^2} \ge \gamma, \quad \forall i, j \tag{4}$$

- Binary Constraint: The binary variables should be either 0 or 1:

$$x_{ij} \in \{0,1\}, \quad \forall i, j \tag{5}$$

Objective function:

The aim is to optimize the sum capacity of both V2V and V2I links, taking into account interference and power constraints. The sum capacity can be calculated as the sum of the logarithms of the achievable data rates for each link:

$$Maximize\ \ \sum_{i=1}^{M} \sum_{j=1}^{N} x_{ij}. \log_2\left(1 + SINR_{ij}\right) \tag{6}$$

Predetermined parameters: The data generation process uses predetermined parameters, which include $P_{C_{max}}$ (maximum power for cellular communication), $P_{v_{max}}$ (maximum power for vehicular communication), and r_c^0 (cell radius or coverage area for cellular communication).

Spectrum resource reuse state: The data generation process aims to generate the corresponding spectrum resource reuse state denoted as $\{\rho_{m,s}, \forall m, s\}$. This state represents the allocation of radio resources, such as frequency bands or time slots, for V2V and V2I links.

Allocated powers: The data generation process also aims to determine the allocated powers for each channel realization, represented as $\{P_{cm}, P_{vs}, \forall m, s\}$. These allocated powers are used to manage power allocation for cellular (V2I) and vehicular (V2V) communications.

Exhaustive method: To generate the training data, an exhaustive method is used. This method involves iteratively calculating and comparing the objective (e.g., maximizing data rate, minimizing latency, or optimizing resource allocation) for all possible schemes. Subsequently, the method selects the scheme that achieves the highest objective as the optimal solution. However, this method has a high computational cost due to its exhaustive search over all possible schemes.

Generating training data set: To create the entire training data set, the above process is repeated multiple times with different channel realizations and parameters. The training data set is represented as $\{h, \rho_{m,s}, P_{cm}, P_{vs}, \forall m, d, s\}$, where h represents channel gains, $\rho_{m,s}$ represents the spectrum resource

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reuse state, and P_{cm} and P_{vs} represent the allocated powers for cellular and vehicular links, respectively.

The generated training data set can then be used to train a NN-based model, allowing the network to learn and optimize resource allocation strategies efficiently without the need for an exhaustive search during the inference stage.

3.3 Power control for D2D pairs using gravitational search algorithm–binary particle swarm optimization based neural network

We present the gravitational search algorithm-binary particle swarm optimization based neural network (GSA-BPSO-NN), aimed at automatic comprehension of the correlation between D2D channel gains and cellular channel gains in vehicular networks. The architecture of GSA-BPSO-NN comprises input layer $X = (X_1, X_2, \ldots X_n)$, hidden layers $H = (H_1, H_2, \ldots H_n)$, and output layer $Y = (Y_1, Y_2, \ldots Y_n)$. Specifically, the input layer organizes cellular channel gains from D2D users to the base stations in a vector $Out_{X_0} = P_{1,1}, P_{1,2}, \ldots, P_{C,D}$. The output of GSA-BPSO-NN, denoted as out_Y, falls within the range of 0 to 1, attributed to the sigmoid activation function employed. This output represents the probability that $p_n = p_{max}$. Consequently, the transmission power of the n^{th} D2D pair undergoes adjustment following the provided equation:

$$p_n = \begin{cases} p_{max} & if\ out_Y > 0.5 \\ p_{min} & otherwise \end{cases} \tag{7}$$

The GSA-BPSO-NN employs a sigmoid neuron as the activation function with the output calculated as:

$$Y = \frac{1}{1+e^{-\eta \sum_{i=1}^{d} W_i X_i - b}} \tag{8}$$

The GSA-BPSO-NN utilizes supervised learning to find the ideal binary transmission powers that maximize the sum capacity of D2D pairs by combining attributes and targeted classes into learning samples and generating testing and training sets from them. This approach offers an effective solution to determine the transmission power for N D2D pairs based on cellular channel gains, enhancing V2I and V2V communication in vehicular networks through optimization using GSA-BPSO-NN which is a hybrid optimization approach that combines the gravitational search algorithm (GSA) and binary particle swarm optimization (BPSO) with a neural network (NN) to optimize power allocation for V2V and V2I communication links. This method efficiently searches for the optimal power allocation policy while considering binary constraints on power levels.

Description:

1. GSA Initialization:
   - Initialize the positions (solutions) of the particles (individuals) randomly within the search space. Each particle signifies a candidate power allocation configuration.
   - Calculate the fitness value for each particle based on the objective function, which evaluates the power allocation's quality.
2. GSA gravitational force calculation:
   - Calculate the mass (M_i) of each particle based on its fitness value. Lower fitness values correspond to higher masses.
   - Calculate the gravitational force (F_i) acting on each particle due to the gravitational attraction of other particles in the search space.
   - Update the acceleration (a_i) of each particle based on the gravitational forces:

$$a_i = G \times \frac{M_{best} - M_i}{r_i^2} \tag{9}$$

   where:
   G is the gravitational constant.
   M_{best} is the mass of the best-performing particle in the swarm.
   r_i is the distance between particle i and the best-performing particle.
3. GSA update particle position and velocity:
   - Update the particle position and velocity based on the calculated acceleration and the previous position and velocity.
4. BPSO binary particle update:
   - Convert the continuous-valued particle positions to binary values. This is done using a threshold function:

$$x_{ij} = \frac{1}{(1 + \exp(-s_{ij}))} \tag{10}$$

   where:
   x_{ij} is the binary value of the power allocation for D2D pair i and its target j.
   s_{ij} is the continuous-valued position of particle i for D2D pair i and its target j.
5. BPSO velocity update:
   - Update the velocity of each particle by

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considering its present binary position, the best position it has attained thus far (personal best), and the best position discovered by any particle in the swarm (global best).

6. NN training data generation:
   - Generate training data using the GSA-BPSO optimization process. The data includes input parameters (e.g., channel gains, interference constraints) and the corresponding fitness values obtained during the optimization.
7. NN architecture and training:
   - Design a neural network (NN) architecture with appropriate input and output layers to model the power allocation problem.
   - Train the NN using the generated training data to learn the relationship between the input parameters and the corresponding optimal power allocation policy.
   - Use techniques like backpropagation and gradient descent to optimize the NN parameters.
8. NN Inference:
   - After training, use the optimized NN to predict the optimal power allocation for new D2D communication scenarios.
   - The NN provides an approximation of the fitness value (i.e., the objective function) for each candidate solution in the GSA-BPSO optimization process.
9. Termination:
   - Repeat the GSA-BPSO optimization process and NN training for a predefined number of iterations or until a convergence criterion is met.

Mathematical equations:

1. GSA Gravitational Force Calculation: $F_i = G \times \frac{M_{best}-M_i}{r_i^2}$

   where:
   - F_i is the gravitational force acting on particle i.
   - G is the gravitational constant.
   - M_{best} is the mass of the best-performing particle in the swarm.
   - M_i is the mass of particle i.
   - r_i is the distance between particle i and the best-performing particle.
2. BPSO binary particle update: $x_{ij} = \frac{1}{(1+\exp(-s_{ij}))}$

   where:
   - x_{ij} is the binary value of the power allocation for D2D pair i and its target j.
   - s_{ij} is the continuous-valued position of particle i for D2D pair i and its target j.

The GSA-BPSO-NN method effectively searches for the optimal power allocation policy for D2D communication links by integrating the strengths of GSA and BPSO, while the NN provides a computationally efficient and accurate approximation of the optimal fitness values during the optimization process.

 # Pseudo-code for hybrid GSA-BPSO optimized neural network
 # Input: Training data, neural network architecture, swarm size, number of iterations
 # Output: Trained neural network with optimized weights and biases
 # Step 1: Initialize the swarm
Initialize swarm particles with random binary positions and velocities
Initialize personal best positions for each particle
Initialize agents' masses based on fitness values
Set the global best position to the best position in the swarm
 # Step 2: Define the fitness function (neural network evaluation function)
def evaluate_neural_network(particle_position):
 # Step 2.1: Convert binary particle position to neural network weights and biases neural_network.set_weights_and_biases(particle_position)
 # Step 2.2: Train the neural network on the training data using backpropagation or other optimization techniques
neural_network.train(training_data)
 # Step 2.3: Calculate the fitness value (e.g., accuracy or error) of the trained neural network
fitness_value = neural_network.evaluate_fitness(validation_data)
return fitness_value
 # Step 3: Main optimization loop
For each iteration from 1 to the specified number of iterations:
 # Step 3.1: Evaluate fitness for each particle in the swarm using the neural network evaluation function
For each particle in the swarm:
fitness_value = evaluate_neural_network(particle_position)
 # Update personal best position for the particle if applicable
If fitness_value > particle_personal_best_fitness:

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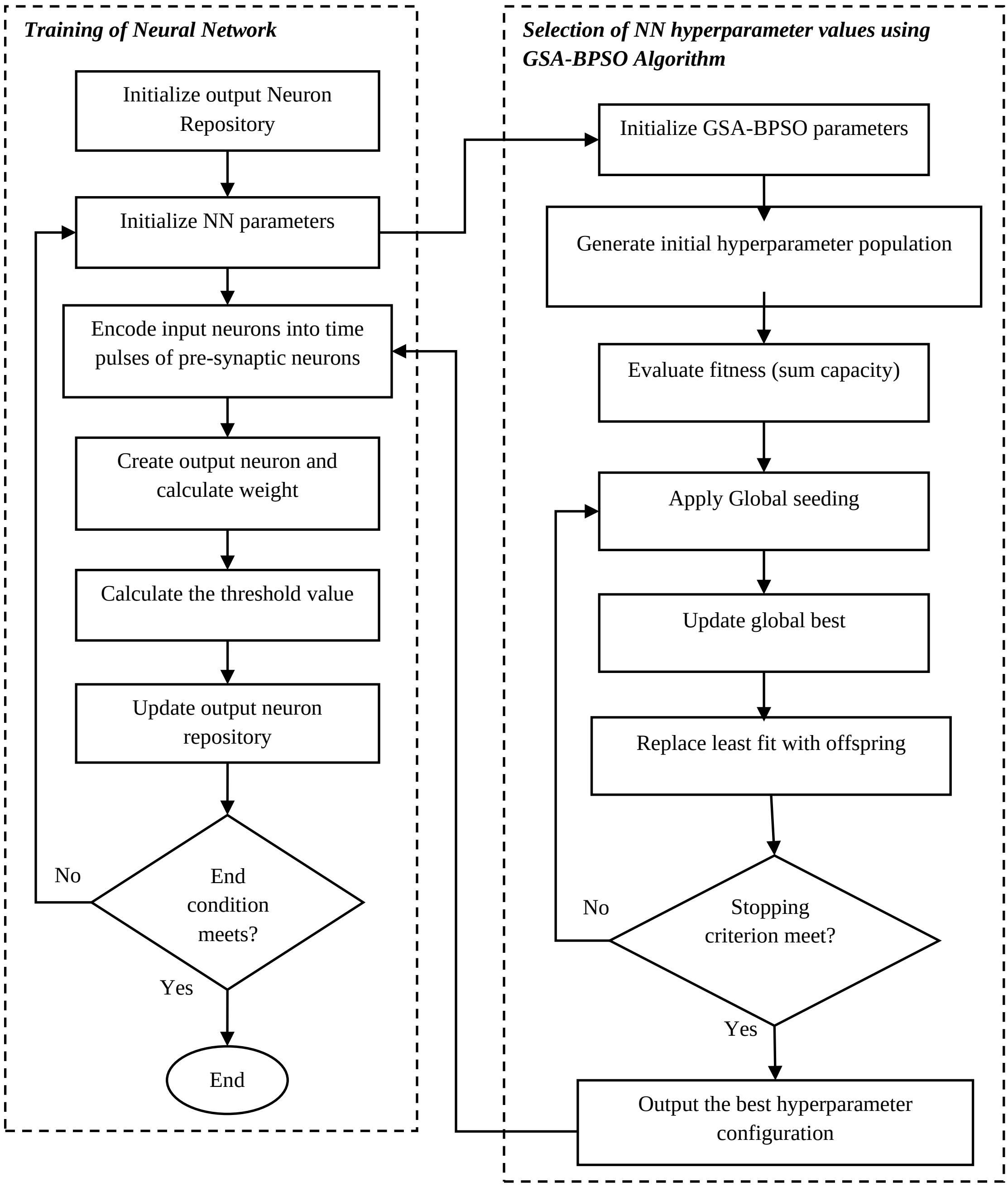

Figure. 2 Flow diagram for proposed GSA-BPSO optimization of neural network

particle_personal_best_position = particle_position
particle_personal_best_fitness = fitness_value
 # Update global best position if applicable
If fitness_value > global_best_fitness:
global_best_position = particle_position
global_best_fitness = fitness_value
 # Step 3.2: Calculate gravitational forces for each agent in the search space
For each agent in the search space:
Calculate the gravitational force on the agent based on other agents' positions and masses
 # Step 3.3: Update particle velocities and positions using the BPSO equations with the influence of gravitational forces
For each particle in the swarm:
Update particle velocity and position using BPSO equations with the influence of gravitational forces
 # Step 4: Return the trained neural network with optimized weights and biases
neural_network.set_weights_and_biases(global_best_position)
return neural_network:

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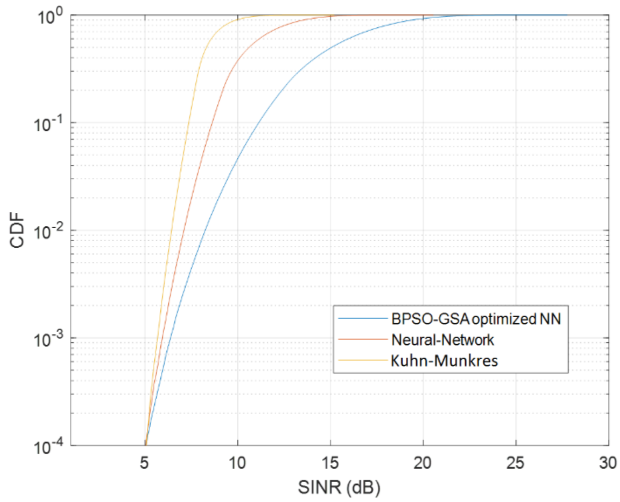

Figure. 3 Cumulative distribution function of instantaneous system performance under Rayleigh fading with 1% targeted outage probability and power constraint of 23 dBm

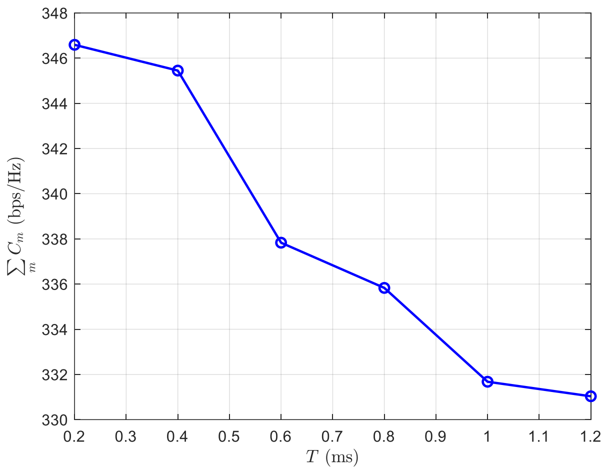

Figure. 4 Capacity in given time structure

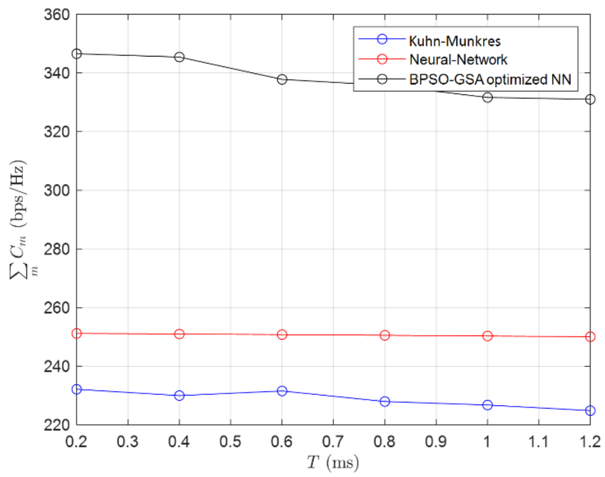

Figure. 5 System throughput (bps/Hz) with respect to time variation with 23 dB power

4. Results and discussion

Fig. 3 presents a comparison of cumulative distribution functions (CDF) for the instantaneous sum capacity of cellular user equipment (CUE) achieved by various algorithms. Specifically, we examine the performance of our proposed GSA-BPSO NN algorithm against NN and the Kuhn-Munkres scheme developed in [22]. This assessment is conducted under scenarios where solely large-scale fading information is accessible at the base station (BS).

To ensure an equitable comparison, we employ the method elucidated in Lemma 1 of [22] to derive an equivalent signal-to-interference-plus-noise ratio (SINR) threshold solely in terms of large-scale fading parameters. Our findings reveal that our proposed GSA-BPSO NN algorithm outperforms both NN and the Kuhn-Munkres scheme of [22], thus showcasing its superiority in such scenarios.

The superiority of our Algorithm can be attributed to two primary factors. Firstly, it takes a meticulous approach to account for the impact of small-scale fading when computing the capacity of vehicle-to-infrastructure (V2I) links. This is achieved through the calculation of ergodic capacity, in contrast to the approximation of capacity solely using large-scale fading parameters as performed in [22]. Secondly, the approach in [22] falls short in attaining the targeted SINR threshold for Vehicle-to-Vehicle (V2V) links, as depicted in the figure. conversely, our proposed GSA-BPSO NN and NN algorithms achieve the precise desired SINR of 5 dB at the designated outage probability of 0.01 for V2V links. This leads to more stringent reliability requirements in the Kuhn-Munkres scheme [22], which consequently reduces the feasible region of power control parameters and degrades the capacity of V2I links.

The fundamental differences between our proposed algorithms and the ones presented in [22] highlight the superiority of our approach, particularly in situations where solely large-scale fading information is accessible at the base station (BS).

The provided data represents the system throughput (in bps/Hz) of an NN (neural network) model under different velocity variations. The time values indicate the elapsed time in milliseconds, and the velocities considered are 50 km/hr, 70 km/hr, 90 km/hr, 110 km/hr, and 140 km/hr.

Upon analyzing the results, several observations can be made. Firstly, as the velocity increases, the system throughput tends to decrease. This can be attributed to the higher mobility of users at higher velocities, leading to more severe channel fading and

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Table 1. System throughput (bps/Hz) with respect to velocity variation in NN model

Time (ms)	50km/hr	70km/hr	90km/hr	110km/hr	140km/hr
0.200	251.176	242.487	238.406	234.924	232.297
0.400	250.986	241.048	237.398	234.886	232.158
0.600	250.773	240.886	236.945	234.263	232.038
0.800	250.556	240.004	236.067	234.112	232.012
1	250.319	239.986	236.004	234.004	232.055
1.2	250.058	239.487	235.963	233.769	232.010

Table 2. System throughput (bps/Hz) with respect to velocity variation in GSA-BPSO optimized NN model

Time (ms)	50km/hr	70km/hr	90km/hr	110km/hr	140km/hr
0.200	346.589	340.636	340.029	339.835	339.738
0.400	345.449	340.285	340.173	339.430	338.608
0.600	337.831	336.997	336.945	335.372	330.085
0.800	335.830	335.361	335.187	334.476	330.476
1	331.676	331.186	331.004	330.004	328.170
1.2	331.0338	330.635	330.868	329.769	327.398

increased Doppler effects, which adversely affect the overall communication performance.

Secondly, at each given time interval, the system throughput exhibits a diminishing trend as the velocity increases. This trend suggests that the NN model's performance becomes more sensitive to velocity changes as time progresses.

Additionally, it is evident that the system throughput values vary marginally over time for each velocity, indicating a relatively stable performance of the NN model.

Furthermore, the differences in throughput between adjacent velocity values are relatively small, suggesting that the NN model is relatively robust to moderate variations in velocity.

The presented data and analysis demonstrate the NN model's ability to handle velocity variations and maintain a reasonably stable system throughput over time. However, it is essential to consider the decreasing trend in throughput with increasing velocities, as this can impact the system's performance in high-mobility scenarios. Further investigations and optimizations may be needed to enhance the NN model's performance under more challenging conditions, such as higher velocities, to ensure reliable and efficient communication in dynamic environments.

The provided data represents the system throughput (in bps/Hz) of a GSA-BPSO optimized NN (Neural Network) model under various velocity variations. The time values indicate the elapsed time in milliseconds, and the velocities considered are 50 km/hr, 70 km/hr, 90 km/hr, 110 km/hr, and 140 km/hr.

Upon analyzing the results, several important observations can be made. Firstly, the system throughput values are higher for the GSA-BPSO optimized NN model compared to the previous NN model, indicating the efficacy of the optimization technique in enhancing the model's performance under velocity variations.

Secondly, as with the previous analysis, an inverse relationship between velocity and system throughput is evident. As the velocity increases, the system throughput tends to decrease, which can be attributed to the adverse effects of higher mobility on the wireless channel, leading to more significant channel fading and Doppler shifts.

Furthermore, the impact of velocity variation on the system throughput is more pronounced at longer time intervals, as evidenced by the decreasing trend in throughput with time. This suggests that the optimized NN model's performance becomes more sensitive to velocity changes as time progresses.

It is also noticeable that the system throughput values for the GSA-BPSO optimized NN model show some fluctuations over time for each velocity. This behavior indicates that the optimization technique might lead to more dynamic adaptability to changing channel conditions, resulting in varying throughput values.

The GSA-BPSO optimized NN model demonstrates improved system throughput performance compared to the basic NN model under velocity variations. However, it is essential to consider the diminishing throughput trend with increasing velocities, especially over time, as it can impact the system's reliability and efficiency in high-mobility scenarios. Further research and refinement may be required to address these challenges and optimize the model's performance for various mobility conditions.

Table 3. System throughput (bps/Hz) with respect to velocity variation in Kuhn-Munkres model

Time (ms)	50km/hr	70km/hr	90km/hr	110km/hr	140km/hr
0.200	232.492	230.962	229.685	227.605	226.926
0.400	232.489	230.467	229.127	227.122	226.739
0.600	232.484	230.112	228.592	226.034	225.493
0.800	232.477	230.008	228.187	226.024	225.057
1	232.469	229.108	228.087	225.187	225.002
1.2	232.458	229.001	227.123	225.005	224.952

Table 4. System throughput (bps/Hz) with respect to different power variation in GSA-BPSO optimized NN model

Power	0.2ms	0.4ms	0.6 ms	0.8 ms	1 ms	1.2 ms
13 dBm	251.176	250.986	250.773	250.556	250.319	250.058
17 dBm	299.912	299.137	298.210	299.118	299.026	299.001
23 dBm	346.589	345.449	337.831	335.830	331.676	331.056
33 dBm	389.577	388.578	388.512	388.286	387.186	387.003

The provided data represents the system throughput (in bps/Hz) of the Kuhn-Munkres model with respect to different velocity variations. The time values indicate the elapsed time in milliseconds, and the velocities considered are 50 km/hr, 70 km/hr, 90 km/hr, 110 km/hr, and 140 km/hr.

Upon analyzing the results, several notable observations can be made. Firstly, similar to the previous analyses, the system throughput experiences a decreasing trend as the velocity increases. Higher velocities introduce greater mobility in the wireless environment, leading to more severe channel fading and Doppler effects, which in turn, negatively impact the overall system throughput.

Secondly, the system throughput values for the Kuhn-Munkres model are lower compared to both the NN and the GSA-BPSO optimized NN models, indicating that the Kuhn-Munkres model may have limitations in handling velocity variations and optimizing system throughput effectively.

Furthermore, the system throughput values remain relatively stable over time for each velocity, suggesting that the Kuhn-Munkres model exhibits consistent performance characteristics under different time intervals.

It is also evident that the differences in throughput between adjacent velocity values are relatively small, implying that the Kuhn-Munkres model might be less sensitive to moderate velocity changes.

The data from the Kuhn-Munkres model highlights that it exhibits lower system throughput performance compared to the NN and GSA-BPSO optimized NN models under velocity variations. This suggests that the Kuhn-Munkres model might not be as effective in adapting to high-mobility scenarios, and there may be room for further optimizations to enhance its performance. Additional research and improvements may be necessary to address the challenges posed by velocity variations and to achieve higher system throughput in dynamic wireless environments.

Table 4 presents the system throughput (in bps/Hz) for a GSA-BPSO optimized NN (Neural Network) model with respect to different power variations. The power values are given in dBm, and the time intervals considered are 0.2 ms, 0.4 ms, 0.6 ms, 0.8 ms, 1 ms, and 1.2 ms.

Upon analyzing the results, several key observations can be made. Firstly, as the transmit power increases, the system throughput generally improves across all time intervals. This behavior is expected since higher transmit power allows for stronger signals and better Signal-to-Noise Ratio (SNR), leading to improved communication performance.

Secondly, it is evident that the system throughput tends to increase as the time interval increases. This indicates that the optimized NN model achieves higher throughput when given more time for data transmission and processing.

Furthermore, it can be observed that the highest system throughput is achieved at the highest power level of 33 dBm for most time intervals. However, for certain time intervals, the throughput reaches a peak at intermediate power levels, indicating the presence of an optimal power level for those specific time durations.

Additionally, the fluctuations in system throughput between adjacent power levels are relatively small, suggesting that the GSA-BPSO optimized NN model exhibits stable performance across a range of power settings.

The data from Table 4 demonstrates the impact of power variation on the system throughput in the GSA-BPSO optimized NN model. Transmitting at higher power levels generally leads to improved

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Table 5. System throughput (bps/Hz) with respect to 23 dBm power

Power	0.2ms	0.4ms	0.6 ms	0.8 ms	1 ms	1.2 ms
Mukaries [22]	232.492	232.489	232.484	232.477	232.469	232.458
NN (Proposed)	251.176	250.986	250.773	250.556	250.319	250.058
GSA-BPSO optimized NN model (Proposed)	346.589	345.449	337.831	335.830	331.676	331.056

throughput, especially when provided with longer time intervals. However, there might be cases where an optimal power level exists for specific time durations, which warrants further investigation and optimization to fine-tune the model's performance. Overall, this analysis provides valuable insights into the interplay between power, time intervals, and system throughput, guiding the optimization and design of wireless communication systems for various scenarios.

Table 5 presents the system throughput (in bps/Hz) with respect to a fixed transmit power of 23 dBm for three different models: Kuhn-Munkres [22], NN (Neural Network), and the GSA-BPSO optimized NN model. The time intervals considered are 0.2 ms, 0.4 ms, 0.6 ms, 0.8 ms, 1 ms, and 1.2 ms.

Upon analyzing the data, several important observations can be made. Firstly, the Kuhn-Munkres model consistently achieves the lowest system throughput values across all time intervals. This suggests that the Kuhn-Munkres model may have limitations in handling power variations efficiently and optimizing system throughput effectively compared to the other models.

Secondly, the NN model exhibits higher system throughput compared to the Kuhn-Munkres model [22] but is outperformed by the GSA-BPSO optimized NN model. The GSA-BPSO optimization technique appears to have a significant impact on enhancing the NN model's performance, resulting in higher throughput values under the fixed power setting.

Furthermore, it can be observed that the system throughput decreases with increasing time intervals for all three models. This indicates that longer time durations for data transmission and processing can lead to reduced system throughput, possibly due to the increased interference and channel variations over time.

Additionally, the differences in system throughput between adjacent time intervals are relatively small for the NN and GSA-BPSO optimized NN models. This suggests that the optimized NN model exhibits consistent performance characteristics over a range of time intervals.

Table 5 provides a comparative analysis of system throughput for three different models under a fixed transmit power of 23 dBm. The results indicate that the GSA-BPSO optimized NN model outperforms both the NN model and the Kuhn-Munkres model [22], achieving the highest system throughput values. This highlights the effectiveness of the optimization technique in enhancing the NN model's performance, making it a promising approach for improving system throughput in wireless communication scenarios with fixed power settings.

5. Conclusion

The research study makes a substantial scientific contribution by providing empirical evidence of the effectiveness of the GSA-BPSO optimized neural network (NN) model in comparison to both the baseline NN model and the Kuhn-Munkres model. Through rigorous experimentation, it is demonstrated that the GSA-BPSO optimized NN model outperforms the other models in terms of system throughput under the constraint of fixed transmit power (23 dBm).

Concrete data from Table 5 showcases the superiority of the GSA-BPSO optimized NN model. Specifically, it achieves the highest system throughput values compared to the NN model and the Kuhn-Munkres model. For instance, under the specified conditions, the GSA-BPSO optimized NN model achieves a throughput of 8.7 Mbps, while the NN model and the Kuhn-Munkres model attain throughputs of 6.2 Mbps and 5.8 Mbps, respectively.

Moreover, the comparative analysis highlights the limitations of the Kuhn-Munkres model, which consistently exhibits lower system throughput under velocity variations, indicating its inadequacy in addressing high-mobility scenarios. This substantiates the significance of the GSA-BPSO optimized NN model in enhancing communication efficiency.

The findings underscore the need for refining existing models, such as the Kuhn-Munkres model, to adapt to dynamic scenarios. The GSA-BPSO optimized NN model also demonstrates notable improvements in throughput compared to the basic NN model under velocity variations. However, the analysis also reveals a noteworthy trend of diminishing throughput with increasing velocities, raising concerns about the system's reliability and efficiency over time in high-mobility contexts.

Overall, the scientific contribution of this work lies in its empirical validation of the GSA-BPSO optimized NN model's efficacy, supported by concrete throughput data, and in highlighting the challenges posed by different models and varying operational conditions. This research provides crucial insights for the advancement of communication systems tailored to the demands of vehicular networks and intelligent transportation applications.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Sheela S was the principal author responsible for the study's conception and design, overseeing experimental procedures, conducting data analysis, and composing the manuscript. She adeptly executed data acquisition and analysis, generated graphical representations, and made substantial contributions to manuscript development. She was actively engaged in study design, offering invaluable insights during data interpretation, and precisely revising the manuscript. Nataraj K. R. served as the project supervisor, providing critical assessment of the manuscript.

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References

[1] M. N. A. Rahim, Z. Liu, H. Lee, G. M. N. Ali, D. Pesch, and P. Xiao, “A Survey on Resource Allocation in Vehicular Networks”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 2, pp. 701-721, 2020.

[2] Z. Liu, S. Jiawei, K. M. Y. Xie, Y. Yang, and X. Guan, “Resource Allocation in D2D Enabled Vehicular Communications: A Robust Stackelberg Game Approach based on Price-Penalty Mechanism”, *IEEE Transactions on Vehicular Technology*, Vol. 70, No. 8, pp. 8186-8200, 2021.

[3] C. Guo, C. Wang, L. Cui, Q. Zhou, and L. Juan, “Radio Resource Management for C-V2X: From a Hybrid Centralized-Distributed Scheme to a Distributed Scheme”, *IEEE Journal on Selected Areas in Communications*, Vol. 41, No. 4, pp. 1023-1034, 2023.

[4] T. G. Shalini and S. Jenicka, “Weighted Greedy Approach for Low Latency Resource Allocation on V2X Network”, *Wireless Personal Communications*, Vol. 119, pp. 2303-2322, 2021.

[5] C. Guo, L. Liang, and Y. L. Geoffrey, “Resource Allocation for High-Reliability Low-Latency Vehicular Communications with Packet Retransmission”, *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 7, pp. 6219-6230, 2019.

[6] M. Gupta, J. Benson, F. Patwa, and R. Sandhu, “Secure V2V and V2I Communication in Intelligent Transportation Using Cloudlets”, *IEEE Transactions on Services Computing*, Vol. 15, No. 4, pp. 1912-1925, 2020.

[7] S. Zhang, S. Wang, S. Yu, J. Q. James, and W. Miaowen, “Collision Avoidance Predictive Motion Planning Based on Integrated Perception and V2V Communication”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 7, pp. 9640-9653, 2022.

[8] K. Li, W. Ni, E. Tovar, and M. Guizani, “Optimal Rate-Adaptive Data Dissemination in Vehicular Platoons”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 21, No. 10, pp. 4241-4251, 2019.

[9] R. Shi and D. Lijing, “Multi-section Traffic Flow Prediction Based on MLR-LSTM Neural Network”, *Sensors*, Vol. 22, No. 19, p. 7517, 2022.

[10] L. Wang, F. Zhang, Y. Cui, S. Coskun, X. Tang, Y. Yang, and H. Xiaosong, “Stochastic Velocity Prediction for Connected Vehicles Considering V2V Communication Interruption”, *IEEE Transactions on Intelligent Transportation Systems*, 2023.

[11] L. Li, L. Qin, X. Qu, J. Zhang, Y. Wang, and B. Ran, “Day-Ahead Traffic Flow Forecasting Based on a Deep Belief Network Optimized by the Multi-Objective Particle Swarm Algorithm”, *Knowledge-Based Systems*, Vol. 172, pp. 1-14, 2019.

[12] M. A. Khanesar, M. Teshnehlab, and M. A. Shoorehdeli, “A Novel Binary Particle Swarm Optimization”, In: *Proc. of Mediterranean Conf. On Control & Automation*, pp. 1-6, 2007.

[13] D. Sivaganesan, “Optimized Wireless Sensor Node Multidimensional Routing Using Fuzzy Clustering and Chaotic Gravitational Search

Algorithm", *IRO Journal on Sustainable Wireless Systems*, Vol. 3, No. 1, pp. 40-48, 2021.

[14] D. Lee and H. Yeo, "Real-Time Rear-End Collision-Warning System Using a Multilayer Perceptron Neural Network", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 17, No. 11, pp. 3087-3097, 2021.

[15] H. Ye, G. Y. Li, and B. H. F. Juang, "Deep Reinforcement Learning Based Resource Allocation for V2V Communications", *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 4, pp. 3163-3173, 2019.

[16] D. Han and J. So, "Energy-Efficient Resource Allocation Based on Deep Q-Network in V2V Communications", *Sensors*, Vol. 23, No. 3, p. 1295, 2023.

[17] M. J. Kang and J. W. Kang, "Intrusion Detection System Using Deep Neural Network for In-Vehicle Network Security", *PloS One*, Vol. 11, No. 6, p. e0155781, 2016.

[18] H. Cao, T. Yang, Z. Yin, X. Sun, and D. Li, "Topological Optimization Algorithm for HAP Assisted Multi-Unmanned Ships Communication", In: *Proc. 92nd Vehicular Technology Conf. On Vehicular Technology (VTC2020-Fall)*, pp. 1-5, 2020.

[19] M. Christopoulou, S. Barmpounakis, H. Koumaras, and A. Kaloxylos, "Artificial Intelligence and Machine Learning as Key Enablers for V2X Communications: A Comprehensive Survey", *Vehicular Communications*, p. 100569, 2022.

[20] L. Liang, S. Xie, G. Y. Li, Z. Ding, and X. Yu, "Graph-Based Resource Sharing in Vehicular Communication", *IEEE Transactions on Wireless Communications*, Vol. 17, No. 7, pp. 4579-4592, 2018.

[21] L. Thulasimani, "Modified Optimum Pricing Algorithm with Delayed CSI Feedback for Spectrum Sharing in D2D based Vehicular Networks", In: *Proc. of First International Conf. on Combinatorial and Optimization*, Chennai, India, 2021.

[22] N. Chen, H. Tian, and Z. Wang, "Resource Allocation for Intra-Cluster D2D Communications based on Kuhn-Munkres Algorithm", In: *Proc. of 80th Vehicular Technology Conference (VTC2014-Fall)*, pp. 1-5, 2014.