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Joint energy and spectral optimization in Heterogeneous Vehicular Network

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ABSTRACT

With the latest developments in both the automotive and communications industries, especially concerning the emerging 5G networks, IoV, and the adoption of Vehicle-to-Everything (V2X) connectivity, there has been a shift towards the establishment of Heterogeneous Vehicular Networks (HetVNets) environments. The rapid growth of data traffic and the drastic expansion of heterogeneous network infrastructure have resulted in a significant increase in energy consumption within wireless communication systems. Balancing energy efficiency and spectral efficiency has become a major challenge in Heterogeneous Vehicular networks, particularly concerning energy optimization, making the design of network systems considerably more challenging. Therefore, this paper attempts to optimize the energy utilized for each packet transmission, considering its stochastic nature and the optimized control parameters of two meta-heuristic algorithms-Particle Swarm Optimization and Artificial Bee Colony Optimization. The optimization process is executed using the Particle Bee Colony Swarm algorithm. Subsequently, a comparison is made with other proposed algorithms, namely LDOD, FO, RO, and MATO, in terms of energy efficiency and spectral efficiency. The performance analysis reveals that the numerical results outperform existing algorithms, demonstrating a 30.32% increase in spectral efficiency and 73.25% increase in energy efficiency.

1. Introduction

Recent advances in information technology have revolutionized the automotive and communications industries, paving the way for next-generation smart and connected vehicles. Emerging 5G networks, the Internet of Vehicles (IoV), and the adoption of vehicle-to-everything (V2X) connectivity have led to the adoption of a heterogeneous vehicular network (HetVNets) environment. The highly dynamic nature of the vehicular networks, along with the heterogeneity of wireless infrastructures for connected cars (e.g., IEEE 802.11p, LTE-A/5G, Cellular Vehicle to Everything (C-V2X), etc.), as well as the variety of vehicular applications (e.g., safety, traffic management, infotainment, etc.), make resource management and low-latency communication requirements a significant challenge to network power consumption [1]. This, in turn, has led to a series of critical problems, such as greenhouse gas emissions due to increased energy consumption. 5G, a significant cellular technology, aims to provide high throughput, a large transmission bandwidth per user, huge capacity in accordance with the number of connected devices, and low latency. Heterogeneity, which is supported in 5G Vision and broadcasted by the 5G-PPP group, achieves high network performance [2]. However, heterogeneity itself is a complicated task to handle which causes network fragmentation and inefficiency in resource utilization. Further, the transition from one radio access to another and the multi-hop process for network traffic routing leads to end-to-end delay [3,4]. These investigations state that careful tackling is needed to optimize spectral and energy efficiency. Particularly in the case of dense HetVNets, the determination of the optimal path within the shortest possible time must be addressed through effective management of network resources and with the assistance of smart routing algorithms. Effective real-time exchange of information among the vehicular systems can be delivered by Dedicated Short Range Communication (DSRC) [5]. Despite mobile networks extensively covering the specifications of vehicular users' need for services with real-time safety but are not guaranteed by cellular networks all the time [6]. Although there exist numerous studies on cellular networks and DSRC, the integrated approach associated with the extraction of reliable outcomes still remains in its infancy. Resource management and the low latency communication requirements are significant challenges to network power consumption. This leads to greenhouse gas emissions due to increased energy consumption. Building this kind of heterogeneous vehicular network needs an in-depth analysis of heterogeneity and its challenges. This section of this research deals with the optimization of energy efficiency and spectral efficiency in a HetVNets environment with the Particle Bee colony swarm algorithm to achieve certain objectives like strong flexibility, simplicity, robustness, handling of

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objectives of stochastic nature, and optimized control parameters. This section has further evaluated and compared the improvised algorithm with state-of-the-art methods in terms of energy and spectral efficiency.

Spectral efficiency defines the quantity of transmitted data with fewer transmission errors over a given bandwidth and provided spectrum in a specific communication system. It is a measure of how efficiently a limited frequency spectrum is utilized by the physical layer protocol and sometimes by the medium or channel access control. It is also equivalent to the maximum number of bits that could be transmitted to a particular number of users per second [7]. It has been stated that for effective usage, large amounts of data have to be transferred over the spectrum. Spectral efficiency generally signifies the efficacy of the digital modulation approach and the decrease in the corresponding signal-to-noise ratio (SNR). The satisfactory values of spectral and energy efficiency must be effectively maintained in practical scenarios for efficient energy management and to decrease the network operation cost.

The main contribution of this paper is to propose a framework for task offloading schemes in HetVNets with optimization of energy efficiency and spectral efficiency using the Particle Bee colony swarm algorithm.

In this paper, we study the efficient task offloading schemes in HetVNets. The vehicles perform the communication, computing resource allocations, and selection of the shortest path to offload the tasks. For this paper, the spectral efficiency and energy efficiency of the wireless communication system have been taken into consideration, keeping in mind the minimum latency of task offloading (T = 0.1 s). To minimize system energy and computing resources, the Particle Bee colony swarm algorithm has been used to keep the latency low in task offloading and also consider the trade-offs between spectral and energy efficiency.

The first section of this paper describes the introduction of the HetVNets and the importance of energy efficiency and spectral efficiency. Section 2 presents the related works in accordance with the proposed methodology. Section 3 covers the proposed methodology and information about the overall architecture of the particle bee colony swarm algorithm in the optimization of spectral efficiency and energy efficiency. Section 4 presents the performance analysis of the improved model, and Section 5 concludes the work with justification.

2. Related works

This section presents information about the methodologies, results, and challenges faced by the existing studies in accordance with the proposed methodology. Most of the conventional HetVNets adoption techniques seem ineffective in real-world scenarios due to their low energy and spectral efficiency. To rectify this problem, [8] suggested a game-based approach for the selection of optimal parameters. The terminals trying to switch over with high evaluation have been framed as a multi-play, non-cooperative system. The characteristics of HetVNets are thoroughly accounted for in adjusting the game strategy, thereby adapting a stable vehicular platform with fast convergence. This model enables the drivers to avoid instability with a probabilistic system prototype. Similarly, to resolve resource allocation in the high mobile scenario, this paper [9] attempted to enhance both the reliability and throughput efficiency of non-orthogonal multiple access (NOMA) based HetVNets through a cascaded Hungarian channel-based algorithm that simplifies the parameters used for power allocation. Chance constraints were transferred to deterministic constraints by the approximation of a non-central chi-square distribution. A reliable framework for the vehicular network has been suggested by [10] that comprises collaborative radio, real-time cloud computing processes, and centralized processing. The study stated that low-distortion compression is essential for improving resource utilization. This research also suggested that it could simplify operational management and the number of base stations. Hence, there is decreased power consumption in the support equipment. In relation to task offloading, a Lyapunov-based dynamic task offloading algorithm has been used to minimize the total network utility under optimal offloading decisions by jointly considering packet drop rate and energy consumption [11], however, the paper does not consider spectral efficiency on mm-wave [12].

The paper compared other algorithms of task offloading, such as the full-offloading (FO) algorithm, the random offloading (RO) algorithm, and the mobility-aware task offloading (MATO) algorithm. In the full offloading algorithm, all the flexible sub-tasks will be offloaded, whereas in the random offloading algorithm, vehicles randomly offload flexible sub-tasks to the server. MATO is proposed in [13] to offload parts of the tasks with the condition that the offloading delay of the sub-task is the same as the local execution delay, thereby minimizing the total delay. Hence, spectral efficiency has not been considered. The FO algorithm provides the advantage of offloading the whole task completely, making the calculation process simple, and involving fewer calculation parameters; however, it suffers from inefficient resource allocation. The RO algorithm also has the advantage of involving fewer calculation parameters; however, it suffers from the same inefficient resource allocation. MATO, on the other hand, is quite effective in efficient resource allocation by splitting the part or whole task to be distributed among the resource points. It also helps in effective energy management [13].

2.1. Energy efficiency in wireless communications

Energy consumption for the accession of the base station is considered the major energy-consuming aspect of HetVNets. To resolve the challenge, it is significant, to begin with, to have a prompt device for decreasing the energy consumption of the base station through precise and reliable scheduling methods in terms of intensity usage. Hence, [14] focused on restrictive flooding that is observed to be highly energy efficient compared to plain flooding under similar reliability factors. Designs with high energy efficiency have been suggested for allocating transmit power and surface-reflecting phase shifts with respect to distinct budget assurance for mobile users. This results in design optimization issues. To solve this, two computationally inexpensive methods—exploiting alternating extensions, Gradient Descent Search (GDS), and Sequential Fractional Programming (SFP)—have been suggested. Particularly, one algorithm applies reconfigurable intelligent surface (RIS) phase coefficients and gradient search to attain fractional programming for the ideal allocation of transmit power. Alternatively, the subsequent algorithm employs SFP to optimize RIS phase shifts. An accurate power consumption framework for systems based on RIS has also been presented. The performance of the suggested techniques has been examined in a real outdoor environment. Outcomes revealed that resource allocation techniques based on RIS have the ability to afford three hundred percent high energy compared to the use of typical Multi-Antenna Amplify and Forward Relaying (MAAFR) [15]. In Wireless Sensor Networks (WSN), it has been a challenging task to fulfil the requirements due to end-to-end delay due to the duty cycle chosen by nodes. This can result in considerable delay as nodes could only transfer or retrieve information in their respective periods (that is, leading to sleep delay). To solve this problem, Dynamic Duty Cycle (DDC) has been recommended to reduce the delay occurring in WSNs. Initially, the way in which the duty cycle impacts network delay has been analysed. Subsequently, the DDC method has been devised for extending the node's active period in areas with no hot spots. With more duty cycles, forwarding nodes stay awake with a high probability. Thus, transmission delay and the node's sleep delay get minimized. The node's remaining energy has been used to improve performance. Hence, DDC does not destroy the network lifetime. Analytical and experimental outcomes revealed the outstanding performance of recommended schemes over traditional schemes. In comparison to the traditional Fixed duty Cycle (FDC), the lifetime gets extended by 16.7% or more. On the other hand, the transmission delay of DDC gets minimized at a rate of 20 to 50% [16].

2.2. Spectral efficiency in wireless communication

Through fixed and identical length periods, synchronized and interfering constraints (SIC) corresponding to cluster heads (CHs) have been formed that afford specific conditions for RPC. All SICs of CHs have been framed as probability constraints due to repeated fluctuations in the channel. Moreover, utility based on pricing has been recommended to avert separate optimization amongst SE and EE and the impact of price on trade-offs amongst them. Due to intractable probability constraints and non-convex unified utility, Bernstein approximation (BA) and successive convex approximation (SCA) have been utilized for transforming the issue into a tractable and convex form. Empirical simulations have also been employed to assess the algorithms' performance in dynamic systems. Further, the comparison has been undertaken to validate the clustering technique and RPC scheme, which confirmed their efficacy [17]. [18] investigated the performance of a vehicular ad hoc network (VANET) as the Cox process; here, the dimensional layout of the roads is modelled by the Poisson Line Process (PLP), and the positions of nodes for each and every line are modelled as a one-dimensional Poisson Point Process (PPP). For this process, the success probability and area spectral efficiency (ASE) of the network assumed ALOHA as the channel of access scheme used. In this study, we examine the trends of success probability parameters and the optimum transmission probability for the Cox process model, which differs from the 1- and 2-dimensional PPP models used in vehicular networks. [19] have deliberated the study on high spectral efficiency on the dual non-orthogonal scheme with three major issues, which are multi-user access, private security, and data rate with the Internet of Things network. It focused on multiple access, spectrum resource pressure, security issues, and bandwidth efficiency. In this study, the high-spectral-efficiency secure access (HSESA) scheme based on dual non-orthogonal is implemented to resolve the issues. The scheme is a hybrid of non-orthogonal multi-access and non-orthogonal multiplex. Compared to ML joined with MPA, the result showed that the detection scheme of ID joined with MPA has a lower level of complexity. The efficiency of spectral has been enhanced with the proposed HSESA method, as it gives better bit error rate performance (BERP).

2.3. Optimized algorithm for energy efficiency

[20] developed an algorithm called two-stage energy-efficient resource allocation for the vehicular network process. The power-contro lled algorithm, auction-matching-based joint-relay selection, and spectrum allocation have been derived in the first stage. In the second stage, the nonlinear fractional programming-based power control algorithm has been developed to maximize the energy efficiency in the base station. In this stage, convergence, stability, and complexity are analysed. Moreover, the proposed algorithm has been evaluated on the basis of real-world road topology and realistic vehicular traffic. The result stated that the proposed algorithm has achieved high performance in terms of network coverage and efficient energy utilization compared to other existing algorithms. [21] has implemented the Adaptive Weighted Clustering Protocol (AWCP) to optimize the network parameters and group the random nodes. The enhanced whale optimization algorithm (EWOA) has been developed to optimize the efficiency of the network. The movement has been analysed with the network mobility routing protocol based on position and speed. The distance between the trusted vehicle node and RSU has been analysed with the proposed EWOA-AWCP method. Finally, the result also stated that mobility and clustering efficiency have been enhanced with the developed model.

In accordance with the literature review, it was observed that both regular VN and HetVN selection techniques lack consideration for changing network efficiency, particularly for the varying terminal number due to network selection [22]. This considerably causes reliability and stability problems in real-time scenarios. Existing network selection methods may cause unexpectedly huge distractions in the network during performance variations. Additionally, the robustness of the system and reliability of the link do get impacted by the errors due to channel estimation occurring in high mobility HetVNet [9]. Generally, the resource allocation issue comprises spectrum resource blocks and time slot variations. To overcome this, [23] formulated average energy effectiveness by transforming the issue into a tractable convex optimization issue with the modifications of different parameters. Because of the constrained computational capability and storage of the devices, conventional security methods face challenges in the process of data transmission. A large amount of energy is consumed with huge data transmission in the insecure network [24]. But it is also to be noted that packets must be delivered to the sink node at the specified time to configure delay-specific applications [25]. In order to overcome these limitations, the proposed study has made use of a particle-bee colony-based swam algorithm. However, PSO also has limitations in terms of convergence. PSO generally converges slowly, especially in high-dimensional spaces or problems where the fitness landscape is rugged. Slow convergence is a significant drawback for this research, particularly in real-time or time-sensitive applications. Hence, PSO's computational complexity increases with the number of particles and dimensions, and scalability can become a big problem for large-scale optimization problems, requiring more computational resources. However, the convergence of PSO can be improved through hybridization (combining PSO with other algorithms) or by using variants of PSO tailored to these specific challenges.

3. Proposed methodology

The overall flowchart of the proposed methodology has been represented below. The system model is configured with the heterogeneous vehicular network with the use of PSO. Heterogeneous vehicular networks often involve dynamic and changing environments. Adapting the PSO algorithm works well in handling dynamic environments, where the optimum can change over time. Secondly, PSO's convergence speed can vary based on the problem and parameter settings. In real-time applications, the algorithm converges quickly to provide timely solutions if the parameters can be tuned with specific values. For example, fixing up the velocity parameter or any other specific parameter. This study addresses the issues of obtaining high spectral efficiency and energy efficiency by using the Particle Bee Colony Swarm optimization algorithm. After initialization, the possible selection of paths has been accomplished. The best agent path prediction by tour construction includes evaluated fitness values. After the requisition of sending and receiving messages, the energy estimated was used to evaluate the fitness values. When the fitness function is easier to optimize, some of the bad particles are deleted. Consequently, the best path was predicted through this mechanism followed by updated velocity and position of agents. If the final iteration is not reached, the cycle has been reversed to a selection of possible paths to reach iteration. After reaching the final iteration the performance analysis has been carried out to evaluate the spectral efficiency and energy efficiency.

The below flowchart is based on the proposed Methodology (see Fig. 1).

3.1. System model

With salient features of agility, scalability, elasticity, re-programmability, and flexibility, the illustration of the system model in HetVNet is represented in Fig. 5. The proposed system model has been designed as a three-tier as well as a heterogeneous network with a single BS (base station) in every tier. The information from the vehicles is transmitted through cellular-based V2V communication to gNodeB (gNB), cellular-based V2I, and DSRC-based V2V communication to the core network for improving locational accuracy and reliability. The user equipment (UE) exploits composite carriers (CC) from all the tiers by accumulating them; thus, their bandwidth could be efficiently utilized.

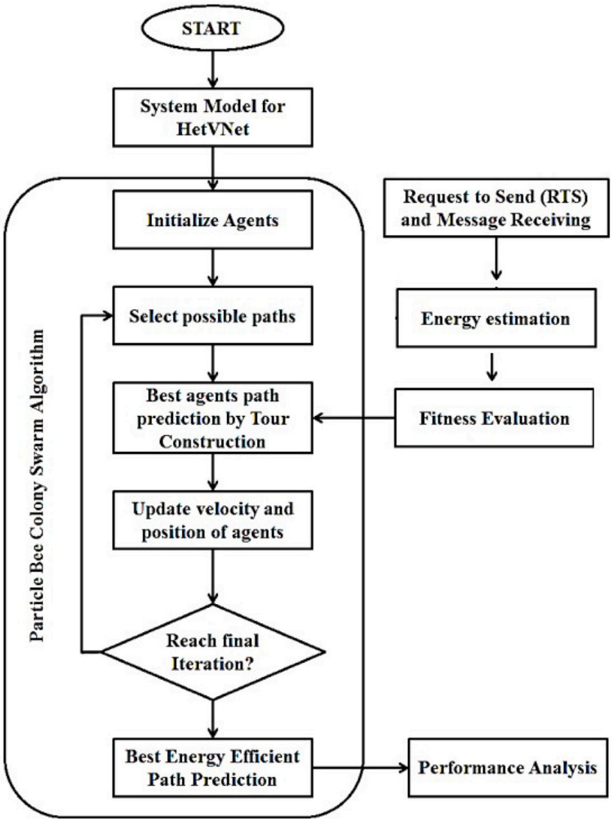

Fig. 1. Flowchart of proposed Methodology.

Further, every BS was presumed to operate in the single frequency band, and hence the intra-brand contiguous carrier aggregation was performed by utilizing adjacent carriers in the frequency band. Later, the spacing between guard band calculations as well as adjacent carriers was obtained.

Below is the System Model (see Fig. 2).

3.2. System parameters

In this section, system parameters are comprehensively explained and presented. System parameters have been defined here that cover the technical specifications for the 5G new radio. The calculation of diverse parameters needs to perform intra-band contiguous carrier aggregation's physical layer simulation [12]. Moreover, the sub-carrier spacing (SCS) of ath composite carriers could be computed as the following Eq. (1),

$$SCS_a = 2^{\mu} * 15 \text{ (KHz)} \tag{1}$$

From the above Eq. (1), μ ranges between 1 and 4. And the sub-carrier numbers of ath composite carriers is computed through the following Eq. (2),

$$n_{sc_a} = NRB_a * 12 \tag{2}$$

From the above Eq. (2), NRB_a indicates the number of resources block for ath composite carrier. Further, the bandwidth (BW) of ath composite carrier is computed with Eq. (3) given below,

$$BW_a = n_{sc_a} * SCS_a \tag{3}$$

The guard band for ath composite carrier is also computed and illustrated as the following equation,

$$GB_a = \frac{BW_a * 1000 \text{ (KHz)} - NRB_a * SCS_a * 12}{2} - \frac{SCS_a}{2} \tag{4}$$

The spacing between the adjacent composite carriers for intra-band contiguous carrier aggregation is computed and it is represented as the following Eq. (5),

$$CC_{spacing} = (BW_a + BW_{a+1} - 2|GB_a - GB_{a+1}|/0.6) * 0.3 \text{ (MHz)} \tag{5}$$

The higher and lower frequency offset $F0_{a_{high}}$ and $F0_{a_{low}}$, which represented as the following Eq. (6),

$$F0_{a_{low}} = \frac{(NRB_{a_{low}} * 12 + 1) * SCS_{a_{low}}}{2} + GB_{a_{low}} \text{ (MHz)} \tag{6}$$

$$F0_{a_{high}} = \frac{(NRB_{a_{high}} * 12 + 1) * SCS_{a_{high}}}{2} + GB_{a_{high}} \text{ (MHz)} \tag{7}$$

From the above Eqs. (5) and (6), $GB_{a_{high}}$, $GB_{a_{low}}$, $SCS_{a_{high}}$, $SCS_{a_{low}}$, $NRB_{a_{high}}$, $NRB_{a_{low}}$ are said to be the guard band, sub-carrier spacing as well as the number of resource blocks of the last and first (CC) component carrier. The higher and lower edge frequencies (EF) were represented as the following Eqs. (8) and (9),

$$EF_{a_{low}} = F_{c,a_{low}} - F0_{a_{low}} \tag{8}$$

$$EF_{a_{high}} = F_{c,a_{high}} - F0_{a_{high}} \tag{9}$$

From the above equations, F_{C_a} indicates the carrier frequency, whereas the high and low represent the maximum and minimum values amid every component carrier. The overall aggregated BW (Bandwidth) is represented [12] as the following Eq. (10),

$$BW_{CA_i} = EF_{a_{high}} + EF_{a_{low}} \tag{10}$$

3.3. Channel model

The downlink channel of every component carrier was modelled as Tapper delay line (TDL) multi-path channel [22]. These tapper delay line models were utilized for simpler non-MIMO evaluations. Further, there is a total number of 5 TDL channels such as TDL-A, B, C, D, and E, in which these models are utilized for evaluating non-line of sight, whereas TDL E and TDL D could be utilized for evaluating line of sight. The TDL B and A possess 23 taps, in every TDL C model has 24 taps, which follows Rayleigh fading distribution. Further, the TDL E and D models possess 14 and 13 taps, in which the first tap follows the Rician fading distribution, while others follow Rayleigh fading distribution. In this study, the TDL A model has been selected, in which the channel was characterized by 23 taps. The Doppler spectrum of every tap has a classical Jake's spectrum shape. The signal-to-noise ratio (SNR) for every composite carrier is computed as the following equation,

$$\gamma_a = \frac{(h_a * P_D(a))}{(N0_a * BW_a)} \tag{11}$$

From Eq. (11), h_a is said to be the average power gain of ath channel, which was obtained after the received signal channel estimation, and $P_D(a)$ represents the transmission power of ath composite carrier (CC). $N0_a$ is considered as Additional white Gaussian noise (AWGN) Power spectral density (PSD).

3.4. Power consumption model

A power consumption model has been exploited in this work, in which the study considered the effectiveness of power amplifiers and static and dynamic power consumption. Further, the total amount of power, required for the transmission of ith carrier is represented as the following Eq. (12),

$$P_{tot}(a) = \alpha * P_D(a) + K \tag{12}$$

In Eq. (12), K indicates the static power consumption of the base station, $1/\alpha$ denotes the power amplifier's drain efficiency and $P_D(a)$ is considered as the transmission power for ath composite carrier and $\alpha * P_D(a)$ is known as the power amplifier's power consumption at BS.

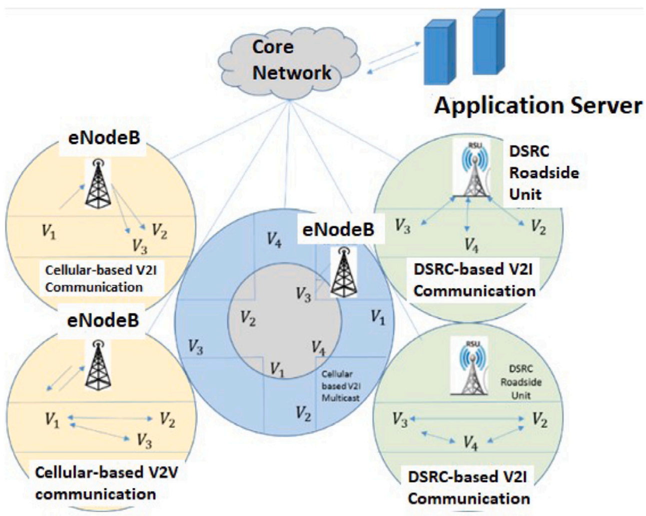

Fig. 2. System model.

The significant performance metrics in this study are considered to be EE (energy efficiency) and SE (spectral efficiency), from which spectral efficiency indicates the effective utilization of a particular spectrum. Further, energy efficiency is measured in bits/J/Hz which indicates the number of bits transmitted by utilizing 1 joule of energy for a specific BW (Bandwidth). The channel capacity for ath composite carrier is represented as the following Eq. (13),

$$C_a = BW_a * log_2 * (1 + \gamma_a) \tag{13}$$

Therefore, the overall capacity of C_{tot} of the system could be represented as the following Eq. (14),

$$C_{tot} = \sum_{a=1}^{n_{cc}} C_a \tag{14}$$

From the above Eq. (14), n_{cc} indicates the number of component carriers, hence, the SE of the proposed system is defined as the ratio of sum capacity across every composite carrier. This can be represented as Eq. (15),

$$SE = \frac{C_{tot}}{BW_{CA}} \text{ (bits/s/Hz)} \tag{15}$$

Moreover, the energy efficiency is represented as the following Eq. (16),

$$EE = SE / \sum_{a=1}^{n_{cc}} P_{tot}(a) \text{ (bits/s/Hz)} \tag{16}$$

3.5. Joint optimization of SE and EE

The multi-objective optimization issue was comprehensively discussed, in which a new resource allocation approach was proposed by utilizing a Genetic algorithm for solving the formulated optimization issues for obtaining optimal EE-SE trade-off.

Problem formulation

The multi-objective optimization (MOO) issue for SE-EE trade-off optimization for the proposed model could be formulated as the following Eq. (17),

$$max : (SE, EE) \tag{17}$$

By utilizing the penalty coefficient method, the above equation has been reformulated to include constraints, and therefore it could be solved by utilizing the Genetic algorithm [12],

$$G_1 = \begin{cases} \sum_{a=1}^{n_{cc}} P_D(a) - 0.2 * P_{max} \geq 0 \\ 0.2 * P_{max} - \sum_{a=1}^{n_{cc}} P_D(a) \leq 0 \end{cases} \tag{18}$$

$$G_2 = \sum_{a=1}^{n_{cc}} P_D(a) - P_{max} \leq 0 \tag{19}$$

By utilizing the quadratic loss function method, the total penalty could be modelled as the following Eq. (20),

$$P = r * (max(0, G_1)^2) + r * (max(0, G_2)^2) \tag{20}$$

In the above Eq. (20), r indicates the penalty coefficient

$$f1 = -(\sum_{a=1}^{n_{cc}} C_a + P) \tag{21}$$

$$f2 = \sum_{a=1}^{n_{cc}} p_{tot}(i) + P \tag{22}$$

From the previous Eqs. (21) and (22), the final optimization is represented by the following Eq. (23),

$$min : f1, f2 \tag{23}$$

3.6. Bee foraging learning PSO (BFL PSO) algorithm

The particle swarm optimization algorithm uses a cluster of particles to search for a better solution. In this algorithm, every particle has its own velocity and position, and it could also update itself by learning from the global best as well as the personal best position. On the other side, the ABC method implements three types of bees, such as scout, onlooker, and employed, which search for food sources and are responsible for diverse tasks [26]. From the inspiration of ABC method, this study proposes a learning model called the BLF PSO (bee foraging learning) method. Moreover, in this method, the population initializes N particles, in which every particle has its own velocity v_a and position a, as well as P_{best_i} personal best position. Later, it enters into three learning phases, such as scout learning, onlooker learning, and employed learning.

Employed learning

In this phase, the particles work like employed bees. Particularly, by learning from g_{best_i}, P_{best_i} global and personal best position, every particle updates its position and velocity. Further, the new positions can be represented as the following equation,

$$\begin{cases} v_a^{new} = \delta * (v_a^{old}, x_a^{old}, p_{best_i}, g_{best_i}) \\ x_a^{new} = x_a^{old} + v_a^{new} \end{cases} \tag{24}$$

From the above equation x_a^{old} and v_a^{old} are considered as position and velocity of ath particle in preceded iterations, whereas x_a^{new} and v_a^{new} indicates position and new velocity of ath particle in present iteration, where δ represents velocity updating approach in PSO. It was noticed that, if x_a^{new} was better than the personal best position, then the personal best position was replaced by x_a^{new}. Consequently, for the particles that fail to update p_{best_i}, their count will be significantly increased, whereas for particles that find a better position, their count will be reset.

Onlooker learning

In this phase, the particles with better fitness values will be selected for performing a better search. Further, the fitness value for every particle is computed on the bases of personal best position, as the following equation,

$$fit(x_a) = \begin{cases} \frac{1}{1+f(p_{best_i})}, if f(p_{best_i}) >= 0 \\ fit(x_a) = 1 + |f(p_{best_i})|, otherwise \end{cases} \tag{25}$$

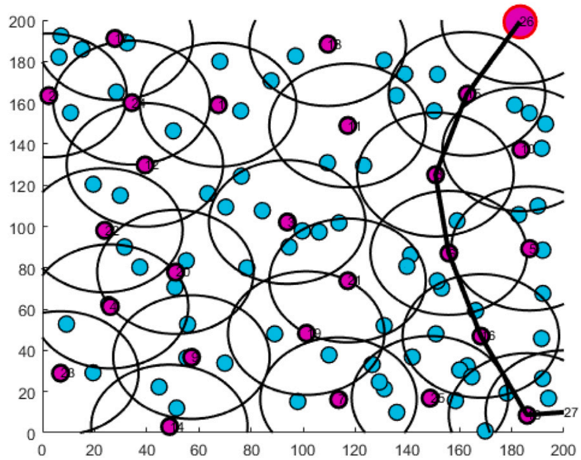

Fig. 3. Mode deployment and its selection using Bee foraging learning.

The probability p_a for the selection of ith particle is computed as the following equation,

$$P_a = fit(x_a) / \sum_{a=1}^{n} fit(x_a) \tag{26}$$

The particles were selected on the basis of probability pa by utilizing the roulette method. Further, the particles which have better p_{best_i} can possibly be selected. When assuming if sth particle x_a was selected, Eq. (26) will be utilized for generating new position x_s^{new}. If this new position was better than p_best_s, then the p_best_s will be replaced by x_s^{new}. Subsequently, for particles that fail to update its p_best_s (personal best position), their counter will be significantly increased, as well as, for the particles which find a better position, their counter gets reset.

Scout learning

In this phase, the particles that fail to update its p_{best_i} (personal best position) in some iterations are considered exhausted. These particles will be abandoned, further, their velocity, position as well as p_{best_i} were randomly initialized in search space.

3.7. BFL PSO algorithm- Description

The study established BFL PSO algorithm on the basis of BFL model, in which the position updating equations and velocity of BLPSO (Bio-geography based learning) PSO were adopted in BFL PSO method. Further, the position updating equations and velocity in BFL PSO algorithm could be represented as the following equation,

$$\begin{cases} v_a^{new} = w.v_i^{old} + c.rand.(pbest_{\tau a} - x_a^{old}) \\ x_a^{new} = x_a^{old} + v_a^{new} \end{cases} \tag{27}$$

From the above equation, w indicates the inertia weight, rand indicates the random vector, which is distributed randomly within [0, 1], whereas c is said to be the learning factor. Further, $p_{best_{\tau a}}$ was constructed by combination of every particles. $p_{best_{\tau a}}$, and τa indicates the index vector for ath particle that was generated by the bio-geography-based exemplar approach. Moreover, the pseudocode of BFL PSO algorithm is presented in the following section. In which the employed learning phase is represented between lines 5 and 14, whereas the onlooker learning phase is represented between lines 15 and 27. The scout learning phase is depicted between 29 and 31 lines.

Pseudocode 1: BFL PSO algorithm

1. Initialize N particles, including velocities v_a,positions x_a ,and personal best p_{besti} positions;
2. Evaluate the particle f(x_a), a=1,….,N;
3. Store the global best position g_{besta}
4. while the terminal condition is not satisfied do
— Employed learning —
5. for each index a=1→N do
6. Generate the learning exemplar index T_a by bio-geography-based exemplar generation
7. Update the velocity v_a and the position x_a using Eq. (24)
8. Evaluate the new position f(x_a^{new})
9. If x_a^{new} is better than $pbest_a$ then
10. $pbest_a = x_a^{new}$,count(a)=0
11. ELSE
12. count(a)=count(a)+1;
13. endIf
14. endfor
— Onlooker learning —
15. Calculate the fitness values fit (x_a) for each particle x_a using Eq. (25)
16. Calculate the probability pa for each particle x_a using Eq. (26);
17. for each $index_a$=1→N do
18. Select a particle x_a using the roulette method based on the probability p_a
19. Generate the learning exemplar index τa by biogeography based exemplar generation
20. Update the velocity v_a and the position x_a using Eq. (24);
21. Evaluate the new position fit(x_a^{new})
22. If x_b^{new} is better than $pbest_b$ then
23. $pbest_b = x_b^{new}$,count(b)=0
24. Else
25. count(b)=count(b)+1;
26. end if
27. end for
28. — Scout learning —
29. for each $index_a$=1→N do
30. if count(a) ⩾ limit then
31. Reinitialize the particle randomly,including its position x_a ,velocity v_a ,and personal best position $pbest_a$

4. Results and discussion

In this section, it compares and evaluates the results of the proposed work in detail with other methods like Lyapunov-based dynamic offloading decision (LDOD) algorithm [11], Random offloading (RO), mobile aware task offloading (MATO) and full-offloading (FO) method [13].

Performance metrics

Energy efficiency is considered the ratio of overall spectral efficiency to overall power consumption. Therefore, the energy efficiency of the hybrid vehicular network can be represented by the following equation,

$$P_{CKT} = N_t * P_R F + P_m + P_{ADC} \tag{28}$$

From the above equation, where P_{CKT} is circuit power consumption, N_t is considered as the number of antennas, whereas P_{RF} indicates the power consumption due to the RF chain. P_{ADC} is the power consumption because of analog to digital conversion (ADC). Spectral efficiency In a similar way, the spectral efficiency for the microwave vehicular networks can be represented as the following equation,

$$\eta_{(ES,\mu)} = \eta_{(S,\mu)} / P_{(T,\mu)} \tag{29}$$

Table 1
Simulations parameters.

Parameters	Values
V	30 km/h
P_{ADC}	$\alpha \times$ Bandwidth, where $\alpha = 10^{-7}$
λ_o	1
σ_m^2, σ_μ^2	$N_o\, B_m,\ N_o\, B_\mu$
Noise power density (N_o)	−174 dBm/Hz
ho, Hu	1 m, 12 m
Microwave band antenna gain	0 dBi
G_M, G_m, ϕ_M	18 dBi, −2 dBi, 10
Number of lanes	4
2W, L	14.8 m, 10 km
α_m, L; α_m, NL	2,4
$\alpha\mu$, L; $\alpha\mu$, NL	2.09. 3.75
P_m, P_μ	30 dBm, 46 dBm
F_μ, F_m	10 MHz, 100 MHz
f_m	26 GHz
f_μ	2 GHz

The spectral efficiency for the hybrid vehicular network is represented as the following,

$$\eta_{ES,PS} = (\eta_{S,PS,m} + \eta_{S,PS,\mu})/(P_{T,m} + P_{T,\mu}) \tag{30}$$

4.1. Performance analysis

For this performance analysis, MATLAB software has been used to carry out the calculation and plotting of the graph. The main parameters used have been presented below, followed by the simulation results of the BFL PSO optimization algorithm. Using MATLAB software, the performance of the proposed algorithm has been evaluated in comparison with different algorithms, i.e., the mobility-aware task offloading (MATO) algorithm, the full-offloading (FO) algorithm, the random offloading (RO) algorithm, and the Lyapunov-based dynamic offloading decision (LDOD) algorithm.

Since this research is considering the mobility of the vehicles, hence V has been considered. Secondly, in this research, optimization of 5G has also been used, and hence, other parameters like noise, bandwidth, antenna gain, area of coverage (W, L), and frequency of 5G have been used (see Table 1).

Fig. 3 represents the node deployment in a heterogeneous vehicular communication platform. It also depicts the cluster formation at the 100th iteration to determine the path. Fig. 4 illustrates the spectral efficiency variation versus λ_m for hybrid vehicular as well as mmWave networks. Further, λ_m was varied and the spectral efficiency curves were plotted for various system configurations. Also, it is observed that the spectral efficiency shadows a similar trend for every configuration. Specifically, this trend seems to be similar to the analysis of spectral efficiency under static vehicular nodes.

We can see in Fig. 4, that the spectral efficiency significantly increases with λ_m, nevertheless, after the density threshold, the spectral efficiency will decrease. It is observed that the spectral efficiency of the hybrid vehicular network is higher than that of the mmWave vehicular network.

Fig. 5 depicts that the spectral efficiency significantly increases for T_s=0.1 s since the probability of vehicular node disconnection from its serving RSU decreases during its slot. From this figure, it is observed that the proposed method was compared to other existing methods such as the Hybrid network and mmWave network in terms of spectral efficiency as well as λ_m. The proposed model has higher spectral efficiency when compared to other prevailing methods. Through this, the information rate of the proposed model could be transmitted over a particular bandwidth in a heterogeneous network.

Fig. 6 depicts the energy efficiency (nats/Hz/Joule) Vs λ_m for the proposed method and compares it with the Hybrid network and mmWave network.

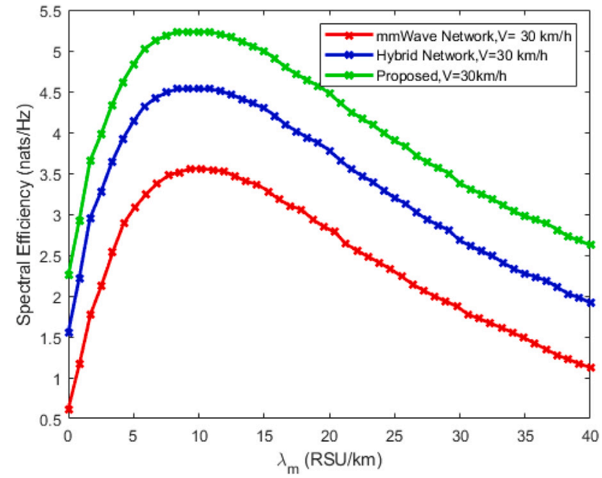

Fig. 4. Spectral efficiency Vs λ_m with Ts = 0.1 s of the proposed and existing method.

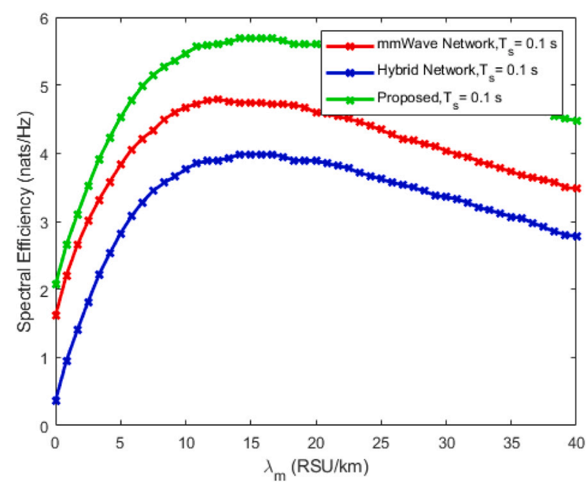

Fig. 5. Spectral efficiency Vs λ_m with Ts = 0.1 s of the proposed and existing method.

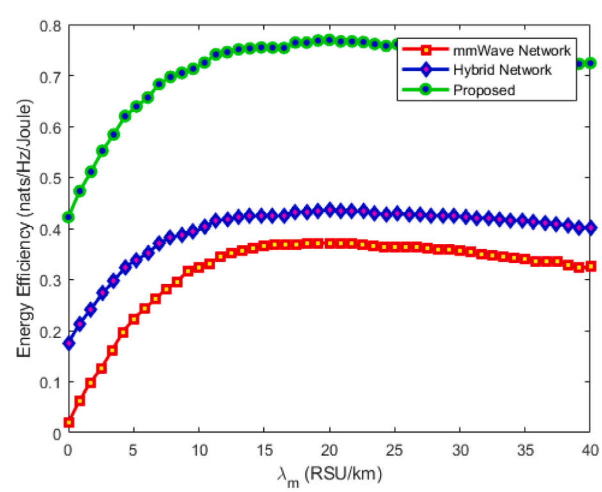

Fig. 6. Energy efficiency Vs control parameter V of the proposed and existing method.

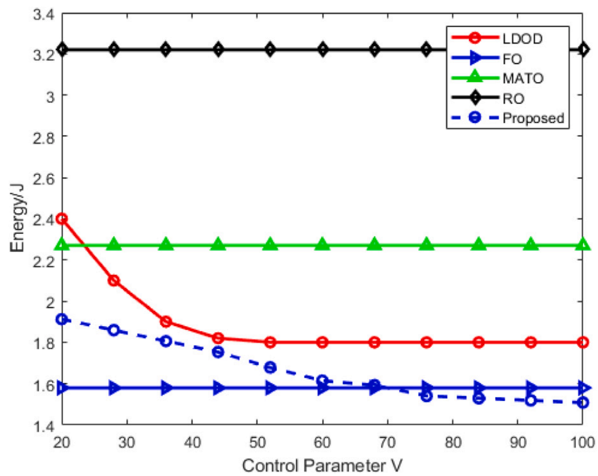

Fig. 7. Energy consumption Vs control parameter V of the proposed and existing method.

It is observed in Fig. 6, that the proposed model has significantly higher energy efficiency than mmWave and hybrid networks because the proposed method has higher spectral efficiency as demonstrated in the previous figure. Since the proposed method is energy efficient, there is very little power consumption.

Fig. 7 deliberates the comparison of the proposed method with other prevailing algorithms in accordance with energy consumption (J). From this figure, it is observed that the energy consumption of the LDOD method significantly decreases with an increase in the control parameter; on the other hand, the RO method has obtained the highest energy consumption. The proposed method has significantly lower energy consumption, which results in better performance than other existing methods like LDOD, RO, MATO, and FO.

5. Conclusion

Ensuring successful conciliation between energy efficiency and spectral efficiency has been considered an interesting design criterion. An improved method with the use of a PBCS optimization algorithm to perform effective power allocation was investigated in this study. This improved algorithm outperforms the prevailing limitations of state-of-the-art existing algorithms, like poor local search capabilities, pre-mature convergence towards optimal solutions, etc. Evaluation of the effectiveness of the proposed system with state-of-the-art methods like LDOD, FO, MATO, and RO showed a 30.32% increase in spectral efficiency and 73.25% increase in energy efficiency.

Hence, the comparison of different algorithms with respect to the proposed algorithm, i.e., the PBCS optimization algorithm, is shown in Fig. 7. Among them, the average energy consumption of the PBCS algorithm decreases with increasing V. In comparison, we can see that the proposed algorithm (PBCS algorithm) consumed less energy in comparison to RO, MATO, and LDOD; however, FO seems to be good in the start, but after the value of 30 (the control parameter, i.e., V), the proposed algorithm starts to perform well as we can see that the overall energy consumption goes down. Based on the simulation results, in addition, we can say that the energy consumption of the RO and MATO algorithms is larger than that of the proposed algorithm (i.e., the PBCS algorithm) with increasing V. In general, the suggested method, PBCS optimization, demonstrates superior performance compared to other algorithms, especially when dealing with 1 KB packet sizes. Recognizing the PSO algorithm's slow convergence rate and smaller packet size, our future research will involve implementing another metaheuristic algorithm like Improved Cooperative Particle Swarm Optimization (ICPSO) [27] or Nonlinear Convex Decreasing Weights Golden Eagle Optimizer (GEO) [28] to minimize computational resource usage while maintaining comparable performance with larger packet sizes. Additionally, we plan to explore the integration of data compression techniques to enhance reliability by reducing packet sizes.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Amjad Alam reports was provided by Middlesex University. Amjad Alam reports a relationship with Middlesex University that includes: non-financial support. Amjad Alam has patent pending to N/A. None.

Data availability

No data was used for the research described in the article.

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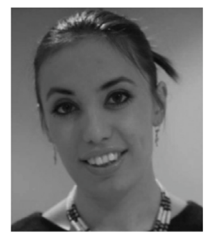

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