Joint Energy and Spectral Optimization in Heterogeneous Vehicular Network

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***Abstract*—With the latest developments in both automotive and communications industries, especially related to the emerging 5G networks, IoV and adoption of Vehicle-to-Everything (V2X) connectivity leading to the adoption of a Heterogeneous Vehicular Networks (HetVNets) environment. Rapid growth of data traffic and drastic expansion of heterogeneous network infrastructure leads to considerable increase of energy consumption in the wireless communication system.This results in the rise of green-house gas emission that seeks a paramount attention in the maintenance and development of sustainable energy as this crisis endangers the natural environment around us, our well-being today. Energy efficiency and spectral efficiency are the main conflicting parameters in Heterogeneous Vehicular network in relation to energy optimisation. Designing a network system for the joint optimization of Energy efficiency and spectral efficiency are critically more challenging. Hence the paper attempted to optimize the energy utilized for each packet transmission with the characteristic features like as simplicity, robustness, flexibility, handling of objective with stochastic nature and optimized control parameters of two meta-heuristic algorithm like Particle swarm optimization and Artificial Bee colony optimization algorithm. The optimization process is performed with the newly developed Particle Bee Colony swarm algorithm followed by the comparison of the effectiveness of the proposed system with the state of art methods like LDOD, FO, RO, and MATO in terms of energy efficiency and spectral efficiency. The performance analysis proves that the proposed system overcomes the existing systems with 30.32% increase in the spectral efficiency and 73.25% increase in the energy efficiency.**

***Index Terms*—Energy efficiency, Spectral efficiency, Artificial Bee-colony, Heterogeneous Vehicular network, Particle swarm optimization**

I. Introduction

Recent advances in information technology have revolutionized the automotive and communications industry, paving the way for next-generation smart and connected vehicles. Emerging 5G networks, Internet of Vehicles (IoV) and adoption of Vehicle-to-Everything (V2X) connectivity has lead to an adoption of a Heterogeneous Vehicular Networks (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.) makes the resource management and the low latency communication requirements a significant challenge on the network power consumption [1]. This in turn will leads to series of critical problems such as greenhouse gas emission due to the increase energy consumption. 5G, a significant cellular technology aims to provide high throughput, large transmission bandwidth per user,huge capacity in accordance to the number of connected-devices and low latency. Heterogeneity which is supported in 5G Vision and broadcasted by 5G-PPP group, achieve high network performance [2]. However heterogeneity itself a complicated task for handling which cause network fragmentation and inefficiency in resource utilization. Further, transition from one radio access to other and 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 the spectral and energy efficiency. Particularly in case of dense HetVNets, determination of optimal path with short 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 Dedication Short Range Communication (DRSC)[5]. Despite mobile networks extensively covers 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 exists numerous studies on the cellular networks and DSRC, the integrated approach associated with the extraction of reliable outcomes still remains to be infancy. Resource management and the low latency communication requirements is a significant challenge on network power consumption. This in turn will leads to series of critical problems such as greenhouse gas emission due to the increase energy consumption. Building this kind of Heterogeneous Vehicular network needs in-depth analysis of heterogeneity and its challenges. Energy efficiency of the future communication systems has been associated with maximization problem and resource allocation problem [7].

Spectral efficiency defines the quantity of the transmitted data with less 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 user per second [8]. It has been stated that for effective usage, huge data has to be transferred over the spectrum. Spectral efficiency generally signifies the efficacy of digital modulation approach and decrease of 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 in decreasing the network operation cost. Hence this study focused on the joint optimization of spectral and energy efficiency scenarios. To overcome the prevailing limitation of the existing algorithm in improving the spectral efficiency and energy efficiency, the present study has made use of the integrated advantages of Artificial Bee colony algorithm and Particle swarm optimization to achieve certain objectives like strong flexibility, simplicity, robustness, handling of objective with stochastic nature and optimized control parameters.

This paper deals with the optimization of energy efficiency and spectral efficiency in a HetVNets environment with the newly developed Particle Bee colony swarm algorithm. The main contribution of this paper are as follows;

- To examine the spectral efficiency of the HetVNets in wireless communication system with the improved Particle Bee colony swarm algorithm.
- To investigate the energy efficiency of the HetVNets in wireless communication system with the improved Particle Bee colony swarm algorithm.
- To evaluate and to compare the improvised protocol with the state of art methods in terms of energy and spectral efficiency.

First section of this paper describes the introduction about the HetVNets and the importance of energy efficiency and spectral efficiency. Section 2 presents the related works in accordance to the proposed methodology. Section 3 covers on the proposed methodology and on the information about the overall architecture of the newly developed 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.

II. Related Works

This section present with the information about the methodologies, results and the challenges faced by the existing studies in accordance with the proposed methodology. Most of the conventional HetVNets adoption techniques seems to possess ineffective in real world scenarios due to low energy and spectral efficiency. To rectify this problem [9] suggested a game based approach for the selection of optimal parameters. The terminals trying to switch over with high evaluation has been framed as multi-play non cooperative system. The characteristics of HetVNets are accounted thoroughly for adjusting the game strategy thereby adapting stable vehicular platform with fast convergence. This model enable the drivers to avoid instability with a probabilistic system prototype. Similarly to resolve resource allocation in high mobile scenario, this paper [10] 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 constrains were transferred to deterministic constraints by approximation of non-central chi square distribution. A reliable framework for vehicular network has been suggested by [11] that comprise collaborative radio, real time cloud computing process, and centralized processing. The study stated that a low distortion compression is more essential for improving the resource utilization. This research also suggested that it could simplify the operational management and number of base stations. Hence there exists decreased power consumption in the support equipment. In relation to tasks offloading, Lyapunov based dynamic task offloading algorithm has been used to minimize the total network utility under the optimal offloading decisions by jointly considering packet drop rate and energy consumption [12], however the paper does not consider on spectral efficiency on mmWave. The paper did compared other algorithms of tasks offloading such as full-offloading (FO) algorithm, random offloading (RO) algorithm, and the mobility aware task offloading (MATO) algorithm. In the full offloading algorithm, all the flexible subtasks will be offloaded whereas in random offloading algorithm, vehicles randomly offload flexible subtasks to the server. MATO is proposed in [13] to offload parts of the tasks having condition that the offloading delay of the subtask is the same as the local execution delay, thereby, to minimize the total delay. Hence in all spectral efficiency has not been considered. Hence the below sections has carried out analysis on spectral and energy efficiency.

A. *Energy efficiency in Wireless communications*

Energy consumption for the accession of base station is considered as the major energy consuming aspect in HetVNets. To resolve the challenge, it is significant to begin with 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 optimisation issues. To solve this, two computationally inexpensive method, exploiting on alternating extension, GDS (Gradient Descent Search) and SFP (Sequential Fractional Programming) has been suggested. Particularly, one algorithm applies re-configurable intelligent surface (RIS) phase coefficients and gradient search to attain fractional programming for ideal allocation of transmit power. Alternatively, subsequent algorithm employs SFP to optimise RIS phase shifts. An accurate power consumption framework for systems based on RIS has also been presented. Performance of suggested techniques have 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 use of typical Multi-Antenna Amplify and Forward Relaying (MAAFR) [15]. In WSN (Wireless Sensor Network), it has been a challenging task to fulfil the requirements due to end-to-end delay due to duty-cycle chosen by nodes. This can results 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, DDC (Dynamic Duty Cycle) has been recommended to reduce the delay occurring in WSNs. Initially, the way in which duty cycle impacts network delay has been analysed. Subsequently, DDC method has been devised for extending the node's active period in areas having no hotspots. With more duty cycle, forwarding nodes stay awake with high probability. Thus, transmission delay and the node's sleep delay gets minimised. The node's remaining energy has been utilised for improving performance. Hence, DDC do not destruct the network lifetime. Analytical and Experiment outcomes revealed the outstanding performance of recommended scheme than traditional schemes. In comparison to traditional FDC (Fixed duty Cycle), lifetime gets extended by 16.7% and more. On the other hand, transmission delay of DDC gets minimised at a rate of 20 to 50%[16].

B. Spectral Efficiency in Wireless Communication

Joint clustering and RPC schemes has been endorsed to optimise SE and EE of HetVNets. Through fixed and identical length periods, SIC (Synchronised and Interference Constraints) corresponding to Cluster Heads (CHs) have been formed that affords specific conditions for RPC. All SICs of CHs have been framed as probability constrains due to repeated fluctuations in channel. Moreover, utility based on pricing has been recommended that averts separate optimisation amongst SE and EE and the impact of price on trade-off amongst them. Due to intractable probability constraints and non-convex unified utility, Bernstein approximation (BA) and Successive Convex Approximation (SCA) has been utilised for transforming the issue into tractable and convex form. Empirical simulations have also been employed to assess the algorithms' performance in dynamic systems. Further, comparison has been undertaken to validate the clustering technique and RPC scheme which confirmed its efficacy [17]. [18] investigated the performance of Vehicular ad-hoc network (VANET) as the cox process, here the dimensional layout of the roads are modelled by PLP (Poisson Line Process) and the positions of nodes for the each and every line are modelled as one dimensional PPP (Poisson Point Process). For this process, success probability and ASE (area spectral efficiency) of network assumed ALOHA as the channel of access scheme used. In this study the trends of success probability parameters and the optimum transmission probability for cox process model, which differs from 1 dimension and 2 dimensional PPP models used in the vehicular networks.[19] has deliberated the study on high spectral efficiency on dual non-orthogonal scheme with three major issues which are multi user access, private security and data rate with Internet of Things network. It focused on multiple access, spectrum resource pressure, security issues and bandwidth efficiency. In this study, The HSESA (high spectral-efficiency secure access) scheme based on dual non-orthogonal is implemented to resolve the issues. The scheme is the 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 the lower level of complexity. Efficiency of spectral has been enhanced with the proposed HSESA method as it gives better bit error rate performances (BERP).

C. Optimized algorithm for energy efficiency

[20] developed an algorithm called two stage energy-efficient resources allocation for the vehicular network process. The power controlled algorithm, auction-matching based joint-relay selection and spectrum allocation has 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. The convergence, stability, and complexity are analysed in this stage. 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 been achieved high performances in terms of network coverage and efficient energy utilisation compared to other existing algorithms.[21] has implemented Adaptive Weighted Clustering protocol (AWCP) to optimise the network parameters and to group the random nodes. The enhanced-whale optimisation algorithm (EWOA) has been developed to optimise the networks efficiency. The movement has been analysed with network mobility routing protocol on position and speed. The distance between trusted vehicle node and RSU has been analysed with proposed EWOA-AWCP method. Finally the result also stated that mobility and clustering efficiency has been enhanced with the developed model.

In accordance with the literature review, it was observed that both regular VN and HetVN selection techniques lacks considering the changing network efficiency particularly for the varying terminal number due to network selection [22]. This considerably cause reliability and stability problems in real time scenarios. Existing network selection methods may cause unexpected huge distraction in the network during the performance variations. Additionally, robustness of the system and reliability of the link does get impacted with the errors due to channel estimation occurring in high mobility HetVNet [10]. Generally the resource allocation issue comprise spectrum resource block and time slot variations. To overcome this [23] formulated average energy effectiveness by transforming the issue to tractable convex optimization issue with the modifications of different parameter. Because of the constrained computational capability and storage of the devices, conventional security methods face challenge in the process of data transmission. Large amount of energy are 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 particle Bee colony based swam algorithm.

III. Proposed Methodology

The overall architecture of the proposed diagram has been represented below. The system model is configured with the heterogeneous vehicular network. This study is addressing the issues in obtaining high spectral efficiency and energy efficiency by using the newly developed Particle Bee

Colony Swarm optimization algorithm. After initialization, possible selection of paths has been accomplished. The best agent path prediction by tour construction includes evaluated fitness values. After 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 best path was predicted through this mechanism followed by updated velocity and position of agents. If final iteration is not reached, the cycle has been reversed to selection of possible paths to reach iteration. After reaching final iteration, the performance analysis has been carried out to evaluate the spectral efficiency and energy efficiency. After reaching final iteration the performance analysis has been carried out to evaluate the spectral efficiency and energy efficiency.

Below flowchart is based on proposed Methodology

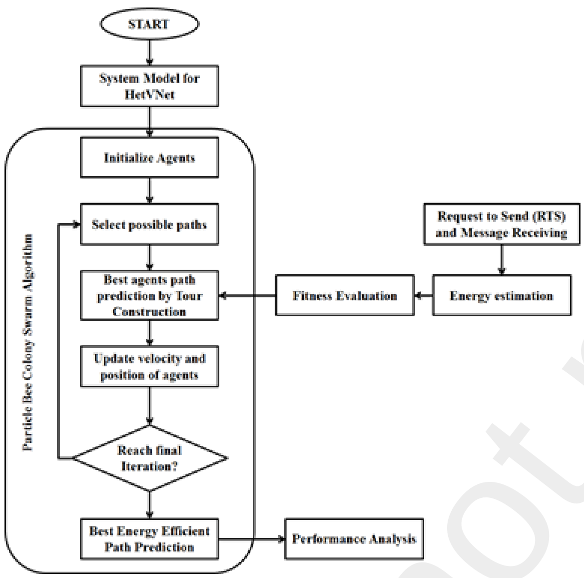

Fig. 1. Flowchart of proposed Methodology

A. System model

With salient features of agility, scalability, elasticity, re-programmability, and flexibility, the illustration of system model in HetV-Net in represented in figure 2. Figure 2 illustrate the proposed system model, which is designed as a three tier as well as a heterogeneous network with single BS (base station) in every tier. The information from the vehicles are transmitted through cellular based V2V communication to gNodeB (gNB), cellular based V2I and DSRC based V2V communication to the core network for improving the 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. Further, every BSs were presumed to operate in single frequency band, and hence the intra brand contiguous carrier aggregation was performed by utilizing adjacent carriers in frequency band. Later, the spacing between guard band calculations as well as adjacent carriers were obtained.

Below is the System Model.

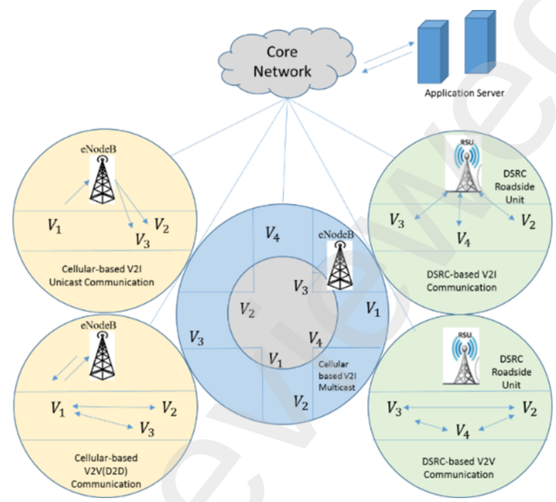

Fig. 2. System model

B. System Parameters

In this section, system parameters are comprehensively explained and presented. System parameters has been defined here that covers its technical specifications for 5G new radio. The calculation of diverse parameters needs to perform intra band contiguous carrier aggregation's physical layer simulation [26]. Moreover, the sub-carrier spacing (SCS) of a^{th} composite carriers could be computed as the following equation 1,

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

From the above equation 1, μ ranges between 1 and 4. And the sub-carrier numbers of a^{th} composite carriers is computed through the following equation 2,

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

From the above equation 2, NRB_a indicates the number of resources block for a^{th} composite carrier. Further, the bandwidth (BW) of a^{th} composite carrier is computed with equation 3 given below,

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

The guard band for a^{th} composite carrier is also computed and illustrated as the following equation,

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

The spacing between the adjacent composite carriers for intra band contiguous carrier aggregation is computed and it is represented as the following equation 5,

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

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

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

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

From the above equation 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 number of resource blocks of the last and first (CC) component carrier. The higher and lower edge frequencies (EF) were represented as the following equations 8 and 9,

$$EF_{a_{low}} = F_{c,a_{low}} - F0_{a_{low}} \quad (8)$$

$$EF_{a_{high}} = F_{c,a_{high}} - F0_{a_{high}} \quad (9)$$

From the above equations, F_{Ca} indicates the carrier frequency, whereas the high and low represents the maximum and minimum value amid every component carriers. The overall aggregated BW (Bandwidth) is represented as the following equation 10,

$$BW_{CA_i} = EF_{a_{high}} + EF_{a_{low}} \quad (10)$$

C. Channel Model

The down-link channel of every component carrier was modelled as TDL (Tapper delay line) 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 model are utilized for evaluating non-line of sight, whereas TDL E and TDL D could be utilised for evaluating line of sight. The TDL B and A possess 23 taps, in which 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 first tap follows Rician fading distribution, while others follows Rayleigh fading distribution. In this study, TDL A model has been selected, in which the channel was characterized by 23 taps as well as the Doppler spectrum of every tap has classical jake's spectrum shape. The SNR (signal to noise ratio) for every composite carrier is computed as the following equation,

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

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

D. Power consumption model

A power consumption model has been exploited in this work, in which the study considered the effectiveness of power amplifier, static and dynamic power consumption. Further, the total amount of power, required for the transmission of i^{th} carrier is represented as the following equation 12,

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

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

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 that indicates the number of bits transmitted by utilizing 1 joule of energy for a specific BW (Bandwidth). The channel capacity for a^{th} composite carrier is represented as the following equation 13,

$$C_a = BW_a * log_2(1 + \gamma_a) \quad (13)$$

Therefore, the overall capacity of C_{tot} of the system could be represented as the following equation 14,

$$C_{tot} = \sum_{a=1}^{n_{cc}} C_a \quad (14)$$

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

$$SE = \frac{C_{tot}}{BW_{CA}}(bits/s/hz) \quad (15)$$

Moreover, the energy efficiency is represented as the following equation 16,

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

E. 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 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 proposed model could be formulated as the following equations 17 and 18,

$$max : (SE, EE) \quad (17)$$

$$max : (f1, f2) \quad (18)$$

By utilizing penalty coefficient method, the above equation has been reformulated to for including constraints, and therefore it could be solved by utilizing Genetic algorithm,

$$\begin{cases} G_1 = \sum_{a=1}^{n_{cc}} P_D(a) - 0.2 * P_{max} \geq 0 \\ = 0.2 * P_{max} - \sum_{a=1}^{n_{cc}} P_D(a) \leq 0 \end{cases} \quad (19)$$

$$G_2 = \sum_{a=1}^{n_{cc}} P_D(a) - P_{max} \leq 0 \tag{20}$$

By utilizing quadratic loss function method, the total penalty could be modelled as the following equation 21,

$$P = r * (max(0, G_1)^2) + r * (max(0, G_2)^2) \tag{21}$$

From the above equation 19c, r indicates the penalty coefficient

$$f1 = -(\sum_{a=1}^{n_{cc}} C_a + P) \tag{22}$$

$$f2 = \sum_{a=1}^{n_{cc}} p_{tot}(i) + P \tag{23}$$

From the previous equation, the final optimization issue is represented as the following equation 24,

$$min : f1, f2 \tag{24}$$

F. Bee foraging learning PSO (BFL PSO) algorithm

The Particle swarm optimization algorithm utilizes a cluster of particles for searching better solution. In this algorithm, every particle has its own velocity and position, and also it could update itself by learning from global best well as personal best position. On other side, the ABC method implements three types of bees such as scout, onlooker and employed, which searches food sources and responsible for diverse tasks [27]. From the inspiration of ABC method, this study proposed a learning model, called BLF PSO (Bee foraging learning) method. Moreover, in this method, the population initializes N particles, in which every particle has own velocity v_a and position a, as well as P_{best_i} personal best position. Later, it enters to 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,

$$\begin{cases} v_a^{new} = \delta(v_a^{old}, x_a^{old}, p_{best_i}, g_{best_i}) \\ x_a^{new} = x_a^{old} + v_a^{new} \end{cases} \tag{25}$$

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

Onlooker learning

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

$$\begin{cases} fit(x_a) = \frac{1}{1+f(p_{best_i})}, iff(p_{best_i}) >= 0 \\ fit(x_a) = 1 + |f(p_{best_i}|, otherwise \end{cases} \tag{26}$$

The probability p_a for the selection of i^{th} particle is computed as the following equation,

$$P_a = fit(x_a) / \sum_{a=1}^{n} fit(x_a) \tag{27}$$

The particles were selected on the basis of probability pa by utilizing roulette method. Further, the particles which has better $p_b est_i$ can possibly be selected. When assuming if s^{th} particle x_a was selected, the equation 25 will be utilized for generating new position x_s^{new}. If this new position was better than $p_b est_s$, then the $p_b est_s$ will be replaced by x_s^{new}. Subsequently, for particles which fails to update its $p_b est_s$ (personal best position), their counter will be significantly increased, as well as, for the particles which finds better position, their counter gets reset.

Scout learning

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

G. 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,

$$\begin{cases} v_a^{new} = w.v_i^{old} + c.rand.(pbest_{\tau a} - x_a^{old}) \\ x_a^{new} = x_a^{old} + v_a^{new} \end{cases} \tag{28}$$

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 a^{th} 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 the lines 5 and 15, whereas the onlooker learning phase is represented between the lines 16 and 29. The scout learning phase is depicted between 30 and 32 lines.

Pseudocode 1: BFL PSO algorithm

Initialize N particles, including velocities v_a,positions x_a ,and personal best p_{besti} positions;
Evaluate the particle f(x_a), a=1,. . . ..,N;
Store the global best position g_{besta}
while the terminal condition is not satisfied do
– Employed learning –
for each index a=1→N do
Generate the learning exemplar index T_a by bio-geography-based exemplar generation
Update the velocity v_a and the position x_a using eq(25)
Evaluate the new position f(x_a^{new})
If x_a^{new} is better than $pbest_a$ then
$pbest_a$=x_a^{new} ,count(a)=0
ELSE
count(a)=count(a)+1;
endIf
endfor
– Onlooker learning –
Calculate the fitness values fit(x_a) for each particle x_a using Eq.(26)
Calculate the probability pa for each particle x_a using Eq.(27);
for each indexa=1→N do
Select a particle x_a using the roulette method based on the probability p_a
Generate the learning exemplar index τa by biogeography based exemplar generation
Update the velocity v_a and the position x_a using Eq.(28);
Evaluate the new position fit(x_a^{new})
If x_b^{new} is better than $pbest_b$ then
$pbest_b$=x_b^{new} ,count(b)=0
Else
count(b)=count(b)+1;
end if
end for
for each indexa=1→N do
if count(a) limit then
Reinitialize the particle randomly,including its position x_a ,velocity v_a ,and personal best position $pbest_a$

IV. RESULTS AND DISCUSSION

In this section, it compares and evaluate the results of the proposed work in detail with other methods like Lyapunov based dynamic offloading decision (LDOD) algorithm [12], Random offloading (RO), mobile aware task offloading (MATO) and full-offloading (FO) method [13].

A. Performance Metrics

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

$$P_{CKT} = N_t * P_R F + P_m + P_{ADC} \tag{29}$$

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 said to be the power consumption because of analog to digital conversion (ADC). Spectral efficiency In similar way, the spectral efficiency for the microwave vehicular networks can be represented as the following equation,

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

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

$$\eta_{ES,PS} = (\eta_{S,PS,m} + \eta_{S,PS,\mu})/(P_{T,m} + P_{T,\mu}) \tag{31}$$

B. Performance Analysis

TABLE I
SIMULATIONS PARAMETERS

Parameters	Values
V	30Km/h
P_{ADC}	α x Bandwidth, where α = 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	1m, 12m
Microwave band antenna gain	0 dBi
G_M, G_m, ϕ_M	18 dBi, -2dBi, 10
Number of lanes	4
2W, L	14.8m, 10km
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	28GHz
f_μ	2Ghz

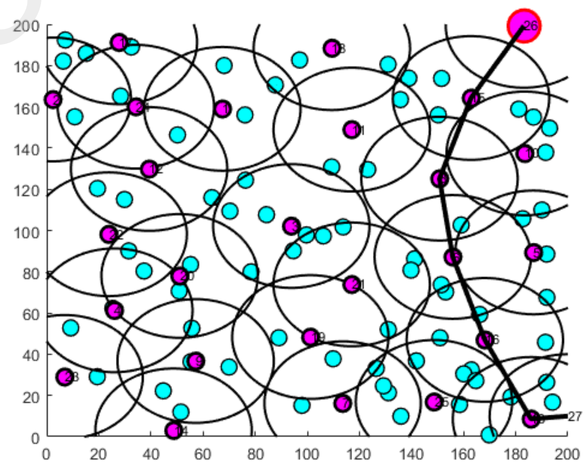

Fig. 3. Mode deployment and its selection using Bee foraging learning

The figure 3 represents the node deployment in heterogeneous vehicular communication platform. Figure 3 depicts the cluster formation at 100th iteration to determine the path. The figure 4 illustrates the spectral efficiency variation versus λ_m for hybrid vehicular as well as mmWave network. 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 similar trend for every configurations. Specifically, this trend seems to be similar to analysis of spectral efficiency under static vehicular nodes. The spectral efficiency significantly increases with λ_m, nevertheless after density threshold, the spectral efficiency will decrease. It is observed that, the spectral efficiency of hybrid vehicular network is higher than that of mmWave vehicular network.

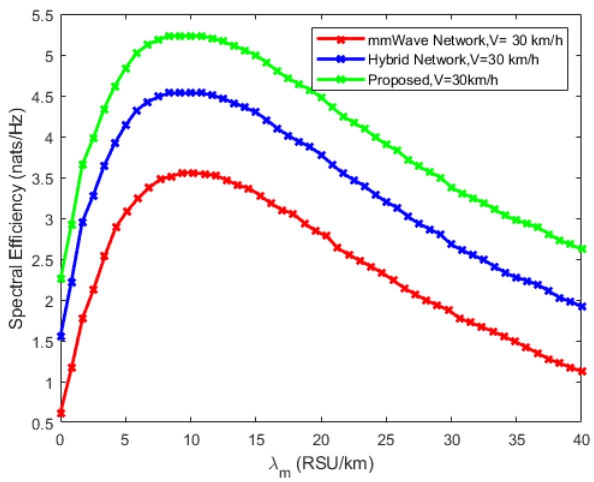

Fig. 4. Spectral efficiency Vs λ_m with Ts=0.1s of the proposed and existing method

Figure 5 depicted that the spectral efficiency significantly increases for T_s=0.1s, 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 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 proposed model could be transmitted over a particular bandwidth in heterogeneous network.

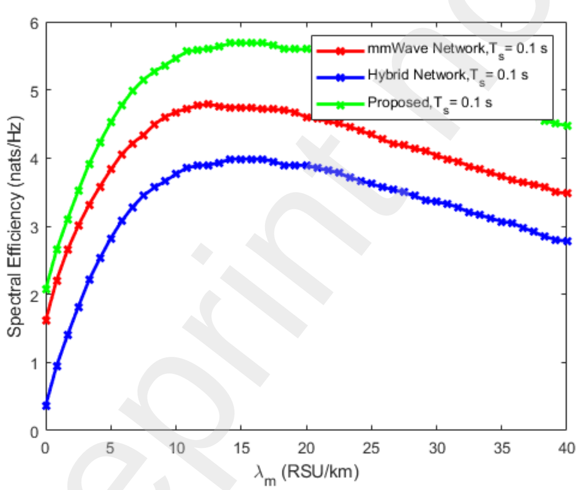

Fig. 5. Spectral efficiency Vs λ_m with Ts=0.1s of the proposed and existing method

The figure 6 depicts the energy efficiency (nats/Hz/Joule) Vs λ_m for proposed method and compared it with Hybrid network and mmWave network. It is observed that the proposed model has significantly high energy efficiency than mmWave and hybrid network because the proposed method was having higher spectral efficiency as demonstrated in the previous figure. Since the proposed method is energy efficient, there is very less power consumption.

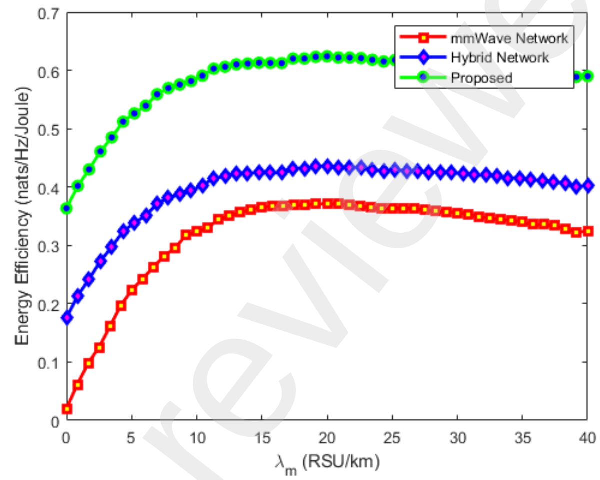

Fig. 6. Energy efficiency Vs control parameter V of the proposed and existing method

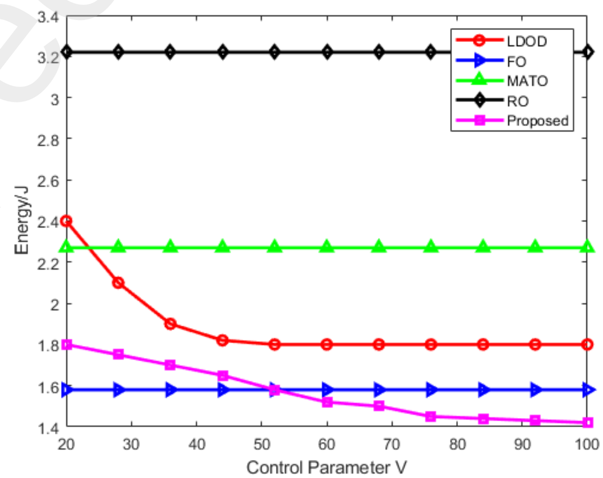

Fig. 7. Energy consumption Vs control parameter V of the proposed and existing method

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

V. Conclusion

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

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