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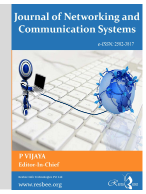

LgDOA: Advanced Dragonfly Optimization for Cross-Layer Virtual MIMO Architectures in WSNs

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Abstract: Wireless Sensor Networks (WSNs) are composed of many sensor nodes that communicate via wireless connections. Virtual MIMO (V-MIMO) improves the reliability of long-range transmissions in WSNs by enabling intermediate nodes to work together during data forwarding. While this collaborative approach enhances communication performance, it also introduces additional system complexity, increases energy usage and can cause greater transmission interference. To address these challenges, this work proposes a novel Levy guided Dragonfly Optimization model for Cross layer Virtual MIMO (LDO-CV-MIMO) systems that significantly enhances communication performance. Specifically, a multihop virtual MIMO communication protocol is developed to improve quality of service (QoS) and energy efficiency in WSNs. Throughput and latency are modeled based on the bit error rate (BER) performance of individual links. In addition, a Levy guided Dragonfly Optimization Algorithm (LgDOA) is employed to optimize the BER of each link while satisfying end-to-end (ETE) QoS requirements with minimal energy consumption. The LgDOA approach has surpassed the LA, PSO and DA methods to obtained lesser joule over energy consumption by 5.8× 10-3 J in 100 nodes and 5.7× 10-3 J in 400 nodes.

Keywords: Virtual MIMO, WSN, Bit Error Rate, Quality of Service, Energy Consumption, LgDOA

Nomenclature

Abbreviation	Description
ADV	Advertisement
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase-Shift Keying
BS	Base Station
CH	Cluster Head
CMIMO	Cooperative MIMO
C-MIMO	Cooperative MIMO
CN	Cluster Nodes
CSI	Channel State Information
DA	Dragonfly Algorithm
ETE	End-To-End
LA	Lion Algorithm
LDO-CV-MIMO	Levy guided Dragonfly Optimization model for Cross layer Virtual MIMO
LgDOA	Levy guided Dragonfly Optimization Algorithm
MIMO	Multiple-Input Multiple-Output
PAR	Packet Arrival Rate
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
QoS	Quality Of Service
RSS	Received Signal Strength
SISO	Single-Input Single-Output
SNR	Signal-To-Noise Ratio
SPT	Shortest Path Tree
STBC	Space-Time Block Codes
TCH	Target Cluster Head
V-MIMO	Virtual MIMO
WSN	Wireless Sensor Networks

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1. Introduction

Multi-antenna (MIMO) techniques can boost channel capacity that offers greater reliability and lower transmission energy than single-input single-output (SISO) systems for the same bit error rate (BER) at a given signal-to-noise ratio (SNR). Energy-efficient MIMO transmission is particularly valuable in wireless sensor networks (WSNs), where nodes must operate for extended periods without battery replacement that makes energy consumption a critical constraint [1].

Direct implementation of MIMO in WSNs is often unfeasible due to the restricted size of sensor nodes, which usually support only a single antenna. However, cooperative MIMO schemes allow multiple sensor nodes to collaborate in transmission and reception. This has motivated extensive research on power minimization strategies across different protocol layers including energy-efficient designs in modulation, coding and routing [2].

Cooperative MIMO (C-MIMO) leverages the energy-efficiency benefits of MIMO, which is particularly significant for long-range transmissions where transmission energy dominates total consumption. Applications such as intelligent transportation systems or agricultural area monitoring often require medium to long-range communication due to the large coverage areas of WSNs [3]. However, C-MIMO also introduces additional energy costs including increased circuit consumption at cooperative nodes, local cooperative data exchange and the extra energy required for more complex digital processing.

In a sensor network, nodes are organized into multiple clusters, where each consisting of a cluster head (CH) and several member nodes. Cluster members send their sensed data to the base station via the CH, which performs additional tasks compared to the members and thus consumes more energy that depletes its battery faster [4]. Cluster-based strategies often employ re-clustering and rotation of CH roles to balance energy consumption across the network. The schedule for cluster updates and the selection of cluster heads significantly affect the overall network lifetime; poor choices can lead to premature energy depletion of nodes [5]. Additionally, existing methods face challenges such as high message overhead and complexity during cluster formation and updates. Hence, this work proposes a novel Levy guided Dragonfly Optimization model for Cross layer Virtual MIMO (LDO-CV-MIMO) systems.

The main contribution of LDO-CV-MIMO system is as follows:

- Contributing the Levy guided Dragonfly Optimization Algorithm (LgDOA) to enhance BER performance by tuning while meeting QoS requirements with reduced energy consumption.

The rest of the section is structured as follows: Section 2 pinpoints features and challenges of extant work on Cross layer Virtual MIMO. Section 3 reveals the LDO-CV-MIMO system. Section 4 reveals the design protocol. Section 5 describes the requirements of QoS and energy consumption. Section 6 analysis the proposed approach and section 7 summarizes the proposed approach.

2. Literature Review

This section discusses the Cross-layer virtual MIMO architectures in WSNs that integrates cooperation across protocol layers to enhance energy efficiency and QoS by enabling coordinated multi-node transmission and reception.

In 2014, Dawei Gong *et al.,* [6] investigated a joint design approach by proposing a novel MAC protocol for clustered WSNs that leveraged both cooperative MIMO and multi-channel communication to enhance network performance. Sensor nodes were structured into clusters and each CH selected cooperative nodes to assist in forwarding or receiving data from neighboring clusters using cooperative MIMO techniques. In addition, a network-wide time organization mechanism was introduced to support the efficient operation of the proposed protocol.

In 2009, Irfan Ahamed *et al.,* [7] designed STBCs to achieve maximum diversity for a given number of transmit and receive antennas while maintaining low decoding complexity. In fading radio channels, STBCs necessitate less transmission energy than SISO techniques to achieve the similar BER. As a result, STBCs can be practically implemented in WSNs through CMIMO schemes. By considering STBCs, the antennas count at both the transmitter and receiver is selected according to the traffic load of each cluster.

In 2009, Marwan Krunz *et al.,* [8] introduced a modified clustering approach that reduces clustering overhead and message exchange costs by efficiently scheduling the clustering process. Clusters were formed based on the residual energy with energy-related parameters determining the auxiliary nodes, selection of CH and member nodes. The roles of CHs were dynamically rotated according to the current state of the nodes. To further minimize energy consumption, re-clustering was performed using an update cycle determined by a fuzzy inference system.

In 2006, Sudharman K. Jayaweera [9] proposed a novel limited-feedback user/antenna scheduling algorithm for MIMO-OFDM broadcast networks. Efficient spectrum utilization required users to provide

CSI feedback to the BS to enable optimal user and antenna scheduling. However, as the users count and subcarriers rises, the feedback overhead grows significantly that consumed valuable uplink bandwidth.

In 2012, Mehwish Nasim *et al.,* [10] presented an energy-efficient hierarchical cooperative clustering scheme for WSNs. The proposed approach enabled nodes to cooperate in forming clusters at different hierarchy levels that ensured minimal energy consumption, maximum coverage and a more balanced load distribution across the network. Network efficacy was further enhanced through CMIMO communication, which enhanced energy efficiency in large-scale WSN deployments. The proposed scheme was evaluated using TOSSIM and compared with existing CMIMO clustering schemes as well as traditional multihop SISO routing approaches.

3. System Model

In the proposed multihop virtual MIMO protocol architecture, data gathered by multiple source nodes is transmitted to a distant sink through multiple hops. During transmission, the sensor nodes are grouped into sN_c clusters. Each hop involves two main phases. In the first phase, the CH broadcasts the data to the cluster nodes (CNs) within its local cluster. Since these intra-cluster communications occur over short distances, they are modeled using an AWGN channel with power path loss. In the second phase, the CNs encode the received data and forward it to the CH of the next hop using orthogonal STBCs.

In this model, G denotes the CNs count participating in each transmission, H indicates the total count of hops, ∂_i represents the distance among a source cluster and the destination cluster or sink and $b\omega$ refers to the system bandwidth. BPSK modulation is employed as it offers efficient performance within the virtual MIMO framework [11].

Fig. 1 illustrates the overall flow of the proposed LDO-CV-MIMO model. In this framework, the output energy from the physical layer and the QoS metrics from the network layers and data link are subjected into the access system from which the relevant parameters are extracted. The parameters δ_b and δ_{bj} are then optimally adjusted using the proposed hybrid LgDOA strategy. Finally, the WSN is configured based on the optimized parameter values.

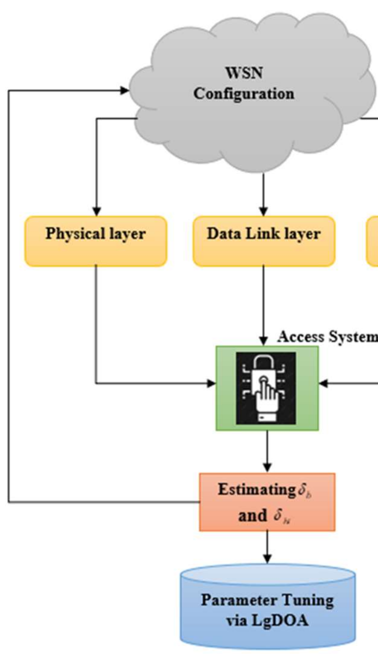

Fig. 1. *System Modelling of LDO-CV-MIMO*

3.1 Cooperative Node Selection Strategy

An effective strategy is required to select the CNs in order to augment the energy efficiency of single-hop communications between CHs. For BPSK modulation, the average energy consumed per transmitted bit using this strategy is given in Eq. (1).

$$\bar{E}_{Bt} = (1+P)\frac{\rho_0}{\frac{1}{\delta_b^G}}\sum_{j=1}^{G}\frac{(4\pi)^2}{A_t A_r \eta^2}L_1\rho_f + \frac{(GC_{ct}+\delta_{cr})}{b\omega} \tag{1}$$

where, P is the power amplifier efficiency, L_1 represents the link margin, A_t and A_r are the receiver and transmitter antenna gains, respectively, ρ_0 denotes the PSD, η is the signal wavelength, ρ_f is the receiver noise figure as well as δ_{ct} and δ_{cr} indicate the power consumption of the receive and transmit circuits, respectively.

Under the assumption of a symmetric channel, when node (τ) transmits a signal with power (δ_{out}), the received signal power at node (j) is denoted by ($\delta_{j\tau}$), is given in Eq. (2). Here, $A\left(\partial_{ij}, g_j\right) = \delta_{out} / \delta_{j\tau} = (4\pi)^2 \partial_{ij}^{g_j} L_1 \rho_f \Big/ A_t A_r \eta^2$. Consequently, Eq. (1) can be reformulated as shown in Eq. (3). Based on Eq. (3), the transmission power δ_{out} required for node j to communicate with the cluster head τ is given in Eq. (4).

$$\delta_{jt} = \delta_{out} \frac{A_t A_r \eta^2}{(4\pi)^2 \partial_{ij}^{k_j} L_1 \rho_f} = \frac{\delta_{out}}{A\left(\partial_{ij}, G_j\right)} \tag{2}$$

$$\bar{E}_{Bt} = (1+\gamma) \frac{\rho_0}{\delta_b^{\frac{1}{G}}} \sum_{j=1}^{\kappa} A\left(\partial_{ij}, G_j\right) + \frac{\left(G\delta_{ct} + \delta_{cr}\right)}{b\omega} \tag{3}$$

$$\delta_{out\ jt} = A\left(\partial_{ij}, G_j\right) \frac{\rho_0 b\omega}{\delta_b^{\frac{1}{G}}} \tag{4}$$

From Eq. (3), the average energy per bit $\bar{E}_{Bt}$ can be minimized by choosing an appropriate set of CNs with lower values of $A\left(\partial_{ij}, G_j\right)$. To achieve better energy balance among nodes, a selection metric is defined as $\beta_{j\tau} = \varepsilon_j \Big/ A\left(\partial_{ij}, G_j\right)$, where, ε_j denotes the remaining energy of node j. This metric favors nodes that require less transmission energy to communicate with the cluster head τ while also having higher residual energy. As a result, the G nodes with the largest $\beta_{j\tau}$ values are chosen as CNs for communication with CH τ.

4. Design Protocol

This work proposes a LDO-CV-MIMO protocol. The protocol operates in rounds and each round consists of three stages: “cluster formation, routing and transmission”.

Phase1- Cluster Formation: During this phase, each node assesses its remaining energy to determine whether it should act as a CH. After the CHs are selected, each CH broadcasts an ADV message containing its ID by δ_{out} using a temporary CSMA-based MAC protocol. When a CH accepts an ADV message from alternative CH with a RSS above a predefined threshold (τhr), it records the sender’s ID and identifies that CH as a neighboring node.

Once the clusters are formed, each CH selects an optimal set of G CNs to participate in CMIMO transmissions with all neighboring CHs.

Phase 2- Routing: The proposed protocol adopts a distance-vector routing scheme to construct routing tables. Each CH keeps a routing table containing the next-hop cluster, IDs of the destination cluster, the average energy consumption per bit and the CNs. Initially, the routing table includes only entries corresponding to directly neighboring CHs.

Each CH then exchanges its routing table with neighboring CHs. Upon receiving routing ADV from adjacent clusters, a CH updates its table according to the associated routing costs and notifies its neighbors of any changes. Through multiple rounds of information exchange and updates, the routing tables at all CHs gradually converge to a complete and optimized state.

Phase 3- Data Transmission: In this phase, cluster members conduct data to the CH over several frames that is followed by a TDMA schedule for each frame. The number of frames sent to the CH per time slot and the duration of each frame are roughly the same across all clusters. Once the CH receives the data frames, it performs data aggregation to remove redundancy. After aggregating the data, the CH forwards the resulting packets to the TCH.

5. QoS and Energy Consumption

5.1 QoS

The average time required to transmit a packet that is represented by $\tau_f = qQ/b\omega(d - pG)$. Consequently, the throughput can be expressed as in Eq. (5).

$$A = \frac{1-\delta_w(\delta_b)}{\tau_f} \tag{5}$$

Performance of QoS: It is modeled based on the BER performance of each link in the SPT. Moreover, the PAR is then given by Eq. (6).

$$\eta_i = \begin{cases} \eta_c, \ (i \in M_s) \\ \sum_{j \in \rho_{si}} \mu_j(\delta_{bj})\Big(1-\delta_0\big(\mu_j(\delta_{bj}),\eta_j\big)\Big) + \eta_c, \ (i \in M_r) \end{cases} \tag{6}$$

where, η_c represents the intra-cluster PAR, M_s denotes the set of child CHs in the SPT and $\mu_j(\delta_{bj}) = \big(1-\delta_w(\delta_{bj})/\tau_f\big)$. For simplicity, η_c is assumed to be the same across all clusters.

Let ${}^{Lt}\xi_j$ represent the route from CH j to the sink in the SPT. The ETE latency and throughput for CH j are given by Eq. (7) and (8), respectively. The average ETE latency and throughput for the entire network are presented in Eq. (9) and (10), respectively. Finally, Eq. (11) represents the total energy consumption of all CHs.

$$\tau hr_j = \prod_{i \in J_j} \Big(1-\delta_\rho\big(\mu_i(\delta_{bi}),\eta_i\big)\Big) \tag{7}$$

$${}^{Lt}\xi_j = \sum_{i \in J_j} \psi\big(\mu_i(\delta_{bi}),\eta_i\big) \tag{8}$$

$$\tau hr\big(\{\delta_{bj}\}\big) = \frac{\sum_{j \in M_s \cup M_r} \eta_j \tau hr_k}{\sum_{j \in M_s \cup M_r} \eta_j} \tag{9}$$

$${}^{Lt}\xi\big(\{\delta_{bj}\}\big) = \frac{\sum_{j \in M_s \cup M_r} \eta_j {}^{Lt}\xi_j}{\sum_{j \in \rho_s \cup \rho_r} \eta_j} \tag{10}$$

$$\bar{E}_{overall} = \sum_{j \in M_s \cup M_r} \frac{1}{1-\delta_w(\delta_{bj})} \times \Big[\bar{E}_{code} + \bar{E}_0(\partial_{i0},G) + \bar{E}_1(\delta_{bj},\partial_{ij},G)\Big] \tag{11}$$

5.2 Energy Consumption

The energy consumed per packet transmission $\bar{E}$ at each hop is primarily due to the decoding and encoding operations. Under the assumption of an AWGN channel with squared power path loss, this energy consumption is expressed in Eq. (12).

$$\bar{E}_0(\partial_0,G) = qr\partial_{i0}^2 + \frac{q\delta_{ct}}{b\omega} + \frac{qG\delta_{cr}}{b\omega} \tag{12}$$

where ∂_{i_0} represents the transmission distance within the local cluster and r is a constant determined by the circuit model.

Let the STBC code have a block size of (Q) symbols with pG training symbols included in each block. Additionally, variations in (∂_{ij}, k_j) for the CNs are considered negligible as inter-cluster distances are much larger than intra-cluster distances. Consequently, the energy consumption ($\bar{E}$) in the j^{th} hop is modeled as shown in Eq. (13), where ∂_{ihj} represents the inter-cluster distance of the j^{th} hop. Based on this analysis, $\bar{E}$ for the j^{th} hop is formulated as in Eq. (14).

$$\bar{E}_1(\delta_b,\partial_{ihj},G) = \frac{qQ}{Q-pG}\left(\frac{G\rho_0}{\delta_b} A(\partial_{ij},k_j) + \frac{G\delta_{ct}+\delta_{cr}}{b\omega}\right) \tag{13}$$

$$\bar{E}_h(j) = \bar{E}_{code} + \bar{E}_0(\partial_{i0},G) + \bar{E}_1(\delta_b,\partial_{ihj},G) \tag{14}$$

Total Energy Consumption: When modeling the overall energy consumption per packet transmission, the average transmission interval must be considered [12]. The word error probability for a linear block code (q,z,τ) is calculated using Eq. (15).

$$\delta_w(\delta_b) = \sum_{i=t+1}^{q} \binom{q}{i} \delta_b^i (1-\delta_b)^{(q-i)} \tag{15}$$

Therefore, the average transmission interval for each hop can be expressed as $(1-\delta_w(\delta_b))$. The overall energy consumption ($\bar{E}_{overall}$) is then specified by Eq. (16). In fact, δ_b affects both the transmission time per interval and the average energy consumption and it must be optimized to lessen the entire energy usage.

$$\bar{E}_{overall}=\frac{1}{\left[1-\delta_w\left(\delta_b\right)\right]}\times\left\{H\left[\bar{E}_{code}+\bar{E}_0\left(\partial_{i0},G\right)\right]+\sum_{j=1}^{H}\bar{E}_1\left(\delta_b,\partial_{ihj},G\right)\right\} \tag{16}$$

5.3 Levy guided Dragonfly Optimization Algorithm (LgDOA)

Dragonflies are small predators that feed on nearly all other small insects in nature. The Dragonfly Algorithm (DA) [13] is inspired by their dynamic and static swarming behaviors. In the exploration phase, dragonflies form sub-swarms as well as move across different areas that mimics the search for new solutions. In contrast, during the exploitation phase, they fly in larger swarms along a single direction that reflects the refinement of solutions in a promising region. However, balancing exploitation and exploration phase is a critical issue. To address this, a Levy guided Dragonfly Optimization Algorithm (LgDOA) has been proposed that balances this both phases and provide better convergence.

5.3.1 Solution Encoding and Objective Function

During the optimization process, the LgDOA procedure takes δ_b and δ_{bj} as input parameters. The fitness function is defined in Eq. (17) and Eq. (18), where $\bar{E}$ represents the energy consumption and ${}^{Lt}\xi$ denotes latency.

$$Ofn_1=\min\left(\bar{E}\right) \tag{17}$$

$$Ofn_2=Desired\left({}^{Lt}\xi\right) \tag{18}$$

5.3.2 Mathematical Modelling

The primary goal of any swarm is survival so that individuals are naturally attracted to food sources while avoiding external threats. Based on these behaviors, five main factors influence how individuals update their positions within the swarm. Each of these behaviors can be represented mathematically. For instance, the separation behavior is calculated as in Eq. (19). The alignment behavior is calculated as in Eq. (20).

$$\varsigma_i=-\Sigma_{j=1}^{N}D-D_j \tag{19}$$

$$Ag_i=\frac{\Sigma_{j=1}^{N}Vl_j}{N} \tag{20}$$

Here, D_j denotes the position of the j^{th} neighboring individual, D represents the position of the current individual, N is the total neighbors count and Vl_j represents the velocity of the j^{th} neighboring individual. The cohesion behavior is calculated as in Eq. (21) and the attraction toward a food source is designed as in Eq. (22).

$$Ch_i=\frac{\Sigma_{j=1}^{N}D_j}{N}-D \tag{21}$$

$$AtF_i=D^{+}-D \tag{22}$$

In this case, N is the neighbors count, D denotes the position of the current individual, D_j represents the position of the j^{th} neighboring individual and D^{+} denotes the position of the food source.

The repulsion or distraction away from an enemy is calculated as in Eq. (23).

$$Dst_i=D^{-}+D \tag{23}$$

Here, D^{-} denotes the enemy position.

In this paper, dragonfly behavior is modeled as a combination of the five corrective patterns. To simulate movement in the search space, each artificial dragonfly has a position vector (D) and a step vector (ΔD). The step vector indicates the movement direction and is defined as in Eq. (24). Although the model is described in one dimension and it can be extended to higher dimensions.

$$\Delta D_{t+1}=\left(s\varsigma_i+aAg_i+cCh_i+fAtF_i+eDst_i\right)+w\Delta D_t \tag{24}$$

Here, a is the alignment weight and Ag_i is the alignment of the i^{th} individual; s represents the separation weight and ς_i is the separation of the i^{th} individual; c is the cohesion weight and Ch_i is the cohesion of the i^{th} individual; e is the enemy factor and Dst_i is the position of the enemy relative to the i^{th}

individual; f is the food factor and AtF_i denotes the food source for the i^{th} individual; t is the iteration number and w is the inertia weight.

In order to obtain better convergence, the Eq. (24) is need to be proposed using "Levy guided adaptive weight calculation" for (s,a,c,f,e) as given in Eq. (25) through Eq. (29).

$$s_{new}(t) = s_{\max}\left(1-\frac{t}{T}\right)+\lambda_s\left|Lvy(t)\right| \tag{25}$$

$$a_{new}(t) = a_{\max}\left(1-\frac{t}{T}\right)+\lambda_a\left|Lvy(t)\right| \tag{26}$$

$$c_{new}(t) = c_{\max}\left(1-\frac{t}{T}\right)+\lambda_c\left|Lvy(t)\right| \tag{27}$$

$$f_{new}(t) = f_{\max}\left(\frac{t}{T}\right)+\lambda_f\left|Lvy(t)\right| \tag{28}$$

$$e_{new}(t) = e_{\max}\left(1-\frac{t}{T}\right)+\lambda_e\left|Lvy(t)\right| \tag{29}$$

Here, $s_{\max}=0.2$, $\lambda_s=0.03$, $a_{\max}=0.2$, $\lambda_a=0.03$, $c_{\max}=0.2$, $\lambda_c=0.03$, $f_{\max}=2$, $\lambda_f=0.05$, $e_{\max}=0.1$, $\lambda_e=0.02$, T denotes total maximum iteration and Levy flight $Lvy(t)$ is formulated as in Eq. (30).

$$Lvy(t)=\frac{m}{|u|^{\frac{1}{\vartheta}}} \tag{30}$$

where, $m \sim N\left(0,\sigma^2\right)$, $u \sim N(0,1)$ and $\vartheta = 1.5$.

Once the step vector is determined, the position vectors are updated as in Eq. (31).

$$D_{t+1}=D_t+\Delta D_{t+1} \tag{31}$$

Neighbors play a key role so that a neighborhood represented as a sphere in 3D, a circle in 2D or a hypersphere in nD and it is defined around each artificial dragonfly.

One may ask how dragonflies converge during optimization. Their weights are adaptively adjusted to transition from exploration to exploitation. As the process progresses, the neighborhood radius increases that allows the swarm to merge into a single group that converges toward the global optimum. This can helps to guide the swarm toward promising regions and away from less promising areas.

To enhance stochastic behavior, randomness and exploration, artificial dragonflies perform a random walk when no neighboring solutions are available. The position of the dragonflies is updated using Eq. (32).

$$D_{t+1}=D_t+Ly(\partial)\times D_t \tag{32}$$

Here, D denotes position vectors' dimension and t indicates current iteration. The Levy flight is estimated using Eq. (33).

$$Ly(z)=0.001\times\frac{\gamma_1\times\sigma}{|\gamma_2|^{\frac{1}{\alpha}}} \tag{33}$$

where, α specifies constant equal to 1.5; γ_1,γ_2 represents arbitrary numbers in [0, 1] and σ is estimated as in Eq. (34). Here, $\Gamma(z)=(z-1)!$.

$$\sigma=\left(\frac{\Gamma(1+\alpha)\times\sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right)\times\alpha\times 2^{\left(\frac{\alpha-1}{2}\right)}}\right)^{\frac{1}{\alpha}} \tag{34}$$

The pseudo code of LgDOA is given in **Algorithm 1**.

Algorithm 1: Pseudo code of LgDOA

Initialize: Dragonfly population $D_i\,(i=1,2,...,n)\rightarrow\delta_b$ and δ_{bj}

Initialize: Step Vector $\Delta D_i\,(i=1,2,...,n)$

while condition is not satisfied
    Compute fitness values for all dragonflies.
    Update enemy and food source
    Update (s,a,c,f,e)
    Compute (s,a,c,f,e) using Eq. (19) to Eq. (23)

Proposed Estimation of $(s_{new}, a_{new}, c_{new}, f_{new}, e_{new})$ using Eq. (25) through Eq. (29).
Update radius of neighbor
if a dragonfly has at least one neighboring dragonfly
    Change velocity vector as in Eq. (24)
    Change position vector as in Eq. (31)
else
    Change position vector as in Eq. (32)
end if
Check and adjust the new positions to ensure they remain within the variable boundaries.
end while

6. Results and Discussion

6.1 Simulation procedure

The proposed model for virtual MIMO-based CHS was designed in MATLAB and their corresponding results were obtained. The performance of proposed scheme is compared over the traditional methods such as LA, PSO and DA in terms of desired latency and energy consumption. Further the evaluation was carried by varying the nodes from 100, 200, 300 and 400.

6.2 Analysis on the objective function

The following section outlines the comparative analysis of proposed methods and baseline methods namely LA, PSO, DA over 100 to 400 nodes with respects to latency and energy consumption. Among this analysis, the ranges should be minimal to prove their betterment. Regarded to latency analysis (Fig. 2), the DA scheme has attained desired latency at 2nd iteration by 0.0139 s, 26th iteration by 0.0137 and followed by PSO has desired latency at 1st iteration and 25th iterations under 100 nodes (Fig. 2(i)). Likewise in 200 nodes, the PSO and DA has reached latency by 0.01375 s, 0.01376 s in 50th iterations (Fig. 2(ii)). But the LgDOA scheme has proven their better capability than the LA, PSO and DA among the 100 nodes and 200 nodes by minimal desired latency at 4th iteration and 7th iteration. Further the analysis with aspects to 300 nodes & 400 nodes is described in Fig. 2(iii) & Fig. 2(iv) respectively.

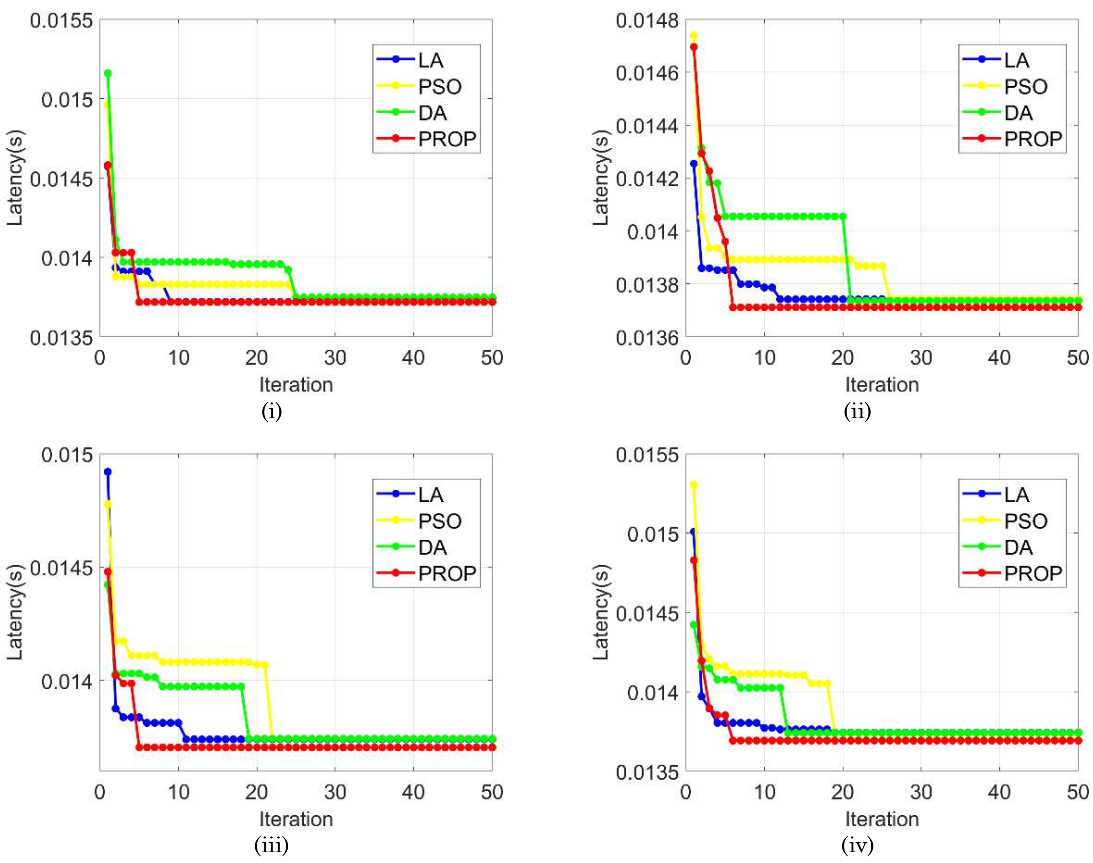

Fig. 2. *Latency analysis among proposed LgDOA versus conventional optimization (i) Under 100 nodes (ii) Under 200 nodes (iii) Under 300 nodes (iv) Under 400 nodes*

Furthermore, the analysis under energy consumption stated that the deployed LgDOA optimization method has yielded lesser energy than the baseline LA, PSO and DA methods (Fig. 3). Notably in 100 nodes, the LA scheme has gained higher energy consumption by 6.4× 10^{-3} J in 0^{th} iteration to 1^{st} iteration and decreased over the iterations to reached by around 6.1× 10^{-3} J to 6.2× 10^{-3} J in 50^{th} iterations. In 200 nodes, they exhibited maximal ranges over 0^{th} to 50h iteration by nearly 6.08× 10^{-3} J to 6.18× 10^{-3} J. The LgDOA method has surpassed the LA, PSO and DA methods to obtained lesser joule over energy consumption by 5.8× 10^{-3} J in 100 nodes, 5.79× 10^{-3} J in 200 nodes, 5.77 × 10^{-3}J in 300 nodes and 5.7× 10^{-3} J in 400 nodes to proven their capability.

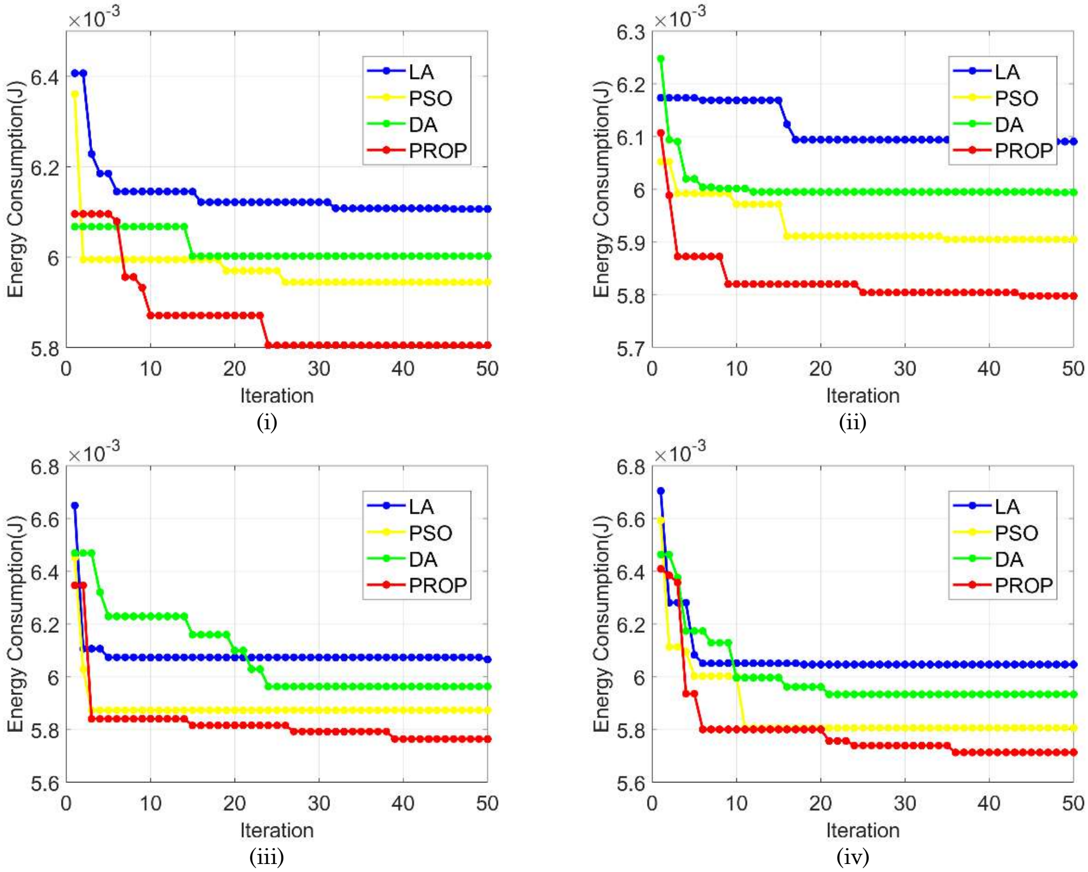

Fig. 3. *Energy consumption analysis of proposed LgDOA versus conventional optimization (i) Under 100 nodes (ii) Under 200 nodes (iii) Under 300 nodes (iv) Under 400 nodes*

7 Conclusion

This work proposed a novel Levy guided Dragonfly Optimization model for Cross layer Virtual MIMO (LDO-CV-MIMO) systems that significantly enhanced communication performance. Specifically, a multihop virtual MIMO communication protocol based on a cross-layer design was developed to improve QoS and energy efficiency in WSNs. Throughput and latency were modeled based on the BER performance of individual links. In addition, LgDOA was employed to optimize the BER of each link while satisfying end-to-end QoS requirements with minimal energy consumption. The LgDOA approach has attained minimal latency levels among 100 and 200 nodes.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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