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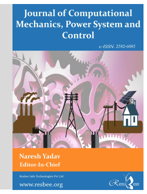

A Two-Stage Levy Jump based Bird Swarm Optimization for Latency Aware Cross-Layer Virtual MIMO Design for WSNs

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Abstract: Cross-layer design combined with cooperative virtual MIMO techniques has emerged as an effective method for enhancing the performance of wireless sensor networks (WSNs). An adaptive virtual MIMO-based cross-layer technique is proposed for multihop WSNs with minimizing the end-to-end latency. This method mainly focusses on the latency that enables improved quality-of-service (QoS) enhancement for delay-sensitive applications. To obtain this enhancement, optimized link-level bit error rate (BER) performance using a Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO) algorithm in Adaptive Virtual MIMO-Based Wireless Sensor Networks is proposed in this paper. The proposed TSLJ-BSO enhances the traditional bird swarm behavior by incorporating a two-stage Levy jump mechanism that improves the global exploration in the initial stage and accelerates convergence. Then, the transmission parameters through the physical and MAC layers are adaptively tuned to minimalize latency while satisfying the reliable link-level BER requirements. Extensive simulation outcomes shows that the proposed TSLJ-BSO based cross-layer design significantly superior than the conventional existing optimization based virtual MIMO schemes in terms of end-to-end latency and validates its suitability for delay-critical WSN applications.

Keywords: Wireless Sensor Network, MIMO, Self-Improved Bird Swarm Optimization, Clustering, Bit Error Rate (BER), Latency

Nomenclature

Abbreviation	Description
ADCPM	Angle-Delay Channel Power Matrix
AWGN	Additive White Gaussian Noise
BSUM	Block Successive Upper-Bound Method
CH	Cluster Head
CKMC	Coding-Aided K-Means Clustering
CMIMO	Cooperative MIMO
Cns	Cooperative Nodes
DSC	Distributed Source Coding
EE	Energy Efficiency
ITS	Intelligent Transportation Systems
MAC	Medium Access Control
MIMO	Multiple-Input Multiple-Output
OFDM	Orthogonal Frequency-Division Multiplexing
PSO	Particle Swarm Optimization
QoS	Quality-Of-Service
SOCP	Second-Order Cone Programming
SSK	Space Shift Keying
STBC	Space-Time Block Codes
TSLJ-BSO	Two-Stage Levy Jump Based Bird Swarm Optimization
V-MIMO	Virtual Multiple-Input Multiple-Output
WKNN	Weighted K-Nearest Neighbor
WSN	Wireless Sensor Network

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1. Introduction

In the Wireless Sensor Networks (WSNs), many sensor nodes are equipped with sensing, processing and communication components that designed to detect and report on the targeted measures. One of the major challenges faced in these sensor nodes are energy efficiency that are typically low-cost, resource-constrained and have limited processing and energy abilities. So, the WSNs frequently utilized hierarchical clustering to address these constraints, where clusters of nodes are report to a Cluster Head (CH). This CH aggregates the data from the sensor node to avoid the redundancy and reduce the communication overhead to the Base Station (BS), thus extending the network lifetime [1]

Despite these approaches, the conventional single-node transmission methods for long-range communication are often variable in WSNs as a result of signal fading, harsh network conditions and energy restrictions [2]. Cooperative communication methods like virtual Multiple-Input Multiple-Output (V-MIMO) have been introduced to improves the reliability and energy efficiency. V-MIMO enables the multiple sensor nodes to transmit collaboratively, which exploit spatial diversity to enhance the communication robustness as well as energy efficiency while maintaining an adequate throughput [3] [4]. The deployment of V-MIMO across the large WSNs faces considerable computational challenges and the process of optimizing transmission parameters being complex as well as resource-demanding [5].

To address these challenges, an adaptive cross-layer designs have been explored, which integrated physical as well as MAC layer parameters to optimize the network performance efficiently. In this structure, intelligent optimization algorithms are essential for tuning transmission parameters through nodes while balancing the reliability, latency and energy efficiency. Based on these considerations, this research proposes an adaptive virtual MIMO cross-layer framework for latency minimization in WSN via TSLJ-BSO. Its primary contributions are proposing an adaptive virtual MIMO-based cross-layer model for multihop WSNs with end-to-end latency as the optimization objective. Optimized the Link-level BER by utilizing a Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO) with a two-stage Levy jump process to enhance the mid-stage convergence. This optimizer adaptively tuned the transmission parameters through layers, which obtained faster convergence and significantly reduced the latency.

After the introduction, the literature review provides in section 2, Proposed system modelling and the protocol design are explained in Section 3. Energy consumption and QoS enhancement are presented in Section 4. Section 5 and Section 6 provides the results and summary of this proposed work.

2. Literature Review

For energy-efficient and reliable communication in WSNs, a review of previous researchers highlights numerous methods. It contains hierarchical clustering, optimization-based cross-layer designs and virtual MIMO techniques, which are reviewed as follows:

In 2018, Yang Liu and Jing Li [6] introduced a new model for linear precoder design in multi-antenna WSNs to optimize the EE, throughput and power consumption. For throughput enlargement, both a centralized algorithm and decentralized algorithm were developed based on a novel SOCP formulation and high efficiency as well as provable convergence, which addresses the drawbacks of the existing fully centralized solutions. Moreover, for power consumption and EE optimization, a decentralized algorithm utilized dual decomposition. Then, proposed the BSUM with careful treatment of initialization, convergence and sufficient conditions for robust duality. Also, extensive numerical outcomes were provided to validate the effectiveness and robustness of the proposed methods through different network systems.

In 2015, Na Li et al., [7] introduced a new data transmission scheme named as DSC-MIMO, which integrated distributed source coding with V-MIMO for WSNs. It enhances the energy efficiency by compressing the correlated source data before transmission that reduces the data length as well as transmission cost. This proposed DSC-MIMO scheme removes the requirement for CHs to gather and forward source data, which saves additional energy. Form the cooperative groups, source nodes directly transmit the data and the multihop V-MIMO supported through the inter-cluster cooperation. Also, introduced an efficient cooperative group allocation algorithm to optimize the communication performance in small and large-scale WSNs. Experimental outcomes display the DSC-MIMO scheme significantly reduces the energy consumption and superior CMIMO in the whole energy efficiency.

In 2018, Sanjeev Sharma et al., [8] proposed an IR-UWB based WSN that utilized massive antenna arrays at the fusion center for the distributed detection. It analyses the coherent and energy-based fusion rules over the multiple access channels, which highlighted the trade-off among the detection performance as well as implementation complexity. The coherent detection obtained the optimal performance and the energy-based detection was preferred due to its lower computational complexity. Using the massive antenna arrays significantly reduces the noise in energy-based fusion, which enable the reliable detection at very low SNR levels. The proposed low-power UWB system was suitable for the precise localization and various 5G-enabled IoT applications such as indoor and short-range circumstances.

In 2015, Han-Wen Liang et al., [9] introduced a CKMC blind transceiver for SSK MIMO systems, which operates without the channel state information. It is well suited for the IoT and WSNs, where the transmitters had limited power as well as processing capability and maintaining spectral efficiency and high energy. CKMC eliminates the training overhead by converting blind detection into clustering and permutation issues. Then, introduced a K-Means Clustering detector to reduce the detection complexity and obtained de-permutation with help of channel coding. To guide system design, analytical error rate expressions were derived, which includes the essential number of random initializations. Moreover, comparisons with training and optimal based detectors validated the spectral efficiency gains achieved by the CKMC scheme.

In 2018, Xiaoyu Sun et al., [10] developed a fingerprint based single-site localization technique for massive MIMO-OFDM systems in rich scattering atmospheres. A new ADCPM fingerprint was extracted from instant CSI by exploiting the high angle as well as delay resolution of massive MIMO. It does not involve extra signal transmission and captures the wide-sense stationary channel features. To accurately measure the distance between fingerprints, a novel fingerprint similarity criterion was introduced. Fingerprint compression and a two-stage clustering preprocessing algorithm are developed to reduce the storage requirements as well as matching complexity. Also, proposed an improved WKNN-based location estimation method to improve the positioning accuracy with limited reference points. Numerical outcomes verified that the proposed approach obtained high localization accuracy and effectual system performance

3. Proposing System Model and Protocol Design

The proposed multihop virtual MIMO model contains multiple source nodes that transmitted data into a remote sink over several hops. Here, the sensor nodes are organized into $G_{\mathbb{C}}$ clusters. Then, the transmission in each hop is splitted into two stages such as Intra-cluster transmission and Inter-cluster transmission

- ***Intra-cluster transmission:*** CHs transmit the data into cooperative nodes (Cns) in the same cluster. Due to the short-range, assumed an additive white Gaussian noise (AWGN) channel with path loss.
- ***Inter-cluster transmission:*** Cns encode the data and forward it into the CH in the subsequent hop via orthogonal space-time block codes (STBCs). Then, the Rayleigh fading with Gth power path loss is considered.

Let M be the number of Cns, $\hat{D}_i$ signifies the distance among the source and target Clusters, $\mathbb{N}$ implies the number of hops and B_W specifies the channel bandwidth. BPSK remains adopted as the modulation scheme due to its efficiency in virtual MIMO systems [11].

3.1 Selection of Cooperative Nodes (Cns)

The Cns Selection is critical for diminishing the energy consumption in a single-hop communications. By using BPSK, the average energy per transmitted bit is modelled as per Eq. (1), wherein, L_1 specifies the link margin, ν signifies the power amplifier efficiency, P_f denotes the receiver noise, A_T and A_R implies the transmitter and the receiver antenna gain, $\hat{\lambda}$ implies the wave length, $\mathbb{Z}_{CT}$ and $\mathbb{Z}_{CR}$ implies the transmit and the receiver circuit power usage.

$$\mathbb{Q}_{bt} = (1+\nu)\frac{P_0}{\frac{1}{\mathbb{Z}_b^l}} \sum_{j=1}^{l} \frac{(4\pi)^2}{A_T A_R \hat{\lambda}^2} L_1 P_f + \frac{(l\mathbb{Z}_{CT} + \mathbb{Z}_{CR})}{B_W} \tag{1}$$

Then, the average channel attenuation for node j is evaluated as follows: Now consider the channel and k transmitted through transmission power signal, $\mathbb{Z}_{out}$ and the received signal power $\mathbb{Z}_{jt}$ is expressed as Eq. (2). In this equation, $A(\hat{D}_{ij}, l_j)$ is evaluated in Eq. (3), the modified average energy per transmitted bit is evaluated in Eq. (4) and $\mathbb{Z}_{out\,jt}$ is calculated in Eq. (5), which is interact with CH.

$$\mathbb{Z}_{jt} = \mathbb{Z}_{out} \frac{A_T A_R \lambda^2}{(4\pi)^2 \hat{D}_{Ij}^{l_j} L_1 P_f} = \frac{\mathbb{Z}_{out}}{A(\hat{D}_{ij}, l_j)} \tag{2}$$

$$A(\hat{D}_{ij}, l_j) = \mathbb{Z}_{out} / \mathbb{Z}_{jt} = (4\pi)^2 \hat{D}_{ij}^{l_j} L_1 P_f \Big/ A_T A_R \hat{\lambda}^2 \tag{3}$$

$$\mathbb{Q}_{bt} = (1+\nu)\frac{P_0}{\mathbb{Z}_b^{\frac{1}{l}}}\sum_{j=1}^{l} A\left(\hat{D}_{ij}, l_j\right) + \frac{\left(l\mathbb{Z}_{CT} + \mathbb{Z}_{CR}\right)}{B_W} \tag{4}$$

$$\mathbb{Z}_{out\ jt} = A\left(\hat{D}_{ij}, l_j\right)\frac{P_0 B_W}{\mathbb{Z}_b^{\frac{1}{l}}} \tag{5}$$

To select an optimal Cns, the energy utilization is computed as per Eq. (6), here the nodes with higher β_{jt} values are chosen as Cns, which balances the energy availability and channel attenuation.

$$\beta_{jt} = EN_j \Big/ A\left(\hat{D}_{ij}, l_j\right) \tag{6}$$

3.2 Protocol Design

In this research work, the proposed cluster-oriented multihop V-MIMO protocol operates in rounds containing of three phases such as Formation of Clusters, Routing and Data Transmission.

- **Cluster Formation Phase***:* Each node assesses it as a potential CH based on the residual energy. CHs broadcast an advertisement (AD) message via non-persistent CSMA MAC. Surrounding non-CH and CHs nodes receive an AD above a threshold compute β_{jt} and $\mathbb{Z}_{out\ jt}$ through Eq. (2) to Eq. (5). Here, non-CH nodes combine the cluster corresponding to the CH by the highest received signal strength (RSS). Then, CHs select the top l CNs for cooperative communication with surrounding (neighboring) CHs.
- **Routing Phase:** At each CH, distance-vector routing is adopted to create the routing table. Consider the entries are Cn IDs, destination cluster, next-hop cluster and average energy consumption per bit. These routing tables are swapped between the neighboring CHs iteratively until the convergence.
- **Data Transmission Phase:** In the data transmission phase, the cluster members are transmit data frames into their CH following a TDMA schedule. CHs achieves the data aggregation to remove the redundancy and forward the packets to the following hop CH. This process repeats until the data reaches to the sink.

3.3 Cross-Layer Parameter Optimization

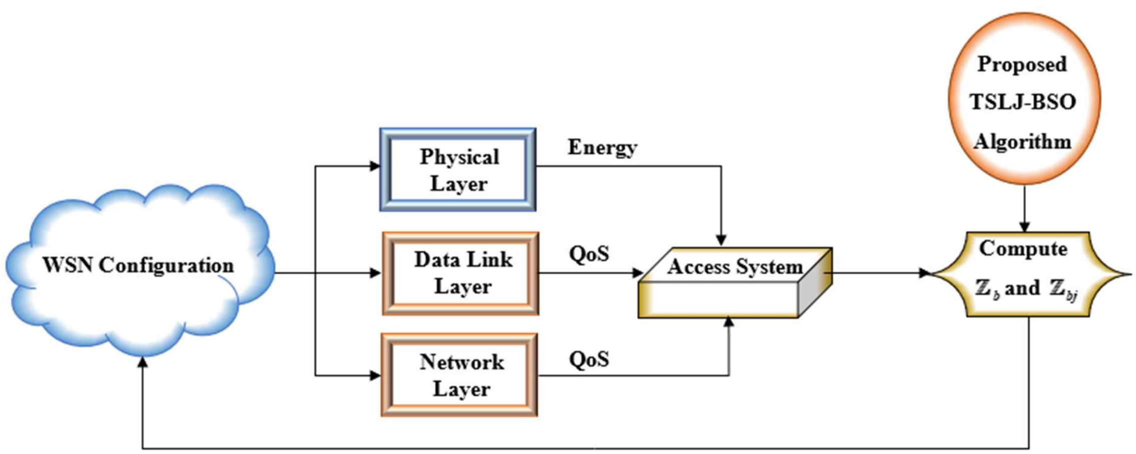

Fig. *1. Entire process of the Proposed model*

From the physical layer and QoS metrics, the output energy from the data link and network layer are utilized as inputs for the cross-layer optimization system. Transmission parameters $\mathbb{Z}_b$ and $\mathbb{Z}_{bj}$ are tuned by using the Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO), which focussed on minimizing the end-to-end latency. These optimized parameters arrange the WSN for reduced latency while maintaining the reliable link-level BER. Fig. 1 shows the entire process of the proposed model.

4. Energy consumption and Enhancing the Quality-of-Service Analysis

4.1 Energy Consumption

In the proposed multihop virtual MIMO framework, the energy consumption mainly rises from encoding, decoding and transmission operations. For an intra cluster communication, assumed an AWGN channel with squared power path loss and the average energy consumption per packet is evaluated in Eq. (7), where R signifies a circuit-dependent constant, $\hat{D}_0$ means the intra-cluster transmission distance, $\mathbb{Z}_{CT}$ and $\mathbb{Z}_{CR}$ indicates the transmitter and receiver circuit power.

$$\mathbb{Q}_0\left(\hat{D}_0, l\right) = nR\hat{D}_{i0}^2 + \frac{n\mathbb{Z}_{CT}}{B_W} + \frac{nl\mathbb{Z}_{CR}}{B_W} \tag{7}$$

For inter-cluster communication, the cooperative nodes utilize the STBC transmission. Assuming a block size of $\hat{D}_i$ symbols with $\wp l$ training symbols and small distance variation between the cooperative nodes, the average energy consumption in the j th hop is expressed as per Eq. (8). Therefore, the total energy consumption in the j th hop is computed in Eq. (9). For a linear block code (n, Y, t), the word error probability is expressed in Eq. (10) [12].

$$\mathbb{Q}_1\left(\mathbb{Z}_b, \hat{D}_{ihj}, l\right) = \frac{nD_i}{D_i - \wp l}\left(\frac{lP_0}{\mathbb{Z}_b} A\left(\hat{D}_{ij}, l_j\right) + \frac{\left(l\mathbb{Z}_{CT} + \mathbb{Z}_{CR}\right)}{B_W}\right) \tag{8}$$

$$\mathbb{Q}_h(j) = \mathbb{Q}_{code} + \mathbb{Q}_0\left(\hat{D}_{i0}, l\right) + \mathbb{Q}_1\left(\mathbb{Z}_b, \hat{D}_{ihj}, l\right) \tag{9}$$

$$\mathbb{Z}_w(\mathbb{Z}_b) = \sum_{i=t+1}^{n} \binom{n}{i} \mathbb{Z}_b^i (1 - \mathbb{Z}_b)^{(n-i)} \tag{10}$$

For Considering the retransmissions, the overall average energy consumption per packet through all hops is modelled as per Eq. (11).

$$\mathbb{Q}_{overall} = \frac{1}{\left[1 - \mathbb{Z}_w\left(\mathbb{Z}_b\right)\right]} \times \left\{A\left[\mathbb{Q}_{code} + \mathbb{Q}_0\left(\hat{D}_{i0}, l\right)\right] + \sum_{j=1}^{G} \mathbb{Q}_1\left(\mathbb{Z}_b, \hat{D}_{ihj}, l\right)\right\} \tag{11}$$

4.2 Quality of Service Model

In the end-to-end quality of the service model, the mean time required to transmit a packet is given $l_f = nD_i / B_W\left(D_i - \wp l\right)$. Therefore, the throughput of a link is computed in Eq. (12). The end-to-end QoS performance is modelled based on the link-level BER characteristics in the SPT. The packet arrival rate at cluster i is expressed in Eq. (13).

$$A = \frac{1 - \mathbb{Z}_w\left(\mathbb{Z}_b\right)}{l_f} \tag{12}$$

$$\lambda_i = \begin{cases} \hat{\lambda}_c, \ (i \in P_S) \\ \sum_{j \in pU_{si}} \mu_j\left(\mathbb{Z}_{bj}\right)\left(1 - \mathbb{Z}_0\left(\hat{\mu}_j\left(\mathbb{Z}_{bj}\right), \hat{\lambda}_j\right)\right) + \hat{\lambda}_c, \ (i \in P_R) \end{cases} \tag{13}$$

Let H_j be the route from cluster head j to the sink. The end-to-end throughput as well as latency for route j are evaluated in Eq. (14) and Eq. (15). The average of end-to-end throughput and latency of the network are computed using Eq. (16) and Eq. (17). The final energy consumption across all cluster heads is computed in Eq. (18).

$$T_j = \prod_{i \in H_j} \left(1 - \mathbb{Z}_P\left(\hat{\mu}_i\left(\mathbb{Z}_{bi}\right), \hat{\lambda}_i\right)\right) \tag{14}$$

$$Lt_j = \sum_{i \in H_j} \omega\left(\hat{\mu}_i\left(\mathbb{Z}_{bi}\right), \hat{\lambda}_i\right) \tag{15}$$

$$T\left(\left\{\mathbb{Z}_{bj}\right\}\right) = \frac{\sum_{j \in V_s \cup V_r} \hat{\lambda}_j T_l}{\sum_{j \in V_s \cup V_r} \hat{\lambda}_j} \tag{16}$$

$$Lt\left(\left\{\mathbb{Z}_{bj}\right\}\right) = \frac{\sum_{j \in V_s \cup V_R} \hat{\lambda}_j Lt_j}{\sum_{j \in V_s \cup V_R} \hat{\lambda}_j} \tag{17}$$

$$\mathbb{Q}_{overall} = \sum_{j \in P_s \cup P_R} \frac{1}{1 - \mathbb{Z}_w\left(\mathbb{Z}_{bj}\right)} \times \left[\mathbb{Q}_{code} + \mathbb{Q}_0\left(\hat{D}_{i0}, L\right) + \mathbb{Q}_1\left(\mathbb{Z}_{bj}, \hat{D}_{ij}, l\right)\right] \tag{18}$$

In this research work, the transmission parameters $\mathbb{Z}_b$ and $\mathbb{Z}_{bj}$ are optimized by using the using a Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO) algorithm to minimize the end-to-end latency, while the energy consumption and QoS models serve as system constraints.

4.3 Solution encoding and Objective function

In the proposed system, model, the solution encoding was defined with respect to the link-level BER parameters, where each candidate solution is represented as $\mathbb{Z} = \left\{\mathbb{Z}_b, \mathbb{Z}_{b1}, \mathbb{Z}_{b2}, .., \mathbb{Z}_{bj}\right\}$, corresponding to the intra as well as the inter-cluster links. These BER parameters are retransmissions and service time and hence determine the latency of the V-MIMO network. The Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO) algorithm was utilized to optimally tune $\mathbb{Z}_b$ and $\mathbb{Z}_{bj}$ using a two-stage Lévy jump process to enhance the mid-stage convergence. The objective function of the TSLJ-BSO is defined in Eq. (19).

$$F = Desired\left(Lt\right) \tag{19}$$

where (Lt) indicates the end-to-end latency of the network. The optimized BER values obtained from TSLJ-BSO enable reduced latency while maintaining reliable communication.

Proposed Two-Stage Levy Jump based Bird Swarm Optimization (TSLJ-BSO) algorithm

Generally, the Bird Swarm Optimization (BSO) [13] is a population-based metaheuristic inspired by the social behaviors like foraging, vigilance, and flight of birds. Each bird signifies a candidate solution and the swarm together searches for the global optimum by sharing the information. The birds are dynamically switch among the different behaviors based on probabilistic rules, which allows a balance between exploration as well as exploitation. Let V be the number of birds and each position of the bird in a d-dimensional search space at iteration t and the maximum number of iterations is denoted as $\mathbb{N}$.

(i) Foraging Behavior

Based on both personal experience and the swarm's collective knowledge, birds search for food in the foraging phase. Each bird remembers its personal best position $\wp_{ij}$ and the global best position G_i . Eq. (20) shows the position update rule for the j th dimension

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + \left(\wp_{i,j} - Y_{i,j}^{t}\right) \times \Re \times Rand\left(0,1\right) + X \times Rand\left(0,1\right) \tag{20}$$

Wherein, $\Re$ and X implies the cognitive as well as social acceleration coefficients, respectively and $Rand\left(0,1\right)$ indicates a uniformly distributed random number.

Then, the switching among the foraging and vigilance is governed by a rule. If a the random number is less than a predefined probability, the bird performs foraging; otherwise, it goes to the vigilance behavior.

(ii) Vigilance Behavior

When the birds show the vigilance behavior, they tend to move to the center of the swarm while competing with other birds. During vigilance, the updated position is expressed in Eq. (21). where $mean_j$ indicates the j th dimension of the average position of swarm and k indicate s a randomly selected bird index. The coefficients $E1$ and $E2$ model indirect and direct competition effects using Eq. (22) and Eq. (23), respectively.

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + E1\left(mean_j - Y_{i,j}^{t}\right) \times Rand\left(0,1\right) + E1\left(\wp_{k,j} - Y_{i,j}^{t}\right) \times Rand\left(-1,1\right) \tag{21}$$

$$E1 = e1 \times \exp\left(-\frac{\wp fit_i}{Sumfit + \varsigma} \times V\right) \tag{22}$$

$$E2 = e2 \times \exp\left(\left(\frac{\wp fit_i - \wp fit_k}{\left|\wp fit_k - \wp fit_i + \varsigma\right|}\right) \times \frac{V \times \wp fit_k}{sumfit + \varsigma}\right) \tag{23}$$

where $\wp fit_i$ and $\wp fit_k$ signify the best fitness values of the i th and k th birds, respectively, $e1$, $e2$ signifies the two positive constant term in the range between 0 to 2. (N) is the swarm size and the small constant term is labelled as ς . Lower fitness values specify better solutions for minimization problems.

(iii) Proposed Flight Behavior based on Two-Stage Lévy Jump Strategy

Conventionally, birds occasionally migrate to a new location due to the environmental factors. During the flight behaviour, birds act as producers and scroungers. The producers actively explore and the scroungers follow the producers. The producer and the scrounger position is expressed in Eq. (24) and Eq. (25), respectively. where $Randn\left(0,1\right)$ signifies a Gaussian random variable and $fl \in \left[0,2\right]$ is the following coefficient. Birds perform this flight operation every iteration and assume each bird travels to another place every fq units of time, which is a positive integer.

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + Randn\left(0,1\right) \times Y_{i,j}^{t} \tag{24}$$

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + \left(Y_{k,j}^{t} - Y_{i,j}^{t}\right) \times fl \times Rand\left(0,1\right) \tag{25}$$

To enhance the convergence performance during the mid-stage of optimization, the conventional producer and scrounger flight behavior in Eq. (24) and Eq. (25) is replaced by a two-stage Levy jump mechanism in the proposed TSLJ-BSO algorithm.

Stage (i): Lévy Macro Jump

In this TSLJ-BSO, the first stage introduces a Levy-based global exploration step, which allows the birds to escape the local optima using Eq. (26). where Y^* signifies the global best position, η implies the Levy jump scale and $L(\beta)$ signifies a Levy flight vector that created by using the Levy distribution with parameter β.

$$\chi_i^t = Y_i^t + \eta L(\beta) \odot \left(Y^* - Y_i^t\right) \tag{26}$$

Stage (ii): Local Refinement

A local exploitation step is applied to improve the solution obtained from the macro jump as per Eq. (27). where ϑ implies the step-size coefficient and υ stands for a uniformly distributed random number between 0 and 1.

$$Y_i^{t+1} = \chi_i^t + \vartheta \upsilon \odot \left(Y^* - \chi_i^t\right) \tag{27}$$

Thus, the two-stage Levy jump approach effectively balances the global exploration as well as local exploitation. The macro-Levy jump ensures that the wide search capability in the early and mid-stages and the local refinement step accelerates the convergence to the global optimum. The pseudocode of the TSLJ-BSO is shown in **Algorithm 1**. This alteration significantly improves the mid-stage convergence and prevents premature stagnation, which makes TSLJ-BSO well suited for optimizing BER parameters to minimize end-to-end latency in the proposed V-MIMO system.

Algorithm 1: Pseudo code of TSLJ-BSO

Initialize: V, $\mathbb{N}$, fq, $\wp$, $\Re$, X, $e1$, $e2$ and fl
Initialize the bird population and define the algorithm parameters
Compute the fitness $\mathbb{N}$ of all birds and find the global best solution
While $(t < \mathbb{N})$
  If $(t\% fq \neq 0)$
    For $i = 1:V$
      If $Rand(0,1) < \wp$
        Obtain foraging behavior as per Eq. (20)
      Else
        Obtain vigilance behavior as per Eq. (21)
      End if
    End for
  Else
    For $i = 1:V$
      Stage 1: Levy Macro Jump- Update the intermediate position as per Eq. (26)
      Stage 2: Local Refinement- Update the final position as per Eq. (27)
    End for
  End if
  Compute fitness of all the updated solutions
  If the new fitness value is better than the prior fitness, then update the present best and global solution
  Increase the iteration count as $t = t + 1$
End while
Output: Best solution with minimum objective function value

5. Results and Discussion

5.1 Simulation Procedure

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

5.2 Analysis on the Objective Function

Under this objective function analysis, the baseline methods such as LA, PSO, DA and proposed methods are compared under varied latency node of 100, 200, 300 and 400. Here, the proposed method has attained lesser latency ranges over all the iterations than the other methods, which is comparatively presented in Fig. 2. In 100 node, the LA method has desired latency at 10^{th} iteration by below 0.014 seconds, 12^{th} iteration by 0.0137 and continued by PSO has desired latency at 4^{th} iteration by nearly 0.014, 19^{th} iteration by 0.0137 (Fig. 2(i)). In 200 nodes, the DA has desired latency at 1^{st} iteration, 17^{th} iterations and LA by 2^{nd} iterations. But the proposed method has attained lesser desired latency at 7^{th} iteration in 100 nodes and 200 nodes, which is extremely lower than the LA, PSO, DA. In addition, the analysis over 300 nodes and 400 nodes are illustrated in Fig. 2(iii) & Fig. 2(iv). Therefore, the superiority of proposed TSLJ-BSO method is described by its ability to reached the desired latency ranges with minimal number of iterations.

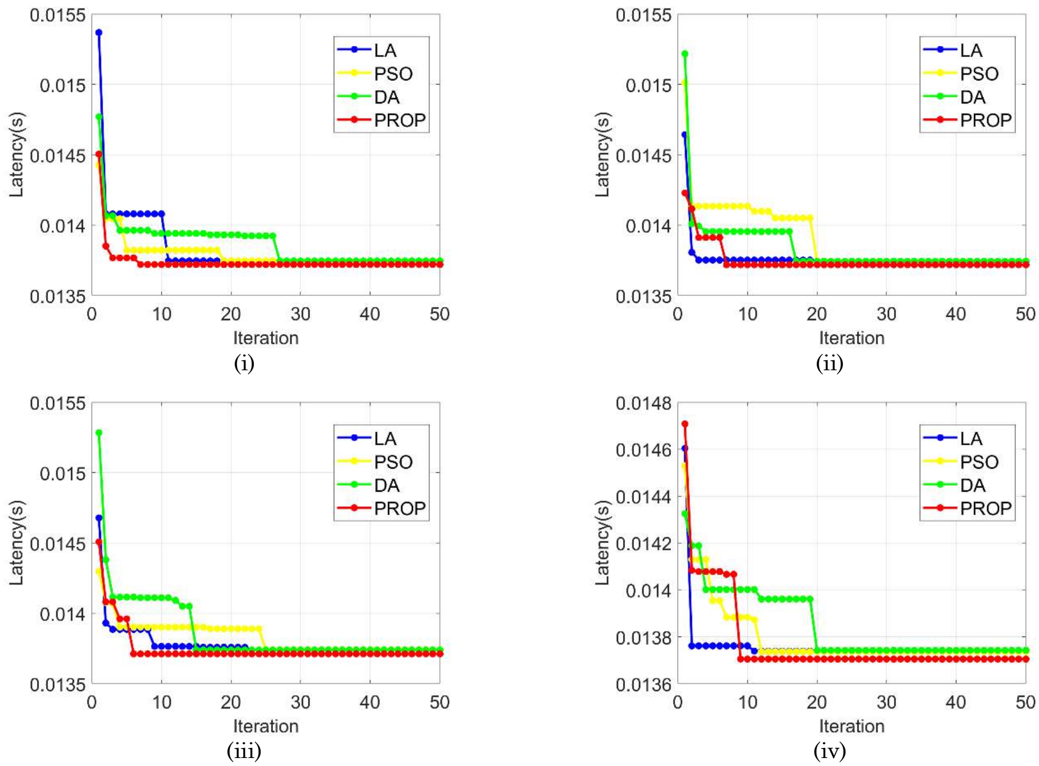

Fig. 2. *Analysis of the objective function: proposed TSLJ-BSO model versus conventional schemes (i) Latency Node-100 (ii) Latency Node-200 (iii) Latency Node-300 (iv) Latency Node-400*

6. Summary

This research presented an adaptive virtual MIMO-based cross-layer design for multihop WSNs with a main importance on minimalizing the end-to-end latency. The link-level BER of each link was optimized through a TSLJ-BSO algorithm, which improved the mid-stage convergence as well as avoided premature stagnation. Here, the transmission parameters through the physical and MAC layers were adaptively tuned to decrease the packet delays while maintaining the dependable communication. Simulation outcomes established that the proposed model obtained faster convergence as well as significantly lower end-to-end latency when compared to the traditional optimization-based virtual MIMO systems.

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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