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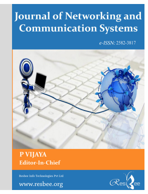

An Enhanced Whale Optimization Algorithm for Massive MIMO System

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Abstract: In Wireless Network Systems, Massive-Multi-Input Multi-Output (M-MIMO) systems based on several antennas to transform numerous data streams simultaneously. The optimal Transmit Antennas selection remains as an important constraint in M-MIMO systems. Additionally, the power or energy consumption increases when the count of antennas is increased. In reality, huge number of transmit antennas is required that leads to an increase in power utilization for obtaining maximum capacity. Therefore, this paper aims to attain the optimal transmit selection of antennas in order to solve these problems in M-MIMO systems, using a multi-objective problem, which increases both the relative Energy Efficiency and capacity. For obtaining this objective, the proposed novel optimization technique not only optimizes the number of transmit antennas but also optimizes the antenna, which antenna has to be selected. Therefore, for optimal selection of antennas, enhanced WOA is exploited, which determines the number of antennas and how to select the antennas in an optimal way.

Keywords*:* MIMO; Antenna; CBF; Optimization; Energy Efficiency

Nomenclature

Abbreviations	Descriptions
BS	Base Station
AOD	Angle of Departure
AOA	Angle of Arrival
MIMO	Multi-Input Multi-Output
BER	Bit Error Rate
TDD	Time-Division Duplex
BAB	Branch and Bound
CBF	Correlation-Based Best First
CSI	Channel State Information
AS	Antenna Selection
SMV	Square Maximum-Volume
BFLS	Burst-Form Least Squares
SPE	Starting Point Estimation
LE	Laplacian Eigenmaps
SINR	Signal-to-Interference-plus-Noise Ratio
DCT	Discrete Cosine Transform
SIQNR	Signal-to-Interference, Quantization and Noise Ratio
SMV	Square Maximum-Volume
RMV	Rectangular Maximum-Volume
ZF	Zero-Forcing
LS-MIMO	Large scale MIMO
MF	Matched filtering
VR	Visibility Regions
CB	Conjugate Beam forming
IUI	Inter user interference
WOA	Whale optimization algorithm
EE	Energy Efficiency
PA	Power Amplifier
GI	Guard interval
TAS	Transmit Antennas Selection
GWO	Grey Wolf Optimization
PSO	Particle Swarm Optimization

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1. Introduction

Generally, Massive MIMO application is an outcome of contemplating the idea of MIMO wireless communications. By maximizing the number of antennas in the BS, it enables each BS to interface with numerous users at a same frequency and time [2]. Moreover, this application minimizes the consequence of supplement thermal noise for the uplink by averaging against a considerable array in the BS and permits the exploit of easy linear processing approaches [3]. In general, the transmitter of mm-Wave massive MIMO communication comprises an analog RF beamformer and a digital baseband beamformer, when the receiver comprises an analog RF combiner and digital baseband combiner respectively [4]. By the analog combiner and analog beamformer the directional beamforming and receiving are mostly performed that are regarded as likely to point at the physically AOD and physically AOA of the channel, correspondingly. Nevertheless, the precise of AOA and AOD depends on channel training before data transmission.

In general, Massive MIMO is considered as an encouraging application in the physical layer of wireless systems to improve the spectral and in addition to energy effectual of future 5G networks [1], [20] [21]. To attain the procures guarantees by the exploit of a huge amount of antennas, the CSI must be attained at the transmitter side with maximum accuracy. The TDD protocol presumes channel reciprocity, in that the uplink, and downlink channels, possess a similar frequency response. The BS side has the ability to access the CSI on the basis of the reciprocity among the channels by exploiting pilot training in the uplink path, whereas the number of pilot symbols is proportional to the number of users [5].

At a recent time, few MIMO AS techniques is made larger to massive MIMO [9]. The AS with the bidirectional BAB search technique was stated in [10], that is also exploited for each subarray in [10]. Here, it is a global optimal searching technique with maximum convolution, as well as just serves as benchmark motivations. A supposed CBF AS technique was presented for massive MIMO in [11], that was somewhat enhanced from the technique in [12]. Nevertheless, it is of minimum performance inability. The AS technique in [13] is exploited from the conventional SMV submatrices in order to find the technique, that can be considered as a development of the technique in [14]. But it cannot work while the number of users is not equivalent to the number of the selection antenna.

However, the conventional SMV AS technique has the ability to attain a nearby the performance of the optimal capability, it can only distribute with a square submatrix. Basically, it happens in the circumstance whereas the number of selected antennas is higher than that of users in massive MIMO systems. That is to say, rectangular submatrices are required to pact within massive MIMO. Hence, it is required to eliminate the restriction.

This major contribution of this article is to develop a method to attain the selection of optimal transmit antennas. It is done by taking into consideration of a multi-objective issue, which can increase both the relative Energy Efficiency and capacity. The presented novel optimization strategy does not only optimize the count of transmit antennas but also tunes that antenna needs to be selection for obtaining this objective. Hence, enhanced WOA algorithm is used for the optimal selection of antennas.

2. Literature Review

In 2019, Soumendu Ghosh and Ribhu Chopra [1], worked on the issue of CSI achievement in massive MIMO systems with the users showing non-identical channel aging profiles. Hence, per user, attainable rates were derived and the equivalent CSI blackout times for various users. They have subsequently utilized these derived outcomes to dispute the scheduling based on the training for all the users, regarding the outage time of the optimal moving user was suboptimal, and outcomes in redundant training overhead. Hence, two simple strategies performance for scheduling was evaluated and performed for the training of users with various mobilities.

In 2019, Mohammad Javad Azizipour et al. [2], presented a burst-form evaluation technique, indicates as the BFLS technique, to completely use the burst-sparsity property of massive MIMO channels. Moreover, the presented technique was on the basis of the knowledge at the user side for the starting position of each burst. For circumstances, whereas the starting positions modify rapidly or else initially unknown at the user, an SPE technique was presented to offer the location for each burst in the channel vector.

In 2019, YongLiao et al. [3], presented a CSI compression feedback technique on the basis of the LE non-linear dealing out for massive MIMO uniform linear array. The Laplacian matrix determined by the spatial correlation of the channel array, and using Laplacian matrix eigenvalue decomposition the channel compression matrix was attained. The experimentation outcomes exhibit that the presented LE technique has the ability to minimize the feedback overhead, and its BER performance, was superior to the DCT sparse compression technique.

In 2019, Azad Azizzadeh et al [4] introduced minimum quantization resolution, to minimize the power utilization of massive MIMO and millimeter wave MIMO systems. Moreover, the performance of BER for quantized uplink massive MIMO using some-bit resolution ADCs was analyzed. A SIQNR to attain an analytical BER approximation was derived considering ZF detection for coarsely quantized M-QAM massive MIMO systems by exploiting a linear quantization technique. The presented expression was a model for the quantization resolution in bits.

In 2016, Yuhan Sun and Chenhao Qi [5] investigated the analog combining and analog beamforming in millimeter wave, in the massive MIMO communications. The weighted sum-rate maximization was examined using jointly regarding the period for receiving SNR and channel training on the basis of a hierarchical codebook. A technique using comprehensive search during the initial level of the codebook and the multi-sectional search at the other levels were presented. The channel gain of the superior path was assessed and the codebook level attaining the weighted sum-rate maximization was predicted using the receiver at each iteration. Subsequently, the predicted level was fed back to the transmitter.

In 2017, Hua Tang and Zaiping Nie [6], studied the AS issue in massive MIMO systems with the contemplation of increasing the channel ability. To eradicate the restriction of the conventional SMV AS technique, the hypothesis of RMV submatrices was developed. Additionally, an AS technique on the basis of the RMV technique was also adopted for massive MIMO, that can be referred post-processing of the outcomes of the SMV technique. On the basis of the outcome attained from SMV technique, the presented technique has the ability to choose a rectangular submatrix.

In 2019, Anum Ali et al [7], developed a massive MIMO system with outsized arrays. Here, the channel turns out to be spatially non-stationary. Using VRs the effect of spatial non-stationarity exemplifies whereas the energy of channel was important on a section of the array was examined. On the basis of the VRs depending on a channel model, the expressions of the SINR of ZF precoders and CB were provided.

In 2018, Manish Mandloi and Vimal Bhatia [8] developed a novel technique on the basis of the fault recovery for recognition in uplink massive MIMO systems. Here, initially, the non-sparse massive MIMO system was converted into a quasisparse fault that was fault vector comprises of a diminutive fraction of important elements system exploiting uneven first access of the transmitted symbol vector. Subsequently, the fault was assessed using a minimum-convolution fault recovery approach that recognizes the fault elements in a controlled model.

3. Problem formulation and System Model

3.1 System Model and TAS

Consider a single isolated cell with terminals and a single BS. In N_t numbers, the BS comprises transmitting (T_s) antennas and each M comprises a single (R_s) antenna. In eq. (1), the received signal vectors is stated in the terminals in that for every M the k state the $M \times 1$ received vector, Q_{t_s} denotes the complete T_s power for forwarding link. O denotes the $M \times N_t$ minute scale Rayleigh fading channel matrix between M terminals and N_t BS antennas and subsequently, Δ signifies the T_s power normalization parameter specifically assessed as $\Delta \approx \sqrt{\frac{N_t}{M}}$. D indicates $N_t \times M$ precoding matrix to reduce IUI, s refers to the $M \times 1$ AWGN noise vector as well as q indicates the $M \times 1$ message signal vector. Here, two common pre-coding matrices for LS-MIMO for precoding matrices, MF $\left(NF : B = N_t^{-1} P^O\right)$ and $\left(YF : B = P^O\left(PP^O\right)^{-1}\right)$ are used. Narrowband signal is only observed as OFDM can contrast the narrowband signal from the wideband signal effectively.

$$k_j = \sqrt{Q_{tz}}\, P \Delta B q + s \tag{1}$$

Let us assume that the transmitter has perfect CSI. On the basis of the norms of thumb, if $N_t > 10\,M$, subsequently the system is referred to as LS-MIMO.

A suitable power consumption design has to be determined in order to estimate the EE of LS-MIMO equipped green BS. Moreover, the sum power, Q_{sum}, a tractable power consumption model comprising definite important LSMIMO power consumption elements are described as exhibited by eq. (2). Here,

Q_{BB} refers the baseband power utilization, Q_{PA} refers the PA power utilization, and $Q_{RF_{front}}$ refers to the RF front-end power utilization that comprises of filter, mixer, and DAC power utilization. For the methodical alleviate, the power utilization Q_c is stated which get higher with the rise in N_t as stated in eq. (3). Therefore, eq. (3) can be stated as eq. (4).

$$Q_{sum} = Q_{PA} + Q_{BB} + N_t Q_{RF_{front}} \tag{2}$$

$$Q_c = \left(Q_{BB} / N_t + Q_{RF_{front}}\right) \tag{3}$$

$$Q_{sum} = Q_{PA} + N_t Q_c \tag{4}$$

Let us consider the OFDM system with superior effectiveness of Class-B (78:5%), (10MHz) with subcarriers (1024), and IBO =11dB. On the basis of the limitations, PA effectiveness is selected as 22%. Due to the superior number of antennas, utilization of PA with maximum effectiveness will be moderately costly. The relation between Q_{tz} and Q_{PA} can be stated in eq. (5).

$$Q_{tz} = \lambda Q_{PA} \tag{5}$$

In Q_{BB}, LS-MIMO baseband power calculation design $q(H\,\text{flops})Q_{BB}$ is exploited and it is stated in [15] [16].

$$z = N_t F. \left[\begin{array}{l} \left(\frac{J_u}{J_s}\right)\log_2(J_u F) + \left(\frac{J_u}{J_s}\right)\left(1 - \frac{J_p}{J_{sl}}\right)M + \left(\frac{J_u}{J_s}\right) \\ \left(\frac{J_p}{J_{sl}}\right)\log_2\left(\frac{J_u J_p}{J_s J_d}\right) + \left(\frac{J_d}{J_{sl}}\right)M^2 \end{array} \right] \tag{6}$$

The description for each constraint in eq. (6) is stated as below:

J_s states Symbol duration with a power utilization of 0.214ms. F states bandwidth with a power utilization of 10MHz. J_{sl} indicates the slot length with a power utilization of 0.5ms. J_p denotes Pilot length in one slot with a power utilization of 0.214ms. J_u indicates a Symbol without GI with a power utilization of 66.7μs. J_d denotes delay spread GI with a power utilization of 4.7μs. J_g indicates GI with a power utilization of 4.7μs.

The limitations were obtained from [17] and the current LTE system [18]. The relation between $q(H\,\text{flops})$ and Q_{BB} is referred to as eq. (7).

$$Q_{BB} = \frac{q(H\,\text{flops})}{\varepsilon(H\,\text{flops}/V)} \tag{7}$$

where ε denoted the effectiveness of VLSI processing, and $\varepsilon = 5G\,\text{flop}/V$ and $50H\,\text{flop}/V$ was selected.

3.2 Optimal Transmit Antenna Selection

The variable obtained using j^{th} user is stated in eq. (8), in that $e:,_j$ indicates the $N_t \times 1$ precoding vector for j^{th} user and $d_j,:$ denotes the $1 \times N_t$ channel vector for j^{th} user. The last variable of eq. (8) is IUI.

$$k_j = \sqrt{\frac{Q_{tz} N_t}{M}} d_j,: e:,_j z_j + n_j + \sqrt{\frac{Q_{tz} N_t}{M}} \sum_{l \neq j} d_j,: e:,_l z_l \tag{8}$$

In eq. (9), the ability of a particular isolated cell is stated, in that $N_0 F$ indicates the noise power in the particular bandwidth F and β indicates the scaling factor for GI and pilot overhead.

$$L = \beta F. \sum_{j=1}^{J} U \left[\log_2 \left(1 + \frac{\frac{Q_{tz} N_t}{M} \left|d_j,: e:,_j\right|^2}{\frac{Q_{tx} N_t}{M} \left|\sum_{l \neq j} d_j,: e:,_l\right|^2 + N_0 F} \right) \right] \tag{9}$$

While the system attains at LS MIMO area, that is $N_t > 10M$, Eq. (9) can be rephrased as eq. (10), in that C indicates IUI.

$$L_{approx}^{LS-MIMO} \approx \beta FM. \left[\log_2 \left(1 + \frac{Q_{tz} N_t}{(C + N_0 F) M} \right) \right] \tag{10}$$

The IUI can be eradicated in an uncomplicated manner in ZF precoding. The EE can be stated as eq. (11) that is referred to as the major contribution model of the recommended function, which needs to be increased.

$$\mathrm{EE} = \mathrm{L} / \mathrm{Q}_{\mathrm{sum}} \tag{11}$$

$$\frac{\partial}{\partial \mathrm{N}_t}\mathrm{EE} = \frac{\partial}{\partial \mathrm{N}_t}\left(\frac{\mathrm{L}_{\mathrm{approx}}}{\frac{1}{\lambda}\mathrm{Q}_{\mathrm{tz}} + \mathrm{N}_t \mathrm{Q}_l}\right)$$

$$\frac{\partial}{\partial \mathrm{N}_t}\mathrm{EE} = \frac{\mathrm{FMQ}_{\mathrm{ty}}}{(\mathrm{L}+\mathrm{N}_0\mathrm{F})\mathrm{M}\left(1+\frac{\mathrm{Q}_{\mathrm{ty}}\mathrm{N}_t}{(\mathrm{C}+\mathrm{N}_0\mathrm{F})\mathrm{M}}\right)\mathrm{Q}_{\mathrm{sum}}\log_2 e} - \tag{12}$$

$$\frac{\mathrm{FMQ}_l . \log_e\left(1+\frac{\mathrm{Q}_{\mathrm{tz}}\mathrm{M}_t}{(\mathrm{C}+\mathrm{N}_0\mathrm{F})\mathrm{M}}\right)}{\mathrm{Q}_{\mathrm{sum}}^2 \log_2 e}$$

$$\frac{\partial}{\partial \mathrm{N}_t}\mathrm{EE} = 0$$

Therefore, the evaluation of $\mathrm{N}_t^{\mathrm{opt}}$ is stated in eq. (13), in that $\delta = \frac{\mathrm{Q}_{\mathrm{tz}}^2 - \mathrm{MN}_0\mathrm{FQ}_c - \mathrm{MCQ}_c}{\mathrm{M}(\mathrm{C}+\mathrm{N}_0\mathrm{F})\mathrm{Q}_c \exp(1)}$ and V indicates the lambert V model which is stated in $\delta = \mathrm{V}(\delta)\exp(\mathrm{V}(\delta))$.

$$\mathrm{N}_t^{\mathrm{opt}} \approx \frac{(\mathrm{C}+\mathrm{N}_0\mathrm{F})\mathrm{M}}{\mathrm{Q}_{\mathrm{ty}}}\left(-1+\exp(1+\mathrm{V}(\delta))\right) \tag{13}$$

Based on eq. (13), $\mathrm{N}_t^{\mathrm{opt}}$ can be simply obtained and the issue here is regarding choosing the number of $\mathrm{N}_t^{\mathrm{opt}}$ antennas from a complete count of the antenna, $\mathrm{N}_t^{\mathrm{total}}$. Conventional antenna selection methods select a predetermined number of antennas out of $\mathrm{N}_t^{\mathrm{total}}$ as channel ability maximization form. The channel ability of $\mathrm{N}_t^{\mathrm{opt}}$ selected antenna system, when selecting columns of P are $\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}$, $\mathrm{L}_{\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}}$ is stated as eq. (14), in that $d_{j,\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}}$ is the $1 \times \mathrm{N}_t^{\mathrm{opt}}$ channel vector for j^{th} user, $e_{\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\},j}$ is the $\mathrm{N}_t^{\mathrm{opt}} \times 1$ precoding vector for j^{th} user, when $(m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}})^{\mathrm{th}}$ is selected.

$$\mathrm{L}_{\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}} = \beta\mathrm{F}.\sum_{j=1}^{\mathrm{M}} \mathrm{U}\left[\log_2\left(1+\frac{\frac{\mathrm{Q}_{\mathrm{ty}}\mathrm{N}_t}{\mathrm{M}}\left|d_{m,\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}} e_{\{m_1, m_2, \ldots h_{\mathrm{N}_t^{\mathrm{opt}}}\},k}\right|^2}{\frac{\mathrm{Q}_{\mathrm{ty}}\mathrm{N}_t}{\mathrm{M}}\left|\sum_{l \neq m} d_{m,\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}} e_{\{m_1, m_2, \ldots h_{\mathrm{N}_t^{\mathrm{opt}}}\},l}\right|^2 + \mathrm{N}_0\mathrm{F}}\right)\right] \tag{14}$$

Rather than maximizing the ability, EE has to be increased for the green BS approach. In this phase, the optimum AS for EE is related to the optimum AS for channel ability from eq. (11). As N_t^{opt} has been selection in advance from (13) and therefore $\mathrm{Q}_{\mathrm{sum}}$ emerge self-governing of AS. For the optimal antenna selection, N_t^{opt} columns encompass to be selected for the uppermost EE as stated in eq. (15), whereas B is the set of all potential amalgamation of $\mathrm{N}_t^{\mathrm{opt}}$ antennas.

$$\{m_1^{\mathrm{opt}}, m_2^{\mathrm{opt}}, \ldots\ldots m_{\mathrm{N}_t^{\mathrm{opt}}}^{\mathrm{opt}}\} = \arg\max_{\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}} \in B\}} \frac{\mathrm{L}_{\{m_1, m_2, \ldots m_{\mathrm{N}_t^{\mathrm{opt}}}\}}}{\mathrm{Q}_{\mathrm{sum}}} \tag{15}$$

4. OPTIMAL TAS in Massive MIMO using Proposed Algorithm

4.1 Conventional WOA

The WOA [19] is a novel dominant population-based technique, which is enthused using the particular spiral bubble-net hunting humpback whales behavior. Every population individual is referred to as $Y_i = [y_{i,1}, y_{i,2}, \ldots y_{i,D}]$, whereas $i = 1,2,\ldots p_s$, p_s refers to the size of the population as well as D refers to the dimension of the problem in WOA. It comprises of three searching phases such as encircling prey, searching for prey, as well as bubble-net attacking technique. The optimal search agent, other humpback whales will try to update their locations to the agent. This can be stated in eq. (16) and (17).

$$M = \left| D \cdot Y_h - Y^t \right| \tag{16}$$

$$Y^{t+1} = Y_h - B \cdot M \tag{17}$$

In eq. (17), $|\cdot|$ indicates the absolute value, t indicates the current iteration, Y_h indicates the optimal location found hitherto. D and B represents the coefficients and that are correspondingly computed and it is stated in eq. (18) and (19).

$$B = 2 \cdot b \cdot rn(0,1) - b \tag{18}$$

$$D = 2 \cdot rn(0,1) \tag{19}$$

In eq. (18), b represents linearly reduced from 2 to 0 against the course of the iteration. $rn(0,1)$ represents a uniformly distributed arbitrary real number in (0, 1).

In the bubble-net attacking process, the whales concurrently use two schemes that are spiraling to spin as well as shrinking encircling regarding update prey locations. WOA presumes that both schemes encompass a similar probability to be done. These two schemes are mathematically stated in eq. (20), correspondingly.

$$Y^{t+1} = Y_h - B \cdot M \text{ if } p < 0.5 \tag{20}$$

$$Y^{t+1} = M' \cdot \exp(sr) \cdot \cos(2\pi r) + Y_h \text{ if } p \geq 0.5 \tag{21}$$

In eq. (21), $M' = \left| Y_h - Y^t \right|$. s represents a constant for describing the form of the spiral logarithmic. p and r represents arbitrary real numbers in $(0,1)$.

In tradition, whales spin arbitrarily in order to look for prey. Its locations are updated based on the in a sequence of each other. The B coefficient can be exploited to decide whether to oblige a whale to progress distant from a whale position. Additionally, it will update its location by exploiting an arbitrary whale rather than the optimal one if $|B| \geq 1$ embrace, this precise model is stated in eq. (22) and (23), where r represents a random whale.

$$M = \left| D \cdot Y_r^t - Y^t \right| \tag{22}$$

$$Y^{t+1} = Y_r^t - B \cdot M \tag{23}$$

4.2 Proposed Enhanced WOA

The conventional WOA has already shown itself a valuable optimization technique. Nevertheless, like other population-based techniques, WOA also has few concerns. It converges rapidly in the start of the evolutionary procedure other than it is simply trapped into local search afterward and as a result of that suffers from prematurity while resolving multimodal problems. The real cause is that the WOA uses the coefficient B in order to balance the exploration as well as exploitation in two manners. Conversely, eq. (23) and (17) are selectively done to strengthen the exploitation and exploration, correspondingly. Nevertheless, the probabilities of performing eq. (23) and (17) are not balanced or equal because of the subsequent cause. Eq. (18) can be rephrased as eq. (24).

$$\begin{aligned} B &= 2 \cdot b \cdot rn(0,1) - b \\ &= [2 \cdot rn(0,1) - 1] \cdot b \\ &= \eta \cdot b \end{aligned} \tag{24}$$

In eq. (24) $\eta = 2 \cdot rn(0,1) - 1$ represents a uniformly distributed arbitrary real number in (−1, 1). Since b is linearly reduced from 2 to 0 against the course of the iteration, hence $|B| = |\eta \cdot b| < 1$ for eternity embrace in the next part of the evolutionary procedure in that Eq. (17) is always done subsequently. In the primary part of the evolutionary procedure, the probability of performing eq. (17) can be computed as eq. (25).

$$P(|B|<1)=P(|\eta\cdot b|<1)=0.5+\int_{0.5}^{1}\int_{1}^{1/\eta}db\,d\eta$$
$$=0.5+\int_{0.5}^{1}\left(\frac{1}{\eta}-1\right)d\eta=0.5+(\ln\eta-\eta)\Big|_{0.5}^{1} \tag{25}$$
$$=\ln\ 2\approx 0.693$$

The whales can be observed through in the initial part of the evolutionary procedure, eq. (17) has a maximum probability of being selection. In reality, the total probability of doing eq. (17) during the complete evolutionary procedure is $P(|B|<1)=0.5+0.5\times\ln 2\approx 0.847$ in the prerequisite $p<0.5$. Hence, eq. (17) extremely controls eq. (23). Conversely, in the premature evolutionary procedure, B referred as comparatively large and can offer a huge perturbation to aid WOA swoop of local optima. Nevertheless it is rapidly minimized with the development of evolution as well as hence the perturbation is little to be helpful for the exploration. From the above evaluation, the WOA exaggerates the exploitation that simply guides to the in advance converging to local optima. To solution the imperfection of the conventional WOA and balance the exploration and exploitation efficiently, here an enhanced WOA indicated as EWOA, is presented. In EWOA, the following two prey searching schemes that are eq. (26) and (27) are utilized to substitute eq. (23) and eq.(17), correspondingly.

$$Y_i^{t+1}=Y_{l_1}^t-B\cdot\left|Y_i^t-Y_{l_1}^t\right| \tag{26}$$

$$Y_i^{t+1}=Y_{l_2}^t-B\cdot\left|Y_h^t-Y_{l_2}^t\right| \tag{27}$$

In eq. (26), l_1 and l_2 represents the two arbitrary individuals. Basic inspiration of the developed searching scheme is on the basis of the three considerations. Initially, eq. (27) uses $Y_{l_2}^t$ rather than Y_h as the base and use $B\cdot\left|Y_h^t-Y_{l_2}^t\right|$ to present a symmetrical perturbation on $Y_{l_2}^t$, that is capable to maximize the diversity of the population. Next, though eq. (27) still influences eq. (26), both eq. (26) and (27) use arbitrary individuals to update the present individual, that is capable to improve the exploration based on the conventional exploitation hence to attain a better equilibrium among them. Subsequently, the rejection of the D coefficient can assurance the reliability of the distance among two individuals and thus ease the vigor. Fig. 1 demonstrates the flowchart of Enhanced WOA. It is important that stating the EWOA stays the fundamental model of the conventional WOA in addition to it does not initiate further parameter which requires being fine-tuned or other intricate searching operators. So, the time complexity of both techniques is similar and equals to $O(t_{max}\cdot P_s\cdot F)$ whereas t_{max} represents the maximum number of iteration.

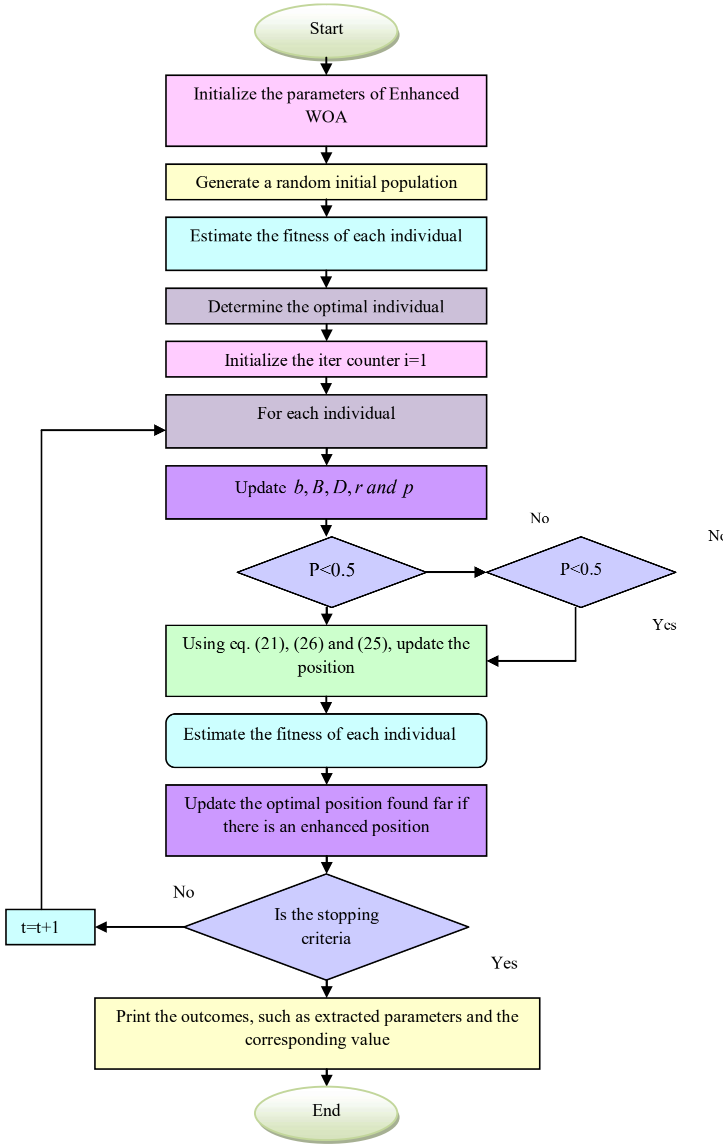

Fig. 1. *Flow Chart of proposed Enhanced GWO*

5. Results and Discussions

5.1 Simulation Procedure

The presented Enhanced WOA algorithm for optimal antenna selection experimented in MATLAB, and the results were attained. In addition, the proposed algorithm was compared with existing methods like GWO, WOA, and PSO and the improved results were attained. The analysis such as relative effectiveness and number of antenna done for ZF coding and MF coding.

5.2 Performance Analysis

Fig. 2 stated the proposed algorithm for optimal TAS in M-MIMO on regarding relative effectiveness. From the figure, the developed algorithm of MF for 5 users is obtained, whereas the proposed method is superior to the conventional methods. In Fig 2, for number of users 5, the proposed method is 12% better than the GWO, 14% better than the WOA, 16% better than the PSO method. Fig 3 states the relative effectiveness of the developed and existing models for zero forcing. Here, the proposed model 21%, 25% and 32% better than the conventional algorithms such as GWO, WOA and PSO models for number of users 15.

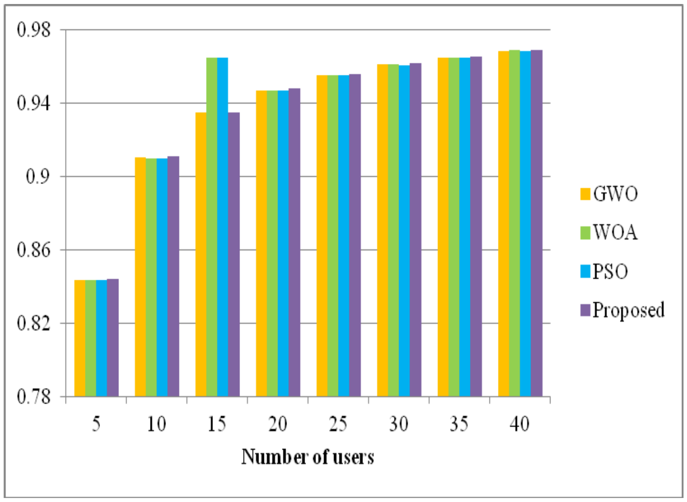

Fig. 2. *Relative effectiveness of the proposed and existing methods for match filtering*

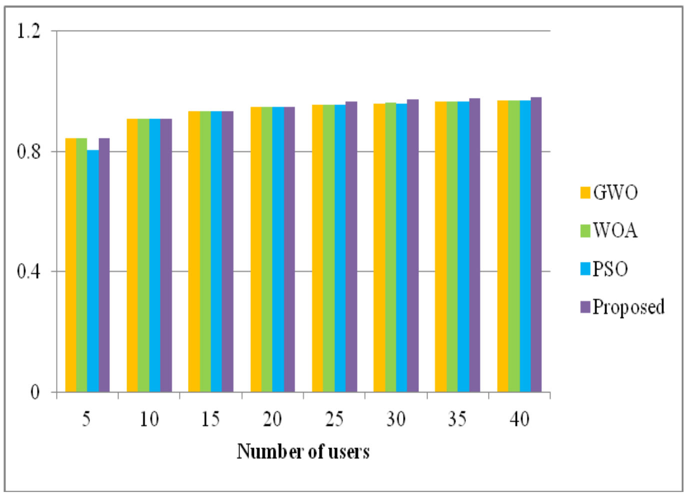

Fig. 3. *Relative effectiveness of the proposed and existing methods for zero forcing*

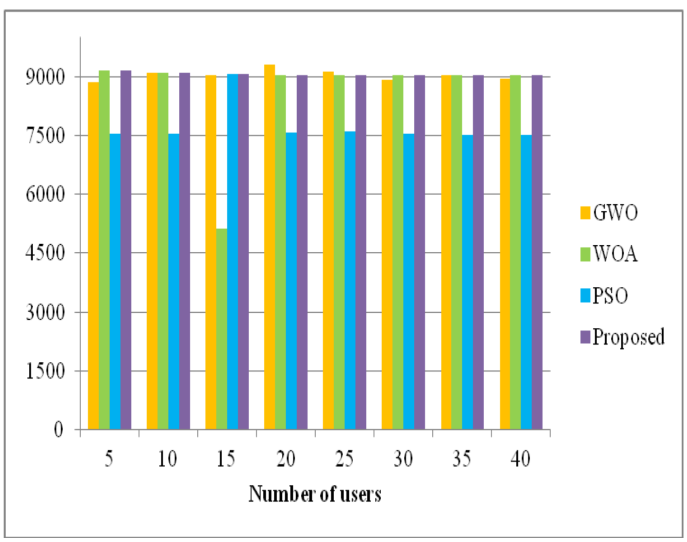

Fig. 4. *Optimal number of TAS proposed and existing methods for match filtering*

The presented enhanced WOA algorithm for the determination of the optimal number of transmitting antennas is stated in Fig 4 and 5. Fig. 4 exhibits the optimal number of TAS of the developed method with existing techniques for match filtering. Here, the proposed method is 22% superior to the GWO, 23% superior to the WOA, 25% superior to the PSO for number for users 15. Likewise, Fig 5 demonstrates the optimal number of TAS of the developed method with existing techniques for ZF. From the simulation outcomes, the optimal antenna selection deviates for ZF and MF on the basis of the number of users. Here, the proposed method is 15% superior to the GWO, 18% superior to the WOA, 22% superior to the PSO for number for users 25.

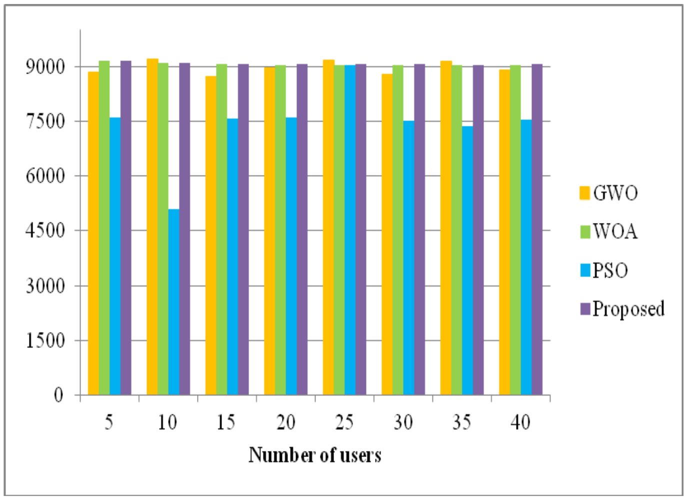

Fig. 5. *Optimal number of TAS proposed and existing methods for Zero Forcing*

6. Conclusion

Generally, MIMO upgrades the radio communication with enhanced reliability and capacity. As there is a incidence of multiple antennas at transmitter and receiver side, an appropriate TAS for obtaining effectual performance was a challenging point. In this paper, a novel Enhanced WOA algorithm was developed to attain the optimal selection of TAS exploiting a multi-objective issue, which can maximize both the relative Energy Efficiency and capacity in M-MIMO system. Therefore, enhanced WOA was used here for optimal selection of antennas, which finds out the number of antennas also how to choose the antennas in the optimal manner. In addition, the proposed method was evaluated with conventional methods such as GWO, WOA and PSO and the outcomes were obtained. The experimentation was performed for evaluating the relative effectiveness, capacity, and the optimal number of transmit antennas.

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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