Node Localization in MIMO-WSN Using Adaptive mutation Artifial Bee colony

Abstract:

In wireless sensor network (WSN) localization of sensor nodes is a fundamental problem. Multi-antenna transmission and reception (known as MIMO) is widely influenced as the key technology for enabling wireless broadband services, whose widespread success will require 10 times higher spectral efficiency than current cellular systems, at 10 times lower cost per bit. In this paper, an optimized mobile terminal localization in MIMO cellular networks is proposed. So that, a signal is generated with some of the initial parameters like, Time of Arrival (ToA), Time Difference on Arrival (TDoA), Angle of Arrival (AoA), Received Signal Strength Indicator (RSSI) etc and transmitted through the channel. During reception, the signal is optimized with an effective optimization algorithm like Adaptive Mutation based Artificial Bee Colony Algorithm (AMABC) in order to reduce the BER (Bit Error Rate). Moreover, beam forming and equalization the localization error is also computed for varying the number of sensor nodes. The technique is performed in the working platform of the MATLAB and its performance is assessed and contrasted with that of the standard Artificial Bee Colony algorithm to effectively illustrate the efficiency in execution of the innovative technique.

1. ***Introduction:***

In the modern day world, communication has become an integral part of our lives in different forms. Many types of communication Systems being used, the three major components of the communication Systems remain the same for all. These include source, channel, and sink (transmitter, channel, and receiver respectively). Both the transmitter and the receiver could either be fixed or mobile, and they are separated by the channel. The channel can be wire line or wireless. [1] A wireless network provides users the opportunity to communicate and access information without using cables. This provides freedom of movement and ability to extend applications in different parts of a building, of a city or almost anywhere in the world. [2]

As wireless signals attenuate quickly over distance, the signal from a local transmitting antenna is hundreds of thousands of times stronger than transmissions from other nodes. Hence it has been generally assumed that one cannot decode a received signal at a radio while it is simultaneously transmitting [3]. More bandwidth is required for higher data-rate transmission. However, due to spectral limitations, it is often impractical or sometimes very expensive to increase bandwidth. In this case, using multiple transmit and receive antennas for spectrally efficient transmission is an alternative solution. [4] Multiple input multiple output (MIMO) systems are a natural extension of developments in antenna array communication. While the advantages of multiple receive antennas, such as gain and spatial diversity, have been known and exploited for some time. [5].However, high transmission rates may result in severe frequency selective fading and inter symbol interference (ISI), when the Bandwidth of the transmitted signal is large compared to the coherence bandwidth of the channel. [6]

Location information of Mobile Terminal (MT) is a demand in many wireless systems. The rule of the FCC for detection of emergency calls requires all wireless providers to locate an E-911caller with an accuracy of 100 m and 300 m for 67% and 95% of calls. [7]There are four widely used measurement methods for localization: Time of Arrival (ToA), Time Difference on Arrival (TDoA), Angle of Arrival (AoA) and Received Signal Strength Indicator (RSSI). [8] Several applications have been proposed for wireless networks that require knowledge of terminal location. The uses of terminal localization include providing user navigation, supplying location context for web browsing, and aiding network resource allocation [10]

The accuracy of localization is limited by the measurement noise which can cause two separate locations to appear identical with respect to RSS measurements. This noise is created by thermal noise and random variations of the RSS created by multipath propagation. [9]Low cost Global Positioning System (GPS) receivers have been shown to give good localization accuracy in outdoor locations but they cannot be used indoors or in dense urban environments since GPS satellite signals are received only intermittently in these locations.[9]

2. Related works

Imran Khan *et al*. [11] have presented an analysis on the capacity and performance of MIMO-OFDM systems. The work was focused on the capacity of MIMO-OFDM systems over rician fading channel, in the case of the channel being known at the receiver only, which is more practical case of the channel. Simple expression for capacity was derived for the case of correlated rician fading. The performance of some MIMO-OFDM implementations with rician fading model is presented using an Alamouti coding scheme and Simulation results are obtained for both capacity and performance analysis.

Xia Liu *et al.* [12] have proposed investigations into capacity of a Multiple Input Multiple Output (MIMO) wireless communication system employing a uniform linear array (ULA) at the transmitter and either a uniform linear array (ULA) or a uniform circular array (UCA) antenna at the receiver. The transmitter was assumed to be surrounded by scattering objects while the receiver was postulated to be free from scattering objects. The Laplacian distribution of angle of arrival (AOA) of a signal reaching the receiver is postulated. Calculations of the MIMO system capacity are performed for two cases without and with the channel estimation errors. For estimating the MIMO channel, the scaled least square (SLS) and minimum mean square error (MMSE) methods are considered.

Varzakas [13] has proposed the problem of estimating the optimal radio capacity of a single-cell spread spectrum (SS) multiple-input multiple-output (MIMO) system operating in a Rayleigh fading environment was examined. The optimization between the radio capacity and the theoretically achievable average channel capacity (in the sense of information theory) per user of a MIMO single-cell SS system operating in a Rayleigh fading environment was presented. The spectral efficiency was estimated in terms of the achievable average channel capacity per user, during the operation over a broadcast time-varying link, and leads to a simple novel-closed form expression for the optimal radio capacity value based on the maximization of the achieved spectral efficiency. Numerical results are presented to illustrate the proposed analysis.

Michael D. Zoltowski *et.al* [14] has presented a pilot-assisted method for estimating the frequency selective channel in a MIMO-OFDM (Multiple Input Multiple Output – Orthogonal Frequency Division Multiplexing) system. The pilot sequence was designed using the DFT (Discrete Fourier Transform) of the Golay complementary sequences. Novel exploitation of the perfect autocorrelation property of the Golay codes, in conjunction with OSTBC (Orthogonal Space-Time Block Code) based pilot waveform scheduling across multiple OFDM frames, facilitates simple separation of the channel mixtures at the receive antennas. The DFT length used to transform the complementary sequence into the frequency domain is shown to be a key critical parameter for correctly estimating the channel. NMSE (Normalized Mean Squared Error) between the actual and the estimated channel was used to characterize the estimation performance.

Parit Kanjanavirojkul *et al*. [15] have examined a performance of compressed beam forming weights feedback technique in generalized triangular decomposition (GTD) based MIMO system. GTD is a beam forming technique that enjoys QoS flexibility. The technique, however, perform at its optimum only when the full knowledge of channel state information (CSI) was available at the transmitter. It would be impossible in the real system, where there are channel estimation error and limited feedback. They have suggested a way to implement the quantized beam forming weights feedback, which could significantly, reduced the feedback data, on GTD based MIMO system, and investigate the performance of the system. Interestingly, they have found that compressed beam forming weights feedback does not degrade the BER performance of the system at low input power, while the channel estimation error and quantization do. For comparison, GTD was more sensitive to compression and quantization, while SVD was more sensitive to the channel estimation error. They have also explore the performance of GTD based MU-MIMO system, and find that the BER performance starts to degrade largely at around -20 dB channel estimation error.

3. Overview of Proposed Technique:

In the domain of radio systems, a stellar surge in the number of mobile users these days has brought in its train the added hassles of the excessive overlap of signal inputs with the attendant and awesome intricacies of the localization procedure. With an eager eye on eradicating the eventual signal overlapping dilemmas, the Multiple Input Multiple Output (MIMO) Cellular networks have been flagged off as a viable solution. The multiple-input and multiple-output, or its abbreviation MIMO with the phonetic representation of "my-moh" or "me-moh", has appeared on the arena as an august approach for the advancement in the ability of a radio link applying a host of transmit and receive antennas to take the added advantage of the multipath transmission. It has set its elegant foot as an indispensable segment of the wireless communication patterns such as the IEEE 802.11n (Wi-Fi), IEEE 802.11ac (Wi-Fi), HSPA+ (3G), WiMAX (4G), and the Long Term Evolution (4G). Striking a discordant chord from the smart antenna approaches it invests itself dedicated for the augmentation in the efficiency of a single data signal, like the beam-forming and diversity.

It has to be earnestly admitted that the MIMO networks offer a host of fruitful benefits. Nevertheless, it is unfortunate that they fail miserable to effectively address the localization hassles completely. Incidentally, there are four vital constraints habitually employed to appraise the localization approaches which include the Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Angle of Arrival (AoA), the Received Signal Strength Indicator (RSSI). In the novel approach, the constraints are initialized in advance and a signal is generated for analysis. Further, an efficient optimization technique termed as the Adaptive mutation based Artificial Bee Colony (AMABC) optimization is kick-started to achieve the superior signal by reducing the BER (Bit Error Rate) values. Finally, beam-forming and equalization is also performed in the realms of the MIMO cellular technologies.

3.1. Proposed Mobile Terminal Localization Technique in MIMO Cellular Networks:

The wireless sensor networks are fundamentally affected by the path loss impact and the path loss incidence is different for diverse directions. The power loss, in turn, is largely triggered by the hindrances by the parallel objects in the vicinity of the receiver and is habitually labelled as the Shadow fading or large-scale fading. The log-normal shadow model surfaces as the ideal candidate for the wireless sensor networks both in respect of the indoor and outdoor applications thanks to its global character and the innate skills of getting duly shaped in accordance with the ecosystem.

A spatially multiplexed MIMO system under the frequency-selective fading channel with L channel taps. N and M denote the numbers of transmit and receive antennas, respectively, and the block transmission environment. A sequence of data bits for a transmission block is modulated into a symbol sequence including KN symbols, where K is the number of transmit signal vectors in a transmission block. Let $X_k = [x_k(1),...,x_k(N)]^T$ denote the kth transmit signal vector of a transmission block for $X_k = [x_k(1),...,x_k(N)]^T$ where $E[X_k X_k^H] = I_N$ with the $N \times N$ identity matrix I_N . Then, the receive signal vector $X_k = [x_k(1),...,x_k(N)]^T$ at time k with $1 \le k \le K + L - 1$ is written as

$$y_k = \sum_{l=0}^{L-1} H_k^l X_{k-1} + n_k$$

Where H_k^l denotes the MN× channel matrix, which corresponds to the channel response of the lth tap at time k, and n_k M×1 additive white Gaussian noise (AWGN) vector with zero-mean and the covariance matrix $E[n_k n_k^H] = \sigma^2 I_M$. The perfect channel estimation at the receiver is assumed, and therefore all H_k^l and σ^2 are perfectly known at the receiver. In addition, no inter-block interference is assumed. Furthermore, it is assumed that each sub-channel has unit energy regardless of k, which is written as

$$\sum_{l=0}^{L-1} E\left[\left|H_k^l(i,j)\right|\right] = 1$$

for any 1 ≤i≤ M and 1 ≤j≤ N, where $H_k^l(\mathrm{i},\ \mathrm{j})$ is the element of H_k^l in the ith row and the jth column. let $\tilde{Y} = \left[Y_1^T,...,Y_{K+l-1}^T\right]^T$ denote the M(K+L-1)×1 receive signal vector including all the received signals for the transmission block. Similarly, let $\tilde{X} = \left[X_1^T,...,X_{K+l-1}^T\right]^T$ denote the NK×1 transmit signal vector including all the transmitted signals for the transmission block. Then, the relationship between $\tilde{Y}$ and $\tilde{X}$ can be written as

$$\tilde{Y} = \tilde{H}\tilde{X} + \tilde{n}$$

where $\tilde{n} = [n_1^T,.....,n_{K+L-1}^T]^T$ denotes the $M(K+L-1)\times 1$ AWGN vector including all the noise components for the transmission block, and $\tilde{H}$ is the $M(K+L-1)\times NK$ channel matrix including the all the channel responses for the transmission block, which is written as

$$\tilde{H} = \begin{bmatrix} H_1^{(0)} & 0_{M\times N} & \dots & 0_{M\times N} \\ \vdots & H_2^{(0)} & \dots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ 0_{M\times N} & 0_{M\times N} & \dots & H_K^{L-1} \end{bmatrix}$$

Where $0_{M\times N}$ is the $M \times N$ all-zero matrix.

3.1.1. Mobile Terminal Localization:

The Location information of Mobile Terminal (MT) constitutes a demand in several wireless mechanisms. In this regard, the localization error is evaluated by means of Equation 4 shown hereunder.

$$L_{error} = \frac{1}{r_{S_N}(S_N - A_N)} \sum_{j=A_N+1}^{S_N} \sqrt{(p'_j - p_j)^2 + (q'_j - q_j)^2} \tag{4}$$

In the captioned equation for the node j , (p_j, q_j) represents the real coordinate of the unidentified node and (p'_j, q'_j) signifies the approximate coordinate of unidentified node. r_{S_N} corresponds to the communication radius of the sensor nodes. S_N indicates the total number of the sensor nodes in the sensor field and A_N reveals the total number of anchor nodes. The lower localization error value exhibits superlative efficiency in accomplishment. The efficiency of the localization technique is significantly affected by the number of unidentified nodes, anchor nodes and the communication radius of the sensor nodes. In the document, the replication outcomes are assessed and appraised for the total number of nodes. In the authentic WSN networks, radio signals are adversely affected by the environ through which they are disseminated.

3.1.2. Types of Mobile Terminal Localization Techniques:

In accordance with the systems employed, various localization techniques may be broadly categorized into three types such as range-based Localization, angle-based Localization and the range-free or proximity-based Localization.

- **Range-based Localization:**

This mode of localization furnishes measurements dependent on the entire distance data among the nodes.

- **Angle-based Localization:**

In this type of localization, measurements are offered by attaining the angle data among the nodes.

- **Range-free or proximity-based Localization:**

In this case, only the connectivity data are presented.

3.1.3. Distance Estimation in Localization:

The ranging between two nodes is unearthed by bringing in two nodes in a network and subsequently locating the distance between them. In this regard, there are four general techniques for measuring in the localization approaches which are shown below.

- The Angle of Arrival (AoA)
- The Time of Arrival (ToA)
- The Time Different of Arrival (TDoA)
- The Received Signal Strength Indicator (RSSI)

- **Time of Arrival:**

The Time of arrival (TOA or ToA), at times termed as the Time of Flight (ToF), represents the travel time of a radio signal from a single transmitter to a far-off single receiver.

The travel time taken by a radio signal to travel from the single transmitter to the far-flung single receiver is represented by means of Equation 5 shown below.

$$t_{ToA} = t_T \simeq t_R \qquad (5)$$

- **Angle of arrival (AoA):**

The Angle of Arrival (AOA) invariably entails a minimum of two towers, identifying the caller at the point of intersection of the lines along the angles from each tower. This type of measurement represents a technique for ascertaining the direction of transmission of a radio-frequency wave incident on an antenna array. The AoA decides the direction by evaluating the Time Difference of Arrival (TDOA) at individual elements of the array and from the corresponding delays the AoA is effectively evaluated.

- **Time Difference of Arrival (TDOA):**

The Time Difference of Arrival (TDOA) functions by means of the multilateration, with the exception that the networks play a vital role in calculating the time difference and hence the distance from each tower (as with seismometers).

Let the receiver be positioned at a distance T_R from the transmitter. The transmitter is placed at the distance T_T. The Time Difference of Arrival is estimated by means of the following Equations 6 and 7.

$$t_{TDoA} = vt_R - vt_T \tag{6}$$

$$t_{TDoA} = T_R - T_T \tag{7}$$

Where, the distance T_R represents the wave speed v times the transmit time t_R.

- **Received Signal Strength Indicator (RSSI):**

In the domain of the telecommunications, the received signal strength indicator (RSSI) constitutes a measure of the power existing in a received radio signal.

The RSSI is habitually invisible to a user of a receiving device. Nevertheless, as the signal strength is capable of fluctuating significantly and having a significant impact on the functionality in the wireless networking, IEEE 802.11 tools generally make the measure accessible to users.

The RSSI is usually performed in the intermediate frequency (IF) stage before the IF amplifier. In the zero-IF mechanisms, it is carried out in the baseband signal chain, before the baseband amplifier. The RSSI output is frequently a DC analog level. It may also be sampled by an internal ADC and the resultant codes accessible directly or through the peripheral or internal processor bus.

Received signal strength (RSS):

The received signal strength represents the easiest and the cost-effective metric to estimate the distance between the sensor nodes for the localization objectives . In the RSS based localization techniques, the signal strength received at the sensor node is mapped into distances by means of certain channel model. The most well-acknowledged channel model is the log normal shadowing model. The received power at the sensor nodes employing the log normal shadowing model is represented by means of the following Equation 5.

$$P_R = P_T - 10\log P_{Loss}\left(\frac{r}{r_0}\right) + \delta \tag{5}$$

The sensor nodes are arbitrarily employed in a square region. All the anchor nodes and unidentified nodes comprise an identical communication radius of 15m.

In our proposed model, a signal is generated with some of the localization parameters. At transmitter side the signal is OFDM modulated. While transmission through the channel, thermal noise is added. In between this, the propagation loss (path loss) and the interferences are measured.

The proposed architecture is shown through the below figure1.

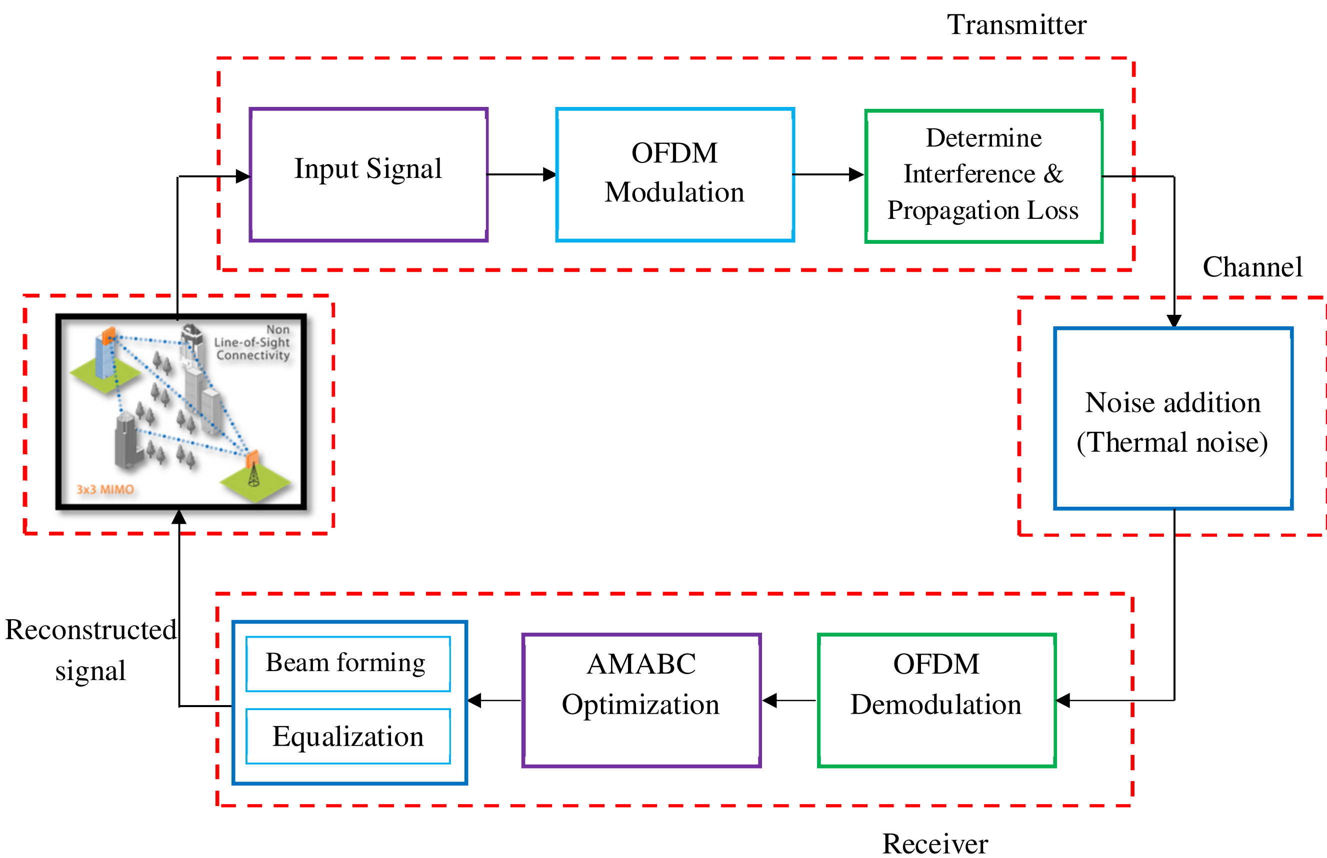


Figure 1: Architecture Diagram

The mathematical equation for the Path Loss Function evaluated and expressed in decibel is represented by the following Equation 1.

$$P_{Loss}(dB) = \overline{P_{Loss}}(r_o)(dB) + 10\gamma\log_{10}\left(\frac{r}{r_o}\right) + \delta(dB) \tag{1}$$

Where,

r relates to the distance between the sending and receiving nodes

r_o denotes the near earth reference distance

γ corresponds to the Path loss index

δ signifies the zero-mean Gaussian random noise

The Path Loss function represented in terms of the Transmitter and Receiver is furnished by Equation 2 given below.

$$P_{Loss}(dB) = 10\log\left(\frac{P_T}{P_R}\right) \tag{2}$$

Where,

P_T symbolizes the Transmitted Signal Power

P_R represents the Received Signal Power. The value of path loss index is invariably dependent on the environment or the transmission scenario. The distance r_o is considered as one meter for the sake of easy evaluation. The basic edition of Equation 1 may be expressed with respect to the received power as shown by Equation 3 given hereunder.

$$\left[\frac{P_R(r_o)}{\overline{P_R}(r)}\right] = \left[\frac{r}{r_0}\right]^{\gamma} + \delta \tag{3}$$

The overall procedure diagram is colourfully pictured in Fig1, where the MIMO cellular network going through the data-sharing procedure is elegantly exhibited.

At the transmitter side, the signal will be OFDM demodulated. Then in order to reduce the noisy content, AMABC algorithm is employed.

3.1.4. Adaptive Mutation based Artificial Bee Colony Optimization Algorithm (AMABC):

The Adaptive Mutation based Artificial Bee Colony Optimization Algorithm is introduced in our proposed method to reduce the BER by optimizing the input signal. The ABC algorithm and its drawbacks are explained below.

- **Artificial Bee Colony Optimization Algorithm:**

The vital objective of the optimization method is to find a set of fittest values for the input parameters. The Artificial bee colony (ABC) optimization represents a swarm intelligence based algorithm which replicates the foraging character of the honey bees. An enormously huge number of bespoke and superior versions like the G best guided ABC, binary version of the ABC known as the DisABC, differential ABC, interactive ABC, and the cooperative ABC have been flagged off and are in vogue at present.

In the ABC model, foraging honey bees are classified into three vital categories such as the Employed bee, Onlooker Bee and the Scout bee.

In accordance with the two essential leading modes of the forages such as the employment to a food source and refusal of a source, the procedure of bees on the hunt for sources with an elevated amount of nectar is the one deployed to ascertain the optimal solution for the specified optimization issue.

- **Steps involved in AMABC:**

The steps involving in AMABC algorithm is detailed in the below section.

Step (1): Initialization:

- An initial population of T_N individuals is created.
- For each and every individual, t_j represents a food source (i.e. solution) consisting of D_N attributes (i.e., dimensionality).

Step (2): Fitness Evaluation of T_N Individuals

- In this phase, the fitness of each individual solution is estimated.

Step (3): Obtain Neighborhood position

- Here, the neighbourhood of the current position of each employed bee is attained to locate a superior food source.

Step (4): New Solution Generation

- Hence, in respect of each and every employed bee, a new solution s_j is produced around its current position, t_j with the help of Equation 6 given below.

$$s_{j,k} = t_{j,k} + \chi_{jk}(t_{j,k} - t_{l,k}) \tag{6}$$

Where,

$j \in \{1,2,..,N_E\}$ and $k \in \{1,2,..,D_N\}$- arbitrarily selected list

N_E - number of employed bees

χ_{jk} - even arbitrary number within range [-1, 1].

Step (5): Selection of Best probability based on Fitness Function

- In this step, the fitness of both t_j and s_j are determined and the selection method is initiated to shortlist the superior among them.

- **Step (5a) : Selection Probability**
  - ❖ Now, the selection probability values, S_p are estimated and standardized for each and every employed bee, t_j with the assistance of the roulette-wheel selection approach.

The selection probability S_P of the k^{th} parameter is given as,

$$S_P = \frac{t_k}{\sum_{k=1}^{D_N} t_k} \tag{7}$$

The adaptive mutation function in the food source position (solution) generation procedure enhances the efficiency in performance of the ABC technique. The novel adaptive mutation function in the AMABC is illustrated as follows.

$$S_{AM} = \delta\left(1 + rand \; \frac{(t_{jk_{\max}} - t_{jk_{\min}})^m - t_{jk_{avg}}^{\;m}}{\zeta\,(t_{jk_{\max}} - t_{jk_{\min}})^m - t_{jk_{avg}}^{\;m}}\right) \tag{8}$$

$$\xi = \left(\frac{t_{jk_{\max}} - t_{jk_{\min}}}{t_{jk_{avg}}}\right)^m \tag{9}$$

Where, δ - mutation probability; m , ξ - mutation coefficient factors; $t_{jk_{\max}}$, $t_{jk_{\min}}$ and $t_{jk_{avg}}$ are the maximum, minimum and average fitness of food sources.

When the evaluation of S_P of the entire k is finished, average of Equation (7) is estimated and k which exceed the valued of the average probability is shortlisted.

$if\ S_P > avg(S_P)$

$then\ k$ is modernized by means of onlooker bee phase

Step (6): Assigning Onlooker Bee

- Here, each and every onlooker bee is allocated to an employed bee, t_j arbitrarily with probability in direct proportion to S_p

- **Step (6a) :**
  - In this stage, new food positions, s_j for each and every onlooker bee, t_j are generated deploying its employed bee as t_l in (6).
- **Step (6b) :**
  - Thereafter, the fitness of each onlooker bee t_j is estimated together with the new solution s_j . Now the greedy selection method is followed to retain the superior bee, after rejecting others.

- ❖ When the evaluation of the best k is finished, the best k outcomes from the onlooker bee phase and employed bee phase are analysed, assessed and contrasted one by one.

Step (7): Replacing with Scout Bee

- In case a specific t_j has not been enhanced even after a number of iterations, it has to be abandoned.
- The solution is replaced by introducing a scout bee at a food source at the search space by means of Equation 7 illustrated as follows.

$$t_{jk} = k_{\min} + rand(0,1) * (k_{\max} - k_{\min}),\ \text{for}\, k \in \{1,2,..,D_N\} \qquad (10)$$

Step (8): Placing Final Best Solution

- In this step, the best food source position (solution) discovered till now, has to be tracked.

Step (9): Termination

- At this juncture, the termination has to be verified. If the best solution discovered is satisfactory or a maximum number of iterations have been reached, the process has to be stopped. When the stoppage standard is satisfied, the best k are shortlisted and replaced in Equation (6) to achieve the ultimate clustered outcome. Or else, return to step 2 and continue the process.

In the long run, the AMABC Optimization technique is carried out for the purpose of reducing noisy contents so as to achieve the lucid communication of the radio signal through the transmitter/receiver units. Subsequently, the MIMO networks are facilitate to carryout the beam-forming so as to evaluate the signal strength at any direction.

3.1.5. Beam forming & Equalization:

The beam forming or spatial filtering represents a signal processing approach extensively employed in the sensor arrays for the directional signal conduction or reception. It is attained by integrating the elements in a phased array in order that the signals at specific angles are subjected to constructive interference while others undergo destructive interference. It is effectively utilized at the communicating and receiving ends so as to attain the spatial selectivity. It is beneficially employed for radio or sound waves. It is widely accepted in a number of applications in the domains of the radar, sonar, seismology, wireless communications, radio astronomy, acoustics, and the biomedicine. Finally, the process of equalization is performed within the MIMO cellular system in order to balance the frequency components of the received signal.

4. Results and Discussion:

The proposed technique for mobile terminal localization is implemented in a system having 8 GB RAM with 32 bit operating system having i5 Processor using MATLAB Version 2013b. The signal power is plotted for a frequency range between 0 to 2.5 KHz.

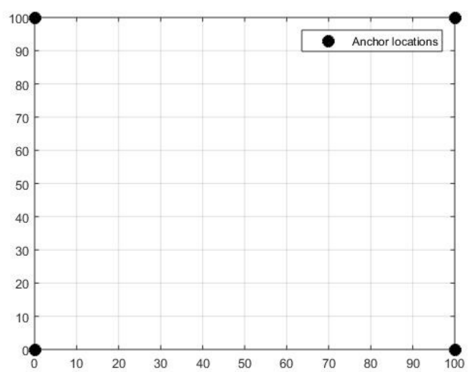
In this paper, Effective AMABC Optimization based Mobile Terminal Localization Technique in MIMO Cellular Networks is used to minimize the localization problems. The localization can be measured by means of four parameters: Time of Arrival (ToA), Time Difference on Arrival (TDoA), Angle of Arrival (AoA) and Received Signal Strength Indicator (RSSI). So, the technique is analyzed with the signal generated with such parameters measuring localization.

The initial parameters were given as below,

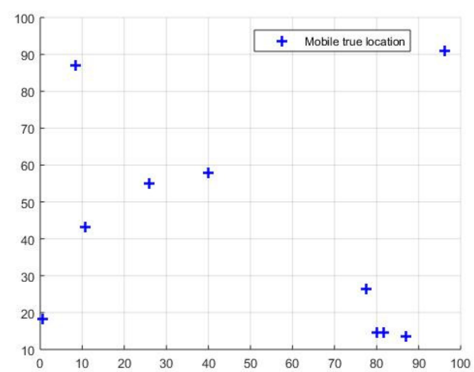
Initial Parameters
Interference Power = -20
Mobile Range = 2750
Mobile Angle = 3
Transmission Power = -8
Interference Range = 9000
Interference Angle = 20
Number of Transmitting Elements = 4

Steering Angle = 0
Receiver Gain = 108.8320 – Transmit Power

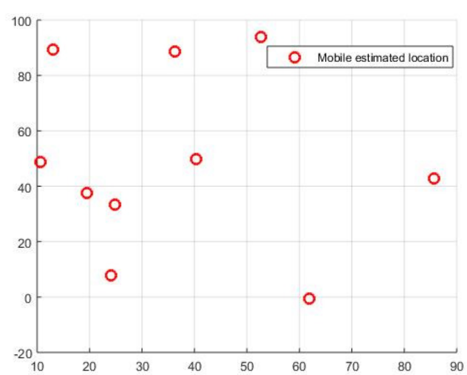
Moreover, the distance is predicted with the help of 4 Anchor Nodes (Known Nodes) and each being placed at the distance of 100m. Fig 2 shows the position of anchor nodes, sensor nodes and the evaluated Position of Sensor Nodes respectively.



(a)



(b)



(c)

Fig 2: Position of (a) Anchor Nodes, (b) Original Mobile Terminal (Sensor nodes), (c) Estimated Mobile Terminal (Sensor nodes)

Moreover, the evaluated position of Sensor Nodes from the Anchor nodes (known Nodes) taken over the area of 100mx100m and the original position of mobile terminal location is given by the below plot (figure 3).

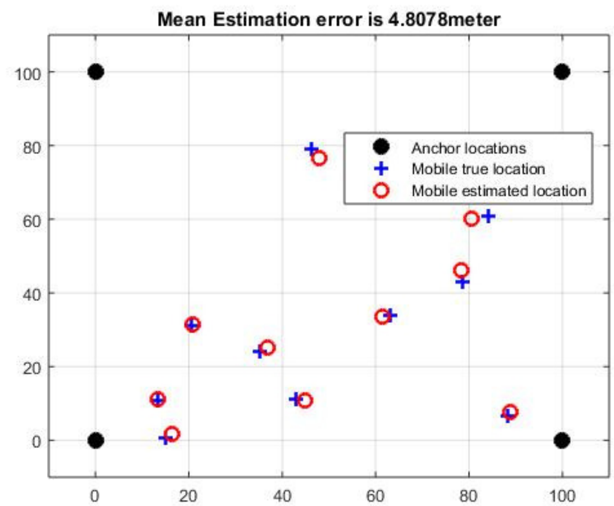


Figure 3: Estimated mobile terminal location

The above graph shows the deviation in mobile location prediction, where the Anchor nodes (location known node) are placed at the four corners. Also, in graph the predicted mobile location as well as the original mobile location is distinguished.

The Localization error is obtained for the sensor with varying number of anchor nodes. Fig 4 shows the Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-10) % and the values are tabulated in table 1.

	For Varying Number of Anchor Nodes					
	50 Nodes	**100 Nodes**	**150 Nodes**	**200 Nodes**	**250 Nodes**	**300 Nodes**
Existing Method	0.406136	0.359405	0.333415	0.246823	0.190892	0.057418
Proposed Method	0.195363	0.194999	0.139543	0.13652	0.099609	0.01864

Table1. Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-10) %

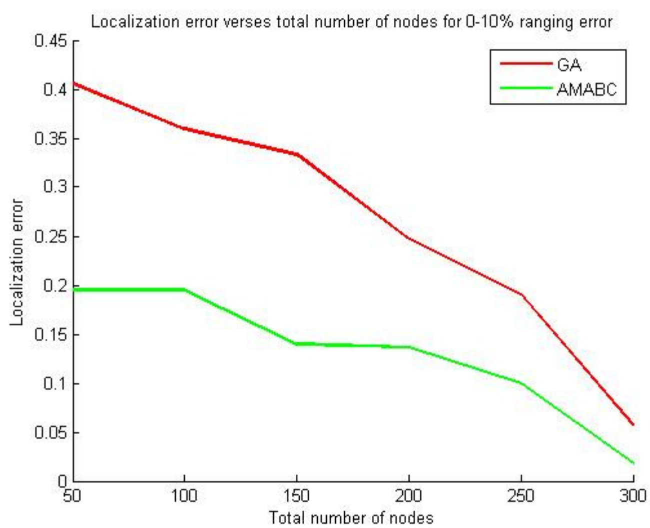


Fig 4: Localization Error Vs Total number of nodes for 0-10% Ranging Error

Fig 5 shows the Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-20) % and the values are tabulated in table 2.

	For Varying Number of Anchor Nodes					
	50 Nodes	**100 Nodes**	**150 Nodes**	**200 Nodes**	**250 Nodes**	**300 Nodes**
Existing Method	0.460622	0.4421803	0.3908244	0.291798151	0.1209579	0.1188496
Proposed Method	0.30358	0.274303	0.2503134	0.229223107	0.0672852	0.0423559

Table2. Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-20) %

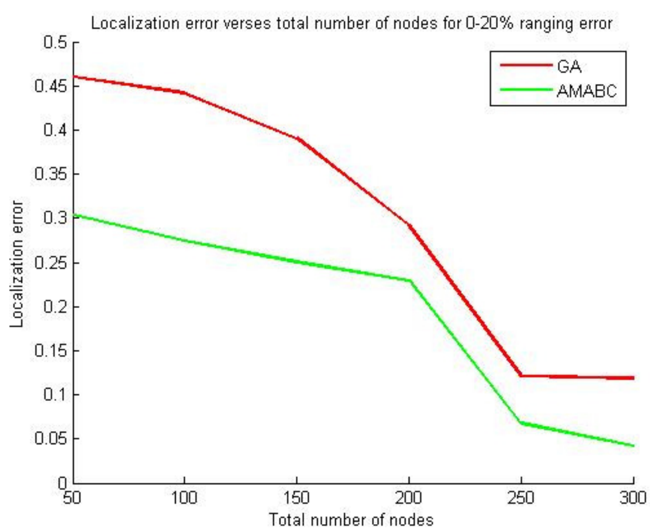


Fig 5: Localization Error Vs Total number of nodes for 0-20% Ranging Error

Fig 6 shows the Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-30) % and the values are tabulated in table 3.

	For Varying Number of Anchor Nodes

	50 Nodes	100 Nodes	150 Nodes	200 Nodes	250 Nodes	300 Nodes
Existing Method	0.44439	0.3930	0.3216	0.30153	0.24557	0.20173
Proposed Method	0.29248	0.275497	0.23606	0.18109	0.03185	0.00356

Table3. Localization error obtained for both proposed and existing method by varying the number of nodes at ranging Error (0-30) %

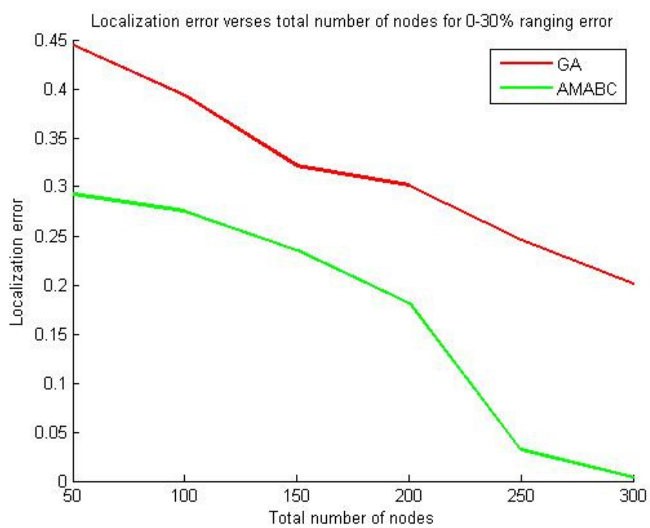


Fig 6: Localization Error Vs Total number of nodes for 0-30% Ranging Error

Also, the Received Signal Strength Indicator Value and the elapsed time for the proposed AMABC and existing GA values are tabulated in table 4.

Technique	**Received Signal Strength Indicator (RSSI)**	**Elapsed Time (Seconds)**

GA	-14.448	23.087793
	-10.5252	
	-14.3084	
AMABC	-0.72664	16.094249
	-6.41546	
	0.799297	

Table 4: Received Signal Strength Indicator Value and elapsed Time for the Proposed AMABC and GA

The process of beam forming is performed finally to increase the SNR and to reduce the BER for the input signal. The beam formed is plotted and is given in the below figure

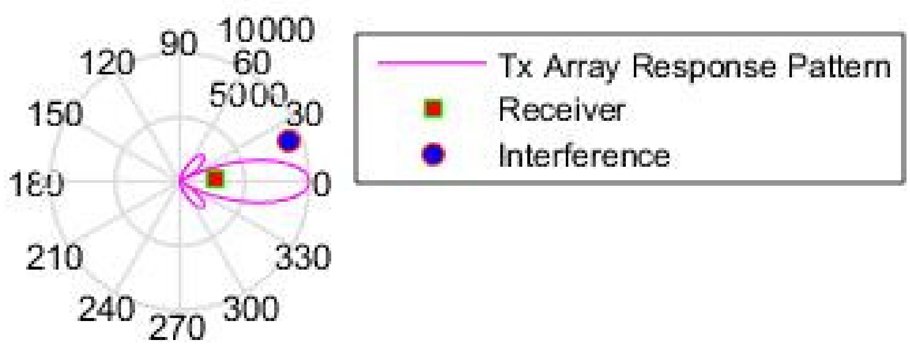


Figure 7: Beam Forming within MIMO environment

Conclusion:

In WSN, localization is very important issue. Localization of sensor nodes is required to know the location of origin of events. In order to obtain high accuracy in node localization, the paper discusses the techniques and algorithms that have been developed and implemented to get a very low cost localization in WSN system. For this the localization error is obtained for varying the ranging error of (0-10) %, (0-20) % and (0-30) %. Also, the received signal strength and time measurements are taken and are analyzed showing the better efficacy of our proposed optimized Mobile Terminal Localization with AMABC technique.