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PSO-optimized Pareto and Nash equilibrium gaming-based power allocation technique for multistatic radar network

Thoka Harikala | **Ravinutala Satya Narayana**

Department of Electronics and Communication, S.V. University, India

Correspondence
Thoka Harikala, Department of Electronics and Communication, S.V. University College of Engineering, Tirupati, Andhra Pradesh, India.
Email: harikala1987@yahoo.com or harikala1987@gmail.com

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At present, multiple input multiple output radars offer accurate target detection and better target parameter estimation with higher resolution in high-speed wireless communication systems. This study focuses primarily on power allocation to improve the performance of radars owing to the sparsity of targets in the spatial velocity domain. First, the radars are clustered using the kernel fuzzy C-means algorithm. Next, cooperative and noncooperative clusters are extracted based on the distance measured using the kernel fuzzy C-means algorithm. The power is allocated to cooperative clusters using the Pareto optimality particle swarm optimization algorithm. In addition, the Nash equilibrium particle swarm optimization algorithm is used for allocating power in the noncooperative clusters. The process of allocating power to cooperative and noncooperative clusters reduces the overall transmission power of the radars. In the experimental section, the proposed method obtained the power consumption of 0.014 to 0.0119 at $K = 2$, $M = 3$ and $K = 2$, $M = 3$, which is better compared to the existing methodologies—generalized Nash game and cooperative and noncooperative game theory.

KEYWORDS
Kernel fuzzy C-means, multiple input multiple output, Nash equilibrium, particle swarm optimization, power allocation

1 | INTRODUCTION

A multiple input multiple output (MIMO) radar uses multiple antennas to transmit different orthogonal waveforms and receives the reflected signals from the target. The performance of the MIMO-radar system is high as compared to conventional radar systems [1–3]. Generally, MIMO radars can be categorized into two types—MIMO with collocated antennas and MIMO with separated antennas. MIMO with collocated antennas enhances the estimation performance of beam-forming using effective spatial degrees of freedom. The coherent signals are detected from the radar target by placing both the transmitter and receiver antennas in MIMO radars. The statistical MIMO radar antenna enhances the detection and estimation of the resolutions using the diversity of transmission paths [4]. The game theory method has been used within the range of the radars. Various techniques have been implemented to optimize the radar's transmission parameters according to underlying scenarios. The detection performances have been improved by implementing the zero sum game in the design of polarimetric waves [5]. Recently, game theory techniques have been extended to address several challenges and optimize various radar parameters [6].

The zero sum game theoretic (ZSGT) technique is employed to examine the interaction between MIMO radars [7]. In the network radar, the features of the radar view point are improved using an adequate coded waveform in frequency. In addition, the signal-to-interference plus noise ratio (SINR) of each radar is improved using noncooperative games [8,9]. The radar network is considered where a generalized Nash game is employed to control the transmission power performance of the radar [9]. The noncooperative game technique is used to address the power optimization issue with a predefined SINR limitation [10]. In radar systems, the problem of power allocation (PA) and distributed beamforming are obtained using various game theoretic methods [11–15]. Improper power allocation to the primary and secondary users affects the performance of the MIMO-radar network. To overcome the aforementioned problem, particle swarm optimization (PSO) is integrated with both the noncooperative game theories based on Nash equilibrium. This integration is used for optimizing the transmission power in a MIMO network. The MIMO radar networks are divided into primary and secondary clusters using the kernel fuzzy C-means (KFCM) algorithm. The KFCM technique is used for clustering/grouping of sensor nodes in the MIMO radar network. The major objective of the KFCM-Pareto optimality Nash equilibrium (PONE)-PSO method is to allocate the power for each antenna of the MIMO radar while maintaining the desired SINR threshold.

This paper is organized as follows. Section 2 presents a detailed literature survey of spectrum sensing techniques for PA in a MIMO network. Section 3 describes the problem statement and solutions of the MIMO radar network. Section 4 briefly describes the proposed KFCM-PONE-PSO method. The comparative experimental results for the proposed KFCM-PONE-PSO method and existing methods are presented in Section 5. The conclusion is drawn in the Section 6.

2 | LITERATURE SURVEY

In this section, a literature review of the existing research studies related to the MIMO-radar system are presented.

Wang and others [16] proposed a jamming PA approach for the MIMO radar; this approach was analyzed based on the performance of minimum mean square error (MMSE) and mutual information. These performances of MMSE and mutual information were utilized as the utility function. The mutual information was used for power allocation between the MIMO radar and jammer. The jamming PA approach is used to increase the target estimation of MMSE and reduce the mutual information between the target impulse response and echo of the MIMO network. The simulation outputs prove that the proposed method increases the MMSE and reduces the mutual information for improving the jamming performance. The MMSE and mutual information based jamming of the PA method were used to obtain the power spectral density (PSD), noise PSD, and radar waveform PA (RWPA). The MMSE value of MMSE-based jamming PA is higher than that obtained using the mutual information based strategy when the radar waveform PA is uniform.

Ma and others [17] introduced the joint scheme of antenna subset selection and an optimal PA to carry out the localization in a MIMO radar network. In this work, sensor management was developed by resolving an optimization issue that was formulated to reduce the error in estimating the target position. A suboptimal technique was used for solving the optimization issues. The proposed scheme divides the optimization into two steps; each step was transformed into second-order cone programming (SOCP) by convex relaxation. The proposed joint approach of the antenna subset selection and optimal PA (OPA) increases the accuracy of localization detection with resource constraints. Ma et al.'s research formulated the issue as an optimization scheme and proposed the two-step suboptimal technique to tackle the complexity in simultaneous optimization. However, the performance of the proposed method is not too efficient for a MIMO radar.

Song and others [18] proposed a joint resource allocation technique for tracking several targets in distributed MIMO radar networks. The residual resources are used to improve the tracking performances for all key targets. The proposed method divides the optimization into three steps, where each step transforms the corresponding mixed Boolean optimization issue into an SOCP issue by convex relaxation. Initially, the cyclic minimization method is used to obtain the approximate optimal solution. The proposed method achieved the lowest velocity estimation in MSE using the smallest number of transmitters. In this technique, the joint resource allocation concentrates only on the key target during target tracking. The proposed algorithm is only applicable to a limited number of users; it is unable to analyze a network with a large number of users.

Lan and others [19] developed a two-step water filling technique for the Stackelberg game between the MIMO radar network and the target in the presence of clutter. The technique was applied to distribute jamming power, and common water filling was applied to distribute signal power based on mutual information. In the Stackelberg equilibrium of radar and target dominance, the optimization technique was achieved in the presence of clutter. Moreover, the optimization with the antenna's state was considered to manage the destruction in MIMO radar transmitting antennas. In this study, the jamming power was focused only on the subspace with less noise.

Panoui and others [20] presented the distributed waveform design for multistatic radar networks. The major objective of this technique is to improve the signal to disturbance ratio

(SDR) of the cluster by selecting the suitable waveforms. Thus, the best waveform for each cluster is determined. The radar performance was improved by determining the equilibrium and establishing interaction between each radar. However, if the number of clusters increases, then the impedance prompted in the system also increases, which reduces the value of SDR for each cluster.

Shi and others [21] presented the low probability of intercept-based optimal power allocation (LPI-OPA) for integrated multistatic radar and communication systems. In each transmitter, the LPI-OPA is used to optimize the transmitted power allocation for reducing the total power consumption. The OPA is used to achieve the predefined target detection for the radar receiver (RR) and an appropriate data rate for the communication receiver (CR). Moreover, linear programming and the Karush-Kuhn-Tucker (KKT) conditions are used to solve the two subproblems—portions of the transmitter power resource and transmitted power allocated for the information waveforms. The requirements of communication rate and target detection are satisfied using the LPI-OPA. The computational complexity of exhaustive search used in the optimization problem is high.

Shi and others [22] developed the power minimization based joint subcarrier assignment and power allocation (PM-JSAPA) for integrated radar and communications systems (IRCSs). The power resource allocation and optimization of available carriers using the PM-JSAPA strategy reduces the IRCS's radiated power. Subsequently, three-step resource allocation is developed for solving the resulting optimization problem, that is, the mixed integer nonlinear programming (MINLP) problem. In the first step, the available subcarriers are allotted to both the radar and communication systems. In the second step, the KKT is used to solve the power resource allocation problem, and the problem of convex power allocation is solved under the conditions of KKT in the third step. The PM-JSAPA does not consider the IRCSs with multiple transmitters, receivers, and downlink communications during power allocation.

Shi and others [23] presented the Nash bargaining solution (NBS)–based game theory for controlling the power in distributed multiple-radar systems (DMRSs). The main objective of NBS is to reduce power consumption along with protection of transmission. The utility function of the DMRS is improved by developing the unified analytical framework. The transmission is protected using the interference power constraints (IPCs) in DMRS. In mathematical formulation, the IPC is transformed into the term of extra pricing for solving the complexity. The NBS developed for DMRS obtains less SINR than the traditional NBS method.

Shi and others [24] developed the robust Stackelberg game–based power control (RSG-PC) for multistatic radar and massive MIMO communication systems. For each radar, the radiated power in the worst case is reduced by RSG-PC. The hierarchical competition among the multiple radars and MIMO-communication base station (CBS) is described by the Stackelberg game model. Here, multiple radars are operated in a noncooperative manner, competing for the power resource. The interference present in the communication is avoided by considering the pricing mechanism and uncertainties in path propagation gains. The RSG-PC model analyzed only a single massive MIMO-based CBS. However, the RSG-PC model failed to analyze multiple CBSs.

3 | PROBLEM STATEMENT

The following section defines the problem statement of PA techniques for the MIMO radar network and provides details on how the proposed methodology addresses the following problems.

- In the MIMO radar network, the problem arises from the distances between the clusters.
- Coexisting multicarrier radar and communication systems require more delay [25].
- PA is the major challenge in the millimeter-wave-based MIMO radar network because of uneven distribution of power in the sensor network.

Solution: In this study, the MIMO radars are initially separated into clusters. The KFCM algorithm is used for clustering the sensor nodes based on the distance between the networks. The classification of primary and secondary users depends on the distance analysis of the network using the KFCM algorithm. Each cluster secures a certain detection in terms of SINR while allocating the minimum possible power to each and every radar. After the clustering process, the power loss is computed based on the threshold between the primary and secondary clusters. After computing the power loss, PSO-based cooperative and noncooperative game theory is used to allocate power in the MIMO network. The PSO-based noncooperative game is used for allocating power for the secondary clusters as well. The major aim of the PSO algorithm is to select the best power to allocate to the clusters of the MIMO network. To apply the game theoretic algorithm, the optimal power value is chosen for each antenna and allocated to the MIMO radar.

4 | KFCM-PONE-PSO METHOD–BASED POWER ALLOCATION IN MIMO RADAR NETWORK

The main challenges in the MIMO radar system are distributive power allocation. To overcome this problem, we implemented PSO with Nash and Pareto game theory to attain

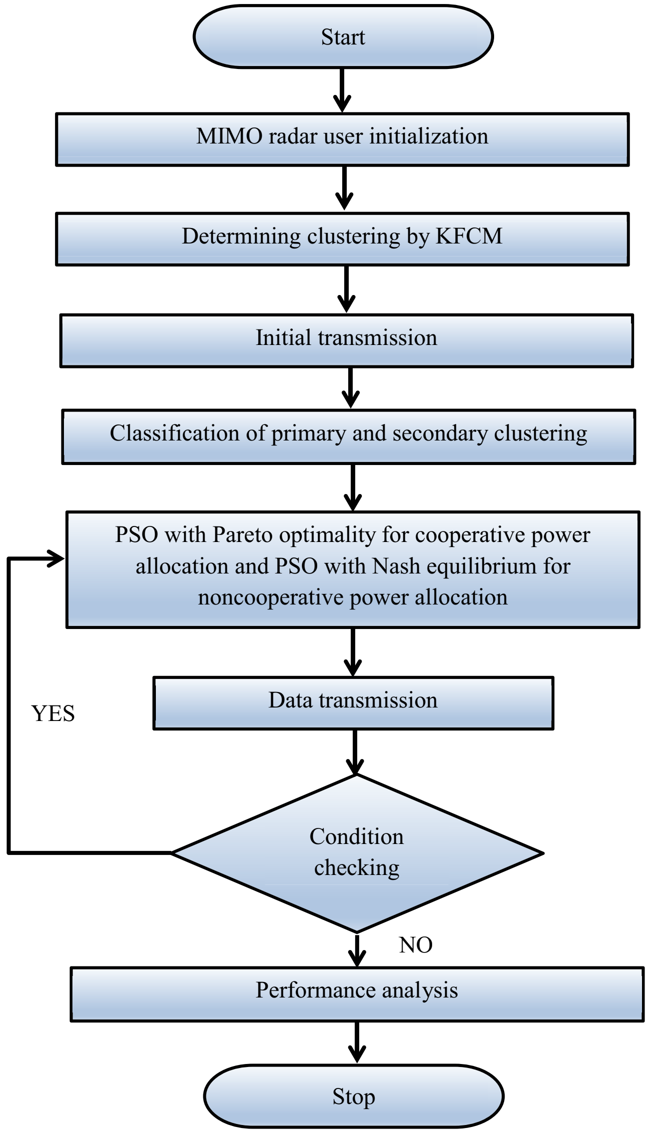

FIGURE 1 Workflow of proposed KFCM-PONE-PSO method

appropriate power allocation in the MIMO radar network. In this study, power allocation of the distributive radars is performed using PSO with Nash equilibrium for noncooperative networks, and PSO with Pareto optimality for cooperative networks is considered as a major objective of the KFCM-PONE-PSO method. Figure 1 depicts the workflow of the proposed KFCM-PONE-PSO method. The principle of the method is described in the following.

4.1 | System model

In KFCM-PONE-PSO, the power allocation problem is analyzed in the distributed multistatic MIMO radar network. Therefore, multiple MIMO radars are divided into clusters for improving the scalability of the system. The proposed method requires efficient detection to recover further information on the target's exact characteristics and positions. Let us consider that the MIMO radars are clustered into K clusters using the KFCM algorithm. The K clusters are denoted as $D_t = \{D_1, D_2, \ldots, D_k\}$, and these clusters from the K-means clustering contain T MIMO radars. The set of radars that belong to the cluster is denoted as $D_k = (M_{rk}, M_{rk2}, \ldots, M_{rkT})$. The goal of the clusters of the network is to utilize the minimum transmission power while generating the waveform. The clusters of the network are processed independently in noncooperative behavior. However, a single cluster is not affected by any other clusters present in the network. The MIMO radar network with the KFCM cluster technique is represented as depicted in Figure 2.

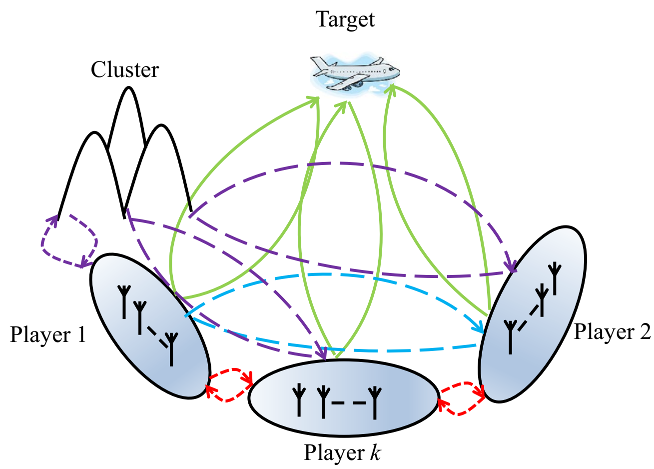

FIGURE 2 MIMO radar network with KFCM clusters

Signal-return samples are received by radars, and hypothesis testing is utilized for making decisions in the presence of targets at each time step. The number of radars in the particular cluster is identified based on the signals transmitted from the radars. These transmitted signals are orthogonal to each other; the waveforms from different clusters are not orthogonal to each other.

4.2 | Pareto optimality using particle swarm optimization

The idea of Pareto optimality gains efficient usage of power resources in the MIMO radar network [26–28]. This section describes the Pareto optimal task using the PSO algorithm for allocating power to the primary clusters (cooperative) of the MIMO network system.

4.2.1 | Pareto optimality

The received signal (b) of the MIMO radar network is expressed as (1):

$$b = Ha + n \tag{1}$$

where the transmitted signal vector is specified as a and the additive white Gaussian noise (AWGN) noise vector with zero mean and variance is represented as n. Equation (2) defines the overall channel capacity (CC) of the MIMO radar network.

$$\mathrm{CC} = B \sum_{j=1}^{r} \log_2 \left(1 + \frac{\lambda_j P_j}{N_0 B}\right) \quad (2)$$

where the system bandwidth is denoted as B, nonzero eigenvalue is λ_j, allocated power to the respective channel is represented as P_j, and power spectral density of AWGN is represented as N_0. The nonzero eigenvalues are similar when the number of transmitting antennas in the transmitter is large. Therefore, the antenna with less power allocation is selected for optimal power allocation in the network. Subsequently, the channel capacity is approximately expressed by (3):

$$\mathrm{CC} \simeq RB\log_2 \left(1 + \frac{\psi L P_t}{N_0 BR}\right) \quad (3)$$

where R represents the receiver antennas, L denotes the selected antenna, and P_t represents the total transmitted power.

The throughput per unit of bandwidth spectrum efficiency (SE) is expressed as

$$\eta_{SE} = \frac{\mathrm{CC}}{B} = R\log_2 \left(1 + \frac{\psi L P_t}{N_0 BR}\right). \quad (4)$$

The ratio of the transmitted number of bits to the total power consumption is expressed as η_{EE}:

$$\eta_{EE} = \frac{\mathrm{CC}}{P\Sigma} = RB\log_2 \left(1 + \frac{\psi L P_t}{N_0 BR}\right) / P\Sigma \quad (5)$$

where the path loss is denoted as ψ and the total power consumption is denoted as $P\Sigma$.

The energy efficiency (EE)-SE tradeoff multi-objective problem is formulated by optimizing EE and SE. Equation (6) provides the formulated optimization problem:

$$\max_{P_t, A} \left\{\eta_{SE}\left(P_t, L\right), \eta_{EE}\left(P_t, L\right)\right\} \quad \text{s.t. } P_t \in P, L \in L \quad (6)$$

where $P = \left\{P_t | 0 \le P_t \le P_t^{\max}\right\}$ and $L = \left\{L | 1 \le L \le T_A\right\}$ represent the transmitted power constraint and set of selected antennas, respectively.

Pareto optimal set

The vector $\vec{a} \in A$ is considered as Pareto optimal when there is no other $\vec{a} \in A$ that satisfies $f_j(\vec{a}) \ge f_j(\vec{a}), \forall = 1, 2, \ldots, m$, where the objective function is represented as $f_j(a)$.

In particular, in this study, $P_t \in P$ or $L \in L$ is a Pareto-optimal solution if there exists no other P_t' or L' that satisfies $\eta_{EE}\, P_t' \ge \eta_{EE}\, P_t$ and $\eta_{SE}\left(L'\right) \ge \eta_{SE}(L)$ or/and $\eta_{SE}\left(L'\right) \ge \eta_{SE}(L)$. The properties of η_{SE} and η_{EE} are as follows: (a) η_{SE} is maximized based on the transmitted power and number of selected antennas; and (b) η_{EE} depends on the transmit power. The fitness function used under the Pareto optimality condition is power allocation. In this study, Nash equilibrium is used to place the radar in the location where it consumes less power during data transmission. Pareto optimality is used only for radars that are present in cooperative clusters. Subsequently, the PSO is used to obtain the minimum least power of radar for different locations of the search area.

4.2.2 | PSO-based power allocation using Pareto optimality for primary clusters

The bi-objective optimization problem is solved using the weighted sum technique, which is significantly easy to solve and produces a single solution. At first, PSO randomly creates a population N in dimension D. In PSO, the particle is represented as X_i and each cluster velocity is represented as v. The position and velocity of the particle are initialized based on the location of the radars and its own speed, respectively, as PSO integrated with Pareto optimality considers only the radars present in the cooperative clusters. The velocity is controlled using $v_{\min}$ and $v_{\max}$. The velocity and location of each particle of PSO is expressed as (7) and (8), respectively:

$$v_{id}^{n+1} = w \times v_{id}^{n} + c_1 \times r_1 \times \left(p\mathrm{best}_{id}^{n} - x_{id}^{n}\right) + c_2 \times r_2 \times \left(g\mathrm{best}_{d}^{n} - x_{id}^{n}\right), \quad (7)$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \quad (8)$$

where $i = 1, 2, \ldots, N$, $n = 1, 2, \ldots, \mathrm{inter}_{\max}$, w is the inertia weight, c_1 and c_2 are two positive constants known as acceleration coefficients, and r_1 and r_2 are the two uniform random numbers distributed in the interval [0, 1]. Every cluster maintains its velocity and position. It remembers the efficient value that η_{SE} has been obtained for the best fitness position. Furthermore, the PSO algorithm maintains the best fitness value obtained among all the clusters in the swarm (global best fitness) and the candidate solution that was used to obtain this global best position fitness. Equations (7) and (8) allow the clusters to search around their individual best positions p_{best} and update the global best position g_{best}.

Algorithm: Particle Swarm Optimization

$P \leftarrow$ Initial population
Evaluate (P)
Initialize p_{best} and g_{best}
While termination criterion not met do
Update velocity (V) as denoted in (1)
Update position (P) as denoted in (2)
Evaluate (P)
Find p_{best} and g_{best}
End while
Output g_{best}

The new task assignment in the problem of power allocation is obtained based on cluster updates using (7) and (8). However, this task assignment achieves floating point values (FPVs) in the continuous domain. Several discrete versions of PSO round off floating point location values and store discrete integer values for the clusters' locations. In this study, we have modified the equation employed to preserve the stochastic nature of the continuous PSO, as expressed by (9):

$$Y_{id}^{n} = \text{ceil}\left(\left(x_{id}^{n} + v_{id}^{n}\right) \times \beta\right); \beta = 10^{y}, \tag{9}$$

$$\text{Loc}_{id}^{n+1} = \left(Y_{id}^{n}\right) \bmod m,$$

$$xc_{id}^{n+1} = \begin{cases} \text{Loc}_{id}^{n+1} & \text{if } \text{Loc}_{id}^{n+1} > 0 \\ m & \text{otherwise.} \end{cases},$$

The multi-objective optimization issue considers an optimization vector, that is, n_{obi} (here, the objective function is $F(x) = f_1(x), f_2(x), \ldots, f_{n\text{obi}}(x)$). The Pareto optimality is easy to solve and produces an individual solution to the problem. The bi-objective optimization problem is expressed as follows:.

$$\text{Minimize } \theta * \text{distance } fn + (1 - \theta) \times \text{time } fn \tag{10}$$

where θ is the relative weight in the range [0, 1]. The optimization problem minimizes the distance fn when $\theta = 0$. The problem reduces time fn when $\theta = 1$. To allocate the power equally to cooperative individuals, Pareto optimality uses the PSO algorithm.

4.3 | Nash equilibrium using PSO

This section describes the PSO-based Nash equilibrium algorithm for allocating power to secondary clusters (noncooperative) in the MIMO network system.

4.3.1 | Nash equilibrium

The various channel matrices are structured based on the Kronecker propagation model for considering the antenna correlation effects in the transmitter. The channel coefficient specified in (1) is expressed as

$$H = r_{\text{r}}^{1/2} H_w r_{\text{t}}^{1/2} \tag{11}$$

where the independent and identically distributed matrix is represented as H_w and the antenna correlation matrices in the receiver and transmitter are represented as r_{r} and r_{t}.

Equation (12) expresses the signal received by the primary user:

$$b_{\text{p}} = S_{\text{p}} + h_{\text{p}} \sum_{i}^{k} \sqrt{p_i} f_i s_i + n_{\text{p}} \tag{12}$$

where the channel coefficient is h_{p}, signal from the primary user transmitter is represented as s_{p}, and AWGN is represented as n_{p}.

Equation (13) represents the SINR (A) of the kth secondary user.

$$A_k = \frac{p_k \left|H f_k\right|^2}{|H|^2 \sum_{i=1, i \neq k}^{k} \left|f_i\right|^2 + \sigma_k^2} \tag{13}$$

where the beam-forming matrix is f_k, the power allocated for the transmitted signals is p_k, and the variance of noise is σ_k^2. The primary user's SINR is expressed as follows:

$$A_{\text{p}} = \frac{p_{\text{p}}}{\sum_{i=1}^{k} p_i \left|h_{\text{p}} f_i\right|^2 + \sigma_{\text{p}}^2}. \tag{14}$$

The condition that the secondary user's SINR should be greater than the threshold (γ_k) is expressed as (15), which is used for ensuring the MIMO radar network performance:

$$A_k \geq \gamma_k. \tag{15}$$

The perceived interference in the primary user should not be greater than the threshold value $\left(I_{\text{th}}\right)$, which is expressed in (16). This condition is used to enhance the performance of the primary user:

$$\sum_{k=1}^{k} p_k \left|h_{\text{p}} f_k\right|^2 \leq I_{\text{th}}. \tag{16}$$

The noncooperative game formulated in (17) is obtained based on the above system model.

$$G = \left\{\Omega\left\{f_k, p_k\right\}_{k \in \Omega}, \left\{u_k\right\}_{k \in \Omega}\right\}. \tag{17}$$

The game strategies used by the players are transmitting power and beam-forming weights. The mutual information contained in (18) is used to design the utility function:

$$u_k = \log_2 \left(1 + A_k\right). \tag{18}$$

The payoff function mentioned in (18) results in inadequate outcome because of the greediness. The reason is that each player of the game concentrates only on increasing its own utility without mitigating the interference that occurs through the primary user. Therefore, the modified utility function of the secondary user, expressed as (19), is used to enhance the system performance:

$$u_k = \log_2 \left(1 + A_k\right) - \lambda p_k \left|h_{\text{p}} f_k\right|^2. \tag{19}$$

Existence of Nash equilibrium

Nash equilibrium is considered as the optimal criterion for analyzing a game. At the point of Nash equilibrium, no player can maximize its effectiveness by varying its own strategy, and each player is unilaterally optimal. The noncooperative game theory attains the Nash equilibrium point when the following conditions are satisfied based on fundamental game theory results:

- The strategies set are closed in the bounded convex set.
- The utility function used in the system is continuous, quasiconcave in the action space.

Subsequently, this KFCM-PONE-PSO verifies whether the above conditions are satisfied or not. The first condition is satisfied because of the limited strategies of the kth secondary users p_k and f_k. Therefore, the KFCM-PONE-PSO is tested to check whether it satisfies the second condition or not. Equations (20) and (21) are obtained by identifying the second derivative $u_k(.)$ based on power and beam-forming:

$$\frac{\partial^2 u_k}{\partial p_k^2} = -\frac{1}{\ln_2 \left(p_k \left|Hf_k\right|^2 \sum_{i=1, i\neq k}^{k} p_i \left|fi\right|^2 + \sigma_k^2\right)}, \tag{20}$$

$$\frac{\partial^2 u_k}{\partial \left[\left|f_k\right|^2\right]^2} = -\frac{1}{\ln_2} \frac{p_k^2 \left|H\right|^4}{\left(p_k \left|Hf_k\right|^2 \sum_{i=1, i\neq k}^{k} p_i \left|f_i\right|^2 + \sigma_k^2\right)^2}. \tag{21}$$

The verification of $\partial^2 u_k / \left[\left|f_k\right|^2\right]^2$ and $\partial^2 u_k / \partial \left[\left|f_k\right|^2\right]^2$ is easy, as it indicates that the utility function is complex. Accordingly, these utility functions satisfy the required conditions for the existence of at least one Nash equilibrium with respect to the noncooperative game with pricing scheme. This Nash equilibrium is used only for the radars present in the noncooperative network. Thereafter, the PSO is used to obtain the minimum least power with minimum distance for the radars present in the noncooperative clusters.

4.3.2 | PSO-based power allocation using Nash equilibrium for secondary clusters

In this study, we used the floating number matrix to represent the power allocation plan. The utility function is defined to optimize distance, execution time, and power consumption. Next, the utility function is used to further represent the fitness function of PSO. The position and velocity of the particles are initialized based on the radar location and its speed, respectively. Moreover, this PSO considers only the radars that are present in the noncooperative clusters. We used a matrix $X_{m,l}$ to code the position or location of a cluster, as expressed in (22):

$$X = \left(x^1, x^2, \ldots, x^i\right)^T = \begin{pmatrix} x_1^1 & \ldots & x_l^1 \\ \vdots & \ldots & \vdots \\ x_1^i & \ldots & x_l^i \end{pmatrix} \tag{22}$$

where x_j^i is the probability of the ith selected task and jth coalition; $x_1^i + x_2^i + \cdots + x_l^i = 1$. For resolving the Nash equilibrium of the mixed strategies, every task t_i is allocated to some coalitions according to the mixed strategy $x^i = \left(x_1^i, x_2^i, \ldots, x_l^i\right)$. In this case, research is required to change the utility function of pure strategies and the expected utility function is expressed as follows:

$$u_i = \left(u_1^i, u_2^i, \ldots, u_l^i\right) \cdot \begin{bmatrix} x_1^i \\ x_2^i \\ \vdots \\ x_1^i \end{bmatrix} = \sum_j^l u_j^i \cdot x_j^i \tag{23}$$

To update the status of the coalition after a task is assigned, the following expression is used:

$$\text{busy}_j = \text{busy}_j + x_j^i * \text{Time}_{ji}, \tag{24}$$

$$e_j = e_j - x_j^i * \text{distance}_{ij}. \tag{25}$$

The fitness function of the PSO is expressed as follows:

$$f X = \sum_i \max\left\{\max\left\{u_i\left(X_{+i,-i}\right) - u_i(X)\right\}, 0\right\}. \tag{26}$$

In (8), the fitness function value of X is zero when X is equal to the best solution X^*. In each cycle, the clusters inform themselves by tracking two types of extreme values such as the optimal solution of the each cluster, denoted by $X^i_{l\text{Best}}$, and the global optimal solution of the entire cluster, represented by $X^i_{g\text{Best}}$. During the cycle of PSO, (27) and (28) update the velocity and location or position of the i^{th} cluster:

$$V^i_k(t+1) = w * V^i_k(t) + c_1 * r_1 * \left(X^i_{l\text{Best}} - X^i_k(t)\right) + c_2 * r_2 * \left(X^i_{g\text{Best}} - X^i_k(t)\right), \quad (27)$$

$$X^i_k(t+1) = V^i_k(t+1) + X^i_k(t). \quad (28)$$

Here, $V^i_k(t)$ is the speed of the i^{th} cluster during the k^{th} iteration, $X^i_t(t)$ is the position of i^{th} cluster during the k^{th} iteration, $X^i_{l\text{Best}}$ is the current local optimal solution of the i^{th} cluster, $X^i_{g\text{Best}}$ represents the current global optimal solution of the entire cluster, r_1 and r_2 are random numbers between 0 to 1, c_1 and c_2 are learning factors, and w is the inertia weight, which is a linearly reducing weight that reduces from $w_{\max}$ and $w_{\min}$ to allocate equal power to noncooperative individuals using Nash equilibrium with the PSO algorithm. The experimental analysis of the proposed KFCM- PONE-PSO method is discussed in Section 5.

5 | RESULT AND DISCUSSION

In this section, we describe the simulation and numerical consequences of implementing the convergence of the KFCM- PONE-PSO method to a unique solution and demonstrate the distributive structure of the MIMO network. The proposed KFCM-PONE-PSO method is simulated using the MATLAB 2018a software tool with 64 GB random access memory (RAM). This method is tested with 32 MIMO radars deployed in the test area, and these radars are clustered using KFCM. Initially, 0.5 J of energy is provided to each MIMO radar. The specifications of the MIMO radar system are presented in Table 1.

TABLE 1 Simulation parameters of MIMO radar system

Simulation parameters	Value/type
Initial power	0.5 J
Number of antennas	4
Motion model	Velocity
Operating frequency	300 MHz
Sample rate	300 kbps
Peak power	2000
Gain	20
Pulse width	6.67e–06
Envelope	Rectangular
Loss factor	0
Temperature	36 °C

5.1 | Performance analysis of KFCM-PONE-PSO

In this section, the performance analysis of KFCM-PONE-PSO is described in terms of power allocation and SINR. Moreover, the node deployment, target detection, and classification of clusters are illustrated in the following section.

Figure 3 represents MIMO radar deployment with target. Target detection based on the generalized likelihood ratio test is depicted in Figure 4. Figure 5 represents the primary and secondary cluster classification of MIMO radars. The distance from the radars to the target is used to classify MIMO radars. In Figure 5, the blue and green colors indicate

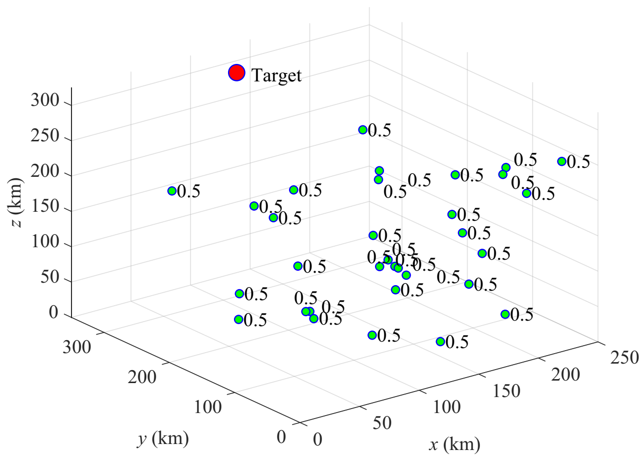

FIGURE 3 MIMO radar deployment with target

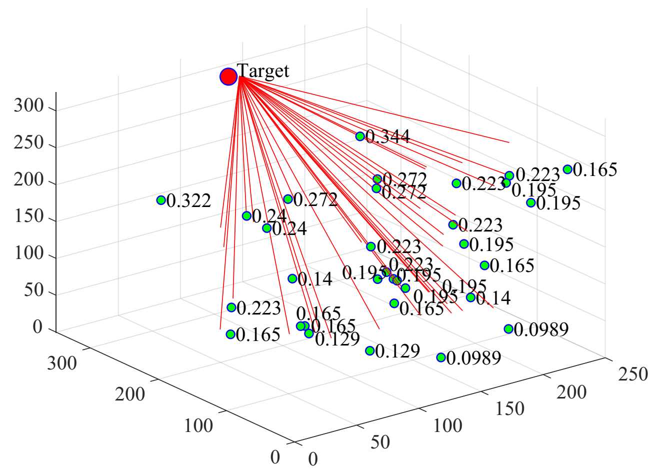

FIGURE 4 Target detection using generalized likelihood ratio test

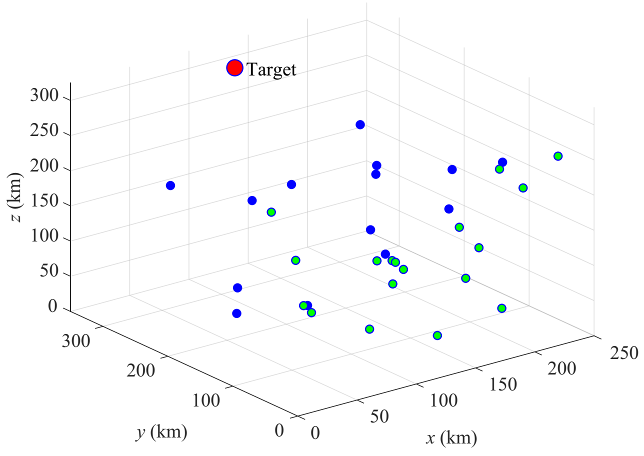

FIGURE 5 Distance-based primary and secondary cluster classification

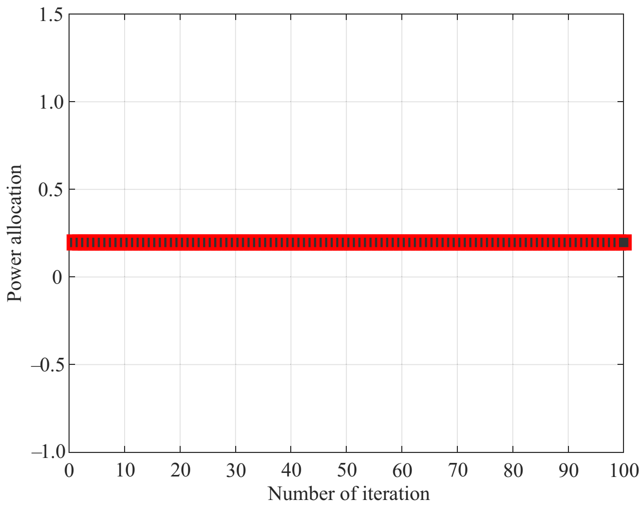

FIGURE 6 Power consumption of entire MIMO network

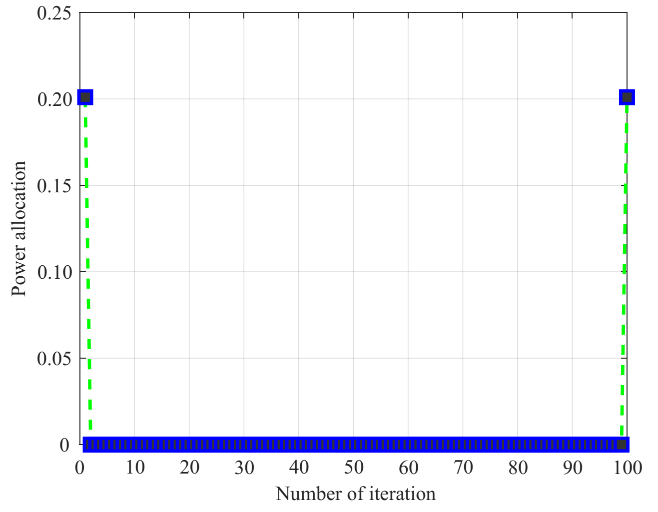

FIGURE 7 Power consumption of secondary cluster

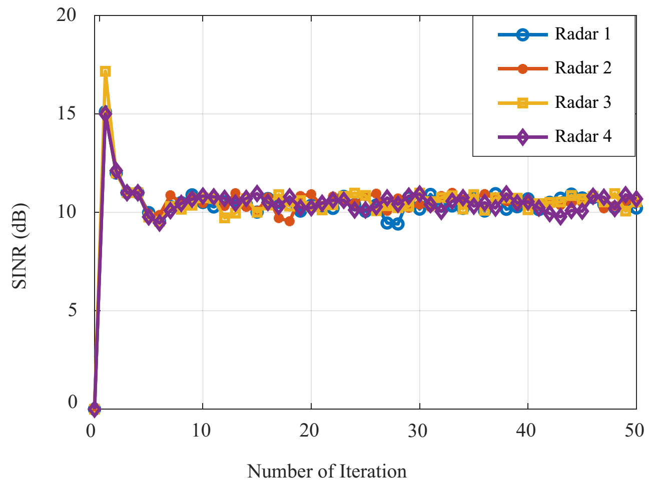

FIGURE 8 SINR of MIMO network

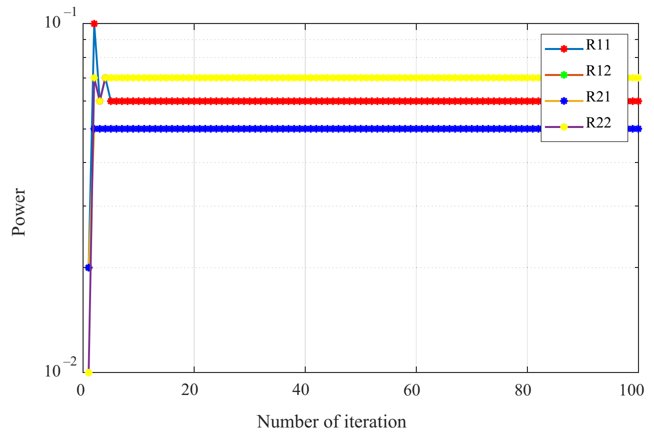

FIGURE 9 Power allocation of MIMO network (when $K = 2$ and $M = 2$ ($P1 = 0.01 \times 1M$, $P2 = 0.02 \times 1M$))

the primary and secondary clusters in the MIMO network, respectively.

Figure 6 presents the power consumption for both the primary and secondary cluster networks. The power consumption of the radar network is stable at 0.2 J from the 10th to the 100th iteration. Figure 7 presents the power consumption of the secondary cluster, which is obtained based on k-means clustering and distance analysis. The power consumption of the secondary cluster is identified after the power allocation of game theory using SINR measures.

The power consumption of the distributive cluster is identified after the power allocation of game theory using SINR measures, which is presented in Figure 8. Here, each radar is required to perform optimization to achieve the PA value. An optimal response function is improved by estimating the SINR factor using the noise variance of intercluster interference.

Figure 9 presents the power allocation of the MIMO network (when K (cluster) = 2 and M (user) = 2 ($P1 = 0.01 \times 1M$, $P2 = 0.02 \times 1M$)). Figure 10 presents the power allocation of

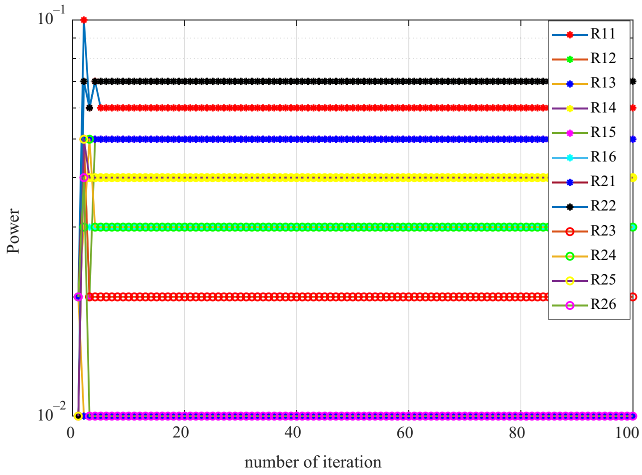

FIGURE 10 Power allocation of MIMO network (when $K = 2$ and $M = 6(P1 = 0.01 \times 1M, P2 = 0.02 \times 1M)$

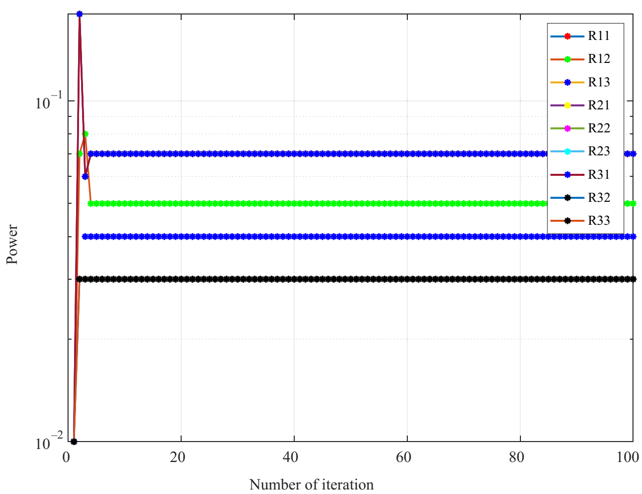

FIGURE 11 Power allocation of MIMO network (when $k = 2$ and $m = 3(p1 = 0.01 \times 1m, p2 = 0.02 \times 1m)$

the MIMO network (when $K = 2$ and $M = 6$ ($P1 = 0.01 \times 1M$, $P2 = 0.02 \times 1M$)). Figure 11 presents the power allocation of the MIMO network (when $K = 2$ and $M = 3$ ($P1 = 0.01 \times 1M$, $P2 = 0.02 \times 1M$)). The proposed KFCM-PONE-PSO method can minimize the power in a totally distributed manner without the need for any communication among the clusters. The problem of PA is particularly of interest in tracking radars; this study helps to analyze the location of the target accurately. In this way, the proposed approach obtained the optimum PA to maintain a specific SINR.

Figures 9–11 present the PA update of the entire MIMO radar network for two different initial PAs in clusters 2 and 3. From this simulation result, it is evident that the number of active radars in both the clusters are the same, regardless of the initial PA. The efficiency of the KFCM-PONE-PSO method illustrates that the process converges to the optimal PA within six iterations.

5.2 | Performance analysis with dissimilar optimization methods

The performance of the KFCM-PONE-PSO method is analyzed in terms of SINR and transmitted power. In addition, the performance of the KFCM-PONE-PSO method is validated using three conventional methods, namely, the KFCM-PONE, KFCM-PONE-cuckoo search (CS), and KFCM-PONE-genetic algorithm (GA) methods. These three algorithms are implemented and simulated in MATLAB with the same specifications mentioned in Table 1. The results are obtained for four different radars that are deployed in four various locations of the search area. Further, the performance analysis is carried out for two different cases. In the first case, the target is located in the selected 2D plane, that is, in (X, Y), (Y, Z), or (X, Z). Meanwhile, in the second case, the target is randomly moved in any one direction, that is, in the X, Y, or Z direction, with minimal speed.

- Case 1: The target is located at [0, 0] of the selected 2D plane.
- Case 2: The target is randomly moving in the selected 2D plane.

Figure 12 presents the comparison of SINR for KFCM-PONE-PSO with those for conventional methods such as KFCM-PONE, KFCM-PONE-CS, and KFCM-PONE-GA. Figure 12A,B depict that the SINR of the KFCM-PONE-PSO is less than that of the conventional methods in Cases 1 and 2, respectively. The KFCM-PONE-PSO has low SINR in the MIMO radar network owing to PSO's higher search probability in the global solution. However, the GA used in KFCM-PONE-GA cannot handle the huge number of constraints in the search area and the CS used in KFCM-PONE-CS has slow convergence. Owing to these properties, the KFCM-PONE, KFCM-PONE-CS, and KFCM-PONE-GA methods produce high SINR during data transmission through the MIMO radar network.

A comparison of the transmitted power for the KFCM-PONE-PSO and conventional methods is presented in Figure 13; the comparisons for Cases 1 and 2 are depicted in Figure 13A and 13B, respectively. Figure 13 indicates that the KFCM-PONE-PSO method has less transmitted power when compared with conventional methods. Owing to faster convergence of the PSO, the optimal solution is achieved during the power allocation of the radars. Thus, it leads to a reduction in the transmitted power in the multistatic MIMO radar network. In the KFCM-PONE-CS method, the CS falls in the local optimal solution during power allocation to the MIMO radars. Moreover, GA leads to an undirected search toward the solution in power allocation. The inappropriate characteristics of the KFCM-PONE, KFCM-PONE-CS, and KFCM-PONE-GA methods fail to perform an appropriate

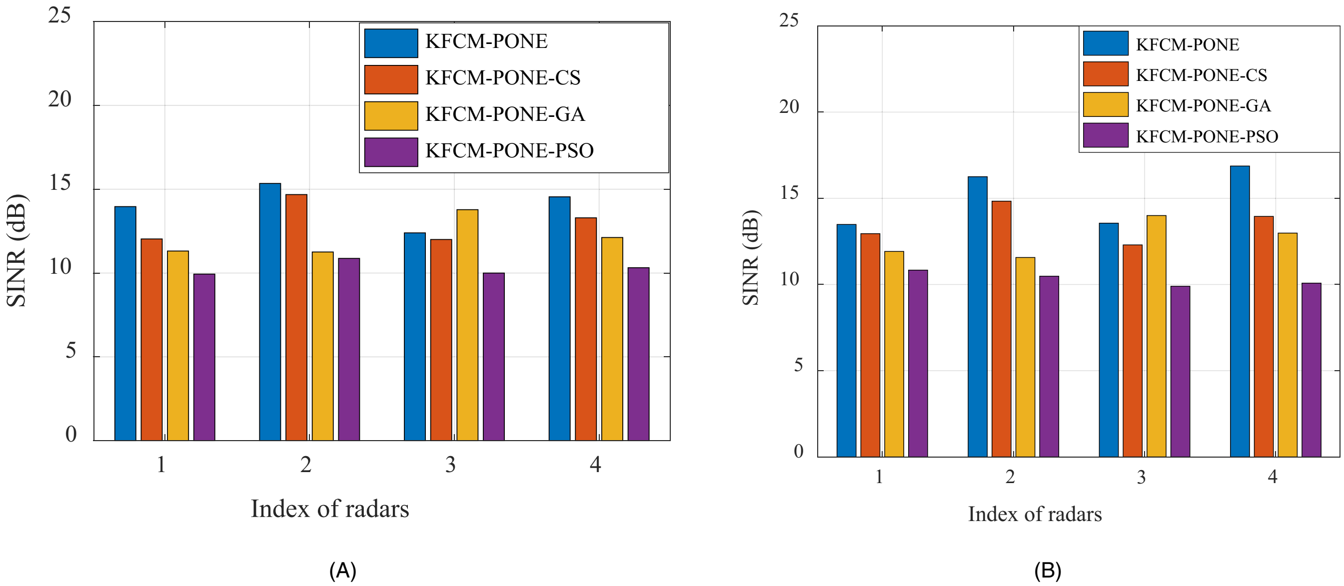

FIGURE 12 Comparison of SINR for KFCM-PONE-PSO with conventional methods: (A) Case 1 and (B) Case 2

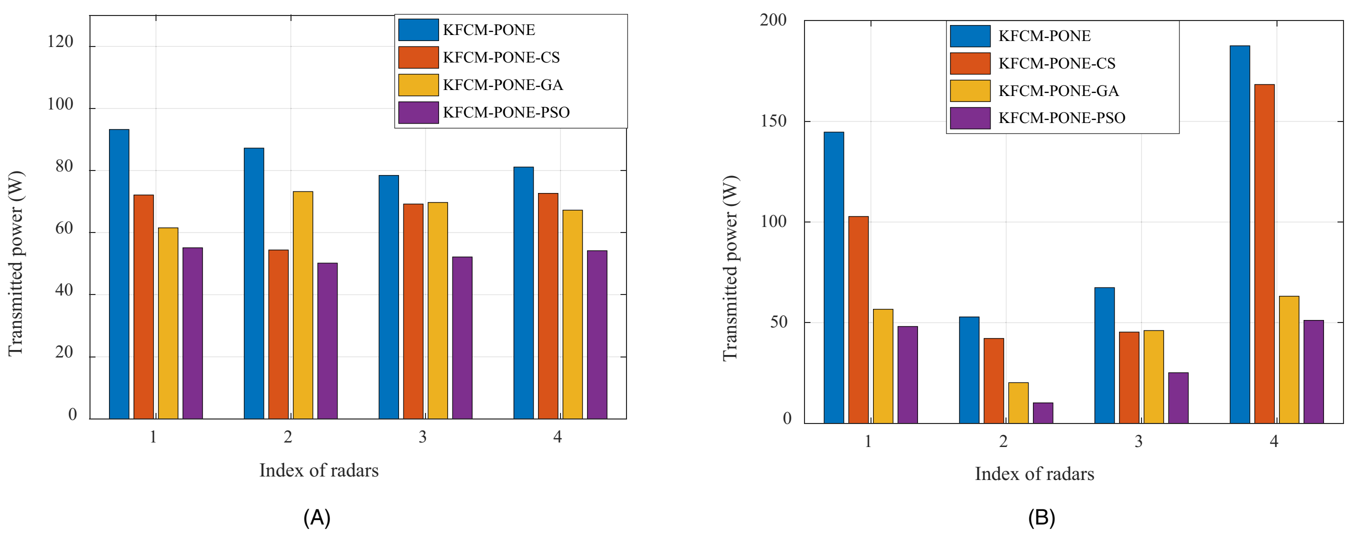

FIGURE 13 Comparison of transmitted power for KFCM-PONE-PSO with conventional methods: (A) Case 1 and (B) Case 2

TABLE 2 Total power consumption in each cluster for three different system realizations

Methodologies	$K = 2, M = 2$		$K = 2, M = 6$		$K = 3, M = 3$			$K = 2, M = 30$	
GNG-PA [6]	**0.0763**	**0.0418**	**0.1382**	**0.1389**	**0.0641**	**0.1191**	**0.0895**	**N/A**	**N/A**
CNCGT-PA [29]	0.0698	0.0384	N/A	N/A	0.0599	0.1167	0.0869	N/A	N/A
KFCM-PONE-PSO	0.0558	0.0297	0.1121	0.1114	0.0480	0.1001	0.0831	0.8576	0.5885

power allocation. However, there is a higher probability of discovering the optimal solution with the PSO used in the KFCM-PONE-PSO method. Therefore, the KFCM-PONE-PSO method effectively allocates optimum power to the radars. This allocation achieves less transmitted power in the multistatic MIMO radar network.

5.3 | Comparative analysis

This section presents a comparative study of the existing works and the proposed KFCM-PONE-PSO method. Table 2 presents the total power consumption in each cluster for three different system realizations. The main aim of the

TABLE 3 Comparison of transmitted power using KFCM-PONE-PSO and NBS [23] methods

	Transmitted power (W)			
	Case 1		Case 2	
Index of radars	NBS [23]	KFCM-PONE-PSO	NBS [23]	KFCM-PONE-PSO
1	75.223	55.127	120.223	48.127
2	75.2231	50.184	20.2231	10.184
3	75.4245	52.162	120.4245	25.162
4	75.24	54.18	310.24	51.18

generalized Nash game based power allocation (GNG-PA) [6] is to secure a certain criterion in each cluster to reduce the SINR while allocating the minimum possible power to every radar. The GNS illustrated that if the number of active radars in a cluster that specify the transmitted signals are similar to the number of radars in a similar cluster, it satisfies the SINR with equality.

Cooperative and noncooperative game theory based PA (CNCGT-PA) [29]—the game theory of Nash equilibrium and Pareto optimality—is implemented for noncooperative and cooperative networks of distributive clusters, respectively. The clustering of the network is carried out using KFCM. Table 2 indicates that the KFCM-PONE-PSO method of cluster 1 produces a power consumption of 0.05, which is less compared to the power allocation using GNG-PA and CNCGT-PA, that is, 0.0763 and 0.0698, at $K = 2$, $M = 2$. The power consumption obtained using the KFCM-PONE-PSO method for cluster 1 is 0.1121, which is less compared to the power allocation using GNG-PA, that is, 0.1382, at $K = 2$, $M = 6$. The power consumption obtained using the KFCM-PONE-PSO for cluster 1 is 0.0480, which is less compared to the power allocation using GNG-PA and CNCG-PA, that is, 0.0641 and 0.0599, at $K = 3$, $M = 3$. The proposed game theoretic technique outperforms the uniform PA in all cases in terms of total power consumption in each cluster. Thus, it is clear that the power is properly allocated to the entire MIMO radar network using the KFCM-PONE-PSO method.

Table 3 presents a comparison of the transmitted power using the KFCM-PONE-PSO and NBS methods [23]. Figure 14A,B present the transmitted power for Cases 1 and 2, respectively. Table 3 and Figure 14 indicate that the transmitted power for both the cases are less when compared with NBS-based power allocation [23]. For example, the transmitted power using the KFCM-PONE-PSO methodology for Case 1 is 50 W–55 W, which is less when compared with NBS (ie, 70 W–75 W). Similarly, the transmit power of KFCM-PONE-PSO for Case 2 is that is less when compared NBS (ie, 20 W–300 W). The reason why the KFCM-PONE-PSO method produces less transmitted power in the multistatic MIMO radar network is an appropriate optimization of power allocation to all the radars in the network. Thus, optimal power allocation to the radars is obtained using the combination of Nash equilibrium and Pareto optimality with PSO.

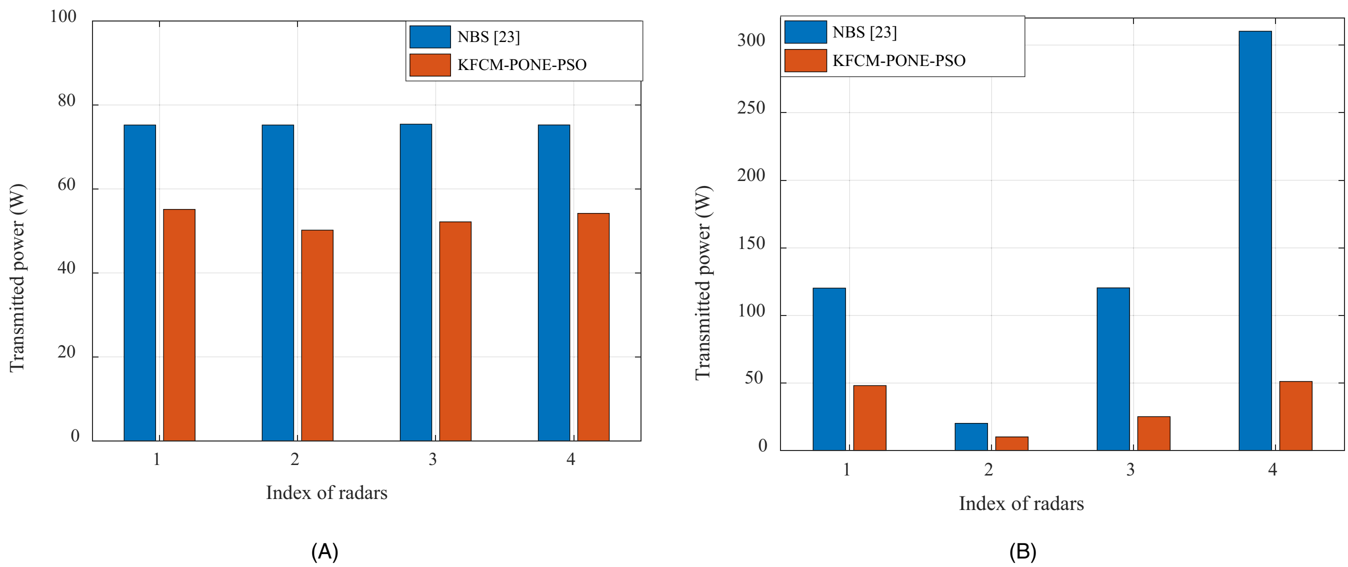

FIGURE 14 Transmitted power: (A) Case 1 and (B) Case 2

6 | CONCLUSION

In this study, the Nash equilibrium and Pareto optimality–based game theories were introduced in the MIMO radar network to allocate power for each antenna of the distributed MIMO radar cluster. These game theories were applied to the distributive network based on the distance from the MIMO radars to the target. The allocated power values depended mainly on the distance from the MIMO radars to the target and the power value of each radar. Subsequently, the optimal power value was selected for each antenna and the selected power was allocated to the MIMO radar. This type of PA led to the reduction of the power consumption of the entire MIMO network. The simulation results proved that the KFCM-PONE-PSO method achieves better performance than conventional methods. For example, the transmitted power using the KFCM-PONE-PSO method for the first radar in Case 1 was 55.127 W, which is less when compared with the NBS method. In future research, relay resource allocation based on the Bayesian game and bio-inspired algorithm can be developed to enhance the performance of multiple users in MIMO radar networks.

ORCID

Thoka Harikala https://orcid.org/0000-0002-3689-3221

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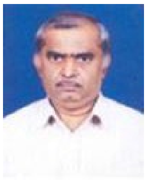
AUTHOR BIOGRAPHIES

Thoka Harikala is a research scholar in the ECE Department, SV University, Tirupati, Andhra Pradesh, India. She received her MTech degree from SV University College of Engineering (SVUCE), Tirupati. Presently she is doing research work on MIMO technology.



Ravinutala Satya Narayana is a professor in the ECE Department, SV University College of Engineering (SVUCE), Tirupati, Andhra Pradesh, India. He completed his PhD in 2003 and has 25 years of teaching and research experience. He has guided four PhD scholars and eight more students are pursuing their PhD programme under his guidance. He received the "Bharat Jyothi Award" conferred by NGO, New Delhi (2011). Two of his papers have been recognized as Best Papers in national conferences.