

Joint Node Selection and Power Allocation for Phased Array Radar Network in Maneuvering Multi-Target Tracking under Non-Ideal Detection

Ting Cheng*, Quan Zhou, and Congchong Cao

Abstract: This paper addresses the problem of joint node selection and power allocation for phased array radar network in maneuvering multi-target tracking under non-ideal detection. Based on the objective of minimizing the total transmission power of all radar nodes while satisfying the target tracking accuracy thresholds and the given system resource constraints, a joint optimization problem model under non-ideal detection condition is established. A closed-form analytical expression for the predicted conditional Cramér–Rao lower bound (PC-CRLB) is derived, which is used as a measure of multi-target tracking accuracy under non-ideal detection. To tackle the nonlinear and non-convex optimization problem, a cyclic iterative framework based on a relaxed interior point method and a heuristic signal-to-noise ratio (SNR)-based initial point selection algorithm is adopted, and a joint node selection and power allocation under non-ideal detection (JNSPA-NID) scheme is proposed. Simulation results indicate that the proposed algorithm effectively reduces the total transmission power of the system while meeting the specified multi-target tracking accuracy requirements under non-ideal detection conditions compared to other comparative algorithms.

Key words: radar resource allocation; phased array radar network; maneuvering multi-target tracking; non-ideal detection; Bayesian Cramér–Rao lower bound (BCRLB)

1 Introduction

In recent years, phased array radar network has been of great interest in various applications such as target detection, localization, and tracking, which have demonstrated impressive system capabilities over traditional single radars^[1–3]. In multi-target tracking, the resources of phased array radar network system need to be allocated among multi-target. To fully utilize the capabilities of the phased array radar network system, it is crucial to optimize the allocation of radiated resources^[4–6].

Currently, the efficient radar node selection and rational allocation of transmission power resources in radar systems to enhance resource utilization have become a focal research topic, which aims to achieve the best tracking accuracy or to minimize the consumed resource consumption.

For single radar platform target tracking, Ref. [7] proposed a multi-beam resource allocation strategy. Subsequent studies extended this approach from single radar platform to multi-radar system, which required rational allocation of radar node resources. References [8–11] focused on optimizing system performance through radar node selection, which was jointly optimized with other system resources. References [12–17] built upon node selection by further optimizing the allocation of radar transmission power. For instance, in Ref. [16], a joint optimization algorithm for node selection and power allocation in a distributed radar network is proposed, specifically

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aimed at multi-target tracking, and Ref. [17] applied this approach to multiple distributed multiple-input multiple-output (MIMO) radar networks. Meanwhile, Ref. [18] addressed both node selection and detection timing optimization.

In the resource management process, a tracking performance metric is essential since it guides the resource allocation during tracking. In Ref. [19], the Bayesian Cramér–Rao lower bound (BCRLB) was first used to measure the tracking performance for each single target, which later has evolved into different metrics according to specific tracking scenes. In Ref. [20], an adaptive channel assignment scheme for maneuvering target tracking was proposed. The predicted conditional Cramér–Rao lower bound (PC-CRLB)^[21] was calculated to predict the tracking performance. Reference [22] was based on PC-CRLB and proposed a joint strategy of power and bandwidth allocation for multiple maneuvering targets tracking in the MIMO radar, introducing the convex relaxation technique and the two-step solution technique.

However, the detection probability of the radar system in the above research was supposed to be one, indicating an ideal detection environment. In actual combat, due to various uncertain factors such as communication interference, dynamic cluster, or electromagnetic attenuation^[23, 24], the radar nodes in the system cannot successfully detect all illuminated targets. In Ref. [23], a joint radar selection and resource allocation strategy was proposed for multi-target tracking in radar networks under communication interference, and the main objective of this strategy was to minimize the tracking error of multi-target while satisfying the budget constraints of transmission resources in the radar network. References [25, 26] considered an imperfect detection environment with the goal of optimizing multi-target tracking accuracy. When calculating the posterior Cramér–Rao lower bound (PCRLB), a two-dimensional (2-D) enumeration method was employed to enumerate all possible detection scenarios. In Ref. [24], under the situation that not all illuminated targets can be successfully detected, a joint optimal allocation algorithm of node selection and transmission resources was studied, and a four-step decomposition algorithm based on the obstacle function method and the loop minimization algorithm was used to solve the problem. Reference [27] extended the work in Ref. [24], considering dwell time in heterogeneous multiple radar networks and proposed a multi-domain resource

allocation strategy for asynchronous multi-target tracking with non-ideal detection performance.

Existing research on radar resource management has made some progress. However, there are still issues in resource allocation for phased array radar network systems during maneuvering multi-target tracking under non-ideal detection condition. References [8–11] focused solely on the radar node selection, while Refs. [12–15], although addressing power allocation and other resource management issues, were limited to single-target tracking or non-maneuvering target tracking scenarios. These references all focused on radar system resource allocation under ideal detection conditions. When considering non-ideal detection conditions, existing literature also has certain limitations. In Ref. [23], when using the relaxed interior-point method to solve the optimization problem, considering only a single solution without iterative solving may lead to significant relaxation errors. In Refs. [25, 26], the 2-D enumeration method to enumerate all possible detection scenarios resulted in a significant computational burden. In Ref. [24], when calculating the BCRLB, all radar nodes were considered to be active. Obviously, this was not always the case, resulting in an inappropriate BCRLB. Additionally, the detection probability was treated as a constant, neglecting the relationship between detection probability and power. This paper introduces improvements in the computation of the PC-CRLB during the process of maneuvering target tracking, making the calculation method more concise and ensuring that only activated radar nodes have the possibility of successfully receiving measurements from the target. Moreover, the detection probability is reformulated as a function of transmit power, thereby capturing the intrinsic trade-off between energy consumption and tracking performance. In summary, these enhancements make the proposed approach more adaptable and practical for real-world, dynamic environments.

This paper establishes a problem model under non-ideal detection conditions, derives the PC-CRLB in such cases, and uses it as an indicator of tracking performance. A cyclic iterative solution method based on a relaxed interior-point method and a heuristic starting point selection method based on signal-to-noise ratio (SNR) is adopted, and a joint node selection and power allocation under non-ideal detection (JNSPA-NID) scheme is proposed.

The main contributions of this paper are summarized as follows:

(1) For maneuvering multi-target tracking in non-ideal detection condition, a new form of PC-CRLB is proposed to characterize the tracking performance. Different detection cases in each node selection situation are considered comprehensively in this new form, and a simpler calculation method is derived.

(2) Based on the new form of PC-CRLB, a joint node selection and power allocation optimization problem under non-ideal detection is established. The total transmission power of the system is minimized under the guarantee of desired tracking accuracy and the given system resource constraints.

(3) For the established optimization problem model, a cyclic iterative solution method based on a relaxed interior point method and a heuristic SNR-based node selection algorithm is proposed, in which a heuristic method is used to obtain the initial point to speed up the computation of the interior point method, and a joint node selection and power allocation under non-ideal detection scheme is proposed.

The rest of this article is organized as follows. Section 2 introduces the system model. A joint optimization model for multi-radar network node selection and power allocation is presented in Section 3. Section 4 introduces the JNSPA-NID scheme for maneuvering multi-target tracking under non-ideal detection. Simulation results are analyzed in Section 5 to check the effectiveness of the JNSPA-NID scheme. Finally, Section 6 concludes this article.

2 System Model

Phased array radar can generate a narrow pencil beam at each moment to illuminate a single target. Multiple phased array radars can work together to form a distributed network, enhancing overall tracking performance^[28]. Consider a phased array multi-radar system consisting of N phased array radars in a 2-D space, where the n -th node is located at $(x_n, y_n) \in \mathbb{R}^2$. Assume that all radar nodes in the system maintain synchronization both in time and space. Furthermore, let there be Q targets moving within the surveillance area of the distributed phased array radar network. The trajectories of these targets are initialized in advance. The state of the target q at time k can be expressed as

$$\mathbf{X}_k^q = [x_k^q, \dot{x}_k^q, \ddot{x}_k^q, y_k^q, \dot{y}_k^q, \ddot{y}_k^q]^T \quad (1)$$

where x_k^q and y_k^q represent the positions of the target, $\dot{x}_k^q$

and $\dot{y}_k^q$ denote the velocities of the target, and $\ddot{x}_k^q$ and $\ddot{y}_k^q$ indicate the accelerations of the target.

The general schematics of the resource-aware closed-loop signal process under non-ideal detection is illustrated in Fig. 1.

2.1 Target dynamic model

Considering the maneuvering characteristics of the targets, we can use a finite number of S models to describe the motion states. The model variable v_k is defined as a discrete stochastic process and takes one of the finite S possible models. The modeling of the motion of target q is represented as

$$\mathbf{X}_k^q = \mathbf{F}_{k-1}^{v_k, q} \mathbf{X}_{k-1}^q + \mathbf{W}_{k-1}^{v_k, q} \quad (2)$$

where v_k represents the model variable acting from time $k-1$ to time k , $\mathbf{F}_{k-1}^{v_k, q}$ is the state transition matrix in the model v_k , and $\mathbf{W}_{k-1}^{v_k, q}$ denotes zero-mean Gaussian white noise with covariance matrix $\mathbf{Q}_{k-1}^{v_k, q}$. The initial model probability can be expressed as $u_{i,1} = \Pr\{v_1 = i\}$, and the model of the sequence can be represented by a Markov chain^[21], with the transition probability given by

$$\pi_{i,j} = \Pr\{v_k = j | v_{k-1} = i\} \quad (3)$$

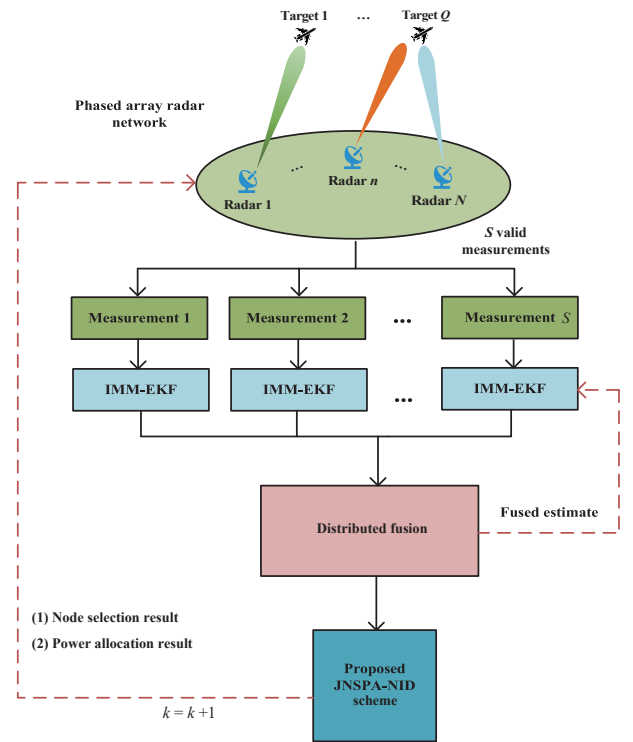


Fig. 1 Working framework for maneuvering multi-target tracking of radar network. IMM: Interacting multiple model; EKF: Extended Kalman filter.

The transition probability matrix $\boldsymbol{\Pi}$ is a $S \times S$ matrix that satisfies $\sum_{j=1}^S \pi_{i,j} = 1, \pi_{i,j} > 0$.

2.2 Radar measurement model

For simplicity, it is assumed that, during each sampling period, each radar node can track at most one target and can only receive the echo of its own. During the process of multi-target tracking, it is essential to rationally allocate the transmission power resources of all radar nodes. This allocation must satisfy the constraints of maneuvering multi-target tracking accuracy requirements while considering the available system resources, ultimately enhancing stealth performance. A binary variable $u_{n,k}^q$ is introduced to describe the matching status between node n and target q , as

$$u_{n,k}^q = \begin{cases} 1, & \text{the radar node } n \text{ illuminates target } q \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

To describe the detection status of the multi-radar system for target q at time k , the binary detection variable is defined as

$$d_{n,k}^q = \begin{cases} 1, & \text{the radar node } n \text{ detects target } q \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Combining the $u_{n,k}^q$, the measurement for radar node n at time k regarding target q can be expressed as

$$\mathbf{Z}_{n,k}^q = \begin{cases} h_{n,k}(\mathbf{X}_k^q) + \mathbf{V}_{n,k}^q, & u_{n,k}^q = 1 \text{ and } d_{n,k}^q = 1 \\ \emptyset, & \text{otherwise} \end{cases} \quad (6)$$

where $\mathbf{Z}_{n,k}^q$ is the measurement vector, $u_{n,k}^q$ is a Boolean variable indicating whether radar node n is used to illuminate target q at time k , $\mathbf{V}_{n,k}^q$ is zero-mean Gaussian white noise, and the nonlinear measurement function $h_{n,k}(\mathbf{X}_k^q)$ can be represented as

$$h_{n,k}(\mathbf{X}_k^q) = \begin{bmatrix} r_{n,k}^q \\ \theta_{n,k}^q \end{bmatrix} = \begin{bmatrix} \sqrt{(x_k^q - x_n)^2 + (y_k^q - y_n)^2} \\ \arctan\left(\frac{y_k^q - y_n}{x_k^q - x_n}\right) \end{bmatrix} \quad (7)$$

where $r_{n,k}^q$ and $\theta_{n,k}^q$ represent the true range and azimuth between radar node n and target q at time k , respectively. In Eq. (6), the measurement noise $\mathbf{V}_{n,k}^q$ is assumed to be Gaussian with zero mean and covariance $\Sigma_{n,k}^q$ as

$$\Sigma_{n,k}^q = \begin{bmatrix} \Sigma_{r_{n,k}^q}^2 & 0 \\ 0 & \Sigma_{\theta_{n,k}^q}^2 \end{bmatrix} \quad (8)$$

where $\Sigma_{r_{n,k}^q}$ and $\Sigma_{\theta_{n,k}^q}$ denote the standard deviations of the target's range and azimuth, respectively. They can be expressed as

$$\begin{cases} \Sigma_{r_{n,k}^q} = \frac{\Delta \text{res}_n}{c_1 \sqrt{2 \text{SNR}_{n,k}^q}} \\ \Sigma_{\theta_{n,k}^q} = \frac{B_n}{c_2 \sqrt{2 \text{SNR}_{n,k}^q}} \end{cases} \quad (9)$$

where Δres_n is the distance resolution, B_n is the beamwidth, c_1 and c_2 are two preset constants, and $\text{SNR}_{n,k}^q$ is the SNR, calculated as

$$\text{SNR}_{n,k}^q = \frac{p_{n,k}^q t_d \alpha_{n,k}^q G_{T,n} G_{R,n} \lambda_n^2}{(4\pi)^3 (r_{n,k}^q)^4 \mathcal{L}_n K T_n \text{NF}_n} \quad (10)$$

where $p_{n,k}^q$ is the transmission power of radar n towards target q , t_d is the dwell time, $\alpha_{n,k}^q$ is the radar cross-section (RCS) of target q at time k , $G_{T,n}$ and $G_{R,n}$ are the transmission and reception gains, respectively, λ_n is the radar signal wavelength, $\mathcal{L}_n$ is the loss factor, K is the Boltzmann constant, T_n is the radar noise temperature, and NF_n is the radar noise figure. It can be inferred from Eq. (10) that, assuming other parameters remain unchanged, SNR is related to the transmission power. Higher SNR results in smaller variances of measurement errors, leading to more accurate measurement results.

3 Joint Optimization Model for Multi-Radar Network Node Selection and Power Allocation under Non-Ideal Detection

For phased array radar systems, it is essential not only to ensure maneuvering multi-target tracking performance, but also to reduce transmission power in order to enhance their radio frequency stealth capabilities. Based on this premise, this section establishes a joint optimization model for node selection and transmission power resources in a multi-radar network for maneuvering multi-target tracking. The model incorporates the tracking accuracy threshold and system resource budget as constraints. Define the node selection vector and transmission power vector concerning target q from different radar nodes in the multi-radar network as

$$\begin{cases} \mathbf{u}_k^q = [u_{1,k}^q, u_{2,k}^q, \dots, u_{N,k}^q]^\top \\ \mathbf{p}_k^q = [p_{1,k}^q, p_{2,k}^q, \dots, p_{N,k}^q]^\top \end{cases} \quad (11)$$

where $\mathbf{u}_k^q$ and $\mathbf{p}_k^q$ are both vectors of dimension N . More specifically, we consider the case of non-ideal detection, which refers to the situation where not all illuminated targets can be successfully detected due to the presence of practical detection imperfections.

3.1 Derivation of the PC-CRLB under non-ideal detection

It is evident that only the radar nodes that illuminate the target can proceed to the next detection process. Assume that according to $\mathbf{u}_k^q$, target q is illuminated by L radar nodes at time k . Denote these radars' indices sequentially in the set ξ_k^q as

$$\xi_k^q = \{n | u_{n,k}^q = 1\} \quad (12)$$

Because each node may or may not detect target q , there are a total of 2^L possible detection cases, which can be expressed as

$$D_k^q = \{D_{i,k}^q | i = 1, 2, \dots, 2^L\} \quad (13)$$

where $D_{i,k}^q$ represents the i -th detection case. $D_{i,k}^q = \left[d_{\xi_k^q(1),i,k}^q, d_{\xi_k^q(2),i,k}^q, \dots, d_{\xi_k^q(L),i,k}^q, \dots, d_{\xi_k^q(L),i,k}^q \right]$, in which $d_{\xi_k^q(l),i,k}^q$ is the detection variable of radar node $\xi_k^q(l)$ in the i -th detection case, taking a value of either 0 or 1. Notably, for different radar nodes, the detection probability of the target varies due to factors such as the target's radar cross-section, the range between the radar node and the target, and the radar's transmission power. The detection probability^[29] of target q by radar node n can be represented as

$$\text{Pd}_{n,k}^q = P_{\text{fa}}^{1/(1+\text{SNR}_{n,k}^q)} \quad (14)$$

where P_{fa} is the false alarm probability. $\text{SNR}_{n,k}^q$, which is shown in Eq. (10), primarily depends on the transmission power. The probability of the i -th detection scenario can be obtained as

$$\Pr(D_{i,k}^q) = \prod_{l \in \xi_k^q} \left[d_{\xi_k^q(l),i,k}^q P_{\xi_k^q(l),i,k}^q + (1 - d_{\xi_k^q(l),i,k}^q) (1 - P_{\xi_k^q(l),i,k}^q) \right] \quad (15)$$

where $P_{\xi_k^q(l),i,k}^q$ means the detection probability in the i -th detection case of radar node $\xi_k^q(l)$ at moment k .

Assuming that the system's process noise is small and that the predicted probability density function of the state can be approximated as a Gaussian distribution, above all, for all possible detection

scenarios under non-ideal detection conditions, the PC-FIM can be approximately represented as^[20]

$$\begin{aligned} \mathbf{J}(\mathbf{X}_{k|k-1}^q) &\approx (\text{Pec}_{k|k-1}^q)^{-1} + \sum_{i=1}^{2^L} \Pr(D_{i,k}^q) \\ &\times \sum_{l \in \xi_k^q} \left[d_{\xi_k^q(l),i,k}^q \left(\mathbf{H}_{\xi_k^q(l),i,k}^q \right)^\top \left(\boldsymbol{\Sigma}_{\xi_k^q(l),i,k}^q \right)^{-1} \mathbf{H}_{\xi_k^q(l),i,k}^q \right] \Big|_{\mathbf{X}_{k|k-1}^q} \end{aligned} \quad (16)$$

$$\begin{aligned} \text{Pec}_{k|k-1}^q &= \sum_{j=1}^S \mu_{k|k-1}^{q,j} \left\{ \mathbf{F}_{k-1}^{q,j} \left(\text{Pec}_{k-1}^q + \mathbf{x}_{k-1}^q (\mathbf{x}_{k-1}^q)^\top \right) (\mathbf{F}_{k-1}^{q,j})^\top \right. \\ &\quad \left. + \mathbf{Q}_{k-1}^{q,j} \right\} - \mathbf{F}_{k-1}^q \mathbf{x}_{k-1}^q (\mathbf{x}_{k-1}^q)^\top (\mathbf{F}_{k-1}^q)^\top \end{aligned} \quad (17)$$

where $\mathbf{J}(\mathbf{X}_{k|k-1}^q)$ represents the PC-FIM, $\text{Pec}_{k|k-1}^q$ is the predicted error covariance matrix; $\mu_{k|k-1}^{q,j}$ stands for the predicted model probability of model j ; $\mathbf{F}_{k-1}^q$ stands for a comprehensive state transition matrix, $\mathbf{F}_{k-1}^q = \sum_{j=1}^S \mu_{k|k-1}^{q,j} \mathbf{F}_{k-1}^{q,j}$; $\mathbf{H}_{\xi_k^q(l),i,k}^q$ and $\boldsymbol{\Sigma}_{\xi_k^q(l),i,k}^q$ represent the Jacobian matrix of the measurement function and the measurement noise covariance matrix, respectively; $|_{\mathbf{X}_{k|k-1}^q}$ means that the calculation is based on the predicted state of target q ($\mathbf{X}_{k|k-1}^q$).

Furthermore, it can be proven that Eq. (16) is equivalent to Eq. (18), with the proof provided in Lemma 2, which can be expressed as

$$\begin{aligned} \mathbf{J}(\mathbf{X}_{k|k-1}^q) &\approx (\text{Pec}_{k|k-1}^q)^{-1} + \sum_{i=1}^L \text{Pd}_{i,k}^q \\ &\times \left[\mathbf{u}_{i,k}^q \left(\mathbf{H}_{i,k}^q \right)^\top \left(\boldsymbol{\Sigma}_{i,k}^q \right)^{-1} \mathbf{H}_{i,k}^q \right] \Big|_{\mathbf{X}_{k|k-1}^q} \end{aligned} \quad (18)$$

Thus, the expression for the PC-CRLB of the target state estimation error under non-ideal detection conditions at time k can be expressed as

$$\mathbf{C}_{\text{PC-CRLB},k}^q = \left[\mathbf{J}(\mathbf{X}_{k|k-1}^q) \right]^{-1} \quad (19)$$

From Eqs. (16) and (19), it can be observed that the PC-CRLB is closely related to the selection of radar nodes and transmission power at time k . The diagonal elements of $\mathbf{C}_{\text{PC-CRLB},k}^q$ represent the lower bound of the root mean square error (RMSE) for the target position estimation.

3.2 Optimization problem formulation

During maneuvering multi-target tracking, the radar nodes and transmission power are optimized adaptively

to minimize the total transmission power while satisfying the constraints of multi-target tracking accuracy and the limitations of system transmission resources. Based on this, the optimization model is established as

$$\begin{aligned} \min_{\mathbf{u}_k^q, \mathbf{p}_k^q} & \sum_{q=1}^Q \sum_{n=1}^N u_{n,k}^q p_{n,k}^q, \\ \text{s.t.}, & \begin{cases} \text{C1: } A(\mathbf{u}_k^q, \mathbf{p}_k^q) \leq a^q, \quad \forall q \\ \text{C2: } p_{\min} \leq p_{n,k}^q \leq p_{\max}, \quad \forall n \\ \text{C3: } \sum_{q=1}^Q u_{n,k}^q \leq 1, \quad \forall n \\ \text{C4: } \sum_{n=1}^N u_{n,k}^q = L_{\max}^q, \quad \forall q \\ \text{C5: } u_{n,k}^q \in \{0, 1\}, \quad \forall n, q \end{cases} \end{aligned} \quad (20)$$

where $A(\mathbf{u}_k^q, \mathbf{p}_k^q)$ represents the measure of maneuvering multi-target tracking accuracy, which is calculated as

$$A(\mathbf{u}_k^q, \mathbf{p}_k^q) = \text{tr}(\mathbf{I}^\top \mathbf{C}_{\text{PC-CRLB},k}^q \mathbf{I}) \quad (21)$$

where the operation of block diagonalization $\mathbf{I} = \mathbf{I}_2 \otimes \text{blkdiag}(1, T_0, T_0^2)$, in which, $\mathbf{I}$ is the normalization matrix, and $\mathbf{I}_2$ stands for the unit matrix with dimension 2. In Formula (20), Constraint C1 indicates the threshold requirement for maneuvering multi-target tracking accuracy, where a^q represents the pre-established tracking accuracy threshold for target q ; Constraint C2 defines the range of transmission power of the radar nodes, with $p_{\max}$ and $p_{\min}$ denoting the upper and lower bounds, respectively; Constraint C3 states that each radar node can track at most one target at a given time; Constraint C4 fixes the number of radar nodes allocated to track target q at time k to be $L_{\max}^q$; Constraint C5 represents the binary variable for radar-target pairing.

4 JNSPA-NID Scheme for Maneuvering Multi-Target Tracking under Non-Ideal Detection

The optimization problem described in Formula (20) involves the optimization of the radar-target pairing indicator $\mathbf{u}_k^q$ and the transmission power variable $\mathbf{p}_k^q$. It is evident that these two optimization variables are coupled with each other. Therefore, Formula (20) is a mixed-integer programming problem that is nonlinear and non-convex.

Firstly, we relax the binary variable $u_{n,k}^q \in \{0, 1\}$ to be a continuous variable $\tilde{u}_{n,k}^q$ between 0 and 1, i.e., $0 \leq \tilde{u}_{n,k}^q \leq 1$. The optimization model then turns to be

$$\begin{aligned} \min_{\tilde{\mathbf{u}}_k^q, \mathbf{p}_k^q} & \sum_{q=1}^Q \sum_{n=1}^N \tilde{u}_{n,k}^q p_{n,k}^q, \\ \text{s.t.}, & \begin{cases} \text{C1} - \text{C4} \\ \text{C5: } 0 \leq \tilde{u}_{n,k}^q \leq 1, \quad \forall n, q \end{cases} \end{aligned} \quad (22)$$

Based on this, a cyclic iterative framework utilizing a relaxed interior-point method and a greedy algorithm is proposed for solving the problem. The steps are as follows.

Step 1: Initialize the current iteration count $i = 1$, the count of successful iterations $\eta_s = 0$, the count of failed iterations $\eta_f = 0$. Set the values of total of iteration number LT, successful iteration number threshold $\eta_{s\text{-th}}$, failed iteration number threshold $\eta_{f\text{-th}}$. $\mathbf{p}_k^{q,0} = p_{\max}$, $\forall n$.

Step 2: Put $\mathbf{p}_k^{q,i-1}$ into Formula (22), then it can be converted into

$$\begin{aligned} \min_{\tilde{\mathbf{u}}_k^{q,i}} & \sum_{q=1}^Q \sum_{n=1}^N \tilde{u}_{n,k}^{q,i} p_{n,k}^{q,i-1}, \\ \text{s.t.}, & \begin{cases} \text{C1: } A(\tilde{\mathbf{u}}_k^{q,i}) \leq \eta^q, \quad \forall q \\ \text{C3: } \sum_{q=1}^Q \tilde{u}_{n,k}^{q,i} \leq 1, \quad \forall n \\ \text{C4: } \sum_{n=1}^N \tilde{u}_{n,k}^{q,i} = L_{\max}^q, \quad \forall q \\ \text{C5: } 0 \leq \tilde{u}_{n,k}^{q,i} \leq 1, \quad \forall n, q \end{cases} \end{aligned} \quad (23)$$

Use the interior point method to solve the above problem, the solution $\tilde{\mathbf{u}}_k^{q,i}$ is obtained. An initial point $\tilde{\mathbf{u}}_{k,(0)}^{q,i}$ is required when using the above method. If $i = 1$, the initial point $\tilde{\mathbf{u}}_{k,(0)}^{q,1}$ can be obtained by Algorithm 1. If $i \neq 1$, take the result of the $(i-1)$ -th iteration as the initial point, i.e., $\tilde{\mathbf{u}}_{k,(0)}^{q,i} = \tilde{\mathbf{u}}_{k,(0)}^{q,i-1}$.

Step 3: According to the larger values in $\tilde{\mathbf{u}}_k^{q,i}$, set the corresponding elements in $\tilde{\mathbf{u}}_k^{q,i}$ to be 1 and set other elements to be 0 while ensuring that they satisfy the constraints C3 and C4 in Formula (20), to obtain $\mathbf{u}_k^{q,i}$. This process is similar to Algorithm 1.

Step 4: Substitute the obtained $\mathbf{u}_k^{q,i}$ into Formula (20) to obtain an optimization problem that is only related to the transmission power, as

Algorithm 1 Heuristic SNR-based node selection**Input:** Initial SNR matrix: $\mathbf{SNR}_0$; initial node selection matrix: $\tilde{\mathbf{u}}_{k,(0)}^{q,1}$ (same size as $\mathbf{SNR}_0$, all elements are 0); $\gamma^q = 0$, $q = \{1, 2, \dots, Q\}$ **Output:** Initial node selection matrix: $\tilde{\mathbf{u}}_{k,(0)}^{q,1}$

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1: for  $i = 1 : \sum_{q=1}^Q L_{\max}^q$  do
2:   Find the maximum value in  $\mathbf{SNR}_0$ ;
3:   Get the position  $[i^*, j^*]$  of the maximum value;
4:   Set  $\tilde{u}_{k,(0)}^{q,1}[i^*, j^*] = 1$ ;
5:   Set  $\mathbf{SNR}_0[:, j^*] = 0$ , to avoid re-selection;
6:    $\gamma^q = \gamma^q + 1$ ;
7:   if  $\gamma^q == L_{\max}^q$  then
8:     Disable all nodes for target  $q$ ;
9:   else
10:    Continue;
11:   end if
12: end for

```

13: **return** the node selection matrix $\tilde{\mathbf{u}}_{k,(0)}^{q,1}$

$$\begin{aligned}
& \min_{\mathbf{p}_k^{q,i}} \sum_{q=1}^Q \sum_{n=1}^N u_{n,k}^{q,i} p_{n,k}^{q,i} \\
& \text{s.t.}, \begin{cases} \text{C1} : F(\mathbf{p}_k^{q,i}) \leq \eta^q, \quad \forall q \\ \text{C2} : p_{\min} \leq p_{n,k}^{q,i} \leq p_{\max}, \quad \forall n \end{cases} \quad (24)
\end{aligned}$$

Apply the interior-point method again to solve for the power distribution matrix, obtaining $\mathbf{p}_k^{q,i}$. Similar to Step 2, if $i = 1$, the initial point $p_{n,k,(0)}^{q,1} = p_{\max}$ for each node. If $i \neq 1$, $\mathbf{p}_{k,(0)}^{q,i} = \mathbf{p}_k^{q,i-1}$.

Step 5: $i = i + 1$, continue the process from Step 2 to Step 4 until $i > \text{LT}$. In the i -th iteration, when the tracking accuracy of all targets is less than the preset accuracy, $\eta_s = \eta_s + 1$. Otherwise, $\eta_f = \eta_f + 1$ and set the elements in $\mathbf{u}_k^{q,i}$ to random values between 0 and 1. If $\eta_s = \eta_{s\text{-th}}$ or $\eta_f = \eta_{f\text{-th}}$, exit the loop, and regard the current $\mathbf{u}_k^{q,i}$ and $\mathbf{p}_k^{q,i}$ as the optimal solution.

To apply the interior-point method to solve the original optimization problem in Step 2, both the objective function and constraints should be convex. It can be observed that the objective function and Constraints C3–C5 are convex. Thus, it is necessary to prove that Constraint C1 in Formula (20) concerning the given power $\mathbf{p}_k^q$ is a convex function with respect to $\mathbf{u}_k^q$ ^[30]. The specific proof steps are provided in Lemmas 1 and 2.

Due to the coupling relationship between $\mathbf{u}_k^q$ and $\mathbf{p}_k^q$, it can be similarly proven that Constraint C1 concerning the given node selection result $\mathbf{u}_k^q$ is a convex function with respect to $\mathbf{p}_k^q$ as well. Therefore, in Step 4, we also use the interior-point method to solve the problem.

The problem in Formula (22) can be solved using the interior-point method, which requires starting from an initial point. Since the interior-point method employs the principles of Newton's descent to find the optimal point^[31, 32], if the initial point in Step 2 lies within the feasible region, the Newton method can quickly converge to the optimal value^[33].

To find a feasible initial point that satisfies the constraints, the initial selection of radar nodes should consider those that yield the greatest improvement in tracking performance. According to Eq. (9), the tracking performance is essentially determined by SNR. Therefore, the selection process of initial point can be realized by a heuristic SNR-based node selection algorithm, which is given in Algorithm 1. The initial SNR matrix $\mathbf{SNR}_0$ represent how much SNR will be obtained if each radar node is assigned to each target, for example, the element $\mathbf{SNR}_0[i, j]$ can be obtained by substituting $i = q$ and $j = n$.

Based on the aforementioned joint allocation method for nodes and power, the optimal operating parameters of the system at time k can be obtained. The system then performs multi-target detection to acquire new measurement information and data processing is conducted using the IMM-EKF method and distributed fusion method. Then initiates the next closed-loop control.

Lemma 1 Constraint C1 is a convex function.

Proof From Eqs. (19) and (21), it can be seen that the convexity of the constraint depends on the properties of the Fisher information matrix (FIM), which is given by

$$\begin{aligned}
J(\mathbf{X}_{k|k-1}^q) & \approx (\text{Pec}_{k|k-1}^q)^{-1} + \sum_{i=1}^{2L} \Pr(D_{i,k}^q) \\
& \times \sum_{l \in \xi_k^q} \left[d_{\xi_k^q(l),i,k}^q \left(\mathbf{H}_{\xi_k^q(l),i,k}^q \right)^\top \left(\boldsymbol{\Sigma}_{\xi_k^q(l),i,k}^q \right)^{-1} \mathbf{H}_{\xi_k^q(l),i,k}^q \right] \Big|_{\mathbf{X}_{k|k-1}^q} \quad (25)
\end{aligned}$$

$$J(\mathbf{X}_{k|k-1}^q) \approx (\text{Pec}_{k|k-1}^q)^{-1} + \sum_{i=1}^L \text{Pd}_{i,k}^q \times \left[\mathbf{u}_{i,k}^q \left(\mathbf{H}_{i,k}^q \right)^\top \left(\boldsymbol{\Sigma}_{i,k}^q \right)^{-1} \mathbf{H}_{i,k}^q \right] \Big|_{\mathbf{X}_{k|k-1}^q} \quad (26)$$

In fact, Eq. (25) can be equivalently represented as

Eq. (26), where $u_{i,k}^q$ is the i -th radar that illuminates target q and $\text{Pd}_{i,k}^q$ is the detection probability. The equivalence of these two equations is proved in Lemma 2. From the definition of the matrix $\Sigma_{i,k}^q$ in Eq. (8), it is evident that it is a positive definite matrix. Therefore, it can be expressed as $\Sigma_{i,k}^q = (\mathbf{C}_{i,k}^q)^\top \mathbf{C}_{i,k}^q$, where $\mathbf{C}_{i,k}^q$ is a real invertible matrix. Consequently, we have $(\mathbf{H}_{i,k}^q)^\top (\Sigma_{i,k}^q)^{-1} \mathbf{H}_{i,k}^q = [(\mathbf{C}_{i,k}^q)^{-1} \mathbf{H}_{i,k}^q]^\top [(\mathbf{C}_{i,k}^q)^{-1} \mathbf{H}_{i,k}^q]$. Therefore, the second term in Eq. (26) is also positive definite. The first term is the predicted error covariance matrix, which is also positive definite.

Next, we need to prove that $A(\mathbf{u}_k^q)$ is positive definite. It can be simplified to represent as $A(\mathbf{u}_k^q) = \text{tr}(\mathbf{R}^\top (\mathbf{J}(\mathbf{X}_{k|k-1}^q))^{-1} \mathbf{R})$, and since $\mathbf{J}(\mathbf{X}_{k|k-1}^q)$ is convex, we can assume $\mathbf{X} = \mathbf{J}(\mathbf{X}_{k|k-1}^q)$, then denote the original function as $A(\mathbf{X}) = \text{tr}(\mathbf{R}^\top \mathbf{X}^{-1} \mathbf{R})$. To prove its convexity, consider any line, letting $\mathbf{X} = \mathbf{K} + t\mathbf{G}$ be defined where $\mathbf{K}$ and $\mathbf{G}$ are positive definite. Let $g(t) = A(\mathbf{K} + t\mathbf{G})$. The detailed proof of strict convexity of $g(t)$ is provided in the appendix of Ref. [30]. Since $A(\mathbf{X})$ is a strictly convex function concerning the positive definite matrix $\mathbf{X}$, it implies that $A(\mathbf{u}_k^q)$ is also a strictly convex function. Therefore, this lemma holds. ■

Lemma 2 Equations (25) and (26) are equivalent.

Proof For simplicity, we take the assumption $\mathbf{J}_i = (\mathbf{H}_{i,k}^q)^\top (\Sigma_{i,k}^q)^{-1} \mathbf{H}_{i,k}^q$, and regard it as a contribution value to the total FIM. The equivalence can be converted to prove that the weighted sum of contributions from all possible detection situations equals the weighted contribution values of individual nodes, which can be described by

$$P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_L \mathbf{J}_L = \sum_{(d_1, d_2, \dots, d_L)} \mathbf{J}(d_1, d_2, \dots, d_L) P(d_1, d_2, \dots, d_L) \quad (27)$$

where $\mathbf{J}(d_1, d_2, \dots, d_L) = \sum_{j=1}^L \mathbf{J}_j d_j$. The combination $(d_1, d_2, \dots, d_L)$, the probability can be expressed as

$$P(d_1, d_2, \dots, d_L) = \prod_{j=1}^L P_j^{d_j} (1 - P_j)^{1-d_j} \quad (28)$$

where $d_j = 1$ denotes that the j -th radar that illuminates target q also detected the target successfully.

We use mathematical induction to prove this equality for any L .

Base case $L = 1$:

$$P_1 \mathbf{J}_1 = \mathbf{J}_1 P_1 \quad (29)$$

Inductive hypothesis: Assume Eq. (30) holds for $L = k$,

$$P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_k \mathbf{J}_k = \sum_{(d_1, d_2, \dots, d_k)} \mathbf{J}(d_1, d_2, \dots, d_k) P(d_1, d_2, \dots, d_k) \quad (30)$$

Inductive step: Now consider $L = k + 1$; the $(k + 1)$ -th node can detect the target with probability P_{k+1} . Therefore, the overall contribution can be expressed as

$$P_{k+1} (\mathbf{J}_1 + \mathbf{J}_2 + \dots + \mathbf{J}_k + \mathbf{J}_{k+1}) + (1 - P_{k+1}) (P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_k \mathbf{J}_k) \quad (31)$$

By the inductive hypothesis, we can rewrite it as

$$P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_k \mathbf{J}_k + P_{k+1} \mathbf{J}_{k+1} \quad (32)$$

Therefore, we have

$$P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_k \mathbf{J}_k + P_{k+1} \mathbf{J}_{k+1} = \sum_{(d_1, d_2, \dots, d_k, d_{k+1})} \mathbf{J}(d_1, d_2, \dots, d_k, d_{k+1}) P(d_1, d_2, \dots, d_k, d_{k+1}) \quad (33)$$

Conclusion: Using induction, we have shown that for any L ,

$$P_1 \mathbf{J}_1 + P_2 \mathbf{J}_2 + \dots + P_k \mathbf{J}_k = \sum_{(d_1, d_2, \dots, d_k)} \mathbf{J}(d_1, d_2, \dots, d_k) P(d_1, d_2, \dots, d_k) \quad (34)$$

This demonstrates that the weighted contribution values of individual nodes equal the weighted sum of contributions from all possible combinations. Therefore, this lemma holds. ■

5 Numerical Result

Consider a distributed phased array radar network consisting of $N = 8$ radars. There are $Q = 2$ moving targets within the surveillance area of the radar system. In the simulation scenario, the entire tracking process consists of 40 frames, totally 120 s. The preset tracking accuracy threshold is set to $\varepsilon^q = 40 \text{ m} (\forall q)$. The maximum number of radar nodes that can be used for each target is set to be $L_{\max}^q = 3$. $\text{LT} = 20$, $\eta_{s\text{-th}} = 2$, $\eta_{f\text{-th}} = 10$. Tables 1 and 2 show the radar system parameters and the initial state of the targets, respectively.

(1) Model 1: The first model is a nearly constant velocity (NCV) model, whose state transition matrix and noise covariance matrix are given by

Table 1 Radar system parameters.

Parameter	Symbol	Value
Radar frequency	f	6 GHz
Wavelength	λ	0.05 m
Maximum transmission power	$p_{\max}$	5 kW
Minimum transmission power	$p_{\min}$	100 W
Antenna gain	G_T	40 dB
Range resolution	ΔR	1.5 m
RCS of target	α	1 m ²
Sampling time	t_0	3 s
Dwell time	t_d	0.005 s

Table 2 Initial state of targets.

Target	Initial state
Target 1	$[0 \text{ m}, -300 \text{ m/s}, 0 \text{ m/s}^2, 40 \text{ km}, -300 \text{ m/s}, 0 \text{ m/s}^2]^\top$
Target 2	$[30 \text{ km}, 300 \text{ m/s}, 0 \text{ m/s}^2 - 20 \text{ km}, 300 \text{ m/s}, 0 \text{ m/s}^2]^\top$

$$\mathbf{F}_{k-1}^1 = \mathbf{I}_2 \otimes \begin{bmatrix} 1 & t_0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (35)$$

$$\mathbf{Q}_{k-1}^1 = \tau \mathbf{I}_2 \otimes \begin{bmatrix} \frac{t_0^3}{3} & \frac{t_0^2}{2} & 0 \\ \frac{t_0^2}{2} & t_0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (36)$$

where $\tau = 1 \text{ m}^2/\text{s}^3$ represents the process noise density.

(2) Model 2: The second dynamic model is the nearly coordinated turn (NCT), which has the same noise covariance matrix as the NCV, i.e., $\mathbf{Q}_{k-1}^2 = \mathbf{Q}_{k-1}^1$.

$$\mathbf{F}_{k-1}^2 = \begin{bmatrix} 1 & \frac{\sin(\Omega T)}{\Omega} & 0 & 0 & \frac{\cos \Omega T - 1}{\Omega} & 0 \\ 0 & \cos(\Omega T) & 0 & 0 & -\sin(\Omega T) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{-\cos \Omega T + 1}{\Omega} & 0 & 1 & \frac{\sin(\Omega T)}{\Omega} & 0 \\ 0 & \sin(\Omega T) & 0 & 0 & \cos(\Omega T) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (37)$$

where the turn rate Ω is set to 2 °/s, and T stands for the sampling period. These two models are integrated into a IMM filtering framework to capture the potential maneuvering of targets. The IMM filter allows dynamic switching between the NCV and NCT models based on the model probabilities. The initial model probability is $[0.8, 0.2]^\top$, and the transition probability matrix is initialized with

$$\mathbf{\Pi} = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix} \quad (38)$$

The model variable sequence of Target 1 is set as $v_2, v_3, \dots, v_{20} = 1$, $v_{21}, v_{22}, \dots, v_{30} = 2$, and $v_{31}, v_{32}, \dots, v_{40} = 1$; Target 2 is set as $v_2, v_3, \dots, v_{15} = 1$, $v_{16}, v_{17}, \dots, v_{25} = 2$, and $v_{26}, v_{27}, \dots, v_{40} = 1$.

Figure 2 shows the distribution of the multi-radar network and the motion trajectories of the targets in the simulation scenario. The red one represents Target 1, while the blue one represents Target 2. The number of Monte Carlo simulations conducted is $N_{\text{MC}} = 500$. The overall position RMSE at time k is used and defined as

$$\text{RMSE}_k^q = \sqrt{\frac{1}{N_{\text{MC}}} \sum_{j=1}^{N_{\text{MC}}} \left[(x_k^q - \hat{x}_{k,j}^q)^2 + (y_k^q - \hat{y}_{k,j}^q)^2 \right]} \quad (39)$$

To better illustrate the patterns and intrinsic relationships of radar node selection and power allocation, the transmission power has been normalized by $p_{\max}$. Figures 3 and 4 display the results of radar node selection and optimized power resource allocation for Targets 1 and 2, respectively. The color gradient in Figs. 3 and 4 indicates the results of power distribution. The black areas in Figs. 3 and 4 represent radar nodes that are not assigned tracking tasks during the corresponding sampling intervals. In contrast, areas of different colors indicate that the radar nodes allocated transmission resources to the targets during those intervals.

From Figs. 3 and 4, it can be observed that the multi-radar system prioritizes radar nodes that are closer to the targets. As the targets get closer to the radar nodes,

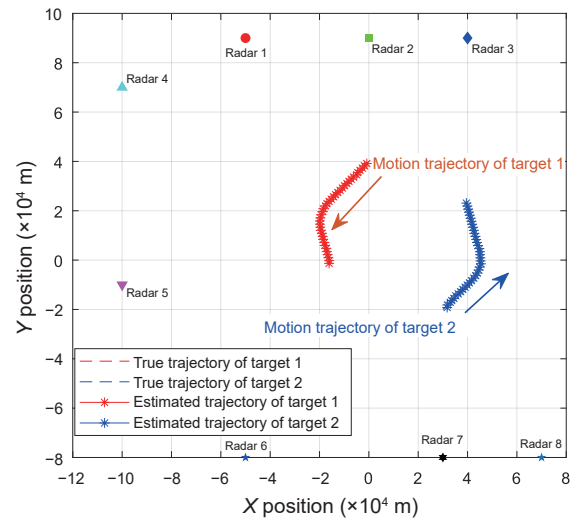


Fig. 2 Distribution of the multi-radar network and the motion trajectories of the targets.

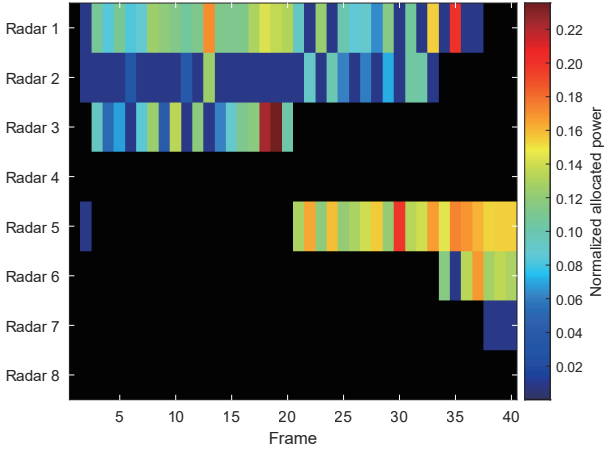


Fig. 3 Power allocation for Target 1 in JNSPA-NID.

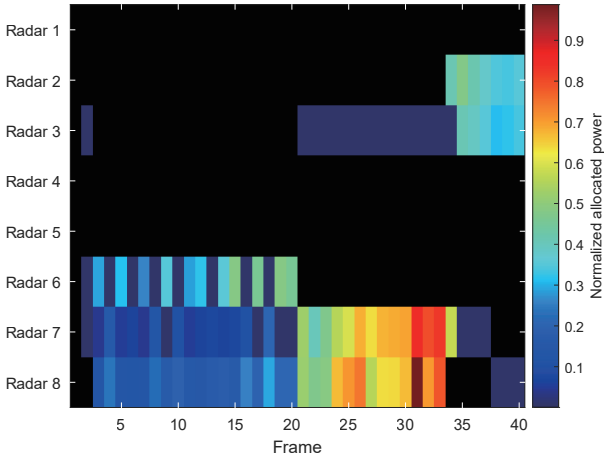


Fig. 4 Power allocation for Target 2 in JNSPA-NID.

the system allocates progressively less transmission power to achieve the optimization goal of minimizing total power consumption, thereby enhancing system performance. For example, regarding Target 1, in the first ten frames, the multi-radar network primarily selects radar nodes 1–3 for tracking. As Target 1 approaches radar nodes 5 and 6, more power is allocated to these nodes to reduce resource consumption. After 20 frames, as Target 1 moves away from radar node 2, radar node 2 is gradually replaced by radar node 5. For Target 2, during the first 35 frames, the system primarily selects radar nodes 6–8. As Target 2 approaches radar nodes 2 and 3, these nodes are allocated more power. As shown in Fig. 4, the energy allocated to Target 2 is greater than that of Target 1. This is because Target 2 is moving away from the radar system, which requires more power allocation to ensure tracking accuracy. It is also observed that Target 1 maneuvers between frames 20

and 30, while Target 2 maneuvers between frames 15 and 25. To ensure tracking accuracy, the radar correspondingly increases the radiation power to cope with the maneuvers of the targets.

Figure 5 presents a comparison between the preset tracking accuracy and the PC-CRLB of targets. The preset tracking accuracy for the targets is set uniformly i.e., $\varepsilon^q = 40$ m. From Fig. 5, it can be observed that through the proposed algorithm for solving the optimization model, the BCRLB for each target is able to effectively meet the predetermined in the majority of time instances.

To better demonstrate the performance improvement of the proposed algorithm under non-ideal detection conditions, four comparative algorithms are evaluated alongside the proposed algorithm to analyze their performance differences. The benchmarks are depicted as follows:

- **Benchmark 1:** Fixed radar nodes with optimized power allocation (NFPO). In this approach, only the power of the radar nodes is optimized during each sampling interval, while the selection of radar nodes remains fixed.
- **Benchmark 2:** Fixed power with optimized radar node allocation (PFNO). In this method, only the selection of radar nodes is optimized during each sampling interval, while the transmission power of the radar nodes is kept constant.
- **Benchmark 3:** Joint node selection and power allocation algorithm without considering non-ideal detection (JNSPA-NND), where non-ideal detection conditions exist, yet they are not accounted for during the joint allocation process.
- **Benchmark 4:** Particle swarm optimization (PSO) algorithm. When dealing with optimization problems,

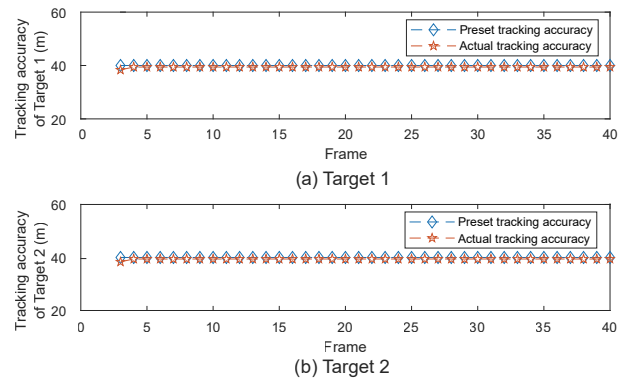


Fig. 5 Comparison between the preset tracking accuracy and the actual tracking accuracy of targets in JNSPA-NID.

PSO is used to search for the optimal solution through iterative searches.

• **Benchmark 5:** Alternating coalition formation and projection gradient (ACFPG) algorithm^[13]. The utility function consisting of the reward function under the quality of service framework and the cost function considering system resources is devised. Task allocation and power allocation are alternately performed to solve the optimization problem.

For the sake of fairness, the gradient projection method used for power optimization in Benchmark 5 (ACFPG) is replaced with the interior point method. The average power consumption of the proposed algorithm and comparative algorithms is shown in Fig. 6.

When using Benchmark 1 method (NFPO), for Target 1, nodes 6–8 are selected, and for Target 2, nodes 2, 4, and 5 are selected. Figure 7 indicates that while the NFPO method can achieve the preset tracking accuracy requirements for the targets, the

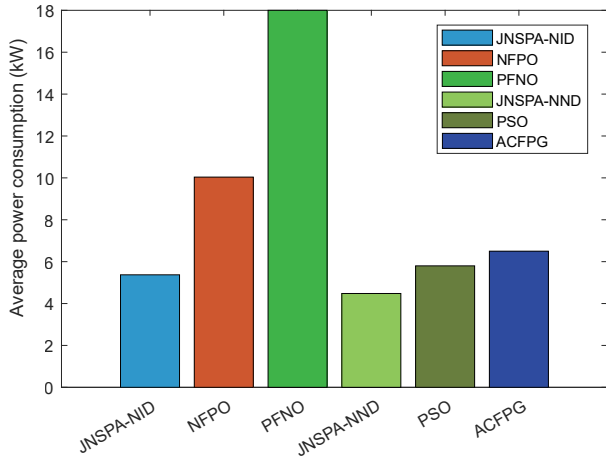


Fig. 6 Average power consumption of the proposed algorithm and comparative algorithms.

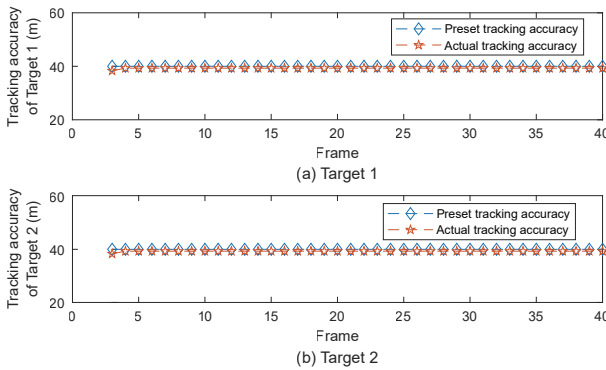


Fig. 7 Comparison between the preset tracking accuracy and the actual tracking accuracy of targets in NFPO.

energy consumption analysis in Fig. 6 shows that the proposed algorithm significantly reduces energy consumption compared with Benchmark 1, because the proposed method offers greater flexibility in selecting nodes.

When using the Benchmark 2 method (PFNO), the transmission power of the selected nodes is fixed at 3000 W. Figure 8 indicates that while the Benchmark 2 method meets the preset tracking accuracy requirements, the large difference from the threshold indicates that excessive transmission power may have been allocated, resulting in excessive energy consumption. Additionally, the energy consumption analysis in Fig. 6 shows that the proposed algorithm consumes significantly less energy than the Benchmark 2 method.

If the non-ideal detection conditions are not considered during performance prediction, the results, as shown in Fig. 9, represent the Benchmark 3 (JNSPA-NND). It can be observed from Fig. 9 that due to the presence of non-ideal detection conditions,

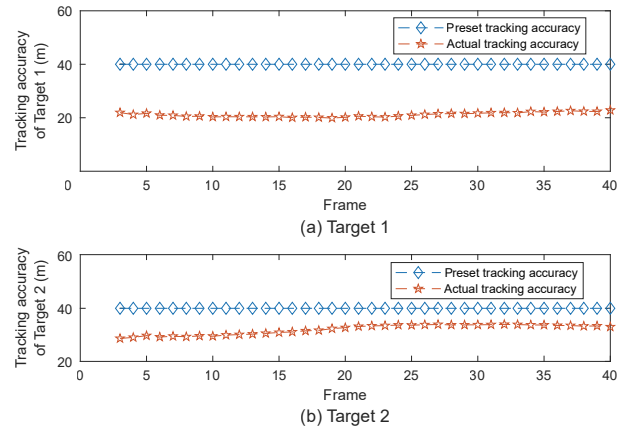


Fig. 8 Comparison between the preset tracking accuracy and the PC-CRLB of targets in PFNO.

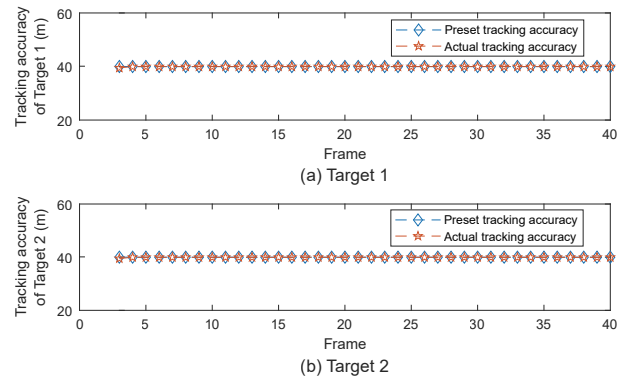


Fig. 9 Comparison between the preset tracking accuracy and the actual tracking accuracy of targets in JNSPA-NND.

which are not considered during performance prediction, the tracking accuracy of the targets is significantly further away from the preset.

When using the method of Benchmark 5 method (ACFPG), in designing the utility function, the tracking accuracy requirement function and the power consumption function are weighted by a manually set factor w . This makes it unlikely to simultaneously achieve both tracking accuracy requirements and power consumption. In the comparison with Benchmark 5, a relatively good weighting factor w has been selected through experimental simulations. When designing the utility function, a trade-off is made between the requirements for tracking accuracy and power consumption, resulting in a certain difference from the tracking accuracy threshold. Figure 10 shows the comparison result.

To further compare the differences between ideal and non-ideal detections, Fig. 11 shows the Accuracy values of the targets. From Fig. 6, it can be observed that although the power consumption of the radar is lower when non-ideal detection is not considered, the tracking accuracy is worse than considering non-ideal detection. This is because under non-ideal detection conditions, not all radars that are allocated energy can successfully detect the targets. As a result, the tracking error in the case of not considering non-ideal detection may not meet the preset values, which aligns with intuitive physical phenomena.

To illustrate the computational complexity advantages of this algorithm, a comparison is made between the proposed algorithm and the Benchmark4 method (PSO). The PSO algorithm primarily searches for the optimal solution to optimization problems through iterative searches^[34].

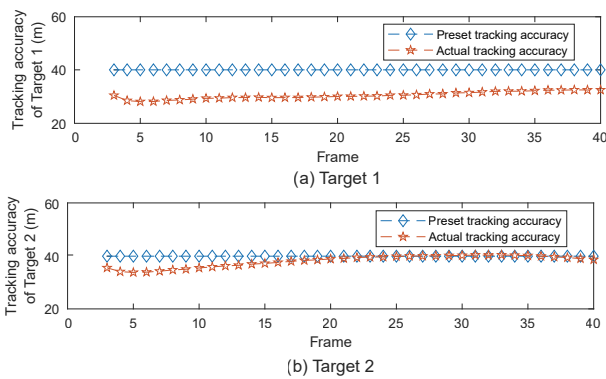


Fig. 10 Comparison between the preset tracking accuracy and the actual tracking accuracy of targets in ACFPG.

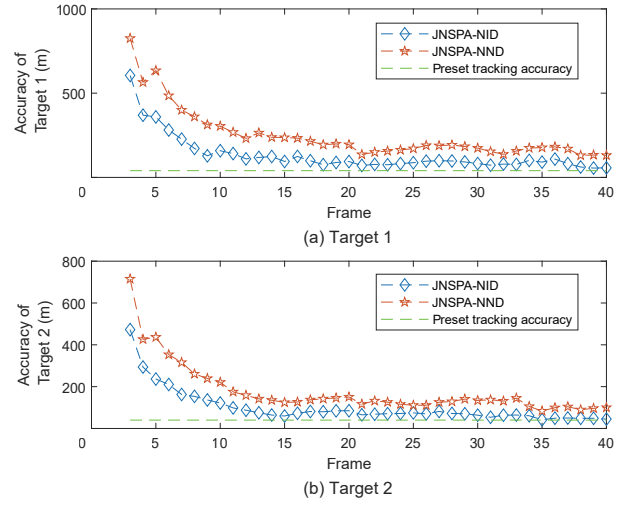


Fig. 11 Accuracy of targets considering and not considering non-ideal detection.

A comparison between the preset tracking accuracy of the targets obtained using the PSO method and the actual BCRLB is presented in Fig. 12. From Fig. 12, it can be seen that while the PSO method can adequately meet the preset tracking accuracy requirements, its final power consumption is comparable to that of the proposed algorithm.

Furthermore, the running times of several well-performing algorithms are compared to verify the effectiveness of the proposed algorithm. As shown in Fig. 13, the average runtime per frame for the proposed algorithm is 0.21 s, whereas the PSO requires 6.7 s. This discrepancy is due to PSO needing to analyze each particle's different potential detection scenarios during iterations, which demands more computational resources. Therefore, the proposed algorithm demonstrates better real-time performance. The ACFPG algorithm shows a slight improvement in

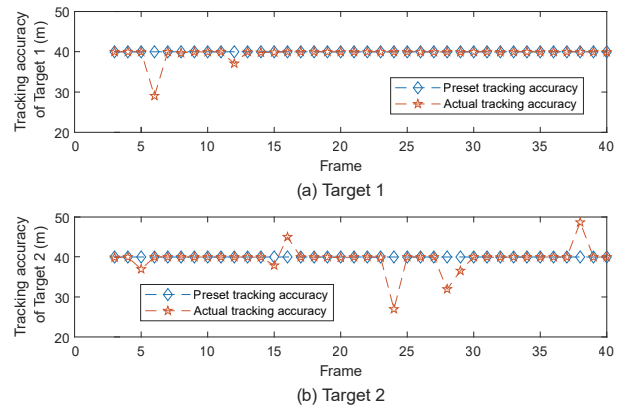


Fig. 12 Comparison between the preset tracking accuracy and the actual tracking accuracy of targets in PSO.

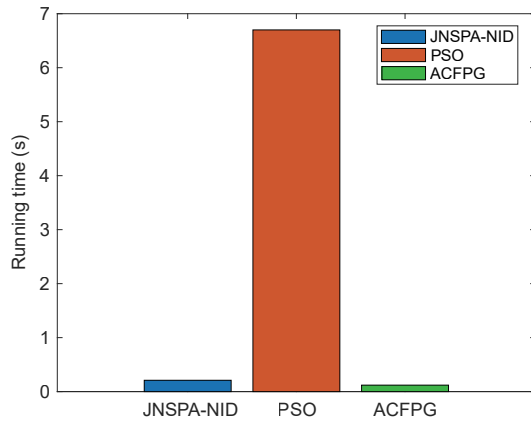


Fig. 13 Comparison of the well-performing algorithms, running times.

running time compared with the proposed algorithm. However, since the radar's sampling time is significantly greater than the running times of these two algorithms, we believe that this improvement is not very meaningful in relation to the required power reduction.

The simulations are conducted on a 2.5-GHz Intel (R) Core (TM) i5-13500 processor with 16 GB of RAM, using MATLAB R 2021b as the simulation software.

Future research directions: Non-ideal detection may be caused by clutter or interference. This paper considers the existence of these phenomena and their impact on resource management under non-ideal detection conditions. Future research will further explore methods to suppress the effects of interference or clutter through resource management.

6 Conclusion

For the scenario of maneuvering multi-target tracking in phased array radar network under non-ideal detection conditions, a joint optimization allocation algorithm for node selection and transmission power has been proposed. This algorithm aims to minimize the total transmission power consumption of a distributed phased array multi-radar network while satisfying multi-target tracking accuracy under given system resource constraints. To solve this mixed-integer programming, nonlinear, and non-convex optimization problem, a cyclic iterative solution method based on a relaxed interior point method and an SNR-based initial point selection algorithm is proposed. Simulation results indicate that the proposed algorithm effectively reduces the total transmission

power of the multi-radar network while meeting maneuvering multi-target tracking accuracy requirements. Furthermore, it performs better than fixed node and fixed power allocation algorithms in meeting tracking task requirements. It also reduces overall resource consumption than the ACFPG method and demonstrates better real-time performance than the PSO method. Compared with JNSPA-NND without considering non-ideal detection situations, it also better satisfies tracking accuracy requirements.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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