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Resource Allocation Optimization for Multi-Target Detection and Tracking in Cognitive Radar Networks

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Abstract. This paper addresses the challenges of power control, radar assignment, and signal timing to improve the detection and tracking of multiple targets within a mono-static cognitive radar network. A fusion center is utilized to integrate target velocity data gathered by radars. The primary objective is to minimize the mean square error in target velocity estimation while adhering to constraints related to global detection probability and total radar power consumption for effective target detection and tracking. The optimization problem is formulated and a low-complexity method is proposed using the genetic algorithm (GA). In this approach, the radars and their transmission powers are represented as chromosomes and the network's quality of service (QoS) requirements serve as inputs to the GA. The output of the GA is the mean error square of the target velocity estimation. Once the problem is resolved, the power allocation for each radar assigned to a specific target is determined. Simulation results demonstrate the effectiveness of the proposed algorithm in enhancing detection performance and improving tracking accuracy when compared to other benchmark algorithms.

Keywords. Target detection, Target tracking, Power allocation, Genetic algorithm.

MSC. 49J15; 49J20; 49N05.

1 Introduction

Radar networks have multiple radar nodes which work together for specified aim [8, 14]. In cognitive radar networks, multiple radars do sensing task. To take the advantages of a cognitive radar network, the radar information combination instead of consideration them individually should be considered. Radar emitter maximizes the transmitted power to increase the detection probability. However, this increment leads to more interception probability. One of the applications of power allocation arises in multi-target tracking [22]. However, one of the critical problems is the power allocation due to the equipment of radar with batteries and thus having limited power resources. On the other hand, power allocation can improve the detection performance while low probability of interception is achieved [6]. In multi-target network, it is shown than target velocity estimation has an important effect for determining the resource allocation results [16]. In this case, the multiple targets velocity estimation is considered by resource allocation.

Bayesian Cramer-Rao Bound (BCRB) is a useful technique for evaluating radar systems' performance. In [4], Cramer-Rao Lower Bound (CRLB) is applied for target localization accuracy and a sequential parameter convex approximation (SPCA) method is considered to solve the problem of the resource allocation. In [20], the strategy of power allocation is proposed for target tracking. The problem solution is proposed based on the two-step semi definite programming method. In [13], a flexible search algorithm is proposed for target assignment using the local detection probability. The goal of the paper is maximizing the total target detection probabilities which can be sub optimal due to low-probability-of-interception (LPI) considerations. In [18], a resource allocation method with transmitters and receivers is proposed to estimate multiple targets' velocity in a multiple-input multiple-output (MIMO) radar network. However, target detection is not addressed in this paper. In [9], LPI is improved by target assignment and power optimization. Target localization error and detection probability are quality of service (QoS) metrics; however, the power consumption constraint of the radars is not considered. In [3], the joint velocity and position of the targets' estimation and the propagation conditions of the urban transmission channel are proposed in a cognitive radar network. However, the radar assignment is not considered. In [22], a power allocation method is proposed for target tracking to maximize the tracking performance. They use the Bayesian Cram r-Rao lower bound and a spectral projected gradient algorithm to find the problem solution. In [5], the detection and tracking of the moving target is considered in the cognitive multimodal radar (CMR). In [1], power allocation based on particle swarm optimization method is proposed in MIMO radar. In [23], a novel method for cognitive radar waveform selection is proposed for the tracking targets with a probabilistic data association (PDA) algorithm. In [11], power allocation and in [10], power transmission and signal bandwidth allocation methods are proposed for target tracking using cooperative game.

Against the main results of the aforementioned works, in this paper, the target detection and target velocity estimation accuracy are improved by joint setting the signal time, optimal transmission power of each radar and radar assignment to each target simultaneously. According to these, the main contributions of this paper are:

- An algorithm is presented for setting the signal time duration, optimal transmission power of each radar and radar assignment to each target in a radar network to improve the target detection and target velocity estimation accuracy.
- The problem of resource allocation, power control and setting signal time is stated based on the target velocity estimation mean square error (MSE) minimization with constraints on the detection performance and total power budget in each time.
- Approximate optimal solution is obtained by applying the GA after relaxations which is used to simplify the solution process, because the problem is non-convex and NP-hard.
- Simulation results demonstrate the proposed algorithm effectiveness in detection performance protection and tracking accuracy improvement in comparison with other bench mark algorithms.

The paper is organized as follows. In Section 2, the network model of a radar network is stated. The problem formulation is presented in Section 3. In Section 4, the GA is introduced and our proposed algorithm is stated in this section. In Section 5, numerical results are demonstrated while analysis results are determined in Section 6. Conclusions are presented in Section 7.

2 Network Model

2.1 Target Detection in Radar Network

Consider a radar system architecture with M mono static search radars and N moving targets. It is assumed that a fusion center (FC) is responsible for information fusion and resource allocation (Figure 1). In this network, proper radars are assigned to each target cooperatively. On the other hand, the assigned radars receive and process the echo signals which are reflected from the targets. Then, transmitted signal from the mth radar and reflected by the nth target, is received by the mth radar. In this case, the received signal can be stated as

$$y_{m,n}(t) = s_{m,n}(t)h_{m,n} + w_n(t), \tag{1}$$

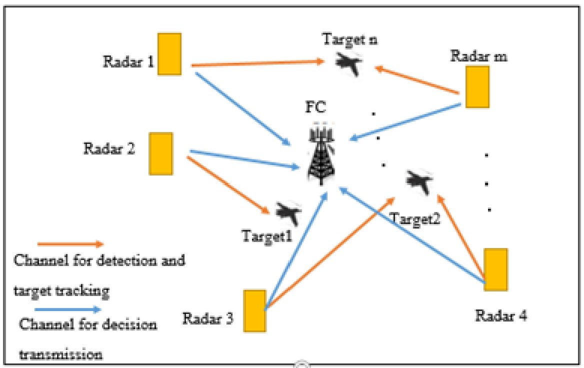

Figure 1: Block diagram showing the radar transmission for detection and target tracking.

where $s_{m,n}(t)$ is the transmitted signal by radar m assigned to nth target and $h_{m,n}$ is the channel gain between mh radar and nth target. $w_n(t)$ is the zero-mean and complex white Gaussian noise with variance σ_W^2. The received signal model from the nth target at the mth radar is also expressed as follows

$$y_{m,n}(t) = \sqrt{\alpha_{nm} P_{t_{m,n}}} \xi_{m,n} x_{m,n}(t - \tau_{m,n}) e^{-jw_{m,n}t} + w_n(t), \tag{2}$$

where α_{nm} denotes the path loss coefficient while $\xi_{m,n}$ is the target reflection coefficient. $P_{t_{m,n}}$ is the transmission power of the mth radar which is assigned to the nth target. $\tau_{m,n}$ denotes the signal propagation time on the corresponding path. $w_{m,n}$ is the doppler frequency shift due to target movement while it is obtained as follows [18]

$$w_{m,n} = \frac{-2\pi}{\lambda}[(2\cos\phi_m^n)v_x^n + (2\sin\phi_m^n)v_y^n], \tag{3}$$

λ is the signal wavelength while ϕ_m^n is the observation angle from the mth radar to the nth target. (v_x^n, v_y^n) is the velocity vector of the nth target. The radars which receive their own echoes from the target, send their estimates about the target existence to the FC to make a final decision using a fusion rule. Therefore, our goal is the radar assignment to each target and manage their transmission power to detect and track the targets with high accuracy. The received power of the mth radar from the nth target is stated as [15]

$$P_{r_{m,n}} = \frac{P_{t_{m,n}} G_{t_m} G_{r_m} \sigma_{m,n} \lambda^2}{(4\pi)^3 R_{m,n}^4 L_m}, \tag{4}$$

where G_{t_m} is the transmission antenna gain and G_{r_m} is the receiving antenna gain. $\sigma_{m,n}$ is the radar cross-section (RCS) of the nth target and L_m is the system loss. $R_{m,n}$ is the distance between mth radar and nth target. According to [15] and using the Swerling model, the local probabilities of false alarm and detection of target n using radar m are obtained, as follows [17].

$$p_{m,n}^f = exp(-\frac{(V^T)^2}{2\psi_0}, \tag{5}$$

and

$$p^d_{m,n} = (p^f_{m,n})^{\frac{1}{1+\gamma_{m,n}}} \tag{6}$$

where V^T is the detection threshold while ψ_0 is the variance of the received noise. $\gamma_{m,n}$ is the average signal to noise ratio of the received signal of the mth radar from the nth target. In fact, the detection probability shows the probability of existence of the target when it really exists while the false alarm probability states the probability of existence of the target when it does not really exist. The results of the radars are transmitted to the FC to make a final decision about the target presence using a fusion rule. We use OR rule due to its simplicity. In this rule, if at least one radar determines the target presence, the final decision is that the target exists. Therefore, the global probabilities of false alarm and detection are obtained, respectively as follows [21].

$$P^F_n = 1 - \prod_{m=1}^{M} (1 - u_{m,n} p^f_{m,n}), \tag{7}$$

and

$$P^D_n = 1 - \prod_{m=1}^{M} (1 - u_{m,n} p^d_{m,n}), \tag{8}$$

where $u_{m,n}$ is the radar assignment index. $u_{m,n} = 1$ presents that mth radar has been assigned to detect the target n while $u_{m,n} = 0$ means that the mth radar has not been assigned.

2.2 Target Parameter Measurement in Radar Network

In this section, BCRB can be applied for parameter estimation error lower bound for target tracking [19]. We define the target state vector $x^n_k = [x^n_k, y^n_k, v^n_{x,k}, v^n_{y,k}]$ for the nth target at state k, where (x^n_k, y^n_k) and $(v^n_{x,k}, v^n_{y,k})$ are the location and velocity of the nth target, respectively. Therefore, the target motion model is considered as follows [18]

$$x^n_{k+1} = F x^n_k + V^n_k. \tag{9}$$

The matrix F is the matrix of state transition and V^n_k is the white Gaussian noise which is zero mean and with the variance matrix Q_k. F and Q_k are defined as follows

$$F = \begin{bmatrix} 1 & \triangle t \\ 0 & 1 \end{bmatrix} \bigotimes I_2, \tag{10}$$

and

$$Q_k = q_0 I_2 \bigotimes \begin{bmatrix} \frac{1}{3}\triangle t^3 & \frac{1}{2}\triangle t^2 \\ \frac{1}{2}\triangle t^2 & \triangle t \end{bmatrix}, \tag{11}$$

where $\bigotimes$ is the Kroneker product symbol while $\triangle t$ is the interval of sample. q_0 states the process noise density. I_2 is a 2×2 unit matrix. By definition of z^n_k as the observation vector which is related to the doppler frequency shift and time of signal propagation, we have

$$z_k^n = [(\tau_k^n)^T (\omega_k^n)^T]^T. \tag{12}$$

In this case, the velocity estimation BCRB for the nth target is required for better target state prediction. Therefore, we have [8]

$$V^n = \frac{g^n + h^n}{\eta(\frac{2\pi}{\lambda})^2[g^n h^n - (z^n)^2]^2}, \tag{13}$$

where g^n, h^n and z^n are defined as follows [18]

$$g^n = \sum_{m=1}^{M} 2|\sqrt{\alpha_{nm}}\xi_{m,n}|^2 (2\cos\phi_m^n)^2 P_{t_{m,n}} t_m^2 u_{m,n}, \tag{14}$$

and

$$h^n = \sum_{m=1}^{M} 2|\sqrt{\alpha_{nm}}\xi_{m,n}|^2 (2\sin\phi_m^n)^2 P_{t_{m,n}} t_m^2 u_{m,n}, \tag{15}$$

and

$$z^n = \sum_{m=1}^{M} 2|\sqrt{\alpha_{nm}}\xi_{m,n}|^2 4\sin\phi_m^n \cos\phi_m^n P_{t_{m,n}} t_m^2 u_{m,n}, \tag{16}$$

where $\eta = \frac{8\pi^2}{\sigma_w^2}$ and t_m is the signal time duration for the mth radar.

3 Problem Formulation

In this paper, due to the radar assignment index and their transmission power in target detection and also setting the signal time duration in target tracking according to (7), (8) and (13), our purpose is minimizing the maximum velocity estimation MSE by assigning the proper radars, adjusting their transmission powers to detect and track the targets and setting the signal time duration for each radar while the detection performance and power consumption constraints are maintained. We note that more transmission power of the radars increases the probability of detection of the targets while increases the power consumption of the radars. Therefore, we define our optimization problem as follows

$$Min\ \ Max_{u_{m,n}, P_{t_{m,n}}, t_m} \quad V^n \tag{17}$$

$$\text{s.t.} \tag{18}$$

$$P_n^D \geq \beta, \qquad n \in \mathbb{N}, \tag{19}$$

$$P_n^F \leq \alpha, \qquad n \in \mathbb{N}, \tag{20}$$

$$P_{total}^n \leq P_{th}, \quad n \in \mathbb{N}, \tag{21}$$

$$P_{\min} \leq P_{t_{m,n}} \leq P_{\max}, \tag{22}$$

$$0 \leq t_m \leq t_{\max}, \tag{23}$$

where P^n_{total} is the total power consumption for detection and tracking of the nth target. The constraints (19) and (20) present the constraints on detection performance. It means that more global probability of detection and less global probability of false alarm improve the detection performance of the radar network. The inequality (21) shows the total power consumption constraint due to the radar equipped with batteries. Relations (22) and (23) state the constraints on the transmission power of each radar and signal time durations respectively. It is clear that problem (17) can be stated as the following problem

$$Min \ \ Max_{u_{m,n}, P_{t_{m,n}}, t_m} \quad MSE \tag{24}$$
$$\text{s.t.} \tag{25}$$
$$P^D_n \geq \beta, \qquad n \in \mathbb{N}, \tag{26}$$
$$P^F_n \leq \alpha, \qquad n \in \mathbb{N}, \tag{27}$$
$$P^n_{total} \leq P_{th}, \qquad n \in \mathbb{N}, \tag{28}$$
$$P_{\min} \leq P_{t_{m,n}} \leq P_{\max}, \tag{29}$$
$$0 \leq t_m \leq t_{\max}, \tag{30}$$
$$V^n \leq MSE. \tag{31}$$

However, we note that P^F_n is independent from the radars. In this case, according to (17) and (27), the maximum number of radars for detection and tracking of each target is obtained as follows

$$\gamma_n \leq \lfloor \frac{\ln(1-\alpha)}{\ln(1-p^f_{m,n})} \rfloor, \tag{32}$$

where, γ_n is the number of radars for detecting and tracking the nth target. Although, the problem is not a standard convex problem, however, convex optimization framework can be utilized to obtain the sub optimal solution. Therefore, Lagrangian function is obtained as follows [2]

$$L = MSE - \lambda_n(P^D_n - \beta) + \zeta_n(P^F_n - \alpha) + \eta_n(P^n_{total} - P_{th}) + \varepsilon_n(V^n - MSE), \tag{33}$$

where λ_n, ζ_n, η_n and ε_n show the Largiangian multipliers. Using the Karush-Kuhn-Tucker (KKT) conditions, the optimal conditions imply that [2]

$$
\begin{cases}
\lambda_n(P_n^D - \beta) = 0 \\
\rightarrow \begin{cases} \lambda_n = 0 \quad P_n^D > \beta \quad (34-1) \\ \lambda_n \neq 0 \quad P_n^D = \beta \quad (34-2) \end{cases} \\
\zeta_n(P_n^F - \alpha) = 0 \\
\rightarrow \begin{cases} \zeta_n = 0 \quad P_n^F < \alpha \quad (34-3) \\ \zeta_n \neq 0 \quad P_n^F = \alpha \quad (34-4) \end{cases} \\
\eta_n(P_{total}^n - P_{th}) = 0 \\
\rightarrow \begin{cases} \eta_n = 0 \quad P_{total}^n < P_{th} \quad (34-5) \\ \zeta_n \neq 0 \quad P_{total}^n = P_{th} \quad (34-6) \end{cases} \\
\varepsilon_n(V^n - MSE) = 0 \\
\rightarrow \begin{cases} \varepsilon_n = 0 \quad V^n < MSE \quad (34-7) \\ \varepsilon_n \neq 0 \quad V^n = MSE \quad (34-8) \end{cases}
\end{cases} \tag{34}
$$

It should be noted that the radars are selected for detecting and tracking the targets so that the problem constraints are maintained. In other words, by selection of more radars for each target, the global probability of detection and velocity estimation error are improved; however, the power consumption and global probability of false alarm are increased. Therefore, (34-2), (34-4), (34-6) and (34-8) are the true conditions. In order to find the optimal radars, an algorithm is proposed to set their transmission power and optimal signal time duration of each radar for detection and tracking the targets, so that the minimum velocity estimation error is obtained while the detection performance and total power consumption constraints are satisfied. We utilize the GA which is an optimization method inspired from nature [7, 12]. The details of this algorithm is described in the next section.

4 Overview of the Genetic Algorithm

Genetic algorithm (GA) is based on the concepts of natural selection and genetics. The GA is a subset of a branch of computation known as evolutionary computation [7].

- **Initialization:** The first step defines the population where its size is the solution numbers. Each solution is called individual which have a chromosome with binary strings.
- **Fitness Function:** Each individual has a fitness value which is considered to select the best individuals. The higher fitness value represents the higher quality of the solution.
- **Selection:** The best chromosomes are selected to generate the off-springs. These chromosomes are called parents. By selection of high-quality individuals, a better quality

offspring than its parents is selected. Roulette wheel method is used generally for selection of the best chromosomes.

- **Crossover:** In fact, by using crossover, new generations are generated the same as natural mutation. In this case, the new generation carries genes from both parents. The percent of the carried genes from the parents can be different.

- **Mutation:** Next variation operator is mutation. For each offspring, some genes are selected and their values are changed. In fact, by applying mutation, the solution may change entirely from the previous solution. Hence, mutation can help to come a better solution.

- Finally, this algorithm will be terminated when the best solution is obtained. Hence, by applying genetic algorithm to the specified problem in the previous section, it can be evaluated the fitness function as follows

$$\text{fitness}(m,n) = MSE - \lambda_n(P_n^D - \beta) + \zeta_n(P_n^F - \alpha) + \eta_k(1^T P_k - P_{\text{total}}) + \varepsilon_n(V^n - MSE). \tag{35}$$

  Algorithm 1 shows the pseudo code for the proposed method which is called Target Detection and Tracking Algorithm (TDTA).

Algorithm 1 Pseudo code for the proposed method

Step 1: Initialize the parameters.
Step 2: Calculate the probabilities of false alarm and detection for each radar when it detects each target according to (5) and (6), respectively.
Step 3: Employ the Genetic Algorithm and the fitness function in (35) to assign the appropriate radars for detecting and tracking each target, as well as to set their transmission power and signal time duration.
Step 4: Calculate the velocity estimation error, power consumption for detection and tracking of each target, and the global probabilities of false alarm and detection for each target.

5 Simulation Results

In this section, the performance evaluation of the proposed algorithm is compared with the random selection method as the bench mark algorithm. MATLAB software is used for simulation of the experiments. The region is considered as a square with the length of 180 m. We consider a network which consists of $M = 12$ radars and $N = 4$ targets. The average RCS of all targets is considered to be $1m^2$. Targets move from their initial positions to their destinations. Threshold of the total power transmitted is $P_{th} = 2\ Mw$ while the upper bound of the power is $P_{\max} = 1.3\ Mw$. The corresponding time constraint is $t_{max} = 0.4s$. Simulation results are obtained for $\alpha = 0.1$ and $\beta = 0.9$. Figure 2 shows the cost function convergence for different values of iterations. In fact, according to this figure, the cost function in (35) is converged to the optimal value. According to the figure, in the $80th$ iteration, the cost function becomes fixed and the best value is obtained. Number of the radars is set to 40. Figure 3 shows the success percent of finding the solution for the proposed algorithm versus different number of radars. This metric shows TDTA algorithm ability in satisfying the problem constraints (26)-(31).

We consider the proposed algorithm with different values of β. According to (8) and (26), more radars increase the global probability of detection while by decreasing the value of β, less radars are required to maintain the detection performance constraint. We also compare the proposed algorithm with random algorithm in which the radars are selected randomly for detecting and tracking the targets. According to Figure 3, the proper selection of radars in detection and tracking the targets leads to have more success percent of finding the solution in comparison with the random selection of radars.

It should be noted, sometimes the problem do not have any solution. In this case, by selection of all radars for each target, the problem constraints are not satisfied. Figure 4 presents the total power consumption for detection and target tracking versus different number of radars. It is shown that random algorithm consumes more power due to the random selection of radars for detecting and tracking the target. On the other hand, proper radar selection for each target leads to have less power consumption. It is important that in all algorithms the constraints of the problem are maintained. Figure 5 shows the signal time duration versus different number of radars. According to (13)-(16), it is shown that signal time duration has a significant effect on the estimation performance. In the proposed algorithm, the signal time duration of the radars is set using the genetic algorithm for detection and tracking each target while in random algorithm the signal time duration is selected randomly.

Figures 6 and 7 present MSE for different number of radars. According to this experiment, it is shown that the random algorithm has more MSE than the other algorithms due to the random selection of radars for detecting and tracking the target. On the other hand, our proposed algorithm has more velocity estimation accuracy due to setting the signal time duration setting, the proper selection of radars for detection and tracking each target and also control their transmission powers. It should be noted that Figure 5 shows MSE of the proposed algorithm when different probability of detection threshold (β) is considered. The results are evaluated for the first target.

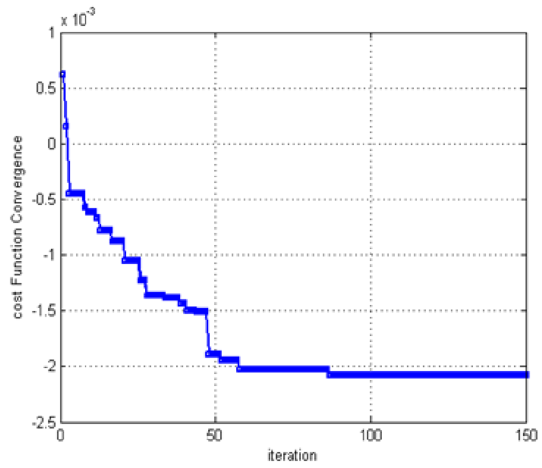

Figure 2: Cost function convergence versus different iterations.

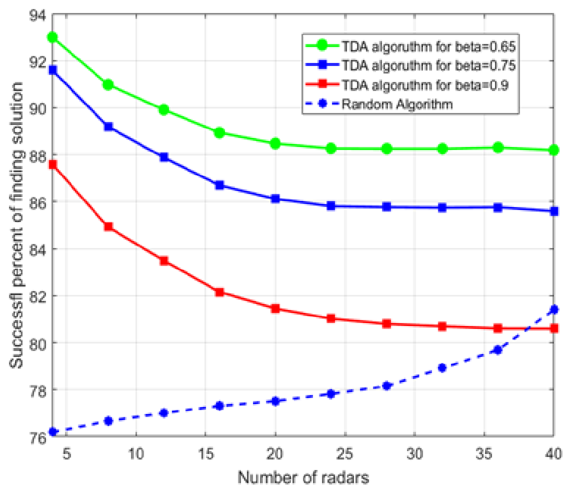

Figure 3: Success percent of finding the solution versus different number of radars.

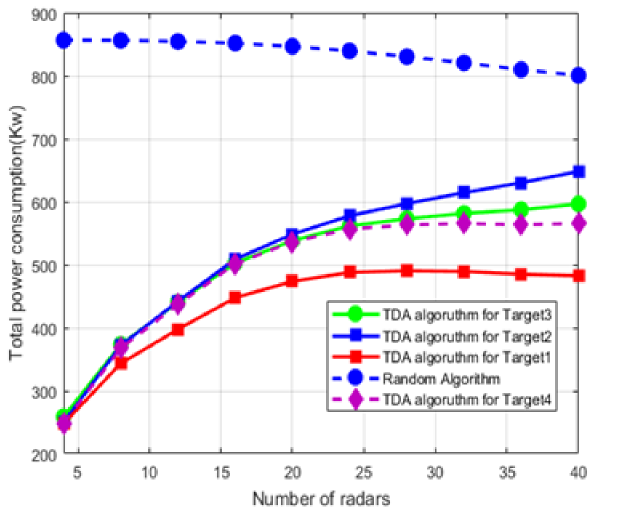

Figure 4: Total power consumption for detection and tracking each object versus different radars.

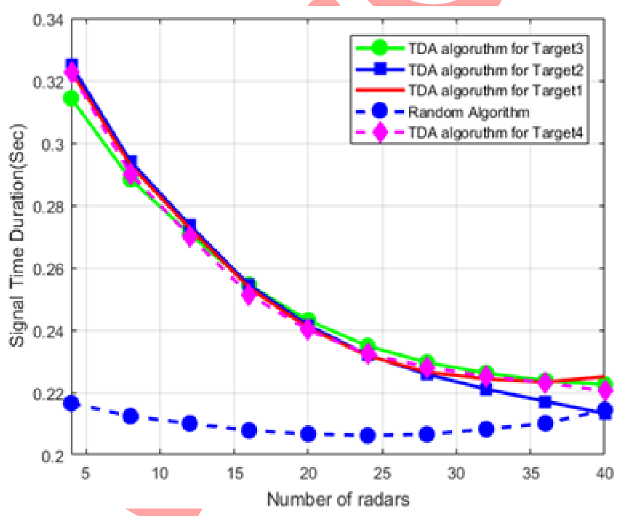

Figure 5: Signal time duration versus different number of radars.

6 Analysis of Results

As discussed in the previous section, we propose the TDTA algorithm, which selects appropriate radars and their transmission powers to enhance the velocity estimation of each target. Additionally, the signal duration for each radar is optimized to improve estimation performance while adhering to constraints on power consumption and detection performance.

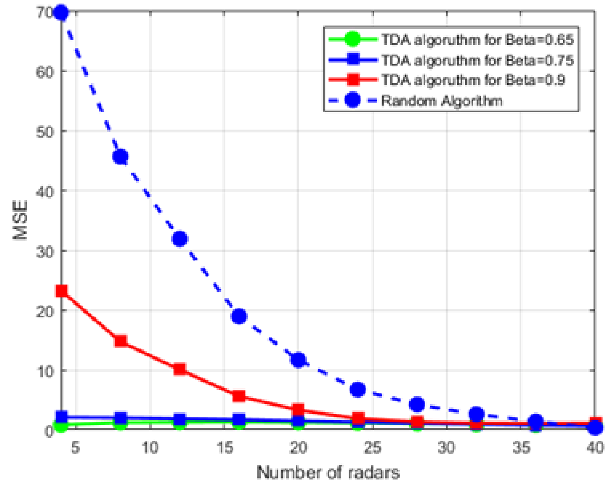

Figure 6: Mean square error for different number of radars.

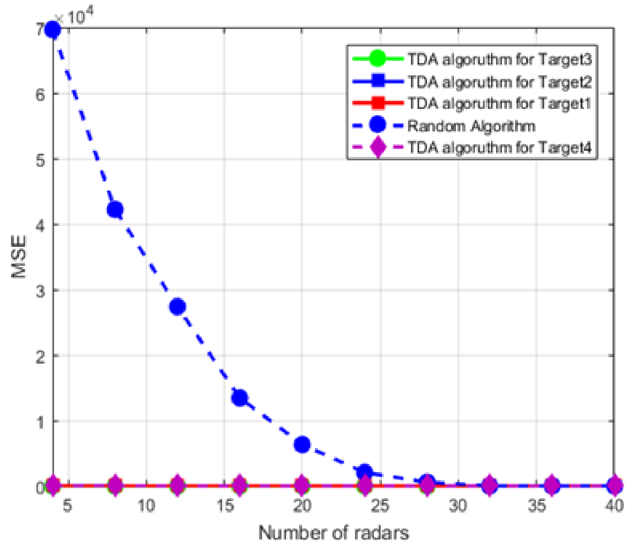

Figure 7: Mean square error for different number of radars.

Figure 2 illustrates the convergence of the cost function using the genetic algorithm. We also employ a random algorithm as a benchmark to demonstrate the effectiveness of our proposed algorithm in enhancing detection performance and tracking accuracy. Figure 3 highlights the algorithm's capability in finding solutions, clearly showing that our approach is more successful in this regard. According to Figure 5, our proposed algorithm consumes less power compared to the random algorithm. Furthermore, Figures 5, 6, and 7 indicate that optimizing the signal duration for each radar significantly improves estimation performance.

7 Conclusions

This study presents a joint power allocation, target assignment for each radar, and the setting of signal duration for velocity estimation in a radar network designed for tracking multiple targets. The constraints of the problem include detection performance and power consumption. After formulating the optimization problem, a suboptimal solution is derived using genetic algorithm. Simulation results demonstrate that the proposed algorithm effectively maintains the quality of service (QoS) constraints while improving overall network performance. Additionally, the algorithm is compared to a random algorithm as a benchmark algorithm to highlight the effectiveness of power control and target assignment in improving estimation performance. This paper investigates resource allocation methods for velocity estimation, with future work focusing on simultaneously improving the location and velocity estimation of the radars.

Declarations

Availability of Supporting Data

All data generated or analyzed during this study are included in this published paper.

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Competing Interests

The authors declare that they have no competing interests relevant to the content of this paper.

Authors' Contributions

The main text of manuscript is collectively written by the authors.

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