

Article

Strategic Deployment of a Single Mobile Weather Radar for the Enhancement of Meteorological Observation: A Coverage-Based Location Problem

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Abstract: Mobile weather radars have been routinely deployed to acquire high-quality meteorological data for research purposes, particularly for monitoring rapidly evolving weather phenomena at low altitudes. However, identifying an optimal location for mobile weather radar deployment is a complex challenge, as it requires consideration of operational safety, data quality, and environmental constraints. In this study, we introduce a framework using a coverage-based location problem to solve the strategic deployment of a single mobile weather radar. This approach aims to enhance weather observation while accounting for the deployment space's safety constraints and geospatial characteristics. The proposed location problem is solved optimally using the geometric branch-and-bound algorithm and heuristically using swarm-based optimization algorithms. The implementation relies entirely on open-source Python packages, allowing the work to be verified, replicated, and expanded upon by the broader scientific community. Results demonstrate that exact solution methods are ideal when ample time is available for decision-making and optimal deployment locations are desired. In contrast, heuristic algorithms can efficiently identify multiple near-optimal deployment locations, making them highly suitable for rapid decision-making and evaluating alternative deployment options. Moreover, the findings highlight the potential of quantitative decision-making techniques in improving the effectiveness of mobile radar positioning, thereby contributing to efficient weather observation, forecasting, and better-informed emergency response strategies.



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Keywords: mobile radar; GIS; spatial optimization; location analysis

1. Introduction

Weather radars have significantly advanced weather observation and forecasting since the mid-20th century, providing more extensive spatiotemporal coverage of regional weather phenomena and more accurate observations than other observation methods [1–3]. A relatively recent advancement in weather radar technology is the development of mobile weather radar systems [4–7]. Mobile radars provide enhanced spatiotemporal resolution and low-altitude coverage compared to static weather radars, thanks to their strategic deployment and the rapid scanning capabilities using smaller, mounted antennas [7]. These features make mobile radars particularly suitable for observing and studying rapidly evolving precipitation systems such as convective precipitation, tornadoes, hurricanes, and hailstorms [8,9]. Mobile weather radars are routinely deployed alone or in coordination with other static and/or mobile radar systems to obtain high-quality data and enhance coverage of weather phenomena [10]. The mobility and data collection capabilities of mobile

weather radars play an essential role in advancing our understanding of rapidly evolving severe weather phenomena, improving the accuracy of weather forecasting models, and enhancing early warning systems and disaster preparedness [5,11,12].

Mobile weather radars are typically designed to operate on X-band or C-band frequencies, with X-band systems operating at wavelengths of approximately 2.5–3.5 cm and C-band systems around 5 cm [8]. Mounted on vehicles, these radars can be rapidly deployed near weather phenomena of interest. Compared to traditional S-band systems (which typically operate at around 10 cm), their smaller antenna sizes enhance portability while still capturing high-resolution data [12,13]. Over the years, various mobile radar systems have been developed and proven effective in monitoring fast-evolving meteorological events. Notable examples include the RaXPol and PX-1000 systems from the University of Oklahoma [6,7], the X-Pol radar from the University of Massachusetts Amherst [5], and the widely recognized Doppler on Wheels [4]. These systems are configured based on their operational scenarios. For instance, the RaXPol system is equipped with an onboard generator, greatly enhancing deployment flexibility by reducing dependency on external power sources. In contrast, some systems require external power access [14]. Additionally, real-time radar data processing necessitates a reliable internet connection to enable immediate data transmission and analysis [14].

The strategic placement of weather radars is crucial for efficient and optimal weather observation [15]. High operational and maintenance costs, along with limitations such as beam blockage [2] and signal attenuation [16], necessitate their strategic deployment. Existing research has been dedicated to location planning for stationary radars, with notable contributions from Minciardi, Sacile, and Siccardi [15], Kurdzo and Palmer [17], Kurdzo et al. [18], and Chandrasekar and Junyent [19], among others. However, most of these works focused on optimizing the observation network for the fixed radars. Unlike fixed radars, mobile radars possess unique characteristics and functionalities—such as mobility, shorter range, the direct involvement of personnel in operation, and specialized observation purposes—that necessitate distinct deployment strategies. However, current research has largely overlooked the need for systematic and optimal deployment of mobile radars.

Determining optimal locations to deploy mobile radar vehicles to observe rapidly evolving weather events, such as supercells and tornadoes, is challenging. First, many factors must be considered when deciding where to deploy a radar. Trees, windmills, high-rise buildings, and other structures can obstruct the radar beam or cause ground clutter in radar observations [20]. Additionally, the radar should not be placed too close to the path of a moving supercell since ensuring the safety of the instrument and its operators is crucial [21]. In addition, scientists involved in the experiment often need to determine mobile radar site selection based on the short-term prediction of weather events swiftly [22]. The process can be overwhelming, as it requires making decisions quickly after analyzing large amounts of data, all while managing other pre-deployment activities, such as testing the radar, driving the vehicle, and defining the scan parameters. So, the key question is as follows: How can we determine deployment locations for mobile radars to ensure compelling weather observations while considering time, safety, and local environmental constraints?

Despite significant advancements in mobile weather radar technology, there is still a lack of research using quantitative methods to determine the optimal deployment sites for mobile weather radars. The major contributions of this research are (1) providing a data-driven framework that supplements human judgment, making radar deployment more objective and replicable; (2) incorporating GIS into the mobile radar deployment decision-making process to account for the local geospatial environment; and (3) applying

exact and heuristic algorithms to solve radar deployment problems. We introduce a spatial optimization-based framework for quantitative decision-making in mobile radar deployment. The deployment problem is formulated as a single-facility coverage-based location problem to achieve optimal weather coverage. Spatial constraints about local geospatial environments, the movement of supercells, and deployment logistics are embedded into the optimization model. The subsequent section briefly details mobile weather radars and coverage location problems. It follows a detailed model solved by exact and heuristic approaches, enabling a precise or rapid decision-making process. This paper concludes with a presentation and discussion of the application results.

2. Background

The characteristics of mobile radars classify their deployment in coverage-based location problems. Firstly, weather radar observations are inherently range-limited [23,24]. With increasing distance from the radar, the radar spokes expand and the cells become coarser, resulting in decreased spatial resolution and complicating the precise identification of hydrometeors beyond a specific range [25]. Additionally, mobile weather radars have a limited detection range and generally cannot fully capture large-scale weather phenomena because their wavelengths are more susceptible to signal attenuation than static weather radars [12,26,27]. Hydrometeors—particles such as raindrops, hailstones, and snowflakes—are the primary targets of radar observations and are distributed heterogeneously over radars' continuous coverage areas. Therefore, the mobile radar deployment problem could be formulated as a continuous coverage-based location problem, where radar placement should be determined to maximize demand coverage within its effective range.

Decisions for deploying mobile weather radars rely on the nature of the weather phenomenon, the objectives of the data collection, and the geospatial context of the deployment area. In different scenarios, deploying mobile weather radars could be represented differently. Under ideal conditions, where the weather phenomenon does not pose a significant threat to the ground and occurs in an open space away from people and interference, the deployment space can be assumed to be continuous and unbounded. After determining the optimal coverage position, observers may find feasible deployment spots around a small area, considering that minor adjustments will not have a significant impact [28,29]. When severe weather damages the ground, we consider a bounded continuous region a suitable region to search for deployment. In the Northern Hemisphere, supercells and tornadoes typically move from the southwest to the northeast [30]. Consequently, radars are commonly positioned to the south of their anticipated path to enhance safety when monitoring supercells with the potential to produce tornadoes. This arrangement prevents the instruments and operators from being exposed to the path of the supercell [21,31,32]. In cases where geospatial context causes great interference with radar deployment, representing the search space as a continuous area with obstacles can better reflect the actual situation. Complex topography, dense urban areas, or tall trees constrain adequate radar coverage [33]. Moreover, objects like wind turbines within the radar's line of sight can result in inaccurate weather observations [34]. Such conditions necessitate a more strategic approach to identify suitable deployment locations with constraints.

Continuous space location problems (CSLPs) have been applied to facilities other than mobile radar vehicles. The deployment problems for these facilities usually have two characteristics: (1) facilities can be placed anywhere in space, and (2) the facility's footprint is relatively small [35]. Even single-facility CSLPs can be non-convex and non-linear due to the infinite number of potential facilities and demand locations [36]. CSLPs are typically addressed using simplified representations of location space and/or demand distribution [35]. For example, Yao and Murray [37] proposed an approach to discretize continuous

heterogeneous demand to solve the continuous Weber problem. Some researchers have assumed uniform demand distributions to simplify CSLPs [38,39]. Approaches for solving CSLPs can be broadly categorized into exact and heuristic methods, depending on their ability to find global optima. Exact algorithms, such as geometric methods [38] and branch-and-bound algorithms [40–42], can guarantee optimal solutions by exhaustively searching the entire space or reducing it with mathematical techniques. However, when demand distribution is heterogeneous and search space is large and/or complex, exhaustive searches can become inefficient [35]. For radar deployment problems, exact approaches are suitable when there is ample time before a weather event, providing sufficient time for decision-making. However, deployment decisions must often be made quickly and in real time. In such situations, heuristic approaches provide faster but approximate solutions that balance speed and accuracy in complex environments. Heuristic algorithms, such as particle swarm optimization (PSO) and genetic algorithms (GAs), have proven to be effective in solving CSLPs efficiently [43,44]. Swarm-based algorithms like PSO are particularly well suited for the proposed radar deployment problem due to their capacity to optimize solutions in continuous space.

Effective spatial coverage, resolution of weather observations, and the safety of both the radar instrument and the personnel involved are significantly influenced by the deployment location of the radar. However, the methodologies for addressing these factors in deployment decision-making are not extensively documented in the existing literature. This gap arises because such decisions are often subjective, relying on the expertise and preferences of weather scientists responsible for data acquisition campaigns. A notable contribution in this area is the work by Feng, Schvartzman, Parajuli, and Wang [29], who proposed a three-phase approach that integrates geographic information systems (GISs) and spatial optimization for optimal radar deployment. Using a gradient-based heuristic algorithm, their model sought to minimize the weighted distance between radar location and hydrometeors. While this approach was innovative, the authors did not assess the performance of the heuristic algorithm against optimal solution methods. Additionally, geospatial data were not directly integrated into the optimization model; instead, spatial analysis was applied post hoc to identify feasible deployment locations near the theoretically optimal sites, which may limit practical applicability. This research builds upon and extends these contributions by addressing key limitations in prior work. Specifically, we integrate the geospatial environment directly into the optimization model as spatial constraints, ensuring that identified deployment locations are theoretically optimal and practically feasible. Furthermore, we evaluate heuristic solutions for their performance and reliability by comparing them with exact solutions. By reformulating the radar deployment problem as a coverage-based location problem, this study offers a more flexible and goal-oriented framework that accommodates diverse deployment objectives. We acknowledge that additional factors, such as interactions between multiple radar systems [10], continuous repositioning, power and internet access [14], and beam blockages [2], are also critical for optimal radar deployment and require further consideration. Our research aims to advance radar deployment studies by developing optimization models and solution algorithms that simultaneously address data quality, spatial constraints, and safety concerns.

3. Methods

The decision to deploy mobile radar systems should carefully consider two factors: meteorological conditions and geospatial characteristics. From a meteorological perspective, the radar must be positioned to ensure optimal weather observation with high spatiotemporal resolution. Equally important is the consideration of the geospatial environment at the deployment location. Features such as tall buildings and trees can create ground

clutter and cause beam blockage, thus affecting the radar's effective spatial coverage. Additionally, road networks and conditions must be considered to ensure accessibility and the availability of potential escape routes in emergencies. This research proposes a framework that integrates spatial optimization and GIS to comprehensively address meteorological and geospatial aspects in deployment decision-making. We present exact and heuristic approaches for addressing the proposed location problem.

Modern weather radar systems are equipped with both single-polarimetric and dual-polarimetric capabilities. Reflectivity, a primary single-polarization variable, measures the intensity of the backscattered signal from hydrometeors. Higher reflectivity values indicate larger or more numerous particles, providing valuable information about storm structure, rainfall intensity, and overall storm severity. Reflectivity and its derived variables help meteorologists study precipitation and storm characteristics, which are essential for the early detection of severe weather events. This research uses reflectivity as a demand parameter for optimizing radar placement. Additional single-polarization variables, such as Doppler velocity and spectral width, further enhance our understanding of storm motion and structure. Dual-polarization radars extend these capabilities by capturing variables like differential reflectivity, differential phase, and correlation coefficient, which are crucial for analyzing weather systems' microphysical properties and dynamics. The proposed model can be expanded to include other variables specific to the goals of weather data acquisition.

GIS facilitates mobile radar deployment decision-making by providing a structured method for managing and analyzing geospatial data [45]. It offers a comprehensive framework to capture, store, and analyze geographical features such as land cover, buildings, and road networks using digital models. These models utilize raster data for continuous variables like land cover and weather forecasts and vector data for discrete features such as roads and building outlines. The strength of GIS lies in its advanced spatial analysis capabilities, which allow for structuring several decision-making criteria into GIS-based operations [46]. For example, GIS can assess potential beam blockages by calculating the proximity of obstructions such as trees or buildings. Additionally, it can evaluate road networks to determine accessibility and identify potential escape routes in the deployment area. By integrating these spatial factors into the planning process, GIS enables data-driven and strategic decision-making for mobile radar deployment.

Facility locations are strategically selected to serve specific functions, such as delivering products or providing services. This decision-making process can be mathematically formulated as an optimization problem. The goal is typically to maximize demand or service coverage or to minimize associated costs. Similarly, deploying mobile weather radar systems can be modeled as an optimization problem. The model's objective should be carefully configured to align with the field observation campaign's goals. For precipitation monitoring, the objective would be to maximize the coverage of weather phenomena within the radar's operational range. Safety considerations and geospatial obstacles in the deployment area act as constraints for the optimization problem. The decision variable is the location for radar deployment that optimizes the objective while conforming to the specified safety and environmental constraints.

The mathematical modeling of the radar deployment problem involves certain simplifications and assumptions. The radar is assumed to be a point-based facility located anywhere in continuous space. Furthermore, it is presumed to have a circular coverage standard determined by its effective observation range. This range is influenced by the radar's radiation wavelength and may be limited by factors such as attenuation. The objective is to maximize reflectivity coverage within this range. While reflectivity is the primary variable, the model can incorporate additional variables depending on the specific goals of the field campaign. Hereafter, the mathematical representation of the mobile radar

deployment problem is presented. The following notations are used to represent the radar deployment problem as a coverage-based facility location problem:

(x, y) = location of hydrometeors in continuous space.

$f(x, y)$ = continuously varying hydrometeors represented by radar reflectivity.

(X, Y) = decision variable indicating the location of mobile radar.

$R_{(X,Y)}$ = the region within the effective range of radar when it is located at (X, Y) .

Ψ = constrained continuous feasible area.

The coverage maximization with single mobile radar, a coverage-based facility in continuous space, can be formulated as follows:

$$\text{Max } Z = \iint_{R_{(X,Y)}} f(x, y) dx dy \quad (1)$$

subject to $(X, Y) \in \Psi$, where Z is the objective value representing the reflectivity covered by the radar within its effective range. The demand function, $f(x, y)$, represents the spatial distribution of hydrometeors in the continuous space (x, y) when scanned at a designated elevation angle. It can be tailored to align with the specific objectives of a field campaign and the operational features of the radar. The scanning elevation angle is selected based on the intended observation target—lower angles are optimal for capturing low-level dynamics, while higher angles are typically employed to study mid-level storm evolution. The characteristics of the feasible area (Ψ) can be different based on the nature of the weather phenomenon and the location of the weather. Three scenarios of radar deployment are presented to address three distinct types of deployment space: continuous space, bounded continuous space, and bounded continuous space with obstacles. While the continuous heterogeneous demand served by a cover-based facility can be approximated by a double integral [39], the exact demand function is often not explicitly known, complicating the precise representation of the demand field using mathematical functions [47]. In this study, the continuous reflectivity field is approximated using discrete points instead. Thus, the objective value, as presented in Equation (1), can be approximated as follows:

$$Z = \left(\frac{1}{n_{R(X,Y)}} \sum_{j=1}^{n_{R(X,Y)}} f(x_j, y_j) \right) \times \text{Area}_{R(X,Y)} \quad (2)$$

where $n_{R(X,Y)}$ is the number of demand points within the coverage R , j is the index of demand points, and $\text{Area}_{R(X,Y)}$ is the area or radar's effective observation range.

3.1. Solution Methods

We present exact and heuristic solutions to the proposed radar deployment problem. The exact solution method is based on a geometric branch-and-bound (B&B) algorithm: Big Triangle Small Triangle (BTST) global optimization. Geometric B&B algorithms simplify the optimization process by breaking down the larger optimization problem into smaller, more manageable tasks [42,48,49]. This approach progressively refines the search space by eliminating or further dividing these smaller segments based on the upper and lower bounds of the objective value in each segment. Additionally, we introduce two variations of particle swarm optimization (PSO)-based heuristic solution approaches. PSO is a swarm-based heuristic known for finding near-optimal solutions even in complex search spaces. Both algorithms are implemented in Python 3.9 using open-source packages such as NumPy, GeoPandas, and Shapely [50,51]. In all studied instances, BTST is considered a standard for evaluating heuristic solutions for computing efficiency and solution quality. The exact and swarm-based heuristic approaches for solving radar deployment problems are described below.

3.1.1. Big Triangle Small Triangle (BTST) Algorithm

The BTST algorithm addresses the optimization problem by systematically breaking down the solution space into smaller geometrics through triangulation [40]. Each smaller triangle is treated as an individual problem. The flowchart illustrating the BTST-based approach for solving the mobile radar deployment problem is shown in Figure 1.

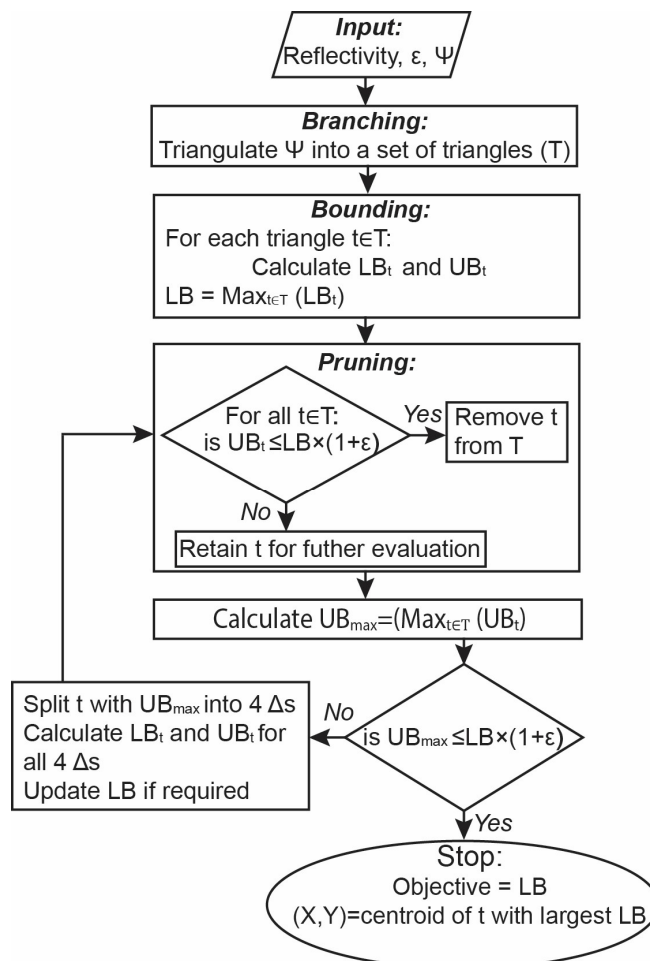


Figure 1. Flowchart for BTST algorithm.

The BTST algorithm starts by dividing the feasible deployment space (Ψ) into a set of triangles (T). Points created along the edges, at the vertices, and randomly within the interior of the potential deployment space are used to create triangles using Delauney triangulation, as illustrated in Figure 2a. Triangles that exceed the boundaries of the feasible space are clipped to fit within the constrained area, as shown in Figure 2b, and any resulting irregular polygons are further decomposed into triangles. The lower and upper bounds of objective values are calculated for each triangle based on the radar coverage. To compute the bounds, the algorithm places a radar with a given radius ' R ' at the centroid of each triangle. The lower bound (LB_t) is defined as the demand covered by this radar, providing a conservative estimate of the radar's effectiveness in that triangle. The upper bound (UB_t) is calculated by extending the radar's range to ' $R + d_{max}$ ', where d_{max} is the longest distance from the triangle's centroid to any of its vertices, thereby capturing the maximum potential demand coverage. The largest lower bound across all triangles becomes the initial lower bound (LB), which serves as a benchmark for evaluating the potential of each triangle to contain the optimal solution.

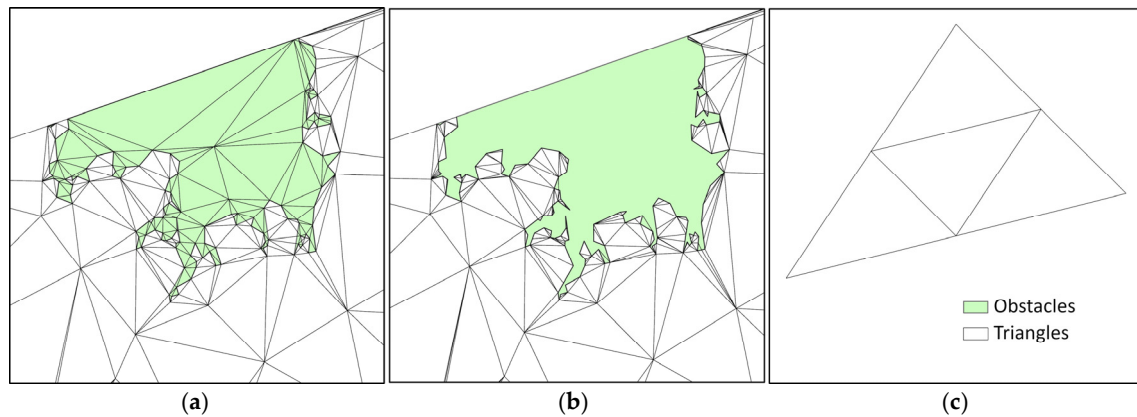


Figure 2. (a) Initial triangles generated using Delauney triangulation, (b) triangles removed from within the obstacles, and (c) division of big triangle into 4 smaller triangles.

During the pruning step, the algorithm compares the upper bounds of each triangle to the current lower bound. Triangles where $UB_t \leq LB \times (1 + \epsilon)$ (where ϵ is a relative accuracy parameter) are eliminated from further consideration, as they cannot contain the optimal solution. The algorithm then calculates the maximum upper bound (UB_{max}) across all remaining triangles. If $UB_{max} \leq LB \times (1 + \epsilon)$, the algorithm terminates, accepting the largest lower bound as the optimal solution. If the stopping condition is not met, the algorithm continues by subdividing the triangle with the largest upper bound into four smaller triangles, as shown in Figure 2c. These new triangles are subjected to the same process, with recalculated bounds, and the algorithm repeats the pruning and subdivision steps. This iterative approach allows the algorithm to gradually refine the search space, focusing on regions that are more likely to contain the optimal radar deployment location.

3.1.2. Heuristic-1: Standard PSO (SPSO)

PSO is a stochastic global optimization algorithm developed by James and Russell [52]. Inspired by bird swarm behavior, it is noted for its simplicity and effectiveness in navigating complex search spaces. PSO enables particles to move freely in continuous space, making it ideal for solving continuous location problems without discretizing the space [43,53]. The flowchart for the SPSO-based heuristic approach for determining the optimal location for mobile radar truck deployment is shown in Figure 3.

The search process in SPSO begins by initializing the positions $X_t = [(x_t^1, y_t^1), (x_t^2, y_t^2), \dots, (x_t^N, y_t^N)]$ and velocities $V_t = [(v_t^{1,x}, v_t^{1,y}), (v_t^{2,x}, v_t^{2,y}), \dots, (v_t^{N,x}, v_t^{N,y})]$ of N particles within the feasible deployment space. Each particle represents a potential radar deployment location. The objective value for each particle is calculated, with each particle's initial location designated as its personal best ($pbest$) and the best location among all particles as the global best ($gbest$). The $pbest$, which represents the optimal position identified by an individual particle (cognitive factor), and the $gbest$, which represents the optimal position identified by the swarm (social factor), are crucial parameters that guide the particle movement in SPSO. The velocity and position of the particles are updated as follows:

$$V_{t+1} = w \times V_t + r1 \times c1(pbest_t - X_t) + r2 \times c2(gbest_t - X_t) \quad (3)$$

$$X_{t+1} = X_t + V_{t+1} \quad (4)$$

where V_t and X_t represent the current velocity and position of the particles, respectively, and V_{t+1} and X_{t+1} indicate the updated velocity and position. The parameters w , $c1$, and $c2$ are the inertia, cognitive, and social coefficients, respectively, which influence the particle's movement toward current moving direction, location of $pbest$, and location of

g_{best} , respectively. Their values can affect the exploration and exploitation characteristics of the particles. Random values $r1$ and $r2$, ranging from 0 to 1, introduce stochasticity to the search process. Following the application of Equation (3) to update velocities, the positions of the particles are adjusted according to Equation (4). Objective values are calculated at the new locations. If a particle moves outside the feasible deployment space, its objective value is penalized to zero, which effectively guides it back into the feasible area. The p_{best} and g_{best} are then updated as needed. After updating the velocities and positions, the termination condition is evaluated. If the objective values at the last 10 g_{best} locations are within a specified tolerance range (ϵ), the search process is stopped, and g_{best} is accepted as the optimal radar deployment location. Otherwise, the process returns to the update step.

In PSO, even identical initial particle configurations can yield different solutions due to the algorithm's randomness. Thus, multiple runs with varying initial configurations are essential to fully explore the search space, avoid local optimum, and assess solution robustness. The optimization was run M times with different initial configurations of particles, producing M distinct solutions, increasing the chances of finding a global optimum and providing insights into solution stability across scenarios.

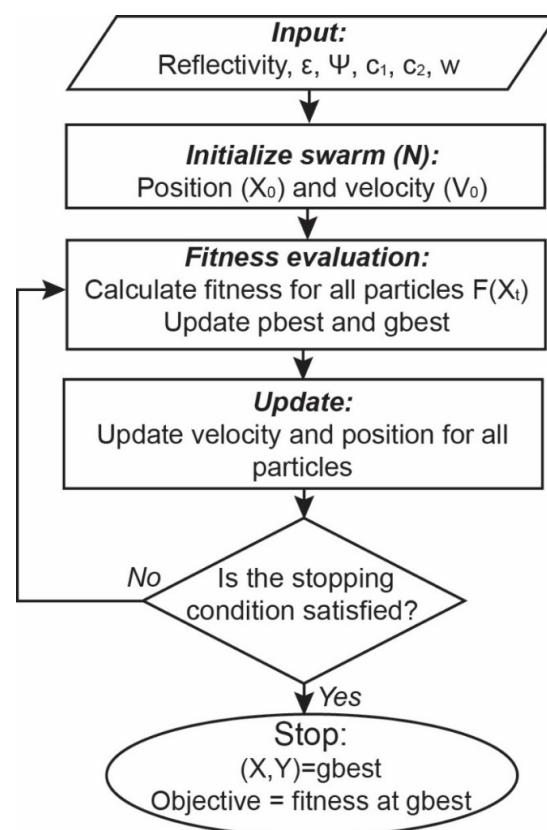


Figure 3. Flowchart for PSO algorithm.

3.1.3. Heuristic-2: Center of Gravity PSO (CoGPSO)

Despite the ability of SPSO to identify near-optimal solutions in challenging scenarios, it may sometimes fail to locate the global optimum if the particles miss the optimal region during the search process. This issue arises if g_{best} represents a local optimum and the other particles are clustered around it, resulting in them becoming trapped at this local optimum [54]. This situation occurs because the second and third terms in the velocity update equation tend to zero when all particles are clustered around the same location. Consequently, this reduces the first term to zero, causing the particles to stop moving. To address these limitations, several enhancements to SPSO have been proposed in the

literature [54,55], with a primary focus on accelerating the search process and enhancing exploration of search space.

In this study, we enhance the SPSO by introducing a center of gravity parameter into the velocity update step. This new algorithm, referred to as center of gravity PSO (CoGPSO), aims to improve the quality and speed of the standard PSO search process. Additionally, it directs the particles towards the center of gravity of the demand. This approach helps reduce the weighted distance between reflectivity covered and the mobile radar location. The center of gravity of g_{best} particles is calculated as follows:

$$COG_t = \left(\frac{\sum_{j=1}^{n_{g_{best}}} (f(x_j, y_j) \times x_j)}{\sum_{j=1}^{n_{g_{best}}} (f(x_j, y_j))}, \frac{\sum_{j=1}^{n_{g_{best}}} (f(x_j, y_j) \times y_j)}{\sum_{j=1}^{n_{g_{best}}} (f(x_j, y_j))} \right) \quad (5)$$

where $n_{g_{best}}$ is the number of demand points in coverage standard of g_{best} particle, and $j = 1, \dots, n_{g_{best}}$ is the index of demand points within the coverage standard of g_{best} particle. The velocity of the particles in CoGPSO is then updated as follows:

$$V_{t+1} = w \times V_t + r1 \times c1(pbest_t - X_t) + r2 \times c2(gbest_t - X_t) + r3 \times c3(COG_t - X_t) \quad (6)$$

where $r3$ is a random number between 0 and 1, and $c3$ is the center of gravity coefficient. Even if the first three components are zero, the last component in Equation (6) will help the particles escape the local optimum. However, the center of gravity might not always be the location that covers the maximum demand. The g_{best} location is updated only if there is an improvement in coverage at the new location. Vector representation of the position update of the particles in SPSO and CoGPSO is shown in Figure 4.

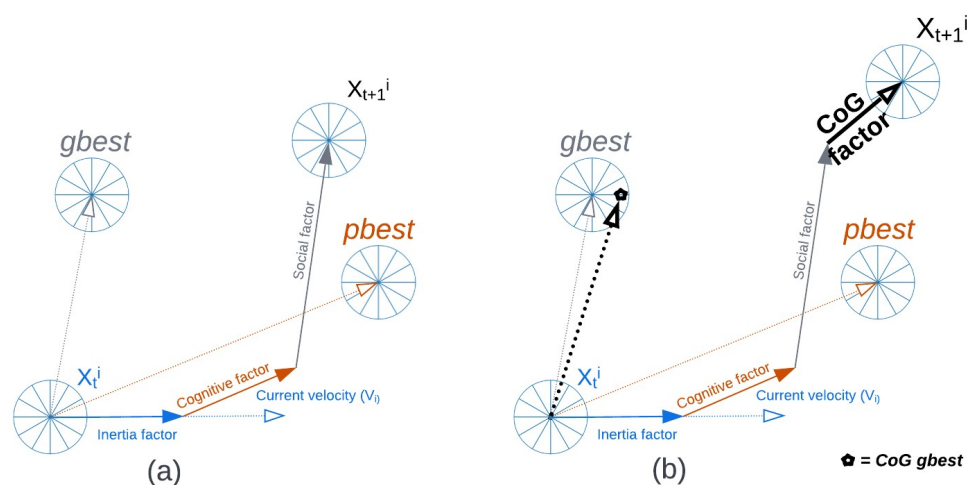


Figure 4. Vector representation of position update for particles in SPSO (a) and CoGPSO (b).

4. Results

4.1. Data and Study Area

In this study, we use a simulated supercell to serve as the demand surface for the proposed radar deployment problem. One important reason for using a simulation is that the spatial resolution of radar data decreases with distance, which can result in inaccuracies when capturing the finer details of supercell structure and dynamics. Simulated supercells offer a more consistent and high-resolution depiction of storm characteristics across the entire affected region, ensuring that no detail is lost due to distance or other observational limitations. The Cloud Model 1 (CM1) simulator, developed by George H. Bryan and Fritsch [56], is particularly suitable for this task. CM1 is designed to simulate atmospheric phenomena on the micro- to mesoscale level, providing detailed cloud-based simulations on a Cartesian coordinate grid

with fine spatial resolutions. For this research, we use the specific CM1-simulated supercell simulated by Feng, Schwartzman, Parajuli, and Wang [29]. This simulation was initialized with parameters to generate a supercell capable of producing large hail and tornadoes. The simulated supercell spans approximately 2500 square kilometers and includes 70 vertical layers, reaching an altitude of 17.5 km. Figure 5 shows the reflectivity fields simulated at a 5° elevation angle, superimposed onto the northwest area of Oklahoma City to illustrate the storm's coverage and potential impact. We consider only positive reflectivity values here to emphasize meaningful precipitation signals and streamline coverage estimations.

We model mobile radar deployment using the University of Oklahoma's Rapid-Scanning X-band Polarimetric (RaXPoL) radar as a reference system [7]. Designed by ProSensing and currently maintained and operated by the Advanced Radar Research Center (ARRC) in Norman, OK, USA, RaXPoL is a highly agile system mounted on a Chevrolet Kodiak 5500 truck, allowing for rapid deployment within minutes [7,29]. It operates at 9.73 GHz (X-band) and completes a full azimuth scan in 2 s and an elevation scan in 5 s, yielding rapid, high-resolution data for a broad range of meteorological applications [29].

The study area is central Oklahoma, a region highly susceptible to extreme weather events such as hailstorms, tornadoes, and severe thunderstorms. Situated in "Tornado Alley", an area extending east of the Rocky Mountains, Oklahoma experiences a disproportionately high number of tornado-producing supercells [57]. In 2019, Oklahoma recorded 149 tornadoes, the highest annual count since records began in 1950 [58]. The frequent occurrence and severity of these storms highlight the urgent need for enhanced radar coverage in this region [7,30]. Mobile radar trucks are routinely used for weather monitoring in Oklahoma. The simulated supercell moves from southwest to northeast through several counties in central Oklahoma, including Oklahoma, Cleveland, and Canadian counties.

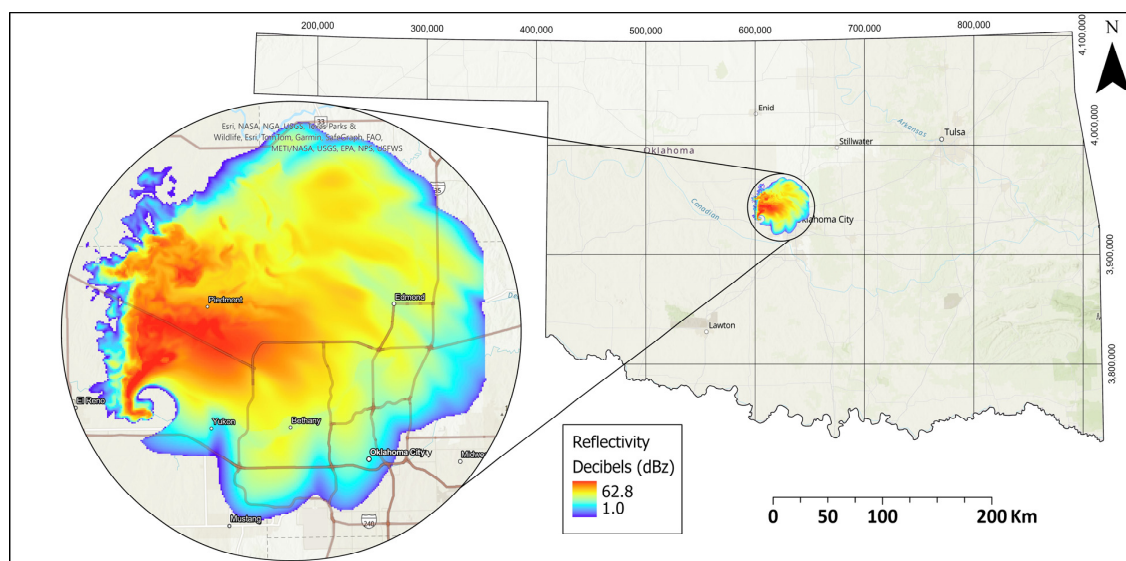


Figure 5. Study area and CM1-simulated reflectivity.

4.2. Case 1: Continuous Deployment Space

Mobile weather radars are frequently deployed to observe weather phenomena such as heavy convective precipitation [11] and hailstorms [59]. Unlike tornadoes, these events pose minimal risk to radar equipment or personnel on the ground, allowing for greater flexibility in deployment. In relatively open areas, far from environmental interference, the assumption of continuous, unbounded potential deployment space becomes more realistic. This scenario enables the radar to be placed at a location that provides optimal coverage of the precipitation system. While minor physical obstacles such as buildings,

trees, or terrain may exist, they do not significantly impact the radar's performance. The radar's wide coverage range ensures that minor adjustments in deployment location will not compromise the quality of weather observations.

In this case study, the simulated thunderstorm is positioned over El Reno, west of Oklahoma City, as depicted in Figure 6 (left). Due to the absence of ground-based risks and the open environment, we assume an unbounded continuous space for radar deployment. The optimal location, which maximizes the objective function described in Equation (2), is identified in the southern part of El Reno, near the intersection of E OKC 10th Street and S Alfadale Road (marked by a black star in Figure 6). This site is free from major obstacles such as tall buildings or dense tree cover, ensuring that radar signals can propagate without obstruction. The clear line of sight allows for optimal radar coverage of the precipitation system, significantly enhancing the accuracy of weather observations. Considering that attenuation can reduce the effective observation range of X-band radars, we evaluated solutions with three different observation radii: 15, 20, and 25 km.

Figure 7 presents the results for BTST, SPSO, and CoGPSO, evaluated with a 25 km range. Optimal deployment locations are marked by black stars, with radar coverage shown as black circles. BTST, an exact algorithm, was run 10 times with varying triangulation point configurations, consistently converging to the same location (Figure 7a). In contrast, the heuristic SPSO and CoGPSO algorithms were run 1000 times with different initial particle configurations. Despite their heuristic nature, both achieved high accuracy relative to BTST. CoGPSO produced solutions within 0.5% of the BTST optimum in all runs, while SPSO reached this threshold in 99.7%. Figure 7b,c display the solution locations and corresponding histograms for SPSO and CoGPSO. The upper panel depicts the spatial distribution of optimal solutions, with grids and labels based on the NAD 1983 projected coordinate system. The lower panel presents histograms of objective values for BTST (a), SPSO (b), and CoGPSO (c) within a 25 km coverage radius.

Table 1 presents the summary of key performance metrics, including the total number of objective function evaluations, computation times, and final objective values achieved by each algorithm. The best results, with the lowest function evaluations, shortest computation times, and highest objective values, are highlighted in bold. In this context, function evaluations represent the total number of objective value computations performed by the algorithm before satisfying the stopping criteria. Notably, SPSO and CoGPSO required fewer function evaluations and significantly less computation time compared to BTST. Of the two heuristic approaches, CoGPSO demonstrated superior performance, with objective values closer to those of BTST and shorter computation times. Additionally, CoGPSO exhibited a lower standard deviation of objective values than SPSO, further confirming its consistency in performance.

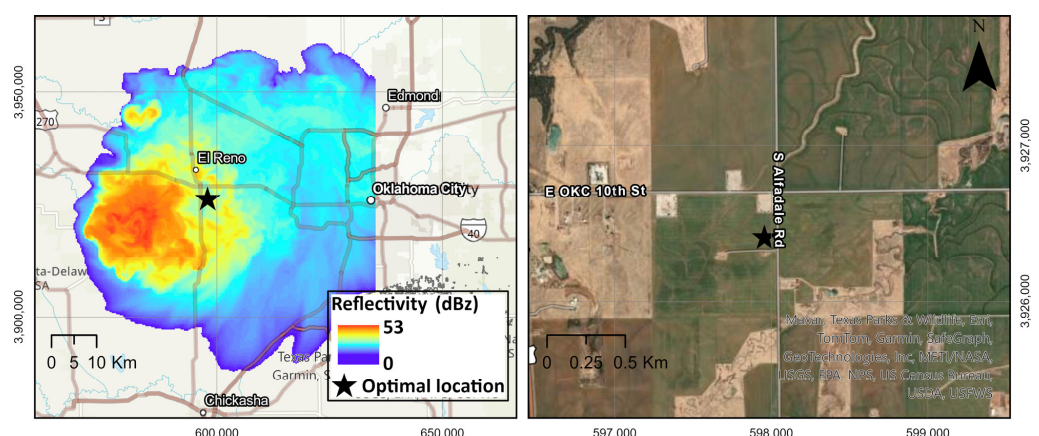


Figure 6. Study area with supercell thunderstorm (left), and optimal location for radar deployment (right).

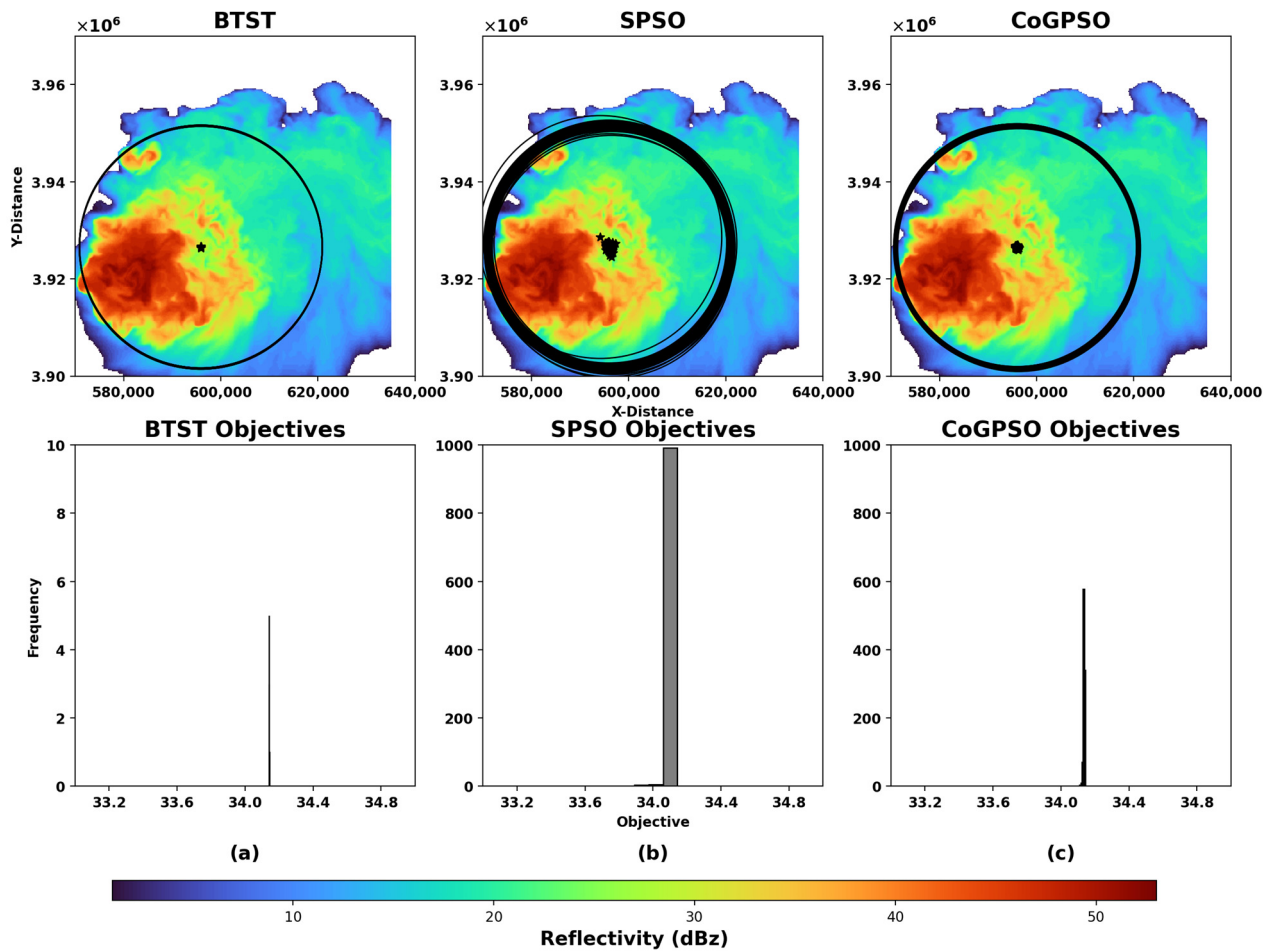


Figure 7. Optimal radar deployment locations in unconstrained continuous space identified by (a) 10 runs of BTST, (b) 1000 runs of SPSO, and (c) 1000 runs of CoGPSO for a 25 km radius. The optimal locations are marked by black stars, while the corresponding effective radar coverage areas are represented by black circles. The upper panels show spatial location for each method's optimal solutions. The lower panels present histograms illustrating the distribution of objective values obtained from BTST (a), SPSO (b), and CoGPSO (c).

Table 1. Performance metrics for 10 runs of BTST and 1000 runs of SPSO and CoGPSO for radar location in unconstrained continuous space.

Radius (km)	Algorithm	Function Evaluations			Time (Seconds)			Objective Value			Standard Deviation
		Min	Max	Average	Min	Max	Average	Min	Max	Average	
15	BTST	42,659	75,856	59,163.7	131.50	238.77	174.36	17.84	17.84	17.84	0.001
	SPSO	1100	3400	2063.9	2.19	10.24	5.35	17.62	17.84	17.83	0.015
	CoGPSO	1100	4800	1826.5	2.22	12.12	4.65	17.81	17.84	17.84	0.003
20	BTST	23,462	44,765	33,475.2	81.62	137.10	100.65	26.25	26.25	26.25	0.001
	SPSO	1100	3300	1893.3	2.26	10.14	4.99	26.05	26.25	26.24	0.018
	CoGPSO	1100	2300	1673.6	2.31	8.55	4.74	26.22	26.25	26.25	0.003
25	BTST	18,157	27,760	23,230.3	64.81	91.70	76.73	34.15	34.15	34.15	0.001
	SPSO	1100	3000	1806.4	2.57	15.59	6.41	33.73	34.15	34.14	0.021
	CoGPSO	1100	2300	1635	2.77	12.15	6.21	34.12	34.15	34.14	0.004

4.3. Case 2: Bounded Continuous Space

When a supercell shows potential for tornado formation, deploying the radar truck directly beneath it or along its projected path poses serious safety risks to both the observer

and the radar equipment. Ensuring the safety of both is a top priority in such scenarios. The CM1-simulated supercell aligns with the path of the Moore tornado on 20 May 2013, based on data from the Storm Prediction Center (<https://www.spc.noaa.gov/gis/svrgis/>, accessed on 1 September 2024). The storm moved from southwest to northeast. To account for this uncertainty and ensure safety, a 3 km buffer zone to the south of the tornado's path was excluded, and the 3 to 20 km buffer zone was deemed a feasible deployment area. This creates a bounded continuous feasible area for potential radar deployment location. As shown in Figure 8, the black line traces the tornado's path, while the light blue region represents the bounded continuous potential radar deployment area. The optimal deployment location, marked by a black star, maximizes the objective function described in Equation (2). It is situated near the southern end of Lake Stanley Draper, along the boundary of the feasible area.

Figure 9 presents the results of 10 runs of the BTST algorithm alongside 1000 runs each of SPSO and CoGPSO within the bounded continuous space. The heuristic algorithms incorporate a penalty function in their objective calculations, which ensures that solutions violating the feasibility constraints are either redirected to the boundary or confined within the permissible region. Unlike Case 1, where the optimal radar deployment location is positioned near the center of the weather system, the optimal location in this scenario lies along the boundary of the designated feasible area. While the heuristic algorithms maintain similar function evaluation counts, as in Case 1, BTST exhibits higher function evaluations in this case, attributed to the different demand distribution. Table 2 provides detailed performance metrics across three observation ranges, demonstrating the efficiency of heuristic algorithms compared to the exact solution. The heuristic methods are significantly faster, requiring fewer function evaluations to achieve near-optimal solutions. Notably, CoGPSO exhibits smaller standard deviations in objective values than SPSO for two of the three observation ranges. Additionally, more than 99.6% of the objective values obtained by both heuristic algorithms fall within 1% of the exact solution's objective value.

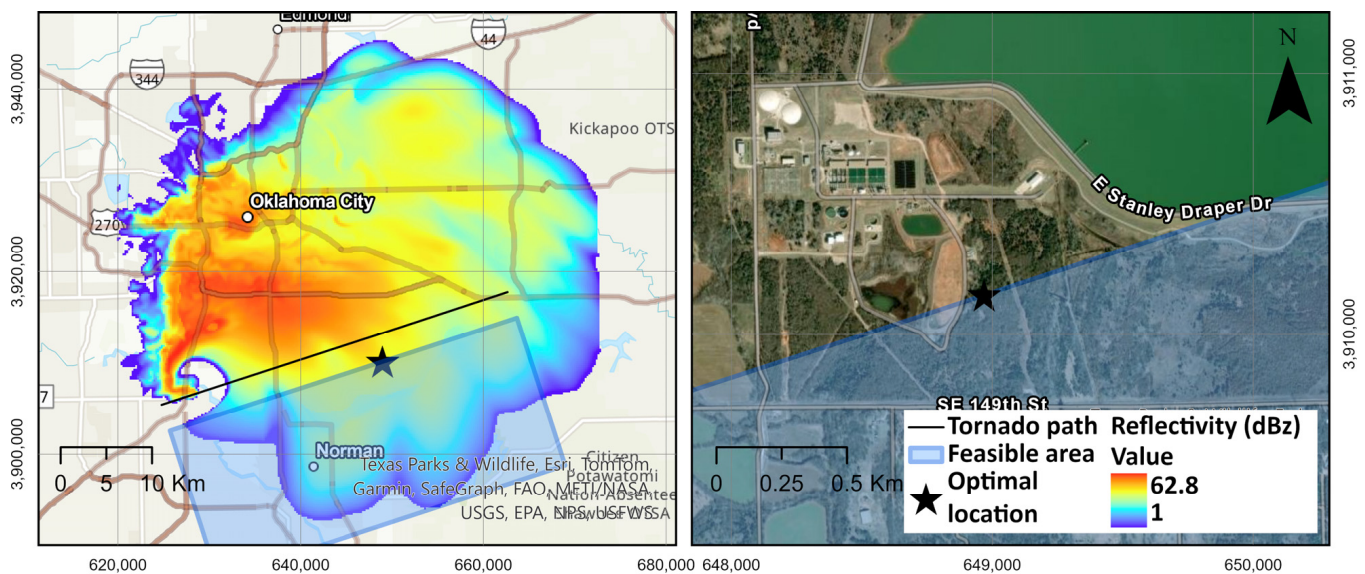


Figure 8. Supercell thunderstorm and bounded continuous feasible area (left), and optimal location for radar deployment (right).

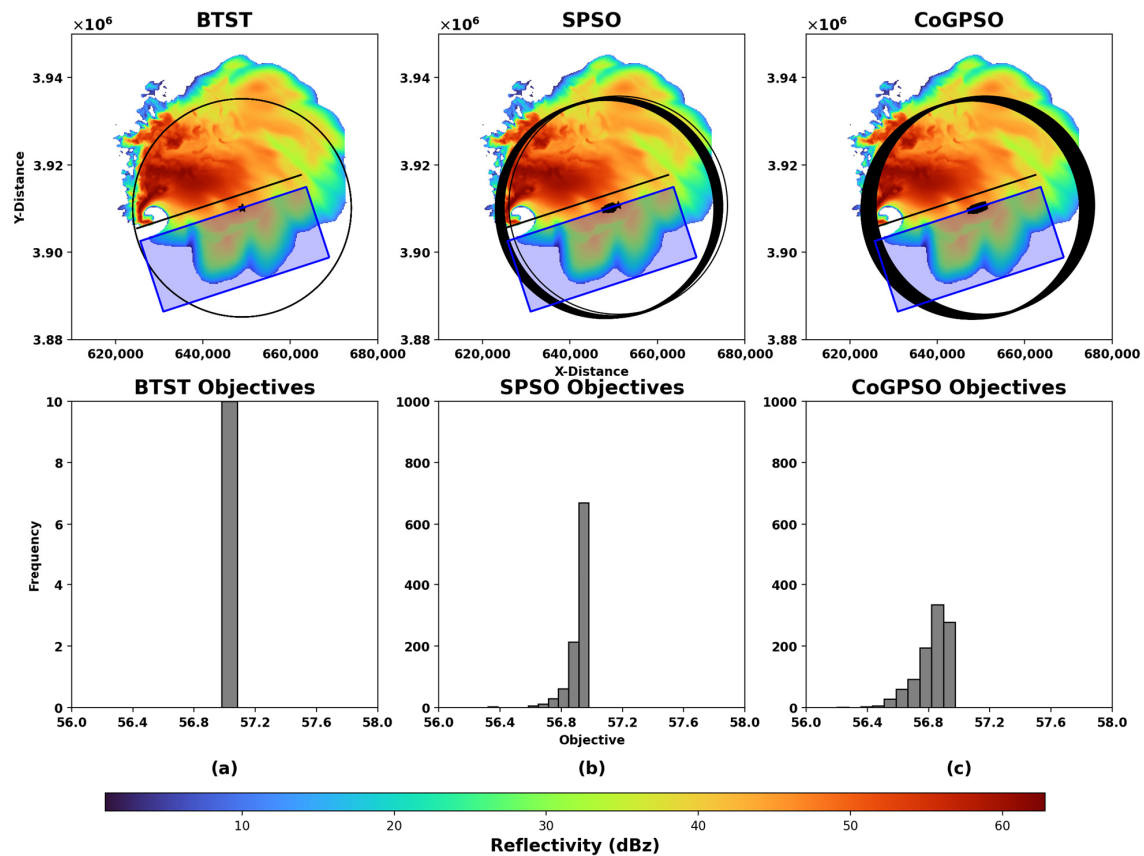


Figure 9. Optimal radar deployment locations in constrained continuous space identified by (a) 10 runs of BTST, (b) 1000 runs of SPSO, and (c) 1000 runs of CoGPSO for a 25 km radius. The optimal locations are marked by black stars, while the corresponding effective radar coverage areas are represented by black circles. The upper panels show the spatial location for each method's optimal solutions. The lower panels present histograms illustrating the distribution of objective values obtained from BTST (a), SPSO (b), and CoGPSO (c).

Table 2. Performance metrics for 10 runs of BTST and 1000 runs of PSO and CoGPSO for radar location in constrained continuous space.

Radius (km)	Algorithm	Function Evaluations			Time (Seconds)			Objective Value			Standard Deviation
		Min	Max	Average	Min	Max	Average	Min	Max	Average	
15	BTST	147,597	150,229	148,853	258.80	323.65	293.10	27.93	27.93	27.93	0.000
	PSO	1100	3100	1899.8	1.68	5.95	3.52	27.36	27.93	27.87	0.060
	CoGPSO	1100	2800	1901.2	1.28	3.68	2.04	27.80	27.93	27.90	0.010
20	BTST	65,502	92,270	88,863.3	140.05	187.54	175.95	41.93	41.93	41.93	0.000
	PSO	1100	3200	1893.6	1.72	6.30	3.67	41.10	41.93	41.87	0.070
	CoGPSO	1100	2600	1734.5	0.90	2.55	1.58	41.49	41.93	41.85	0.050
25	BTST	34,990	35,669	35,321	86.88	93.46	89.46	57.00	57.00	57.00	0.000
	PSO	1100	2900	1864.2	1.94	7.84	4.65	56.33	56.99	56.93	0.070
	CoGPSO	1100	2300	1577	0.84	3.25	1.43	56.21	56.99	56.84	0.110

4.4. Case 3: Bounded Continuous Space with Physical Obstacles

In environments with significant obstacles, the assumption that radar can be freely deployed in continuous space becomes unrealistic. For example, dense forests near a deployment site can lead to ground clutter and beam blockages, reducing the radar's effectiveness. Additionally, placing the radar too close to tall buildings or settlements introduces the risk of beam obstruction and potential radiation exposure to the public,

rendering these areas unsuitable. Open spaces that are inaccessible to radar trucks further limit deployment options. In this case study, spatial analysis, and local geospatial data, such as land cover and accessibility, are integrated into the optimization model to redefine feasible deployment areas.

Land cover and tree canopy data were sourced from the National Land Cover Database (NLCD) [60], while settlement areas were identified using Microsoft’s building footprints dataset [61]. The road network shapefile was obtained from the Oklahoma GIS Data Clearinghouse (<https://okmaps.org/ogi/>, accessed on 4 March 2024). The second case study excluded regions within 100 m of buildings and trees from the deployment space. We selected 100 m as a distance threshold based on the radar’s typical elevation and average tree heights in Oklahoma, with the flexibility to adjust for other local geospatial conditions. Areas not intersected with the road network were also removed to ensure accessibility for radar trucks. The remaining potential deployment space is represented as a bounded continuous area with obstacles. The BTST algorithm was adapted to exclude any triangles that overlapped with obstacles. Additionally, penalties were introduced into the objective functions of heuristic algorithms when particles moved outside feasible zones. This ensured that if particles entered unsafe or inaccessible areas during optimization, they were penalized and redirected back into the viable deployment space. Furthermore, for PSO-based methods, particles were initialized to ensure at least one particle was positioned in each geometric fragment of the feasible area, guaranteeing a comprehensive search across all potential sites. This approach effectively balanced geographical and safety constraints while maintaining optimal radar coverage. The final optimal location identified was on E Stanley Draper Road—an elevated site with no nearby trees, making it an ideal spot for radar deployment, as shown in Figure 10.

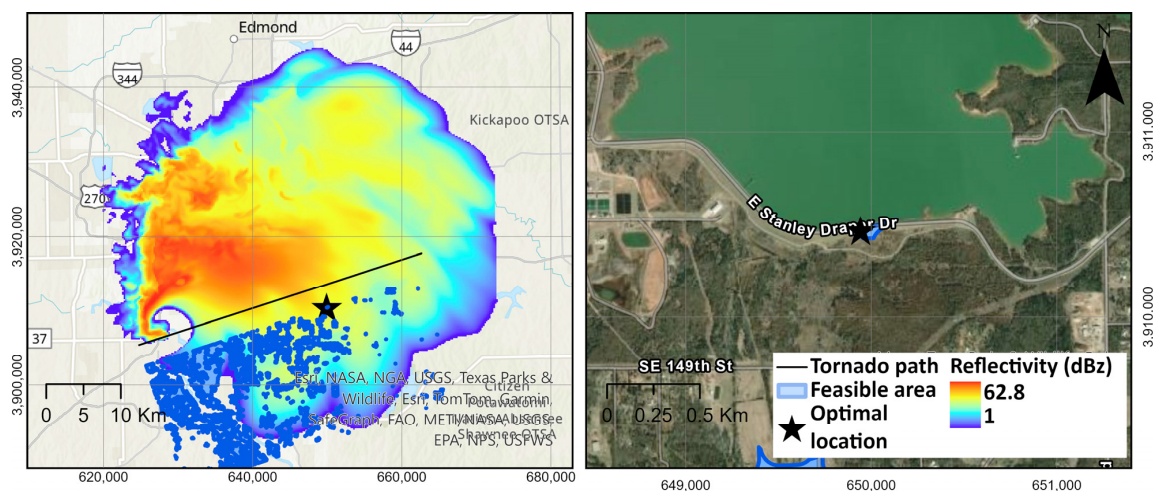


Figure 10. Supercell thunderstorm and bounded continuous feasible area and holes (left), and optimal location for radar deployment (right).

Figure 11 illustrates the solutions generated by the three algorithms for a radius of 25 km. The performance of all solution methods in identifying the optimal feasible location was comparable. This is mainly due to the initialization of particles within each geometric fragment of the feasible deployment space, which allowed the swarm-based heuristics to effectively locate the optimal site as well. The performance metrics for the three solution methods across three different radii are shown in Table 3. The PSO-based heuristics exhibited significantly longer computation times than the previous two case studies, averaging around 28 s per run. This increase in computation time is attributed to the complexity of evaluating particle positions within the bounded continuous space with holes. Despite the added

complexity, the average number of objective function evaluations for the heuristic algorithms remained comparable to those in the previous cases. Surprisingly, the exact BTST algorithm is only four times slower than the heuristic algorithms. Additionally, the number of function evaluations for the BTST algorithm was notably lower than in the unbounded and bounded continuous cases. This is due to the significantly smaller potential deployment area after removing the regions that are not feasible for radar deployment.

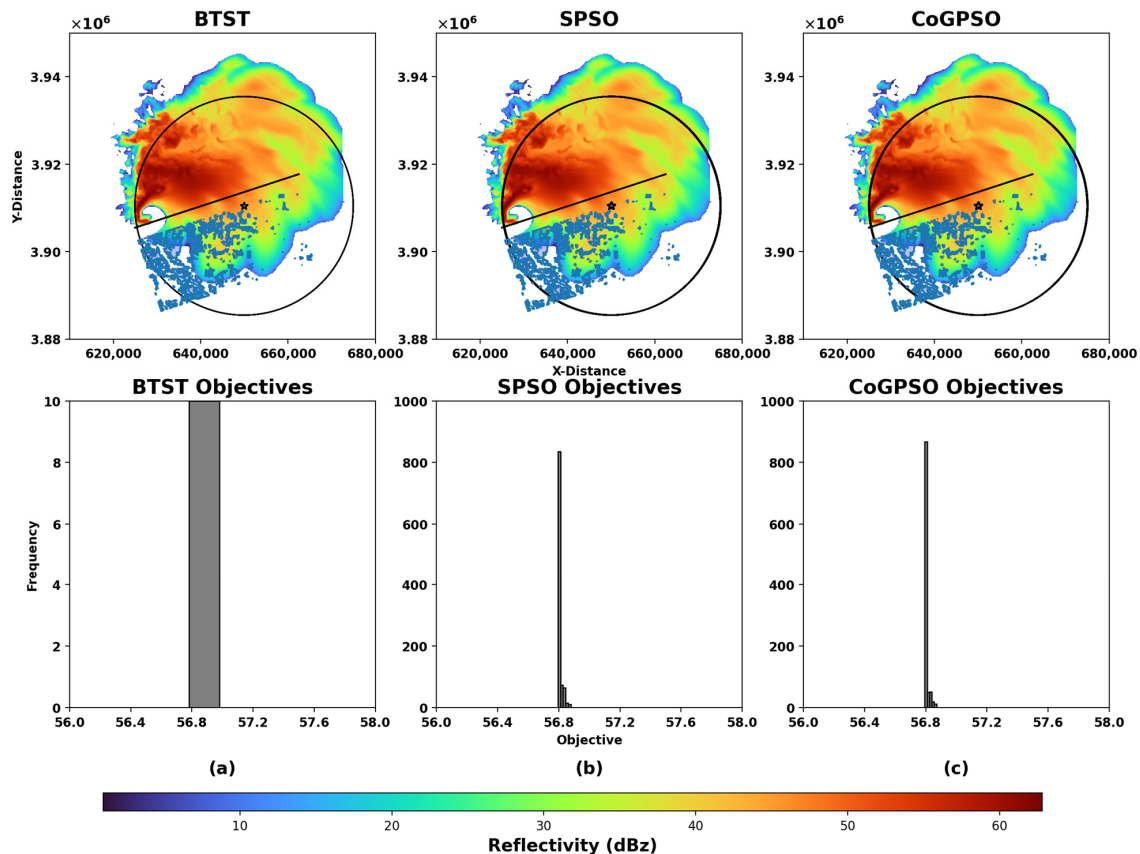


Figure 11. Optimal radar deployment locations in constrained continuous space with obstacles identified by (a) 10 runs of BTST, (b) 1000 runs of SPSO, and (c) 1000 runs of CoGPSO for a 25 km radius. The optimal locations are marked by black stars, while the corresponding effective radar coverage areas are represented by black circles. The upper panels show spatial location for each method's optimal solutions in the feasible area. The lower panels present histograms illustrating the distribution of objective values obtained from BTST (a), SPSO (b), and CoGPSO (c).

Table 3. Performance metrics for 10 runs of BTST and 1000 runs of PSO and CoGPSO for radar location in constrained continuous space with obstacles.

Radius (km)	Algorithm	Function Evaluations			Time (Seconds)			Objective Value			Standard Deviation
		Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	
15	BTST	27,907	29,441	28,486.2	92.55	159.57	120.35	27.67	27.67	27.67	0.001
	PSO	2585	5875	2700.62	23.06	62.76	31.15	27.61	27.67	27.61	0.012
	CoGPSO	2585	4700	2654.795	22.26	54.43	27.90	27.61	27.67	27.61	0.010
20	BTST	26,921	27,300	27,160.8	89.40	200.62	128.71	41.84	41.84	41.84	0.000
	PSO	2585	4700	2707.67	24.73	64.21	31.46	41.77	41.84	41.77	0.017
	CoGPSO	2585	4700	2657.145	23.89	52.02	28.64	41.77	41.84	41.77	0.013
25	BTST	27,018	27,531	27,287.1	129.59	166.09	141.00	56.90	56.90	56.90	0.000
	PSO	2585	4230	2606.855	25.21	45.06	28.64	56.81	56.89	56.81	0.016
	CoGPSO	2585	4700	2608.265	22.50	55.88	29.52	56.81	56.89	56.81	0.014

5. Discussion

The integration of polarimetric weather radars into mobile units has significantly enhanced our ability to capture high-resolution observations of rapidly evolving extreme weather events. However, deploying mobile weather radars presents complex challenges since the deployment process must consider varying meteorological conditions, environmental factors, and safety constraints. In this study, we proposed a GIS- and spatial optimization-based framework for the optimal deployment of a mobile weather radar. This framework enhances weather observation while ensuring the safety of operators and vehicles. The radar deployment problem is formulated as a coverage-based facility location problem and solved using exact and heuristic solution methods. The exact BTST algorithm identifies an optimal deployment site, while swarm-based heuristic algorithms offer near-optimal alternatives when rapid deployment is crucial, balancing speed with accuracy in site selection.

To navigate the complexities introduced by safety constraints and physical obstacles at deployment sites, we made key improvements to spatial optimization algorithms. The BTST algorithm was modified to effectively handle geospatial data by clipping triangles that intersect physical obstacles or fall outside the feasible area, followed by re-triangulation of the resulting non-triangle geometries. In swarm-based heuristics, we introduced a penalty function that prevents particles from moving outside the feasible deployment space, actively guiding them back to safe areas. This direct incorporation of geospatial data into the optimization process ensures that the locations identified are optimal and practical for radar deployment. This method proves more efficient in urban or forested areas than relying on post-optimization GIS analysis to adjust for nearby feasible sites.

Despite the quantitative approach for optimizing the deployment of mobile radar vehicles, several critical factors require further consideration. Radar beam blockage is a particularly challenging issue in regions with complex terrain, such as the undulating landscapes of Colorado. This factor is less significant in Oklahoma's flat terrain, but thorough terrain analysis is crucial for deployments in geographically varied regions. High-resolution lidar-derived digital surface models (DSMs) and elevation data could be used to perform terrain analysis to more accurately identify obstacles and detect beam blockages. Moreover, depending on operational objectives, radar coverage may prioritize areas with higher storm velocities or significant meteorological changes. This could be achieved by refining the objective function to include additional radar parameters—such as differential reflectivity, echo broadening, and velocity data—to enable a more targeted and strategic deployment. Insights from numerical weather predictions and data assimilation can further improve mobile radar deployment decision-making [62]. The simultaneous deployment of multiple mobile radars in coordination with existing static radars is a promising direction worth exploring in the future. This approach will allow for more effective mesoscale supercell monitoring, improving the accuracy and coverage of weather observations [10].

6. Conclusions

Mobile weather radars play a critical role in meteorological observation by offering flexible deployment and high-resolution data capture for rapidly evolving atmospheric events. In this study, we presented a GIS- and spatial optimization-based framework for guiding the deployment of mobile weather radars, integrating meteorological objectives, safety considerations, and geospatial constraints. Through three case studies, we demonstrated how spatial optimization techniques can enhance radar placement strategies, ensuring broad coverage while safeguarding equipment and personnel. The major strength of our approach is its data-driven methodology, which complements human judgment by providing an objective foundation for radar deployment. We further demonstrate that heuristic algorithms, particularly CoGPSO, provide an effective balance of speed

and accuracy in urgent, on-site decision-making scenarios. While BTST provides an ideal benchmark, CoGPSO consistently provides near-optimal results in significantly less time, highlighting its usefulness in real-world applications. Moving forward, refining and expanding this framework to include additional real-world constraints holds substantial promise for improving meteorological observations.

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