

Simulation of Radar-Based Object Detection for Railway Safety in Foggy Conditions Using MATLAB

Malateshwari Aski

Research scholar of electronics department KSAWUV Vijayapur

Swetha.N

Assistant professor of electronics department of KSAWUV Vijayapur

Abstract

This research presents a technique that Identifies objects over railway tracks in foggy weather using radar technology. A simulation software named MATLAB is used to model the railway track with a granite basis and random impediments on the track. A radar system with multiple frequencies is modelled to identify these objects using received reflected power. The impact of fog attenuation on the proposed strategy is evaluated by considering variables such as carrier frequency, antenna gain, radar cross-section (RCS), and detection threshold. The detection range is estimated by calculating the received power for the distances of up to 2000 meters. The simulation findings showed that fog significantly impacts high and millimetre radar signals, and results into accurate Detection to a limited area. which confirmed the fog-attenuation hypothesis. However, the low frequency radar systems are very effective in early-warning systems under the foggy conditions.

Keywords: *Railroad detection, fog attenuation, radar signal modeling, object detection, MATLAB simulation, railway safety, remote sensing.*

1 Introduction

In recent times, the upkeep of existing transportation infrastructure has grown crucial due to the growing demand for freight and mass transit worldwide. Transportation systems that provide a dependable, economical, and environmentally friendly means of transportation must include railway systems. With their affordable fares, dependable pace, and little environmental effect, railway services are often regarded as a safe method to travel (or move freight) (Schneider, 2020). The majority of the current railway infrastructure is outdated and needs constant maintenance to remain operational, which is quite expensive (Gao & Touran, 2020). Furthermore, these structures have deteriorated quickly over time due to increased train frequencies, quicker train speeds, and larger axle loads (Malekjafarian et al., 2021).

Every year, train accidents that might have been avoided result in thousands of severe injuries and hundreds of fatalities. Level crossing and trespasser accidents are the two primary categories into which train-pedestrian incidents are often divided depending on pedestrian intent. Users of level crossings include pedestrians who cross railway tracks at specified shared

locations, including grade crossings.

On the other hand, trespassers enter restricted and unapproved railway zones by crossing the railway right of way. Trespassing was the leading cause of railway-related deaths from 2013 to 2022, accounting for about 59% and 64% of deaths in Canada and the US, respectively. 200 people were killed and 256 seriously injured in 1,581 railway-road level crossing crashes between 2013 and 2022, according to the Transportation Safety Board (TSB) of Canada. Furthermore, 409 people were killed and 190 people were seriously injured in 654 trespassing events. In the same time frame, the US had 21,385 crossing crashes with 2,507 fatalities and 8,480 injuries, as well as 9,635 trespasser occurrences with 5,062 fatalities and 4,909 injuries, according to the Federal Railroad Administration (Nateghinia & Miranda-Moreno, 2025).

Train operations may be significantly impacted if railway tracks are not properly and promptly maintained (Asada et al., 2013). For the system to function effectively, fractures must be identified. Therefore, to guarantee that these systems function properly and at a fair price, effective and dependable infrastructure monitoring solutions are required. The initial point of contact between the railroad structure below and the heavy, traversing trains is the railway rails. As a consequence, the track experiences high longitudinal and transverse strains, which causes it to deteriorate severely over time (Koks et al., 2019), (Azim & Gül, 2019), (Rageh et al., 2020), (Quirke et al., 2022). To ensure an efficient initial train–rail contact, the structural state of the railroad tracks must be routinely inspected and necessary repairs must be scheduled.

Traditionally, railroad tracks are inspected visually on a regular basis by walking along them while using portable surveying tools, such as a leveler or tachometer. When the whole network is taken into account, this approach is costly to use often and intensive (Barke & Chiu, 2005), (Malekjafarian et al., 2023). Furthermore, this approach is ineffective at identifying internal defects, which are only seen when a train passes over, and it only finds significant flaws that are visibly noticeable. The employment of a dedicated vehicle, known as a Track Recording Vehicle (TRV), which is outfitted with optical and inertial sensors to gather track geometry data while traveling, is another often used technique for track monitoring (Berggren et al., 2014). Through the use of GPS and displacement sensors, these vehicles are able to monitor the rail's level and alignment, track gauge, cross level, rail twist, curvature/curve radius, gradient, and track position. TRVs can be used to implement the EN13848 standard (Andrade & Teixeira, 2014), which requires regular measurements of the railway track's geometric characterization. Temporary speed restrictions or the suspension of train operations may be imposed if any of the characteristics exceed the tolerance limit. Even while TRVs provide accurate inspection data, their deployment is quite costly, and they cause traffic interruptions during inspection by

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occupying tracks and limiting traffic speeds. To lessen the negative effects, it is necessary to develop and evaluate the viability of a low-cost automated traditional cart system that can monitor the condition of the railway track. This will aid in the accurate and efficient diagnosis and maintenance of tracks, preventing accidents. The railway track system must include automatic defect detection in order to reduce human error.

To address safety concerns and avoid or lessen railway-related casualties, a number of countermeasures are often put in place throughout railway infrastructure. Engineering, enforcement, and education initiatives are the three main categories into which these remedies often fall (Havârneanu et al., 2015). The goal of educational and enforcement initiatives is to raise knowledge and accountability among those who live or work close to railway infrastructure. Geometry-related interventions and technical solutions are the two categories of engineering countermeasures. Redesigning or altering railway infrastructure to prevent unwanted access is known as geometric engineering intervention (Fitzpatrick et al., 2015). Technology plays a key role in rail facility monitoring by identifying, alerting, and limiting access via gates, noises, and signals. In a typical setup, a detection system notifies authorities, activates warning devices, and confirms the existence of unlawful road users (daSilva et al., 2012). Such system incorporates alternative technologies such as cameras, thermal cameras, stereo cameras, ultrasonic sensors, active or passive infrared sensors, and radars (Amaral et al., 2016), (Horne et al., 2016).

There are now more chances to enhance railway track monitoring systems and provide precise and affordable solutions thanks to recent research on the use of sensor technologies and computing power (Barke & Chiu, 2005), (Wei et al., 2017). Installing sensors on the track and keeping an eye on track accelerations to identify any issues is standard procedure. Despite their effectiveness, direct track monitoring technologies are impractical for the intricate and extensive network of railway infrastructure (Malekjafarian et al., 2021). In recent years, indirect monitoring techniques also referred to as "drive-by" monitoring have drawn a lot of interest. These techniques are based on installing sensors on a passing train for railway bridge and track health monitoring (Lederman et al., 2017) (Molodova et al., 2011). These techniques evaluate the dynamic reactions of train components that are closer to the track, including suspensions, and may also use real-time data from a passing train. This makes it possible to instrument many passenger trains and utilize them for ongoing railway track monitoring, which may identify problems early on. Drive-by track monitoring systems have been developed using

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a variety of sensor types, including inertial sensors (OBrien et al., 2018), cameras (Bar-Am, 2015) and laser technology (Fallah Nafari et al., 2018).

Despite the distinct advantages of alternative systems, certain limitations must be highlighted. For example, low light negatively impacts the visual spectrum camera-based system. Furthermore, in order to precisely estimate the x-y coordinates of road users, a camera-based system must be manually geometrically calibrated at each location. Stereo and infrared cameras could help with these problems, but they are expensive to construct and need sophisticated processing units to function in real time. On the other hand, infrared, ultrasonic, and radar sensors have trouble correctly identifying road users and are greatly impacted by unfavorable weather and precipitation.

This study presents a methodology for radar-aided railway monitoring systems designed specifically to function in the low-visibility environments like fog—filling a vital void in existing railway safety technologies. Although radar technology has penetrated various automotive and surveillance applications extensively, its use in the railway context, especially for track monitoring under poor weather conditions, is vastly underdeveloped. Previous methods are usually vision-centric or dependent on enormous, human-annotated datasets for sensor fusion, and many are not capable of realistically modeling environmental phenomena such as radar attenuation caused by atmospheric conditions. This research fills that gap by synergistically integrating geometric railway topology modeling, fog-induced radar signal degradation, and object detection thresholds into one, MATLAB-based simulation framework. The main contributions of this research are:

- To augment the traditional radar range equation by including an exponential radar attenuation model that realistically simulates signal degradation in fog, allowing prediction of detection performance loss over distance.
- To create a holistic MATLAB-prototyped framework that unifies railway geometric setup, radar signal attenuation, and detection thresholds, offering a cost-efficient and scalable testbed without the need for expensive physical prototypes.
- To analyze detection performance under different power thresholds, providing insights into how radar sensitivity impacts the effective monitoring range in various environmental and operational conditions.

- To develop an adaptive simulation platform that, while currently focused on radar, is designed to support integration of other sensor modalities such as LiDAR, thermal imaging, and computer vision, enabling future advancements in sensor fusion techniques.
- To make available a low-cost, customizable, and user-friendly simulation tool that supports rapid experimentation and parameter tuning, suitable for academic researchers, railway authorities, and technology developers.

In summary, the present research bridges a critical knowledge gap through the investigation of radar attenuation effects under low-visibility railway surveillance scenarios and provides a solid basis for promoting intelligent and resilient railway safety technology.

The paper is structured into six main sections. Section 2 reviews the relevant literature on radar technology applications in railway monitoring and the effects of fog on signal propagation. Section 3 details the methodology, including the modeling of the railway layout, radar signal attenuation due to fog, and the object detection simulation implemented in MATLAB. Section 4 presents the simulation results, showcasing the 3D railway visualization, received signal power analysis, and object detection outcomes. Section 5 discusses the implications of the findings, addressing the strengths and limitations of the proposed model in real-world scenarios. Finally, Section 6 concludes the study, summarizing key contributions and suggesting directions for future research.

2 Literature Review

Studies on several sensor fusion technologies in relation to perimeter intrusion detection techniques have been carried out by both local and foreign research organizations (Zhangyu et al., 2021); (Garcia-Dominguez et al., 2008). Nevertheless, there are still issues, such as poor monitoring accuracy in bad weather and the incapacity to identify tiny, far-off objects.

Another method is creating a number of detection boxes using image detection algorithms, then projecting the 3D pyramids that the detection boxes produce into 3D point cloud space to aid in identification (Wang & Jia, 2019). Furthermore, (Shuai et al., 2021) investigated fusion techniques for millimeter-wave radar and cameras in situations with limited visibility or illumination, greatly enhancing detecting capabilities in lowlight situations. In the area of advanced driving assistance systems, (Chen et al., 2023) recently studied a generic fusion framework for millimeter-wave radar, lidar, and cameras. They were successful in achieving

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positive target identification findings on publically accessible multi-source data fusion datasets. However, in order to properly train models, camera and radar fusion mostly depends on pre-training data and needs a significant volume of manually labeled intrusion data. It's possible that current training datasets don't accurately depict actual railroad situations.

The infrared thermography approach allows for remote operation without interfering with train transit, making it both efficient and easy. By displaying the defect's contour, the edge detection image processing can further quantify the defect degeneration. Furthermore, accurate identification of spontaneous fracture flaws is provided by the ideal settings for different edge operators (Cui et al., 2024). A study by (Çalışkan, 2024) introduces a Rail Transit Fuzzy Logic Model to assess the necessity of expanding rail networks for sustainable transport development. Using five key input parameters slope, geology, population, land use, and stream the model generates a spatial Suitability Score through a fuzzy inference system (FIS) with 108 If-Then rules, all implemented in MATLAB. The methodology involves developing the FIS, designing a graphical user interface using the GUIDE toolbox, and producing a suitability score database for a study area modeled as a 216-by-208 matrix. This spatially oriented fuzzy approach, rarely applied to large-scale urban rail networks, offers a systematic and cost-effective framework to support data-driven decision-making in rail infrastructure planning.

(Lederman et al., 2017) presented an energy-based technique to examine track modifications by using acceleration data from the train body. They deployed a feature detection indicator and analyzed the signal energy from multiple runs of an operational train to detect changes in the track over time. Similarly, (Fallah Nafari et al., 2018) utilized the relative vertical distance between the rail surfaces at two sites, observed from the train via a laser-based rolling deflection measuring device, to determine the track stiffness profile. Although these methods yielded effective results, they focused only on specific damage scenarios.

(Malekjafarian et al., 2019) applied the Hilbert–Huang transformation to determine the instantaneous amplitudes of acceleration signals recorded on a train. They proposed representing the signal's energy as a function of train localization to identify track anomalies. Later, . (Malekjafarian et al., 2021) demonstrated that the recorded drive-by acceleration could be used to numerically calculate the bogie-filtered displacement (BFD), validating the method with data from an operational Irish rail train. While the BFD is sensitive to signal noise and train speed, it effectively identifies loss of stiffness on track using data from train passes at varying forward speeds.

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Train-track interaction modeling has been approached in various ways (Zhai et al., 2019). (OBrien et al., 2017) developed a computational model to deduce a track longitudinal profile from drive-by measurements. In their model, the rail was treated as a beam supported by a three-layer sprung mass system representing ballast, pads, and sleepers, while the train was modeled as a 10-degree-of-freedom (DOF) half-train. To validate this approach, (OBrien et al., 2018) compared field test measurements with numerical simulations, employing an irregular longitudinal track profile to accurately depict track–train interaction. Their method quantifies the dynamic responses of both the train and railway infrastructure using numerical techniques. (Marini et al., 2024) proposed a real-time active damping methodology for front-end inverters connected to the railway catenary in energy recovery applications. Their system consists of a three-phase 2.5 MW inverter connected to the AC grid via a suitable filter and sharing the DC-side with the railway plant, where traction inverters and auxiliary systems are connected. The proposed method addresses the issue of resonance caused by the energy recovery converter operating under almost constant power load. It estimates the DC-side resonant frequency, isolates voltage oscillations around this frequency, and attenuates their effects through inverter current control. Experimental validation using a hardware-in-the-loop (HIL) real-time emulator, modeled with real data from a train operator, demonstrated the method's effectiveness in detecting and reducing resonance, enhancing catenary robustness and enabling proper integration of energy recovery systems.

A comprehensive description of how to utilize MATLAB to find rail track faults was given to readers by (Sharma & Swet, 2016). This is accomplished via a methodical procedure that begins with the fundamental rail track examination in railroad maintenance. Any engineer, scientist, or practitioner interested in the analysis and processing will find this self-contained book useful. Using a vision-based approach and calibration to find the track's fault site, the system offers real-time monitoring and structural status information for railroad tracks. Track flaws, missing bolts, anchors, tie plates, and clips, among other things, are found during inspections. A 25 kV, 50 Hz AC traction system was modeled and simulated by (Shenoy et al., 2004) using SIMULINK software and the Power System Block set (PSB). The model includes a three-phase system with substations, a rail section with DC trains supplied by rectifiers, and extensive traction loads. The research looked at how loads and fault circumstances affected the 25 kV AC traction system. Additionally, a relay feature based on the X-R plane's combination of two quadrilaterals was suggested. This relay characteristic was implemented and verified using a Texas Instruments TMS320C50 digital signal processor (DSP) hardware configuration.

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The fusion algorithms of millimeter wave radar and cameras in the context of advanced driver assistance systems (ADAS) have been the subject of much study in recent years. These algorithms may be divided into three primary categories based on the degrees of content and fusion: data-level fusion, feature-level fusion, and decision-level fusion (Wei et al., 2022). In decision-level fusion, two distinct sensors independently identify targets, gather target information, and then combine the detection outcomes from several sensors. In order to further improve the identification performance across modes, feature-level fusion usually projects the radar features into the relevant 2D picture plane. Regions of interest (ROIs) are first created via data-level fusion using radar points, and then feature extractors and classifiers are used within ROIs to find targets.

An obstacle identification technique that integrates millimeter-wave radar and cameras was proposed by (Zhang et al., 2019). The method first locates the target using millimeterwave radar. The ROI of the target in the picture is then determined by the camera's coordinate transformation, after which the object concurrently detects targets, and finally the camera's detection findings are linked to radar data. A unique fusion point pruning technique was presented by (Stäcker et al., 2022). It automatically determines the best fusion point for radar and image characteristics within a neural network framework. A three-level fusion architecture including target trajectory prediction, sensor data association, and sensor data selection was suggested by (Liu & Liu, 2021). (Yao et al., 2021) proposed a three-level fusion architecture that includes sensor data selection, sensor data association, and target trajectory prediction.

2.1 Research Gap

Even with various developments in railway fault detection and monitoring systems, there is still a vital lack in successful simulation and implementation of radar-based systems during low-visibility situations like fog. Although radar and sensor fusion algorithms have been largely used in vehicular and surveillance applications, they have not been widely adopted in railway applications especially for track observation in poor weather conditions. Current approaches typically concentrate on signal analysis, energy-based detection, or vision-based systems, which are either extremely reliant on clear conditions or need large labeled datasets and expensive physical infrastructure. In addition, most models do not integrate environmental conditions such as radar attenuation due to fog into detection algorithms, and very few are capable of 3D visualizations for sensor coverage and blind spot analysis. Moreover, existing tools lack a low-cost, user-extensible simulation platform for assessing radar performance over actual railway geometries. To overcome these limitations, the current work proposes a new

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MATLAB-based simulation platform integrating geometric modeling, realistic radar signal degradation, object detection functionality, and 3D visualization within a modular, scalable setting. This method bridges an important research gap by making feasible, affordable analysis of foggy condition radar-aided railway monitoring possible, facilitating infrastructure planning as well as the creation of robust smart transportation systems.

3 Methodology

The goal of this project is to develop radar technology to create a whole railway monitoring system that works in foggy weather and the flow chart is shown in figure1. The simulation has three main parts: building a 3D railway layout, modelling how fog weakens radar signals as they travel, and finding objects that are randomly put on the tracks. The system is built in MATLAB and combines ideas from both geometric visualizations and signal processing by considering the parameters presented in table 1.

Table 1 Parameters Table

Parameter	Description	Value	Units
length	Track length	2000	meters (m)
width	Track width	2	meters (m)
sleeper_spacing	Distance between sleepers	0.6	meters (m)
track_height	Rail height	0.2	meters (m)
foundation_depth	Depth of granite foundation	0.5	meters (m)
c	Speed of light	3×10^8	m/s
f_carrier	Radar carrier frequency	77×10^9	Hz
lambda	Wavelength	c / f_{carrier}	meters (m)
Pt	Transmitted power	1	Watts (W)
Gt	Transmitter gain	30	dB
Gr	Receiver gain	30	dB
sigma	Radar cross-section of object	5	m ²
alpha	Fog attenuation factor	0.05	dB/m
R	Range vector	1 to 2000	meters (m)
threshold	Minimum detectable power	1×10^{-9}	Watts (W)
num_objects	Number of objects on track	10	count
object_positions	Positions of objects on track	Random 0 to 2000	meters (m)
object_heights	Heights of objects	0.3	meters (m)

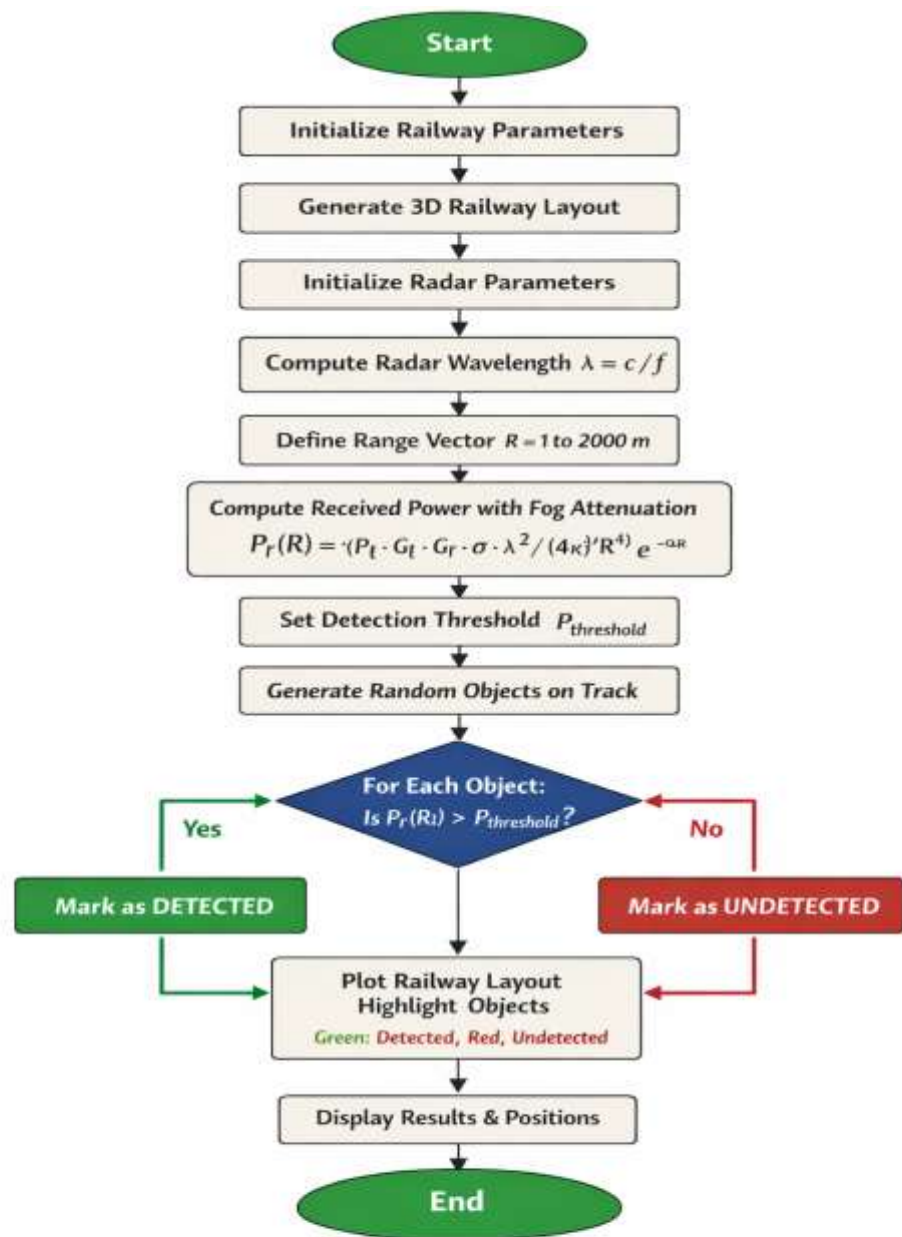


Figure 1 Flowchart

3.1 Railroad Layout Modeling

3.1.1 Objective

The initial step in the simulation is to build a three-dimensional model of a railway track. This pattern is a physical guide for imitating how items are placed and found. A realistic railway setting lets you see how the track, objects, and sensor signals are all related in space.

3.1.2 Implementation

MATLAB's mesh grid tool to create a 3D mesh grid that looks like the track. Users choose the length and width of the track, and the distance between the sleepers decides how dense the mesh is. There are two layers: one for the top of the steel rail and one for the granite base underneath it. The surf function in MATLAB is then used to generate these surfaces, making it easy to see the difference between the track and its base.

3.1.3 Parameters Used

- Track Length: $L=2000$
- Track Width: $W=2$ m
- Sleeper Spacing: $s=0.6$ m
- Rail Height: $h=0.2$ m
- Foundation Depth: $d=0.5$ m

3.2 Fog Attenuation and Radar Signal Modeling

3.2.1 Objective

The second phase shows how radar signals act when there is fog in the air. Fog weakens electromagnetic waves, which has a big effect on how well radar-based object identification works. This module shows how fog affects signal strength and finds the range at which signals may be detected.

3.2.2 Signal Propagation Model

The simulation is based on the classical radar range equation, which calculates the received power P_r as a function of the transmitted power P_t antenna gains G_t and G_r radar cross-section σ and signal wavelength λ . An additional exponential term is introduced to model attenuation due to fog over distance R , characterized by an attenuation coefficient α .

Radar Equation with Fog Attenuation:

$$P_r(R) = \frac{P_t \cdot G_t \cdot G_r \cdot \sigma \cdot \lambda^2}{(4\pi)^3 \cdot R^4} \cdot e^{-\alpha R} \quad (1)$$

Where:

- P_t : Transmitted power (W)
- G_t, G_r : Transmitter and receiver gains (linear scale)
- $\lambda = \frac{c}{f}$: Wavelength (m), with c as the speed of light and f as the carrier frequency
- σ : Radar cross-section (m²)
- α : Fog attenuation coefficient (dB/m)
- R: Distance to target (m)

The resulting power P_r is computed over a range of 1 to 2000 meters, and the values are plotted in decibels (dBm) to visualize signal decay.

3.2.3 Detection Criteria

A minimum power threshold $P_{threshold}$ is defined to represent the radar's sensitivity. Any signal with received power below this threshold is considered undetectable. Detection is thus a binary outcome determined by comparing (R) against $P_{threshold}$

$$Detection\ Flag = \begin{cases} 1, & \text{if } P_r > P_{threshold} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

This helps simulate the realistic limitation of radar sensors in adverse weather conditions.

3.3 Object Placement and Detection Simulation

3.3.1 Objective

This module puts random items along the track and checks how easy they are to find depending on the intensity of the radar signal that was computed in the previous phase. The goal is to simulate situations in the actual world when there are foreign items on the track that need to be found for safety reasons.

3.3.2 Implementation

The rand function in MATLAB randomly places a specified number of items along the length of the track. We set the Y-coordinate to 0, which means that all objects are on the centerline of the track, and we give them all the same height. The nearest index in the pre-computed range vector RRR is used to map the location of each item. Then, the value of P_r that goes with it is compared to the detection threshold. If the value is higher than the threshold, the item is said to be detected. To make it easier to see, detected items are shown in a distinct color.

Algorithm 1 Railway Monitoring and Object Detection Under Fog

1. Initialize railroad parameters: length, width, sleeper spacing, track height, foundation depth
2. Generate mesh grid for 3D railroad layout using the specified dimensions
3. Plot steel track and granite foundation using surface rendering
4. Initialize radar parameters: P_t , G_t , G_r , f , c , σ , α
5. Compute wavelength: $\lambda = fc$
6. Define range vector R from 1 m to 2000 m
7. Calculate received power with fog attenuation:
8.
$$P_r(R) = \frac{P_t G_t G_r \sigma \lambda^2}{(4\pi)^3 R^4} \cdot e^{-\alpha R}$$
9. Define detection threshold $P_{threshold}$
10. Mark all ranges where $P_r > P_{threshold}$ as detectable
11. Generate N random object positions along the track length
12. for each object $i=1$ to N do
13. Find nearest index in $R_{corresponding}$ to object position
- 14.
15. if $P_r(R_i) > P_{threshold}$ then
16. Mark object I as detected
17. Else
18. Mark object I as undetected
19. End if

20. End for
21. Plot all objects on track layout
22. Highlight detected objects in green, undetected in red
23. Display positions of detected objects

4 Results

The simulation works well to mimic how a radar system with fog-attenuated radar may find things on a train track. The numbers below show that the results are split into three main phases:

4.1 Railroad Layout Visualization

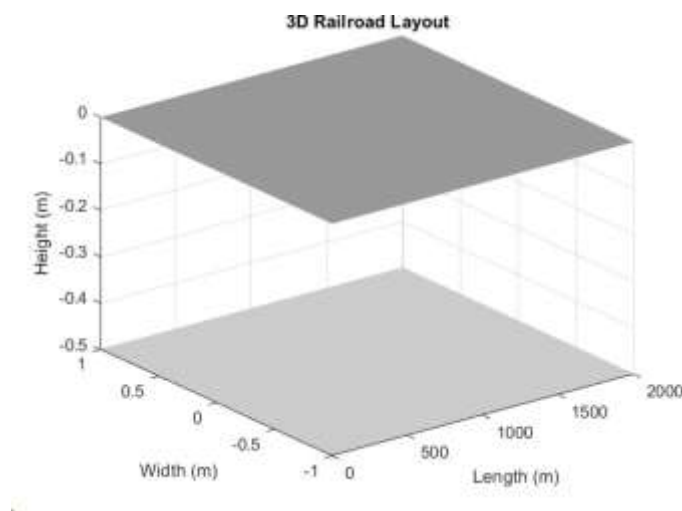


Figure 2 3D Railroad Layout

The first result, Figure 1, shows a 3D model of the layout of the railway. The granite foundation is shown on the bottom plane, while the steel rail is shown on the top plane. The pattern is 2000 meters long and 2 meters wide. The visualization shows that the spatial arrangement is proper, which is important for inserting and finding things correctly later in the experiment.

4.2 Received Signal Power Analysis

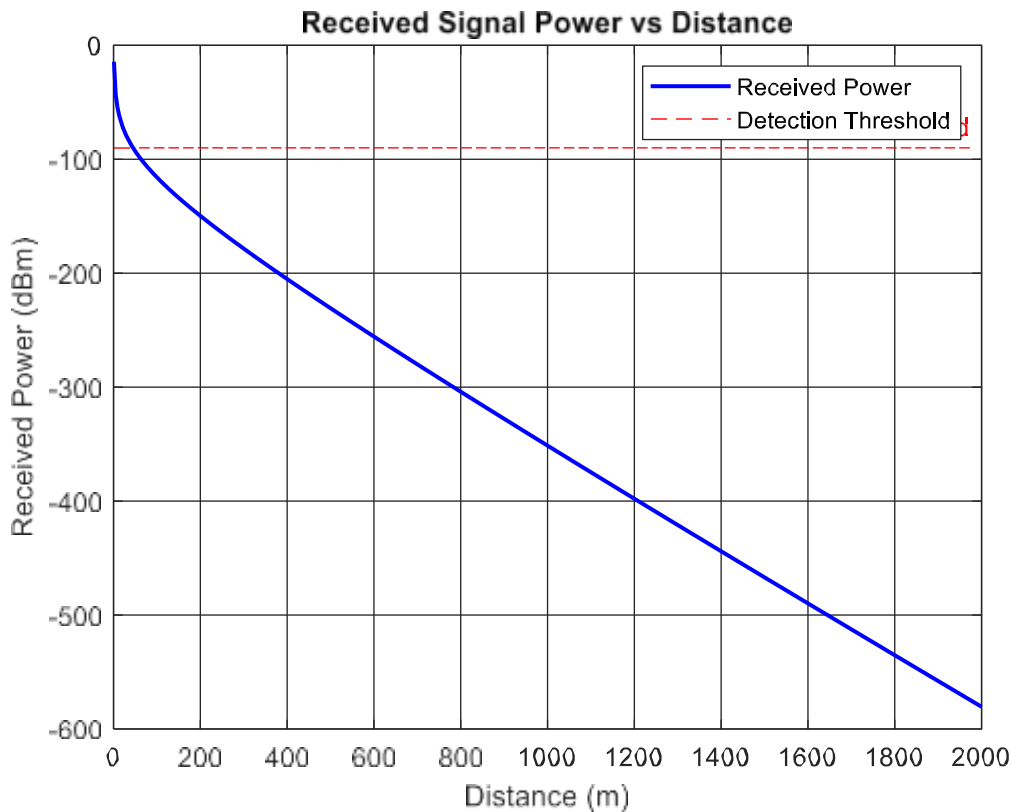


Figure 3 Received Signal Power vs Distance

Figure 2 shows how the strength of the received radar signal changes at a distance of 1 to 2000 meters, taking into account how fog weakens the signal. The blue curve shows the logarithmic (dBm) scale of received power. This power diminishes exponentially with distance because of both spreading loss and exponential fog attenuation.

The detection threshold is shown by a red dashed line. If the power received falls below this line, it is not enough to identify an item. The graphic makes it evident that detection is only possible up to a certain distance (around the first few hundred meters), beyond which the signal drops below the threshold.

4.3 Object Detection Outcome

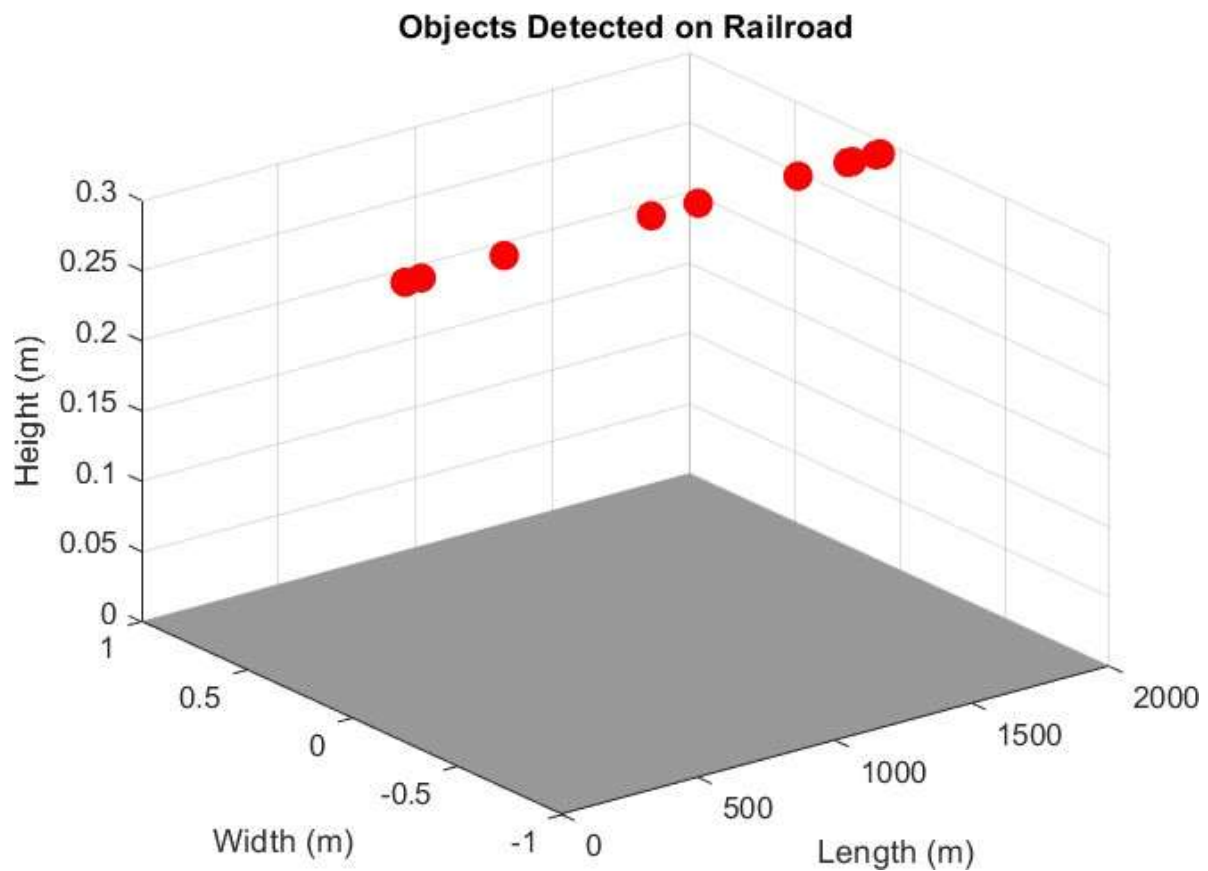


Figure 4 Objects Detected on Railroad

Figure 3 shows where things are really placed and how they are found along the railway. There were 10 items put randomly on the course. The red dots show these things, which are all at a height of 0.3 meters above the track surface. The system figures out which of these items are detected by looking at the computed received power levels and their locations. Only those that fall within the effective range, where the received power is over the threshold, are recorded as detected. The graphic shows that some items at the beginning of the track (closer range) are identified correctly, but others further away are not, which is in line with the signal power analysis.

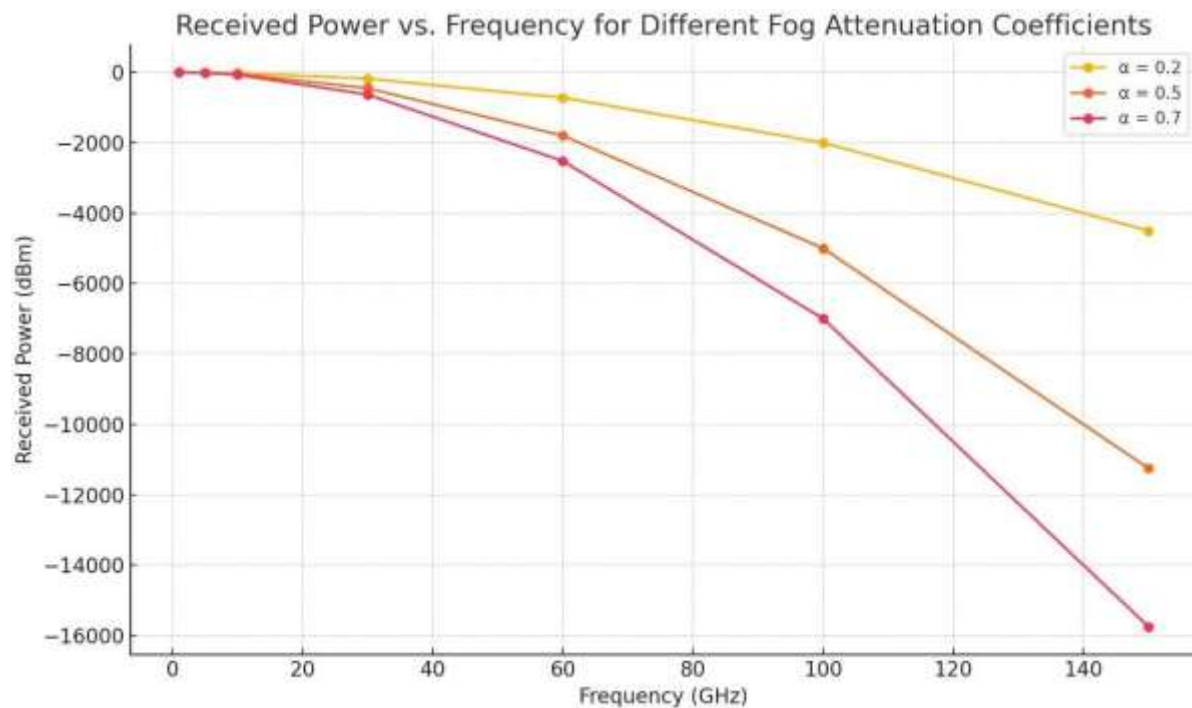


Figure 5 Received power vs frequency for different fog attenuation coefficients

The Fig 4 illustrates the relationship between received power and frequency for different fog attenuation coefficients. The graph shows three distinct curves, each corresponding to a specific fog attenuation coefficient (α). Where the $\alpha=0.2$, indicates the lowest attenuation, with received power starting near 0 dBm at 0 GHz and gradually decreasing to about -4500 dBm at 150 GHz. The second fog attenuation coefficient $\alpha=0.5$, showing a more significant drop in received power to approximately -11500 dBm at 150 GHz. The third fog attenuation coefficient $\alpha=0.7$, exhibits the highest attenuation, with the most rapid decline in received power, plummeting to roughly -16000 dBm at 150 GHz. Across all the tested attenuation coefficients, there is a clear trend of decreasing received power as frequency increases. Moreover, a higher fog attenuation coefficient consistently results in a more pronounced reduction in received power over the entire frequency spectrum from 0 to 150 GHz.

5 Discussion

The study's simulation does a good job of modelling a real-life situation when radar-based object identification is used on a foggy train track. The algorithm takes into account important physical and environmental factors, such how fog weakens radar signals, how big the tracks are, and how many randomly placed obstructions there are. The power attenuation model, which is an exponential loss with distance, does a good job of showing how air fog makes radar

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signals less clear. The simulation shows that the received signal strength drops quickly as the range grows, which limits the system's ability to identify things. This is in line with what we would anticipate from theory and gives us a better idea of the real-world limits of radar-based systems in bad weather. The 3D view of the railway and item placements makes it much easier to understand how the system works. It helps you understand where detection is possible in space and helps you figure out the system's effective range. The model is easy to understand and works well since it makes basic geometric assumptions, including that the height of an item stays the same and the fog attenuation factor stays the same. But the simulation also shows that there are some big problems with it. First, the attenuation model doesn't take into account the fact that fog density and environmental conditions aren't always the same, which is what happens in the real world. Second, it's assumed that the items have a consistent radar cross-section (RCS), however this could not be true for real trash or barriers that come in different shapes, sizes, and materials. The model also doesn't take into account changes in the topography, which might affect how well signals travel and how reliable they are for detection. Even with these simplifications, the model does a good job of showing the main trade-offs between radar sensitivity, environmental attenuation, and detection range. The fact that the model can find adjacent objects shows that it can be used in real-life early-warning railway systems. Also, it makes it possible to use sensor fusion methods like LiDAR or thermal imaging to improve the performance of radar when visibility is limited or cloudy.

6 Conclusion

This paper shows how to use radar to simulate railway track monitoring in foggy situations using a simulation-based method. The implementation has three main parts: making the railway layout, modeling signal power with environmental attenuation, and finding objects based on signal thresholds. The findings show that radar may be a useful tool for finding obstacles on trains, but its efficacy is greatly affected by things like fog. The received signal strength decreases exponentially with distance because of air attenuation, which restricts the effective detection zone. This shows how important it is to locate radar strategically and improve signal processing. Overall, the experiment shows that it is possible to use radar devices to keep an eye on trains when visibility is low. It also lays the groundwork for future research and development, such as applying dynamic environmental modeling, improving item categorization using machine learning, and leveraging multi-sensor fusion to make things more resilient. The technique and results are not just interesting from an academic point of view, but they also help

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make train infrastructure smarter and safer, especially in places where weather makes it hard to see. Future work should concentrate on fine-tuning system parameters, testing the model with real-world data, and looking into how well it can scale up to handle bigger and more complicated railway networks.

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