



Enhancing Pavement-Encoded Signages for Precise Driving Automation

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16. Abstract A field study was developed combining an automated driving system (ADS) vehicle and magnetometer-based sensing system to test the detectability, repeatability, and reliability of pavement encoded electromagnetic (EM) strips placed on the surface of concrete and asphalt pavement. The objective was to define the EM strips' patterns, lateral vehicle position, and speed accuracy at several vehicle speeds (15 to 55 mph) and weather conditions on a closed traffic concrete pad and a low-volume rural road. The closed area concrete pad consisted of two test segments that evaluated construction work zone warning patterns, lane shifting, lateral vehicle position, vehicle speed, and unsignalized intersection stop warning pattern with the ADS vehicle testing conducted between 25 and 55 mph. The second test section on a rural road placed 36 longitudinal EM strips spaced at 15 and 20 ft on a tangent and horizontal curve, respectively. The vehicle traversed this section in several weather conditions (normal, snow, ice) and compared its lateral position and speed to a camera-based ground truth measure and GPS speed indicator. The refined signal-processing algorithms enabled reliable and repeatable detection of the EM strips when the minimum signal threshold was set to 30 nT/ms. To minimize the effects of electromagnetic interference from the ADS vehicle, two bandpass filtering configurations were employed successfully with 15–55 Hz for < 35 mph and 20–80 Hz for > 35 mph along with a notch filter at 60 Hz to remove adjacent powerline noise. A noise rejection framework was deployed based on top-row sensor coincidence screening, which filtered out disturbances from embedded ferromagnetic elements in or near the pavement. With the V2I EM strips, sensors, and filtering system refined, more than 90% of the EM strips were detected in all weather conditions. For the rural road section, the mean lateral position accuracy varied between 1.3 to 2.6 in. for all weather conditions, while the difference in calculated and GPS speed was < 1 mph. The new signal-processing enhancements and testing at various speeds confirmed the V2I system is detectable, interpretable, and repeatable, which can now lead to additional V2I testing in more complex testing configurations and sites.			
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EXECUTIVE SUMMARY

This report investigated the reliability and applicability of electromagnetic (EM)-based pavement-encoded signage for enhancing precise driving automation at various speeds, ranging from 15 mph to 55 mph, under normal and adverse weather conditions. Past research has shown that automated driving systems (ADS) could potentially address crash risks posed by driver error. The integration of the proposed pavement-encoded signage could be used as complementary roadway cues for current ADS perception systems. The objective of this research was to evaluate the detectability, interpretability, reliability, and accuracy of the proposed pavement-encoded signage.

The initial experimental phase conducted vehicle-to-infrastructure (V2I) experiments that focused on the validation of signal response from multiple pavement-encoded signages, including construction work zone (CWZ) speed warnings, CWZ lane merge warnings, lateral positioning, CWZ lane shift guidance, and intersection warnings. Sixteen test cases were conducted in a closed test area under these conditions. Next, the signal-processing framework was further refined to accommodate higher speeds, electromagnetic interference (EMI), and signal disturbances unrelated to the EM strips. Several key differences were identified between the 2024 low-speed movable cart testing and the higher-speed vehicle testing. First, the EM disturbances influencing the reliability of EM signal detection came from the EMI caused by the harmonic motion of the vehicle's wheel and tire. This EMI was speed dependent: as wheel angular velocity increased, the EMI frequency also increased with speed from 0 to 20 Hz. Second, EM disturbances near the test section from adjacent powerlines could reduce the clarity of the EM response from the pavement-encoded signage. Powerline EMI was constant at 60 Hz and was successfully filtered with an updated notched signal-processing framework. Lastly, differences in EM signature captured by the top-row sensors versus the main-row sensors were used to successfully differentiate the encoded EM signage from erroneous disturbances beneath the pavement surface.

The next experimental phase validated the V2I system's effectiveness on a two-lane rural road with a horizontal curve in Rantoul, Illinois. The accuracy of the system in determining the vehicle's lateral position and speed was validated under normal and adverse weather conditions. First, the EM-based sensing system consistently detected more than 90% of the EM strips. Moreover, the results showed that the proposed EM-based sensing system could achieve a lateral position deviation from the referenced ground truth of between 1.3 and 2.6 in. and a speed deviation of less than 1 mph under both normal and adverse weather conditions.

This study also presented an experimental evaluation of the proposed motion-planning framework under different lateral offset scenarios. Simulations were performed to safely assess the planner's behavior under frequent and extreme offsets that exceed those expected in real-world operation. These simulations demonstrated that the motion-planning framework remains stable even under large offset perturbations and that incorporating more frequent and accurate offset information led to improved lane-keeping performance. The results also showed that steering behavior remained bounded and that offset errors alone did not destabilize the vehicle, even in aggressive scenarios on horizontal curves without any transition curves.

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CHAPTER 1: INTRODUCTION

BACKGROUND

Driver error has historically been identified as the primary cause of roadway accidents (Rumar, 1985; Singh, 2018) with 94% of accident related to driver error. These driver-initiated accidents occur across various collision scenarios such as lane departures (SIKA, 2001; NHTSA, 2024), intersections (Wang and Qin, 2015), and construction work zones (Raub et al., 2001; Pigman & Agent, 1990; Bai & Li, 2006; El-Rayes et al, 2013). According to NHTSA, nearly half of all driver errors were related to recognition errors such as inattention, distractions, and inadequate surveillance, while one-third resulted from decision errors such as driving too fast for conditions and illegal driving maneuvers (Singh, 2018). These issues are particularly pronounced in rural areas. According to the National Center for Statistics and Analysis (NCSA, 2024), the fatality rate per 100 million vehicle miles traveled in rural areas was 1.5 times higher than in urban areas in 2022. Although only 20% of the U.S. population resides in rural areas, these crashes account for 43% of all roadway fatalities.

Roadway departure crashes and intersection crashes are among the leading contributors to traffic fatalities in the United States (NHTSA, 2024; FHWA, 2020). Rural roadway departures are associated with 12,000 fatalities per year (Satterfield & Albin, 2021). Furthermore, traffic fatalities at unsignalized intersections, which are primarily located in rural areas, represent nearly two-thirds of all intersection-related fatalities each year. As expected, driver errors contribute to about 80% of these intersection crashes with driver awareness and speeding identified as primary contributors to severe and fatal outcomes (FHWA, 2003; Haleem & Abdel-Aty, 2010; Wang & Qin, 2015). Additionally, many unsignalized intersections provide inadequate visibility for approaching drivers, particularly those on major roads without stop or yield signs. This lack of awareness often leads to high-speed intersection approach crashes, as drivers fail to anticipate potential cross-traffic conflicts.

Several measures have been developed to reduce fatal crashes caused by driver errors. Speed warning and enforcement measures can effectively reduce mean speeds, which leads to a decrease in injuries and fatalities as well as decrease in property-damage-only crashes where unsafe speed is the primary collision factor (FHWA, 2003; Meuleners et al., 2020). Recently, a simulated study on intersection collision warning systems showed that in-vehicle auditory warning outperformed the no-warning and visual-only warning scenarios (Bella & Silvestri, 2017). With the in-vehicle auditory warning, driver reaction time was reduced compared to the other two scenarios, which allowed the driver to reduce speed earlier than the no-warning or visual-only warning scenarios.

Recently, automated driving systems (ADS) have illustrated the potential to reduce crashes by eliminating common human errors. Scharber (2024) analyzed Fatality Analysis Reporting System data (2016–2022) and found that vehicles equipped with lane-keeping assistance were approximately 24% less likely to be involved in fatal single-vehicle road departure crashes compared to non-equipped vehicles (95% confidence interval: 2%–42%), although other relevant crash types were not included in the analysis. According to Mueller et al. (2020), approximately 33% of crashes involve either incapacitation (10%) or sensing/perceiving failures (23%), such as failing to recognize hazards in time. These are the types of crashes that could be directly mitigated if ADS systems maintain superior

perception capabilities across all driving conditions. However, ADS perception systems remain vulnerable under adverse weather conditions. In scenarios involving rain, fog, snow, or degraded pavement markings, visual and signal-based sensors often suffer reduced accuracy and reliability. These conditions obscure critical roadway features, which assist in accurate vehicle positioning, and ultimately pose risks to vehicle safety and limit real-world effectiveness of ADS. According to Aldibaja et al. (2020), the accuracy of lateral localization is an important factor affecting the performance of driving automation. Their research indicated that the lateral positioning precision of LiDAR-equipped vehicles deteriorates by 40 to 300 cm in snow or wet pavement conditions. This level of error in adverse conditions exceeds the typical safety threshold of 10 to 20 cm for precise lateral control.

To address these limitations, recent research by Dahal and Roesler (2021) introduced a pavement-assisted passive sensing system designed to improve lateral positioning accuracy in adverse weather and complement ADS-equipped vehicles that use systems such as computer vision. The material sensing system functions by locally altering the electromagnetic (EM) field of the pavement surface, enabling passive vehicle-to-infrastructure (V2I) communication. Unlike traditional vision-based systems, this approach does not rely on a clear visual line of sight, making it significantly more adaptable during adverse weather conditions. However, the practicality and reliability of these secondary systems under real-world speed and weather conditions have not yet been proven.

Recent CCAT research by Sakulneya and Roesler (2023, 2024) developed a pavement-assisted passive sensing system called pavement-encoded signage—programmable coatings made from ferromagnetic oxide materials—to enhance the practical implementation of passive sensing signatures relative to previously embedded methods (Dahal, 2022). These pavement-encoded signages were designed for temporary applications that require minimal installation time, limit damage to existing pavement, and are easily removable. Potential use cases include ADS-equipped vehicles approaching construction work zones to provide in-vehicle speed and lane-merge warnings. Sakulneya and Roesler's (2024) proof-of-concept study, validated through experiments using a movable cart equipped with sensors, demonstrated that pavement-encoded signage can be used to estimate a vehicle's real-time speed. By measuring the time between successive detection signals, the system calculates the vehicle's speed, which can then be compared with a predefined threshold based on the spacing of the encoded signage markings. If the vehicle's travel time between pavement-encoded signage falls below the predefined threshold, the ADS could then issue a warning to the driver before entering the work zone (Sakulneya & Roesler 2024).

Building on the previous findings by Sakulneya and Roesler (2023, 2024), the goal of the current study is to validate the pavement-encoded signages with an ADS-equipped vehicle under realistic speeds and environmental conditions. The experiments focused on assessing the detectability and interpretability of various pavement-encoded signages, including construction work zone (CWZ) speed warnings, CWZ lane-merge warnings, end-of-CWZ signages, lane-keeping maneuvers on horizontal curves, lane-shifting maneuvers, and STOP warnings at unsignalized intersections for ADS-equipped vehicles.

RESEARCH OBJECTIVES

The objective of this research is to enhance driving safety through the integration of pavement-encoded signages coated on roadway surfaces that provide passive communication between ADS-equipped vehicles and the roadway. This study implements and validates the lateral accuracy and high-speed reliability of pavement-assisted passive sensing systems using an ADS-equipped vehicle. The system was evaluated to support automated driving functions such as lane keeping on tangent sections and horizontal curves, lane-shifting maneuvers, varying speed conditions, and diverse weather environments, especially in rural roadway settings.

OVERVIEW OF THE REPORT

This report is organized into seven chapters with Chapter 1 providing background on the research problem, research objectives, and scope of research work. Chapter 2 illustrates the background and current limitations of driving automation. This chapter briefly discusses development of driving automation, collision-avoidance features in ADS, contributing factors to crashes in automated vehicles, the impact of adverse weather on automated vehicle sensors, and potential features of pavement-assisted passive sensing systems for automated driving systems. Chapter 3 defines the experimental setups and data collection plans from the closed-area pilot experiment to open-driving environments on a rural roadway. Chapter 4 presents the electromagnetic signal-processing and filtering procedures along with the interpretation of data from multiple pavement-encoded signages collected during pilot testing: CWZ speed warnings, CWZ lane-merge warnings, end-of-CWZ signages, lane-shifting maneuvers, and STOP warnings at unsignalized intersections. Chapter 5 details the field test results conducted on a rural road, focusing on the detection and interpretation of lane-keeping maneuvers and vehicle speed control during horizontal curve navigation by the ADS-equipped vehicle. Chapter 6 discusses the motion-planning algorithm for autonomous driving and presents the simulation and experimental results from the rural road tests. Finally, Chapter 7 synthesizes the experimental findings into conclusions and offers recommendations for implementing pavement-encoded signage to support and enhance ADS.

CHAPTER 2: DRIVING AUTOMATION

DEVELOPMENT OF DRIVING AUTOMATION

Driving automation systems are categorized by the level of driver involvement and system capability. The SAE J3016 standard defines six levels (0 to 5), ranging from no automation to full automation (Figure 1).

- Level 0: No driving automation. The human driver performs all tasks.
- Level 1: Driver assistance. The system assists with either steering or speed, but not both. The driver is fully responsible.
- Level 2: Partial automation. The system can assist with both steering and speed simultaneously under specific conditions. Continuous driver supervision is required.
- Level 3: Conditional automation. The system performs all dynamic driving tasks within limited environments. The driver must take over when requested.
- Level 4: High automation. The vehicle performs all driving functions within a limited operational design domain. Human intervention is not required within this domain.
- Level 5: Full automation. The system can operate under all conditions without any human input. No steering wheel or pedals are necessary.

Currently, most deployments remain at Level 4, where automated vehicles operate independently within constrained conditions, such as low-speed urban environments or predefined service zones. Advancing beyond Level 4 requires extending system capabilities to complex and unstructured scenarios, including rural or remote areas under adverse weather conditions.

SAE J3016™ LEVELS OF DRIVING AUTOMATION™

Learn more here: [sae.org/standards/content/j3016_202104](https://www.sae.org/standards/content/j3016_202104)

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	SAE LEVEL 0™	SAE LEVEL 1™	SAE LEVEL 2™	SAE LEVEL 3™	SAE LEVEL 4™	SAE LEVEL 5™
What does the human in the driver's seat have to do?	You are driving whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			You are not driving when these automated driving features are engaged – even if you are seated in “the driver's seat”		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	

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	These are driver support features			These are automated driving features		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering OR brake/acceleration support to the driver	These features provide steering AND brake/acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met	This feature can drive the vehicle under all conditions	
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering OR • adaptive cruise control	• lane centering AND • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

Figure 1. Diagram. Levels of driving automation.

Source: SAE International (2021)

COLLISION AVOIDANCE IN AUTOMATED DRIVING SYSTEMS

In automated driving systems (ADS), collision avoidance is a core safety function that operates alongside perception and planning modules to prevent or mitigate imminent crashes. These systems are responsible for detecting hazards, assessing collision risks, and executing evasive maneuvers—such as braking or steering—without human intervention (Ahangarnejad et al., 2020).

The fundamental architecture of automated collision avoidance includes environment sensing, threat assessment, and automated control execution. Advanced collision avoidance in ADS typically integrates vehicle-to-infrastructure (V2I) interactions, vehicle-to-vehicle (V2V) interactions, automated lane keeping, and automated lane changes. These functions can operate at high speeds and without driver input. ADS platforms rely on sensor fusion (e.g., radar, LiDAR, and vision systems) to identify surrounding objects and their trajectories. Once a collision risk is detected, the system generates control actions using real-time vehicle dynamics models and motion-planning algorithms (Ahangarnejad et al., 2020).

Lane-keeping systems are a fundamental component of collision avoidance in ADS. These systems rely on accurate lane detection to maintain the vehicle's lateral position within the driving lane and to perform corrective steering when necessary. Zhaoxue and Pengfei (2004) emphasized that vision-based lane detection must be capable of recognizing various types of lane markings across different road conditions. McCall and Trivedi (2004) further highlighted that lane-detection systems must provide reliable estimates of vehicle position relative to the lane center to ensure consistent lateral control.

The initial development of these systems can be attributed to Bertozzi et al. (2000), who performed a vision-based lane-keeping function on a test platform at the University of Parma. Subsequent studies, including those by Netto et al. (2004) and Liu et al. (2007), focused on lateral control performance by incorporating road curvature and wind disturbances into the vision-based assessment methodology. Wu et al. (2005) introduced a steering automation system based on lane detection, which was validated through motor vehicle testing.

The major issue with vision-based systems is sensor degradation, especially in inclement weather, when visual input can be obstructed or lost. Son et al. (2015) proposed using a multirate Kalman filter to reduce delays in vision-based lane detection. Further lane-keeping performance developments have focused on predictive control frameworks under uncertainty and varying external influences. Liu et al. (2015) proposed a model predictive control strategy that incorporates driver behavior as a Gaussian disturbance, modeled within a linear time-varying human–vehicle system.

Despite these control advancements, most lane-keeping systems remain highly dependent on reliable vision-based sensing, which can degrade significantly in low-visibility or adverse weather scenarios. These limitations present a barrier to reliable collision avoidance in autonomous vehicles.

FACTORS CONTRIBUTING TO AUTONOMOUS VEHICLE CRASHES

As ADS advance, understanding the potential failure points in autonomous vehicle (AV) operations becomes increasingly important. Although AVs are expected to reduce crash rates by eliminating human driver error, recent research suggests that simply removing human involvement does not guarantee crash-free performance. A comprehensive study by Mueller et al. (2020) analyzed the causes of driver-related crashes using data from the National Motor Vehicle Crash Causation Survey and identified five main categories of contributing behaviors, as shown in Table 1: (1) sensing/perceiving—failures to detect or notice critical roadway information; (2) predicting—errors in anticipating the actions or movements of other road users; (3) planning/deciding—poor judgment in choosing safe or lawful driving strategies; (4) execution/performance—ineffective or incorrect control of the vehicle; and (5) incapacitation—driver impairment due to alcohol, drugs, fatigue, or medical conditions. Table 2 presents a derived analysis estimating the proportion of crashes that would remain if errors related to sensing/perceiving and incapacitation were eliminated through automation. The findings indicate that about two-thirds of crashes are associated with complex behavioral factors—specifically planning/deciding (41%), execution/performance (23%), and predicting (17%). Within the planning/deciding category, key contributors include speeding (23%) and illegal maneuvers (15%), highlighting the need for AVs to consistently make safe and lawful decisions

in dynamic traffic environments. In contrast, one-third of crashes involved only sensing/perceiving (23%) or incapacitation (10%), both of which AVs are expected to manage more effectively. These anticipated achievements assume robust and reliable perception systems capable of operating across diverse conditions, including adverse weather, low visibility, and pavement surface wear. Because sensor performance can degrade significantly in such scenarios, the actual crash reduction achieved by AVs may fall short of this reported theoretical maximum.

Table 1. Percentage of Crashes Involving Various Driver-Related Contributing Factors (Mueller et al. (2020))

Factor type (mutually inclusive)	Weighted %
Sensing and perceiving	61.8
Incapacitation	10.5
Planning and deciding	43.9
Execution and performance	26.7
Predicting	17.3
<i>Any driver-related factor</i>	<i>94.5</i>
<i>Unavoidable by driver and unknown factors</i>	<i>5.5</i>

Table 2. Derived Analysis Estimating the Proportion of Crashes That Would Remain by Driver-Factor Category if Crashes Related to Sensing/Perceiving and Incapacitation Were Eliminated by AVs (Mueller et al. (2020))

Factor type (mutually exclusive)	Weighted %
Only sensing and perceiving	22.6
Incapacitation	10.5
<i>Crashes preventable by AVs (Assuming robust and reliable perception systems)</i>	<i>33.1</i>
Planning and deciding	41.3
Execution and performance	23.2
Predicting	17.0
<i>Remaining crashes with a predicting, planning and deciding, or execution and performance factor</i>	<i>61.4</i>

IMPACT OF ADVERSE WEATHER ON ADS SENSORS

The effectiveness of ADS is critically dependent on the reliability of their onboard sensor systems, which typically comprise LiDAR, cameras, radar, and ultrasonic sensors. These sensors support key perception functions, including lane detection, obstacle identification, object tracking, and environmental modeling. However, performance can degrade substantially in low-visibility environments (Amditis et al., 2012; Aldibaja et al., 2020; Dahal & Roesler, 2021; Dahal, 2022). These environmental factors introduce sensor noise, diminish visibility, and interfere with signal returns,

thereby compromising the accuracy of perception and the overall reliability of ADS decision-making. Sensor-specific vulnerabilities under such conditions may result in missed detections, object misclassification, or localization errors, all of which present serious risks to safety and operational performance.

Chen et al. (2021) conducted a comparative evaluation of various ADS sensors, including laser sensing (LiDAR), visual sensing, millimeter-wave and microwave radar, ultrasonic sensing, and sensor-fusion systems (Figure 2). Their analysis considered ten key performance indicators, such as detection range, performance under different lighting conditions, and robustness in rain and snow. A summary of each sensor type is provided below.

- **LiDAR (Laser sensors):** LiDAR sensors are unaffected by lighting conditions, making them suitable for use in various environmental scenarios. They excel in detection range, speed, and object separation. However, their large physical size, high cost, and performance degradation in rain or snow limit their scalability for widespread vehicular deployment.
- **Camera-based (vision) sensors:** These sensors are highly sensitive to ambient light and adverse weather, performing best in clear, well-lit environments. Nevertheless, they offer high-resolution imagery, accurate color representation, and spatial detail while still being compact and cost-effective.
- **Millimeter-wave and microwave radars:** These radars are largely insensitive to lighting conditions and offer reliable detection speed, moderate range, and compact form factors. However, their limited sensing distance and susceptibility to blockage from physical obstructions, such as heavy precipitation or snow accumulation, reduce their performance in extreme weather conditions.
- **Ultrasonic sensors:** Known for their low cost and compactness, ultrasonic sensors are unaffected by lighting but have very short detection ranges, slow responsiveness, and poor performance in rain or snow. Additionally, they cannot capture visual or color-based information, limiting their utility for scene understanding.

Sensor fusion is one means of overcoming the limitations of individual sensing modalities. ADS platforms that integrate data from multiple sensors can improve perception accuracy, environmental robustness, and redundancy (Chen et al., 2021).

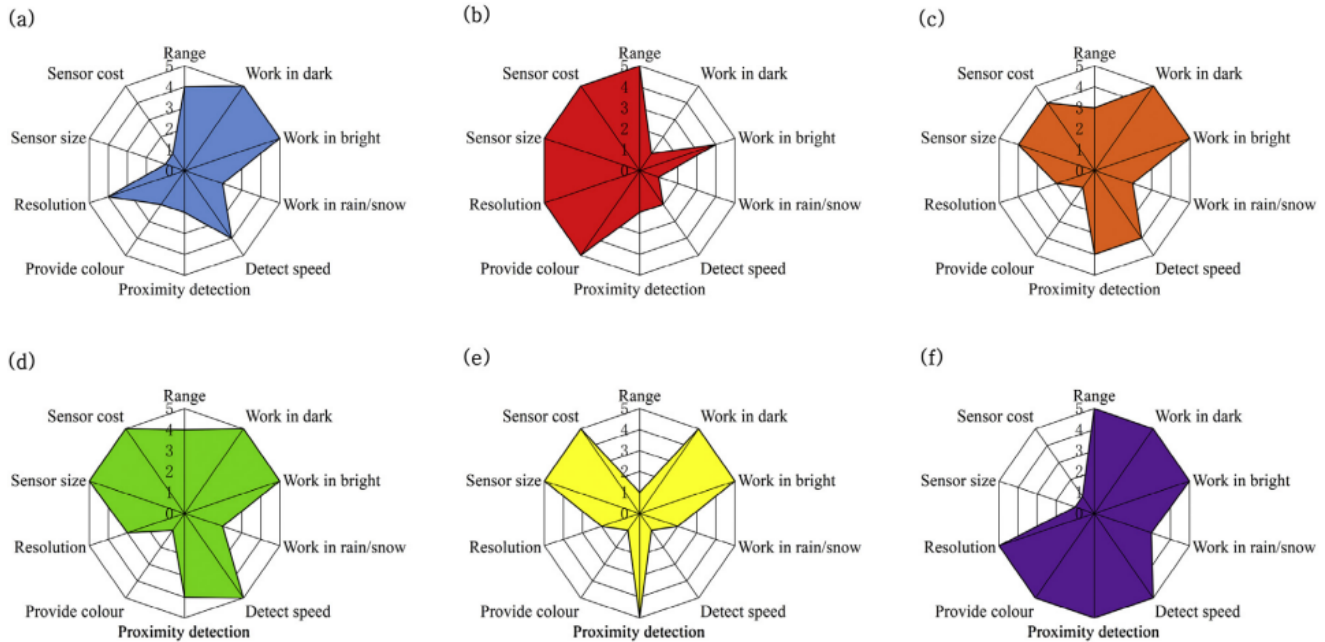


Figure 2. Chart. Comparison of sensing performance: (a) laser sensing, (b) visual sensing, (c) millimeter-wave radar sensing, (d) microwave radar sensing, (e) ultrasonic sensing, and (f) fusion sensing.

Source: Chen, Q., Xie, Y., Guo, S., Bai, J., and Shu, Q. (2021).

PAVEMENT-ENCODED SIGNAGES FOR ASSISTING DRIVING AUTOMATION

With the growing demand for robust and weather-resilient perception systems in ADS, infrastructure-based solutions are gaining attention as viable complements to traditional onboard sensors. Among these, pavement-encoded signages represent a novel approach to passive V2I communication, providing lateral positioning cues directly from the road surface. Unlike vision-based or active sensor methods, this system is infrastructure driven, weather tolerant, and passive, requiring no powered transmission from the pavement. The following subsections outline the underlying concept and system architecture of pavement-encoded signages, followed by a discussion of their key features relevant to automated driving applications.

Concept of Pavement-Encoded Signages

Pavement-encoded signages refer to magnetically altered regions embedded within or encoded on the pavement surface in specific patterns or sequences. Initially, this concept was introduced to overcome the limitations of vision-based systems under low visibility, when lane markings may be obscured by snow, fog, or poor lighting. These signages locally modify the ambient electromagnetic (EM) field, enabling passive detection by vehicles equipped with fluxgate magnetometer sensor arrays. As the vehicle traverses the roadway, the sensor array captures changes in magnetic flux density, which are then interpreted to determine the vehicle's lateral position relative to the EM-encoded pathway.

In contrast to active radio-frequency or vision-based localization methods, this technique enables fully passive perception: the vehicle senses the infrastructure without requiring any electronic emissions from the pavement. This design makes the system inherently resilient to weather, immune to lighting conditions, and compatible with temporary deployments in construction zones or detours.

Potential Features of Pavement-Encoded Signages

Pavement-encoded signages are designed not only for passive lateral positioning but also to enable a wide range of advanced vehicle –infrastructure interactions critical for driving automation. By encoding specific patterns, spatial sequences, and signal intensities into the pavement surface, these signages can convey actionable information to ADS without relying on visual cues or electronic transmission. Key potential features include:

- **High-precision lateral positioning:** Through magnetic field variations detected by onboard magnetometers, the system enables accurate vehicle localization relative to the lane centerline.
- **Speed warning and automated speed limit control:** Encoded magnetic sequences can communicate roadway speed limits to ADS platforms. This enables in-vehicle speed warnings or real-time vehicle speed regulation, supporting both driver-assistance and fully autonomous functionalities.
- **Temporary lane merge control:** In work zones or areas with revised traffic patterns, magnetic patterns can inform ADS-equipped vehicles of upcoming lane closures or merges, allowing safe, timely lane-change maneuvers without reliance on visible signage or cones.
- **Automated control through construction zones:** Pavement-encoded signages can serve as a navigational layer for ADS in temporary or dynamic work zone environments, guiding path following and speed adaptation where traditional markings are removed or unclear.
- **Support at unsignalized intersections:** Magnetic encoding can alert ADS-equipped vehicles to approaching unsignalized intersections and suggest right-of-way rules, improving vehicle decision-making where visual signage is unavailable, blocked, or ambiguous—particularly in rural areas.
- **Passive V2I communication via pattern recognition:** By varying the spatial layout and intensity of magnetic signatures, the system can encode identifiers analogous to road signs (e.g., STOP, YIELD), allowing vehicles to interpret roadway rules passively and autonomously. This supports infrastructure-based interpretation of traffic control, independent of visual signage.
- **Redundancy to vision-based systems:** In degraded sensing environments (such as heavy rain, snow, fog, or pavement glare), pavement-encoded signages provide a robust backup perception system, increasing the reliability of decision-making and path planning in ADS.
- **Support for permanent and temporary applications:** The magnetic materials can be embedded during road construction or retrofitted on existing pavements, making the system scalable for

permanent infrastructure or temporary deployments, such as detours or short-term lane shifts.

Collectively, these features make pavement-encoded signages a versatile, infrastructure-based tool for enhancing the perception and control capabilities of ADS. They provide a passive, reliable, and weather-resilient channel for lane positioning, roadway regulation, and dynamic maneuvering, especially in scenarios where conventional sensors may be impaired.

CHAPTER 3: FIELD EXPERIMENTAL PLAN FOR VEHICLE TESTING OF PAVEMENT-ENCODED SIGNAGES

TEST LAYOUT AND SCHEMATICS

The goal of the field experiments was to carry out larger-scale deployment of the vehicle-passive pavement sensors at higher speeds and under variable weather conditions. The experimental plan was designed to build on the findings of the 2024 experiments with a human-directed movable cart in a controlled parking lot area. The new test setup was deployed at the Illinois Center for Transportation (ICT) test facility, with the objective of validating the feasibility of pavement-encoded signages for high-speed ADS operations at vehicle speeds ranging from 20 mph up to approximately 55 mph.

Diagram of Test Scenarios

Pilot experiment. As shown in Figure 3, the experimental layout consists of two vehicle trajectories (between yellow and white longitudinal markers) designed to evaluate a variety of pavement-encoded signage scenarios at higher speed and various weather conditions. The first test lane is a 350 ft tangent section, while the second 350 ft test lane has both a tangent part and lane-shift maneuver. The EM strips shown in Figure 3 were constructed with a mixture of epoxy containing 20% chromium dioxide (CrO_2) by weight that was then coated on the pavement surface as black pavement markers. The test lanes can be broken down into the following four functional zones that simulate roadway situations relevant to driving automation:

- Construction work zone (CWZ) segment: 8 ft wide by 6 in. transverse EM strips that are spaced at 20 ft intervals that communicate information about a CWZ, such as lane merge, vehicle speed warning, and end of CWZ.
- Lateral positioning segment: 3 ft long by 6 in. wide EM strips spaced at 20 ft intervals for assessing the vehicle's lateral positioning accuracy.
- Unsignalized intersection segment: 4 ft wide by 6 in. EM strips applied at variable spacing of 20 ft, 10 ft, and 5 ft to communicate and simulate intersection approaches under limited visibility or with an automated vehicle.
- Lane merge and shift CWZ segment: A combination of 8 ft and 3 ft by 6 in. EM strips placed along a lane merge warning area and shifted lane path to replicate temporary lane realignments in active construction zones.

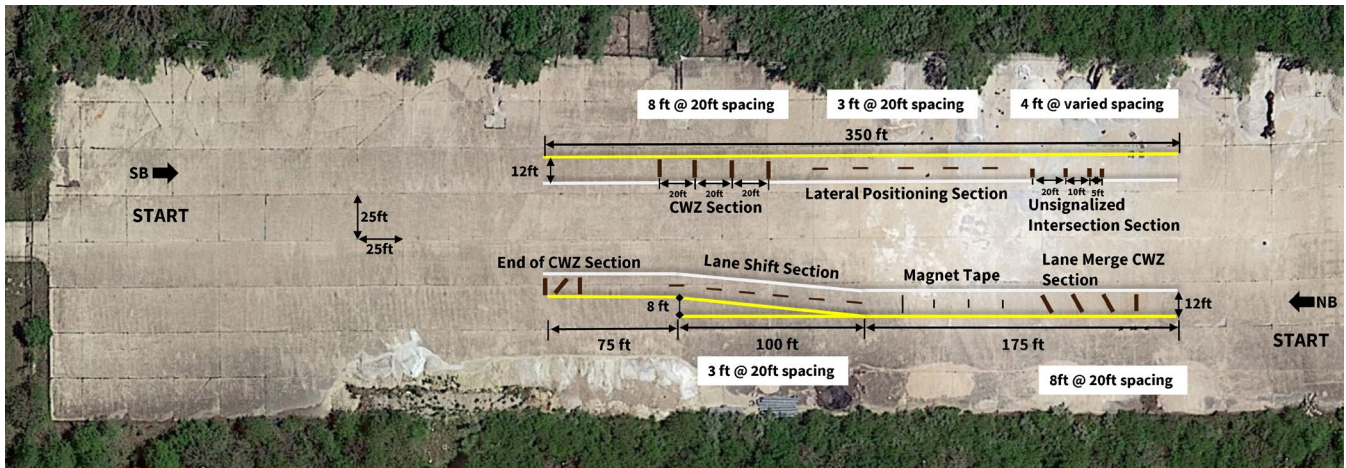


Figure 3. Diagram. Layout of EM pavement signages for northbound and southbound higher-speed experiments at the Illinois Center for Transportation closed-area test facility. The southbound and northbound sections are located in the east and west parts of the closed apron area, respectively.

Rural road driving experiment. To further validate the pavement passive sensing system for high-precision lateral positioning of ADS, a second full-scale experiment was conducted, as illustrated in Figure 4, primarily to evaluate ADS on a horizontal curve. This test evaluated the performance of pavement-encoded signages in supporting both lateral positioning control and approach speed regulation during horizontal curve maneuvering. The experiment was divided into two sequential sections:

- Preparation for horizontal curve segment
- Horizontal curve maneuvering segment

The 560 ft long test section was established along the westbound lane of Titan Drive in Rantoul, Illinois, adjacent to the ICT facility. To maintain consistent lateral positioning, all pavement-encoded electromagnetic (EM) signages were installed longitudinally along the lane centerline, approximately one-quarter of the total roadway width from the right pavement edge. This placement ensured that the ADS-equipped vehicle could reliably detect the EM signature while maintaining alignment throughout the test sequence. Initially, the ADS-equipped vehicle accelerated to a target speed of 20 mph before entering the first segment approaching the horizontal curve. In this zone, the strip spacing was set to 20 ft to illustrate the maximum suggested approaching speed of 20 mph. Then, in the horizontal curve maneuvering section, the EM strip spacing was shortened to 15 ft, corresponding to a speed of 15 mph during horizontal curve maneuvering. This change in strip spacing enabled the vehicle to adjust its speed in anticipation of the horizontal curve while monitoring lateral alignment.



Figure 4. Diagram. Horizontal curve test section (560 ft) on Titan Drive (westbound), Rantoul, Illinois.

Test Plan and Vehicle Trajectories

Table 3 summarizes the test cases conducted across closed concrete test pads and a rural roadway segment as part of the field experiments. A total of 21 test cases were executed, encompassing both pilot- and full-scale evaluations. Test Cases 1 and 2 were performed on concrete pavement at the closed-area test facility to assess system performance under high-speed and complex motion conditions. Specifically, Test Case 1 was designated as a critical speed pilot test, representing the maximum achievable velocity (> 50 mph) within the spatial constraints of the closed test area. Test Case 2 involved wandering motion above 25 mph to simulate critical lateral offset detection scenarios. Test Cases 3–5 and 6–8 focused on evaluating optimal signal-filtering parameters under low-speed (< 35 mph) and high-speed (> 35 mph) straight-line motion, respectively, along the southbound segment shown in Figure 3. These evaluations were mirrored in the northbound direction in Test Cases 9–11 and 12–14. Test Cases 15–16 conducted for evaluating the system performance under adverse conditions in controlled area. The final phase of testing assessed the detectability, repeatability, and overall system performance of pavement-encoded signages in realistic roadway conditions and geometries. Test Cases 17–20—were conducted on Titan Drive, a rural flexible-pavement segment shown in Figure 4, where the vehicle navigated a horizontal curve at speeds exceeding 15 mph. Test Case 21 focused on the system’s navigation performance on a horizontal curve under adverse conditions.

Table 3. Test Cases for Field Experiments in Closed Area and Rural Road Segments

Test Case	Location	Approaching Speed (mph)	Vehicle Direction	Motion	Pavement Type	Remarks
1	Concrete pads (closed area)	> 50	SB	Straight	Rigid pavement	Critical speed pilot-test
2	Concrete pads (closed area)	>25	SB	Wandering	Rigid pavement	Complex motion pilot-test
3–5	Concrete pads (closed area)	<35	SB	Straight	Rigid pavement	Low-speed pilot test for evaluating optimal filtering frequency
6–8	Concrete pads (closed area)	>35	SB	Straight	Rigid pavement	High-speed pilot test for evaluating optimal filtering frequency
9–11	Concrete pads (closed area)	<35	NB	Straight/Lane Shift	Rigid pavement	Low-speed pilot test for evaluating optimal filtering frequency
12–14	Concrete pads (closed area)	>35	NB	Straight/Lane Shift	Rigid pavement	High-speed pilot test for evaluating optimal filtering frequency
15	Concrete pads (closed area)	<35	SB	Straight	Rigid pavement	Low-speed pilot test for evaluating optimal filtering frequency under adverse weather condition

Test Case	Location	Approaching Speed (mph)	Vehicle Direction	Motion	Pavement Type	Remarks
16	Concrete pads (closed area)	<35	NB	Straight/Lane Shift	Rigid pavement	Low-speed pilot test for evaluating optimal filtering frequency under adverse weather condition
17–20	Titan Drive	>15	WB	Horizontal Curve	Flexible pavement	Evaluating EM signal detection while maneuvering through horizontal curve
21	Titan Drive	>15	WB	Horizontal Curve	Flexible pavement	Evaluating EM signal detection while maneuvering through horizontal curve covered with snow

Sensor Array Placement and Vehicle Mounting Configurations

To evaluate the magnetic field signatures generated by the pavement-encoded signages, a high-resolution sensor array was mounted at the rear bumper of the test vehicle, as shown in Figures 5–9. The array consisted of 15 single-axis fluxgate magnetometers (Stefan Mayer FLC100), each oriented to detect the vertical component of magnetic flux density, which was previously identified as the most responsive axis to pavement-induced electromagnetic signals.

The lower row comprised 12 sensors, spaced at 3 in. horizontal intervals (center to center), providing high spatial resolution for precise lateral positioning detection. An upper row of three sensors was mounted 6 in. above the lower array, spaced 12 in. apart, and configured in a gradiometer setup to assist with background-noise correction. These top-row sensors continuously monitored the ambient electromagnetic environment, such as Earth's magnetic field, interference from nearby ferromagnetic structures, and localized ferromagnetic signatures, to assist in removing background noise. See Chapter 4.

Magnetometers with a 1,000 Hz sampling rate and $\pm 100 \mu\text{T}$ measuring range provide sufficient spatial and intensity resolution to detect magnetic field strength variations at highway speeds. Compared with the three-axis array employed in previous studies, the single-axis array allowed denser lateral sensor coverage, lowered onboard vehicle computational demand, and simplified data processing while preserving precise magnetic signature detection and lane tracking.

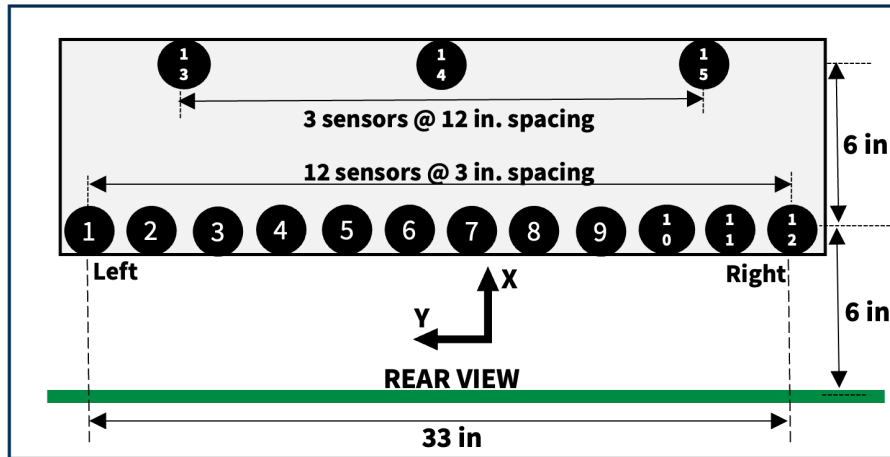


Figure 5. Diagram. Test vehicle magnetometer sensor array setup oriented as a gradiometer.

Vehicle Sensor Suite and Design

This study used an automated vehicle (Figure 6) equipped with a drive-by-wire system to easily implement changes to the autonomous driving algorithms. Figures 7 and 8 present the sensing and computing equipment installed on the vehicle. Specifically, the vehicle was outfitted with one front-bumper radar, five cameras, three LiDAR units, and a global navigation satellite system (GNSS) mounted on the roof. All sensors were connected to an onboard computer (Figure 8) running Ubuntu 18.04, located in the trunk and operated through the Robot Operating System (ROS). Figure 9 shows how the magnetometer sensor array was installed on the vehicle's rear bumper.



Figure 6. Photo. Autonomous test vehicle.

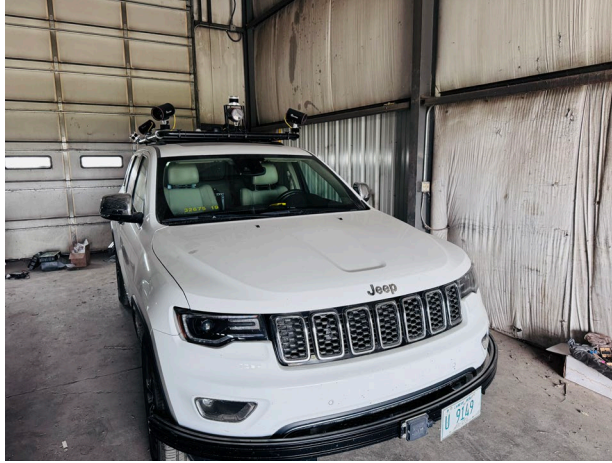


Figure 7. Photo. Sensor arrays on the vehicle.

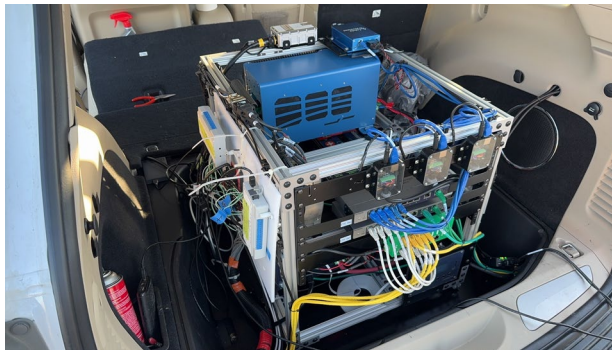


Figure 8. Photo. Vehicle computer and data acquisition system.



Figure 9. Photo. Magnetometer sensor array setup on the rear bumper of the test vehicle.

Implementation and Magnetization of Pavement Signages

The pavement encoded signage was created by applying a marking material composed of 20% CrO₂ by weight to the pavement surface. This concentration was chosen based on previous studies indicating that 20% CrO₂ generates more robust and stable EM signals compared with lower concentrations, ensuring repeatability, detection sensitivity, and reliable signal filtering, especially under high-speed testing conditions.

The markings were 6 in. wide with specified lengths of 3 ft, 4 ft, or 8 ft, depending on the test zone configuration. After the marking had been placed and cured, each strip was subjected to a magnetization process to align the CrO₂ particles and establish a stable, permanent electromagnetic signature.

As shown in Figure 10, the magnetization procedure began by heating the coated pavement surface using a 2,500 W infrared heating lamp powered by a portable electric generator. Surface temperature was monitored using an infrared laser thermometer, and external magnetization was initiated once the surface temperature exceeded 120°C. At that point, permanent magnets were positioned approximately 0.5 in. above the pavement, spaced 6 in. apart, with orientation patterns adjusted depending on whether the strip was longitudinal or transverse. The electromagnetic alignment configurations for both transverse and longitudinal orientations are illustrated in Figures 11 and 12, respectively.

After the surface cooled to below 60°C, the magnets were carefully removed to lock in the induced polarity of the CrO₂ particles. This magnetization method was uniformly applied to all field test sections. The resulting magnetic signatures exhibited sufficient intensity and clarity to enable lateral positioning detection and event-based triggering at vehicle speeds ranging from 20 to nearly 55 mph, as described in subsequent chapters.



a.



b.

Figure 10. Photo. Photo taken during magnetization process with infrared heater and permanent magnets above the marking at (a) transverse EM strip and (b) longitudinal EM strip.

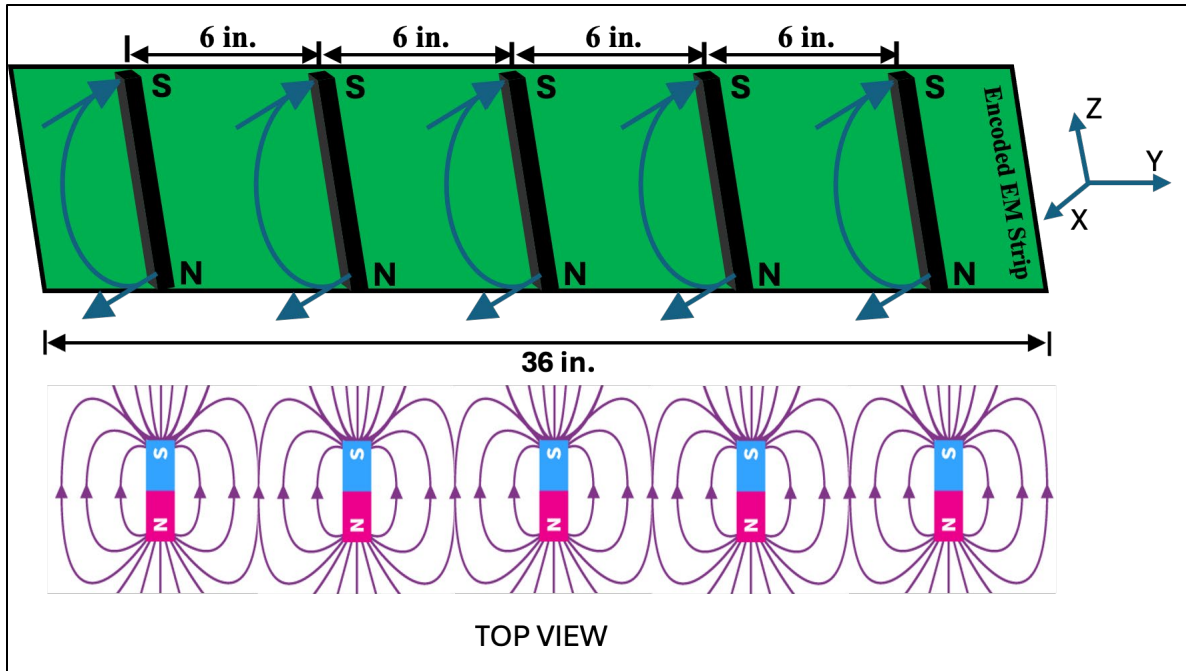


Figure 11. Diagram. Electromagnetic diagram of magnetized transverse EM strip (pattern A).

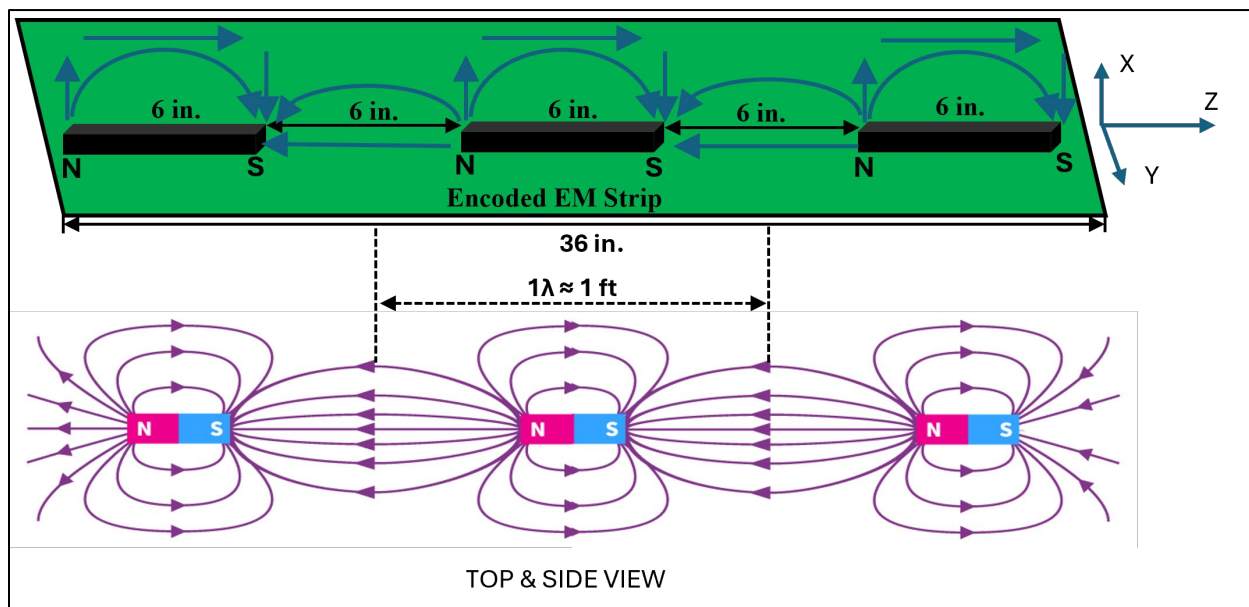


Figure 12. Diagram. Electromagnetic diagram of magnetized longitudinal EM strip (pattern B).

CHAPTER 4: SIGNAL PROCESSING AND FILTERING OF PAVEMENT-ENCODED SIGNAGE

To extract distinguishable electromagnetic (EM) flux signatures from the pavement-encoded signages, the research team implemented a robust signal processing pipeline to account for high-intensity and multi-frequency background noise. These signal interferences included contributions from the Earth's magnetic field, buried metallic infrastructure, and ambient electromagnetic fields from nearby vehicles, utilities, and the roadway environment.

Given the high sampling rate (1000 Hz) and increased vehicle speed in this study, both low-frequency drift and high-frequency EM interference were amplified in the raw data. Therefore, precise filtering procedures were necessary to isolate valid magnetic signal events from the background signals and ambient noise fluctuations.

NOISE FILTERING PROCEDURES

To accurately extract the expected EM signatures generated by pavement-encoded signages, a signal-processing framework was applied to minimize background noise and enhance signal clarity. This multistage process was designed to suppress both low-frequency drift and high-frequency environmental interference affecting the raw EM signal.

The procedure began with three critical pre-processing steps. First, each sensor's signal was zeroed by subtracting its initial value at approximately $t = 0$ seconds, effectively removing sensor and hardware bias. For sensor number $n = 1$ to 15, the magnetic fluxes ($EM_{n(i)}$) referenced to zero were calculated by subtracting the initial raw reading ($Raw_{n(0)}$) from the current raw reading ($Raw_{n(i)}$) at time index i , where i represents the discrete time index corresponding to each sampled data point from zero.

Second, to lessen low-frequency components and enhance signature contrast, the effect of low-frequency noise was reduced by taking the derivative of the processed signal to achieve the rate of change of the EM flux density between consecutive data points ($\Delta EM_{n(i)}$), emphasizing localized distinctions due to the encoded EM strips while diminishing slow-changing background noise.

Mathematically, this process was implemented by calculating the difference in processed EM flux density between the current and previous timestamps for each sensor and normalizing it by the corresponding time-step interval. In this calculation, EM_n represents the magnetic flux density measured by the n^{th} sensor, and the subscript i indicates the current timestamp. Therefore, $\Delta EM_n(i)$ represents the temporal rate of change in magnetic flux density for the n^{th} sensor at the i^{th}

timestamp ($\Delta EM_{n(i)} = \frac{dEM_{ni}}{d_i} = \frac{EM_{n(i)} - EM_{n(i-1)}}{(i) - (i-1)}$).

The resulting signal was then passed through a Butterworth bandpass filter to isolate the most responsive frequency bands. For the primary sensing channels (C1–C12, mounted in the lower row of the sensor array), the passband was defined between 25–80 Hz, while for the noise reference

channels (C13–C15, mounted in the upper row of sensor array), the band was broadened to 1–100 Hz to capture higher-variance environmental interference.

The Butterworth filter is a type of signal processing filter designed to have a frequency response that is as flat as possible within the passband (Butterworth, 1930). Mathematically, an n th-order Butterworth bandpass filter is defined by applying the standard low-pass prototype to the bandpass frequency transformation, yielding the magnitude response.

The bandpass Butterworth magnitude response is calculated by first evaluating how far the input angular frequency is from the filter's center frequency ($\omega_0 = \sqrt{\omega_1 \omega_2}$), relative to the filter bandwidth ($B = \omega_2 - \omega_1$). This normalized frequency term is then squared and raised according to the filter order (n). The magnitude response is obtained by adding this order-dependent term to one and taking its reciprocal. As a result, frequencies near the center of the passband produce a response close to one, while frequencies farther from the passband are increasingly attenuated depending on the filter order ($|H_{BP}(j\omega)|^2 = \frac{1}{1 + [\frac{\omega^2 - \omega_0^2}{B\omega}]^{2n}}$)

This filter characteristic, shown in **Figure 13**, helps preserve the true shape of the electromagnetic signal without introducing ripple distortion, i.e., small oscillations in amplitude within the passband that can distort the intended signal. It is commonly used to separate one band of frequencies from another and is effective in both analog and digital implementations (Smith, 2007). This filter type provides rapid roll-off while keeping the passband flat, making it particularly suited for high-speed detection scenarios where signal integrity is critical.

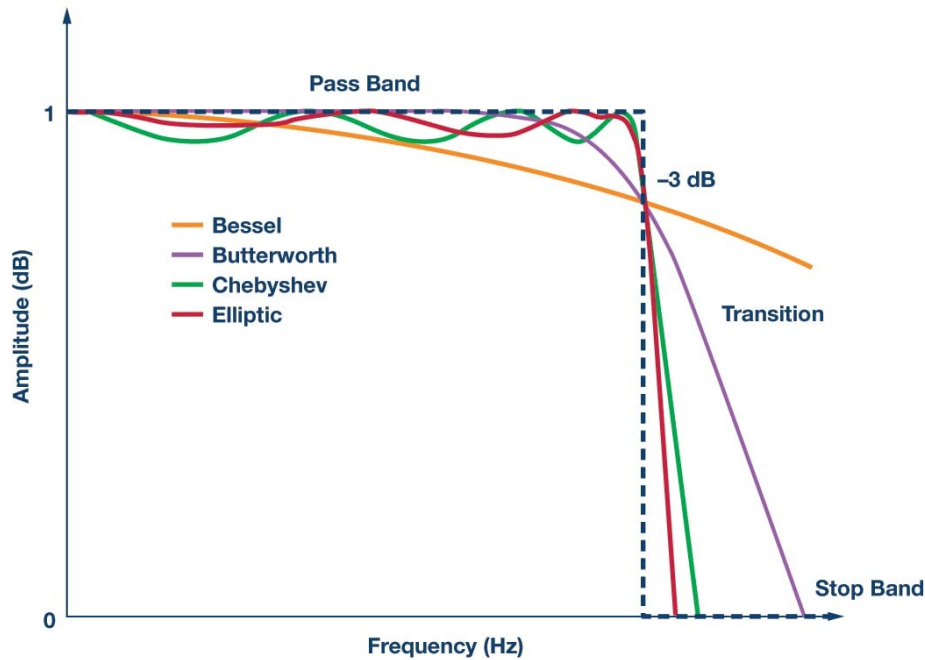


Figure 13. Chart. Ideal filter (dashed line) vs. candidate filters amplitude response.

Source: Xie (2016)

Following the filtering step, interference perception and event detection procedures, described in the next section, were performed. The top row of sensors (C13–C15) was retained not for direct subtraction from the lower sensor array but for independent monitoring of ambient electromagnetic disturbances. Their outputs were used as check to flag and exclude any peaks on the main sensor array that coincided with high-intensity background noise, ensuring that only true signage-induced events were retained for analysis.

IDENTIFYING AND FILTERING HIGH-INTENSITY BACKGROUND EM INTERFERENCE

Given the relatively small amplitude changes in the magnetic flux caused by pavement-encoded signages, typically in the nanotesla (nT) range, compared with the ambient electromagnetic disturbances, it was essential to distinguish actual signage-induced events from high-intensity environmental interference.

In this research, three upper-row sensors (C13–C15) installed 6 in. above the primary sensor array shown in Figure 5 were used as dedicated noise reference channels. These sensors, positioned farther from the pavement surface, are less sensitive to CrO_2 -induced magnetic changes, but remain responsive to larger ambient electromagnetic interference such as other metallic materials embedded in the pavement, roadside guardrails, or transitory vehicle-generated disturbances.

Rather than employing a conventional gradiometer subtraction approach, the system adopted a time-based noise-coincidence screening strategy. After filtering and amplitude thresholding, signals from the primary sensor array (C1–C12) were evaluated against those from the top-row reference channels (C13–C15). If a peak was detected in any top-row sensor within ± 50 milliseconds of a peak in the primary bottom-row sensor array, and if its amplitude exceeded a predefined threshold, the event was classified as noise-induced and excluded from further analysis.

Threshold levels were defined to balance sensitivity and robustness across speed conditions. For the top-row noise reference sensors, a uniform minimum threshold of 60 nT was applied under all conditions. For the bottom-row primary sensors, the threshold was set at 30 nT during low-speed tests and increased to 50 nT for high-speed tests. This adjustment accounted for the increased signal magnitude generated by signage detection at higher speeds, as well as the higher levels of vibration-induced EM noise that could otherwise result in false positives if the threshold remained at lower levels. The CrO_2 signage signals were only detected by bottom-row sensors, whereas the strong background interference was observed in both sensor rows. Therefore, the system filtered out high-intensity noise while preserving signage detections by using spatial and amplitude-based asymmetry. This step was crucial to improving lateral positioning and speed estimation in complex disturbance environments.

FIELD PILOT EXPERIMENTS

After the introduction of the passive pavement sensing system was presented at various venues, questions were raised regarding its performance under real-world vehicle speeds. This concern stemmed from prior experiments reported in the 2023 and 2024 CCAT reports, which primarily involved a movable cart operating at speeds below 15 mph.

To address these limitations, the first field pilot experiments conducted in 2025 were designed to validate the system's performance under higher-speed conditions. During testing, the ADS-equipped vehicle operated at speeds ranging from 20 mph to approximately 55 mph, under two motion patterns: straight-line motion and wandering motion. The wandering motion was characterized by deliberate and rapid changes in lateral position.

Two types of pavement-encoded signage segments were selected for this test evaluation, located on a single straight-line tangent as illustrated in Figure 14: construction work zone (CWZ) segments and the lateral positioning segments. The signal processing employed in this test followed the Butterworth bandpass filtering and the temporal coincidence-based screening for high-intensity EM background interference discussed earlier in the chapter.

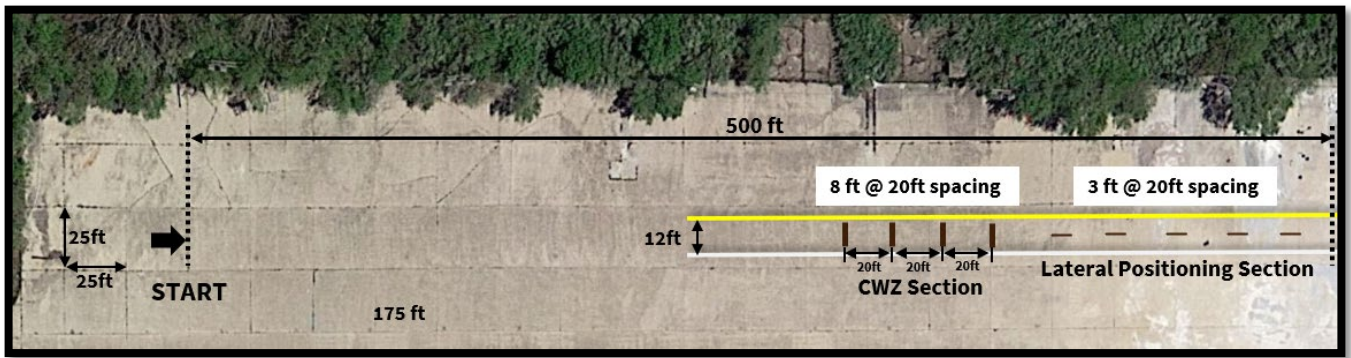


Figure 14. Diagram. Higher-speed pilot test on a straight-line tangent section.

Field Pilot Experimental Results

Case 1: High-Speed Test (Straight Motion)

Figures 15 through 21 illustrate the signal-processing steps for Case #1, in which the ADS-equipped vehicle traveled in a straight line at higher speed (> 20 mph). The raw EM flux signals, shown in Figure 15, revealed significant variation across all sensors. This variation originated from multiple sources, including the Earth's magnetic field, localized magnetic interference, and sensor-specific voltage offsets from wiring inconsistencies. To enable comparative analysis across sensors, the signals were normalized by subtracting the initial value from each sensor output, as shown in Figure 16.

Despite normalization, low-frequency drift remained visible in the data, largely due to fluctuations in the Earth's magnetic field as the vehicle moved. To address this, the first-order derivative of the EM flux signal was computed to enhance localized transitions while minimizing slow background variation. The resulting rate of signal change, $\Delta EM_n(i)$, is shown in Figure 17, with the periodic electromagnetic signatures induced by the pavement-encoded signages indicated.

Even after this transformation, both low- and high-frequency interference remained present. These artifacts were attributed to several possible sources: induction effects from buried metallic structures (e.g., dowel bars or steel conduits), vibrations from the vehicle's chassis, and rotating components

such as steel-belted radial tires. The fast Fourier transform (FFT) spectrum analysis shown in Figure 18 confirmed the dominance of interference components below 25 Hz and above 100 Hz.

Prior research has shown that vehicle tires can emit magnetic fields exceeding 2 μT at frequencies usually below 20 Hz within the vehicle cabin (Milham et al., 1999). Considering these factors, the FFT results and the physical nature of the EM signage layout, the expected signal frequency band was determined as follows:

- The minimum full EM wavelength from a pavement-encoded signage is 1 ft (see Figure 12).
- At a maximum vehicle speed of 55 mph (80 ft/s), this corresponds to a maximum signage-induced signal frequency of 80 Hz (80 ft/s divided by 1 ft).

Therefore, the Butterworth bandpass filter for the primary sensing array (C1–C12) was configured with a passband of 25–80 Hz to isolate signage-induced signals. In contrast, the top-row noise reference sensors (C13–C15) used a broader 1–100 Hz filter to capture more generalized ambient EM noise.

Figure 19 displays the ΔEM flux after bandpass filtering, with distinct peaks observed at 4.448 s, 5.553 s, 6.232 s, 8.054 s, 11.558 s, 11.805 s, 12.044 s, 12.280 s, 12.494 s, 12.741 s, 13.019 s, 13.299 s, and 13.608 s, corresponding to both localized EM disturbances and pavement-encoded signage. In Figure 20, these filtered signals are mapped spatially over the pavement-encoded signage area, clearly showing signage-induced changes in magnetic flux and successful detection of the peaks.

Finally, Table 4 presents the automated output from the signal-processing algorithm implemented using Python 3.0. The analysis confirms that the system successfully estimated both vehicle speed and lateral offset with inch-level precision, closely aligning with the ground-truth data recorded by the externally mounted GPS camera on the vehicle's rear tailgate. It is worth noting that electromagnetic sources not associated with the sensing system—including vehicle-induced noise and metallic objects embedded on or beneath the pavement—were classified as noise in Table 4, because they represent external disturbances rather than intended signage signals. In addition, a strong braking event occurred as the vehicle crossed CWZ Strip #4, resulting in a noticeable discrepancy between the back-calculated speed and the ground-truth speed. Specifically, the back-calculated speed represents the average speed between adjacent EM strips, whereas the ground-truth speed corresponds to the instantaneous speed at the moment the vehicle crosses an individual EM strip.

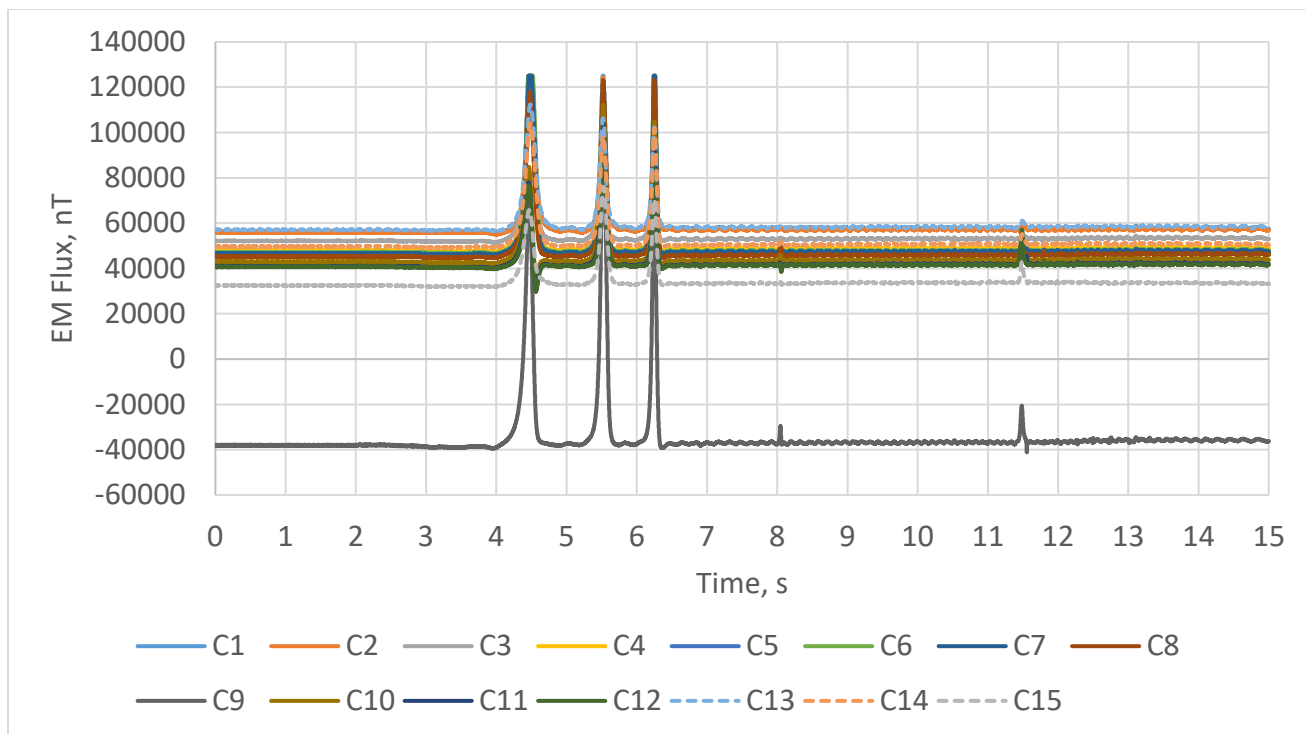


Figure 15. Chart. Raw EM flux with time for Case #1.

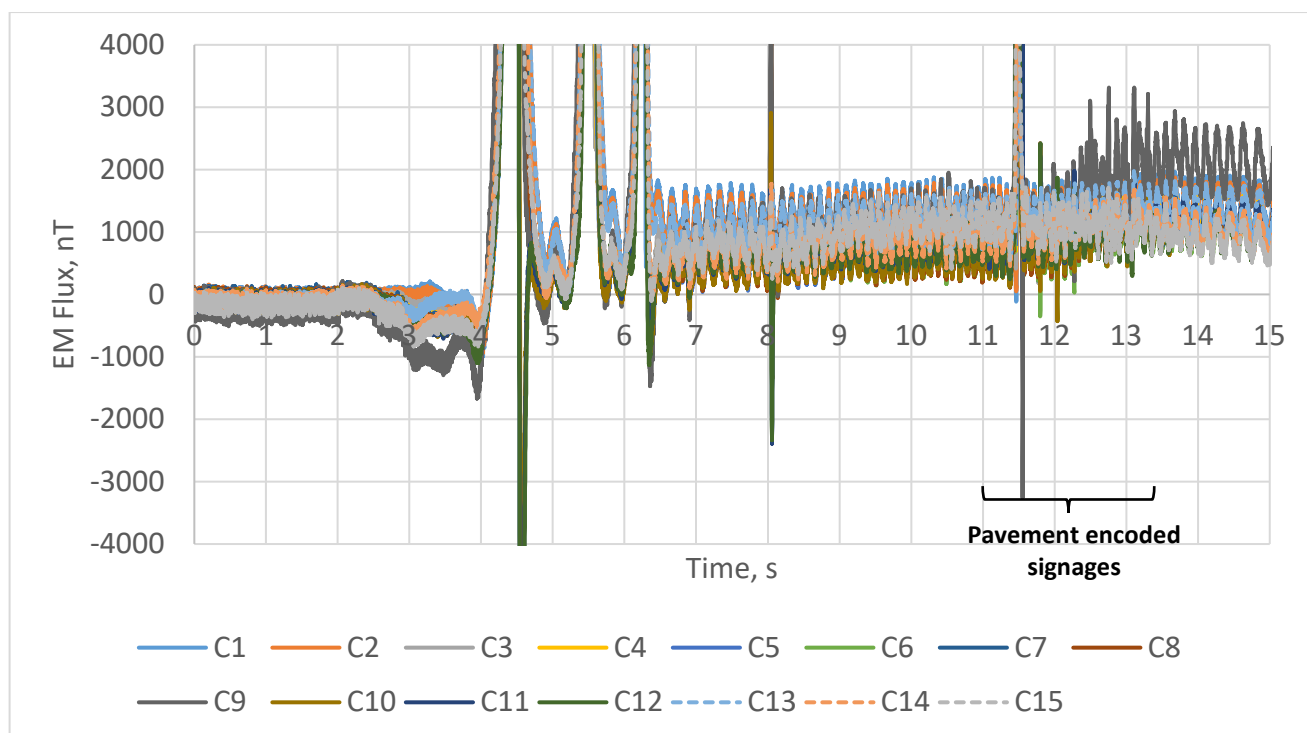


Figure 16. Chart. Referenced EM flux signal after initial reading zeroed at time zero (Case #1).

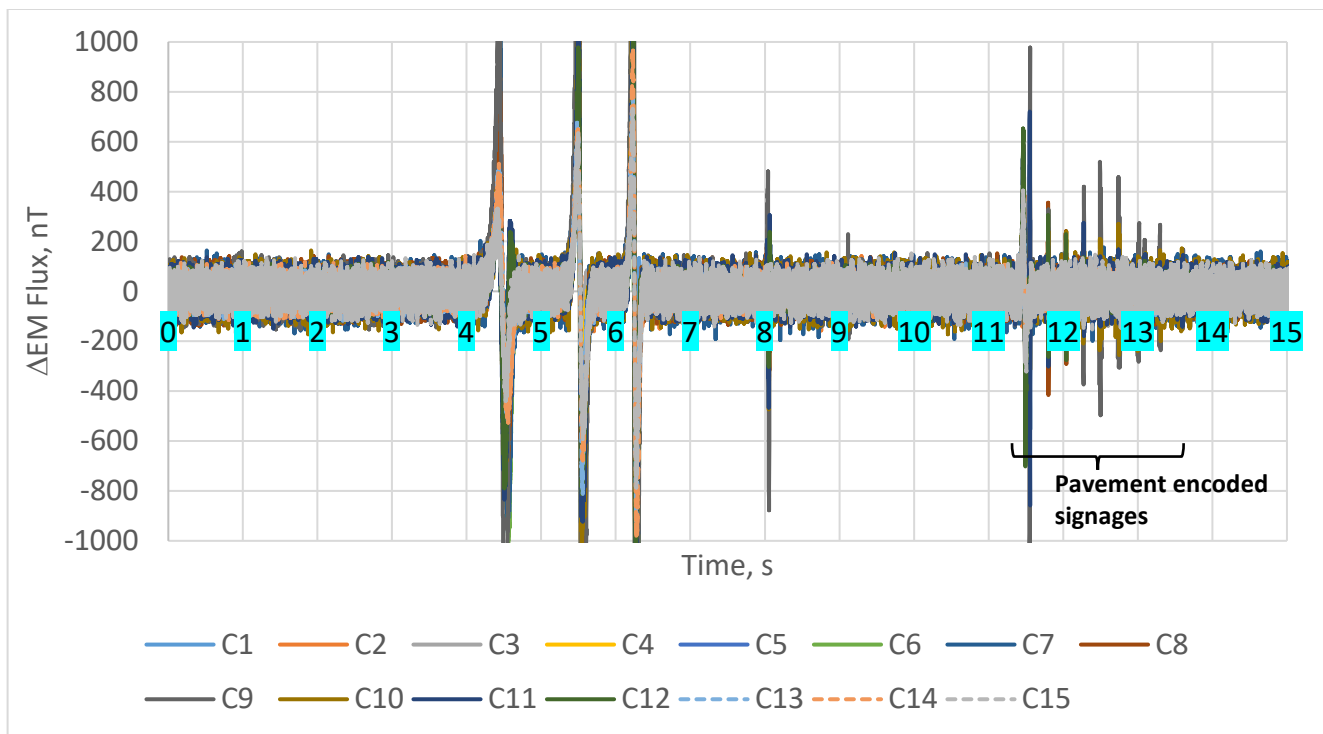
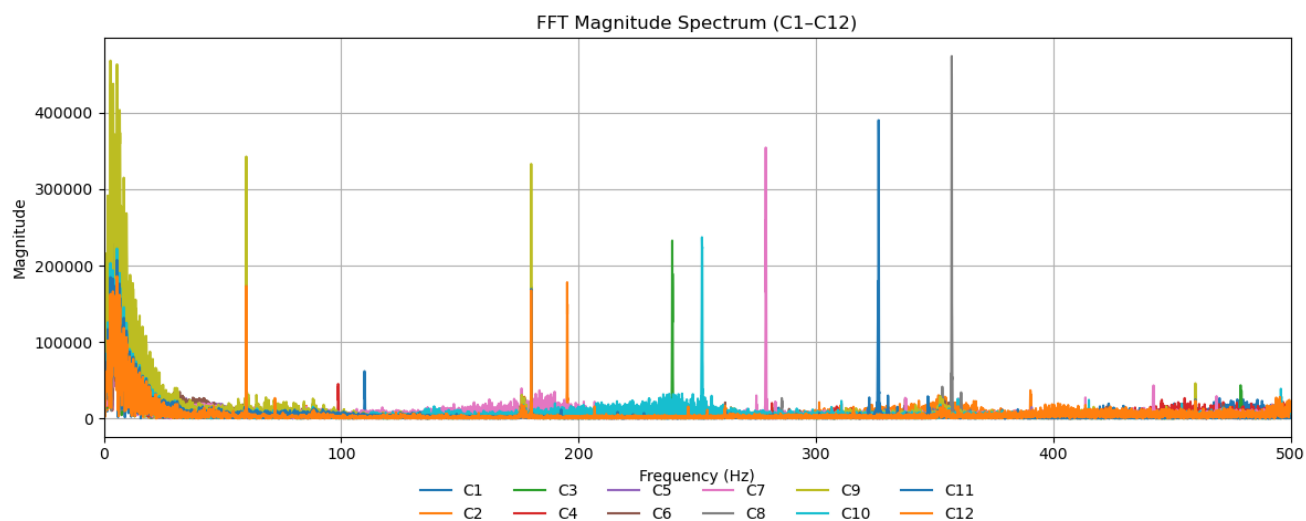
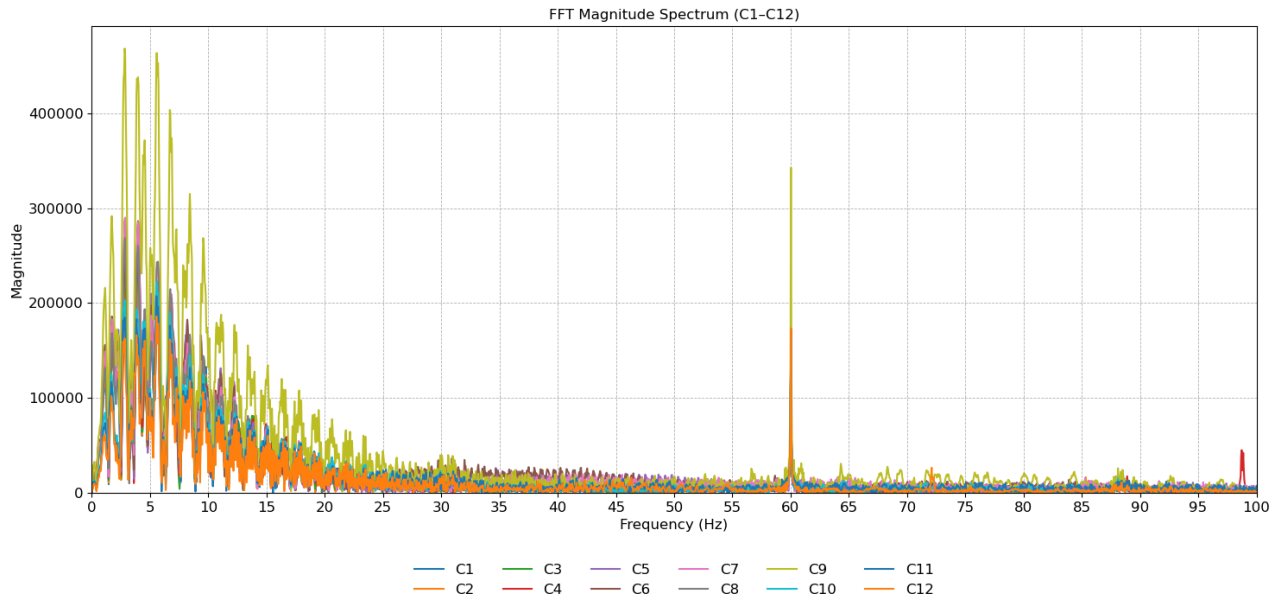


Figure 17. Chart. Δ EM flux for sensors with time (Case #1).



a. FFT of signal to identify EM magnitude spectrum (0–500 Hz).



b. EM magnitude spectrum (0 –100 Hz).

Figure 18. Chart. Frequency band spectra from 0–100 Hz (Case #1).

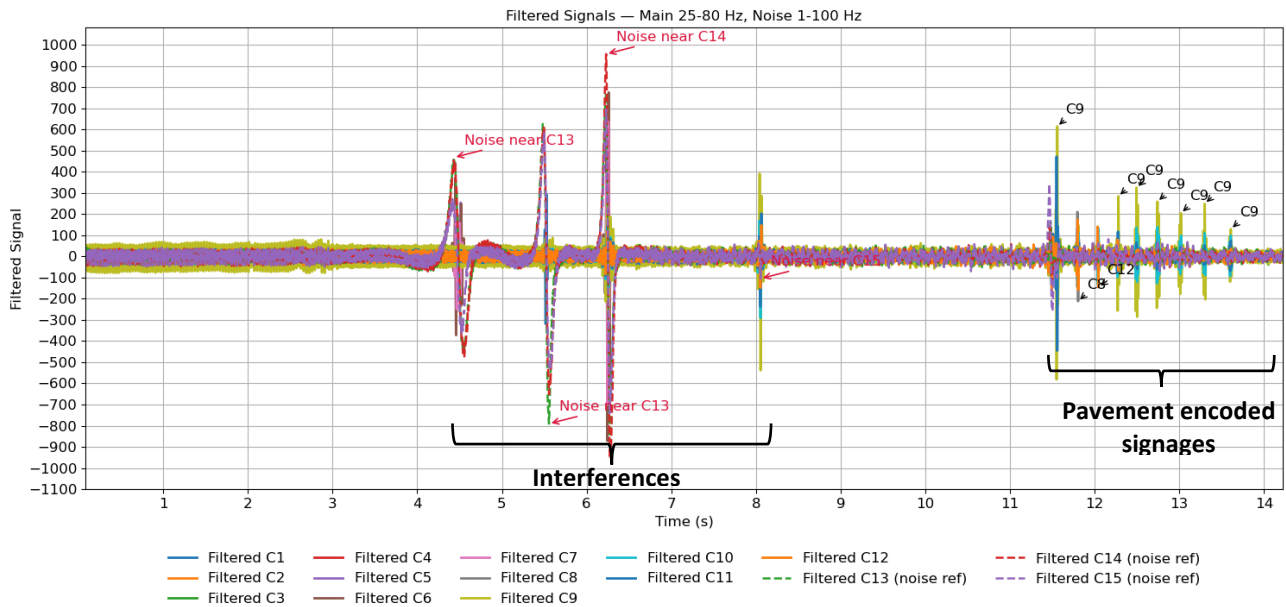


Figure 19. Chart. Δ EM flux (nT) with time (s) after applying Butterworth filter (Case #1).

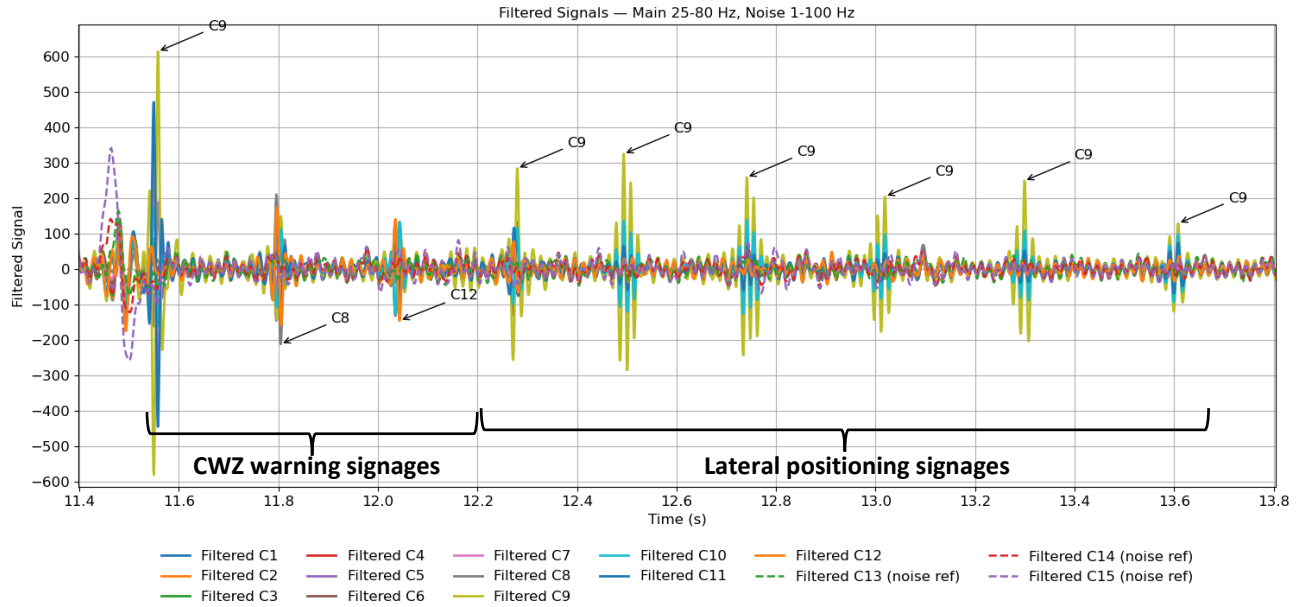


Figure 20. Chart. Δ EM flux(nT) with time (s) after Butterworth filter on CWZ and lateral positioning segments (Case #1).

Table 4. Summary of Automated Signal Analysis After Applying Butterworth Filter (Case #1)

#EM Strip	Time (s)	Peak Value Δ EM Flux (nT)	Channel	Lateral Offset (in.)	Speed (mph)	Ground Truth Offset (in.)	Ground Truth Speed (mph)
N/A	4.448	167.0	Noise (C13)	N/A	N/A	N/A	N/A
N/A	5.553	-489.0	Noise (C13)	N/A	N/A	N/A	N/A
N/A	6.232	772.0	Noise (C14)	N/A	N/A	N/A	N/A
N/A	8.054	-103.0	Noise (C15)	N/A	N/A	N/A	N/A
CWZ Strip #1	11.558	614.0	C9	N/A	N/A	N/A	55
CWZ Strip #2	11.805	-211.8	C8	N/A	55.2	N/A	55
CWZ Strip #3	12.044	-145.6	C12	N/A	57.1	N/A	55
CWZ Strip #4	12.280	284.2	C9	N/A	57.8	N/A	55
Lateral Strip #1	12.494	324.8	C9	7.5" (Left)	N/A	7.5" (Left)	53
Lateral Strip #2	12.741	258.8	C9	7.5" (Left)	55.2	7.5" (Left)	49
Lateral Strip #3	13.019	204.5	C9	7.5" (Left)	49.1	7.5" (Left)	47
Lateral Strip #4	13.299	248.8	C9	7.5" (Left)	48.7	7.5" (Left)	43
Lateral Strip #5	13.608	128.8	C9	7.5" (Left)	44.1	9.0" (Left)	38.5

Case #2: Wandering Motion Test on Mixed Pavement-Encoded Signages

For Case 2, the same test segment used in Case 1 was driven again (see Figure 14), but the vehicle moved in a purposeful wandering motion rather than in a straight-line trajectory. The raw EM flux data were processed using the same signal-conditioning sequence established in Case #1. The final filtered results are presented in Figure 21. For this test, the Butterworth bandpass filter applied to the primary sensing array (C1–C12) was configured with a passband of 20–80 Hz, optimized to isolate signage-induced magnetic flux signals. The top-row noise reference sensors (C13–C15) were again filtered using a broader 1–100 Hz band to capture a wider range of ambient EM disturbances.

As shown in Figure 21, the filtered Δ EM flux signals detected by the lower-row sensors exhibited clear peaks at timestamps 6.700 s, 17.754 s, 18.245 s, 18.749 s, 19.693 s, 20.185 s, 20.684 s, 21.203 s, and 21.698 s, corresponding to both encoded signage and localized EM interference. These events are spatially mapped in Figure 22, which highlights successful detection and localization of the pavement-encoded signage signals during the wandering vehicle trajectory.

Table 5 presents the automated output generated by the Python-based signal-processing algorithm. The results confirm that the system accurately estimated both vehicle speed and lateral position with inch-level resolution, validated against the ground-truth data recorded by the externally mounted GPS camera on the vehicle's rear tailgate.

A sequence of top-view photographic frames along the lateral positioning section, shown in Figures 23 through 27, was captured during the Case #2 vehicle test. For example, Figure 23, corresponding to the 19.693 s timestamp, confirms strong alignment between the detected peak position from the magnetometer (offset of 1.5 in. to the right of the centerline) and the position of the sensor (#6 at offset of 1.5 in. to the right of the centerline) over the signage strip in the image. Similarly, at 20.185 s, Figure 24 shows that the vehicle's centerline was directly above Sensor #9 (offset of 7.5 in. to the left of the centerline), corroborating the automated signal analysis offset of 7.5 in. to the left of the centerline. Subsequent images (Figures 25 through 27) consistently illustrate strong spatial correlation between detected magnetic peaks and vehicle position relative to the EM strip centerline. Additionally, the back-calculated vehicle speeds from the automated signal analysis showed excellent agreement with the GPS-derived speed captured by the GoPro Hero11 Black, with differences of less than 2 mph across all detected events.

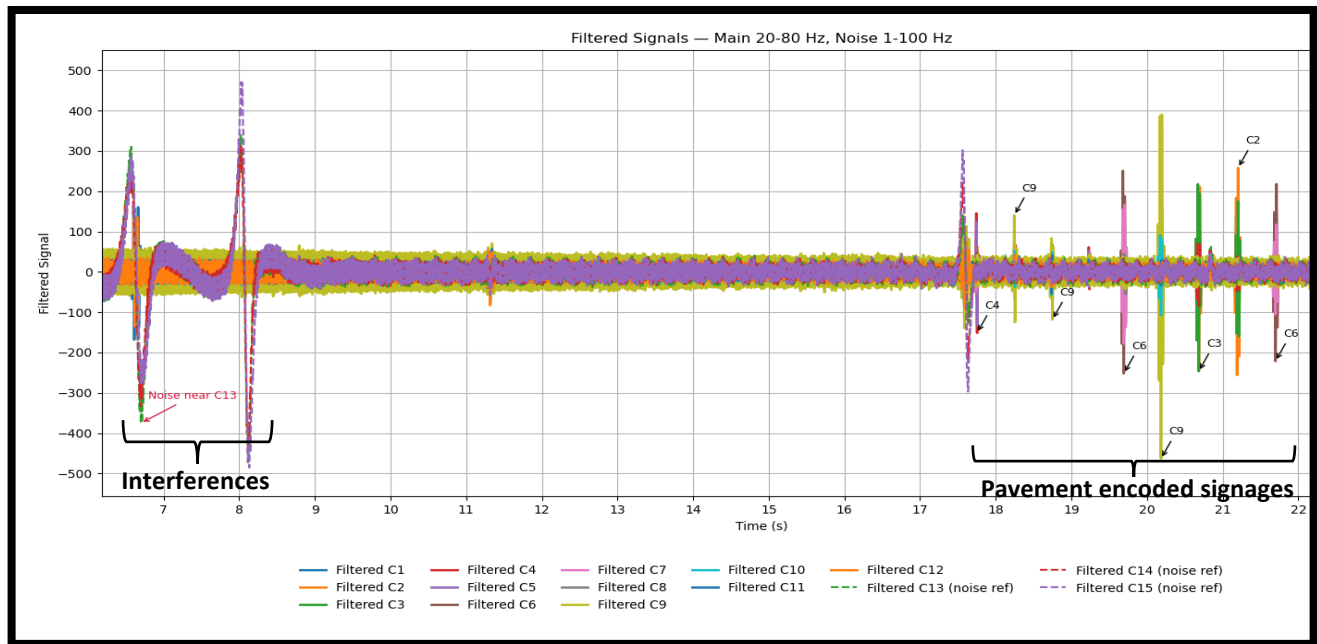


Figure 21. Chart. Filtered Δ EM flux (nT) vs time (s) (Case #2).

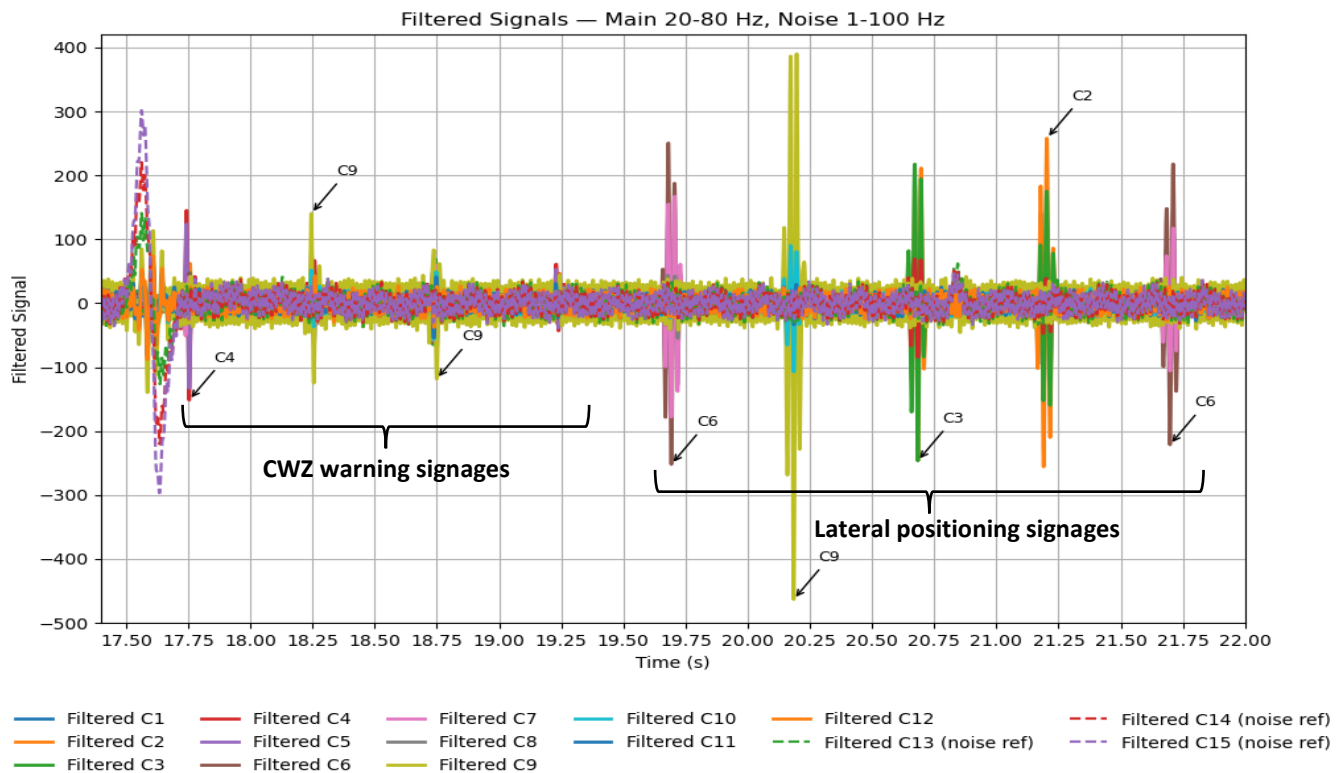


Figure 22. Chart. Filtered Δ EM flux (nT) vs time (s) on CWZ and lateral positioning segments (Case #2).

Table 5. Summary of Automated Signal Analysis with Filtering (Case #2).

#EM Strip	Time (s)	Peak Value Δ EM Flux (nT)	Channel	Lateral Offset (in.)	Speed (mph)	Ground Truth Offset (in.)	Ground Truth Speed (mph)
N/A	6.700	-375.0	Noise (C13)	N/A	N/A	N/A	N/A
CWZ Strip #1	17.754	-151.4	C4	N/A	N/A	N/A	27
CWZ Strip #2	18.245	140.4	C9	N/A	27.8	N/A	27
CWZ Strip #3	18.749	-118.5	C9	N/A	27.1	N/A	27
CWZ Strip #4	NA	NA	NA	NA	NA	N/A	27
Lateral Strip #1	19.693	-252.0	C6	1.5" Right	N/A	1.5" Right	27
Lateral Strip #2	20.185	-463.3	C9	7.5" Left	27.7	7.5" Left	27
Lateral Strip #3	20.684	-246.5	C3	10.5" Right	27.3	12" Right	27
Lateral Strip #4	21.203	258.0	C2	13.5" Right	26.3	12" Right	27
Lateral Strip #5	21.698	-221.4	C6	1.5" Right	27.6	1.5" Right	25



Figure 23. Photo. GPS-camera image when the test vehicle was over the longitudinal strip #1.

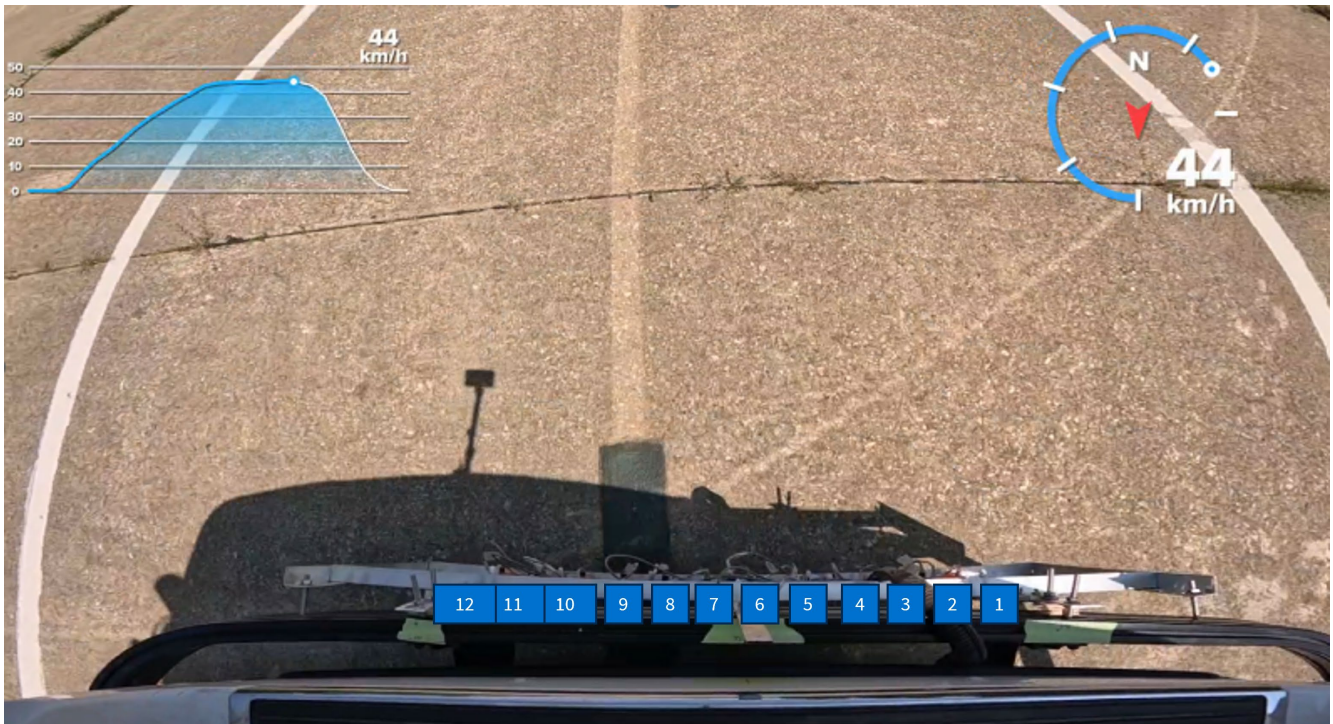


Figure 24. Photo. GPS-camera image when the test vehicle was over the longitudinal strip #2.



Figure 25. Photo. GPS-camera image when the test vehicle was over the longitudinal strip #3.



Figure 26. Photo. GPS-camera image when the test vehicle was over the longitudinal strip #4.



Figure 27. Photo. GPS-camera footage when the vehicle crosses the longitudinal strip #5.

Evaluations of Optimal Filtering Frequency Band for Broad Applications of Pavement-Encoded Signages

Effect of Vehicle Speed on the Magnetic Field Spectra

Based on the findings of Paniagua et al. (2017), the magnetic field spectra near a moving vehicle are primarily influenced by wheel rotation, with emission frequency increasing in proportion to vehicle speed. As shown in Figure 28 from their experimental study, the dominant spectral peaks were observed at approximately 8 Hz for 60 km/h (≈ 37 mph), 12 Hz for 90 km/h (≈ 56 mph), and 16 Hz for 120 km/h (≈ 75 mph), with additional harmonic peaks extending up to nearly 100 Hz. Figure 29 confirms the linear relationship between vehicle speed and emission frequency, with the slope of the harmonic trendline corresponding to the main frequency component—validating that the frequency of wheel-induced magnetic generation scaled directly with vehicle speed. Although the overall magnetic field intensity remained relatively constant across different speeds, its spectral composition shifted toward higher frequencies at increased velocities. This past finding independently confirms that vehicle-induced electromagnetic interference (EMI) is fundamentally speed dependent, supporting the need for speed-specific filtering strategies.

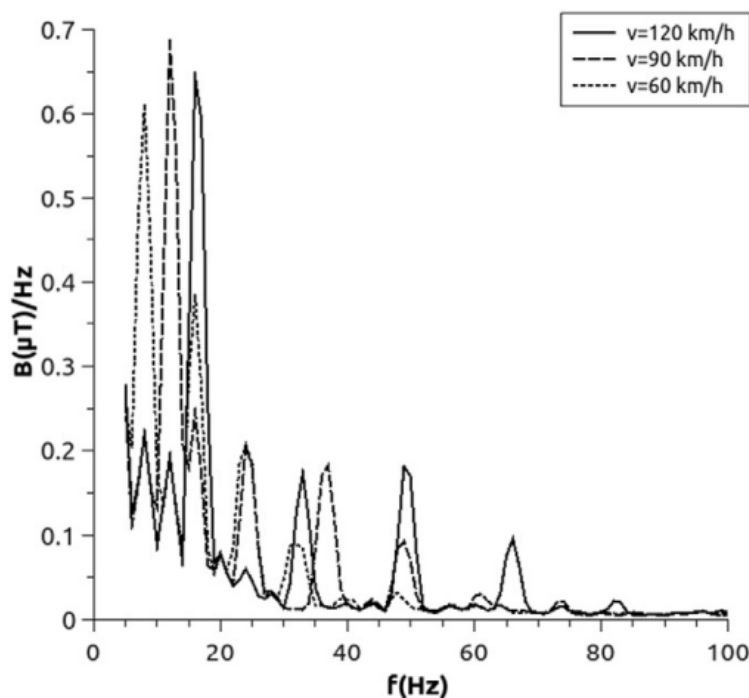


Figure 28. Chart. EMF spectra acquired on a vehicle moving at 60, 90, 120 km/h.

Source: Paniagua et al. (2017)

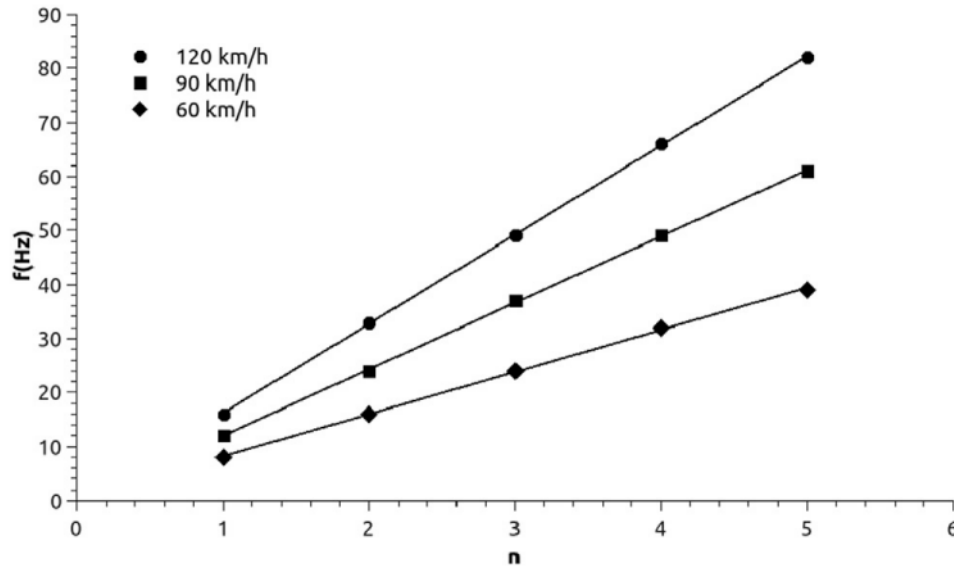


Figure 29. Chart. Relationship between EMF frequency and harmonic order for different vehicle speeds.

Source: Paniagua et al. (2017)

Analysis of Magnetic Field Spectra from Field Pilot Experiments, Cases 3–16. The additional tests investigated optimal bandpass filtering ranges tailored for low-speed (< 35 mph) and high-speed ($\geq$ 35 mph) driving conditions to ensure robust and accurate detection of pavement-encoded signage signals across diverse vehicle operations.

In the eastern test section (Figure 3) with the vehicle trajectory southbound, the pavement-encoded signages were arranged to evaluate multiple sensing functionalities. The first four EM strips were installed transversely to the direction of vehicle travel and served as an in-vehicle speed warning system, as previously described in Sakulneya and Roesler (2023). These were followed by five longitudinal EM strips placed along the centerline of the lane to support lateral offset detection and assess the vehicle's deviation from the lane center. The final four EM strips introduced progressively decreasing intervals, simulating a STOP warning pattern for an unsignalized intersection. This southbound layout in Figure 3 was tested under both low-speed (Cases 3–5) and high-speed (Cases 6–8) conditions.

In the western test section (Figure 3) with the vehicle trajectory northbound, the first group of signages replicated a lane-merge warning setup in a construction work zone (CWZ), consistent with previous work by the authors (Sakulneya & Roesler, 2024). The configuration included one transverse EM strip, followed by three EM strips inclined at a 45° angle to indicate a right-lane merge. Next, a sequence of magnetic tapes (three 6 in. by 1 in. and one 96 in. by 1 in. strip) was placed transversely across the lane to compare their signal characteristics with those of the ferromagnetic oxide pavement-encoded signages. This was followed by six longitudinal EM strips used for lane-shift guidance. At the end of the section, an end-of-CWZ signage pattern was included to denote the

transition out of the work zone. The northbound vehicle trajectory tests also included both low-speed (Cases #9–11) and high-speed (Cases #12–14) evaluations.

Adverse-weather testing was incorporated into the experimental plan to determine detection accuracy when visibility of the lane markings was compromised. Case #15 was conducted on the southbound section and Case #16 on the northbound section, with pavement surfaces partially or fully covered in water, ice, and/or snow.

To characterize the spectral content of the signals collected from all test cases, an FFT was applied to the Δ EM flux data for each scenario. Representative results from Cases 3, 6, 9, 12, 15, and 16 are shown in Figures 30 through 35, while the complete set of spectral analyses for all test cases is provided in Appendix A. The FFT analysis indicated that lower vehicle speeds (e.g., Cases 3, 9, 15, and 16) produced dominant spectral components at lower frequencies, primarily associated with wheel rotation. In contrast, higher-speed cases (e.g., Cases 6 and 12) exhibited dominant frequencies shifted upward, consistent with previous findings by Paniagua et al. (2017), who reported a positive correlation between wheel-induced magnetic emission frequency and vehicle speed.

Beyond these vehicle-speed-dependent components, two recurring interference bands were observed across all test cases. A 60 Hz peak was consistently detected, corresponding to ambient power line EMF noise. Additionally, a less-defined but persistent interference band was found in the 80–90 Hz range. This band did not vary with vehicle speed and may be attributed to structural vibrations, vehicle electrical systems, or other unknown noise sources. These interference patterns informed the design of bandpass filter settings applied during post-processing.

Based on the spectral observations, the Butterworth bandpass filter was configured with a low-frequency cutoff of 15 Hz for low-speed cases and 20 Hz for high-speed cases. The signal energy from the pavement-encoded signage was concentrated within the 15 to 55 Hz range for low-speed tests and 20 to 80 Hz for high-speed tests. Therefore, final bandpass ranges of 15 to 55 Hz and 20 to 80 Hz were selected for low- and high-speed conditions, respectively. These ranges were chosen to maximize detection of the pavement-encoded EM signatures while attenuating low-frequency signal drift because of the harmonic motion of wheel and tire rotations and high-frequency interference from on-board electronic devices.

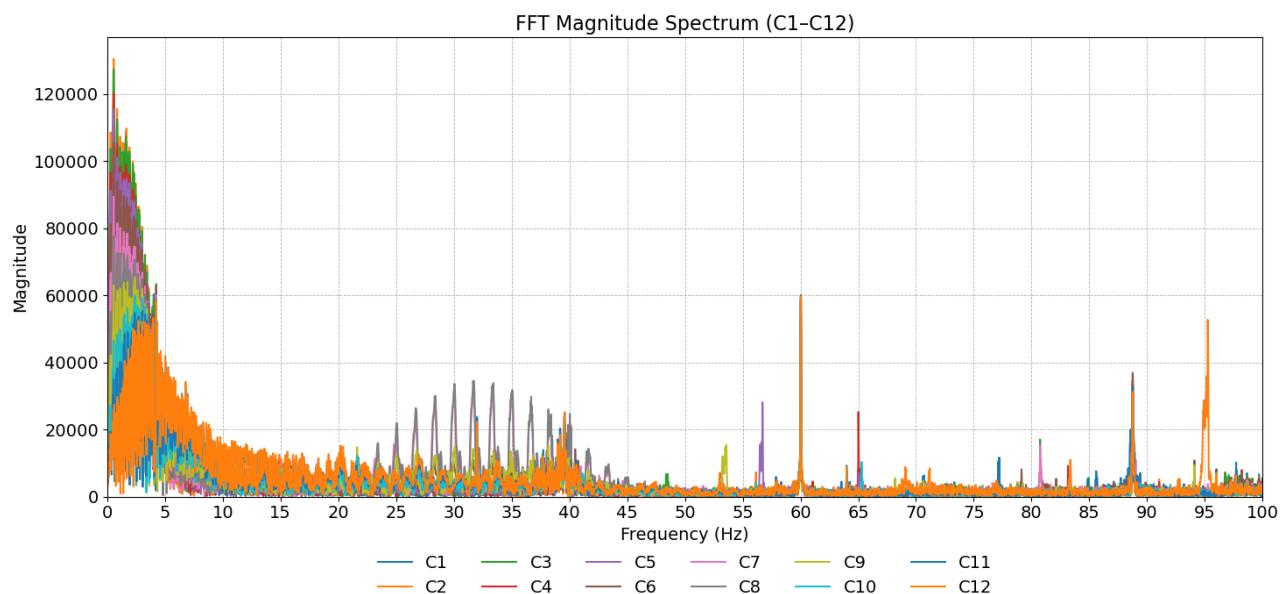


Figure 30. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed below 35 mph (Case #3).

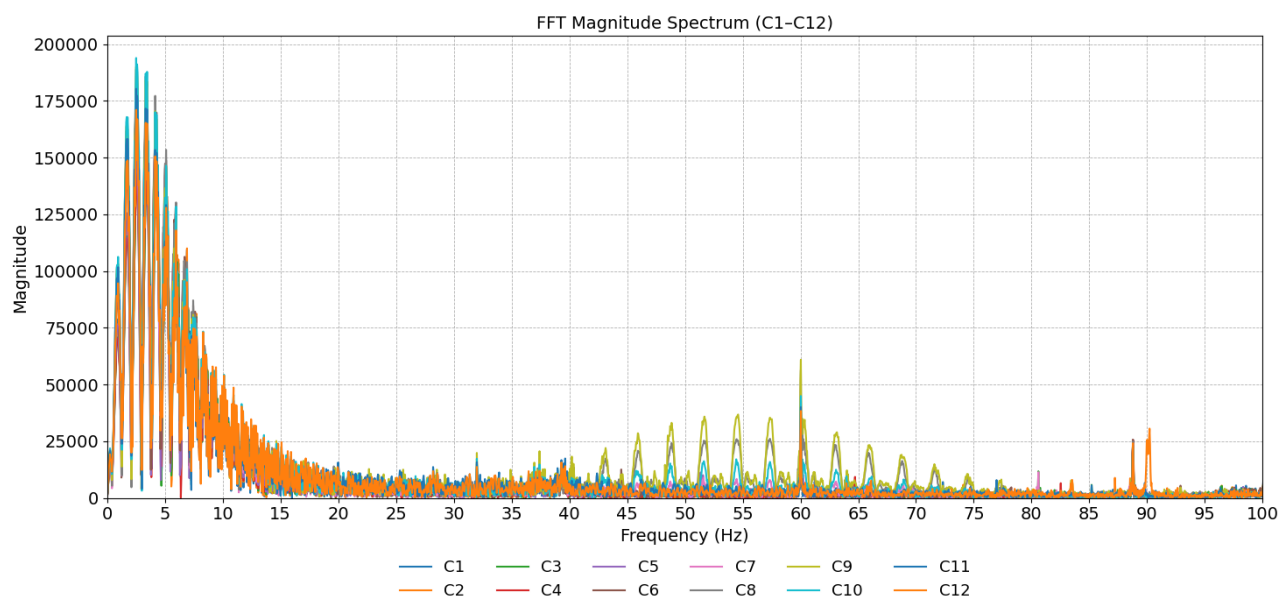


Figure 31. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed above 35 mph (Case #6).

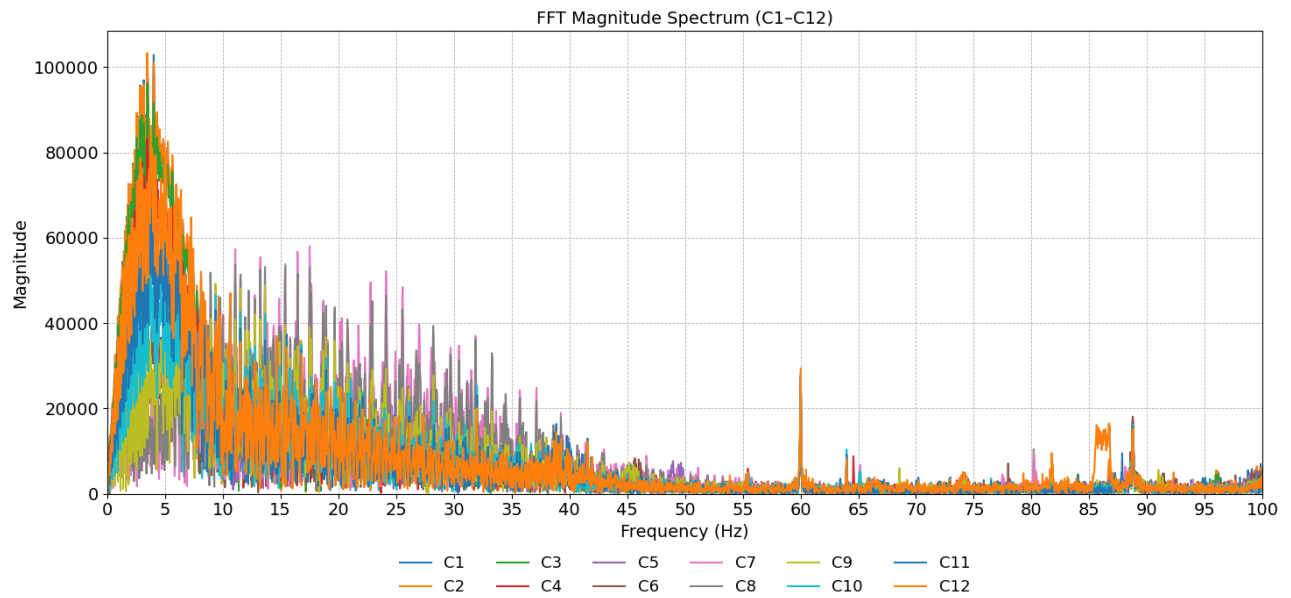


Figure 32. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed below 35 mph (Case #9).

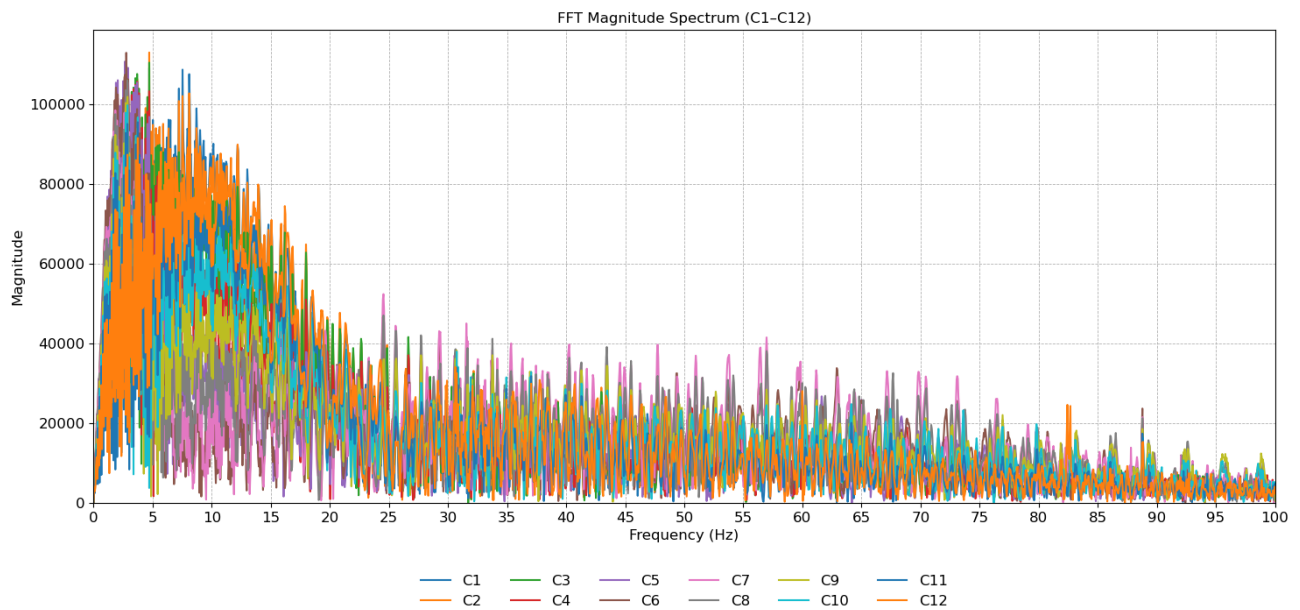


Figure 33. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed above 35 mph (Case #12).

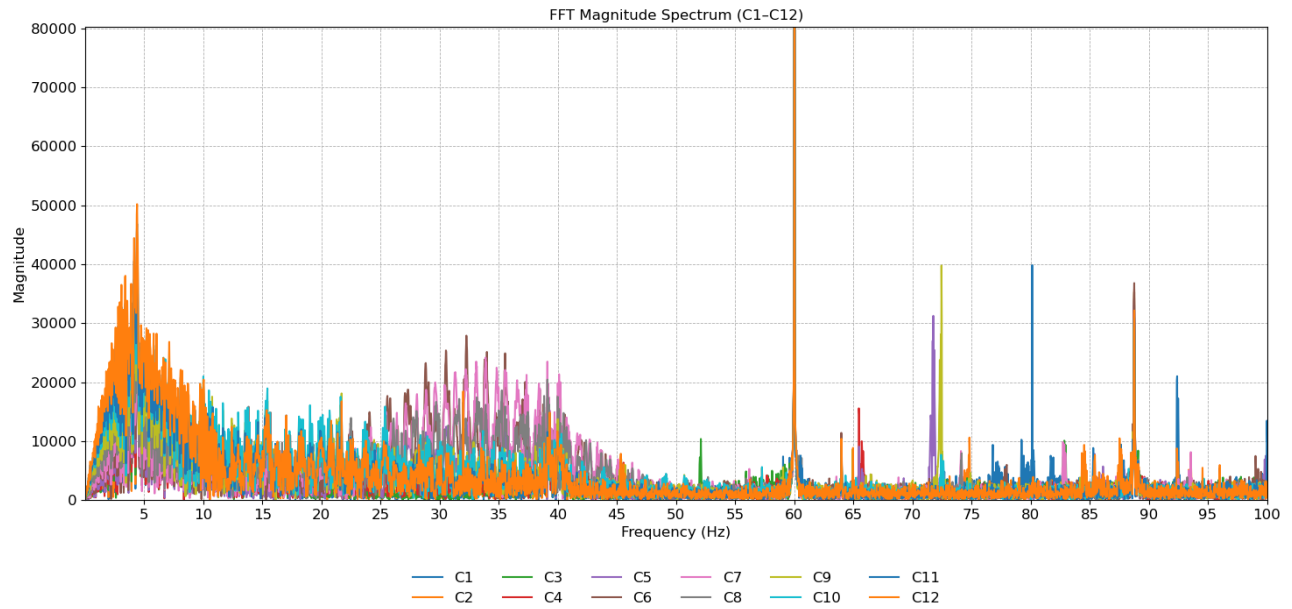


Figure 34. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed below 35 mph (Case #15).

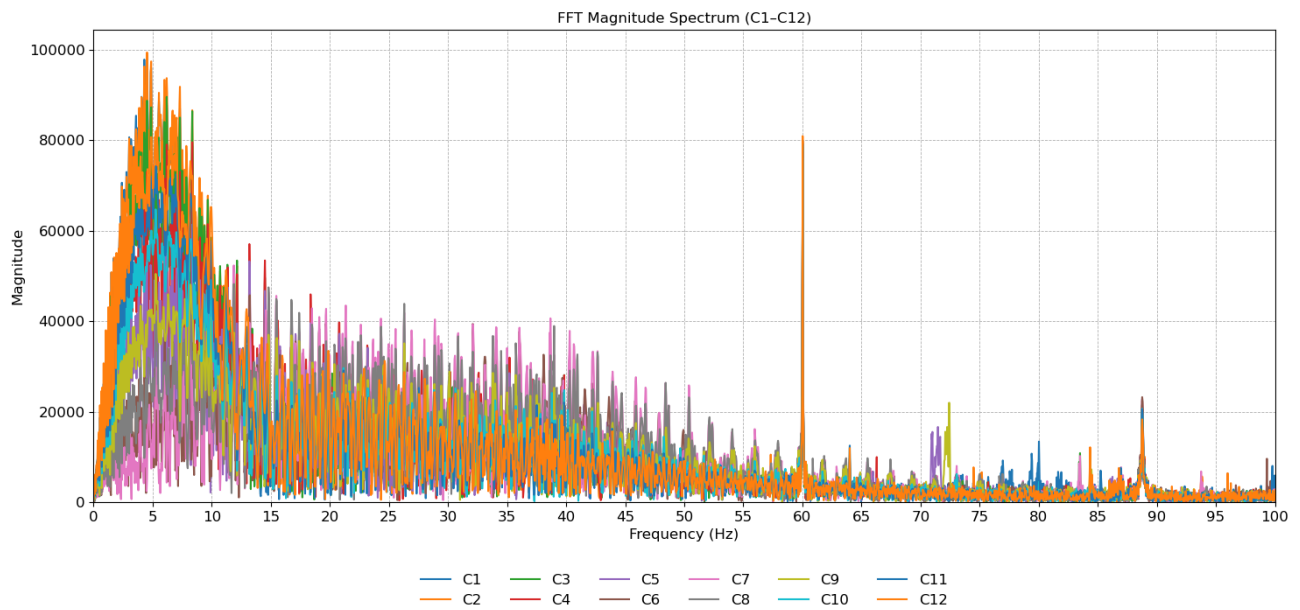


Figure 35. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed ranged between 15 and 25 mph (Case #18).

Cases 3–8: Low- and High-Speed Detection Performance on the Southbound Vehicle Trajectory Test Section

Figures 36 through 38 illustrate the processed EM signals obtained from Test Cases #3 to #5, which represent low-speed runs conducted on the southbound section (Figure 3). The results confirm that the Butterworth bandpass filter with a frequency range of 15 to 55 Hz was effective in isolating the EM signatures. This filter range successfully captured the spatial patterns associated with various pavement-encoded signage placements, including transverse, longitudinal, and decreasing peak-interval patterns. The peak detection algorithm clearly distinguished the intended signage signals from ambient EM interference.

Even under increased speed conditions in the same test section (Test Cases #6 to #8), the system maintained reliable performance using the 20 to 80 Hz bandpass filter, as illustrated in Figures 39 to 41. The captured EM flux signatures remained well aligned with the predefined pavement-encoded signage configurations, demonstrating that the adapted high-speed filter range successfully compensated for speed-dependent spectral shifts and removed other localized interferences. These initial results validated the robustness and scalability of the filtering strategy across varying vehicle speeds for the southbound vehicle trajectory and pavement-encoded signage.

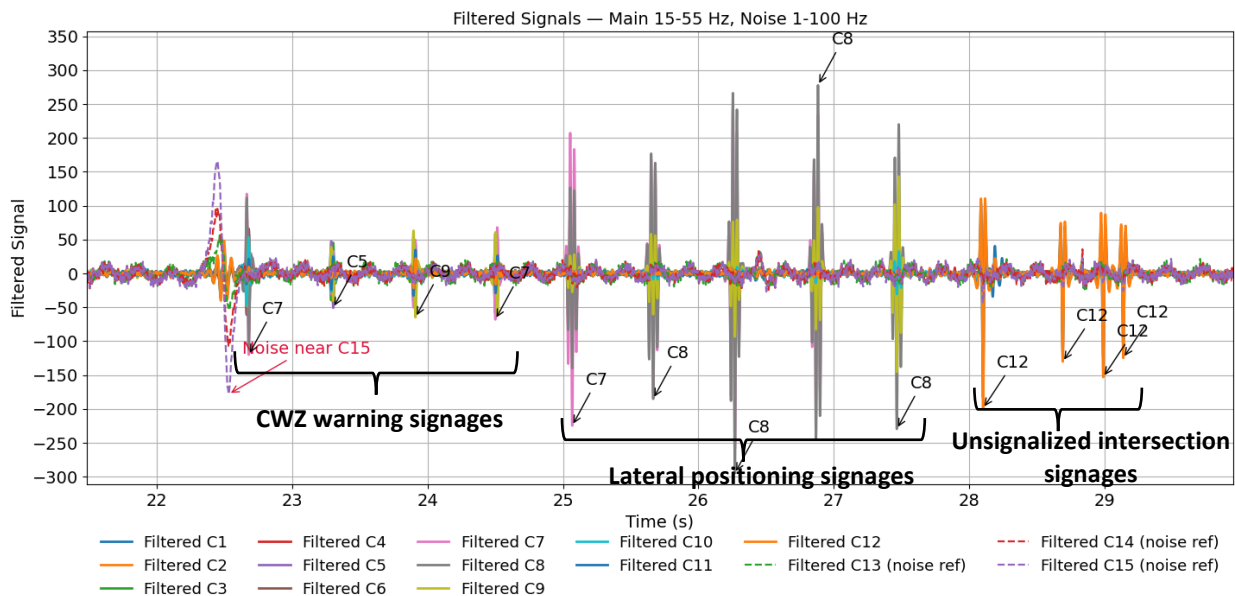


Figure 36. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #3).

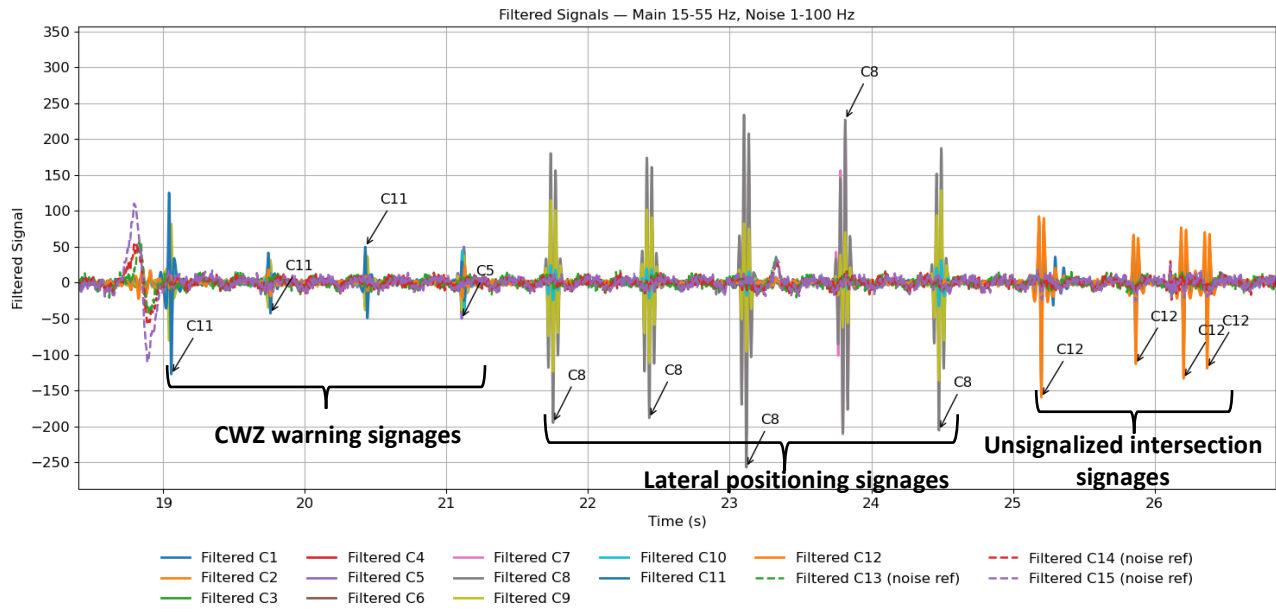


Figure 37. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #4).

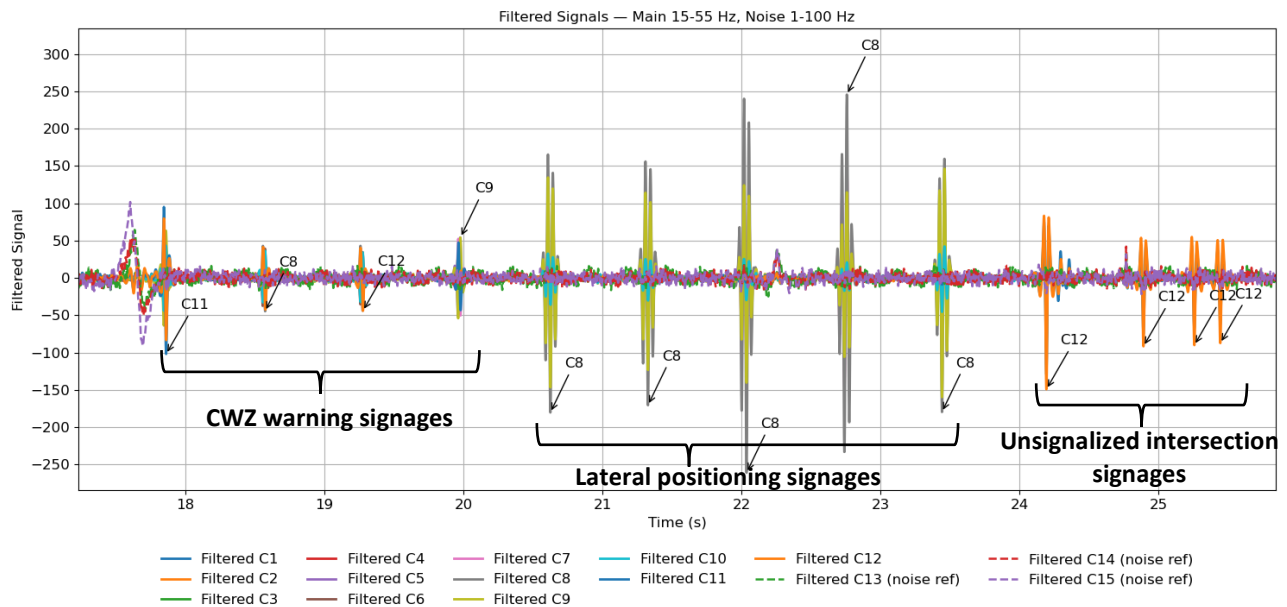


Figure 38. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #5).

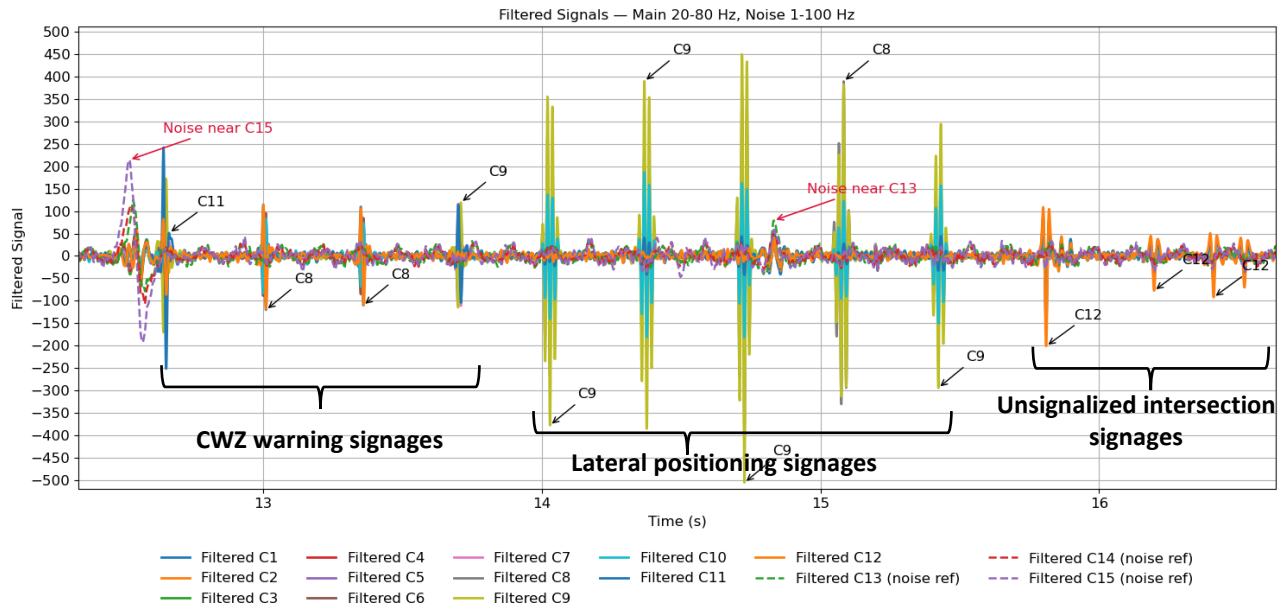


Figure 39. Chart. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph (Case #6).

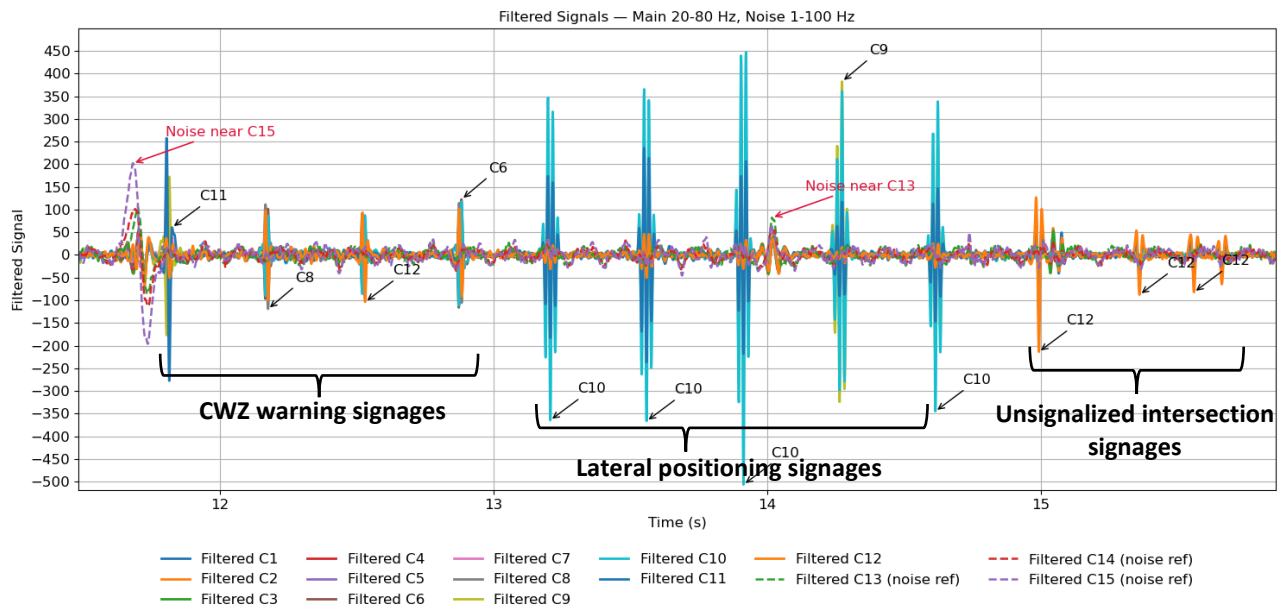


Figure 40. Chart. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph (Case #7).

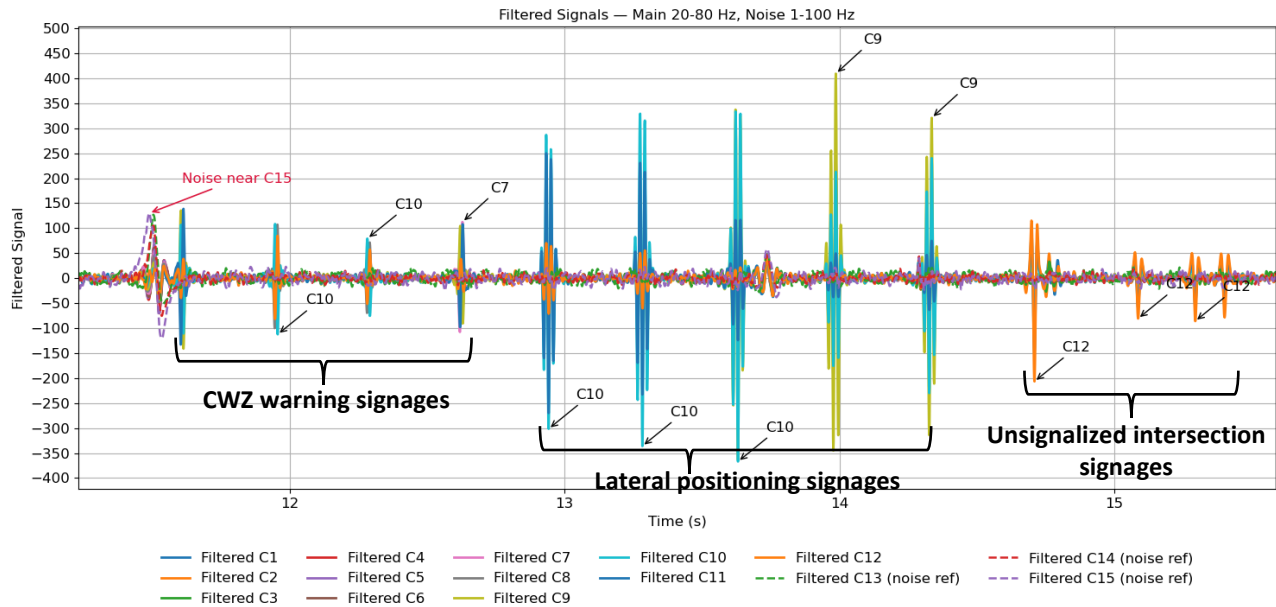


Figure 41. Chart. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph (Case #8).

Cases 9–14: Low- and High-Speed Detection Performance on the Northbound Vehicle Trajectory Test Section

The western test section (Cases #9 to #14) shown in Figure 3, where the vehicle trajectory was northbound, presented a more complex and challenging testing environment than the southbound trajectory because of both layout and surface conditions. This segment included a purposeful lane-shift maneuver, requiring the vehicle to travel along the concrete longitudinal construction joint, a zone characterized by steel dowels and embedded steel hooks for aircraft tiedowns, both of which introduced localized EMI. Additionally, several commercially available magnetic tapes were installed transversely across the lane to compare their signal characteristics with those of the magnetized pavement-encoded signages.

Despite these challenges, the same signal-processing framework from the southbound vehicle tests was applied. A Butterworth bandpass filter with a 15–55 Hz range was used for low-speed test cases (Cases #9 to #11), while the high-speed tests (Cases #12 to #14) used a slightly broader band of 20–80 Hz. As shown in Figures 42 to 44, the processed and filtered EM signals from the low-speed conditions clearly revealed both magnetic tape and pavement-encoded signage detections while effectively suppressing interference from structural metallic components. The signal strength from the transverse and inclined strips—used in the CWZ lane-merge pattern—was significantly lower than that of the longitudinal EM strips used for lane-shift signages. In Case #9, three of the transverse/inclined strips failed to trigger detections, as their peak magnitudes fell below the system’s predefined threshold of 30 nT. Under higher-speed conditions (Figures 45 to 47), those same strips became more detectable. This detection improvement occurred because the system relied on the rate of change in EM flux (Δ EM) between consecutive data points rather than EM flux magnitude

alone. Therefore, faster vehicle movement resulted in steeper signal gradients, enhancing detectability even for lower-strength EM fields.

The longitudinal EM strips produced filtered signal amplitudes comparable to those of magnetic tapes but had greater robustness against misclassification by the detection algorithm. Although the top-row sensors (C13–C15) effectively captured high-intensity ambient EM interference—such as signals from buried metallic structures or nearby electrical utility emissions—they also occasionally responded to the signals generated by the permanent magnetic tapes. Because the detection framework flags any peak coinciding with top-row sensor activity as noise, resulting in false negatives where valid magnetic tape signals were erroneously suppressed. For example, between 8.0 s and 9.3 s in Figure 48 to 50, the system disregarded a legitimate magnetic tape event because of simultaneous activity in the noise reference channel. In contrast, none of the pavement-encoded signals triggered responses in the top-row sensors throughout all test cases. This clear separation between signage signals and ambient noise enhanced their detectability and reliability. Part of the success of the pavement-encoded signage may be attributed to the fact that the magnetic tapes were purchased commercially and not tailored to the intended application, whereas the longitudinal EM strips were magnetized to maximize detection at the tested vehicle speeds and sensor-to-surface spacing.

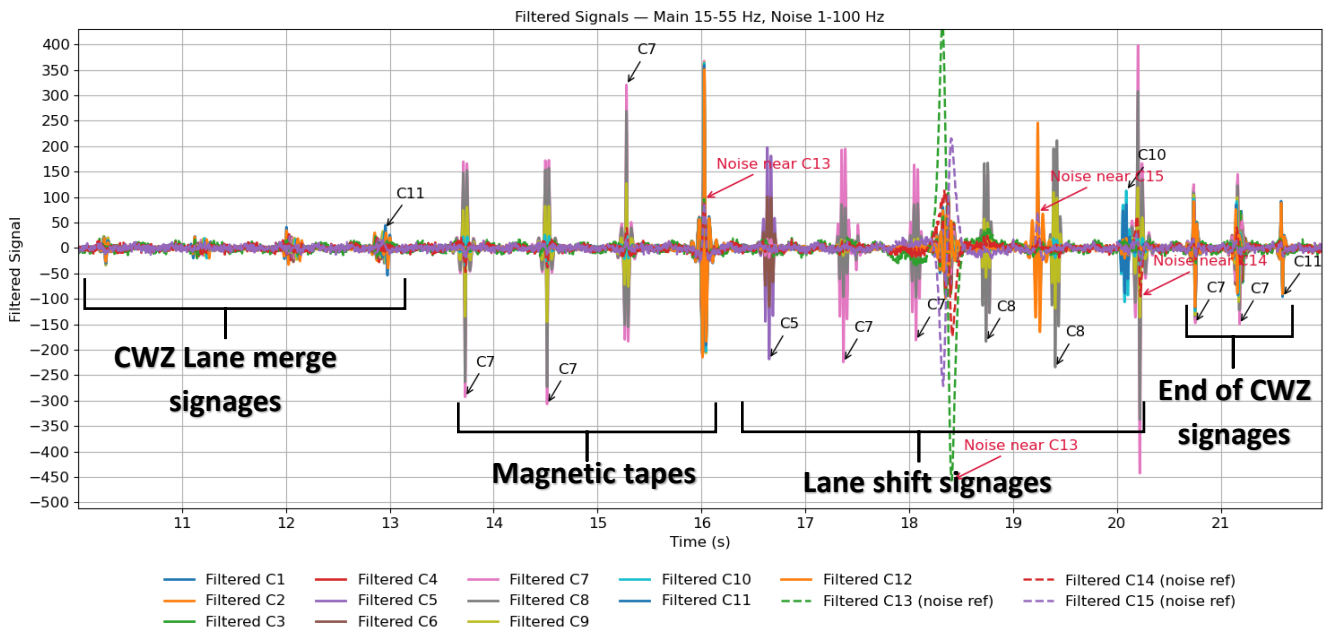


Figure 42. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #9).

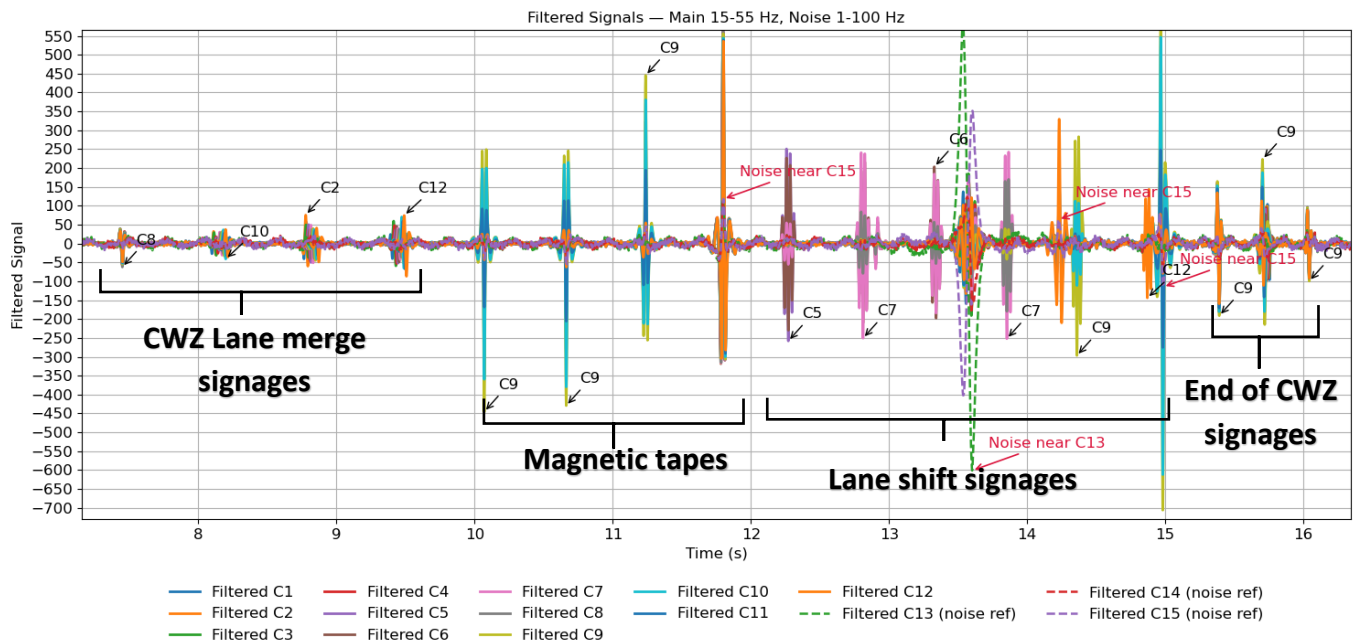


Figure 43. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #10).

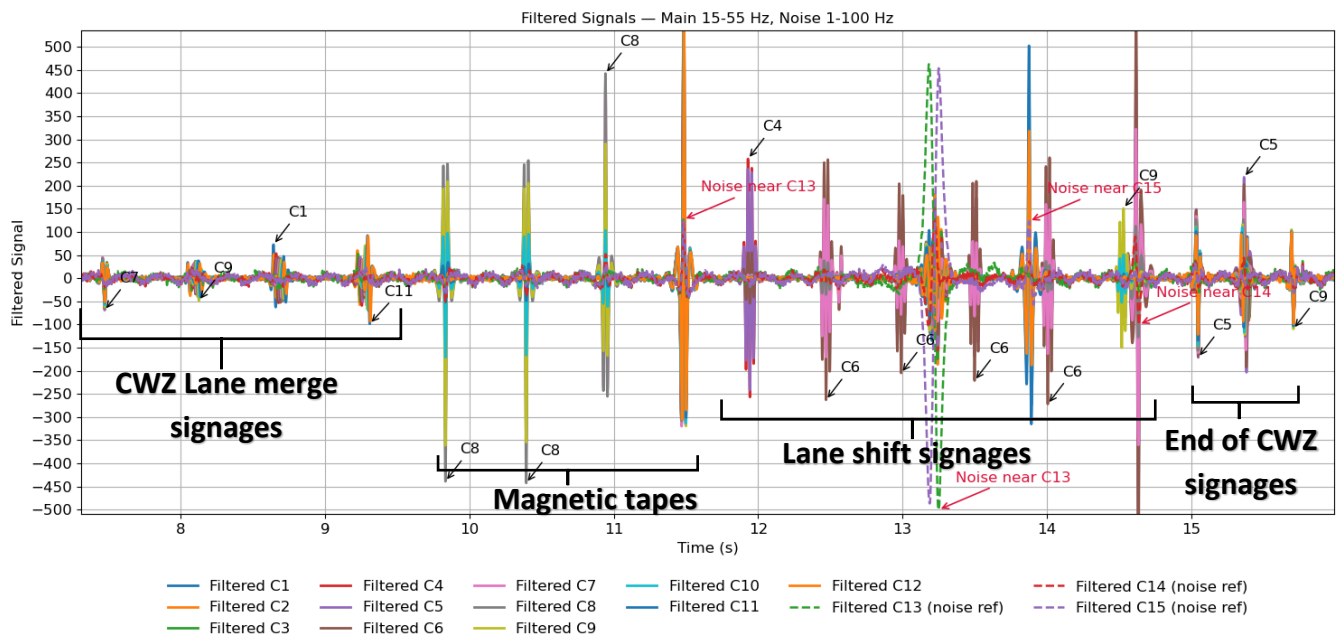


Figure 44. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph (Case #11).

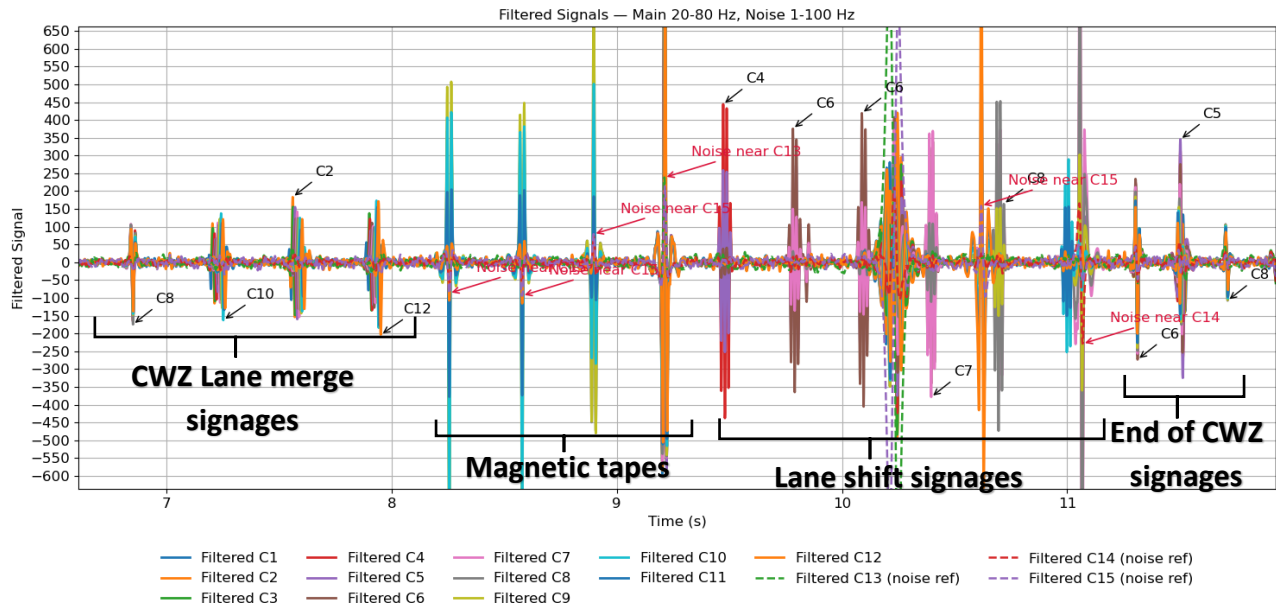


Figure 45. Chart. Filtered $\Delta\Delta\text{EM}$ flux (nT) vs time (s) at speed above 35 mph (Case #12).

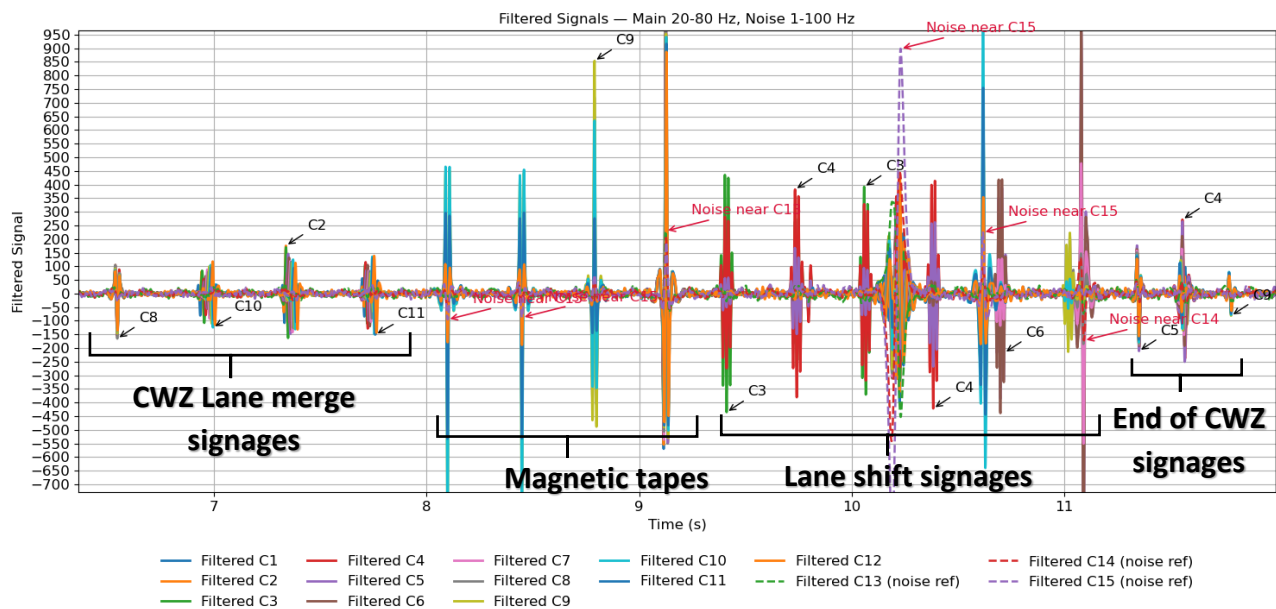


Figure 46. Chart. Filtered ΔEM flux (nT) vs time (s) at speed above 35 mph (Case #13).

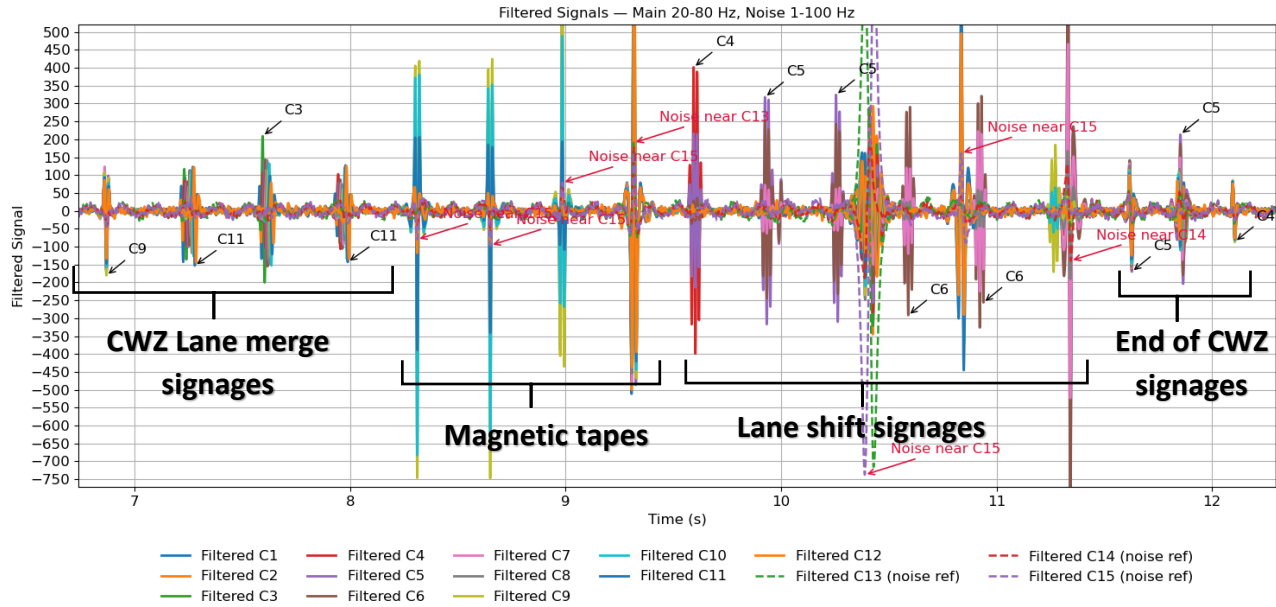


Figure 47. Chart. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph (Case #14).

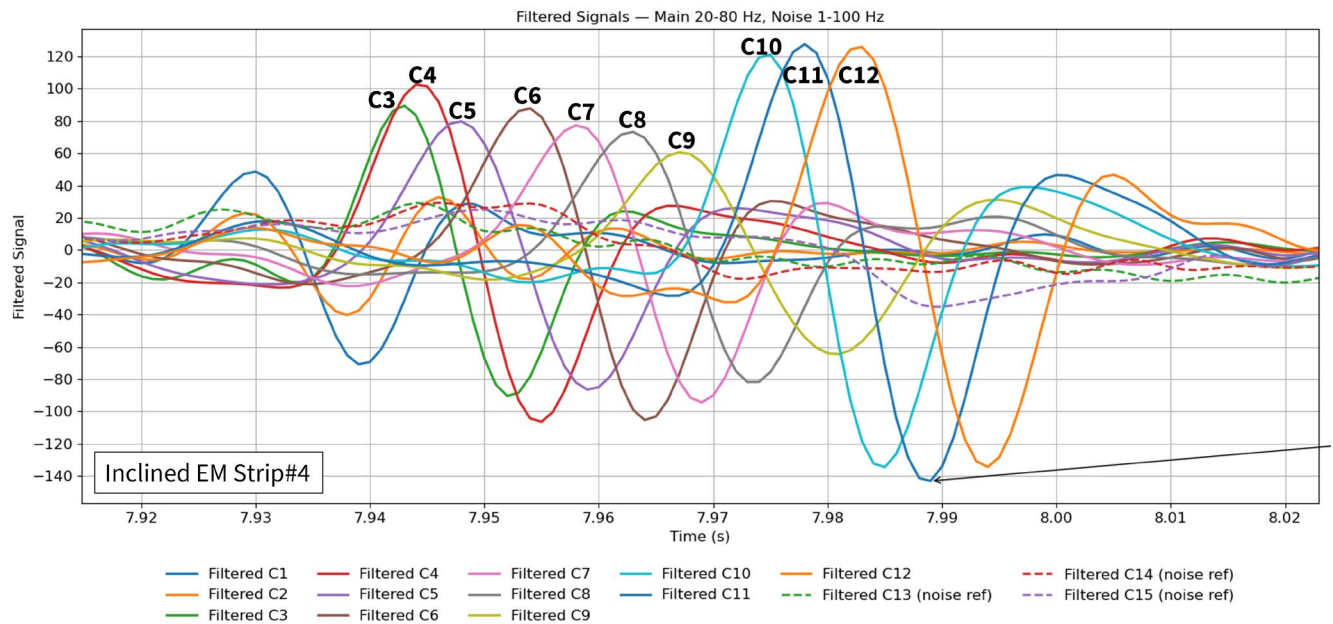
Figures 48a through 48d present filtered Δ EM flux signals for Case #14, representing signal profiles for different pavement-encoded signages and EMI along the northbound vehicle trajectory. In Figure 48a, the signal from a single inclined EM strip—used to generate a sequence of peaks warning of a lane merge in a CWZ—demonstrates clear, structured peaks across bottom-row sensors sequentially from sensor C3 ($t = 7.943$ s) to C12 ($t = 7.982$ s). The spatially and temporally distributed pattern was effective in triggering a sequence of offset detections, supporting the intended interpretation of a right-lane merge (Sakulneya and Roesler, 2024).

In contrast, Figures 48b and 48c display peak signals generated by different EM strip materials with distinct spatial signal distributions. Figure 48b shows the response of a 6 in. transverse magnetic tape, which yields a broad waveform with high amplitude spanning nearly all bottom-row sensors (C7 to C12). This confirms the magnetic tape’s strong detectability under the applied filtering parameters, but the signal also triggered a response in the top-row noise reference sensors, indicating that the magnetic field strength from the tape was sufficiently high to be detected as potential background interference. This wide signal response across sensor channels, coupled with top-row sensor activation, may introduce false negatives in event classification.

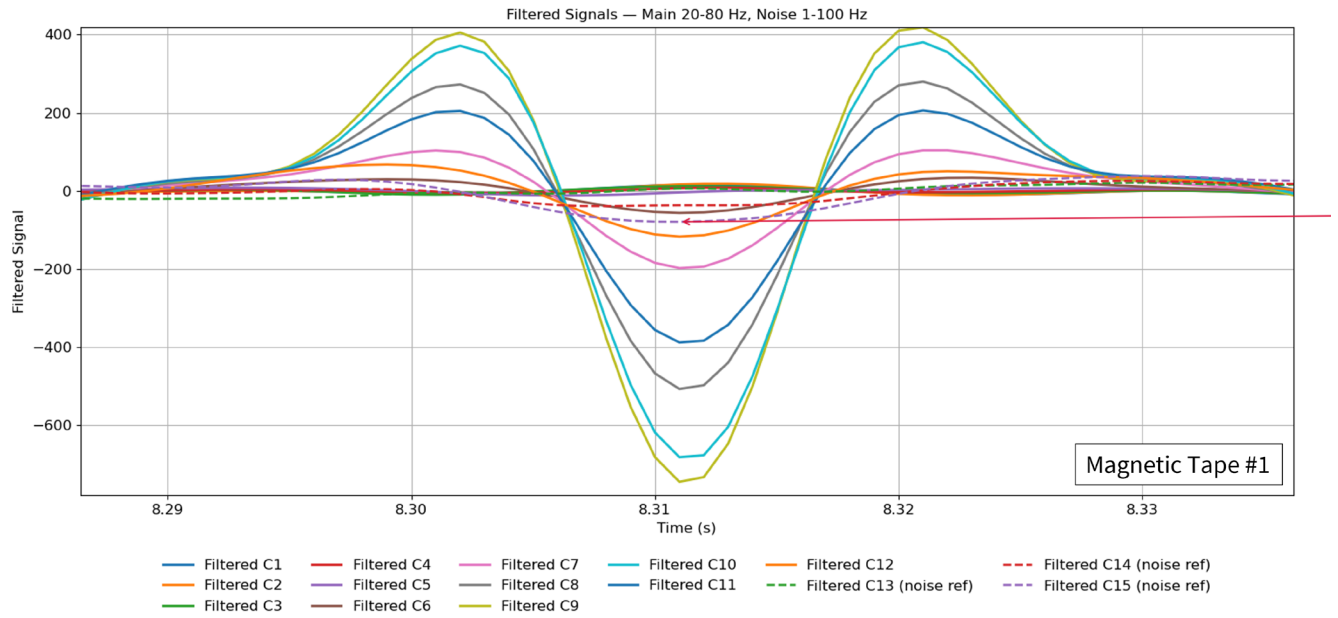
Figure 48c displays the signal response from a longitudinal pavement-encoded EM strip, which achieves an amplitude similar to that of the magnetic tape but features a shorter wavelength and a more spatially confined waveform. While both the magnetic tape (Figure 48b) and the longitudinal EM strip exhibit symmetric profiles, the response in Figure 48c shows a more pronounced amplitude contrast between the dominant sensor and adjacent channels. The peak is clearly centered at sensor C4, with significantly lower amplitudes at neighboring sensors C3 and C5. This distinct differentiation makes it easier for the detection algorithm to isolate the principal detection channel, thereby

enhancing lateral localization accuracy. These characteristics make longitudinal EM strips particularly advantageous for lane keeping and precise positioning in automated driving scenarios.

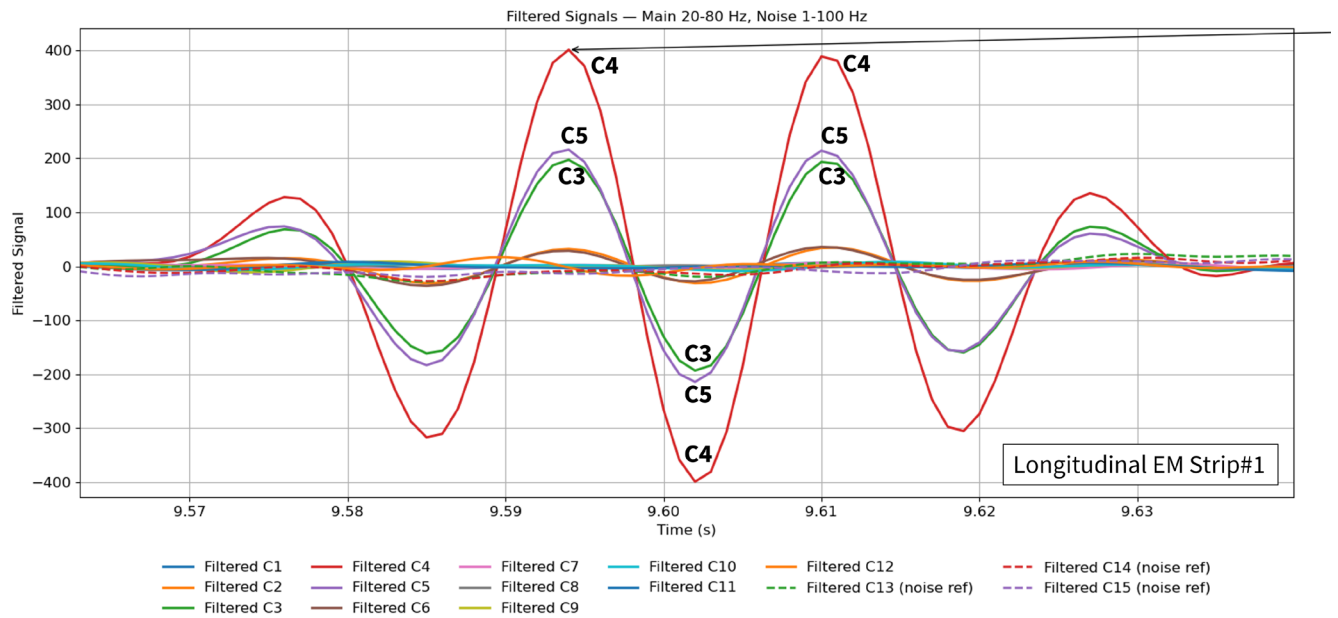
Figure 48d illustrates a representative disturbance below the concrete surface, where a dashed-line trace from a top-row sensor (e.g., C15) momentarily exceeded the detection threshold, appropriately triggering the system's noise or disturbance detection mechanism. Notably, signage-induced signals such as those in Figure 48c did not activate top-row sensors. This contrast reinforces the effectiveness of the coincidence-check strategy for filtering ambient EMI disturbances and preserving valid pavement-encoded signage detections.



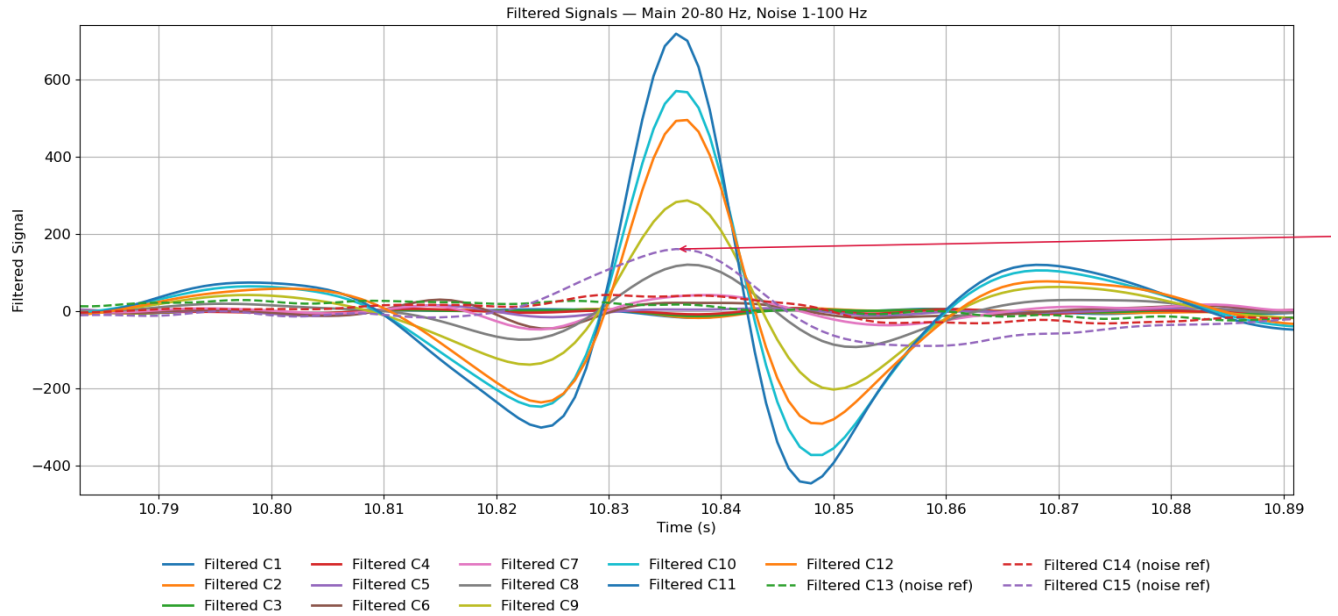
a. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph for Case #14 and inclined EM strip.



b. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph for Case #14 and transverse magnetic tape.



c. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph for Case #14 and longitudinal EM strip.



d. Filtered Δ EM flux (nT) vs time (s) at speed above 35 mph for Case #14 with disturbance detected beneath the concrete surface

Figure 48. Chart. Signal characteristics of various EM sources (case #14).

Cases 15 and 16: EM Strip Detection Accuracy Under Adverse Weather Conditions

To evaluate the robustness of the pavement-encoded signage detection system under adverse environmental conditions (rain, ice, snow), Cases #15 and #16 were conducted when the pavement surface was partially covered with a combination of standing water, ice sheets, and melting snow to a depth of 1 in. Representative images of these tests are shown in Figure 49 for inclined, longitudinal, and transverse EM strips. The processed Δ EM flux signals under these adverse weather conditions are presented in Figures 50 and 51 for Case #15 (southbound) and Case #16 (northbound), respectively. Despite the presence of surface moisture and ice, the detection system successfully identified signage-induced magnetic peaks with signal profiles comparable to those observed during dry-condition testing. The processed Δ EM flux signals under normal weather conditions for Cases #3 to #5 ranged approximately from -250 nT and 250 nT (Figures 36 to 38). Similarly, for the same location under adverse weather conditions (Case #15), the processed Δ EM flux signals remained within a comparable range of -250 nT to 250 nT (Figure 50). Given the similar detections and mean signals observed under normal and adverse weather conditions, the results indicate that the pavement-encoded signage detection system for ADS applications is robust, especially under adverse roadway conditions.



a. Inclined EM strip.



b. Longitudinal EM strip in the lane-shift area.



c. Transverse EM strip in the End-of-CWZ signage pattern.

Figure 49. Photo. Downward image of vehicle crossing EM strip under combination of snow, ice, and water in northbound vehicle trajectory section.

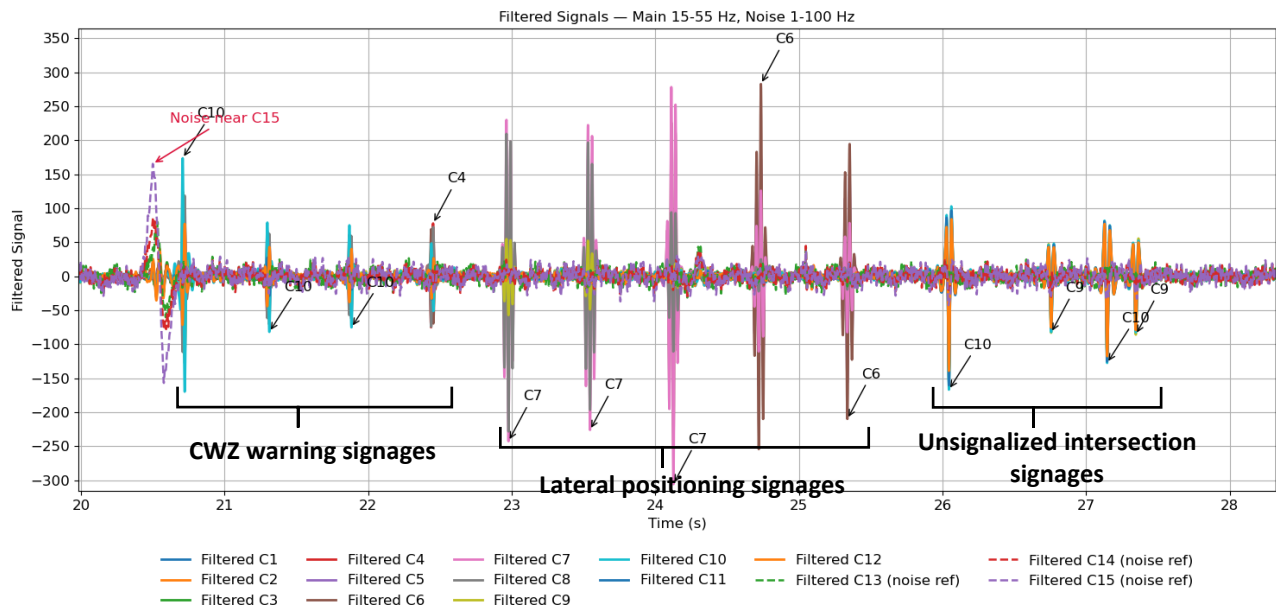


Figure 50. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph for Case #15 and southbound vehicle trajectory.

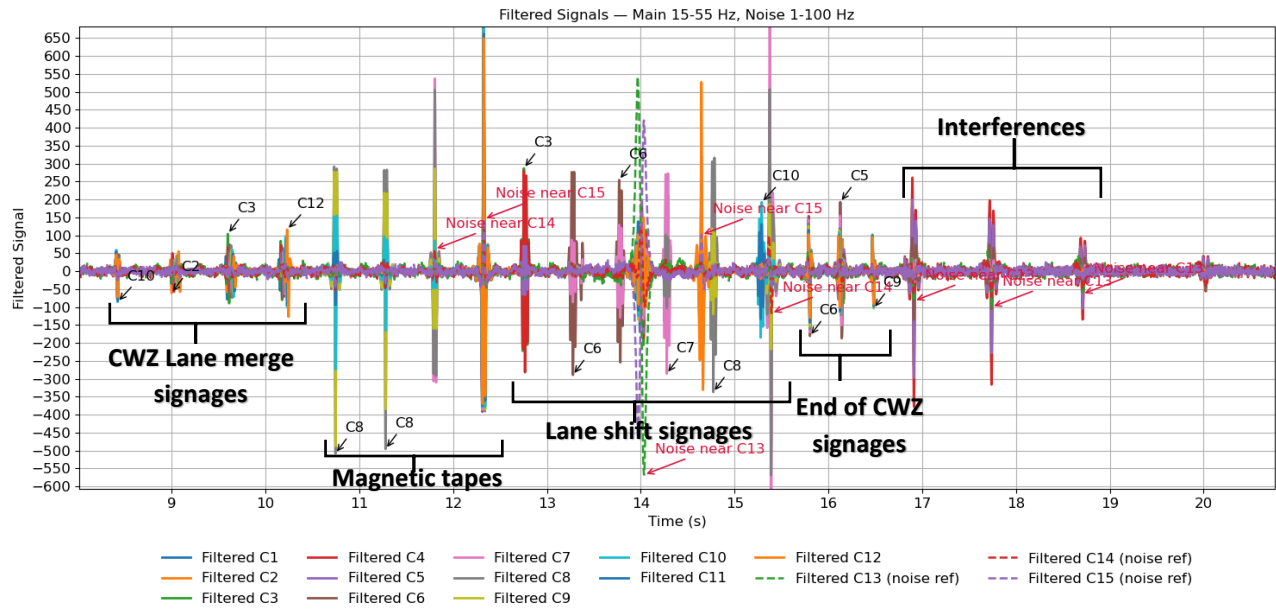


Figure 51. Chart. Filtered Δ EM flux (nT) vs time (s) at speed below 35 mph for Case #16 and northbound vehicle trajectory.

Discussion

The field pilot experiment conducted in a closed area on jointed concrete pavement demonstrated the effectiveness of the developed signal-processing framework—particularly the bandpass filtering and event-rejection procedures presented in this chapter—for detecting pavement-encoded EM signals across varied operating conditions, including speed, direction, and weather conditions. Throughout all test cases (Table 6), the system consistently identified signage-related events while effectively rejecting false positives arising from ambient EMI, particularly those associated with dowelled joints embedded in the concrete pavement. Notably, no false detection events from other EM sources were recorded in the filtered signals, other than the intended pavement-encoded signages and magnetic tapes, validating the robustness and reliability of the proposed filtering and noise-rejection algorithm. To further review the system’s performance, the raw and filtered signal results from the field pilot experiments are provided in Appendix A.

A limited number of missed EM strip detections were observed and can be attributed to two primary causes. First, certain EM signage signals occurred in close temporal proximity (≤ 50 ms) to EM interference peaks, placing them within the system’s predefined signal-rejection window. This resulted in the suppression of valid detections, including one CWZ strip in Case #8 and one longitudinal strip each in Cases #12, #13, and #14. Second, several EM signages generated signal magnitudes below the detection threshold of 30 nT, specifically one CWZ speed-warning strip in Case #2 and three CWZ lane-merge strips in Case #9. As noted earlier, the processed signal in this study represents the rate of change in EM flux (Δ EM) between consecutive data points. Accordingly, as vehicle speed increases, the Δ EM per unit time becomes more pronounced, enhancing signal

detectability. As a result, no EM signage signals fell below the detection threshold during higher-speed test conditions of >35 MPH.

As previously discussed, the transverse magnetic tapes produced broad lateral waveforms with high amplitude, which in several instances were strong enough to trigger detections in the top-row noise reference sensors, particularly under high-speed conditions. This led the system to classify these events as EMI and exclude them from further analysis. Specifically, 11 of 12 magnetic tape signals were rejected during the high-speed tests (Cases #12 to #14), and 3 of 12 were rejected during the low-speed tests (Cases #9 to #11). The commercially purchased magnetic tapes would need to be adjusted to lower the peak ΔEM flux and reduce the lateral spread of the EM signal to other sensor channels.

Table 6. Field Pilot Experiment Summary in Closed Concrete Test Area

Test Case	Max. Recorded Speed (mph)	Total EM Strips	Main Sensors Band-pass (Hz)	No. of False Event Rejections	Successful Detections	Missed Detections	Type of Missed Strip	False Detections
1	58	9 EM	25 - 80	4/4	9	0	N/A	0
2	28	9 EM	20 - 80	2/2	8	1	1-CWZ strip	0
3	24	13 EM	15 - 55	3/3	13	0	N/A	0
4	21	13 EM	15 - 55	1/1	13	0	N/A	0
5	21	13 EM	15 - 55	2/2	13	0	N/A	0
6	43	13 EM	20 - 80	2/2	13	0	N/A	0
7	42	13 EM	20 - 80	2/2	13	0	N/A	0
8	43	13 EM	20 - 80	2/2	12	1	1-CWZ strip	0
9	20	13 EM + 4 Magnetic tape	15 - 55	6/6	13	4	3-CWZ strips, 1-Magnetic tape	0
10	27	13 EM + 4 Magnetic tape	15 - 55	5/5	16	1	1-Magnetic tape	0
11	27	13 EM + 4 Magnetic tape	15 - 55	5/5	16	1	1-Magnetic tape	0
12	45	13 EM + 4 Magnetic tape	20 - 80	7/7	12	5	1-Longitudinal EM strip, 4-Magnetic tape	0
13	42	13 EM + 4 Magnetic tape	20 - 80	6/6	13	4	1-Longitudinal EM strip, 3-Magnetic tape	0
14	41	13 EM + 4 Magnetic tape	20 - 80	6/6	12	5	1-Longitudinal EM strip, 4-Magnetic tape	0
15	26	13 EM	15 - 55	1/1	13	0	N/A	0
16	27	13 EM + 4 Magnetic tape	15 - 55	6/6	15	2	2-Magnetic tape	0

CHAPTER 5: EXPERIMENTAL RESULTS FROM RURAL ROAD SITE

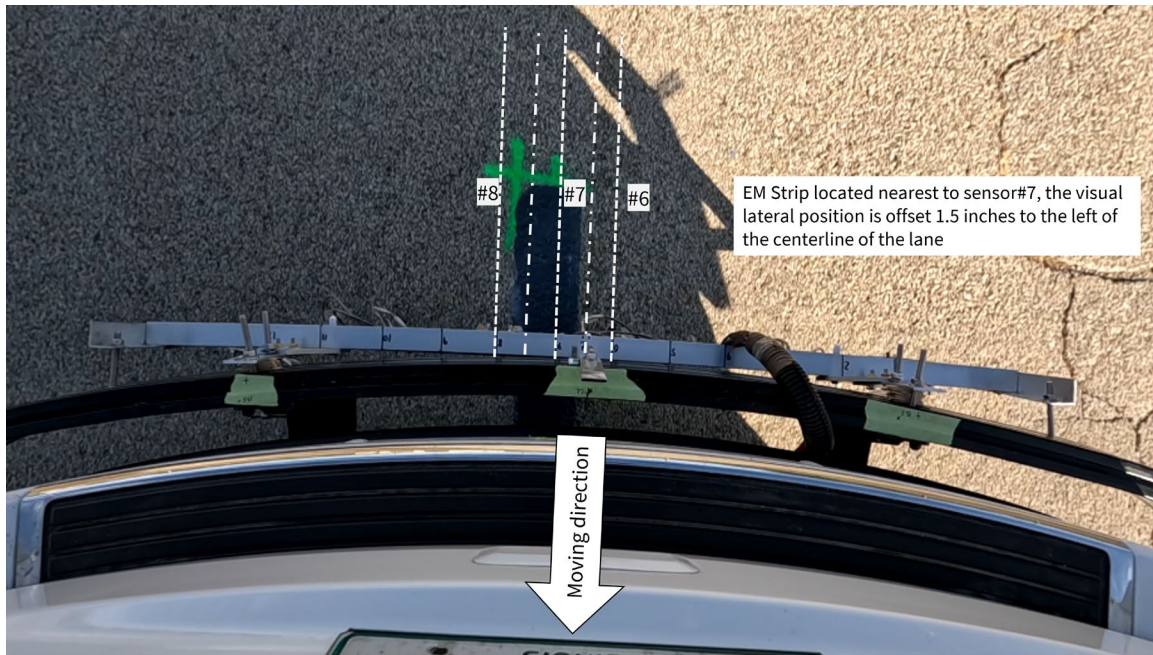
FIELD TEST RESULTS ON PRECISE MANEUVERING IN HORIZONTAL CURVE

To evaluate the performance of the pavement-assisted passive sensing system under actual rural road geometry, Cases #17 through #21 were conducted along a horizontal curve segment of Titan Drive in Rantoul, Illinois. The primary objective of these tests was to assess the system's ability to reliably detect and interpret pavement-encoded electromagnetic (EM) signage signals and to evaluate the accuracy of vehicle lateral positioning and speed detection during curve maneuvering relative to visual-based observations and GPS-derived speed measurements. Test Cases #17 to #20 were carried out under normal weather conditions and included multiple runs to validate the consistency and repeatability of EM signal detection along the horizontal curve. In contrast, Case #21 was conducted on the same segment during adverse weather, with snow partially covering the pavement surface. This test case examined the system's robustness under reduced road surface visibility, simulating real-world challenges for automated vehicle operation.

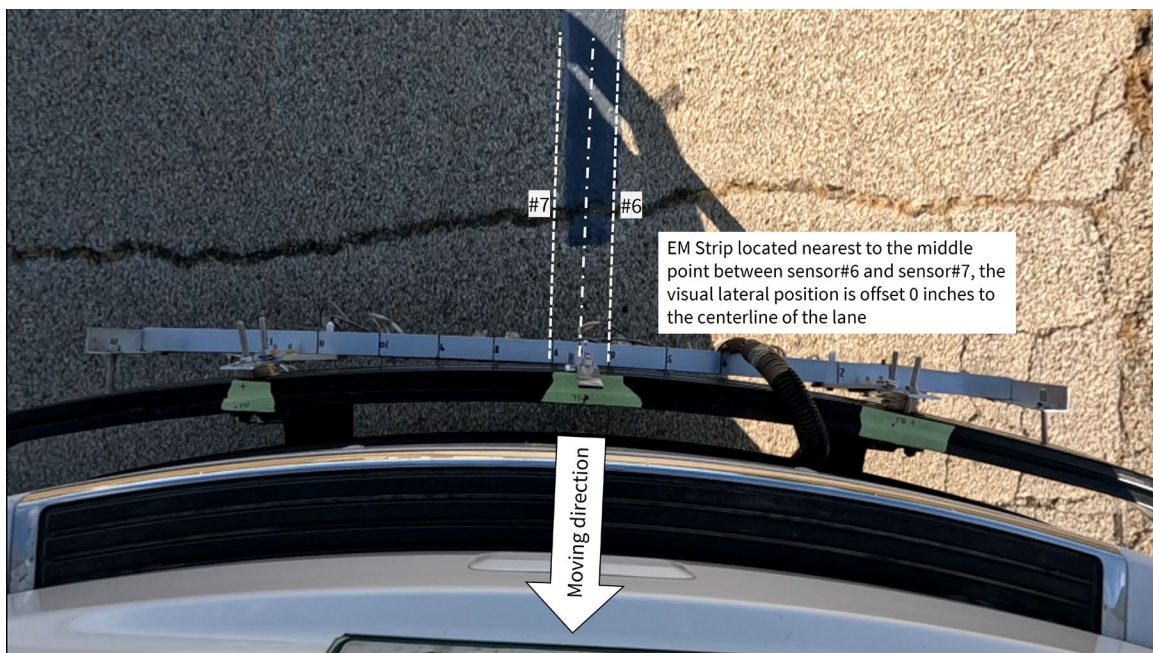
Figure 52 illustrates the methodology used to determine the visual-based lateral offset of the vehicle relative to the lane centerline using images recorded from a vertically mounted camera. This camera was positioned above the EM sensor array, which was fixed to the rear bumper of the test vehicle. The sensor array consists of 12 sensors, laterally spaced at 3 in. intervals, with Sensor #1 located on the far left and Sensor #12 on the far right relative to the vehicle's forward motion. The center of the vehicle is defined as the midpoint between Sensor #6 and Sensor #7.

To estimate lateral offset visually, reference positions were established at 1.5 in. intervals, including the centerlines of each sensor and the midpoints between adjacent sensors. The lateral offset at each EM signage location was then determined by identifying which reference point lay closest to the center of the EM strip directly beneath the array. For example, in Figure 52a, the center of the EM strip is nearest to Sensor #7, indicating that the vehicle's center is offset by approximately 1.5 in. to the left of the EM marking. In contrast, Figure 52b shows the EM strip aligned with the midpoint between Sensors #6 and #7, resulting in a visual-based lateral offset of 0 in.

These visual-based lateral offset values were subsequently compared with the corresponding EM-based offset estimates at each signage location for all test runs. This comparative analysis was statistically evaluated to quantify the accuracy, reliability, and repeatability of the ADS's lateral positioning capability under both normal and adverse weather conditions.



a. Example image #1.



b. Example image #2.

Figure 52. Photo. Visual method to determine the lateral offset of the vehicle relative to the lane centerline using image recorded from a vertically mounted camera.

Lateral Offset and Speed Test Results for a Vehicle in a Horizontal Curve

To evaluate the system's detection performance during curve navigation, Test Case #17 was conducted under normal weather conditions along the westbound horizontal curve of Titan Drive. In this test, the driver maintained the vehicle's position in the lane using visual cues. Figure 53 shows the filtered Δ EM flux signals for Test Case #17, confirming that the system successfully detected each pavement-encoded EM strip placed along the curve. Each peak represented an EM strip, serving as a reference point for lateral positioning and vehicle motion tracking. Figure 54 compares the vehicle's lateral offset estimated from downward-facing video recordings with the offset calculated by the passive sensing detection and filtering algorithm. The two methods show close agreement throughout the horizontal curve between the EM and image detections, with a mean difference of 2.6 in. and a standard deviation of 2.2 in., supporting the accuracy of the EM-based estimate. Figure 55 presents the comparison between GPS-measured vehicle speed and the speed calculated from the known EM strip spacing and timing between event detections. Both speed profiles align closely, with the mean difference of 0.84 mph and standard deviation of 0.76 mph, demonstrating the system's ability to provide reliable speed estimates. Test Cases #18 to #20 were repeats of Case #17 and are illustrated in the Appendix B.

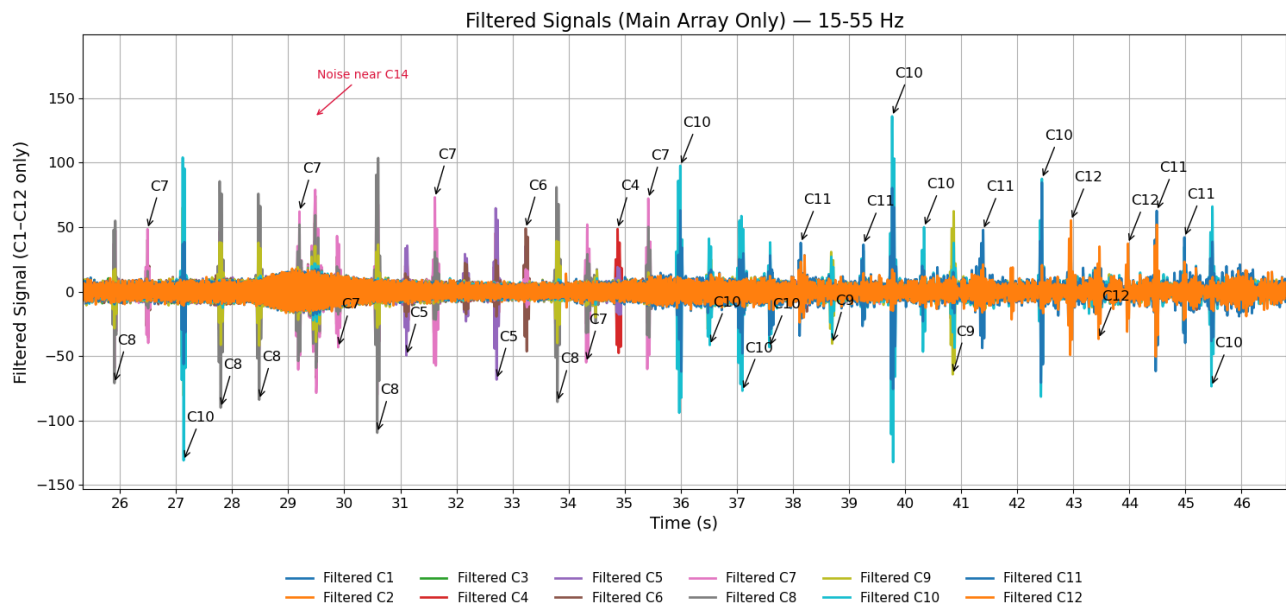


Figure 53. Chart. Filtered Δ EM flux (nT) vs time (s) at speed above 15 mph for Case #17 and westbound vehicle trajectory on Titan Drive.

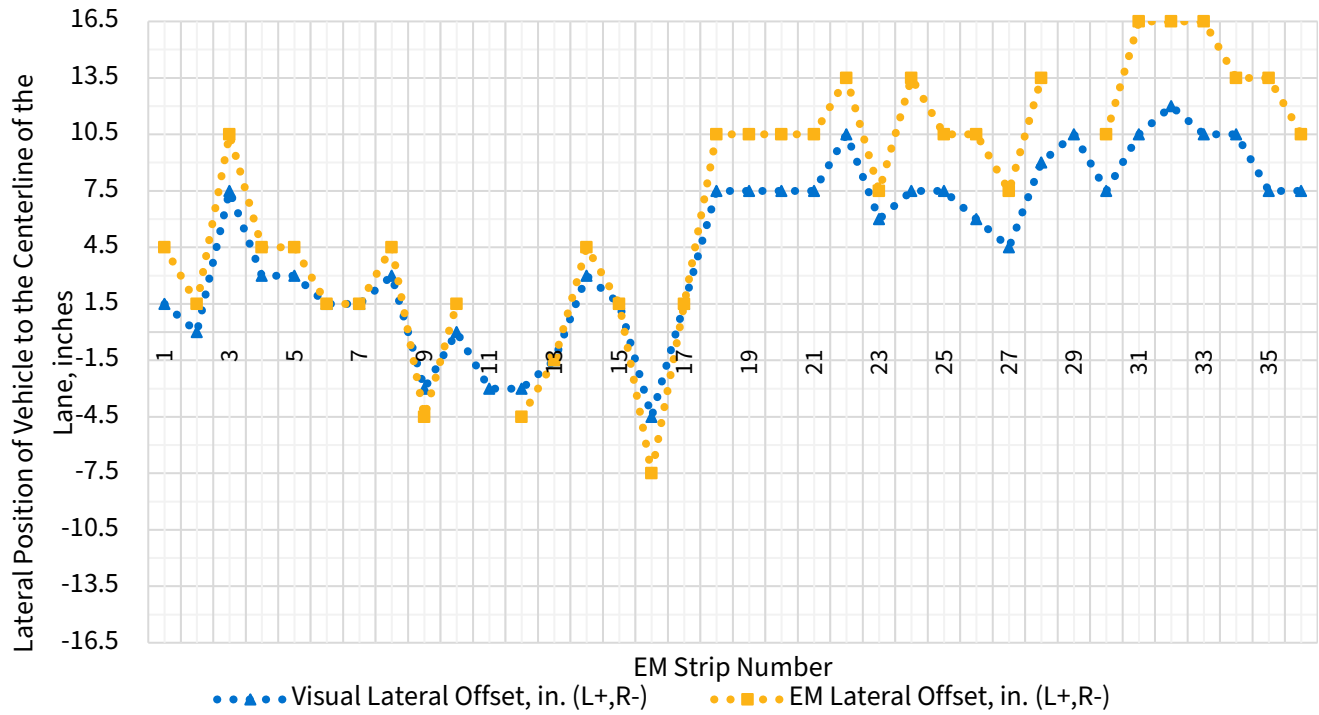


Figure 54. Chart. Comparison of the lateral position of vehicle from visual detection and pavement-assisted passive sensing detection at speed below for Case #17.

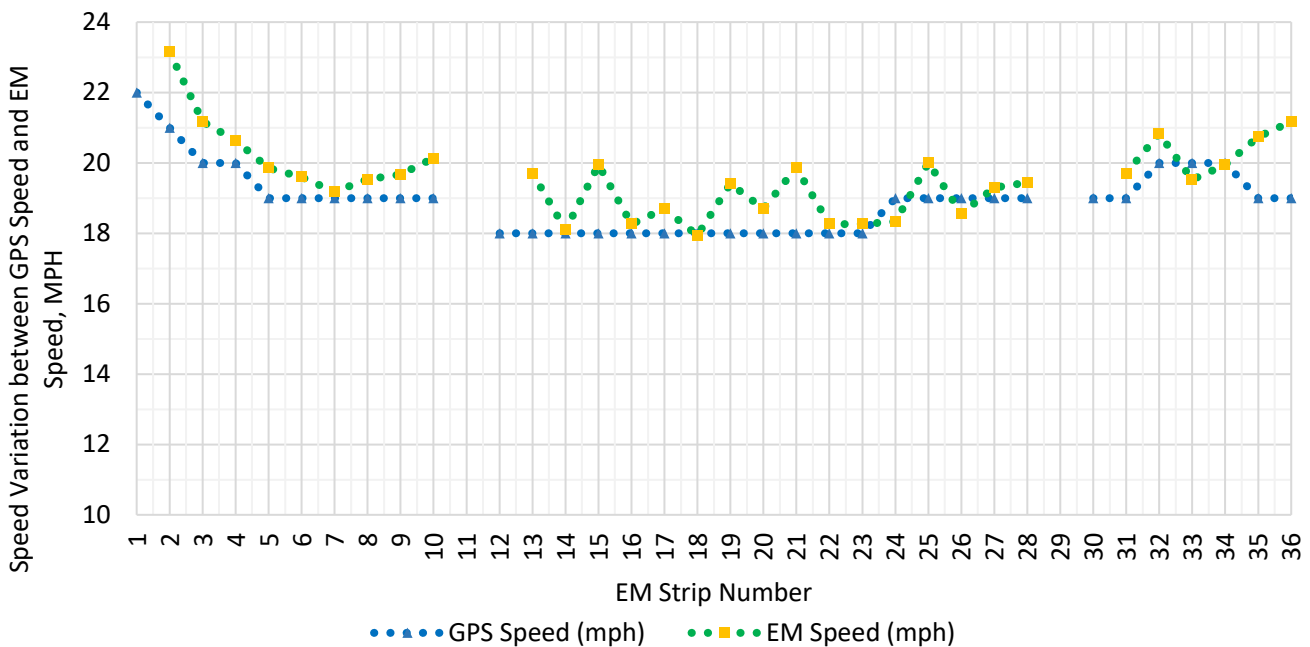


Figure 55. Chart. Comparison of the vehicle speed through GPS and EM strip detection for Case #17.

Signal Reliability and Detectability

To evaluate system vehicle detection and EM strip performance under adverse surface conditions, Test Case #21 was conducted along the same horizontal curve with snow and ice partially covering the pavement surface. The signal frequency spectra captured during normal surface conditions and snow-covered conditions are shown in Figures 56 and 57, respectively. Under snow-covered conditions, a pronounced interference peak was observed near 60 Hz. This increase may be related to higher electrical demand during winter conditions, which can intensify electromagnetic interference from nearby power infrastructure.

Figures 58 through 61 present the processed Δ EM flux signals corresponding to EM Strip #1 using various high-pass filter settings. These results reveal that when the high-pass cutoff frequency exceeded 50 Hz, the signage signals became noticeably distorted and peak clarity was reduced because of overlap with the strong interference band.

To further investigate the filtering strategy, Figures 62 through 64 compare the processed signals using high-pass cutoff frequencies of 55 Hz, 50 Hz, and 45 Hz. The results indicate that the 45 Hz configuration provided the clearest and most distinguishable peak events, with improved signal-to-noise contrast and reduced distortion from EMI.

To specifically target the interference centered at 60 Hz, a notch filter was applied. The resulting frequency spectrum after applying the 60 Hz notch filter is shown in Figure 65, and the revised Δ EM flux signals after filtering are presented in Figure 66. A direct comparison between the bandpass-only approach (15–55 Hz) without the notch filter (Figure 59) and the updated approach with the notch filter included (Figure 67) highlights the improvement in peak clarity. The addition of the notch filter substantially suppressed 60 Hz interference, resulting in cleaner waveforms and improved detection confidence for events at EM Strip #1.

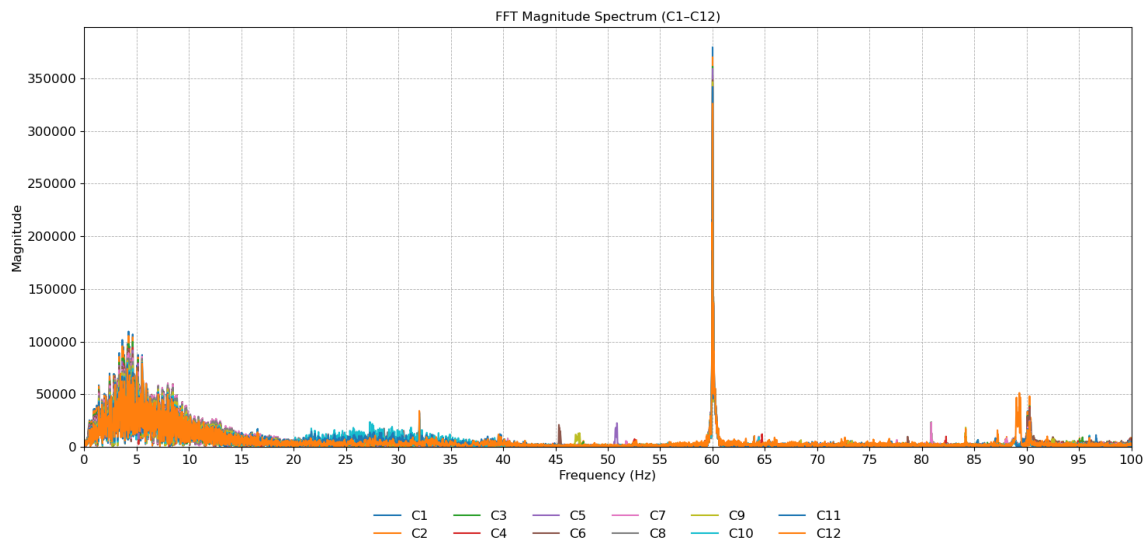


Figure 56. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed above 15 mph during normal surface conditions on Titan Drive (Case #17).

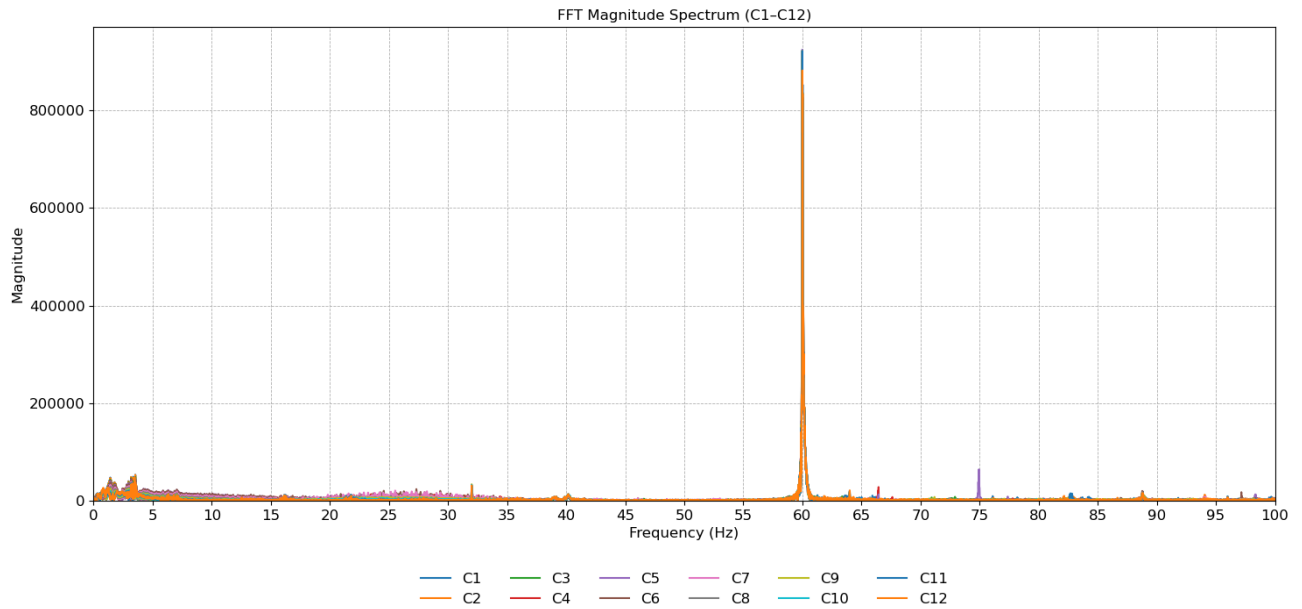


Figure 57. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels at speed above 15 mph during surface conditions with snow on Titan Drive (Case #21).

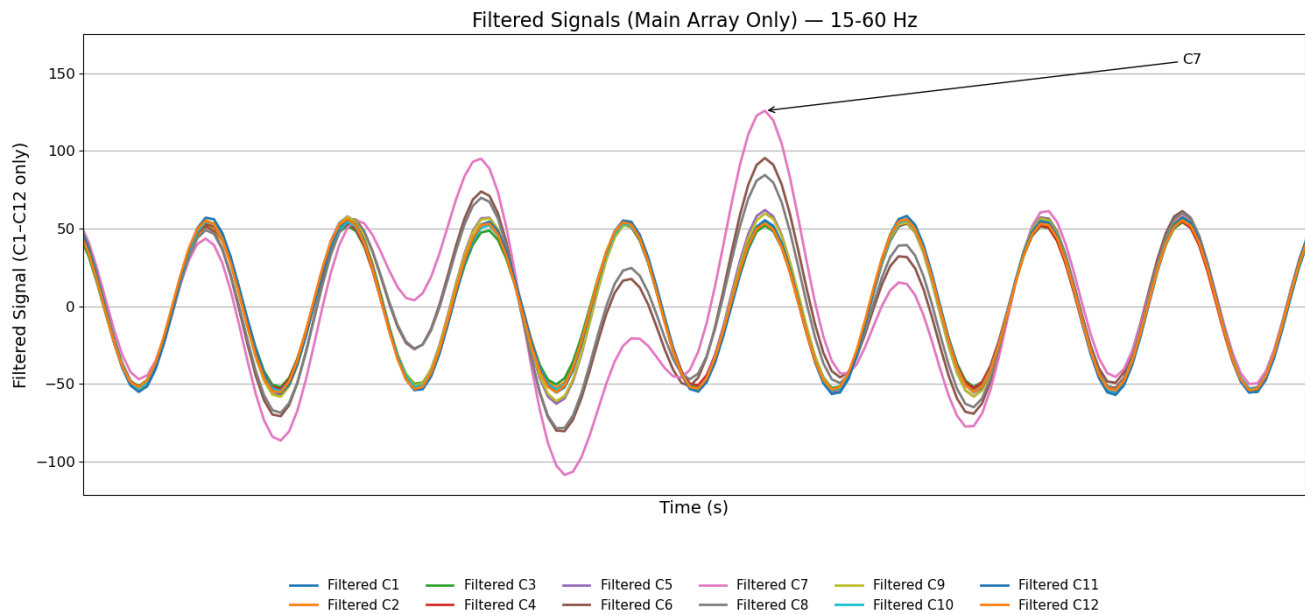


Figure 58. Chart. Δ EM flux (nT) vs time (s) of collected data on EM strip #1 with 15 to 60 Hz bandpass (Case #21) with peak signal at sensor #7 with EMI noise.

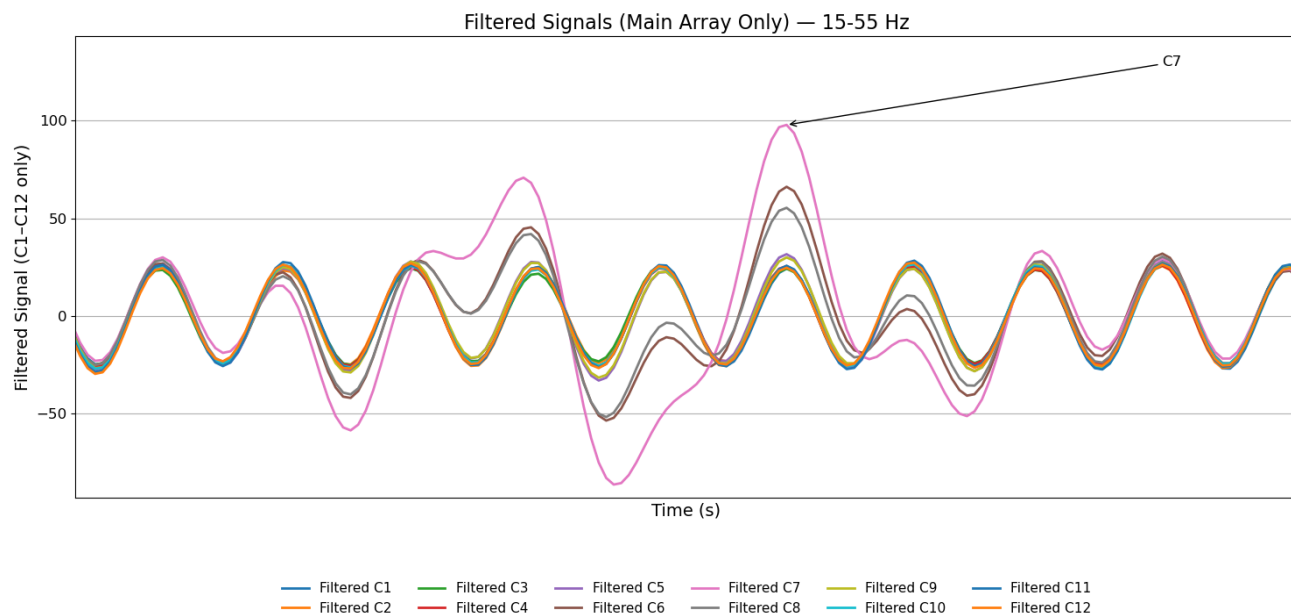


Figure 59. Chart. Δ EM flux (nT) vs time (s) of collected data on EM strip #1 with 15 to 55 Hz bandpass (Case #21) with peak signal at sensor #7 with EMI noise.

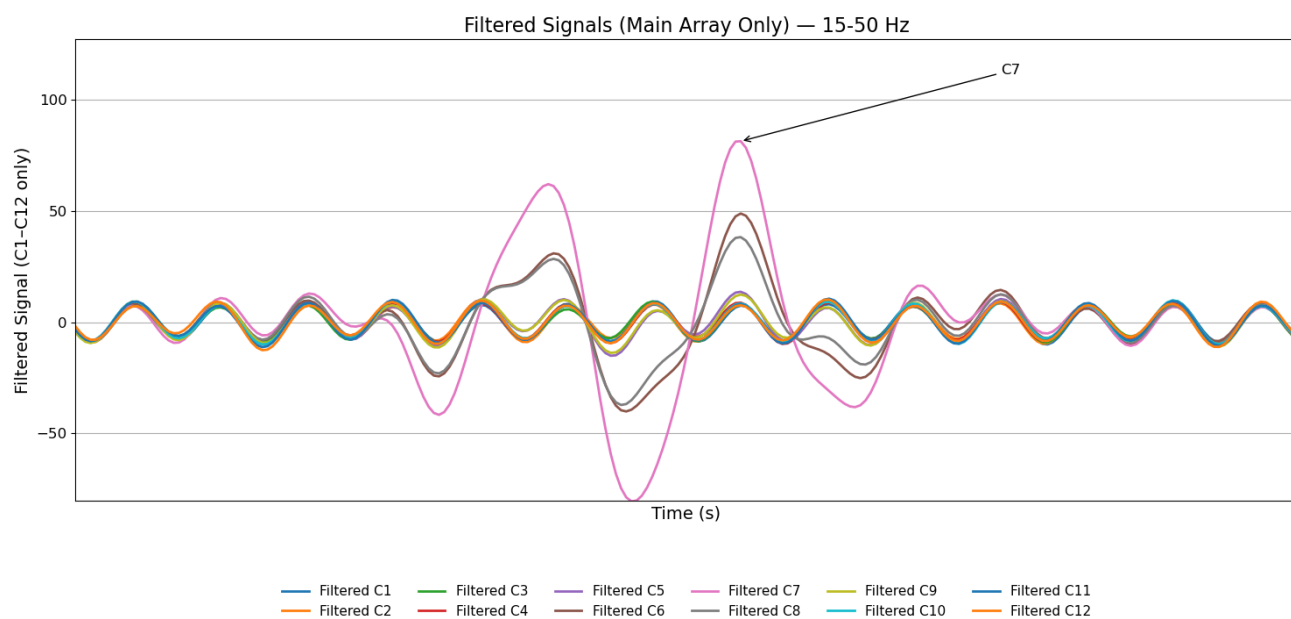


Figure 60. Chart. Δ EM flux (nT) vs time (s) of collected data on EM strip #1 with 15 to 50 Hz bandpass (Case #21).

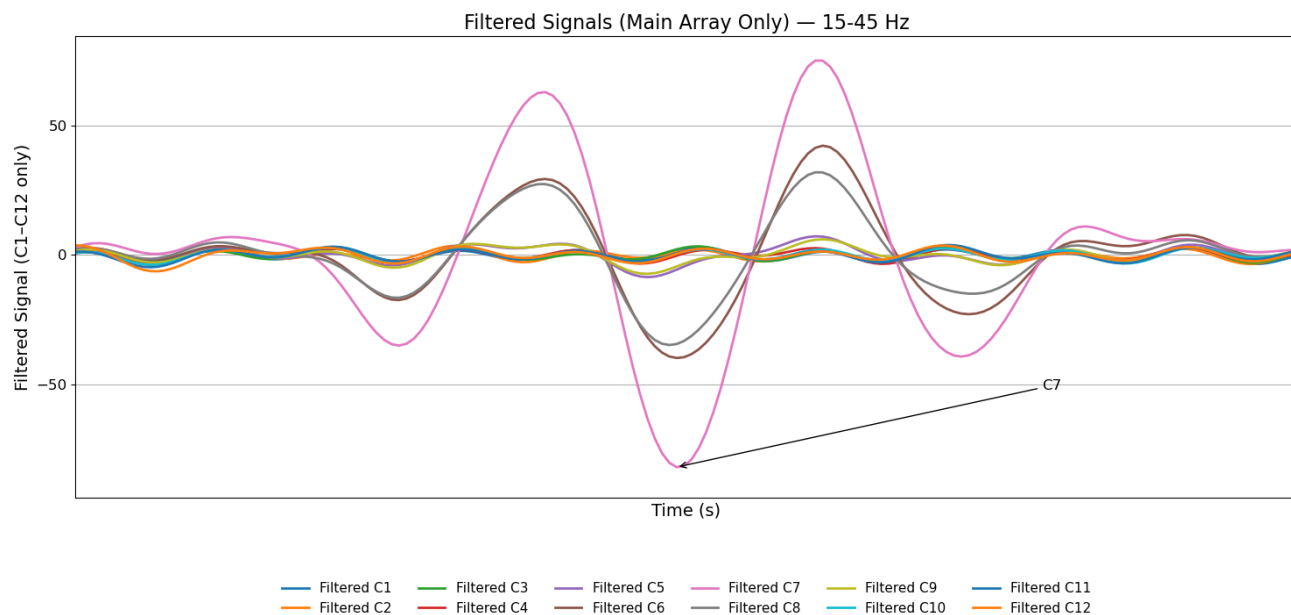


Figure 61. Chart. Δ EM flux (nT) vs time (s) of collected data on EM strip #1 with 15 to 45 Hz bandpass (Case #21) with peak signal at sensor #7 with EMI noise.

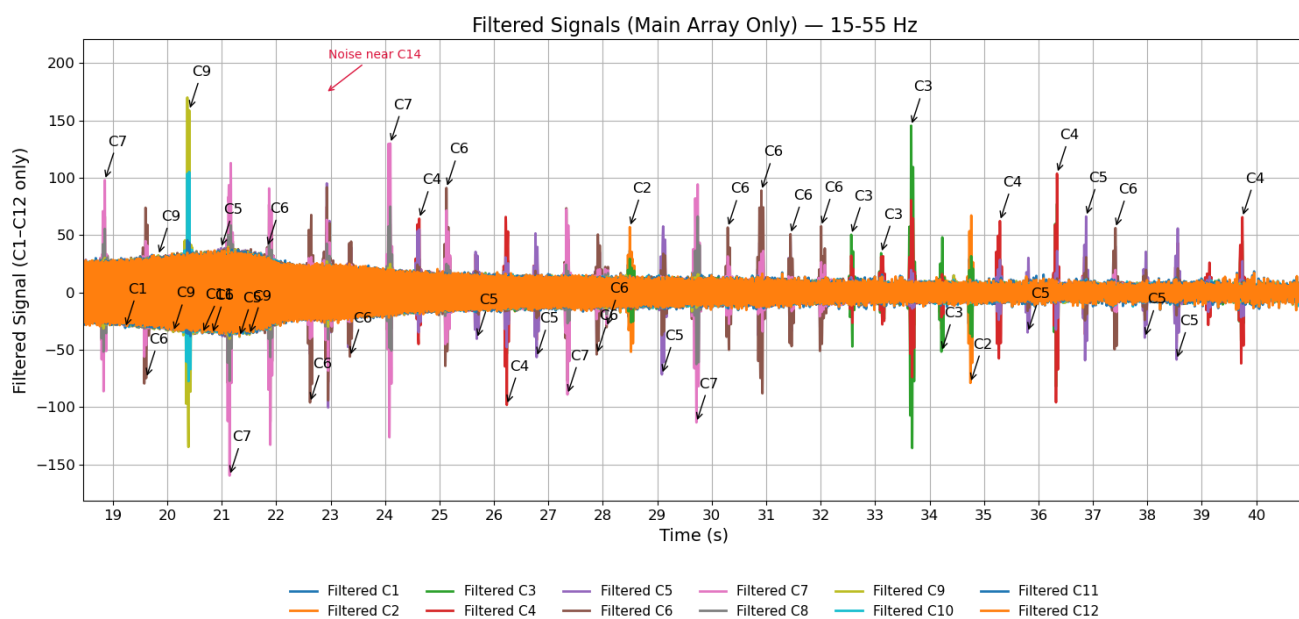


Figure 62. Chart. Δ EM flux (nT) vs time (s) of collected data with 15 to 55 Hz bandpass (Case #21).

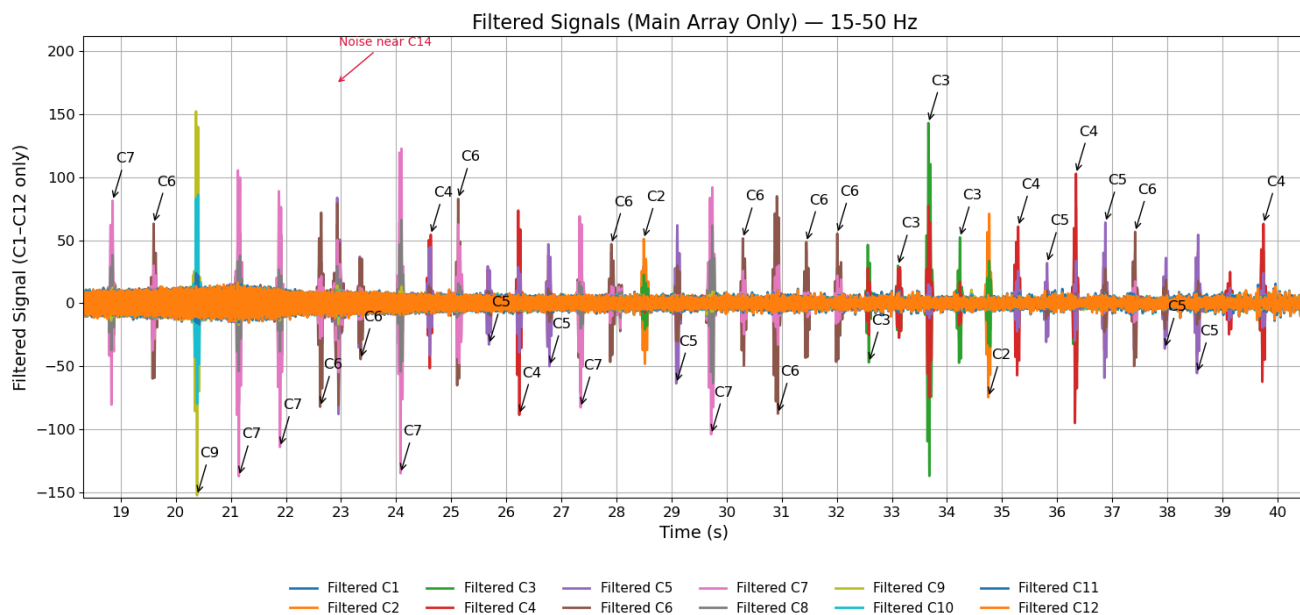


Figure 63. Chart. Δ EM flux (nT) vs time (s) of collected data with 15 to 50 Hz bandpass (Case #21).

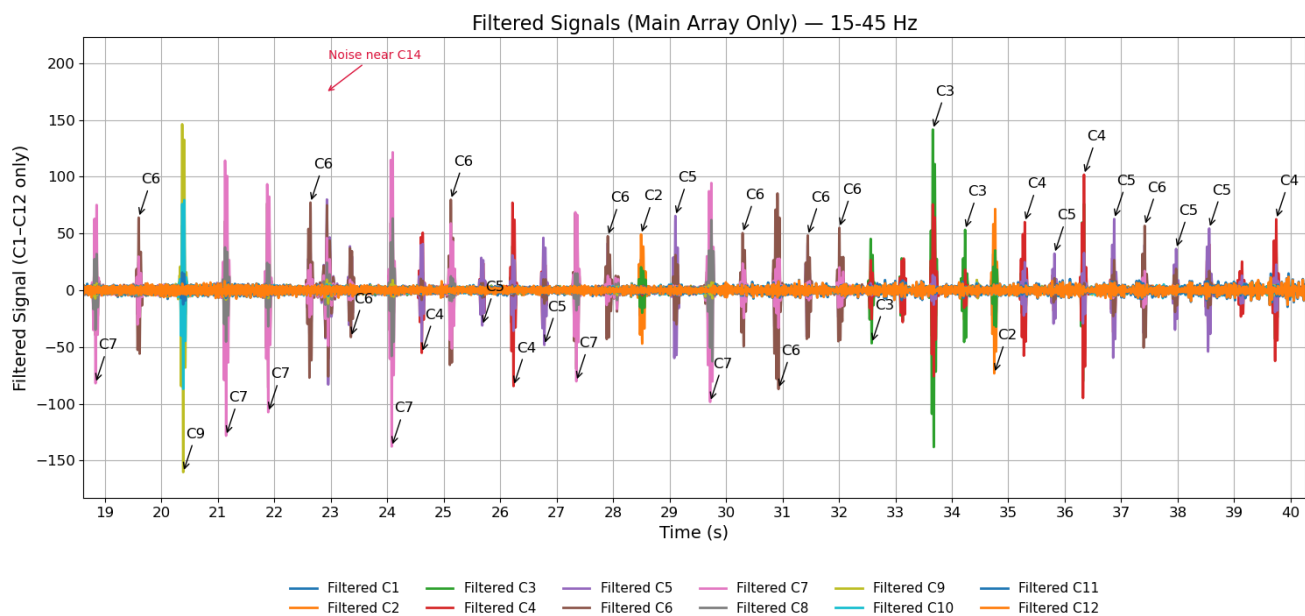


Figure 64. Chart. Δ EM flux (nT) vs time (s) of collected data with 15 to 45 Hz bandpass (Case #21).

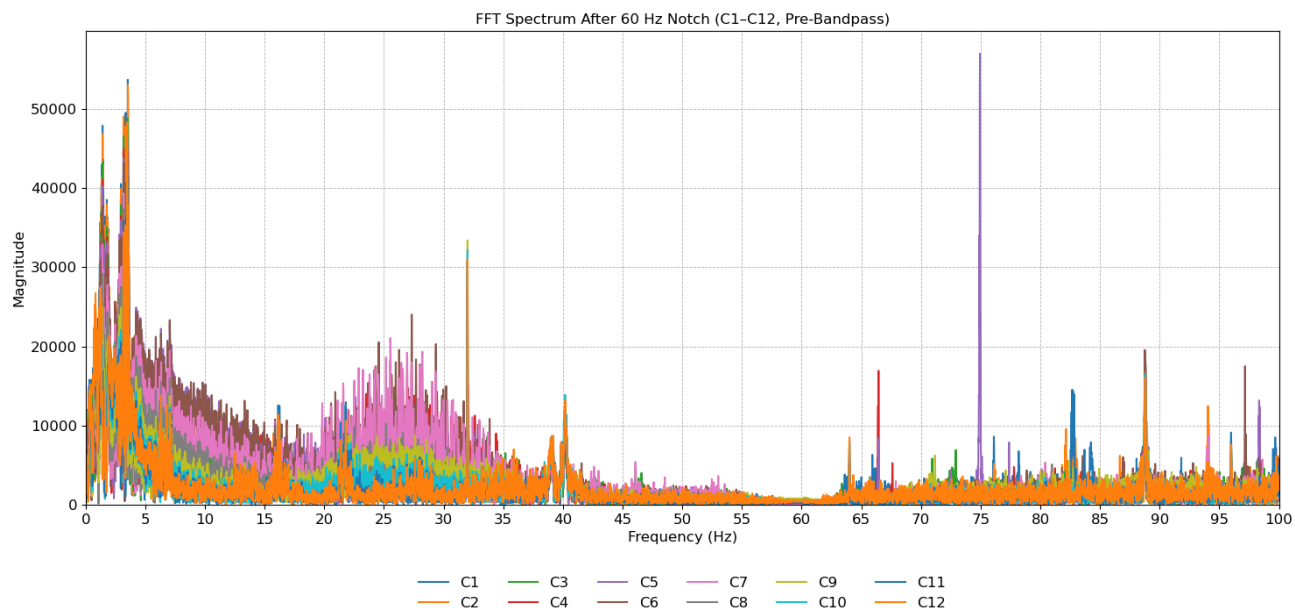


Figure 65. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels during surface conditions with snow on Titan Drive after applying 60 Hz notch bandpass filter (Case #21).

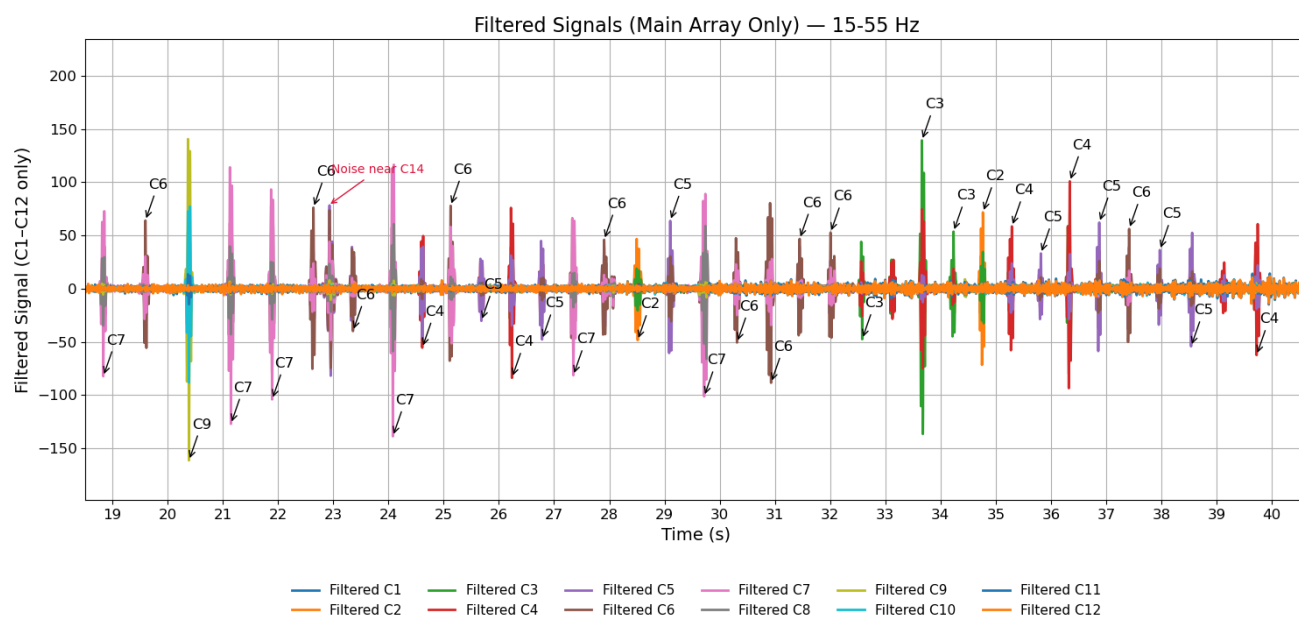


Figure 66. Chart. Δ EM flux (nT) vs time (s) of collected data after taking 60 Hz notch and 15 to 55 Hz Butterworth bandpass filters (Case #21).

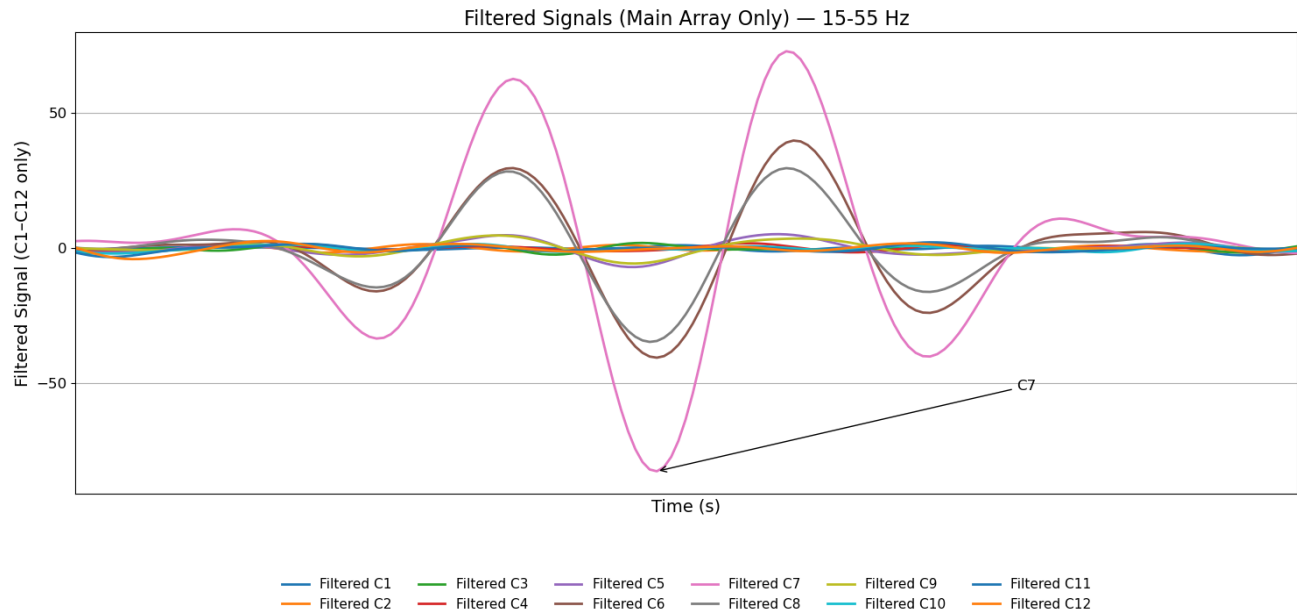


Figure 67. Chart. Δ EM flux (nT) vs time (s) of collected data on EM strip #1 with 15 to 55 Hz bandpass and 60-Hz notch filters (Case #21).

As shown in Figure 66, the vehicle sensor system continued to detect EM strips despite the surface being partially covered with snow. In fact, seven EM strips—Strips 20 through 25 and Strip 35—were fully obscured and could not be visually identified in the recorded images, as shown in Figure 68. Of these, five were successfully detected by the EM-based sensing system, while the remaining two were detected but failed to exceed the minimum Δ EM flux detection threshold of 30 nT. Figure 69 compares lateral offset measurements obtained from visual observation and EM-based detection under these snow-covered surface conditions, while Figure 70 presents the comparison between vehicle speeds derived from vehicle GPS and those estimated by the passive sensing system. A summary of lateral offset comparisons for Cases #17 to #21 is shown in Figure 71 and Table 7. Across these tests, the mean absolute lateral difference between visual-based and EM-based positioning ranged from 1.3 to 2.7 in., with standard deviations less than 3 in. This level of accuracy between the ground-truth measurements and EM strip detection, less than 3 in., is consistent with the magnetometer sensor spacing of 3 in. Vehicle speed differences between GPS-based and EM strip-based estimates remained within 1 mph on average for all cases, further supporting the reliability of the passive sensing system. Detailed test results for Cases #18 to #20, conducted under normal weather conditions to confirm detection repeatability, are summarized in Appendix B.

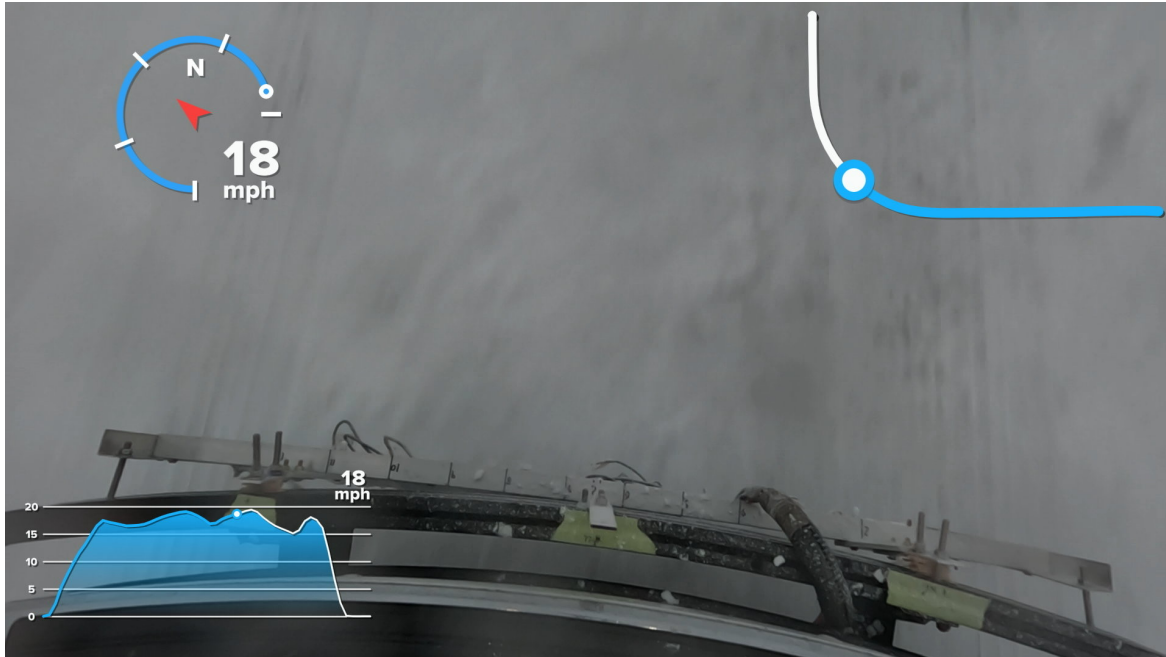


Figure 68. Photo. Example of top-view recorded image for EM strip #35 during test Case #21.

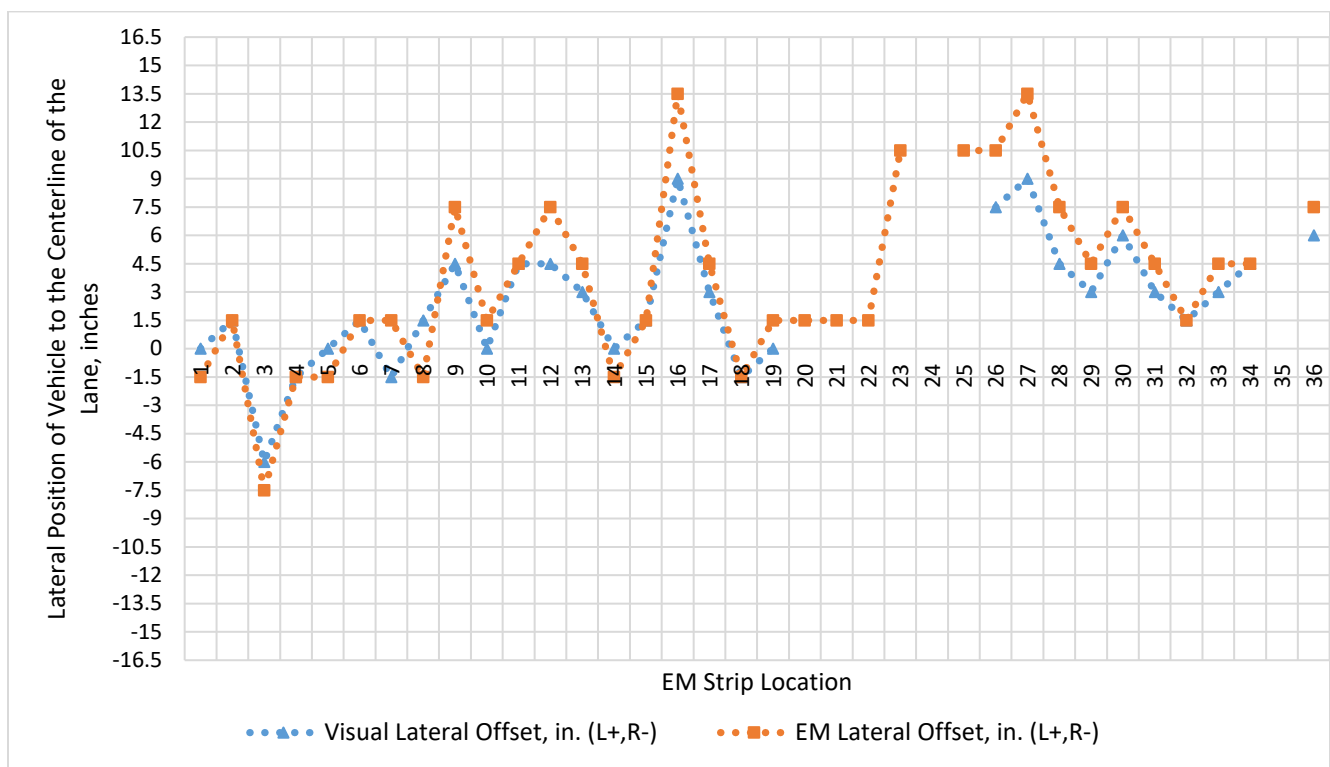


Figure 69. Chart. Comparison of the lateral position of vehicle from visual detection and EM sensor detection at speed above 15 mph for Case #21.

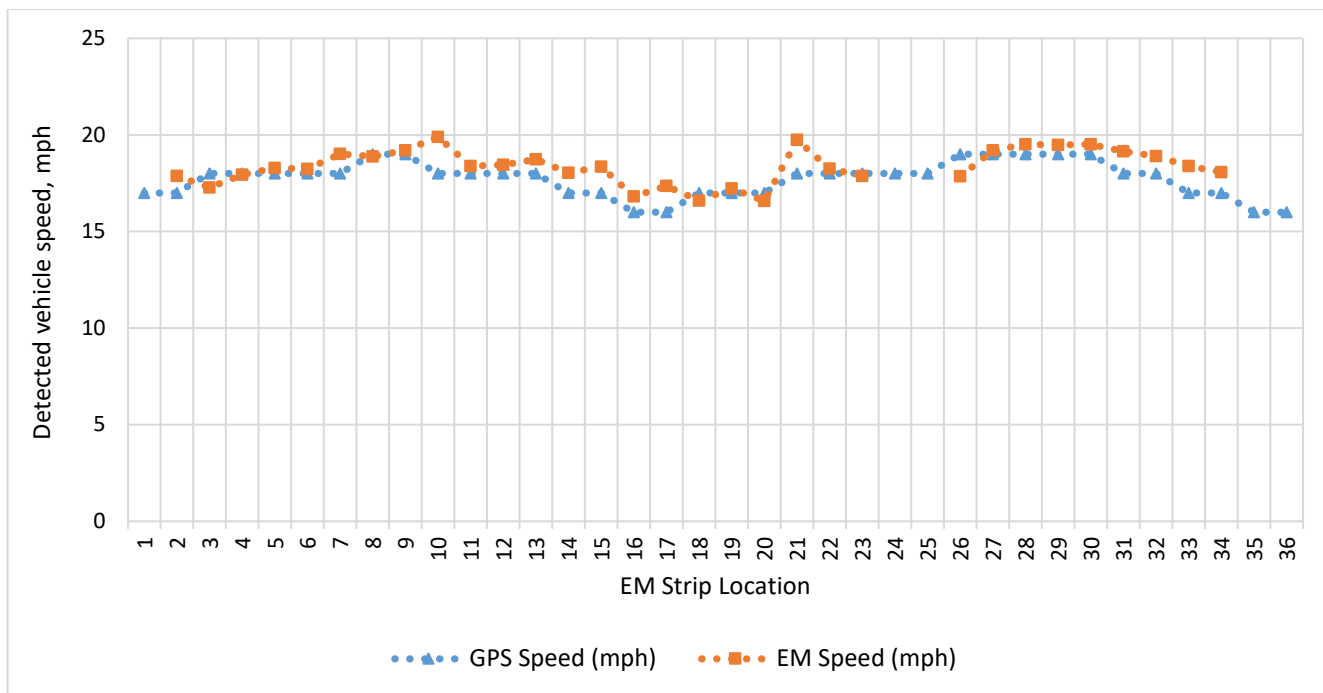


Figure 70. Chart. Comparison of the vehicle speed from GPS and EM strip detection (Case #21).

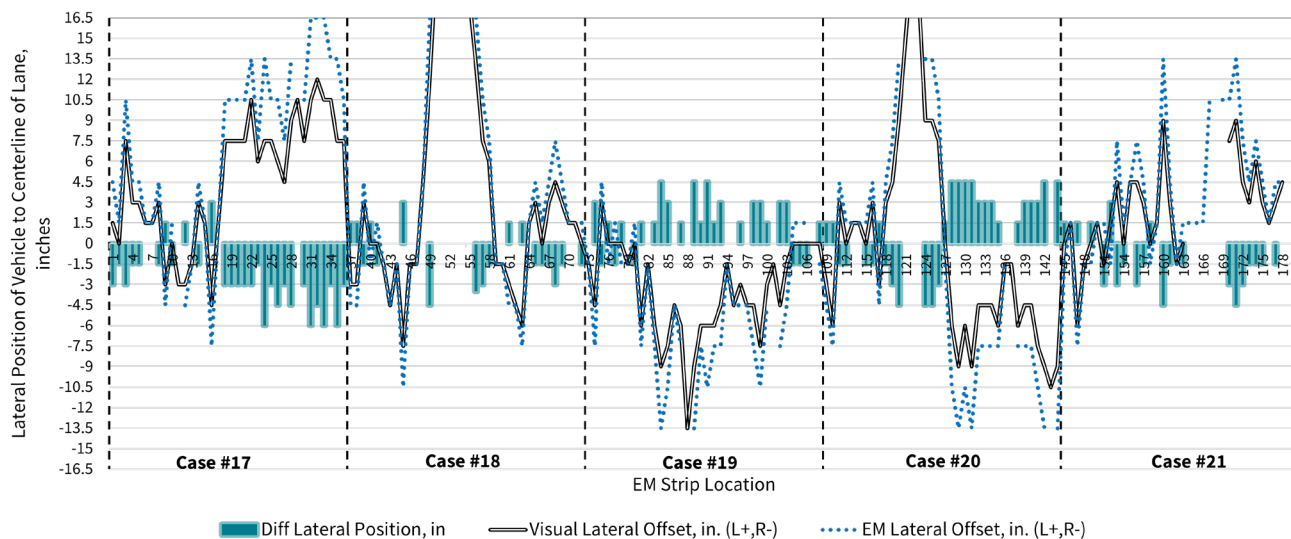


Figure 71. Chart. Comparison of the repeated performance of vehicle lateral position by visual and EM strip detection (Cases #17 to #21).

Table 7. Summary of Lateral Positioning and Speed Detection Performance for Test Cases #17 to #21 between Visual and EM Strips

Test Case	% EM Strip Detection	Mean $ Visual_i - EM_i $ Offset (in.)	SD, in.	Mean $ GPS_i - EM_i $ Vehicle Speed (mph.)	SD, mph.
17	94.4 (34/36)	2.6	2.2	0.8	0.8
18	96.7 (29/30)	1.3	1.7	0.7	0.8
19	91.7 (33/36)	1.8	1.8	0.7	0.8
20	93.9 (31/33)	2.6	2.9	0.8	0.7
21	94.4 (34/36)	2.1	2.8	0.7	0.7

CHAPTER 6: MOTION PLANNING IMPACTS WITH EM SENSOR DATA

The commonly adopted sensor-based offset extraction approach relies on offline processing of sensor time-series data, as detailed in the previous chapter. The method proposed in Chapter 5 requires batch-level signal analysis, in which the entire signal segment is first filtered using frequency-domain techniques such as fast Fourier transform (FFT)-based noise suppression and then analyzed through peak detection to infer the lateral offset. Although this approach is effective for post-processing and offline evaluation, its reliance on complete temporal windows limits its applicability to real-time lateral control, which requires instantaneous offset estimation at each control step. Development of such a real-time offset estimation strategy is underway during the next phase of the project. In this report, however, sensor readings are introduced based on GPS readings and a predefined error structure.

Building on the preceding discussion, this chapter presents and analyzes the robustness of motion planning under the experimental scenarios described earlier. This chapter first introduces the planner used in the experiments. It then analyzes the experimental results from both longitudinal and lateral control perspectives. All experiments were conducted on the rural road located in front of the ICT building, Titan Drive, in Rantoul, Illinois, as illustrated in Figure 4.

INTRODUCTION TO THE MOTION PLANNING FRAMEWORK

This section presents a motion planning framework for autonomous ground vehicles based on optimal trajectory generation in a Frenet coordinate system. The planner is designed to generate smooth, dynamically feasible trajectories in real time while respecting roadway geometry, vehicle kinematic constraints, and safety requirements. The approach follows a sampling-based, optimization-driven paradigm in which a dense set of candidate trajectories is generated over a short planning horizon and evaluated using a multi-objective cost function (Werling et al., 2010; Paden et al., 2016).

This motion planning system emphasizes a clear separation between global route planning and local motion generation, continuous replanning at high frequency, and explicit evaluation of multiple candidate motions rather than reliance on a single long-horizon optimization. Such semi-reactive architectures have been shown to be effective for autonomous driving in complex, uncertain, and dynamic environments (Thrun et al., 2006; Dolgov et al., 2008).

The planner operates within a hierarchical architecture consisting of a global planner and a local planner. The global planner produces a reference path that encodes roadway geometry and high-level navigation intent. This path is assumed to be collision-free at a coarse spatial resolution and is represented as a smooth parametric curve, consistent with standard autonomous driving system architectures (Dolgov et al., 2008; Paden et al., 2016). In the context of rural autonomous driving, the reference path represents a safe driving path on marked or unmarked roads. To avoid the scaling issues of high-definition maps, the global path is generated using satellite images. In this method, the drivable area is automatically detected, and a safe path is generated to serve as the global path for

the local planner. Using satellite images and automating this global path extraction provides a scalable approach to enabling autonomy in rural communities without the need for high-definition maps.

The local planner operates relative to this reference route and is responsible for generating executable vehicle trajectories. Its role is not to modify the global route but rather to compute locally feasible, and preferably close to optimal, trajectories that track the route while accounting for obstacles, speed targets, and vehicle dynamics. This decomposition reduces computational complexity and improves robustness by restricting local decision-making to a short horizon, where perception and prediction are most reliable (Dolgov et al., 2008).

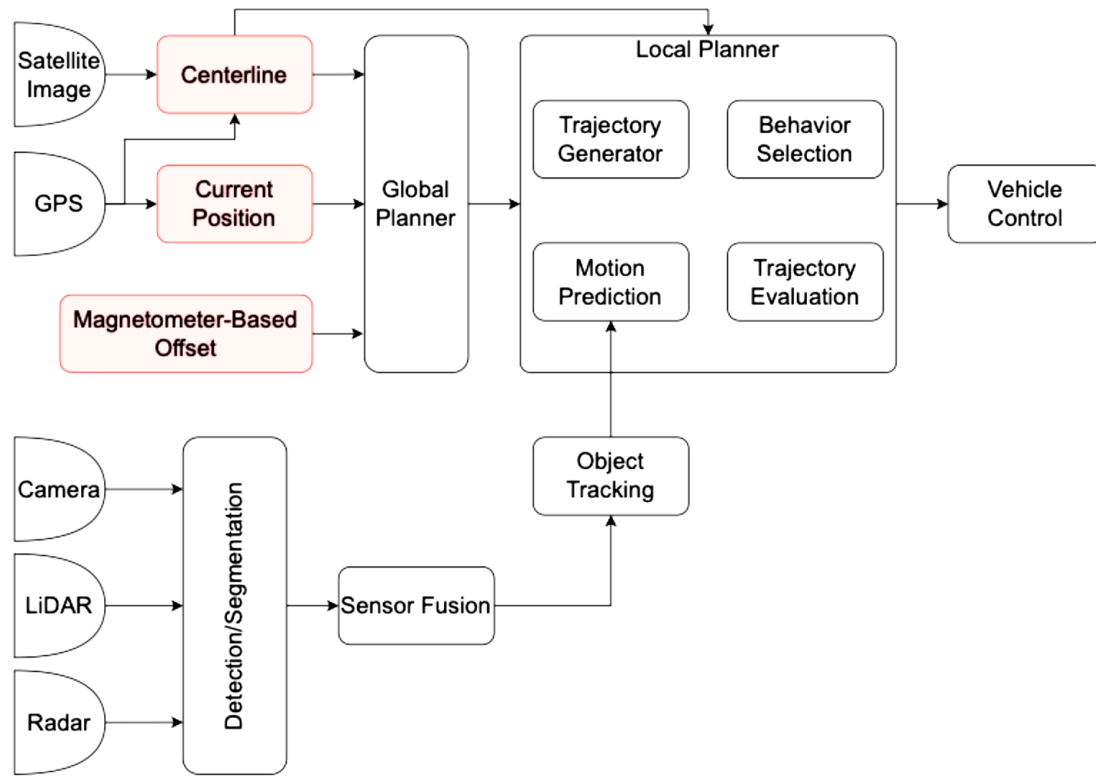


Figure 72. Chart. Structure of the motion planning framework developed for this project, with magnetometer sensor readings integrated into the planner to frequently update the vehicle offset from a reference path.

LOCAL PLANNER

This section discusses the underlying details of the local planner that enables the use of data from the magnetometer sensors for robust motion planning.

Frenet Coordinate Representation

Trajectory planning directly in Cartesian coordinates couples lateral and longitudinal vehicle motion, particularly on curved roadways. To simplify the planning problem, the local planner operates in a

Frenet coordinate system defined relative to the global reference path. In this coordinate system, vehicle motion is decomposed into:

- longitudinal distance along the reference path, denoted by s , and
- lateral offset from the reference path, denoted by d .

This representation enables structured reasoning about lane keeping, lane changes, and roadway boundaries while maintaining a compact planning space. Frenet-frame formulations have become a standard tool for road-aligned trajectory planning in autonomous driving applications (Werling et al. 2010; Ziegler et al. 2014).

Using this coordinate system is also critical for this project. While this offset is typically estimated using either camera-based perception or a combination of GPS and an inertial measurement unit (IMU), the proposed magnetometer-based detection approach enables direct and accurate measurement of the vehicle's offset relative to the global path. Accordingly, this study prioritizes magnetometer-based offset measurements and falls back on GPS-IMU estimation when those measurements are unavailable.

Reference Path and Projection

The reference path is represented as a continuously differentiable spline parameterized by arc length. At each planning cycle, the vehicle state is projected onto the reference path to obtain the corresponding Frenet coordinates. Candidate trajectories are generated in the Frenet frame and subsequently mapped back to Cartesian coordinates for feasibility evaluation and execution.

The Frenet formulation employed in this planner closely follows the optimal trajectory generation framework introduced by Werling et al., which demonstrated that complex urban driving scenarios can be addressed efficiently through polynomial trajectory generation in curvilinear coordinates (Werling et al., 2010). Figure 73 illustrates this concept.

Trajectory Generation Using Polynomial Motion Primitives

The motion planning framework employs polynomial motion primitives to generate a set of dynamically feasible candidate trajectories.

Polynomial Parameterization: Candidate trajectories are parameterized using time-based polynomials. Lateral motion is represented using quintic polynomials to ensure continuity of position, velocity, and acceleration at both the initial and terminal states. Longitudinal motion is represented by using quartic or quintic polynomials, allowing control over terminal speed while maintaining smooth acceleration profiles. A general quintic polynomial was used to represent lateral motion as a fifth-order time-dependent trajectory function. In this formulation, the lateral position is expressed as the summation of six polynomial terms, ranging from a constant term to a fifth-order time term. The corresponding coefficients are uniquely determined from the prescribed boundary conditions on lateral position, velocity, and acceleration at the initial and final states. This formulation guarantees

bounded jerk, which is critical for passenger comfort and stable vehicle control (Werling et al., 2010; Paden et al., 2016).

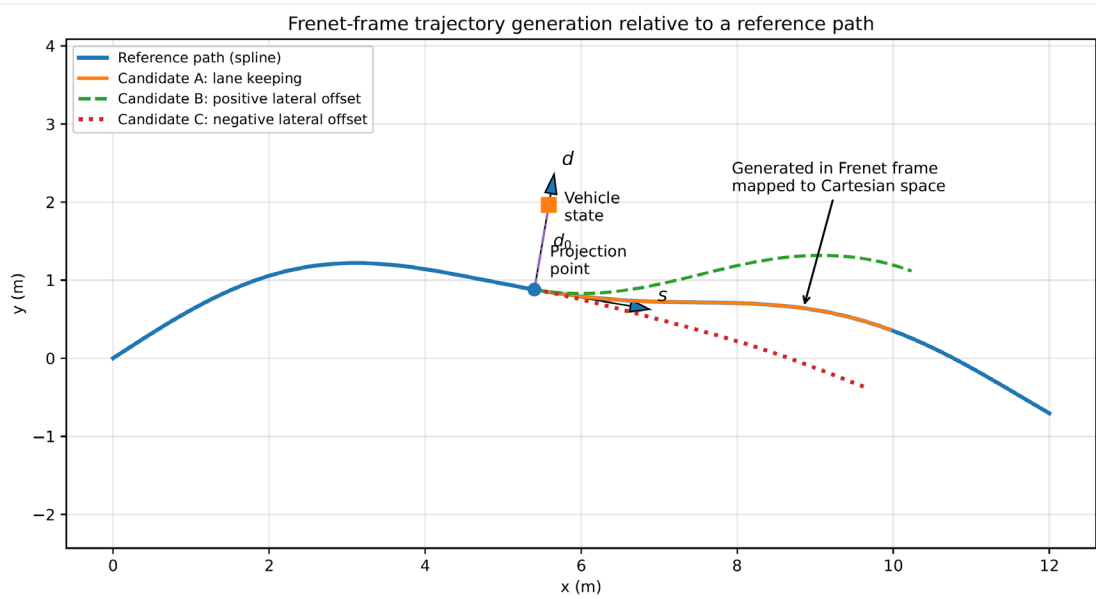


Figure 73. Chart. Frenet-frame planning relative to a reference path. The vehicle state is projected onto a continuously differentiable spline reference path to obtain Frenet coordinates (s, d) . Candidate trajectories are generated in the Frenet frame and mapped back to Cartesian space for feasibility evaluation and execution, consistent with Werling et al. (2010).

Sampling of Terminal Conditions: Rather than optimizing directly over control inputs, the planner samples terminal conditions over a finite horizon. These samples include target lateral offsets, target longitudinal velocities, and trajectory durations. Each sampled terminal condition defines a unique candidate trajectory. This approach is critical to ensuring fast trajectory generation that meets the requirements of real-world driving. The sampling-based strategy enables systematic exploration of feasible maneuvers, including lane keeping and lane changes, while avoiding the nonconvex optimization challenges associated with continuous trajectory optimization in dynamic driving environments (Dolgov et al., 2008).

Cost Function and Trajectory Selection

Each candidate trajectory was evaluated using a weighted cost function that combines multiple performance and safety criteria. Separate cost terms were assigned to lateral deviation and lateral acceleration, inefficient longitudinal progress, deviation from the desired speed, jerk for passenger comfort, and proximity to obstacles. Each term was multiplied by a corresponding weighting factor, allowing the trajectory planner to prioritize safety, comfort, speed tracking, and efficient motion according to the selected design objectives.

Such a cost function can be easily calculated for each generated trajectory and provides a balanced evaluation across multiple objectives. Cost formulations of this type are widely used in autonomous driving to balance safety, comfort, and efficiency, and they are a central component of optimal

trajectory generation methods (Werling et al., 2010; Paden et al., 2016). The weights can be adjusted based on the overall goals of the planner. In this study, greater weights were assigned to penalize deviation from the reference path.

Obstacle Handling and Feasibility Constraints

Obstacle avoidance is performed by projecting detected obstacles into the Frenet frame and evaluating the distance between each obstacle and candidate trajectory over time. Trajectories that violate minimum safety distances, kinematic limits, or roadway constraints are discarded prior to cost evaluation.

This filter-then-rank strategy ensures strict enforcement of safety constraints while maintaining computational efficiency. Similar approaches have been successfully applied in real-world autonomous vehicle systems to enable real-time operation in crowded environments (Thrun et al., 2006; Ziegler et al., 2014).

An extended Kalman filter is employed to predict the motion of surrounding objects over the planning horizon. Accordingly, the collision detection process evaluates both vehicle and obstacle trajectories over time to identify any violation of minimum safety-distance constraints. The minimum safety distance is selected conservatively to prioritize operational safety.

Receding-Horizon Execution

The planner operates in a receding-horizon manner. At each planning cycle, only the initial segment of the selected trajectory is executed, after which the planning process is repeated using updated state and perception information. This approach provides robustness to disturbances, modeling uncertainty, and dynamic obstacles, enabling continuous adaptation to changing environments (Dolgov et al., 2008; Paden et al., 2016).

EXPERIMENTAL RESULTS

This section presents the results of the experiments conducted to assess the robustness of planning under the proposed precise driving automation strategy. The key focus is to evaluate whether integrating readings from the magnetometer sensors can enhance the safety and efficiency of motion planning.

Experimental Setup

To enable real-time experiments, the current study uses a GPS-based lateral control strategy. A reference trajectory is prerecorded using GPS coordinates, and the planner computes the lateral offset in real time by comparing the vehicle's current GPS position with the reference path. This offset is then provided directly to the controller for lateral actuation. As discussed, the control framework is designed to support a dual-source offset estimation scheme, in which sensor-based offset measurements are used when available, and GPS-based offset estimation serves as a fallback to ensure continuous lateral control. In practice, sensor-based offsets can be obtained only when the vehicle traverses pavement segments equipped with EM strips, and reliable real-time sensor-based offset estimation is not yet available in the current system. As a result, the experiments presented in

this chapter rely exclusively on GPS-based offset estimation. To mimic the offsets provided from magnetometer sensors, random noise is added to GPS-based offset. This process simulates readings from the magnetometer sensors by assuming that GPS errors create discrepancies between GPS readings and magnetometer-based offsets. This setup provides the necessary data to assess the performance of the motion planning framework integrated with the magnetometer-based offset calculations. Nevertheless, the overall motion planning structure is formulated in a modular manner with respect to the offset source. Once a reliable real-time sensor-based offset estimation becomes available, it can be integrated alongside the GPS-based offset within the same control framework, without requiring modifications to the planner or controller.

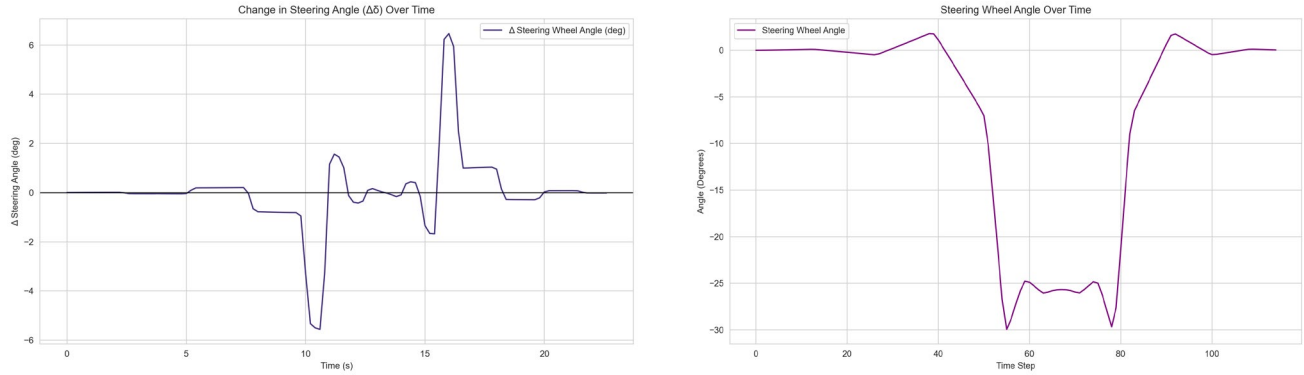
Simulation Results

To safely assess the performance of the motion planning framework under frequent offset adjustments—the condition expected from integrating the magnetometer-based offset readings with the GPS-based offset calculations—this project conducted extensive simulation studies before performing any field experiments. While the simulation studies focused on scenarios similar to those expected to be tested in the field, they provided the opportunity to push the planner to the limits by imposing extreme discrepancies between GPS-based offset and magnetometer-based offset.

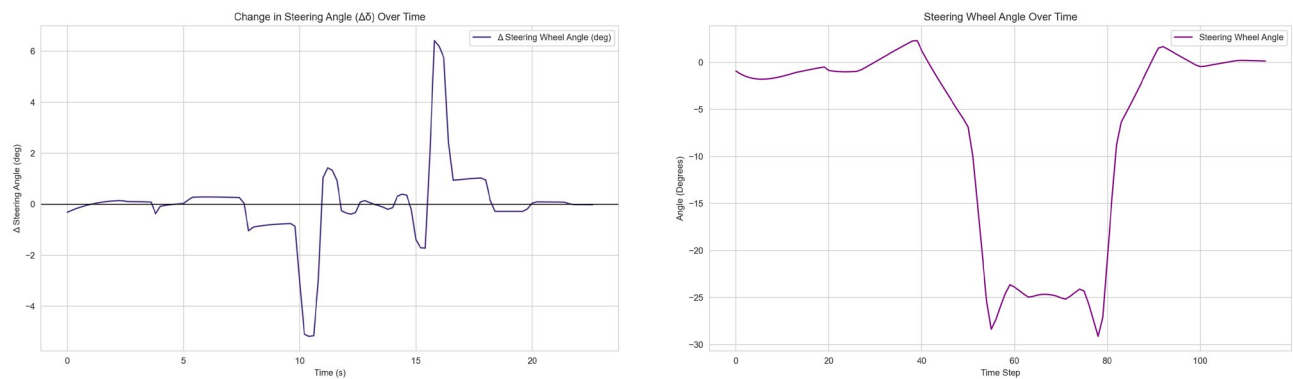
Figure 74 presents the steering wheel angle and changes in steering wheel angle when driving through a curve similar to the one shown in Figure 4. Two cases of small random offsets, within $(-4, 4)$ in., and very large offsets, within $(-40, 40)$ in. are presented. The key finding from these simulation efforts was that the motion planning framework is robust to discrepancies between GPS-based offset and magnetometer-based offset. In fact, using magnetometer-based offset when available resulted in better performance than using only GPS-based offset. In other words, frequent and accurate offset information resulted in more robust lane keeping. The steering angles and changes in steering angle (as shown in Figure 74) also show that the amount of offset error did not have a significant impact on the lane-keeping outcome. The jumps in steering angle changes in Figure 74 are due to the lack of a transition curve in these scenarios. This was intentional and was designed to push the planner to its limits. Adding a transition curve further smooths the steering angles and changes in steering angle, resulting in significantly more comfortable ride experience.

Field Experiments

After the simulation studies confirmed the safety and robustness of the motion planning framework integrated with the magnetometer-based offset detection system, extensive field experiments were conducted. These tests were conducted at ICT (Figure 4). Compared with the simulation study, the field experiments were conducted under significantly more restrictions and prioritized safety while ensuring a comprehensive evaluation of the proposed framework. The following sections present selected results from these experiments.



a. Changes in steering angle (left) and steering angle (right) in small offsets (–4, 4) in.



b. Changes in steering angle (left) and steering angle (right) in large offsets (–40, 40) in.

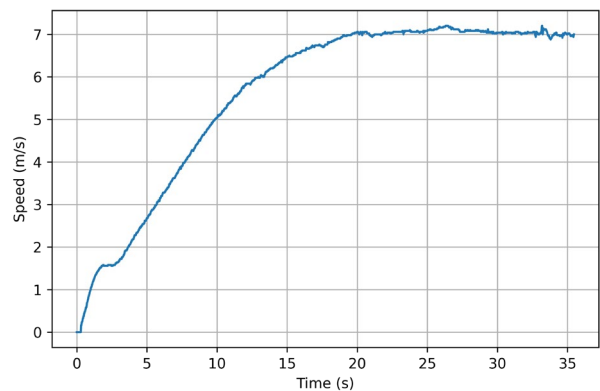
Figure 74. Chart. Simulation results for (a) small and (b) large random offsets.

Longitudinal Control Analysis

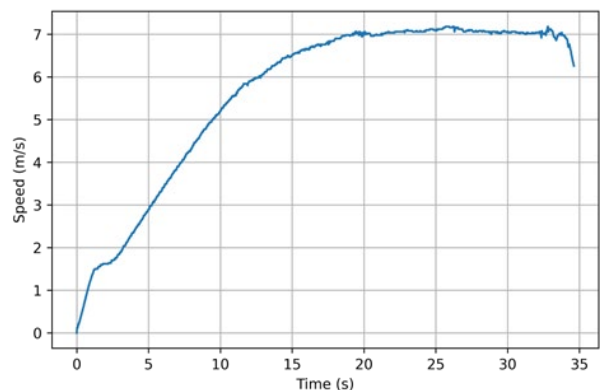
The longitudinal control performance is analyzed using the time-speed and time-acceleration diagrams. In the experiments, the maximum vehicle speed is set to 7 m/s (approximately 15.7 mph). As shown in the time-speed profile (Figure 75), the vehicle exhibits a relatively large acceleration during the initial launch phase to overcome inertia and reach the desired speed. This is followed by a phase of approximately constant acceleration, during which the vehicle speed increases smoothly toward the target value. Once the desired speed of 7 m/s is reached, the controller maintains a nearly constant cruising speed with only minor fluctuations. The corresponding time-acceleration diagram in Figure 76 further illustrates this behavior. Higher acceleration is observed at the beginning of the maneuver, after which the acceleration gradually decreases as the vehicle approaches the target speed. This transition reflects the longitudinal controller's ability to regulate acceleration and ensure a smooth convergence to steady-state cruising.

To simulate a sensor-based offset source, a small amount of randomness was introduced to the original GPS-based offset. Specifically, the offset is perturbed by a uniformly distributed random term within the range of $[-0.1, 0.1]$ relative to its nominal value. This formulation was intended to approximate the variability that may arise from magnetometer-based offset measurements. From a

longitudinal control perspective, the introduction of offset randomness did not produce a noticeable effect. As shown by the time-speed and time-acceleration diagrams in Figures 75 and 76, the longitudinal response remains nearly unchanged compared to the pure GPS-based case. The impact of offset randomness therefore appears primarily in the lateral control behavior, which is examined in detail in the subsequent lateral control analysis. This is expected because longitudinal behavior changes only during extreme lateral movements, when stabilization is needed, and the small offset values used in this test were not sufficient to push the vehicle to its operating limits.

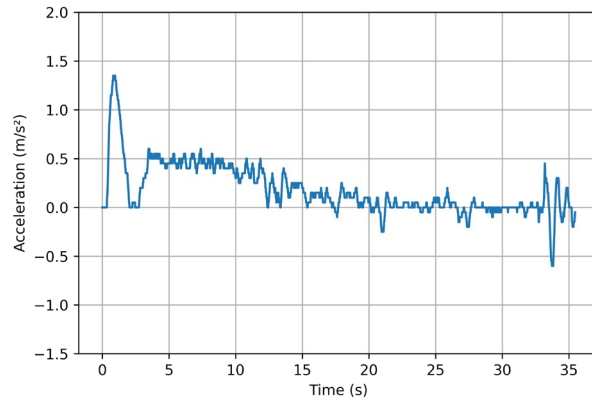


a. Without Random Noise

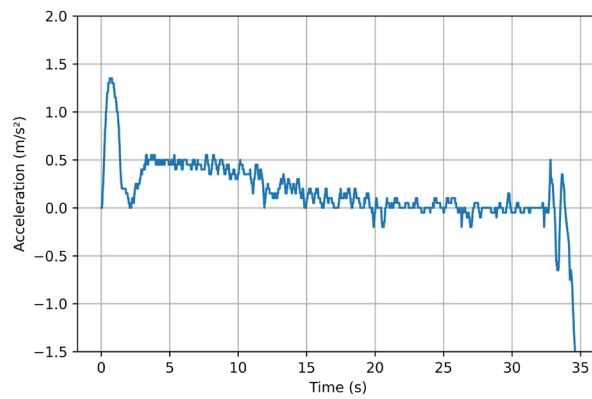


b. With Random Noise

Figure 75. Chart. Longitudinal speed profiles.



a. Without Random Noise

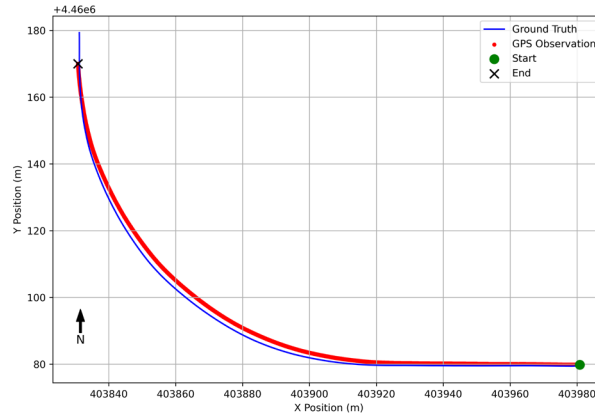


b. With Random Noise

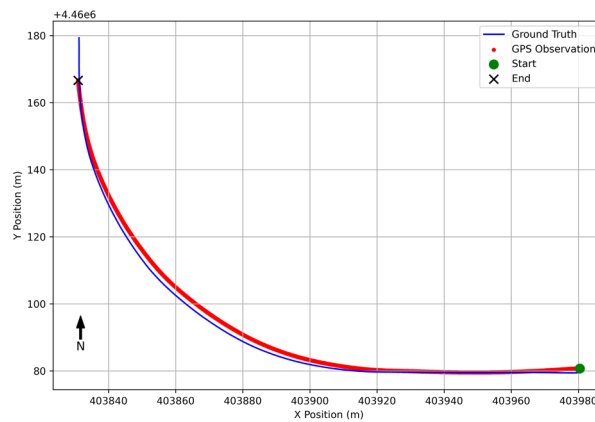
Figure 76. Chart. Longitudinal acceleration profiles.

Lateral Control Analysis

The lateral control performance is first evaluated by comparing the vehicle's actual trajectory with the ground-truth trajectory under two conditions: without random offset and with random offset. As shown in Figure 77, during straight-line driving, the vehicle trajectory closely follows the ground-truth path in both cases. In contrast, larger deviations between the actual trajectory and the ground truth are observed in curved road segments, where lateral control demands are higher. When random offset is introduced to emulate sensor-based offset measurements, the overall lateral deviation increases. This result is expected because GPS had very small errors during these tests, and the additional offsets were creating unnecessary errors in tracking. Such behavior, however, is not expected when GPS accuracy is low and the magnetometer-based offset is more accurate.



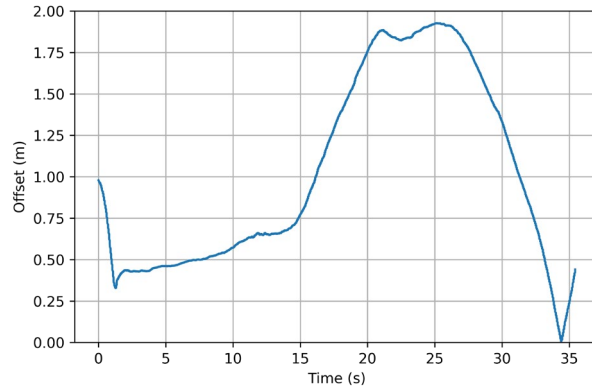
a. Without Random Noise



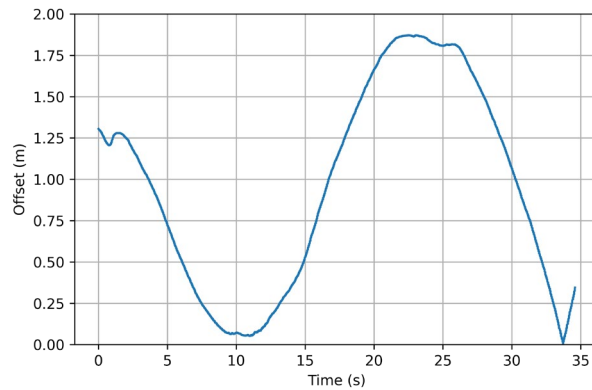
b. With Random Noise

Figure 77. Chart. Comparison of actual vehicle trajectory and ground truth.

A consistent observation can also be made from the time-offset diagram in Figure 78. During straight-line driving, the lateral offset remains relatively small in both cases. After introducing random offset to emulate sensor-based measurements, the lateral offset during straight segments becomes slightly larger than in GPS-only case. This increase reflects the direct influence of offset perturbations on the lateral tracking error, even when the vehicle is operating under low-curvature conditions.



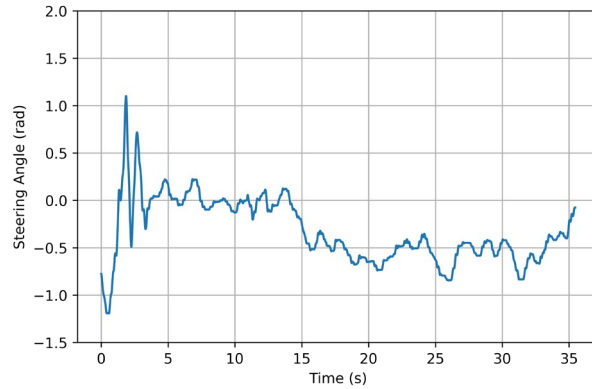
a. Without Random Noise



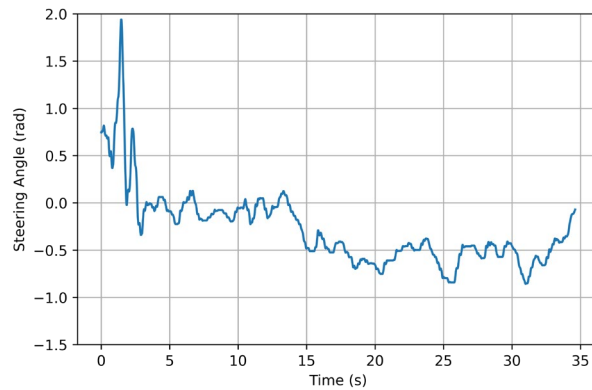
b. With Random Noise

Figure 78. Chart. Lateral offset profiles.

The lateral control behavior is further examined by comparing the steering angle over time under the two conditions. At the beginning of the maneuver, a relatively large steering angle is observed as the controller initiates vehicle motion and corrects the initial lateral deviation. Following this initial adjustment, the steering angle gradually settles and remains within a relatively stable range. In this study, a negative steering angle corresponds to a rightward steering input. As shown in the time-steering-angle diagram in Figure 79, the vehicle enters a curved road segment approximately between 10 s and 15 s, during which the steering angle deviates more significantly from zero to accommodate the required turning maneuver. Upon exiting the curve, the steering angle gradually returns toward zero as the vehicle transitions back to straight-line driving. Throughout the maneuver, the steering angle exhibits continuous small adjustments rather than remaining constant. When the steering angle becomes excessively large or small, corrective steering inputs in the opposite direction are observed. This behavior reflects the controller's ongoing effort to regulate lateral deviation and maintain stable trajectory tracking.



a. Without Random Noise

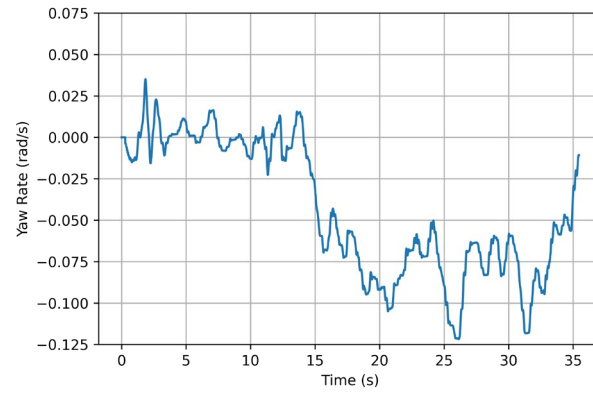


b. With Random Noise

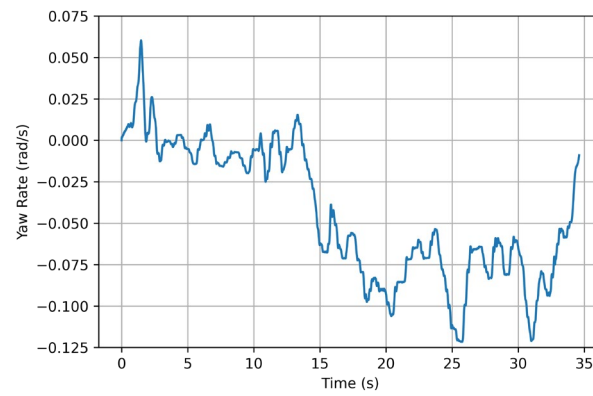
Figure 79. Chart. Steering angle profiles.

A similar pattern can also be observed in the time-yaw-rate response (see Figure 80). Consistent with the steering angle behavior, the vehicle's yaw rate exhibits larger variations after the introduction of random offset. Compared with the case without random offset, the yaw rate magnitude increases, indicating a more active lateral response to compensate for the perturbed offset input.

Overall, the experimental results demonstrate that the proposed control framework can be successfully implemented using GPS-based lateral offset estimation. The GPS-based configuration enables stable real-time longitudinal and lateral control and serves as an effective means to validate the overall control architecture under current sensing constraints. However, GPS-based offset estimation alone is not sufficient to fully replace sensor-based lateral offset information, particularly in curved road segments where higher lateral accuracy is required. Sensor-derived offset measurements remain essential for precise lateral control when reliable real-time sensing is available. Once real-time sensor-based lateral offset estimation is achieved, the envisioned dual-source offset framework can be realized. By leveraging sensor-based offsets when available and GPS-based offsets as a fallback, the system can seamlessly transition between offset sources while preserving the existing planner and controller structure.



a. Without Random Noise



b. With Random Noise

Figure 80. Chart. Yaw rate profiles.

CHAPTER 7: SUMMARY AND CONCLUSIONS

A field study was developed with an automated driving system (ADS) vehicle and magnetometer-based sensing system to test the detectability, repeatability, and reliability of pavement-encoded EM strips placed on the surface of concrete and asphalt pavements. The objective of the study was to detect and define the electromagnetic (EM) strip patterns (pavement-encoded signage), evaluate vehicle lateral position and speed accuracy for a variety of vehicle speeds, 15 to 55 mph, and weather conditions, including normal, rain, and snow/ice conditions, on both a closed-traffic concrete pad and a low-volume rural road. Both test sections were in Rantoul, Illinois, adjacent to the Illinois Center for Transportation facility.

The closed-area concrete pad consisted of two test segments: (1) a 350 ft tangent section that tested the construction work zone signage, vehicle speed, lateral position of the vehicle within the lane, and an unsignalized intersection stop-warning pattern; and (2) a 350 ft section with a lane-merge EM strip pattern, commercial magnetic tape compared with metal oxide magnetized strips, lane shift, and an end-of-CWZ pattern. ADS vehicle testing was conducted between 25 and 55 mph for both test segments.

The second main test section for the vehicle-to-infrastructure (V2I) system involved placement of longitudinal EM strips spaced 20 ft and 15 ft apart on a rural road tangent and horizontal curve, respectively. There were 36 longitudinal EM strips (8 ft long by 6 in. wide) fabricated using epoxy containing magnetizable metal oxide and placed on the asphalt pavement surface. The vehicle traversed this section under different weather conditions, and its lateral position was compared with a ground-truth measure (downward-facing camera) and GPS speed indicator at speeds between 15–20 mph. The findings from the testing on these two main sections are summarized in the next few sections related to detectability, repeatability, and reliability.

DETECTABILITY OF PAVEMENT-ENCODED SIGNAGES

This field study demonstrated the robust detectability of pavement-encoded electromagnetic (EM) strips across several road geometries, vehicle speeds, weather conditions, and strip configurations, or signage patterns. The detection algorithm reliably identified diverse EM signage patterns, including transverse strips for speed detections and warnings, inclined strips for lane-merge cues, longitudinal strips for lateral positioning and lane-shift maneuvers, and spatially encoded patterns for end-of-zone and STOP warnings at unsignalized intersections. The minimum reliable signal detected after filtering was determined to be 30 nT. Across all 21 test cases, including both rigid concrete and flexible asphalt pavements, straight and curved segments, and normal and adverse weather conditions, the system consistently captured signage-induced EM signals with clarity and minimal distortion after signal processing, with overall detectability greater 90% of the EM strips.

Even under adverse weather conditions, including snow-covered pavement scenarios (Case #15, #16, and #21), the V2I sensing system successfully detected signage events that were fully obscured from visual observation. This performance demonstrates the potential of the pavement-assisted passive sensing framework to serve as a redundant and resilient input layer for advanced driver-assistance

systems (ADAS) and ADS, particularly in situations where visual sensors may be compromised by environmental occlusion or surface contamination.

ACCURACY OF LATERAL POSITIONING AND SPEED ESTIMATION

Across all rural road test cases (Cases #17 to #21), the mean absolute lateral difference between visual-based and EM-based measurements ranged from 1.3 to 2.6 in., with standard deviations below 3 in. including under the snow-covered conditions of Case #21. The lateral position accuracy was directly linked to the spacing of the magnetometer sensors, which was fixed at 3 in. This confirms the system's capability to provide < 3 in. lateral positioning accuracy. Vehicle speed estimations derived from EM strip spacing and detected signal time were also benchmarked against GPS-derived speed data. The mean absolute difference between the two methods remained consistently below 1 mph across all test runs confirming the reliability of the system for speed estimation and warning. These results validate the V2I system's potential to support vehicle guidance and control functions in automated driving applications.

ROBUSTNESS OF MOTION PLANNING FRAMEWORK

The simulations and field experiments confirm that the proposed offset detection framework can be safely integrated with the present motion planning framework. The results indicate that adding accurate magnetometer-based offset measurements to adjust vehicle offset can improve both safety and comfort. The evaluation of steering angle, changes in steering angle, acceleration, and yaw rate indicated that by leveraging sensor-based offsets when available and GPS-based offsets as a fallback, the system can seamlessly transition between offset sources while preserving the existing planner and controller structure. This is a critical finding toward the development of a robust lane-keeping strategy capable of operating in any weather and roadway conditions.

KEY FINDINGS AND PERFORMANCE EVALUATION

Several key findings emerged from the pavement-encoded signage and ADS vehicle field experiments:

- **Interference and Filtering Strategy:** The system effectively identified and suppressed low-frequency ambient interferences that varied with ADS vehicle speed. These interferences were strongly correlated with wheel and tire harmonics. To address this EMI, two bandpass filtering configurations were employed: 15–55 Hz for speeds below 35 mph and 20–80 Hz for speeds above 35 mph. Both configurations preserved EM signals while minimizing noise, validating the need for speed-adaptive filtering strategies. Notch filtering at 60 Hz was also applied to the collected signals and was sufficient to suppress noise generated by adjacent electric power lines.
- **Weather Resilience:** The detection system maintained high repeatability and reliability even under adverse weather conditions, including the presence of snow, ice, and water on the pavement surface. Notably, the EM strip and signage signals remained detectable by the

magnetometer sensors and filtering strategies even when the road was visually obscured by snow.

- **False Detection Control:** A noise-rejection framework was developed based on top-row magnetometer sensor coincidence screening. This framework successfully filtered out disturbances from embedded metallic elements, such as dowel bars and steel tie bars, subsurface ferromagnetic materials, and other ambient EM sources. With this new false detection control, no false positives were recorded from non-EM strip sources across both test sections and all test runs.

Recommendations for future development and deployment include:

- **Extended Field Testing and Real-Time System Integration:** Future work should include expanded field testing across diverse roadway types (functional classifications, curves, intersections, tangents), speeds, and vehicle platforms. This includes integrating the V2I sensing system into real-time vehicle control environments to assess system responsiveness, latency, and detection robustness under live ADS operations.
- **Multimodal Sensor Fusion:** To enhance fault tolerance and improve redundancy, future development should explore integrating pavement-assisted EM sensing with other onboard sensor modalities, such as camera-based vision, radar, and LiDAR. Multi-sensor fusion would allow for complementary strengths—using EM signals for robust lane-level localization in low-visibility conditions, and computer vision/LiDAR for broader situational awareness—thereby improving overall safety and system reliability.

The results of this study support the viability of pavement-encoded EM signages as a passive, infrastructure-integrated solution for improving automated vehicle guidance, particularly in work zones and complex road geometries where visual perception alone may be unreliable.

PROJECT OUTPUTS, OUTCOMES, AND IMPACTS

OUTPUTS

This project produced a field-validated passive V2I sensing framework using pavement-encoded electromagnetic (EM) strips and vehicle-mounted magnetometers. The work developed EM signage patterns for construction work zones, speed warnings, lane-merge cues, lane shifts, end-of-work-zone messages, rural road lateral positioning, and unsignalized intersection STOP warnings. A detection and signal-processing framework was also developed to capture true EM signage responses while rejecting false positives caused by local EM disturbances. Field testing was conducted on concrete and asphalt pavements, tangent and horizontal curved roadway sections, normal and adverse weather conditions, and vehicle speeds ranging from 15 to 55 mph.

- Sakulneya, A., & Roesler, J. R. (2025). Passive Sensing Communication to Vehicles in Construction Work Zones through Signage Coded on Pavement Surface. *Transportation Research Record: Journal of the Transportation Research Board*, 2679(9), 847-857. <https://doi.org/10.1177/03611981251340399>
- Hsiao, C-C., An, G., & Talebpour, A. (2025) Optimizing for Ride Comfort: A Model Predictive Control Framework with Frequency-Domain Analysis of the Acceleration Sequence. Presentation at IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hangzhou, China, Oct. 25, 2025.
- Hsiao, C-C., An, G., & Talebpour, A. (2026) Comfort-Aware Control Strategy for Autonomous Vehicles: Shaping Acceleration Profile in the Frequency Domain. Presentation at the 105th Annual Meeting of the Transportation Research Board (TRB), Washington D.C., January 11-15, 2026.
- Sakulneya, A., "Precise Connected Automated Vehicle Motion Planning with V2I Passive System. CCAT Global Symposium on Mobility Innovation," Ann Arbor, MI, April 17, 2026.
- Roesler, J., "V2I Communication: Lane Keeping and Construction Work Zone Systems," UC Davis/Caltrans Seminar, University of California, Davis, July 17, 2025.
- Sakulneya, A., Liu, P., Hsiao, C-C, Hsiao, Talebpour, A., & Roesler, R. (2026). Enhancing Pavement-Encoded Signages for Precise Driving Automation [Dataset]. Purdue University Research Repository. <https://doi.org/10.4231/EVQN-EP06>

OUTCOMES

The system demonstrated reliable detection, lateral positioning, and speed-estimation performance across 21 test cases. Pavement-encoded EM strips achieved greater than 90% detectability, including under snow-covered road conditions where visual observation was occluded. Rural road testing showed mean absolute lateral-position differences of 1.3 to 2.6 in. compared with visual observations, confirming less than 3 in. positioning accuracy. Speed estimates derived from EM strip spacing and detection timing remained within 1 mph of GPS-based speed across test runs. The filtering and false-detection framework suppressed vehicle-motion interference, power-line noise, embedded metallic elements, and other ambient EM sources, with no false positives recorded from non-EM strip sources.

IMPACTS

This project demonstrates that pavement-encoded EM signage can serve as a passive, infrastructure-integrated, and weather-resilient sensing layer for ADAS and ADS applications. Its primary impact is improved vehicle guidance and warning capability in critical roadway areas, including work zones, rural roads, curves, lane shifts, and intersections, where camera- or LiDAR-based perception may be degraded by snow, rain, occlusion, or pavement contamination. By enabling inch-level localization, speed warning, and roadway guidance, the system can improve the safety and reliability of vehicles equipped with ADAS and ADS. The study also supports future integration with real-time vehicle control and multimodal sensor fusion to enhance redundancy and safety in complex roadway environments.

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APPENDIX A: SIGNAL-PROCESSING RESULTS FROM EXPERIMENTS ON CONCRETE PAD LOCATION – CASES 1-16

CASE #1

Referenced ground-truth data



Figure 81. Photo. Referenced photo for CWZ strip #1 (Case #1).



Figure 82. Photo. Referenced photo for CWZ strip #2 (Case #1).



Figure 83. Photo. Referenced photo for CWZ strip #3 (Case #1).



Figure 84. Photo. Referenced photo for CWZ strip #4 (Case #1).



Figure 85. Photo. Referenced photo for Lateral strip #1 (Case #1).



Figure 86. Photo. Referenced photo for Lateral strip #2 (Case #1).



Figure 87. Photo. Referenced photo for Lateral strip #3 (Case #1).



Figure 88. Photo. Referenced photo for Lateral strip #4 (Case #1).



Figure 89. Photo. Referenced photo for Lateral strip #5 (Case #1).

EM spectral analysis

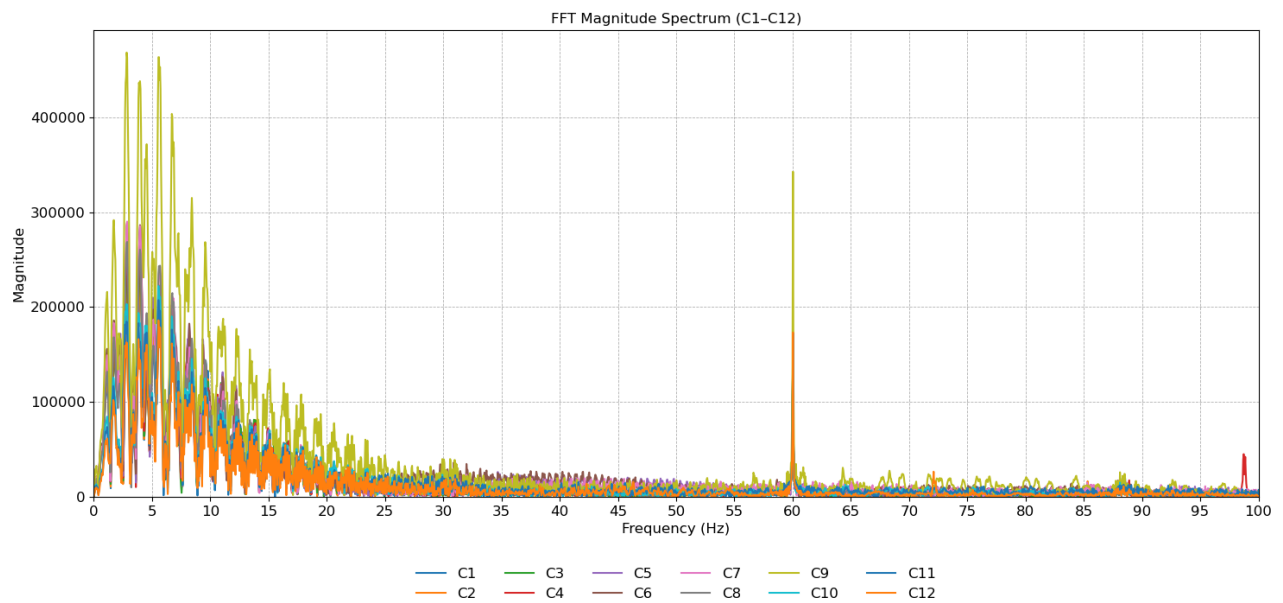


Figure 90. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #1).

CASE #2

Referenced ground-truth data

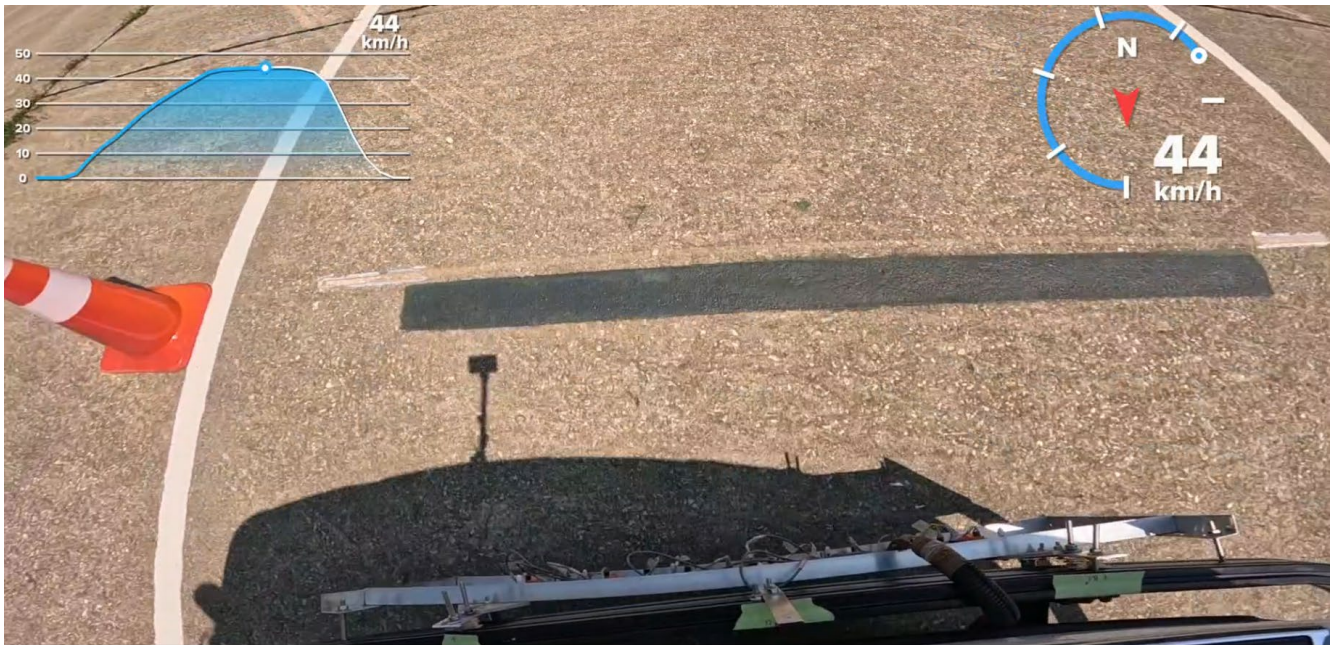


Figure 91. Photo. Referenced photo for CWZ strip #1 (Case #2).

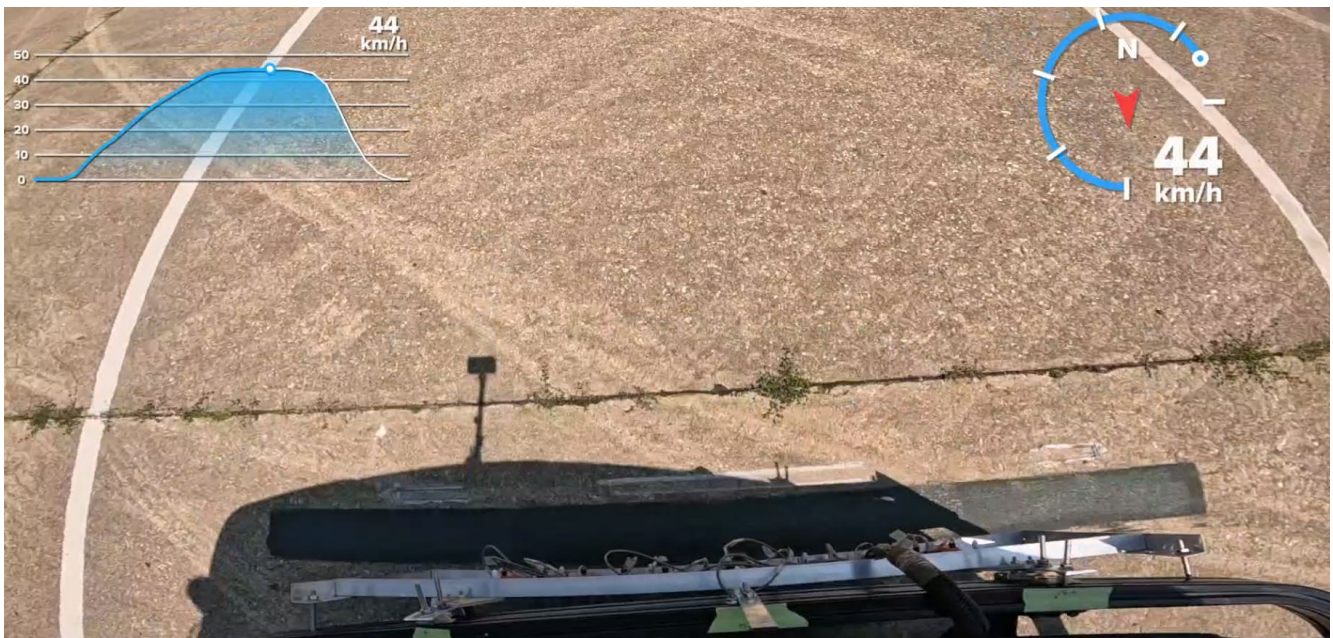


Figure 92. Photo. Referenced photo for CWZ strip #2 (Case #2).

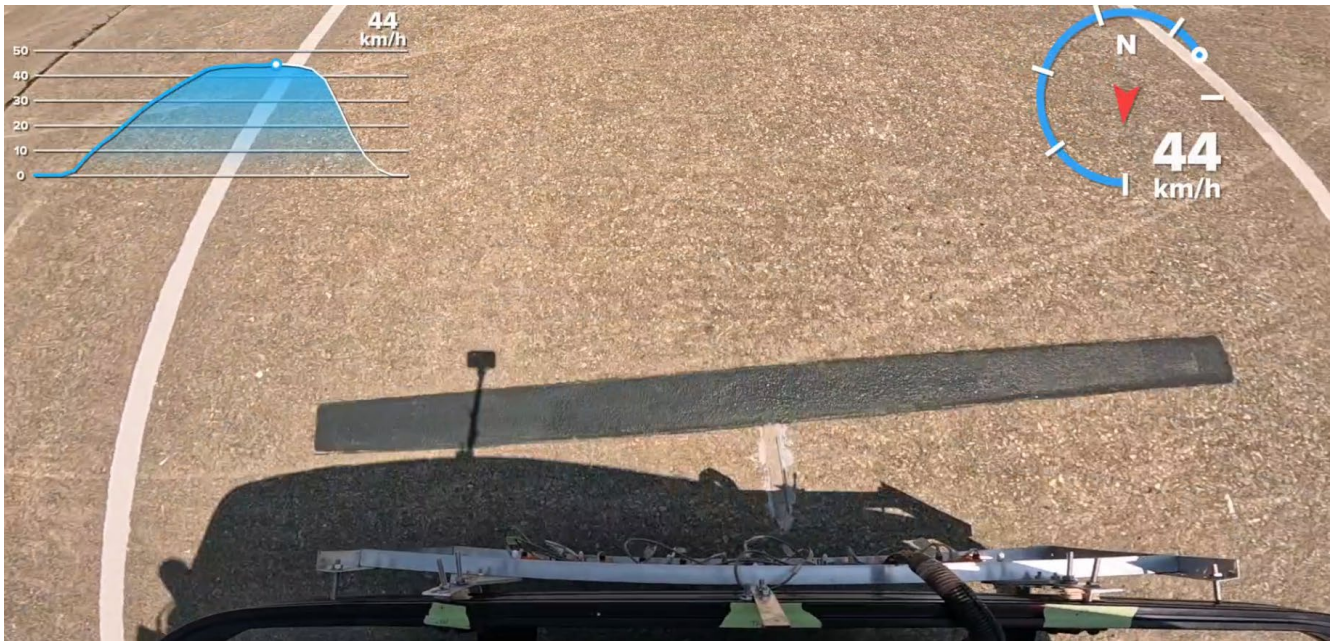


Figure 93. Photo. Referenced photo for CWZ strip #3 (Case #2).



Figure 94. Photo. Referenced photo for CWZ strip #4 (Case #2).

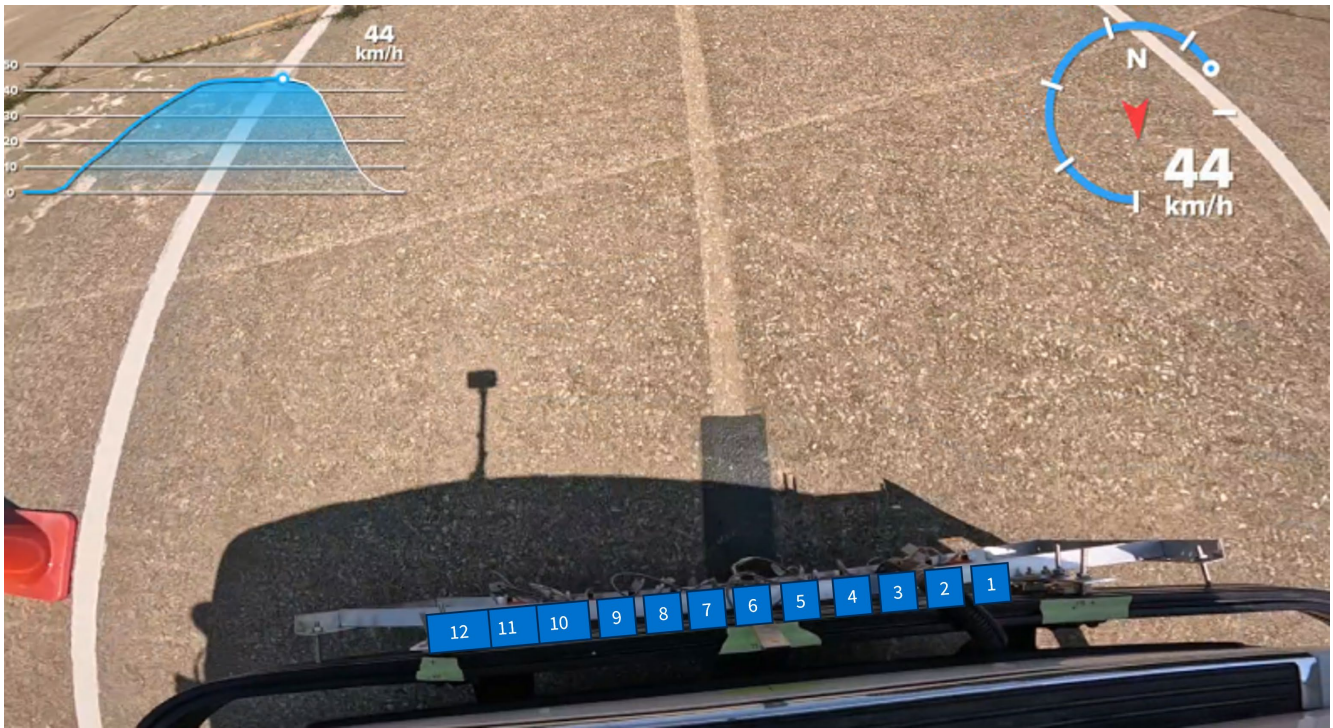


Figure 95. Photo. Referenced photo for longitudinal strip #1 (Case #2).

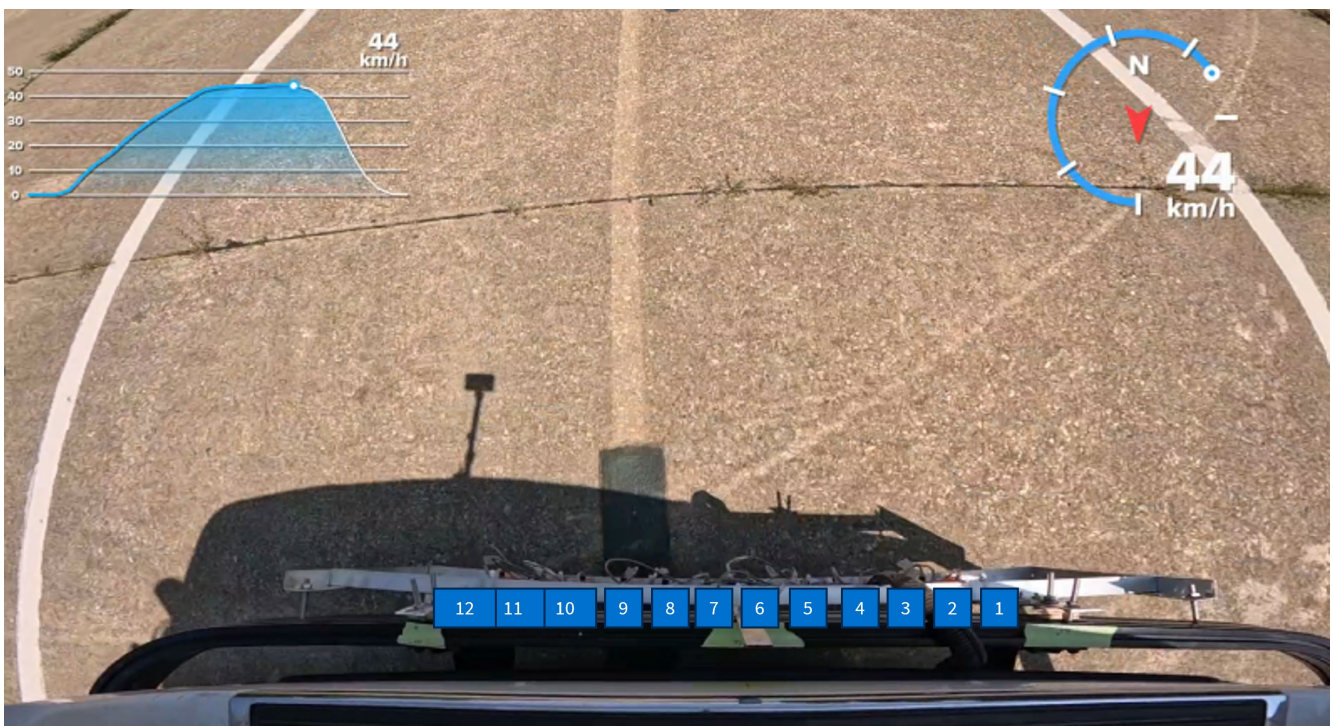


Figure 96. Photo. Referenced photo for longitudinal strip #2 (Case #2).



Figure 97. Photo. Referenced photo for longitudinal strip #3 (Case #2).



Figure 98. Photo. Referenced photo for longitudinal strip #4 (Case #2).



Figure 99. Photo. Referenced photo for longitudinal strip #5 (Case #2).

EM spectral analysis

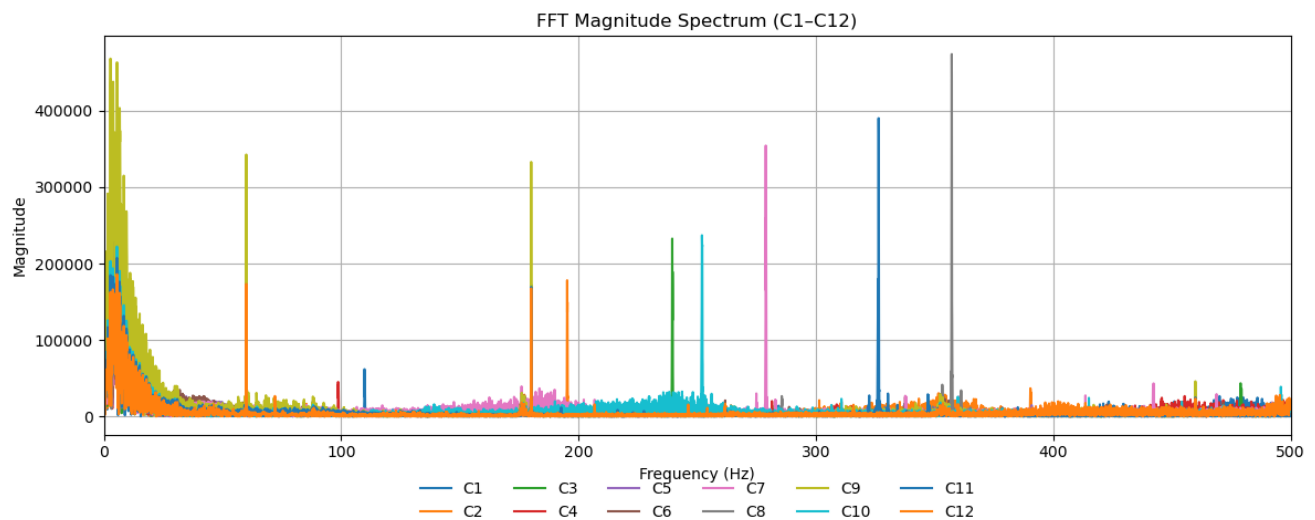


Figure 100. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #2).

Raw EM Flux

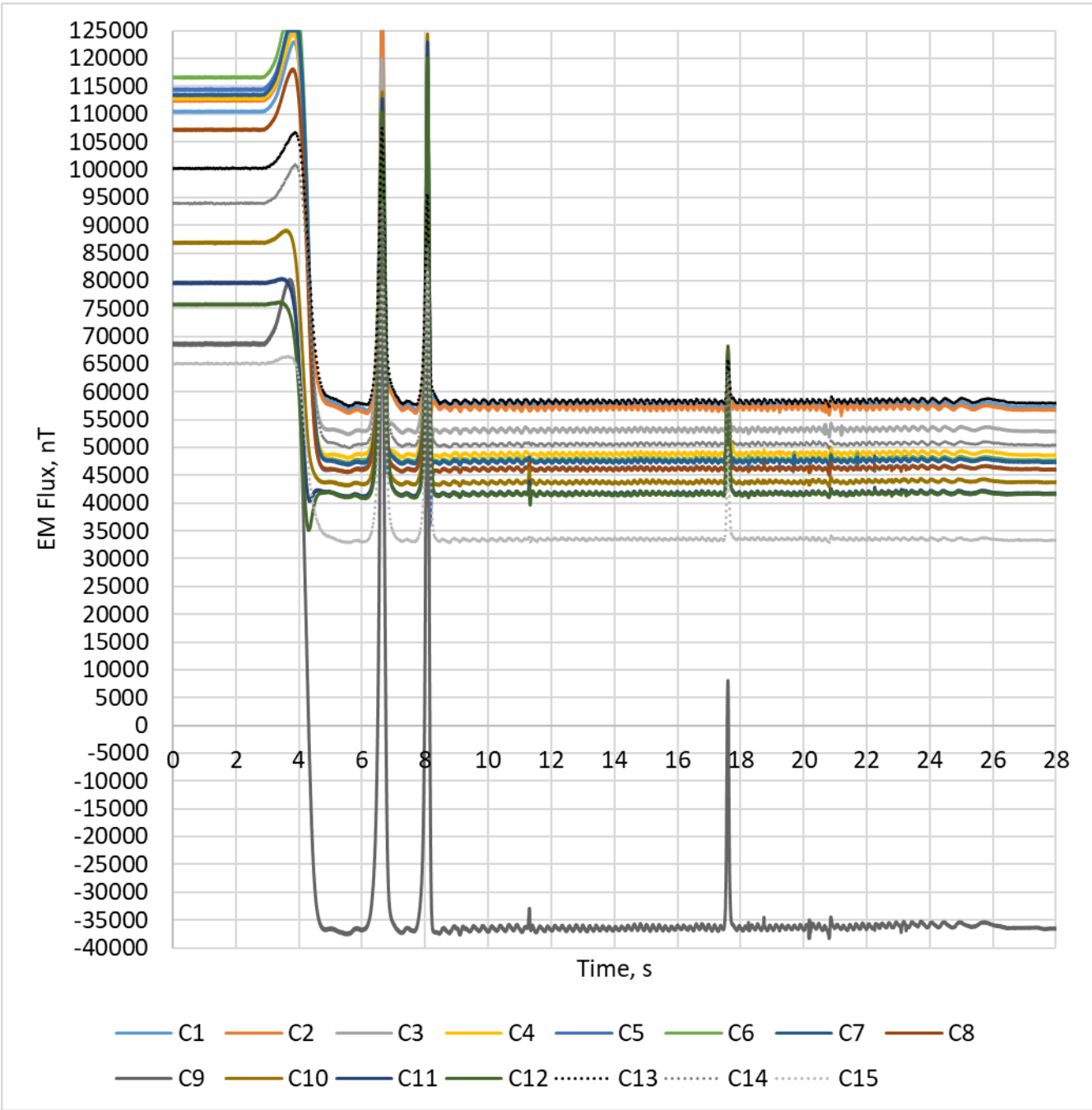


Figure 101. Chart. Signal characteristics of various EM sources (Case #2).

Processed EM Flux

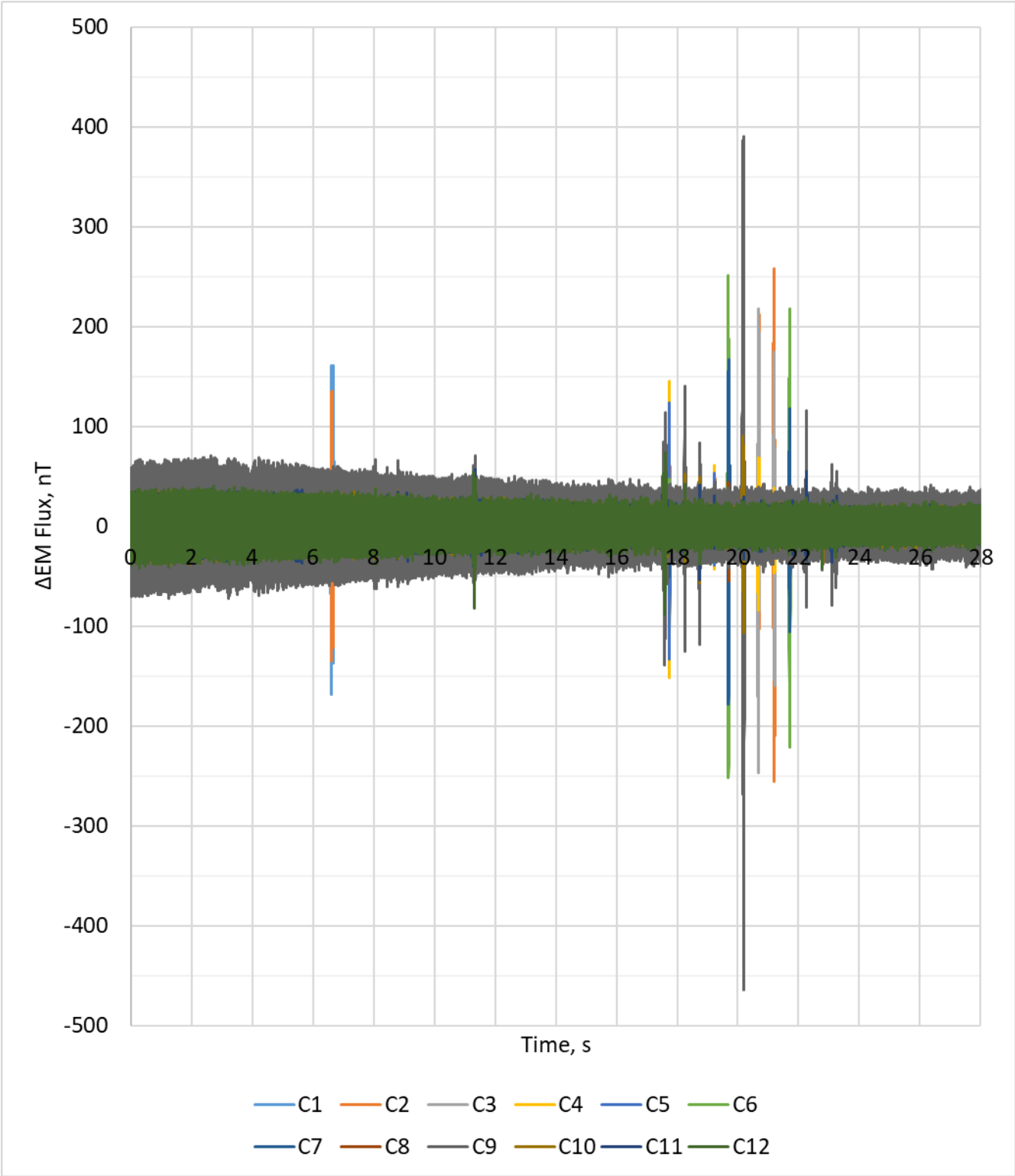


Figure 102. Chart. Signal characteristics of various EM sources (Case #2).

CASE #3

EM spectral analysis

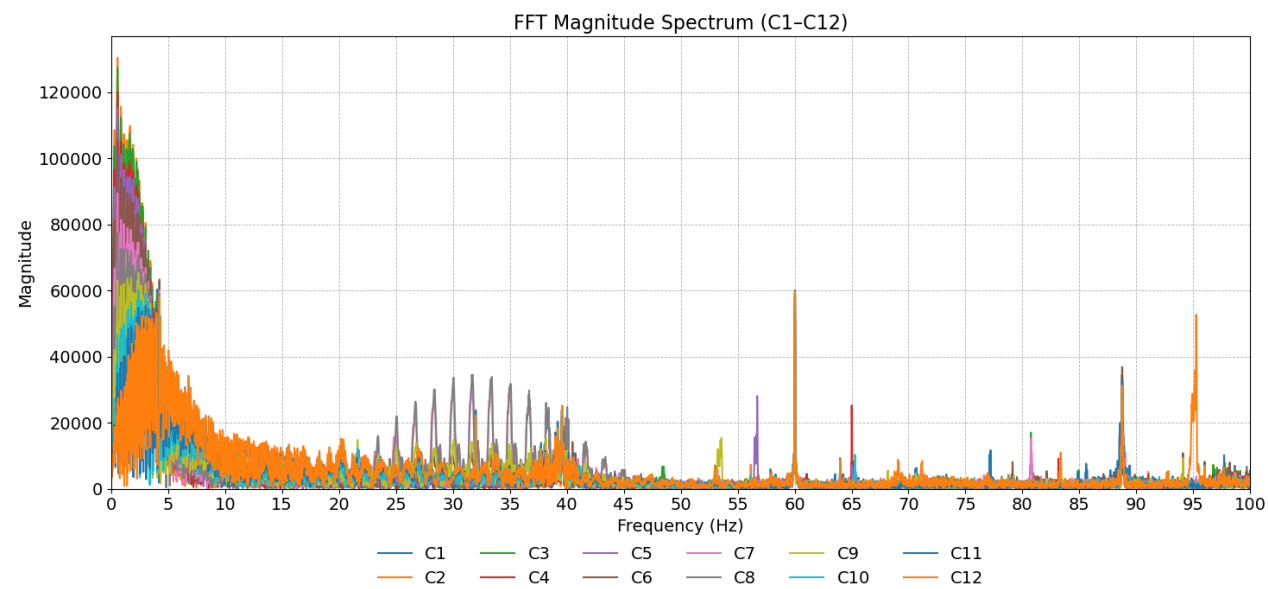


Figure 103. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #3).

Raw EM Flux

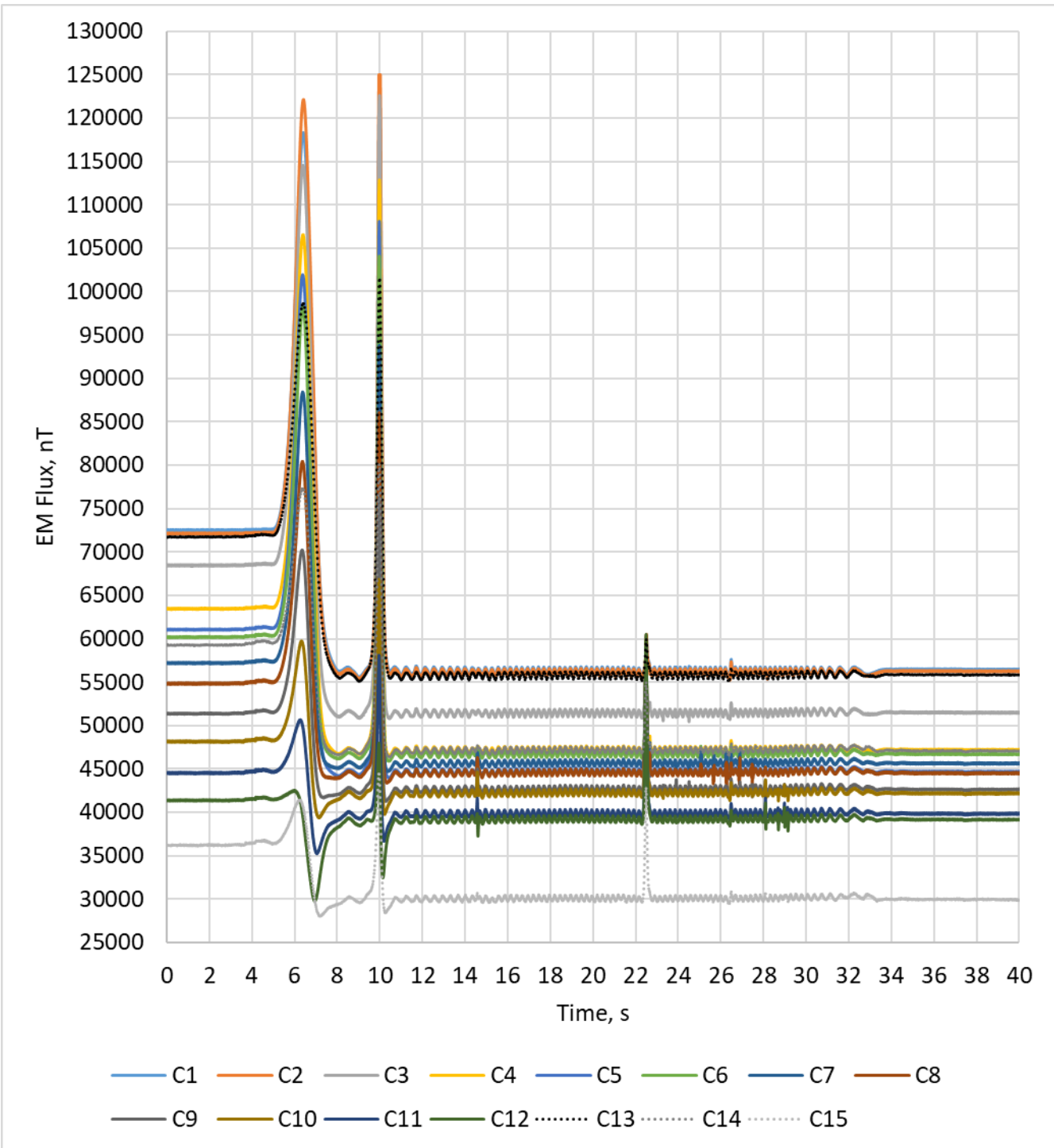


Figure 104. Chart. Signal characteristics of various EM sources (Case #3).

Processed EM Flux

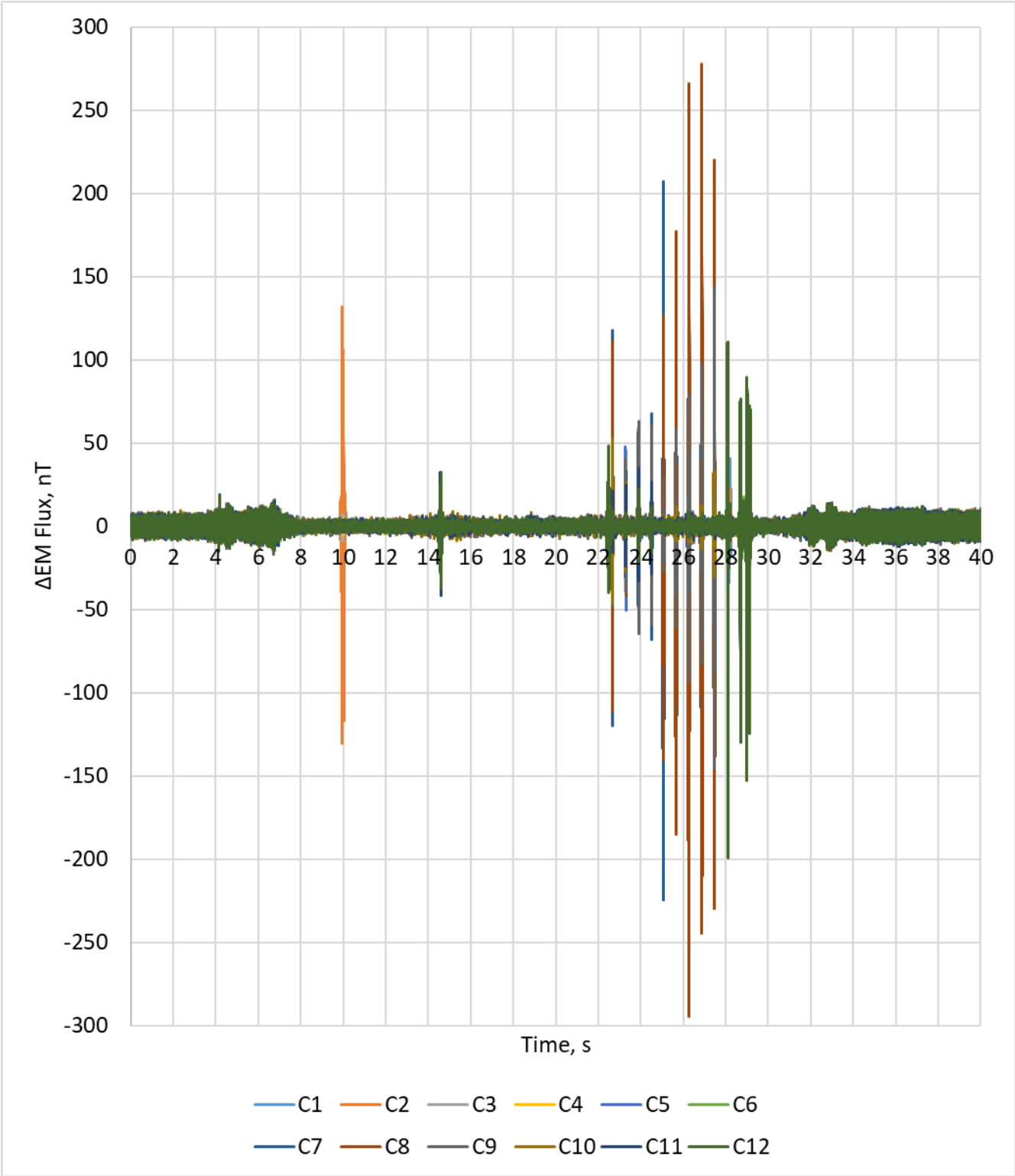


Figure 105. Chart. Signal characteristics of various EM sources (Case #3).

CASE #4

EM spectral analysis

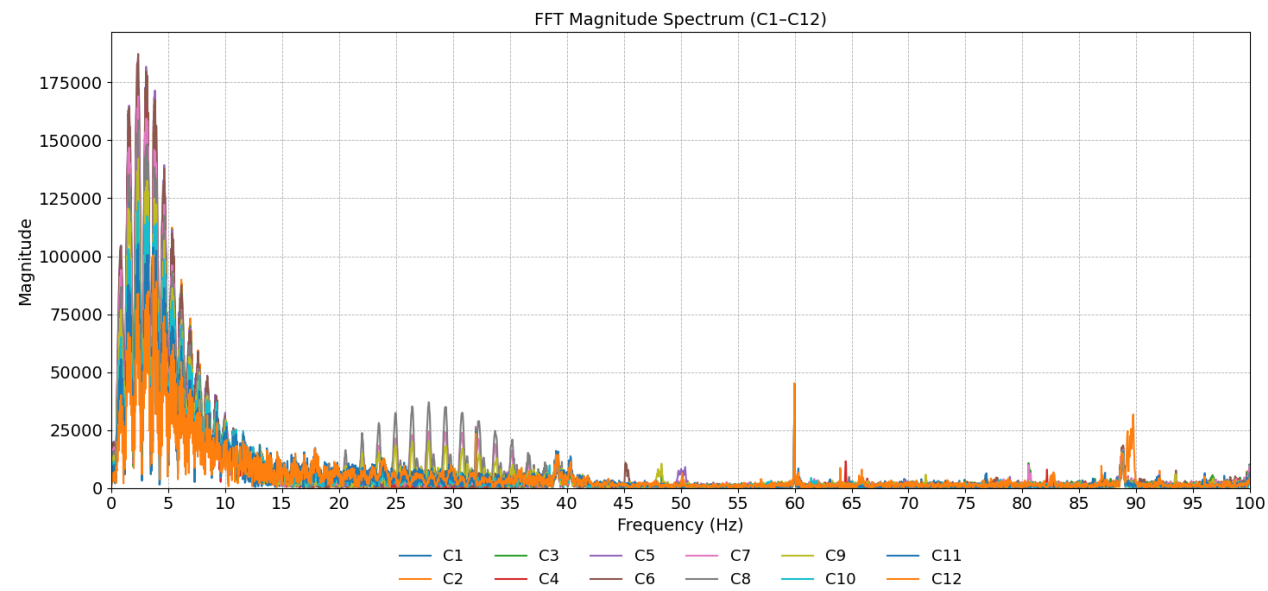


Figure 106. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #4).

Raw EM Flux

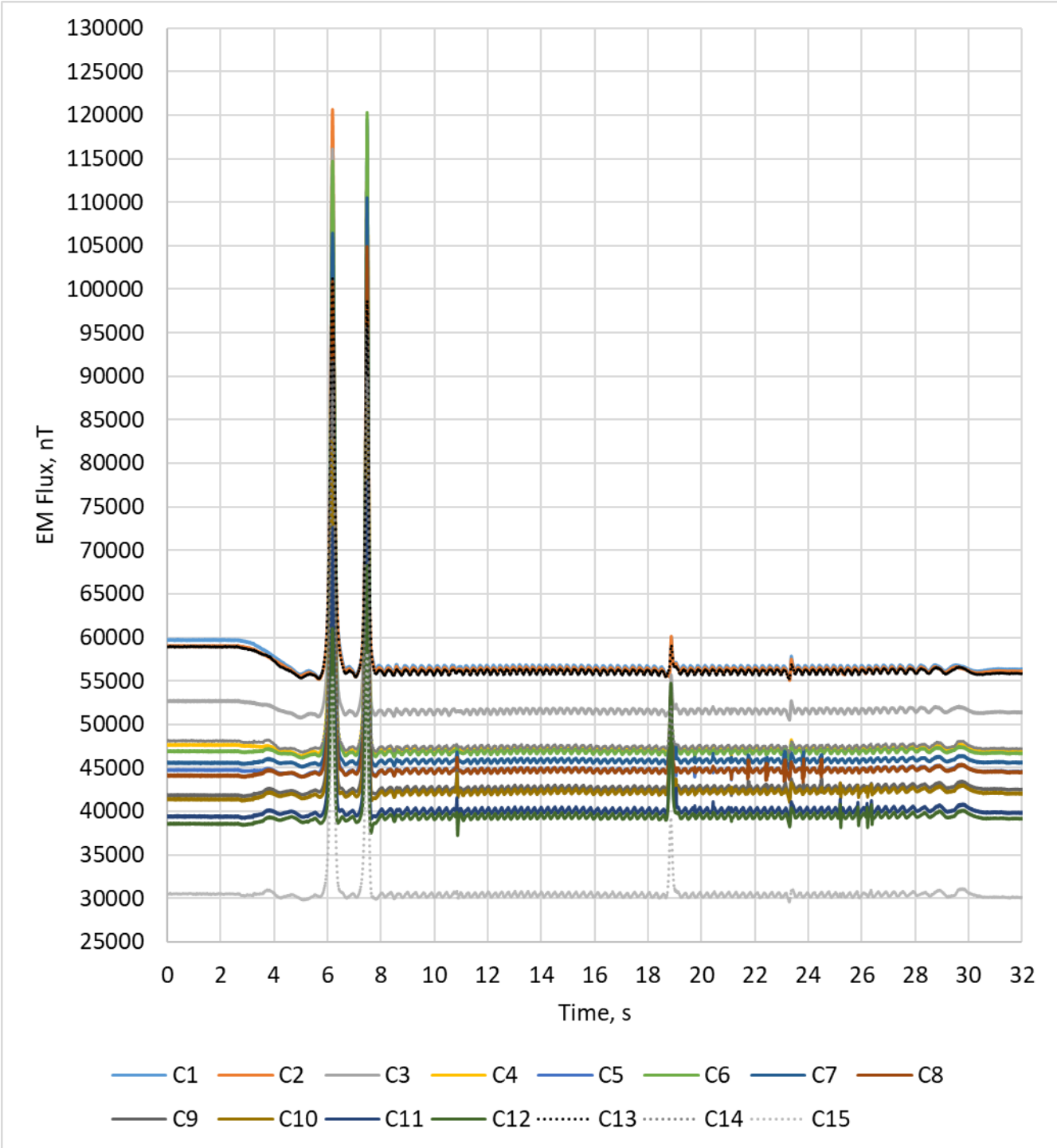


Figure 107. Chart. Signal characteristics of various EM sources (Case #4).

Processed EM Flux

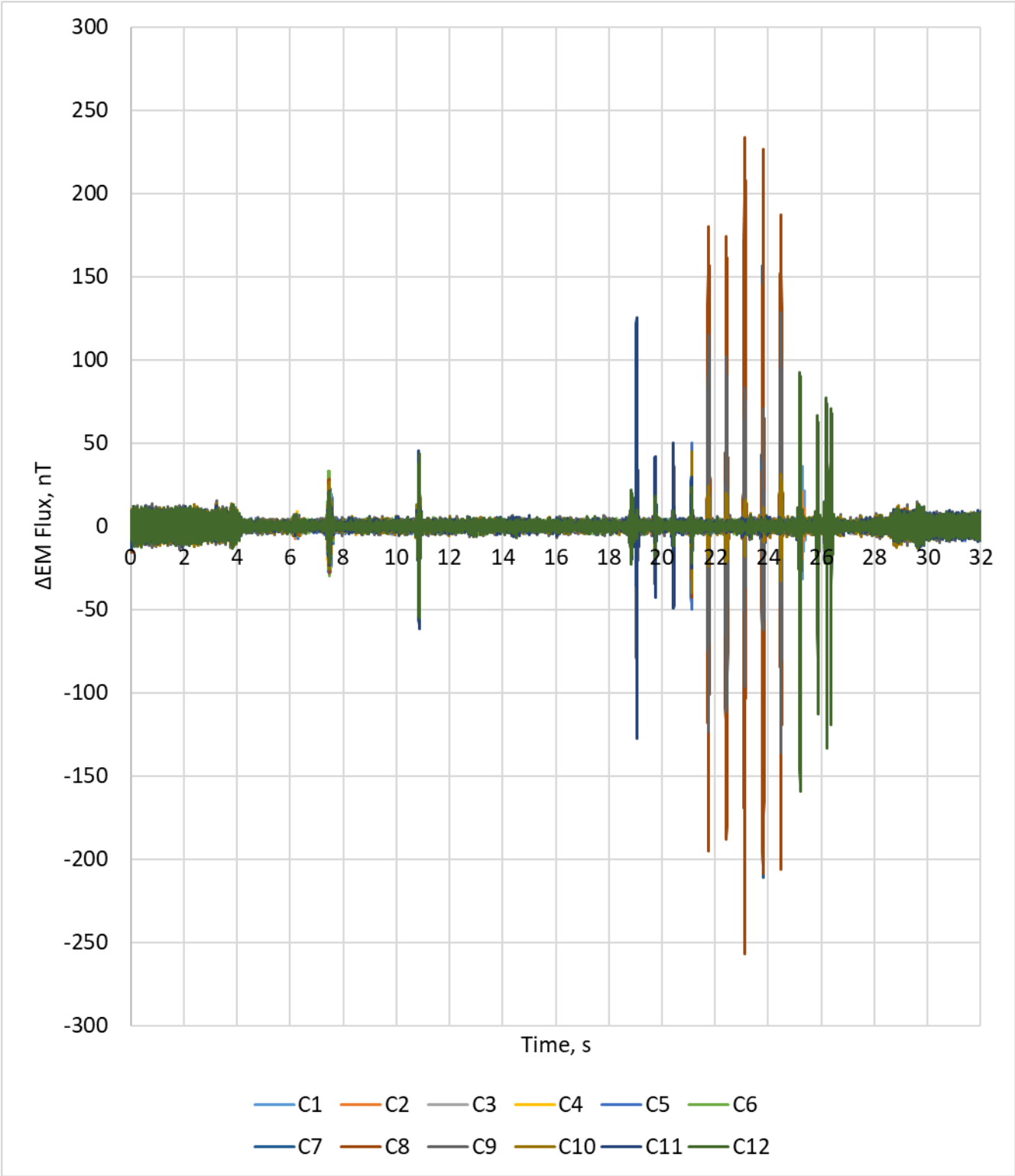


Figure 108. Chart. Signal characteristics of various EM sources (Case #4).

CASE #5

EM spectral analysis

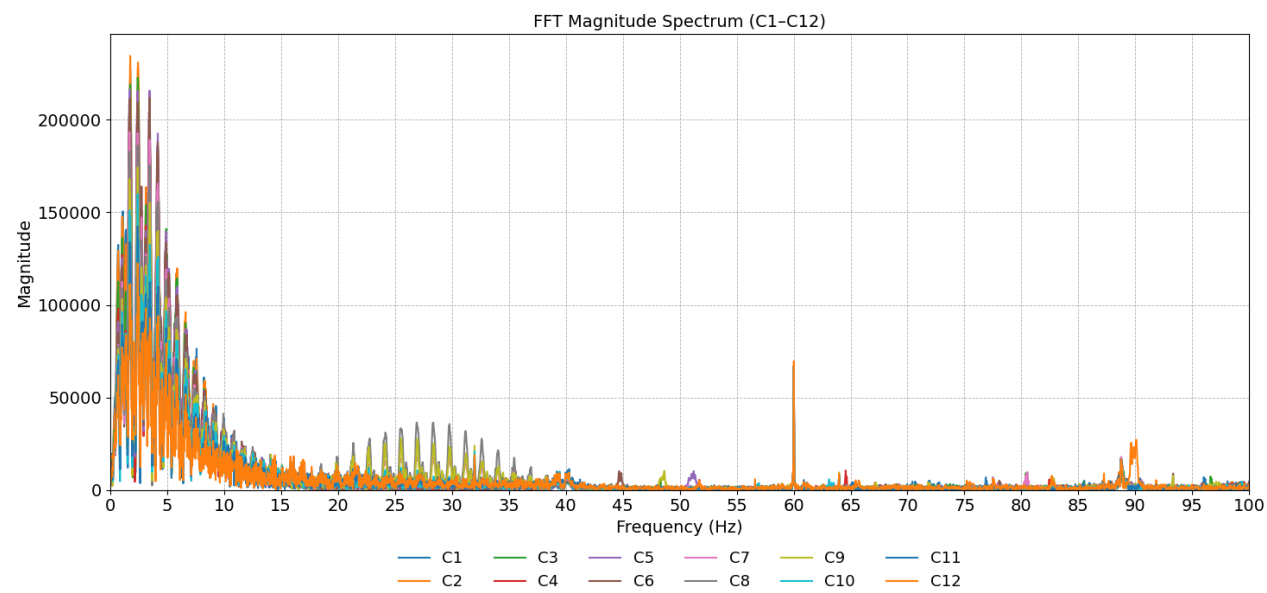


Figure 109. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #5).

Raw EM Flux

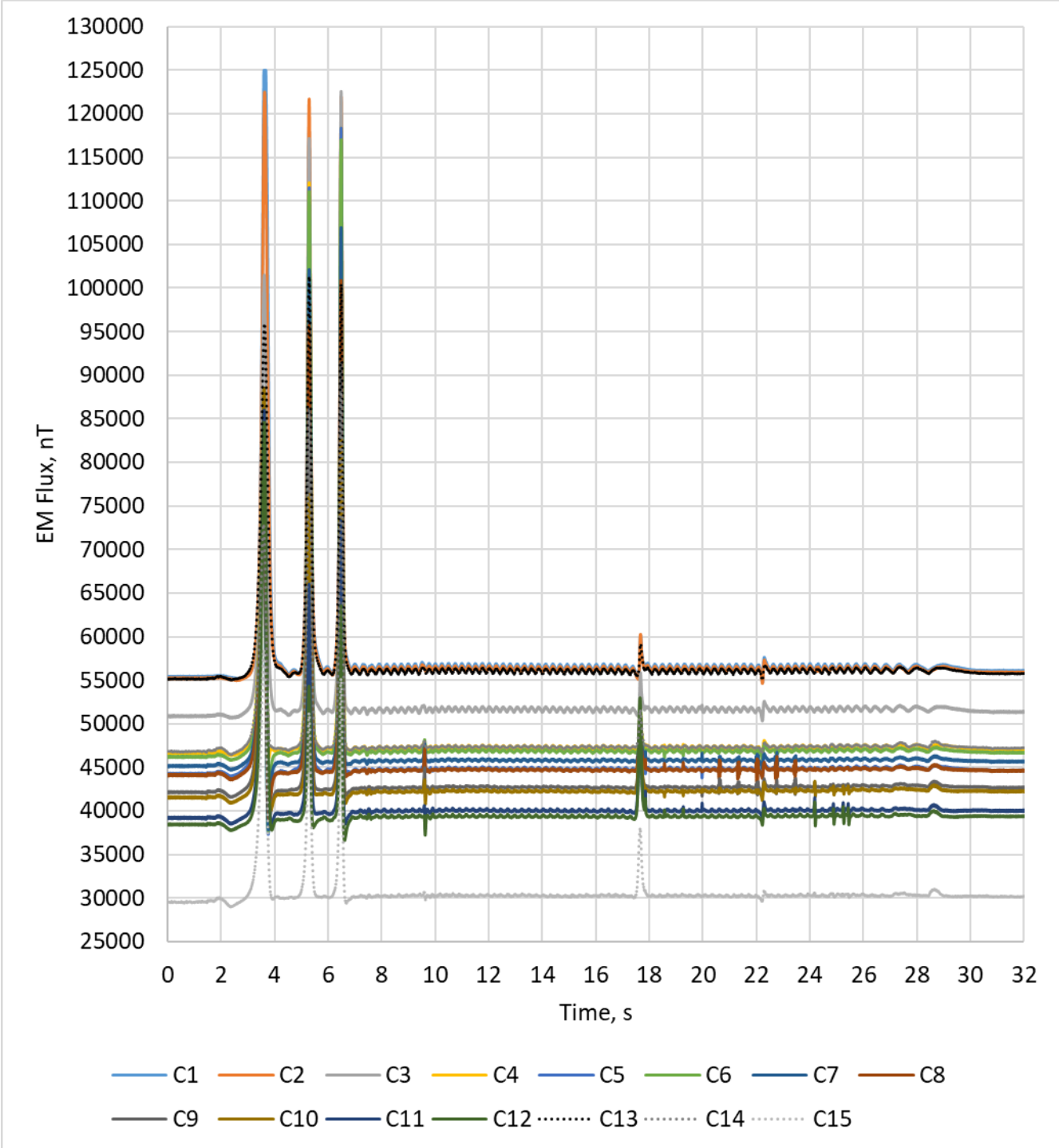


Figure 110. Chart. Signal characteristics of various EM sources (Case #5).

Processed EM Flux

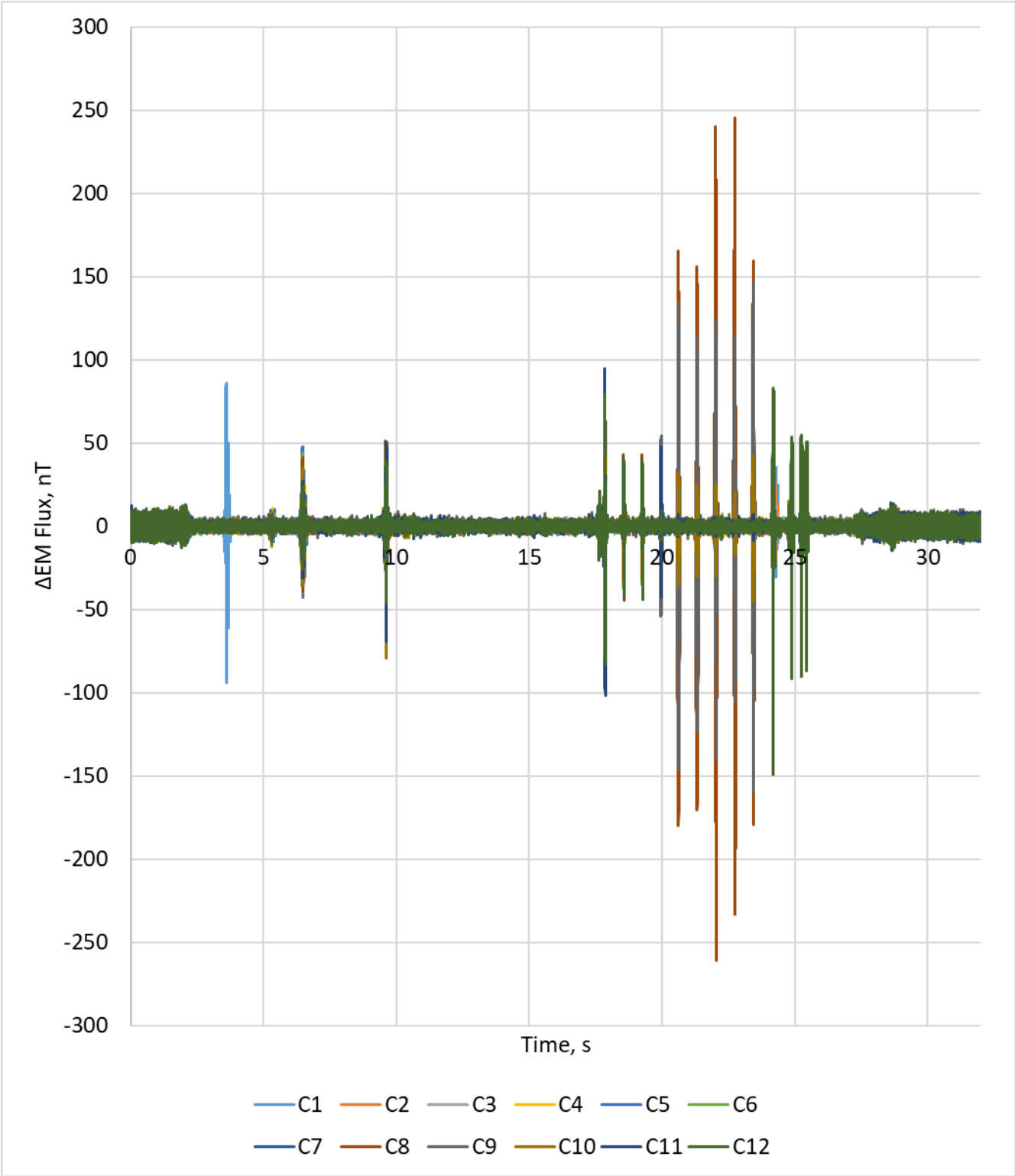


Figure 111. Chart. Signal characteristics of various EM sources (Case #5).

CASE #6

EM spectral analysis

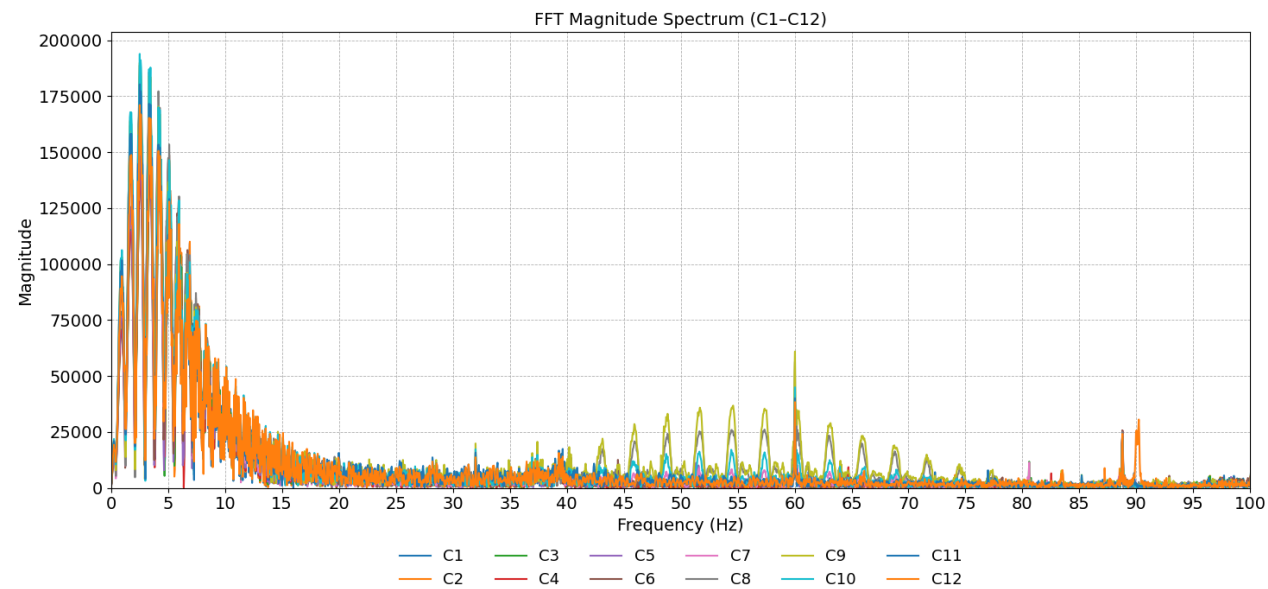


Figure 112. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #6).

Raw EM Flux

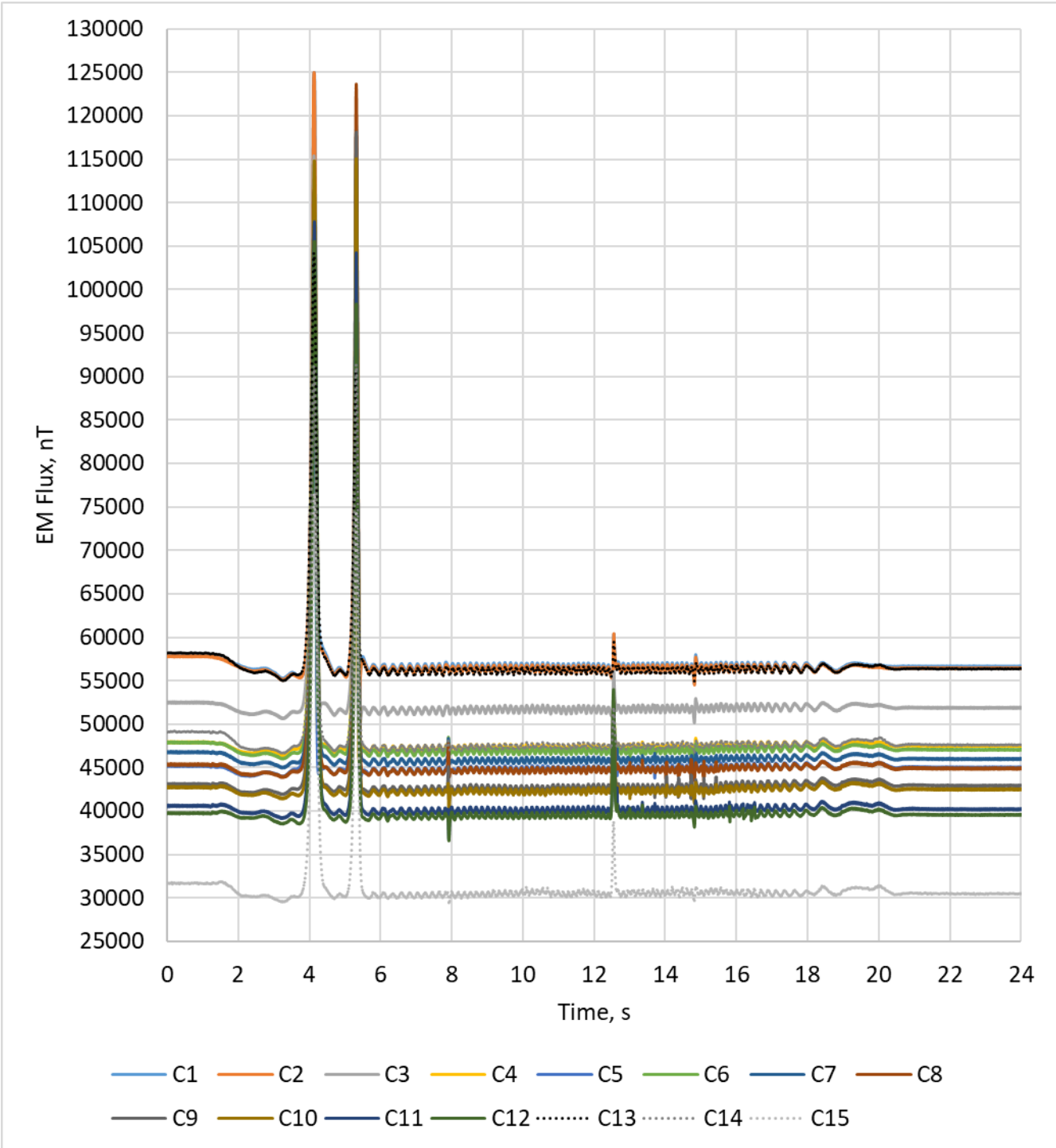


Figure 113. Chart. Signal characteristics of various EM sources (Case #6).

Processed EM Flux

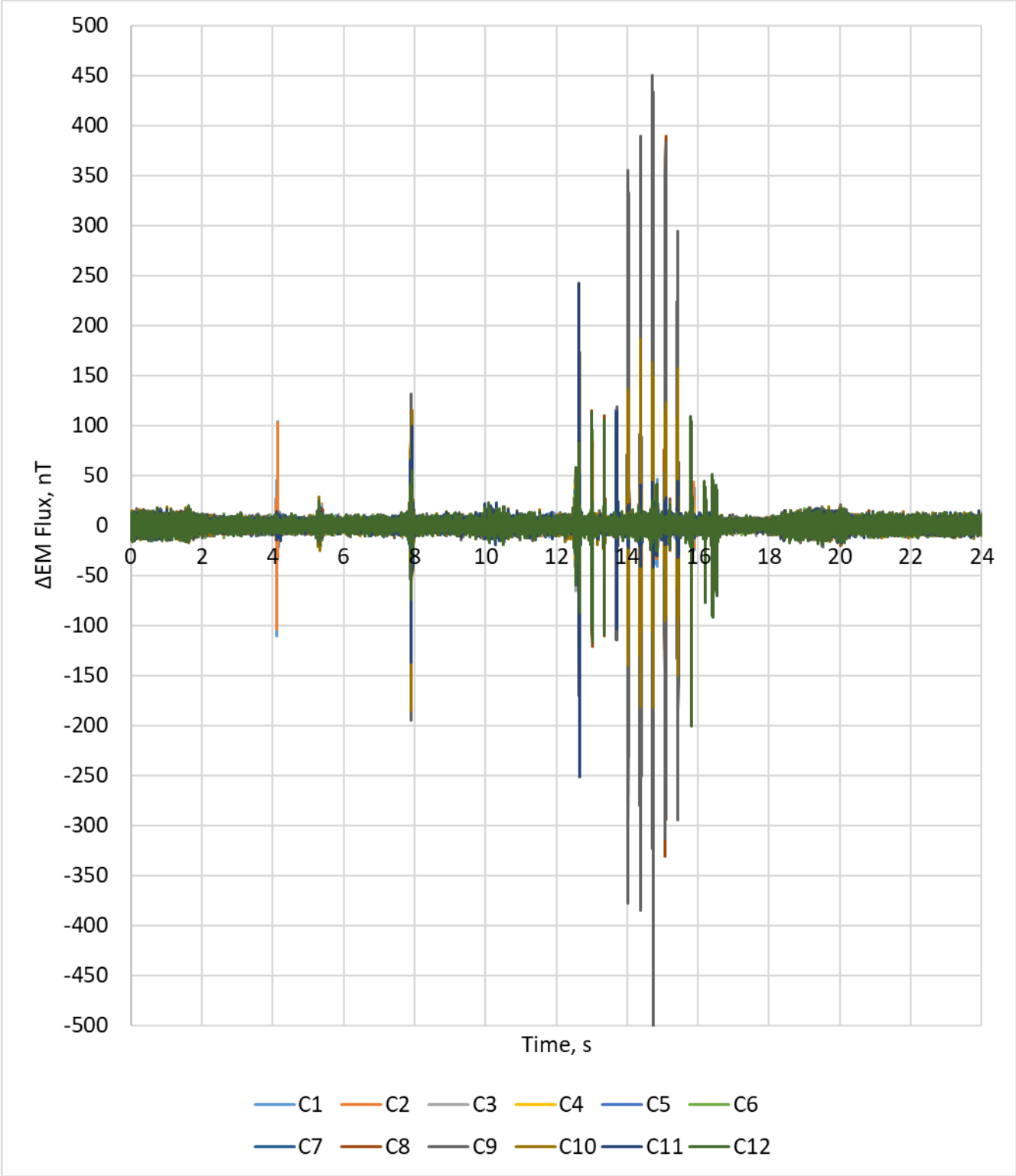


Figure 114. Chart. Signal characteristics of various EM sources (Case #6).

CASE #7

EM spectral analysis

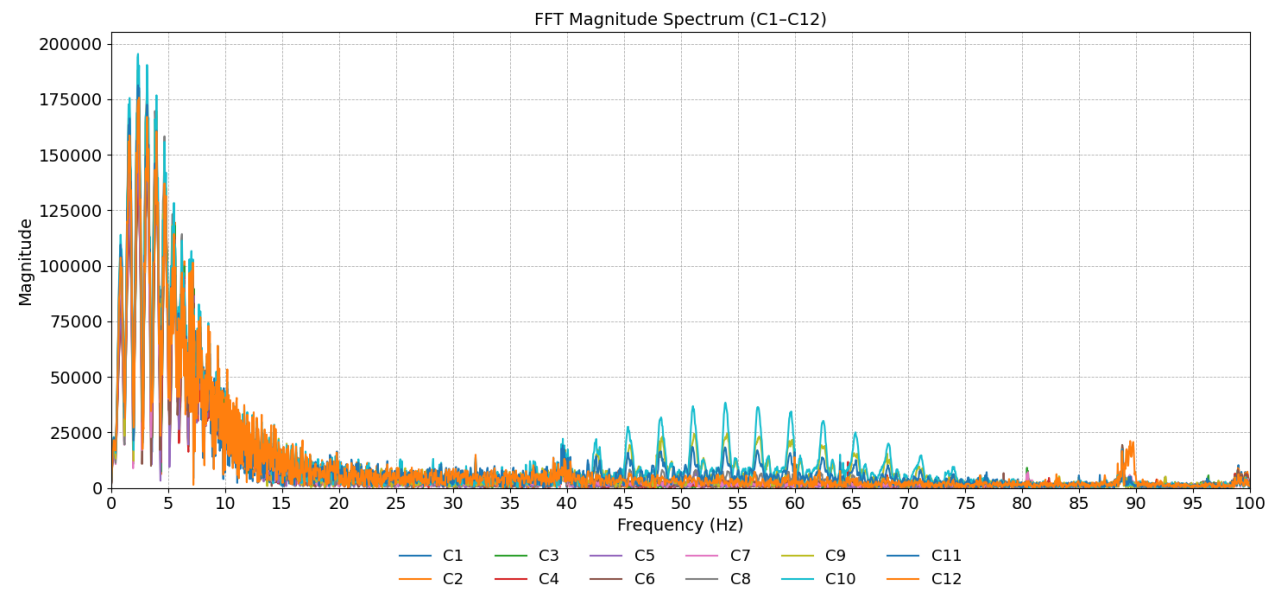


Figure 115. Photo. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #7).

Raw EM Flux

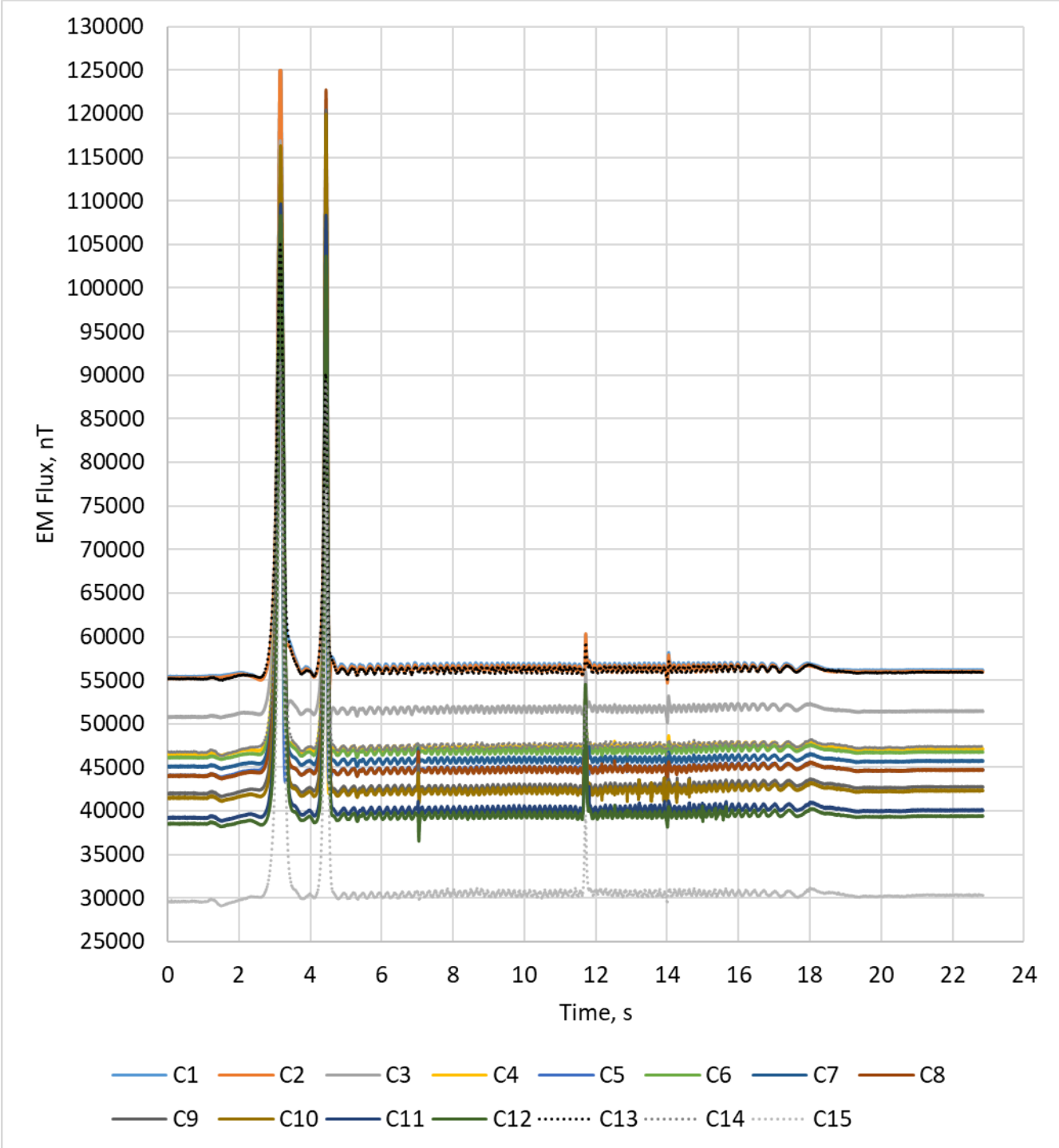


Figure 116. Chart. Signal characteristics of various EM sources (Case #7).

Processed EM Flux

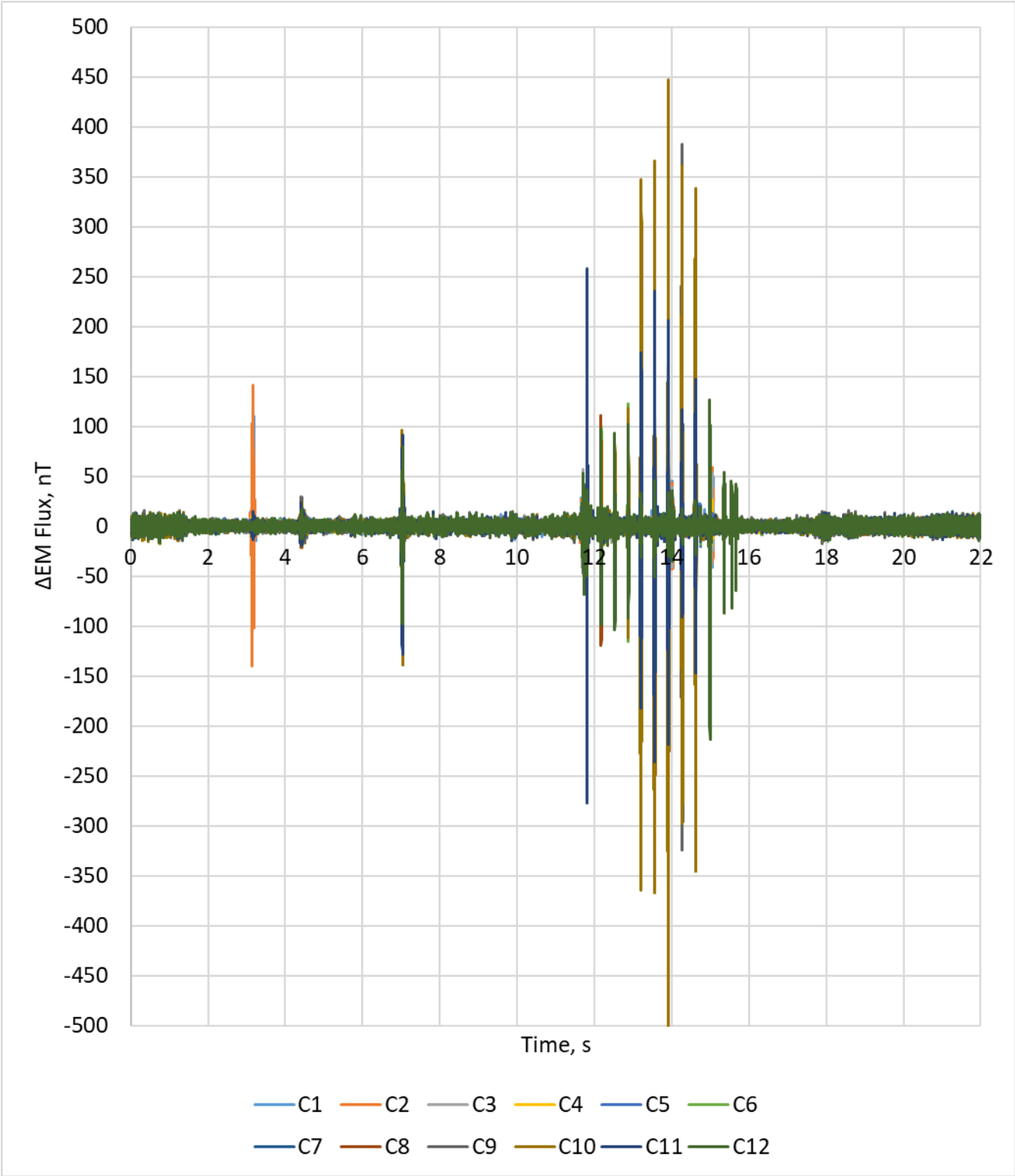


Figure 117. Chart. Signal characteristics of various EM sources (Case #7).

CASE #8

EM spectral analysis

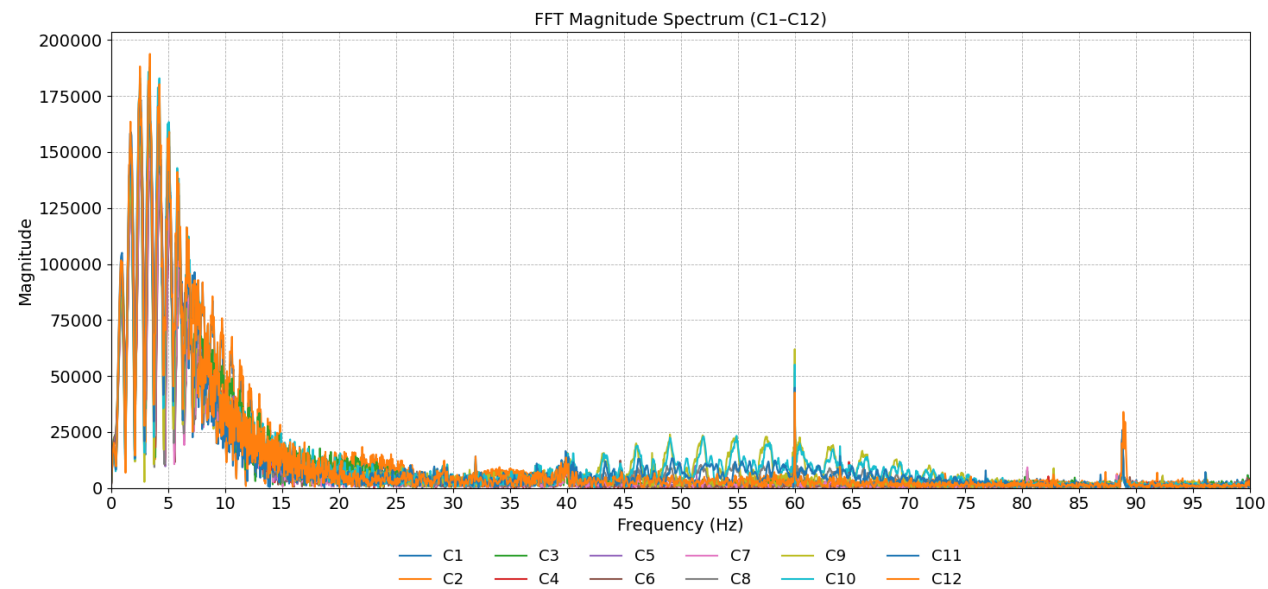


Figure 118. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #8).

Raw EM Flux

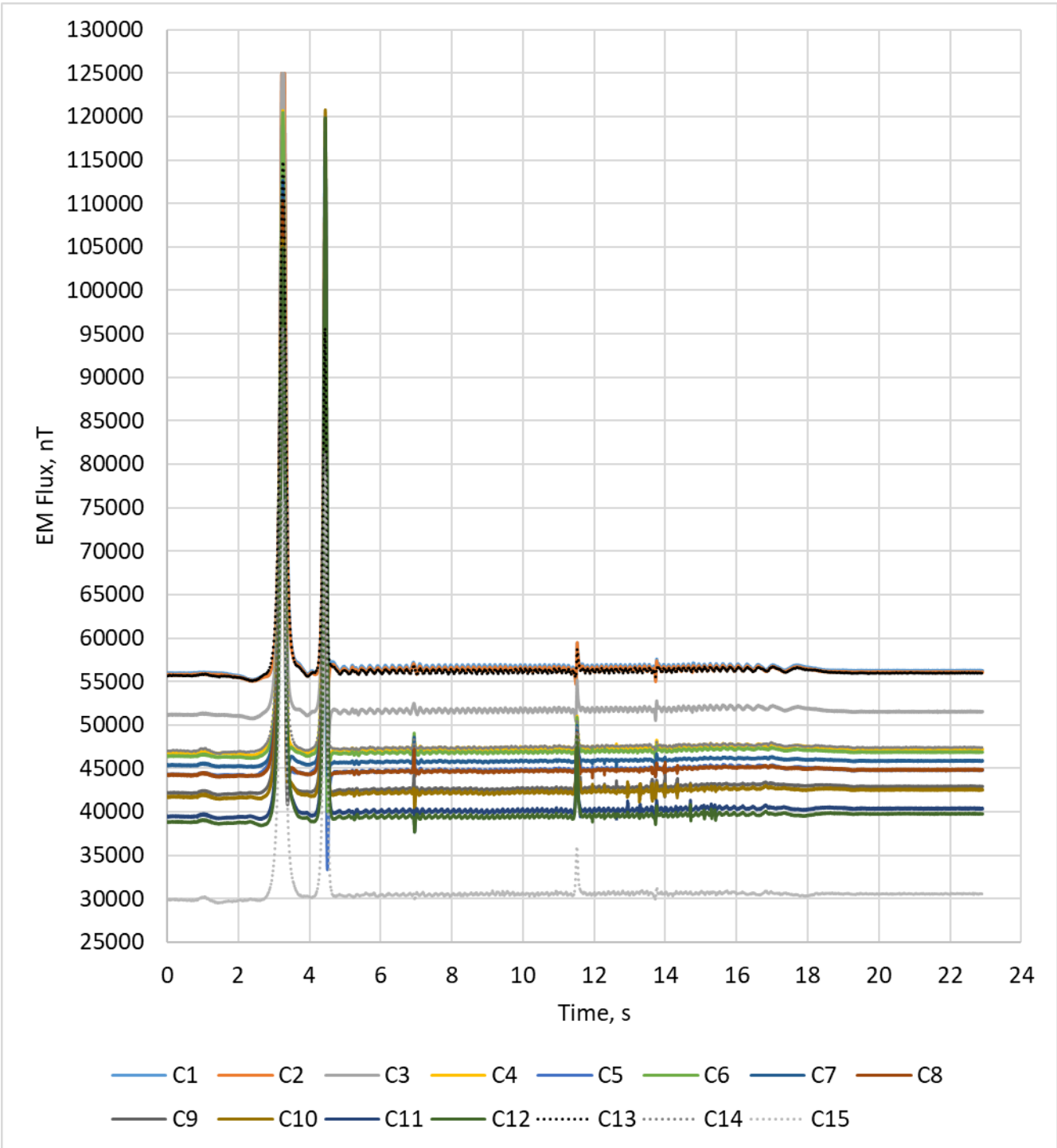


Figure 119. Chart. Signal characteristics of various EM sources (Case #8).

Processed EM Flux

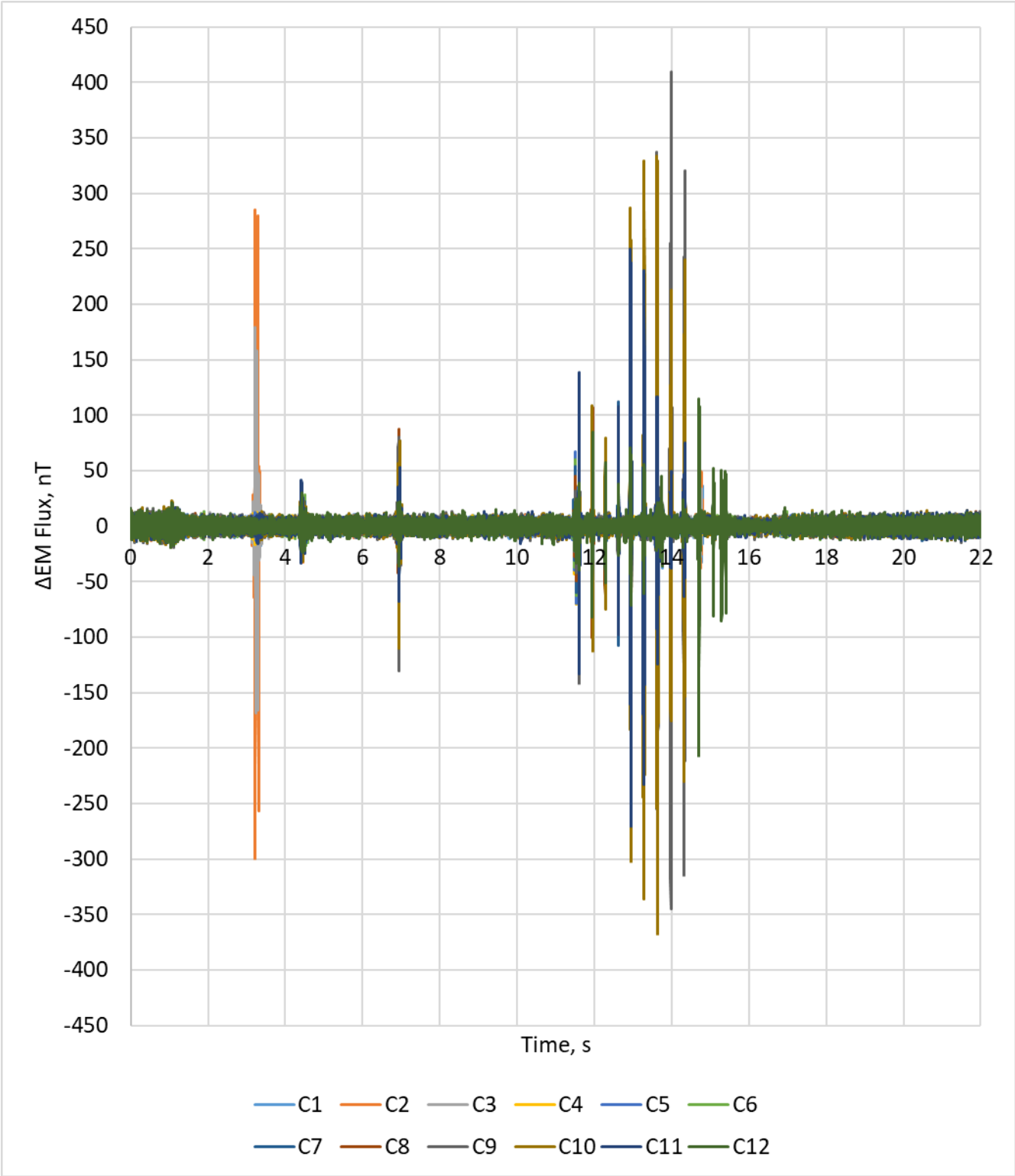


Figure 120. Chart. Signal characteristics of various EM sources (Case #8).

CASE #9

EM spectral analysis

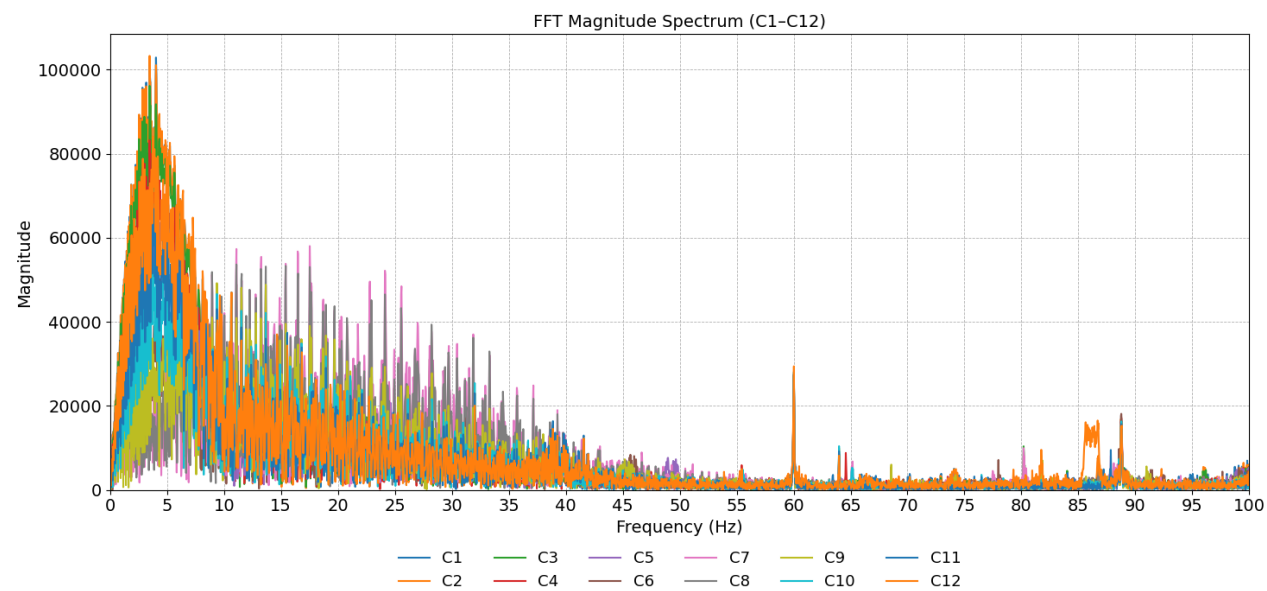


Figure 121. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #9).

Raw EM Flux

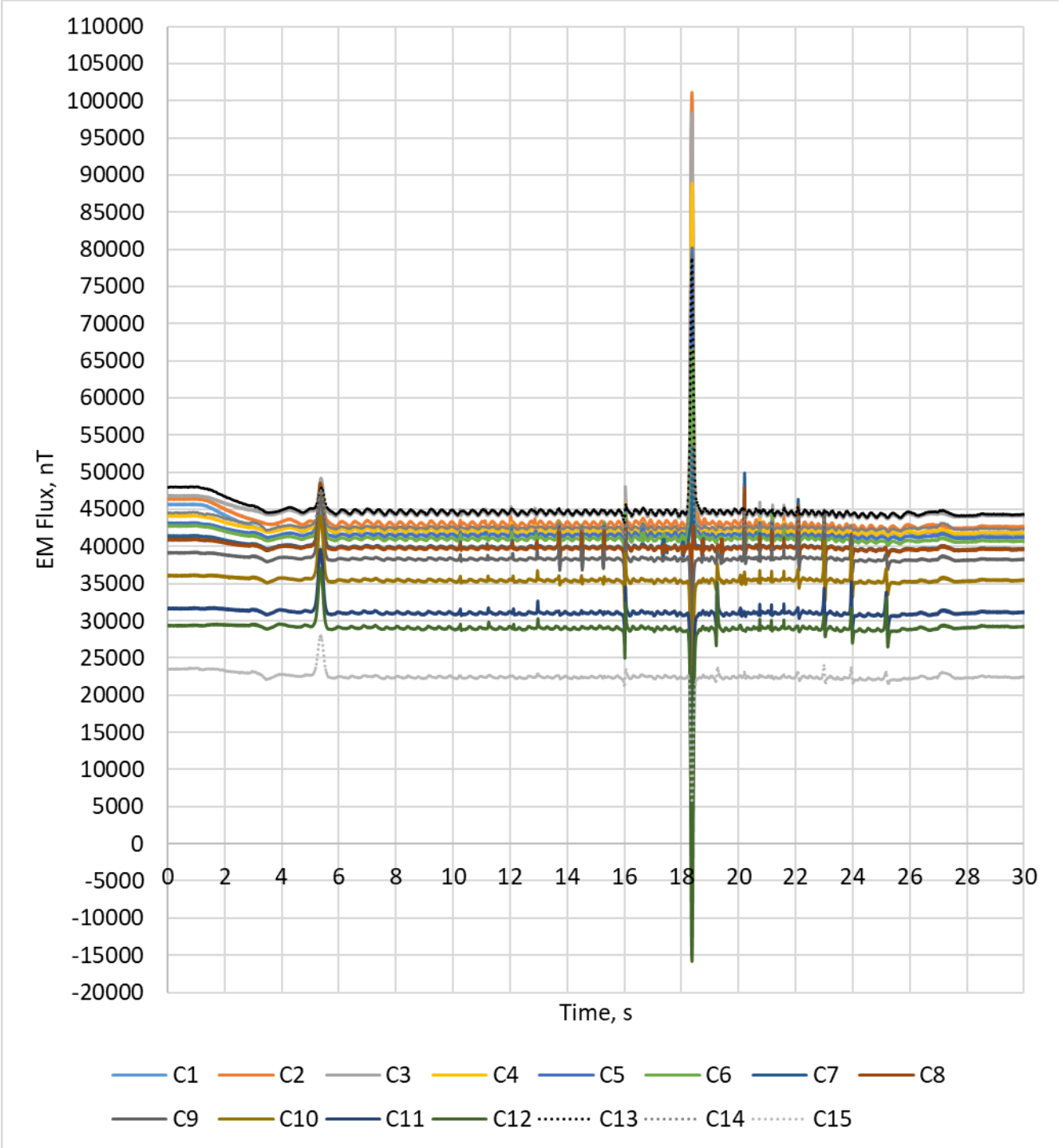


Figure 122. Chart. Signal characteristics of various EM sources (Case #9).

Processed EM Flux

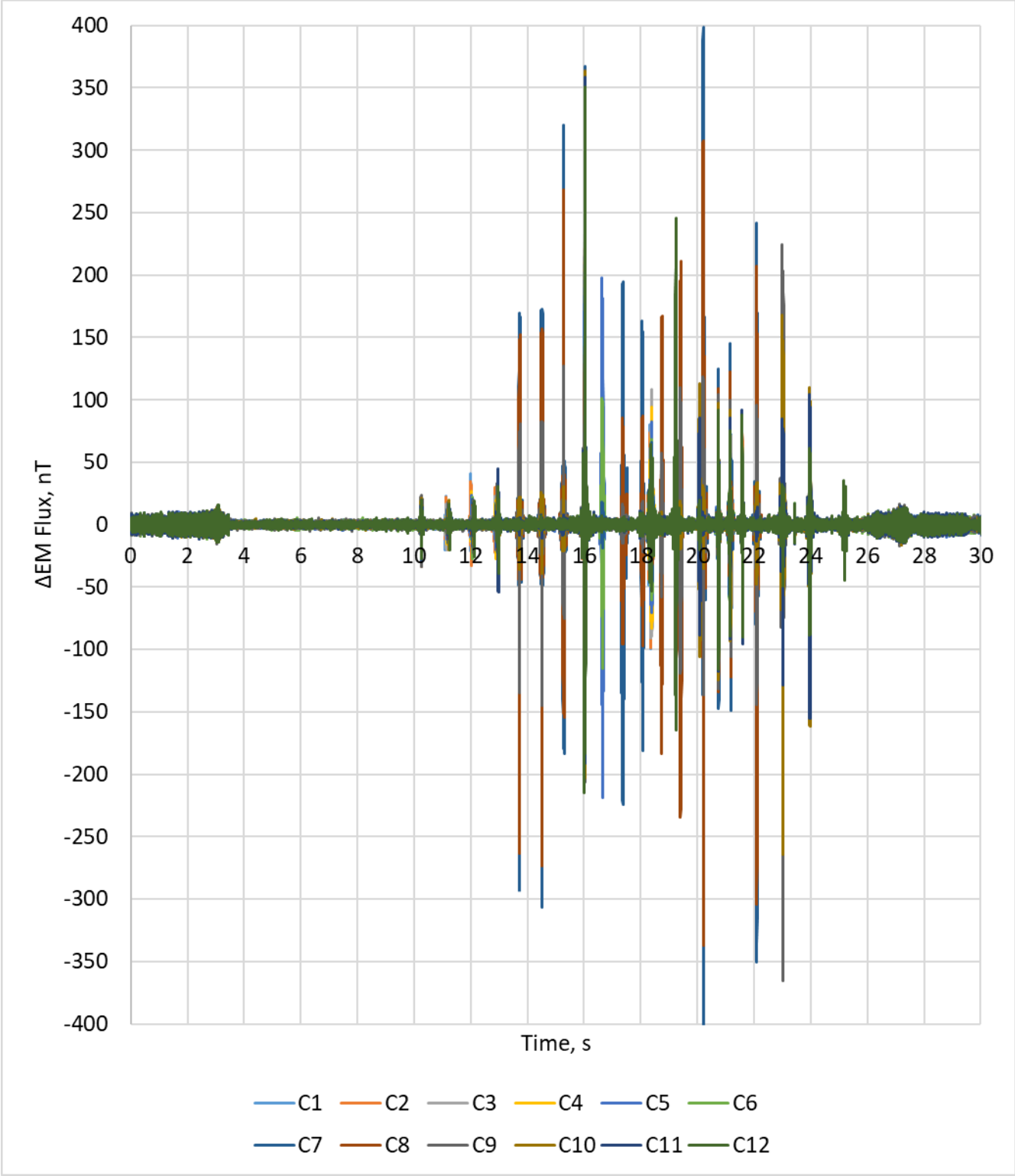


Figure 123. Chart. Signal characteristics of various EM sources (Case #9).

CASE #10

EM spectral analysis

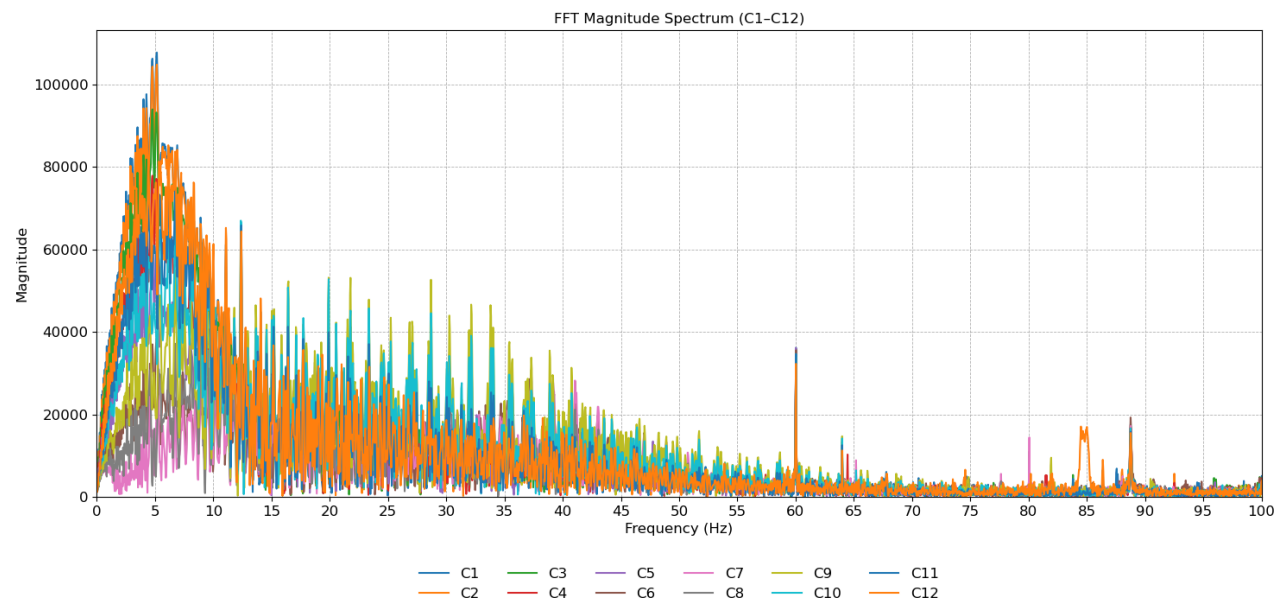


Figure 124. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #10).

Raw EM Flux

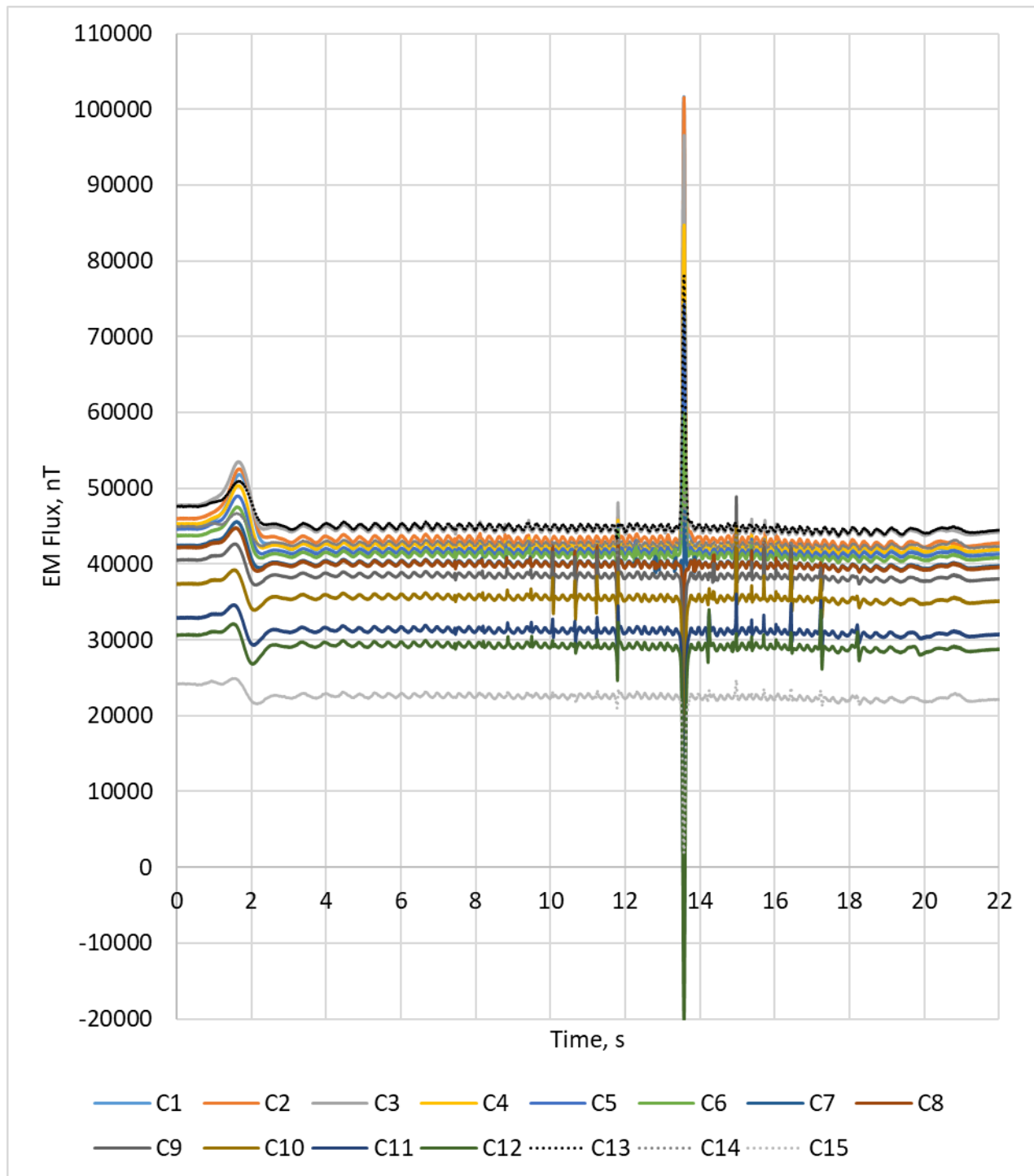


Figure 125. Chart. Signal characteristics of various EM sources (Case #10).

Processed EM Flux

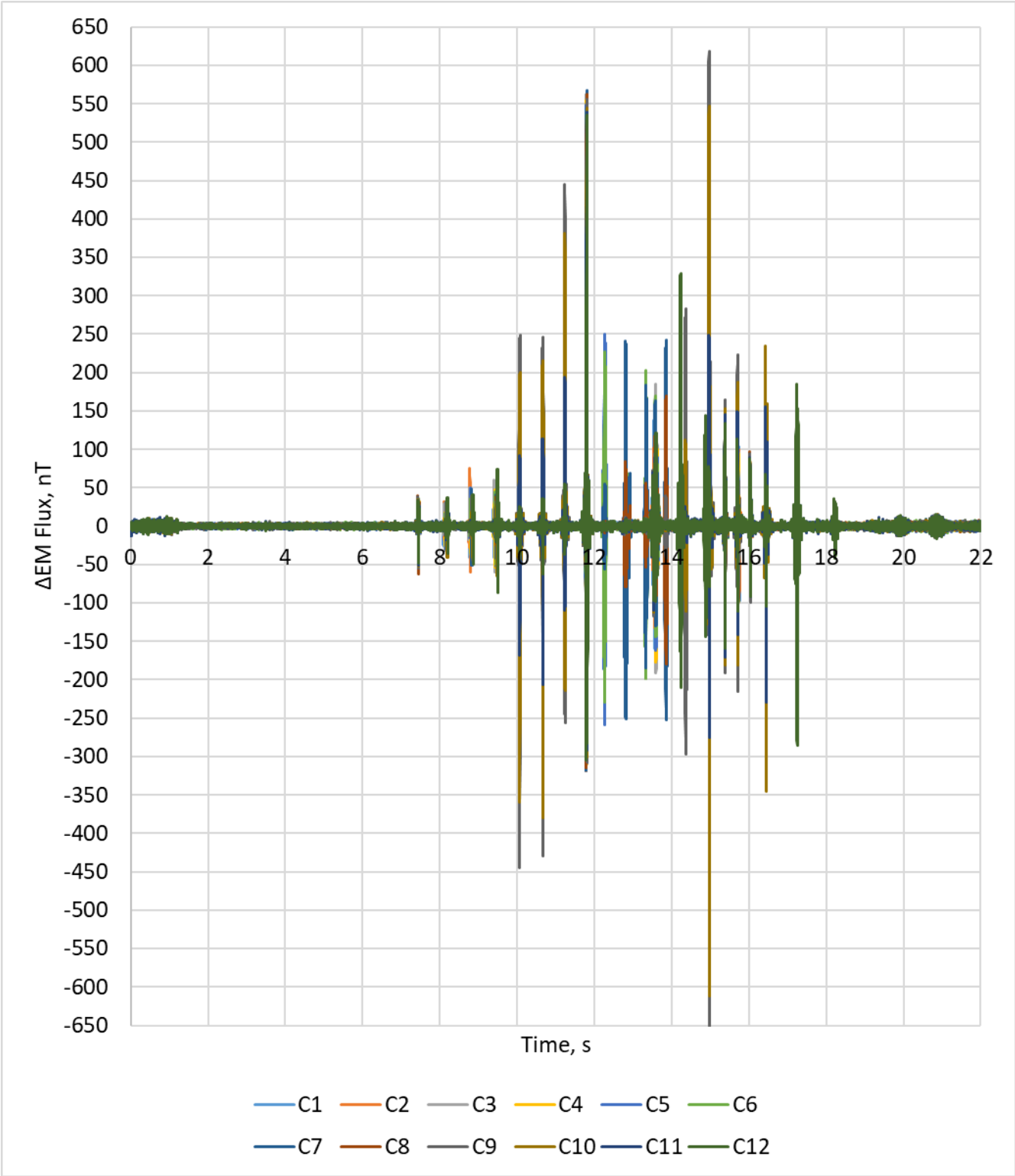


Figure 126. Chart. Signal characteristics of various EM sources (Case #10).

CASE #11

EM spectral analysis

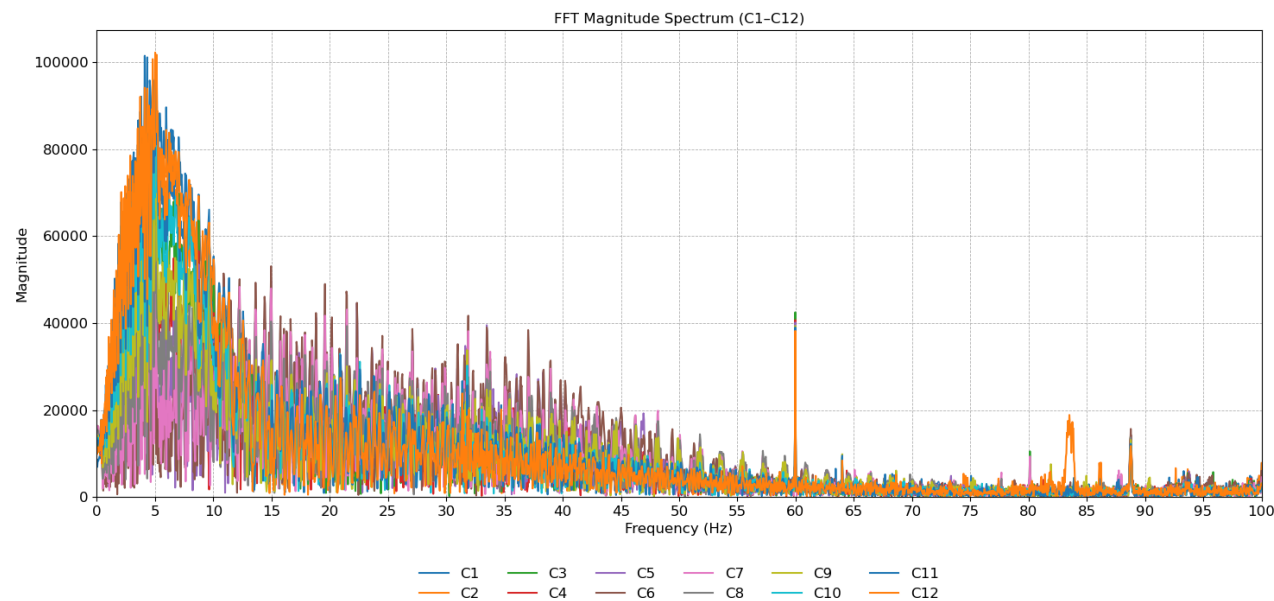


Figure 127. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #11).

Raw EM Flux

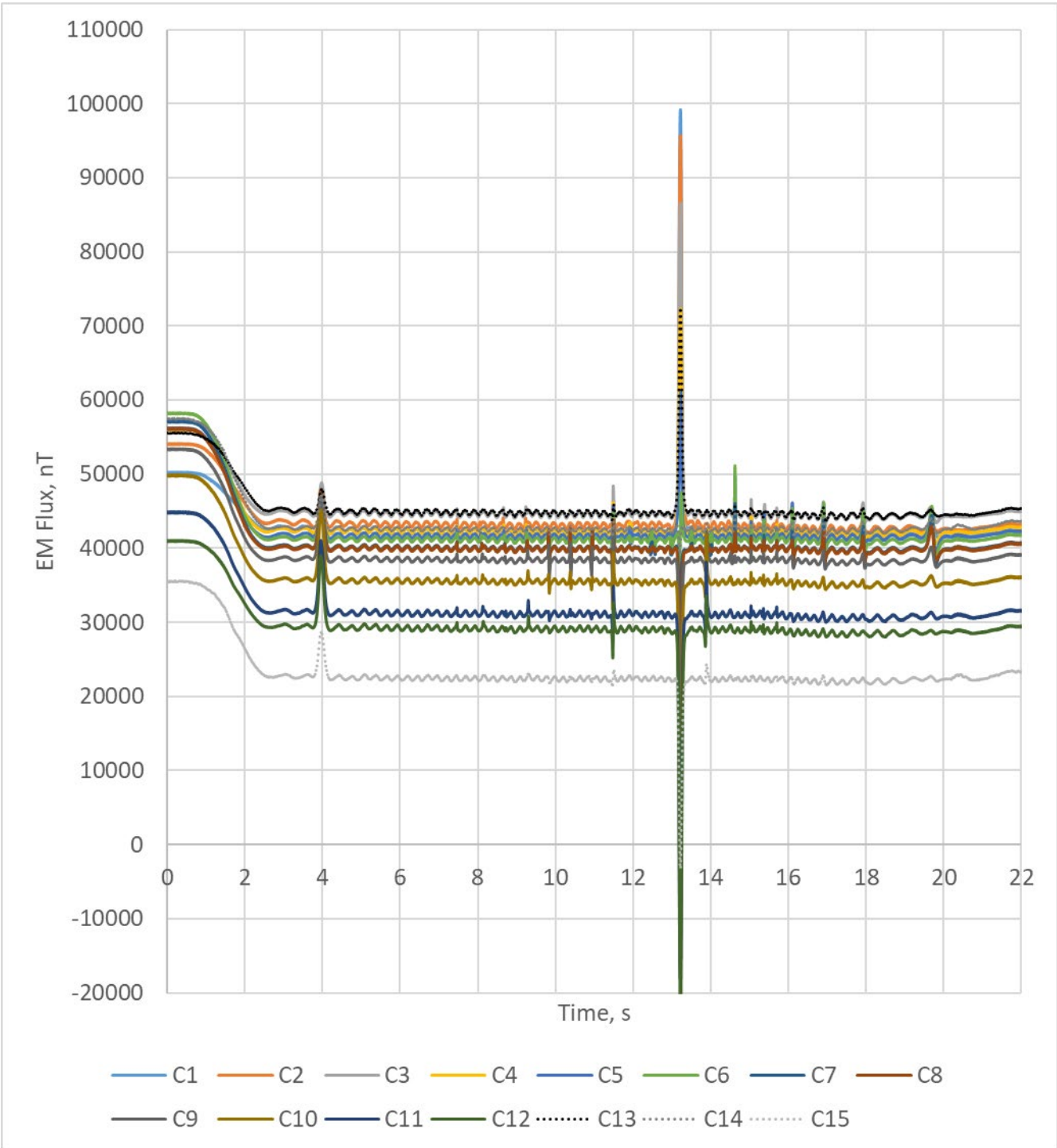


Figure 128. Chart. Signal characteristics of various EM sources (Case #11).

Processed EM Flux

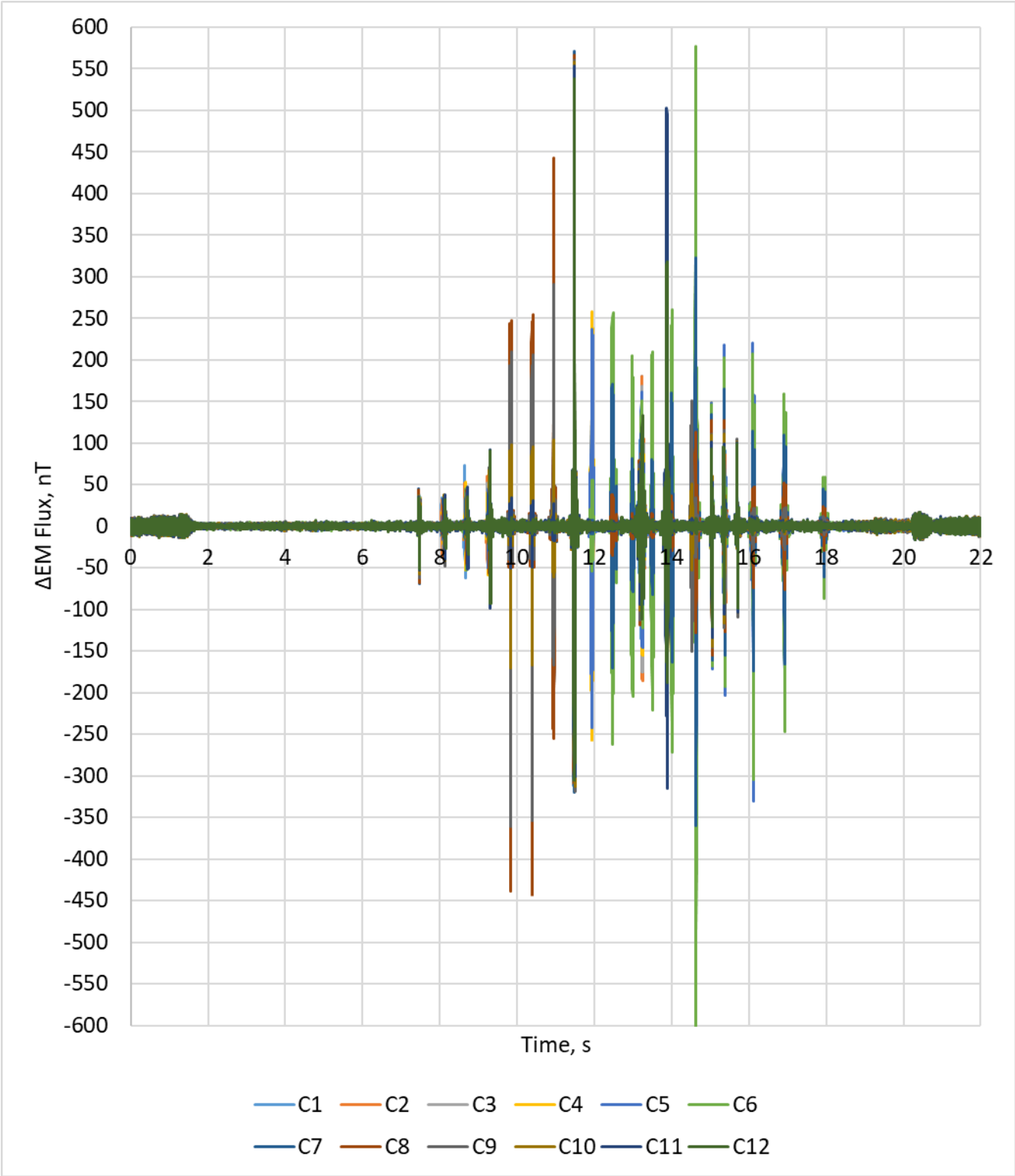


Figure 129. Chart. Signal characteristics of various EM sources (Case #11).

CASE #12

EM spectral analysis

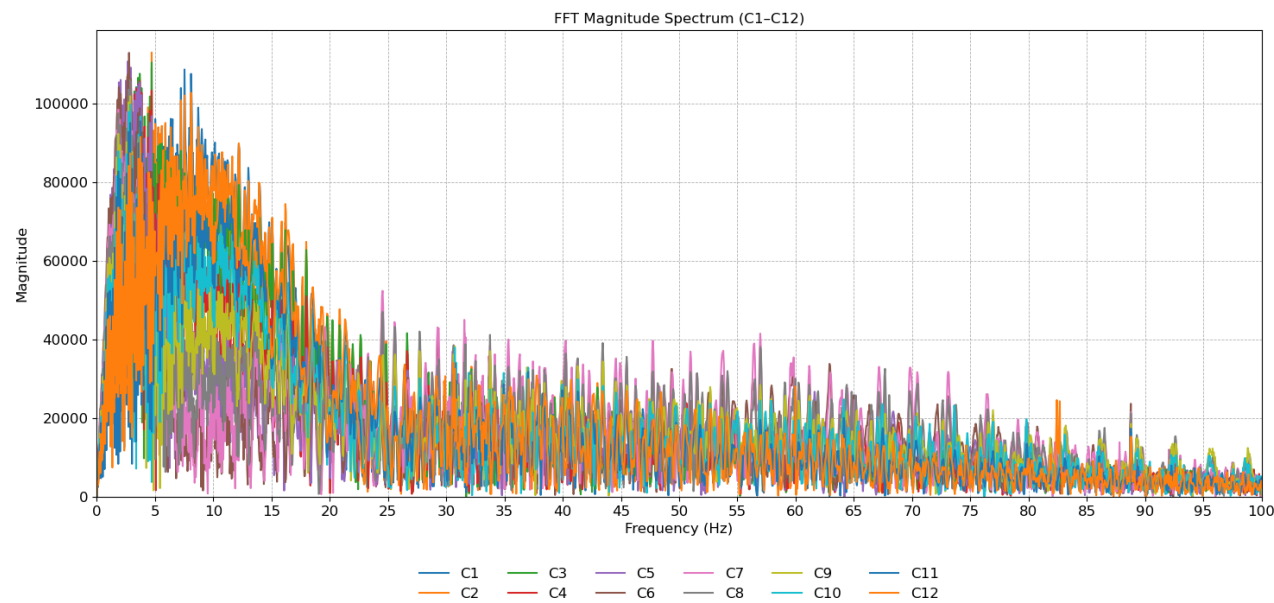


Figure 130. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #12).

Raw EM Flux

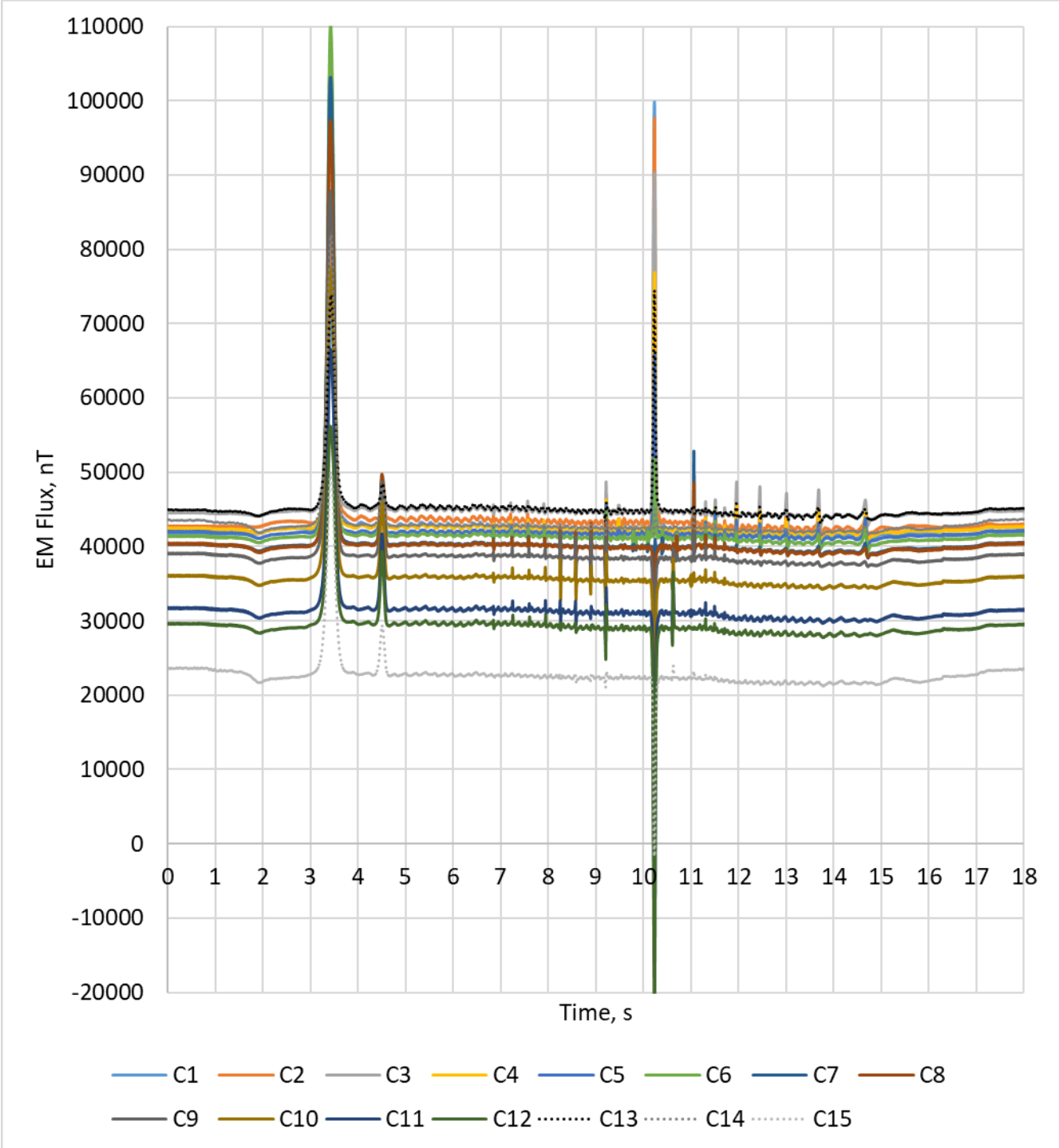


Figure 131. Chart. Signal characteristics of various EM sources (Case #12).

Processed EM Flux

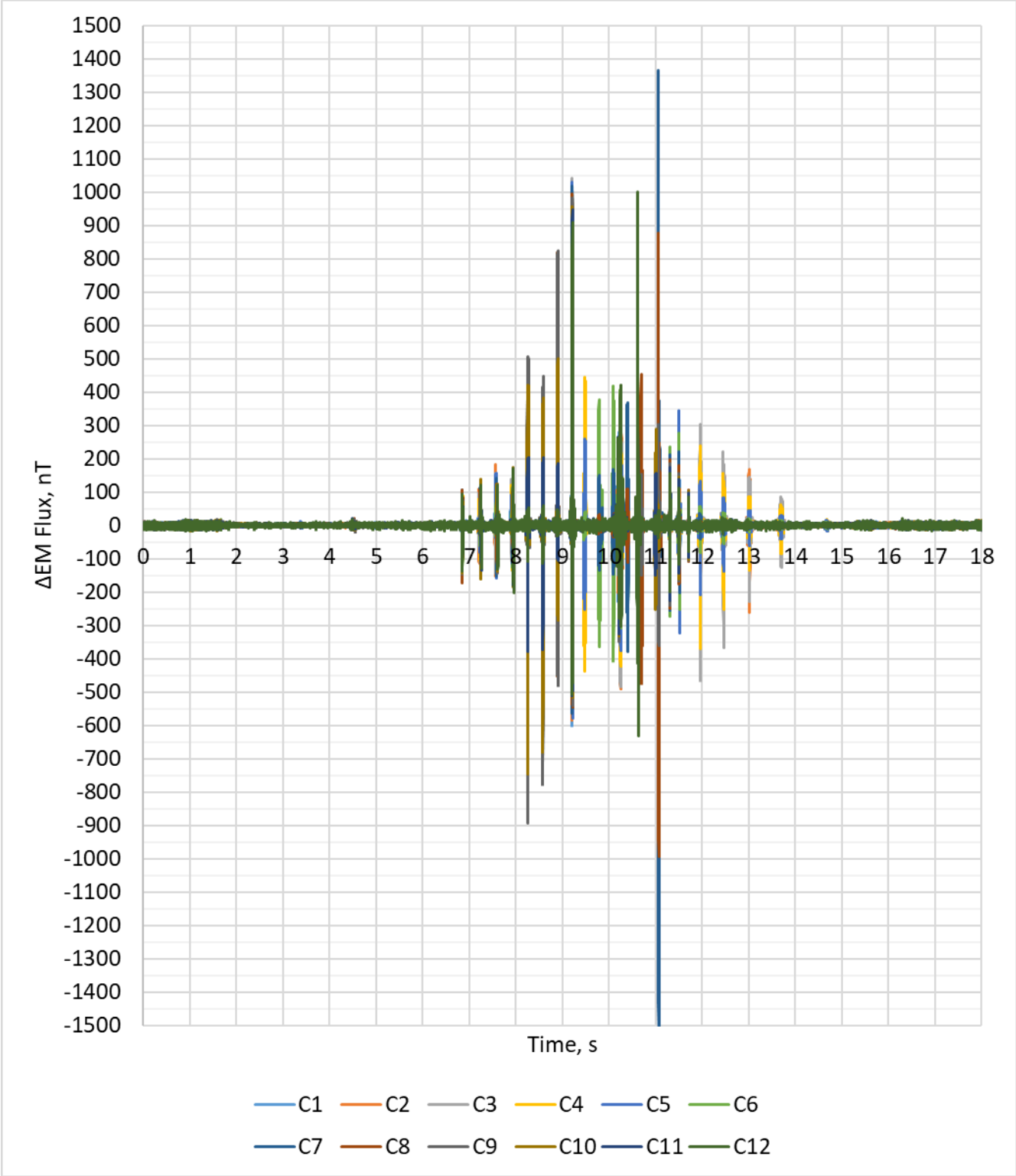


Figure 132. Chart. Signal characteristics of various EM sources (Case #12).

CASE #13

EM spectral analysis

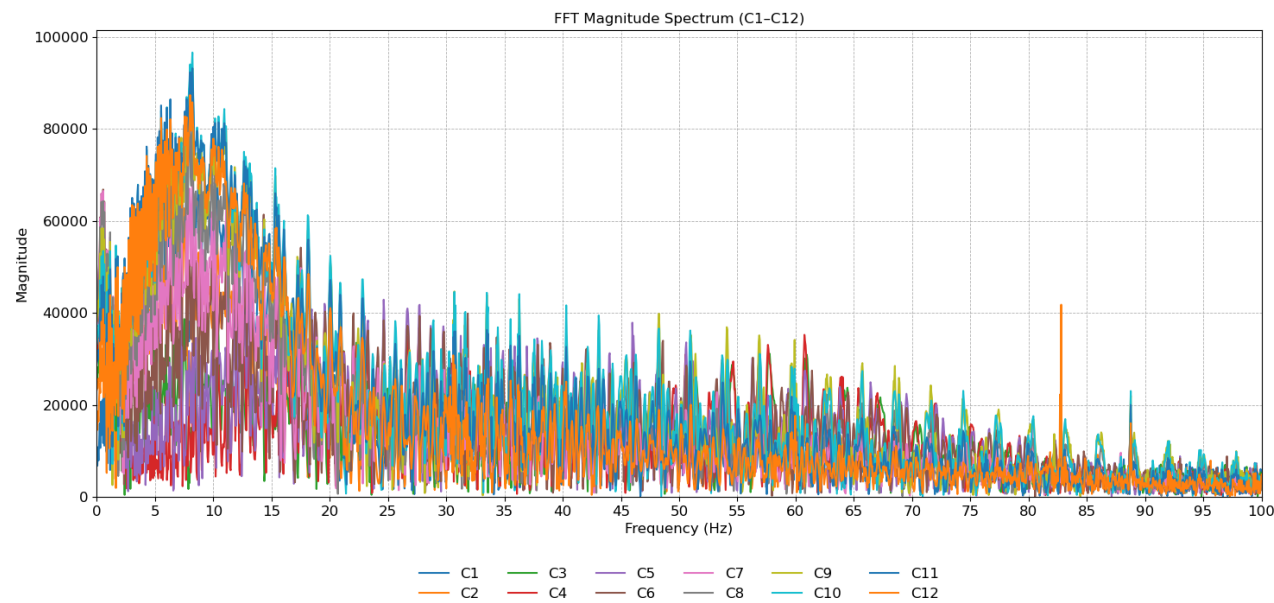


Figure 133. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #13).

Raw EM Flux

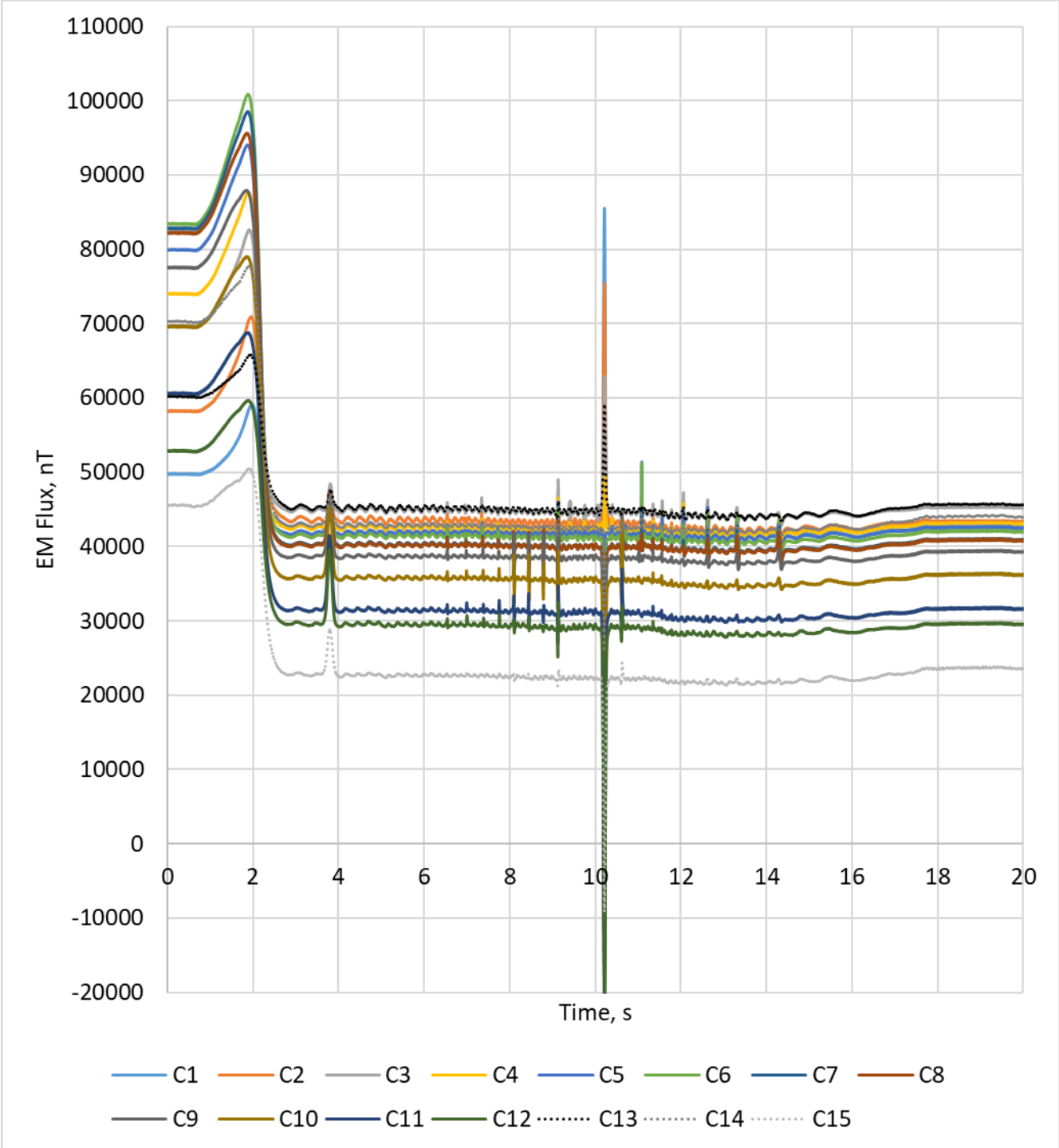


Figure 134. Chart. Signal characteristics of various EM sources (Case #13).

Processed EM Flux

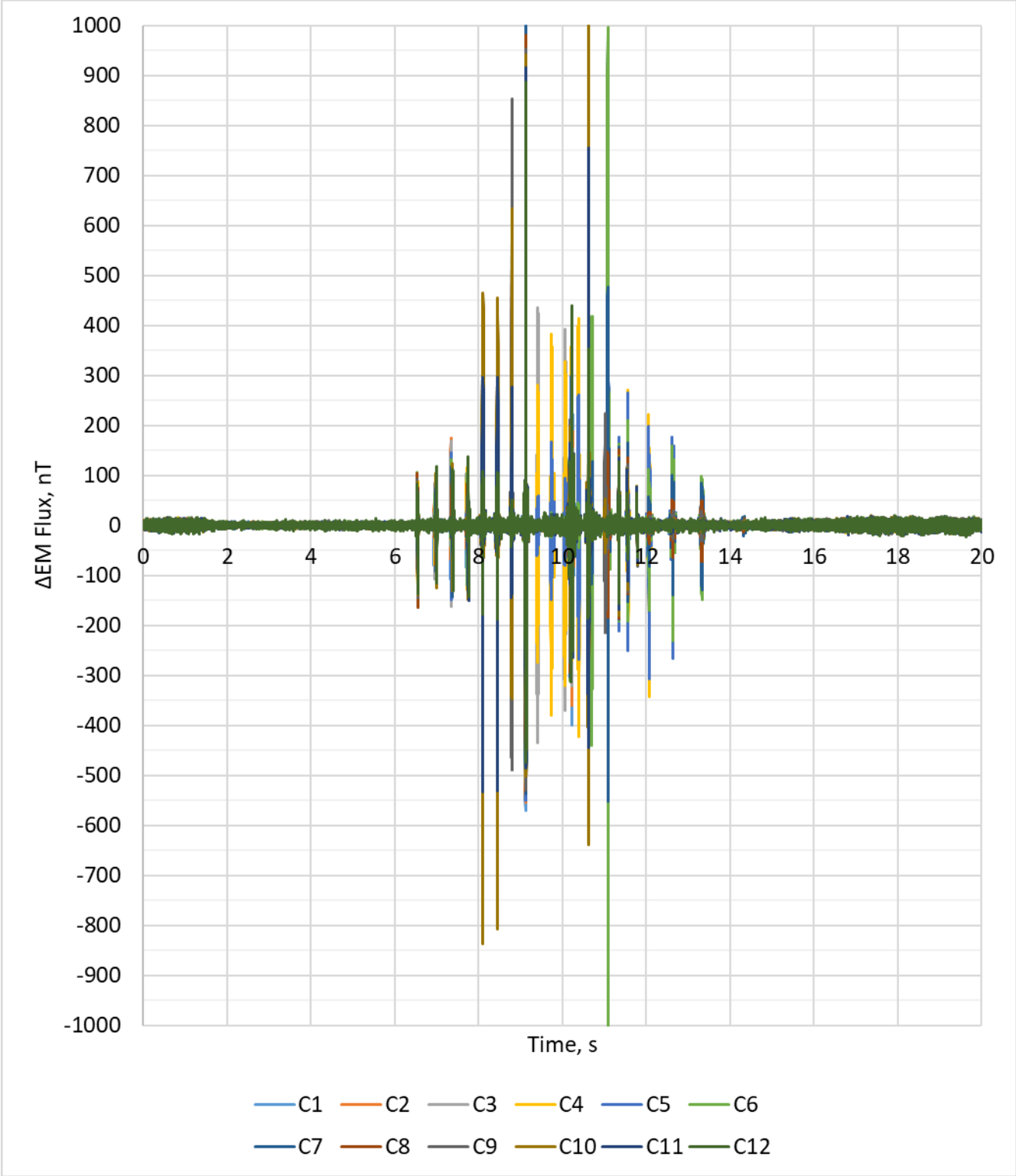


Figure 135. Chart. Signal characteristics of various EM sources (Case #13).

CASE #14

EM spectral analysis

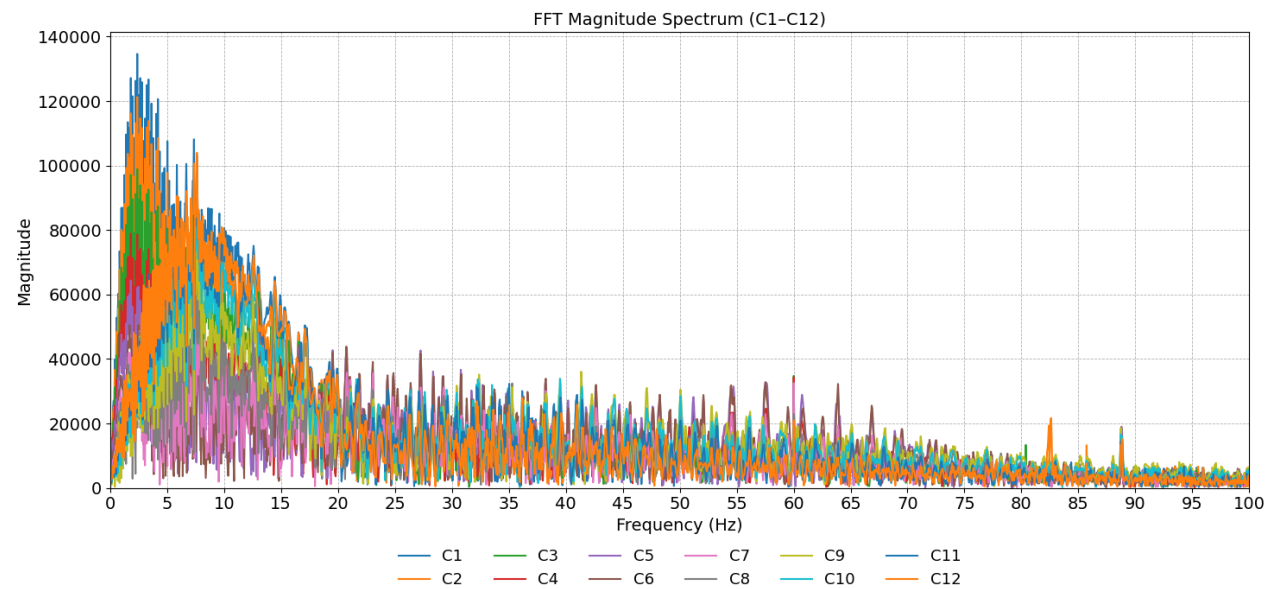


Figure 136. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #14).

Raw EM Flux

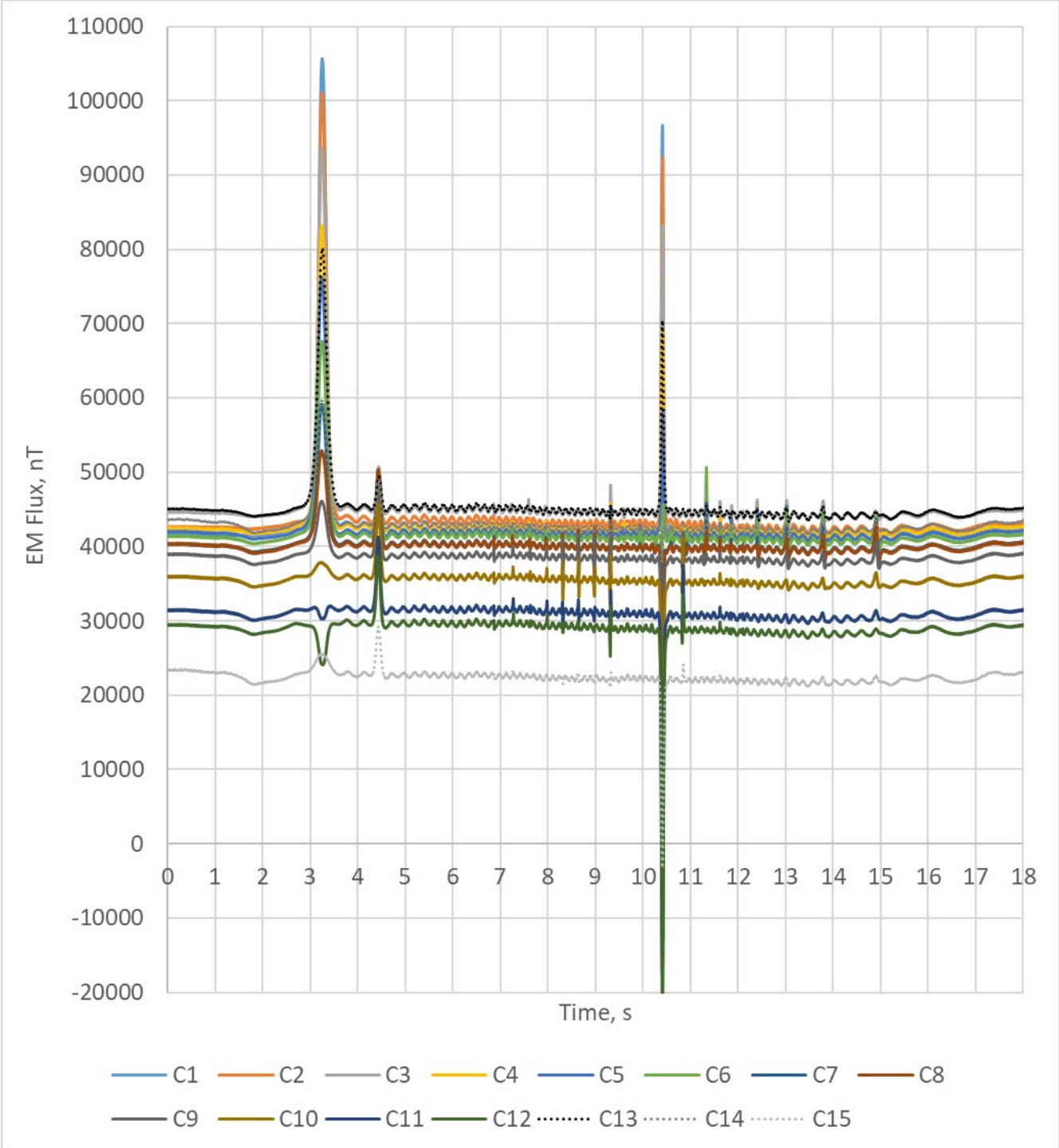


Figure 137. Chart. Signal characteristics of various EM sources (Case #14).

Processed EM Flux

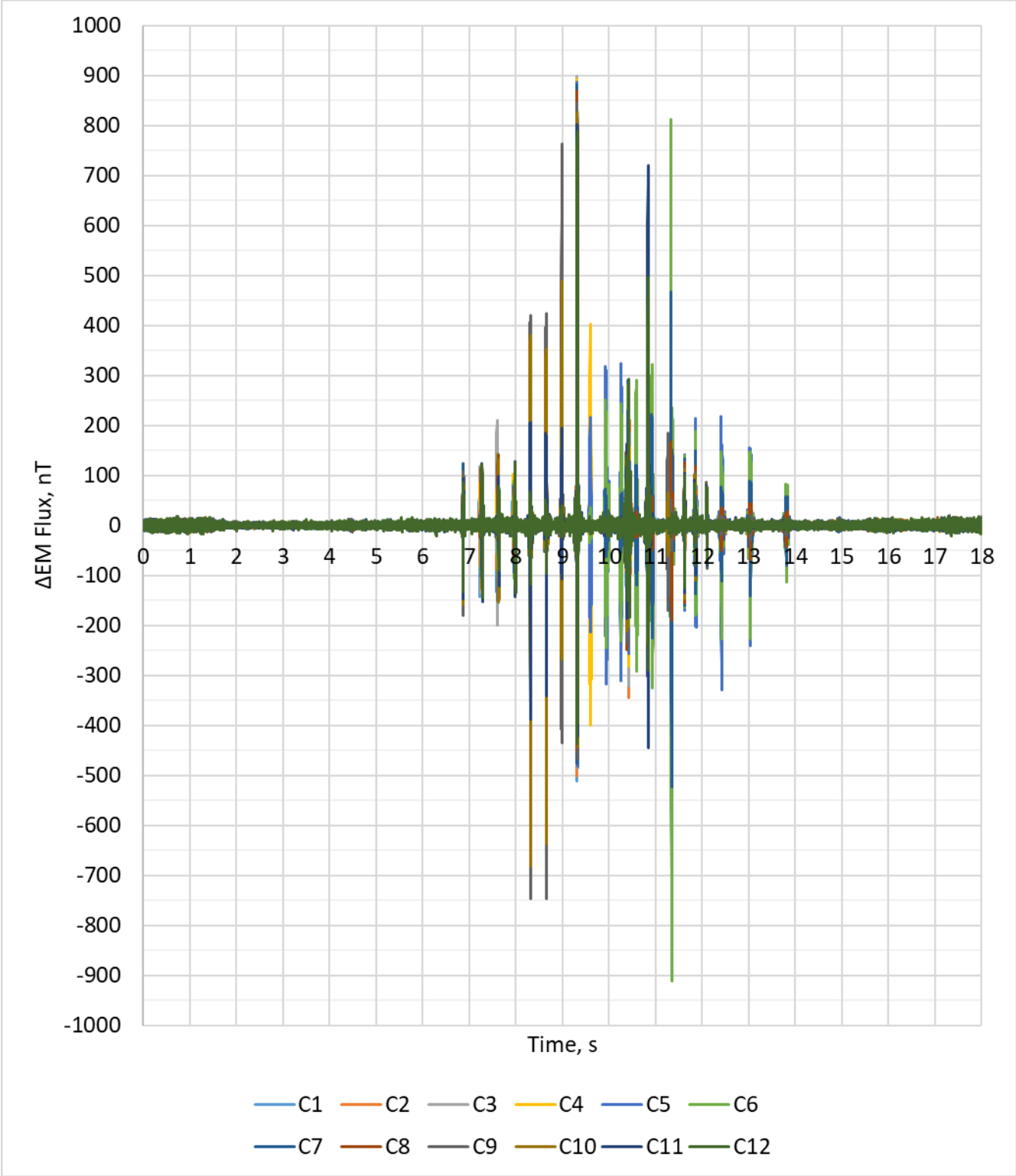


Figure 138. Chart. Signal characteristics of various EM sources (Case #14).

CASE #15

EM spectral analysis

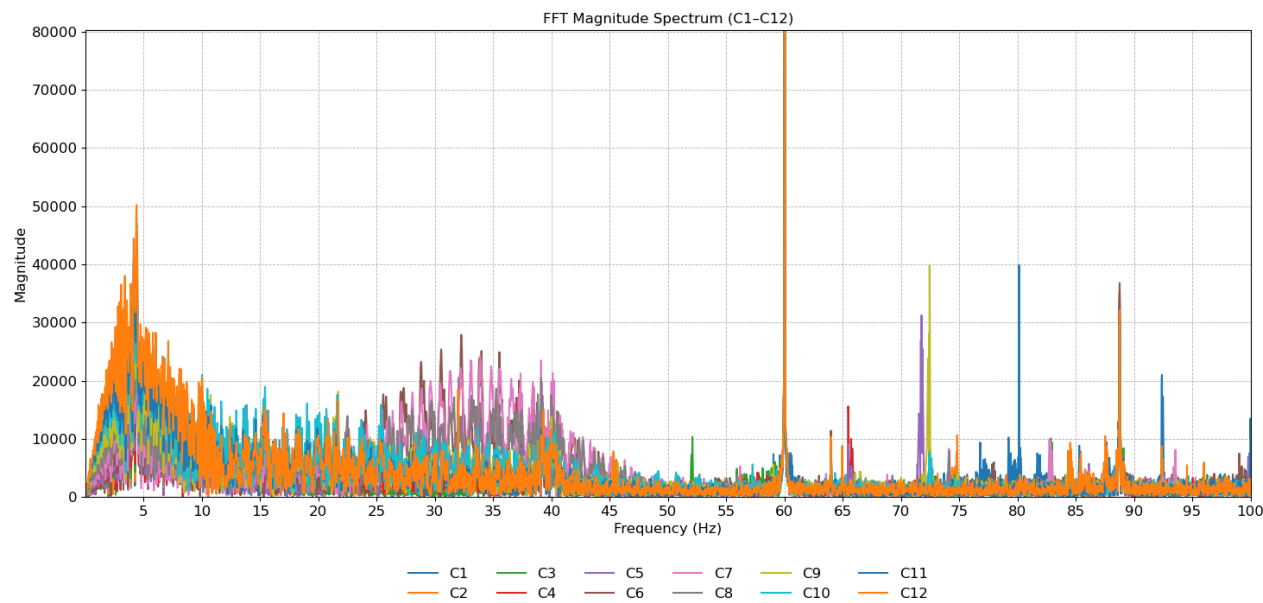


Figure 139. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #15).

Raw EM Flux

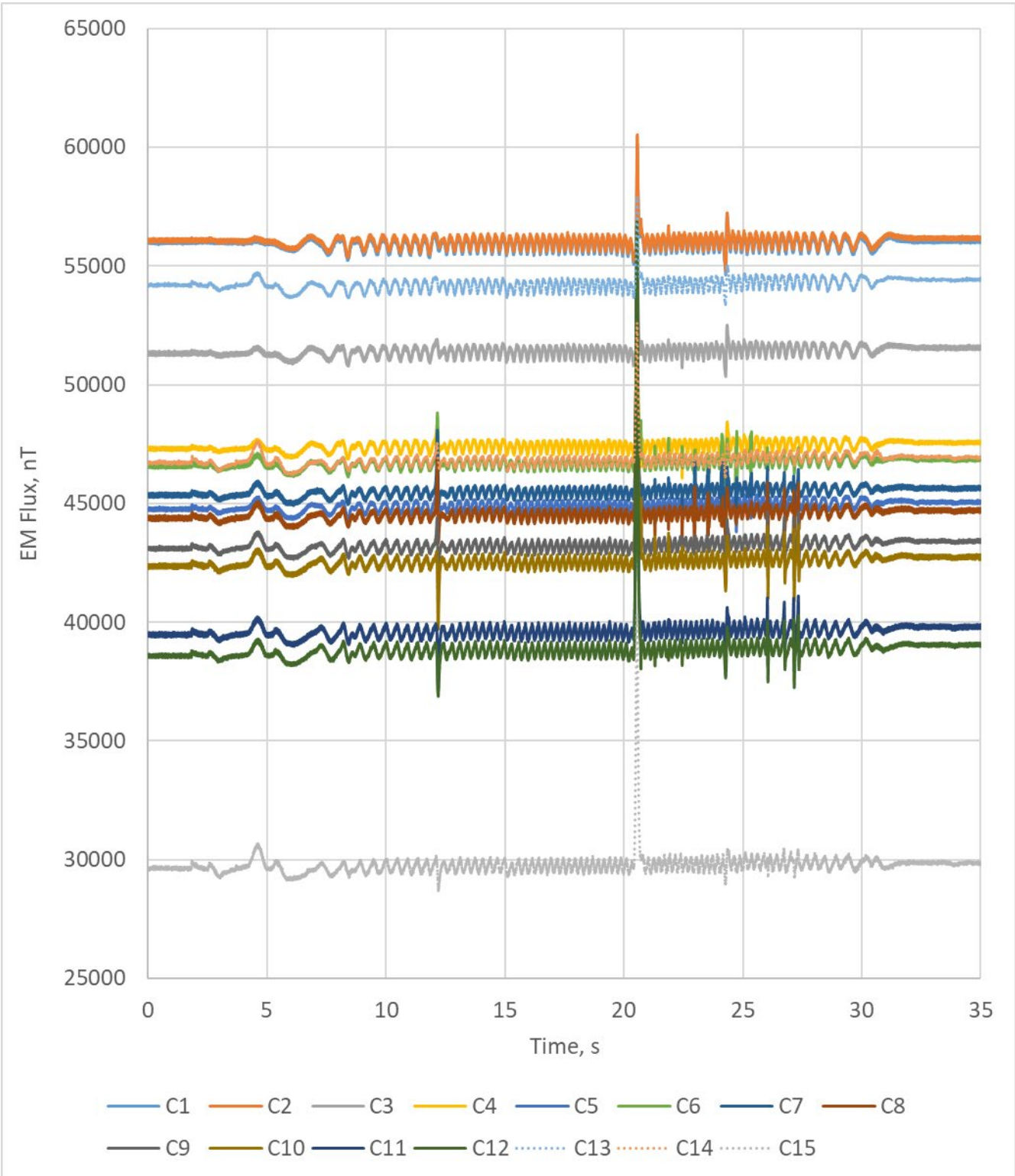


Figure 140. Chart. Signal characteristics of various EM sources (Case #15).

Processed EM Flux

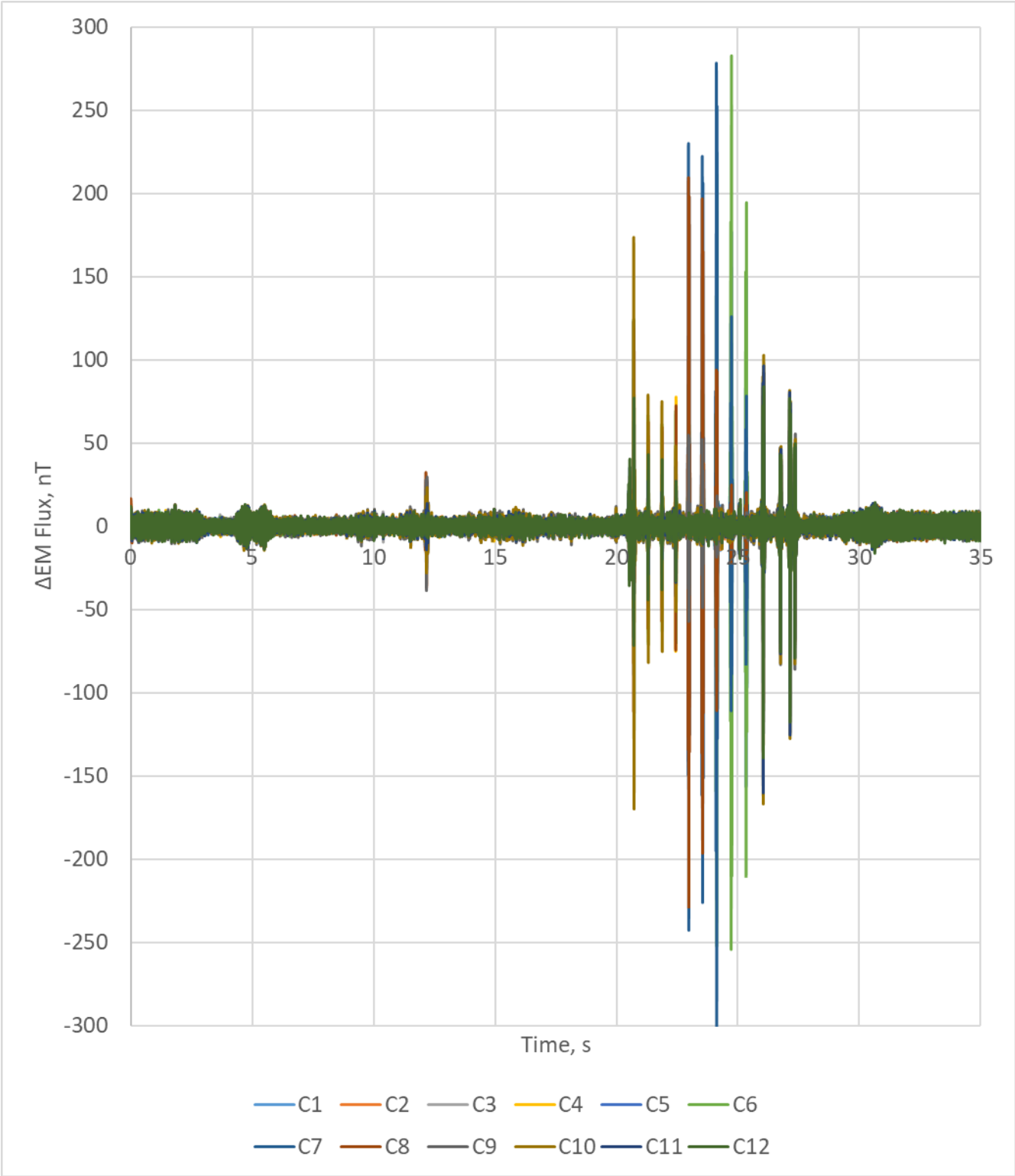


Figure 141. Chart. Signal characteristics of various EM sources (Case #15).

CASE #16

EM spectral analysis

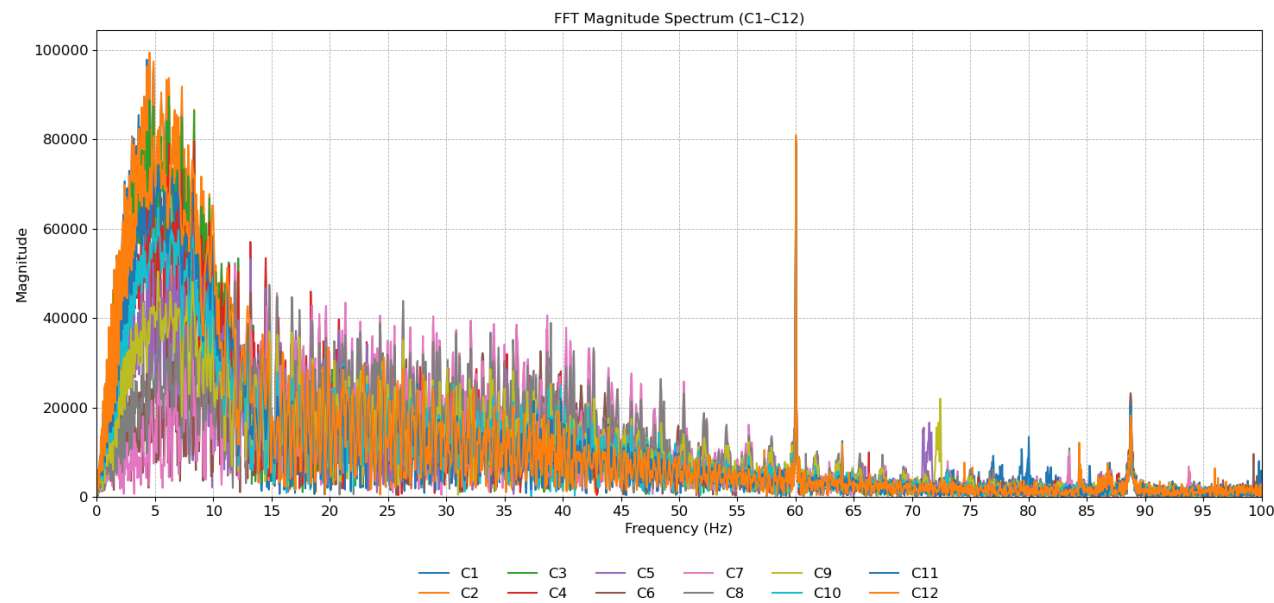


Figure 142. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #16).

Raw EM Flux

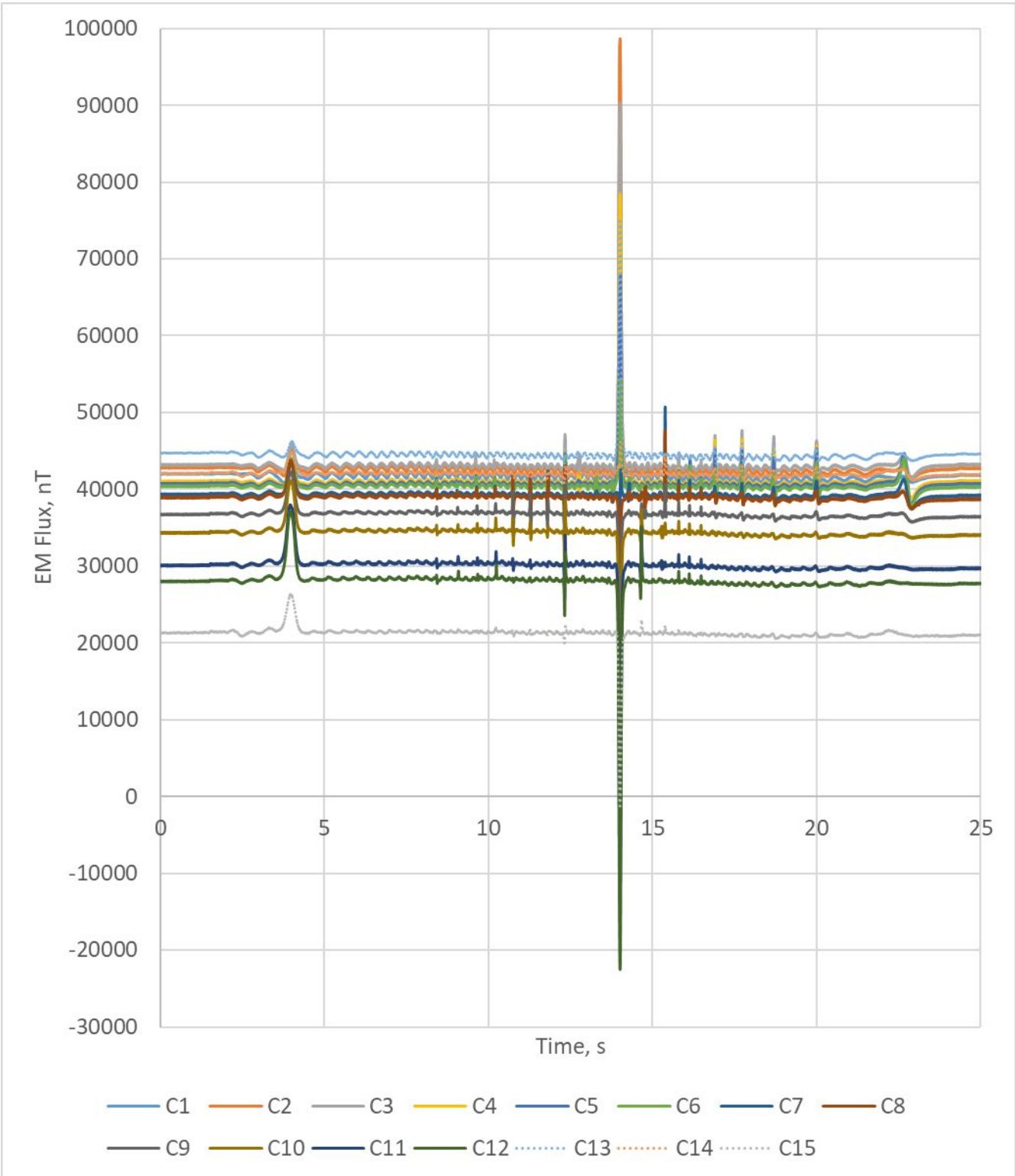


Figure 143. Chart. Signal characteristics of various EM sources (Case #16).

Processed EM Flux

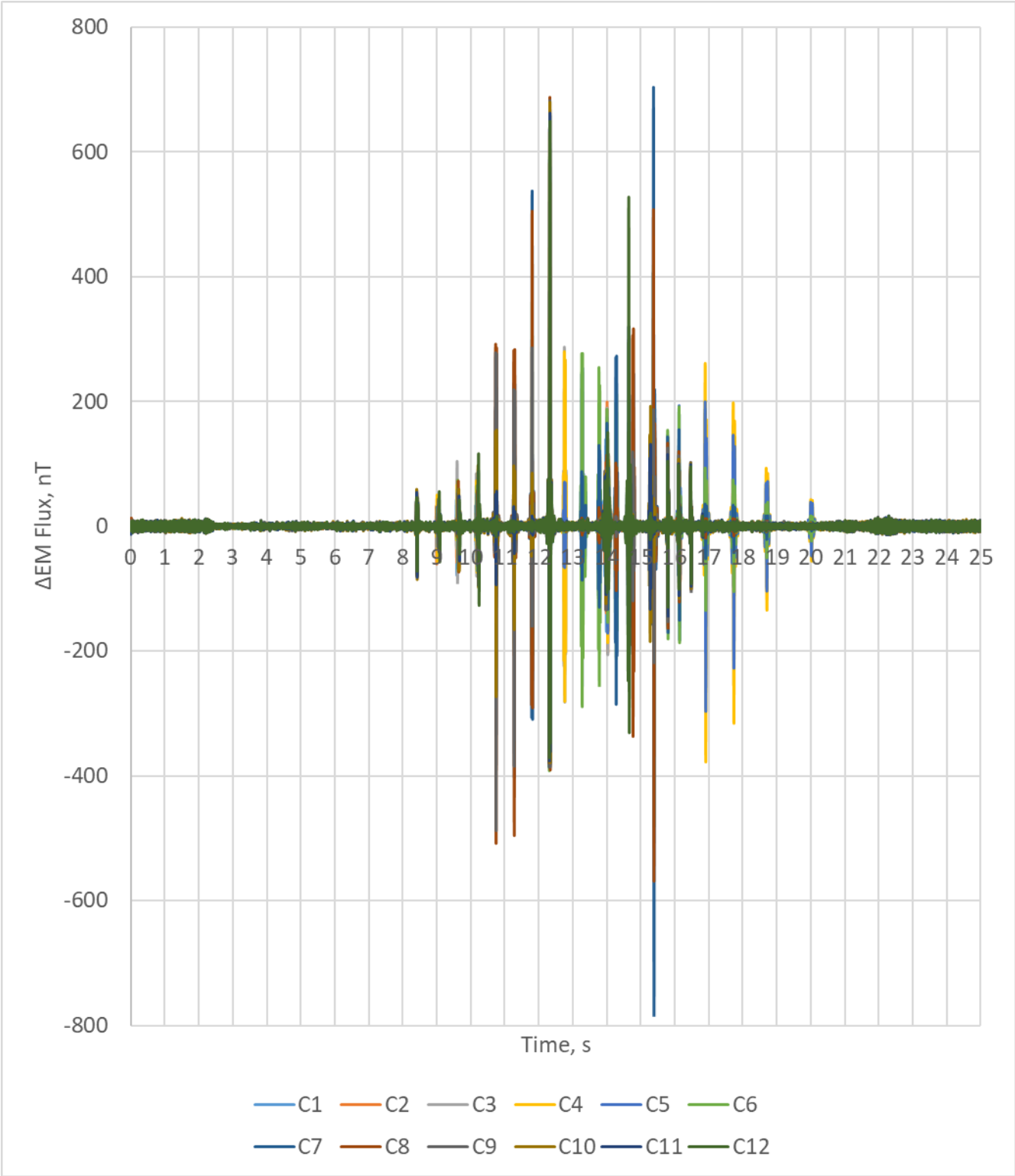


Figure 144. Chart. Signal characteristics of various EM sources (Case #16).

APPENDIX B: SIGNAL-PROCESSING RESULTS FROM EXPERIMENTS ON TITAN DRIVE - CASES 17-21

CASE #17

Referenced ground-truth data



Figure 145. Photo. Referenced photo for longitudinal strip #1 (Case #17).



Figure 146. Photo. Referenced photo for longitudinal strip #2 (Case #17).



Figure 147. Photo. Referenced photo for longitudinal strip #3 (Case #17).



Figure 148. Photo. Referenced photo for longitudinal strip #4 (Case #17).



Figure 149. Photo. Referenced photo for longitudinal strip #5 (Case #17).



Figure 150. Photo. Referenced photo for longitudinal strip #6 (Case #17).



Figure 151. Photo. Referenced photo for longitudinal strip #7 (Case #17).



Figure 152. Photo. Referenced photo for longitudinal strip #8(Case #17).



Figure 153. Photo. Referenced photo for longitudinal strip #9 (Case #17).



Figure 154. Photo. Referenced photo for longitudinal strip #10 (Case #17).



Figure 155. Photo. Referenced photo for longitudinal strip #11 (Case #17).



Figure 156. Photo. Referenced photo for longitudinal strip #12 (Case #17).



Figure 157. Photo. Referenced photo for longitudinal strip #13 (Case #17).



Figure 158. Photo. Referenced photo for longitudinal strip #14 (Case #17).



Figure 159. Photo. Referenced photo for longitudinal strip #15 (Case #17).



Figure 160. Photo. Referenced photo for longitudinal strip #16 (Case #17).

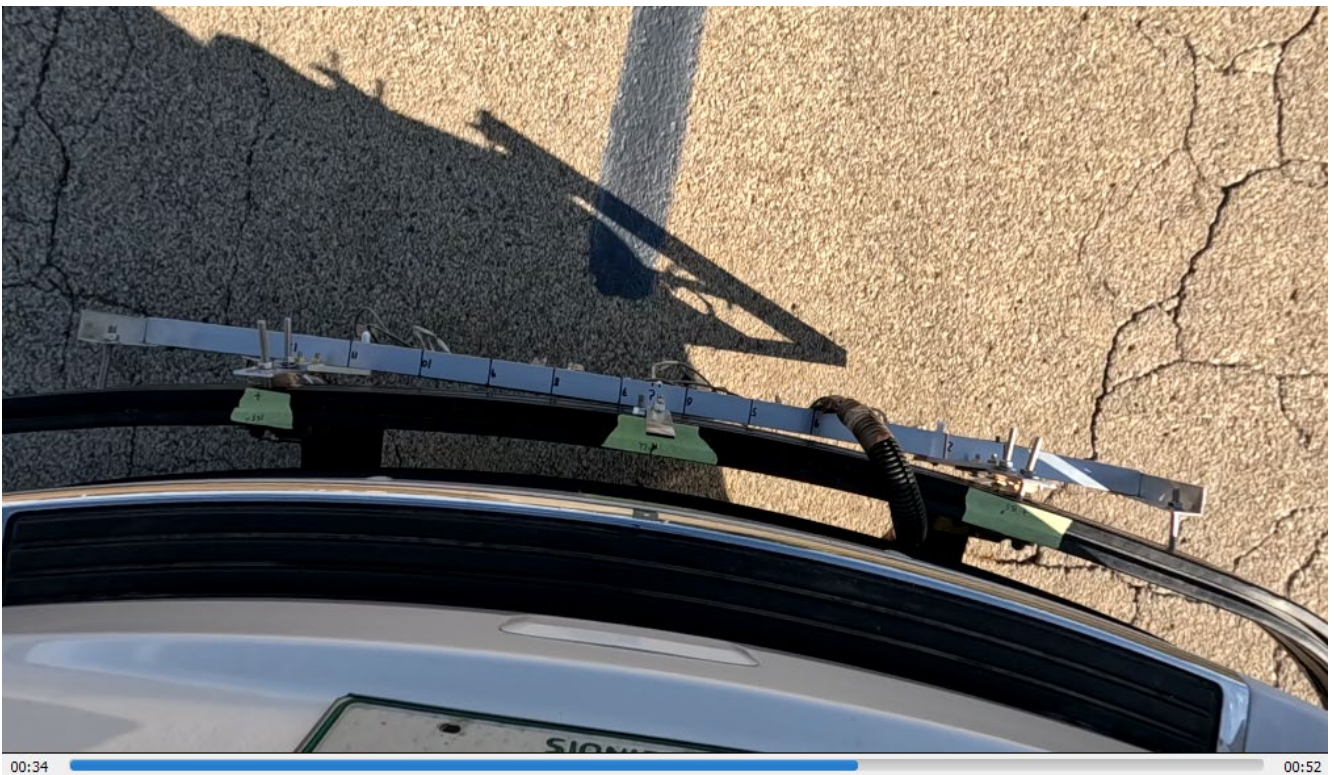


Figure 161. Photo. Referenced photo for longitudinal strip #17 (Case #17).

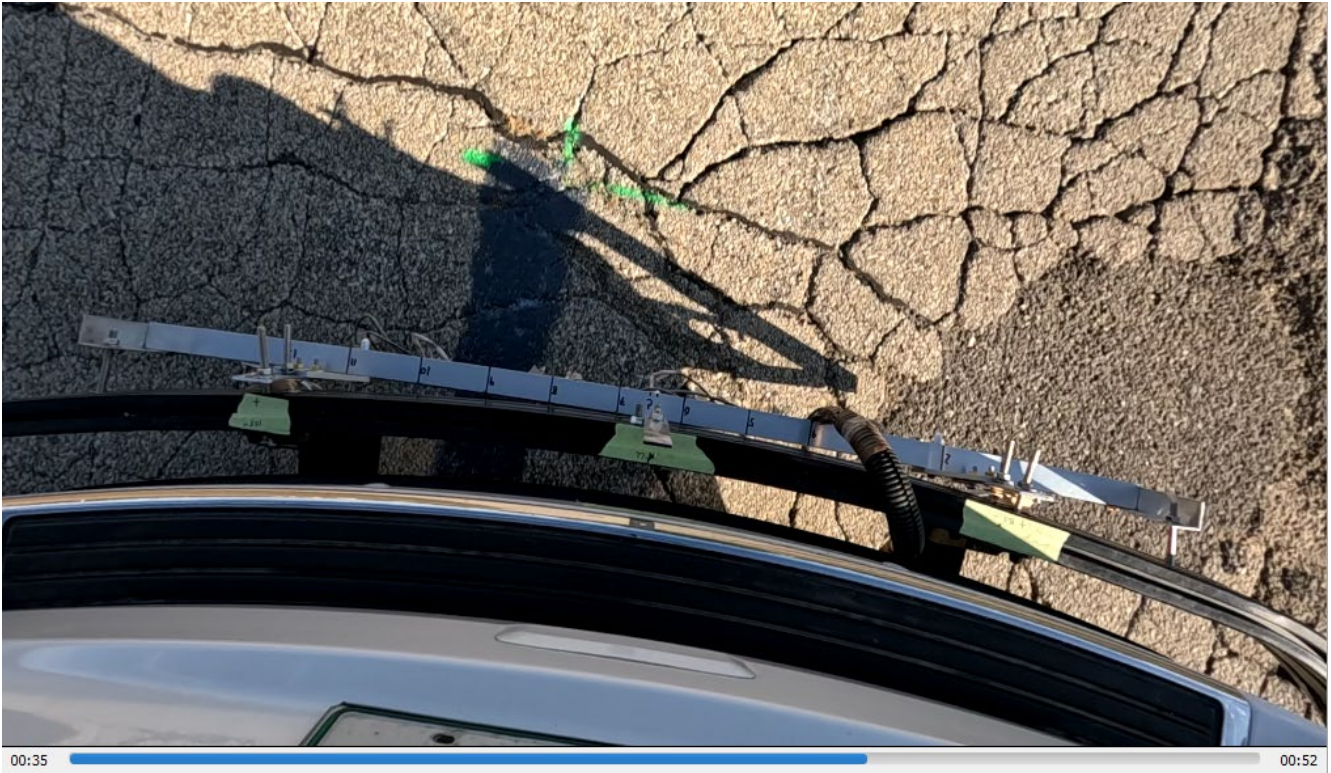


Figure 162. Photo. Referenced photo for longitudinal strip #18 (Case #17).



Figure 163. Photo. Referenced photo for longitudinal strip #19 (Case #17).



Figure 164. Photo. Referenced photo for longitudinal strip #20 (Case #17).



Figure 165. Photo. Referenced photo for longitudinal strip #21 (Case #17).



Figure 166. Photo. Referenced photo for longitudinal strip #22 (Case #17).



Figure 167. Photo. Referenced photo for longitudinal strip #23 (Case #17).



Figure 168. Photo. Referenced photo for longitudinal strip #24 (Case #17).



Figure 169. Photo. Referenced photo for longitudinal strip #25 (Case #17).

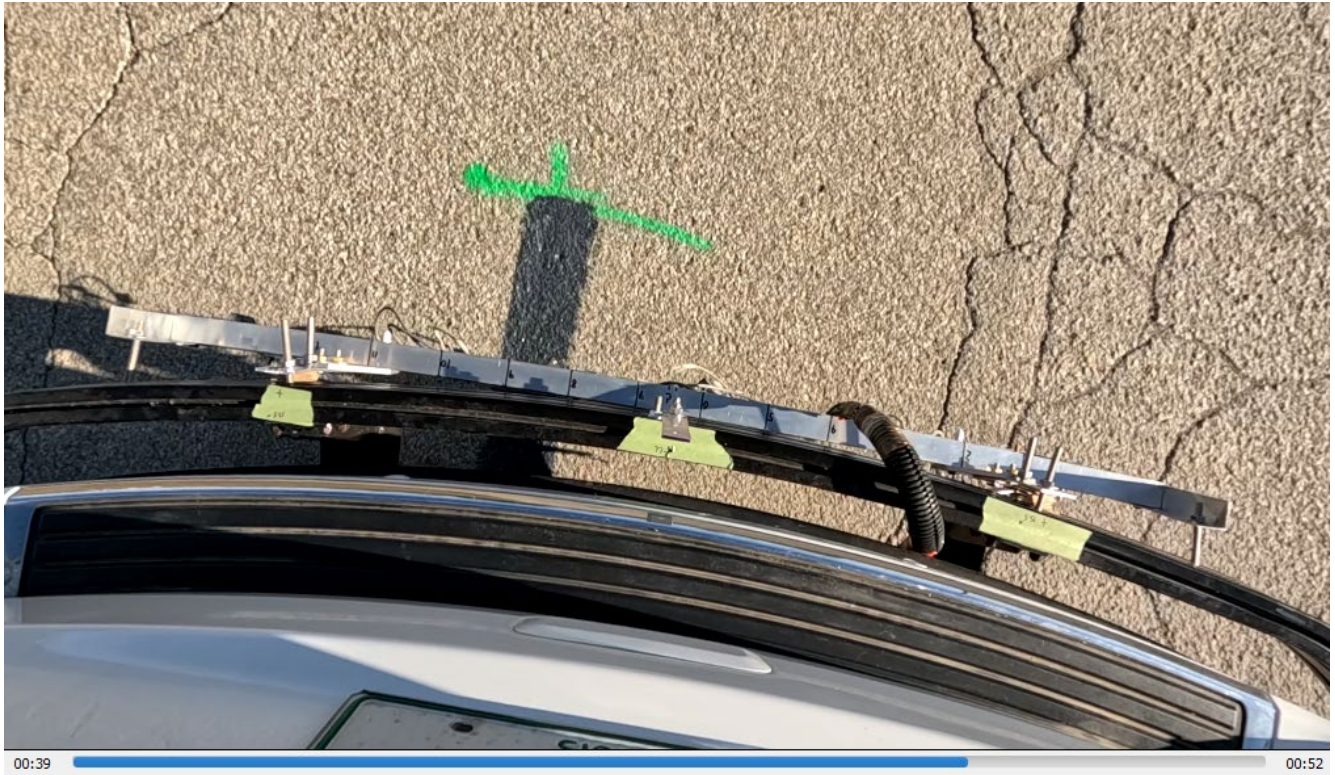


Figure 170. Photo. Referenced photo for longitudinal strip #26 (Case #17).

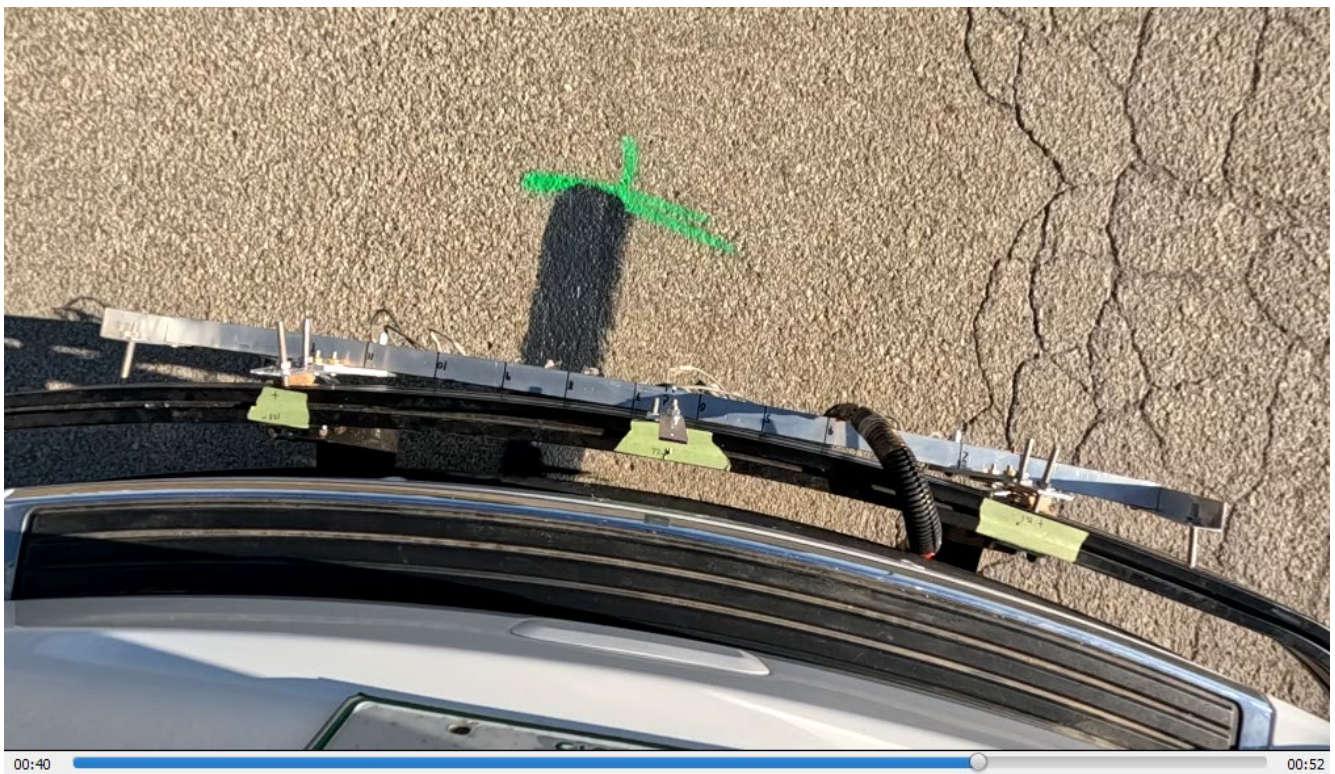


Figure 171. Photo. Referenced photo for longitudinal strip #27 (Case #17).

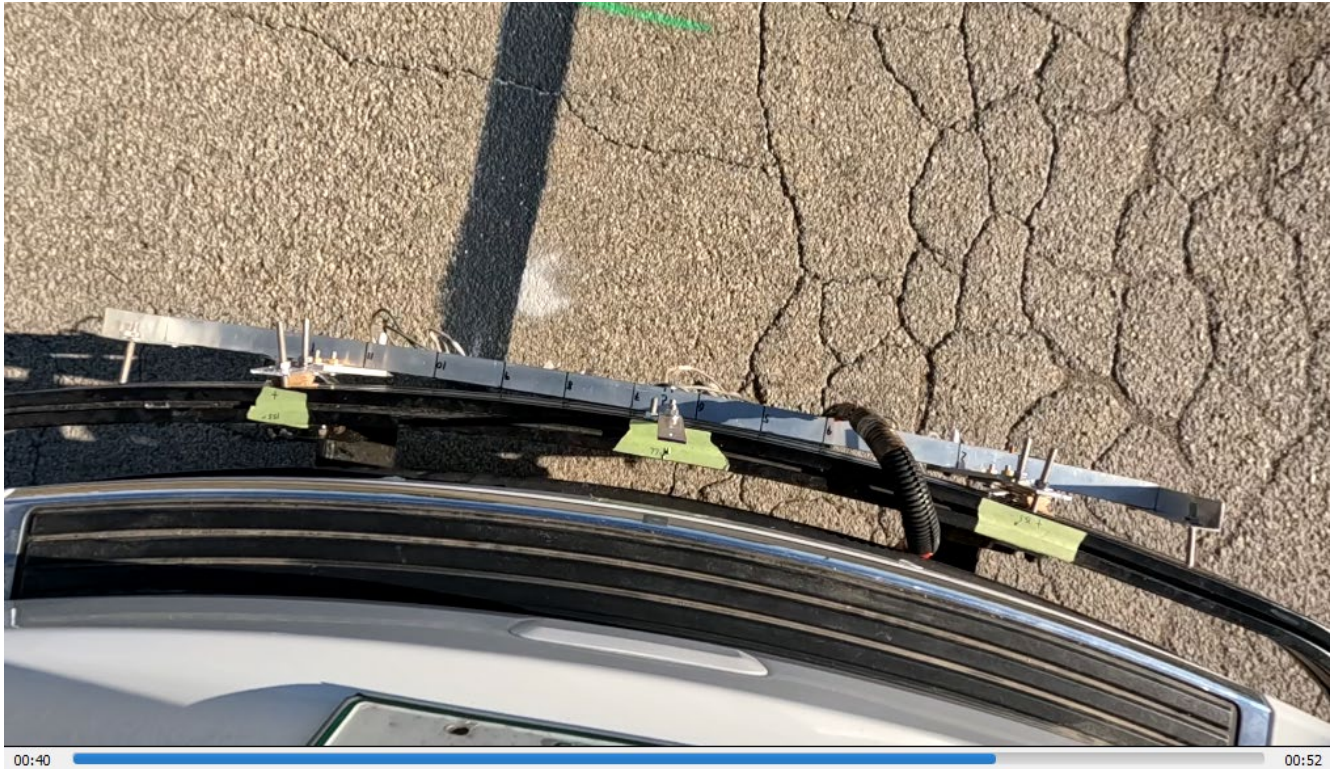


Figure 172. Photo. Referenced photo for longitudinal strip #28 (Case #17).

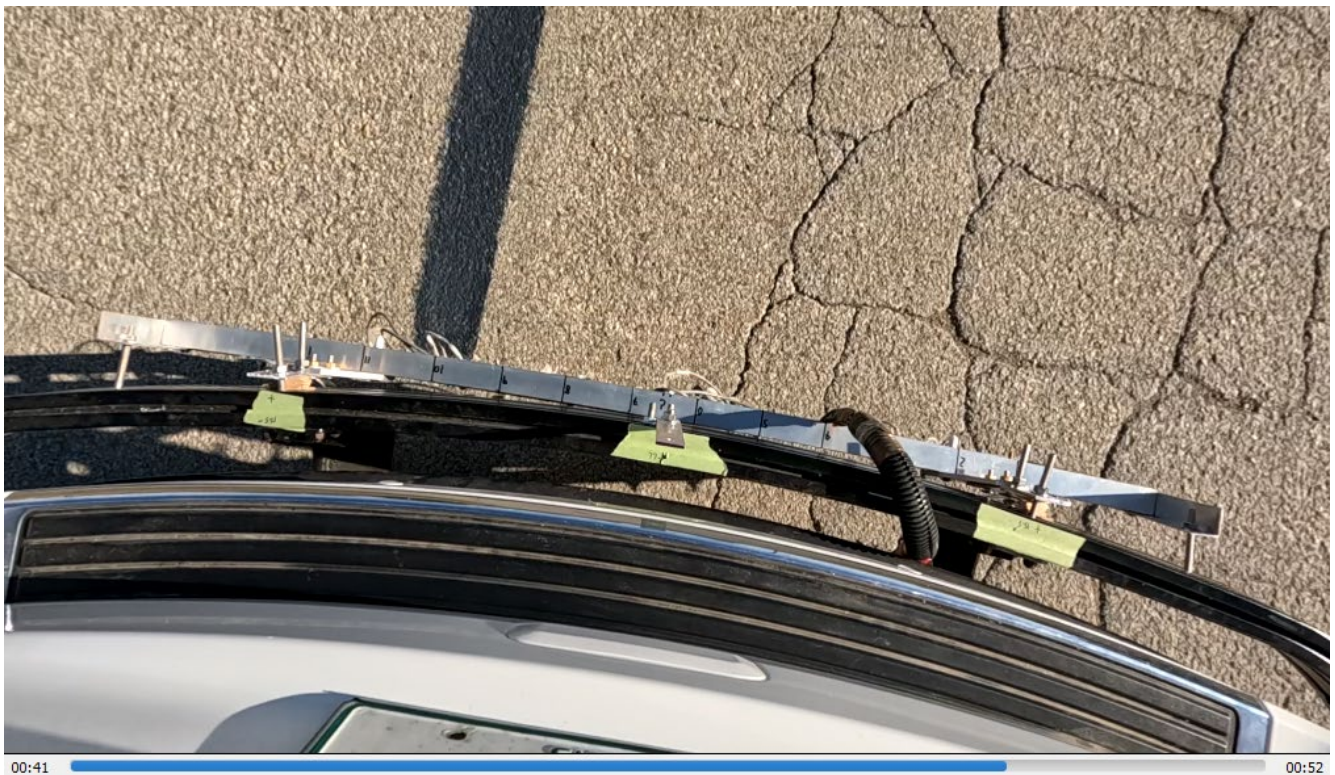


Figure 173. Photo. Referenced photo for longitudinal strip #29 (Case #17).



Figure 174. Photo. Referenced photo for longitudinal strip #30 (Case #17).



Figure 175. Photo. Referenced photo for longitudinal strip #31 (Case #17).

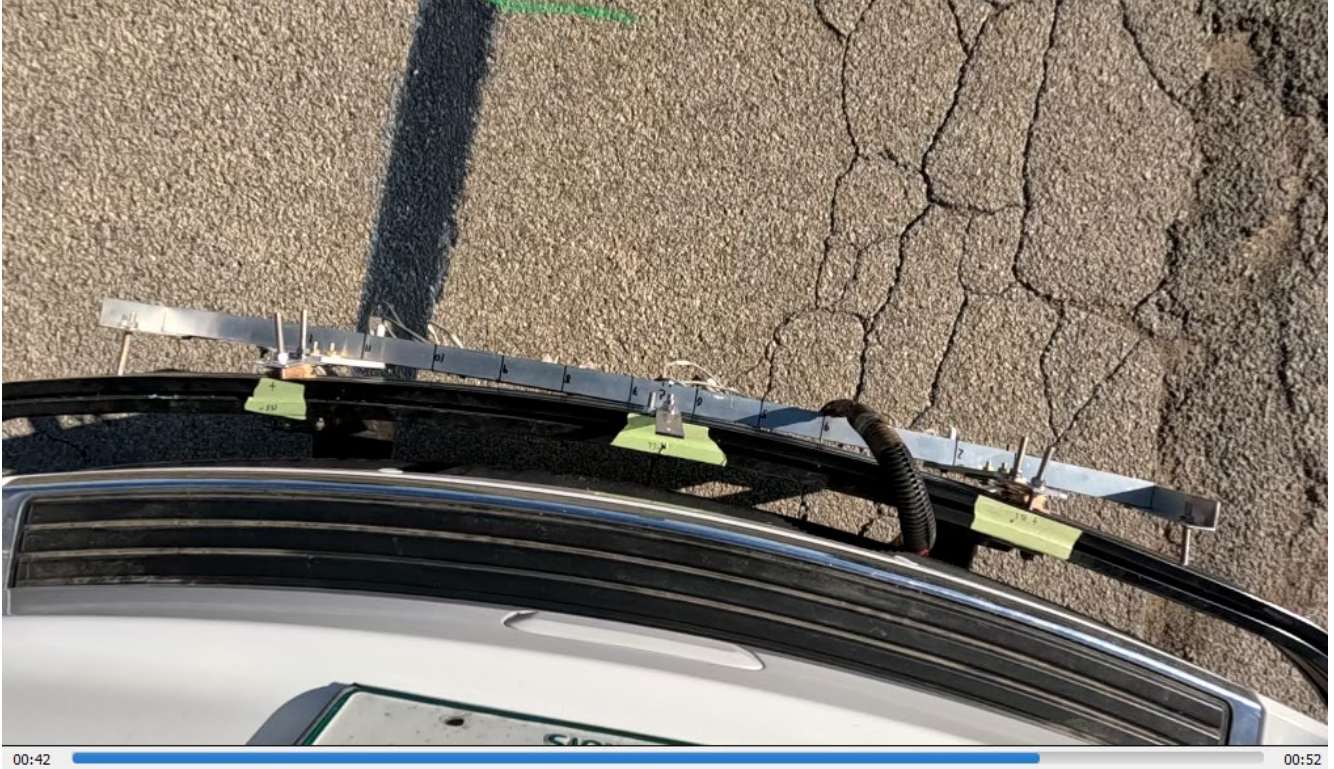


Figure 176. Photo. Referenced photo for longitudinal strip #32 (Case #17).

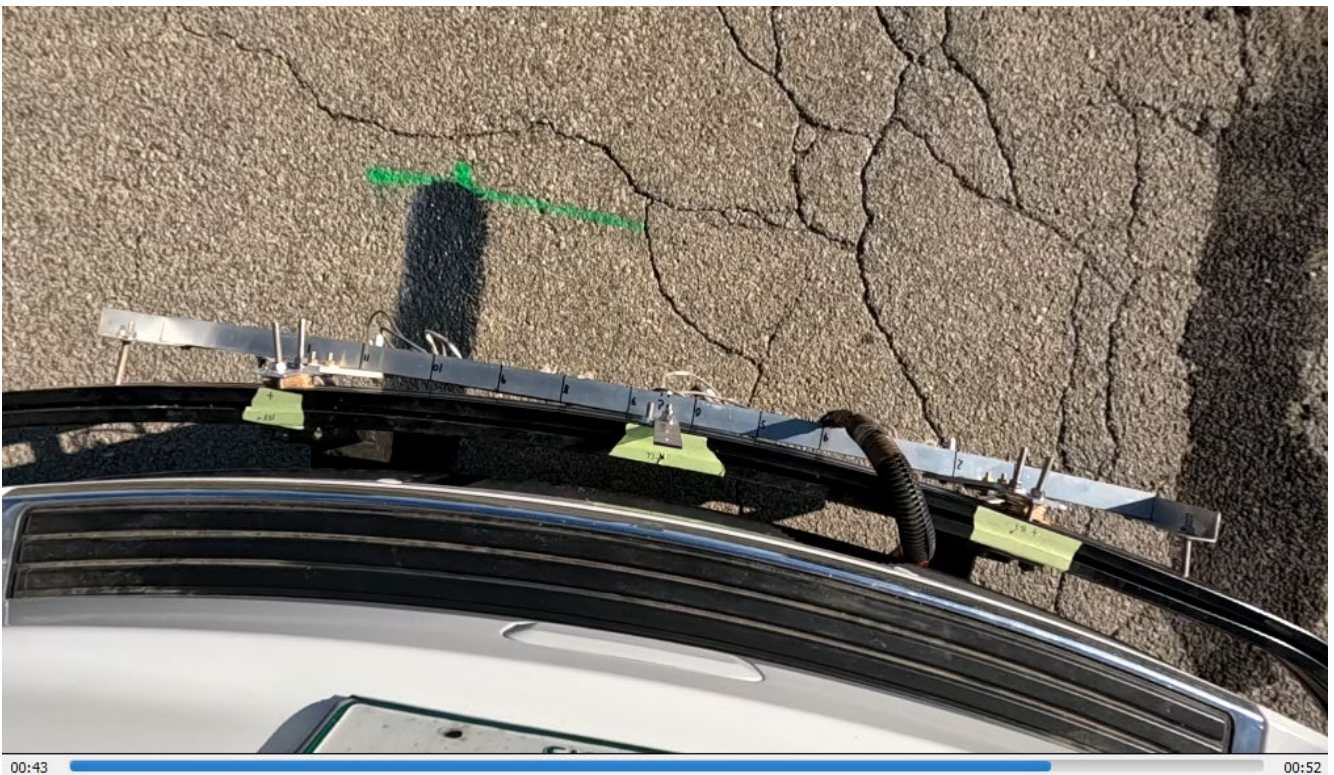


Figure 177. Photo. Referenced photo for longitudinal strip #33 (Case #17).

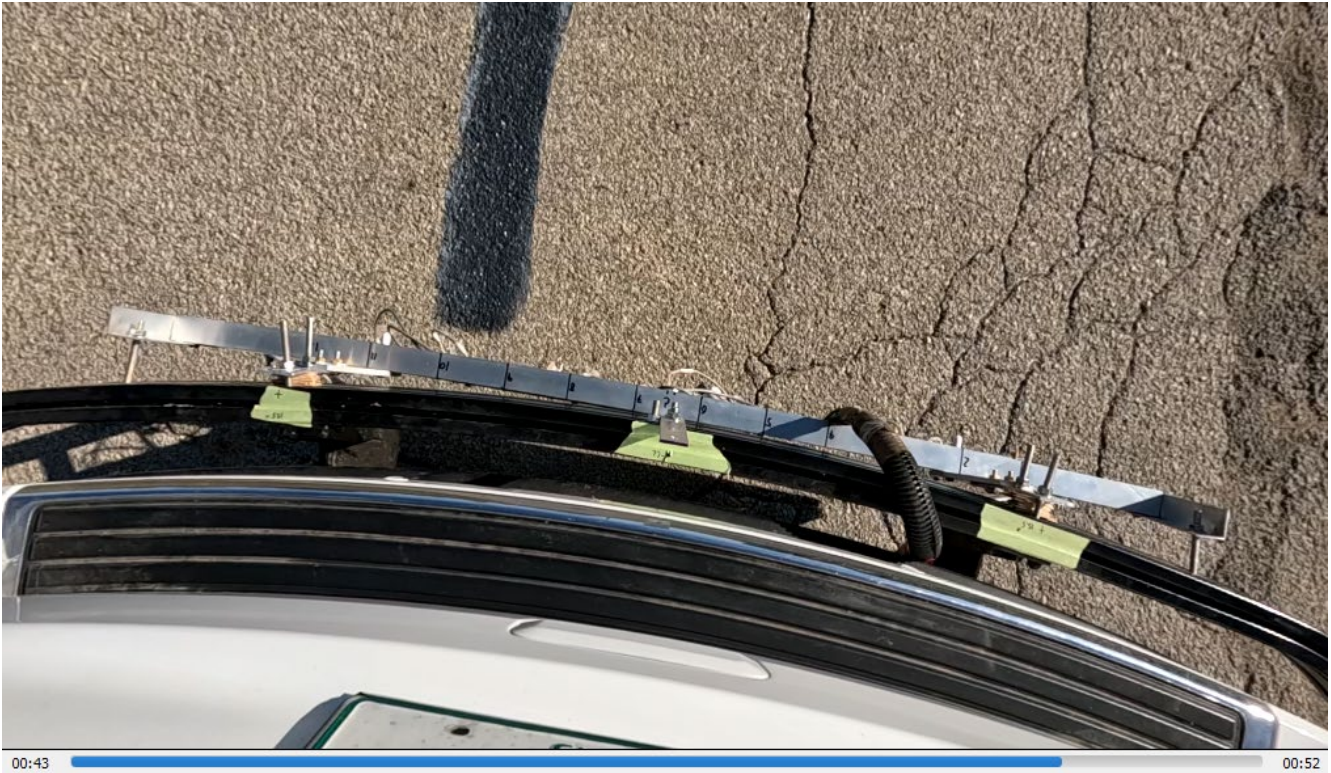


Figure 178. Photo. Referenced photo for longitudinal strip #34 (Case #17).

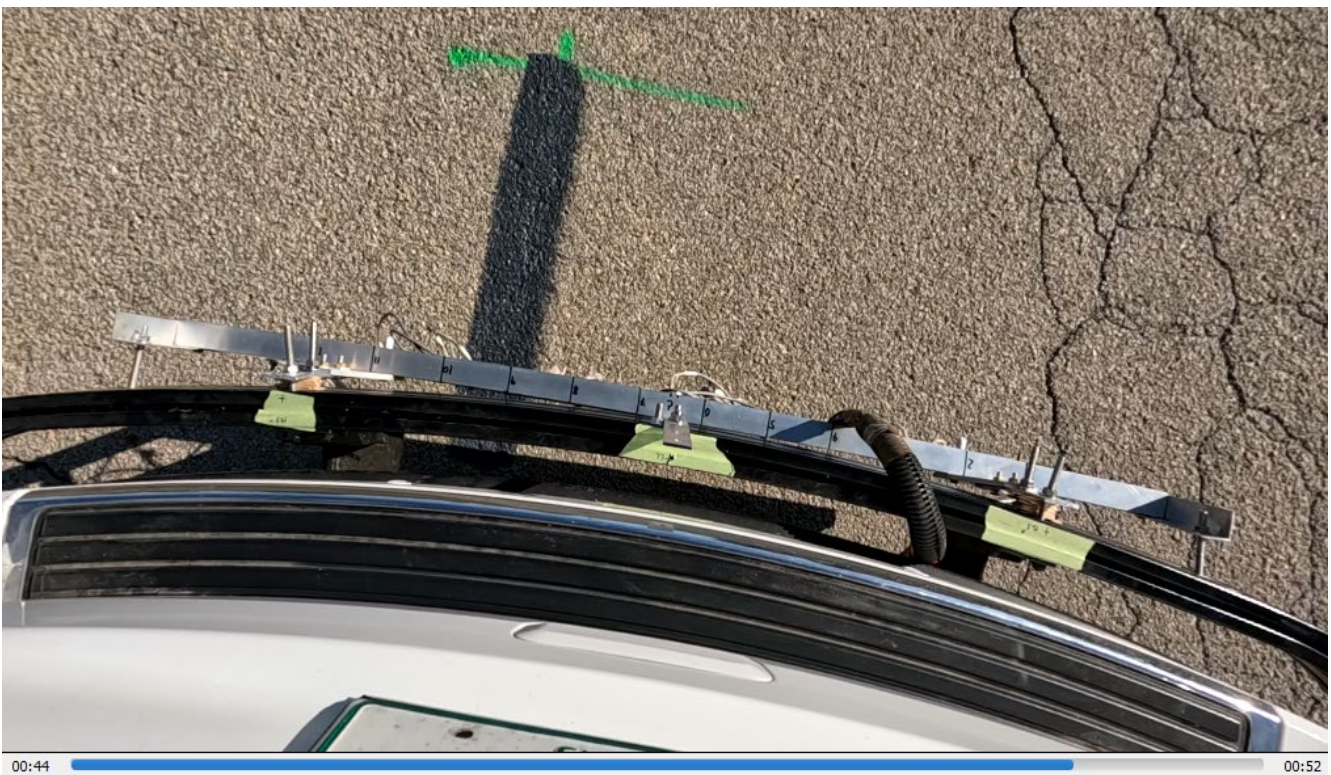


Figure 179. Photo. Referenced photo for longitudinal strip #35 (Case #17).

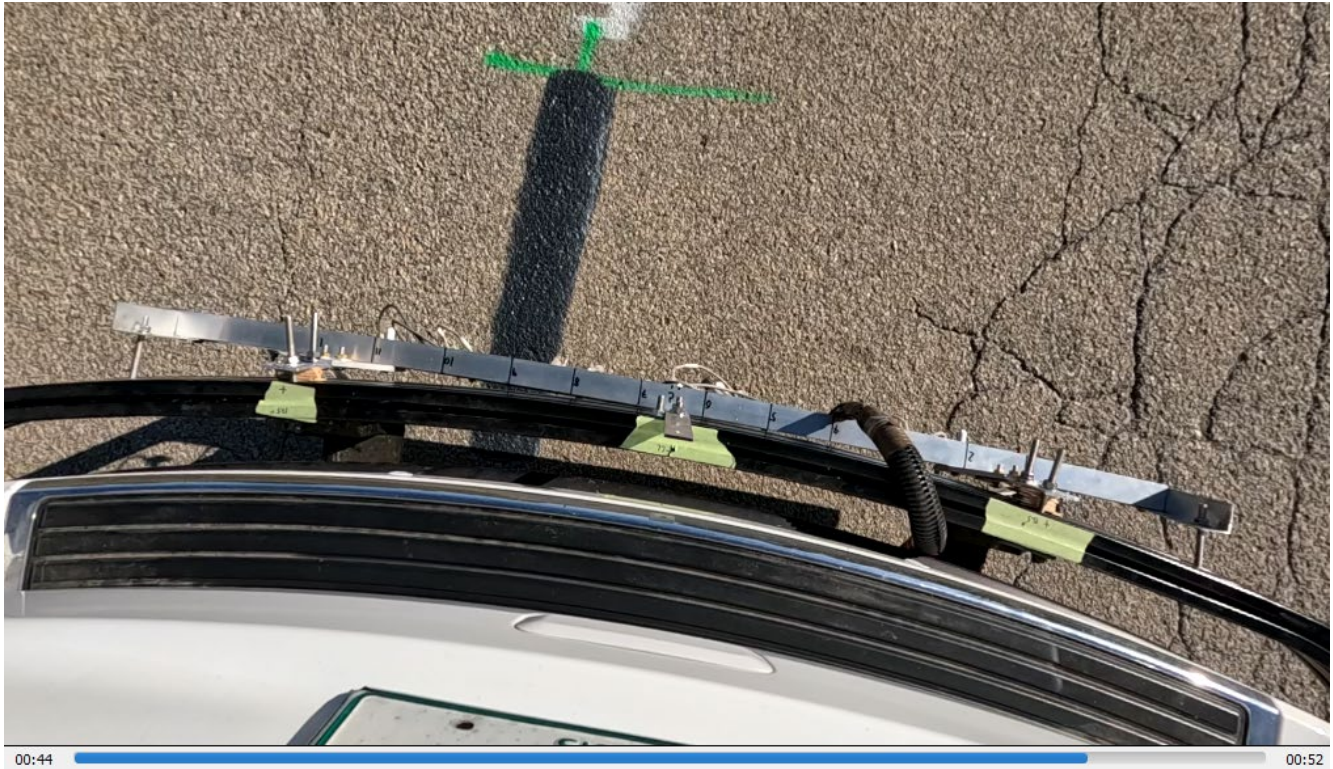


Figure 180. Photo. Referenced photo for longitudinal strip #36 (Case #17).

EM spectral analysis

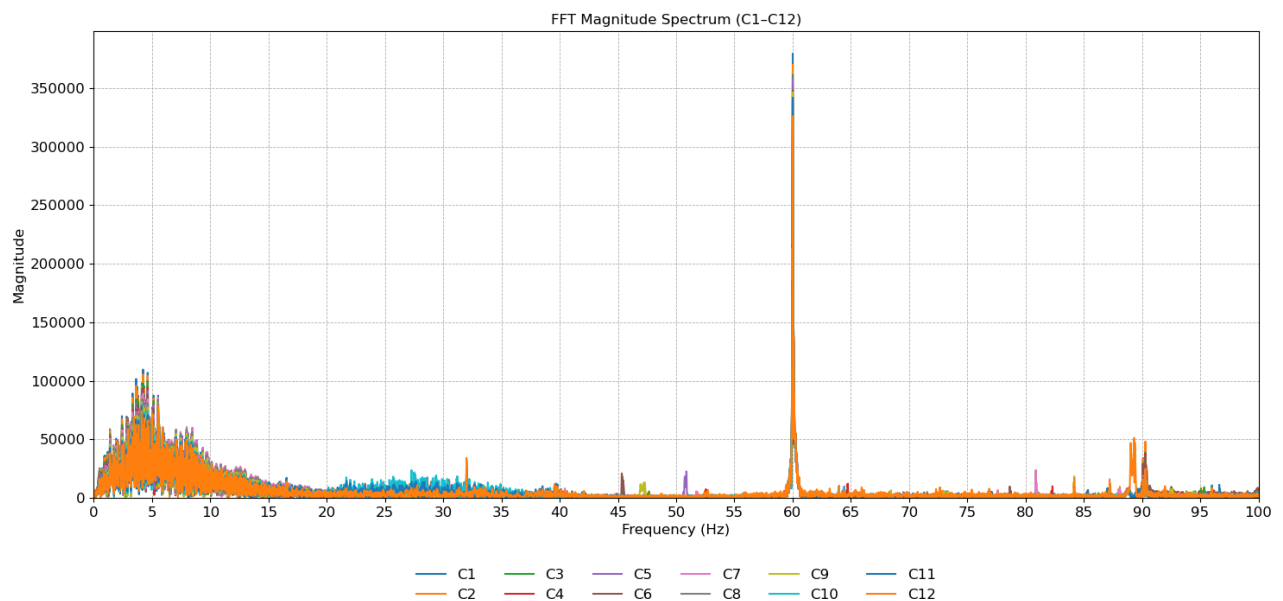


Figure 181. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #17).

Raw EM Flux

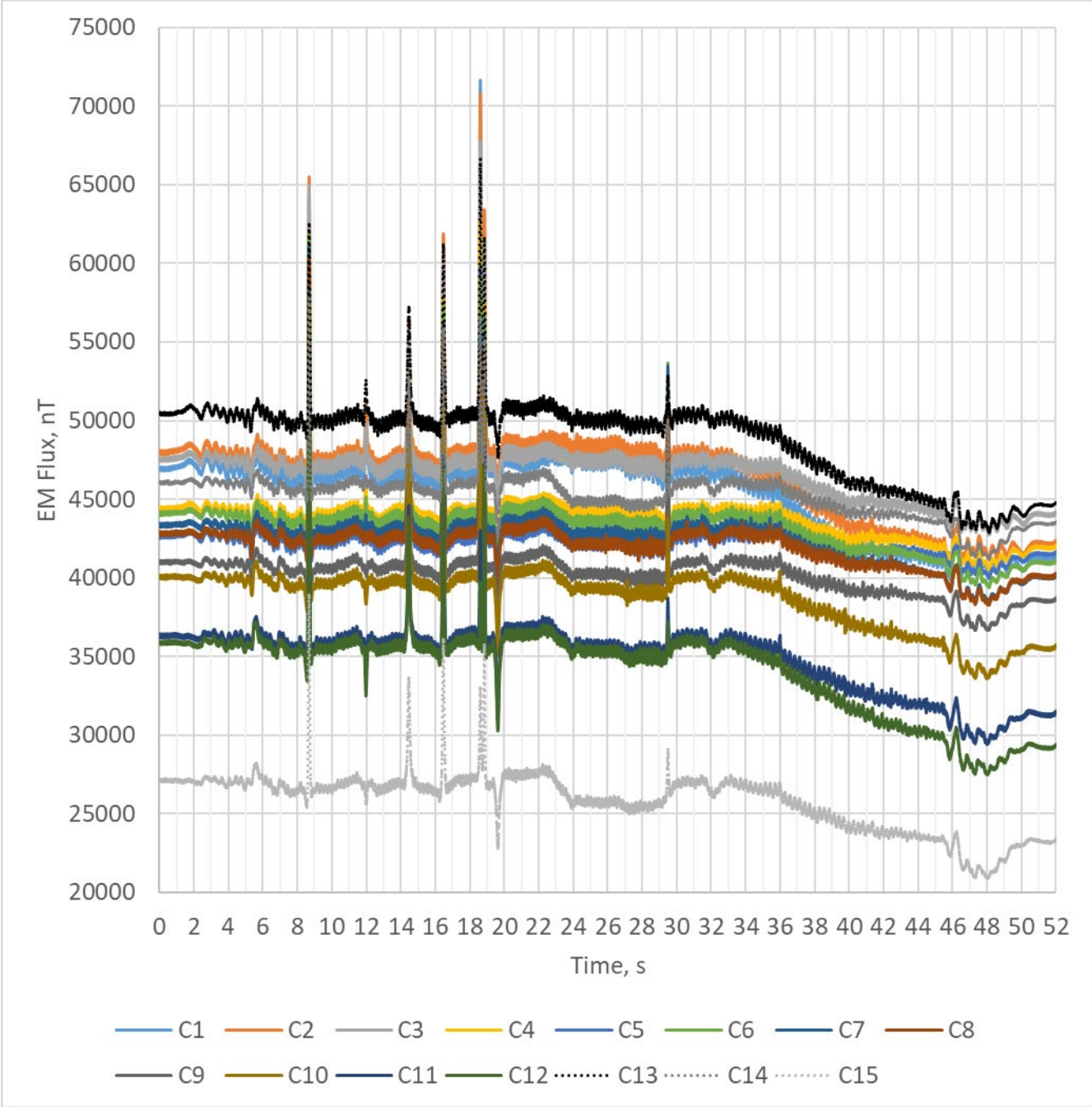


Figure 182. Chart. Signal characteristics of various EM sources (Case #17).

Processed EM Flux

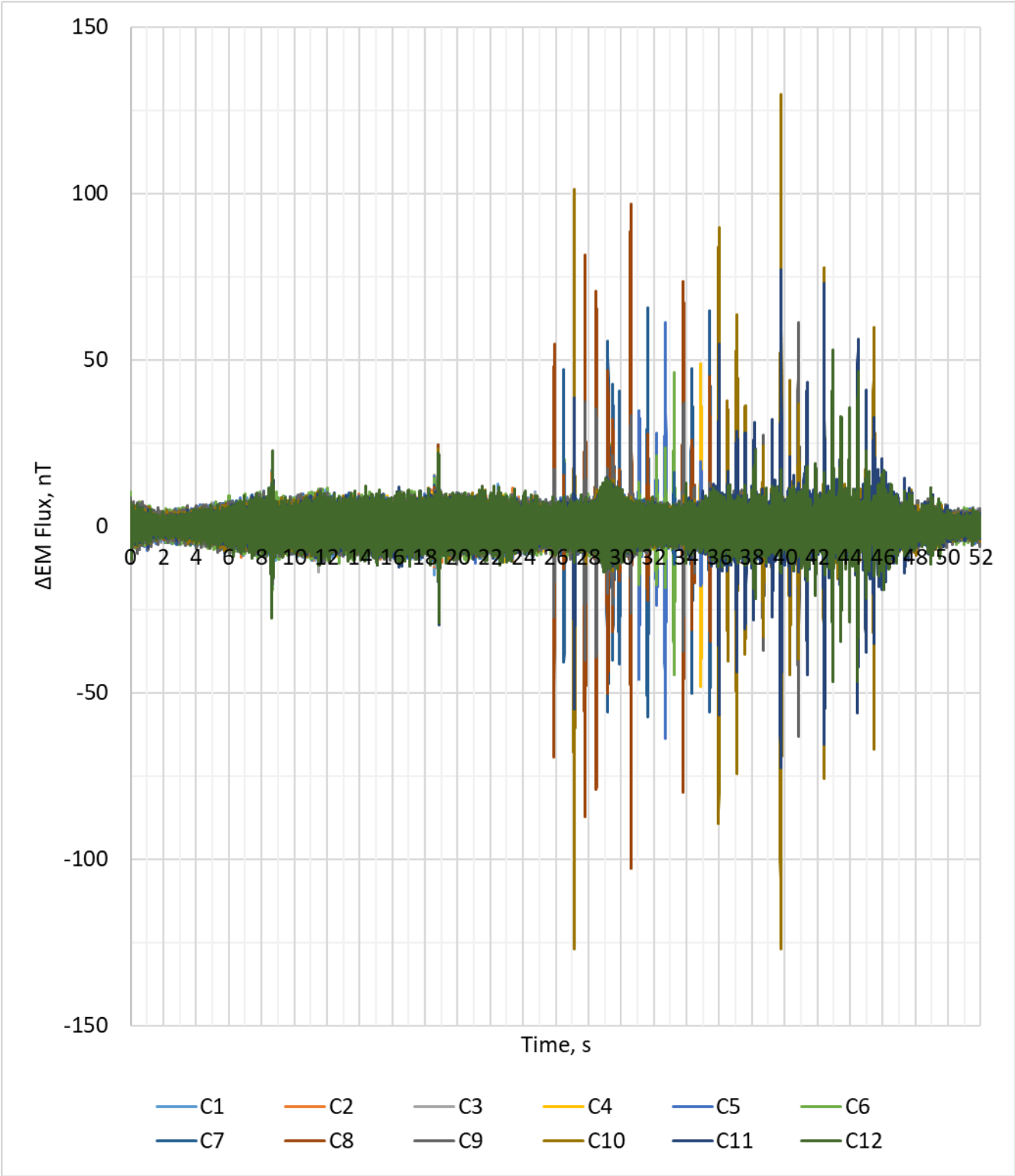


Figure 183. Chart. Signal characteristics of various EM sources (Case #17).

CASE #18

EM spectral analysis

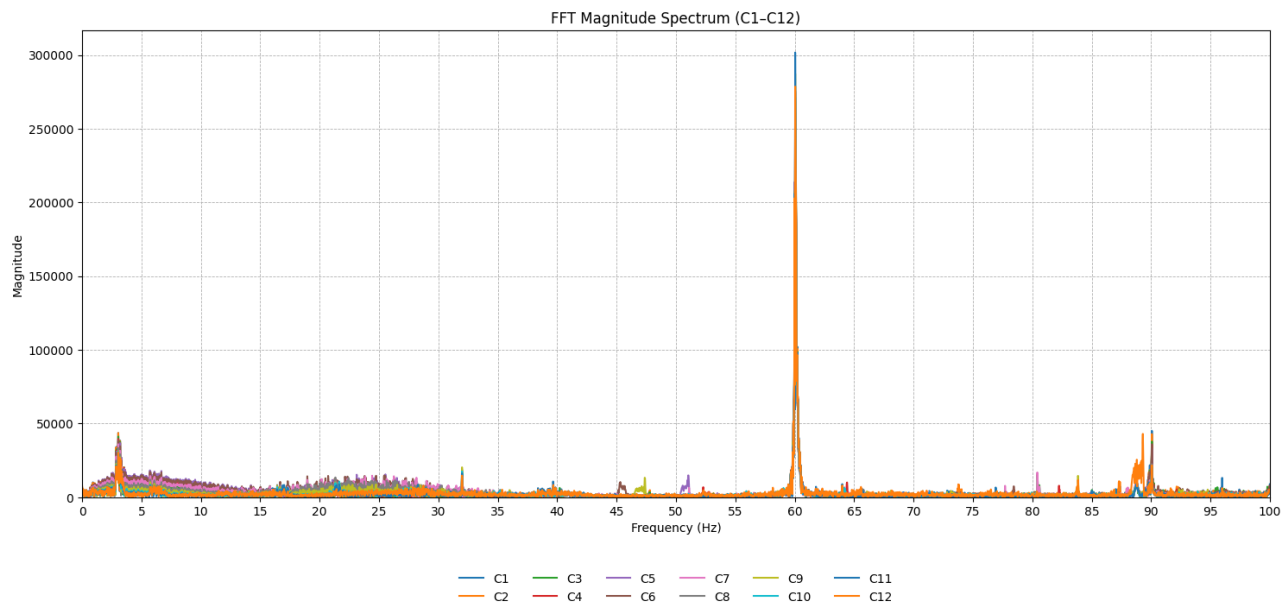


Figure 184. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #18).

Raw EM Flux

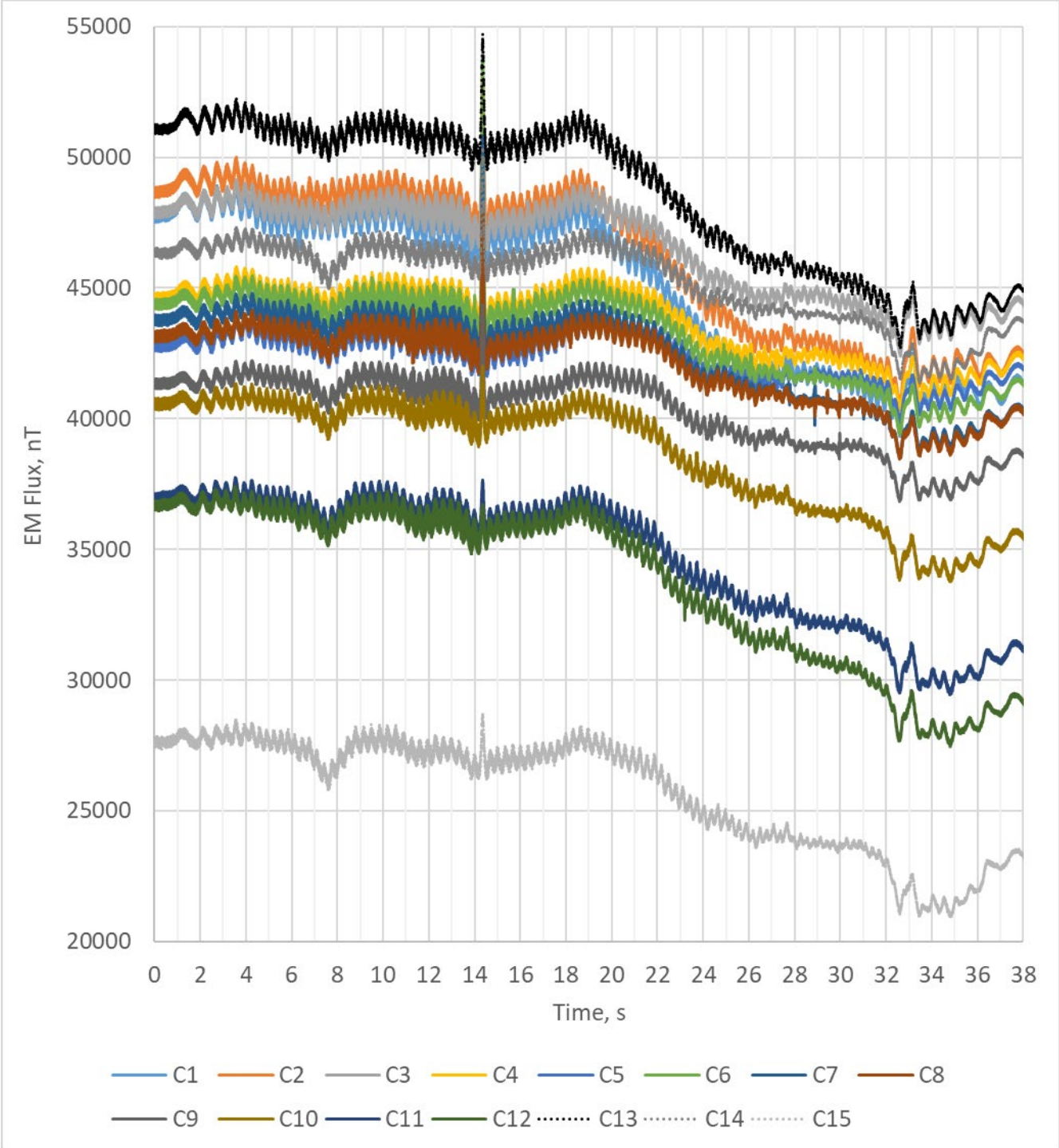


Figure 185. Chart. Signal characteristics of various EM sources (Case #18).

Processed EM Flux

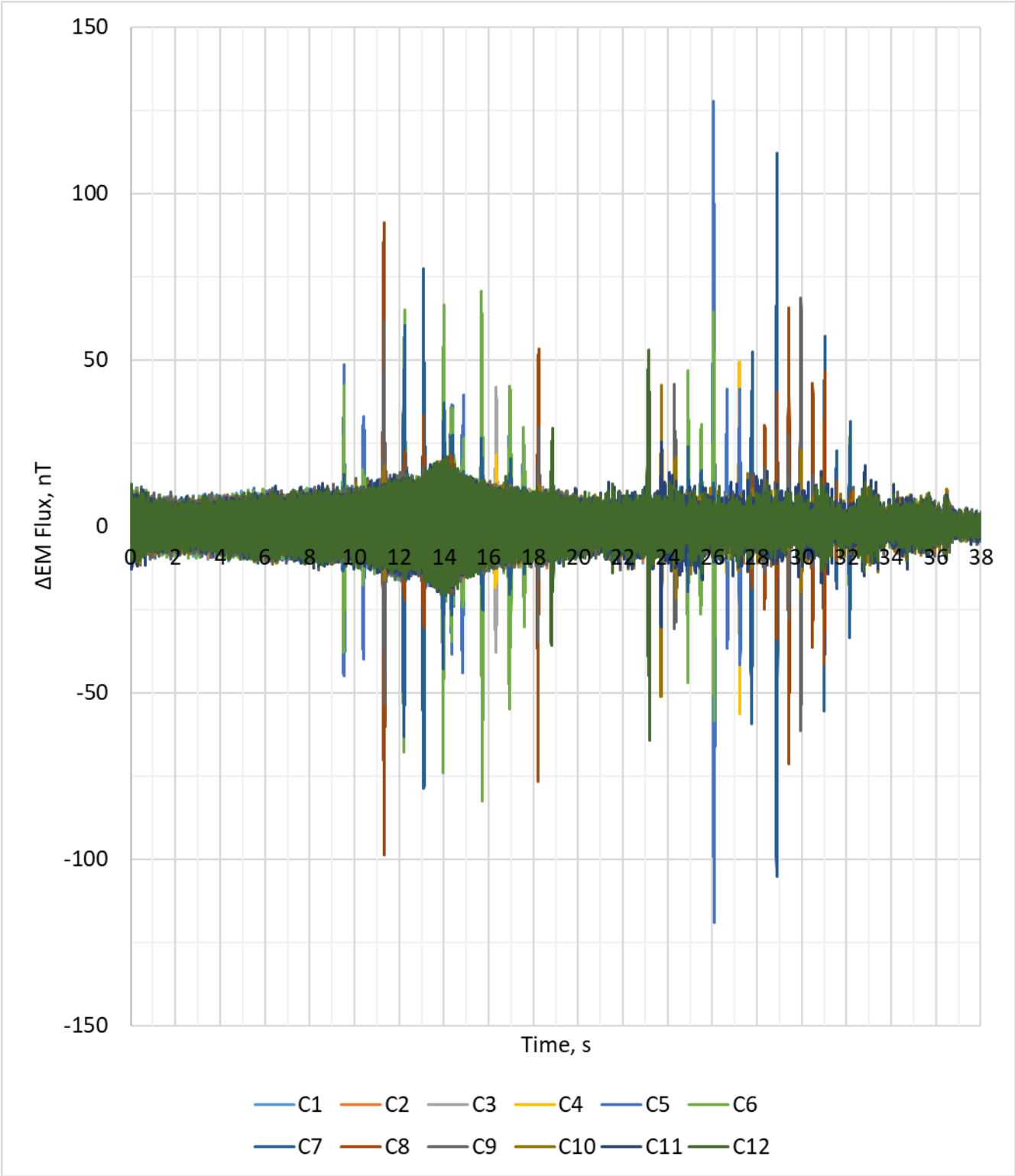


Figure 186. Chart. Signal characteristics of various EM sources (Case #18).

CASE #19

EM spectral analysis

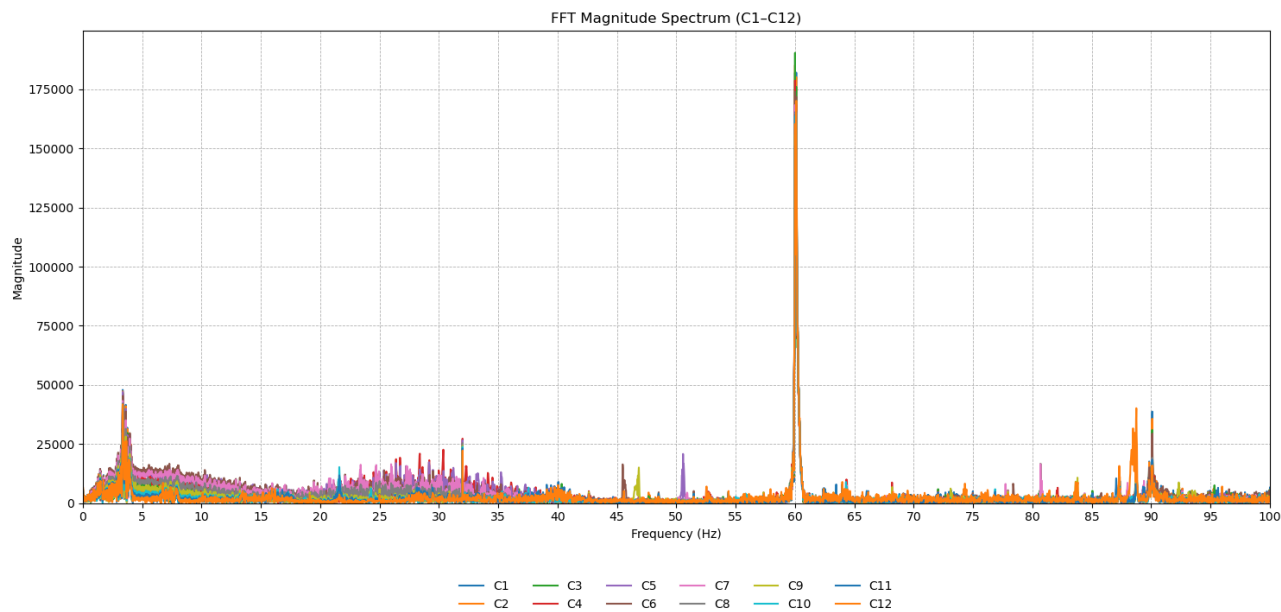


Figure 187. Photo. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #19).

Raw EM Flux

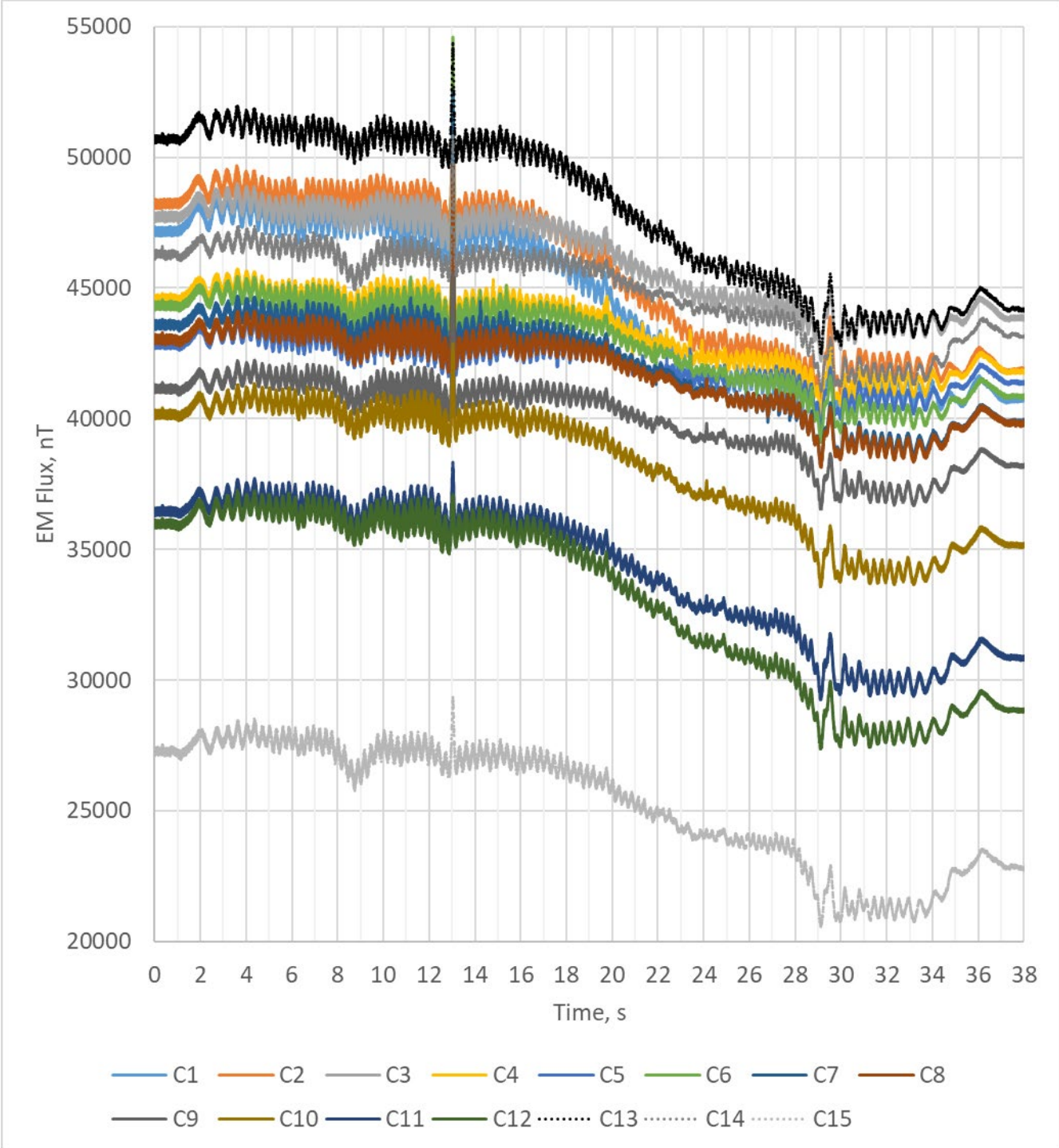


Figure 188. Chart. Signal characteristics of various EM sources (Case #19).

Processed EM Flux

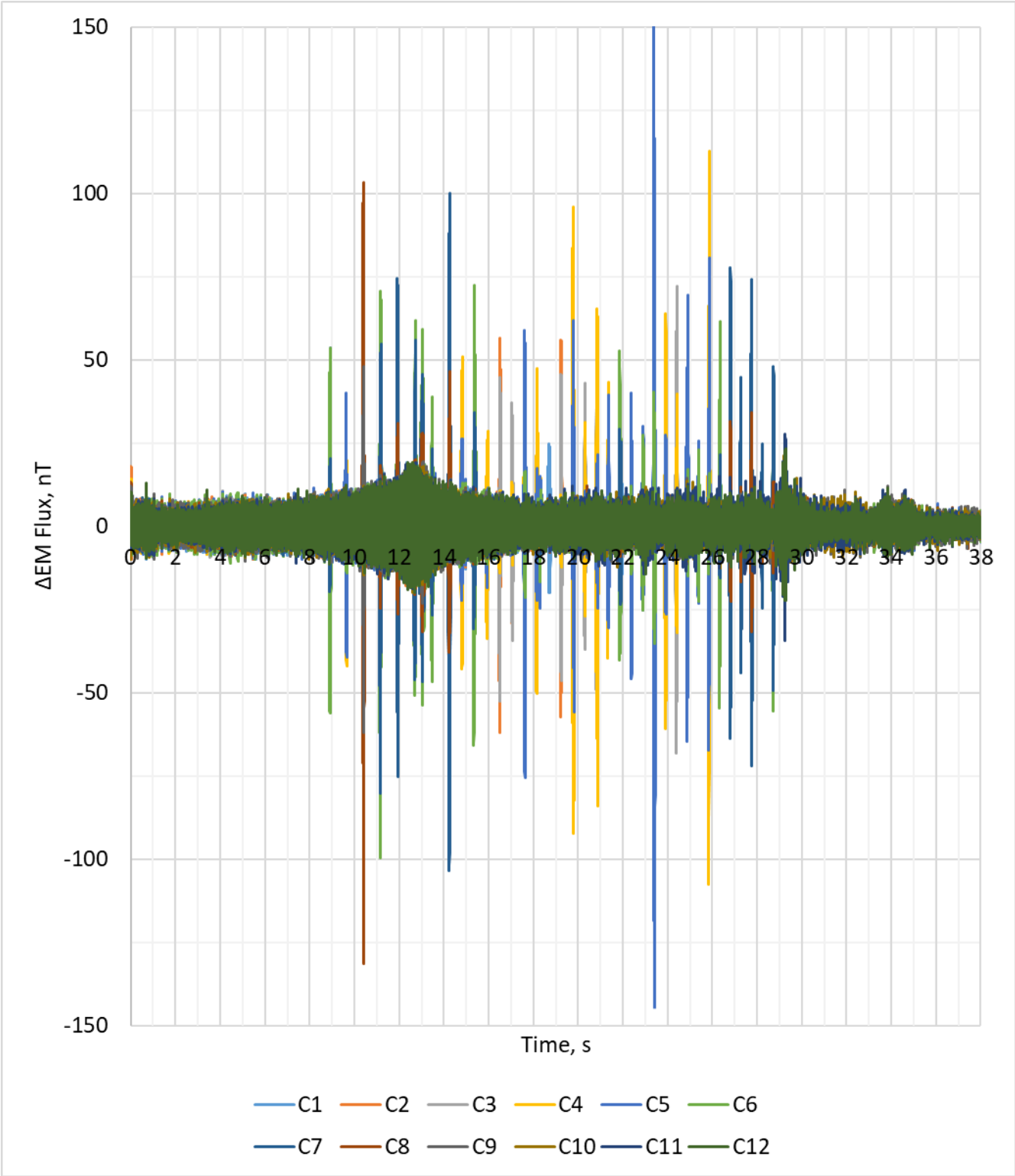


Figure 189. Chart. Signal characteristics of various EM sources (Case #19).

CASE #20

EM spectral analysis

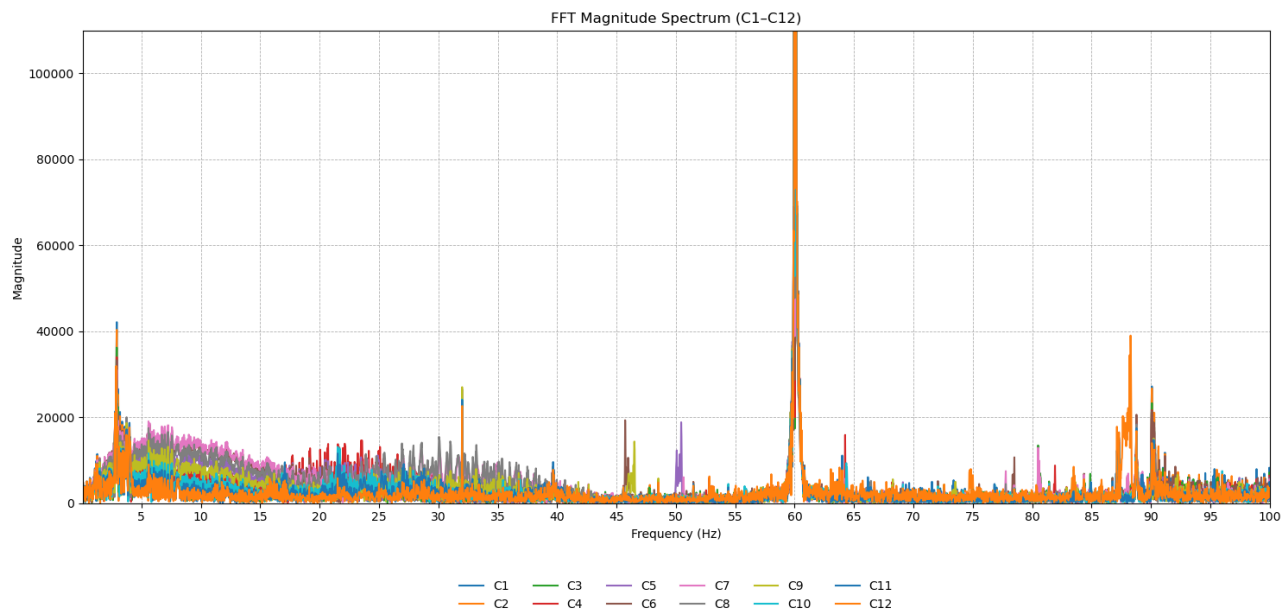


Figure 190. Photo. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #20).

Raw EM Flux

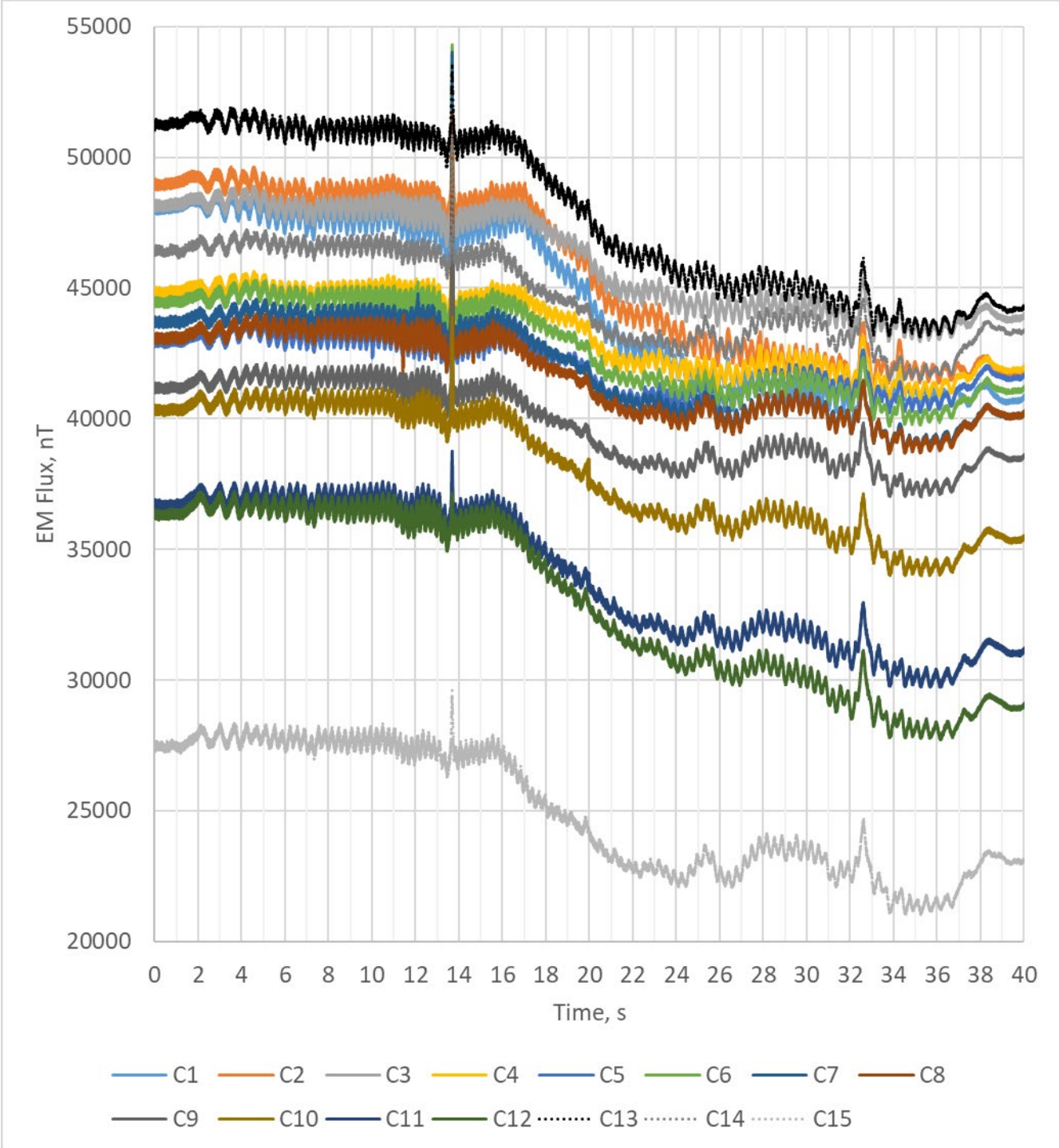


Figure 191. Chart. Signal characteristics of various EM sources (Case #20).

Processed EM Flux

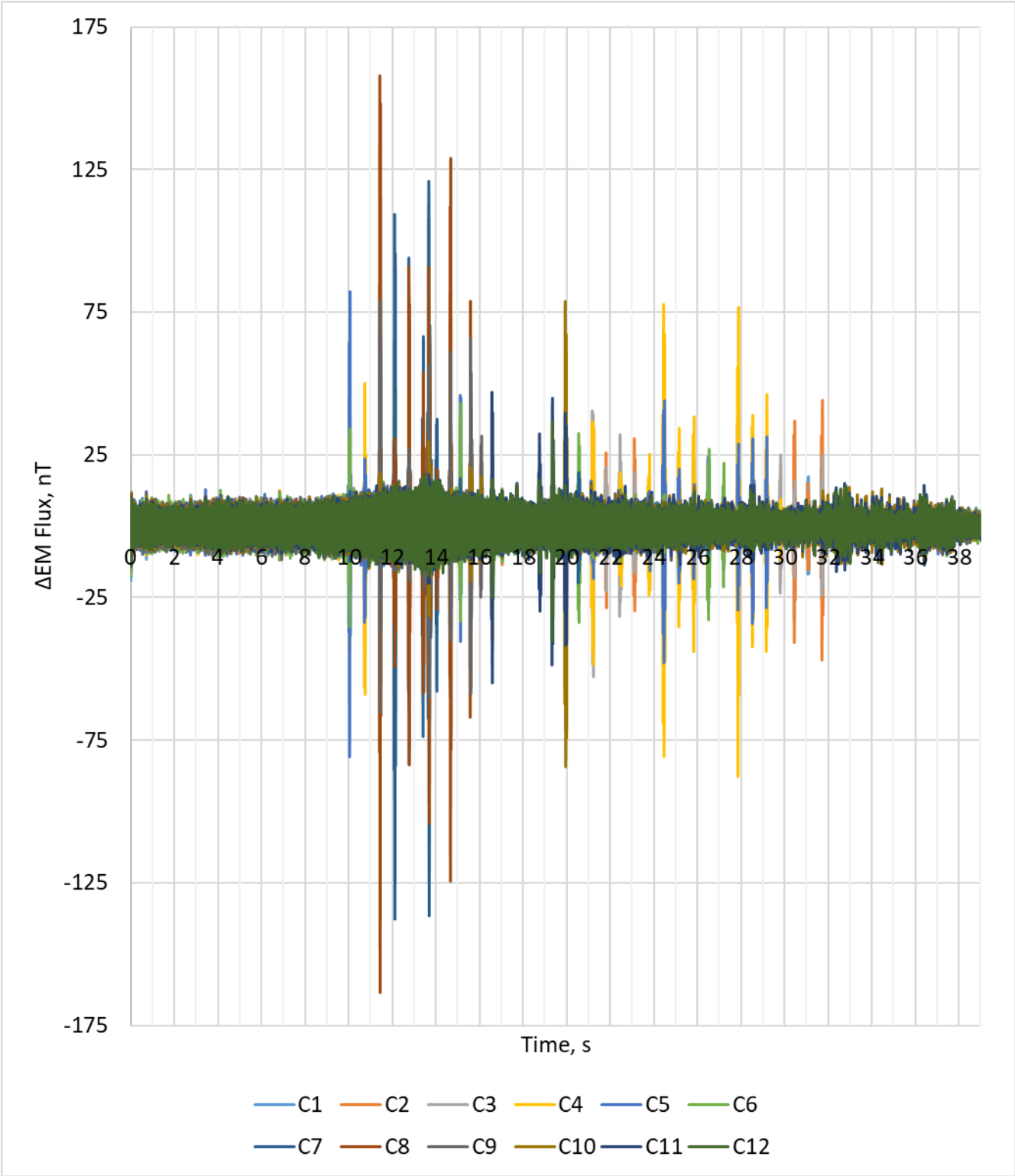


Figure 192. Chart. Signal characteristics of various EM sources (Case #20).

CASE #21

Referenced ground-truth data



Figure 193. Photo. Referenced photo for longitudinal strip #1 (Case #21).



Figure 194. Photo. Referenced photo for longitudinal strip #2 (Case #21).

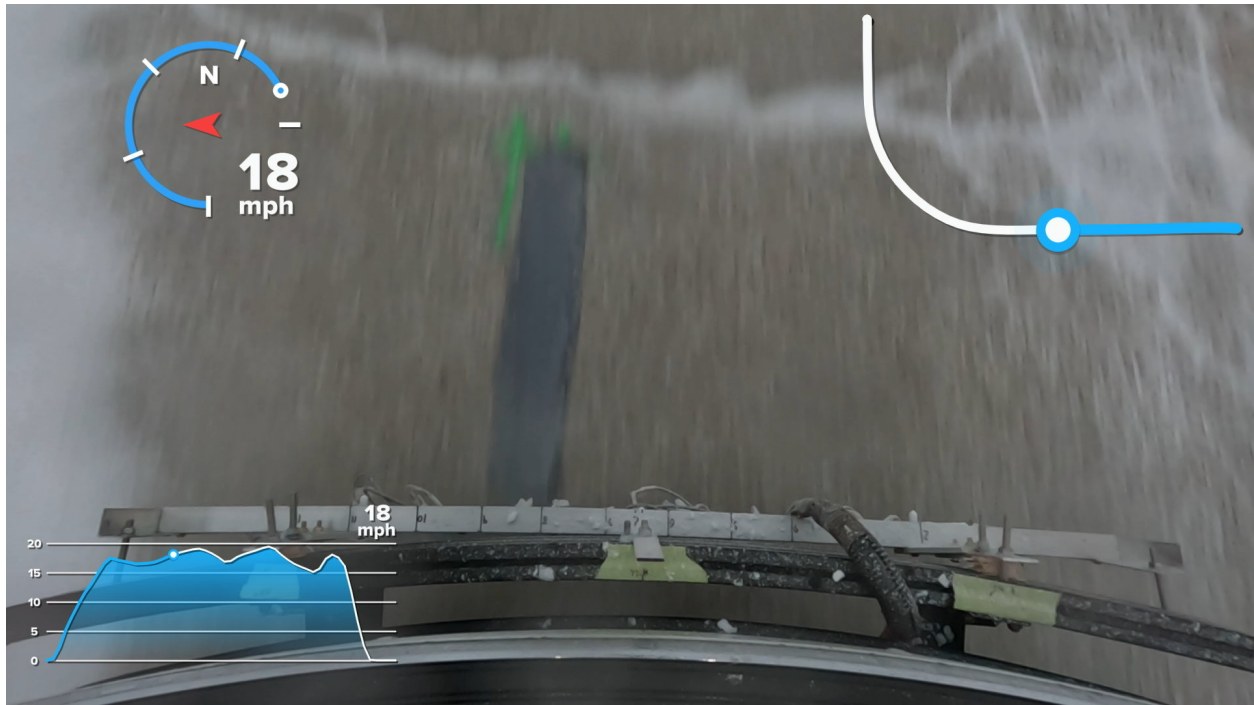


Figure 195. Photo. Referenced photo for longitudinal strip #3 (Case #21).



Figure 196. Photo. Referenced photo for longitudinal strip #4 (Case #21).



Figure 197. Photo. Referenced photo for longitudinal strip #5 (Case #21).



Figure 198. Photo. Referenced photo for longitudinal strip #6 (Case #21).

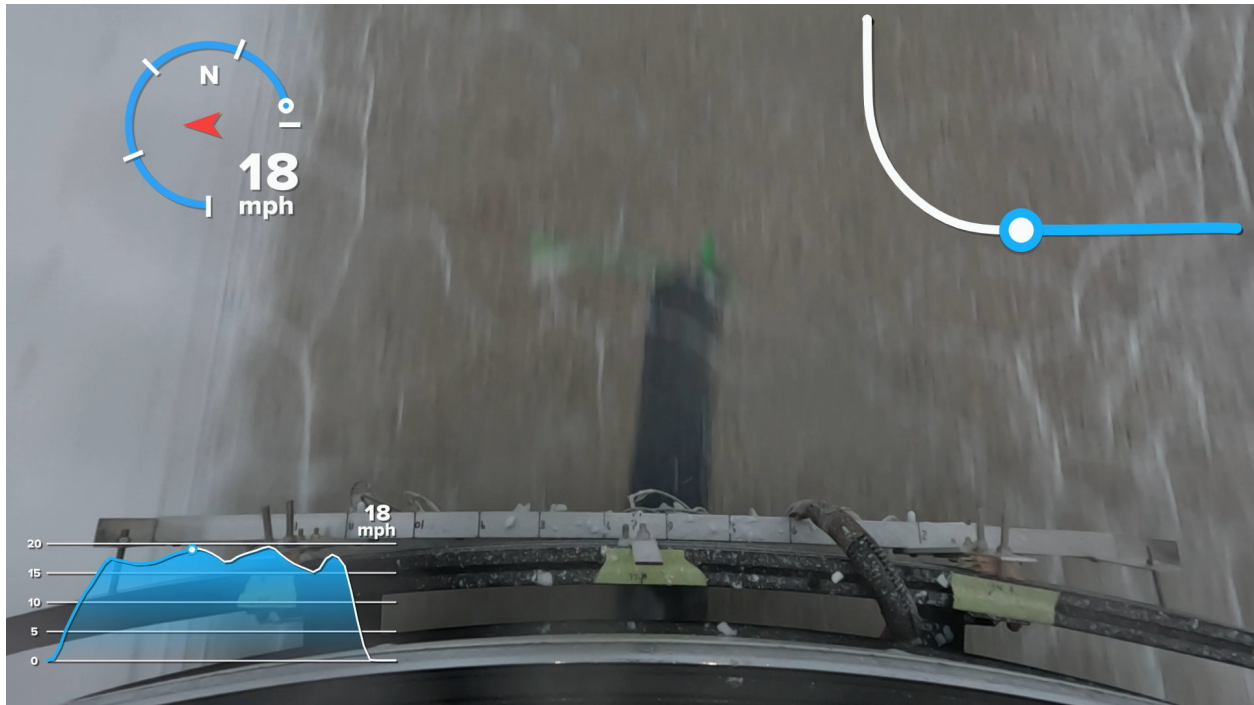


Figure 199. Photo. Referenced photo for longitudinal strip #7 (Case #21).



Figure 200. Photo. Referenced photo for longitudinal strip #8 (Case #21).



Figure 201. Photo. Referenced photo for longitudinal strip #9 (Case #21).



Figure 202. Photo. Referenced photo for longitudinal strip #10 (Case #21).

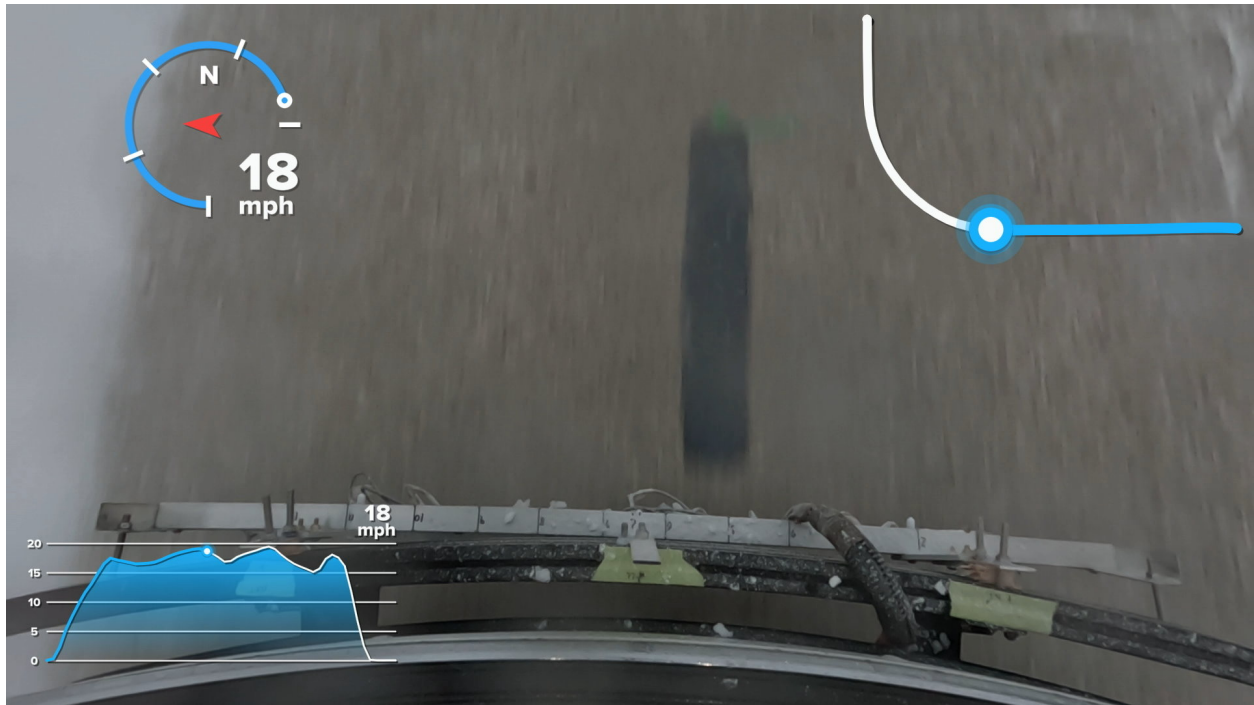


Figure 203. Photo. Referenced photo for longitudinal strip #11 (Case #21).

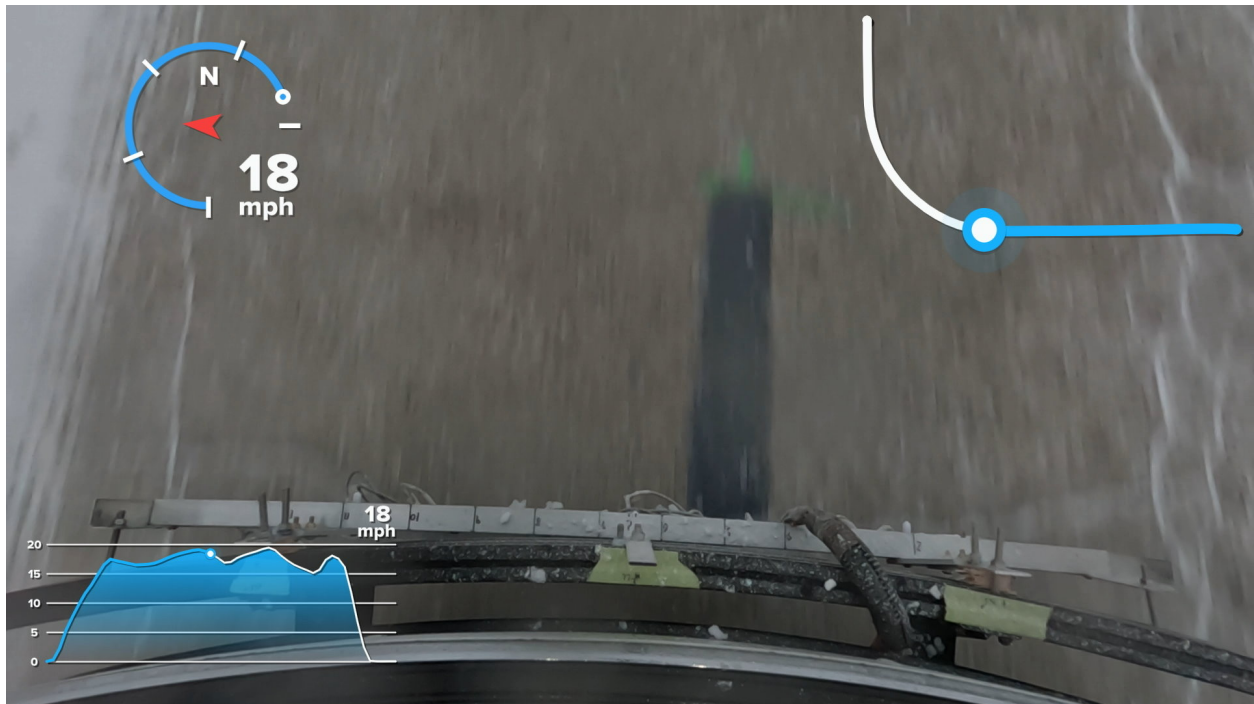


Figure 204. Photo. Referenced photo for longitudinal strip #12 (Case #21).



Figure 205. Photo. Referenced photo for longitudinal strip #13 (Case #21).



Figure 206. Photo. Referenced photo for longitudinal strip #14 (Case #21).



Figure 207. Photo. Referenced photo for longitudinal strip #15 (Case #21).

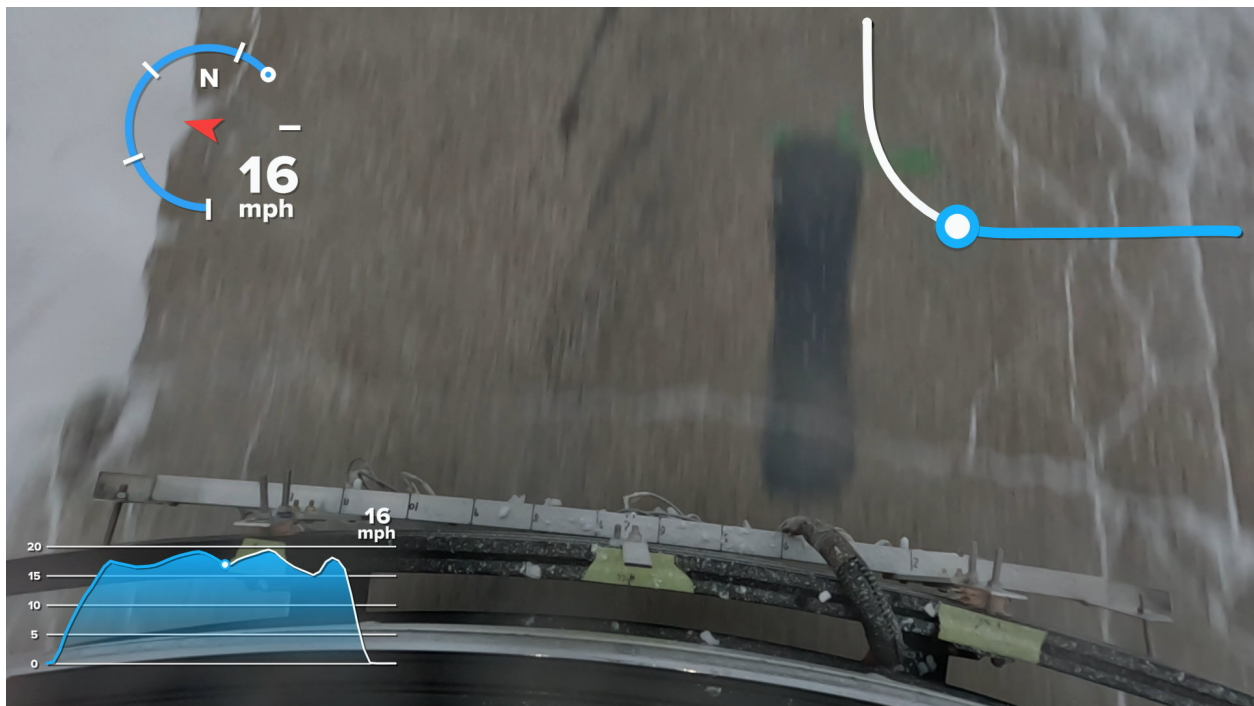


Figure 208. Photo. Referenced photo for longitudinal strip #16 (Case #21).



Figure 209. Photo. Referenced photo for longitudinal strip #17 (Case #21).



Figure 210. Photo. Referenced photo for longitudinal strip #18 (Case #21).



Figure 211. Photo. Referenced photo for longitudinal strip #19 (Case #21).



Figure 212. Photo. Referenced photo for longitudinal strip #20 (Case #21).

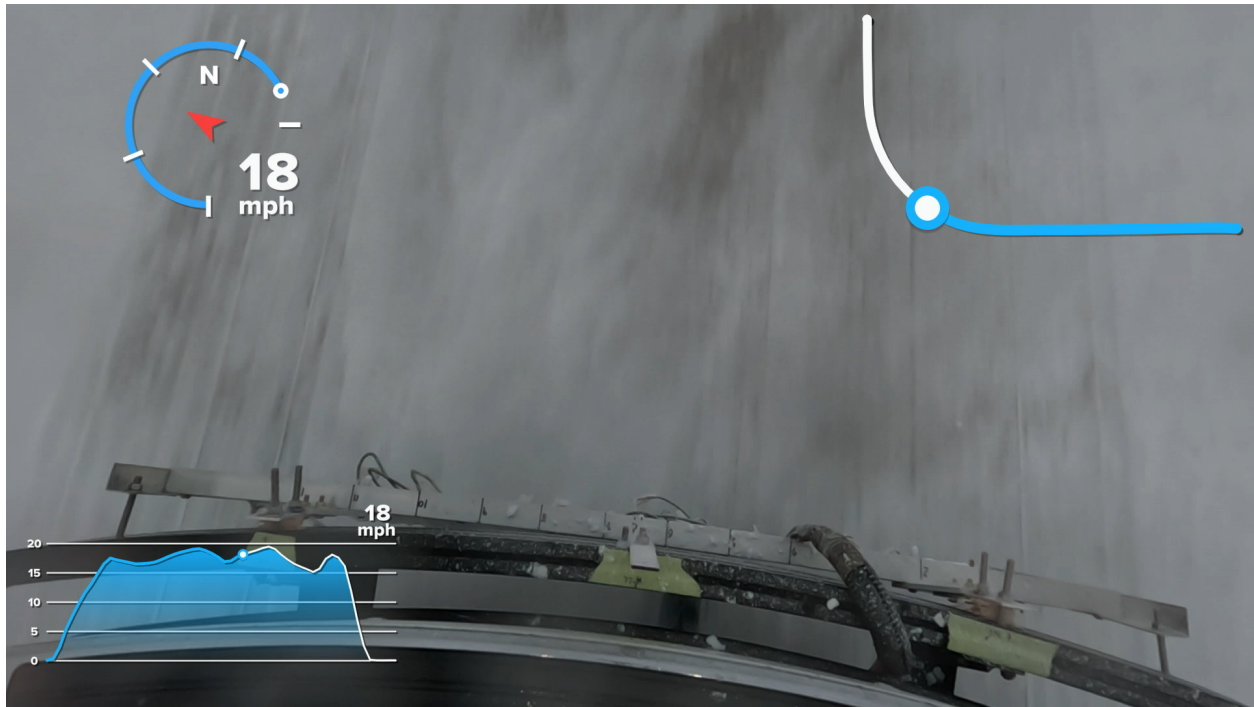


Figure 213. Photo. Referenced photo for longitudinal strip #21 (Case #21).

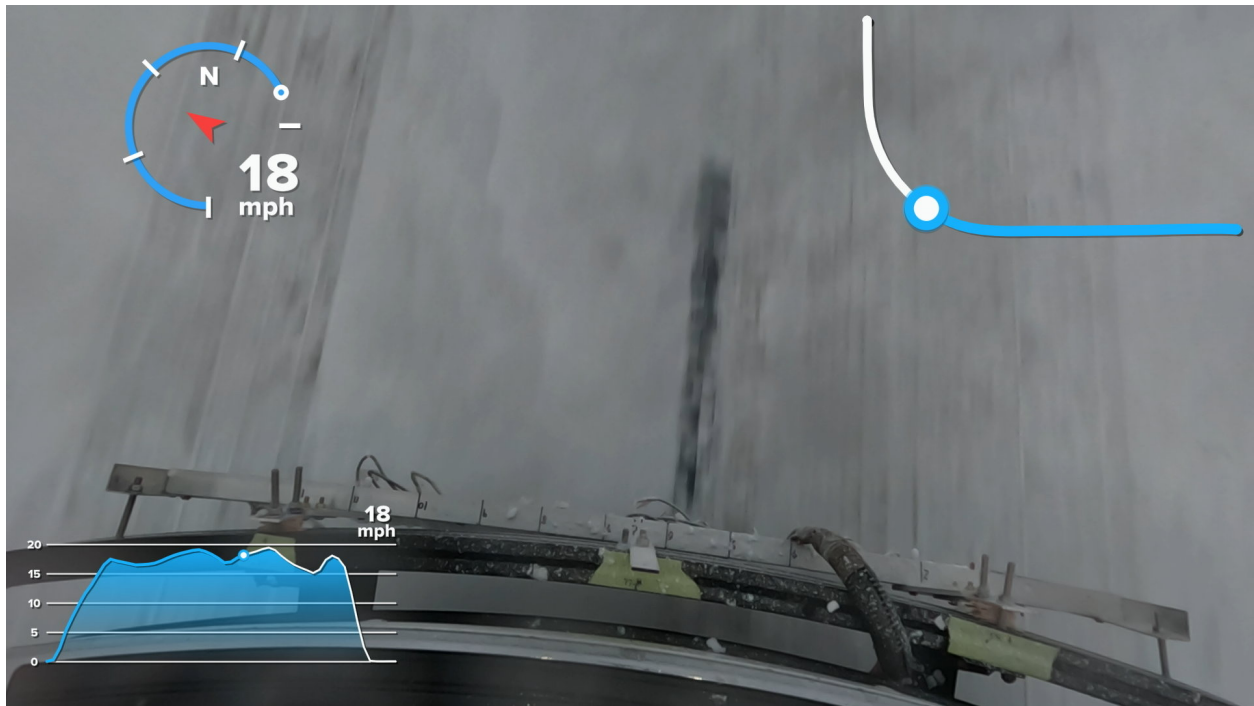


Figure 214. Photo. Referenced photo for longitudinal strip #22 (Case #21).

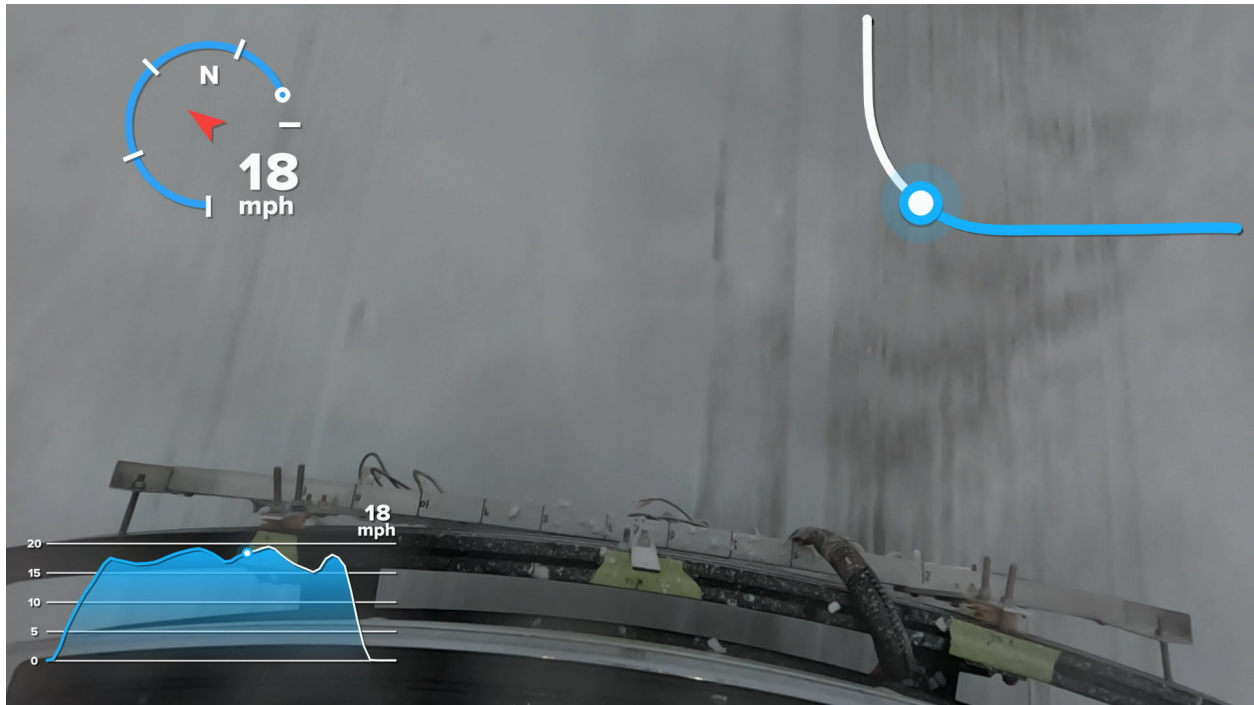


Figure 215. Photo. Referenced photo for longitudinal strip #23 (Case #21).

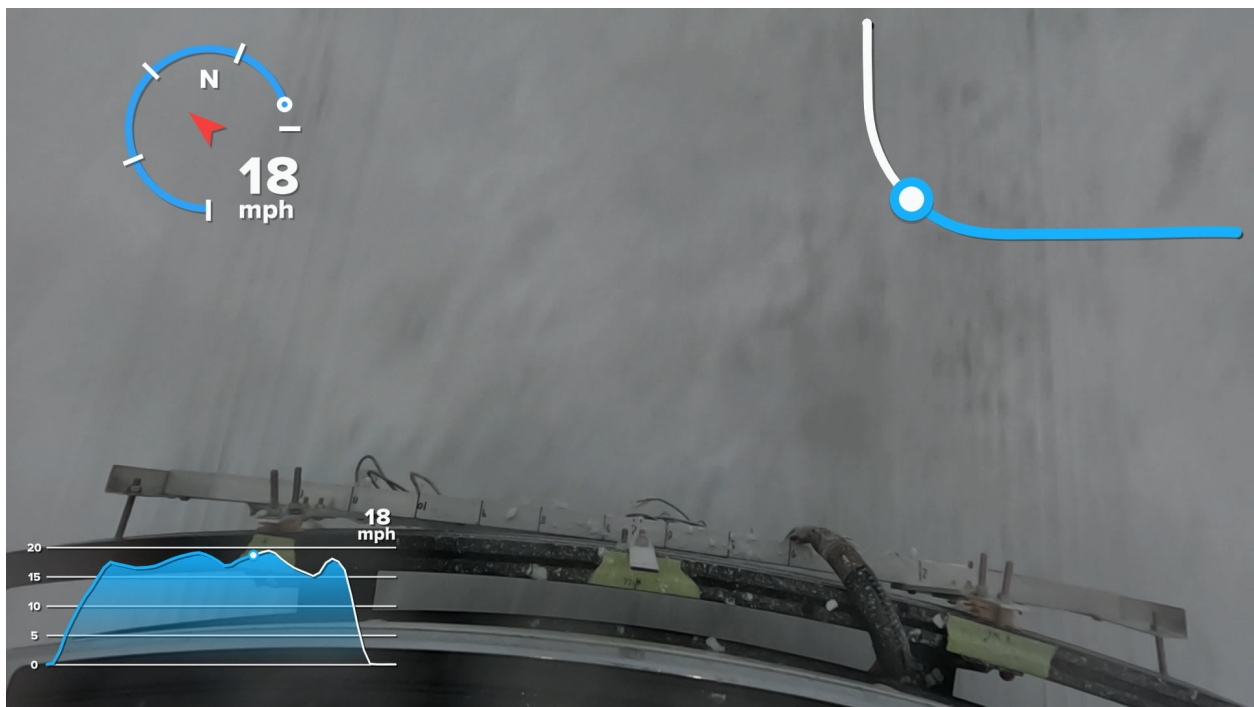


Figure 216. Photo. Referenced photo for longitudinal strip #24 (Case #21).

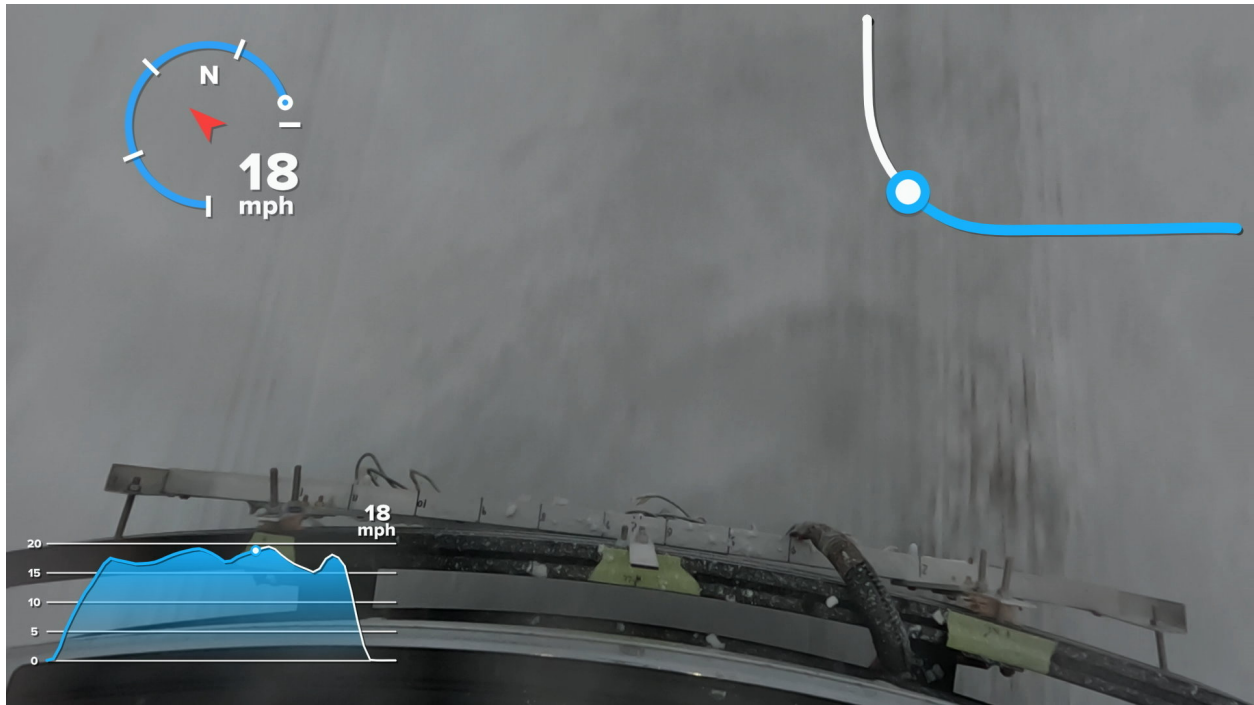


Figure 217. Photo. Referenced photo for longitudinal strip #25 (Case #21).



Figure 218. Photo. Referenced photo for longitudinal strip #26 (Case #21).

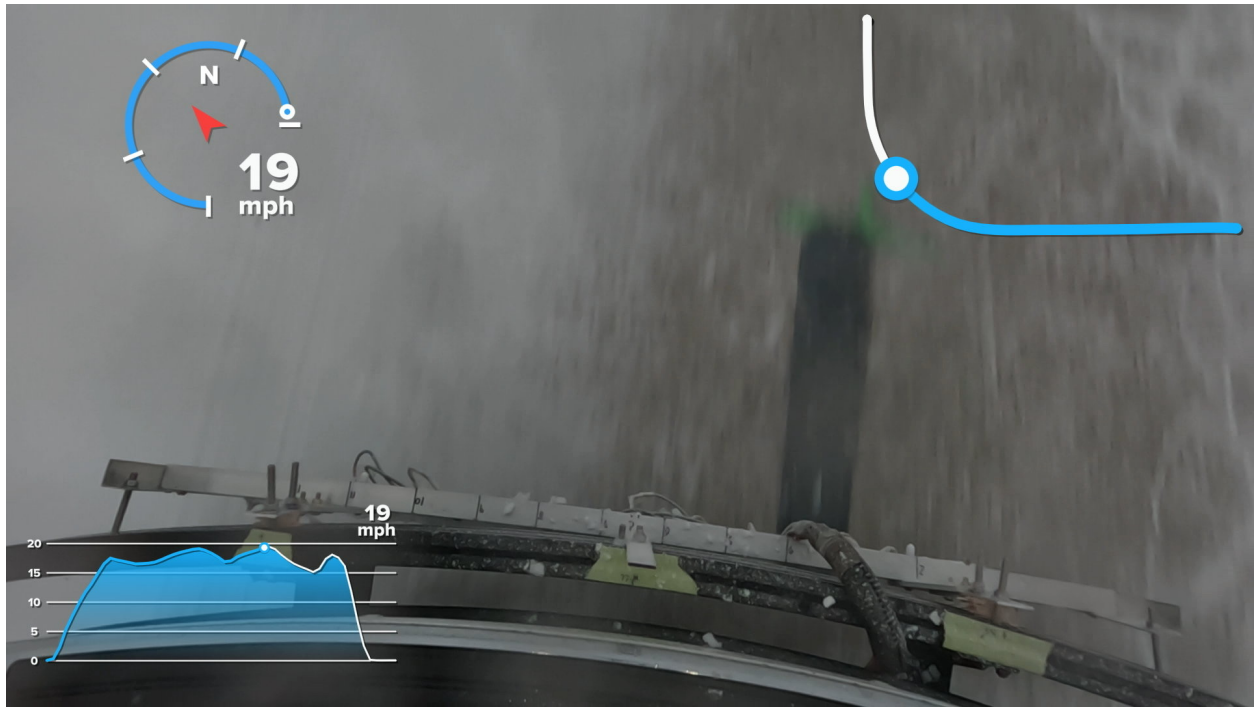


Figure 219. Photo. Referenced photo for longitudinal strip #27 (Case #21).

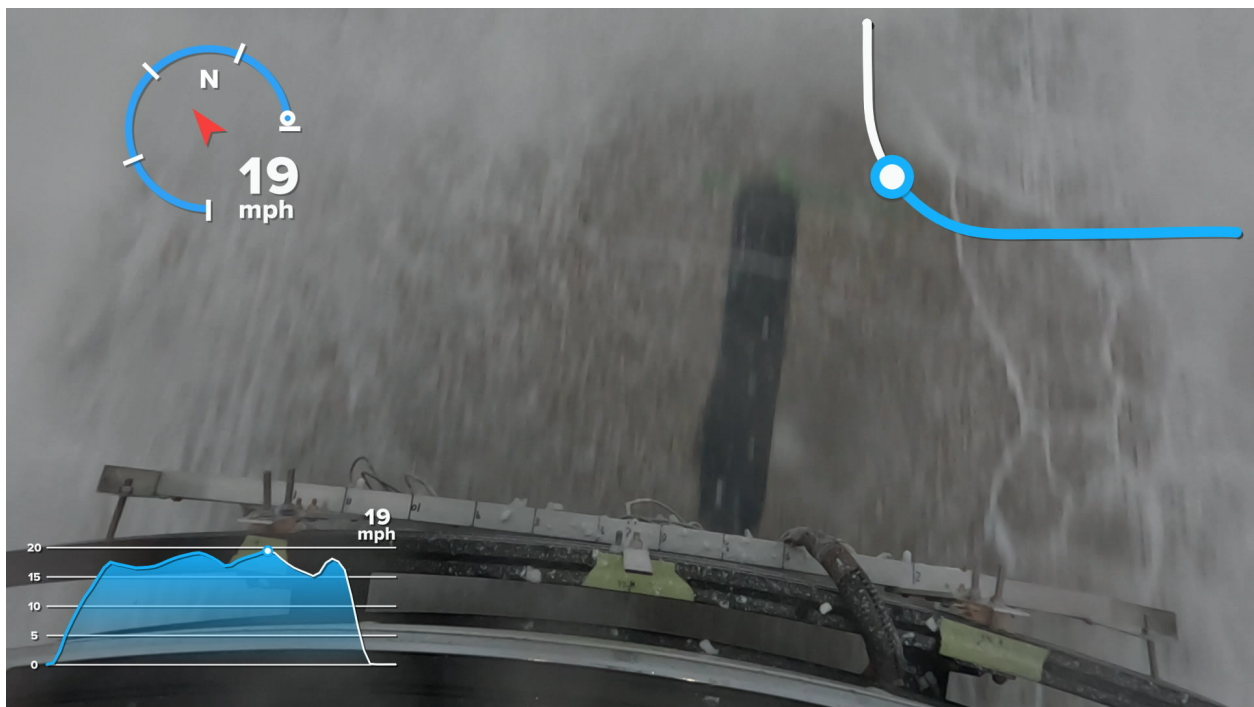


Figure 220. Photo. Referenced photo for longitudinal strip #28 (Case #21).



Figure 221. Photo. Referenced photo for longitudinal strip #29 (Case #21).

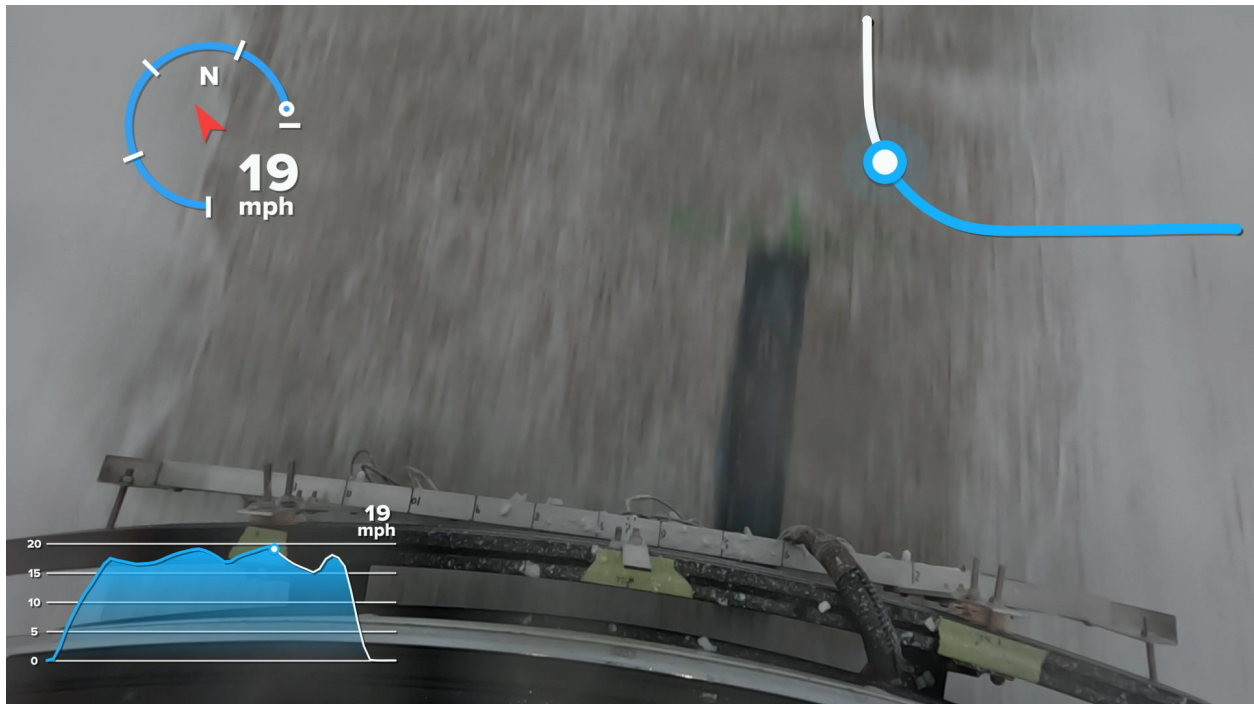


Figure 222. Photo. Referenced photo for longitudinal strip #30 (Case #21).



Figure 223. Photo. Referenced photo for longitudinal strip #31 (Case #21).

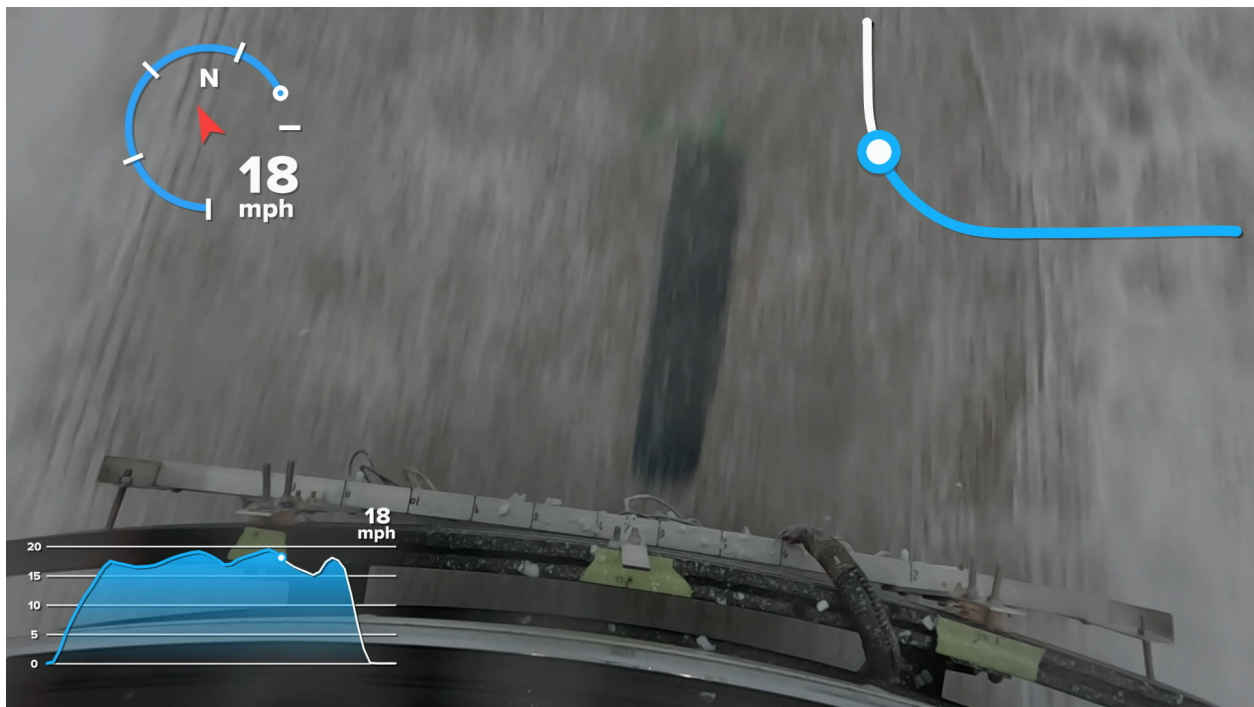


Figure 224. Photo. Referenced photo for longitudinal strip #32 (Case #21).



Figure 225. Photo. Referenced photo for longitudinal strip #33 (Case #21).

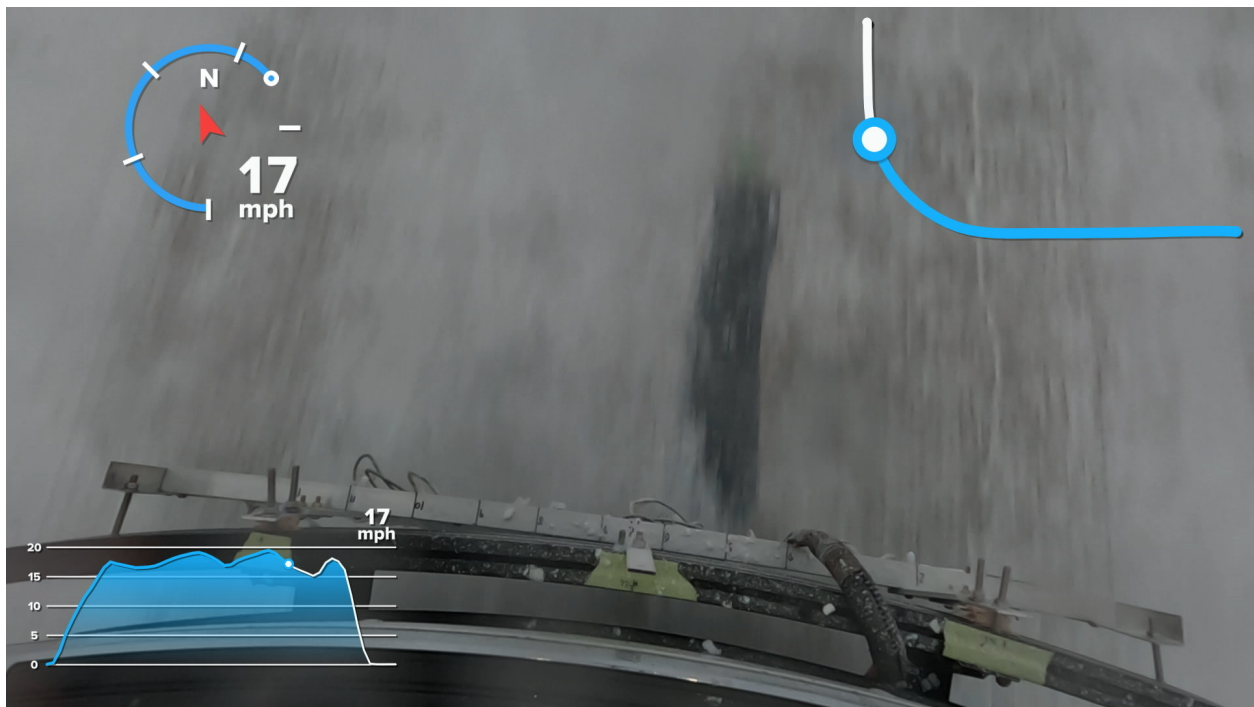


Figure 226. Photo. Referenced photo for longitudinal strip #34 (Case #21).



Figure 227. Photo. Referenced photo for longitudinal strip #35 (Case #21).

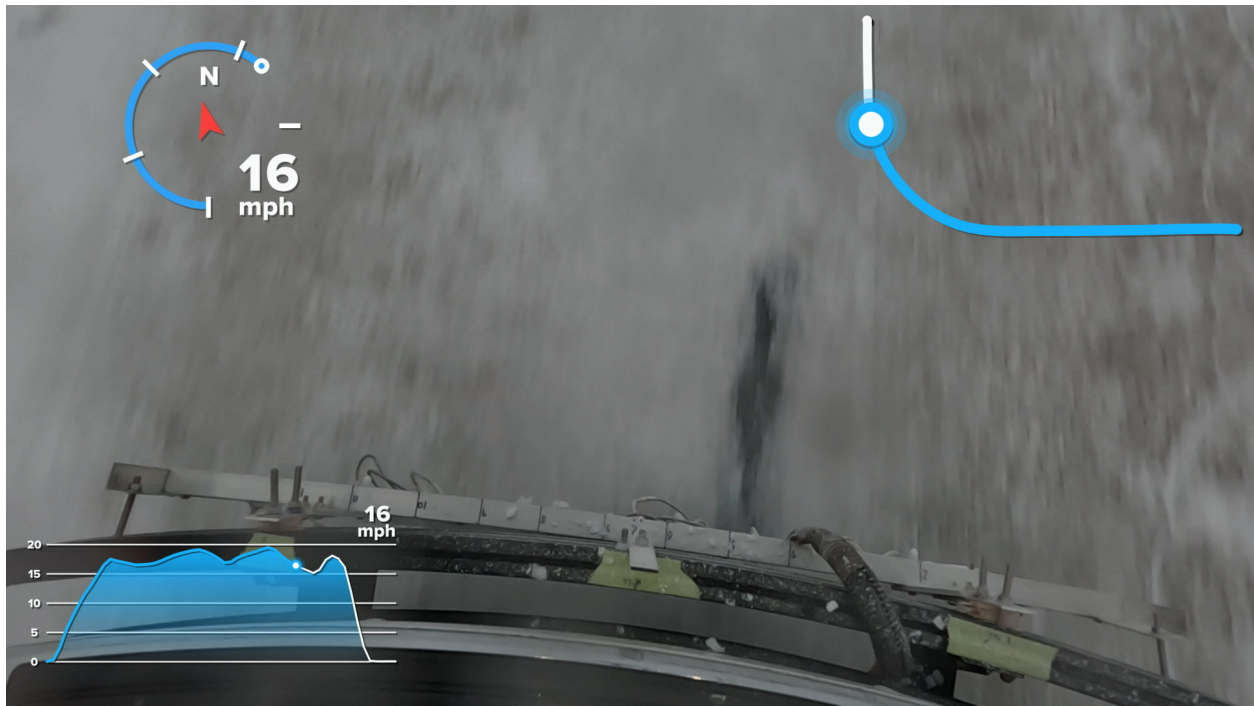


Figure 228. Photo. Referenced photo for longitudinal strip #36 (Case #21).

EM spectral analysis

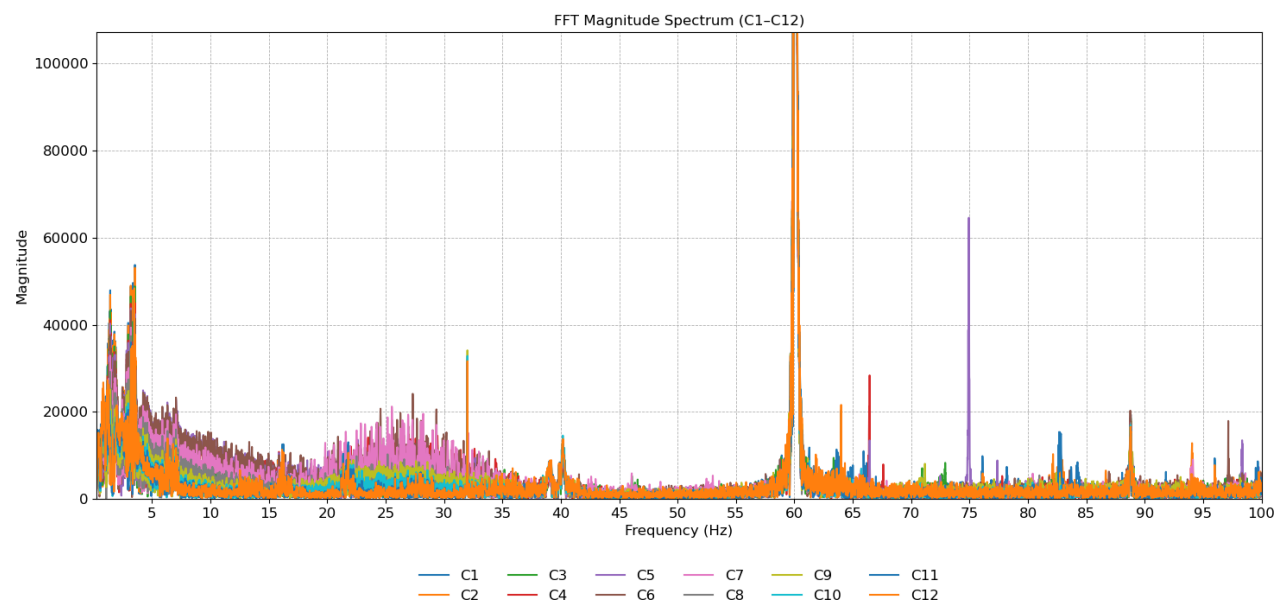


Figure 229. Chart. FFT frequency band spectra of Δ EM flux of all sensor data channels (Case #21).

Raw EM Flux

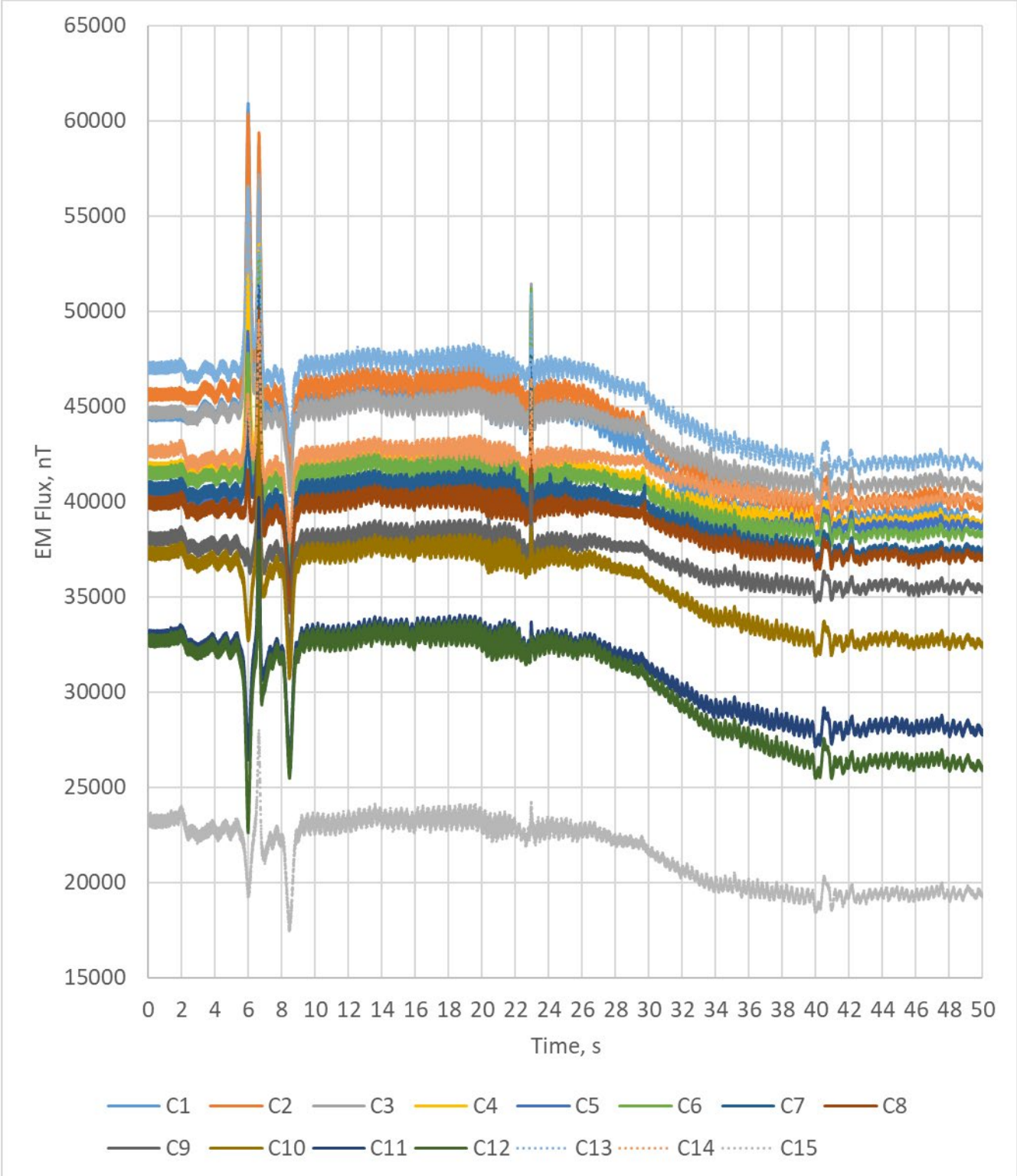


Figure 230. Chart. Signal characteristics of various EM sources (Case #21)

Processed EM Flux

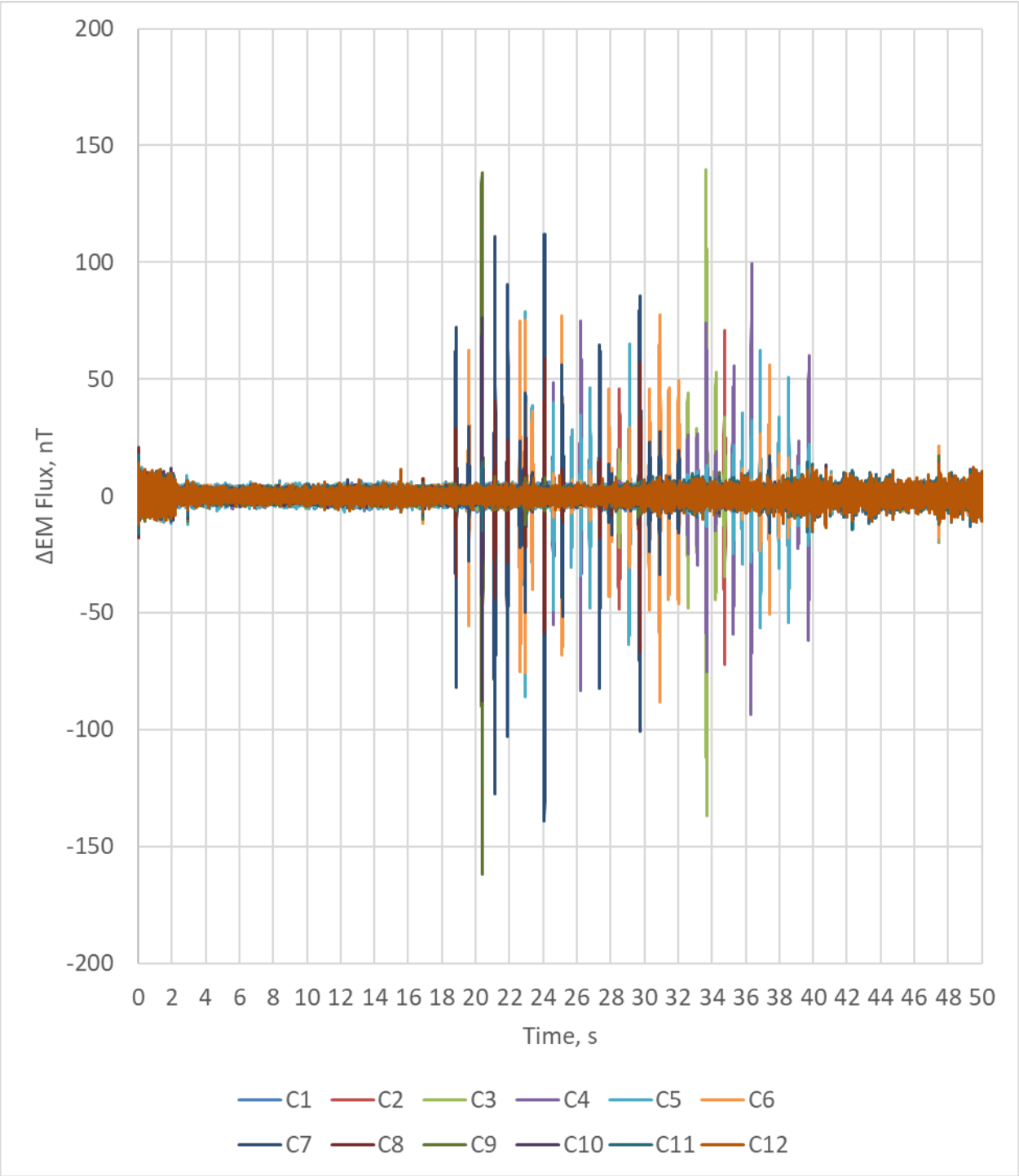


Figure 231. Chart. Signal characteristics of various EM sources (Case #21)