Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 24, 2025
*A Regional Conference of the Society for Industrial and Systems Engineering*

# Autonomous Ground Vehicle Simulation: An Agile Research Study

**Matthew Rhodes, Benjamin Gaucher, Tommy Zitiello, and Brandon Thompson**

Department of Systems Engineering, United States Military Academy, West Point, New York 10996

Corresponding Author's Email: Bgaucher87@gmail.com

**Author Note:** The authors would like to extend our thanks to the Engineer Research and Development Center (ERDC) Information Technology Laboratory (ITL) and Institute for Systems Engineering Research (ISER) for providing the opportunity to participate in Autonomous Ground Vehicle (AGV) simulation development and research. The views expressed herein are those of the authors and do not reflect the position of the United States Military Academy, the Department of the Army, or the Department of Defense.

**Abstract:** Autonomous Ground Vehicles (AGVs) can be significant force multipliers on the battlefield, reducing risk to soldiers and increasing logistical capability. These AGVs must be thoroughly tested under various conditions before being incorporated into missions. This requires not only physical testing but virtual testing through simulation to reduce cost and increase the scope of testing environments and conditions. This study involved virtually testing AGVs using a Software-in-the-Loop (SIL) simulation developed by the Engineer Research and Development Center (ERDC). The researchers conducted an agile research methodology to iteratively identify problems and develop solutions to establish the SIL and simulate AGV performance. Each agile iteration included data collection and analysis to compare vehicle performance under three weather conditions while using three path planning algorithms. The results of this study helped the Army refine their own AGV simulation, integrate a new autonomy stack, and evaluate three path planning algorithms for implementation in military AGVs.

*Keywords:* Autonomous Ground Vehicle Simulation, Path Planning Algorithm, Agile Methodology

## 1. Background

The United States Army is developing Autonomous Ground Vehicles (AGVs) to operate alongside humans to provide new ways of fighting and offer new capabilities on the battlefield (Heckmann, Magnuson, & Park, 2023). Developing, testing, and integrating AGVs within the Army is a time-consuming and costly endeavor. The Engineer Research and Development Center (ERDC) is tasked with developing an AGV simulation that measures and tests vehicle performance in a virtual environment under various weather conditions and multiple terrain models in an effort to reduce testing costs, provide more timely results, and enable a broader range of testing scenarios. The Army is currently assessing multiple path planning algorithms to evaluate autonomous decision making to identify the optimal solution for military AGVs. By using simulation, users can perform numerous tests while controlling the environment, route, terrain, and other independent variables to systematically assess their effects on AGV performance. Leading this endeavor, ERDC developed a high-performance computing simulation titled, Virtual Autonomous Navigation Environment (VANE) Software-in-the-Loop (SIL) simulation, that contributes to the set of simulation tools available for assessing autonomy (Jones et. al., 2008). As a precursor to this research, ERDC installed a SIL at West Point that was comprised of four integral systems. The West Point VANE-SIL includes an autonomy stack for path planning decision making, an Environmental and Sensory Engine (ESE) which virtually simulates a LiDAR sensor, a VIGOR Unreal Engine 4 that creates the virtual environment, and a Warfighter Machine Interface which acts as the user interface. These interconnected computer systems facilitate seamless communication between hardware and software components, thereby generating a comprehensive virtual simulation testing environment. The research team aimed to augment ERDC's virtual AGV testing through this study by conducting an agile research study consisting of three iterative research cycles. In Iteration I, the team worked with EDRC to install and test a new autonomy stack software, evaluating vehicle performance against the previously provided autonomy software. Iteration II involved the addition of testing three levels of path planning aggressiveness settings. In iteration III, the team integrated and evaluated a total of three path planning algorithms, referenced as path planning algorithms P1, P2 and P3.

## 2. Introduction

A previous study using the West Point SIL tested AGV performance under three weather conditions using the path planning algorithm P1. The simulation demonstrated surprising results as the AGV seemed to perform more aggressively under rainy and foggy conditions, compared to conditions with no precipitation (Caldwell, Cross, Oglesbee, & Thompson, 2024). The researchers hypothesized that the path planning algorithm was able to find a more direct path under degraded LiDAR conditions presented by the rain and fog as the autonomy is programmed to identify an optimal path through all visible obstacles (Caldwell et al., 2024). However, the team also noted gaps in the cost map where the virtual LiDAR was missing data points in front of the vehicle.

The current research effort began by investigating the cost map anomalies. The team discovered the AGV path planning was only using the rear virtual LiDAR sensor which resulted in a blind spot to the front, left of the vehicle. The blind spot in the cost map negatively affected the path planning algorithm. ERDC requested the team test the AGV performance differences when both the front and rear LiDAR sensors were utilized. In addition, the team was tasked to update the autonomy to a new version. Lastly, the team was asked to test two new path planning algorithms under three weather conditions and three routing aggressiveness settings. The researchers decided to tackle each of these initiatives in a separate iteration using an agile research methodology.

## 3. Agile Research Methodology

The agile research methodology is characterized by the division of tasks into short phases of work and frequent reassessment and adaptation of plans (Conforto, 2010). The agile methodology promotes an iterative and incremental developmental approach that is beneficial when the projects require continuous feedback during the development and testing phases. Each iteration is a specific sprint beginning with analysis, followed by design, implementation, and testing to accomplish a specific task (Cohen & Costa, 2004). The conclusion of each sprint or iteration can bring to light existing or new problems to work on during the next iteration.

Agile research was determined as the most effective approach for this study because it allows for continuous iteration, rapid problem identification, and quick adaptation. Agile ensures that errors and deficiencies such as incorrect LiDAR settings are identified and corrected at the end of each iteration rather than waiting until the end of the study. This research required the implementation of several new features to the West Point SIL to include adjustments to the LiDAR sensor, incorporation of a new autonomy stack, addition of two path planning algorithms, and new testing of routing aggressiveness settings. The agile methodology ensured that each new feature was integrated and tested prior to starting the next task. Without this iterative process, the team risked not being able to properly attribute errors in the SIL to one of the new features implemented. Agile also focuses on flexibility in consistently changing requirements. This was important for the study as several changes occurred throughout the study as problems were identified with the post-processing data analysis script and unexpected vehicle behavior under different routing aggressiveness settings. By utilizing agile, this study ensured that AGV testing was adaptive, iterative, and efficient, leading to a more robust and reliable simulation for military applications.

### 3.1 Agile Iteration I: SIL Updates and Sensor Integration

During the first agile cycle, the researchers worked with ERDC engineers to incorporate both the front and rear LiDAR sensors and installed and debugged the updated autonomy software. Analyzing the previous study conducted on the West Point SIL, the team identified a gap in the LiDAR scan displayed in the cost map, a two-dimensional representation of the virtual LiDAR scan. Figure 1 displays the LiDAR sensor output displaying a 360-degree scan of the environment next to the system-produced cost map displaying a missing wedge of data to the front left of the vehicle, seen as a missing pie piece in the top left of the picture. Though sensor dropout is possible in field testing or real-world system deployment, this is not the expected operating condition for the system. The missing LiDAR output often caused the path planning algorithm to route the vehicle to the right, as seen in the green planned path line. This resulted in a sub-optimal path, increasing the total distance traveled. Interestingly, the degraded LiDAR sensor under rainy and foggy conditions was less impacted by the missing sensor data, resulting in a more direct path than under normal conditions. The research team worked with ERDC to alter the SIL to reliably turn on the LiDAR sensors for every run. This resulted in a more consistent perception across runs and more similar results under the three weather conditions.

The second requirement in the first cycle was to install and troubleshoot the autonomy stack. After the addition of the new autonomy, the team tested the simulation and noticed the AGV was lurching, quickly accelerating, followed by quickly stopping. The team also observed the AGV tires spinning while the vehicle was stuck or moving at a slow rate. Working with ERDC, the researchers attributed the vehicle dynamics issues to a soft-soil model problem where the vehicle interactions between terrain and wheels were not parametrized correctly for the soil type. This soft-soil model is a complex algorithm that is used to make the simulated environment as realistic as possible by adjusting how the vehicle interacts with different ground types. For example, in real life, a vehicle will drive differently on a muddy surface versus a paved road. However, in the virtual environment, the soft-soil model was inaccurately causing decreased friction between the tires and the soil, resulting in the tires slipping and the vehicle lurching during testing runs. ERDC adjusted the soft-soil model in the simulation, fixing the vehicle dynamics. The research team tested the updated model and was able to achieve expected vehicle performance metrics. The team also verified the simulated vehicle performance with results from the ERDC SIL. This marked the end of the first agile iteration.

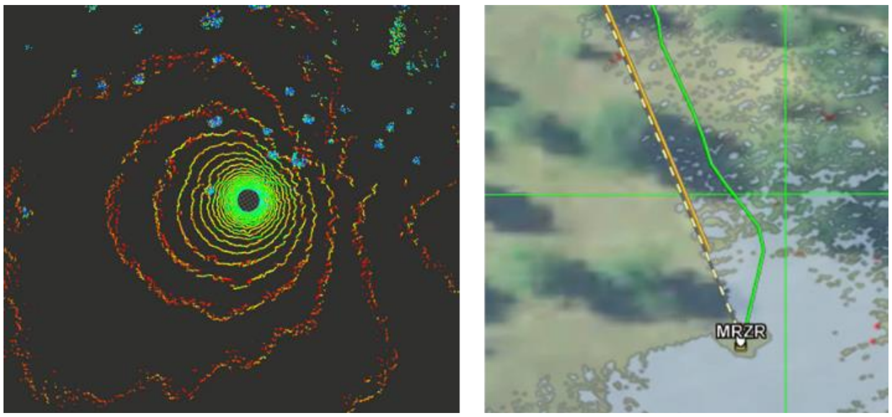


Figure 1: LiDAR Scan (left) and Cost Map Displaying Missing Sensor Data (right)

## 3.2 Iteration II: Routing Aggressiveness

The primary task for the second agile cycle was to implement and test various routing aggressiveness settings to identify the effects on AGV performance. This task required the team to use an alternate user interface where the aggressiveness setting could be adjusted. The aggressiveness setting is a level of tolerance for obstacles, where the lowest setting, A1, would avoid driving through a potential obstacle, while the highest setting, A9, would allow the vehicle to drive through obstacles it thinks the vehicle could penetrate, such as bushes and small diameter trees. The default setting under path planning algorithm P1 is set to A4.

The team developed an experimental design to test three aggressiveness settings (A1, A4, and A9), under three weather conditions (normal, rain, and fog), using three path planning algorithms (P1, P2, & P3). For this agile cycle, only path planning algorithm P1 was tested since it was previously verified to work during the first agile cycle. Three testing runs were performed, recorded, and analyzed under each combination of independent measure. Under each testing run, the virtual AGV was programmed to autonomously navigate a route consisting of segments of heavy, medium, and light vegetation by planning routes to avoid obstacles while following waypoints (Figure 2).

After post-processing, the team discovered inconsistencies in the AGV performance and dependent measure data. In Caldwell et al. (2024), the researchers split the AGV course into three segments. The total distance traveled on the three courses usually averaged over 800-meters. However, the total distance traveled on almost all the runs using path planning algorithm P1 and new autonomy averaged only 45 meters. Similar issues were discovered when analyzing the average speed and percent moving data points. Evaluation of the recorded AGV route showed the vehicle successfully navigated around the entire course, which should have resulted in approximately 800-meters total distance. The team narrowed down the issue to an error in the post-processing analysis that inaccurately summarized the data for path planning algorithm P1. The research team worked with ERDC engineers to update the post-processing code resulting in metrics consistent with the actual vehicle performance.

## 3.3 Agile Iteration III: Additional Path Planning Algorithms P2 & P3

ISBN: 97819384969-9-8

The final agile research cycle involved testing two additional path planning algorithms, referred to as P2 and P3. Algorithm P2 uses a rapidly exploring random trees optimization-based path planner that updates paths to the changing environmental conditions during execution. Path planning algorithm P3 utilizes the LiDAR sensor feedback as a georeferencing tool, a process of applying a coordinate system to the point cloud so it can be accurately located on a map. Path planning algorithm P3 then specializes in localizing navigation systems that provide optimal estimates of position, velocity, and attitude. The team conducted the same experimental runs for path planning algorithms P2 and P3 under the three aggressiveness settings and three weather conditions, three runs in each category for a total of 27 runs for each path planner. Table 1 displays the average distance traveled and average speed for each category with omitted failed runs and italicized data for categories with less than three successful runs.

## 4. Results by Iteration

For the post-processing results, the team compared AGV performance under the three path planning algorithms, three aggressiveness settings, and three weather conditions using several dependent measures to include total distance traveled, average speed, percent moving, average moving speed, and percent stopped. The results discussed below primarily focus on total distance traveled and average speed under each category. Table 1 displays the average distance traveled and average speed across the three runs for each aggressiveness setting, path planning algorithm, and weather condition. Data from failed runs is omitted and categories with a mix of failed and successful runs show the averages of only successful runs in italicized font.

Table 1. AGV Performance by Path Planning Algorithm, Aggressiveness, and Weather Condition; Mean (Standard Deviation)

| | | **Normal** | | **Rain** | | **Fog** | |
|---|---|---|---|---|---|---|---|
| Path Planning Algorithm | Aggressiveness Setting | Distance Traveled (meters) | Average Speed (km/hr) | Distance Traveled (meters) | Average Speed (km/hr) | Distance Traveled (meters) | Average Speed (km/hr) |
| **P1** | **A9** | 855.5 (2.3) | 1.9 (<0.0) | 839.5 (4.4) | 1.8 (0.1) | 879.1 (11.0) | 1.9 (<0.0) |
| | **A4** | 883.9 (21.0) | 1.9 (<0.0) | 852.4 (13.3) | 1.8 (0.1) | | |
| | **A1** | *866.3 (2.7)* | *1.9 (<0.0)* | *936.1 (49.8)* | *1.3 (<0.0)* | | |
| **P2** | **A9** | 882.7 (19.1) | 2.9 (0.2) | 861.3 (22.9) | 2.7 (0.1) | 872.4 (17.9) | 2.7 (0.1) |
| | **A4** | 901.1 (5.1) | 2.8 (0.3) | 846.3 (1.9) | 2.7 (<0.0) | 863.4 (7.7) | 2.8 (0.1) |
| | **A1** | 884.5 (19.8) | 2.8 (0.1) | 901.8 (9.0) | 2.1 (0.1) | | |
| **P3** | **A9** | 885.1 (25.9) | 2.5 (0.2) | 864.5 (10.8) | 2.4 (0.3) | 863.5 (2.2) | 2.6 (0.1) |
| | **A4** | 905.1 (43.9) | 2.7 (0.2) | *853.8 (4.2)* | *2.3 (0.3)* | *871.7 (4.0)* | *2.5 (<0.0)* |
| | **A1** | 987.5 (122) | 2.4 (0.2) | 900.7 (18.9) | 2.4 (0.1) | | |

### 4.1 Path Planning Algorithm P1 Results

Out of all the aggressiveness settings, the vehicle was more consistent under the A9 setting, the highest aggressiveness. The vehicle completed the course with the lowest mean distance traveled and highest percentage of successful runs under the A9 setting. The researchers attribute this to the vehicle planning more aggressive routes toward obstacles that were in its path. The AGV also seemed to have less hesitation when creating a path upon encountering an obstacle. Under setting A1, the AGV experienced the most issues, failing to complete the course on one normal run, one rain run, and all three fog runs, as indicated by the omitted data and italicized results in Table 1. In addition, the A1 setting resulted in the AGV often struggling to determine a feasible path when it encountered an obstacle and sometimes completely stopping. For runs using setting A4, the AGV successfully completed runs under normal and rain conditions but failed to complete any of the three runs under the fog weather condition. Simulated fog conditions limited the LiDAR sensor's ability to detect obstacles until it was too close to the vehicle, causing it to navigate into positions where it could not find a feasible path to complete the route. This problem was exacerbated by the low routing aggressiveness setting often resulting in the vehicle failing to complete the route.

### 4.2 Path Planning Algorithms P2 & P3 Results

Results for path planning algorithms P2 and P3 followed similar overall trends as planning algorithm P1. Algorithm P2 had the highest successful route completion rates followed by algorithm P3 and then P1. On average, runs under aggressiveness setting A9 resulted in lower mean total distances traveled for all path planning algorithms across all weather conditions. This indicates that the routing aggressiveness setting effects how direct of a path is planned for the AGV. Path planning algorithm P2 had slightly lower mean total distances traveled and higher mean average speeds when compared to algorithm P3. The simulated weather conditions also influenced the path planning algorithm's route with rain conditions resulting in the lowest mean total distance traveled under most routing aggressiveness settings. Again, the AGV failed to complete the course most often under the fog weather conditions with more failures under lower aggressiveness settings.

The AGV course is plotted onto an overhead image of the virtual environment in the top image in Figure 2. The three route paths at the bottom of Figure 2 show the AGV route recorded for path planning algorithm P2 under aggressiveness setting A9 and the three weather conditions, normal (left), rain (center), and fog (right). The routes confirm the AGV took a more direct path under the rain condition. The AGV route deviates the most along areas with higher vegetation as seen at the top of the route curves where the AGV under normal condition changes directions several times after the top waypoint and where the AGV under fog condition performs a complete loop at the top waypoint. The effect of vegetation can also be seen by the similar direct paths under all three weather conditions toward the end of the route where there are very few obstacles, shown at the bottom of the images. Similar route paths were seen under path planning algorithm P3. In addition, the route paths became less direct as the routing aggressiveness decreased.

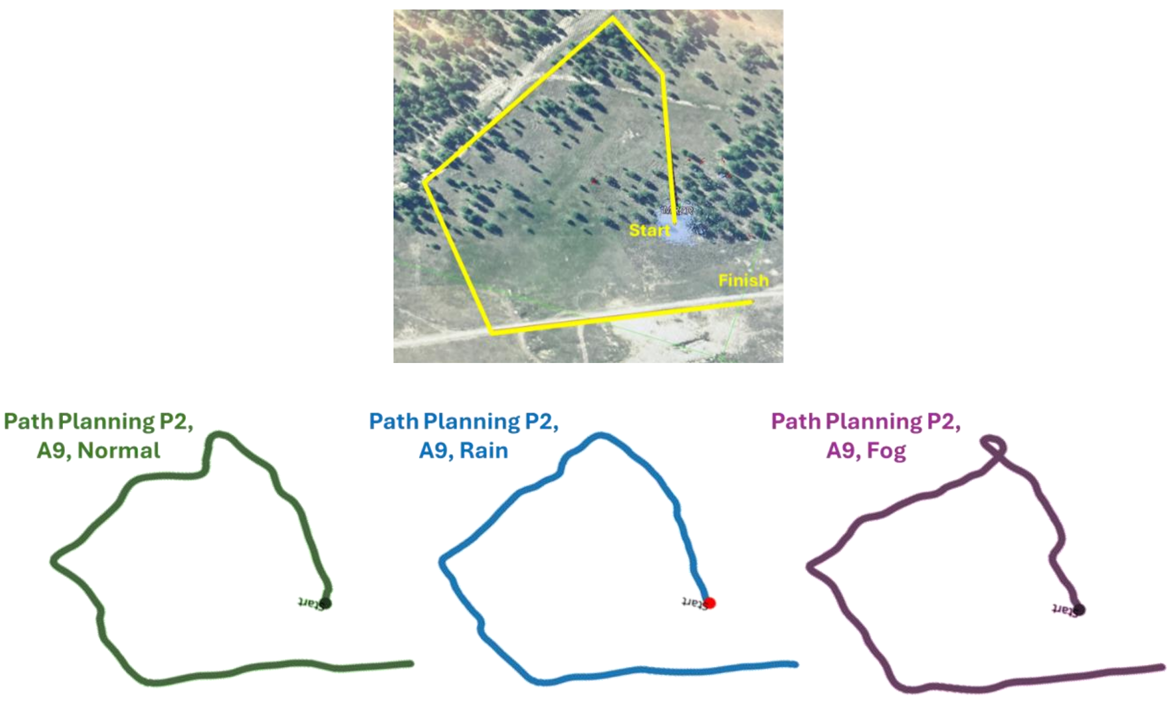


Figure 2: AGV Course (top), Path Planning Algorithm P2 Routes under Normal (left), Rain (center), and Fog (right) Conditions

## 5. Discussion

The results of this study demonstrate the importance of simulating autonomous ground vehicle performance under various conditions. While there was little difference seen between path planning algorithms P2 and P3, weather

ISBN: 97819384969-9-8 

conditions and routing aggressiveness settings highly affected the route path and successful completion of the course. The percentage of successful course completions makes it easy to identify the best independent measure combinations. However, the slight differences in dependent measures and variations in route path are not as easy to interpret. A more direct path may not equate to a better path planning algorithm decision. The research team recommends testing the AGV path planning algorithms in a shorter controlled test where a smaller number of obstacles are placed in front of the vehicle with a known optimal path. In addition, while aggressiveness settings A4 and A9 resulted in more successful runs, it is not clear whether a more aggressive routing plan produces a more optimal route. Again, the research team recommends additional testing under shorter, controlled settings to better understand the impacts of routing aggressiveness on vehicle performance.

This study was limited in scope to one type of vehicle and one course. While the terrain on the course varied in vegetation density, additional terrain models should be tested to determine their effects on AGV performance. One advantage of simulating AGV performance is that parameters can be changed fairly quickly and much cheaper than moving a physical AGV test site to different terrain features. Another study limitation involves how the current SIL simulates weather conditions. The rain and fog weather conditions impact the virtual LiDAR sensor but do not alter the terrain or vehicle dynamics. This means rain never results in muddy terrain. Testing various types of terrain models along with the LiDAR sensor degradation will provide a more realistic operating environment for AGV testing. A final limitation with this study was the lack of validity testing. The research team verified the West Point SIL model and results at every stage of testing with the ERDC SIL and with subject matter experts at ERDC and the autonomy stack developers. However, there is a lack of physical AGV testing under similar conditions to validate the model, specifically weather conditions and routing aggressiveness settings. As a proxy validation measure, the team presented results to ERDC researchers familiar with physical AGV testing and confirmed the overall test result trends under normal weather conditions. The experts at ERDC highlighted that, while the overall model validity is hard to test, each component of the model to include the virtual environment and virtual lidar has been through a rigorous validation process.

Applying an agile research methodology allowed the research team to iteratively integrate, test, and evaluate new features into the West Point SIL. The research team encountered several issues during the testing and evaluation phases of each agile cycle that may not have been as easy to identify had this research followed a traditional waterfall methodology. The team will continue to perform agile iterations to isolate optimal combinations of path planning algorithms and routing aggressiveness settings as additional tests are performed under new weather conditions and on various terrain models.

## 6. References

Agile Alliance. (n.d.). *12 principles behind the Agile Manifesto*. Agile Alliance. https://www.agilealliance.org/agile101/12-principles-behind-the-agile-manifesto/

Caldwell, J., Cross, J., Oglesbee, P., and Thompson, B. (2024). Autonomous Ground Vehicle Simulation: Usability and Evaluation Study. Proceedings of the Annual General Donald R. Keith Memorial Conference, West Point, NY, May 2. ISBN: 97819384962-4-0, 172-177. https://www.ieworldconference.org/content/WP2023/Papers/GDRKMCC23_50.pdf

Cohen, David & Costa, Patrícia. (2004). An Introduction to Agile Methods. Advances in Computers. 62. 1-66. 10.1016/S0065-2458(03)62001-2.

Conforto, E.C. and Amaral, D.C. (2010), Evaluating an agile method for planning and controlling innovative projects. Proj Mgmt Jrnl, 41: 73-80. https://doi.org/10.1002/pmj.20089

Heckmann, L., Magnuson, S., & Park, A. (2023, December 12). Army Lays Out Plans for Robotic Combat Vehicles. *National Defense*. Retrieved March 20, 2024, from

Jones, R., Priddy, J., Horner, D., Peters, J., Howington, S., Ballard Jr., J., Gates, B., & Cummins, C. (2008). Virtual Autonomous Navigation Environment (VANE). *Earth & Space2008: Engineering, Science, Construction, and Operations in Challenging Environments*. https://doi.org/10.1061/40988(323)114