Open Access

Recent Progress in Science and Engineering

LIDSEN Publishing Inc.

Review

Simulation Software in the Design and AI-Driven Automation of All-Terrain Farm Vehicles and Implements for Precision Agriculture

Mrutyunjay Padhiary *, Pankaj Roy, Kundan Kumar

Department of Agricultural Engineering, Triguna Sen School of Technology, Assam University, Silchar-788011, India; E-Mails: mrutyu@gmail.com; pankaj8638.9846@gmail.com; kkazad6200@gmail.com

* **Correspondence:** Mrutyunjay Padhiary; E-Mail: mrutyu@gmail.com

Academic Editor: Danilo Avola

Recent Prog Sci Eng
2025, volume 1, issue 2
doi:10.21926/rpse.2502006

Received: August 26, 2024
Accepted: March 23, 2025
Published: April 01, 2025

Abstract

Precision agriculture depends on the automation and mechanization of agricultural equipment and vehicles in a variety of terrains, which increases productivity and sustainability. This review presents a comparative analysis of significant simulation software used in designing and developing automated agricultural systems, emphasizing their methodologies and significance in advancing farm technology. Artificial intelligence (AI) and machine learning (ML) methods are modeled, optimized, and integrated using key technologies such as MATLAB/Simulink, SolidWorks, ANSYS, AirSim, and Gazebo. The results demonstrate how these technologies improve agricultural automation's real-time decision-making, predictive maintenance, and system accuracy. Case studies illustrate their practical application in simulating all-terrain farm vehicles and specialized implements. The best tools for simulating autonomous navigation are AirSim and Gazebo, although MATLAB/Simulink is particularly adept at system-level AI modeling. This study takes a new approach to improving design, control, and environmental interactions by combining many modeling tools. This makes it easier to make agricultural automation systems that last longer and work better. It is suggested that future studies investigate the relationship between agricultural automation, AI, and simulation in greater detail to propel precision agriculture forward.

Keywords
Precision agriculture; farm automation; simulation software; artificial intelligence (AI); machine learning (ML); all-terrain vehicles

1. Introduction

Precision agriculture is a substantial advancement in improving the efficiency and sustainability of farming. Precision agriculture strives to improve resource use, minimize environmental footprint, and enhance crop productivity using advanced technologies such as automation, artificial intelligence, and machine learning [1, 2]. Farm automation, an essential element of precision agriculture, utilizes sophisticated machinery and equipment, including all-terrain vehicles and automated tools, to carry out tasks with little human involvement [3]. These technologies play a crucial role in contemporary agriculture, where there is a growing need for increased production and sustainability. The incorporation of AI and ML into the design of farm machinery has added numerous advantageous transformations in the agricultural industry. This integration has allowed for the emergence of intelligent systems capable of making decisions in real-time, predicting maintenance needs, and optimizing operations [4]. The design and modeling of these automated systems, including all-terrain vehicles and implements, are crucial for guaranteeing their efficiency and dependability in various farming conditions [5]. Simulation software is vital since it offers a virtual environment for testing, refining, and validating design concepts before creating prototypes. Software applications such as MATLAB/Simulink, SolidWorks, ANSYS, AirSim, and Gazebo have become essential in the design and development of modern agricultural systems. Each tool provides distinct capabilities and approaches to address specific design difficulties.

The main goals of this study are to examine and contrast various simulation software utilized in the design and automation of farm vehicles and implements. The study evaluates their methodology, accuracy, and significance in the design process. Also, this work seeks to assess the incorporation of AI and ML into these simulation procedures, investigating how these technologies improve the design, functionality, and efficiency of automated agricultural machinery. The study combines advanced simulation tools with AI and machine learning algorithms to optimize farm machinery design and automation. It explores hybrid AI/ML algorithms for predictive maintenance, optimization, and real-time decision-making. The research suggests using MATLAB/Simulink to improve control systems for self-driving cars and using AirSim and Gazebo to help train AI models for navigation and avoiding obstacles [6]. This approach addresses challenges in terrain adaptability, resource optimization, and operational efficiency. Hybrid algorithms, like real-time plant disease detection and R-CNN and SVM, may be used to monitor farm equipment health and dynamic resource allocation in machinery [7]. These algorithms are also used for crop classification and variable-rate fertilizer application based on real-time crop and soil data.

2. Application in Agriculture

2.1 Precision Agriculture and Farm Automation

In recent decades, advances in technology and data analysis have significantly advanced the field of precision agriculture [1]. Centered initially on enhancing agricultural productivity and optimizing resource utilization using simple instruments, it has now integrated advanced technology like GPS, remote sensing, and real-time data analytics [8]. The latest developments in precision agriculture prioritize utilizing Internet of Things (IoT) devices, drones, and automated machinery to gather and evaluate data with unparalleled precision. These advancements empower farmers to make better-informed choices, optimize the utilization of resources, and improve overall output [9]. Automation is essential in this evolution as it simplifies agricultural procedures and decreases the requirement for manual labor [10]. Automated technologies, such as all-terrain vehicles and precision implements, enable more accurate delivery of inputs like fertilizers and pesticides, enhancing crop health and decreasing environmental impact [11]. Many challenges in precision agriculture require creative solutions. Terrain adaptation is one of the most serious issues as agricultural equipment must work effectively on various terrains, such as rocky, muddy, and steep areas [12]. When machines cannot adapt dynamically to such circumstances, they frequently suffer from performance degradation or complete failure. Another major challenge is real-time decision-making, which requires self-driving vehicles to process vast amounts of sensor data and react instantly to environmental changes [13-15]. IoT device integration is equally important, but it presents technological challenges including latency, connectivity, and device compatibility. Resource optimization is crucial to managing inputs like water, fertilizer, and pesticides to reduce waste and maximize efficiency [16]. Lastly and most importantly, predictive maintenance is a significant concern because equipment failures during crucial farming times, such as planting or harvesting, lead to substantial losses in productivity. AI-enhanced simulation tools may be essential in resolving these issues by enabling predictive analytics and real-time system adjustments.

2.2 AI and ML in Agricultural Machinery

AI and ML have become essential components of contemporary agricultural technology, enhancing the design and operation of farm vehicles and equipment. AI and ML algorithms improve several aspects of agricultural machinery, such as autonomous navigation, real-time monitoring, and data-driven decision-making [17]. These technologies facilitate the ability of farming vehicles to carry out duties such as planting, harvesting, and spraying with exceptional accuracy and productivity [18]. Predictive maintenance is a significant usage of AI and ML, where information from sensors and past performance is utilized to forecast equipment malfunctions and plan maintenance promptly, reducing downtime and repair expenses [19]. Optimization algorithms enhance operating efficiency by dynamically altering settings in response to environmental conditions and crop requirements. AI-powered solutions offer crucial decision-making assistance by analyzing intricate datasets to deliver insights and recommendations that improve farm management and productivity [20, 21].

In precision agriculture, artificial intelligence and machine learning play various roles that greatly enhance operational effectiveness, lower costs, and promote sustainability. AI models detect patterns indicating probable failures by tracking vibration, temperature, and wear-and-tear data from components such as power engines or hydraulic systems [22]. Artificial intelligence may optimize irrigation by assessing soil moisture data, weather forecasts, and crop requirements. This enhances agricultural yields and minimizes water waste by enabling precision watering. Similarly, artificial intelligence may dynamically modify spray patterns in the context of pesticide application based on real-time data from sensors and drones [23]. This ensures that pesticides are only applied where necessary, reducing environmental effects and chemical use. AI and machine learning are also essential in real-time decision-making. AI-enabled autonomous cars are capable of navigating across challenging agricultural terrain, making judgments in real time about load distribution, speed, and route based on the surrounding conditions [24]. Thus, a tractor or harvest robot may change its route or speed according to the unevenness of the terrain, avoiding obstacles and guaranteeing consistent functioning. AI models also help optimize fertilizer by detecting soil and crop health, enabling variable-rate applications customized for certain field zones. Through increased production and resource efficiency, these AI/ML technologies are crucial to advancing precision agriculture. By using such adaptive, real-time technologies, farmers may maximize their agricultural yields while minimizing their environmental impact.

2.3 Simulation in Agricultural Engineering

Simulation techniques are crucial in the design and development of agricultural machinery and implements, as they offer a virtual environment for testing and improving design concepts before creating actual prototypes [25]. Simulation tools like MATLAB/Simulink, SolidWorks, ANSYS, AirSim, and Gazebo provide various capabilities for modeling and assessing the performance of agricultural vehicles and implements [26]. These tools aid in several phases of the design process, such as kinematic and dynamic analysis, assessment of structural integrity, and optimization of systems. Comparative studies of current simulation tools emphasize the advantages and drawbacks of each tool, providing valuable insights into their suitability for various design difficulties. For example, AirSim and Gazebo are highly valuable tools for simulating the behavior of autonomous vehicles in intricate surroundings. At the same time, MATLAB/Simulink and ANSYS are well-known for their extensive capabilities in modeling and analysis [27, 28]. Using these simulation tools, engineers and researchers may maximize the effectiveness of designs, improve functionality, and guarantee the dependability of agricultural machinery in practical situations.

3. Comparative Analysis of Simulation Software

3.1 Selection Criteria for Simulation Software

When assessing simulation software for the design and automation of farm vehicles and implements, it is crucial to examine many essential aspects and capabilities [29]. Usability refers to the simplicity with which users can use the software, configure simulations, and understand the outcomes. Precision is essential to ensure that the simulations accurately depict real-world situations and behaviors, which is key for making well-informed design choices. Integrating AI and ML algorithms is a crucial aspect that enhances predictive capabilities, optimization, and real-time decision-making in the simulation environment [30]. Software that enables seamless interaction with AI/ML algorithms can significantly improve the efficiency of the simulation process by enabling more advanced analyses and automated modifications using real-time data. Various simulation programs are listed in Table 1, with information on their payment and open-source status and their main characteristics, usability, accuracy, and AI/ML integration.

Table 1 Comparison of simulation software features.

Software	**Key Features**	**Usability**	**Accuracy**	**Integration with AI/ML**	**Type**
MATLAB/Simulink	System-level simulation, control design	High	High	Extensive	Paid
SolidWorks	3D CAD modeling, structural analysis	Moderate	Moderate	Limited	Paid
ANSYS	Structural and thermal analysis	Moderate	High	Moderate	Paid
AirSim	Autonomous vehicle simulation, environment	Moderate	High	High	Open-source
Gazebo	Robotics simulation, environmental interaction	High	High	Moderate	Open-source
COMSOL Multiphysics	Multi-physics simulations	High	High	Extensive	Paid
PTC Creo	3D CAD design and simulation	Moderate	High	Limited	Paid
Blender	3D modeling and rendering	High	Moderate	Limited	Open-source
OpenModelica	System modeling and simulation	Moderate	Moderate	High	Open-source
Simulink (MATLAB)	System simulation and model-based design	High	High	Extensive	Paid
DynamiCs	System-level dynamics simulation	Moderate	Moderate	Moderate	Paid
Unity	Real-time 3D development and simulation	High	Moderate	High	Paid
V-REP (CoppeliaSim)	Robotics simulation and control	Moderate	High	Moderate	Open-source
ModelSim	Hardware description language simulation	High	High	Limited	Paid
Scilab	Open-source computational software	Moderate	Moderate	Moderate	Open-source

3.2 Software Options for Farm Vehicles and Implement Design

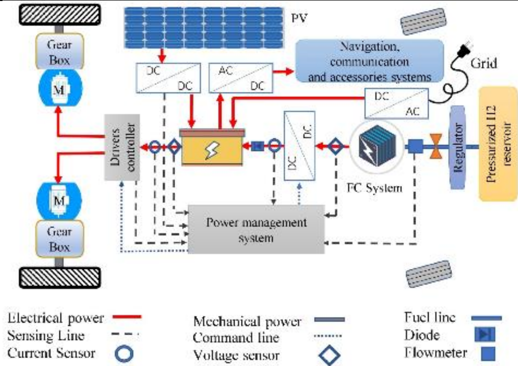
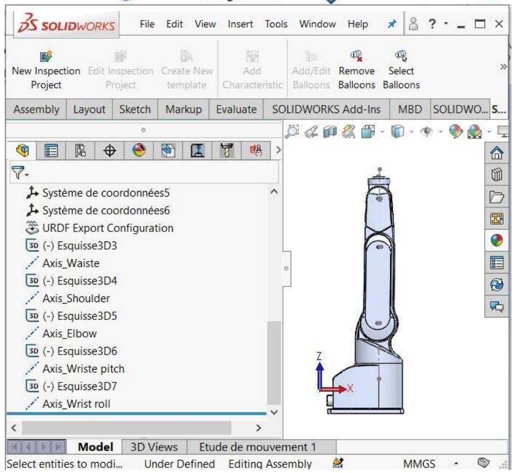
Various simulation software alternatives are extensively utilized in the design of agricultural vehicles and equipment. MATLAB/Simulink is well-known for its strong modeling and simulation abilities, providing a wide range of toolboxes for system-level simulation and control design [31]. SolidWorks offers sophisticated 3D computer-aided design (CAD) modeling and simulation capabilities, enabling precise design and structural analysis of agricultural machinery. ANSYS is renowned for its extensive finite element analysis (FEA) software, which assesses the structural soundness and efficiency of components in different scenarios [32]. AirSim and Gazebo are highly beneficial for simulating the behavior of autonomous vehicles and their interactions with intricate environments. They offer realistic situations for testing and improving control algorithms and navigation systems.

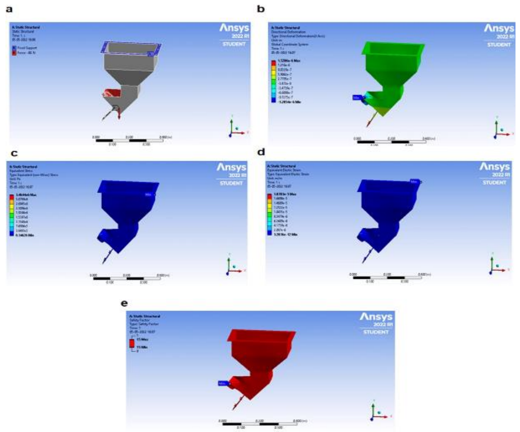
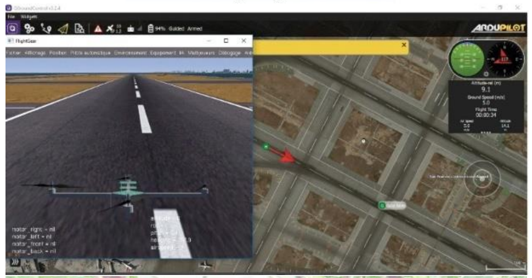
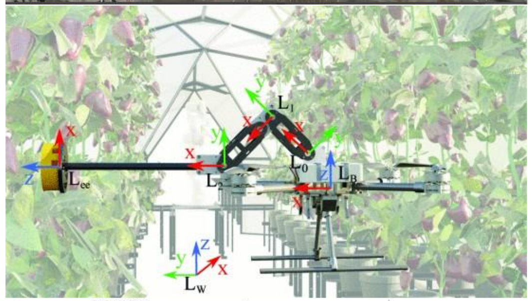
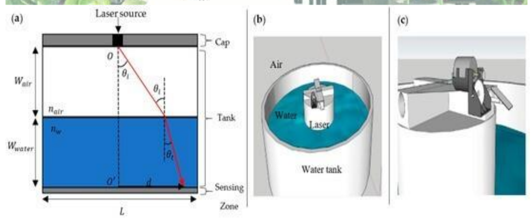
3.3 Performance Evaluation

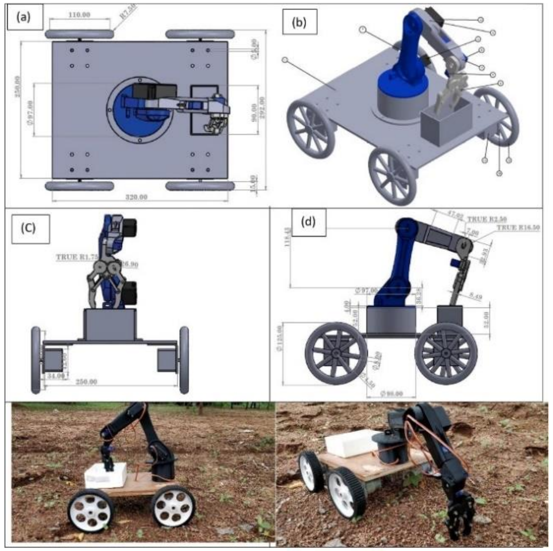
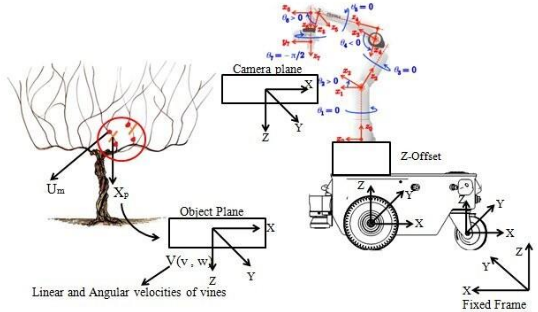
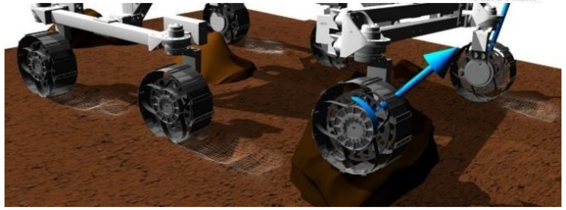
In order to assess these simulation tools, a performance evaluation is undertaken, taking into account several variables such as accuracy, computational efficiency, learning difficulty, and interface software. MATLAB/Simulink is proficient at conducting system-level simulations with exceptional precision and intricate control methods, demanding substantial computer resources for intricate models [33]. SolidWorks provides outstanding accuracy in 3D modeling and structural analysis, along with user-friendly design features that facilitate design revisions. However, its simulation capabilities may be somewhat restricted regarding dynamic system modeling compared to alternative tools [34]. ANSYS offers exceptional precision in structural analysis and thermal simulations. However, it may require significant computer resources. AirSim and Gazebo are highly effective at simulating the dynamics of autonomous vehicles and their interactions with the environment. The computing efficiency of these simulations varies depending on the complexity of the scenarios being simulated [35]. Illustrative case studies or examples showcasing the utilization of these software tools in the construction of all-terrain vehicles and farm implements can effectively demonstrate their practical applications and performance in real-life situations.

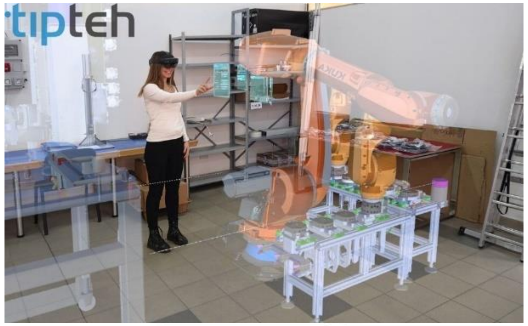
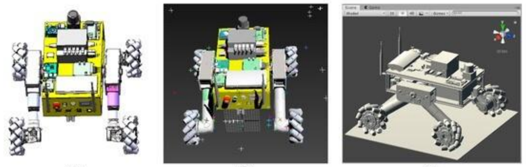
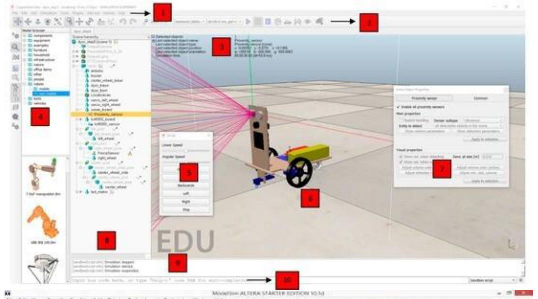
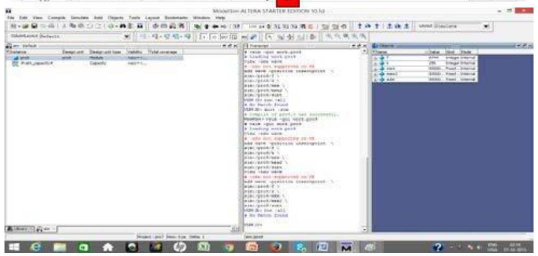
Table 2 presents a comparison of different simulation software utilized in the field of agricultural engineering. The assessment evaluates each software based on its computational efficiency, computational power requirements, and learning curve, providing insights into its performance and usability. It also discusses the types of related software, microcontrollers, or systems often used with each tool. This gives us a bigger picture of how these software solutions can be combined with other technologies. Using illustrative figures and references, the software is situated within the more extensive study of the paper, facilitating readers' comprehension of the practical applications and significance of each instrument in precision agriculture and farm automation. The price for the regular version in India is provided. Free versions of software such as ANSYS are accessible for students.

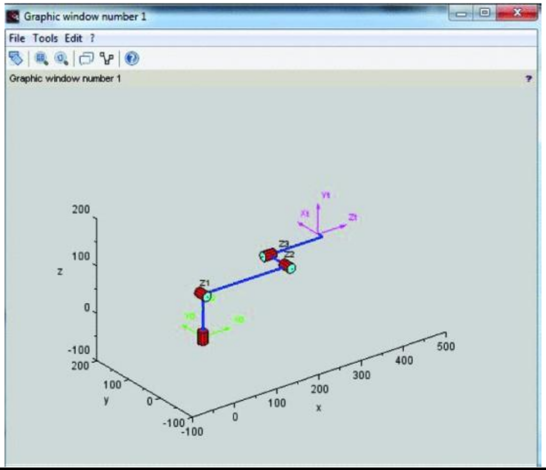
Table 2 Performance metrics and characteristics of simulation software.

Software	Computational Efficiency	Computational Power Requirement	Learning Curve	Type of Allied Software/ Microcontroller/System	Illustrative Figure	Ref.	Subscription Cost (Annual)
MATLAB/Simulink	High	Moderate	Steep	Arduino, Raspberry Pi, Simscape		[36]	$900
SolidWorks	Moderate	High	Moderate	3D CAD, PLM Systems, FEA		[37]	$2,797

ANSYS	Low	High	Steep	FEA, CFD, Thermal Analysis Tools		[38]	$1,000
AirSim	Moderate	Moderate	Moderate	UAV Simulation, Python, Unreal Engine		[39]	-
Gazebo	High	Moderate	Moderate	ROS, UAV Systems, Robotics		[40]	-
COMSOL Multiphysics	Low	High	Steep	Multiphysics, MATLAB, FEA Tools		[41]	$4000

PTC Creo	Moderate	High	Moderate	3D CAD, PLM Systems, IoT		[42]	$2400
Blender	High	Low	Moderate	3D Modeling, Python, Animation Software		[43]	-
OpenModelica	Moderate	Low	Moderate	Modelica, System Simulation Tools		[44]	-

DynamiCs	Moderate	Moderate	Moderate	MATLAB, Control Systems, Dynamics		[45]	$2000
Unity	High	Moderate	Moderate	C#, Visual Studio, 3D Simulation Tools	 (a) (b) (c)	[46]	$2,040
CoppeliaSim	Moderate	Moderate	Moderate	ROS, Python, Lua Scripting		[47]	-
ModelSim	High	High	Steep	VHDL/Verilog, FPGA, Hardware Simulation		[48]	$1,995

Scilab	Moderate	Low	Moderate	Xcos, Control Systems, Simulation		[49]	-

3.4 Integration with AI and ML

By incorporating AI and ML into simulation software, the capacity to model and optimize farm vehicles and implements is significantly improved. Because it has a lot of tools and data analysis features, MATLAB/Simulink makes it easy to use AI and machine learning algorithms [50]. This lets you do complex modeling and forecasting. SolidWorks can connect with other artificial intelligence and machine learning tools to enhance optimization and analysis. However, its built-in artificial intelligence features are not as advanced. ANSYS enables the integration of machine learning models to enhance predicted accuracy and optimize material performance [51]. AirSim and Gazebo allow the integration of AI/ML by offering simulation settings that assist in the development and testing of AI-driven control systems for autonomous vehicles. These environments support real-time data processing and are crucial for implementing autonomous vehicle algorithms. Every program has its own set of benefits and constraints when integrating AI/ML, with specific options providing more smooth and sophisticated functionalities compared to others. Comprehending these factors is essential for choosing the suitable tool for design and automation assignments.

4. Design and Simulation of All-Terrain Vehicles and Automated Implements

4.1 Methodology

A systematic approach is used to design and simulate all-terrain vehicles and automated implements. This approach utilizes specific simulation software to enhance performance and functionality [52]. The process commences with establishing the design prerequisites and goals, subsequently proceeding to create a conceptual design and its representation through tools such as SolidWorks for 3D computer-aided design (CAD). MATLAB/Simulink is subsequently employed to design and evaluate control systems and algorithms, incorporating dynamic simulations to evaluate vehicle performance in different scenarios [53]. ANSYS is utilized for structural analysis to verify the ability of components to endure operational pressures and environmental conditions. The software tools AirSim and Gazebo replicate self-governing movement and engagement with intricate landscapes, offering a valuable understanding of how vehicles behave in actual situations [54]. The simulation workflow entails a process of iterative testing and refinement, wherein design improvements are implemented based on simulation results to improve the overall efficacy and dependability of the vehicle or implementation. Computational efficiency analyzes the performance of simulation tools based on processing time and resource utilization for complex models, highlighting tools that optimize computational requirements without sacrificing accuracy. Integration capabilities evaluate how well the tool integrates with other software, AI/ML algorithms, or hardware systems like IoT devices and robotic platforms [55, 56]. Scalability investigates whether the tool can handle increasing complexity, such as larger datasets or more detailed models, without performance degradation. Finally, cost and accessibility provide a detailed cost analysis, including licensing fees, free versions, and open-source alternatives, while considering the availability of academic or student licenses for resource-constrained users [57]. By systematically applying these parameters, researchers and practitioners can make informed decisions about selecting the most suitable simulation tool for their needs. Figure 1 visually illustrates the complete process of creating and simulating all-terrain vehicles. It emphasizes the incorporation of many software tools and processes, illustrating the contribution of each step to the ultimate design.

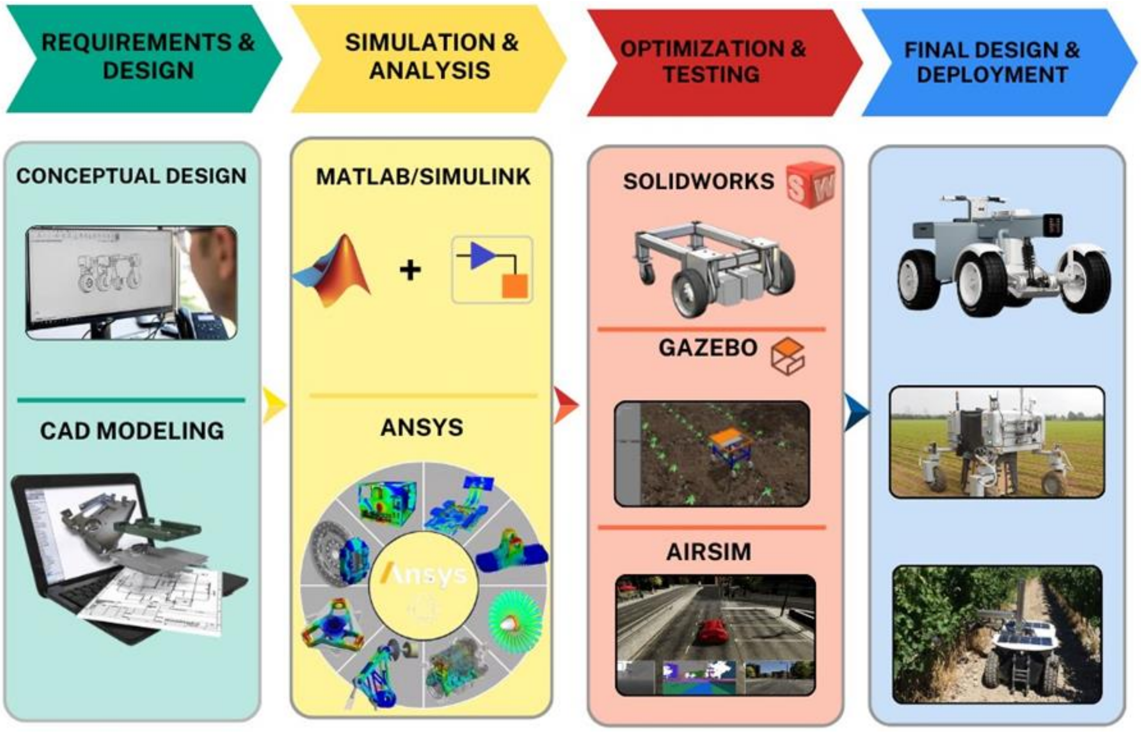


Figure 1 Workflow for simulation of all-terrain vehicles.

4.2 AI-Driven Design and Automation

Integrating AI and ML algorithms into the design and modeling process amplifies the capabilities of all-terrain vehicles and automated implements. AI and ML can be included in simulations to optimize design parameters, forecast performance results, and streamline decision-making procedures [58]. For example, artificial intelligence algorithms can examine simulation data to determine the best setups for car parts or control systems. At the same time, machine learning models can forecast maintenance requirements and adapt operational settings instantly. These technologies also enable adaptive learning, wherein the simulation environment constantly enhances itself by incorporating new data and performance feedback [59]. This AI-powered methodology allows for more streamlined and precise design procedures, making sophisticated automated systems more suitable for dynamic agricultural settings. Figure 2 illustrates the contribution of AI and ML in enhancing the simulation process. The article delineates the utilization of these technologies in scrutinizing data, modifying parameters, and improving design choices, resulting in simulations that are more proficient and impactful.

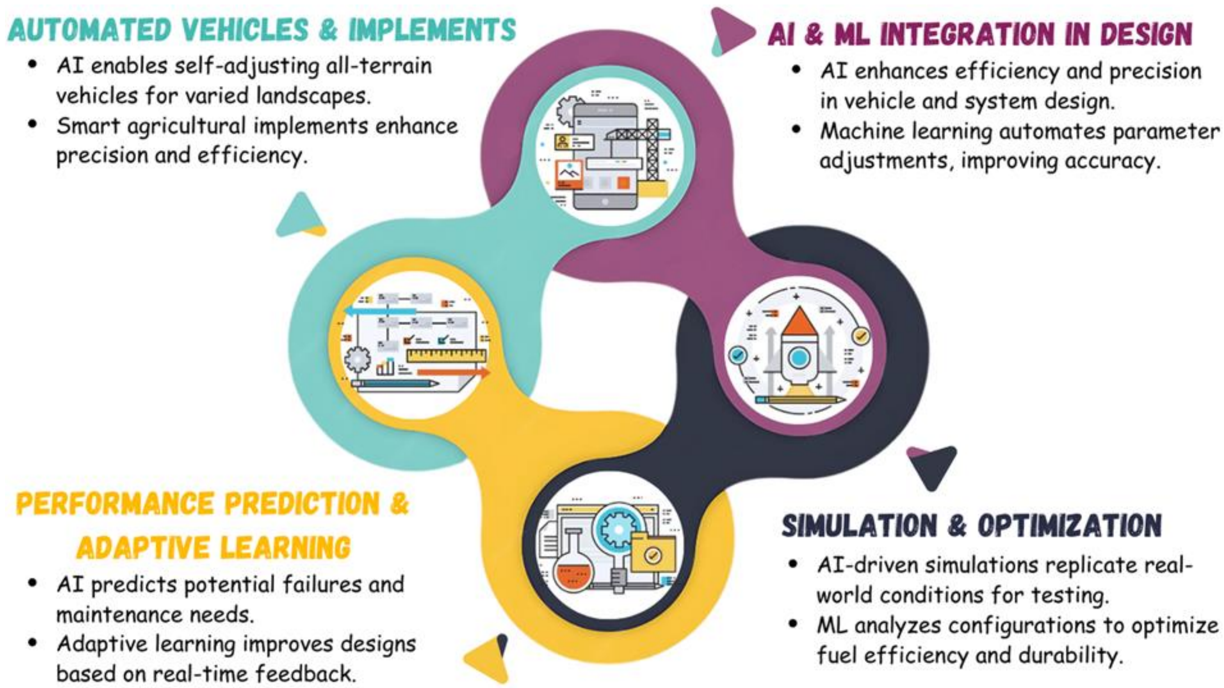


Figure 2 AI and ML integration in simulation.

4.3 All-Terrain Farm Vehicle Simulation

All-Terrain Farm vehicles with automation features to carry out precision agriculture activities are designed to function on various terrains, such as rocky, muddy, or sloping terrain. Numerous studies have been undertaken to examine the design and simulation of a prototype agricultural vehicle capable of operating in all types of terrain [60]. The design process commences by establishing the vehicle's functional prerequisites, including its ability to adapt to different terrains, its capacity to carry loads, and its operating effectiveness. SolidWorks is utilized for the creation of complex 3D models of the various parts of the vehicle. In contrast, MATLAB/Simulink is employed for the development and simulation of control systems for navigation and automation [61]. ANSYS offers structural analysis capabilities to verify the ability of the vehicle's structure and components to withstand the stresses experienced during operation [62]. AirSim and Gazebo are utilized for simulating the vehicle's performance in different types of terrain, enabling real-time evaluation of autonomous navigation algorithms and environmental interactions. The case study illustrates how incorporating these technologies leads to a resilient and effective design capable of fulfilling the requirements of contemporary agriculture. Figure 3 offers an elaborate depiction of the prototype of the all-terrain vehicle that was created using simulation. It also provides a detailed analysis of the design features and components, providing valuable information on how simulation tools are applied in the development process.

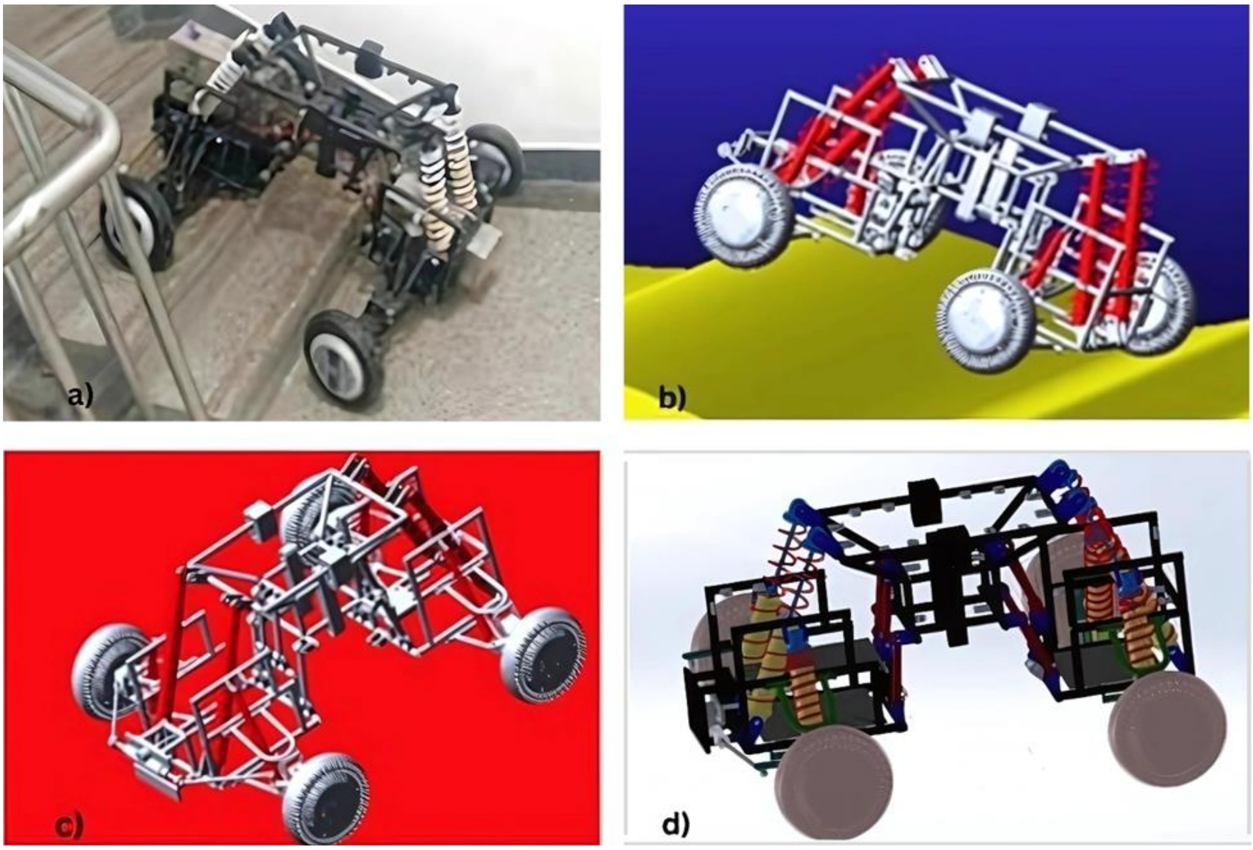


Figure 3 All-terrain vehicle design and simulation a) vehicle crossing beam test b) Animation simulation of obstacle crossing experiment c) The vehicle model imported into simulation d) Vehicle structure [63].

A different study centers on the design and simulation of a particular automated agricultural device, such as a precision sprayer or planter. The design process entails establishing the implementation specifications, such as application precision, capacity, and operational efficiency [64]. The implement's structure and components are modeled using SolidWorks, while control algorithms for accurate application and automation are developed and tested using MATLAB/Simulink. ANSYS is utilized to conduct structural and thermal analyses to verify the ability of the implement to endure operational conditions. AirSim and Gazebo offer a simulation environment to evaluate the performance of the implementation in several field conditions, such as interacting with crops and soil. This case study showcases the benefits of utilizing simulation software to enhance the design and performance of automated tools, illustrating enhancements in efficiency and accuracy through the utilization of advanced design and simulation methods [65]. The Valley Dairy Farm Automation project utilized SolidWorks to design and simulate a robotic milking system, significantly improving farm efficiency [63]. The software enabled precise modeling and testing of the system's components, while AI and automation were integrated to optimize the milking process, resulting in increased productivity and reduced labor costs. This case exemplifies the effectiveness of combining advanced design tools with automation in agricultural applications [66].

4.4 AI-Driven Autonomous Harvesting Systems

With advancements in precision agriculture, AI-driven autonomous harvesting systems are changing modern farming practices. These systems integrate AI, robotics, and simulation software to optimize harvesting efficiency while reducing human labor and crop losses. One notable example is autonomous combine harvesters, which leverage MATLAB/Simulink for control system modeling, AirSim for navigation simulation, and ANSYS for structural and fatigue analysis of mechanical components [67]. These tools enable the simulation of various environmental conditions, ensuring real-time adaptability to terrain variations and crop density. A case study explored AI-powered drones for real-time fruit-picking operations. The study integrated the Gazebo to train—AI models for obstacle detection and robotic arm movements [24]. Implementing reinforcement learning algorithms in MATLAB/Simulink allowed continuous adaptation, improving fruit-picking precision while minimizing damage. Similarly, it demonstrated how sensor fusion techniques enhance AI-driven harvesting efficiency by combining LiDAR, computer vision, and ML algorithms to optimize crop selection and picking strategies [68]. Another case study involved a robotic apple harvester using optimized picking patterns and an anthropomorphic picking pattern; success rates using two picking motions were 80.17% and 82.93%, respectively [69]. Machine learning models integrated with AI-based decision-making algorithms improved harvesting and reduced 31% post-harvest damage compared to conventional methods [70]. These studies emphasize integrating AI, simulation tools, and automation technologies in agricultural harvesting systems. By simulating real-world conditions, engineers can refine AI models, optimize mechanical designs, and improve harvesting precision before real-world deployment. The combination of MATLAB/Simulink, AirSim, Gazebo, and SolidWorks has proven highly effective in developing intelligent harvesting solutions, paving the way for more efficient and sustainable farm automation.

5. Results and Discussion

5.1 Comparative Results of Simulation Software

Upon conducting a comparative examination of simulation software, it becomes evident that each tool exhibits unique performance metrics, accuracy levels, and usability outcomes. MATLAB/Simulink is highly proficient in delivering comprehensive system-level simulations with exceptional precision and powerful control design capabilities [31]. However, it can be demanding regarding resources and challenging for certain users to navigate. SolidWorks has exceptional accuracy in 3D modeling and structural analysis, incorporating user-friendly features. However, its dynamic system simulation capabilities are less sophisticated than competing tools. ANSYS provides exceptional precision in structural and thermal simulations, while it requires significant computer resources and may present a steep learning curve for inexperienced users [43]. AirSim and Gazebo excel at mimicking the behavior of autonomous vehicles and their interactions with the environment. They provide realistic scenarios and allow for flexible testing. However, using them may need additional setup and integration work [71]. Integrating AI and machine learning algorithms in simulations has proven to significantly reduce fuel consumption and enhance navigation efficiency [72]. However, the software's difficult learning curve and high computational resource requirements have significant limits in practical agricultural contexts, particularly on small-scale or resource-constrained farms. Also, configuring simulations for complicated situations in

MATLAB/Simulink often requires considerable expertise, which is not always available to all practitioners [73]. These limitations focus on the requirement for more efficient processes or add-on tools, such as AirSim or Gazebo, which are more affordable and easier to use for simulating dynamic field conditions. In general, the selection of simulation software relies on the individual requirements of the design project, with each tool providing distinct advantages that can be utilized according to the design objectives and goals.

5.2 AI and ML Integration Impact

Incorporating AI and ML into the design and simulation process dramatically enhances the efficiency and efficacy of farm vehicles and implements development. AI algorithms improve the simulation process by offering sophisticated predictive skills, allowing for more precise performance predictions and optimization of design parameters [74]. Machine learning models enhance real-time decision-making and adaptive learning by utilizing simulation data and operational input, leading to ongoing improvement. This integration enables more accurate and automated design modifications, resulting in enhanced performance and decreased development time [75]. Simulating and testing AI-driven control systems in virtual environments speeds up the development of modern agricultural machinery, providing notable benefits in terms of operational efficiency and adaptability in dynamic farming situations. For example, MATLAB/Simulink uses reinforcement learning algorithms to optimize control systems, allowing for real-time changes to vehicle speed and route depending on sensor response [76]. Similarly, AirSim enables the training of neural networks for autonomous navigation by simulating complex, dynamic environments, such as fields with obstacles and uneven terrain [77]. These implementations typically involve data preprocessing pipelines, where raw sensor data is fed into AI models trained to predict outcomes, such as machinery performance or maintenance requirements. However, the study is unclear about the architectures that are used (e.g., gradient-boosted decision trees for predictive maintenance or convolutional neural networks for image-based decision-making) and the way they are incorporated into simulation workflow [78]. By offering insights into the operational challenges of these instruments and their applicability to various farming contexts, an in-depth investigation of these issues might significantly enhance the paper's contribution.

5.3 Practical Implications

The practical ramifications of employing sophisticated simulation software and integrating artificial intelligence/machine learning in precision agriculture are significant. Through the utilization of these technologies, farmers and agricultural engineers can create and install automated systems, such as versatile vehicles and precise tools, that improve production and sustainability [79]. Utilizing virtual environments to simulate and optimize machinery before accurate installation mitigates the potential for expensive errors and enhances the dependability of the equipment. In addition, AI-powered solutions offer practical analysis and automation features that simplify agricultural tasks, improve resource efficiency, and enhance crop supervision [80]. The tangible advantages encompass higher crop production, diminished ecological footprint, and improved operational effectiveness, thus promoting the general progress of precision agriculture methodologies.

During the design stage, model and optimize the structural elements and control systems of machinery using programs like ANSYS and MATLAB/Simulink [81]. Use AI/ML to optimize resources and make decisions in real-time. Collect and analyze field data by integrating IoT-enabled devices with simulation frameworks. For flexibility and cost savings, give open-source simulation tools like Gazebo and OpenModelica preference [82]. Sustainable farming results, decreased resource waste, and increased operational efficiency are all possible with this strategy. AirSim and Gazebo can simulate autonomous navigation in realistic field environments, allowing farmers to train AI models for obstacle detection and path planning before deploying vehicles in real-world conditions; ANSYS offers wear and tear analyses to ensure structural durability under varying field conditions; and MATLAB/Simulink can simulate real-time system dynamics, enabling precise calibration of autonomous vehicles for terrain adaptability [83-85]. AI algorithms combined with drones or sensors allow them to assess crop health and modify inputs in real-time, depending on data.

5.4 Challenges and Limitations

The report showcases notable progress in integrating simulation and AI/ML, but it also acknowledges various hurdles and limitations. An obstacle lies in the high computational intensity and intricate nature of specific simulation software, necessitating significant resources and knowledge for optimal utilization [86]. Various issues related to the integration of AI/ML algorithms, such as data quality, algorithm correctness, and compatibility with simulation tools, can impact the success of the design and automation process [87, 88]. Furthermore, simulation software may not consistently convey the complexity of real-world events despite its ability to depict complex environmental variables and interactions [89] accurately. To overcome these constraints, continuous research and development efforts are necessary to strengthen the precision of simulations, integrate artificial intelligence and machine learning more effectively, and ensure that the tools employed align with the practical requirements of precision agriculture.

5.5 Future Directions in Simulation and AI Integration

Integrating AI and simulation tools has helped agricultural automation, but several advancements are needed to enhance efficiency, real-time adaptability, and sustainability. One promising direction is the development of hybrid simulation environments, where real-world sensor data from IoT-enabled farm equipment is continuously fed into virtual models to refine AI-driven decision-making. As AirSim and Gazebo may simulate farm vehicle navigation, integrating LiDAR-based real-time field data may improve terrain adaptability and path optimization algorithms. Researchers have demonstrated that using sensor fusion techniques in AI-based simulation environments reduces navigation errors by 30% compared to static simulation models [90]. Another emerging approach is real-time AI-driven feedback systems, where reinforcement learning algorithms dynamically adjust simulation parameters based on live data. In a recent study, MATLAB/Simulink was integrated with IoT soil sensors to optimize irrigation schedules, leading to a 25% improvement in water efficiency [91]. Such frameworks may also enhance predictive maintenance models, where machine learning algorithms process real-time wear-and-tear data from farm machinery to anticipate failures before they occur.

Additionally, future AI-driven simulations should focus on multi-tool interoperability, where software like MATLAB, ANSYS, and AirSim seamlessly exchange data without manual preprocessing.

Current challenges include data standardization, as different tools use incompatible file formats (e.g., Simulink's. mdl vs. ANSYS's. cdb format), making integration cumbersome. Recent research suggests that cloud-based AI simulation frameworks might enable real-time model updates, reducing computation time by 40% compared to local simulation environments [92]. Another key advancement lies in AI-enhanced crop modeling, where machine-learning models predict crop health based on weather forecasts, soil quality, and past yield data. Recent deep-learning applications for disease detection in crop simulation environments have shown accuracy improvements of up to 92% compared to conventional rule-based models [76]. Combining AI-driven plant growth simulation with precision agriculture tools such as drone-based spectral imaging can significantly improve yield prediction accuracy. As AI and simulation tools evolve, future research should focus on developing standardized testing frameworks to validate AI-driven control systems for agricultural automation. This includes creating benchmark datasets for training AI models across various farm conditions, ensuring robust performance across geographical and environmental settings. By integrating real-world data with virtual simulation environments, the future of precision agriculture will see improved efficiency, cost-effectiveness, and sustainability.

6. Conclusion

This study provides a comprehensive comparison of simulation software and the integration of AI and ML in designing and automating agricultural tractors and all-terrain farm machinery. Key simulation tools, including MATLAB/Simulink, SolidWorks, ANSYS, AirSim, and Gazebo, were reviewed for their capabilities in predictive maintenance, real-time decision-making, and system optimization. The results show that MATLAB/Simulink is great for system-level modeling and integrating complex AI, while AirSim and Gazebo are great for simulating autonomous navigation under challenging environments. The study also talks about how to improve design features using different modeling tools and how to combine these processes. This will lead to more sustainable and effective agricultural automation systems. MATLAB/Simulink demonstrates exceptional precision in system-level simulations and comprehensive control design. SolidWorks, proficient in accurate 3D modeling and structural analysis, has limitations in dynamic simulations. ANSYS offers high accuracy in structural and thermal simulations but demands substantial computational resources. Meanwhile, AirSim and Gazebo effectively replicate the behavior of autonomous vehicles and their interactions with the environment, though they require additional configuration and integration. By allowing advanced prediction, instantaneous decision-making, and adaptive learning, AI and ML improve the simulation process. This leads to better designs and shorter development times.

In the future, researchers should work on making computers faster and easier for people to use, integrating AI and machine learning better in simulations, and finding new ways to test and confirm AI-driven control systems in different farming situations. Collaboration among software developers, agricultural engineers, and researchers will be essential in overcoming current challenges and driving technological advancements in precision agriculture. As simulation and AI technologies keep improving, they will have a significant effect on the future of precision agriculture by making it easier to design more accurate equipment, lowering the cost of development, and making systems more reliable.

Author Contributions

Mrutyunjay Padhiary: Writing-original draft, Writing- review & editing, Visualization, Resources, Methodology, Investigation, Conceptualization. Pankaj Roy: Writing- original draft, Writing- review & editing, Conceptualization, Supervision, Software, Resources. Kundan Kumar: Data curation, Formal analysis, Resources.

Competing Interests

The authors would like to state that there is no conflict of interest.

Data Availability Statement

This is a review article and the data has been collected from literature, Internet Articles, and Government official websites. All the citations are included in the reference section.

References

1. Shaikh TA, Mir WA, Rasool T, Sofi S. Machine learning for smart agriculture and precision farming: Towards making the fields talk. Arch Comput Methods Eng. 2022; 29: 4557-4597.
2. Debnath J, Kumar K, Roy K, Choudhary RD, PU AK. Precision agriculture: A review of AI vision and machine learning in soil, water, and conservation practice. Int J Res Appl Sci Eng Technol. 2024; 12: 2130-2141.
3. Padhiary M, Sethi LN, Kumar A. Enhancing hill farming efficiency using unmanned agricultural vehicles: A comprehensive review. Trans Indian Natl Acad Eng. 2024; 9: 253-268.
4. Foresti R, Rossi S, Magnani M, Bianco CG, Delmonte N. Smart society and artificial intelligence: Big data scheduling and the global standard method applied to smart maintenance. Engineering. 2020; 6: 835-846.
5. Padhiary M, Kumar R, Sethi LN. Navigating the future of agriculture: A comprehensive review of automatic all-terrain vehicles in precision farming. J Inst Eng India Ser A. 2024; 105: 767-782.
6. Zhang T, Liu H, Wang W, Wang X. Virtual tools for testing autonomous driving: A survey and benchmark of simulators, datasets, and competitions. Electronics. 2024; 13: 3486.
7. Jayapalan DF, Ananth JP. Root disease classification with hybrid optimization models in IoT. Expert Syst Appl. 2023; 226: 120150.
8. Sishodia RP, Ray RL, Singh SK. Applications of remote sensing in precision agriculture: A review. Remote Sens. 2020; 12: 3136.
9. Padhiary M, Kyndiah AK, Kumar R, Saha D. Exploration of electrode materials for in-situ soil fertilizer concentration measurement by electrochemical method. Int J Adv Biochem Res. 2024; 8: 539-544.
10. Hoque A, Padhiary M, Prasad G, Kumar K. Real-time data processing in agricultural robotics. In: Computer vision techniques for agricultural advancements. Hershey, PA: IGI Global Scientific Publishing; 2025. pp. 431-468.
11. Padhiary M, Saha D, Kumar R, Sethi LN, Kumar A. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. Smart Agric Technol. 2024; 8: 100483.

12. Wang B, Zhu J, Chai X, Liu B, Zhang G, Yao W. Research status and development trend of key technology of agricultural machinery chassis in hilly and mountainous areas. Comput Electron Agric. 2024; 226: 109447.
13. Padhiary M, Roy P, Dey P, Sahu B. Harnessing AI for automated decision-making in farm machinery and operations: Optimizing agriculture. In: Enhancing automated decision-making through AI. Hershey, PA: IGI Global Scientific Publishing; 2025. pp. 249-282.
14. Padhiary M, Kumar R. Enhancing agriculture through AI vision and machine learning: The evolution of smart farming. In: Advancements in intelligent process automation. Hershey, PA: IGI Global Scientific Publishing; 2025. pp. 295-324.
15. Kumar D, Kumar K, Roy P, Rabha G. Renewable energy in agriculture: Enhancing aquaculture and post-harvest technologies with solar and AI integration. Asian J Res Com Sci. 2024; 1: 201-219.
16. Panhwar QA, Ali A, Naher UA, Memon MY. Fertilizer management strategies for enhancing nutrient use efficiency and sustainable wheat production. In: Organic farming. Thorston, UK: Woodhead Publishing; 2019. pp. 17-39.
17. Mishra H, Mishra D. AI for data-driven decision-making in smart agriculture: From field to farm management. In: Artificial Intelligence Techniques in Smart Agriculture. Springer Singapore; 2024. pp. 173-193.
18. Abdullahi HS, Mahieddine F, Sheriff RE. Technology impact on agricultural productivity: A review of precision agriculture using unmanned aerial vehicles. Proceedings of the Wireless and Satellite Systems: 7th International Conference, WiSATS 2015; 2015 July 6-7; Bradford, UK. Cham: Springer International Publishing.
19. Zhu T, Ran Y, Zhou X, Wen Y. A survey of predictive maintenance: Systems, purposes and approaches. arXiv:1912.07383 [Internet]. arXiv; 2024. Available from: https://arxiv.org/abs/1912.07383.
20. Javaid M, Haleem A, Khan IH, Suman R. Understanding the potential applications of artificial intelligence in agriculture sector. Adv Agrochem. 2023; 2: 15-30.
21. Padhiary M, Kumar K, Hussain N, Roy D, Barbhuiya JA, Roy P. Artificial intelligence in farm management: Integrating smart systems for optimal agricultural practices. Int J Smart Agric. 2025; 3: 1-11.
22. Hassan IU, Panduru K, Walsh J. An in-depth study of vibration sensors for condition monitoring. Sensors. 2024; 24: 740.
23. Taseer A, Han X. Advancements in variable rate spraying for precise spray requirements in precision agriculture using unmanned aerial spraying systems: A review. Comput Electron Agric. 2024; 219: 108841.
24. Sai S, Garg A, Jhawar K, Chamola V, Sikdar B. A comprehensive survey on artificial intelligence for unmanned aerial vehicles. IEEE Open J Veh Technol. 2023; 4: 713-738.
25. Kabir MR, Ray S. Virtual prototyping for modern internet-of-things applications: A survey. IEEE Access. 2023; 11: 31384-31398.
26. Padhiary M, Tikute SV, Saha D, Barbhuiya JA, Sethi LN. Development of an IOT-based semi-autonomous vehicle sprayer. Agric Res. 2024; 14: 229-239.
27. Symeonidis C, Nikolaidis N. Simulation environments. In: Deep learning for robot perception and cognition. New York, NY: Academic Press; 2022. pp. 461-490.

28. Hung KY, Liu NW, Yang SC. A method for constructing synchronous electrical machine equivalent circuit models for motor-drive co-simulation. IEEE Trans Ind Appl. 2025. doi: 10.1109/TIA.2025.3531828.
29. Nazar M, Alam MM, Yafi E, Su'ud MM. A systematic review of human-computer interaction and explainable artificial intelligence in healthcare with artificial intelligence techniques. IEEE Access. 2021; 9: 153316-153348.
30. Adeyeye OJ, Akanbi I. Artificial intelligence for systems engineering complexity: A review on the use of AI and machine learning algorithms. Comput Sci IT Res J. 2024; 5: 787-808.
31. Sharma R, Vashisht V, Singh U. Modelling and simulation frameworks for wireless sensor networks: A comparative study. IET Wirel Sens Syst. 2020; 10: 181-197.
32. Liang C. Application and prospect of analysis of structures based on finite element method. Highlights Sci Eng Technol. 2022; 28: 53-60.
33. Wang W, Yang W, Dinavahi V. Co-simulation interfacing capabilities in device-level power electronic circuit simulation tools: An overview. Int J Power Electron Drive Syst. 2015; 6: 665-682.
34. Hunde BR, Woldeyohannes AD. Future prospects of computer-aided design (CAD)-A review from the perspective of artificial intelligence (AI), extended reality, and 3D printing. Results Eng. 2022; 14: 100478.
35. Rosique F, Navarro PJ, Fernández C, Padilla A. A systematic review of perception system and simulators for autonomous vehicles research. Sensors. 2019; 19: 648.
36. Ghobadpour A, Cardenas A, Monsalve G, Mousazadeh H. Optimal design of energy sources for a photovoltaic/fuel cell extended-range agricultural mobile robot. Robotics. 2023; 12: 13.
37. Benotsmane R, Dudás L, Kovács G. Simulation and trajectory optimization of collaborating robots by application of solidworks and matlab software in industry 4.0. Acad J Manuf Eng. 2020; 18: 191-197.
38. Poojari M, Hanumanthappa H, Prasad CD, Jathanna HM, Ksheerasagar AR, Shetty P, et al. Computational modelling for the manufacturing of solar-powered multifunctional agricultural robot. Int J Interact Des Manuf. 2024; 18: 5725-5736.
39. Hentati AI, Krichen L, Fourati M, Fourati LC. Simulation tools, environments and frameworks for UAV systems performance analysis. Proceedings of the 2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC); 2018 June 25-29; Limassol, Cyprus. Piscataway, NJ: IEEE.
40. Ivanovic A, Polic M, Tabak J, Orsag M. Render-in-the-loop aerial robotics simulator: Case study on yield estimation in indoor agriculture. Proceedings of the 2022 International Conference on Unmanned Aircraft Systems (ICUAS); 2022 June 21-24; Dubrovnik, Croatia. Piscataway, NJ: IEEE.
41. Mourched B, Ferko N, Abdallah M, Neji B, Vrtagic S. Study and design of a machine learning-enabled laser-based sensor for pure and sea water determination using COMSOL multiphysics. Appl Sci. 2022; 12: 6693.
42. Kumar P, Ashok G. Design and fabrication of smart seed sowing robot. Mater Today Proc. 2021; 39: 354-358.
43. Katyara S, Ficuciello F, Caldwell DG, Chen F, Siciliano B. Reproducible pruning system on dynamic natural plants for field agricultural robots. Proceedings of the 13th International Workshop on Human-Friendly Robotics (HFR 2020); 2020 October 1-2; Innsbruck, Austria. Cham: Springer International Publishing.

44. Buse F, Lichtenheldt R, Krenn R. SCM - A novel approach for soil deformation in a modular soil contact model for multibody simulation. Proceedings of the 4th Joint International Conference on Multibody System Dynamics; 2016 May 29-June 2; Montreal, Canada. Berlin, Germany: ResearchGate.
45. Danilov I, Šaponjić Đ, Bojović B. Implantation of mixed reality tools in design enhancement application. Art Sci Appl Exper Vision. 2022; 2: 246-261.
46. Li Y, Dai S, Shi Y, Zhao L, Ding M. Navigation simulation of a Mecanum wheel mobile robot based on an improved A* algorithm in Unity3D. Sensors. 2019; 19: 2976.
47. Ribeiro JP, Gaspar PD, Soares VN, Caldeira JM. Computational simulation of an agricultural robotic rover for weed control and fallen fruit collection-algorithms for image detection and recognition and systems control, regulation, and command. Electronics. 2022; 11: 790.
48. Rana S, Deepu MP, Sivanantham S, Sivasankaran K. Face detection system using FPGA. Proceedings of the 2015 Online International Conference on Green Engineering and Technologies (IC-GET); 2015 November 27; Coimbatore, India. Piscataway, NJ: IEEE.
49. Yudha HM, Dewi T, Risma P, Oktarina Y. Arm robot manipulator design and control for trajectory tracking; A review. Proceedings of the 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI); 2018 October 16-18; Malang, Indonesia. Piscataway, NJ: IEEE.
50. Jha KA. AutoAgri: A comprehensive research on automation and artificial intelligence in agriculture. San Francisco, CA: San Francisco State University; 2021.
51. Zhou HR, Yang H, Li HQ, Ma YC, Yu S, Shi J, et al. Advancements in machine learning for material design and process optimization in the field of additive manufacturing. China Foundry. 2024; 21: 101-115.
52. Etezadi H, Eshkabilov S. A comprehensive overview of control algorithms, sensors, actuators, and communication tools of autonomous all-terrain vehicles in agriculture. Agriculture. 2024; 14: 163.
53. Gietelink O, Ploeg J, De Schutter B, Verhaegen M. Development of advanced driver assistance systems with vehicle hardware-in-the-loop simulations. Veh Syst Dyn. 2006; 44: 569-590.
54. Jiang W, Han H, He M, Gu W. Network simulation tools for unmanned aerial vehicle communications: A survey. Int J Commun Syst. 2024; 37: e5878.
55. Schizas N, Karras A, Karras C, Sioutas S. TinyML for ultra-low power AI and large scale IoT deployments: A systematic review. Future Internet. 2022; 14: 363.
56. Padhiary M. The convergence of deep learning, IoT, sensors, and farm machinery in agriculture. In: Designing sustainable internet of things solutions for smart industries. Hershey, PA: IGI Global Scientific Publishing; 2025. pp. 109-142.
57. Agbeyangi A, Suleman H. Advances and challenges in low-resource-environment software systems: A Survey. Informatics. 2024; 11: 90.
58. Di Stefano AG, Ruta M, Masera G. Advanced digital tools for data-informed and performance-driven design: A review of building energy consumption forecasting models based on machine learning. Appl Sci. 2023; 13: 12981.
59. Padhiary M, Rani N, Saha D, Barbhuiya JA, Sethi LN. Efficient precision agriculture with python-based raspberry pi image processing for real-time plant target identification. Int J Res Anal Rev. 2023; 10: 539-545.

60. Ospina R, Noguchi N. Real-time work progress estimation based on GIS remote monitoring system for agricultural robot vehicles. Comput Electron Agric. 2025; 234: 110313.
61. Padhiary M, Roy P. Advancements in precision agriculture: Exploring the role of 3D printing in designing all-terrain vehicles for farming applications. Int J Sci Res. 2024; 13: 861-868.
62. Paul S, Roy P, Chatterjee A, Pandit P, Mukherjee R, Ghosh M. Design and analysis of automotive vehicle components with composite materials using Ansys 18.1. J Inst Eng India Ser D. 2024; 105: 1537-1550.
63. Wang Z, Zhao J, Zeng G. Modeling, simulation and implementation of all terrain adaptive five DOF robot. Sensors. 2022; 22: 6991.
64. Saha D, Padhiary M, Barbhuiya JA, Chakrabarty T, Sethi LN. Development of an IOT based solenoid controlled pressure regulation system for precision sprayer. Int J Res Appl Sci Eng Technol. 2023; 11: 2210-2216.
65. Kamel E, Memari AM. Review of BIM's application in energy simulation: Tools, issues, and solutions. Autom Constr. 2019; 97: 164-180.
66. Gargiulo JI, Lyons NA, Clark CE, Garcia SC. The AMS integrated management model: A decision-support system for automatic milking systems. Comput Electron Agric. 2022; 196: 106904.
67. Ramasamy MN, Slíva A, Govindaraj P, Nag A. Topology optimization and testing of connecting rod based on static and dynamic analyses. Appl Sci. 2025; 15: 2081.
68. Kargar SM, Yordanov B, Harvey C, Asadipour A. Emerging trends in realistic robotic simulations: A comprehensive systematic literature review. IEEE Access. 2024; 12: 191264-191287.
69. Bu L, Chen C, Hu G, Sugirbay A, Sun H, Chen J. Design and evaluation of a robotic apple harvester using optimized picking patterns. Comput Electron Agric. 2022; 198: 107092.
70. Mohyuddin G, Khan MA, Haseeb A, Mahpara S, Waseem M, Saleh AM. Evaluation of machine learning approaches for precision farming in smart agriculture system-a comprehensive review. IEEE Access. 2024; 12: 60155-60184.
71. Kang J, Han W, Kim S, Jun J. Comprehensive analysis of design and performance evaluation methodologies for a high-resolution read-out IC with ultralow 1/f corner for DC measurement applications. IEEE Trans Instrum Meas. 2025; 74: 2003914.
72. Peng T, Yang X, Xu Z, Liang Y. Constructing an environmental friendly low-carbon-emission intelligent transportation system based on big data and machine learning methods. Sustainability. 2020; 12: 8118.
73. Boll A, Brokhausen F, Amorim T, Kehrer T, Vogelsang A. Characteristics, potentials, and limitations of open-source Simulink projects for empirical research. Softw Syst Model. 2021; 20: 2111-2130.
74. Jenis J, Ondriga J, Hrcek S, Brumercik F, Cuchor M, Sadovsky E. Engineering applications of artificial intelligence in mechanical design and optimization. Machines. 2023; 11: 577.
75. Javaid M, Haleem A, Singh RP, Suman R. Enhancing smart farming through the applications of agriculture 4.0 technologies. Int J Intell Netw. 2022; 3: 150-164.
76. Maheedhar M, Deepa T. A behavioral study of different controllers and algorithms in real-time applications. IETE J Res. 2024; 70: 1657-1681.
77. Chan JH, Liu K, Chen Y, Sagar AS, Kim YG. Reinforcement learning-based drone simulators: Survey, practice, and challenge. Artif Intell Rev. 2024; 57: 281.
78. Guo K, Wu M, Soo Z, Yang Y, Zhang Y, Zhang Q, et al. Artificial intelligence-driven biomedical genomics. Knowl Based Syst. 2023; 279: 110937.

79. Hati AJ, Singh RR. Smart indoor farms: Leveraging technological advancements to power a sustainable agricultural revolution. AgriEngineering. 2021; 3: 728-767.
80. Subeesh A, Mehta CR. Automation and digitization of agriculture using artificial intelligence and internet of things. Artif Intell Agric. 2021; 5: 278-291.
81. Mersha TK, Du C. Co-simulation and modeling of PMSM based on ANSYS software and Simulink for EVs. World Electr Veh J. 2021; 13: 4.
82. Platt J, Ricks K. Comparative analysis of ros-unity3d and Ros-gazebo for mobile ground robot simulation. J Intell Robot Syst. 2022; 106: 80.
83. Saraf V, Patil DD. Advancing smart autonomous systems: Simulation and testing platforms. Proceedings of the 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS); 2024 December 17-18; Bengaluru, India. Piscataway, NJ: IEEE.
84. Singh V, Rooprai RS, Kunal G, Vishnoi M, Bansal A, Singla AK, et al. Finite element analysis driven study on SS316 cladding of mild steel for enhanced durability in agricultural tools. Int J Interact Des Manuf. 2024. doi: 10.1007/s12008-024-02192-4.
85. Horri N, Pietraszko M. A tutorial and review on flight control co-simulation using matlab/Simulink and flight simulators. Automation. 2022; 3: 486-510.
86. Chen M, Voinov A, Ames DP, Kettner AJ, Goodall JL, Jakeman AJ, et al. Position paper: Open web-distributed integrated geographic modelling and simulation to enable broader participation and applications. Earth Sci Rev. 2020; 207: 103223.
87. Padhiary M. Status of farm automation, advances, trends, and scope in India. Int J Sci Res. 2024; 13: 737-745.
88. Rabha G, Kumar K, Kumar D, Kumar D. A comprehensive review of integrating AI and IoT in farm machinery: Advancements, applications, and sustainability. Int J Res Anal Rev. 2024; 11: 62-78.
89. Pianosi F, Beven K, Freer J, Hall JW, Rougier J, Stephenson DB, et al. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environ Model Softw. 2016; 79: 214-232.
90. Ušinskis V, Nowicki M, Dzedzickis A, Bučinskas V. Sensor-fusion based navigation for autonomous mobile robot. Sensors. 2025; 25: 1248.
91. Kaur C, Sharma A. Enhancing predictive maintenance with ai: applications and impact. Proceedings of the 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI). 2025 January 07-08; Goathgaun, Nepal. Piscataway, NJ: IEEE.
92. Velu S, Gill SS, Murugesan SS, Wu H, Li X. CloudAIBus: A testbed for AI based cloud computing environments. Cluster Comput. 2024; 27: 11953-11981.