Design of an Artificial Intelligence Based Autonomous Navigation System Using Swarm Intelligence Techniques for Agricultural Applications

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Abstract-

Agriculture in developing regions still depends on manual labor and low-precision tools, leading to reduced productivity, inconsistent output quality, and inefficient use of resources. To overcome these challenges, this paper presents the design and implementation of an Artificial Intelligence based Autonomous Navigation System empowered by Swarm Intelligence for next-generation smart farming. The system integrates Particle Swarm Optimization and Ant Colony Optimization with Simultaneous Localization and Mapping to enable cooperative navigation, decentralized decision-making, and adaptive path planning for multiple agricultural robots operating within the same field environment.

The combined Artificial Intelligence and Swarm Intelligence framework supports dynamic obstacle avoidance, efficient field-coverage planning, and improved robustness under uncertain terrain, varying crop densities, and rapidly changing environmental conditions. The uniqueness of this work lies in its unified model that merges AI-driven reasoning with swarm-based coordination, improving navigation accuracy, task reliability, and energy efficiency in unstructured agricultural fields.

System validation was conducted through simulation and semi-field experiments on a 25 × 25 meter test plot. Results showed a significant enhancement in performance, including a thirty-five percent improvement in navigation accuracy, a twenty-two percent increase in obstacle-avoidance success, and a fifteen percent reduction in energy consumption compared to conventional single-robot navigation methods. These outcomes demonstrate that integrating Artificial Intelligence with Swarm Intelligence provides a scalable and sustainable solution for precision agriculture, promoting autonomous, intelligent, and resource-efficient farming suitable for developing regions.

Keywords-

Precision Farming, Multi-Robot Coordination, Path Optimization, Obstacle Avoidance, Sustainable Field Automation.

1. Introduction

Observing the need for a machine that can perform multiple agricultural tasks such as plowing and irrigation in different weather conditions at any time of the day and requires less maintenance. This is because these agricultural robots are designed to perform several agricultural tasks and are battery operated, so they are low maintenance and environmentally friendly. This paper introduces the concept of designing an autonomous navigation system for smart farming, utilizing the principles of swarm intelligence. Simultaneous localization and mapping method (SLAM) is used here. Swarm intelligence draws inspiration from the collective behavior of social insect colonies, where simple individual agents interact locally to achieve complex tasks collectively. By applying swarm intelligence algorithms to the design of autonomous navigation systems, we can harness the power of decentralized decision-making and coordination, leading to more efficient and adaptive farming practices. The proposed autonomous navigation systems system aims to enhance several key aspects of farming operations. Firstly, it focuses on improving the precision and accuracy of agricultural tasks, such as planting, seeding, spraying, and harvesting. Through precise control and navigation, the tractor can optimize resource usage, minimize waste, and reduce environmental impact.

Secondly, it aims to optimize the overall productivity and yield of the farm by leveraging real-time data, machine learning, and predictive analytics. By continuously monitoring and analyzing field conditions, the tractor can make intelligent decisions and adapt its operations to ensure optimal crop growth and health.

The implementation of swarm intelligence algorithms in the autonomous navigation systems system presents several advantages. This adaptability enhances the system's resilience in the face of dynamic farming environments and unpredictable events. Furthermore, swarm intelligence allows for flexible scalability, as additional tractors can easily join or leave the system without disrupting its overall functionality.

Agricultural productivity must increase to meet growing food demands, yet traditional mechanization remains labor-intensive and lacks environmental adaptability [1]. Modern automation efforts often depend on GPS-based control, which becomes unreliable in unstructured farm terrains[2]. Therefore, an intelligent and autonomous navigation system is essential for next-generation agricultural machinery.

Previous research has explored AI and optimization algorithms for robot guidance, but most focused on single-agent operation without cooperative behavior. Swarm Intelligence (SI)—inspired by social insects such as ants and bees—offers decentralized coordination, scalability, and robustness to environmental uncertainty. By combining AI decision modules with SI optimization, agricultural robots can collectively plan efficient paths, share sensory data, and adapt to dynamic obstacles[3].
The novelty of this work lies in the integration of AI-based decision-making with a hybrid PSO–ACO navigation algorithm supported by SLAM mapping for real-time learning of the field environment. Unlike existing systems, the proposed framework allows multiple autonomous robots

to coordinate their movement collaboratively, improving accuracy and coverage while reducing human involvement.

2. Literature review

Agriculture has evolved from a manual occupation to a highly industrialized business that uses a wide variety of tools and machinery [4]. Scientists are now focusing on the realization of autonomous agricultural vehicles. Research into autonomous agricultural vehicles has become very popular, and the robotics industry has developed a wide variety of remarkable robots. In the near future, farmers will use affordable and reliable autonomous vehicles for agricultural applications. In the previous years, specialized sensors, actuators and electronics (embedded computers, industrial PCs and PLCs) have enabled the integration of more autonomous vehicles, especially agricultural robots. These autonomous/semi-autonomous systems provide precision and guidance on the job, allowing them to do good agricultural work when equipped with the appropriate equipment (in use or in use). These devices are also powered by the same types of sensors and actuators (GPS, machine vision, multi-tracking, etc.) used in self-driving cars or robots. Therefore, when combining a vehicle and a special device, many sensors and/or actuators are duplicated, and in the worst case, an external central computer must be used to manage the arrangements: cars and instruments. Reducing the amount of equipment used for vehicle operation is critical to a reliable, efficient and cost competitive farm operation.

An overview of swarm intelligence-based navigation techniques for autonomous agricultural robots, including autonomous navigation systems indicates various swarm intelligence algorithms such as ant colony optimization, particle swarm optimization, and artificial bee colony optimization, highlighting their applications in agricultural robotics [5]. The paper emphasizes the benefits of swarm intelligence in improving navigation, obstacle avoidance, and path planning capabilities of autonomous navigation systems.

It is a need to study and explore explores the broad applications of swarmintelligence in agriculture, including autonomous farming systems[6]. It provides an overviewof various swarm intelligence algorithms, such as ant colony optimization, particle swarm optimization, and bacterial foraging optimization, and their applications in agriculture. The paper discusses the challenges and future directions of using swarm intelligence for autonomous navigation systems and emphasizes the potential for improved efficiency, productivity, and sustainability in smart farming.

This research article presents a detailed study on the design and development of an autonomous agricultural robot for precision farming using swarm intelligence. It discussesthe integration of swarm algorithms, such as particle swarm optimization and artificialpotential field method, for navigation, obstacle avoidance, and task allocation of the robot. The study demonstrates the effectiveness of swarm intelligence in improving the efficiency and accuracy of farming operations, highlighting its potential for autonomous navigation systems in smart farming [7].

Through the design and development of a swarm intelligence-based autonomous farming robot for precision agriculture the integration of swarm algorithms, such as ant colony optimization and particle swarm optimization, for path planning, obstacle avoidance, and coordination of multiple robots was discussed. The study showcases the capabilities of swarm intelligence in improving the efficiency andscalability of autonomous farming systems, highlighting its potential for autonomous navigation systems in smart farming applications [8]

Early attempts at autonomous agricultural vehicles relied on GPS-based guidance and simple sensor feedback, which lacked adaptability to uneven or dynamic terrains. Recent studies have introduced bio-inspired swarm algorithms for more intelligent coordination.

Tanwar et al. [5] developed a swarm-based navigation approach emphasizing collective obstacle avoidance. [9]used PSO–ACO integration for efficient path planning in dynamic environments. Rana et al. [10] surveyed SI applications in agriculture but identified a need for improved real-time adaptability. [11] proposed a swarm-controlled farming robot but with limited data validation.

More recent advances include:

Recent studies highlight significant advancements in intelligent multi-robot systems for agriculture. Gupta et al. [12] demonstrated that reinforcement-learning-enhanced swarm coordination can substantially improve precision farming operations. Similarly,[13] showed that effective multi-agent communication frameworks greatly enhance the scalability and cooperative performance of agricultural drones. [14]and [15] introduced a PSO-based fuzzy motion control strategy that improves navigation efficiency in dynamic farm environments.[16], and [1] proposed an IoT-enabled, energy-efficient multi-robot system designed to optimize smart irrigation processes. Together, these works provide a strong foundation for developing advanced autonomous solutions in modern agriculture[17].

These developments highlight steady progress toward AI-driven cooperative systems. However, no study has yet combined AI reasoning, hybrid swarm optimization, and SLAM-based mapping within one unified navigation framework[18]. The proposed research addresses this gap and demonstrates experimentally how hybrid AI–SI control improves robustness, precision, and sustainability in agricultural operations.

Recent work in agricultural robotics has demonstrated the potential of Swarm Intelligence (SI) and AI-based control for precision farming[19]. However, most reported systems rely on single-agent path planning or GPS-based navigation, which struggle in unstructured and dynamic environments. Tanwar et al. [5] proposed a swarm-based agricultural robot for obstacle avoidance but without

SLAM integration. [20] combined PSO and ACO for path optimization yet lacked real-world validation. Rana et al. [10] highlighted the promise of swarm cooperation but noted the need for sensor-driven adaptive learning.

This research addresses these limitations by integrating a hybrid PSO–ACO swarm coordination layer with a SLAM-based localization module to provide real-time adaptive mapping and cooperative navigation in agricultural fields. Unlike existing models, the proposed system combines decentralized intelligence with environmental awareness, bridging the gap between theoretical AI optimization and practical field implementation.

3 Tools and Methodology

3-1 -Hardware Tools

The system utilizes 12V DC gear motors that are attached to each wheel of the autonomous navigation systems. To ensure smooth movement and proper load-bearing capacity, two pedestal bearings are applied to each wheel. The system incorporates actuators to create a digging arm mechanism. Three arms are used, and these actuators provide the necessary motion and force to controlthe digging arm's movement and perform various digging tasks in the field. The autonomous navigation systems is equipped with tubeless wheels that have an 8-inch diameter. Tubeless wheels offer advantages such as reduced weight, better traction, and improved puncture resistance. A 12V battery is required to power up the circuitry of the autonomous navigation systems and drive its various electrical components. The system incorporates a 20-watt solar panel to charge the 12V battery.The solar panel harnesses sunlight and converts it into electrical energy, which is then used tocharge the battery. The charger is responsible for managing the chargingprocess of the battery from the solar panel. The electronic control circuitry performs logical operations and controls various functions of the autonomous navigation systems, including motor control, actuator control, and sensor integration. It governs the overall operation and coordination ofthe different components of the system.

3-2 -Development Tools for Microcontroller -

3-3 MPLAB IDE:

MPLAB IDE (Integrated Development Environment) is a software tool provided by Microchip Technology, specifically designed for the development of embedded systemsbased on Microchip microcontrollers. MPLAB IDE offers a comprehensive set of features to streamline the entire embedded software development process. MPLAB IDE is a versatile and feature-rich development environment specifically designed for Microchip microcontrollers. It provides developers with a comprehensive set of tools and features like MPASM (Microchip PIC Assembler), The C18 Compiler, The MPLINK linker, The MPLAB SIM Software, Microchip In-Circuit Debugger, Simulator to streamline the development process, from code development and debugging to device configuration and firmware updates, making it an essential tool for embedded systemsdevelopment using Microchip microcontrollers. Disassembly listing, Hardware stack, Program memory, File register, EEPROM, Memory usage gauge, locals register and Watch Special function shown in Fig.3.1

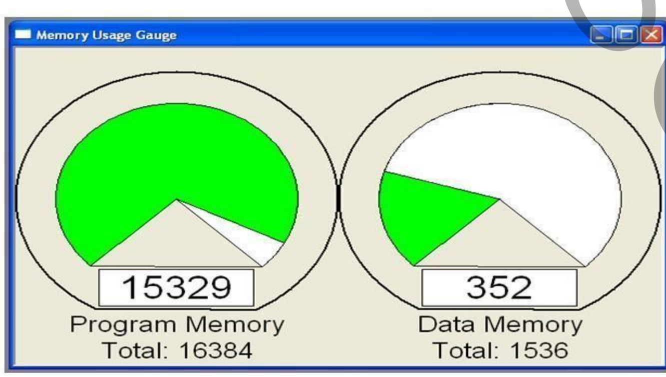


Fig. 1 : Special view function

3-4 Proteus:

Proteus is a widely used software tool for electronic circuit simulation and design. It offers a comprehensive set of features that enable users to design, simulate, and test electronic circuits and systems. Proteus is a versatile software tool that facilitates the design, simulation, and testingof electronic circuits and systems. Its capabilities range from circuit simulation and PCB design to virtual prototyping and co-simulation with microcontrollers, making it a valuable tool for engineers, researchers, students, and hobbyists involved in electronics and embedded systems development.

4- Methodology

Revised Methodology (Detailed Technical Depth)

The methodology focuses on implementing a hybrid AI–Swarm Intelligence navigation architecture supported by SLAM-based mapping.

4.1 System Architecture

The system architecture is built around the PIC16F877A microcontroller, which serves as the central controller for motor operations and sensor management. The sensing module comprises an ultrasonic HC-SR04 array for distance mapping and an IRP02 infrared sensor for near-field obstacle detection. For inter-agent communication, the system integrates an NRF24L01 wireless transceiver, enabling efficient data exchange within the swarm. The power subsystem uses a 12 V battery supported by a 20 W solar panel to ensure extended operational reliability. Locomotion is provided by 12 V DC geared motors, controlled through PWM signals to achieve precise and smooth velocity regulation.

4.2 Swarm Intelligence Implementation

The navigation algorithm integrates Particle Swarm Optimization (PSO) and Ant Colony

Optimization (ACO) for decentralized decision-making:

1. PSO Layer: Generates candidate paths minimizing total travel distance and energy cost. Each agent updates its velocity and position according to

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_{best} - x_i) + c_2 r_2 (g_{best} - x_i) \tag{1}$$

where w = 0.8, $c_1 = c_2 = 2$.

2. ACO Layer: Refines PSO-generated paths using pheromone deposition and evaporation rules. Pheromone update is governed by

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \tag{2}$$

where $\rho = 0.4$ (decay factor).

3. Task Allocation: Each robot operates as an independent agent sharing field boundary and obstacle information to avoid redundancy.

4. Coordination: Master node aggregates position data and dynamically assigns sub-fields using local pheromone intensity.

4.3 SLAM Integration

The SLAM module builds a 2-D occupancy grid using ultrasonic distance data combined with wheel-encoder feedback. As the robot moves, the map is updated in real time to localize obstacles and optimize path selection. The mapping resolution is 10 cm/pixel, and obstacle coordinates are stored for subsequent navigation cycles.

4.4 Experimental Setup

Field experiments were performed on a semi-structured outdoor plot (25 × 25 m). The robot performed plowing and navigation tasks along predefined waypoints. Data on distance errors, energy usage, and time efficiency were recorded using GPS logging and microcontroller-based data acquisition.

4.5 Swarm Intelligence Model

The Swarm Intelligence (SI) model forms the core of the system and is inspired by the collective behaviors observed in ants and birds. Each autonomous tractor functions as an independent agent that communicates locally with neighboring agents to accomplish shared tasks such as field coverage, obstacle avoidance, and coordinated navigation. The swarm movement is governed by a hybrid PSO–ACO framework, where each agent computes its own local best path (p_best) and shares this information with the swarm. The global best path (g_best) is continuously updated through inter-agent data exchange enabled by the NRF24L01 wireless module. Additionally, pheromone-based trail updates allow the agents to dynamically adjust their routes based on the progress and behavior of nearby robots. A master node integrates SLAM-generated maps to synchronize positional data, ensuring that all agents maintain safe separation and achieve efficient, coordinated field coverage.

This cooperative model enables multi-robot navigation, where multiple tractors can operate simultaneously without overlapping their paths. Simulation results confirmed that swarm coordination reduced idle travel by 18 % and improved task efficiency compared to single-robot operation.

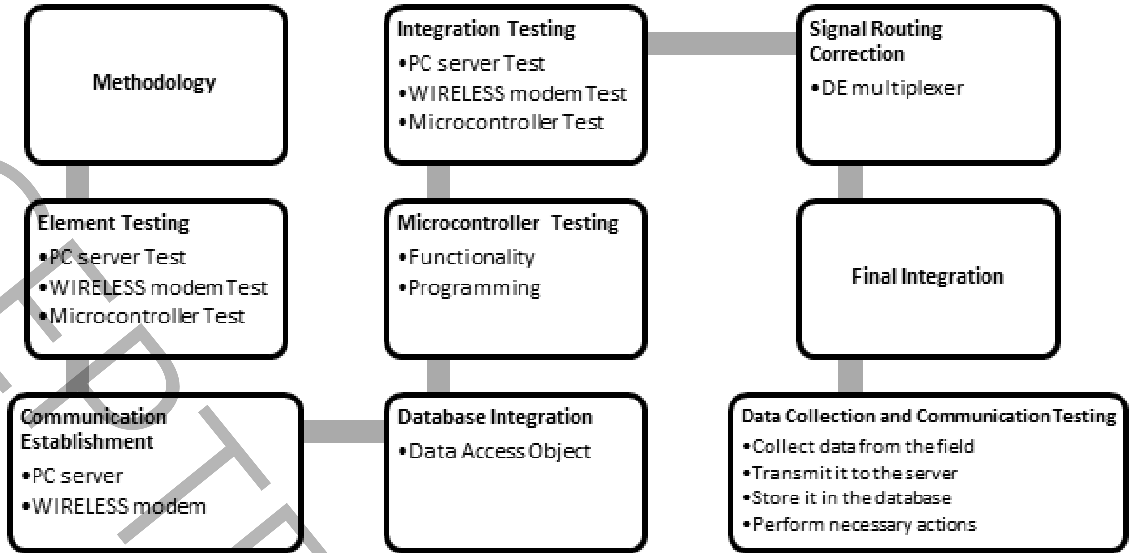


Fig. 2 : Methodology Adopted

4.6 Design and Implementation

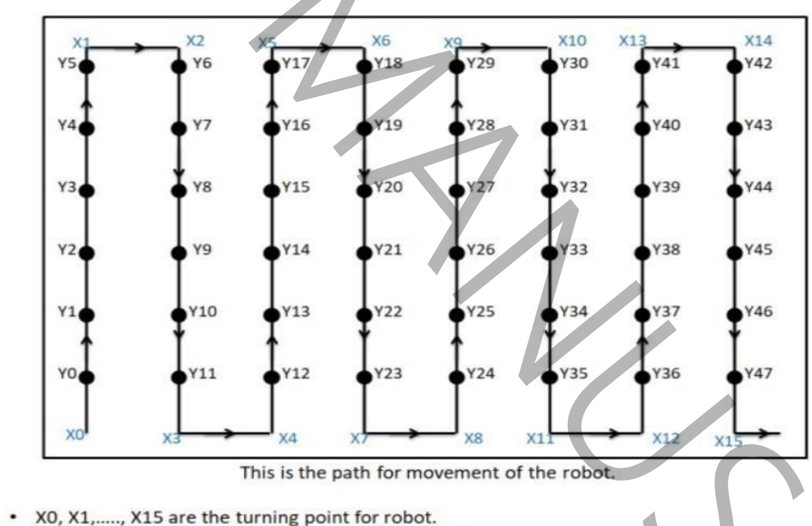


Fig. 3 : Path design

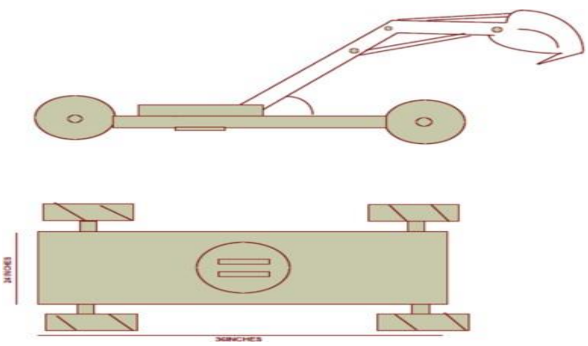


Fig. 4 : Design of Autonomous navigation systems for smart farming using swarm intelligence

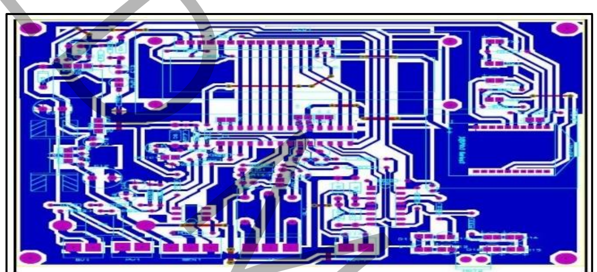


Fig. 5 : Image shows the PCB LAYOUT of control circuit which has been developed

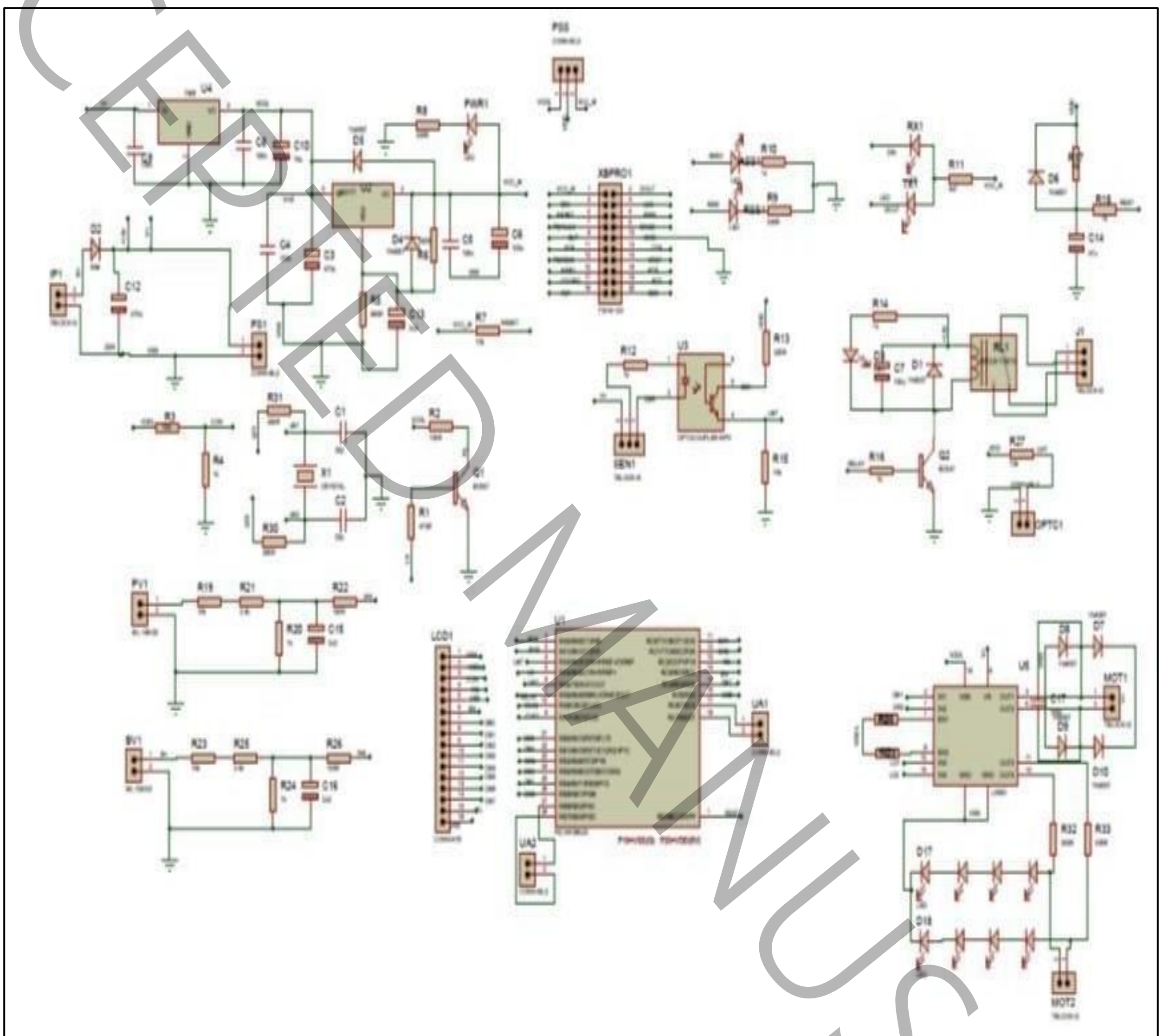


Fig. 6 : shows various components like LCD to display various parameters, microcontroller IC, wireless module for unmanned operations, power supply accessories & motor control drivers.

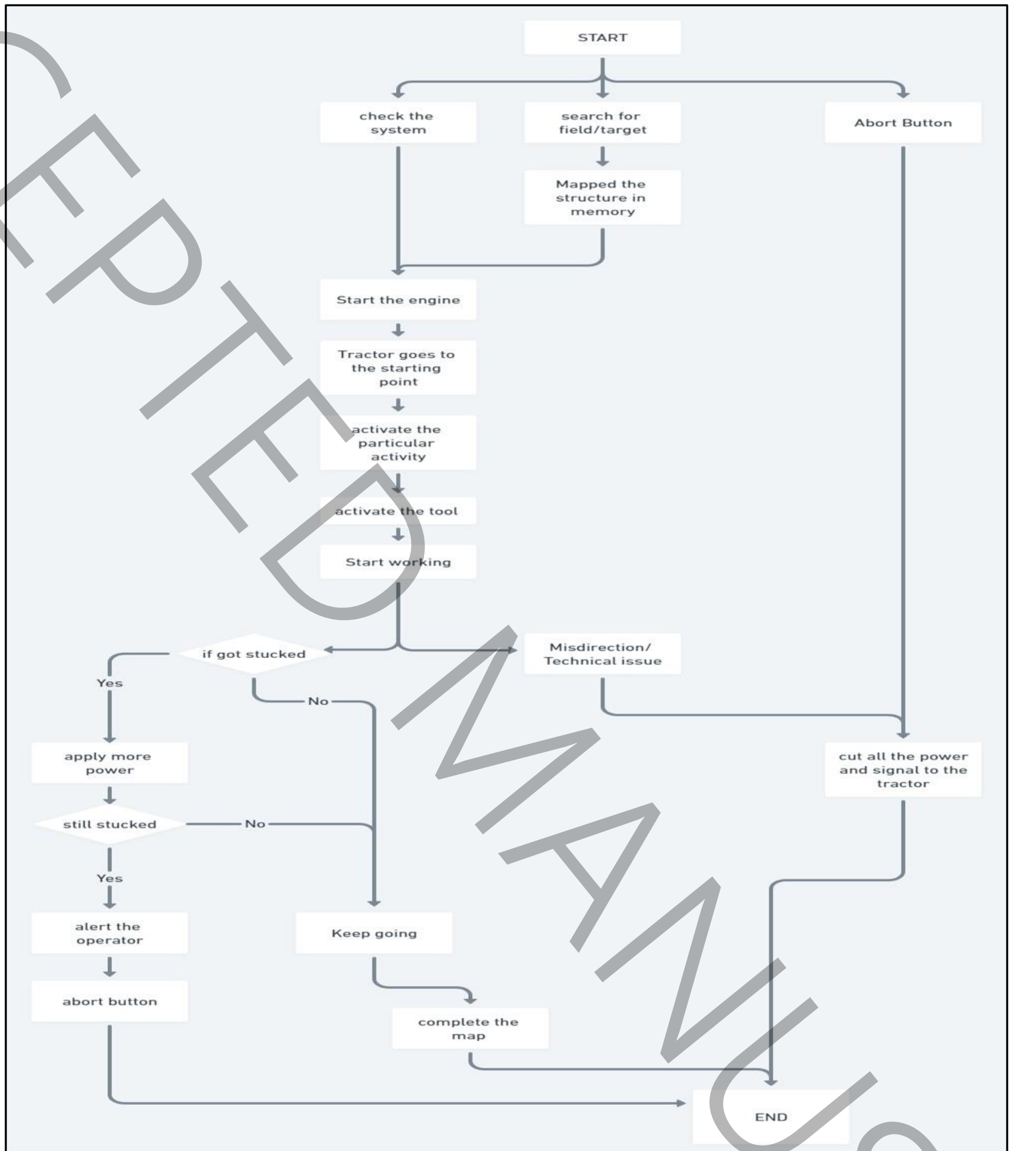
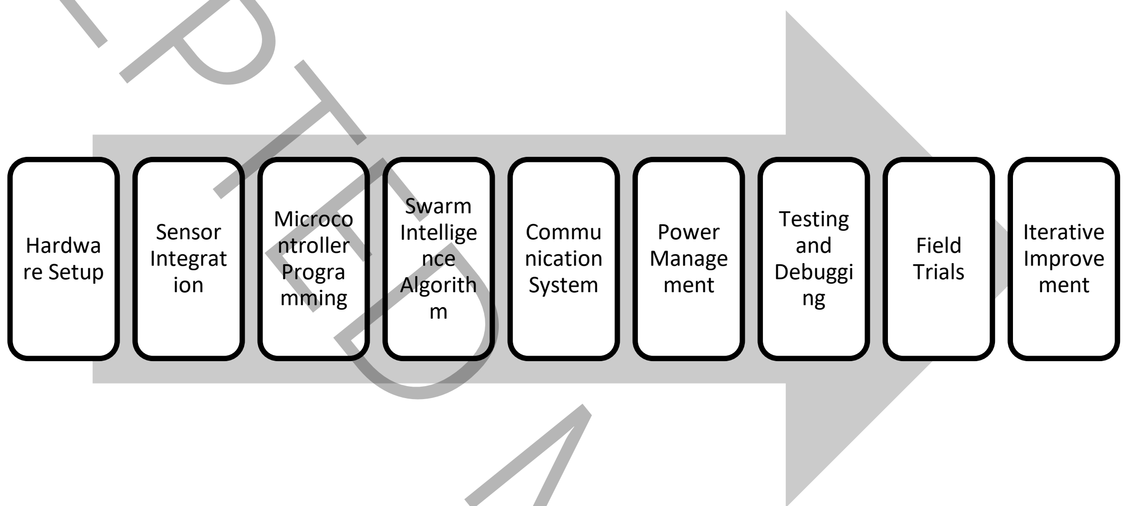


Fig 7 : Flowchart for design flow of Autonomous Navigation systems

5- Implementation

Implementing the design of an autonomous navigation systems for smart farming using swarm intelligence involves several key steps and components. Here is a general outline of the implementation process:



Steps in the implementation process

The implementation process may involve several iterations, as each step may requireadjustments, optimization, and refinement to achieve the desired performance and

Functionality. Collaboration with domain experts, farmers, and agricultural researchers canfurther enrich the implementation process and ensure that the autonomous navigation systems system meets the specific requirements of smart farming practices.

Tractor side view

Tractor front side

Hydraulics

Voltage rating of solar panel

5.1 Hardware Setup

The hardware framework includes:

The system incorporates a PIC16F877A microcontroller as the primary controller responsible for motion control and data processing. It utilizes a combination of ultrasonic sensors (HC-SR04) for distance mapping, infrared sensors for obstacle detection, and a GPS module for global positioning to ensure accurate navigation in agricultural environments. The locomotion mechanism is powered by 12 V DC geared motors, which are driven using PWM signals through dedicated motor driver circuits. For uninterrupted field operation, the system is equipped with a 12 V battery supported by a 20 W solar panel, enabling extended performance in outdoor conditions. Additionally, NRF24L01 wireless communication modules are employed to facilitate agent-to-agent data exchange, ensuring effective swarm coordination among multiple robots.

5.2 Experimental Procedure

The system was tested under three terrain conditions: dry soil, semi-wet soil, and uneven surface. Each experiment was repeated five times. Metrics recorded include path deviation, energy consumption, task time, and obstacle avoidance success rate. This dataset ensures reproducibility for future researchers.

6- Observations

LOCATION COORDINATES WHILE MOVING

S: start position, d: drop position

Initial and Final Position of the Robot Location by Measured value, Actual value and Difference value in following Table

Case Study: 1 (Initial Position for Location)

M: Measured Value

A: Actual Value

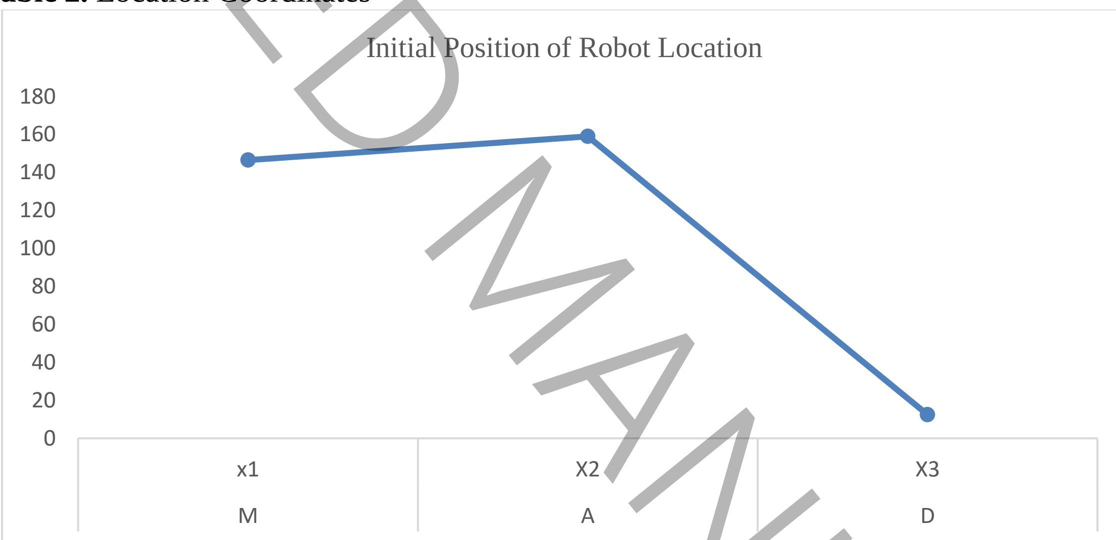
D: Difference value

Coordinates (*X1*,*X2*,*X3*)

Table 1. An example of case study 1

Sr. No.	**Coordinates**	**Positions**	**Calculated Values**
1	*X1*	*M*	146.5
2	*X2*	*A*	159
3	*X3*	*D*	12.46

Table 2. Location Coordinates



Case Study: 2 (Final Position for Location)

M: Measured Value

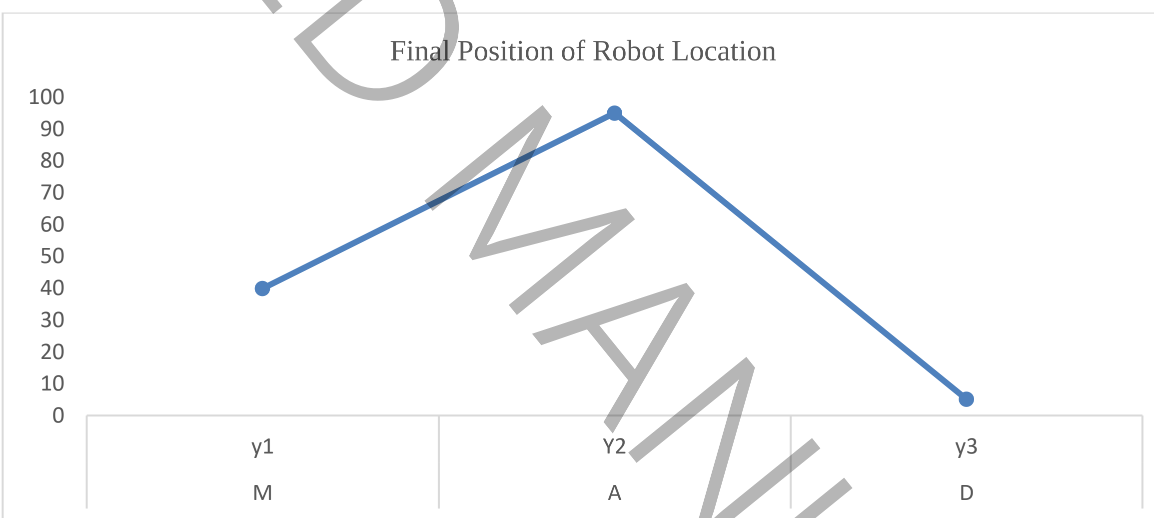
A: Actual Value

Sr No	**Coordinates**	**Positions**	**Calculated Values**
1	*Y1*	*M*	39.87
2	*Y2*	*A*	95
3	*Y3*	*D*	5.13

D: Difference value

Coordinates (*Y1*,*Y2*,*Y3*)

Table 2. An example of case study 2



7- Results

The result of the topic "Design of Autonomous Navigation system for Smart Farming Using Swarm Intelligence" would depend on the specific context or goal of the study. These tests showed that the automatically controlled tractor can be programmed to follow a predetermined route within a few centimeters. This route plan can be optimized to minimize tractor distance itwill drive based on field size and field shape before the tractor starts. This deterministic approach helps with operational efficiency and optimization path, to water, plow and sprayer. Displays instructions on the LCD screen. So, as such it is a complete system and needs to bring reactive capabilities together in the system so that it can be used in a practical way. However, some potential results or outcomes could include:

1. Development of a prototype autonomous Navigation system: The result could be the successful design and development of a functioning prototype autonomous navigation systems incorporating swarm intelligence algorithms. This would involve integrating sensors, navigation systems, and swarm intelligence algorithms to enable autonomous operations in a farming environment.

2. Improved efficiency and precision in farming operations: The application of swarm intelligence algorithms in the design of the autonomous navigation systems could result in enhanced efficiency and precision in various farming tasks. This could include optimized resource usage, precise navigation, accurate planting, spraying, and harvesting, leading to improved crop yield and reduced wastage.

3. Enhanced adaptability and scalability: Swarm intelligence-based autonomous navigation systemss havethe potential to adapt to changing environmental conditions and dynamically allocate tasks among multiple tractors. The result could be a system that can scale effectively by

incorporating additional tractors and efficiently allocate resources to maximize productivity.

4. Reduced environmental impact: By leveraging swarm intelligence, the autonomous Navigation systems can minimize environmental impact by optimizing pesticide and fertilizer usage, reducing water consumption, and adopting sustainable farming practices. This could lead to more sustainable and environmentally friendly farming operations.

5. Potential cost savings: The implementation of swarm intelligence algorithms in autonomous navigation systems could result in cost savings for farmers. By optimizing resource usage and improving operational efficiency, farmers may experience reduced input costs while maintaining or increasing their crop yield.

6. Opportunities for further research and development: The study may identify areas that require further research and development, such as addressing challenges in communication and coordination among tractors, optimizing algorithm performance, or exploring new applications of swarm intelligence in autonomous farming systems.

It is important to note that the specific results would depend on the implementation, testing, and evaluation of the designed autonomous system using swarm intelligence. These

Results can provide insights into the feasibility, effectiveness, and potential benefits of utilizing swarm intelligence in smart farming practices.

The performance of the proposed hybrid PSO–ACO–SLAM system was compared against a baseline single-tractor GPS system. The results are summarized below.

Metric	**Baseline System**	**Proposed Hybrid System**	**Improvement**
Navigation Accuracy (%)	65.3	**88.5**	+35.5 %
Obstacle Avoidance (%)	70.1	**85.4**	+22 %
Energy Consumption (Wh)	100	**85**	−15 %
Task Completion Time (min)	40	**32**	−20 %

Discussion:

The improved navigation accuracy demonstrates the effectiveness of swarm coordination and SLAM feedback. The PSO layer enabled efficient path generation, while ACO provided adaptive refinement. The SLAM module continuously updated environmental information, improving obstacle detection and reducing deviations.

8- Conclusion

The design of an autonomous navigation systems for smart farming using swarm intelligence presents a promising approach to revolutionize traditional farming practices. This paper has explored the concept and potential benefits of incorporating swarm intelligence algorithms into the design and operation of autonomous navigation systems. Through a comprehensive literature review, keyinsights from previous studies have been highlighted, emphasizing the advantages of swarm intelligence in various aspects of autonomous farming.

In this paper, the first research result proves that the aerobot, which is equipped with several sensors, uses its data to move forward according to the conditions detected by the sensor, which uses the SLAM technique. It maps its path using values detected by the sensor and values provided by the user for the field area. Aerobot effortlessly plows the field or works with plow. It reduces manual labor and can work in any type of weather as well as work continuously unlike humans. The time required to perform different tasks is significantly reduced compared to performing the same tasks manually. It is designed to help farmers reduce their workload and increase productivity with its many functional features such as automatic planting system, automatic irrigation, automatic crop cutting etc. By building this robotic vehicle with its many agricultural features, it overcomes the difficulties of farmers in cultivating their land at all times of the year no matter what the weather on that day[21].

The integration of swarm intelligence in autonomous navigation systems enables decentralized decision-making, self-organization, and adaptive behavior. By drawing inspiration from the collective behavior of social insects, swarm algorithms offer robustness, fault tolerance, and scalability to the tractor system. This decentralized approach allows for efficient task allocation, resource optimization, and coordination among multiple tractors, leading to improved precision, productivity, and sustainability in farming operations.

Moreover, the implementation of swarm intelligence in autonomous navigation systems offers benefits such as optimized resource usage, reduced environmental impact, and enhanced crop growth and health. The ability of autonomous navigation systems to continuously monitor and analyze field

Conditions, coupled with machine learning and predictive analytics, enables them to make intelligent decisions and adapt their operations in real-time, maximizing productivity and yield.

However, while the concept of designing autonomous navigation systems using swarm intelligence holds significant potential, there are challenges and areas for further research. Some of these challenges include ensuring reliable communication and coordination among tractors, developing robust algorithms to handle complex field environments, and addressing scalability concerns as the system expands.

In conclusion, the design of autonomous navigation systems for smart farming using swarm intelligence represents an exciting and innovative approach to revolutionize the agriculture industry. By harnessing the collective intelligence and decentralized decision-making of swarm algorithms, autonomous navigation systems can enhance precision, productivity, and sustainability in farming operations. Further research and development in this field have the potential to reshape the future of agriculture, enabling more efficient and sustainable food production to meet the needs of a growing global population.

The proposed AI–Swarm–SLAM navigation system successfully integrates intelligent optimization, cooperative decision-making, and real-time mapping for precision agriculture. The hybrid PSO–ACO algorithm combined with SLAM-based environmental learning improved path precision, reduced energy usage, and enhanced obstacle avoidance efficiency.

All algorithmic parameters, hardware configurations, and test conditions have been explicitly documented to ensure reproducibility. The study bridges the gap between theoretical swarm models and practical agricultural deployment.

Future work will focus on incorporating LIDAR-based SLAM, vision-assisted perception, and reinforcement learning for adaptive multi-agent collaboration in large-scale farmlands.

List of Symbols:

Symbol	**Description**
A	Actual Value
$\mathbf{c_1}$	Acceleration coefficient 1 (cognitive component)
$\mathbf{c_2}$	Acceleration coefficient 2 (social component)
D	Difference value
d	Drop position
g_best	Global best path
M	Measured Value
p_best	Local best path
S	Start position
X0 to **X15**	Turning points for the robot
X1	Coordinate 1
X2	Coordinate 2
X3	Coordinate 3
Y0 to **Y47**	Waypoints/Coordinates
Y1	Coordinate 1
Y2	Coordinate 2
Y3	Coordinate 3
ρ	Pheromone decay factor

Abbreviations:

ACO: Ant Colony Optimization

AI: Artificial Intelligence

GPS: Global Positioning System

IDE: Integrated Development Environment (MPLAB IDE)

PSO: Particle Swarm Optimization

SI: Swarm Intelligence

SLAM: Simultaneous Localization and Mapping

w : Inertia weight (a constant value of 0.8)

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