Metaverse in InterPlanet Internet: Application of Artificial Intelligence Solution That Uses Swarm Intelligence and Evolutionary Algorithm to Enable Collective Behavior and Self-Organization

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ABSTRACT

The interplanet internet is a conceived computer network in space, consisting of a set of network nodes that can communicate with each other. These nodes are the planet's orbiters (satellites) and landers (e.g. robots, autonomous machines, etc.) and the earth ground stations, and the data can be routed through Earth's internal internet. As resource depletion on Earth becomes real, the idea of extracting valuable elements from asteroids or using space-based resources to build space habitats becomes more attractive, one of the key technologies for harvesting resources is robotic space mining (minerals, metals, etc.,) or robotic building of space settlement. The metaverse is essentially a simulated digital environment mimicking the real world. The metaverse would be something very similar to real world planetary activities where users (space colonies or internet users on Earth) interact with overlaying objects represented by robots, drones, etc. for real-world planetary activities like space mining, building space settlements, etc. in a completely virtual manner. Here we show how swarm intelligence which is a branch of artificial intelligence is applied and to give intelligence and collective knowledge to space robots in operation and also their interactions with the environment. The swarm intelligence algorithms are nature-inspired based on the interactions between space robots and this behaviour of robots is simulated in the metaverse environment and the algorithm so designed is a variant of ant colony optimization(ACO) to arrive at collective behaviour of robots in their colony. In this way, a group of swarm computing units assisted robotics with reconfigurable system consisting of self-organized that is part of space robots is feasible for automated operations and in that respect an implementation of ant colony optimization algorithm for managing swarm of robots as a part of space application unit based on small model is presented. In this way, the desired response was measured, and new operational conditions and robotic predictions were synergistically

combined for diverse outcomes. The results of the study show that the real individual behaviour on a distant planet of undertaking of space related activities with swarm intelligence using evolutionary learning models could be of reality even in interplanet environment provided the interplanet internet is available as pathway communication.

INTRODUCTION

Inter-planetary exploration, be it Lunar habitation, asteroid mining, Mars colonization or planetary science/mapping missions of the solar system, will increase demands for inter-planetary communications. The movement of people and material throughout the solar system will create the economic necessity for an information highway to move data throughout the solar system in support of inter-planetary exploration and exploitation. The communication capabilities of this interplanet information highway need to be designed to offer; 1) continuous data, 2) reliable communications, 3) high bandwidth and 4) accommodate data, voice and video.

The interplanetary Internet is a conceived computer network in space, consisting of a set of network nodes that can communicate with each other. These nodes are the planet's orbiters (satellites) and landers (e.g., robots), and the earth ground stations. For example, the orbiters collect the scientific data from the Landers on Mars through near-Mars communication links, transmit the data to Earth through direct links from the Mars orbiters to the Earth ground stations, and finally the data can be routed through Earth's internal internet. Interplanetary communication is greatly delayed by interplanetary distances, so a new set of protocols and technology that are tolerant to large delays and errors are required. The interplanetary Internet is a store and forward network of internets that is often disconnected, has a wireless backbone fraught with error-prone links and delays ranging from tens of minutes to even hours, even when there is a connection. In the core implementation of Interplanetary Internet, satellites orbiting a planet communicate to other planet's satellites. Simultaneously, these planets revolve around the Sun with long distances, and thus many challenges face the communications. The reasons and the resultant challenges are: The interplanetary communication is greatly delayed due to the interplanet distances and the motion of the planets. The interplanetary communication also suspends due to the solar conjunction, when the sun's radiation hinders the direct communication between the planets.

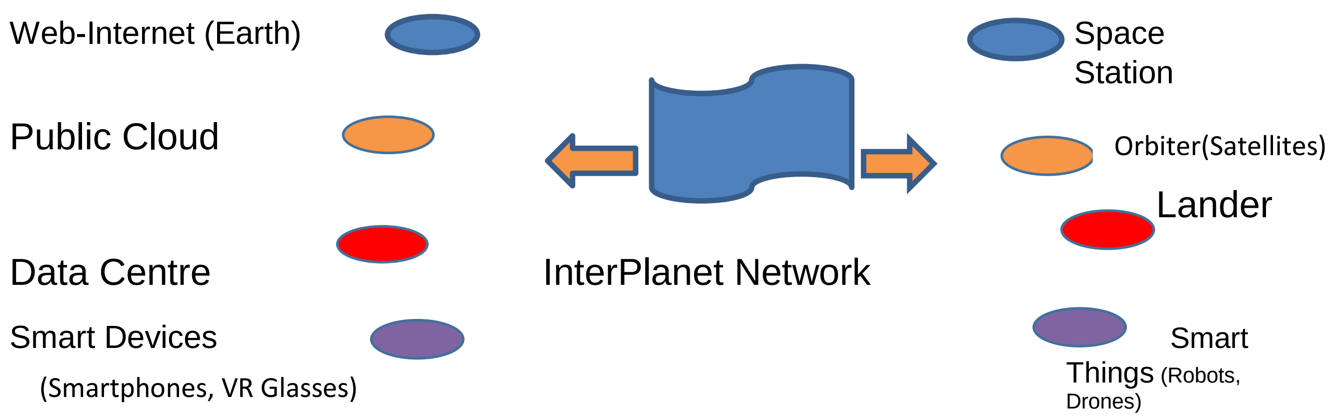
NETWORK ARCHITECTURE

A **Computer Network Architecture** is a design in which all computers in a computer network are organized. An architecture defines how the computers should get connected to get the maximum advantages of a computer network such as better response time, security, scalability, etc.

Network architecture refers to the way network devices and services are structured to serve the connectivity needs of client devices.

- Network devices typically include switches and routers.
- Types of services include DHCP and DNS.
- Client devices comprise end-user devices, servers, and smart things.

The network architecture for the planet Mars or the Moon is as shown in below figure: -

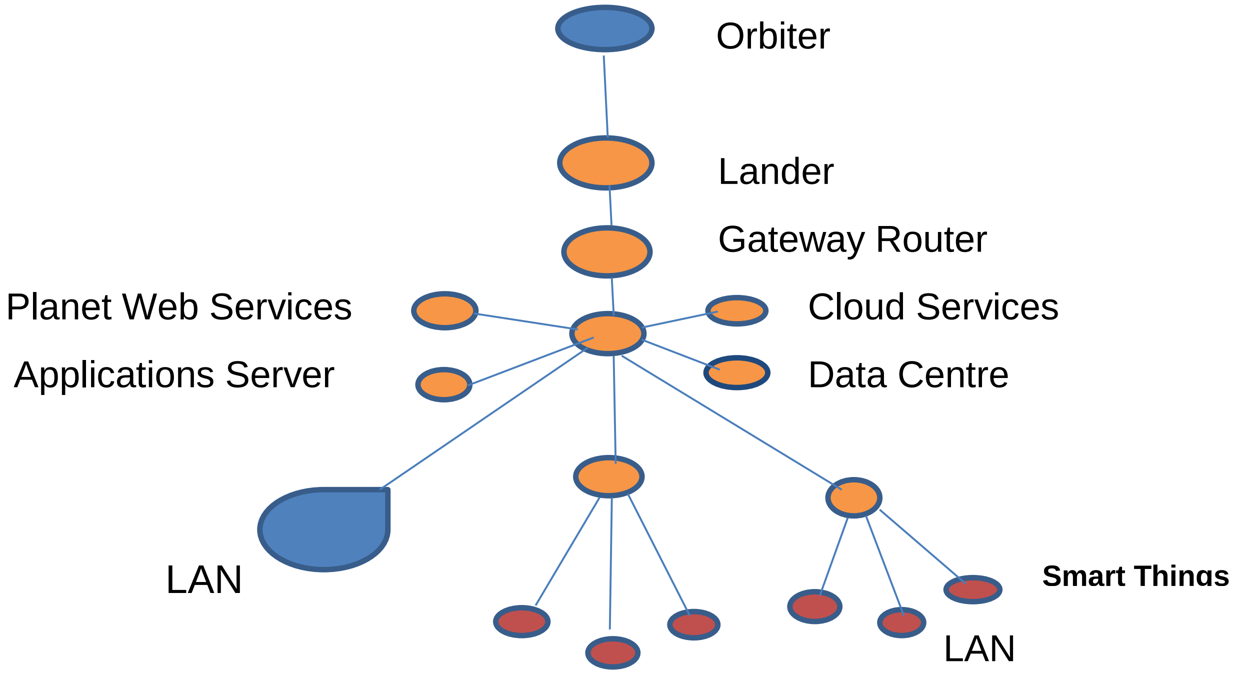


Computer networks are built to serve the needs of certain functionality and also their clients. Described below are three types of planetary networks:

- Access networks, for campuses and local areas, are built to bring machines and things onboard, such as connecting robots, drones, etc. within a location.
- Networks for data center connect servers that host data and applications and make them available to smart devices.

- Wide-area networks (WANs) connect robots and others to applications, sometimes over long distances, such as connecting robots to cloud applications related to space mining operations.

We give below the architecture of network on the planet Mars or the Earth's Moon is as shown in below figure: -



Local Area Network

An Internet is a "network of networks" in which routers move data among a multiplicity of networks with multiple admin. domains.

The main aim of networks is to connect remote endpoints with end-to-end principle and network should provide only those services that cannot be provided effectively by endpoints.

Since the networks are predominantly wireless, the fundamental impact of distance due to speed-of-light delays and impact on interactive applications – for both data and control is to be considered. Also power consumption of wireless links as a function of distance is to be examined.

The interplanetary internet is a conceived networks of nodes and these nodes are space station, planet's orbiters (satellites), planet's landers, robots (drones, autonomous machines, etc.), earth ground stations and earth's internal internet.

METHODOLOGY

1. Augmented Reality

The word ‘augmented’ means to add. Augmented reality uses different tools to make the real and existing environment better and provides an improved version of reality.

As Augmented Reality (AR) technologies improve, we are starting to see use cases and these include product visualization. There are AR apps that allow a customer to place virtual furniture in their house before buying and it is also a powerful tool for marketing as it allows users to try products before buying.

At its core, AR is driven by advanced computer vision algorithms that compares visual features between camera frames in order to map and track the environment. **But we can do more.** By layering machine learning systems on top of the core AR tech, the range of possible use cases can be expanded greatly.

Augmented Reality (AR) can be defined as a system that incorporates three basic features: a combination of real and virtual worlds, real-time interaction, and accurate 3D registration of virtual and real objects

2. Camera Representation

A camera is a device that converts the 3D world into a 2D image. A camera plays a very important role in capturing three-dimensional images and storing them in two-dimensional images. And the following equation can represent the camera.

$$x=PX$$

Here x denotes 2-D image point, P denotes camera matrix and X denotes 3-D world point.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

The above is vector representation of x=PX [1].

The camera representation method is frequently used in image processing and is intended to identify the geometric characteristics of the image creation process. This is a vital step to perform in many computer vision applications, especially when metric information on the scene is needed.

3. *Metaverse Algorithm*

1. **Physical Reality Modeling -** required information
   - The goal of the agent/robot
   - What the robot sees, Materials & location
   - Real Simulation for Task Execution
2. **Task Execution (Simulation)**
   - Generating actual materials (how materials arrive at the site)
   - Robots arrive in the environment (speed and goal)
   - Task Execution (Simulation Steps), is updated as the work process progresses in line with the simulation
   - Task execution performance, as we have fully functional simulator and to make a realistic system, we would like to see how well it performs and mirrors real world execution(Artificial Intelligence)
   - Implementation of Graphical Version of the Task Execution

Models for Metaverse & Algorithm

Minimum amount of required information

- The current state of the robot/agent and its environment
- The goal of the agent/robot
- What the agent sees, materials & it's location

Agents – Attributes

We opt for the agents and they have the attributes: the sight and the goal. While the goal is chosen randomly when an agent arrives on the location, the sight is always fixed to the some value. We define the autonomous robots as entities whose primary concern is to avoid failure; they should consequently not exhibit any preference for a certain speed as long as they are working safely. Furthermore, we add an attribute to these learning agents; this is their probability of choosing a random action at each time step.

Agents as workmen

Given that we define learning agents the same way as the type of workers, we can seamlessly add them at the location. The only difference is how they will choose an action: by using their learning model, a neural network. We can therefore adapt the site's time step's algorithm to take the learning agent into account for the observation step. To decide what action it should take, the learning agent uses a neural network to approximate the Q-function. Thus, at every time step t, the agent c observes its state $s_{c,t}$; this state is then processed in some way so that it can be passed to a neural network.

Neural Network Models

Presently different neural network models are available that we will use to train our autonomous robots. These models define what information the learning agents use and how they are encoded as inputs to the neural networks. Before we start with our model, we need to define the building structure; how these neural networks are used by the learning agents. We use a feedforward neural network whose outputs correspond to the possible actions. Our models define different ways of using information about the agent's current state.

Required Information

We start by defining the minimum amount of information that an autonomous robot should have. Consequently, the model that we design will possess these pieces of information. They are:

- The goal of the agent/robot
- What the robot sees, Materials & location
- The current location that the agent is in
- The current speed of the agent
- Real Simulation for Task Execution

Task Execution (Simulation)

- Generating actual materials (how materials arrive at the site)
- Robots arrive in the environment (speed and goal)
- Task Execution (Simulation Steps), is updated as the work process progresses in line with the simulation
- Task execution performance and to make a realistic system, we would like to see how well it performs and mirrors real world execution (Artificial Intelligence with learning algorithm)

Robotic Design and Placement

Robots are **collections of task executors** and have no brain system of their own. But they can be programmed to work autonomously and collaborate with other robots, or eventually to do other things tackling everything from space mining to deep space exploration.

Robots can be programmed as specific executor of an assigned task for a number of situations and also using artificial intelligence to figure out the best shape for the Robots to perform in group on a more consistent basis to have better control over performance of assigned work.

Using a computational model that simulates the nature of work and everything of the Robot Capability, the process yields the robotic shape best suited to ensure the shape of the actual Robots into more efficient form suitable to a particular situation/task and accordingly enables robots to gather together in their environment forming them into groups with the same capability.

The revolution of modern computing has been largely enabled by remarkable advances in robotics however, majority of today's robots designed are not suitable for high-end space exploration, resulting in the need to speculate about how to optimize the next generation of robots for the machine learning (ML) models. Further, dramatically shortening the robot design/shape requirement would allow hardware to adapt to the rapidly advancing field of ML. The ML itself could provide the means to the robot design/shape requirement , creating a more integrated relationship between space exploration and ML.

Vast arrays of robots with different make are required for complex space applications thus, improving the selection of design patterns of these autonomous robots would be critical in improving the performance and efficiency of remote space applications and use of AI to achieve high-performance execution and robotic performance relevant to the work.

In order for the AI to design with an RL agent and the technique proved that AI can not only learn to design robotic patterns from scratch but that those structural patterns are accurate and faster than designed using any of the latest validation tools. Here an AI agent could design neural graphs and such a graph is converted into a class of robots with connection (relevant shapes) using a link generator.

Swarm Intelligence

Swarm intelligence is the collective behaviour and decision-making based on decentralized, self-organized systems, natural or artificial. Natural examples are commonplace—flocks of birds and schools of fish act and react as groups, without instruction or direction from any single leader.

Examples in natural systems of swarm intelligence include **bird flocking, ant foraging, and fish schooling**. Inspired by swarm's such behavior, a class of algorithms is proposed for tackling optimization problems, usually under the title of swarm intelligence algorithms

The research findings suggest animal collective behavior has very early evolutionary origins. Examples of biological swarming are found in **bird flocks, fish schools, insect swarms, bacteria swarms, molds, molecular motors, quadruped herds and people**

Swarm learning is **a decentralized machine learning solution that uses edge computing and blockchain technology to enable peer-to-peer collaboration**.

The algorithm used in swarm intelligence is

- Evolutionary algorithms (EA), particle swarm optimization (PSO), differential evolution (DE), ant colony optimization (ACO) and their variants dominate the field of nature-inspired metaheuristics.

Swarm Intelligence:

- One Million Heads, One Beautiful Mind.
- Agents interacting locally with each other and the environment.
- Agents follow simple rules.
- **Emergence of Intelligent, Collective, Self-organised, Global behaviour.**
- Decentralized and artificial or natural.
- Very adaptive.

There are two types of Optimization algorithms in Swarm Intelligence:

- The first one is *Ant Colony Optimization(ACO)*. Here the algorithm is based on the collective behaviour of ants in their colony.
- The second technique is *Particle Swarm Optimization(PSO).*

Ant colony optimization (ACO) is **a metaheuristic algorithm that simulates the foraging behavior of an ant colony to discover the shortest path to the food**. As ants search for food, they leave behind pheromones that attract other ants to follow their path.

The ant colony optimization is useful in artificial intelligence as Ant colony optimization (ACO) is a population-based metaheuristic that can be used **to find approximate solutions to difficult optimization problems**. In ACO, a set of software agents called artificial ants search for good solutions to a given optimization problem.

The methodology primarily consists of following parts:-

1. Swarm intelligence is a branch of Artificial Intelligence where we observe robotic units and try to learn how different space related process phenomenon can be imitated in a swarm of robots to optimize the applications
2. In swarm intelligence, we focus on the collective behavior of robot units in operation and their interactions with the space environment
3. In space applications, the focus is on a group of robotic units and this group is referred to as 'swarm'
4. The robotic units on a space operation can be correlated with the tasks in a space application which are awaiting for resources with best suitable environmental conditions. On careful observation of Swarm, the robotic units do not know where the resources are located, but they do know what is to be achieved.
5. Thus, the best approach for finding the target, is to follow the robotic units which are operating nearest to the set target
6. This behavior of robotic units is simulated in the computation environment and the algorithm so designed is variant version of Ant Colony Optimization.

All the robots work together in a group, just like ant colony, as robots search for resources, they leave behind pheromones that attract other robots to follow their path either to aggregate debris scattered along the surface into neat piles or possibly, to build a space settlement/ 'carry out space mining'. They can survive for long-time without recharge and heal themselves after any damage/confusion. The shape of a robot's body, and its distribution of legs and structure are automatically designed in simulation to perform a specific task in space environment. Also, A fleet of robots are divided into dozens of blocks, each of which is an individual robotic module, such as a memory subsystem, compute unit, or control logic system and these blocks are represented as a interconnected class of components consisting of robot types and adjacency information for collaborative outcomes.

ARCHITECTURE

Robotic Microcontroller

A **microcontroller** is a compact integrated circuit designed to govern a specific operation in an embedded system. A typical microcontroller includes a processor, memory and input/output (I/O) peripherals on a single chip.

A robot microcontroller is basically the brain of the robot. It is used to collect the information from various input devices such as sensors, switches and others. Then it executes a program and in accordance with it controls the output devices such as motors, lights and others

Microcontrollers are used in automatically controlled products and devices, such as automobile engine control systems, implantable medical devices, and other embedded systems and one of the main application of Microcontroller is sensing and controlling devices and this feature will be used in automatically controlling flow of resources in space applications.

Ant Colony Optimization

Particle Swarm Optimization and **Ant Colony Optimization** are examples of the swarm intelligence algorithms. The objective of the swarm intelligence algorithms is to get the optimal solution from the behaviour of insects, ants, bees, etc.

Algorithms such as the Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are examples of swarm intelligence and metaheuristics. The goal of swarm intelligence is to design intelligent multi-agent systems by taking inspiration from the collective behaviour of social insects such as ants, termites, bees, wasps, and other animal societies such as flocks of birds or schools of fish.

Ant colony optimization (ACO) is **a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems**. In ACO, a set of software agents called artificial ants search for good solutions to a given optimization problem.

To apply an ant colony algorithm, **the optimization problem needs to be converted into the problem of finding the shortest path on a weighted graph**. In the first step of each iteration, each ant stochastically constructs a solution, i.e. the order in which the edges in the graph should be followed.

Principle of Ant Colony Optimization

Ant Colony Optimization technique is purely inspired from the **foraging** behaviour of ant colonies, and this technique is derived from the behaviour of ant colonies. Ants are social insects that live in groups or colonies that prefer community survival and sustaining rather than as individual species. For communication, they use pheromones. Pheromones are the chemicals secreted by the ants on the soil, and ants from the same colony can smell them and follow the instructions.

To get the food, ants use the shortest path available from the food source to the colony. Now ants going for the food secret the pheromone and other ants follow this pheromone to follow the shortest route. Since more ants use the shortest route so the concentration of the pheromone increase and the rate of evaporation of pheromone to other paths will be decreased, so these are the two major factors to determine the shortest path from the food source to the colony.

Algorithmic Design and Implementation: Pertaining to the above behaviour of the ants, an algorithmic design suiting to group of space robots can now be developed. For simplicity, a two source resource and single ant colony have been considered with just three paths of possible traversal. The whole scenario can be realized through weighted graphs where the ant colony and the mineral/material source act as vertices (or nodes); the paths serve as the edges and the pheromone values are the weights associated with the edges. Let the graph be **G = (V, E)** where V, E are the edges and the vertices of the graph. The vertices according to our consideration are $\mathbf{V_s}$ (Source vertex – ant colony) and $\mathbf{V_d}$ (Destination vertex – mineral/material source), The three edges are $\mathbf{E_1}$, **E2**and $\mathbf{E_3}$ with lengths $\mathbf{L_1}$, $\mathbf{L_2}$ and $\mathbf{L_3}$ assigned to each. Now, the associated pheromone values (indicative of their strength) can be assumed to be $\mathbf{R_1}$, $\mathbf{R_2}$ and $\mathbf{R_3}$ for vertices E_1, E_2 and E_3 respectively. Thus for each ant, the starting probability of selection of path (between E_1, E_2 and E_3) can be expressed as follows:

$$P_i = R_i \Big/ (R1 + R2 + R3) \; ; \quad I = 1,2,3$$

Evidently, if $R_1 > R_2$, the probability of choosing E_1 is higher and vice-versa. Now, while returning through this shortest path say E_i, the pheromone value is updated for the corresponding path. The updation is done based on the length of the paths as well as the evaporation rate of pheromone. So, the update can be step-wise realized as follows:

1. **Concentration of pheromone according to the length of the path-**

$$Ri = Ri + \frac{K}{Li}$$

In the above updation, i = 1, 2, 3 and 'K' serves as a parameter of the model. Moreover, the update is dependent on the length of the path. Shorter the path, higher the pheromone added.

2. **Change in concentration according to the rate of evaporation -**

$$Ri = (1 - v) * Ri$$

The parameter 'v' belongs to interval (0, 1] that regulates the pheromone evaporation. Further, i = 1, 2,3.

At each iteration, all ants are placed at source vertex V_s (ant colony). Subsequently, ants move from V_s(food source) to V_d (food destination) following step 1. Next, all ants conduct their return trip and reinforce their chosen path based on step 2.

Procedure AntColonyOptimization:
  Initialize the necessary parameters and pheromone concentration;
  while not termination **do**:
    Generate ant population;
    Calculate the fitness values associated with each ant of the colony;
    Find best solution using selection methods;

Update pheromone concentration;
end while
end procedure

RESULTS

In order to do implementation, we must define parameter values such as number of trials, evaporation variable, pharmone left by each ant, antfactor (no. of ants per resource), and random factor. We set these values randomly to 4, 0.5, 500, 0.9, and 0.01.

First we initiated implementation by providing trials and ants matrices, and setup the ants matrices with a random resource location.

For each iteration, we performed move ants operation where each ant tries to follow other ants trials with properly selecting the next resource to choose.

As a next step, we updated the trials and left the pharmone trace, and finally we updated the best solution with reference.

It was found that after all the iterations, the final result was indicative of the best path in a combinatorial situation found by the ACO.

CONCLUSION

The interplanetary computer network in space is a set of computer nodes that can communicate with each other. We proposed a network architecture with planet's orbiters, landers (robots, etc.), as well as the earth ground stations and linked through Earth's internal internet, and consisted of complex information routing through relay satellites. As we know, the metaverse will be very different from the internet of today due to massive parallelism, three-dimensional (3D) virtual space and multiple real-world spaces like space mining, building space habitats, etc. We presented a swarm intelligence of collective knowledge of robotic deployment equipped with AI-model driven learning that can effectively execute complex applications in space environment. As a part of sharing intelligence and collective knowledge, we implemented nature-inspired swarm intelligence algorithm for optimizing interactions between space robots in the simulated metaverse environment and the algorithm so designed is ant colony optimization to arrive at collective behaviour of robots in their colony for sharing knowledge/intelligence for successful execution. In this way, an AI - model of swarm intelligence system with ant colony optimization for collective intelligence that is part of

Metaverse is feasible for automated execution of diverse space related outcomes depending on the applications and in that respect an implementation of varied version of ant colony optimization based on small model is presented. Although the platform model with AI learning model with swarm intelligence and evolutionary strategy given us a method of optimizing space applications however, this need to be tested using natural allocation for real space applications.

REFERENCE

1. **Poondru Prithvinath Reddy**: **“Metaverse in InterPlanet Internet: Modeling, Validation, and Experimental Implementation”, Google Scholar**