"Enhancing Autonomy on Construction Sites through Implementation of Swarm Robotics as adaptive Material-Handling logistics system".

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Source: OpenAI. "Image generated by ChatGPT." OpenAI. 2024.

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Acknowledgment

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Abstract

This thesis explores the application of swarm robotics in addressing construction sites' dynamic and complex challenges by using them as material handling units. Despite significant technological advances, the construction industry continues to face substantial challenges related to the human workforce including skilled labor shortages, high safety risks, and inefficient communication, all of which impede productivity and safety. Swarm robotics, inspired by the decentralized behaviors of social insects, offers a promising solution to these issues by enabling distributed task management and enhanced flexibility and robustness in dynamic environments.

The research specifically investigates the implementation of swarm robotics as an adaptive on-site logistics system for dynamic construction sites. Using Ant Colony Optimization, a path-planning swarm intelligence-based algorithm derived from the foraging behavior of ants, this study examines the algorithm's applicability for enhancing material handling within the unpredictable conditions of construction sites. The study includes the development of an architectural scenario for a virtual simulation environment and practical experiments on two different architectural scenarios to evaluate the effectiveness of swarm robotics in real construction scenarios.

This study demonstrates the advantages of decentralized control in swarm robotics for enhancing operational efficiency, reducing safety risks, and improving communication on construction sites. The outcomes include the development of a Design-to-Construction workflow using a scalable and resilient construction logistics system that takes advantage of the unique capabilities of swarm robotics. This outcome has the potential to revolutionize construction practices through the integration of advanced robotic technologies and decentralized management systems.

Additionally, virtual experiments results as a part of the workflow indicate that achieving optimal values for parameters in the simulation, such as the required number of robots and pheromone evaporation rate, is highly scenario-dependent. This conclusion highlights the necessity of using the developed workflow that enables designers and construction groups to create their desired architectural layouts, simulate their construction process, and optimize them for further construction using swarm robots, effectively bridging the gap from initial design to final construction.

Table of Contents

Acknowledgment 1

Abstract 2

1- Introduction 5

1-1 Problem Statement 6

1-2 Context 7

1-2-1 Construction Site Challenges 7

1-2-2 Robotic Construction 10

1-3 Approach 13

1-4 Research Question 14

1-5 Thesis Objective 14

2- Literature Review 16

2-1 Construction Site....17

2-2 Swarm Intelligence....21

2-3 Swarm Robotics....27

3- Case Studies....33

3-1 Operating Robotic System and Technical Features....35

3-1-1 Projects by Swarm Robots 35

3-1-2 Autonomous Mobile Robots as Logistics in Industry 37

3-2 Architectural & Construction Site Layout 40

3-3 Virtual Simulation 44

4- Implementations....50

4-1 Architectural layout....52

4-2 Construction Site....54

4-3 Structure 56

4-4 Material....58

4-5 Simulation....58

5- Methodology....60

5-1 Design Phase 62

5-1-1 Architectural Layout....64

5-1-2 Booth Parametric Script....72
5-1-3 Structural Analysis....76
5-1-4 Brick Estimation....81
5-1-5 Data Export for Simulation and Design Analysis....85
5-1-6 Selected Layout....86
5-2 Simulation Phase....87
5-2-1 Python Code Overview....88
5-2-2 Simulation Setup....89
5-2-3 Part A as Tetris-Style Construction Site Visualization....91
5-2-4 Part B as Ant Colony Optimization (ACO)....94
5-2-5 Simulation Loop....109
6- Experiments....110
7- Results....116
8- Discussion....122
8-1 Limitations....123
8-2 Opportunities and Future Research....126
9- Conclusion....129
9-1 Answers to Research Question....132
10- Reflection....140
11- References....148
12- Appendix....153

1

Introduction

1-1 Problem Statement

The construction industry, while rapidly growing and expanding, faces countless numbers of challenges that limits its efficiency and safety. Despite technological advancements, the sector continues to struggle with several persistent issues on construction sites. Some of these issues originate from the high dependency of the construction industry on the human workforce followed by the challenges related to their presence on the construction site.

The high demand for human labor in the construction industry has led to a shortage of skilled workers, which is one of the industry's biggest problems. Since the worldwide pandemic, this issue has gotten worse, increasing labor expenses, project cancellations, and delays. After the pandemic, some labor markets, such as the Dutch labor market, have demonstrated resilience by quickly recovering to pre-pandemic levels. Despite this recovery, these markets remain highly competitive, with low unemployment rates and labor shortages in certain areas of the country (OECD, 2023).

As the human workforce as the main labor is present on the construction sites, safety remains a critical concern, as these sites are some of the most hazardous workplaces. Workers in this sector are significantly more likely to experience serious or fatal accidents compared to other industries. These incidents put the lives of workers highly at risk from getting injured to potentially endangering their lives. Regarding the project’s process, these incidents also disrupt project timelines and inflate costs due to delays and compensation claims (Muñoz-La Rivera et al., 2021).

Lastly, the present human workforce on the construction site requires effective communication for coordination, highlighting another significant issue: poor communication. This prevalent issue substantially affects project outcomes, resulting in delays, cost overruns, and conflicts. Ineffective communication in the construction sector can be attributed to several factors such as poor management and supervision, a lack of technical knowledge, the complex nature of the industry, and language barriers (Ohueri et al., 2023).

To address these critical challenges- **skilled labor shortages, safety risks**, and **Poor Communication -** happening on the construction sites at once, there is a growing interest in utilizing advanced technological solutions such as robotic construction. Utilizing robotic construction reduces the construction industry's reliance on the human workforce for specific tasks, thereby minimizing challenges associated with human labor. However, traditional robots widely used for small-scale construction projects, while beneficial, have shown limitations in robustness and flexibility, particularly in dynamic and unpredictable construction environments (Davila Delgado et al., 2019).

As a result, a new approach toward robotic construction has been studied in this thesis. Swarm robotics, inspired by the decentralized and cooperative behavior of social insects, presents a promising solution. By distributing tasks among simple, autonomous robots that work collaboratively, swarm robotics can enhance robustness and adaptability on construction sites. These robots can dynamically adjust to environmental changes, manage logistical tasks, and reduce human exposure to hazardous conditions, thereby improving overall site efficiency and safety (Brambilla et al., 2013).

The potential of swarm robotics in partially assisting the human workforce and transforming construction sites by addressing labor shortages, enhancing safety, and improving communication methods forms the basis of this thesis. The research aims to explore how swarm robots can function as an adaptive material handling logistic system on dynamic construction sites, offering a scalable and resilient solution to the industry's challenges.

1-2 Context

In this section, to provide more context about the mentioned challenges at construction sites, a subsection titled "Construction Site Challenges" will explain these issues. Another subsection titled "Robotic Construction" will offer a general review of robotic construction and its role in addressing these specific challenges at construction sites.

1-2-1 Construction Site Challenges

Skilled Labor Shortage

According to a Following the epidemic, there is a worldwide shortage of skilled labor, which is affecting a variety of sectors throughout the world. This scarcity is especially critical in the construction industry, where skilled labor is in great demand, worsening an already tight labor market. Most European Union countries are dealing with labor shortages and inflationary pressures on building supplies and equipment (Jones, 2022).

As highlighted in the introduction, the Dutch labor market, despite its robustness, is anticipated to face labor shortages. This is attributed to several factors, including a quick recovery from the pandemic, continually evolving skill demands, low working hours, and the dissolution of the labor market. These factors collectively contribute to labor shortages that limit economic potential and pose risks to the green and digital transitions (Gonne, 2023).

The worldwide labor shortage in the construction sector has a substantial influence on project performance, and economic growth. Studies show that a lack of competent labor impedes project success, lowers productivity rates, raises labor expenses, and results in inadequate compensation for workers, which restricts skill development (Ekwuno, 2022).

Construction Safety and Health

The construction industry has a high rate of accidents due to its active and dynamic work environment. Compared to the manufacturing sector, construction workers are 2.5 times more likely to experience a serious accident and five times more likely to suffer a fatal accident. Globally, about 30–40% of accidents in construction result in fatalities (Muñoz-La Rivera et al., 2021).

There are two types of safety-related categories. The first one is on-site accidents, and the other one happens in a long-term period.

Accidents: Accidents on construction sites are caused by worker ignorance of safe work procedures, insufficient safety warnings/signs, working under the influence of drugs/alcohol, working with defective equipment, and insufficient working platforms. According to HSE (2015) the most frequent causes of accidental death and injury are:

Table 1- Frequent Causes of Accidental Death on Construction Sites

Table Source: (HSE, 2015)

Falls • *Inadequate access to workplace* • *Working at heights*	***Mobile plant*** • *Operating on muddy and uneven* • *Poor driver's visibility* • *Getting hit by moving vehicles* • *overturning vehicles and plant*
Falling material and collapses • *material falling from loads being lifted* • *material rolls or kicked off work platforms* • *struck or buried by falling materials when excavations* • *buildings or structures collapse.* • *Scaffolds collapse*	***Electrical accidents*** • *electric shock and burns by contacting overhead power lines and buried cables.*
Slip • *Spills* • *Wet Surfaces* • *Footwear* • *Slippery Surfaces (Anderson, 2022)*	***Trips*** • *changes in the level of floors* • *damaged flooring* • *ineffective management of access routes such as corridors, stairwells, and footpaths*

Health: The construction industry has a poor health record. Construction workers are likely to suffer ill health as a result of their work in the industry after exposure to both harsh working conditions and hazardous substances (HSE, 2015).

Table 2-Long-term Health problems

Table Source: (HSE, 2015)

<table>
<tr>
<td>Asbestos
serious respiratory diseases such as asbestosis and cancer</td>
<td>Manual handling
Lifting heavy and awkward loads causes back and other injuries.
Long-term injury because of repeated minor injury due to repetitive lifting
Musculoskeletal disorders, skin problems, eye and skin injuries, and cuts and wounds.</td>
</tr>
<tr>
<td>Noise and vibration
High levels of noise causing hearing loss
repeated use of vibrating tools causes hand-arm vibration syndrome</td>
<td>Chemicals
Exposure to materials such as cement and solvents causing skin problems such as dermatitis</td>
</tr>
</table>

Poor Communication on a Construction Site

Poor communication is a common problem in the construction industry, leading to project delays, mistakes, and even accidents. According to the Project Management Institute (PMI), about one-third of construction projects fail due to communication issues.

Effective communication is crucial in construction for better project quality, increased efficiency, time-saving, enhanced budget management, and reduced accidents. However, communication can be obstructed by various factors, related to inefficiencies in verbal and digital methods (Hazlegreaves, 2022).

Verbal communication can be challenging due to difficulties in accessing the right person on a scattered construction site, confusion over terminology, fear of criticism, and hearing comprehension issues.

Digital communication also has its challenges, such as the need for technological knowledge, lack of access to information, cultural barriers, delayed information delivery, technical language complexities, lack of feedback, and teamwork issues (Safety, 2023; Akunyumu et al., 2019).

1-2-2 Robotic Construction

Robotic construction, which has been used since the 1960s and 1970s, offers significant advantages in automating construction tasks through specialized robotic equipment. This technology has the potential to revolutionize construction by enabling tasks to be performed by robots created for specific construction requirements, and to a greater extent it may even be integrated as a structural component in the future (Davila Delgado et al., 2019; Allwright et al., 2017).

Within the scope of this thesis, it is stated by Xiao et al. (2022) and Pan et al. (2018) that challenges such as skilled labor shortages, high safety risks, and the growing demand for sustainability, efficiency, and productivity in the construction industry can be mitigated using automation methods in construction. However, the unique characteristics of the construction process such as unpredictability and complexity compared to other industries necessitate the adoption of more advanced automation methods, such as robotic construction (Dias et al., 2021).

The Role of Robotic Construction in Addressing Construction Industry Challenges

In this section, how robotic construction particularly can address the challenges of skilled labor shortages, construction safety, and poor communication will be elaborated.

- **Skilled Labor Shortage:** Robots in construction can perform a wide array of tasks, ranging from simple deliveries to intricate assemblies. With the ongoing challenge of skilled labor shortages in the industry, there is a tremendous need to achieve greater efficiency with fewer personnel. This raises the question: *Is there a way to bridge this gap by ensuring that a smaller workforce can be as productive as a larger one?*
  The key to addressing this challenge lies in optimizing the workforce's focus on their specialized expertise while delegating tasks requiring lower levels of expertise, such as on-site material handling and logistics, to robots. By doing so, workers can allocate 100% of their attention to their specialized tasks. This approach not only enhances productivity but also saves time by eliminating the need for workers to manually handle materials. In this way, a group of robots can complement the human workforce.

- **Construction Safety and Health:** While it's true that the health and safety risks on construction sites cannot be completely eradicated, the industry is not yet fully digitalized and automated, and human presence especially for supervision remains necessary. However, by delegating certain tasks like on-site material handling and delivery to robots, we can significantly reduce workers' exposure to risks, thereby lowering the probability of them being affected by accidents.
  Moreover, in the unfortunate event of injuries to human workers, there's no way to fully compensate for the consequences. In contrast, robots offer advantages in terms of replaceability and

repairability. Additionally, they have the flexibility to operate in hazardous areas, providing a safer alternative for completing tasks in dangerous zones on construction sites (Cheraghi et al., 2021).

- **Poor Communication on a Construction Site:** As mentioned earlier, both verbal and digital communication systems face challenges when operating on a scattered, large-scale construction site. What if, in this communication network, human involvement in communication diminishes, and another method of communication is embraced? Robots come equipped with their own built-in communication and storage tools, which enhance communication on the construction site, ensuring efficiency and productivity.

Limitations of Current Robotic Systems

Despite all of the advantages of using robots in construction, Construction Automation and Robotics (CAR), particularly in construction site applications, have not yet experienced widespread real-world implementation on a large scale (Pan et al., 2018).

According to Davila Delgado et al. (2019), there are several limiting factors to the adoption of robotics and automated systems in large-scale construction which are lack of robustness and flexibility.

The robots currently employed in construction projects are primarily tasked with pre-programmed and intricate assignments, overseen by a centralized authority. Consequently, if one robot malfunctions, the entire system is at risk of failure. Moreover, replacing malfunctioning robots entails significant capital and maintenance expenses, given the technology's high costs and customized tasks. This process not only experiences substantial budgetary consequences but also consumes valuable time, as it involves replacing the robot and recalculating the plan.

Overall, these systems, often controlled by centralized algorithms, suffer from a lack of adaptability to dynamic environments and high costs related to maintenance and failure management. Built up on these reasons, another new approach toward robotic construction will be explored in this thesis.

Introduction to Swarm Robotics

Swarm robotics offers a promising alternative by utilizing decentralized, multi-agent systems where robots operate cooperatively. Inspired by natural swarms, these systems focus on simple, adaptable agent behaviors without centralized control, offering unique solutions to the limitations of traditional robotic systems (Zheng et al., 2021).

Two main Advantages of Swarm Robotics over the current systems

Swarm Robotic systems should display certain properties common with natural swarms. According to Beni (2004) proposed properties for swarm robotics to be identified as swarm systems are Robustness, Flexibility, and Scalability. All three features are the main advantages of swarm robotics over the current systems.

- **Robustness**

  A system is considered robust when it can continue functioning despite environmental disturbances or system faults. These interruptions may include changes in surroundings, increased obstacles, or weather changes (Beni, 2004).

  In a swarm robotic system, individual robots are simple and cannot perform significant tasks alone. Therefore, the system should be resilient to malfunctions or failures of some members. The loss of individuals can be compensated for by others, ensuring tasks continue with consistent efficiency. As a result, a decentralized system of cooperative swarm robots offers advantages by operating locally with minimal resources, avoiding the necessity to comprehend the entire system's complexity. This decentralized approach ensures robustness, as the failure of individual entities does not lead to overall system or task failure (Brambilla et al., 2013).

- **Flexibility**

  According to Costa et al., (2019) the solutions offered by centralized algorithms widely used in robotic construction frequently provide optimal and ideal solutions. However, since these solutions are precomputed, any robotic or structural failure would need additional costly recomputation. Therefore using these robots to adapt to dynamic environments since they need effective and efficient sequence planning for construction tasks, with current approaches is challenging (Ruan et al., 2023). Therefore, as the scale of the problem grows, fully centralized systems become impractical, and to avoid recomputing, approximations should be applied in centralized solutions.

- **Scalability**

  Scalability in swarm robotics implies the ability to function effectively with varying group sizes. The system should perform tasks successfully regardless of the global number of robots, ensuring that different sizes can still achieve effectiveness. The system must operate efficiently with both small and large swarm sizes, supporting coordination and cooperation among members as needed.

Therefore, while traditional robotic construction offers substantial benefits for the construction industry, swarm robotics presents an innovative approach to overcoming the inherent limitations of these systems. By enhancing robustness and flexibility, swarm robotics could revolutionize construction automation, making it more adaptable, efficient, and resilient.

1-3 Approach

According to Davila Delgado et al. (2019), There are four broad areas of construction automation and robotic technology. Among these, "On-site automated and Robotic systems," which involves the direct use of automated and robotic systems on the construction site, is identified as the primary area for this thesis. This category is particularly suited for dynamic environments such as construction sites.

The proposed solution to enhance the construction autonomy on dynamic construction sites while addressing the challenges previously mentioned is to explore the potential of swarm robotics by implementing them as on-site logistics responsible for material handling.

At this point, swarm robotics seems to be a compelling approach. However, while promising in theory, the effectiveness of them must be verified in practice. This requires designing a realistic workflow and conducting experiments to assess its practical application and results.

Table 3- Construction Automation and Robotic Categories

Table Source: Table by author based on (Davila Delgado et al., 2019)

1- Off-site prefabrication systems

2- On-site automated and robotic systems

- Single task construction robots (STCRs) for bricklaying, steel-truss assembly, steel welding, façade installation, wall painting, concrete laying, etc.
- Robotic on-site factories
- Swarms and robots for building component assembly

3- Drones and autonomous vehicles

4- Exoskeletons

1-4 Research Question

In this research, the objective is to evaluate the performance of swarm robots as a more robust and adaptable solution for dynamic construction sites. The central research question to be addressed is:

"How can swarm robots function as an adaptive on-site logistics system in a dynamic construction environment?"

Sub- Questions

- How will tasks be allocated among the swarm robots based on real-time demands and resource availability?
- What coordination mechanisms are required to ensure efficient collaboration among the swarm robots?
- How can robots perceive and respond to obstacles?
- How can the swarm robots adapt their behavior in response to the parameters of different demands, resources, obstacles, changing priorities or unexpected events?

1-5 Thesis Objective

The proposed solution to address the challenges of a dynamic and unpredictable construction site involves implementing swarm robotics for on-site logistics and material handling within a predefined construction scenario.

In this scenario, parameters related to real construction sites are considered, including:

- The presence of static obstacles like excavations
- Dynamic obstacles such as in process buildings, equipment, material depot
- Multiple placement points to deliver the material to them instead of a single food source for robots
- Multiple pick-up points due to multiple material supplies instead of a single nest for robots
- Varying material demands based on the structure's size workers' working rate and their presence
- The construction stage of the structure
- The availability of materials in stock

The main objective of this project is to get adaptive responses from swarm robots to the defined changes relevant to a real construction site by using the Ant Colony Optimization (ACO) path-planning algorithm.

While this algorithm has studied ants' foraging behavior and their response to static and dynamic obstacles, there are additional parameters on a construction site that on-site logistics agents need to be aware of and respond to.

The main outcomes of the project are as follows:

- **Developing a Three-Stage Workflow:** Create a design-to-construction workflow that replicates the whole process within a dynamic construction site, focusing on swarm robots' ability to respond effectively to changing conditions.

- **Configuring an Architectural Layout:** Utilize Grasshopper to set up an architectural layout and construction site model. This model will serve as the foundation for virtual simulations designed to replicate the adaptive behavior of swarm robots in a dynamic construction environment.

- **Establishing Simulation:** Set up a virtual simulation as the foundation for conducting experiments across various construction scenarios, allowing for comprehensive testing and observation of the robots' performance.

- **Analyzing Experiment Results:** Examine the outcomes of the swarm robots' simulations, focusing on construction performance metrics within a dynamic construction environment.

2

Literature Review

Introduction

In this literature review, the aim is to explore two interconnected fields: construction sites and swarm-related areas. The section on construction sites will cover the features that define and influence construction operations, define logistics within the construction context, explore the principles of safe site layout, and discuss the integration of robots for on-site logistics. Following this, the swarm section will begin with an explanation of swarm intelligence, introduce the specific algorithm selected for this thesis, and detail the features of swarm robots. It will also review their applications in industry and practice.

2-1 Construction Site

The Dynamic Feature of Construction Site

The construction industry is intricate and ever-changing, with each project presenting its own set of challenges. It involves the collaboration of various professionals from different backgrounds and organizations, each bringing their unique perspectives and expertise to the table. These diverse elements must seamlessly integrate to achieve the project's specific objectives. Consequently, the construction site itself is distinct, characterized by factors that complicate construction and safety management.

Factors such as unpredictable weather conditions, including rain, wind, and varying light levels, pose challenges beyond the control of the project team. Additionally, the presence of heavy machinery, hazardous tools, and the transportation and handling of materials on a large scale further contribute to the complexity. Moreover, the diverse workforce, comprising individuals with different roles and levels of training, adds another layer of complexity to ensuring comprehensive safety control measures are in place (Muñoz-La Rivera et al., 2021).

Logistics

Logistics deals with the overall process of planning, coordinating, and executing several tasks related to the purchase, supply, storage, transportation, maintenance, and handling of resources such as materials, labor, and equipment (Regassa, 2015; Magill et al., 2020).

In construction, logistics mainly refers to the movement of materials and construction equipment on-site. Additional factors that play an important role in efficiently managing construction resources on-site include material purchase, handling, and storage (Tunji-Olayeni et al., 2017; Misron et al., 2018).

A successful site logistics plan needs significant amounts of pre-planning and coordination between various trades and is, therefore, considered a complicated task (TunjiOlayeni et al., 2017).

Effective and transparent planning of construction site logistics is crucial for ensuring safety, productivity, and adherence to schedules, serving as the base of a successful building project. Developing, executing, and adapting these plans over time to accommodate changes is a skill that necessitates practice and thinking to achieve efficiency and continual improvement. (Dustin, 2021).

Ineffective site logistics plans result in significant waste and material losses, leading to delays and increased costs, as highlighted by Tunji-Olayeni et al. (2017) and Misron et al. (2018). Ogundipe et al. (2020) identified 25 factors hindering the full utilization of effective building materials management (EBMM), many of which originate from inadequate material handling and inefficient site logistics. Similarly, Owolabi et al. (2021) discussed how inadequate material management due to poor construction site logistics planning can result not only in material wastage but also in delays and cost overruns.

Construction Site Layout regarding Logistics

Construction site layout planning (CSLP) is a subset of project planning. An optimal CSLP improves project productivity and the level of safety on a construction site. Since construction activities are usually performed in sequential or parallel stages, the late completion of a construction task can affect the start time of the next task. For example, poor weather conditions, moving equipment/labor, improper packaging, using improper equipment to offload material, poor staging conditions, or improper staging placement, may damage construction materials stored on-site (Ying et al., 2014; Misron et al., 2018).

As a result, the material may need to be reordered, delaying its availability to the workforce. This emphasizes the necessity of effectively managing material logistics on a building site. (Misron et al., 2018; Owolabi et al., 2021).

To ensure a safe and productive construction site, it's mandatory to design the site based on Health, Safety, and Environment (HSE) principles and set up essential elements accordingly. When designing a construction site, the following factors should be considered and arranged:

1. Safe Site Access
2. Fenced and protected site boundaries
3. Proper Welfare Facilities including:
   - Sanitary conveniences
   - Washing facilities
   - Rest facilities
   - Storing and drying clothing and personal protective equipment
   - Drinking water
4. Good order, storage areas, and waste materials

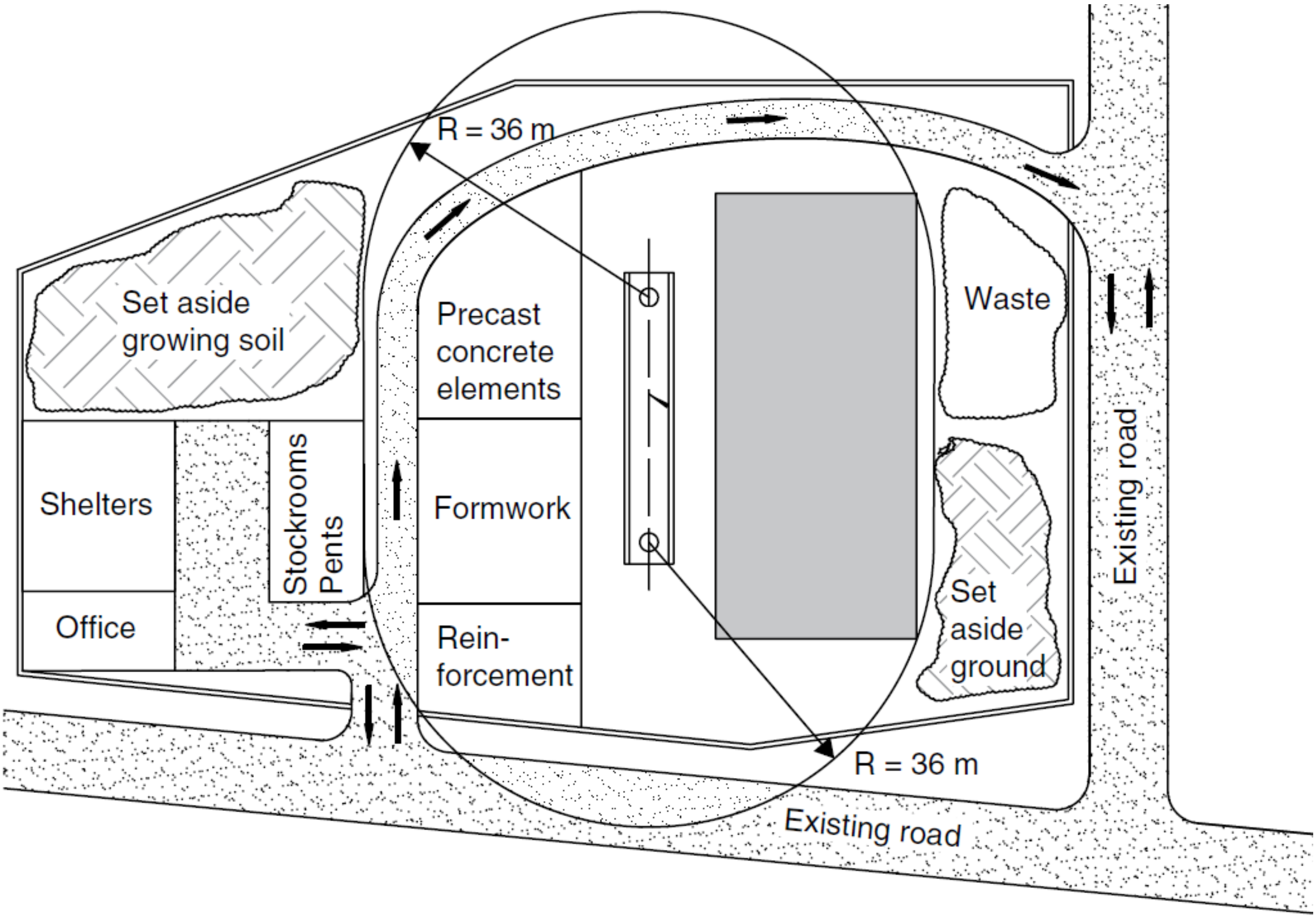


Figure 1- Site layout in the preliminary stages

Image Source: (Sutt et al., 2013)

Robot Navigation as Logistics

As mentioned earlier, inadequate material handling is one of the factors that significantly affects construction efficiency. Robots can play a crucial role in addressing this issue by utilizing their advanced navigation technology. Robot navigation is the process of navigating a mobile robot to its destination to execute tasks. There are two methods of navigation: reactive navigation and map-based navigation. In the first method, the mobile robot has no map or knowledge of where it is. The mobile robot moves randomly and obtains information about its surroundings just via the contact sensor, proving that the machine is capable of perceiving and acting. Map-based navigation, on the other hand, is the process of creating a path for a mobile robot to travel from one location to another that meets certain criteria, such as the shortest distance and/or the lowest cost. The machine can perceive, plan, and act, which is known as path planning (Ajeil et al., 2020).

Path planning is an interesting subject in mobile robotics that focuses on autonomous navigation in a given environment. It is about finding the shortest, collision-free, and smooth path for the robot to follow from a set starting location to a fixed target point in an environment containing moving or stationary objects. This challenge is complex to solve, especially in dynamic environments like construction sites, where the ideal path must be re-planned in real-time as new obstacles appear.

In general, there are various pathways for the robot to take in order to reach its destination, but the ideal path is chosen based on several guidelines. These guidelines are: shortest path, least energy consumed, or shortest time (SinghPal & Sharma, 2013).

Discussion

Construction sites are dynamic workplaces characterized by their ever-changing and unpredictable nature. Numerous factors influence their efficiency, from controllable aspects such as strong management, timely deliveries, and well-organized logistics, to uncontrollable variables like weather and unexpected incidents. All these elements must work together to streamline the construction process. Among these, inadequate material handling and inefficient site logistics are significant contributors to construction disruptions. Utilizing robotic navigation, which encompasses the ability to perceive, plan, and act—commonly known as path-planning—can greatly enhance efficiency and safety on construction sites.

As a result, within the scope of this thesis, the direction will be towards on-site robotic logistics with reactive navigation system responsible for material handling. This system will use path-planning algorithms to continuously adapt and re-plan the optimal path in real time, ensuring operational efficiency and safety.

2-2 Swarm Intelligence

Swarm intelligence is a discipline based on natural and artificial systems, involving numerous individuals that coordinate through decentralized control and self-organization (Dorigo & Birattari, 2007). This collective behavior, observed in entities like ants, bees, and birds, enables them to accomplish complex tasks more efficiently than a single individual (Altshuler, 2023).

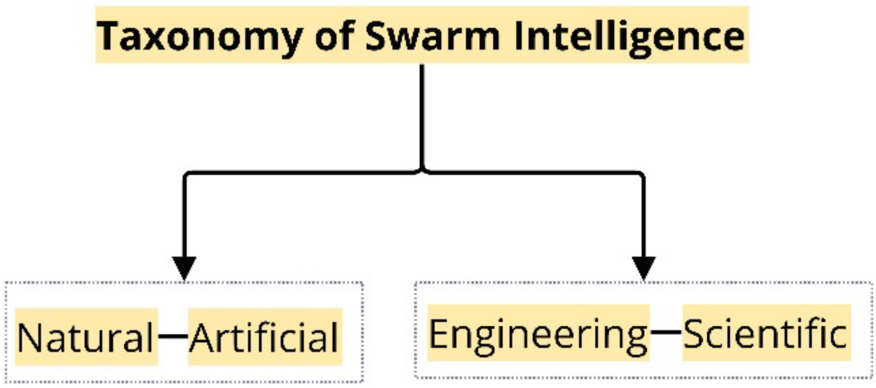


Figure 2- Taxonomy of Swarm Intelligence

Image Source: Diagram by Author Based on (Dorigo and Birattari 2007)

According to (Dorigo & Birattari, 2007) Swarm intelligence research is commonly categorized into two areas based on the systems analyzed. The first one is Natural/ Artificial. Natural swarm intelligence studies biological systems, and artificial swarm intelligence focuses on human-made artifacts.

And the other category is Scientific/ Engineering. Scientific, aims to model and understand the mechanisms of coordinated behavior in swarm systems, and engineering, seeks to apply this understanding to design practical problem-solving systems.

The categories of natural/artificial and scientific/engineering are separate, and some research involves both. For example, some studies use robot swarms (artificial and engineering) to test mathematical models of biological systems (natural and scientific).

Swarm Intelligence- based Algorithms

Swarm-based algorithms are classified under Multi-Agent Systems (MAS) algorithms. A Multi-Agent System (MAS) consists of independent software agents collaborating within an environment to accomplish tasks. These agents, capable of autonomous actions, communicate and coordinate through networked message exchange (Cheraghi et al., 2021).

By translating multi-agent systems’ behaviors to mathematical models, multiple algorithms have been created. As shown in the figure below, Swarm Intelligence-based algorithms are a subset of Bio-Inspired Metaheuristic algorithms. Swarm Intelligence-based algorithms have a high variety, each with unique collective behaviors adapted to specific tasks based on different live species in nature.

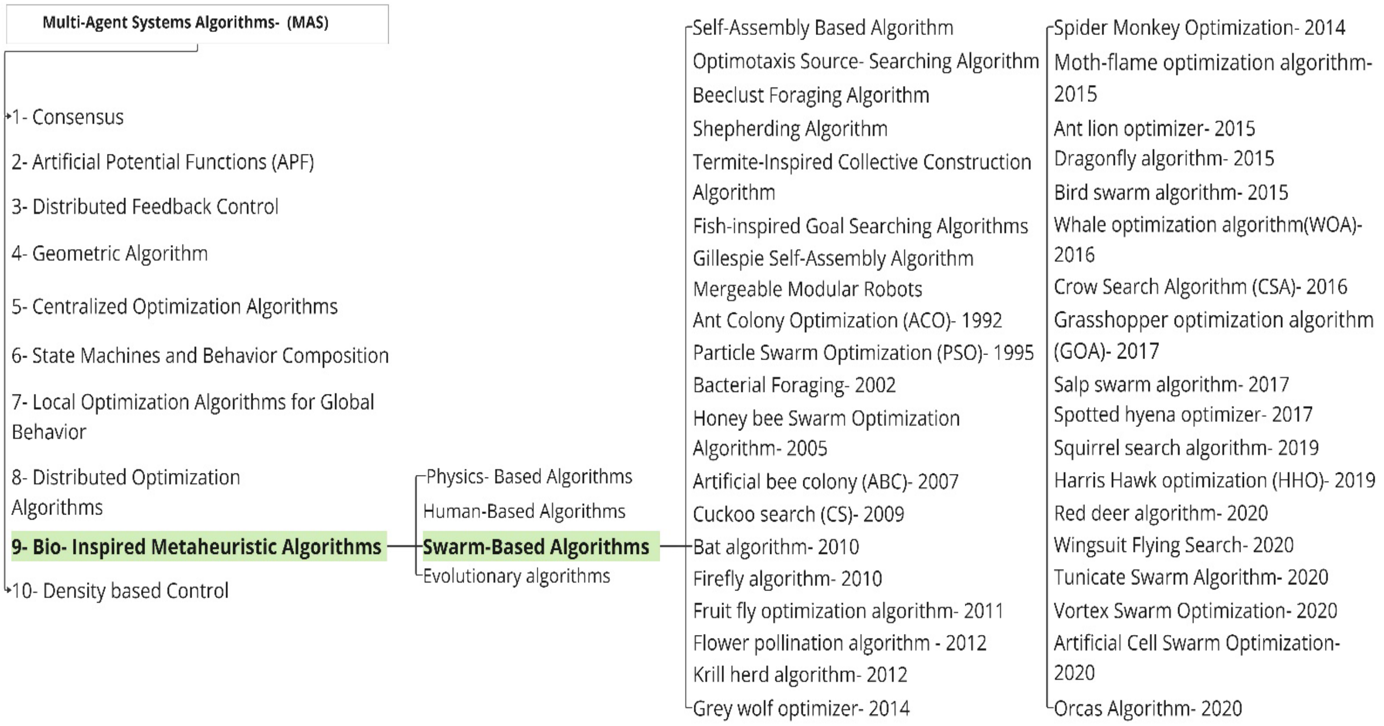


Figure 3- Categorization of MAS algorithms based on their mathematical approach

Image Source: Diagram by Author Based on (Rossi et al. 2018; Mohamed, Hadi, and Mohamed 2020; Dutta et al. 2020)

Taxonomy of Swarm Collective Behaviors

The collective behaviors of each swarm species to achieve their goals are different. The categorization of these behaviors helps to understand the types of collective behaviors observed in swarms and how these behaviors lead to specific outcomes. The figure below features a task and swarm behavior categorization taxonomy proposed by Brambilla et al. (2013) and an additional taxonomy by Schranz et al. (2020) complements it, introducing new behaviors like Collective Localization, Collective Perception, Synchronization, Self-Healing, and Self-Reproduction into existing categories.

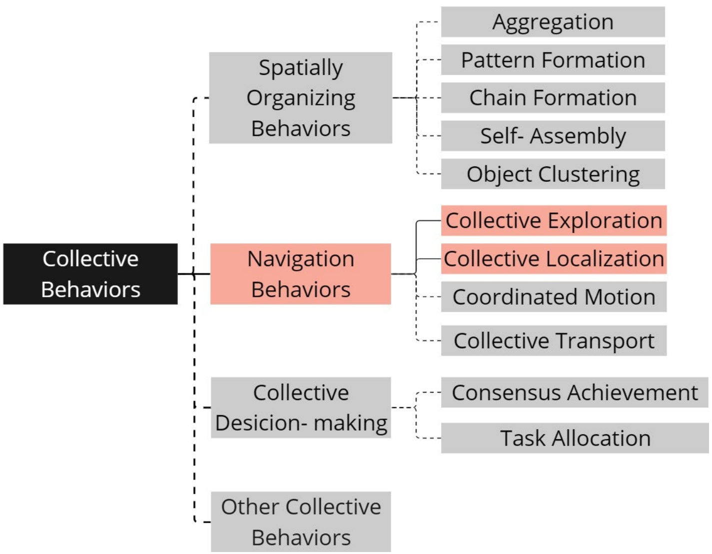


Figure 4- Taxonomies of Swarm Behaviors

Image Source: Diagram by Author based on classifications in (Brambilla et al., 2013; Schranz et al., 2020)

Algorithms with Navigation Behaviors

Dynamic problems are characterized by a solution search space that evolves, which means that as the search progresses, the conditions, problem definitions, and the quality of potential solutions may change. This concept applies to the dynamic environment of a construction site, the primary focus of this research. The study requires an algorithm showing navigation behaviors of swarms in such dynamic search spaces, particularly how they move and coordinate together within the environment.

On a construction site, two essential behaviors are collective exploration and collective localization. Collective exploration involves the swarm agents working together to survey and understand the construction site environment. Collective localization requires the agents to determine their positions and orientations relative to each other, effectively establishing a local coordinate system within the swarm to maintain coordination and accuracy in their tasks (Schranz et al., 2020).

SinghPal & Sharma (2013) noted that in recent years, four swarm-based algorithms—Ant Colony Optimization (ACO), Particle Swarm Optimization, Bee Colony Optimization (BCO), and Firefly Algorithm (FA)—have been widely utilized in path-planning problems. In the table below, four algorithms are described, each followed by a more detailed elaboration of their methods.

Table 4- Algorithms based on Swarm Intelligence

Table Source: Table by Author Based on (SinghPal & Sharma, 2013; Dorigo and Birattari 2007; Valdez 2021; Dutta et al. 2020)

Parameter	**Ant Colony Optimization (ACO) - artificial/engineering**	**Particle Swarm Optimization- artificial/engineering**	**Bee Colony Optimization (BCO) artificial/engineering**	**Firefly Algorithm (FA) Natural/Scientific**
Proposed by	M.Dorgio- 1990	Kennedy and Eberhart- 1995	Dervis Karaboga- 2005	X.S. Yang- 2008
Inspired by	foraging behavior of ant colonies.	social behaviors in flocks of birds and schools of fish.	The foraging behavior of honeybees.	The flashing patterns and behavior of fireflies.
Based on	Pheromone Trails	Communication between particles	Mysterious dance inside the hive	Flashing light of fireflies
Applied to	Discrete combinational optimization problems	Continuous optimization as well as discrete problems	Constraint and unconstraint optimization problems	Multimodal optimization applications
Solutions represented by	The path constructed by the ants	The positions of the particles	The position of bee's in the neighborhood of breakpoint	Agent movements along line-of-sight with a neighbor
Knowledge stored in	The pheromone levels associated with the path trails	The previous local/global best positions of all particles	The dance which is performed by employed bee's	Variation of light intensity and formulation of the attractiveness
Application Area	• Traveling salesman problem • Scheduling • Network Model Problem • Vehicle Routing • Set Problem	• Function optimization • Artificial neural network training • Fuzzy system control • Grammatical Herding • Mobile sensor navigation	• Clustering • neural network training • structural optimization • multi-level thresholding • face pose estimation	• Digital image compression • image processing, • clustering, • scheduling and TSP • Antenna Design

- **Particle Swarm Optimization (PSO)** is an artificial/engineering type of Swarm Intelligence algorithm. In PSO, a group of software agents known as particles explore the solution space of a continuous or discrete optimization problem. Each particle represents a potential solution and navigates the search space by leveraging both its own experience and the experiences of neighboring particles. The movement of each particle is influenced by stochastic (random) processes, allowing for a diverse exploration of possible solutions.

- **Bee Colony Optimization (BCO)** falls into the artificial/engineering category of algorithms. In this algorithm, artificial bees are used to explore the solution space to find high-quality solutions. These bees mimic the behavior of real bees in nature, systematically searching and communicating about promising solution areas.

- **Firefly Algorithm (FA)** is categorized under the artificial/engineering group of swarm intelligence algorithms, despite it being inspired by the natural behavior of fireflies. In this algorithm, the brightness of each firefly is associated with the value of the objective function at a candidate solution. Fireflies in the algorithm are attracted to others with higher brightness, simulating the natural attraction behavior seen in actual fireflies toward brighter light, which helps them navigate toward potentially better solutions.

- **Ant Colony Optimization (ACO)** is categorized under the artificial/engineering group of swarm intelligence algorithms. This stochastic optimization method is inspired by the foraging behavior of real ants, developed by Dorigo. It finds the shortest route from an ant colony to food sources through collaborative information exchange. Ants follow each other along the same path as they leave a chemical substance known as pheromone while moving. In traditional ACO, the quantity of pheromone deposited by the ants is considered constant (SinghPal & Sharma, 2013).
  ACO algorithms are considered state-of-the-art techniques for addressing dynamic path-planning problems. An ACO algorithm has also been utilized for dynamic vehicle routing problems, demonstrating effective performance on both randomly generated and real-world instances (Reshamwala & Vinchurkar, 2013).

Regarding the dynamic nature of construction sites and the material-handling task combined with a path-planning method to be investigated in this thesis, Ant Colony Optimization (ACO) appears to be well-aligned with this research direction. This algorithm's strong ability to navigate and find the most optimal path in discrete dynamic search spaces is the reason for its selection.

In the following parts, this algorithm's different features will be explained.

The basic ACO algorithm is summarized in the following steps:

- Step 1

  Establish the free space model for the search environment, identifying the starting and ending points.

  In this scenario, the construction site serves as the free space model, with the material supply points (nest) as the starting point and the material placement points (food sites) as the endpoints.
- Step 2

  Determine the optimal next move for the ants by evaluating the intensity of pheromone deposits.
- Step 3

  Calculate the transition probabilities for each unit and develop multiple routes from the start point to the endpoint, with each route depicting an ant's journey.
- Step 4

  Assess the length of each route and adjust the pheromone levels accordingly, taking into account the rate of pheromone evaporation.

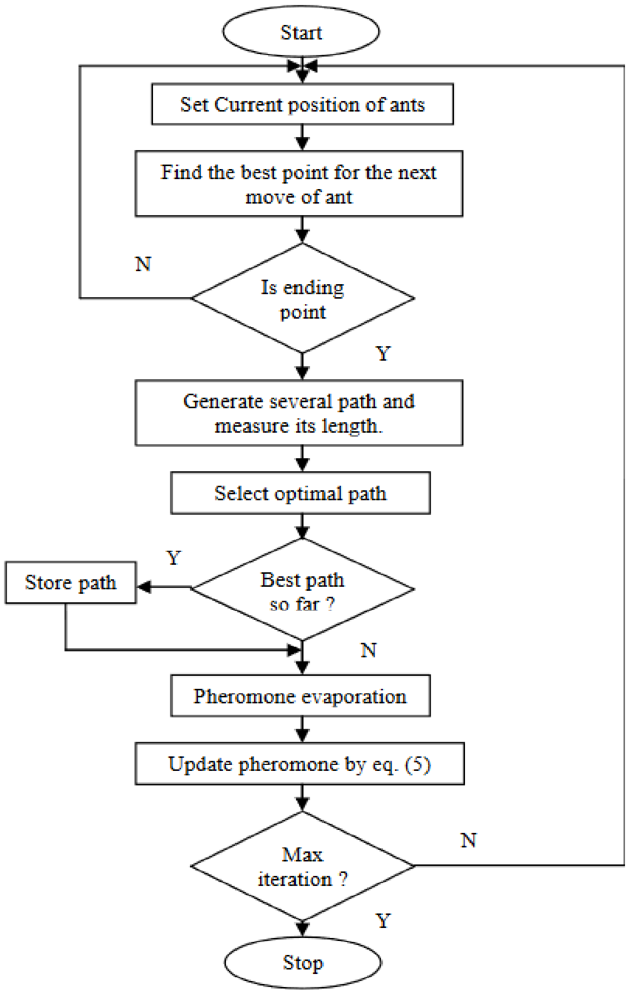


Figure 5- Flowchart of ACO

Image Source: (SinghPal & Sharma, 2013)

Indirect Communication Method (Stigmergy & Pheromones)

In the realm of swarm robotics, storing information in the environment, known as stigmergy, serves as an indirect form of communication (Werfel, 2012).

Stigmergy, proposed by Grasse in 1959, allows coordination by agents responding to environmental changes instead of direct communication. Stigmergy is employed by robots to assess the local configuration of building materials, determining where to add additional material (Lieveloo 2023).

Pheromones serve as a form of indirect or stigmergic communication among ants, allowing them to store information in the environment. By depositing pheromones as they move, ants efficiently find the shortest routes to food and their nest. Other ants can detect these chemical trails and are more likely to follow paths with higher pheromone levels. This enables ants to adapt to sudden changes in the terrain, such as obstructions blocking previously used paths, by reconstituting shorter paths with increased ant traffic.

This behavior of ant colonies has inspired the Ant Colony Optimization algorithm, where artificial ants cooperate to find solutions to optimization problems by depositing pheromone trails. The algorithm has been successfully applied to various combinatorial optimization problems within discrete search spaces, demonstrating reliability and efficiency (Reshamwala & Vinchurkar, 2013).

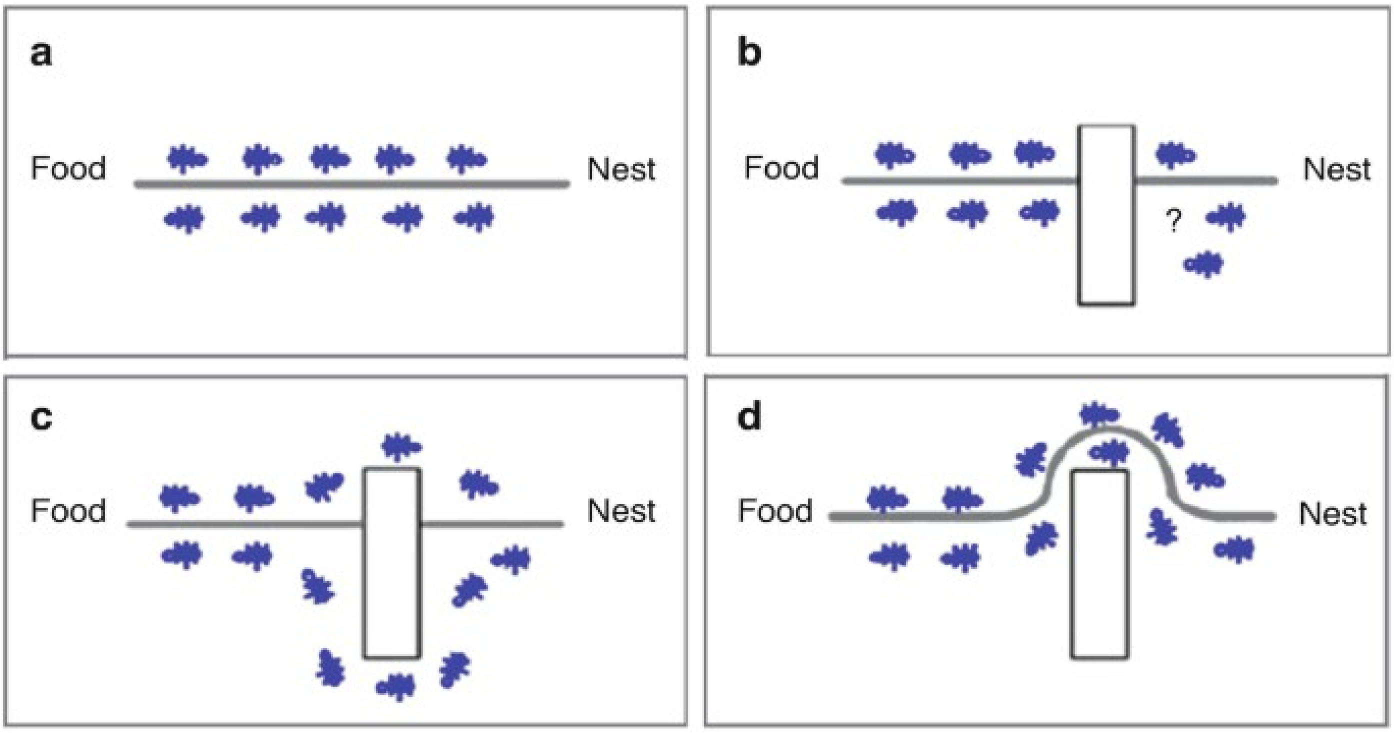


Figure 6- Pheromone build-up allows ants to reroute to the shortest path

Image Source: (Gupta et al., 2021)

2-3 Swarm Robotics

Swarm robotics is the application of **swarm intelligence** principles to the control of swarms of robots. Swarm Robotics (SR) represents an extension of the field of Multi-Robot Systems, focusing on leveraging communication, coordination, and collaboration among a large group of robots. These robots enable tasks to be completed more efficiently compared to a single complex robot (Nedjah & Junior, 2019).

In the field of swarm robotics, individual robots display behavior governed by a local set of rules, ranging from simple reactive mappings of sensor inputs to sophisticated local algorithms. Typically, these local behaviors involve interactions with the physical environment, including both the surroundings and other robots (Floreano and Mattiussi, 2008).

Each interaction consists of gathering and interpreting sensory data, processing this information, and then adjusting the actuators. This series of steps forms a basic behavior that repeats continuously, either without end or until a specific goal is reached (Schranz et al., 2020).

Types of Swarm Robots

Swarm robotics comprises two primary types: homogeneous and heterogeneous. In homogeneous swarm robotics, identical robots collaborate to achieve common goals, taking advantage of collective intelligence for decision-making. This type offers built-in redundancy, enhancing robustness, as damaged or malfunctioning robots can be easily replaced without affecting overall performance. The Kilobot swarm, a small $14 open-source robot shown in Figure 7, exemplifies homogeneous swarm robotics. On the other hand, heterogeneous swarm robotics involves robots with varied capabilities and strengths, allowing for task assignments based on individual abilities. The Swarmanoid project by Dorigo et al. in 2012, depicted in Figure 8, is an example of a heterogeneous swarm where three foot-bots collaborate to transport one hand-bot, showcasing the efficiency of diverse capabilities within the swarm.

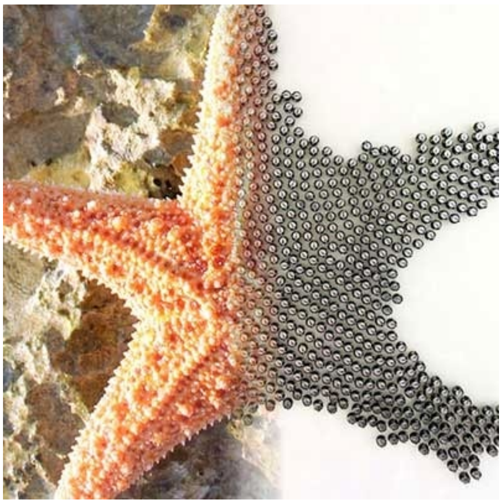


Figure 7- Kilobot Self-Organizing Swarm Project (2014)- homogeneous robots

Image Source: https://seas.harvard.edu/news/2014/08/self-organizing-thousand-robot-swarm (on the left), https://en.m.wikipedia.org/wiki/File:Kilobot_robot_swarm.JPG (on the right)


Figure 8- The Swarmanoid Project (2012) made up of three families

Image Source: https://www.semageek.com/swarmanoid-film-avec-des-robots-colaboratif/

Areas of Using Swarm Robots

Swarm Robotics is a relatively new field to be applied in all fields, According to Cheraghi et al., (2021) the diverse applications of swarm robotic systems due to their features are:

- **Specific Region Tasks:** Swarm robotics excels in large, designated areas where robots collaborate to perform tasks like garbage collection in cities.

- **Dangerous Zone Tasks:** Robot swarms are deployed in hazardous environments, such as searching for dangerous objects or extinguishing fires in buildings, where human presence is impractical or unsafe.

- **Scalable Tasks**: Swarm robotics is advantageous for tasks that can dynamically scale up or down based on circumstances, such as responding to natural disasters that require rapid scalability.

- **Redundancy Requirements**: Swarm robotic systems exhibit robustness and redundancy, enabling them to continue functioning effectively even in the event of individual robot failures, ensuring uninterrupted task performance.

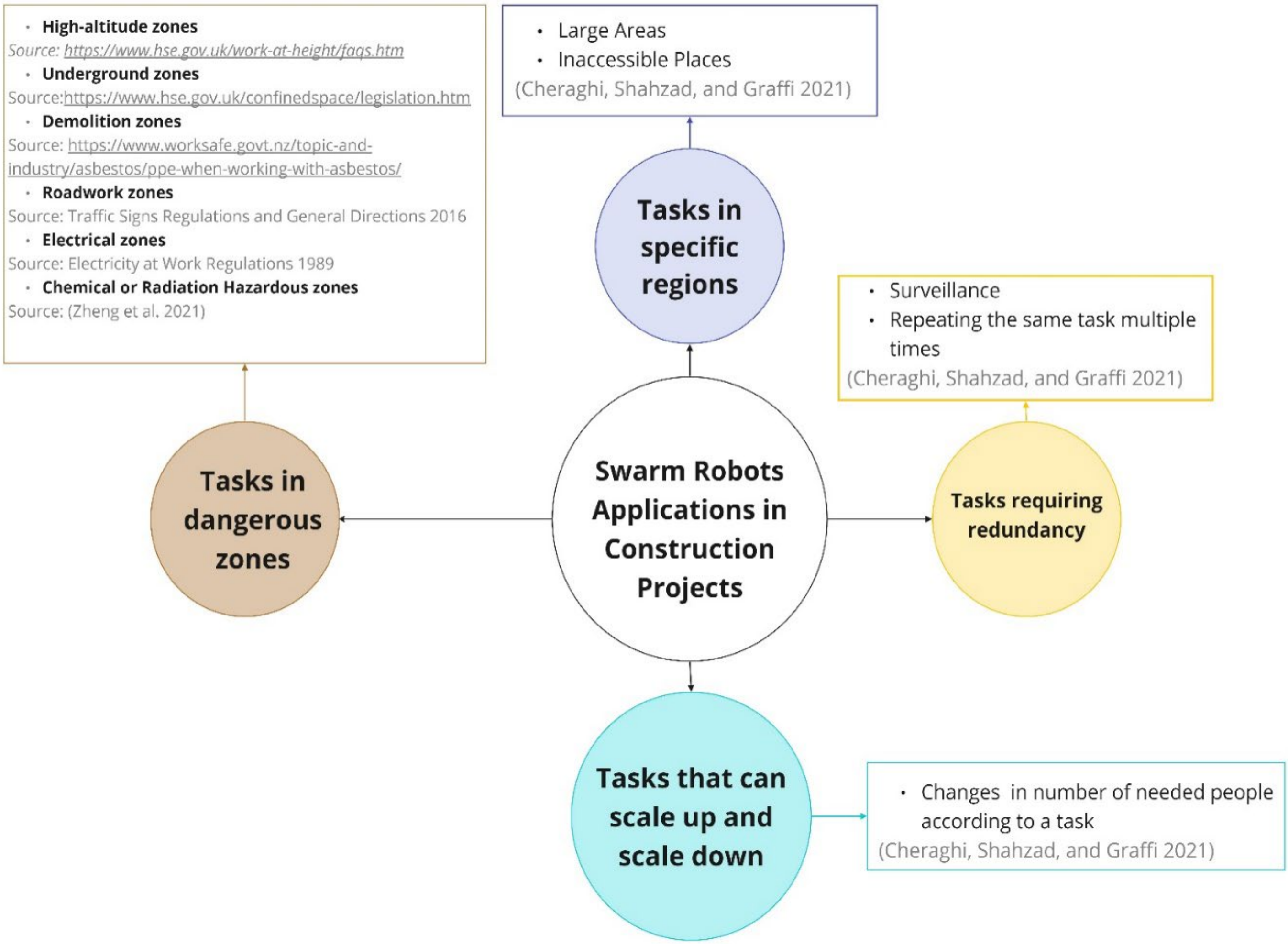


Figure 9- Swarm Robots Applications in Construction Projects

Image Source: Diagram by Author based on the written Sources

Swarm Applications Fields in Industry and Construction

A classification of Swarm Robotics industrial projects, depicted in Figure 10, classifies them based on their operational environments, categorizing robots as unmanned ground vehicles (UGV), unmanned aerial vehicles (UAV), unmanned surface vehicles (USV), unmanned underwater vehicles (UUV) (Schranz et al., 2020).

As it can be seen in the picture several industries are taking advantage of swarm robots in all available operational environments. However, it seems that in a real-scale construction project, swarm robots have not been used yet highlighting a gap in the application of this technology within construction industrial sector.

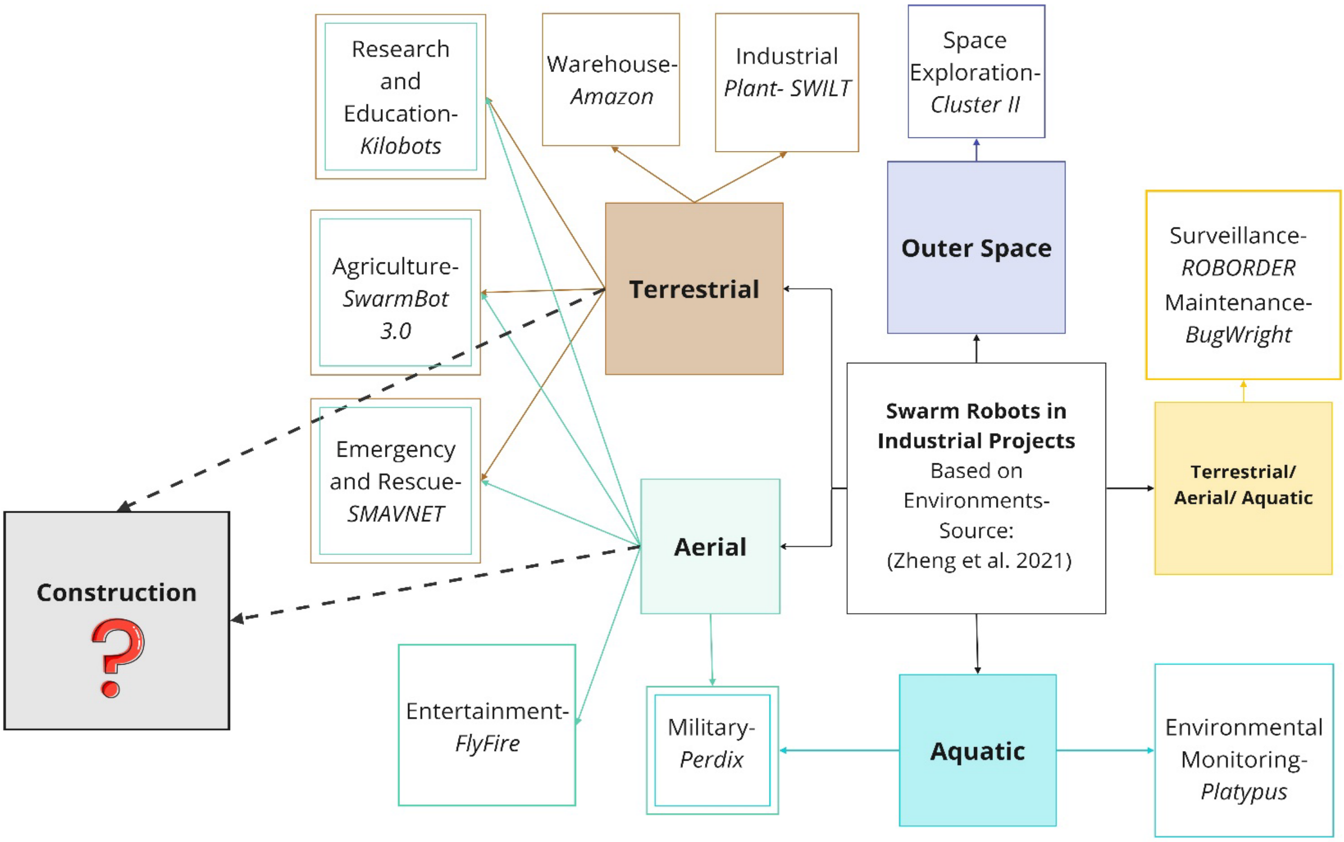


Figure 10- Industrial Swarm Robots Projects Classification based in their environment

Image Source: Diagram by Author based on classifications in (Schranz et al. 2020)

Challenges of Implementation of Swarm Robots in Construction

As was covered in earlier sections, swarm robots haven't been applied in a legitimate building project. This is due to the reasons below.

- **Centralized Control in Swarm Robotics**

The field of swarm robotics faces several challenges as identified by Schranz et al. (2020) and others. One major issue is the over-reliance on centralized control due to its accurate solutions, despite the centralized decision-making that can limit the flexibility and adaptability of swarm robotics systems. This centralization impedes the potential benefits arising from decentralized interactions among multiple robots.

- **Neglect of Swarm Robotics and Distributed Decision Making**

Another significant challenge is the neglect of swarm robotics and distributed decision-making. Ignoring the concept and benefits of distributed systems can prevent desirable swarm behaviors that typically emerge from local interactions between individual robots (Schranz et al., 2020).

- **Difficulty in Predicting Swarm Behavior**

Additionally, there is difficulty in predicting swarm behavior, which results from the complex and emergent nature of local interactions among robots. This unpredictability makes it hard to accurately predict the collective actions of a swarm (Schranz et al., 2020).

- **Challenges in Testing for Industrial Applications**

When it comes to industrial applications, testing poses its own set of challenges. Proving the eligibility of swarm robotics for industrial applications is difficult due to the risks associated with testing swarms in real-world environments and achieving realistic simulations.

- **Communication Architecture Mismatch**

Communication within swarms also presents challenges; the current communication architectures often do not meet the requirements of swarm robotics. These systems require decentralized and dynamic communication strategies, which are not sufficiently supported by centralized communication infrastructures (Schranz et al., 2020).

- **Localization Challenges**

Werfel (2012) identifies additional challenges such as localization difficulties, where the unreliability of GPS and odometry in dynamic environments complicates the establishment of a global coordinate system necessary for coordinated operations.

- **Control Complexity**

Furthermore, controlling complexity in unconstrained environments like construction sites challenges precise object manipulation by robots, necessitating advancements in manipulation algorithms(Werfel, 2012).

Potential Benefits of Decentralized solutions over Centralized ones in Construction

Swarm robots offer significant benefits through simple agent behaviors without centralized control, inspired by natural swarms. Centralized control systems in construction can create bottlenecks in computational and communication throughput and introduce a single point of failure (Zheng et al., 2021).

In contrast, decentralized systems with cooperative swarm robots operate locally with minimal resources, enhancing robustness and flexibility. The failure of individual robots does not compromise the overall system, which remains resilient and avoids communication bottlenecks (Brambilla et al., 2013). The simplicity and high number of robots allow for significant parallelism and reduced chances of malfunction (Werfel, 2012).

However, implementing decentralized control poses challenges, limiting coordination to local perception, direct communication with nearby robots, and indirect communication through the environment (Allwright, Bhalla, and Dorigo, 2017). Furthermore, decentralized systems offer weak guarantees of optimality compared to centralized algorithms, which excel in structure assembly and minimizing travel distance and assembly time (Costa et al., 2019). Centralized solutions, however, require costly recomputation in case of robotic or structural failure. As the problem scale increases, fully centralized systems become impractical, and approximations should be applied to avoid frequent recomputing.

Discussion

Swarm robots utilize algorithms based on swarm intelligence, which draw inspiration from natural swarm behaviors and get translated into mathematical models. These models facilitate the control of agents in multi-agent simulations and swarm multi-robot systems, showcasing various collective behaviors designed to achieve specific objectives. In dynamic environments such as construction sites, where conditions are constantly evolving, two key navigation behaviors—collective exploration and collective localization—are crucial.

Among the path-planning algorithms rooted in swarm intelligence, Ant Colony Optimization (ACO) is particularly fitting for its high optimization potential in both discrete and continuous environments, and its similarity to material handling operations, which is the focus of this thesis.

Transitioning from theoretical concepts to practical applications, the discussion covers different types of swarm robots, their optimal application areas, and their current industrial uses. Swarm robots are especially suited for tasks in specific, hazardous, or scalable zones due to their unique capabilities. Given that material handling is a repetitive and dangerous task on construction sites, using swarm robots for this purpose is highly advantageous.

Despite their potential, swarm robots have not yet been widely adopted in the construction industry due to various challenges. However, their decentralized control systems offer significant benefits over centralized systems, particularly in terms of flexibility and robustness.

Therefore, this research aims to implement swarm robots as an on-site logistics system for construction sites to address these challenges and improve construction efficiency. By integrating swarm robots into the construction process, this thesis seeks to demonstrate how they can enhance productivity, safety, and adaptability in dynamic construction environment.

3

Case Studies

Introduction

In this section, the practical implementation of swarm robotics within the logistic frameworks of construction sites will be explored by studying case studies. The aim is to align the experimental design closely with the operational and environmental realities of real-world construction settings. To design a realistic integration of swarm robots for this thesis, it is essential to do these five steps one by one in the details. Therefore, before designing the framework, case studies corresponding to each of these key areas will be thoroughly examined to gather accurate and relevant information.

Framework Design Essential Steps

- **Operating Robotic System and Technical Features**

  Specify the technical features of the operating robotic system. This includes the type of current swarm robots' status in construction projects, their control algorithms, navigation capabilities, sensor configurations, and payload capacities. Understanding the technical aspects of the robotic system ensures that it can meet the demands of the construction project and integrate seamlessly with the architectural and site-specific requirements.

- **Architectural Scenario and Function**

  Clearly outline the architectural design and its intended function. This involves specifying the purpose of the construction. Understanding the architectural scenario helps in planning the logistics and requirements for the swarm robots.

- **Construction Site's Condition and Layout**

  Describe the construction site's conditions and layout in detail. This includes the terrain, size, obstacles, and any dynamic elements that might change during the construction process.

- **Structure Type and Used Material**

  Define the type of structures that will be created and the materials that will be used. This involves detailing the construction methodology. The choice of materials affects the swarm robots' handling and operational strategies.

- **Virtual Simulation**

  Implement a virtual simulation to test and refine the integration of swarm robots within the construction environment. This simulation should replicate the construction site, the robots' movements, and their interactions with the environment and materials.

3-1 Operating Robotic System and Technical Features

3-1-1 Projects by Swarm Robots

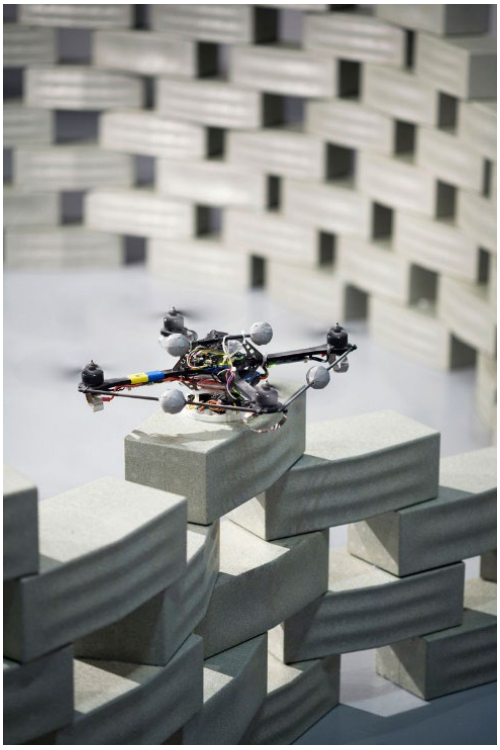
In this section, the capabilities and applications of swarm robots are assessed through an examination of real projects conducted either in the industry or as academic research. This investigation is necessary to discover the swarm robots' strengths and weaknesses to assess the feasibility of using swarm robots as the primary logistics system on a construction site.

Flight Assembled Architecture, 2011-2012

This project is known for being the first architectural installation assembled entirely by flying robots, without human intervention. A fleet of quadrotor helicopters placed over 1500 modules to create the installation, coordinating through mathematical algorithms that translated digital design data into their actions. This project introduced a visionary architectural concept—a 600-meter-high "vertical village" designed to accommodate 30,000 inhabitants on a 1:100 scale model. However, it is evident that this project operated on an unrealistic scale of construction, with each robot handling only a single lightweight polystyrene foam module at a time. The materials were discrete and simply stacked without further connections (Gramazio et al., 2012).

Figure 11- Flight Assembled Architecture

Image Source: https://gramaziokohler.arch.ethz.ch/web/e/projekte/209



Termes Project

In this project, the research group investigated the construction capabilities of social insects, specifically termites, to develop a decentralized control system for swarm robotic construction without centralized planning. This effort led to the development of algorithms and robotic designs inspired by termite construction behavior, allowing robots to build specified structures autonomously. These robots, capable of climbing and assembling modular structures from foam blocks embedded with magnets and plastic, highlight a significant advance. Each block measures 21.5 × 21.5 × 4.5 cm, with a weight of 165–210g, while the robot's footprint is 17.5 cm × 11.0 cm. (Petersen et al., 2012).

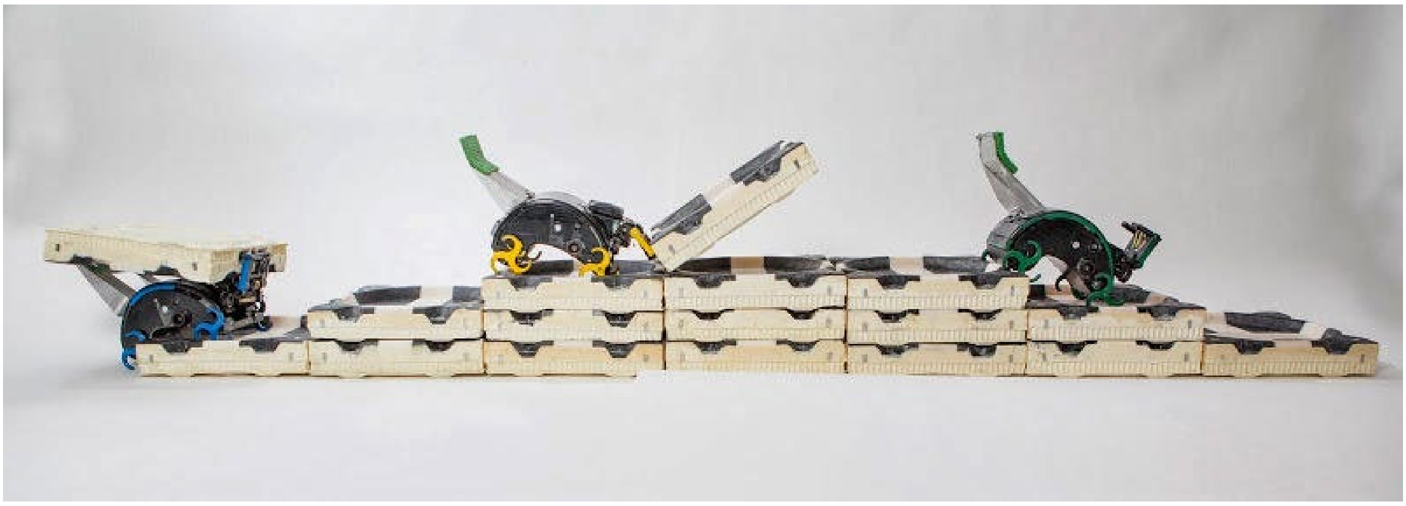


Figure 12- Termes Project

Image Source: https://ssr.seas.harvard.edu/termes

BuilderBot Project

An extension of the BeBot mobile robotics platform, BuilderBot, was utilized for allocating construction tasks through the collective perception of a dynamic environment. This project focused on an abstract construction scenario where a swarm of robots estimated the density of building blocks around a site, as represented by 2D tiles. Robots assigned to foraging tasks moved these tiles to a cache area, and those tasked with construction picked up the tiles to build structures. The BuilderBot itself has dimensions of 38.8 cm in height and a square footprint 14 cm per side, weighing 2.1 kilograms, with each building block weighing 110 grams and measuring 55 mm on each side. BuilderBot uses camers to see the blocks on the ground up to approximately 35 cm away from the center of the robot (Khaluf et al., 2020; Allwright et al., 2018).

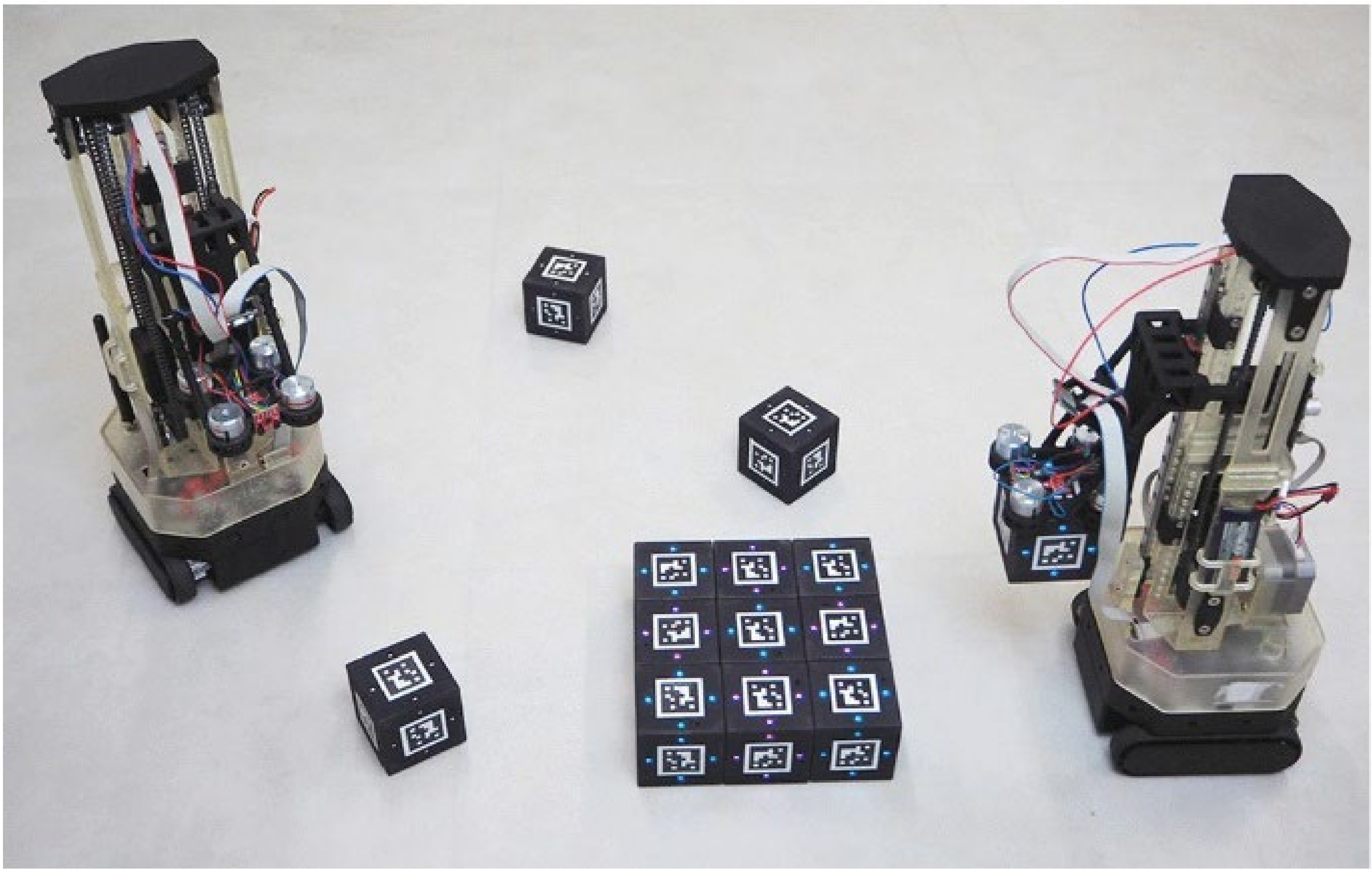


Figure 13- Simulation Environment

Image Source: (Khaluf et al., 2020)

Discussion

These projects demonstrate that while swarm robots can handle discrete, lightweight materials, they face practical limitations in larger-scale construction environments where heavier materials are prevalent. Since the project's objective is to act on a larger construction site, these swarm robots with lightweight materials cannot be used. As a result, the next step will involve examining autonomous mobile systems used in industry to evaluate their control systems and physical properties, determining their potential as logistics systems. However, these mentioned projects illustrate that using simple, discrete materials stacked by robots offers a focused approach to handling materials, albeit limited to simpler tasks rather than complex assembly stages.

3-1-2 Autonomous Mobile Robots as Logistics in Industry

In this section, after identifying limitations related to payload, size, and scalability in previous studies, attention is shifted towards industrial projects that utilize autonomous mobile robots (AMRs) with larger sizes and higher load capacities. These robots, such as Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs), are extensively employed for tasks like warehouse automation and materials handling in manufacturing industries, aiming to enhance output efficiency (Velis, 2023; Rajan &

De La Cruz, 2022). Although previously noted that AMR robots typically employ centralized control systems, this part will focus solely on the robots' usage not regarding their control algorithms, concentrating on tasks like navigation, path-planning, and material handling in warehouse settings.

LoadRunner

A notable advancement in the deployment of larger-scale swarm robots with distributed systems is the LoadRunner, developed by the Fraunhofer Institute IML and the KION Group. These robots, which are undergoing testing in a DPD Germany warehouse, communicate via 5G and are equipped with cameras that allow for localization at 400 frames per second. The robots have a maximum speed of 10 m/s, which theoretically could increase to 25 m/s, with an acceleration capacity of up to 5 m/s². Each robot can handle a payload of approximately 30 kg. According to a report by the KION Group, these robots are capable of sorting up to 10,000 shipments per hour with a fleet of 60 units. The physical size of these robots was not specified, but they are designed to handle standard-sized packages, with designated pickup and placing points within the warehouse (Fraunhofer Institute IML and KION Group, 2021).

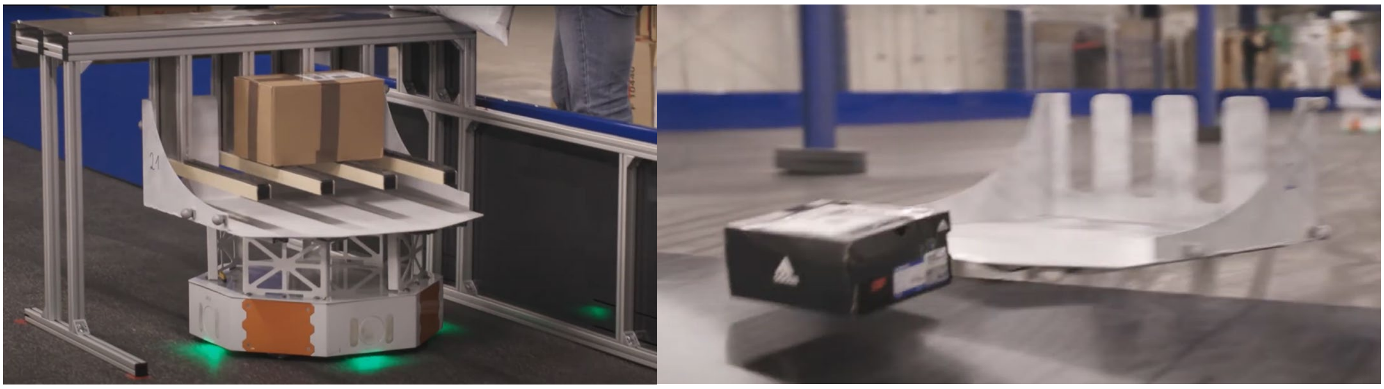


Figure 14- Load Runner Picking and Placement
Image Source: https://www.youtube.com/watch?v=XtDjhCBFe7Y

Husky

Another AMR robot is the Husky Unmanned Ground Vehicle (UGV), a medium-sized robotic platform well-suited for construction site applications. The Husky's design allows for a large payload capacity, and its power systems support a wide range of payloads. It can be customized with various devices such as stereo cameras, LIDAR, GPS, IMUs, and manipulators, facilitated by integration experts. The Husky is robustly constructed with a high-torque drivetrain that enables operation in diverse environments. It has a maximum speed of 1.0 m/s and can run for up to 3 hours. The external dimensions of the Husky are 990mm x 670mm x 390mm, with a payload capacity of 75 kg, and it is fully compatible with a wide range of robotic accessories, supported in ROS with community-driven open-source code and examples.

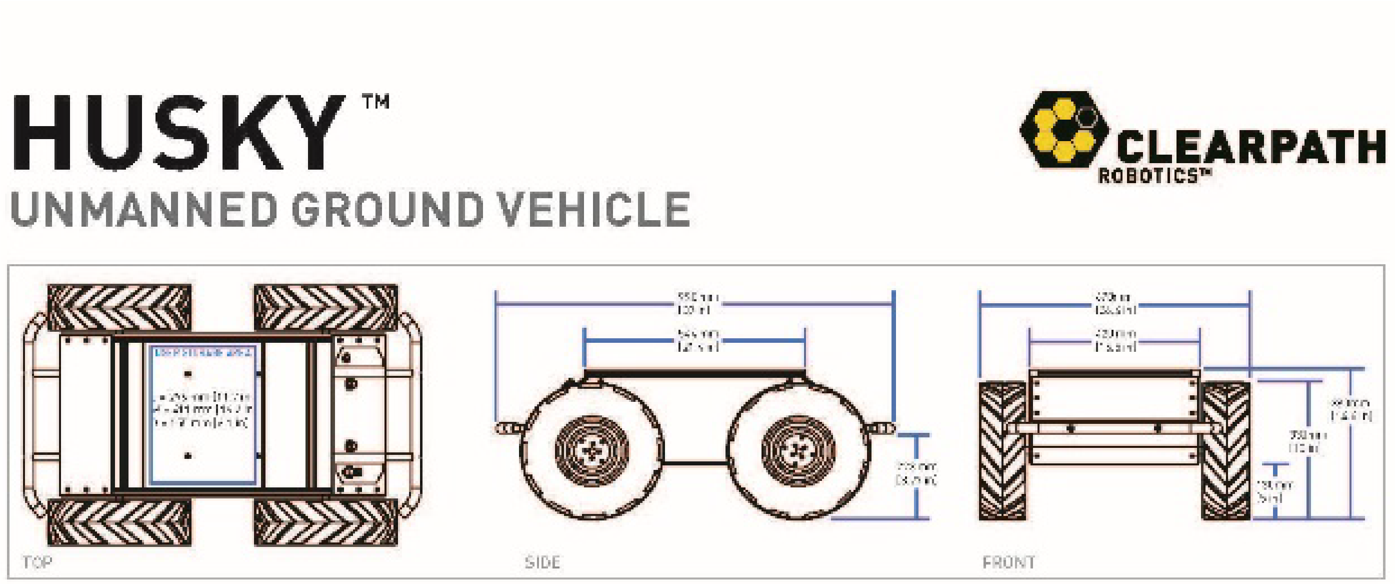


Figure 15- Husky Robot's Dimension

Image Source: https://clearpathrobotics.com/husky-unmanned-ground-vehicle-robot/

Figure 16- Husky Robot

Image Source: https://clearpathrobotics.com/husky-unmanned-ground-vehicle-robot/

Discussion

The examination of these projects demonstrates that robots with higher payload capacities are increasingly adaptable to varied tasks and environments, enhancing their utility in unmanned operations. The technical properties of robots like LoadRunner and Husky vary significantly across manufacturers, which impacts their application potential. The high speed of the LoadRunner, compared to the slower Husky, highlights the trade-offs between speed and payload capacity in different operational contexts. However, the systematic pickup and placement stations utilized by LoadRunner in warehouse environments present a valuable model for material handling processes on construction sites. While the LoadRunner benefits from a decentralized control system, the focus here is on technical properties relevant to construction scenarios, making the Husky a more viable option due to its all-terrain capabilities and higher load capacity. Moreover, Husky's compatibility with additional equipment installations enhances its functionality, allowing for the integration of robotic arms and other devices, thereby broadening its application in construction environments.

3-2 Architectural & Construction Site Layout

In the previous section on the "Capabilities and Applications of Swarm Robots," it was determined that using simple, discrete materials that can be easily stacked in scattered locations across a construction site emphasizes material handling as a primary task focus. Building on this finding, the current section aims to explore architectural layouts that are distributed around the site to make the swarm robots as on-site logistics the most important feature of this construction. Specifically, the goal is to identify designs featuring monolithic structures that require the minimum variety of material types and construction stages, thereby highlighting the role of swarm robots in material handling tasks. Regarding the Framework Design Essential Steps, this section’s case studies cover all three areas of Architectural Scenario and Function, Construction Site’s Condition and Layout, Structure Type and Used Material.

Riyadh Houses

The speculative proposal utilizes advanced eco-friendly technology and a contemporary reinterpretation of traditional atrium and dome designs to create luxurious, serene, and harmonious habitats that blend seamlessly with the surrounding nature. This project is a competition entry for two expansive villas situated on the outskirts of Riyadh, Saudi Arabia. The program calls for spacious residences with various zones for both public and private use, including areas for meetings, work, and relaxation, amounting to over 2000 square meters per villa. Despite their proximity to the city, the immediate surroundings of the villas are characterized by rocky desert terrain (COLLARCH, 2022).

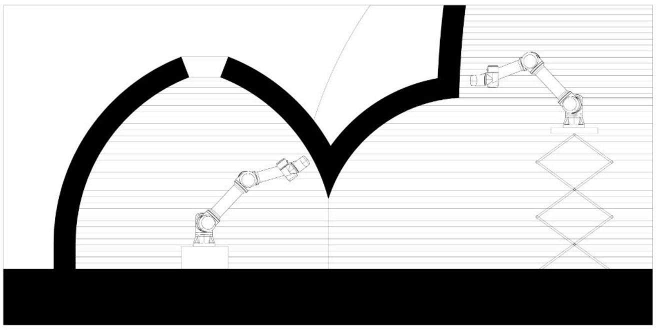
Figure 17- Riyadh Dream Villas

Image Source:(COLLARCH, 2022)

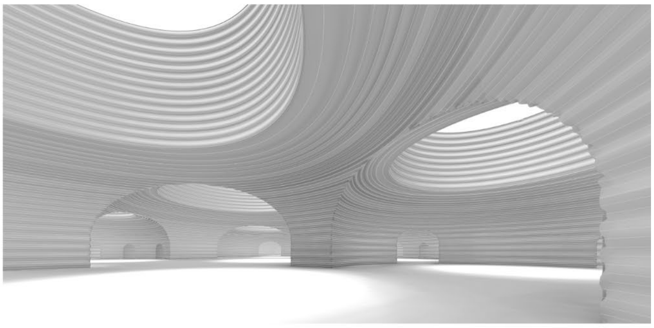
The images displayed reveal two predominant architectural styles. Villa A is characterized by several domes that surround garden atriums. These domes intersect with the atriums, creating varied geometrical forms that not only meet the complex requirements of the program but also contribute to an elegant and timeless architectural style. Given the harsh climatic conditions, the living areas are designed to face these shaded atriums instead of the harsh external environment, providing protection from both sunlight and wind. The overall external design of the residence echoes vernacular architecture with local material.

In contrast, Villa B's external design appears as the inverse of Villa A, with domes and atriums seemingly sculpted from the residence's substantial volume.

The project's geometry and material choices stem directly from its primary construction method—additive manufacturing using locally sourced materials. Elements such as local soil, clay, and concrete—derived and colored from local sand and gravel—are robotically 3D printed. Traditional construction techniques are employed as needed to enhance the structures. The selected geometries are particularly suited to this construction method; a centrally positioned robotic arm can efficiently fabricate the walls of a dome or atrium. Furthermore, the dome shapes are structurally advantageous as they generate compressive forces, aligning well with the material properties.



THE STRUCTURES ARE BUILT USING ROBOTIC ADDITIVE FABRICATION OUT OF LOCAL MATERIALS



THE INTERSECTION OF THE DOMES AND ATRIUMS PRODUCES COMPLEX SEQUENCE OF VARYING SPACES.

Figure 18- Structures built using Robotic Arm
Image Source: (COLLARCH, 2022)

The floor plan displayed in the image below uses different colors to delineate various program areas. It is clear that the design is structured around multiple areas as main cores, with surrounding spaces varying in scale, evident at both the site level and on a more detailed scale. This layout effectively emphasizes the main gathering spaces and facilitates easy access to other areas.

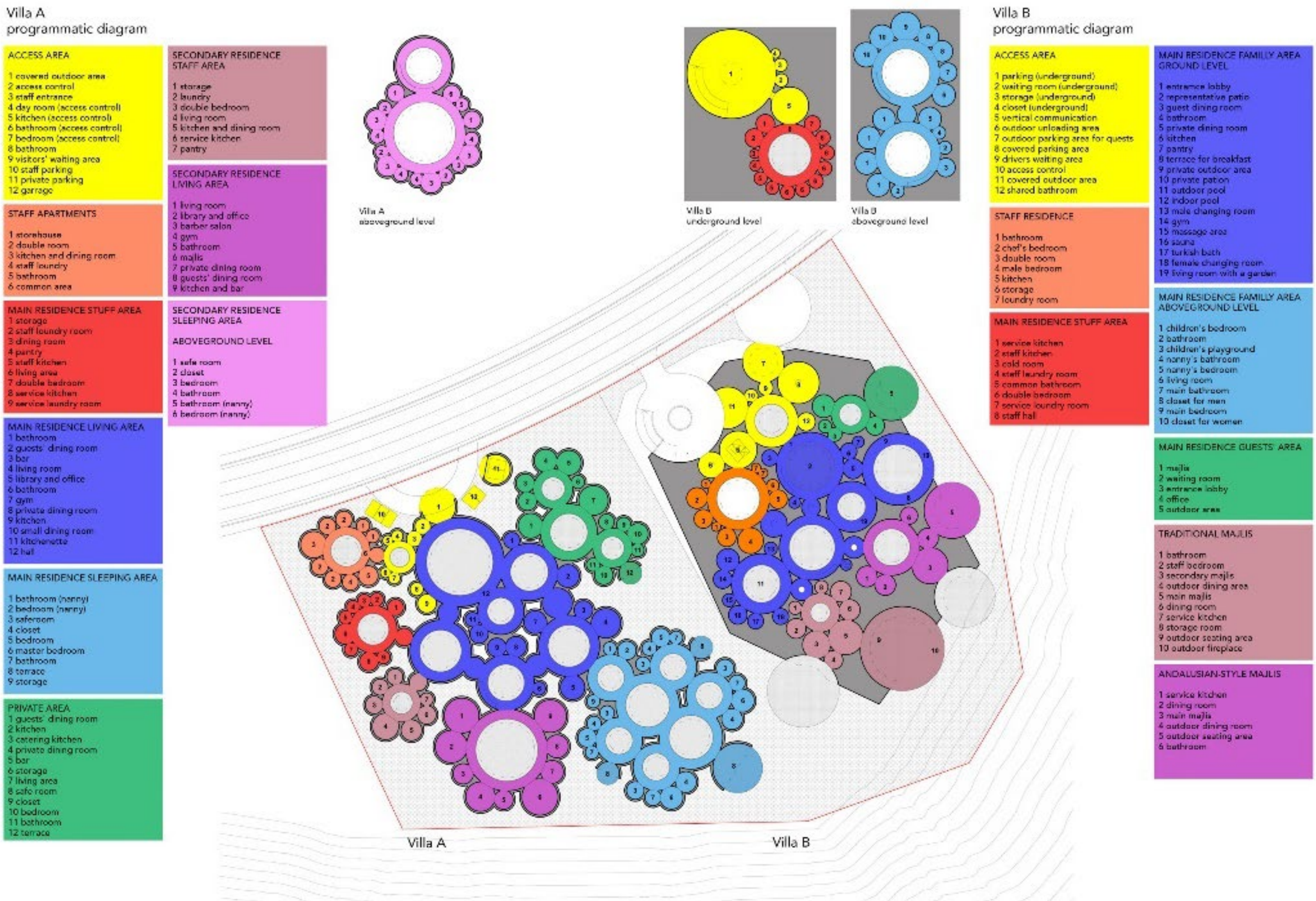


Figure 19_ Architectural Layout
Image Source: (COLLARCH, 2022)

Wasp

TECLA is an innovative eco-sustainable 3D printed habitat designed by MC A – Mario Cucinella Architects and engineered by WASP. It represents a groundbreaking achievement in construction technology, being the first and unique fully 3D-printed habitat based on natural materials. Constructed in Massa Lombarda, Italy, TECLA is made using Crane WASP, a brand-new 3D printer in the construction sector, and multiple collaborative printers operating simultaneously. The habitat is circular in shape and built with reusable and recyclable materials sourced from local soil, making it carbon-neutral and adaptable to any climate and context. TECLA showcases the potential of 3D printing technology to optimize construction processes, minimize resource usage, and pave the way for a greener economy. The construction process is replicable with the WASP Maker Economy Starter Kit, which includes multiple 3D printers and a system for picking, mixing, and pumping materials. Overall, TECLA exemplifies a sustainable approach to housing design and construction, using advanced technology to create environmentally friendly and adaptable living spaces (WASP, 2021).

Figure 20- 3d-printed eco-sustainable habitats

(WASP, 2021)Image Source:

This sustainable housing project, featuring compression structures and scattered buildings around the site, resembles the previous case study. The layout with scattered core models provides a large space for robotic arms and swarm robots as logistics to navigate freely between the structures.

Discussion

As depicted in both case studies, compression-only structures have been used for creating innovative and free-form architecture. These structures rely only on compression forces for stability without the need for reinforcement or mortar, showcasing a unique blend of traditional techniques and advanced technologies(Carbonell-Márquez et al., 2016; Akbarzadeh et al., 2014). By utilizing force density methods and topological mapping, compression-only structures can be efficiently form-found, allowing for rapid adjustments in equilibrium configurations (Zhang, 2011). The benefits of compression-only structures include material efficiency, simplified construction processes, and the creation of visually striking and innovative architectural solutions.

Given the exclusive focus on using swarm robots for material handling, it is advisable to select discrete, dry conventional materials such as wooden elements, cork blocks, and bricks that lend themselves to easy stacking. These materials are particularly suited for creating compression-only structures, which emphasizes their stacking capabilities to handle compressive loads effectively.

3-3 Virtual Simulation

This section is dedicated to the study of computational simulations relevant to this thesis, focusing on scenarios where agents engage in specific behaviors crucial for construction site operations. These behaviors include path-planning, material detection for picking and placement, and obstacle and collision detection and avoidance. Through these simulations, settings that mimic a realistic construction site are extracted to enhance the virtual simulation framework, with a focus primarily on simple tasks that focus on swarm behaviors.

Construction Task Allocation Through the Collective Perception of a Dynamic Environment

In the 2020 study by Khaluf et al., an abstract construction scenario is presented where a swarm of robots is tasked with estimating the density of building blocks around a construction site. Robots are allocated to foraging tasks to maintain the desired block density in a cache area, represented as 2D tiles in the simulation model. This stochastic process aims to minimize idle time and maximize construction rates by ensuring a continuous supply of materials necessary for construction tasks. Robots not only retrieve but also position these tiles within a designated construction zone, emphasizing efficiency in both material handling and structural assembly.

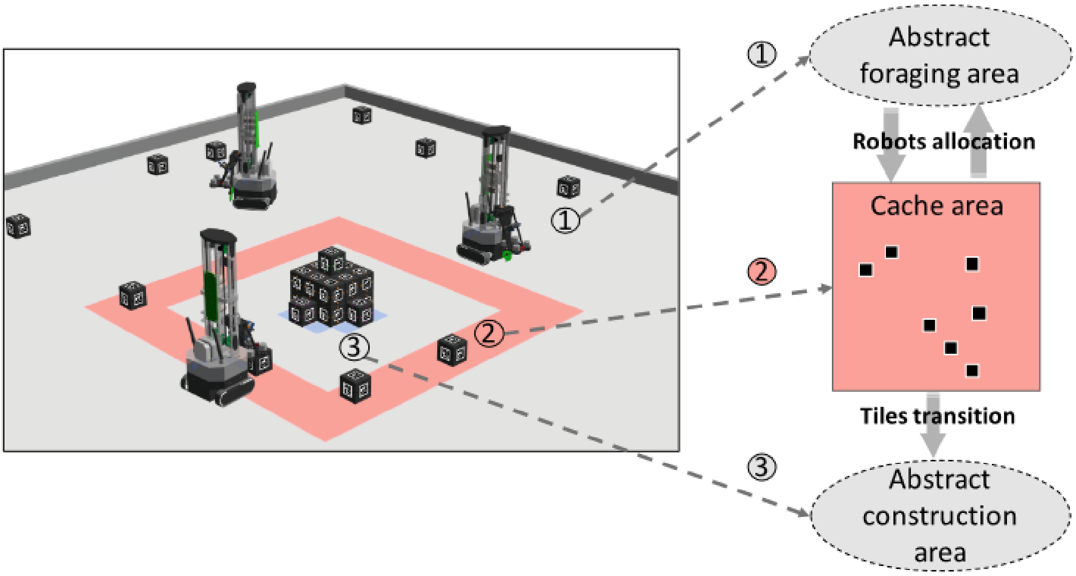


Figure 21- Simulation Environment

Image Source: (Khaluf et al., 2020)

The objective of this study is to construct a simple structure using stigmergic blocks, with a focus on the collective perception of the swarm. Observed behaviors include material detection and the accurate pickup and placement of blocks. In this experiment, every component was meticulously designed and engineered, including the hardware of the robots themselves. The measure of success for the experiment is determined by comparing the idle time, which is directly related to the rate of construction.

Grid-Based Mobile Robot Path Planning Using Aging-Based Ant Colony Optimization Algorithm in Static and Dynamic Environments

In this article, a variation of the standard ant colony optimization known as aging-based ant colony optimization (ABACO) has been developed. ABACO incorporates the age of the ant into the optimization process. It was integrated with grid-based modeling for both static and dynamic environments to address path-planning problems. Simulations revealed that the proposed path planning algorithms exhibit improved performance, successfully identifying the shortest and least collision-prone paths across various static and dynamic scenarios (Ajeil et al., 2020).

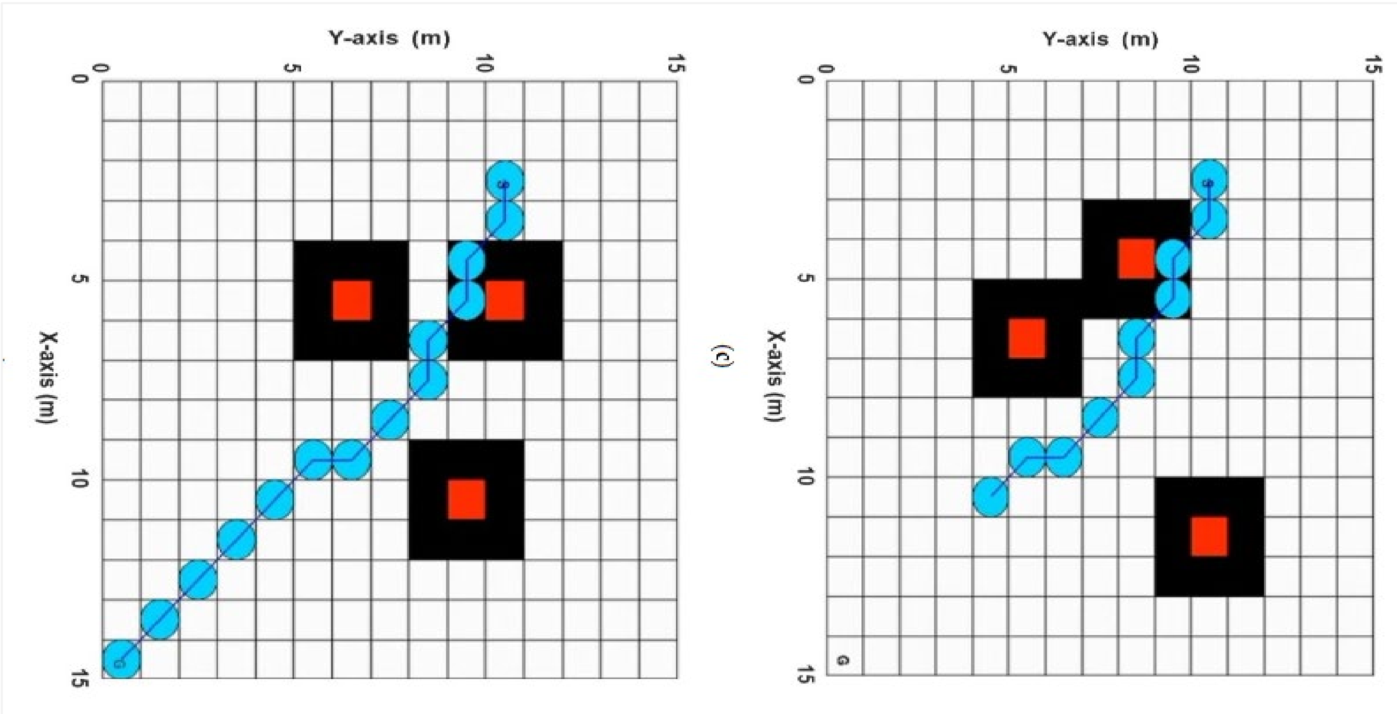


Figure 22- Simulation in a 2D dynamic environment

Image Source:(Ajeil et al., 2020)

The experimental environment is defined as a grid-based 2D space, where grids represent the workspace of mobile robots as equal square cells. Each cell is either traversable, denoted as logic 0, or obstructed by an obstacle, marked as logic 1. Each cell is uniquely identified by an "address.

If a cell is blocked by an obstacle, as shown in the figure, the robot is programmed to look for nearby open cells to keep moving. During the simulation, the robot can move from its current position to any adjacent cell that is not occupied, as illustrated in Figure 23 (Ajeil et al., 2020).

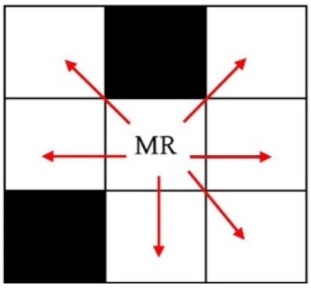


Figure 23- Possible path directions for the robot

Image Source: (Ajeil et al., 2020)

Additionally, the physical dimensions of the robots are considered as the agents' dimensions in this study. The experiment examines parameters such as path length and execution number, both correlated with the number of iterations. Notably, this experiment is conducted under multiple scenarios featuring static and dynamic obstacles across various time frames.

Optimal Path Planning Applied to Ant Foraging

In this paper, the authors propose a hybrid approach that combines the pheromone method with path-planning techniques to enhance the performance of basic mobile robots. By integrating path planning, the time required for locating food sources can be minimized by eliminating the random exploration phase inherent in the standard ant foraging technique. This novel hybrid technique, applicable in various environments such as assembly systems with components distributed across multiple locations or in dynamic industrial settings where workers' positions are not fixed and tools need to be allocated to them efficiently, is both proactive and passive in nature (Veeraswamy et al., 2016).

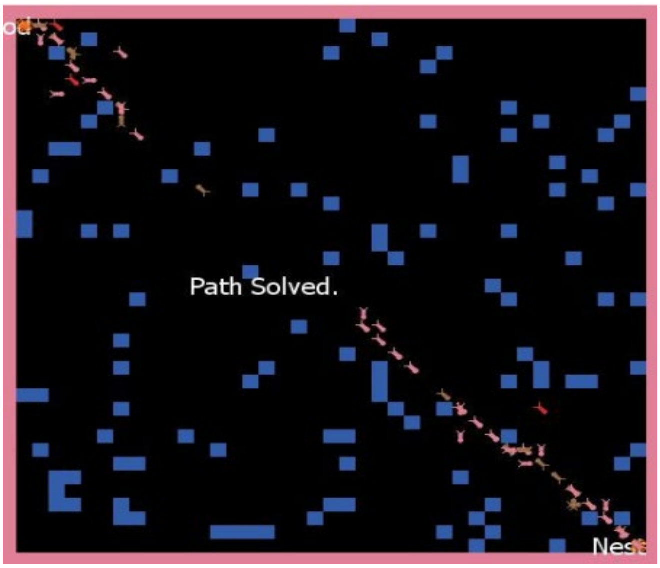


Figure 24- Ant foraging in an environment with random obstacles

Image Source: (Veeraswamy et al., 2016)

Figure 25- Ant foraging in an environment with bar like obstacles

Image Source: (Veeraswamy et al., 2016)

This approach is particularly valuable as it conserves the time initially spent on random exploration by robots on construction sites. The experiment features a single ant tasked solely with identifying the optimal path to the food source and depositing pheromones, without the burden of carrying food. This experiment, similar to the previous one, is conducted across multiple scenarios that incorporate both static and dynamic obstacles over various time frames.

A Novel Swarm Robot Simulation Platform for Warehousing Logistics

In this experiment, a novel simulation platform known as MultiBots is employed, which utilizes a multi-agent pathfinding (MAPF) method and a collision avoidance strategy to effectively evaluate task allocation strategies in warehouse logistics scenarios. This platform also incorporates a designed charging process to manage the energy consumption of the robots, which is crucial for extended operations.

The experimental setup is conducted within a simulated warehouse environment, represented as an 800* 550 white rectangle, which serves as the working area for the robots tasked with loading and unloading goods. The warehouse is organized with six designated departure zones and six corresponding unloading zones, as depicted in Figure 26. Additionally, the warehouse includes eighty 50*50 red squares, divided into ten groups of eight, which represent the storage areas for the goods and are sequentially numbered from 0 to 79. The color of these squares indicates the presence of goods: a red square signals goods are present, while a square filled with black indicates an absence of goods.

Navigational pathways between these groups are defined by a 50-width passageway, allowing circle robots with a radius of 12.5 to pass through successfully. The robots are represented with a circle marked with a straight line indicating the robot's head, and a life bar at the end, indicating the robot's current status. The circles are filled with three different colors to represent the operational status of the robots: blue for robots on route to pick up goods, red for robots actively transporting goods, and green for idle robots either completing a task or returning to charge. Above the operational floor, six charging zones are available, as shown in Figure 26. A small red square positioned left below the warehouse denotes the goods that have been picked up.

The performance outcomes of this experiment are measured based on task completion time, correlated with the number of goods handled, the number of multi-agent interactions, and the occurrence of collisions. The experiment involves five groups of goods locations, which are used to set up various testing scenarios.

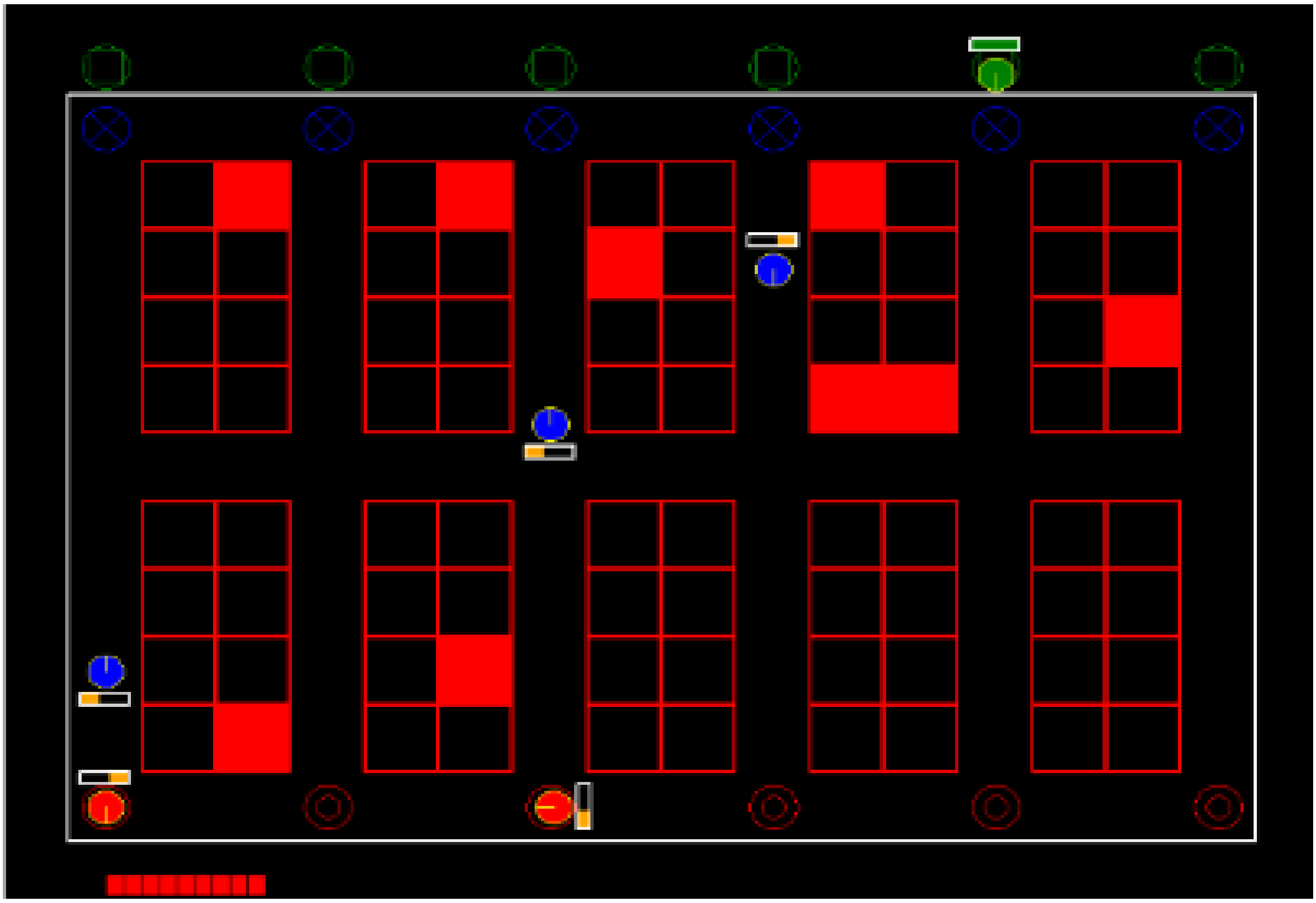


Figure 26- Warehouse Simulation Settings
Image Source: (Liu et al., 2017)

The MultiBots simulation platform demonstrates its capability to fulfill the requirements for evaluating task allocation strategies within warehouse logistics environments, confirming its applicability for assessing the efficiency of such strategies in real-world logistics systems.

Discussion

Overall, these four experiments establish a solid foundation for identifying the necessary parameters to define a simulation. The parameters extracted, as detailed by Bonabeau et al. (1999) and Lieveloo (2023), are crucial for setting the simulation framework of future research. These parameters include:

- **Environment: size- type**
- **Multiagent system: size- type- tasks-technical features**
- **Agent's Detection Method**
- **Agent's Communication System**
- **Agent's Control Algorithm**
- **Simulation Environment**
- **Simulation Scenarios**

These parameters are essential for creating a virtual simulation and objectives of subsequent studies and ensure that evaluations of robot efficiency are accurate and applicable to the scenarios being investigated.

The main takeaways from all the studied case studies are recapped in the form of a diagram. These insights have been incorporated into the thesis framework which will be presented in the next chapter.

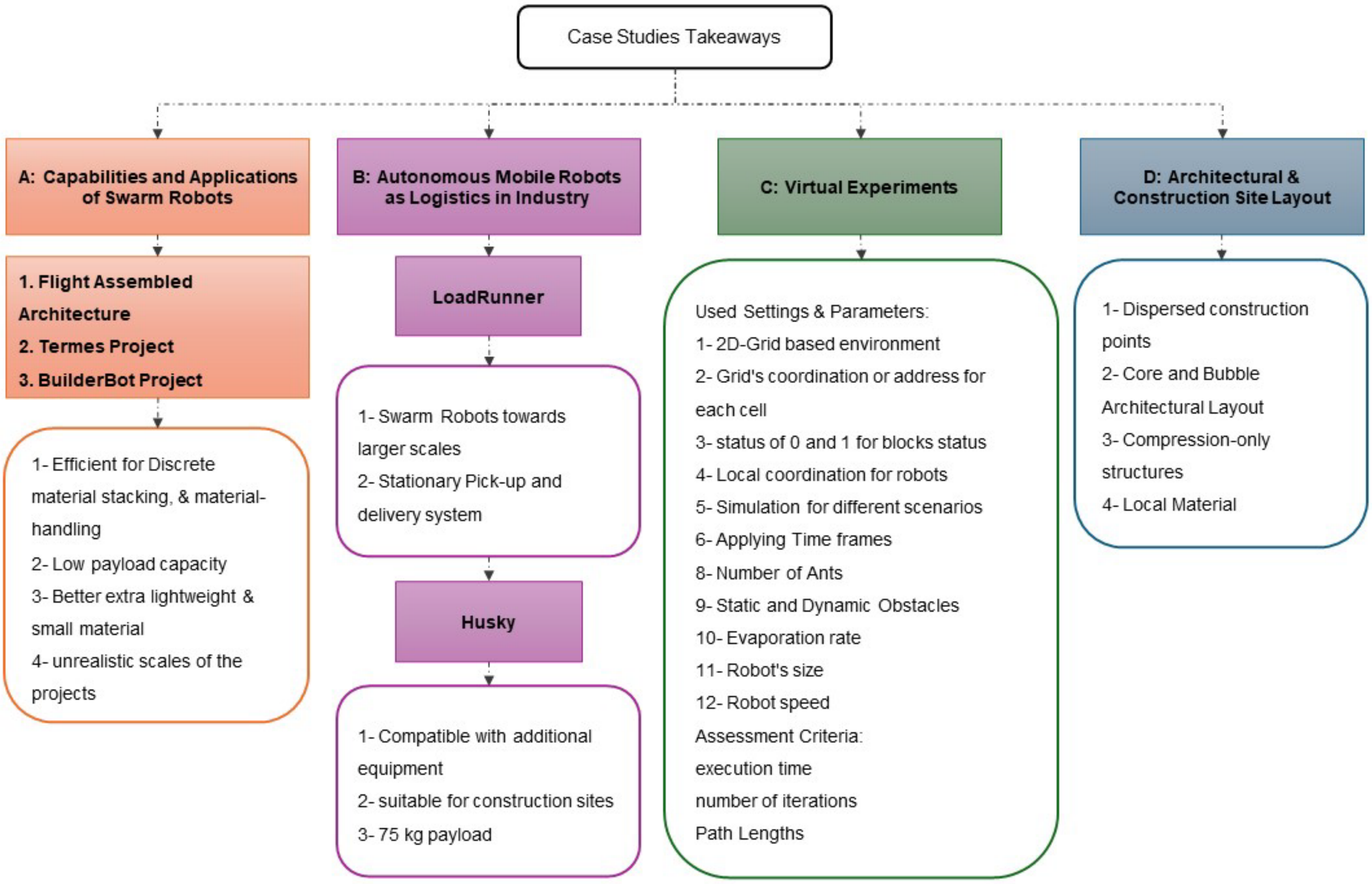


Figure 27- Extracted results from the case studies

4

Implementations

Introduction

In this section, the final implementations derived from all the studied case studies will be presented. These implementations are categorized into two areas: Architectural and Simulation. For clarity and ease of understanding, they will be depicted in a diagram below.

In the subsequent section, the architectural layout style will be finalized, focusing on a compression-only structure that is ideal for this scenario. Then a general review of selected discrete material will be conducted followed by developing a construction scenario specifically tailored to this research. This scenario will incorporate characteristics from previous case studies, ensuring that this approach is both innovative and rooted in established practices.

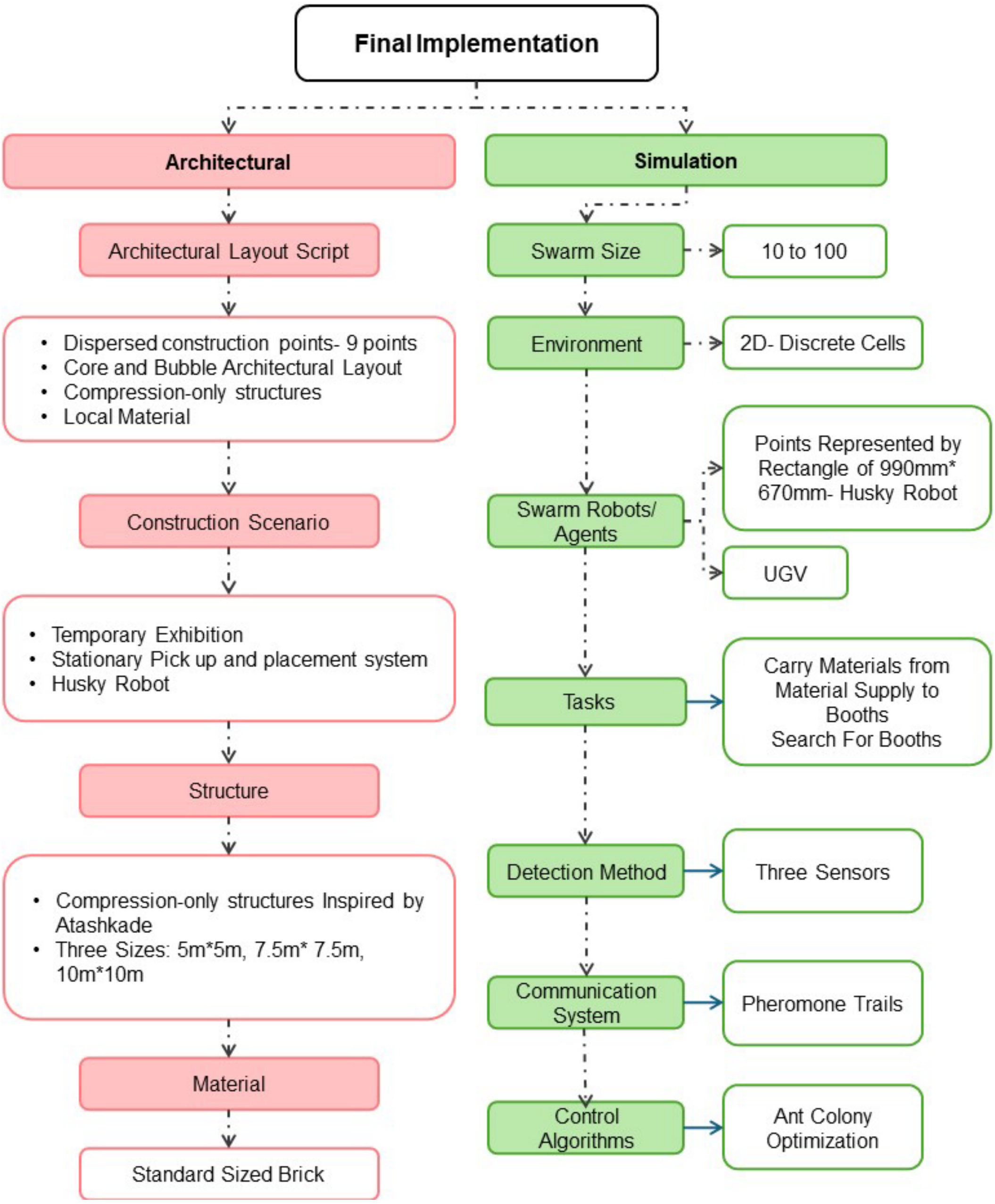


Figure 28- Simulation Initial Settings

4-1 Architectural layout

In the Riyadh houses and Wasp project, the central takeaway was the use of main core areas surrounded by other spaces, which serve as gathering points and facilitate access throughout the site. This centralized design simplifies controlling the layout compactness and density and offers flexibility in architecture and simulation simplicity. Initially, the construction site will be imagined with multiple scattered points, functioning as the main cores of the project. This layout enhances the ease of robot movement around the site.

For this research, a complex consisting of nine main points designed as exhibition booths is proposed. Given the focus on the material handling capabilities of swarm robots, these exhibition booths are intended to be temporary, allowing for multiple assembly and disassembly. This flexibility requires the exhibition organizer and architect to customize the space according to specific needs, ensuring a seamless integration of the initial design with the logistics plan handled by the swarm robots. The plan is to create three types of booths of varying sizes to meet different design and exhibition requirements. To improve the visitor experience, seven ponds are included in the layout, and a walking path that connects all the booths while navigating around the ponds is planned to provide an enjoyable experience.

The images below show one layout option with different degrees of compactness. The first focuses only on the cores, showing the essential elements for setting up a simplified simulation. The second presents a more connected and compact design, where all booths and their surrounding areas are linked. The exhibition layout includes three functions: red zones as main exhibition booths, larger middle zones for community activities like cafes and restaurants, and blue zones for services such as washrooms.

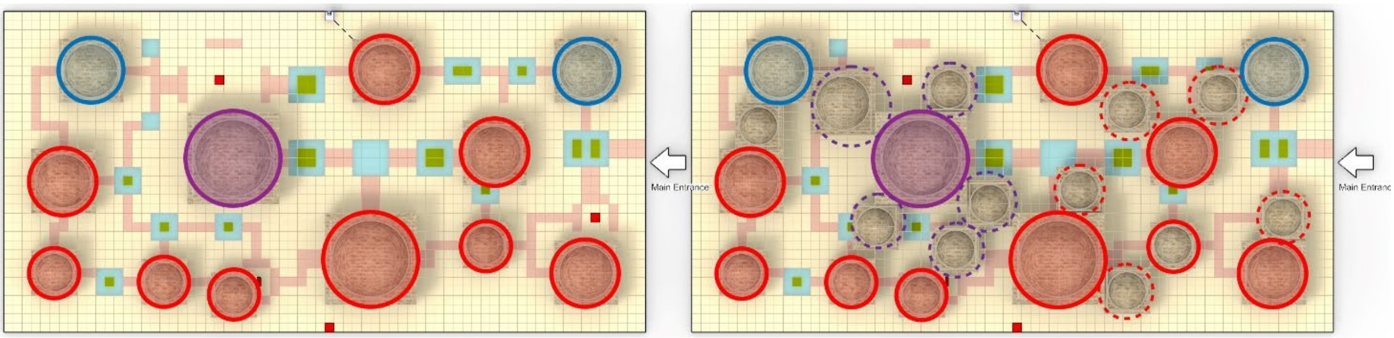


Figure 29- Two Densities of the Architectural Layout

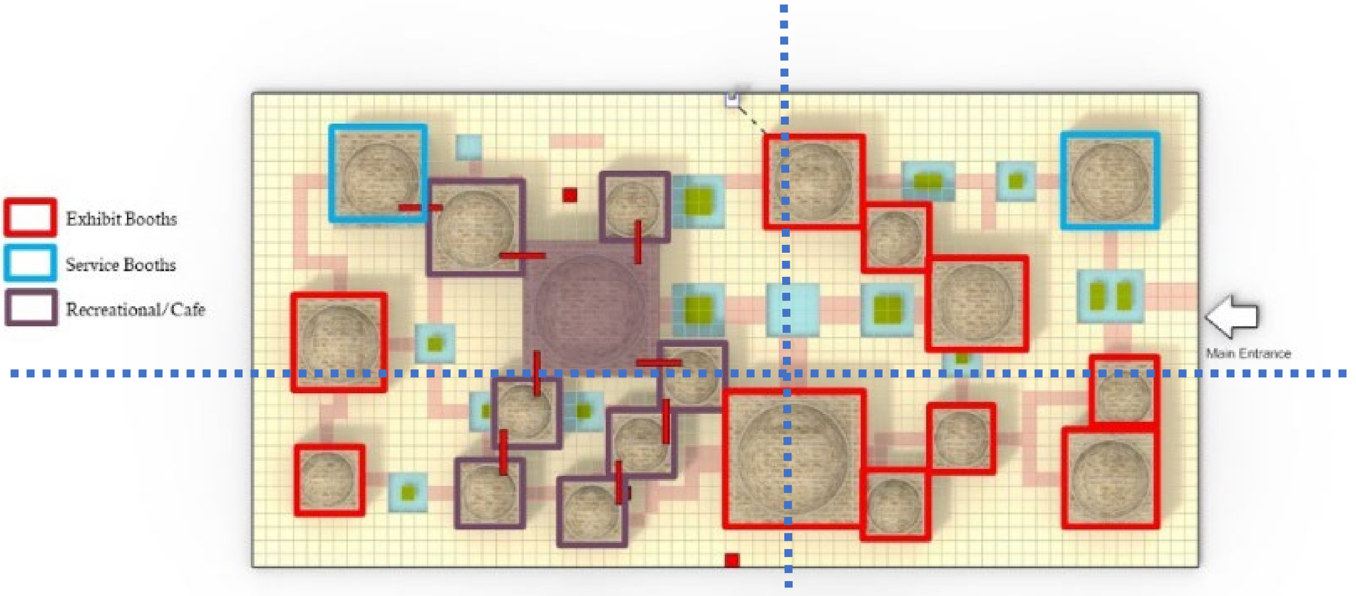


Figure 30- Architectural Plan

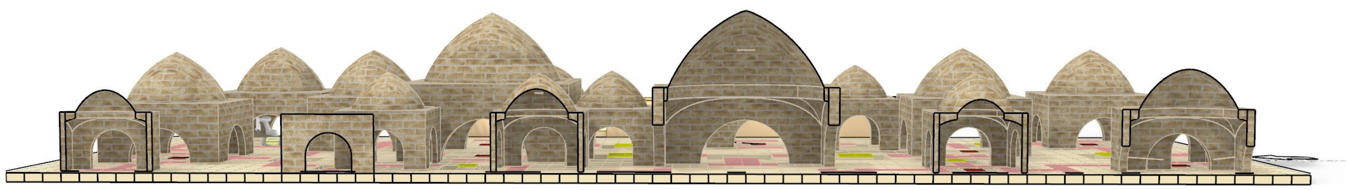


Figure 31- Section A-A

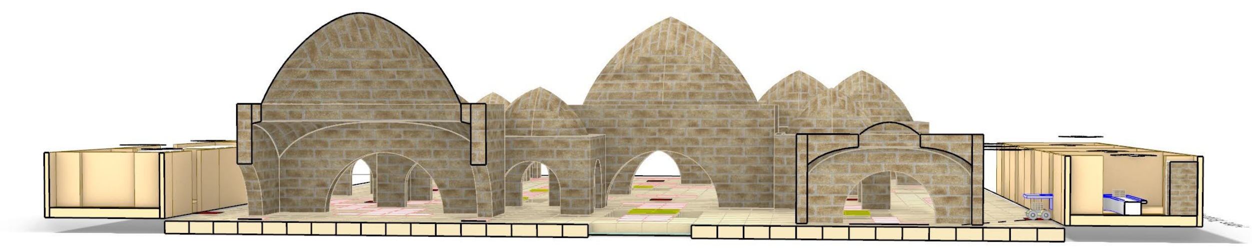


Figure 32- Section B-B

4-2 Construction Site

As outlined in the "Construction Site Layout regarding Logistics" section of the background review, it is crucial to design construction sites based on Health, Safety, and Environment (HSE) principles to ensure safety and productivity. The design process typically begins with a preliminary freehand sketch, which is refined as the layout is finalized. The following factors are critical in arranging a construction site effectively:

Safe Site Access:

Ensuring there is a secure and clearly defined entry point for personnel and equipment.

Fenced and Protected Site Boundaries:

Installing barriers to delineate the site and protect it from unauthorized access.

Proper Welfare Facilities:

- Sanitary conveniences
- Washing facilities
- Rest facilities
- Storage and drying areas for clothing and personal protective equipment
- Drinking water provisions

Good Order and Management of Storage Areas and Waste Materials:

Organizing storage and disposal areas to maintain cleanliness and order.

To facilitate these requirements, the plan includes a single-lane, one-way temporary road with a width sufficient for a standard truck. All facilities are arranged within a 5-meter margin around the site perimeter. The layout includes two rest areas, two welfare facilities, two material supply points, two robot maintenance stations, and two construction waste disposal areas, positioned across from each other on opposite sides of the site. Additional space is allocated at the entrance for offices. This setup allows trucks to enter from one side, load supplies, or remove waste in a single circuit, enhancing the logistics system and preventing collisions. Two material storage areas are strategically placed on opposite sides of the site to further facilitate efficient movement and access.

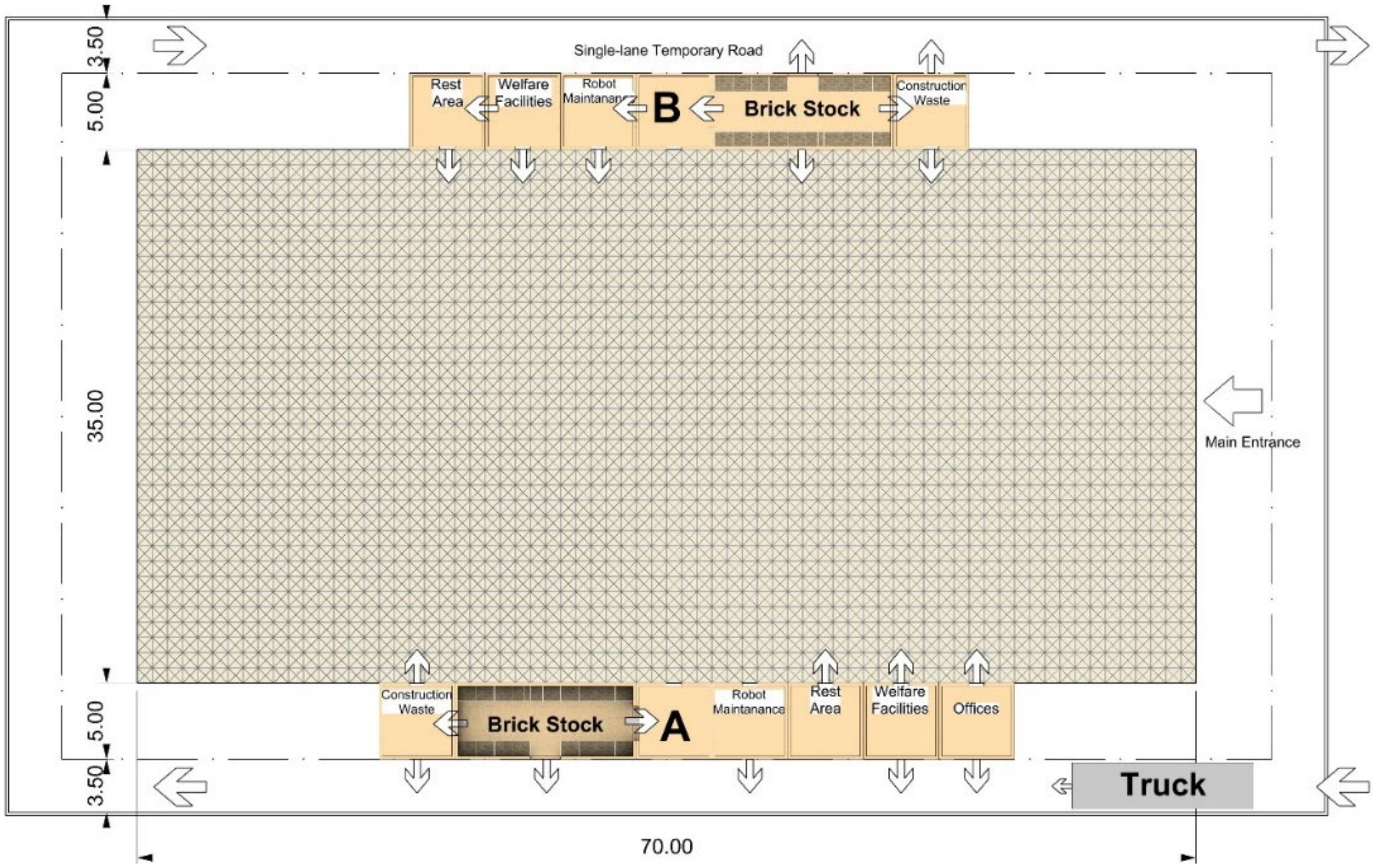
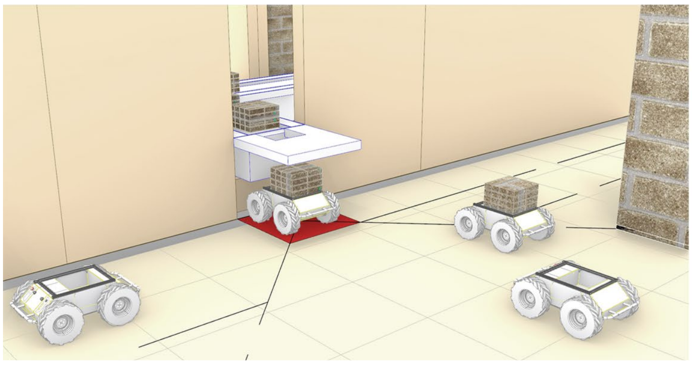


Figure 33- 2D Grid-based construction site Layout

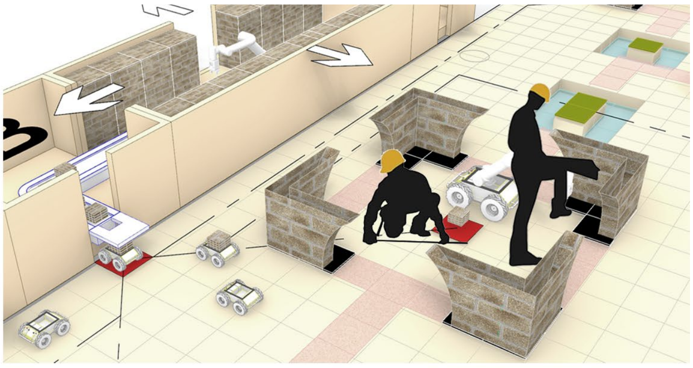
In the outlined construction scenario, once the exhibition holder's design is approved, the coordinates of the booths are transmitted to swarm robots. These coordinates are designated as specific delivery points where the robots are tasked with carrying materials from the material supplies. After the temporary exhibition period is ended, workers will dismantle the structures and return the bricks to the material supplies for reuse in the next exhibitions.

Drawing inspiration from the "LoadRunner" project, a system featuring stationary pickup and placement stations is adopted. The material supplies are designated as two fixed pickup stations. To fully automate the material handling process, it is assumed that the materials are pre-packaged according to the robots' payload capacity. Upon arrival at these stations, a package of materials is automatically loaded onto each robot's tray, ready to be transported to the designated booth locations. This setup streamlines the logistics and ensures efficient material distribution across the exhibition site.



Pick up Station

1



Placement

2

Figure 34- Material Handling Process Pick up and Place

4-3 Structure

In the direction of utilizing swarm robots for material handling, the preference lies in selecting discrete, dry materials like wooden elements, cork blocks, and bricks. These materials are chosen for their feature for easy stacking, aligning with the selection of compression-only structures. This choice is driven by the effectiveness of such structures in managing compressive loads, taking advantage of the stacking capabilities of the materials to their fullest potential.

As part of this project, the objective is to design a booth structure that aligns with the selected architectural layout. The booths are ideally square shaped to be compatible with the squared grid system. Since these booths serve as exhibition spaces, they must provide shelter from sun, wind, and rain while also being open enough to ensure proper air ventilation and daylight penetration.

The design of the booths is inspired by the **"Atash Kade"**, a term from Persian architecture that refers to a fire temple or a place of worship for Zoroastrians. These temples, significant in ancient Persian culture, typically featured a dome supported by four columns and four arches, and were built using local materials such as stone and brick(Ahmadi, 2021).

In this modern application, the booths are constructed using monolithic sustainable materials, with each booth serving as a designated placement point for materials by the swarm robots. The booths are designed in three sizes: 5m x 5m, 7.5m x 7.5m, and 10m x 10m, each requiring a different volume of materials.

To save materials and simplify the parametric model, the traditional flat roof of the Atash Kade is adapted into a curved roof in our design. This adjustment not only enhances the structural integrity but also adds an aesthetic value to the booths. The parametric design allows for structural analysis based on the selected materials and aids in estimating the quantity of materials that swarm robots need to transport.

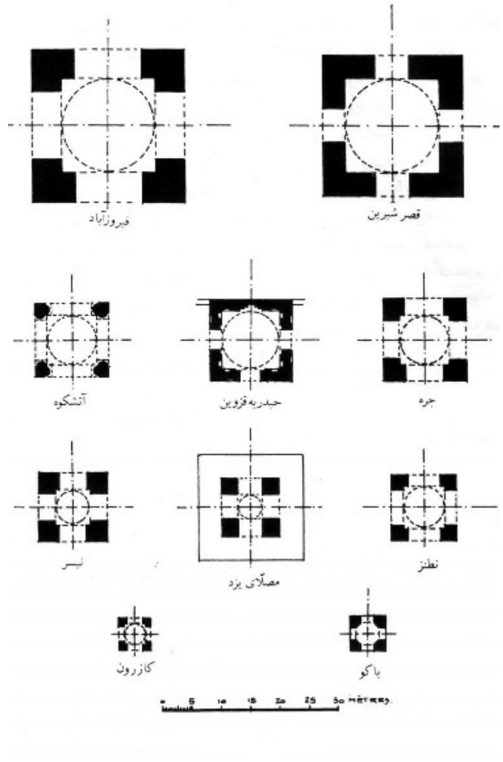


Figure 35- Atashkade Plans

Image Source:(Ahmadi, 2021)

Figure 36- Famous Atashkad, Niasar, Iran.

Image Source: (Ahmadi, 2021)

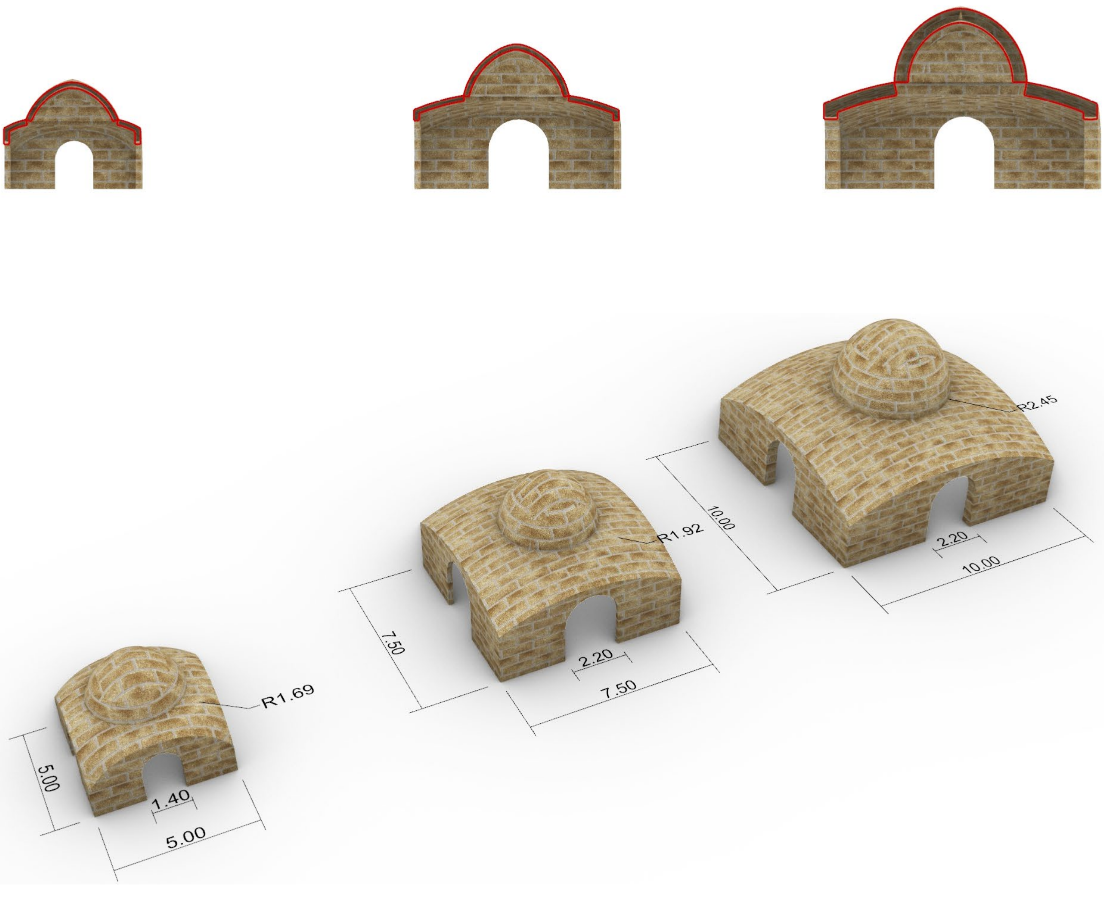


Figure 37- Adjusted Booths' Design

Below, images compare the traditional “Atash Kade” with its common plans to the newly designed booths for this research project, highlighting both the traditional and modern adaptations.

4-4 Material

As outlined in the previous section, the selection of a suitable material is necessary for conducting the experiment. In line with the type of structure and research objectives, the exploration of discrete block-shaped materials is intended. The goal is to develop a highly sustainable construction approach by maximizing the reusability of materials. To achieve this, either fully sustainable materials may be employed, or less sustainable materials may be utilized repeatedly to extend their usability. The use of dry connections, such as stacking or interlocking, is proposed to simplify the assembly and disassembly processes, thus enhancing the overall sustainability of the structure.

Another vital factor that has been considered is the availability of these materials, ensuring that the construction practices are both practical and sustainable. In this study, several materials were considered, including interlocking cork blocks, hempcrete blocks, and high-density foam blocks. However, to render the construction scenario more realistic and to accommodate conventional materials, simple standard-sized bricks have been chosen for dry stacking. The brick that is selected for this experiment is a standard size brick of 92mm x 57mm x 203mm.

4-5 Simulation

In this section, the simulation is informed by insights drawn from various projects, with all assumptions, constraints, and settings explicitly outlined.

Swarm Size: Despite natural swarms typically consisting of a high number of agents, a large swarm in this context not only increases the probability of collisions but also proves less efficient in terms of time and cost. However, to check the impact of the number of robots on the construction time, the experiments will be conducted with a swarm size ranging from 10 to 100 agents.

Environment: As influenced by "Grid-Based Mobile Robot Path Planning Using Aging-Based Ant Colony Optimization Algorithm in Static and Dynamic Environments," the selected simulation environment is a 2D grid-based model. This model is established as the initial step in mobile robot path planning, where grids represent the mobile robot workspace as equal square cells.

Swarm Robots or Agents: Within the simulation, each agent is represented by a central point at the center of a rectangle, measuring 990mm by 670mm, corresponding to the dimensions of the Husky Unmanned Ground Vehicle provided by Clear path. The maximum speed of these robots is restrained to 1m/s.

Detection Method: Each agent is equipped with three sensors on the front side.

Communication Method: Drawing from the principles of Ant Colony Optimization as well as studies mentioned earlier, the communication among agents is designed to be stigmergic and indirect, based on the intensity of the deposited pheromone.

Control Algorithm: A simple Ant Colony Optimization algorithm will be implemented as previously stated.

Assumptions

- All robots are maintained in a constantly charged state, eliminating the need for recharging.
- Workers are continuously available.
- As soon as the robots deliver the bricks to the booths, they will return to the closest nest without any delays.
- Although the booths represent food sources and the nests represent material supplies in this scenario, the process involves transporting materials from the nests to the food sources, reversing the typical foraging model.
- All booth points function for both of the material supplies or nests, with a similar number of agents assigned to each nest. This setup ensures that no single food source or booth is exclusive to any nest.

Operational Dynamics

- Due to varying booth sizes, the required number of trips by robots differs which will be calculated to be implemented in the simulation.

Behavioral Dynamics

- Agents emerge sequentially from two nests with delays, engaging in random direction movements to locate and retrieve materials to the designated booths. After the successful material delivery, the agents return for additional materials until the booth is completed.

Assessment Criteria

Evaluations will be based on the total construction time and total walking distance required to complete construction, and these two parameters in correlation to the parameters of number of robots and Pheromone evaporation rate will be analyzed.

This structured approach ensures a comprehensive and systematic assessment of the swarm robots' performance in constructing the exhibition booths.

5

Methodology

Introduction

This study aims to replicate a realistic construction scenario where swarm robots perform site logistics and material-handling tasks. So far, the thesis completed the “**Framework Design Essential Steps”** including the following steps.

- Specifying the technical features of the operating robotic system.
- Outlining the architectural design and its intended function.
- Describing the construction site’s conditions and layout in detail.
- Defining the type of structures that will be created and the materials that will be used.
- Extracting the essential parameters for virtual simulation

The next step is to integrate the architectural layout and swarm robots within one construction environment by translating them using both visual and text programming languages in a virtual environment. The primary methodology employed is a simulative approach.

The workflow of methodology is structured into three distinct phases: Design Phase, Simulation Phase, and Experiments & Analysis. In this workflow, all required elements are first translated and integrated into a unified environment. Then, different scenarios are defined to conduct experiments on them for further analysis.

Design Phase

At this stage Grasshopper, a visual programming language, is used to parametrically design the architectural layout on the construction site, including architectural and structural analysis of the booths and their brick demand estimation.

Simulation Phase

Then Python, a text-based programming language is employed to simulate the ant-like behaviors of the robots within the virtual construction site.

Experiments and Analysis

The final step is defining different construction scenarios with two levels of compactness to conduct virtual experiments on them, allowing for comprehensive testing and assessing the robots' performance based on the simulations time and robots’ walking distances.

In this chapter only two stages of Design Phase and Simulation Phase will be explained in detail. The two next chapter dedicate to Experiments and Result Analysis respectively.

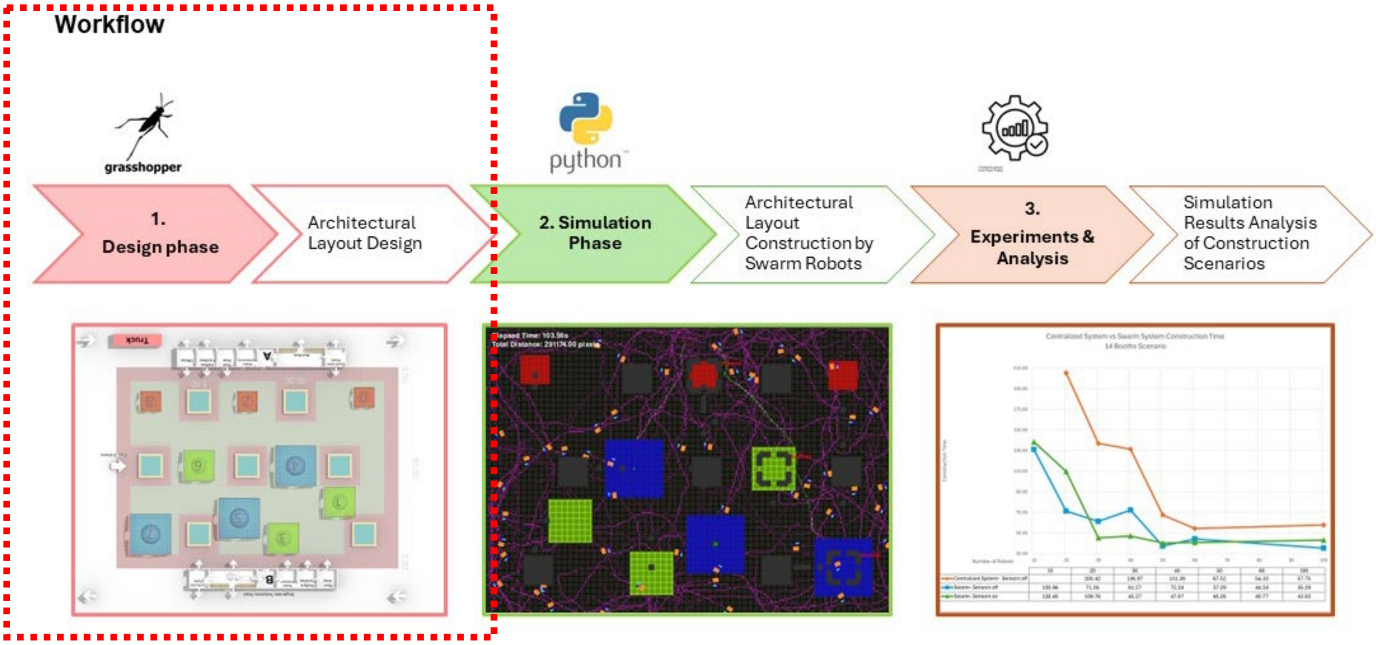


Figure 38- Workflow

5-1 Design Phase

The Grasshopper code employed in the study is divided into five distinct categories, each contributing to the comprehensive simulation of the construction site dynamics:

1. Architectural Layout

The construction site setup is initialized with the establishment of grids that define the spatial layout. Material supply points are designated as nest locations, while booths positions are defined as food sources. Additionally, dynamic obstacles and pond locations are incorporated as static obstacles within the site, contributing to the complexity of the navigational environment.

2. Booth Parametric Design

Parametric designs for the booths are generated, serving as inputs for the following structural and material demand analytical processes. This design flexibility allows for adaptations based on varying site conditions and requirements.

3. Structural Analysis of Booths

A structural analysis of each booth is conducted, assessing their stability and integrity under simulated environmental conditions. This analysis ensures that the booths are capable of withstanding real-world physical stresses.

4. Demand Estimation for Materials

An estimation of the brick demand for each booth is calculated. This process involves determining the quantity of materials required based on the booth designs and structural necessities.

5. Data Exportation

The final component involves exporting the necessary data to a CSV file. This file contains all relevant information from the architectural layout, parametric designs, structural analyses, and material demands. It is then imported into the Python script for further processing and simulation of swarm behaviors.

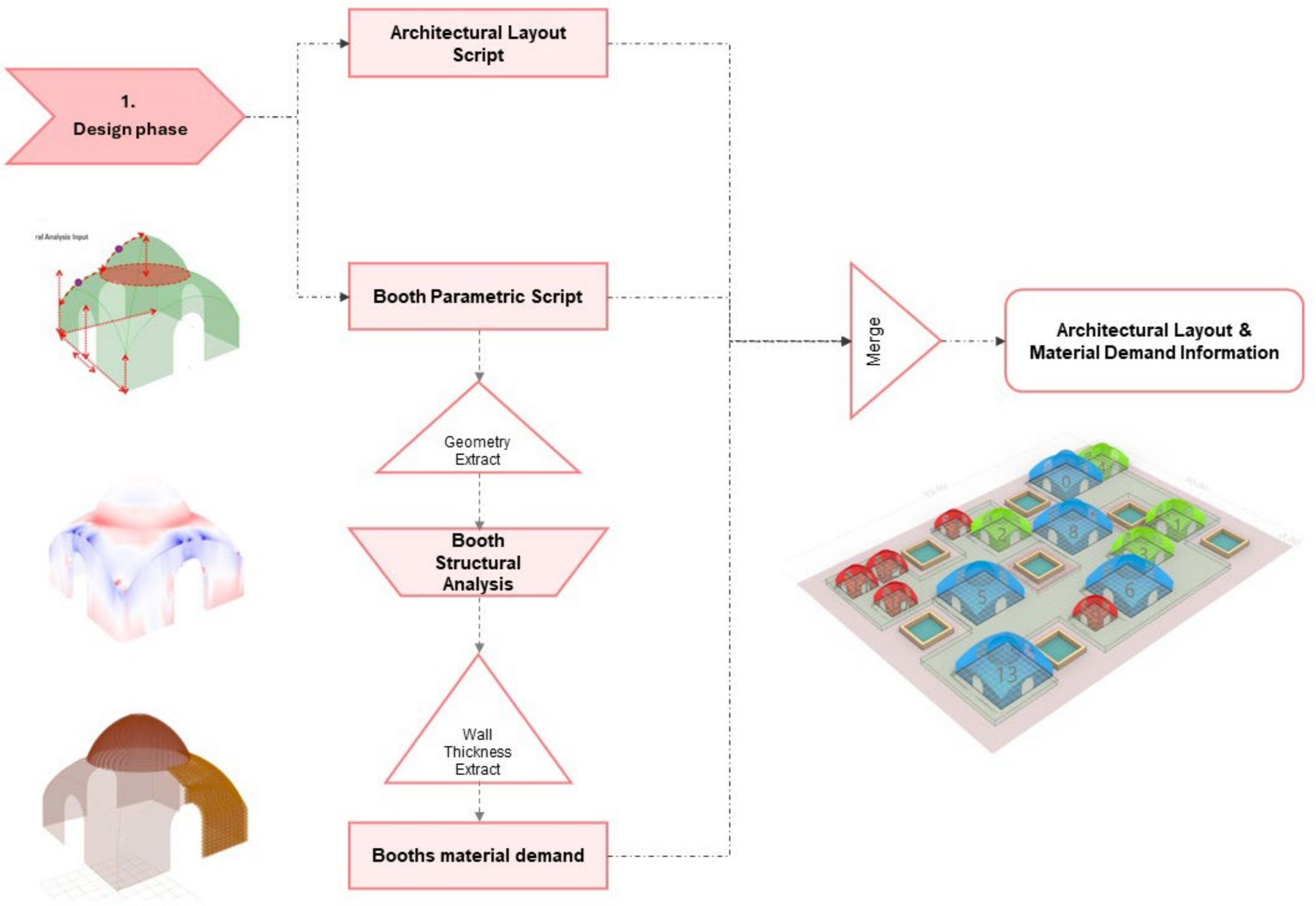


Figure 39- Grasshopper Code Overview

5-1-1 Architectural Layout

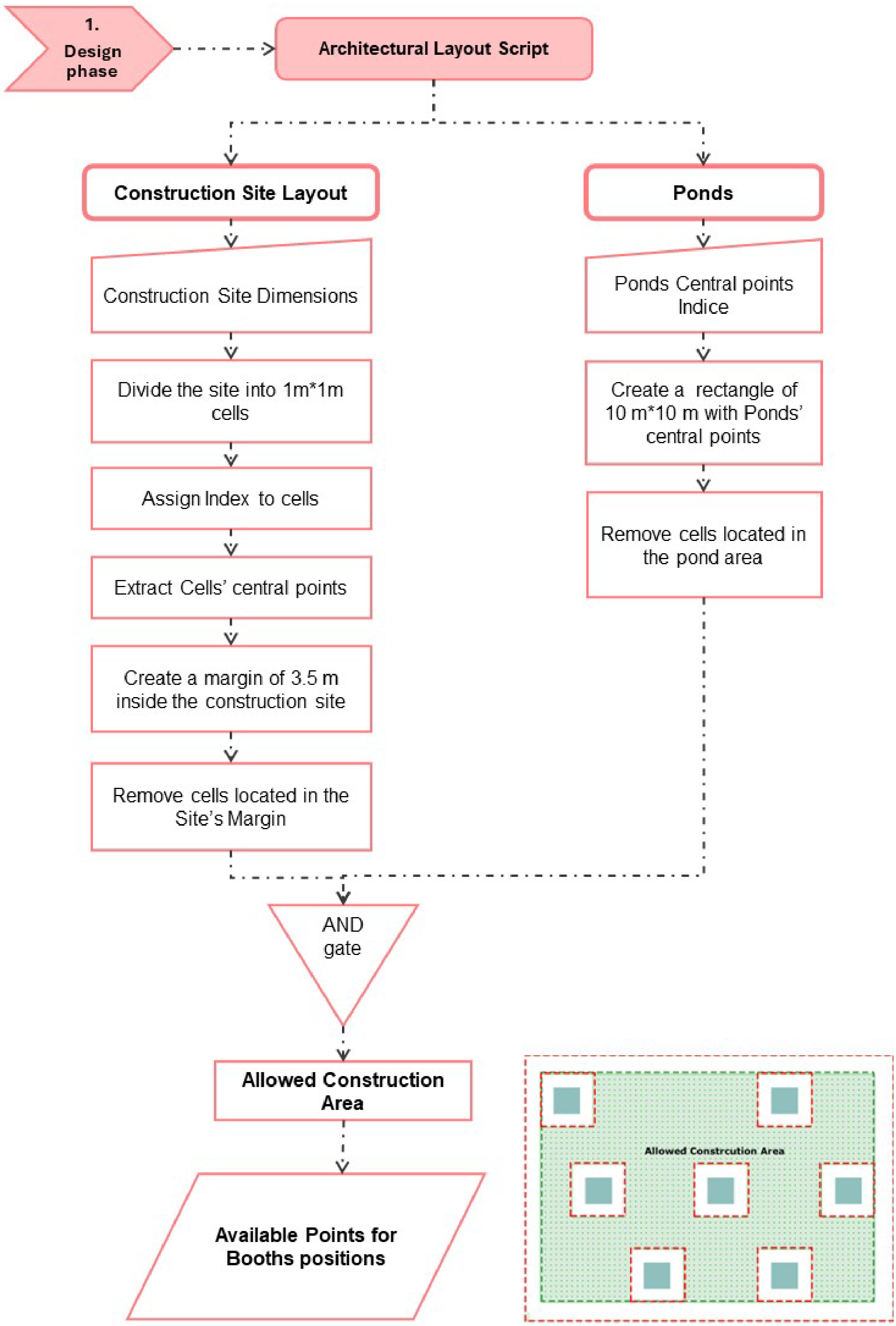


Figure 40- Architectural layout Script- Construction site & Ponds' Creation

1- Construction Site Layout Initialization

The initialization of the construction site's layout is executed by establishing a grid system. This grid is organized into 1m x 1m cells, facilitating the spatial arrangement and placement of various elements across the site. An adjustable margin of 2.5m is applied around the perimeter of the construction site to ensure unobstructed boundaries. The margin width is adjustable based on the requirements.

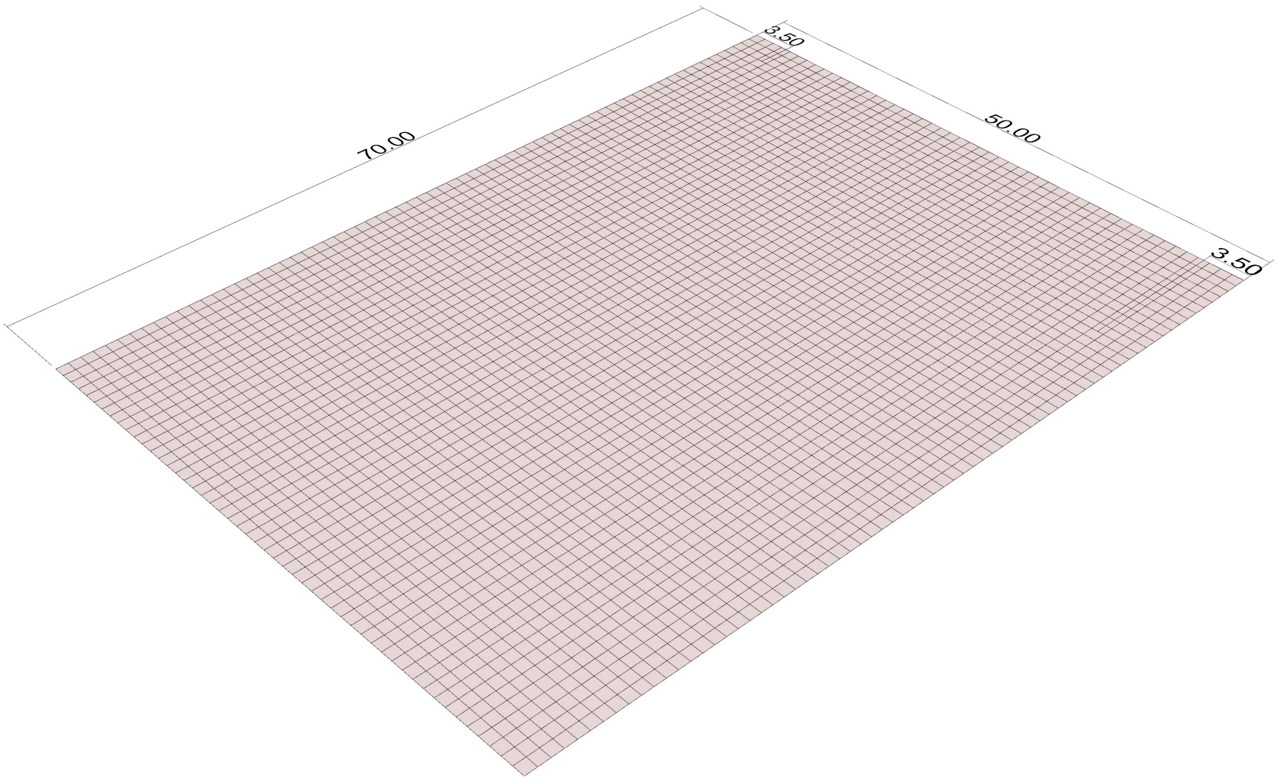


Figure 41- Construction site Grids Settings

2- Ponds- Static Obstacle Configuration

Within the architectural layout, ponds are fixed as seven squares, each measuring 5m x 5m. The central points of these ponds are specified and displayed in a panel as indices of the cells. Surrounding each pond, an additional margin of 2.5m is imposed, further defining the restricted areas within the grid. The indices of cells occupied by the ponds, their margins, and the external margin of the construction site are systematically extracted and removed from the overall list of cell indices. This extraction process results in the identification of all available points that do not fall within the margins of the construction site or the ponds, marking them as suitable locations for placing the booths' central points.

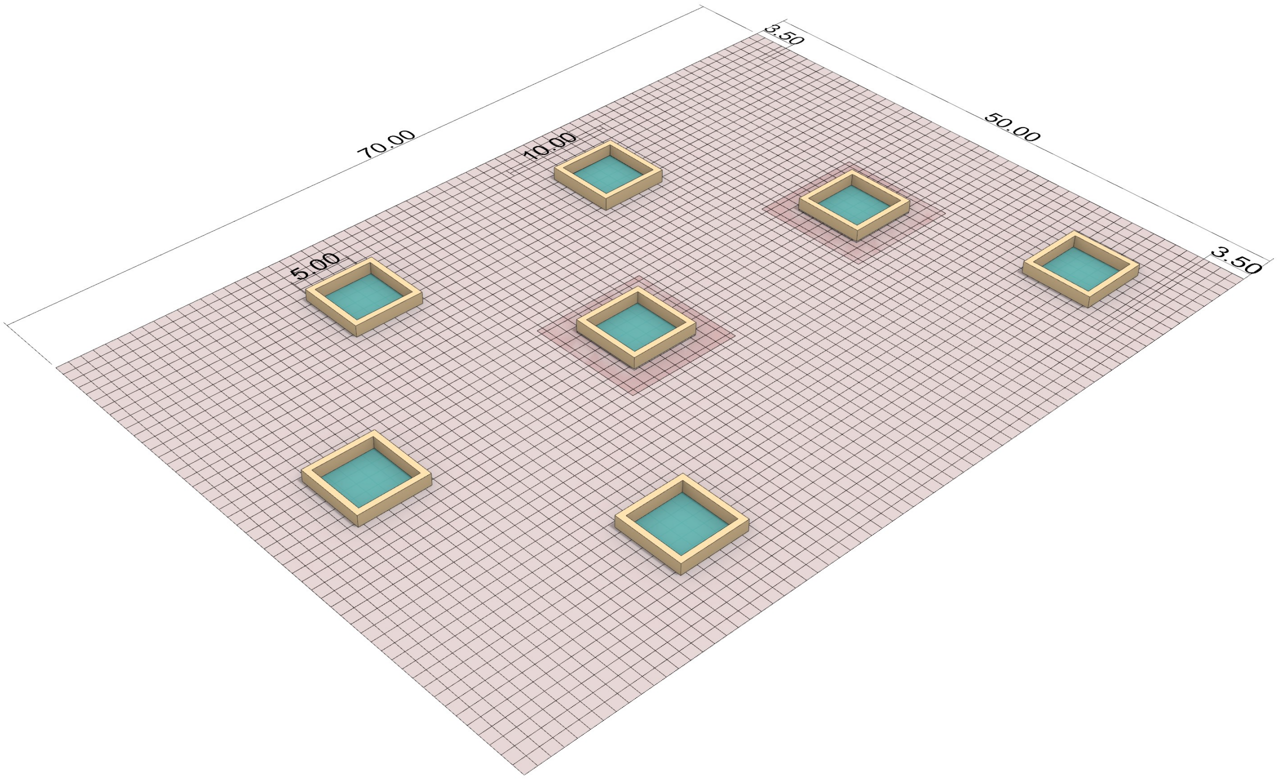


Figure 42- Ponds' Positioning on the Construction Site

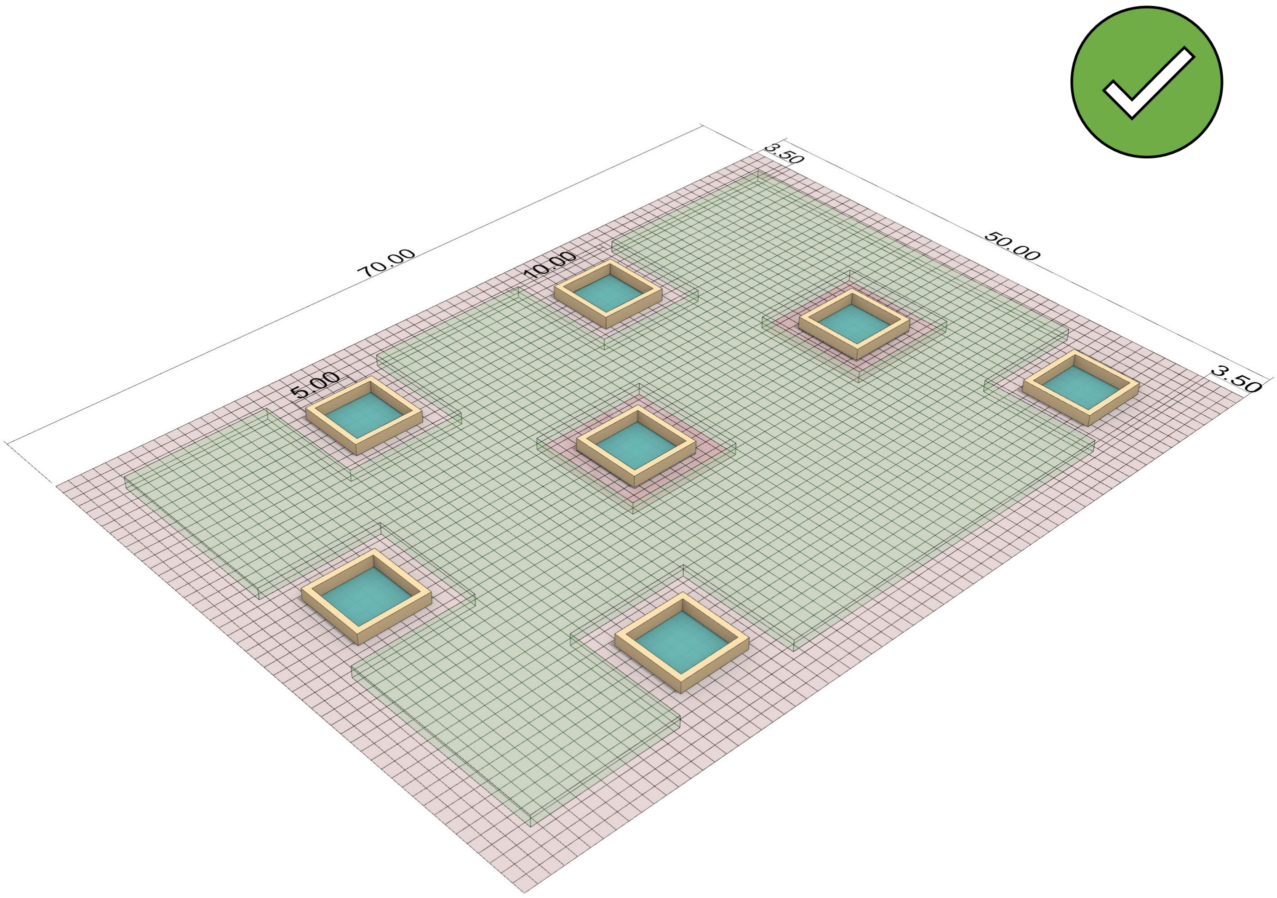


Figure 43- Allowed Construction Area

3- Booth Placement and Distance Validation

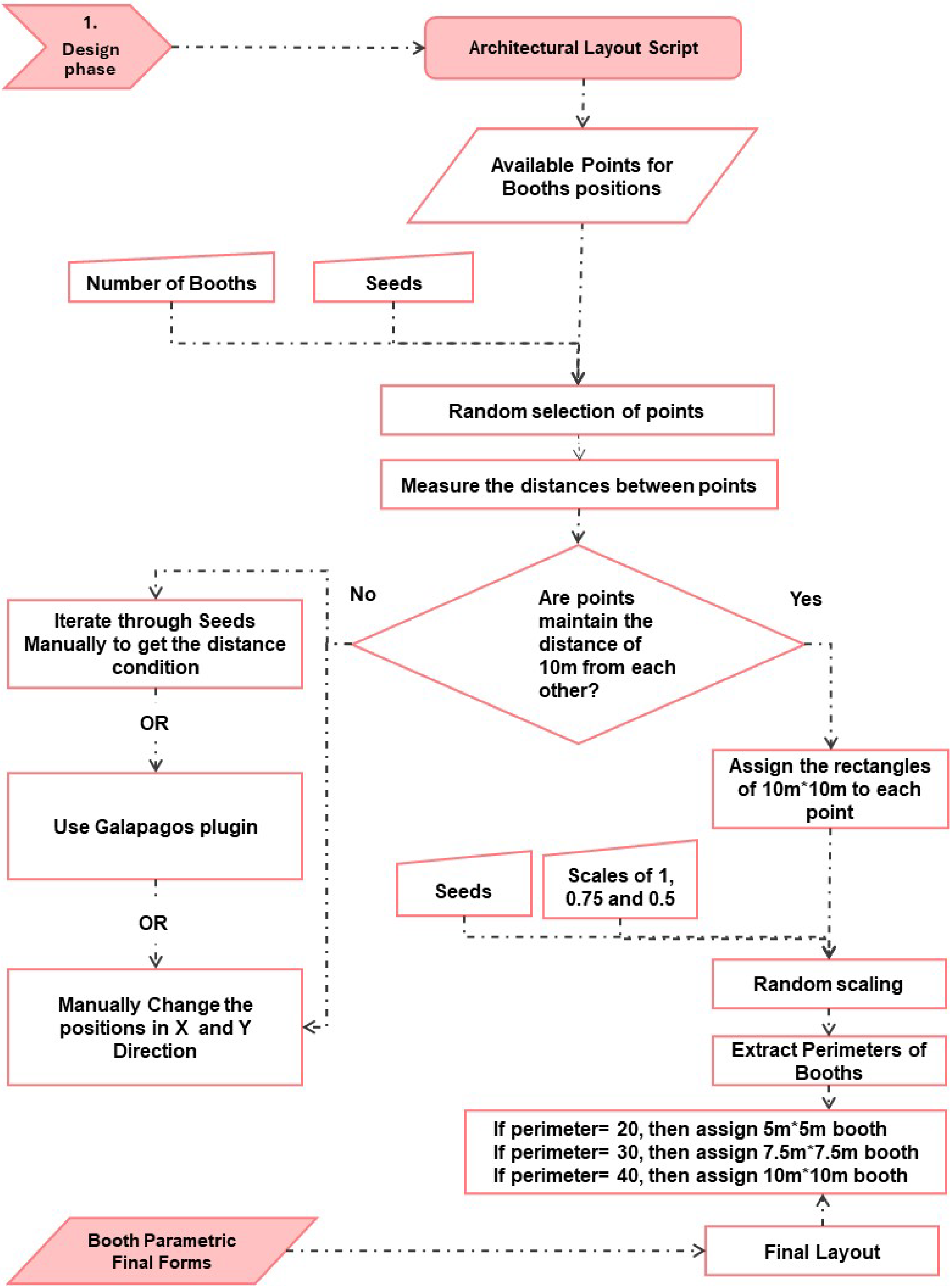
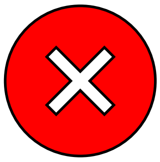


Figure 44- Architectural layout Script- Booths' Location Creation

From the refined list of available points, the desired number of points- in this case nine points- are randomly selected to serve as central locations for the booths, which function as food sources within the simulation. A condition is imposed where each chosen point must maintain a minimum distance of 10 meters from any other booth’s central point. This criterion is essential to prevent any intersection between booths. A Python script evaluates this criterion, returning a boolean value (True or False) for each point, indicating whether it meets the distance requirement. If nine "True" statements are received, it confirms that all booths are appropriately distanced from one another.



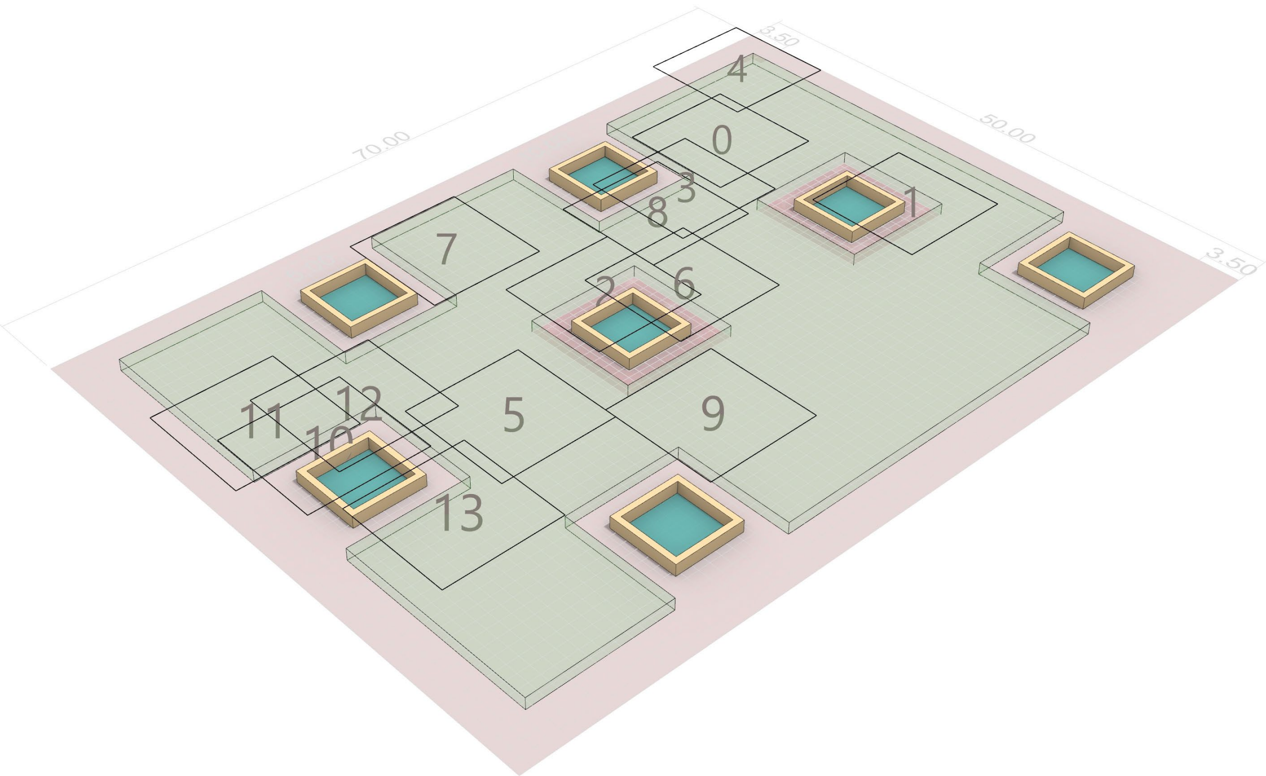


Figure 45-Booths' undesirable Positioning on the Construction Site

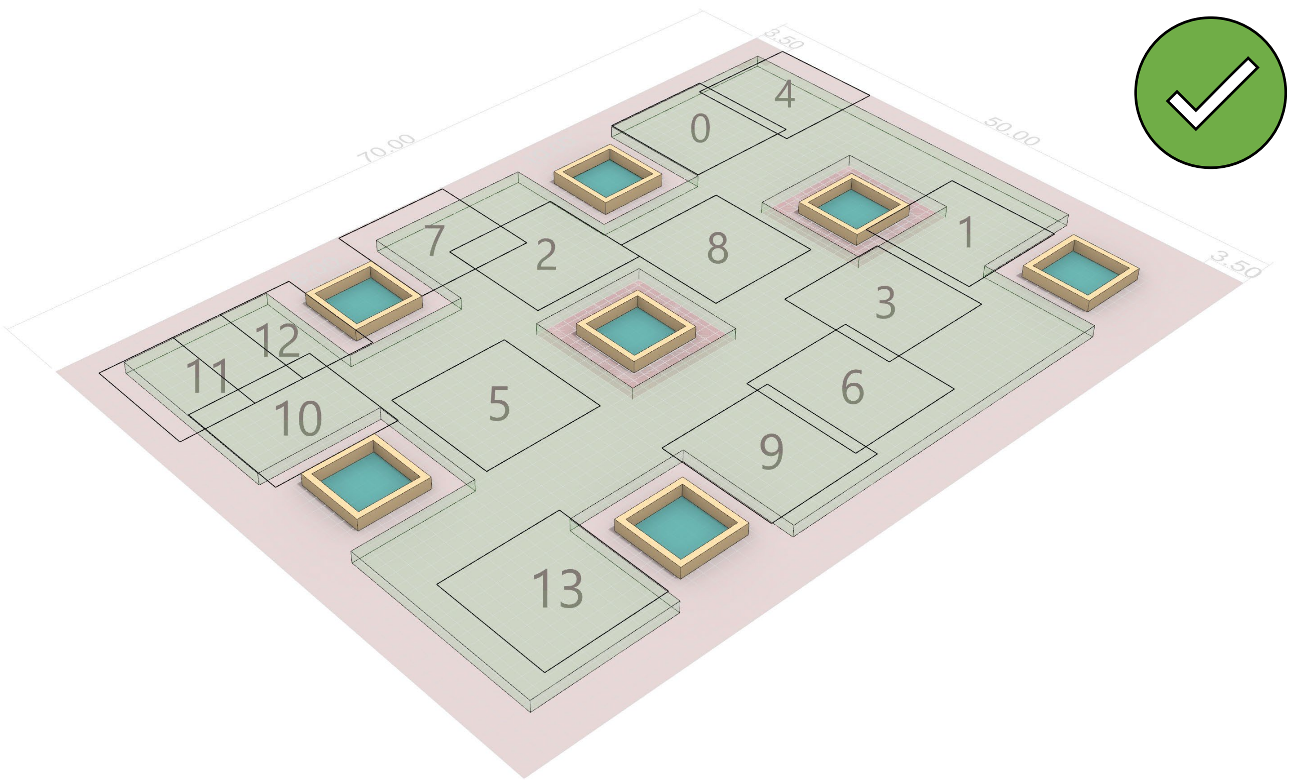


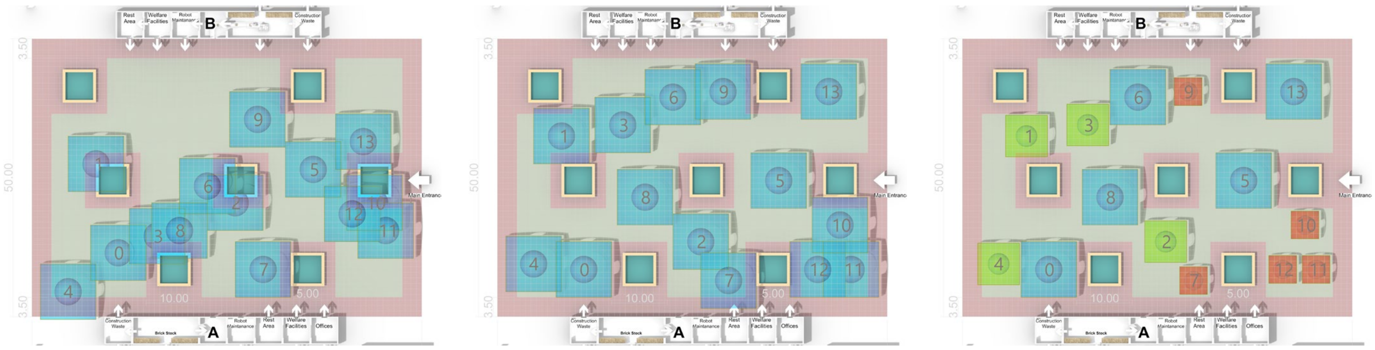
Figure 46- Booths' Desirable Positioning on the Construction Site

Optimization and Manual Adjustment

To maximize the occurrence of "True" values, three methods are employed:

1. Manual adjustments of the booths' positions in the X and Y directions are facilitated through user interaction with number sliders. These adjustments are by using the number sliders for each point.

Figure 47- Manual Control of the Layout



2. Utilization of the Galapagos optimization plugin to automatically adjust points by maximizing the number of “True” values to satisfy the distance criterion.

3. Iterative testing of various layouts, which are then exported to visual interfaces such as DesignExplorer for further refinement until nine "True" values are consistently achieved.

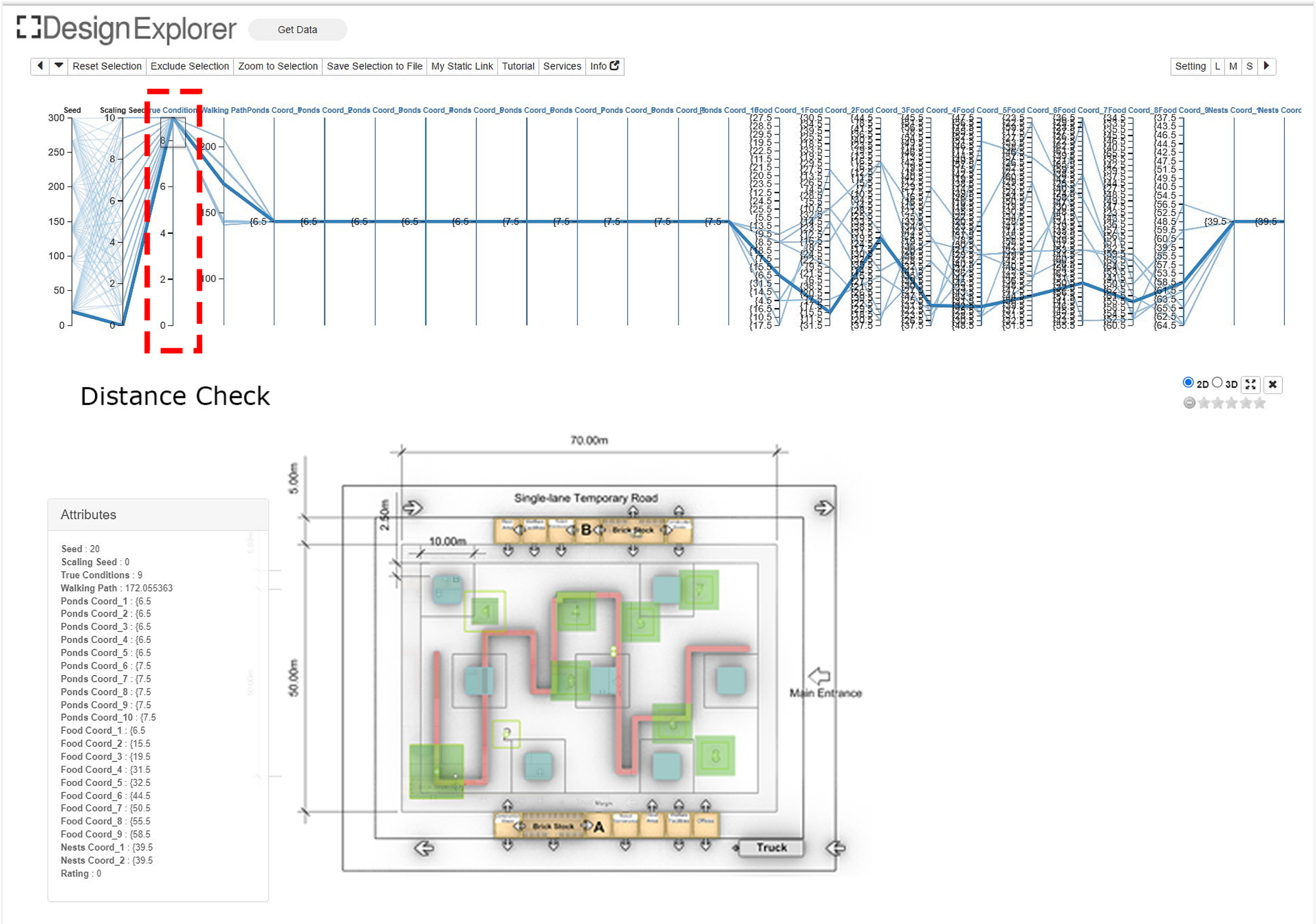


Figure 48- Design Explorer Showing All Results

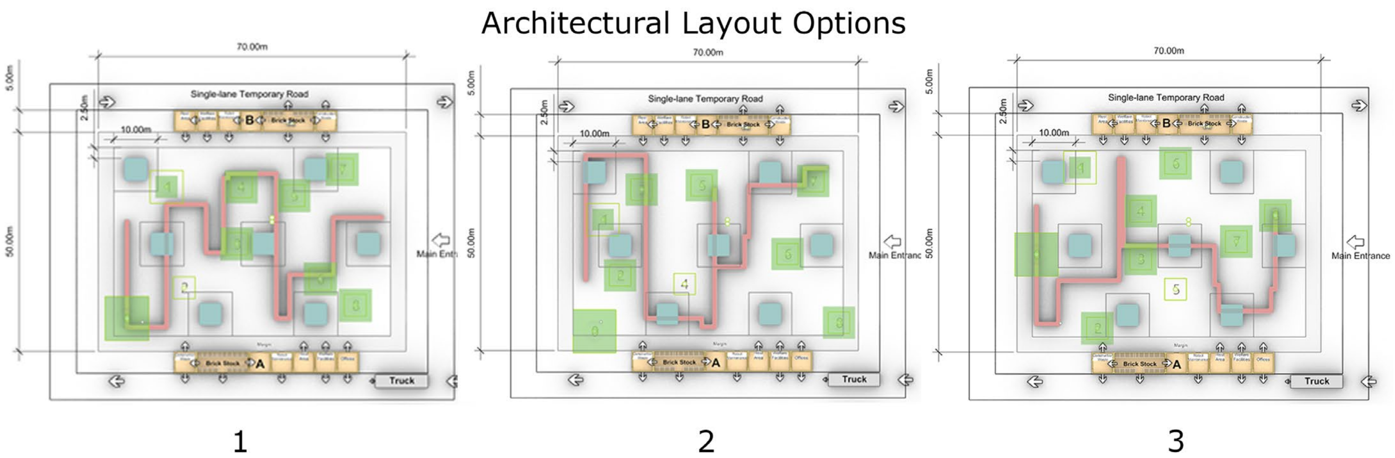


Figure 49- 3 Layouts with correct distance criteria

4- Booth Sizing and Location

Each booth location is marked with a 10m x 10m rectangle to ensure no overlaps or intersections occur. Manual adjustments can still be made to the positions of these rectangles using number sliders, providing flexibility in the layout design. Subsequently, the booths are randomly scaled using factors of 0.5, 0.75, and 1, leading to three possible booth sizes. Depending on the resulting perimeter of these rectangles—20m, 30m, or 40m—booths are assigned dimensions of 5m x 5m, 7.5m x 7.5m, or 10m x 10m respectively. This step also allows for various combinations of booth sizes, achieved through the use of random number generators.

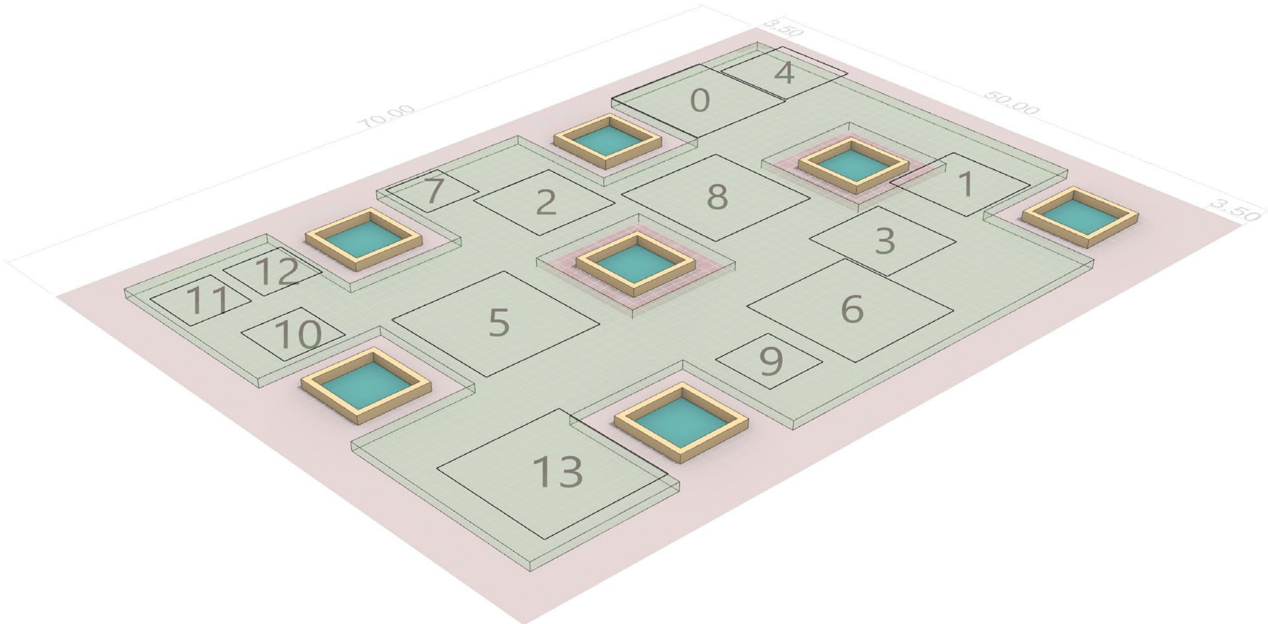


Figure 50- Booths' scaling on the Construction Site

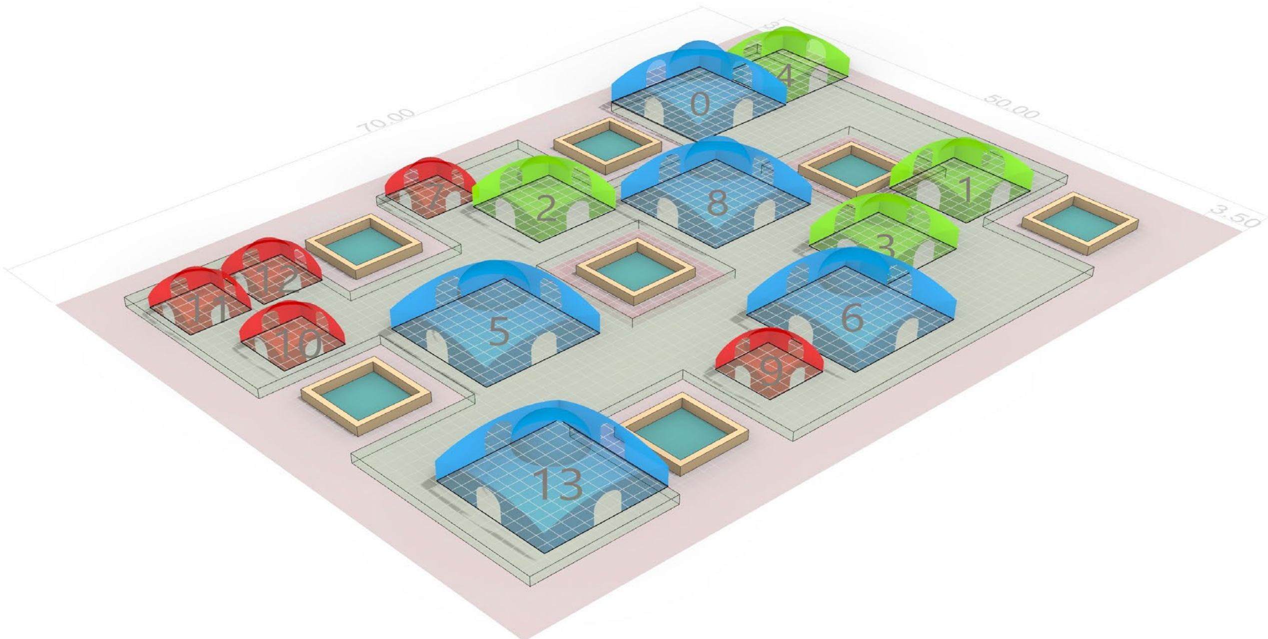


Figure 51- Assigning the booths to their corresponding position

5-1-2 Booth Parametric Script

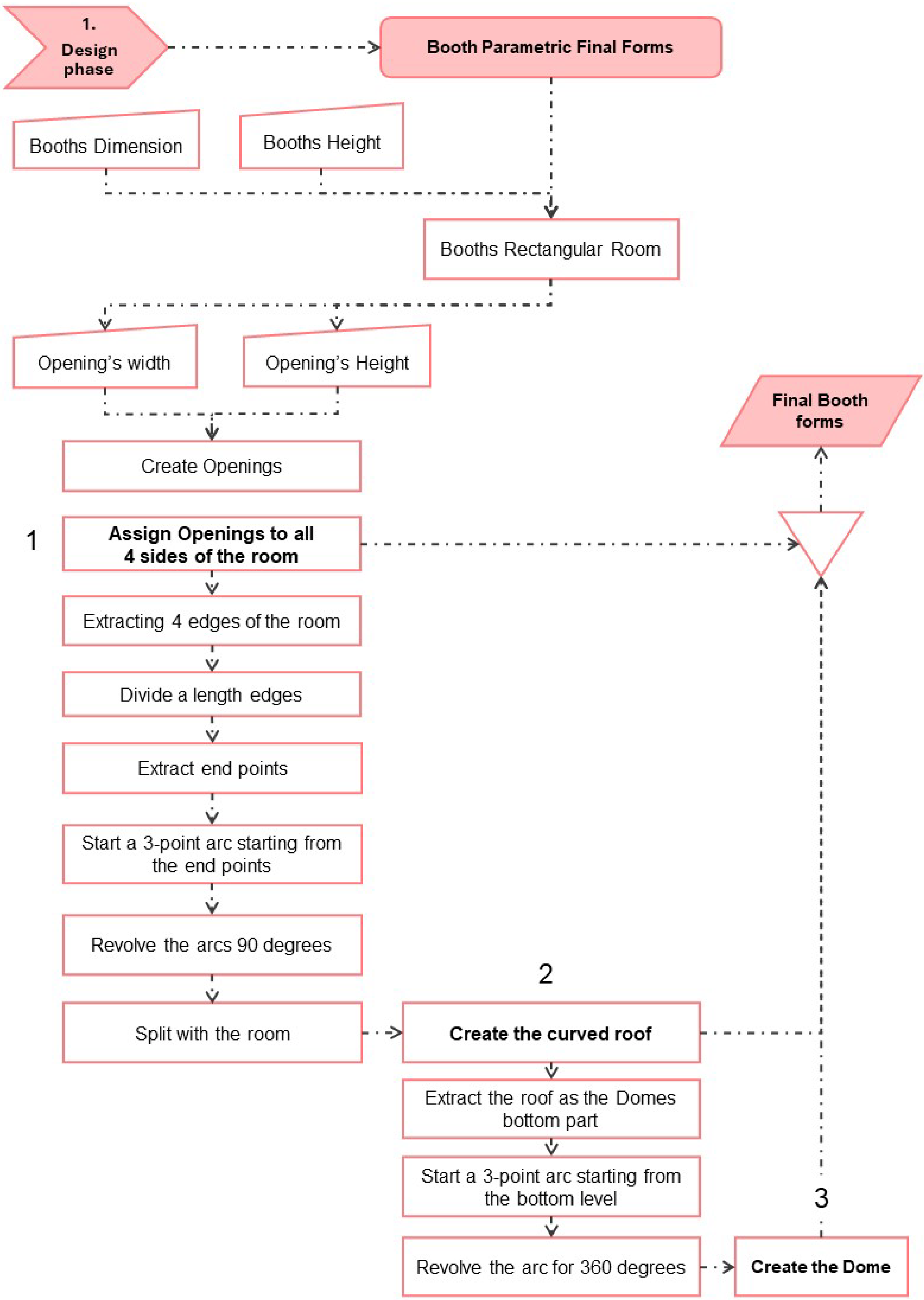


Figure 52- Booth Parametric Design Script

1- Booth Design Initialization

Rectangular bases of three predetermined sizes—5m x 5m, 7.5m x 7.5m, and 10m x 10m—are defined as the initial step in the booth design process. Each rectangle is then extruded to a variable height, which is adjustable, setting the preliminary structure up to the point where the dome begins.

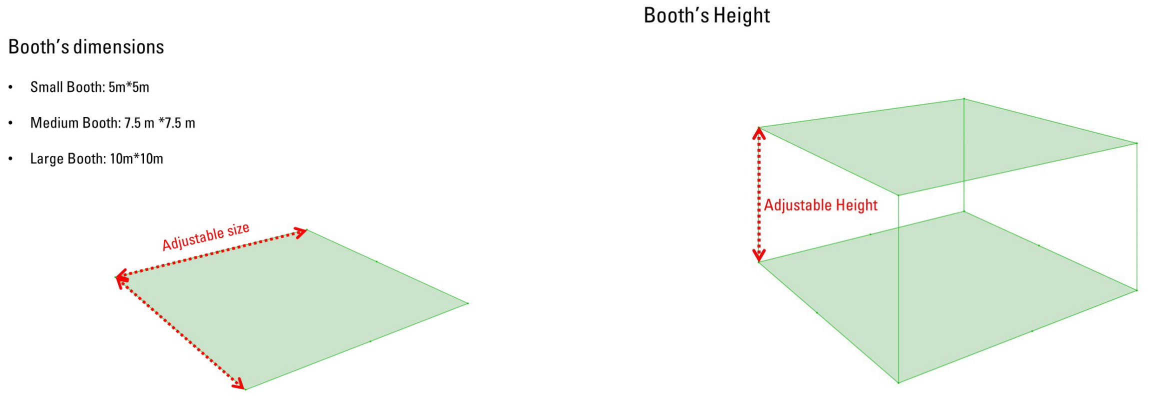


Figure 53- Booth's Rectangular Base and Extrusion

2- Openings and the Roof

Around the perimeter of the extruded rectangle, adjustable circular arcs are projected on each side. These arcs, having adjustable heights and widths, serve as openings in the structure. Subsequently, the creation of the roof is initiated by generating four adjustable arcs that extend from each vertical edge of the room toward the center. These arcs are revolved 90 degrees to form arced surfaces that span over the room.

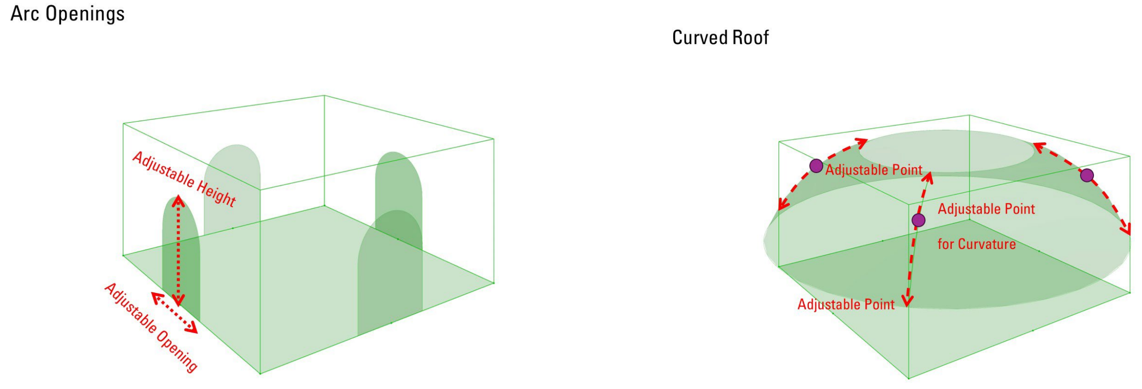


Figure 54- Booth's Opening and Roof Creation

3- Roof Modification and Dome Preparation

Of the arced surfaces created, only the inner parts are required for the final structure. The inner segments of these arced surfaces are split and then integrated with the room's vertical walls. An adjustable circular opening is then added to the center of the roof to serve as the base for the dome.

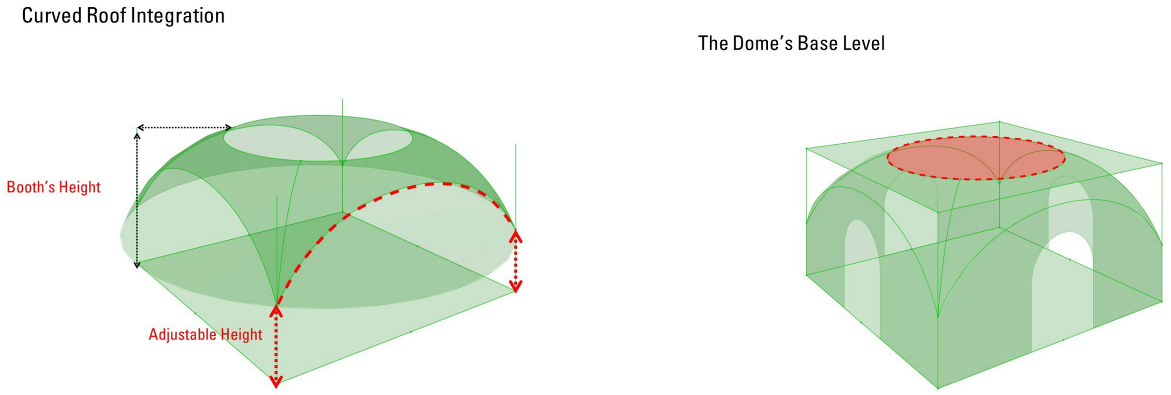


Figure 55- Booth's Roof Modification and Dome Base

4- Dome Construction

At this stage, the radius and height of the dome are specified. Another arc, serving as the profile for the dome, is created and subjected to a 360-degree revolution to form the dome's surface.

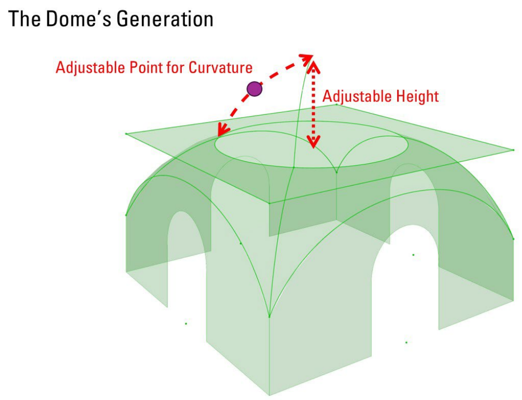


Figure 56- Booth's Dome Creation

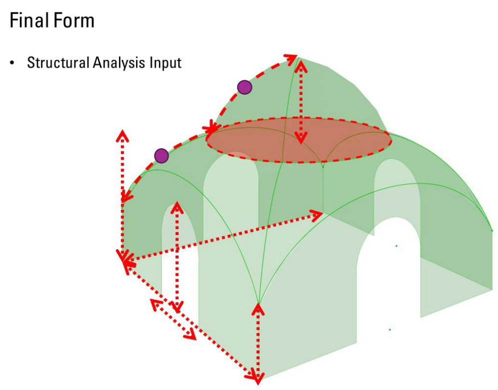


Figure 57- Booth's Adjustable Parameters

5- Structural Assembly and Integration

Upon the completion of these steps, all surfaces are combined to form the primary layer of the structure. This assembled surface is then prepared to receive a specified wall thickness. It is placed within the architectural layout that was previously described, positioning each booth according to the designed site plan.

6- Structural Analysis Preparation

Finally, the surface of the structure is used as a shell surface in the subsequent part of the script dedicated to structural analysis. This analysis determines the required wall thickness to ensure the structural integrity of the booths under the given loads.

5-1-3 Structural Analysis

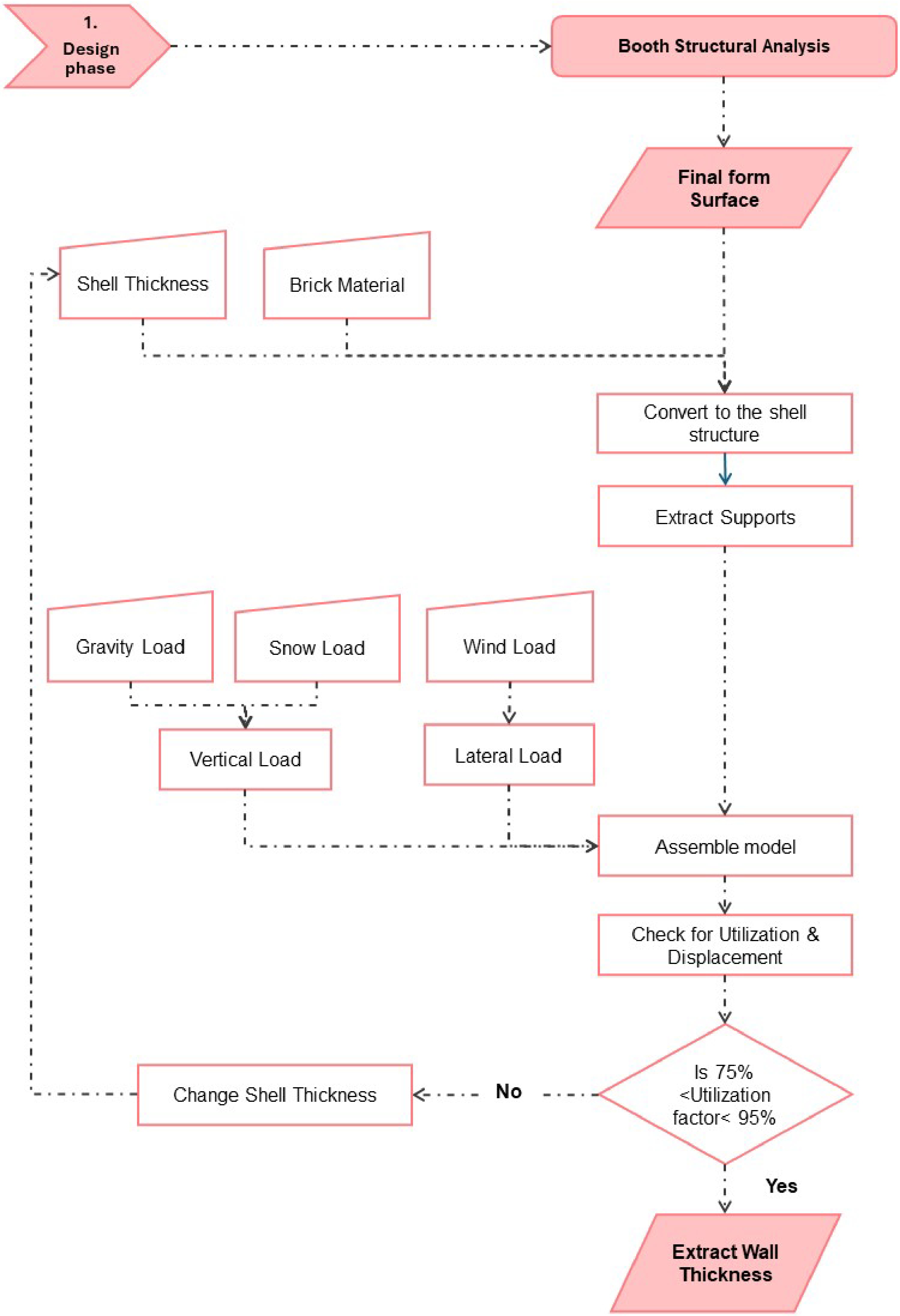


Figure 58- Structural Analysis Script

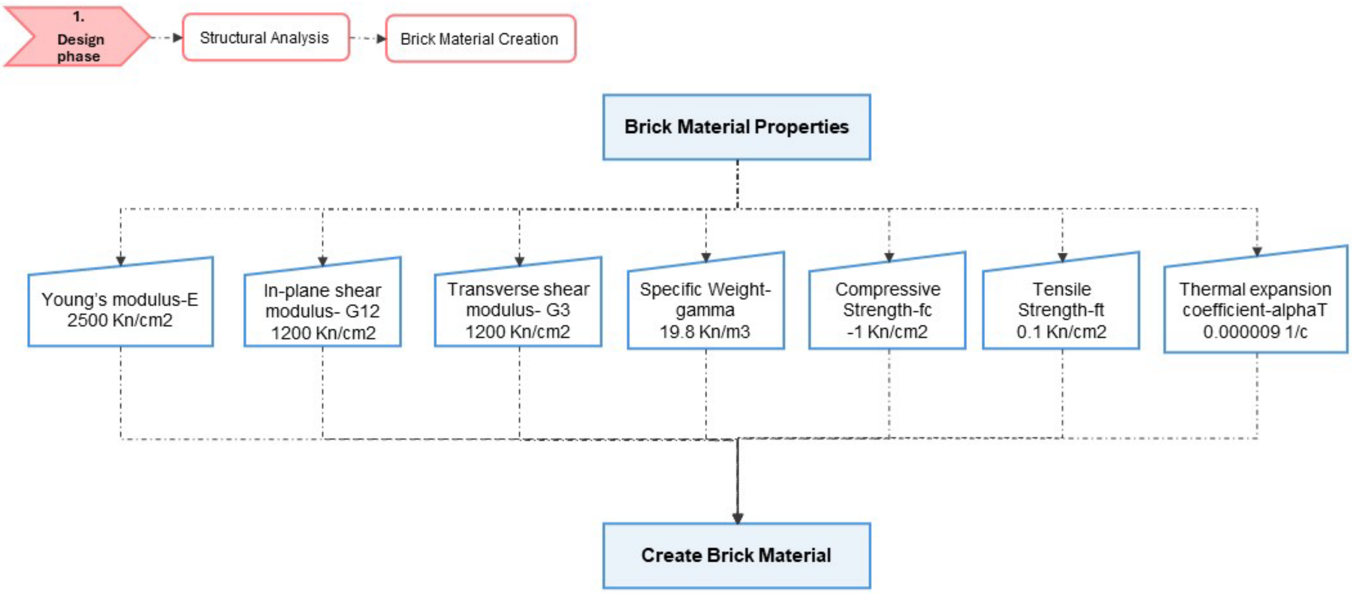


Figure 59- Brick Material Creation

Structural Analysis Using Karamba Plugin

In this phase of the project, the surfaces of the booths are inputted into the Karamba Plugin for structural analysis. Due to the computational intensity associated with brick simulation, which involves a high number of components, a simplified method is adopted. The surfaces are treated as shell structures with specific thicknesses, and the material selected for these analyses is brick, with properties derived from Granta Edu pack software.

Load Considerations

The design of the structure necessitates consideration of various external forces, which are categorized into dead loads and live loads:

- Dead Loads: These are constant loads exerted on the structure by gravity. For this study, the dead load includes the own weight of the structural elements and the roof. According to Eurocode, it is noted that for roofs not used as terraces, a load of 1 Kn/m2 should be considered for every 10 m2 (Arends, 2017). This same load of 1 Kn/m2 is applied throughout the research.

- Live Loads: These are variable loads that a structure encounters during its operational life, including snow loads, wind loads (suction), and maintenance loads. For the simulation, the case study location is in the Netherlands is used to determine specific values:

- Snow Load: Uniformly, a load of 0.7 Kn/m2 is applicable across the Netherlands (Arends, 2017).

Load Case Scenarios

Multiple load scenarios are combined to simulate conditions where several forces act simultaneously:

LC1 (Dead Load Dominant): 1.4 times the weight of the structure.

LC2 (Combined Dead and Snow Load): 1.2 times the structure's weight plus 1.5 times the snow load.

LC3 (Maintenance Consideration): 1.2 times the structure's weight plus 1.5 times the maintenance load (applicable in scenarios with maintenance walkways).

LC4 (Comprehensive Environmental Load): 1.2 times the structure's weight plus 1.2 times each for suction and maintenance.

LC5 (Suction Dominant): 1.2 times the structure's weight plus 1.5 times the suction load.

Dominant Load Scenario Analysis

Load Case 2 has been identified as the dominant scenario, taking into account not only the snow load but also the impact of wind loads on the façade. The wind load is specifically calculated based on prevalent conditions in the Netherlands, where the standard wind load is 0.46 Kn/m2. This value is then multiplied by a factor of 1.5 to account for potential increases in wind intensity under certain conditions. Consequently, the wall thickness for the booths is determined based on the highest stress levels presented by this demanding load case. This approach ensures that the structural integrity and functionality of the booths are maintained, even under severe environmental stresses.

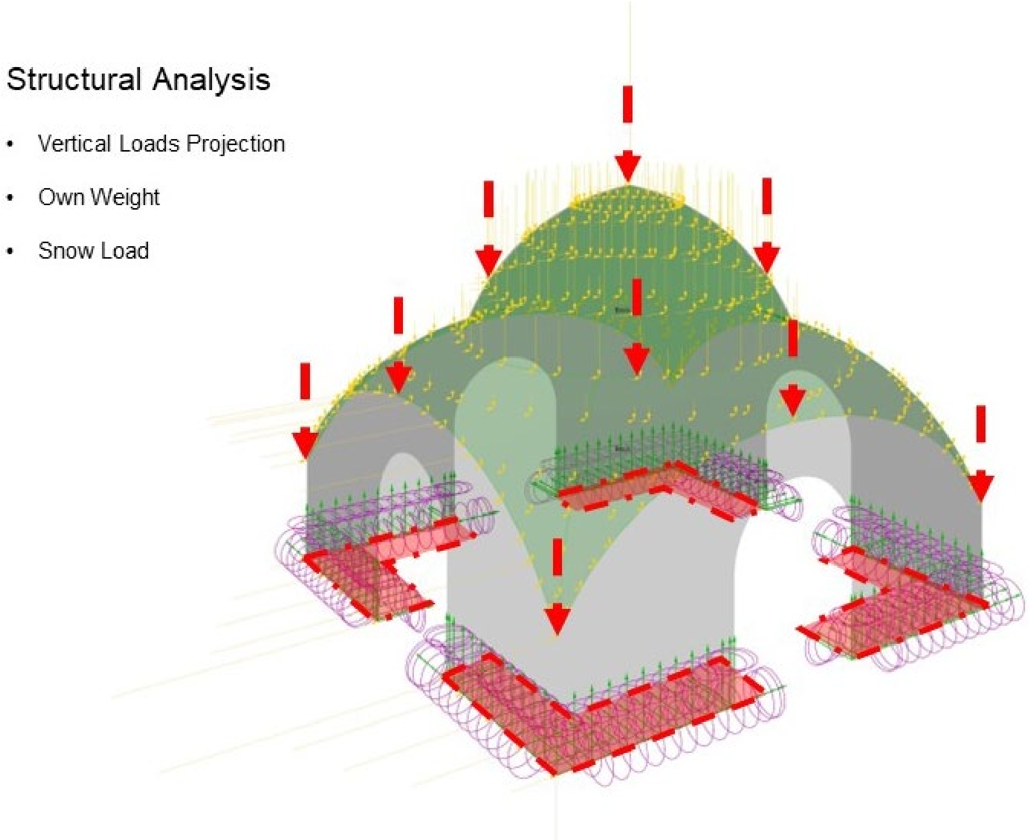


Figure 60-Vertical Load Projection

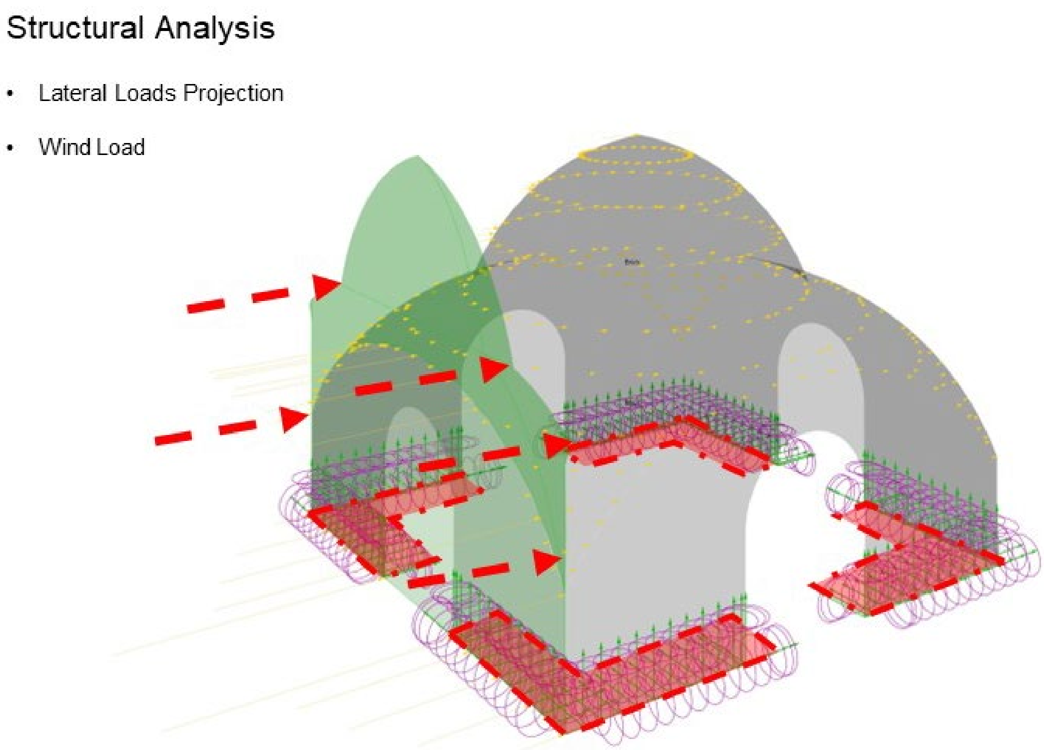
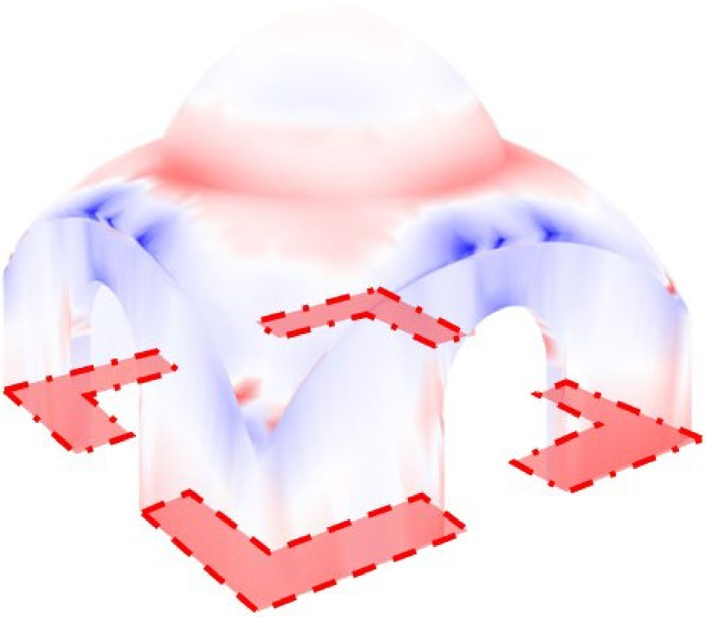


Figure 61- Lateral Load Projection

Structural Analysis

- As a shell structure
- Utilization Factor
- Extract Wall Thickness



- Small Booth: 20cm
- Medium Booth: 20cm
- Large Booth: 50 cm

Figure 62- Utilization of the Material

5-1-4 Brick Estimation

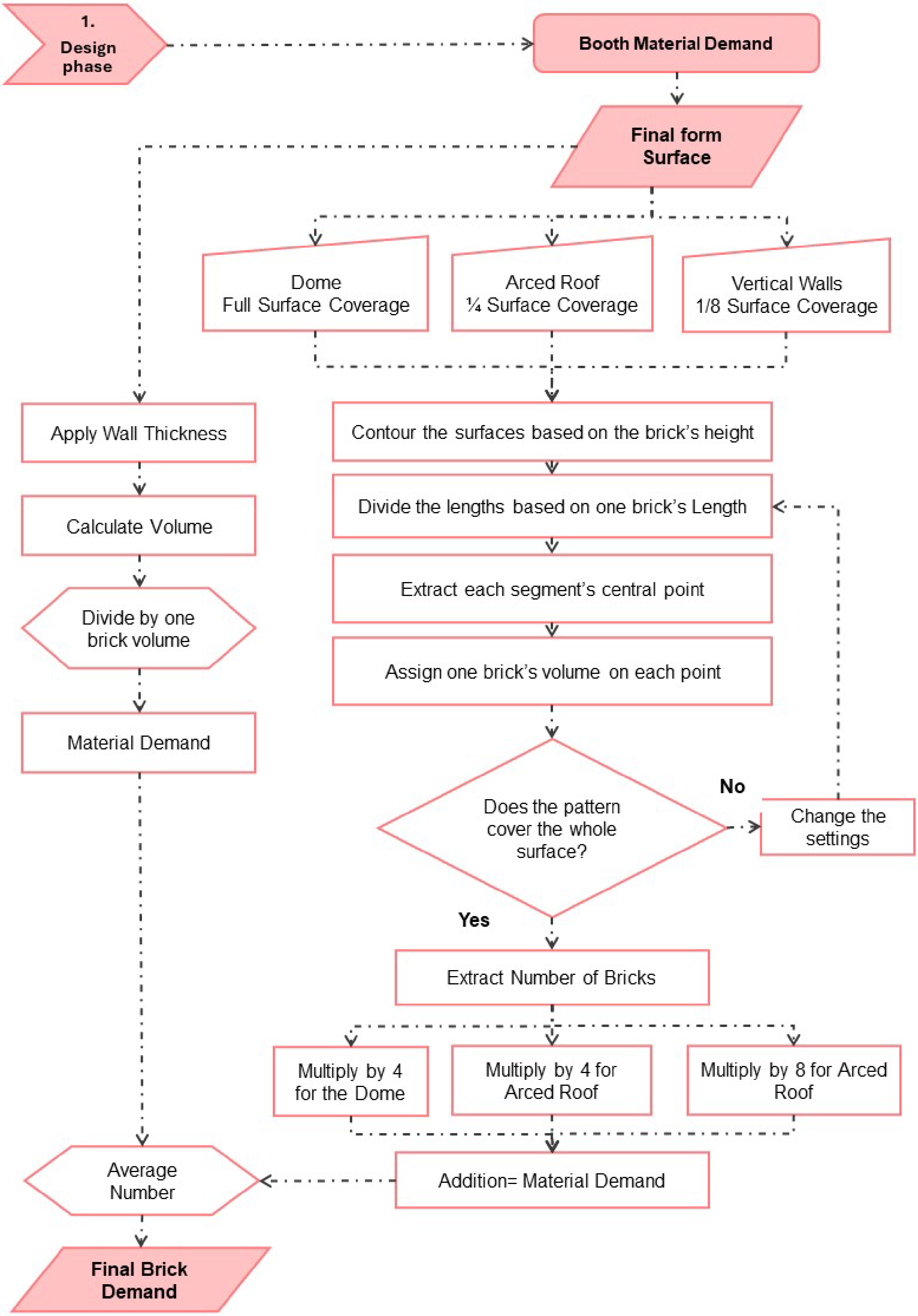


Figure 63- Parametric Brick laying Script

Volume Calculation and Initial Estimation

Upon determining the wall thickness for each booth, the approximate volume of each structure is calculated. This volume is then divided by the volume of a standard-sized brick to produce a preliminary estimate of the brick demand for each booth.

Detailed Surface Coverage Simulation

To verify the accuracy of this initial estimation, a detailed script is employed to simulate the complete coverage of the booth surfaces with bricks. The script specifically analyzes:

- ¼ of the top half of the arced roof
- ¼ of the bottom half of the arced roof
- 1/8 of the vertical walls
- The entire surface of the dome

This analysis involves creating points on these surfaces, spaced to accommodate the placement of a standard-sized brick. These points are generated by dividing the contour lines of each surface with intervals equal to a brick's height, adjusted to match the length of a brick. Due to the uneven nature of the surfaces, the number of divisions is adjusted within a range to ensure a realistic representation of brick coverage.

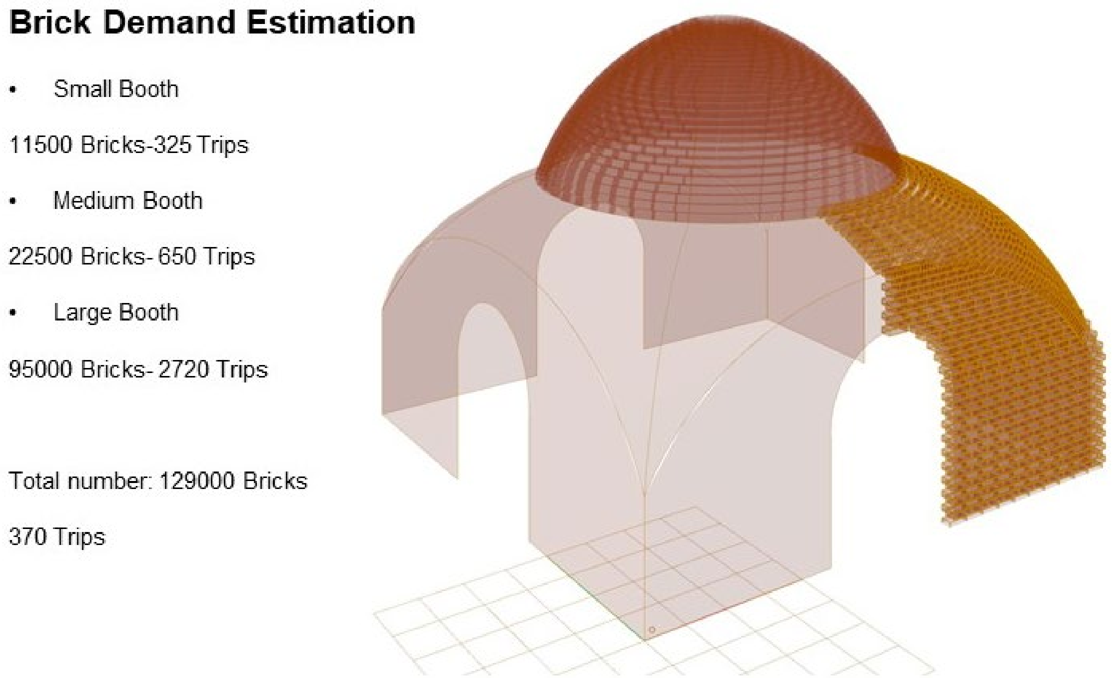


Figure 64- Parametric Bricklaying

Brick Placement and Final Count

The derived points serve as the centers for placing the bricks. The total number of bricks, calculated by adding the numbers from each surface and multiplying by the wall thickness, is then compared to the initial rough estimation. An average of these two figures is calculated to obtain a more precise estimate of the required bricks.

The results of this detailed estimation process are summarized in the following table:

Table 5- Structural Analysis and Brick Estimation Results

<table>
<tr><th>Type</th><th colspan="2">Number of Bricks</th><th>Utilization Factor</th></tr>
<tr><td>5 m* 5 m Booth</td><td colspan="2">Dome: (full coverage)
918* 2 Layers
1836</td><td rowspan="2">Tension:
-7.6%
Compression:
82.3%</td></tr>
<tr><td>Wall Thickness:
20 cm</td><td colspan="2">Roof- Top: (quarter coverage)
304 * 4 Srf *2 Layers
2432</td></tr>
<tr><td>Volume:
11.5 m3</td><td colspan="2">Roof- Bottom: (quarter coverage)
198 * 4 Srf *2 Layers
1584</td><td rowspan="2">Displacement:
7.84 e-3 cm</td></tr>
<tr><td>Footprint: 25 m2</td><td colspan="2">Walls: (1/8 coverage)
390 * 8 Srf *2 Layers
6240</td></tr>
<tr><td>Total Number of Bricks</td><td>Volume Estimation:
11525</td><td>Parametric Estimation:
11156</td><td>Total Trips:
325 Times</td></tr>
<tr><td>7.5 m* 7.5 m Booth</td><td colspan="2">Dome: (full coverage)
1440 * 2 Layers</td><td>Tension:
-10.2%
Compression:
74.9%</td></tr>
<tr><td>Wall Thickness:
20 cm</td><td colspan="2">Roof- Top:
702 * 4 Srf *2 Layers
5616</td><td></td></tr>
<tr><td>Volume:
24 m3</td><td colspan="2">Roof- Bottom: (quarter coverage)
253 * 4 Srf *2 Layers
2024</td><td rowspan="2">Displacement:
2.86e-2 cm</td></tr>
<tr><td>Footprint: 56.25 m2</td><td colspan="2">Walls: (1/8 coverage)
706 * 8 Srf *2 Layers
11296</td></tr>
<tr><td>Total Number of Bricks</td><td>Volume Estimation:
23999</td><td>Parametric Estimation:
21816</td><td>Total Trips:
655 Times</td></tr>
<tr><td>10 m * 10 m Booth</td><td colspan="2">Dome: (full coverage)
2789 * 5 Layers
13945</td><td rowspan="2">Tension:
-11.2%
Compression:
97.2%</td></tr>
<tr><td>Wall Thickness:
50 cm</td><td colspan="2">Roof- Top: (quarter coverage)
1481* 4 Srf *5 Layers</td></tr>
</table>

	29620		
Volume: **95 m3**	Roof- Bottom: (quarter coverage) 520 * 4 Srf *5 Layers 10400		Displacement: 2.30e-2 cm
Footprint: 100 m2	Walls: (1/8 coverage) 1026 * 8 Srf *5 Layers 41040		
Total Number of Bricks	Volume Estimation: 95347	Parametric Estimation: 95005	Total Trips: 2720 Times

This methodological approach ensures that the brick demand for each booth is accurately assessed, providing a reliable basis for material planning and allocation in the construction simulation.

5-1-5 Data Export for Simulation and Design Analysis

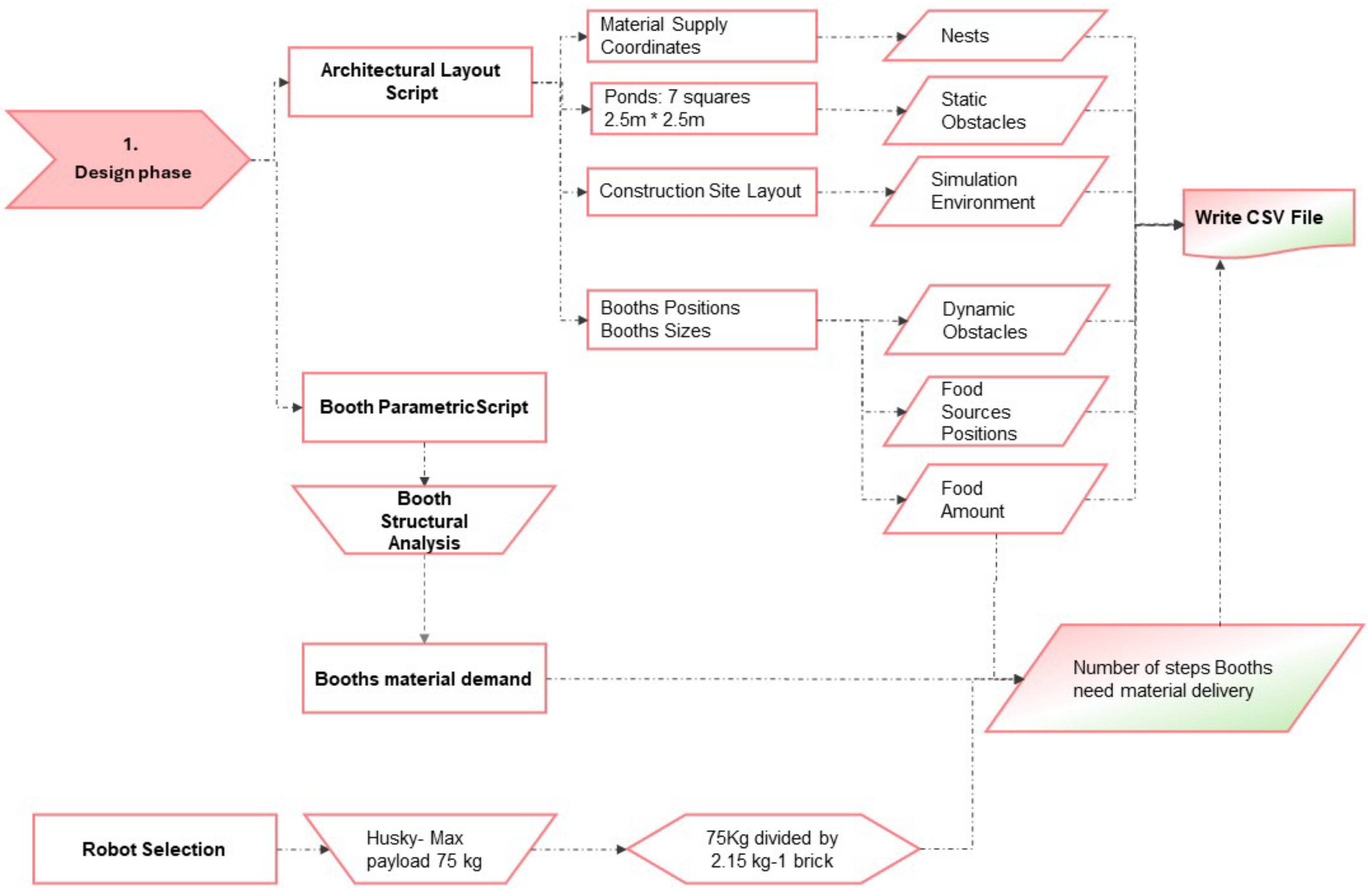


Figure 65- Data Export Stage

In the concluding segment of the simulation process, key data elements are systematically prepared for export to facilitate the subsequent phase of simulation. The specific data exported includes:

- **Material Supplies Locations:** Identified as nests, these coordinates denote critical resupply points within the simulation environment.
- **Ponds Cells' Coordinates:** These are recorded as static obstacles to inform the layout and navigational restrictions within the simulation.
- **Booths Central Coordinates and Size:** Represented as food points and dynamic obstacles, these data points provide essential details on the location and scale of interaction points for the simulated agents.

All data is compiled and written into a CSV file, structured to ensure compatibility and ease of integration with the Python script designated for running the Ant Colony Optimization.

5-1-6 Selected Layout

For moving forward to the next step one of the layouts is chosen for the simulation. This layout contains 3 booths of each type scattered all over the construction site. All the parameters and extracted data about this layout will be imported to our python to replicate the exact same layout.

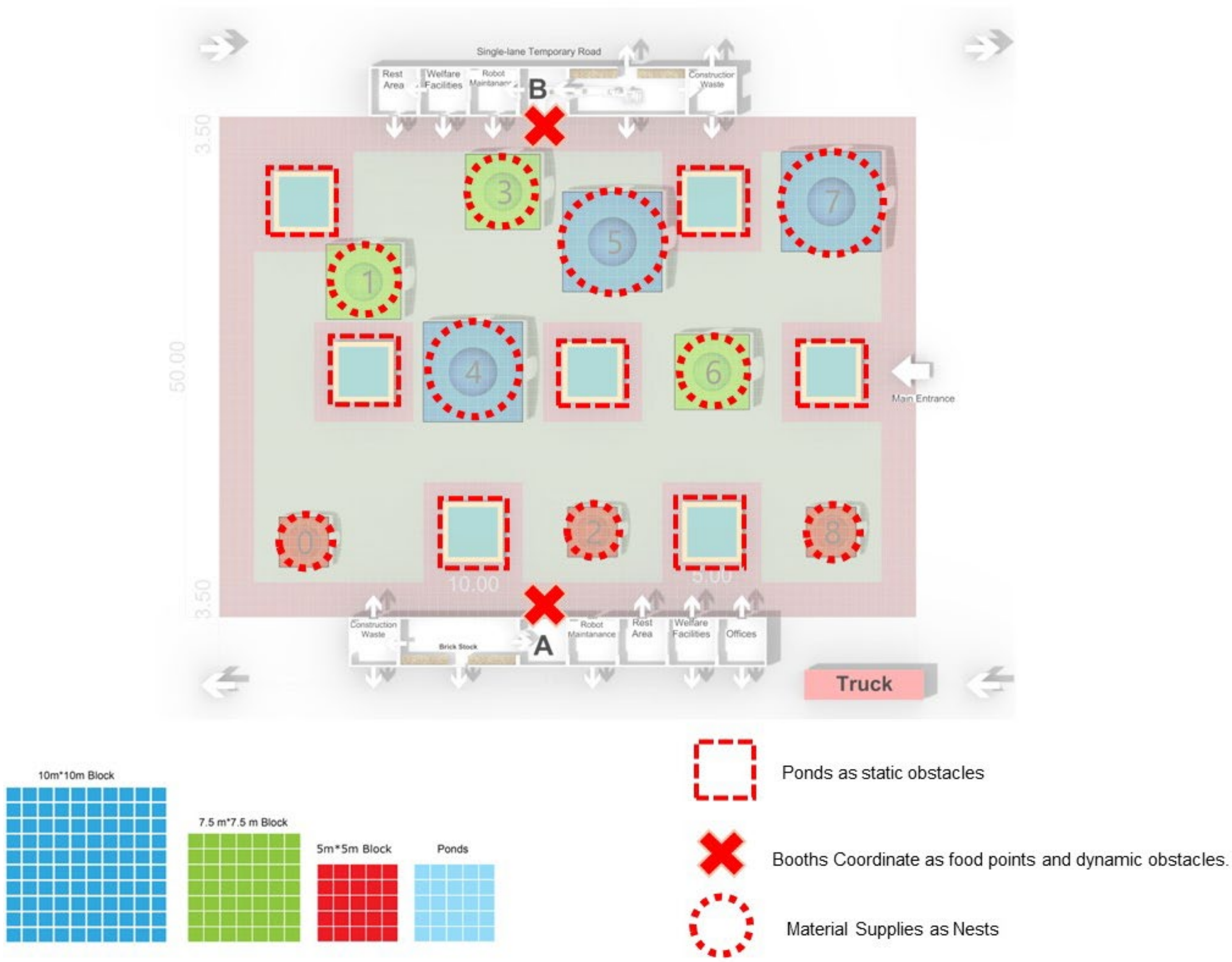


Figure 66- Selected Layout and Exported Elements

5-2 Simulation Phase

The process starts by defining the physical parameters of the construction site in the simulator, setting up material stocks, and locating booth centers as starting and destination points. In the next step, by building up on a code[1] replicating Ant Colony Optimization is adjusted based on the requirements.

An initial simulation run tests the algorithm's functionality within the established construction environment. In terms of algorithm responsiveness and progress, new adjustments, functions or parameters will be added or changed to comply to this project's goal which is to ensure that the algorithm effectively interacts with all defined elements of the simulation, particularly in fully utilizing the resources designated as food sources.

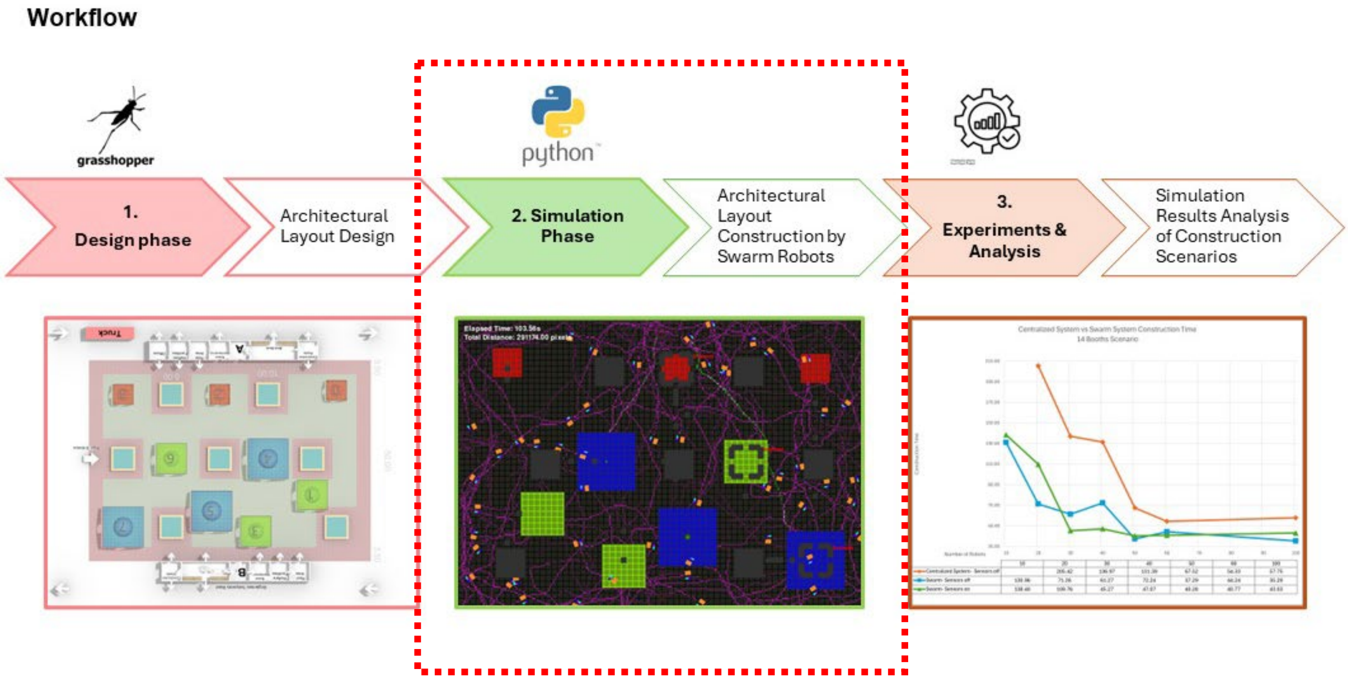


Figure 67- Project's workflow

[1] A code written by Nik Stromberg
Source: PyNAnts/nants_3sens.py at main · Nikorasu/PyNAnts · GitHub

5-2-1 Python Code Overview

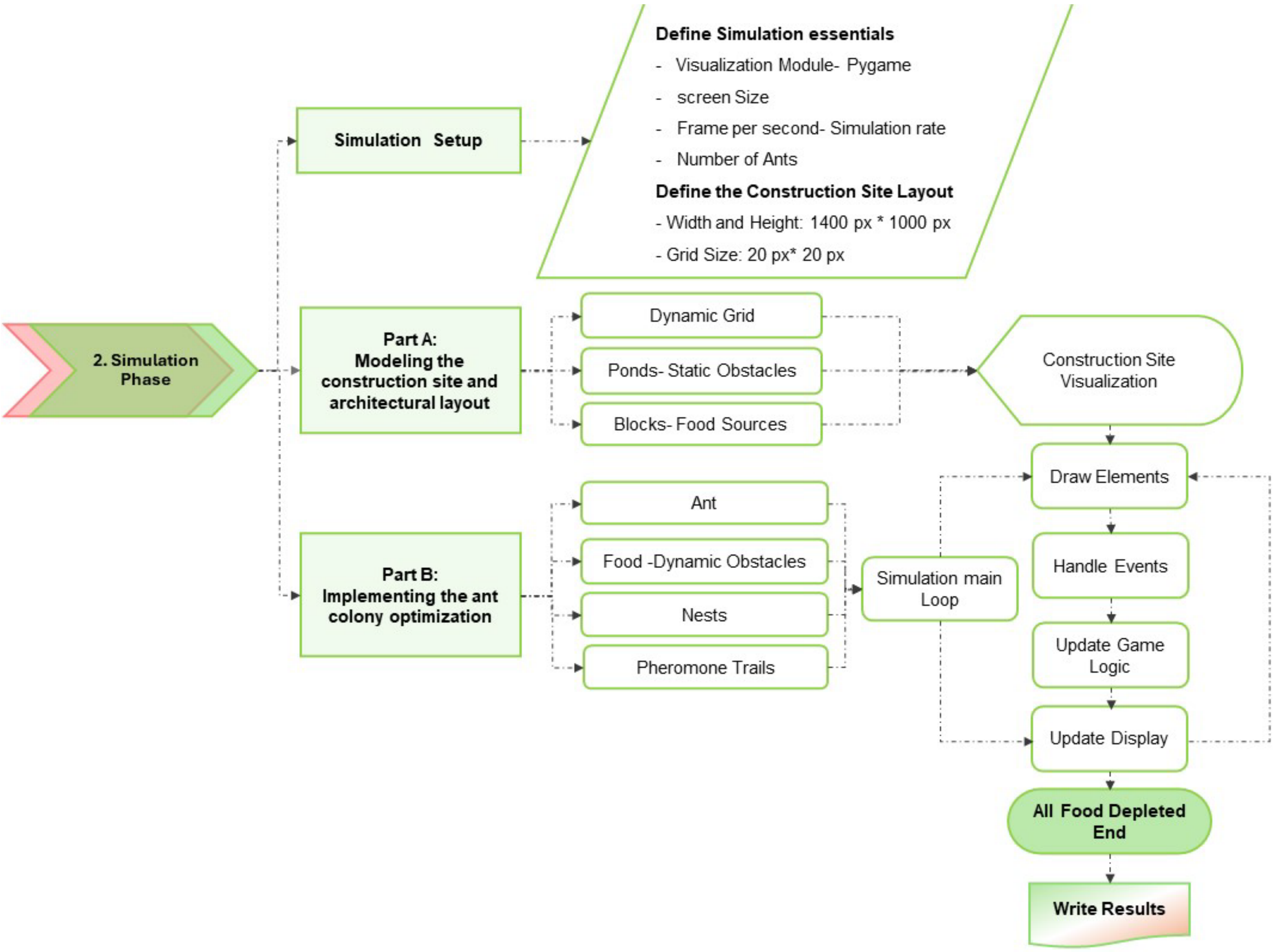


Figure 68- Python Workflow

The flowchart illustrates the simulation phase, starting with establishing the simulation environment setups, which is compared to an initial game setup. These setups include the fundamentals of visualization and simulation environment within Python and required parameters for each simulation.

Then, The Python code structure will be implemented within the defined simulation setup. The code written integrates two main components:

- **Part A: Construction Site Visualization** - Utilizing the logical framework of a Tetris game for the construction site visualization and layout control, this part of the simulation focuses on arranging and managing the construction site's grid. It provides a dynamic environment where construction materials and booths can be moved and organized within the grid.
- **Part B: Ant Behavior Control** - This segment is inspired by ant foraging behavior, controlling how the swarm agents (ants) interact with their environment. It includes searching for resources, returning them to designated points, and navigating around obstacles.

All the events happened by the written code, enter the simulation's main loop, where is responsible to handling the events, update the status, draw the newly updated elements and update them on display continuously until the simulation concludes. In the next part, each step will be explained in detail.

5-2-2 Simulation Setup

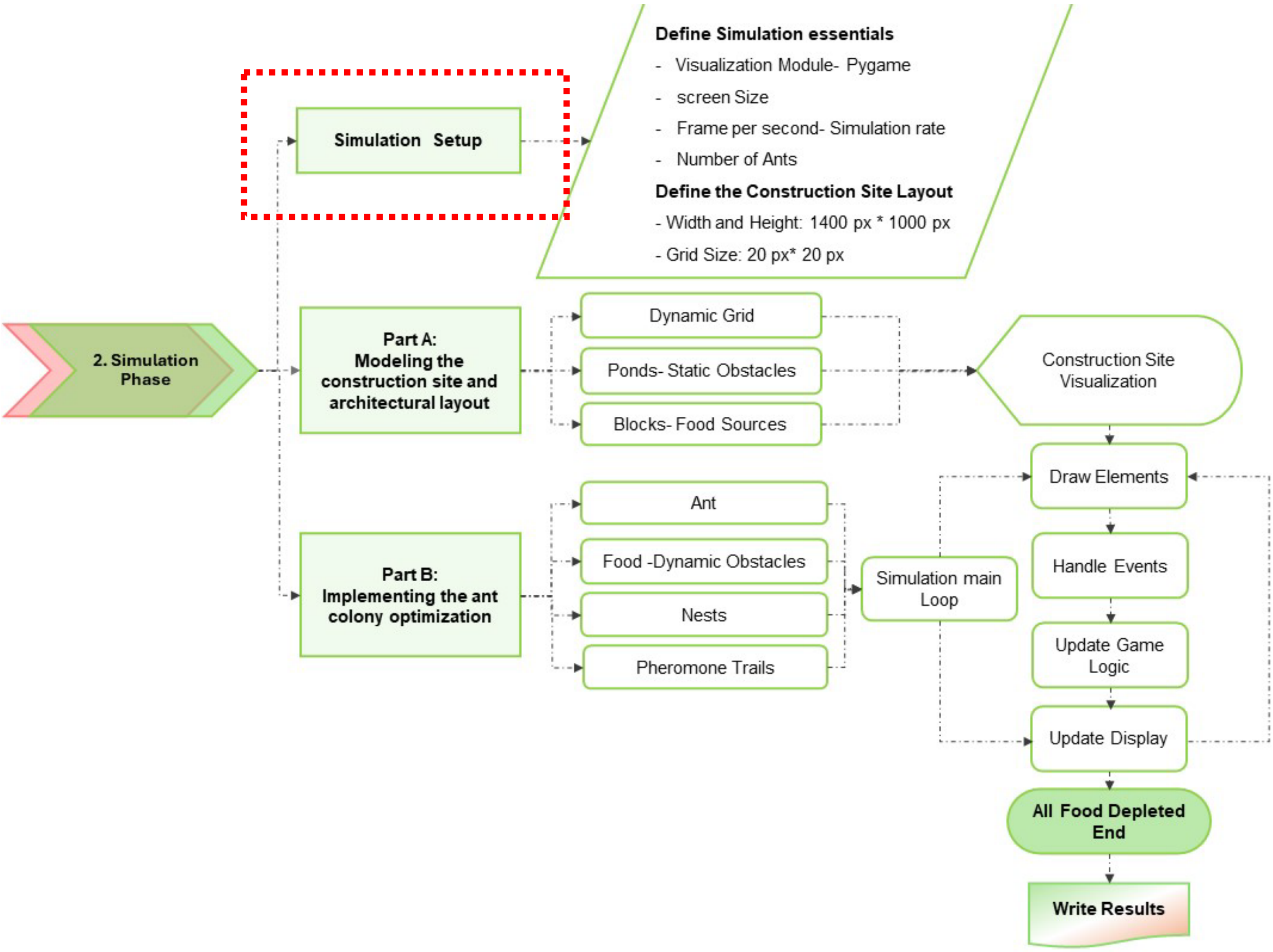


Figure 69- Python Workflow

Pygame Implementation

The entire simulation process utilizes Pygame, a robust toolkit for the development of Python multimedia applications. Pygame simplifies the handling of common multimedia functionalities through its use of the

Simple Direct Media Layer library and other utilities, effectively supporting the visualization and interaction dynamics of the simulation. By selecting Pygame, the coordination system will be also defined within.

Path-finding Logic

At the beginning of the process construction site is defined and visualized by the creation of a grid system, employing a binary logic where each cell holds a status of 0 or 1 or if they are occupied by a block, they get that block's specific ID. This binary ID setup is designed to facilitate the transfer of location data, and identification of food points and nests. However, this logic only gets used for the construction site visualization in Part A and not for the swarm robots' path-finding logic. To enhance the interaction capabilities and data richness, the simulation logic transitions to color detection. This shift involves using RGB values for detection tasks, which enables the ants, equipped with sensors, to detect and adapt to their surroundings based on color signals on the screen.

Unit Conversion and Display Setup

All units from the Grasshopper workflow, initially in meters, are converted to pixels to suit the Pygame environment. The construction site is represented in a game window measuring 1400 pixels in width and 1000 pixels in height, corresponding to a real-world size of 70 meters by 50 meters. This setup results in a grid where each cell represents a 1 meter by 1 meter area, scaled up to 20 pixels by 20 pixels on the display.

Variable Definitions

The simulation defines several fixed variables to maintain consistency and control over the simulation environment:

- Number of Ants: Ranges from 10 to 100, depending on the scenario.
- FPS (Frames Per Second): Set at 60 to ensure smooth simulation progression.
- Pheromone scale-down Ratio: Defined as 5, representing the pixel size for the pheromone grid, crucial for the visualization of ant trails and pheromone deposition.

5-2-3 Part A as Tetris-Style Construction Site Visualization

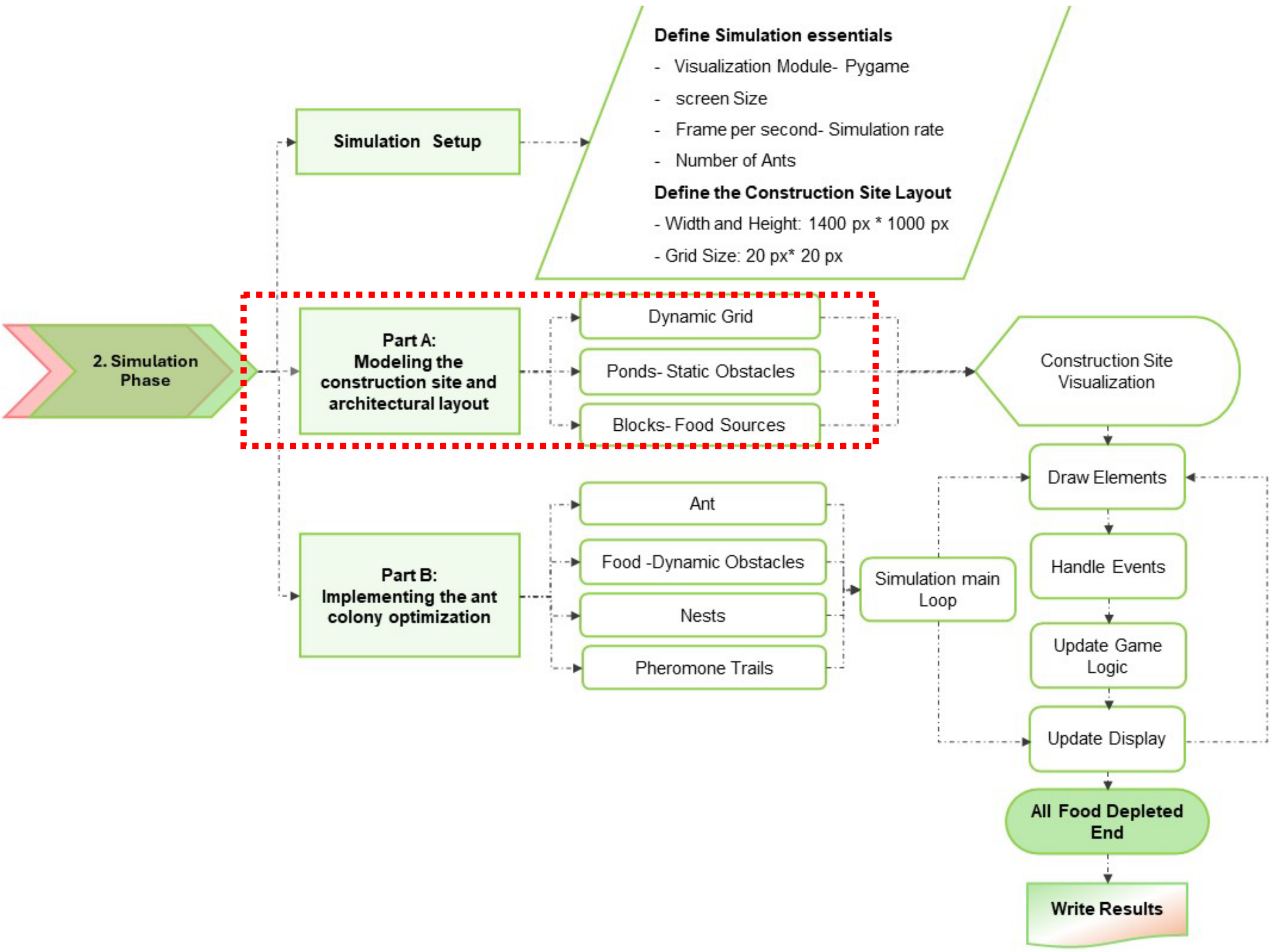


Figure 70- Python Workflow

At the inception of integrating the construction site into the Python environment, various algorithms are tested to develop smart grids in a rectangular configuration. This smart grid ensures that each cell provides comprehensive information including its central and corner coordinates, a distinct index, and its status (either occupied or unoccupied).

Given the dynamism like an empty construction site populated with various blocks, Tetris game code[2] structure is adopted to manage the spatial dynamics efficiently. The steps involved, derived from this framework, include:

1. Creating the Grid that represents the construction site.
2. Create the Blocks which symbolize construction units.

[2] a code written by Nick Koumaris (Koumaris, 2023).

3. Move the Blocks to simulate unit handling and placement.
4. Rotate the Blocks to fit into the designated construction areas.

Classes Used in Part A

Classes in Python are a blueprint for creating objects (a particular data structure), providing initial values for state (member variables or attributes), and implementations of behavior (member functions or methods). They define the structure and behavior that the objects created from the class can have. In this context, the objects that these classes have created are required simulation elements.

Class Grid: Represents and manipulates the grid for the construction simulation. Each cell's information is projected onto our virtual construction site, with indices and statuses updated from Grasshopper data.

Class Position: Manages block movements based on grid positions rather than pixel coordinates, enhancing the logic handling and movement precision.

Class Block: Acts as the base class for different block types or booths, allowing movement and interaction within the grid based on Tetris logic. This class is extended by specific block classes

- Class FiveBlock: Represents a 5m x 5m booth.
- Class SevenBlock: Represents a 7.5m x 7.5m booth.
- Class TenBlock: Represents a 10m x 10m booth.
- Class Pond: Represents a 2.5m x 2.5m Pond

In the simulation, static obstacles are predefined and do not change position or characteristics throughout the simulation process. These obstacles are represented by extracting the coordinates of ponds within the virtual construction site. Each pond is represented as a rectangular block, specifically a 20-pixel by 20-pixel square, centered on the extracted pond coordinates. These blocks serve as impassable areas that the robots (ants) must navigate around, simulating real-world physical barriers that restrict movement.

The image displays how adjustments made to the Tetris blocks' definitions now effectively represent the booths.

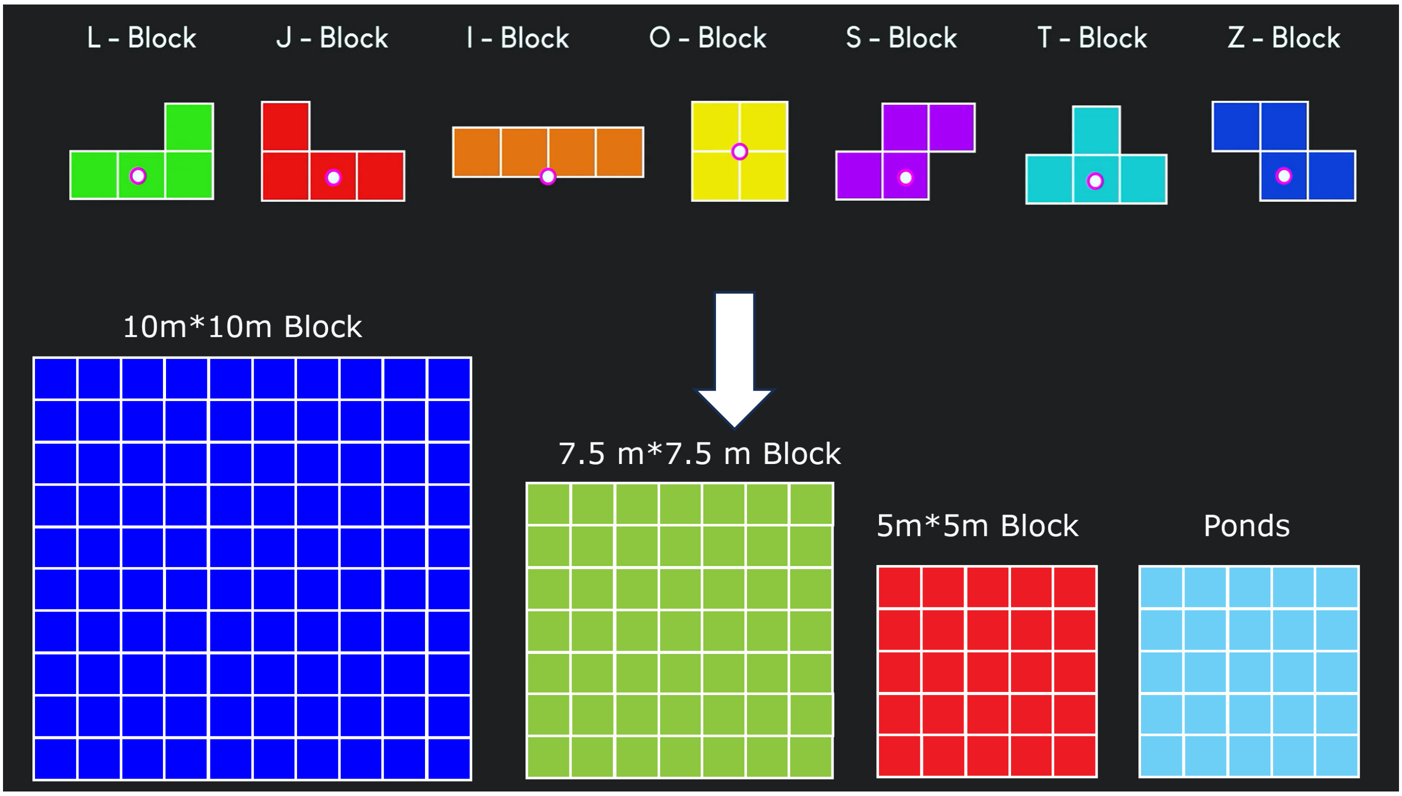


Figure 71- Transition from Tetris to Booths & Ponds
Image Source: https://www.youtube.com/watch?v=nF_crEtmpBo&t=725s

Class Game: Retrieves and utilizes food point data and booth size information from a CSV file, aligning each block with its correct position on the grid. At this step, as shown in the picture below the construction site with its elements are visualized and translated as the exact design layout.

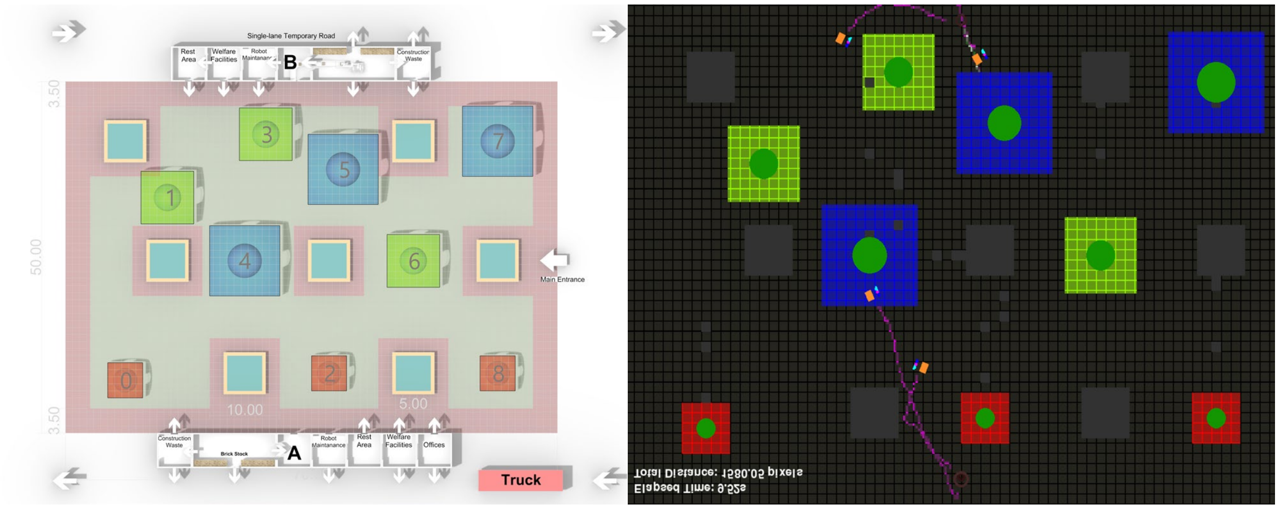


Figure 72- Final translation to Python

5-2-4 Part B as Ant Colony Optimization (ACO)

In this segment of the simulation, the behavior of the robots, represented as ants, is managed. The implementation encompasses the classes for ants, food, pheromones. All of the changes have been made built up on a code written by Nik Stromberg (Stromberg, 2021).

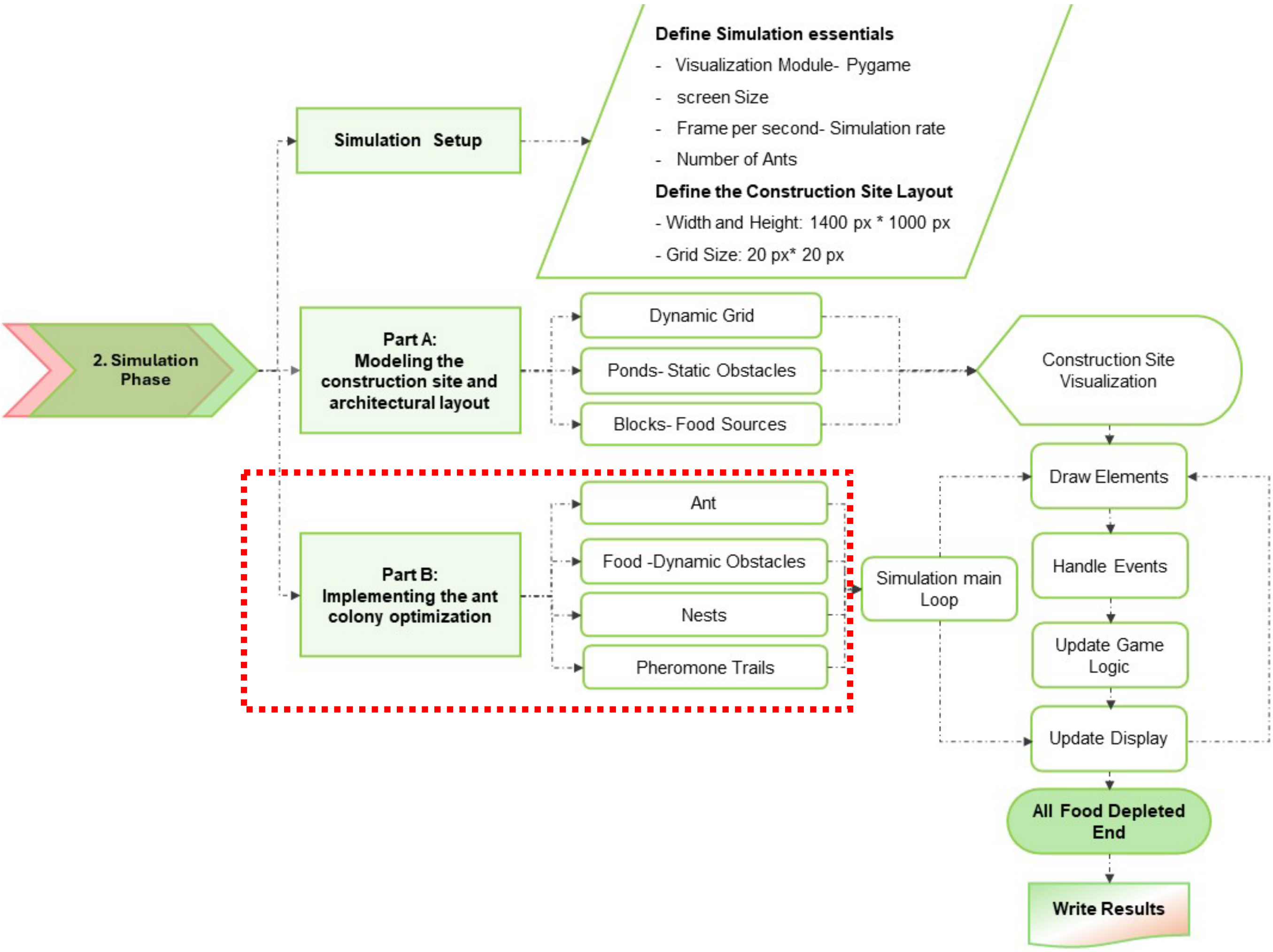


Figure 73- Python Workflow

Classes Used in Part B

Class Ant: This class stores and updates essential attributes and behaviors of each ant.

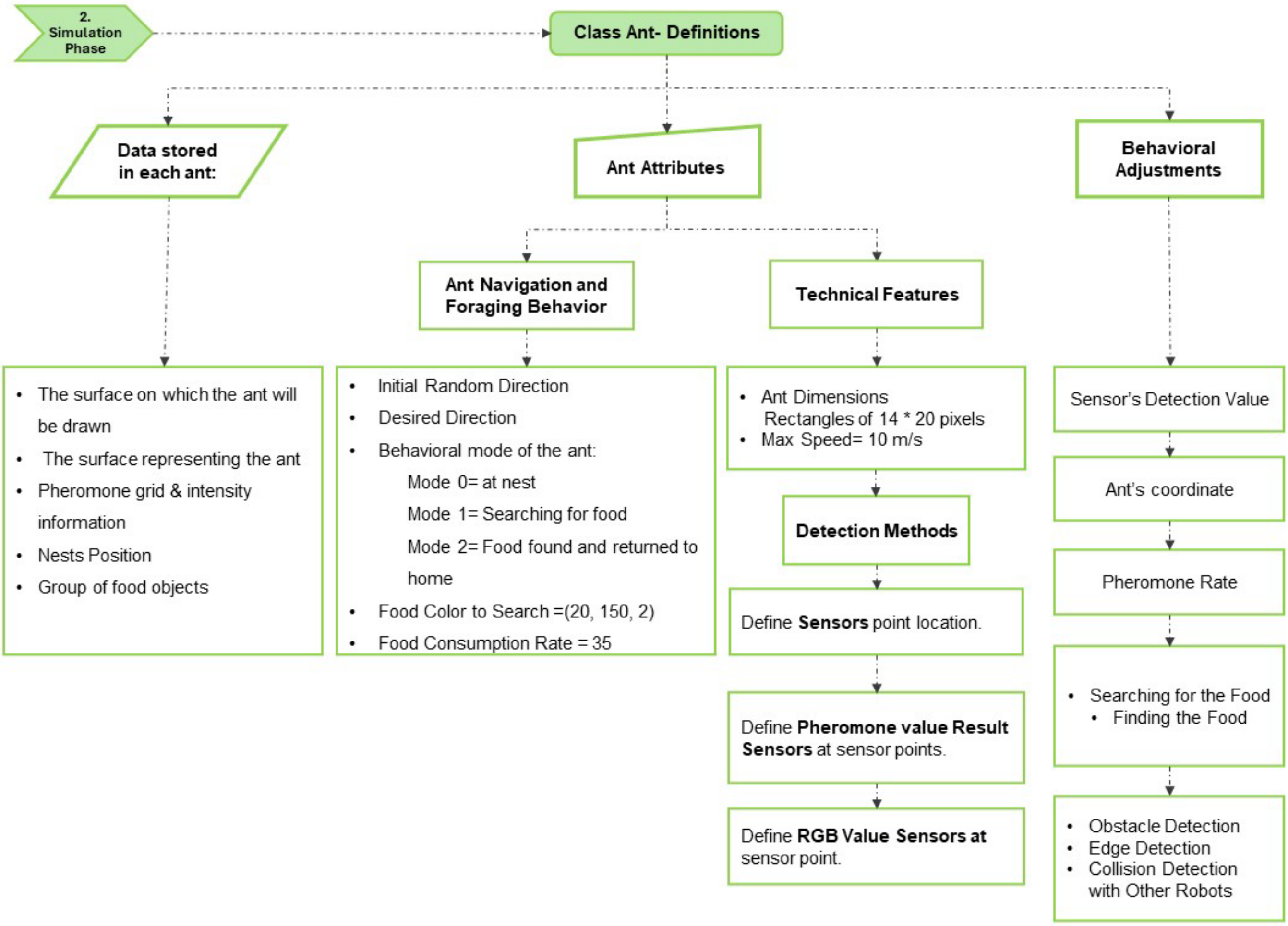


Figure 74- Class Ant's Description

Storage of Information

The first defined attribute in this class is **Storage of Information.** It means that this class holds data concerning the ant's image, pheromone value, food detection and nest detection.

Ant Attributes

Ant Attributes is divided into two groups of technical features and Foraging and Navigation behavior.

Technical Features

The ant and in this case the robot's features are defined as manual inputs. To define the robot's technical features the Dimension Specification is set to reflect the Husky robot's size, scaled to 13.4 pixels by 19.8 pixels, representing the robot's actual dimensions of 670 mm by 990 mm. Although the Husky robot's actual speed is 1 m/s, for showing the movements better in the simulation, the max speed is set to 10m/s. As the ants navigate the construction site searching for food, they leave behind a trail of magenta pheromones of 5 pixels grids. When they find the food the color turns to green in visualization.

Detection Method

Each robot is equipped with three sensors that detect RGB values 20 pixels away from its central point on the front side. One of the sensors detect the RGB Values In the simulation for all elements and the other sensor checks the green colors intensity in the detected RGB value to check if its pheromone left by food founders. In the simulation, each ant is visualized as an orange rectangle equipped with three color sensors for distinction.

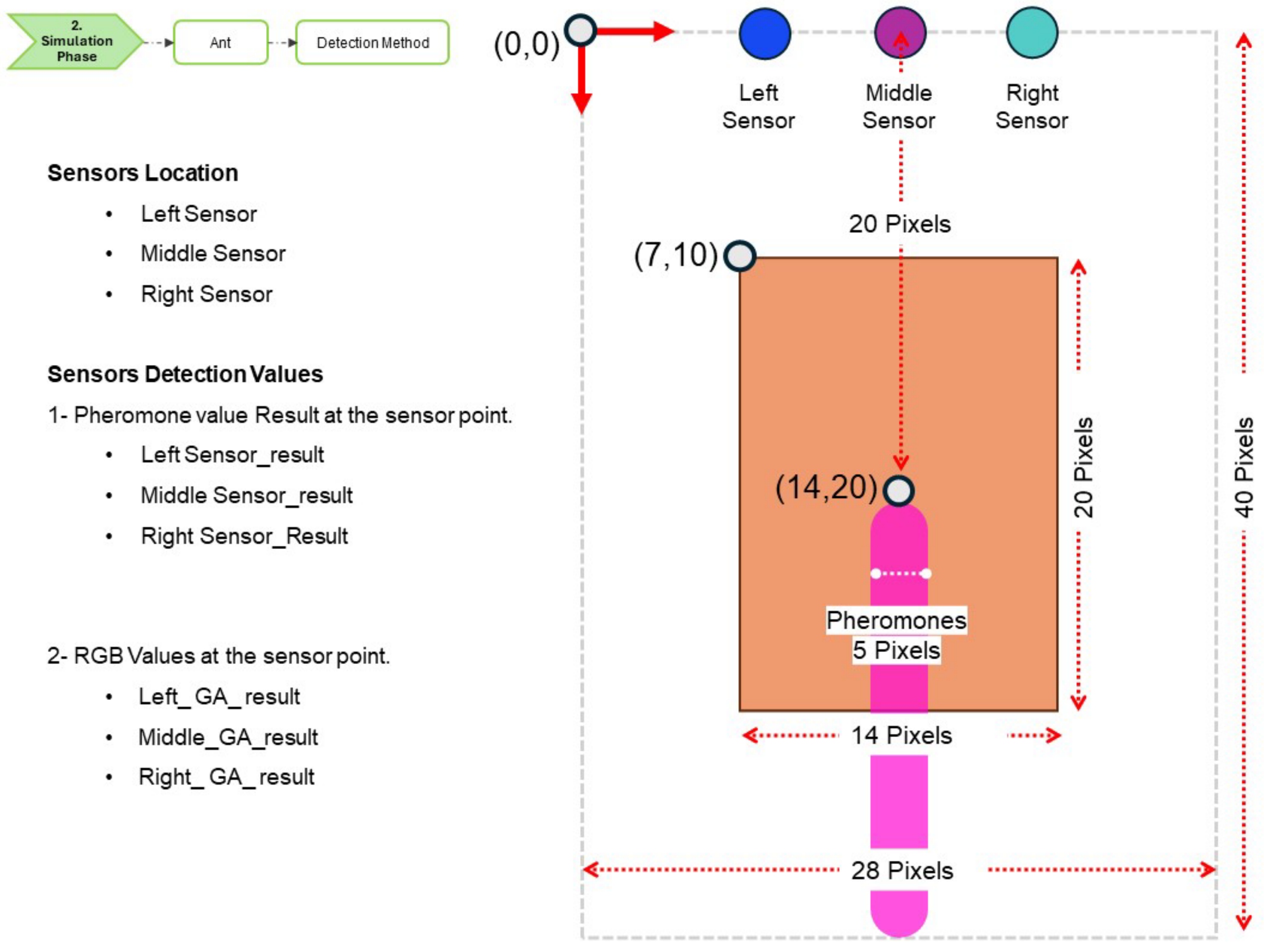


Figure 75- The Robot's Technical Information

Ant Navigation and Foraging Behavior

These ants emerge from their nests at random angles to ensure minimal initial collision, particularly at material pickup points. This randomized direction is crucial for simulating the chaotic nature of a real construction site where space management is essential.

Following the logic common to ant foraging, ants exit their nests to search for food. For ant's different conditions three modes are defined.

- Mode 0= when the ant is at nest.
- Mode 1= When the ant comes out of the nest and its distance to the nearest nest is more than 25 pixels.
- Mode 2= When the ant finds the food and carries it back to the nearest nest.

The food color that ants should look for is also defined in this part to enhance their sensitivity to this color. When they find the food as defined ants are allowed to consume 35 parts of the food.

Behavioral Adjustments

The final part of the Class Ant involves adjusting their paths due to their path-finding capabilities. These adjustments occur under several conditions: detecting an obstacle, encountering another robot, reaching the edges of the construction site, or finding food. Throughout the simulation, each robot's coordinates, desired direction, detected RGB values, and pheromone levels are continually updated and stored. The robots' desired direction is determined by specific rules defined for each of these conditions.

Searching for the Food

In this condition, when a robot navigates the construction site in search of food, the desired direction is determined by the robot's RGB value sensor, which captures the RGB values of all the pixels it has walked on. The pheromone rate detection sensor then compares the green component's value among these pixels. If the intensity of the green component is higher in the middle pixel, the robot will continue moving straight. If the intensity is higher in the right pixel, the robot will turn to the right, and if it is higher in the left pixel, the robot will turn to the left. This mechanism allows the robot to make informed decisions based on the detected pheromone trails, optimizing its path towards the food source.

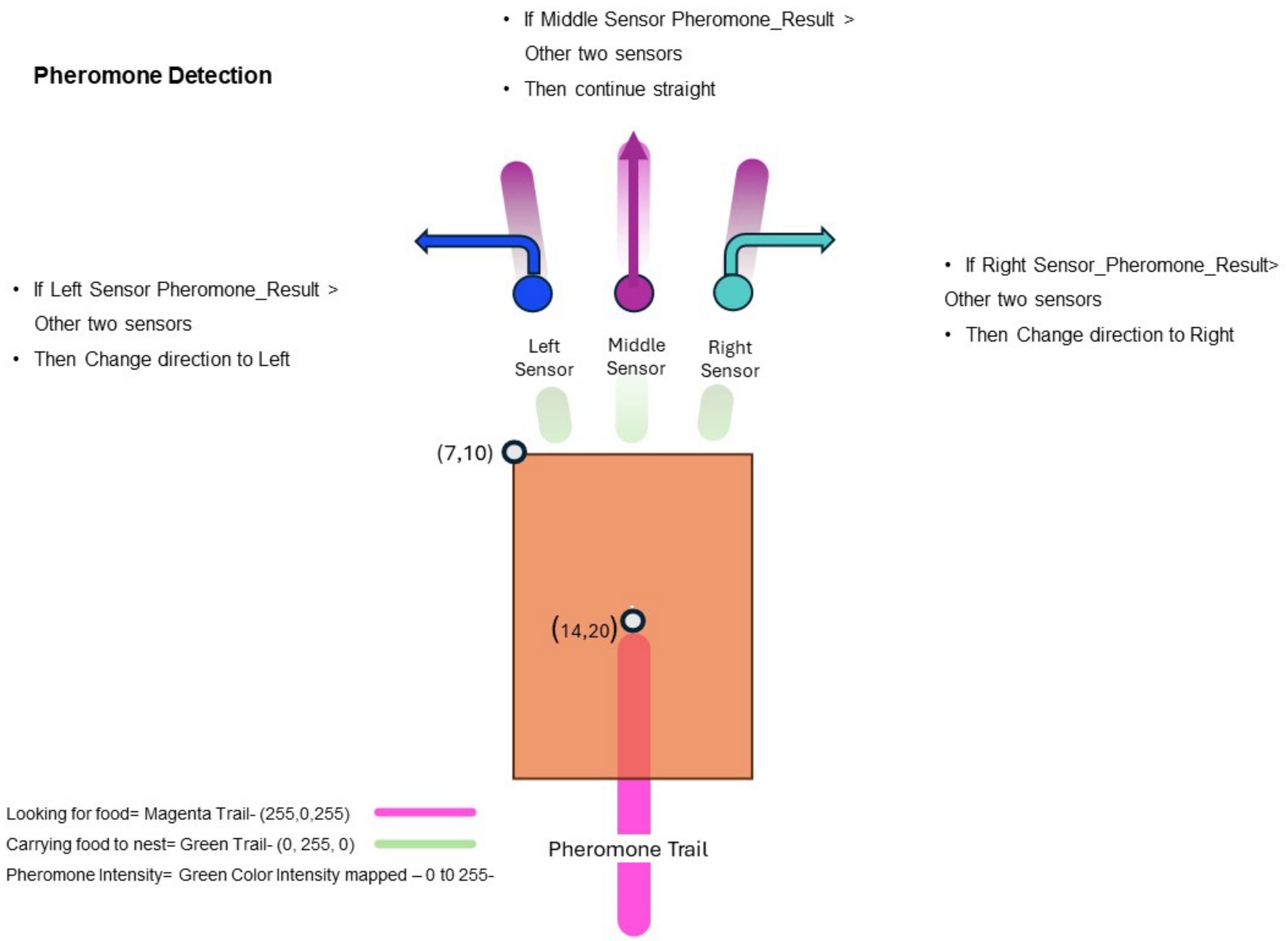


Figure 76- Searching for Food Movement Behavior

Finding the Food

In this condition, when a robot finds the food, the desired direction is determined by the RGB value sensor, which detects the exact food color value of (20,150,2) from the walked-on pixels. If the middle sensor detects this color, the robot will move forward. If the right sensor detects the color, the robot will turn to the right. Similarly, if the left sensor detects the color, the robot will turn to the left. This mechanism ensures that the robot accurately navigates towards the food source based on the specific color detection.

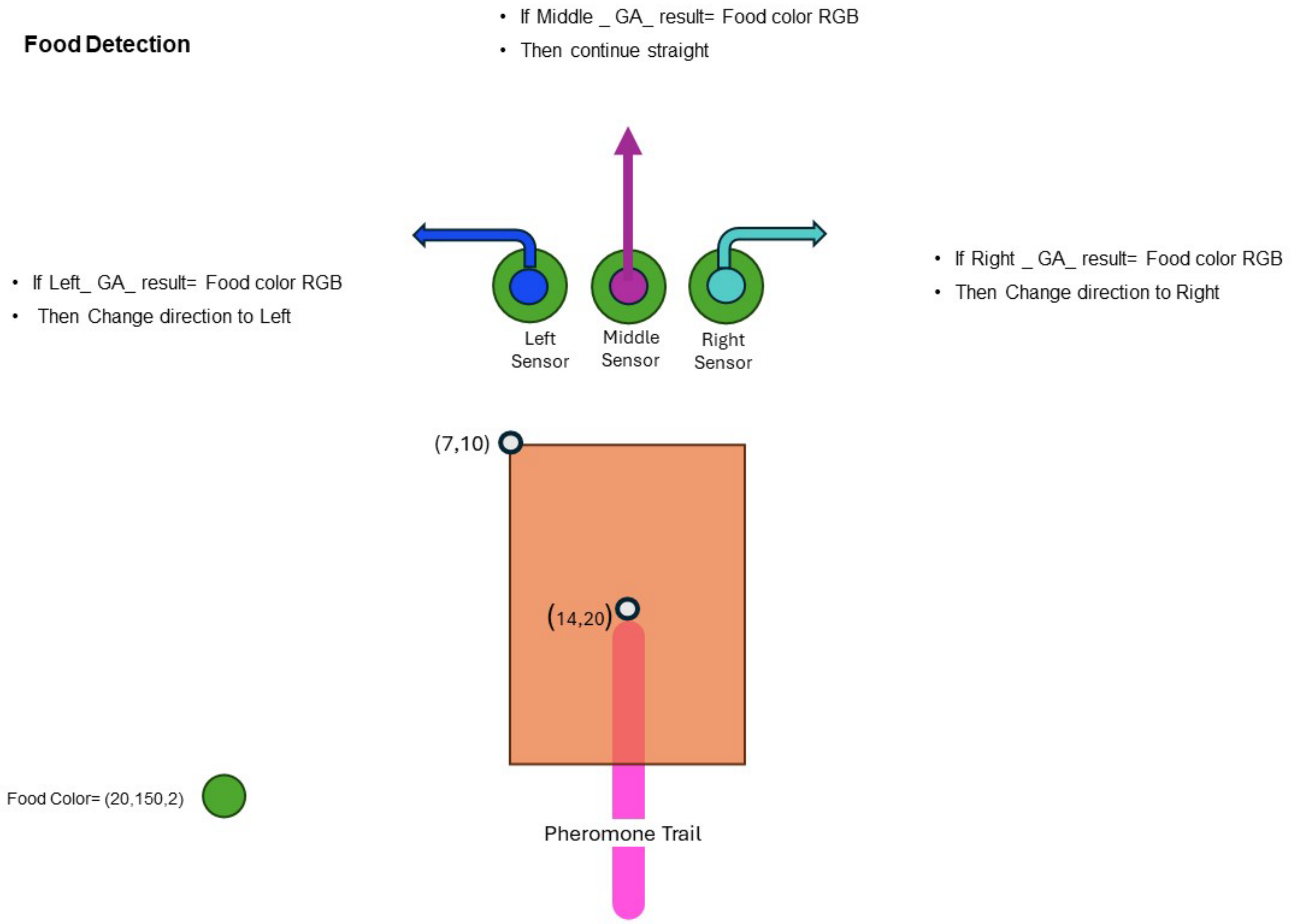


Figure 77- Finding the Food Movement Behaviors

Static & Dynamic Obstacles

The robots' reaction to all kinds of obstacles is consistent. The only difference between static and dynamic obstacles is that static ones are always present, while dynamic ones appear after a food source is depleted. In this case, static obstacles, represented as rectangular blocks with an RGB value of (50,50,50), are ponds on the construction site. Dynamic obstacles are booths that, once completed, change the layout of the construction site by introducing new walls with the same RGB value of (50,50,50) as new obstacles. This addition of new obstacles requires the robots to continuously adjust their navigation strategies to avoid collisions and efficiently move around the site. When the robots' RGB sensors detect the RGB value of (50,50,50), they recognize it as an obstacle. If the middle sensor detects it, the robot will rotate 180 degrees and move backward. If the right sensor detects it, the robot will turn left, and if the left sensor detects it, the robot will turn right.

Edge Detection

The robots avoid the construction site edge when their sensors coordinates are placed outside the defined construction site area. In this case, their path is corrected same as the previous condition. If the middle sensor's coordinate is out of the boundary, the robot will rotate 180 degrees and move backward. If the right sensor is outside, the robot will turn left, and if the left sensor's coordinate is outside, the robot will turn right.

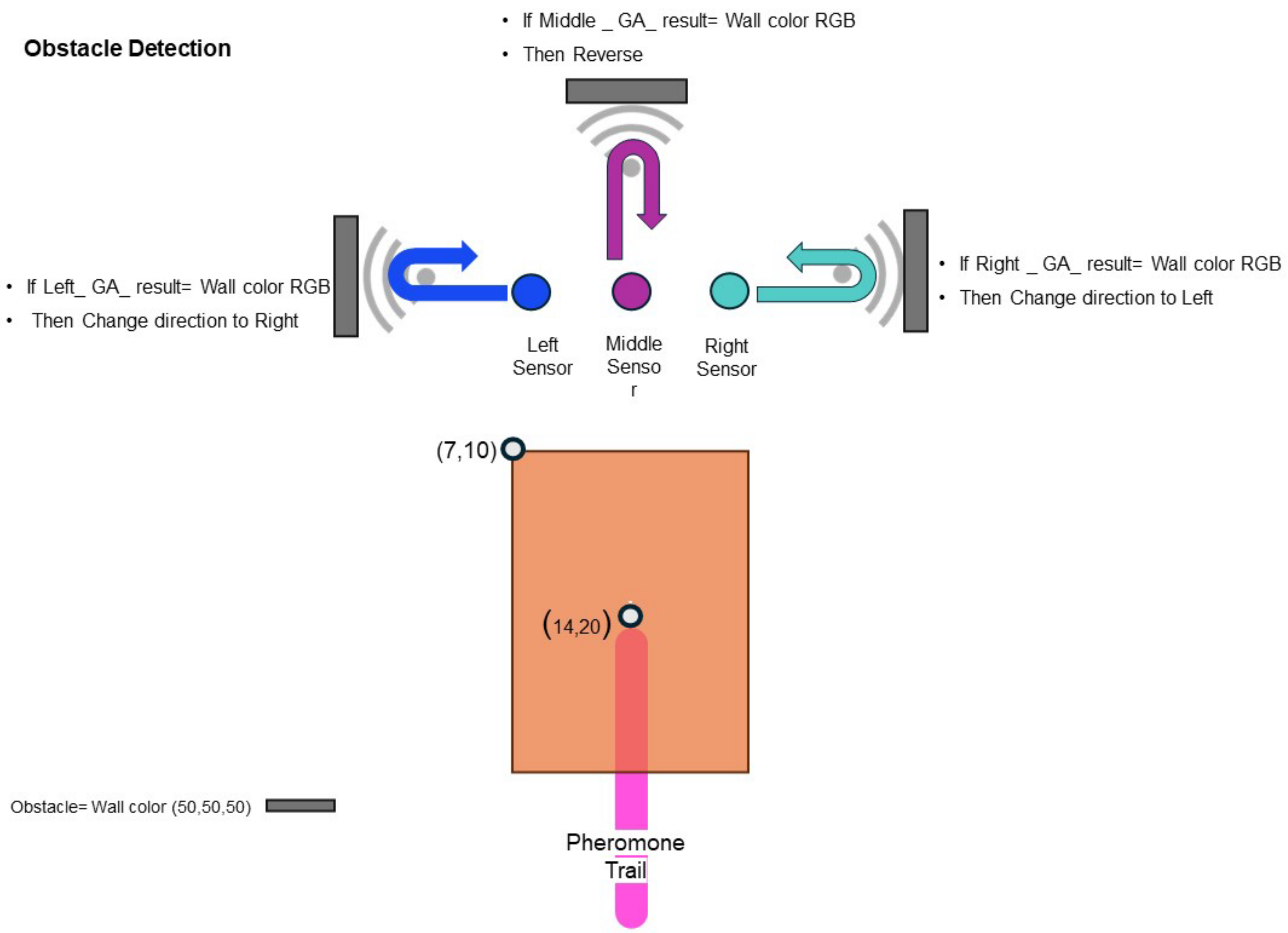


Figure 78- Obstacle Detection Movement Behaviors

Collision Detection with Other Robots

A similar approach is used when the middle sensor detects the RGB value of orange, which is the robot's own color. If the middle sensor detects it and the distance between the robots' central points is more than 25 pixels, ensuring the detection does not belong to the robot itself, the robot will change direction and move backward.

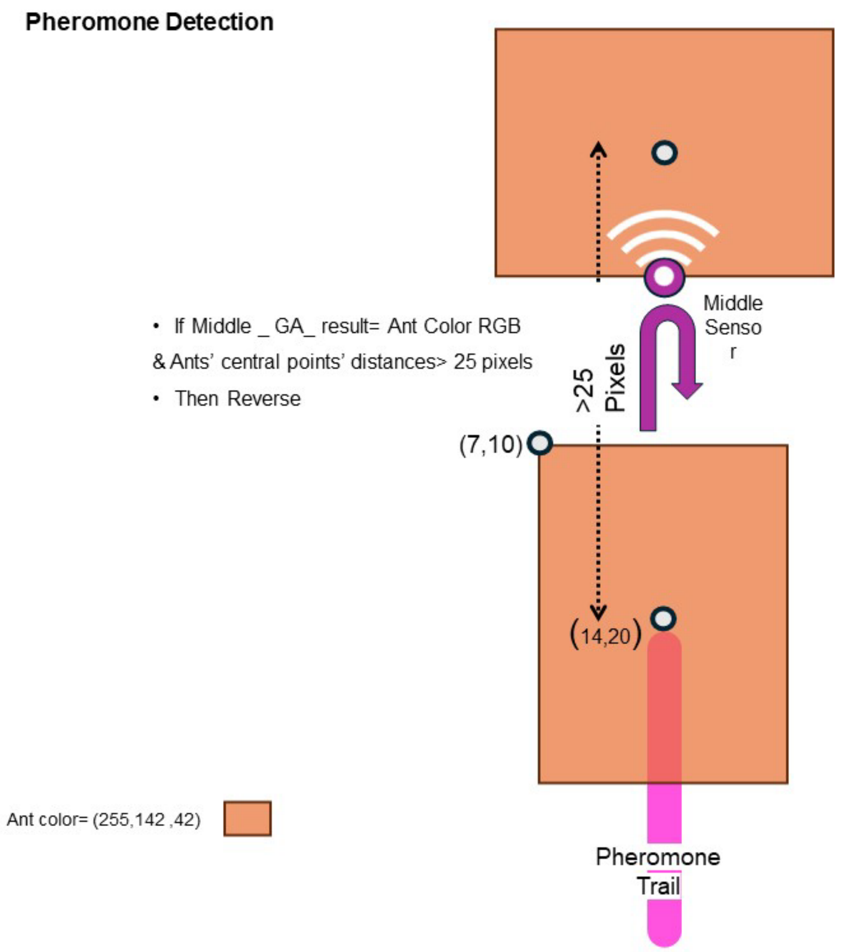


Figure 79- Collision Detection Movement Behavior

The picture below shows the robots movement behavior logic summarized in a flowchart.

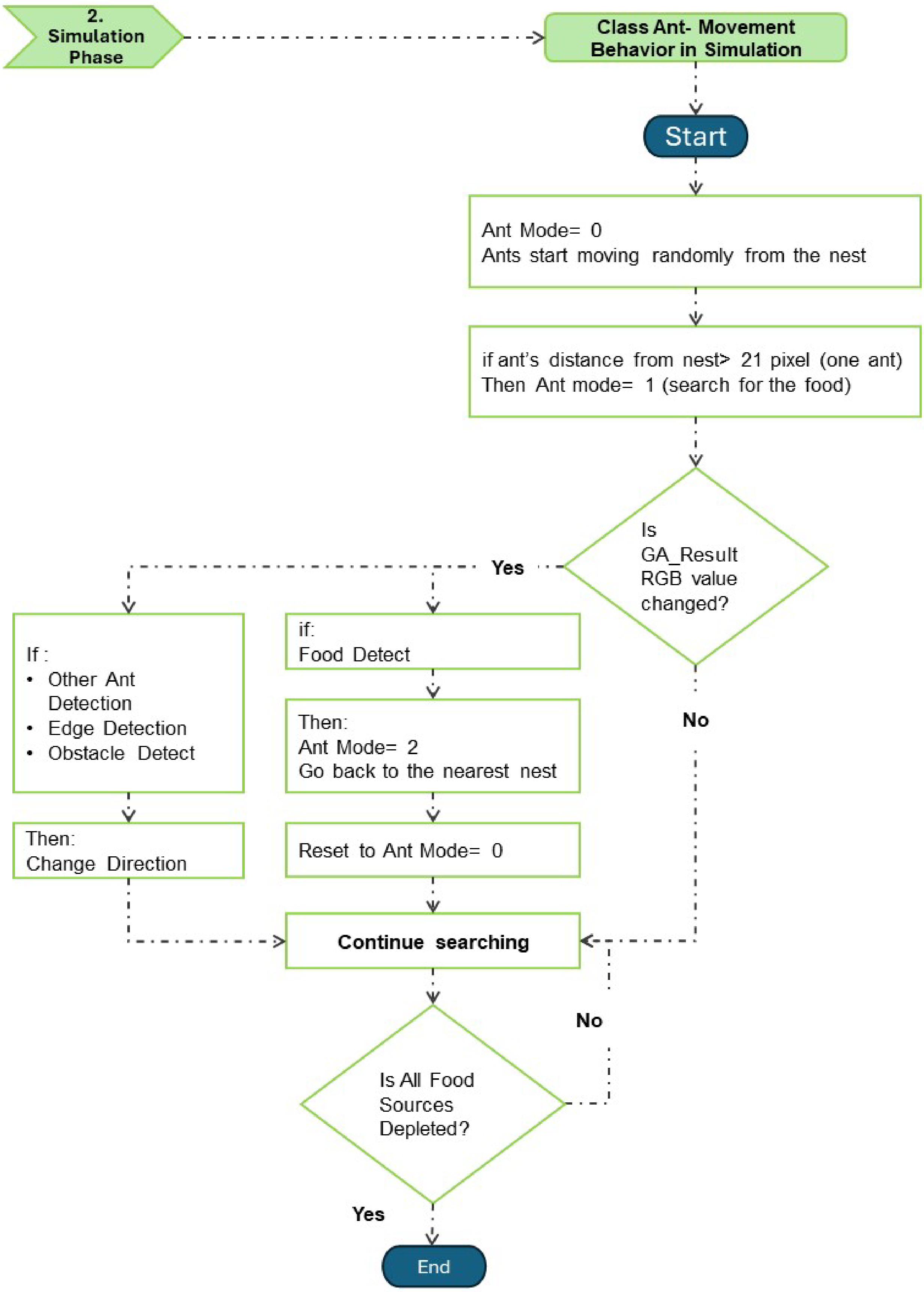


Figure 80- Robots' Movement Behavior Logic

Class Pheromone: The pheromone deposition and evaporation processes are crucial for guiding the robots along efficient paths. The evaporation rate must be adjusted to ensure that pheromones neither fade too quickly nor persist too long, which could mislead the robots. As the robots navigate the construction site searching for food, they leave behind a trail of magenta pheromones with a width of 5 pixels. Upon finding food, the trail color changes to green (0,255,0). Both trails evaporate over time. The pheromone evaporation rate, which updates the pheromone intensity, is governed by the following equation:

New Pheromone Intensity= (1−Evaporation Rate) $\times \Delta T + \sum$Pheromones Deposited Previously

When robots deposit trails on the screen, their RGB value visibility duration gets updated by this equation. When multiple green trails overlap, the pheromone detection sensor perceives a higher level of the green component, which helps the robots locate food.

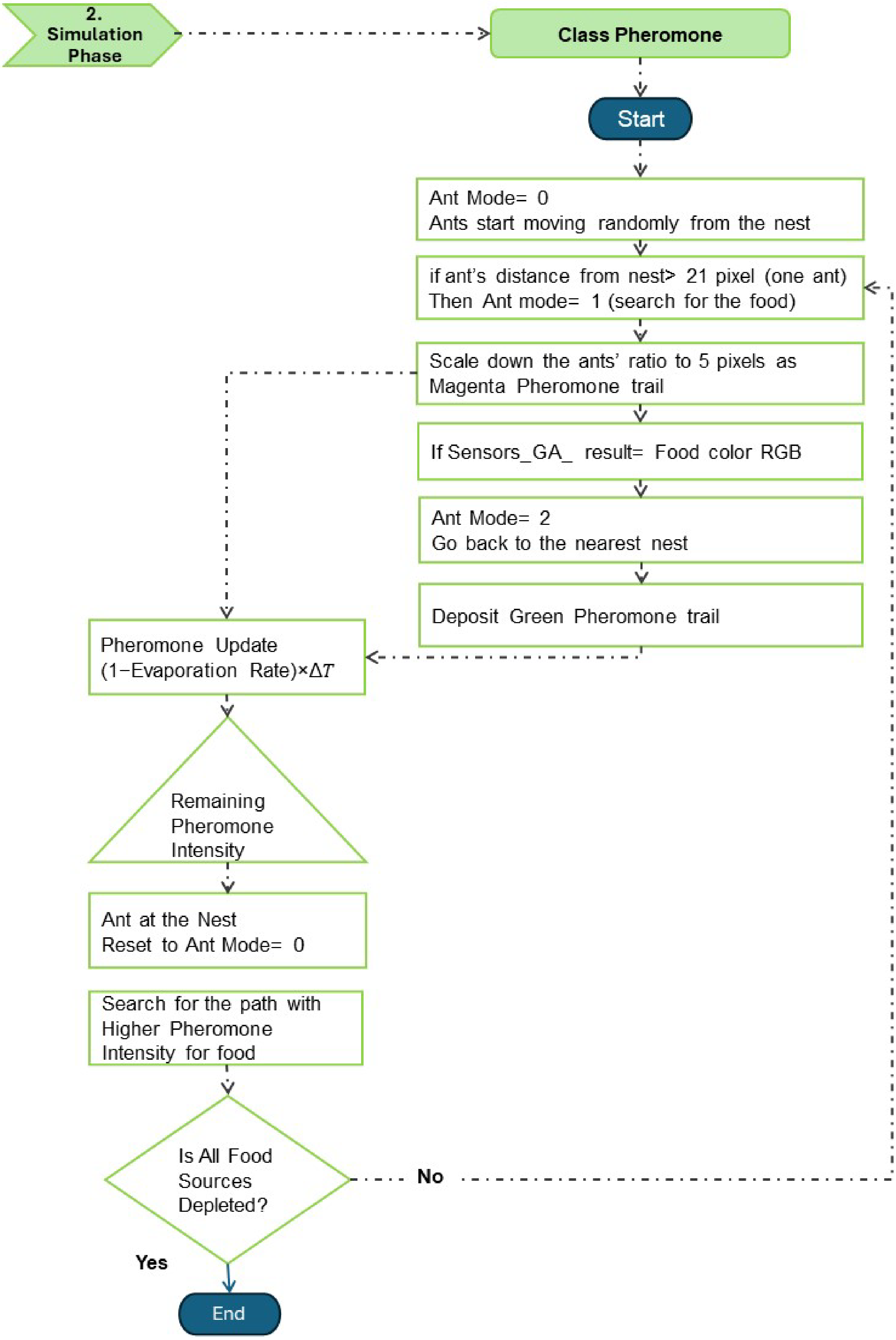


Figure 81- Pheromone Update Logic

Class Food: Oversees the positions, visualization size, index, and consumption rates of food sources, ensuring each interaction is logged and adjusted in real-time. The initial information is imported from a CSV file extracted from the Design phase.

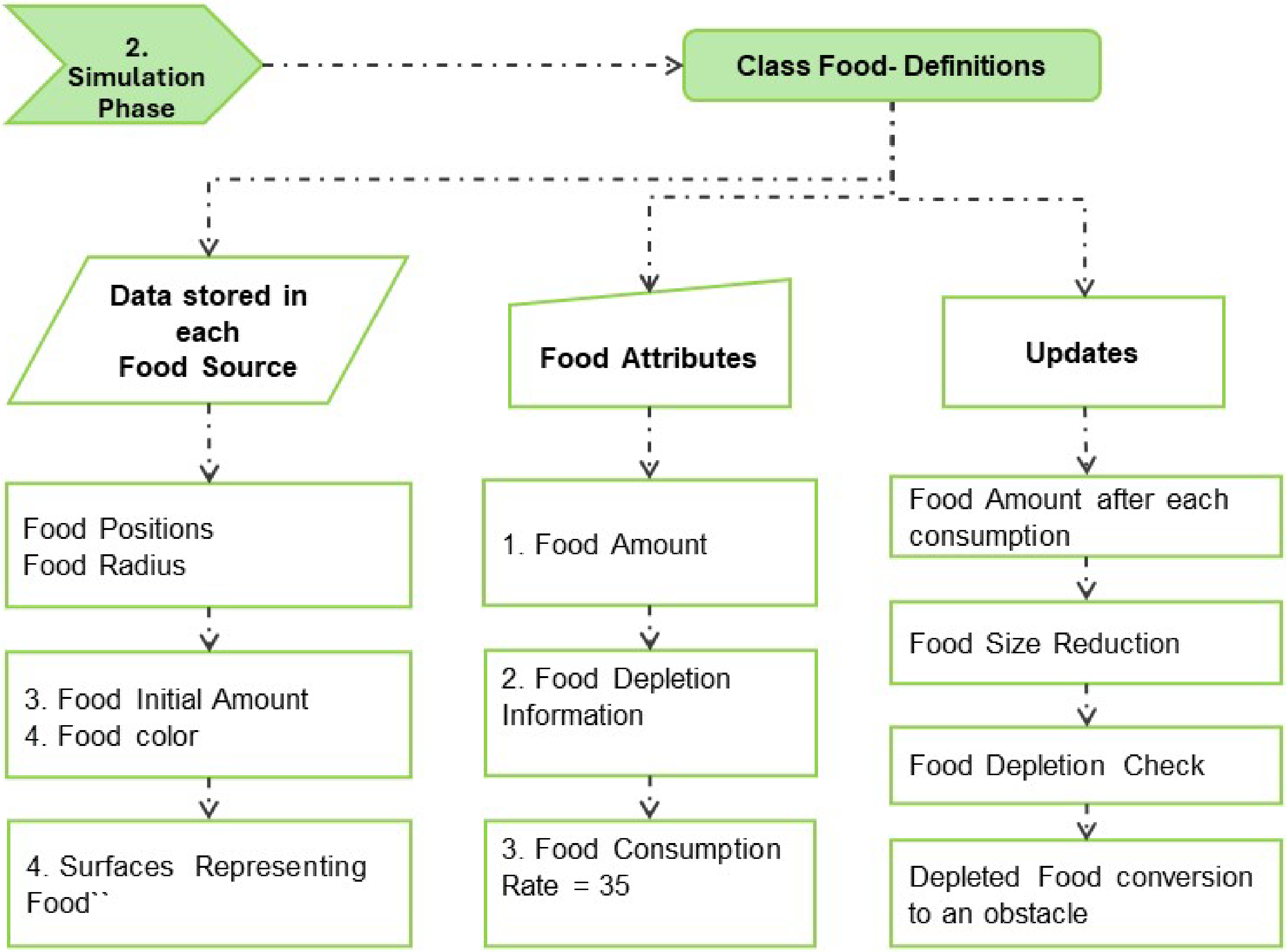


Figure 82- Class Food's Description

Dynamic Changes Upon Food Sources

In the simulation, food sources are represented as green circles centered at the booth coordinates. The radius of each circle corresponds to the booth's perimeter extracted from the design phase. The perimeters for each booth size are 20, 30, and 40 meters, from smallest to largest. The amount of food assigned to each type of booth is also related to their perimeters. To convert booth sizes to their corresponding food amounts and ensure that the food amount reflects a coefficient of the actual material demand, the following formula is used:

$$\textbf{Initial Food Amount} = (\text{radius} \times 100) + 35 \times 37$$

This formula gives a food amount equal to the real material demands divided by 10. Each time a robot hits a food source, the food amount is reduced by 35 units. This reduction is visualized by the circle shrinking in size. The process continues until the food amount reaches 0, at which point the source is announced as a "Depleted Food Source."

Updates in food sources occur each time a robot visits the

A significant dynamic change occurs when a food source is completely depleted: the green circle is replaced by a representation of a room with four walls, indicating that a structure has been completed in that location. This transformation highlights the progress in the construction process and introduces new obstacles that the ants must navigate around, adjusting their routes accordingly.

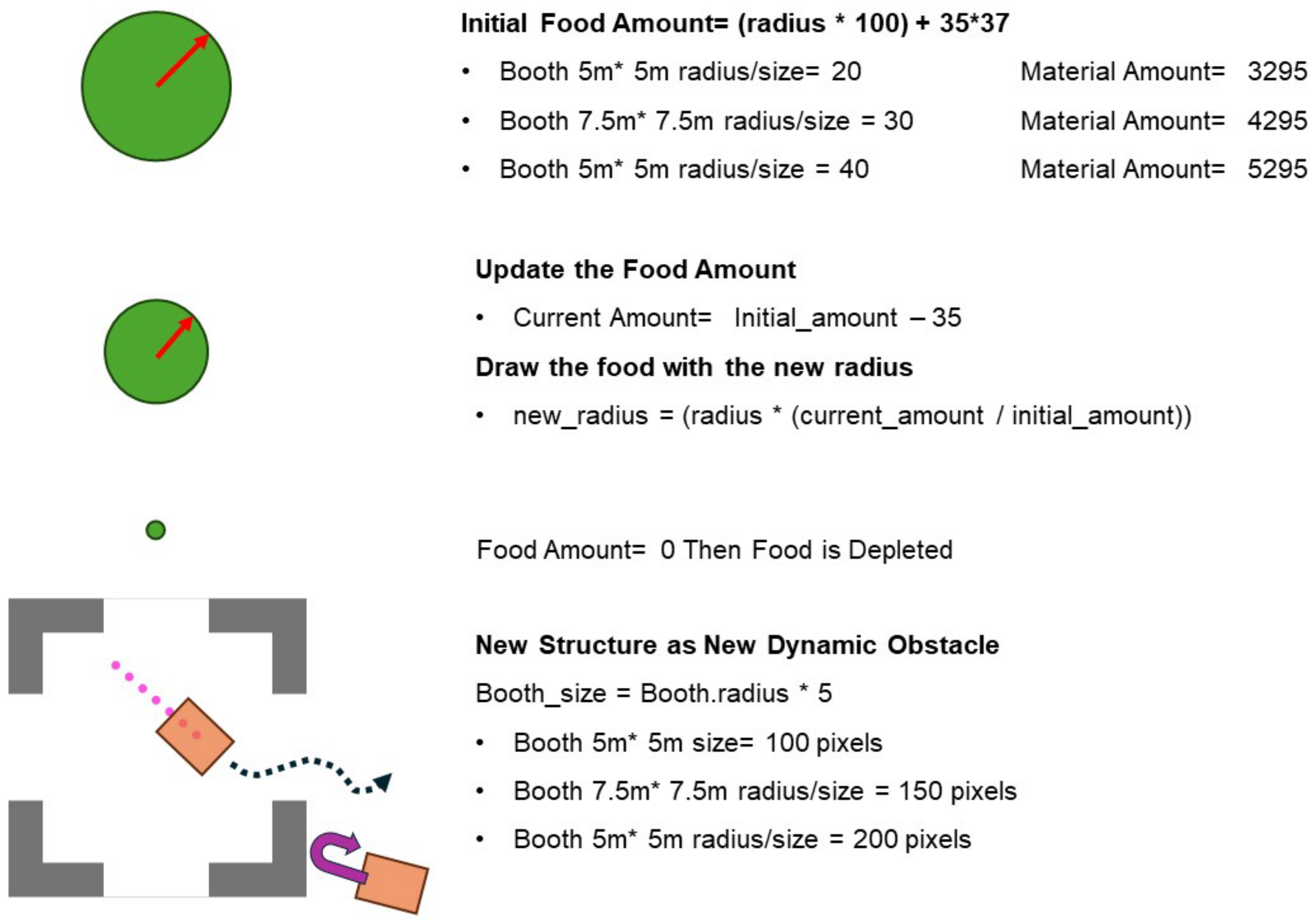


Figure 83- Dynamic Changes of Food Sources

In the picture below, a frame of simulation is rendered where almost all food sources are completed.

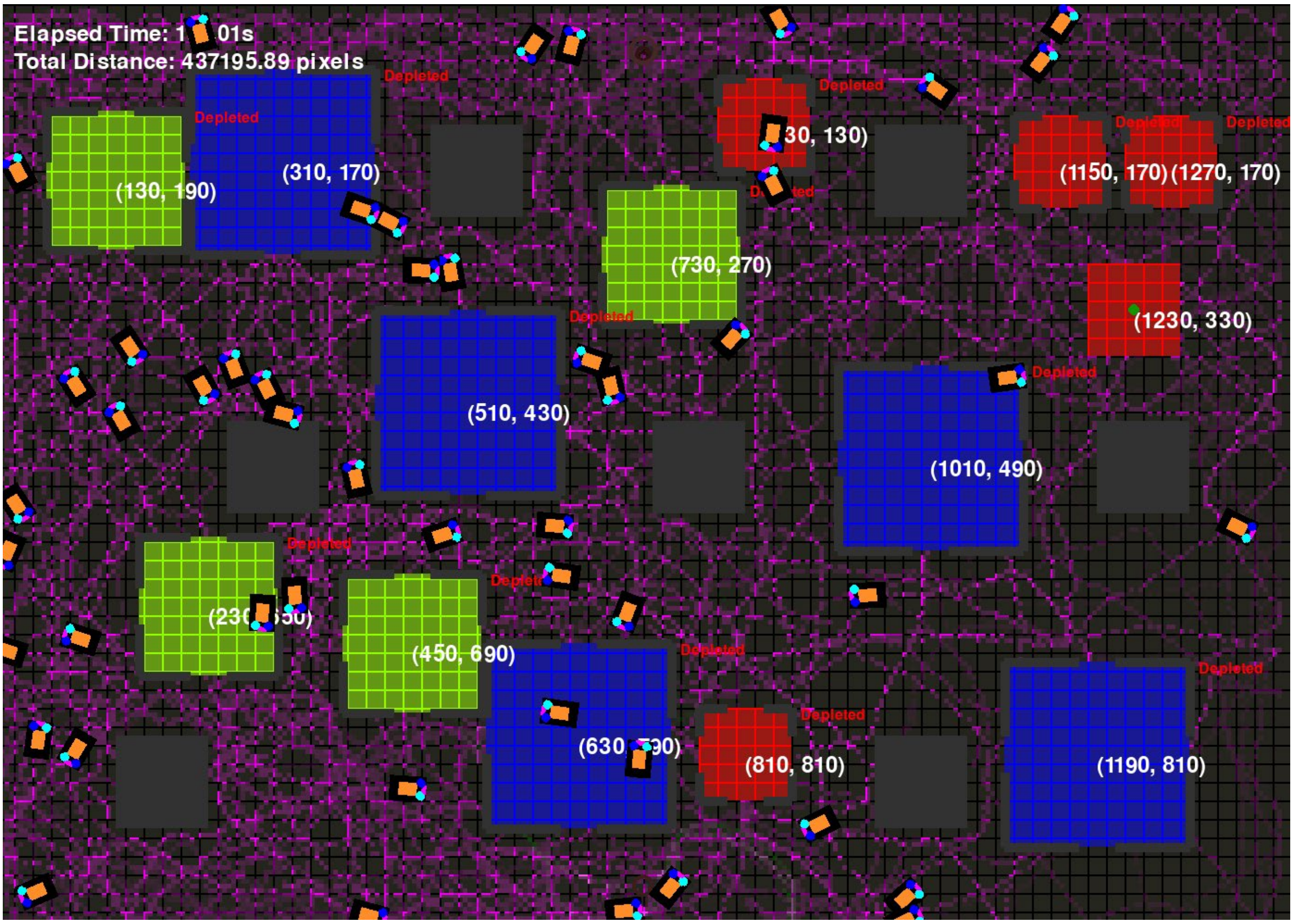


Figure 84- Food Depletion

The flowchart below, shows the updates in the food consumption process.

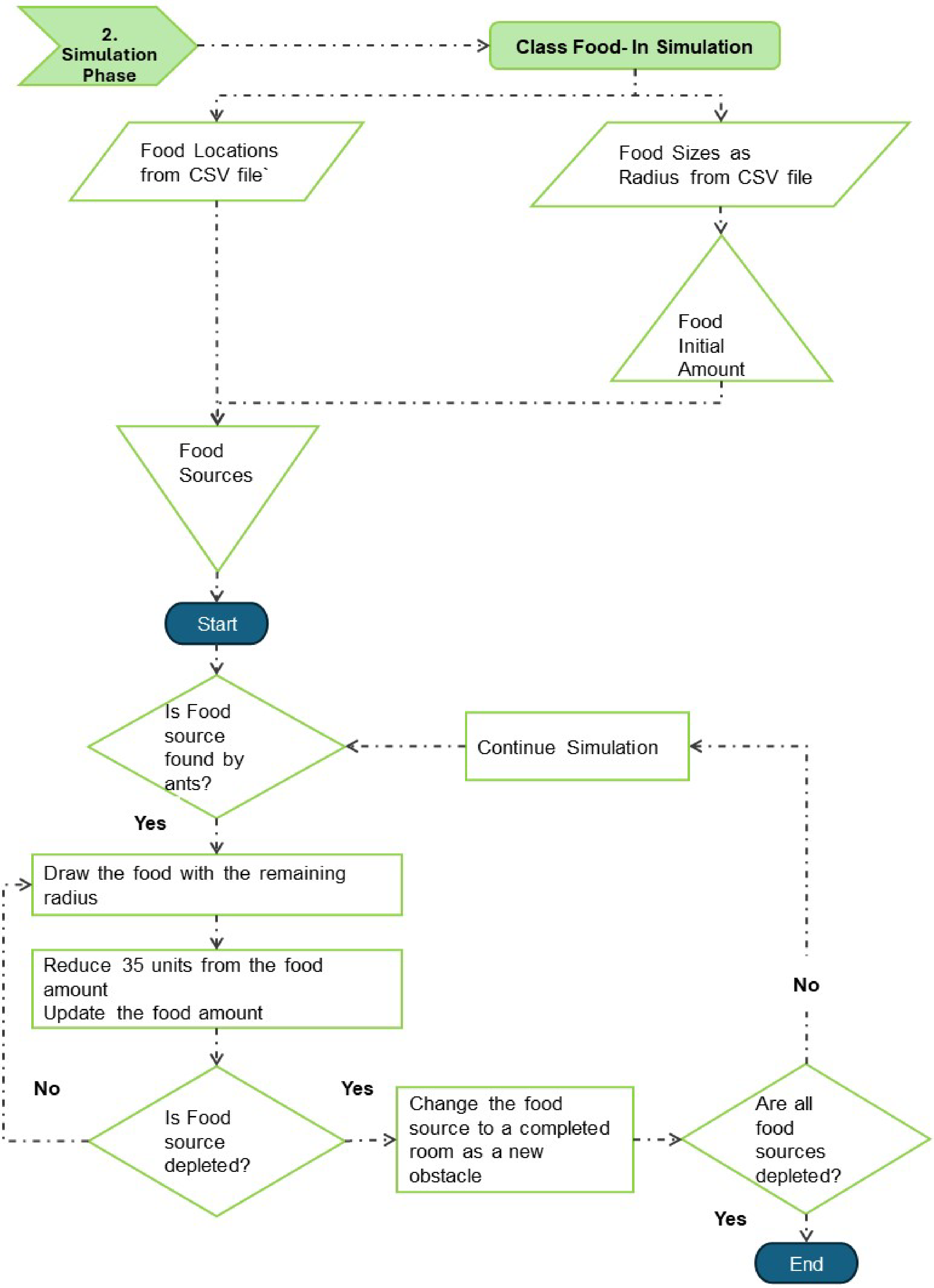


Figure 85- Food Update Logic

5-2-5 Simulation Loop

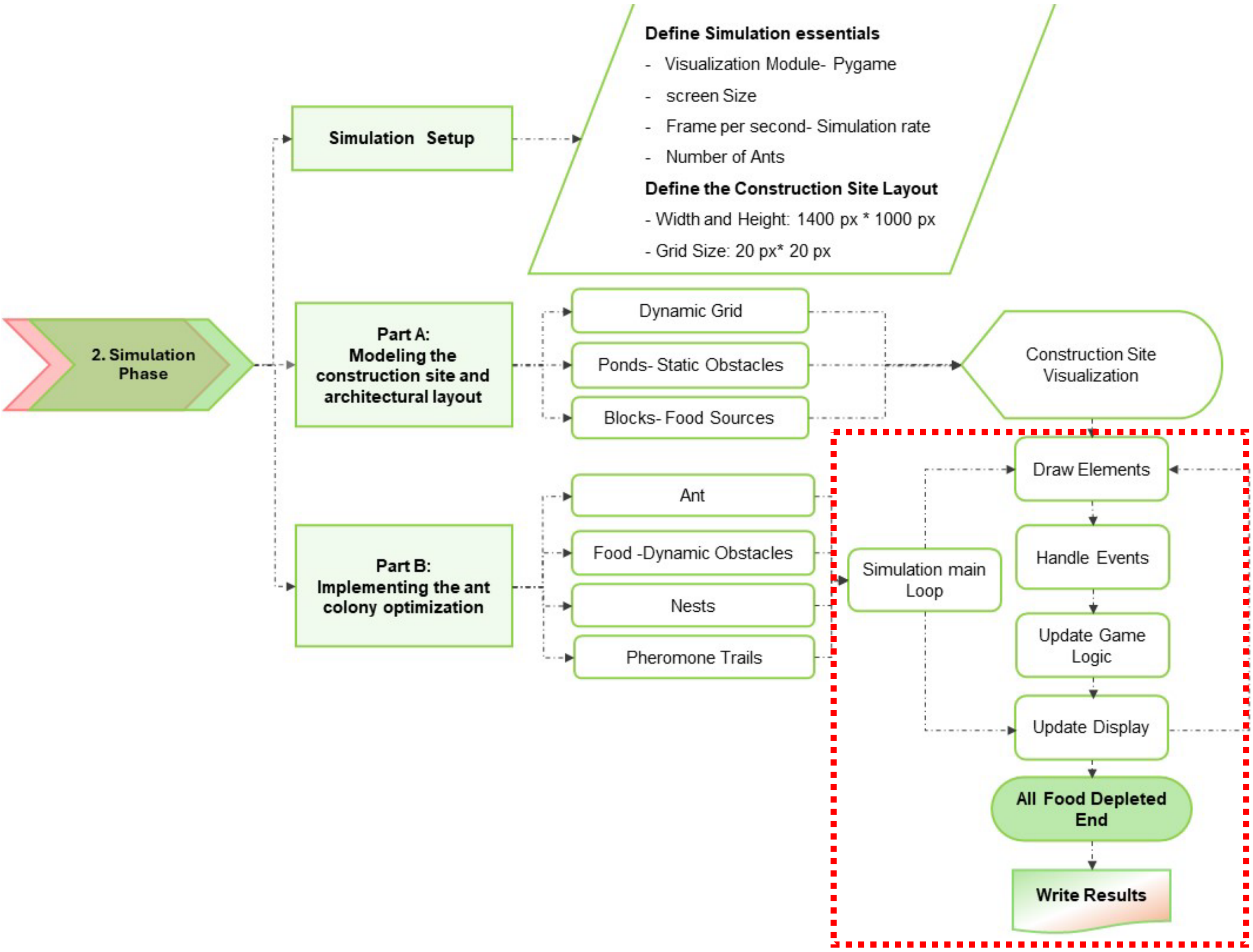


Figure 86- Python Workflow

The last part of the code's structure is the simulation's main loop. This part is designed for defining game elements, drawing them and continuously updating their states within the game loop. This part is responsible for actively displaying key metrics such as the total construction time in seconds and the total walking distance in pixels covered by all robots. These parameters end results are calculated when all food sources have been depleted. To align the simulation speed with realistic construction timelines, this time is multiplied by 1000, accounting for the accelerated frame rate and the increased speed and quantity of materials handled in the simulation setting.

6

Experiments

Introduction

In this part, after setting up the simulation, the aim is to evaluate how different parameters influence the swarm robots' performance. To assess their performance under varying architectural layouts and settings, different combinations of parameters are tested in two scenarios with differing levels of compactness within the same construction site size. The compactness level affects the robots' ease of movement, their response to different spatial layouts, the complexity of their paths, and the material demand for each scenario. At the end of the simulations, referred to as "Experiments," the impact of the changed parameters on the construction process will be analyzed.

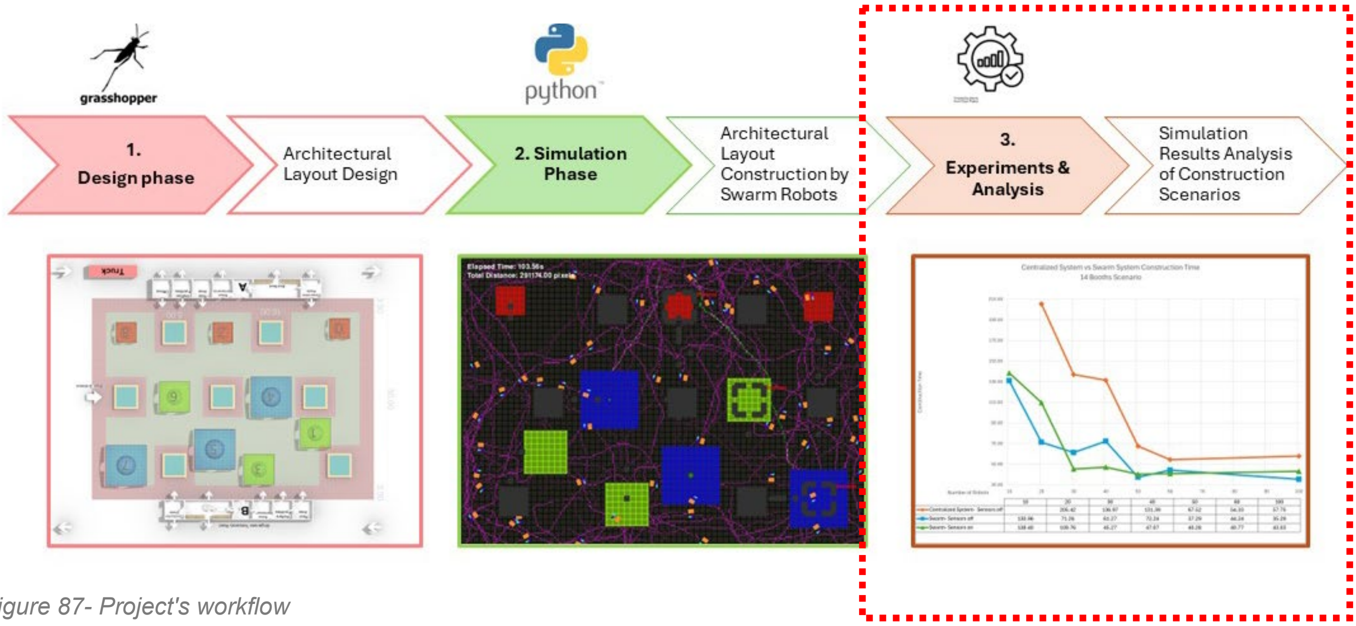


Figure 87- Project's workflow

Experiments

As previously mentioned, translating the entire construction process into a digital simulation and studying all variables may not be fully feasible due to its complexity. Therefore, the experiments are simplified to provide an overview of the construction process.

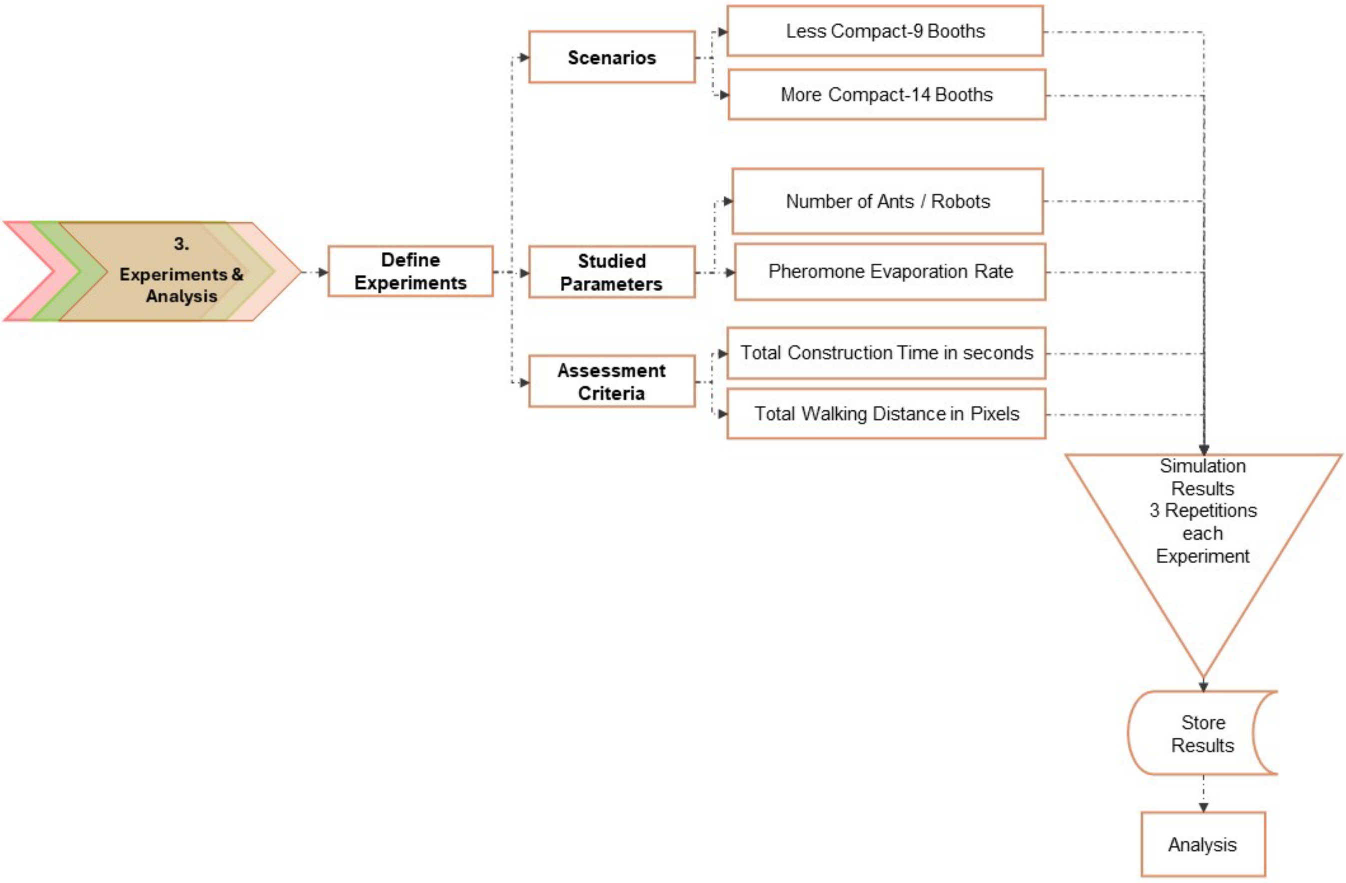
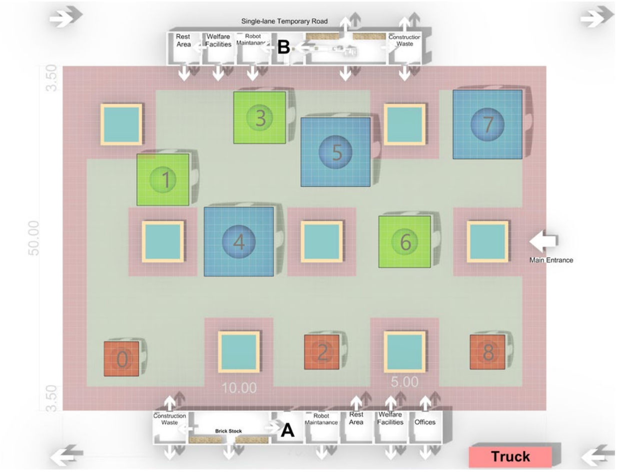


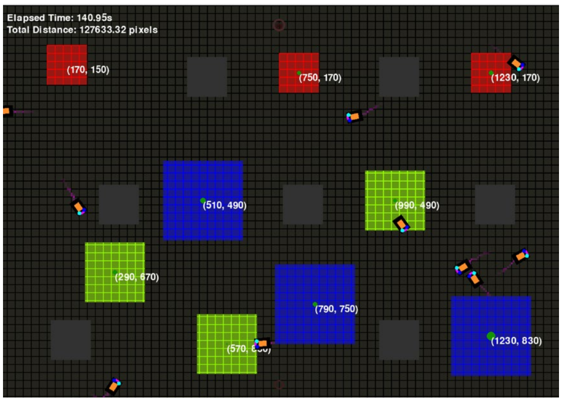
Figure 88- Experiment Phase Workflow

Evaluated Scenarios

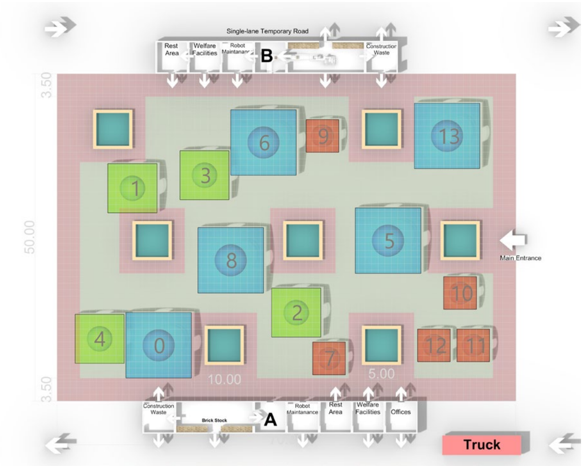
To represent the complexity and variety of architectural designs, two selected scenarios are used. The first scenario involves a less compact site with 9 booths, while the second scenario is more compact, featuring 14 booths within the same construction site of 1400 pixels* 1000 pixels. Both scenarios incorporate seven static obstacles, each measuring 2.5 m by 2.5 m. Booths are treated as dynamic obstacles once they are fully constructed, or their food sources are completely depleted. In the pictures below, two scenarios and their translation into Python environment are depicted.

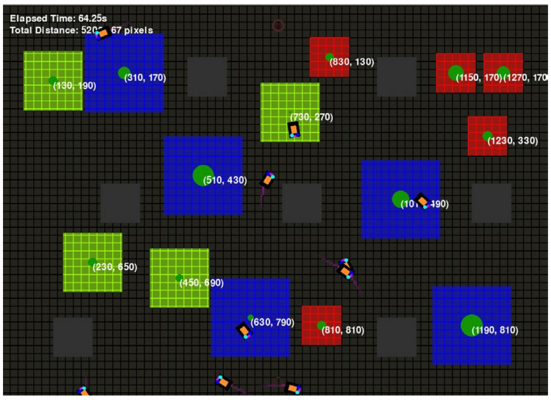
- 9 Booths with Ant Foraging Behavior-





- 14 Booths with Ant Foraging Behavior-





Variables Under Investigation

The studied parameters include the number of robots and the pheromone evaporation rate, both of which are closely related to swarm discipline. While swarms typically have a high number of individuals, practical considerations such as the cost of robots and physical environment limitations necessitate optimizing their numbers. The pheromone communication method, which is crucial for the optimal functioning of the ant foraging process, is also explored to understand its effect on the overall construction process.

Number of Robots:

- Tested with 10, 20, 30, 40, 50, 80, and 100 robots.
- These numbers are evenly divided between two nests.

Pheromone Evaporation Rate:

- Eight values tested: 0 (No evaporation), 0.01, 0.05, 0.1, 0.2, 0.3, 0,5, 0.8 and 1(Complete evaporation).

- The optimal number of robots, determined from the first variable, is fixed during this evaluation.

Fixed Variables and Assumptions

- Robot Speed: Max speed is set at 10 m/s, ten times faster than the actual Husky robot.
- Wall Colors: Represented as RGB (50,50,50).
- Consumption Rate: Each robot handles 35 units of material.
- Food Amount: Ten times less than actual demand to match simulation constraints.
- Simulation Speed: Ten times faster than real-time.
- Sensor Configuration: Three sensors positioned on the front side of each robot.
- Self-Detection Distance: The robots can detect each other if the other robot's distance from the other's center is more than 25 pixels.

Simulation Steps

To assess the impact of robot numbers, initial tests are conducted with the number of robots as the only variable. The objective is to identify the optimal number for each scenario, where both the number of robots and the construction time are minimized. Once the optimal numbers are determined, they are applied as fixed parameters in the next step.

Next, the focus shifts to evaluating the pheromone evaporation rate. The goal is to determine the optimal rates that balance the intensity, duration, and effectiveness of the pheromone trails, ensuring minimizing the construction time.

Final Assessment Parameters

In terms of assessment criteria, the construction process can be evaluated based on various aspects such as financial efficiency, timing, human resources, equipment resources, and maintenance. To simplify the experiment, only construction time (as measured by simulation time) and the robots' walking distance are considered. This focused approach helps in isolating the effects of the chosen parameters on the efficiency of the construction process.

- Total Construction Time or simulation time: Measured in Seconds.
- Total Walking Distance: Measured in pixels, divided by 20 to convert to meters.

Conclusion

The aim of this experiment is to explore in optimal configuration of swarm robots and control mechanisms that minimize construction time and walking distance, thereby improving efficiency and effectiveness on dynamic construction sites. The results will provide insights into whether these parameters can be universally applied or need adjustment based on specific site conditions.

7

Results

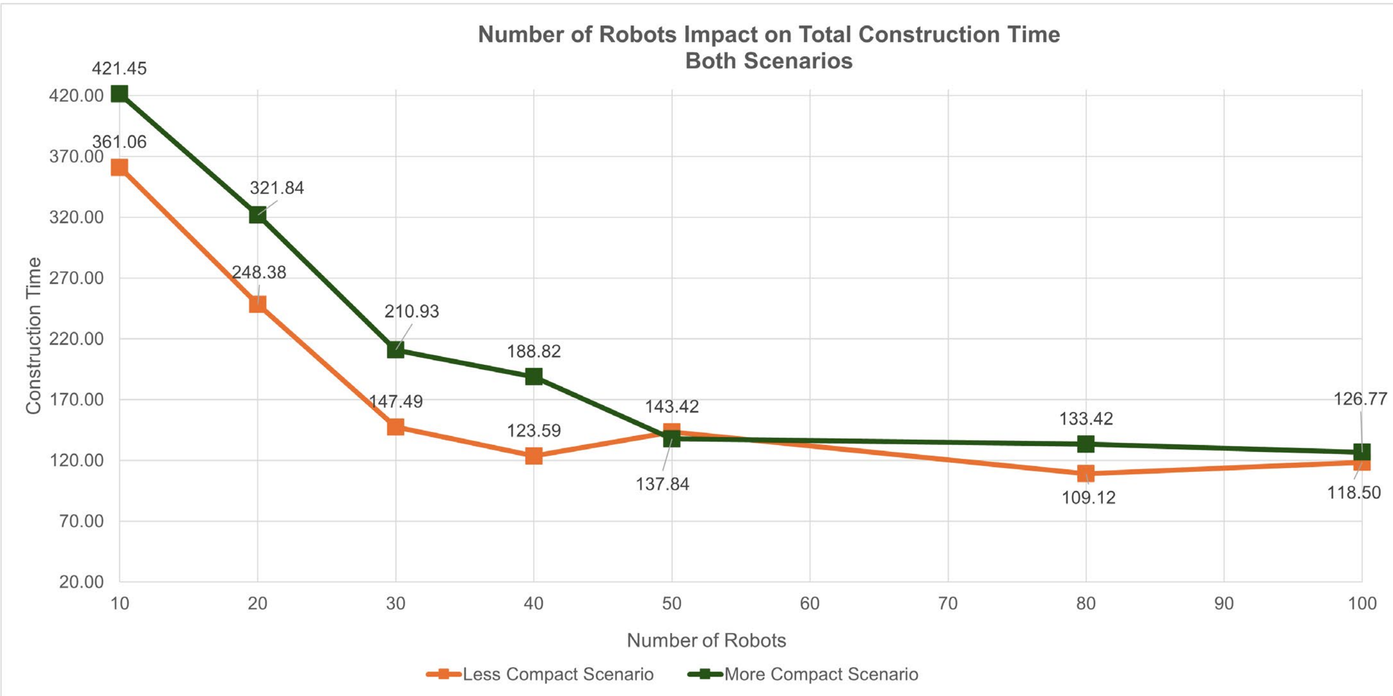
Introduction

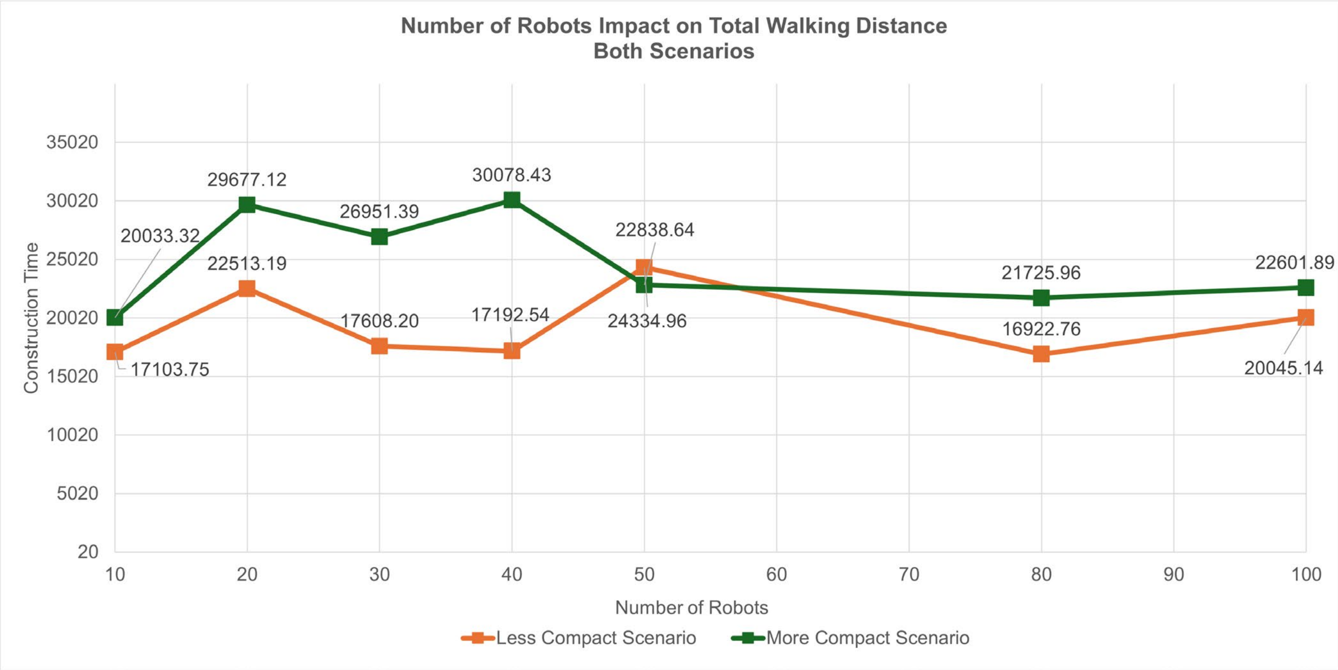
In this section, the results of the simulations are presented in graphs. For each scenario, 15 experiments and 30 in total have been conducted. Each repeated three times to moderate the impact of the randomness in the ants' movements. Among these 30 experiments, 14 investigated the number of robots impact on the construction process and other 16 is related to the pheromone evaluation rate impact. The total construction time recorded in these experiments is multiplied by 1000 to adjust for compensating the amount of material, robot speed, and simulation speed. The total walking distance, initially measured in pixels, is converted to meters by dividing by 20. Although the total walking distance is considered, the primary assessment parameter is the total construction time due to the inherent randomness of the ants' movements and the complex interactions on a dynamic construction site, which make it challenging to assess performance based solely on walking distance. However, both criteria will be observed to check whether there is a correlation.

1- The Impact of the Number of Robots on Construction Time and Walking Distance

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario





Construction Time

The graph comparing the two scenarios for total construction time reveals several key insights. Firstly, the construction time is higher in the more compact scenario, which is logical given the increased complexity and density of the environment. Both scenarios follow a similar pattern, with the maximum construction time occurring when there are 10 robots. As the number of robots increases, the construction time decreases in both scenarios. However, the reduction rate slows down after a certain number of robots—40 for the less compact scenario and 50 for the more compact scenario. Beyond these points, the convergence of construction times suggests diminishing returns on adding more robots. This indicates that adding more robots does not significantly improve performance and can add unnecessary costs. This phenomenon can be interpreted in two ways: either additional robots are not assigned tasks and keep wandering, or by the time construction ends, not all robots are released from the material supply.

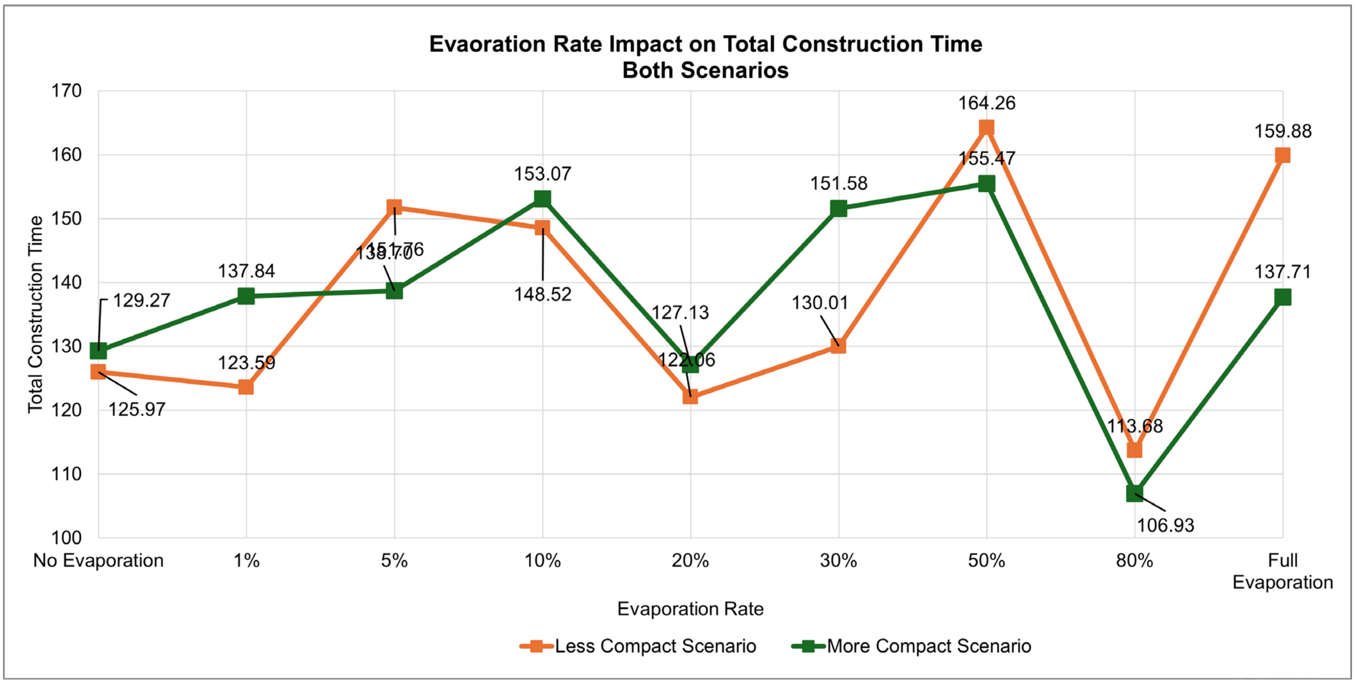
Walking Distance

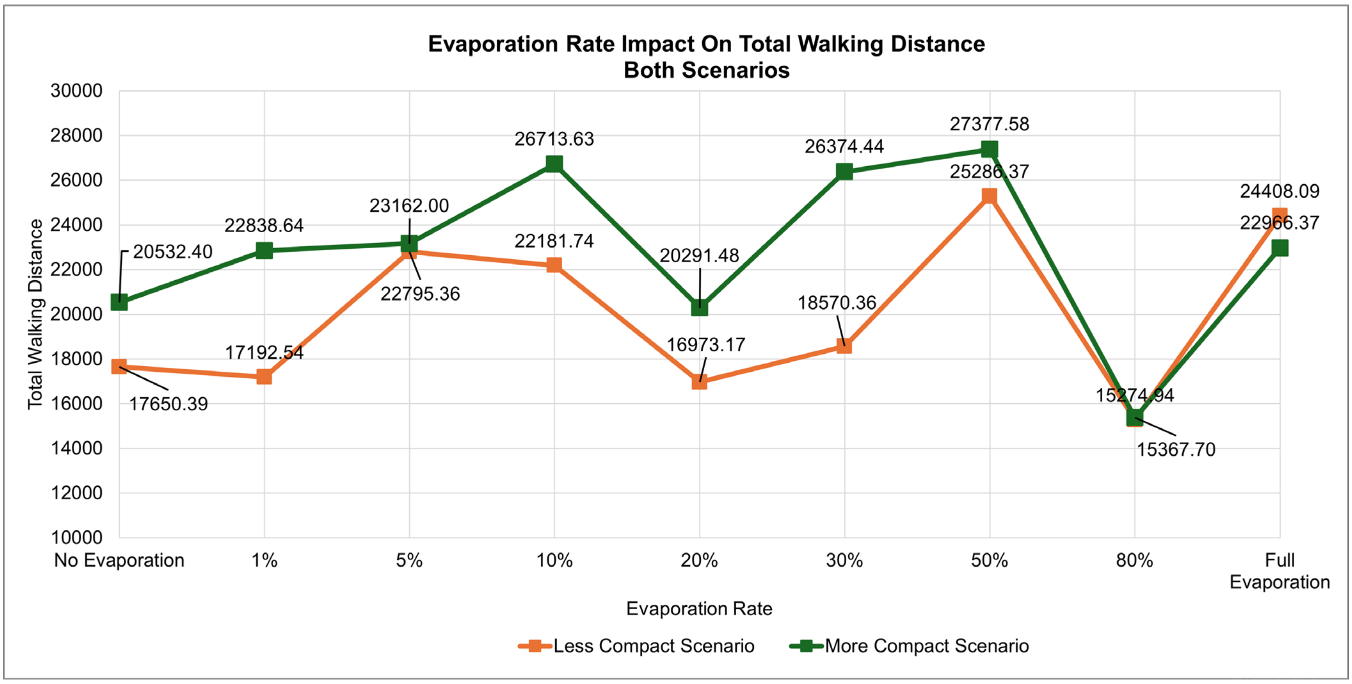
Similarly, the walking distance is higher in the more compact scenario. While the graphs for both scenarios show some similarities in peak points, they do not follow the same patterns as the construction time graphs and exhibit more fluctuations. These fluctuations may be related to the random movements of the robots, as they might get stuck in unfavorable conditions such as loops or corners depending on the directions they randomly choose. Both scenarios demonstrate that adding more robots does not necessarily improve construction time and may lead to inefficiencies. Although walking distance has more complex correlations, it appears that at 40 robots for the less compact scenario and 50 for the more compact scenario, the walking distance is relatively low, mirroring the trends observed in construction time.

2- The Impact of Pheromone Evaporation Rate on Construction Time and Walking Distance

Scenarios: Less Compact - 9 Booths Scenario

More Compact - 14 Booths Scenario





Construction Time

In the graph showing the impact of the evaporation rate on total construction time for both less compact and more compact scenarios, construction time varies with changes in the evaporation rate. Unlike the number of robots graph, the more compact scenario does not consistently show higher construction times as expected. This indicates that the evaporation rate has a more complex correlation with the level of compactness.

Another observation is that with no evaporation, the pheromone paths should ideally maintain the same amount of pheromones, leading to the shortest construction time. However, because the food sources are dynamic and get depleted over time, trails with high pheromone durability can mislead robots to unavailable food sources. Consequently, the experiment with no evaporation rate shows only a slight difference compared to full evaporation. This suggests that the pheromone evaporation rate needs to find a balance where it neither misleads the robots nor vanishes too quickly. Both scenarios achieve their lowest construction times at an 80% evaporation rate and peak at a 50% evaporation rate.

Walking Distance

In the walking distance graph, similar variations are observed rather than a consistent pattern. The 80% evaporation rate also results in the minimum walking distance for both scenarios, reinforcing that 80% is the optimal value for this construction site.

Discussion

After evaluating all the graphs related to the two main categories of 9 booths and 14 booths, based on total construction time and total walking distance, the following conclusions are drawn:

Number of Robots (9 Booths Scenario and 14 Booths Scenario)

This parameter has a more straightforward impact on construction time, indicating that as the number of robots increases, construction time decreases. However, this pattern is not consistently linear and exhibits some irregularities. These irregularities might be due to the random movements of the robots or increased collision detection followed by more direction changes. Overall, the graph shows that after a certain number of robots, construction time starts to stabilize, indicating that adding more robots does not necessarily decrease construction time. This suggests that fewer robots can be selected for the scenario, ensuring lower costs and maintaining the same efficiency.

The optimal number of robots for achieving minimum construction time differs for each scenario. This is logical, as within the same construction site, the higher material demands in the more compact scenario require a higher number of robots. Consequently, this parameter is scenario-dependent, and each change in the scenario necessitates studying the optimal value.

Evaporation Rate Impact

The graphs illustrating the impact of the pheromone evaporation rate demonstrate a more complex relationship between evaporation rate, construction time, and walking distance. Initially, based on articles studied in the background information, an evaporation rate range of 95% to 99% was examined (please refer to the Appendix). This narrow range exhibited several variations. However, in the presented graphs, the range is broader, from no evaporation to full evaporation, with steps of 1%, 5%, 10%, 20%, and 30%. Fluctuations are still evident across all ranges.

By expanding the investigation range, both scenarios show the minimum construction time and walking distance at an 80% evaporation rate. The optimal value for the evaporation rate is highly sensitive, as failing to detect the correct number can mislead the robots or prevent them from receiving any guidance for the correct paths. This is particularly crucial in dynamic environments where food source availability, material stock availability, or the presence of other obstacles change over time.

In summary, the optimal parameters are highly scenario-dependent. A unique set of parameters cannot be applied universally to all scenarios, even within the same construction site with varying levels of compactness. Therefore, each scenario should be individually optimized before construction due to the dynamic nature of the construction environment and complex interactions.

8

Discussion

Introduction

Although several steps have been taken to develop this workflow, including an extensive literature review, studying several case studies, developing Design, Simulation, and Experiments & Results phase, several issues have been detected that still need to be addressed. The aim of this thesis is to replicate a dynamic construction site comprehensively. However, achieving full replication remains a challenging and distant goal. This current version is a simplified model and cannot fully represent the complexities of a real construction site. Despite its limitations, this research represents a critical first step towards enabling the use of swarm robots in future construction projects. Further refinement and development are required to move closer to a fully realistic and functional simulation of dynamic construction sites.

8-1 Limitations

In this section, the limitations and opportunities of the workflow including the Grasshopper and Python simulation and results are reflected on. This helps to better understand how to interpret the output results of the simulation, as well as indicating where future improvements can or should be made. The limitations of this workflow are listed in this paragraph.

Fully Replicating a Dynamic Construction Site and Construction Process

This simulation demonstrates some features of a dynamic construction site but remains highly simplified. It involves constructing with only one type of material by stacking, which does not fully represent the complexity of real construction sites. Real-world construction involves multiple materials and components that must be assembled in a specific order.

In a more accurate scenario, structures should be divided into groups for sequential construction, but in this simulation, all food sources are available to the robots simultaneously. Additionally, the material supplies, represented as nests, are always fully stocked and static, unlike in the real world, where stock availability and delivery times vary.

The Husky robot's maximum payload of 75 kg on flat surfaces is considered here, but in reality, this payload decreases to 20 kg on rough terrain. Construction sites often feature uneven terrain, a factor not accounted for in this simulation, which assumes a flat site.

Robotic Physical Translation

While the simulation investigates parameters like evaporation rate, translating these into the physical hardware of robots presents significant challenges. For instance, pheromones in the simulation can be translated to memory storage of optimized routes, which are continually updated. Alternatively, using chemicals that evaporate at a certain rate could be considered, but this introduces complexities. Sensors in the simulation are represented by simple RGB value detection, but in practice, this could involve cameras, LIDAR, or other technologies. The physical translation of obstacle detection and avoidance using these sensors is a separate field of investigation.

The simulation does not account for robots' operating time and charging cycles, which would make some robots unavailable when recharging. While charging points are considered, the time required for charging is not factored in. Additionally, the time for picking up and placing materials is also not considered.

Understanding when robots should return to the stock after delivering materials, considering the workers' speed, and determining what tasks they should perform while waiting are also complex issues not addressed here. The randomness in ant behavior sometimes increases construction time, which, if mirrored in real-world applications, could lead to wasted power and energy.

Efficient collision detection is achievable at 25 pixels but reducing it to 20 pixels for more accurate collision avoidance causes movement disruption and rotation issues. In reality, collisions might still occur, and implementing elastic materials around the robots could mitigate damage.

Simulation Observations

The simulation's visualization should be well-coordinated with the robots' movements to accurately reflect their behavior. Occasional lags in frame updates lead to robots passing through obstacle walls. Despite running each experiment three times to reduce the effect of randomness, variability in results persists. Sometimes, robots get stuck in completed rooms or at the site margins, wasting time and energy. They also occasionally miss or double-hit small food points due to sensor limitations. Other parameters related to ant behavior, such as Wander Strength, Maximum Speed, and Steering Strength, are not studied and depend heavily on the robots' technical features.

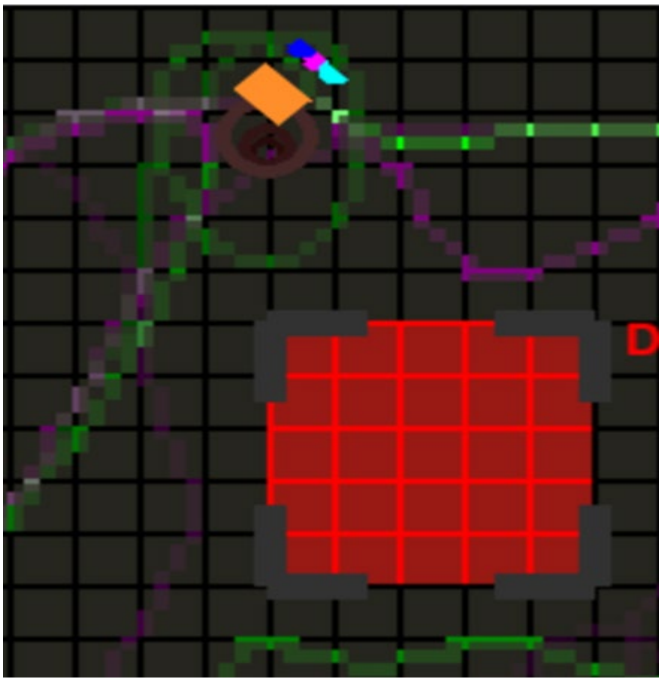


Figure 89- Robot Getting Stuck in a Loop

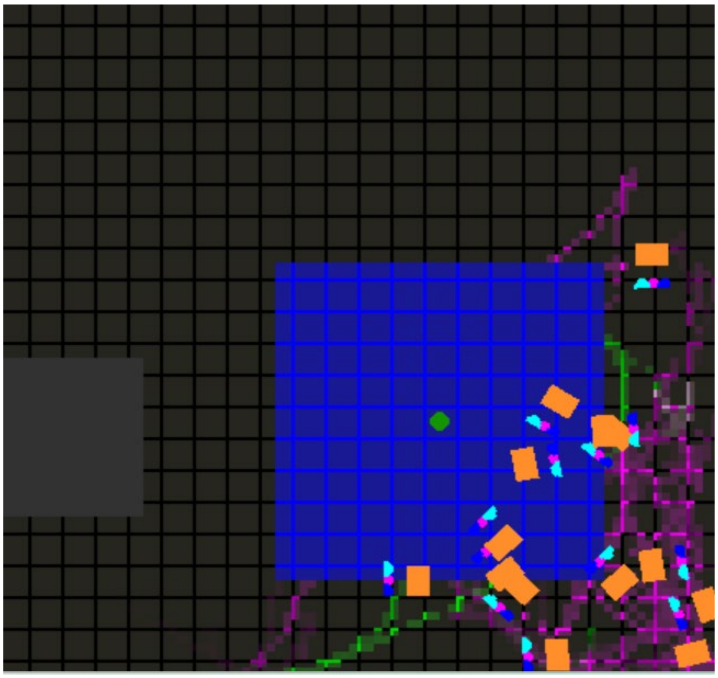


Figure 90- Robot Getting Stuck in a Loop

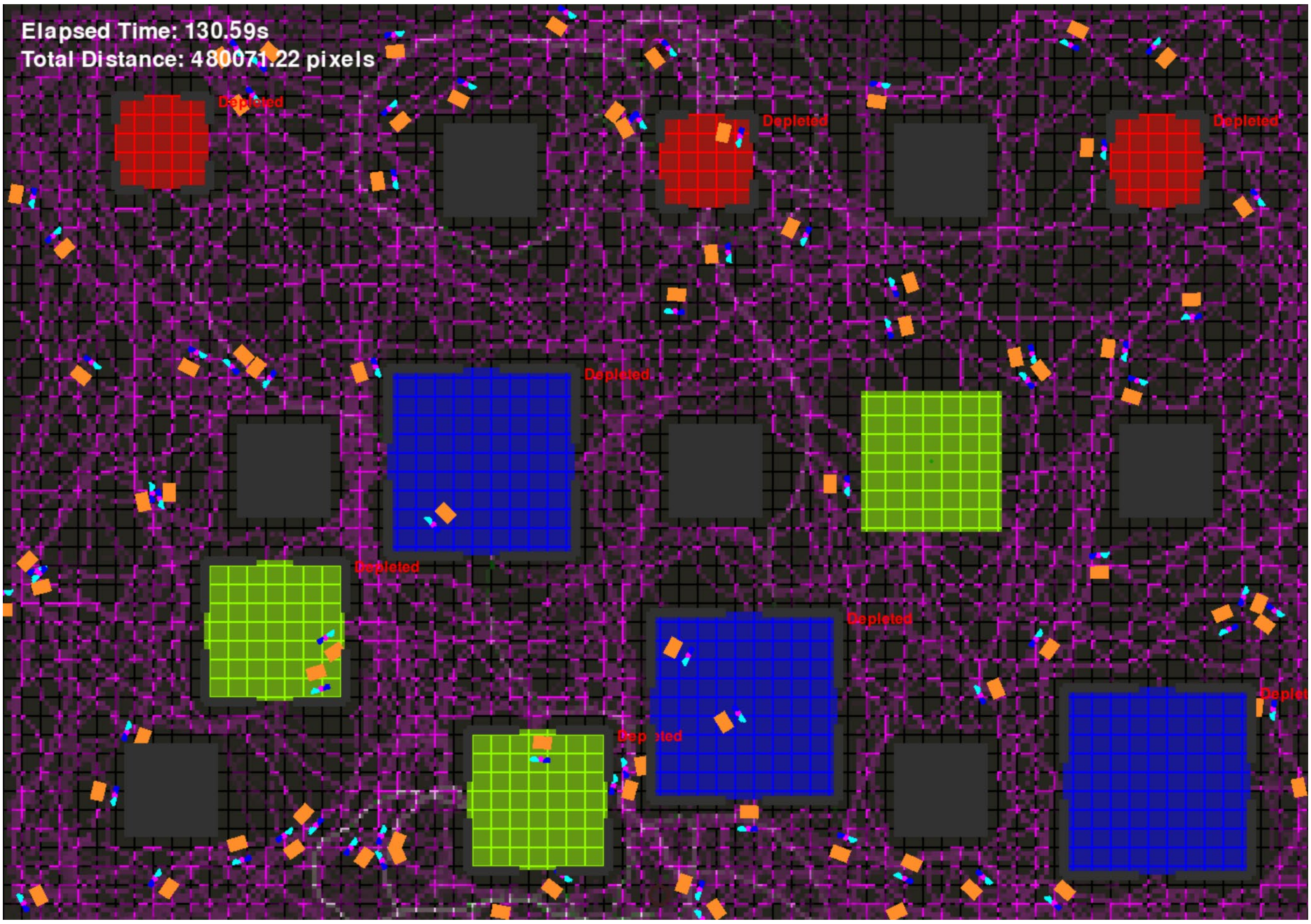


Figure 91- Robots not being able to find the Small Amount of Food

8-2 Opportunities and Future Research

Exploring Other Algorithms

This research could expand by exploring other swarm algorithms with navigation capabilities, such as Particle Swarm Optimization, Bee Colony Optimization, and Firefly Algorithm. Hybrid algorithms combining ant-colony optimization with path-planning techniques, like A* mentioned in the article “Optimal Path Planning Applied to Ant Foraging,” could reduce randomness and improve efficiency.

Towards 100% Dynamic Construction Sites

The goal of replicating a fully dynamic construction site is vast, requiring robust coding skills and a deep understanding of construction management. Adding more parameters to the simulation could bring it closer to a realistic model, reflecting the intricate logistics of a real construction site.

Enhancing Robotic Features

Replicating the robots' technical features more accurately is a promising area for future work. This includes considering operating time, charging cycles, obstacle and collision avoidance methods, and sensor configurations.

Incorporating More Variables

This thesis examines only two parameters: the number of robots and evaporation rate. Future studies could include variables like sensor number and positioning, Movement Control Attributes (Wander Strength, Maximum Speed, Steering Strength), optimal search distances from nests, dynamic material supplies, and different construction groups.

Developing a Unified Tool

This workflow can be developed into a comprehensive tool for using swarm robots in various architectural designs. Such a tool could provide initial settings for dynamic construction processes, improved through increased accuracy and additional parameters. By integrating the separate steps into a single, cohesive tool, construction teams, and architects could upload their designs and optimize their swarm-based logistics systems. Furthermore, there should be a new function for a person with knowledge of computer science, coding and robotics responsible for optimizing the swarm robots for each scenario.

Exploring Different Materials

While this thesis focuses on conventional brick materials, it could extend to other materials, such as long wooden bars or fluids like mortar and clay, enhancing the simulation's applicability to diverse construction scenarios.

Automating the Entire Construction Process

Another opportunity is to automate the entire construction process, from material handling by robotic arms to transportation by swarm robots and final placement by bricklaying robotic arms, eliminating the need for human intervention.

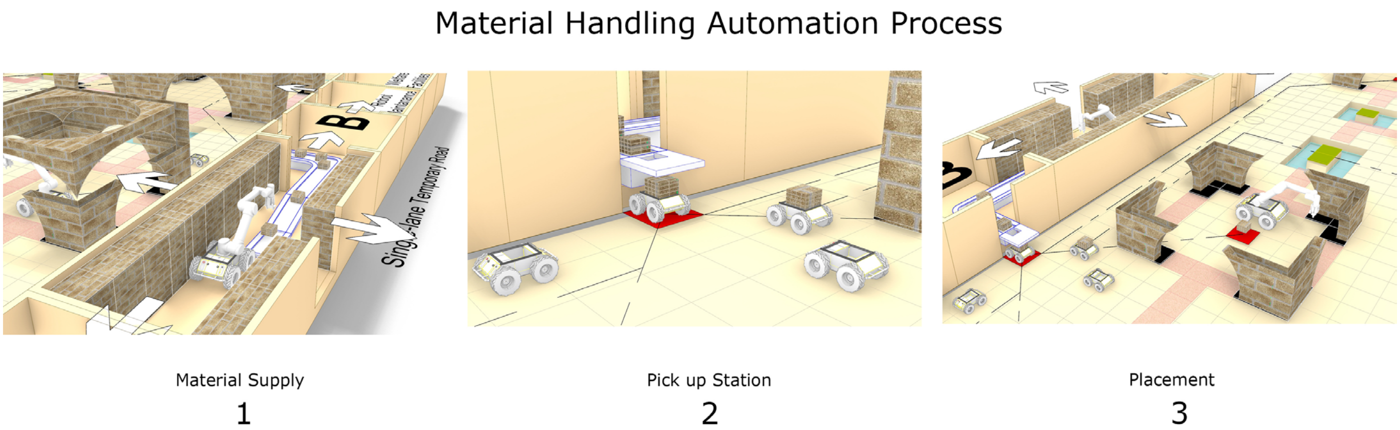


Figure 92- Automatic Material Handling

Conducting Physical Tests

Translating the simulation to real-world tests with small-scale swarm robots and booth models could provide valuable insights, validating the simulation results against physical experiments.

Linking the Workflow to Machine Learning Models

Optimizing parameter values for each construction scenario is essential but highly scenario-dependent. By running simulations with various parameter configurations, comprehensive datasets can be generated. These datasets, which include booth coordinates, material supply locations, construction site size, and outcomes like total construction time and walking distance, can be used to train a machine learning model. The trained model can predict optimal values for parameters such as the number of robots, pheromone evaporation rates, and sensor distances based on initial fixed parameters. This integration allows for efficient and adaptive optimization, enabling rapid adjustments for new scenarios, thereby enhancing the performance of swarm robots in dynamic construction environments.

Discussion

Overall, this research attempts to summarize the fundamental requirements for operating a dynamic construction site with swarm robots as the material handling system. While there are numerous limitations and opportunities for further exploration, addressing all of them is beyond this research's scope.

9

Conclusion

Introduction

This thesis begins by addressing critical issues related to the human workforce in the construction industry, such as the shortage of skilled labor, safety concerns, and poor communication. These challenges significantly impact the industry's efficiency and speed. Faced with these serious issues, the question arises: how can we improve this situation? The answer may lie in taking advantage of a system that is always available, compensates for the shortage of human labor, faces no safety threats, and uses standardized communication technology. This led to the exploration of using robots in construction, assisting the human workforce by performing repetitive and simple tasks.

Consequently, the approach of allocating certain tasks to robots and transitioning towards robotic construction was explored. The potential benefits include enhanced efficiency and speed. However, delegating complex tasks to robots, especially on a large scale, remains challenging. Thus, this research focuses on a simpler task on a large-scale construction site: material handling without complex assemblies. This investigation began with exploring autonomous mobile systems that use centralized control systems for path planning and navigation. The high costs and limitations associated with centralized systems prompted a shift towards decentralized systems, particularly swarm intelligence-based robots. These robots are not only suitable for simple tasks but also offer promising advantages due to their scalability, resilience, and reduced dependency on centralized control.

Given that these robots are intended to function as a workforce, their workplace will be construction sites. A construction site is characterized by complex interactions and constant changes. Therefore, any system operating in such an environment must adapt to these changes. Swarm intelligence was selected for its high adaptability, aligning with the dynamic nature of the construction process. This context raises the question: ***"How can swarm robots perform as an on-site adaptive logistic system on a dynamic construction site?"***

In the next section, a recap of all the work conducted and conclusions drawn in this research is presented.

Research

The research on swarm robotics began with a comprehensive literature review. This review explored fundamental concepts such as dynamic construction sites, logistics, robotic construction, swarm intelligence, behaviors, and swarm robotics. To better understand how a construction site should be designed and what parameters make it a dynamic workplace, an investigation into logistics was conducted. It was concluded that the nature of constant changes and complex interactions at construction sites requires a highly responsive logistic system that can adapt to these changes. This necessitated a system where updating and recalculating were easily achievable.

A comprehensive study of swarm intelligence, and swarm robots was also conducted. It was concluded that swarms, performing simple tasks collectively, can complete more complex tasks. Swarms exhibit high scalability, robustness, and adaptability. Among these behaviors, navigation and indirect communication are well-aligned with the simple task considered: navigating and finding their path on a construction site. One highly adaptable path-finding behavior is ant foraging, mathematically modeled by Dorigo (1992) as Ant Colony Optimization (ACO). This control algorithm was chosen as the basis for the robots' behavior, where agents (robots) find the optimal route to food and carry it to the nest. Thus, swarm intelligence-based robots seem to be an ideal solution for the dynamic nature of construction sites.

Next, the investigation focused on swarm robots in practice. It was found that swarm robots have not yet been used in real large-scale construction processes with conventional materials. Therefore, a simple architectural scenario was designed to start answering the research question. Case studies of Riyadh House and Wasp inspired a design with a central core and smaller surrounding areas, resembling an atomic model. This model allowed for flexible control of the degree of compactness across the construction site. Additionally, these case studies emphasized using compression-only structures, constructible with a single material of high aesthetic value.

From an architectural perspective, this simple layout with scattered structures is suitable for a temporary exhibition with several booths. Ponds and walking paths were also designed for this complex. To make the scenario more realistic, the booths' identity was defined. Inspired by the Atashkade structure, a compression-only design was chosen, allowing construction with conventional bricks. Three sizes—5m x 5m, 7.5m x 7.5m, and 10m x 10m—were designed, with three of each size located on a 70m x 50m construction site.

After establishing these parameters, the next step was to validate the booths structurally and determine the number of materials required. Structural analysis provided the necessary wall thickness to calculate the brick requirements. This architectural layout, each structure, and the construction site were translated into a parametric model in Grasshopper. This parametric model allowed manual control by architects, enabling them to manage the scenario, calculate material demand, analyze the booths structurally, and ultimately import all data into the Python simulation.

The structural analysis concluded that the material requirements varied: 95,176 bricks for a 10m x 10m booth, 22,908 bricks for a 7.5m x 7.5m booth, and 11,340 bricks for a 5m x 5m booth. To calculate the number of trips required for construction, a suitable autonomous robot with higher payload capacity was selected. The Husky robot from ClearPath Robotics was chosen, assuming that its control algorithms would be based on ant colony optimization. Considering the Husky's payload capacity of 75 kg, it was determined that constructing the booths would require 2,720 trips for a 10m x 10m booth, 655 trips for a 7.5m x 7.5m booth, and 325 trips for a 5m x 5m booth. These high numbers of trips highlight how robots can save human workers from short-term and long-term injuries caused by repetitive material handling tasks.

The second part of the workflow, the Python simulation, began with binary logic visualization of the construction site. However, RGB values proved to be a better logic for the entire simulation. After adjusting the code to reflect the dynamic nature of the construction site, two main layouts were tested: 9 booths (less compact) and 14 booths (more compact). The results showed that swarm systems outperformed centralized systems in both scenarios. It was also concluded that increasing the number of robots beyond a certain number dependent on each scenario did not significantly enhance performance. The main conclusion regarding the evaporation rate was that these parameters are unique to each condition and highly scenario-dependent. Therefore, before each construction, the swarm robots should be optimized for the specific scenario. In the next section, the sub-questions of the research will be answered.

9-1 Answers to Research Question

In this literature review, the aim is to answer this research question “***How can swarm robots perform as an on-site adaptive logistic system on a dynamic construction site?”***

Swarm robots have multiple strengths that make them a potential candidate for dynamic workplaces. However, practical limitations present a serious challenge for fully utilizing these robots. This thesis attempts to exclude these challenges by implementing swarm-intelligence-based algorithms in large-scale robots and only focusing on their control algorithm's performance.

To answer how swarm robots can perform as an on-site adaptive logistic system on a dynamic construction site, a three-stage workflow is proposed in the thesis. This workflow begins with the architectural design phase, simulates the construction process in a dynamic construction environment, and optimizes the setup for the specific scenario before the actual construction starts. This workflow necessitates collaboration across various fields, including architecture, construction management, robotics, and computer science.

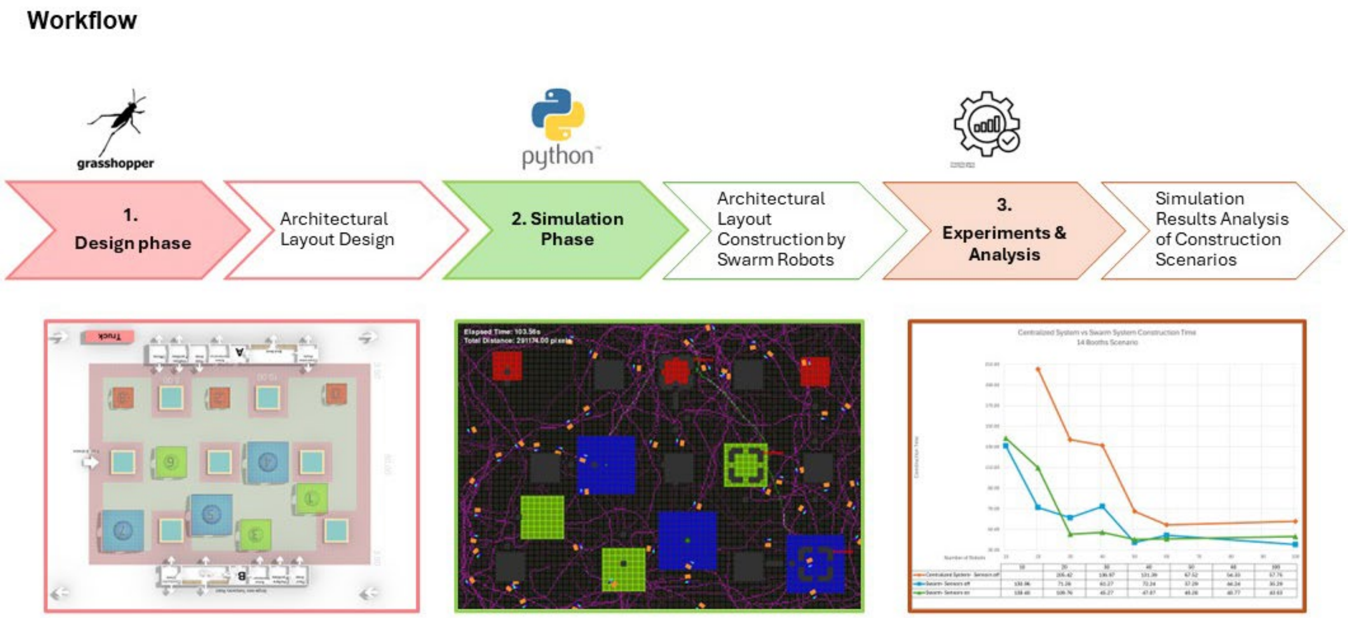


Figure 93- Project's workflow

How would this workflow reflect in the real-world construction industry?

The envisioned commercialization of this workflow involves construction companies owning the necessary equipment. These companies could offer material-handling services by deploying a fleet of robots, managed by experts responsible for both software and hardware maintenance. Software experts would adjust the swarm-intelligence-based control algorithms for each project, while hardware experts would handle the operational features and repairs both on-site and off-site.

Clients utilizing these services could import their architectural designs into user interfaces provided by these companies. All necessary information, such as time plans, material types, material demands, obstacles, and other details, would need to be defined.

Figure 94- Design Phase User Interface Sketch

The next step involves simulation, where clients can select available robot types based on cost and preferences. Construction files, including topography and project planning files, should be imported as well. Clients can then choose the desired number of robots, initiating the simulation process.

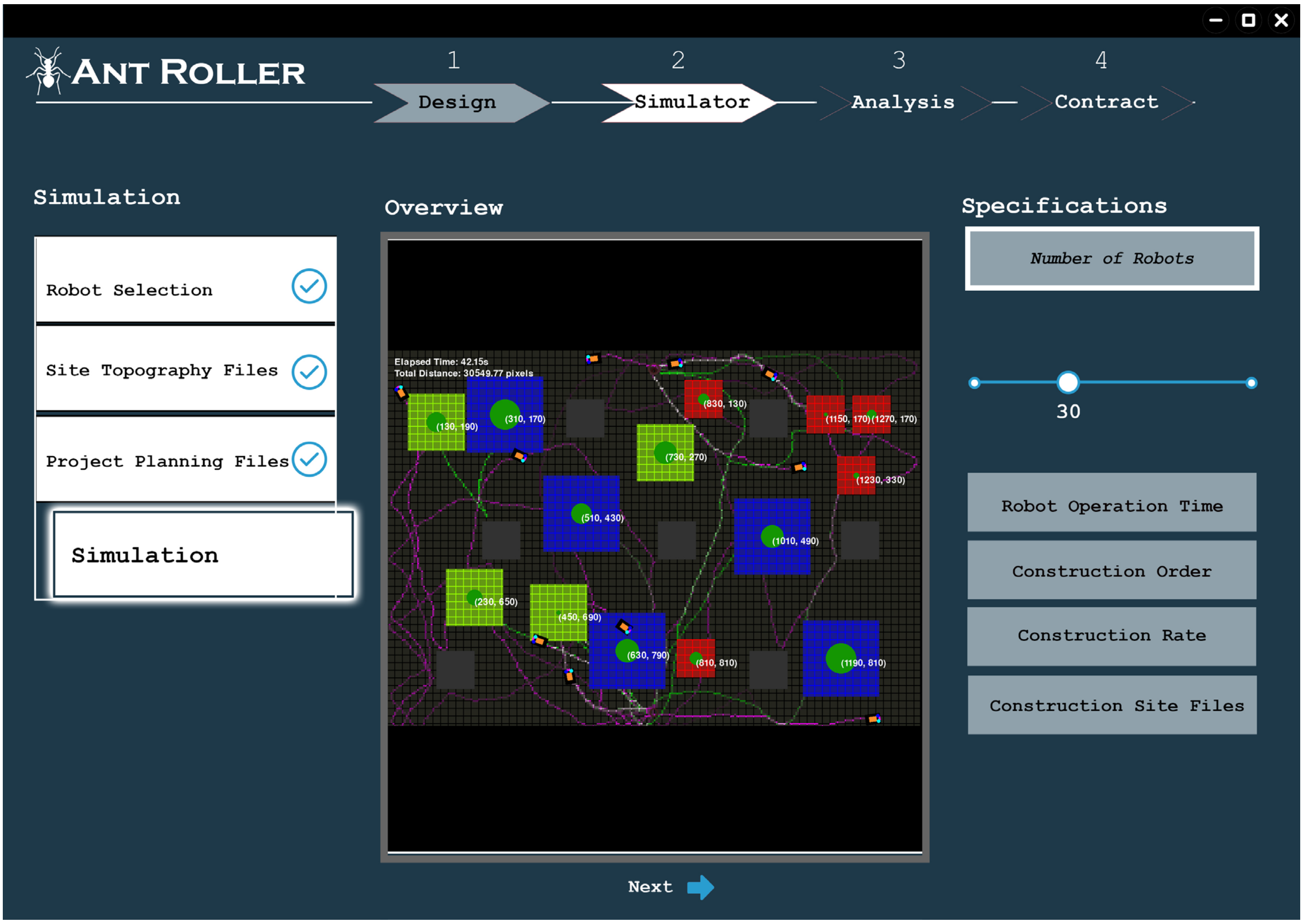


Figure 95- Simulation Phase User Interface Sketch

During the analysis phase, construction reports detailing construction time, walking distances, and robots' operational statuses would be recorded and displayed in real-time simulations. These reports would be ready for client review based on their preferences. Additionally, the technical support team could offer scenario-specific optimizations to reduce costs and enhance construction performance.

Finally, the client can decide whether to rent the swarm robots for their on-site logistic system and proceed with signing a contract

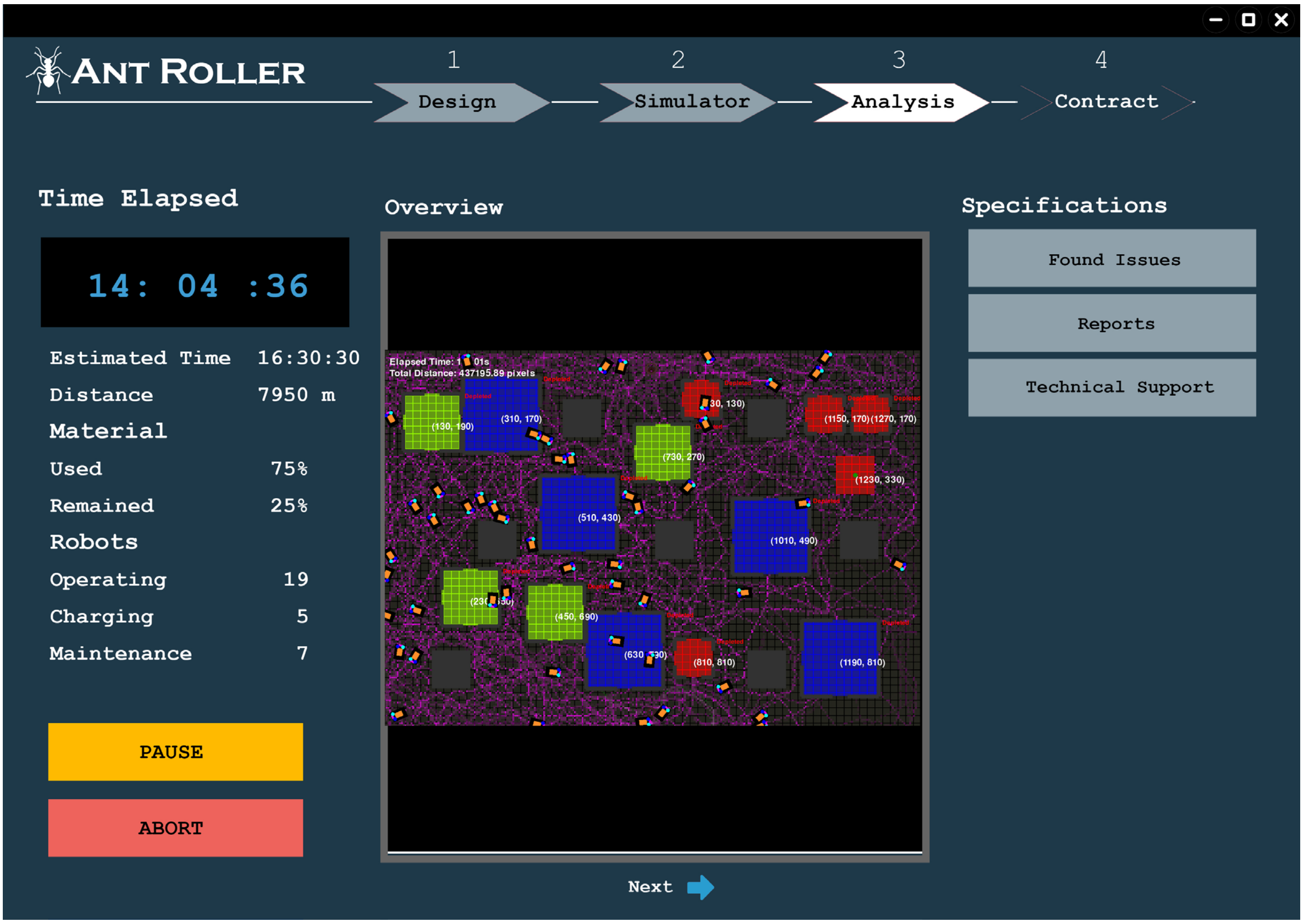


Figure 96- Analysis Phase User Interface Sketch

Sub- Questions

How will tasks be allocated among the swarm robots based on real-time demands and resource availability?

- Regarding real-time demands, the primary task of the swarm robots is to carry materials by picking them up from the material supply points, or nests, and placing them in the centers of the booths, which are defined as food sources in the simulation. All robots are assigned the same task and emerge from their nests one by one, starting their search for food in random directions. The task of delivering materials to the booths is determined by the robots that randomly visit the booths and follow the path to the food sources. There are no specific robots assigned to particular booths. Instead, each robot that visits a food source or booth will decrease the amount of required bricks for that booth with each visit. This decentralized approach ensures that tasks are allocated based on real-time demands and the availability of resources.

- Material supplies are considered to be static and always available in terms of real-time resources.

2- What coordination mechanisms are required to ensure efficient collaboration among the swarm robots?

- Two types of coordination mechanisms are employed in this simulation to ensure efficient collaboration among the swarm robots.
- Firstly, each robot maintains knowledge of its own position. This is achieved by tracking its movements from the initial starting point at the nests or material supplies. As each robot begins its journey from these sources, its initial coordinates are recorded. The subsequent movements of the robot are tracked by measuring its speed and time, creating a direction vector that indicates both the magnitude and direction of movement. This method continuously updates the robot’s position, allowing it to navigate accurately. In a real project, the localization method used depends on the robot's technology and may include options such as GPS (Global Positioning System), infrared and visual markers, and odometry which is out of this research’s scope.

- Secondly, indirect communication is facilitated through pheromone trails. As robots travel, they deposit pheromones along their paths. The intensity and concentration of these pheromone trails serve as signals to other robots, indicating the likelihood of a particular path being the shortest and most efficient route between the food sources (booths) and the nests. This pheromone-based communication allows robots to indirectly share information about optimal paths, thereby enhancing their collective efficiency and coordination. As mentioned before, in a real project, either evaporative chemicals or temporary built-in memory based on the robot’s technology might be implemented.

- These two mechanisms—self-coordination through position tracking and indirect communication through pheromone trails—ensure that the swarm robots can collaborate effectively and adaptively in the dynamic construction environment.

3- How can robots perceive and respond to obstacles?

- Each robot is equipped with three sensors positioned on the front side of its rectangular body, at a distance of 20 pixels (or 1 meter) from the central axis. These sensors play a crucial role in obstacle detection and navigation.

- When these sensors detect the RGB value (50,50,50) within a 1-meter range, which indicates the presence of an obstacle, they command the robot to change its direction in the opposite direction. The robot responds by rotating at half of its maximum speed and attempting to move in a different direction. This response mechanism helps the robot avoid collisions and navigate around obstacles effectively.

- By using these sensors, robots can perceive and react to obstacles in their environment, ensuring smooth and efficient navigation within the dynamic construction site.

- In a real project, the choice of technology such as cameras, LIDAR, infrared transceiver sensors, ultrasound emitter/receivers, tactile sensors and other tools may vary depending on the technical features of the robot.

4- How can the swarm robots adapt their behavior in response to the parameters of different demands, resources, obstacles etc. changing priorities or unexpected events?

Swarm robots exhibit several adaptive behaviors in response to various parameters such as demands, resources, obstacles, changing priorities, and unexpected events.

Obstacle Response

Each robot is equipped with three sensors on the front side of its rectangular body, positioned 20 pixels (or 1 meter) from the central axis. When these sensors detect the RGB value (50,50,50) within a 1-meter range, indicating an obstacle, they command the robot to change direction. The robot rotates at half of its maximum speed and attempts an alternate path, effectively navigating around obstacles.

Demand Response

Robots adapt to changing demands by perceiving the size of the food sources. As robots consume material from the food sources, the food size decreases, and the area with the corresponding RGB value also reduces. This decrease in size and area correlates with the diminishing material demand, signaling the robots to adjust their focus to other food sources as needed. In a real project, this demand might be controlled either by the worker's signals to getting more material or by using visual markers at each booth representing the remaining demand.

Resource Availability

The resource is assumed to be always available in a static condition. However, for implementing dynamic resource availability, two potential methods can simulate this behavior in future steps.

Temporary Obstacle Simulation: When a material supply stock is temporarily empty, a block with the RGB value indicating an obstacle appears. Robots perceive this as an obstacle until the stock is reloaded.

Removal from Nests List: Temporarily remove the empty stock from the nests list in the simulation, causing robots to redirect to other available stocks. This method mimics ant behavior by gradually increasing pheromone intensity towards the remaining material stocks, guiding robots to these sources.

Changing Priorities

Currently, all booths are assigned the same level of priority, but to accommodate different construction groups with varying priorities, two potential methods could be used to simulate this behavior in future steps.

Changing construction priorities can be simulated by introducing higher-priority booths earlier in the simulation. By presenting these booths as food sources first, robots will recognize and prioritize them over others. This mechanism allows the robots to adapt to changes in the construction order.

Unexpected Events

Unexpected events must be accurately translated into the simulation to ensure correct adaptive responses. For example, if a robot fails in the middle of the construction site, it should be treated as an obstacle until addressed. This ensures that other robots can navigate around the failed robot, maintaining efficiency and safety.

By employing these adaptive behaviors, swarm robots can respond effectively to various changes and challenges in a dynamic construction environment, ensuring continuous and efficient operation.

10

Reflection

Introduction

This reflection evaluates the graduation process and discusses the potential societal impact of my thesis, which focuses on implementing swarm robots as a material-handling logistics system on construction sites. The aim is to enhance efficiency and safety by reducing dependency on the human workforce. This interdisciplinary approach is central to the Building Technology Graduation Studio, where balancing knowledge from various domains is crucial for developing innovative solutions with a positive impact.

The thesis integrates computational programming skills from the Design Informatics (DI) Department and the Robotics Department of the Industrial Design Faculty with structural knowledge from the Structural Design (SD) Department. This combination ensures a realistic and accurate framework for creating an architectural design-to-construction workflow. The goal is to enable swarm robots to perform the construction process, transforming traditional human-dependent construction sites into more efficient and safer environments. By leveraging expertise from different fields, this thesis demonstrates the potential for interdisciplinary collaboration to drive advancements in construction technology.

Graduation process

This thesis journey has been filled with new experiences and significant learning. The initial plan was to research within a framework focused on robotic construction using robotic arms, influenced by the Design Informatics course of the Building Technology Track. This plan involved working with reclaimed wood and robotic arms in the Lama Lab. However, the research direction evolved towards the entirely new and abstract field of swarm robots. This field was unfamiliar to me, and acquiring the necessary knowledge presented a substantial challenge.

After becoming acquainted with the fundamentals of swarm robotics, formulating a precise research question became the next obstacle. The process was marked by confusion over technical terms and the overall direction of the research. Through guidance from mentors and numerous discussions, a clear and exciting new direction emerged. This shift required delving deeper into path-planning algorithms, necessitating significant revisions to my report. The interdisciplinary nature of this research spanned computer science, robotics, structural design, and design informatics.

Executing this research required integrating considerations from various fields to create a realistic construction scenario. This demanded a coherent and robust structure to tie together diverse areas such as structural analysis, brick demand estimation, and the parametric design of booths. Each task, although seemingly small, was a critical piece of a larger puzzle.

The first part of the workflow involved programming in Grasshopper to make all components parametric, which aligned well with my background and skills, making this phase relatively smooth. However, the second part of the workflow—replicating a dynamic construction site and ant behaviour in Python—was a new challenge. This phase required understanding the mathematical modelling of ant colony optimization and significantly improving my Python programming skills. Writing even simple tasks involved multiple attempts, proving to be time-consuming and stressful, especially when debugging.

Furthermore, consulting computer science experts did not provide the answer either, as they lacked an understanding of the architectural concepts crucial to the research. This highlighted the need for me, as a building technologist, to enhance my Python coding skills to better address the specific requirements of the project.

Despite these challenges, the simplified version of the intended research was successfully completed after many trials. This journey has imparted substantial experience and knowledge in new fields, which I am eager to continue mastering in the future. The interdisciplinary and practical aspects of this project have enriched my understanding and capabilities, preparing me for more complex and innovative endeavours in the realm of robotic construction and beyond.

Societal impact

The construction industry is rapidly growing, but it faces significant challenges such as a shortage of skilled labor, safety concerns, and poor communication on construction sites. These issues not only impact the efficiency of construction processes but also pose serious risks to the lives of workers. The shortage of labor can lead to overwork, while inadequate safety measures can result in severe injuries or fatalities. This thesis aims to address these problems by employing swarm robots for repetitive and simple tasks like material handling. By taking over these tasks, robots can prevent various short-term and long-term injuries and accidents, creating a safer work environment. This allows human workers to focus on tasks that require their expertise, leading to a more balanced and healthy work environment, both mentally and physically.

Another noteworthy societal impact is the subjective issue of safety. While using robots on construction sites may appear safe due to their sensors and detection tools, true safety extends beyond the robots themselves. The human workers who interact with these robots must also feel safe. Enhancing safety can be approached from two aspects: technical improvements and the perceived safety by human workers. Technical improvements can be addressed through engineering solutions, ensuring the robots' detection and navigation systems are robust and reliable. On the other hand, perceived safety involves the role of industrial designers who can work to enhance the safety image of robots. By focusing on design elements that make the robots appear more user-friendly and less intimidating, industrial designers can help create a sense of security among workers. This dual approach ensures both the actual safety, and the perceived safety of the working environment are optimized.

Additionally, the capabilities of swarm robots can mitigate disruptions, delays, and inefficiencies caused by the mentioned issues. Enhanced efficiency in the construction industry can drive economic growth, making the industry more resilient and productive. By improving safety, reducing physical strain on workers, and increasing overall efficiency, the integration of swarm robots can have a profound positive impact on the construction industry and society as a whole.

Figure 98- Construction Site

Image Source: OpenAI. "Image generated by ChatGPT." OpenAI. 2024.

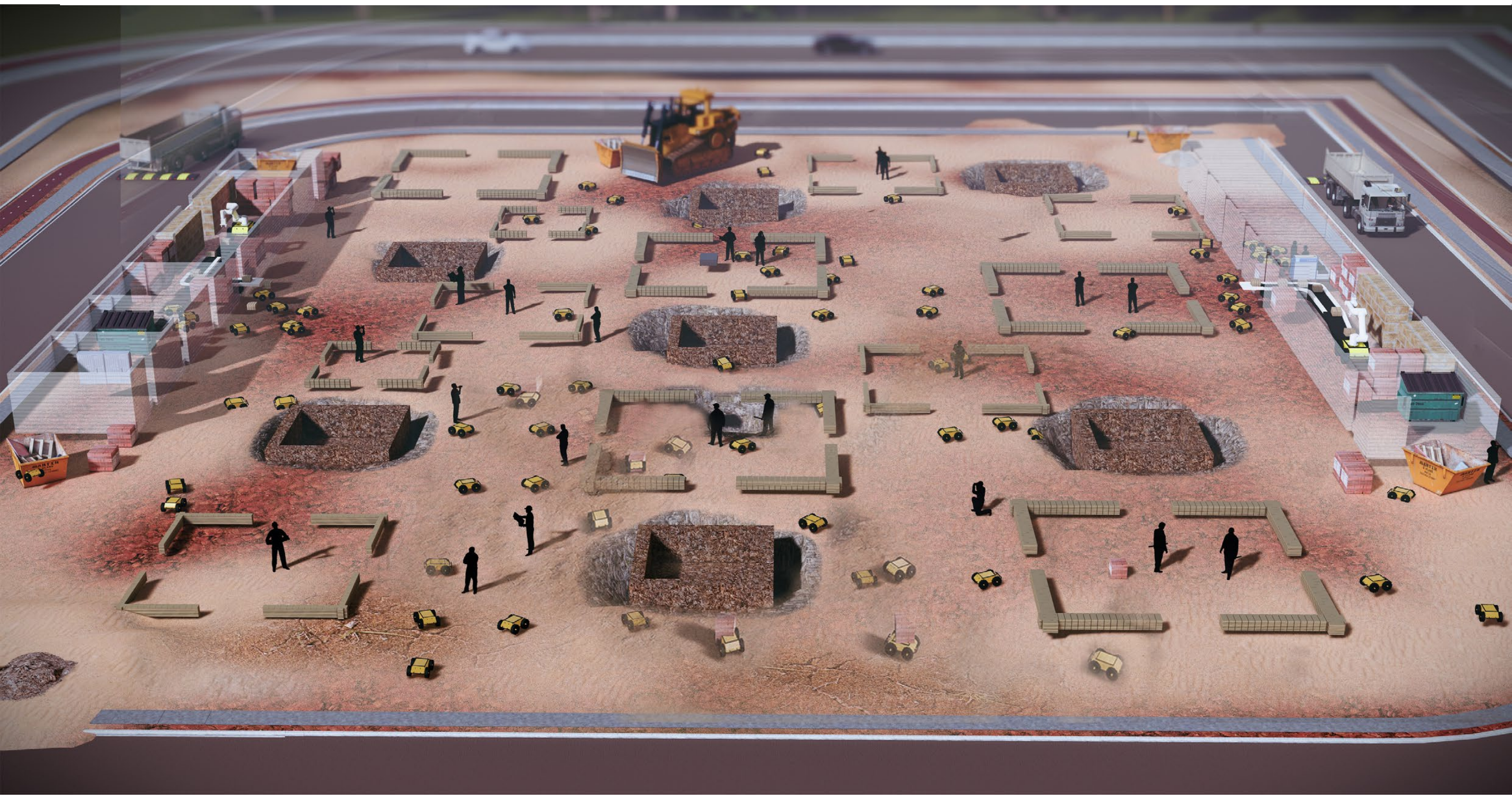


Figure 97- Render of Construction Stages

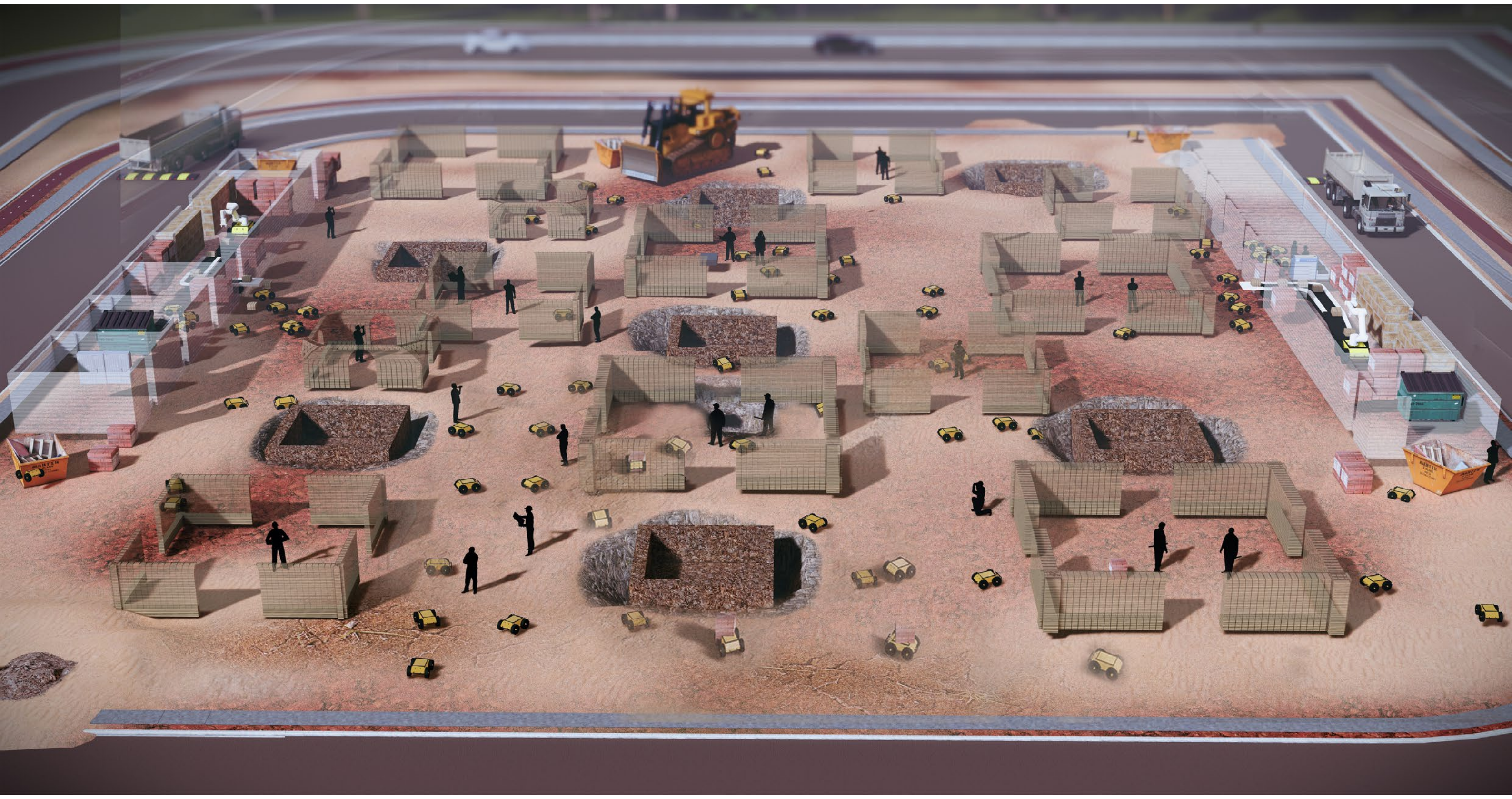


Figure 99- Render of Construction Stages

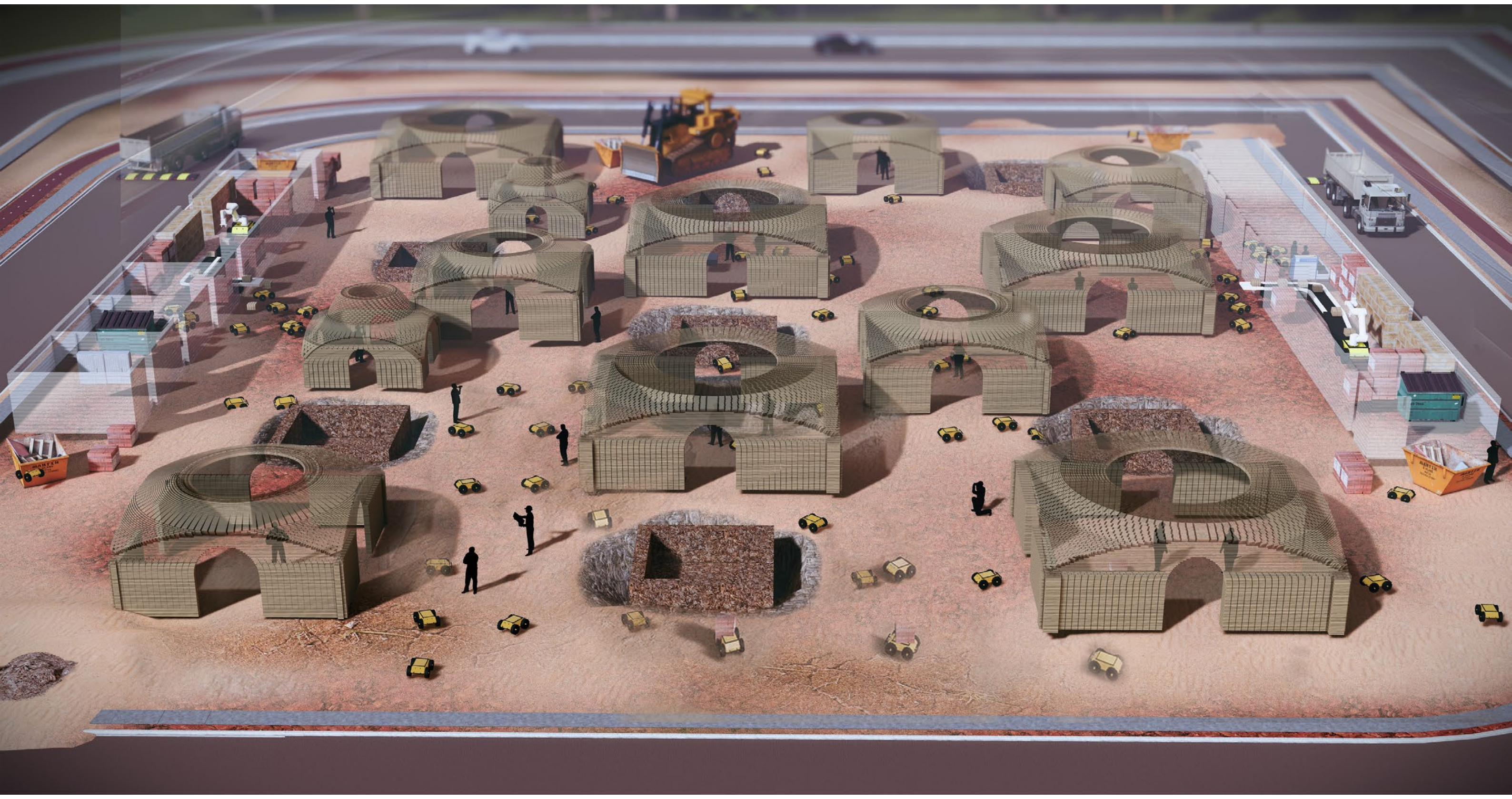


Figure 100- Render of Construction Stages

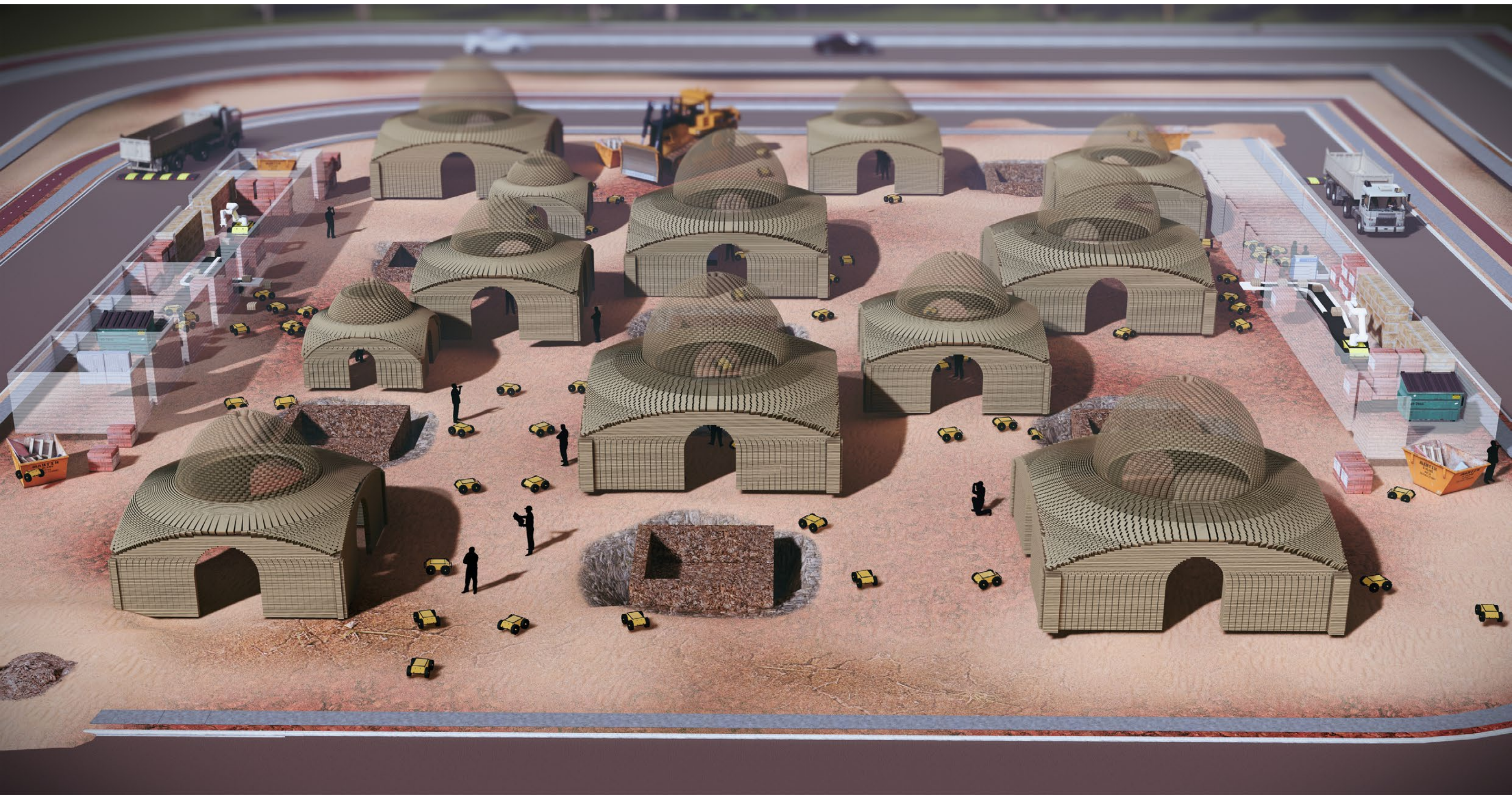


Figure 102- Render of Construction Stages

Figure 101- Final Architectural Render

Figure 103- Eye-level Perspective

11

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12

Appendix

Introduction

In this section, the new results are presented with two major differences from the previous ones.

Firstly, in the previous results, the robots had their sensors located on their right side. In the new setup, the sensors have been relocated to the front of the robot, 20 pixels ahead of the central point. This new position provides more accuracy on both sides. Additionally, while the previous results studied varying sensor detection distances, the new setup fixes this distance at 20 pixels, which is both the optimal number from previous studies and the length of one robot. Since this feature is mainly a technical specification provided by the manufacturer, using a fixed number seemed more rational. To evaluate the impact of this repositioning on construction time and walking distance, two identical experiments with only the sensor positions differing were conducted. The results show that the new adjustments reduced both construction time and walking distance, enhancing overall performance.

Secondly, the previous study used smaller steps for the evaporation rate, ranging from 0.01 to 0.05. In the final results, this range has been expanded to cover a spectrum from no evaporation to complete evaporation.

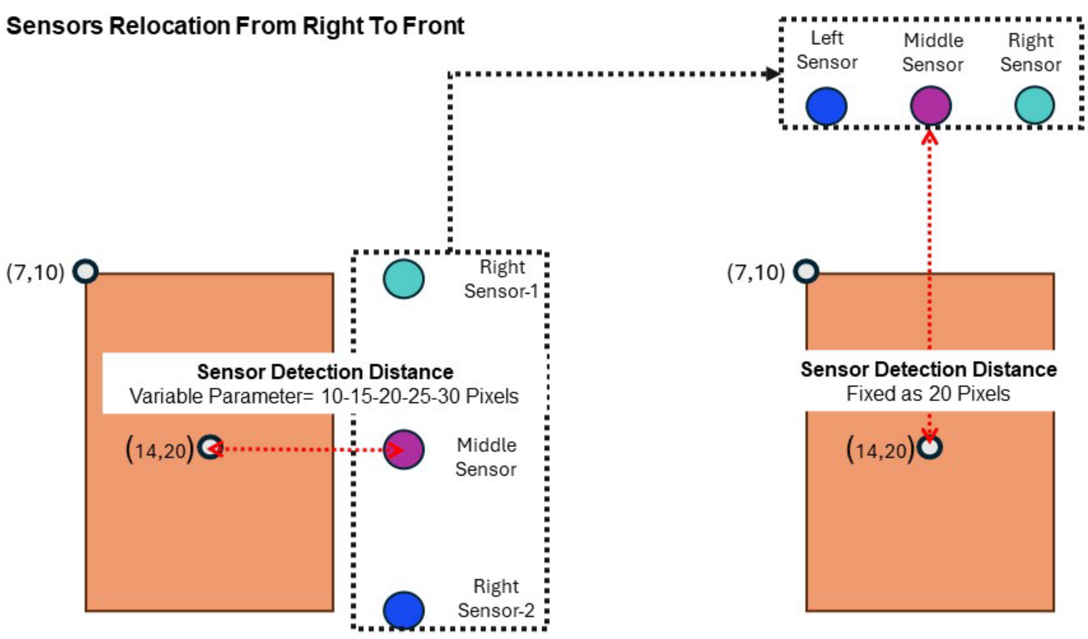
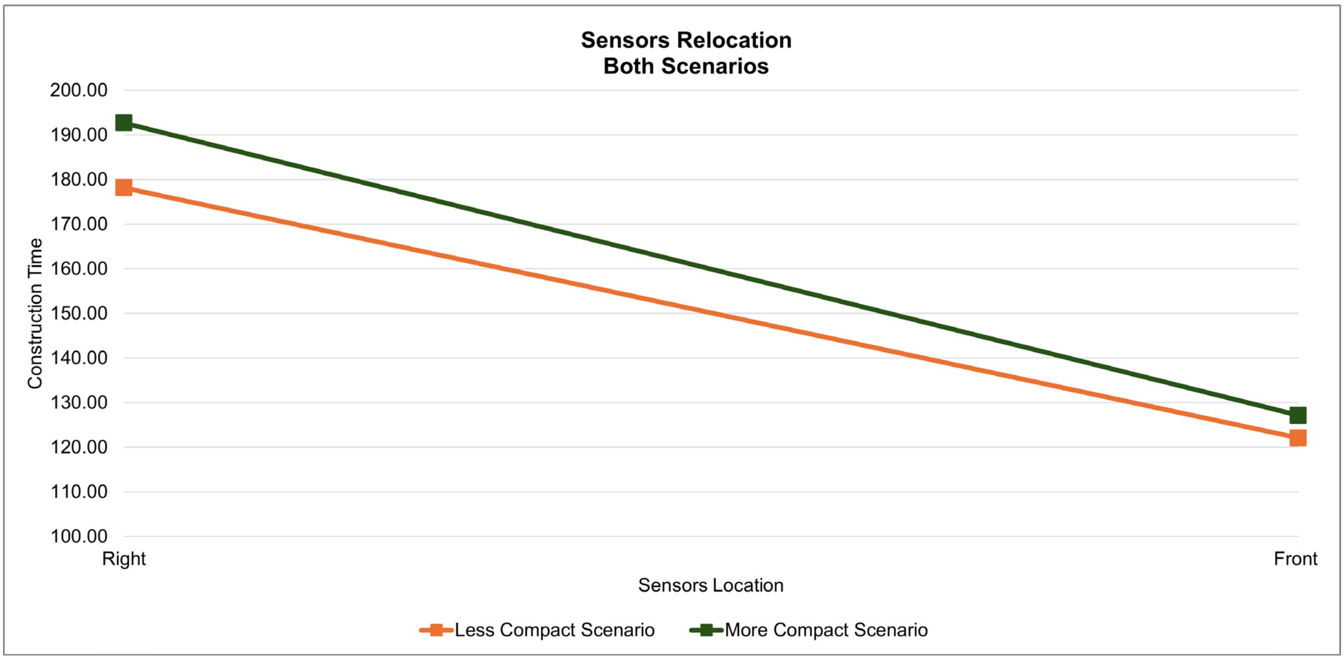


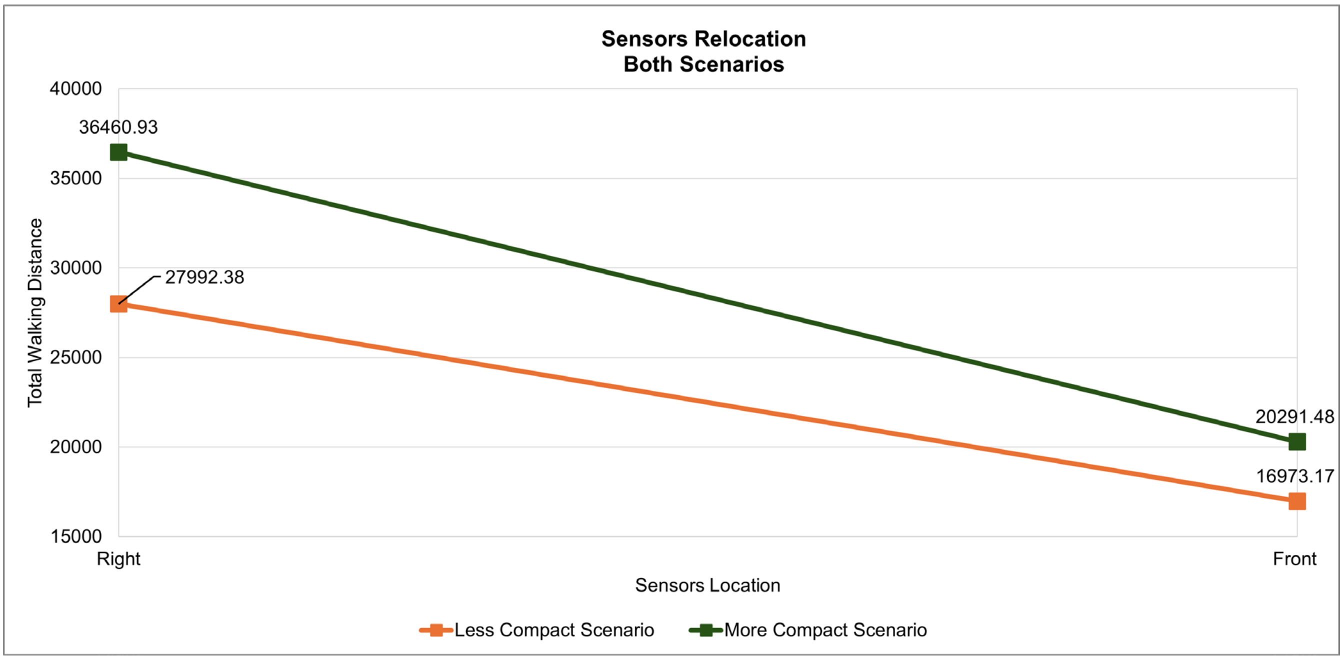
Figure 104- Sensors' Relocation

1- The Impact of sensor Relocation on Construction Time and Walking Distance

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario



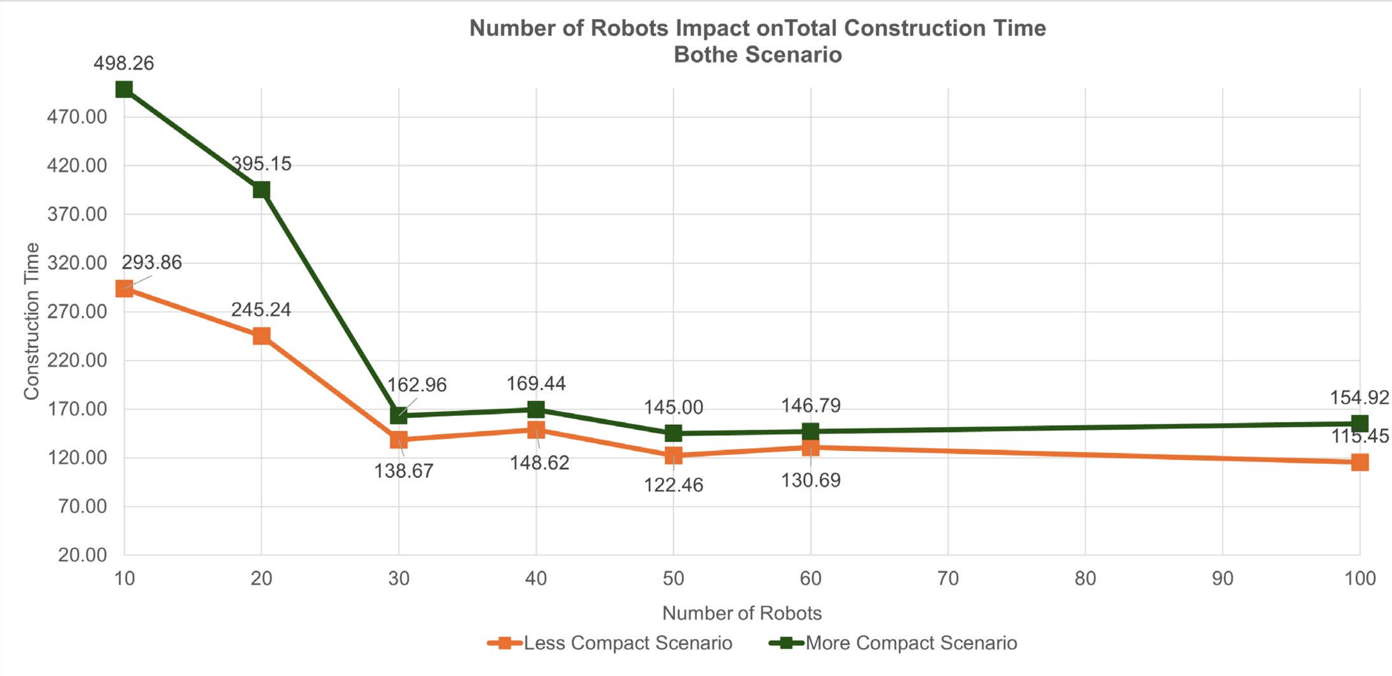


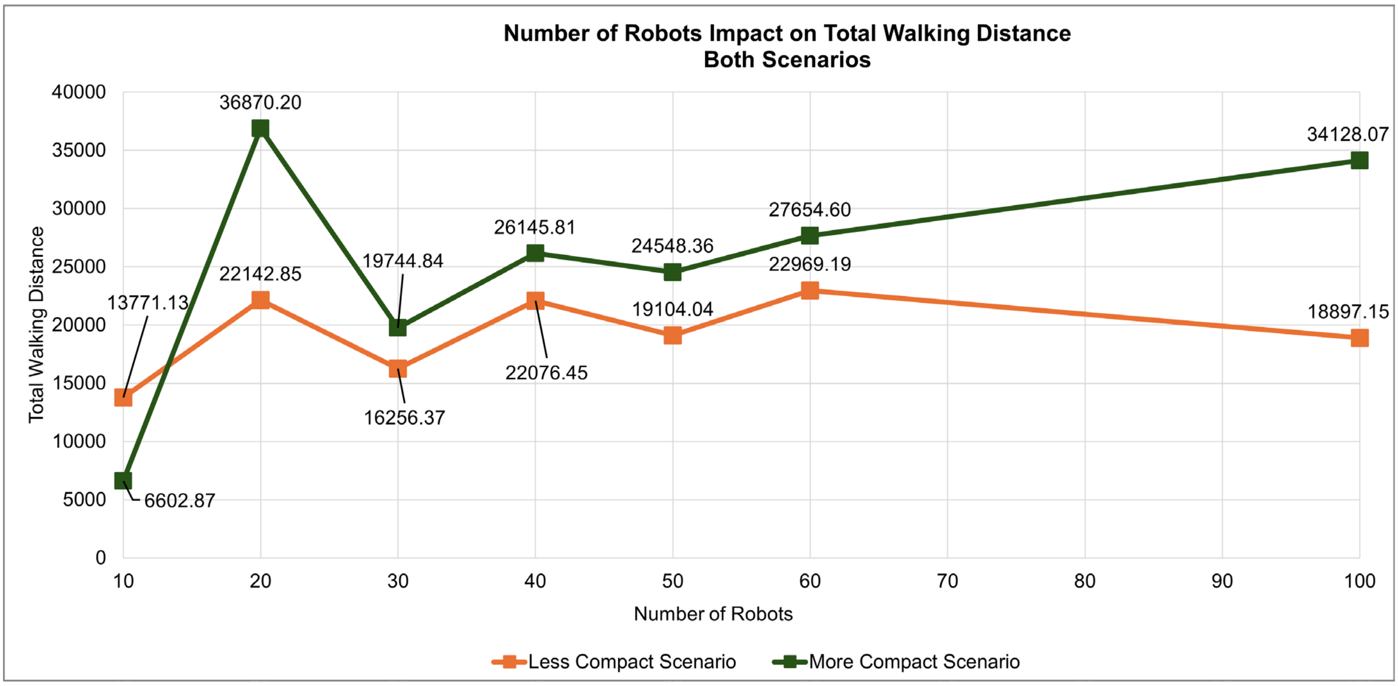
The following sections present the graphs that examine the impact of the number of robots, pheromone evaporation rate, and sensor detection distance on construction time and walking distance. By adjusting the sensors' positions, it is observed that the patterns remain consistent with the final results, although there are changes in the optimal values.

2- The Impact of the Number of Robots on Construction Time and Walking Distance

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario

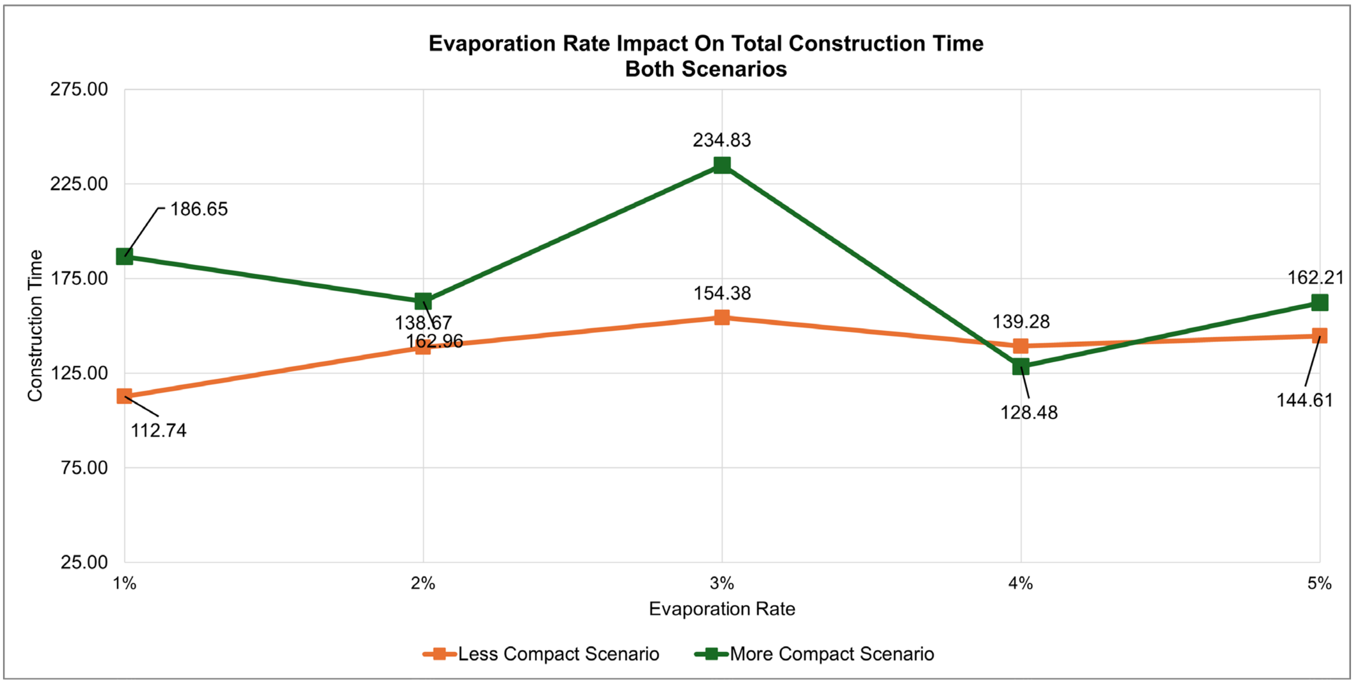


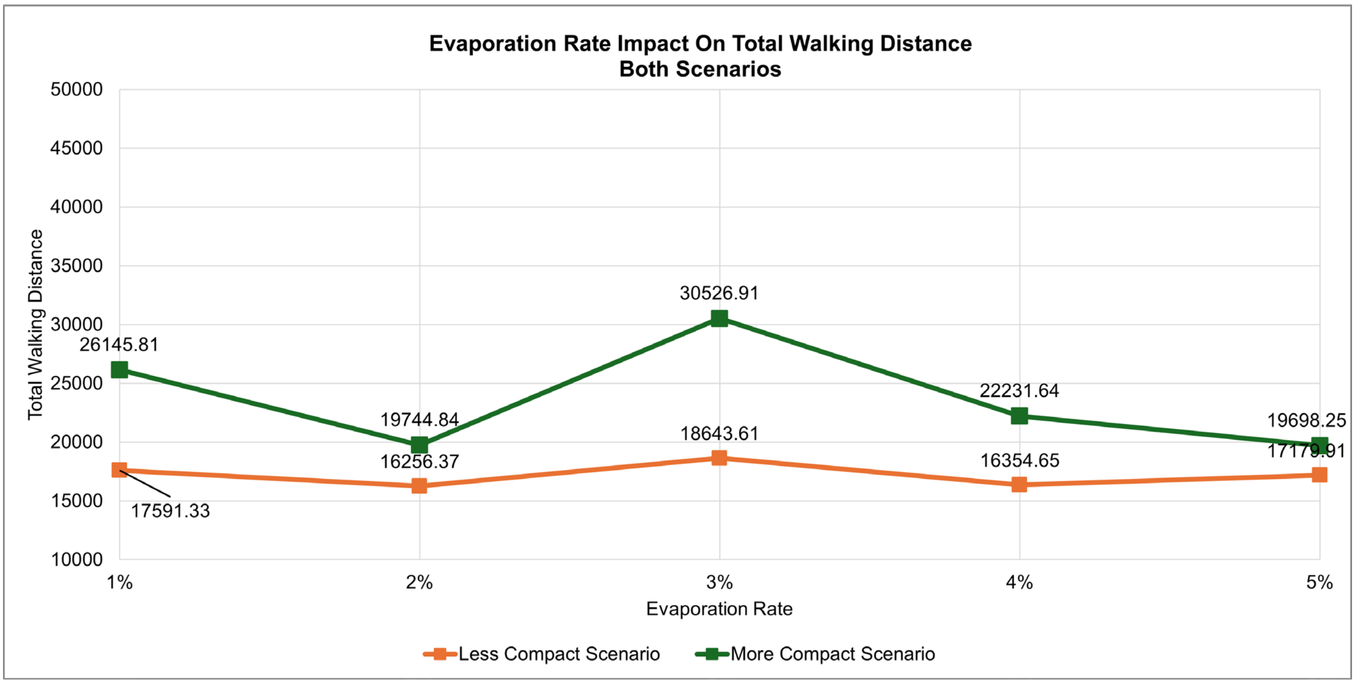


3- The Impact of Pheromone Evaporation Rate on Construction Time and Walking Distance

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario

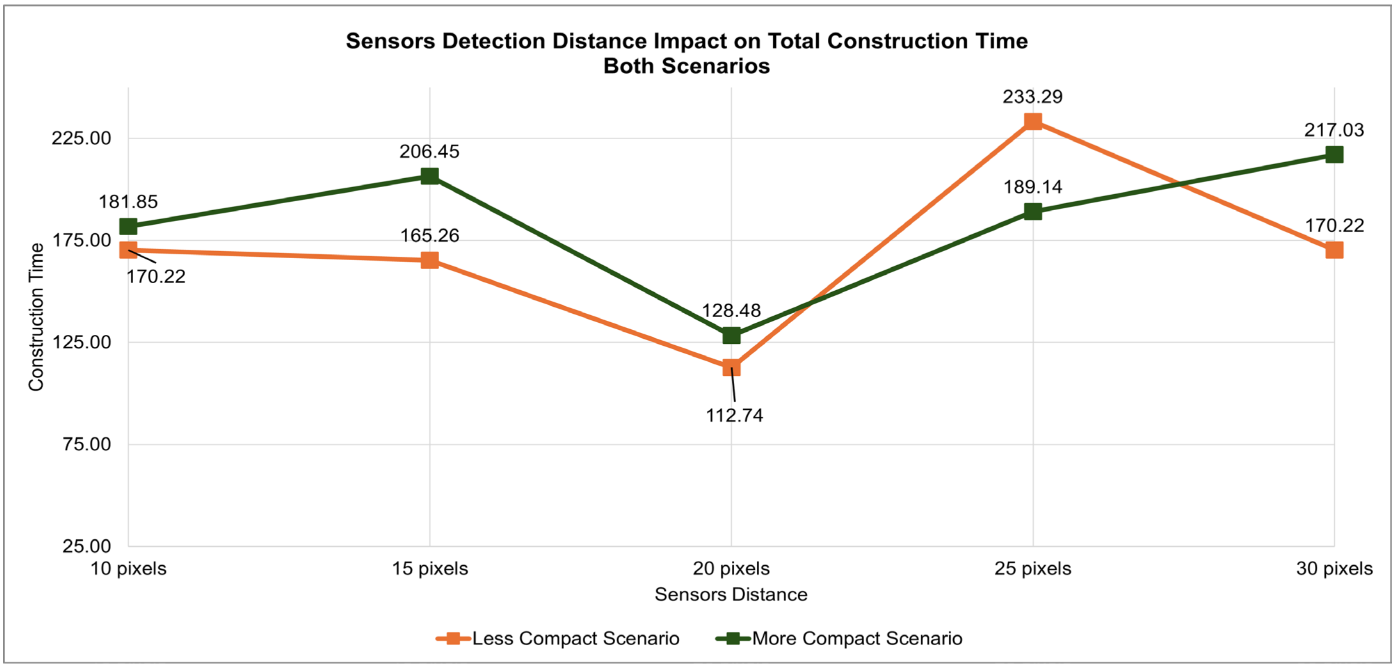


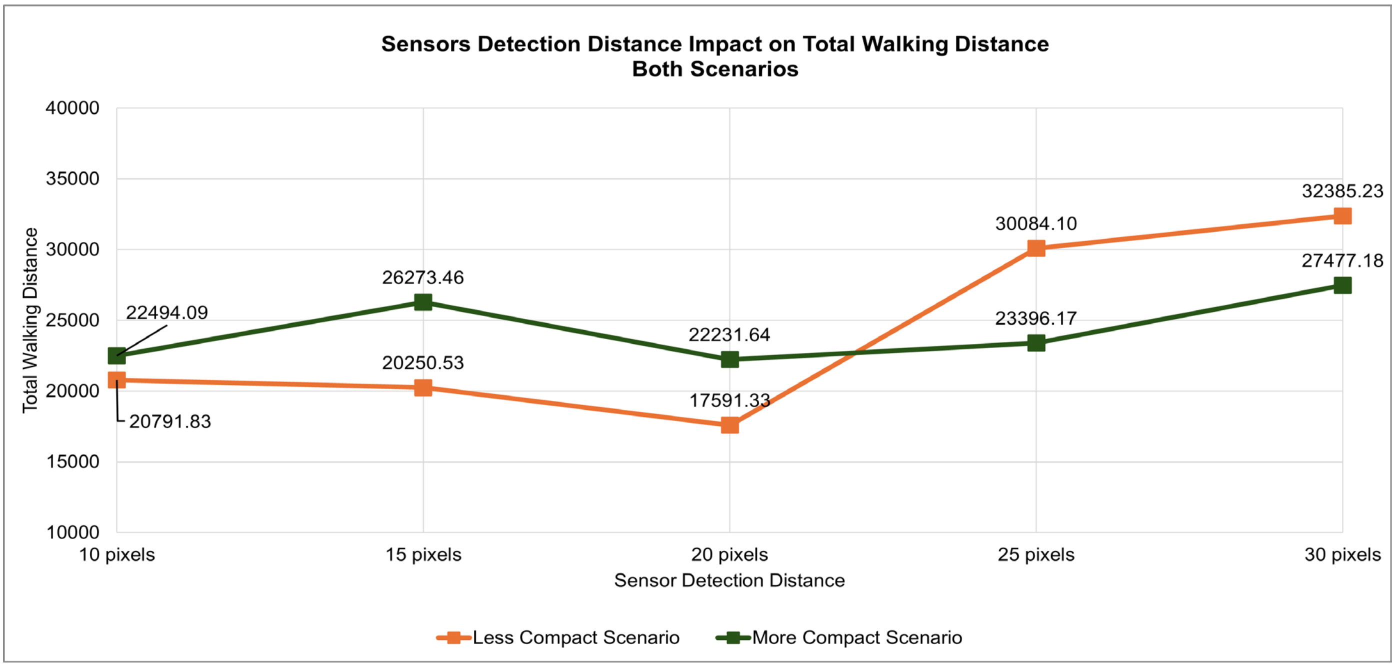


4- The Impact of Sensor Detection Distance on Construction Time and Walking Distance

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario

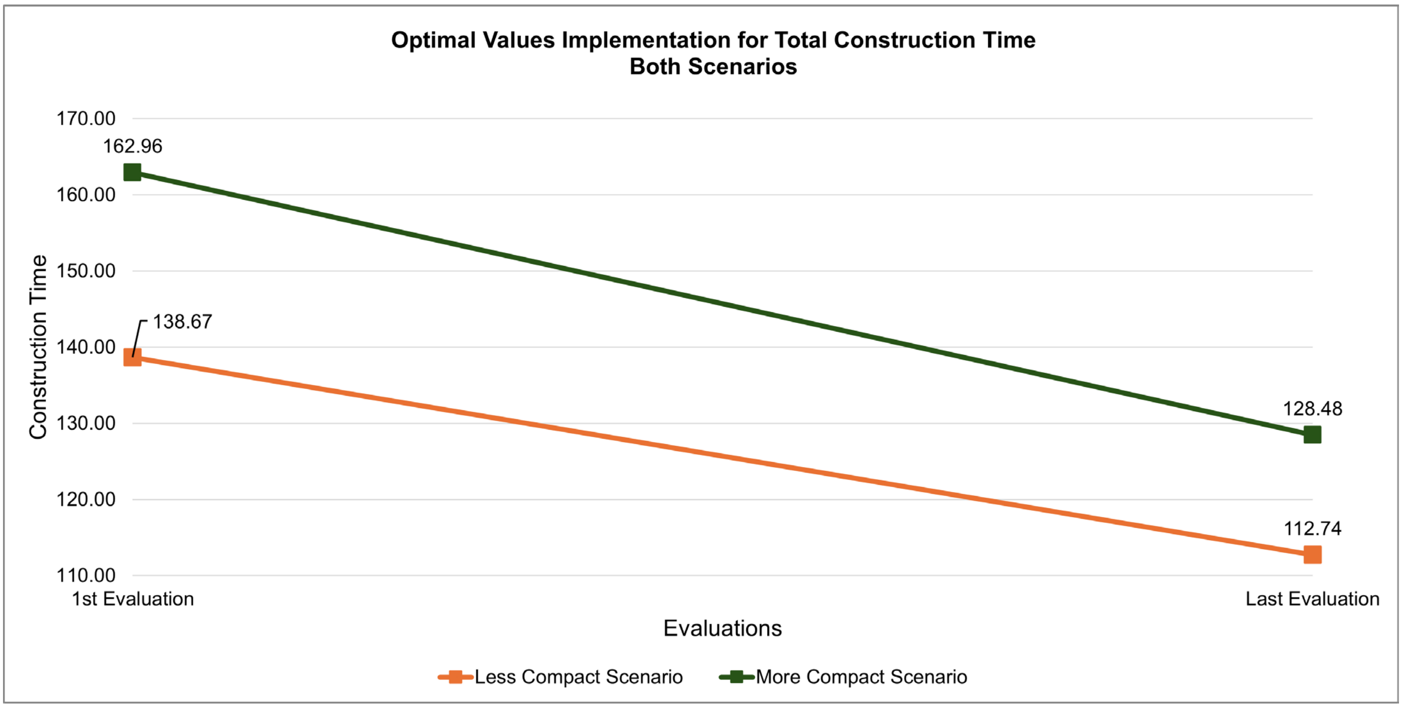


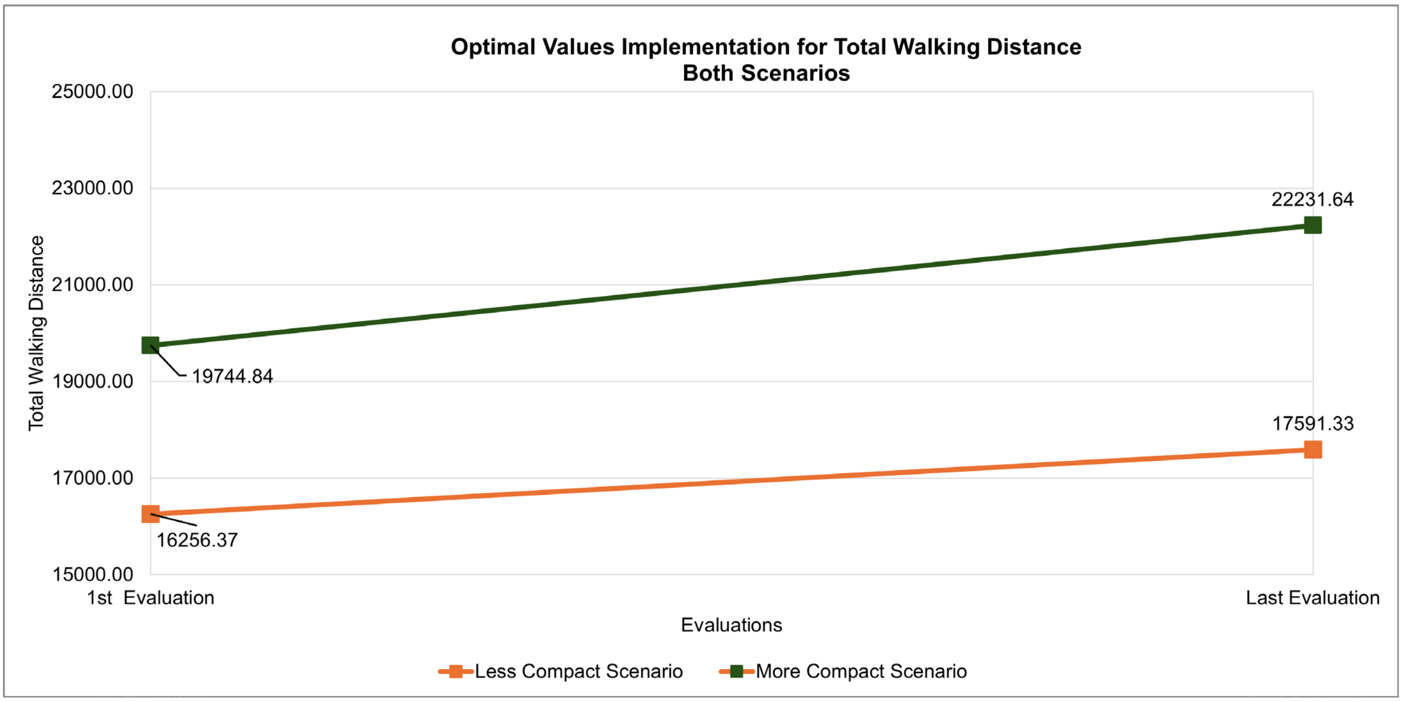


5- Implementations of optimal values for the number of robots, pheromone evaporation rate, and sensors' detection distances

Scenarios: **Less Compact - 9 Booths Scenario**

More Compact - 14 Booths Scenario





Final Results

9 booths Simulations

Number of Ants Evaluation

Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1
Experiment 1	1400*1000	9	12,885	370	7	9	2	10	0.01	R1	454635.32	473.23
										R2	368178.18	388.23
										R3	308528.12	326.5
										R4	277579.35	294.9
										R5	301453.67	322.46
										Average	342074.93	361.06
										Standard Deviation		71.38245043
Experiment 2	1400*1000	9	12,885	370	7	9	2	20	0.01	R1	221485.75	132.22
										R2	700375.47	374.59
										R3	712055.47	380.12
										R4	393187.63	220.75
										R5	224214.94	134.22
										Average	450263.85	248.38
										Standard Deviation		123.0583803
Experiment 3	1400*1000	9	12,885	370	7	9	2	30	0.01	R1	400926.37	163.36
										R2	331168.18	140.67
										R3	324397.19	138.43
										Average	352163.91	147.49
										Standard Deviation		13.79225991
Experiment 4	1400*1000	9	12,885	370	7	9	2	40	0.01	R1	239931.33	96.97
										R2	333369.95	120.8
										R3	458250.95	152.99
										Average	343850.74	123.59
										Standard Deviation		28.11377302
Experiment 5	1400*1000	9	12,885	370	7	9	2	50	0.01	R1	302525.45	106.14
										R2	695417.29	185.66
										R3	462154.9	138.45
										Average	486699.21	143.42
										Standard Deviation		39.99197961
Experiment 6	1400*1000	9	12,885	370	7	9	2	80	0.01	R1	351504.94	112.01
										R2	229109.19	90.95
										R3	434751.61	124.4
										Average	338455.25	109.12
										Standard Deviation		16.91123
Experiment 7	1400*1000	9	12,885	370	7	9	2	100	0.01	R1	434751.61	124.40
										R2	267152.9	97.92
										R3	500803.69	133.17
										Average	400902.73	118.50
										Standard Deviation		18.35150221

Final Results **Pheromone Evaluation**

Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1
Experiment 8	1400*1000	9	12,885	370	7	9	2	40	0	R1	261055.63	102.75
										R2	429405.79	145.31
										R3	226449.23	93.94
											495120.81	161.88
										Average	353007.87	125.97
										Standard Deviation		32.80575661
Experiment 4	1400*1000	9	12,885	370	7	9	2	40	0.01	R1	239931.33	96.97
										R2	333369.95	120.8
										R3	458250.95	152.99
										Average	343850.74	123.59
										Standard Deviation		28.11377302
Experiment 9	1400*1000	9	12,885	370	7	9	2	40	0.05	R1	598445.98	187.57
										R2	297550.86	111.39
										R3	471724.97	156.33
										Average	455907.27	151.76
										Standard Deviation		38.29476378
Experiment 10	1400*1000	9	12,885	370	7	9	2	40	0.1	R1	634364.30	196.63
										R2	419711.87	142.47
										R3	276828.35	106.47
										Average	443634.84	148.52
										Standard Deviation		45.38379153
Experiment 11	1400*1000	9	12,885	370	7	9	2	40	0.2	R1	410324.73	139.81
										R2	315972.4	116.32
										R3	292092.82	110.06
										Average	339463.32	122.06
										Standard Deviation		15.6845476
Experiment 12	1400*1000	9	12,885	370	7	9	2	40	0.3	R1	485021.85	158.66
										R2	308594.28	114.17
										R3	320605.52	117.2
										Average	371407.22	130.01
										Standard Deviation		24.8578378
Experiment 13	1400*1000	9	12,885	370	7	9	2	40	0.5	R1	539337.91	172.45
										R2	505801.6	164
										R3	472042.87	156.34
										Average	505727.46	164.26
										Standard Deviation		8.058227679
Experiment 14	1400*1000	9	12,885	370	7	9	2	40	0.8	R1	292501.05	110.19
										R2	333191.44	120.96
										R3	290804	109.88
										Average	305498.83	113.68
										Standard Deviation		6.309455867
Experiment 15	1400*1000	9	12,885	370	7	9	2	40	1	R1	701553.31	213.61
										R2	367866.01	129.7
										R3	395066.36	136.32
										Average	488161.89	159.88
										Standard Deviation		46.65200353

Final Results

14 booths Simulations

Number of Ants Evaluation

Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1

Experiment 16	1400*1000	14	60,130	1718	7	14	2	10	0.01	R1	400251.78	421.81
										R2	337471.57	357.44
										R3	346332.89	366.89
										R4	610440.08	632.2
										R5	308836.03	328.93
										Average	400666.47	421.45
										Standard Deviation		122.5252179
Experiment 17	1400*1000	14	60,130	1718	7	14	2	20	0.01	R1	506306.25	279.13
										R2	573048.66	310.82
										R3	701272.42	375.57
										Average	593542.44	321.84
										Standard Deviation		49.15535271
Experiment 18	1400*1000	14	60,130	1718	7	14	2	30	0.01	R1	580723.16	224.52
										R2	463265.45	186.23
										R3	573094.92	222.03
										Average	539027.84	210.93
										Standard Deviation		21.42414604
Experiment 19	1400*1000	14	60,130	1718	7	14	2	40	0.01	R1	551480.86	176.35
										R2	742083.08	224.71
										R3	511141.58	165.4
										Average	601568.51	188.82
										Standard Deviation		31.56017586
Experiment 20	1400*1000	14	60,130	1718	7	14	2	50	0.01	R1	530574.10	152.31
										R2	443611.01	135.48
										R3	396133.02	125.72
										Average	456772.71	137.84
										Standard Deviation		13.450741
Experiment 21	1400*1000	14	60,130	1718	7	14	2	80	0.01	R1	387556.58	123.96
										R2	453523.65	137.11
										R3	462477.2	139.18
										Average	434519.14	133.42
										Standard Deviation		8.254855137
Experiment 22	1400*1000	14	60,130	1718	7	14	2	100	0.01	R1	522867.90	136.37
										R2	447324.9	126.46
										R3	385920.79	117.49
										Average	452037.86	126.77
Final Results				**Pheromone Evaluation**						Standard Deviation		9.443899265
Experiment 23	1400*1000	14	60,130	1718	7	14	2	50	0	R1	352460.73	117.32
										R2	500229.45	147.85
										R3	481013.13	143.71
											308888.62	108.21
										Average	410647.98	129.27
										Standard Deviation		19.49406811
Experiment 20	1400*1000	14	60,130	1718	7	14	2	50	0.01	R1	530574.10	152.31
										R2	443611.01	135.48
										R3	396133.02	125.72
										Average	456772.71	137.84
										Standard Deviation		13.450741
Experiment 24	1400*1000	14	60,130	1718	7	14	2	50	0.05	R1	311016.51	107.89
										R2	613750.57	169.22
										R3	464953.11	139
										Average	463240.06	138.70
										Standard Deviation		
Experiment 25	1400*1000	14	60,130	1718	7	14	2	50	0.1	R1	409132.93	127.98
										R2	590512.52	164.32
										R3	603172.11	166.9
										Average	534272.52	153.07
										Standard Deviation		21.76395491
Experiment 26	1400*1000	14	60,130	1718	7	14	2	50	0.2	R1	402795.69	126.35
										R2	419854.21	130.17
										R3	394838.95	124.88
										Average	405829.62	127.13
										Standard Deviation		2.730610432
Experiment 27	1400*1000	14	60,130	1718	7	14	2	50	0.3	R1	635348.73	173.38
										R2	369123.04	119.56
										R3	577994.69	161.81
										Average	527488.82	151.58
										Standard Deviation		28.32996
Experiment 28	1400*1000	14	60,130	1718	7	14	2	50	0.5	R1	500327.91	145.84
										R2	596841.21	165.43
										R3	545485.43	155.15
										Average	547551.52	155.47
										Standard Deviation		9.79900165
Experiment 29	1400*1000	14	60,130	1718	7	14	2	50	0.8	R1	332652.67	112.15
										R2	284216.17	102.31
										R3	305193.32	106.34
										Average	307354.05	106.93
										Standard Deviation		4.946759882
Experiment 30	1400*1000	14	60,130	1718	7	14	2	50	1	R1	343832.53	114.28
										R2	603909.21	167.08
										R3	430240.19	131.77
										Average	459327.31	137.71
										Standard Deviation		26.89651836
Final Results				**Sensor Repositioning**								
Experiment 31	1400*1000	9	12,885	370	7	9	2	40	0.2	R1	486718.89	159.62
										R2	650037.82	201.18
										R3	542786.18	173.69
										Average	559847.63	178.16
										Standard Deviation		21.13803286
Experiment 30	1400*1000	14	60,130	1718	7	14	2	50	0.2	R1	821853.13	211.58
										R2	599535.02	166.36
										R3	766267.53	200.15
										Average	729218.56	192.70
										Standard Deviation		23.51332034
P4 Results				**9 booths Simulations** **Number of Ants Evaluation**								

P4 Results

9 booths Simulations

Number of Ants Evaluation

											Standard Deviation	23.51332034	
Parameters	**Construction site**	**Number of Foods**	**Total Number of Bricks**	**Total Number of Travels**	**Number of Static Obstacles**	**Number of Dynamic Obstacles**	**Number of Nests**	**Number of Robots/ants**	**Sensors Distance**	**Evaporation Rate**	**Parameters**	**Total Walking Distance(m)-1**	**Construction Time(s)-1**
Experiment 1	1400*1000	9	12,885	370	7	9	2	10	20 pixels	0.98	R1	272600.17	291.03
											R2	295658.04	314.76
											R3	258009.73	275.78
											Average	275422.65	293.86
											Standard Deviation		19.64313196
Experiment 2	1400*1000	9	12,885	370	7	9	2	20	20 pixels	0.98	R1	483583.15	266.22
											R2	355770.1	201.62
											R3	489217.88	267.89
											Average	442857.04	245.24
											Standard Deviation		37.78814144
Experiment 3	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.98	R1	446950.60	180.36
											R2	275492.34	121.6
											R3	252939.3	114.05
											Average	325127.41	138.67
											Standard Deviation		36.30141457
Experiment 4	1400*1000	9	12,885	370	7	9	2	40	20 pixels	0.98	R1	544091.64	174.58
											R2	308281.41	114.67
											R3	472213.95	156.61
											Average	441529.00	148.62
											Standard Deviation		30.74381401
Experiment 5	1400*1000	9	12,885	370	7	9	2	50	20 pixels	0.98	R1	437323.31	134.02
											R2	381743.45	122.23
											R3	327175.53	111.14
											Average	382080.76	122.46
											Standard Deviation		11.44178453
Experiment 6	1400*1000	9	12,885	370	7	9	2	60	20 pixels	0.98	R1	504597.25	138.53
											R2	343825.53	111.22
											R3	529728.72	142.31
											Average	459383.83	130.69
											Standard Deviation		16.96423984
Experiment 7	1400*1000	9	12,885	370	7	9	2	100	20 pixels	0.98	R1	484065.92	131.04
											R2	291508.1	102.16
											R3	358254.69	113.15
											Average	377942.90	115.45
											Standard Deviation		14.57673146
P4 Results				**Pheromone Evaluation**									
Experiment 8	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.95	R1	532744.19	208.93
											R2	258638.77	115.77
											R3	239411.38	109.12
											Average	343598.11	144.61
											Standard Deviation		55.80478504
Experiment 9	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.96	R1	426663.57	173.07
											R2	226037.82	104.71
											R3	328577.41	140.05
											Average	327092.93	139.28
											Standard Deviation		34.18656071
Experiment 10	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.97	R1	557719.60	216.47
											R2	317523.48	135.84
											R3	243373.3	110.84
											Average	372872.13	154.38
											Standard Deviation		55.20249662
Experiment 3	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.98	R1	446950.60	180.36
											R2	275492.34	121.6
											R3	252939.3	114.05
											Average	325127.41	138.67
											Standard Deviation		36.30141457
Experiment 11	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.99	R1	395577.11	120.18
											R2	366033.68	115.18
											R3	293869.24	102.86
											Average	351826.68	112.74
											Standard Deviation		8.914078752
P4 Results				**Sensor Detection Distance**									
Experiment 12	1400*1000	9	12,885	370	7	9	2	30	10 pixels	0.99	R1	539993.89	211.24
											R2	382762.38	159.64
											R3	324753.33	139.79
											Average	415836.53	170.22
											Standard Deviation		36.88198521
Experiment 13	1400*1000	9	12,885	370	7	9	2	30	15 pixels	0.99	R1	450662.19	180.13
											R2	416475.98	168.91
											R3	347893.51	146.75
											Average	405010.56	165.26
											Standard Deviation		[illegible]
Experiment 11	1400*1000	9	12,885	370	7	9	2	30	20 pixels	0.99	R1	395577.11	120.18
											R2	366033.68	115.18
											R3	293869.24	102.86
											Average	351826.68	112.74
											Standard Deviation		8.914078752
Experiment 14	1400*1000	9	12,885	370	7	9	2	30	25 pixels	0.99	R1	716388.39	272.32
											R2	524248.72	207.1
											R3	564409.13	220.46
											Average	601682.08	233.29
											Standard Deviation		34.45189303
Experiment 15	1400*1000	9	12,885	370	7	9	2	30	30 pixels	0.99	R1	578691.19	226.44
											R2	697360.70	266.96
											R3	667061.96	257.01
											Average	647704.62	250.14
											Standard Deviation		21.1163357

P4 Results

14 booths Simulations

Number of Ants Evaluation

Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Sensors Distance	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1
Experiment 16	1400*1000	14	60,130	1718	7	14	2	10	20 pixels	0.98	R1	669315.38	693.33
											R2	403072.95	425.73
											R3	353832.47	375.71
											Average	132057.48	498.26
											Standard Deviation		170.7796947
Experiment 17	1400*1000	14	60,130	1718	7	14	2	20	20 pixels	0.98	R1	645809.31	349.18
											R2	835105.93	444.21
											R3	731296.97	392.05
											Average	737404.07	395.15
											Standard Deviation		47.59062127
Experiment 18	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.98	R1	463093.26	186.16
											R2	352202.45	148.5
											R3	369394.81	154.23
											Average	394896.84	162.96
											Standard Deviation		20.29217173
Experiment 19	1400*1000	14	60,130	1718	7	14	2	40	20 pixels	0.98	R1	430435.57	145.66
											R2	615374.02	193.04
											R3	522938.72	169.61
											Average	522916.10	169.44
											Standard Deviation		23.69047558
Experiment 20	1400*1000	14	60,130	1718	7	14	2	50	20 pixels	0.98	R1	661836.27	179.24
											R2	358400.84	118.11
											R3	452664.41	137.65
											Average	490967.17	145.00
											Standard Deviation		31.22076392
Experiment 21	1400*1000	14	60,130	1718	7	14	2	60	20 pixels	0.98	R1	641445.64	161.90
											R2	471387.05	132.99
											R3	546443.13	145.47
											Average	553091.94	146.79
											Standard Deviation		14.4999046
Experiment 22	1400*1000	14	60,130	1718	7	14	2	100	20 pixels	0.98	R1	605468.50	146.41
											R2	786952.95	166.55
											R3	655262.56	151.81
											Average	682561.34	154.92
											Standard Deviation		10.42470783

P4 Results

Pheromone Evaluation

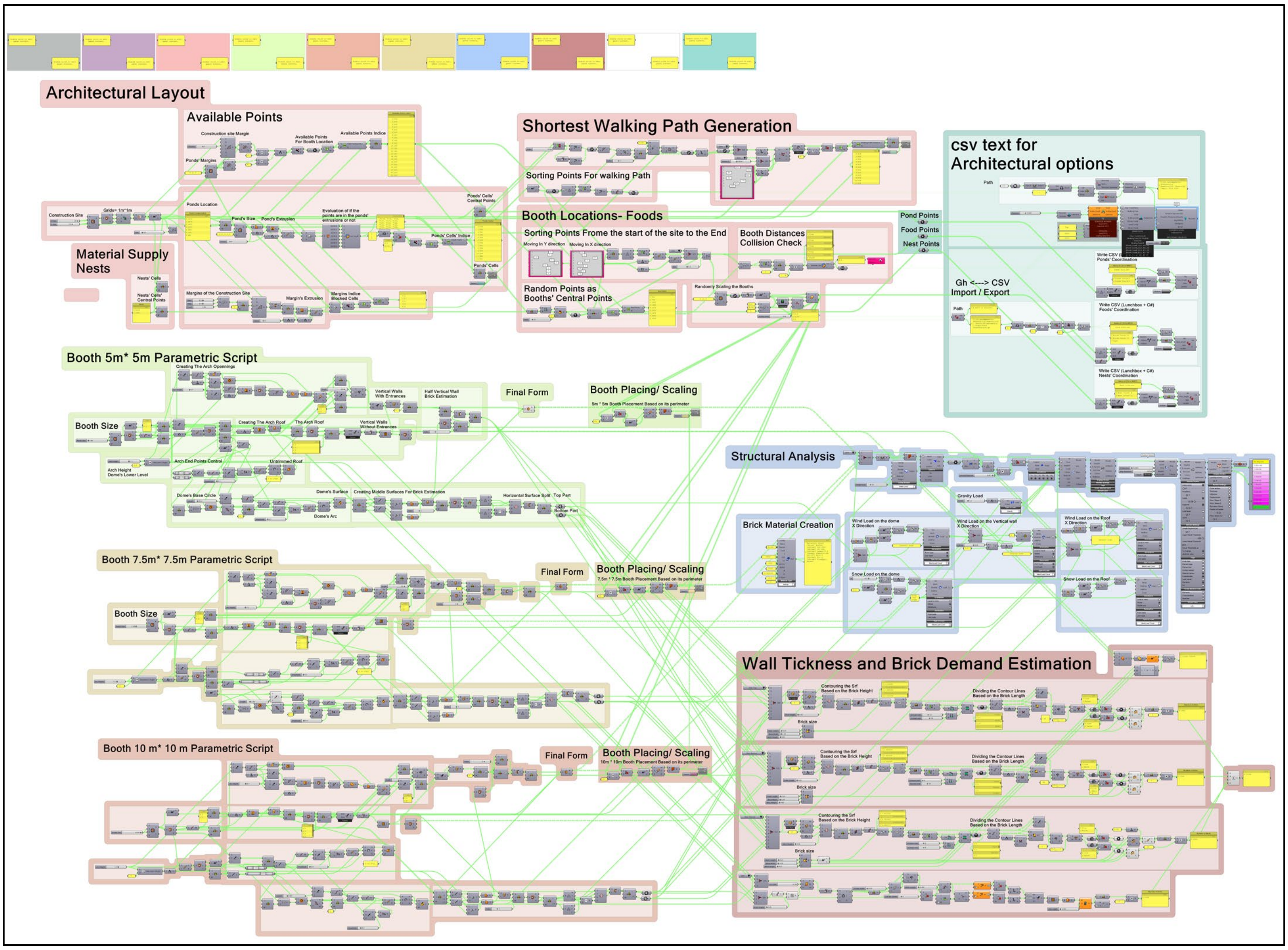
Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Sensors Distance	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1
Experiment 23	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.95	R1	464521.26	185.58
											R2	332996.61	141.92
											R3	384376.88	159.12
											Average	393964.92	162.21
											Standard Deviation		21.99305648
Experiment 24	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.96	R1	373650.17	116.38
											R2	477306.44	133.94
											R3	482941.51	135.12
											Average	444632.71	128.48
											Standard Deviation		10.4955038
Experiment 25	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.97	R1	510507.96	201.02
											R2	628775.82	241.06
											R3	692330.67	262.41
											Average	610538.15	234.83
											Standard Deviation		31.16556914
Experiment 18	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.98	R1	463093.26	186.16
											R2	352202.45	148.5
											R3	369394.81	154.23
											Average	394896.84	162.96
											Standard Deviation		20.29217173
Experiment 26	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.99	R1	367851.91	154.34
											R2	481790.5	192.08
											R3	546315.5	213.53
											Average	129255.36	186.65
											Standard Deviation		29.96627604

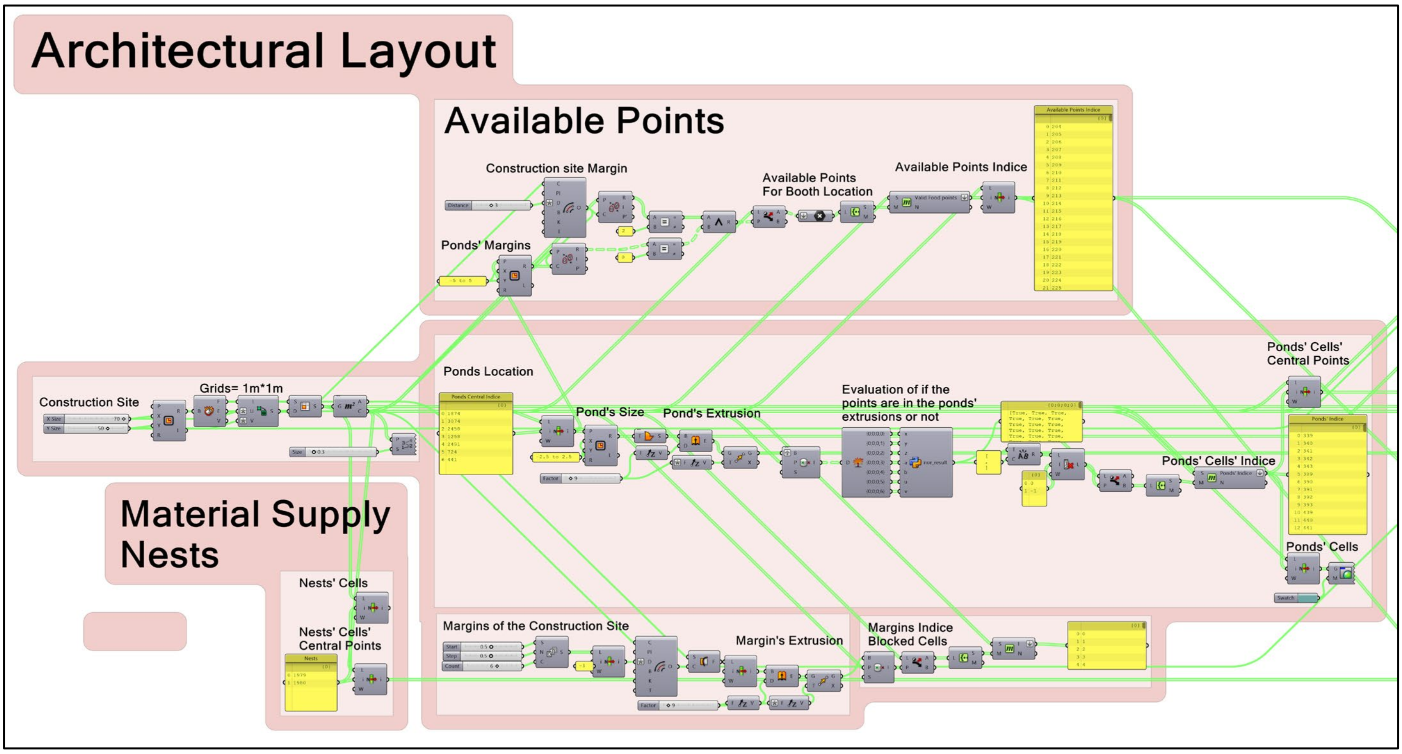
P4 Results

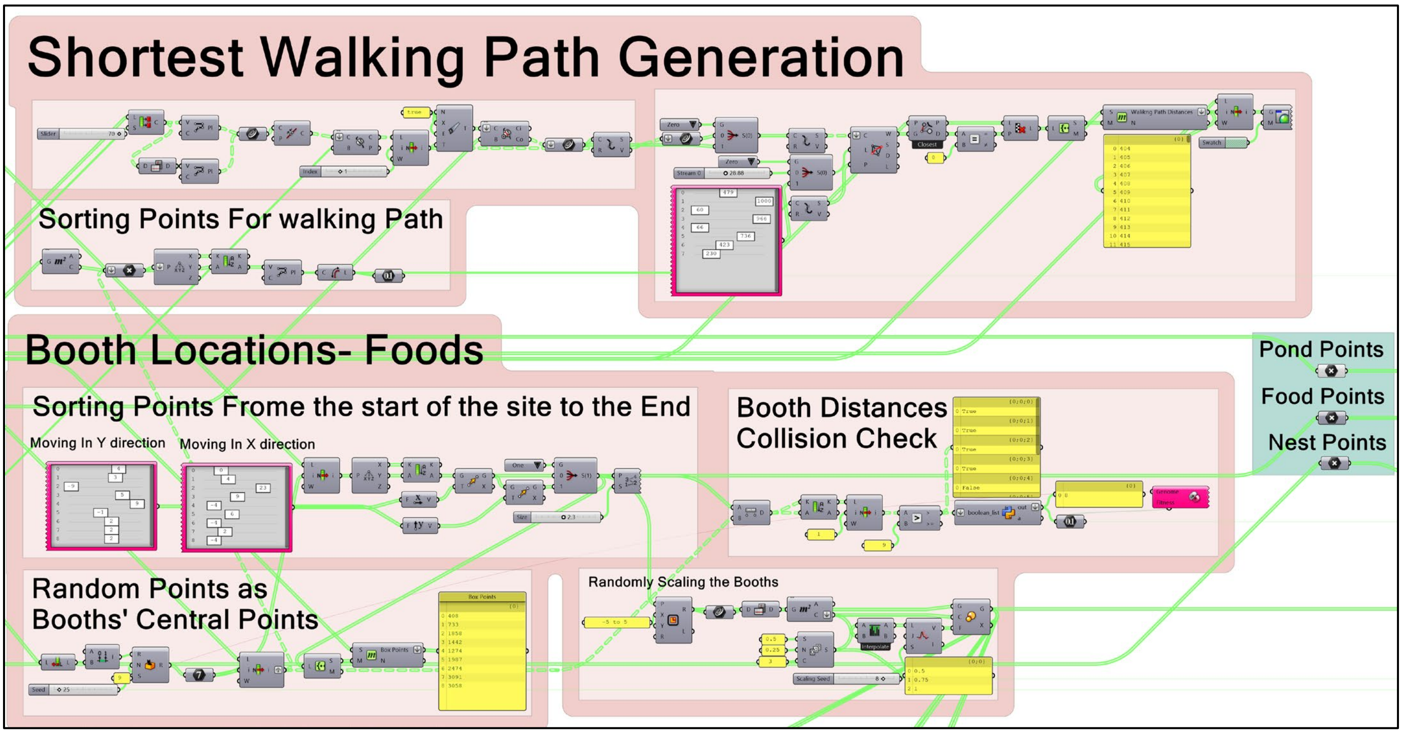
Sensor Detection Distance

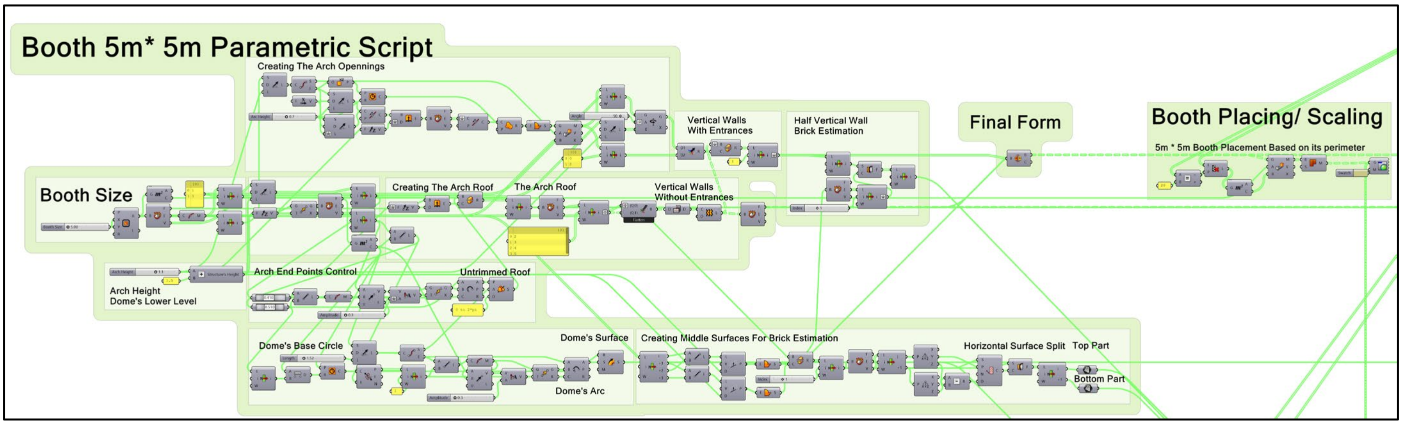
Parameters	Construction site	Number of Foods	Total Number of Bricks	Total Number of Travels	Number of Static Obstacles	Number of Dynamic Obstacles	Number of Nests	Number of Robots/ants	Sensors Distance	Evaporation Rate	Parameters	Total Walking Distance(m)-1	Construction Time(s)-1
Experiment 27	1400*1000	14	60,130	1718	7	14	2	30	10 pixels	0.96	R1	436605.99	176.40
											R2	464207.58	187.95
											R3	448831.91	181.21
											Average	449881.83	181.85
											Standard Deviation		5.801812935
Experiment 28	1400*1000	14	60,130	1718	7	14	2	30	15 pixels	0.96	R1	375390.65	156.26
											R2	636712.16	243.87
											R3	564304.68	219.23
											Average	525469.16	206.45
											Standard Deviation		45.18086357
Experiment 24	1400*1000	14	60,130	1718	7	14	2	30	20 pixels	0.96	R1	373650.17	116.38
											R2	477306.44	133.94
											R3	482941.51	135.12
											Average	444632.71	128.48
											Standard Deviation		10.4955038
Experiment 29	1400*1000	14	60,130	1718	7	14	2	30	25 pixels	0.96	R1	412096.42	169.85
											R2	396371.43	164.25
											R3	595302.61	233.32
											Average	467923.49	189.14
											Standard Deviation		38.36331972
Experiment 30	1400*1000	14	60,130	1718	7	14	2	30	30 pixels	0.96	R1	782007.50	295.97
											R2	426524.97	175.53
											R3	440098.49	179.6
											Average	549543.65	217.03
											Standard Deviation		68.39144123

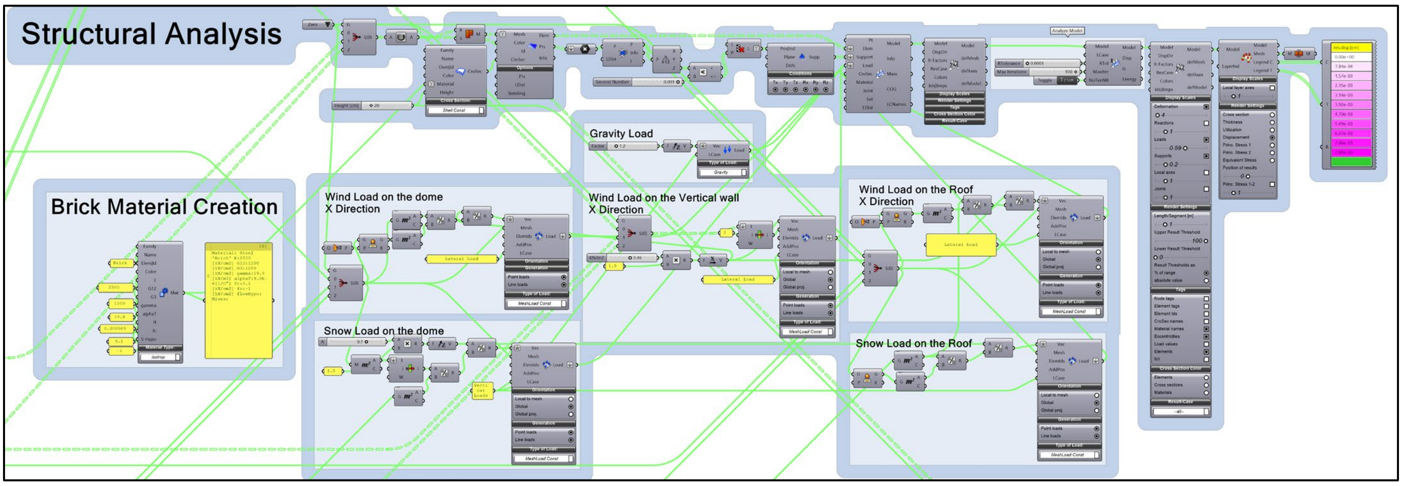
Grasshopper Code

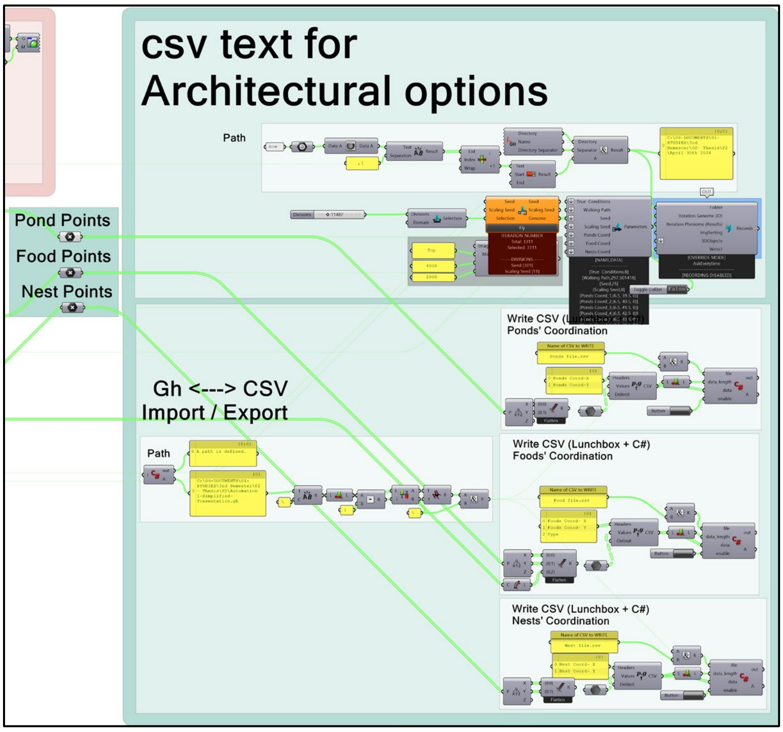


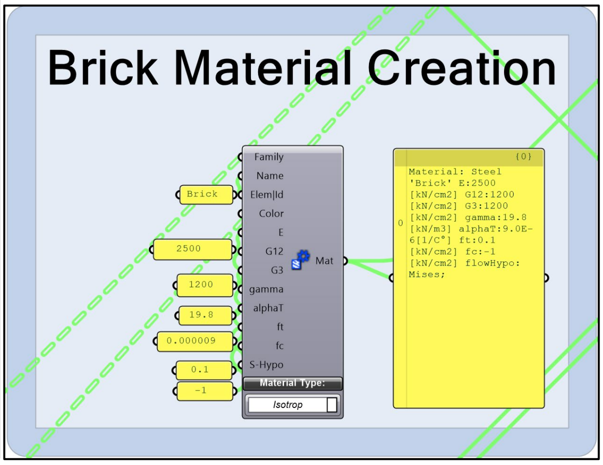


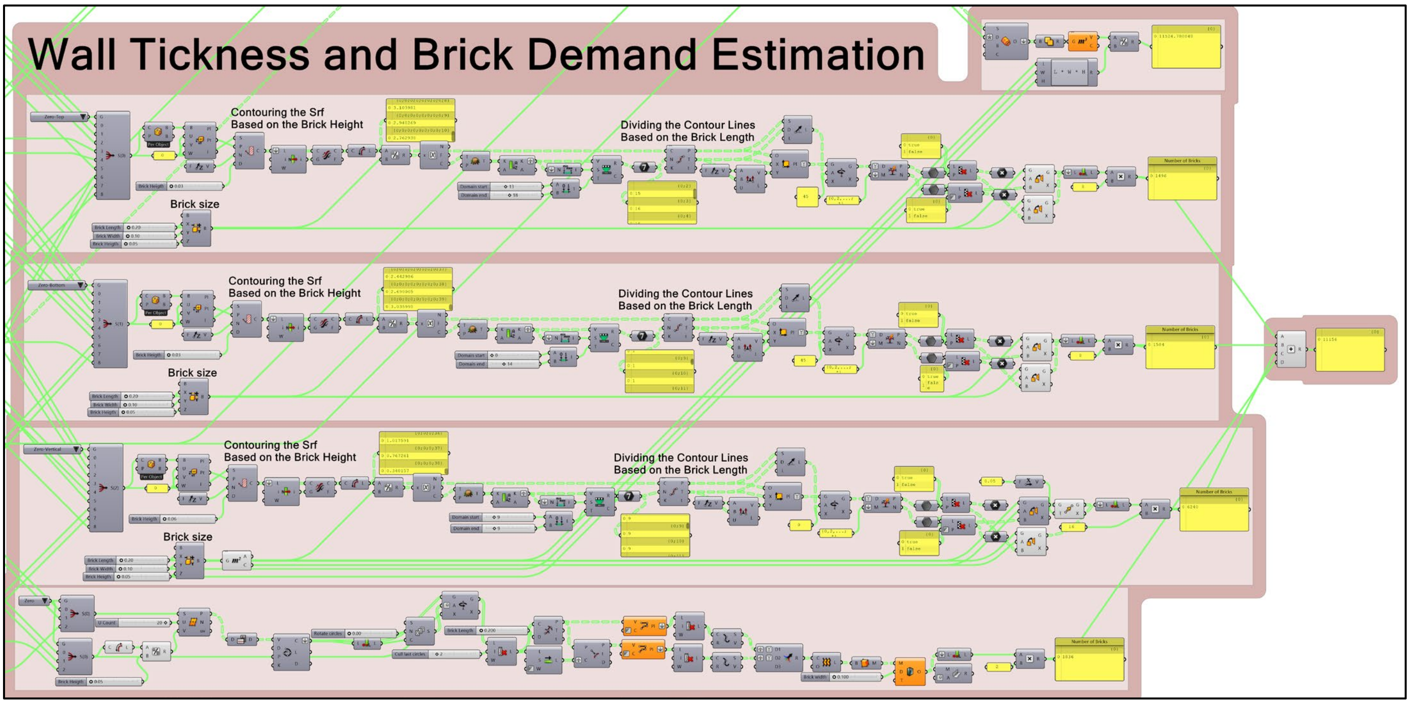

Shortest Walking Path Generation
Sorting Points For walking Path
Booth Locations- Foods
Pond Points
Food Points
Nest Points
Sorting Points Frome the start of the site to the End
Moving In Y direction
Moving In X direction
Booth Distances
Collision Check
Random Points as
Booths' Central Points
Randomly Scaling the Booths


Booth 5m* 5m Parametric Script
Creating The Arch Opennings
Vertical Walls
With Entrances
Half Vertical Wall
Brick Estimation
Final Form
Booth Placing/ Scaling
5m * 5m Booth Placement Based on its perimeter
Booth Size
Creating The Arch Roof
The Arch Roof
Vertical Walls
Without Entrances
Arch Height
Dome's Lower Level
Arch End Points Control
Untrimmed Roof
Dome's Base Circle
Dome's Surface
Creating Middle Surfaces For Brick Estimation
Horizontal Surface Split
Top Part
Bottom Part
Dome's Arc


Structural Analysis
Gravity Load
Brick Material Creation
Wind Load on the dome
X Direction
Wind Load on the Vertical wall
X Direction
Wind Load on the Roof
X Direction
Snow Load on the dome
Snow Load on the Roof


csv text for
Architectural options
Path
Pond Points
Food Points
Nest Points
Gh <---> CSV
Import / Export
Write CSV (L
Ponds' Coordination
Path
Write CSV (Lunchbox + C#)
Foods' Coordination
Write CSV (Lunchbox + C#)
Nests' Coordination


Brick Material Creation
Family
Name
Elem|Id
Color
E
G12
G3
gamma
alphaT
ft
fc
S-Hypo
Mat
Brick
2500
1200
19.8
0.000009
0.1
-1
Material Type:
Isotrop
Material: Steel
'Brick' E:2500
[kN/cm2] G12:1200
[kN/cm2] G3:1200
[kN/cm2] gamma:19.8
[kN/m3] alphaT:9.0E-6[1/C°] ft:0.1
[kN/cm2] fc:-1
[kN/cm2] flowHypo:
Mises;


Wall Tickness and Brick Demand Estimation
Contouring the Srf
Based on the Brick Height
Dividing the Contour Lines
Based on the Brick Length
Brick size
Contouring the Srf
Based on the Brick Height
Dividing the Contour Lines
Based on the Brick Length
Brick size
Contouring the Srf
Based on the Brick Height
Dividing the Contour Lines
Based on the Brick Length
Brick size