Self-organisation in Intralogistics

An Intuitive Modelling Approach to Study Emergent Behaviour

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primevision

Self-Organization in Intra-Logistics: An Intuitive Modelling Approach to Study Emergent Behaviour

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Preface

Culminating the journey at the Delft University of Technology, this thesis project has been the product of academic skills gained in the past two years and previous industrial work experience. My first gratitude is to my parents, for the person I am today.

I would like to express my sincere thanks to Prof.dr.ir. Lóri Tavasszy for being ever approachable, and for connecting me with Prime Vision for this exciting topic. My supervisors at TU Delft, Dr. Ron van Duin, and Ir. Mark Duinkerken, have been supportive throughout this journey and helped maintain structured progress with their constructive criticism and guidance. My utmost gratitude to them. I would like to express my appreciation to Prime Vision, for this wonderful opportunity, especially Bernd van Dijk and Diego Valdivia, for their confidence in me and the freedom provided to steer the project. This made my entire project duration a smooth voyage.

With most of my Master's program being shrouded by the ramifications of the pandemic, it would not have been possible to complete on time, without the support of my friends at Delft. Under the academic pressure and new-normal conditions, they were key to sound mental health. On that note, a special mention and gratitude to Mahesh, for all the venting sessions and late-night beers.

Finally, but most importantly, heartfelt gratitude for my wife, Harshini. The unwavering support from her and her parents fuelled me through my studies.

V. Chandrashekar
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Summary

Self-organisation has been referred to as, “creating order out of chaos” in multiple literatures and is being researched in various fields ranging from biology to astrophysics. Its application in logistics has seen accelerated development in the recent past, owing to the shifting pattern towards digitisation and automation. Globalisation, mass customisation, and shorter product life cycles being the key drivers, have led the industry and researchers to explore the potential of self-organisation to improve efficiency and robustness in different levels of logistics. Treading this path, Thymo Vlot’s thesis dealt with the development of an algorithm for self-organisation in last-mile logistics, enabling multi-modal transport and collaborative delivery, together with Prime Vision. Continuing the work, Diego Valdivia’s thesis synthesised the software architecture of the logistics planning system. This thesis project intends to investigate the potential contribution of decentralised material handling system in intra-logistics, considering its crucial position in the supply chain. The complex emergent behaviour of locally interacting agents, coupled with the lack of extensive operational studies have made quantifying, and generalising the efficiency and robustness of such systems challenging. This project approaches the topic by developing an intuitive, adaptable, and scalable simulation model to study the emergent behaviour of a system of self-organising robots for material transport in a self-contained company site. Here, intuitive refers to the ease of usage and understanding of the developed model, not only to the developer but also to aid the presentation to relevant stakeholders in the business. The model is intended to function as a support tool for strategic decision-making in the current case study and is adaptable to future business applications.

A self-contained company site such as a manufacturing facility, warehouse, or distribution centre has multiple associated logistics functions including transport, storage, and picking, packing, handling. The challenges for digital transformation have been the lack of digital culture, training, and a clear vision towards digital operations. This project’s focus is on introducing automation in vehicle-based in-house material transportation, by choosing a manufacturing facility as the case study. In the existing system, the components are transported from the central warehouse to different assembly stations using manually driven reach trucks and manual carts. Collating the orders from the assembly stations raised in the Warehouse Management System (WMS), a warehouse operator prepares a packing list to retrieve the materials from storage, pack, and dispatch in the vehicles. Certain urgent orders are catered in manual pushcarts. The current form of operation increases the manually travelled distance, thereby higher fatigue in the employees and resulting in order fulfilment time of around one day. The new system of self-organised robots is expected to reduce the manual transport activities and add robustness to the system, by adapting to the varying scenarios and reducing the order fulfilment time to the stations.

The key control strategy problems to be addressed for automation in an intra-logistics facility have been identified as load-vehicle assignment, empty vehicle management, routing, and deadlock avoidance. To design solving approaches to these problems, the principal functionalities of self-organisation, openness, intelligence, and decentralisation are used as the foundation. Multiple literatures suggest control strategies with varying degrees of decentralisation in decision making and information usage. Most of the approaches consider the load-vehicle assignment and empty vehicle management as a combined dispatching problem and propose multi-agent-based strategies including CNET protocol based on auctioning, emitted field-based assignment, feedback-based dispatching, forecast based dispatching, and more. The selection of a suitable approach is dependent on the variation of demand, size of the layout, and arrangement of different nodes. For the given case and the purpose of the study, Klein’s static dispatching for decentralised control has been chosen which is suitable for smaller layouts and high variation in demand. With a central warehouse and loading point, a central parking position is considered for the robots. Routing uses the information on global topology and the shortest path between the nodes is used during operation. Deadlock avoidance at the intersection, merges, and switches are governed by First Come First Serve (FCFS) and supported by onboard proximity sensors. The order for components raised by the assembly stations is attached with a task priority. These are collated and queued by the central platform on FCFS basis, but the higher priority task skipping to the front of the queue behind other high priority tasks in the queue. While most transport requests are from warehouse to stations, a small percentage of orders also move from station-station. A delay for order preparation is considered for orders with the warehouse as the source and the duration is lesser than the existing system due to the smaller size of the orders. The case at the front of the queue raises a transport request to the set of robots. Depending on their availability to accept a new task, the robots respond with the shortest distance to the loading point.

The nearest robot gets assigned to the case, where the case is loaded manually, to be transported to its destination. After every delivery, the robot has an internal check of the battery level before becoming available for the next task. If the battery level is critical or no tasks are available, the robots always return to the home position, if not the next assigned task.

Considering the dynamic and decentralised nature of the system, and the need for easy understanding and adaptability, a multi-method modelling approach has been used for implementation. Using Anylogic as the platform, the flow of the operations involved in the vehicle-based material transport is represented using a process-centric model (discrete event modelling) and the individual behaviour of the agents is represented using statecharts which is a part of agent-based modelling. Anylogic's attributes including an easy-to-use interface (UI and Java), material handling and process modelling libraries, 2D and 3D animations, and visualisation (performance indicators) have been the reasons for its choice. The existing operation has not been implemented in the simulation model and hence, a discussion on the calculated performance indicators for the existing operation and the generalised results of the simulation model has been done. A direct comparison would not be appropriate, given the difference in order consolidation, limitation on the load-carrying capacity of the robots, and other underlying assumptions.

For the new model to be effectively used in decision-making in business applications, it must provide insight on the system performance under different operating conditions, so that the involved stakeholders can take a call on its feasibility and investment. Although the economic perspective on the matter is not touched upon in this project, the model intends to answer questions on the efficiency and robustness of the system under different configurations and scenarios. From the experiments conducted on the simulation model, it is learned that the system can adapt to varying scenarios, such as high demands, skewed patterns, and breakdowns. For a given system design, a balance between desired robot utilisation and demand satisfaction under varying conditions can be achieved. However, there would be a compromise in the performance indicators such as the total distance travelled (directly related to energy consumption) and order fulfilment time in extreme conditions. Compared to the existing manual operation, this would still be a positive takeaway considering the reduction in manual effort and faster delivery. With the increase in the number of robots in the system, the throughput stabilises for a given rate of demand, but the orders are delivered faster. This factor helps in system design by finding a balance between acceptable service time and investment in robots. It is also to be noted that, although the decentralised operations provide flexibility, the suitability of a control strategy strongly depends on the configuration and scenario. During experimentation, point of release positioning served better for demands originating around the facility, while central positioning performs better when orders from warehouse to stations are higher. Incorporating the option to switch between the strategies and necessary infrastructure during implementation would provide better control over the adaptability of the system.

Based on the findings in this project, the conclusion is that the conceptualised system of self-organising robots, considering its current capabilities and constraints, would supplement the existing in-house material transport to improve robustness and reduce human fatigue. Factors such as the limit on the load-carrying capacity of the robots, expected changes in order placement, infrastructural changes required, and acceptance level of human-robot symbiotic work environment would be the challenges to overcome for a full transformation. However, introducing a fleet of robots to handle the logistics of small components and spares would reduce the manual movement, mainly the usage of pushcarts which are the key cause of fatigue. Reducing the order fulfilment time to a great extent, the robots would also be able to cater to skewed demands and urgent requirements. Multiple recommendations are made on method extension and improvements, implementation, and from a managerial perspective. A possible course of action to adapt and scale the model to other types of intra-logistics facilities has also been presented. This thesis is expected to contribute to science, society, and industry for a better tomorrow.

Most of the reviewed literature focus on a particular form of self-organisation varying in the extent of decentralisation or the control strategy problem addressed. There is a need for the development of more holistic research in self-organisation. The existing research papers although dwelling deeply into the concepts they address, lack in operational study and involvement of stakeholders, mainly the end-users of the technology. This research has attempted to cover these aspects by developing an intuitive platform to quickly and conveniently include the industry expectations and feedback in the research and evaluation. In business cases, this simulation model functions as a support tool for decision-makers even without in-depth knowledge on self-organisation, enabling them to get a prima facie impression on the performance of the system.

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1 Introduction

With changing times and newer challenges, Transport & Logistics (T&L) has been a part of the 'shifting pattern' as in the case of many other industries. New technology, new market entrants, new customer expectations and new business models have brought about both risk & opportunity in the field. Surviving through the tumultuous phase such as the pandemic, the push towards higher robustness and efficiency has taken precedence and in light of this, digitisation and automation have been experiencing greater importance. The key drivers influencing logistics, including the in-house logistical systems are (Schmidt et al., 2020):

- Globalisation of operations
- Mass customisation
- Shorter product life cycles

These drivers have led to increase in complexity and dynamics at an operational level. T&L sector is one in which around 90% of the experts ascribe for digital transformation in the next five years. However, this is still a challenge with the top reason being the lack of digital culture and training, followed by constraints in investment and a clear vision towards digital operations (PwC, 2016). Thus there is an immense potential for disruptive technologies, including the increased degree of automation.

As quoted by Thomas A. Edison, *"There's a way to do it better - find it"* (quoteresearch, 2018). This graduation project in MSc. Transport, Infrastructure & Logistics, focuses on exploring an intuitive approach to study the emergent behaviour of an intralogistics system working on the principles of self-organisation. To begin with, it would be worthwhile to introduce the key terminologies & concepts.

Intralogistics is an umbrella term referring to the organisation, control, execution and optimisation of internal material flow and logistics technologies, usually within self-contained company sites such as factories, warehouses or distribution centres (Fottner et al., 2021). Dealing with the in-house logistical challenges, it encapsulates a manual or automated material handling system to perform tasks at an operational level. Some typical tasks associated with this are storage systems, transport systems, sorting systems and more.

As discussed above, there is a push towards automation in the logistics domain. As defined by Fottner et al. (2021) *"autonomous intralogistics systems enable self-contained, decentralised planning, execution, control and optimisation of internal material and information flows through cooperation and interaction with other systems and with humans"*. **Self-organisation** is a terminology used in this context and can be best described with an analogy to social insects, like ants or bees, where every being acts towards a common goal based on certain instincts, but without central control. In a logistics system, this can be considered as functioning without significant intervention by managers, engineers or software control. Being a loosely defined term, the main functionalities of a Self-organising Logistics System (SoLS) can be specified as (Pan et al., 2017):

- Openness: Boundaries of the system are open for actors to enter and leave.
- Intelligence: Agents are capable of autonomous decision-making by collecting and processing information.
- Decentralised Control: Actions of every agent are based on contextual local interactions.

Depending on the system, environment and context, the degree to which each of these functionalities is applicable and thus the degree of automation varies. While in an ideal case the system is expected to self-organise towards optimality, the phenomenon may result in complex structures emerging from the behaviour and contextual local interactions between the agents (Bartholdi et al., 2010).

Various control strategies have been suggested in publications for decentralised architecture. However, the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents (Schmidt et al., 2020) and lack of extensive operational studies. The emergent behaviour may not always be desirable. Hence, different modelling paradigms, such as simulation modelling and building of digital twins are required to observe and analyse the system performance before proceeding towards implementation. With the lack of methods to implement decentralised system and choose the level of decentrality in real world, it is challenging to quantify and generalise efficiency and robustness of such systems (Schmidt et al., 2020). Hence, the development of an intuitive, adaptable and scalable method to study this is necessary.

1.1 Context & Problem Statement

The research in this graduation project is being conducted in cooperation with Prime Vision, a systems integrator in the global logistics market. As a project within the Innovations team, Prime Vision is exploring the possibilities with self-organisation at different levels of logistics. Previous projects have focused on developing methods for self-organisation in last-mile logistics and collaborative delivery.

In this project, the case is of intralogistics. A prominent manufacturer in the market, a client of Prime Vision, has an assembly facility with multiple assembly stations. The components necessary for assembly are transported from the stock room to the requested assembly stations by manually driven reach trucks or manual carts. The orders are first raised by each station in the Warehouse Management System (WMS), after which, the stockroom in charge consolidates and manually prepares the packing list before dispatching to the various requirement points. However, when there is an urgent or off-the-schedule request, the requirement is catered manually, outside the WMS. These requests are usually served by manual carts. The current system results in a high manually travelled distance, inaccuracy, labour intensive and also fatigue, considering the manual nature of the operation.

As a solution, stage-wise implementation of automation is being considered. Starting with the commissioning of a single robot with simple signalling to transport the components, Prime Vision wishes to implement a decentralised, self-organising system with multiple robots to carry out the logistics within the facility. This transformation is expected to improve the robustness and system performance. A decentralised system with multiple intelligent agents interacting with each other fits the definition of a multi-agent system. However, as mentioned in the previous section, the emergent behaviour of a decentralised multi-agent system is complex and needs to be analysed. This leads to the problem statement,

Develop an intuitive, adaptable and scalable model to study the emergent behaviour of a self-organising intralogistics system

Here, *intuitive* refers to the ease of usage and understanding of the developed model, not only to the developer but also to aid the presentation to relevant stakeholders in the business. While the research methodology is to be based on solid scientific underpinning, the results should be comprehensible by stakeholders from various backgrounds. The terms *adaptable* and *scalable* refer to the ease of customising the model to different use cases with varying configurations, sizes and scenarios.

1.2 Expectations & Objectives

In the context of the problem statement, the expectations of Prime Vision from the thesis project is explicitly mentioned below. These points have been put together based on an interview with Mr. Bernd van Dijk, Director Innovation at Prime Vision.

- Insight into the performance of the self-organised system of robots, as an alternative to the existing manual operation.
- Robustness of the new system for different demand conditions of the case under study. Here demand refers to the fluctuation in the components to be transported between different points within the facility.
- Recommendations on adaptability and scalability of the model for future projects.

To visualise the path of the project in line with the above expectations, the following objectives have been drawn:

- Conceptualise a system of robots with the defined level of self-organisation to replace the existing manual operation of material movement within the intralogistics facility.
- Develop a model to function as a Decision Support Tool for Prime Vision, with a capability to reconfigure demand, number of robots and other system parameters and record the performance indicators for further analysis.
- Conduct experiments and compare the performance indicators under different demand scenarios to study the robustness of the system of robots and also against the existing manual operation to obtain insight on system performance
- Recommend on the adaptability and scalability of the model for future projects of Prime Vision

1.3 Research Questions

Self-organisation in logistics (SoLS) is a relatively new and developing field of research. Although various literatures point to an increase in robustness in a decentralised system, the outcome in the real-world application is still unclear owing to complex multi-agent interaction and emergent characteristics. With this in mind and the expectations of the industry as mentioned in the previous section, this project has been set out to develop a model to simulate a self-organising intralogistics system in a real industry environment and analyse the same.

Towards science, this case study aims to shed more light on the system performance and robustness due to the emergent characteristics of a decentralised multi-agent system. To the industry, this project aims to develop an interactive approach to simulate the case and present the results to all stakeholders in an easy to understand manner and enable strategical decision-making. From a holistic perspective, the thesis expects to contribute towards the resilience of society.

With this aim, the main research question can be stated as:

Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?

The following sub research questions will guide in answering the main research question:

1. *What is the status quo of logistics operations and actors involved in a self-contained company site?*

   This sub-research question sets the stage of the intralogistics environment, introducing the actors involved and the current state of operations.

2. *What are the indicators that define system performance in an intralogistics operation?*

   To compare the system performance of the new system with robots operating on principles of self-organisation, it is necessary to define performance indicators. This question aims to define the appropriate performance indicators for the given intralogistics environment.

3. *How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?*

   Depending on the forms of decentralisation adopted, the level of automation varies and thus the solving approach for the control strategy problems. While building a model, it is required to define this framework and identify the suitable solving approach.

4. *What modelling technique would be the most suitable to study the emergent behaviour of the system?*

   To study the emergent behaviour of the multi-agent system a suitable technique has to be established for modelling as well as software implementation.

5. *For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?*

   While the model helps study the emergent performance of the multi-agent system, it is also a necessity to use the results to support decision making for implementation in business applications by understanding the scale, number of required robots and balance between performance indicators. Apart from answering the questions for the chosen case study, the model must be adaptable for future projects too. This sub-research question serves this purpose.

1.4 Scope

In an intralogistics environment like the assembly facility considered in this project, there are numerous operations happening simultaneously, including transportation, storage, retrieval and sorting. The material movement occurs within the facility as well as with external stakeholders. The focus of this project is material transportation from the stockroom/warehouse to the different assembly stations which can be considered as internal customers. The look-ahead being the automation of the material transportation, the segment under consideration is the dispatch point in the stockroom to the delivery point at multiple assembly stations. This process has the involvement of multiple control strategy problems and the influence of decentralisation on these is the scope of the study. The material movement to and from the facility, storage and retrieval lies outside the scope of this study.

1.5 Methodology

The system under consideration is dynamic and consists of multiple agents which are expected to possess a certain degree of autonomy to perform tasks and make their own decisions. Although the decisions are based on a set of protocols, the emergent behaviour of every system can vary depending on the characteristics such as scale, environment and more (Fottner et al., 2021). Given the dynamic and decentralised nature of the multi-agent system, simulation modelling would be a suitable approach which has been further elaborated in Chapter 5. To answer the research questions mentioned in the previous section, the case study of the Assembly Facility (client of Prime Vision) will be used as a test-bed in this project.

Simulation can be described as "*The process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behaviour of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system.*" (Shannon, 1975) Simulation models do not generate the alternatives or provide optimum, solution, but helps evaluate the performance of the alternative, the human interaction is not allowed at intermediate stages of the model computations. These models are inductive in nature(Maknoon, 2017). A simulation model is often referred to as a structural model and is developed for a specific purpose. Based on the logical and causal relationships occurring in the system, multiple iterations are involved before arriving at a valid model. Sargent, 2015 ((Sargent, 2015) suggests a Simplified View of Model Development Process, presenting a graphical paradigm for model development. The presentation of steps for the development of Simulation Model by University of Houston, based on the book *Simulation with Arena* (Kelton, 1998) has also supplemented the understanding. Based on these frameworks, adaptation has been done to formulate the methodology for this project. The overview of this methodology is mentioned below.

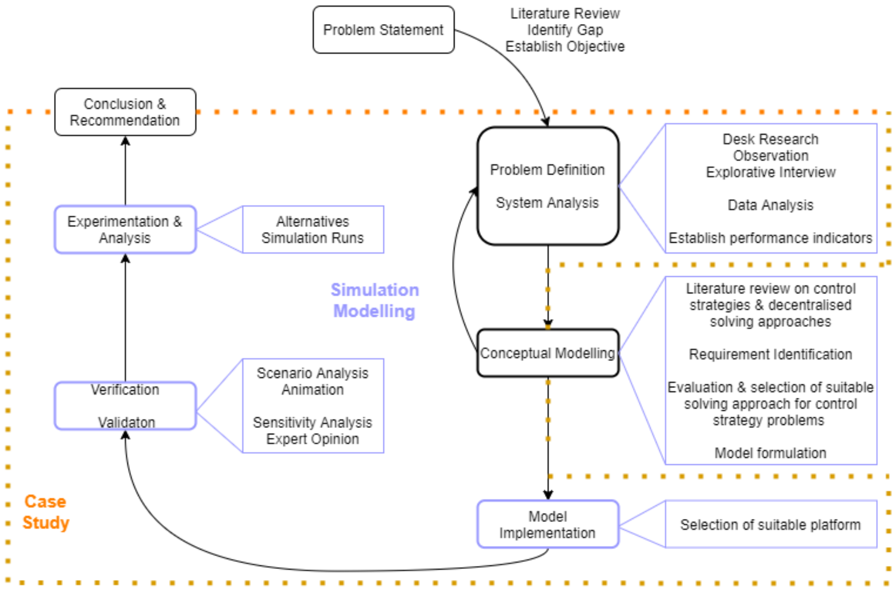


Figure 1: Overview of Methodology in this project, adapted from (Kelton, 1998; Sargent, 2015; UH)

The trigger and the motivation for the project is the *problem statement* from Prime Vision to study the emergent behaviour of self-organisation in an intralogistics system. Using this as the base, the goals of the study are defined with a scientific underpinning supported by an extensive *literature review* to identify the research gap. These objectives have been broken down into milestones to fit within the feasible duration of the project.

Problem Definition & System Analysis
As discussed before, a simulation model is built for a specific purpose and enable the evaluation of alternative. Hence before building the model, it is key to identify the objectives. Based on the interview with the key stakeholder, Prime Vision, the initial objective have been set as mentioned in section 1.2. A deeper dive into this is done in the phase of *Problem Definition & System Analysis*. To build a simulation model, it is necessary to define the system under consideration. This involves defining actors involved, processes involved, variables to consider and establishing performance indicators. This step, augmented by desk research allows establishing the nature of the data to be collected or gathered. The system analysis and data collection is an iterative process to establish closeness to reality. Data collection for analysis is mainly through explorative interviews with the robotics team members within Prime Vision and the head of warehouse at the Assembly Facility. Regular follow-ups and observation at the facility are done during the process of model building to better understand the 'as-is' state and establish the performance indicators. The data obtained from the relevant stakeholders is volume-intensive and raw. Data Analysis is done to clean and summarise the raw data to extract a usable form in the upcoming stages.

Conceptual Modelling
The next key stage is to *formulate the model* by understanding the behaviour of the desired system and determining the basic requirements. Through literature review, different decentralised solving approaches for the control strategy problems are evaluated, to select the suitable form for implementation in the chosen intralogistics environment. Appropriate visual representation, such as the Swim-lane flowcharts are created to explain the agents and the interactions involved in the system. Certain acceptable assumptions and simplification have to be made in order to facilitate the simulation. Using literature review and the characteristics of the system involved, it is also essential to establish a suitable simulation paradigm at the operational level.

Model Implementation
After this, is the building of the model itself in a suitable platform. The criteria for deciding the software is based on the intuitiveness of usage for the end-user and a GUI based platform. The platform should

be plausibly adaptable and scalable for future projects and cases.

Verification & Validation

The built simulation model has to be verified and validated. *Verification* is done through scenario analysis and animation to ensure correct representation. The input data and parameters are modified to check the output against expectation. This step ensures the correctness of the translation of the conceptualised method into the model. *Validation* is the model's conformity to reality. This is obtained through sensitivity analysis and expert opinion.

Experimentation & Analysis

This phase is conducted as per the established experimental plan with various alternatives and multiple simulation runs. Along with statistical analysis of the performance indicators for various configurations and scenarios, a comparison of the results with respect to the 'as-is' scenarios is also done. The objective of this stage is to compare the performance indicators under different demand scenarios to study the robustness of the system of robots and also against the existing manual operation to obtain insight on system performance.

Conclusion & Recommendations

Finally, the results and interpretations will be used to arrive at a conclusion attending to the initial problem statement. Recommendations regarding the usage of the model for decision-making, guidelines for adaptability and scalability are mentioned.

The methodology explained above is used to answer the sub-research questions along the way to present the solution to the main research question. The different methods corresponding to answer them are mentioned in the table below:

Table 1: Research Questions - Methods

(Sub) Research Questions	Methodology
What is the status quo of logistics operations and actors involved in a self-contained company site?	**Problem Definition & System Analysis**: Desk research, Observation, Explorative interview, Data analysis, Establish performance indicators
What are the indicators that define system performance in an intralogistics operation?	
How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies? What modelling technique would be the most suitable to study the emergent behaviour of the system?	**Conceptual Modeling**: Literature review on control strategies & decentralized solving approaches, Requirement identification, Evaluation & selection of suitable solving approach for control strategy problems, Choosing suitable modelling approach, Model formulation
For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?	**Model Implementation:** Selection of suitable platform **Verification & Validation:** Scenario analysis, Animation Sensitivity analysis, Expert opinion **Experimentation & Analysis:** Alternatives, Simulation runs
Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?	**Conclusion & Recommendation**

1.6 Relevance

This project aims to contribute both in the scientific and societal realms. A significant segment involves studying and choosing from the multiple decentralised solving approaches that have been published, which can be implemented for the chosen intralogistics environment. The output of the project aims to provide a platform to simulate and compare the different configurations of the automation. While this provides an insight into the co-relation between the scale of the system, level of decentralisation and the performance of the system, the industry benefits from the resulting system design needed for strategic business decisions.

From a societal perspective, the project is a step forward towards building resilience. With scenarios such as the pandemic creating a volatile environment in the demand and supply, shift towards increasing robustness to handle the variations is the key. Self-organising systems aid in this, by incorporating flexibility and smartness. The results of this project aim to facilitate this.

1.7 Stakeholder Expectations

This thesis project is a part of the program MSc. Transport, Infrastructure & Logistics being done in collaboration with industry. Hence three parties, namely, the student, university and industry are the major stakeholders and it is essential to manage the expectations judiciously. In view of this, the below figure presents the overview of *Stakeholder Expectations*.

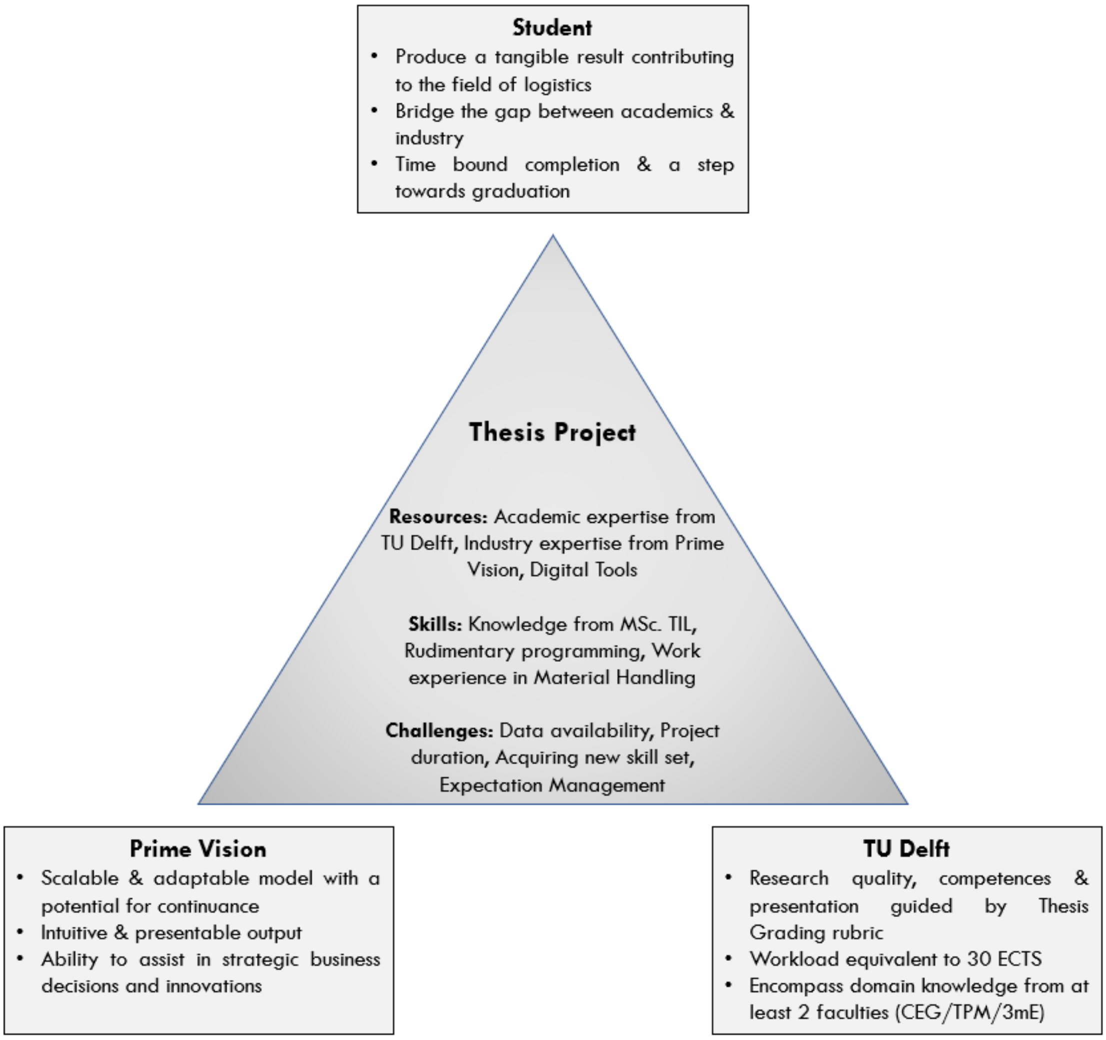


Figure 2: Stakeholder Expectations

1.8 Thesis Outline

The thesis report starts with *Chapter 1: Introduction* defining the context, research questions and the methodology. The next section, *Chapter 2: Intralogistics* dwells deeper into the logistics operations in a self-contained company site, the state-of-art and the actors involved. *Chapter 3: System Analysis of Existing In-house Material Transport* introduces the case study, the system parameters, along with the establishing of performance indicators. In *Chapter 4: Self-organisation & Control Strategies*, the control strategy problems and the decentralised solving approaches are addressed to achieve the desired level of automation and define a framework to specify the degree of automation, which are later used to build the model as explained in *Chapter 5: Conceptual Model of New In-house Material Transport.* The objective of *Chapter 6: Model Implementation* is to justify the modelling technique and describe the process of implementation in the software. *Chapter 7: Experimentation* describes the experimental plan and the results of running the model with different configurations and scenarios. Finally, *Chapter 8: Conclusions & Recommendations* addresses the emergent behaviour of the system by comparing different scenarios, configurations and also against the current manual operation. This chapter also discusses the limitations, recommendations and scope for future work.

The table below outlines the research questions addressed by each chapter.

Table 2: Research Questions - Report Chapters

(Sub) Research Questions	Report Chapters
Introduction	Chapter 1: Introduction
What is the status quo of logistics operations and actors involved in a self-contained company site? What are the indicators that define system performance in an intralogistics operation?	Chapter 2: Intralogistics Chapter 3: System Analysis of Existing In-house Material Transport
How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies? What modelling technique would be the most suitable to study the emergent behaviour of the system?	Chapter 4: Self-organisation & Control Strategies Chapter 5: Conceptual Model of New In-house Material Transport
For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?	Chapter 6: Model Implementation Chapter 7: Experimentation
Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?	**Chapter 8: Conclusions & Recommendations**

2 Intralogistics

The aim of this chapter is to set the context of the system and type of operations under focus. Before introducing the new system of robots in an intralogistics environment, the state-of-art, desired features and the need for automation are explained. Later, the key stakeholders in an in-house transport system are presented in light of this project. This is the first phase of this project and its position in the overall methodology is shown below (Figure 3).

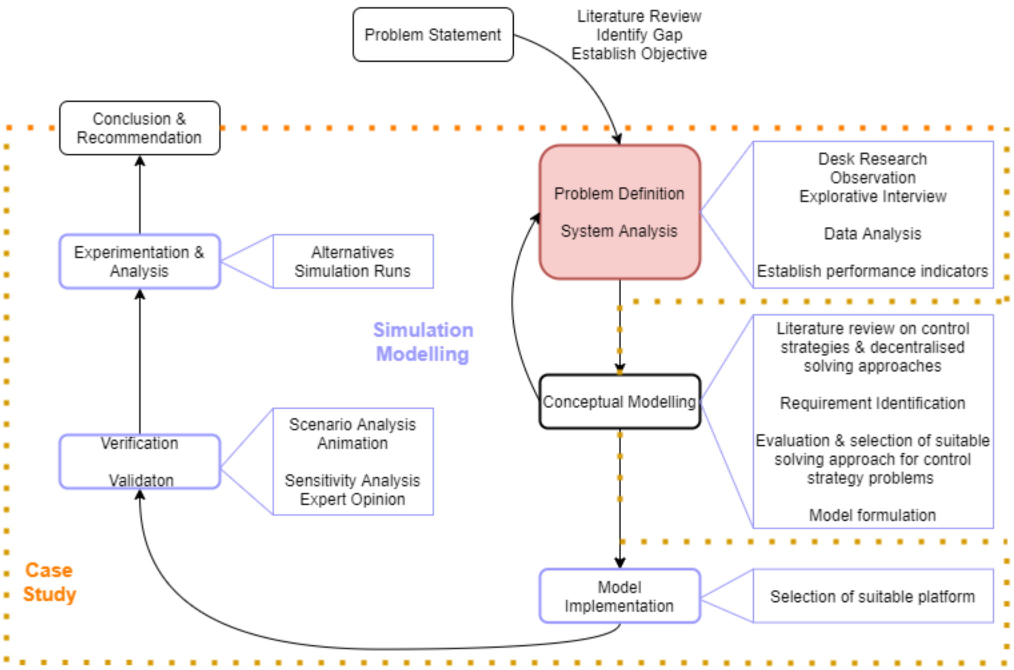


Figure 3: Phase: Problem Definition, adapted from (Kelton, 1998; Sargent, 2015; UH)

2.1 Intralogistics, Basic Functions & Evolution

Intralogistics is an umbrella term referring to the organisation, control, execution and optimisation of internal material flow and logistics technologies, usually within self-contained company sites such as factories, warehouses or distribution centres (Fottner et al., 2021). Dealing with the in-house logistical challenges, it en-capsules manual or automated material handling systems to perform tasks at the operational level. Some typical tasks associated with this are storage systems, transport systems, sorting systems and more.

The push for intralogistics stems from the post-war economic and industrial development when manufacturing was the key driver. Starting with equipment such as bag carts, trolleys and overhead cranes, the standardisation of pallets opened up a whole new avenue of developments, including, forklifts and stacker cranes. With the increase in global demand and consequently the production, growth in storage and distribution technology became inevitable. However, this was also accompanied by escalating labour and material cost (Kartnig et al., 2012). This was countered by the research and incorporation of automation in the field of intralogistics. Automated Guided Vehicles, Automated Storage and Retrieval Systems, and more microprocessor-based technologies entered the stage and have been in continuous development ever since. Explosive globalisation necessitated the merging of supply chains across the world and intralogistics has been an integral part of it. The dynamics and complexity of the systems have been increasing with the goal to have more robust configurations.

Basic Functions

A self-contained company site such as a manufacturing facility, warehouse or distribution centre is actively connected to the supply chain enabling the inflow and outflow of materials to and from the facility. The focus here is the in-house material flow and logistics which are enabled by certain basic functions as mentioned in Figure 4 depending on the nature of the facility.

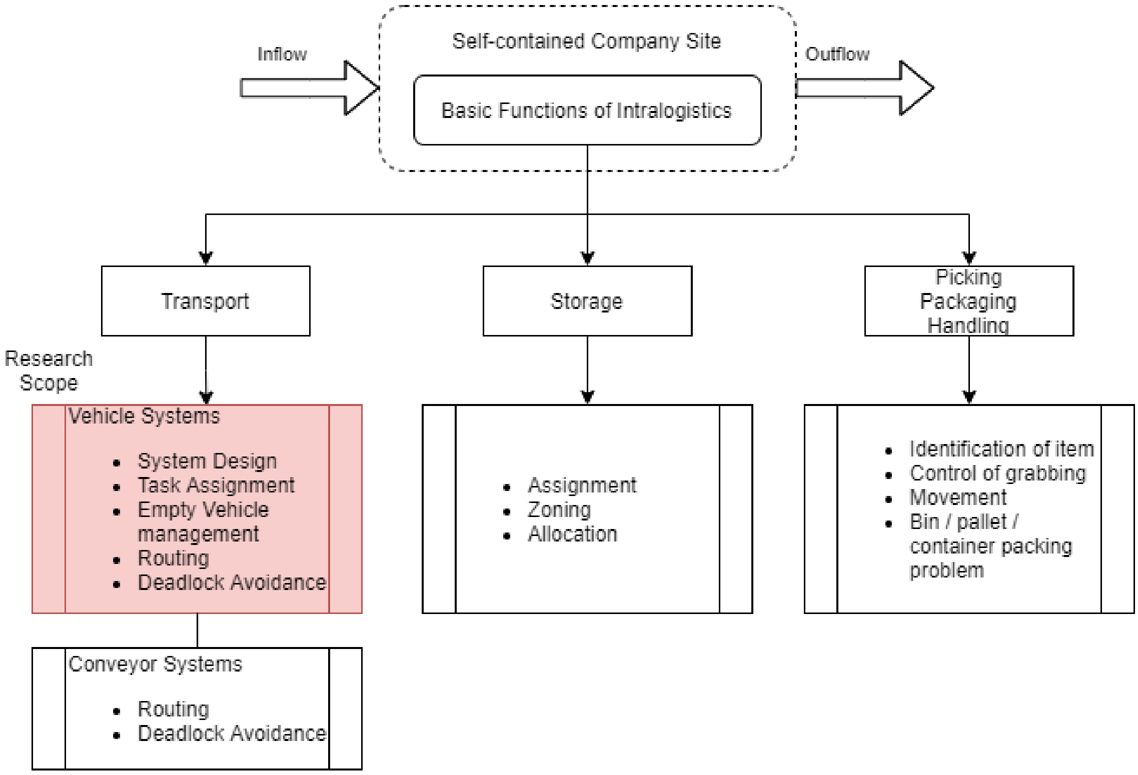


Figure 4: Basic Functions of Intralogistics, adapted from (Fottner et al., 2021)

As depicted above, the key functions of intralogistics are segregated into *Transport, Storage and Picking, Packing, Handling.*

Depending on the nature of the facility, the proportion of these functions vary. In the case of this project, the focus is on a manufacturing facility with assembly stations and a central stockroom or warehouse which stores the components needed for manufacturing. Based on the request raised by the assembly stations, the components need to be transported to the destinations. Also, being a systems integrator, Prime Vision is keen on the implementation of a self-organising system of robots in such a facility. In this context, we concentrate on the Transport function, particularly the Vehicle System in this thesis.

The approach towards Vehicle System involves addressing the control strategy problems to understand and build its functioning. These are:

- System Design (number of vehicles in system)
- Task Assignment (assigning vehicle to task or task to vehicle)
- Empty Vehicle Management (behaviour of vehicles without an active task)
- Routing (route to be taken to the destination)
- Deadlock Avoidance (avoiding obstacles including other vehicles)

The functions of intralogistics mentioned in the above section are simplified and general. The detailed system analysis is presented in Chapter 3. Further, the above control strategies and appropriate solving approaches are discussed in Chapter 4.

Evolution & Challenges

The importance of the logistics industry and its impact on society has been continuously growing. The counter effect is also existent, where the logistics world is continuously influenced by the evolving societal needs and newer challenges. Globalisation, Mass Customisation and Shorter Product Life Cycles are the key drivers that have been influencing the logistics world, including in-house logistics (Schmidt et al., 2020). The challenges brought about by the pandemic have accelerated the 'shifting pattern' in Transport & Logistics (T&L), with the push towards higher robustness and efficiency taking precedence. This has paved the way for the spike in digitisation & automation.

To adapt to the evolving conditions, the logistics system at different levels are desired to have the following specifications (Furmans et al., 2011; Klein, 2013):

- Flexibility (eg. modular design)
- Reconfigurability
- High Availability
- Plug & Play Configurability (standardisation of interfaces and communication)
- Scalability
- Re-usability
- Adaptivity
- Energy-efficiency and resource-efficiency

In view of the above features, a manual or a semi-automated system would be preferred in view of the high degree of freedom regarding changeability. A central controller would present resistance to flexibility and adaptivity in the case of a dynamic and growing environment. Some disadvantages of such a centralised structure are:

- Higher efforts for modifications
- Limited flexibility
- Test efforts for updating procedures is high
- Expensive hot or warm standby systems as they have a single point of failure
- Manufacturer restrictions on hardware

As mentioned by (Kartnig et al., 2012), the major challenges in the growth of intralogistics will be Green Logistics, Internet of Things and Cellular Technology (Decentralisation). A key approach towards these challenges is transformation from a centralised, hierarchical organisation principles and structures to a dynamic, networked, autonomous system cooperative based on contextual interactions optimising themselves to a dynamic environment(Fottner et al., 2021).

2.2 Actors Involved

An intralogistics facility involves interactions among various internal and external stakeholders. However, there is usually no comprehensive and generally accepted list available (Crostack and Mathis, 2008), as the actors involved depend on the type of facility, for example, warehouse, manufacturing facility, etc, the type of activities and also the equipment used within. Excluding the major external stakeholders such as the suppliers and customers, certain key actors necessary for the functioning of an intralogistics facility can be categorised as mentioned in Figure 5. These actors are the internal customers for each other as they are co-dependent on either product or service provided by the other and have their own interests (Crostack et al., 2008).

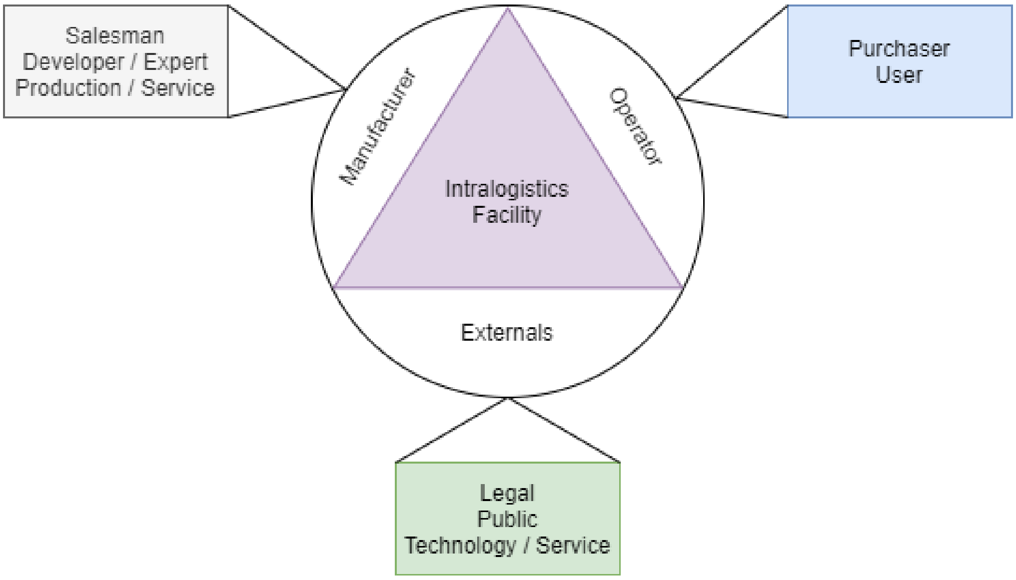


Figure 5: Actors in Intralogistics, adapted from (Crostack et al., 2008)

The stakeholders in an intralogistics facility can be broadly categorised into - manufacturer, operator and externals. Here, manufacturer refers to all the stakeholders are linked to the processing or assembly of the product which directly contributes to the revenue of the facility. The stakeholders in the operator category are responsible for the day to day operations supporting the manufacturing. This includes quality management, maintenance, in-house transportation and more. The externals are mainly the stakeholders who are consulted or services are availed to take care of aspects such as legal, environmental, governmental and technology services to augment the functioning of the facility.

Based on the type of facility under focus in this project, the major actors identified are as follows:

- Assembly Station Operators (Manufacturer - Production / Service)
- Warehouse Operators (Operator - User)
- In-house Transportation Operators (Operator - User)
- Head of Warehouse (Operator - User Management)
- Technology Developers (External - Technology / Service)

The roles, responsibilities and interests of each of the actors have been described below based on the Interview with the Head of Warehouse (personal communication dt. 19 March 2021, Appendix A.2) and the framework of stakeholders in intralogistics described in (Crostack et al., 2008) & (Crostack and Mathis, 2008).

2.2.1 Assembly Station Operators

The assembly station operators are responsible for the manufacturing or assembly at their respective stations. In coordination with the Head of Assembly, they place orders for components to be supplied from the warehouse. These orders may be a schedule for future consumption or required urgently for immediate requirement. Depending on the lead time of the components, the operators need to plan the order placement of the components required. This leads to the consolidation of requirements over a period of time and raising an order. In the case of the facility under consideration, the orders are raised in the Warehouse Management System (WMS). This is a centralised platform that collates orders from all the assembly stations to be catered to from the warehouse.

The primary interest of this stakeholder is to receive the required components on time and in sufficient quantity. This depends on the planning capabilities of the operators in collaboration with the Head of Assembly. However, the constraint faced by these actors includes the availability of the required components in the warehouse, the efficiency of in-house transport operation and the efficiency of operation of warehouse staff.

2.2.2 Warehouse Operators

The warehouse operators refer to the employees at the warehouse who are an interface between the reception of material from external stakeholders and dispatching them to the respective consumption points within the facility. In collaboration with the Head of the Warehouse, these actors forecast the demand for various components based on the consumption pattern and requests, while being responsible for the stock levels. The employees in this category also plan the dispatch of components based on the requests raised in the WMS. Collating the orders, preparing a packing list and raising a transportation request is a part of the activities performed.

The interest of this actor category is efficient order management. The more the volume of orders received, the higher is the workload. Major constraints for the warehouse operators are the availability of the required components in the warehouse, the capacity of the in-house transport vehicles and the number of vehicles available.

2.2.3 In-house Transportation Operators

The employees dedicated to transportation and the activities performed by them are a key focus in this project. They are primarily responsible for the transportation, storage, picking and all other material handling activities within the intralogistics facility. The material movement from the reception area (area receiving material from external stakeholders) to storage, retrieval from storage for order preparation and transportation to the assembly stations are the responsibility of this stakeholder. Depending on the size and priority of the orders, the mode of transportation used varies. While for large volume or weight of orders (in pallets), a motorised vehicle such as a reach truck or forklift is used, for smaller as well as urgent orders, manual carts are used. The usage of a manual cart results in increased physical manual activity causing fatigue. The management of these employees, their duties and protection of interest is usually taken care of by the Head of Warehouse.

The key interest of the transportation employees is the reduction of the total distance travelled and the reduction in the fatigue caused by manual operations. The main constraint faced is the arrival of urgent tasks to be transported manually and the availability of transport vehicles.

2.2.4 Head of Warehouse

The Head of Warehouse is a key stakeholder and the representative of the intralogistics facility for the purpose of discussions in this project. The responsibilities of the role include optimisation and day to day management of the critical functions including transportation, storage, picking and other material handling activities. Planning of activities as well as human resource management falls under the tasks of this stakeholder. The warehouse operators and the in-house transportation operators report to the Head of Warehouse. There is close collaboration and planning with the management of the manufacturing team for tactical and strategic level planning. The Key Performance Indicators (KPIs) of the warehouse are tracked by the Head of Warehouse to analyse performance and implement steps to optimise the operations and reduce the bottlenecks. Being the link to the higher management, planning operational level activities to implement broader level objectives are key to this role.

The primary interests of this stakeholder are to ensure sufficiency in throughput and aim to increase it, reduce the lead time of component delivery to the assembly stations, balance the workload of the resources available including humans and vehicles, ensure an acceptable level of fatigue due to manual operations of transportation and aim to reduce it. The balance between increased operational performance and protecting the interests of the warehouse employees with the constraint of available resources is a challenge for the Head of Warehouse.

2.2.5 Technology Developers

The final actor discussed is the Technology Developer who is external to the intralogistics facility and in this context, Prime Vision. Being a systems integrator in the parcel logistics sector, Prime Vision is expanding the boundaries beyond optical character recognition and parcel sorting technologies. The aim of Prime Vision in this project is to explore the possibility of a self-organised system of robots in an intralogistics environment that can contribute to the robustness of operation and reduction in fatigue due to manual operations.

Prime Vision is a co-initiator for this thesis project. Starting with the commissioning of a single robot with simple signalling to transport the components, the lookahead is towards a decentralised, self-organising system with multiple robots to carry out the logistics within the facility. The context and objectives of Prime Vision are explained in detail in Section 1.1 & 1.2.

2.2.6 Actor Relations & Interactions

Figure 6 depicts the relation between the actors explained above, the interactions and transportation in the system. The operation is generally triggered by the request for the components from the assembly station operators which are prepared and dispatched by the warehouse operators. The focus of this project is mainly on the operations performed by the in-house transportation operators and mainly the vehicle transportation functions. A self-organised system of robots is being considered to replace a part of these operations to reduce the fatigue due to manual transport activities within the intralogistics facility.

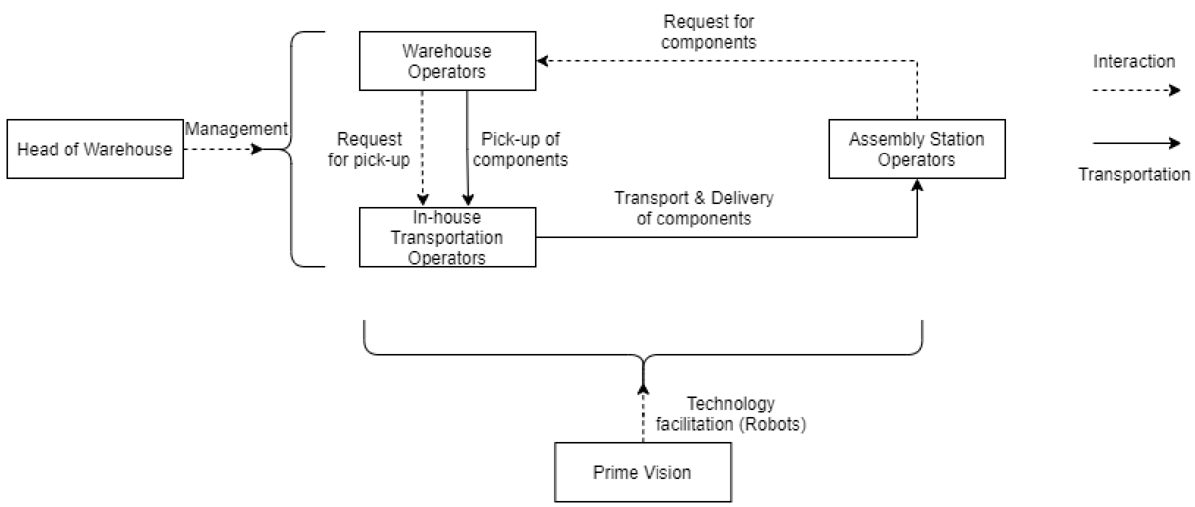


Figure 6: Actor Interactions

2.3 Summary

The intent of this chapter has been to introduce the intralogistics system, functions and actors involved. This section is in view of the first sub-research question, *"What is the status quo of logistics operations and actors involved in a self-contained company site?"*. This question has been partly addressed by introducing the concept of intralogistics and describing the basic functions involved in a self-contained company site. Providing this overview, the focus of this project and the relevant functions are also listed. As explained, this thesis deals with the in-house transportation function using vehicles which requires developing solving approaches to address the control strategy problems. System design, task assignment, empty vehicle management, routing and deadlock avoidance are important control strategies identified which are explained in detail in Chapter 4. Further, the evolution in intralogistics and the desired features have been presented.

The next major section of this chapter provides an overview of the actors involved in an intralogistics facility. Although it is challenging to list a generalised set of actors in an intralogistics facility, the closest categories of stakeholders has been presented. Using this structure, the key actors in a manufacturing facility have been elaborated with their responsibilities, interests and constraints. While the assembly station operators usually trigger the material transportation by raising a request in the WMS, the warehouse operators are responsible for catering to this as well as stock planning in the warehouse. The main focus of this project is on the functions performed by the in-house transportation operators, to reduce the manual transportation activities and thereby fatigue. This project also intends to analyse the robustness contributed by the new self-organised system of robots to the existing operations by measuring the KPIs such as total distance travelled, lead time and resource utilisation. These factors fall under the interests of the Head of Warehouse who is responsible for the optimisation of in-house transportation and also protecting the interests of related employees. Prime Vision envisages catering to this with the self-organised system of robots.

Chapter 3 supplements this chapter in completing the picture to answer the first sub-research question. The next chapter analyses in detail, the intralogistics system under study using the data obtained from scanned transactions of in-house transportation activities.

3 System Analysis of Existing In-house Material Transport

In the previous chapter, a general introduction to the intralogistics system, basic functions and actors were introduced. This chapter focuses on the case study that is being dealt with in this project and its analysis. This chapter starts with the introduction to the existing state of operations in the intralogistics facility and its key characteristics. Diving deeper into the data collected from the facility, demand patterns and performance indicators are established. With this, the need for an innovative transformation in the system is discussed. In conjunction with the previous chapter, the aim is to complete the answer for the sub-research question, *"What is the status quo of logistics operations and actors involved in a self-contained company site?"* and also attend to the next sub-research question, *What are the indicators that define system performance in an intralogistics operation?*. This chapter falls under the problem definition and system analysis phase of the methodology as shown in Figure 7.

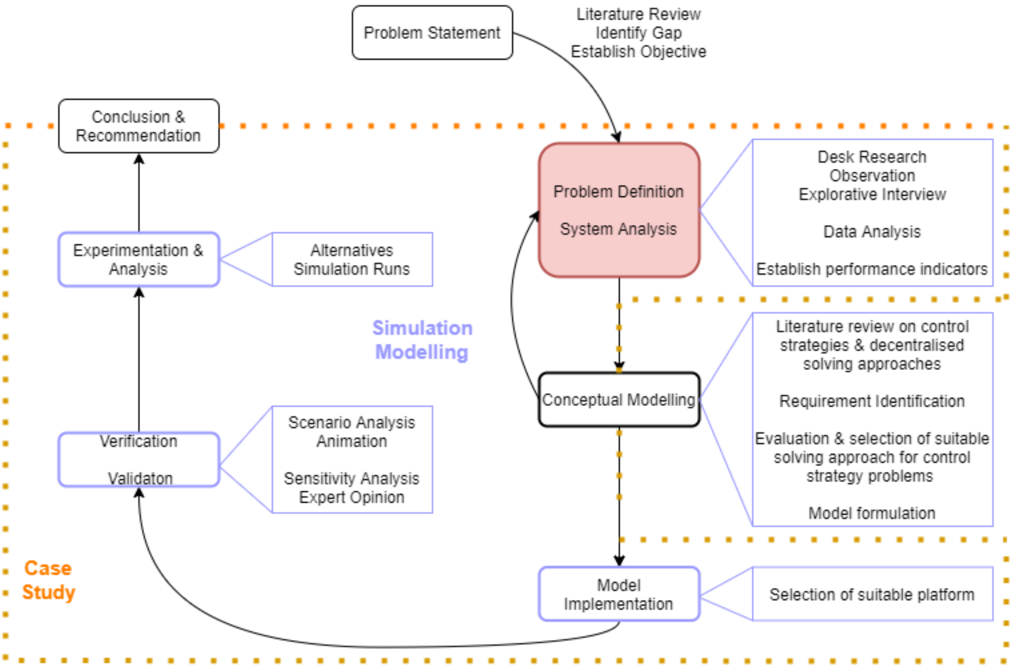


Figure 7: Phase: Problem Definition & System Analysis, adapted from (Kelton, 1998; Sargent, 2015; UH)

3.1 Existing In-house Material Transport System: Case Study

The key to proposing an innovation in an existing system is to understand the nuances of the current structure and operations. An interview with the Head of Warehouse of the intralogistics facility (personal communication dt. 19 March 2021, Appendix A.2) was conducted for this purpose. Figure 8 shows the overview of the existing operations in the in-house material transport system based on the data gathered.

As explained in sections 2.1 and 2.2, an intralogistics facility is actively connected with the global supply chain, with the continuous movement of materials in and out of the facility. However, in this project, the focus is on vehicle-based in-house material transport. Thus, for the purpose of study, it is essential to establish the system, its boundary, elements within and the considered simplification.

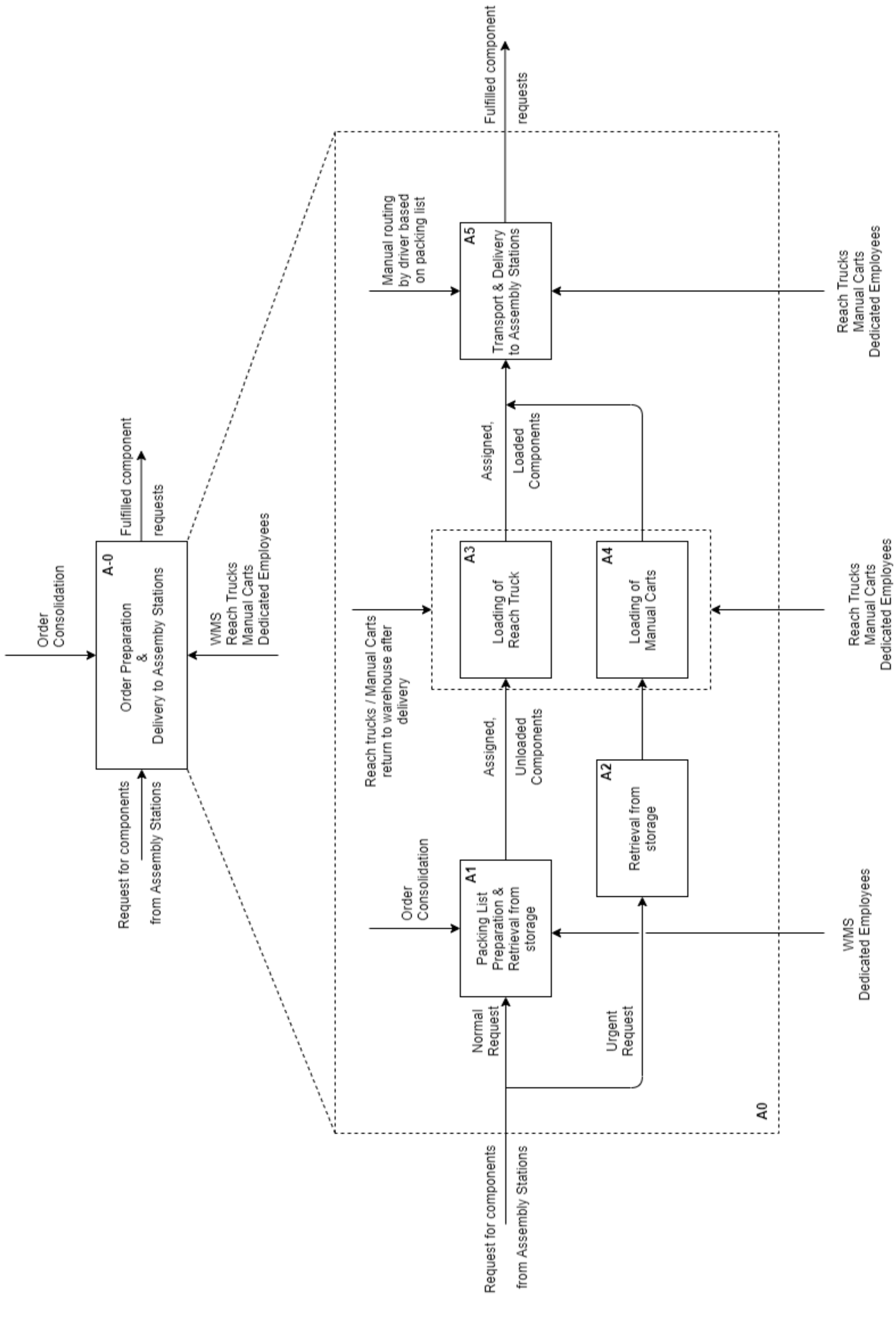


Figure 8: IDEF0 diagram of existing in-house material transport

3.1.1 System Definition & Boundary

A system has been defined in multiple ways. One of the most widely used and apt to this case is that a system is a collection of interconnected and interdependent elements, or subsystems, that work together to achieve a common purpose (Ackoff, 1971). The basic characteristics of a system include organisation, interaction, interdependence, integration and central objective.

In the previous chapter, the key actors and basic functions of an intralogistics system, specifically the vehicle based in-house transport were introduced. The intralogistics facility in this project is a manufacturing facility. Thus, there is a continuous inflow of raw materials into the facility, which are transported and stored in the warehouse. These materials or components are transported to the required assembly stations upon request for further processing. The next stage may include the movement of half-products between the stations or movement of the fully finished product to the dispatch area from where it is shipped out of the facility to an external customer.

The defined system consists of multiple elements and interactions. For the purpose of the study, the focus area needs to be demarcated by establishing a boundary. This is to distinguish a system from its environment and is called the system boundary. The input and output for the system traverse across this boundary (Veeke et al., 2008). The A-0 level in the IDEF0 diagram (Figure 8) depicts this. As seen, the focus is mainly on the preparation of the order and delivery to assembly stations. The input to the system is the request for components from the different assembly stations and the output is the delivered components (and in turn fulfilled requests). The key actors involved in the process are the Warehouse Management System (WMS) which consolidates orders from different assembly stations, warehouse employees and manually driven reach trucks and carts to transport the components.

In the explanation below, the information flow and physical flow have been merged. In the existing system, the trigger is the request from the assembly stations for the components from the warehouse. It is assumed that the required components are already available in the storage. The raised requests are populated in the WMS which is proprietary in-house software. These orders are consolidated manually by the warehouse employee in charge to prepare the packing list. The preparation of the packing list is the assignment process of linking tasks to the vehicles. In the existing operation, this is done at the discretion of the employee and on First Come First Serve (FCFS) basis. The consolidation also takes into account the destination of orders and vehicle capacity chosen for transportation. These components in the packing lists are manually retrieved from storage, prepared in pallets to be loaded onto the assigned reach trucks. Since the reach trucks are driven manually, the routing choice is by the driver of the vehicle. Depending on the destinations on the packing list assigned, the length of the route varies. Usually, a milk run is followed for delivering the components to their assigned destinations before returning to the warehouse (Brar and Saini, 2011). About 5% of the orders may be raised as urgent requests, needed at a short notice (personal communication dt. 19 March 2021, Appendix A.2). These orders are either raised through the WMS or manually conveyed to the warehouse in charge. The urgently required components are retrieved at the earliest, skipping the existing queue of tasks, loaded onto manual carts and transported to the destination. It is to be noted that all the orders are loaded and dispatched from a central point in the warehouse. As informed by the Head of Warehouse, given the consolidation and order preparation, the average lead-time for delivery of components is one day.

Type of System

Type of system can be classified based on different perspectives such as interaction with the environment, type of occurrences and more. In this case, it can be defined as one that is closed to all other interactions except the flow-in of information and flow-out of the required components. The required components are assumed to be already available in the storage. Based on the output or occurrences, a system is classified as deterministic if it is perfectly predictable and probabilistic if not. As stated above, in reality, a system involves a combination of parameters that can be probabilistic or deterministic. For example, while the daily demand generation is probabilistic, the distance travelled and the travel time for a certain combination of orders in the packing list is deterministic. However, with a strong human influence in the process and uncertainty involved, the probabilistic feature dominates.

3.1.2 Layout & Elements

Within the system boundary described above, a few key actors and elements need to be explicitly mentioned for a better understanding. The layout of the system is mentioned below in Figure 9, along with the distances between different stations in the intralogistics facility. Above each of the assembly stations, the daily demand in terms of the number of transactions has been mentioned. This aspect is further explained in Section 3.2.2.

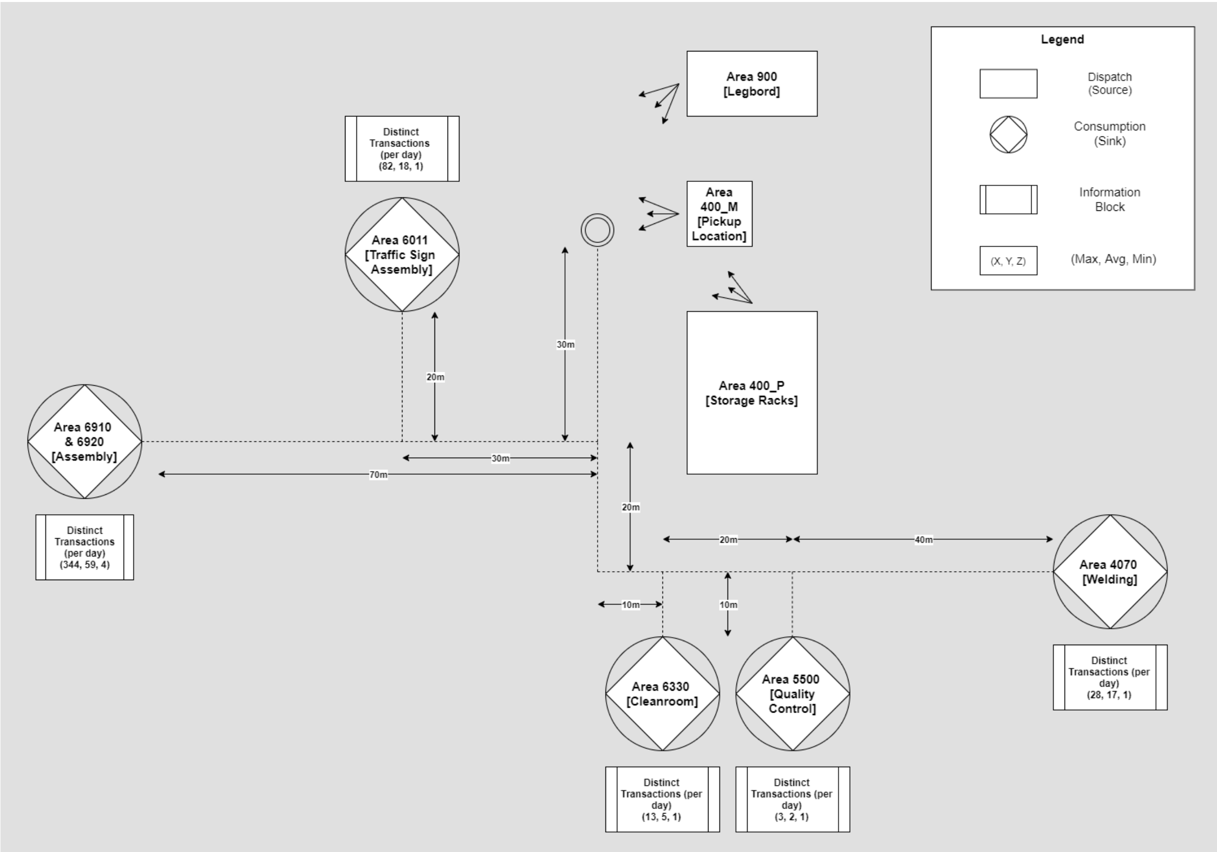


Figure 9: Layout of Intralogistics Facility: Case Study

In the existing operation, there is a central source for the in-house dispatch of all components. This is the *loading and dispatch point in the warehouse (Area 400M)*. The storage rack is located in the same area where the inbound material from outside the facility is stored. There are multiple manufacturing areas in the facility which use the components from the warehouse storage. Based on the interview with the Head of the Warehouse, the key delivery points or *sinks* have been identified *(Area 6910, 6011, 6330, 5500 and 4070)*. The main actors in the material transport involve: *WMS, reach trucks and manual carts, warehouse operators and drivers.* As explained in Section 3.1.1, the orders raised by the assembly stations are populated by the WMS and manually consolidated into a packing list which is prepared for dispatch. Every packing list is assigned to a reach truck that initiates its operation. Following a milk run and a route at the discretion of the vehicle driver, components are delivered to each of the sinks. The manual carts are used to deliver urgent orders which bypass the WMS and order consolidation. A *dedicated path* is present on the floor of the warehouse to guide the movement of vehicles.

3.2 Operational Data

This section deals with the data collected, used and processed in an intralogistics facility in the perspective of this project. This data, which is usually captured and managed through a Warehouse Management System (WMS), can be classified into Master Data (data on suppliers, customers and items), Business

Data (for mapping and configuration WMS as per requirements) and Transaction Data (data collected on the movement of items within the facility and inventory levels) (Andiyappillai, 2019). This classification is illustrated in Figure 10 below. For the scope of study in this project, the focus is on the transaction data, mainly obtained from the scanning of materials dispatched and received at different stations. The data used in the following sections to establish the demand pattern and the performance indicators for this case has been obtained from the data extract of around 107,000 scanned transactions of material movement within the intralogistics facility.

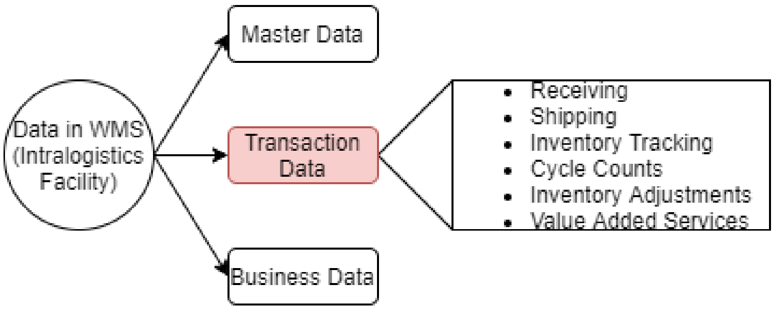


Figure 10: Types of Data in Intralogistics, adopted from (Andiyappillai, 2019)

3.2.1 Operating Conditions & Simplifications

Before presenting the results of the data analysed, it is important to lay out the operating conditions and the simplifications considered. It is important to mention that the basis for most of the operating conditions is the interview with the Head of Warehouse (personal communication dt. 19 March, 2021, Appendix A.2). All the dispatches of in-house material transport happen from a single point, Area 400M to the key assembly areas as shown in Figure 9. No component is transported back to the warehouse from the assembly stations or between assembly stations. Only small components and spares are in the scope of this project and not the large, heavy frames and half-products that are also transported in the facility. This consideration is based on the limitations of the robots that are later proposed as innovation. Further details are discussed in Chapters 5 and 6. Most of the orders placed by the assembly stations are of normal priority and are consolidated and dispatched with a lead time of around one day. Around 5% of the orders in a day are of urgent priority and has to be dispatched at the earliest, usually in manual carts. The individual characteristics and the quantity of components have not been considered as the variations are too many. For the purpose of simplification and to suit the modelling requirements, the movement has been tracked in terms of the number of daily transactions to each of the assembly stations. Dedicated warehouse operators (including drivers) and vehicles are available to handle WMS, component retrieval from storage and transport to different destinations. The resource specifications are mentioned in Table

Table 3: Summary of resource specifications

Resource Specification	Value
Number of reach trucks	5
Number of manual carts	Multiple
Dedicated warehouse operators (including drivers)	7
Average number of employees on shopfloor	100
Maximum speed of reach trucks	7 km/h
Maximum speed of manual carts	3 km/h
Working shift per day	8 hours
Average loading and unloading time per transaction	1 minute

3.2.2 Demand Pattern

As explained in Section 3.1.2, the current operation in the intralogistics facility consists of multiple assembly stations to which the components are supplied from the warehouse. However, the requirement is not deterministic and varies over a period of time. Since the individual characteristics and quantities of each type of the components are not being focused on, the key is to track the count of transactions to each of the stations. The data extract of about 107,000 scanned transactions has been analysed using the software Tableau to identify the demand and thus movement pattern to the different assembly stations. Based on the discussion with the Head of Warehouse (personal communication dt. 19 March, 2021, Appendix A.2), a period of one month has been considered to track this pattern given the recent start of data collection of scanned transactions. Figure 11 shows the result of the data analysis, with the variation of the distinct daily number of transactions to each of the assembly stations. In figure 12, the histogram of the demand distribution has been represented with an attempt to recognise the type of distribution. It is seen that the pattern of demand for each assembly station varies, also given the shorter duration of data collection. Considering this uncertainty, a triangular distribution has been considered for all stations. Further recommendation on data collection and establishing a distribution has been mentioned in Chapter 8.

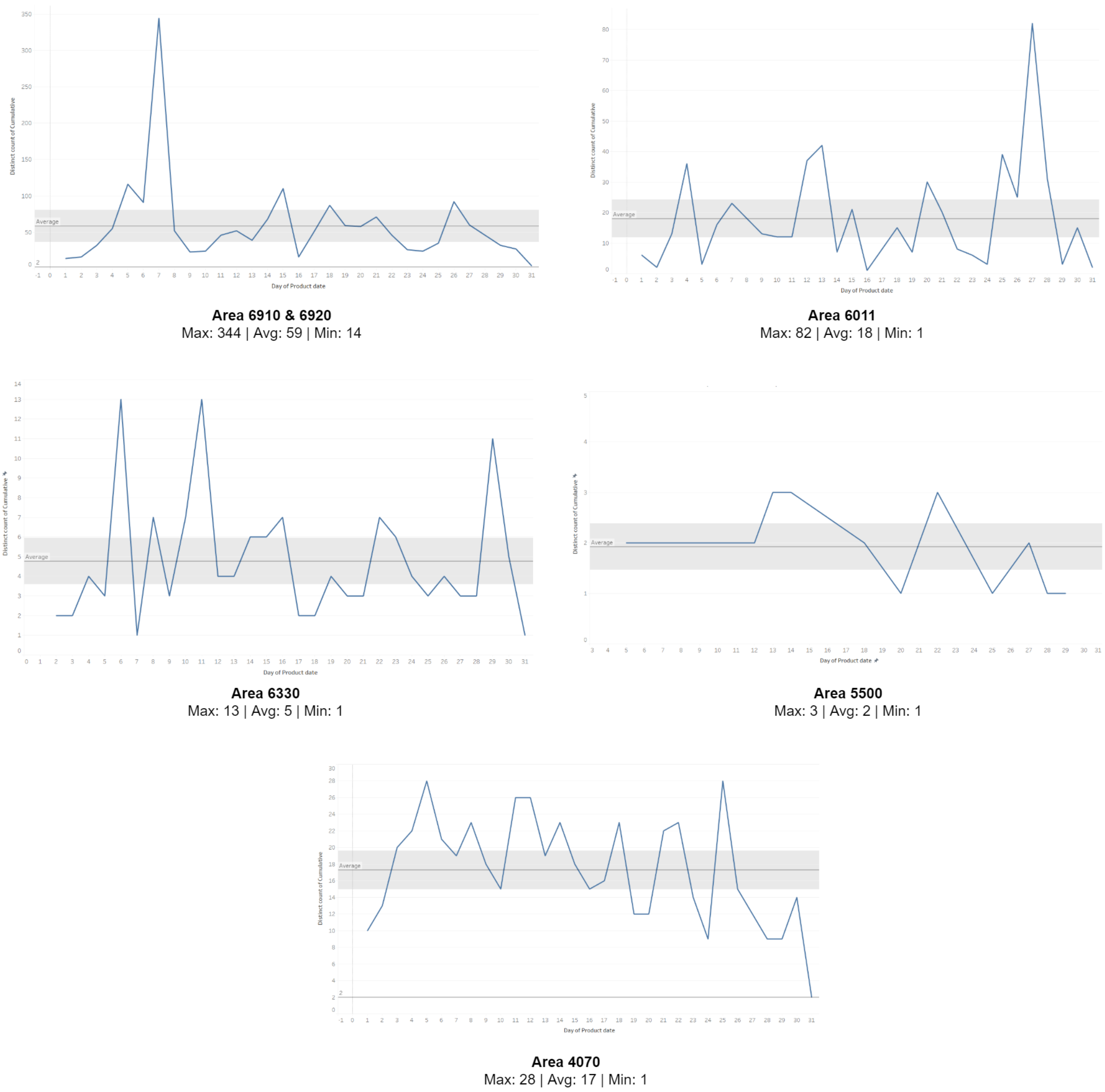


Figure 11: Demand Distribution (Number of distinct transactions per day)
x-axis: day of the month; y-axis: number of distinct transactions

In the results, the maximum, average and minimum daily transactions have been identified for each of the assembly stations. This helps identify the variation in demand and the stations which are more frequently visited. It is observed that Area 6910 & 6920 is the most visited station, while Area 5500 has one of the least consumption. However, even with the individual stations, the variation is quite widespread. Area 6910 & 6920 has a peak only once a month, while most of the other days, the number of transactions is around the average. Area 6330 has peaks and troughs in demand fluctuating all through the month.

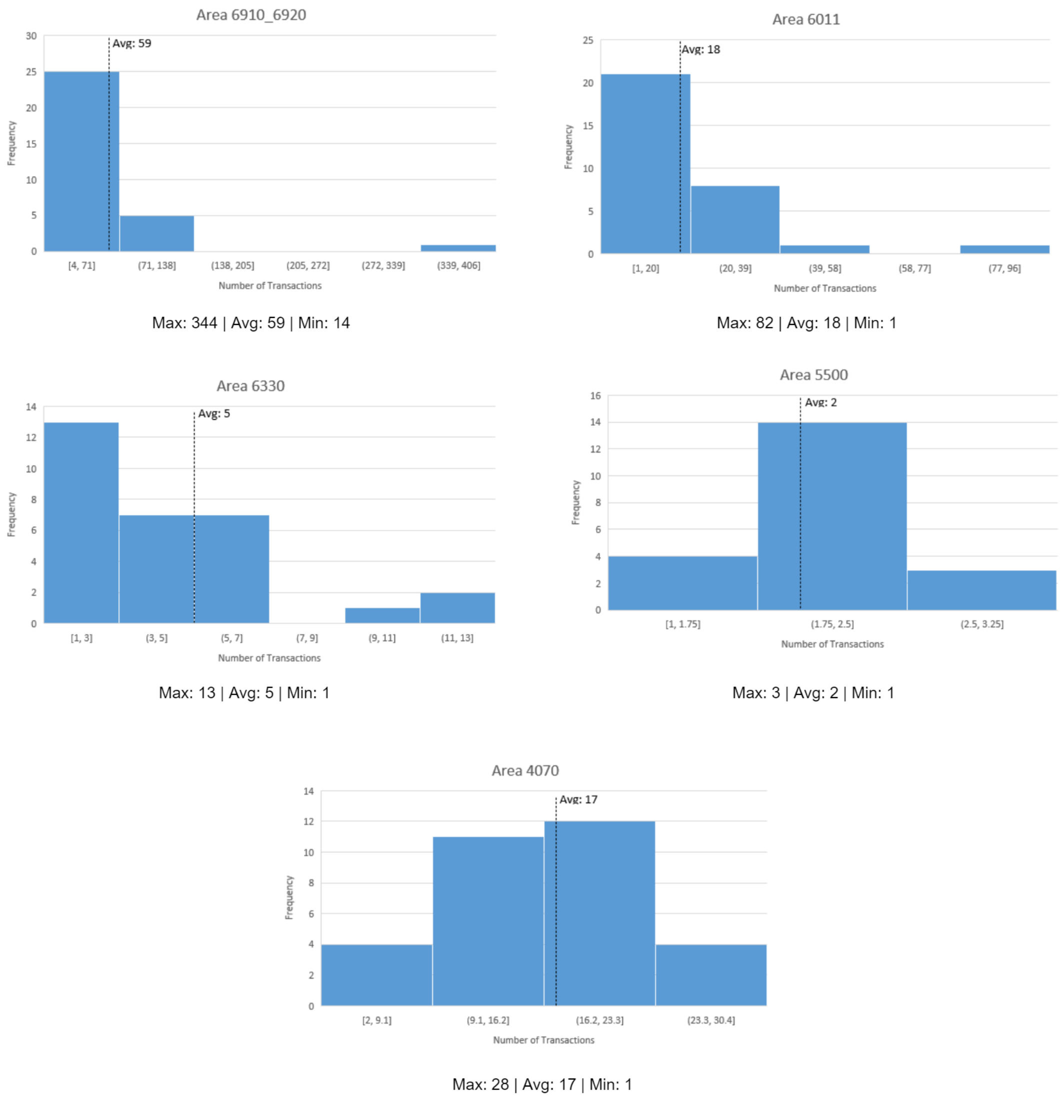


Figure 12: Histogram of Demand Distribution
x-axis: Number of transactions; y-axis: Frequency

The takeaway from this study is the high demand variability. The current situation, which is dominated by manual operation, leads to increased fatigue, high lead time and increased inefficiency. This result is used in the next section to calculate the performance indicators for the existing operations. Also, this provides the demand pattern (number of cases per station) to be used as a triangular distribution in the implementation of the self-organising simulation model explained in Chapter 6.

3.2.3 Performance Indicators

The performance indicators for an intralogistics facility can be measured in various ways. It is key to note that, in this project, although the performance indicators for the existing form of operations are measured, they are not used as benchmarks to directly compare the results from the self-organised system of robots. The main reason for this is the assumptions and simplifications considered in measuring the parameters of the existing configuration which is dominated by manual operations. Also, the existing configuration will be not be simulated and run on the same platform as the new method. Hence, a direct comparison of the performance indicators would not be appropriate.

However, the takeaway from this would be the estimation of manual effort in the current form, the reduction in fatigue contributed by the self-organised system of robots and the robustness of the new system to varying demands. The performance indicators should enable a quick understanding and judgement of the system for various configurations without the need to physically observe them (Klein, 2013). With this motive and based on discussion with the key stakeholders (Prime Vision and Head of Warehouse), the following performance indicators are used.

- *Vehicle distance travelled*: The total distance travelled by the vehicles is an important indicator for any kind of material transport as also mentioned regularly in literature (Sun et al., 2018). In an intralogistics facility dominated by manual operation, travelling, whether driving reach trucks or manual carts contribute to human fatigue and thus the distance travelled is an indicator of this. However, with the varying demand pattern, it is to be noted that the average values have been used to calculate the distance in the existing operation. In the new system, although the robots have lesser load carrying capacity compared to the reach trucks and thus leads to increased frequency of material movement, the robustness and order fulfilment time is expected to improve. In the case of robot operation, this indicator also allows the robot manufacturers with the design aspects including, active run time, battery capacity and durability.
- *Vehicle utilisation*: Vehicle utilisation refers to how efficiently the vehicles are used. In this case, it is intended to track the active duration of the vehicle in the fixed duration of the study considered. In the existing configuration, this is directly derived from the estimate of the number of transactions and the distance between the stations. For the new system of robots, this indicator helps in the system design to choose the most appropriate configuration and required number of robots for a scenario.
- *Order fulfilment time*: The order fulfilment time can also be called the service time. In the given intralogistics system, this is considered as the time between the raising of request by an assembly station to the time at which the components are delivered (Van der Meer, 2000). In the existing configuration, while the order fulfilment time has not been actively tracked, the average value has been based on the interaction with the Head of Warehouse (personal communication dt. 19 March, 2021, Appendix A.2). In the new method with the self-organised system of robots, this value can be actively tracked (maximum, minimum and average) to understand the performance of the system. The new method is expected to reduce the order fulfilment time.

Based on the above description, the performance indicators for the existing manual configuration has been calculated with plausible assumptions and considering the specifications mentioned in Table 3. The summary of the same is mentioned in Table 4 . The detailed calculation and considered simplifications have been elaborated in Appendix A.6.

Table 4: Summary of performance indicators: Existing configuration

Performance Indicator	Value
Vehicle travel distance per shift (based on average demand values)	17020 metres
Vehicle utilisation per shift (active duration during a working shift, based on average demand values)	156 minutes
Order fulfilment time (based on interview with Head of Warehouse)	1 day

3.3 Innovation

As introduced in Section 1.2, the primary expectation from this project is to gain insight into the performance of the self-organised system of robots as an alternative to the existing manual operation for material transport in the intralogistics facility. In most literature, self-organised systems and thus decentralisation is expected to improve the qualitative aspects of robustness and adaptivity (Klein, 2013). Thus, the new system is expected to improve the robustness of the system and reduce the human fatigue caused by manual movement in the existing configuration. Robustness can be defined as *"the ability of a system to continue to operate correctly across a wide range of operational conditions, and to fail gracefully outside of that range"* (Gribble, 2001). This project aims to analyse the performance of the system of self-organised robots in case of disturbances. With changing configurations and varying environmental conditions that may influence the system performance, the ability of the system to adapt is to be studied (Ay, 2006).

One of the key stakeholders in the project, Prime Vision, is considering the implementation of a self-organised system of robots in the intralogistics facility. However, as discussed before, the feasibility in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents and lack of extensive operational studies. Through this project, it is intended to conceptualise this new system of robots and develop a model to study the system performance under conditions of varying demand and configuration.

3.4 Summary

This chapter is aimed at answering the sub-research question, *"What are the indicators that define system performance in an intralogistics operation?"*. A case study of a manufacturing facility has been chosen, where Prime Vision is considering implementing a self-organising system of robots. The chapter starts with the study of the state of operations in the existing configuration of the facility using the IDEF0 diagram. It is observed that manual operation is dominant and the lead time for the components to be delivered to each of the assembly stations is pretty high. As a result of manual operations, mainly the transport of components across significant distances between the warehouse and assembly stations, there is a high factor of human fatigue involved. To understand the system better, the system boundary has been established to focus the study and identify the elements involved. Addressing high demand variability and flexibility in the deployment of resources (transport vehicles) are the advantages of a decentralised system identified in the literature. In view of this, the data analysis of the scanned material movement transactions has helped identify the demand pattern among the different assembly stations. A wide range of variation was observed in the requirement of components between different assembly stations in a given period of time as well as in the demand for components by a single station over a period of time. Utilising these numbers and plausible assumptions, the performance indicators for the system: vehicle distance travelled, vehicle utilisation and order fulfilment time have been established which are intended to give an impression on the system performance at a quick glance. Since the existing configuration (manual) of material transport is not being simulated on the same platform as that of the new system of self-organising robots, a direct comparison would not be appropriate. However, the takeaway from this would be the estimation of manual effort in the current form, the reduction in fatigue contributed by the self-organised system of robots and the robustness of the new system to varying demand.

With this as the foundation, the project proceeds with conceptualising the self-organised system of robots. Before formulating the model, it is key to understand the control strategy problems in intralogistics, principles of self-organisation and the various decentralised solving approaches in the literature. Chapter 4 deals with this aspect.

4 Self-organisation & Control Strategies

In the previous chapters, the basic functions in an intralogistics system and analysis of the existing system at the assembly facility have been discussed. As presented in Section 3.3, the key focus of this project has been to introduce automation, particularly with a self-organised system of robots as an alternative to the existing in-house material transportation dominated by manual operation. While formulating the conceptual model of the new system of robots, it is necessary to define the control strategy problems that need to be addressed and the various decentralised solving approaches. This provides the research base to choose the appropriate technique to implement in the chosen case study. This chapter also aims to define the level of automation for the facility under study using a classification matrix. The intent of this chapter is to partially answer the sub-research question, *"How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?"*. Figure 13 shows the position of this phase in the overall methodology.

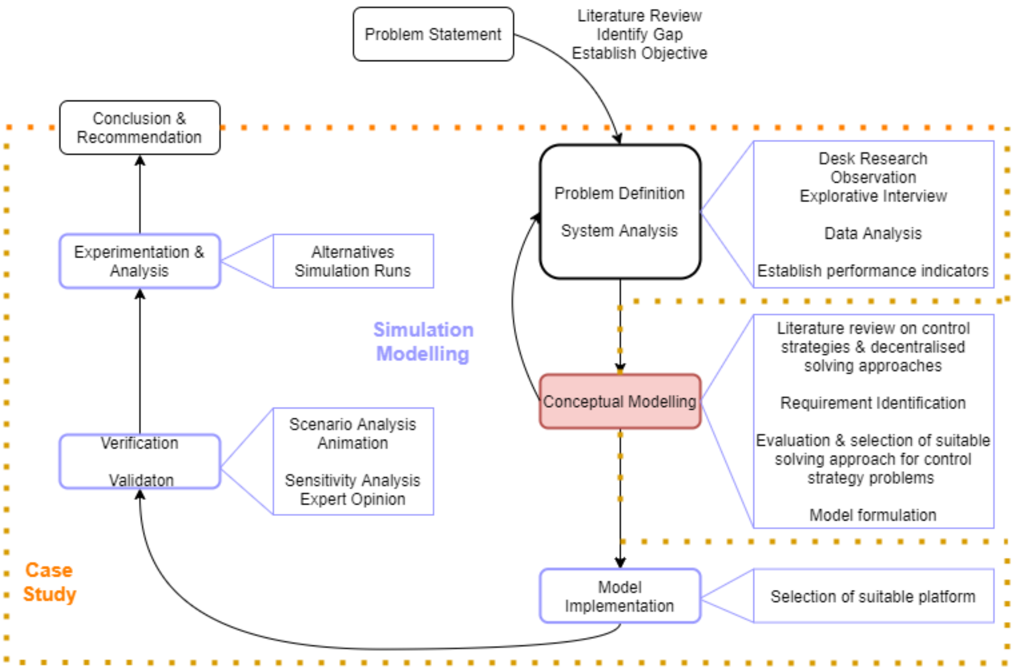


Figure 13: Phase: Conceptual Modelling, adapted from (Kelton, 1998; Sargent, 2015; UH)

4.1 Automation & Self-organisation

As discussed in Chapter 1, factors such as globalisation in industries, volatility in the markets, shorter product life cycle and increasing product variety have all been the drivers of the shifting pattern (Wilding, 1998; Windt et al., 2008). In view of this, the lookahead is for robust systems which can adapt to fast-paced changes. One of the vital approaches to deal with these challenges is the transformation from centralised, hierarchical principles to networked, autonomous systems that can collaborate with each other to optimise and adapt to the dynamic environment (Schmidt et al., 2020; Van Brussel et al., 1998).

As defined by Fottner et al. (2021) *"autonomous intra-logistics systems enable self-contained, decentralised planning, execution, control and optimisation of internal material and information flows through cooperation and interaction with other systems and with humans"*. A key perspective of autonomy is its relative characteristic, that is, the degree of autonomy based on the subsystem and its freedom of action. Based on this, the autonomous system can be classified as per the following characteristics (Rammert, 2009):

- autonomy over behaviour
- autonomy in decision-making
- autonomy in information processing/gathering

Fottner, 2021, also suggests a two-dimensional classification for defining the degree of automation in an intra-logistics system based on this definition, with task level and automation stage. The task levels represent the different types from physical control to overall system planning in a hierarchical manner. Although in an autonomous system, this hierarchy dissolves, the distinction among the type of tasks is still applicable. The level of automation for intralogistics is similar to the framework published by the Society of Automotive Engineers for autonomous driving, including not only the physical level of vehicles but a higher level of monitoring and control (soc). The framework, as shown below, classifies the different stages of automation over the various levels of intra-logistics tasks.

Table 5: Classification matrix - Level of automation in intralogistics, adapted from (Fottner et al., 2021)

	Automation Stages					
Task Level	No Automation **Stage 0**	Assistance Systems **Stage 1**	Partial Automation **Stage 2**	Conditional Automation **Stage 3**	High Automation **Stage 4**	Autonomy **Stage 5**
Overall System Planning **Level 4**	Manual decision making in overall system planning	Decision support system in overall system planning	Partly centralised decision making in overall system planning	Centralised decision making in overall system planning	Partly decentralised decision making in overall system planning	Decentralised decision making in overall system planning
Overall System Control **Level 3**	Manual decision making in overall system control	Decision support system in overall system control	Partly centralised decision making in overall system control	Centralised decision making in overall system control	Partly decentralised decision making in overall system control	Decentralised decision making in overall system control
Process Control and Monitoring **Level 2**	Manual decision making in process control and monitoring	Decision support system in process control and monitoring	Partly centralised decision making in process control and monitoring	Centralised decision making in process control and monitoring	Partly decentralised decision making in process control and monitoring	Decentralised decision making in process control and monitoring
Device Control and Information Processing **Level 1**	Manual search and transfer of information on demand	Assisted search and transfer of information on demand	Assisted and partly self-contained information acquisition and processing	Fully self-contained information acquisition, generation of information and interaction with central system	Fully self-contained information acquisition, generation of information and partly interaction with other system elements	Fully self-contained information acquisition, generation of information and interaction with other system elements
System Execution and Real Time Control **Level 0 and 1**	Manual execution in static environment	Manual assisted execution in static environment	Assisted and partly self-contained execution in static environment	Partly self-contained execution in infrequently changing environment	Fully self-contained execution in dynamic environment	Fully self-contained execution in complex and dynamic environment

Co-relating the basic functions of a vehicle based in-house transport system addressed in Chapter 2, the control strategy problems which are further described in section 4.4 can be categorised as per the task levels stated in the above table (Schmidt et al., 2020):

- System Design -> Level 4
- Load-Vehicle Assignment -> Level 3
- Empty Vehicle Management -> Level 3
- Routing & Deadlock Avoidance -> Level 2

With the framework for autonomous logistics system as established in this chapter, we next dwell on the aspects of self-organisation and the decentralised solving approaches for the control strategy problems.

4.1.1 Self-organisation

With the shift towards decentralised autonomous control, the barriers between different hierarchy levels are disappearing. Self-organisation is a terminology used in this context and can be best described with an analogy to social insects, like the ants or bees, where every being acts towards a common goal based on certain instincts, but without central control. This phenomenon results in the emergence of complex structures due to the behaviour and interaction of local agents (Bartholdi et al., 2010). The principles of self-organisation have also been applied in other fields such as sociology, biology and chemistry (Serugendo et al., 2011). In a logistics system, this can be considered as functioning without significant intervention by managers, engineers or software control. Being a loosely defined term, the main functionalities of a Self-organising Logistics System (SoLS) can be specified as (Pan et al., 2017):

- Openness: Boundaries of the system are open for actors to enter and leave. Thus, like computers in an internet network, connecting and disconnecting will be convenient, making the system more flexible.
- Intelligence: Agents are capable of autonomous decision-making by collecting and processing information. These decisions are made based on the interaction of the actors between each other and the environment.
- Decentralised Control: Actions of every agent is based on contextual local interactions and thus self-controlling. However, to avoid undesirable results, the protocols and regulations of the environment they operate in are respected. Self-Organisation in Logistics System will involve a rule-based decentralised control which is expected to improve the flexibility and robustness of the system (McFarlane et al., 2016).

The characteristics mentioned form the basis of the design requirement for the new system.

4.1.2 Type of Information and Implementation

When discussing decentralisation, which is a key aspect of self-organisation, the focus can be on two aspects: internal structure and implementation, type of information used (Klein, 2013).

As compared to a hierarchical structure in a conventional control system, a decentralised system sheds the usage of one central controller which is responsible for collecting information as well as decision making. The system allows the decisions to be taken by distributed and autonomous units. The next aspect is the extent of usage of global information. A decentralised system intends to work with locally available information to a possible extent.

With the above aspects, it is important to understand that in most systems, there is no clear distinction between centralised and decentralised systems. Implementing a 'truly decentralised' system has limitations when it comes to usage of purely local information which hampers optimisation and incorporates randomness. Thus, it is very common and practical for the existence of systems with units capable of autonomous decision making, but knowledge of pending transportation tasks are still available as global information (Schmidt et al., 2020).

4.2 Design Requirements for the New System

Section 4.1.1, which explains the main functionalities of a self-organising system, has set the precedence for the design requirements (Pan et al., 2017). In this project, the design requirements originate from the requirements of Prime Vision towards developing a self-organised system of robots in an intra-logistics environment. The case chosen, which is an assembly facility and the focus of incorporating automation in the intra facility material movement sets the constraints.

- **Openness:** In the system being considered, the actors which are mainly the 'cases' and 'robots' must be able to enter or leave the established system boundary. Although there is homogeneity in the type of cases and robots considered, the addition of new entities, removal or breakdown of existing entities should be accommodated by the system.
- **Intelligence:** Intelligence refers to the autonomous characteristics. Using the onboard sensors and communication between the agents, the assignment of the best available task must take place and the

robot must find its own path to the relevant destination while avoiding or resolving obstacles. The demand with different priority levels must be catered to accordingly between the origin-destinations pairs.

- **Decentralised Control:** Decentralisation primarily refers to the 'cases' and 'robots' functioning based on local contextual interactions. However, this shall be applicable at different degrees in each of the control strategy problems. This method while allowing simple computational requirements, also makes the model scalable and adaptable. Decentralisation is implementable in decision-making as well as information usage.
- **Collision Avoidance and Resolution:** In contrast to the transporters operated by humans, autonomous robots require a sound and precise sensing and feedback arrangement to avoid and resolve obstacles. The floor of the facility being an environment comprising of humans, other static and moving infrastructure needs to be considered while developing the logic for resolving the situation. The behaviour at the intersections in the path shall also be defined.
- **Battery Management (Soft Requirement):** The battery capacity of the robots is limited and is a critical consideration during the operation. The task assignment and routing need to consider this factor during decision-making. As per discussion with Prime Vision, the incorporation of battery management is a soft requirement.

4.3 Method Conceptualisation

In Chapter 3, the existing mode of operation has been described. Figure 8 depicted the IDEF0 diagram of the existing operation in the intralogistics facility, identifying the actors involved and the process of material movement from the stockroom to the assembly stations. In the existing operation, we see the dominance of manual operation as well as decision making. As depicted in Figure 8, we see three major stages in the operation. Consolidation and order preparation, Loading onto vehicles and transport to the destination. In the new system, these stages are similar but vary in the level of consolidation of orders and extent of manual operation, thereby level of automation.

4.3.1 Actors Involved

The new method depicted in Figure 14 has three main actors: robots, cases and a central platform. Apart from these actors, the interaction of human operators are involved at different stages: operators at the assembly station raising orders and warehouse employees retrieving components from storage and preparing for dispatch.

Robots are key in this operation which are capable of communicating with the cases and other robots. Compared to the existing case, where the transportation is done through manually driven reach trucks and carts, robots move autonomously to the loading location and later to the assigned destination. With the assistance of onboard sensors, the robots are capable of detecting and resolving obstacles. Another key difference between the existing transport vehicles, i.e., reach trucks and robots is the reduced carrying capacity. Both the volume and weight of the goods that can be carried by the robot is limited. This in turn affects the level of consolidation of orders and the size of each shipment to the assembly stations. However, the lead time for each order and the flexibility in order size is expected to improve.

The cases of components are the next key actor in this system. The case is manually prepared by the human operators after retrieving the components from storage. The number of components filled in each case is at the discretion of the warehouse operator but limited to the volume and weight capacity. In this model, for simplicity, every order raised has been assumed to be fulfilled by a case. The prepared cases represent the task in queue and are intelligent to communicate with the robot and assign itself.

The third actor in the system is the central platform which is responsible for consolidating the raised orders in a queue, based on a combination of first come first serve and task priority. This process is further explained in the upcoming sections.

4.3.2 Key Stages & Actor Interactions

The new method for transporting the components within the facility can be broadly divided into three stages: order queuing and preparation, assignment and transport, action after task completion.

The operators at the assembly station raise the order for components from their consoles. These orders are to be attached with priority levels: normal or urgent. These orders are populated in the central platform. The components are retrieved from storage and prepared into cases by warehouse operators. In this model, for simplicity, every order raised has been assumed to be fulfilled by a case. The central platform also generates a queue based on First Come First Serve. However, the tasks with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority orders. The case at the front of the queue sends a transportation request to the robots.

The next stage is the assignment and transport. The robots are capable of responding to the transport request by the cases with their task status and battery status. An idle robot, with sufficient battery level, nearest to the task is assigned. The robots may be located at the home position or at any other point in the layout. Once the case is picked up at the pick-up point, where the case is manually loaded, the robots can autonomously move to the assigned destination along a guided but shortest path. The cases are unloaded manually.

Once the task is completed, the robots check for their battery status. If it is below the critical level, they return to the home position for charging. If not, based on the chosen mode of operation, they can always return to the home position or get assigned to the next task.

The control strategy design of the system is explained in detail in Section 5.4 with a swim-lane flowchart.

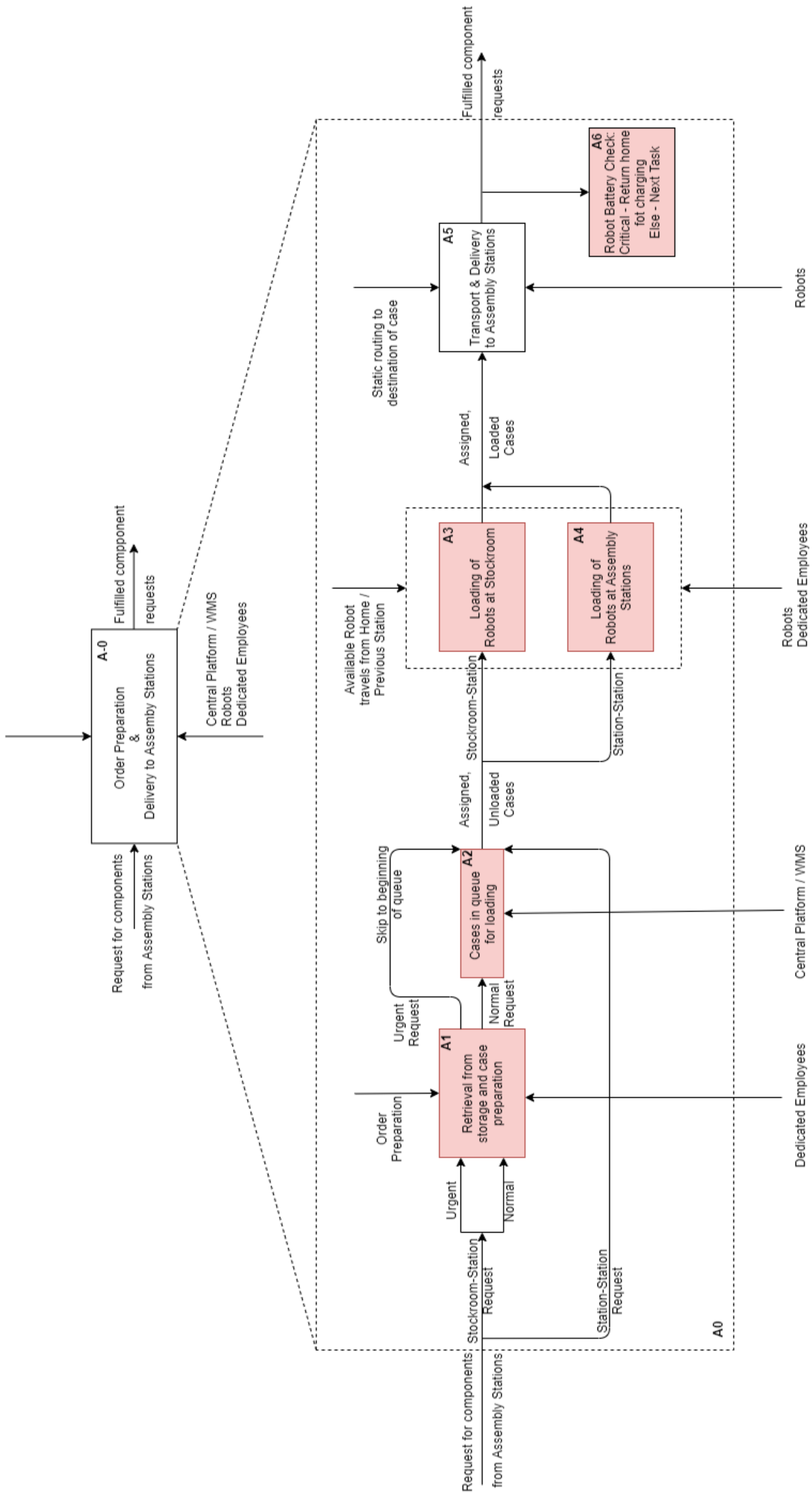
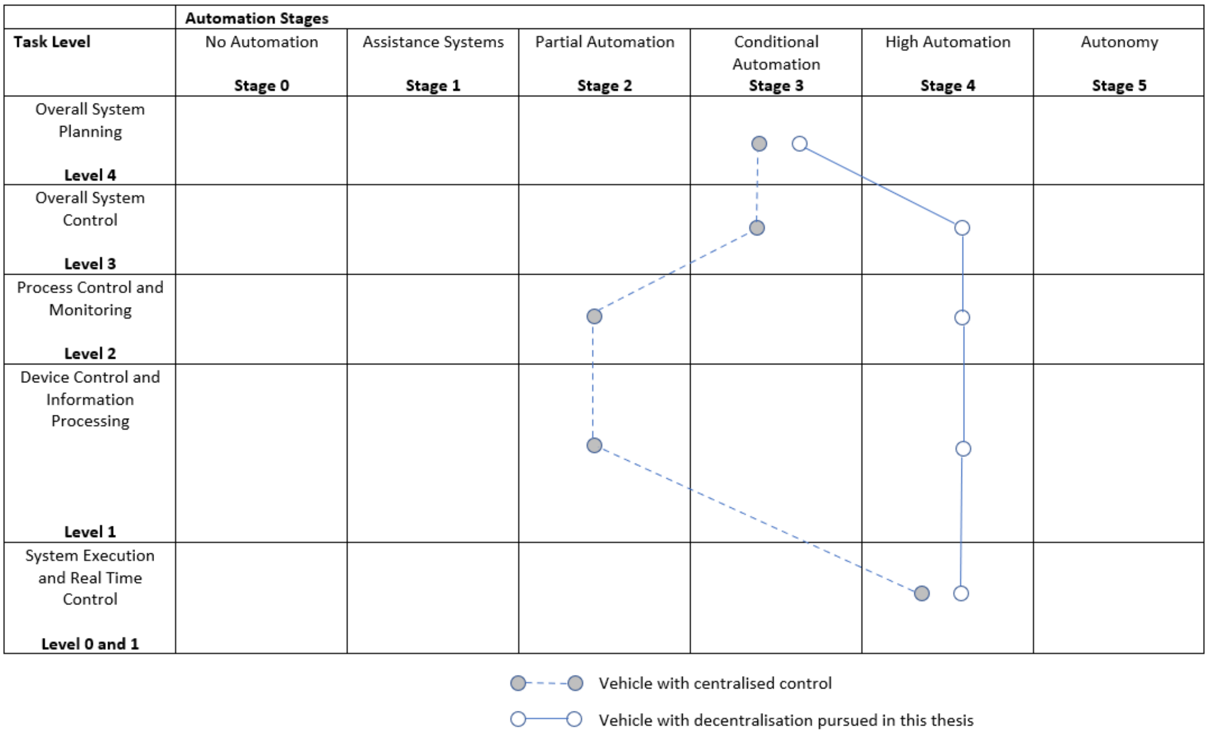


Figure 14: IDEF0 diagram of new in-house material transport

4.3.3 Mapping Level of Automation in this Project

In Section 4.1 and Table 5, the framework to map the level of automation on a two-dimensional matrix was described (Fottner et al., 2021). Based on the operation of the new system described above and discussion with Prime Vision, the level of automation has been charted in Table 6 for the degree of decentralisation being incorporated. We observe that the lower levels of tasks including the onboard sensors (Level 0 & 1), robot controls (Level 1), routing and coordination (Level 2) and order management (Level 3) are all highly automated and decentralised. However, the overall system planning or resource planning is mapped to conditional automation as there is a centralised collation of orders to form a queue and the decision to add or remove a robot from the system can be taken manually. From the literature, the mapping for an Automated Guided Vehicle (AGV) with centralised control has also been done for comparison (Fottner et al., 2021).

Table 6: Mapping - Level of Automation in this project, based on Figure 5



4.4 Control Strategy Problems

As described in Chapter 2, we are dealing with a vehicle-based in-house transport system in this project. The vehicle-based refers to systems such as Automated Guided Vehicles (AGV), Autonomous Mobile Robots (AMR) and Overhead Hoist Transport (OHT) system used for material transport within an intralogistics facility. As mentioned in (Sinriech and Tanchoco, 1993), the design of such systems includes unit load sizing, development of layout, choosing the type and quantity of vehicle and design of a suitable control system. In the context of this project, the type of robot available, and thus its characteristics and load carrying capabilities are fixed. With the intent of commissioning the new system in an existing self-contained company site, there are also layout restrictions in place. Thus, the focus of the upcoming sections will mainly be on the control system including system design.

Figure 15 presents an overview of the key control strategy problems to be addressed in a vehicle based in-house transport system. System design is usually a higher-level task, referring to the number of vehicles in the system and decision is usually taken based on a comparison of outputs of simulation runs. The other control strategy problems, load-vehicle assignment, empty vehicle balancing, routing and deadlock avoidance deal with lower-level controls and is necessary to design appropriate solving approaches before building a model. In the context of in-house vehicle transport, load-vehicle assignment and empty vehicle balancing can be considered under the umbrella term 'dispatching'. It is important to note that, although separate controls, strong inter-dependencies exist between them which leads to a high degree of complexity during the design of autonomous controls (Fottner et al., 2021).

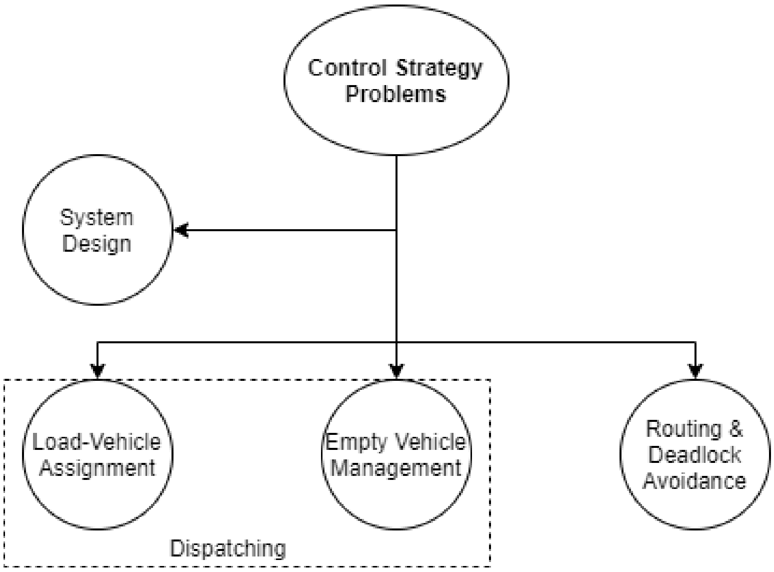


Figure 15: Control Strategy Problems, adapted from (Schmidt et al., 2020)

Vehicle and layout considerations

Certain vehicle and layout considerations have to be established before proceeding with the different control strategy problems. It is to be noted that the vehicle fleet is considered to be homogeneous in terms of characteristics and technical specifications. The maximum speed, load-carrying capacity, battery time, etc. are the same for all vehicles. Also, from the layout consideration, the vehicles are path guided and not free-ranging. The layout primarily consists of loading points, unloading points, merges, switches and parking locations for the vehicles. All these aspects are discussed further with the relevant control strategy problems.

4.4.1 System Design

As stated by Han et al., in a vehicle transport system, system design refers to "determining the optimal number of vehicles" (Han et al., 2017). It is a part of resource planning and the complexity depends on multiple variables and factors. The design of solving approaches for the other control strategy problems influences the system design. While various analytical methods are available for this, Vivaldini et. al., mentions an iterative procedure of simulation and adjusting the input parameters to determine the optimal number. Chang et al., also suggests comparing multiple simulation runs ((Chang et al., 2014; Vivaldini et al., 2016).

4.4.2 Load-vehicle Assignment

Load-vehicle assignment or task assignment refers to the assigning of vehicles (in this context, robots) to the new transport requests or tasks (at a given location) or vice-versa. The method of assignment depends on the characteristics of the vehicle being considered and the overall objective, such as reduction of overall distance travelled, shortest response time and more. The assignment process can be presented in two broad perspectives (Egbelu and Tachoco, 1984):

- Load or Workstation initiated: Load or the work station selects the best vehicle based on the arrival of the task in the system
- Vehicle initiated: It is the responsibility of the vehicle to choose the next appropriate task or load.

Based on these perspectives, the basic triggers that are responsible for the assignment process an intralogistics facility are:

- Arrival of a new load or task in the system (load or workstation initiated)
- Vehicle delivers its load to destination (vehicle initiated)
- Vehicle reaches parking (vehicle initiated)

Most of the real-world applications involve the combination of these perspectives and triggers. For example, load searches for an idle vehicle (maybe within a fixed distance radius) and if no 'idle' vehicles are available, the radius of search expands. If still, no vehicles are available, it stops searching. When a vehicle becomes available, the vehicle searches for an open task in a similar way.

4.4.3 Empty Vehicle Management

Empty vehicle management governs the behaviour of the idle vehicle when there are no available tasks in the system. Addressing this problem is key to the system performance, especially with a high variation of loads, as this decides the empty vehicle travel time and the response time for new pick-ups. The vehicle has to efficiently find a parking location or dwell point. For autonomous systems, four approaches have been identified with varying degrees of complexity (Hu and Egbelu, 2000; Le Anh, 2005; Schmidt et al., 2020):

- Central Zone Positioning: The idle vehicles always return to a central home position. This is more suitable for smaller layouts and if the parking location is near to the loading point.
- Point of Release Positioning: The idle vehicles stay at the same position where they complete or are released from the task. However, this may lead to congestion in a layout where there is a spike in demand for one of the stations.
- Distributed Positioning: In this approach, there are multiple home or parking locations for the vehicles. Based on simple or complex logic, the vehicles travel to these locations and the balance of the number of vehicles at each location is maintained. One example of such logic is maintaining a minimum number of vehicles at each location.
- Circulatory Loop Positioning: This approach dictates the continuous movement of the vehicles in single or multiple loops without any parking location. The assignment takes place on the move. Although there is a possibility of a shorter response time, this leads to higher energy consumption and chances of blockage with other vehicles.

One aspect of empty vehicle management is the presence of a loop siding, which is a separated area from the actual travel path to avoid idle vehicles from obstructing other vehicles (Schmidt et al., 2020). The placement of this would depend on the layout and travel path itself.

4.4.4 Routing & Deadlock Avoidance

The routing problem is to find the optimal route from source to sink. Here the consideration for optimal may differ from case to case, such as shortest path, fastest (considering traffic and other factors), objective to minimise the total travel distance or individual travel distances ((Klein, 2013). It is to be noted that the objective also depends on the extent of global information available and at what point in time. Although routing is typically executed after the dispatching function (load-vehicle assignment or empty vehicle management), parallel computation is also possible in some cases (ex. if all load information is available at the beginning of operation) (Schmidt et al., 2020). In case of multiple routes available between the source and the sink, routing can be executed in stages of, route planning and route execution. However, this depends on the complexity of the overall layout. In an intralogistics facility, if there is limited or only one shortest path available, the fixed routing algorithm to the destination is usually executed after the assignment process.

Deadlock avoidance basically refers to avoiding and resolution of obstacles and the behaviour of the vehicle at merges and splits. This function is strongly related to routing and depends on the extent of global information being used, as it involves other vehicles in the system. This control strategy problem is also addressed using onboard sensors on the vehicles (ex. robots) to detect the presence of other vehicles and obstacles.

4.5 Decentralised Solving Approaches: A Literature Survey

This section describes the various decentralised solving approaches from literature for the control strategy problems mentioned in Section 4.4. It is important to note that, when an approach is defined as 'decentralised', the aspect of decision-making process and the type of information used is examined. Also, there is no clear cut demarcation between centralised and decentralised approaches, but varying degrees in each of the aspects. For a vehicle based in-house transportation system, the following static and dynamic information are utilised at different levels.

Table 7: Static and Dynamic Information - Vehicle based in-house transport system, adapted from (Schmidt et al., 2020)

Static & Dynamic Information		
Layout Specific [usually static] • Path Layout • Sinks & Sources in Layout • Parking Locations	**Vehicle Specific [dynamic, per entity]** • Current Position • Velocity, Acceleration, Deceleration • Current Status: Idle / Busy • Battery Level • Other Info	**System Specific [dynamic, aggregated]** • Position of other vehicles • Destinations • Path of other vehicles • Queues sizes at source and waiting times • Open Tasks

4.5.1 Load-Vehicle Assignment

As discussed in Section 4.4.2, load-vehicle assignment is one of the preliminary and key step in the control of a vehicle transport system. When it comes to central assignment, it can be classified based on (Le Anh, 2005): a) number of attributes considered in decision-making (rules based on single-attribute or multi-attributes),
b) look ahead period (dynamic rules),
c) possibility of job reassignment
d) possibility of sequential or hierarchical decision making

With the above set of rules, the central computing or decision-making increases in complexity with the increase in problem size, thereby reaching the complexities of computing time and capabilities (Garey and Johnson, 1978). As a result, most central control strategies are heuristics and looking over a certain time horizon rather than aiming for the global optimum. Various decentralised approaches are being researched to address the shortcomings and complexities of the centralised approach to reduce the complex calculations and lower the amount of information required. In the case of load-vehicle assignment, this leads to a) each vehicle or load is assigned independently the next task (decentralised decision-making), b) these decisions are made based on less global information.

In the approaches discussed below, one of the considerations is that there is no complete pre-arrival information for the assignment process. Also, the path layout for the vehicle-based system are classified into: a) single-loop systems, b) tandem systems and c) conventional systems (Le-Anh, 2005). A single loop system is a layout with one guide path loop with multiple loading and unloading stations, while a tandem system consists of multiple single loops. It is typically considered that only one vehicle is used in each of the loops and a transfer point is used for any exchange. Conventional systems represent real-world in-house transportation with multiple vehicles, loops and control complexities.

Based on various literature mentioning decentralised solving approaches for load-vehicle assignment, they can be broadly classified into a) layout transformation and b) multi-agent system.

Layout Transformation
The layout transformation approach is primarily to improve the performance of the decentralised control strategies. Most literature focus on single-loop layouts.

First Encountered First Served (FEFS) for a single-loop layout has been evaluated by Bartholdi and Platzman, where a single vehicle continuously circulates in the loop and as soon as a load is encountered and if the vehicle is idle, the load is picked up and delivered at its destination in the loop itself. This logic is greedy from the individual vehicle perspective. A greedy rule from the load perspective is the First Come First Serve (FCFS), where the time of arrival of the task is used as the deciding factor for assignment. As per the simulation studies performed, FEFS showed better results than FCFS ((Bartholdi and Platzman, 1989). However, FEFS may also result in longer distance travelled, particularly the empty travel distance.

Multiple literatures also mention and evaluate the layout simplification approach. In this, a conventional system is split into multiple single loops, thereby resulting in a tandem system or a single loop is split into multiple segments served by individual bi-directional vehicles, thereby distributing and decentralising the control (Sinriech and Tanchoco, 1993). For the purpose of the assignment, sequential logic is used (Bozer and Srinivasan, 1992).

Compared to the above-mentioned approaches, multi-agent systems, also referred to as agent-based systems are more prevalent in recent times and are discussed in the next section.

Multi-agent Systems
Multi-agent systems consist of two or more agents which interact during the functioning through direct or indirect communication. With the growing interest in decentralised operations, this approach has been the most widely used as it allows plug and play functionality, eliminating a single point of failure and allowing the entry and exit of the agents (Weyns et al., 2008a). This builds in flexibility in behaviour, making the system adaptable to changing conditions. However, in complex systems, the outcome of the interaction between multiple agents becomes unpredictable and may not always be desirable or optimal.

Many multi-agent systems make use of auction-based algorithms. The contract net (CNET) protocol by Smith (Smith, 1980) sets the framework for most auction based control strategies. This describes the sequence of negotiation, the way the task needs to be announced and also the offer by vehicle and task assignment. This protocol has been further extended to reassignment of tasks which encapsulates robustness to the variations in the agents' awareness to the status of the system (Choi et al., 2009). As a continuation to the CNET protocol, but with a multi-agent load vehicle assignment, another method was suggested where the loading station offers the tasks on the market which are evaluated by the vehicles based on ttance to pick-up and the current utilisation of e route for task assignment (Fay and Fischer, 2005). FiTA and DynCNET are two other auction-based protocols suggested in the reviewed literature (Weyns et al., 2008a,b). The former function on the basis of emitted fields both by the loads and the vehicles in the virtual environment. While the vehicle field repels, the load field attracts the vehicle. The assignment process is based on the resultant gradient field and pre-defined paths. In DynCNET, the difference is the stipulated radius of search for both load and vehicles in the process of assignment and the possibility of reassignment or switching. The Foundation for Intelligent Physical Agents (FIPA) CNET suggested by Schwartz et al., modifies the CNET with the possibility of vehicles bidding in multiple an auctions,-but resulting in only one task allocation (Schwarz et al., 2013). Here, the assignment is based on delivery time of the current job and future position. Another interesting two-level decentralised solving approach has been suggested for assignment (Giordani et al., 2013). In the first level, the number of required robots for the tasks in a given time period is calculated based on an iterative auction algorithm, while the second level is for the assignment. Among the literature reviewed for auction-based algorithm, the modified CNET protocol allows the contracting of two vehicles, where the second one behaves as a backup in case of failure (Martin et al., 2017). The assignment takes into account various factors including distance to load, battery level and more.

Apart from the CNET based decentralised solving approaches mentioned above, other forms of task assignment have also been put forth. Since in an intralogistics environment, the utilised time of the vehicle is pretty high, vehicle-based information collection and vehicle-initiated dispatching have been presented (Berman and Edan, 2002). This is aimed at reducing the communication overhead which might be the case in a workstation initiated dispatch. The moving vehicles collect information from all stations and the assignment is done based on the distance to workstations and the due time of tasks. This method is considered partially decentralised as there is a consolidation of information to some extent. For smaller layouts with high demand variability, Klein suggests different strategies of decentralised approaches for load-vehicle assignment (Klein, 2013).

- Random dispatching: Vehicles continuously move in the loop until the encounter of a new open task. While it is truly decentralised and does not use central information for assignment, the energy consumption is expected to be very high due to the continuous movement.
- Static destination dispatching: Having a fixed home position, the vehicle always returns to it after every task completion. Classified as truly decentralised, this logic may not realise in the most optimised travel distances.
- Forecast dispatching: Forecast is done based on the aggregation of information at the sink of the sources of the loads. The aggregated information is used to direct the vehicle to the source with a higher probability of an open task. Although no global information is used, the calculation is still probabilistic.
- Feedback-based dispatching: This is based on a continuously updated probability table at the switches. Here, switches refer to the points at which the vehicle loads or unloads. The feedback provided by the vehicle on waiting times at the sources updates the probability table at the given switch based on which the vehicle is forwarded to the next location.

The above section has presented the studied decentralised solving approaches for load-vehicle assignment. It can be observed that in most of the approaches, while the implementation or the decision making was distributed among the agent the usage of information and communication witnessed some form of consolidation. Very few truly decentralised methods were mentioned, which were also not very practical or optimal. A summary of the studied literature and a discussion is presented in Section 4.5.4.

4.5.2 Empty-Vehicle Management

As explained in Section 4.4, empty vehicle management is strongly connected to load-vehicle management and considered under the umbrella of dispatching. Among the different positioning approaches explained in Section 4.4.3, the central positioning and point of release are pretty straightforward and decentralised as there is no system status that is required and the decision-making is not complex. The circulatory loop positioning, although known for quick response time, results in peaked energy consumption due to continuous movement.

The distributed positioning has been discussed in some literature from two aspects: planning and controlling (Schmidt et al., 2020). In the case of multiple parking or dwell locations, the planning aspect refers to the selection of optimal dwell locations after a task has been executed in an in-house logistics environment. This aspect is strongly influenced by the layout of the facility and the number of vehicles. With the objective of reducing the maximum response time, four different setups: single vehicle-unidirectional traffic, single vehicle-bidirectional traffic, multiple vehicle-unidirectional traffic and multiple vehicle-bidirectional traffic were studied by Egbelu to find the optimum dwell location (Egbelu, 1993). Multiple literatures have researched on the same objective of minimisation of maximum response time, but with various layout configurations. It has been shown that the problem of optimal dwell location is more complex in the case of bidirectional traffic compared to unidirectional loops (Gademann and Van De Velde, 2000). The controlling aspect deals with the problem of distributing a single vehicle between the parking locations. This depends on factors such as the number of vehicles already at the location, the number of vehicles in a loop, required fill levels and more. A study by Le-Anh and de-Koster explored a system with a less number of vehicles parked at the dwell locations and the rest circulating in the loop in idle status (Le-Anh and de Koster, 2004).

From the above description, it can be noted that empty-vehicle management is an integral part of the dispatching process and is ideal to be combined with the logic of the load-vehicle assignment. From the literature, it can be understood that, for distributed positioning, a certain extent of global information of the system is required and sometimes can be a centralised logic. However, the other types of empty vehicle positioning utilise very little or no central information. A summary of the studied literature and a discussion is presented in Section 4.5.4.

4.5.3 Routing & Deadlock Avoidance

The destination is a result of the dispatching process and thus the routing usually follows it. However, in some cases where pre-arrival information is available, dispatching and dynamic routing can happen simultaneously in an iterative process (Schmidt et al., 2020). In any case, it is to be noted that routing cannot occur purely on the basis of local information, but knowledge of the global topology of the system would be required. If not, the forwarding would be random and the destination would not be reached (Klein, 2013).

Klein mentions two types of routing for a decentralised implementation: random routing and central static routing. In random routing, the vehicle chooses the next path randomly without a routing table, leading to a purely stochastic movement. This can apply either only to empty vehicles or all vehicles. In central static routing, shortest paths from all sources to sinks are calculated using the Dijkstra algorithm and stored in a routing table at every switch. At the switch and during the next destination assignment, this information is passed to the vehicle. The tables are created only at the beginning of the simulation. While this uses only local information and not the entire system status, global knowledge of topology is still needed (Klein, 2013).

Multiple other decentralised approaches have been suggested in the literature for routing. However, most of them use the central information or system status to some extent. One such algorithm (Taghaboni-Dutta and Tanchoco, 2007) allows the incremental selection of the next node or segment to ensure a clash-free transport. However, this uses the central system status to track the estimated waiting time at the subsequent nodes. Nishi et al. considered a process where the initial route planning is done by the individual vehicles, but communicated and verified with other vehicles for feasibility and rescheduling (Nishi et al., 2006). While the communication is between agents, the range of communication is something to be pondered about in a decentralised system.

In line with the discussion above, deadlock avoidance is closely related to the approach adopted in routing. As explained in Section 4.4.4, this is applicable at the switches, merges, splits and encountering of obstacles on the route. For an optimum execution, information on system status would be needed to predict the congestion or obstacles in different segments along the route to avoid them. Moving to a more decentralised approach, First Come First Serve basis is a commonly used logic to resolve conflicts (Klein, 2013) at merges and splits. The onboard sensors of the vehicles also help in the localised detection and resolution of obstacles.

A truly decentralised approach whether with regard to information usage or implementation is not feasible in routing and deadlock avoidance. In most approaches, we see the usage of central information or at least the global topology to some extent. A summary of the studied literature and a discussion is presented in Section 4.5.4.

4.5.4 Discussion: Emergent Behaviour & Need for Study

Various control strategies have been suggested in publications for decentralised architecture. It is to be noted that the extent of decentralisation and functioning purely on local information vary. Most of the publications discuss the conceptual nature of the systems. However, the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents. As a consequence, predicting the performance of a decentralised system can be hard (Shen et al., 2006). The emergent behaviour may not always be desirable.

Table 8: Decentralised Solving Approaches: Summary of Literature

Control Strategy	Approach	Paper	Remarks
Load-Vehicle Assignment	Layout Transformation	Bartholdi and Platzman, 1989	First Encountered First Serve, First Come First Serve
		Sinriech and Tanchoco, 1993 Bozer and Srinivasan, 1992	Layout simplification
	Multi-Agent System	Smith, 1980 Choi et al., 2009	Auction based on CNET protocol
		Fay and Fischer, 2005	Multi-agent Load-Vehicle assignment based on CNET
		Weyns and Holvoet, 2008 Weyns et al., 2008	FiTA DynCNET
		Schwarz et al., 2013	Foundation for Intelligent Physical Agents (FIPA) CNET
		Giordani et al., 2013	Two level multi-agent framework
		Martin et al., 2017	Modified CNET
		Berman and Edan, 2002	Vehicle-initiated dispatching
		Klein, 2013	Multi-agent decentralized approach
Empty Vehicle Management	Planning Aspect	Egbelu, 1993	Different layout configurations
		Gademann and Van De Velde, 2000	Layout comparison for optimal dwell location
	Controlling Aspect	Le-Anh and de Koster, 2004	Vehicles distributed between parking and circulatory loop
Routing & Deadlock Avoidance	Multi-Agent System	Klein, 2013	Random routing Central static routing First Come First Serve (deadlock avoidance)
		Taghaboni-Dutta and Tanchoco, 2007	selectnextnode algorithm
		Nishi et al., 2006	Initial individual planning and rescheduling

System robustness and flexibility has always been claimed as an upside of decentralised systems. Also, the rapid installation process has always justified the push towards autonomy and decentralisation. But the actual estimation of the benefits of such a system is still lacking. The conditions under which a decentralised control would be more profitable or results in higher performance requires further research (Fragapane et al., 2021). The influence on system performance by multiple decision variables such as the number of vehicles, zoning, simultaneous scheduling and path planning, all based on contextual local interactions in a dynamic environment needs to be studied further.

One powerful method to deal with the above-mentioned challenge is through modelling. Different approaches such as virtualisation by digital twins and simulation modelling would help in understanding and predicting the emergent system behaviour under a specified set of ground rules. For a given case, studying the emergent behaviour of a self-organising system in a virtually developed ecosystem would substantiate future investment. Although multiple such models are already being developed, the challenge is the extent of decentralisation and the complexity of real-world application. Developing such a model will also help in preparedness for predictive maintenance in the future(Fottner et al., 2021).

4.6 Summary

The purpose of this chapter is to set the framework for conceptualising the self-organising system of robots for the intralogistics facility in focus. This chapter in conjunction with the next one is aimed at answering the sub-research question, *"How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?"*. Setting the stage for automation and a framework to explain its extent is the first step. A two-dimensional classification with task level and automation level is drawn, which is later used to specify the degree of automation in the system under focus. It is understood that openness, intelligence and decentralised control are the key functionalities of a self-organised system. However, the degree of self-organisation varies with the type of information used and decision making. On the basis of this, the design requirements of the new system are laid out and conceptualised as illustrated in Figure 14, including the key actors and interactions involved. The new system aims to reduce the fatigue due to manual operations in the existing system and incorporate robustness.

Next, the control strategy problems for a vehicle based in-house transport system are explored. Load-vehicle assignment and empty vehicle management, coming under the umbrella of dispatching are usually addressed together while designing the solving approach. The dispatching function can be either vehicle-initiated or load initiated with the corresponding actions being the trigger. Routing and deadlock avoidance generally follows after the destination assignment but is also possible to have the process run in parallel to dispatching in case of dynamic routing. It is understood from the literature that system design, mainly concerning the optimum number of vehicles in a system is achieved through comparative simulation runs.

This leads the way to exploring the decentralised solving approaches for the control strategies in intralogistics. The critical aspects defining decentrality in an in-house vehicle transport system are the type of information and decision making process. While in load-vehicle assignment, the multi-agent approach is most commonly used in recent times, various literatures explore the auction-based approach mainly with the CNET framework. Approaches based on the modifications of the CNET framework use system information with varying extents between purely local and global. But most of the decision making appears to be distributed or decentralised. Klein suggests four interesting and simple approaches for implementing decentralisation in the dispatching process. Empty vehicle management is closely linked to load-vehicle assignment and is mostly referred to together as dispatching in many papers. Minimisation of the maximum response time is the key over here. In the various approaches studied for routing and deadlock avoidance, the takeaway is that a truly decentralised approach whether with regard to information usage or implementation is not feasible. Using purely local information leads to random forwarding of vehicles and the desired destination might not be reached. We see the usage of central information or at least the global topology to some extent.

It is key to note that there is no clear cut demarcation between central control and decentralised control. Based on the usage of information and the type of decision making, the level of decentrality varies. However, from a multi-agent perspective, the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between the agents. Robustness and flexibility which are considered as the motivators for the push towards self-organised systems need to be tested more for real-world applications. Simulation modelling is one of the ways forward.

In Chapter 5, this literature research and motivation are used to build a conceptual model for the envisioned self-organising system of robots for material transport in the intralogistics facility.

5 Conceptual Model of New In-house Material Transport

The previous chapter established the framework of control strategies to be focused on a vehicle based in-house transportation system and also the various decentralised solving approaches in the literature. It is also understood that the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents. One of the ways to move forward and understand such a system is through modelling, and a critical step is to formulate a conceptual model based on the objectives and requirements set for the case.

This chapter lays down the concept and the detailed specifications of the self-organised system of robots being considered in the intralogistics facility. In continuation to Chapter 4, this chapter aims to complete the answer for the sub-research question, *"How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?"*. In addition, it also attends to the sub-research question, *"What modelling technique would be the most suitable to study the emergent behaviour of the system?"*. Figure 16 specifies the stage in the planned methodology. Starting with the objectives and suitable modelling technique, detailed model specifications and implementation of control strategies are explained.

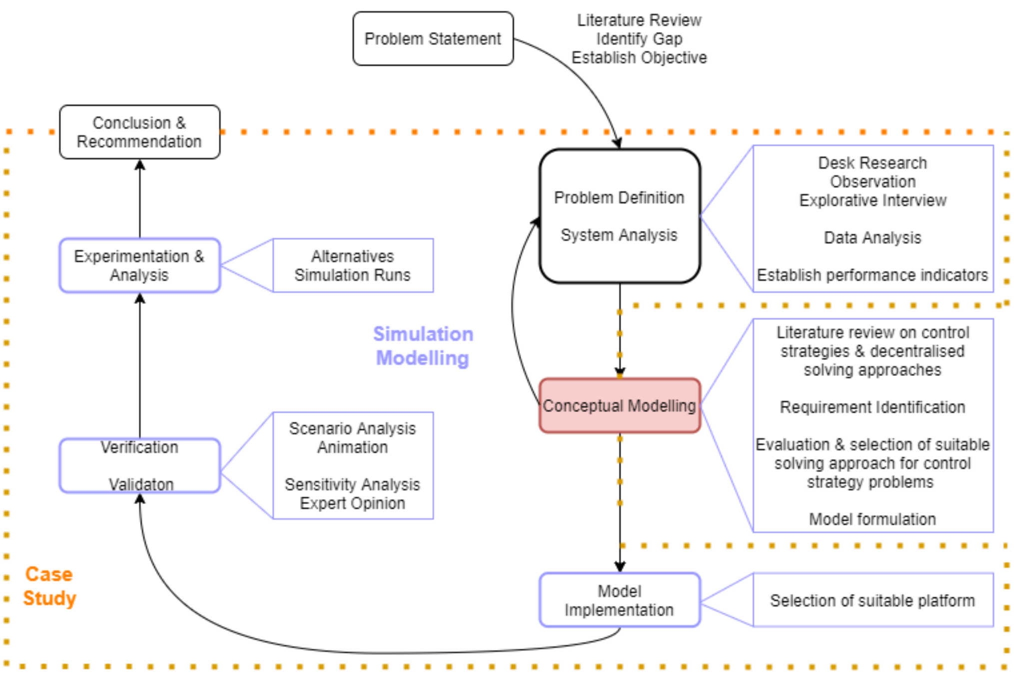


Figure 16: Phase: Conceptual Modelling, adapted from (Kelton, 1998; Sargent, 2015; UH)

5.1 Model Objectives

Before conceptualising, it is imperative to revisit the problem statement mentioned in Chapter 1 that was chalked out in discussion with Prime Vision. *"Develop an intuitive, adaptable and scalable model to study the emergent behaviour of a self-organising intralogistics system"*. With this statement and an interview with Mr. Bernd van Dijk, Director Innovation at Prime Vision, the objectives for the project were laid out which are also the foundation for building the model.

- The model should incorporate the defined level of automation and self-organisation as conceptualised in Section 4.3 to replace the existing manual operation of material movement within the intralogistics facility.

- It should function as a Decision Support Tool for Prime Vision, with a capability to reconfigure demand, number of robots and other system parameters and record the performance indicators for further analysis.
- The model should facilitate the conducting of experiments to compare the performance indicators under different configurations and demand scenarios to study the efficiency and robustness of the system.

These objectives in conjunction with the need for studying the emergent behaviour of a multi-agent system as explained in Section 4.5.4 guide the course of the conceptual model.

5.2 Modelling Technique

There are various approaches to analyse a material handling system subject to the situation, including operating principle, budget, available time and other factors (Daniluk and Chisu, 2010). Although experiments in real-world is one of the most intuitive approaches, it proves to be expensive, time-consuming and disrupts existing operations. As mentioned in the introduction, in the case of the self-organised system of robots, the added challenge is the emergence of complex system characteristics arising from the interaction of multiple agents and their decentralised decision making (Schmidt et al., 2020). Each agent is capable of performing autonomous, local action to achieve its own goal (Abar et al., 2017). An analytic, static modelling technique is not suitable for such a multi-agent system due to its dynamic and decentralised character. Instead, a simulation model would steer the system through state changes as model time progresses (Borshchev and Filippov, 2004).

The level of abstraction is a factor that influences the approach chosen for simulation modelling. For the operational level focused in the case of this project, the level of abstraction is low and the suitable approaches include Discrete Event Modelling (Process-Centric Modelling) and Agent-Based Modelling (Borshchev, 2013; Borshchev and Filippov, 2004). In discrete event modelling, the sequence of operation is the focus and the same can be represented in the form of a flowchart. The elements (usually passive) or the resources pass through a sequence of events as the system status changes, triggering more actions (Mahdavi, 2020). Agent-Based Modelling is suited for systems with active sub-systems or elements which interact with each other locally and the system characteristics are due to the collective behaviour (Klügl and Bazzan, 2012).

ABM (Agent-Based Modelling) is the most widely used method for simulating complex systems with multiple interacting and autonomous agents (Nikolic and Ghorbani, 2011). The modelled system in ABM is made up of numerous software agents living in a bounded environment. Agents are dedicated to achieving their personal goals by interacting with other agents and the environment while adhering to a set of rules (Klügl and Bazzan, 2012). ABM is very beneficial for observing this emergent behaviour and performance, as well as understanding how a system responds to changes in rules, for example. This is accomplished via Agent-Based Simulation (ABS), which entails simulating how agents behave and interact with other agents and their surroundings across a finite number of time steps(MacAl and North, 2010).

In this project, a multi-method modelling approach has been adopted. This means the characteristics of the above mentioned two approaches have been combined to form a hybrid method. While the flow of the operations involved in the vehicle-based material transport is represented using a process-centric model, the individual behaviour of the agents is represented using statecharts. The reason for following this method is to capture the nature of the intralogistics operations involved in an intuitive way and make the model easy to use. This form of model building also gives more control over the details to be focused upon and makes it convenient to extend and adapt the model for different business cases (Borshchev, 2013).

5.3 Model Specification: Components

The conceptualisation of the new system is described in Section 4.3 and the modelling objectives are set in Section 5.1. Before proceeding to describe the control strategy design, it is important to mention the detailed specifications and operating conditions. The description of the model specification is broadly divided into components and process. The active and passive components of the model are described in this section. The process including the control strategy design is explained in section 5.4.

5.3.1 Active Components: Actors & Attributes

Section 4.3.1 introduced the actors involved in the new method. In this section we discuss the attributes associated with each of these actors. While some of these attributes are static, such as the load-carrying capacity of the vehicle, maximum speed, battery discharge rate and more, the dynamic attributes change through time such as the status of the robot and distance travelled.

Robots
The current specifications and features of the robots are based on an equivalent to the ones manufactured by Prime Vision. At the start of operations, the robots are located at the home or parking location which also has the charging facility. This can be situated closely to the loading point in case of a central loading location. The key attributes of the robots are as follows:

- The structure of the robot includes a load-carrying platform of fixed dimension. The robots are battery powered and move on a smooth industrial floor. It is to be noted that the weight carrying capacity of the robot is not simulated in the model.
- The robots have a maximum limit on velocity, acceleration and deceleration. Apart from normal operation, the maximum speed is also restricted in the case of obstacle detection.
- Being battery powered, the robots need to be charged when the level reaches critical status. For the purpose of design, the battery percentage is considered to vary between 0 - 100% and 15% is considered as critical level when charging is recommended. The discharge rate of the battery is different during the operation and idle conditions. The battery can be an inbuilt or removable one. The specific details on the type of recharging are not in the scope of this simulation.
- The robots have onboard sensors such as the Lidar to detect and resolve obstacles. Although the sensor itself is not considered for simulation, there is a fixed distance range within which an obstacle can be detected and the action for resolution can be taken.
- Every robot is considered as an agent and is capable of communicating with other robots as well as the cases. This communication is used for the assignment process and resolving obstacles.
- Upon assignment, the case needs to be manually loaded onto and later unloaded from the robots.
- Based on the operation, the robot can have three possible states: (1) Seized: After a case has been assigned to the robot, (2) Released: After the delivery of a case to the destination or when in idle condition at the parking location, (3) Charging: When the battery level goes below critical
- Certain performance indicators of the robots are continuously tracked during the operation including (1) Distance Travelled (unit of distance), (2) Total Busy / Idle Time (unit of time), (3) Utilisation (in %), (4) Total cases delivered (number)

Cases
In this context, the case is considered a container to carry the components from the source to the destination. The key attributes of a case are as follows:

- A case has a dimension corresponding to the loading platform of the robot. As mentioned before, weight is not simulated in the model.
- Once an order is raised with a task priority, a case is automatically allocated to the task and carries all the attributes of the task. For simplicity, every order raised is considered as one case. Also, to ensure ease of unloading and avoid mix-up of components, every case is dedicated to one destination.

- The retrieval of components from storage and preparation of the case is done manually by the warehouse operators. This process is to be included as a time delay in the simulation.
- Based on the order being served, the following attributes are linked to the case: (1) Case ID, (2) Destination, (3) Task Priority (Normal or Urgent)
- If the task priority is normal, the case passes through the queue on a First Come First Serve Basis. Cases with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority cases.
- The cases have a fixed order preparation, load and unloading time.
- The case can be defined under two states: (1) Generated (recorded as 'entry time' of the case) (2) Delivered (recorded as 'exit time' of the case)
- Once at the front of the queue, the cases can send a transport request to the robot. Based on the response from the robot on its availability and battery status, the assignment takes place.
- Certain performance indicators of the cases are continuously tracked during the operation including (1) Order fulfilment or service time (unit of time), (2) Number of cases delivered or throughput (number)

Platform
The central platform is mainly responsible for consolidating the raised orders in a queue based on the set logic. This facilitates the load-vehicle assignment. The normal mode of operation is the First Come First Serve mode for the orders. However, cases with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority cases. An attribute linked with the platform is the queue size.

The project-specific attributes used in model implementation are mentioned in detail in Chapter 6.

5.3.2 Passive Components: Network Elements & Topology

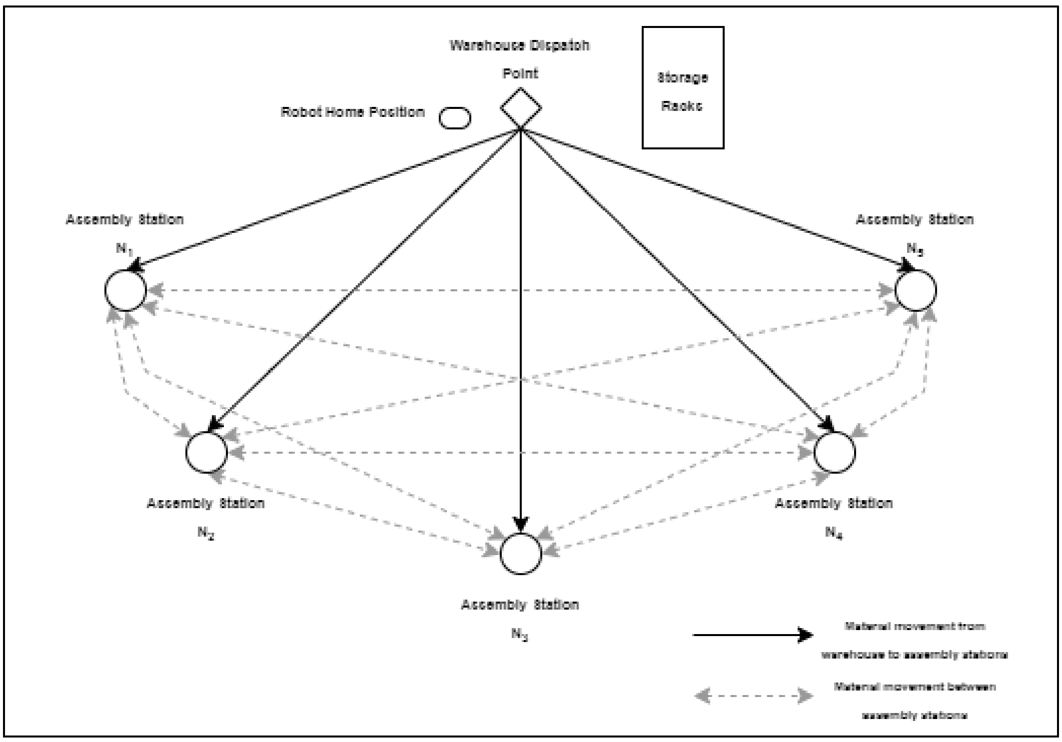


Figure 17: Network topology

It is important to mention network topology to enable a better understanding of the solving approaches. Section 3.1.2 and Figure 9 present the layout and elements involved in the existing in-house transportation. The new system is based on the same. Most material movement is from the warehouse dispatch point to the different assembly stations. There is also material movement between the different assembly stations. The warehouse dispatch point and the different assembly stations are the nodes or switches in the network. the vehicular movement between these nodes takes place on a dedicated path. This network topology is mentioned in the Figure 17.

5.3.3 Operating Conditions & Assumptions

Now that the actor attributes have been specified, the important operating conditions and assumptions need to be set before dwelling on the control strategy design. This helps set a context to the content in the next section.

First of all, the fleet of robots considered for the operations are homogeneous in terms of features such as dimension, maximum speed, load-carrying capacity and other auxiliary characteristics. Although there are no physical markers, the robots are still path-guided virtually. Each robot can handle only one transport request at a time. Thus planning of vehicle tasks is not possible. Also, re-assignment or split up of loads is not possible. Every order is considered to be catered to by a case. Mixing and match of components from different orders, even from the same assembly station has not been considered. Even if done, it is at the discretion of the warehouse operators. For ease of unloading and to avoid mixing of components, every case consists of order to only one destination.

In terms of layout, one central home or parking location is considered near the warehouse loading location. The same location also serves as the battery charging point for the robots. The majority of the demand is from the central warehouse to the fixed assembly stations. However, there is also a part of demand between different assembly stations. No movement is considered back to the warehouse based on the discussion with the Head of the Warehouse (personal communication dt. 19 March, 2021, Appendix A.2). While the communication and collation of orders with task priority occur across the network in a central platform, most of the control strategy decisions occur in a decentralised form based on limited, local information. This is further explained in Section 5.4 A dedicated two lanes, but a uni-directional path is considered for the movement of the robots.

5.4 Model Specification: Process (Control Strategy Design)

In Chapter 4, the different control strategy problems that need to be addressed in an intralogistics system were discussed in detail along with the various decentralised solving approaches available in the literature. This section deals with the control strategy design for the new method as explained in Section 4.3. The static and dynamic information as listed in Table 7 have already been taken into account while stating the model specification. The approach for solving the control strategy problem has been explained in two stages. The first is the dispatching including load-vehicle assignment and empty vehicle management. The aspect of battery management has also been included in this step. Next is the routing and deadlock avoidance. With the modelling technique mentioned in Section 5.2, these steps are aimed at satisfying the design requirements set in Section 4.2 and aid the implementation of the model.

5.4.1 Dispatching: Load-Vehicle Assignment & Empty Vehicle Management

The new method for dispatching being discussed here is based on the **Static Destination Dispatching** (Klein, 2013), which is a decentralised solving approach presented by Klein. However, it has been modified to suit the intralogistics facility under focus and the type of robots being considered. In the literature, Klein describes this method as having a fixed home position and the vehicle returning to the home position always after task completion. With limited knowledge of the network, i.e., coordinates of the home position and the coordinates of the next destination of the assigned, the vehicles move in the network. The vehicles do not actively search for the next task after completion. The task assignment happens with the one with the highest waiting time. Based on the information usage and type of decision making, the approach is tagged as truly decentralised and no major problems were experienced during the implementation.

The key reason for choosing this method is the suitability of the method for small layouts with high demand variability (Schmidt et al., 2020). Also, in the chosen intralogistics facility, we observe the smaller shipment sizes and more frequent movement. Once the components are ordered, there is no customer (assembly station operators) interaction. Considering the short travel time and no transfer of shipment between different vehicles, this method fits the purpose. Adapting this method to the case being dealt with in this project, the following major changes have been made:

- Load initiated dispatch is followed as in Klein's method. However, after task completion, the robots also search for an open task. The robots return to the home position only if there are no active tasks at any of the sources. This has been done to accommodate the transport requests at any of the stations and reduce the distance travelled.
- Shortest distance is considered as a deciding criterion for load-vehicle assignment.
- Tasks with different priority levels have been incorporated in the system as against the simple First Come First Serve in the literature.
- Battery level of the robots has been considered as an attribute to allow recharging at the required moments.

In section 4.4.2 and 4.4.3, the basic characteristics and types of load-vehicle assignment and empty vehicle management are discussed. Since both these control strategy problems are closely interlinked, they are being dealt with under the common umbrella of dispatching. As discussed in the previous paragraph, a *combination of load initiated and vehicle initiated dispatch* is considered in the new method. The two types of triggers considered here are: *arrival of a new case in the system (load initiated) and vehicle delivers its load to the destination (vehicle initiated).* For empty vehicle management, *central zone dispatching* is used, as there is a single warehouse loading point. This can be classified as a multi-attribute dispatching approach. Figure 18 shows the swim-lane flowchart of the conceptual model of the new self-organising system of robots. Below is a step by step description of the dispatching process:

- In the new method, each of the assembly stations raises an order for components required from the stockroom. These orders are attached with the priority level: urgent or normal by the assembly station operator responsible for raising the order. Another type of order also exists, which are the transport requests from one station to the other. These may arise due to re-routing of the received components or transport of half products and are always tagged as urgent.
- A central platform is responsible for receiving both these orders and queuing them based on the priority levels attached. Although the basic policy is First Come First Serve, the tasks with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority orders. Order preparation includes the warehouse operator retrieving the components from the storage location and preparing the case ready for loading. The order preparation time is to be incorporated as a delay in the model. However, no delay is considered for the station to station transport requests.
- At the initialisation of the system, all robots are present at the home position in fully charged (100%) condition and 'Released' state.
- The case at the front of the queue sends a transport request to all the robots. The initial internal check in the robots is for their current status. If in the 'Released' state, the robot responds with the shortest distance to the source of the case or transport request. Among them, the robot nearest to the case is assigned and the robot moves to the loading point.
- Manual loading of the case takes place after which the robot moves to the assigned destination to deliver the case. Unloading is also a manual operation. Loading and unloading times are incorporated as delays during modelling.

(contd. after figure)

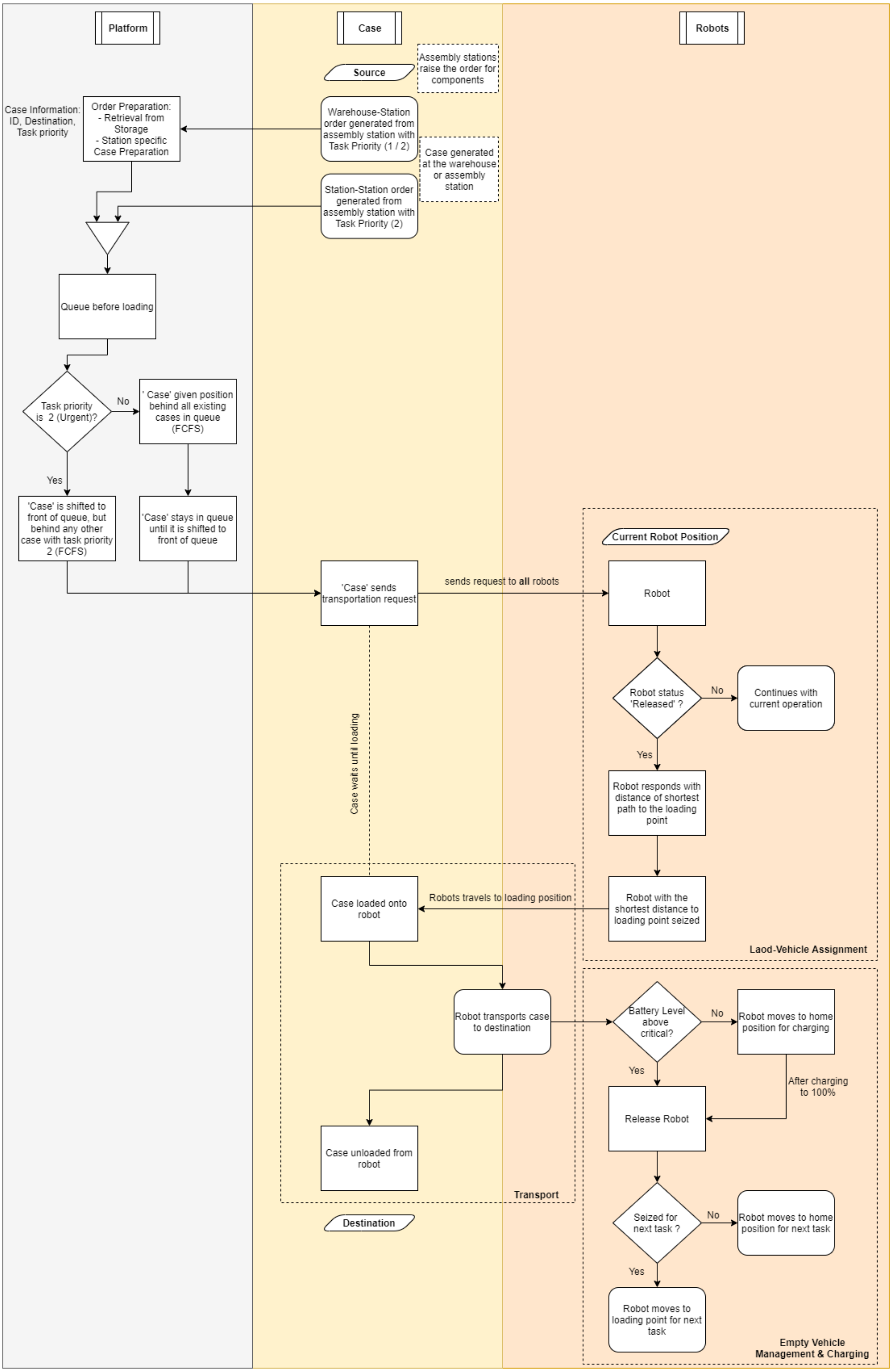


Figure 18: Swim-lane Flowchart: Conceptual Model of New Method

- Once a task is completed, the internal state-chart of the robot checks for the battery level. If the same is above the critical state, the state of the robot changes to 'Released' and checks for open transport requests. If there is an open request and the assignment condition explained above is satisfied, it moves to the new loading position. If no active tasks are present, the robot moves to the home position.
- If the battery level is detected as critical, then the state of the robot changes to 'Charging' and moves to the home position for charging. After the delay for the re-charging period, the state of the robot changes to 'Released' and is available for a new assignment.

5.4.2 Routing & Deadlock Avoidance

In section 4.5.3, it has been discussed that the routing process usually follows dispatching. However, when it comes to a decentralised approach, routing cannot occur purely on the basis of local information, but knowledge of the global topology of the system would be required. If not, the forwarding would be random and the destination would not be reached. Section 5.3.2 briefly presents the topology of the network with the key nodes and arcs. The nodes are also called the switches, representing the home position of the robots, loading and unloading points.

The routing in the new method is based on Klein's Central Static Routing (Klein, 2013). As per this, the shortest path from the source to the destination is calculated using Dijkstra's algorithm and stored in a routing table at every switch. Here switch refers to the home position, loading point or any of the assembly stations. At every switch, after the next destination assignment occurs, the robot follows the shortest route to the next destination. Hence the robot need not be aware of the entire system status, but only the network topology. The choice of method for routing would also depend on the size of the layout, route options available and total traffic in the system. The capabilities of the simulation software is also a factor to be considered. In this case, the major focus has been on the decentralised dispatching strategy. Also, considering the smaller layout and fewer route options in the intralogistics facility, the chosen method for routing is suitable. The path for the movement of the robots is a two-lane, unidirectional path.

Deadlock avoidance is closely related to routing and the onboard sensors of the robot. The possibilities of deadlock are mainly at the intersections, splits and merges. At these junctions, First Come First Serve has been used as the logic to resolve conflicts. The Lidar on the robots is used to detect obstacles including humans, structures and other robots. The minimum distance to the obstacle needs to be defined at which the robot identifies the object as an obstacle. On detection, the robot decelerates and later stops until the obstacle is removed. As a safety feature, the robots also decelerate before a curve or intersection.

5.5 Summary

This chapter along with the previous one, completes answering the sub-research question, *"How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?"* Motivation stemming from the problem statement by Prime Vision, objectives for the model are specified. It is concluded to use a multi-method simulation modelling, involving a hybrid of agent-based and process-centric approach to addressing the dynamic and decentralised system. This also answers the sub-research question, *"What modelling technique would be the most suitable to study the emergent behaviour of the system?"*. With the existing operations as explained in Chapter 3 as a reference, the new method for vehicle-based in-house material transport has been conceptualised in Section 4.3. The principles of self-organisation and mainly decentralised control strategies are utilised to formulate the new method involving the actors: robots, cases and central platform.

Before proceeding to the control strategy design, method specification is critical. In this section, the detailed attributes of the actors or agents in the system, as well as the environment, are defined. The robot attributes use the robots manufactured by Prime Vision as a reference. The cases are the next important agent in the system and are capable to communicate with the robots by raising a transport request and assigning themselves to a suitable robot. The task priority is an attribute attached to the case or task which factors in the queue formation by the platform, which is its main function. While the normal mode of operation is First Come First Serve, cases with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority cases. The layout of the intralogistics facility consists of a single stockroom and multiple assembly stations which request the components. Although less, transport requests are also raised for the station to station movement. The rate of demand keeps fluctuating.

The decentralised control strategy design is based on the literature review presented in Chapter 4. The network topology as represented in Figure 17, consists of nodes or switches (home position of robots, loading and unloading points) and arcs. The decentralised approach to deal with the dispatching problem is based on Klein's Static Destination rule. With appropriate modifications to include the shortest distance criteria for the assignment, check on battery level and inclusion of task priority, the method is represented in a swim-lane flowchart to also show the agent interactions. As opposed to robots always returning to the home position after task completion in Klein's method, this method involves the robots having an additional check for open tasks before returning home. The check for critical battery level and return to home for charging is a feature that has been included. The routing makes use of a central static approach with fixed routing tables based on Dijkstra's algorithm at the switches. Although this information is locally communicated at the switches, knowledge of network topology is still required. Deadlock avoidance is mainly achieved through FCFS at the intersections and through onboard sensors to detect and resolve obstacles.

All the above steps are aimed at satisfying the set design requirements. With the conceptual model in place, the next chapter moves towards the implementation of the model on a suitable platform. Chapter 6 describes this in detail.

6 Model Implementation

The problem statement for this thesis is *"Develop an intuitive, adaptable and scalable model to study the emergent behaviour of a self-organising intralogistics system"*. Considering the implementation of automation in an intralogistics facility where the vehicle-based material transport is dominated by manual operation, Prime Vision's look ahead is to explore the feasibility of a self-organising system of robots. Robustness under high demand variability has been one of the hypothesised advantages of self-organisation. However, given the complex emergent system characteristics arising from the multi-agent interaction and the lack of extensive operational studies, this thesis set out to develop an intuitive decision support tool to study the system performance of a self-organised system of robots under different configurations and varying demand. Until Chapter 4, the premise was set to describe the existing system and the different forms of decentralised solving approaches for the control strategy problems of intralogistics. In Chapter 5, a conceptual model was formulated to implement automation and self-organisation in intralogistics. The next step is to implement this model on a suitable platform that allows the user to interact, manipulate demand and configuration and analyse the results. As shown in Figure 19, this chapter deals with the model implementation, verification and validation.

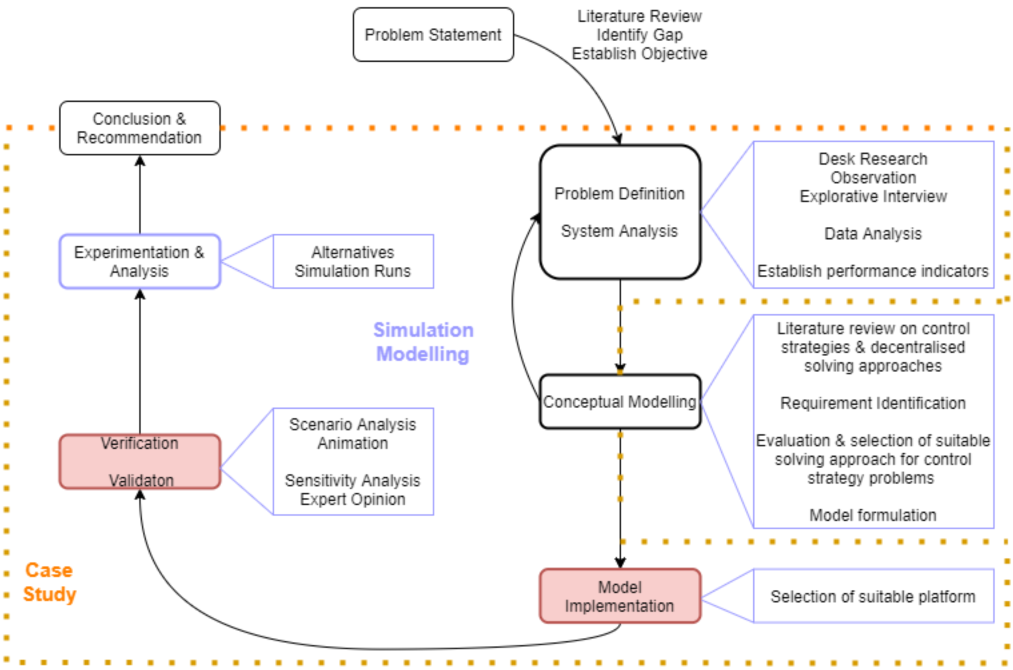


Figure 19: Phase: Model Implementation, Verification & Validation, adapted from (Kelton, 1998; Sargent, 2015; UH)

The main intent of this chapter is to implement the conceptualised model keeping in mind the requirements of the industry, thus addressing the sub-research question, *"For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?"*. In Chapter 3, the existing state of operations and its performance indicators in the chosen case of intralogistics facility were discussed. The existing case dominated by the manual operation is not being simulated on the platform. Hence a direct comparison of the performance indicators would not be appropriate. However, while the system analysis of the existing case provided an estimation of the manual effort involved, the simulation of the new system of self-organised robots with a similar demand pattern would assist in the system design. Also, with the option to analyse the performance indicators resulting from varying demands, it would be possible to study the robustness of the new system.

6.1 Modelling Platform

In Section 5.2, it was established that the modelling technique used in this project is a multi-method simulation involving a hybrid of agent-based and process-centric modelling. Considering the dynamic and decentralised nature of the system under consideration, this method provides more control over the details to be focused upon and makes it convenient to extend and adapt the model for different business cases. Anylogic is a software that facilitates an intuitive platform for multi-method modelling. While providing an easy-to-use interface for implementation using UI and Java-based programming, multiple libraries like the material handling and process modelling provides comprehensive features for simulating complex real-world operations. The options available for animation (2D and 3D) and visualisation (performance indicators) are added attributes that help build an easy to understand interface for the end-user in case of tool development.

6.2 Implementation

This section describes the implementation of the conceptual model presented in Sections 5.3 and 5.4. Anylogic has been used to build the floor of the intralogistics facility as per the dimensions on the actual shop floor. The demand generated by each of the assembly stations is stochastic, based on the demand pattern of the existing operation which is obtained through data analysis as presented in Section 3.2.2. While a process flow with relevant blocks takes care of the sequence of operation, the agent has a built-in state chart to control the individual behaviour of the agents. The simulation runs over the defined time period in discrete steps. The collective behaviour of the system can be observed through the animation and analysed using the graph of performance indicators.

6.2.1 Simulation Specifications

The simulation model has certain inputs from the user, resources that are configured by parameters and output. In this model, the key input is the demand at different stations. However, the details on the number of robots, loading and unloading time, type of control strategy and order preparation time can also be configured by the user before the simulation. Other elements are configured within the model. The upcoming sections explain these in detail. The output of this model is the performance indicators which are later described in the Section 6.3.

A: Agent Properties
We have three types of agents defined in this project: robots, cases and the platform. The attributes associated with these agents have been laid out in 5.3.1. In this section, specifications of these agents as implemented in Anylogic is presented.

Robots
Robots are created as agents with its own state-chart and homogeneous characteristics. Figure 20 shows the states, transitions and the relevant conditions within the robot agent. It is seen that there are mainly three states 'Released', 'Seized' and 'Charging' through which every robot transits. All the robots initialised in the 'Released' state. When the transport request is received from the cases and the load-vehicle assignment happens as per the specified conditions, a message is sent from the assigned case. Based on the message, the state of the robot changes to 'Seized'. Similarly, after the completion of the task (delivery of the case to its destination), a message is received by the robot, based on which the next transition towards 'Released' starts. However, during this transition, an internal check on the battery level occurs. If the battery level is more than 15%, the state transition to 'Released' takes place. The robot either stays at the point of release or moves to the home position based on the selected logic in the process flow. If the battery level is critical (less than 15%), the state changes to 'Charging' and the robot moves to the home position for charging until it is fully charged to 100%. The simulation of battery charge and discharge is achieved through an internal transition command within each state. When the robot is in 'Released' or 'Seized' states, the battery counter decreases at a specified rate. When the robot enters the charged state, there is a timeout (charging time), before the transition to the 'Released' state occurs.

Within the robot agent, the variables created are mentioned below:

- *Robot Status:* To store and track the state of the robot
- *Battery Level:* Counter to track the battery level of the robot between 0 to 100% in steps of 1%.
- *Timer (Released, Seized and Charging):* Time counter to track the time spent by the robot in each of the states

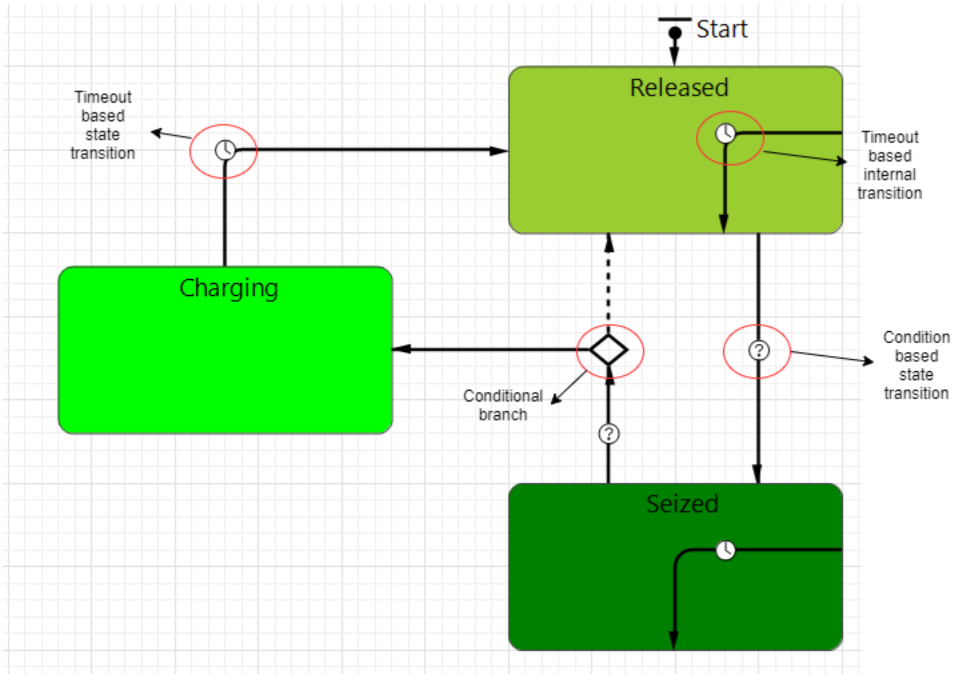


Figure 20: Robot state chart (as implemented in Anylogic)

All the robots are grouped in a population or a 'Robot Fleet'. This block is used to specify the characteristics of the robots. Since a homogeneous group is considered, all individual specifications remain the same.

- *Capacity(number of robots):* The total number of the robots at any point during the simulation run is defined by the parameter mentioned on the Control Dashboard. Refer 6.2.3.
- *Dimensions:* Defined as per the dimensions of the robot in Prime Vision's specification sheet. Length: 0.75 metres, Width: 0.51 metres, Height: 0.2 metres
- Maximum Speed: Defined by the parameter mentioned on the Control Dashboard. Refer 6.2.3.
- *Home location:* A central home position is defined near the loading point in the warehouse as defined in the layout.
- *Reaction to obstacles:* Defined as per Prime Vision's specification sheet. Minimum distance to obstacles is defined as 0.5 metres and the speed of the robot near the obstacles reduces to half the originally defined speed.
- *Load capacity:* The simplification considered is that every robot can carry 1 case at any point in time. The dimensions of the cases are homogeneous and the weight of the cases has not been taken into consideration.

Cases
Similar to the robots, cases (containers carrying components to assembly stations) are also created as agents with homogeneous characteristics. They consist of a simple statechart that starts as 'Unassigned' at the time of the creation of the order and leaves the system when delivery is completed. As stated in 5.3.1, a case is intelligent and can communicate with and choose a robot to satisfy the transport requirement to its destination. The cases are a part of the population, which are created based on the order generation at each of the assembly stations. The following variables are specified within the individual 'case' agent:

- *Destination ID:* At the time of order generation, a Destination ID is assigned to the case. The ID is the name of the destination assembly station. The assigning of this is based on the stochastic (triangular distribution) order generation parameters entered for the simulation run.
- *Task Priority:* Similar to the Destination ID, a task priority number is assigned to each case at the time of order generation. Task Priority: 1 indicates normal task and Task Priority: 2 indicates urgent task. The ratio of the tasks of different priorities is based on the parameter 'Percentage of Urgent Tasks' entered for the simulation run.
- Case Status: This variable tracks the status of the case once it enters the system as 'Unassigned' and later leaves the system after delivery at its destination.
- *Timer:* The counter variable associated with each case, tracks the time from the moment the order or case is generated to the moment it is delivered at its destination (and thus exits the system).
- *Dimension:* The dimensions of the case are designed to fit the load-carrying base of the robots.

Platform
The platform is represented by the dispatch queue block in the process flow. As explained in 5.3.1, the main function of the platform is to consolidate the raised orders in a queue based on the set logic. before load-vehicle assignment. The normal mode of operation is the First Come First Serve mode for the orders. However, cases with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority cases. An attribute linked with the platform is the queue size, which is currently set as unlimited.

B: Environment
For the agent to function as intended, the environment matching the intralogistics facility needs to be created. As shown in Figure 21, the floor plan of the intralogistics facility under study is drawn to scale as per the dimensions on the actual site (Figure 9). We see that there is a single loading area which is a source node located near the storage warehouse. The home position for the robots is located on a loop siding near the loading area. The block next to the loading area is a virtual representation of the orders or cases generated before loading. The assembly stations are created as nodes (source or sink) at different locations in the warehouse. A uni-directional path is created to link the different nodes. with each other. Different camera positions have been defined to observe the 3D animation during the simulation run. The key elements associated with the environment are:

- *Nodes:* Node defines the place where the agents reside (source or sink). In this case, the loading point in the warehouse, the parking location of the robots and the assembly stations are all located by nodes.
- *Attractors:* Attractor allows controlling agent's location inside a node. For example, the exact loading point with the loading area or the position of each robot within the parking area can be located using an attractor.
- *Network*: Network is a graphical representation of the path for the movement of the agents between different nodes. The paths are unidirectional and the speed limit on each segment can be specified. The maximum number of robots on each of the paths can be specified. Using graphical representation, the behaviour of the robots at the intersections, merges and splits on the path can also be defined. In the current project, the robots drive on the left side of the path and follow left-hand traffic rules at turns and intersections. To resolve conflicts and collisions at the intersections, First Come First Serve logic is followed.

- *Graphic elements:* Different graphic elements are created to make the simulation more intuitive during the simulation run. This includes the coloured blocks to indicate the shop floor, loading area, parking area, different assembly stations and the movement path for robots. Walls have also been set up which behave as obstacles for robots. The dimensions between different areas have been indicated in Figure 21.

- Camera: Cameras can be located at different points in the environment to view the 3D animation during the simulation run.

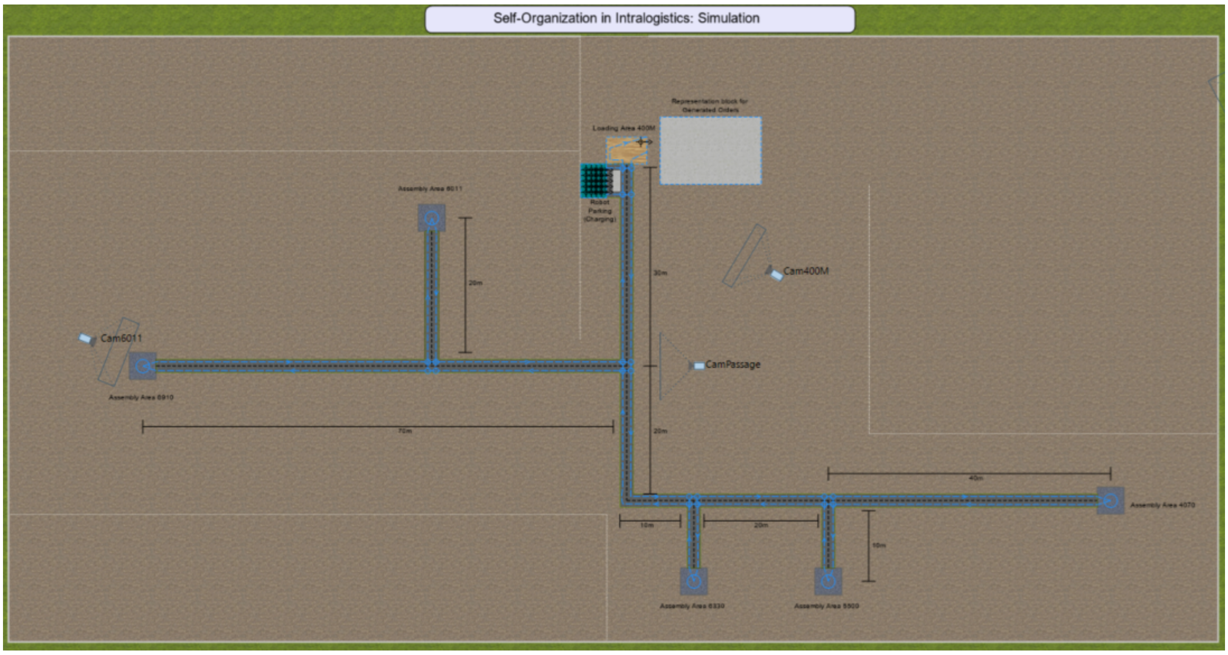


Figure 21: Floor plan of intralogistics facility (as implemented in Anylogic)

C: Parameters Parameters are used to represent the characteristics of the modelled object. Apart from the parameters specified within an agent, certain parameters are defined in the main environment to govern the behaviour of the system and the agents. The following are the key parameters defined in the model:

- *Number of robots:* This parameter is specified at the beginning of each simulation run. Based on the number specified, the robots are initialised in the home position at the attractor points.

- *Speed of robots:* The speed of the robots is a parameter that is set at the beginning of the simulation run. It can be varied within the specified range. It depends on the specification of the robot and the regulations on the shop floor.

- *Battery usage rate (charge/discharge):* The battery discharge parameter is entered as the time for the drop of 1 percentage of battery level, separately for 'seized' and 'release' state. The battery charge parameter is specified as the time required for the battery to charge to 100% from any level which can be used as a timeout in the 'charging' state. These parameters directly impact the internal state chart of every robot agent.

- *Order preparation time:* The order preparation time is the time delay that occurs once an order is generated at the warehouse before entering the queue. This is specified in terms of a triangular distribution between a maximum and minimum value to take into account the variation in the required time to retrieve the order from the warehouse rack and prepare the case.

- *Loading and unloading time:* Loading and unloading times are separate parameters that determine the time for which the robots wait at the designated point for loading and unloading.

- *Rate of demand:* The rate of demand is the rate at which orders are generated for each of the assembly stations. The demand can be either from warehouse to assembly station or between different assembly stations. These values are mentioned in the form of a triangular distribution (maximum, mean minimum) based on the data analysis of the demand in the existing operations as mentioned in Section 3.2.2. Based on the mentioned distribution, stochastic values are generated during the simulation run.

- *Percentage of urgent tasks:* This parameter decides the percentage of tasks that are tagged as urgent (task priority 2) during the order generation. The set percent of urgent tasks is uniformly distributed across the orders.

- *Type of operation:* The type of load-vehicle assignment and empty vehicle management is entered in this section. Based on the input, the robots can return to parking after unloading or stay at the point of release. The section also allows deciding whether the robot should return to parking always before being assigned to the next task or only if there is no other available task. This allows the user to test the system performance under different configurations.

Based on discussion with the Head of Warehouse and robot specifications from Prime Vision (refer Appendix A.5), default values have been set for all the above parameters. However, these values can be changed to test different scenarios and configurations.

Table 9: Parameters and default values(as implemented in Anylogic)

Parameter	**Default Value (can be varied during simulation)**	**Reference**
Number of robots	2	System design
Speed of robots	1 m/s	Robot specification sheet and considering battery swap / quick recharge
Battery recharge time	20 mins	
Battery discharge time in seized state (per % drop)	5 mins	
Battery discharge time in released state (per % drop)	8 mins	
Order preparation time	Triangular distribution (60 mins, 20 mins)	Interview with Head of Warehouse
Loading and unloading time	30 secs	
Percentage of urgent tasks	5%	
Rate of demand	Varies for each assembly station	Data analysis on existing system operation

6.2.2 Process Flow

This section describes the implementation in Anylogic based on the conceptual model of the new self-organised system of robots presented in Section 5.4.1. As explained in Section 5.2, multi-method modelling has been used in this project. While the behaviour of the individual agents is described using statecharts, the flow of the operations involved in the vehicle-based material transport is represented using a process-centric flowchart. Figure 22 describes the process flow and the different blocks involved. As seen, the process starts with order generation at different assembly stations which are sent to the central platform or the queue. Two types of transport requests can be generated: warehouse-station and station-station. For transport requests from warehouse to station, a delay is considered in terms of order preparation time signifying the retrieval of order from storage and preparing the case. Once the queue rearranges the orders as per the task priority and FCFS, the case at the front of the queue sends a transport request to the robots. The load vehicle assignment occurs as described in Section 5.4.1. The robot moves to the relevant loading point and the case with components is transported to the relevant destination. The 'case' agent exists in the system and the next action of the robot is to stay at the point of release or always return to the home position or move to the next available task, based on the set logic. The following are the blocks and related properties of the process flow:

- *Demand generation (source):* This block is responsible for generating the 'case' agents at an arrival rate mentioned at the input (refer section 6.2.1 for details). At the exit of this block, every 'case' agent is assigned a Destination ID and task priority as per the set parameters. The orders may be generated as warehouse-station or station-station (re-route blocks).

- *Order preparation:* Only warehouse-station transport requests pass through the delay block representing order preparation. This signifies the retrieval of order from storage and preparing the case. The delay time is a triangular distribution as explained in Section 6.2.1.

- *Dispatch queue:* The dispatch queue is a block that represents the 'platform' agent in the system. An unlimited queue capacity is defined and the queuing logic is a combination of task priority and FCFS as described in Section 6.2.1. In the animation, the cases in the queue are shown in the virtual order generation area.

- *Move by robot:* This is a key block that takes care of the load-vehicle assignment, empty vehicle management as well as the movement of the robots. This block starts with the logic for assigning a case to the robot. Based on the state of the robot and the shortest distance of the robot to the loading point, the case at the end of the queue is assigned to a robot (refer section 5.4.1 for details). This block also specifies the loading and unloading time for the operations. As explained in 6.2.1, the 'case' agent sends a message to the robot, based on which the state transitions from 'Released' to 'Seized' occurs. This feature is taken care of by this block. The next main feature of this block is the definition of the robot's behaviour after being released, i.e after delivery of the case to its destination. The specification of the logic of whether to stay at the point of release or always return to the home position or move to the next available task is done here.

- *Assembly stations (sink):* The assembly stations are the destinations or sinks for all types of orders. The cases are unloaded at these stations and exit the system.

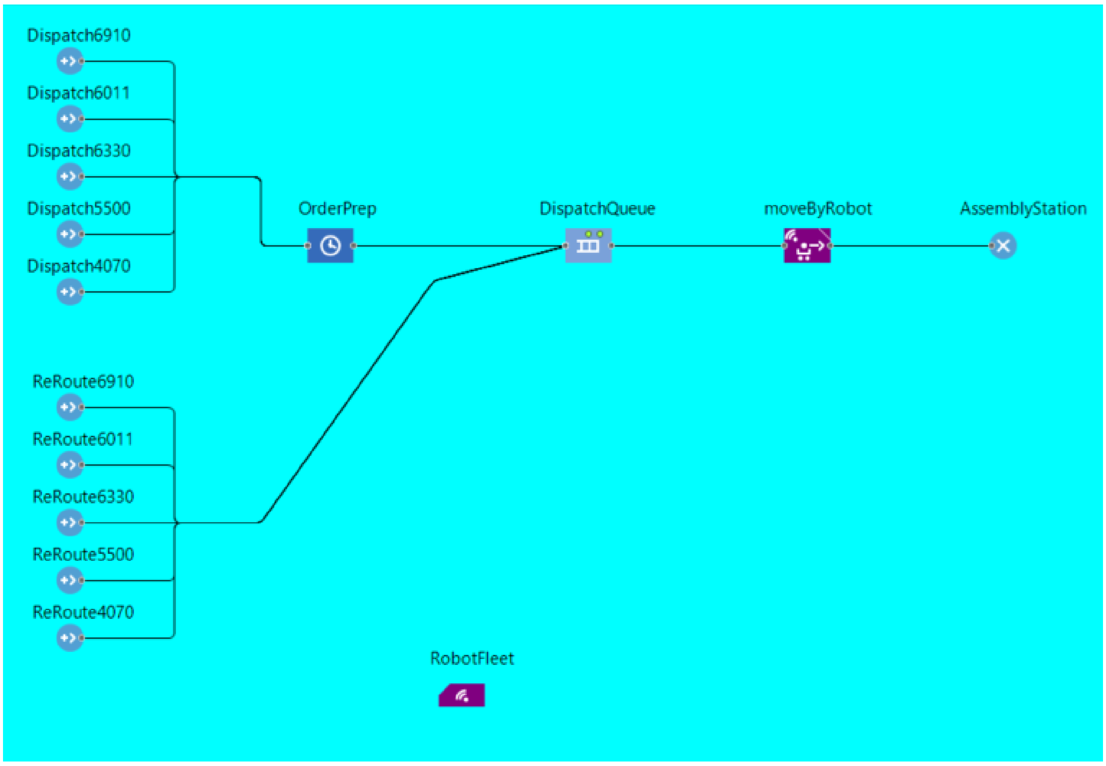


Figure 22: Process Modelling(as implemented in Anylogic)

6.2.3 User Interface

This is the interface available to the user at the time of the simulation run. Figure 23 shows the options available in the control dashboard. The values are usually set at the beginning of the simulation run. The details of each of the parameters have been described in Section 6.2.1. Figure 24 shows the 3D animation windows. These are the output from the cameras placed in the environment. The main purpose of these windows are an intuitive understanding of the simulation and also helps in verification.

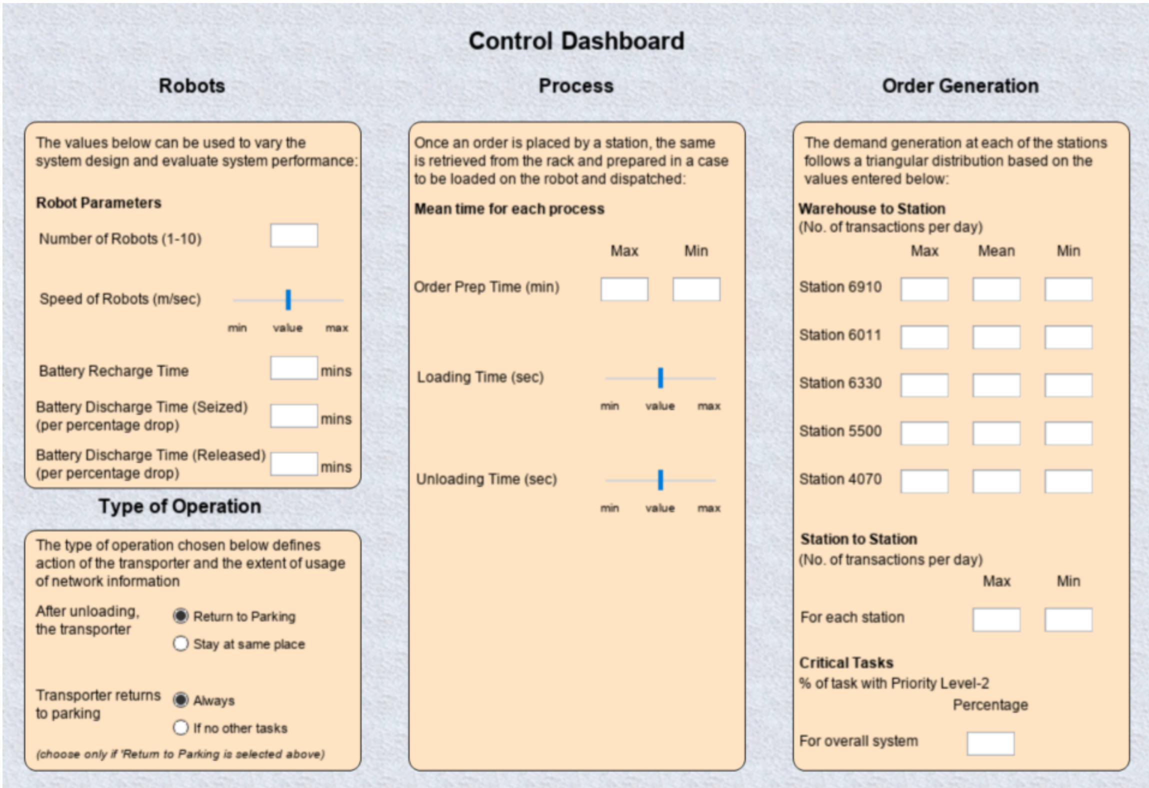


Figure 23: Model interface (as implemented in Anylogic)

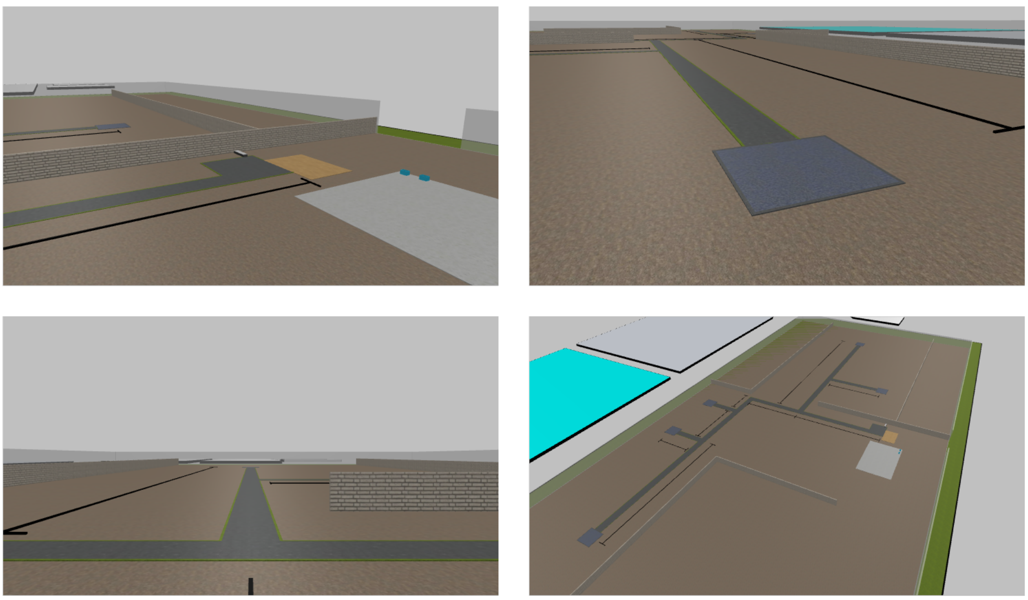


Figure 24: 3D animation windows (as implemented in Anylogic)

6.2.4 Simulation Run

The simulation run is the default experiment that is executed in Anylogic. Other experiments can be set up depending on the intent. The simulation run window allows the play, pause and stop of the simulation. The model time can be modified as a scale of the real-time and thus allowing the increase or decrease of the speed of the run. The following are the properties that can be set for the running of the simulation model.

- *Time Progression:* When the simulation run is initiated, the agents and the process flow are loaded and the model time starts running. The time step of the model set is 1 minute, and thus the collection of statistics can be defined based on this interval. Considering the work shift of 8 hours, the total model run time is set for 480 steps. This property also allows setting the scale of time progression, which is currently set as the same as real-time.
- *Randomness:* This property allows the control of the initialisation of the random number generator. Based on the type of experiment being run, the property may be set at a random seed (unique simulation runs) or fixed seed (reproducible simulation runs). For efficiency experiments under different configurations, the fixed seed may be used and random seed supports the robustness experiments.
- *Replication:* Replication is a repeating run of a simulation experiment which are based on scenarios with a stochastic parameter (Anylogic, 2021) when a single run might not produce a statistically significant result. Anylogic provides the option to set the number of replications. This is further explained in Chapter 7 during relevant experiments.
- *Performance indicators:* Relevant statistics for tracking the performance indicators are collected and displayed in real-time during the simulation run. The performance indicators can be collected in a database and also displayed in a time plot during the run. Further explanation for this is provided in Section 6.3.

6.3 Specification of Performance Indicators

In this section, the specification of performance indicators as introduced in Section 3.2.3 and its implementation in Anylogic is described. Since the existing configuration has not been simulated in the same platform as the new method, a direct comparison of the performance indicators would not be appropriate. However, the aim of measuring these performance indicators is to help measure the efficiency of the new system of self-organised robots under different configurations and to analyse the robustness of the system in varying scenarios, mainly the demand fluctuations. These indicators mainly represent costs and service level. While costs are indicated by the total distance travelled (operational costs) and utilisation (investment on number of robots), the evaluation of the service level is enabled by the order fulfilment time and throughput. Most of the below-mentioned performance indicators are measured on a time plot in real-time and the simulation can be paused to check these indicators at any instant of time. Also, these indicators are recorded in a database for further analysis.

- *Total distance travelled by robots:* The floor plan of the intralogistics has been drawn to scale and the path for the movement of the robots is specified in the network. With this set-up, it is possible to track the total distance travelled by the robots. This includes the actual distance for the transportation of the cases from the source to destination and the movement of the robot from the home position to the loading point and from the unloading point to the home position. The total distance travelled by the vehicles is an important indicator for any kind of material transport as also mentioned regularly in literature (Sun et al., 2018). Studying the total distance travelled by the robots helps in analysing the efficiency of a configuration, choose a system design with the optimum number of robots and allows the manufacturers with the design aspects such as active run time, battery capacity and durability.
- *Utilisation of robots:* Utilisation of robots is measured by keeping track of the time spent by robots in 'busy' and 'idle' states. In this project, the utilisation is indicated in the number of hours spent in 'busy' and 'idle' state, as well as in terms of utilisation ratio. All these indicators are indicated in

real-time on a time plot. Similar to the total distance, this utilisation indicator helps measure the efficiency of a particular configuration and in identifying the suitable system design for the given intralogistics facility.

- *Fulfilment time for orders:* Order fulfilment time can also be called the service time. In the given intralogistics system, this is considered as the time between the raising of request by an assembly station to the time at which the components are delivered (Van der Meer, 2000). This indicator is measured by tracking the time at which the 'case' agent enters the system (birth) and the time at which it exits (death). The time counter in the 'case' agent is used to track this and print the results in a database. Analysing the fulfilment time for different configurations and scenarios helps to analyse the robustness of the self-organised system of robots.
- *Throughput:* Throughput is an indicator that helps measure the efficiency of a system design (number of robots). For a given demand scenario, different configurations of system design can be experimented with to identify the suitable form for the given intralogistics system. In this project, the total number of cases delivered are tracked for the given model run time which is also represented in a time plot.

All the above performance indicators are recorded, analysed and inferences are drawn for combinations of configuration and scenarios. This is elaborately discussed in Chapter 7.

6.4 Verification

The purpose of verifying a model is to ensure the correct implementation of the conceptual model in the software. This step checks if the model is doing what it is supposed to do. The inputs, parameters and configuration are varied and the outputs are checked for changes as expected. The verification step is not an isolated one, but a part of model building and iterative. The discrepancies observed help identify the errors before experiments are conducted or the model is put to use in business applications. In the case of this project, scenario analysis is used to verify the model.

The model is verified for the assembly stations that have been considered in the case study of the manufacturing facility. There are 5 assembly stations that are located at a fixed distance from the central dispatching point in the stockroom. The distances and the approximate position of the stations match the layout of the facility. The robots have a central parking location and travel along the dedicated path for vehicle movement. This layout and description of the environment are elaborated in Section 6.2.1 and Figure 21.

The specifications and parameters considered for the verification are mentioned below:

- **Robots**
  - Homogeneous fleet
  - Number of robots: Varied as per scenario (refer Appendix A.7)
  - Maximum speed: 1m/s
  - Acceleration and deceleration: 1m/s^2
  - Minimum distance to obstacles: 0.5m
  - Reduced speed near curves, intersections & obstacles: 0.5m/s
  - Battery recharge time: 20 minutes
  - Battery discharge time (busy): 5 minutes per percentage drop
  - Battery discharge time (idle): 8 minutes per percentage drop
- **Operation**
  - Order preparation time: Triangular distribution (60 minutes (max), 20 minutes(min))
  - Loading time: 30 seconds
  - Unloading time: 30 seconds

  - Type of operation: Varied as per scenario (refer Appendix A.7)

- **Runtime**
  - Total runtime: 8 hours
  - Time step: 1 minute
  - Number of time steps: 480
  - Run duration: 08:00 – 16:00

- **Order Generation**
  - Warehouse to stations (all values in (max, mean, min) orders per day, based on existing demand pattern as mentioned in section 3.2.2)
    * Station 6910: Triangular distribution (344, 59, 14)
    * Station 6011: Triangular distribution (82, 18, 1)
    * Station 6330: Triangular distribution (13, 5, 1)
    * Station 5500: Triangular distribution (3, 2, 1)
    * Station 4070: Triangular distribution (28, 17, 1)
  - Station to station (all values in (max, min) orders per day)
    * All stations: Triangular distribution (10, 1)
  - Percentage of urgent tasks: 5% of total orders generated, uniformly distributed

The verification of the implemented model has been done in three phases as suggested by (Nikolic and Ghorbani, 2011) for agent-based models:

- *Single-agent testing:* In this phase, only a single agent is considered. The generation of the agent, both case and robot, loading in the model, the state of the agent and behaviour through one shift is verified.

- *Interaction testing:* The main aim of this phase is to verify the interaction between the agents, case and robot. Hence one agent of each category is loaded in the model to check the basic aspect of the case reaching its destination.

- *Multi-agent testing:* In the final phase, the input demand is as obtained from the data analysis of the existing operation (values mentioned in the above section). Five robots are loaded and the complete model run is executed to check the performance indicators. This gives a complete picture of the agents and their interactions.

The check of the hypothesis and result for the scenarios in the above phases of testing are tabulated and the complete process of verification has been explained in Appendix A.7. The model is verified successfully.

6.5 Validation

In the previous section, the implemented model was verified against the formulated concept. Validation is the process of checking the model to its conformity to reality. As explained in section 5.2, experimenting with a model in the real world would be one of the most desired options. However, given the costs and operational constraints, the simulation model has to be validated in other ways. In this project, sensitivity analysis and expert opinions have been used to validate the model. In sensitivity analysis, the results of the model are analysed to check if it behaves as expected, for varying inputs and parameters. Expert opinion has been used to validate the implementation (Nikolic and Ghorbani, 2011) from different perspectives of Prime Vision expectations, a reality check with the Head of Warehouse and the implementation in Anylogic.

Sensitivity Analysis
A quick sensitivity analysis is performed to see if the simulation model reacts realistically and predictably

to changes in inputs and parameters. For this, two types of analyses have been done. One is to vary the number of robots and the other is to vary the demand. The changes is performance indicators are analysed for the varying inputs. A detailed explanation of the sensitivity analysis and the results are presented in Appendix A.8.1.

When the number of robots is varied, a fixed seed has been used for the demand at different stations assembly stations. For the fixed seed, the number of robots is varied between 1 to 5 to study the changes in performance indicators, total distance travelled by the robots, average robot utilisation, busy and idle duration of robots and throughput. The model is run over 8 hours of model time for all tests. The same performance indicators are also studied for varying demands at 1 station, where only the demand for station 6910 is opened and varied between the rate of 100 to 500 cases per day. The number of robots is constantly maintained as 2.

In all the above tests, the behaviour of the system has been in line with the expectations and reality. Refer Appendix A.8.1 for details.

Expert Opinion
The process of expert opinion to validate the method and implementation has been done from three perspectives.

The first interview is from the perspective of the Head of Warehouse (personal communication dt. 09/06/2021, refer A.8.2) validating the model for the practicality of the operations. Keeping in mind that the new system of self-organised robots is a look ahead for the future, the model was found to be sufficient and practical for the movement of small components such as screws, panel pins and other spares which form almost 30% of the current components which are transported. In the current form of operation, this adds to the fatigue due to increased manual movement. However, the size of a single shipment (volume and weight) is mentioned as a concern as it is limited to the capacity of the robot. This is a point of improvement to be considered for the future. The parameters considered for the model were deemed feasible, however, the order preparation time was suggested to be considered as a triangular distribution between 20 minutes and 60 minutes. While the performance indicators being measured were found to be useful from the interviewee's position, a live dashboard to keep track of the same was suggested. From a real-world implementation and managerial point of view, the human factor and safety during the movement of robots was a key concern to be dealt with.

The next perspective is that of the product owner at Prime Vision and the validity of the simulation model as a decision support tool (personal communication dt. 10/06/2021, refer A.8.3). The simulation model was found to be a sound and satisfactory representation as per requirement. While adding value as a decision support tool for Prime Vision, the performance indicators are found to be useful for decision making. However, further development was suggested in terms of making a direct comparison of the new method with the existing operation, as under the current consideration, the shipment sizes vary. Dealing with the human factor and safety concerns was mentioned as a challenge for implementation.

The last interview is with the researcher from TU Delft with expertise in Anylogic (personal communication dt. 10/06/2021, refer A.8.4). The model implementation in Anylogic was found to be sufficient and sound with the usage of best practices, given the fact of the learning curve involved. A recommendation was to include comments along the relevant Java codes to make the model more clear and understandable for future developers.

The complete process of validation including the transcripts of the interview is available in Appendix A.8.

6.6 Summary

The main intention of this chapter has been to implement the conceptual model as explained in the previous chapter keeping in mind the requirement of the industry and its usage as a decision support tool. It provides the crucial link to the experimentation which is dealt in the next chapter. As concurred in multiple literatures, a simulation model is one of the aptest methods to study a system with a dynamic and decentralised nature. Starting with the choosing of a suitable modelling platform, it is made clear that multi-method modelling is a suitable approach to address the problem at hand. While the flow of the operations involved in the vehicle-based material transport is represented using a process-centric model, the individual behaviour of the agents is represented using statecharts. The reason for following this method is to capture the nature of the intralogistics operations involved in an intuitive way and provide better control over the details.

Anylogic is considered as the choice of the platform which uses a GUI and Java-based environment for modelling. Defining the characteristics of individual agents and building state charts, the agents are linked with the environment with the help of a process-centric model represented as a flowchart. The process-centric model is made of individual blocks to characterise the flow of operations. The intricate details can be controlled by linking the parameters to these blocks and coding the behaviour of each block. The case agent is generated at the beginning of this flowchart and passes through various blocks until it is transported to the destination by a robot that exits the system. An intuitive user interface consisting of a control dashboard and 3D animation windows has been incorporated for the simulation. The necessary performance indicators based on Section 3.2.3 and interviews with relevant stakeholders are tracked in real-time during the running of the model.

The built model has been verified through scenarios analysis to check the compliance with the conceptualised model. The validation process through sensitivity analysis for varying inputs and expert interviews has confirmed the behaviour of the model in line with the expectations and reality. This chapter, in conjunction with the next one, answers the sub-research question, *"For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?"*. In Chapter 7, the different scenarios and configurations are tested to get a better insight into the self-organised system of robots.

7 Experimentation

This chapter is dedicated to experimenting on the implemented model, described in the previous chapter. In combination with Chapter 6, this chapter completes answering the sub-research question, *"For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?"*. As explained in the methodology, the implemented model is run with various alternatives involving a combination of configurations and scenarios. The aim of the experiments is to gain insight into the efficiency and robustness of the new self-organised system of robots. Also, the model's functionality as a decision support tool to aid the industry in system design, including a suitable number of robots for a given scenario is tested here. Figure 25 shows the current stage in the overall methodology. This chapter is one of the final sections before moving towards the conclusion and paving the way to answer the main research question.

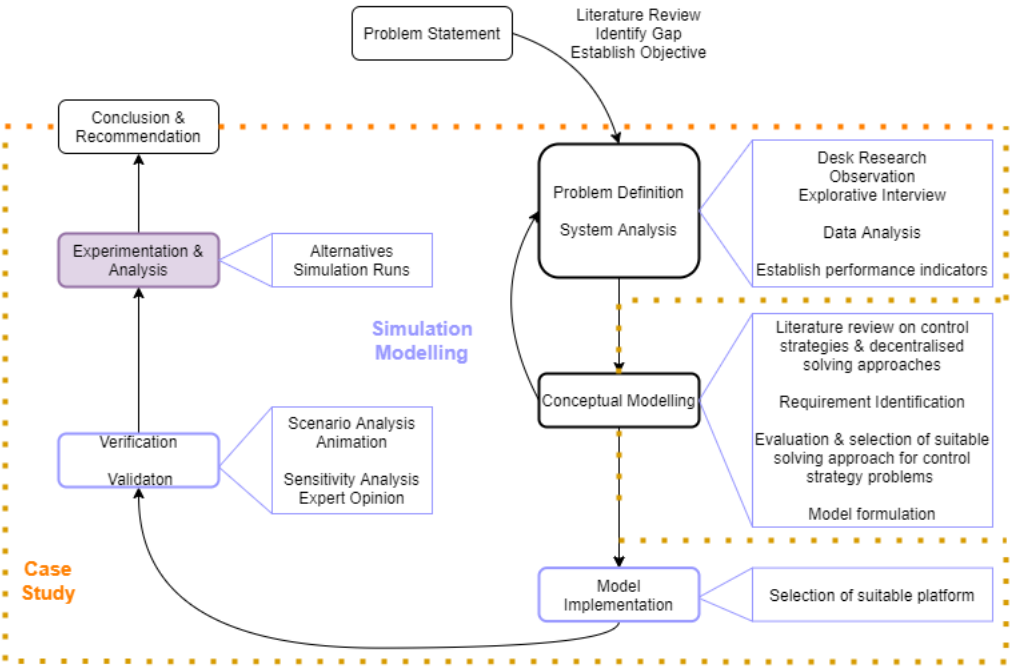


Figure 25: Phase: Experimentation, adapted from (Kelton, 1998; Sargent, 2015; UH)

7.1 Objective

Before proceeding to explain the experiments, it is key to establish the objectives. As discussed in 1.2, the key goal of this project has been to explore if the self-organised system of robots can serve as an alternative to the existing vehicle-based in-house material transport dominated by manual operation. The existing configuration is not simulated in this project. The data and performance indicators have been obtained through observation, interviews and data analysis. Hence, a direct comparison of the performance indicators would not be appropriate. However, the takeaway from this would be the estimation of manual effort in the current form, the reduction in fatigue contributed by the self-organised system of robots. The performance indicators of the new system will enable a quick understanding and judgement of the system for various configurations without the need to physically observe them (Klein, 2013). Literature suggests that self-organised systems improve the robustness of a system. This model and its usage in the chosen case study helps perform the operational study in this regard. The experiments are designed to test the efficiency and robustness of the new system. Along with this, the usability of the model as a decision support tool to check the optimum number of robots required for a given setup is tested. The following points summarise the objectives:

- *Insight into system design:* Before the implementation of the system in real-world, the system design, simply put as the number of robots required, is one of the basic necessities to understand the scale of the system. For a given configuration and scenario, experiments are conducted to gain insight into the suitable number of robots required.
- *Study the efficiency of the new system for different alternatives:* Various scenarios (demand conditions) and configurations (number of robots, type of operation) are possible in the real world, where the system is put into practice. A set of experiments are conducted to analyse the system performance (costs and service level as explained in section 6.3) under different demand conditions and modes of operation to understand the efficiency and suitability of these alternatives.
- *Test robustness of the new system under varying conditions during operation:* Robustness is the ability of the system to continue operating under a varying and wide range of operational conditions (Gribble, 2001). These experiments are aimed to test the performance of the system when a change in scenario or breakdown occurs during the run-time.

All the above experiments measure the performance indicators described in Section 6.3. The comparison between different alternatives provides an insight into the emergent characteristics of the new system.

7.2 Experimental Setup

In this section, the experimental setup is explained, with the system and run-time parameters used. While some of these are constant for all the experiments, the necessary variations are explained in the experimental plan in Section 7.3 and further in relevant experiments.

7.2.1 System Parameters

The case under study is a manufacturing facility with 5 assembly stations that are located at a fixed distance from the central dispatching point in the stockroom. The distances and the approximate position of the stations match the layout of the facility. The robots have a central parking location and travel along the dedicated path for vehicle movement. This layout and description of the environment is elaborated in Section 6.2.1 and Figure 21. The request for components is made by assembly stations by raising orders, which is also addressed as demand generation in the model. After order preparation, the central platform queues the orders and rearranges if necessary based on task priority. The case at the front of the queue sends a transport request and load-vehicle assignment takes place, before being transported to the destination. The detailed process flow is as explained in Section 6.2.2. The key parameters for the simulation model address the robots, operation, and order generation. The following are elaborated below:

- **Robots**
  - Homogeneous fleet
  - Number of robots: Varied as per experiment (maximum 20 parking locations are considered in the simulation model)
  - Maximum speed: 1m/s
  - Acceleration and deceleration: 1m/s^2
  - Minimum distance to obstacles: 0.5m
  - Reduced speed near curves, intersections & obstacles: 0.5m/s
  - Battery recharge time: 20 minutes
  - Battery discharge time (busy): 5 minutes per percentage drop
  - Battery discharge time (idle): 8 minutes per percentage drop
- **Operation**
  - Order preparation time: Triangular distribution (60 minutes (max), 20 minutes(min))

  - Loading time: 30 seconds
  - Unloading time: 30 seconds
  - Type of operation: Varied as per experiment Considered options are:
    * Central positioning: Robots return to a central home position when idle or when no tasks are available after completion of delivery.
    * Point of release positioning: The idle robots stay at the same position where they complete or are released from the task.

- **Order Generation**
  - Warehouse to stations (all values in (max, mean, min) orders per day, based on existing demand pattern as mentioned in section 3.2.2)
    * Station 6910: Triangular distribution (344, 59, 14)
    * Station 6011: Triangular distribution (82, 18, 1)
    * Station 6330: Triangular distribution (13, 5, 1)
    * Station 5500: Triangular distribution (3, 2, 1)
    * Station 4070: Triangular distribution (28, 17, 1)
  - Station to station (all values in (max, min) orders per day)
    * All stations: Triangular distribution (10, 1)
  - Percentage of urgent tasks: 5% of total orders generated, uniformly distributed

7.2.2 Runtime Parameters

The runtime parameters define the model time progression, randomness and replication during the simulation run.

- Total runtime: 8 hours
- Time step: 1 minute
- Number of time steps: 480
- Run duration: 08:00 – 16:00
- Randomness: Varied as per experiment. Fixed and Random Seed options available.
- Replication: Varied as per experiment. Options of fixed replications and defining replications based on desired confidence interval are available.

7.3 Experimental Plan

Based on the objectives of the experiment presented in Section 7.1, the experimental plan has been developed. System design, efficiency and robustness being the focus, various experiments have been designed with varying scenarios and configurations. The summary of the plan is presented in Table 10. It is to be noted that, in the table, base demand refers to the demand as presented in Section 7.2.2.

Table 10: Summary of Experimental Plan

<table>
<tr><th colspan="4">Summary of Experimental Plan</th></tr>
<tr><th colspan="2">Experiment Type</th><th>Scenario</th><th>Configuration</th></tr>
<tr><td>System Design / Efficiency Experiment</td><td>Variation in number of robots</td><td>- Base demand (Warehouse-Station)
- Base demand (Station-Station)
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 1- 8</td></tr>
<tr><td rowspan="4">Efficiency Experiments</td><td rowspan="2">Variation in control strategy</td><td rowspan="2">- Base demand (Warehouse-Station)
- Base demand (Station-Station)
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 2</td></tr>
<tr><td>- Point of release positioning
- Robots: 2</td></tr>
<tr><td>High demand</td><td>- High demand (2 x Base demand) (Warehouse-Station)
- High demand (2 x Base demand) (Station-Station)
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 2</td></tr>
<tr><td>Variation in battery life</td><td>- Base demand (Warehouse-Station)
- Base demand (Station-Station)
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 2
- Battery life: 500, 400 & 300 minutes</td></tr>
<tr><td rowspan="4">Robustness Experiments</td><td>Fluctuation in demand</td><td>- Base demand (Warehouse-Station)
- Base demand (Station-Station)
- Multiple replications with random seed</td><td>- Central positioning
- Robots: 2</td></tr>
<tr><td rowspan="2">Skewed demand</td><td rowspan="2">- Base demand (Warehouse-Station)
- Station-Station demand higher than Warehouse-Station
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 2</td></tr>
<tr><td>- Point of release positioning
- Robots: 2</td></tr>
<tr><td>Breakdown of robots</td><td>- Base demand (Warehouse-Station)
- Base demand (Station-Station)
- Multiple replications with controlled seed</td><td>- Central positioning
- Robots: 2
- 1 robot breaks down during runtime</td></tr>
</table>

7.4 Experiments

7.4.1 System Design Experiments

The system and efficiency experiments aim at finding a suitable configuration of the system, whether the number of robots or the type of control strategy for a given scenario. Hence multiple alternatives are simulated to compare the performance indicators to support decision making.

A. Variation in the number of robots

The aim of this experiment is to find a suitable number of robots to handle the delivery of the cases to different assembly stations and thus aiding system design. The decision on the number of robots required, will be based on a combination of throughput, order fulfilment time, distance travelled and the utilisation of the robots. The pattern of transport requests, both warehouse-station and station-station are considered as mentioned in Section 7.2.2. Considering the stochastic nature of the orders generated, 5 replications have been considered for each variation, i.e., the number of robots. The number of robots is varied from 1 to 8 and only central positioning is considered. As seen in Figure 26, with the increase in the number of robots the throughput increases initially. However, after a brief drop, the throughput remains almost the same with a minor variation. This variation can be attributed to the following reason. In the simulation model, the rate of order generation is set on a per-day basis, but there is a cutoff on the run time of the model. Distance to the robot being one of the key conditions for the assignment of a case, the sequence and timing of the assignment varies with the number of robots.

When the number of robots increases from 1 to 2, the increase in throughput is 47%. When more than 2 robots are used, there is no significant change in the number of cases delivered, while it also results in a drop in robot utilisation. For the increase of robots from 1 to 2, there is an increase in the throughput with a decrease in utilisation.

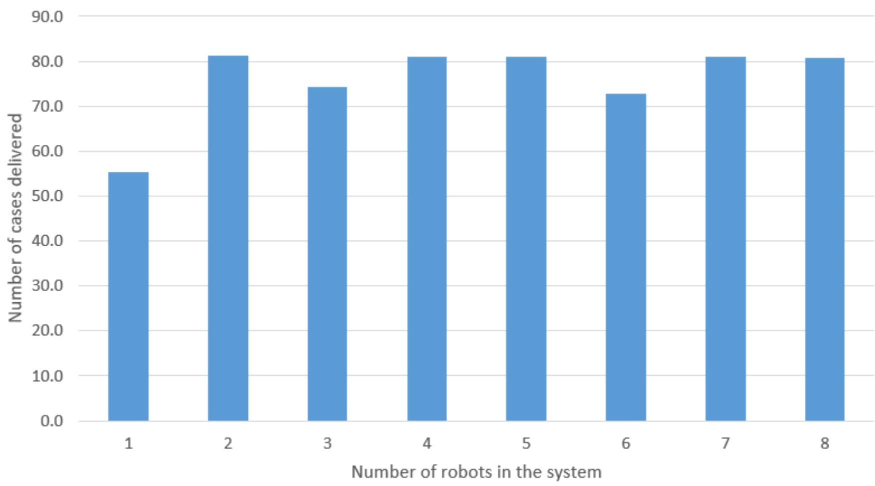
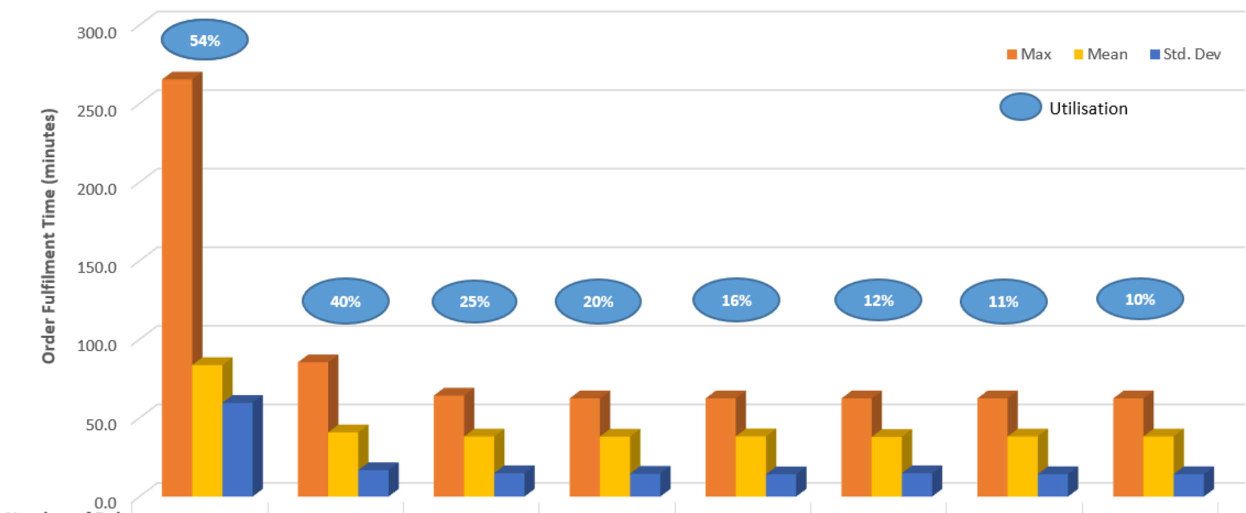


Figure 26: Total cases delivered with varying maximum number of robots



Number of Robots	1	2	3	4	5	6	7	8
Max	265.4	85.4	64.3	62.5	62.5	62.5	62.5	62.5
Mean	83.7	40.9	38.2	38.2	38.4	38.0	38.3	38.3
Std. Dev	59.7	16.8	14.9	14.6	14.2	14.9	14.3	14.3

*All the above values are in minutes

Figure 27: Order fulfilment time with varying maximum number of robots

In Figure 27, it is observed that the maximum order fulfilment time decreases significantly (by more than 200%) when the number of robots increases from 1 to 2. The average fulfilment time as well the standard deviation also show a considerable decrease indicating improvement in service. However, for more than 2 robots, this improvement is not so significant and later remains almost the same. This comparison between investment and acceptable service time helps in the decision on system design. Although this choice varies based on decision-makers, for the considered demand pattern, it is recommended to use two robots for the operation, with average utilisation of around 40%.

Figure 28 shows the change in the total distance travelled with the varying number of robots. As seen in the case of throughput, with the increase of robots from 1 to 2, the total distance travelled increases by 47%. This can be directly attributed to the increased throughput. The less significant variations later can be attributed to the limited model run time and variation in the sequence and timing of assignment. Figure 29 shows the distance travelled over the time progression for 1 replication. It is observed that, after the increase of distance travelled from 1 robot to 2 robots, there is no further increase. This corroborates the usage of 2 robots for the considered demand pattern.

For experiments in the upcoming sections, unless the case demands, the default number of robots has been considered as 2. The other aspects including delivery time and different types of operation are explored further.

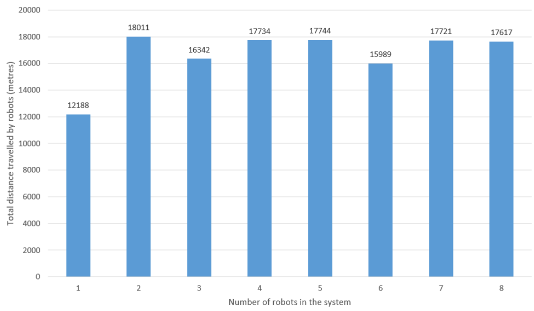


Figure 28: Total distance travelled with varying maximum number of robots

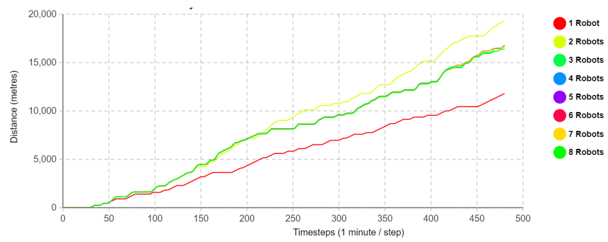


Figure 29: Total distance travelled over time progression
for varying maximum number of robots

7.4.2 Efficiency Experiments

B. Variation in control strategy

The control strategy to manage empty vehicles has an impact on the system performance. In this experiment, two types: central positioning and point of release positioning are explored to study the difference in system performance. The demand considered is the base demand as mentioned in section 7.2.2. For each of the strategies, 3 replications of the simulation are conducted and the mean values of the performance indicators are analysed.

Table 11: Comparison of performance indicators for different control strategies

	Central Positioning	**Point of Release Positioning**
Total distance travelled (metres)	18011	16823
Robot utilisation (%)	40,3	37,9
Throughput (Nos.)	81	79
Order fulfilment time (minutes)		
Maximum	80,24	133,22
Minimum	2,56	2,76
Mean	40,8	47,81
Std. Dev	17,49	23,07

In the given alternative, similar to the current demand pattern in the case study, the movement of the components from the warehouse to the assembly stations are predominant. As seen in Table 11, the central positioning strategy results in a higher travelled distance (about 7.5%), as the robots always travel to the home position if no other available tasks are present. Unless the source of the case is from one of the assembly stations (which is comparatively less in this case), the robots mostly travel to either the home position or the warehouse pick-up point. This clearly explains the increased travel distance. The utilisation of the robots is also consequently lower in the point of release positioning, as the robots stay at the delivery point unless the next task is assigned. In both configurations, there is not much change in the throughput. The reason for this is that the robots are not fully utilised and thus are capable of catering to the demand similarly.

However, an interesting observation is in the order fulfilment time. The maximum value in the case of point of release positioning is 66% higher than in the case of central positioning. This is an expected consequence, as the robots released and parked at the assembly station have to travel to the warehouse loading point in case of a new task assignment. Most of the transport requests being originated at the warehouse, the response time of the robots are higher. The comparison of the performance indicators in Table 11 show that, for the demand pattern similar to the case study, central positioning would be an appropriate control strategy for empty vehicle management. However, the response of the system with point of release positioning in case of an increased station-station demand would be intriguing to study. This is explored in the sections further.

C. High demand (warehouse-station & station-station)

This experiment is to analyse the system performance for higher demand. In this case, the rate of daily demand has been considered twice that of the base demand mentioned in section 7.2.2. The rate of demand is doubled both for warehouse-station and station-station. From the previous experiment, it is learnt that, for the scenario where the warehouse-station demand is dominant, the central positioning strategy is more suitable. Hence, for this experiment, the same is considered. Also, for the base demand, the number of robots required was observed as 2. Hence, initially, we study the response of the system with 2 robots and later examine the effect of the increased number of robots.

Table 12: Comparison of performance indicators for base & high demand

	Number of robots: 2 (Central Positioning)	
	Base Demand	High Demand (double)
Total distance travelled (metres)	18011	29287
Robot utilisation (%)	40,3	65,8
Throughput (Nos.)	81	134
Order fulfilment time (minutes)		
Maximum	80,24	181,92
Minimum	5,56	2,56
Mean	40,8	65,94
Std. Dev	17,49	38,39

Table 12 summarises and compares the response of the system with 2 robots to base and higher demand. In the first case, we see that the robot utilisation is only 40%. Due to the availability of time, the 2 robots are still able to cater to the increased demand with the increase in throughput by almost 65%. Consequently, there is also an increase in the distance travelled by the robots. However, the downside of this situation is the increase in the order fulfilment time. While the maximum time for fulfilment has increased more than double, the mean time is 62% higher. The higher variation in the delivery time is also seen due to the increased movement of the robots and the additional distances travelled to cater to the new demand. The practical implication of this experiment is that, a system of 2 robots can be used for catering to increased demand in the future, but with a compromise in the service time.

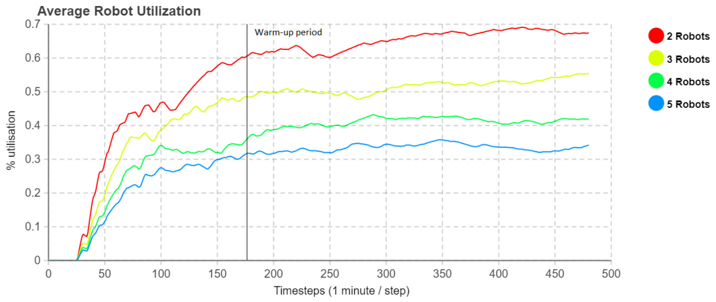


Figure 30: Change in utilisation with varying maximum number of robots: High demand

High demand	Number of robots			
	2	3	4	5
Total distance travelled (metres)	29287	35104	35747	37477
Throughput (Nos.)	134	159	162	170
Max Order fulfilment time (minutes)	181.92	70.54	65.07	61.74
Mean Order fulfilment time (minutes)	65.94	40.04	36.37	35.46
Min Order fulfilment time (minutes)	2.56	2.55	2.53	2.53
Std. Dev Order fulfilment time (minutes)	38.39	15.25	17.54	16.96

Table 13: Comparison of performance indicators for varying maximum number of robots: High demand

Table 13 shows the variation in performance indicators for a scenario with high demand, but with the increase in the number of robots. While the increase in the number of robots from 2 to 3 leads to 19% higher throughput, a further increase in the number of robots does not have a significant impact on throughput. As seen in Figure 30, the utilisation of the robots also decreases with the increasing number of robots. However, the interesting point is the decrease in order fulfilment time. The increase in the number of robots from 2 to 3 decreased the maximum order fulfilment time by more than half and the mean time by 40%. Hence, a key factor to consider during the system design is the balance between the investment in robots and the acceptable value of throughput and order fulfilment time similar to the discussion done in Experiment A.

In the context of Figure 30, it is necessary to mention the warm-up period. This is the delay in the time period considered generally in discrete event simulation run while collecting data on steady-state performance. Some literatures mention the detrimental effect of considering the initialisation period (Grassmann, 2008). However, Anylogic provides flexibility based on user requirements and real-time visualisation of the collected data along with time-stamps for the entire duration of the simulation run. This makes it convenient to consider the steady-state for calculation. As seen in Figure 30, a warm-up period of 180 minutes is considered for calculating the utilisation.

D. Variation in battery life

In this simulation model, the functioning of the battery system has been incorporated at a rudimentary level. Section 6.2 explains this in detail. The battery discharge rate is mentioned in terms of time taken for a percentage drop (based on the battery life) and the battery recharge is a fixed duration. This experiment explores the change in system performance for different battery lives. For this, a system of 2 robots with homogeneous characteristics and the base demand conditions as mentioned in Section 7.2.2 is considered. The system performance is recorded over different battery levels with 3 replications each.

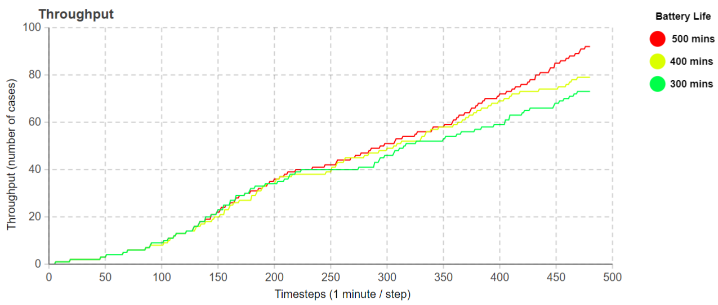


Figure 31: Variation in throughput for change in battery life

Battery life (minutes)	500	400	300
Total distance travelled (metres)	18011	17035	16700
Robot utilisation (%)	40,3	38,2	37,4
Throughput (Nos.)	81	77	76

Table 14: Comparison of performance indicators for different values of battery life

The battery life is varied over 500, 400 and 300 minutes from a fully charged condition. 500 minutes correspond to around 8 hours of battery life. Once the robot reaches a critical battery level, it moves to the home position to be fully charged at a fixed duration. As seen in Figure 31 and Table 14, reduced battery life leads to a decrease in the throughput of the system as well as robot utilisation. However, For every 100 minutes of reduction in battery life, the drop in the number of cases delivered is less than 5% and the utilisation of robots is less than 2%. Due to the decreased battery life, the robots undergo recharging more frequently and thus are not available for task assignment.

Although the simulation of battery operation is in a basic stage, this gives a brief idea of the effect of battery life on the system performance of the robot. It is recommended to model the battery simulation more accurately and in detail for future models for a more specific understanding.

7.4.3 Robustness Experiments

Robustness is the ability of the system to continue operating under varying and wide range of operational conditions (Gribble, 2001). These experiments are aimed to test the performance of the system when a change in scenario or breakdown occurs during the run-time. In the upcoming sections, some of these situations are tested to study the response of the system.

E. Fluctuation in demand

Fluctuating demand and the flexibility of the system to adapt is one of the reasons for exploring the self-organised system of robots. Hence, the rate of demand used as input to the model is considered as a triangular distribution with a wide range. Also, the rate of demand is based on the data analysis conducted on the current system to identify the demand pattern. In this experiment, the base rate of demand as mentioned in Section 7.2.2 is considered. However, 10 iterations of the simulation run are conducted with a random seed. Thus, the demand fluctuates for every iteration. Considering a system of 2 robots, the system performance is analysed, with the main intention to study the response of the system to the changes.

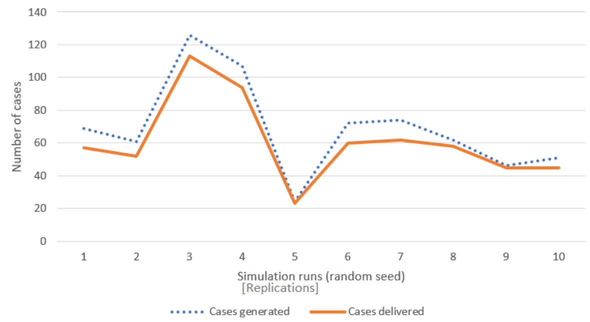


Figure 32: Variation in throughput for fluctuating demand

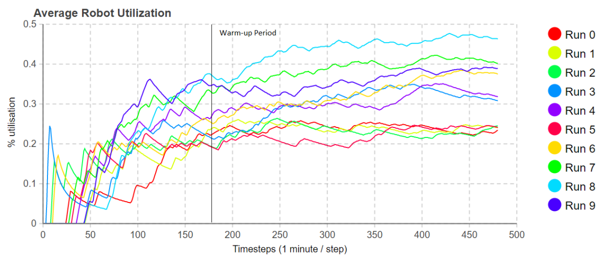


Figure 33: Variation in utilisation for fluctuating demand

Table 15: Summary of performance indicators for fluctuating demand

Fluctuating Demand	Min	Max	Mean	Std. Dev
Total distance travelled (metres)	5243	25130	13364	5318
Throughput (Nos.)	23	113	60.9	24.2
Order fulfilment time (minutes)	2.6	104.1	40.7	19

Figure 32 shows the variation in the number of cases delivered during every run, Figure 33 shows the change in utilisation over the time progression for each of the runs and Table 15 summarises the performance indicators over all replications. Over the period of 8 hours, it is seen that the system of 2 robots was able to handle a throughput between 23 cases to 113 cases, while the utilisation of the robots stayed within the range of 20% to 48% (warm-up period 180 minutes). Even at the highest generated demand, around 10% of the cases were undelivered, which is mainly attributed to the model runtime and sequence of operation rather than available capacity. Table 15 also shows the variation in order fulfilment time with an average of 40.7 minutes. Running more replications with random seeds and observing the variation in fulfilment time helps the user to choose a suitable system. This conveys the robustness of the system of 2 robots to function over a wide range, with the ability to further increase its utilisation to handle higher demand. In the upcoming experiments, the response of the system to a breakdown of one of the robots and skewed demand conditions are studied.

F. Skewed demand (station-station demand higher than warehouse-station demand)

The current state of operation in the considered case study is the demand mainly from the warehouse to the assembly stations. However, there is also a certain proportion of components moving between the stations. These may be due to the movement of half-products or components that need to be re-routed to other stations. Due to the constraint on the load-carrying capacity of the robot, there is not much station-station demand considered in the main case. However, to test the robustness of the new system of self-organised robots, this experiment considers the case of increased station-station demand. The warehouse-station demand is considered the same as the base demand values mentioned in section 7.2.2. However, the rate of daily demand for station-station is increased to a triangular distribution between (400, 20). This leads to higher inter-station material movement as well as increases the overall load on the system. As discussed in the experiment on the variation of control strategy, central positioning favoured a demand pattern with a central origin. Hence for this case of skewed demand, both the central positioning and point of release positioning are tested. For all the replications, the 2 robots are considered in the operation.

Table 16: Comparison of performance indicators for different control strategies: Skewed demand

	Central Positioning	Point of Release Positioning
Total distance travelled (metres)	35210	30694
Robot utilisation (%)	79,5	69
Throughput (Nos.)	158	142
Order fulfilment time (minutes)		
Maximum	400,79	439
Minimum	2,56	2,9
Mean	109,12	99,68
Std. Dev	117,67	121,49

The major observation in Table 16 is the decrease in the mean order fulfilment time by 10% in the case of point of release positioning compared to central positioning. As the majority of the demand generated is for station-station, the parking of the robots at the point of delivery before the next task assignment decreases the response time. In Table 11, it was observed that point of release positioning increased the mean delivery time when most orders were generated at the warehouse. However, in both cases, the coefficient of variation is very high (greater than 100%) and the variance in point of release is higher than central positioning. This is explained by the extremely distributed pattern of material movement. In point of release positioning, the fulfilment time is significantly less if the next station is nearby than if the next station is at the other end of the facility which explains the higher variance than central positioning.

Despite the total increased demand in this case, as well as a skewed demand pattern, a commonality observed both in Table 16 and Table 11, is the decrease in the total travelled distance by the robots. This can be attributed to the avoided travel to the central home position when no task assignment takes place. In both cases, the decrease in the total travelled distance is between 11%-15%. However, this gain is at the cost of slightly decreased throughput because of only 2 robots in the system and the demand distributed between 5 stations. In the case of Point of Release Positioning, the distance travelled per delivered case is lesser. Exploring the concept of distributed positioning for empty vehicle management would be a recommendation for future projects in these scenarios. While this analysis helps demonstrates the robustness of the current system for a skewed demand, it also guides the choice of the control strategy.

G. Breakdown of robots

One of the functionalities of a self-organised system is the ability of the agents to enter and leave the system. This nature is expected to build robustness in the system. There is a possibility that one of the robots in the system experiences a breakdown or needs to go offline for maintenance. In case such a situation occurs during the daily operation, it would be worthwhile to study the effect on system performance. To test this, a situation with a base demand as mentioned in section 7.2.2 is considered with 2 robots in operation according to central positioning. The breakdown of one of the robots is simulated at t=240. The effect on system performance is analysed and also compared against normal operation without a breakdown.

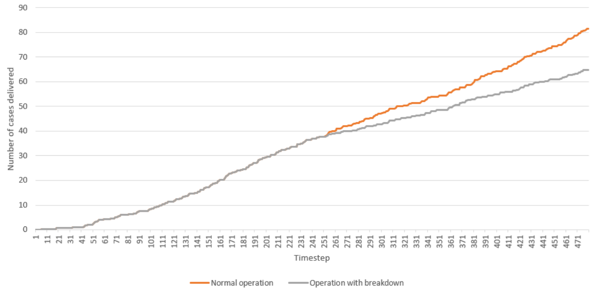


Figure 34: Total cases delivered over time progression with and without breakdown

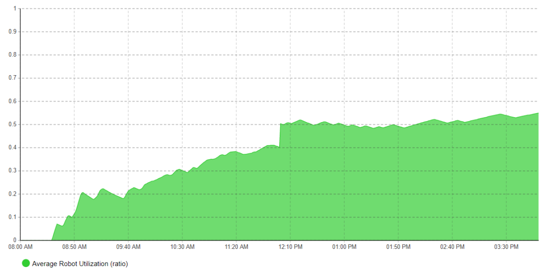


Figure 35: Utilisation of robots over time progression during breakdown

Table 17: Comparison of performance indicators with and without breakdown

	Operation without breakdown	Before Breakdown	After Breakdown
Total distance travelled (metres)	18011	11333	
Robot utilisation (%)	40,33	36,33	50,47
Throughput (Nos.)	81	34	31
Order fulfilment time (minutes)			
Maximum	80,24	75,29	188,49
Minimum	2,56	2,56	2,75
Mean	40,8	37,87	77,21
Std. Dev	17,49	16,82	43,33

Figure 34 shows the difference in throughput between the two situations. In Figure 35 the jump in the utilisation at the time of breakdown is observed from 36.33% to 50.47%. The breakdown of one of the robots leads to a decrease in the travelled distance by 37% compared to the operation without breakdown. However, it is interesting to note that the throughput decreases from 81 to 65, which is just a 19% drop. Also, the difference in the number of cases delivered before (34) and after breakdown (31) is less. This is a positive indication of the capability of the system to respond to the change or breakdown. Since the two robots were not completely utilised in the normal case, the single operating robot is able to increase its utilisation to cater to the higher demand. However, since only one robot operates, the waiting time for every case increases and thus the order fulfilment time rises. As seen in Table 17, the mean order fulfilment time doubles after the breakdown. There is also a steep rise in the maximum order fulfilment time. Since only one robot is catering to all the demand, high variation is seen over the fulfilment times. For a given type of control strategy, particularly central positioning, the self-organised system of robots exhibits increased contribution to robustness in the overall throughput as compared to the order fulfilment time.

7.5 Discussion: Self-organised Robots versus Existing Operation

In the case study, the existing operations of the vehicle based in-house material transportation are dominated by manual activities. After the order for components is placed by the assembly stations from the warehouse, the consolidation is done manually to fit the shipment size of a pallet to be transported in a reach truck. As a result, the average time for order fulfilment is almost 1 day. Also, when there is an urgent requirement for a component, it is transported in a manual cart and the long distances lead to increased human fatigue. From the data analysis and plausible assumption, it is found that the total travelled distance by manually driven reach trucks is around 17km in a day within the facility. The above experiments explored the various scenarios in which a self-organised system of robots can serve as an alternative to existing material transport. As explained in Section 3.2.3, a direct comparison of the performance indicators of the existing operations and the new system of robots would not be appropriate, as the exiting system has not been simulated. Also, the level of consolidation of the transported components is different in both methods. The limitation of the load-carrying capacity of the robots supplements this.

However, the self-organised system of robots is being introduced to reduce human fatigue by automating the material transport activities to a certain extent. Because of the open and decentralised nature, it incorporates robustness in the system for varying conditions. From the above set of experiments, it is observed that for the base demand conditions as specified in section 7.2.2, the average order fulfilment time is just 40 minutes. This is a significant improvement as compared to the waiting time of almost 1 day in the current operation and thus catering even to urgent requirements. As explored in the experiments, a system of just 2 robots will be able to provide an average throughput of 81 cases per shift, thereby serving the transportation demand of small components. The new system of robots can adapt to increased or skewed demand with minimum impact on the system performance.

One of the drawbacks of the robots would be the limit on the load-carrying capacity. As mentioned in Appendix A.5, the maximum load-carrying capacity of the current version of robots is 30kg. The components moved in the intralogistics facility includes large and heavy components also. The smaller components which can be carried by the robots account to 30% of the total material movement (personal communication dt. 09/06/2021, refer Appendix A.8.2). Thus the new self-organised system of robots will need to work in tandem with the existing vehicles and supplement the operations. As discussed above, this results in the reduction of human fatigue, faster order fulfilment and a robust material transport system.

Further discussion on this is conducted in Chapter 8.

7.6 Discussion: Model as a Decision Support Tool

One of the objectives of the simulation model is to function as a decision support tool for Prime Vision in the given case study and upcoming projects. For the implementation of the self-organised system of robots in an intralogistics facility, multiple factors have to be considered and explored to find a suitable setup to cater to the requirement. This requires making a decision on the configuration of the vehicle based in-house material handling system considering the possible scenarios during the operation. The key scenarios that affect the system performance are the demand pattern and the ability of the system to respond and adapt to fluctuations. The developed simulation model helps test these conditions.

As seen in the experiments, for the considered base demand conditions, the number of robots required can be established. This would be the first step towards understanding the scale of the system. By comparing the system performance under varying demand distribution and different control strategies, the suitable form of task assignment and empty vehicle management can be decided. The model also helps study the performance indicators in case of extreme conditions of demand whether high or skewed. With the ability to incorporate the battery operation (basic in this case) and breakdowns in the simulation and analyse the impact of the same, the tool helps the robot manufacturers to optimise the vehicle and build necessary redundancy in the system. Being a decentralised system with the agents having localised behaviour, the simulation model helps witness and analyse the emergent behaviour in the form of animation and visualised statistics. The intuitive control dashboard allows the user to modify the parameters and configuration conveniently. Further discussion on this perspective is conducted in Chapter 8 with the scalability and adaptability aspects.

7.7 Summary

Table 18 summarises the results of the experiments conducted.

Table 18: Summary of Experiment Results

Experiment		Summary of results
System Design / Efficiency Experiment	Variation in number of robots (central positioning, 1-8 robots)	Considering the balance between the investment on robots, order fulfilment time, throughput, and robot utilisation, it is recommended to use 2 robots for the considered demand pattern. With an average utilisation of 40%, around 80 cases can be delivered with a mean order fulfilment time of 40 minutes. Beyond 2 robots, the improvement in service (increase in throughput & decrease in fulfilment time in comparison to utilisation) is not significant.
Efficiency Experiments	Variation in control strategy (central & point of release positioning, 2 robots)	For a demand pattern dominated by central origin, although Central Positioning leads to 7.5% higher travelled distance, the longest order fulfilment time is lesser by 66% than Point of Release Positioning. Given the availability of sufficient resources, the throughput remains almost the same in both cases.
	High demand (central positioning, 2 robots)	With the doubling of the demand rate (central positioning), there is an obvious increase in robot utilisation (40% to 66%), but also the throughput increases by 65%. While the maximum time for fulfilment increases more than double, the mean time is 62% higher with increased variance. Although 2 robots can handle the increased demand (with compromise in order fulfilment time), having 3 robots leads to 40% better order fulfilment time.
	Variation in battery life (central positioning, 2 robots)	Simulation of battery is basic in this model. For base demand and decreased battery life (100 mins) there is a slight decrease (5%) in throughput as the frequency of recharging increases. Sufficient availability of robot idle time compensates for this.
Robustness Experiments	Fluctuation in demand (central positioning, 2 robots)	For random seed of demands at the base rate (triangular distribution) f0r 10 replications, the robots delivered between 23 to 113 cases in each instance. With an average order fulfilment time of 40.7 minutes, just around 10% of cases were undelivered even at the highest demand rate, which is mainly attributed to the model runtime and sequence of operation rather than available capacity.
	Skewed demand (central & point of release positioning, 2 robots)	With a higher station-station demand than warehouse-station, Point of Release Positioning leads to 10% lower order fulfilment time (mean) and lesser distance travelled per delivered case. However, this gain is at the cost of slightly decreased throughput because of only 2 robots in the system and the demand distributed between 5 stations. In both central and point of release, a very high variance is observed owing to the distributed pattern of material movement.
	Breakdown of robots (central positioning, 2 robots)	With the breakdown of 1 robot, the overall utilisation jumps from 36.3% to 50.5%, but the system can handle the load with a throughput drop of just 19%. This is a positive indication towards the capability of the system to respond to the change or breakdown. The total distance travelled decreases by 37% as compared to normal operation. However, after the breakdown, the mean order fulfilment time doubles with also increase in the variance.
Comparison with manual operation		With almost 17km travelled per day in the exiting material movement operation (manual driven reach truck & manual push carts), human fatigue is high. The self-organised system of robots support in reducing this. However, the current version of robots has a load carrying capacity of 30kg, thus limiting the components it can carry. From the experiments, it is found that robots provide a mean order fulfilment of 40 minutes with the base demand rate, while the manual operation delivers components usually the next day. Thus, the robots can be used to supplement the existing operations mainly for small components (approx. 30% of current material movement) and urgent orders. The decentralised nature of the new system incorporates robustness in the operation to handle varying demand pattern and breakdowns.

This chapter is aimed at exploring the implemented simulation model with different scenarios and configurations to test the efficiency and robustness of the new system of robots. Also, the function of the simulation model as a decision support tool to the industry is scrutinised. This chapter in conjunction with the previous one completes the answer to the sub-research question, *"For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?"*. Deriving the objective of the experiment from the project goals, the experiments dive into checking the suitability and efficiency of the new system of robots under varying system design, control strategies and demand scenarios. The experiments are mainly divided into two categories to analyse efficiency and robustness.

While it is found that for the base demand conditions as specified in Section 7.2.2, 2 robots suitably cater to the demand, the effects of central positioning and point of release positioning is explored in the next experiments. It is found that, for a given demand, by increasing the number of robots, the throughput and order fulfilment time stabilise at a certain fleet size. However, a further increase in the number of robots decreases the order fulfilment time at the cost of increased investment and decreased utilisation. Hence for any system, it is key to find a balance between the investment, and the acceptable values of the performance indicators. The type of empty vehicle management depends on the demand pattern and contributes to the robustness of the system. The experiment to test the system response (same number of robots) to high demand presents that the most adverse effect is on the order fulfilment time. Due to the availability of unutilised time, the robots cater to the increased number of cases. Reduced battery life contributes to decreased throughput, due to increased frequency of recharging and non-availability of the robots for task assignment. Although this drop is not significant, it is recommended to explore further by simulating the battery functioning more in detail. The robustness experiments test the adaptability of the system of robots to changing conditions such as skewed demand, fluctuating demand and breakdown of robots. The response of the system of two robots to fluctuating demand was positive with the utilisation varying between 20% to 48%. This indicates that the robots were not overloaded and have further potential to handle higher demand. The skewed demand, with increased station-station demand, is handled better by the system with point of release positioning as the mean order fulfilment time reduces. The next sections discuss the new system in comparison to the existing manual operation and the simulation model's function as a decision support tool. Considering the limitations in the load-carrying capacity of the robots, the self-organised system of robots will need to work in tandem with the existing vehicles and supplement the operations, to reduce human fatigue, enable faster order fulfilment and build a robust material transport system. The simulation model with the animation and an intuitive user interface supports witnessing and analysing the emergent behaviour of the decentralised system of robots. The extracted performance indicators would help in exploring the system design and decision making before implementation.

In the next chapter, conclusions are drawn from the research, design and experiments conducted till now to answer the main and the sub-research questions.

8 Conclusions and Recommendations

8.1 Conclusions

Addressing and adapting to the 'shifting pattern' towards digitisation and automation in logistics has been the stimulus for this thesis project. In-house or intralogistics is a key link in this domain and since the pandemic, the push towards building resiliency has been more than ever. Self-organisation, with its functionalities of openness, intelligence and decentralisation has been the look ahead. Owing to the complex emergent behaviour of locally interacting agents, coupled with a lack of operational studies, quantifying and generalising the efficiency and robustness of such systems have always been challenging. Considering a case of a prominent manufacturer where the in-house material transport is dominated by manual operations, Prime Vision's aim is to develop and implement a self-organised system of robots for intralogistics to reduce human fatigue and improve robustness. In this context, the pursuit of this project has been the development of a simulation model to explore the emergent system characteristics of a self-organised system (problem statement in Section 1.1). The implementation of this model has been done to enable its functionality as a decision support tool that is intuitive, adaptable and scalable. To operationalise this, the main research question was set as:

Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?

In the final chapter, this question is answered guided by the following sub-research questions, which also built the storyline of this report.

What is the status quo of logistics operations and actors involved in a self-contained company site?

A self-contained company site includes a variety of facilities including manufacturing and assembly, warehouse, distribution centre and more. The associated functions and actors vary depending on the type of facility. However, the key and common functions have been identified as transport, storage and picking, packing, handling. In this project, the focus has been on the vehicle based in-house transport system for a manufacturing and assembly facility. With around 90% of the experts, ascribing for digital transformation in the transport and logistics sector, the challenge to it has been the lack of digital culture, training and a clear vision towards digital operations (PwC, 2016). Globalisation has been pushing towards mass customisation and shorter product life cycles which necessitates the incorporation of flexibility, reconfigurability, scalability, adaptability and re-usability in the existing industry including logistics (Furmans et al., 2011; Klein, 2013). Multiple internal and external stakeholders influence this transformation (Figure 5) and understanding their responsibilities, interests and constraints is a key aspect.

In the considered case study, the head of the warehouse, warehouse operators (including vehicle drivers) and assembly station operators are invested in the performance of in-house material transportation. Based on the orders placed by the assembly stations, the components are mainly transported from the central warehouse to the assembly stations spread across the facility in reach trucks. While the assembly station expects speedy delivery of components and flexibility to facilitate urgent requirements, the warehouse operators have a constraint of fatigue due to multiple movements. In the current state, the orders are consolidated to a pallet size shipment and the order fulfilment takes 1 day on average. Apart from the usual manually driven reach trucks, pushcarts are also used to serve urgent requirements. The long distances and multiple visits increase human fatigue. The spread of transported materials include small spares to large components and the intent of this project is to explore the possibility of using a self-organised system of robots for material transport. However, owing to the constraint on the load-carrying capacity of robots (30kg), the focus is on smaller components accounting for around 30% of the transported materials. The way this can be enabled is discussed in the answer to the main research question. The next sub-research question addresses the performance indicators to define the system performance of the existing and future systems.

What are the indicators that define system performance in an intralogistics operation?

The current operations for material transport in the intralogistics facility include multiple human-made decisions and activities, from the point of raising an order, consolidation, retrieval and transport. When some of these decisions and activities are fulfilled by the system of self-organised robots, changes in system performance are expected. To analyse the performance of such a system, it is necessary to establish performance indicators suited to the type of facility and nature of the operation. However, a direct comparison between both the cases would not be suitable considering the limited availability of data on the current operation, the difference in consolidation and shipment size, and simplifications considered as mentioned in Section 3.2.1. From the literature review and interviews with relevant stakeholders, the performance indicators for the existing operations have been decided as total vehicle distance travelled, vehicle utilisation and order fulfilment time. To obtain these, data analysis has been conducted on a sample set of scanned material movement transactions within the facility. The data analysis gives a rudimentary idea of the demand pattern between the assembly stations and helps in calculating the performance indicators. As mentioned in Table 4, the total travelled distance per day by the vehicles is around 17km with an active vehicle utilisation time of around 2.5 hours. As reported by the Head of Warehouse, the order fulfilment takes around 1 day, considering the consolidation, preparation of packing list, retrieval and transport. It is to be noted that, in these calculations, movement both by reach trucks and manual carts are included with plausible considerations on routing, number of visits and speed of movement. These values indicate that the manual movement involved and service time of orders are high with a scope to reduce human fatigue and improve robustness.

With the introduction of the self-organised system of robots, the shipment size per robot is reduced to the capacity constraint of the robot. However, the fulfilment time of orders for small components is expected to reduce significantly while reducing the manual effort. They understand the capabilities of the new system, similar performance indicators are used including total robot distance travelled, robot utilisation, order fulfilment time and the number of cases delivered during a shift. By conducting experiments on the implemented new method, these indicators have been used to analyse the efficiency and robustness of the system under different configurations and scenarios. The next sub-research question describes the control strategies considered and modelling of the self-organised system of robots.

How can a vehicle based in-house transportation system be modelled to enable the study of the emergent characteristics under different decentralised control strategies?

Self-organisation has been a term used under different perspectives, varying in extent of automation, decision-making and information usage. Openness, intelligence and decentralisation being the foundation, the system advocates the autonomous behaviour of individual agents based on local interaction, with a common system goal such as delivering the components to the destination. While the emergent characteristics may not be the most optimised, it is expected to contribute towards flexibility and robustness. In the newly conceptualised method, the robots, cases carrying the components and a central platform are the agents which communicate with each other to enable the material transport. To model such a system, it is necessary to design appropriate decentralised solving approaches for the control strategy problems. For an intralogistics environment, system design, load-vehicle assignment, empty vehicle management, routing and deadlock avoidance are considered as the key tasks. Multiple literatures suggest control strategies varying in degree of decentralisation in decision making and information usage. Most of the approaches consider the load-vehicle assignment and empty vehicle management as a combined dispatching problem, and propose multi-agent based strategies including CNET protocol based on auctioning, emitted field-based assignment, feedback based dispatching, forecast based dispatching and more. The selection of a suitable approach is dependant on the variation of demand, size of the layout and arrangement of different nodes. For the given case and for the purpose of study, Klein's static dispatching for decentralised control has been chosen which is suitable for smaller layouts and high variation in demand (Klein, 2013; Schmidt et al., 2020). With a central warehouse and loading point, a central parking position is considered for the robots. Routing uses the information on global topology and the shortest path between the nodes are used during operation. Deadlock avoidance at the intersection, merges and switches is governed by FCFS and supported by onboard proximity sensors.

Based on the above principles, a swim-lane flowchart has been used to present the conceptual model of the new system (Figure 18). The order for components raised by the assembly stations are attached with a task priority which is collated and queued by the central platform on a FCFS basis, but the higher priority task skipping to the front of the queue behind other high priority tasks. While most transport requests are from warehouse to stations, a small percentage of orders also move from station-station. A delay for order preparation is considered for orders with the warehouse as the source and the duration is lesser than the existing system due to the smaller size of the orders. The case at the front of the queue raises a transport request to the set of robots. Depending on their availability to accept a new task, the robots respond with the shortest distance to the loading point. The nearest robot gets assigned to the case, where the case is loaded manually, to be transported to its destination. After every delivery, the robot has an internal check of the battery level before becoming available for the next task. If the battery level is critical or no tasks are available, the robots always return to the home position, if not the next assigned task. To enable the study of different alternatives and emergent characteristics, variation in the empty vehicle management between central positioning and point of release positioning for different demand scenarios, with the varying number of robots are considered during experiments.

What modelling technique would be the most suitable to study the emergent behaviour of the system?

Although experiment in real-world is one of the most intuitive approaches, it proves to be expensive, time-consuming and disrupts existing operations. In the case of a self-organised system of robots, the added challenge is the emergence of complex system characteristics arising from the interaction of multiple agents and their decentralised decision making (Schmidt et al., 2020). Considering the dynamic and decentralised nature, a simulation model steering the system through state changes as model time progresses is a suitable technique to study such a system. The type of simulation modelling used depends on the comfortable abstraction level. To capture the nature of the intralogistics operations involved in an intuitive way and make the model easy to use, multi-method modelling is implemented in this project. In this method, the flow of the operations involved in the vehicle-based material transport is represented using a process-centric model (discrete event modelling) and the individual behaviour of the agents is represented using statecharts which is a part of agent-based modelling. This form of model building gives more control over the details to be focused upon and makes it convenient to extend and adapt the model for different business cases. Anylogic which facilitates an intuitive platform for multi-method modelling was found suitable for this project. Its attributes including an easy-to-use interface (UI and Java), material handling and process modelling libraries, 2D and 3D animations and visualisation (performance indicators) has helped build an intuitive model and interface for the end-user to use as a decision support tool. The next sub-research question describes the model's functionality as a decision support tool.

For an industry, how can the model support strategic decision-making in the implementation of self-organising robotic system in business applications?

"Strategic decision-making is the process of charting a course based on long-term goals and a longer-term vision" (Gartenstein, 2019). For a model to be effectively used in such business applications, it must provide insight on the system performance under expected operating conditions, so that the involved stakeholders can take a call on its feasibility and investment. Although the economic perspective on the matter is not touched upon in this project, the model intends to answer questions on the efficiency and robustness of the system under different configurations and scenarios. Also, during the implementation of the model in Anylogic, the aspect of providing a lucid user interface has been focused upon, to ensure convenient usability to the decision-maker without dwelling on the details of programming. The user would be able to modify types of control strategy, number of robots, robots specification, operating conditions and more from a single dashboard and run the simulation to visualise the performance indicators live.

The implemented simulation model allows conducting experiments with controlled seed, random seed, and comparative runs to analyse and compare the performance indicators for different alternatives. As seen in the experiments, for the considered base demand conditions, the number of robots required can be established. This would be the first step towards understanding the scale of the system. By comparing the system performance under varying demand distribution and different control strategies, the suitable form of task assignment and empty vehicle management can be decided. The model also helps study the performance indicators in case of extreme conditions of demand whether high or skewed. With the ability to incorporate the battery operation (basic in this case) and breakdowns in the simulation and analyse the impact of the same, the tool helps the robot manufacturers to optimise the vehicle and build necessary redundancy in the system. The animation also allows quick verification of the operation and the model.

Based on the course set by the answers to these sub-research questions, the primary objective and the main research question is answered.

Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?

Based on the findings in this project, a quick answer to the main research question would be that the conceptualised system of self-organising robots, considering its current capabilities and constraints, would supplement the existing in-house material transport to improve robustness and reduce human fatigue. Factors such as a limit on the load-carrying capacity of the robots, expected changes in order placement, infrastructural changes required and acceptance level of human-robot symbiotic work environment would be the challenges to overcome for a full transformation. However, introducing a fleet of robots to handle the logistics of small components and spares would reduce the manual movement, mainly the usage of pushcarts which are the key cause of fatigue. Reducing the order fulfilment time to a great extent, the robots would also be able to cater to skewed demands and urgent requirements.

Understanding the emergent behaviour of a self-organised system in an intralogistics environment has been the pivot of this initiative. From the experiments conducted on the simulation model, it is learnt that the system is able to adapt to varying scenarios, such as high demands, skewed patterns and breakdowns. For a given system design, considering enough margin in the robot utilisation would ensure that most of the demand is satisfied for the varying conditions. However, there would be a compromise in the performance indicators such as the total distance travelled (directly related to energy consumption) and order fulfilment time in extreme conditions. For the base demand conditions considered in this project, it is recommended to use 2 robots for material movement, considering the balance between the investment in robots, order fulfilment time, throughput, and robot utilisation. With an average utilisation of 40%, around 80 cases can be delivered with a mean order fulfilment time of 40 minutes. Compared to the existing manual operation, this would still be a positive takeaway considering the reduction in manual effort and faster delivery. Beyond 2 robots, the improvement in service (increase in throughput decrease in fulfilment time in comparison to utilisation) is not significant. This factor helps in system design by finding a balance between acceptable service time and investment in robots.

It is also to be noted that, although the decentralised operations provide flexibility, the suitability of a control strategy strongly depends on the configuration and scenario. During experimentation, point of release positioning served better for demands originating around the facility, while central positioning performed better when orders from warehouse to stations were higher. For a demand pattern dominated by central origin, although central positioning leads to a 7.5% higher travelled distance, the longest order fulfilment time is lesser by 66% than the point of release positioning. Given the availability of sufficient resources, the throughput remains almost the same in both cases. Incorporating the option to switch between the strategies and necessary infrastructure during implementation would provide better control over the adaptability of the system. During the experiments, the new system of robots was found to robustly manage high demand, fluctuating demand as well as skewed demand (increased station-station movement). While the throughput shows small changes in all these cases compared to the base demand, the order fulfilment time shows a significant increase and variance in case of high and skewed demand. Under base demand conditions and the same model run time, the breakdown of 1 robot caused a drop of throughput by just 19%, indicating the robustness of the system.

To accommodate the new system of robots on the shop floor, a few changes would be required in the exiting mode of operations on the shop floor. The smaller components which can be transported in a case on the robot need to be identified. The orders for such components need to be placed separately by the assembly stations considering the size of the case. However, the upside would be that these orders can be of smaller sizes and due to faster replenishment, smaller stock of components can be maintained at the assembly stations, promoting a just-in-time strategy. The developed simulation model provides a platform to analyse and compare the performance indicators for various alternatives before making a decision as per the case. Through the course of this project, it is learnt that self-organisation is an umbrella term encompassing numerous pioneering concepts. In this project, a limited set of control strategies, implementation options and application environment have been explored. For accelerated growth in this field and shift towards digitisation, a close collaboration between technology developers, end-users and researchers is key.

8.2 Recommendations

The method for the self-organising system of robots proposed in this project and the simulation model developed supports the decision making in future implementation. However, being the initial step towards a limitless technology, it opens up multiple areas of extension and improvement. Some of these are mentioned below.

8.2.1 Method: Extension and Improvements

The points below address the possible improvement in the developed method:

- *Refine demand distribution:* The current demand values considered are based on the data collected over a short period of time and unrefined. A triangular distribution has been established because of this limited availability. The demarcation between the loads carried by reach trucks and manual carts were not present. The characteristics of the material transported were unclear and the scanned transactions were prone to human error. For future developments, a more focused data collection and over a longer period of time would help refine the model and establish a more accurate distribution curve for the demand.
- *Improve logic for battery management:* Battery management is an important characteristic in robots and will impact the throughput and robustness of the system. In the current model, considering the primary focus and time constraint, the logic for the functioning of the battery has been built within the state-chart of the robot agent in a rudimentary form. The discharge rate is constant and a fixed recharging time has been incorporated. In the upcoming models, a more intelligent battery management system, with options for battery swapping or dynamic dispatching decisions based on battery level can be incorporated.
- *Method for order consolidation:* In the current state of operations, order consolidation to pallet size shipments are done manually. In the new system of self-organising robots, the orders are assumed to enter the system as 1 case size. For incorporating more accurate order consolidation, characteristics of the components including size and weight would be needed. However, this would be a salient improvement to the model.
- *Incorporate multiple delivery points:* Related to the above point, each case is considered to have a fixed destination. This has been done considering the complexities of mixing of components, challenges in retrieving components from a small case and dispatching decisions. Understanding the characteristics of components and clarity on-demand distribution would help including multiple delivery points in a single run of the robot.
- *Explore other forms of decentralised control strategy for dispatching:* The choice for the control strategy in the current model is based on the smaller layout and high demand variation. Depending on the business case for implementation, other forms of decentralised dispatch control strategies can be explored. One such suggestion is to have multiple home positions of the robot depending on the demand. While considering this, it is important to define a logic that maintains a balance between the number of robots at multiple locations.

8.2.2 Implementation and Evaluation

The developed model has been implemented in Anylogic and multiple experiments have been conducted. These recommendations are related to the model and the evaluation of the system:

- *Improve accuracy of robot characteristics:* In the implementation of the model in Anylogic, simplifications have been considered in the robot characteristics. Although the size is similar to the dimensions of the current version of Prime Vision's robots, more specific details and functioning can be incorporated including the conveyor on the top, actual method of loading, charging hub and more accurate onboard sensor functions. While improving the accuracy of the current model, standardisation of these features would help in adaptability to other projects.

- *Evaluation of more scenario-configuration combinations:* In the experimentation section, the full factorial of scenario-configuration combinations haven not been tested. Only the experiments fitting the context of the discussion and the available time have been conducted. However, evaluating more alternatives such as distributed positioning, sensitivity analysis of battery recharge time, more scenarios of skewed demand would provide more insight into the system behaviour.
- *Interface with other software:* The simulation model implemented in Anylogic currently is a standalone model where the inputs are entered manually in the dashboard and live performance indicators are visualised. Further analysis of the recorded run-time data needs manual extraction and analysis. Further possibilities to interface the inputs and output with other software can be explored. The possibility to accept input from a database and providing an output of performance indicators in a prescribed format would be a value addition.
- *Economic analysis:* The current evaluation of the system has been purely on the basis of comparison of performance indicators such as throughput, order fulfilment time, total distance travelled and robot utilisation. While this gives a significant platform for decision making on the system design and suitability, an economic analysis involving investment, operational cost and energy consumption would prove useful for more informed decisions.
- *Measuring empty kilometres:* Measuring empty kilometres is an effective way to evaluate the efficiency of the model. Comparing the empty kilometres run by the robot in different configurations of decentralisation helps decision making and steps towards further optimisation. A suitable logic can be incorporated to enable this.

8.2.3 Adaptability and Scalability

The simulation model built in Anylogic represents the chosen case study in layout and operations. However, the model can be conveniently adapted and scaled to other business cases and type of intralogistics facility. The following are a few guidelines and examples on the same:

- *Scale:* The scale of the model can be extended by including additional nodes in the graphical interface. Multiple palette options are available to draw the type of node and its characteristics. The same can be included in the process model to integrate with the existing model.
- *Storage racks:* In the case of applications such as distribution centres, warehouses can be modelled as models with specific details such as size, layout, filling and retrieval pattern. This would help considering the inventory status and automatic replenishment in the logic.
- *Pedestrian movement:* Most of the intralogistics facilities have movement of human operators on the shop-floor. Anylogic provides the option to include this in the simulation with a stochastic pattern for the movement. This would help understand the human-robot interaction and its impact on system behaviour.
- *Other material handling equipment:* Intralogistics facilities have multiple material handling equipment working in tandem. Anylogic with its inbuilt material handling library enables the inclusion of these equipment including conveyors, forklifts ad cranes. For a more complex environment, these equipment can be included in the layout and interfaced with each other to simulate real-world operations.

8.2.4 Managerial Recommendations

The new system of self-organised robots supplements the exiting operation by reducing the fatigue due to manual operations and improves the robustness of the system. This being the look ahead for the intralogistics facility, multiple hurdles have to be crossed moving towards implementation.

- The results of the simulation model shows the operational efficiency of the system of robots for various conditions. However, the development of robots with the technical specifications to enable self-organisation would incur significant investment and time. Multiple field tests would be required before the commercial launch of such a system. Also, the system requires intelligent cases (carrying components) capable of simple, but efficient communication with the other agents and a central platform similar to WMS. Development of these and integrating them into the existing client operations is a challenge to overcome.
- The existing version of robots have a limitation on the load-carrying capacity, both weight and volume. Implementation of the robots in multiple types of intralogistics facilities would require robust load carrying options for components and half-products of various sizes. Development of this design and associated auxiliaries such as a suitable motor, battery and guidance system is necessary to expand the application.
- Apart from the development of technology, the resistance to experimental design and automation is an inherent challenge in most industries. Although the efficiency of the system can be proven, ensuring the trust of the employees working around such a system is quintessential to ensure synergy in operation. Incorporating necessary safety measures and pleasant interaction protocols would support this cause.
- Proceeding with this technology, market research among the potential customers and users of intelligent in-house material transport systems would add value to the design. Understanding the nuances of their requirement would help refine the design and focus the investments in the right technology.

8.3 Bigger Picture

Based on the conclusions drawn in this thesis and the recommendations, Figure 36 shows an overview of the path ahead for Prime Vision towards further development of this project.

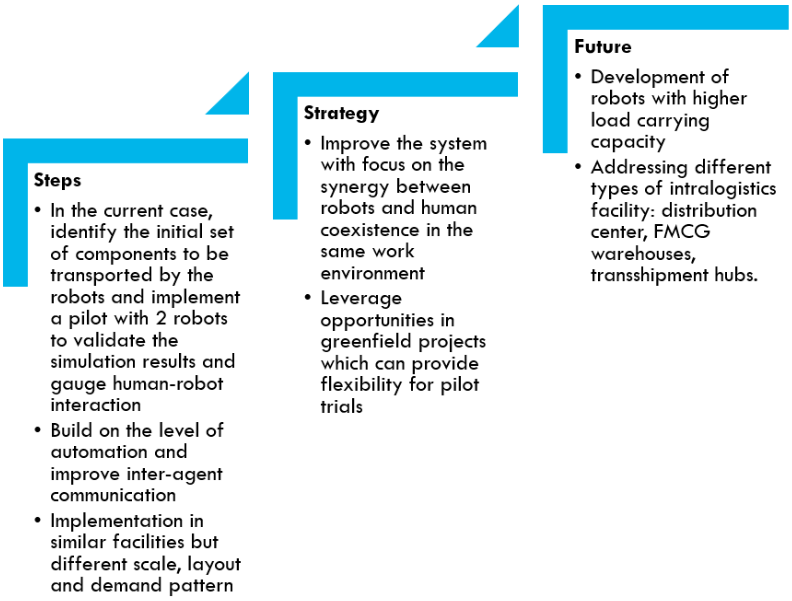


Figure 36: Path ahead for Prime Vision

In this project, the discussion and research have been focused on a manufacturing and assembly facility of a given scale. In Section 8.2.3, the recommendations on adaptability scalability from the perspective of the simulation model has been mentioned. However, on a practical note, self-organisation has wider applicability in other domains too. As shown in Figure 37, distribution centres, warehouses, ports and last-mile delivery are some key areas where logistics can benefit from decentralised and intelligent systems.

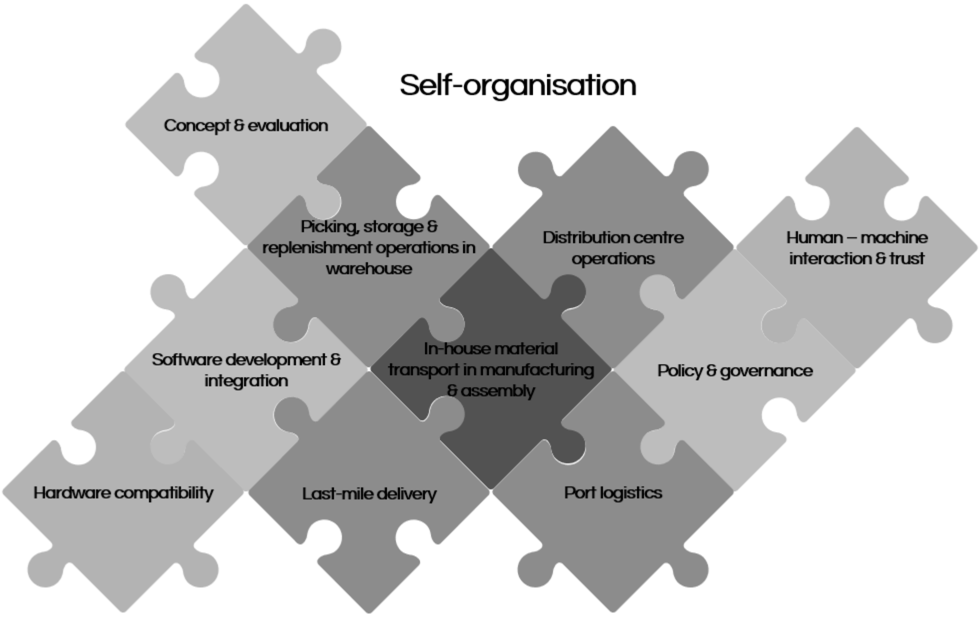


Figure 37: Wider Application of Self-organisation

However, in reference to this project, a few concerns need to be addressed while expanding the scale or adapting to a different environment. In a similar facility, but on a bigger scale, more robots would be required, increasing the communication load and complicated human-machine interaction. Necessary hardware needs to be developed to handle heavier and bigger loads with increased safety. Compatible software with quick integration with the client's existing platform would be necessary. In facilities with larger layouts and distributed load origins, distributed positioning of robots can be explored for better flexibility. Optimised batching and route selection for multi-point delivery under a short time horizon can be improved by investigating other forms of decentralised solving approaches. Adapting the system to a different environment of material movements such as ports or last-mile would require improved coordination with other vehicles, equipment and personnel. On-boarding of relevant stakeholders and consideration of governing policies is also a key factor to be considered for wider application.

8.4 Reflection

This project began with the spark to explore the possibilities of a technology that can take automation and digitisation to the next level. Self-organisation is an organic part of living beings, society and their growth. Incorporating this in an optimised and tangible way for industrial applications is a challenge. The intent of this project has been to contribute to this, even if in the smallest way possible. Banking on the knowledge of transport and logistics from the MSc. TIL program, previous work experience in material handling system and acquiring of new skill sets on simulation including the usage of Anylogic, was a testing path, but exciting.

Most of the reviewed literature focus on a particular form of self-organisation varying in the extent of decentralisation or the control strategy problem addressed. The types of facilities addressed are also limited within a given research paper. There is a need for the development of more holistic research in self-organisation. The existing research papers although dwelling deeply into the concepts they address, lack of operational study and involvement of stakeholders, mainly the end-users of the technology. This research attempts to cover these aspects by developing an intuitive platform to quickly and conveniently include the industry expectations and feedback in the research and evaluation. Apart from focusing on the chosen case study, this thesis project also provides a connecting link to adapt and scale the system to a bigger and different environment, thus an attempt towards holism. Exploring different forms of decentralised control strategies for an intralogistics system, a platform is set for further research to critically analyse them. The developed conceptual model and its implementation provide a comprehensible way to study the emergent behaviour of the multi-agent interactions and trim the parameters for optimisation. This research can be extended to other intralogistics facilities like distribution centres and warehouses, adapting to the change in the type of activities.

For industry, the simulation model developed functions as a decision support tool. Even without in-depth knowledge of self-organisation, a decision-maker will be able to get a prima facie impression on the performance of the system. This would assist in the conceptualisation of new business cases and discussions. From a societal perspective, the project is a step forward towards building resilience. With scenarios such as the pandemic creating a volatile environment in the demand and supply, there has been a push to increase robustness to handle the variations. Self-organising systems aid this, by incorporating flexibility and smartness in the logistics system.

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A Appendices

A.1 Scientific Paper Draft

Self-organisation in Intralogistics: An Intuitive Modelling Approach to Study Emergent Behavior

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Abstract—Intralogistics is a crucial part of the supply chain and is continuously influenced by the drivers such as globalisation, mass customisation, and shorter product life cycles. The challenges brought about by the pandemic have accelerated the 'shifting pattern' towards automation in transport & logistics. With the push towards higher robustness and efficiency, self-organisation is the next step to incorporate flexibility, reconfigurability, scalability, re-usability, adaptivity, and energy-efficiency in the material handling system. This aims to reduce human fatigue and inaccuracy in in-house logistics and also improve the response time. However, the feasibility of such systems in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents and the lack of extensive operational studies. This research attempts to develop an intuitive, adaptable and scalable model to study the emergent behaviour of a system of self-organising robots for in-house material movement. By considering the industry expectations and feedback in the research and evaluation, the model also functions as a decision support tool for business cases, providing a prima facie impression on the system performance.

Keywords— *Intralogistics, Self-organisation, Emergent behaviour, Multi-method simulation, Decision support tool*

1. Introduction

With changing times and newer challenges, Transport & Logistics (T&L) has been a part of the 'shifting pattern' as in the case of many other industries. New technology, new market entrants, new customer expectations, and new business models have brought about both risk & opportunity in the field. Surviving through the tumultuous phase such as the pandemic, the push towards higher robustness and efficiency has taken precedence and in light of this, digitisation and automation have been experiencing greater importance. The key drivers influencing logistics, including the in-house logistical systems are (Schmidt et al., 2020):

- Globalisation of operations
- Mass customisation
- Shorter product life cycles

These drivers have led to an increase in complexity and dynamics at the operational level. T&L sector is one in which around 90% of the experts ascribe for digital transformation in the next five years. However, this is still a challenge with the top reason being the lack of digital culture and training, followed by constraints in investment and clear vision towards digital operations (PwC, 2016). Thus there is an immense potential for disruptive technologies, including an increased degree of automation.

Intralogistics is an umbrella term referring to the organisation, control, execution, and optimisation of internal material flow and logistics technologies, usually within self-contained company sites such as factories, warehouses, or distribution centres (Fottner et al., 2021). Dealing with the in-house logistical challenges, it encapsulates a manual or automated material handling system to perform tasks at the operational level. Some typical tasks associated with this are storage systems, transport systems, sorting systems, and more.

As defined by Fottner et al. (2021) *"autonomous intralogistics systems enable self-contained, decentralised planning, execution, control and optimisation of internal material and information flows through cooperation and interaction with other systems and with humans"*. **Self-organisation** is a terminology used in this context and can be best described with an analogy to social insects, like ants or bees, where every being acts towards a common goal based on certain instincts, but without central control. In a logistics system, this can be considered as functioning without significant intervention by managers, engineers, or software control. Being a loosely defined term, the main functionalities of a Self-organising Logistics System (SoLS) can be specified as openness, intelligence, and decentralised control (Pan et al., 2017).

Depending on the system, environment, and context, the degree to which each of these functionalities is applicable and thus the degree of automation varies. While in an ideal case the system is expected to self-organise towards optimality, the phenomenon may result in complex structures emerging from the behaviour and contextual local interactions between the agents (Bartholdi et al., 2010).

Various control strategies have been suggested in publications for decentralised architecture. However, the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents (Schmidt et al., 2020) and lack of extensive operational studies. The emergent behaviour may not always be desirable. Hence, different modelling paradigms, such as simulation modelling and the building of digital twins are required to observe and analyse the system performance before proceeding towards implementation. With the lack of methods to implement decentralised systems and choose the level of decentrality in the real world, it is challenging to quantify and generalise the efficiency and robustness of such systems (Schmidt et al., 2020).

In this context, this research attempts to answer the question, *"Can a self-organised system of robots serve as a robust alternative to existing in-house material transportation with predominant manual operations?"*. Hence, the development of an intuitive, adaptable and scalable method to study this is necessary. Section 2 explores the literature on self-organisation and various decentralised solving approaches for the control strategy problems in intralogistics. Identifying the scientific gaps, Section 3 describes the new method of self-organised robots for in-house material movement. Section 4 specifies the implementation and Section 5 presents the results of the experiments. The conclusion based on the findings and further recommendations form the last Section 6.

2. LITERATURE REVIEW

2.1 Current State of Intralogistics

The push for intralogistics stems from the post-war economic and industrial development when manufacturing was the key driver. With the increase in global demand and consequently the production, growth in storage and distribution technology became inevitable. However, this was also accompanied by escalating labour and material cost (Kartnig et al., 2012). This was countered by the research and incorporation of automation in the field of intralogistics. Globalisation, Mass Customisation, and Shorter Product Life Cycles are the key drivers that have been influencing the logistics world, including in-house logistics (Schmidt et al., 2020). The challenges brought about by the pandemic have accelerated the 'shifting pattern' in Transport & Logistics (T&L), with the push towards higher robustness and efficiency taking precedence. To adapt to the evolving conditions, the logistics system at different levels is desired to have flexibility, reconfigurability, scalability, re-usability, adaptivity, and energy-efficiency (Furmans et al., 2011; Klein, 2013).

An intralogistics facility involves interactions among various internal and external stakeholders. However, there is usually no comprehensive and generally accepted list available (Crostack and Mathis, 2008), as the actors involved depend on the type of facility, for example, warehouse, manufacturing facility, etc, the type of activities, and also the equipment used within. Excluding the major external stakeholders such as the suppliers and customers, key actors in an intralogistics facility can be broadly categorised into - manufacturer, operator, and externals. For a manufacturing & assembly facility and the topic of focus in this research, the actors under consideration are assembly station operators, warehouse operators, in-house transportation operators, head of warehouse, and external technology developers. Interests of the stakeholders and interaction between them have to be considered during problem-solving.

2.2 Automation & Self-organisation

The definition of an autonomous intralogistics system has been introduced in Section 1. A key perspective of autonomy is its relative characteristic, that is, the degree of autonomy based on the subsystem and its freedom of action. Based on this, the autonomous system can be classified based on autonomy over behaviour, autonomy in decision-making, and autonomy in information processing/gathering (Rammert, 2009). Fottner, 2021, also suggests a two-dimensional classification for defining the degree of automation in an intra-logistics system based on this definition, with task level and automation stage. The task levels represent the different types from physical control to overall system planning hierarchically.

With the shift towards decentralised autonomous control, the barriers between different hierarchy levels are disappearing. Self-organisation is a terminology used in this context and can be best described with an analogy to social insects, like the ants or bees, where every being acts towards a common goal based on certain instincts, but without central control. This phenomenon results in the emergence of complex structures due to the behaviour and interaction of local agents (Bartholdi et al., 2010). Being a loosely defined term, the main functionalities of a Self-organising Logistics System (SoLS) can be specified as (Pan et al., 2017):

- Openness: Boundaries of the system are open for actors to enter and leave. Thus, like computers in an internet network, connecting and disconnecting will be convenient, making the system more flexible.

- Intelligence: Agents are capable of autonomous decision-making by collecting and processing information. These decisions are made based on the interaction of the actors between each other and the environment.

- Decentralised Control: Actions of every agent is based on contextual local interactions and thus self-controlling. However, to avoid undesirable results, the protocols and regulations of the environment they operate in are respected. Self-Organisation in Logistics System will involve a rule-based decentralised control which is expected to improve the flexibility and robustness of the system (McFarlane et al., 2016).

When discussing decentralisation, which is a key aspect of self-organisation, the focus can be on two aspects: internal structure and implementation, type of information used (Klein, 2013). A decentralised system intends to shed central control and hierarchical structure and enable decision-making based on locally available information. However, in most systems, there is no clear distinction between centralised and decentralised systems. Implementing a 'truly decentralised' system has limitations when it comes to usage of purely local information which hampers optimisation and incorporates randomness. Thus, it is very common and practical for the existence of systems with units capable of autonomous decision making, but knowledge of pending transportation tasks are still available as global information (Schmidt et al., 2020).

2.3 Control Strategy Problems & Decentralised Solving Approaches

A self-contained company site such as a manufacturing facility, warehouse, or distribution centre is actively connected to the supply chain enabling the inflow and outflow of materials to and from the facility. Concentrating on the in-house material flow, key functions include transport, storage, and picking, packing, handling. The focus of this research is vehicle-based in-house transportation. As mentioned in (Sinriech and Tanchoco, 1993), the design of such systems includes unit load sizing, development of layout, choosing the type and quantity of vehicle, and design of a suitable control system. In the context of this project, the type of robot available, and thus its characteristics and load carrying capabilities are fixed. With the intent of commissioning the new system in an existing self-contained company site, there are also layout restrictions in place. Thus, the focus of the upcoming sections will mainly be on the control system including system design. Figure 1 presents an overview of the key control strategy problems to be addressed.

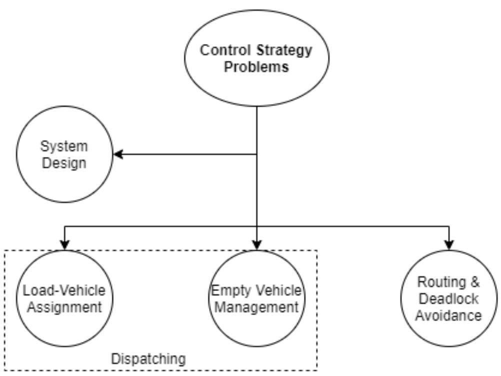

Fig. 1: Control Strategy Problems, adapted from (Schmidt et al., 2020)

System Design

As stated by Han et al., in a vehicle transport system, system design refers to "determining the optimal number of vehicles" (Han et al., 2017). It is a part of resource planning and the complexity depends on multiple variables and factors. The design of solving approaches for the other control strategy problems influences the system design. While various analytical methods are available for this, Vivaldini et. al., mentions an iterative procedure of simulation and adjusting the input parameters to determine the optimal number. Chang et al., also suggests comparing multiple simulation runs ((Vivaldini et al., 2016; Chang et al., 2014).

Load-Vehicle Assignment

Load-vehicle assignment or task assignment refers to assigning vehicles to the new transport requests or tasks or vice-versa depending on the overall objective. It can be either load or workstation initiated (arrival of a new load) or vehicle initiated (vehicle delivers load or reaches parking) (Egbelu and Tachoco, 1984). Most of the real-world applications involve the combination of these perspectives and triggers.

Based on various literature mentioning decentralised solving approaches for load-vehicle assignment, they can be broadly classified into a) layout transformation and b) multi-agent system. Layout transformation involves breaking down the layout into simpler forms and most literature focus on single-loop layouts. In this paper, the focus is on multi-agent system approaches. Multi-agent systems consist of two or more agents which interact during the functioning through direct or indirect communication. With the growing interest in decentralised operations, this approach has been the most widely used as it allows plug and play functionality, eliminating a single point of failure and allowing the entry and exit of the agents (Weyns et al., 2008a). Many multi-agent systems make use of auction-based algorithms. The contract net (CNET) protocol by Smith (Smith, 1980) sets the framework for most auction-based control strategies. This describes the sequence of negotiation, the way the task needs to be announced, and also the offer by vehicle and task assignment. This protocol has been further extended to the reassignment of tasks which encapsulates robustness to the variations in the agents' awareness of the status of the system (Choi et al., 2009). As a continuation to the CNET protocol, but with a multi-agent load vehicle assignment, another method was suggested where the loading station offers the tasks on the market which are evaluated by the vehicles based on the distance to pick-up and the current utilisation of the route for task assignment (Fay and Fischer, 2005). FiTA and DynCNET are two other auction-based protocols suggested in the reviewed literature (Weyns et al., 2008a,b). For smaller layouts with high demand variability, Klein suggests different strategies of decentralised approaches for load-vehicle assignment including random dispatching, static destination dispatching, forecast dispatching, and feedback-based dispatching (Klein, 2013). While these are the few key approaches, a summary of other methods which were studied are mentioned in Table 1.

Empty Vehicle Management

Empty vehicle management governs the behaviour of the idle vehicle when there are no available tasks in the system. Addressing this problem is key to the system performance, especially with a high variation of loads, as this decides the empty vehicle travel time and the response time for new pick-ups. For the idle vehicles in autonomous systems, four approaches that have been identified with varying degrees of complexity are central zone positioning (returns to central home position), point of release positioning (stays at the same position of task completion), distributed positioning (distributed between multiple home positions) and circulatory loop positioning (continuous movement in a loop without parking location) (Hu and Egbelu, 2000; Schmidt et al., 2020; Le Anh, 2005). One aspect in the empty vehicle management is the presence of a loop siding, which is a separated area from the actual travel path to avoid the idle vehicles from obstructing other vehicles (Schmidt et al., 2020). The placement of this would depend on the layout and travel path itself.

Central positioning and point of release are pretty straightforward and decentralised as no system status is required and the decision-making is not complex. The circulatory loop positioning, although known for quick response time, results in peaked energy consumption due to continuous movement. The distributed positioning has been discussed in some literature from two aspects: planning and controlling (Schmidt et al., 2020). In the case of multiple parking or dwell locations, the planning aspect refers to the selection of optimal dwell locations after a task has been executed in an in-house logistics environment. This aspect is strongly influenced by the layout of the facility and the number of vehicles. The controlling aspect deals with the problem of distributing a single vehicle between the parking locations. This depends on factors such as the number of vehicles already at the location, the number of vehicles in a loop, required fill levels, and more. It can be noted that empty-vehicle management is an integral part of the dispatching process and is ideal to be combined with the logic of the load-vehicle assignment. While distributed positioning uses global information to a certain extent, other types of empty vehicle positioning utilise very little or no central information.

Routing & Deadlock Avoidance

The routing problem is to find the optimal route from source to sink. Here the consideration for optimal may differ from case to case, such as shortest path, fastest (considering traffic and other factors), objective to minimise the total travel distance, or individual travel distances ((Klein, 2013). It is to be noted that the objective also depends on the extent of global information available and at what point in time. The destination is a result of the dispatching process and thus the routing usually follows it. However, in some cases where pre-arrival information is available, dispatching and dynamic routing can happen simultaneously in an iterative process (Schmidt et al., 2020). In any case, it is to be noted that routing cannot occur purely based on local information, but knowledge of the global topology of the system would be required. If not, the forwarding would be random and the destination would not be reached (Klein, 2013).

Klein mentions two types of routing for a decentralised implementation: random routing (leads to purely stochastic movement) and central static routing. In central static routing, shortest paths from all sources to sinks are calculated using the Dijkstra algorithm and stored in a routing table at every switch. At the switch and during the next destination assignment, this information is passed to the vehicle. The tables are created only at the beginning of the simulation. While this uses only local information and not the entire system status, the global knowledge of topology is still needed (Klein, 2013). Other studies forms are mentioned in Table 1.

Deadlock avoidance is applicable at the switches, merges, splits, and encountering of obstacles on the route. For an optimum execution, information on system status would be needed to predict the congestion or obstacles in different segments along the route to avoid them. Moving to a more decentralised approach, First Come First Serve basis is a commonly used logic to resolve conflicts (Klein, 2013) at merges and splits. The onboard sensors of the vehicles also help in the localised detection and resolution of obstacles.

TABLE 1: DECENTRALISED SOLVING APPROACHES: SUMMARY OF LITERATURE

Control Strategy	Approach	Paper	Remarks
Load-Vehicle Assignment	Layout Transformation	Bartholdi and Platzman, 1989	First Encountered First Serve, First Come First Serve
		Sinriech and Tanchoco, 1993 Bozer and Srinivasan, 1992	Layout simplification
	Multi-Agent System	Smith, 1980 Choi et al., 2009	Auction based on CNET protocol
		Fay and Fischer, 2005	Multi-agent Load-Vehicle assignment based on CNET
		Weyns and Holvoet, 2008 Weyns et al., 2008	FiTA DynCNET
		Schwarz et al., 2013	Foundation for Intelligent Physical Agents (FIPA) CNET
		Giordani et al., 2013	Two level multi-agent framework
		Martin et al., 2017	Modified CNET
		Berman and Edan, 2002	Vehicle-initiated dispatching
		Klein, 2013	Multi-agent decentralized approach
Empty Vehicle Management	Planning Aspect	Egbelu, 1993	Different layout configurations
		Gademann and Van De Velde, 2000	Layout comparison for optimal dwell location
	Controlling Aspect	Le-Anh and de Koster, 2004	Vehicles distributed between parking and circulatory loop
Routing & Deadlock Avoidance	Multi-Agent System	Klein, 2013	Random routing Central static routing First Come First Serve (deadlock avoidance)
		Taghaboni-Dutta and Tanchoco, 2007	selectnextnode algorithm
		Nishi et al., 2006	Initial individual planning and rescheduling

2.4 Emergent Behaviour & Need for Study

Various control strategies have been suggested in publications for decentralised architecture. It is to be noted that the extent of decentralisation and functioning purely on local information vary. Most of the publications discuss the conceptual nature of the systems. However, the feasibility of these in real-world applications often remains unclear owing to the complex emergent system characteristics as a result of local interactions between multiple agents. As a consequence, predicting the performance of a decentralised system can be hard (Shen et al., 2006). The emergent behaviour may not always be desirable.

System robustness and flexibility has always been claimed as an upside of decentralised systems. Also, the rapid installation process has always justified the push towards autonomy and decentralisation. But the actual estimation of the benefits of such a system is still lacking. The conditions under which a decentralised control would be more profitable or results in higher performance require further research (Fragapane et al., 2021). The influence on system performance by multiple decision variables such as the number of vehicles, zoning, simultaneous scheduling, and path planning, all based on contextual local interactions in a dynamic environment needs to be studied further.

One powerful method to deal with the above-mentioned challenge is through modelling. Different approaches such as virtualisation by digital twins and simulation modelling would help in understanding and predicting the emergent system behaviour under a specified set of ground rules. For a given case, studying the emergent behaviour of a self-organising system in a virtually developed ecosystem would substantiate future investment. Although multiple such models are already being developed, the challenge is the extent of decentralisation and the complexity of the real-world application. Developing such a model will also help in preparedness for predictive maintenance in the future(Fottner et al., 2021).

3. Self-organised Robots for Intralogistics

3.1 Case Study & Existing Material Handling Operations

For this research, the case of a prominent manufacturer with an assembly facility with multiple assembly stations is chosen. In the existing system, the components are transported from the central warehouse to different assembly stations using manually driven reach trucks and manual carts. Collating the orders from the assembly stations raised in the Warehouse Management System (WMS), a warehouse operator prepares a packing list to retrieve the materials from storage, pack, and dispatch in the vehicles. Certain urgent orders are catered in manual pushcarts. The current form of operation results in a high manually travelled distance (almost 17km in manual driven reach truck manual pushcarts) and labour intensive, thereby higher fatigue in the employees and resulting in order fulfilment time of around one day. Figure 2 shows the layout of the facility along with the indicative movement paths. Without dwelling on the individual characteristics of the components, the count of transactions of the material movement has been tracked based on the data analysis of around 107,000 scanned transactions.

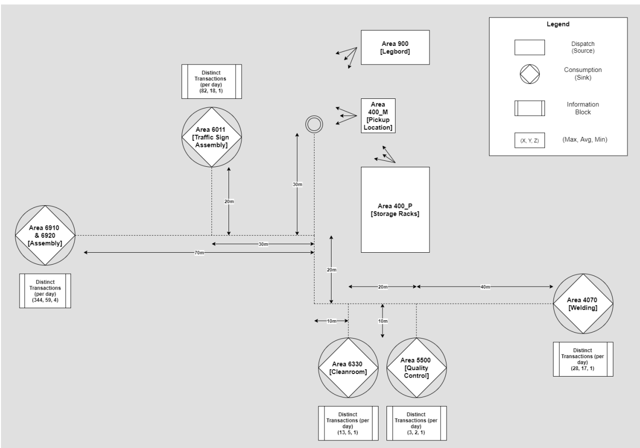

Fig. 2: Layout of Intralogistics Facility: Case Study

The primary expectation from this research is to gain insight into the performance of the self-organised system of robots as an alternative to the existing manual operation for material transport in the intralogistics facility. In most literature, self-organised systems and thus decentralisation is expected to improve the qualitative aspects of robustness and adaptivity (Klein, 2013). Thus, the new system is expected to improve the robustness of the system and reduce the human fatigue caused by manual movement in the existing configuration. This research intends to conceptualise this new system of robots and develop a model to study the system performance under conditions of varying demand and configuration.

3.2 New Method Overview

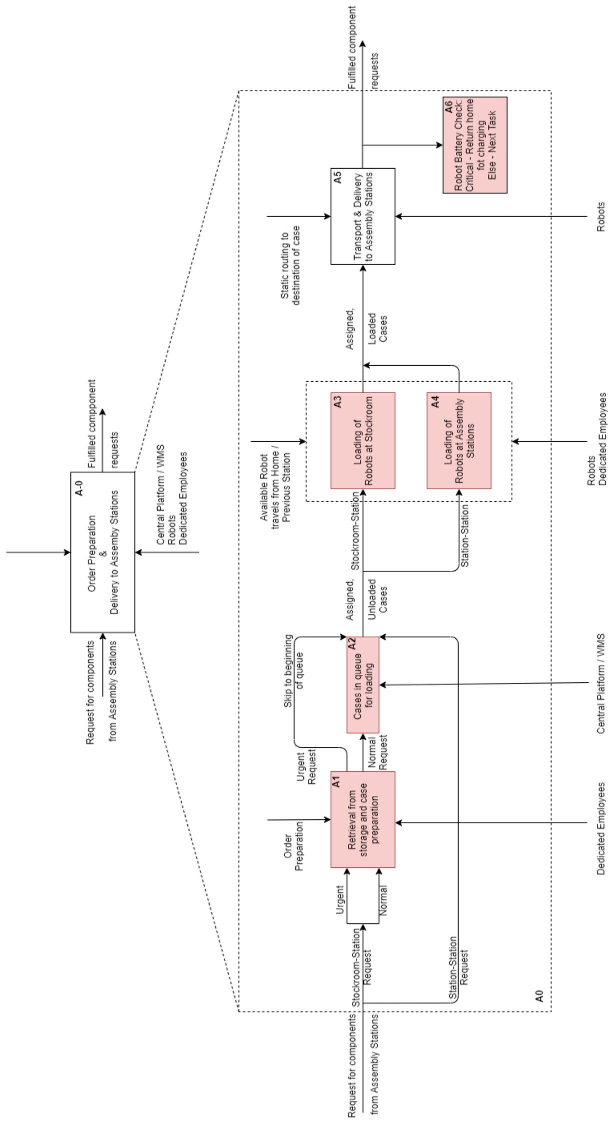

Fig. 3: IDEF0 diagram of new in-house material transport

The new method for transporting the components within the facility can be broadly divided into three stages: order queuing and preparation, assignment and transport, action after task completion. The operators at the assembly station raise the order for components from their consoles. These orders are to be attached with priority levels: normal or urgent. These orders are populated in the central platform. The components are retrieved from storage and prepared into cases by warehouse operators. In this model, for simplicity, every order raised has been assumed to be fulfilled by a case. The central platform also generates a queue based on First Come First Serve. However, the tasks with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority orders. The case at the front of the queue sends a transportation request to the robots. The next stage is the assignment and transport. The robots are capable of responding to the transport request by the cases with their task status and battery status. An idle robot, with sufficient battery level, nearest to the task is assigned. The robots may be located at the home position or any other point in the layout. Once the case is picked up at the pick-up point, where the case is manually loaded, the robots can autonomously move to the assigned destination along a guided but shortest path. The cases are unloaded manually. Once the task is completed, the robots check for their battery status. If it is below the critical level, they return to the home position for charging. If not, based on the chosen mode of operation, they can always return to the home position or get assigned to the next task. The new method is depicted in the form of an IDEF0 diagram in Figure 3.

3.3 Model & Control Strategy Design

The modelling for the new method is based on the objectives set for the project.

- The model should incorporate the defined level of automation and self-organisation as conceptualised to replace the existing manual operation of material movement within the intralogistics facility.
- It should function as a Decision Support Tool, with a capability to reconfigure demand, number of robots, and other system parameters and record the performance indicators for further analysis.
- The model should facilitate the conducting of experiments to compare the performance indicators under different configurations and demand scenarios to study the efficiency and robustness of the system.

These objectives in conjunction with the need for studying the emergent behaviour of a multi-agent system guide the course of the conceptual model.

Key actors in the new method are the robots, cases carrying the components, and the central platform. The robots are battery-operated, have onboard sensors to detect and avoid obstacles and have the capability to carry 1 case at a time. Based on the operation, the robot can have three possible states: (1) Seized: After a case has been assigned to the robot, (2) Released: After the delivery of a case to the destination or when in idle condition at the parking location, (3) Charging: When the battery level goes below critical. Once an order is raised with a task priority, a case is automatically allocated to the task and carries all the attributes of the task including task id, priority (normal or urgent), and destination. For simplicity, every order raised is considered as one case. Also, to ensure ease of unloading and avoid mix-up of components, every case is dedicated to one destination. If the task priority is normal, the case passes through the queue on a First Come First Serve Basis. Cases with priority 'urgent' jump to the front of the queue behind the previously lined up higher priority cases. The central platform is mainly responsible for consolidating the raised orders in a queue based on the set logic. The fleet of robots considered for the operations are homogeneous in terms of features and are path-guided virtually. Each robot can handle only one transport request at a time and re-assignment or split up of loads is not possible. In terms of layout, one central home or parking location is considered near the warehouse loading location which also serves as the battery charging point.

The new method for dispatching being discussed here is based on the **Static Destination Dispatching** (Klein, 2013), in which there is a fixed home position and the vehicle always returns to it after every task completion. However, it has been modified to suit the intralogistics facility under focus and the type of robots being considered. The robots return to the home position only if there are no active tasks at any of the sources to accommodate the transport requests at any of the stations and reduce the distance travelled. The shortest distance is considered as a deciding criterion for load-vehicle assignment. The battery level of the robots has been considered as an attribute to allow recharging at the required moments. The key reason for choosing this method is the suitability of the method for small layouts with high demand variability (Schmidt et al., 2020). Also, in the chosen intralogistics facility, we observe the smaller shipment sizes and more frequent movement. Once the components are ordered, there is no customer (assembly station operators) interaction. Considering the short travel time and no transfer of shipment between different vehicles, this method fits the purpose.

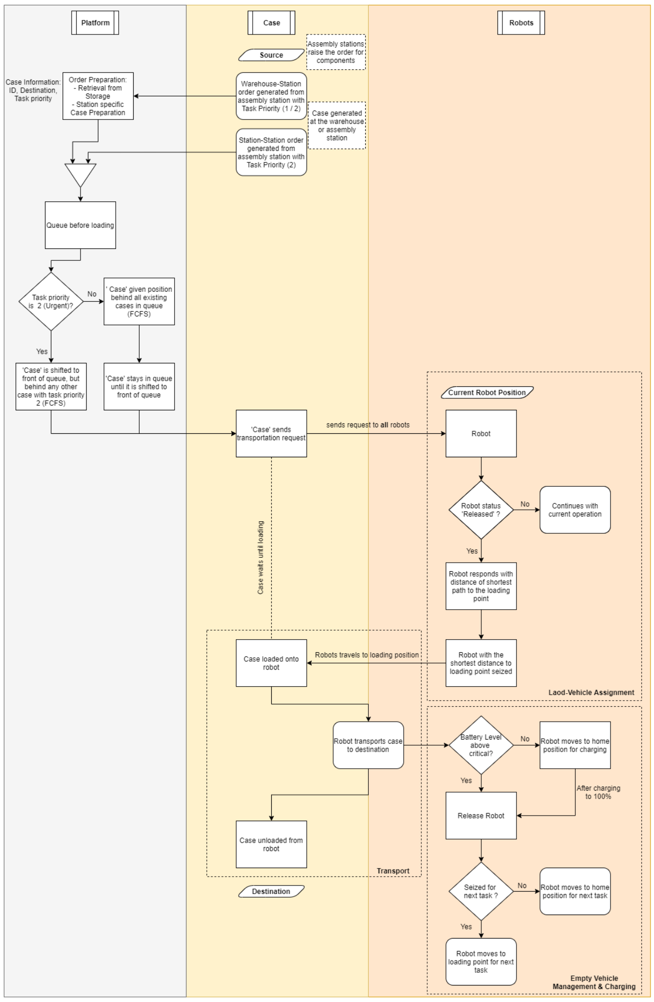

Fig. 4: Swim-lane Flowchart: Conceptual Model of New Method

Figure 4 shows the conceptual model of the new method. The dispatching (load-vehicle assignment & empty vehicle management) followed the modified version of the Static Destination rule. are as described in the previous section. The routing in the new method is based on Klein's Central Static

Routing (Klein, 2013). The shortest paths from all sources to sinks are calculated using the Dijkstra algorithm and stored in a routing table (created only at the beginning of the simulation) at every switch. At the switch and during the next destination assignment, this information is passed to the vehicle.

4. Implementation

4.1 Modelling Technique & Platform

Although experiments in real-world are one of the most intuitive approaches, it proves to be expensive, time-consuming and disrupts existing operations. For a self-organised system of robots, the added challenge is the emergence of complex system characteristics arising from the interaction of multiple agents and their decentralised decision making (Schmidt et al., 2020). An analytic, static modelling technique is not suitable for such a multi-agent system due to its dynamic and decentralised character. Instead, a simulation model would steer the system through state changes as model time progresses (Borshchev and Filippov, 2004). In this research, a multi-method modelling approach has been adopted. The characteristics of two approaches: Discrete Event Modelling (Process-Centric Modelling) and Agent-Based Modelling (Borshchev and Filippov, 2004; Borshchev, 2013) have been combined to form a hybrid method. While the flow of the operations involved in the vehicle-based material transport is represented using a process-centric model, the individual behaviour of the agents is represented using statecharts. The reason for following this method is to capture the nature of the intralogistics operations involved intuitively and make the model easy to use. This form of model building also gives more control over the details to be focused upon and makes it convenient to extend and adapt the model for different business cases (Borshchev, 2013).

Anylogic has been used for implementing the model, given the easy-to-use UI and Java-based programming. Built-in libraries provide comprehensive features for simulating complex real-world operations with animation (2D and 3D) and visualisation (performance indicators) in case of tool development.

4.2 Implementation

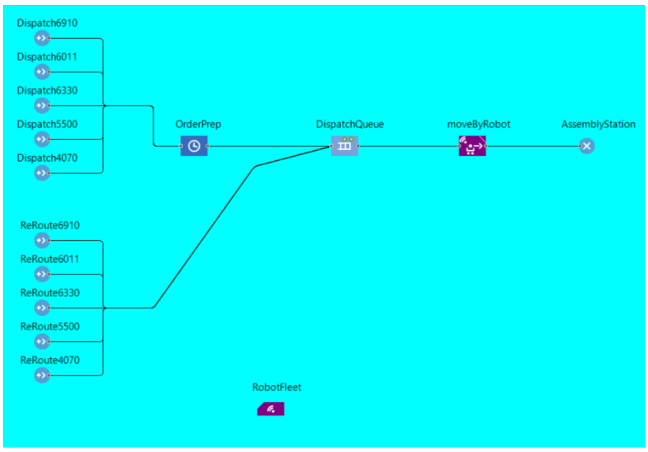

Fig. 5: Process Modelling(as implemented in Anylogic)

Anylogic is used to build the floor of the intralogistics facility as per the dimensions on the actual shop floor. The simulation model has certain inputs from the user, resources that are configured by parameters, and an output. The key input is the demand generated by each of the assembly stations which is stochastic and based on the demand pattern of the existing operation which is obtained through data analysis. While a process flow with relevant blocks takes care of the sequence of operation, the agent has a built-in state chart to control the individual behaviour of the agents. The simulation runs over the defined period in discrete steps. The details on the number of robots, loading and unloading time, type of control strategy, and order preparation time can be configured by the user before the simulation. The collective behaviour of the system can be observed through animation and analysed using the graph of performance indicators.

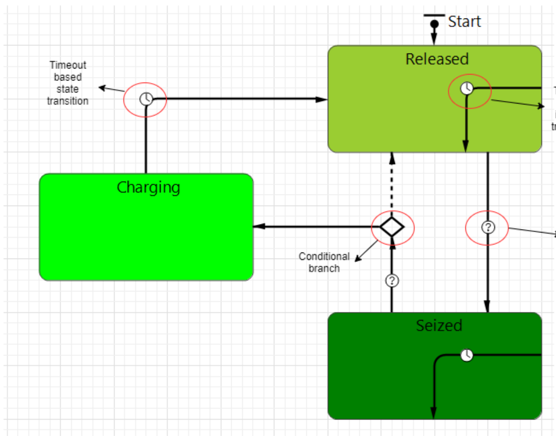

Fig. 6: Robot state chart (as implemented in Anylogic)

Table 2: Model Specification (as implemented in Anylogic)

	Specification	Value
ROBOTS	Fleet	Homogenous
	Number of robots	Varied as per scenario
	Max. speed	1m/s
	Acceleration & deceleration	$1m/s^2$
	Maximum distance to obstacles	0.5m
	Reduced speed near curves, intersections & obstacles	0.5m/s
	Battery recharge time	20 mins
	Battery discharge time (busy)	5 mins per % drop
	Battery discharge time (idle)	8 mins per % drop
OPERATION	Order preparation time	Triangular distribution (60 mins (max), 20 mins (min))
	Loading time	30 secs
	Unloading time	30 secs
	Type of operation	Varied as per scenario
RUNTIME	Total runtime	8 hours
	Time steps	1 min
	Number of time steps	480
	Run duration	08:00 – 16:00
ORDER GENERATION	Warehouse to stations (all values in triangular distribution (max, mean, min) orders per day, based on existing demand pattern	
	Station 6910	(344, 59, 14)
	Station 6011	(82, 18, 1)
	Station 6330	(13, 5, 1)
	Station 5500	(3, 2, 1)
	Station 4070	(28, 17, 1)
	Station to stations (all values in triangular distribution (max, mean, min) orders per day	
	All stations	(10, 1)
	Percentage of urgent tasks	5%, uniformly distributed

Figure 6 shows the statechart within the robot agent governing its behaviour and Figure 5 shows the process flow. Table

2 lists the model specifications including the inputs and parameters. The input demand is not deterministic and varies over a period of time. This is based on the data collection and analysis of the scanned transactions over one month. Given the varied demand distribution and shorter period of data collection, triangular distribution has been considered for the simulation model.

4.3 Performance Indicators

Since the existing configuration has not been simulated in the same platform as the new method, a direct comparison of the performance indicators would not be appropriate. However, the aim of measuring these performance indicators is to help measure the efficiency of the new system of self-organised robots under different configurations and to analyse the robustness of the system in varying scenarios, mainly the demand fluctuations. These indicators mainly represent costs and service level. While costs are indicated by the total distance travelled (operational costs) and utilisation (investment on number of robots), the evaluation of the service level is enabled by the order fulfilment time and throughput.

- *Total distance travelled by robots:* This includes the actual distance of transportation of the cases from source to destination and movement of the robot from the home position to loading point and return to the home position. The total distance travelled by the vehicles is an important indicator for any kind of material transport as also mentioned regularly in literature (Sun et al., 2018). Studying the total distance travelled by the robots helps in analysing the efficiency of a configuration, choose a system design with an optimum number of robots, and allows the manufacturers with the design aspects such as active run time, battery capacity, and durability.

- *Utilisation of robots:* Utilisation of robots is measured by keeping track of the time spent by robots in 'busy' and 'idle' states. In this project, the utilisation is indicated in the number of hours spent in 'busy' and 'idle' state, as well as in terms of utilisation ratio.

- *Fulfilment time for orders:* Order fulfilment time or service time is the time between the raising of request by an assembly station to the time at which the components are delivered (Van der Meer, 2000). This indicator is measured by tracking the birth (enter) and death (exit) of the 'case' agent. Analysing the fulfilment time for different configurations and scenarios helps to analyse the robustness of the self-organised system of robots.

- *Throughput:* Throughput is an indicator that helps measure the efficiency of a system design (number of robots). For a given demand scenario, different configurations of system design can be experimented with to identify the suitable form for the given intralogistics system.

5. Experimentation & Results

The existing configuration is not simulated in this project. The data and performance indicators have been obtained through observation, interviews, and data analysis. Hence, a direct comparison of the performance indicators would not be appropriate. However, the takeaway from this would be the estimation of manual effort in the current form, the reduction in fatigue contributed by the self-organised system of robots. The performance indicators of the new system will enable a quick understanding and judgement of the system for various configurations without the need to physically observe them (Klein, 2013). The key objectives of the experiment are:

- Insight into system design

- Study the efficiency of the new system for different alternatives

- Test robustness of the new system under varying conditions during operation

Considering the stochastic nature of demand generation, multiple replications of simulation are used in each of the experiments to compare the mean values and standard deviations between various scenarios and configurations. Except for the scenario of fluctuating demand where a random seed is used, a controlled but fixed variation of seed is used in the experiments.

5.1 System Design

The system and efficiency experiments aim at finding a suitable configuration of the system, whether the number of robots or the type of control strategy for a given scenario. Hence multiple alternatives are simulated to compare the performance indicators to support decision making.

Variation in number of robots

The number of robots is varied between 1 to 8 with central positioning configuration. Considering the balance between the investment in robots, order fulfilment time, throughput, and robot utilisation, it is recommended to use 2 robots for the considered demand pattern. With an average utilisation of 40%, around 80 cases can be delivered with a mean order fulfilment time of 40 minutes. Beyond 2 robots, the improvement in service (increase in throughput decrease in fulfilment time in comparison to utilisation) is not significant. (Figure 7 & Figure 8)

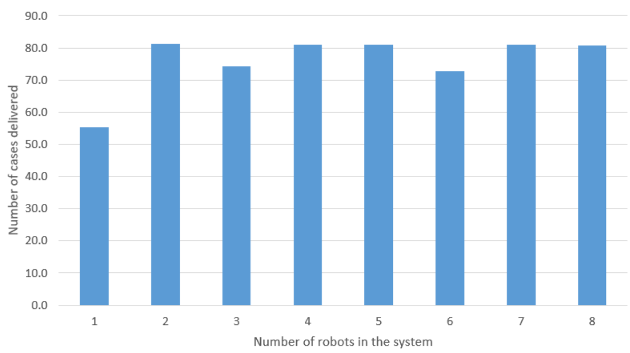

Fig. 7: Total cases delivered with varying maximum number of robots

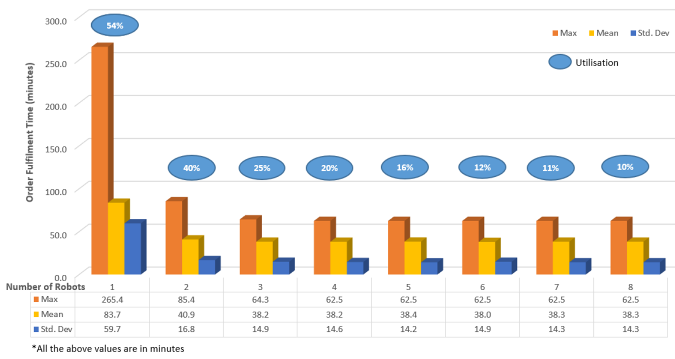

Fig. 8: Order fulfilment time with varying maximum number of robots

5.2 *Efficiency*

Variation in control strategy

Considering 2 robots, the performance indicators are compared between central positioning and point of release positioning. For a demand pattern dominated by central origin, although Central Positioning leads to a 7.5% higher travelled distance, the longest order fulfilment time is lesser by 66% than Point of Release Positioning. Given the availability of sufficient resources, the throughput remains almost the same in both cases. (Table 3)

TABLE 3: COMPARISON OF PERFORMANCE INDICATORS FOR DIFFERENT CONTROL STRATEGIES

	Central Positioning	Point of Release Positioning
Total distance travelled (metres)	18011	16823
Robot utilisation (%)	40,3	37,9
Throughput (Nos.)	81	79
Order fulfilment time (minutes)		
Maximum	80,24	133,22
Minimum	2,56	2,76
Mean	40,8	47,81
Std. Dev	17,49	23,07

High demand

Two robots are considered and a central positioning configuration is used to compare the system performance under a doubled rate of demand.

TABLE 4: COMPARISON OF PERFORMANCE INDICATORS FOR BASE & HIGH DEMAND

	Number of robots: 2 (Central Positioning)	
	Base Demand	High Demand (double)
Total distance travelled (metres)	18011	29287
Robot utilisation (%)	40,3	65,8
Throughput (Nos.)	81	134
Order fulfilment time (minutes)		
Maximum	80,24	181,92
Minimum	5,56	2,56
Mean	40,8	65,94
Std. Dev	17,49	38,39

With the doubling of the demand rate (central positioning), there is an obvious increase in robot utilisation (40% to 66%), but also the throughput increases by 65%. While the maximum time for fulfilment increases more than double, the mean time is 62% higher with increased variance. Although 2 robots can handle the increased demand (with compromise in order fulfilment time), having 3 robots leads to 40% better order fulfilment time. (Table 4)

5.3 *Robustness*

Robustness is the ability of the system to continue operating under a varying and wide range of operational conditions (Gribble, 2001). These experiments are aimed to test the performance of the system when a change in scenario or breakdown occurs during the run-time.

Fluctuation in demand

2 robots are considered and a central positioning configuration is used to compare the system performance under fluctuating demand conditions. For a random seed of demands at the base rate (triangular distribution) f0r 10 replications, the robots delivered between 23 to 113 cases in each instance. With an average order fulfilment time of 40.7 minutes, just around 10% of cases were undelivered even at the highest demand rate, which is mainly attributed to the model runtime and sequence of operation rather than available capacity. (Figure 9 & Table 5)

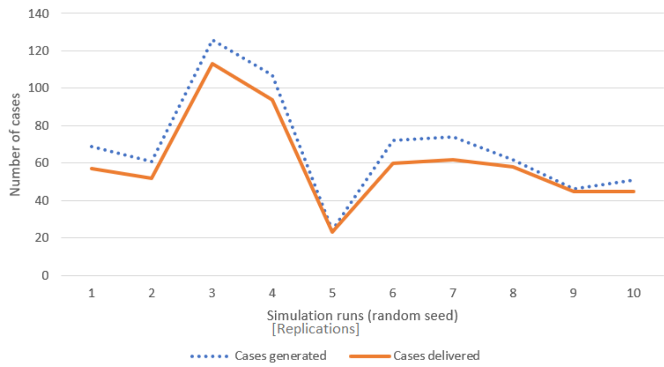

Fig. 9: Variation in throughput for fluctuating demand

TABLE 5: SUMMARY OF PERFORMANCE INDICATORS FOR FLUCTUATING DEMAND

Fluctuating Demand	Min	Max	Mean	Std. Dev
Total distance travelled (metres)	5243	25130	13364	5318
Throughput (Nos.)	23	113	60.9	24.2
Order fulfilment time (minutes)	2.6	104.1	40.7	19

Skewed demand

Considering 2 robots, the performance indicators are compared between central positioning and point of release positioning. With a higher station-station demand than warehouse-station, Point of Release Positioning leads to 10% lower order fulfilment time (mean) and lesser distance travelled per delivered case. However, this gain is at the cost of slightly decreased throughput because of only 2 robots in the system and the demand distributed between 5 stations. In both central and point of release, very high variance is observed owing to the distributed pattern of material movement. (Table 6)

TABLE 6: COMPARISON OF PERFORMANCE INDICATORS FOR DIFFERENT CONTROL STRATEGIES: SKEWED DEMAND

	Central Positioning	Point of Release Positioning
Total distance travelled (metres)	35210	30694
Robot utilisation (%)	79,5	69
Throughput (Nos.)	158	142
Order fulfilment time (minutes)		
Maximum	400,79	439
Minimum	2,56	2,9
Mean	109,12	99,68
Std. Dev	117,67	121,49

Breakdown of robots

With the breakdown of 1 robot, the overall utilisation jumps from 36.3% to 50.5%, but the system can handle the load with a throughput drop of just 19%. This is a positive indication of the capability of the system to respond to the change or breakdown. The total distance travelled decreases by 37% as compared to normal operation. However, after the breakdown, the mean order fulfilment time doubles with also increase in the variance. (Table 7)

TABLE 7: COMPARISON OF PERFORMANCE INDICATORS WITH AND WITHOUT BREAKDOWN

	Operation without breakdown	Before Breakdown	After Breakdown
Total distance travelled (metres)	18011	11333	
Robot utilisation (%)	40,33	36,33	50,47
Throughput (Nos.)	81	34	31
Order fulfilment time (minutes)			
Maximum	80,24	75,29	188,49
Minimum	2,56	2,56	2,75
Mean	40,8	37,87	77,21
Std. Dev	17,49	16,82	43,33

Comparison with manual operation

With almost 17km travelled per day in the exiting material movement operation (manual driven reach truck manual pushcarts), human fatigue is high. The self-organised system of robots supports in reducing this. However, the current version of robots has a load-carrying capacity of 30kg, thus limiting the components it can carry. From the experiments, it is found that robots provide a mean order fulfilment of 40 minutes with the base demand rate, while the manual operation delivers components usually the next day. Thus, the robots can be used to supplement the existing operations mainly for small components (approx. 30% of current material movement) and urgent orders. The decentralised nature of the new system incorporates robustness in the operation to handle varying demand patterns and breakdowns.

6. CONCLUSION

Based on the findings in this project, a quick answer to the main research question would be that the conceptualised system of self-organising robots, considering its current capabilities and constraints, would supplement the existing in-house material transport to improve robustness and reduce human fatigue. Factors such as a limit on the load-carrying capacity of the robots, expected changes in order placement, infrastructural changes required and acceptance level of human-robot symbiotic work environment would be the challenges to overcome for a full transformation. However, introducing a fleet of robots to handle the logistics of small components and spares would reduce the manual movement, mainly the usage of pushcarts which are the key cause of fatigue. Reducing the order fulfilment time to a great extent, the robots would also be able to cater to skewed demands and urgent requirements.

Understanding the emergent behaviour of a self-organised system in an intralogistics environment has been the pivot of this initiative. From the experiments conducted on the simulation model, it is learned that the system can adapt to varying scenarios, such as high demands, skewed patterns, and breakdowns. For a given system design, considering enough margin in the robot utilisation would ensure that most of the demand is satisfied for the varying conditions. However, there would be a compromise in the performance indicators such as the total distance travelled (directly related to energy consumption) and order fulfilment time in extreme conditions. For the base demand conditions considered in this project, it is recommended to use 2 robots for material movement, considering the balance between the investment in robots, order fulfilment time, throughput, and robot utilisation. With an average utilisation of 40%, around 80 cases can be delivered with a mean order fulfilment time of 40 minutes. Compared to the existing manual operation, this would still be a positive takeaway considering the reduction in manual effort and faster delivery. Beyond 2 robots, the improvement in service (increase in throughput decrease in fulfilment time in comparison to utilisation) is not significant. This factor helps in system design by finding a balance between acceptable service time and investment in robots. It is also to be noted that, although the decentralised operations provide flexibility, the suitability of a control strategy strongly depends on the configuration and scenario. During experimentation, point of release positioning served better for demands originating around the facility, while central positioning performed better when orders from warehouse to stations were higher. Incorporating the option to switch between the strategies and necessary infrastructure during implementation would provide better control over the adaptability of the system.

To accommodate the new system of robots on the shop floor, a few changes would be required in the exiting mode of operations on the shop floor. The smaller components which can be transported in a case on the robot need to be identified. The orders for such components need to be placed separately by the assembly stations considering the size of the case. However, the upside would be that these orders can be of smaller sizes, and due to faster replenishment, smaller stock of components can be maintained at the assembly stations, promoting a just-in-time strategy. The developed simulation model provides a platform to analyse and compare the performance indicators for various alternatives before deciding as per the case. Future improvements for this research would be to obtain more refined input data on-demand distribution. Based on this, a method for order consolidation can be conceptualised with multiple delivery points on a single run. Other forms of decentralisation can be explored to get a more holistic perspective of self-organisation. For future implementation, energy usage and economic factor can be included for a more accurate analysis. The current simulation model, although focuses on a particular case, is adaptable and scalable for other types of intralogistics facility like distribution centres and warehouses with the convenient inclusion of other material handling equipment and structures.

Most of the reviewed literature focus on a particular form of self-organisation varying in the extent of decentralisation or the control strategy problem addressed. There is a need for the development of more holistic research in self-organisation. The existing research papers although dwelling deeply into the concepts they address, lack operational study and involvement of stakeholders, mainly the end-users of the technology. This research has attempted to cover these aspects by developing an intuitive platform to quickly and conveniently include the industry expectations and feedback in the research and evaluation. In business cases, this simulation model functions as a support tool for decision-makers even without in-depth knowledge on self-organisation, enabling them to get a prima facie impression on the performance of the system.

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A.2 Interview: Head of Warehouse (Case Study)

Interviewee: Head of Warehouse (for intralogistics facility considered in the case study)
Date of interview: 19/03/2021

- *Q: Can you describe the layout of the current facility related to material transport to the assembly station?*

  A: The layout of the current facility along with the distances is explained in the layout drawing (refer Figure 38). Storage racks are present in the magazijn area. The order preparation and the loading point for the vehicles is located near this. From here, the different components are transported to the assembly station spread across the facility. The main delivery points to be considered are Area 6910 & 6920 (assembly station), Area 6011 (traffic sign assembly), Area 6330 (cleanroom), Area 5500 (quality control) and Area 4070 (welding).

- *Q: What is the sequence of activities for the material transport in the facility?*

  A: The materials procured externally are received in the reception area and stored in the racks. The orders for components are raised by the assembly stations in the WMS. The operator at the warehouse collates these orders and prepared the packing list for the dispatch of each shipment. Based on the packing list, the components are retrieved from the storage racks and prepared for dispatch based on the type of vehicle being used. Usually, manually driven reach trucks are used for transport and the pallets are prepared accordingly. These are transported to the different assembly stations. However, around 5% of orders are urgent orders which might bypass the WMS and are carried to the assembly stations as soon as possible in manual carts or directly by the warehouse operators. All the movement is from the warehouse to the different assembly stations and not the other direction. There is not much movement of material between the assembly stations too.

- *Q: What resources are used, humans and vehicles for material transport in the current operation?*

  A: For the transportation of components, there are 5 reach trucks on-site and multiple manual carts. 7 dedicated employees including drivers are present during a shift of 8 hours for warehouse operations.

- *Q: What kind of data is available to understand the demand pattern of the current state of operations?*

  A: We have just started with collecting the data on scanned transactions for material movement. These scans include the outbound and inbound materials at different points in the facility. The data extract of the same can be provided. It is to be noted that the materials include large structures as well as small components. Only around 30% of the components are small.

- *Q: Are there any performance indicators tracked currently?*

  A: Currently, no performance indicators are tracked. The order fulfilment time for the assembly stations is approximately around 1 day. However, for the new system, it would be helpful to measure the total distance travelled, capacity utilisation and throughput.

- *Q: What is the major concern in the existing operation that requires attention?*

  A: The exiting operation includes a major share of manual activities. The long distances between different points lead to an increase in fatigue for the operators. Also, when there is an urgent requirement, the operator has to walk with the component or the cart to the respective assembly station to deliver. This is undesirable and makes the system inefficient.

A.3 Layout of the Intralogistics Facility

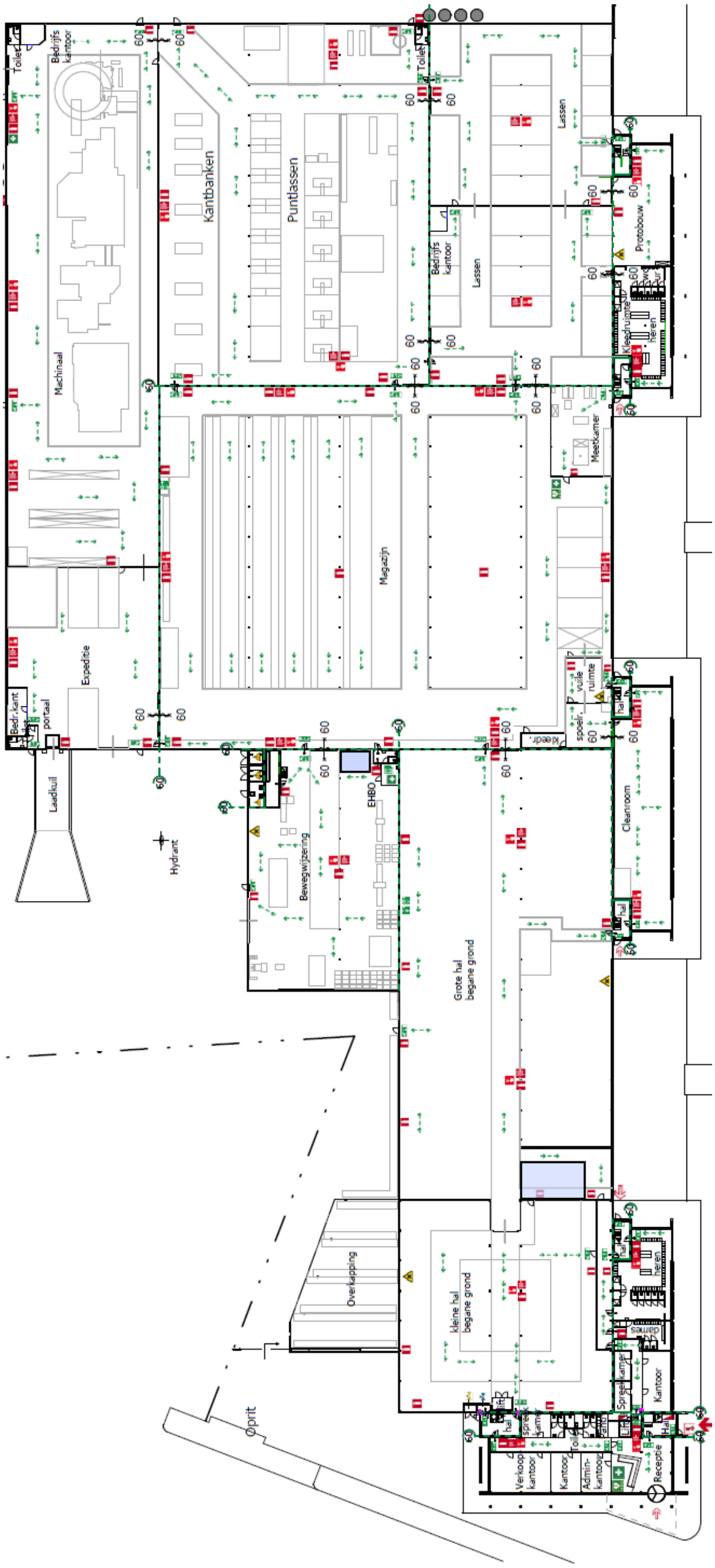

Figure 38: Layout of the intralogistics facility

A.4 Interview: Director Innovations, Prime Vision

Interviewee: Director Innovations, Prime Vision
Date of interview: 01/06/2021

- *Q: One of the comments from the mid-term meeting was to operationalise the research question. With the current research going on, what would be the primary expectation of Prime Vision?*

  A: Prime Vision is considering the implementation of a self-organised system of robots in a facility where material movement is dominated by manual operations. This is expected to happen in stages, starting with one robot with a milkrun and later developing a system with self-organisation. We would want to understand how the new system of robots with decentralised control would behave in that environment and whether they can function as an alternative to the existing system.

- *Q: What features would be useful for Prime Vision, considering that the functionality of the simulation model as a decision support tool?*

  A: The simulation model should provide an idea of the scale of the system and the number of robots required for a given scenario. The performance indicators should give an idea of the efficiency of the system and how robust the system would be and adapt for variation in configuration and scenarios. Also, the model with necessary recommendations must support scaling and adapting to other intralogistics facilities, for the size of the layout, different arrangements and equipment.

A.5 Robot Specification Sheet, Prime Vision

General

Name	Autonomous sorting system	
Device type	R007C	
Emission of noise A-weighted	Average Peak	55 dB(A) 72 dB(A)
Maximum speed	2 m/s	
Power consumption	60 W	
Battery lifetime	8 hrs	

Mechanical

Lenght	0.75 m
Width	0.51 m
Height	1.12 m
Weight	65 kg
Load surface	0.65 x 0.50 m
Max. load	30 kg
Color	Black

Power

Battery type	Lithium-ion, 25.9V, 42Ah	**NOTICE** See safety notes for the battery in "Power source"
Charging voltage	29.4V	
Time for full recharge	7 hrs	
Operating temperature	Discharge: Charge:	-20 ~ 60 °C 0 ~ 45 °C
Storage temperature	Less than 1 year: Less than 3 months:	-20 ~ 25 °C -20 ~ 40 °C
Charger	Fuyang FY2907000, 29.4V 7A DC	

Connections

Wifi	Dual-band wireless AC/G/N/B
Digimesh	2.4GHz wireless

Safety sensors

Pepperl+Fuchs lidar	Detection of objects ahead

Figure 39: Specifications of Robots (source: Prime Vision)

A.6 Performance Indicator Calculation: Existing Operation

The performance indicators for the existing manual configuration has been calculated with plausible assumptions and considering the specifications mentioned in Table 3. Interview with the Head of Warehouse (refer Appendix A.2) and the data extract of scanned transactions have been used as references for these calculations. No performance indicators are measured currently, and thus the resulting numbers are an approximation. However, they have been validated by discussing with the relevant stakeholders to provide an indication of the current state of operations.

Vehicle travel distance per day

Distances between different points in the warehouse are known from the layout. Data analysis on the scanned transaction provides rudimentary information on the number of distinct transactions to the assembly stations. Every distinct transaction is considered as a visit from the dispatch point to the assembly station and return to the dispatch point in the warehouse. The average value of the per day transactions has been considered for calculation. All delivery visits to Area 6011 are considered a part of the delivery route to Area 6910 & 6920 since they are on the same part of the facility. All delivery visits to Area 6330 & Area 5500 are considered a part of the delivery route to Area 4070 since they are on the same part of the facility.

Table 19: Vehicle travel distance calculation

Area_6910 & 6920 Area_6011	2 x [(100m x 59) + (20m x 18)]	**12520m**
Area_4070 Area_6330 Area_5500	2 x [(120m x 17) + (5m x 10) + (16m x 10)]	**4500m**
Average Transport Distance (per day)		**17020m**

Vehicle utilisation

In this calculation, the active hours of the vehicles during a shift is calculated. This is based on the distances calculated, speed of vehicles and handling duration. Speed of reach truck is considered as 7 km/h, considering safe operating speeds in an environment with human interactions. Speed of manual cart is considered as 3 km/h. 5% of the orders in a day are urgent orders served in manual carts. Loading time and unloading time are together assumed as 1 minute per transaction.

Table 20: Vehicle utilisation calculation

Loading, Unloading, Waiting	1 min x 101	**101 mins**
Transport time_Manual (5% of total distance)	0,85km/3kmph	**17 mins**
Transport time_Reach Truck	16,17km/7kmph	**139 mins**
Capacity Utilization (Active Hours per day)		**156 mins**

Order fulfilment time

The data extract does not give information on the order fulfilment time and it is also not tracked at the facility. Based on an interview with the Head of Warehouse, it has been found that the components ordered by a consumption station is delivered the next working day of the order placement. Hence the average fulfilment time has been considered as 1 day.

A.7 Verification

This appendix explains in detail the three-phase verification process: single-agent testing, interaction testing and multi-agent testing (Nikolic and Ghorbani, 2011) for the implemented model for self-organised robots in the intralogistics facility. The hypothesis and the results are verified for relevant scenarios.

Table 21: Phases of verification (1)

Single-agent testing		
Description	**Hypothesis**	**Result**
Case		
Generation	Agent generated and performance indicator loaded.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Simulation run without robot: Warehouse as source	Agent generated at the warehouse, but not assigned to a robot and thus not transported to destination.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Simulation run without robot: Station as source	Agent generated at an assembly station, but not assigned to a robot and thus not transported to destination.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Robot		
Generation	Agent generated at the home location and performance indicator loaded.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Simulation run without case	Agent generated at the home location but does not move, as no case is assigned to the robot.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Interaction testing		
Description	**Hypothesis**	**Result**
Warehouse to Station		
Order generation	'Case' agent generated in demand generation block 6910 and animation of case appears in virtual order representation block.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Order preparation	'Case' agent passes through delay block of order preparation and animation of case stays in virtual order representation block for the delay period.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Queue block	'Case' agent passes through queue block and order is rearranged as per task priority. Animation of case stays in virtual order representation block.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Assignment	'Case' agent enters Move by Robot block, nearest robot in home position assigned. Animation of case stays in virtual order representation block and robot stays in home position.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Transport	Robot moves from home position to loading point of warehouse, stays in loading position for 30 seconds. Case animation is loaded onto robot, and robot moves to destination 6910.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Case Delivery	'Case' agent exits Move by Robot block and moves to sink block. In the animation, case is unloaded from robot onto destination 6910 area and disappears (exits system).	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check

Table 22: Phases of verification (2)

Robot Returns always	In the animation, robot returns to home block after delivery after staying at destination for 30 seconds (unloading).	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Robot Stays at Sink until next assignment	In the animation, robot stays at sink and does not return as there is only 1 case generated and no next assignment is present.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Station to station		
Order generation	'Case' agent generated in reroute generation block and animation of case appears in virtual order representation block.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Order preparation	'Case' agent skips delay block of order preparation and animation of case stays in virtual order representation block for the delay period.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Queue block	'Case' agent passes through queue block and order is managed on FCFS as all cases have urgent task priority. Animation of case stays in virtual order representation block.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Assignment	'Case' agent enters Move by Robot block, nearest robot in home position assigned. Animation of case stays in virtual order representation block and robot stays in home position.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Transport	Robot moves from home position to assembly station block, stays for 30 seconds. Case animation is loaded onto robot, and robot moves to destination.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Case Delivery	'Case' agent exits Move by Robot block and moves to sink block. In the animation, case is unloaded from robot onto destination area and disappears (exits system).	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Robot Returns always	In the animation, robot returns to home block after delivery after staying at destination for 30 seconds (unloading).	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Robot Stays at Sink until next assignment	In the animation, robot stays at sink and does not return as there is only 1 case generated and no next assignment is present.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check
Multi-agent testing		
Description	**Hypothesis**	**Result**
Testing simulation model with 2 robots and given triangular distribution of order generation (both warehouse-station & station-station) & 5% critical tasks. Robots return to home after delivery only if no other task assigned. (refer section 6.4 for details)	Model runs through 480 time steps. At the end of the time steps, there is match between total orders generated versus sum of orders in order preparation block, in move by robot block and sink. Animation displays all the movement and performance indicators are calculated.	Logic block: Check Database: Check Animation: Check Performance Indicator Charts: Check

A.8 Validation

A.8.1 Sensitivity Analysis

A quick sensitivity analysis is performed to see if the simulation model reacts realistically and predictably to changes in inputs and parameters. For this, two types of analyses have been done. One is to vary the number of robots and the other is to vary the demand. The changes is performance indicators are analysed for the varying inputs. A detailed explanation of the sensitivity analysis and the results are presented in Appendix A.8.1.

The specifications and parameters considered for validation are mentioned below:

- **Robots**
  - Homogeneous fleet
  - Number of robots: Varied as per scenario
  - Maximum speed: 1m/s
  - Acceleration and deceleration: $1m/s^2$
  - Minimum distance to obstacles: 0.5m
  - Reduced speed near curves, intersections & obstacles: 0.5m/s
  - Battery recharge time: 20 minutes
  - Battery discharge time (busy): 5 minutes per percentage drop
  - Battery discharge time (idle): 8 minutes per percentage drop
- **Operation**
  - Order preparation time: Triangular distribution (60 minutes (max), 20 minutes(min))
  - Loading time: 30 seconds
  - Unloading time: 30 seconds
  - Type of operation: Return to the home position after delivery if no other available task, else move to next task
- **Runtime**
  - Total runtime: 8 hours
  - Time step: 1 minute
  - Number of time steps: 480
  - Run duration: 08:00 – 16:00
- **Order Generation**
  - Warehouse to stations (all values in (max, mean, min) orders per day, based on existing demand pattern as mentioned in section 3.2.2)
    - Station 6910: Triangular distribution (344, 59, 14)
    - Station 6011: Triangular distribution (82, 18, 1)
    - Station 6330: Triangular distribution (13, 5, 1)
    - Station 5500: Triangular distribution (3, 2, 1)
    - Station 4070: Triangular distribution (28, 17, 1)
  - Station to station (all values in (max, min) orders per day)
    - All stations: Triangular distribution (10, 1)
  - Percentage of urgent tasks: 5% of total orders generated, uniformly distributed
  - Fixed seed has been considered for all the tests below

Variation in the number of robots

Considering the parameters and the demand values mentioned above with a fixed seed, the number of robots are varied between 1 to 5 to study the changes in performance indicators, total distance travelled by the robots, average robot utilisation, busy and idle duration of robots and throughput. It is observed that the variation in the result is in line with expectation and reality.

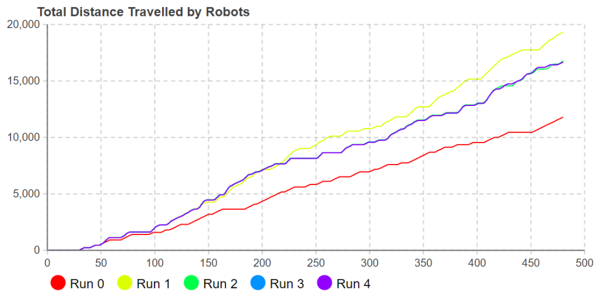

Figure 40: Variation in total distance travelled

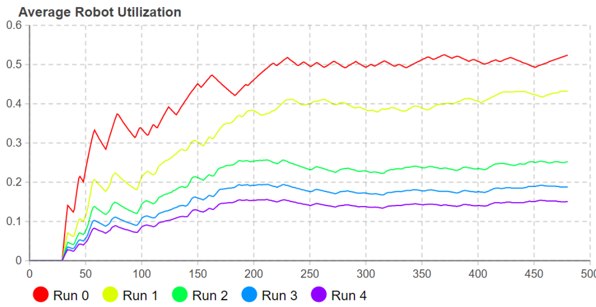

Figure 41: Variation in average robot utilisation

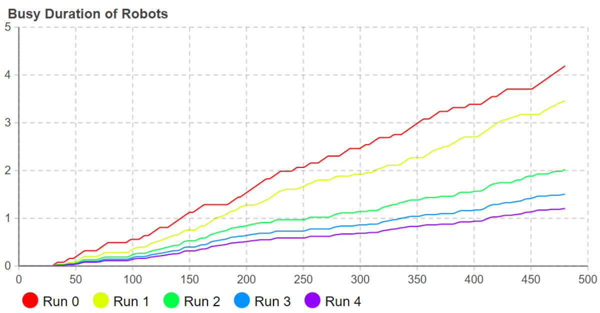

Figure 42: Variation in average busy duration of robots

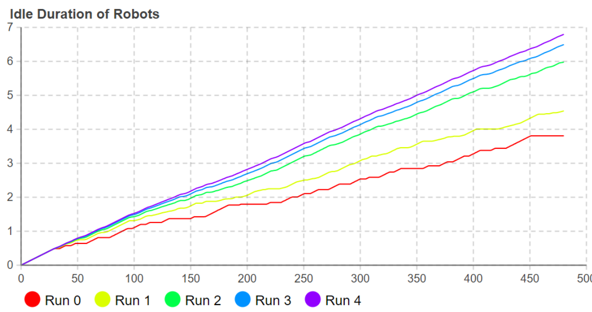

Figure 43: Variation in average idle duration of robots

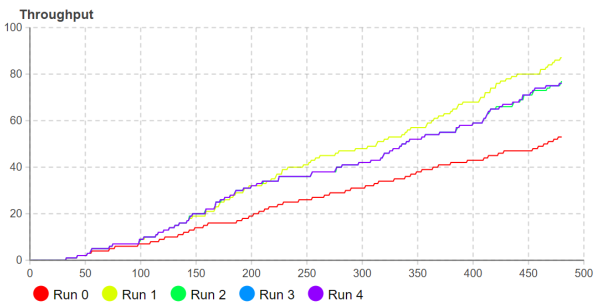

Figure 44: Variation in throughput

Run	Number of robots (# of robots)	Distance (metres)	Robot utilisation (percentage)	Robot busy duration (hours)	Robot idle duration (hours)	Throughput (# of cases)
0	1	11799	52%	4,19	3,81	53
1	2	19312	43%	3,46	4,54	87
2	3	16808	25%	2,02	5,98	77
3	4	16656	19%	1,50	6,50	76
4	5	16656	15%	1,20	6,80	76

Figure 45: Results of variation in the number of robots

In the above test of a varying number of robots, it is seen that, for a fixed demand, as the number of robots increase, the total distance travelled increases to a certain extent (up to 2 robots in this case). Later with the increase in the number of robots, the total distance decreases slightly and almost remains constant. This indicates the increase in the number of cases handled by the robots and then reaching an optimised state, serving the entire demand. The average utilisation of the robot follows an expected pattern, with the decrease in utilisation with the increase in the number of robots. This is directly a result of the increase in the idle duration of the robots and a decrease in the busy time. When it comes to throughput, like in the total distance travelled, it increases initially with the increase in the number of robots before reaching a stable or optimised state and remains almost constant.

The above inference confirms the behaviour of the model in line with the expectation and reality.

Variation in demand

The next phase for validation is to observe the performance indicators for change in demand. To study this, the number of robots have been fixed at 2 and the demand values of all the assembly stations were reduced to zero, except for 1 station 6910. The demand values of triangular distribution (max, mean and min) are all maintained the same for a run of the test. The rate of demand is varied between 100 to 500 per day as shown in Figure 51.

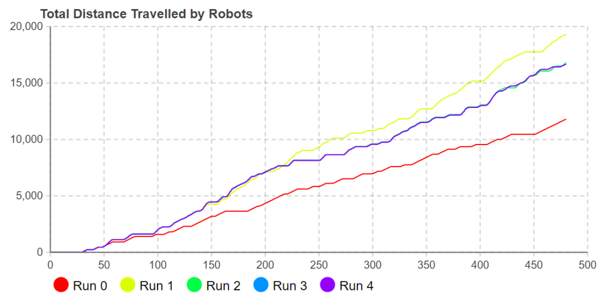

Figure 46: Variation in total distance travelled

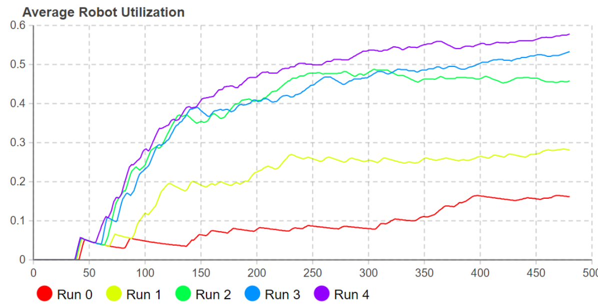

Figure 47: Variation in average robot utilisation

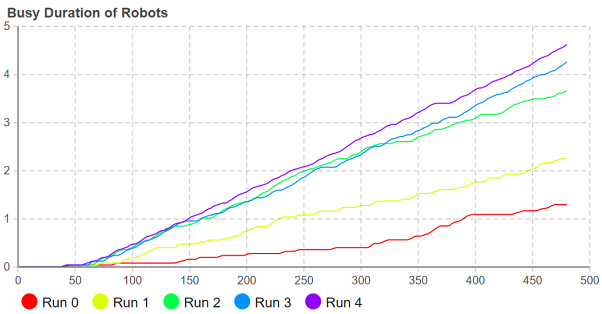

Figure 48: Variation in average busy duration of robots

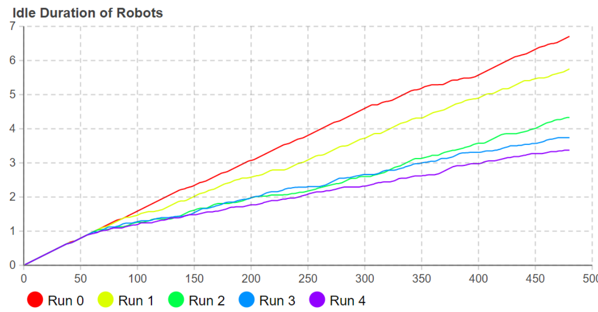

Figure 49: Variation in average idle duration of robots

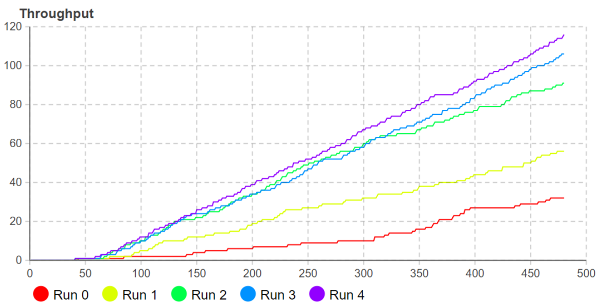

Figure 50: Variation in throughput

Run	Demand Variation (# of cases / day)	Distance (metres)	Robot utilisation (percentage)	Robot busy duration (hours)	Robot idle duration (hours)	Throughput (# of cases)
0	100	7242	16%	1,29	6,71	32
1	200	12670	28%	2,25	5,75	56
2	300	20546	46%	3,67	4,33	91
3	400	23986	53%	4,26	3,74	106
4	500	25902	58%	4,63	3,38	116

Figure 51: Results of variation in demand

As observed in the case of the varying number of robots, the varying demand leads to an expected behaviour of the model. For the purpose of simplicity and understanding, the demand for only 1 station is considered here. With the fixed number of robots and increasing demand, the total distance travelled increases continuously as there is still idle time available for the robots. Corresponding to this, the spike in busy time compared to idle time is seen for the increase in demand, thereby increasing the utilisation of the robots. As expected, the demand increase leads to an increase in throughput, with the robots trying to satisfy the transport requests raised.

The above inference confirms the behaviour of the model in line with the expectation and reality.

A.8.2 Validation interview: Head of Warehouse (Case Study)

Interviewee: Head of Warehouse (for intralogistics facility considered in the case study)
Date of interview: 09/06/2021

- *Q: The operations simulated in the model is a look ahead. Considering the smaller size of each shipment carried by the robots, the number of trips will be more, but faster response time to orders, lesser consolidation and provides flexibility. Mainly lesser fatigue to human operators. What is your view on this?*

  A: The model is interesting and sufficient from the point of view of simulating the future operations. This would be very useful for the movement of small components including screws, panel pins and more, which currently is adding to the fatigue due to manual operations. However, the concern is regarding the size of the single shipment which the robot would be able to carry. Currently, most of the components moved are heavy components including sheet metal. Only 30% of the total movement may be small components. Hence, we should investigate increasing the load-carrying capacity of the robots.

- *Q: What are your comments on the parameters considered for the model, particularly the order preparation time of 20 minutes?*

  A: Order prep time of 20 minutes per case seems logical at this stage. However, instead of a single number, a variation between 20-60 minutes can be considered, taking into account the type components, retrieval and consolidation.

- *Q: What are your comments on the performance indicators currently used are total travelled distance, utilisation of robots and delivery time (response time) and total cases handled in the given duration?*

  A: The considered KPIs are sufficient and useful for us too. It would help us track performance. Mainly the lead time for each package can be investigated to identify the root cause in case of extreme delays.

- *Q: What would your recommendation be, for the size of the case carrying components to each station?*

  A: Currently considering a case to carry the small components is feasible. However, given the ratio of larger and heavier components, the possibility to carry them need to be investigated.

- *Q: What are the challenges you foresee in the implementation of this system with multiple robots?*

  A: Human factor and simultaneous interaction on the shop floor is something that needs to be worked out. Safety aspects must be ensured. Employees are concerned about the safety protocol. Employees at the source and destination are proficient to interact with such a system.
  From the managerial point of view, robots replacing a part of manual operation is a point of attention from the perspective of the current employees responsible for the operation. However, these employees will not lose their jobs, but be efficiently used for other operations and leads to a reduction in fatigue which will be a convincing factor.

- *Q: What are your recommendations for extending the model?*

  A: A live dashboard of a similar interface would be useful after the implementation of the robots.

A.8.3 Validation interview: Product Owner, Prime Vision

Interviewee: Product Owner, Prime Vision
Date of interview: 10/06/2021

- *Q: From the perspective of using the model as a decision support tool, what is your feedback on the sufficiency of the current state of the model?*

  A: The current model is a satisfactory representation of the physical warehouse and the generated demands per station as far we know them. Therefore, it would be a valuable decision support tool when evaluating the effect of our autonomous sorting robots on VDL's operations, and hopefully other clients in the future.

- *Q: What are your comments on the performance indicators currently used are total travelled distance, utilisation of robots and delivery time (response time) and total cases handled in the given duration?*

  A: The change from large, consolidated orders transported by a tug cart to individual cases handled by small robots needs to be comparable in an apples-to-apples manner so that warehouse managers have a clear understanding of the difference between the solutions. The KPIs need to be a practical way of reflecting this comparison. From that point of view, these seem to be functional and practical KPIs to compare with the current operations. When comparing both cases (current operations and several versions of the new operations), I would recommend communicating the percentage of time saved to satisfy demand from the working stations, especially since we expect substantial differences in lead time. Besides that, it would be good to corroborate these particular KPIs with the warehouse expert.

- *Q: What are your recommendations for extending the model?*

  A: The robots in the current model only have local information available to them. It would be interesting to add global information as a toggle on/off feature, where robots can be updated of the other robots' activities and incoming demand from workstations is published.

- *Q: What are the challenges you foresee in the implementation of this system with multiple robots with self-organising capability?*

  A: We need to make sure that the paths are as cleared as the model assumes. If in practice, the forklifts frequently use this space, we might run into some security hazards on site. This is also applicable for access to the workstations, which employees will need to keep clear of tools in the ground which a driver in a tug cart would have easily avoided.
  From a managerial point of view, any innovative project needs to wrestle with the status quo, and employees are often resistant to change. The new solution needs to surpass the original in many regards before it is completely accepted by all workers. As we conceive it right now, this solution would not require much change on the side of the workers, which makes our expectations optimistic.

A.8.4 Validation interview: Researcher, TU Delft (Anylogic)

Interviewee: Researcher, TU Delft (Anylogic user)
Date of interview: 10/06/2021

- *Q: From the perspective of implementing the conceptual model in Anylogic, what is your feedback on the sufficiency of the current state of the model?*

  A: Based on the conceptual model, I feel the implementation in Anylogic is sufficient and sound. Given no prior experience with Anylogic and the learning curve involved, I am satisfied with the implementation and the followed best practices.

- *Q: What are your recommendations to make the model more convenient to work with for future developers?*

  A: At the relevant logic blocks and Java codes, comments can be added to explain what exactly the block does so that it will be convenient for future developers. A user manual or report with the scheme and flow will be useful for future users or developers of the model.

- *Q: What are your recommendations for extending the model?*

  A: Extension of the model should directly come from the requirement. Recommendation on other logic of operation (centralised/decentralised) can be a part of the report.