# Designing an Automatic Load Planning Tool for Military Transport Aircraft

Iris van Alkemade

Master Thesis Aerospace Engineering

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by

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| Supervision | Ir. D. Wiltenburg | NLR – Netherlands Aerospace Centre |
| Supervision | Ir. P. Roling | Delft University of Technology |
| Faculty | Aerospace Engineering | Delft |



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## Preface

So this is the last piece of text I will write for the Aerospace Engineering program ... For the past nine months I have been working on this master's thesis, starting and ending with fresh enery. I was happy and lucky having the chance to dive into a sector which I find very interesting together with a topic that drew my interest.

First of all I would like to thank Daan, my supervisor at NLR, for your continuous commitment and feedback throughout the entire project. I enjoyed our collaboration and white board sessions we had in which we played around with various algorithms (and sometimes struggled to fully understanding them). Paul, you have been my supervisor from the TU and I want to thank you for your guidance in this project. You have introduced me to the concept of bit flips, and it's one of my favourite words to say now – *bit flip*.

I would also like to thank my colleagues at NLR for the great atmosphere and the lunch runs to Nieuwe Meer. To my fellow graduate students: thank you for turning long days of screen time into such an enjoyable experience. The conversations, short and longer coffee breaks made this period both productive and a lot of fun. And to my housemates, friends, teammates, and family: thank you for your energy, encouragement, and support.

I had an amazing time in Delft during my studies, and I am happy to close this chapter with this thesis.

Please enjoy!

*Iris van Alkemade*
*Delft, June 2026*

## Outline

Good preparation is crucial for the success of any military operation. Effective logistical support is essential for any type of mission, no matter the scale, complexity or urgence of the conflict. Mission planning is a key component of this support, outlining not only what needs to be done to succeed but also how it will be accomplished. This includes determining which assets and troops are needed and how they will operate. The efficiency of mission planning depends on many factors, making it a complex process.

Since the arrival of military aircraft they are widely used to deliver air support. Fighter jets provide direct air support, while military transport aircraft offer combat support, transferring goods and people. The unique characteristics for airpower are altitude, speed and range [1]. Transport aircraft can operate under different conditions, carry large loads, passengers (pax), can perform medical evacuations, airdrops and cover big distances. For effective use of this type of air support, proper mission planning is essential. This ranges from making flight schedules to where and when the aircraft should fly, to planning what they will transport and how they will deliver. For the latter, the packing order and configuration in the cabin is of importance, next to the weight distribution of the loads. The loading configuration how the cargo and/or pax are positioned in the aircraft directly influence the safety, efficiency, and overall effectiveness of operations. This problem is called the load planning problem (LPP).

The loadmasters, the operational staff that plan how the loads will be placed in the cabin, are responsible for making a feasible load plan. A poor loading configuration can result in decreased flight performance and can even result in dangerous situations. If the balance of the loads exceed the allowable limits, the pilots potentially lose control over the aircraft. A bad load plan can result in having to move items during intermediate landings in one mission and low efficiency during (un)loading. Currently, load planning is a manual process that works under low-pressure conditions but becomes challenging in acute crisis situations or when mission complexity increases.

In this report, the outline for an automatic load planning tool is presented. Two optimisation methods are desinged to solve the LPP for military purposes. Semi-structured interviews are performed with loadmasters and planners of the Royal Netherlands Air and Space Force (RNLASF) to gain insight in the loadplanning process and to learn about current procedures and limitations.

This report is structured as follows: Part 1 introduces the scientific article, Part 2 provides the literature review, and defines the research gap and presents research proposal. The document concludes with a Gantt chart in Part 3.

# Contents

Part 1

# Scientific Article

# Designing an Automatic Load Planning Tool for Military Transport Aircraft

**I.P. van Alkemade**
Under the supervision of Ir. P. Roling (TU Delft) and Ir. D. Wiltenburg (NLR)
*Faculty of Aerospace Engineering, Delft University of Technology*

This paper proposes two complementary optimisation approaches to support the the load planning problem (LPP) for military transport aircraft. A mixed-integer linear programming (MILP) model is designed as a baseline method to find exact, high-quality solutions. The model includes operational procedures derived from semi-structured interviews with loadmasters and mission planners. To address scalability limitations from the traditional MILP formulation, a hybrid TS-MILP approach is designed. It combines tabu search (TS) in a first layer for fast global assignment of items over a fleet, and MILP refinement in a second layer for constraint-accurate positioning optimisation within each aircraft. MILP and TS-MILP are evaluated across three realistic scenarios on the C-130 Hercules military transport aircraft, where the fleet size is increased from 1 to 16 aircraft, and the input size and composition varies for troops and cargo. MILP shows best results for the LPP with palletised cargo only, where up to a fleet of 6 aircraft, a feasibility success rate of 45.5 to 100% is achieved within a time limit of 600 seconds. For more complex item compositions, TS-MILP proves scalability and a better success rate and runtime than MILP while maintaining solution quality. The study demonstrates that by leveraging the strengths of both exact and heuristic methods, load planning can be effectively automated and be used as a decision-making tool for military operations.
**Keywords:** Load planning problem; Mixed-integer linear programming; Tabu search

**Abbreviations**

| | |
|---|---|
| C-130H(- 30) | C-130 Hercules (extended version) |
| CDS | Container Delivery System |
| CG | Centre of Gravity |
| FS | Fuselage Station |
| IATA | International Air Transport Association |
| IUR | Item Unfulfillment Rate |
| LEMAC | Leading Edge Mean Aerodynamic Chord |
| LPP | Load Planning Problem |
| LS | Load Station |
| LW | Landing Weight |
| MAC | Mean Aerodynamic Chord |
| MILP | Mixed Integer Linear Programming |
| MTOW | Maximum Take-Off Weight |
| Pax | Passenger |
| RNLASF | Royal Netherlands Air and Space Force |
| RPC | Residual Payload Capacity |
| TS | Tabu Search |

## 1 Introduction

Good preparation is crucial for the success of any military operation. Effective logistical support is essential throughout its execution, and mission planning is a key part of this support. It outlines what needs to be done and how it will be accomplished, including which assets and troops are needed.

In crisis situations, military transport aircraft provide vital support by delivering cargo and personnel. It is often the best way to deliver goods to remote locations. Time pressure may play a role and expose pressure on the operational staff. Military transport aircraft can pick up and deliver different types of vehicles and goods, can perform airdrops, drop paratroopers and transport people and pax (personnel). This makes planning complicated, and can be different for each operation.

The process of deciding which goods are transported and how they are loaded involves cooperation between different parties from different levels and teams. Load planning is a manual process currently, and is performed by experienced staff. When missions get larger, the planning process gets significantly more complicated. Different parties must also communicate well to ensure efficient operations. That is why this research proposes a load planning help tool that can be used by any planner, for any kind of mission.

Previous research efforts explore optimisation techniques for the load planning problem (LPP), intended for two main applications: commercial airline cargo transport and military transport aircraft.

Safe and efficient flight operations are directly influenced by the weight and balance of an aircraft's configuration [8]. A study by Van Es [26] found that cargo flights have an 8.5 times higher risk of weight and balance-related accidents compared to passenger flights. Aviation accidents resulting from aircraft operating above the maximum allowed weight limitations and/or flights where aircraft operate outside of its centre of gravity (CG) envelope have a high risk of fatality [3]. Many papers aim to optimise the CG location, by placing the loads such that the final aircraft's CG is near the optimal CG position for lower fuel consumption and better stability [27][13]. Optimising cargo loading can save significant amounts of fuel and money [15].

Tools exist to aid the planning process for transport aircraft, both for civil and military applications. Scientific papers discuss how optimisation algorithms can be designed to support the generation of feasible load plans and can aid as a decision support tool [7, 23].

In contrast to commercial cargo airlines, military transport operations are not primarily profit-driven, they aim to optimise efficiency and effective operations. Commercial airlines work with cargo delivered in standard unit load devices or cargo delivered on pallets with standard dimensions. Aircraft taking passengers and cargo have different compartments for both. In military transport, all passengers and cargo are placed altogether in one cabin, introducing the need of safety rules and extra regulations.

The LPP can be divided into two layers: (1) to select the aircraft to be used from an available fleet and (2) to determine the load placement within each aircraft [10]. in both layers the models decide how goods can be loaded into aircraft while meeting safety and operational constraints [13]. Various optimisation methods have been proposed to solve these problems, including hybrid genetic algorithms [4], mixed integer programming models [27, 13, 18], and heuristic algorithms [10, 18].

Currently, load planning is a manual process that usually works under low-pressure conditions and becomes challenging in acute crisis situations or when mission complexity increases. This research aims to design a hybrid TS-MILP optimisation approach to support the load planning process for military transport aircraft. The purpose is to guarantee feasible and safe load configurations and optimise the value of items with a given load priority. This paper addresses the following research question for a proof of concept model:

*How can an automatic optimisation model support the load planning process for military transport aircraft, such that feasible and safe load configurations are guaranteed and the loading of high prioritised items is optimised?*

The purpose of this research is to use an implementation of traditional MILP and design a hybrid TS-MILP optimisation model to support the load planning process for a loadplanner, applied to military transport aircraft. Then the application and scalability of the models will be tested and compared on a C-130 military transport aircraft with mixed-type cargo loads.

# 2 The load planning problem: literature review

Aircraft load planning problems are generally solved for two primary applications: commercial and military. Commercial applications focus on cost efficiency, often by maximising profit or load, and minimising trim drag or fuel consumption [7, 12, 13, 16, 18, 27, 28, 30]. Profit results from loading and delivering cargo with a specific value, and costs are determined by fuel consumption. Military applications, on the other hand, prioritise operational efficiency rather than profit. Objectives include maximising loaded priority per flight [6], or minimising the total number of aircraft needed for a mission [24, 20, 29]. Depending on the problem formulation, mathematical models or heuristics are used to solve these optimisation problems.

## 2.1 Bin packing methods

Optimisation algorithms that investigate how equipment can be best positioned within a given surface or volume is called the bin packing problem (BPP). For aircraft cargo, items are generally not stacked, resulting in a 2-dimensional problem BBP where only the width and length of each item are considered. Physical limits constrain the solution space for the loading possibilities. Due to the combinatorial complexity of arranging cargo within all constraints, the load planning problem is classified as a nondeterministic polynomial (NP)-hard problem [1, 21]. The solvation time can scale with $O(n^k)$ for some constant k [1]. Typical for nondeterministic algorithms is that they can explore multiple options at once to find possible solutions [9].

## 2.2 Weight and balance

A variety of papers describe bin packing algorithms to solve the weight and balance (W&B) problem [28, 20, 27, 13] . As freighter aircraft primarily transport ULDs, the main question is how to position all the ULDs in the cabin to generate maximal revenue. Revenue is optimised by maximising the profit of loaded cargo value, and minimising cost, mainly through limiting fuel use per flight and reducing the number of flights needed [28].

A feasibility envelope defines the upper and lower bounds for CG location of the aircraft during different flight stages [27]; the bounds depend on total aircraft weight and change during flight as fuel is consumed. Nonlinearities in the envelope induce nonlinear CG constraints which are handled differently across studies. Vancroonenburg et al. [27] linearise constraints at critical moments, Zhao et al. [30] linearise the nonlinear CG problem and solve it as MILP, and Lu et al. [16] keep the nonlinear constraints and solve the model as MIP. Mongeau and Bès [18] approximate the nonlinear constraints using a centering tolerance $\epsilon$ as a percentage of the reference CG position.

Finally, structural limitations per aircraft section and overlapping areas are considered by Limbourg, Schyns, and Laporte [13]. Their approach, calculating the moment of inertia of the full aircraft rather than only the CG, results in a program that runs 16 times faster while respecting structural and balance constraints.

## 2.3 Aircraft loading

Previous studies often focus on single-type loading. Troop transport introduces additional safety requirements and operational constraints and is only included by Gueret et al. [10] who consider both troops and cargo items. For standardised ULD sets Vancroonenburg et al. [27] demonstrate improvements in lateral balance by an optimisation algorithm up to 89% compared to expert plans. However, non-standardised items introduce new parameters and constraints, which have not been fully addressed. Single-aircraft load planning is often simpler, while multi-aircraft scenarios require additional heuristics to distribute items efficiently across a fleet [4]. Table 1.3 presents an overview of the different methods used for different applications to varying LPP optimisations.

Vancroonenburg et al. [27] propose a MILP model for single-aircraft load planning, whereas Roesener and Barnes [24] apply Tabu Search for multi-aircraft problems. Both focus on single-type ULDs, highlighting a limitation in scaling to multiple aircraft or mixed cargo sizes. Chenguang, Hu, and Yuan [4] address this by proposing a hybrid genetic algorithm (hybrid GA) that combines a traditional GA with heuristics. The heuristics solve the 2D bin packing problem while the GA allocates the loads to multiple aircraft, decoding candidate solutions using rules to generate feasible load plans.

The placement of items within the aircraft cabin is another key consideration. Some studies, such as Vancroonenburg et al. [27], place ULDs in fixed position slots to minimise fuel consumption, where larger items may occupy multiple slots, limiting possible configurations. Other approaches, such as Chenguang, Hu, and Yuan [4], allow ULDs to be placed freely within the cabin, increasing the solution space and problem complexity. Heuristic algorithms based on item priority, e.g., longest side length first, are used to manage loading efficiently [4]. CG limits are incorporated in various ways: Wesolkowski, Mazurek, and Stuive [29] apply maximum load capacity per aircraft without explicit CG constraints, Mongeau and Bès [18] set a maximum allowable CG deviation, and Limbourg, Schyns, and Laporte [13] calculate the moment of inertia for the full aircraft to improve computational efficiency.

## 2.4 Military applications

Despite extensive research in aircraft load planning, a substantial gap remains for military applications. Most existing studies focus on loading one cargo type in to minimise fuel consumption or maximise profit. In commercial applications, the primary objective is often weight and balance optimisation. In contrast, military operations rarely have a profit motive. Instead, the focus is on using each flight efficiently, either by maximising the loaded priority of items per flight or effectively using the least number of aircraft needed for a mission.

A key gap in existing research is the inclusion of troops *and* cargo, which introduces additional safety requirements and operational constraints. While some studies discuss the combination of troops and cargo items [10], most models focus solely on pallets or cargo, without considering other cargo types such as smaller items or vehicles. Roesener and Barnes [24] are unique in including temporal constraints, specifying the earliest possible and latest required delivery dates for each cargo item. However, their work still considers only pallets and does not include troop transport.

Another gap relates to the variability of item priorities in military missions. Dahmani and Krichen [6] assign fixed priorities to items, but in military operations, the priority of an item may change depending on the situation. Similarly, Richardson et al. [23] highlight the complexity of military load planning, noting the diversity of equipment, mission-specific requirements, and safety constraints. A model for military applications must therefore provide a situational, mission-dependent load plan capable of handling multiple item types, troops, priorities, and operational requirements.

Finally, existing research often addresses only one of the three fundamental questions of load planning: *what* is transported, *when* it is picked up and delivered, and *how* it is placed in the aircraft. Optimising the loading of high prioritised items ensures that all necessary items are transported [10], while maximising loaded weight or profit can also determine *what* is loaded [6, 18, 30, 27, 28]. Time constraints are addressed only by Roesener and Barnes [24], which determines *when* items must be transported. The placement of items (*how*) is often optimised to achieve the smallest deviation from a given centre of gravity, improving fuel efficiency [7, 12, 13, 16, 27, 28, 30]. However, no single objective integrates all three questions for military operations, including both cargo and troop transport, situational priorities, and mission-dependent constraints.

## 2.5 Literature review summary

In summary, the state of the art demonstrates the current methods and approaches to load planning optimisation, particularly for commercial applications. Military-specific requirements, including troop transport, situational priorities, multi-aircraft fleets, non-standardised items and temporal constraints, remain underexplored. These gaps form the foundation for further research and the development of situationally and mission-dependent

Table 2.1: Overview of methods used for load planning optimisation in relevant papers

| First Author | Year | Application | Method | Objective | Item prioritisation |
|---|---|---|---|---|---|
| Chenguang [4] | 2018 | Commercial | HGA | Min. fuel | |
| Dahmani [6] | 2016 | Military | PSO | 1: Max. weight, 2: Max. priority | x |
| Desai [7] | 2023 | Commercial | MINLP | Min. CG deviation | |
| Gueret [10] | 2003 | Military | Heuristics | Min. flights | x |
| Li [12] | 2012 | Commercial | Heuristics | 1: Min. trim drag, 2: Max. load factor | |
| Limbourg [13] | 2012 | Commercial | MILP | 1: Min. MoI, 2: Min. CG deviation | |
| Lu [16] | 2023 | Commercial | MIP then GA | 1: Min. CG deviation, 2: Max. load | |
| Lurkin [17] | 2015 | Commercial | MILP | Min. CG deviation | |
| Mongeau [18] | 2003 | Commercial | MILP | Max. load | |
| Nance [20] | 2011 | Military | TS | Min. number of aircraft | |
| Roesener [24] | 2016 | Military | TS | Min. flights | |
| Vancroonenburg [27] | 2014 | Commercial | MIP | 1: Max. profit, 2: Min. CG deviation | x |
| Verstichel [28] | 2011 | Commercial | MIP | 1: Max. profit, 2: Min. CG deviation | x |
| Wesolkowski [29] | 2010 | Military | GA | Min. number of aircraft | |
| Zhao [30] | 2021 | Commercial | MILP | 1: Max. load, 2: Min. CG deviation | |

load planning models.

The main objective of this study is to develop a load planning model that is situationally and mission-dependent, taking into account the priorities and urgency of the items to be transported. This will be achieved by incorporating input from the loadmaster, including items with special priority, situationally dependent levels of urgency, and time constraints, as well as mission-dependent objectives. Further interviews with loadmasters are conducted to work towards determining the optimal number of alternative load-plan suggestions and the preferred level of detail in each, ensuring the model effectively supports operational decision-making. The goal is to provide a suggested load configuration that meets the operational requirements and preferences of the loadmasters.

# 3
# Problem description

To gain a deeper understanding of the LPP and its requirements, six semi-structured interviews are conducted with subject matter experts, all having more than three years of experience as loadmasters or planners at the Royal Netherlands Air and Space Force (RNLASF). These interviews provide valuable insights into the current state of loadplanning. The operational experience and expertise of the interviewees form the foundation for the model's objective function, constraints, input parameters, and constants. This section presents relevant terminology, current practices and regulations related to load planning, as well as summarised findings from the interviews.

## 3.1 Planning at different levels

The full planning process for transport aircraft consist of two phases. Table 3.1 summarises the differences between the two distinct planning processes at higher level, and from a more detailed point of view. The planners at both levels have the same goal: to complete the mission successfully.

**Deployment planning:** The Army planning team plans the overall mission, deciding when and where to deploy transport aircraft, personnel, and cargo. They specify quantities and locations for all goods, and order the Air Force for execution if aerial support is needed. The main considerations for a planner at this level is to gain insight in how many aircraft are needed to transport the concerned goods. A planner tries to make a best estimation of which loads fit in the available space and how the items would be assigned over the fleet. Load plans for larger fleet on mission-planning level are usually made up to weeks before departure.

**Loadmaster planning:** Loadmasters are the operational staff that plan the configuration and position the cargo within the cabin of each aircraft individually. Other responsibilities include checking the prepacked loads, performing preflight procedures and informing staff and passengers about the upcoming flight.

## 3.2 General overview problem

To ensure safe flight operations, loadmasters manually plan and iterate on loading configurations, typically on the day of flight or one to three days prior to departure. For standard missions, the configuration of fixed load plans can be used using load plan documentation. Under new circumstances and when flying with new cargo types or non-standard equipment new configurations have to be made and verified to guarantee feasibility. Limited preparation time, intermediate stops with cargo and troop exchanges, and complex cargo arrangements add complexity to load planning. Loadmasters must carefully place and restrain equipment, pallets, containers, and personnel within the cabin, adhering to safety regulations, structural constraints, and aviation rules.

While loadmasters iterate on loading configurations, it is the higher level-planning that assigns the loadmasters which goods they must load. For mission-planning staff it is helpful to know limitations and possibilities of cabin loading to plan most efficiently, and use the available

**Table 3.1:** Load planning tasks at different operational levels

| Deployment planning | Loadmaster planning |
|---|---|
| Weeks to days before departure | 0–3 days before departure |
| Determine what needs to be transported | Determine how items are transported |
| Assign priorities to cargo (1=high, 2=medium, 3=low) | Must guarantee that items with highest priorities are always transported |
| Estimate total cargo weight and volume | Know exact weight and spatial limits per aircraft |
| Want to know how much capacity and weight remain available for additional cargo | Plan configurations with the given set of assigned cargo only |
| May have mismatches between estimated and actual capacity | Must create feasible configurations within real constraints |
| Estimated planning process for large fleet | Manual planning process per aircraft individually |

space most effectively.

While planning the load configuration, loadmasters must follow strict regulations for weight distribution, balance, and safety. Load planning is a largely manual and time-consuming task. In case of last-minute changes loadmasters have to quickly adapt and make changes to the configuration, still ensuring mission requirements and safety standards are met. These last-minute changes in load delivery add complexity and cause higher work load. Large temperature fluctuations can affect fuel requirements, potentially reducing the amount of cargo that can be transported. When an aircraft malfunctions, loads must be redistributed across the remaining available aircraft, always keeping in mind that items with the highest priorities must be transported.

The LPP in this research poses to solve two main challenges: (1) mismatch between planning stages, where Army plans may not align with loadmasters' capabilities, leading to delays and inefficiencies; and (2) complex loading configuration planning by loadmasters, which becomes increasingly difficult with large numbers of loads, multiple aircraft, and last-minute changes. For each load plan, loadmasters must balance competing focusses, such as CG constraints, item prioritisation, and compliance with regulations for non-compliant or dangerous items. To address these challenges, the optimisation models presented in this research incorporate operational preferences and insights from subject matter experts (experienced loadmasters and planners), translating their expertise into mathematical constraints and objectives.

## 3.3 Cargo types and specific constraints from operations

Four types of cargo are considered in this research: pallets, vehicles, pax and container delivery system (CDS) bundles. Each cargo type is treaded differently in load planning and will be described in this section.

### 3.3.1 Description of load types

For regular transport flights, loads are prepacked on 463L Master Pallets, being 108 inch wide and 88 inch long. The standard palletised cargo have a fixed system on the cabin floor where they can be positioned and restrained to. The cargo loaded on the pallets have a fixed height that always fits in the cabin. The loadmasters determine the loading order of the pallets which determines where the pallets are positioned. For regular missions, standard pallet positions are taken to calculate the weight and balance. In this model, all pallets can be moved over the length of the cabin, allowing more precise CG balancing. When dangerous (DGR) items are packed, the goods and are given a hazard label $S$. When shipping DGR goods by air, the IATA Dangerous Goods Regulations define standards that must be followed [25]. Non-compliant goods, which do not meet standard safety regulations, require additional constraints. Two types of DGR goods are distinguished in this model by their hazard label, with different segregation rules applying depending on the label. DGR goods are typically placed at the rear such that in case of an emergency, the ramp can be opened and the load can be quickly unloaded.

Various types of vehicles can be transported by air, ranging from small lightweight vehicles to large vehicles with trailers. Large vehicles are typically very heavy and have limited placement options in the cabin due to compartment load limits. Whereas pallets are tied down on the fixed rail system on the cabin floor, vehicles can be placed freely in the cabin compartment. Vehicles impose strict tie-down requirements in forward, rearward, side and upward directions for multiple gs (accelerations). The vehicles are restrained using cables that occupy extra space. Vehicles are always planned to be placed on the cabin's centerline, and are not placed in the most forward compartment.

When missions involve moving pax or dropping paratroopers, pax are accomodated to seats with fixed positions. When the seats are not in use, they can be stowed away making place for other items. When they are in use, each seat positions two pax. Normally, loadmasters assign pax to seats starting at the front of the cabin. In this model, there is more freedom to move the pax.

CDS bundles are 48 x 48 inch squared prepacked packages that are used for airdrops. A parachute is attached to each CDS bundle, and as the ramp is open and the cables are cut, all bundles on the rails are dropped. The CDS are positioned on either of the two rails along the cabin, enabling sequential release and ejection. It is crucial to sort CDS bundles by weight along each rail, from lightest at the front to heaviest at the rear, to ensure safe unloading during flight.

### 3.3.2 Operations

The development of a load planning model can provide significant benefits to anyone involved in tasks related to load planning operations. By implementing the model as an automated tool, commanders can optimise aircraft allocation for given load combinations, while planners can verify the feasibility of their planned loads within the constraints of the available fleet. The tool should provide a visual representation of the loading configuration, as well as an overview of the load distribution within the cabin. At the mission-planning level, planners with limited loadmaster experience can utilise the tool to estimate the transport capacity of aircraft under expected conditions, where the model automatically incorporates factors such as weight and balance and operational constraints. Loadmasters can also employ the tool as a decision-support tool to evaluate loading configurations and flight plans, ensuring safe and efficient cargo transport.

## 3.4 Simplifications

The following simplifications and assumptions are made in order to design the LPP models. These simplifications are considered sufficient for the minimum required detail necessary for the proof of concept of this LP tool.

- The model accounts for **longitudinal balance** only. Subject matter experts do not include vertical balance in their calculations. The horizontal balance is mentioned as CG position; the x-position of the CG from the reference datum in inches. The reference datum is located just in front of the nose of the aircraft at $x = 0$.
- The LPP is a **2D bin packing problem**; the heigts of the cabin and items are not included in the model. One assumes that the items delivered for transport fit in the height of the cabin *and* can be loaded into the cabin through the ramp.
- A **standard of 2 crew members** are included in the basic operating weight (BOW) of each aircraft. The crew members (loadmasters) have fixed positions in the cabin and are therefore not visualised in the final load suggestions.
- **Fixed fuel weights** are used for simulation purposes and consistency. An arbitrary value for the preferred CG location, the *target CG* of the aircraft at take-off weight (TOW) is taken.
- Two arbitrary values for the **minimum and maximum CG position** at take-off are taken (larger than the actual limits).
- The variety of interrelated **interactions between non-compliant goods** is simplified to two separation rules: DGR goods labelled as Hazard Type S1 must be separated by a minimum distance, and Hazard Type S2 items must be separated by at least one other physical item.

Weights are given in pounds (lbs), and dimensions in inches (in).

## 3.5 Objectives of the tool

The aim of this report is to introduce two optimisation models designed as a proof of concept for a load planning decision making tool. Finally, the results of the two methods are compared and tested on different use cases.

The tool aims to support both planning mission planning and operational planning by providing:

1. **Optimised loading configurations:** The tool suggests how to divide cargo across multiple aircraft and how to position items within each aircraft.
2. **Feasible solutions:** All suggested configurations guarantee that the aircraft is properly balanced (centre of gravity within acceptable limits) and meets safety regulations.
3. **Load capacity insights:** The tool shows how much cargo weight and space remain available after loading, which can be useful for planning additional cargo.
4. **Visual representations:** The tool provides top-view diagrams showing exactly how each aircraft is loaded, making it easy to understand the configuration.
5. **Practical output format:** The tool presents weight distributions in a format that loadmasters can directly use for their official flight documentation.

# 4
# Model design

To address the LPP, two complementary optimisation approaches are developed and compared. First, a MILP framework is designed as the baseline method to provide exact, high-quality reference solutions. Mixed-integer linear programming is selected for this role because it is one of the most popular methods in operations research [5], proving optimality and having the ability to incorporate complex operational constraints. The MILP model in this work incorporates geometric constraints and operational constraints derived from the semi-structured interviews with subject matter experts. To handle the originally nonlinear centre of gravity calculations, linearisation techniques are applied.

However, MILP becomes computationally expensive as problem size increases, particularly when dealing with large fleets, mixed cargo types, and strict operational rules. As the problem size increases, the computational complexity of MILP grows exponentially [14]. To address this scalability limitation while preserving the exactness and credibility that MILP provides, a hybrid TS-MILP approach is designed. This hybrid strategy leverages the strengths of both methods: it uses TS as a fast global heuristic in the first layer to quickly explore the item-to-aircraft assignment space, followed by MILP refinement in subsequent layers to guarantee operational feasibility. In this way, the hybrid method combines the popularity and proven reliability of MILP with the speed and scalability of metaheuristics. The method is designed to be practical for large and time-critical load planning scenarios where exact optimality may be less critical than rapid feasible solutions.

TS is a stochastic optimisation method that begins with an initial solution and iteratively explores the best new neighbouring solutions [2]. The search is guided by a tabu list that prevents revisiting solutions that are already recently explored. The algorithm is good for avoiding local optima, and the quality of the solution depends on how the parameters are tuned [22]. The algorithm stops when a stopping criterion is met, either when an acceptable solution is found or when a maximum number of iterations or computational effort is reached. TS is effective for large, complex LPPs but does not guarantee a global optimum. The algorithm explores many candidate solutions from which the preferred *best* solution can be chosen [24].

In this chapter, the methodologies for both the MILP and TS-MILP approaches are described in detail. The chapter begins with input parameters and constants that define the problem, followed by the full MILP formulation including the objective function and operational constraints. Next, the tabu search design is introduced, and finally the hybrid TS-MILP framework is presented, explaining how the two methods are combined to balance solution quality with computational efficiency.

## 4.1 Input Parameters

This section describes the input parameters used in the model, including item-specific, aircraft-specific, and compartment-specific parameters. The different item types pallets (PAL), vehicle (VEH), pax (PAX), and container delivery system bundles (CDS) are sorted in sets $I_{\text{PAL}}$, $I_{\text{VEH}}$, $I_{\text{PAX}}$, and $I_{\text{CDS}}$, respectively. Each pallet, pax and CDS has fixed dimensions in length and width, and four different vehicles dimensions are taken. Additionally, each item has a load priority ($LP$) value on a scale from one to three. Critical items are given value $LP1$, and the items of lowest priority are given value $LP3$. The priority of an item can differ per situation and per mission. To incorporate DGR goods in the model, two types of non-compliancies are included. These items are given a hazard label $S1$ or $S2$.

Aircraft-related sets and parameters provide information about the fleet, including dimensions of the cabin and mass and balance requirements. Table 4.1 presents the sets used throughout the model and Table 4.2 presents a lists of input parameters.

**Table 4.1:** LPP sets

| Notation | Description |
|---|---|
| $I$ | Set of all items available for loading, indexed by $i$ |
| $A$ | Set of all aircraft available, indexed by $j$ |
| $K_j$ | Set of compartments in aircraft $j$, indexed by $k$ |
| $P_j$ | Set of all available seating positions in aircraft $j$, indexed by $p$ |
| $I_{S1}$, $I_{S2}$ | Set of DGR goods items with hazard label S1 and S2, indexed by $i$, with $I_{S1}, I_{S2} \subseteq I$ |
| $I_{\text{PAX}}$,$I_{\text{PAL}}$, $I_{\text{PAL}}$,$I_{\text{CDS}}$ | Item subsets of passengers, pallets, vehicles and CDS bundles, indexed by $i$, with $I_{\text{PAX}}, I_{\text{PAL}}, I_{\text{VEH}}, I_{\text{CDS}} \subseteq I$ |
| $P_{jC}, P_{jW}, P_{js}$ | Seat subsets in aircraft $j$ (centre, wheelwell, side), with $P_{jC}, P_{jW}, P_{js} \subseteq P_j$ |

All binary and continuous decision variables are listed in Table 4.3. The variables are further explained in the context of the relevant LPP model constraints.

**Table 4.2:** LPP parameters

| Notation | Description |
|---|---|
| $L_i$, $W_i$ | Length, width of item $i$ ($x$-direction) |
| $M_i$ | Weight of item $i$ |
| $LP_i$ | Loading priority of item $i$ |
| $Type_i$ | Type of cargo item $i$ |
| $Haz_i$ | Hazard label class $S$ of item $i$ (0, 1, or 2) |
| $L_j$,$W_j$ | Cabin length, width of aircraft $j$ |
| $ZFW_j$ | Zero fuel weight of aircraft $j$ |
| $BOW_j$ | Basic operating weight of aircraft $j$ (including crew) |
| $FuelW_j$ | Total fuel weight available in aircraft $j$ at take-off |
| $MTOW_j$ | Maximum take-off weight of aircraft $j$ |
| $BOWcg_j$ | $x$-coordinate of centre of gravity of aircraft $j$ at BOW |
| $Fuelcg_j$ | $x$-coordinate of centre of gravity of total fuel in aircraft $j$ |
| $Crew_j$ | Number of crew members in aircraft $j$ |
| $LEMAC_j$ | $x$-coordinate of the leading edge of the mean aerodynamic chord |
| $MAC_j$ | Length of the mean aerodynamic chord (MAC) |
| $CG\_to_j^{\min}$ | Minimal allowable CG position at take-off (% of MAC) of aircrft $j$ |
| $CG\_to_j^{\max}$ | Maximal allowable CG position at take-off (% of MAC) of aircrft $j$ |
| $XCG\_target_j$ | Target CG position for aircraft $j$ |
| $X0_{jk}$ | Starting $x$-coordinate of compartment $k$ in aircraft $j$ |
| $Loadlim_{jk}$ | Maximum load (weight limit) for compartment $k$ in aircraft $j$ |
| $Xcg_{jk}$ | $x$-coordinate of the centre of gravity of compartment $k$ in aircraft $j$ |

## 4.2 Solution presentation

A graphical representation is used to present the final loading solution. This output supports the loadmaster in the planning proces and during operations. The solution contains information on the item placement in the cabin, and presents aircraft W&B details. For each aircraft used in the solution, a loadsheet is generated.

If an item cannot be accommodated in the final loading solution, the item must be left behind on the ground. This reflects day-to-day operations, where delivered cargo may exceed spatial or weight limits, or where the combination of items and flight conditions prevents compliance with operational regulations. To model this, the $ground$ is represented as a large bin with unlimited space and no weight restrictions. This big bin (BB) is implemented as a dummy aircraft index within the aircraft set $A$.

When an item is assigned to the BB, it is indicated by the variable $p_{i,bb} = 1$. This implies that the item is not part of the current loading solution and will be left behind. The BB allows the MILP to generate a feasible solution by assigning items to the BB instead of resulting in an infeasible solution.

**Table 4.3:** LPP decision variables

| Notation | Description |
|---|---|
| $p_{ij} \in \{0,1\}$ | 1 if item $i$ is assigned to aircraft $j$, 0 otherwise, for $i \in I,\ j \in A$ |
| $u_j \in \{0,1\}$ | 1 if aircraft $j$ is used, 0 otherwise, for $j \in A$ |
| $z_{ijk} \in \{0,1\}$ | 1 if item $i$ is in aircraft $j$ in compartment $k$, 0 otherwise, for $i \in I,\ j \in A,\ k \in K_j$ |
| $xp_{il} \in \{0,1\}$ | 1 if item $i$ is positioned more aft than item $l$, 0 otherwise, for $i,l \in I,\ i \neq l$ |
| $yp_{il} \in \{0,1\}$ | 1 if item $i$ is to starboard of item $l$, 0 otherwise, for $i,l \in I,\ i \neq l$ |
| $haz\_dx_{il} \in \{0,1\}$ | 1 if S1 hazard items $i$ and $l$ are separated, 0 otherwise, for $i,l \in I_{S1},\ i < l$ |
| $haz\_b_{ilkj} \in \{0,1\}$ | 1 if S2 hazard items $i$ and $l$ are separated by non-S2 item $k$ in aircraft $j$, 0 otherwise, for $i,l \in I_{S2},\ i < l,\ k \in I \setminus I_{S2},\ j \in A$ |
| $paxpos_{ip} \in \{0,1\}$ | 1 if passenger item $i$ is assigned to seat position $p$, 0 otherwise, for $i \in I_{\text{PAX}},\ p \in P_j,\ j \in A$ |
| $c\_pax_i \in \{0,1\}$ | 1 if passenger item $i$ is assigned to a centre seat, 0 otherwise, for $i \in I_{\text{PAX}}$ |
| $w\_pax_i \in \{0,1\}$ | 1 if passenger item $i$ is assigned to a wheelwell seat, 0 otherwise, for $i \in I_{\text{PAX}}$ |
| $pax\_exit^L_{ij} \in \{0,1\}$ | 1 if passenger item $i$ in aircraft $j$ can use front exit $L$, 0 otherwise, for $i \in I_{\text{PAX}},\ j \in A$ |
| $pax\_exit^R_{ij} \in \{0,1\}$ | 1 if passenger item $i$ in aircraft $j$ can use rear exit $R$, 0 otherwise, for $i \in I_{\text{PAX}},\ j \in A$ |
| $rail_{ijr} \in \{0,1\}$ | 1 if CDS bundle $i$ on aircraft $j$ is on rail $r$, 0 otherwise, for $i \in I_{\text{CDS}},\ j \in A,\ r \in R$ |
| $\beta_{ij} \in \{0,1\}$ | 1 if item $i$ is positioned closest to or on the ramp in aircraft $j$, 0 otherwise, for $i \in I,\ j \in A$ |
| $x_i \in \mathbb{R}$ | x-coordinate of the bottom-left corner of item $i$, for $i \in I$ |
| $y_i \in \mathbb{R}$ | y-coordinate of the bottom-left corner of item $i$, for $i \in I$ |
| $x'_i \in \mathbb{R}$ | x-coordinate of the top-right corner of item $i$, for $i \in I$ |
| $y'_i \in \mathbb{R}$ | y-coordinate of the top-right corner of item $i$, for $i \in I$ |
| $xcg_{ij} \in \mathbb{R}$ | Linearised product variable for item CG contribution in aircraft $j$, for $i \in I,\ j \in A$ |
| $tow_j \in \mathbb{R}$ | Take-off weight of aircraft $j$, for $j \in A$ |
| $Q_j \in \mathbb{R}$ | Total moment of aircraft $j$, for $j \in A$ |
| $d_j \in \mathbb{R}$ | Absolute deviation between desired and actual CG at take-off for aircraft $j$, for $j \in A$. |

## 4.3 Mathematical representation of MILP model

As a baseline method, traditional MILP is set up to assign a full set of items to a given fleet. The decision variable $p_{ij}$ indicates which item $i$ is allocated to aircraft $j$. The variables $x_i$ and $y_i$ indicate the lateral and longitudinal position of each item within the cabin of the aircraft, respectively.

A multi-objective approach is employed, combining three normalised objective terms and an additional penalty term. The MILP is solved using the Gurobi commercial solver with a predefined maximum time limit. During optimisation the solver explores and prunes parts of the solution space using branch and bound method, extended with cutting planes, presolve techniques and heuristics. Solver parameters are automatically activated and applied when the solver is initiated, limiting the size of the branch and bound tree that is to be explored [11].

MILP is an exact method which allows the solver to provide the *optimality gap* of each solution, presenting the quality of the solution. Optimal solutions have a gap of 0%. Solutions with a non-zero gap present a feasible solution for which the solver can potentially still improve the solution towards optimallity. For example, a gap of 24% indicates that the current solution is at most 24% worse than the best known lower bound found by LP relaxation.

### 4.3.1 MILP Objective function

The objective function optimises a weighted sum of four criteria: (1) minimisation of the unloaded item priority values to ensure operational preferences, (2) minimisation of aircraft use to incentify effective aircraft use; (3) the minimisation of the CG deviation to achieve best performance during flight; (4) a penalty when critical items with highest priority are not assigned to an aircraft in the fleet. The BB is modelled as a real aircraft, as a part of the fleet $A$. The BB has index $bb$ in set $A$.

$$\text{Min} \quad W_1 \cdot o_1 + W_2 \cdot o_2 + W_3 \cdot o_3 + P_{\text{LP1}} \tag{4.1}$$

with:

$$o_1 = \frac{\sum_{i \in I, j=bb} (LP_{\max} - LP_i + 1) \cdot p_{ij}}{\sum_{i \in I} LP_i} \tag{4.2}$$

$$o_2 = \frac{1}{|A|-1} \sum_{j \in A} u_j \tag{4.3}$$

$$o_3 = \frac{1}{|A|-1} \sum_{j \in A} \frac{d_j}{CG\_dev\_cap_j} \tag{4.4}$$

$$P_{LP1} = \frac{\sum_{i \in I: LP_i = 1} p_{ij}}{|\{i \in I : LP_i = 1\}|} \tag{4.5}$$

, with the deviation from the target CG location to the bounds per aircraft described by:

$$CG\_dev\_cap_j = \max\left( \left| XCG_j^{\text{target}} - XCG_j^{\min} \right|, \left| XCG_j^{\max} - XCG_j^{\text{target}} \right| \right) \cdot MTOW_j, \quad \forall j \in A \tag{4.6}$$

The first objective term $o_1$ minimises the placement of items in the BB based on their LP value (eq. 4.2). To promote effective fleet utilisation use $o_2$ is introduced to minimise the number of aircraft used (eq 4.3). In order to minimise deviations from the target CG in the aircraft, $o_3$

is introduced to focus on the placement of items within the aircraft cabin (eq 4.4).

For critical items an extra penalty $P_{LP1}$ is introduced to minimise the number of $LP1$ items in the BB (eq 4.5). The $P_{LP1}$ penalty is intentionally added to the objective function instead of being included as a constraint in the model. This decision is made to increase the likelihood of obtaining a feasible solution. In this context, a suboptimal solution is preferable to no solution at all. $P_{LP1}$ is used to discourage the model from assigning critical items with the highest priority to the BB, thereby promoting the assignment of these critical items to an aircraft in the fleet. The values for each objective term and the penalty are determined through further model validation to ensure that the optimisation aligned with operational priorities and constraints.

The effect of the objective weights is visible in the balance between loading priority, fleet utilisation, and CG deviation. A higher weight on priority causes the model to always load high-priority items, while a higher fleet-use penalty encourages the model to use fewer aircraft. The CG term improves the balance of the aircraft, but if its weight is too strong, the model may prefer to leave items behind rather than accept a small CG deviation-which is not desired. The final weight settings therefore reflect a compromise between operational priorities and feasibility. All objective terms are normalised and can be scaled directly using the weighting factors.

The following auxiliary constants are used to formulate tight big-M constraints.

$$L = \max L_j, \quad W = \max W_j, \quad M = L + W$$

### 4.3.2 Fundamental and geometric constraints

The following constraints are fundamental to this LPP to define the main decision variables and physical and geometric constraints.

$$\sum_{j \in A} p_{ij} = 1, \quad \forall i \in I \tag{4.7}$$

$$p_{ij} \leq u_j, \quad \forall i \in I, \ \forall j \in A \tag{4.8}$$

$$x'_i - x_i = L_i, \quad \forall i \in I \tag{4.9}$$

$$y'_i - y_i = W_i, \quad \forall i \in I \tag{4.10}$$

$$x'_l \leq x_i + (1 - xp_{il})L, \quad \forall i, l \in I, \ i \neq l \tag{4.11}$$

$$x_i + 1 \leq x'_l + xp_{il}L, \quad \forall i, l \in I, \ i \neq l \tag{4.12}$$

$$y'_l \leq y_i + (1 - yp_{il})W, \quad \forall i, l \in I, \ i \neq l \tag{4.13}$$

$$y_i + 1 \leq y'_l + yp_{il}W, \quad \forall i, l \in I, \ i \neq l \tag{4.14}$$

$$xp_{il} + xp_{li} + yp_{il} + yp_{li} \geq p_{ij} + p_{lj} - 1, \quad \forall i, l \in I, \ i \neq l, \ \forall j \in A \tag{4.15}$$

$$\sum_{j \in A} \sum_{k \in K_j} z_{ijk} = 1, \quad \forall i \in I \tag{4.16}$$

$$xcg_i = x_i + \frac{x'_i - x_i}{2}, \quad \forall i \in I \tag{4.17}$$

$$x_i \geq \sum_{j \in A} X0_{j,0}\, p_{ij}, \quad \forall i \in I \tag{4.18}$$

$$x'_i \leq \sum_{j \in A} (X0_{j,-1} + L_{j,-1})\, p_{ij}, \quad \forall i \in I \tag{4.19}$$

$$y_i \geq y_{\text{left},jk}\, p_{ij} - W(1 - z_{ijk}), \quad \forall i \in I, \ \forall j \in A, \ \forall k \in K_j \tag{4.20}$$

$$y'_i \leq y_{\text{right},jk}\, p_{ij} + W(1 - z_{ijk}), \quad \forall i \in I, \ \forall j \in A, \ \forall k \in K_j \tag{4.21}$$

The constraints are formulated as follows: each item is assigned to exactly one aircraft (C4.7), and an item can only be assigned to an aircraft if that aircraft is active (C4.8). To convert the item dimensions to positions in the cabin, the horizontal ($x$, over the length) and vertical ($y$, over the wirdt) positions are defined (C4.9, C4.10). To prevent overlap between two items assigned to the same aircraft C4.15 is formulated, where variables $xp_{il}$ and $xp_{il}$ define the horizontal and vertical relationships between two items (C4.11, C4.12, C4.13, C4.14). Each item is assigned to exactly one compartment with C4.16, with its CG calculated as the midpoint of an item's length along the horizontal axis, see C4.17. To ensure the item fitting within the cabin boundaries, C4.18 and C4.19 are used for the most forward and aft locations, and C4.20 and C4.21 for the sides of the cabin.

### 4.3.3 Weight & balance constraints

The following constraints describe weight and moment calculations for the loaded aircraft.

$$\sum_{i \in I} z_{ijk} M_i \leq \text{Loadlim}_{jk}, \quad \forall j \in A, \ \forall k \in K_j \tag{4.22}$$

$$\text{TOW}_j = \text{BOW}_j\, u_j + \text{FuelW}_j\, u_j + \sum_{i \in I} M_i p_{ij}, \quad \forall j \in A \tag{4.23}$$

$$\text{TOW}_j \leq \text{MTOW}_j, \quad \forall j \in A \tag{4.24}$$

$$\text{X}^{\text{min}}_{\text{cg},j} \text{TOW}_j \leq Q_j, \quad \forall j \in A \tag{4.25}$$

$$Q_j \leq X^{\text{max}}_{\text{cg},j} \text{TOW}_j, \quad \forall j \in A \tag{4.26}$$

$$Q_j = \text{BOWcg}_j\, \text{BOW}_j\, u_j + \text{Fuelcg}_j\, \text{FuelW}_j\, u_j + \sum_{i \in I} M_i\, xcg_{ij}, \quad \forall j \in A \tag{4.27}$$

$$d_j = \left| \text{X}_{\text{target},j} \cdot \text{TOW}_j - Q_j \right|, \forall j \in A \tag{4.28}$$

The weight and balance constraints are formulated to ensure that the loads placed in the cabin correctly balance the aircraft. C4.22 ensures that weight of all items within one compartment can not exceed the compartment's maximum load limit. The TOW is calculated as the sum of the basic operating weight, fuel weight, and total loaded cargo weight with C4.23. The TOW can never exceed each MTOW due to C4.24. The CG at take-off must always remain within the foward and rear bounds (C4.25, C4.26). The total moment at take-off is calculated as the sum of moments from basic operating weight, fuel, and all loaded items (4.27). To calculate the absolute deviation of the aircraft at take-off from the target CG is calculated using C4.28.

$\mathrm{xcg}_{ij}$ is the linearised result of the original bilinear term, being the product of a continuous variable $xcg_i$ and binary variable $p_{ij}$. The following linearisation is performed.

$$xcg_{ij} \leq \mathrm{Ub}\, p_{ij}, \quad \forall i \in I,\ \forall j \in A \tag{4.29}$$

$$xcg_{ij} \geq \mathrm{Lb}\, p_{ij}, \quad \forall i \in I,\ \forall j \in A \tag{4.30}$$

$$xcg_{ij} \leq xcg_i - (1 - p_{ij})\mathrm{Lb}, \quad \forall i \in I,\ \forall j \in A \tag{4.31}$$

$$xcg_{ij} \geq xcg_i - (1 - p_{ij})\mathrm{Ub}, \quad \forall i \in I,\ \forall j \in A \tag{4.32}$$

The linearised variable describes the CG of a placed item $i$ in aircraft $j$. The lower and upper bound (LB and UB) for the variable are the start $x = X0_{j,0}$ and end of the cabin $X0_{j,0} + L_j$, see eq 4.29 and eq 4.30. Eq 4.31 and eq 4.32 are derived via the McCormick envelope [19]. The bounds ensure that the linearised variable accurately represents the product of the original variable terms.

### 4.3.4 Operational constraints

The following listed constraints cover the operational and item type specific constraints.

$$x_i \geq x'_l + S_i - L(1 - xp_{il}), \quad \forall i, l \in I_{\mathrm{VEH}} \cup I_{\mathrm{PAL}},\ i \neq l \tag{4.33}$$

$$x_l \geq x'_i + S_l - L(1 - xp_{li}), \quad \forall i, l \in I_{\mathrm{VEH}} \cup I_{\mathrm{PAL}},\ i \neq l \tag{4.34}$$

The operational constraints are formulated as such that various logistical and safety considerations are captured. Horizontal separation between vehicles and pallets is ensured through constraints C4.33 and C4.34, to allow for restraint systems spacing.

$$\sum_{p \in P_j} paxpos_{ip} = p_{ij}, \quad \forall i \in I_{\mathrm{PAX}}, ; \forall j \in A \tag{4.35}$$

$$x_i = \sum_{j \in A} \sum_{p \in P_j} x_p, paxpos_{ip}, \quad \forall i \in I_{\mathrm{PAX}} \tag{4.36}$$

$$y_i = \sum_{j \in A} \sum_{p \in P_j} y_p, paxpos_{ip}, \quad \forall i \in I_{\mathrm{PAX}} \tag{4.37}$$

$$c\_pax_i = \sum_{j \in A} \sum_{p \in P_{jC}} paxpos_{ip}, \quad \forall i \in I_{\mathrm{PAX}} \tag{4.38}$$

$$w\_pax_i = \sum_{j \in A} \sum_{p \in P_{jW}} paxpos_{ip}, \quad \forall i \in I_{\mathrm{PAX}} \tag{4.39}$$

$$x_i + 1 \leq x_l + M\left(2 - c\_pax_i - w\_pax_l\right), \quad \forall i, l \in I_{\mathrm{PAX}}, ; i \neq l \tag{4.40}$$

$$x_l + 1 \leq x_i + M\left(2 - c\_pax_l - w\_pax_i\right), \quad \forall i, l \in I_{\mathrm{PAX}}, ; i \neq l \tag{4.41}$$

$$x_i \leq x_k + M\left(1 - c\_pax_i\right), \quad \forall i \in I_{\mathrm{PAX}}, \forall k \in I_{\mathrm{VEH}} \cup I_{\mathrm{PAL}} \tag{4.42}$$

Passenger seating is managed through constraints that assign each passenger to exactly one predefined seat position with C4.35. Note that in this problem each seat has space for two passengers, so all pax are added in pairs. Binary variables indicate the occupation of the centre-line and wheel-well seats. Constraint C4.40 ensure that centre-line and wheel-well passengers are not positioned simultaneously. Due to the tightness of the cabin one of the two seats must be stowed away. Furthermore, centre-line seats are always positioned in front of cargo items such as pallets or vehicles to prevent obstruction, see C4.42.

$$x_i + \mathrm{DGRx}_i - x_l - \mathrm{DGRx}_l \geq HS - M(1 - haz\_dx_{il}), \quad \forall i, l \in I_{S1},\ i < l \tag{4.43}$$

$$x_i + \mathrm{DGRx}_i - x_l - \mathrm{DGRx}_l \leq -HS + M\, haz\_dx_{il}, \quad \forall i, l \in I_{S1},\ i < l \tag{4.44}$$

$$haz\_dx_{il} \geq p_{ij} + p_{lj} - 1, \quad \forall i, l \in I_{S1},\ i < l,\ \forall j \in A \tag{4.45}$$

$$haz\_b^{i,l,k,j} \leq xp_{ik}, \quad \forall i, l \in I_{S2},\ i < l,\ \forall k \in I \setminus I_{S2},\ \forall j \in A \tag{4.46}$$

$$haz\_b^{i,l,k,j} \leq xp_{kl}, \quad \forall i, l \in I_{S2},\ i < l,\ \forall k \in I \setminus I_{S2},\ \forall j \in A \tag{4.47}$$

$$\sum_{k \in I \setminus I_{S2}} haz\_b^{i,l,k,j} \geq 1, \quad \forall i, l \in I_{S2},\ i < l,\ \forall j \in A \tag{4.48}$$

For items classified as non-compliant, specific segregation rules apply. To simulate the handling of dangerous goods two types of non-compliants are introduced: S1 and S2 items. Items with hazard label S1 need to maintain a minimum horizontal separation of $HS$ inches with C4.43 and C4.44. The separation is in compliance with IATA Dangerous Goods Regulations, with this separation enforced only when both items are assigned to the same aircraft (C4.45). For hazard label S2 items, constraints C4.46 and C4.47 ensure that at least one non-S2 item phisically separates the two S2 items on the same aircraft (C4.48).

$$\sum_{r \in R} rail_{ijr} = p_{ij}, \quad \forall i \in I_{\mathrm{CDS}},\ \forall j \in A \tag{4.49}$$

$$y_i \geq 10\, rail_{ij,0} + 65\, rail_{ij,1} - W(1 - p_{ij}), \quad \forall i \in I_{\mathrm{CDS}},\ \forall j \in A \tag{4.50}$$

$$y_i \leq 10\,rail_{ij,0} + 65\,rail_{ij,1} + W(1 - p_{ij}),$$
$$\forall i \in I_{\text{CDS}},\ \forall j \in A \tag{4.51}$$

$$x_{\text{lighter}} \leq x_{\text{heavier}} + M(2 - rail_{\text{lighter},j,r} - rail_{\text{heavier},j,r}),$$
$$\forall(\text{lighter, heavier}) \in I^2_{\text{CDS}},\ M_{\text{lighter}} \leq M_{\text{heavier}},$$
$$\forall j \in A,\ \forall r \in R \tag{4.52}$$

$$x_p \leq x_i + M\left(2 - p_{pj} - p_{ij}\right), \forall p \in I_{\text{PAX}},$$
$$\forall i \in I_{\text{CDS}},\ \forall j \in A \tag{4.53}$$

CDS bundles are assigned to exactly one rail in each real aircraft through C4.49. The rail choice fixes the vertical CDS line at two y-coordinates with a Big-M activation in C4.50, C4.51, so the relation is only active when the bundle is actually assigned to that aircraft. For each CDS pair on the same rail, the lighter bundle is forced to be forward (lower (x)) than the heavier one by C4.52. Finally, passengers are kept forward of CDS in the same aircraft by C4.53.

## 4.4 TS model approach

This section describes the TS algorithm implementation as a first layer of the hybrid optimisation method to the LPP. The goal of TS is to explore the search space quickly to find a good solution for the distribution of all cargo items over the available fleet using a bitstring representation. A simplified algorithm is set up for the LPP to serve as a starting point for further refinement in the second layer of the hybrid model, using MILP. The TS is capacity-oriented and works with violations for a solution rather than hard constraints (as for MILP). By correct implementation of the tabu algorithm, the metaheuristic approach is designed to escape local optima and present the best solution found from the performed iterations.

At first an initial solution is generated using a bitstring formulation, serving as a starting point for the TS. At each iteration, individual bits are flipped and a new candidate solution is generated. The objective value is calculated for the new candidate and its value is saved in a tabu list, next to the bit flip history. The tabu list keeps track of previously visited candidate solutions for a specified number of iterations (tabu tenure $\tau$) to keep track of the visited and unvisited solutions. For each iteration, the candidate bitstring itself is stored in the tabu list (first-in first-out, tenure $\tau$) to prevent immediate revisits. The searching algorithm can be initiated as a parallel search where the bitflips are randomised, enlarging the total searched solution space within a given number of maximum iterations. The best solution (with lowest objective value for this minimisation problem), is decoded, resulting in a representation of how the loads can be assigned over the fleet.

### 4.4.1 Bitstring Representation

The load plan is encoded as a concatenated bitstring $b = [b_{\text{pax}}|b_{\text{pallets}}|b_{\text{vehicles}}|b_{\text{CDS}}]$. The length of the bitstring depends on the number of items and the number of available aircraft. Just like in the MILP formulation, the set of aircraft includes the BB. The number of bits required to encode item $i$ is $b = \lceil \log_2(A) \rceil$. Each item in the bitstring occupies an identical number of bits, and its decoded value directly maps item $i$ to aircraft $j$. The BB is always represented by the decoded bit value *zero* ($j = 0$). Real aircraft are assigned indices $j \in \{1, \ldots, A-1\}$. If a decoded bit segment results in a decimal value that exceeds the number of available aircraft, counting restarts by assigning the items starting at $j = 0$. The total bitstring length $B_{\text{total}}$ is given by:

$$B_{\text{total}} = I \cdot \lceil \log_2(A) \rceil \tag{4.54}$$

**Example encoding:** A load plan with 10 items $|I|= 10$ and a fleet of two aircraft, $A = 3$ (BB included) results in $\lceil \log_2(3) \rceil = 2$ bits per item: two bits per item are required to map one item to one of the three aircraft options. The total bitstring length is $B = 10 \cdot 2 = 20$. A bitstring of length 20 will be used in the TS.

**Example decoding:** Consider a randomly generated bitstring segment for three items and five aircraft options: $b = [001000100]$. The first three bits **001** decode to decimal 1, assigning Item 0 to Aircraft 1. The next three bits **000** decode to decimal 0, assigning Item 1 to BB. The final three bits **100** decode to decimal 4, resulting in Item 2 being placed in Aircraft 4. The bitstring ordering allows the algorithm to move items between aircraft with a single bit flip.

### 4.4.2 Initial solution generation

To accelerate convergence, the initial bitstring is generated in a semi-random mode: $LP1$ items are placed in real aircraft, while $LP2$ and $LP3$ items are randomly assigned over all aircraft options, including the BB. The result is that capacities may be fulfilled and exceeded and the initial solution is a (highly) penalised baseline solution. The searching algorithm is encouraged to add and relocate all items into other aircraft or the BB during the search process.

### 4.4.3 Dynamic capacity restrictions

The capacity-based TS uses a dynamic relation between the number of loaded items. To simplify calculations, all items are approximated as part of *1 seat (= 2 pax)* units. The total number of available units expresses the capacity of the aircraft.

The following conversions are used to calculate capacity usage:

1 pallet = 5 seats
1 vehicle = 25 seats
1 CDS = 1.8 seats

**Example capacity-oriented configuration:** a set of eight pax and four pallets is presented to an aircraft with a capacity of 20 units. Eight pax occupy four seats, leaving 16 units of space available for other cargo. Four pallets occupy $4 \cdot 5 = 20$ units of space. The remaining capacity is $20 - 4 - 20 = -4$ units of space, indicating that the capacity is exceeded.

The total available capacity is based on the capacity of each aircraft and the fleet size. Note that the BB has unlimited units capacity. Initially, all pax are assigned to the fleet, and the remaining capacities per aircraft are based on the remaining units space per aircraft.

### 4.4.4 Objective Function

In contrast to MILP models that only present results when a feasible solution is found satisfying all constraints, TS will always provide a solution. Since this model does not include any hard constraints, a solution is the result of evaluating a candidate bitstring $B$ with a penalty-based objective value. The objective is a weighted sum of penalty terms. The coefficients $\lambda_r$ are only non-zero when the violation applies.

$$\text{Min} \quad \lambda_1 P_{\text{MTOW}} + \lambda_2 P_{\text{Cap}} + \lambda_3 P_{\text{LP1}} + \lambda_4 P_{\text{BB}} + \lambda_5 P_{\text{AC usage}} + \lambda_6 P_{\text{unused cap}} \tag{4.55}$$

The **MTOW penalty** $P_{\text{MTOW}}$ penalises each aircraft $j$ that exceeds its maximum take-off weight. For each aircraft, the total operating weight $TOW_j$ is calculated as the sum of the basic operating weight $BOW_j$, fuel weight $FuelW_j$, and the mass of all assigned items $\sum M_{ij}$ in $j$. If $TOW_j > MTOW_j$, a fixed penalty is added to the objective. The dynamic **capacity trade-off penalty** $P_{\text{Cap}}$ enforces the physical space limitations between pax and cargo. For each aircraft, the algorithm identifies the number of maximum allowable cargo slot units as explained in subsection 4.4.3. The decoded bits base the remaining cargo slots for pallets, vehicles and CDS on the current number of assigned pax. If the assigned cargo exceeds the capacity threshold, a penalty is applied per violating item. For each item that is placed in the BB instead of an active aircraft, **BB (ground) penalty** $P_{\text{BB}}$ applies. To ensure that mission-critical items are loaded, an additional **priority 1 penalty** $P_{\text{LP1}}$ is applied for every item $i$ with $LP_i = 1$ that is assigned to the BB. To make efficient use of the available aircraft, **aircraft usage penalty** $P_{\text{AC usage}}$ applied to each aircraft when in use. To further enforce full capacity use, the dynamic penalty **capacity usage** $P_{\text{Cap usage}}$ is added that penalises when there are empty spaces left in an active aircraft.

### 4.4.5 TS algorithm and neighbour generation

At each iteration, the TS generates one candidate neighbour. First, an item is sampled from a biased pool. The biased pools are pools filled with items that are in the BB, items that are placed in an aircraft whose capacity is exceeded, and the remaining items. The sampling priority follows the implemented probabilities $p_{\text{item\_in\_BB}}$ and $p_{\text{exceeded\_capacity}}$, that indicate from which pool an item is selected. Next, one random bit from the selected item address segment is flipped, producing a candidate bitstring. The new candidate is decoded and evaluated with the penalty-based objective.

The candidate is accepted when its bitstring is not currently present in the tabu list $T$. If accepted, the candidate becomes the current solution and its bitstring is appended to $T$. The tabu list is maintained with finite tenure $\tau$ using a first-in first-out rule: once $|T| > \tau$, the oldest element is removed. If the accepted candidate also improves the global best objective, the best solution so far, is updated, and the iteration number is saved. This logic allows a neighbour that does not directly improve the solution to be accepted. Accepting non-improving moves when they are non-tabu, supports search space exploration and helps to avoid local minima.

### 4.4.6 Tabu list management and termination

The tabu list stores recently accepted candidate bitstrings for $\tau$ iterations. This short-term memory prevents immediate cycling to recently visited solutions. In each iteration, if a candidate is accepted, its string is added to T and the oldest entry is removed when the list exceeds $\tau$. The search terminates after $I_{\max}$ iterations, and the algorithm returns the best solution found and its objective value.

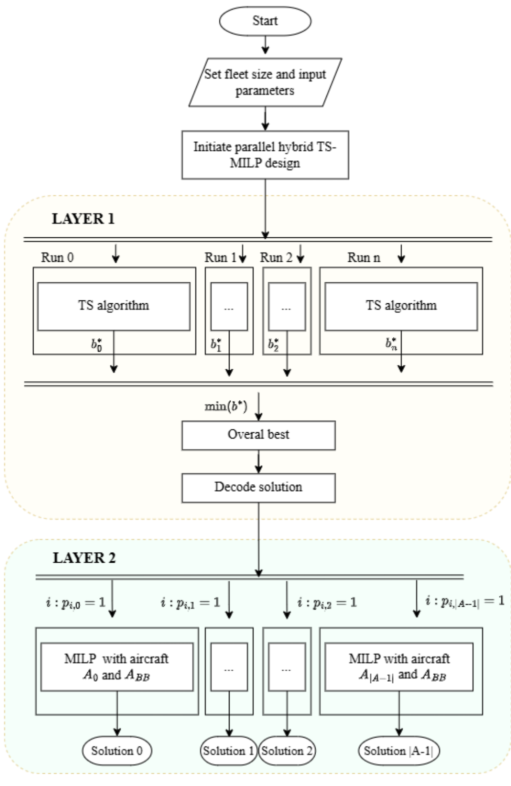



**Figure 4.1:** Flowchart hybrid TS-MILP model

## 4.5 Hybrid TS-MILP design

Now that the workings of TS and MILP have been described, the hybrid design will be outlined. The hybrid approach is visualised in Figure 4.1, consisting of two layers.

**Layer 1-TS (fleet assignment):** The TS runs through $I_{\max}$ iterations for multiple parallel runs to explore a larger part of the search space. The best solution is decoded to find which items are assigned to which aircraft. The output of this layer is a set of item-to-aircraft assignments $p_{ij}$.

**Layer 2-MILP per aircraft (item placement):** For each aircraft used in Layer 1, a MILP subproblem is solved to determine the exact position of each assigned item within the cabin. The subproblem includes only the items assigned to aircraft $j$ and a dummy BB aircraft. This results in $A$ simultaneous MILP operations that can be solved in parallel. Items that cannot be feasibly placed within the cabin, due to geometric or operational constraints, are returned to the BB.

# 5 Methodology

The load planning tool is designed to aid the load planning process during different phases in planning. A methodology is set up to evaluate the suitability of each model under varying conditions. To assess the effectiveness of the models, a set of scenarios are presented in this section. The scenarios simulate different applications and are used to evaluate and compare the results for the traditional MILP model and the hybrid TS-MILP method. The performane of each model is analysed and multiple metrics will support a the trade-off between them.

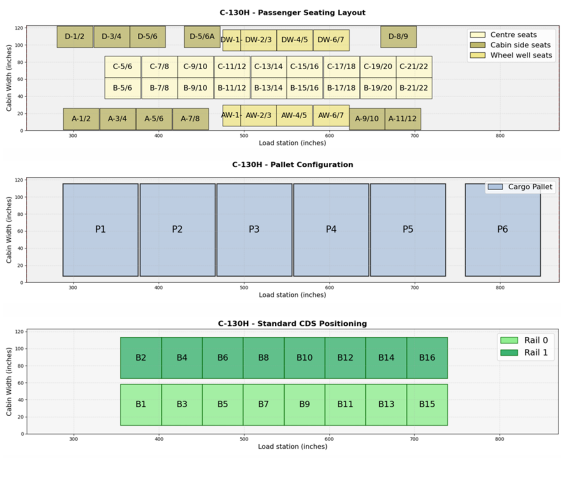



**Figure 5.1:** Standard positions for pax, pallets and CDS in a C-130H

## 5.1 Scenarios

Three scenarios are designed to simulate different applications of military load planning. The scenarios are designed to test how well each model handles different cargo types, constraints, operational requirements and fleet size.

For each scenario specific test instances are introduced for small, medium and large fleet sizes ranging from 1 to 16 aircraft. In this research the C-130H and C-130H-30 military transport aircraft are selected, where the Hercules-30 variant is the extended version of the regular Hercules. For single-type loading the standard configuration for pax, pallets and CDS is presented in Figure 5.1. The horizontal placement of pallets and CDS may differ from the standard configuration.

For each test instance, the fleet size considers a random mix of the short and long aircraft type.

**Scenario 1 - Pallet transportation** This scenario focusses on the weight distribution of palletised cargo, including compliant and non-compliant goods. The cargo are delivered on 463L pallets. The goal is to ensure that weight restrictions are met and safety regulations are adhered to. The type of dangerous goods are simplified to three different categories; compliant (no extra regulations), non-compliant S1-type (minimum separation required), and non-compliant S2-type (physical separation required).

**Scenario 2 - Multi-role deployment:** This scenario involves a mix of item types, including pax, pallets, and vehicles. Passenger placement limits available positions for pallets and vehicles, while vehicles require extra space for tie-down requirements.

**Scenario 3 - Airdrops** This scenario involves the placement of CDS bundles only in combination with pax. The bundles are placed on two fixed rails and are deployed during flight. CDS bundles can be loaded with pax (normal or paratroopers) and follow strict order placement rules.

### 5.1.1 Input cargo generation

The primary objective of the input generation is to test model behaviour under both under-demand and over-demand conditions, i.e. cases where relatively few items are offered and cases where demand exceeds practical fleet capacity. For each generated instance, total demand is scaled by a load factor $L \in [0.5, 1.2]$, representing a target utilisation between 50% and 120% of fleet capacity.

The load factor is sampled from a left-skewed piecewise-linear distribution to generate most cases toward moderate-to-high utilisations while still including low and overload cases.

Input counts are generated per scenario using fleet-level capacities from Table 5.1: for Scenario 1, $N_{\text{PAL}} = \text{round}(L \cdot N_{\text{PAL}}^{\max})$. For mixed scenarios, cargo types compete for the same physical space through a passenger-equivalent unit model. In Scenario 2 (PAX + pallets + vehicles), unit values are set to 1 (for pax), 5 (for pallets), and 25 (for vehicles). A target number of equivalent units is computed with $L$ and the fleet capacity. In Scenario 3 (PAX + CDS), PAX has unit value 1 and CDS uses a fleet-dependent equivalent value 1pax : 1.8CDS. PAX and CDS counts are then derived from the same target-space principle with $L$.

Item attributes are generated as follows. The passenger weight is fixed and pallet and CDS weights are sampled uniformly within operational ranges. Vehicle attributes are sampled from a predefined vehicle database with fixed dimensions, weight, and priority class. The priority classes are uniformly sampled for pax, pallets, and CDS as $LP1$, $LP2$, $LP3$.

DGR goods flags are only applied to pallets. For each instance a random subset is labelled as S1 and/or S2 non-compliant, with an intended share of 0% to 10% of the complete pallet set.

The maximum capacity for a C-130H and C-130H-30 aircraft are given in Table 5.1.

**Table 5.1:** Capacity per aircraft for single item type loading

| Item type | C-130H | C-130H-30 |
|---|---|---|
| Pax | 29 | 45 |
| Pallets | 6 | 8 |
| Vehicles | 1 | 2 |
| CDS bundles | 16 | 24 |

## 5.2 Experiment plan

An experimental framework with the three outlined scenarios to evaluate the performance of the MILP and hybrid TS-MILP approach. Each method will be evaluated on temporal performance, quality of the solution, parameter sensitivity and scalability.

### 5.2.1 Temporal performance and feasibility

Efficiency is measured by the time required to find the first feasible solution and the time required to prove optimality. A global time limit of 600 seconds is enforced for all models. If the model can be solved within ten minutes, great advantage is achieved compared to manual loadplanning that may take up to hours. The temporal performance of the hybrid model is tested by adding the time to solve TS in Layer 1, and the duration for further MILP refinement in Layer 2. The suitability of the model for operations is partially dependent on the total optimisation duration.

When MILP reaches the time limit, two outcomes are possible. If no feasible solution is been found, the model has not yet produced an incumbent and the solution status is infeasible. If a feasible solution is found, the solver reports its incumbent objective value together with the remaining optimality gap. The incumbent is the best known feasible solution found by the solver in the search tree [5].

When MILP search has not encountered a feasible solution yet that satisfies all constraints within the given time limit, no solution is presented. The number of simplex iterations that must be solved increase exponentially as the problem size increases. When the model does find a solution within the time limit, the gap presents the quality of the solution. The gap is presented as a percentage from the objective value when all constraints would be relaxed (best bound), see Equation 5.1. With MILP one can track the convergence rate to evaluate the speed at which the lower bound approaches the incumbent. The incumbent is The optimal solution for a minimisation problem is found when the upper bound is equal to the lower bound and a gap of 0% is achieved. Checking the feasibility for the TS algorithm is slightly less clear. The algorithm can in theory present an infeasible solution as best solution. But as Layer 2 prosecutes the optimisation, infeasilibities in Layer 1 will be solved with MILP.

Two important quality measures are the mean CG centre of gravity deviation and fleet use. Mean CG deviation indicates how well the loaded aircraft are balanced around their target CG positions, which is important for flight safety and operational efficiency. Fleet use indicates how effectively the available aircraft are exploited, for example by avoiding unnecessary aircraft activation and by concentrating cargo in fewer aircraft when feasible.

$$\text{Gap} = \frac{|\text{Objective value} - \text{Best bound}|}{|\text{Objective value}|} \tag{5.1}$$

**Fleet effectiveness**

To provide an overview of the planning status and to support the loadmasters' decision-making process, the load plans are evaluated using two metrics: Item Unfulfilment Rate (IUR) and Residual Payload Capacity (RPC). The IUR (eq 5.2) measures the proportion of individual items that cannot be accommodated within the current fleet, and being being left behind in the BB. However, IUR alone does not provide enough information for planners to decide whether to leave cargo behind or add an aircraft to accommodate left-behind items. To address this limitation, the IUR is supplemented with RPC (eq 5.3), which measures available payload capacity in pounds (lbs). Together, these metrics inform loadmasters about excluded cargo and potential additional loading capacity if fleet size increases. The IUR and RPC are supported with figures.

$$IUR_A = \left(\frac{I_{BB}}{I_{total}}\right) \tag{5.2}$$

$$RPC_{A+1} = \left(\text{AllowablePayload}_j - \text{Mass}_{I_{BB}}\right) \tag{5.3}$$

IUR and RPC are complementary, but they do not fully describe all unused capacity. An aircraft may still contain leftover payload space even when it is considered used, but this local residual space is intentionally not counted in RPC. RPC is defined at fleet level and focuses on the remaining capacity after the current allocation, while IUR captures the number of items that could not be accommodated at all. Consequently, a solution may report one item left in the BB even though part of the remaining cargo could still theoretically fit in a partially used aircraft, because the excluded item may violate weight, priority, or placement constraints rather than pure capacity limits.

### 5.2.2 Scalability analysis

The scalability analysis evaluates how computational effort and solution quality change as instance size increases, and identifies when the hybrid TS-MILP approach becomes operationally preferable to pure MILP. Instance size is increased through both fleet size and generated demand level (via $L$), creating small, medium, and large cases with different numbers of items and mix of item types.

Performance is evaluated on two dimensions: (i) computational performance and (ii) solution quality. Computational performance is measured by total runtime and feasibility within the time limit. To evaluate whether TS-MILP is faster *and* remains sufficiently accurate, solution quality is compared using the final objective function value of each method, denoted as $Z^{\text{MILP}}$ and $Z^{\text{TSMILP}}$.

For the hybrid method, runtime is split by layer (TS assignment and MILP refinement, and optional recovery layer) to determine where computational gains or losses occur. This decomposition is used to explain whether speed improvements originate from reducing MILP problem size, improved assignment quality from TS, or both.

The final comparison is used to define a practical preference: a model is preferred when it obtains high quality solutions within reasonable time limits. This directly links scalability results to real mission-planning requirements, where timely decision support is critical.

# 6
# Results

This chapter presents the results for the LPP based on three realistic scenarios, evaluated on the C-130 Hercules military transport aircraft. The results are used to compare the exact MILP model to the hybrid TS-MILP approach and to asses their suitability for real-world operations.

## 6.1 Constants

The objective function balances loading priority, fleet efficiency, and CG quality, while penalising critical items left in the BB. To set the relative influence of each objective term, a parameter-tuning phase was performed on smaller test instances. The selected MILP weights below are used throughout this chapter and serve as the fixed baseline for comparison with the hybrid TS-MILP method.

$$w_1 = 5.0; \quad w_2 = 0.1; \quad w_3 = 1.0; \quad p_1 = 50$$

TS does not enforce hard constraints directly; instead, it evaluates candidate assignments using penalties for rule violations. As a result, TS always returns a solution, whereas MILP may terminate without a feasible solution within the time limit. The values for the TS penalty constants used in this study are as follows.

$$P_{\text{MTOW}} = 10000; \quad P_{\text{Cap}} = 10000; \quad P_{\text{LP1}} = 7500$$
$$P_{\text{BB}} = 300; \quad P_{\text{AC usage}} = 200; \quad P_{\text{Unused cap}} = 10$$

To demonstrate how the TS behaves, controlled test runs are performed on Scenario 2 with a fixed fleet of 2, 6, and 12 aircraft. The maximum iteration value $I_{\max}$ is varied, while tabu tenure is fixed at 10% of total iterations. Each TS is run ten times in parallel, and the best objective is selected. Table 6.1 summarises the results. Per fleet combination and per $I_{\max}$, 100 runs are performed, all with a randomised set of input data with pax, pallets and vehicles. For 8 instances a $LP1$ item is assigned to the BB. For the hybrid TS-MILP an $I_{\max}$ of 1000 iterations is used, with a tabu tenure of 100.

**Table 6.1:** Evaluation of $I_{\max}$ on the quality of the TS and the solution for a fleet size of two aircraft for a load factor between 70 and 100% capacity for a Scenario 2 test

| Fleet size | $I_{\max}$ | LP 1 items in BB / $N_{\text{runs}}$ | Solution value | Runtime |
|---|---|---|---|---|
| 2 | 100 | 3 / 100 | 3581 | 13 s |
| | 1000 | 1 / 100 | 2768 | 112 s |
| | 10000 | 0 / 100 | 2704 | 471 s |
| 6 | 100 | 2 / 100 | 15375 | 63 s |
| | 1000 | 1 / 100 | 14210 | 136 s |
| | 10000 | 0 / 100 | 13573 | 721 s |
| 12 | 100 | 1 / 100 | 49829 | 43 s |
| | 1000 | 0 / 100 | 47012 | 291 s |
| | 10000 | 0 / 100 | 43095 | 1150 s |

## 6.2 Load configuration

A feasible Scenario 2 solution is presented in Figure 6.2 for an input of 24 pax and four pallets. An optimal configuration is obtained with an objective value of 0.004. Each aircraft cabin is shown as a rectangular box divided into compartments. The dark green dot represents the aircraft's longitudinal CG, while the green dashed line indicates the target CG location. The yellow area represents the MAC over the full cabin width, and the green area indicates the feasible CG region. The RPC reflects the additional transport capacity that could be used if the loadmaster decides to schedule an extra aircraft to carry BB items. This solution, with $L$=1.103%, has an IUR of 0.06 and an RPC of 42844 lbs.

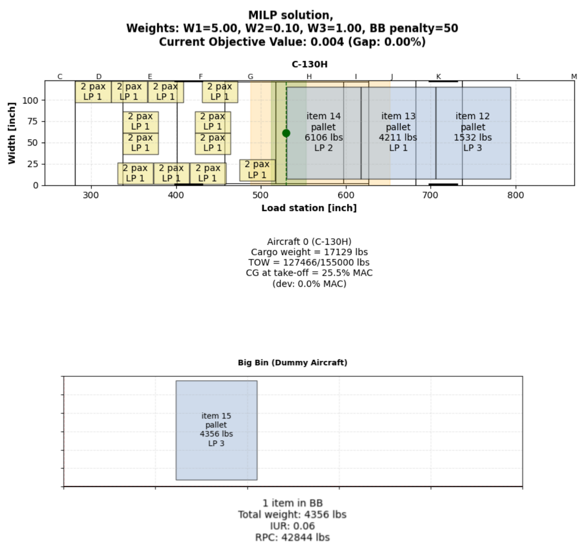
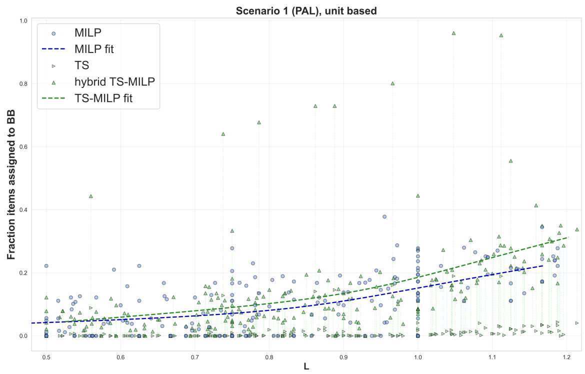


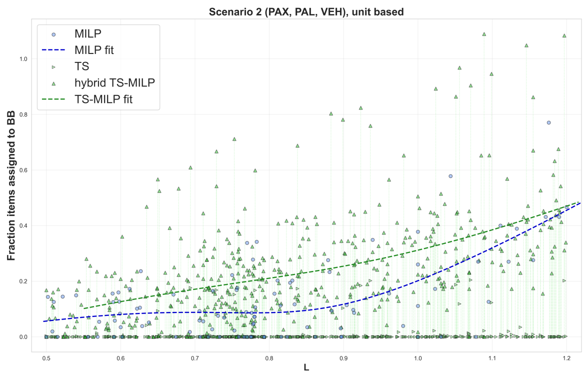

**Figure 6.2:** A Scenario 2 load configuration

## 6.3 Effect of load factor and item composition

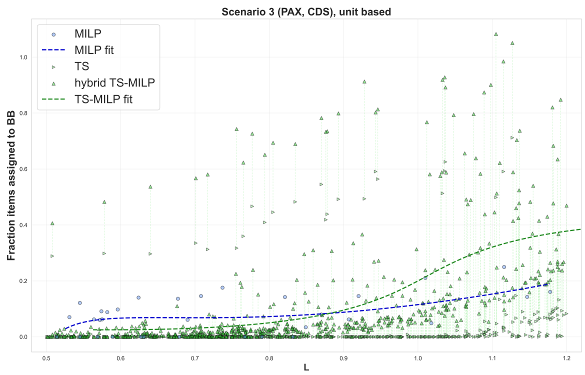
The load factor $L$ is used to scale the input instances and to control the amount of cargo relative to the available fleet capacity. A low value of $L$ represents a relatively light mission, while a high value of $L$ creates a harder planning problem in which the fleet is closer to or above capacity. Then the importance to the load priorities of the items are addressed.




**(a)** Scenario 1 (PAL)




**(b)** Scenario 2 (PAX/PAL/VEH)




**(c)** Scenario 3 (PAX/CDS)

**Figure 6.3:** Unit Based IUR: the trendlines describe the number of items assigned to the BB as a fraction of the total number of input items, al converted in spatial unit costs

Figure 6.3 presents the effect of $L$ on the number of items being assigned to the BB in the final solution of the hybrid TS-MILP model, as expressed in IUR. Recall that the IUR describes the number of items placed in the BB as a fraction of the total number of items available. For Scenario 2 and 3 all items are converted to the spacial unit costs, as described in subsection 5.1.1.

The blue datapoints in Figure 6.3 present MILP results, where the dots present the IUR for varying values of $L$. The blue trendline is a parametric fit to the generated results. The green right-pointing triangles show the IUR after Layer 1 in the hybrid model. When the fraction of items assigned to the BB is zero, it means that the nominator is zero and no items are placed in the BB. The right-pointing triangles are connected with a vertical green line to green upward-pointing triangles depicting the IUR after MILP refinement in Layer 2. The dark green dashed trendline is fitted to the TS-MILP results.

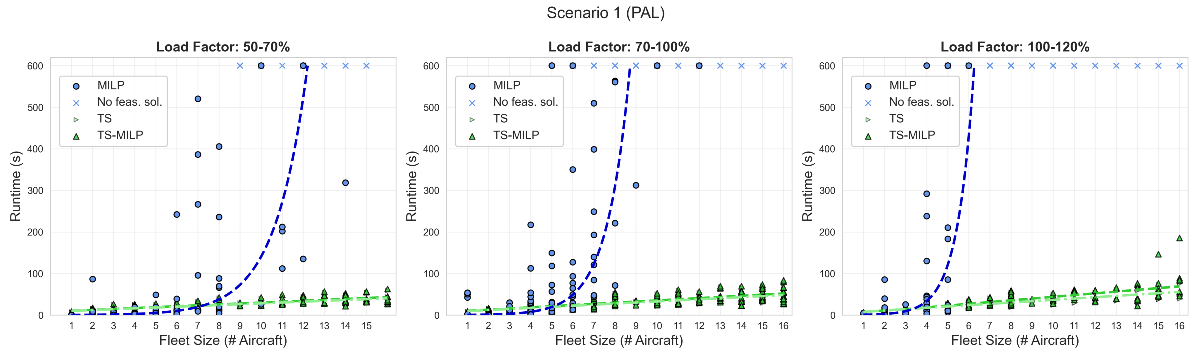
## 6.4 Scalability

The temporal performance of MILP and TS-MILP is reported in Figure 6.4. A time limit of 600 s is imposed for all runs. The horizontal axis represents fleet size and the vertical axis represents runtime in seconds. In the figure, MILP outcomes are shown in blue, where circles indicate runs that return a solution within the time limit and crosses indicate runs that terminate at the limit. The runtime trend shown for MILP is exponential. Linear trendlines are reported for Layer 1 TS and for the total TS-MILP runtime.

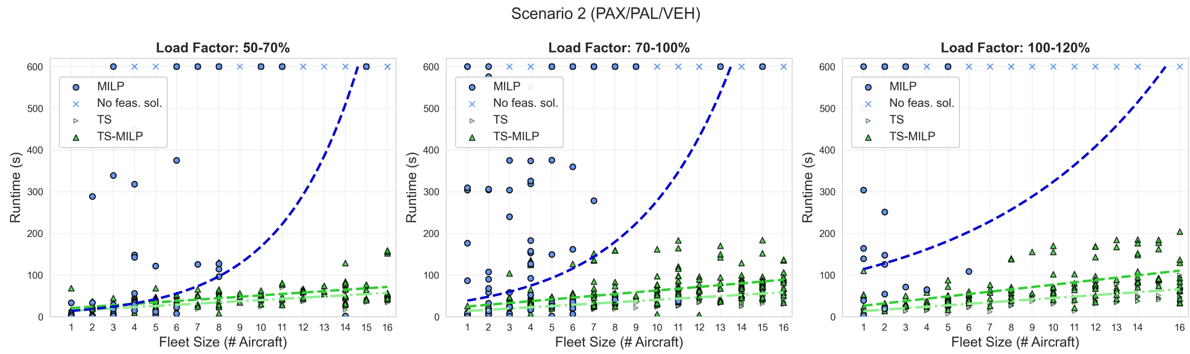
## 6.5 Quality of final results

The quality of the final results is reported using two groups of metrics: mean objective value and success rate. Table 6.2 is sorted by fleet-size (1–2, 3–4, 5–8, 9–16) and scenario, and includes separate run counts for MILP and TS-MILP. For TS-MILP, the reported objective is the final aggregated objective after per-aircraft MILP refinement, so that values are derived equally as for the full MILP model, filling in the decision variables in the objective function.

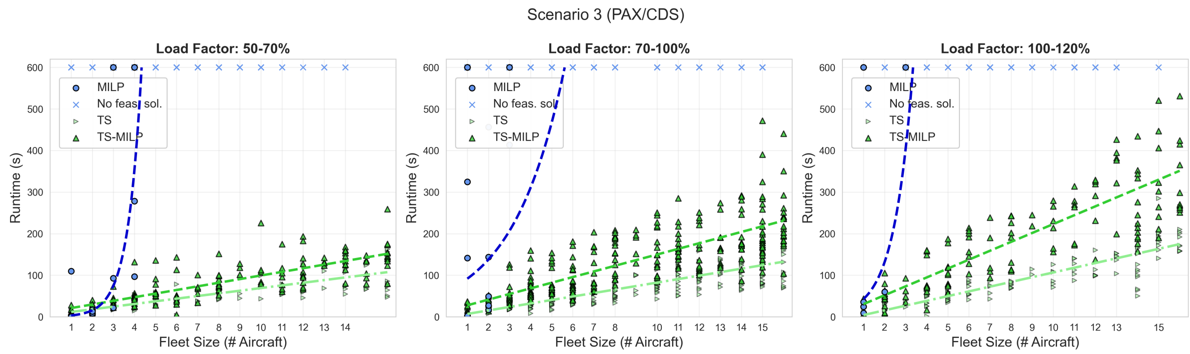
The objective value columns show that values vary across both scenario and fleet size. In MILP rows, objective values are reported for all Scenario 1 and Scenario 2 bins, while for Scenario 3 no MILP objective is available in the largest two fleet bins (shown as "–"). The success-rate columns report different value ranges by method: MILP spans from 0.0% to 100.0% across the table, while TS-MILP ranges from 93.4% to 100.0%. These percentages are calculated from the full set of runs listed in the corresponding $N_{\text{runs}}$ columns.




**(a)** Scenario 1 (PAL)




**(b)** Scenario 2 (PAX/PAL/VEH)




**(c)** Scenario 3 (PAX/CDS)

**Figure 6.4:** Runtime versus fleet size for all scenarios and varying load factor

**Table 6.2:** Quality of results

| | | $N_{runs}$ | | Objective value mean | | Success rate | |
|---|---|---|---|---|---|---|---|
| Fleet size | Scenario | MILP | TS-MILP | MILP | TS-MILP | MILP | TS-MILP |
| 1-2 | 1 | 77 | 50 | 0.0100 | 0.0137 | 100.0% | 100.0% |
| | 2 | 50 | 50 | 0.0148 | 0.0193 | 94.0% | 98.0% |
| | 3 | 55 | 50 | 0.0108 | 0.0035 | 45.5% | 100.0% |
| 3-4 | 1 | 94 | 80 | 0.0223 | 0.0111 | 97.9% | 100.0% |
| | 2 | 56 | 80 | 0.0188 | 0.0525 | 73.2% | 94.8% |
| | 3 | 72 | 80 | 0.0625 | 0.0218 | 16.7% | 98.8% |
| 5-8 | 1 | 142 | 150 | 0.0281 | 0.0394 | 61.3% | 99.9% |
| | 2 | 90 | 150 | 0.0121 | 0.0581 | 36.7% | 95.1% |
| | 3 | 102 | 150 | – | 0.0490 | 0.0% | 96.7% |
| 9-16 | 1 | 145 | 240 | 0.0347 | 0.0781 | 9.0% | 99.7% |
| | 2 | 81 | 240 | 0.0154 | 0.1103 | 11.1% | 93.2% |
| | 3 | 50 | 240 | – | 0.1339 | 0.0% | 89.8% |

# 7
# Discussion

This section discusses the outcomes of the results, followed by identifying the strengths and limitations for solving the LPP optimisation. The results show a clear difference in performance for both models. The solution runtime for MILP increases exponentially, leading to a low success rate within the set time limit. The exact MILP approach is valuable when the problem size remains small and an optimal or near-optimal solution is required. When the fleet size and the load factor increase, runtime grows exponentially and practical use for operations becomes limited. TS-MILP bridges this gap and with a layered approach finds solutions quickly. When a "good" solution is sufficient for mission planning, introducing TS-MILP is of great value to aid the planning process. Further research is needed to determine whether a mission planner would want to use the tool as a fully standalone planning solution.

## 7.1 Solution quality

Using MILP as a baseline for comparing solution quality is tricky. MILP proves to find the optimal solution, but only few solutions are found for large test instances. Table 6.2 shows that when MILP does find a solution, the mean objective value is better for MILP (lower objective) compared to TS-MILP. There are two exceptions. Both are discussed below.

For single-type loading in Scenario 1 with pallets, the trendline in Figure 6.3a shows that MILP has a more effective item sorting than TS-MILP. So how can the optimal MILP objective be lower than TS-MILP? The objective value is a function of effective fleet use, prioritised item loading and CG balancing. One reason could be that the item allocation in Layer 1 is less efficient in fleet utilisation, but the CG refinement in Layer 2 is more precise. The final objective value of a multi-objective algorithm does not directly indicate whether a solution is good or bad. Each solution should be inspected individually.

TS-MILP for Scenario 3 shows a higher solution quality than MILP. Figure 6.4c reflects in this principle, where, at the 600-second time limit, MILP is suboptimal. Many CDS are assigned to the BB for both methods, indicating that the constraints in the model may clash. Placing CDS bundles safely in the cabin is a task that is highly dependent on the interrelating weights of each bundle. The high success rates for TS-MILP always being above 89%, may show that MILP especially struggles to allocate items over the fleet. The success rate for TS-MILP is based on Layer 2 successes, and while the runtime increases for Layer 2 for larger fleets, a solution is often found.

## 7.2 Model effectiveness

For Scenario 1, MILP performs well for low cargo density in runtime for small fleet sizes, having a high overall success rate and few BB assignments. As fleet size and $L$ increase, fewer solutions are found within the time limit TS-MILP remains fast and keeps a high success rate above 99% from Table 6.2 for all fleets showing a slow linear increase in total runtime. The quality decreases slightly, caused by the basic TS algorithm that does not include compartment weight limits. To give an example, regarding space in the cabin, a C-130H can always fit 6 pallets. However, the load limit for the compartments at the rear of the cabin are 2500 lbs. If the lightest item of a given set of pallets weighs more than 2500 lbs, no item can be placed on the ramp and one item has to be left on the ground. As long as the MTOW is not exceeded, the TS will not know recognise the situation.

For Scenario 3 MILP has the lowest success rate in the reported results. The MILP formulation seems to be restrictive. A cause can be the constraint formulation for distributing and placing CDS in combination with pax on aircraft. For single-aircraft loading Scenario 3 works, and that is why the hybrid approach is so useful: Layer 1 already determines a CDS distribution, so Layer 2 can focus on exact per-aircraft refinement instead of solving the full assignment from scratch.

The TS is designed to fill the capacities of the real aircraft. When in Layer 1 an item is placed in the BB, the item has no chance of returning back to the final load configuration. An advantage of this mechanism is that a first good selection is made from all items based on priority value. Also, it means temporary capacity or MTOW infeasibilities can appear in Layer 1, but will be corrected in Layer 2. Layer 2 correction results in many additional items to be placed in the BB, indicating that the TS is not precise enough. Compartment weight limits and a more precise interrelated rules between item types could be included.

For TS-MILP, objective values are available for all fleet bins and the success-rate range remains high (93.4% to 100.0%). This indicates that the hybrid model consistently returns feasible refined outcomes, even in settings where full MILP frequently reaches the time limit.

### 7.3 Strengths and limitations

This section will discuss strengths and limitations regarding the modelling of TS and MILP algorithms applied to solving the LPP.

An important limitation of the layered TS-MILP architecture appears in Scenario 3 at high load factors. The CDS constraints create a small feasible region because bundles must follow strict weight-order rules. This means that small assignment errors in Layer 1 can still lead to weak final solutions after Layers 2 and 3. A more detailed TS objective could improve this by including weight distribution and cargo-combination effects already in Layer 1, instead of only capacity. In the same way, equal-weight passenger swaps can be reduced because they add little value to the search. So, the current capacity-based TS is not a perfect distribution method, but it does provide MILP with a useful head start.

An important finding is that objective weights and penalty values strongly influence the solution quality and behaviour of the model. This is a major advantage: loadmasters and planners can tune the model to mission priorities, for example prioritising critical cargo, reducing aircraft usage, or improving CG quality. At the same time, this sensitivity is also a challenge, because small changes in weights can lead to significantly different solutions, and to unintended behaviour. There is a fine line between the BB assignment objective term and making efficient use of the fleet. Using an available aircraft should always be preferred over assigning an item to the BB. Therefore, careful tuning and validation are essential before deployment, which can involve critically evaluating the configuration solution figures.

TS proves to be a good starting point for the LPP to help MILP find solutions. For a fleet of one to four aircraft, MILP can always be used. In small instances MILP proves to find the optimal solution in short runtimes. If the problem size gets larger, and a decision has to be made on multiple aircraft, TS-MILP should always be used. For pallet, troops or vehicle transportation, a loadmaster can explore multiple configurations within only 100 seconds. The model takes out all manual steps a loadmaster has to perform when making the distribution and puzzling where all items are positioned to be within the safety limits.

Having an automated tool that guarantees to find a feasible option is a great step. The TS-MILP does not guarantee global optimal solutions, but the heuristic first layer allows the generation of multiple configurations for one input set. A loadmaster can use the hybrid approach multiple times to generate multiple load plans, presenting more options to help in the decision-making process during planning.

### 7.4 Future directions

TS runs with BB assignments show large variability. The current scenarios may be too large and too random. Studying more specific scenarios, starting with single-type cargo and gradually increasing complexity, could improve understanding of algorithm behaviour.

A way to include more specific item constraints in a hybrid model, is to incorporate MILP in each TS iteration. Per iteration, the bitstring is decoded and the items are forwarded to an aircraft. Then, MILP refinement is perfomed per which is optimised using MILP. By using the exact objective value, a smart next neighbour can be generated in the tabu algorithm. The effect of merging Layer 2 in Layer 1 as a hybrid approach on the runtime and effectiveness of the algorithm can be investigated in future research.

Future work should focus on further refinement of cargo constraints and CDS handling, including the integration of additional weighting schemes into the TS objective function. Solely looking The successful application of TS as a first layer for capacity-based assignment, followed by MILP refinement, demonstrates significant potential for hybrid heuristic-exact approaches in military logistics.

## 8
## Conclusion

Depending on the type and size of military LPP, MILP and/or TS-MILP are suitable methods to guarantee a feasible load plan solution.

The complete MILP model is a strong baseline to find a solution. When the model finishes before the 600-second limit is reached, it shows that an optimal solution is found. The hybrid TS-MILP method combines a fast global assignment step (TS) with exact per-aircraft refinement (MILP), which makes the method usable in higher LPP complexity. When either of the models finish, a figure of the optimal configuration can be used as input for a load sheet with the configuration details for the loadmaster to use before take-off. The models provide a good starting point for a loadmaster by presenting feasible solutions. As the models are higly dependent on problem size, a loadmaster should remain in the loop to judge the results.

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**Part 2**

# Literature Review

## Nomenclature

| Abbreviation | Definition |
|---|---|
| BB | Big Bin |
| BOW | Basic Operating Weight |
| CG | Centre of Gravity |
| BPP | Bin Packing Problem |
| GA | Genetic Algorithm |
| HGA | Hybrid Genetic Algorithm |
| LPP | Load Planning Problem |
| LEMAC | Leading Edge Mean Aerodynamic Chord |
| LHS | Left Hand Side |
| LS | Load Station |
| LW | Landing Weight |
| MAC | Mean Aerodynamic Chord |
| MAR | Military Aviation Regulation |
| MILP | Mixed Integer Linear Programming |
| MLA | Militaire Luchtvaart Autoriteiten |
| MTOW | Maximum Take-Off Weight |
| NLD | Netherlands |
| NP | Nondeterministic Polynomial |
| OEW | Operational Empty Weight |
| Pax | Passenger |
| PSO | Particle Swarm Optimisation |
| RHS | Right Hand Side |
| RNLASF | Royal Netherlands Air and Space Force |
| SMLE | Speciale Militaire Luchtwaardigheids Eisen |
| TOW | Take-Off Weight |
| TS | Tabu Search |
| ULD | Unit Load Device |
| W&B | Weight and Balance |
| ZFW | Zero Fuel Weight |

# 1
# Literature review
## 1.1 Introduction

In crisis situations, airpower is often the only way to transport goods and troops to the relevant position/location. As pressure mounts or mission complexity grows, loadmasters' workload increases significantly. Compliance with (military) aviation regulations including tie-down requirements induce extra complexity. Loadmasters may struggle to fit all items into the cabin (and) to fulfill the operational needs and comply to the regulations, highlighting the need for more efficient load planning methods.

This Resarch Proposal document proposes a method to develop an automatic load planning model to improve the efficiency and performance of loadplanning for military transport aircraft.

To ensure the aircraft's centre of gravity (CG) remains within limits, loadmasters perform a manual, iterative loading process typically at the day of flight or one or two days before. For standard missions, fixed load configurations are usually sufficient. However, when non-standard cargo is transported and airdrop operations are involved, new configurations must be evaluated to guarantee feasibility. In situations with limited preparation time before flight or missions including intermediate stops with unloading and loading of cargo and troops, extra complexity is added to load planning.

How military aircraft are deployed within an operation depends on the mission. When aircraft fly under safe conditions from A to B at high altitudes and operate from designated runways, the mission is so called "strategic". Tactical missions are flown under more severe conditions. Runway conditions may be harsh and the aircraft fly at low altitudes (below 1,000 ft). The aircraft may directly participate in combat, combat support, and combat service, and the crew is trained in tactical operations in situations under threat [6]. Through air-drop operations, aircraft can launch paratroopers or deliver cargo loads by parachute directly over the deployment area. Flying tactical missions also imposes additional restraints on equipment on board due to more extreme manoeuvres and the possibility of unexpected movements. This is particularly relevant during emergency airlifts, where preparation time is limited and operational risks are high.

Air mobility supports the rapid movement of personnel and equipment globally and locally. The air force operate fixed-wing aircraft and helicopters for these missions. Troops and crews are trained to conduct aeromedical evacuations (medevacs), air-to-air refuelling, tactical airlanding operations, airdrop missions, and air-mobile operations [6].

It is the loadmaster's task to load the aircraft in such a way that all equipment, pallets, containers, and personnel are properly placed and restrained. The cabin is designed to accommodate different types of cargo: seats for troops are arranged in fixed configurations, equipment can be transported on pallets, in containers, or as loose items. All material must be tied down to handle g-forces in forward, aft, up, down, and lateral directions. The freedom to place items is limited by safety regulations, structural constraints, and aviation rules.

A critical constraint in load planning is the aircraft's CG, which must remain within strict limits defined by the aircraft manufacturer at all times. These limits ensure the aircraft remains controllable and stable under all phases of flight. If the CG is too far forward (nose-heavy), the aircraft requires greater elevator input to lift the nose, resulting in slower pitch response. If the CG is too far aft (tail-heavy), the aircraft becomes unstable, with a higher risk of over-rotation, loss of longitudinal stability, and difficulty in recovering from stalls. There is also an optimal CG position, at which trim drag is minimal and fuel consumption is optimised.

Optimisation algorithms support the generation of feasible load plans. Load planning determines where all equipment can be positioned in the cabin to ensure safe flight. This is called the Bin Packing Problem (BPP). Given a set of cargo items with specific dimensions, weight, and operational constraints, BPP optimisation produces a complete loading configuration. In transportation and logistics, BPPs are typically used to maximise load utilisation, maximise profit, minimise unused space, or optimise other operational objectives. For aircraft cargo, items are generally not stacked, resulting in a two-dimensional problem of where to place the cargo on the floor of the cabin/cargo space. Due to the combinatorial complexity of arranging cargo within all constraints, the load planning problem is classified as a nondeterministic polynomial (NP)-hard problem [3]. Typical for nondeterministic algorithms is that they can explore multiple options at once to find possible solutions [11].

This research proposes a model that automates the load planning process to reduce the workload for loadmasters and the logistic planning squadrons. The model will give optimised load planning suggestions, ensuring that the CG limits are always met, resulting in a more effective and efficient load planning process. Based on existing literature and existing bin packing methods, a model will be developed with optimisation techniques to suggest a load plan for an aircraft within the available fleet.

From the given introduction to the problem the following research question and research objectives follow:

**Research question**

How can an automatic optimisation model support the load planning process for military transport aircraft, such that feasible and safe load configurations are guaranteed and the loading of high prioritised items is optimised?

**Research objectives**

1. To identify key differences between civil and military load planning processes, focussing on mission objectives, cargo types, bin-packing methods and centre of gravity optimisation.
2. To review and evaluate the state of the art in load planning and optimisation algorithms, assessing their suitability for a military use case.
3. To define the specific constraints and performance criteria relevant to military load planning, including CG limits, airdrop considerations, operational preferences, and loading sequence priorities.
4. To develop a proof of concept automatic load planning model that generates feasible and optimised loading configurations based on the defined constraints and objectives.
5. To compare different optimisation techniques in terms of computational performance and the resulting load plan.
6. To evaluate the performance of the model in terms of solution quality compared to conventional load planning, examining improvements in feasibility, safety, and load-priority optimisation.
7. To conduct a case study on a representative military use case to validate the model and assess its operational applicability.

## 1.2 Background

This section provides the background needed to understand the load planning problem and the context in which this research is positioned. It introduces the operational environment of military air transport, the types of missions and cargo involved, and the constraints that shape load planning decisions. The section also gives an overview of relevant literature, including existing optimisation methods and current approaches to weight and balance.

At first the context for military load planning and air transport is presented in subsection 1.2.1. Then in **??** literature is discussed, focussing on design choises for load planning optimisation algorithms in existing studies across different domains. The state of the art for optimisation methods load planning is discussed in section 1.3 with an overview to current methods found in literature. Then section 1.4 identifies the research gap that motivates the work presented in this proposal.

### 1.2.1 Terminology and context

Military transport aircraft are designed to operate under a wide range of conditions and mission profiles. Within military air mobility, four main types of missions are distinguished: Air Transport, Airborne Operations, Aeromedical Evacuation and Personnel Recovery [6].

### 1.2.2 Strategic and tactical missions

Tactical aviation supports the army in combat, combat support, and combat service support [31]. This means that aircraft contribute to land-force operations by, for example, providing situational awareness throughout the area of operations and rapidly transporting tactical units and supplies over long distances. Each type of operation requires specific preparations to the aircraft and appropriate configuration of its cargo. In addition to these operational categories, missions are further distinguished by their operational risk level, which reflects the expected intensity of manoeuvring, environmental unpredictability, and urgency.

**Low-risk strategic missions**: These correspond to regular, planned transport flights conducted under predictable conditions. Threat levels are minimal and no tactical manoeuvres are anticipated.

**Medium- to high-risk tactical missions**: These represent operations with increasing operational complexity and risk. Tactical manoeuvring, low-level flying (below 1,000 ft), airdrop activities, and non-standard procedures may be required. At the highest risk levels, missions may approach near-combat conditions.

**Emergency airlift**: Highly time-critical operations conducted under significant urgency and elevated risk. Preparation time is limited, and cargo information may be incomplete.

The mission's risk category determines the expected aircraft manoeuvring profile and the required tie-down strength for equipment in the cabin. Higher-risk missions impose additional safety requirements. Emergency airlift operations fall outside the standard categories and are defined by intense time pressure and uncertainty regarding the cargo to be transported. When preparation time is limited, the workload placed on loadmasters increases significantly. Under higher-risk or time critical conditions, load planning becomes more demanding because every step—verifying cargo compatibility, restraint requirements, CG limits, and sequencing—must be carried out with full attention

Because operational conditions influence cargo-restraint requirements and feasible loading arrangements, the selected risk category directly shapes the solution space of the load planning problem. Different risk environments may lead to different optimal or near-optimal loading configurations, even when the cargo set remains unchanged. Therefore, these operational risk levels form an essential component of the optimisation model developed in this research.

### 1.2.3 Goods and equipment

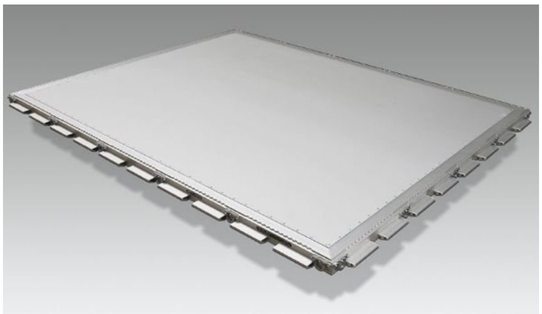
Commercial airlines transport freight on pallets or in containers with fixed dimensions, called a Unit Load Device (ULD). The use of ULDs with fixed dimensions provide easier handling and more efficient (un)loading for transportation [36]. Figure 1.1 shows an overview of commercial cargo, loose (Figure 1.1a, 1.1b) and fit in the cabin (Figure 1.1c, 1.1d). The cabins of freighter aircraft are typically only filled with ULDs.

Next to standardised aircraft cargo pallets, military air transport involves transporting a larger variety of cargo types and dimensions, see Figure 1.2. Common example of cargo are pallets, vehicles, trailers, airdrop platforms and loose equipment. Next to items, the aircraft carry two or more loadmasters in the cabin. The aircraft also transport paratroopers, wounded passengers, and normal passengers. Airdrop operations of both equipment and troops are also a core component of military air mobility. Special constraints apply with mixed configurations of cargo and people to the restraints of cargo in the cabin.

Special attention must be given to transporting dangerous goods, which can vary from flammable liquids and batteries to ammunition and hand grenades. These items are subject to strict handling, segregation, and stowage requirements to prevent accidents, ensure the safety of personnel, and maintain aircraft airworthiness. For example, incompatible dangerous goods must be separated by a minimum distance or by a physical barrier. The procedures for transporting these goods are detailed in the MAR-OPS X.1160 [34]. Compliance with these regulations is mandatory, and any deviations require prior authorisation from the responsible aviation authority.

The wide variety of cargo and operations in military air transport adds complexity to the load planning process. Also because items may impose additional constraints to other items and the loading configuration. In the case of airdrops, the aircraft must be well balanced before and after the dropping, and dropping sequence of cargo and/or troops also influence how the loads are arranged in the cabin. For missions with one or more intermediate stops for ressuply or goods delivery also introduce arrangement complexity. All of these factors are relevant to designing a complete load planning model.

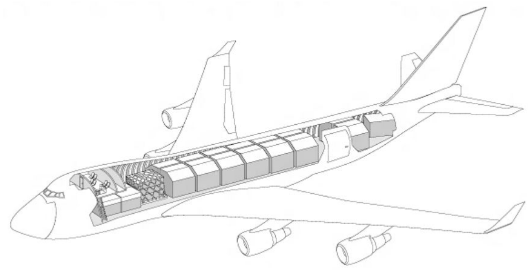
Load planning for transport aircraft which involves deciding how goods can be loaded into aircraft while meeting safety and operational constraints [17]. The problem can be divided into two phases: (1) to select the aircraft to be used from an available fleet and (2) to determine the load placement within each aircraft [12]. Various optimisation methods have been proposed to solve these problems, including hybrid genetic algorithms [5], mixed integer linear programming (MILP) [39][17][22], and heuristic



**(a)** Unloaded standard 463L pallet, from Noe [25]

**(b)** Standard cargo ULD, from Taiwan Fylin Industrial Co. [32]

**(c)** Loaded pallets in cabin, from International Air Transport Association [14]



**(d)** Loaded ULDs in cargo aircraft, from LogCluster [18]

**Figure 1.1:** Examples commercial air cargo

algorithms [12][22].

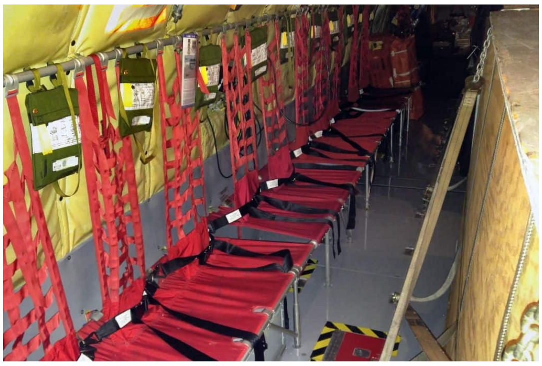
This section reviews the relevant literature in three domains: (1) weight and balance optimisation in subsection 1.2.4, (2) optimisation algorithms used in load planning in subsection 1.2.5, and (3) load planning in the military context in subsection 1.2.7.

### 1.2.4 Weight & balance

A variety of papers describe bin packing algorithms to solve the weight and balance (W&B) problem. Freighter aircraft primarily transport ULDs, so for those problems the main question is how to fit all the ULDs in the cabin for commercial purposes. This reflects in the objectives seen in the papers. A MILP mehod is described by Vancroonenburg who optimises revenue from transporting a set of cargo with given monetary value while also approaching the target CG [39]. The CG is a critical factor in load planning, as it directly affects the stability and efficiency of the aircraft [17]. A study from NLR stated that cargo flights compared to passenger flights have a 8.5 times higher risk of having W&B related accidents [38]. The CG should therefore always be within the limits that are defined by the aircraft manufacturer. CG limits are always taken as a constraint in weight and balance problems however, the CG can also be optimised. Each aircraft has a CG location measured from a reference datum at the front of the aircraft that is related to minimum trim drag during cruise[30]. This CG position is called the *optimal CG*. Therefore many papers aim to optimise this location, also as deviations from the optimal CG can result in increased fuel consumption and reduced stability [39].

Figure 1.3 shows a graphical representation of the CG limits during flight with the distance (in inches) from the reference datum on the x-axis, and the total weight of the aircraft (in lbs) on the y-axis. The green line represents the zero-fuel weight (ZFW), the red line the take-off weight (TOW), and the purple line the landing weight (LW). It is important to notice that the ZFW already includes weights of the cargo and operational staff on board the aircraft.

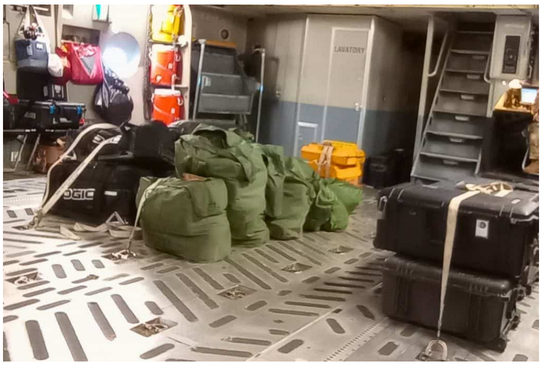
Research by Lurkin and Schyns [20] extends the W&B framework introduced by Limbourg, Schyns, and Laporte [17] to address the sequencing problem. The sequencing problem concerns the order



**(a)** A seating configuration on a KC-135 aircraft, from PoppinsSmoke [27]

**(b)** Unloaded standard wooden pallet, from U.S. Army [37]

**(c)** Combination of cargo and pax, from Ministerie van Defensie [21]



**(d)** Loose equipment loaded on a C-17, from PoppinsSmoke [27]

**(e)** Combination of different cargo types, from Think Defence [35]

**(f)** Tank loaded in cabin with help of loadmasters, from DVIDS [9]

**Figure 1.2:** Examples military air cargo

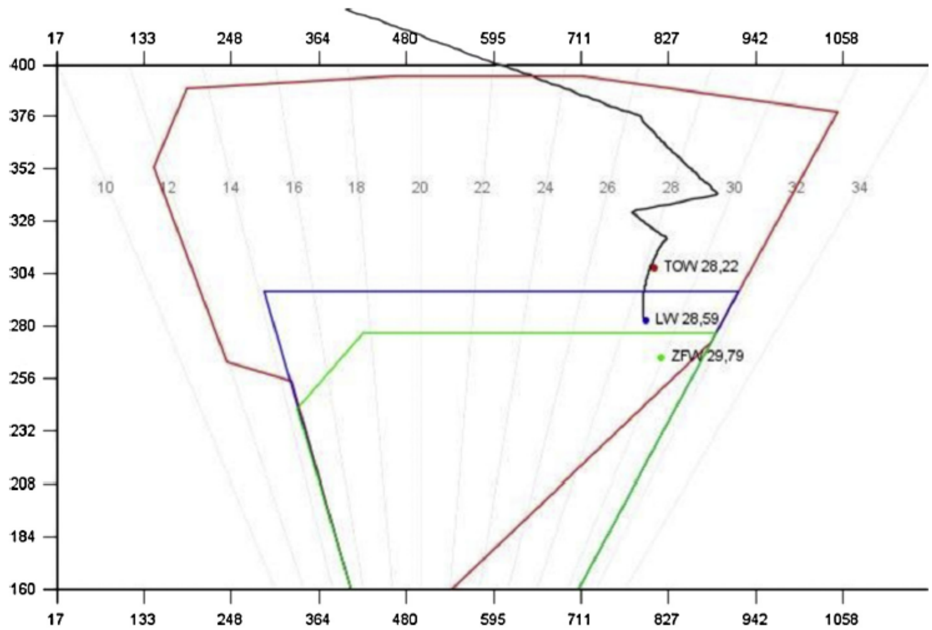



**Figure 1.3:** CG limits during flight[39]

in which cargo items are loaded and unloaded across multiple flight legs and how this affects the prescribed loading configuration. Sequencing is directly linked to W&B feasibility: an item that must be unloaded at an intermediate stop should not be obstructed by another item positioned between it and the exit. Reshuffling after unloading, or during the loading of new ULDs, may be required to restore an optimal CG for the next flight segment. In multi-leg missions—particularly when multiple cargo doors are available and different loading routes are possible—sequencing and W&B constraints interact closely, increasing the overall complexity of the problem.

### 1.2.5 Optimisation algorithms

The load planning problem (LPP) can be approached with different optimisation techniques. Each technique has different properties and comes with specific capabilities and limitations. Depending on the type of constraints and input paramters some techniques may be more favourable than others. Main factors to consider are (non)linearity of the problem and the desired outcome, so whether the model guarantees to give the best solution, or a solution that is good enough. Table 1.1 presents an overview of relevant optimisation algorithms for the LPP.

**MILP** is a popular optimisation method. For MILP the constraints, as the name indicates, are linear. The optimal solution might be a non-integer number, so then the program evaluates the objective function at possible solutions in the solution space using branch-and-bound [13]. The combination with the best value (either minimum or maximum depending on the objective) is the optimal solution. The corresponding values for the decision variables are the solution to the optimisation problem. As being an exact algorithm, the optimal solution is guaranteed to be optimal.

For problems that are not linear, mixed integer progamming (MIP) can be used. It works through the same method as MILP, but can now handle nonlinear objective or constraints [13].

Where MILP is an exact algorithm that might take some time to converge towards the global optimum, metaheuristics come in handy. Metaheuristics are becoming more popular lately as succesful alternatives to exact optimisation problems[4]. Within the solution space of the problem, heuristics search for a good solution, and are hence called approximate algorithms. The strategy for how the search spaces are explored depend on the type of algorithm.

**Genetic Algorithms (GA)** simulate natural selection to search for finding approximate solutions[40]. Candidate solutions, represented as chromosomes, undergo operations that look like the biological processes of mutation, crossover, and selection to evolve successive generations. GAs produce a set of high-quality solutions rather than always the global optimum. As a heuristic method, there is no guarantee of optimality, but GAs are particularly useful for multi-objective or combinatorial problems like LPP, where multiple feasible load plans are desirable.

**Tabu Search (TS)** is a stochastic optimisation method that begins with an initial solution $x_0$ and iteratively explores the best new neighbouring solutions[4]. The search is guided by a tabu list that prevents revisiting solutions that are already recently explored. The algorithm is good for avoiding local optima, and the quality of the solution depends on how the parameters are tuned [26]. The algorithm stops when a stopping criterion is met, either when an acceptable solution is found or when a maximum number of iterations or computational effort is reached. TS is effective for large, complex LPPs but does not guarantee a global optimum. The algorithm produces an array of solutions from which the preferred "best" one can be chosen [29].

**Particle Swarm Optimisation (PSO)** can quickly converge to a near-optimal solution[40] and is one of the most successful optimisation algorithms [2]. This method is popular due the simple structure and large search range[44]. A swarm of particles explores the solution space, updating their positions based on individual and collective experience[7]. The algorithm iterates until a stopping criterion is met, typically when the particle with the best fitness value satisfies predefined conditions. The final solution corresponds to the particle with the best fitness. PSO can require considerable execution time but is particularly suited for problems with complex, nonlinear relationships between variables. For multi-objective optimisation PSO can divide the problem into sub problems and simultaneously optimise two objective function[44]. Research by Tayebi, Nejad, and Mola [33] compared a case study by solving the problem with PSO and GA. They concluded that PSO is more accurate and faster than GA, and that PSO is easier to use.

**Table 1.1:** Optimisation methods to solve LPP

| **Optimisation method** | Mixed-Integer Linear Programming | Genetic Algorithm | Tabu Search | Particle Swarm Optimisation |
|---|---|---|---|---|
| **Type of solution** | Exact | Approximate | Approximate | Approximate |
| **Method** | Exact | Metaheuristic | Metaheuristc | Metaheuristic |
| **Search strategy** | Tree search | Population-based | Local Neighbourhood | Swarm-based |
| **Problem type** | Linear | Nonlinear | Nonlinear | Nonlinear |
| **Tools** | Gurobi, CPLEX | - | - | C language |
| **Global optimum** | Yes | No | No | No |

### 1.2.6 Multi objective optimisation

When solving a single-objective optimisation problem, the result is one solution being either the highest (for maximisation) or lowest (for minimisation) value of the objective function. The values of the decision variables in the objective form the solution to the problem. In contrast, multi-objective optimisation involves two or more objectives that typically conflict with one another. Instead of a single optimum, the solution space of a bi-objective problem forms a two-dimensional field. The set of solutions for which no objective can be improved without worsening another defines the Pareto front.

A multi-objective problem can be forulated as a vector $Z(x) = (Z_1(x), ..., Z_n(x))$ with $n$ objectives. In this case there is not one single optimal solution, but a set of feasible solutions $S$ that optimise the objective functions $Z_n$ [7]. The Pareto-set $P$ contains all Pareto optional solutions. The Pareto front is used to choose the best solution: the best trade-off among the solutions in the objective space is up to the decision maker [15].

A visual representation of the Pareto front for a bi-objective optimisation problem is presented in Figure 1.4. The figure presents an example of a problem that optimises engine noise (on the x-axis) and BSFC (y-axis) and show the trade-off of the objectives along the Pareto-optimal front.

A common scalar formulation for a bi-objective optimisation problem is $O = (O_1K_1 + O_2K_2)$ where $K_1 + K_2 = 1$. Weighting factors $K_1$ and $K_2$ express the relative importance of each objective. A scaling factor is often used for $O_1, O_2$ such that the objectives can be compared and such that the convergence criteria on the parameter changes become the same [10].

### 1.2.7 Military load planning

Military and civil load planning have much in common. Both parties have to comply to many regulations for air transport. Additional military regulations are bundled in Military Aviation Regulation

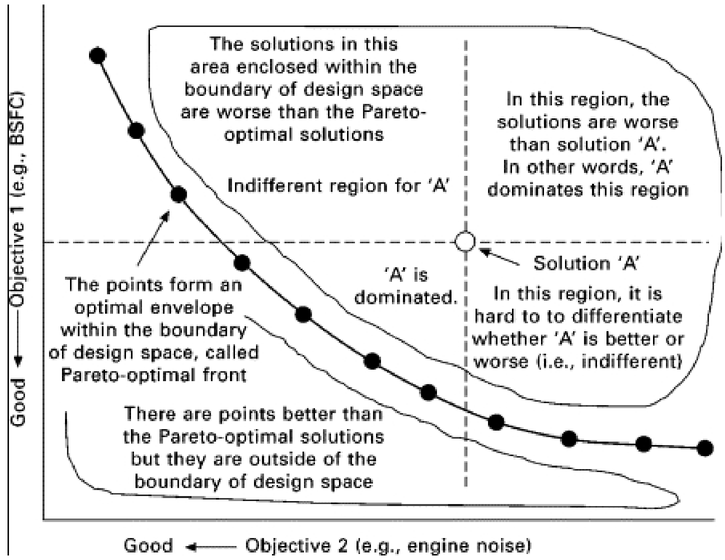



**Figure 1.4:** Figure supporting the concept of Pareto front [43]

(MAR) documents set by the Military Aviation Authority Netherlands (MLA, NLD).

Military load planning has different requirements than civil load planning. Due to the diversity of transported items, the presence of troops on board in the same cabin as cargo and mission-dependent constraints extra rules are induced to military aviation.

In preparation for this research, field interviews were conducted with loadmasters from the RNLASF who plan and execute cargo loading on C-130 and CH-47 aircraft. These interviews show that current military load planning is predominantly a manual, experience-driven process. For standard missions with familiar cargo types, load planning is relatively straightforward. However, complexity increases rapidly when multiple cargo items, mixed passenger configurations, or multiple available aircraft must be coordinated. Loadmasters typically explore loading options through trial-and-error until they find a configuration that both fits physically and satisfies the safety constraints.

A critical aspect of military load planning is ensuring that the aircraft's CG remains within allowable limits. Loadmasters must distribute mass such that the CG stays within the envelope at all phases of flight. If these limits are exceeded, the aircraft is not allowed to take off. After completing the weight and balance calculations, the loadmaster reports the final cargo configuration and CG position.

When troops or paratroopers are transported, the available cargo space becomes dependent on the required seating configuration. Seats are installed in fixed blocks (typically per eight seats), and reducing or expanding passenger capacity changes the remaining usable cabin floor area. Mixed configurations of cargo, standard passengers and paratroopers introduce additional constraints, especially regarding tie-down rules and access routes within the cabin.

Military load planning is governed by requirements set by the MLA, including tie-down procedures and load-restraint rules (MAR-OPS X.1160 [34]). When passengers and cargo are transported together, tie-down requirements become significantly stricter.

Operational practice also includes rules not typically found in civilian operations. For example, dangerous goods—such as ammunition, flammable liquids or batteries—are preferably loaded next to the ramp such that in case of emergency, they can throw the dangerous goods out.

Operational staff that plans the mission set up a priority list for the cargo that are to be transported. When cargo does not fit, this priority list determines which items must be flown.

The cargo floors of military transport aircraft are equipped with tie-down points arranged in a fixed grid. Each item must be restrained to withstand forces from all directions and must typically be tied to at least four independent floor stations. Unlike automated models, loadmasters use practical experience to judge how items interact, how loading sequences should be organised, and whether a configuration is realistically feasible—even if it technically satisfies dimensions and CG limits.

An overview of the aircraft considered in this research, including representative payload limits and

**Table 1.2:** Description of aircraft in the available fleet

| Aircraft type # | Available in fleet | Aircraft name | Cargo | Maximum pax | Maximum normal paylaod (lbs) |
|---|---|---|---|---|---|
| A1 | 2 | C-130H [1] | 6 pallets | 92 combat troops or 64 paratroopers | 36,500 (42,000 max) |
| A2 | 2 | C-130H-30 [1] | 8 pallets | 128 combat troops or 92 paratroopers | 36,000 (44,000 max) |
| A3 | 4 | CH-47D [23] | 3 pallets | 33 combat troops | 24,000 (27,700 max) |

cabin capacities, is shown in Table 1.2. These reflect typical operational characteristics rather than manufacturer-maximum values, as used in day-to-day planning.

## 1.3 Current state of LPP optimisation algorithms

Aircraft load planning problems are generally solved for two primary applications: commercial and military. Commercial applications focus on cost efficiency, often by maximising profit or load, and minimising trim drag or fuel consumption [8, 16, 17, 19, 22, 39, 41, 45]. Profit results from loading and delivering cargo with a specific value, and costs are determined by fuel consumption. Military applications, on the other hand, prioritise operational efficiency rather than profit. Objectives include maximising loaded priority per flight [7], or minimising the total number of aircraft needed for a mission [29, 24, 42]. Depending on the problem formulation, mathematical models or heuristics are used to solve these optimisation problems.

**Table 1.3:** Overview literature load planning

| First author | Year article | Application | Nonlinearity | Prioritised items | Method | Objective |
|---|---|---|---|---|---|---|
| Chenguang[5] | 2018 | commercial | | | HGA | min fuel |
| Dahmani[7] | 2016 | military | | x | PSO | 1: max weight, 2: max priority |
| Desai[8] | 2023 | commercial | nonlinear outer-envelope & linearised envelope | | MINLP | min CG deviation |
| Gueret[12] | 2003 | military | | x | heuristics | min flights |
| Li[16] | 2012 | commercial | | | heuristics | 1: min trim drag, 2: max load factor |
| Limbourg[17] | 2012 | commercial | linearised cumulative weight distribution | | MILP | 1: min MoI, 2:min CG deviation |
| Lu[19] | 2023 | commercial | linear and nonlinear constraints | | first MIP, then GA | min CG deviation, 2: max load |
| Lurkin[20] | 2015 | commercial | | | MILP | min CG deviation |
| Mongeau[22] | 2003 | commercial | approximated constraints to avoid nonlinearity | | MILP | max load |
| Nance[24] | 2011 | military | nonlinear objective function | | TS | min number of aircraft |
| Roesener[29] | 2016 | military | nonlinear objective function | | TS | min flights |
| Vancroonenburg[39] | 2014 | commercial | nonlinear cumulative load constraints | x | MIP | 1: max profit, 2: min CG deviation |
| Verstichel[41] | 2011 | commercial | linearised envelope constraints | x | MIP | 1: max profit, 2: min CG deviation |
| Wesolkowski[42] | 2010 | military | | | GA | min number of aircraft |
| Zhao[45] | 2021 | commercial | linearised nonlinear CG constraints | | MILP | 1: max load, 2: min CG deviation |

The methods used in the literature include exact optimisation, such as MILP, and metaheuristics, including GAs, PSO and TS. Problems that optimise for minimum CG deviation typically employ MILP formulations [8, 17, 19, 39, 41, 45], mainly for commercial applications. Metaheuristics are commonly used for problems with complex priorities or multi-aircraft load planning. For example, PSO can be used to maximise loaded priority [7], TS to minimise the number of flights [29, 24], and GA for fleet-level load planning [42, 5]. An overview of the reviewed papers, including their methods, objectives, and constraints, is provided in Table 1.3. The $x$ in the column *Prioritised items* tell whether the author included a priority factor for the cargo.

In addition to weight and balance optimisation, a MILP formulation has also been used to address the sequencing problem in multi-leg missions, ensuring correct unloading sequencing. Lurkin and Schyns [20] demonstrate that MILP can effectively integrate sequencing decisions with CG feasibility, allowing reshuffling strategies to be evaluated while maintaining stability and operational constraints. This highlights MILP's ability to couple spatial placement with temporal logistics decisions in transport scenarios.

Compared to conventional optimisation algorithms, stochastic and evolutionary methods handle nonlinear constraints and objective functions more naturally. For example, Desai et al. [8] attempted to solve the load planning problem as a nonlinear mixed-integer problem, where two constraints related to the aircraft's CG are nonlinear due to the longitudinal and lateral positions of assigned ULDs. The resulting model took over 13 minutes to generate a solution. By applying a linearisation technique, they reformulated the problem as a MILP, achieving near-optimal solutions within 120 seconds for all tested configurations, particularly for double-row ULD arrangements. Desai et al. [8] also compared their model to a simpler approach used by a large air cargo operator, which suffices for single-row configurations but is less efficient for more complex layouts.

Vancroonenburg et al. [39] propose a MILP model for single-aircraft load planning, whereas Roesener and Barnes [29] apply Tabu Search for multi-aircraft problems. Both focus on single-type ULDs, highlighting a limitation in scaling to multiple aircraft or mixed cargo sizes. Chenguang, Hu, and Yuan [5] address this by proposing a hybrid genetic algorithm (HGA) that combines a traditional GA with heuristics. The heuristics solve the 2D bin packing problem while the GA allocates the loads to multiple aircraft, decoding candidate solutions using rules to generate feasible load plans.

Existing models often focus on loading pallets or cargo only or the combination of cargo and troop transport. Troop transport introduces additional safety requirements and operational constraints. Only Gueret et al. [12] consider both soldiers and cargo items. For standardised ULD sets Vancroonenburg et al. [39] demonstrate improvements in lateral balance up to 89% compared to expert plans. However, non-standardised items introduce new parameters and constraints, which have not been fully addressed. Single-aircraft load planning is often simpler, while multi-aircraft scenarios require additional heuristics to distribute items efficiently across a fleet [5].

The placement of items within the aircraft cabin is another key consideration. Some studies, such as Vancroonenburg et al. [39], place ULDs in fixed position slots to minimise fuel consumption, where larger items may occupy multiple slots, limiting possible configurations. Other approaches, such as Chenguang, Hu, and Yuan [5], allow ULDs to be placed freely within the cabin, increasing the solution space and problem complexity. Heuristic algorithms based on item priority, e.g., longest side length first, are used to manage loading efficiently [5]. CG limits are incorporated in various ways: Wesolkowski, Mazurek, and Stuive [42] apply maximum load capacity per aircraft without explicit CG constraints, Mongeau and Bès [22] set a maximum allowable CG deviation, and Limbourg, Schyns, and Laporte [17] calculate the moment of inertia for the full aircraft to improve computational efficiency.

The feasibility envelope defines the upper and lower bounds for CG location, which depend on total aircraft weight and change during flight as fuel is consumed. Nonlinearities in the envelope induce nonlinear CG constraints, which are handled differently across studies. Vancroonenburg et al. [39] linearise constraints at critical moments, Zhao et al. [45] linearise the nonlinear CG problem and solve it as MILP, and Lu et al. [19] keep the nonlinear constraints and solve the model as MIP. Mongeau and Bès [22] approximate the nonlinear constraints using a centering tolerance $\epsilon$ as a percentage of the reference CG position.

Finally, structural limitations per aircraft section and overlapping areas are considered by Limbourg, Schyns, and Laporte [17]. Their approach, calculating the moment of inertia of the full aircraft rather than only the CG, results in a program that runs 16 times faster while respecting structural and balance constraints.

In summary, the state of the art demonstrates the current methods and approaches to load planning optimisation, particularly for commercial applications. Military-specific requirements, including troop transport, situational priorities, multi-aircraft fleets, non-standardised items and temporal constraints, remain underexplored. These gaps form the foundation for further research and the development of situationally and mission-dependent load planning models.

## 1.4 Research gap

Despite extensive research in aircraft load planning, a substantial gap remains for military applications. Most existing studies focus on loading pallets or cargo in ways that minimise fuel consumption or maximise profit. In commercial applications, the primary objective is often weight and balance optimisation for efficiency. In contrast, military operations rarely have a profit motive. Instead, the focus is on using each flight efficiently, either by maximising the loaded priority of items per flight or effectively using the least number of aircraft needed for a mission. Depending on the chosen objectives and constraints, these problems are solved using mathematical models or heuristics.

A key gap in existing research is the inclusion of troops *and* cargo, which introduces additional safety requirements and operational constraints. While some studies discuss the combination of soldiers and cargo items [12], most models focus solely on pallets or cargo, without considering timing constraints or the varying priorities of items. Roesener and Barnes [29] are unique in including temporal constraints, specifying the earliest possible and latest required delivery dates for each cargo item. However, their work still considers only pallets and does not include troop transport.

Another gap relates to the variability of item priorities in military missions. Dahmani and Krichen [7] assign fixed priorities to items, but in military operations, the priority of an item may change depending on the situation. Similarly, Richardson et al. [28] highlight the complexity of military load planning, noting the diversity of equipment, mission-specific requirements, and safety constraints. A model for military applications must therefore provide a situational, mission-dependent load plan capable of handling multiple item types, troops, priorities, and operational requirements across single or multiple-leg flights.

Another gap concerns the operational relationships between items, which have not been addressed in the literature. Military missions frequently involve items that must be transported together, in a particular order, or under specific conditions that depend on other items. For example, when specialised equipment is delivered on the first flight, a specific number of troops may be required to accompany and secure it until the remaining equipment arrives on a subsequent flight. Such operational requirements affect both the load plan and the feasible loading configuration, yet these dependencies are not incorporated in current models.

Finally, existing research often addresses only one of the three fundamental questions of load planning: *what* is transported, *when* it is taken and delivered, and *how* it is placed in the aircraft. Optimising the priorities of items ensures that all necessary items are transported [12], while maximising loaded weight or profit can also determine *what* is loaded [7, 22, 45, 39, 41]. Time constraints are addressed only by Roesener and Barnes [29], which determines *when* items must be transported. The placement of items (*how*) is often optimised to achieve the smallest deviation from a given centre of gravity, improving fuel efficiency [8, 16, 17, 19, 39, 41, 45]. However, no single objective integrates all three questions for military operations, including both cargo and troop transport, situational priorities, and mission-dependent constraints.

The main objective of this study is to develop a load planning model that is situationally and mission-dependent, taking into account the priorities and urgency of the items to be transported in single flight leg missions. This will be achieved by incorporating input from the loadmaster, including items with special priority, situationally dependent levels of urgency, and time constraints, as well as mission-dependent objectives. Further interviews with loadmasters will be conducted to work towards determining the optimal number of alternative load-plan suggestions and the preferred level of detail in each, ensuring the model effectively supports operational decision-making. The goal is to provide a suggested load configuration that meets the operational requirements of the loadmasters and complies with military aviation regulations.

# 2
# Research Proposal

Section 2.1 presents the research question and objectives for this master's thesis, including a proposed methodology. The topic builds upon the literature and reserach gap presented in the previous section. The expected results, strengths and limitations are presented in section 2.3

## 2.1 Research question

Given an introduction to the project the following research question arised.

*How can an automatic loadplanning model be developed to optimise the load planning process for military aircraft to guarantee feasible and safe loadplans?*

### 2.1.1 Research objectives

1. To identify key differences between civil and military load planning processes, focussing on mission objectives, cargo types, bin-packing methods and centre of gravity optimisation.
2. To define specific constraints and performance criteria (CG limits, loading sequency prioritisation) for military load planning.
3. To develop an automatic load planning model that generates feasible and optimised loading configurations based on the defined constraints.

4. To evaluate effect of the model's performance on planning time and accuracy compared to manual load planning.
5. To conduct a case study on a specific military aircraft type to validate the model and asses its operational applicability.
6. To develop a scalable model capable of optimising load allocation for the use of multiple aircraft within a fleet.

### 2.1.2 Methodology

1. Literature review of existing load planning strategies and bin-packing optimisation models (military & civil cases). This will provide insight to the current state of the art.
2. The specific operational constraints and requirements for military cargo, troops and aircraft will be analysed. This includes weight and balance calculations, CG limits, loading sequence, prioritisation, and mission specific objectives. Analysis specific requirements and constraints military cargo, troops, and military aircraft
3. An automatic load planning model will be developed, integrating optimisation techniques to generate feasible and efficient load configurations complying to all limits and constraints. The model will also be scalable to optimal usage of aircraft when performing loadplanning for multiple available aircraft in a fleet.
4. A case study will be conducted on the use of the model by loadmasters of the C-130 Hercules transport aircraft, an aircraft type that is currently operational and in use by the RNLASF.
5. The model's performance will be evaluated based on workload, accuracy and time savings in the planning process.
6. The results of the validation and case study will be analysed to identify the model's benefits, limitations and areas for improvement. Reccommendations will be made for future research and development.

## 2.2 Method

The methodology used to develop the proof-of-concept automatic optimisation model for military load planning will be outlined. The approach consists of: defining the model structure in subsection 2.2.1, including constants, parameters, objectives, and constraints; subsection 2.2.5 selecting and justifying the optimisation methods; subsection 2.2.6 outlining the operational assumptions and simplifications.

### 2.2.1 Model

The load planning problem (LPP) is formulated as an optimisation problem in which a set of cargo items and passengers must be assigned to available aircraft during a mission. The model aims to generate feasible and safe loading configurations that respect aircraft and mission constraints while maximising operational priorities.

### 2.2.2 Constants and parameters

The model uses input parameters that describe the mission profile, cargo and passenger characteristics, and aircraft-specific details. Table 2.1 summarises all required inputs. These values may vary per operation and can be manually adjusted by loadmasters during planning.

Cargo is defined as any item that is not a passenger. This includes vehicles, pallets, aircraft floor plates, bags, ammunition boxes, containers, trailers, and other equipment types.

Passengers (pax) are categorised into regular passengers, combat troops, and paratroopers, each associated with a predefined standard weight. Paratroopers may have an airdrop classification equal to 1, indicating that they will exit the aircraft during a flight leg. For all other passenger types, the airdrop classification is set to 0.

Aircraft parameters include the aircraft type, fuel level, required crew, number of flight legs, and mission type. A mission is defined as a sequence of flight legs from the origin to the final destination.

Aircraft-specific structural constants such as fuel tank locations, CG envelopes, and maximum allowable cabin weight are included once the model is applied to real aircraft.

**Table 2.1:** Input parameters for the LPP

| | |
|---|---|
| **Cargo** | Identification number, cargo type, total weight, length, weight, spatial priority, loading priority dangerous goods classification, origin, destination, airdrop |
| **Pax** | Identification number, passenger type, total weight, equipment coupling, spatial priority, loading priority, origin, destination, airdrop |
| **Aircraft** | Identification number, aircraft type, origin, destination, number of flight legs, crew, fuel level, mission type |

### 2.2.3 Objective function

The primary objective is to maximise the operational priority of loaded items. This ensures that the model reflects practical considerations used by loadmasters. The LPP is treated as a multi-objective optimisation problem with two types of priorities:

$O_1$**: Spatial priority** reflects the preferred placement of items within the aircraft cabin:

- Placement of items in preferred compartments
- Separation of dangerous cargo and pax: if dangerous goods and pax are to be moved, they are preferably in different aircraft
- Proximity to exits for items that must be unloaded at intermediate stops.
- Proximity requirements between items or between pax and equipment.

$O_2$**: Loading priority** defines which items should be included on the flight:

- Mission-dependent priority of each item.
- The selection of items to be loaded when the cabin capacity is insufficient for all cargo.

In mathematical formulation the LPP objectives are given as follows:

$$O = \text{Maximise}\ (O_1K_1 + O_2K_2) \tag{2.1}$$

where $K_1$ and $K_2$ are weighting factors that can be adjusted to generate a Pareto front of optimal solutions, reflecting different trade-offs between spatial and loading priorities. By changing the ratios of $K$, multiple loading suggestions can be generated. Different correction factors and weighting factors will be tested and evaluated for the model

### 2.2.4 Constraints

To ensure the model generates feasible solutions, several constraints are incorporated into the optimisation model. These constraints guarantee that the load plan and pickup and delivery sequence are feasible and safe. The model accounts for operational, physical, and safety constraints. The following constraints are considered:

- **Centre of gravity (CG)**: Linear functions define the forward and aft CG limits as a function of the total aircraft weight. The CG must remain within allowable bounds throughout all flight phases and legs to maintain aircraft stability.
- **Position slots**: The cabin floor is divided into discrete position slots. Each cargo item occupies multiple slots depending on its size and shape. Free slots beneath an item cannot be used for other cargo.
- **Capacity and geometry**: Cargo items must fit within the cabin's length and width. Some items (e.g., pallets or loose items) can be rotated, while others (e.g., vehicles) cannot be rotated due to accessibility constraints (e.g., a vehicle cannot be driven in or out of the cabin if positioned sideways).
- **Aircraft limits**: The cabin's loaded weight must always be below the predefined load limits. Other structural limits include maximum container ramp loads, pallet loads, and maximum gross weight limits to prevent overloading and ensure aircraft safety.
- **Airdrop requirements**: Cargo or passengers designated for airdrop must be positioned next to an exit to facilitate quick accessibility during the corresponding flight leg.
- **Separation of dangerous goods**: Dangerous items must maintain minimum distances from passengers and other equipment or be assigned to separate aircraft when feasible to ensure safety.
- **Loading sequence**: Items can only be unloaded at an intermediate stop if there are no items between the unloaded item and the exit. This means that the path to the exit must be clear to facilitate efficient

unloading.

### 2.2.5 Proposed method

The core LPP model is implemented as a multi-objective MILP. MILP is chosen because it can handle discrete decisions (assignment of items to position slots) and continuous variables (weights, CG), while guaranteeing exact optimisation under linear constraints. The decision variables include:

- A binary variable indicating whether a cargo item or passenger is assigned to a specific cabin slot, at specific flight leg(s) of an aircraft from the fleet.
- Continuous variables for CG calculation.

The model explores the solution space using branch-and-bound methods, ensuring that the optimal configuration maximising the weighted sum of spatial and loading priorities is found. By varying $K_1$ and $K_2$, the MILP produces multiple solutions along the Pareto front, allowing loadmasters to select configurations according to operational preferences.

MILP is well-suited for the proof-of-concept due to its ability to enforce all constraints simultaneously, including CG, cabin capacity, and separation rules. However, MILP performance decreases for:

- nonlinear constraints (e.g. nonlinear CG envelopes)
- large fleets

To address these limitations,the research will compare MILP solutions with those generated by the metaheuristic algorithms Tabu Search and Particle Swarm Optimisation (PSO). These methods are capable of efficiently exploring nonlinear and large search spaces while providing near-optimal solutions. GA is not selected as PSO is easier to use and operates faster and gives more accurate results than PSO [33].

This proof-of-concept load planning mode will then be tested on a representative military use case. The case study will serve to validate the model and assess its ability to generate feasible and optimised loading configurations. Following this, the model will be tested with loadmasters to identify potential improvements and to determine the optimal number of load plan suggestions that should be provided for most effective load planning support.

### 2.2.6 Assumptions and simplifications

The following aspects are assumed and simplifications are made in the model.

**Assumptions**

- Lateral balance is assumed to remain within limits and is therefore not explicitly modelled.
- No items are stacked and the model is two dimensional; all items are assumed to fit in cabin height ($H_i < H_{cabin}$).
- Each item occupies four cabin position slots. $H_i < H_{cabin}$ So the height of the item is always smaller than the cabin.
- A mission may contain multiple flight legs; the number of legs equals the number of intermediate stops minus one.

**Simplifications**

- For an item with surface area $S$, the full weight is applied at the longitudinal CG point, ignoring distributed loading effects.
- External sling loads (e.g. CH-47 hooks) are not considered; only internal loading is modelled.

## 2.3 Scope

In this section the expected results for this project are presented.

### 2.3.1 Outcome

A proof-of-concept load planning model will be developed to support military aircraft operations. The model enables loadmasters to evaluate and test multiple load configurations for a given mission while automatically ensuring compliance with operational, safety, and aircraft-specific constraints. By integrating cargo characteristics, passenger types, and aircraft parameters, the model produces feasible loading plans that respect CG limits and spatial requirements.

The model is designed to be scalable and adaptable to different aircraft types and fleet sizes. It can optimise the allocation of cargo and passengers across single or multiple aircraft, allowing mission planners to explore alternative configurations efficiently. The results of this research will provide a foundation for a practical decision-support tool for military load planning and could inform future extensions such as real-time planning under dynamic operational conditions.

### 2.3.2 Impact

Currently, load planning for military missions is a largely manual and time-consuming process, particularly for large equipment sets, non-standard cargo, or high-risk operations. Loadmasters rely on experience and trial-and-error approaches, which are prone to errors and inefficiencies. The proposed model addresses these challenges by generating feasible and optimised load plans automatically, reducing cognitive load and saving planning time.

By providing multiple alternative configurations, the model allows loadmasters to evaluate trade-offs and choose solutions that best meet operational priorities. It ensures compliance with spatial, loading, and safety constraints, including centre-of-gravity limits, thereby improving the reliability and safety of missions. The model has the potential to enhance mission efficiency, operational flexibility, and situational awareness, forming a basis for a future operational load planning tool.

### 2.3.3 Limitations

A key limitation of this project is its scope. Military cargo and passenger operations are governed by extensive regulations, and missions often involve last-minute changes, exemptions, or unusual circumstances. As such, the model should be viewed as a decision-support tool rather than a fully autonomous planner.

The model does not cover all possible mission-specific scenarios, such as transporting heavy equipment in combination with troops, medical evacuation under non-standard conditions, or other exceptional operational cases. Additionally, while the proof-of-concept demonstrates feasibility and scalability, full operational deployment would require extensive validation, certification, and integration with existing mission planning systems, which is beyond the scope of this research.

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**Part 3**

# Gantt Chart

| **Milestone** | **Original planning made at the start** | **Actual dates milestone meetings** | **Max. milestone deadlines according to part-time thesis** |
|---|---|---|---|
| Kick-off Meeting | 01-Oct-2025 | 01-Oct-2025 | |
| Literature Proposal | Week 13-Dec-2025 | 14-Dec-2025 | Week 29-Dec-2025 |
| Midterm | Week 23-Mar-2026 | 18-Mar-2026 | Week 06-Apr-2026 |
| Green Light | Week 01-June-2026 | 26-May-2026 | Week 06-Jul-2026 |
| Final Thesis Presentation | Week 06-Jul-2026 | 23-June-2026 | Week 27-Jul-2026 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Year | 2025 | | | | | | | | | | | | | | | | | | | |
| | | september | | october | | | | november | | | | december | | | | | january | | | | |
| | Week | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 1 | 2 | 3 | 4 | 5 | 6 |
| | Date | 22-09-2025 | 29-09-2025 | 06-10-2025 | 13-10-2025 | 20-10-2025 | 27-10-2025 | 03-11-2025 | 10-11-2025 | 17-11-2025 | 24-11-2025 | 01-12-2025 | 08-12-2025 | 15-12-2025 | 22-12-2025 | 29-12-2025 | 05-01-2026 | 12-01-2026 | 19-01-2026 | 26-01-2026 | 02-02-2026 |
| | Extra | | | | | | | | | | | | | | Christmas holidays | | | | | | Out of office |
| | Thesis week count | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
| 1 | Milestones | | | | | | | | | | | | | | | | | | | | |
| | Kick-off meeting | 25-09-2025 | | | | | | | | | | | | | | | | | | | |
| | Start thesis | | 01-10-2025 | | | | | | | | | | | | | | | | | | |
| | Research proposal Review | | | | | | | | | | | | hand in draft | Research Prop pres | | | | | | | |
| | Mid-term Review | | | | | | | | | | | | | | | | | | | | |
| | Green light Review | | | | | | | | | | | | | | | | | | | | |
| | Thesis Defence | | | | | | | | | | | | | | | | | | | | |
| 2 | Literature study | | | | | | | | | | | | | | | | | | | | |
| | Orientation topic | | | | | | | | | | | | | | | | | | | | |
| | Understand & Scope (read 20 papers) | | | | | | | | | | | | | | | | | | | | |
| | Description and comparison existing models | | | | | | | | | | | | | | | | | | | | |
| | Draft "state-of-the-art" section | | | | | | | | | | | | | | | | | | | | |
| | Find and describe research gap | | | | | | | | | | | | | | | | | | | | |
| | Propose 4-5 research questions | | | | | | | | | | | | | | | | | | | | |
| | Exploratory interviews | | | | | | | | | | | | | | | | | | | | |
| | Set up hypothesis + methods to test hypothesis | | | | | | | | | | | | | | | | | | | | |
| | Draft Timeline complete thesis | | | | | | | | | | | | | | | | | | | | |
| | Draft final Research Proposal | | | | | | | | | | | | | | | | | | | | |
| 3 | Conceptual design | | | | | | | | | | | | | | | | | | | | |
| | Decide on method & read about method | | | | | | | | | | | | | | | | | | | | |
| | start building model structure & framework | | | | | | | | | | | | | | | | | | | | |
| 4 | Model development | | | | | | | | | | | | | | | | | | | | |
| | build MILP | | | | | | | | | | | | | | | | | | | | |
| | build tabu search algorithm | | | | | | | | | | | | | | | | | | | | |
| 6 | Verification & Validation | | | | | | | | | | | | | | | | | | | | |
| | verify methods | | | | | | | | | | | | | | | | | | | | |
| | write thesis | | | | | | | | | | | | | | | | | | | | |
| 7 | Operational analysis | | | | | | | | | | | | | | | | | | | | |
| | perform operational analysis and test models | | | | | | | | | | | | | | | | | | | | |
| | plot results | | | | | | | | | | | | | | | | | | | | |
| 8 | Project conclusion | | | | | | | | | | | | | | | | | | | | |
| | 8.1 Synthesise main findings | | | | | | | | | | | | | | | | | | | | |
| | 8.2 Finalise thesis paper draft version | | | | | | | | | | | | | | | | | | | | |
| | 8.3 Prepare Greenlight | | | | | | | | | | | | | | | | | | | | |
| | 8.4 Finalise thesis paper | | | | | | | | | | | | | | | | | | | | |
| | 8.5 Prepare Defence | | | | | | | | | | | | | | | | | | | | |

| | |
|---|---|
| **Student Name** | **Iris van Alkemade** |
| **Student ID** | **508291** |
| **Principal Supervisor** | **Paul Roling** |

- planned milestone week
- deadline week draft versions
- deadline week
- holidays or out of office week
- planned dates to work on topic

| 2026 | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| february | | | march | | | | | april | | | | may | | | | june | | | | | july | |
| 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 |
| 09-02-2026 | 16-02-2026 | 23-02-2026 | 02-03-2026 | 09-03-2026 | 16-03-2026 | 23-03-2026 | 30-03-2026 | 06-04-2026 | 13-04-2026 | 20-04-2026 | 27-04-2026 | 04-05-2026 | 11-05-2026 | 18-05-2026 | 25-05-2026 | 01-06-2026 | 08-06-2026 | 15-06-2026 | 22-06-2026 | 29-06-2026 | 06-07-2026 | 13-07-2026 |
| 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 |
| | | | hand in draft | | Midterm presentation | planned midterm | | max DL midterm | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | hand in draft | | Green light | planned GL | | | | | max DL green light | |
| | | | | | | | | | | | | | | | | | hand in final | | Thesis defence | | planned defence | |
| | | start TS | | | | | | | | integrate hybrid method | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | | | 23-06-2026 | | | |