Optimisation of pipe system routing and space reservation in ship design with regards to production cost drivers

Damen Offshore & Specialized Vessels

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based on the cost drivers in production, during ship design at Damen Offshore Specialised Vessels.

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Use of Artificial Intelligence

During the writing of this thesis, AI-assisted tools (including large language model-based tools such as ChatGPT and Gemini) were used for the following purposes: (1) literature search support and keyword generation, (2) language editing and proofreading of draft text, and (3) assistance in structuring and reformulating written content. All technical content, analysis, conclusions, and interpretations are the sole work of the author. Any AI-generated suggestions were critically evaluated, and the author takes full responsibility for the accuracy and integrity of this thesis.

Preface

This thesis marks the end of my 5-year engineering education at the TU Delft. 5 years of experience and lessons I will carry with me forever. During the past 9 months, completing this research at Damen Offshore Specialised Vessels in the expertise center has been a very pleasurable and insightful experience. I would like to thank Pieter Klasens and the other experts in the center for their insightful conversations and guidance while developing the Damen Routing Tool. I would also like to thank them for the laughs and stories exchanged. I would also like to thank Jeroen Pruyn for his ever-sharp thinking skills and laughs in his office.
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Finally, I extend my deepest gratitude to the ancient people of Ethiopia and Yemen for their discovery of coffee. Your centuries-old agricultural breakthrough remains the cornerstone of modern engineering.

Laurens Sebastian Ooms
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Abstract

Piping systems account for nearly half of all detailed engineering time in shipbuilding and exert a disproportionate influence on total production costs. In the competitive Engineering-to-Order (ETO) market, where profit margins typically lie between 2 and 6%, labour efficiency during pipe installation represents a far greater cost lever than material savings alone. Yet existing Automated Pipe Routing (APR) algorithms optimise almost exclusively for material reduction (minimising pipe length and the number of bends), while largely neglecting ease of installation as a design objective. This thesis addresses that gap by proposing a combined methodology that integrates production cost drivers directly into the pipe routing and space reservation process during the design phase.

The approach proceeds in three stages. First, Value Stream Mapping (VSM) is applied to the production process at Damen Offshore Specialised Vessels (OSV), identifying installation as the primary bottleneck by non-value-added duration. Second, Fuzzy Logic (calibrated through expert questionnaires with ten industry specialists) translates physical clearance distances around pipes into a quantitative Installability Index (II) and Time Multiplier (TM), bridging the gap between vague engineering descriptions and the crisp numerical inputs required for algorithmic optimisation. Third, these metrics are embedded as penalty terms within an A^* pathfinding algorithm that simultaneously enforces Classification Society hard constraints governing hazardous zone separation and vertical routing restrictions.

The methodology is tested in a case study on the engine room of the *Windcat Amsterdam*, a CMB.TECH vessel built by Damen. Rerouting key pipe systems yielded a theoretical 18% reduction in installation time, corresponding to a potential saving of 12,498 man-hours for a single engine room. These results demonstrate that installation-aware routing is a practically achievable and financially meaningful improvement to current design practice.

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Nomenclature

Abbreviations

Abbreviation	Description
ACO	Ant Colony Optimisation
APR	Automated Pipe Routing
BFS	Breadth-First Search
BV	Bureau Veritas
CAPEX	Capital Expenditure
CO	Change-Over time (Value Stream Mapping)
CT	Cycle Time
DN	Diameter Nominal (nominal pipe size)
DNV	Det Norske Veritas
DRL	Deep Reinforcement Learning
ER	Engine Room
ETO	Engineering-to-Order
FIFI	Fire Fighting
FRAM	Functional Resonance Analysis Method
GA	Genetic Algorithm
HP	High Pressure
IACS	International Association of Classification Societies
II	Installability Index
ILP	Integer Linear Programming
IMO	International Maritime Organization
JPS	Jump Point Search
KPI	Key Performance Indicator
LR	Lloyd's Register
MA	Machinery Arrangement
MRP	Manufacturing Resource Planning
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NVA	Non-Value Added
OD	Outer Diameter
OSV	Offshore Specialised Vessel
PSO	Particle Swarm Optimisation
RL	Reinforcement Learning
SID	System Identification code (Cadmatic)
SOLAS	Safety of Life at Sea
SQ	Sub-Question
TM	Time Multiplier
TSK	Takagi-Sugeno-Kang (fuzzy logic variant)
VA	Value Added
VSM	Value Stream Mapping
WT	Wall Thickness

Latin Symbols

Symbol	Description	Unit
a, b	Fuzzy logic universe boundary values	mm
B	Number of pipe bends	–
$c(n \rightarrow n')$	A* step cost from node n to candidate node n'	–
c_B	Cost per bend	€
C_{inst}	Installability cost penalty at candidate node	–
C_{PM}	Total pipe production cost (Hadelkamp)	€
c_p	Unit cost per running metre of straight pipe	€ m^{-1}
c_W	Cost per running metre of weld	€ m^{-1}
$d(n)$	BFS clearance distance at grid node n	grid units
⌀	Diameter (nominal pipe size indicator)	mm
$d_{mm}(g_x, g_y, g_z)$	Clearance distance at grid cell	mm
$f(n)$	Total A* path cost function	–
F	Finishing costs (painting, galvanising)	€
g	Goal node in A* search	–
$g(n)$	Accumulated path cost from start node to n	–
g_x, g_y, g_z	Grid cell indices	–
$h(n)$	A* heuristic cost estimate from n to goal	–
h_{tonne}	Installation labour rate	hr kg^{-1}
L	Pipe length	m
L_p	Pipe segment length	m
L_W	Weld length	m
$L_{\text{existing},i}$	Existing pipe length for system i	m
$m(x)$	Defuzzified time multiplier at clearance x	–
m_{avg}	Average time multiplier over all route waypoints	–
m_k	Time multiplier for fuzzy category k	–
$M_L(DN)$	Pipe mass per unit length as function of DN	kg m^{-1}
n	Grid node; or number of pipe components	–
n'	Candidate next node in A* search	–
N	Number of waypoints in a pipe route	–
n_x, n_y, n_z	Coordinates of current grid node	–
P_i	Purchase parts cost (flanges, fittings)	€
r	Grid resolution	m
r_{pipe}	Pipe outer radius	mm
R^2	Pearson correlation coefficient squared	–
$s(x)$	Defuzzified installability score at clearance x	–
s_{avg}	Average installability score over all waypoints	–
s_{dist}	Euclidean distance from grid node to BFS seed	grid units
s_{inst}	Installability score at candidate node (cost function)	–
s_k	Normalised installability score for fuzzy category k	–
s_x, s_y, s_z	Coordinates of BFS seed node	–
w_1, w_2, w_3	General cost function component weights	–
w_{bend}	Bend penalty weight	–
w_{dist}	Base movement cost weight (default: 1.0)	–
w_{inst}	Installability penalty weight	–
w_{par}	Parallel pipe preference weight (cost discount)	–
w_{vert}	Vertical movement penalty weight	–
w_{wc}	Wall/ceiling preference weight (cost discount)	–
x	Crisp clearance value input to fuzzy system	mm
x_{eff}	Effective clearance (clearance minus pipe radius)	mm
x, y, z	World coordinate axes	m

Greek Symbols

Symbol	Description	Unit
δ_{bend}	Bend indicator: 1 if movement direction changes, else 0	–
$\delta_{\text{parr}}(n')$	Parallel routing indicator: 1 if n' is adjacent to a routed pipe	–
δ_{vert}	Vertical movement indicator: 1 if $\Delta z \neq 0$, else 0	–
$\delta_{\text{wc}}(n')$	Wall/ceiling adjacency indicator at n'	–
ΔCost	Change in theoretical installation cost	man-hours
ΔL_i	Fractional change in pipe length for system i	–
ΔTM_i	Fractional change in time multiplier for system i	–
μ	Fuzzy membership degree, $\mu \in [0, 1]$	–
$\mu_k(x)$	Membership degree of clearance x in fuzzy category k	–

Summary

In the current shipbuilding market, intense competition has placed significant pressure on design and engineering teams to deliver complex, Engineering-to-Order (ETO) vessels with reduced lead times and costs. While design costs represent only approximately 5% of a project's total expenditure, they influence up to 70% of the overall costs. Piping systems are a critical component of this influence, accounting for nearly 50% of the detailed design time and a substantial portion of production man-hours. This research identifies a significant gap in current automated pipe routing (APR) literature: while existing algorithms successfully optimise for material reduction, such as length and frequency of bends, they largely fail to incorporate the **ease of installation**, a primary driver of production costs.

This thesis proposes a novel methodology to optimise pipe system routing and space reservation by integrating **production cost drivers** directly into the design phase. The research utilised a three-tiered approach:

1. **Identification**: Value Stream Mapping (VSM) was employed to analyse the production process at Damen shipyards. The analysis confirmed that **installation** is the key bottleneck, characterised by the highest absolute duration of non-value-added time. At Damen Galati, the ratio of material costs to man-hour costs was documented at 1:4, emphasising that labour efficiency is a more impactful optimisation target than material savings. In addition, it allows for a numerical indication of production times, enabling further analysis of the optimisation.
2. **Quantification**: To bridge the gap between vague human descriptions (e.g., ”tight fit” vs. ”sufficient space”) and the crisp numerical inputs required for algorithmic optimisation, **Fuzzy Logic** was implemented. Using expert knowledge from ten industry specialists, membership functions were developed to translate physical clearance distances into an **Installability Index (II)** and a **Time Multiplier (TM)**. This technique allows for optimising based on subjective installation ease in a mathematical algorithm.
3. **Optimisation**: These quantified production cost drivers were integrated as penalty terms within an A^* **pathfinding algorithm**. This enables the router to evaluate the trade-off between a shorter, more difficult-to-install path and a longer, more accessible route. The algorithm also incorporates hard constraints based on **Classification Society rules** regarding hazardous zones and vertical exclusions.

The methodology was validated through a case study involving the engine room of the *Windcat Amsterdam* vessel from CMB.TECH. By rerouting key systems such as seawater cooling and fire-fighting mains, the tool achieved a theoretical **18% reduction in installation time** across the analysed systems. When accounting for changes in both length and installation ease, the optimisation demonstrated a potential saving of **12,498 man-hours** for a single engine room.

These results indicate that shifting the optimisation focus from material reduction to **installation-aware routing** provides a practically achievable improvement with measurable financial impact. This research provides Damen OSV with a schematic assistance tool that bridges the gap between practical engineering judgement and quantitative algorithmic optimisation, ultimately improving profit margins in a low-margin industry.

1 Introduction

The maritime industry forms a critical backbone of global industry. As vessels grow in complexity and customer demands diversify, the pressure on shipbuilders to deliver quality products faster and at lower cost has never been greater. In competitive, low-margin industries such as shipbuilding, where profit margins typically range between 2–6% (Group, 2009), even marginal improvements in design and production efficiency can have significant financial impact.

To properly understand the issue at hand, a problem description is crucial. As the American inventor and head of research at General Motors, Charles Kettering has stated: "*A problem well stated is a problem half solved*" (Boyd, 1957). Staying true to this, describing the problem at hand at Damen OSV is important to fully comprehend what is to be solved.

1.1. Problem Definition

In the modern shipbuilding market the level of competition is at an all-time high (Visser, 2025; Thawornwichian, 2018). This puts high pressure on design and engineering teams to deliver on time with increasingly lower costs. Moreover, with shipbuilding only yielding a 2-6% profit margin (Group, 2009; Alblas and Pruijn, 2024; Levering, 2015), every saving is crucial for increasing the profitability of a build. The difference of increasing from 2% to 2,5% is a 25% increase in net returns. Costs are split into material costs, that are in turn driven by external factors, and operational costs. Only operational efficiency is always in the direct control of the shipbuilder. The labour costs range from 20% (Alblas and Pruijn, 2024) up to 60% (Asmara, 2013). Hence, it is up to the ship designer to optimise operational efficiency during manufacturing to increase the profit margins.

Within the shipbuilding process, nearly 50% of the total detailed design time is allocated to the piping (Park and Storch, 2002). While design costs only account for 5% of the total, they impact 70% of the total costs in shipbuilding (Matuszek et al., 2020; Hagen, 2013). Recognising the moments, tasks or stages of production cycles that drive the costs in the process from initial concept design up to production at the yard, leads to an understanding of where optimisation is most effective.

At Damen Offshore & Specialized Vessels (OSV), almost all vessels built are on an Engineering-to-Order (ETO) basis. As there is a lack of similarity per project, it is difficult to use a different project to estimate costs for a new project. Therefore, it is key to identify activities in the production process that are always the main cost drivers, as these can be scaled per project. To achieve this, the overview of cost drivers needs to be clearly defined in the product manufacturing process. With 50% of detailed-design time being dedicated to piping (Park and Storch, 2002), it is key to understand what drives the costs in the product development of the piping systems onboard complex vessels to reduce the costs made per design hour.

Currently, at Damen OSV there is no structured insight into the relevant cost drivers within the pipe system routing and spatial reservation. Piping is highly relevant in the scope of production, as nearly 50% of the total design process consists of the piping or related matters (Park and Storch, 2002). Furthermore, Damen OSV operates in multiple countries during the production of a vessel. The headquarters is located in Gorinchem, the Netherlands, basic engineering in Gdansk, Poland and detailed engineering is stationed in Galati, Romania. This geographical spread of different departments leads to complexities in communications between departments. A socio-technical issue arises when considering the inefficient communication between the teams on small, easy-to-solve issues, possibly saving rework in the long run. The absence of a structured framework to capture the influence of pipe system design on total production costs hinders Damen OSV's ability to maximise the narrow profit window. A method to create structure in the pipe routing design,based on optimising the main cost drivers in manufacturing, is to be developed for design engineers. This should introduce structure to the way of working, allowing for more efficient communication across the geographical spread, and assists in decreasing time spent on pipe design processes.

There are two clear sides to the optimisation problem at hand. These are complementary; focusing on identifying the key cost drivers during manufacturing and implementing these in an optimisation technique for the design phase.
The first side involves analysing all the processes and tasks that occur during the complete conceptual design, basic and detailed engineering, and the manufacturing of the piping systems. Understanding and quantifying the vague engineering terms communicated between teams that indicate the cost drivers in manufacturing is necessary to create user incentive.
The second side would be analysing how the pipes are routed. Pipe routing is defined as follows: *"The basic approach to pipe routing is developing a collision free route of a pipe between two or more connection points in a 3D, obstacle-scattered environment, according to the rules and standards"(Asmara, 2013)*. The pipe routing in the engine room should be analysed to determine whether it is cost-efficiently designed. This means no unnecessary routing around objects or repeated highly complex installation routines. This contributes heavily to cost savings, as material costs are directly saved as well as man-hours. Moreover, investing increased amounts of time earlier in the process can save a substantial amount of time in manufacturing, resulting in cost savings for man-hours (Boehm, 1981).
Both of the approaches lead to the same goal: reducing the costs of the design and manufacturing process of the piping systems in Damen OSV new build vessels. That in turn, delivers a significant cost-saving in the total picture resulting in a maximised profit margin per vessel.

Due to the time constraints of this research, the research will be limited to and around the engine room of the OSV's. This is the most complex part of the design within the vessel ((Asmara, 2013); (Gunawan et al., 2020)).

Firstly, the background of the problem will be further explained. This defines the reasoning for Damen OSV to conduct such an optimisation research. Then, the research will start with a literature review to determine the techniques available to optimise the problem. A wide range of possible solutions will be analysed, ranging from operational optimisation to algorithmic approaches to the piping optimisation problem, a wide range of possible solutions will be analysed. From the options considered, the best solution will be chosen and fully decomposed. During the literature review, it will also be key to understand the production process behind the problem. Through interviews and discussions with stakeholders, an overview of the design-to-manufacturing process will be formed. Following the method choice and approach description, a pioneering method to optimise the process will be described. This method, which combines different state-of-the-art techniques, will be tested on a case study to confirm the effectiveness of the methodology or tool. This will be demonstrated with a maximal theoretical cost saving.
Finally, a conclusion will be drawn concerning the problem and the fitting solution, and any further research needed will be discussed.

To solve the problem that has arisen, different issues need to be addressed. Initially, a method needs to be used to properly map the spread of the costs during the design and manufacturing process. Having this knowledge creates opportunities to understand what drives the costs. Acknowledging these points factually is crucial to being able to optimise the process based on the cost drivers. Secondly, a methodology needs to be created to simplify the process and reduce the number of iterations needed in the design spiral with regard to the engine room layout, which is driven by the pipe layout. Third, the efficiency increase should also result in less man-hours being required in the manufacturing of the pipe systems and reduce the costs of the materials in the process.

1.2. Problem Background

1.2.1. Current design and manufacturing process

The current process follows a straightforward four step global process. Beginning with the conceptual design, where the initial arrangements are made in the general design of the vessel. An engineer has full freedom of choice where to place the equipment, so long as all is included. Moving on to the basic engineering, not dissimilar from the conceptual, the design is still at a global level. In this step, the engineers describe the rough routing of pipe systems and other connections between equipment in schematic overviews. Subsequently, detailed engineering maps out the precise routing of the piping in 3D and alters the layout of the equipment if necessary. Finally, the designs are manufactured at the yard.

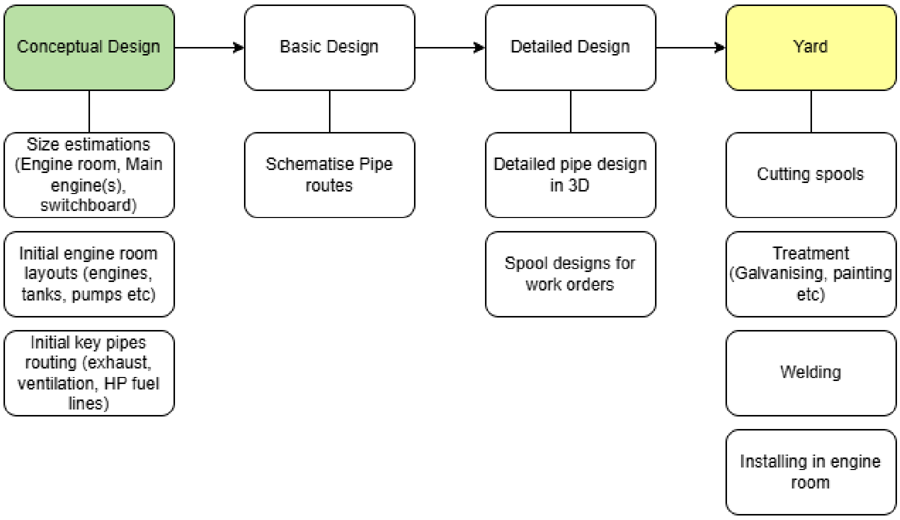


Figure 1.1: Current product development process. The flow of arrows represents the process, and each process is broken down below.

As is the nature of such information flow, conceptual design decisions influence what happens in all the next processes. Meaning, if any adjustments can be made in the early stages, then this has a larger impact on the overall efficiency than managing the operational efficiency later on (Hagen, 2013; Matuszek et al., 2020). Addressing the costs incurred in the yard (yellow) during the conceptual design (green) significantly reduces the necessary rework.

1.2.2. Previous DAMEN Research

In 2021 a research was conducted by DAMEN together with Targus Management Consulting AG to optimise the production process of piping across two different yards in Romania, Mangalia and Galati, combining the pre-assembly manufacturing processes all onto one yard. In this research different conclusions were drawn based on certain cost savings that are achievable for small investments earlier in the piping process. For example, in Figure 1.2, the most right pillar for waste reduction, states that if design processes are improved in combination with understanding of these designs by the manufacturing team, there are considerable savings achievable.

It was further found that at the Galati yard, the division of the work done in time is as shown below in Figure 1.3. It is clear that more than half of the work completed is dedicated to the Assembly process within the manufacturing.

Furthermore, this data is backed up by a separate research into the data from the Galati yard by Damen. Over the past projects, the budgeted man-hours demonstrate the following division, as shown below in Figure 1.4.

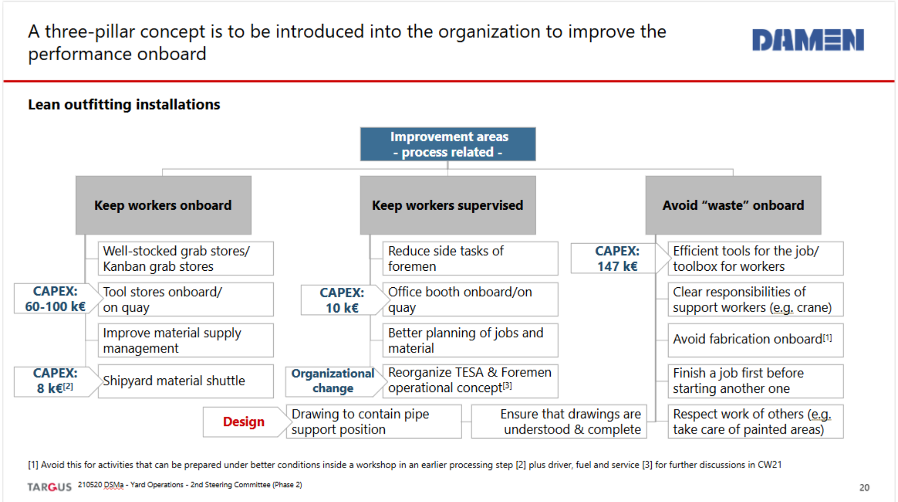


Figure 1.2: Three pillars of possible savings

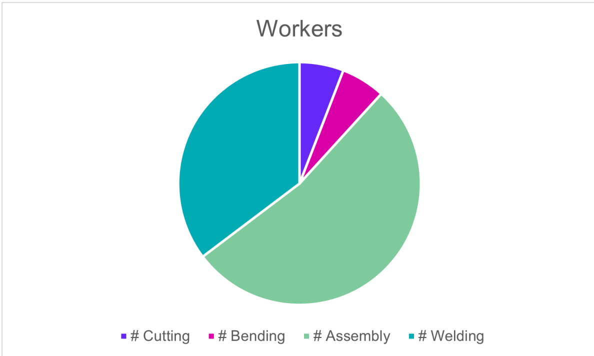


Figure 1.3: Work Division at Galati

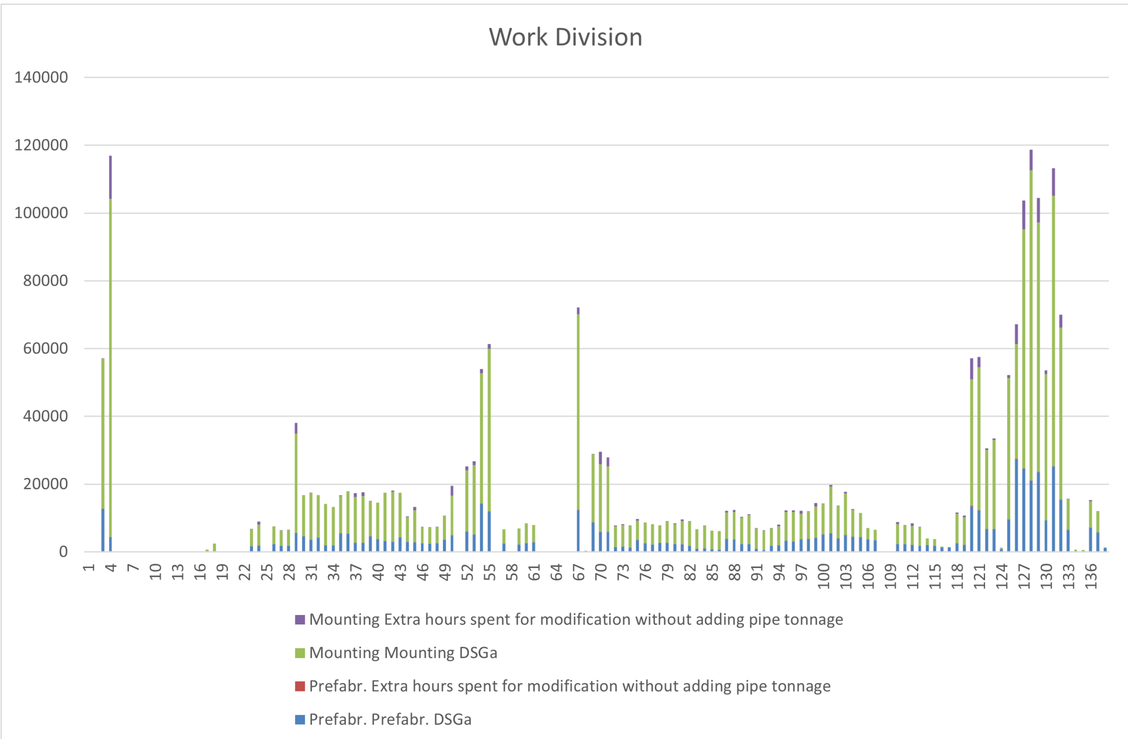


Figure 1.4: Work division from Galati per Project

On average, most of the hours are dedicated to the installation of the piping, meaning there is much to be saved in this part of the process in terms of man-hours. Creating piping that is less complex to install, or making the space in which it is installed more accessible, allows man-hours to be saved. These are choices that need to be made in the design phase of the piping, costing possibly only a few hours, and possibly saving dozens of man-hours in the installation process. A problem arises when considering how to quantify the 'install-ability' of pipes when creating the pipe routing. In Figure 1.4 it is also visible that each of the projects contains a certain amount of 'extra hours spent for modifications without adding pipe tonnage'. This indicates that, without fail, adjustments that are made during mounting are presumably not fully taken into account earlier on in the design process.

There is a necessity to clearly find and state the main cost drivers. In doing so, the clarification of the possible cost reduction from certain efficiency gains can be demonstrated as well. This problem consists of two parts:

1. Identifying the main cost drivers in the process and finding areas to reduce these.
    - How can these be quantified so that they can be considered during the design phase?
2. Implement the optimisation into a usable method in the real world.

Between the first and the second step, a complexity arises in that the 'installation ease' is not easily quantified. A quantification is needed in order to be usable in a cost function for the optimisation in the second step (Wu et al., 1998; Kim et al., 2009). This is something that is stated in vague terms, for example: too tight, tight, or sufficient spaces within an engine room. A translation from the process analysis to the implementation of the cost optimisation is necessary to properly use the methodology in the design phase.

1.2.3. Problem Division

Assembly and installation are the most man-hour expensive parts of the piping (Figure 1.2). Besides this, half of the detailed engineering time is spent on the pipe routing (Park and Storch, 2002). Furthermore, during the design of the pipe systems, less attention is put towards creating installable piping than to creating shorter pipes that cost less in material. The choice to prefer one over the other often leads to rework needing to be done because a pipe cannot be installed by the yard. The pipe routings are often complex and intertwined, and an experienced builder is needed at the yard to properly install the pipes. If the pipes are simple to install, creating slightly more expensive pipes could be compensated by the fact that fewer man-hours are needed to install that same pipe system.

1.2.3.1 Identifying and Quantifying Cost Drivers

As stated and shown in section 1.2.2, there are specific phases that take up most of the man-hours during the manufacturing stage. To confirm this, research must be conducted to define the specific points or actions that are driving the costs. This will also involve quantifying these costs in both man-hours and monetary values to validate the achievable amount of savings.

1.2.3.2 Increase Design Efficiency

To implement an optimisation during the pipe routing design, the use of algorithms is a proven technique. There is significant research done looking into the automatic pipe routing (APR). Blokland et al. (2023) has conducted extensive research into all the automatic pipe routing techniques available at the time and what cost drivers are included. Markhorst et al. (2025) developed a more recent algorithm that aims to make future-proof routing, using an adjustable cost function in their algorithm. A review of the existing literature will determine which techniques are available and where the gaps remain regarding the specific cost drivers relevant to this problem (see Section 2.8).

In this conducted research it was found that none of the techniques translate the ease of install from a human perspective, but all include factors such as: aligning pipes as much as possible and keeping them within certain proximities of walls or objects to ensure structural supports can be placed. This only solves the fact that the way the pipes are routed makes them physically installable in the room. Installing ease, such as if somewhere is easily accessible with a large and heavy pipe spool, is not taken into account for any cost functions. Dong and Bian (2020) take an approach using A* and a Genetic algorithm, combining the reliability for pathfinding of A* with the search power of evolution. Blokland et al. (2023) scores this case study as medium complexity, compared to Blokland et al. (2023)'s scoring of the case study by Asmara (2013), which has a highly complex case with a higher number of pipes. This research is further elaborated on in Section 2.

1.3. Research Goal

The goal of this thesis is to improve the cost driver quantification for the cost functions of an optimisation algorithm to improve the pipe routing based on production costs. Having completed this, a tool will be created using this as a back-end to aid the design engineers in creating more efficient pipe designs. To do this, three requirements need to be fulfilled:

- Create a clear overview of how the costs during the manufacturing process of pipe systems in the engine room of an offshore support vessel are distributed.
- Create a cost function that can be used as a cost function of an algorithm.
- Develop a method for the design teams to use as support when developing a pipe routing plan.

1.4. Research Question

To encapsulate the problem at hand and drive the research in a structured manner, the following main research question and sub-questions are formulated.

"What is the potential cost saving for the pipe production process by implementing the pipe routing optimisation in the design phase, focusing on cost drivers within the production process?"

To properly understand and correctly address this main question, the following sub-questions have been developed:

1. **SQ** What research on piping has already been performed?
    - How applicable is Automatic Pipe Routing currently?
2. **SQ** What are the primary sources for piping costs?
    - How can these be quantified?
3. **SQ** How can the design process implement optimisation for the pipe routing production costs?
4. **SQ** What is the theoretically maximal achievable cost saving?

2
Literature research

Isaac Newton once said: *"If I have seen any further, it is by standing on the shoulders of giants ."*(Newton, 1959). He implied that without prior research and knowledge attained by those before him, he could not have made the progress he did. The following section relies on the same implication he made.

The literature research is structured around four steps. First, the current APR literature is reviewed to identify how costs are modelled and where the gap between optimisation objectives and actual cost drivers lies. Second, a method for quantifying the unrepresented cost driver, 'installability', is examined, leading to the selection of Fuzzy Logic. Third, the most suitable routing algorithm for incorporating this cost term is selected from a full comparison of available options. Finally, a process analysis technique is chosen to translate the theoretical framework into concrete numerical values from the production process.

With the keywords visible in Appendix A.1, Scopus, Google Scholar, Google Gemini, Chat-GPT and different AI search engines were used to find papers relevant to the problem at hand (see Section 1.2). In addition to these keywords being searched, through 'snowballing' from paper's sources other information has been found. In the first stage, abstracts were scanned and only if slightly applicable saved. Then, these paper's introductions, summaries and conclusions were read to determine if they were still relevant. If so, the paper would be read.

2.1. APR State of the Art

There is over 50 years of research into the automating pipe routing (APR) (Blokland et al., 2023). Automatic Pipe Routing algorithms aim to optimise pipe routes based on the specific optimisation goal, that is based on a cost function coherent with that algorithm. The survey conducted by Blokland et al. (2023) is an extensive and relatively up-to-date survey, completed with the intention of providing a complete overview of the current APR literature. Many of the research studies completed find methods that are currently unattainable due to the computational complexity of the pipe routing, a non linear and endless probability problem and solution. Moreover, current research into piping optimisation,specifically within shipbuilding, is limited to the routing optimisation problems. Different researches have been done with many facets, all aiming to create an algorithm that routes the piping as efficiently and cost-effectively as possible (Markhorst et al., 2025). Incidentally, in different industries, including aerospace and the petrochemical industry, the optimisation and automation of the pipe routing process is a highly researched optimisation problem. Hadelkamp (2017) has researched the possibility of decreasing piping costs within shipbuilding based on pipe penetration. In this research a formula for the manufacturing and production costs has been created (see Equation 2.1). This, however, does not fully encapsulate the effects that a more efficient design (team) can have. Moreover, Blokland et al. (2023) researched the possibilities of automating the layout of piping. This was proven to be nearly possible, but still needs some external input presently. Again, this does not take any of the design spiral and costs thereof into account.
Blokland et al. (2023) structure the objectives used in APR into three categories in section 3.2.2:

- *geometric objectives (pipe length and bend count)*
- *structural objectives (clearance constraints, support placement, hazardous zone avoidance)*
- *operational objectives (accessibility, maintainability and producibility)*

The studies literature is dominated by geometrical objectives, as these are the most straightforward to quantify and implement. Structural objectives are addressed through hard constraints in most algorithms. Operational objectives, however, while identified as a separate category, are rarely incorporated into cost functions. They are described qualitatively or left out to the designer's professional opinion.
Wu et al. (1998) developed the most notable attempt to optimise the system design for the machinery arrangement and pipe routing. They focus on producibility, engine room size as input and convenience (degree of access to machinery that needs to be used frequently). This research is a strong base point, thus being a starting point for Damen OSV's design cycle, possibly decreasing the number of design iterations in the conceptual phase. The study, however, does not quantify the cost savings of the new method for a shipbuilder. Besides that, no unpredictability is taken into account, such as designs needing to change in the (near) future. Similarly, Kim et al. (2009) established an objective evaluation function for the machinery arrangement design. This was also done based on maximising the producibility while aiming to minimise undesirable outcomes.

More recently, research was conducted on the piping monitoring using a digital twin, conducted by Jiao et al. (2026). This moves beyond only the construction phase and also considers the monitoring of the pipe systems. This could provide information and feedback from previous designs to achieve more efficient designs in the future, based on data-rich feedback.
As found by Blokland et al. (2023), there is a considerable amount of research done the past 50 years towards APR, but is all focused on the algorithmic solutions for routing the piping. Very little research is conducted into the combination of practical costs and pipe routing. More specifically, the installation ease of the designed piping systems is not accounted for, only whether it *can* be installed. Furthermore, it is clear that the research completed has found methods of optimising the layout of the engine room and piping routing, but does not yet incorporate the operational side of the design process. Research done about the operational effectiveness has not yet incorporated the technical side of the design process. They either focus on the output efficiency, looking into decreasing material usage or increasing work output. None focuses on the financial gains that can possibly be achieved using the techniques developed.

2.2. Cost factors in automated pipe routing

The different objectives for the routing optimisations found in Section 2.1 demonstrate the dominance of material cost minimisation. However, the spread of costs in reality consists of material and operational costs.

2.2.1. Engineering and Production Costs

Estimating costs within shipbuilding is complex and difficult to standardise (Alblas and Pruijn, 2024). The expenses estimation will need to be done based primarily on the data available within Damen. To properly understand where costs can be saved in the production of pipe systems, an overview of all costs in the creation of a ship is needed. Ship production consists of the engineering hours and production hours. As previously stated from research done internally at Damen, a significant amount of man-hours is spent on the installation of the piping (Figure 1.4).

The costs of a pipe production (C_{PM}) in material and several physical factors are combined in a formula created by (Hadelkamp, 2017):

$$C_{PM} = \sum_{ps}\left(\sum_{p}(c_p L_P + c_B B) + c_W L_W + \sum_{pp} P_i + F\right) \tag{2.1}$$

This bases the costs on the following factors:

- **Raw Material Cost:** This depends on the material. This means length (L_p), diameter, thickness and type of pipe used (Asmara, 2013). The unit cost per straight pipe (c_p) is based on the cost per running meter (rm).
- **Bending costs:** The bending of piping costs significant amounts of money (Hadelkamp, 2017). The formula takes the cost per bend (c_B) and multiplies it by the number of bends (B).
- **Welding Costs:** The costs per weld are also calculated for the welding length (L_W) by multiplying with the costs per running meter of the weld (c_W).
- **Purchase Parts and Finishing:** This factor accounts for parts that need to be purchased(P_i), such as flanges, and finishing costs (F), such as painting or galvanising.

The formula shows that there is room for optimisation based on the situation. One could compare making a pipe with multiple bends or multiple pipes with only one bend (Hadelkamp, 2017). This does not take the installation costs into account; only material and parts costs are considered.

2.2.2. Manhours and Monetary Values

Evaluating the manhours per tonne (Mh/t) of production is a valuation of time. Be decreasing this value and maintaining output, the efficiency of the production is increasing. This measurement is very valuable for efficiency measuring as it is equal across all yards. The economic benefit changes when analysing different yards in the world, as hourly wages differ drastically. Using the man-hours is thus a clear indication of efficiency increase or decrease.

Also in different industries, the reduction of man-hours leads to the most effective cost reduction during construction (Jarkas and Bitar, 2012), such as the petrochemical industry (see Appendix A.3.1). In this research it is stated that labour costs compromise 30% to 50% of the total project costs, in line with Alblas and Pruijn (2024). It is also stated that these costs are the most volatile but controllable. The authors subsequently argue that human productivity is the truest reflection of the economic success of a project. Keorapetse et al. (2024) states that a modular construction that saves rework can reduce man-hours by 35%, resulting in an overall cost savings of 6% to 20% because overhead costs are avoided with the reduction in labour time.

In the total costs, the design is relatively small compared to the material costs. However, the material costs can not be controlled as these are externally priced by a fluctuating market. While these markets fluctuate, the efficiency of labour (specifically in assembly and installation) is where shipbuilders can exercise control. Alblas and Pruijn (2024) put emphasis on optimising the construction process and reducing non-value adding activities (waste). This is crucial for improving the profit margin.

2.3. Underrepresented operational optimisation

The survey of APR literature in Section 2.1 and the cost breakdown in Section 2.2 together expose a structural misalignment between what existing algorithms optimise and where costs actually arise in practice. Existing APR cost functions are dominated by geometric objectives ,primarily pipe length and bend count, because these are directly derivable from the routing geometry and straightforward to minimise mathematically (Blokland et al., 2023). Structural objectives such as clearance and support placement are typically handled as hard constraints rather than cost terms. Operational objectives (accessibility, maintainability, and producibility) are identified as a category in the literature (Blokland et al., 2023) but are rarely incorporated into cost functions. Where they appear at all, they are expressed qualitatively or left to the designer's professional judgement.

This stands in contrast to what the cost data show. As established in Section 1.2.2, assembly and installation are the most man-hour intensive phases of pipe system production at Damen OSV. In addition, Park and Storch (2002) reports that approximately half of the total detailed engineering time in shipbuilding is spent on pipe routing alone. Labour costs in construction represent 30% to 50% of total project costs and are the most controllable cost category available to a shipbuilder (Alblas and Pruijn, 2024; Jarkas and Bitar, 2012). Yet the Hadelkamp cost formula (Equation 2.1), which represents the state of the art in piping cost modelling, accounts only for material and fabrication costs: raw material, bends, welds, and purchased parts. Installation cost is absent entirely.

The consequence is clear: current APR optimises for the cheapest pipe to *make*, not the cheapest pipe to *install*. A routing that minimises material cost may simultaneously maximise installation labour by routing pipes through confined, difficult-to-access spaces. The preference for shorter and geometrically efficient routes over more accessible ones in practice leads to rework, because pipes that cannot be physically installed by yard workers must be redesigned after the engineering phase (Section 1.2.2). This rework itself generates additional engineering and production hours that are not captured in any current cost function.

The gap is therefore not a minor omission, but a systematic one. The cost driver with the highest absolute share of production man-hours, installation, is the one least represented in APR optimisation objectives. Addressing this gap requires three steps. First, a method is needed to quantify the ease of installation in numerical terms suitable for inclusion in a cost function; this is addressed in Section 2.4. Second, once the cost function structure is defined, an algorithm must be selected that can incorporate this additional cost term efficiently; this is addressed in Section 2.5.3. Third, the numerical values for the cost drivers must be determined from the actual production process; this is addressed in Section 2.6

2.4. Quantification Theory

There exists a necessity to have crisp value inputs for an optimisation problem. This is due to the fact that an optimisation always coincides with a cost function, which consists of numeric values so that the function can be mathematically solved (Wu et al., 1998; Kim et al., 2009; Xu et al., 2007). Norman and Kirakowski (2018) explain Fitt's Law, the pre-eminent technique for quantifying the difficulty of manually installing or placing an object. Douglas (2021) explains fuzzy logic, a very effective way of capturing what avague human language means in numeric values. Fitt's law is a predictive model that is used in human-computer interaction to analyse the speed with which someone can point at and address a target. For the situation of addressing the ”install-ability” of pipes in the engine room, Fuzzy logic is a better fit due to the fact it can define the quality of a design. This is crucial in defining a cost function for optimisation.

2.4.1. Fuzzy Theory

Fuzzy theory is a way to quantify the vague dependencies of a system. It can be useful to create a logical overview in a non-binary situation and aid in decision-making. When a value is neither true nor false, the fuzzy theory creates a spectrum of absolutely true to absolutely false. Using a fuzzy inference system is a form of artificial intelligence (Douglas, 2021), as the system is created in such a way that the feedback is as a human would give it. This theory can aid in understanding the feedback given by engineers and production workers and increase the value of the given feedback. Or for quantifying vague communications into monetary values.

2.4.1.1 Basic mechanism

Fuzzy logic is essentially a conversion mechanism to transforms traditionally illogical data into quantifiable amounts with which decision making can be aided. The difference is the creation of a scale instead of using binary data:

- **Traditional Logic:** True/False or 0/1
- **Fuzzy logic:** scaled between absolutely True and absolutely False or some numerical values a and b such that $a \leq x \leq b$.

To transform the vague data into a quantified output, that is interpreted as a human would fuzzy uses 2 or 3 steps between input and output: **fuzzification → (inference) → defuzzification**. Babuška and Mamdani (2008) uses inference as an additional step using IF THEN logic based on rules, where the TSK fuzzy logic variant (Sugeno and Kang, 1988; Takagi and Sugeno, 1985) transfers a crisp fuzzified value directly to a crisp defuzzified output. The full process is explained in chapter 3.3.1.

2.4.2. Quantification Technique Conclusions

Fuzzy logic is identified as the sole quantification technique applicable to the goal of algorithm cost function integration. Other techniques have not been identified that can translate a human (subjective) vague input to a numerical value. Proven by Wu et al. (1998) in a similar quantification problem, Fuzzy Logic is therefore the selected method.

2.5. Pipe routing algorithms

With methods to identify and quantify the cost drivers during the installation/assembly being researched, choosing the best fitting algorithm is key for correct implementation of the objective optimisation. Leveraging research by Blokland et al. (2023) to begin with in the algorithm identification. In section 5, table 3 of Blokland et al. (2023) the wide variety of pipe routing algorithm papers are organised.

2.5.1. Deterministic Algorithms

2.5.1.1 Dijkstra's

This algorithm finds the shortest routes from a given position to the destination according to **Dijkstra's theory** (Dijkstra, 1959). This theory is based on an iterative process in a grid of points called 'nodes'. A path from node x to node y is to be found. Dijkstra's algorithm will go across all the vertices (lines connecting nodes, sing. 'vertex') and each time find the shortest distance to an undiscovered node (Choi and Lee (2024); Jacobse (2021)). This is done uniformly in all directions. The path with the lowest cost function is selected as the optimal path. The cost function for Dijkstra's algorithm is:

$$f(n) = g(n) \tag{2.2}$$

This reflects that the cost function per path is taken to the start node. Dijkstra's algorithm ensures no local optima are given as the best solution, but it will always return the global optimal solution. The downside for this algorithm is the computing time. As every path is researched, in complex problems with many different nodes, this computing time increases exponentially. Choi and Lee (2024) recognised that this algorithm does not reflect the decision variables that a design engineer keeps in mind.

2.5.1.2 A*

This version of pathfinding is an extension to Dijkstra's original, developed by Hart, Nilsson, and Raphael in Powell et al. (1968). This type uses a heuristic that always finds the path most in the direction of the destination. This is shown in the cost function of A*:

$$f(n) = g(n) + h(n) \tag{2.3}$$

Where $g(n)$ is the total cost function to the start node and $h(n)$ is the estimated cost from the current node to the target node (Liao et al. (2020); Jacobse (2021); Dong and Bian (2020)). This ensures the heuristic part of the cost function, which is based on a directional cost towards the final destination. With this non-uniform search approach, not all vertices need to be explored to find the shortest path. Thus, this means that the computational time to find the shortest path is drastically reduced.

Min et al. (2020) continues developing the A* algorithm by adding the **Jump Point Search** or JPS. This algorithm "jumps" over intermediate nodes in the grid, creating more straight lines, resulting in a faster computation time. The increase in speed is reported to be 300x-1000x faster than A* when tested in specific environments. The downside is that it is limited to uniform grids, resulting in difficulties in indicating weighted areas within a grid. Meaning adjusting the cost function becomes difficult.

2.5.2. Artificial Intelligence

Different relevant research studies have been conducted on the subject of pipe routing and spatial reservation within shipbuilding with special consideration of artificial intelligence. In a research by Cahya (2025) the use of Deep Learning (DL) as a surrogate for early stage ship design proved to be promising in predicting key metrics such as power requirements and steel weight. Using Multi-Layer Perceptrons (MLP) and Autoencoders (AEs), the DL model demonstrated a strong nonlinear fitting capability and achieved competitive predictive accuracy (R^2 values of 0.986 for MLP and 0.984 for AE). In some optimisation tasks, the combination of MLP and algorithms such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) achieved 58% lower power requirements and 20% less steel weight compared to the original expert design (Cahya, 2025). In another research completed by Kong et al. (2025), Reinforcement Learning (RL) A.4.4.1 is explored as a potential method to automate the pathfinding process for pipe systems.

Liao et al. (2020) conducted extensive research into the use of reinforced learning to optimise global routing problems. In this research, Deep Reinforced Learning (DRL, more specifically using Deep W-Network, see Appendix A.4.4.1) to minimise two measurable cost proxies: Total Wirelength and Total Overflow. **Total Wirelength** in a pipe routing problem is considered a primary cost, as the material costs are a significant part of the total costs. **Total Overflow (OF)**, considered as the second primary objecting, is interpretable as the congestion, constraint violations or physical interference. DRL shows successful optimisation reaching *zero OF* compared to A, which has the *occasional OF*. Liao et al. (2020)'s research was focussed on the pathfinding for small to medium scale complexities, for cable routing on small chips.

The use of AI in the design stage of the pipe system routing and spatial reservation for those systems, could significantly speed up the initial process. Giving the conceptual designers a starting point that is identical for all allows for fewer iteration steps and could possibly remove the need for a design spiral.

2.5.3. Comparing Algorithms

In Table 2.1 below, the main algorithms considered are compared and defined if it is useful for the research problem.

Algorithm Category	**Algorithm**	**Primary Use Case**	**Speed**	**Optimality**	**Why use or not**
Deterministic	Dijkstra	Baseline pathfinding in static environments	Slow	Guaranteed	Cannot handle complexity of 3D grids effectively.
↑	A*	Single Pipe Routing	Fast	Guaranteed	Good balance of speed, accuracy and adjustability of the cost function.
↑	Mikami-Tabuchi	Blockage check	Very Fast	No	Can be used as check, not as optimiser
Meta-heuristic	Genetic Algorithm	Multiple objective or Sequencing optimisation	Slow	Approximately	Good at defining ideal pipe installation sequence or space reservation
↑	Ant Colony Optimisation	Discrete Graphs	Medium	Approximately	Alternative for GA, but slower than A*
↑	Particle Swarm Optimisation	Continuous or Discrete graphs	Fast	Approximately	Fast conversion to an optimum, but risks finding local optima
Mathematical	Integer Linear Programming	Robust/Future proof	Varies	Exact	Best for uncertainty influenced optimisation, but scaling to large scales can pose problematic
↑	Deep Reinforcement Learning	Complex or dynamic routing	Fast	Learned	State-of-the-art technique, but teaching can be a cumbersome process

Table 2.1: Comparison of algorithms. See Blokland et al. (2023) section 5, table 3, for a further detailed version

Table 2.1 highlights the trade-offs of routing algorithms. While deterministic algorithms find optimised routes at high speeds and allow cost function adjustability, they rely on simple cost functions and route pipes sequentially. In contrast, meta-heuristic and mathematical routing approaches handle uncertainty and complexity well, but are sluggish and computationally expensive when scaling to larger grids.

The gap in the literature lies not in the path-finding logic itself, but in the lack of integration of the real-world applicability of the optimised paths. When considering the options outlined in this section, the most applicable algorithm for customising the cost function is the A^*. However, adding an integration step such as ILP by Markhorst et al. (2025) to identify the prioritisation of the pipe selection or defining better space reservation for the pipes could lead to a more refined solution integrating installation difficulty.

2.6. Process Analysis

The theoretical framework (cost function structure and routing algorithm) is now established. However, applying it requires concrete numerical values for the cost of the drivers. To achieve this different techniques are discussed in order to find the ideal method for identifying the cost drivers numerical values. As found in Chapter 1.2 and Section 2.2.2, man-hours are a key cost within the shipbuilding industry. These costs are also generalisable, as building a ship in different yards may have different hourly wages, but man-hours do not change.
Lean management techniques are a proven way of identifying cost bottlenecks in production processes (See Appendix A.1.2). For this reason, Value Stream Mapping (Section 2.6.1) is researched from this management principle for its time capturing properties.
Visser (2025) conducted research on the socio-technical side of the misalignment between formal managerial processes and production environments. This study demonstrates the possible gains of improving operational effectiveness and productivity.

2.6.1. Value Stream Mapping (VSM)

Value Stream Mapping is a Lean management tool used to visualise and analyse the flow of materials and information required to deliver product or service (Rother et al., 1999). It encompasses value adding and non-value adding from Lean Management principles A.1.2, thus creating a clear overview of where the costs and wastes are located in the value stream.

VSM consists of 3 parts:

1. **Visualisation:** VSM breaks down the process, from order entry to delivery, into its component steps

2. **Waste Identification:** Its primary purpose is to identify ”Waste” in the process at both micro (individual tasks) and macro (overall value stream) levels. Can be done with cycle time (VA Time) or waiting/delay time.

3. **Current and Future state:** A VSM typically involves a Current state map and a Future state map, illustrating what the starting point is and where optimisation will lead (goal).

VSM is relevant for shipbuilding as the Engineering-To-Order (ETO) nature of the industry need to reduce inefficiencies and waste (Kong et al. (2025); Kunkera et al. (2025)). However, VSM has some limitations regarding the non-linearity of shipbuilding and the socio-technical variability that is inevitable in large, bespoke projects (Visser, 2025). Creating a VSM of a single project can give a snapshot overview of where the main cost drivers in terms of time are located in the process chain.

VSM mainly demonstrates the time losses for different parts of a process. It shows where the information or product streams are going and the time each process takes, but also the lead times between the processes. This allows for a fast overview what moments during the entire process cost the most unnecessary time. Multiplying the man-hours by the cost of type of man-hour, engineering or yard work, gives the economic cost per process.

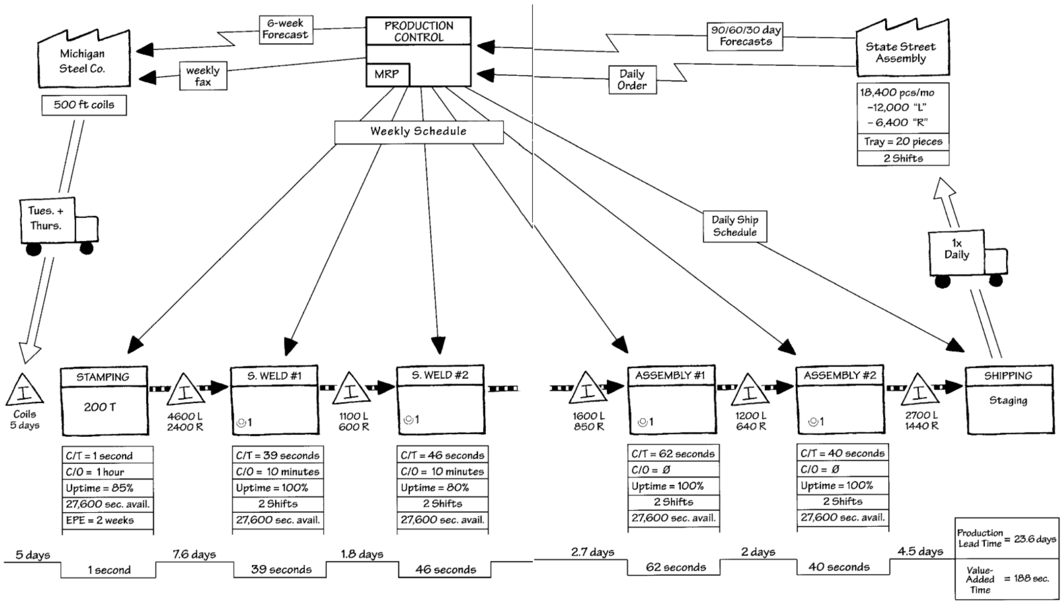


Figure 2.1: Value Stream Map from (Rother et al., 1999, p. 40). In this example a value stream map is created for de door-to-door flow by walking the shop floor. This follows the material stream for a "stamped-steel steering bracket" for the automotive industry.

In Figure 2.1 a mapping of a single part is shown. All the included steps to create such a part from start to finish are shown. The arrows show the relationships between steps, including the durations it takes and whether it is information or material goods. Per material altering activity (value adding), the Cycle Times (CT), Change Over times (CO) and Uptime are defined. At the bottom of the value stream map there is a stepped summation of the duration of each step. This is stepped, with the top being the production lead time, and the lower being the value-adding durations. Here, the key steps that add value can clearly be identified, and non-value adding periods can be addressed as well.

2.6.2. Functional Resonance Analysis Method; FRAM

Besides VSM, the Functional Resonance Analysis Method is considered for process analysis. Functional Resonance analysis method (FRAM) used by Visser (2025) is enriched with an abstraction hierarchy to systematically compare the Work As Intended (WAI) and Work As Done (WAD). This innovation allows the "granularity problem" (Visser, 2025) (the complex task of comparing high-level management plans with detailed yard-floor actions) to be tackled. In this technique the following structure is necessary:

- **Work-As-Intended:** Top-down processes. Business process management planning. In Visser (2025)'s case study, this is linear and assumes ideal conditions
- **Work-As-Done:** These are process bottom-up. Information gathered from informal conversations and observations in the yard.

Using these models, they can be analysed from three different hierarchical levels:

1. **Functional Purpose:** High-level goals such as *deliver a vessel*.
2. **Abstract Function:** This is the causal network and how the information flows between tasks.
3. **Generalised Function:** Actual operational processes governing behaviour.

In contrast to VSM 2.6.1, FRAM allows the process analysis to be done for non-linear systems where information not only flows downstream (linear) (Rother et al., 1999), but also includes feedback loops or interdependencies.

2.6.3. Process Analysis technique choice

For the goal of this research, the identification of time per process step is crucial, as this directly translates to the cost drivers that need to be addressed. VSM is therefore chosen over FRAM for three reasons. First, VSM explicitly captures Cycle Times, Change Over times, and lead times between steps, providing a directly quantifiable output that can be used to rank process activities by their time impact. FRAM, by contrast, is better suited to understanding the functional interdependencies and socio-technical dynamics of a process, rather than producing quantified time breakdowns. Second, the shipbuilding process for a single vessel at Damen OSV, while complex, can be meaningfully captured as a linear flow from design to delivery — a structure that VSM is designed for. The non-linear feedback modelling strength of FRAM is therefore less critical here. Third, VSM is already established in the ETO context of shipbuilding to identify waste and cost drivers (Kong et al., 2025; Kunkera et al., 2025), lending external validity to the results. FRAM remains a useful tool for future socio-technical analysis, as demonstrated by Visser (2025), but falls outside the quantitative scope of this research.

2.7. Rules and Regulations

When considering the optimal pipe routing and spatial reservation, it is key to clearly define the boundary conditions, some of these being the rules and regulations defined by different class societies. There are three main societies Damen adhere to, depending on what the client requires: Bureau Veritas (BV), Det Norske Veritas (DNV) and Lloyd's Register. All of these adhere to the same general piping rules imposed by IACS Unified Requirements and IMO SOLAS regulations. The rules on piping can be found in the following locations per classification society:

Society	**Primary Rule Document**	**Section**
Bureau Veritas (BV)	*Rules for the Classification of Steel Ships*	Part C, Chapter 1, Section 10: Piping Systems
DNV	*DNV Rules for Classification: Ships*	Part 4, Chapter 6: Piping Systems
Lloyd's Register	*Rules & Regulations for the Classification of Ships*	Part 5, Chapter 12: Piping Design Requirements / Part 5, Chapter 13: Ship Piping Systems

Table 2.2: Classification Societies and Piping Rules location

As the scope of this research is limited to the engine room, only the rules regarding this area will be analysed. However, some general rules need to be addressed. Areas around electrical switchboards need to be kept free from pipes carrying liquid. The exhaust pipes (or other pipes transporting heated liquid or gas) need to have a radius surrounding them to prevent heating other surfaces. Escape routes must be kept clear of pipes, and walking zones in general must have sufficient headroom for operators to move safely. A full overview of the rules in visible in Appendix B. The integration of the rules is further explained in Section 3.5.6.

2.8. Literature Conclusions

2.8.1. Identified gap in existing APR literature

Having reviewed all available literature on APR in Sections 2.1 - 2.6, the following gap has been identified: all existing cost functions focus on the length of the pipe and the number of bends, and some also focus on operational factors, but none incorporate the ease of installation of the piping designs. Grouping certain types of pipes is not considered in terms of 'installability', only in terms of an aesthetic objective. Moreover, research by Zhu and Latombe (1991) addresses the idea of macro-piping (Blokland et al., 2023), but does not incorporate it in any practical methods. Three researches do include some form of grouping (Zhao et al., 2019; Dong and Bian (2020); Yuan et al., 2021), but again do not consider this from an 'ease of installation' perspective. These implement the macro-piping to use create more efficient bending patterns as all these pipes can bend together, reducing the overall number of bends.

2.8.2. Technique requirement matching

To make an informed decision on which methods best solve the research problem, each technique identified in Chapter 2 is evaluated against the three requirements of this research: identifying the cost drivers in pipe production, quantifying those costs and translating them into a cost function, and implementing a routing optimisation that reflects those costs. It is key to note that no new algorithm is developed in this research. Instead, existing and proven techniques are combined in a way that directly addresses the gap identified in Section 2.1 the lack of installation-ease integration in automated pipe routing. The evaluation of each technique against the three requirements is summarised in Table 2.3.

Table 2.3: Method Selection Table

Requirement → / Method ↓	Identify Cost Drivers	Quantify Costs	Optimise Routing	Use	Arguments
Lean Management & VSM	++	+	-	Yes	Clearly defines non-value adding activities
FRAM	+	-	-	Possible	Does not identify key costs as well as VSM, but can be used to validate
Fuzzy Theory	-	++	-	Yes	Ideal for quantifying installability
Reinforcement Learning (AI)	-	-	++	No	Too data expensive
Genetic Algorithm	-	-	+	Yes	For spatial reservation and sequencing
A*	-	-	++	Yes	Good balance of speed, and cost function adjustability

2.8.3. Process Analysis Method Selection

For identifying cost drivers, Value Stream Mapping (VSM) is the most appropriate technique. As demonstrated in Section 2.6, VSM maps every step of the production process and separates value-adding from non-value-adding activities. Crucially, it does so in a way that is directly quantifiable: Cycle Times, Change Over times, and Uptime are all expressed as durations, making it straightforward to identify where the largest potential savings lie. FRAM, while useful for non-linear and feedback-driven process analysis (Rother et al., 1999), does not produce this level of quantitative clarity and is better suited to safety-critical functional analysis than cost driver identification. For the purpose of this research, VSM is selected.

2.8.4. Quantification Method Selection

Translating the ease of installation into a numeric value for the cost function requires capturing how engineers and workers describe the working space around a pipe. The two techniques considered are Fitt's Law and Fuzzy Logic. Fitt's Law is a predictive model from human-computer interaction research that estimates movement speed to a target (Norman and Kirakowski, 2018). While it has been applied to physical assembly tasks, the model is parametric and requires precise ergonomic measurements that are not practically obtainable for shipyard installation work. Furthermore, the task of installing a large-diameter pipe in a confined engine room is not well described as a pointing movement, like pointing a mouse on a computer is. Fuzzy Logic (Douglas, 2021) is a better fit for this problem. It directly converts vague, linguistically expressed engineering descriptions — such as 'tight fit' or 'sufficient space' — into numeric membership values, and can be parameterised using expert questionnaire data. As shown by Wu et al. (1998), Fuzzy Logic has already been applied to similar spatial quantification problems in pipe routing. Fuzzy Logic is therefore selected for the quantification step.

2.8.5. Routing Algorithm

Several algorithms are considered for the routing optimisation. The key requirements for this research are:

- Routing on a static 3D grid
- Guaranteed or near-guaranteed optimality
- Adjustability of the cost function
- Computational feasibility for a grid of approximately a couple 100,000 cells

Dijkstra's algorithm guarantees the global optimum but explores every node without directional guidance. This results in computation times that scale poorly with grid size. For a 100×80×50 grid, this is prohibitively slow for iterative use in a design tool (Choi and Lee, 2024). Genetic Algorithms (GA) handle multi-objective and sequencing problems well, as shown by Asmara (2013), but are stochastic and slow when applied to individual pipe routing in static environments. The lack of a guaranteed solution and the additional complexity of population management make GA unsuitable as the core routing method.

Ant Colony Optimisation (ACO) is an alternative to GA that can handle discrete graph problems at medium speed, but also requires a large number of iterations to converge, which makes it slower than A* for single-pipe routing in complex 3D grids (Blokland et al., 2023).

Particle Swarm Optimisation (PSO) converges quickly to a solution but is known to settle on local optima (Kennedy and Eberhart, 1995). For pipe routing in an engine room, where a globally optimal path is the objective, PSO introduces an unacceptable risk of suboptimal results.

Reinforcement Learning (RL) has been shown to work for dynamic, multi-scale routing problems (Liao et al., 2020; Kong et al., 2025), but requires training on existing routed pipe data. This data is not available in the required volume at Damen for the early design stage, making RL data-expensive and impractical for immediate application.

Integer Linear Programming (ILP), as applied by Markhorst et al. (2025), is exact and future-proof, but is NP-hard and does not scale to full 3D geometric routing grids without simplification. It is well-suited to sequencing and space reservation but not to the geometric routing problem addressed here.

The A* algorithm meets all requirements. It guarantees the globally optimal path on the grid through the use of an admissible heuristic (Powell et al., 1968), while its directed search reduces computation time significantly compared to Dijkstra. The cost function is directly adjustable, allowing the installability score derived from the fuzzy logic module to be integrated as a penalty term — which is the core contribution of this research. This adjustability has been demonstrated in similar piping contexts: Kang et al. (2024) achieved a 36-times faster routing plan time than manual design using an A*-based approach in the petrochemical industry. A* is therefore selected as the routing algorithm.

2.8.6. Combined Methodology

No single technique from the literature is in itself sufficient to solve the research problem. The combination of VSM, Fuzzy Logic and A* uniquely bridges the gap identified at the end of Section 2.1. VSM numerically identifies installation as the primary cost driver. Fuzzy Logic translates the vague descriptions of installation space into a numeric installability score. A* uses that score within a cost function to find the pipe route that minimises both length and installation difficulty simultaneously. This combined methodology is the basis for the research presented in Chapter 3 onwards.

3 Methodology and Approach

The current state of research primarily optimises the routing of piping in shipbuilding and other industries, based on reducing material cost and waste as stated in Chapter 2. The reality is that man-hours contribute to a larger portion of the costs than the material costs, found both by previous research as well as being documented by Damen Galati engineers (these stated 1:4 cost ratio of material to man-hours). Consequently, to achieve substantial cost reduction, the underlying philosophy behind the routing algorithms needs to pivot to different primary minimisation. Instead of saving on materials through minimising spool length and frequency of bends, the installation capability of each spool needs to be optimised. Using the conclusions drawn in section 2.8, the tools are then identified to match the requirements necessary to address the optimisation.

The approach will require (1) the numerical identification of the cost drivers, down to detail, in the work processes to produce the most effective optimisation process. Then (2) the cost bottlenecks will need to be integrated in an optimisation technique that can be developed into a tool version for Damen OSV to use in the production process. The bridging step to translate the human interpretations that induce the cost drivers will be achieved using fuzzy logic.

3.1. Scope and boundaries

The final goal of this thesis is to develop a functional routing optimisation tool for Damen to use in their ETO design process, to reduce the costs of piping in the final product. To achieve this most effectively in this thesis, the scope is limited to the engine room of the vessel, as this is widely considered the most complex space where optimisation is most cost-effective. Besides this, the complexity makes the engine room the ultimate benchmark for an automated design tool. Thus, a proven tool for this area of the vessel leads to the applicability of the tool to other, less complicated rooms or areas of a vessel.

Although the machinery arrangement is of strong influence on the routing of pipes, for this thesis a static predetermined (by users of the final tool) MA is set as a boundary condition. Furthermore, to prevent computational overload or out-of-memory errors the 3D environment will be limited to orthogonal grid lines and shapes will be simplified into rectangular boxes.

Moreover, the tool will focus on the main rigid steel piping systems such as fuel, cooling water and bilge water pipes. Small-bore pipes (below 50mm diameter) or plastic/composite pipes will be excluded from the scope.

Additionally, the tool must at all times adhere to the class rules of the classification society involved in the design of the vessel.

Finally, the optimisation will only focus on the immediate installation costs and production costs (CAPEX). Any operational costs (OPEX) will be left out of the cost function of the optimisation algorithm.

3.2. Identification with Value Stream Mapping

With data acquired from yards regarding the hours spent on pipe production processes, a value stream map can be created to demonstrate the time costs and effectiveness per step in the production. This can prove the misalignment in man-hours and find the point of production where the key cost drivers are located. To implement, each step of the process needs to have a start and end time, and an effective working time (value added time). The hypothesis is that the most man-hours are spent in the installation process of the full production cycle of a spool. The first VSM will be created focusing on the final of the 4 main steps of the total design to production process:

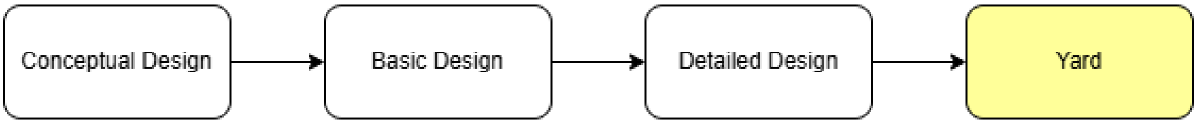


Figure 3.1: Full overview of design to production process, VSM focusses on the yard step

Once an overview is created on what production process the efficacy of the man-hours is least, a new VSM is created in more detail for that specific process. Then with the precise data on what specific parts of the installation process cause excess man-hours, this can be implemented in the cost function.
The KPIs that define the bottlenecks of production are the 'value added' and 'non-value added'.

- Value added: any time spent altering the product for the final stage, that is productive such as changing inherent properties (shape, weight, material etc.).
- Non Value added: lead times where spools lay unused on the work-racks or waiting for next value added step.

Data for the VSM is attained from two different yards, one in Galati, Romania, and the other in Sharjah, UAE. Galati will be visited for interviews with engineers and production teams, as well as data attainment through Spool Tracing™. Due to current circumstances, Sharjah will only be available through digital tracking software and short online meetings.

3.3. Incorporating cost drivers in a cost function

Once the cost drivers are identified, the way it is incorporated into the final algorithm depends on how the cost driver can be formulated in numerical values. Fuzzy logic will be used to translate the difficult-to-quantify cost drivers. A questionnaire will be made to attain the human perspective on the matter to convert to final numerical value. Fuzzy meets the requirements to get measurable values from non-numeric inputs from humans.

3.3.1. Fuzzy Logic

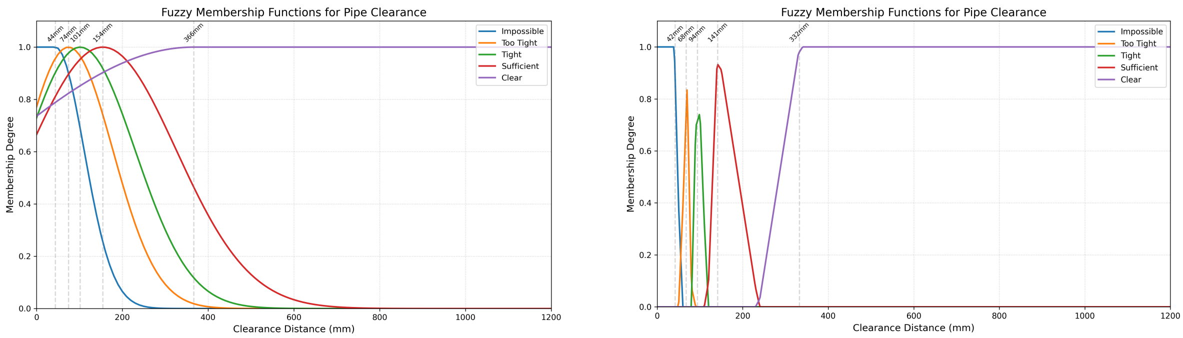
To incorporate the installability into the algorithm, that parameter must be numeric as to be usable in a cost function. **Fuzzy Logic** bridges the gap between human vague language that describes the ease of install to the numbers necessary for the cost function of the optimisation algorithm. A hybrid approach between the Mamdani (Babuška and Mamdani, 2008) and TSK (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) fuzzy logic methods is used. Mamdani-style linguistic membership functions are defined over the input universe, while TSK-style crisp consequents are assigned to each category. Because the system has a single input variable, a full IF-THEN rule base would reduce to five trivial singleton rules — one per linguistic category — with no combinatorial interaction effects. The inference step therefore collapses into a direct weighted-average defuzzification, where each category's firing strength equals its membership degree at the observed clearance value.

3.3.1.1 Fuzzification

Fuzzification constitutes the first stage of the fuzzy inference process. It is a process in which a precise, deterministic value (referred to in fuzzy logic as a *crisp value*) is mapped onto one or more fuzzy sets. These sets are characterised by a *membership function* that assigns a degree of membership $\mu \in [0, 1]$ (Zadeh, 1965; Douglas, 2021).

To translate the first step is fuzzification. This is done by creating membership functions, dictating a degree of truth for which a crisp value belongs to a vague description given by humans. A questionnaire filled in by **10** experts on the subject of piping gives the membership functions. In the questionnaire, the questions are asked about what minimum distances are associated with the outermost limit of a pipe spool to the nearest wall or obstacle when considering descriptions as 'too tight', 'tight', 'sufficient' and 'clear'. With all the data combined, the membership functions defined by the values given by the engineers and workers can be used to define a degree of truth of a distance. Either a Gaussian distribution or triangular functions can be used for the membership functions.

Although Gaussian functions can reflect the statistical spread across many responses, this research adopts this only when there are sufficient responses (≥ 50). There are three reasons to use the triangular distributions over the Gaussian. First, there needs to be sufficient data to develop a reliable probability distribution, something that is difficult to attain for novel complex systems (Lin et al., 2012), such as enough inputs from experts. The uncertainty captured by the fuzzy membership functions are possibilistic rather than probabilistic. Expert language such as 'tight' or 'sufficient' describes subjective, vague interpretations and not statistically random values (Zadeh, 1965; MacKenzie, 2015). Second, the triangular functions are also the most economical to define, requiring only three inputs per function. This matches the output from questionnaires structured with a lowest value, the peak value (most recurring or average), and a maximum value. Finally, triangular fuzzy membership functions are noted to be easier to compute than probability distributions, making them highly applicable in practical industry tools (Lin et al., 2012; Matuszek et al., 2020). For example, figure 3.2a shows the Gaussian distribution of the expert input and figure 3.2b shows the triangular function.



(a) Gaussian Membership functions as defined by experts

(b) Triangular Membership functions as defined by experts

Figure 3.2: Expert-defined fuzzy membership functions for analysis.

In figure 3.2 it shows that Gaussian functions do not correctly represent the distribution of overlapping agreement in subjective vagueness that triangular does. The distributions shown in Figure 3.2b will be incorporated into the cost function. The distances to surrounding objects will be computed, inserted, and then assessed based on how 'installable' the chosen routing is.

It is important to only have input from experts in the field of pipe installation. More inputs are not inherently better, as low quality inputs can lead to more noise than added value and/or increased accuracy of the fuzzy logic.

3.3.1.2 Defuzzification

Using the values extracted from the membership functions, a time multiplier is determined through the data from the expert input about 'How much longer installation takes considering the (too) tight, sufficient or clear space'. The distribution of the questionnaire output is visible in figure 3.3 below.

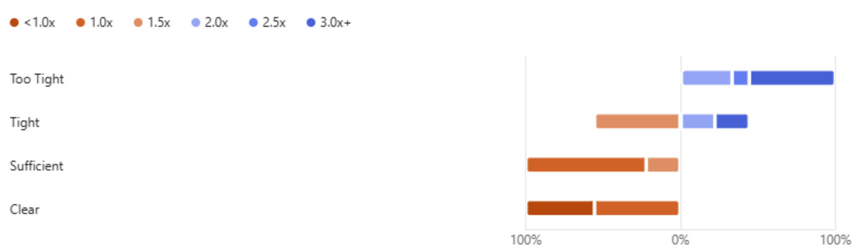


Figure 3.3: Time Multiplier estimations by piping experts per space of working description

Translating these values using the fuzzy value inputs creates the following distribution :

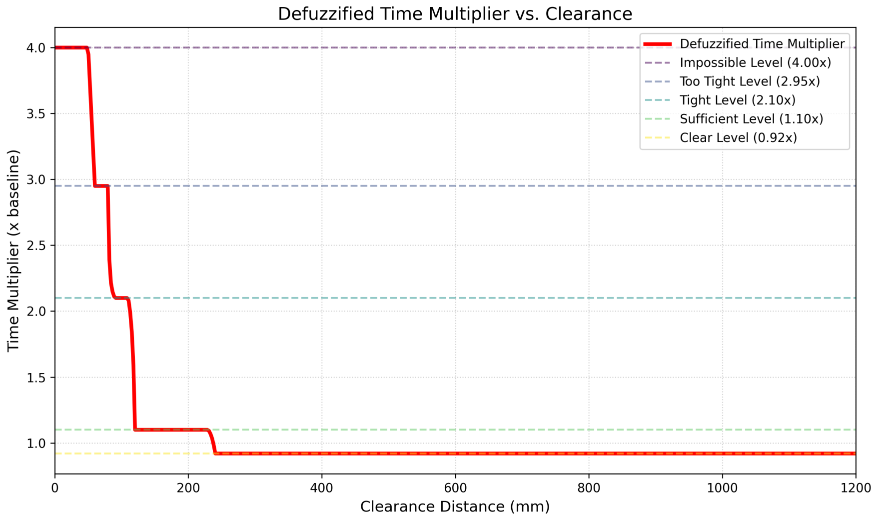


Figure 3.4: Defuzzification of the installation distances to time multiplier

Through the questionnaire, the inputs for the membership functions are made with definitions as follows:

- **Installation distance:** the distance form the outermost part of a spool to the nearest (non-fastening) wall or object in millimeters.
  - Impossible
  - Too Tight
  - Tight
  - Sufficient
  - Clear
- **Time cost per space definition:** If 'Sufficient' is the baseline duration (*1.0x*), how is duration affected by the different spacial definitions? *For each distance definition, <1,0x, 1.0x 1.5x 2.0x 2.5x 3.0x+ is selected.*

This provides the data distribution necessary to create the membership function and to create the defuzzification step from the degrees of truth to the cost function input value. An example of what this will look like is demonstrated in figure 3.5. These Gaussian distribution are now randomly generated based on estimates of spaces. This is under the circumstances of there being hundreds of input values from the questionnaire to be able to sufficiently demonstrate the probabilistic distribution in Gaussian.

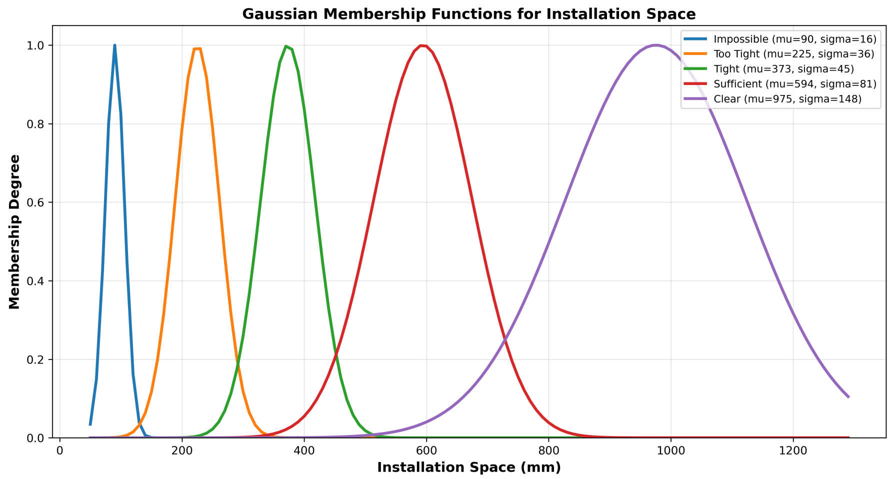


Figure 3.5: Membership Function examples, based on random distributions

This gives degrees of truth. For the example in figure 3.5, the value of 250mm space gives the following membership degrees:

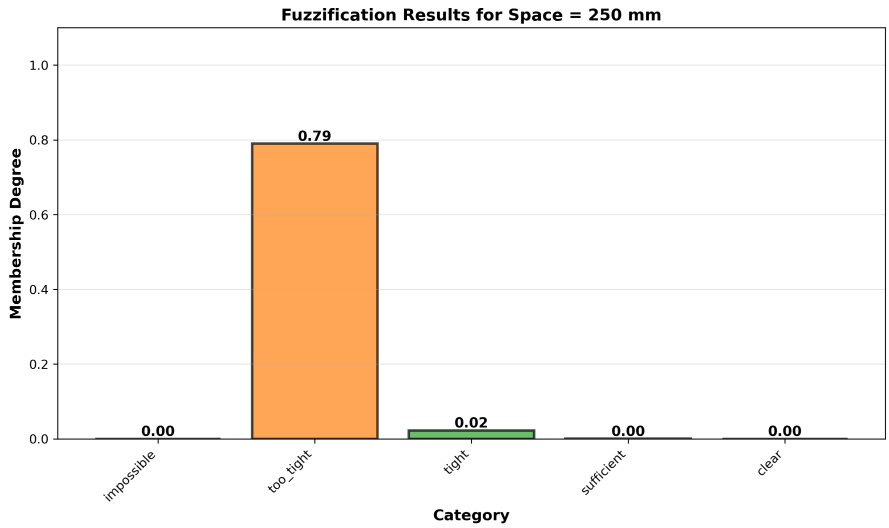


Figure 3.6: Membership degree 250mm for functions in fig. 3.5

Finally, the reverse of this will be done to give the penalty amount to the degree of installability for the algorithm cost function.

Besides this, the rule-based function will also consider congestion and 'parallelism'. If many pipes do not align in the same direction and cross paths, a rule to align pipes as much as possible will be implemented. This significantly aids the installation process, as stated by the project completion engineers at the Galati shipyard.

3.4. Broad Implementation Description

The identified costs will be integrated into an A* algorithm, finding a balance between cost function adaptability, speed and optimal route finding. In comparison to other optimisation techniques using artificial intelligence, it requires no prior data training models to achieve the optimisation. Developing the back-end in python, a software tool will be created, with A* algorithm as the base pathfinder, and the previous human inputs translated by Fuzzy Logic as the definer of the key cost drivers in the algorithm's cost function. The front end will be a usable 3D routing visualisation for the engineers to use as a base for their designs.

The cost function of an A* algorithm consists of 2 parts:

$$f(n) = g(n) + h(n) \tag{3.1}$$

Where $g(n)$ is the accumulative cost of a pipe up till the point of the route, and $h(n)$ is a heuristic cost function estimating the cost from the current node to the destination node. $g(n)$ can be adjusted to account for different cost penalties for the path.

$$g(n) = w_1 \cdot L + w_2 \cdot B + w_3 \cdot f(fuzzy) \tag{3.2}$$

Now, with w_1, w_2, w_3 being the different weights and L being length, B is bend and $f(fuzzy)$ being a fuzzy numerical value corresponding to the 'installability', the weight can be assigned based on what is considered more crucial. This formula is a simplified preview of full equation 3.7. The integration of the ease of installation concerning pipe spools into optimisation algorithms designed to find the shortest path, is a novel technique not yet identified in different studies. Based on real data from the yard assessed with VSM, converting the subjective labour constraints to crisp numerical values using fuzzy logic and using these values as the cost function within the A* pathfinding algorithm is currently nonexistent. Development of a design software based on this mathematical model enhances design efficiency, reducing the man-hours in both engineering and production.

The accumulated cost $g(n)$ is constructed as the sum of all step costs $c(n_i \rightarrow n_{i+1})$ along the path from the start node $n_0 = s$ to the current node n_k:

$$g(n_k) = \sum_{i=0}^{k-1} c(n_i \rightarrow n_{i+1}) \tag{3.3}$$

Since every step cost satisfies $c(n \rightarrow n') \geq w_{\text{dist}} > 0$, the function $g(n)$ is strictly monotonically increasing with path length, and no local minima exist in the accumulated cost landscape. The heuristic $h(n)$ is the Manhattan distance to the goal (Equation 3.8), which is an L_1-norm and therefore a convex function of node coordinates. As the sum of two convex functions, $f(n) = g(n) + h(n)$ is itself convex. Crucially, $h(n)$ is *admissible*: it never overestimates the true remaining cost $h^*(n)$, i.e. $h(n) \leq h^*(n)$ for all $n \in \mathcal{V}$. This admissibility condition, combined with the convexity and non-negativity of $g(n)$, guarantees that A* identifies the **globally optimal path** when the goal node is first expanded, without the risk of convergence to local optima (Powell et al., 1968).

The basic primary rule set that is satisfied at all times must be the class rules as stated in section 3.1. These will be integrated based on rules such as: *IF switchboard THEN no fluid pipes above*. Such an implementation would then take the $[x, y]$ coordinates of the said switchboard and block any $[z]$ coordinate above for fluid-containing pipes.

The following tests will be performed to ensure basic benchmarks are met:

- **Pathfinding check:** in an empty space, the routing should have the shortest route, aligning multiple pipes to allow simple installation.
- **Class Rule check:** implement simple rules (e.g. switchboard), to ensure the rules are enforced
- **Implement correct prioritisation:** the order of installation given by the engineer should be the order of installation. Theoretically, heavy, larger-diameter pipe spools have priority.

Maximal Theoretical cost saving
The final step of development is validating the software. Here, a case study will be performed with an existing engine room and the registered time it took for all spools to be installed. With the theoretical time savings using the software, a cost savings calculation can be performed. Hence, demonstrating the efficacy of the software.

3.5. Routing Tool Design and Implementation

The routing algorithm is the computational core of the pipe routing optimisation tool developed in this research. Continuing the theoretical framework laid out in section 3.4, the following section will describe the complete implementation of the routing system. The tool takes a defined engine room (given by the user), a set of placed machinery (given by the user) and a list of pipes to route with start and end points and returns optimised three-dimensional pipe paths. This solution balances pipe length, number of bends and installation accessibility. The tool is written in Python and made accessible (and shareable) for engineers through the Streamlit web interface.
The backend of the tool is composed of four interconnected modules:

- **Spatial discretisation:** converts the engine room to a grid;
- **Clearance mapper:** predetermines the grid's available spaces before calculation;
- **Fuzzy installability module:** translates the clearance of all the grid points to an installability score and a time multiplier;
- **A* router:** uses the previous three to find the cost-optimal pipe path.

Below each module is described in more detail.

3.5.1. Spatial Discretisation

To calculate the paths, the A* algorithm requires the space to be discretised. This is achieved by creating a uniform three-dimensional grid in the room volume. Each grid represents a corner point of a volume cell with edge length r, referred to as the grid resolution.

3.5.1.1 Grid resolution

For all the path finding computations, a resolution of r=0.1m is used. For example, in a 10x8x5 m engine room, the room is discretised to $100 \times 80 \times 50 = 400,000$ cells. The world coordinates associated with grid cell [gx, gy, gz]^T is therefore:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} r + \begin{bmatrix} 0 \\ 0 \\ -0.5 \end{bmatrix} \tag{3.4}$$

The final vector offsetting the grid -0.5 in z is to create the half a meter clearance for pipes to run below the engine room, as is common practice. The choice is made for a grid resolution of 0.1 m, although this is a trade-off. A coarser 0.5 m grid, more common in literature (Blokland et al., 2023; Dong and Bian, 2020), could miss crucial clearance variations around machinery corners and/or small passages. A finer 0.05 m grid would increase the amount of grid points by 8 (2^3), vastly increasing the computational power necessary to solve the optimisation. Adjusting the grid resolution therefore exponentially affects either the accuracy or the computational time.

3.5.2. Environment Modelling

3.5.2.1 Obstacle encoding

Before the routing begins, the tool builds a static obstacle set based on the locations given by the user. A grid cell is marked as an obstacle if its corresponding world position falls in a bounding box of any of the following:

- Machinery items; these occupy a rectangular volume defined by the position, length, width and height
- No-go zones; defined by an engineer as explicit forbidden areas
- Walking spaces; these are areas that block routing for z = 0 m to z = 2.1 m. This is in line with class rules as head-clearance requirements for crew working zones.

For each bounding box, any grid cells whose indices fall within the box boundaries are added to the obstacle set. The conversion from world coordinates to grid index utilises integer rounding as follows:

$$gx = round(\frac{x}{r}) \tag{3.5}$$

Then these obstacles are stored as a Python set (gx, gy, gz) of integer tuples. This data is continuous through time, meaning it does not change no matter the amount of new pipes. This is noted as O(1) membership test. This results in a significant decrease in computation time as each A* node expansion checks up to 6 neighbouring points.

Routing trays
Routing trays are also obstacles, pipes cannot run through these. The spaces are reserved for cable routing.

3.5.3. A* algorithm

Implementing A* algorithm is adjusting the initial cost function explained in section 2.5.1.2. Implementation is done using 6-connectivity: each cell can expand to the neighbouring orthogonal nodes $[\pm x, \pm y, \pm z]$. For the sake of the computational power, diagonal moves are excluded. This produces axis-aligned piping, in accordance with standard practice in shipbuilding piping.

3.5.3.1 Cost function

The routing problem is formulated as a shortest-path optimisation over the discretised engine room grid. Let $\mathcal{V}$ denote the set of all free (non-obstacle) grid nodes, and let $\mathcal{P}(s,t) \subseteq \mathcal{V}$ denote the set of all collision-free, class-rule-compliant paths from start node s to goal node t, where each path $P = (n_0, n_1, \dots, n_N)$ satisfies $n_0 = s, n_N = t, n_i \in \mathcal{V}$ for all i, and $n_{i+1} \in \mathcal{N}(n_i)$ (the six orthogonal neighbours of n_i). The optimal pipe route P^* is defined as:

$$P^* = \underset{P \in \mathcal{P}(s,t)}{\arg\min} \sum_{i=0}^{N-1} c(n_i \to n_{i+1}) \tag{3.6}$$

where $c(n \to n')$ is the step cost from node n to candidate node n', defined in full below (Equation 3.7). The accumulated cost $g(n_k) = \sum_{i=0}^{k-1} c(n_i \to n_{i+1})$ therefore represents the objective value of the partial path to n_k, and minimising $g(n_N)$ at the goal node t is equivalent to solving Equation 3.6. The A* algorithm solves this exactly by evaluating $f(n) = g(n) + h(n)$ at each candidate node, where $h(n)$ is an admissible lower bound on the remaining path cost from n to t.

The standard cost function with the fuzzy part comes from equation 3.2. The complete adjustment for A* is expressed for the calculation of the costs from node n to the next node n':

$$c(n \to n') = w_{dist} + w_{bend} \cdot \delta_{bend} + w_{vert} \cdot \delta_{vert} + w_{inst} \cdot (1 - s_{inst}(n')) - w_{parr} \cdot \delta_{parr}(n') - w_{wc} \cdot \delta_{wc}(n') \tag{3.7}$$

The 5 terms used are integrated and used as follows:

- w_{dist} is the base movement cost (default: 1.0). Every step carries this cost, ensuring that all other factors equal, the router prefers shorter routes.
- $w_{bend} \cdot \delta_{bend}$ is the bend penalty. $\delta_{bend} = 1$ when the movement direction changes relative to the immediately preceding step, 0 otherwise. Each direction change corresponds to a physical pipe bend, which adds fabrication cost and reduces the accessibility of the resulting spool (Hadelkamp, 2017).
- $w_{vert} \cdot \delta_{vert}$ is the vertical penalty. $\delta_{vert} = 1$ when $dz \neq 0$, penalising upward and downward routing segments that require additional support structures and are more difficult to install in confined spaces.

- $w_{inst} \cdot (1 - s_{inst}(n'))$ is the fuzzy installability penalty, derived from the clearance map and fuzzy system (Section 3.5.5). This is the key term added by this research relative to conventional A* pipe routing formulations.

- $w_{par} \cdot \delta_{par}(n')$ is a cost discount applied when cell n' is in the preferred-cell set adjacent to a routed pipe. This term is subtracted, reducing the total step cost and guiding the router towards parallel piping locations.

- $w_{wc} \cdot \delta_{wc}(n')$ is a cost discount that is applied when cell n' lies adjacent to a structural wall or ceiling, in this case being the outer lateral and vertical boundaries of the engine room dimension. This is a subtraction term, encouraging the router to route along walls and ceilings, as is common practice in shipbuilding.

All weights are configurable parameters for users of the tool, allowing full control over how the optimisation is tested. This additionally allows validation of the tool by adjusting weights and analysing path differences.

3.5.3.2 Heuristic

Manhattan distance is used for the heuristic of the A* algorithm. This is computed in grid coordinates between the current node n and the goal node g:

$$h(n) = |n_x - g_x| + |n_y - g_y| + |n_z - g_z| \tag{3.8}$$

w_{dist} from equation 3.7 is set to have a minimum value of 1.0. This, combined with the Manhattan distance, which counts the minimum number of orthogonal steps to the goal, makes the heuristic admissible.

3.5.4. Clearance Map pre-computation

Fuzzy logic requires the distance to the nearest obstacle in millimeters for each grid cell. An on-the-fly method during the A* route search is computationally taxing at the resolution of 0.1 m. Thus, a full clearance map is computed once before the routing begins and stored in a 3D array.

The method used is the Breadth-First Search (BFS) (Wikipedia contributors, 2026) over the 26 connected neighbouring cells. This 26 comes from the 6 orthogonal $\pm x, \pm y$ or $\pm z$ where grid distance is 1, 12 diagonal in plane $[\pm x, \pm y]$ with grid distance $\sqrt{2}$ and the 8 diagonal cells $[\pm x, \pm y, \pm z]$ with grid distance $\sqrt{3}$. This results in a spherical searching shape, speeding up the process of finding the Euclidean distance for each grid cell to the nearest object. The seed (starting point) is in the object cells, all assigned with a seed distance of 0 m. Boundary cells beside walls and ceilings get the clearance to the nearest obstacle and not to the wall or ceiling beside it. This is simplified compared to reality, but leads to installation also being nearer to walls and ceilings (clearance may still be overestimated for these cells). The BFS wave front propagates outward, updating the distance of each free cell (no distance assigned yet) to the accumulated distance to the nearest seed:

$$d(n) = \min[s_{\text{distance}}(n)] \tag{3.9}$$

$$s_{\text{dist}} = \sqrt{(n_x - s_x)^2 + (n_y - s_y)^2 + (n_z - s_z)^2} \tag{3.10}$$

As the distances are determined in all directions for each step is pre-computed (1 for orthogonal, $\sqrt{2}$ for face diagonal, $\sqrt{3}$ for body diagonal), the BFS calculated the Euclidean distance without transforms for each grid cell. The transform is then as follows to millimeters to the nearest obstacle:

$$d_{mm}(g_x, g_y, g_z) = d(g_x, g_y, g_z) \cdot r \cdot 1000 \tag{3.11}$$

Where r is the grid distance and multiplication by 1000 to match the questionnaire fuzzy membership function's values.

3.5.5. Fuzzy Installability

In Section 3.3.1 a more complete explanation is given about the initial definition of the fuzzy membership functions used in the tool.

3.5.5.1 Fuzzification

Using the fuzzy membership functions attained from the questionnaire and described in chapter 3.3.1, the distances for each grid node can be categorised in a membership function, thus determining the degree of 'installability'. This is based on the clearance value x for each node, measured as the distance to the nearest object (section 3.5.4).

3.5.5.2 Defuzzification

With the degree of memberships known, the defuzzification step calculating the installability score s and installation time multiplier m are obtained with the weighted averages from all the active categories:

$$s(x) = \frac{\sum_k [s_k \cdot \mu_k(x)]}{\sum_k [\mu_k(x)]} \tag{3.12}$$

$$m(x) = \frac{\sum_k [m_k \cdot \mu_k(x)]}{\sum_k [\mu_k(x)]} \tag{3.13}$$

Where $s_k \in 0.00, 0.341, 0.617, 0.942, 1.00$ are the normalised installability scores based on responses from the questionnaire (values visible in Figure 3.3) and m_k are the installation time multipliers, based on the values from the Installability questionnaire. An $s_k = 1.0$ corresponds to a completely clear space and $s_k = 0.0$ to a space impossible for installation. The normalisation is taken by normalising over maximum and minimal values of the time multiplication (output value) defined by the experts.

3.5.5.3 A* Penalty integration

Each candidate cell n' considered during the A* search, the effective distance to the nearest obstacle is extracted from the clearance map:

$$x_{eff} = max(50, d_{mm}(n') - r_{pipe}) \tag{3.14}$$

For equation 3.14, r_{pipe} is the pipe radius (half the nominal outer radius of the pipe, dictated by the user). By subtracting the radius from the clearance, a meaningful value of the space around the pipe can be defined. This value is physically meaningful for the installation ease. A lower boundary of at least 50 mm is taken to ensure that there is always a calculable value, preventing sluggish responses from the algorithm.

The installability score in equation 3.12 can be calculated with the x_{eff} for the effective score. The penalty is calculated as follows:

$$C_{inst} = w_{inst} \cdot (1 - s_{inst}) \tag{3.15}$$

This value ranges from 0 to w_{inst} where a cell is considered impossible to install $s_{inst} = 0$. The continuous nature of this cost integration, results in pathfinding not fully avoiding spaces but rather preferring through the least constrained areas even if the path is longer, with more accessible space.

3.5.6. Class Rules Constraints

As stated in 3.1 class rules are a hard constraint for this tool. The rules are derived and shown in Appendix B. Rules are implemented per pipe routed as an additional pre-processing step. This ensures that enforcing a rule on one pipe does not obstruct the routing of another pipe. Specific rule obstacle cells are added to a local copy of the obstacle set in question, allowing the global obstacle set to remain untouched.

The foundation of most rules is based in the pipe content types. This is assigned by the user for each pipe. There are nine categories:

Table 3.1: Pipe Content Category Membership for Routing Rules

Content Category	Liquid Set	Flammable Set
1. General Fluid	Yes	No
2. Fuel / Flammable Oil	Yes	Yes
3. HP Fuel (Injection)	Yes	Yes
4. Lubricating Oil	Yes	Yes
5. Seawater / Ballast	Yes	No
6. Bilge	Yes	No
7. Freshwater / Cooling	Yes	No
8. Gas / Compressed Air	No	No
9. Exhaust / Steam	No	No

3.5.6.1 Switchboard Vertical Volume Exclusion

As stated in Lloyd's Register (LR Pt 5, Ch 13, 5.5), no liquid carrying pipes should travel over the vertical volume above a switchboard. To adhere, any objects tagged as '*Switchboard*' have the vertical column of grid cells marked as obstacles for the current pipe's search if the pipe's contents type belongs to the liquid set.

3.5.6.2 Hot Surface to Flammable Pipe

BV (Pt C, Ch 1, Sect 10 [11]) states that flammable pipes require a minimum distance of 500 to any surface reaching temperatures above 220°C; if it should be less than 500 mm of clearance, pipe shielding is required. The tool marks any spaces surrounding an object tagged '*Hot Surface*' within 500 mm as an exclusion area for pipes transporting contents in the *Flammable Set*. While hot surfaces are mandatory to insulate, enforcing the rule in such a way is according to industry standard practice.

3.5.6.3 Bilge and Ballast line separation

BV (Pt C, Ch 1, Sect. 10[7]) dictates that bilge lines must be kept entirely separate from seawater and ballast lines to prevent accidental pollution through shared manifolds or cross contamination during fault conditions. To implement this rule, when routing a 'Bilge' pipe, any grid cells within 300mm of an already routed ballast or seawater pipe are added as hard objects. The process works vice versa for the opposite pipe types.

3.5.6.4 Post Routing Compliance Check

In addition to the rules implemented above, any rules further applying to piping to do with supports or bending due to length are checked post routing. These are then flagged for the engineer to keep in mind for further development.

3.5.7. Multi Pipe Routing Strategy

Due to the selection of A* algorithm, the ability to also determine the order of pipes routed is lost. This is compensated by allowing the pipe priority to still be determined by the user of the tool. The pipes are sorted in ascending order of the priority index. Once a pipe has been routed, the grid cells used by the newly routed pipe are added to the obstacle set used by subsequent pipes. This prevents the intersection of pipes without implementing a multi-commodity formulation that would require large computational power.

3.5.8. Output and Performance Metrics

Subsequent to the routing process, all pipes are assigned the 2 metrics previously mentioned: **Installability Index (II)** and **Time Multiplier (TM)**. The II is calculated by taking the average installability quality over all N waypoints of a pipe route:

$$II = s_{avg} = \frac{1}{N}\sum_{i=1}^{N} s(x_{eff}, i) \tag{3.16}$$

A value of $s_a vg = 1$ indicates a fully clear route with no obstacle encountered. Values of $s_{avg} \leq .85$ indicate that somewhere in the route the pipe passes tighter clearance zones. This metric provides a single numerical value indicating the ease of install of a full pipe route. The MP is calculated similarly:

$$TM = m_{avg} = \frac{1}{N}\sum_{i=1}^{N} m(x_{eff}, i) \tag{3.17}$$

This metric is representative of the estimated installation time for pipe relative to the baseline route through an unobstructed space. A value of $m_{avg} = 1.4$ indicates that the estimated installation duration will take 40% longer than the baseline time. Together **II** and **TM** represent the primary numerical outputs allowing for quantitative validation and a case study.

4 Implementation and Case Study

In this chapter the routing algorithm is tested through controlled tests and then applied to a real vessel case study. The verification tests shall test the basic functionalities and a toy-problem will verify the working principle of the tool's algorithm. The case study will describe the theoretically achievable profit of the use case of the routing tool on a real-world vessel.

4.1. Algorithm Verification Tests

Preceding the case study, the tool must be validated first to ensure the efficacy of the algorithm. 3 tests are run to verify the 3 core goals of the pathfinding. Each of these tests isolates a specific capability of the A* algorithm implementation, thereby ensuring the algorithm performs correctly under verifiable, controlled and repeatable conditions. The tests are performed in a fixed box, where the start and end points of the route can be precisely defined and an expected outcome can be analytically determined. Each time the algorithm is adjusted, these tests are performed to ensure that the underlying logic is preserved.

4.1.1. Straight path test

In an empty bounded box, defined to replicate the engine room dimensions, a start and end node are selected that share the same axis (X, Y or Z). The expected result is a perfectly straight line that follows the shortest path between these two points. This test verifies the heuristic that guides the solution to the shortest path without making any detours. Besides this, it also verifies that the cost function does not introduce any bias that could cause deviation from the shortest Euclidean route.

Table 4.1: A* Routing Algorithm Test 1: Straight-Line Path Verification

Parameter	**Result / Observation**
Test Identifier	TEST 1: No obstacle — path should be (near) straight
Path Found	YES
Total Waypoints	17
Final Path Length	8.00 m
Theoretical Minimum	8.00 m
Max Lateral Deviation	0.000 m
Path Characteristic	Perfectly straight (□Passed)
Status	**PASSED □**

4.1.2. Shortest path around obstacle

A single obstacle is placed between the start and end nodes of the path, blocking the direct path between these two predetermined points. The shortest path is analytically computable, thus allowing a direct comparison between the expected path and the routed one. This test validates that the route finding avoids obstacles logically and that the A* heuristic remains functional.

Table 4.2: A* Routing Algorithm Test 2: Shortest Path Optimisation around obstacle

Parameter	**Result / Observation**
Test Identifier	TEST 1: Shortest path ($w_{\text{installability}} = 0$)
Path Found	YES
Total Waypoints	29
Final Path Length	14.00 m
Obstacle Avoidance	YES (□Passed)
Straight-line Dist (2D)	10.00 m
Path Efficiency	40.0% longer due to obstacle detour
Status	**PASSED □**

4.1.3. Fuzzy Installability cost integration

Two possible routes are presented: one shorter that passes close to an obstacle (low clearance) and a longer route that has more clearance around the object. The fuzzy membership functions, determined every 10 cm along a route, should assign a high cost to the low-clearance route, adding a high Time Multiplier (TM), and a lower cost to the longer route with better clearance, receiving a lower Time Multiplier. Through this test, the algorithm should select the longer route, as due to the low TM, although the longer route is favoured in terms of 'installability'. This confirms that the total weighted cost (pipe weight · Time Multiplier) is correctly integrated into the A* algorithm's cost function.

Table 4.3: Test 3: Fuzzy Logic and Routing Results

Category	**Center**	**Mult.**	**Score**
Impossible	133.3	4.00	0.00
Too Tight	200.0	3.17	0.36
Tight	316.7	2.33	0.63
Sufficient	533.3	1.33	0.94
Clear	1033.3	1.00	1.00

Parameter	**Result**
Test ID	TEST 3 ($w_{\text{inst}} = 2.0$)
Data	3 responses
Path Found	YES
Waypoints	29
Path Length	14.00 m
Avg. Inst.	1.000
Avg. TM	1.000×
Obstacle	YES □
Status	**PASSED □**

4.2. Verification toy problem

To evaluate the efficiency of the implementation of the fuzzy logic of installability in the cost function of the A* logic, the II and TM are assessed when changing the weights of the algorithm. This validation is done by creating a realistic engine room, with the following machinery and locations visible below in table 4.3. The room's initial dimensions are [12, 10, 5].

Machinery Name	Type	LxWxH (m)	X	Y	Z	Constraint
Main Engine Starboard	General	$4.5 \times 1.8 \times 2.0$	2.0	1.0	0.0	floor
Main Engine Port	General	$4.5 \times 1.8 \times 2.0$	2.0	6.2	0.0	floor
Gearbox Starboard	General	$1.5 \times 1.8 \times 1.5$	0.5	1.0	0.0	floor
Gearbox Port	General	$1.5 \times 1.8 \times 1.5$	0.5	6.2	0.0	floor
Diesel Generator 1	General	$3.0 \times 1.8 \times 1.8$	7.5	0.5	0.0	floor
Diesel Generator 2	General	$3.0 \times 1.8 \times 1.8$	7.5	7.2	0.0	floor
Main Switchboard	Switchboard	$3.0 \times 1.0 \times 2.0$	5.0	9.0	0.0	wall
Emergency Switchboard	Switchboard	$1.5 \times 1.0 \times 2.0$	9.5	0.0	0.0	wall
Turbocharger Starboard	Hot Surface	$0.7 \times 0.7 \times 0.6$	4.5	2.1	2.0	free
Turbocharger Port	Hot Surface	$0.7 \times 0.7 \times 0.6$	4.5	6.2	2.0	free
Central Cooler	General	$2.0 \times 2.0 \times 1.5$	9.0	3.5	0.0	floor
Fuel Oil Purifier	General	$0.8 \times 0.8 \times 1.2$	8.0	2.5	0.0	floor
Lube Oil Purifier	General	$0.8 \times 0.8 \times 1.2$	9.0	2.5	0.0	floor
Air Compressor	General	$1.0 \times 1.0 \times 1.2$	10.5	5.5	0.0	floor
Bilge Pump	General	$0.8 \times 0.8 \times 0.8$	1.0	4.5	0.0	floor

Table 4.3: Machinery information used in validation test

Table 4.4: OSV Engine Room Test Dataset – Pipe List

ID	Pipe Name	Content Type	System Type	DN	Priority
p_0	ME STB HP Fuel Supply	HP Fuel (Injection)	Closed / Pressurised	32	1
p_1	ME PORT HP Fuel Supply	HP Fuel (Injection)	Closed / Pressurised	32	1
p_2	ME STB Jacket Cooling	Freshwater / Cooling	Closed / Pressurised	80	2
p_3	ME PORT Jacket Cooling	Freshwater / Cooling	Closed / Pressurised	80	2
p_4	ME STB Lube Oil Supply	Lubricating Oil	Closed / Pressurised	50	2
p_5	ME PORT Lube Oil Supply	Lubricating Oil	Closed / Pressurised	50	2
p_6	DG1 Fuel Supply	Fuel / Flammable Oil	Closed / Pressurised	25	3
p_7	DG2 Fuel Supply	Fuel / Flammable Oil	Closed / Pressurised	25	3
p_8	Sea Water Cooling Main	Seawater / Ballast	Closed / Suction	100	2
p_9	Ballast Main	Seawater / Ballast	Closed / Pressurised	100	3
p_10	Fire Main	Seawater / Ballast	Closed / Pressurised	80	2
p_11	Bilge Main Discharge	Bilge	Closed / Suction	80	4
p_12	Bilge STB Collection	Bilge	Closed / Suction	65	5
p_13	Bilge PORT Collection	Bilge	Closed / Suction	65	5
p_14	Starting Air STB	Gas / Compressed Air	Closed / Pressurised	40	2
p_15	Starting Air PORT	Gas / Compressed Air	Closed / Pressurised	40	3
p_16	Fuel Oil Transfer	Fuel / Flammable Oil	Closed / Pressurised	50	5

Name Walkway	X min	X max	Y min	Y max
Centre Walkway	0.0	12.0	3.3	5.2
Cross Passage	6.8	7.5	3.0	6.2

Table 4.5: Walkways used in validation tests

4.2.1. Installability Index

By varying the weighting of the installability fuzzy logic within the cost function, the effectiveness of the part of the algorithm can be validated and demonstrated. In Figure 4.1 the analysis is shown. The lower X-axis is the weight of the installability part of the cost function. The Y-axis, the installability index is displayed. The values calculated and displayed are derived for the described engine room in section 4.2 previously by calculating the average II across all pipes, for different w_{inst} from equation 3.7 each time.

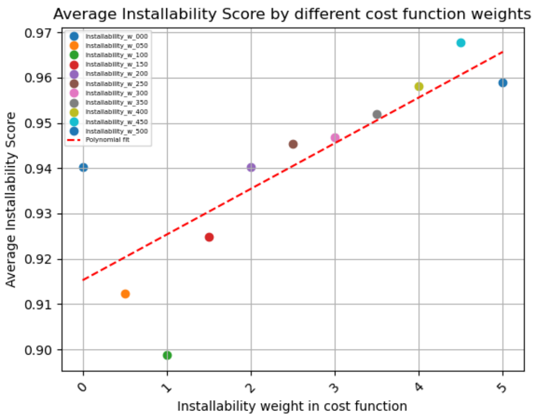


Figure 4.1: Installability Index averaged for different cost function weights

Interestingly, the II decreases initially when increasing the w_{inst}. This phenomenon can be explained by the fact that the cost function still prefers the shortest route, but attempts to steer to less congested areas. The priority order of the pipes comes in to play here. The lower priority pipes **decrease** in II for the values of $0.5 \leq w_{inst} \leq 1.5$ when compared to no installability cost at all in the cost function. This is due to the higher-priority pipes blocking paths, therefby increasing the costs (due to no shorter paths being accessible), and thus decreasing the installability index. However, once the installation ease becomes dominant in the cost function for $w_{inst} \geq 2$, the II increases almost linearly. Looking at lower-priority pipes confirms this in figure 4.2. The Lowest priority pipe (5), is the last to be routed and is the bilge system. This is routed below the engine room in the free 0.5 meters below and encounters almost zero obstacles, hence the consistently high II.

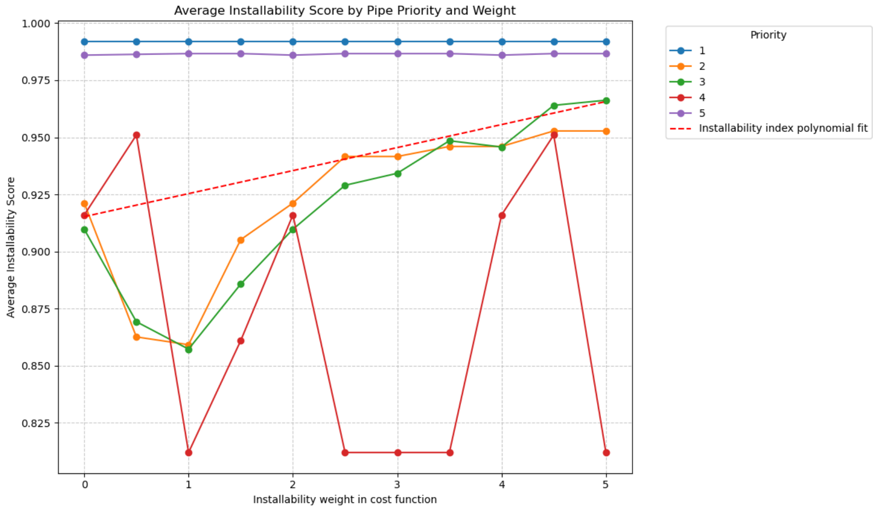


Figure 4.2: II categorised by priotiry demonstrating the mid level priority has largest affect on II

4.2.2. Time Multiplier

As done in section 4.2.1, the average values for the TM for each different w_{inst} are calculated and plotted below in 4.3:

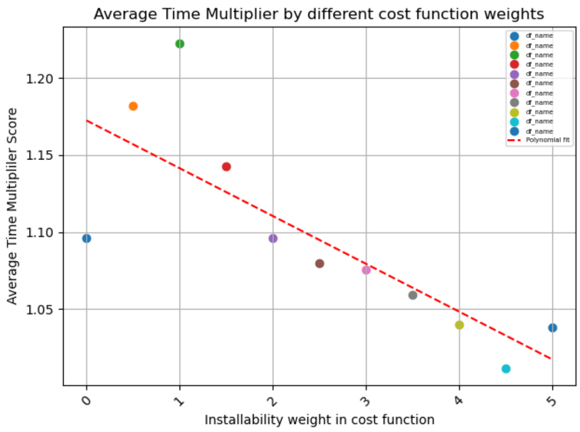


Figure 4.3: Time Multiplier averaged for different cost function weights

Similar to the installability index, the time multiplier gets 'worse' for the first increase in w_{inst} and then the time multiplier decreases. The inverse relation of the two performance indicators is discussed further in section 4.2.3.

4.2.3. II and TM relationship

As the II and TM are based on data acquired through the questionnaire, filled in by industry experts, some correlation is to be expected. It becomes clear that the experts strongly agree on the extent that the space of an installation affects the time to install. This validates the internal consistency of the expert knowledge. When calculating the Pearson correlation value for each of the different w_{inst}, a trend can be observed about the relation between II and TM in table 4.6:

Table 4.6: Pearson Correlation Squared values across varying Weights.

Weight	Pearson Correlation
0.0	-0.99975
0.5	-0.99989
1.0	-0.99995
1.5	-0.99986
2.0	-0.99975
2.5	-0.99986
3.0	-0.99983
3.5	-0.99978
4.0	-0.99949
4.5	-0.99946
5.0	-0.99980

The Pearson relation being so near to -1, demonstrates the strong negative linear relationship between II and TM. Squaring these values gives a positive value, now only showing the level of linear relationship. In figure 4.4 demonstrates the extreme linear behaviour of II and TM, showing these values have large relationship and is replicated correctly by the tool's underlying fuzzy logic rules.

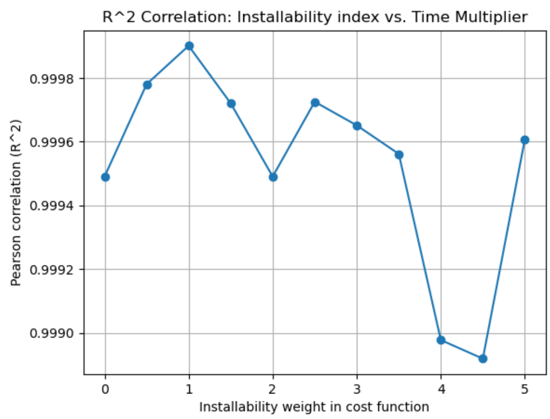


Figure 4.4: Pearson Correlation squared for Installability Score vs Time Multiplier

4.2.4. Pipe Length changes

Another key validation point, is the length of the piping. In figure 4.5 the change in pipe length is shown. The pipes increase in length, but overall the increase is only 3% of the initial pipe length.

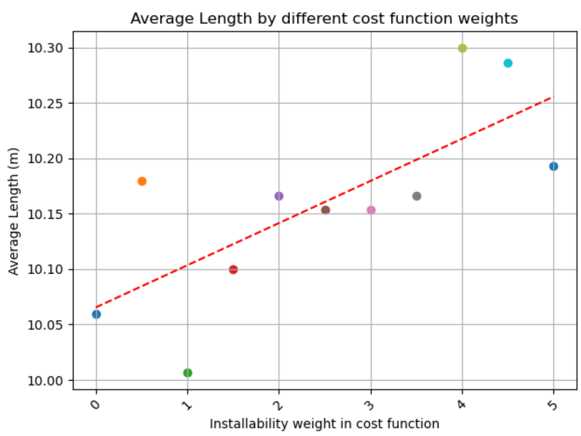


Figure 4.5: Average pipe length for different w_{inst}

4.2.5. Verification Conclusion

When considering the variation of II, TM and pipe length over the different w_{isnt} values, the implementation of installability in the cost function is verified to work as expected. When increasing the dominance of the installability in the cost function, the install score averaged and time multiplier improve by 5% and 17% respectively. Consequently, the pipe length only increases by 3%.

Having completed and analysed the verifications and toy problem allows the tool to be used to analyse a real-world problem. Moving from a generated pseudo-realistic engine room to an actual implemented design to analyse the performance of the tool. Through the case study theoretical effects of the methodology implementation can be observed in a realistic scenario.

4.3. Case Study

4.3.1. Cost Drivers Identification

From data attained at the Damen Galati yard where the OSVs are built fully and yachts are built to casco, the hypothesis that there is a considerable amount of time to be saved in installation processes is confirmed. With the material cost to man-hours cost ratio being 1:4 for every project, the contribution of a reduction in man-hours by optimisation has a larger impact than the material savings. Below some findings are stated.

Many times the 'Spool tracing™' software has been referenced by people at the yard. With data attained from multiple projects from the Spool Tracing software, the durations of each activity are normalised by dividing the time it takes per kg of piping handled. Unfortunately, because Spool Tracing relies on the worker pressing start and end activity, this is sometimes forgotten. Leading to inconsistent data and huge outlier values or a lack of sufficient values altogether. Besides this, many small pipes are also included in the data and the time stamps are 24/7. The data is therefore filtered for pipes with a diameter larger than 50 millimeters and only Monday to Friday 8 hours working days are taken into account.

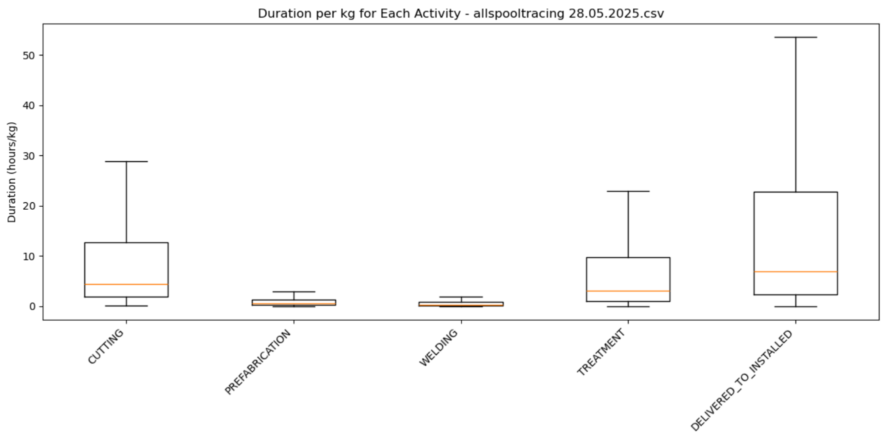


Figure 4.6: Data attained from Galati Spool tracing software

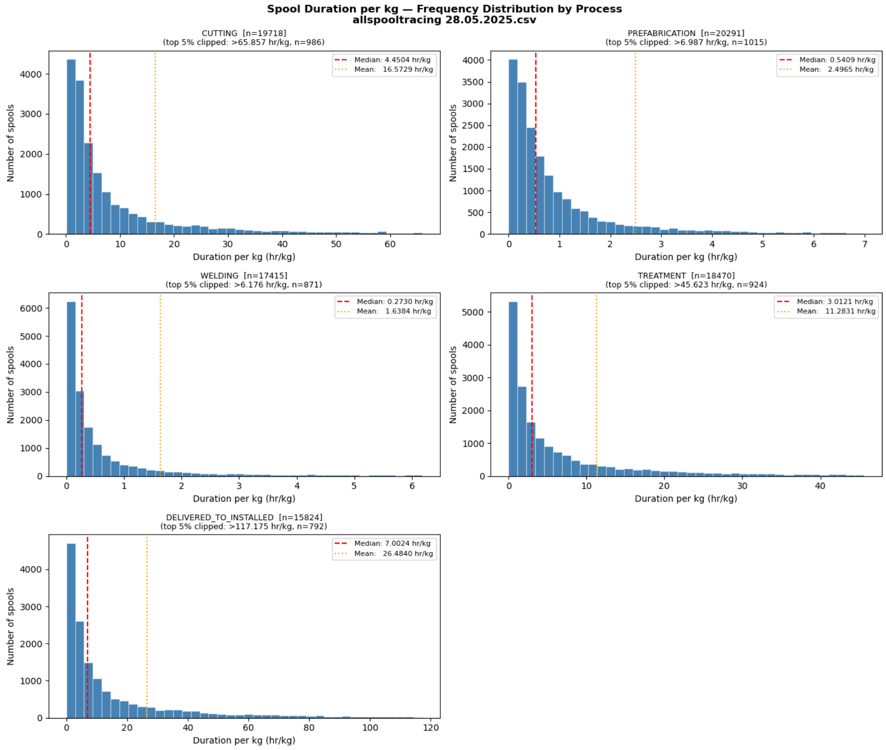


Figure 4.7: Distribution per kilogram of spools analysed from project 28th of May 2025

In both figure 4.6 and the boxplots in Appendix C the longest average durations occur in the installation phase of the spools. Complementing this, the means and medians of all the durations further strengthen the hypothesis. In table 4.7 the means and medians are visible for each process spread across different projects. As the scope of the tool is on creating schematic designs to assist the development of the pipe routing, any pipes smaller than 50mm in diameter are filtered out to remove the noise of 'easy-to-route' or very lightweight pipes that are poorly tracked in the spool tracing software. Now, only pipes of significant weight and length are considered in the analysis of process durations per kilogram.

Table 4.7: Project completion data (Values in hr/kg spool, pipes DN ≥ 50 mm)

Project completion date	**02.06.2025**	**04.07.2025**	**24.06.2025**	**28.05.2025**	**18.02.2026**
Cutting	*Values in hr/kg spool*				
Mean	16.50	15.83	15.95	16.57	–
Median	4.45	4.19	4.27	4.45	–
Bending					
Mean	–	–	–	–	2.48
Median	–	–	–	–	1.67
Prefabrication					
Mean	2.48	2.29	2.36	2.50	0.05
Median	0.54	0.51	0.52	0.54	0.00
Welding					
Mean	1.63	1.62	1.65	1.64	0.14
Median	0.27	0.28	0.28	0.27	0.03
Treatment					
Mean	11.20	11.12	11.07	11.28	6.25
Median	2.99	2.96	2.92	3.01	2.11
Installation					
Mean	26.11	24.19	24.61	26.48	9.02
Median	6.87	6.13	6.37	6.72	3.76
Weights (kg)					
Mean	21.32	21.49	21.54	21.28	23.62
Median	14.66	14.60	14.67	14.66	19.91

Using these values, the differences between the mean and median show the gaps between in value added and non-value added work. The mean is often much larger than the median indicates that there are outliers in the data, skewing the average. However, as each has very large data sets, it is not down to individual outliers, but rather multiple, as is visible by the highest quartiles in figures C. Using this, the value-added times are the medians of the data, as the median is resistant to large outliers in the data. This resistance incorporates the resistance to include the unnecessary work or time taken in the average by outliers. The mean is then an average that includes all the 'excess' time, such as waiting or rework. Therefore, $NVA = means - medians$. In 4.8, the global VSM is visible. Here, the two processes with the longest overall duration are pipe cutting and installation. Pipe cutting's man-hours per kilogram is likely to be heavily skewed due to how the spool tracing is used by workers in the factory. They get large bulk of pipe spools that need cutting, and mark multiple pipes as completed at once, or later after all in the bulk are done. In some cases, they may mark a spool as completed before the pipe has been marked as starting to be cut. This results in some negative cutting times, visible in C.3.

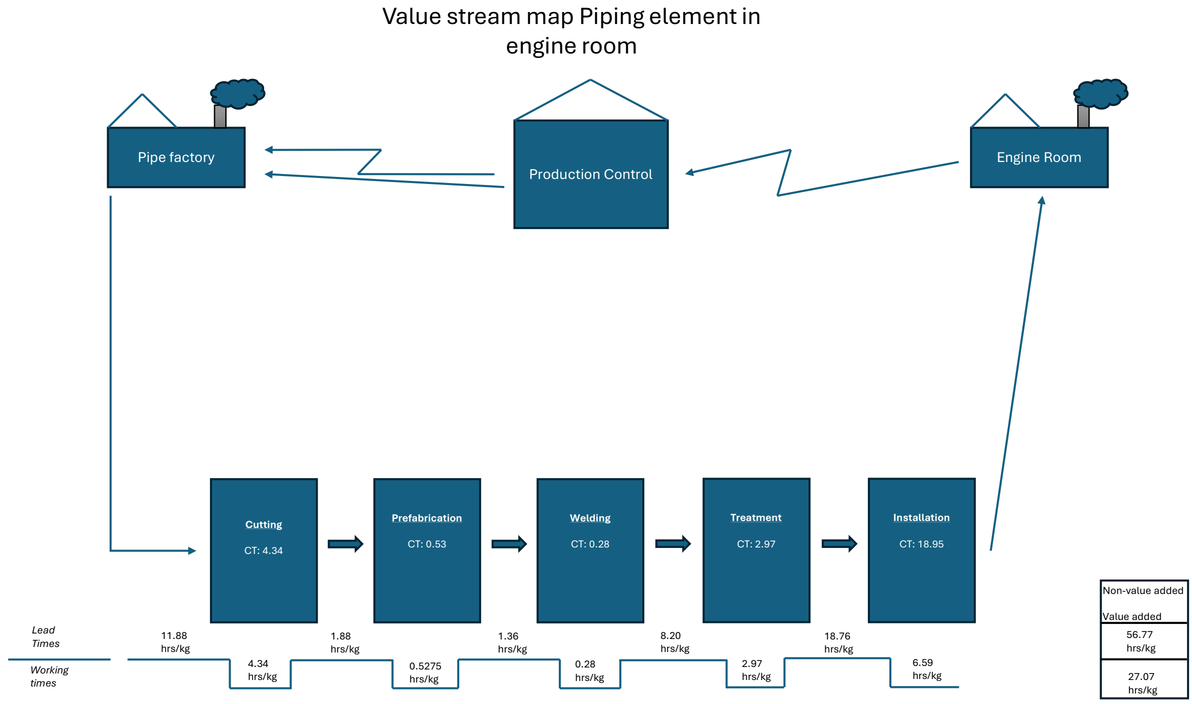


Figure 4.8: Value Stream Map based on spool tracing data

- **Cutting** (CT: 4.34 hr/kg): Raw pipe stock is cut to the required spool lengths. Workers collect bulk batches from storage; timing inconsistencies in spool tracing inflate the measured lead time.
- **Prefabrication** (CT: 0.53 hr/kg): Pipe ends are prepared for joining — including bevelling, flange fitting, and bend preparation — before entering the welding station.
- **Welding** (CT: 0.28 hr/kg): Spools are welded into their final form, joining pipe sections, flanges, and fittings. This is the shortest value-added step by cycle time.
- **Treatment** (CT: 2.97 hr/kg): Spools are surface-treated — typically sandblasted, primed and painted. Lead times here are extended by drying and curing times that cannot be reduced by labour input.
- **Installation** (CT: 6.59 hr/kg): Completed spools are transported to the vessel and physically installed in the engine room, including alignment, bolting, and welding to flanges in situ. This step has the largest absolute cycle time and lead time, making it the primary target for cost reduction. Extended lead times are from waiting to install time of the spool at the installation location.

The VSM in Figure 4.8 must be interpreted as follows:
The values in Table 4.7 and in the VSM should be interpreted with some caution. The Spool Tracing software is dependent on manual worker input, and the distributions per kilogram, visible in figure 4.7, show the spread of the available data of hours per kilogram and the frequency thereof. This indicates that the absolute values are not a precise measure of the true cycle times.

However, these values represent the **best available quantitative indicator** of the man-hours per kilogram of the spools throughout the building process.

Beyond this data, higher-level data from previous projects do provide more concrete information. In this data, it is demonstrated that most man-hours are invested in to the installation of piping during the block building and completion of projects than in pipe production. In Figure 4.9, the split between block factory, project completion and pipe factory is seen in man-hours as a percentage of the total man-hours on the piping for the project.

The VSM also demonstrated the following about the efficiencies per process. The value added time ratio's of the total are shown below in table 4.8. This demonstrates that in terms of VA ratio, installation is not the worst, on the contrary it is the best. However, due to the total time consumption of the process, marginal gains have a larger impact on overall time savings.

Table 4.8: Value-added ratios per process step

Process	**CT (hr/kg)**	**Lead Time (hr/kg)**	**VA Ratio (%)**
Cutting	4.34	11.87	26.8
Prefabrication	0.53	1.88	21.9
Welding	0.28	1.36	16.8
Treatment	2.97	8.2	26.6
Installation	6.59	18.75	26.0
Total	**14.71**	**42.07**	**25.9**

		Complete vessel		% for each Category			
Total Hours	**Hours**			**Block Factory**	**Project Completion**	**Aluminum Factory**	**Piping Factory**
95,560	90,060	Piping, Class I,II,III (300)	Piping, Class I,II,III (300)	33.50%	43.50%		23%
	1,500	Piping, Class I,II,III (300)	Piping for commisioning		100%		
	4,000	Piping, Class I,II,III (300)	Flushing		90%		10%
4,253		Piping, St.st., Cunifer, (300)		33.50%	43.50%		23%
9,072		Piping, GRE, Ameron		33.50%	43.50%		23%

Figure 4.9: How the piping man-hours are split across the different building stages

For a complete build vessel at Galati yard, most of the man-hours are in the installation and finalisation of the piping. The reason project completion takes the longest is that, during this stage, the blocks previously built are attached to full sections and then to a full hull, requiring made-to-measure piping for all connections.

		Casco vessel					
Total Hours	**Hours**			**Block Factory**	**Project Completion**	**Aluminum Factory**	**Piping Factory**
24,334	21,634	Piping, Class I,II,III (300)	Piping, Class I,II,III (300)	54.00%	22.00%		24%
	-	Piping, Class I,II,III (300)	Piping for commisioning		100%		
	2,700	Piping, Class I,II,III (300)	Flushing		90%		10%
	55,368	Piping, St.st., Cunifer, (300)		54.00%	22.00%		24%
	7,794	Piping, Aluminum (300)			22.00%	54.00%	24%

Figure 4.10: man-hours division for Casco build vessel

For a casco vessel the division is even more clear that installation is the man-hours cost driver, see Figure 4.10. Here, over half of the hours that are in the piping are 'spent' on installation of the pipes during block building.

4.3.1.1 Pipe installation bottlenecks

It becomes clear from the data that the highest absolute amount of man-hours is spent during the installation phase of piping. Although this stage does yield the highest VA-ratio of the different processes, shown in table 4.8 is that both cutting and treatment have higher VA-ratios, due to the longer cycle time relative to the other processes, installation has the greatest effect per saved man hour than any other process. Cutting processes are highly automated, and increased lead times here are due to a lack of equipment and not real man-hours. The treatment process takes relatively longer due to waiting times for drying or other chemical reactions not receptive to human adjustments. The installation times are operational and can be impacted by adjusting the routes. Through discussions about how installation speeds can be increased, it was found that often pipes are installed in difficult spaces or need rework due to poor design choices. It is consistently demonstrated from both high level and more detailed data, from independent projects, that most man-hours are spent on installation.

4.3.2. Routing Tool Case Study

To assess the optimisation of the routing compared to the routes created by engineers, a previous project is imported and the II and TM values are determined. Then, pipes will be routed by the routing algorithm with an integrated installability cost function.

The input for the case study is the engine room from the 'Windcat Amsterdam' vessel in figure 4.11:

Figure 4.11: Windcat Amsterdam (Damen, 2026)

Extracting the layout from the Cadmatic model of the vessel to a .3dm model, the engine room's systems can be dissected in subsystems. Pipes are recognised by analysing the aspect ratio's of the volumes from the .3dm model when being extracted to a .json file. Using the Damen in house codes in the 'Type' description of each volume, it can be further categorised in to the correct system. Thus resulting in an ordered .json file of the systems and pipes, accessible for the tools backend.

Running the fuzzy logic algorithm over the systems to analyse the II and the TM of the designed and implemented engine room explained in section 3.5.8. The results of the average per system are displayed below in table 4.9.

Table 4.9: Baseline installability scores and estimated pipe lengths — Cadmatic ER 552205

SID	System	n	Span (m)	Length (m)	Avg II	Avg TM
322	Fuel Oil HFO	3	6.0	6.0	0.896	1.234×
322	Fuel Oil MDO	4	11.9	12.7	0.966	1.017×
322	Fuel Oil Service	29	19.1	48.5	0.949	1.070×
321	Fuel Oil Transfer	6	6.2	7.4	0.977	0.982×
361	Lube Oil	16	19.1	33.4	1.000	0.911×
311	Bilge	4	11.1	13.7	0.848	1.383×
362	Bilge Oily Water	3	14.2†	~21†	0.554	2.289×
312	Ballast	9	14.8	23.9	0.851	1.372×
351	Sounding / Air Vent	14	13.3	32.5	0.932	1.120×
313	Fire Fighting Main	42	18.2	54.1	0.648	1.999×
670	Fire Fighting Local	40	14.7	71.3	0.596	2.160×
331	Sea Water Cooling	134	18.7	88.6	0.928	1.135×
331	Sea Water Cooling (alt)	1	—	—	0.995	0.926×
333	Sea Water Cooling (br.)	35	17.4	60.3	0.654	1.981×
346	Overboard / Discharge	2	2.1	2.1	1.000	0.911×
380	Exhaust Gas	1	—	—	0.999	0.915×
Overall					**0.862**	**1.338×**

n = number of Cadmatic model components. Length is estimated via nearest-neighbour chain through component centres: span is the straight-line start-to-end distance. Systems 331 (alt) and 380 have ≤3 clustered components and no meaningful routed length. SIDs follow the Cadmatic ER 552205 system tree; systems 322 (HFO, MDO, Service) and 331 (main, alt) are sub-groups within the same Cadmatic system code.
† System 362 has only 3 co-located components in the Cadmatic export (the OWS unit); span and length are taken from the tool-routed result, which at ~21 m is consistent with a full bilge collection run.

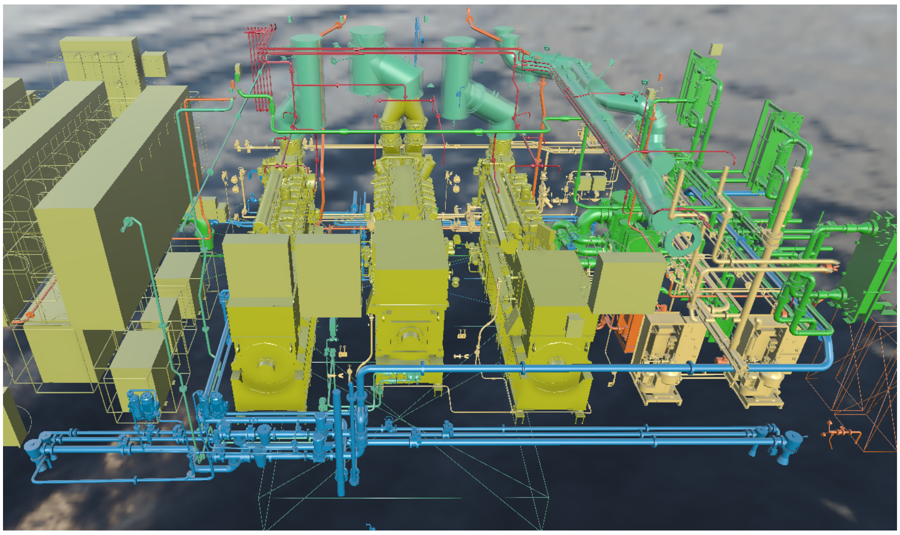


Figure 4.12: As-was routing of key systems in the Windcat Amsterdam. This image also includes small-diameter pipes (≤ 50 mm). Pipes split and routed in parallel are considered a single pipe.

This demonstrates the complexity of the engine room, as the average install index of all systems is only **0.862**. This average however is skewed by the *Fire Fighting Local* piping. These pipes are located above the engine room in cramped spaces. The reason behind this is that FIFI (Fire-Fighting) systems tend to be implemented late in the design process, but are bound by classifications to specific locations. However, it must be stated that the pipes have relatively small diameters with main and local being 10 cm and 8 cm in diameter, respectively. The local, having the smaller diameter, could be put in less accessible places, resulting in the lowest Install Index average.

4.3.3. Rerouted solutions

To compare the tool with the final use case in mind to the routed piping, only significant routing will be used. As the final goal of the tool is to be used in schematic, pre-detail design stage, highly detailed routing with small diameter pipes falls beyond the bounds of the scope defined.

As such, the following systems are rerouted: Bilge pipes (2 subsystems), lube oil pipes (2 subsystems), seawater cooling, FIFI, Fuel oil HFO and Fuel oil MDO, and the exhaust system. The settings used for the rerouting are the following in table 4.10. These values are chosen based on the time share of the total added value from the VSM in Figure 4.8. Additionally, expert input is taken into account for what they consider to be how important each weight is.

Installability Weight	4.00 out of 5.00
Bend Penalty	1.50 out of 5.00
Parallel Preference	0.50 out of 2.00
Suction low-z preference	5.00 out of 10.00
Wall/Ceiling Preference	1.00 out of 2.00

Table 4.10: Routing variable's weight settings for case study

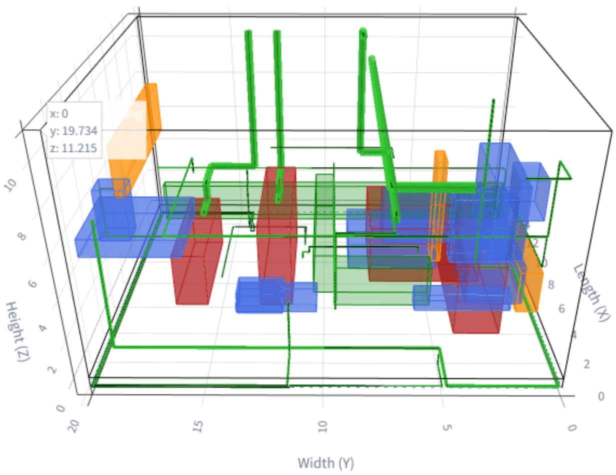


Figure 4.13: Rerouted key system pipes in the Windcat Amsterdam engine room. Red indicates hot surfaces (e.g., engines or generators), orange represents switchboards, and blue denotes general machinery. Pipe colours range from red to green based on the installation index of the specific pipe.

This comparison takes the exact situation the engineers routed the primary pipes before moving on to the highly detailed piping design. Simulating the actual process step in which the tool is to be used.

4.3.3.1 Comparison

When comparing the results from the original pipe routing and the key systems rerouted in a populated engine room, excluding all other piping to simulate a situation where the tool is to be used, the following results are 4.12:

Pipe	Ø (mm)	Priority	Length (m)	Install score	Time mult
Fuel Oil HFO — HP Supply (322)	100	1	6.8	0.953	1.05×
Fuel Oil MDO — HP Supply (322)	100	8	20.5	1.000	0.91×
Fuel Oil Service (322)	80	4	31.3	0.992	0.94×
Fuel Oil Transfer (321)	80	10	7.4	1.000	0.91×
Lube Oil (361)	80	3	22.9	0.999	0.91×
Bilge (311)	100	1	38.2	0.956	1.05×
Bilge Oily Water (362)	80	2	39.6	1.000	0.91×
Fire Fighting Main (313)	100	6	33.1	0.991	0.94×
Sea Water Cooling (331)	150	5	48.5	0.938	1.10×
Exhaust Gas (380)	400	2	16.9	0.990	0.94×

Table 4.11: Keysystems rerouted by Damen pipe route installation priority tool

Table 4.12: Comparison of existing pipe routing versus A* routed paths. $\Delta = \frac{\text{A*}-\text{existing}}{\text{existing}} \times 100\%$. A negative ΔLength and negative ΔTM indicate A* performs better. A positive ΔII indicates A* performs better. †Length estimated from tool routing (sparse Cadmatic component coverage).

Sys.	Pipe System	ΔLength (%)	ΔII (%)	ΔTM (%)
322	Fuel Oil HFO — HP Supply	+13	+6	−15
322	Fuel Oil MDO — HP Supply	+61	+4	−11
322	Fuel Oil Service	−35	+5	−12
321	Fuel Oil Transfer	0	+2	−7
361	Lube Oil	−31	0	0
311	Bilge	+179	+13	−24
362	Bilge Oily Water†	+89	+81	−60
313	Fire Fighting Main	−39	+53	−53
331	Sea Water Cooling	−45	+1	−3
380	Exhaust Gas†	+58	−1	+3

The length of the pipe systems varies significantly, with some being longer and others shorter. This is due to the different routing limitations in the final result, induced by changes necessary because of accessory equipment added later in the process. Install Index increases for all pipes other than Lube Oil (361) and Exhaust Gas (380). This is due to the II already being 1 in the original design, no improvements are achievable. Crucially, for the Exhaust System, the time multiplier is slightly increased. Although 1% increase is negligible in the total time, the indication of the fuzzy system inferring slightly tighter fits than the original demonstrates the pathfinding was considered ever slightly tighter by engineering estimations.

Table 4.13: Nominal pipe weight per meter by diameter — ASME B36.10M Schedule 40, carbon steel

DN	Nominal size	OD (mm)	WT (mm)	kg/m	Applied to systems
80	DN80 (3 in)	88.9	5.49	11.29	322 (Service), 321, 361, 362
100	DN100 (4 in)	114.3	6.02	16.07	322 (HFO), 322 (MDO), 311, 313
150	DN150 (6 in)	168.3	7.11	28.26	331
400	DN400 (16 in)	406.4	12.70	123.30	380

Wall thickness (WT) and bare pipe weight (kg/m) from ASME-B36.10. Weights exclude fittings, flanges, supports, and insulation. A fitting and support factor of 1.2–1.4× is typical for marine installations (Watson, 1998).

When taking the values for weight per unit of length of each system, and the Δ TM, a theoretical cost change can be determined. Below the results are displayed for :

$$\Delta Cost_{theoretical} = \sum_{Sid=i} L_{exisiting,i} \cdot M_L(DN) \cdot TM_{existing,i} \cdot h_{tonne} \cdot [(1+\Delta L_i)(1+\Delta TM_i) - 1] \quad (4.1)$$

In this formula, h_{tonne} is the added value installation time found in chapter 4.3.1: 6.59 $\frac{hours}{kg}$. Calculating gives a theoretical decrease of 12,498 units of man-hours visible in table 4.14.

Table 4.14: System Comparison and Cost Variation Analysis

System ID	System Type	DN	L_{existing} [m]	TM_{existing}	Length Δ	Time Δ	Δ Cost
322	Fuel Oil HFO	100	6	1.234	13%	-15%	-27.9
322	Fuel Oil MDO	100	12.7	1.017	61%	-11%	6.7.7
322	Fuel Oil Service	80	48.5	1.07	-35%	-12%	-1672.9
321	Fuel Oil Transfer	80	7.4	0.9818	0%	-7%	-39.6
361	Lube Oil	80	33.4	0.911	-31%	0%	-713.8
311	Bilge	100	13.7	1.3825	179%	-24%	2241.9
362	Bilge Oily Water	80	21	2.289	89%	-60%	-895.8
313	Fire Fighting Main	100	54.1	1.999	-39%	-53%	-8157.8
331	Sea Water Cooling	150	88.6	1.135	-45%	-3%	-8792.2
380	Exhaust Gas	400	10.7	0.915	58%	3%	4952.9
						Total:	-12,497.5

The overall achieved saving of 18% when considering only the simple average of the ΔTM, excluding the length cost increase or decrease. The length increase or decrease is taken into account in the formula to determine the mass per unit of length to achieve the theoretical man-hour savings.

4.3.4. Results Discussion

The main gains are achieved by the rerouting of the 313 and 331 systems; the fire fighting main and sea water cooling systems. Each of these systems saves a considerable amount of man hours for installation. On the contrary, the exhaust gas system is increasing in length, resulting in an increase in man-hours for installation. This increase it due to a slight reroute to create more space between the exhaust and upper level equipment. In reality, exhaust pipes are thin walled large diameter pipes with lower mass per unit of length displayed in table 4.13. This lower mass per unit of length results in lower installation times than calculated. Besides this, the length of the Bilge system is increased 179%. This is due to the routing preference near walls and by the enforcement of the separation rule of seawater/ballast lines, which the original path enforced less strictly.

4.3.4.1 Spatial routings

A limitation of the tool not functioning in highly crowded engine room, as the goal of the tool is to use the optimisation algorithm earlier in the design process leads to slight discrepancy in the engine room layout in the initial analysis and the final rerouting.

4.4. Conclusion

In spite of the difference in applicability of the tool in the detailed engine room and the design analysed in the case study, the A* algorithm improved the Instal Index for all but one pipe system, it improved the length of half the piping and decreased the Time Multiplier for all but one pipe. This exhaust pipe is limited by the necessity of routing upward as straight as possible being the exhaust pipe.

Through optimising the algorithm using a novel technique, optimising for man hour reduction, in contrast to optimising by pipe material reduction a reduction of **18%**[1]. This is translated to man-hours, including the change in length from the original engine room from the Windcat Amsterdam to the rerouted solution from the routing tool, resulting in 12,498 man-hours saved.

[1]The simple average ΔTM is taken here for the systems in table 4.14, excluding the change in pipe length, the length is also changed by the algorithm but left out for this partial result to only demonstrate installation ease increase.

5 Research Results

This chapter presents the consolidated quantitative outcomes of the research. The results are structured to directly address the research question by combining the cost driver analysis, algorithm verification, and case study findings into a coherent summary.

5.1. Cost Driver Identification

Through Value Stream Mapping of the complete piping production cycle at the Damen Galati shipyard, **installation** was identified as the primary cost driver. Installation carries the highest absolute cycle time (CT: 6.39 hr/kg) and the highest lead time (18.75 hr/kg) of all process steps. Although cutting and treatment have marginally higher value-added ratios, the total installation time makes it the process with the greatest potential for man-hour savings per unit of improvement. This is consistently confirmed across five independent project datasets and across two vessel build stages (complete build and casco build), as detailed in section 4.3.1.

5.2. Algorithm Verification

The A* routing algorithm was verified through three controlled tests in a defined bounding box environment:

- **Test 1 — Straight path:** In an obstacle-free space, the algorithm returns a perfectly straight 8.00 m route with zero lateral deviation. **PASSED.**
- **Test 2 — Shortest path around obstacle:** With a single obstacle blocking the direct route, the algorithm returns the analytically optimal 14.00 m detour path. **PASSED.**
- **Test 3 — Fuzzy installability integration:** Given two route options of equal length but different clearance, the algorithm correctly selects the higher-clearance route when the installability weight $w_{inst} \geq 2$. **PASSED.**

The toy-problem verification on a realistic synthetic engine room confirmed that increasing w_{inst} improves the average Installability Index by 5% and the average Time Multiplier by 17%, with a pipe length increase of only 3%. This demonstrates that the cost function trades minimal additional pipe length for substantially better installation conditions.

5.3. Case Study: Windcat Amsterdam

Applying the routing tool to the engine room of the Windcat Amsterdam (Damen OSV), the following key outcomes were obtained. The baseline installability scan of the existing design revealed an average II of 0.862 across all systems, driven down primarily by the Fire Fighting piping routed in congested above-engine-room spaces.

After rerouting the ten primary pipe systems with the A* tool using the settings in Table 4.10, the results in Table 4.12 show the following headline outcomes:

- **Installability Index improved** in 8 out of 10 systems. The remaining 2 (Lube Oil, Exhaust Gas) had an II already at or near 1.0 in the original design, leaving little to no room for improvement.
- **Time Multiplier decreased** in 9 out of 10 systems. The Exhaust Gas system increased by 3%, attributable to necessary clearance rerouting around upper-level equipment — a negligible change on a large-diameter, thin-walled pipe with low mass per meter.
- **The simple average ΔTM across all systems is** -18%, indicating that on average the rerouted pipes require 18% less installation time per kilogram than the original design.
- **Theoretical man-hour saving: 12,498 man-hours**, calculated using Equation 4.1, accounting for both the change in TM and the change in pipe length for each system.

The Fire Fighting Main (313) and Sea Water Cooling (331) systems account for the majority of the savings, contributing −7,910 and −8,525 man-hours respectively. These systems are characterised by large pipe counts, significant total lengths, and routes that in the original design pass through congested overhead spaces — exactly the scenario where the installability cost function provides the greatest benefit.

6 Discussions

6.1. Discussion of Methodology and Tool

6.1.1. Validity of Combined Methodology

The case study's results demonstrate that the combined VSM-Fuzzy Logic- A* algorithm methodology is an effective approach to installation-aware pipe routing. Each individual part contributes to the final objective of optimising the routing system based on the cost drivers of production. VSM provides the empirical grounding that installation is the primary cost driver of the production process. Fuzzy logic then bridges the gap between the subjective expert knowledge and the crisp numerical input necessary of an algorithmic objective optimisation. A* provides a guaranteed global optimum routing with a specialised cost function incorporating the 'installability' in the objective, without the need for prior knowledge of the pipe routing systems. Together, this combination of process analysis, quantification and optimisation is without precedent in the researched APR literature.

6.1.2. Significance of 18% Improvement

The 18% reduction of the Time Multiplier and the corresponding saving of 12,498 man-hours are significant results, but must be understood in the correct context. The case study compares the tool's ability to optimise in a simulated, gridded engine room to the real-world, final-result piping engineered by experts. The fact that the algorithm, operating without any visual or contextual understanding of the engine room, improves 8 of the 10 pipe systems and achieves near-equivalent results on the final 2, indicates that the fuzzy logic installability integration into the cost function correctly represents the engineer's subjectivity. It will not replace the engineer's judgement, but it will replicate it and speed up the design progress in the meantime.

6.1.3. Practical Implications for Damen OSV

At the Galati shipyard, the installation process constitutes the largest portion of man-hours across both complete build and casco vessel production. An 18% reduction in installation time for the primary pipe systems in one engine room, requiring only an early-stage routing pass through the tool, represents a cost intervention that is both significant in magnitude and low in effort to implement. Assuming a conservative fully-loaded labour rate, a 12,498 man-hour saving translates directly to project cost reduction and schedule compression.

The tool requires no prior training data, exports to existing CAD export formats (.3dm and .json), and produces results within minutes on standard hardware. The barrier to adoption is therefore primarily procedural (embedding the tool into the early design workflow) rather than technical.

In addition to this, the 3D renders also potentially improve the communication between departments by providing a single source of truth to start design discussions from.

6.2. Limitations

The results of this research are promising. However, there are several limitations that must be acknowledged. First, the current implementation of the tool operates in a simplified 3D-grid environment to simulate an engine room. In reality, engine rooms have complex geometries, structural obstacles and dynamic constraints that are not fully captured by the current tool. It is currently best understood as an early-stage schematic design assistant rather than a complete production-ready routing software tool.

Second, as the case study is performed on a single engine room (Windcat Amsterdam) the statistical confidence of the reported 18% improvement is limited. A broader validation across multiple engine rooms for multiple vessels would strengthen the statistical quality of the results.

Third, the data collected for the VSM has an unknown unreliability due to the human error factor associated with the Spool Tracing software. Some data may be slightly misrepresented by inputs errors such as forgetting to scan a spool and therefore adding large time fluxes to the hour per kilogram representative value.

Fourth, the Installation Index and Time Multiplier associated with the Fuzzy Logic are derived from a questionnaire filled out by Damen experienced engineers (Gorinchem) and yard workers with years of relevant experience (Damen Galati). The generalisability of this data has not been proven to work for other shipyards, vessel types, or highly complex, late stage design piping configuration. The weights of the cost function parameters may need recalibrating for different production conditions.

Finally, the Fuzzy Logic translation relies on the input from ten experts whose knowledge reflects Damen-specific working conditions and spatial conventions. The subjective nature of these values inherently brings uncertainty regarding the generalisability of the resulting Installation Index to other yards or vessel types, and recalibration with experts from different organisations would be required before broader application.

6.3. Recommendations

Based on the limitations and findings within this research, the following recommendations are made for future work on this subject:

- **Validation across vessel types:** The pipe routing tool should be validated across multiple different engine rooms from different vessels to further test the robustness and scalability of the Installation Index and the cost function. The expansion of the results pool would increase the statistical significance of the research results.
- **Refinement of Fuzzy Logic:** Currently, the fuzzy logic membership functions are derived from a small number of experts. Increasing the number of inputs for the Fuzzy Logic membership functions from a systematic elicitation process will result in a more reliable and representative distribution of truths. Furthermore, a sensitivity analysis of the membership function parameters improves the reliability of the Install Index further.
- **Integration of existing CAD and design tools:** For maximum practical impact, the tool should be integrated into a CAD tool used by the engineers in the earlier stages of design. Integrating would lower the entry barrier to use the tool within the way of working.
- **Extension to full piping network:** Future expansion from solely engine room individual pipe routing to multi-system routing would accurately reflect real-world dynamical conflicts. Using Reinforcement Learning or alternative Machine Learning methods to create a realistic understanding of dynamical problems within multi-system simultaneous routing would further increase the effectiveness of the tool. The key bottleneck for this technology is the lack of data available at this moment.

7
Conclusions

The research question for this thesis is:

"What is the potential cost saving for the pipe production process by implementing the pipe routing optimisation in the design phase, focusing on cost drivers within the production process?"

To answer this question, the subquestions in section 1.4 are answered as follows.

What literature on piping has already been performed? (Chapter 2)

Automatic pipe routing is a highly researched phenomenon within engineering, spanning from maritime and petrochemical fields to nano-scale chip infrastructure . The main goal for APR in this research is to find the shortest path possible, without considering the manner of creation of said routes. Throughout all the research, starting over 50 years ago with Dijkstra's algorithm, ranging through to the most state-of-the-art Artificial Intelligence integrated or Reinforcement learning implementing techniques have been explored. Though the APR techniques are becoming more complex and powerful, the human applicability of these routes is still lacking in research.

This gap is addressed in the presented thesis by adapting the A* cost function to incorporate this ease of installation.

What are the primary sources for piping costs? (Chapter 3.2)

Identifying the primary piping cost sources has been achieved through Value Stream Mapping (Section 4.3.1), the processes done during the entire production loop at a yard. Discussed in Section 2.8, the VSM technique demonstrates a fast and clear overview of processes that have larger non-value added activities. Using the overview of data acquired from Galati and Sharjah Damen shipyards, a value stream map is created for the full final design to installation cycle for piping. It is found that **Installation** is the key process due to the absolute longest duration of non value added time. It is therefore the process with the greatest potential for saving man-hours.

How can these be quantified? (Chapter 3.3)

Having identified where the cost savings are most effective, incorporating the 'ease of installation' into an algorithm requires a crisp numerical input to allow for optimisation. Through Fuzzy Logic, the vague engineering 'jargon' such as 'Tight fit' or 'Sufficient' space can be quantified and used in the algorithm's cost function. Furthermore, this allows the duration of processes to be more narrowly estimated using expert knowledge. This creates a measurable and comparable value for efficiency analysis.

How can the design process implement optimisation for the pipe routing production costs? (Chapter 3.5)

With the creation of the pipe routing tool for Damen, an early-stage schematic assistance tool has been developed. The tool is to be used in the initial design phases to aid engineers in creating an engine room layout, prioritising the ease of installation as the primary optimisation criterion.

The core of the algorithm in the tool is the A* algorithm with an adjusted cost function to find the path with the best 'Installation Index' , explained in detail in section 3.5. Integrating the needs from engineers and yard workers at Damen Shipyard Galati have lead to the cost function 3.7:

$$c(n \rightarrow n') = w_{dist} + w_{bend} \cdot \delta bend + w_{vert} \cdot \delta_{vert} + w_{inst} \cdot (1 - s_{inst}(n')) - w_{parr} \cdot \delta_{parr}(n') - w_{wc} \cdot \delta_{wc}(n') \quad (3.7)$$

This takes the key things engineers need to consider into account when determining the installability of a pipe. Keeping pipes near walls and ceilings, routing parallel where possible, reducing bends yet all of these variables are left adjustable for the engineer to prioritise for any certain situation.

The integration of this tool into the early design process elicits the best response for the reduction of man-hours through pipe routing design.

What is the theoretically maximal achievable cost saving? (Chapter 4)

Comparing an existing engine room's (the Windcat Amsterdam) piping of the key systems that are also to be routed in the stage where the tool will be used, demonstrates a 18% decrease in installation time 4.3. In man-hours this is a 12,498 saving. This cost saving is substantial and only necessitates a small integration in the design period of the vessel's engine room.

Main Research Question

The separate parts of the main question have been answered by the sub-questions. The final answer, although not exact due to limitations, is as follows:

This result demonstrates that integrating installation-aware routing into the early design phase is not merely a theoretical enhancement, but a practically achievable improvement with measurable financial impact. The combination of Value Stream Mapping, Fuzzy Logic, and the A* algorithm provides a complete methodology that bridges the gap between practical engineering judgement and quantitative algorithmic optimisation.

The potential cost saving is up to 18% of man-hours per engine room using an adjusted A algorithm cost function to focus on the ease of installation during the production process of the pipe systems in the engine room.*

A

Literature Research

Keyword	Where	Why
Shipbuilding	Scopus, Google Scholar, Gemini	Identify relevance in research field
Piping	Scopus, Google Scholar, Gemini	Relevance in pipe routing
Piping systems	Scopus	Relevance in pipe routing
Optimisation	Scopus, Google Scholar, Gemini	Optimisation techniques
Concurrent Engineering	Scopus, Google Scholar	Process Analysis
Fuzzy logic	Scopus, Google (Scholar), Gemini	Quantifying vague terms
Project Planning	Scopus, Gemini	Process analysis
Lean Management	Scopus	Process analysis
Artificial Intelligence	Scopus	Optimisation algorithms
A* pathfinding	Scopus, Google Scholar	Optimisation algorithms
Petrochemical	Scopus, Google Scholar	Relevance in different industries
Aerospace	Scopus	Relevance in different industries
Cost Division	Scopus, Google Scholar	Cost driver identification
Value Stream Mapping	Scopus, Google Scholar, Google	Process analysis
Reinforced Learning	Scopus, Google Scholar	Optimisation algorithms
Deep Learning	Scopus, Google Scholar	Optimisation algorithms
Space Reservation	Google Scholar	Previous research identification

Table A.1: Keywords used for literature research

A.1. Process Analysis

A.1.1. The 7 Muda

- Waiting: idle time for employees, material or information
- Inventory: Excess raw materials, working-in-progress, or finished goods (not sold)
- Motion: Unnecessary movement of people (e.g., walking back and forth for tools or documents)
- Transportation: Unnecessary movement of materials or products
- Defects: Errors or mistakes that require rework or scrap
- Overproduction; Producing too much, too soon or faster than necessary.
- Over-processing: Doing more work than required by the customer.

A.1.2. Lean Management

Lean management is a systematic approach to process engineering, originally from Toyota Production Systems (TPS), that focuses on maximising customer value while minimising waste. It aims to eliminate waste (Muda A.1.1) from production processes (Rother et al., 1999). In the case of the piping problem, customer value is the efficiency of the build. In research by Kunkera et al. (2025) it was found that applying the Japanese lean method in shipbuilding the lead times could be reduced by 54%. Besides the Muda, lean management uses value adding and non value adding activities. Non value adding are activities that cost money and to not add any monetary or operational value to a product. To make it **value adding** it needs to (1) transform the product (material, information, physically changing), (2) be done correctly the first time and (3) the customer must be willing to pay (Womack and Jones, 1996).

A.2. Quantification Techniques

A.2.1. Analytical Hierarchy Process (AHP)

AHP is a multi-criteria decision-making technique that is commonly used to structure and analyse multi-attribute and multi-period problems hierarchically (Xu et al., 2007). It consists of 4 steps, the fourth one being optional:

1. Determining the relative importance of attributes
2. Determining the relative standing (weight) of each alternative with respect to each attribute and sub-attribute.
3. Determination of the overall priority weight (score) of each alternative with respect to each attribute
4. Determination of consistency indicator(s) in comparing pairwise.

AHP compares different criteria and identifies how much more important criterion A is than B. It cannot convert a continual space description to an 'ease of installation' description, let alone to a numerical value.

A.3. State of the art techniques explored

A.3.1. Petrochemical Research

A research by Kang et al. (2024) was conducted to look at automatic pipe routing in the petro-chemical industry. This industry has highly complex pipe routing systems that also need to optimised based on the pipe lengths and bends to keep costs low. The research uses a Dijkstra path finding algorithm 2.5.1.1 as the base for the routing automatisation. Then a priority system is introduced. Using Line Cost *(Pipe weight×Material Ratio)* priority is given to higher-cost pipe lines. Furthermore, a distinction is made between **main lines** and **branch lines**, making sure that more expensive or complex conduits are placed first to prevent suboptimal detours. Kang et al. (2024) also included a voxel-based approach allowing for obstacle avoidance. This APR design is also applicable in the shipbuilding industry, as all points focus on reduction of costs also encountered in this industry.

In the research, a dramatic engineering man-hour reduction is realised. The ARS implemented by Kang et al. (2024) achieved a 36-times faster routing plan time than an experienced engineer [(Kang et al., 2024), table 13]. It also achieved 3 time faster 3D layouts than manual design [(Kang et al., 2024), table 12]. Finally, in validation test the automatic routing system produced shorter routes than the base-case manual designs, achieving a 98.9% weight match but with 84.9% of the original length. Meaning that the ARS found more direct routes than the originally design by engineers.

A.3.2. Automated Planning techniques

In research conducted by Rose (2017), the possibilities of Automatic Production Planning are explored. This research was conducted at a high level, considering the section building and outfitting. The base for this research is Wei and Nienhuis (2012), who focusses on the outfitting planning. Each concluded that the difficulty lies in the planning of multiple subcontractors doing the outfitting process. Yards function as project managers making a global planning and each subcontractor makes a more detailed plan. However many tasks by different contractors rely on the tasks done by others (Wei and Nienhuis (2012); Rose (2017)). Integrating the plans all into one will increase the operational efficiency decreasing the need for rework and communication failures.

A.4. Path optimisation algorithms

Pathfinding algorithms have been highly research over the past 70 years. The following section will lay out the options considered for this optimisation problem.

A.4.1. Line search algorithms

Mikami-Tabuchi

This algorithm, created by Mikami and Tabuchi (1968) and mentioned for pipe routing use by Asmara (2013), uses orthogonal lines from the start to the target grid until these sections intersect or encounter an object. This method is extremely fast and requires very little computing power. This pathfinding technique does not, however, ensure the optimal paths between two points in a complex grid. Furthermore, it can create excessive amounts of bends or straight sections. Asmara (2013) uses this technique to check if routes are even possible before committing to different path finding algorithms that are more computationally expensive.

A.4.2. Meta-Heuristic or Stochastic Algorithms

These algorithm types use iterations or randomisations to improve routes until a route that is defined 'good enough' is found. These kinds of algorithms are based on how nature optimises systems, and can be used to generate multifaceted solutions for problems that are too complex for deterministic methods.

A.4.2.1 Genetic Algorithm

Genetic algorithms (GAs) are metaheuristic optimisation techniques based on Charles Darwins theory of evolution and natural selection (AKAN and ALKAN, 2023). They are designed to solve complex, non-linear problems like pipe routing or resource-constrained project scheduling in situations when traditional deterministic methods to not suffice (AKAN and ALKAN (2023); Asmara (2013)).

Key Components Implementing GAs requires the following:

- **Gene:** These represents a specific part of a solution. In routing this would be a grid location or parameter of the grid AKAN and ALKAN (2023).
- **Chromosome:** Chromosomes are a compination of genes. Meaning for piping, this could be a section of pipes in a solution or the location of bends of a piping section (Asmara (2013); Rose (2017)).
- **Population:** This is the set of candidate solutions (the chromosomes) that are being simultaneously searched. The larger the population, the better the chances are of finding the single optimal solution, but also the longer the computation time.
- **Fitness Function:** This is a mathematical function that evaluates the 'fitness' of a chromosome. Doing so allows the 'survival of the fittest' principle to work. The best scoring chromosomes are more likely to continue on in the process than the less fit chromosomes.

GAs then follow the evolution steps. **First,** the process is initiated by generating a population of possible solutions, randomly based on priority rules (i.e. this pipe first, then that pipe etc.). **Second,** the fitness function evaluates the current quality or cost function of each chromosome in the generated population. **Third,** Chromosomes are selected as parents for the next generation. High scoring chromosomes get a higher probability of selection, and low scoring get a small probability to maintain diversity. **Fourth,** the chromosomes start the reproduction by connecting 'genetic information' between them. In this stage, convergence towards a high-quality population is promoted. **Fifth,** slight mutations (alterations) are sometimes introduced to the a part of the chromosomes. This is critical to endure genetic diversity and prevent local optima. **Sixth and finally,** the process is repeated until the stopping condition is met. This can be either a maximum number of generations or a satisfactory fitness level.

GAs introduce the possibility to optimise a sequence of pipes rather than routing a single pipe each time. However, this is a specific boundary condition that a design engineer might want to alter depending on the design case. Besides the piping, this algorithm does also introduce the option to look in to the machinery arrangement of the engine room with relation to specific cost functions, that are defined by piping.

A.4.2.2 Ant Colony Optimisation (ACO) (DORIGO, 1992)

As ants search for food and leave cents for the rest to follow, this algorithm creates virtual "pheromone trails" that mark the shortest or better paths depending on the cost function given (Blokland et al. (2023); Asmara (2013)). The downsides to this algorithm are the vast number of iterations needed to find the optimal path.

A.4.2.3 Particle Swarm Optimisation (Kennedy and Eberhart, 1995)

Similar to ACO, this algorithm has a large amount of particles move through the solution space, each based on their best known position towards the solution (vectors and velocities). In comparison to GA, it converges faster to the optimal solution (Asmara, 2013). However, this technique tends to find the local optima and not the global optimum (Kennedy and Eberhart, 1995).

A.4.3. Mathematical and Artificial Intelligence

The most modern of all optimisation techniques, aimed at creating systems that can optimise for situations with uncertainty and handle non-linear issues. Besides this, multiple optimisation can be done concurrently instead of sequentially.

A.4.3.1 Integer Linear Programming and Steiner Forest (Markhorst et al., 2025)

In Markhorst et al. (2025) an algorithm is developed for solving an NP-hard '2 Stage Steiner Stochastic Tree Problem' using integer linear programming. The cost function is based on the possible bends, length of the pipe, rework amount and feasibility. But also a factor for uncertainty is included for future retrofitting for alternative fuels. However, the cost function focuses heavily on expected future retrofit costs and keeping these as low as possible. For the current problem at Damen OSV, it would need to be reassessed to optimise for the current expected costs. The downside of this technique is the fact that it is NP-hard, meaning that for highly complex systems need to be simplified in order so solve them.

A.4.4. Artificial Intelligence

A.4.4.1 Reinforcement Learning

Deep Reinforcement Learning (DRL) is a technique that combines deep learning with reinforcement learning, making it suitable for tackling complex sequential decision-making problems (Liao et al., 2020). This is based on the Markov Decision Process (MDP), developed by Bellman (1957). MDP by Richard Bellman layed the groundwork for Reinforcement Learning. This technique is a dynamic programming technique that does not always only consider the best outcome for one step ahead, but for a sequence of decisions, what is the expected optimal outcome. This can be described by function $Q^*(s,a)$, where the maximising expected return from starting state s through action a, and then following policy π from there that gives rise to the subsequent action-state configurations (Sutton and Barto, 1998):

$$Q^*(s,a) = \max_{E}[Rt|st = s, at = a, \pi] \tag{A.1}$$

- Q: Quality of the solution
- *: Optimality sign, indicating that the Quality (Q) is to be optimised.
- max: Finding the maximum value possible by varying the policy π
- E: expected value

- R: Discounted total return. This is what is expected from time t until the end of the task

What is key in this formula is that each step taken, the previous information is only kept from the last step. This leads to the function being a 'memoryless' system. The use of Deep Reinforced Learning is significantly faster than traditional A* path finding algorithms, because it has the ability to simultaneously optimise interrelated variables instead of only sequentially.

The limiting factor for DRL is that a large amount of data is needed for the algorithms to learn. Currently, the public availability of piping data is limited (Liao et al., 2020). Besides this, currently only models with single agents have been created. Single agents do not naturally extend from global route optimisation that contain multiple points that need connecting simultaneously.

B

Detailed Classification Rules for Piping Systems

This appendix details the technical requirements for piping systems as defined by Bureau Veritas, DNV, and Lloyd's Register. These rules directly influence space reservation and cost drivers in ship design.

B.1. Detailed Routing Regulations

Table B.1: Detailed Piping Routing and Construction Requirements

Category	Detailed Requirement	Source Reference
Separation	**Oil vs. Hot Surfaces:** Flammable oil pipes must not be routed within a zone of risk near surfaces $> 220°$C. Physical steel shielding is required if clearance is < 500mm.	BV Pt C, Ch 1, Sec 10 [11]
Electrical	**Switchboard Exclusion:** No piping is permitted over the front/rear of switchboards. If unavoidable, pipes must have no joints and be fitted with a continuous drip tray.	LR Pt 5, Ch 13, 5.5
Structural	**Collision Bulkhead:** Only one pipe (forepeak) may pierce the collision bulkhead. It must have a screw-down valve on the forepeak side operable from the weather deck.	DNV Pt 4, Ch 6, Sec 3
Maintenance	**Component Access:** Space reservation must account for "pull-out" distances for heat exchanger bundles and filter basket removal without cutting main lines.	LR Pt 5, Ch 12
Integrity	**Bulkhead Penetrations:** Watertight integrity must be maintained using certified bulkhead pieces. Plastic pipes require fire-resistant sleeves in A-60 divisions.	BV Pt C, Ch 1, Sec 10 [5]
Protection	**Cargo Holds:** Pipes in holds must be protected against mechanical impact by steel covers (≥ 6mm) or placed in a pipe tunnel.	DNV Pt 4, Ch 6, Sec 10
Expansion	**Hull Flexing:** Long runs (> 20m) must include Ω-loops or bellows to absorb thermal expansion and the ship's natural hogging/sagging.	LR Pt 5, Ch 12, 3.2
Safety	**Jacketed HP Fuel:** All HP fuel injection lines must be double-walled (jacketed) with a leak detection alarm system connected to the AMS.	SOLAS II-2, Reg 4
Support	**Vibration Control:** Maximum distance between pipe supports is determined by diameter (e.g., DN50 = 3.0m, DN100 = 4.0m) to avoid resonance.	DNV Pt 4, Ch 6, Sec 10
Drainage	**Bilge Suctions:** Bilge lines must be entirely separate from seawater/ballast lines to prevent accidental pollution (no common manifolds).	BV Pt C, Ch 1, Sec 10 [6]

B.2. Minimum Wall Thickness (IACS UR P1)

Class societies require a minimum thickness t for steel pipes to account for corrosion and mechanical strength, calculated as follows:

$$t = t_0 + b + c$$

Where:

- t_0: Theoretical thickness for internal pressure.
- b: Allowance for bending (typically 12.5%).
- c: Corrosion allowance (typically 2.5mm to 5.0mm for sea water lines).

C

Galati process duration statistics

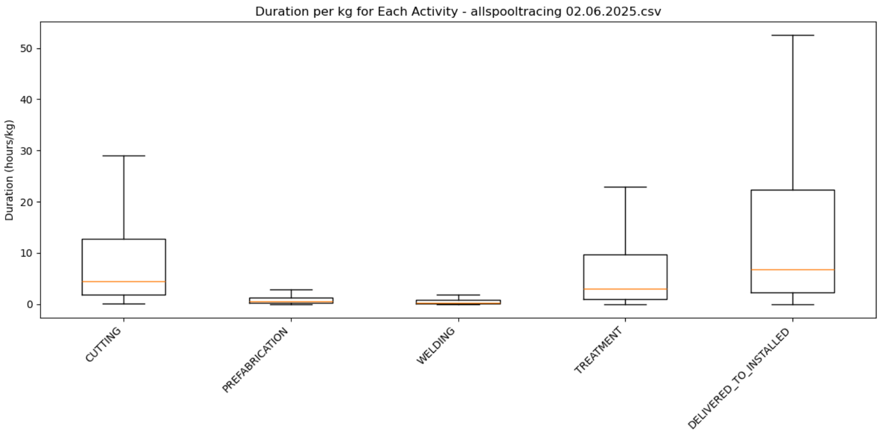


Figure C.1: Pipe process boxplots for 02.06.2025

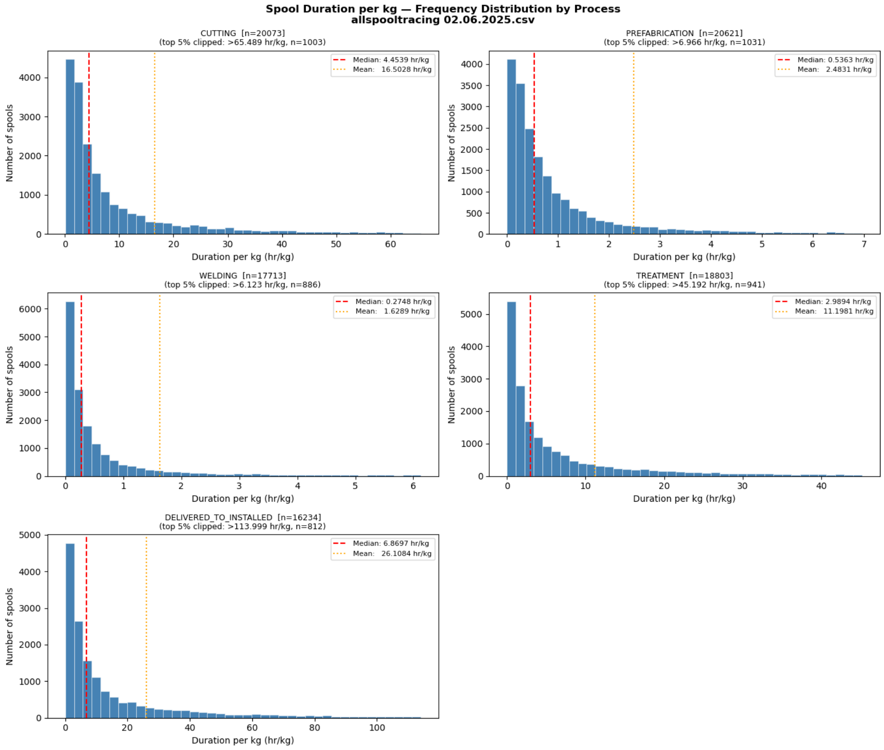


Figure C.2: Pipe spools distribution of data sorted by hours per kilogram 02.06.2025

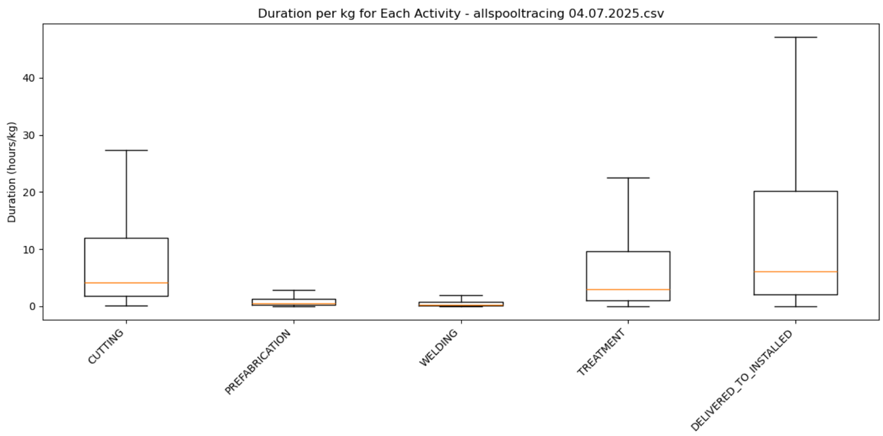


Figure C.3: Pipe process boxplots for 04.07.2025

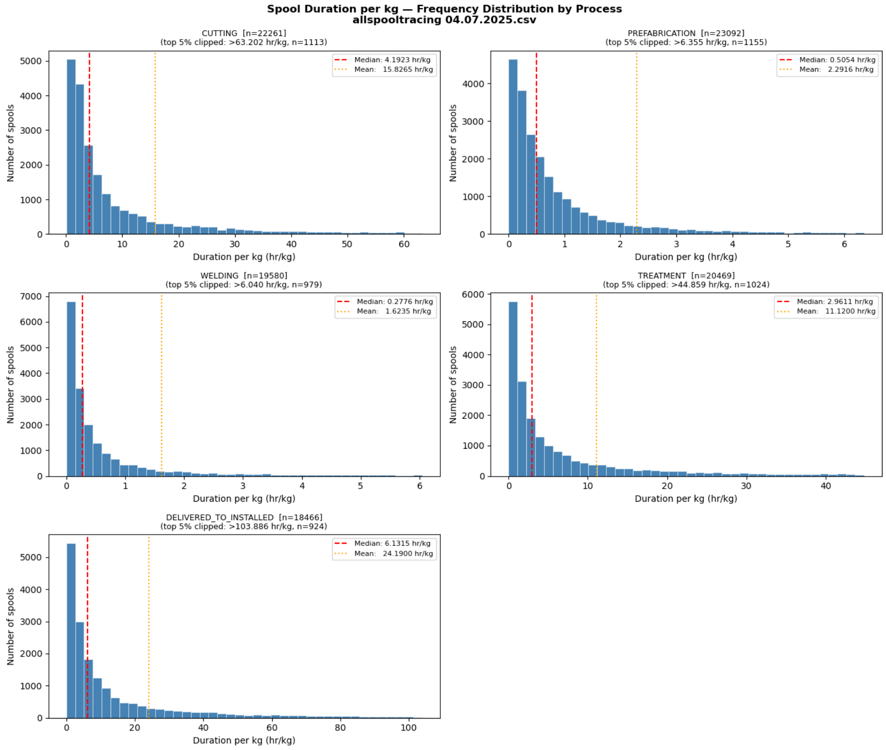


Figure C.4: Pipe spools distribution of data sorted by hours per kilogram 04.07.2025

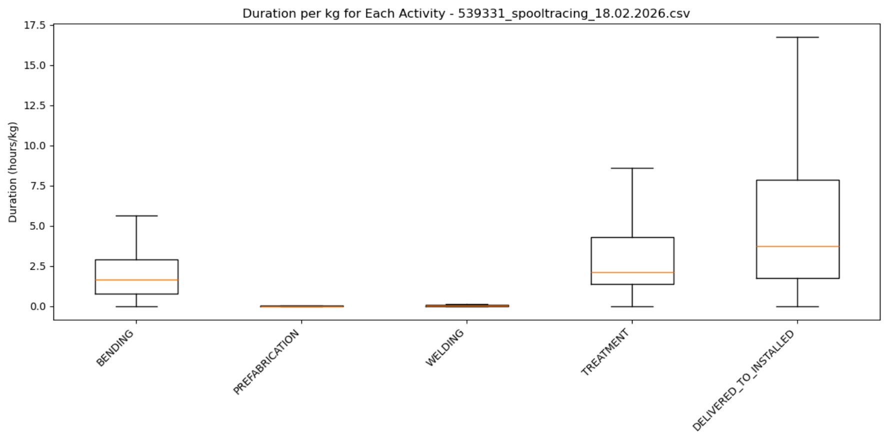


Figure C.5: Pipe process boxplots for 18.02.2026

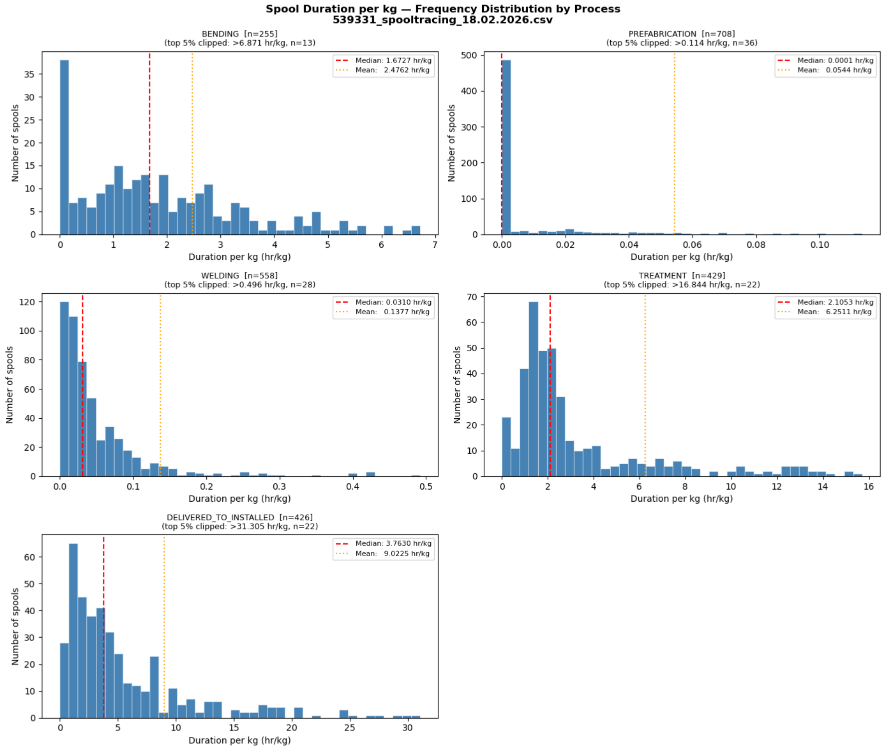


Figure C.6: Pipe spools distribution of data sorted by hours per kilogram 18.02.2026

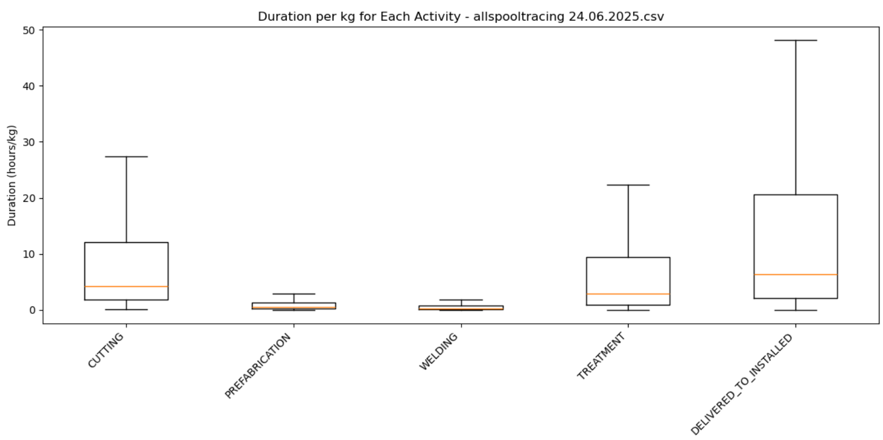


Figure C.7: Pipe process boxplots for 24.06.2025

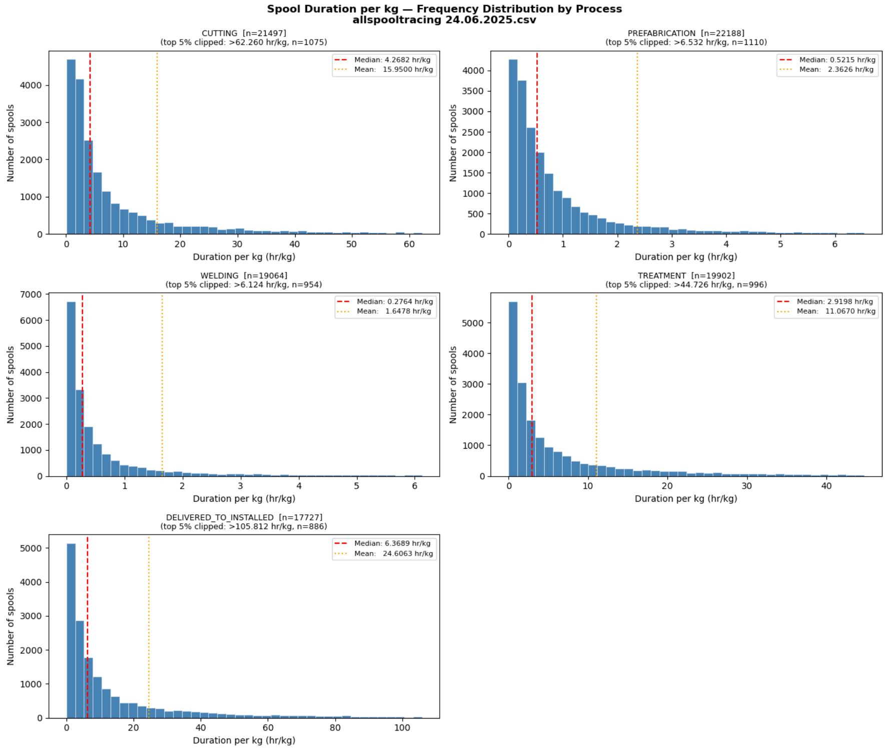


Figure C.8: Pipe spools distribution of data sorted by hours per kilogram 24.06.2025

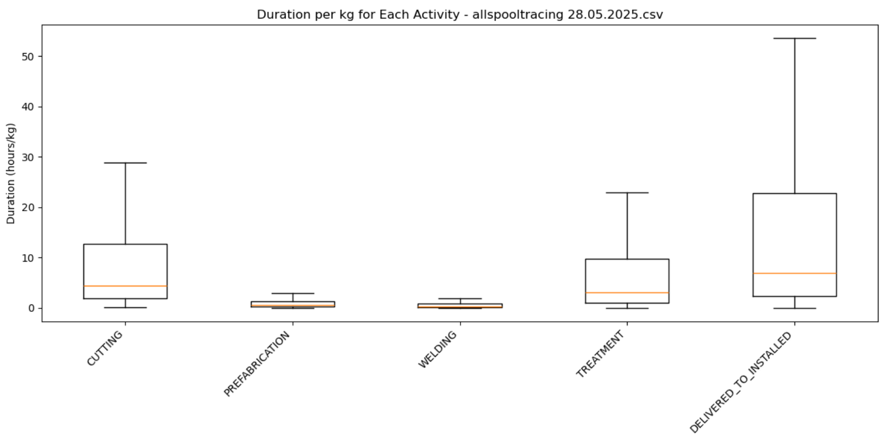


Figure C.9: Pipe process boxplots for 28.05.2025

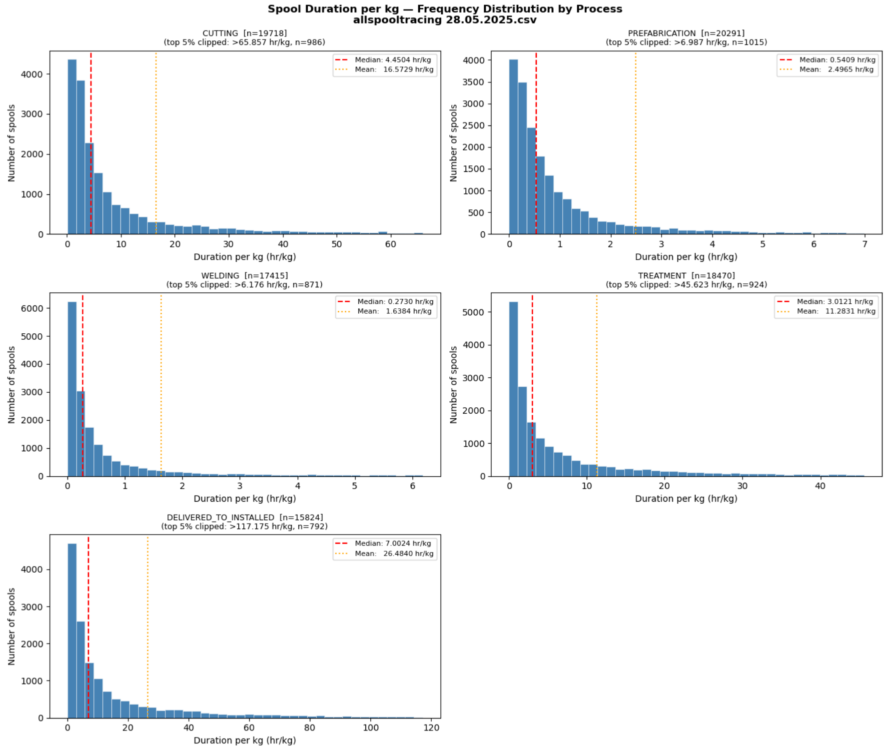


Figure C.10: Pipe spools distribution of data sorted by hours per kilogram 28.05.2025

D
Questionnaire data

Table D.1: Complete Expert Questionnaire Raw Data (Damen Shipyards)

			Spatial Thresholds (mm)					Time Multipliers				Base	Affecting Factors			
ID (Yr) (min)	Occupation Imp Dia	Exp T.T Len	Tgt Hgt	Suf Wld	Clr	T.T	Tgt	Suf	Clr	Time						
5	Technical Specialist Mech. & Piping Standards	27.0	5	10	25	50	100	3.0x+	2.0x	1.0x	1.0x	15	SA	SA	SA	A
6	Project Completion Manager	15.0	10	30	50	100	200	2.0x	1.5x	1.0x	<1.0x	10	A	A	SA	SA
7	HSSEQ Manager	17.0	1	5	10	50	100	2.0x	1.5x	1.0x	<1.0x	15	SA	SA	A	A
8	Technical Specialist Mechanical	12.5	10	20	30	40	50	3.0x+	2.0x	1.0x	1.0x	3	A	A	A	A
9	Technical Expert (Mechanical)	24.0	0	25	50	100	600	3.0x+	1.5x	1.5x	1.0x	30	A	A	A	A
10	Technical Specialist Shipbuilding	15.0	20	50	100	200	200	2.5x	1.5x	1.0x	<1.0x	15	N	SA	A	D
11	Expertise Center Engineering OSV	10.0	100	200	300	400	500	2.0x	1.5x	1.0x	<1.0x	5	SA	SA	SA	N
12	Manager Mfg. Engineering & Job Prep.	12.0	200	300	350	500	1500	3.0x+	3.0x+	1.5x	1.0x	15	A	A	A	A
13	Technical Specialist	4.0	50	50	50	50	50	3.0x+	3.0x+	1.0x	1.0x	60	A	SA	A	N

Spatial Condition Keys: Imp = Impossible, T.T = Too Tight, Tgt = Tight, Suf = Sufficient, Clr = Clear.
Likert Agreement Keys: SA = Strongly Agree, A = Agree, N = Neutral, D = Disagree.
Affecting Factors Columns: Dia = Pipe Diameter, Len = Spool Length, Hgt = Installation Height, Wld = Welding vs. Bolting.

D.1. Data distribution of answers

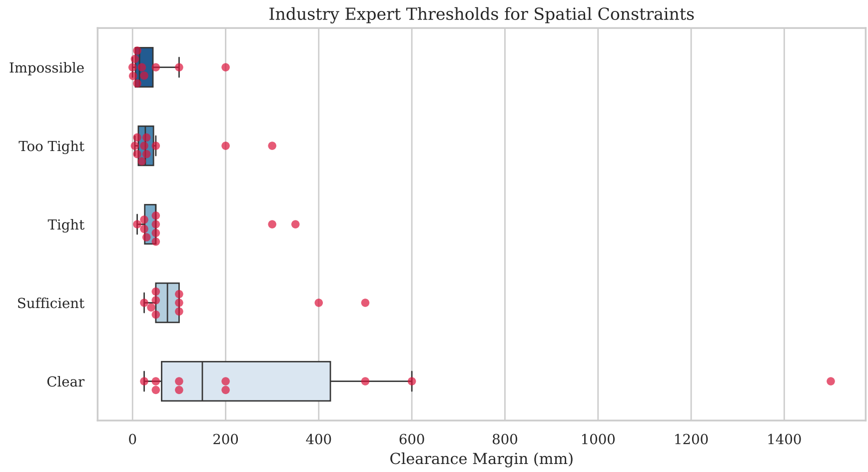


Figure D.1: Distribution of experts' answers in response to: *Estimate the **typical** distance between the pipe and a wall/obstacle that matches the following description about ease of install*

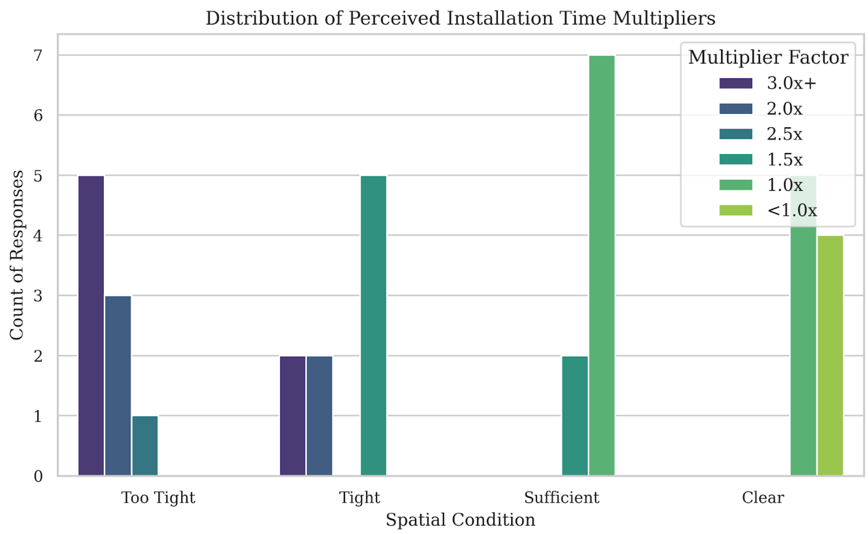


Figure D.2: Distribution of time multipliers estimated by engineers per cleanance description.

Bibliography

AKAN, E. and ALKAN, G. (2023). Optimizing shipbuilding production project scheduling under resource constraints using genetic algorithms and fuzzy sets. *Marine Science and Technology Bulletin*, 12:380–401.

Alblas, G. and Pruijn, J. (2024). Are current shipbuilding cost estimation methods ready for a sustainable future? a literature review of cost estimation methods and challenges.

Asmara, A. (2013). •**4»>fr pipe routing framework for detailed ship design. Technical report.

Babuška, R. and Mamdani, E. (2008). Fuzzy control. *Scholarpedia*, 3(2):2103. revision #91287.

Bellman, R. (1957). A markovian decision process. *Indiana University Mathematics Journal*, 6(4):679–684.

Blokland, M., van der Mei, R. D., Pruyn, J. F., and Berkhout, J. (2023). Literature survey on automatic pipe routing. *Operations Research Forum*, 4.

Boehm, B. W. (1981). *Software Engineering Economics*. Prentice-Hall, Englewood Cliffs, NJ.

Boyd, T. A. (1957). *Professional Amateur: The Biography of Charles Franklin Kettering*. E.P. Dutton & Co., New York. Foreword by Alfred P. Sloan, Jr.

Cahya, Z. (2025). Comparison of deep learning and ensemble learning as surrogate models in the early stage of ship design. Technical report.

Choi, S. W. and Lee, E. B. (2024). Application of an advanced dijkstra algorithm for automation systems of 3d piping routing. In *2024 8th International Conference on Communication and Information Systems, ICCIS 2024*, pages 213–217. Institute of Electrical and Electronics Engineers Inc.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. Technical report.

Dong, Z. R. and Bian, X. Y. (2020). Ship pipe route design using improved a* algorithm and genetic algorithm. *IEEE Access*, 8:153273–153296.

DORIGO, M. (1992). Optimization, learning and natural algorithms. *Ph. D. Thesis, Politecnico di Milano*.

Douglas, B. (2021). What is fuzzy logic? | fuzzy logic, part 1. `https://www.youtube.com/watch?v=__0nZuG4sTw`. YouTube video, published August 17 2021.

Group, E. S. (2009). Study on the competitiveness of the european shipbuilding industry: Within the framework contract of sectoral competitiveness studies – entr/06/054. Technical Report ENTR/06/054, European Commission, Directorate-General Enterprise Industry, Rotterdam. Final Report, 239 pp. Available from: `https://ec.europa.eu/docsroom/documents/10506/attachments/1/translations/en/renditions/native`.

Gunawan, Yanuar, Waskita, F. A., and Kurniawan, A. (2020). Modularization of ship engine room using design structure matrix (dsm) based on the genetic algorithm. *Engineering Journal*, 24:205–216.

Hadelkamp, V. D. (2017). Reducing pipe penetration costs in shipbuilding a new engineering & production approach to eliminate manual cutting by use of large predetermined openings. Technical report.

Hagen, A. (2013). Shipbuilding cost estimation parametric approach haakon shetelig, ntut. Technical report.

Jacobse, L. (2021). Initial pipe routing optimization for ship conversion report. Technical report, Technical University Delft.

Jarkas, A. M. and Bitar, C. G. (2012). Factors affecting construction labor productivity in kuwait. *Journal of Construction Engineering and Management*, 138:811–820.

Jiao, T., Zeng, J., Zhang, Y., Gu, H., and Ding, W. (2026). Research on intelligent monitoring of ship piping systems based on digital twin. *Journal of Ship Production and Design*, pages 565–571.

Kang, D. H., Choi, S. W., Lee, E. B., and Kang, S. O. (2024). Auto-routing systems (arss) with 3d piping for sustainable plant projects based on artificial intelligence (ai) and digitalization of 2d drawings and specifications. *Sustainability (Switzerland)*, 16.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks*, volume 4, pages 1942–1948. IEEE.

Keorapetse, M. P., Utzig, H., and Formoso, C. T. (2024). Cost control in modular construction: A taxonomy for effective cost management. In *Annual Conference of the International Group for Lean Construction, IGLC*, volume 32, pages 167–178. International Group for Lean Construction.

Kim, S.-Y., Moon, B.-Y., and Shin, S.-C. (2009). Journal of ship production evaluation criterion of machinery arrangement design in a ship engine room. Technical report.

Kong, M. C., Roh, M. I., Han, I. S., Lee, I., Lee, H., Kim, M., Kim, J., and You, J. (2025). A representation method of pipe connections and routing space in pipe auto-routing using graph and octree structures. *Ocean Engineering*, 329:121204.

Kunkera, Z., Runje, B., Tošanović, N., and Hadžić, N. (2025). Lean tools implementation model in shipbuilding processes under conditions of predominantly custom production. *Machines*, 13.

Levering, R. C. (2015). Coordination, learning and multi-organizational projects: The case of the dutch shipbuilding industry. Technical report.

Liao, H., Zhang, W., Dong, X., Poczos, B., Shimada, K., and Kara, L. B. (2020). A deep reinforcement learning approach for global routing. *Journal of Mechanical Design*, 142.

Lin, J., Qian, Y., Yassine, A. A., and Cui, W. (2012). A fuzzy approach for sequencing interrelated activities in a dsm. *International Journal of Production Research*, 50:7012–7025.

MacKenzie, I. S. (2015). Fitts' throughput and the remarkable case of touch-based target selection. In *Proceedings of HCI International—HCII 2015 (LNCS 9170)*, pages 238–249, Heidelberg. Springer.

Markhorst, B., Berkhout, J., Zocca, A., Pruyn, J., and van der Mei, R. (2025). Future-proof ship pipe routing: Navigating the energy transition. *Ocean Engineering*, 319.

Matuszek, J., Seneta, T., and Moczała, A. (2020). Assessment of the design for manufacturability using fuzzy logic. *Applied Sciences (Switzerland)*, 10.

Mikami, K. and Tabuchi, K. (1968). A computer program for optimal routing of printed circuit conductors. In *Proceedings of the IFIP Congress*, volume 68, pages 1475–1478, Amsterdam, Netherlands. North-Holland Publishing Company.

Min, J. G., Ruy, W. S., and Park, C. S. (2020). Faster pipe auto-routing using improved jump point search. *International Journal of Naval Architecture and Ocean Engineering*, 12:596–604.

Newton, I. (1959). Letter from newton to hooke, 5 february 1675/6. In Turnbull, H. W., editor, *The Correspondence of Isaac Newton, Volume 1: 1661–1675*, page 416. Cambridge University Press, Cambridge. Published for the Royal Society.

Norman, K. L. and Kirakowski, J. (2018). The wiley handbook of human computer interaction. Technical report.

Park, J.-H. and Storch, R. L. (2002). Pipe-routing algorithm development: case study of a ship engine room design. Technical report.

Powell, M. J. D., Lasdon, S., Schoeffler, J. D., Dzielinski, B. P., Gomory, R. E., Hart, P. E., Nilsson, N. J., and Raphael, B. (1968). The gradient projection method for nonlinear programming, pt. i, linear constraints. Technical report.

Rose, C. (2017). Automatic production planning for the construction of complex ships.

Rother, M., Shook, J., Womack, J., and Jones, D. (1999). Learning to see value stream mapping to create value and eliminate muda. Technical report.

Sugeno, M. and Kang, G. T. (1988). Structure identification of fuzzy model. *Fuzzy Sets and Systems*, 28(1):15–33.

Sutton, R. S. and Barto, A. G. (1998). Reinforcement learning: An introduction second edition, in progress. Technical report.

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-15(1):116–132.

Thawornwichian, W. (2018). An analysis of market-distorting factors in shipbuilding the role of government interventions.

Visser, B. (2025). Bridging operations and management on the shipyard production floor.

Watson, D. G. M. (1998). Elsevier ocean engineering book series volume 1 practical ship design. Technical report.

Wei, Y. and Nienhuis, U. (2012). Automatic generation of assembly sequence for the planning of outfitting processes in shipbuilding. *Journal of Ship Production*, 28:49–59.

Wikipedia contributors (2026). Breadth-first search — Wikipedia, the free encyclopedia. [Online; accessed 16-April-2026].

Womack, J. P. and Jones, D. T. (1996). Notes on continuous process improvement lean thinking banish waste and create wealth in your corporation. Technical report.

Wu, B. C., Young, G. S., Schmidt, W., and Choppella, K. (1998). Applying fuzzy functions and sequential coordination to optimization of machinery arrangement and pipe routing. *Naval Engineers Journal*, 110:43–54.

Xu, L., Li, Z., Li, S., and Tang, F. (2007). A decision support system for product design in concurrent engineering. *Decision Support Systems*, 42:2029–2042.

Zadeh, L. A. (1965). Fuzzy s e t s *. Technical report.