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# THÈSE DE DOCTORAT EN COTUTELLE

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## *Seafaring Staff Scheduling Problem with Workload Fairness and Incompatibility: Modeling and Resolution*

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**Abstract**

Staff scheduling challenges have been extensively studied in transportation sectors like airlines, railways, and urban buses, yet their application in sea transport remains notably underexplored. This work addresses a seafaring staff scheduling problem inspired by a real case study, where a shipowner operates multiple vessel categories requiring specific skills. The objective is to achieve a fair workload distribution, minimize worker incompatibility, and comply with legal requirements such as mandatory rest periods and shift intervals. The novelty of this work lies in the integration of these multiple objectives and constraints into a Mixed Integer Linear Programming (MILP) model, supported by experimental results that assess the model's performance under varying parameters. This research demonstrates that the problem is NP-hard, justifying the use of heuristic methods. The heuristic approach, rigorously tested against exact methods, is shown to effectively manage scheduling while adhering to the problem's constraints. Benchmarking results reveal that the heuristic yields near-optimal solutions with significantly reduced computation times, offering a practical decision-support tool for complex maritime staff scheduling

**Résumé**

Les employés sont souvent la ressource la plus coûteuse pour de nombreuses entreprises. Par conséquent, optimiser leurs horaires de travail est crucial pour garantir que l'employé le plus qualifié et le plus approprié soit affecté aux bonnes tâches aux moments opportuns. Ce processus peut être compliqué et chronophage, surtout lorsque la planification du personnel est encore gérée à la main. La définition de la planification du personnel varie depuis 1950 une conception très large par Dantzig, qui considérait que la planification est liée au nombre total d'heures nécessaires pour la journée, au nombre d'employés nécessaires, et aux heures de début et de fin. Cette définition a évolué au fil du temps. Pour A.T. Ernst et al. (2004) : « La planification du personnel, ou la gestion des horaires, est le processus de construction des horaires de travail pour son personnel afin qu'une organisation puisse satisfaire la demande de ses biens ou services ».

Ces dernières années, le processus de la planification du personnel a subi des changements significatifs en raison de la complexité croissante des processus organisationnels. Les entreprises doivent désormais prendre en compte plus de facteurs, y compris les compétences des employés, leur satisfaction, leurs préférences, le stress, la fatigue et d'autres facteurs pertinents liés aux employés. Par conséquent, la prise en compte de ces multiples facteurs rend difficile la prise de décisions basées sur des preuves concernant cette question. Ainsi, la réalisation de revues de littérature devient cruciale car elles peuvent éclairer les défis communs rencontrés dans la PP.

Ce travail traite d'un problème de planification du personnel navigant inspiré d’un cas réel, où l'armateur exploite plusieurs catégories de navires nécessitant des compétences spécifiques visant à atteindre une répartition équitable de la charge de travail et à minimiser les incompatibilités entre les travailleurs tout en respectant les exigences légales, telles que les intervalles de repos, les heures de travail, les jours de congés.

La nouveauté de cette thèse réside dans l'intégration de ces multiples objectifs et contraintes dans une formulation de problème linéaire en nombres entiers mixtes (MILP) accompagnée de résultats expérimentaux qui testent les performances du modèle à travers divers ajustements de paramètres. Ces résultats contribuent au support décisionnel, en éclairant le comportement du modèle face aux complexités de la planification du personnel dans le domaine maritime.

Les objectifs principaux de cette thèse sont :

1) Réaliser une étude préliminaire afin de comprendre les besoins techniques.

2) Se positionner par rapport aux travaux antérieurs et examiner comment ce type de modèle a été intégré dans d'autres domaines.

3) Développer un modèle de programmation linéaire mixte en nombres entiers (MILP) qui intègre les multiples contraintes et objectifs de la planification des employés maritimes. Valider le modèle à l'aide d'une méthode exacte, tester ses performances en ajustant divers paramètres et révéler la complexité du modèle.

4) Résoudre le problème à l'aide d'une méthode approchée.

Ces objectifs s'étalent sur plusieurs chapitres dans mon mémoire de thèse :

- **Chapitre 1 :** Le premier chapitre d'une thèse est considéré comme l'opportunité de présenter les concepts clés et les notions fondamentales liées à notre thématique de recherche. Cependant, nous étudions la gestion de la chaîne d'approvisionnement qui implique la coordination de diverses activités, notamment la logistique, la planification et l'optimisation. Nous nous concentrons sur la planification dans la gestion de la chaîne d'approvisionnement, en particulier la planification des effectifs dans le transport maritime. Nous explorons la modélisation générale du problème de planification des effectifs, y compris les contraintes et les fonctions objectives. Nous présentons également diverses techniques et méthodes de résolution, notamment des approches exactes et approximatives.

- **Chapitre 2 :** Pour répondre au besoin d'un processus d'affectation efficace pour un armateur tunisien, notre étude a employé un processus à quatre étapes. Tout d'abord, nous avons mené des entretiens semi-structurés pour identifier les objectifs clés qui devaient être atteints. Ensuite, nous avons examiné ces objectifs pour détecter des contradictions potentielles en utilisant la méthodologie de résolution de problèmes inventifs (TRIZ). En construisant un Système de Contradictions (SoC) et en alignant les paramètres TRIZ avec les paramètres d'évaluation, nous avons pu résoudre de manière systématique les conflits inhérents en proposant des solutions pratiques. Cependant, certaines solutions se sont avérées complexes à mettre en œuvre immédiatement, ce qui a nécessité des décisions clés, notamment la suppression de la rotation du processus de qualification des employés et la conduite du processus de qualification en dehors du processus de planification. En outre, nous avons élaboré sur les problèmes d'incompatibilité pour satisfaire les préférences et les affinités simultanément.

- **Chapitre 3 :** Pour répondre aux besoins de l'armateur, il est crucial d'examiner si ce problème a été abordé dans la littérature. Nous avons donc élaboré une revue de littérature pour identifier les travaux les plus significatifs, nous permettant de mieux comprendre notre problématique et le contexte de la recherche. Ces travaux se concentrent principalement sur les problèmes d'affectation rencontrés dans divers domaines, en utilisant une revue exploratoire (Scoping Review). Cette revue est basée sur le diagramme de flux PRISMA. Notre approche a cartographié un total de 122 études pertinentes issues de plusieurs bases de données, identifiant les lacunes de la recherche et couvrant les limites de ce domaine. La littérature actuelle présente un écart dans le domaine maritime concernant la minimisation des incompatibilités en tant qu'objectif. Il est essentiel de combiner cette minimisation avec une répartition équitable de la charge de travail pour répondre aux besoins spécifiques de l'armateur, tout en tenant compte des qualifications et des contraintes légales. Cette approche intégrée n'a pas été abordée dans les travaux existants, ce qui représente un écart significatif dans la planification du personnel maritime.

- **Chapitre 4 :** Les résultats de la littérature nous ont inspirés pour développer un modèle mathématique pour répondre aux besoins spécifiques des armateurs, qui sera discuté dans ce chapitre. Nous avons intégré ces objectifs et contraintes multiples dans une formulation de problème linéaire mixte entière (MILP) accompagnée de résultats expérimentaux qui testent le comportement du modèle en fonction des ajustements de paramètres variés. Ces résultats contribuent à l'appui à la décision, éclairant sur le comportement du modèle en ce qui concerne les complexités de la planification du personnel navigant dans le domaine maritime.

Les fonctions objectives de notre modèle sont présentées comme suit :

- **Équité de la répartition de la charge de travail** : Cette fonction objectif cherche à garantir une distribution équilibrée des tâches parmi les employés, évitant ainsi une surcharge de travail pour certains et une sous-utilisation pour d'autres. Cela aide à maintenir un niveau élevé de satisfaction et de motivation parmi les employés.

$$\boldsymbol{f1} = \left| \sum_{j}^{J} (\boldsymbol{X_{j,w}} * \boldsymbol{B_{l,j}}) - \boldsymbol{ANA_l} \right|$$

Nous constatons que la présence de la valeur absolue dans cette fonction introduit une non-linéarité. Pour la linéariser, nous utilisons une variable auxiliaire et la fonction objectif prend la forme suivante :

$$\boldsymbol{MIN\ f_1} = \sum_{w=1}^{W} \sum_{l=1}^{L} \boldsymbol{y_{l,w}}$$

En revanche, deux inégalités linéaires distinctes doivent être ajoutées aux contraintes, comme suit :

$$Y_{l,w} \geq (\sum_{j=1}^{J} (X_{j,w} * B_{l,j}) - ANA_l) \ \forall w \ \forall l$$

$$Y_{l,w} \geq -(\sum_{j=1}^{J} (X_{j,w} * B_{l,j}) - ANA_l) \ \forall w \ \forall l$$

- **Minimisation des incompatibilités :** Cette fonction objectif vise à réduire les conflits potentiels entre les employés, en tenant compte de leurs compétences, préférences et disponibilités.

$$\boldsymbol{f2} = (\frac{\mathbf{1}}{\boldsymbol{W}}) \sum_{w=1}^{W} \sum_{v=1}^{W} \sum_{j=1}^{J} \boldsymbol{H_{w,v}} * \boldsymbol{Z_{w,v,j}}$$

Plusieurs contraintes ont été abordées dans ce travail, qui sont bien détaillées à la page 104 et 105.

Pour résoudre et valider notre Model nous avons utilisés le solveur XPRESS à travers des tests et des exemples concrets, confirmant ainsi sa validité.

Pour comprendre comment le modèle réagit aux variations de paramètres clés, une étude de sensibilité a été réalisée, permettant d'évaluer les performances du modèle en ajustant différents paramètres. Cette étude garantit la robustesse et l'efficacité de notre modèle dans diverses conditions.

Notre modèle joue également un rôle crucial dans la prise de décisions managériales. En permettant la variation du paramètre alpha, qui agit comme un poids ajustable, les décideurs peuvent privilégier un objectif spécifique et observer son impact sur l'ensemble du modèle.

$$\textbf{MIN} \, f = \propto f1 + (1-\propto) \; f2$$

Cette flexibilité offre une visibilité accrue sur les décisions et leurs conséquences potentielles, offrant aux gestionnaires la capacité de prendre des décisions éclairées et stratégiques. Les principaux avantages de cette approche comprennent :

- L'augmentation du nombre de travailleurs qualifiés entraîne généralement des gains significatifs. Toutefois, ces gains peuvent atteindre un plafond à un certain niveau de qualification. Au-delà de ce seuil, des qualifications supplémentaires peuvent engendrer des coûts sans ajouter de valeur au profit.

- Assurer la compatibilité entre les travailleurs a un impact positif sur les profits. Cette influence a été observée dans deux cas étudiés : des matrices de compatibilité générées aléatoirement et des scénarios de compatibilité prédéfinis. Les scénarios prédéfinis offrent des interprétations claires mais peuvent ne pas refléter la complexité du monde réel, tandis que les matrices aléatoires fournissent une évaluation plus réaliste mais introduisent une incertitude dans la prédiction du niveau de profit potentiel.

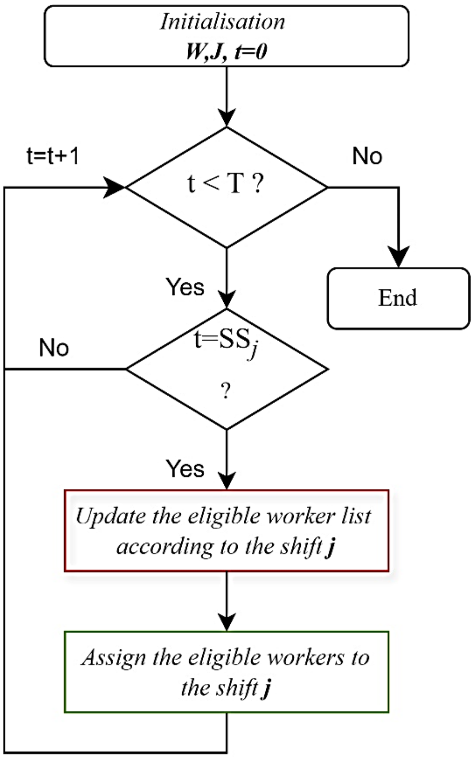
- Le temps d'exécution peut être augmenter non seulement avec le nombre croissant de travailleurs, mais aussi en raison des incompatibilités entre eux, conduisant à des temps d'exécution excessifs ou même à l'incapacité de trouver une solution pour certaines tailles de groupes de travailleurs.

Les études menées ont mis en évidence que la méthode exacte atteint ses limites lorsqu'elle est appliquée à des problèmes de grande envergure. En effet, le problème traité dans cette étude est un problème NP-difficile, ce qui signifie qu'il est impossible de trouver une solution exacte en temps raisonnable pour des instances de grande taille. Par conséquent, l'utilisation de méthodes approchées, telles que les heuristiques, est essentielle pour résoudre notre problème.

**Chapitre 5 :** Les chapitres précédents ont mis en évidence les défis posés par le problème de planification du personnel, notamment sa complexité NP-dure et les limitations des méthodes exactes pour fournir des solutions dans un délai raisonnable, ce qui soulève la question d’une approche plus pratique. L'objectif de ce chapitre est et d’appliquer une méthode approchée et de comparer les résultats avec ceux obtenus à l'aide de la méthode exacte.

L'algorithme heuristique développé dans ce travail vise à affecter efficacement les travailleurs éligibles aux postes de travail en fonction du temps qui passe jusqu'à ce que le temps final T soit atteint. Lorsqu'un poste de travail est identifié à l'horizon, le processus d'affectation commence et les travailleurs sont choisis à partir d'une liste dynamique de travailleurs éligibles. Cette liste est mise à jour en fonction des exigences spécifiques de ce poste de travail et devrait inclure uniquement les travailleurs qui sont éligibles pour l'affectation.

L'algorithme tente ensuite de satisfaire des objectifs tels que la minimisation de l'incompatibilité parmi les travailleurs affectés au même poste de travail et l'assurance de la justice dans la répartition du travail lorsque l'on sélectionne parmi. Les étapes impliquées dans ce processus sont détaillées dans le diagramme de flux présenté dans la figure ci-dessous.




Les résultats de cette étude ont montré que notre approche donne des résultats similaires à ceux obtenus avec la méthode exacte pour des instances de même taille, tout en étant capable de traiter des instances de grande taille que la méthode exacte ne peut pas gérer.

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I would like to express my profound gratitude to my parents, family. I am deeply grateful for the sacrifices **they have made for me and for the unconditional love they have shown me.**

Also, my friends who have never ceased to help and encourage me you have all been a vital part of my success.

# Dedication

*This work is dedicated to*

*My Parents,*

*My Husband,*

*My beloved sisters,*

*To our pride brother Chiheb, and his beautiful wife Nihel*

*My Brothers in law*

*My parents-in-law,*

*To my great sisters-in-law,*

*To my second brother Rami,*

*To all family members*

*To all my Friends…*

*Your encouragement, understanding, and belief in me have been the guiding lights that fueled my determination and perseverance throughout this long trip. As I celebrate the culmination of this endeavor, I dedicate my success to each of you, whose unwavering presence has been my source of strength and inspiration*

*Thank you……*

*"The PhD is a path, not an end"*

*Rishabh Jain*

# OUTLINE

# List of Abbreviations

**SS:** Staff Scheduling

**SRs:** Systematic Review

**ScR:** Scoping Review

**SSI:** Semi -Structured Interview

**SC:** Supply Chain

**SCM:** Supply Chain Management

**ASLOG : LOG**istics **AS**sociation

**TRIZ:** Théorie de la Résolution des Problèmes Inventifs

**UNCTAD:** United Nations Conference on Trade and Development

**SoC: S**ystem **o**f **C**ontradiction

**IP:** Integer Programming

**MIP:** Mixed-Integer Programming

**QP:** Quadratic Programming

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# General Introduction

Employees are often the most valuable and costly resource for many companies. Therefore, optimizing their work schedules is crucial to ensure that the most suitable employee, with the appropriate qualifications, is assigned to the right tasks at the appropriate times. This process can be complicated and time-consuming, especially when Staff Scheduling (SS) is still managed using spreadsheets.

The definition of SS has evolved over time. Initially, a broad conception was introduced by Dantzig in the 1950s, who considered scheduling to be related to the total number of hours needed for the day, the number of employees required, and their start and end times. This definition has since expanded. As A.T. Ernst et al. (2004) stated: "Personnel scheduling, or rostering, is the process of constructing work timetables for staff so that an organization can satisfy the demand for its goods or services."

In recent years, the staff scheduling (SS) process has undergone significant changes due to the growing complexity of organizational processes. Companies now need to account for a wider range of factors, such as employee skills, satisfaction, preferences, stress, fatigue, and other employee-related considerations. These multiple factors make it increasingly challenging to develop a comprehensive innovative solution to the scheduling problem. Our work is inspired by a maritime shipowner who aims to address a staff scheduling problem in preparation for a future project involving the acquisition of new, diverse vessels.

To address this challenge, we proceed as follows

- ❖ **Chapter 1:** introduces the fundamentals of staff scheduling within the supply chain context, focusing on the specific challenges faced by a maritime shipowner. It covers essential techniques and methods used to solve scheduling problems in maritime transportation, setting the groundwork for the more detailed models developed later.
- ❖ **Chapter 2:** In this chapter, we aim to define our research problem, which is rooted in the real-world challenges faced by the shipowner in staff scheduling. Through semi-structured interviews, we gathered insights into the operational constraints and specific needs of the organization. We then analyzed the contradictions that

emerged from these interviews, such as conflicting objectives, and resolved them using the TRIZ framework.

- **Chapter 3:** A literature review is essential to understand how similar problems have been addressed in the maritime domain. Due to the limited studies in this field, we conducted a scoping review using the PRISMA flow diagram to explore the existing literature and frameworks from other domains. This comprehensive analysis helped guide our approach to maritime scheduling.
- **Chapter 4:** Since our focus is on staff scheduling, this chapter formulates the problem mathematically as a Mixed Integer Linear Programming (MILP) model. The objective of the model is to balance fair workload distribution, minimize worker incompatibility, and ensure compliance with legal constraints such as rest periods. Additionally, the chapter presents experimental results to assess the model's performance under different conditions.
- **Chapter 5** introduces a heuristic method designed to provide a practical and scalable solution to the scheduling problem, particularly given its NP-hard complexity. We discuss how the heuristic serves as a viable alternative to exact methods, offering improved efficiency and comparable solution quality, making it well-suited for real-world applications.

# Chapter 1. Staff Scheduling Problem

## Introduction

Supply chain management involves coordinating various activities, including logistics, scheduling, and optimization. This chapter focuses on scheduling in supply chain management, specifically staff scheduling in maritime transportation. We explore the general modeling of the staff scheduling problem, including constraints and objective functions. We also present various techniques and resolution methods, including exact and approximate approaches. The chapter concludes with an introduction to our industrial partner.

## 1 Supply chain Management: general concepts

Logistics, supply chain, and supply chain management (SCM) are interrelated concepts that are essential for the efficient and effective movement of goods, information, and finances in modern business. Logistics refers to the planning, execution, and control of the movement and storage of goods and related information. A supply chain is a network of organizations, activities, and resources involved in the production and delivery of a product or service. SCM is the coordination and management of these activities to maximize value for customers and stakeholders. Understanding the relationships between logistics, supply chain, and SCM is critical for businesses seeking to improve their operations and gain a competitive advantage.

### 1.1 Logistic: Definition

The term "logistics" includes various concepts and has evolved over time. According to Pons J., and Chevalier P., (1996), indicate that the term logistics comes from a Greek word meaning the art of reasoning and calculation. the term originates from a Greek word meaning "the art of reasoning and calculation." Historically, logistics was used in a military context, referring to the activities that support armies, enabling them to live, move, fight, and evacuate and treat combatants (Ben kahla-Touil, 2011). After the Second World War, logistics expanded to the industry, and today, it plays a vital role in ensuring continuity. ASLOG (French **LOG**istics **AS**sociation) defines logistics as "the art and manner of making a given product available at the right time, in the right place, at the lowest cost and with the best quality". Other researchers, such as Nadine and Patrick, (2010) view logistics as the management of both physical and information flows, aimed at minimal costs while respecting deadlines and quality. Logistics involves various activities, such as handling, inventory management, warehousing, transportation, packaging, procurement, and international trade techniques. These activities can be further categorized into distinct areas or functions such as;

- ***Inbound Logistics:*** deals with the transportation of raw materials and products from suppliers to production facilities. It involves order fulfillment systems and efficient transportation methods.
- ***Outbound Logistics****:* involves moving finished goods from production centers to customers. It is crucial for order fulfillment and maintaining customer satisfaction.
- ***Reverse Logistics****:* Deals with the transportation of goods from customers back to the supply chain for purposes like returns, repairs, or recycling.
- ***Third-Party Logistics (3PL)****:* Outsourcing logistics operations, including inventory management and delivery, to a third-party logistics provider, allowing businesses to focus on core activities.
- ***Fourth-Party Logistics (4PL)****:* Comprehensive logistics outsourcing where a single partner manages the entire supply chain, including design, implementation, and tracking of solutions.

Logistics plays a crucial role in ensuring the smooth flow of operations within a company, encompassing activities such as transportation, warehousing, and inventory management to ensure timely delivery of goods to customers, However, logistics is just one piece of the puzzle. It's part of a broader framework known as the supply chain.

## 1.2 Supply Chain

A supply chain (SC) is a network of actors that work together to transform raw materials into finished products and deliver them to external customers.

A SC is a network of actors that work together to transform raw materials into finished products and deliver them to external customers. It can be visualized as a logistical network composed of various actors, including suppliers, producers, warehouses, distributors, and customers, all working towards satisfying customer demand (Simchi-levi et al., 2008)(see figure 1).

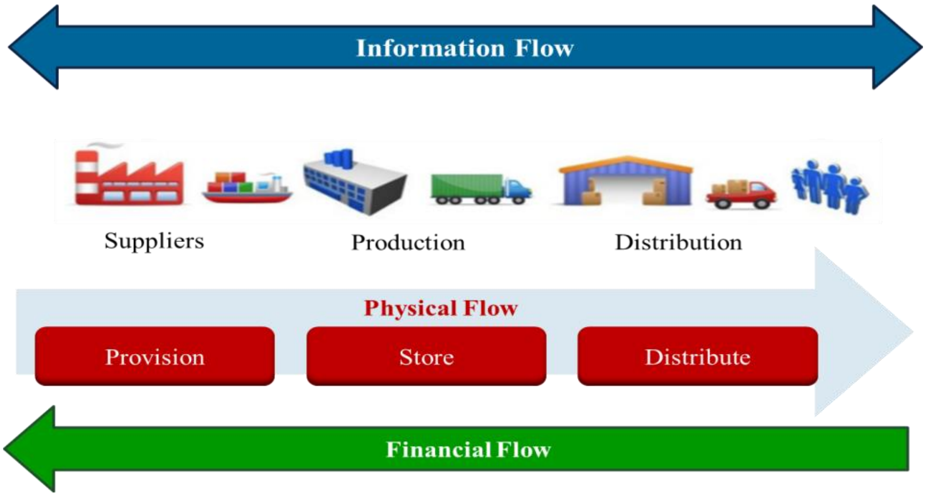



**Figure 1**:Supply Chain structure

In a typical supply chain, raw materials are sourced from one or multiple suppliers, transported to production facilities, and transformed into finished products. These products are then stored temporarily in warehouses before being delivered to distribution centers or directly to customers. The manufacturing process involves various activities, such as storage and the creation of intermediate products, highlighting the complexity and multiple stages of the supply chain. This network can be better understood by examining its structural components: upstream, internal, and downstream segments.

### 1.2.1 Supply Chain structure

Understanding the role of each of these links is crucial for comprehending how the supply chain operates in a holistic manner.

- ***Upstream Supply Chain:*** involves activities such as sourcing raw materials, supplier selection, procurement, and inbound logistics.
- ***Internal Supply Chain:*** covers internal operations like manufacturing, assembly, and quality control, focusing on optimizing processes for efficient production.
- ***Downstream Supply Chain:*** also known as physical distribution, refers to the set of activities involved in the collection, storage, and distribution of products to

buyers. It includes the management of finished goods warehouses, goods handling, operation of delivery vehicles, order processing, and scheduling (Rémy, 2013).

Understanding the structural components of the supply chain is fundamental to grasping the complexities of decision-making within its framework. As the supply chain operates through various stages, each level of decision-making—strategic, tactical, and operational—plays a crucial role in ensuring its efficient operation.

### 1.2.2 Decision Levels in a Supply Chain

Decision-making in supply chain is typically addressed sequentially and hierarchically, resulting in independent decision-making processes at different levels. However, each decision-making level has an impact on the others. For example, the possible decisions at the tactical or operational level are heavily dependent on those made at the strategic level (Phouratsamay, 2017).

- ***Strategic Level****:* at this level, long-term decisions shape the overall supply chain strategy to align with company objectives. These decisions involve network design, supplier selection, and major investments in infrastructure or technology, aiming to achieve desired results through careful planning.
- ***Tactical Level:*** this level involves a set of medium-term decisions that range from a year to a week. These decisions include production planning, inventory management, transportation routing, and distribution center operations (Phouratsamay., 2017). The goal at this level is to balance efficiency and flexibility while meeting customer demand and minimizing costs.
- ***Operational Level:*** involves making short-term decisions to execute the tactical plans and ensure the smooth flow of goods and information throughout the supply chain. Operational decisions include tasks such as order processing, scheduling of production activities, managing warehouse operations, and coordinating transportation activities.

Effective collaboration is crucial for a successful supply chain, as it enables seamless communication and coordination. Without it, minor issues can escalate into financial losses. The bullwhip effect, where small demand changes lead to exaggerated inventory fluctuations, is a prime example.

### 1.2.3 The Bull-Whip Effect (BWE)

The bullwhip effect, as defined by Buzon, (2007), refers to the phenomenon where small fluctuations in consumer demand result in increasingly larger variations in orders placed upstream in the supply chain. This effect arises from several factors, including inaccuracies in information, a lack of supply chain transparency, extended lead times for delivery, and a significant disconnect between consumption (actual customer demand) and production (actual factory activity). Figure 2 below provides a visual representation of this concept.

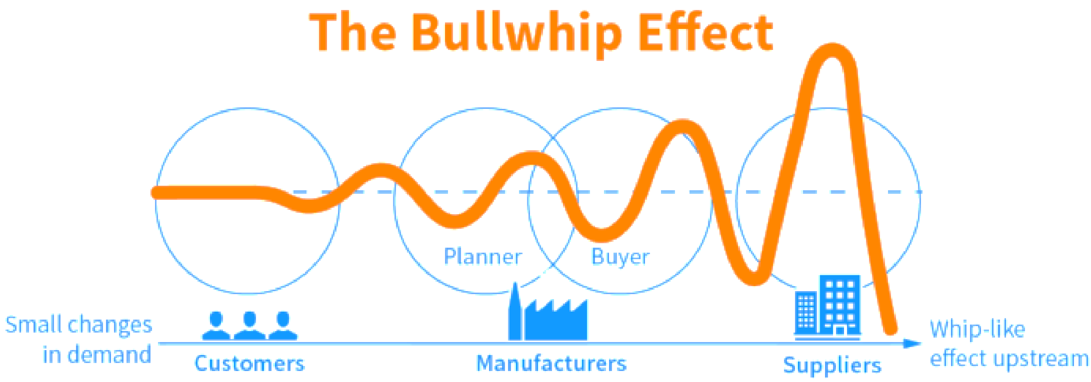



**Figure 2**:The bullwhip effect

When observing the bullwhip effect within supply chains, it becomes evident that fluctuations in consumer demand can lead to significant disruptions and inefficiencies throughout the entire supply chain. To mitigate and avoid such problems, effective supply chain management practices are essential, as a well-managed supply chain can help stabilize demand, reduce uncertainties, and improve overall operational efficiency.

## 1.3 Supply Chain Management

Supply Chain Management (SCM) coordinates all activities to deliver a product from raw materials to the end customer, including sourcing, manufacturing, assembly, inventory management, order processing, distribution, and customer delivery, supported by information systems. Unlike a supply chain, which begins with collaboration between at least two businesses (Mentzer et al., 2001), SCM focuses on the comprehensive management of these interconnected processes to ensure efficiency, reduce costs, and improve lead times (Lummus et al., 2003). SCM has experienced significant developments in recent years due to digital transformation, globalization, customer-centric approaches, and a growing emphasis on sustainability.

Artificial Intelligence (AI) has transformed SCM by enhancing demand forecasting, inventory management, logistics optimization, and risk management. AI-powered tools enable real-time data analysis, predictive maintenance, and improved interactions with suppliers and customers, leading to more efficient, adaptable, and resilient supply chains. These advancements make SCM more data-driven, agile, and sustainable, offering greater value to all stakeholders. As companies navigate complex and changing business environments, adopting AI technologies is crucial for optimizing supply chain planning and decision-making by analyzing extensive data, detecting patterns, and generating insights for improved efficiency, responsiveness, and resilience (Khoa & Toai, 2024).

Within this evolved framework, SCM involves managing various types of flows to ensure smooth operations and value creation:

- ***Physical flows:*** include raw materials, intermediate products, and finished goods, typically moving upstream to downstream, with recent challenges necessitating reverse flows for after-sales service and recycling.
- ***Financial flows***: associated with physical flows move downstream to upstream in a conventional supply chain. These include production costs, transportation costs, storage costs, and financial immobilization costs, among others.
- ***Information flows:*** can exchange in both directions within the supply chain. As entities within a supply chain are independent, information exchanges may occur among them. These exchanges may involve external customer demand, operational costs, or inventory levels, for example.

The beforementioned flows circulate between different operations within the supply chain. Physical, financial, and information flows move through various stages such as procurement, logistics, planning, and analysis, ensuring efficient and seamless operations. Each type of flow interacts with the others to support overall supply chain effectiveness and value creation.

# 2 Scheduling in Supply Chain Management

SCM is the central function that oversees and coordinates all sub-operations involved including logistics, planning, analysis, procurement, and successful operations (Figure 3).

Each component is integral to effective SCM, ensuring smooth operations from start to finish. Successful Operation ensures overall efficiency, while Logistics coordinates transportation, warehousing, and inventory management.

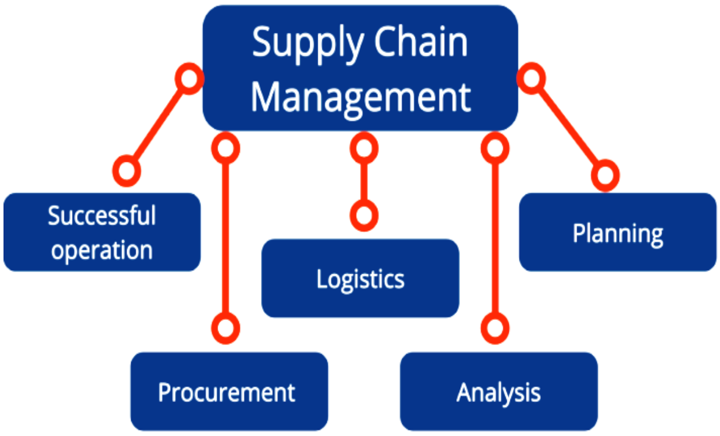



**Figure 3:**Essential Elements of Supply Chain Operations

Procurement involves sourcing materials and services, and Analysis evaluates data to improve performance. Planning stands out for its strategic role, covering demand forecasting, capacity planning, production scheduling, and resource allocation to meet market demands efficiently. Effective scheduling is crucial in SCM, optimizing task planning, personnel, equipment, and production. It ensures timely task completion, efficient resource use, and achievement of production goals while identifying potential bottlenecks for proactive problem-solving.

## 2.1 Types of scheduling

Scheduling involves planning the use of resources whether they are personnel, equipment, materials, or transportation to ensure that operations run smoothly and efficiently. Various types of scheduling are utilized depending on the specific needs and goals of the organization. Here, we explore the main types of scheduling, each with its unique focus and key factors:

- ***Production scheduling****:* This involves creating a schedule for producing goods, taking into account factors such as production capacity, lead times, and material availability.
- ***Distribution scheduling****:* This involves creating a schedule for the distribution of goods, taking into account factors such as transportation capacity, delivery times, and inventory levels.
- ***Equipment scheduling****:* This involves creating a schedule for equipment, taking into account factors such as maintenance schedules, capacity, and availability.
- ***Material scheduling****:* This involves creating a schedule for the procurement and delivery of materials, taking into account factors such as lead times, delivery schedules, and inventory levels.
- ***Workforce scheduling****:* This involves creating a schedule for personnel, taking into account factors such as staff availability, skill sets, and workload. Workforce scheduling helps to ensure that the right staff are available at the right time, reducing labor costs and improving productivity.

In SCM, various types of scheduling are employed to optimize the flow of goods and resources. These include production scheduling, distribution scheduling, workforce scheduling, equipment scheduling, and material scheduling. Among these, Staff Scheduling (SS) stands out as a critical aspect of supply chain operations. As employees are often the most expensive resource, optimizing their work schedules is essential. This involves ensuring that the right employee with the right qualifications is assigned to the right tasks at the right time. Effective SS is crucial in supporting supply chain operations, minimizing delays, and maximizing productivity.

### 2.2 Staff scheduling

Many companies consider their employees to be their most valuable and costly resource. As such, optimizing employee work schedules is crucial to ensure that the right employee with the appropriate qualifications is assigned to the right tasks at the appropriate times. However, this process can be complex and time-consuming, particularly when SS is managed using spreadsheets. The use of manual methods for SS can lead to inefficiencies, errors, and increased labor costs. Therefore, there is a need for more effective and efficient approaches to SS that can help companies save time, reduce costs, and improve productivity. The definition of SS has evolved significantly over time. In the 1950s, Dantzig defined scheduling in terms of the total number of hours needed for the day, the number of employees required, and their start and end times. By 2004, A.T.Ernst et al.,. described SS as the process of constructing work timetables for staff to meet the demand for an organization's goods or services. In recent years, the SS process has undergone significant changes due to the increasing complexity of organizational processes. Companies now need to consider a broader range of factors in SS, including employee skills (Kasirzadeh et al., 2015), satisfaction (Lorenzo-Espejo et al., 2021), preferences (Quesnel et al., 2019), stress, fatigue (Mohammed Othman, et al., 2012), and other relevant employee-related factors.

By considering factors such as employee qualifications, preferences, and well-being, these systems ensure employees are assigned tasks where they can perform most effectively and safely in various fields such as healthcare, manufacturing, services, and maintenance. Specifically, in transportation, this issue has been extensively studied across air, road, and rail transport but remains underexplored in the maritime sector, which is our focus.

# 3 General Modeling of The Staff Scheduling Problem

SS is a crucial aspect of workforce management, ensuring that the right number of employees with the appropriate skills are available to meet organizational needs. It involves various interconnected processes, and each process indeed depends heavily on the specific requirements of the organization, as each organization has unique operational needs, workforce compositions, and regulatory constraints that influence their scheduling processes. These requirements shape how demand modeling, shift scheduling, day-off scheduling, tour scheduling, and cyclic scheduling are implemented.

## 3.1 Components of Staff Scheduling

The process of staff scheduling is multifaceted, involving various components that address different aspects of workforce planning. In this section, we delve into the essential components of staff scheduling, each contributing to the creation of effective and efficient schedules:

- ***Demand modeling:*** the process of determining demand levels, converting them into work requirements, and evaluating staff needs for each planning period, shift, or task. This strategic decision-making step considers not only the number of employees but also their skills and contract types. In service operations with random customer arrivals, forecasting, queueing theory, and simulation techniques are used to estimate demand and staff requirements. In transportation and similar sectors, demand is modeled based on individual tasks and employee (driver) requirements.

- ***Shift scheduling:*** the process of designing work periods for employees, considering daily planning horizons, start and end times, work rules, and breaks. Shifts can be fixed or flexible, impacting staff costs and problem complexity. Other factors include shift sequences, forbidden shift sequences, demand coverage, and rest periods. Various shift scheduling problem variations exist.

- ***Day-off-scheduling:*** addresses determining the most appropriate rest days for employees within a planning horizon while considering work days. This problem is relevant when labor costs vary based on different rest patterns, aiming to minimize total labor costs. An example is a 5-day work week for employees and a 7-day operating week, with the possibility of consecutive days off.

- ***The tour scheduling:*** Tour scheduling is common in 24/7 operations, combining shift and day-off scheduling. Employees need daily and weekly breaks, requiring specific work hours and days. The complexity of tour scheduling depends on factors like the minimum planning interval, which can range from 15 minutes to 8 hours. Tour scheduling is found in various service sectors and production systems. An example of tour scheduling output with staff assignment is shown in Figure 2.4. Staff assignment can occur in the final phase or during the construction of work lines, especially when employees have different scheduling constraints.

- ***Cyclic scheduling***: also referred to as workforce rotating scheduling, is a method of assigning employees to the same work line with a set time lag, and this pattern repeats regularly. This approach is well-suited for demand patterns that consistently repeat, such as scheduling for bus or train drivers. Cyclic scheduling offers several benefits, including equal distribution of shifts and days off, stability, and advance scheduling knowledge. However, it lacks flexibility and the ability to adapt to last-minute changes.

### 3.2 Mathematical Modeling

SS is a common problem that has been addressed using various mathematical techniques, with Integer Programming (IP) being one of the most popular approaches. Many IP formulations are based on the set covering model introduced by Dantzig in 1954).

$$Minimize \sum_{j=1}^{n} C_j x_j$$

S.t.

$$\sum_{j=1}^{n} a_{ij} x_j \geq r_i \quad i = 1,2,\ldots,m$$

$$x_j \geq 0, and\ integer$$

This model could be applied to solving problems related to shift scheduling, days off, and tour planning by appropriately defining the following variables and parameters:

$x_j$ = a decision variable representing the number of employees assigned to schedule $j$.
$r_i$ = Number of employees needed to work during the $i^{th}$ time period.
$C_j$ = Cost associated with assigning an employee to shift $j$.
n = Total number of daily shift types to be considered.
m = Total number of time periods that need to be planned for a single day
$a_{ij}$= 1 if time period $i$ is covered by a shift pattern $j$; 0 otherwise.

This model aims to minimize the total cost of assigning employees to various shifts. The cost function to be minimized is represented by $\sum_{j=1}^{n} C_j x_j$, where $C_j$ is the cost of assigning an employee to shift $j$, and $x_j$ is the number of employees assigned to shift $j$. The constraints ensure that for each time period $i$ (from 1 to m), the number of employees working meets or exceeds the minimum required, $r_i$. This is expressed as $\sum_{j=1}^{n} a_{ij} x_j \geq r_i$ for each $i$. The decision variables $x_j$ are restricted to be non-negative integers. The coefficients $a_{ij}$ are set to 1 if time period $i$ is a work period in the daily shift pattern $j$, and 0 otherwise. This model is adaptable to various scheduling formats by adjusting the definitions of shifts and time periods.

The general model of SS has expanded in recent times and could include several factors. These problems can differ significantly based on the work environment, with various factors contributing to these differences, such as:

- ***Planning period:*** ranging from a few days to several months or up to a year, or user-defined.
- ***Operating hours:*** continuous 24-hour or discontinuous operations.
- ***Workforce:*** employees with single or mixed contract types, different skills, productivity levels, availability, and personal preferences. Shift flexibility can be fixed or vary in terms of starting time, length, breaks, and overlaps.

***Employee substitutability rules***: based on hierarchy or specific skills, can be considered.

These factors must be carefully considered to create effective and efficient staff schedules that meet organizational needs while also accommodating objectives and constraints.

### 3.3 Constraints and objective functions

When developing a model for a problem, both the constraints and objectives will vary depending on the specific features of the problem. Here are some common types of constraints that are often found in the literature:

As a result, the enterprise decision-maker is faced with an assignment problem that must simultaneously preserve the Constraints inspired by (Draghici, 2006):

- ***Legal***: Pertains to labor law regulations regarding work and rest periods over various time horizons (daily, weekly, monthly, and annually). This includes the required or allowed sequence of consecutive working or rest days as mandated by law. Examples include the maximum/minimum number of consecutive working/rest days and mandatory days off after a night shift.
- ***Social:*** Ensures the equitable distribution of tasks among employees, considering factors such as gender, unavailability, individual preferences, and other employee requests. It also involves the fair allocation of working hours and rest periods.
- ***Technical:*** Includes regulations of the different trades of the company (taking into account skills and required levels);

- ***Economic:*** This aspect involves aligning staffing plans with the organization's operational requirements at every point in the planning horizon. This means ensuring that the right number of employees are assigned to each shift to meet business needs, such as setting minimum or maximum staffing levels to maintain optimal coverage and efficiency.

In problem modeling, constraints can be expressed as soft objectives to provide more flexibility and adaptability in solutions. For instance, the constraint of coverage can be formulated as an objective function aimed at minimizing the gap between assignments and demand. This objective ensures that the number of staff assigned to shifts closely matches the labor demand, thereby avoiding situations of under or over coverage. By treating constraints as soft objectives, the modeling process can better balance practical limitations with the overall goals, leading to more realistic and achievable solutions. Other objectives that can be considered include:

- ***Coverage:*** Ensures that the number of staff assigned to shifts matches the labor demand as closely as possible, avoiding under or over coverage.
- ***Minimizing total labor costs:*** Aims to reduce the overall cost of labor by minimizing the number of staff assigned to shifts or reducing the number of overtime hours worked.
- ***Maximizing the percentage of contractual work hours assigned or minimizing the percentage of unassigned hours***: Ensures that as many contractual work hours as possible are utilized.
- ***Minimizing workforce size:*** Aims to reduce the number of staff required to cover shifts, helping to lower labor costs.
- ***Minimizing the gap between assignments and employees' preferences***: Assigns staff to shifts that align with their preferred working hours, enhancing employee satisfaction.
- ***Balancing the workload between employees***: Distributes the workload evenly between employees, preventing overburdening or underutilization.
- ***Maximizing employee satisfaction***: Creates schedules that meet the needs and preferences of employees, improving morale and reducing turnover.

In certain Staff Scheduling (SS) problems, the objective of achieving a balanced and fair schedule is explicitly stated in the objective function. However, in other cases, this objective is indirectly achieved by balancing multiple objectives that collectively contribute to a fair and balanced schedule (Ferreira & Rocha, 2013).

Having explored how objective functions are tailored to ensure fairness and balance in specific staff scheduling scenarios, it is evident that these practices are a subset of the broader field of optimization.

# 4 Optimization: Modelling Techniques and Resolution Methods

Optimization plays a crucial role not only in operations management but also in engineering, finance, and other disciplines where the best solutions must be identified from a range of possible options. Whether dealing with discrete, continuous, or mixed variables, the essence of optimization involves either maximizing or minimizing a real function based on selected input values, as defined in various sectors including mathematics and computer science (Sadrehaghighi, 2022). This perspective sets the stage to delve into an overview of basic optimization techniques and solutions, providing a foundation for understanding the wide array of applications and methodologies in this expansive field.

## 4.1 Modeling Techniques

Mathematical modeling involves representing real-world problems with mathematical expressions and then solving them using optimization techniques. Advanced optimization techniques such as Integer Programming (IP), Mixed-Integer Programming (MIP), and Quadratic Programming (QP) play crucial roles in tackling complex decision-making problems across various industries. Each technique offers unique capabilities tailored to handle specific types of mathematical models and constraints, and range from handling discrete choices and integer constraints to integrating continuous variables and modeling nonlinear relationships.

### 4.1.1 Integer programming (IP)

IP is a type of optimization where decision variables are restricted to integers, ideal for yes/no decisions and scenarios requiring whole numbers, like scheduling. Useful for discrete choices such as manufacturing units or dispatching trucks, IP faces challenges in computational complexity. As the number of integer variables increases, the solution space expands exponentially, complicating optimal solution finding.

#### 4.1.2 Mixed Integer Programming (MIP)

MIP combines integer and continuous variables, ideal for complex tasks like airline crew scheduling. It integrates discrete decisions (number of pilots per flight) and continuous decisions (pilot working hours), making it versatile for logistics planning but also difficult to solve due to the mix of variable types.

#### 4.1.3 Quadratic Programming (QP)

QP is a type of optimization technique where the objective function is quadratic, meaning it includes terms where decision variables are squared. This allows QP to model problems where relationships between variables are nonlinear. A straightforward example of QP is managing work shifts at a retail store, where the goal might be to minimize both direct labor costs and indirect costs related to employee fatigue, which increases quadratically with longer hours.

#### 4.1.4 Linearity

Integer Programming (IP), Mixed Integer Programming (MIP), and Quadratic Programming (QP) differ in their handling of linearity and non-linearity, which impacts their applications and complexities. IP primarily deals with linear relationships (ILP) where decision variables and constraints involve basic arithmetic operations. However, introducing non-linear equations in IP leads to Non-linear Integer Programming, which can model complex phenomena but is more challenging to solve. MIP expands on IP by allowing both integer and continuous variables, typically within a linear framework (MILP). But when MIP includes non-linear functions in constraints or objectives, it becomes Mixed Integer Non-linear Programming (MINLP), suitable for addressing real-world industrial scenarios with non-linear production costs. Finally, QP inherently involves non-linearity through its quadratic terms in the objective function, enabling it to capture intricate interactions between variables that linear models cannot, such as risk optimization in finance where the relationship between risk factors is multiplicative. This inherent non-linearity makes QP uniquely suited for scenarios requiring detailed interaction modeling.

### 4.2 Resolution Methods

Several methods are available for solving SS problems (Figure 4), including exact and approximate approaches. Exact methods, also known as complete methods, guarantee an optimal solution but can be computationally expensive and time-consuming, particularly for large-scale problems. Conversely, approximate methods do not guarantee an optimal solution but can provide a good solution within a reasonable timeframe. These approximate methods are often used to solve large-scale integer programming (IP) models that are impractical for exact methods due to their complexity and computational demands.

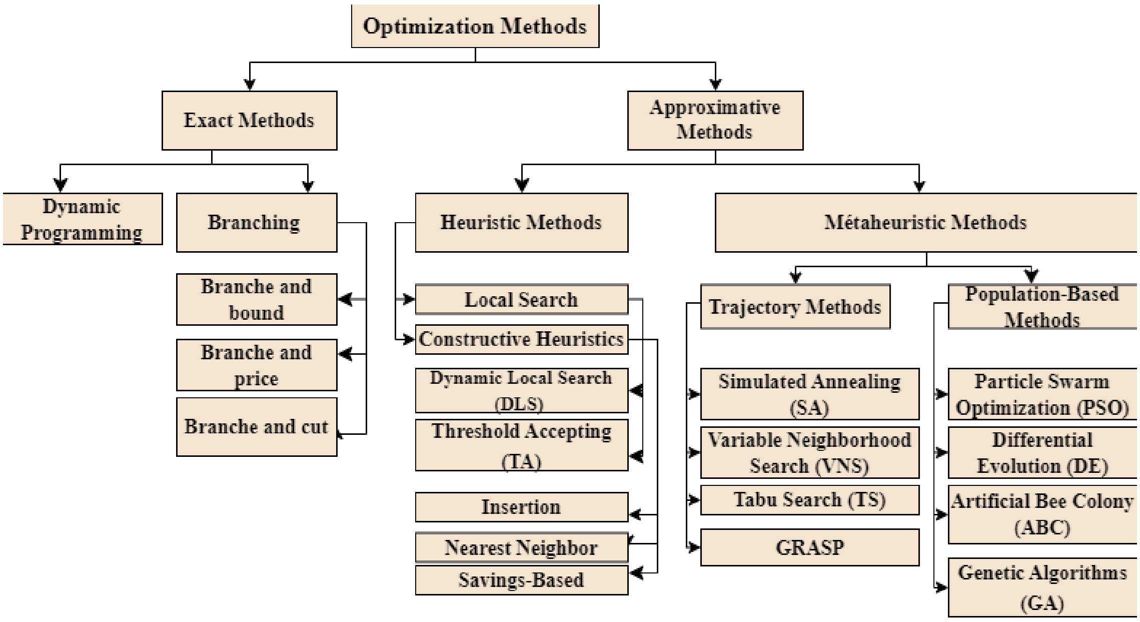



**Figure 4**:Resolution Methods

#### 4.2.1 Exact Approach

Exact algorithms are designed to guarantee finding the optimal solution to an optimization problem under specific conditions. These methods are particularly valuable when precision is crucial, as they can ensure the quality of the obtained solution. These methods are particularly useful for solving combinatorial optimization problems where the solution space is discrete and often very large. One of the most well-known enumerative methods is Branch and Bound and its extensions.

- ***Branching**:* The Branch and Bound algorithm, developed in 1960, solves optimization problems using a structured tree-based approach, combining evaluation, separation, and traversal strategies. It reduces the search space by applying bounding techniques, decomposes problems into smaller subproblems, and employs traversal strategies like breadth-first, depth-first, and best-first to optimize search efficiency and memory usage. While effective, Branch and Bound can be computationally expensive for large or complex problems. To address this, "Branch and Cut" and "Branch and Price" were developed as extensions. Branch and Cut integrates cutting planes to tighten bounds and accelerate convergence, while Branch and Price uses column generation to selectively add variables, making it more efficient for large-scale integer programming problems.
- ***Dynamic programming:*** is a problem-solving technique that breaks down complex problems into simpler sub-problems, solves each sub-problem only once, and stores solutions to avoid redundant calculations. It's effective for recursive problems with overlapping sub-problems, optimizing computation time. Applications include inventory management, project scheduling, and combinatorial problems.

#### 4.2.2 Approximate Approach

When exact solutions are computationally impractical due to problem complexity or size, approximate algorithms are used. These methods do not guarantee an optimal solution but can often find good solutions more quickly than exact methods.

### *Heuristic Methods*

heuristics are valuable problem-solving tools that can be categorized into two main types: general heuristics and problem-specific heuristics. General heuristics are versatile and can be applied across a wide range of problems without significant modifications, making them ideal when specific problem details are unknown or when development resources are limited. However, they may be less effective than problem-specific heuristics, which are tailored to leverage unique features of a particular problem, often resulting in more efficient solutions but at a higher development cost. The choice between using general or problem-specific heuristics largely depends on the knowledge of the problem, available resources, and the desired solution quality. In practice, it's common to start with general heuristics for an initial solution and refine this solution with more targeted heuristics to improve outcomes, such as:

- ***Local Search**:* includes methods like Dynamic Local Search (DLS) and Threshold Accepting (TA), which iteratively explore the solution space by making local changes to a current solution.
- ***Constructive Heuristics**:* Constructive heuristics create feasible solutions from scratch by progressively adding components until the solution is complete, commonly used in combinatorial optimization problems. Notable methods include: Closest Neighbor (Nearest Neighbor), which selects the nearest unvisited option at each step, often used in routing problems; Insertion, which builds a solution by adding elements one by one to minimize cost increases; and Savings-Based, which merges individual components to maximize cost savings.

***Metaheuristic Methods***

These methods are higher-level strategies that guide the search process to explore the solution space more thoroughly, capable of escaping local optima by employing mechanisms that promote diversification and intensification.

- ***Trajectory Methods**:* Such as Simulated Annealing (SA), Tabu Search (TS), and Variable Neighborhood Search (VNS), Greedy Randomized Adaptive Search Procedure (GRASP) which modify a single solution over time.

  *Simulated Annealing (SA):* Inspired by the annealing process in metallurgy, SA is a probabilistic technique for approximating the global optimum of a given function. It starts with an initial solution and iteratively makes small random changes to the solution.

  *Variable Neighborhood Search (VNS):* VNS systematically changes the neighborhood structure during the search process to escape local optima. It combines local search with systematic changes in the neighborhood.

  *Tabu Search (TS):* An iterative optimization algorithm that uses memory structures to avoid cycling back to previously visited solutions. It enhances local search methods by maintaining a tabu list of recently visited solutions or moves.

*Greedy Randomized Adaptive Search Procedure (GRASP):* An iterative process that involves two main phases: construction and local search. In the construction phase, a feasible solution is built in a greedy randomized manner. In the local search phase, this solution is iteratively improved by exploring its neighborhood. The process is repeated multiple times, and the best solution found across all iterations is selected.

- ***Population-Based Methods****:* Employ a set of potential solutions which evolve over time, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), Artificial Bee Colony (ABC).

  ***Particle Swarm Optimization (PSO):*** Inspired by the social behavior of birds flocking or fish schooling. It optimizes a problem by iteratively trying to improve candidate solutions with regard to a given measure of quality.

  *Differential Evolution (DE):* A population-based optimization method that optimizes a problem by iteratively improving candidate solutions with regard to a given measure of quality. It uses vector differences for perturbing the population members.

  *Artificial Bee Colony (ABC)****:*** A tool which simulates the intelligent foraging behavior of a honey bee swarm. It consists of three types of bees: employed bees, onlooker bees, and scout bees, each contributing to the search for the optimal solution in a different way.

  *Genetic Algorithms (GA*): are a type of evolutionary algorithm, which are a subset of population-based methods. All evolutionary algorithms use populations of solutions to find optima, inspired by the biological mechanisms of evolution. GAs are specifically inspired by natural selection and genetics. They solve combinatorial and continuous optimization problems by evolving a population of candidate solutions over several generations. GAs simulate natural evolution using mechanisms like selection, crossover, and mutation to iteratively improve the population towards an optimal or near-optimal solution.

# 5 Staff Scheduling in Maritime Transportation

Ports play a critical role in driving trade, travel, and economic growth for countries worldwide. In fact, according to the United Nations Conference on Trade and Development (UNCTAD), approximately 80% of global trade by volume and over 70% of global trade by value are transported by sea and managed by ports globally. As such, ports serve as vital gateways for the movement of goods and people, and their efficient operation is essential for supporting economic development and growth. Given the importance of ports in facilitating global trade, it is crucial to ensure their smooth and efficient operation, which can be achieved through effective management practices, investment in infrastructure and technology, and the adoption of innovative solutions to address emerging challenges and opportunities in the maritime industry. However, a transshipment terminal is an extremely complex system requiring a wide array of manpower that need to interact in a 24-hour operating cycle. Workers and their time are important factors, but they represent the costliest elements for any business constituting up to 80% of total costs. Therefore, there have been significant efforts made to reduce the maritime transportation cost by efficiently recruiting, training, and well scheduling staff members. The effectiveness of SS plays a pivotal role in ensuring optimal performance of such a transshipment terminal. Crew members on vessels, including cargo ones, follow strict schedules for duty rotations, rest periods, and port calls. SS in maritime field involves coordinating crew assignments, ensuring compliance with maritime regulations, and managing staff fatigue to maintain safety standards at sea. Moreover, in port operations, SS extends to dockworkers, crane operators, and port administrators, ensuring seamless vessel handling and cargo movement.

In maritime transport, two types of scheduling are crucial for ensuring the smooth flow of goods/passengers. dock workers scheduling refers to the efficient allocation of scheduling staff responsible of the loading and unloading of cargo ships, ensuring that ships are loaded and unloaded promptly, minimizing turnaround times and optimizing port operations. Seafaring staff scheduling, on the other hand, focuses on the efficient allocation of seafaring workers to ensure the safe and efficient operation of ships at sea. This involves scheduling captains, officers, engineers, and crew members to navigate ships, monitor equipment, and perform maintenance tasks, thereby minimizing risks and ensuring the safe and efficient transport of goods/passengers by sea.

### 5.1 Dock staff

Dock staff play a crucial role in maritime transportation, handling the loading and unloading of cargo ships and ensuring the smooth flow of goods through ports. Their responsibilities may include operating cranes and other equipment to move cargo, securing cargo for transport, and maintaining cleanliness and safety on the docks. Efficient scheduling of dock workers is essential to ensure that ships are loaded and unloaded promptly, minimizing turnaround times and optimizing port operations.

### 5.2 Seafaring staff

This study focuses on seafaring staff, inspired by a real-world shipowner operating a fleet of car-ferries. The shipowner aims to allocate workers to vessels while adhering to several objectives and constraints. To better understand the shipowner's requirements, we conduct a field study involving semi-structured interviews with key stakeholders. This approach provides insights into the specific needs and challenges in allocating seafaring staff. However, before moving forward, it is important to introduce the industrial partner.

## 6 Presentation of the Industrial Compagny

The New Transportation Company of Kerkennah, "SONOTRAK", is a public limited company established in July 1976, with a social capital of 970,000 dinars. The company's social objective is to provide public transportation services for passengers, vehicles, goods, and merchandise between Sfax and the Kerkennah islands. SONOTRAK fleet consists of five car ferries namely: **Cercina, Loud Tunisie**, **Kerkennah, Hached, Elmouhit, Habib Achour** and **Kyrannis** (figure 5).


**Figure 5**:Operating a fleet of SONOTRACK vessels

As shown in Figure 5, SONOTRAK operates several vessels, but each with a different capacity. Table 1 presents the capacity of these vessels in terms of the number of vehicles and passengers they can accommodate.

**Table 1:**Vessels Capacity

| | Capacity | |
|---|---|---|
| | **Vehicles** | **Passengers** |
| **Loud Tunisie** | 120 | 600 |
| **Kerkennah** | 68 | 900 |
| **Hached** | 67 | 900 |
| **Elmouhit** | 210 | 900 |
| **Habib Achour** | 172 | 800 |
| **Kyrannis** | 52 | 900 |
| **Cercina** | 150 | 800 |

The operating fleet has a total capacity of approximately 689 vehicles and 5000 passengers.

To understand the operations of SONOTRAK in recent years, it is important to review data from this period. Therefore, we present statistics sourced from the official website of the company, reflecting SONOTRAK's operations over the period from 2015 to 2020.

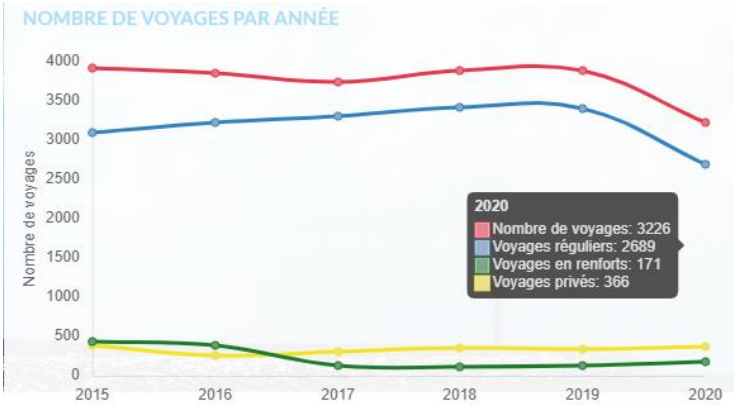



**Figure 6:**Annual Trips Statistics by Category (2015-2020)

Figure 6, presents a graph depicting the number of trips conducted by SONOTRAK per year from 2015 to 2020. The organization offers three different types of trips: regular voyages, reinforcement voyages, and private voyages.

In addition to the different types of voyages, the company offers various fares for passengers: normal fare, reduced fare, and free fare.

The two graphs illustrate trends in SONOTRAK's operations from 2015 to 2020, focusing on the number of voyages and passengers. These trends indicate a general reduction in both voyages and passengers over the period, potentially due to changes in demand, operational adjustments, or external factors affecting SONOTRAK's operations.

The shipowner recognizes the significance of their fleet and seeks to optimize the staff scheduling process as a critical component of the company's success. To gain a deeper understanding of the organization's requirements, a primary analysis is conducted through semi-structured interviews with stakeholders. This approach helps better understand the technical problems explored in the next chapter. This approach helps identify the challenges faced by the company and inform the development of effective staff scheduling strategies that align with the organization's goals.

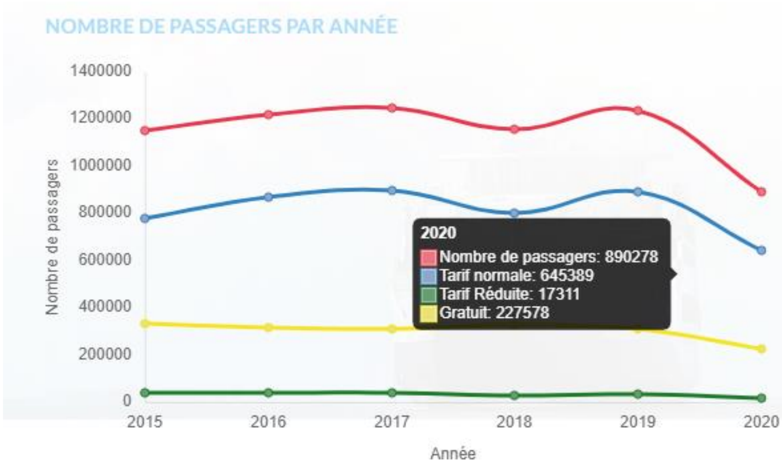



**Figure 7**:Annual Passenger Statistics by Ticket Type (2015-2020)[1]

## Conclusion

This chapter has provided a comprehensive overview of staff scheduling (SS) in the maritime industry, highlighting its importance for optimizing resources and ensuring safety. The discussion covered various resolution methods, including exact and approximate methods, and explored the constraints and objective functions involved in SS modeling. The chapter also introduced an industrial partner, whose challenges will be the focus of the next chapter as technical problem that need to be met.

[1] https://www.sonotrak.tn/fr/statistiques

# Chapter 2. Research Problem Statement: Semi Structured Interview and TRIZ

## Introduction

To gain a comprehensive understanding of the unique needs and challenges faced by a shipowner, it is essential to conduct field studies with preliminary analyses. This approach ensures that research efforts are aligned with the real-world requirements and constraints of the context being studied. In this chapter, we present the preliminary findings of a comprehensive study on seafaring Staff Scheduling (SS) within the maritime shipowner. We used Semi-Structured Interviews (SSI) as a research method to gather in-depth insights from the shipowner. During the analysis of the findings, we identified conflicts in the results, which is why we employed the TRIZ Framework to resolve these contradictions and match them with the organization's challenges.

## 1 Preliminary qualitative research

The primary objective of a preliminary analysis is to develop a thorough understanding of the topic, thereby avoiding unnecessary time, effort, or financial investment (Roche, 2009). It can be conducted using both qualitative and quantitative methods, each offering unique insights and benefits. In contrast to quantitative research, qualitative research does not aim to quantify or measure. Instead, it often involves collecting verbal data to facilitate an interpretative approach. According to (Roche, 2009), the objective of qualitative research is to better understand and get closer to the study's target to illuminate various elements. (Triki, 2008) asserts that qualitative research is a very powerful tool with an exploratory objective. It is often used to deepen knowledge in fields subject to study. Here are the main characteristics of qualitative research:

- It asks open-ended questions without presumptions about cause-and-effect relationships, resulting in subjective data related to motivations, attitudes, perceptions, etc.
- It is synonymous with richness and detail, providing reasons behind the numbers.

- It allows listening to the respondent and learning their language.
- It is useful for identifying problems as an initial step for subsequent study.

To conduct qualitative research effectively, several techniques are available: Focus Groups, Observations and interviews

### 1.1 Focus groups

The focus group approach is a qualitative method for gathering data on a specific topic through a structured and focused discussion with a small group of people. This method is particularly valuable as a complement to other data collection techniques, as it can provide rich and detailed information within a relatively short time frame (Gundumogula, 2020).

### 1.2 Observations

Observations involve recording detailed notes of what has been seen, heard, or encountered in the field. They can serve as an effective form of qualitative data in situations where individuals are unable or unwilling to express themselves in interviews, or when the researcher can directly observe the phenomenon of interest in its natural setting. This method can also complement interviewing by allowing the researcher to compare and contrast the codes and themes that emerge from the observations with the findings from the interviews (Poth & Searle, 2021).

### 1.3 Interviews

The interview format is the most common form of data collection in qualitative research (Jamshed, 2014). Interviews can be structured, unstructured, or semi-structured.,.

#### 1.3.1 Structured interviews

Structured interviews involve asking a predetermined set of questions to each participant in the same order. This format is similar to a questionnaire and ensures that all respondents are asked the same questions, allowing for easier comparison and analysis of the data. The advantages of structured interviews include consistency, ease of replication, and straightforward analysis. However, they may limit the depth of responses and restrict the ability to explore unexpected topics or responses in detail.

#### 1.3.2 Unstructured interviews

Unstructured interviews are more flexible and open-ended, allowing respondents to express themselves freely without being confined to specific themes or questions. This format encourages in-depth responses and can provide rich, detailed data. However, the lack of a standardized framework can lead to a deluge of data, making it challenging to manage and analyze. Additionally, the varying responses across participants can make it difficult to compare and contrast data, which can hinder the ability to draw meaningful conclusions.

#### 1.3.3 Semi-Structured Interviews (SSI)

SSI offer a balance between structure and flexibility. By using an interview guide with a set of pre-determined questions or topics, researchers can establish a coherent framework for analysis, while also allowing for spontaneous discussions and explorations of emerging themes. This format combines the depth and richness of unstructured interviews with the comparability and consistency of structured interviews, making it a popular choice in qualitative research. Semi-structured interviews enable researchers to gather detailed, nuanced data while maintaining a level of consistency across interviews, allowing for more meaningful comparisons and insights.

### 1.4 Semi-Structured Interviews applied to the maritime transportation company

Our research aimed to gain insights into the SS practices and difficulties faced by the shipowner. To accomplish this, we conducted SSI with stakeholders to gather information about their requirements, objectives, and challenges related to SS. We used a pre-established theme list to guide the interviews, which helped us identify the underlying needs and reasons for implementing a scheduling process. Additionally, the theme list ensured that crucial topics such as workforce management objectives, regulatory requirements, operational constraints, and best practices were consistently addressed.

To ensure that the study provides rich and relevant information related to the research question, it is essential to identify and select participants who have the necessary expertise, experience, and knowledge to provide valuable insights.

### 1.4.1 Sample selection

Sample selection is a pivotal step within the SSI process. It serves to identify participants who can offer insights into the research topic. This could include a diverse range of stakeholders. According to Table 2, Eight interviews were conducted, each lasting between 1 to 1.5 hours, with participants who had various levels of experience and expertise.

**Table 2**:Stakeholder’s interview

| Interviewer | Stakeholders | | | | | Duration (min) |
|---|---|---|---|---|---|---|
| | Senior management employee | Armament Director | Captain | Head mechanical-Engineer | Syndical agent | |
| **1** | x | | x | | | 78 |
| **2** | x | | | | | 65 |
| **3** | x | | | | | 73 |
| **4** | | x | x | | | 82 |
| **5** | | x | x | | | 76 |
| **6** | | | x | | x | 67 |
| **7** | | | | x | | 62 |
| **8** | | | | | x | 58 |

The SSI were conducted with intention to guide the respondents' answers around various themes that were predetermined by the interviewers in an interview guide.

### 1.4.2 Conducting and analyzing interviews using the interview guide.

Themes previously identified by the interviewers and documented in the interview guide were explored during the SSI.

***Topic 1: Investigating the Requirements for a New Decision Support Tool for Seafaring Staff Scheduling***

1) **What are the reasons behind the need for a new decision support tool?**

- All participants (100%) concurred that the addition of new vessels and categories (car ferries with maximum length 93.5 meters) to the fleet requires a new decision support tool that considers new constraints and objectives.

3) **How have unexpected situations been handled?**

- According to 88% of the interviewees, some dock personnel have the necessary qualifications to work on ships in various positions and can be assigned if needed.

***Topic 2: Perspectives and Challenges of the New Decision Support Tool for Seafaring Staff Scheduling***

1) **What is the assignment process that is used for assigning the staff member*?***

- 100% of the participants stated that the used DMP (Decision making Process) incorporates regulatory constraints such as rest hours, days off, and workload fairness.

2) **Are there any changes of objectives, constraints related to the assignment process?**

- Maintain the existing constraints and objectives in the decision-making process (100%).
- Maintain a stable team composition in order to maintain affinity between workers (65%).
- Implement a personnel rotation policy to enhance competencies and skills (58%).
- Ensure that workers with the necessary qualifications are assigned to the right type of vessel (100%).

3) **Are there any other relevant factors that should be considered in the scheduling process to ensure effective resource allocation?**

- Trying to satisfy employee preferences: a worker could choose coworkers in a team in which he is assigned (75%).

- Develop an online platform that enables employees to submit their preferences or request schedule permutations, with approval required from their supervisors (25%).

***Topic 3: In the new assignment process, it is essential to identify the key stakeholders involved and understand their respective roles and responsibilities.***

**1) Who are these stakeholders, and what are their contributions to the allocation process?**

- The shipowner determines the positions that each employee is eligible for, according to the visa maiming (100 %).
- The Director of Armament has an influence on the final decision regarding the ship allocation schedule (50%).

***Topic 4: Is there any further information or context that would be helpful to consider in the new assignment process?***

1) Create a DMP for the scheduling of Dock Workers (13%).

Once the results from the SSI are extracted, it's essential to make these results easier to understand and actionable, rather than trying to interpret them directly from the analysis. The results will be translated into objectives, creating a clear and concise framework that outlines what needs to be achieved.

### 1.4.3 Extracting relevant goals.

We are committed to preserve the same objectives as the current decision support system used in the maritime company, including regulatory constraints such as working hours and rest periods, as well as workload fairness. It is important to note that the future decision-making process will be constructed upon these goals and incorporate new ones that are derived from the latest SSI results.

*Pre-existing Goals Adopted in the Current Scheduling process*

- **Working Hours (G1):** limit the number of shifts an employee can work per week/day to ensure compliance with legal standards and to promote employee well-being.
- **Rest Day (G2):** ensure a rest day after a certain number of consecutive working days, generally after five or six days of work.
- **Rest Hours (G3):** ensure a minimum rest period between the end of one shift and the start of the next.
- **Workload Fairness (G4):** Distribute the workload fairly among employees to prevent equal salaries

*Required Goals for the future Scheduling process*

- **Affinity Between Workers (G5):** Avoid scheduling employees with conflicts on the same shift to minimize incompatibility and ensure affinity in a harmonious work environment.
- **Qualification (G6):** confirm that each employee has the necessary skills and qualifications before assigning them to a specific shift or task.
- **Employee Preferences (G7):** take into account individual employee preferences, a worker could choose coworkers in a team in which he is assigned
- **Rotation Between Vessels (G8): i**mplement a rotation system to ensure that employees work on different vessels over time to gain qualification.

When pursuing several goals concurrently, it is possible for conflicts to emerge between them. As a result, it is essential to meticulously examine the relationships between these objectives to identify any potential contradictions and determine the most effective way to manage them. The adapted and new objectives may align or conflict with each other. Such conflicts could lead to challenges in decision-making, making it crucial to establish strategies for resolving these issues effectively in the scheduling process.

### 1.5 Identifying contradiction between objectives

In this step, we elaborate on the **S**ystem **o**f **C**ontradictions (SoC) concept to identify potential conflicts that may arise between objectives and try to solve them using TRIZ method. It is essential to note that we are focusing on non-technical parameters, and therefore, we need to establish a connection between TRIZ parameters and the evaluation parameters of our system. Contradictions are identified with TRIZ expert according to the context of application and the shipowner requirement.

#### 1.5.1 Construction of the System of Contradiction (SoC)

Our proposed SoC addresses the conflicting goals shown in Figure 8, specifically G5, G6, and G8. Notably, each type of vessel requires specific skills, and shipowners aim to ensure that their staff members are qualified to work on various types of vessels (G6). One solution is to rotate staff members among different types of ships (G8). However, it's important to consider the potential drawbacks of frequent rotation, such as difficulties in maintaining a stable team and increase employee affinity with coworkers (G5).

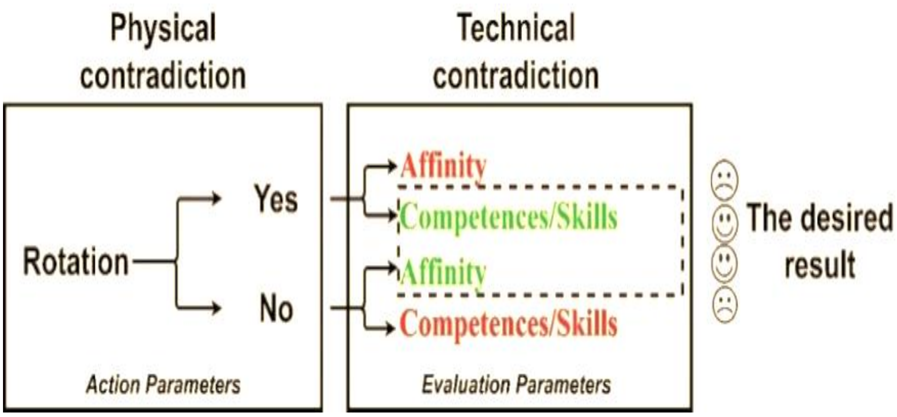


**Figure 8**:System of Contradictions (SoC)

As shown in the figure 8, employee rotation among different ships can be considered a controllable action parameter, as it is an action that can be adjusted to achieve specific objectives within our system. affinity and skills can be used as evaluation parameters in relation to rotation as an action parameter, as they are directly affected by employee rotations.

Once contradictions are identified, it's important to consider whether two objectives are truly in conflict and, if so, how to use the technical TRIZ matrix to address and solve a non-technical problem.

### 1.5.2 Fitting between TRIZ parameters and evaluation parameters of the system

In our initial study, we discovered contradictions between two distinct parameters. It is important to note that this type of contradictions is classified as "technical contradictions" rather than “physical contradictions” (need to have 2 different values for the same parameter). To analyze and address these contradictions, we employed the matrix of contradictions along with relevant guiding principles. Therefore, TRIZ parameters need be translated into non-technical terms that are relevant to the case study. Table 3 shows the adoption of TRIZ parameters to evaluations parameters of the system based on brainstorming with TRIZ experts available in our team research which is a leader team in France about TRIZ and inventive design.

**Table 3:**Fitting TRIZ parameters with Evaluations parameters of the system

| | Evaluation parameters of the system | TRIZ parameters |
|---|---|---|
| **(35) Adaptability or versatility** | Qualification: the ability to perform a task or job effectively and efficiently, using a combination of knowledge, experience, and abilities. | The extent to which a system/object positively responds to external changes. Also, a system that can be used in multiple ways for un-der a variety of circum-stances. |
| **(27) Reliability** | is the degree of mutual understanding, trust and collaboration among team members | A system’s ability to perform its intended functions in predictable ways and conditions. |

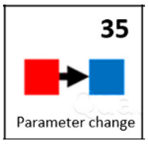
### 1.5.3 Inventive principles and solutions using TRIZ matrix

The main idea of the inventive principles solution in TRIZ is to identify and resolve contradictions between two or more parameters to a wide range of systems, including non-technical ones in order to generate inventive solutions (Table 4). According to the above-mentioned contradictions, the contradictions matrix proposes the following inventive principles as follow:

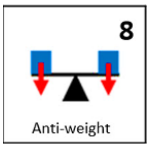
**Table 4**:Contradiction matrix of the objectives

| | **Improving features** | **Worsening features** | **Inventive principles** |
|---|---|---|---|
| **Scenario 1** | (27) Reliability | (35) Adaptability or versatility | 13, 35, 8, 24 |
| **Scenario 2** | (35) Adaptability or versatility | (27) Reliability | 35, 13, 8, 24 |

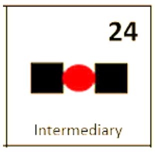
The inventive principles extracted from the TRIZ matrix are typically applied to technical contradictions involving tangible elements. Given that this specific problem has not been previously addressed in the literature, we have attempted to adapt these inventive technical solutions to non-technical contexts to better address the challenges of our problem:




*For the solution principle 35 Change of physical and chemical parameters:* in this case we propose to change the degree of flexibility of the system, it means the possibility of creating a pool of employees who are trained in multiple skills, allowing for more flexibility in assigning them to different boats and roles.




*For the solution principle 8 Anti-weight*: This involves introducing elements flexibility into the system to counteract the decrees rigidity and complexity. In our case, it could involve creating a person for workers that allowed to express their preferences for which team they would like be assigned.




*For the solution principle 24 Intermediary*: the concept of "intermediary" in TRIZ refers to creating an element that resolves a conflict or problem by finding a tiers object/element that complete the super-system and satisfies all parties involved. In our case, intermediary could be a member of a seafaring staff who is responsible for assigning employees to different boats. This worker could be a point of contact for employees who have preferences about their co-worker assignment and try to meet their needs while maintaining balance and stability for the team.

After conducting semi-structured interviews and studying contradictions, it is crucial to hold a multidisciplinary meeting to discuss and finalize the objectives to be included in the final model. This meeting allowed us to synthesize the insights gathered during the interviews and ensure that the final decisions are well-founded and accepted by all stakeholders.

### 1.6 Results discussion and multidisciplinary meeting

A multidisciplinary meeting with stakeholders assessed the challenges of integrating innovative solutions into the worker rotation scheduling model, we have concluded that such solutions would significantly increase the model's complexity by adding numerous variables and constraints.

Solutions obtained from TRIZ were discussed and several modifications were made with explanations, including:

*Change of physical and chemical parameters:* the first inventive principle of TRIZ which consist of managing rotation between vessels in order to maintain qualification, it suggests to create a pool of multi-skilled employees to enhance flexibility in assigning them to different vessels and roles. However, this approach introduces its own set of complications:

1) **Complex Training Needs:** developing multi-skilled employees demands considerable additional resources, time, cost and meticulous planning to ensure comprehensive training across various competencies.
2) **Dynamic Scheduling Complexity:** allocating specific time slots for training on different vessel types is challenging. These slots need to be scheduled well in advance to avoid disrupting regular vessel operations while meeting the required training hours.

- **Solution:** to address workforce challenges, the shipowner has to implement alternative strategies by scheduling dedicated training sessions outside of the primary scheduling process. These sessions occur during low-activity periods, such as winter, or during maintenance windows to minimize operational disruption. Consequently, worker rotation between vessels will be excluded from the primary scheduling to simplify operations and reduce complexity.

*Anti-weight*, *Intermediary:* the second and the third inventive principles have almost the same idea about creating a point of contact for employees who have preferences about their co-worker assignment and try to meet their needs in order to maintain affinity and stability between workers.

1) **Risk of bias:** Assigning an intermediary can introduce bias if the person favors certain employees or viewpoints, whether due to personal relationships or unconscious preferences. This can lead to unequal treatment and worsen conflicts.

- **Solution:** To foster a harmonious work environment, it is more crucial to minimize incompatibility among workers rather than maximize their affinity. Incompatibility, as identified in our multi-disciplinary meeting, refers to the friction arising from several factors such as:

  - *Work Styles:* One crew member might prefer a highly organized, structured approach, while another might be more adaptable and spontaneous. This can lead to disagreements about how tasks should be completed.
  - *Communication Preferences:* Different styles of communication (e.g., direct vs. indirect) can cause misunderstandings.
  - *Personal Values and Cultural Backgrounds:* Diverse cultural norms and personal values can influence how crew members interact with each other, affecting everything from conflict resolution to daily routines.

Differences in work styles, communication preferences, personal values, or cultural backgrounds among team members can lead to misunderstandings, conflicts, and Incompatibility. This is accomplished by strategically grouping workers with compatible work styles and personalities into the same teams, enabling them to work effectively with their preferred colleagues and enhancing collaboration and cohesion. The multidisciplinary meeting resulted in modifications to the scheduling goals, which will be considered in the final scheduling process.

## 2 Final goals included in scheduling process

Figure 9 illustrates the transition from the current scheduling process to the new approach, incorporating additional goals identified from recent SSI results and the multidisciplinary meeting

These results are integrated in this work into the model as either objectives or constraints. Objectives are included as criteria to be maximized, or minimized while constraints are incorporated as limitations or requirements that must be adhered to.

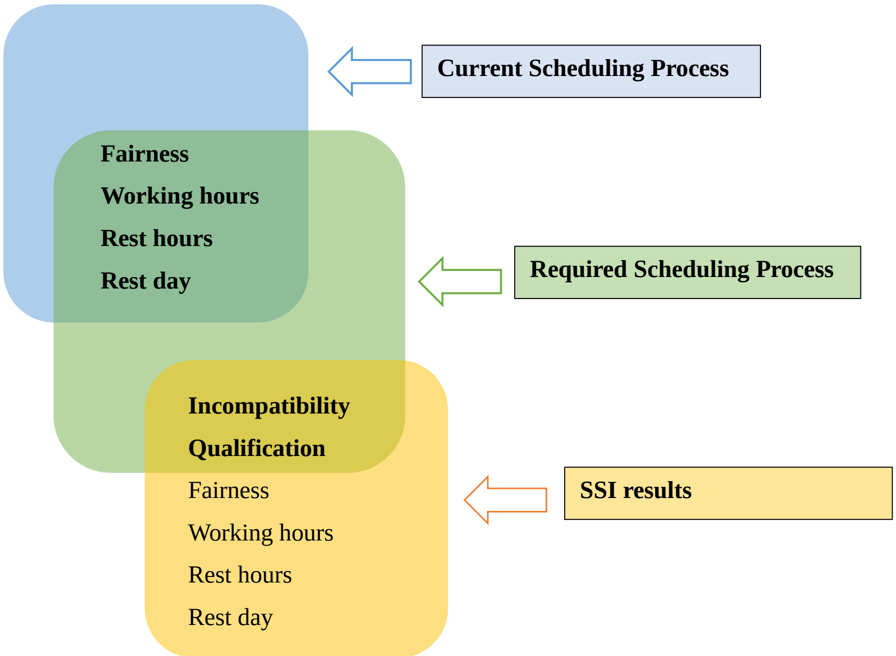



**Figure 9**:Evolving Scheduling Processes with New SSI Insights

### 2.1 Objectives

We have chosen workload fairness and incompatibility between Workers as objectives for our scheduling model because they are key performance indicators that we want to optimize. These objectives are not hard constraints that must be strictly adhered to, but rather goals that we aim to achieve to the greatest extent possible.

1) **Workload Fairness**

To promote fairness and equity among employees despite equal salaries, it's essential to distribute the workload evenly. In practice, a shift is a trip which can be categorized into reinforcement, regular, and special trips. While employees who undertake special trips may receive a risk premium, it's crucial to ensure that everyone receives an equal number of each category to guarantee fairness in the overall workload. By doing so, employees will be treated equally, regardless of the type of trip they're assigned, and the workload will be distributed fairly, preventing disparities and promoting a sense of equity among team members.

2) **Incompatibility Between Workers**

Avoid scheduling employees with low compatibility on the same shift to minimize incompatibility and promote a harmonious work environment and avoid risks and bad performance. Incompatibility is represented by scores that prioritize workers with lower levels of incompatibility.

### 2.2 Constraints

Certain goals are classified as hard constraints due to their non-negotiable nature. These constraints must be met to ensure compliance with strict legal regulations, such as the labor code (e.g., working hours, rest periods). Failure to adhere to these constraints can lead to severe consequences, including legal penalties, safety risks, and reputational damage. The constraints are categorized as follows:

1) **Working Hours**

Limit the number of shifts an employee can work per week/day to comply with legal standards and promote employee well-being. Note that in our case, shifts and their lengths are predefined, but a restriction on the number of shifts per day is imposed.

2) **Rest day**

Ensures a rest day after a certain number of consecutive working days, five days in our case.

3) **Rest hours**

Ensure a minimum rest period between the end of one shift and the start of the next, as fixed by the shipowner in adherence to regulatory constraints.

4) **Qualifications**

Confirm that each employee has the necessary skills and qualifications before assigning them to a specific shift or task. In our case, qualifications are assumed to be known before scheduling workers and represented as an input in a binary matrix, indicating whether a worker is qualified for a particular shift. Note that qualifications are not related to shift categories but to the type of vessel associated with the shift, which is not included in our work. Therefore, before scheduling, the ship owner should verify and note if the worker is qualified according to the visa manning

## Conclusion

Our study employed a four-step process to address the need for an efficient assignment process for a Tunisian shipowner. First, we conducted semi-structured interviews to identify the key objectives that needed to be achieved. Second, we examined these objectives for potential contradictions using the Theory of Inventive Problem Solving (TRIZ) methodology. By constructing a System of Contradictions (SoC) and aligning TRIZ parameters with evaluation parameters, we were able to systematically address and resolve inherent conflicts by proposing practical solutions. However, some solutions proved complex to implement immediately, so we made key decisions, including removing rotation from the employee qualification process and conducting the qualification process outside the scheduling process. Additionally, we elaborated on incompatibility issues to satisfy preferences and affinities simultaneously.

The final results, representing the research problem statement, were presented as constraints and objectives in a model to be optimized.

As a limitation, the future scheduling process does not include rotation as a constraint, and the elaborate solutions found by TRIZ are considered as perspectives for future research.

Once the research problem has been identified, we need to position ourselves in relation to previous works to see how such problems have been solved in the literature in the next chapter.

# Chapter 3. Exploring Staff Scheduling Problems: A Scoping Review Framework

## Introduction

In this chapter, we conduct an in-depth analysis of the existing research on staff scheduling to gain a comprehensive understanding of the current state of knowledge in this maritime area. The limited number of papers in the maritime domain prompted us to extend our exploration to other domains through a Scoping Review (ScR) framework. This helped us understanding how the constraints and requirements of staff scheduling can be effectively integrated into other domains, allowing us to identify best practices and innovative approaches that can be applied to our problem.

## 1 Review types

In recent years, the SS process has undergone significant changes due to the increasing complexity of organizational processes. Companies now need to consider a broader range of factors in SS, including employee skills, satisfaction, preferences, stress, fatigue, and other relevant employee-related factors. Therefore, considering these multiple factors makes it challenging to make evidence-based decisions regarding this issue. Accordingly, conducting literature reviews becomes crucial as they can shed light on the common challenges encountered in SS. various typologies of literature reviews are serve different purposes depending on the scope, methodology, and objectives of the review. According to Grant and Booth, (2009), there are 14 distinct types of literature reviews. However, classical literature reviews (or narrative review), Systematic Reviews and ScR, are the most common and crucial to uncover common challenges. Choosing the right review type must align with the specific research objectives for a comprehensive and relevant exploration of the field.

Literature reviews provide an examination of recent or current literature, covering a wide range of subjects and levels of completeness. However, they lack a systematic method and are susceptible to bias due to their subjective summaries of findings (Grant and Booth., 2009). Systematic reviews are, therefore, emerged to fill this gap while robustly addressing a well-defined question using a rigorous and transparent methodology to identify, evaluate, and synthesize all relevant studies on a particular topic. This helps to provide a completer and more unbiased summary of the evidence than traditional narrative reviews. While they offer a more comprehensive and unbiased summary, they depend on the quality of primary studies and may face challenges when the topic hasn't been thoroughly reviewed before. However, they might need a methodologically rigorous and structured preliminary scoping activity to inform how future Systematic reviews are done. Therefore, ScRs are a type of literature review that are conducted when the body of literature on a particular topic has not been comprehensively reviewed before, or when the literature is complex or heterogeneous and not suitable for a more precise Systematic review. According to Peters et al. (2015), ScR is a useful tool for mapping the existing literature, identifying gaps in the research, and determining the value of conducting a more in-depth systematic review. They can be particularly helpful for researchers who are just starting to explore a new topic, as they provide a broad overview of the existing research and can help to identify key themes and trends.

Each type of review serves a distinct purpose, with systematic reviews providing depth and rigor, narrative reviews offering comprehensive summaries, and ScRs mapping out research territory.

For our work, we focus on ScRs due to their suitability in mapping out broad topics and uncovering research gaps, with further details provided in the following sections.

## 2 Scoping Review: definition and generalities

As their name suggests, scoping reviews are particularly suited for assessing the breadth and scope of literature on a specific topic. They provide a clear indication of the volume of available literature and studies, offering either a broad or detailed overview of the subject matter. Scoping reviews are especially valuable when dealing with emerging evidence, where it is not yet clear which more specific questions could be effectively aaddressed by a systematic review. They can also highlight the types of evidence that contribute to practice in the field and the methodologies used in the research (Munn et al., 2018).

The primary goal of conducting a scoping review is to identify and map the available evidence. Arksey and O'Malley (2005), in their seminal paper, outlined four specific reasons for conducting scoping reviews. This framework was later refined and expanded by (Levac et al., 2010), who pointed out that, at the time, there was no universally accepted definition or purpose for scoping reviews. In 2015, a methodological working group from the Joanna Briggs Institute (JBI) provided formal guidance for conducting scoping reviews. However, the specific purposes and indications for conducting scoping reviews had not been thoroughly explored until now. Building on previous work, we suggest the following purposes for conducting a scoping review:

Since we are working in the maritime field, a primary research effort was undertaken to address our research problem. We conducted a comprehensive investigation of previous studies on this understudied topic and identified only few studies within the maritime realm. However, these studies typically do not integrate all the necessary constraints into a single planning model. Notably, none of these studies consider the concept of incompatibility at all. The ambiguity surrounding this issue and the lack of comprehensive studies in the literature necessary to meet our shipowner's challenges highlight the need for a ScR. By expanding our search to include other domains, we aim not only to see how such problems have been resolved but also to provide future researchers with a comprehensive map of the existing literature using a structured methodology.

## 3 Scoping Review Framework

Our study methodology follows the five-stage framework outlined by Arksey et al. (2005), which includes:

1) ***Identifying the Research Question:*** we define our research question, which guided our search for relevant literature.
2) ***Identifying Relevant Studies:*** we perform an extensive search of electronic databases to find studies that addressed our research question, ensuring that we captured all relevant studies as comprehensively as possible.
3) ***Study Selection:*** we select studies that met the following inclusion criteria and we excluded studies that did not meet these criteria, as well as those that were not relevant to our research question.

4) ***Charting the Data:*** we extract relevant data from each selected study, we use a standardized data extraction form to ensure consistency and accuracy.
5) ***Collating, Summarizing, and Reporting the Results:*** we collate and summarize the extracted data to identify patterns, themes, and gaps in the literature. We report our findings in a narrative format, highlighting the key findings and implications for future research.

### 3.1 Identification of the research question

A well-defined research question is critical for a successful research study, as it keeps the study relevant by specifying the topic or problem under investigation. Careful crafting of the question is necessary for clarity, guidance, and effective communication of the study's goals and results. Therefore, using the PICO components (Population, Intervention, Comparison, and Outcome) framework from the "JBI Manual for Evidence Synthesis" can be helpful, (Table 5).

**Table 5**:PICO research question

| **P: Population** | **I: Intervention** | **C: Comparison** | **O: Outcome** |
|---|---|---|---|
| Workers with diverse skills, who performs a job. | Staff scheduling optimization methods and approaches | Real-life constraints in the maritime domain compared to other domains | Optimized scheduling that balances multiple constraints and objectives |

Using the beforementioned framework, we elaborate our question as shown on the Table 5: "*What research has been conducted on optimization methods and approaches for assigning workers with diverse skills to positions or shifts while balancing multiple constraints and objectives, and how applicable are they across different domains compared to maritime field?*".

To effectively address the research question, it is crucial to identify relevant studies by conducting a comprehensive search across various sources to gather literature that is pertinent to the research topic.

### 3.2 Searching relevant studies

The primary objective of conducting an ScR is to systematically identify and summarize the available primary studies and reviews that are relevant to the research question of interest. In order to achieve this, we employed a comprehensive search strategy that involved searching multiple sources, including electronic databases, hand-searching key journals, and reviewing the reference lists of relevant studies. This approach allowed us to thoroughly and efficiently identify a wide range of relevant literature, ensuring that our ScR was as comprehensive and inclusive as possible.

***Electronic data basis:*** The search was running, at first, using two databases (Scopus, and Web of Science) listed by discipline in Table 6. The key words were extracted after broad research of required topic and every word was verified. We used Boolean terms, such as “AND”, “OR”, and “AND NOT” to separate keywords.

**Table 6:**Pilot database search results

| Nº | | Keywords | Relevant items | Data-Base | Row of search |
|---|---|---|---|---|---|
| **# 1** | Date of search 25/12/2022 | Staff | ("human resource" **OR** "employee" **OR** "staff" OR "crew" **OR** "team" **OR** "personnel" **OR** "operator" **OR** "manpower" **OR** "workforce" **OR** "resource") | Scopus and web of science | Search within article title |
| | | **AND** | | | |
| **# 2** | | Scheduling | ("Timetable" **OR** "pairing" **OR** "allocation" **OR** "assignment" **OR** "time-table" **OR** "schedul*" **OR** "roster*" **OR** "planning") | | |
| | | **AND** | | | |
| **# 3** | | ("shift" **OR** "optimaz*" **OR** " modelling" **OR** "skill*" **OR** "qualifi*" **OR** "competenc*" **OR** "Expertise" **OR** "senior*" ) | | | Search within article title, abstract and keywords |
| | | **AND NOT** | | | |
| **#4** | | ("stochastic*" **OR** "real" **OR** "uncertain*" **OR** "reschedul*" **OR** "dynamic*") | | | Search within article title and keywords |
| **(# 1 AND # 2 AND # 3 AND NOT #4).** | | | | | |

The title must include the two first key words or synonyms (# 1 AND # 2) defining the core issue, otherwise, the search going to take other deviation.  Since the SS problem is a very broad term, some key words have been added to the abstract to avoid the number of unmanageable papers without influencing its direction (# 1 AND # 2 AND # 3). Our research concerning only deterministic research, therefore ("stochastic*" OR "uncertain*" OR "reschedul*" OR "dynamic*") should not be included (# 1 AND # 2 AND # 3 AND NOT #4).

Since the same search concept used on Scopus and Web of Science couldn't be applied to other databases, we resort to manually searching key journals to find relevant studies.

***Hand-searching of key journals:*** It is important that key journals are hand-searched to identify articles that have been missed in database, and to make research on data bases in which we cannot put too long searched chain. Four principal data bases are used in this discipline: Science Direct, Taylor and Francis, Emerald Insight, Google scholar.

***References list:*** after initial database searches, we cross-checked bibliographies from relevant papers for missed articles. This process reveals additional references until saturation is reached, and articles begin to repeat.

## 3.3 Study selection

The study selection process involved a rigorous evaluation of each potential study to ensure that it effectively addressed the main research question (Peters et al., 2017). To facilitate this process, we established specific inclusion and exclusion criteria

### 3.3.1 Inclusion and exclusion criteria

Once keywords are identified, it is essential to establish a preliminary criterion of inclusion to manage the number of papers and ensure that only relevant and high-quality studies are included in the review.

Some common criteria of inclusion are outlined in Table 7.

**Table 7**:Inclusion and exclusion criteria

| | |
|---|---|
| **1** | Articles and conference papers are included |
| **2** | Books, book chapters and Lecture Notes are removed |
| **3** | Only English papers are selected |
| **4** | Only period between 2011 -2023 is taken |

1. *Inclusion of Articles and Conference Papers*: Articles and conference papers were considered for inclusion in our study due to their relevance and focus on specific research topics.
2. *Exclusion of Books, Book Chapters, and Lecture Notes:* Books, book chapters, and lecture notes were excluded from our study. This decision was based on the challenges associated with accessing comprehensive information from these sources and the difficulty in extracting relevant data for analysis.
3. *Selection of Only English Papers*: Only English papers were selected for inclusion in our study. This decision was made due to the limited relevance and difficulty in understanding non-English articles, even after translation.
4. *Focus on Publications from 2011 Onwards:* We focused on publications from 2011 onwards to ensure that we captured the latest findings, theories, and methodologies in our field of study. This approach is particularly important in rapidly evolving fields such as technology, medical research, and certain sciences.

These criteria were consistently applied throughout the study selection process to ensure that only the most relevant and up-to-date literature was included in our analysis. By adhering to these criteria, we were able to streamline the study selection process and ensure the validity and reliability of our findings.

Even if a preliminary number of papers has been identified through previous steps, including searching relevant studies with keywords on databases and filtering according to primary inclusion and exclusion criteria, non-relevant papers may still occur. This can happen for various reasons (out of scoop, no access, review paper…). This process is detailed on PRISMA flow diagram.

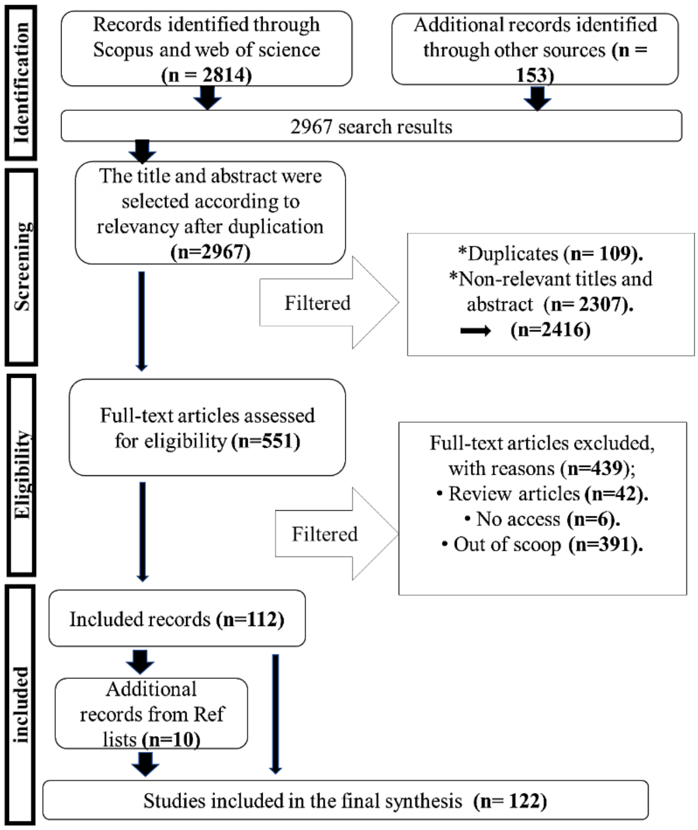



**Figure 10:**PRISMA flow Diagram

### 3.3.2 PRISMA diagram

In this section of the review, the outcomes of the ScR process are outlined through the PRISMA diagram, which illustrates how the initial pool of studies previously identified is screened, assessed for eligibility, and included in the final analysis (Figure 10).

As seen in Figure 10, several steps were involved in identifying relevant literature using the PRISMA diagram which provide a clear representation of the study selection and how the researcher progressed from the initial search to the final selection of relevant studies. The subsequent paragraph offers a more comprehensive about each step of the process.

1. The identification step involved searching electronic databases and hand-searching journals, resulting in the initial identification of 2,967 studies. Specifically, 2,814 studies were identified from Scopus and Web of Science, and 153 studies were identified from other sources of hand-searching journals.
2. After identifying papers through a search of relevant databases and application of primary inclusion and exclusion criteria, the first step is to screen the titles and

abstracts of these papers. This initial screening helps to reduce the number of papers that need to be retrieved and reviewed in detail, as papers may include one or several main keywords but may not necessarily represent the same scope. During the screening process, a total of 2,307 irrelevant articles were identified and excluded. Additionally, 109 duplicates were identified and removed, resulting in a total of 551 articles that were exported to Mendeley software for full text review.

3. The eligibility stage is an important step in the review process, as it involves a more detailed assessment of the papers to determine their relevance and quality. This stage typically involves a full-text review of the papers, as the title and abstract may not always provide sufficient information to determine whether the paper is within the scope of the research. Out of the 551 articles that were subjected to a comprehensive full-text review 439 were excluded for various reasons. Specifically, 391 articles were out of scope, 6 articles were not accessible, and 42 articles were review papers. As a result, a total of 112 relevant papers were included in the review.
4. After identifying final relevant studies, a review of their reference lists was conducted to discover any potentially overlooked articles suitable for inclusion. An additional 10 relevant papers were identified from the bibliographic references, resulting in a total of 122 articles.

After identifying 122 relevant articles, we implemented a data charting process to provide a comprehensive overview of the results. We chose to emphasize charting data across various fields because these factors are crucial for understanding the context and gaining valuable insights into the literature landscape and its implications for staff scheduling practices. The study selection and data charting were performed independently by two reviewers using standardized forms, with any disagreements resolved through discussion.

### 3.4 Charting the data

SS complexities affect multiple sectors like healthcare, manufacturing, transportation, and services (Figure 11). The transportation sector, representing 29% of these challenges. as reported by Čižiuniene, *et al.* (2016), there are 6,714 companies in Lithuania employing a total of 81,192 employees. Healthcare system of any country is undoubtedly one of the most crucial components (Bhattacharjee & Ray, 2014). Today, hospitals allocate over 50% of variable costs to personnel payroll (Nobil, *et al*. 2022). This importance is particularly pronounced in the case of Japan, where the aging population (27.7% aged 65+)[2] increases demand for nursing care increases demand for nursing care increases demand for nursing care (22%).

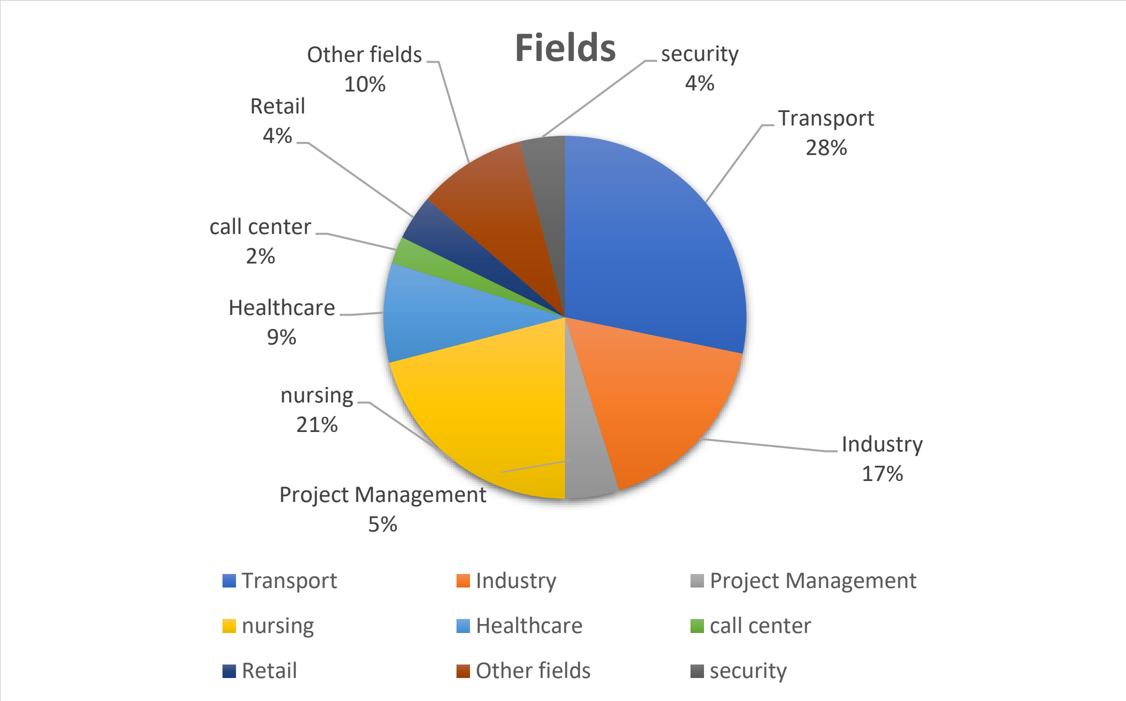



**Figure 11**:Staff scheduling among several fields

Alongside nurse scheduling, physician planning has gained recent focus (9%). Notably, physician scheduling differs from nurses due to individual contractual duties for physicians whereas nurses operate under collective agreements (Bruni and Detti, 2014).

Additionally, nurse schedules must balance both preference satisfaction and cost considerations, whereas physician scheduling primarily focuses on physician satisfaction. Efficient personnel management is a significant challenge in healthcare, as well as in industry, where workforce management is crucial for productivity, representing 17% among other sectors. This complex problem extends to activities like maintenance (Nearchou and Lagodimos, 2013), and other activities in the industrial domain. Effective SS is crucial for organizational success in industrial operations, including project management, which engages around 16 million professionals globally representing 5%

[2] (Statistics Bureau & Ministry of Internal Affairs and Communications, 2018)

compared to other sectors (Huemann, et al. 2004). In project management, human resources play a vital role in ensuring project quality, success, and customer satisfaction.

Staffing strategies play a key role in managerial functions, notably in growing service sectors like call centers, where labor costs can reach 60%–80% (Xu & Wang, 2021). However, existing studies largely concentrate on demand forecasting and stochastic aspects, which don't align with our study objectives. Consequently, call center-related studies make up only 2% of our total focus.

In large-scale retail, staff costs typically range from 8 to 20% of sales, and approximately 30% of personnel are directly involved in serving customers at the cash registers (Talarico & Maya Duque, 2015). Despite its importance (4%), attention is less directed toward this sector compared to transportation and healthcare.

Many jobs, like air traffic control, security, and assembly line work, require constant focus to prevent dangerous situations. scheduling security staff is crucial for safety, as they must be in peak physical, mental, and emotional condition to safeguard property and people (4%).

Other fields like bank, postal service and other service agency are grouped into same category as it exists but not with the same frequency as other fields and present 10% of the total works.

Once the data has been gathered and charted from various studies spanning multiple sectors, it's essential to summarize and report the information to provide a comprehensive and interpretive analysis of the literature.

### 3.5 Collating, summarizing and reporting the results

Our objective is to provide Our own classification of the literature on staff scheduling problems that reflects our vision for the field. This classification is presented in a summary table (Appendix A) and provides a brief overview of the gathered studies, highlighting two primary aspects: Decisional and Methodological. While the table offers a concise summary of the studies, we will provide a more detailed analysis of it in the upcoming sections.

### 3.5.1 Decisional aspects

In this section, we focus on the characteristics of the problem, namely the assignment decision, additional assignment and planning horizon (Figure 12).

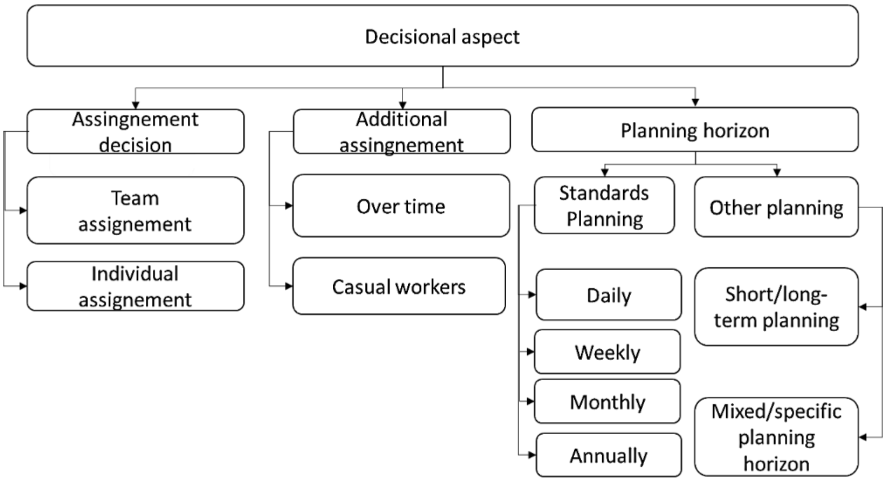



**Figure 12:**Decisional Aspects

*Assignment decision:* Some problems require the scheduling of team instead of considering each employee on their own. And this type of decision is commonly used in the transportation area. In this field we mention Di Francesco *et al.*, (2016), Ammar, *et al.*, (2014) who have examined the activities carried out by teams, with each member responsible for a task or role.

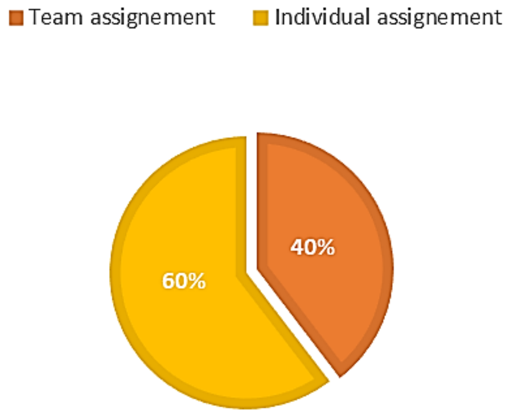



**Figure 13**:Assignment decision

An example of airline crew scheduling can be found in Kasirzadeh, *et al.*, (2015), Armas *et al.*, (2016), Hadianti *et al.*, (2014) and Chutima and Arayikanon, (2020) works. In public transport, Kang, *et al.*, (2019) have made a study deal with a group of drivers scheduling problem, by considering practical mealtime windows for a single bus route.

In bus crew scheduling, most studies focus on individual task assignments since bus drivers typically work alone. This individual approach is also common in sectors like healthcare, where the aim is to improve job satisfaction and address preferences (Mohammadian et al., 2019).

As Figure 13 illustrates, individual assignments are more commonly used (60%) rather than team assignment (40%) due to the advantages of efficiency, and suitability for tasks that require specialized skills making it easier to evaluate individual performance. However, the choice between individual and team assignments should depend on the task's nature and goals.

*Additional assignment*:  The scheduling problem must meet manpower requirement, which is defined as the number of workers required to perform task(s). When the regular workforce cannot meet the workload, scheduling casual workers (flexible) or assigning overtime becomes necessary to prevent understaffing (Figure 14). Some organizations prefer overtime over hiring temporary workers for cost savings, skill availability, and operational continuity, while complying with labor laws (19%). Healthcare Organizations utilize overtime due to intense pressures, when nurses take on extra shifts beyond the minimum required, this time is classified as overtime. El Adoly, *et al.*,(2018), proposed a model, where minimizing the overtime cost of nurses, is the main objective of the problem.

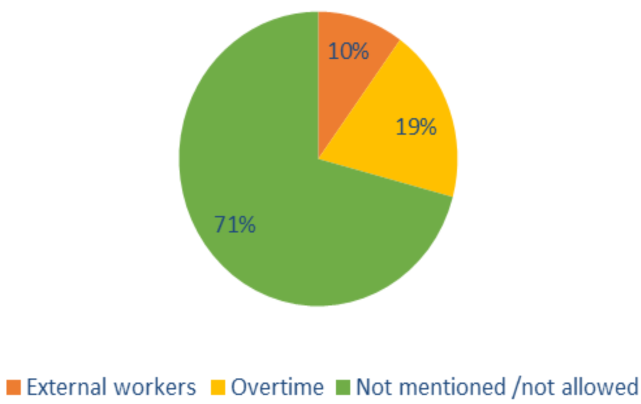



**Figure 14**:Additional assignment

According to some authors (10%), overtime costs are higher than other alternatives, therefore, external workers can be employed when internal ones are in short supply.

Some organizations like maritime terminals for example cannot pay penalties for delays caused on ships, it is essential to detect and correct the problem of an understaffing by adding external workers to provide additional manpower (Di Francesco et al., 2016).

It's important to note that in the majority of articles (71%), these options aren't mentioned, either because they're not considered or because the authors don't allow them.

*Planning horizon:* Planning is a systematic and formal process that organizations use to accomplish specific objectives within a designated timeframe. Plans can be developed for varying durations, ranging from short-term to long-term, and can be tailored to meet the unique requirements of the organization. The planning process involves specifying goals, identifying necessary resources, and outlining the steps required to achieve the desired outcome (Figure 15).

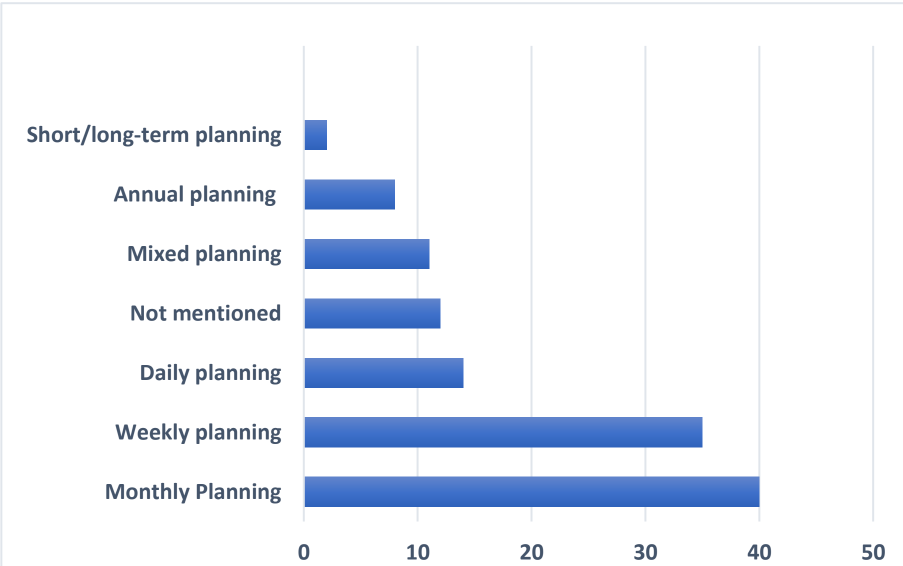



**Figure 15**:Planning Horizon

It's crucial to mention that the planning horizon is determined by various factors, including decision level (strategic, tactical, or operational), the product or service's lifecycle, and the duration of tasks to be accomplished.

Crafting new schedules daily is under the concept of a short schedule horizon. The primary advantage of this practice lies in its ability to consistently refine schedules to align closely with the changing workload forecasts day by day. Valouxis *et al.*, (2012), created a two-phase strategy: initially deciding the workload for each nurse and day of the week, followed by assigning specific daily shifts in the second phase. Despite effective work shift systems, retailers struggle with unpredictable staffing demands due to seasonality or absenteeism. Adapting daily staffing is crucial to manage surplus or shortage situations (Alvarez et al., 2020). Daily planning is frequently used also on bus drivers scheduling problem where the objective is To determine the minimum number of staff members needed to cover all daily tasks (Öztop et al., 2017). Kang, *et al.*, (2019) addressed a daily crew rostering challenge, assuming prior knowledge of crew availability, days-off schedules, and crew shift assignments for the working week.

Alongside daily planning, extending the schedule horizon to a weekly basis offers a broader overview, potentially providing greater stability to workers but typically requiring more forecasting and planning. However, Weekly schedules are less adaptable to daily fluctuations in demand or unforeseen events. Additionally, this horizon is commonly used in industry when Soriano *et al.*, (2020) have proposed a model that incorporates all employee weekly schedules, break times, work conditions, and preferences while adhering to predefined constraints.

Having a monthly work schedule is crucial for maintaining adequate shift coverage and ensuring that employees can effectively manage their time around other commitments. In the airline industry, weekly horizons are often used for flight schedules that are set in advance. During this timeframe, crew members are assigned to weekly shifts, which consist of seven daily shifts. These daily shifts must be feasible, as defined by Talarico and Maya Duque, (2015), and adhere to legal and contractual requirements for crew members.

When it comes to calculating the total working hours in a weekly shift, it involves summing up the daily workload for each of the daily shifts within the weekly shift. According to Kasirzadeh, et al. (2015), a monthly time horizon is considered the most practical, taking into account vacation periods and fluctuations in flight schedules. Other organizations create schedules and leave them in place for a while between 3 or 6 months but some as long as a year or more. The extended schedule horizon minimizes staff disruption and reduces the workload for scheduling specialists. However, it may impact schedule efficiency when unexpected situations arise in real-life practice. Akyurt *et al.*, (2021) made a study that primarily aims to minimize the vital number of pilot employments while planning, training of pilots between fleets and annual leaves. The study by, Rocha, et al.,(2014) tackled SS in a glass industry operating 24/7, 365 days a year. Using an annual planning approach, it considered variations in demand between winter and summer months due to holidays.

There is no specific timeframe for long/short-term planning, it's mean that it's not limited to a particular time and can be applied to various horizons depending organization's need. Long-term planning is commonly used in airline companies where timetable has much longer planned horizon, (planning at least 13/14 weeks ahead), than other transportation settings and managers need to arrange travel in advance for the crew (Leggate et al., 2018) (Lorenzo-Espejo et al., 2021). Meanwhile, short-term planning, encompassing the establishment of immediate future, is employed when incorporating flexible workers and covers a planning horizon ranging from one to several days (Di Francesco et al., 2016).

Organizations sometimes choose to define their own planning horizons to meet their specific needs. This tailored approach, seen in industries like aviation, public transit, and maritime shipping, addresses specific challenges. For instance, Ladier et al., (2014) addressed the workforce planning problem into two stages: weekly timetabling and daily rostering. Integrating mixed schedules, such as monthly and daily, is demonstrated in aviation (Shiau et al., 2020). Authors like Baeklund (2014) and Louly (2013) employ different time slots and periods, such as two-week or six-week cycles, to optimize planning efficiency. Lorenzo-Espejo et al., (2021) explored planning horizons of one, two, and three months.

### 3.5.2 Methodological aspects

In this section, we discuss the approaches, which include modelling techniques, algorithms, and solvers, used to address the main problems along with the constraints involved (Figure 16).

***Used approach***

Figure 17 illustrates the SS displays a variety of research methodologies that combine a particular analytical approach with a solution or assessment technique.

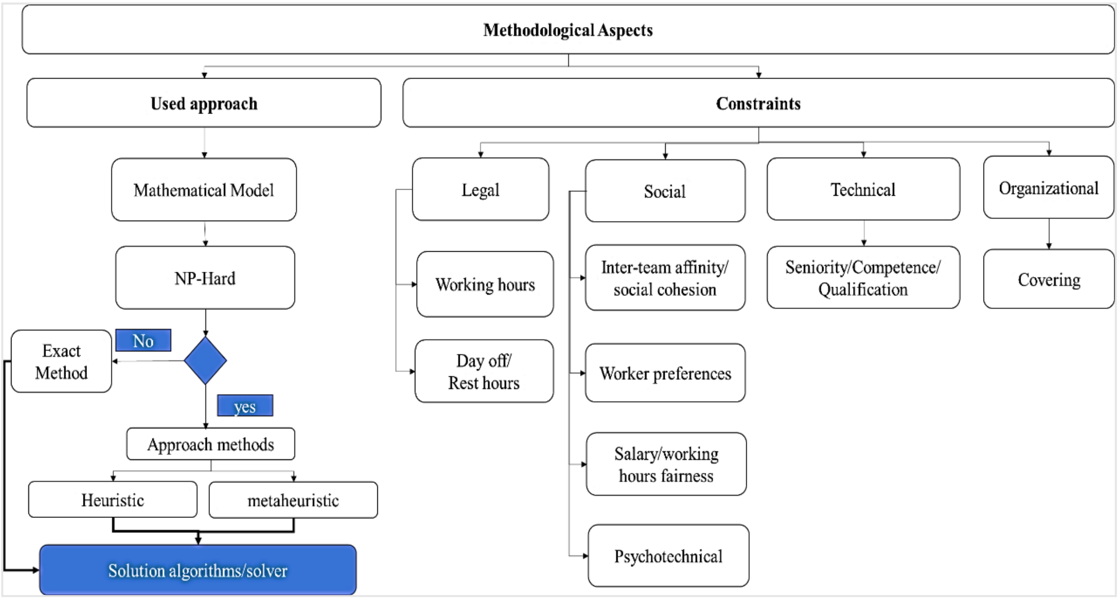



**Figure 16:**Methodological aspects

Lot of studies have used exact methods to find an optimal solution to a given problem, but they run the risk of not returning any feasible solution for a long time especially for difficult NP-ones. Therefore, approach methods are used to fill this gap. Otherwise, the creation of a mathematical model is a crucial step in the optimization process because it facilitates understanding, structuring and efficient resolution of complex problems, ensuring that tools and algorithms are applied appropriately to obtain high-quality solutions. Consequently, the choice of model depends on the problem's complexity and characteristics.

Linear Programming (LP) is well-suited for problems characterized by linear relationships, as emphasized by Strandmark *et al*, (2020), Sumathy and Amirthalingam (2021), Park and Ko ( 2022). As mentioned by Baidya *et al.*, (2017), the Transportation Problem is widely recognized as one of the most well-known linear programming problems, as highlighted in Khmeleva *et al.*, (2014), Rama *et al.*, (2017) works. Nevertheless, nonlinear optimization handles more complex, nonlinear relationships Othman *et al.*, (2012a). When dealing with discrete decision variables, Integer Programming (IP) model (Guo et al., 2014), (Cezik & L'Ecuyer, 2008), and Mixed-Integer Programming (MIP) model (Leggate et al., 2018) are employed. Furthermore, there exist problems that combine linearity with integer or non-integer variables, such as Non-linear Integer Programming (NLIP), where integer variables interact with a nonlinear objective function or constraints (Amindoust et al., 2021), (Hadianti et al., 2014), (S. H. Huang et al., 2011). Similarly, Linear Integer Programming (LIP) combines discrete decision variables with linear relationships (Constantino et al., 2017). For even more complex scenarios, Mixed-Integer Linear Programming (MILP) models, such as those proposed by (Moosavi et al., 2022), (Nobil, et al., 2022) can be used, which incorporate both integer and continuous variables along with linear on Non-Linear relationships (NLMIP), (Peng-Sheng & Yi-Chih, 2021), (R Chen et al., 2017). In cases where a combination of different optimization techniques is required to tackle multifaceted problems, hybrid programming Models, may be employed to achieve better results (Rahimian et al., 2017). Additionally, Goal Programming is employed when there are multiple conflicting objectives that need to be simultaneously optimized (Mohammadian et al., 2019), (Rerkjirattikal et al., 2020).

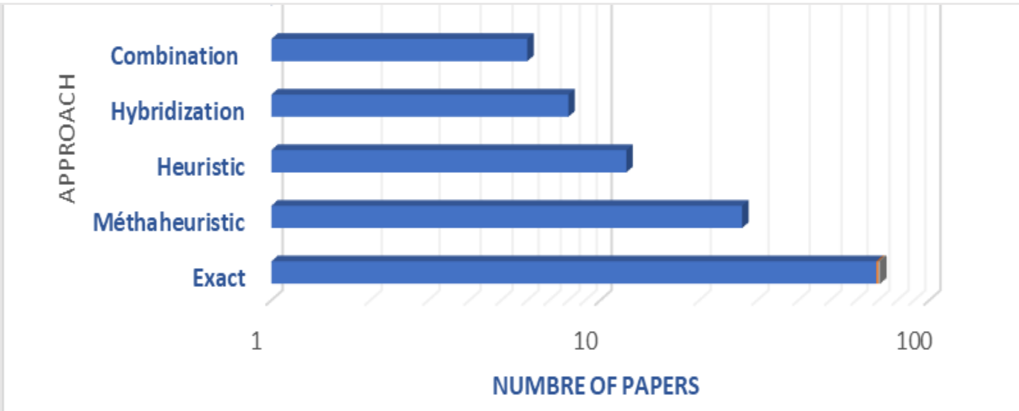



**Figure 17**:Used Approach

When an author chooses to validate one or several of the aforementioned models with algorithm(s) and solver(s) consecutively, it indicates the use of an exact method to find a solution. The solver like CPLEX, GPLK, GUROBI, GAMS... acts as a powerful computational tool that works in the background, employing algorithms like branch and bound (Nishi et al., 2014) (El Adoly et al., 2018) or brunch and cut (Mobasher et al., 2011) to navigate the mathematical model and find the most favourable outcome. for solving large-scale integer programming problems, some authors such as Lin & Tsai, (2019) who have introduced a branch-and-price-and-cut algorithm. This method employs a two-level decomposition approach, dividing the problem into an upper-level master problem and a lower-level subproblem, iteratively solving subproblems and adding cuts to the master problem.

In order to meet reality, authors are trying to add a number of constraints based on their own particular needs. Many of these variations tend to create linear/mixed integer programs with a huge number of variables. Researchers tried to over-come these large-scale formulations even by decomposition techniques (as shown previously) or/and heuristic algorithms. Kasirzadeh *et al.*, (2015) applied two heuristic strategies: column fixing and heuristic inter-task fixing, Armas *et al.*, (2016) proposed a multi-start randomized heuristic for solving real-life crew rostering problems in airlines. Radar Cross Section (RCS) are heuristics based on algorithms column generation algorithm that is used for solving large real-world test instances with thousands of trips (Jütte, *et al.*, 2017). The decomposition leads to a more efficient algorithm by breaking the problem into smaller, manageable subproblems, reducing computation time. However, using heuristics, comes with drawbacks as they may not guarantee optimal solutions or reduced search space (Van Den Bergh et al., 2013).

Metaheuristics form an important class of methods are used to solve problems that cannot be solved by traditional heuristics or exact solution approaches. Metaheuristics are typically hybrids of heuristic algorithms, and combine different base methods under one framework. For Boschetti and Maniezzo (2022) Metaheuristics are heuristic algorithms based on mathematical tools such as the ones provided by mathematical programming. These algorithms demonstrate a broad structural adaptability, enabling their application across diverse problem sets with minimal modifications to their foundational structure. In this context, Guo et al., (2014) have used an efficient Genetic Algorithm (GA) is proposed based on the IP formulation due to the computational complexity of the integrated scheduling problem. This method was adapted also by Ballesteros-Pérez *et al.*, (2019), Costa et al., (2013), Khmeleva et al., (2014). When author need to solve NP-hard multi-objective optimization problem The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is designed to tackle this issue (R Chen et al., 2017). Abdoul Soukour et al.,(2013) have proposed a metaheuristic based on a Memetic Algorithm (MA) which merged an Evolutionary Algorithm (EA) and Local Search (LS) techniques in order to model and solve a SS problem in airport security service. Lin *et al.*, (2015) also have adapted this algorithm. Today, the population-based meta-heuristics are widely used for the optimization of NP-hard problems, among these meta-heuristics, Tabu-Search (TS) algorithm that has been proposed by Chen and Niu (2012) to minimize the total idle time of crew for a circle bus line while considering the mainly various working rules and duties. Boyer, et al., (2018) developed Variable Neighborhood Search (VNS) metaheuristic where the objective is to minimize operational costs, considering vehicle usage and driver wages, while meeting operational constraints and labor regulations. Other uses of this algorithm is in nurse department, where the purpose is to assign each month shifts to the nursing staff subject to various requirements (Della Croce and Salassa, 2012). Another example of modern meta-heuristics is Ant Colony Optimization (ACO) introduced by Achmad et al., (2021). It's used to improve nurse rostering using semi-random initialization to prevent hard constraint violations and ACO to minimize soft constraint violations. In 2011, Huang, et al.,(2011) used ACO on Taiwan Railways data, finding that allowing "dead-heading" improved solutions with less drivers and idle time. Modern metaheuristic algorithms are being applied across various domains for optimization tasks. For instance, in seafaring SS, Ammar et al., (2014) successfully utilized the Greedy Random Adaptive Search Procedure GRASP based on real data from the SONOTRAK maritime company. It worth noting that Authors initially attempted an exact method for their problem but later proved its NP-Hard complexity, consequently they turned to metaheuristics. However, it's important to note that this wasn't the universal approach. For instance, Koubaa et al., (2016) responded to Ammar's findings by applying directly the Artificial Bee Colony ABC metaheuristic, and proved that ABC has the ability to outperform the GRASP and deliver better results in solving the same issue. On the other hand, it's worth noting that in 2022, (Koubaa et al., ) applied a different metaheuristic to the same problem, yielding results that outperformed the previous two studies. In the same context, ABC was applied also to nurse scheduling evaluated under different working environments (Buyukozkan & Sarucan, 2013).

The concept of combination involves merging two approaches: exact and heuristic methods. Ammar et al., (2014) explored the synergy between these methods, and a similar fusion is evident in the research of (Cildoz et al., 2021), where a combination of continuous linear algorithms and the GRASP metaheuristic was employed for scheduling emergency physicians. Other work of Brech et al., (2019) which combined Benders Decomposition (BD) and (ACO) to elaborate monthly training schedules for medical residents with the objective of minimizing the tardiness of their training (Costa Filho et al., 2012). In the work of Talarico and Maya Duque (2015), a mathematical problem formulation and hybrid heuristic approach for daily shift scheduling is presented. Their approach efficiently manages different planning intervals and complex constraints. In addition, Quesnel et al., (2019) proposed a diving heuristic alongside with CG (Column Generation) to address the challenge of long computation times in a single step.

While combination process serves as the bridge between the realms of exact and heuristic/metaheuristic, the 'Hybridization' section delves into the integration of algorithms within the same approach. This section highlights instances where multiple algorithms are merged to create more robust, efficient, and specialized solutions for specific problem classes within a single approach. Hybrid metaheuristic algorithms are commonly used in optimization. Chutima and Arayikanon (2020) have designed the MOEA/D (Decomposition-based Multi-objective Evolutionary Algorithm)-HBMO (Honey Bee Mating Optimization) hybrid algorithm for cockpit crew rostering for a low-cost airline, balancing multiple conflicting objectives. Hybrid Genetic Algorithm (HGA) is commonly used due you to their efficiency, by Costa et al., (2013) Amindoust et al., (2021). Campos Ciro et al., (2016) have choose to merge between two Meta-heuristics GA and ACO to solve an open shop scheduling problem with a multi-skills resource constraint. Wang et al., (2021) have proposed a heuristic algorithm that utilizes k-Opt as a diversification strategy within TS to address the simultaneous assignment of multi-skilled workers to tasks with varied skill requirements in both single and multiple period operations. The choice of mixing algorithms from heuristic and metaheuristic was also adopted by Hoffmann et al., (2017) applying a hybrid CG approach, which solves the pricing problem by means of a GA. Genetic Algorithms were also combined with heuristic to solve certain problems in health care department such as Peng-Sheng and Yi-Chih (2021) and Koruca et al., (2023). Some authors have chosen to tackle small to medium-sized problems by combining exact algorithms with heuristic ones. Hojati and Patil (2011), outlined a two-stage approach for employee scheduling in services with part-time workers using small integer linear programs-based heuristic to efficiently find suitable shifts to employees. The decision to employ the hybrid strategy often stems from the nature and scale of the specific problem. Firat et al., (2016) have used CG and B&P algorithm in order to hierarchically assign skilled technicians to jobs by considering their preferences. A similar fusion of techniques was established by Maenhout and Vanhoucke

(2013). A Hybrid Integer and Constraint Programming approach was established by Rahimian et al.,(2017) to Solve Nurse Rostering Problems.

Based on Figure 17, we could conclude that exact methods are prioritized for their ability to ensure a globally optimal solution, especially for small and well-structured problems. Metaheuristics follow, offering efficiency in exploring complex solution spaces. Heuristics, though less rigorous, are next in line, suitable for simpler problems or when computational time is restricted. Hybridization, while powerful, often demands the development of new algorithms as it combines existing ones. This approach, is less commonly used due to its complexity. Combination between methods, that is based on using two different approaches, is less used as author often proceed directly to only one approach (generally approach methods). It's more rigorous to first try exact methods and show they can't find a fast solution, providing a solid basis for using heuristics or Meta-heuristics.

***Constraints***

To succeed in the modern global economy, organizations must efficiently plan and organize their employees' work, matching capacities to future activities and staffing requirements while adhering to specific constraints (figure 18). In our work we are inspired by Chan (2002) which elaborated covering of the bellow aspects;

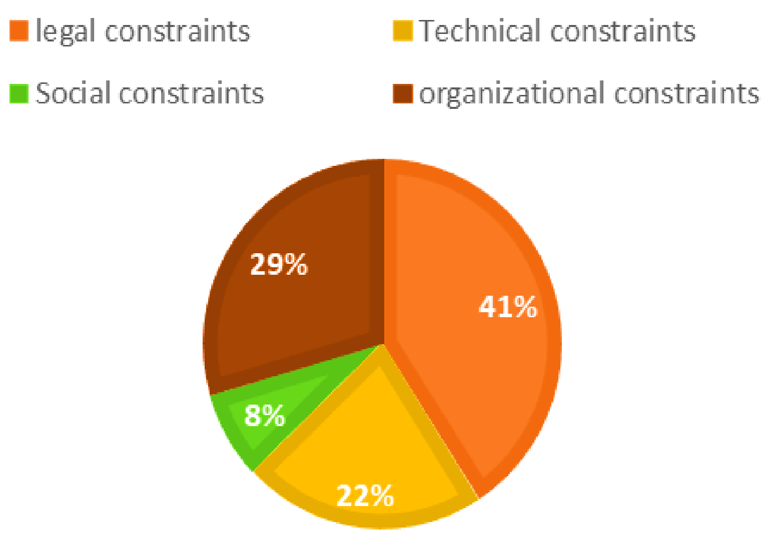



**Figure 18:** Constraints

*Legal constraints:* it’s about shift scheduling problems according to the labour standards law concerning working hours and rest periods. As shown in Figure10, this category is used frequently and almost standard in order to not offend the low. In the context of the railway industry, Khmeleva et al., (2014) employed it to address the crew scheduling problem in the rail freight sector, which entails assigning drivers to working days while complying with authorized working hours. Lim et al., (2016) have introduced an optimization model for assigning nurses to surgery cases, ensuring lunch breaks are provided, when necessary, without disrupting ongoing surgeries. The same for call centres where a minimum amount of rest is required after each shift (Türker & Demiriz, 2018). The interval of weekly rest hours/ day-off and the interval of hours between consecutive posts present an important criterion of the problem according to (Ammar et al., 2014). Moving to airline context where Quesnel et al.,(2019) have presented an individual schedules which are constrained by a set of rules . A schedule must contain at least 10 days off and at most 6 consecutive work days. It must contain no more than 85 hours of leg time, and 2 successive pairings must be separated by at least 12 hours of rest.

*Ergonomic constraints:* One of the typical challenges for managers is to establish an appropriate schedule for their employees' shifts. How an individual's work schedule is structured can greatly affect their job satisfaction and likelihood of staying in the job (Brusco et al., 2018). achieving workers’ satisfaction requires to ensure a fair distribution of work and rest hours while considering individual preferences and other employee needs. It also addresses psychological conditions like depression, stress, and anxiety, impacting mental health and overall workforce well-being. Hospitals, nowadays, care about this topic and specially with nurses who play a key role as the main healthcare workforce, and their satisfaction and high performance contribute to the quality of services. Mohammadian et al.,(2019), focused on nurses' interests, satisfaction, and preferences for days off and rest periods. Airlines use operations research to cost management, ranking crew scheduling as their second most important cost after fuel expenses. To maximize employee satisfaction, airlines tailor schedules to individual preferences, including preferred destinations and flight legs. Quesnel et al., (2019) consider that crew preferences known beforehand, the set of requested off-periods and the set of preferred legs for crew member preferences. Today, managers in charge of planning must consider not only traditional scheduling elements like personnel availability, training and shift preferences but also specific worker requirements. Di Martinelly and Meskens, (2017) emphasize the importance of considering affinities between team members, their willingness to work together, as an essential scheduling element. In order to ensure that no staff member is significantly disadvantaged of preferences or salary or workload, day off. Ammar et al., (2014) highlighted this issue and aimed that all workers need to have an equal workload to have the similar salary. Ergonomics aspects have been given consideration by Othman et al.,(2012b) who studied a workforce scheduling model that includes human breaks and worker fatigue. Fatigue can notably impact system performance and human productivity, especially with excessively long working hours and poorly planned shift work.

*Technical constraints:* we focus here on various business activities of the company taking into account the skills and expertise levels required. In a shift, various tasks with diverse skill requirements may be present. In cases where multiple skills are necessary, the highest-level skill required for the shift is chosen as the essential skill for that specific shift. Abdoul Soukour et al., (2013) have presented a model, where there are many kinds of skills with different levels are required. For Lim et al., (2016), the initial step is to assess the required staff numbers and skills to meet service demand, especially in specialized units with diverse skill requirements. Employees with higher skills can perform tasks of lower-ranked employees, but not the other way around, allowing for differentiation based on education, training, experience, and seniority. Seniority can impact decision-making policies, leading to privileges for older employees, such as more days off or priority in preferences. Additionally, higher-qualified workers can perform tasks that require lower qualifications, optimizing the workforce. Seniority constraint is applied between crew members; for instance, in the cockpit (pilot or co-pilot), if one flight crew member is junior, the other must be senior. Seniority ensures less experienced members are paired with more experienced (Dawid et al.,2001).

*Organizational constraints:* Respect for the company requirements at each point in the planning horizon. In our case, we consider that optimally covering manpower demands is the most constraint that could influence the economy of any organization according to his cost effect, and majority of authors have considered it.

All collected data are summarized in tables that provide a clear overview of our classification of the relevant papers we found.

Table 8 presents the research related to the maritime domain, highlighting the studies specifically focused on SS in this area. In contrast, Table 9 explores research from other domains, offering insights into how these fields approach similar issues. Comparing these tables, allow us to gain a comprehensive understanding of research in maritime studies and identify gaps, and recognize where maritime research is lacking and where insights from other domains might be applied to enhance our understanding and address challenges within the maritime sector.

**Table 8:**Novel Classification for Seafaring Staff Scheduling

| | **Decisional Aspects** | | | | | | | | **Methodological Aspects** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Assignment Decision | | Additional assignment | | planning horizon | | | | Used approach | | Constraints | | | | | | | |
| | | | | | | | | | | | legal | | Technical | Ergonomic | | | | Operational |
| | Team assignment | Personal assignment | External workers | Overtime | Daily | Weekly | Monthly | Annual | Modelling technic | Solution algorithms/ solver | Working hours | Day off / rest hours | Seniority/ Skills/ Qualification | Workload fairness | Psycho-technical | Worker preferences | affinity/ Compatibility | covering |
| **Maritime staff scheduling** | | | | | | | | | | | | | | | | | | |
| (Koubaa *et al.*, 2022) | x | | | | | | x | | - | MH (COA) | x | x | | x | | | | x |
| (Lorenzo-Espejo et al., 2021) | | x | Not allowed | | 14 weeks | | | | MILP | EX | x | x | | x | | x | | x |
| (Leggate et al., 2018) | | x | | x | 13 weeks | | | | MIP | EX | x | x | x | | | | | x |
| (Massimo et al., 2016) | | x | x | | Short term | | | | LIP | EX(CPLEX+ GPLK) | x | x | x | | | | | x |
| (koubaa *et al*, 2016) | x | | | | | | x | | - | MH (ABC) | x | x | | x | | | | x |
| (Ammar *et al.*, 2014) | x | | | | | | x | | LIP | EX + MH(GRASP) | x | x | | x | | | | x |
| (Francesco *et al.*, 2014) | x | | x | | Short term | | | | LIP | EX (CPLEX) | x | x | x | | | | | x |

***Ex:** Exact Method, ***MH:** Meta-Heuristic, ***MILP:** Mixed Integer Linear Programming, ***MIP:** Mixed Integer Programming ***LIP:** Linear Integer Programming, ***LP:** Linear Programming ***ABC:** Artificial Bee Colony, CPLEX/GPLK**: Solvers, *GRASP:** Greedy Randomized Adaptive Search Procedure, ***COA:** Cuckoo Optimization Algorithm

**Table 9:** Novel Classification for Staff Scheduling

| | Decisional Aspects | | | | | | | | Methodological Aspects | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | Constraints | | | | | | | |
| | Assignment Decision | | Additional assignment | | Planning horizon | | | | Used approach | | legal | | Technical | Ergonomic | | | | Operational |
| | Team | individual assignment | External workers | Overtime | Daily | Weekly | Monthly | Annual | Model | Solution algorithms/ | Working hours | Day off / rest hours | Seniority/ Skills/ Qualifica-tion | Workload Fairness | Psychotechnical | Worker preferences | Inter-team affinity | covering |
| **Airline Staff scheduling** | | | | | | | | | | | | | | | | | | |
| (Kasirzadeh et al., 2015) | x | | | x | | | x | | NLMIP | EX(CG) | | | | | | x | | x |
| (Armas et al., 2016) | x | | | | | | x | | - | H | x | x | | | | | | x |
| (Hadianti et al., 2014) | x | | | | | | x | | NLIP | MH (SA) | x | x | | | | | | x |
| (Quesnel et al.,2019) | | x | | | | | x | | NLMIP | EX(CG)+H | x | | | | | x | | x |
| (Chutima & Arayikanon, 2020) | x | | | | | | x | | - | MH (MOEA/D-HBMO) | x | x | x | x | | x | | x |
| (Shiau et al., 2020) | | x | | | | | x | | MIP | EX (LINGO) | x | | x | | | | | x |
| (Pereira et al., 2021) | x | | | | | | | | NLMIP | EX (GLPK) | x | | x | x | | | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Akyurt et al.,2021) | x | | | | | | | x | MIP | EX (CPLEX) | | x | x | x | | | | |
| **Railway Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (Khmeleva et al., 2014) | | x | | | x | | | | LP | MH (GA) | x | x | | | | | | x |
| (Hoffmann et al., 2017) | | | | | | x | | | MILP | MH (GA) + H (CG) | x | x | | | | | | x |
| (Jütte et al., 2017) | | x | | | | | | | MILP | EX (CG) | x | x | | | x | | | x |
| (Nishi et al., 2014) | | x | | | | x | | | IP | EX (BB) | x | x | | | x | | | x |
| (Lin & Tsai, 2019) | x | x | | | | x | | | IP | EX (BPC) | x | x | | | | | | x |
| (Raehlmann et al., 2020) | | | | | x | | | | MIP | EX(CG) | x | x | | | | | | x |
| (Khosravi et al., 2017) | x | | | | x | | | | IP | EX (CPLEX) | x | x | | | x | | | x |
| (S. H. Huang et al., 2011) | | | | | x | | | | NLIP | MH (ACO) | x | x | | | | | | |
| **Public transport Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (M. Chen & Niu, 2012) | | x | | | x | | | | 0-1 IP | MH(TS) | x | x | | | | | | x |
| (Li & Gupta, 2014) | | x | | x | | | x | | MILP | H | x | | | | | | | x |
| (Öztop et al., 2017) | | x | | | x | | | | NLMIP | EX (CPLEX) | x | x | x | | | | | x |
| (Rama et al., 2017) | | x | | | | x | | | LP | EX (MATLAB) | x | | | | | | | x |
| (Constantino et al., 2017) | | x | | x | | | | | ILP | H | x | x | | | | | | x |
| (Boyer et al., 2018) | | x | | x | x | | | | MIP | MH (VNS) | x | x | x | | | | | x |
| (Kang et al., 2019) | x | | | | x | | | | MILP | MH (SASA) | x | x | | | | | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Hajdu et al.,2020) | | x | | x | 1-3 months | | | | IP | H | x | x | | | | | | |
| **Industry Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (M Othman et al., 2012a) | | x | | x | | x | | | NLP | EX (LINGO) | x | x | x | | x | | | x |
| (Hasani-Goodarzi et al., 2012) | x | | x | | x | | | | MILP | EX (GAMS) | x | x | x | | | | | x |
| (Othman et al., 2012b) | | x | | x | | | x | | MILP | EX (LINGO) | x | x | x | | x | | | x |
| (Costa et al., 2013) | x | | | | | | | | MILP | MH (Hybrid GA) | | | x | | | | | |
| (Frihat et al., 2022) | x | | | | 3 months | | | | MILP | EX (CP) | x | | x | | | | | x |
| (Ramya & Chandrasekaran, 2014) | | x | | | | | | | IP | H | x | x | x | | | x | | |
| (Ladier et al.,2014) | | x | x | | x | x | | | MILP | EX(CPLEX) | x | x | x | x | | | | x |
| (Agrali et al.,2017) | | x | | x | | | | | MIP | EX | x | x | x | x | | | | |
| (Sifaleras et al., 2020) | x | | | | | | x | | MIP | EX (Gurobi) | x | | | | | | | x |
| (Campos Ciro et al., 2016) | | x | | | | x | | | MILP/ NLMIP | MH (GA/ACO) | x | | x | | | | | |
| (Rocha et al., 2014) | x | | | | | | | x | MIP | H | x | x | | *x* | | | | |
| (Firat et al., 2014) | x | | | | | | | | IP | H | x | | x | | | x | | |
| (Nearchou et al., 2015) | x | | | | 10 days | | | | LIP | H | x | | | | | | | |
| (Firat et al., 2016) | x | | | | | | | | IP | EX (CG + BP) | x | | x | | *x* | x | | |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Mahmud et al., 2018) | | x | | | | | x | | IGP | EX (lingo) | x | x | | | | x | | |
| (Özder et al., 2019) | | | | | | | x | | IGP | EX(CPLEX ) | x | x | x | *x* | | | | |
| (Soriano et al., 2020) | x | | x | x | | x | | | MILP | EX | x | x | | | | x | | |
| (Park & Ko, 2022) | | x | x | x | | | | | LP | EX(CPLEX ) | x | x | | | | | | x |
| **Project management Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (R Chen et al., 2017) | | x | | | | | | | NLMIP | MH (NSGAII) | | | x | | | | | |
| (Ballesteros-Pérez et al., 2019) | x | | | | | | | | NLMIP | MH (GA) | x | | x | | | | x | |
| (Sarihi et al., 2020) | | x | x | | | | x | | | EX (CP) + Simulation | x | | x | | | | | |
| (Rong Chen et al., 2020) | | x | | | | | | | | MH (Pareto-ACO) | x | | x | | | | | |
| **Nurse Scheduling** | | | | | | | | | | | | | | | | | | |
| (Mobasher et al., 2011) | | x | | x | x | | | | MIGP | EX (BC) | x | x | x | | | x | | x |
| (M'Hallah & Alkhabbaz, 2013) | x | | | | | x | | | MIP | EX | x | x | | | | | | x |
| (Guo et al., 2014) | | x | | | | x | | | IP | MH (GA) | x | x | | | | | | x |
| (Mandana & Reza, 2022) | x | | | | | | x | | MIP | EX (GAMS) | x | x | | | | x | | |
| (Silva et al., 2015) | | x | | | x | | | | IP | H | x | | x | | | | | x |
| (Lim et al., 2016) | | x | | x | | x | | | MILP | EX (CG) | x | x | x | | | x | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Di Martinelly & Meskens, 2017) | x | | | | | x | | | IP | EX (CP) | x | | x | | | | x | x |
| (Rahimian et al., 2017) | x | | | x | | x | | | IP | EX (CP) | x | x | | | | x | | x |
| (El Adoly et al., 2018) | | x | | x | | x | | | LIP | EX(BB) | x | x | | | | x | | |
| (Mohammadian et al., 2019 | | x | | x | | | x | | MIGP | EX | x | x | | | | x | | |
| (Strandmark et al., 2020) | | x | | | | x | | | LP | EX+H | x | x | | | | | | x |
| (Rerkjirattikal et al., 2020) | | x | | x | | | | | MIGP | EX | x | x | | x | | x | | |
| (Mischek & Musliu, 2019) | | x | | | | x | | | IP | EX | x | x | | | | x | | x |
| (Hamid et al., 2019) | x | | | | | | x | | IP | MH(MOKA /NSGAII/ MOTS) | x | x | x | | | x | | x |
| (Jenal et al., 2011) | | x | | | 3 weeks | | | | 0-1 IGP | EX (LINGO) | x | x | | | | x | | x |
| (Della Croce & Salassa, 2012) | | x | x | | | | x | | ILP | MH (VNS) | x | x | | | | | | x |
| (He & Qu, 2012) | x | | | | | x | | | LIP | EX | x | x | | x | | x | | x |
| (Huang et al., 2016) | | x | | | 2 weeks | | | | IP | EX | x | x | x | x | | x | | x |
| (Baeklund, 2014) | | x | | x | 2 weeks | | | | IP | EX (CSP-BCP-CG) | x | x | x | | | x | | x |
| (Legrain, et al.,, 2015) | x | | | x | | | x | | IP | H | x | x | x | | | x | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Buyukozkan & Sarucan, 2013) | x | | | x | | | x | | | MH (ABC) | x | x | x | x | | | | x |
| (Jafari & Salmasi, 2015) | | x | | | | | x | | IP | MH (SA) | x | x | | | | x | | x |
| (Awadallah et al., 2015) | x | | | | | x | | | IP | MH (hybrid ABC) | x | x | x | | | x | | x |
| (Amindoust et al.,2021) | | x | | | | | x | | NLIP | MH (Hybrid GA) | x | x | | | x | | | x |
| (Achmad et al., 2021) | | x | | | | | x | | LIP | MH (ACO) | x | x | x | x | | | | x |
| (Lin et al., 2015) | | x | | | | | x | | IP | MH (MA) | x | x | | x | | x | | x |
| (Wright & Mahar, 2013) | x | | | x | | | x | | LIP | EX | x | x | | | | x | | x |
| (Maenhout & Vanhoucke, 2013) | x | | x | x | | | x | | LIP | EX (CG/BP) | x | x | | x | | x | | x |
| (Santos et al., 2016) | | x | | | | x | | | MIP | H | x | x | x | x | | x | | x |
| **Health Care Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (Brunner & Edenharter, 2011) | | x | | | | | | x | MIP | EX (CG based H/ BP) | x | x | x | | | | | x |
| (Costa Filho et al., 2012) | x | | | | | | x | | CSP | EX (CSP) +H | | | | | | | | |
| (Bruni & Detti, 2014) | | x | | | | | | x | MILP | EX (BC) | x | x | | x | | x | | x |
| (Elomri et al., 2015) | | x | | | 2-Months | | | | MIP | EX | x | x | | x | | x | | x |
| (Smalley & Keskinocak, 2016) | x | | | x | | | | x | IP | EX(CPLEX ) | x | x | | | | x | | |
| (Volland et al., 2017) | | x | | | | x | | | MIP | EX (CG) | x | x | x | | | | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Praveen Kumar et al., 2018) | x | | | | | x | | | MIGP | EX | x | x | | x | | | | |
| (Brech et al., 2019) | | x | | | | | x | | MIP | EX(BD)+MH (ACO) | x | | x | | | | | x |
| (Peng-Sheng & Yi-Chih, 2021) | | x | | | | | | | NLMIP | H (HGA) | x | x | x | | | x | | |
| (Cildoz et al.,2021) | | x | | | | | | x | LIP | EX+MH (GRASP) | x | x | | x | | | | x |
| (Guerriero & Guido, 2021) | | x | | | | x | | | MIP | EX | x | x | | | | x | | x |
| (Moosavi et al.,2022) | | x | x | x | | x | | | MILP | H | x | | x | | | | | |
| (Nobil et al., 2022) | | x | | x | | | x | | MILP | EX (lingo) | x | x | | | | | | x |
| (Koruca et al., 2023) | | x | | | | x | x | | IP | H (based on GA) | x | | x | x | | x | | x |
| **Call Center Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (Louly, 2013) | X | | | | 6 weeks | | | | BIGP | EX | x | x | | x | | | | |
| (Türker & Demiriz, 2018) | | X | | | | x | | | IP/CP | EX | x | x | | | | | | |
| (Xu & Wang, 2021) | | X | | | | | x | | LIP | MH (ABC) | x | x | | | | x | | x |
| (Xu & Wang, 2022) | | x | | | | | | x | IP | MH (Hybrid IP and ABC) | x | x | | x | | x | | x |
| **Retail Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| ( Henao et al., 2015) | x | | | | | x | | | MILP | EX | x | x | x | | | | | x |
| (Talarico & Maya Duque, 2015) | | x | | | | x | | | MP | EX+H | x | x | | | | | | x |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Porto et al., 2019) | x | | | | | x | | | MILP | EX | x | x | x | | | | | x |
| (Alvarez et al., 2020) | x | | | | x | | | | MIP | EX | x | x | | | | | | x |
| (Curebal et al., 2022) | | x | x | | | | x | | 0-1 IP | Ex | x | | x | | | | | |
| **Security Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (Soukour et al., 2013) | | x | | x | | | x | | IP | MH (MA) | x | x | x | | | x | | x |
| (Todovic et al., 2015) | | x | | | | | x | | MIGP | EX | x | x | | | | x | | x |
| (Özcan et al., 2018) | | x | | | | | x | | IGP | EX | x | x | | | | | | x |
| (Ang et al.,2019) | | x | | | | x | | | LIP | EX | x | x | | | | x | | |
| (Alfares & Alzahrani, 2020) | x | | | | | | x | | IP | EX | x | x | | | | | | |
| **Other fields Staff Scheduling** | | | | | | | | | | | | | | | | | | |
| (Hojati & Patil, 2011) | | x | | | | x | | | | EX (LIP-based H) | x | x | x | | | | | x |
| (Özgüven & Sungur, 2013) | | x | | | | x | | | IP | EX | x | x | x | | | | | |
| (Akbari et al., 2013) | | x | | | | x | | | IP | MH (SA/ VNS) | x | | x | | x | x | | |
| (Veldhoven et al., 2016) | | x | | | | | | | LIP | EX | x | x | x | | | x | | |
| (Wang et al., 2021) | | x | | | | | | | MIP | H+ MH (TS) | x | | x | | | | | |
| (Sumathy & Amirthalingam, 2021) | | | | | | | | | LP | EX | x | x | | | | | | x |
| (Ryu et al., 2023) | | x | | | | | x | | LIP | EX | x | x | x | x | | x | | |
| (Brunner & Bard, 2013) | | x | | | | | x | | MILP | EX (CG) | x | x | | | | | | x |
| (Labidi et al., 2014) | | x | | | x | | | X | | MIP | x | x | x | x | | x | | |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Smet et al.,2016) | | x | | | x | x | | LIP | EX (CG) | x | x | x | | | | | x |
| (Ozturk, 2019) | | x | | | x | | | IP | EX | x | x | | x | | x | | |
| (Doan et al., 2021) | x | | | | x | | | MILP | EX | x | x | x | x | | x | | |

***Ex:** Exact Method**, *MH:** Meta-Heuristic**, *MILP:** Mixed Integer Linear Programming**, *MIP:** Mixed Integer Programming ***LIP:** Linear Integer Programming**, *LP:** Linear Programming ***NLMIP:** Non Linear Mixed Integer Programming**, * I-GP:** Integer Goal Programming, ***BI-GP**: Binary Integer Goal Programming *MIGP: Mixed Integer Goal Programming ***BPC:** Branch-And-Price-And-Cut,***BC**: Branch & Cut, ***BP**: Branch-And-Price**, *BB**: Branch and Bound **, *ABC:** Artificial Bee Colony**,** CPLEX/GPLK**: Solvers, *GRASP:** Greedy Randomized Adaptive Search Procedure**, *SA:** Simulated Annealing**, *GA:** Genetic Algorithm**, *CG:** Column Generation**, *VNS:** Variable Neighborhood Search, ***TS**: Tabu-search, , ***ACO**: Ant Colony Optimization,* **MOKA**: Multi-Objective Keshtel Algorithm, ***MOTS**: Multi-Objective Tabu Search, ***NSGAII**: Non-Dominated Sorting Genetic Algorithm II, ***CSP**: Constraint Satisfaction Problem, ***HBMO:** Honeybee Mating Optimization. ***MOEA/D**: Decomposition-based Multi-objective Evolutionary Algorithm. **SASA:** self-adaptive search algorithm

## Discussion

While staff scheduling has been extensively studied in various industries, it remains a relatively underexplored issue in the maritime sector. Specifically, concepts such as affinity and incompatibility have not been thoroughly examined in this context, as highlighted by the red-coloured column in Table 8. To address this research gap, we drew on studies from other domains. As shown in Table 9, we found a significant number of articles on staff scheduling from various fields, although no one addressed the dual objectives of workload fairness and incompatibility minimization, which are crucial for shipowners. Previous research, such as Blochliger's work in 2004, has discussed similar concepts using mathematical models, but noted that resolving these issues would require heuristic approaches, which were not implemented. Table 9 show also that ergonomic constraints are less commonly used compared to other constraints, and they should receive more attention to tackle current challenges. With an increasing number of constraints, complexity grows proportionally, and metaheuristics are a popular approach for addressing complex optimization problems. These methods provide practical solutions to NP-hard problems without relying on exact methods, using strategies such as problem decomposition and hybridization without optimality

## Conclusion

Efficient SS is a critical challenge for many organizations, as it directly impacts service quality and operational efficiency. To effectively address this issue, it is crucial to have a comprehensive understanding of the current research landscape, including the available tools and methodologies. This study conducts a ScR to systematically examine recent research on tools for addressing key staff scheduling problems, which are essential for delivering high-quality services in various sectors, both public and private. We employed a PRISMA flow diagram-based approach to conduct a scoping search of the literature on SS, analysing a total of 122 relevant studies across multiple databases. The results were categorized using our own classification system, which enabled us to identify research gaps and limitations within the field.

The insights gained from this review have inspired us to develop a mathematical model to address the specific needs of shipowners, which will be discussed in the following chapter.

# Chapter 4. A New Mixed Integer Linear Program (MILP) For Seafaring Staff Scheduling Problem– Real Case Study

## Introduction

This chapter addresses a real-world problem of scheduling seafaring staff, where a shipowner operates multiple vessel categories that require specific skills to achieve a fair workload distribution and minimize incompatibility between workers while meeting legal requirements including requirements for days off and rest intervals between shifts. The goal of this chapter is to integrates these multiple objectives and constraints, and to test its performance across varying parameter adjustments. This work's novelty lies in integrating these multiple objectives and constraints into a Mixed Integer Linear Problem (MILP) formulation accompanied by experimental results that test the model's performance across varying parameter adjustments. These findings contribute to decision support, shedding light on the model's behavior in addressing the complexities of SS in the maritime domain.

## 1 Problem description

To better present our issue, Figure 19 illustrates a schematic representation outlining the fundamental aspects of our model and its structure. It's important to emphasize that in our model, shifts are predetermined, and our objective revolves around efficiently assigning workers to their respective shifts. This assignment process considers various constraints and two objectives.

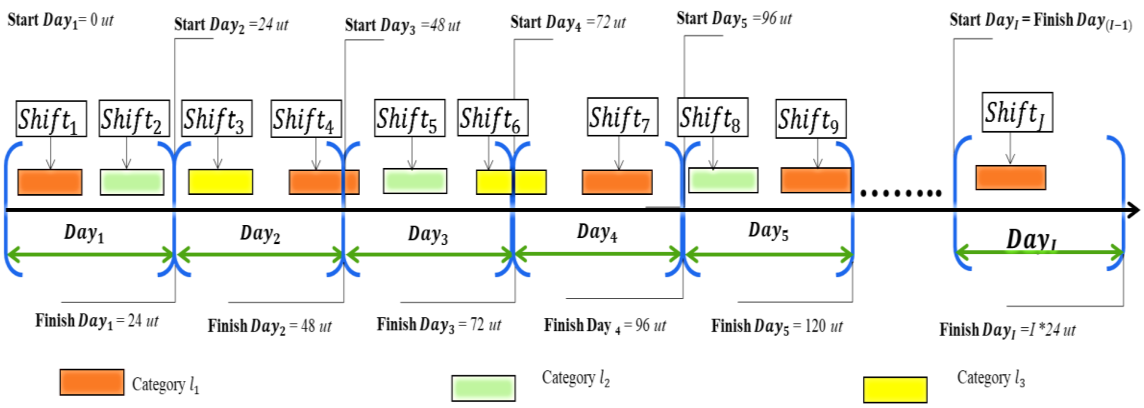



**Figure 19**:Model Structure

The SS Problem involves the allocation of specific number of workers $W$ to a set of shifts $J$ of categories $L$ in days $I$. $w = \{1, \ldots, W\}$, $j = \{1, \ldots, J\}$, $l = \{1, \ldots, L\}$, *and* $i = \{1, \ldots, I\}$ are respectively the index of worker, shift, category and day. The shipowner requires round-the-clock operations and, therefore, need workers to cover the overnight hours. However, the challenge arises when a shift starts on a day and extends to finish in the next day, causing an overlap in workdays for a single shift $j$, and both days count as workdays for a worker $w$, as is the case of shift 4 and 6 of Figure1. To tackle this issue, we've opted for a unified temporal division where each day is divided into 24 unit of time (*ut*) where $SS_j$ and $FS_j$ are respectively the starting and finishing time of shift $j$. After a certain number of successive days, denoted by *SWD*, workers must have a day off. A day may consist of one or multiple shifts, and it's crucial for the shipowner to maintain, for each worker, a rest interval *Bmin* between two successive shifts. In the case of the shipowner, three categories of shift are considered: i) regular shift, $l$=1, refers to standard shift, ii) reinforcement shift: $l$=2, refers to an additional or supplementary shift introduced to bolster the existing workforce for unexpected circumstances or to cover shortages in staffing. The shipowner might assign deck personnel (often sailors) to join the navigating team, iii) premium shift , $l$=3, which is designated for transporting hazardous products may come with a risk premium. Therefore, we introduce a binary parameter $B_{l,j}$ that helps us identify and label which category $l$ that the shift $j$ belongs to. It's essential to note that different shift categories come varying salaries, emphasizing the need for fairness in shift assignments. Hence, we've introduced an Average Number assignment to category $l$, $ANA_l$. It designates the average balanced workload to be reached. Each shift is defined by a set number of workers designated as *NRP*. Given that the shipowner operates various categories of shift moving between categories typically requires an additional qualification obtained either through specific training or after accruing a defined number of hours accompanied by seniors. Therefore, $QP_{j,w}$ defines the qualification of worker $w$ to shift $j$, $QP_{j,w} \epsilon \{0,1\}$. Given that shifts require different qualifications, this notation indicates whether a worker has the necessary qualifications for a specific shift. We also define a symmetric matrix to illustrate the incompatibility scores $H_{w,v}$ when worker $w$ works with worker $v$. $H_{w,v}$ ranges from 1 to 4, where 1 indicates the lowest level of incompatibility and 4 indicates the highest level of incompatibility. This scale was chosen to simplify the model and maintain a clear distinction between incompatibility levels.

In the upcoming section, we detail all index, decision variables and parameters, along with their application in our model.

# 2 Problem Modelling

The mathematical model consists of four components, which are decision variable, parameters, objective function and constraints.

## 2.1 Decision Variables

$$Y_{i,w} \begin{cases} = 1 \text{ } if \text{ } the \text{ } worker \text{ 'w' is on duty on day 'i'} \\ = 0 \text{ } otherwise \end{cases}$$

$$X_{j,w} \begin{cases} = 1 \text{ } if \text{ } the \text{ } the \text{ } worker \text{ } 'w' \text{ is assigned to shift 'j'} \\ = 0 \text{ } otherwise \end{cases}$$

$$Z_{w,v,j} \begin{cases} = 1 \text{ } if \text{ } the \text{ } worker \text{ 'w' is on duty with the worker 'v' on shift 'j'} \\ = 0 \text{ } otherwise \end{cases}$$

## 2.2 Parameters

| | |
|---|---|
| $\boldsymbol{I}$ | *: Set of days* |
| $\boldsymbol{i}$ | *: Index of day, i= 1,…,I* |
| $\boldsymbol{W}$ | *: Set of workers* |
| $\boldsymbol{w,v}$ | *: Index of workers, w=1,..,W, v= 1,..,W* |
| $\boldsymbol{J}$ | *: Total number of shift* |
| $\boldsymbol{j}$ | *: Index of shift, j= 1,..,J* |
| $\boldsymbol{L}$ | *: Total categories of shifts* |
| $\boldsymbol{l}$ | *: Index of shifts' category, l=1,…,L* |
| $\boldsymbol{H_{w,v}}$ | *: Incompatibility score between two workers 'w' and 'v'* |
| $\boldsymbol{SS_j}$ | *: Start time of the shift 'j'* |
| $\boldsymbol{FS_j}$ | *: Finishing time of the shift 'j'* |
| $\boldsymbol{NRP}$ | *: Number of required workers on a shift* |
| $\boldsymbol{Bmin}$ | *: Minimal rest hours for a worker between every two consecutive shifts.* |
| $\boldsymbol{SN_l}$ | *: Total shift of category l* |

$\boldsymbol{ANA_l}$ : *Average number of assignments to 'l' category, ANA*$_l$$=NRP * \frac{SN_l}{W}$

$\boldsymbol{QP}_{j,w}$ : $\begin{cases} = 1 \; if \; the \; worker \text{ 'w' is qualified to shift'j'} \\ \qquad = 0 \; otherwise \end{cases}$

$\boldsymbol{A_{i,j}}$ : $\begin{cases} = 1 \; if \; the \; shift \; 'j' \text{ occurs on day } \; 'i' \\ \qquad = 0 \; otherwise \end{cases}$

$\boldsymbol{B_{l,j}}$ : $\begin{cases} = 1 \; if \; the \; shift \text{ 'j' blongs to category 'l'} \\ \qquad = 0 \; otherwise \end{cases}$

$\boldsymbol{SWD}$ : *Number of* ***S****uccessive* ***W****orking* ***D****ays*

$\boldsymbol{M}$ : *High Value*

$\boldsymbol{y_{l,w}}$ : *A*uxiliary *variable*

### 2.3 Objective Function

The overall objective function $\boldsymbol{f}$ aims to minimize two objective functions: $\boldsymbol{f}_1$ and $\boldsymbol{f}_2$.

The first objective function $\boldsymbol{f}_1$ reduces the gap between the number of assignations to category 'l' and $ANA_l$ .The aim is to ensure that all workers have the same number of assignations to category 'l'.

$$\boldsymbol{MIN\, f}_1 = \left| \sum_{j}^{J} (\boldsymbol{X_{j,w}} * \boldsymbol{B_{l,j}}) - \boldsymbol{ANA_l} \right|$$

We observe that this function introduces non-linearity due to the presence of the absolute value. Therefore, by introducing the auxiliary variable $\boldsymbol{y_{l,w}}$. we replace the absolute value with two distinct linear inequalities, allowing the problem to be expressed and solved using linear programming techniques. These two inequalities are then transformed into the constraints (10) and (11) as explained in section 3.4. As a result, $\boldsymbol{f}_1$ becomes:

$$\boldsymbol{MIN\, f}_1 = \sum_{w=1}^{W} \sum_{l=1}^{L} \boldsymbol{y_{l,w}}$$

The second objectives $\boldsymbol{f}_2$ is to minimize incompatibility between workers, based on the incompatibility matrix score $H_{w,v}$.

$$\boldsymbol{MIN\, f}_2 = (\frac{1}{\boldsymbol{W}}) \sum_{w=1}^{W} \sum_{v=1}^{W} \sum_{j=1}^{J} \boldsymbol{H_{w,v}} * \boldsymbol{Z_{w,v,j}}$$

It's important to acknowledge that the matrix $H_{w,v}$ is symmetric, meaning each interaction between workers w and v is counted twice. Without normalization, this would double the contribution of each interaction. By dividing by the number of workers $(\frac{1}{W})$, we correct for this double counting and ensure each interaction is counted only once, providing an accurate result.

The global objective function $\boldsymbol{f}$ aims to simultaneously ensure workload fairness, represented by $\boldsymbol{f_1}$, and minimize incompatibility, represented by $\boldsymbol{f_2}$. The parameter α represents the weight of $\boldsymbol{f_1}$, while 1-α represents the weight of $\boldsymbol{f_2}$. Therefore, the objective is to minimize $\boldsymbol{f}$, as shown in the equation:

$$\mathbf{MIN}\,\boldsymbol{f} = \propto \boldsymbol{f_1} + (1-\propto)\,\boldsymbol{f_2}$$

$$\boldsymbol{MIN\,f} = \propto \left(\sum_{w}^{W}\sum_{l}^{L} \boldsymbol{y_{l,w}}\right) + (1-\propto)\left(\left(\frac{1}{\boldsymbol{w}}\right)\sum_{w=1}^{W}\sum_{v=1}^{WV}\sum_{j=1}^{J} \boldsymbol{H_{w,v}} * \boldsymbol{Z_{w,v,j}}\right)$$

For first resolution tests, we assume equal importance, α=0.5, it means that both criteria have equal weight in the objective function. In the following sections, we vary α to understand the relative impact of each criterion on the final solution. By adjusting α, we aim to analyze how changes in the weight assigned to each criterion influence the optimization results.

These two objectives depend on several constraints detailed in subsequent sections.

### 2.4 Constraints

$$\mathrm{X}_{j,w} \leq QP_{j,w}\ \forall j, \forall w \tag{1}$$

$$\sum_{\mathrm{j=1}}^{\mathrm{J}} (\mathrm{X}_{j,w} * \mathrm{A}_{i,j}) \leq 1\ \forall i, \forall w \tag{2}$$

$$\sum_{\mathrm{j=1}}^{\mathrm{J}} (\mathrm{X}_{j,w} * \mathrm{A}_{i,j}) = \mathrm{Y}_{i,w}\ \forall i, \forall w \tag{3}$$

$$\sum_{w=1}^{W} X_{j,w} = \text{NRP} \quad \forall j \tag{4}$$

$$Y_{(i+SWD),w} + M * \left( \sum_{x=i}^{i+(SWD-1)} Y_{x,w} - SWD \right) \leq 0 \;\forall i \in \{1,..,I - SWD\}, \forall w \tag{5}$$

$$Z_{w,v,j} \leq X_{j,w} \;\forall w\; \forall v\; \forall j \tag{6}$$

$$Z_{w,v,j} \leq X_{j,v} \;\forall w\; \forall v\; \forall j \tag{7}$$

$$Z_{w,v,j} \leq X_{j,v} + X_{j,w} - 1 \;\forall w\; \forall v\; \forall j \tag{8}$$

$$(X_{jb,w} * SS_{jb}) - (X_{ja,w} * FS_{ja}) - M * ((X_{jb,w} + X_{ja,w}) - 2) \geq \text{Bmin} \;\forall w,\; \forall ja,\; \forall jb \text{ with } ja<jb \tag{9}$$

$$X_{j,w} Y_{i,w}\, Z_{w,v,j} \in \{0,1\} \;\forall w\; \forall v\; \forall j \tag{10}$$

$$Y_{l,w} \geq -\left(\sum_{j=1}^{J} (X_{j,w} * B_{l,j}) - ANA_l\right) \forall w\, \forall l \tag{11}$$

$$Y_{l,w} \geq \left(\sum_{j=1}^{J} (X_{j,w} * B_{l,j}) - ANA_l\right) \forall w\, \forall l \tag{12}$$

- Constraint (1): A worker is Scheduled if he is qualified to the shift.
- Constraint (2): Each worker is assigned or not to one shift per day
- Constraint (3): A worker is on duty for a shift if he is not on rest day.
- Constraint (4): A shift must have a required number of workers.
- Constraint (5): Every worker should have a day off after a set of consecutive workdays.
- Constraint (6), (7) and (8): A worker *w* is assigned or not with the worker *v* in the same shift *j*.
- Constraint (9): Between two shifts, a worker should have minimum rest hours *Bmin*.
- Constraint (10): The decision variable is made binary.

- Constraint (11) and (12): linear constraints that ensures that all workers work the same number of shifts of category *l*.

## 3 Experimental Results

Once the mathematical model is established, it must be executed to validate its effectiveness and ensure that objectives are met and constraints are respected. This involves implementing the model into a computational algorithm using FICO Xpress optimizer (figure 20). The model is executed on a laptop equipped with an Intel Core i7-10700K processor, boasting a clock speed of 3.80 GHz (3792 MHz), 8 physical cores, and 16 logical processors, supported by 32GB of RAM, and running on the Windows 10 operating system.

The results are then analyzed in two sections: first we focus on testing the model to ensure its effectiveness, and if the model does not meet the objectives or violates constraints. The second section conducts a sensitivity analysis that involves understanding how changes in input parameters affect the model's outputs.

### 3.1 Model validation

To test and validate the model, we present examples tested on the instance showed in Table 10, with $QP_{j,w}$ and $H_{w,v}$ hereafter presented. We chose to use small instances to simplify and better understand the problem. The aim is to check if the model appropriately assigns the workers while fulfilling the objectives and adhering to the previously mentioned constraints.

**Table 10**:Example instance for testing and validating the model

| | |
|---|---|
| ***I*** | 4 |
| ***J*** | 5 |
| ***W*** | 4 |
| ***L*** | 2 |
| ***NRP*** | 2 |
| ***Bmin*** | 8 |
| ***Alpha*** | 0.5 |

$$\boldsymbol{QP_{j,w}} \begin{pmatrix} & w_1 & w_2 & w_3 & w_4 \\ j_1 & 1 & 1 & 1 & 1 \\ j_2 & 1 & 1 & 1 & 1 \\ j_3 & 1 & 1 & 1 & 1 \\ j_4 & 1 & 1 & 1 & 1 \\ j_5 & 1 & 1 & 1 & 1 \end{pmatrix} \quad \boldsymbol{H_{w,v}} \begin{pmatrix} & w_1 & w_2 & w_3 & w_4 \\ w_1 & 0 & 1 & 1 & 1 \\ w_2 & 1 & 0 & 1 & 1 \\ w_3 & 1 & 1 & 0 & 1 \\ w_4 & 1 & 1 & 1 & 0 \end{pmatrix}$$

#### 3.1.1 Ensuring fair assignment of shifts

Since one of our primary objectives is to ensure fairness, we evaluate whether the program maintains equitable assignment among workers. To do that, we assume that all workers are qualified and compatibles, see the matrix $H_{w,v}$ and $QP_{j,w}$. The result is presented in Figure 20.

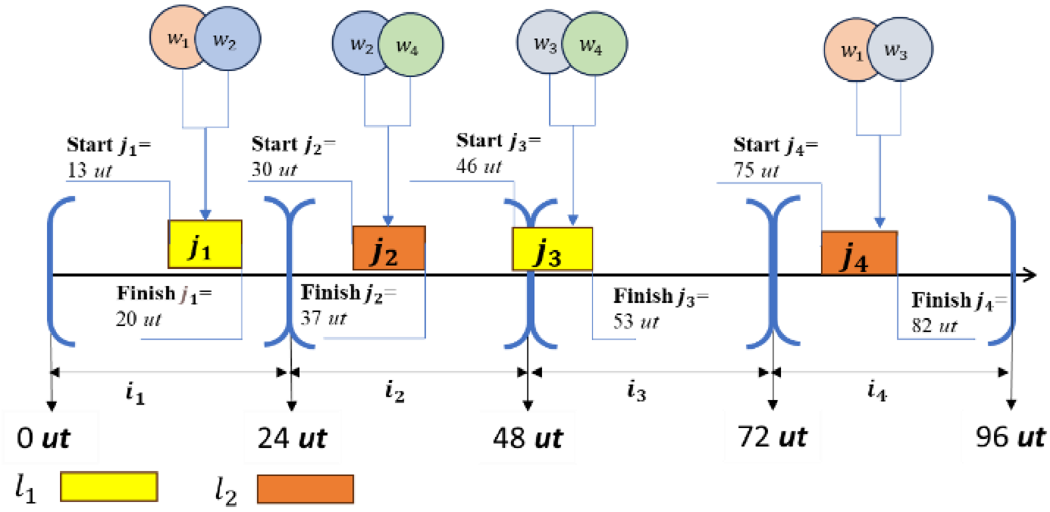



**Figure 20:**Fair scheduling with predefined shifts and overlap days

According to Figure 20, the program assigns workers to shifts in a fair and equitable way, with two individuals per shift *NRP*=2, ensuring that each employee *w* is assigned to different shift categories, 2 categories of shift per person in this example. In the tested instances, $w_4$ is assigned to two shifts: $j_2$ and $j_3$. However, it's important to note that shift $j_3$ is considered to belong to the day $i_3$, and not to $i_2$, due to the model's assumption that shifts starting on day *i* and ending on day *i+1* are considered to belong to day *i+1*.Given that we are testing the program on small instance with 4 shifts/workers, we pre-defined shifts in a way that shifts are spaced through the time horizon and *Bmin* is systematically respected. Therefore, in the section 5.1.2, we focus on reducing the time interval between two consecutive shifts, in order to not exceed *Bmin*. This allows us to verify both the adherence to *Bmin* and that a worker cannot perform two shifts on the same day.

### 3.1.2 Validation of the minimum rest period and single shift per day constraint

In this section, we verify if the program adheres to the minimum rest period *Bmin* requirement and one single shift par day. On the day $i_4$, two shifts $j_4$ and $j_5$ are planned for testing both constraints.

According to Figure 21, the program successfully identified that workers $w_1$ and $w_3$ were not eligible for assignment to $j_5$, they were already scheduled to work on the same day in the shift $j_4$. The program recognized that the minimum rest period *Bmin* was not respected between the two shifts, leading to the assignment of workers $w_2$ and $w_4$ instead, which confirms our initial hypothesis.

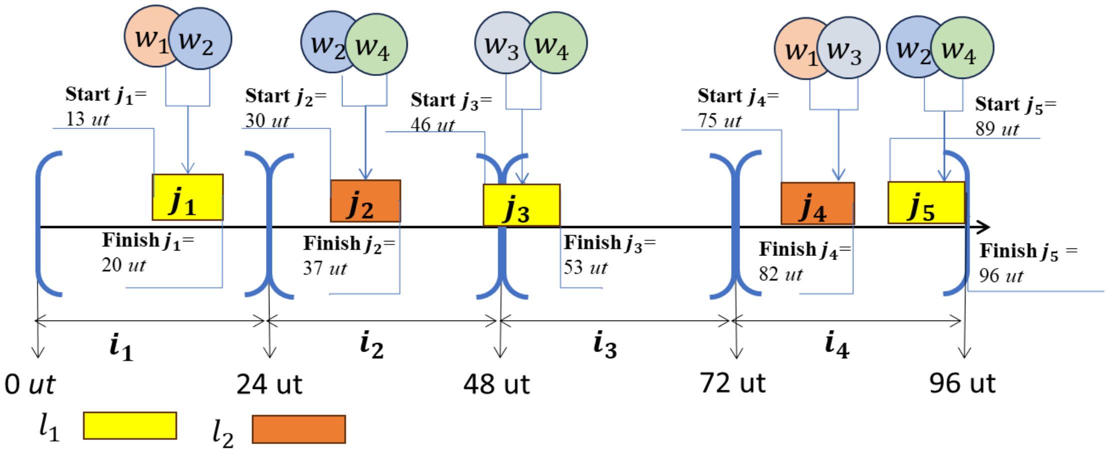



**Figure 21:**Adherence to the minimum rest period and single shift per day

### 3.1.3 Assessing the Program's Ability to Handle $QP_{j,w}$ and $H_{w,v}$

In this scenario, we assess the program's ability to manage incompatibility. Specifically, we have chosen two individuals, $w_1$ and $w_2$, who typically work together and were initially assigned to the same shift $j_1$.

4 $H_{1,2}$

$$H_{w,v}\quad \begin{array}{cc} & \begin{array}{cccc} w_1 & w_2 & w_3 & w_4 \end{array} \\ \begin{array}{c} w_1 \\ w_2 \\ w_3 \\ w_4 \end{array} & \begin{pmatrix} 0 & \cancel{\boxed{1}} & 1 & 1 \\ 4 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \end{array}$$

0 $QP_{1,1}$

$$QP_{j,w}\quad \begin{array}{cc} & \begin{array}{cccc} w_1 & w_2 & w_3 & w_4 \end{array} \\ \begin{array}{c} j_1 \\ j_2 \\ j_3 \\ j_4 \\ j_5 \end{array} & \begin{pmatrix} \boxed{1} & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} \end{array}$$

As shown on $H_{12}$ and $H_{21}$ , was set to 1 at first, indicating a good working relationship. However, we later adjusted their compatibility level to 4, indicating that they were no longer compatible. Additionally, we assume that $w_1$ is not qualified to perform $j_1$.

In Figure 22, we show that $w_1$ not assigned to $j_1$, and notably, $w_1$ and $w_2$ did not work together in any shift. This outcome highlights the program's ability to provide a fair schedule that minimize workers incompatibility while adhering to qualification constraints and the breaks' respect.

### 3.2 Sensitivity Analysis

After testing our model, evaluating its performance is crucial. This involves studying how changes in input parameters affect the model's outputs, providing insights into the model's behavior and effectiveness. In this study, we firstly varied $QP_{j,w}$ to evaluate its impacts on

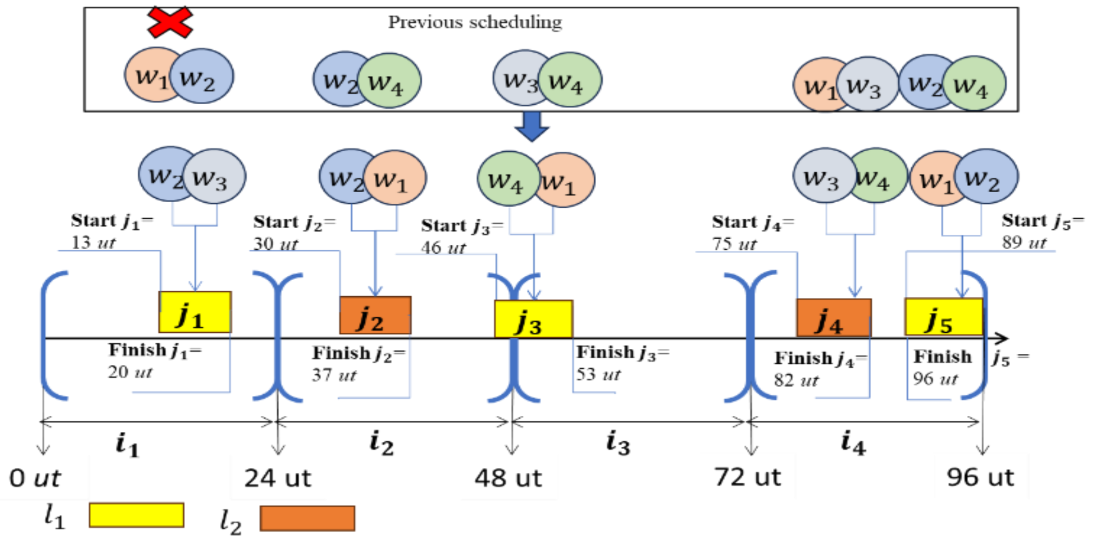



**Figure 22:**The Impact of adjusting $\mathbf{QP_{j,w}}$ and $\mathbf{H_{w,v}}$

the objectives. Then, we explored the model's execution time limits by varying $w$. However, it is essential to note that these experiments rely on the generation of specific instances to create relevant scenarios.

#### 3.2.1 Instance Generation

The aforementioned two studies are based on the data presented in Table 11. The only difference is that in the second study, the parameter $w$ will be varied.

**Table 11:**Initial parameters used in sensitivity analysis

| Parameters | Value |
|---|---|
| $\alpha$ | 0.5 |
| ***NRP*** | 2 |
| ***W*** | 10 |
| ***I*** | 6 |
| ***J*** | 9 |
| ***L*** | 3 |
| ***SWD*** | 5 |
| ***Bmin*** | 8 |
| $w$ | {9,..,14} |
| $QP_{j,w}$ | From 50% to 100% of qualified workers |

The minimization of incompatibility highly depends on $H_{wv}$, this means that even a minor change in that a simple change on $H_{w,v}$ could significantly impact the results. Relying on a random matrix may not reflect significant results due to the large number of configurations that could exist. Therefore, we need further robustness exploration to confirm if our results remain reliable when the $H_{wv}$ is modified.

Consequently, we create the values of $H_{wv}$ for different scenarios. Thus, we create a compatibility scale that categorizes the level of incompatibility between two workers into four distinct levels: highly compatible, compatible, moderately compatible, incompatible, each level is represented by a number ranging respectively from 1 to 4, see Table 12.

**Table 12**:Scale for categorizing incompatibility levels

<table>
<tr><th></th><th colspan="2">Levels</th><th>Significance</th></tr>
<tr><td rowspan="2">Compatibility class</td><td>Highly compatible</td><td>1</td><td>Workers have strong preferences to work together and collaborate effectively</td></tr>
<tr><td>Compatible</td><td>2</td><td>Workers generally prefer to work together, although there may be some minor differences in their preferences or work styles.</td></tr>
<tr><td rowspan="2">Incompatibility class</td><td>Moderately incompatible</td><td>3</td><td>Workers have significant differences in their preferences or work styles, which can sometimes lead to friction or inefficiencies.</td></tr>
<tr><td>Incompatible</td><td>4</td><td>Workers have very different preferences or work styles, often resulting in conflicts or difficulties in working together</td></tr>
</table>

In the following, we categorize levels 1 and 2 as the compatibility class, and levels 3 and 4 as the incompatibility class. While we do not consider the specific distribution of percentages between the sub-classes (levels) within each class, it is important that the total percentage of levels within a class meets the required percentage. For instance, a matrix may consist of 70% compatibility, meaning that levels 1 and 2 together make up 70% of the entries in the matrix.

Using the aforementioned compatibility scale, we concentrated our analysis on specific compatibility scenarios that explore various distributions within a single matrix, such as:

- ✓ Scenario 1: 70% of compatibility class and 30% of incompatibility class (meaning 70% of the matrix values are either 1 or 2 and 30% of are either 3 or 4).
- ✓ Scenario 2: 50% of compatibility class and 50% of incompatibility class.
- ✓ Scenario 3:30% of compatibility class and 70% of incompatibility class.

We've provided an example of a matrix $H_{w,v}$ sized 10x10. This matrix illustrates compatibility level among a group of 10 workers. Each worker is represented both in the rows and columns, emphasizing the symmetry of the matrix. This symmetry has two important implications:

Firstly, $H_{w,v}$ is identical to $H_{v,w}$. Secondly, the matrix has zero values on the diagonal, indicating that a worker's compatibility with themselves is not applicable.

$$H_{w,v} = \left(\begin{array}{c|cccccccccc} & \mathrm{w}_1 & \mathrm{w}_2 & \mathrm{w}_3 & \mathrm{w}_4 & \mathrm{w}_5 & \mathrm{w}_6 & \mathrm{w}_7 & \mathrm{w}_8 & \mathrm{w}_9 & \mathrm{w}_{10} \\ \mathrm{w}_1 & 0 & 1 & 1 & 1 & 1 & 1 & 3 & 2 & 1 & 3 \\ \mathrm{w}_2 & 1 & 0 & 1 & 2 & 1 & 4 & 1 & 4 & 2 & 4 \\ \mathrm{w}_3 & 1 & 1 & 0 & 4 & 2 & 2 & 1 & 3 & 1 & 1 \\ \mathrm{w}_4 & 1 & 2 & 4 & 0 & 2 & 2 & 3 & 2 & 2 & 4 \\ \mathrm{w}_5 & 1 & 1 & 2 & 2 & 0 & 3 & 2 & 1 & 3 & 3 \\ \mathrm{w}_6 & 1 & 4 & 2 & 2 & 3 & 0 & 2 & 2 & 1 & 1 \\ \mathrm{w}_7 & 3 & 1 & 1 & 3 & 2 & 2 & 0 & 2 & 1 & 2 \\ \mathrm{w}_8 & 2 & 4 & 3 & 2 & 1 & 2 & 2 & 0 & 4 & 2 \\ \mathrm{w}_9 & 1 & 2 & 1 & 2 & 3 & 1 & 1 & 4 & 0 & 1 \\ \mathrm{w}_{10} & 3 & 4 & 1 & 4 & 3 & 1 & 2 & 2 & 1 & 0 \end{array}\right)$$

In the provided matrix, we applied the first scenario and assumed a distribution of 70% compatibility, where 35% of the cells contain the value 1, and another 35% contain the value 2. For the incompatibility class, which makes up 30% of the entries, 15% of the cases contain the value 3, and the remaining 15% contain the value 4. And for each scenario, we generate 10 different matrices, not directly adhering to the subclasses (levels) distribution but rather to the distribution of incompatibility/compatibility classes.

In the next sections, we randomly generate different matrix of $H_{w,v}$ using the explained three scenarios.

### 3.2.2. Impact of the workers qualification on the objectives

In this section, we choose to vary $QP_{j,w}$ due to its significant impact on SS. It is important to highlight that worker qualification generates a cost. This is due to the training that workers must undergo for a certain number of hours to achieve a particular skill level.

This study consists to vary, at each step, $QP_{j,w}$ from 50% to 100%, with a step of 10% to evaluate its impact on the objectives for 10 different $H_{w,v}$. 50% means that half of the workers are qualified, while 100% means that all workers are qualified. However, when generating $QP_{j,w}$, we do not select the shifts for which the workers will be qualified. These steps are identically applied to all three different scenarios resulting in a total of 180 = 6*10*3 different instances, 6 matrices of $QP_{j,w}$ and 3 scenarios of compatibility tested on 10 instances. Throughout this process, we evaluated the effects of these changes on $f$, $f_1$, and $f_2$. This approach involves conducting the analysis by comparing results when transitioning from one percentage to another one progressively, starting from 50% means that no comparisons are made with previous levels, resulting in zero gain percentages for the objective functions generated in this case. However, in the subsequent cases, from 60% to 100%, the gain is calculated in a comparison with 50% to highlight the progression. The results are presented in Table 13.

**Table 13:** Impact of qualified workers' percentage on the objective functions through different incompatibility levels.

| **70% compatible and 30% incompatible** | | | | | | |
|---|---|---|---|---|---|---|
| ***%qualified workers*** | ***Average f2*** | ***Average f1*** | ***Average f*** | ***% of compatibility profit*** | ***% of fairness profit*** | ***% of objective function profit*** |
| **50%** | 11,76 | 13,12 | 12,53 | 0% | 0% | 0% |
| **60%** | 10,74 | 11,4 | 11,1 | 9% | 14% | 11% |
| **70%** | 8,76 | 9,8 | 9,28 | 26% | 26% | 26% |
| **80%** | 7,98 | 9,8 | 8,89 | 32% | 26% | 29% |
| **90%** | 7,63 | 9,80 | 8,74 | 35% | 26% | 30% |
| **100%** | 7,30 | 9,8 | 8,39 | 38% | 26% | 33% |
| **50% compatible and 50% incompatible** | | | | | | |
| ***%qualified workers*** | ***Average f2*** | ***Average f1*** | ***Average f*** | ***% of compatibility profit*** | ***% of fairness profit*** | ***% of objective function profit*** |
| **50%** | 10,08 | 13,3 | 11,75 | 0% | 0% | 0% |
| **60%** | 9,22 | 11,58 | 10,4 | 9% | 14% | 11% |
| **70%** | 7,56 | 9,8 | 8,68 | 25% | 27% | 26% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **80%** | 7,08 | 9,8 | 8,44 | 30% | 27% | 28% |
| **90%** | 6,58 | 9,8 | 8,19 | 35% | 27% | 30% |
| **100%** | 6,52 | 9,8 | 8,16 | 35% | 27% | 31% |
| **30% compatible and 70% incompatible** | | | | | | |
| ***%qualified workers*** | ***Average f2*** | ***Average f1*** | ***Average f*** | ***% of compatibility profit*** | ***% of fairness profit*** | ***% of objective function profit*** |
| **50%** | 14,96 | 13,42 | 14,04 | 0% | 0% | 0% |
| **60%** | 13,94 | 11,4 | 12,67 | 7% | 13% | 10% |
| **70%** | 11,52 | 9,8 | 10,66 | 23% | 25% | 19% |
| **80%** | 10,6 | 9,8 | 10,2 | 29% | 25% | 27% |
| **90%** | 9,82 | 9,8 | 9,81 | 34% | 25% | 30% |
| **100%** | 9,72 | 9,8 | 9,78 | 35% | 25% | 30% |

In Table 13, we observe that the gains of *f*, $f_1$, and $f_2$ increase proportionally with the percentage of qualified workers. This trend highlights the positive influence of qualification in the overall objective functions. Since there are several qualified workers, it is easier to find a fair scheduling with fewer incompatibilities. Notably, the increase in gain of *f* is more significant in the first scenario compared to the other scenarios indicating that the program has a greater ability to assign workers when they are more compatible, leading to higher profit gains. However, to obtain a comprehensive understanding of the impact of $QP_{j,w}$ we

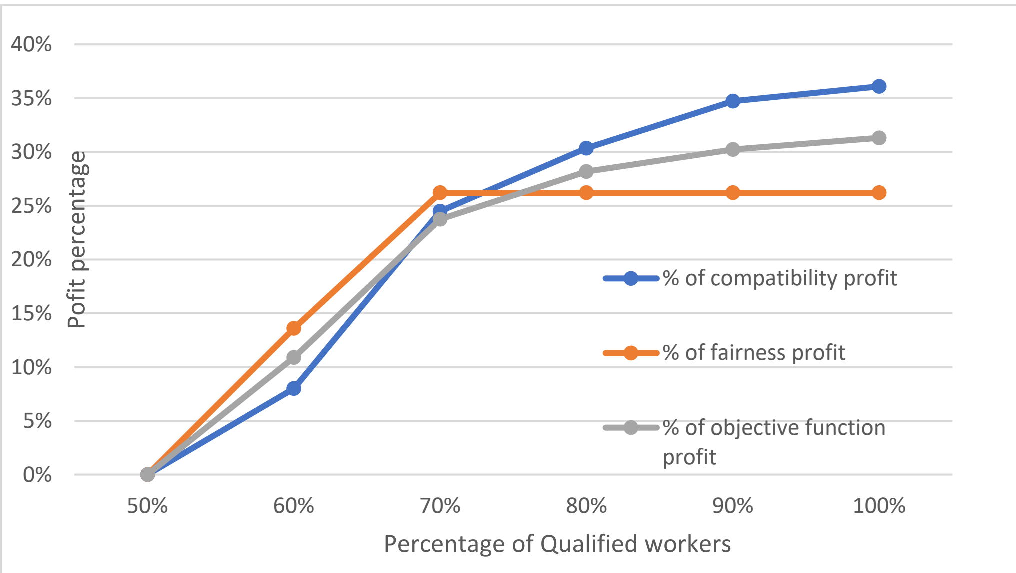



**Figure 23:**Objective function gains averaged by qualified worker percentage

have calculated the average profit gains of $f$, $f_1$, and $f_2$, for each qualification level over three scenarios.

Results are shown on Figure 23 which had illustrates that increasing qualification, from 50% to 80%, leads to a significant improvement. This can be attributed to the program's access to a larger pool of qualified workers, making it easier to find combinations of workers that can work effectively together, thus reducing compatibility issues while maximizing equity profit.

Beyond 80%, gains start to increase only marginally or may even stagnate for certain objective functions such as fairness.
This behavior could indicate either a threshold in the model's optimization is reached or meeting the boundaries of optimality, where future improvements might be marginal. In such cases, future improvements might be marginal, such as fairness, where the model has reached its limits at 70% of the qualification level, signifying its capacity to maintain an optimal workload balance and any further increase in qualifications beyond this threshold may potentially incur additional costs without significant added value in the objectives' gains.

The results show that an increase in the percentage of qualified workers generally leads to significant improvements in the objective functions. They also reveal the positive impact of the compatibility increasing on the profit's gains. However, in the real world, the distribution of $H_{w,v}$ may not always follow a predictable pattern. Factors such as personality differences, varying levels of experience, and differing skill sets can make influence on the workers' collaboration. Therefore, testing with random matrix provides decision-makers with a more comprehensive understanding of potential outcomes across diverse and unpredictable conditions they might face. To do so, we test our model using randomly generated $H_{w,v}$ and observe if we can confirm the previous curve. The outcomes of these tests are presented in Table 14.

**Table 14**:Impact of percentage of qualified workers on the objective functions

| *% of qualified workers* | *Average f2* | *Average f1* | *Average f* | *% of compatibility profit (f2)* | *% of fairness profit (f1)* | *% of objective function profit (f)* |
|---|---|---|---|---|---|---|
| **50%** | 11,45 | 10,8 | 11,0 | 0% | 0% | 0% |
| **60%** | 10,08 | 5,38 | 7,85 | 12% | 50% | 29% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **70%** | 8,65 | 5,4 | 7,02 | 24% | 50% | 36% |
| **80%** | 8,14 | 5,4 | 6,77 | 29% | 50% | 39% |
| **90%** | 7,66 | 5,4 | 6,53 | 33% | 50% | 41% |
| **100%** | 7,56 | 5,4 | 6,48 | 34% | 50% | 41% |

According to Table 14, we observe similar behavior when $H_{w,v}$ is predefined, with the gain increasing proportionally to the number of qualified workers. This trend is further supported by Figure 24, which shows curves remarkably similar to those in Figure 23. However, fairness reaches its threshold at 60% of qualified workers in this case, compared to 70% in the previous analysis. Therefore, the random nature of $H_{w,v}$ introduces greater uncertainty in predicting specific levels of gains, making it challenging for decision-makers to pinpoint exact outcomes.

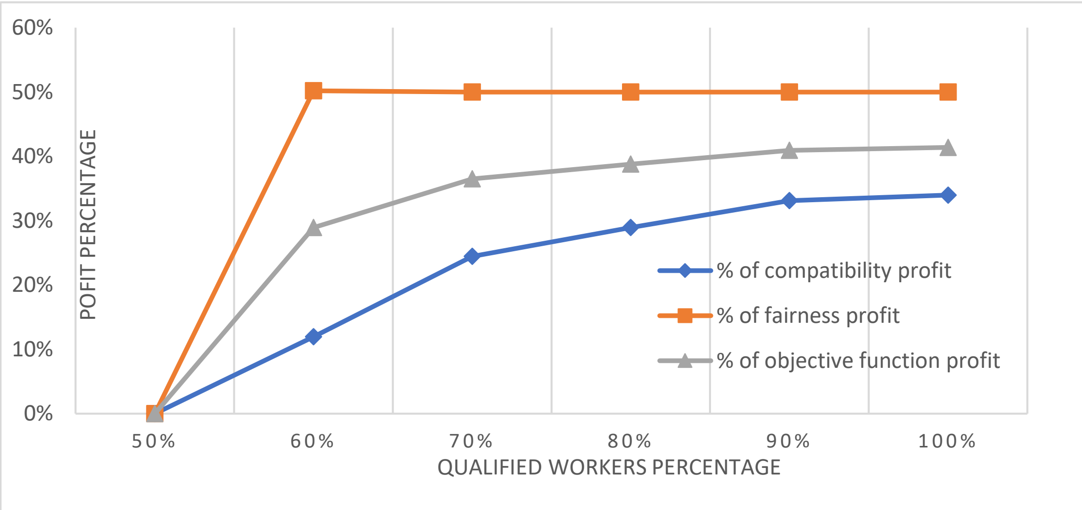



**Figure 24**:Average gains of objective functions using random instances of $H_{w,v}$

The comparison highlights that predefined scenarios provide clear trends but may not capture real-world complexity, while random matrix provides a more realistic but introduce uncertainty in predicting specific outcomes.

Although our previous study reflects general trends and directions, it does not fully explore the limits of the model and the factors that could increase its complexity. This will be elaborated in Section 4.2.3.

#### 3.2.3. Exploring the impact of workers number and incompatibility levels on the execution time

As a fundamental parameter in SS, the number of workers is a key factor whose importance extends far beyond the composition of work teams. In this study, we analyze who this number impacts the execution time. So, Table 15 presents the execution time in second for different $W$ in the 3 scenarios.

**Table 15:** Number of workers and incompatibility levels impact on execution time

| | $W$=9 | $W$=10 | $W$=11 | $W$=12 | $W$=13 | $W$=14 |
|---|---|---|---|---|---|---|
| | **Execution Time (Second)** | | | | | |
| **70% compatibility, 30% incompatibility** | 2.19 | 3.36 | 9.09 | 86.84 | 694.25 | 79085 |
| **50% compatibility, 50% incompatibility** | 2.21 | 4.37 | 31.12 | 100.56 | 870.23 | > 24h |
| **30% compatibility, 70% incompatibility** | 2.30 | 7.28 | 43.37 | 165.25 | 2431.1 | > 24h |

In this study, we assumed that all workers were fully qualified and investigated how varying the number of workers, under the three different compatibility scenarios, impacted the execution time of the program. We established a baseline of 9 workers, determined by input data constraints, and then iteratively increased this number to 14. For each problem size, we consistently applied the same parameters that already used in the previous section. Table 15 shows that execution time proportionally increases with the number of workers. The execution time is also influenced by the level of incompatibility, it is noticeable that as the number of incompatible workers increases, the execution time extends eventually reaching a stopping point when $W$ =14. For the first scenario, an execution time of 79085 seconds was recorded. However, for the subsequent scenarios, the running time surpassed 24 hours without producing any results, making further continuation of the process impractical. To confirm the trend observed in Table 15, we can refer to Figure 25, which shows the curve of execution time in function of worker size and incompatibility levels.

Figure 25 reveal that higher incompatibility results in longer execution times. For example, when $W$= 12, an execution time of 86.846 seconds is recorded when 70% of workers are compatible. However, when only 30% of workers are compatible, the execution time increases significantly to 165.250 seconds. This trend is observed across all problems size, suggesting that the optimization process becomes increasingly complex as worker incompatibility increases, leading to longer execution times.

Figure 25 not only illustrates the impact of incompatibility on the execution time but also demonstrates the effects of increasing the workforce size since the time scale increase at each case of $W$. To further clarify this relation, Figure 8 presents the average execution times of the three different scenarios, for each case of $W$, from 9 to 13 workers.

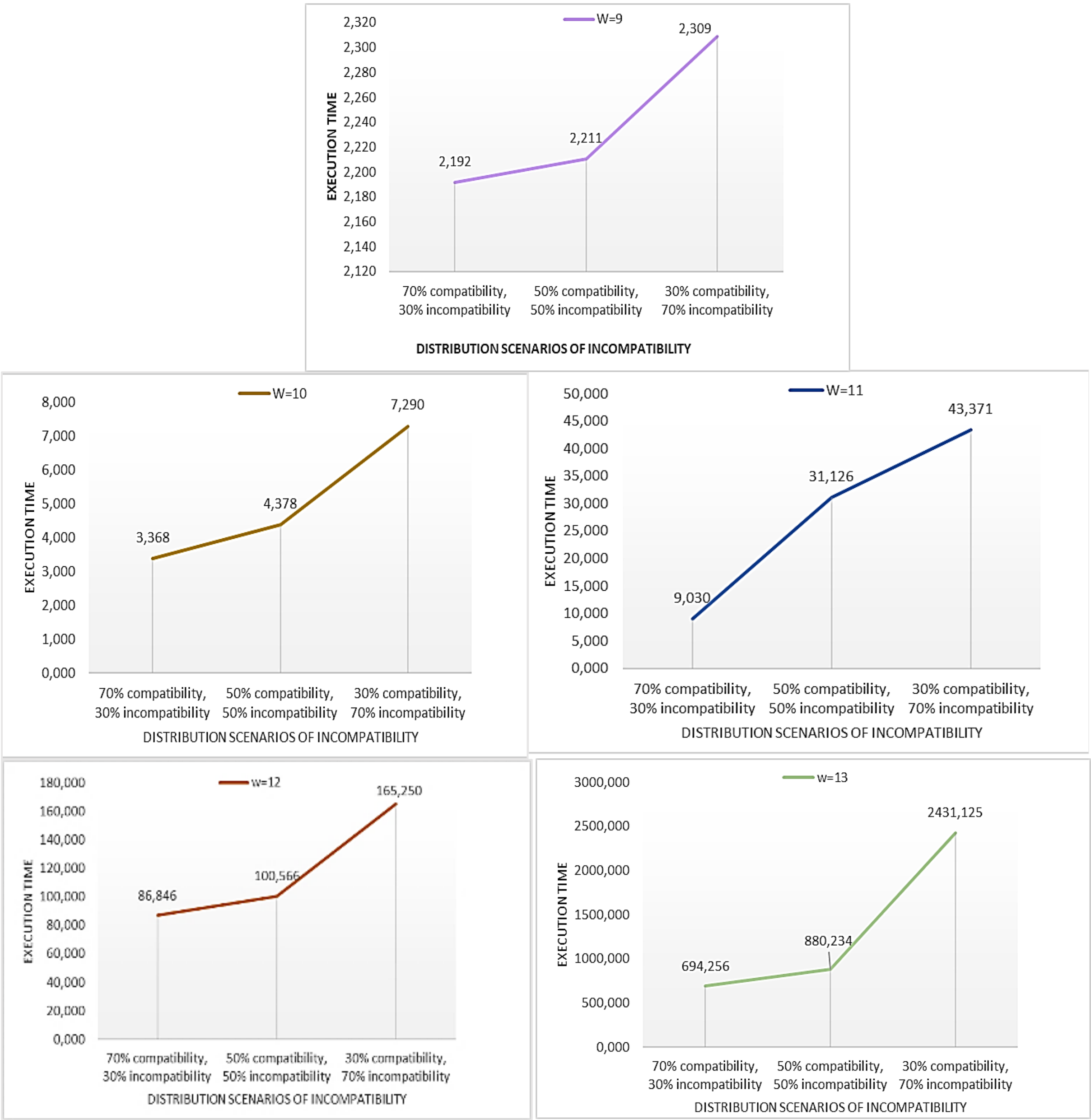



**Figure 25:**Illustration of execution time variations based on the number of workers and their compatibility

The idea behind averaging the execution time is to mitigate the potential ambiguity caused by the significant deviation of execution time values across different scenarios for each workforce size. This deviation makes it difficult to align these values on the same scale, leading to potential ambiguity in interpreting the curve.

As illustrated in Figure 26, the execution time tends to increase as the number of workers grows, particularly when $W$=13, resulting in an execution time of 1335.20 seconds. This phenomenon can be attributed to two factors. Firstly, a larger workforce leads to an exponential increase in possible combinations to evaluate, necessitating more computational time or demanding greater computational resources. Secondly, the input data also has an

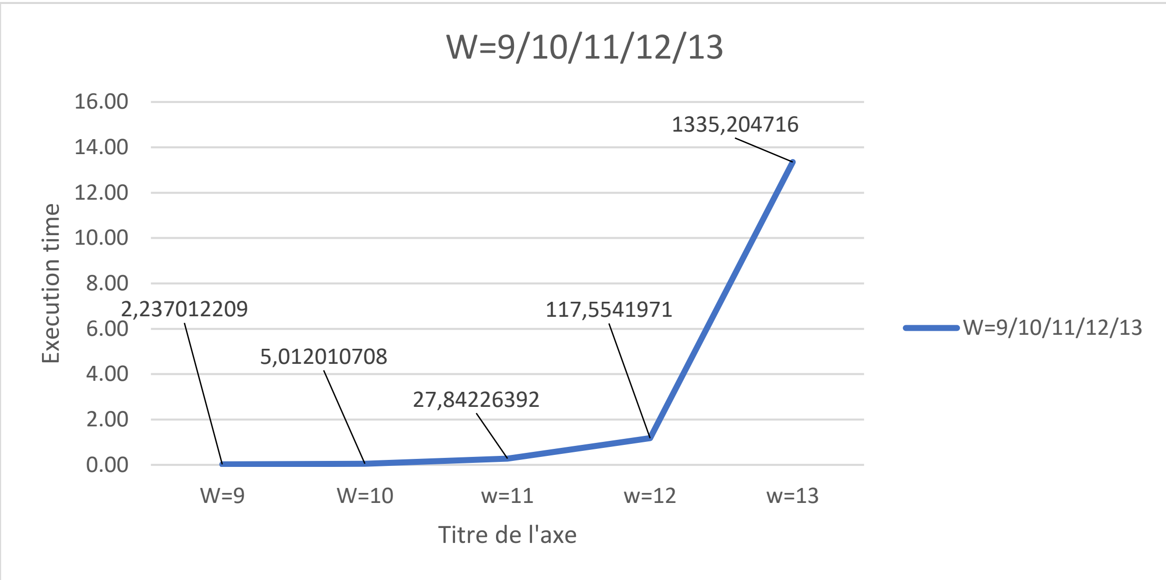



**Figure 26:** Worker size effect on execution time (average across three scenarios)

impact on the solution, as working with fewer instances makes it increasingly complex to distribute workers throughout the horizon and shifts while respecting constraints and meeting the objectives.

## Conclusion

This chapter presents a novel model for staff scheduling problem in the maritime transportation sector, which is based on a real-world case study and can be adapted to other domains due to its generic nature. The novelty of this work lies in the incorporation of worker incompatibilities as an objective, while also prioritizing workload fairness and adhering to various constraints, such as qualifications, rest hours, the number of workers per shift, and days off. This problem is mathematically formulated as a Mixed Integer Linear Programming (MILP) model, implemented using XPRESS solver and complemented by experimental results that evaluate the model's performance under varying parameter adjustments.

The main conclusions are as follows:

- Increasing the number of qualified workers typically results in significant improvements in gains, but these gains can reach a limit at a certain worker qualification level. Further increases in qualification beyond this threshold may incur costs without adding value to the gain profit.
- Ensuring compatibility between workers has a positive impact on profits. This influence was observed in two studied cases, randomly generated compatibility matrices and predefined compatibility scenarios. Thus, the predefined scenarios offer clear interpretations but may not reflect real-world complexity, while the random matrices case provides a more realistic assessment but introduce uncertainty in predicting the level of gain profit that a decision maker could.
- Execution time can increase not only with the growing number of workers but also with incompatibility between them, leading to excessive execution times or even the inability to find a solution for certain group sizes of workers.

The development of a mathematical model was essential to gain a deep and precise understanding of the problem at hand. Demonstrating that the problem is NP-hard provided a theoretical foundation justifying the subsequent use of approximative methods. This foundation not only strengthens the credibility of our solutions but also facilitates effective validation and benchmarking. In the next chapter, we delve into the heuristic technique used and compare the results with the insights gained from our mathematical formulation.

# Chapter 5: Heuristic Approach for Seafaring Staff Scheduling

## Introduction

In light of the complexities discussed in previous chapters, particularly the NP-hard nature of the crew scheduling problem and the limitations of exact methods in providing solutions within a practical timeframe, the need for an alternative approach becomes evident. To address the scalability and flexibility required for real-world applications, this chapter introduces a heuristic method designed to efficiently assign workers to shifts while adhering to operational constraints.

## 1 Heuristic Design and Workflow

The heuristic algorithm developed in this work aims to efficiently assign eligible workers to shifts as time advances until the final time $T$ is reached. When a shift is identified on the horizon, the assignment process begins and workers are chosen from a dynamic list of eligible workers, noted as $W_{var}$. This list is updated based on the specific requirements of that shift and should include only those workers who are eligible for assignment. The algorithm then tries to satisfy objectives such as minimizing incompatibility among workers assigned to the same shift and ensuring fairness in workload distribution when selecting from $W_{var}$. The steps involved in this process are detailed in the flowchart presented in Figure 27.

1) **Initialization**:

   The process begins with the initialization of variables:

   - ✓ *W:* This is the initial list that contains all workers.
   - ✓ *J:* all shifts initially predefined but no worker is yet assigned
   - ✓ *t:* the current time unit which is set to 0 initially marking the begin of the horizon and increments with each step of the algorithm.
   - ✓ *T:* This variable denotes the finish unit time of the horizon. It represents the total time frame or limit within which all tasks, shifts, or assignments must be completed.

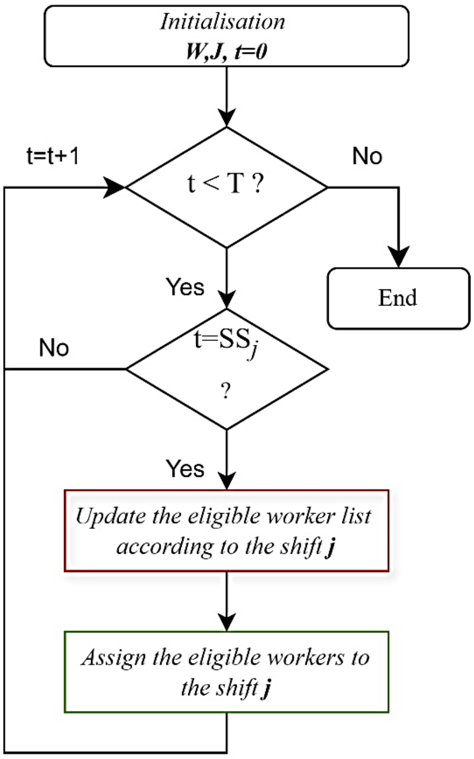



**Figure 27:** Heuristic flowchart

2) **Check Current Time Against Total Time**:

The flow proceeds to check if $t$ is less than $T$. This check acts as a boundary condition. It ensures that the algorithm does not proceed beyond the defined time frame which is essential for preventing errors, such as attempting to assign workers or tasks outside of the valid scheduling period.

- ✓ If **Yes**: The process continues to the next step.
- ✓ If **No**: The process terminates, leading to the end of the flow.

3) **Check Current Time Against Shift Start Time**

The next decision point verifies whether $t = SS_j$, which indicates the start time of shift $j$. This condition marks the beginning of the assignment process for that particular shift.

- ✓ If **Yes**: The flow proceeds to update the list of eligible workers.
- ✓ If **No**: The flow loops back to increment t by 1 and checks again (step 2).

4) **Update Eligible Workers**

When time progresses, the list of Eligible workers noted as $W_{var}$ should be updated according to the specific requirements of shift j through several setup:

- ✓ ***Initial Setup:*** $\boldsymbol{W_{var}}$***= W , t = 0 ut:*** This marks the start $t$ of the planning period, although assignments may not begin immediately, as the first shift could occur after *t =0 ut*. At this stage, all workers ***W*** are included in $\boldsymbol{W_{var}}$, since there are no prior assignments.
- ✓ ***Dynamic Update: t =*** $\boldsymbol{SS_j}$ ***,*** $\boldsymbol{W_{var}}$***= W-***$\boldsymbol{\overline{W}}$ ***:*** As time progresses towards $t$, reaching the **S**tart of the **S**hift ($SS_j$), indicating the start of it and the assignment for this shift begins. $\boldsymbol{W_{var}}$ is updated by removing workers who do not meet the constraints for shift $j$, represented as $\boldsymbol{\overline{W}}$. For every shift $\boldsymbol{W_{var}}$ is always equal to ***W***, ensuring that all workers undergo an eligibility check for every shift**.**
- ✓ ***Final setup: t = T ut:*** At *t = T ut*, the allocation process concludes, marking the end of the planning horizon T. By this time, all workers have been assigned, and $W_{var}$ becomes static, reflecting the final state after all assignments and eligibility checks are completed.

5) **Assign Workers to Shift**

Following the update, the algorithm continues to assign workers to shift $j$ from $W_{var}$ until he reaches the required number of workers per shift (NRP), while adhering as much as possible to fairness and compatibility.

6) **Final Check**: I**ncrement t and Check Again**:

After the workers are assigned, the program increments t by 1 and verify if is still less than T.

- ✓ If **Yes**: the loop continues and the program checks the next shift or waits for the right time to assign workers to the next shift.
- ✓ If **No**: The program ends when t ≥T, meaning the total time or iteration limit has been reached, and all shifts that were scheduled have been assigned workers.

The heuristic outlined in the flowchart consists of two principal steps. The first step involves updating the list of eligible workers $W_{var}$, to ensure adherence to various constraints by filtering the initial list of workers (presented in red color in figure 27). The second step focuses on assigning workers from the updated $W_{var}$ while striving to meet defined objectives (outlined in green color in figure 27). However, each of these main steps encompasses several sub-steps that detail the specific actions needed to achieve the overall goals of the heuristic, including checks for availability and qualifications, as well as evaluating compatibility scores for optimal assignments.

### 1.1 Updating the Eligible Workers List

Updating the list involves adding and removing workers based on specific constraints, ensuring that only those who meet the shift requirements are included. The dynamic list $W_{var}$ changes according to the specific requirements of each shift. A flowchart (figure 28) illustrates the decision-making process for selecting workers eligible to be assigned on a shift $j$ based on a series of conditions and steps as mentioned below:

1. **Initialization (w = 1):**

The process starts by initializing the worker index $w$ to 1. This indicates the first worker in the list or set of workers to be evaluated. $W_{var}$ is updated with adding the worker who satisfy all the criteria, meaning he is eligible to be assigned to the task.

2. **Qualification Check:**

   *Condition:* Is the worker qualified for the shift $j$ ?

   - ✓ **If** Yes: Proceed to the next condition.
   - ✓ **If** No: Worker will be not included on $W_{var}$ and moved to $\overline{W}$.

3. **Rest Period Check:**

   *Condition:* Has the worker completed the required rest period (Bmin) between his previous and current shift?

   - ✓ **If** Yes: Continue to the next condition.
   - ✓ **If** No: Worker will be not included on $W_{var}$ and moved to $\overline{W}$.

4. **Already Assigned Check:**

   *Condition:* Is the worker not already assigned to another shift on that day?

   - ✓ **If** Yes: Continue to the next check.

✓ **If** No: Worker will be not included on $\boldsymbol{W_{var}}$ and moved to $\overline{\boldsymbol{W}}$**.**

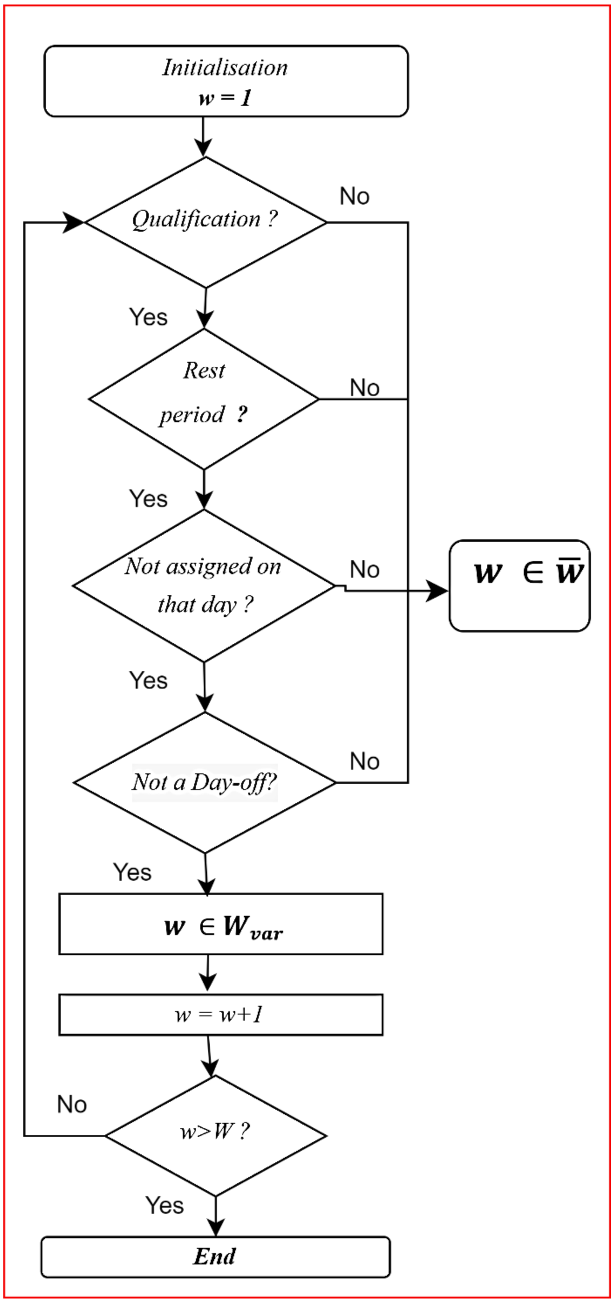



**Figure 28**: Updating the Eligible Workers List $\boldsymbol{W_{var}}$ Flowchart

**5. Day-Off Check:**

*Condition:* Is the worker not on a day off?

✓ **If** Yes: The worker is valid and should be included in $\boldsymbol{W_{var}}$**.**

✓ **If** No: Worker will be not included on $W_{var}$ and moved to $\overline{\boldsymbol{W}}$.

**6. Update Worker List:**

If all the constraints are satisfied, the worker is added to the list of eligible workers $W_{var}$, meaning that he could to be assigned to the task.

7. **Move to the Next Worker ($w = w + 1$):**

   The index $w$ is incremented to check the next worker in the list.

8. **Check End of Worker List (w > W?):**

   *Condition:* Have all workers been evaluated?

   - ✓ **If** Yes: End the process.
   - ✓ **If** No: Return to the qualification check and repeat the process for the next worker.

The objective of this process is to generate a list of workers who have satisfied all the constraints set by the decision-maker and eligible for assignment to Shift j.

### 1.2 Assignment Considering Objectives

At this stage, workers to be assigned to shift $j$ should be chosen from the pre-established list $W_{var}$, which takes all relevant constraints into account. The selection process prioritizes achieving objectives such as workload fairness and minimizing conflicts among workers assigned to the same shift. This means we will aim to select as many workers as possible who help meet these objectives effectively.

This step is highlighted in green on the principal heuristic flowchart (Figure 27). However, this step consists of several underlying sub-steps, which are detailed in the flowchart (Figure 29) and outlined afterward:

1) **Use the Pre-filtered List of Eligible Workers $W_{var}$**

   The primary purpose of this step is to initialize the process with a list of workers that have already been determined to be eligible for assignment.

2) **Calculate the Deviation of each Eligible Worker**

   For fairness, each worker's deviation is calculated. This deviation represents how far a worker’s current assignment count is from an equitable workload.

   - ✓ *Implementation:* The deviation is computed using the formula of deviation:

$$\boldsymbol{Deviation} =: \frac{\boldsymbol{Number\ of\ \ assignments\ of\ each\ worker\ on\ a\ category\ of\ shift}}{\boldsymbol{ANA_l}}$$

*$ANA_l$ is the average number of assignments per shift type. The goal is to prioritize workers who are under-assigned.

**3) Sort the Workers by Deviation**

To ensure equitable assignment, workers on $W_{var}$ list are sorted based on their deviation in ascending order. Workers with the least deviation (those who have been assigned the fewest shifts) are prioritized for assignment.

**4) Assign the First Worker with the Minimum Deviation to the Current Shift**

The algorithm begins by assigning the first worker for the shift, specifically the worker with the lowest deviation, who is implicitly the first one on the sorted $W_{var}$ list.

**5) Find a Partner for the First Worker**

The algorithm assigns workers in pairs for each shift. After assigning the first worker, the algorithm looks for a compatible partner among the remaining eligible workers. fairness (deviation) is the second factor considered in selecting a partner after Compatibility. This process is made in three steps:

- ✓ ***Step 1: Calculate the Incompatibility Score for Each Remaining Worker:*** For each remaining worker, an incompatibility score is computed using the incompatibility matrix $H_{w,v}$which measures their compatibility with the initially selected worker. A lower score indicates a higher level of compatibility.
- ✓ ***Step 2: Sort Potential Partners by Incompatibility:*** After extracting incompatibility scores for all remaining workers, the potential partners are sorted in ascending order of incompatibility. This ensures that the algorithm selects the most compatible partner for the initially selected worker.
- ✓ **Step 3: *Select the First Partner with Minimum Incompatibility and Deviation:*** The partner with the lowest incompatibility score is selected as a partner. If there are multiple workers with the same compatibility score, the one with the least deviation from the ideal partner is chosen.

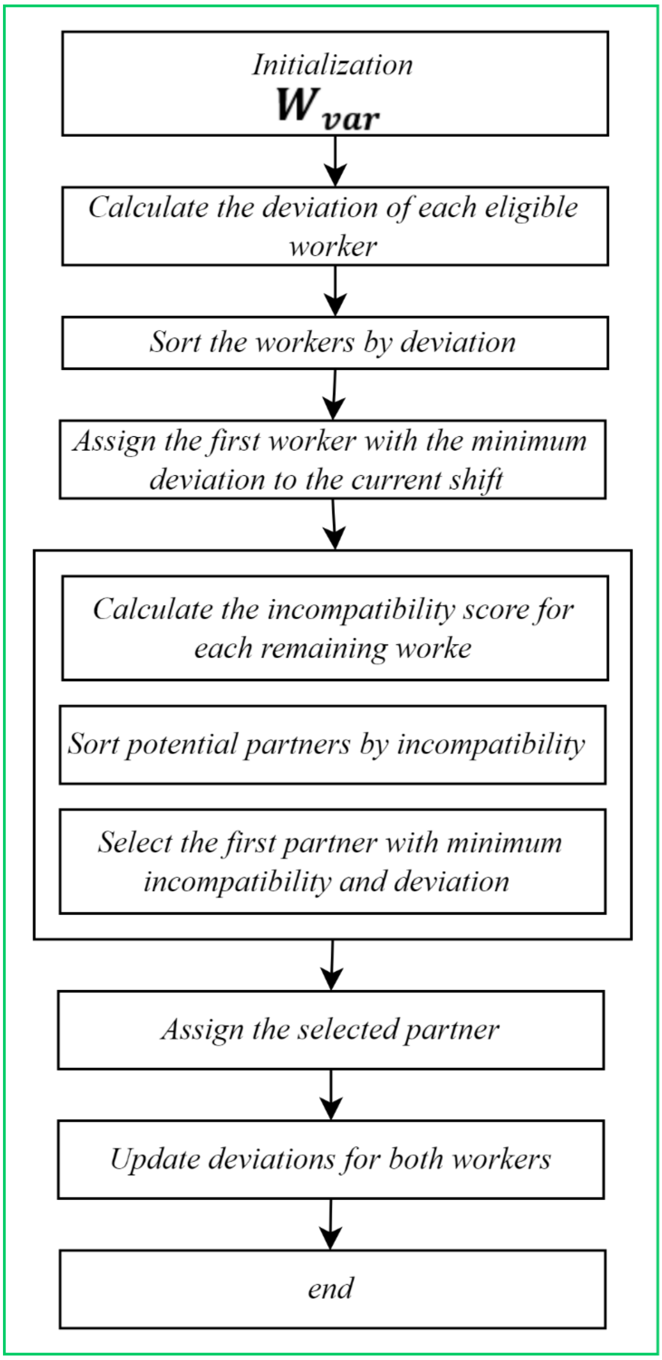



**Figure 29:** Flowchart for assignment process

### 6) Assign the Selected Partner

Once partner is founded the next step is to be assigned to the same shift as the initially selected worker.

### 7) Update Deviations for Both Workers

After assigning both workers to the shift, their deviations need to be recalculated based on their new total number of assignments.

Having established the allocation process, the next step is to test our algorithm on a specific example to ensure its validity. Testing the algorithm in a practical scenario allows us to evaluate its adherence to the defined constraints and objectives.

## 2 Validation of the proposed heuristic

Our heuristic is validated through an example, in figure 30, that illustrates $W_{var}$?, processes through the assignment of shifts. Given that this list is the cornerstone of our work, its dynamicity depends on the constraints of each shift. The algorithm has been coded in Python and executed on a laptop equipped with an Intel Core i7-10700K processor, boasting a clock speed of 3.80 GHz (3792 MHz), 8 physical cores, and 16 logical processors, supported by 32GB of RAM, and running on the Windows 10 operating system.

To start we need to initialize instances and inputs as mentioned below:

**Table 16:** Example instance for testing and validating Heuristic

| | |
|---|---|
| *I* | 3 |
| *J* | 4 |
| *W* | 4 |
| *L* | 2 |
| *NRP* | 2 |
| *Bmin* | 8 |
| *Alpha* | 0.5 |

$$\boldsymbol{QP_{j,w}} \quad \begin{array}{c|cccc} & w_1 & w_2 & w_3 & w_4 \\ \hline j_1 & 1 & 1 & 1 & 4 \\ j_2 & 1 & 1 & 1 & 1 \\ j_3 & 1 & 1 & 1 & 1 \\ j_4 & 1 & 1 & 1 & 1 \\ j_5 & 1 & 1 & 1 & 1 \end{array} \qquad \boldsymbol{H_{w,v}} \quad \begin{array}{c|cccc} & w_1 & w_2 & w_3 & w_4 \\ \hline w_1 & 0 & 4 & 1 & 1 \\ w_2 & 4 & 0 & 1 & 1 \\ w_3 & 1 & 1 & 0 & 1 \\ w_4 & 1 & 1 & 1 & 0 \end{array}$$

Initially, before proceeding with the assignments, $\mathrm{W_{var}}$ contain all workers $\mathrm{w_1}$, $\mathrm{w_2}$, $\mathrm{w_3}$, and $\mathrm{w_4}$, assuming that all workers are eligible since no prior assignments have been made. This list will be updated as the process progresses according to each shift requirement(s) :

- ***Shift 1:*** the pool of eligible workers $\mathrm{W_{var}}$ is limited to $\mathrm{w_1}$, $\mathrm{w_2}$, $\mathrm{w_3}$, as $\mathrm{w_4}$ do not meet the qualification criteria (constraint (1)). The algorithm selects $\mathrm{w_1}$, and $\mathrm{w_3}$ are selected for assignment due to their lowest incompatibility score of 1, even though $\mathrm{w_2}$ and $\mathrm{w_3}$ could also form a suitable pair.

The algorithm prioritizes $w_1$ based on its selection logic. The choice of $w_1$ as the first worker to assign is due to the calculation of deviations among workers in $W_{var}$. The workers are sorted in ascending order of deviation, so the one with the lowest deviation appears first on the list and is chosen for the shift. Initially, all deviations are zero, making $w_1$ the first in the list for assignment.

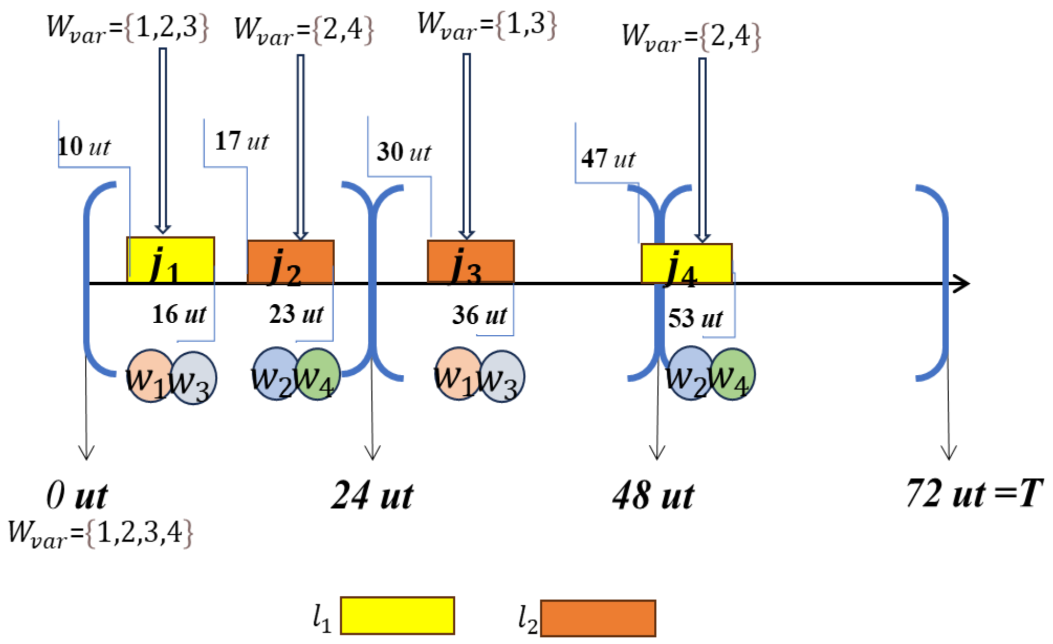



**Figure 30:** Heuristic validation through constraints and objectives

- ***Shift 2:*** For Shift 2, only $w_2$ and $w_4$ remain in $W_{var}$ since $w_1$ and $w_3$ have already been assigned to Shift 1, which occurred on the same day as Shift 2. This adheres to constraint (2).

- ***Shift 3:*** In Shift 3, $W_{var}$ contains $w_1$ and $w_3$ because the minimum rest period Bmin is not satisfied with the assignments from Shift 2. This validates constraint (9).

- ***Shift 4:*** It is crucial to note that Shift 4 is considered to belong to the day 2, rather than the third day, due to the model's assumption that shifts beginning on day (*i)* and ending the next day (*i+1*) are classified under the day (*i+1*). Only $w_2$ and $w_4$ remain in $W_{var}$ since $w_1$ and $w_3$ are assigned to two consecutive days, rendering them ineligible for the third day, which serves as a Day-off (Constraint 5).

The validation of our proposed heuristic has shown that it can successfully manage worker assignments while meeting specified constraints. To further assess the heuristic's performance, we conduct in the next section a benchmarking analysis comparing it to the exact method.

## 3 Benchmark with exact method

A benchmarking process is essential for assessing the effectiveness of our algorithm. The primary goal is to determine how closely the heuristic can replicate the results obtained by the exact method while considering various performance metrics such as, $f, f_1$ , $f_2$, and computation time. Both approaches utilize the same set of instances, as detailed in Section 3.2.1 of Chapter 4.

In this analysis, we focused on a single example scenario to evaluate the performance of the heuristic method against the exact method. The primary aim of this comparison is to check the validity of the heuristic approach in achieving acceptable objective function values in a reasonable computation time rather than to guide a decision-maker in evaluating qualifications or making operational decisions.

### 3.1 Comparative Study of Objective Function Metrics

This section provides a comparison of the objective function values produced by the Exact Method (yellow color) and the Heuristic Approach (green color), focusing on instances where 50% and 100% of the workers are qualified. The goal is to evaluate the accuracy of the heuristic method in approximating the exact method's results and to identify whether it follows a similar pattern in minimizing objective values as compatibility and qualification levels change. The comparison is presented across the three compatibility levels.

Table 17 showcases the performance of each method in terms of these metrics, emphasizing the differences in results and the heuristic's closeness to the exact method's solutions.

**Table 17:** Benchmark of Objective Function: Exact Method (yellow) vs. Heuristic Approach (green) Across Compatibility Scenarios

| **70% compatible and 30% incompatible** | | | |
|---|---|---|---|
| | $\boldsymbol{f_2}$ | $\boldsymbol{f_1}$ | $\boldsymbol{f}$ |
| 50% qualified | 11,9 | 14,869 | 13,389 |
| | 11,76 | 13,12 | 12,53 |

| | | | |
|---|---|---|---|
| 100% qualified | 9,6 | 14,55 | 12,939 |
| | 7,30 | 9,8 | 8,39 |
| **50% compatible and 50% incompatible** | | | |
| | $f_2$ | $f_1$ | $f$ |
| 50% qualified | 13,4 | 16,62 | 14,869 |
| | 10,08 | 13,3 | 11,75 |
| 100% qualified | 10,2 | 16,39 | 13,418 |
| | 6,52 | 9,8 | 8,16 |
| **30% compatible and 70% incompatible** | | | |
| | $f_2$ | $f_1$ | $f$ |
| 50% qualified | 16,199 | 18,838 | 17,487 |
| | 14,96 | 13,42 | 14,04 |
| 100% qualified | 13,1 | 17,236 | 14,986 |
| | 9,72 | 9,8 | 9,78 |

### 3.1.1 Overall Trend

In the overall comparison, both the Exact Method and the Heuristic Approach demonstrate similar trends in minimizing the objective function. The heuristic method, although not as precise as the exact method, provides results that are relatively close. There is a consistent variation between the two methods, which becomes more noticeable as the levels of qualification and compatibility change.

### 3.1.2 Impact of Compatibility Scenarios

As shown in Figure 31, the objective function is minimized when a larger proportion of workers are compatible. For example, in the scenario where 70% of workers are compatible and 30% are incompatible, the value of $f_1$ is 10.75, compared to 14.64 when only 30% are compatible. The total objective function increases from 13.164 to 16.213 as incompatibility rises.

In this case, the heuristic approach performs more closely to the exact method, benefiting from the larger pool of compatible workers. This scenario allows for more opportunities to find optimal worker combinations with minimal incompatibility, resulting in a lower objective function. However, as compatibility decreases (e.g., 50% or 30% compatible), the objective function increases due to the reduced pool of compatible workers, making it more difficult to find optimal or near-optimal assignments.

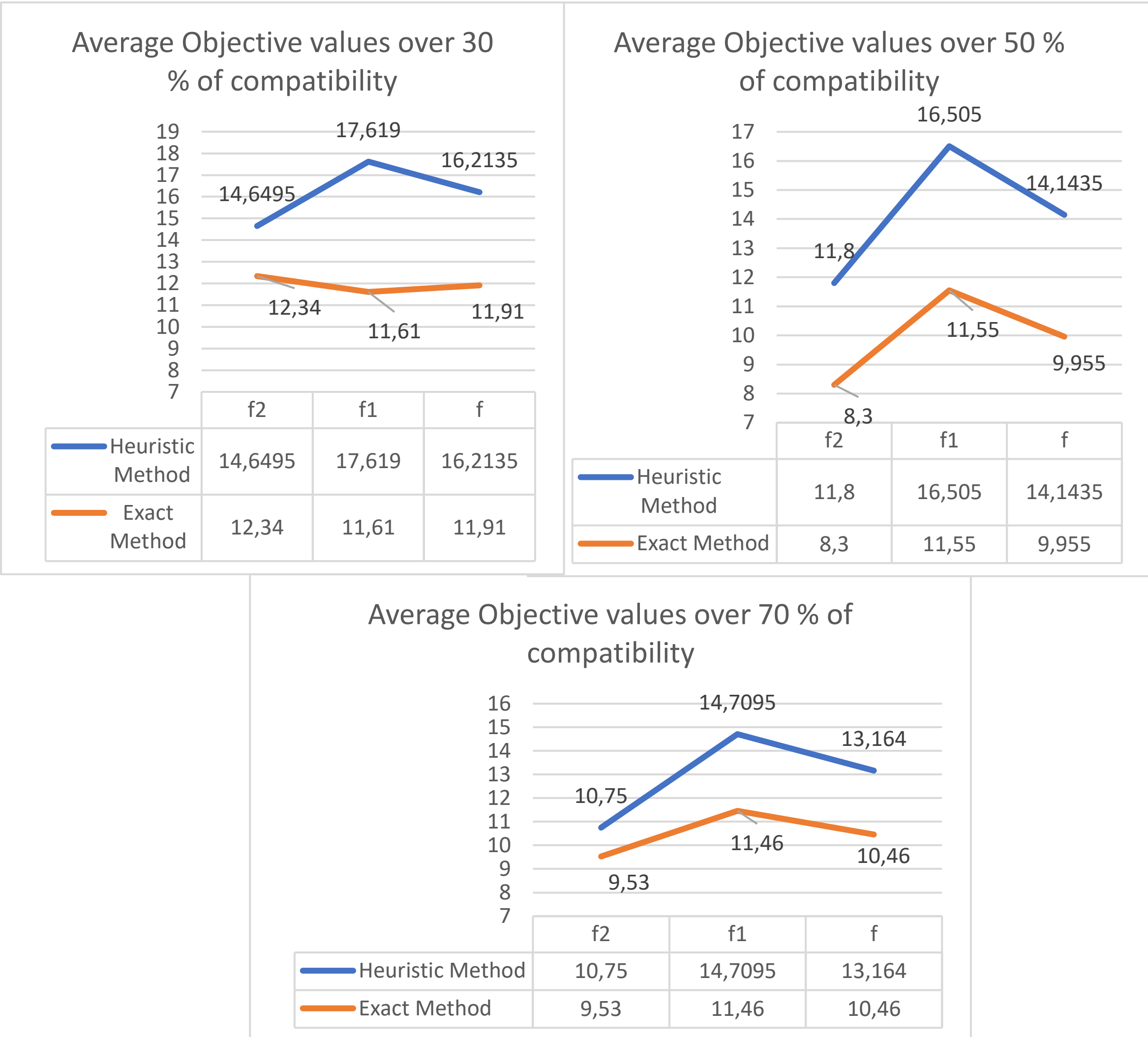



**Figure 31**:Average objective function values over the three different scenarios

It is worth noting that the values presented on the graph are calculated as the average of the objective function values at both 50% and 100% worker qualification levels across each scenario.

### 3.1.3 Effect of Qualification Increasing

Figure 32 illustrates the objective function values averaged over three different Compatibility scenarios. When worker qualification increases from 50% to 100%, the objective function values tend to decrease for both methods. The comparison between 50% and 100% qualified workers shows that the exact method consistently outperforms the heuristic method in both cases, but the performance gap narrows as the number of qualified workers increases.

For example, at 50% qualification, the heuristic yields a higher average objective value for $f_2$ with 13.83, compared to 10.97 when 100% are qualified, indicating difficulty in finding optimal solutions with fewer qualified workers. However, with 100% qualified workers, the heuristic performs closer to the exact metho, as it benefits from the larger pool of qualified workers, allowing for more optimal assignments.

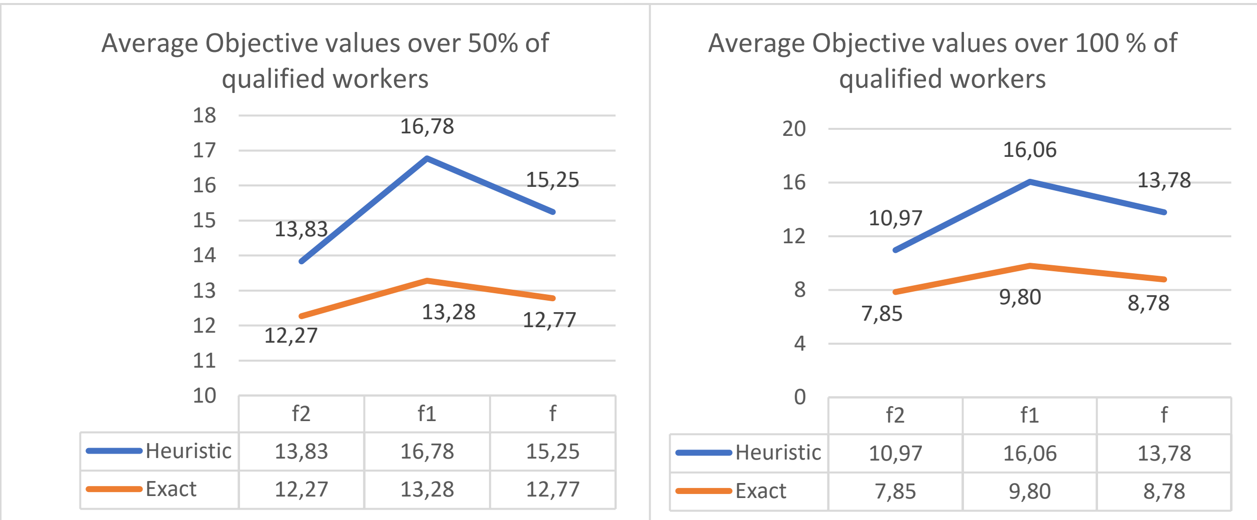



**Figure 32**: Average Objective Values Across Worker Qualification Levels

In the overall comparison, both methods demonstrate similar trends in minimizing the objective function. Although not all qualification levels are evaluated, since the primary objective is not to provide managerial insights but to confirm the trend in how the objective function decreases or increases as qualification levels rise,

### 3.1.4 Key Insights from Metrics Comparison

The results showcase overall similar trends between the exact and heuristic methods, with relatively close values in many cases. However, in some scenarios, the exact method shows a much larger decrease in the objective function compared to the heuristic method. This can be attributed to several factors:

- *Global Optimization:* the exact method seeks the optimal solution by considering all possible combinations and adjusting constraints like equity and compatibility in a balanced and comprehensive way. It explores all potential assignments and finds the one that minimizes differences in workload or task allocation most effectively, which explains the lower objective value.
- *Sequential Decision-Making:* the Heuristic Approach focuses on faster, sequential decisions. It prioritizes one criterion (e.g., assigning the least worked worker) and then moves on to the next (e.g., selecting based on compatibility). However, these decisions are treated separately and are not necessarily optimized together.

As a result, the heuristic may settle for a suboptimal solution, as it does not always adjust for the global set of constraints at once. This can lead to a higher objective function value than the exact method, even when 100% of workers are qualified, as observed with the heuristic producing a higher value of **16.**06 compared to **9.8** with the exact method.

The Exact Method and the Heuristic Approach share similar trends in minimizing the objective function, making execution time a critical metric to evaluate. Demonstrating that the heuristic yields comparable objective values is essential, as the heuristic method is specifically designed to deliver faster solutions while preserving a close approximation to the exact method's performance.

## 3.2 Computation Time Comparison

In this section, we analyze the computation times associated with both the Exact Method and the Heuristic Approach under a scenario where 100% of the workers are qualified. The comparison focuses on the execution times across various worker sizes, ranging from 9 to 14 workers, as presented in Table 18.

**Table 18.** Computation Time: Exact Method vs. Heuristic Approach

| 100% of qualified workers | W=9 | W=10 | W=11 | W=12 | W=13 | W=14 |
|---|---|---|---|---|---|---|
| | Execution Time (Second) | | | | | |
| Heuristic | 0,01631 | 0,01879 | 0,02099 | 0,02244 | 0,02451 | 0,02484 |
| Exact Method | 2.21 | 4.37 | 31.12 | 100.56 | 870.23 | > 24h |

The comparison of execution times between the Exact Method and the Heuristic Method reveals stark differences in performance as the worker size increases from 9 to 14. The heuristic method demonstrates impressive efficiency, with execution times remaining within fractions of a second even as the number of workers grows. In contrast, the Exact Method experiences an exponential increase in execution time without yielding a solution is such cases. For $W = 9$, the heuristic method executes in just 0.01631 seconds, significantly faster than the Exact Method at 2.21 seconds. At $W = 10$, the heuristic remains efficient at 0.01879 seconds, while the Exact Method nearly doubles to 4.37 seconds. The gap widens at $W = 11$ with the heuristic at 0.02099 seconds compared to 31.12 seconds for the Exact Method. By $W = 12$, the Exact Method exceeds 100 seconds, while the heuristic stays stable at 0.02244 seconds. For $W = 13$, the Exact Method's performance deteriorates to 870.23 seconds (about 14.5 minutes), whereas the heuristic remains efficient at 0.02451 seconds. Finally, at $W = 14$, the Exact Method fails to provide results in under 24 hours, while the heuristic completes the assignment in just 0.02484 seconds. For the maximum worker size, the exact method fails to produce a result within a reasonable timeframe, exceeding 24 hours. Meanwhile, the heuristic remains stable, completing the assignment in less than a quarter of a second.

Our heuristic has proven its value not only in terms of generating objective function values that are close to optimality but also in its remarkably low execution times, making it a practical option for decision-makers.

Our heuristic approach has demonstrated its ability to balance the quality of objective values and execution time. Although it tends to sacrifice some accuracy for faster solutions compared to the exact method, it still provides reasonably accurate objective values while substantially decreasing computation time. Consequently, the heuristic method emerges as a practical alternative when prioritizing speed is essential.

Even though we have not yet tested our heuristic on very large instances, the results obtained are still highly satisfactory. We have demonstrated that, when the exact method faced difficulty in finding a solution for an instance with $W$ =14 our heuristic was able to generate a solution in just 0.024 seconds. This shows the efficiency and practicality of the heuristic, particularly in time-sensitive applications.

## Conclusion

In summary, this chapter has conducted a thorough examination of the heuristic approach developed for worker assignment inspired by a real-world case in maritime transportation, emphasizing its effectiveness in efficiently managing scheduling while adhering to predefined constraints. The benchmarking process was crucial in evaluating the heuristic's performance in comparison to the exact method. By analyzing objective function values and execution times, we demonstrated that the heuristic not only produces results closely aligned with optimal solutions but also achieves this with significantly reduced computation times. This efficiency is particularly advantageous for decision-makers who require prompt and effective solutions in fast-paced and dynamic environments.

Currently, Given the complexity of the problem, we employ a heuristic that assigns exactly two workers per shift, focusing on simplicity and ensuring manageable pairwise compatibility. However, we acknowledge that this is a limitation, and in future work, we plan to extend the heuristic by allowing a number of required workers (NRP) determined by a decision maker to handle a variable workforce per shift, accommodating operational needs where more than two workers are necessary, while maintaining fairness and compatibility among larger groups of workers. Additionally, real-world data could be incorporated to validate the heuristic’s scalability and adaptability, allowing for the accommodation of larger and more complex workforce needs, while maintaining fairness and compatibility.

# General Conclusion

This research has extensively studied the complexities of staff scheduling in the maritime field, aiming to develop a solution that balances fairness and compatibility. Our research, inspired by a real case study, has been structured across five chapters, each contributing to a comprehensive solution for staff scheduling in the maritime industry.

In the first chapter, we focused on scheduling within supply chain management, particularly staff scheduling in maritime transportation. We examined the general modeling of the scheduling problem, outlining constraints and objectives, and presented various resolution methods, including exact and approximate approaches, as well as introducing our industrial partner. To better understand the shipowner's requirements and to develop our research problem statement, in the second Chapter, we conducted Semi-Structured Interviews (SSIs) to identify the key objectives that needed to be addressed in the scheduling process. Following this, we applied the Theory of Inventive Problem Solving (TRIZ) methodology to examine these objectives for potential contradictions. By constructing a System of Contradictions (SoC) and aligning TRIZ parameters with evaluation criteria, we systematically resolved conflicts and proposed inventive solutions. However, some solutions were too complex to implement immediately, leading us to make key decisions, such as removing rotation from the employee qualification process and separating the qualification process from scheduling. Additionally, we addressed incompatibility issues to simultaneously account for worker preferences and affinities.

Once our problem was outlined, we aimed to evaluate how similar challenges have been addressed in previous research in Chapter Three. To achieve this, we conducted a Scoping Review (ScR) using a PRISMA-based approach, reviewing 122 relevant studies. This analysis revealed significant gaps in the literature, particularly in relation to worker incompatibility in the maritime sector. The insights from this review informed the development of a new scheduling model, ensuring our approach effectively addressed these identified gaps in the Chapter Four. we have introduced a Mixed Integer Linear Programming (MILP) model. Although inspired by a real-world case, the model was designed to be adaptable to other industries due to its general formulation. One of the key contributions of the MILP model was the inclusion of both worker incompatibility and workload fairness in the objective function. Additionally, the model adhered to critical constraints such as qualifications, rest hours, day-off requirements, and the number of shifts per day. Additionally, experimental results were presented to assess the model's performance under different conditions. These findings contribute to decision support, shedding light on the model's behavior in addressing the complexities of staff scheduling in the maritime domain.

Acknowledging the limitations of exact methods when increasing instances size, we transitioned to a heuristic approach in the Fifth chapter, effectively managing larger problem sets. The heuristic produced results closely aligned with optimal solutions but with significantly reduced computation time. This efficiency is crucial for decision-makers in dynamic environments requiring timely solutions.

Currently, the heuristic assigns two workers per shift, but future research aims to give decision-makers the flexibility to determine the number of workers per shift based on operational needs. Future work will focus on extending the heuristic to address larger and more complex workforce requirements. Real-world data will be used to validate its scalability and adaptability. Additionally, we plan to test solutions derived from the TRIZ methodology, even those deemed complex, in real-world scenarios to evaluate their efficiency and practical applicability.

By building on the insights gained from this research, we aim to enhance the model's practical applications while continuing to refine its performance in real-world scenarios.

**Scientific Production**

| | |
|---|---|
| **Paper 1** | *New classification relative to Seafaring Staff scheduling: Literature Review* |
| **Submitted journal** | : *Transactions on Maritime Science* |
| **Status** | : **Submitted** |
| **Authors** | : Marwa BEN MOALLEM, Mohamed Haykal AMMAR, Remy HOUSSIN, Diala DHOUIB, Amadou COULIBALY |

| | |
|---|---|
| **Paper 2** | Factors Affecting Employees Scheduling: An Approach to a Theoretical Framework Model with a Scoping Review. |
| **Submitted journal** | *Int. J. of Logistics Systems and Management* |
| **Status** | **Published** |
| **Authors** | Marwa BEN MOALLEM, Remy HOUSSIN, Diala DHOUIB, Mohamed Haykal AMMAR, Amadou COULIBALY |

| | |
|---|---|
| **Paper 3** | MILP Model for Workload Fairness and Incompatibility in Seafaring Staff Scheduling Problem. |
| **Submitted journal** | *Maritime Business Review* |
| **Status** | **Published** |
| **Authors** | Marwa BEN MOALLEM, Ayoub TIGHAZOUI, Rémy HOUSSIN, Mohamed Haykal AMMAR, Diala DHOUIB, Amadou COULIBALY |

| | |
|---|---|
| **Book chapter** | Incorporating TRIZ Methodology into Semi-structured Interviews for Innovative Insights |
| **Book** | *Towards AI-Aided Invention and Innovation* |
| **Status** | **Published** |
| **Authors** | Marwa BEN MOALLEM, Rémy HOUSSIN, Amadou COULIBALY, Mohamed Haykal AMMAR, Diala DHOUIB & Mohamed ABDELLATIF |

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