DEPARTMENT OF MATHEMATICS

NOVA SCHOOL OF SCIENCE & TECHNOLOGY

INÊS DOURADINHO

BSc in Mathematics Applied to Risk Management

SCHEDULING RESERVE DUTIES IN PASSENGER RAIL TRANSPORT

MASTER IN MATHEMATICS AND APPLICATIONS

NOVA University Lisbon
September, 2024

DEPARTMENT OF MATHEMATICS

SCHEDULING RESERVE DUTIES IN PASSENGER RAIL TRANSPORT

INÊS DOURADINHO

BSc in Mathematics Applied to Risk Management

Adviser: Ricardo Saldanha
Head of Innovation Department, SISCOG - Sistemas Cognitivos, SA

Co-adviser: Nelson Chibeles Martins
Assistant Professor, Universidade NOVA de Lisboa

Examination Committee

Chair: Maria Isabel Azevedo Rodrigues Gomes
Associate Professor with Habilitation, Universidade NOVA de Lisboa

Rapporteur: Ana Paula Barroso
Assistant Professor, Universidade NOVA de Lisboa

Adviser: Ricardo Saldanha
Head of Innovation Department, SISCOG - Sistemas Cognitivos, SA

MASTER IN MATHEMATICS AND APPLICATIONS

NOVA University Lisbon
September, 2024

Scheduling Reserve Duties in Passenger Rail Transport

This document was created with the (pdf/Xe/Lua)LaTeX processor and the NOVAthesis template (v7.1.18) [1].

Acknowledgements

Queria começar por agradecer ao meu orientador, o Professor Nelson Chibeles Martins, que, além de ser um rosto conhecido durante este ano cheio de novidades, me recebeu sempre com um abraço ou uma palavra de conforto.

Gostaria também de agradecer à SISCOG pela oportunidade e por tornar este processo muito mais agradável e desafiante. Agradeço ao meu orientador Ricardo Saldanha por me ter acompanhado nesta jornada; ao Jorge Roussado e à Ana Wemans por me terem acolhido na sua equipa e por estarem sempre a uma chamada no *Teams* de distância, sempre com um sorriso, prontos para esclarecer qualquer dúvida. E, por fim, a todos os que fazem parte do Departamento de Inovação, por tornarem a minha entrada no mundo do trabalho numa experiência acolhedora e por todas as sugestões que tornaram o meu trabalho mais rico.

Quero agradecer aos meus pais por investirem na minha educação e por estarem sempre presentes nas minhas pequenas derrotas, para me reconfortarem, e nas minhas pequenas vitórias. Sei que, mesmo um pouco excessiva, a exigência da minha mãe é uma das razões para ter chegado onde cheguei.

Neste percurso académico, tenho de destacar dois grupos que mudaram a forma como vivi os últimos cinco anos. A Praxe de LMAGR, que me proporcionou momentos inesquecíveis e me deu uma segunda familia: a *Dreamy Family*. E a TunaMaria, um grupo que, apesar de me ter dado muitas dores de cabeça, tem um lugar muito especial no meu coração. Deu-me a conhecer imensas pessoas que espero levar para a vida e continua a desafiar-me de maneiras que nunca pensei serem possíveis. Quero agradecer especialmente às minhas companheiras de dois anos de direção, a Splash e a Reverse, por estarem sempre presentes, cada uma à sua maneira, e por terem tornado este caminho menos solitário. Também quero agradecer às novas aquisições da direção, a Juro Joca e a Barilla, que, com a sua leveza, tornam qualquer reunião, evento ou ensaio mais divertido.

Por fim, quero agradecer a três pessoas muito especiais. A Margarida, a minha *buddy* da faculdade, que, para além de me aturar diariamente, está sempre pronta para me ajudar, ouvir e dar um abraço amigo. O Diogo, que está sempre lá para me reconfortar nos momentos difíceis e se torna no meu maior fã nas vitórias da vida. Obrigada por me ouvires, aturares, por me tirares de casa e por tornares qualquer lugar onde estou contigo num espaço reconfortante e cheio de alegria. A Sofia, a minha irmã, a minha companheira de todas as horas, que me ajuda diariamente a crescer. Obrigada por, além de seres minha irmã, seres também a minha melhor amiga.

Abstract

The railway industry facilitates global transportation, enabling the movement of passengers and goods across local and long-haul distances. Despite significant evolution, the industry continues to encounter significant challenges, particularly managing disruptions. This Master's Thesis develops an algorithm that takes daily schedules with assigned work, regular duties, as input to generate duties without work assigned, known as reserve duties.

The initial set of reserve duties is created through the utilisation of three methodologies: Peak approach, Window approach and Random Selection approach. Furthermore, two additional approaches can be used to improve an existing solution of reserve duties: Change Procedure and Simulated Annealing.

To test these approaches, a real-world dataset from a Northern European train operating company was used, comprising 881 duties and 28 operational bases. The efficacy of the reserve duties is evaluated using one of the most frequent types of disruptions in railway operations - crew absence. The disruption scenarios are generated with a stochastic simulator. Two methods were employed to evaluate the reserve duties obtained from the algorithms. The first method, intermediate evaluation, is a fast approach that makes use of some empirical guessing due to the lack of information. The second method, the SISCOG optimiser, provides a more robust and realistic evaluation, reflecting the real conditions of the operation.

The results of both evaluation methods enabled the comprehension of the effectiveness and adaptability of each solution methods to different failure scenarios, as well as the identification of the most effective solution methods. These results represent a significant advance in this area.

Keywords: Reserve Crew, Reserve Duty Scheduling, Absenteeism, Crew Absence, Rail Transport, Stochastic Simulation, Simulated Annealing

Resumo

O setor ferroviário facilita o transporte global, permitindo a circulação de passageiros e mercadorias em distâncias locais e de longo curso. Apesar da evolução significativa, o setor continua a enfrentar desafios importantes, nomeadamente a gestão das perturbações ferroviárias. Esta dissertação desenvolve um algoritmo que utiliza os turnos com trabalho atribuído, turnos regulares de maquinistas, para gerar turnos sem trabalho atribuído, denominados como turnos de reserva.

O conjunto inicial de turnos de reserva é criado através da utilização de três metodologias: *Peak approach*, *Window approach* and *Random Selection approach*. Para além disso, podem ser utilizadas duas abordagens adicionais para melhorar uma solução existente de turnos de reserva: *Change Procedure* e *Simulated Annealing*.

Para testar as abordagens, foi utilizado um conjunto de dados de um operador ferroviário do Norte da Europa, que inclui 881 turnos e 28 bases operacionais. A eficácia dos turnos de reserva é avaliada utilizando um dos tipos de perturbações mais frequentes nas operações ferroviárias - o absentismo. Os cenários de falha são gerados por um simulador estocástico. Foram utilizados dois métodos para avaliar os turnos de reserva obtidos. O primeiro método, a avaliação intermédia, é uma abordagem rápida que recorre a algumas suposições empíricas devido à falta de informação. O segundo método, o otimizador da SISCOG, proporciona uma avaliação mais robusta e realista, refletindo as condições reais da operação.

Os resultados de ambos os métodos de avaliação permitiram compreender a eficácia e adaptabilidade de cada método de resolução a diferentes cenários de falha, bem como identificar os método de resolução mais eficazes. Estes resultados representam um avanço significativo nesta área.

Palavras-chave: Turnos de Reserva, Planeamento de Turnos de Reserva, Absentismo, Ausência de Maquinistas, Transporte Ferroviário, Simulação Estocástica, Simulated Annealing

Contents

List of Figures

List of Tables

Acronyms

C	cost *(pp. 11, 17–21)*
DS	Duty Scheduling *(pp. 2, 6–9)*
FC	final cost *(pp. 17, 18)*
MIP	Mixed Integer Programming *(p. 7)*
MIPSSM	Mixed Integer Programming Simulation Scenario Model *(p. 7)*
RCRP	Robust Crew Recovery Problem *(p. 7)*
RDU	reserve duty utility *(pp. 16, 18)*
RS	Roster Scheduling *(pp. 2, 6–8)*
UT	Uncovered Tasks *(pp. 17, 18)*

Symbols

α	cooling ratio *(pp. 12, 20, 26–28, 36, 39, 42–46, 55–58)*
$c_{current}$	current cost *(pp. 20, 21)*
c_{new}	new cost *(pp. 20, 21)*
$nIRes$	number of insufficient reserve duties *(p. 19)*
$nReg$	number of regular duties *(pp. 10–13)*
N_{rej}	Number of Consecutive Rejections *(pp. 20, 21)*
$nRes$	number of reserve duties *(pp. 10, 12, 13)*
nUD	number of unmanned duties *(p. 15)*
p	probability of acceptance *(pp. 20, 21, 26)*
$pRes$	percentage of reserve duties *(pp. 10, 12, 30)*
pUD	percentages of unmanned duties *(pp. 11, 15, 30)*
$S_{current}$	Current set of reserve duties *(pp. 20, 21)*
S_{new}	New set of reserve duties *(pp. 20, 21)*
$N_{stop\ criteria}$	Stop Criteria - Number of Consecutive Rejections *(pp. 12, 20, 21)*
T_0	Initial Temperature *(pp. 12, 20, 26, 28, 36, 39, 42–46, 55–58, 62–66)*
T_k	Temperature in iteration k *(p. 20)*
$wIRes$	insufficient reserve duties workload *(p. 17)*
$wRes$	reserve duties workload *(p. 17)*
$wURes$	unmanned reserve duties workload *(p. 17)*

1

Introduction

This work was developed in a business context at SISCOG – Sistemas Cognitivos, S.A., leading to the completion of a Master's Thesis in Mathematics and Applications from NOVA FCT. SISCOG is a company that specialises in optimising the resources of public transport operators, namely time, space, vehicles and personnel. Working with SISCOG constitutes an excellent opportunity to have real data, work alongside experts in the field and also have a real impact on society. This document reports the work developed to determine an algorithm for scheduling reserve railway duties, with the objective of reducing the number of cancelled trips when disruptions occur.

The global railway market is growing every year and it "is expected to grow at a compound annual growth rate (CAGR) of 5.6% from 2023 to 2030" [2]. More people choose public transport as their main way of transportation due to high gasoline prices, traffic congestion and even climate change. The railway industry stands out for its comfort, affordability, and for being the friendliest way of transportation. Technology is evolving to make railway trips even more eco-friendly. The hydrogen train technology [3], used in some European countries [4], reduces CO_2 emissions, making the railway cleaner than ever before mode of mass transportation.

The railway industry requires railroad tracks, vehicles, and staff to provide the desired transport services. These resources are limited and expensive, therefore it is necessary to optimise the available resources. The objective is to provide transport services while maximising revenue and customer satisfaction.

Unfortunately, during the day, a number of unexpected events may occur which prevent the original plan from being followed. These unexpected events, also called disruptions, can be due to the weather, crew illness, rolling stock engine break down, incidents in railroad tracks and many other factors.

This chapter begins with an overview of railway planning, which is inserted in Section 1.1. Section 1.2 describes the types of disruptions that may occur and some potential solutions. Section 1.3 explains the concept of reserve duties and their defining characteristics. Section 1.4 delineates the main goals of this thesis, the methodologies used and the contribution given to the field. Finally, Section 1.5 presents the main structure of the document.

1.1 Railway Planning

The scheduling problem arises from the necessity of planning the utilisation of limited resources: railroad tracks, vehicles and staff. Railway planning has four phases, schemed in Figure 1.1.

Strategic planning is where "decisions on investing in new rail-infrastructure (network design), fleet management and human resource management" [5] are made.

Tactical planning is where "a detailed plan is created for generic pattern days" [5], which means a plan that deals with generic days of the week (Monday to Sunday), "including the timetable, the rolling stock schedules, the shunt plans and the crew schedules" [5]. There are two crucial steps in crew scheduling: Duty Scheduling (DS) and Roster Scheduling (RS). The Duty Scheduling or pairing problem consists of producing daily working schedules in the form of feasible sets of trips (duties). The Roster Scheduling is responsible for assigning people to a line of work, a set of workdays and days off, where each workday already has a set of trips that need to be covered.

In operational planning "plans are created for calendar days" [5] and specific resources where "only necessary changes are made to the generic plans" [5].

The only phase that occurs in the present is operational control. It is required when an unexpected event causes the initial plan to become unfeasible. In this case, a process “very similar to operational planning, with the major difference that decisions need to be made in minutes" [5].

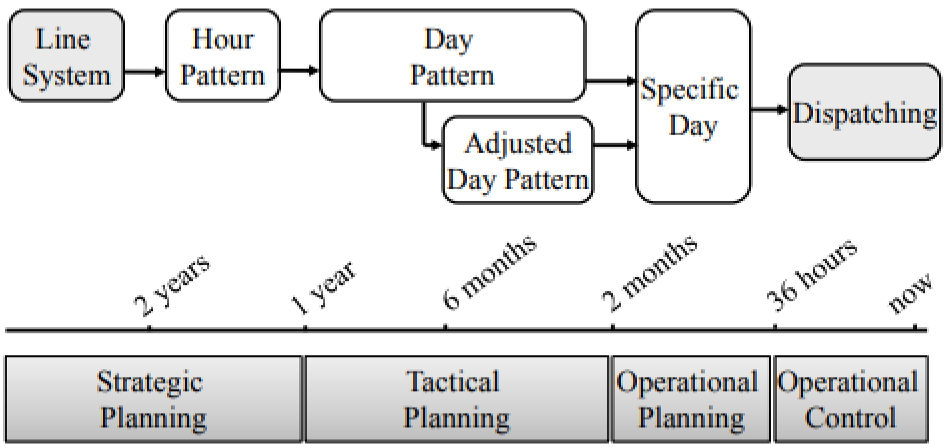


Figure 1.1: Railway Planning Phases [5]

The team responsible for staff management in SISCOG, is called CREWS, within which this project is positioned. There are two algorithms used in CREWS for Duty Scheduling: the scheduling algorithm and the rescheduling algorithm. The scheduling algorithm is used for long-term scheduling, which corresponds to the tactical planning phase. The rescheduling algorithm is used for short-term scheduling and real-time dispatching, which correspond to the operational planning and operational control phases.

1.2 Disruptions in Passenger Transport and How to Cope with Them

Disruptions can be classified as small perturbances, medium disruptions and large disruptions. The small perturbances, such as departure delays due to overcrowded stations, mechanical issues that force reduced train speeds, or late arrival of crew members, result in delayed train trips, which might be solved with time, or can escalate into a more significant problem. Medium disruptions, such as engine breakdowns in station yards or absent crew members, can result in the cancellation of train trips if any reserve resource is unavailable. Large disruptions, such as forced stops of trains on the main line, extreme weather, collisions with other vehicles, or derailments usually require high-level adjustments which result in a new scheduled plan made in the operational control phase [6].

In disruption scenarios, the goal is to quickly adjust the original plan to accommodate the unexpected condition with minimal changes. However, due to the strong interdependency nature of the railway network and resource allocation focused on cost efficiency, disruptions tend to spread over the network in space and time, causing the phenomenon called the knock-on effect [7].

Reserve resources have no specific job assigned and are set aside for future use. They offer additional options for support systems, that can lead to a better scheduling solution. Sometimes, the original plan can be maintained by substituting original resources with reserve resources, providing a quicker and simpler resolution. It is crucial to have backup resources during peak times to ensure that you can promptly replace original resources with reserve resources, minimising the impact on overall operations.

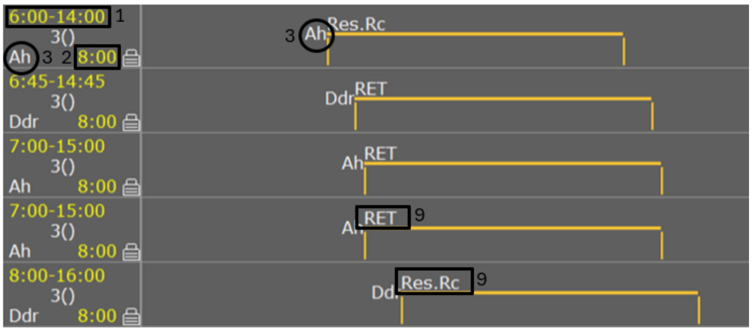
1.3 Reserve Duties

The term reserve duty scheduling is used to describe the process of planning reserve duties. A reserve duty has no specific job assigned in the tactical or operational phases. The only information needed is the time and location of the start and end of each reserve duty. The objective is to attribute trips to these empty duties when these trips become unassigned due to disruptions in train operation. The timetables are selected based on the regular duties provided as input. The workers typically alternate between regular duties and reserve duties.

Figure 1.2(a) illustrates the regular duties from two bases Ddr and Ah. Each has a start time, an end time, a base, a duration, a list of trips, a meal break and a train number. The trips are represented by the green lines and have the intermediate stop stations indicated below. Meal periods are indicated by an asterisk (*). Some regular duties require positioning trips, defined as trips where the crew member travels as a passenger, represented by a light yellow line and a P above the line.

Figure 1.2(b) illustrates the reserve duties represented by the yellow lines, for the same bases, Ddr and Ah. In this case, each has a start time, an end time, a base, a duration, and a type of reserve duty. The reserve duties can be classified into two categories: RET and Res.Rc. RET are reserve duties typically used for local manoeuvres, while the Res.Rc are used for real time disruptions.

(a) Regular Duties from two bases



(b) Reserve Duties for two bases

Legend:
1: Duty start and end time (sign in and sign out time);
2: Duty duration;
3: Duty start or end station;
4: Positioning trip (trip where the crew member travels as a passenger);
5: Train number;
6: Line drawn under sequences of trips performed with the same rolling stock;
7: Intermediate stop stations;
8: Meal Break;
9: Type of reserve duty.

Figure 1.2: Duties from Two Bases

1.4 Goals and Contributions of this Thesis

The railway industry is a crucial component of global transportation, facilitating the movement of passengers and products from short local journeys to long-haul international trips.

The industry has evolved significantly over time. However, despite these developments, the industry continues to encounter challenges, particularly in managing disruptions caused by unexpected events.

The primary objective of this thesis is to develop an algorithm that takes regular duties as input and generates reserve duties. The efficacy of the reserve duties is evaluated using one of the most frequent types of disruptions in railway operations - crew absence. The challenge is to develop schedules for reserve duties at the appropriate time and location, not knowing the circumstances of when and where crew members will be absent. Different numbers of reserve duties were defined to understand the impact of absent workers. By addressing these challenges, this thesis contributes to the field by implementing metaheuristics to tackle combinatorial optimisation problems and utilising simulation techniques to create uncertainty.

This work was executed in two distinct phases. In the initial phase, which took place between 4 September 2023 and 9 February 2024, it was performed introductory work on the topic, identified potential methods for solving it, and presented a report that included a proposed work plan for completing the dissertation. The project was evaluated and approved at a public session, thus allowing it to be pursued. The second phase, which took place from 9 February 2024 to 30 September 2024, focused on the practical aspects of the problem. This involved the construction of various algorithms to generate reserve duties and simulation techniques to introduce uncertainty, to achieve the stated goals of the dissertation.

1.5 Document Structure

The first chapter provides a more detailed introduction of the railway sector, how the scheduling process is phased and what are the remaining challenges of this industry. This was followed by a definition of reserve duties and the benefits of these types of duties. The chapter concludes with an explication of the main goals of this thesis.

In Chapter 2, it is presented scientific work related to the proposed topics or other topics with a similar problem, the algorithms used and how the schedules are tested.

Chapter 3 presents the structure of the proposed algorithm, followed by a definition of the type of input data and parameters needed to set the algorithm. It also describes the simulation process responsible for creating disruptions, which introduces the uncertainty present in the real world to the evaluation process. Lastly, every method is explained in detail, and the metrics needed to compare the different schedules are explained.

Chapter 4 presents the input data and the experiences made to determine some parameters. Chapter 5 demonstrates the results obtained with the models. Lastly, Chapter 6 presents the final conclusions of the results shown and outlines potential future approaches for further improvement of the work presented in this thesis.

2

Literature Review

In this chapter, a literature review of reserve crew scheduling and other resource allocation problems are introduced.

The literature found was the result of searches in Google Scholar, in the SISCOG database, in elicit and in b-on. The keywords used to find the documents were Reserve Crew, Scheduling, Airline Reserve Crew, Stochastic Simulation, Simulated Annealing, Uncertainty demand and Duty Scheduling.

2.1 Previous Work on Reserve Crew Scheduling

Resource optimisation is an essential process within the domain of railway operations. To ensure that crew is available for operating trips, mathematical algorithms are used to optimise schedules before they are executed.

The crew scheduling problem, presented in the previous chapter, is divided into two categories: Roster Scheduling and Duty Scheduling, explained in the Chapter 1. Some studies solve both problems ([8], [9]), others focus just on the roster scheduling problem and others solve the Duty Scheduling problem ([10], [11]). The focus of this thesis will be the Duty Scheduling problem.

Determining the right amount of reserve duties is a complex problem. Some studies decide to consider the number of reserve duties as an input parameter and compare different numbers ([11], [8]), and others simulate the quantity needed based on reserve crew demand ([10], [9]). Usually, some sort of disruption is also an input parameter, like simulated disruptions scenarios ([10]) or probabilities of disruptions, for example, crew absence ([11], [9]).

Since scheduling reserve duties is a problem of uncertainty, simulation is a common method used to create disruption scenarios, some based on data ([8]) and others based on statistics distributions like negative binomial ([9]) or Poisson distribution. The studies that have probabilities use uniform distribution for simulating probabilities of crew members absence ([12]) or even make an algorithm to do so ([11]). In this study, a Poisson distribution is going to be used to determine the number of disruptions for each base, utilising a mean of disruptions per base as a parameter.

The approaches found in the literature are based on probabilities, metaheuristics, simulation, and linear optimisation. There are many objective functions like minimise a cancellation metric ([10], [11]), minimise costs ([9]) or minimise the number of reserve duties needed and other resources. In Table 2.1, there is a summary of all the references related to reserve Duty Scheduling mentioned in this subchapter.

Table 2.1: Related Studies on the Reserve Duty Optimisation

References	Domain	Type of Scheduling	Input Data	Simulations	Granularity	Approach	Objective Function	Size of Problem
[8]	Airline	DS + RS	Probability of disruptions (historical data)	No	4 Hours	MIP + RCRP + Branch-and-price	Minimise cost	309 Flights
[9]	Bus	DS + RS	Schedules and probability of crew absence	yes	1 Hour	Greedy Approach	Minimise cost	60-124 Operators
[10]	Airline	DS	Number of reserve crew members and disruption scenarios (simulated)	yes, 20 000 disruption scenarios	-	MIPSSM + Heuristics	Minimise cancellation measure	243 Flights legs
[11]	Airline	DS	Probabilities of crew absence	yes, 20 000 disruption scenarios	-	Metaheuristics	Minimise cancellation measure	566 Flights
[12]	Airline	-	Reserve crew demand	yes, 2 000 disruption scenarios	-	Probabilistic + Heuristics	Minimise probability of crew un-availability	25 Flights

2.2 Previous Work on Other Resource Scheduling Problems

The reserve scheduling problem has not been extensively explored, although many other areas also have a similar problem dealing with uncertainty demands and resource optimisation.

Scheduling cashier's shifts in a supermarket has similarities when compared to the reserve scheduling problem. Boths have hours when the demand is higher, one due to having more trips and the other because of a higher customer flow. In reference [13], the problem is solved by giving as an input the number of employees recommended at each hour of the day and the type of cashier shifts there are. With an integer linear programming approach, the program gives the number of shifts and length to minimise the total number and time of employees shifts required per day while covering the recommended cashier's demand.

The procedure to assign the events of a university to the various resources such as lecturers, classrooms and time slots can also solve the reserve scheduling problem. In reference [14] the approach used was Simulated Annealing. The initial solution was randomly obtained. The new solutions are generated in three different ways. The initial approach is the simple searching neighbourhood, where an activity and a time slot are randomly chosen. The second approach is the swapping neighbourhood, where two activities and two time slots are selected and their time slot is swapped. The third approach is the simple searching and swapping neighbourhood, where two activities and two time slots are randomly chosen and assigned. The initial temperature used was 10000 and the cooling method used, the method responsible for reducing the temperature, was geometric cooling. The cooling ratio, alpha (α), is calculated as shown in equation 2.1, where t is the current temperature, t_f is the final temperature and N_{move} is a fixed value that affects the duration of the temperature decrease and also the stop criteria. Many experiences were made variating the N_{move} and the method responsible for creating new solutions. The execution time and the cost were the detectors of the best solutions. The best method to create new solutions was the simple searching neighbourhood and the best N_{move} was 500.

$$\alpha = 1 - (\ln t - \ln t_f)/N_{move} \tag{2.1}$$

In Table 2.2, there is a summary of the two studies presented in this chapter.

Table 2.2: Related Studies on Other Resource Allocation

References	Domain	Type of Scheduling	Input Data	Evaluation Scenarios	Granularity	Approach	Objective Function	Size of Problem
[13]	Supermarket cashiers	DS	Clients data from 4 weeks and type of shifts	No	hour	Linear integer programming	Minimise total number of employees time per day	103 scheduling hours, 18 cashiers
[14]	School time slots	DS + RS	Problem information and restrictions	No	time slots	Simulated Annealing	Minimise cost of conditions violated	5 classes, 5 classrooms, 20 lectures, 8 instructors

3

Railway Reserve Duty Scheduling

The focus of this chapter is to explain the process of solving the Reserve Duty Scheduling problem. Figure 3.1 presents a diagram of the algorithm. Firstly, the input data and parameters are defined. In the second phase, an initial set of reserve duties is generated using one of the three alternative approaches shown. To evaluate the initial reserve duties, a set of disruption scenarios is simulated, and a cost is assigned to the set of reserve duties calculated. There are two options to improve the schedules obtained in the second phase, Change Procedure or Simulated Annealing. These algorithms continually evaluate the reserve duties to determine whether or not to make further changes.

The final assessment is made by the SISCOG optimiser with a more realistic view to validate the reserve duties.

3.1 Input Data and Parameters

To initialise the algorithm, it is first necessary to receive the input data and set certain parameters.

The input data is a set of regular duties and each duty needs to have the following information:

- Base: operational base of the regular duty (location where the crew member signs in and out).
- Start time: start time of the regular duty.
- End time: end time of the regular duty.
- Duration: time length of the regular duty, in other words, End time - Start time.
- Trips: a sequence of trips to be performed by the crew member that will be assigned to the regular duty.

With this information, a workload will be created for each base, to be used in the scheduling phase. This analysis, in the algorithm, is done for each base.

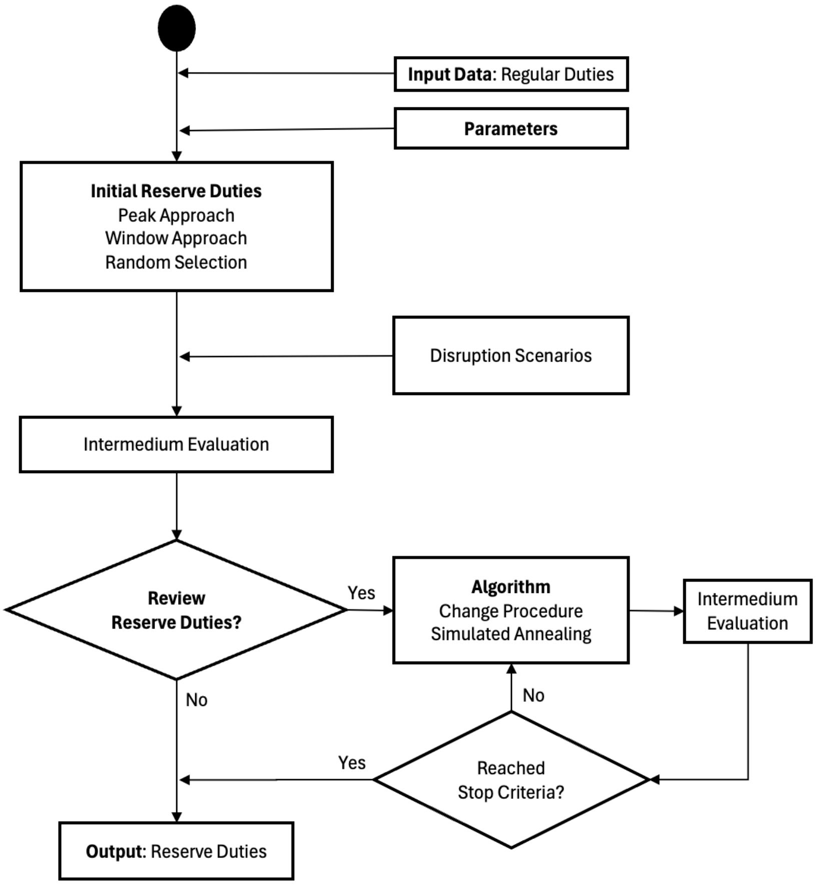


Figure 3.1: Diagram of Reserve Duty Scheduling Algorithm

The type of approach used to determine the initial schedules is an input parameter, which receives as value a number from 0 to 2 and represents one of the three algorithms developed: Peak, Window and Random Selection.

In the Peak and Window approach, the number of reserve duties ($nRes$) to be produced for the several operational bases is computed based on Reserve Duties Percentages ($pRes$), a list of input parameters specifying the percentage of reserve duties per operational base. The number of reserve duties for each base is the result of the percentage of reserve duties given for that base, multiplied by the number of regular duties ($nReg$) of that base, as shown in Equation 3.1. In the Random Selection approach, the number of reserve duties is an input parameter, which receive as value a sole number since the specification of quantities per base is not necessary.

$$nRes = pRes \times nReg \tag{3.1}$$

A list of disruption scenarios is created to introduce uncertainty to the problem, and is then used to evaluate the quality of the reserve duties produced. Each scenario has regular duties that become unmanned. This usually happens because the crew members responsible for executing them become suddenly absent due to illness or another unexpected incident.

The parameter designated as Disruptions can receive one of two values: the word "Read" or a list with percentages of unmanned duties (pUD). If the parameter receives the word "Read" as a value, the system will then proceed to read a file with information on a number of disruption scenarios. In the event that the parameter receives as value a list with percentages of unmanned duties, then it is necessary to define another parameter called Day Period, along with the number of scenarios. The Day Period parameter offers the possibility of allocating additional unmanned duties to a specific portion of the day. The parameter may be assigned the value "No" or a set of vectors. If the parameter receives the value "No", then the unmanned duties are distributed uniformly throughout the day. Alternatively, if the parameter is provided with a set of vectors, each vector corresponds to a period of the day, and another parameter is required, the percentage of unmanned duties per period of the day. This parameter receives as its value a vector with a percentage for each period of the day defined, representing the percentage of unmanned duties selected for that period of the day. It is necessary to ensure that the sum of these percentages is 100%. The following parameter to be defined is the number of disruption scenarios. This parameter receives as value an integer representing the number of disruption scenarios the algorithm will simulate.

In order to attribute uncertainty to the disruption scenarios, the number of unmanned duties per period of the day, per base and scenario is randomly generated using the Poisson distribution. Consequently, the number of unmanned duties for a given period of the day and base will vary across scenarios. To use the Poisson distribution, it is necessary to define a parameter, lambda (λ), which, in this case, represents the mean number of unmanned duties. Equation 3.2 provides a visual representation of the calculation of the mean number of unmanned duties (λ) per period of the day and base. This is obtained through a multiplication of the percentage of unmanned duties (pUD) and the number of regular duties ($nReg$).

$$\lambda = pUD \times nReg \tag{3.2}$$

To improve the initial reserve duties there are two additional algorithms: Change Procedure and Simulated Annealing.

The parameter Change can receive as value the word "Fixed", "Best" or "No". The word "No" means that the user does not want any changes. The word "Fixed" means that the user wants to have a fixed number of changes, in this case, another parameter is needed to represent the number of changes the algorithm will make. If the parameter receives as value the word "Best", the algorithm makes changes until the cost starts increasing.

Finally, the parameter Simulated Annealing can receive as value the word "Yes" or "No". The word "No" means that the user does not want to use this last algorithm. The word "Yes" means that the user wants to use the Simulated Annealing algorithm and more parameters are needed: Initial Temperature (T_0), Alpha (α) and Number of Consecutive Rejections ($N_{stop\ criteria}$).

3.2 Initial Reserve Duties

There are three different approaches to create the first set of reserve duties.

The reserve duties will be scheduled at times when there are regular duties scheduled. In order to demonstrate the methodology of the three proposed approaches, it is necessary to consider the workload represented in Figure 3.2. It is possible to conclude that the working window in this base is between 5h and 1h of the next day. The range of hours corresponding to the subsequent day is shown with an apostrophe at the end, for example, 0h-1h'.

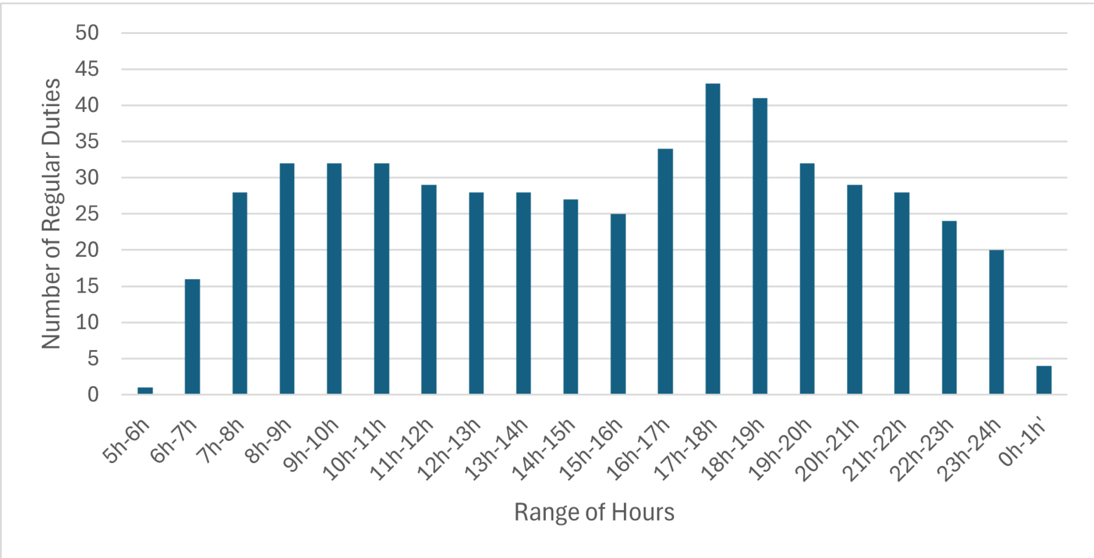


Figure 3.2: Regular Duties Workload in Each Hour

3.2.1 Peak and Window Approach

In the first two approaches, Peak and Window approach, the reserve duties are generated based on duties workload because it is an approximation of reserve duty demand.

First, the algorithm computes the number of reserve duties ($nRes$) in each base. For example, a base with 77 regular duties and a percentage of reserve duties of 8%, according to expression below, the number of reserve duties needed, for that base, will be 7. This algorithm rounds up the number of reserve duties to approximate the required percentage at each base.

$$nRes = pRes \times nReg = 0.08 \times 77 = 6.16 \approx 7$$

The next step is to generate a reserve duty with one of the approaches described below. After each reserve duty is completed, an intermediate regular duties workload is created to establish the new reserve duty demand and to provide different schedules in the following iterations. During the scheduled hours of the new reserve duty, a load is removed from the regular duties workload, as illustrated in Equation 3.3, creating the intermediate reserve duties workload.

$$load = \frac{nReg}{nRes} \tag{3.3}$$

The same process repeats for the next reserve duty created.

The algorithm schedules reserve duties base by base. The two different approaches for generating a new reserve duty in each iteration of the algorithm, namely the Peak and Window approach, are explained in the following two subchapters.

3.2.1.1 Peak Approach

In this first approach, the scheduling method starts to select the hour when there is the highest number of regular duties . This hour will be the first working hour of the reserve duty selected. After that, it will compare the workload of the previous and next adjacent hours and select the hour with the highest number of regular duties . This procedure will continue until the reserve duty is complete, which means 8 hours of work.

In Figure 3.3, there is a sequence of the Peak approach to form a reserve duty.

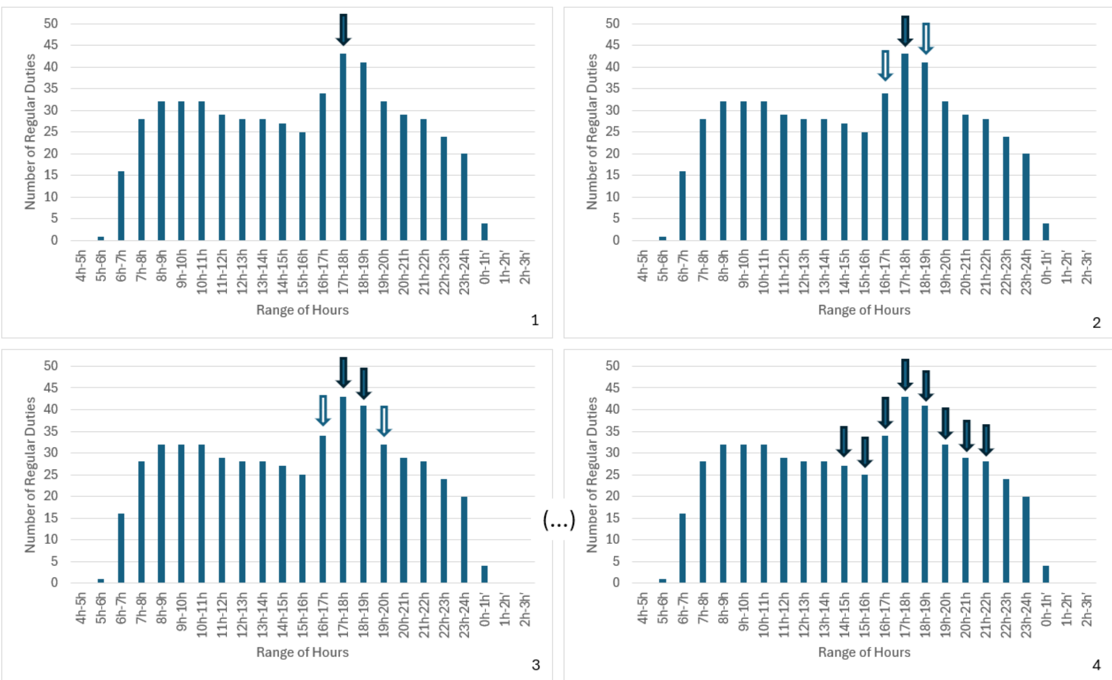


Figure 3.3: Peak Approach Sequence

3.2.1.2 Window approach

The Window approach selects the schedule for reserve duties based on the sum of the number of regular duties (i.e. crew working) at every eight hours interval. Every interval of eight hours is a possible schedule. The algorithm sums the number of regular duties and selects the one with the highest sum. Then, it assigns these eight hours as working hours, finishing the reserve duty.

To exemplify, the schedule options for the reserve duties are represented in the first column of the Table 3.1.

In the Window approach, the schedule with the highest sum is selected to be the reserve duty because it represents the schedule where reserve duties are needed the most. When two time intervals or more have the same sum, the earliest one will be chosen, which means that the earliest is used as a tiebreaker. In the example shown in Table 3.1 both the schedules 13h-21h and 14h-22h represent the highest sum, and it is selected the earlier schedule 13h-21h.

Table 3.1: Sum of Workload

Time Interval	**number of regular duties**
05h-13h	198
06h-14h	225
07h-15h	236
08h-16h	233
09h-17h	235
10h-18h	246
11h-19h	255
12h-20h	258
13h-21h	259
14h-22h	259
15h-23h	256
16h-00h	251
17h-01h	221

3.2.2 Random Selection Approach

The last approach of this subsection is Random Selection approach, the simplest one. The number of reserve duties is an input, decided by the user. To determine the start time and the base of the reserve duty two lists are needed, one with all the bases and the other with the viable hours to start the duty.

The start time and the base are selected randomly with a uniform distribution. In Figure 3.4 can be seen how the reserve duties workload is distributed in the timeline, when compared with the regular duties workload or with any other approach. This approach reveals a lack of knowledge, as evidenced by the absence of a decrease in the amount of workload during off-peak hours and at night.

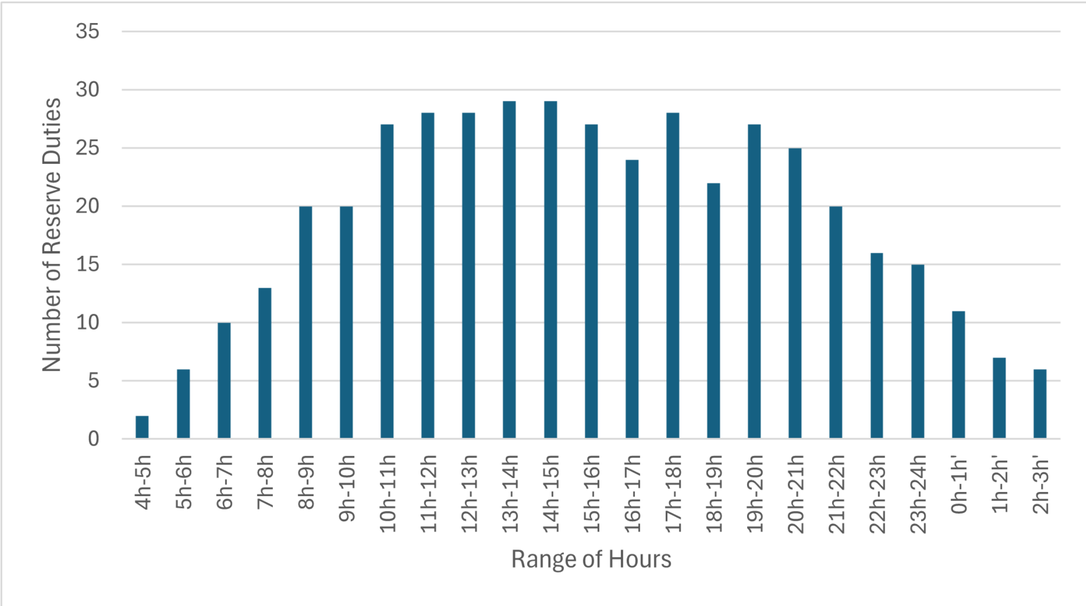


Figure 3.4: Reserve Duties Workload with Random Selection Approach

3.3 Disruption Scenarios Simulation

The only disruption considered when testing reserve duties is crew absence. When a crew member is absent his duty becomes unmanned, and the trips must be assigned to someone else in a few minutes, namely the worker with a reserve duty at that day.

The process of selecting unmanned duties with different percentages for different bases is initiated by defining the number of unmanned duties per base. For each scenario, a number of unmanned duties (nUD) per base (due to crew absence) is modelled using a Poisson distribution. The Poisson parameter, lambda, is the expected number of unmanned duties per base. To calculate lambda, a percentage of unmanned duties pUD at that base is used, and it is obtained as shown in Equation 3.2. To determine the number of unmanned duties per base a Poisson function was computed. The unmanned duties are chosen using a uniform distribution based on the assumption that each individual has an independent probability of being absent. For each base, a vector of regular duties is ordered randomly, and the first ones are selected.

The process of selecting unmanned duties with different percentages for different bases and different periods of the day are very similar. The only difference between the two processes is the manner in which the duties are divided. The first process divides duties according to bases, whereas the second process additionally subdivides duties according to both bases and periods of the day.

The percentage of unmanned duties per base and period of the day may be affected by factors such as seasonal and personal tendencies. Therefore, it is important to test the methodologies presented with different disruption scenarios in order to evaluate their adaptability.

3.4 Evaluation

There were two methods used to evaluate the reserve duties obtained from the algorithms. The first one, the intermediate evaluation, is a fast approach used in the algorithms described in Section 3.5, giving knowledge about their performance to improve initial solutions, modelled by the algorithm from Section 3.2. This approach considers some empirical guessing due to the lack of information. The SISCOG optimiser is used as a second evaluation method and it tests the reserve duties in a more realistic situation.

These two methods are needed because the SISCOG optimiser requires approximately 15 minutes to evaluate a set of reserve duties in one disruption scenario, whereas the intermediate evolution can be completed in less than one second. This discrepancy can be attributed to the quantity of information available for each. The granularity of the information present in the SISCOG optimiser is in minutes, whereas the information in the algorithm is processed in hours. The SISCOG optimiser has access to a more extensive range of information and requirements than the algorithm does, which results in a more complex problem to compute. Therefore, the intermediate evaluation will be used to shape the reserve duties schedules using a vast number of disruption scenarios, while the SISCOG optimiser will be used to validate solutions.

3.4.1 Intermediate Evaluation

The intermediate evaluation computes several metrics to evaluate the behaviour of the reserve duties in the different simulated disruption scenarios.

The variable reserve duty utility (RDU) represents the total number of hours each reserve duty is utilised. In order to determine the value of this variable for each reserve duty, it is necessary to consider all potential scenarios, bases and hours, and to establish whether or not each reserve duty is required. In the event that the number of unmanned duties exceeds the number of reserve duties in that scenario, base and hour, all reserve duties are utilised. The value of the variable is then incremented by one for each reserve duty. Conversely, if the opposite happens, there are more reserve duties than unmanned duties, resulting in the utilisation of some reserve duties. This implies that, for some reserve duties, the value of the variable is increased by one (the reserve duties used), while for others it is not (the reserve duties not unused). The $\overline{RDU}$ represents the average hours per scenario each reserve duty is used. This parameter is calculated by summing the hours that the reserve duties are used to cover the unmanned work in each scenario and dividing it by the number of disruption scenarios. This is demonstrated in Equation 3.4.

$$\overline{RDU} = \frac{\sum_{s=1}^{n_{scenarios}} RDU\,[s]}{n_{scenarios}} \tag{3.4}$$

The intermediate evaluation compares the workload of regular duties that became unmanned with the workload of reserve duties at each base. The workload of the unmanned duties represents the reserve demand profile and the workload of the reserve duties represents the reserve supply profile.

In the periods of the day where the workload of the unmanned duties is larger than the workload of the reserve duties, it assumes the work will not be performed and therefore the corresponding trips will be cancelled.

It is important to note that this is an effective method for rapidly evaluating reserve duties. However, it is not the most accurate due to the absence of comprehensive details. Specifically, the distance between the base of the reserve duty and the location of the piece of unmanned work is not taken into account. Consequently, the unmanned piece of work is attributed to a reserve duty with the same base as the regular duty where that piece of work was originally planned.

The insufficient reserve duties workload ($wIRes$) represents the number of insufficient reserve duties in each hour of the day. When the number of reserve duties is higher than the number of unmanned duties, then there are enough reserve duties and the workload value is 0 at that hour, base and scenario. When the number of reserve duties is smaller than the number of unmanned duties, then there are not enough reserve duties to cover the unmanned work. In this case, the number of insufficient reserve duties is the difference between the number of unmanned duties and the number of reserve duties, shown in Equation 3.5.

$$wIRes = \begin{cases} 0, & \text{if } wURes - wRes \leq 0 \\ wURes - wresd, & \text{otherwise} \end{cases} \tag{3.5}$$

The cost (C) represents the average of insufficient reserve duties per hour, base and scenario shown in Equation 3.6.

$$C = \frac{\sum_{s=1}^{n_{scenarios}} \sum_{b=1}^{n_{bases}} \sum_{h=1}^{n_{hours}} wird[s][b][h]}{n_{scenarios}} \tag{3.6}$$

3.4.2 Final Evaluation

The final evaluation is made in the SISCOG optimiser, a powerful tool that uses a considerable amount of computation time. It gives a more robust evaluation because it uses full detail and disruption management methods used in practice by rail operators. The SISCOG optimiser only evaluates one disruption scenario at a time and receives as input reserve duties and a list with the unmanned duties of a given disruption scenario. The output is a list of tasks, train trips, that could not be covered by any of the given reserve duties. With that list, the final cost (FC) is calculated based on the duration of these tasks. The number of trips that could not be covered and the final cost will be two metrics use to compare the different sets of reserve duties.

The final cost represents the uncovered reserve demand (measured in hours) as shown in Equation 3.7. The variable UT represents the Uncovered Tasks and the $duration[UT]$

represents the duration of an Uncovered Tasks (measured in seconds). To transform the result from seconds to hours the sum is divided by 3600.

$$FC = \frac{\sum_{UT=1}^{n_{UT}} duration[UT]}{3600} \tag{3.7}$$

Two metrics will be employed for the purpose of comparing the various methods: the number of trips that could not be covered and the final cost.

3.5 Review Reserve Duties

This section presents two algorithms that improve an existing solution of reserve duties. Change Procedure and Simulated Annealing need a first set of reserve duties given by one of the algorithms of Section 3.2. The intermediate evaluation is used to guide the next steps of these algorithms to improve the cost results.

3.5.1 Change Procedure

The Change Procedure algorithm starts by selecting the reserve duty that was less used and then selects the hour and the base with the highest value in the insufficient reserve duties workload. The objective is to reallocate reserve duties in a more efficient time and place.

The reserve duty that was less used is the one that minimises the reserve duty utility variable. The reserve duty selected will have its base, start time and end time replaced. It maximises the number of reserve duties in the insufficient reserve duties workload to select the hour and base. How the reserve duty utility variable and the insufficient reserve duties workload are obtained is explained in the Section 3.4.1.

The reserve duty selected will have its base changed to the one where there is the maximum number of insufficient reserve duties. The rescheduling process uses the Peak approach, explained in Section 3.2.1.1, but in this context, it utilises the insufficient reserve duties workload of the selected base. The new start time will automatically allow this reserve duty to be working in the hour selected because it is the one with the highest load of insufficient reserve duties.

The insufficient reserve duties workload is updated after each reserve duty change. The procedure repeats the steps described above all over again until the maximum number of changes (user-defined parameter) is reached or until the cost no longer increases.

For a better understanding of the procedure, the following example is provided. First, the algorithm selects the reserve duty with less use and the hour and base with the highest number of insufficient reserve duties, shown in Table 3.2.

Table 3.2: The Hour with the Highest Number of Insufficient Reserve Duties and the Reserve Duty less used

Hour with the Highest $nIRes$	**Reserve Duty less used**
$nIRes$ (mean): 3.204 Hour: 14 Base: 24	Utility: 0.1202 hours Schedule: 13h-21h Base: 19

In the next phase, the objective is to change the base and schedule of this reserve duty to cover the hour and base with the highest number of insufficient reserve duties, which is in base 24 at 14h. The schedule is remade with the Peak approach, using the workload graph from base 24. The process is represented in Figure 3.5. The new schedule is from 13h-21h, in base 24.

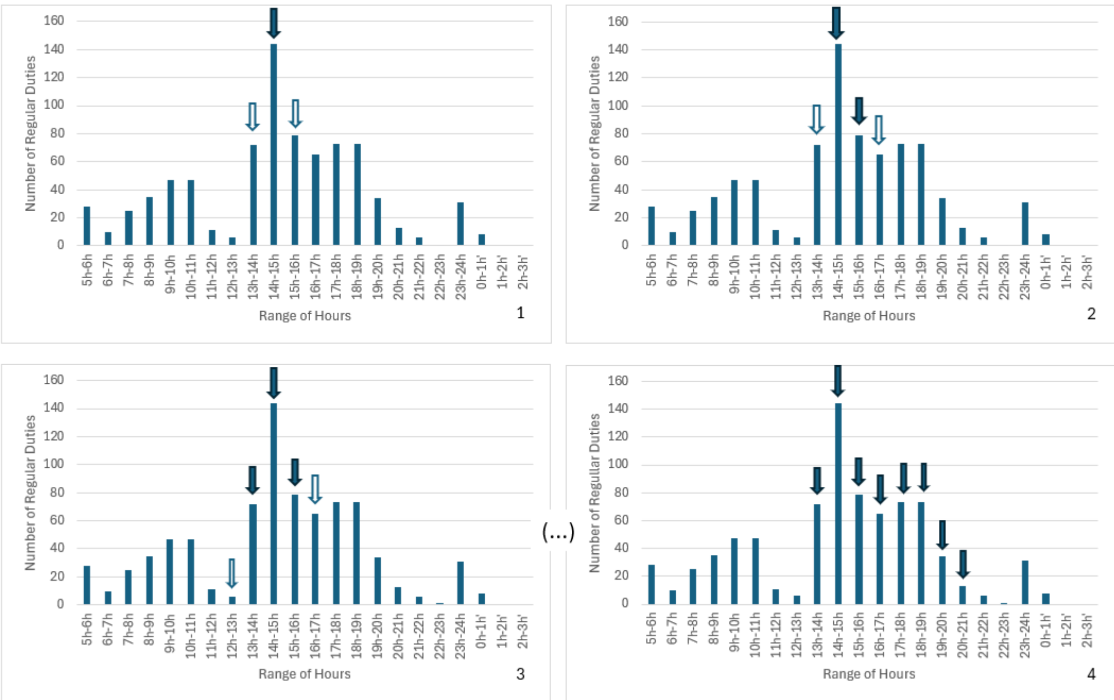


Figure 3.5: Peak Approach Squence in the Change Procedure

The number of changes made to the schedules depends on the values chosen for the Change parameter. If the parameter has the value "Fixed", the number of changes will be a fixed number, even if the cost increases. If the parameter has the value "Best", the number of changes will depend on the evaluation of the cost. If the cost decreases, the change is made and the change procedure continues, calculating a new possible change. If the cost increases or is equal to the previous cost, the change is not made and the change procedure stops.

3.5.2 Simulated Annealing

Simulated Annealing is a metaheuristic used for optimisation problems with large search spaces. In this case, Simulated Annealing is used to minimise the cost.

"Simulated annealing is so named because of its analogy to the process of physical annealing with solids, in which a crystalline solid is heated and then allowed to cool very slowly until it achieves its most regular possible crystal lattice configuration (i.e., its minimum lattice energy state), and thus is free of crystal defects. If the cooling schedule is sufficiently slow, the final configuration results in a solid with such superior structural integrity. Simulated annealing establishes the connection between this type of thermodynamic behaviour and the search for global minima for a discrete optimisation problem. Furthermore, it provides an algorithmic means for exploiting such a connection."[15]. This algorithm searches results with a lot of variety which tends to prevent it from being stuck in a local minimum, always searching for the global minimum solution.

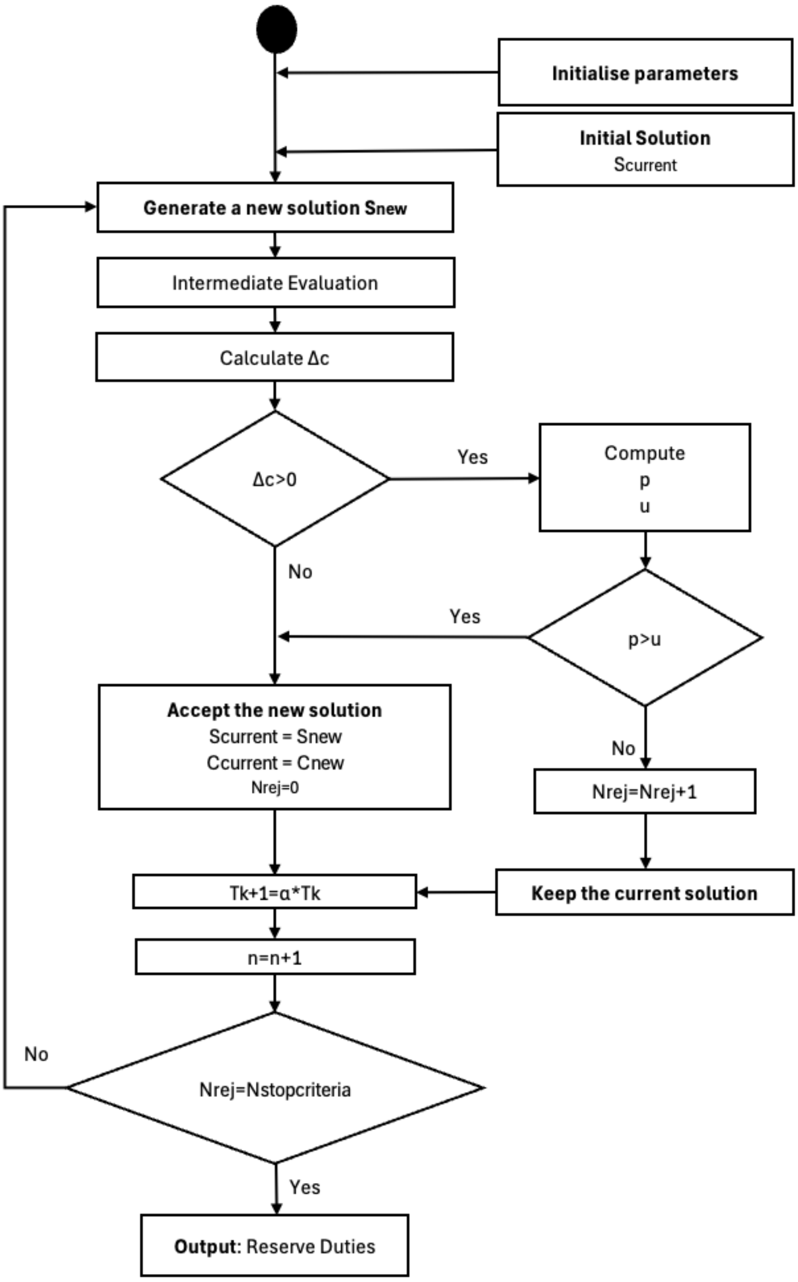
This algorithm needs three parameters: initial temperature (T_0), cooling ratio (α) and stop criteria ($N_{stop\ criteria}$). Equation 3.8 shows the reduction function, it uses the geometric reduction rule, and alpha is the parameter used to reduce the temperature in every iteration (T_k). The condition responsible for stopping the algorithm is reaching a certain number of consecutive rejections (N_{rej}), a parameter set by the user.

$$T_{k+1} = \alpha \times T_k \tag{3.8}$$

The initial solution, $S_{current}$, is obtained by one of the algorithms presented in Section 3.2, namely the Peak, Window or Random Selection approach. In every iteration, a reserve duty is randomly selected and its start time, end time and base are changed. The new set, S_{new} , is evaluated. The difference between the costs (Δc) is represented in Equation 3.9. If the cost decreases, i.e., the difference in cost is less than zero, the new solution is better, and it is accepted. Otherwise, the current set is potentially better. However, there is still the possibility that the new set, even having a higher cost, will be accepted. In this case, the percentage of acceptance (p), shown in Equation 3.10, is compared with a random number between 0 and 1. If the percentage of acceptance is greater than the random number, the new solution is accepted even with a higher cost. The objective of this process is to search for a variety of results and avoid getting stuck at a local minimum. Figure 3.6 illustrates the entire diagram of the algorithm.

$$\Delta c = c_{new} - c_{current} \tag{3.9}$$

$$p = e^{\frac{-\Delta c}{T_k}} \tag{3.10}$$



Legend:
$S_{current}$: Current set of reserve duties;
S_{new}: New set of reserve duties;
Δc: Difference between the costs;
p: percentage of acceptance;
$c_{current}$: current cost;
c_{new}: new cost;
u: Random number between 0 and 1;
N_{rej}: Number of consecutive rejections;
$N_{stop\ criteria}$: Stop criteria;
n: Number of iterations.

Figure 3.6: Simulated Annealing Diagram

Each reserve duty is defined by three key parameters: an operational base, a start time, and an end time. A set of reserve duties will be created with each methodology and tested with the evaluation methods. The following chapter provides a detailed description of the input data utilised in Chapter 5, as well as explanations and tests of decisions that had to be conducted to define the last details of the methodologies described.

4

Data description and Model Specifications

This chapter provides a detailed analysis and description of the input data provided by SISCOG. This is followed by the experiences made to determine the appropriate number of disruption scenarios for the parameterisation and evaluation of the results derived from the algorithms described in the Chapter 3. Finalises by comparing different values for Simulated Annealing parameters, with the objective of identifying those that most align the output (reserve duties) with this type of problem.

4.1 Input Data

The data used in this thesis for testing purposes is provided by SISCOG. The data set includes regular duties from one of the northern European railway companies that is a customer of SISCOG. The data set contains 881 regular duties and 28 bases. Each regular duty is associated with a base, a start time, an end time, a duration, and a sequence of trips.

Through the workload graph of Figure 4.1, it can get a small insight into the regular duties distribution throughout the day. The data reveals a higher number of regular duties in the morning and afternoon periods, with a decrease at lunchtime. Also, their working window is very extensive, starting at 5h and concluding at 2h of the following day, which represents a break in the trip services from 2h to 5h In the morning, at 9h, the highest number of regular duties working at the same time is recorded, which is 401 regular duties.

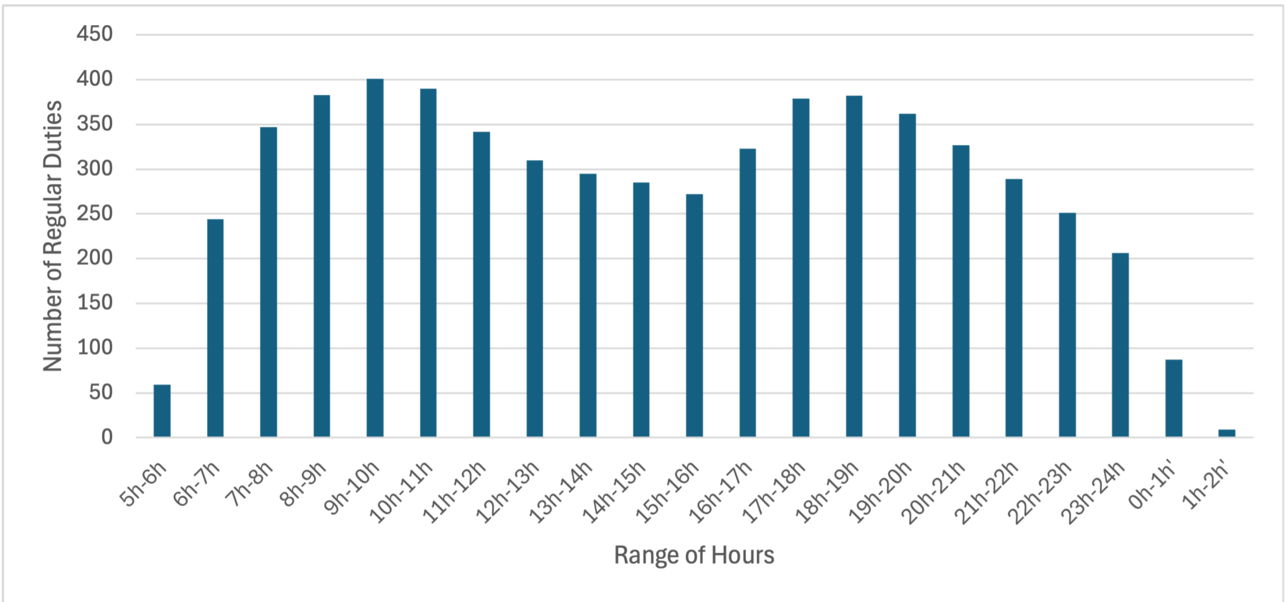


Figure 4.1: Workload of Regular Duties

The objective is to develop an algorithm that generates reserve duties that help the dispatcher solve disruption scenarios. In other words, the reserve duties should be capable of covering as many tasks as possible that would otherwise remain uncovered due to disruption scenarios.

4.2 Disruption Scenarios

The disruption scenarios have an impact on the evolution of the reserve duties in the Simulated Annealing and the Change Procedure. It is crucial to incorporate variety in the disruption scenarios in order to achieve a more precise cost. A higher number of disruption scenarios results in a more precise evaluation, although this is accompanied by a higher computational cost. The objective of the following subsection is to select the ideal number of disruption scenarios that provide sufficient precision to select the most appropriate parameters for Simulated Annealing and to evaluate the reserve duties in the intermediate evaluation.

The set of regular duties presented in this chapter, are derived from a distinct dataset. This approach was employed to prevent the parameters of Simulated Annealing and the number of disruption scenarios from being entirely adapted to the dataset under examination. This dataset comprises 719 duties with similar information to that presented in Section 4.1.

4.2.1 Disruption Scenarios Precision

Precision, in the simulation field, can be defined as the variability of simulation results. The term high precision is used to describe a situation in which the results of repeated simulations are very similar, indicating a low level of variability. To test the precision, the reserve duties used were obtained from the algorithms that create them without the influence of the disruption scenarios. This ensures that the precision calculated accurately reflects the variability and accuracy of the simulation under the specific conditions it is intended to model.

To determine the precision, 250 disruption scenarios were simulated, generating a result's dataset. Then, the mean and the standard deviation of the results were determined to understand their central tendency and variability. Next, the amplitude of the 95% confidence interval was determined using the formula writen in Equation 4.1, where $Z_{0.975}$ (also known as the critical value or Z-score) is approximately 1.96, σ is the standard deviation, and n is the sample size. This critical value of 1.96 corresponds to the 97.5th percentile of the standard normal distribution, used for a two-tailed 95% confidence interval. Finally, the precision was obtained as referenced in Equation 4.2.

$$\text{Amplitude} = 2 \times Z_{0.975} \times \frac{\sigma}{\sqrt{n}} \tag{4.1}$$

$$\text{Precision} = 1 - \frac{\text{amplitude}}{\text{mean}} \tag{4.2}$$

In Table 4.1, it is shown the precision from the cost obtained by 73 reserve duties calculated with Peak, Window and Random Selection approaches. These are the algorithms that can create reserve duties.

Table 4.1: Precision per Number of Scenarios and Approaches

Number of Consecutive Rejections	**250**	**500**	**1000**	**1500**	**2000**	**3000**	**4000**	**5000**
Peak Approach	82%	88%	91%	93%	94%	95%	96%	96%
Window Approach	74%	81%	87%	89%	91%	92%	93%	94%
Random Selection Approach	84%	88%	92%	93%	94%	95%	96%	96%

Given that determining the best parameters for the Simulated Annealing algorithm should be a relatively straightforward process, 250 disruption scenarios will be used, since they have an accuracy rate of at least 74%, which is considered sufficient for determining the parameters.

To present the results of this thesis in greater detail, a higher precision is required. However, higher precision implies higher computational time. Therefore, 2000 disruption scenarios were selected, since this number has a precision between 91% and 94%.

4.3 Setting Simulated Annealing Parameters

In order to implement the Simulated Annealing algorithm, it is necessary to define three of parameters: the initial temperature, the alpha, and the stop criteria (a limited number of consecutive rejections). To determine the best values for these parameters, a series of tests were performed. These tests were performed with the same input as that described in Section 4.2. Initially, a series of tests were performed to investigate the influence of varying the initial temperature and alpha. The sets that exhibited the lowest cost were selected. Then, the stopping criterion was defined, taking into account the cost and computational time.

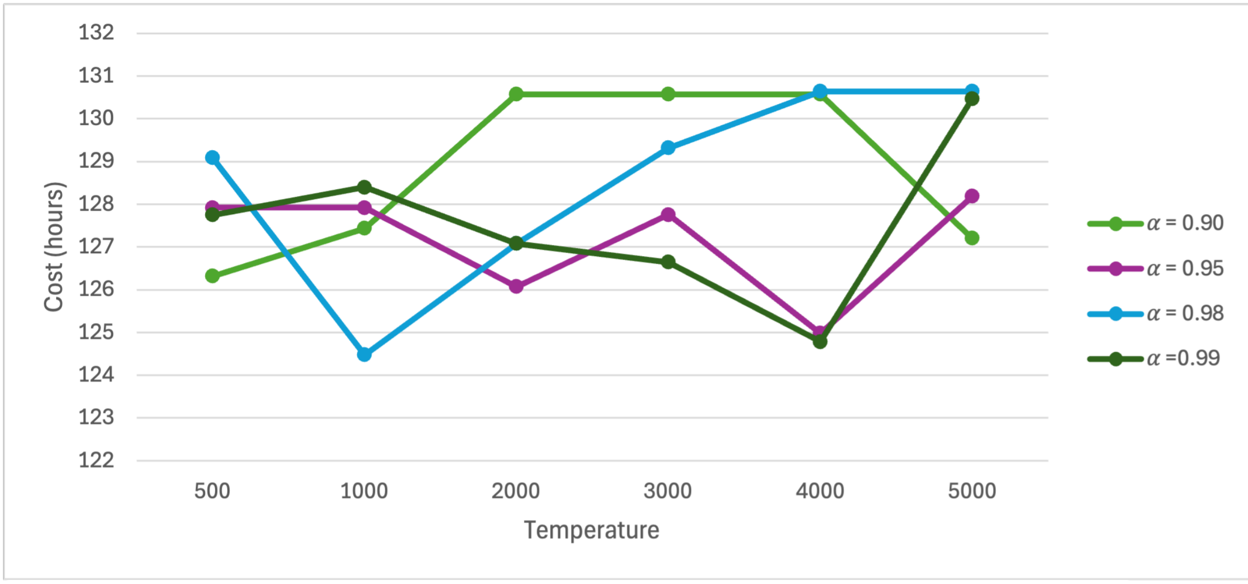
4.3.1 Initial Temperature and Alpha

The initial temperature (T_0) selected must be sufficiently high to ensure that the , as defined in Equation 3.10, is close to 1. This results in the acceptance of new solutions even if they have a higher cost, enabling the algorithm to identify and consider a wider range of potential solutions, rather than settling on the first good solution it finds. It should be noted that an increase in the initial temperature usually correlates with an increase in the computation time as well.

The cooling ratio, represented by alpha (α), which is used to reduce the temperature in the reduction function (Equation 3.8), is also a parameter that must be determined. This parameter can have values between 0 and 1. It is recommended that its numerical value should not be lower than 0.8 to allow for a gradual reduction in temperature, thereby facilitating the search for additional solutions.

The parameters were tested with 73 reserve duties, 250 disruption scenarios and 1000 as the number of consecutive rejections. The initial temperature was tested with values ranging from 500 to 5000. The cooling ratio was tested with the values 0.9, 0.95, 0.98 and 0.99.

Figure 4.2 illustrates the impact of varying initial temperature and cooling ratio values on the cost. It can be observed that there is no linear correlation between the cost and the parameters, however, minimum values can be identified.



Legend:
α 0.90: Alpha of 0.90;
α 0.95: Alpha of 0.95;
α 0.98: Alpha of 0.98;
α 0.99: Alpha of 0.99.

Figure 4.2: Cost from Different Initial Temperature and Alpha Pairs

In order to obtain a more comprehensive understanding of the costs associated to this test, Table 4.2 is presented. From the data presented in the table, it can be observed that the lowest cost is associated with an alpha value of 0.98 and an initial temperature of 1000. Similarly, there are some comparable costs values associated with an alpha of 0.99 and an initial temperature of 4000, as well as an alpha of 0.95 and an initial temperature of 4000. These three pairs of alpha and initial temperatures are selected for further analysis.

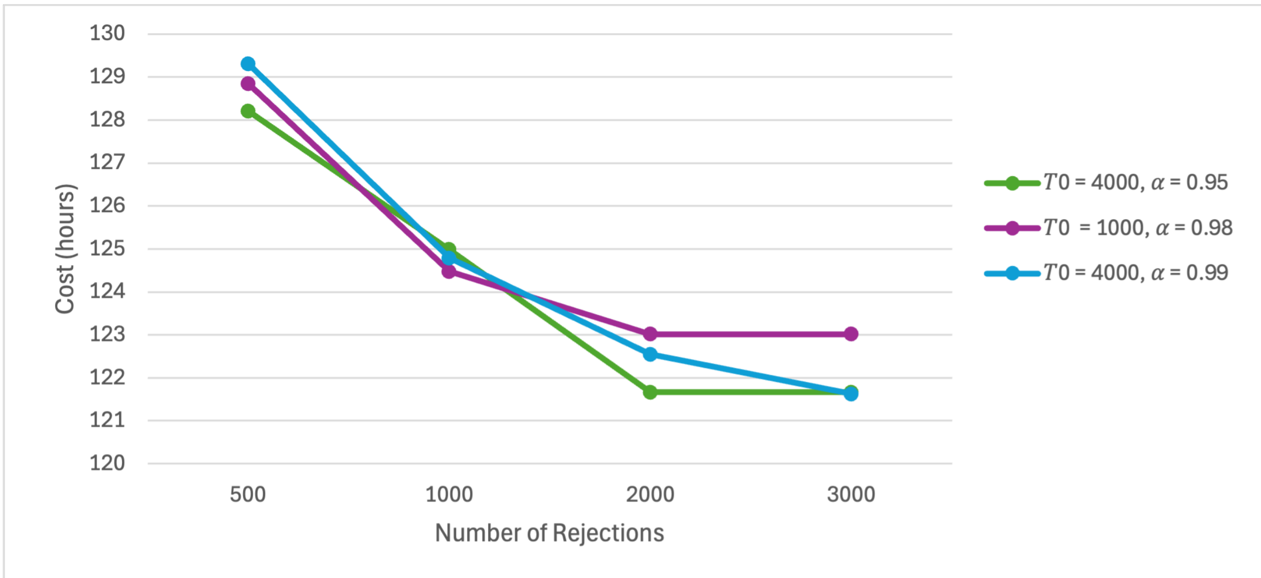
Table 4.2: Cost from Different Initial Temperature and Alpha pairs

Alpha	**Initial Temperature**					
	500	1000	2000	3000	4000	5000
0.90	126.320	127.436	130.572	130.572	130.572	127.204
0.95	127.924	127.924	126.072	127.756	124.980	128.188
0.98	129.088	124.476	127.084	129.320	130.640	130.640
0.99	127.748	128.396	127.084	126.644	124.784	130.472

4.3.2 Stop Criteria: Number of Consecutive Rejections

The final parameter that requires definition is the stop criteria. This parameter defines the limit number of consecutive rejections made in order to choose the set of reserve duties. A higher number of consecutive rejections is typically associated with a higher computation time and a higher number of iterations, which can be observed in the test results. Tests were conducted with three pairs of initial temperature and alpha, the ones selected in the previous section, with the number of consecutive rejections ranging from 500 to 3000.

Figure 4.3 illustrates the cost of the reserve duties. The initial temperature is represented by a T_0, while alpha is represented by its symbol, α. It can be observed that there is a decrease in the cost when the number of consecutive rejections increases. In order to determine the best number of consecutive rejections, it is necessary to consider the computation time.



Legend:
T_0 4000 α 0.95: Initial Temperature of 4000 and an Alpha of 0.95;
T_0 1000 α 0.98: Initial Temperature of 1000 and an Alpha of 0.98;
T_0 4000 α 0.99: Initial Temperature of 4000 and an Alpha of 0.99.

Figure 4.3: Cost from Different Numbers of Consecutive Rejections

As evidenced in Tables 4.3 and 4.5, the last increase of the number of consecutive rejections has no impact on the cost. In Table 4.4, the cost always decreases when the number of consecutive rejections increases. However, in this final instance, the increase is less than an hour. This indicates that elevating the number of consecutive rejections to 3000 is not the best strategy, as it prolongs the computation time without demonstrating a cost-effective outcome. The number of consecutive rejections selected is 2000, which increases the computation time but is compensated by a significant decrease in the cost, as presented in the tables.

Table 4.3: Comparing Different Numbers of Consecutive Rejection from Reserve Duties obtained with an Initial Temperature of 1000 and an Alpha of 0.98

Number of Consecutive Rejections	**500**	**1000**	**2000**	**3000**
Number of Iterations	6400	14758	22955	23956
Time (sec)	78	187	282	295
Cost (hours)	128.848	124.476	123.016	123.016

Table 4.4: Comparing Different Numbers of Consecutive Rejection from Reserve Duties obtained with an Initial Temperature of 4000 and an Alpha of 0.99

Number of Consecutive Rejections	**500**	**1000**	**2000**	**3000**
Number of Iterations	4486	10528	17680	31141
Time (sec)	54	129	216	383
Cost (hours)	129.304	124.784	122.548	121.624

Table 4.5: Comparing Different Numbers of Consecutive Rejection from Reserve Duties obtained with an Initial Temperature of 4000 and an Alpha of 0.95

Number of Consecutive Rejections	**500**	**1000**	**2000**	**3000**
Number of Iterations	3396	11301	20432	21433
Time (sec)	42	137	254	259
Cost (hours)	128.208	124.980	121.664	121.664

Having now established the details of the Simulated Annealing algorithm and the best number of disruption scenarios, it is possible to proceed to the presentation of the results. The following chapter will present the results obtained with the intermediate evaluation, conducted with 2000 disruption scenarios, and with the final evaluation.

5

Results and Discussion

This chapter analyses the results obtained by the models described in Chapter 3. Section 5.1 compares the results obtained by the Peak, Window, and Random Selection approaches, the models responsible for the initial reserve duties. Section 5.2 presents the results obtained with the initial reserve duties and the application of the Change Procedure. The Change Procedure is applied using the best method and the fixed method. Section 5.3 analyses the results obtained with the initial reserve duties methods along with the Simulated Annealing method. Section 5.4 presents the results obtained with the previously described approaches, but using different disruption scenarios. In these scenarios, the number of unmanned duties varies per base and per period of the day. The last section, 5.5, presents the results obtained by the SISCOG optimiser.

The input data utilised in this chapter is described in the Section 4.1. The disruption scenarios are crucial for modelling the uncertainty present in real-world scenarios. As mentioned in the previous chapter, the results are obtained with 2000 disruption scenarios. The number of unmanned duties is calculated using the Equation 3.2. A statistical analysis was conducted using data from one of SISCOG's clients, which revealed a crew absence rate of 8% among employers. Accordingly, the used was 8%. The number of reserve duties obtained is calculated using Equation 3.1. The used were 8% as well, equal to the crew absence rate, and 16% the double. This resulted in 82 reserve duties and 152 reserve duties, respectively. With these two percentages, it is possible to observe how the reserve duties are distributed with an identical and the influence of a higher percentage of reserve duties on the cost.

The measure employed for comparative analysis in Sections 5.1, 5.2, 5.3 and 5.4 is named cost and it is detailed in the Subsection 3.4.1. The cost is rounded up to three decimal places. In the Sections 5.1, 5.2 and 5.3 the disruption scenarios are created with the same percentage of unmanned duties for each base and part of the day, in order to study the adaptability of a simpler scenario.

In the Section 5.4, the disruption scenarios are created with different percentages of unmanned duties. In Subsections 5.5.2, the percentages differ by base, while in Subsection 5.5.3, the percentages differ by period of the day. The objective of this study is to demonstrate the adaptability of the various methods in response to different disruption scenarios.

In the last section, 5.5, a second evaluation is conducted utilising the SISCOG optimiser. The final cost, described in reference Subsection 3.4.2, is employed as the metric for this evaluation.

5.1 Initial Reserve Duties Evaluation

Table 5.1 presents a cost analysis of the initial models, which reveals a correlation between an increase in the number of reserve duties and a reduction in the costs.

It can be concluded that the Window approach is the most effective method for both 82 and 152 reserve duties. Conversely, the Random Selection approach is the least effective, as would be anticipated given that this approach randomly selects the start time and the base of the schedule, only using the working time window. The other two approaches utilise information from the duties to generate the reserve duties.

Table 5.1: Performance Measure obtained from the Initial Reserve Duties Models

Method **Number of Reserve Duties**	**PA** **82**	**WA** **82**	**RSA** **82**	**PA** **152**	**WA** **152**	**RSA** **152**
Time (seconds)	2	2	2	3	2	2
Cost (hours)	193.546	129.811	237.463	101.725	39.847	140.372

Legend: *PA: Peak Approach; WA: Window Approach; RSA: Random Selection Approach.*

Table 5.1 is used for the comparison of the results obtained with the additional methods, namely the Change Procedure and Simulated Annealing.

The workload of the Initial Reserve Duties with 82 Reserve Duties is presented in A.1, and with 152 Reserve Duties is presented in A.2.

5.2 Change Procedure Evaluation

The Change Procedure comprises two processes for defining the number of changes to be made to the initial reserve duties: the Best method and the Fixed method. In the Best method, the number of changes is variable and dependent on the cost progression. In contrast, the Fixed method requires the definition of a fixed number of changes, which, in this case, will be 50 changes. Once this number has been defined, the algorithm automatically makes the requisite number of changes.

Table 5.2 presents the cost obtained from the Best method of the Change Procedure. Additionally, it is evident that this method is very rigid, preventing the processes from exploring further opportunities for reducing the cost, which ultimately results in a reduced number of changes. The initial reserve duties obtained with the method Window approach do not suffer any change, remain unaltered because the suggested change would increase the cost. With the method Peak approach, few changes are made to the initial reserve duties, and the cost is not significantly improved. Lastly, with Random Selection approach, the initial reserve duties suffer the higher number of changes and show a significant improvement in the cost.

Table 5.2: Performance Measure obtained from the Initial Reserve Duties Models used in conjunction with the Best Method of the Change Procedure

Method **Number of Reserve Duties**	**PA** **82**	**WA** **82**	**RSA** **82**	**PA** **152**	**WA** **152**	**RSA** **152**
Number of Changes	1	0	9	2	0	10
Time (seconds)	3	2	5	3	3	5
Cost (hours)	190.849	129.811	198.032	97.048	39.847	91.951

Legend: *PA: Peak Approach; WA: Window Approach; RSA: Random Selection Approach.*

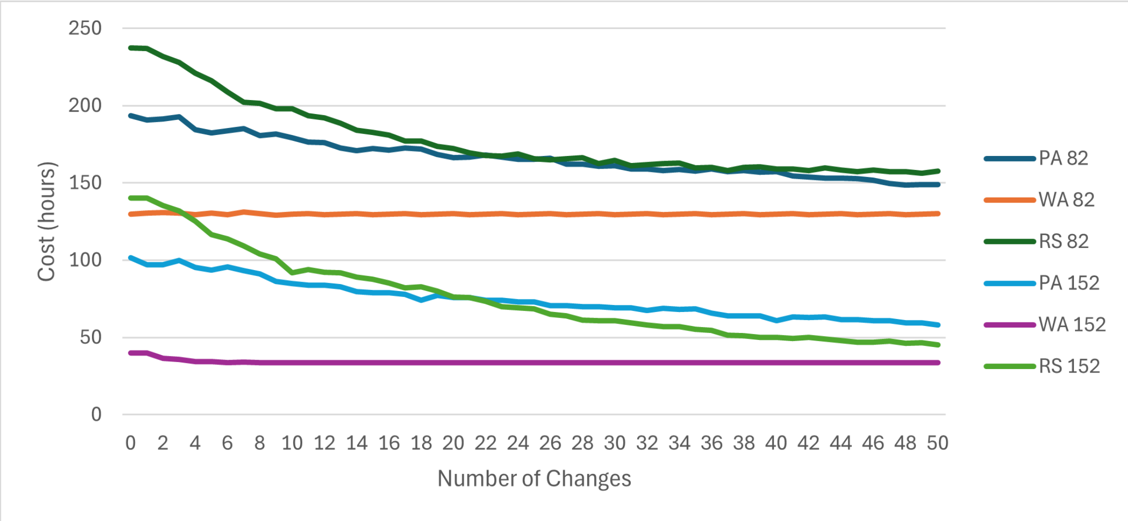
Table 5.3 presents the cost obtained from the Fixed method of the Change Procedure, with 50 changes. This number of changes allows for an examination of the cost evolution and the impact of different initial reserve duties on this evolution. Furthermore, it is evident that the Window approach with 82 reserve duties has resulted in a higher cost when compared to its initial reserve duty, as presented in Table 5.1. Even though, the Change Procedure does not result in any modifications, the Window approach remains the best solution for 82 reserve duties. Similarly, for 152 reserve duties, the Window approach continues to be the most cost-effective method.

Table 5.3: Performance Measure obtained from the Initial Reserve Duties Models used in conjunction with the Fixed Method of the Change Procedure

Method **Number of Reserve Duties**	**PA** **82**	**WA** **82**	**RSA** **82**	**PA** **152**	**WA** **152**	**RSA** **152**
Number of Changes (Fixed)	50	50	50	50	50	50
Time (seconds)	19	16	18	17	18	18
Cost (hours)	148.869	130.077	157.753	58.171	33.754	45.226

Legend: *PA: Peak Approach; WA: Window Approach; RSA: Random Selection Approach.*

Figure 5.1 illustrates the evolution of the cost per number of changes obtained from the Fixed method of the Change Procedure with 50 changes. For 82 reserve duties, the Peak approach begins with a lower cost than Random Selection approach. Following approximately 25 changes, the Random Selection approach exhibits a lower cost than the Peak approach. For 152 reserve duties, the Peak approach begins with a lower cost than Random Selection approach. Following approximately 25 changes, the Random Selection approach demonstrates a lower cost than the Peak approach. However, a number of changes after the Peak approach cost starts to reduce, resulting in a lower cost than Random Selection approach. For both 82 and 152 reserve duties, the cost of the Window approach decreases slowly but remains the lowest throughout the number of changes.



Legend:
PA 82: Peak Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RS 82: Random Selection Approach with 82 Reserve Duties;
PA 152: Peak Approach with 152 Reserve Duties;
WA 152: Window Approach with 152 Reserve Duties;
RS 152: Random Selection Approach with 152 Reserve Duties.

Figure 5.1: Cost Evolution per Number of Changes from the Initial Reserve Duties Models used in conjunction with the Fixed Method of the Change Procedure

The workload of the reserve duties obtained with the Best method with 82 Reserve Duties, is presented in Figure A.3, and with 152 Reserve Duties is presented in Figure A.4. The workload of the reserve duties obtained with the Fixed method with 50 changes and with 82 Reserve Duties is presented in FigureA.5, and with 152 Reserve Duties is presented in FigureA.6.

5.3 Simulated Annealing Evaluation

In Section 4.3, the parameters necessary for the execution of the Simulated Annealing algorithm were defined. Those included the initial temperature, alpha, and stop criteria, defined as the number of consecutive rejections. Three sets of initial temperature and alpha values were identified as particularly noteworthy. The first set has an initial temperature of 1000 and an alpha of 0.98. The second set has an initial temperature of 4000 and an alpha of 0.95. The third set has an initial temperature of 4000 and an alpha of 0.99. These three sets were then tested using three different approaches: the Peak, the Window, and Random Selection approaches.

The following three tables present four measures: best iteration, total number of iterations, time (seconds), and cost (hours). Achieving the stopping criterion of 2000 consecutive iterations results in different total numbers of iterations per method. A higher total number of iterations also correlates with an increased computational time. The best iteration is defined as the number of iterations to which the best cost was achieved.

Table 5.4 presents a cost analysis obtained from the Peak approach used in conjunction with Simulated Annealing, with the three sets of initial temperatures and alphas. In the case of 82 reserve duties, the set with the lowest cost is that with an initial temperature of 4000 and an alpha of 0.99. However, for 152 reserve duties, this set of parameters presents the highest cost. Conversely, for 82 reserve duties, the set with an initial temperature of 1000 and an alpha of 0.98 presents the highest cost of the group, while for 152 reserve duties with the same parameters, presents the lowest cost. The final set, with an initial temperature of 4000 and an alpha of 0.95, represents the intermediate cost for both 82 and 152 reserve duties. The application of Simulated Annealing to the Peak approach, regardless of the set applied, resulted in a significant improvement in the cost for both 82 and 152 reserve duties. The reduction in the cost for 82 reserve duties ranges from 54.772 to 65.854 hours, while for 152 reserve duties it ranges from 69.673 to 71.696 hours, depending on the initial temperature and alpha set applied.

Table 5.4: Performance Measure obtained from the Peak Approach used in conjunction with Simulated Annealing

Number of Reserve Duties	82	82	82	152	152	152
Alpha	0.98	0.95	0.99	0.98	0.95	0.99
Temperature	1000	4000	4000	1000	4000	4000
Best Iteration	3809	9264	28161	31493	22152	16907
Total Number of Iterations	5813	11267	30169	33498	24158	18912
Time (seconds)	658	1277	3203	3536	2478	2007
Cost (hours)	138.774	130.766	127.692	30.029	31.608	32.052

Table 5.5 presents a cost analysis obtained from the Window approach used in conjunction with Simulated Annealing, with the three sets of initial temperatures and alphas. For 82 reserve duties the set with the lowest cost is with an initial temperature of 1000 and an alpha of 0.98. However, for 152 reserve duties, this set presents the higher cost. It is noteworthy that two sets of reserve duties exhibited no change in cost following the application of Simulated Annealing. These were obtained with 82 reserve duties, with an initial temperature of 4000 and alphas of 0.95 and 0.99. For 152 reserve duties, the cost decreased for each set in comparison with the application of the Window approach alone. The set with an initial temperature of 4000 and an alpha of 0.95 exhibits the lowest cost, although the difference between the three costs are not sufficient to be considered meaningful. The application of the Simulated Annealing to the Window approach resulted in a modest reduction in the cost when compared with the reduction achieved by the Peak approach. The reduction in the cost for 82 reserve duties ranges from 0 to 2.466 hours, while for 152 reserve duties it ranges from 8.393 to 9.715 hours, depending on the set of initial temperatures and alphas applied.

Table 5.5: Performance Measure obtained from the Window Approach used in conjunction with Simulated Annealing

Number of Reserve Duties	82	82	82	152	152	152
Alpha	0.98	0.95	0.99	0.98	0.95	0.99
Temperature	1000	4000	4000	1000	4000	4000
Best Iteration	32361	0	0	11852	21160	24422
Total Number of Iterations	34364	9516	11503	13860	23168	26429
Time (seconds)	3592	978	1165	1448	2457	2775
Cost (hours)	127.345	129.811	129.811	31.454	30.132	30.778

Table 5.6 present a cost analysis obtained from the Random Selection approach used in conjunction with Simulated Annealing, with the three sets of initial temperatures and alphas. For 82 reserve duties, the set with the lowest cost is achieved with an initial temperature of 4000 and an alpha of 0.95. However, for 152 reserve duties, the set with the lowest cost is achieved with an initial temperature of 4000 and an alpha of 0.99. The reduction in the cost for 82 reserve duties ranges from 108.103 to 112.103 hours, while for 152 reserve duties it ranges from 108.244 to 108.701 hours, depending on the set of initial temperatures and alphas applied.

Table 5.6: Performance Measure obtained from the Random Selection Approach used in conjunction with Simulated Annealing

Number of Reserve Duties	82	82	82	152	152	152
Alpha	0.98	0.95	0.99	0.98	0.95	0.99
Temperature	1000	4000	4000	1000	4000	4000
Best Iteration	15990	30490	29001	24306	21231	21519
Total Number of Iterations	17998	32497	31008	26308	23237	23527
Time (seconds)	1886	3353	3207	2739	2391	2394
Cost (hours)	129.360	125.381	127.037	32.128	32.043	31.671

A review of the three tables presented in this section reveals that the cost range is from 125.381 hours to 138.774 hours for 82 reserve duties and from 32.128 hours to 30.029 hours for 152 reserve duties. Additionally, no set of an initial temperature and an alpha exhibits a distinctive or noteworthy characteristic.

Although the Simulated Annealing method requires a longer time to achieve improvements in solutions, it is more robust than the Change Procedure. This suggests that the model is less sensitive to the initial solution, which may explain why no initial reserve duty models exhibited distinctive characteristics.

The workload of the reserve duties obtain from the Peak approach used in conjunction with Simulated Annealing with 82 Reserve Duties is presented in Figure A.7, and with 152 Reserve Duties is presented in Figure A.8. The workload of the reserve duties obtain from the Window approach used in conjunction with Simulated Annealing with 82 Reserve Duties is presented in Figure A.9, and with 152 Reserve Duties is presented in Figure

A.10.The workload of the reserve duties obtain from the Random Selection approach used in conjunction with Simulated Annealing with 82 Reserve Duties is presented in Figure A.11, and with 152 Reserve Duties is presented in Figure A.12.

5.4 Different Percentage of Unmanned Duties

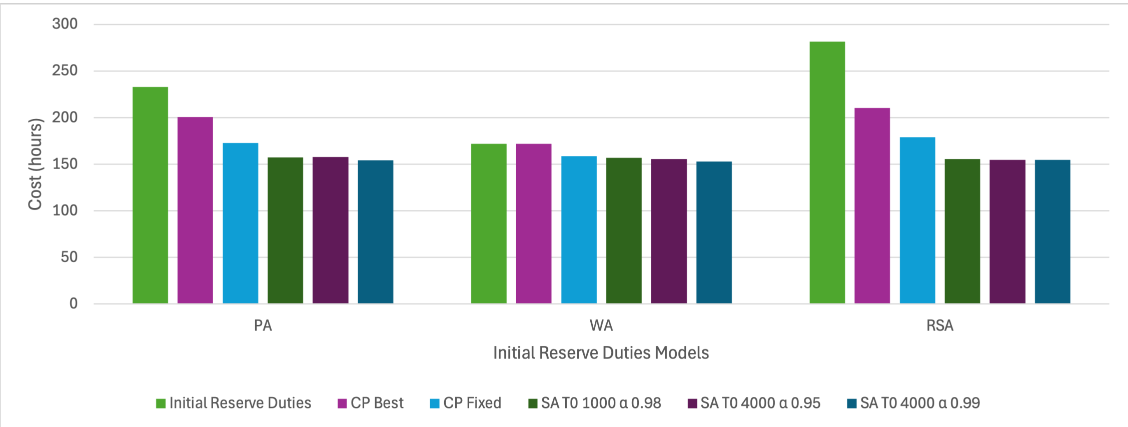
This chapter tests the adaptability of the models presented by looking at different disruption scenarios. The scenarios are constructed by assigning distinct percentages to different bases and periods of the day.

The assignment of different percentages to bases and periods of the day results in different numbers of unmanned duties, which consequently creates different cost ranges. It is therefore not appropriate to compare the results presented in this section with those of other sections.

5.4.1 Different Percentage of Unmanned Duties per Base

In order to allocate different percentages of unmanned duties to the 28 operational bases, four bases were assigned a value of 0%, another four a value of 16%, and the remaining a value of 8%.

Figure 5.2 presents a cost analysis of the initial reserve duties models, the methods of the Change Procedure and Simulated Annealing, with the disruption scenarios created with different percentages of unmanned duties per base.



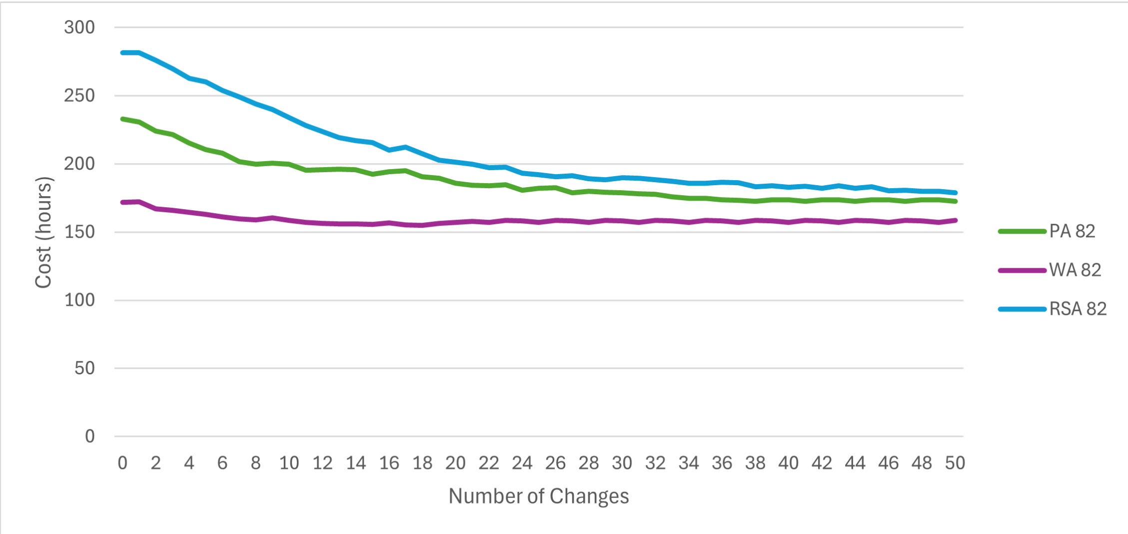
Legend
CP Best: Change Procedure Best method;
CP Fixed: Change Procedure Fixed method; SA T_0 1000 α 0.98: Simulated Annealing with an initial temperature of 1000 and an alpha of 0.98;
SA T_0 4000 α 0.95: Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95;
SA T_0 4000 α 0.99: Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99.

Figure 5.2: Cost obtained from the Initial Reserve Duties Models, Change Procedure and Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

The three initial reserve duties models, represented in the Figure 5.2 in light green, create reserve duties based on the input data exclusively. It should be noted that this column serves only as a reference for the initial models, as it is acknowledged that they lack the capacity to adapt to new disruption scenarios. The table with the cost and time of the initial reserve duties models with the disruption scenarios created with different percentages of unmanned duties per base is presented in Table A.1.

As observed in the previously disruption scenarios, the Fixed method once again obtained better costs than the Best method. Table A.2 presents the cost, time, and number of changes of the initial reserve duties models used in conjunction with the methods Best and Fixed from Change Procedure, with the disruption scenarios created with different percentages of unmanned duties per base. Furthermore, it is evident that the Window approach, when applied in conjunction with the Best method of the Change Procedure, resulted in no alteration, despite exhibiting the lowest cost of the method.

The Fixed method demonstrates a reduction in cost, as evidenced by Figure 5.3. However, it is notable that this decline is not linear, with some values remaining constant or even increasing throughout the changes. This phenomenon is observed across all initial reserve duties models.



Legend:
PA 82: Peak Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RS 82: Random Selection Approach with 82 Reserve Duties.

Figure 5.3: Evolution of the Cost per Number of Changes with Different Initial Reserve Duties

In both approaches of the Change procedure, the initial model with the lowest cost is Window approach, while Random Selection approach exhibits the highest cost.

In Figure 5.2, it can be seen that the costs resulted from the different initial temperature and alpha sets of the Simulated Annealing are very similar, it is not possible to identify in this figure which one has the lowest cost.

Tables A.3, A.4 and A.5 presents a cost analysis of the Peak, Window and Random Selection approaches, respectively, used in conjunction with Simulated Annealing, with the disruption scenarios created with different percentages of unmanned duties per base. A comparison of the three tables reveals that the lowest cost is obtained with the Window approach with an initial temperature of 4000 and an alpha of 0.99. Furthermore, it can be seen that the range of costs in the three tables reveals a relatively similar range of costs. However, there is a significant variation in computation time and the number of iterations.

A detailed examination of the costs associated with disruption scenarios created with different percentages of crew unmanned duties per base reveals that the Simulated Annealing exhibits a lower cost than the Change Procedure. Simulated Annealing is a more robust method than the Change Procedure, necessitating a longer time to achieve improvements, typically between 15 and 50 minutes.

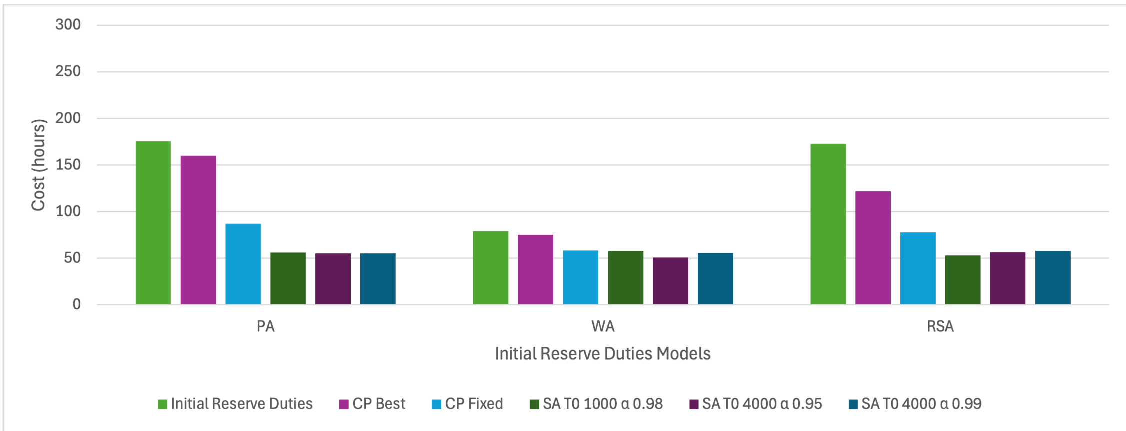
5.4.2 Different Percentage of Unmanned Duties per Day Period

In order to allocate different percentages of unmanned duties to different parts of the day, the day was partitioned at 12 o'clock. This implies that every duty starting between 12 a.m. and 12 p.m. is associated with the initial period of the day, and every duty starting after 12 p.m. is associated with the second period of the day. Given that afternoon shifts are associated with a higher probability of unmanned duties [16], a higher percentage of unmanned duties was attributed to the second period. Consequently, 80% of unmanned duties was attributed to the second period of the day, while the remaining 20% of unmanned duties was attributed to the first period of the day. This also means that 80% of the unmanned duties will start after 12pm, while 20% of them will start before 12pm.

Figure 5.4 presents a cost analysis of the initial reserve duties models, the methods of the Change Procedure and Simulated Annealing, with the disruption scenarios created with different percentages of unmanned duties per period of the day.

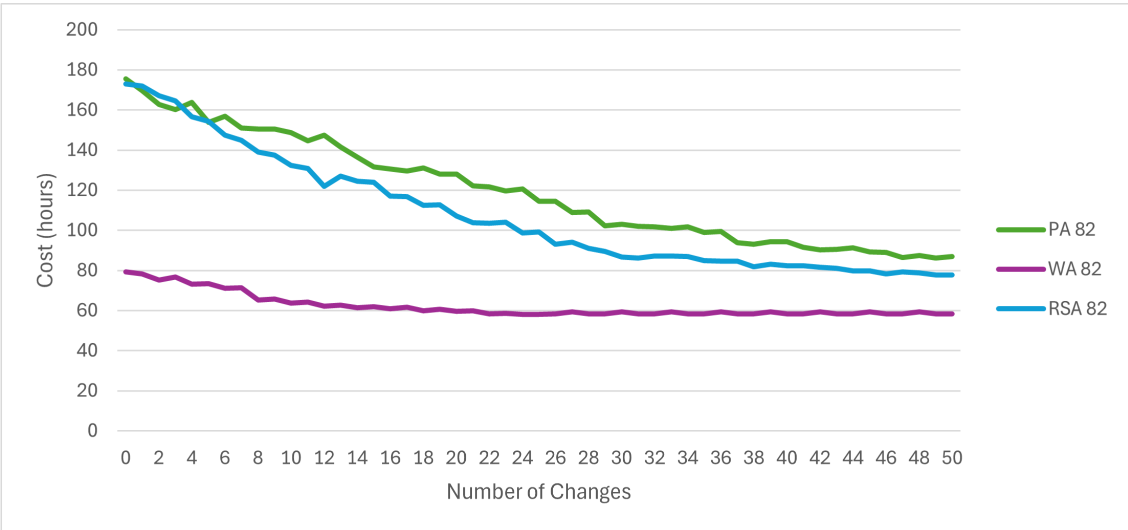
As previously stated, the three initial reserve duties models, represented in the Figure 5.4 in light green, are only intended to serve as a reference for the initial models due to of their lack of capacity to adapt to new disruption scenarios.

Figure 5.5 illustrates the evolution of the cost per number of changes. The Fixed method resulted in a reduction in cost, with some fluctuations, but still produced better costs when compared to the Best method. Table A.7 presents a cost analysis of the initial reserve duties models, used in conjunction with the methods Best and Fixed from Change Procedure, with different percentages of unmanned duties per period of the day. The Best method resulted in a reduction of the cost for every initial reserve duties model, with a total of three to six changes in the reserve duties. The lower costs were obtained with the Window approach for both methods, Best and Fixed.



Legend:
CP Best: Change Procedure Best method;
CP Fixed: Change Procedure Fixed method;
SA T_0 1000 α 0.98: Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98;
SA T_0 4000 α 0.95: Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95;
SA T_0 4000 α 0.99: Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99.

Figure 5.4: Cost obtained from the Initial Reserve Duties Models, Change Procedure and Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day



Legend:
PA 82: Peak Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RS 82: Random Selection Approach with 82 Reserve Duties.

Figure 5.5: Evolution of the Cost per Number of Changes with Different Initial Reserve Duties

Tables A.8, A.9 and A.10 present a cost analysis of the Peak, Window and Random Selection approaches, respectively, used in conjunction with Simulated Annealing, with the disruption scenarios created with different percentages of unmanned duties per period of the day.

A comparison of the three tables reveals that the lowest cost is obtained with the Window approach with an initial temperature of 4000 and an alpha of 0.95. Furthermore, it can be seen that the range of costs in the three tables reveals a relatively similar range of costs. However, there is a notable variation in computation time and the number of iterations.

Similarly, as outlined in Section 5.5.2, the analysis of the costs associated with disruption scenarios created with different percentages of unmanned duties per period of the day reveals that the Simulated Annealing exhibits a lower cost than the Change Procedure. However, the Change Procedure continues to requires a relatively brief period of time when compared with the Simulated Annealing. This can once again be explained by the difference in the robustness of the methods. Simulated Annealing, being more robust, also takes longer to compute.

5.5 SISCOG Optimiser

The SISCOG optimiser is a tool designed to assess the behaviour of the methods in a disruption scenario, utilising comprehensive information pertaining to the problem. Given the increased computational burden, a smaller number of methods and disruption scenarios had to be selected. In order to obtain measurements from the SISCOG optimiser, three sets of 20 disruption scenarios and four methods were selected.

The three sets of 20 disruption scenarios were selected from the sets used previously in this chapter. One set comprises disruption scenarios with the same percentage of unmanned duties for each base and part of the day. Another set includes disruption scenarios with different percentages for different bases, as detailed in Subsection 5.5.2. A third set of disruption scenarios with different percentages for different parts of the day, as detailed in Subsection 5.5.3.

Given that only 20 scenarios are employed in this section, it was necessary to exercise control over the variation in the number of unmanned duties. The percentage of unmanned duties selected for the simulation of disruption scenarios was 8%. Given that 8% of the total number of duties is 70, it was decided that 65 to 75 unmanned duties would be the best range. The first 20 scenarios of the 2000 disruption scenarios with that range of unmanned duties between 65 and 75 were selected. A similar number of unmanned duties is associated with a similar distribution of costs, with no disruption scenario exhibiting a higher impact than another.

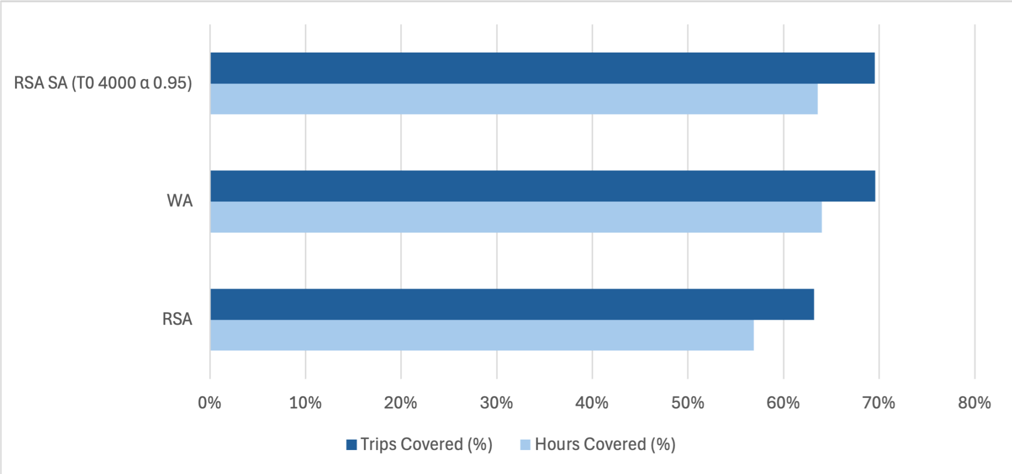
A comparative analysis will be conducted using the number of hours and trips that were covered by the reserve duties and the number of hours and trips that would not be covered if there were any reserve duties in each disruption scenario. To facilitate comparison, the number of hours and trips in each scenario are summed and, a percentage of hours covered and a percentage of trips covered per method and set of disruption scenarios is created. The percentage of hours covered is calculated by dividing the sum of hours of trips that were covered by the reserve duties by the sum of hours of trips that would not be covered if there were any reserve duties. The percentage of trips covered is the result of the division between the sum of trips that were covered by the reserve duties and the sum of trips that would not be covered if there were any reserve duties.

In order to obtain measurements from the SISCOG optimiser, four distinct methods were employed. Two initial reserve duties models were used: Random Selection approach, which produced the worst results in intermediate evaluation and Window approach, which produced the best results in intermediate evaluation. One method from the Change Procedure and one method from Simulated Annealing were selected based on the best costs demonstrated in the intermediate evaluation.

5.5.1 Equal Percentage of Unmanned Duties per Base and Day Period

The first set of 20 disruption scenarios were tested with 82 reserve duties and 152 reserve duties. The method employed for the 82 reserve duties was that of Simulated Annealing, utilising a Random Selection approach with an initial temperature of 4000 and an alpha value of 0.95. For 82 reserve duties, no method of the Change Procedure was employed, as the best result of the Window approach was with the Best method with 0 changes, which is equivalent to the Window approach solely. In regard to the 152 reserve duties, the methods used were the Window approach with the Fixed method from the Change Procedure and the Peak approach with an initial temperature of 1000 and an alpha of 0.98 from Simulated Annealing.

From Figure 5.6 to Figure 5.7 it is notable an increase, approximately 20%, in both the percentages of hours and number of trips covered, resulting from the increase in the number of reserve duties from 82 to 152. It is also evident that the method with the lowest percentages of hours and trips covered is Random Selection approach, for both 82 reserve duties and 152 reserve duties. The highest percentages of hours and trips covered are achieved by the Window approach for 82 reserve duties and the Simulated Annealing for 152 reserve duties. The discrepancy between the percentages of hours and number of trips covered is attributable to the varying lengths of trips that became covered.



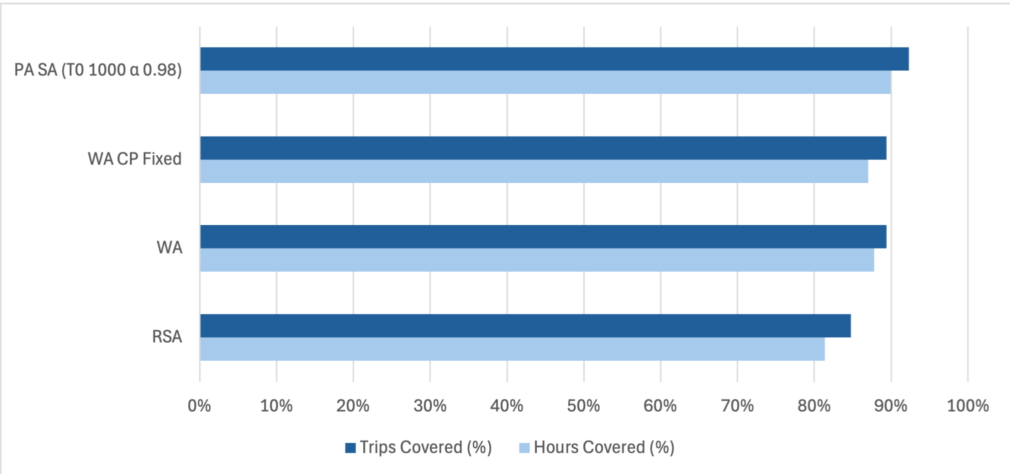
Legend:

RS SA (T_0 4000 α 0.95): Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95;

WA: Window Approach;

RSA: Random Selection Approach.

Figure 5.6: Percentage of Hours and Number of Trips Covered in 20 Disruption Scenarios for 82 Reserve Duties- Results from SISCOG Optimiser



Legend:

PA SA (T_0 1000 α 0.98): Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98;

WA CP Fixed: Window Approach used in conjunction with Change Procedure Fixed method;

WA: Window Approach;

RSA: Random Selection Approach.

Figure 5.7: Percentage of Hours and Number of Trips Covered in 20 Disruption Scenarios for 152 Reserve Duties- Results from SISCOG Optimiser

Table 5.7 compares the cost obtained with the intermediate and the final evaluations. It can be seen that the results show similar outcomes for all methods except for Random Selection approach, which demonstrates inferior results. This may indicate that the SISCOG optimiser, even when presented with poor sets of reserve duties, is capable of allocating trips that start in another base when necessary, a capability that the intermediate evaluation does not possess. The remaining methods have similar results, exhibiting a maximum difference of 10 hours.

Table 5.7: Comparison of the Cost obtained with Intermediate Evaluation and Final Evaluation

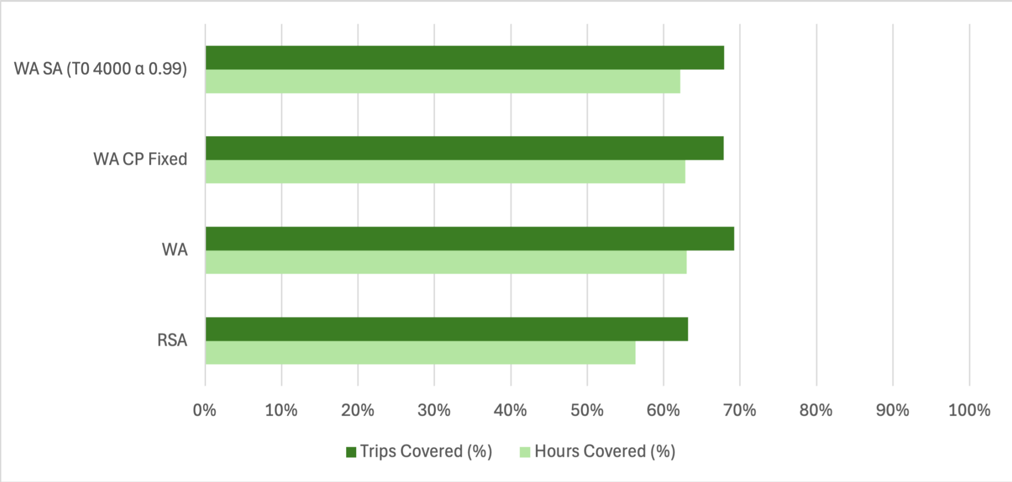
Method	**Number of Reserve Duties**	**Intermediate Evaluation Cost (hours)**	**Final Evaluation Cost (hours)**
RSA	82	237.463	143.586
WA	82	129.811	119.832
RSA SA (T_0 4000 α 0.95)	82	125.381	121.158
RSA	152	140.372	62.303
WA	152	39.847	40.590
WA CP Fixed	152	33.754	43.193
PA SA (T_0 1000 α 0.98)	152	30.029	33.389

Legend: *PA: Peak Approach; WA: Window Approach; RSA: Random Selection Approach; CP: Change Procedure; SA: Simulated Annealing; T_0: Initial Temperature; α: Alpha.*

5.5.2 Different Percentage of Unmanned Duties per Base

The second set of 20 disruption scenarios, with different percentages of unmanned duties per base, were tested with 82 reserve duties. The methods employed from Change Procedure was the Window approach Fixed method and from Simulated Annealing was the Window approach with an initial temperature of 4000 and an alpha of 0.99.

Figure 5.8 demonstrates the adaptability of the methodologies in the context of different percentages of unmanned duties per base. It is evident that the method with the lowest percentages of hours and trips covered is Random Selection approach. The Window approach method achieves the highest percentages of hours and trips covered, which is contrary to expectation, given that this method has no access to the disruption scenarios. Consequently, it should lack the ability to adapt to new scenarios. This phenomenon can be attributed to the flexibility of the SISCOG optimiser for being able to assign unmanned trips to duties from bases different from the base of the duty where the task was originally assigned (with the use of positioning trips), which is not an option for the intermediate evaluation. The discrepancy between values obtained for percentages of hours and number of trips covered is attributable to the varying lengths of trips that became covered.



Legend:
WA SA (T 4000 α 0.99): Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99;
WA CP Fixed: Window Approach used in conjunction with Change Procedure Fixed method;
WA: Window Approach;
RSA: Random Selection Approach.

Figure 5.8: Percentage of Hours and Number of Trips Covered in 20 Disruption Scenarios with Different Percentages of Unmanned Duties per Base for 82 Reserve Duties- Results from SISCOG Optimiser

Table 5.8 compares the costs obtained with the intermediate and the final evaluations. It can be seen that the final evaluation results, in this disruption scenarios, show lower costs when compared to the intermediate evaluation. This discrepancy can be attributed to the fact that the intermediate evaluation does not take into account the possibility of unmanned trips being assigned to a duty form another base (with the use of positioning trips).

Table 5.8: Comparison of the Cost obtained with Intermediate Evaluation and Final Evaluation for 82 Reserve Duties - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

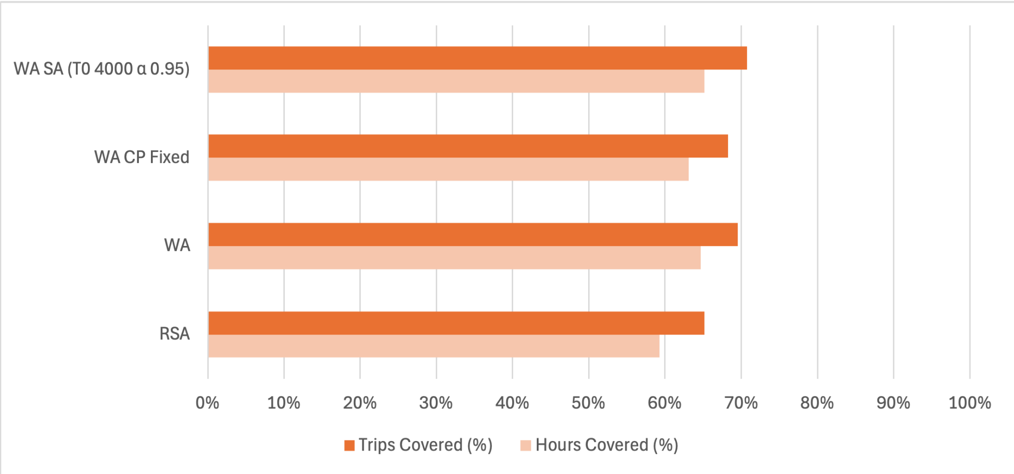
Method	**Intermediate Evaluation Cost (hours)**	**Final Evaluation Cost (hours)**
RSA	281.634	146.516
WA	171.981	124.021
WA CP Fixed	158.627	124.643
WA SA (T_0 4000 α 0.99)	152.660	126.668

Legend: *WA: Window Approach; RSA: Random Selection Approach; CP: Change Procedure; SA: Simulated Annealing;* T_0*: Initial Temperature;* α*: Alpha.*

5.5.3 Different Percentage of Unmanned Duties per Day Period

The third set of 20 disruption scenarios, with different percentages of unmanned duties per period of the day, were tested with 82 reserve duties. The methods employed from Change Procedure was the Window approach Fixed method and from Simulated Annealing was the Window approach with an initial temperature of 4000 and an alpha of 0.95.

Figure 5.9 demonstrates the adaptability of the methodologies in the context of different percentages of unmanned duties per period of the day. It is evident that the method with the lowest percentages of hours and trips covered is Random Selection approach. The highest percentages of hours and trips covered are achieved by the Simulated Annealing method. The discrepancy between values obtained for percentages of hours and number of trips covered is attributable to the varying lengths of trips that became covered.



Legend:
WA SA (T_0 4000 α 0.95): Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95;
WA CP Fixed: Window Approach used in conjunction with Change Procedure Fixed method;
WA: Window Approach;
RSA: Random Selection Approach.

Figure 5.9: Percentage of Hours and Number of Trips Covered in 20 Disruption Scenarios with different percentages of Unmanned Duties per Period of the Day for 82 Reserve Duties- Results from SISCOG Optimiser

Table 5.9 compares the costs obtained with the intermediate and the final evaluations. In this disruption scenario, in contrast with the behaviour observed in previous sets of disruption scenarios, it can be observed that the final evaluation results of every method except for Random Selection approach demonstrated higher costs when compared to the intermediate evaluation. This discrepancy may be attributed to the quality of the disruption scenarios chosen, with the 20 scenarios from the final evaluation representing the least favourable results when compared to the overall of the 2000 from the intermediate evaluation.

Table 5.9: Comparison of the Cost obtained with Intermediate Evaluation and Final Evaluation for 82 Reserve Duties - Disruption Scenarios with Different Percentages of Unmanned Duties per Part of the Day

Method	**Intermediate Evaluation Cost (hours)**	**Final Evaluation Cost (hours)**
RSA	172.961	135.483
WA	79.140	117.418
WA CP Fixed	58.219	122.550
WA SA (T_0 4000 α 0.95)	50.683	115.960

Legend: *WA: Window Approach; RSA: Random Selection Approach; CP: Change Procedure; SA: Simulated Annealing;* T_0*: Initial Temperature;* α*: Alpha.*

More information about each result for each method and disruption scenario can be found in the Appendix B.

Taking the optimiser's outcomes into account, it becomes evident that the methods that possess knowledge of the problem consistently achieve better results when compared with the method that does not, namely Random Selection approach. The discrepancy between the intermediate and the final evaluations can be attributed to the lack of problem information in the intermediate evaluation. The Window approach and Simulated Annealing were the methods that demonstrated better results. The difference in their cost was minimal, making it challenging to identify the best method for this problem. Simulated Annealing changes the set of reserve duties according to the given disruption scenario, unlike the Window approach. Therefore, despite the additional computational time this method requires, it proves to be the best method.

6 Conclusion

This chapter begins with an overview of the main conclusions, presented in Section 6.1. Section 6.2 identifies prospective avenues for future investigation that could be incorporated into the present work.

6.1 Main Conclusions

The use of public transportation is increasing, particularly trains, due to the enhanced comfort, reliability and reduced environmental impact. One of the most significant challenges currently facing the rail industry is the occurrence of train trip cancellations, which can have a negative impact on passengers' lives. Consequently, there is a greater focus on the allocation and planning of reserve resources and the prediction of the train trip cancellations.

The main objective of this thesis was the development of an algorithm for scheduling reserve railway duties, aiming at reducing the number of cancelled trips when disruptions occur.

Three initial methodologies were employed: Peak, Window and Random Selection approaches. In addition, two approaches for improving reserve duties were utilised: Change Procedure and Simulated Annealing. To test these new approaches, a SISCOG dataset was used, comprising 881 regular duties and 28 operational bases. To introduce uncertainty, stochastic simulation was used to create disruption scenarios. The disruption scenarios are represented as a set of unmanned duties, which were created to represent the absence of crew members. This was the only disruption considered in this study.

In consideration of the outcomes of the initial reserve duties, the Window approach was the method that stood out in all sets of disruption scenarios. This approach offers a rapid solution, making it particularly suited to problems characterised by uniform disruptions.

Although the initial reserve duties models showed satisfactory results, approaches for reviewing reserve duties were implemented. The Change Procedure is composed by two distinct methods: Fixed and Best. The method Best is a very demanding method because it only accepts solutions that improve the result. When it is considered the method Fixed with 50 changes, it is evident that the result is frequently improved. Nevertheless, the Change Procedure is a rapid method that typically enhances the preliminary outcomes and demonstrates the capacity to adapt to diverse disruption scenarios. The Simulated Annealing is a method that requires parameterisation for the initial temperature and the alpha. Three sets were chosen, which adapted the metheuristic to this type of problem. This is the method that takes the longest time to compute due to its complexity and robustness. Regardless, it is also the method that is most responsive to changing disruption scenarios and typically produces the best results.

The final evaluation, performed using the SISCOG optimiser, yielded comparable results to the intermediate evaluation The Random Selection approach demonstrated a higher discrepancy, but the other methods used, the ones with knowledge of the problem, showed similar good costs. This emphasises that, despite the limited information available, the intermediate evaluation was a success because it was able to obtain cost results that were similar to those that would be observed in real life. The approaches highlighted are the Window approach and Simulated Annealing. Despite these results, the Simulated Annealing should be the method of choice due to its ability to adapt to every given disruption scenario, which is not a feature of the Window approach.

6.2 Future Perspectives

The development of this algorithm represents an evolution to schedule reserve duties problem, although some improvements could be made in the work revealed.

The intermediate evolution could have more information of the characteristics of the rail trips, the conditions to make feasible schedules, and information about the distance between bases. The incorporation of additional data into the intermediate evaluation would facilitate the generation of more precise costs and the creation of more effective schedules. An alternative approach would be to incorporate the SISCOG optimiser into the evaluation process. However, this approach would prevent the testing of schedules with extensive data sets, which could result in schedules being modified only to align with the presented cases.

The Best method of the Change Procedure is very rigid, which leads us to the conclusion that it would be more beneficial to relax the acceptance assumption. The objective would be to accept unfavourable costs with the aim of reaching a better one. This could be achieved by accepting a fixed number of unfavourable results.

In the context of simulating disruption scenarios, one potential avenue for exploration would be the introduction of the possibility of reserve crew members being absent.

Another potential approach to addressing this type of problem is the use of genetic algorithms. A meteurisctic used in similar problems, exhibiting favourable outcomes in multiple domains. One possible strategy for implementing this approach is to divide the chromosome into three parts. The first section could represent the number of reserve crew members considered in that chromosome, the second section could represent the bases of each reserve crew member, and the final section could represent the start time of the reserve crew schedules.

Finally, it would also be interesting to evaluate these methodologies with actual data on employee absences, rather than relying on simulated disruption scenarios.

Bibliography

[1] J. M. Lourenço. *The NOVAthesis LaTeX Template User's Manual*. NOVA University Lisbon. 2021. URL: https://github.com/joaomlourenco/novathesis/raw/main/template.pdf (cit. on p. i).

[2] *Railroad Market Size, Share Growth Analysis Report, 2030*. 2022. URL: https://www.grandviewresearch.com/industry-analysis/railroads-market (cit. on p. 1).

[3] M. Gallucci. *Hydrogen trains and trucks are coming — for better or worse*. 2024. URL: https://www.canarymedia.com/articles/transportation/hydrogen-trains-and-trucks-are-coming-for-better-or-worse (cit. on p. 1).

[4] *FCH2Rail – The First Hydrogen Train Carried Out Tests On The Portuguese Railway Network*. 2024. URL: https://hydrogen-central.com/fch2rail-the-first-hydrogen-train-carried-out-tests-on-the-portuguese-railway-network/ (cit. on p. 1).

[5] E. J. W. Abbink. *Crew Management in Passenger Rail Transport*. Erasmus Research Institute of Management-ERIM, 2014. ISBN: 978-90-5892-374-5 (cit. on p. 2).

[6] R. Saldanha. *The show must go on*. 2024. URL: https://www.siscog.pt/en-gb/blog/the-show-must-go-on/ (cit. on p. 3).

[7] D. Potthof. "Railway Crew Rescheduling: Novel approaches and extensions". PhD thesis. Erasmus University Rotterdam, 2010 (cit. on p. 3).

[8] A. H. Schrotenboer et al. "Reliable reserve-crew scheduling for airlines". In: *Transportation Research Part E: Logistics and Transportation Review* 178 (2023), p. 103283. ISSN: 1366-5545. DOI: https://doi.org/10.1016/j.tre.2023.103283. URL: https://www.sciencedirect.com/science/article/pii/S1366554523002715 (cit. on pp. 6, 7).

[9] Q. Y. Wang. "Transit extraboard operator scheduling". Master's thesis. Cambridge, Massachusetts, Estados Unidos: Massachusetts Institute of Technology, 2020 (cit. on pp. 6, 7).

[10] C. Bayliss et al. "A simulation scenario based mixed integer programming approach to airline reserve crew scheduling under uncertainty". In: *Annals of Operations Research* 252 (2017), pp. 335–363. DOI: 10.1007/s10479-016-2174-8. URL: https://doi.org/10.1007/s10479-016-2174-8 (cit. on pp. 6, 7).

[11] C. Bayliss et al. "Scheduling airline reserve crew using a probabilistic crew absence and recovery model". In: *Journal of the Operational Research Society* 71 (2019-04), pp. 1–23. DOI: 10.1080/01605682.2019.1567649 (cit. on pp. 6, 7).

[12] C. Bayliss et al. "Probabilistic Airline Reserve Crew Scheduling Model". In: *OpenAccess Series in Informatics*. Open Access Series in Informatics (OASIcs) 25 (2012), pp. 132–143. ISSN: 2190-6807. DOI: 10.4230/OASIcs.ATMOS.2012.132. URL: https://drops.dagstuhl.de/entities/document/10.4230/OASIcs.ATMOS.2012.132 (cit. on pp. 6, 7).

[13] E. Melachrinoudis and M. Olafsson. "A microcomputer cashier scheduling system for supermarket stores". In: *International Journal of Physical Distribution Logistics Management* 25 (1995-02), pp. 34–50. DOI: 10.1108/09600039510080180 (cit. on pp. 7, 8).

[14] E. Aycan and T. Ayav. "Solving the Course Scheduling Problem Using Simulated Annealing". In: *2009 IEEE International Advance Computing Conference, IACC 2009* (2009-04), pp. 462–466. DOI: 10.1109/IADCC.2009.4809055 (cit. on p. 8).

[15] D. Henderson, S. Jacobson, and A. Johnson. "The Theory and Practice of Simulated Annealing". In: *Handbook of Metaheuristics*. Ed. by F. Glover and G. Kochenberger. Vol. 57. International Series in Operations Research & Management Science. Boston, MA: Springer, 2003. DOI: 10.1007/0-306-48056-5_10 (cit. on p. 20).

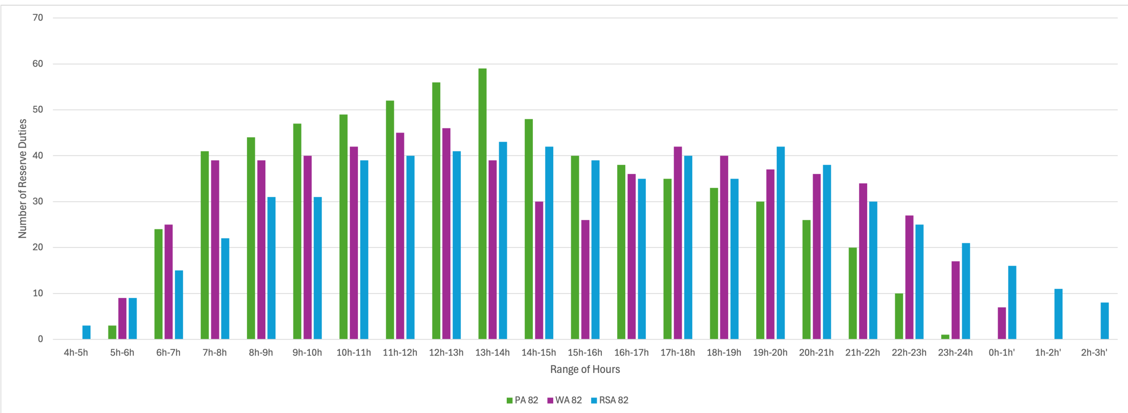
[16] R. S. F. S. Bernd Frick. "Timing matters: worker absenteeism in a weekly backward rotating shift model". In: *The European Jornal of Health Economics* 21 (2020), pp. 1399–1410. DOI: https://doi.org/10.1007/s10198-020-01232-6 (cit. on p. 38).

A

Intermediate Evaluation

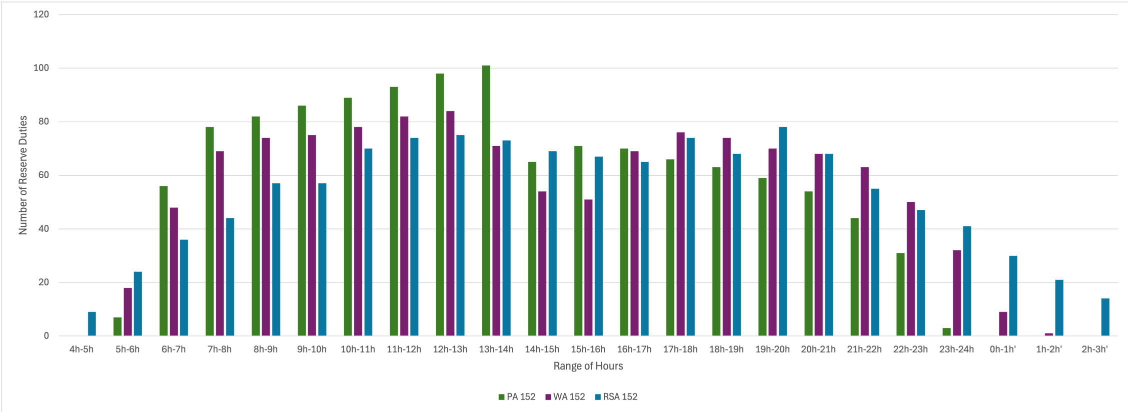
This Appendix shows additional results obtained with the intermediate evaluation.

A.1 Workload from Initial Reserve Duties



Legend:
PA 82: Peak Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RSA 82: Random Selection Approach with 82 Reserve Duties.

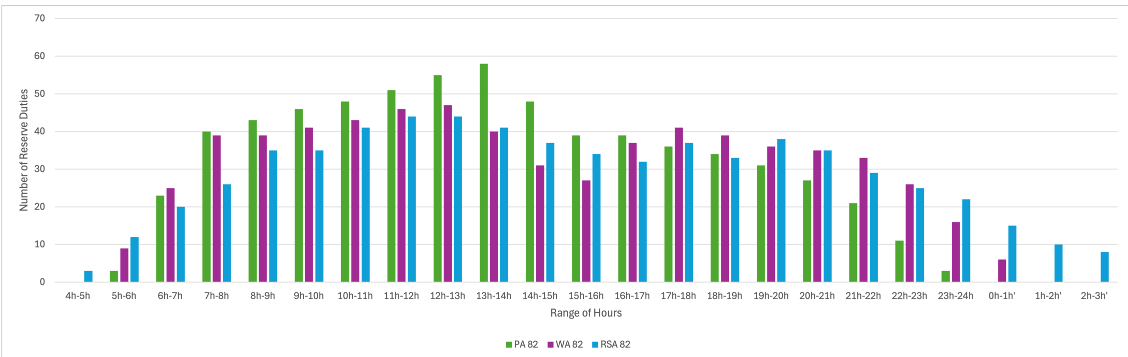
Figure A.1: Workload of 82 Reserve Duties obtained with the Initial Reserve Duties with 82 Reserve Duties



Legend:
PA 152: Peak Approach with 152 Reserve Duties;
WA 152: Window Approach with 152 Reserve Duties;
RSA 152: Random Selection Approach with 152 Reserve Duties.

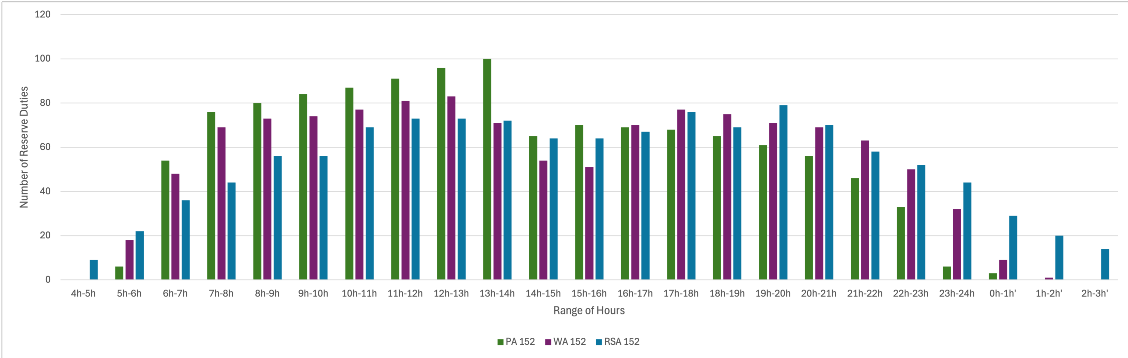
Figure A.2: Workload of 152 Reserve Duties obtained with the Initial Reserve Duties Models

A.2 Workload from Change Procedure



Legend:
PA 82: Peak Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RSA 82: Random Selection Approach with 82 Reserve Duties.

Figure A.3: Workload of 82 Reserve Duties obtained with the Initial Reserve Duties Models used in conjunction with the Method Best



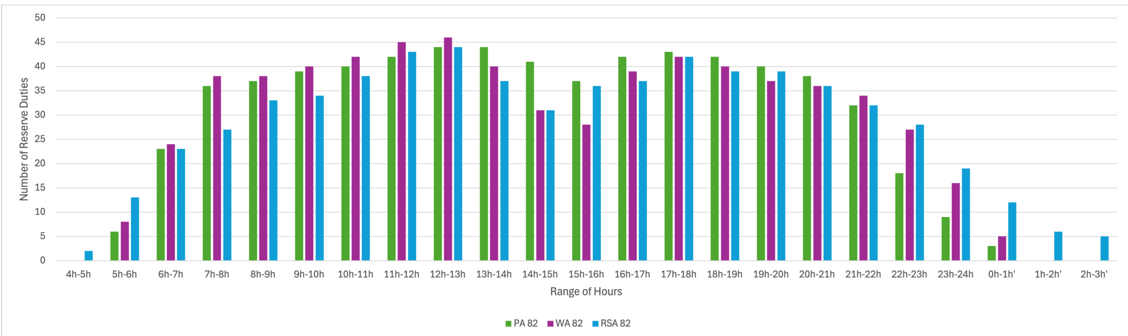
Legend:

PA 152: Peak Approach with 152 Reserve Duties;

WA 152: Window Approach with 152 Reserve Duties;

RSA 152: Random Selection Approach with 152 Reserve Duties.

Figure A.4: Workload of 152 Reserve Duties obtained with the Initial Reserve Duties Models used in conjunction with the Method Best



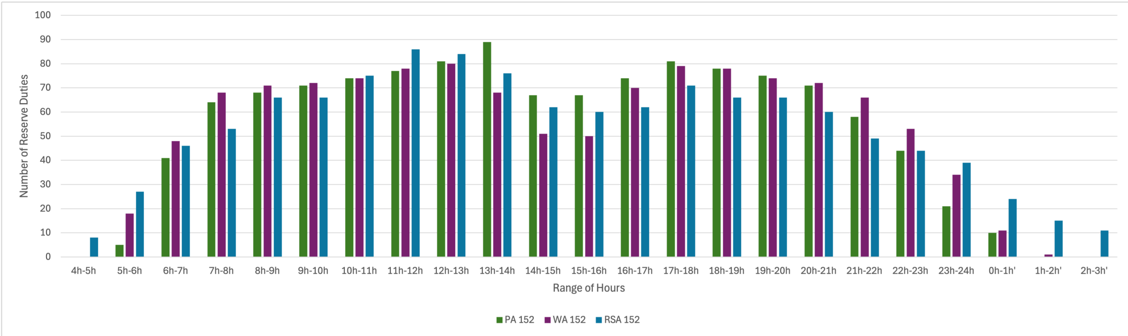
Legend:

PA 82: Peak Approach with 82 Reserve Duties;

WA 82: Window Approach with 82 Reserve Duties;

RSA 82: Random Selection Approach with 82 Reserve Duties.

Figure A.5: Workload of 82 Reserve Duties obtained with the Initial Reserve Duties Models used in conjunction with the Method Fixed with 50 Changes



Legend:

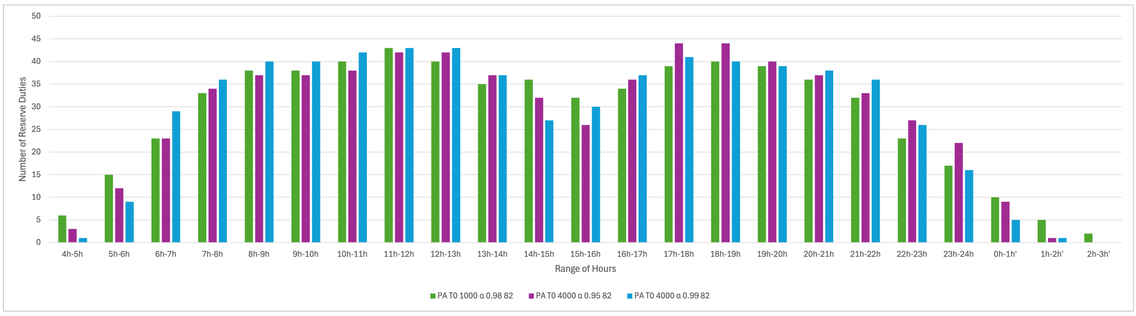
PA 152: Peak Approach with 152 Reserve Duties;

WA 152: Window Approach with 152 Reserve Duties;

RSA 152: Random Selection Approach with 152 Reserve Duties.

Figure A.6: Workload of 152 Reserve Duties obtained with the Initial Reserve Duties Models used in conjunction with the Method Fixed with 50 Changes

A.3 Workload from Simulated Annealing



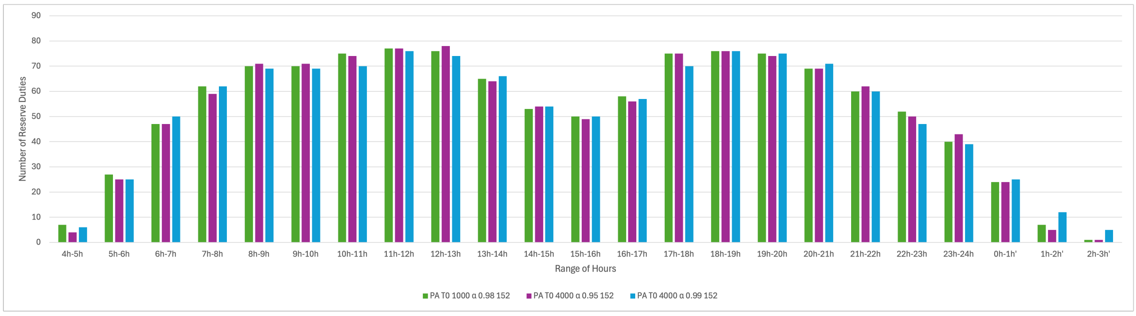
Legend:

PA T_0 1000 α 0.98 82: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 82 Reserve Duties;

PA T_0 4000 α 0.95 82: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties;

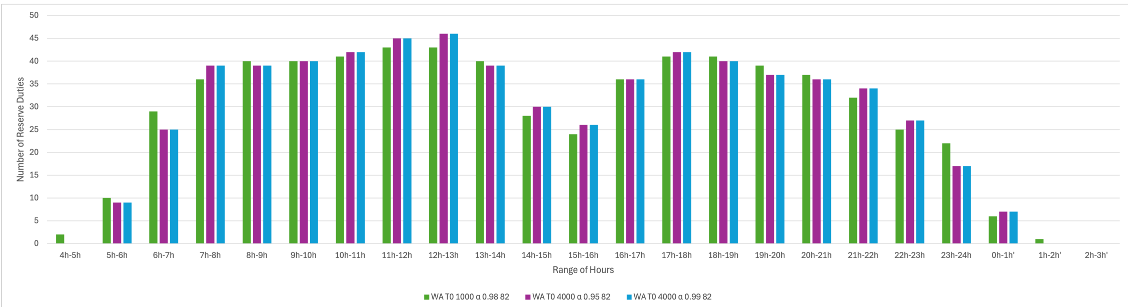
PA T_0 4000 α 0.99 82: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 82 Reserve Duties.

Figure A.7: Workload of 82 Reserve Duties obtained with Peak Approach used in conjunction with Simulated Annealing



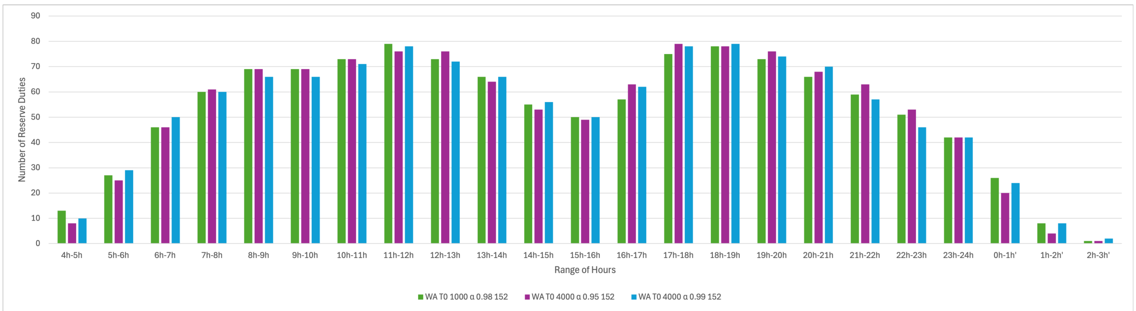
Legend:
PA T_0 1000 α 0.98 152: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 152 Reserve Duties;
PA T_0 4000 α 0.95 152: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 152 Reserve Duties;
PA T_0 4000 α 0.99 152: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 152 Reserve Duties.

Figure A.8: Workload of 152 Reserve Duties obtained with Peak Approach used in conjunction with Simulated Annealing



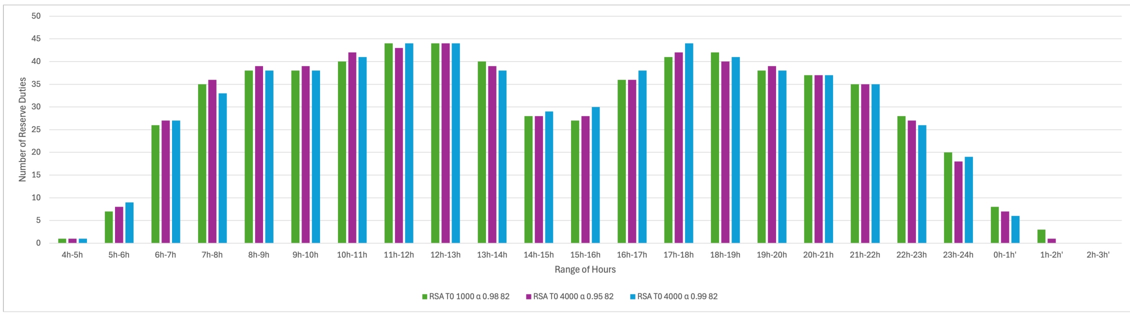
Legend:
WA T_0 1000 α 0.98 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 82 Reserve Duties;
WA T_0 4000 α 0.95 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties;
WA T_0 4000 α 0.99 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 82 Reserve Duties.

Figure A.9: Workload of 82 Reserve Duties obtained with Window Approach used in conjunction with Simulated Annealing



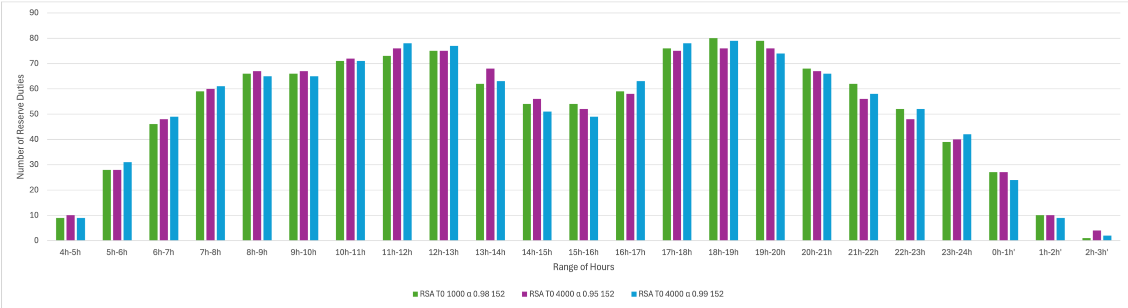
Legend:
WA T_0 1000 α 0.98 152: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 152 Reserve Duties;
WA T_0 4000 α 0.95 152: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 152 Reserve Duties;
WA T_0 4000 α 0.99 152: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 152 Reserve Duties.

Figure A.10: Workload of 152 Reserve Duties obtained with Window Approach used in conjunction with Simulated Annealing



Legend:
RSA T_0 1000 α 0.98 82: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 82 Reserve Duties;
RSA T_0 4000 α 0.95 82: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties;
RSA T_0 4000 α 0.99 82: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 82 Reserve Duties.

Figure A.11: Workload of 82 Reserve Duties obtained with Random Selection Approach used in conjunction with Simulated Annealing



Legend:
RSA T_0 1000 α 0.98 152: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 152 Reserve Duties;
RSA T_0 4000 α 0.95 152: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 152 Reserve Duties;
RSA T_0 4000 α 0.99 152: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 152 Reserve Duties.

Figure A.12: Workload of 152 Reserve Duties obtained with Random Selection Approach used in conjunction with Simulated Annealing

A.4 Results from Different Percentage of Unmanned Duties

Table A.1: Performance Measure obtained from the Initial Reserve Duties Models - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

Method	**PA**	**WA**	**RSA**
Time (sec)	2	2	2
Cost (hours)	232.795	171.981	281.634

Legend: *PA- Peak Approach; WA- Window Approach; RSA- Random Selection Approach.*

Table A.2: Performance Measure obtained from the Initial Reserve Duties Models used in conjunction with the Methods Best and Fixed from Change Procedure - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

Initial Method **Change Procedure Method**	**PA** **Best**	**WA** **Best**	**RSA** **Best**	**PA** **Fixed**	**WA** **Fixed**	**RSA** **Fixed**
Number of Changes	8	0	16	50	50	50
Time (sec)	5	2	7	17	17	17
Cost (hours)	200.684	171.981	210.171	172.572	158.627	178.938

Legend: *PA- Peak Approach; WA- Window Approach; RSA- Random Selection Approach.*

Table A.3: Performance Measure obtained from the Peak Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Base Peak Approach Method

Alpha	0.98	0.95	0.99
Initial Temperature	1000	4000	4000
Best Iteration	17477	8948	20017
Total Number of Iterations	19487	10952	22025
Time (sec)	2178	1188	2475
Cost (hours)	157.142	157.494	154.189

Table A.4: Performance Measure obtained from the Window Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

Alpha	0.98	0.95	0.99
Initial Temperature	1000	4000	4000
Best Iteration	11520	8700	24309
Total Number of Iterations	13529	10706	26316
Time (sec)	1484	1167	2851
Cost (hours)	156.712	155.605	152.66

Table A.5: Performance Measure obtained from the Random Selection Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Base

Alpha	0.98	0.95	0.99
Initial Temperature	1000	4000	4000
Best Iteration	23304	19205	17930
Total Number of Iterations	25308	21210	19934
Time (sec)	2710	2283	2073
Cost (hours)	155.706	154.747	154.484

Table A.6: Performance Measure obtained from the Initial Reserve Duties Models - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day

Method	**PA**	**WA**	**RSA**
Time (sec)	2	3	3
Cost (hours)	175.515	79.1395	172.961

Legend: *PA- Peak Approach; WA- Window Approach; RSA- Random Selection Approach.*

Table A.7: Performance Measure obtained from the Initial Reserve Duties Models used in conjunction with the Methods Best and Fixed from Change Procedure - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day

Initial Method **Change Procedure Method**	**PA** **Best**	**WA** **Best**	**RSA** **Best**	**PA** **Fixed**	**WA** **Fixed**	**RSA** **Fixed**
Number of Changes	3	2	12	50	50	50
Time (sec)	3	3	6	20	19	19
Cost (hours)	160.065	75.2355	121.824	86.873	58.219	77.828

Legend: *PA- Peak Approach; WA- Window Approach; RSA- Random Selection Approach.*

Table A.8: Performance Measure obtained from the Peak Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day

Alpha **Initial Temperature**	0.98 1000	0.95 4000	0.99 4000
Best Iteration	14474	20682	17612
Total Number of Iterations	16492	22688	19621
Time (sec)	2280	3121	2733
Cost (hours)	55.969	55.108	55.340

Table A.9: Performance Measure obtained from the Window Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day

Alpha **Initial Temperature**	0.98 1000	0.95 4000	0.99 4000
Best Iteration	8722	38295	17460
Total Number of Iterations	10732	40303	19465
Time (sec)	1491	5600	2705
Cost (hours)	57.752	50.683	55.789

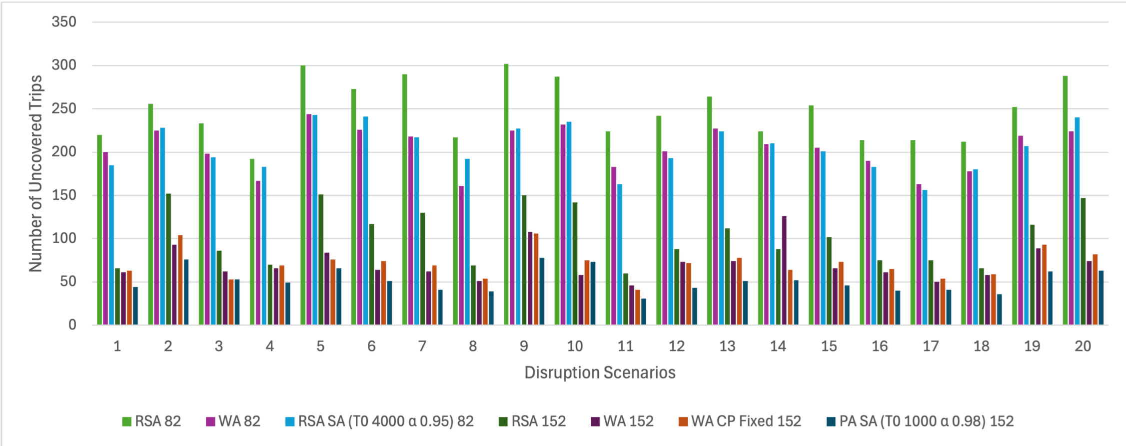
Table A.10: Performance Measure obtained from the Random Selection Approach used in conjunction with Simulated Annealing - Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day

Alpha **Initial Temperature**	0.98 1000	0.95 4000	0.99 4000
Best Iteration	25105	13328	11883
Total Number of Iterations	27113	15338	13888
Time (sec)	3743	2151	1939
Cost (hours)	52.827	56.642	57.599

B

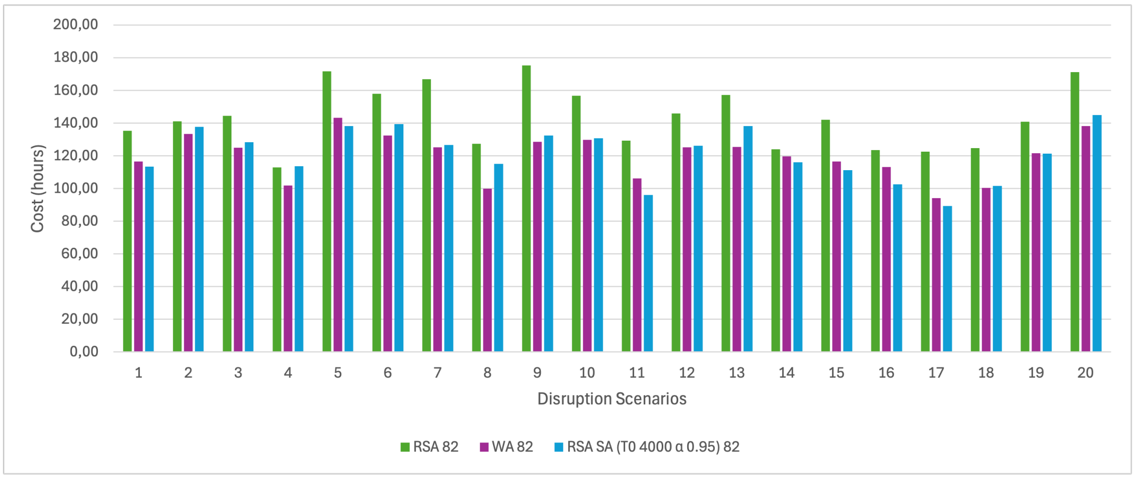
Final Evaluation

This Appendix shows additional results obtained with the final evaluation.



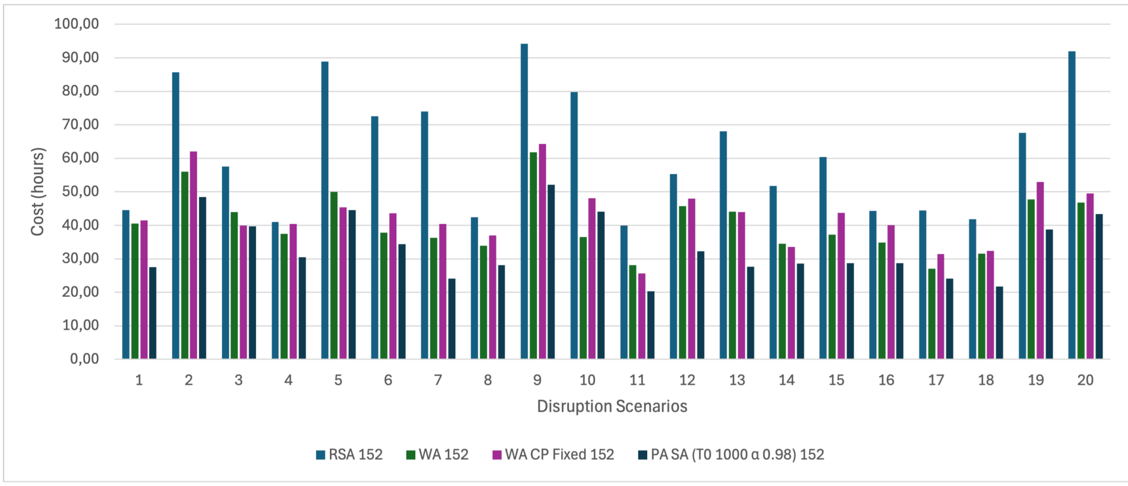
Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RSA SA (T_0 4000 α 0.95) 82: Random Selection Approach, Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties;
RSA 152: Random Selection Approach with 152 Reserve Duties;
WA 152: Window Approach with 152 Reserve Duties;
WA CP Fixed 152: Window Approach used in conjunction with Change Procedure method Fixed with 152 Reserve Duties;
PA SA (T_0 1000 α 0.98) 152: Peak Approach used in conjunction with Simulated annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 152 Reserve Duties.

Figure B.1: Number of Uncovered Trips in 20 Disruption Scenarios - Results from SISCOG Optimiser



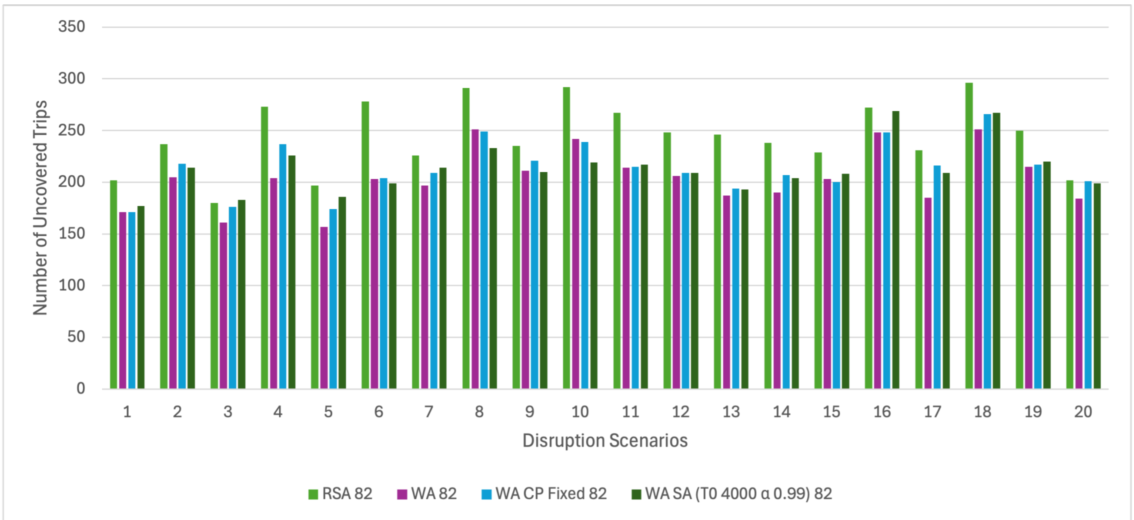
Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
RS SA (T_0 4000 α 0.95) 82: Random Selection Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties.

Figure B.2: Cost of 82 Reserve Duties in 20 Disruption Scenarios - Results from SISCOG Optimiser



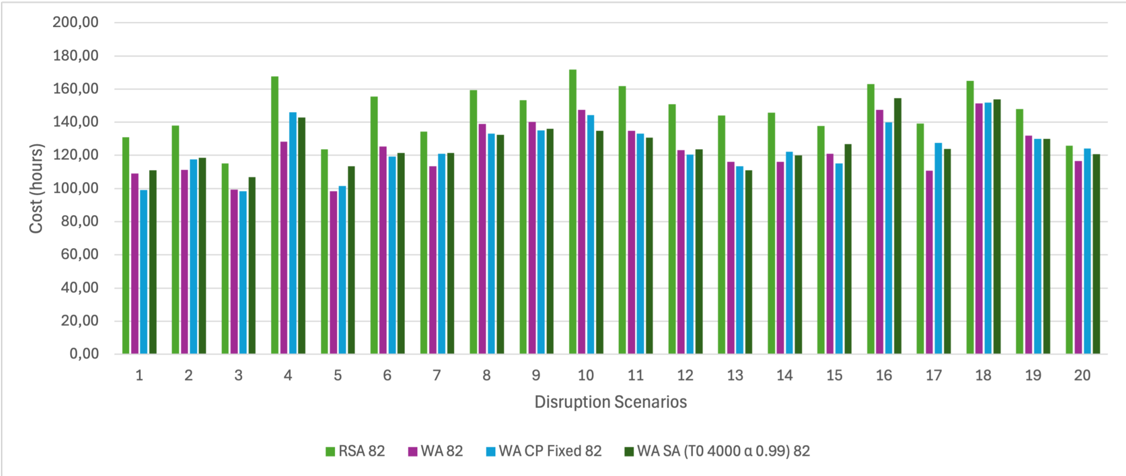
Legend:
RSA 152: Random Selection Approach with 152 Reserve Duties;
WA 152: Window Approach with 152 Reserve Duties;
WA CP Fixed 152: Window Approach used in conjunction with Change Procedure method Fixed with 152 Reserve Duties;
PA SA (T_0 1000 α 0.98) 152: Peak Approach used in conjunction with Simulated Annealing with an Initial Temperature of 1000 and an Alpha of 0.98 with 152 Reserve Duties.

Figure B.3: Cost of 152 Reserve Duties in 20 Disruption Scenarios - Results from SISCOG Optimiser



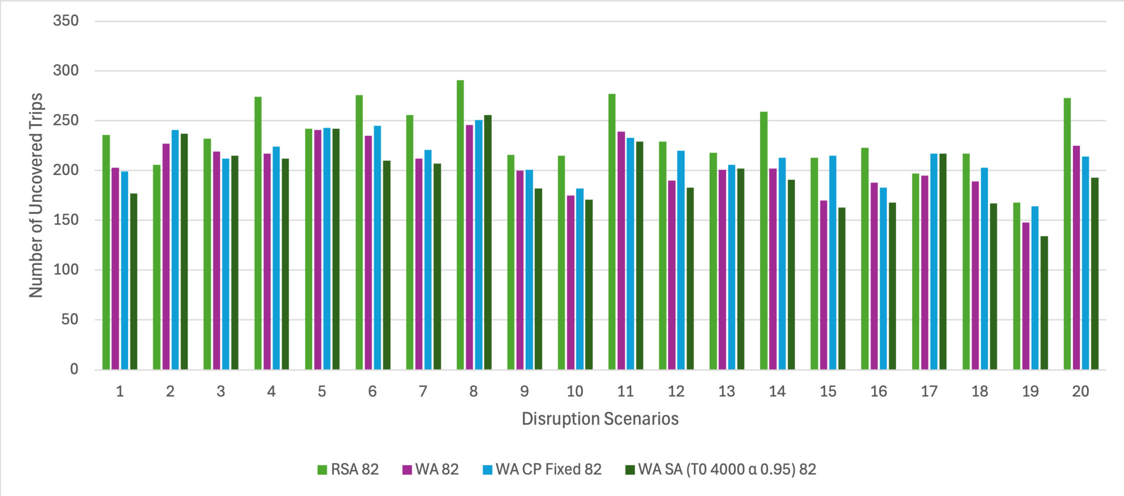
Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
WA CP Fixed 82: Window Approach used in conjunction with Change Procedure method Fixed with 82 Reserve Duties;
WA SA (T_0 4000 α 0.99) 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 82 Reserve Duties.

Figure B.4: Number of Uncovered Trips in 20 Disruption Scenarios with Different Percentages of Unmanned Duties per Base - Results from SISCOG Optimiser



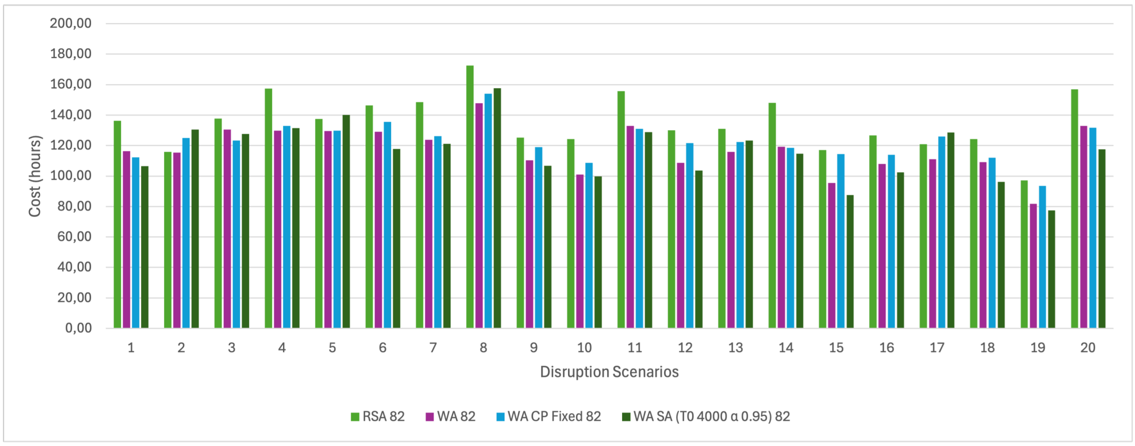
Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
WA CP Fixed 82: Window Approach used in conjunction with Change Procedure method Fixed with 82 Reserve Duties;
WA SA (T_0 4000 α 0.99) 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.99 with 82 Reserve Duties.

Figure B.5: Cost of 82 Reserve Duties in 20 Disruption Scenarios with Different Percentages of Unmanned Duties per Base - Results from SISCOG Optimiser



Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
WA CP Fixed 82: Window Approach used in conjunction with Change Procedure method Fixed with 82 Reserve Duties;
WA SA (T_0 4000 α 0.95) 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties.

Figure B.6: Number of Uncovered Trips in 20 Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day - Results from SISCOG Optimiser



Legend:
RSA 82: Random Selection Approach with 82 Reserve Duties;
WA 82: Window Approach with 82 Reserve Duties;
WA CP Fixed 82: Window Approach used in conjunction with Change Procedure method Fixed with 82 Reserve Duties;
WA SA (T_0 4000 α 0.95) 82: Window Approach used in conjunction with Simulated Annealing with an Initial Temperature of 4000 and an Alpha of 0.95 with 82 Reserve Duties.

Figure B.7: Cost of 82 Reserve Duties in 20 Disruption Scenarios with Different Percentages of Unmanned Duties per Period of the Day - Results from SISCOG Optimiser

NOVA SCHOOL OF SCIENCE & TECHNOLOGY