Staff rescheduling with minimum disruption at Emergency Medical Services

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Abstract

Emergency Medical Services (EMS) play a critical role in pre-hospital care and directly affect the medical outcome of emergency patients. Given the increase of emergency requests and the restricted resources that EMS systems have at their disposal, there is an urgency to operate at the highest efficiency. In order to find fields to improve, planning problems at EMS were studied and it was found that rescheduling, which is the process of finding a new feasible schedule after a disruption, constitutes an interesting area to develop further analysis.

Since the Portuguese Emergency Medical Institute – INEM – still performs this complex task manually and, being an almost daily activity, there is the opportunity to improve its efficiency by developing more sophisticated methods capable of providing strong insights to decision-makers. Therefore, a mathematical model was developed in order to assist EMS systems on their rescheduling activity, providing accurate solutions in a short amount of time. To test its effectiveness, the model was tested for different INEM scenarios, including the most extreme absenteeism cases in the EMS sector and delivered optimal solutions always in less than 11 minutes. Additionally, it was also possible to compare the differences between starting the month with a cyclic and a non-cyclic schedule. Results show that the non-cyclic outperforms the cyclic in both under and oversupply situations due to its flexibility to adapt to different contexts. Therefore, as INEM currently builds a cyclic initial schedule, it could be beneficial to consider a shift to non-cyclic.

Keywords: Emergency Medical Services, Staff Rescheduling, Optimization, Mathematical Programming, Health Services, Human Resources Planning

1. Introduction

Technological improvement and easier access to health care services, alongside a better distribution of goods and better living conditions, have increased the medium life expectancy worldwide (Simões *et al.* 2017), hence contributing to a rise in the proportion of elder people in society (PORDATA, 2020). Consequently, the need for proper health care services has been increasing over the past years. Effectively, in 2018, Portugal spent 18,300 million euros on health care, which represents 9.1% of the national Gross Domestic Product – GDP (INE, 2019). Within the health care service, there are emergency medical services, which are designated to save lives and play a key role in pre-hospital medical care, directly impacting the medical outcome of emergency patients (World Health Organization, 2005). Although, in 2018, Portugal had the same percentage of expenses allocated to emergency medical services as the average of the European Union, the percentage of the GDP allocated to health care services was almost 10% lower when compared to the average of 9.9% from the European Union (Eurostat, 2021). These factors may indicate that, in Portugal, the Emergency Medical National Institute – INEM – operates with scarce resources. Thus, in this context, arises the need to deliver the most effective and efficient service to patients using restricted available resources. Operations Research techniques have been applied to a variety of problems in health care environments and have largely contributed to providing better solutions for these problems (Brailsford & Vissers, 2011). Personnel scheduling is one of the most extensively studied topics as it can directly influence the performance of the health organization and staff costs to have the highest proportion on the overall costs of a health organization (Clark *et al*. 2015).

However, staff rescheduling, which is the task of rebuilding a schedule that suffered a disruption by an absent employee, has not received a lot of attention. Despite being considered as a complex and time-consuming activity, accounting for 10-20% of managers' day-to-day activities, few academic research has been made on this topic (Clark *et al*., 2015). In most organizations, rescheduling is still a task performed manually and few models have been implemented due to lack of staff training, high complexity of solutions or lack of financial resources to implement them. INEM is no exception and still performs this activity manually. In fact, INEM's planners must often rely on intuition and experience to make challenging planning decisions in the face of uncertainty, limited by budget restrictions and balancing various stakeholders' objectives. Therefore, there is room for improvement, to achieve a higher efficiency which will lead to a higher service level.

This context motivates the present study, which addresses the staff rescheduling problem in the EMS field, exploiting particularly the case of INEM. The use of more sophisticated techniques to support decision-making could potentially contribute to more effective and efficient solutions, which may enhance the overall performance of an organization.

1.1 Methodology

The first step is of the methodology is the problem definition, enabling to have a clear overview of the context. The second is the literature review, which assesses previous literature on both the emergency medical services field and the rescheduling process. Following, the third step is the first mathematical problem definition. This is done taking key aspects from the literature studied, namely from the most relevant studies from Maenhout & Vanhoucke (2011), Maenhout & Vanhoucke (2018), Wickert *et al.* (2019) and Wolbeck *et al*. (2020). Then, a first draft of the problem and its characteristics are presented to INEM's TEPHs, in order to get a clear overview of what are the most important factors to take into account and if those being considered are relevant, e.g., it is crucial to understand if the different stakeholders prefer fairness and employees' satisfaction over service quality or overall costs for the organization. The data collected from these interactions is treated, extracting the main conclusions that will be then presented to TEPH's responsible, following a review, having in mind its validation. In case of validation, it is possible to construct the final mathematical problem definition, determining then sets, subsets, parameters, decision variables, the objective function and constraints. Afterwards, it will be possible to implement the model with CPLEX. The model can then be solved considering progressively more complex instances from INEM's dataset. If these solutions are validated, then a strong analysis will be performed, intending to understand which is the best initial schedule type, cyclic and non-cyclic and how it can affect the results. Then, the analysis will be presented, reviewed and subject to validation from the TEPH's responsible. Additionally, recommendations to INEM are given.

2. Problem Definition

2.1 Portuguese Emergency Medical Service

The Medical Emergency National Institute, INEM, was established, in 1981, as the entity of the Portuguese Health Ministry responsible for running the Integrated Medical Emergency System, SIEM, ensuring a prompt and correct pre-hospital health care provision in mainland Portugal (INEM, 2020). To achieve its mission, INEM must define, organize, coordinate and assess SIEM operation.

SIEM is a set of coordinated activities executed by different entities within the emergency medical care delivery structure, including INEM, firefighters, police officers, the Portuguese Red Cross, hospitals and health units.

Firstly, an incident that requires emergency assistance is detected, usually by civilians near the event, that must call the emergency number which, in case of a medical emergency, is directed to a Centre of Orientation of Urgent Patients – CODU. After receiving the information and prioritizing the case, an emergency vehicle – EV – with a crew may be dispatched (normally, at least one TEPH – Pre-Hospital Emergency Technician – is present). While it is reaching the incident, if needed, the caller may be receiving instructions on Basic Life Support by the TEPH at the CODU. Once the emergency vehicle arrives, medical care to stabilize the victim is provided. Then, the victim is transported to a health unit (Ferreira dos Santos, 2019). Finally, the victim is received at the closest health unit to continue the required treatment. At this moment, the vehicle and the crew are released and become available for the next operation (INEM, 2020).

Since 2017, the number of answered calls from INEM has been increasing at a rate of approximately 2% per year. However, the rate of required TEPHs, i.e., the number of TEPHs divided by the number of TEPHs needed to perform the tasks, has oscillating between 72.2% and 79.4% (INEM, 2021). Therefore, to respond to the demand increase and regarding the scarce human resources, it is essential that INEM operates with high efficiency and where that does not happen, gather the means to do so.

2.2 Staff Rescheduling at INEM

Managing staff properly is of crucial importance as these represent a vast percentage of INEM's operational costs. Nowadays, both INEM's scheduling and rescheduling for Lisbon's CODU area (which is the area considered in this dissertation's case study) are performed by three local TEPHs. TEPHs operate under a cyclical schedule where they give their available shifts to the responsible, who will later build the schedule based on the following 10 days cycle: *M – M; A – A; O; N – N; O – O – O*. These letters represent the shift that is done in a specific day (N – Night (00:00 a.m. – 8 a.m.), M – Morning (08:00 a.m. – 04:00 p.m.), A – Afternoon (04:00 p.m. – 12:00 p.m.) and O – Day Off). Concerning rescheduling, it is an informal process, where the three rebuild the schedule by calling other TEPHs to determine whether or not they are available for the disrupted shift. Typically, they contact people that are in one of the three consecutive days off (Table 1) and try to maintain equity factors – extra hours, weekends availability, legal constraints and others – immutable. Often, TEPHs communicate between themselves to assure that another worker replaces the absent.

Table 1: 10 days cycle used at INEM

TEPH/Day	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
TEPH 1	M	M	A	A	O	N	N	O	O	O

To evaluate the process performance, INEM intends to achieve neither overtime nor undertime. On the one hand, overtime must happen only when strictly necessary, as the entity is incurring higher costs. On the other hand, undertime might not fulfil demand, causing understaffing, which is also undesirable. Additionally, some issues related to TEPHs' wages arise when working hours are not constant. However, another interesting performance indicator could be the time spent to rebuild a schedule or the number of changes from the previous schedule to the updated version.

2.3 Problem Definition

Currently, INEM's managers reconstruct disrupted schedules manually, which makes it a time-consuming task. As it is a frequent task, it happens almost every day, the time spent can be higher than what would be desired. Moreover, the rescheduling process has more factors needed to be taken into account than the scheduling, which increases its complexity. Thus, being an informal process, some errors may occur. These are, certainly, not desired, since when equity is not accomplished, employees' satisfaction may decrease, which will ultimately affect the quality of the service provided.

Therefore, this dissertation aims to develop and apply a mathematical model that can act as support to the rescheduling process at INEM. The main goal of the model is to provide a tool for this process to perform this activity in a short amount of time and causing as little disorder as possible for TEPHs. Ultimately, it aims as well to improve the quality of current solutions. It should automate the process of constructing a new updated schedule after a disruption caused by a worker.

3. Literature Review

The staff rescheduling is a common problem for most organizations where each worker operates a shift. This chapter explains the reasons why it should be more studied, especially in the EMS context.

3.1 Planning Problems in EMS

Planning in EMS has the goal to measure the performance and costs of the system, as well as to assess its process quality. Moreover, planning also aims to compute the expected service level based on the current state and future changes to be implemented (Reuter-Oppermann *et al.* 2017). These authors divided EMS planning into three main groups: (i) the general design, (ii) the logistics and (iii) the analytics. This thesis focus on the logistics field, concerning a specific planning problem: workforce planning. Reuter-Oppermann *et al*., (2017) split EMS staff into two groups: (i) staff working in the ambulances and (ii) staff working in dispatching centres. Furthermore, staff scheduling has been widely discussed in the literature, which is motivated by economic factors, since labour cost is the major direct cost component in many cases (Van Den Bergh *et al*. 2013).

Despite shift scheduling being an extensively studied subject, rescheduling has not received the same consideration in the literature (Maenhout & Vanhoucke, 2011). The importance of staff rescheduling as an every-day complex and time consuming task has not been widely recognized, although some authors have noted that the lack of a specific methodological base that considers its complexity increases the likelihood to prejudice patients and stress working staff and managers (Clark *et al*., 2015). Therefore, this thesis will focus on this gap, studying the staff rescheduling in EMS.

3.2 Staff Rescheduling Problems

In any organization, staff scheduling is a balancing act between service needs and the available workforce resources. Poor scheduling decisions carry risks that may negatively impact the staff and, ultimately, the performance of the service provided. Rescheduling is the act of rediscovering this balance in a short period. Thus, poor rescheduling decisions may also prejudice the effectiveness of the service (Clark *et al.*, 2015). Clark *et al.* (2015) concluded that, as well as nurse scheduling, data suggests that rescheduling can impact patient care, staff morale and costs. Regarding the deterioration of patient care, it can be originated by three consequences of poor rescheduling decisions: (i) poor skill mix, (ii) under-staffing and (iii) long hours. McGillis Hall *et al*. (2004) found that, in the hospital context, inappropriate staff skill mix results in higher medication errors and wound infections, especially concerning more complex problems. Aiken *et al.* (2002) and Taylor *et al.* (1999) identified that when there are high patient-to-nurse ratios, there is also a higher mortality risk and failure-to-rescue rate. It can be transposed to the EMS, as when there are fewer technicians, response time – both on the dispatching centre and for the ambulance – may be higher, causing a delayed service, which may lead to mortality risk increase. Finally, Rogers et al. (2004) detected that when shift durations exceeded 12.5 hours per day, nurses were more fatigued, leading to an increase in errors occurrence.

Considering staff morale decline, it can be caused by three consequences of poor rescheduling: (i) long hours (ii) inequitable shifts and (iii) excessive changes on the initial schedule. As observed in Rogers *et al.* (2004), when working long hour shifts, staff will be more fatigued, which according to Hegney et al. (2006), can lead to a decrease in nurse morale. According to Wilson, (2002), several of characteristics contribute to the acceptability of shift work, including equitable shift rotas. Also, these rotas must be as regular as possible, having few changes so that employees can find a routine for themselves. Finally, low staff morale can lead to high staff turnover and high absenteeism (Silvestro & Silvestro, 2008).

Concerning the loss of costs effectiveness, it can be generated by two consequences of poor staff morale already mentioned, high staff turnover and high absenteeism, and two consequences of poor rescheduling decisions, over-staffing and low efficiency in the rescheduling process. Bland

Jones (2008) conducted a study where the most obvious insight was that by building an environment that increases nurse retention and mitigates its absence, the health organization would save money from turnover costs and other indirect gains, such as improved staff and patient satisfaction. Hayes & Bonnet, (2010) also concluded that it is possible to decrease costs by retaining valued staff. In addition, overstaffing can directly increase costs (Newbold, 2008). Finally, Clark *et al.* (2015) described rescheduling as time-consuming, as some managers were spending 10-20% of most working days rescheduling, repairing absenteeism and changing required staff. When poorly done, rescheduling in a health organization can, indirectly, hinder patient care, staff morale and costs increase. Thus, it can affect the whole performance of the health organization, being a topic demanding urgent attention.

3.3 Methodologies

In the rescheduling problem, some characteristics are translated into a mathematical formulation through an accurate modelling.

This section introduces first the most important decision criteria. Then, the most common constraints to which rescheduling decisions are subjected will be discussed. Finally, it presents some different modelling strategies regarding the horizon and the number of workers considered, and their impact on the quality of the final solution.

The reconstructed schedule quality is measured by multiple goals with different priority levels which can be grouped in health organisation's and staff related objectives. The objectives related to the health organization are as i) Maximize or maintain the quality of service as was intended in the original roster before disruptions and ii) Maintain or minimize labour cost (Maenhout & Vanhoucke, 2011, 2013; Mutingi & Mbohwa, 2015).

The staff related objectives are iii) Maintain or maximize or the satisfaction of individual nurse preferences, iv) Maintain or maximize schedule fairness and v) Maintain or minimize workload variation and vi) Maintain or minimize schedule changes as much as possible (Maenhout & Vanhoucke, 2011, 2013; Mutingi & Mbohwa, 2015; Wolbeck et al., 2020).

Rescheduling models share many constraints with scheduling models. Regarding scheduling, following the work done by Cheang *et al*. (2003) and Namorado Rosa, (2017), it is possible to divide these constraints into four groups: (i) coverage requirements, (ii) time-related constraints, (iii) work regulation constraints and (iv) internal ward constraints. Maenhout and Vanhoucke (2011) added one more group concerning rescheduling (v) disruption constraints.

When constructing a schedule, it is logical that the whole time horizon must be considered. However, when rebuilding an affected schedule, it may not be necessary to reschedule for the whole horizon. Maenhout and Vanhoucke (2013) concluded that it is not required to rebuild for the complete horizon. In truth, to effectively perform this task, the planning period must start two days before the first schedule disruption. Additionally, Wickert *et al. (2019)* generated near-optimum results confirming that if the planning period had already started, it may only be necessary to consider from the first day of absence. Moreover, Maenhout & Vanhoucke, (2013) also considered the variation of the number of workers on to reroster. In traditional rescheduling, the whole staff size is considered. They hypothesized that with fewer workers, solutions could still achieve a good quality in less time. However, this theory fell apart, as they identified that a higher number of workers would lead to lower variation, which would, in turn, guarantee higher quality.

3.4 Solutions

Several solution techniques have been applied to solve the personnel rescheduling problem. Based on the different classifications proposed, these techniques will be divided into exact algorithms and heuristic algorithms (Clark *et al*., 2015; Mutingi & Mbohwa, 2015; Namorado Rosa, 2017).

Starting with exact solutions, the first researchers to approach the rescheduling problem were Moz & Pato (2003), who conducted the tests for the ILP formulation of the integer multicommodity flow model. Moz & Pato (2004) presented two new integer multicommodity flow models. Later, Do *et al*. (2017) proposed a method based on MIP to provide a new schedule with minimum changes, while satisfying all constraints as in the original situation, for the Lai Chau hydropower station. Wolbeck *et al*. (2018) used a dynamic approach where a monthly schedule is created and then uncertain events such as illness are generated stochastically. Wolbeck *et al.* (2020) developed a MIP model where instead of penalizing each shift change equally, they evaluated them according to a Fair Shift Change Penalization Scheme. Finally, Paias *et al.* (2021) approached the bus driver rerostering problem with a MIP multicommodity flow assignment model, enabling the reconstruction based on calling standby drivers, good candidates to replace absents, depot drivers, those who have no duties in that day, and the postponement of already assigned days off.

Regarding heuristics solutions, Moz & Vaz Pato (2007) were the first to propose heuristic methods for the rescheduling problem. Pato & Moz (2008) developed an utopic Pareto genetic heuristic to deal with a bi-objective nurse rerostering problem. Kitada & Morizawa (2010) proposed a heuristic model incorporating a tree-search algorithm into the recursive search algorithm to achieve an optimal roster while minimizing reassigned tasks. In Maenhout & Vanhoucke (2011), the authors developed an evolutionary meta-heuristic model. Bäumelt *et al*. (2013) dealt with the rerostering problem by performing a parallel algorithm (constructive heuristic) on a Graphics Process Unit (GPU) to shorten the required computational time. Chiaramonte & Caswell (2016) developed a modified agent-based nurse rostering system that provides solutions for both scheduling and rescheduling. Mutingi & Mbohwa (2016) created a Fuzzy Multi-criteria Simulated Evolution (FMSE) approach, an iterative algorithm generated from the general Simulated Evolution (SE), where some of the original SE operators are fuzzified. Finally, Wickert *et al.* (2019) presented a Variable Neighbourhood Descent (VND) heuristic, a simple algorithm but able to integrate several neighbourhood structures and generate good results quickly.

4. Mathematical Formulation

This chapter presents an optimization model to solve EMS staff rescheduling problems, where the parameters, sets and subsets, the objective function and constraints are introduced. This model is supported by the methodologies explored in the literature review and INEM's case study.

The following are the sets and indices used in the mathematical model:

- $\boldsymbol{i} \in \boldsymbol{I}$ is the set of individuals
- $\boldsymbol{t} \in \boldsymbol{T}$ is the set of tasks
- $\boldsymbol{d} \in \boldsymbol{D}$ is the set of days in the planning horizon
- $\boldsymbol{s} \in \boldsymbol{S}$ is the set of working shifts, (e.g., S = {1(Night), 2(Morning), 3(Afternoon)})
- $\boldsymbol{g} \in \boldsymbol{G}$ is the set of teams
- $\boldsymbol{w} \in \boldsymbol{W}$ is the set of Sundays on the planning horizon

The following are the subsets:

- $\boldsymbol{I_g^G}$ is the set of workers that belong to team g
- $\boldsymbol{I_t^T}$ is the set of workers that have the required skills to perform task t
- $\boldsymbol{T_i^I}$ is the set of tasks that can be performed by worker i
- $\boldsymbol{I_t^{Td}}$ is the set of workers that have the desired skills to perform task t
- $\boldsymbol{T_g^G}$ is the set of tasks that are assigned to team g
- $\boldsymbol{H_i^I}$ is the set of holidays scheduled by worker i

The parameters used are defined as:

- $\boldsymbol{\theta_{days}^{max}}$ as the maximum number of consecutive working days
- $\boldsymbol{\theta_{nights}^{max}}$ as the maximum number of consecutive working nights
- $\boldsymbol{\theta_{d-off}^{max}}$ as the maximum number of consecutive days off
- $\boldsymbol{\theta_i^{min}}$ as the minimum number of working hours for worker i
- $\boldsymbol{\theta_{s-off}^{min}}$ as the minimum number of Sundays off that worker must have during the planning horizon
- $\boldsymbol{\theta_s^{min-s}}$ as the minimum number of shifts that must be performed for each shift s
- $\boldsymbol{L_t}$ as the length of the task t
- η as the number of public holidays on the planning horizon
- ξ as the number of hours to discount from the contract hours
- $\boldsymbol{R_{d,s,t}}$ as the staff requirements for day d, shift s and task t
- $\boldsymbol{z_{i,d,s,t}^0}$ as the initial schedule for worker i
- $\boldsymbol{z_{i,d}^D}$ as the disruptions caused by worker i and day d
- $|\boldsymbol{D}|$ as the number of days during the planning horizon
- $|\boldsymbol{W}|$ as the number of Sundays during the planning horizon

The objective function weights are now defined as:

- $\boldsymbol{w^{WF-}}$ the weight of the penalty variable for understaffed tasks for a certain day and shift
- $\boldsymbol{w^{WF+}}$ the weight of the penalty variable for overstaffed tasks for a certain day and shift
- $\boldsymbol{w^{OT-}}$ the weight of the penalty variable for shortage of hours worked
- $\boldsymbol{w^{OT+}}$ the weight of the penalty variable for excess of hours worked
- $\boldsymbol{w^{Sun}}$ the weight of the penalty for worker i being assigned to work on Sunday w but not on Saturday $w-1$
- $\boldsymbol{w^{Sat}}$ the weight of the penalty for worker i being assigned to work on Saturday $w-1$ but not on Sunday w
- $\boldsymbol{w^{G}}$ the weight of the penalty for team swaps
- $\boldsymbol{w^{Dist}}$ the weight of the penalty for tasks performed outside of workers' location
- $\boldsymbol{w^{R-}}$ the weight of the penalty variable for decrease in working hours by worker i from previous schedule
- $\boldsymbol{w^{R+}}$ the weight of the penalty variable for increase in working hours by worker i from previous schedule

Regarding decision variables, this problem presents only a set of decision variables, concerning the assignment of a tasks on a day and shift to a worker:

- $\boldsymbol{x_{i,d,s,t}} \in \{0,1\}$ is a decision variable that determines if worker i is assigned on day d and shift s to task t (1) or not (0)

There are various auxiliary/penalty variables, which account for the quality of the reschedule solution, as these are present in the objective function. In this model, the auxiliary variables are the following:

- $\boldsymbol{Y_i^{OT-}} \in \mathbb{N}_0$ is the auxiliary/penalty variable for the number of deficit working hours by worker i
- $\boldsymbol{Y_i^{OT+}} \in \mathbb{N}_0$ is the auxiliary/penalty variable for the number of excess working hours by worker i
- $\boldsymbol{Y_{d,s,t}^{WF-}} \in \mathbb{N}_0$ is the auxiliary/penalty variable measuring the lack of workers on day d, shift s to perform task t
- $\boldsymbol{Y_{d,s,t}^{WF+}} \in \mathbb{N}_0$ is the auxiliary/penalty variable measuring the excess of workers on day d, shift s to perform task t
- $\boldsymbol{Y_{i,w}^{Sun}} \in \mathbb{N}_0$ is the auxiliary/penalty variable defining if worker i is assigned to work on Sunday w but not on Saturday $w-1$
- $\boldsymbol{Y_{i,w}^{Sat}} \in \mathbb{N}_0$ is the auxiliary/penalty variable defining if worker i is assigned to work on Saturday $w-1$ but not on Sunday w
- $\boldsymbol{Y_g^{G}} \in \mathbb{N}_0$ is the auxiliary/penalty variable for allocating tasks to team g to workers that do not belong to team g
- $\boldsymbol{Y_{i,d,s}^{R+}} \in \mathbb{N}_0$ is the auxiliary/penalty variable measuring the increase in working hours by worker i from previous schedule
- $\boldsymbol{Y_{i,d,s}^{R-}} \in \mathbb{N}_0$ is the auxiliary/penalty variable measuring the decrease in working hours by worker i from previous schedule

The objective function presented in equation (1) aims to minimize the weighted sum of the penalty variables.

$$
\begin{aligned}
\boldsymbol{Min} \quad & \left(\sum_{d\in D}\sum_{s\in S}\sum_{t\in T} \boldsymbol{w^{WF-}} \times \boldsymbol{Y_{d,s,t}^{WF-}} + \boldsymbol{w^{WF+}} \times \boldsymbol{Y_{d,s,t}^{WF+}}\right) \\
& + \left(\sum_{i\in I} \boldsymbol{w^{OT-}} \times \boldsymbol{Y_{i}^{OT-}} + \boldsymbol{w^{OT+}} \times \boldsymbol{Y_{i}^{OT+}}\right) \\
& + \left(\sum_{i\in I}\sum_{w\in W} \boldsymbol{w^{Sat}} \times \boldsymbol{Y_{i,w}^{Sat}} \right. \\
& \left. + \boldsymbol{w^{Sun}} \times \boldsymbol{Y_{i,w}^{Sun}}\right) \\
& + \left(\sum_{g\in G} \boldsymbol{w^{G}} \times \boldsymbol{Y_{g}^{G}}\right) \\
& + \left(\sum_{i\in I}\sum_{d\in D}\sum_{s\in S} \boldsymbol{w^{R-}} \times \boldsymbol{Y_{i,d,s}^{R-}} \right. \\
& \left. + \boldsymbol{w^{R+}} \times \boldsymbol{Y_{i,d,s,t}^{R+}}\right)
\end{aligned}
\tag{1}
$$

Additionally, constraints were developed based on previous works done by various authors (Carmo, 2021; A. Clark & Walker, 2011; Maenhout & Vanhoucke, 2018; Rosa, 2017; Wickert et al., 2019; Wolbeck et al., 2020). Constraints can be divided into two categories, hard and soft constraints and it is important to note that there are constraints that concern the building of any schedule, so an initial schedule can be built applying this set of constraints. Moreover, there are also constraints related to rebuilding a new schedule from a previous one. Therefore, with the same set of constraints, it is possible to build scheduling and rescheduling models (Wickert et al., 2019).

Hard constraints are those that must not be violated and soft are those that can be violated with a penalization in the objective function. All constraints are in Appendix A.

5. INEM Case Study

This chapter presents the problem context, detailing the demand area, the tasks needed to be done, the workforce and respective team allocation to both services, CODU and EVs, and introduces the different types of disruptions generated and the test instances made to assess the model's accuracy.

5.1 Problem Context

This study focuses on rescheduling for both INEM's services in the areas that respond to the Lisbon CODU displayed, which encompasses CODU's location, several areas of the Lisbon Metropolitan Area and also other cities, scattered through the south to the centre region of Portugal.

For each of the two services, there are specific tasks. In CODU, there are two tasks for each one of the five teams: CODU shift responsible and CODU task. Considering EVs service, each task is called for the kind of medical vehicle to which it is linked. To illustrate, SIV task is related to the SIV vehicle. There is just one exception for the AEM category, because this vehicle demands two distinct tasks, requiring two TEPHs. These TEPHs have separate roles: one is in charge of driving the AEM, while the other is in charge of the shift, as an AEM team responsible.

The workforce considered in this case study is composed of 266 Pre-Hospital Emergency Technicians (TEPHs). At INEM, every TEPH holds a full-time contract, working 35 hours per week, which corresponds to 7 hours per day, 5 days a week. As the time horizon in this case study is 31 days, if there are no public or scheduled holidays, TEPHs must work 156 hours. TEPHs can be allocated to one or more teams and each team is responsible for certain tasks that belong to one or the other service. At CODU, there are 5 teams and each one is formed by 23 TEPHs, having a total of 115 technicians that can perform CODU's tasks. In the EVs case, there are 194 TEPHs capable of performing this service's tasks.

5.2 Disruptions Generation

Since it was not possible to access the records of disruptions and changes on the initial schedule at INEM for a month, disruption generation was based on the works done by Ingels & Maenhout, (2015), Wolbeck *et al*., (2018) and Wickert *et al*., (2019) and interactions with the decision maker, deciding for an initial absenteeism rate of 1.6%.

For type I, disruptions were generated with a Binomial distribution with binary scenarios (success – 1 or unsuccess – 0) with a probability of success of 1.6%. The number of trials was the number of TEPHs multiplied by the number of days in the planning horizon (266 x 31). Disruptions could happen every day for any TEPH. Disruption of type II was generated since the study made by Vahtera et. al (2001) showed that there are week days where the probability to be absent is higher. According to the work developed, people tend to be absent more in the beginning – Monday – or in the end of the week – Friday. They found that the absenteeism rates on these days is up to 1.9 times higher than on others. Therefore, for each day, it was generated a trial using a Binomial distribution where the probability of being a day with a disruption was 80% for Mondays and Fridays and 40% for the rest of the days. This resulted in 14 days with disruptions, 6 Fridays or Mondays and 8 from the other weekdays, which accounts for around 45% of the days in the planning horizon. Then, to equal the probability of 1.6% of the previous type, disruptions were generated again for each worker on the days with disruptions using a Binomial distribution where the probability of each person being absent was 3.6% (3.6% x 45% = 1.62%).

5.3 Test Instances

The model was tested on real data provided by INEM and the tests made can be divided into four groups.

The first group concerns a comparison between rescheduling starting from a cyclic schedule and from a non-cyclic schedule with the same disruptions scenario for CODU's TEPHs. The cyclic initial schedule was generated from previous works at INEM and the non-cyclic schedule was generated from the model presented in this thesis.

The second group concerns tests for an initial cyclic schedule for the universe of EVs and for the whole INEM service.

The third group includes tests for an initial schedule for the whole INEM service, with three variants of the first type of generated disruptions. The first variant starts from the disruptions used in the second group (with an absenteeism rate of 1.6%) but the next day of the schedule for each TEPH is also a disruption day. This results in two consecutive absent days, which accounts for an absenteeism rate of approximately 3.2%. The second variant is very similar but the two next days of a disruption also have disruptions. Hence, three consecutive absent days are generated, which accounts for an absenteeism rate of approximately 4.8%. The third variant is equal to type I, disruptions are also generated randomly using Binomial distribution but different values of probability will be used, 5% and 10%, because these are the highest absenteeism rates reported for emergency services in the literature (Wickert et al., 2019).

The fourth group includes tests for an initial schedule for the whole INEM service, with an absenteeism rate of 5%, starting from a cyclic and a non-cyclic schedule. In this case, it is intended to study the effect on the other variables of the objective function after varying the weight of changing shifts from the previous schedule w^{R-} and w^{R+}. These will have a value of 1000, equal to the weight of understaffing, and 500, half of the weight of understaffing so that in the objective function two changes (remove a shift from an absent person and add one to another person) have the same value, in theory, of an understaffed task. It is also intended to go deeper in the study of the differences between starting with a cyclic and a non-cyclic schedule.

Table 2 displays a summary of the test instances.

Table 2: Test instances

Nbr.	Instance	TEPHs	Tasks	Rate (%)	w^{R-}/w^{R+}
1.1	CODU Cyclic Schedule – Type I	115	10	1.6	20
1.2	CODU Cyclic Schedule – Type II	115	10	1.6	20
1.3	CODU Non-Cyclic Schedule – Type I	115	10	1.6	20
1.4	CODU Non-Cyclic Schedule – Type II	115	10	1.6	20
2.1	EVs Cyclic Schedule – Type I	194	54	1.6	7000
2.2	EVs Cyclic Schedule – Type II	194	54	1.6	7000
2.3	INEM Cyclic Schedule – Type I	266	64	1.6	7000
2.4	INEM Cyclic Schedule – Type II	266	64	1.6	7000
3.1	INEM Cyclic Schedule – Type I Variant I	266	64	3.2	7000
3.2	INEM Cyclic Schedule – Type I Variant II	266	64	4.8	7000
3.3	INEM Cyclic Schedule – Type I	266	64	5	7000
3.4	INEM Cyclic Schedule – Type I	266	64	10	7000
4.1	INEM Cyclic Schedule – Type I	266	64	5	1000
4.2	INEM Cyclic Schedule – Type I	266	64	5	500
4.3	INEM Non-Cyclic Schedule – Type I	266	64	5	1000
4.4	INEM Non-Cyclic Schedule – Type I	266	64	5	500

Table 3 displays the parameters and weights used for all cases, except when w^{R-}/w^{R+} are changed.

Table 3: Parameters and Weights

Parameter	Value	Weight	Value
θ_{days}^{max}	6	w^{EV_WF-}	1000
θ_{nights}^{max}	3	w^{EV_WF+}	10
θ_{d-off}^{max}	3	w^{CODU_WF-}	100
θ_{i}^{min}	156	w^{CODU_WF+}	10
θ_{s-off}^{min}	1	w^{OT-}	1
θ_{s}^{min-s}	3	w^{OT+}	50
$\|\boldsymbol{D}\|$	31	$w^{Sun}/w^{Sat}/$	10
$\|\boldsymbol{W}\|$	4	w^{EV_G}	5
η	0	w^{CODU_G}	1
ξ	8	w^{R-}/w^{R+}	7000

It is important to remark that a month was simulated and the model only run in the days where there was a disruption, day r. In this case, the past schedule was blocked from day 1 until day (r – 3) and, from day (r – 2) until day 31, variables were free to change from the previous schedule. It means that TEPHs must notice the manager until two days before their absence, which seems reasonable. Therefore, during the month the number of variables for this instance is expressed by the following equation:

$$\#\,\boldsymbol{variables} = \mathbf{115} \times \mathbf{10} \times \mathbf{3} \times (\mathbf{31} - (\mathbf{r} - \mathbf{2})) \qquad (18)$$

6. Results and Discussion

The model is implemented in Python with the combination of the library Docplex - IBM Decision Optimization CPLEX and solving through IBM ILOG CPLEX Optimizing Studio. All tests were executed on a PC with an Intel Core i7- 1165G7 processor of 2.4 GHz and 16 GB of RAM running under the Windows 10 operating system. All models were run until optimality.

6.1 Results Presentation

Regarding first group, in table 4, after running the monthly simulations, it was observed that better solutions are achieved when rescheduling for schedules that start the month with a non-cyclic than with a cyclic schedule. For CODU instance, where there is an oversupply, the reason behind is related to the number of incomplete weekends off – IWO. Cyclic schedule is not flexible and not capable of adapting. Non-cyclic is capable of adapting, having less IWO. Additionally, in a scenario with no IWO both cyclic and non-cyclic have similar Objective Function Value average – OFV.

Table 4: First group results

Instance	Time (Avg.)	Changes (+)	Changes (-)	OFV (Avg.)	IWO
CODU Cyclic Schedule – Type I	6.58	0.46	1.50	3,519.77	183.92
CODU Non-Cyclic Schedule – Type I	3.37	1.81	1.85	2,901.15	126.42
CODU Cyclic Schedule – Type II	5.22	1.21	2.50	3,923.57	191.25
CODU Non-Cyclic Schedule – Type II	7.17	2.64	2.36	3,213.43	126.92
CODU Cyclic Schedule – Type II	4.57	1.21	2.50	1,988.14	0
CODU Non-Cyclic Schedule – Type II	6.79	2.64	2.36	1,928.43	0

The second group results, in table 5, show that the model is able to find optimal solutions in a short amount of time for EVs and INEM service, changing always less than 0.26% of the previous schedule.

Table 5: Second group results

Instance	Time (Avg.)	Changes (+)	Changes (-)	OFV (Avg.)
EVs Cyclic Schedule – Type I	178.45	1.28	4.76	46,601.38
EVs Cyclic Schedule – Type II	159.62	2.07	7.29	73,712.36
INEM Cyclic Schedule – Type I	212.08	2.13	6.00	42,965.00
INEM Cyclic Schedule – Type II	214.71	2.29	7.64	52,609.07

The third group results, in table 6, show that the model is able to deal with the strictest scenarios that can happen in the emergency services sector regarding two consecutive and three consecutive absent days and 5% and 10% absenteeism rates.

Table 6: Third group results

Instance	Time (Avg.)	Changes (+)	Changes (-)	OFV (Avg.)
INEM Cyclic Schedule – Type I Variant I	234.58	2.87	6.06	70,699.29
INEM Cyclic Schedule – Type I Variant II	257.63	5.03	8.84	104,613.13
INEM Cyclic Schedule – Type I	192.91	3.58	7.94	88,849.61
INEM Cyclic Schedule – Type I	148.94	6.42	16.45	169,199.35

The fourth group presents results, in table 7, to determine the effects of varying the weight of making changes from previous to new schedules for both cyclic and non-cyclic starting schedules and that will be discussed in the next section.

Table 7: Fourth group results

Instance	Time (Avg.)	Changes (+)	Changes (-)	OFV (Avg.)
INEM Cyclic Schedule – Type I	198.18	3.58	7.94	19,036.58
INEM Cyclic Schedule – Type I	205.36	4.03	7.90	13,111.68
INEM Non-Cyclic Schedule – Type I	156.52	2.06	8.87	18,844.61
INEM Non-Cyclic Schedule – Type I	72.40	3.13	8.84	10,074.58

6.2 Discussion

In this section, scenarios 3.2, 3.3, 4.1, 4.2, 4.3 and 4.4 were studied. First, it was observed that for scenarios 3.3 and 4.1, despite having such different penalizations of changes from previous schedule (w^{R-}/w^{R+}), react very similarly to the same disruptions scenario, showing that if this penalization is higher or equal to the weight regarding understaffing, the model respond in the same way. Then, as expected, when decreasing the value of w^{R-}/w^{R+}, there will be more changes (+). This aspect must be discussed with the decision-maker in order to define this weight in a way that benefices more the organization. Additionally, although scenario 3.2 has a lower absenteeism rate than scenario 3.3, the first has worse results, because since the maximum of consecutive days off is three, after being absent three consecutive days, TEPHs must work in the following day. Additionally, IWO are strongly related with the disruption scenario, i.e., scenarios with the same disruption have the same number of IWO. Finally, starting the month with a non-cyclic schedule still produces better results than with a cyclic due to its flexibility in adapting to situations. In this case, the non-cyclic responds to the undersupply by decreasing understaffing and reducing overtime. However, due to non-cyclic strictness, the latter cannot adapt, having always more penalizations.

Concluding, scenarios starting with non-cyclic initial schedules provide better results for cases with under and over supply compared to the demand. Being less strict than the cyclic initial schedule, the non-cycle initial schedule appears as a good alternative for INEM current way of operating.

7. Conclusions and Future Work

Rescheduling is a daily and time-consuming task, which nowadays, many organizations still perform manually. Thus, this thesis aimed to create a model to solve the rescheduling process for EMS, taking into consideration INEM's case. The model was capable of providing optimal results for INEM's instances and showed consistency for cases with two and three consecutive absent days and also for the highest absenteeism rates observed in the emergency services sector ranging from 5% to 10%.

Since INEM currently operates under a cyclic initial schedule, the differences between starting the month with a cyclic and a non-cyclic schedule were studied. For scenarios with oversupply and undersupply compared to the demand, the non-cyclic initial schedule month simulation outperformed the cyclic, mainly due to the lack of flexibility shown by the latter. Hence, the recommendation to INEM holds with rethinking the way its initial schedule is being generated.

Despite the advancements made, there are still numerous ways to develop this subject. The results obtained in this dissertation aimed to create new schedules in a matter of minutes and with little perturbation for the workers, only considering three groups of elements in the objective. In severe cases, where a quick response is required, it may be fair but performing it every day may neglect important aspects, such as staff preferences and hours allocated to each service. Thus, it would be interesting to solve rescheduling also concerning those key factors even if periodically during the month, to adjust the latter, assuring that staff satisfaction is being considered.

Regarding INEM, it is essential to study TEPHs absenteeism more in-depth in order to better understand the reasons behind them and, possibly, introduce factors taking that into consideration in the initial schedule to reduce disruptions. It would also be interesting to have the records of one month of the created schedules after disruptions to be able to precisely compare the solutions provided by the model and those obtained by performing this task manually. Furthermore, as abovementioned, schedule managers, often spend 10-20% of their days performing this task. Hence, it would be a great advantage if this process could be automatized. For its implementation, there are two tools that outstand to be critical for its acceptance. The first is a Graphical User Interface, which must be user-friendly and intuitive to ease managers job. The second is concerned with the difficulty for the manager to communicate with TEPHs and get people to perform tasks that were going to be done by an absent worker. It is a tool that sends a message to a TEPH's phone in case her/his initial schedule was reshaped. This message contains the substitution of shifts dictated by the model. Then, if the TEPH agrees with the change, s/he must send a message with "YES" and the schedule is updated, accepting the new schedule. If the TEPH does not agree, s/he must send a message with "NO" and the model must consider the shift as disruption for this worker, i.e., TEPH cannot work on that shift and the model must find a new solution. This procedure is repeated until all the people with reshaped schedules confirm that they accept schedule changes

Appendix A

Scheduling Constraints

$$x_{i,d,s,t} = 0 \,, \forall\, i \notin I_t^T \,, \forall\, d \in D \,, \forall\, s \in S \,, \forall\, t \in T \qquad \textbf{(1)}$$

$$\sum_{t\in T_i^I} x_{i,d,1,t} + \sum_{t\in T_i^I} x_{i,d,2,t} + \sum_{t\in T_i^I} x_{i,d,3,t} \le 1 \,, \forall\, i \in I \,, \forall\, d \in D \qquad \textbf{(3)}$$

$$\sum_{t\in T_i^I} x_{i,d+1,1,t} + \sum_{t\in T_i^I} x_{i,d,2,t} + \sum_{t\in T_i^I} x_{i,d,3,t} \le 1 \,, \forall\, i \in I \,, \forall\, d \in D \setminus \{|D|\} \qquad \textbf{(2)}$$

$$\sum_{t\in T_i^I} x_{i,d+1,1,t} + \sum_{t\in T_i^I} x_{i,d+1,2,t} + \sum_{t\in T_i^I} x_{i,d,3,t} \le 1 \,, \forall\, i \in I \,, \forall\, d \in D \setminus \{|D|\} \qquad \textbf{(3)}$$

$$\sum_{r\in\{d,d+1,\dots,d+\theta_{days}^{max}\}} \sum_{s\in S} \sum_{t\in T_i^I} x_{i,r,s,t} \le \theta_{days}^{max} \,, \forall\, i \in I \,, \forall\, d \in D \setminus \{|D|, |D|-1, \dots, |D|-\theta_{days}^{max}\} \qquad \textbf{(4)}$$

$$\sum_{r\in\{d,d+1,\dots,d+\theta_{days}^{max}\}} \sum_{s\in S} \sum_{t\in T_i^I} x_{i,r,1,t} \le \theta_{nights}^{max} \,, \forall\, i \in I \,, \forall\, d \in D \;\{|D|, |D|-1, \dots, |D|-\theta_{nights}^{max}\} \qquad \textbf{(5)}$$

$$\sum_{r\in\{d,d+1,\dots,d+\theta_{d-off}^{max}+1\}} \sum_{s\in S} \sum_{t\in T_i^I} x_{i,r,s,t} \ge 1 \,, \forall\, i \in I \,, \forall\, d \in D \setminus \{|D|, |D|-1, \dots, |D| - \theta_{d-off}^{max} - 1\} \qquad \textbf{(6)}$$

$$\sum_{r\in W} \sum_{s\in S} \sum_{t\in T_i^I} x_{i,r,s,t} \le |W| - \theta_{s-off}^{min}, \forall\, i \in I \qquad \textbf{(7)}$$

$$\sum_{d\in D} \sum_{t\in T_i^I} x_{i,d,s,t} \ge \theta_s^{min-s} \,, \forall\, i \in I, s \in S \qquad \textbf{(8)}$$

$$\sum_{d\in H_i^I} \sum_{s\in S} \sum_{t\in T_i^I} x_{i,d,s,t} = 0 \,, \forall\, i \in I \qquad \textbf{(9)}$$

$$\sum_{d\in D} \sum_{s\in S} \sum_{t\in T_i^I} L_t \times x_{i,d,s,t} = \theta_i^{min} - (\eta + H_i^I) \times \xi + Y_i^{OT+} - Y_i^{OT-} \,, \forall\, i \in I \qquad \textbf{(12)}$$

$$\sum_{i\in I_t^T} x_{i,d,s,t} = R_{d,s,t} - Y_{d,s,t}^{WF-} + Y_{d,s,t}^{WF+} \,, \forall\, d \in D \,, \forall\, s \in S \,, \forall\, t \in T \qquad \textbf{(13)}$$

$$\sum_{s\in S} \sum_{t\in T_i^I} (x_{i,w,s,t} - x_{i,w-1,s,t}) - Y_{i,w}^{Sun} + Y_{i,w}^{Sat} = 0, \forall\, i \in I \,, \forall\, w \in W \qquad \textbf{(14)}$$

$$\sum_{d\in D} \sum_{s\in S} \sum_{t\in T_g^G} \sum_{i\in I_t^T \setminus I_g^G} x_{i,d,s,t} - Y_g^G = 0 \,, \forall\, g \in G \qquad \textbf{(15)}$$

Rescheduling Constraints

$$\sum_{s\in S} \sum_{t\in T_i^I} x_{i,d,s,t} + z_{i,d}^D \le 1 \,, \forall\, i \in I \,, \forall\, d \in D \qquad \textit{(16)}$$

$$\sum_{t\in T_i^I} (x_{i,d,s,t} - z_{i,d,s,t}^0) + Y_{i,d,s}^{R+} - Y_{i,d,s}^{R-} = 0 \,, \forall\, i \in I \,, \forall\, d \in D \,, \forall\, s \in S \qquad \textit{(17)}$$

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