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A rostering approach to minimize health risks for workers: an application to a container terminal in the Italian port of Genoa

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Abstract

The evolving safety regulation is pushing seaports to comply with safety measures for workers performing heavy loads handling and repetitive movements. This paper proposes a risk-aware rostering approach in maritime container terminals, i.e., it addresses the rostering problem of minimizing and balancing workers' risk in such terminals. To this end, a mixed integer mathematical programming model incorporating workforce risks is proposed, considering constraints such as the satisfaction of the workforce demand to perform the terminal operations, the worker-task compatibility and restrictions on the sequence of tasks assigned to the same worker. The model has been successfully applied to plan workforce over a six months horizon in a real container terminal located in Northern Italy, the Southern European Container Hub (SECH) in Genoa. As the workforce demand in SECH terminal is available at most two weeks in advance, a rolling horizon planning approach is devised. Experimental tests on real data provided by SECH terminal over a six months planning horizon highlight the effectiveness of the approach - the maximum monthly risk for workers is reduced by 33.9% compared to the current planning - and suitability to other container terminal contexts. Moreover, the model is applicable to a broad range of port situations, and robust enough to need little adaptation.

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Keywords: Container Terminal Rostering, Safety, Risk Balance, Mathematical Modeling, Rolling Horizon, OCRA and NIOSH methods

1. Introduction

Personnel scheduling or rostering is a combinatorial optimization problem that continues receiving a relevant attention in the literature [1]. This problem consists in assigning shifts to workers over a scheduling period taking into account different classes of constraints usually related to the involved organization, the regulation in force and the individual worker preferences [2]. With specific regards to transportion, staff scheduling and rostering have been widely considered in airline (e.g., [3], [4] and [5]) and railway transport (e.g., [6] and [7]). The concept of *safety* in work environments started to be recently taken into account also in rostering and scheduling approaches. This is done especially for contexts where jobs may cause injury, health diseases to workers and accidents. A relevant example of the inclusion of safety aspects in crew scheduling is provided by [8], where personnel fatigue aspects are modelled in order to improve safety in the airline sector.

Greater attention and stricter rules to safeguard workers' health and increase safety are beginning to be adopted also in maritime container terminals. In such contexts, operative workers are subject to musculoskeletal disorders of the spinal column, which in industrialized countries represent the most important cause of disability and absence from work due to illness. The National Institute of Occupational Safety and Health (NIOSH) ranks such pathologies at the second place in the list of the ten most important health problems in workplaces. These diseases cause low worker return, absenteeism, low efficiency and quality, and the need of new staff training. This translates also in significant costs for companies that directly impact their performances. An European survey on employment conditions carried out in 2005 by the European Foundation for the Improvement of Living and Working Conditions [9] has highlighted that incorrect load manual handling (LMH) and repetitive movements (RM) have very negative health consequences:

- 24% of workers suffers from back pain and an almost similar percentage is affected by muscle disorders;
- 50% of premature retirements is caused by back-related diseases;
- 15% of cases of unsuitability at work is due to back injuries;
- 43% of occupational diseases is related to upper bio-mechanical overload pathologies;
- 33% of workers, for the majority of their working time, is employed in activities involving repetitive movements of upper limbs.

Therefore, in rostering it is fundamental to evaluate and minimize the risk associated with activities that may affect the health of workers. In particular, the health risk due to physical activities in work environments must be assessed in relation to three kinds of actions: (i) manual handling of loads, (ii) repetitive movements, and (iii) tractions and thrusts.

The contribution of this paper stands in the incorporation - in the mathematical model - of health and safety issues related to manual handling of load and repetitive movements (since these are the main activities carried out in a container terminal), based on the NIOSH and OCRA (Occupational Repetitive Actions) methods, and in its application to a real case study.

In Section 2 the first two kinds of critical movements are analyzed in detail, together with the methodologies used to evaluate them.

1.1. Literature review

Personnel scheduling and rostering are usually considered as synonymous [10]. Rostering is primarily concerned with the allocation of tasks among the available workforce in order to satisfy a given time-dependent demand. Rostering models and their possible solution approaches usually differs according to the specific application context considered, but they are commonly characterized by a high degree of complexity.

The literature regarding rostering problems is wide and consolidated; extensive related surveys are provided in [1], [10], [11] and [12]. In particular, Ernst et al. [10] provide a review of staff scheduling and rostering in specific application areas, together with the models and algorithms reported in the literature for their solution. As pointed out in [10], personnel scheduling, or rostering, is the process of constructing work timetables for the staff so that an organization can satisfy the demand for its goods or services. In the service sector, staff rostering is a major challenge since costs are essentially made up of staffing costs. In the hospital context the rostering problem has been extensively studied [13], [14]; in particular, much attention has been devoted to the NP-hard *Nurse Rostering Problem* (NRP), whose goal is to find an optimal way to assign shifts to nurses [15], [16], [17], [18], [19]. The home health care (HHC) problem is faced in [20] and in [21], where a NRP and a vehicle routing problem with time windows (VRPTW) are jointly considered. Recently, in [22], the problem of defining stable shift rosters in presence of uncertain demand forecast has been faced.

The survey provided in [1] focuses on algorithms for generating rosters and personnel schedules, but it also covers related areas such as workforce planning and staffing requirements estimation. Papers are classified according to the types of problem addressed, the application areas covered and the methods used. Morever, in the survey of Van den Bergh et al. [11], the papers considered are classified according to different personnel categories, such as contract types (full-time, part-time, casual), skills and entity (individual and crew), type of decisions taken (i.e., related to tasks, groups, shift sequence, time or other), coverage constraints (i.e., ensuring the presence of the number of employees needed to cover the workload), skills (modelled either as a hard or a soft constraint), level of flexibility with respect to breaks and skills, financial measures, time-related constraints, solution techniques, incorporation of uncertainty, application area and applicability of the research. With respect to such criteria, this paper considers a problem where the required tasks are known and already associated with the shifts over a fixed time horizon; then, the decisions consist in assigning full-time workers with different skills to indivisible tasks (i.e., to cover the whole task demand); legal and time-related constraints are also imposed. The objectives of our real world problem are novel, they are not considered in the survey [11]. The goal is to minimize the maximum cumulative risk borne by the workforce over the planning period, while balancing this risk among workers.

Other recent surveys are: [23], where routing and scheduling problems are considered, summarizing the key features of the problems and the solution methodologies developed and applied to realistic problem settings; [24] that introduces a new classification scheme for integrated staff rostering and job scheduling problems, extending existing schemes for project and machine scheduling; [25], where a survey on resource constrained routing and scheduling is provided, considering characteristics with respect to resource qualifications, service requirements and problem objectives, and identifying the most effective exact and heuristic algorithms for this class of problems.

With regard to solution approaches, many heuristics have been proposed to solve staff scheduling problems, including simulated annealing (e.g., [26] and [27]), tabu search (e.g. [28]), and genetic algorithms (e.g., [29]). Exact approaches, such as column generation methods, have also been used, e.g., in [30] and [31]. Belin and Demeulemeester [32] make a comparison of several MILP models in scheduling nurse trainees. Smet et al. [2] introduce the concepts of local and global consistency in constraint evaluation processes regarding the personnel rostering problem and propose a general methodology to address these challenges in integer programming approaches. Ramesh et al. [33] propose a new approach to the personnel task scheduling problem based on decomposition and develop several new exact and heuristic techniques to solve the resulting sub-problems.

In the last few decades, Operational Research methods and approachess have been extensively used to tackle and solve problems arising in port contexts (see the surveys [34] and [35]). However, the research works that are specifically focused on container terminal rostering problems are scarce. The rostering problem is solved in [36] for a real container terminal in Gioia Tauro port, taking into account the uncertainty of the workforce demand and the need of ensuring a time continuous efficiency of the terminal. The problem is decomposed into two phases associated with long-period planning and daily planning. A heuristic approach based on a set-covering model is then used for the long-term planning, whereas a branch-and-bound heuristic is adopted for the short-term planning.

The problem of assigning an operator to each piece of equipment during each operating time segment scheduled for the equipment is tackled in [37] by defining a constraint-satisfaction problem and solving it by utilizing a commercial software; the solution procedure is applied to a real container terminal located in Pusan, Korea.

More recently, Di Francesco et al. [38] investigated the short-term manpower planning problem, i.e., the determination of shifts, tasks and activities of the manpower working in transhipment container terminals, by formulating an integer linear programming model with the goal of properly serve vessels. The optimal model solutions have been compared with the decisions made by a real transhipment container terminal.

To the best of our knowledge, there are no publications regarding the rostering problem in container terminals that take into account the risk for workers' health due to the assigned tasks. All the research in literature carried out so far on rostering in container terminals is motivated by economic considerations, neglecting worker safety aspects, since, for many companies, the labor cost is the major direct cost component. This paper tries to fill this gap, providing a planning approach based on a mathematical programming model which is able to effectively generate roster plans in a seaport container terminal, i.e., to assign manpower to the required operational tasks, with the goal of minimizing the risks for workers related to the manual handling of loads and repetitive movements. This paper explicitly accounts for workers' risks in the mathematical model by means of a quantitative approach.

Different kinds of operations are performed in container terminals [39], [40] and each activity is related to a different level of risk in terms of injury occurrence and development of health pathologies. Lower risks arise when considering, for instance, the driving of a trailer or a reach stacker, whereas very high risks occur when dealing with the unstuffing (stripping) of containers for customs check purposes or with lashing and unlashing operations (necessary to properly secure containers on board of containerships).

Risks related to workers are rarely considered in the literature concerning logistics and transportation. Some papers considering this issue are [41], [42] and [43]. More specifically, Spieler [41] examines, from a legal standpoint, the costs due to injuries in working places and investigates the workers compensation paradigm and insurance; besides, the author analyzes the implication of safety and health reforms on injury prevention. In [42] Wang et al. identify the critical factors and paths that influence workers safety risk tolerance and then develop an influencing path model to estimate the effects of external factors on risk tolerance. In [43] Lin et al. investigate the feasibility of a real-time tunnel location-based services system to provide workers safety protection; they proposed a location algorithm for providing real-time positioning service and assure workers' safety on tunnel site.

The present paper proposes a mathematical model to optimally solve the rostering problem in real container terminals, considering several sets of constraints that are analogous to some of those already introduced in the literature, as better pointed out in Section 3. The novelty of the paper stands in the incorporation of the risks for workers when performing heavy loads and repetitive movements and, also, in the successful application of the model to a real container terminal. Moreover, a rolling horizon approach is used to consider the occurrence of unpredictable events, such as sudden illness or injuries, when performing roster plans.

The remainder of the paper is organized as follows. Section 2 provides a short description of the NIOSH and OCRA methods through which the risk for workers health respectively due to manual handling of heavy loads and repetitive movements can be evaluated. Section 3 describes in more detail the problem under investigation and the paper contribution. In Section 4 a mathematical model to solve the addressed problem is introduced and described, while in

Section 5 the overall workforce planning approach adopted and experimented in a real container terminal located in Northern Italy, the Southern European Container Hub (SECH) in the Genoa port, is outlined. Section 6 provides an extensive experimental and computational analysis to test the model performance, also comparing the obtained plans with the ones actually adopted in the SECH terminal. Finally, concluding remarks are reported in Section 7.

2. The methods for evaluating risks for container terminal workers

In this section the two methods adopted to evaluate the risk for workers due to manual handling of loads and performing repetitive movements are briefly described.

Load Manual Handling (LMH) operations are regulated by the international ISO (International Organization for Standardization) 11228-1 Norm and regards "the operations of transportation and support of a load by one or more workers, including the actions of lifting, holding, pushing, pulling, carrying or moving a load which, due to their characteristics or as a result of unfavorable ergonomic conditions, result in risk of biomechanical overload diseases, especially back-lumbar ones (Article 167 of Italian Legislative Decree 81/08 [44])".

The elements to consider for the definition of the risk level associated with the LMH are the load characteristics (too heavy, i.e., greater than 30 Kg for men and 20 kg for women; too bulky; unstable, etc.), the positions assumed during the lifting operation (low back, trunk twist, excessive load distance from the trunk, etc.), the size of the physical stress (high frequency of lifting actions or high prolonged lift time) and the characteristics of the working environment (presence of slopes, pavement status, non-optimal microclimate, etc.). In general, there are risks associated with the LMH when the load weight is more than 3 kilograms. LMH may be the cause of the development of pathologies due to the gradual cumulative wear of the musculoskeletal system, particularly the lumbar spine. It represents one of the main causes of absence from work for illness or injury.

LMH operations are assessed through the *NIOSH method* ([45], [46]) that is applied in accordance to the European Standard UNI EN 1005-2 and ISO 11228-1. This method analyses the fatigue deriving from the lifting of heavy loads and transportation of heavy objects, and defines the so called NIOSH index (LI), allowing to evaluate whether the working conditions for jobs including such operations are safe and physically acceptable. This index is computed as follows:

$$LI = \frac{lifted \quad weight}{RWL} \tag{1}$$

where RWL is the Recommended Weight Limit for lifting actions [47], estimated from the maximum weight that can be lifted under ideal conditions (denoted as constant weight or reference mass), and is then reduced according to other risk factors (multiplicative factors of reduction).

The values of the LI for the analysed tasks are compared with a set of risk thresholds, shown in Table 1, to evaluate the need of preventive and/or corrective actions.

Repetitive movements (RM) refer instead to the high frequency handling of small loads [48]. Repetitive tasks are identified as “work activities characterized by repeated cycles composed of technical actions”, where the cycle is a “sequence of relatively short duration actions, several times repeated and equal to itself”. Diseases related to RM are defined as musculoskeletal disorders due to biomechanical overload, i.e., to the alterations of the osteo-muscle-neuro-tendon units related to the presence of a constant functional engagement of upper limb joints (shoulder, elbow, wrist). Such diseases are related to endogenous factors (sex, age, strength, chronic illnesses, psychological conditions), exogenous factors (repetitive movements, high frequency and speed, force use, incongruous posture and stereotyped gestures, work cycle times, insufficient recovery times, imposed rhythms, not ergonomic workstations and tools), and complementary factors, which depend on the type of work performed and can act as risk amplifiers.

RM operations are assessed by means of the international OCRA (Occupational Repetitive Actions) method [49], which is the reference method in the

Table 1: NIOSH LI values and related corrective actions

LI value	**Exposure level**	**Interpretation**	**Consequences**
LI <0.85	Acceptable, no risk	Acceptable exposure for most of the working population	Acceptable, no consequences
0.85 <LI <1	Borderline or very low exposure	Acceptable exposure for most of the working population, but a negligible part could be exposed to very low risk levels	If possible, improve structural factors or take other organizational measures; train workers
1 <LI <2	Risk at a low level	A significant part of the working population may be exposed to a low risk level	Redesigning tasks and jobs with low priority; train workers and activate health surveillance
2 <LI <3	Risk at a significant level	A larger part of the working population could be exposed to a significant level of risk	Redesigning tasks and jobs with medium priority; train workers and activate health surveillance
LI >3	Risk at a high level	Absolutely not adequate for the most of the population	Redesigning tasks and jobs with high priority; train workers and activate health surveillance

11228-3 ISO Norm and in the 1005-5 EN- CEN (European Committee for Standardization).

The OCRA checklist is a simplified procedure for assessing and managing the risk of biomechanical overload of the upper limbs, analyzing four major risk factors (shortage of recovery periods, frequency, strength and incongruous posture). This checklist estimates a risk index both for the right and left upper limbs. Once quantified, the risk of a task is compared with specific risk thresholds and some corrective actions are possibly suggested, as shown in Table 2.

The NIOSH and OCRA methods have been successfully applied to various working fields, but only recently some relevant Italian terminal operators have

Table 2: OCRA risk levels and corrective actions

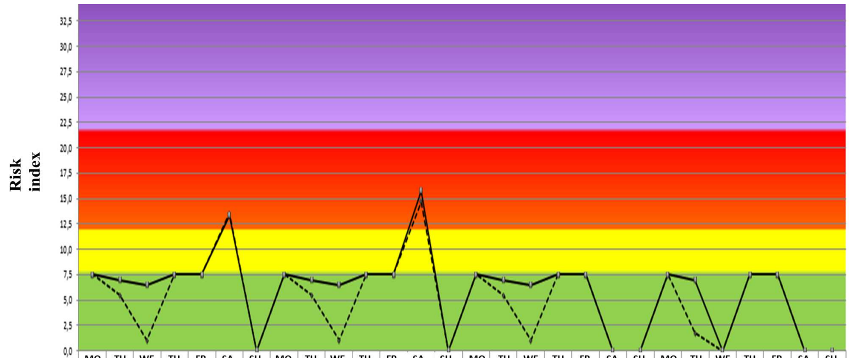
Ocra Index Limit	**Band**	**Risk**	**Corrective actions**
<2.2	green	Acceptable risk	None
2.3-2.5	yellow	Borderline or very light	Health surveillance
3.6-4.5	light red	low risk	Reduction of risk by priority (e.g. redisign workplace), health surveillance, training
4.6-9	medium red	medium risk	Reduction of risk by priority (e.g. redisign workplace), health surveillance, training
> 9.1	purple	high risk	Reduction of risk by priority (e.g. redisign workplace), health surveillance, training

started to adopt them in order to quantitatively evaluate the risks related to the operative tasks performed by workers [44].

The graph in Figure 1 provides an example of the risk levels, both for the right and left limb, incurred during a typical month by an operator of the SECH Italian container terminal qualified to perform different tasks, calculated by means of the OCRA checklist. Figure 1 shows that the risk levels reach the critical red band in two days (in particular, 13.5 and 15.8 respectively in the first and second Saturday of the month), so requiring some actions to reduce the risk for that worker.

3. Problem description

Safety of workers in seaport container terminals is getting an increasing importance worldwide, since many operations are characterized by a certain level of risk for workers. Very recently, some Italian seaports of the Northern Range (such as Genoa and Venice seaports [50]) have started to successfully apply the NIOSH and OCRA methods described in Section 2 with the goal of obtaining a



	MO	TU	WE	TH	FR	SA	SU	MO	TU	WE	TH	FR	SA	SU	MO	TU	WE	TH	FR	SA	SU	MO	TU	WE	TH	FR	SA	SU
Right limb	7,5	5,5	1,0	7,5	7,5	13,5	0,0	7,5	5,5	1,0	7,5	7,5	14,7	0,0	7,5	5,5	1,0	7,5	7,5	0,0	0,0	7,5	1,7	0,0	7,5	7,5	0,0	0,0
Left limb	7,5	7,0	6,5	7,5	7,5	13,4	0,0	7,5	7,0	6,5	7,5	7,5	15,8	0,0	7,5	7,0	6,5	7,5	7,5	0,0	0,0	7,5	7,0	0,0	7,5	7,5	0,0	0,0

Figure 1: Right and left limbs risk levels incurred by a multi-tasking operator of the SECH terminal during a representative month, calculated by using the weighted average method of the OCRA checklist.

quantitative evaluation of the risk for workers' health when performing activities in the container terminal. The levels of risks related both to the handling of loads and to repetitive movements have to be strictly taken into account when planning manpower over the shifts of a certain time period (e.g., a month), in order to minimize the occurrence of accidents and health diseases for workers.

In the following we formally define the rostering planning problem faced in this paper. Let S denote the set of shifts to be planned over the planning horizon and T the set of tasks that must be performed in such shifts. The set S corresponds to an ordered sequence of shifts that can be partitioned in sub-sequences associated with the shifts in each working day. Specifically, if D denotes the set of days in the planning horizon, then S_d , $d \in D$, is the set of daily shifts for the particular day d. In the SECH terminal, working days generally include four daily shifts, but during weekend or holidays the daily shifts may be reduced to three. According to the workload scheduled (mainly related to containerships' arrivals), the terminal defines for each shift $s \in S$ the required set of tasks T_s that must be performed, specifying the number of workers n_{ts} needed for each task $t \in T_s$. The overall set of terminal workers O

is then partitioned according to the skills of workers and their availability in the shifts; in particular, the workers assigned to perform a given task in a given shift must be qualified for that kind of operation and be available (not in vacation or absent due to illness) in that shift. In addition, the rostering must respect union and safety rules, limiting the workload that can be assigned to workers during shifts, i.e., imposing appropriate rest periods. Specifically, in the SECH terminal the assignment of workers to the tasks scheduled in the shifts must satisfy the following classes of operational constraints:

(a) in each shift the workforce demand must be satisfied, i.e., each scheduled task must be performed by the required number of workers;

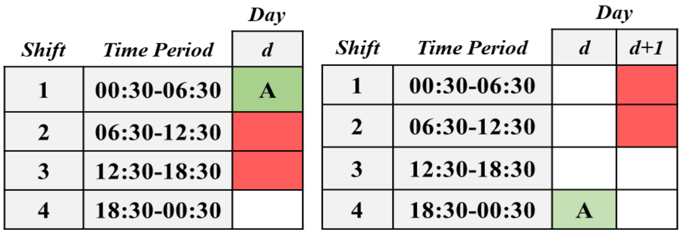
(b) each worker can be assigned to at most a single task in a shift;

(c) each worker should not work in two consecutive shifts. This is considered a hard constraint only if both the tasks assigned to the worker have a risk exposure, otherwise the assignment to two consecutive shifts can be accepted but it must be avoided as much as possible. In addition, no worker can be assigned to tasks in more than two consecutive shifts;

(d) two sets of time-related constraints must be respected, the first regarding forbidden shift sequences and the second the maximum number of assignments in a given time period;

(e) a maximum monthly accumulated risk level for the right and left limbs of workers must not be exceeded.

In class (d) constraint, the forbidden shift sequences (i.e., the first time-related constraint) specify infeasible assignments of tasks to a worker in subsets of shifts in a working day or in two consecutive working days that do not depend on the kind of assigned tasks. As an example, Figure 2 shows the two cases of forbidden sequence of shifts characterizing the SECH terminal. The figure reports the time periods for the four daily shifts: with the letter A (that stands for *Assigned*) in the green box the shift during which a task is assigned to the worker is denoted; the red boxes highlight the shifts during which no assignment is allowed for the same worker as a consequence of the previous assignment. In particular, in Figure 2, case (a) shows that a task assignments in the first shift of a day, which is considered particularly burdensome, prevents any assignment both in the second and third shift. Two consecutive days are considered in case (b) of Figure 2, where a task assignment in the last shift of a day rules out assignments in the first two shifts of the next day.



Shift	*Time Period*	*Day* *d*
1	**00:30-06:30**	🟩 **A**
2	**06:30-12:30**	🟥
3	**12:30-18:30**	🟥
4	**18:30-00:30**	

(a)

Shift	*Time Period*	*Day* *d*	 *d+1*
1	**00:30-06:30**		🟥
2	**06:30-12:30**		🟥
3	**12:30-18:30**		
4	**18:30-00:30**	🟩 **A**	

(b)

Figure 2: The forbidden shift sequences for the SECH Genoa terminal.

As regards the second type of time-related constraints, in the SECH terminal a limit of at most three assignments in non-consecutive shifts in two days is imposed. Note that, considering the class of constraints (b) in the previous list and the forbidden shift sequences in Figure 2, this limit can be modeled imposing that the maximum number of assignments in two consecutive days cannot exceed four. Hence, in the Genoa terminal, the resulting allowed patterns of assignments to the shifts in two consecutive days that include four or three assignments are those reported in Figure 3. Note that the set of rules defining the time-related constraints may vary from terminal to terminal, but this does not affect the structure of the mathematical model for this problem.

Finally, feasible rostering plans are evaluated according to two types of performance indices, both related to the value of cumulative risk for an individual worker in a specified time period (e.g., a month for the SECH terminal). The maximum cumulative risk among the workers must be minimized and the values of the cumulative risk of the workers must be balanced. The set of feasible plans

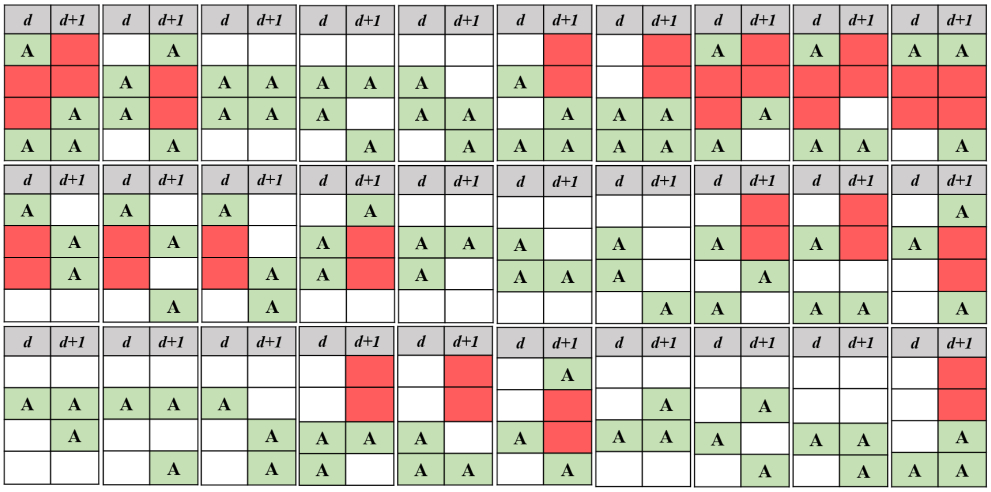


Figure 3: The possible patterns for three or four assignments to a worker in two consecutive days in the SECH Genoa terminal.

is restricted to those which least violate conditions (c) and (e).

As already anticipated in the Introduction, the novelty of the model presented in the following Section 4 consists in dealing with condition (e) and in taking into account the risks of workers in the rostering objective. On the other hand, the classes of constraints related to the operational condition (a)-(d) are not new, since they are usually included in rostering problems. Such classes of constraints are analogous to some of the ones reported in the surveys [51] and [13]: more specifically, from the ones listed in [51], constraints related to consecutive working shifts, skill categories, free time between working shifts, number of shift assignments (in our model with reference to certain time periods), shift patterns (in our model some patterns are prohibited) and constraints among shifts; from the ones in [13], the classes of constraints referred to as "*Meeting demand*", "*One shift at a time*", "*No backward rotation*" and "*Minimum rest*". Finally, note that, different from the majority of the approaches presented in the literature, in the this paper we do not directly balance the workload or shifts of workers: through the balance of risk we indirectly balance the workload/shifts as well.

In the next Section, the mathematical formulation designed for solving the roster planning problem when considering risks deriving from LMH and RM is presented.

4. The mathematical model

In this section, a mixed integer linear programming (MILP) model is defined for the roster planning problem described in Section 3. The model has the purpose of assigning a set of required tasks to the available workers over a given time horizon in order to satisfy the whole task demand, minimizing the total risk for the right and left upper limbs sustained by workers and balancing the risks among workers. The notation is introduced in the following.

Sets and parameters:

- O, the set of operators (workers);
- H, the last day in the planning horizon;
- $D = \{0, \cdots, H\}, W, M$, respectively the set of days, weeks and months in the planning horizon;
- $L_d, \forall d \in D$, the last shift in day d;
- $S_d = \{0, \cdots, L_d\}, \forall d \in D$, the set of daily shifts;
- $S = \{(d,p) : d \in D, p \in S_d\}$, the set of planning shifts. S is ordered so that $s = (d,p) < s' = (d',p'), \forall d < d', \forall p, p'$ and $s = (d,p) < s' = (d,p'), \forall p < p', \forall d$. Given a shift s, its successor is denoted as $s+1$ and defined $\forall s \in S \setminus \{s_{last}\}$, where $s_{last} = (H, L_H)$ is the last shift in the planning horizon, whereas its predecessor is denoted as $s-1$ and defined $\forall s \in S \setminus \{(0,0)\}$;
- $w_s \in W, \forall s \in S$, the week of shift s;

- $m_s \in M, \forall s \in S$, the month of shift s;
- $d_s \in D, \forall s \in S$, the day of shift s;
- T, the set of tasks;
- $T^R \subseteq T$, the subset of risky tasks (i.e., with an associated risk);
- $T_s \subseteq T, \forall s \in S$, the subset of tasks required during shift s;
- $T_o \subseteq T, \forall o \in O$, the subset of tasks for which operator o is qualified;
- $T^C \subseteq T$, the subset of critical tasks, i.e., tasks with a maximum limit of assignments to each qualified worker in a week;
- $O_s \subseteq O, \forall s \in S$, the subset of operators that are available in shift s;
- $O_t \subseteq O, \forall t \in T$, the subset of operators qualified to perform task t;
- $F_s \subseteq S, \forall s \in S$, the forbidden shift list associated with shift s, i.e., the subset of shifts that cannot be assigned to a worker who is on duty in shift s;
- R_{max} the maximum cumulative risk for both the right and left upper limb of a worker allowed in a month;
- $R_t^R, R_t^L, \forall t \in T^R$ the risk value respectively for the right and left limb associated with the risky task t;
- $n_{ts}, \forall s \in S, t \in T_s$ is the number of operators required to perform task t in shift s;
- $N^{(2)}$, the maximum number of assignments of tasks to a worker in two consecutive days;
- N^W, the maximum number of assignments of tasks to a worker in a week;
- N_t^W, the maximum number of assignments of a task $t \in T^C$ to a worker in a week;

- α, β, γ, the priority weights in the objective function respectively for the violation of soft constraints, the maximum monthly cumulative risk and the risk imbalance.

Decision variables

- $x_{ost} \in \{0,1\}, \forall o \in O, s \in S, t \in T$, the assignment variables; $x_{ost} = 1$ if operator o is assigned to task t in shift s, 0 otherwise;
- $v^1_{os} \geq 0$, $\forall s \in S, s < s_{last}, o \in O_s \cap O_{s+1}$, the violation variables for the soft constraints related to two consecutive shift assignments;
- $v^2_{ow} \geq 0$, $w \in W, o \in O$, the violation variables for the soft constraints related to the maximum number of assignments in a week;
- $0 \leq r^R_{om} \leq R_{max}, o \in O, m \in M$, the monthly cumulative right limb risk variable;
- $0 \leq r^L_{om} \leq R_{max}, o \in O, m \in M$, the monthly cumulative left limb risk variable;
- $r_{max} \geq 0$, the maximum monthly cumulative risk variable of any operator;
- $r_{min} \geq 0$, the minimum monthly cumulative risk variable of any operator.

The problem formulation follows.

$$min \quad Z = \alpha F_1 + \beta F_2 + \gamma F_3 \tag{2}$$

where the three objective components are

$$F_1 = \sum_{\substack{s \in S: \\ s < s_{last}}} \sum_{o \in O_s \cap O_{s+1}} v^1_{os} + \sum_{w \in W} \sum_{o \in O} v^2_{ow} \tag{3}$$

$$F_2 = r_{max} \tag{4}$$

$$F_3 = r_{max} - r_{min} \tag{5}$$

subject to

$$\sum_{o \in O_t \cap O_s} x_{ost} = n_{ts} \qquad \forall s \in S \qquad \forall t \in T_s \tag{6}$$

$$\sum_{t \in T_0} x_{ost} \leq 1 \qquad \forall s \in S \qquad \forall o \in O_s \tag{7}$$

$$\sum_{t,t' \in T_0 \cap T^R} (x_{ost} + x_{os+1t'}) \leq 1 \qquad \forall s \in S, s < s_{last} \qquad \forall o \in O_s \cap O_{s+1} \tag{8}$$

$$\sum_{t \in T_0} (x_{ost} + x_{os+1t}) \leq 1 + v^1_{os} \qquad \forall s \in S, s < s_{last} \qquad \forall o \in O_s \cap O_{s+1} \tag{9}$$

$$\begin{aligned} &\sum_{t \in T_0} (x_{ost} + x_{os+1t} + x_{os+2t}) \leq 2 \qquad \forall s \in S, s < s_{last} - 1 \\ &\qquad\qquad\qquad\qquad \forall o \in O_s \cap O_{s+1} \cap O_{s+2} \end{aligned} \tag{10}$$

$$\sum_{t \in T_0} x_{ost} + \sum_{t \in T_0} x_{os't} \leq 1 \qquad \forall s \in S, F_s \neq \oslash, s' \in F_s, o \in O_s \cap O_{s'} \tag{11}$$

$$\begin{aligned} &\sum_{\substack{s \in S: \\ d(s)=d}} \sum_{t \in T_0 \cap T_s} x_{ost} + \sum_{\substack{s \in S: \\ d(s)=d+1}} \sum_{t \in T_0 \cap T_s} x_{ost} \leq N^{(2)} \\ &\qquad\qquad\qquad\qquad \forall d \in D, d < H, o \in O \end{aligned} \tag{12}$$

$$\sum_{\substack{s \in S: \\ w(s)=w}} \sum_{t \in T_0 \cap T_S} x_{ost} \leq N^W + v^2_{ow} \qquad \forall w \in W \qquad \forall o \in O \tag{13}$$

$$\sum_{\substack{s \in S: \\ w(s)=w \wedge \hat{t} \in T_s}} x_{os\hat{t}} \leq N^W_t \qquad \forall w \in W \qquad \forall o \in O_t : t \in T^C \tag{14}$$

$$r^R_{om} = \sum_{\substack{s \in S: \\ m(s)=m}} \sum_{t \in T_s \cap T_o} R^R_t \cdot x_{ost} \qquad \forall m \in M \qquad \forall o \in O \tag{15}$$

$$r^L_{om} = \sum_{\substack{s \in S: \\ m(s)=m}} \sum_{t \in T_s \cap T_o} R^L_t \cdot x_{ost} \qquad \forall m \in M \qquad \forall o \in O \tag{16}$$

$$r_{max} \geq r^R_{om} \qquad \forall m \in M \qquad \forall o \in O \tag{17}$$

$$r_{max} \geq r^L_{om} \qquad \forall m \in M \qquad \forall o \in O \tag{18}$$

$$r_{min} \leq r^R_{om} \qquad \forall m \in M \qquad \forall o \in O \tag{19}$$

$$r_{min} \leq r^L_{om} \qquad \forall m \in M \qquad \forall o \in O \tag{20}$$

$$\begin{aligned} & x_{ost} \in \{0,1\} \qquad o \in O \qquad \forall s \in S \qquad \forall t \in T \\ & v^1_{os} \geq 0 \qquad \forall s \in S, s < s_{last} \qquad \forall o \in O_s \cap O_{s+1} \\ & v^2_{ow} \geq 0 \qquad \forall w \in W \qquad \forall o \in O \\ & r_{max} \geq 0 \\ & r_{min} \geq 0 \end{aligned} \tag{21}$$

The roster planning is modeled as a multi-objective optimization problem. In the formulation the three objectives (3), (4) and (5) are simultaneously optimized. In particular, the objectives are aggregated into the scalar objective function (2) by means of the weights α, β and γ, whose values are fixed to impose a predefined lexicographic priority order according to the container terminal preferences. In practice this means that the three objectives are minimized hierarchically. In particular, for SECH terminal, the minimization of F_1 (i.e., the soft constraints violations (3) related to constraints (9) and (13)) is considered the highest level priority objective, followed by the minimization of F_2

(i.e., the maximum accumulated risk (4)), which represents the second priority level objective; the minimization of F_3 (i.e., the maximum risk imbalance (5)) is the lowest priority objective for SECH container terminal. Therefore, in order to reflect such hierarchical priority and to avoid possible trade-offs among the objectives, the weights must be chosen with very different magnitude, i.e., $\alpha >> \beta >> \gamma$. Such a priority order can be easily modified by properly changing the values assigned to weights α, β and γ in order to adapt the method to a different terminal. Note that, as an alternative, a lexicographic multi-objective method can also be used to solve the model. This means solving in sequence three scalar MILP problems, optimizing one objective at a time according to the hierarchical priority order with additional constraints for the second and third problem. Such constraints are needed to guarantee that the higher priority objectives are not worsen with respect to their optimal values obtained, i.e., they impose $F_h \leq F_h^*$, with $h = 1, 2$, where F_h^* denotes the optimal value for objective h obtained when solving the h-th scalar problem. However, the experiments that we performed to compare the solutions obtained when optimizing the single scalarized objective (2) and the ones obtained by using the lexicographic method show the equivalence of the two approaches, also from the standpoint of the required computational time.

The role of the different sets of constraints introduced in the MILP model is described in the following. Constraints (6) impose the satisfaction of the workforce demand in each shift, whereas constraints (7) ensure that at most one task per shift is assigned to a worker. Constraints (8) prevent the assignment of two tasks in two consecutive shifts to the same worker if both tasks have an associated risk. In case at least one of the two involved tasks has no associated risk, this condition becomes violable and it is modeled by soft constraints (9). Constraints (10) assure that any worker is never assigned to tasks in more than two consecutive shifts. Forbidden sequences of shifts are prevented by constraints (11). For example, in the case (a) of Figure 2, a task assignment to a worker in the first shift $s = (0, d)$ of a day d determines a forbidden shift list $F_s = \{(1, d), (2, d)\}$, whereas in the case (b) of the same Figure, the forbidden shifts due to an assignment to the shift $s = (3, d)$ are $F_s = \{(0, d + 1), (1, d + 1)\}$. Constraints (12)-(14) deal with maximum number of assignments in a period for a given worker. Specifically, constraints (12) impose the upper bound for the assignments in two consecutive days, whereas constraints (14) ensure the respect of the maximum number of assignments to qualified workers of a critical task (e.g., driving a trailer in the SECH terminal) in a week. Differently, constraints (13) are soft ones since they prescribe the desired maximum number of assignments in a week. Constraints (15) and (16) define, respectively, the monthly accumulated risk for the right and left limb for each worker, constraints (17) and (18) provide the maximum monthly accumulated risks over all workers, whereas (19) and (20) determine the minimum monthly accumulated risks over all workers. Finally, constraints (21) define the decision variables of the problem.

Note that the model (2)-(21), even if designed with reference to the case of the SECH Genoa terminal, has a general structure and it can be easily extended to other terminal contexts.

5. The planning approach

The mathematical model (2)-(21) may be termed *risk-aware rostering* as it takes into account the health risk for workers. This model has been exploited to define an overall workforce planning approach for the SECH Genoa terminal, that can be easily applied to other terminals with similar characteristics and requirements. Rostering plans are currently carried out in the SECH terminal according to the schema in Figure 4 (a).

In particular, a roster is defined weekly for the successive week (*W*), considering the demand for tasks due to the arrivals of ships scheduled for that week. This activity is performed by a planning team using only the support of spreadsheets, and mainly guided by the experience on the field. Actually, SECH terminal also knows approximately the ship arrivals for the second future week (*W+1*). Since this sort of forecast (note that in this context the term "forecast" does not refer to a prediction generated by a forecast model on the basis of his-

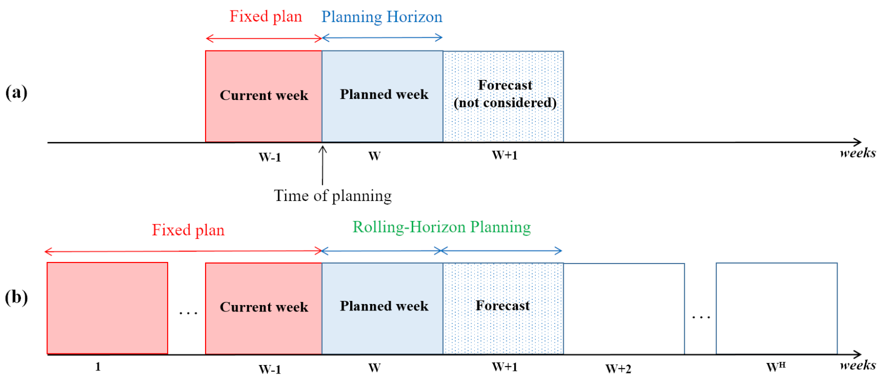


Figure 4: The current planning approach at SECH terminal (a) and the rolling-horizon planning approach (b).

torical data) on the ship arrivals for the second future week (*W+1*) is in general subject to changes, the terminal does not currently take it into account in the planning process. On the other hand, the Genoa terminal has recently started the collection and analysis of data with the purpose of determining the risk indexes for the different tasks performed by workers utilizing the NIOSH and OCRA methods. However, such evaluations of the tasks' risk are not considered by the terminal when determining roster plans.

This work proposes a new planning approach which incorporates risk-awareness into rostering. Its main features are described in Figure 5. This approach consists in a rolling horizon planning method based on the mathematical model introduced in Section 4, which needs three kinds of input: the first one concerns the risk indexes related to LMH and RM operations, computed and possibly revised by the off-line analysis of tasks performed at the terminal; the second input regards the task requirements for the week W to plan and the forecast of such requirements for the successive week $W+1$; the third derives from the plan for the current month up to week $W-1$ and consists in the accumulated risks for the limbs of each worker, as well as the task assignments in the last shift of the last day of week $W-1$. As shown in Figure 4 (b), the approach

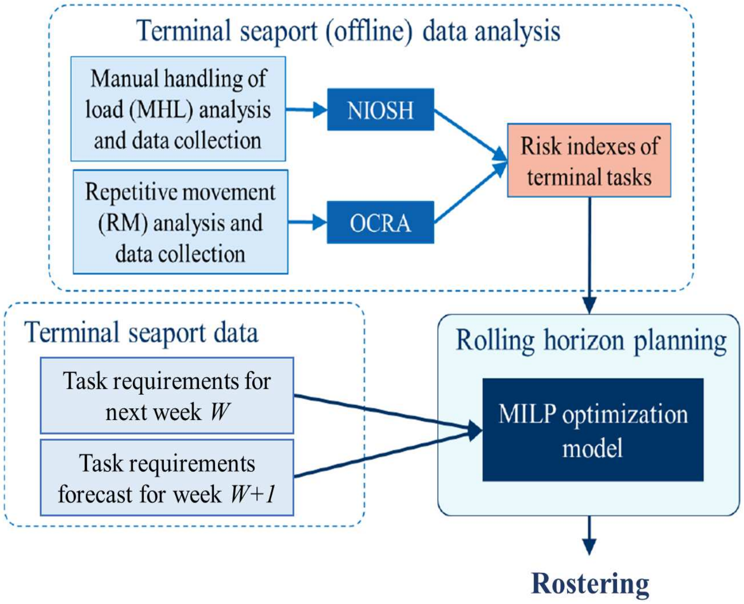


Figure 5: The risk-aware rostering approach.

then defines the rostering for weeks W and $W + 1$ taking into account both the cumulative monthly risk for the right and left upper limbs of workers due to the rostering in the weeks of the current month up to week $W - 1$, and the assignments of tasks to workers in the last day of week $W-1$ to properly impose the time-related constraints. Afterward, the roster for week W is implemented and the procedure is iterated whenever the definitive task requirements and the new forecasts are available respectively for the next weeks $W + 1$ and $W + 2$. Since the maximum limit for the upper limbs risk is imposed by the terminal on a monthly base, the cumulative worker risks are reset accordingly. It is worth noting that the forecasts may be exploited optionally in our approach and in the next section the possible improvement due to their use is analyzed.

6. Experimental analysis

In order to evaluate the effectiveness of the methodology and in particular that of the MILP model introduced in Section 4, a set of tests was performed using the real data provided by SECH Genoa terminal. This was possible since SECH performed the data analysis included in the scheme of Figure 5, having recently started to apply the NIOSH and OCRA methods to monitor and reduce the risks for its workers' health.

The available data correspond to the roster planning over 6 months (from January 2016 to June 2016) and include 26 weeks and 614 shifts. A set of 27 different tasks is required in the considered shifts. In particular, Table 3 provides for each of such tasks the risks deriving from RM both for the right and left limbs, respectively denoted as RLR and LLR, computed with the OCRA methodology. Note that the terminal has not yet completed the data analysis for the risk due to LMH; in addition, for confidentiality reasons, the risk values shown in Table 3 correspond to the real risk values provided by the terminal multiplied by a proportionality factor. Finally, the last column of Table 3 reports, for each task, the total demand of workers over the six months planning period.

As pointed out by Table 3, only 10 tasks out of the 27 have an associated risk. However, the cumulative demand for the risky tasks covers the 74.2% of the total demand. Figure 6 reports an analysis of the demand for the risky tasks, highlighting for each of them the average risk for the upper limbs. The figure shows, for each risky task, the frequency over the shifts in the considered six months planning period, i.e., the percentage of the shifts in which each task is required, and the percentage of the total demand of workers needed for that task. Figure 6 then underlines how the two tasks with the highest average risk are not frequently required, but a set of significant tasks with medium risk level is needed very frequently with a high demand of workers.

At SECH terminal 94 workers were available in the analyzed period; all workers were qualified to perform at least one risky task, in particular workers

Table 3: Tasks, OCRA risk factors and requirements/demand in the six month planning period

at SECH Terminal of Genoa port

Task	**Description**	**RLR**	**LLR**	**Worker demand**
1	Customs check operator	14.7	15.8	69
2	Rail wagon checker	13.5	13.4	68
3	Quay crane driver	7.5	7.5	1931
4	RTG crane operator	7.5	7.5	102
5	RMG crane operator	7.5	7.5	2651
6	Generic operator	5.38	7.1	754
7	Reach stacker driver	5.5	7	1881
8	Generic	3.8	3.3	2
9	Weighing operator	1	6.5	1301
10	Trailer driver	1	6.5	25
11	Stevedor instructor	0	0	1230
12	Trainstainer instructor	0	0	333
13	Instructor	0	0	75
14	Theoretical instructor	0	0	21
15	Maintenance	0	0	13
16	General cargo	0	0	4
17	Checker	0	0	30
18	Truck gate	0	0	27
19	Rail gate	0	0	27
20	Trainstainer informer	0	0	10
21	Rail crane instructor	0	0	17
22	Stevedor	0	0	2
23	Quay crane instructor	0	0	1
24	Team leader	0	0	50
25	RTG instructor	0	0	1088
26	Document operator	0	0	55
27	Reach stacker instructor	0	0	70

were qualified to perform on average 8.6 out of the 10 risky tasks.

In this section the results of the several kinds of analysis performed are reported. In all these tests the weights in the objective function (2) were fixed to the following values in order to comply with the lexicographic priority order determined during the meetings with SECH terminal managers: $\alpha = 10^4$, $\beta = 10^3$ and $\gamma = 1$.

The maximum risk allowed by the terminal for any single worker, calculated

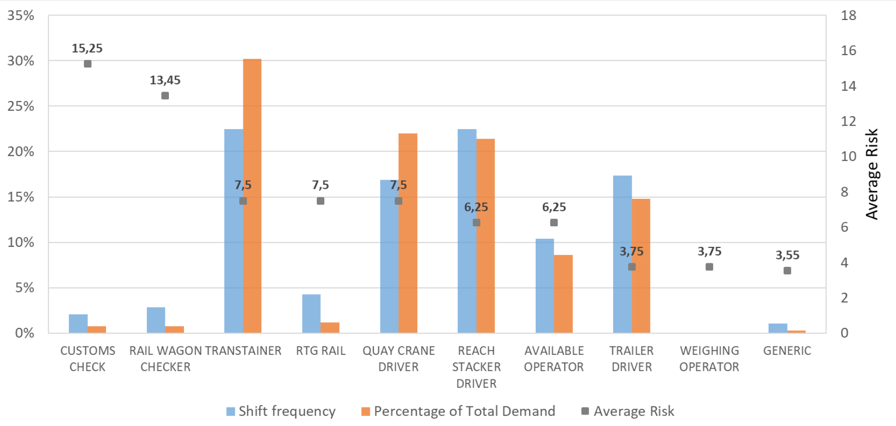


Figure 6: Characteristics of frequency and risk factor of the demand for the risky tasks of SECH terminal.

according to the OCRA procedure and again corrected according to a proper multiplying factor for confidentiality issues, is equal to 293.

In addition, the maximum number of assignments to a worker in two consecutive days was fixed as $N^{(2)} = 4$, whereas in a week $N^W = 6$; only for one task, the quay crane driver, the maximum number of assignments in a week was fixed as $N_t^W = 3$.

The approach was implemented in C♯ programming language using Cplex 12.6.3 as MILP solver, and all tests were performed on a laptop having the following features: Processor i7-6820HQ, 2.70GHz, 16 Gb Ram. All tests described in the following were performed with a maximum time limit of 600 seconds for each MILP solver run, since this time was sufficient to obtain solutions with optimality gap not greater than 1%.

6.1. Comparison of the actual terminal planning with the rolling horizon planning approach

The first test had the purpose of comparing the actual planning produced by SECH terminal with the rolling horizon planning (RHP) approach described in Section 5. In particular, the RHP was used to determine the rostering over the six months planning period proceeding one week at a time, as it is actually done at SECH container terminal. Hence, with this method, called *1-Week Planning* (1-WP), the rostering for the next week W was determined on the basis of the demand for the tasks in week W, disregarding the forecast for week $W + 1$.

Table 4: Comparing the actual and 1-Week planning over six months.

	Terminal Planning (TP)	**1-Week Planning (1-WP)**
Objective	62,120,715.13	5,845,888.0
Objective gap		-90.59 %
Consecutive shifts violation	304	38
Shifts over 6 in a week violation	315	19
Weeks involved	23	9
Average for week	13.7	2.1
Max risk	220.5	145.75
Max risk gap	215.12	138.25
Right limb risk mode	100	96
Right limb risk average	95.76	93.72
Left limb risk mode	146	117
Left limb risk average	116.16	113.86

The results are shown in Table 4, where SECH terminal planning (TP) and the 1-Week Planning (1-WP) over six months are compared and the objective function is the one defined in (2) as Z. As shown in the row *Objective gap*, computed as $100 \cdot (Z_{1-WP} - Z_{TP})/Z_{TP}$, the 1-WP produced an improvement of more than 90% with respect to the overall objective function generated by the TP. This is due to the very large number of violations of the soft constraints included in the TP (304 violations for assignments in consecutive shifts and 315 assignments beyond the weekly limit). The analysis of the results pointed out that in almost all the weeks (23 out of 26) some soft constraints violation occured in the TP and that, on average, the number of such violations is about 13 per week. Differently, in the 1-WP these values reduced to 9 weeks with violations and about 2 violations on average per week.

The next group of rows in Table 4 considers the maximum risk in a month and the maximum risk gap, i.e., the difference between the maximum and minimum monthly risk among workers. The 1-Week Planning reduces the maximum risk value by 33.9% and the maximum risk gap by 35.74% with respect to the TP results.

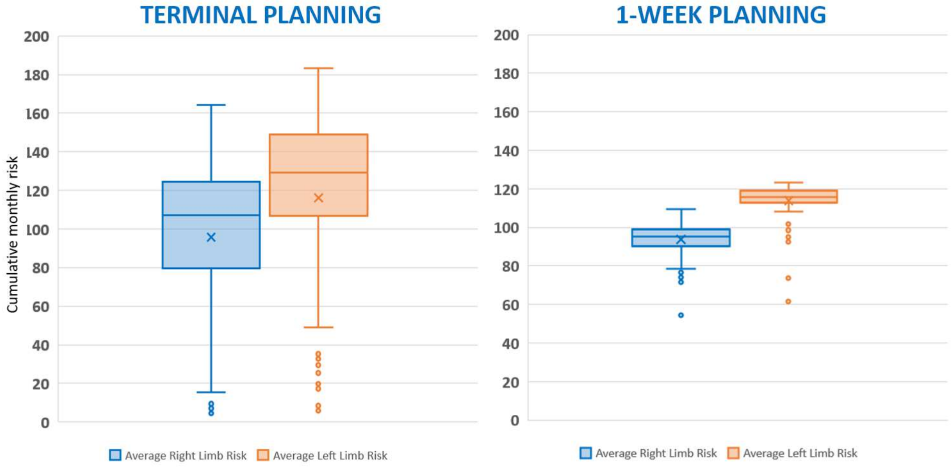
The last four rows report both the mode and the average for the right and left limb risk, showing in this case slightly better values for the 1-WP. A final important observation relates to the violations of hard constraints: these cannot occur for the MILP solution, whereas in 3 cases the TP includes assignments of risky tasks in consecutive shifts.

To better evaluate the quality of the 1-WP rostering, an important aspect is how the risk is distributed over the available workers. To this aim, the diagrams reported in Figure 7 shows an aggregate picture of the distribution of the risk among workers; more specifically Figure 7 compares, for the TP (on the left) and the 1-WP (on the right), the box plot diagrams of the monthly risk for the two upper limbs over the six months period (the × symbols in the boxes denote the average values). These diagrams also highlight the better fairness in distributing the risk among workers provided by the 1-WP, as well as a significant reduction of the maximum risk levels and gap.

A similar conclusion is supported by the diagrams in Figure 8, where the evolution over the six months of the average monthly risk for the upper limbs over all workers is shown, including the 5% confidence bands around the averages.

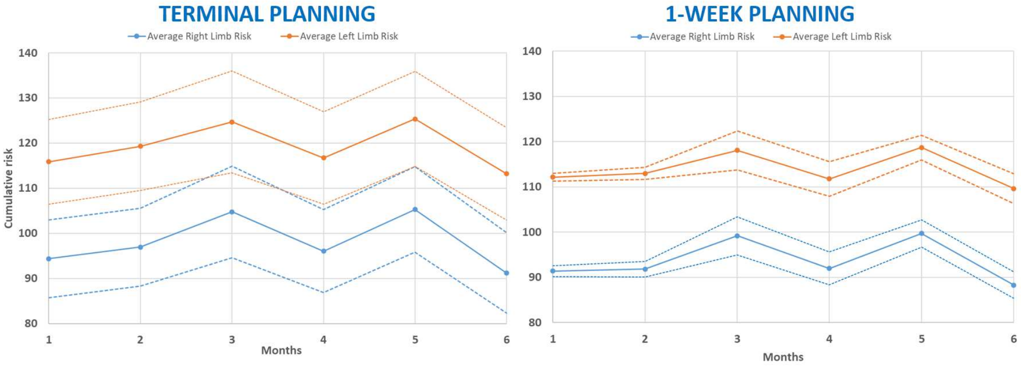
The two diagrams in Figure 9 show, instead, for each worker, the maximum (full points) and minimum (circles) cumulative monthly risks for the two upper limbs over the six months planning period. The upper diagram of Figure 9 provides the real distribution of risks among workers over six months due to the terminal planning. In this figure the points are very scattered among workers, pointing out very heterogeneous risk levels. By contrast, the corresponding diagrams for the 1-WP planning show much more balanced risk levels among workers.

This result would be greatly appreciated by the terminal managers, whose goal is to both distribute the risky tasks among workers with fairness and reduce the cumulative risk levels to prevent health diseases, as well as legal con-



(a) (b)

Figure 7: Dispersion of the average risk for the right and left limb on all workers over the six months period: Terminal planning (a) versus 1-Week Planning (b).



(a) (b)

Figure 8: Dispersion of the average risk for the right and left limb on all workers for each month in the six months period: Terminal planning (a) versus 1-Week Planning (b).

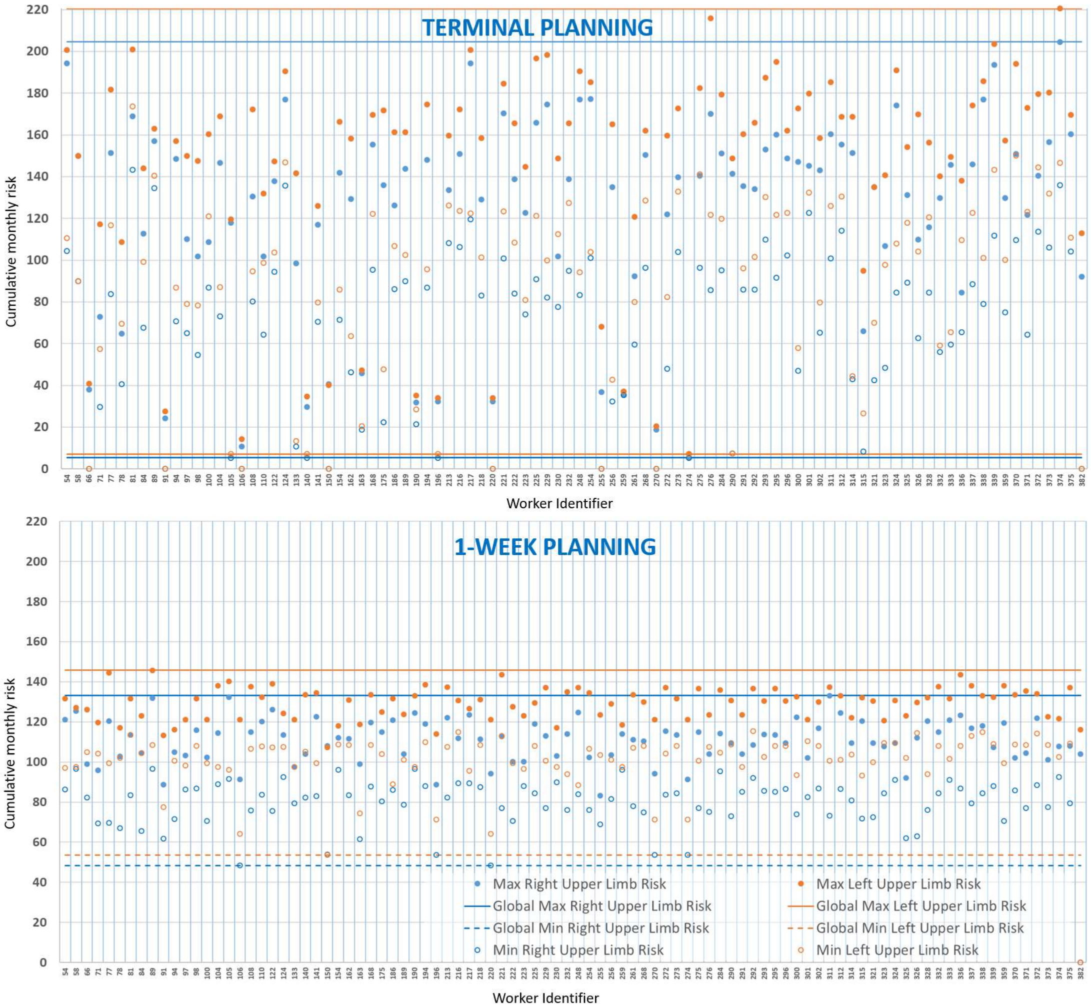


Figure 9: Comparison between the maximum and minimum cumulative monthly risks for workers over the six months planning period provided by the TP and 1-WP.

sequences.

6.2. Analisys of the rolling horizon planning approach

A second test aims at comparing the results obtained by the 1-WP with an "ideal" planning (IP) approach. In particular, the IP corresponds to the solution generated by the MILP model considering the whole planning horizon of six months and the related tasks demand. This rostering is an ideal one since it assumes that all the information about the demand is available at the first planning time, whereas, in practice, the demand for the tasks is known only one week in advance, with the addition of the forecast for the successive week. However, the results obtained in this way provide lower bounds that can be used to evaluate the quality of the results produced by the 1-WP.

A third test has the purpose of evaluating the possible benefit of including, in the RHP for a week W, also the information from the forecast for week $W+1$. This test is based on a planning, called *2-Week Ideal planning* (2-WIP), which determines the rostering for the next week W on the basis of the demand for the tasks in week W and week $W+1$. Note that also this rostering is an ideal one, since only approximate information is usually available for week $W+1$ at SECH terminal. Therefore, this test allows to determine what benefit can result if the perfect information on week $W+1$ is included in the planning model.

Finally, the last planning tested, called *2-Week Planning with Estimated Forecast* (2-WPEF), is a tentative approach to the sensitivity of the plan produced by 2-WIP to the uncertainty in the demand for the tasks in week $W+1$. In particular, the 2-WPEF determines the rostering for the next week W on the basis of the demand for the tasks in week W and of an estimation of the forecast of the demand for week $W+1$. Since no data about the actual forecasts were recorded at SECH terminal, the forecast for week $W+1$ was estimated by applying a random disturbance to the real demand for week $W+1$, i.e., assuming $n'_{ts} = max[0, n_{ts} + \delta]$, where $\delta \sim [-2, 2]$ (the level of this disturbance was considered significant since the average number of workers required for a task in a shift over the six months horizon is 3.2 with a mode of 1).

The results obtained for the three above described planning tests are collected in Table 5, which compares the overall objective for the 1-WP, 2-WIP and

2-WPEF with the lower bound represented by the objective of the IP with full information, here used as reference for the objective gap computation. In addition, Table 5 provides also the values for the maximum risk and the maximum risk gap generated by the different tests. From Table 5 it can be observed that the result provided by the 1-WP, that is, by the RHP that exploits the same information currently used by the actual terminal planning, is sufficiently close to the ideal planning (5.85%). In addition, the tests revealed that including in the RHP also the information derived from the forecast of the demand for week $W + 1$ allows to produce plans very close to the ideal one, with a gap of 0.40% when the perfect information is used for week $W + 1$, and a gap of 0.42% when instead the forecast for week $W + 1$ is estimated. However, it is worth to underline that both the maximum risk and the maximum risk gap for the 1-WP, 2-WIP and 2-WPEF are very similar, so that the improvements in the objective gap for the 2-WIP and 2-WPEF with respect to the 1-WP are mainly due to the large weight assigned in the objective function (2) to the violations of soft constraints.

Table 5: Comparison between the different tested plannings

		Objective	Objective gap	Max risk	Max risk gap
	IP	5,522,615.0		122.50	115.0
RHP	1-WP	5,845,888.0	5.85 %	145.75	138.25
	2-WIP	5,544,637.0	0.40 %	144.50	137.00
	2-WPEF	5,545,763.1	0.42 %	145.60	138.12

The quality of the RHP approach can also be observed considering the dispersion of the cumulative monthly risk for the two upper limbs to which the workers are exposed according to the different plans. In particular, Figure 10 shows, for the two upper limbs, the box plot diagrams of the risk for workers resulting for the TP, IP, 1-WP, 2-WIP and 2-WPEF. The box plots are reported for each month and the figure reveals that the left upper limb is the most critical for the tasks performed at SECH terminal. The comparison in the various months of the box plots of the different plans shows the quality of the RHP, since, in all the scenarios tested, the RHP was able to fairly distribute the risk among the workers as obtained by the IP.

7. Conclusion

In this paper the rostering problem in seaport container terminals is addressed, considering specific constraints and objectives that take into account the risk for workers' health when performing repetitive movements and manual handling of loads.

A MILP model is formulated taking into account operative, legal and time-related constraints; the mathematical model is then validated by using real data and information provided by a real container terminal located in the Italian port of Genoa, i.e., the SECH terminal.

In practice, planning needs to be done on a rolling horizon basis. A rolling horizon planning approach based on the MILP model is therefore proposed. Computational comparison on real data provided by SECH terminal is made between our MILP approach and the actual plans. Our MILP model outperforms SECH real planning in determining feasible rostering plans while minimizing the risks for workers and fairly distributing the risks among them. More specifically, our MILP approach is able to reduce the maximum monthly risk for workers by 33.9% compared to the actual SECH planning. Additional computational experiments are performed to explore whether the safety benefits of our approach can be further improved if more data are available. In particular, we compare our rolling horizon MILP results with an ideal planning when all delivery and personnel information at SECH terminal is known in advance. Such comparisons show that the rolling horizon method provides very close results to the ones obtained by the ideal planning. Then, we consider two further planning tests to evaluate the possible improvement if forecast data are included in the rolling horizon planning. These tests revealed that the use of forecasts does not produce a significant reduction of risk, but it can contribute to better satisfy the operational (soft) constraints.

Finally, it is worth pointing out that the present work has been appreciated by SECH container terminal, highlighting the usefulness of the approach. Moreover, after little adaptation, the model can be successfully applied to numerous container terminals located worldwide.

8. Acknowledgments

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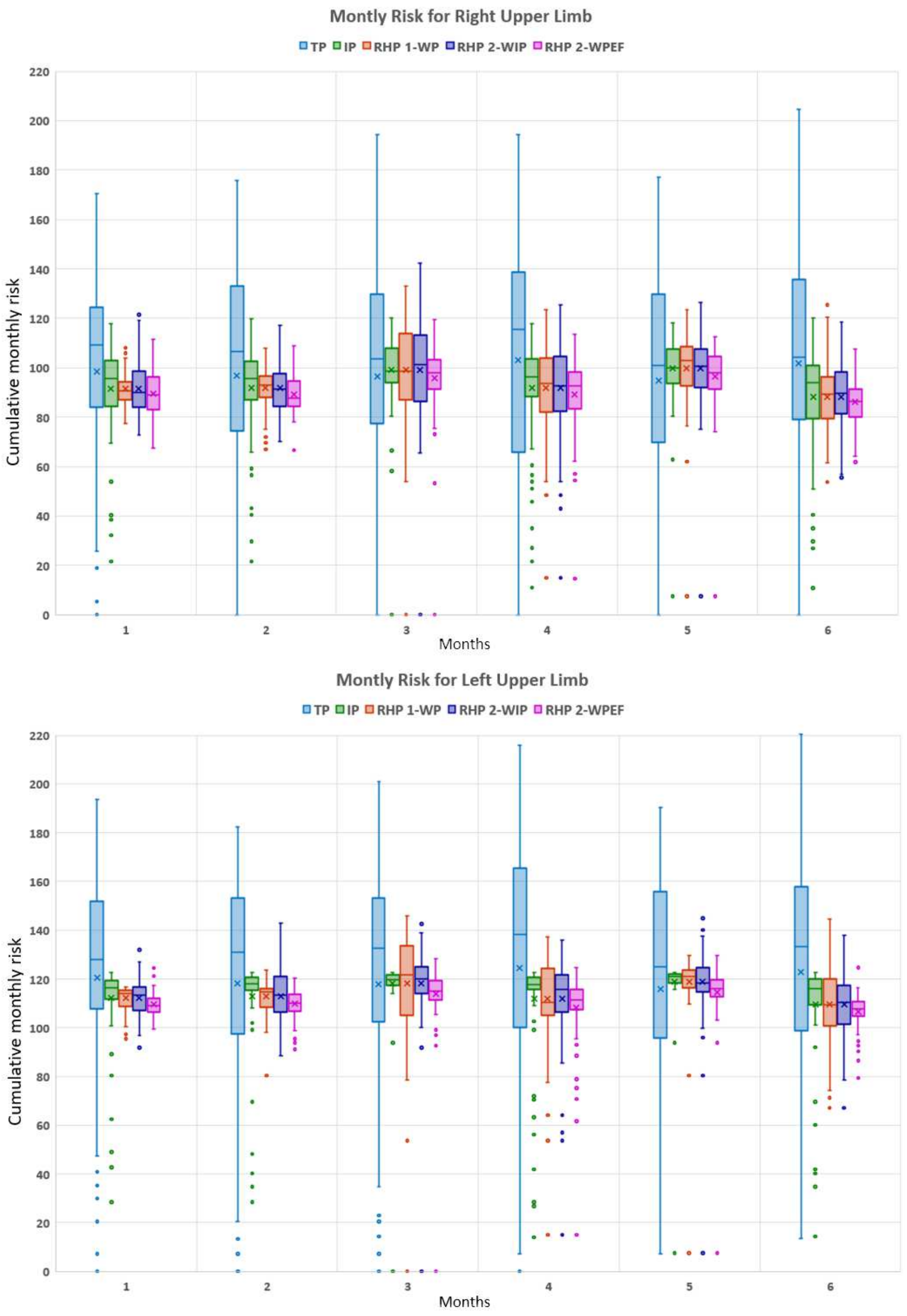

Figure 10: Dispersion of the accumulated monthly risks of workers for the compared planning over six months.