A Mathematical Programming Approach for Minimizing Occupational Exposures to Chemical Agents

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The occupational exposure to hazardous chemical agents is a problem acknowledged by international and European institutions and organizations. To assess and manage risks arising from work activities involving chemical agents, safety managers should rely on several tools, including models and algorithms, available in the literature. However, to the best of our knowledge, no models dealing with reducing chemical risk through the scheduling of work tasks have been defined. The aim of this paper is to propose an optimization tool to identify the best scheduling of tasks for minimizing occupational exposures to inhaled chemical substances. This tool is based on a two-phase algorithm, with each phase exploiting a different single period Mixed Integer Linear Programming (MILP) compact formulation encompassing real constraints such as the Threshold Limit Values (TLVs®) for chemicals, in terms of TLV-TWA (Time-Weighted Average) and TLV-STEL (Short-Term Exposure Limit). Besides the TLV restrictions, the models include classical preemptive job scheduling constraints, such as the assignment of tasks to workers and preemption handling. In order to test our algorithm, we solved a real exposure scenario in a foundry by means of a MILP solver (Gurobi). The optimal scheduling of tasks, obtained in a reasonable amount of time, reduces the adverse effects due to occupational exposures to chemical agents.

Keywords: Chemical risk, inhalation, occupational exposure limit value, occupational health and safety, exposure duration, risk assessment, Mixed Integer Linear Programming, scheduling, foundry.

1. Introduction

Both large and small enterprises employ considerable amounts of chemicals in virtually all work activities all over the world (ILO 1993, European Agency for Safety and Health at Work 2018). Moreover, Eurofound (2017) has recently emphasized a trend of growing exposure to chemical risks. In such a context, any risk to the safety and health of workers arising from the presence of those chemical agents should be assessed, considering several determinants including the level, type and duration of exposure (Council of the European Union 1998). As well underlined by Riedmann et al. (2015), a variety of models for assessing the occupational exposure to chemicals is available. With particular regard to the inhalation route, frequently mentioned tools for estimating exposures to hazardous substances are: Stoffenmanager (Marquart et al. 2008), Estimation and Assessment of Substance Exposure (EASE) developed by UK Health and Safety Executive (HSE), Metals' EASE by EBRC, European Centre for Ecotoxicology and Toxicology Of Chemicals (ECETOC) Targeted Risk Assessment (TRA) (ECETOC 2012), Advanced REACH Tool (ART) (Fransman et al. 2011), EMKG-EXPO-TOOL, and SEiRiCH by the French Research and Safety Institute (Institut National de Recherche et de Sécurité - INRS). Savic et al. (2016) propose TRanslation of EXposure MOdels (TREXMO) tool integrating six common occupational exposure models for producing a single interface that helps users to select the correct parameters and facilitate the simultaneous use of several models for evaluating the same exposure

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situation. These models are characterized by various complexity and refinement levels. Interesting concise descriptions of some of these models can be found in Lamb et al. (2015) and ECHA (2016). Some scientific papers discuss the performance, and compare accuracy and robustness levels among such models: e.g., Riedmann et al. (2015), Spinazzè et al. (2017), and van Tongeren et al. (2017). Finally, the recent Italian standard UNI/TR 11707:2018 (UNI 2018) is noteworthy: it proposes a survey about some tools and predictive models (e.g., Stoffenmanager) to evaluate the occupational risk from chemicals. However, to the best of our knowledge, no models dealing with reducing chemical risk through the scheduling of work tasks have been defined. For this reason, the aim of this paper is to present an optimization tool based on two single period Mixed Integer Linear Programming (MILP) compact formulations to identify the best scheduling of tasks for minimizing occupational exposures to inhaled chemical substances. The paper is organized as follows. In Section 2, we summarize the details about the literature review conducted for this research and the employed optimization solver. The developed optimization tool is presented in Section 3, and its application to a real case study is described in Section 4. Concluding remarks are provided in the final section.

2. Materials and methods

We carried out a literature review about the available tools and models for estimating occupational inhalation exposure. For each identified model, we focused on the assumptions, inputs, considered parameters, mathematical relationships, and outputs, highlighting strengths and weaknesses. We also analyzed scientific and technical documents related to chemical risk assessments in order to understand the main parameters affecting the risk and those related to the inhalation exposure. We manually browsed catalogues of technical standards currently available to identify interesting documents concerning the management and assessment aspects of workplace exposure to chemical agents. We discussed with safety managers in Italian companies to comprehend the available data and information for performing chemical risk estimations. The evidences captured during site audits and measurements in a foundry allowed to characterize a real exposure scenario for testing our optimization tool. The literature on occupational exposure limits permitted us to study in depth assumptions, recommendations for users, and formulas related to the various possible limits for chemical substances. For pointing out a complete overview, we consulted limits published by both organizations (e.g., ACGIH 2019) and legislative institutions (e.g., European Commission 2017). We also considered management science and resource management books, scientific papers, and technical reports for defining plausible organizational and production constraints.

The developed optimization tool encompasses two MILP scheduling models, one for each of the phases of the implemented solution algorithm, which we solved by employing the mathematical optimization solver Gurobi (version 9.0.0). We refer the interested reader to Pinedo (2012), a study of different ways of modeling scheduling problems, and to Mansini and Zanotti (2019) for an analysis of how effective the use of a scheduling model can be in a real case scenario.

3. Optimization tool

The aim of our optimization tool is to minimize workers' exposure to chemical substances inhaled during performed tasks. It assumes no additive effects among chemicals and does not consider individual susceptibility. The optimization tool is composed of a two-phase algorithm, each phase associated with a distinct MILP model, with two different objective functions, and various constraints related to safety and organizational issues. In particular, a specific set of constraints regards the possibility that a worker can not perform a task because of the lack of fitness and/or qualification for work.

3.1. *Notation*

Let us define $J = \{1, \ldots, m\}$ as the set of tasks (jobs) that have to be scheduled, and $W = \{1, \ldots, n\}$ as the set of workers that have to perform these jobs. We also define $W_j \subseteq W$ as the subset of workers that are capable of performing task j. Constant d_j determines the duration of task j. Preemption is allowed: a worker does not have to perform a task for its whole duration, but can stop and possibly resume performing it later. Additionally, the same task can be performed by multiple workers, even in parallel. It is worth noticing that, for example, two workers simultaneously performing the same task for one hour are counted as two hours of performed task. The main restriction regarding preemption is associated with the minimum duration d_j^{min}: when a worker starts a task, he/she can not stop (and switch to a different task) before d_j^{min} minutes. The working day has a duration equal to D minutes, and is partitioned into a set $S = \{1, \ldots, q\}$ of non-homogeneous time slots. Each time slot can have a different duration, from 0 minutes (which means that the time slot is unused) to D minutes. At most one task can be performed in each time slot. For instance, if a worker performs a single task for D minutes during the day, a single time slot is used, while all the others have duration equal to 0. The minimum duration of a time slot in which a task is performed is δ. In order to introduce the chemical exposure constraints, we define $C = \{1, \dots, k\}$ as the set of all the types of the chemical substances to which a worker can be exposed while performing tasks. We define constant e_{cj} as the concentration of substance c while performing task j, expressed in mg $\cdot$ m^{-3}. We also define $C^{TWA} \subseteq C$ and $C^{ST} \subseteq C$ as the subsets of chemical substances that are associated with TLV-TWA and TLV-STEL constraints, respectively. Furthermore, constants TWA_c and ST_c indicate the TLV-TWA and the TLV-STEL for chemical agent c, respectively. Additionally, constant ST_c^{max} represents the maximum exposure allowed for chemical substance c, while ST_{limit} indicates the maximum number of times the TLV-STEL of a substance can be exceeded by a worker during a day. Finally, constant ST_{time} identifies the maximum duration of a slot in which the TLV-STEL is exceeded, while constant ST_{wait} determines the time that must elapse between two TLV-STEL violations for the same worker and the same chemical substance. For constants ST_{limit}, ST_{wait}, and ST_{time}, values equal to 4, 60 minutes, and 15 minutes are suggested by ACGIH (2019), respectively.

In addition, we designate several sets of variables. Let us define, for each $j \in J$, for each $w \in W$, and for each $s \in S$, a continuous variable x_{js}^w indicating the amount of time spent by worker w performing job j in time slot t. We also introduce, for each $j \in J$, for each $w \in W$, and for each $s \in S$, a binary variable y_{js}^w, which takes value 1 if and only if worker w performs task j in time slot s, 0 otherwise. Additionally, let us define, for each $w \in W$, and for each $s \in S$, a continuous variable t_s^w indicating the time instant in which worker w finishes to work in time slot s. We also need to define an additional continuous variable, γ, which indicates the worst exposure to any substance experienced by any of the workers. For each chemical substance and for each worker, our tool computes the average daily exposure and compares it to the TLV-TWA (by performing the ratio). Variable γ takes as value the worst (highest) of these ratios. Additionally, let us introduce, for each $j \in J$, for each $w \in W$, and for each $s \in S$, an auxiliary integer variable g_{js}^w, which is used to restrict the possible duration of a time slot. Finally, we need to include, for each $w \in W$, for each $s \in S$, and for each $c \in C$, binary variable z_{sc}^w, which indicates whether the exposure to substance c in time slot s for worker w exceeds ST_c.

3.2. *Two-phase algorithm*

In the first phase of our algorithm we exploit a MILP model that has the goal to identify a schedule for all the tasks with the minimum worst exposure among the considered chemical substances. It includes 19 classes of constraints and makes use of the sets of variables presented in Section 3.1. The problem can be formulated as follows:

$$\text{Minimize } \gamma \tag{1}$$

subject to:

$$\gamma \geq \frac{1}{D \cdot TWA_c} \sum_{s \in S} \sum_{j \in J} e_{cj} x_{js}^w \qquad w \in W, c \in C^{TWA} \tag{2}$$

$$x_{js}^w \leq D y_{js}^w \quad j \in J, s \in S, w \in W \tag{3}$$

$$\sum_{j \in J} y_{js}^w \leq 1 \quad s \in S, w \in W \tag{4}$$

$$\sum_{j \in J} \sum_{s \in S} x_{js}^w = D \quad w \in W \tag{5}$$

$$\sum_{s \in S} \sum_{w \in W_j} x_{js}^w = d_j \quad j \in J \tag{6}$$

$$x_{js}^w \geq d_j^{min} y_{js}^w \quad j \in J, s \in S, w \in W \tag{7}$$

$$\sum_{j \in J} x_{j1}^w = t_1^w \quad w \in W \tag{8}$$

$$t_s^w = \sum_{j \in J} x_{js}^w + t_{s-1}^w \quad s \in S \setminus \{1\}, w \in W \tag{9}$$

$$x_{js}^w = \delta g_{js}^w \quad j \in J, s \in S, w \in W \tag{10}$$

$$\sum_{j \in J} (e_{cj} - ST_c) y_{js}^w \leq ST_c^{max} z_{sc}^w \qquad c \in C^{ST}, s \in S, w \in W \tag{11}$$

$$\sum_{s \in S} z_{sc}^w \leq ST_{limit} \quad c \in C^{ST}, w \in W \tag{12}$$

$$t_{s_1}^w + D(1 - z_{s_1 c}^w) \geq t_{s_2}^w + \sum_{j \in J} x_{j s_1}^w + ST_{wait} z_{s_2 c}^w \qquad c \in C^{ST}, w \in W, s_1, s_2 \in S, s_1 > s_2 \tag{13}$$

$$\sum_{j \in J} x_{js}^w \leq ST_{time} + D(1 - z_{sc}^w) \qquad s \in S, c \in C^{ST}, w \in W \tag{14}$$

$$\sum_{s_1 \in S, s_1 > s} \sum_{j \in J} y^w_{js_1} \leq \sum_{j \in J} |S| y^w_{js} \quad s \in S, w \in W \tag{15}$$

$$x^w_{js} \geq 0 \quad j \in J, s \in S, w \in W \tag{16}$$

$$y^w_{js} \in \{0, 1\} \quad j \in J, s \in S, w \in W \tag{17}$$

$$t^w_s \geq 0 \quad s \in S, w \in W \tag{18}$$

$$z^w_{sc} \in \{0, 1\} \quad s \in S, c \in C, w \in W \tag{19}$$

$$g^w_{js} \geq 0, integer \quad j \in J, s \in S, w \in W \tag{20}$$

The objective function (1) establishes the minimization of the worst exposure γ. Since other exposures are lower than the worst exposure, this allows to minimize the exposures by inhalation of all workers. Constraints (2) impose that variable γ takes at least a value equal to the worst exposure (expressed as a ratio between the actual exposure and the TLV-TWA) to any substance experienced by any worker during the working day. Jointly considering objective function (1) and constraints (2) clearly identifies this formulation as a min-max model. Constraints (3) link variables x and y together, and ensure that variable x^w_{js} can take values greater than 0 if and only if variable y^w_{js} takes value 1. Constraints (4) guarantee that a worker can perform at most one task in each time slot. Constraints (5) are included to ensure that each worker performs tasks for exactly D minutes, while constraints (6) guarantee that each task is performed for the required amount of time. Constraints (7) impose that, when task j is assigned to a worker in a time slot, he/she has to perform it for at least d^{min}_j minutes. Indeed, our model assumes that certain activities are characterized by a minimum duration: if such tasks are undertaken, workers are exposed to chemical substances for at least the period of exposure. Constraints (8) and (9) link variables x and t together, and impose that variable t^w_s takes as value the ending time of task j in time slot s, performed by worker w. Constraints (10) ensure that the duration of a time slot is always a multiple of δ. These constraints are added in order to obtain a more realistic and usable schedule. By using $\delta = 15$ or $\delta = 30$, we can obtain a schedule much easier to apply and execute in real scenarios (a task switch can happen only in 4 or 2 possible times during an hour), whereas if we remove these constraints, a task switch could occur at any point in an hour. Constraints (11) activate variable z^w_{sc} whenever the TLV-STEL of chemical substance s is violated in slot s for worker w. Constraints (12) ensure that the TLV-STEL of a certain chemical substance is violated at most ST_{limit} times for a worker during the day. Constraints (13) ensure that, when the TLV-STEL of a chemical substance is exceeded for a worker, at least one hour elapses before the same worker is exposed to the same chemical substance. Constraints (14) limit the duration of a time slot to ST_{time} when a TLV-STEL is exceeded. Constraints (15) guarantee that only consecutive time slots are used during the day for every worker. Constraints (16)–(20) are binary and non-negative conditions on variables.

This mathematical model produces, if it exists, a feasible schedule than can be used in a real case scenario. Two different kinds of solution can occur:

(i) the value of γ is lower than or equal to 1, which means that the schedule produced complies with all TLV-TWA constraints;
(ii) the value of γ is greater than 1, which means that at least one TLV-TWA constraint is violated.

In the first case, the solution can be accepted and applied in a real scenario. In the second case, if the obtained solution is optimal and γ is greater than 1, it is proven that no solution that complies with all the TLV-TWA restrictions exists. When this situation arises, our optimization tool proceeds to a second phase, in which the goal is to produce a solution in which the violation of TLV-TWA restrictions is allowed, although as limited as possible. It is worth noticing that, when γ is greater than 1, we can obtain solutions that are mathematically equivalent for our model (i.e., they have the same objective function value), but are extremely different if we consider the exposure to all chemical substances, and not just the worst one. This is best explained with a simple example. Assume there are only two chemical substances (c_1 and c_2) in our scenario, and the optimal solution is equal to $\gamma = 2$. This means that there is at least one worker whose exposure to one chemical substance (e.g., substance c_1) is twice its related TLV-TWA. For our first mathematical model, the exposure level to substance c_2 is irrelevant, as long as it does not exceed $\gamma = 2$. This means that a solution in which the exposure to c_2 is equal to $0.5TWA_{c_2}$ for all workers is equivalent to a solution in which the exposure to c_2 is equal to $1.5TWA_{c_2}$ for some of the workers.

In the second phase of our algorithm, we consider an additional objective, in contrast with the initial one. Indeed, we consider the minimization of the total violation of TLVs-TWA, defined as the sum, for each worker and each chemical substance, of the violation (in percentage) of the associated TLV-TWA. When dealing with multi-objective problems, a common approach in the scientific literature is to develop methods that try to generate the set of efficient points, i.e., the set of solutions for which it is impossible to improve the value of an objective function without deteriorating the value of at least one of the remaining ones. Since identifying the exact Pareto frontier (i.e., the set of all the efficient points) is too demanding for this problem, both in terms of computational power and required time, we restrict our tool to the generation of few efficient points (possibly only one). To this aim, we introduce a second MILP model, which differs from the first one only for the objective function and a couple of constraints. We include, for each $c \in C$ and for each $w \in W$, a new continuous variable θ_{cw}, representing by how much the TLV-TWA for chemical substance c is violated for worker w. Then, we introduce a new set of constraints as follows:

$$\sum_{s \in S} \sum_{j \in J} x_{js}^{w} e_{cj} \leq TWA_c + \theta_{cw} \qquad w \in W, c \in C^{TWA} \tag{21}$$

Constraints (21) ensure that if the exposure to chemical substance c is higher than its TLV-TWA TWA_c, θ_{cw} represents the amount by which the restriction is violated. Additionally, we impose that the worst exposure can not exceed a predefined value $\bar{\gamma}$:

$$\gamma \leq \bar{\gamma} \tag{22}$$

By using different values of $\bar{\gamma}$, we can generate different efficient points. For example, we can solve this model considering as $\bar{\gamma}$ the value of the optimal solution identified by the first phase of the algorithm. Finally, objective function (1) is replaced by objective function (23):

$$\text{Minimize} \sum_{c \in C^{TWA}} \sum_{w \in W} \frac{1}{TWA_c} \theta_{cw} \tag{23}$$

that minimizes the sum of the violation of all the TLV-TWA restrictions. By utilizing this objective function we try to mitigate the drawbacks emphasized above and we are able to overcome the situation described in our simple example.

4. Case study

In order to test our optimization tool, we considered a real exposure scenario in a foundry. Activities undertaken in the iron and steel industry can expose workers to a variety of health and safety hazards, causing different types of adverse effects (Stefana et al. 2019b). In such an industry, the risks arising from the presence and production of a plethora of chemicals require particular attention by safety managers. In the case study described in this paper, we analyzed 6 departments, where 15 work tasks are usually performed by 10 workers. A typical foundry process is described in Stefana et al. (2019a). The duration of the working day for all workers is equal to 8 hours (480 minutes). Details about input data, including the minimum period required for each work activity, are shown in Table 1. Workers' characterization is presented in Table 2 (for privacy reasons we only report worker initials), where fitness for work based on the judgment of the occupational physician, qualification for work, and thus non assignable work tasks are highlighted. Seven chemical substances present in each department and work activity were selected for safety relevance and sampled according to the measurement strategies defined in EN 689:2018+AC:2019 (CEN 2018): their airborne concentrations are reported in Table 3. The chemical substances are sampled considering the presence of any engineering control (e.g., ventilation system). For conservative estimates, the exposures are determined without considering the use and effectiveness of respiratory protective devices. Although our optimization tool allows to take into account chemical agents having TLV-TWA and TLV-STEL, the substances in this case study are only characterized by the first one. TLVs-TWA referred to each substance are equal to the following values, as reported in ACGIH (2019):

- respirable crystalline silica: 0.025 mg · m^{-3};
- respirable particles not otherwise specified: 3 mg · m^{-3};
- inhalable particles not otherwise specified: 10 mg · m^{-3};
- chromium: 0.5 mg · m^{-3};
- lead: 0.05 mg · m^{-3};
- manganese: 0.1 mg · m^{-3};
- nickel: 1.5 mg · m^{-3}.

The entire set of the above data and information identifies the main exposure determinants that safety managers should gather for a chemical risk assessment. Figure 1 illustrates the current (initial) scheduling of tasks and worker exposure sequence: each row reports the tasks that are assigned to each worker (identified by initials) during a working day. The different tasks are visualized as colored bars within which the number # exposure/work task of Table 1 is introduced.

The analysis of the initial workers' exposure points out that the F.B.'s exposure to nickel is the most severe one (the ratio between average daily exposure and TLV-TWA is equal to 2.56). This and other exposures with a ratio higher than 1 require the adoption of adequate control measures: a new scheduling of work tasks can solve these criticalities. The application of the optimization tool presented in Section 3 to the scenario under investigation permits to obtain the optimal scheduling of work tasks (Figure 2).

This scheduling permits to reduce the ratios between average daily exposure and TLV-TWA to values lower than 1, for each substance and for each worker. Therefore, such workers' exposures, day after day, to the airborne concentrations of

Table 1. Exposure/work task characterization.

# Exposure/ Work task	Work task	Process phase or department	Minimum period (min)	Total duration (min)
1	Load and unload	Moulding	60	120
2	Manual moulding	Moulding	240	960
3	Handling	Moulding	60	240
4	Other tasks	Moulding	120	240
5	Manual core making	Core making	15	240
6	Handling	Core making	60	120
7	Load and unload	Furnace work	60	240
8	Handling	Furnace work	120	240
9	Quality control and other tasks	Furnace work	15	480
10	Manual casting	Casting	240	480
11	Manual knockout	Casting	120	240
12	Handling and other tasks	Casting	60	240
13	Manual fettling	Fettling	15	600
14	Cutting and other tasks	Finishing	60	180
15	Welding	Finishing	15	180

Table 2. Workers' characterization.

Worker	Fitness for work	Qualification for work	Non assignable exposures/work tasks
M.A.	Yes	Yes	-
F.B.	Yes	Yes	-
S.G.	Yes	Partially (no welding)	15
S.P.	Yes	Partially (no welding, no cutting)	14, 15
P.F.	Partially (no heavy manual work)	Yes	2, 5, 10, 11, 13
D.N.	Yes	Yes	-
C.P.	Yes	Partially (no welding, no cutting)	14, 15
H.M.	Yes	Partially (no welding, no cutting)	14, 15
F.M.	Partially (no heavy manual work)	Partially (no welding)	2, 5, 10, 11, 13, 15
A.L.	Yes	Partially (no welding)	15

Table 3. Chemical substance concentrations ($mg \cdot m^{-3}$).

#Exposure/	Chemical substances						
Work task	RCS	R-PNOS	I-PNOS	Cr	Pb	Mn	Ni
1	0.027	1.13	6.86	0.040	0.051	0.011	0.019
2	0.014	0.77	4.62	0.032	0.009	0.007	0.014
4	0.011	0.58	3.62	0.019	0.004	0.006	0.012
5	0.008	0.49	4.10	0.016	0.007	0.008	0.019
6	0.007	0.44	3.41	0.006	0.003	0.004	0.013
7	0.028	1.19	11.84	0.210	0.092	0.084	0.068
8	0.013	0.55	5.92	0.058	0.043	0.068	0.023
9	0.009	0.86	4.67	0.061	0.052	0.078	0.022
10	0.029	1.04	9.55	0.038	0.008	0.031	0.030
11	0.029	1.12	15.54	0.008	0.011	0.073	0.008
12	0.028	1.23	5.65	0.015	0.006	0.012	0.014
13	0.017	4.82	16.74	1.020	0.061	0.230	3.840
14	0.070	6.91	22.65	1.640	0.005	0.104	6.540
15	0.045	3.42	7.36	0.544	0.048	0.680	0.316

Note: RCS: Respirable Crystalline Silica; R-PNOS: Respirable Particles Not Otherwise Specified; I-PNOS: Inhalable Particles Not Otherwise Specified; Cr: Chromium; Pb: Lead; Mn: Manganese; Ni: Nickel.

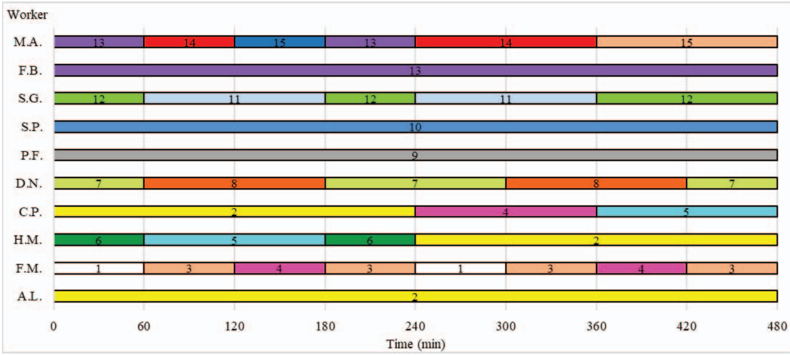

Fig. 1. Current exposure sequence and scheduling of tasks assigned to each worker in the foundry.

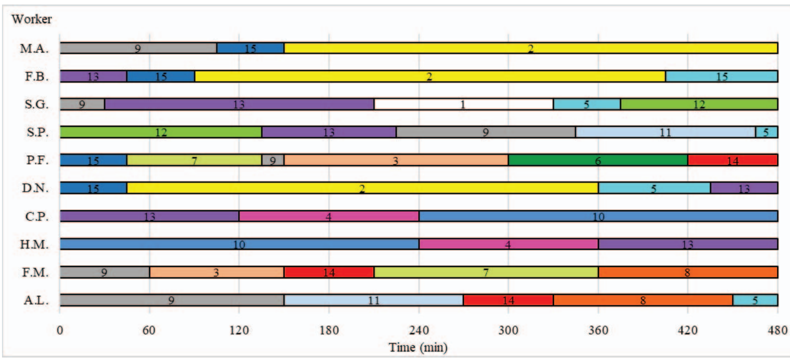

Fig. 2. Resulting exposure sequence and the optimal scheduling of tasks for each worker in the foundry.

the chemical agents present in the working environment are unlikely to result in adverse effects. Since the first phase of our algorithm identified a solution with $\gamma \leq 1$, the second phase was not executed for this particular scenario. The comparison between the initial and the resulting scheduling of tasks highlights that the minimization of occupational exposures to chemical agents is achievable through the assignment of the same activity to several workers for a shorter duration. For instance, the activity "quality control and other tasks" (# exposure/work task = 9) was initially conducted only by worker P.F. for the entire 8-hour workday. In the final scheduling produced by our optimization tool, 6 workers (i.e., M.A., S.G., S.P., P.F., F.M., and A.I.) carry out this task during the shift for time intervals ranging from 15 to 150 minutes. However, the obtained solution requires frequent work task changes, also in different departments. This is justified by the absence of constraints related to the task dependencies in our current scheduling model. Since these changes are not always feasible in real working environments, an improved version of the tool should include other real constraints about the relative tasks order and their dependencies.

5. Conclusions

This article presents the first optimization tool for identifying the best scheduling of work tasks able to minimize workers' exposures to inhaled chemical substances. A two-phase algorithm, exploiting two single period MILP compact formulations, and different constraints related to occupational exposure limits, work task duration, and organizational aspects, is proposed. A real case study in a foundry was solved and the optimal scheduling of tasks obtained. The considered scenario highlights the capability and adequacy of the proposed optimization tool, based on the data and information typically available by safety managers for assessing chemical risks. Furthermore, the computing time required for the search of solutions seems acceptable for routine model applications. Indeed, our tool, implemented in Java, takes on average less than five minutes to obtain an optimal/quasi-optimal solution. The computation time can increase up to one hour if we also consider the time needed to mathematically prove the optimality of the solution. Future research should focus on the development of a scheduling model based on a multi-period formulation, with other real constraints (e.g., relative tasks order and their dependencies), and further objective functions to deal with scenarios in which the first phase of our approach is not able to identify a solution that respects both TLV-TWA and TLV-STEL. How to handle the multi-objective nature of the problem and how to efficiently generate its set of efficient points is an additional aspect that deserves further investigation.

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