How to front the physical distancing requirement within workforce scheduling: empirical investigation through an optimization model

Riccio Carlo, Menanno Marialuisa and Savino Matteo M.

*Department of Technic and Industrial Systems Management, University of Padua, Vicenza, Italy; 
*Department of Engineering, University of Sannio, Benevento, Italy

**ABSTRACT**

This work is focused on workforce scheduling for assembly lines with the additional constraint of workforce distancing. The aim is to warrant the necessary safety and health requirements due to COVID-19. The research stems within an industrial case in which a methodology has been developed with the objectives of i) developing a constraint optimization model considering the social distancing of workers as part of the workforce scheduling requirements and ii) investigating how the workforce distancing can affect certain production performances. Through an empirical investigation the impact of distancing on workforce allocation is appraised in terms of daily production capacity. Then, different distancing thresholds are assessed to seek the optimal balance among production performances and safety requirements. The research resulted in a tool able to adapt the scheduling sequence to those health/safety situations where the production manager needs to minimize losses in terms of production capacity, warranting the safest working conditions.

**1. Introduction**

Workforce scheduling (WS) concerns the allocation of the type and number of workers at the right time and on the right machine in production systems. Generally, WS is needed when the number of available workers is less than the number of workstations, or when not all workers have the skills for all operations, thus generating a potential shortage of work (Thompson & Goodale, 2006).

Typically, a WS problem regards the assignments of workers to workstations for a certain time period. Over the past few decades, WS problems have been extensively studied and further research has been conducted on a range of decision variables (Dolgui & Proth, 2010).

An event like COVID-19 puts a strain on the workforce to adapt to the new regime of a production process. Hence, within production systems, numerous changes occurred, such as changes in processes and production, along with new operating procedures.

**CONTACT** Menanno Marialuisa marialuisa.menanno@unisannio.it Department of Engineering, University of Sannio, Piazza Roma, 21 - 82100, Benevento, Italy

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aimed to keep social distancing in workplaces. These changes put a strain on the achievement of employee productivity targets, as more time is needed to follow the new regime (Armenta et al., 2022).

The present work fronts the WS problem under the perspective of the workforce distancing to ensure the respect of safety and sanitary requirements that may also be needed due to COVID-19. The motivation for this research is the belief that in the next future, workforce distancing will be a cogent issue to consider in defining process layouts and in WS methods and algorithms.

The contribution of this paper regards the integration of the distancing constraint between workers in the WS.

The paper is organized as follows. After the literature review, section 3 describes the methodology used. Section 4 details the model and the constraints, section 5 analyzes the industrial case, while in sections 6 and 7, we find the results with the discussions and conclusions, respectively.

2. Literature review

2.1. Pandemic and social distancing

Due to COVID-19 disease, and the relative countermeasures, many countries have implemented social distancing as one of the main actions to ‘flatten the curve’ of the ongoing epidemics (Teslya et al., 2020). Among these countermeasures, distancing has proven to be effective in mitigating and delaying the epidemic, resulting in reductions in the incidence of COVID-19 globally (Islam et al., 2020).

Ahmed et al. (2018) demonstrated that social distancing should be employed over the whole population during an epidemic or pandemic. Social distancing is practiced within contained environments (e.g. homes, offices) and even in shared or open spaces. However, it can be culturally and socially challenging to enforce social distancing. The importance of distancing has also stimulated the research as regards real-time monitoring methods. Cristiani et al. (2020) introduced Visual Social Distancing method to automatically appraise the inter-personal distance by an image, and to evaluate whether the social behavior in the scene is compliant with the distancing restrictions.

Within working environments, the term Social Distancing, due to its wider meaning, should be better mentioned as Physical Distancing because it may avoid closer contacts among people thus reducing the potential cross-transmission of virus-carrying droplets from human respiration (Sun & Zhai, 2020). The analysis of recent studies on physical distancing shows discrepancies on the correct distance; the Word Health Organization recommends at least 1 m, Güner et al. (2020) suggest at least 3 feet, and Huremovic (2019) recommends that a minimum of 2 m (about two arms’ length) should be kept between each other, while others believed that 2 m may not be adequate during this COVID-19 outbreak (Setti et al., 2020).

Many studies highlight that workplaces may expose a high risk of infection in a pandemic situation (Golbabaei & Kalantari, 2020) and they are susceptible places to outbreak the SARS-CoV-2 due to the closeness of many people together. Various cases have demonstrated work-related situations where individual contacts occurred and the virus had spread easily (Wang & McLaren, 2020). Despite the considerable number of
group infections occurring in workplaces, the guidelines against infection prevention need to include protocols for workplace sanitation and distancing (Kim, 2020). Provided that above all in working activities, the use of the term Social Distancing appears to be inappropriate due to its wider meaning; within this study, we shall use the term Physical Distancing. Hence, this paper investigates the possibility that Physical Distancing among workers may enter as a cogent constraint of workforce scheduling.

2.2. The workforce scheduling problem

WS is one of the major problems that manufacturing companies have to face, in which workers can be assigned to one or several tasks within a certain period of time (Ammar & Elkosantin, 2013). The WS problem occurs when the number of available workers is less than the number of operations, as in dual resources constrained (DRC) systems where workers can be relocated across various workstations (Xu et al., 2015). Some studies have addressed worker allocation through the implementation of a Constraint Optimization Model (COP) that is able to find the optimal distribution of the workforce one or several performance criteria, as cycle time, the lead times, the production cost, and the level of workers in process (Battaia & Dolgui, 2012; Savino and Neubert (2009) combined COP and Constraint Satisfaction Problem (CSP) techniques to get optimal utilization of workforce, together with a maximization of throughput and makespan in an assembly line composed of six workstations.

In many WS studies, an important factor is workers’ flexibility, intended as the ability to conduct several different types of jobs, which may allow to assign workers to several different operations (Alfares et al., 1999).

Workforce set can be homogeneous or heterogeneous according to the skill level of workers (Cagliano et al., 2014), with different repercussions on the search for optimal allocation (Felan & Fry, 2001; Nakade & Nishiwaki, 2008). Another aspect that has stimulated the research is walking time, that is defined as the time needed by the operator to move from one station to another and its impact on WS efficiency (Sirovetnukul & Chutima, 2010; Wang et al., 2009). The distinction between collaborative and non-collaborative systems has been also addressed in other studies, like collaborative systems, in which more than one worker can be assigned to a task at once. Yet, in this case, the absence of collaboration between workers is assumed as a fundamental hypothesis (Sennott et al., 2006).

The literature analysis has shown that many researches focused on the evolution of the WS, both by including aspects related to the characteristics of the workforce and through the use of different techniques to implement the models (Lagodimos & Paravantis, 2006).

Some researches focused their efforts on how workers’ skills can be considered in task allocation. On this line, Techawiboonwong et al. (2006) address the WS problem of temporary workers in mixed-model flow lines with both skilled and unskilled workplaces, taking a cue from reality in labor-intensive export-oriented factories located in the Far East. Othman et al. (2012) include into WS some human aspects such as skills, training, and workers’ personalities and motivation through a multi-objective non-linear programming model that minimizes costs. Thompson and Goodaleb (2006) consider the problem of developing workforce schedules using groups of employees having different productivity through a nonlinear representation.
Mixed-integer linear programming (MILP) is used by Safaei et al. (2009) to propose a multi-objective WS for maintenance with the aim of simultaneously minimizing the workforce cost and maximizing the equipment availability. Niemi’s model (2009) uses MILP to optimize the allocation of workers to the products in a make-to-order manufacturing of large variable products, with the purpose of meeting the deadline and minimizing the labor costs, and by Gebennini et al. (2016) which in their minimize operators’ walking times into a linear system layout with flexible workstations.

Savino et al. (2014) explored the use of multi-agent system (MAS) for dynamic workforce allocation with a two-step approach made of a centralized scheduling based on initial operator scheduling, and a decentralized MAS in case of unforeseen events.

2.3. Workforce scheduling and workers’ features

Genetic algorithm is the basis for the metaheuristics developed and compared in the research of Costa et al. (2013) to address the WS problem with multi-skilled human resources, and impact of workers’ skills on the work cell performance has been analyzed; the goal is to build the optimal workers’ profiles to ensure makespan reduction and minimize manpower costs. Algethami and Landa-Silva (2019) present an adaptive multiple crossover genetic algorithm to tackle the combined setting of a WS and Routing Problem.

Regarding workforce’s skills in WS, a multi-agent reinforcement learning approach has been proposed by Qu et al. (2016) for the optimal scheduling of a manufacturing system producing multiple types of products with multi-skilled workforce.

Previous studies have also analyzed the possibility of including some personal features of operators as variables for determining the optimal allocation (Techawiboonwong & Yenradee, 2003).

Work overload in mixed-model assembly lines is analyzed by Aroui et al. (2017) for truck production and solved through three heuristic methods with different reactions against work overloads. Visentin et al. (2018) improved the scheduling model with a physical fatigue assessment for workers performing manual material handling activities. The goal of Moussavi et al. (2019) was to balance the global daily workload of the workers, through an optimal sequence of jobs for each worker. The physical workload has been appraised through an ergonomic analysis of the workstations. On this research stream, Savino et al. (2019) integrated the ergonomic assessment into a COP model for WS to i) appraise the impact of ergonomic load of workers on production performances and ii) schedule workers on workstations based on their ergonomic parameters.

2.4. Summary of the literature review

Table 1 offers an overview of the findings relative to the goals pursued by the authors in WS and social distancing, within the relative industrial areas and the approaches used.

Based on the extant literature, we may argue that currently there may be a lack of investigations in which WS considers the physical distancing of workers. It should be noted that the need for workers’ distancing arose in the last two years of the pandemic as
### Table 1. Literature classification regarding workforce scheduling and social distancing.

| Domain/Area | Subject | Main Goal | References |
|-------------|---------|-----------|------------|
| Pandemic and social distancing | Social distancing in pandemic | Countermeasures to flatten pandemic curve, Evaluate the effect of social distancing on pandemic curve | Teslya et al., 2020, Islam et al., 2020 |
| Distance evaluation | | Estimation of interpersonal distancing | Cristani et al. (2020) |
| Social distancing in workplace | | Evaluate the effect on Physical Distancing in workplaces | Sun & Zhai, 2020 |
| The correct distance | | Recommended minimal distance | Güner et al. (2020), Huremovic (2019), Setti et al. (2020), Ammar and Elkositin (2013), Xu et al. (2015), Battaia and Dolgui (2012), Savino and Neubert (2009) |
| The workforce scheduling problem | Definition of a WS problem COP model | Define the goal of workforce scheduling Model to represent a WS problem | |
| Workforce set | Impact of the flexibility and collaboration of the workforce set on the WS | Alfares et al. (1999), Cagliano et al. (2014), Nakade and Nishiwaki (2008), Felan and Fry (2001), Sirovetnukul and Chutima (2010), Wang et al. (2009), Sennott et al. (2006) |
| Workers’ skills | Impact of the workers’ skills on the WS | Techawahoonwong et al. (2006), Othman et al. (2012), Thompson and Goodaleb (2006) |
| WS model resolution techniques | | Mixed-integer linear programming (MILP), Multi-agent system (MAS) | Safaei et al. (2009), Niemi (2009), Gebennini et al. (2016), Savino et al. (2014) |
| Genetic algorithm | Combination of WS problem with workers' skills and routing | Algethami and Landa-Silva (2019), Costa et al. (2013) |
| Multi-agent approach | Multi-agent reinforcement learning approach for a WS with multi-skilled workers | Qu et al. (2016) |
| Workers physical features | Personal features of operators included in WS, Physical fatigue assessment in WS, Reduce workers overload, Ergonomic assessment integrated into WS | Techawahoonwong and Yenradee (2003), Visentin et al. (2018), Aroui et al. (2017), Mussavi et al. (2019), Savino et al. (2019) |

A means of preventing contagion. The goal of this work is to provide a workforce scheduling tool that takes into account the distance of workers as a safety constraint, while ensuring production objectives.

### 3. Research questions and research methodology

The first research question (RQ) focuses on the basic feasibility of a WS model that considers the distancing constraint.

**RQ1:** How is it possible to include the physical distancing as a variable into a WS problem?
The second RQ explores how the distance can affect production performances within the WS.

RQ2: Is it possible to optimize production capacity with regard to the distancing among workers?

Within RQ2, the main goal is to i) define the impact of the distancing constraint on workforce allocation, ii) appraise, throughout the case study, the optimal scheduling in terms of production capacity with a certain distancing requirement, and iii) appraise how the production capacity may vary when the distancing constraint varies.

The research methodology of Figure 1 has been designed to appraise the possible effects on the WS of the distancing constraint. The same Figure 1 shows the research steps in which the RQs find answer.

Within the study, WS and Distancing Model (WSDM) has been designed to answer to the RQs raised by the analysis of the extant literature.

In the first step (S1), an existing COP model for WS has been analyzed. In this step, a Distance Matrix (DM) is purposely conceived as mathematical model of the distance among workers. DM is used to evaluate the average distance among workers of the current WS configuration.

The second step (S2) has been addressed with the Constraint Optimization Problem (COP) approach (Savino & Neubert, 2009), by realizing a COP model that includes the distancing constraints that result from S1.

In S3, the impact of distancing on the production capacity has been appraised. In the S4 step, an analysis of the outputs of the WSDM has been performed with a goal to find a balance between production performances and workers’ distancing.

4. Workforce scheduling and distancing model

The test bed of this study is an assembly flow shop composed of 10 workstations (Figure 2) where electromechanical device is assembled. All operations are manual or they require the use of manually operated tools.

The operations are conducted by two workers (wk1 and wk2) in a single shift of 7 hours and 15 minutes. This production system, in which the number of operators is less than the number of workstations, is usually modeled as a flow shop with similar characteristics (Savino et al., 2014; Savino & Neubert, 2009). Table 2 reports the operations with the respective cycle times and constraints.

According to Table 2, this flow shop needs to schedule wk1 and wk2 on the opi where i = [1, . . . , 10].

The basic COP model has the following notations:

- wk = {1, . . . , wkM} the number of available workers
- op = {1, . . . , opN} the number of operations
- t = {0, . . . , tS} the workday length, in S time slots
- xwk(op)(t) operator’s state
- xwk(op)(t) = \begin{cases} 
1 & \text{if } wk \text{ is working on the } op \text{ at time } t \\
0 & \text{otherwise}
\end{cases}
This number can be expressed by the ratio between the time spent by the $w_{kj}$ on a workstation and the cycle time of a single workpiece on that workstation, according to Equation (1):
where

- $\Pi$ is the time to conduct $op_i$ by the $wk_j$
- $t_uop$ is the cycle time of the workstation

With these variables, we adapted the objective function $f_i(t)$ of Savino et al. (2019) to maximize the Daily Production Capacity (DPC) that can be expressed as (Equation 2).

$$
\max(DPC) = \max \frac{\sum_{wk} z_{op}(t)}{t_uop},
$$

where

- $N$ is the total number of operations of the line
- $t_5$ is the final time slot
Equation (2) states that maximizing DPC implies maximizing the number of pieces worked at the last operation of the cycle \( op_N \) at \( t_5 \), \( p_{op_N}(t_5) \).

The constraints of the model are the following:

- \( p_{op}(t_0) = 0 \forall op \) This constraint ensures that at the beginning of the working day, no workpieces are on the workstation.
- \( p_{op}(t) \leq \sum_{\Delta t_{op}} \forall op \) ensuring that the maximum number of workpieces that can be worked in each operation is equal to the maximum production capacity of the optimal case, i.e. when there is no idle time. This optimal case corresponds to the ratio between the duration of the working shift and the time required to carry out all the activities.

\[
\begin{align*}
  p_7(t) & \leq p_1(t) \\
  p_7(t) & \leq p_2(t) \\
  p_7(t) & \leq p_3(t) \\
  p_7(t) & \leq p_4(t) \\
  p_7(t) & \leq p_5(t) \\
  p_7(t) & \leq p_6(t) \\
  p_8(t) & \leq p_7(t) \\
  p_9(t) & \leq p_8(t) \\
  p_{10}(t) & \leq p_9(t)
\end{align*}
\]

The priority constraints are translated into constraints relative to the number of pieces that have already been worked in each \( op_i \).

\[
\begin{align*}
  p_{10}(op_n) & \leq p_4(op_n) \\
  p_{10}(op_n) & \leq p_5(op_n) \\
  p_{10}(op_n) & \leq p_6(op_n)
\end{align*}
\]

These operations have no priority constraints, but they must be completed within the end of the working shift.

\[ \sum_{wk} z_{op}^{wk}(t_0) = 0 \forall op \] initially, all the times spent on the operations, by each operator, are equal to 0;

\[ \sum_{op} z_{op}^{wk}(t) \leq t_S \forall wk \] the time that each worker can spend for all the operations is equal to the duration of the working day;

\[ \sum_{wk} x_{op}^{wk}(t) \leq 1 \] each workstation can be used by a single worker or, similarly, an operation can be carried out by a single worker at a time;

Each operation needs to be completed within \( t_{uo} \) time according to the cycle time of Table 2;

\[ \sum_{wk} z_{op}^{wk}(t) - \sum_{wk} z_{op}^{wk}(t - 1) - \sum_{wk} x_{op}^{wk}(t) = 0. \] The time spent on an operation can increase only if a worker has been assigned to that operation.

To assess the distance between the workers at each time slot, we need to know the distance between each couple of workstations (WS). Since each \( op_i \) is conducted on one WS, the distance between each couple of workstations is also intended as the distance \( (d_{ij}) \) between a couple of operations \( op_i \) and \( op_j \). Within this study, \( d_{ij} \) is modeled by a DM (Equation 3):

\[
DM = \begin{bmatrix}
  d_{1,1} & \ldots & d_{1,N} \\
  \vdots & \ddots & \vdots \\
  d_{N,1} & \ldots & d_{N,N}
\end{bmatrix}
\]

where \( i, j = \{1, \ldots, op_N\} \), \( d_{i,j} = 0 \) if \( i = j \).

Figure 3 shows an example of the distances between the workstations of the flow shop as elements of the DM.

At each time slot \( t = \{0, \ldots, t_S\} \), the function \( DIS(t) \) models the distance between \( wk_1 \) and \( wk_2 \) and at time \( t \) (Equation 4):

![Figure 3. Elements of the Distance Matrix.](image-url)
\[ DIS(t) = x_{opi}^{wk1}(t) \times x_{opi}^{wk2}(t) \times d_{ij} \] (4)

The new additional objective function \( f_2(t) \) maximizes the average distance \( DIS_{AVG} \) between \( wk_1 \) and \( wk_2 \) within the working shift of duration \( t_s \) (Equation 5):

\[
\max DIS_{AVG} = \max \frac{\sum_{t=0}^{t_s} DIS(t)}{t_s}
\] (5)

The maximization of (2) and (5) has been addressed (Chircop & Zammit-Mangion, 2013) through the Bi-Objective Optimization Problem (BOOP) as shown in Equation (6):

\[
\begin{align*}
\max f_1(t) &= \max DPC = \max \frac{\sum_{op} x_{opi}^{wk1}(t_s)}{t_{op}} \\
\max f_2(t) &= \max DIS_{AVG} = \max \frac{\sum_{ni=1}^{ni} DIS(t)}{t_s}
\end{align*}
\] (6)

BOOP can be reduced to a Single Objective Optimization Problem (SOOP) with \( \epsilon \)-constraints method (Haines et al., 1971). In this method, one of the objective functions is optimized while the other is transformed into an additional constraint. Thus, we obtain a solution that can always be proved as weakly Pareto optimal, which is to say that there does not exist another point in the feasible space of solutions that improves all of the objective functions simultaneously (Singh Arora, 2017). Hence, the system of (6) is converted into:

\[
\begin{align*}
\max f_1(t) \\
f_2(t) \geq \epsilon_1
\end{align*}
\] (7)

Systematic modification of the values of the objective functions forming the additional constraints generates a Pareto front that is the boundary defined by the set of all points mapped from the feasible solutions. In our case, the \( \epsilon \)-constraints method introduces a threshold on the workers distancing expressed by (5), as follows:

\[
f_2(t) = \frac{\sum_{t=0}^{t_s} DIS(t)}{t_s} \geq DIS_{MIN} = \epsilon_1
\] (8)

where \( DIS_{MIN} \) is the minimum value of workers’ distance that may be allowed by safety regulations.

Thus, the final model is the original COP that maximizes both DPC (through an objective function) and workers distancing (through an \( \epsilon \)-constraint):

\[
\begin{align*}
p_{op}(t_0) &= 0 \\
p_{op}(t) &\leq \frac{t_s \times wk_1}{t_{op}} \\
p_{op}(t) &= \sum_{op} \frac{x_{opi}^{wk1}(t)}{t_{op}} \\
p_{10}(t) &\leq p_1(t) \\
p_{10}(t) &\leq p_2(t)
\end{align*}
\]
\[
\begin{align*}
& p_7(t) \leq p_5(t) \\
& p_7(t) \leq p_4(t) \\
& p_7(t) \leq p_5(t) \\
& p_7(t) \leq p_6(t) \\
& p_8(t) \leq p_7(t)
\end{align*}
\]

\[
\begin{align*}
& p_9(t) \leq p_8(t) \\
& p_{10}(t) \leq p_9(t) \\
& p_{10}(op) \leq p_4(op) \\
& p_{10}(op) \leq p_5(op) \\
& p_{10}(op) \leq p_6(op)
\end{align*}
\]

\[
\begin{align*}
\sum_{wk} z_{wk}^{op}(t_0) &= 0 \\
\sum_{op} z_{op}^{wk}(t) &\leq t_s \\
\sum_{op} x_{op}^{wk}(t) &\leq 1 \\
\sum_{wk} x_{wk}^{op}(t) &\leq 1 \\
\sum_{wk} z_{wk}^{op}(t) - \sum_{wk} z_{wk}^{op}(t-1) - \sum_{wk} x_{wk}^{op}(t) &= 0
\end{align*}
\]

\[
\begin{align*}
\sum_{t=t_s}^{u} DIS(t) \geq DIS_{MIN} \\
x_{op}^{wk}(t) = \{0, 1\} &\forall wk, op, tp_{op}(t) \in N \\
z_{op}^{wk}(t) \in N
\end{align*}
\]

5. Results

The model has been implemented in Mosel language and solved through Xpress solver. The first test has been run to appraise the ability of the model to modify the allocation of workers due to the possible changes of the minimum distancing threshold. Under a practical perspective, it may occur that the two workers are never allocated in any time slot on those workstations whose relative distance is less than the safety distance. The time slot in which the workers is not at a safe distance is therefore defined ‘critical slot’.

5.1. Case #1

Table 3 shows the results obtained within 29 time slots, equal to 435 minutes, with the distancing constraint set \(DIS_{MIN} = 2\) mt. (Huremovic, 2019).

According to Table 3, the WS algorithm allows keeping a distance greater than distance \(DIS_{MIN}\) in 21 time slots, while in the remaining six time slots, the operators are allocated to adjacent workstations whose relative distance is less than the safe distance. This distance is marked in red in Tables 3 and 4 and the corresponding time slot is critical. This behavior of the
model derives from the minimum distance constraint expressed by Equation 5. The constraint is accomplished by comparing this distance with the average distance between workers over the entire shift, and not over the single time slot.

From Table 3, we may see that when just one wk is scheduled on a time slot, it is assumed that the other wk is allocated on the Rest Station (RS, WS₀). In this case, \( d_{0,j} \) is the distance between the RS and the workstation allocated (Figure 4).

Figure 5 provides a different representation for the scheduling in Table 3, where the value 0 on y-axis is the RS.

### 5.2. Case #2

From Case #1, we may argue that, by setting \( DIS_{\text{MIN}} = 2 \text{ mt.} \), the model does not guarantee that the constraint is respected on all time slots. Hence, to ensure that in each time slot the operators may be correctly distanced, it is necessary to test the model at increasing values of the average distancing threshold.

For this Case #2, we attempted to obtain a scheduling with a lower number of critical slots. Table 4 shows the results obtained with \( DIS_{\text{MIN}} = 7 \text{ mt.} \).

According to Table 4, in Case #2, the number of critical slots has been decreased to 4, keeping the production capacity of the shift at the same value of 52 pieces.

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### Table 3. WS with \( DIS_{\text{MIN}} = 2 \text{ mt.} \)

| Time slot | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Distance (mt) |
|-----------|---|---|---|---|---|---|---|---|---|----|--------------|
|           |   | wk₁|   | wk₁|   | wk₀|   | wk₁|   | wk₀| 6.2          |
|           | wk₂| wk₁| wk₁| wk₀| wk₁| wk₁| wk₁| wk₁| wk₁| wk₁| 5.7          |
|           | wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| wk₁| 2.2          |
|           | wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| wk₁| 0.9          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₀| wk₁| wk₁| 1.1          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₀| 5.7          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.8          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 5.8          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 1.3          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.1          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 0.8          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 8.6          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 11.7         |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.1          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 3.9          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 1.3          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 11.7         |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 4.1          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.0          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 0.8          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.0          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 4.1          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.8          |
|           | wk₂| wk₂| wk₂| wk₂| wk₂| wk₁| wk₁| wk₁| wk₁| wk₁| 2.0          |

**Number of critical slots** 6

**Shift production (pcs)** 52
Figure 6 provides the time graph for the scheduling of Table 4.

Thus, the results of Tables 3 and 4 may answer RQ1. The WSDM has proven to be able to consider the distance constraint to generate the scheduling. In answering RQ1, analysing Case #1 and let us argue that, by varying the $DIS_{MIN}$ threshold, it is possible to obtain an allocation that even guarantees greater safety. Yet, in Case #2, there are still four critical slots in which $DIS(t) < DIS_{MIN}$.

5.3. Case #3

In contrast with Case #1 and Case #2, this third case, through setting $DIS_{MIN} = 7.6$ mt., allows a WS with no critical slot (Table 5).

The data of Table 5 let us infer that the increase in the $DIS_{MIN}$ threshold has led to a decrease in the critical slots up to zero. Yet, the increase of this constraint has also caused the decrease in the DPC from 52 pieces – maximum theoretical value – to 47 pieces.

Figure 7 provides the worker assignment vs time slots for the scheduling in Table 5.

6. Discussions

Table 6 shows the results of the three cases.
Analyzing the results of Tables from 2-3-4-5, we may see how the WSDM is able to modify the scheduling sequence for both workers to keep $DIS(t) > DIS_{MIN}$.

Thus, from these results, we may better answer $RQ_1$ by arguing that it is possible to include the distancing among workers into a WS problem with an approach that constrains the COP model with the threshold value of the $DIS_{MIN}$ required by safety and sanitary rules.
Figure 6. Workers assignment in the 29 time slot for Case #2.

Table 5. WS with $DIS_{\text{MIN}} = 7.6 \text{ mt.}$

| Time slot | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Distance (mt) |
|-----------|---|---|---|---|---|---|---|---|---|----|-------------|
| 1         |   |   |   |   | $wk_2$ |   |   |   |   |    | 6.2         |
| 2         |   |   |   |   | $wk_2$ | $wk_1$ |   |   |   |    | 3.9         |
| 3         |   |   |   |   | $wk_2$ | $wk_1$ |   |   |   |    | 2.6         |
| 4         |   | $wk_2$ |   |   |   | $wk_1$ |   |   |   |    | 5.7         |
| 5         | $wk_2$ |   |   |   |   | $wk_1$ |   |   |   |    | 5.8         |
| 6         | $wk_2$ |   |   |   |   | $wk_1$ |   |   |   |    | 5.7         |
| 7         | $wk_2$ |   |   |   |   | $wk_1$ |   |   |   |    | 8.1         |
| 8         | $wk_2$ |   |   |   |   | $wk_1$ |   |   |   |    | 5.8         |
| 9         |   | $wk_1$ |   |   |   | $wk_1$ |   |   |   |    | 9.4         |
| 10        |   | $wk_2$ |   |   |   | $wk_1$ |   |   |   |    | 10.2        |
| 11        |   | $wk_1$ |   |   |   | $wk_1$ |   |   |   |    | 5.8         |
| 12        | $wk_1$ |   |   |   |   | $wk_1$ |   |   |   |    | 10.2        |
| 13        | $wk_2$ |   |   |   |   | $wk_1$ |   |   |   |    | 9.7         |
| 14        | $wk_2$ | $wk_1$ |   |   |   | $wk_1$ |   |   |   |    | 5.8         |
| 15        | $wk_2$ |   |   |   | $wk_1$ |   |   |   |   |    | 6.2         |
| 16        | $wk_1$ | $wk_1$ |   |   |   | $wk_1$ |   |   |   |    | 9.4         |
| 17        | $wk_2$ |   |   |   | $wk_1$ |   |   |   |   |    | 12.2        |
| 18        | $wk_2$ | $wk_1$ |   |   | $wk_1$ | $wk_1$ |   |   |   |    | 8.1         |
| 19        | $wk_2$ | $wk_1$ |   |   | $wk_1$ | $wk_1$ |   |   |   |    | 7.1         |
| 20        | $wk_2$ | $wk_1$ | $wk_1$ |   |   | $wk_1$ |   |   |   |    | 5.7         |
| 21        | $wk_2$ | $wk_1$ |   |   |   |   | $wk_1$ |   |   |    | 8.1         |
| 22        | $wk_2$ |   |   |   | $wk_1$ |   |   |   |   |    | 12.2        |
| 23        | $wk_2$ | $wk_1$ |   |   |   | $wk_1$ |   |   |   |    | 7.7         |
| 24        | $wk_2$ | $wk_1$ | $wk_1$ |   | $wk_1$ |   |   |   |   |    | 9.4         |
| 25        | $wk_2$ | $wk_1$ |   |   |   | $wk_1$ | $wk_1$ |   |   |    | 10.2        |
| 26        | $wk_2$ | $wk_1$ |   |   |   | $wk_1$ | $wk_1$ |   |   |    | 10.2        |
| 27        | $wk_2$ |   |   | $wk_1$ |   |   |   |   |   |    | 12.2        |
| 28        | $wk_2$ | $wk_1$ |   |   | $wk_1$ |   |   |   |   |    | 7.1         |
| 29        | $wk_2$ | $wk_1$ |   |   | $wk_1$ |   |   |   |   |    | 12.2        |

Number of critical slots: 0
Shift production (pcs): 47
To answer RQ2, the second part of the study has been oriented to explore the behavior of certain parameters as regards the $DIS_{MIN}$ value. This investigation provided the analysis of the possible correlations of workers’ distancing with $DPC$, idle time, and critical slots.

Figures 8–10 report the WSDM functions for $DPC$, idle time, and number of critical slots, respectively, when the $DIS_{MIN}$ increases.

From Figures 5–7, we may see that up to the value $DIS_{MIN} = 6.5$ mt., the $DPC$ remains on the same value of $DPC = 52$ pieces. In contrast, increasing the $DIS_{MIN}$ over 6.5 mt. causes a strong decreasing of the $DPC$. This result corresponds to an increased idle time of the operators, in particular for wk2, that is the lower production capacity is linked to a greater interval of time in which the workers are inactive. Another result from this portion of the study is that increasing the $DIS_{MIN}$ generates a scheduling with fewer critical slots, and therefore safer for workers.
It is worth mentioning (Figure 5(b)) that there is a $DIS_{MIN}$ threshold, appraised in $DIS_{MIN} = 8.5$ mt., beyond which the model does not generate a realistic scheduling. Yet, from this last empirical result, we may argue that starting from a $DIS_{MIN} = 6.5$ mt., the model increases the idle time of wk$_2$ to keep the distancing threshold.

Thus, the WSDM can suggest to practitioners and/or production managers how to balance the distancing up to the most feasible value in regard to the production capacity.
In all three test cases, a value of $DIS_{\text{MIN}} = 7.6$ mt. allows to get a safer allocation with no critical slots, but the $DPC$ value is equal to the 90% of the maximum available $DPC$ (47 pcs vs 52 pcs). Another possibility is to prioritize the maximization of $DPC$ against $DIS_{\text{MIN}}$ by setting $DIS_{\text{MIN}} = 7.0$ mt; in this case, the four time slots in which the effective distance is less than $DIS_{\text{MIN}}$ can be made more ‘safe’ by modifying, for example, the workstations with physical separators.

Figure 5(a–) may better answer $RQ_2$ in terms that the $WSDM$ is a system allowing i) to choose the optimal production capacity in respect to the safer allocation of the workers and ii) to keep the distancing threshold as highest as possible while keeping constant the production capacity. Thus, the system can be a useful tool in a health emergency situation in which the production manager must guarantee the least loss in terms of production capacity and at the same time safe working conditions for workers.

7. Conclusions

Physical Distancing is worldwide acknowledged as the basic need for all activities in which humans have to cooperate or work in the same working environment, especially with actual regulations to contrast COVID-19 pandemic. This study was mainly motivated by this basic and vital need but also from the awareness that in the next future, Physical Distancing will be a fundamental issue in defining the layout to optimize logistics, ergonomics, and safety.

Within this focused-on-practice research, we investigated how the requirement of distancing among workers may impact on workforce scheduling solutions and the relative production parameters. The research methodology set within the study explored the possibility of linking the Physical Distancing to the distance between the workstations, thus assessing the impact of the distancing requirement in regard to the main production parameters.

This portion of the study has been addressed through a WS model in which we compared the distance between workers at each time slot with a predefined threshold based on safety needs. The amount of time slots in which the minimum distance can be respected allowed to define i) how the distancing impacts on the production parameters of our scheduling and ii) a strategy to balance the distance requirement with the production capacity. The research methodology has been designed to fit other production problems, and the $WSDM$ can be applied to similar assembly lines.

Despite the results obtained, two main technical limitations affect the $WSDM$ developed.

The first one regards the impossibility of setting the $DIS_{\text{MIN}}$ on the individual time slots that might guarantee the absence of critical slots. Hence, it requires an in-depth study to evaluate any impacts on the feasibility of scheduling. Further works might investigate the impact of constraints on the distance at each time slot instead of the average distance in the whole working shift. Alternatively, further investigation might appraise the possibility to include a constraint on the number of critical slots allowed, and to consider those critical slots in which the possible lower distance between operators is balanced by other personal protection devices such as masks or face shields. Towards this direction, the scheduling model should consider a global coefficient, such as a sanitary score, as main WS parameter.
The second limitation is that the WSDM does not balance the idle time of the workers if a higher $DIS_{MIN}$ is required. This may result in a high concentration of $op$, on one or more wks, with the other(s) highly under-saturated. Hence, possible concerns may be raised under both ergonomic and ethical point of views. Further development of this study may regard the evaluation of a ‘balancing factor’ among the constraints of the model.

Despite these unavoidable limitations, the empirical results of the WSDM show that safety conditions for the workers in some cases can be implemented without affecting production performances, giving to companies a flexible tool to verify in advance the correct distancing threshold as regards their local shop floors spaces and constraints before making layout investments to accomplish safety and sanitary restrictions.

Future research will focus on the generation of a scheduling with different spacing constraints between one workstation and another, in the event when a greater safety distance is required for a specific workstation in relation to the operation carried out; further studies may concern the impact of the distance constraint on the path of workers to move between workstations.

8. Managerial implications

This work resulted from industrial activities aimed at developing a model for the control of the distancing between the workers in relation to production targets. The model has been developed as Single Objective Optimization Problem, with an $\epsilon$-costraint representing the workers distancing, to support the Safety and Production Managers with the following tasks: (i) to include the physical distancing into a WS problem and (ii) to optimize the production capacity based on a distancing threshold among workers.

From a managerial perspective, this study and its activities have addressed the assessment of distancing requirements based on the sequence of assigned tasks, the impact of distancing constraints on production, and the identification of the workstations that do not allow to guarantee the safe distance, supporting Safety Managers and Production Managers in evaluating possible modifications of the layout or on the installation of additional protection systems.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Savino Matteo M. http://orcid.org/0000-0002-7266-8849

References

Ahmed, F., Zviedrite, N., & Uzicanin, A. (2018). Effectiveness of workplace social distancing measures in reducing influenza transmission: A systematic review. BMC Public Health, 18(1), 1–13.https://doi.org/10.1186/s12889-018-5446-1
Alfares, H. K., Bailey, J. E., & Lin, W. Y. (1999). Integrated project operations and personnel scheduling with multiple labour classes. Production Planning and Control, 10(6), 570–578. https://doi.org/10.1080/095372899232867

Algethami, R. L. P., & Landa-Silva, D. (2019). A genetic algorithm for a workforce scheduling and routing problem. IEEE Congress on Evolutionary Computation (CEC) (pp. 927–934). https://doi.org/10.1109/CEC.2016.7743889.

Ammar, A., & Elkosantin, S. (2013). Worker assignment problems in manufacturing systems: A literature analysis. International Conference on Industrial Engineering and Systems Management (IESM), 1(7), 1–7. https://ieeexplore.ieee.org/abstract/document/6761486.

Armenta, J. M. L., Josafat, R. C., Macam, F. J. L., Minas, C., Austin, T., & Cabal, E. M. (2022). Perception of Employees in the Implementation of a Safe Workplace in the Municipal Offices of a Local Government in Zamboales. 6(4), 18–23.

Aroui, K., Alpan, G., & Frein, Y. (2017). Minimising work overload in mixed-model assembly lines with different types of operators: A case study from the truck industry. International Journal of Production Research, 55(21), 1–22. https://doi.org/10.1080/00207543.2017.1346313

Battaia, O., & Dolgui, A. (2012). A taxonomy of line balancing problems and their solution approaches. International Journal of Production Economics, 142(2), 259–277. https://doi.org/10.1016/j.ijpe.2012.10.020

Cagliano, R., Caniato, F., Longoni, A., & Spina, G. (2014). Alternative uses of temporary work and new forms of work organisation. Production Planning and Control, 25(9), 762–782. https://doi.org/10.1080/09537287.2012.750387

Chircop, K., & Zammit-Mangion, D. (2013). On epsilon-constraint based methods for the generation of pareto frontiers. David Publishing.

Costa, A., Fichera, S., & Cappadona, F. A. (2013). A genetic algorithm for scheduling both jobs and skilled workforce. International Journal of Operations and Quantitative Management, 19(4), 221–247.

Cristani, M., Del Bue, A., Murino, V., Setti, F., & Vinciarelli, A. (2020). The visual social distancing problem. IEEE Access, 8, 126876–126886. https://doi.org/10.1109/ACCESS.2020.3008370

Dolgui, A., & Proth, J. M. (2010). Supply chain engineering: Useful methods and techniques (Vol. 539). Springer.

Felan, J. T., & Fry, T. D. (2001). Multi-level heterogeneous worker flexibility in a dual resource constrained (DRC) job-shop. International Journal of Production Research, 39(14), 3041–3059. https://doi.org/10.1080/00207540110047702

Gebennini, E., Zeppetella, L., Grassi, A., & Rimini, B. (2016). Minimizing operators’ walking times into a linear system layout. IFAC-PapersOnLine, 49(12), 1709–1714. https://doi.org/10.1016/j.ifacol.2016.07.828

Golbabaei, F., & Kalantari, S. (2020). A review of the strategies and policies for the prevention and control of the COVID-19 at workplaces. International Journal of Occupational Hygiene, 12(1), 60–65.

Güner, H. R., Hasanoglu, İ., & Aktaş, F. (2020). COVID-19: Prevention and control measures in community. Turkish Journal of Medical Sciences, 50(SI–1), 571–577. https://doi.org/10.3906/sag-2004-146

Haimes, Y. Y., Lasdon, L. S., & Wismer, D. A. (1971). On a bicriterion formulation of the problems of integrated system identification and system optimization. IEEE Transactions on Systems, Man, and Cybernetics, 1(3), 296–297 https://doi.org/10.1109/TSMC.1971.4308298.

Huremovíc, D. (2019). Psychiatry of Pandemics. Springer International Publishing.

Islam, N., Sharp, S. J., Chowell, G., Shabnam, S., Kawachi, I., Lacey, B., Massaro, J. M., D’Agostino, R. B., & White, M. (2020). Physical distancing interventions and incidence of coronavirus disease 2019: Natural experiment in 149 countries. British Medical Journal, 370. https://doi.org/10.1136/bmj.m2743

Kim, E. A. (2020). Social distancing and public health guidelines at workplaces in Korea: Responses to coronavirus Disease-19. Safety and Health at Work, 11(3), 275–283. https://doi.org/10.1016/j.shaw.2020.07.006
Lagodimos, A. G., & Paravantis, J. A. (2006). Improved heuristic for manpower shift planning with modified shift priorities. Production Planning and Control, 17(3), 301–310. https://doi.org/10.1080/09537280500285631

Moussavi, S. E., Zare, M., Mahdjoub, M., & Grunder, O. (2019). Balancing high operator’s workload through a new job rotation approach: Application to an automotive assembly line. International Journal of Industrial Ergonomics, 71, 136 144.

Moussavi, S. E., Zare, M., Grunder, O., & Mahdjoub, M. (2019). Balancing high operator’s workload through a new job rotation approach: Application to an automotive assembly line. International Journal of Industrial Ergonomics, 71, 136–144. https://doi.org/10.1016/j.ergon.2019.03.003

Nakade, K., & Nishiwaki, R. (2008). Optimal allocation of heterogeneous workers in a U- shaped production line. Journal of Computers and Industrial Engineering, 54(3), 432–440. https://doi.org/10.1016/j.jcie.2007.08.007

Niemi, E. (2009). Worker allocation in make-to-order assembly cells. Robotics and Computer Integrated Manufacturing, 25(6), 932–936. https://doi.org/10.1016/j.rcim.2009.04.008

Othman, M., Bhuiyan, N., & Gouw, G. J. (2012). Integrating workers’ differences into workforce planning. Computers & Industrial Engineering, 63(4), 1096–1106. https://doi.org/10.1016/j.cie.2012.06.015

Qu, S., Wang, J., Govil, S., & Leckie, J. O. (2016). Optimized adaptive scheduling of a manufacturing process system with multi-skill workforce and multiple machine types: An ontology-based, multi-agent reinforcement learning approach. 9th CIRP Conference on Manufacturing Systems - Procedia CIRP 57, 55–60. https://doi.org/10.1016/j.procir.2016.11.011.

Safaei, N., Banjевич, D., & Jardine, A. K. S. (2009). Multi-objective maintenance workforce scheduling in a steel company. IFAC Proceedings, 42(4), 1049–1054. https://doi.org/10.3182/20090603-3-RU-2001.0106.

Savino, M. M., & Neubert, G. (2009). Flow shop operator scheduling through constraint satisfaction and constraint optimization techniques. International Journal of Productivity and Quality Management, 4(5), 549–568. https://doi.org/10.1504/IJPQM.2009.025185

Savino, M. M., Brun, A., & Mazza, A. (2014). Dynamic workforce allocation in a constrained flow shop with multi-agent system. Computers in Industry, 65(6), 967–975. https://doi.org/10.1016/j.compind.2014.02.016

Savino, M. M., Riccio, C., & Menanno, M. (2019). Empirical study to explore the impact of ergonomics on workforce scheduling. International Journal of Production Research, 58(2), 415–433. https://doi.org/10.1080/00207543.2019.1591645

Sennott, L. I., Van Oyen, M. P., & Iravani, S. M. R. (2006). Optimal dynamic assignment of a flexible worker on an open production line with specialists. European Journal of Operational Research, 170(2), 541–566. https://doi.org/10.1016/j.ejor.2004.06.030

Setti, L., Passarini, F., De Gennaro, G., Barbieri, P., Perrone, M. G., Borelli, M., Palmisani, J., Di Gilio, A., Piscitelli, P., & Alessandro Miani, A. (2020). Airborne transmission route of COVID-19: Why 2 meters/6 feet of inter-personal distance could not be enough. International Journal of Environmental Research and Public Health, 17(8), 2932. https://doi.org/10.3390/ijerph17082932

Singh Arora, J. (2017). Introduction to optimum design (Fourth ed.). Elsevier.

Sirovetnukul, R., & Chutima, P. (2010). The impact of walking time on U-shaped assembly line worker allocation problems. Engineering Journal, 14(2), 53–78. https://doi.org/10.4186/ej.2010.14.2.53

Sun, C., & Zhai, Z. (2020). The efficacy of social distance and ventilation effectiveness in preventing COVID-19 transmission. Sustainable Cities and Society, 62, 102390. https://doi.org/10.1016/j.scs.2020.102390

Techawiboonwong, A., & Yenradee, P. (2003). Aggregate production planning with workforce transferring plan for multiple product types. Production Planning and Control, 14(5), 447–458. https://doi.org/10.1080/09537280310001597343
Techawiboonwong, A., Yenradeea, P., & Dasb, S. K. (2006). A master scheduling model with skilled and unskilled temporary workers. *International Journal of Production Economics, 103*(2), 798–809. https://doi.org/10.1016/j.ijpe.2005.11.009

Teslya, A., Pham, T. M., Godijk, G. N., Kretzschmar, M. E., Bootsma, M. C. J., Rozhnova, G., & Guo, Y. (2020). Impact of self-imposed prevention measures and short-term government-imposed social distancing on mitigating and delaying a COVID-19 epidemic: A modelling study. *PLoS Medicine, 17*(7), e1003166. https://doi.org/10.1371/journal.pmed.1003166

Thompson, G. M., & Goodaleb, J. C. (2006). Variable employee productivity in workforce scheduling. *European Journal of Operational Research, 170*(2), 376–390. https://doi.org/10.1016/j.ejor.2004.03.048

Visentin, V., Sgarbossa, F., Calzavara, M., & Persona, A. (2018). Fatigue accumulation in the assignment of manual material handling activities to operators. *IFAC-PapersOnLine, 51*(11), 826–831. https://doi.org/10.1016/j.ifacol.2018.08.441

Wang, Q., Lassalle, S., Mileham, A. R., & Owen, G. W. (2009). Analysis of a linear walking worker line using a combination of computer simulation and mathematical modeling approaches. *Journal of Manufacturing Systems, 28*(2–3), 64–70. https://doi.org/10.1016/j.jmsy.2009.12.001

Wang, S., & McLaren, J. (2020). *Effects of reduced workplace presence on COVID-19 deaths: An instrumental-variables approach*. National Bureau of Economic Research.

Xu, J., Xu, S., & Xie, S. Q. (2015). Recent developments in Dual Resource Constrained (DRC) system research. *European Journal of Operational Research, 215*(2), 309–318. https://doi.org/10.1016/j.ejor.2011.03.004