Production scheduling optimization for parallel machines subject to physical distancing due to COVID-19 pandemic

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Abstract
This paper, for the first time, presents a production scheduling model for a production line considering physical distancing between the machines' workforces. The production environment is an unrelated parallel-machine, in which for producing each part, different machines with different production rates and the required number of workers are available. We propose a three-objective mixed-integer linear programming mathematical model that aims to maximize the manufacturer's total benefit, parts' safety stock (SS) index, and the workforce's physical distance over a finite horizon (one year) by determining the optimal scheduling of the parts on the machines. Since a large production scheduling problem belongs to the Np-Hard category of problems, a non-dominated sorting genetic algorithm, and a non-dominated ranked GA algorithm are developed to solve the presented model in two stages using the empirical data from a Canadian plastic injection mold company. In the first stage, the LP-metrics approach is utilized for validating the meta-heuristics on a reduced-size problem. In the second stage, the validated meta-heuristics are utilized to optimize the company’s yearly production schedule. The results indicate both metaheuristics are performing well in determining the optimal solution. Moreover, implementing physical distancing in the company reduces the company’s monthly net benefit by around 9.56% compared to the normal operational conditions (without considering physical distancing).

Keywords COVID-19 pandemic · Physical distancing · Plastic injection mold · Parallel machines · Production planning-scheduling · NSGA-II · NRGA

1 Introduction
Workplace safety guidelines, i.e., face covering, physical distancing, and self-isolation (Ontario Agency for Health Protection and Promotion 2020) were published during the COVID-19 pandemic to help employers keep their workers safe and healthy while continuing their business operations. These instructions are often restrictive and costly, but are mandatory to be considered in the planning.

Production machines in manufacturing companies are usually fixed-in-place due to certain requirements, such as specific concrete foundations required for proper functioning of the machines. Moreover, at the design stage, the production line designers try to minimize the distance between the machines because of space limitations (Papadopoulos et al. 2009). Therefore, the layout of the machines that require labor forces may not fulfill physical distancing guidelines. It is challenging for manufacturers to incorporate physical distancing guidelines by revising fixed-in-place machines' layouts for a limited time period (during the pandemic). A feasible approach to overcome the problem is to incorporate the distance constraint in a production schedule.

This paper considers an unrelated parallel machines environment of a plastic injection mold production line. The production line has 32 different machines with various characteristics, producing 95 different parts. The parts can
be produced using a number of machines in the production line. However, the parts’ production rate depends on different parameters, such as the number of mold cavities. The production time horizon is one year, and the yearly demand for the parts is known. The parts can be produced in different time intervals during the production horizon, and there is a fixed setup time for producing the parts on the machines. The setup time is required to change the machines’ mold and prepare the machines for the part production in changeovers.

The machines’ layout is fixed, and there is not enough space to increase the distance between the machines. Since the machines need workforces for handling the production of the parts, considering the workforces’ physical distancing must be taken into account.

We present a three-objective mixed integer linear programming (MILP) model to overcome parts backorder. The presented model aims to simultaneously maximize the company’s net benefit, the parts’ SS index, and the workforces’ physical distance. The planning horizon is divided into daily time intervals, so the production scheduling problem is broken into a daily production scheduling problem. The motivation behind the study is to optimize a production schedule considering the physical distancing constraint during the COVID-19 pandemic. The proposed model provides the answer to the question “which part should be produced on which machine in which daily time interval?”.

The literature is limited on how physical distancing constraint at different stages of a pandemic can be incorporated in production scheduling environments, such as shop floors or parallel machines. Therefore, in this study for the first time, a new mathematical model is developed for optimizing the production schedule during a pandemic. The developed model consists of three objectives for quantifying the adverse effects of physical distancing constraint on the total net benefit. The proposed model is applied for scheduling a real-world smart manufacturing. Since the mathematical model is a non-linear complex mixed integer multi-objective optimization, GA-based optimization algorithms are utilized to determine the Pareto front.

Since the guidelines for physical distancing differ depending on the pandemic’s types and levels, we consider the workforce’s physical distance as one of the model’s objective functions. The proposed methodology is capable to be utilized for any level of physical distancing. In other words, considering the physical distancing as a model’s constraint, for example, more than two meters, is a special case of the current model that leads us only to the results in which the distance between the workforces is more than two meters. To explore the effects of incorporating the physical distancing restriction in a company with a set of fixed-in-place production machines, the production performance is investigated and compared for two specific scenarios, A and B. Scenario A represents the best-known operation during the normal condition, and Scenario B represents the best-known production during COVID-19 pandemic incorporating the mandatory 6-feet physical distancing.

Due to the complexity of the proposed mathematical model, and the superiority of the GA-based metaheuristic algorithms in solving the production scheduling problems (i.e., Berrichi et al. (2009); Rabiee et al. (2012); Yuan and Xu (2013); Han et al. (2014); Xi et al. (2015); Ahmadi et al. (2016); Shahriari et al. (2016); Musavi and Bozorgi-Amiri (2017); Afzalirad and Rezaeian (2017); Sheikhi et al. (2018); Nasiri et al. (2018); Tirkolaee et al. (2019); Yazdani et al. (2019); Salimifard et al. (2020)), we develop a non-dominated sorting Genetic algorithm (NSGA-II), and a non-dominated ranked Genetic algorithm (NRGA) to solve the model. Our approach consists of two stages. In the first stage, for validating the algorithms, the problem is narrowed down to a critical zone of the studied manufacturing company. In the next stage, the validated algorithms are utilized for solving the actual size problem. We consider a reduced size problem for the algorithms’ validation, consisting of 5 machines and 14 parts. We then solve the proposed multi-objective model using the Lp-Metrics for a one-month time interval, and validate the algorithms’ performance with the result of the Lp-Metrics.

The rest of the paper is organized as follows: in Sect. 2, the related works are summarized, and the gap of the literature is presented. In Sect. 3, the multi-objective mathematical model is presented in detail. Section 4 deals with the solving methodology. In Sect. 5, a real-case study is presented in detail and solved using the metaheuristics, followed by the managerial insights. Finally, the conclusion and some directions for further studies are presented in Sect. 6.

2 Literature review

Optimization of machine scheduling problems is one of the most critical issues in modern manufacturing. Therefore, many studies on optimizing production schedules have been conducted (Yamashiro and Nonaka 2021). However, all the studies to date have considered manufacturing operations during normal conditions. Currently, many manufacturing companies around the globe are expected to implement workplace safety guidelines in response to the COVID-19 pandemic, which impacts the production scheduling of machines. Given the paper’s focus, the related literature is divided into two parts: COVID-19 and parallel machines scheduling. Since the start of the COVID-19 pandemic in late 2019, some publications have studied the impact of COVID-19 on businesses, including manufacturing. For example, the effect of COVID-19 has been investigated on sustainable production (Kumar et al. 2020), supply chain resilience (Handfield et al. 2020; Gunese and Subramanian 2020; Sarkis 2020; Ivanov and Das 2020), manufacturing...
supply chains (Paul and Chowdhury 2020; Qin et al. 2021; Wen and Liao 2021; Hajiagha et al. 2021), intelligent manufacturing technologies (Shen et al. 2020), medical applications production (Malik et al. 2020; Patel and Gohil 2020), manufacturing technologies (Tarfaoui et al. 2020; Chen and Lin 2020), learning and image processing (Jiang et al. 2021), Internet of Things (Singh et al. 2020; Nasajpour et al. 2020; Tan et al. 2020; Li et al. 2018a), and Industry 4.0 content (Czifra and Molnár 2020).

Kumar et al. (2020) provided a path-breaking idea to deal with the current business’s pandemic situation and make a contingency plan to control and revamp future events. They also recommended various pandemic control systems to improve the resilience and sustainability of production systems. Ivanov and Das (2020) modeled the effect of epidemic outbreaks (especially COVID-19/SARS-CoV-2 virus) on a global supply chain. To build their model, they considered the pandemic propagation’s velocity, the duration of the production, and the market disruption, distribution, and demand decline. They also analyzed the pandemic supply risk mitigation and potential recovery paths. Paul and Chowdhury (2020) developed a mathematical model to produce essential high-demand items during the COVID-19 pandemic. They analyzed the recovery plan’s attributes, and maximized the production’s profit in the recovery windows.

Qin et al. (2021) examined the impact of COVID-19 and health expenditure on the global supply chain by utilizing balanced panel data (balanced multi-dimensional data involving measurements over time) for the period from January 2020 to June 2020. Wen and Liao (2021) captured the attitudinal characteristics of decision-makers in a large-scale group decision-making process to ensure the comprehensiveness and reliability of decision recommendations for mitigating the negative impact of COVID-19. Hajiagha et al. (2021) considered the problem of time–cost tradeoff in supply chains project management, and extended it to time, cost, and risk tradeoff. The risk factor was considered to convey the uncertainty arising from the COVID-19 pandemic situation.

Shen et al. (2020) discussed how during the COVID-19 pandemic, collaborative intelligent manufacturing technologies could improve collaborative supplier networks’ resilience and address supply chain breakages and workforce shortages on shop floors. Malik et al. (2020) proposed the integration of human–robot teams to ramp up production while maintain social distancing. Patel and Gohil (2020) investigated the key role of additive manufacturing in stopping the spread of COVID-19 by providing customized parts on-demand quickly and locally, reducing waste, and eliminating the need for an extensive manufacturer.

Tarfaoui et al. (2020) provided a background study of COVID-19, its conventional preventive measures, and described the latest additive manufacturing role in the fight against COVID-19. Using an evolving fuzzy assessment approach, Chen and Lin (2020) worked on the effect of smart and automation technologies to ensure a factory’s long-term operation amid the COVID-19 pandemic. Czifra and Molnár (2020) used renowned experts’ publications to answer some COVID-19-related questions, such as “How can we handle this situation?”, “How does business flexibility help us?”, “How can we use modern technology to restore the functioning of the economy?”, and “How can losses be reduced?”.

Malik et al. (2020) and Murray (2020) conducted the only physical distancing-related work. Murray (2020) used a spatial optimization approach to plan classrooms considering physical distancing. He implemented the model in a university campus to illustrate how spatial optimization can support safety enhancements. However, to the best of the authors’ knowledge, the current paper is the first one that addresses the optimization of the production schedule with the consideration of physical distancing.

In the viewpoint of parallel machines scheduling, Centeno and Armacost (1997) presented an algorithm to minimize the maximum lateness in a parallel machines environment with release dates. Kim et al. (2002) presented a scheduling problem for unrelated parallel machines with sequence-dependent setup times and solved the presented model using simulated annealing (SA). They assumed the job refers to a lot composed of \( N \) items, in which the items in the same lot were assumed to have the same processing times with the same machine. The machine in their model had different processing times according to the characteristics of the machine and the type of allocated job. Liao and Sheen (2008) considered a scheduling problem with independent jobs, and incorporated machines’ availability and eligibility constraints to minimize the makespan. They proposed a polynomial-time binary search to find the optimal solution when it exists.

Berrichi et al. (2009) presented a bi-objective production and maintenance scheduling problem to find the compromised solutions between the production objectives and maintenance ones. Unlu and Mason (2010) provided four MIP formulations for different parallel machines scheduling problems. They provided these models based on the type of the decision variables. They considered four different types of objective functions: minimizing the total weighted completion time, minimizing total weighted tardiness, minimizing the maximum lateness, and minimizing the total number of tardy jobs. They aimed to identify the challenges of optimization formulations for solving large-scale scheduling problems and providing tighter lower solution bounds. Bulin (2011) proposed a new crossover operator and a new optimality criterion to adapt a genetic algorithm (GA) for a non-identical parallel machines scheduling problem, and minimized the makespan. Lee et al. (2013) considered the sequence-dependent setup times for an unrelated parallel machines scheduling environment with independent jobs.
and minimized the total tardiness. They presented a general integer programming model considering a sequence-based jobs’ completion time constraint. They used a tabu search (TS) algorithm and an iterated greedy algorithm to solve the proposed model. The results showed the superiority of the TS in solving the problem.

MILP is a practical modeling approach, which due to its solution stability and global search capabilities has been used by many researchers for optimizing scheduling problems. For example, Tirkolaee et al. (2020) recently used it for flow shop scheduling, and Goli et al. (2021) for scheduling the parts within cells in a cellular manufacturing system. Şen and Bulbül (2015) developed a new preemptive relaxation for total weighted tardiness and total weighted earliness/tardiness MILP problems. They solved the proposed problems using an effective benders decomposition algorithm.

Joo and Kim (2015) provided a MIP mathematical model to minimize the total completion time of an unrelated parallel machines scheduling problem with sequence- and machine-dependent setup and processing times. They used a hybrid GA (HGA) meta-heuristic to solve the proposed mathematical model with three different dispatching rules. Xi et al. (2015) proposed a linear binary programming model to minimize the total weighted tardiness of identical parallel machines and solved the proposed model using a look-ahead and look-back heuristic. They considered when a machine becomes idle, it selects a job from available jobs and near-future jobs to process. Avalos-Rosales et al. (2015) studied an unrelated parallel machines scheduling problem with sequence and machine-dependent setup times, and minimized the makespan. They developed a MILP mathematical model that minimized the total jobs’ completion time, and proposed a metaheuristic algorithm to solve the model, which worked based on a multi-start and variable neighborhood descent meta-heuristic. Afzalirad and Rezaeian (2016) worked on an unrelated parallel machines scheduling problem with resource constraints, sequence-dependent setup times, different release dates, machine eligibility, and precedence constraints. They developed a pure integer mathematical model to minimize the makespan. They used a GA and an artificial immune system to solve their developed model. Fanjul-Peyro et al. (2017) presented two integer linear programming problems to minimize the makespan of a parallel machines scheduling problem with scarce resource-required machines and limited and fixed production horizon. They proposed three meta-heuristic algorithms for solving the model.

Woo and Kim (2018) studied a parallel machines scheduling problem with time-dependent deterioration and multiple rate-modifying activities (RMAs). They developed a MILP mathematical model which simultaneously determines the number and positions of RMAs and the jobs schedule on parallel machines to minimize the makespan. The provided model was then solved using GA and simulated annealing (SA) metaheuristics. Li et al. (2018b) worked on two uniform parallel machines scheduling problems with fixed machine cost, aiming to minimize the makespan with a given budget. Afzalirad and Shafipour (2018) presented an integer programming mathematical model that minimizes the makespan for an unrelated parallel machines scheduling problem with machine eligibility restrictions. They solved their model using GA and hybrid GA algorithms. Hung et al. (2019) proposed a non-standard MILP mathematical model that maximizes the proportion of each job to be processed in each interval. They presented a classical preemptive parallel machines scheduling problem to maximize the number of on-time jobs, and proposed heuristics based on different design strategies. Bektur and Saraç (2019) provided a MILP mathematical model to minimize the weighted tardiness of an unrelated parallel machines scheduling problem with shared servers, sequence-dependent setup times, and machine eligibility restrictions. They solved the developed MILP using tabu search and SA metaheuristics.

Caricato et al. (2020) addressed a parallel machines scheduling problem with sequence-dependent setup times and additional resource constraints related to workforce management, and proposed an ad hoc procedure to solve the model. Soper and Strusevich (2018) presented a parametric analysis of a scheduling problem with three uniform parallel machines to minimize the makespan. They compared the quality of a schedule with at most one preemption with the quality of the global optimal schedule with any number of preemptions. Agung et al. (2021) proposed a parallel-job scheduling method that effectively uses shared heterogeneous systems for urgent computations. Their method employed an in-memory process swapping mechanism to preempt jobs running on the coprocessor devices.

Although many production scheduling problems are solvable in polynomial times, the production planning-scheduling problems are NP-hard in nature (Ghaleb et al. 2020a, b; Sharifi and Taghipour 2021). Thus, many heuristics and metaheuristics (single-objective and multi-objective) were developed to solve them. Examples include NSGA-II and NSGA-III (Berrichi et al. 2009; Xi et al. 2015; Rabiee et al. 2012; Yuan and Xu 2013; Han et al. 2014; Ahmadi et al. 2016; Shahriri et al. 2016; Musavi and Bozorgi-Amiri 2017; Afzalirad and Rezaeian 2017; Sheikh et al. 2018; Nasiri et al. 2018; Tirkolaee et al. 2019; Yazdani et al. 2019; Salimifard et al. 2020), NRGA (Berrichi et al. 2009; Rabiee et al. 2012; Ahmadi et al. 2016; Shahriri et al. 2016; Nasiri et al. 2018; Yazdani et al. 2019), multi-objective genetic algorithm (Ahmadi et al. 2016), Pareto archive evolutionary strategy (Rabiee et al. 2012), multi-objective ant colony optimization (Afzalirad and Rezaeian 2017), multi-objective particle swarm optimization (Shahriri et al. 2016; Sheikh et al. 2018; Salimifard et al. 2020), and multi-objective simulated annealing algorithm (Tirkolaee et al. 2019).
This paper filled the literature gap by presenting a three-objective MILP mathematical model for a parallel machines production planning-scheduling problem considering physical distancing. The novelty of this paper can be summarized as follows:

- Presenting a new three-objective MILP model for a parallel machines production-scheduling and workforce planning problem with the consideration of physical distancing,
- Optimizing the model using empirical data, and
- Determining the investment opportunity cost during the COVID-19 (and other future pandemics).

Presenting a mathematical optimization model for production scheduling considering physical distancing is the main difference between the current study and other existing models. To the best of our knowledge, no other studies considered the physical distancing between the workforces in production lines.

### 3 Problem formulation

In this paper, a thermoplastic manufacturing company that must be active during the pandemic is considered. The company produces various plastic components for the automation industry using thermoplastic injection machines. For producing a part, there is a specific mold that should be installed on the machines. The molds have different sizes and cavity numbers. Depending on the parts’ characteristics, there is a set of alternative machines where the mold can be installed on them. Thus, the problem is categorized under a parallel machines scheduling environment. Installing the molds on the machines requires setup time. The production cycle times are part-dependent. Cycle time in this paper refers to two consecutive mold injections. Moreover, the parts’ production is preemptive, implying that the parts can be produced at different times. We considered the time windows are daily, which means the goal is to determine the production planning-scheduling for each day.

Moreover, the workforces must follow the physical distancing constraint during the pandemic. Thus, the workforces need to be planned. Produced parts have certain net benefits, which are part-dependent. On the other hand, the overdue production is subject to considerable penalty, namely shortage cost. To combat the production fluctuations, the manufacturers usually include an inventory buffer capacity. In addition to fulfilling the demand, maintaining the buffer capacity to the maximum attainable amount is a task that should be taken to reduce the risk of failure in the demand fulfillment in the next periods.

We formulate the governing constraints and the objectives of the problem. The required primary data and information for the case study are collected from a Canadian company. The data is then utilized for designing the model and the test problems. We address the nomenclature, the model’s assumptions, and the developed mixed integer linear problem in the following sub-sections, and utilize the metaheuristic algorithms. We consider the physical distancing as an objective function for the presented model. The aim is to maximize the distance. This consideration is to allow the evaluation of the outcomes for different distancing scenarios, including the six feet established for the COVID-19 pandemic.

#### 3.1 Nomenclatures

##### 3.1.1 Dimensions

| Symbol | Description |
|--------|-------------|
| $T$    | Planning horizon, |
| $N_i$  | Number of parts, |
| $N_m$  | Number of machines, |
| $N_t$  | Number of time windows, $N_t = T/\delta$ |

##### 3.1.2 Indices

| Symbol | Description |
|--------|-------------|
| $t$    | Period index, $t = 1, 2, \ldots, N_t$ |
| $i$    | Part type index, $i = 1, 2, \ldots, N_i$ |
| $m$    | Machine number index, $m = 1, 2, \ldots, N_m$ |

##### 3.1.3 Parameters

| Symbol | Description |
|--------|-------------|
| $\delta$ | Duration of each time window, |
| $\delta_i$ | Setup time duration, |
| $V_i$ | Number of cavities of the mold utilized for producing part type $i$, |
| $Y_i$ | Production cycle time of part type $i$, |
| $D_i$ | The demand for part type $i$, |
| $B_i$ | The net benefit of part type $i$, |
### 3.1.4 Auxiliary Variables

- \( C_i \): Unit shortage cost of part type \( i \),
- \( W_{i,m} \): Number of workers required to produce part \( i \) on machine \( m \), \( W_{i,m} \in \{0, 1\} \)
- \( L_i \): The initial quantity of part type \( i \),
- \( E_i^{\text{Req}} \): Required quantity buffer capacity target for part type \( i \),
- \( d_{m_1,m_2} \): The distance between machines \( m_1 \) and \( m_2 \),
- \( a_{i,m} \): 1, if machine \( m \) can produce part type \( i \); 0, otherwise

### 3.1.5 Decision variables

- \( S_{i,m,t} \): 1, if machine number \( m \) is allocated for producing part type \( i \) at time window \( t \); 0, otherwise

### 3.2 Assumptions

The following assumptions have been considered to formulate the problem based on the company’s production process:

- The machines’ layout is fixed,
- For producing a part, there is a specific mold with known cycle time, number of cavities, and required workers,
- At the beginning of the production period, the set of jobs based on specific demand and SS is available,
- The jobs can be scheduled on different (not all) machines,
- A machine might be busy with a specific job, or be idle without any allocated job,
- Setup time is required for each production changeover,
- The critical distance between the machines is the minimum distance between the workers who are working with any two active machines,
- A two-week SS is assumed as the target buffer capacity, \( D_i^{\text{Req}} \). For any part \( i \), the value of two-week SS is equal to 1/25 of the parts’ demand, considering that each year has 50 working weeks,
- For any specific job, there is a set of alternative machines that can be utilized for the production,
- Two types of shortages, namely minor and major, are considered in this study. The minor shortage is the number of parts required to fulfill the demand. The major shortage is the number of parts required to be produced for fulfilling the demand and meet the two weeks SS.
- Only one mold is available to be installed on the machines for production. Therefore, at each time window, we cannot produce a part in parallel on several machines,
- No constraint on the total number of required workers is considered,
- The developed model is general enough to model all the operating machines in the company,
- There is no limitation on the number of jobs and the length of the planning horizon,
- Since the mission horizon is one year, the time value of money is not considered in this model.

### 3.3 Optimization model

The feasible state of any individual production machine can be summarized as (i) idle mode, (ii) busy with producing parts, where their production is possible without any worker, and (iii) busy for producing parts that require worker(s) for production. Therefore, in some specific cases, the optimization model is free to choose idle status for a limited time to fulfill the physical distancing requirement while maximizing the total net benefit. Choosing a proper production status for a specific machine depends on the type of produced parts, demand, the parts’ net benefit, inventory status, overdue penalty of the parts, and the list of available alternative machines that could be utilized for production. The objective functions and the constraints of the proposed optimization model are discussed in detail in the following subsections.

#### 3.3.1 Objective functions

The proposed model’s goal can be divided into the following objectives: maximizing the net benefit, maximizing the SS index, and maximizing the physical distance between the workers. These objectives contrast with each other since when we maximize the net benefit, the optimal solution occurs on the minimum level of the SS index and the physical distance. When we intend to maximize the physical distance, the optimal solution
is around the minimum SS index, and is very costly. Finally, when we maximize the SS index, the optimal solution is around the minimum physical distance value, and it is again expensive.

1. **Maximizing the net benefit**: Manufacturers are willing to maximize their benefit by choosing a proper production schedule considering the physical distancing constraint. Since manufacturers might not be physically able to fulfill the usual demands due to the pandemic-related conditions, the overdue cost must be considered. Therefore, the net benefit is the difference between the total benefit received by selling the parts produced at the end of the planning horizon and the overdue cost the company is charged if it fails to fulfill the production commitment. In the presented mathematical model, the net benefit is calculated by summing the benefits and subtracting the production costs from it. Therefore, in quantifying the net benefit of each type of part, the production costs and the revenue from its sale are considered and integrated into parameter \( B_i \). The net benefit is formulated as follows:

\[
\text{Max } Z_1 = \sum_{i=1}^{N_i} (P_i - R_i - C_i)
\]

(1)

2. **Maximizing the SS index**: Production downtime is challenging for manufacturing companies. Since downtime is generally unexpected and unavoidable, companies try to provide a buffer capacity for combating the problem. The minimum required SS (\( E_i^{\text{Req}} \)) for unexpected downtime is part-dependent, and is pre-defined based on the historical data. Maximizing the SS index, \( Z_2 \), presented in Eq. (2), is considered for maintaining the minimum SS required for combating failure events.

\[
\text{Max } Z_2 = \sum_{i=1}^{N_i} \sum_{j=1}^{N_i} \min \{ 1, E_i/E_i^{\text{Req}} \}
\]

(2)

3. **Maximizing critical physical distance (\( D_{cr} \))**: Maintaining the critical distance between the individual workers is a top priority during the pandemic. However, the allowable critical distance for different pandemics and different stages of pandemics might change over time. The machines’ layout is fixed. Therefore, the critical physical distance can be determined at any specific time window based on the machines’ layout and the machines’ working zone. This study considers the critical physical distance (\( D_{cr} \)) between the individual workers. Let us define the distance matrix between the workers at \( t^{th} \) time window, as follows:

\[
D^{(t)} = \left( d_{m_1,m_2}^{(t)} \right)_{N_m \times N_m} \text{ For } m_1, m_2 = 1, \ldots, N_m
\]

(3)

In Eq. (3), the main diagonal of matrix \( D^{(t)} \) refers to the condition that \( m_1 = m_2 \). The values of the main diagonal are equal to +\( \infty \). For other elements, when \( \sum_{i=1}^{N_i} W_{i,m_1} = \sum_{i=1}^{N_i} W_{i,m_2} = 1 \), machines \( m_1 \) and \( m_2 \) are two different machines that are producing one specific part which needs a workforce. So, in this condition \( d_{m_1,m_2}^{(t)} = d_{m_1,m_2} \). Nevertheless, when \( \sum_{i=1}^{N_i} W_{i,m_1} = 0 \) or \( \sum_{i=1}^{N_i} W_{i,m_2} = 0 \), at least one of these two machines are idle, so the value of the corresponding element is equal to \( d_{m_1,m_2}^{(t)} = +\infty \).

Equations (19), (20), (21), (22), (23), and (24) are the constraints that define the values of matrix \( D^{(t)} \) at time interval \( t \). The critical distance in this study is defined as follow:

\[
D_{cr} = \min_{\forall t \in T} D_{cr}^{(t)}
\]

(4)

To study the influence of different minimum required distance between the workers on the manufacturing performance, \( D_{cr} \) is considered as an objective to be maximized. Maximizing the critical distance (\( Z_3 \)), which accounts for taking into account the effect of physical distancing constraint, is considered as the third objective:

\[
\text{Max } Z_3 = D_{cr}
\]

(5)

### 3.3.2 Constraints

Since the problem consists of an integer and non-integer variables, the MILP programming approach is deployed to include the objectives described in Eqs. (1), (2), and (5). With the notation defined in the previous sub-sections (Eqs. 1, 2, 3, 4, and 5), the problem can be formulated as the following mixed-integer linear programming model. Equations (6) to (24) are the constraints derived through the analysis of the problem. In the proposed approach, it is assumed that each machine in each specific time window can be utilized for producing a specific part (Eq. 6). All machines require a setup time at the start of the scheduling, \( t = 1 \), for installing the proper mold for a part production (Eq. 7).

\[
\sum_{i=1}^{N_i} S_{i,m,t} \leq 1; \quad \forall m, \forall t
\]

(6)

\[
\delta_{i,m,t} = (\delta - \delta_i)S_{i,m,t}, \quad \forall t = 1, m, i
\]

(7)

In case of a changeover, a portion of the time window must be allocated to setting the new mold, which results in a reduced time window for the part production. For determining the effective duration of each time window that could be used for
the production, Eqs. (8), (9), and (10) are included. Using this set of equations, the efficient time window is reduced to zero, if no job is allocated to a specific machine during a time window. Moreover, if during two consecutive time windows $t - 1$ and $t$, the same product is scheduled on the same machine, there is no need for setup time at the beginning of the time window $t$. In this case, we have $\delta_{i,m,t} = \delta$. Finally, if a new product is scheduled on machine $m$ for time window $t$, we have $S_{i,m,t-1} = 0$ and $S_{i,m,t} = 1$, and we conclude that $\delta_{i,m,t} = \delta - \delta_s$.

$$\delta_{i,m,t} \leq \delta - (S_{i,m,t} - S_{i,m,t-1}).\delta_s + (1 - S_{i,m,t}).T; \quad \forall t \geq 2, m, i$$  
(8)

$$\delta_{i,m,t} \geq \delta - (S_{i,m,t} - S_{i,m,t-1}).\delta_s - (1 - S_{i,m,t}).T; \quad \forall t \geq 2, m, i$$  
(9)

$$\delta_{i,m,t} \leq S_{i,m,t}.T; \quad \forall t \geq 2, m, i$$  
(10)

Equation (11) is used to calculate the total number of part type $i$ produced during the planning horizon, which depends on the number of the mold cavity and the production cycle of this product.

$$P_i = \sum_{m=1}^{N_m} \sum_{t=1}^{T} \frac{V_i.S_{i,m,t}}{Y_i}; \quad \forall i$$  
(11)

Equations (12), (13), (14), (15), and (16) are used to incorporate the governing rules of the shortage and SS of any part type $i$ at the end of the planning horizon, where $M$ is a very large positive number. In Eq. (12), $P_{i}^{m'}$ is a binary auxiliary variable that helps to make a balance between the produced quantity, the initial inventory, and the demand of part $i$. According to Eq. (12), the value of the sold production type $i$ should only be equal to $D_t$ (demand) or $P_i + L_i$ (produced quantity plus the initial inventory). If $P_i + L_i < D_t$, the sold quantity is equal to $P_i + L_i$, and the value of $P_{i}^{m'}$ is equal to zero. If $P_i + L_i > D_t$, the sold quantity is equal to $D_t$, and the value of $P_{i}^{m'}$ is equal to one. In Eqs. (15), (16), (17), and (18), $R_i$ is a binary auxiliary variable to ensure we only have shortage or SS at the end of the mission horizon, not both. If $P_i + L_i < D_t$, at the end of the mission horizon, we will face a shortage. In this case, the value of $R_i$ is equal to one, and $E_i = 0$, which means we have no SS. If $P_i + L_i > D_t$, at the end of the mission horizon, we will have SS. In this case, the value of $R_i$ is equal to zero, and $E_i = 0$, which means we have no shortage.

$$P_i \leq P_i + L_i + P_{i}^{m'},M; \forall i$$  
(12)

$$P_i \geq P_i + L_i - P_{i}^{m'},M; \forall i$$  
(12)

$$P_i \leq D_t + (1 - P_{i}^{m'}).M; \forall i$$  
(12)

$$P_i \geq D_t - (1 - P_{i}^{m'}).M; \forall i$$  
(12)

$$P_{i}^{m'} \leq P_i + L_i; \quad \forall i$$  
(13)

$$P_{i}^{m'} \leq D_t; \quad \forall i$$  
(14)

$$R_i - E_i = D_t - (P_i + L_i); \quad \forall i$$  
(15)

$$R_i \leq R_i^{'},M; \quad \forall$$  
(16)

$$E_i \leq (1 - R_i^{'}).M; \quad \forall i$$  
(17)

$$E_i \leq E_i^{Req}, \quad \forall i$$  
(18)

The critical distance is essential for any two machines at each time window, if both machines are active and require a workforce (Eqs. 19, 20, 21, 22, 23, and 24). The required number of workers for the production is part-dependent. It is assumed that there is enough workforce in each time period. Equations (19) and (20) ensure if, in time interval $i$, the machine number $m$ is producing a part which needs a workforce, the value of $S_{i,m,t}$ is equal to one, and if the machine is idle or producing a part that does not need a workforce, the value of $S_{i,m,t}$ is equal to zero. Equation (21) defines that for the main diagonal of matrix $D_{cr}$, $d_{m_1,m_2} = \infty$. Equations (22), (23), (24), and (25) determine the actual distance between all workers in each time interval, depending on the condition of the machines and the type of the allocated parts to them.

$$\sum_{i=1}^{N_i} S_{i,m,t}.W_{i,m} \leq S_{i,m,t}^{m'},M; \quad \forall m, t$$  
(19)

$$S_{i,m,t}^{m'} \leq M. \sum_{i=1}^{N_i} S_{i,m,t}.W_{i,m}; \quad \forall m, t$$  
(20)

$$d_{m_1,m_2}^{i} = \infty; \quad \forall m_1, m_2, t, m_1 = m_2$$  
(21)

$$d_{m_1,m_2}^{i} \leq d_{m_1,m_2}^{i} + (1 - S_{i,m,t}^{m'}).M + (1 - S_{i,m,t}^{m'}).M; \quad \forall m_1, m_2, t$$  
(22)

$$d_{m_1,m_2}^{i} \geq d_{m_1,m_2}^{i} - (1 - S_{i,m,t}^{m'}).M - (1 - S_{i,m,t}^{m'}).M; \quad \forall m_1, m_2, t$$  
(23)

$$d_{m_1,m_2}^{i} \leq \max(d_{m_1,m_2}^{i}), \quad \forall m_1, m_2, t$$  
(24)

$$D_{cr} \leq d_{m_1,m_2}^{i}; \quad \forall m_1, m_2, t, m_1 \neq m_2$$  
(25)

Equation (26) defines that only pre-defined set of parts (based on the value of $a_{i,m}$) can be allocated to each machine.

$$\sum_{i=1}^{N_i} S_{i,m,t} \leq a_{i,m},M; \quad \forall m, i$$  
(26)

Equation (27) is used for defining the non-negative and integer variables.
For solving the proposed model, the value of $M$ is set to $M = 1,000$.

### 3.3.3 Model complexity

The mathematical optimization model presented in the previous subsections (Sects. 3.3.1 and 3.3.2) is a MILP for production planning and scheduling. Production planning and scheduling problems are generally classified as NP-hard problems (Lenstra et al. 1977). Therefore, the problem under investigation can be classified as an NP-hard problem. Moreover, the proposed case study has 20,400 decision variables and 118,460 constraints that make it hard to be solved using the known solvers, such as CPLEX. So, due to the complexity of this problem, the use of the proposed MILP solver to solve the problem is not sufficient, as it may not result in good quality solutions for large-scale problems (i.e., the proposed case study). Therefore, we use an Lp-Metrics method from scalarizing approach and NSGA-II and NRGA from evolutionary algorithms to solve the model. The proposed algorithms are described in Sect. 4.

### 4 Solving methodology

In general, there are two approaches to solve multi-objective problems. These two approaches include scalarizing and evolutionary algorithms. Scalarizing a multi-objective optimization problem is a method that turns the problem into a single-objective problem, such that the optimal solution of the single-objective optimization problem is Pareto optimal solution of the multi-objective optimization problem. Evolutionary algorithms are popular approaches to generate Pareto optimal solutions for a multi-objective optimization problem.

In this research, the Lp-Metrics method, a scalarizing approach, and NSGA-II and NRGA, evolutionary algorithms have been used to solve the proposed model. Since the Lp-Metrics is an exact solution method for MILP, it has been used to validate NSGA-II and NRGA.

NSGA-II and NRGA algorithms have been widely used in solving production planning problems (i.e., Berrichi et al. 2009; Rabiee et al. 2012; Yuan and Xu 2013; Han et al. 2014; Xi et al. 2015; Ahmadi et al. 2016; Shahriari et al. 2016; Musavi and Bozorgi-Amiri 2017; Afzalrad and Rezaeian 2017; Sheikh et al. 2018; Nasiri et al. 2018; Tirkolaee et al. 2019; Yazdani et al. 2019; Salimifard et al. 2020). The main advantages of these approaches are their scalability with the number of objectives and insensibility to the nonconvexity of the Pareto optimal front. Given the acceptable performance of these algorithms in optimizing complicated scheduling problems, they are used to optimize the presented MILP model. In this section, the structures of the solving algorithms are presented.

#### 4.1 NSGA-II

This algorithm, presented by Deb et al. (2000), is one of the most practical algorithms to solve multi-objective scheduling problems. The mechanism of NSGA-II is shown in Fig. 1 (Deb et al. 2000).

#### 4.2 NRGA

Al Jadaan et al. (2008) presented a population-based multi-objective non-dominated ranking genetic algorithm (NRGA) evolutionary algorithm to solve non-convex, discrete non-linear optimization problems (similar to the current paper’s problem). NRGA is developed based on a novel ranking-based roulette wheel selection approach to find Pareto fronts, and has a wide range of applicability in solving multi-objective scheduling problems (i.e., Berrichi et al. 2009; Rabiee et al. 2012; Ahmadi et al. 2016; Shahriari et al. 2016; Nasiri et al. 2018; Yazdani et al. 2019). The flowchart of NSGA-II and NRGA algorithms is shown in Fig. 2. In this flowchart, the selection operators for NSGA-II and NRGA are “binary tournament selection” and “roulette wheel selection”, respectively.
4.3 Chromosome structure and the algorithms’ operators

The chromosome structure used in this study is a matrix of size \( N_m \times N_t \), shown in Fig. 3. Any specific elements of this matrix, \( O_{m,t} \), represents the status of machine \( m \) at time window \( t \). The status of a machine is an integer number that varies in the range \([0, N_i]\). If machine number \( m \) is allocated for producing part type \( i \) at time window \( t \), \( O_{m,t} = i \). It is worth noting that \( O_{m,t} = 0 \) represents the idle status of machine number \( m \) at time window \( t \).

The decision variable, \( S_{i,m,t} \), initializes using Eq. (28) in accordance with the chromosome structure:

\[
\forall i, m, t : \begin{cases} 
S_{O_{m,t}, m, t} = 1; & \text{if } O_{m,t} \neq 0 \\
S_{i, m, t} = 0; & \text{if } O_{m,t} = 0 
\end{cases}
\]  

(28)

In this paper, the solution procedure is population-based, in which the initial solutions are randomly generated. Through an evolutionary approach, the algorithms converge to the non-dominated solution set. The crossover and mutation are used as search operators. The crossover operator is a continuous type of uniform crossover (Gen and Cheng 1997) using a mask matrix (Tavakkoli-Moghaddam et al. 2008). The genomes of the two offspring are generated using \( Parent_1 \times Mask + Parent_2 \times (1 - Mask) \) and \( Parent_1 \times (1 - Mask) + Parent_2 \times Mask \). For the mutation, parent chromosomes are randomly selected and muted using a mask matrix. If an element of the mask matrix is smaller than a threshold value, namely mutation rate, \( \mu \), the corresponding element in the parent chromosome mutates. Equation (29) is the utilized fitness function for guiding the solutions toward the feasible region. In this approach, the procedure stops at a certain number of generations.

\[
Fitness \ function (Objective \ function(j)) = \frac{Z_j}{1 + \sum_{i=1}^{N_i} \max (E_i - E^{req}_i, 0)}; \quad j = 1, 2, 3
\]  

(29)

4.4 Multi-objective metrics

In this paper, “diversity”, “spacing”, “the number of non-dominated solutions in the final Pareto”, “mean ideal distance”, and “time” are used as the measures to evaluate the algorithms’ performance. Table 1 summarizes these measures. The readers are referred to the references shown in the first column of this table for more details.

\[
\begin{bmatrix}
O_{1,1} & \cdots & O_{1,N_t} \\
\vdots & \ddots & \vdots \\
O_{N_m,1} & \cdots & O_{N_m,N_t}
\end{bmatrix}
\]

\( N_m \times N_t \)
Case study

The empirical data used in this paper is obtained from a Canadian plastic injection mold company. The company produces different products with different unrelated parallel machines. In this section, first, we develop and solve a model for a critical zone of the studied company that covers any level of physical distancing restrictions. Then, the algorithms’ parameters are tuned using Response Surface Methodology (RSM), and the performance of the algorithms is validated.

To explore the effects of physical distancing, the company’s production scheduling during the COVID-19 period (Scenario B) is selected among the obtained set of optimal solutions, and compared with the production before COVID-19 (Scenario A) for the considered critical zone. Scenario B is also a special output of the developed model that can be extracted from the outputs of the algorithms with the tuned parameters. Finally, we analyzed the obtained results of solving the algorithms. The algorithms are coded using MATLAB R2019b. All codes run on an Intel(R) Core (TM) i7-4500U CPU @ 1.80 GHz 2.39 GHz laptop with 8.00 GB RAM.

Table 1 Performance measures of the multi-objective algorithms (Zaretalab et al. 2015)

| Description                                      | Formula                                                                 | Metric |
|--------------------------------------------------|-------------------------------------------------------------------------|--------|
| Diversity (Zitzler 1999)                         | $D = \sqrt{\sum_{j=1}^{m} \left( \max_{i} f_j^i - \min_{i} f_j^i \right)^2}$ | evaluates the spread of the curve ($m$ is the number of objectives and $f_j^i$ is the $i$th value of the $j$th objective) |
| Spacing (Schott 1995)                            | $S = \sqrt{\sum_{i=1}^{n} (d_i - \bar{d})^2 / (n - 1)}$                  | evaluates the uniformity of the solutions’ distribution within a front ($n$ denotes the size of the Pareto front), $d_i = \min_{k \in \omega, k \neq i} \sum_{j=1}^{m} |f_j^i - f_j^k|$, $\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n}$ |
| Number of non-dominated solutions in final Pareto (NOS) | -                                                                      | It measures the number of Pareto solutions |
| Mean Ideal Distance (MID) (Zitzler and Thiele 1998) | $MID = \sum_{i=1}^{NOS} c_i / NOS$                                    | evaluates the closeness of the solutions of a Pareto front to an ideal point ($c_i$ represents the distance of each member of the population from the best possible value) |
| Time                                             | -                                                                      | computational time in second |

Fig. 4 The layout of the machines in the studied company (for the reduced size problem, only machines 15, 16, 27, 29, and 30 are considered)
5.1 Algorithms’ validation

A reduced-size instance containing five machines (machines number 15, 16, 27, 29, and 30) is considered for evaluating the algorithms’ performance. The layout of the studied machines is shown in Fig. 4.

The distance matrix for these machines is presented in Table 2. Fourteen different products are produced using these machines and are presented in Table 3. The demand and needed quantity for each product are presented in Fig. 5. Finally, the mold’s characteristics for producing each job, and the required number of workers for the production are presented in Table 4.

The presented model for the reduced-size instance is solved using both algorithms. The Pareto front of the NSGA-II incorporating Lp-Metric is presented in Fig. 6. As is shown in the figure, the Pareto front of the NSGA-II algorithm is not dominated by the result of Lp-metric technique, which validates the NSGA-II algorithm’s performance to achieve reasonable solutions. The NRGA algorithm is validated by achieving the same results as the NSGA-II.

5.2 Algorithms parameters’ tuning

In the literature, there are two main techniques for parameters tuning of algorithms: RSM and Taguchi. Based on our experience in using Taguchi and RSM for optimizing production scheduling problems (i.e., Shahriari et al. 2016; Ghaleb et al. 2020a; Sharifi and Taghipour 2021) and the related literature (i.e., Assid et al. 2015; Najafi and Behnoud 2015; Azadeh et al. 2016; Zahraee et al. 2018), we decided to use the RSM technique for tuning the parameters of the provided NSGA-II and NRGA algorithms.

Through the calculation of SN ratio, Taguchi provides a better graphical visualization of the optimum settings for each parameter. However, finding the degree of significance of each parameter requires additional examination using ANOVA. On the other hand, in RSM, ANOVA is an important element in the analysis process. Thus, the degree of significance can be easily determined. In addition, the availability of desired criteria in the RSM software, makes it easier to determine the optimum settings for each parameter. This can be only achieved if a user has enough data for the analysis; for example, to use CCD or Box Bunking arrays. Therefore, we used the RSM technique for tuning the parameters of the provided NSGA-II and NRGA algorithms. RSM was also used for algorithm parameter tuning in several related research (e.g., Assid et al. 2015; Najafi and Behnoud 2015; Azadeh et al. 2016; Zahraee et al. 2018).

RSM is a statistical optimization method that fits a curve to the problem’s outputs for different input parameters. Each algorithm has three initial parameters, which are: the initial population size ($N_{pop}$), crossover probability ($p_c$), and mutation probability ($p_m$). Using Box-Bunking’s method, three different input parameters’ combinations are needed for the algorithm’s parameters’ tuning. We set the algorithms to solve 60,000 individuals for parameter tuning. Thus, the algorithms’ iteration can be calculated as $NoAI = 60000/N_{pop}$. The range of the input parameters and the optimized values for NSGA-II and NRGA are presented in Table 5.

Since the optimal value of $N_{pop}$ for both algorithms is equal to 500, the number of the algorithms’ iterations is set to $NoAI = 60000/500 = 120$.

5.3 Production scheduling during the COVID-19 pandemic

The detailed results for solving the reduced-size problem are presented in Figs. 6 and 7 and Tables 6, 7, 8, and 9. Figure 6a shows that the best obtained Pareto-front from the NGSA-II algorithms contains 13 solutions, presented in detail in Table 6. Figures 6b–d are the two-dimensional Pareto-fronts. The results show no significant change in the values of the objective function number 2 with and without
consideration of physical distancing. The first and the third objective functions are more critical for the company. So, considering Fig. 6d, the solutions are divided into three categories. The first and the second categories are related to when the workers’ minimum physical distance is less than two meters. Between the solutions which belong to the first and the second categories, the solution number 1 has the best value for the objective function 1. This solution can be considered the best in terms of net benefit without considering the physical distancing (Scenario A). The detailed schedule of all solutions is presented in Table 6. The third category is related to when the minimum physical distance between the workers is about three meters. This category contains the solutions number 2, 4, 5, 7, 8, 10, and 12 (Scenario B). Between these solutions, the solution number 12 has better values for the objective function 1. The schedule of this solution is also presented in Table 6. Moreover, the values of all objective functions for all solutions are presented in Table 7.

The detailed schedule of all solutions is presented in Tables 6 and 7. It contains the daily schedule of the considered five machines for one month with 21 business days. For example, as shown in Table 7, in the solution number 12, the workers’ critical physical distance is 2.97 m, which absolutely satisfies the minimum 6ft physical distancing recommended for COVID-19. The machines are fixed in place, and the distance between the machines is pre-defined (Table 2). Thus, finding a closer solution to 6ft is physically infeasible. For this solution, the machine number 15 is scheduled to produce part number 12 for 5 days (9, 10, 11, 17, and 19) and part number 13 for two days (13 and 14). For the machine number 16, the part number 8 is scheduled for the 2nd and 7th days, and the part number 6 is scheduled for the 5th day. The part number 7 is scheduled for day 18. For the machine number 27, the part number 2 is scheduled in time windows 3 and 20; the part number 3 is scheduled in time windows 6 and 21, and the part number 11 is scheduled in time windows 14. For the machine number 29, the part number 4 is scheduled in time

---

**Table 4** Mold’s parameters and the required number of workers for each product

| Parameter                        | Production ID |
|----------------------------------|---------------|
|                                  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 |
| Cycle time (seconds)             | 28 | 28 | 28 | 27 | 27 | 35 | 35 | 35 | 35 | 35 | 45 | 16 | 35 | 16 |
| Number of cavities               | 4  | 4  | 4  | 8  | 4  | 4  | 4  | 4  | 4  | 4  | 8  | 4  | 4  | 8  |
| Hourly production rate (unit per hour) | 514 | 514 | 514 | 1067 | 533 | 411 | 411 | 411 | 411 | 411 | 320 | 1800 | 411 | 1800 |
| Required number of workers       | 0.25 | 1  | 1  | 0.5 | 0.5 | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0.5 | 0.5 |
Fig. 6 Pareto-front of the NSGA-II incorporating Lp-Metrics

**a:** Three-dimensional front (Objectives 1 and 3).

**b:** Two-dimensional front (Objectives 1 and 2).
Fig. 6 (continued)

c: Two-dimensional front (Objectives 1 and 3).

d: Two-dimensional front (Objectives 2 and 3).
windows 8, 13, and 15, and the part number 14 is scheduled in time windows 12 and 19. Finally, for the machine number 30, the part number 4 is scheduled in time windows 1 and 4, and the part number 5 is scheduled in time windows 10 and 16. For this solution, the SS index equals 6.6903, while the net benefit equals $108,397. Relaxing the physical distancing limit to 1.5 m will not lead to a considerable benefit for this specific problem. However, if the next stages of a pandemic require the physical distancing of 1.00 m, the solution no. 1 would be a feasible solution that is more beneficial in terms of objectives 1 and 2.

Considering physical distance between the machines in the solution number 1 (the best net benefit for Scenario A), the machines numbers 16 and 17 are working simultaneously in time window 5, while the distance between these two machines is 1 m. The same issue is for producing the parts on the machines numbers 15 and 16 in time window 9, the machines numbers 15 and 30 in time window ten, etc., all with the distance less than 2 m. Nevertheless, in the solution number 12, only the machines number 15 and 29 in time windows 11, 12, 14, and 18, and the machines number 15 and 27 in time window 13 are working simultaneously, while the distance between these machines is more than 2 m (refer to Table 2). The changes of these machines’ schedules due to the physical distancing constraint result in a reduced net benefit value.

As shown in Fig. 7a, the best-known Pareto-front of the NRGA contains nine solutions, presented in detail in Table 9. Figures 7b–d are the two-dimensional Pareto-fronts. Considering Fig. 7d, the solutions are divided into two categories. The first category is related to when the workers’ minimum physical distance is about one meter or less. Among the solutions in the first category, the solutions number 1, 3, 6, and 9 have the best values for the objective function 1. This solution can be considered the best solution for its net benefit, without considering the physical distancing (Scenario A). The detailed schedule of all solutions is presented in Table 8. The second category is related to when the minimum physical distance between the workers is about three meters. This category contains the solution numbers 3, 5, and 7. The solution number 5 has the best value for the objective function number 1 (Scenario B) between these solutions. The schedule of these solutions is also presented in Table 8.

The measures outputs for both algorithms are presented in Table 10. As is presented in this table, the spacing, NOS, MID, and the time of both algorithms are the same. The diversity of NSGA-II is significantly better than NRGA, which shows the superiority of NSGA-II in solving the presented model.

The developed model is general enough and covers any levels of physical distancing constraint. Production scheduling before the pandemic is a special output of the model described above. The solution for this case corresponds to when the lowest workforce’s physical distance is in place (Objective 3). The value of the solutions’ objective functions and the details of the schedules for before-the-pandemic in the studied instance is available in the presented solution no. 3 of the NSGA-II (Tables 6 and 7) and the solution no. 2 of the NRGA (Tables 8 and 9). These solutions can be taken into account as the model’s optimal solutions for normal operation (Table 10).

According to the NSGA-II solutions, the net benefit for the normal operating condition is $114,464, and the SS index is over 8, which implies the solution achieves at least 57% of the required SS. When the workforce’s physical distance is more than (or is about) two meters (i.e., the solutions number 2, 4, 5, 7, 8, 10, and 12 in Table 7), the net benefit is lower. At the same time, the SS index does not have a significant change. So, if we focus on the net benefit among these solutions, the solution number 12 has the highest net benefit ($108,397), which is %5.3 less than the optimal net benefit without considering physical distancing. Similarly, the NRGA solution is $114,464 for normal operating condition, where the physical distancing constraint is neglected, and the SS index is over 8. However, to maintain the required 6-feet physical distancing, the solutions number 3, 5, and 7 would be the feasible solutions corresponding to different levels of the net benefit drop while the SS index is still more than six. So, if we focus on the net benefit among these solutions, the solution number 5 has the highest net benefit ($108,977). That shows a reduction of %4.79.

### 5.4 Sensitivity analysis of the results

The proposed multi-objective MILP has several parameters, from which, two of the critical ones, i.e., physical distancing

| Parameter | Lower bound | Average | Upper bound | Optimal value (NSGA-II) | Optimal value (NRGA) |
|-----------|-------------|---------|-------------|-------------------------|----------------------|
| Npop      | 100         | 300     | 500         | 500                     | 500                  |
| p_c       | 0.80        | 0.85    | 0.90        | 0.8321                  | 0.8617               |
| p_m       | 0.01        | 0.04    | 0.07        | 0.0623                  | 0.0517               |
Fig. 7 Pareto front of NRGA incorporating Lp-Metrics

**a:** Three-dimensional front (Objectives 1, 2, and 3).

**b:** Two-dimensional front (Objectives 1 and 2).
Fig. 7 (continued)

**c**: Two-dimensional front (Objectives 1 and 3).

**d**: Two-dimensional front (Objectives 2 and 3).
Table 6  The detailed schedules of the NSGA-II’s best-known front

| Solution No | Machine | Period (20 working days in a month) |
|-------------|---------|-------------------------------------|
|             | 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 |
| 1           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 0 12 12 12 0 13 0 0 12 0 12 13 0 |
| 16          |         | 0 8 0 0 6 0 8 0 11 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 0 0 0 2 0 0 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 2           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 3           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 4           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 5           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 6           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 7           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 8           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 0 12 13 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
| 9           |         |                                     |
| 15          |         | 0 0 0 0 0 0 0 0 0 12 12 12 13 0 0 12 0 12 0 0 |
| 16          |         | 0 8 0 0 6 0 8 0 0 0 0 0 0 0 0 0 7 0 0 0  |
| 27          |         | 0 0 2 0 1 3 0 0 0 0 0 0 11 0 0 0 0 2 3 |
| 29          |         | 0 0 0 0 0 0 14 4 0 0 14 0 0 4 0 0 0 14 0 0 |
| 30          |         | 4 0 0 4 0 0 0 0 0 5 0 5 0 0 4 0 0 0 14 0 0 |
Table 6 (continued)

| Solution No | Machine | Period (20 working days in a month) |
|-------------|---------|-------------------------------------|
|             |         | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| 10          | 15      | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 0 | 12 | 13 | 12 | 12 | 0 | 12 | 0 | 12 | 0 | 0 |     |
| 16          | 0       | 8 | 0 | 0 | 6 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 0 |     |
| 27          | 0       | 0 | 11 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 |
| 29          | 0       | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 14 | 4 | 0 | 4 | 0 | 0 | 0 | 14 | 0 | 0 |     |
| 30          | 4       | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 |     |
| 11          | 15      | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 12 | 12 | 13 | 0 | 0 | 12 | 0 | 12 | 0 |     |
| 16          | 0       | 8 | 0 | 0 | 6 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 |     |
| 27          | 0       | 0 | 2 | 0 | 0 | 3 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 |     |
| 29          | 0       | 0 | 0 | 0 | 0 | 0 | 14 | 4 | 0 | 0 | 14 | 4 | 0 | 4 | 0 | 0 | 14 | 0 | 0 |     |
| 30          | 4       | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 |     |
| 12          | 15      | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 12 | 12 | 13 | 12 | 0 | 12 | 0 | 12 | 0 |     |
| 16          | 0       | 8 | 0 | 0 | 6 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 |     |
| 27          | 0       | 0 | 2 | 0 | 0 | 3 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 |     |
| 29          | 0       | 0 | 0 | 0 | 0 | 0 | 14 | 4 | 0 | 0 | 14 | 4 | 0 | 4 | 0 | 0 | 14 | 0 | 0 |     |
| 30          | 4       | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 |     |
| 13          | 15      | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 12 | 12 | 13 | 12 | 0 | 12 | 0 | 12 | 0 |     |
| 16          | 0       | 8 | 0 | 0 | 6 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 |     |
| 27          | 0       | 0 | 2 | 0 | 0 | 3 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 |     |
| 29          | 0       | 0 | 0 | 0 | 0 | 0 | 14 | 4 | 0 | 0 | 14 | 4 | 0 | 4 | 0 | 0 | 14 | 0 | 0 |     |
| 30          | 4       | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 |     |

Table 7 The value of the solutions’ objective functions using NSGA-II

| Solution No | Objective 1 ($10,000) | Objective 2 (Part unit) | Objective 3 (m) |
|-------------|-----------------------|-------------------------|-----------------|
| 1           | 11.4464               | 8.1613                  | 1.00            |
| 2           | 8.5090                | 6.2696                  | 3.04            |
| 3           | 11.4464               | 8.2536                  | 0.94            |
| 4           | 10.4981               | 5.7815                  | 3.04            |
| 5           | 5.2194                | 6.6410                  | 3.04            |
| 6           | 10.7925               | 7.0978                  | 1.58            |
| 7           | 10.7925               | 7.0234                  | 2.97            |
| 8           | 5.2667                | 6.3079                  | 3.04            |
| 9           | 10.9891               | 7.2528                  | 1.12            |
| 10          | 10.4508               | 6.1147                  | 3.04            |
| 11          | 11.0364               | 6.9197                  | 1.12            |
| **12**      | **10.8397**           | **6.6903**              | **2.97**        |
| 13          | 10.8397               | 6.7647                  | 1.58            |

between the workforce and the SS index are considered as the objective functions of the models. In this section, we consider the effects of these two parameters, individually and jointly, on the total net benefit. Combining the non-dominant solutions of both algorithms presented in Tables 7 and 9, we will have 9 different non-dominated solutions for the problem. These nine different non-dominant solutions are presented in Table 11.

Table 7 The value of the solutions’ objective functions using NSGA-II

| Solution No | Objective 1 ($10,000) | Objective 2 (Part unit) | Objective 3 (m) |
|-------------|-----------------------|-------------------------|-----------------|
| 1           | 11.4464               | 8.1613                  | 1.00            |
| 2           | 8.5090                | 6.2696                  | 3.04            |
| 3           | 11.4464               | 8.2536                  | 0.94            |
| 4           | 10.4981               | 5.7815                  | 3.04            |
| 5           | 5.2194                | 6.6410                  | 3.04            |
| 6           | 10.7925               | 7.0978                  | 1.58            |
| 7           | 10.7925               | 7.0234                  | 2.97            |
| 8           | 5.2667                | 6.3079                  | 3.04            |
| 9           | 10.9891               | 7.2528                  | 1.12            |
| 10          | 10.4508               | 6.1147                  | 3.04            |
| 11          | 11.0364               | 6.9197                  | 1.12            |
| **12**      | **10.8397**           | **6.6903**              | **2.97**        |
| 13          | 10.8397               | 6.7647                  | 1.58            |

We used a multi-variable non-linear regression model to fit a curve to the data in Table 11 as follows:

\[ y = b_0 + b_1 \times x_1 + b_2 \times x_2 + b_{12} \times x_1 \times x_2, \]  

(30)

in which \( y \) is the net benefit (Objective 1), and \( x_1 \) and \( x_2 \) are the SS index (Objective 2) and the physical distance (Objective 3), respectively. The \( R^2 \) for this model is equal to 0.9695, which shows a significant relation between these variables. \( b_1 = -0.2705 \), which indicates a unit increase in the SS index, results in about 0.27 units decrease in the net benefit. \( b_2 = -1.6271 \), which shows each unit increase in the physical distance, decreases the net benefit by about 1.63 units. Finally, \( b_{12} = +0.1777 \), which indicates each unit increase in both physical distance and the SS index, decreases the net benefit by about 1.78 units.

5.5 Whole company’s production-scheduling optimization

Since scenario A is the pre-COVID optimal production scheduling and scenario B is the post-COVID optimal production scheduling, by comparing the results of these two scenarios, we can find the financial (the net benefit) and technical (the SS index) effects of the COVID-19 pandemic. In this regard, the first objective function determines the effect of the COVID-19 pandemic on the company’s net
Table 8 The detailed schedules of the NRGA’s best-known front

| Solution No | Machine | Period |
|-------------|---------|--------|
|             | 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 |
| 1           | 15      | 0 12 13 12 0 13 0 0 0 0 0 0 0 12 0 0 12 12 0 7 0 |
| 2           | 15      | 0 12 13 12 0 13 0 0 0 0 0 0 0 12 12 0 12 0 0 0 0 |
| 3           | 15      | 0 12 0 12 0 13 0 0 0 0 0 0 0 12 0 0 0 0 0 7 12 |
| 4           | 16      | 0 0 0 0 8 0 0 0 6 0 0 0 0 0 0 0 0 11 0 8 0 0 |
| 5           | 16      | 0 0 0 0 8 0 0 0 6 0 0 0 0 0 0 0 0 12 0 0 0 0 0 |
| 6           | 15      | 0 12 13 12 0 13 0 0 0 0 0 0 0 12 12 0 0 0 0 12 |
| 7           | 16      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 11 0 8 0 0 |
| 8           | 16      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 12 0 0 0 0 0 |
| 9           | 15      | 0 12 13 12 0 13 0 0 0 0 0 0 0 12 12 0 0 0 0 7 12 |
| 10          | 16      | 0 0 0 0 8 0 0 0 6 0 0 0 0 0 0 0 0 11 0 8 0 0 |
| 11          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 12          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 13          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 14          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 15          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 16          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 17          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 18          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 19          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |
| 20          | 27      | 0 0 0 0 8 0 0 0 6 0 7 0 0 0 0 0 0 1 2 0 0 0 0 |

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benefit, and the second objective function determines the effect on the company’s SS index. The value of the SS index clarifies the company’s capability to overcome the problem of the parts’ fluctuations during the pandemic.

To optimize the whole company's production planning-scheduling problem, we consider a one-year horizon and solve the presented MILP model using the NSGA-II and NRGA algorithms (with the tuned input parameters). We schedule the production of 95 different parts on 32 existing machines for both Scenario A (normal operation without the consideration of physical distancing) and Scenario B (considering physical distancing between workforce). Then, the better output for each month (net benefit) is reported in Table 12.

The result of Table 12 shows that the reduction in the company’s monthly net benefit subject to physical distancing constraint varies from 0.02% to 22.34%; while the average yearly reduction is 9.64%. The difference between these numbers is due to different parameters, such as the number of scheduled parts, the parts’ SS, and the demand for the parts. As an instance, in month ten, only 36 parts should be scheduled; while in months number 4, 5, and 11, the number of scheduled parts to be produced are 56, 58, and 64, respectively. Moreover, the parts’ demand in months number 1, 2, 6, and 10 is significantly less than the parts’ demand of the other months.

Moreover, for all production days, the SS index for Scenario A is between 7.23 to 8.64, while for Scenario B is between 5.13 and 6.86, which shows the adverse effects of incorporating physical distancing on the company’s buffer capacity. Finally, for all production days in Scenario A, the minimum physical distance is between 0.58 m and 0.96 m; while for Scenario B, the minimum physical distance is between 2.18 m to 2.36 m, which is more than 2 m. Although the results of NRGA in terms of net benefit are better than NSGA-II, the SS index reported by NSGA-II is better than NRGA, which implies no algorithm has significant superiority compared with the other one.

In this paper, the LP-metrics approach was first used to measure and validate the efficiency of the developed metaheuristic algorithms for solving the model for a reduced-size problem. The validated meta-heuristics were then used to optimize the company’s yearly production schedule. The results indicate both metaheuristics are performing well in determining the optimal solution.
5.6 Managerial insights

Given the pandemic will continue for at least one more year, $181,397, which is the difference between the company’s yearly net benefit in normal operation and in the pandemic, is the company’s opportunity cost to re-locate the machines in the production line (new machines’ layout) to ensure the physical distance for every two workers is at least 2 m. This means if the company pays about $180,000 for the re-arrangement of the production line’s layout, it has no loss in its yearly net benefit. Moreover, the new layout ensures the company is ready for any possible upcoming pandemics. In other words, the company can make investment decisions based on the net benefits of various shop floor layouts with different physical distancing scenarios.

6 Conclusion and further studies

This study aimed to develop a new mathematical model for incorporating the physical distancing constraint in the scheduling of fixed-in-place production machines. The paper presented a new MILP mathematical model for optimizing the production planning-scheduling of a plastic injection mold company with a parallel-machine production environment, considering the physical distancing. Two different scenarios (with and without considering physical distancing) were presented to investigate the impacts of physical distancing on the company’s yearly net benefit. Since the production planning-scheduling problem belongs to the Np-Hard category of problems, a Non-Dominated Sorting Genetic Algorithm (NSGA-II) and a Non-Dominated Ranked Genetic Algorithm (NRGA) algorithms were used to solve the presented model. Considering that the physical distancing may force the company to leave some machines idle during different production intervals, we have a reduction in the yearly net benefit. The results showed that considering physical distancing as a restrictive instruction may reduce the company’s monthly net benefit up to 22.34% (the average of 9.64% in one year). The company’s yearly net benefit reduction (which is about $181,397 for the under-studied company in one year) can be considered as the investment opportunity cost for re-arranging the production line’s machines. Moreover, the results indicate that an increase in the considered physical distance (the third objective function) results in a significant reduction in the SS index (up to 39.67%), i.e., the second objective function.

The current work can be extended to include other activities in a factory, by such as supply chain, transportation, and production, given the pandemic-related restrictive instructions.

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Data availability The data used to support the findings of this study are included in the article.

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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