Simulated Annealing Heuristic for Disposable Medical Face Mask Production Scheduling Problem

Yagmur Selenay SELCUK, Elvin COBAN, Burcu BALCIK
Department of Industrial Engineering
Ozyegin University
Istanbul, Turkey
yagmur.selcuk@ozu.edu.tr, elvin.coban@ozyegin.edu.tr, burcu.balcik@ozyegin.edu.tr

Abstract

With the outbreak of the new coronavirus (Covid-19), many countries adapted mandatory mask policies to curb the spread of the virus. Even if some countries start to loosen the disposable mask requirements, mask policies are still mandatory at least during transportation and people are highly recommended to wear them in public spaces. Due to all these preventive mask policies, the demand for medical face masks has increased tremendously, and mask manufacturers began to take orders for varying types of masks in large quantities that have to be fulfilled within a short response time. Thus, it is significant for the manufacturer to schedule medical face mask production tasks as efficiently as possible. In this paper, disposable medical face mask production planning is studied when the orders have different release dates, due dates, and set-up times. The problem studied in this paper is motivated from a real-life mask manufacturer and a flow shop production scheduling problem is formulated with sequent two machines and set-up times while minimizing the total tardiness. A simulated annealing heuristic is proposed to solve this problem and we conclude that applying a simulated annealing heuristic results in a fast and efficient production plan.

Keywords
Medical face mask production, scheduling, release dates, due dates, simulated annealing

1. Introduction
After the coronavirus first appeared in China in 2019, there was a rapid increase in cases and spread all over the world. With the outbreak of the Covid- 19, the disposable medical mask has become a basic need and the amount of demand has increased day by day. Since masks are the key measure for protection from viruses, reducing transmission, and saving lives. Due to the filtration feature of the disposable medical mask, WHO recommended disposable medical masks, not only for those who are sick due to Covid-19 but also for those who feel the symptoms, are in the community and are over 60 age (WHO 2022). Hence, many countries have made it mandatory to wear masks to reduce or even prevent the spread of Covid19. For example, while in Italy, Germany, Australia, Brazil, and the UK wearing mask is required in certain spaces or regions, in Spain, France, India, and

Philippines wearing mask is required in public nationwide (Felter and Bussemaker 2020). Even the recommendations may vary according to countries, still many people are expected to continue wearing masks. Consequently, mask manufacturers began to take orders continuously for masks in large quantities that have to be fulfilled within a short response time. Thus, the mask manufacturers need good production planning and scheduling that will avoid any delays. However, there are different types of masks with varying fabric, ear loops, and packaging, complicating problems as producing different types of masks requires set-up times.

We are motivated from a real-life mask manufacturer and formulate its production process via a flow shop problem with two machines. This manufacturer receives multiple orders with varying release dates and due dates. Due to varying requirements of each order, set-up time is spent, such as time spent due to fabric changes between orders. The objective is to minimize the total tardiness. The two-machine flow-shop problem with total tardiness as the scheduling criterion is shown to be NP-complete. A simulated annealing (SA) heuristic is proposed to overcome this

combinatorial complexity. A numerical study is performed based on the real-life motivated data, and insights on results of the disposable medical mask production scheduling during pandemic are summarized.
The remaining sections of this paper are organized as follows. In Section 2, we briefly review the relevant papers from the literature. In Section 3, the background information of disposable medical mask production planning and scheduling problem is introduced. In Section 4, the constructive heuristic, first improvement algorithm and a simulated annealing heuristic are explained. In section 5, data collection is explained. Then, the computational results of the algorithms are summarized in Section 6. Finally, the conclusion is presented in Section 7.

2. Literature Review

Scheduling is defined as a decision-making process by which limited resources are allocated to tasks over given time periods while optimizing one or more objectives (Pinedo 2002). There are many different classes of scheduling problems of which a commonly observed one is flow shop problems. Many manufacturing and production facilities need to solve flow shop problems during which each job undergoes the same series of operations while machines are assumed to be set up in series. Production planning and scheduling problems have been vastly studied with varying extensions, such as set-up times. Allahverdi et al. (1999) provided detailed research of the literature on scheduling problems with setup times. They categorized the scheduling problems with set-up times into two major groups: sequence-independent setup times and sequence-dependent setup times. Wu and Lee (2006) and Shiau et al. (2007) studied a two-machine flow shop scheduling problem with linear deterioration, and they aimed to minimize the mean flow time by applying branch-and-bound. Malapert et al. (2012) studied a constraint programming (CP) approach for a batch processing machine with a finite number of jobs with non-identical sizes. The aim was to minimize the maximal lateness. The CP approach may compute an optimal solution for the small-sized problems, however; when the instance sizes grow, the computational time of the CP approach increases. Additionally, due to the large sizes and variability of instances, exact algorithms can compute the optimal solution(s) in a long computation time. Therefore, varying heuristic algorithms have been suggested in the literature. Rajendran and Zeigler (1997) proposed a heuristic technique to minimize total weighted flowtime.

The heuristic consists of two phases: i) an insertion heuristic that uses as the initial seed sequence and ii) the improvement phase based on an insertion algorithm to improve the seed sequence based on the total weighted flowtime of jobs. Crauwels et al. (1998) applied the neighborhood search and the genetic algorithm for the single machine problem to minimize total weighted tardiness, whereas Mendes et al. (2002) studied on identical parallel machine scheduling to minimize the makespan. They applied tabu search-based heuristic and memetic approach and they evaluated the performance of the two meta-heuristic algorithms. Pereira and Santoro (2011) introduced an integrative scheduling simulation that is based on the usage of sequencing principles. The impact of product structure, scheduling mechanism, and sequencing rules on system performance was investigated. Kirlik and Oğuz (2012) developed a neighborhood search algorithm to minimize total weighted tardiness. They considered sequence-dependent setup times on a single machine. Bhongade and Khodke (2012) proposed two heuristics to deal with assembly flow shop scheduling problem where every part may not be processed on each machine. He et al. (2017) presented a modified variable neighborhood search algorithm for two-machine flow shop scheduling problems with deterioration jobs and setup time. Zhou et al. (2018) proposed a modified particle swarm optimization (MPSO) algorithm for the single batch-processing machine problem with non-identical job sizes and release times. They aim to minimize the maximum tardiness of the jobs. The MPSO algorithm provides incorporation between diversification and a local search strategy into a basic particle swarm optimization algorithm. Therefore, the algorithm increases the efficiency of the solution.

More specifically, there are few works in the literature about the application of medical mask production as producing medical masks becomes more important with the pandemic. Wu et al. (2020) developed a neural network scheduler to efficiently solve the emergency medical mask production task scheduling problem. The authors applied a heuristic solution to the model and used the Monte Carlo simulation for the comparison of instances. Lee et al. (2020) investigated the dynamic response system of healthcare mask production and analyzed the global supply chain of mask production and distribution systems during the Covid19 pandemic. With the outbreak of the pandemic, it is also mentioned in the paper that how difficult it is to make emergency production and supply planning for both domestic and foreign markets due to the high amount of need.

For a more complete review of recent literature on production scheduling problems, we refer to the works of Framinan et al. (2004), Hejazi & Saghafian (2005), Allahverdi et al. (2008), and Fuchigami & Rengel (2018).

As a result, we contribute to the literature by studying a real-life-motivated medical mask production scheduling problem when the orders have different release dates and due dates. We propose heuristics including the simulated annealing heuristic; hence, rapid production schedules can be computed.

3. Problem Background and Assumptions

In this paper, disposable medical mask production planning is studied when the manufacturer receives many orders with varying release dates and due dates. The problem studied in this paper is motivated from a real-life mask manufacturer. We formulate a flow shop production scheduling problem with sequent two machines while minimizing the total tardiness. The production process is represented in Figure 1. There are three processes and two types of machines: the first two processes are done in the first machine, whereas the last process is performed on the second machine as shown in Figure 1. The first machine creates the three-ply mask structure using each order's fabric requirement, inserts an aluminum wire into the masks, and presses the ear loops to the masks, whereas the second machine packs these masks based on their requirements, such as 50 masks in a large box and 5 packs 10 masks in a large box.

Spunbonded and meltblown are the two types of fabrics used. Spunbond masks have three layers with three-ply materials of spunbonded non-woven fabric between two spunbonded non-woven fabrics. On the other hand, for meltblown masks three layers with three-ply materials of a meltblown non-woven fabric between two spunbonded non-woven fabrics. Depending on the type of the mask, the first process is performed in the first machine where the fabrics will be assembled to form the three-layer structure. The production processing times also differ as processing the meltblown fabric takes a longer time than the spunbonded fabric. Regardless of type of the fabric, the aluminum wire on the nose is attached in the intermediate process in a very short amount of time, hence we ignore this time in our paper. Afterward, the ear loops are assembled to the partially processed mask. We consider two types of ear loops which are also the ones used in the real-life company: (i) classical elastic ear loops, and (ii) elastic round-shaped ear loops. Due to the shape of the elastic round-shaped ear loops, the processing time takes longer than the processing time of classical elastic loops. The last process is packaging that is performed on the second machine. Packaging has two types that are boxes and bags, depending on the order requirement.

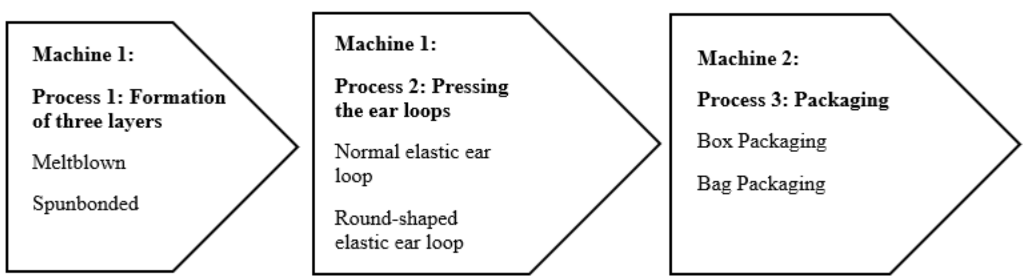

Figure 1. Production and packaging processing model of disposable medical mask

Corresponding to the real process in the real-life mask manufacturer, we assume only one order can be processed at the machines and there is no preemption as it may disrupt the sterilized process that has to be followed until the finishing time of the packaging. The orders have different release dates, the earliest time the production of that order can start, and due dates. Once an order's production process finishes after its due date, the manufacturer pays a penalty due to that order's tardiness. Our aim is to minimize the total tardiness of all jobs.

In Section 4, we introduce our heuristics to solve our disposable medical face production scheduling problem with set-up times and orders with different release dates and due dates.

4. Methods

In this section, we introduce the heuristic algorithms applied in the paper. First, a constructive heuristic is defined, then first improvement algorithm and the simulated annealing heuristic with its parameters are introduced.

Constructive Heurist A constructive heuristic is a type of heuristic that starts with an empty solution and continuously at each iteration, the current solution is expanded until the complete solution is reached. In this paper, the job insertion technique is used as a type of machine scheduling problem is studied. The constructive heuristic steps applied in this study are as follows:

Step 1: Create an empty set.
Step 2: Calculate the total processing times and setup times of the jobs in all machines.
Step 3: Calculate the ratio of (due date – release time) / (total processing time + setup time).
Step 4: Sort the ratios in ascending order.
Step 5: Insert each of the sorted orders into the created empty set and calculate the current total tardiness.
Step 6: After all orders are inserted, calculate the current solution's objective function value.

First Improvement Algorithm

The First improvement algorithm generates the neighborhood incrementally and chooses the first solution of a better objective value than the current one. When applying the first improvement algorithm for this problem, swapping between jobs was applied and it was checked whether the value after the swap was better or not. The first improvement algorithm steps applied in this study are as follows.

Step 1: Consider the order sequence and its objective function that is obtained by the constructive heuristic as an initial solution.
Step 2: Randomly choose two orders and swap them.
Step 3: Calculate the total tardiness of the orders in the current order sequence.
Step 4: If the current total tardiness value is less than the candidate tardiness value, it is improved, and the current tardiness becomes the best objective function value.
Step 5: Stop the algorithm, when the objective function first improved.
Step 6: If the current total tardiness value is greater than the candidate tardiness value, it is not improved, and the same process continues to be applied to other orders until improvement occurs.

Simulated Annealing

Callo and Capozzi (2019) described that simulated annealing (SA) is an algorithm based on statistical mechanics concepts, and it is motivated by an analogy with the behavior of physical systems during the cooling process. SA is a heuristic method for global optimization which requires no assumption on the objective function. One of the most significant features of this heuristic is that the value of the best objective function is not related to the value of the initial solution. A SA heuristic is applied in this paper and the parameters chosen for the SA phase are as follows.

- **Initialization:** The SA heuristic begins with creating an initial solution. In the algorithm, the constructive heuristic result is chosen as the initial solution.
- **Selection of a mechanism:** This is part of generating neighborhood solutions. To find a neighborhood solution, the swapping method is applied. Random numbers are generated and are exchanged places for the jobs that in the scheduling queue occupy the positions relative to the random numbers chosen.
- **Temperature:** The initial temperature for the SA phase is set in the temperature parameter. In the paper, T=1000 and T=10000 are chosen.
- **Cooling:** At each iteration, the temperature is cooled by this parameter. In the paper, α=0.5 and α=0.9 are chosen.
- **Epoch length:** It is the length of the following steps where an epoch length of 1 is used.

- **Algorithm termination criteria:** The algorithm will stop when the temperature achieves a very small value. It is determined as to when T ≥ 0.1 then, stop!

5. Data Collection

The data we used in our numerical analysis is from a real disposable medical face mask manufacturer in Turkey. The manufacturer has two shifts from 8 am to 4 pm and from 4 pm to 12 am. The machines are used in the production of masks for 16 hours (i.e., 8 am to 12 am). The manufacturer usually receives orders at the beginning of the month; however, the orders have different release times and due dates. The orders vary with respect to their fabric, earloop, packaging types, and their amounts. These differences may result in varying processing times and may require varying set-up times. One of five data sets including 20 orders is summarized in Table 1 representing each order's fabric, earloop, packaging, amount, release date, due date, processing times, and set up times. For instance, the first order requires 150,000 masks whose fabric, ear loop, and packaging types are meltblown, classical elastic ear loop, and box, respectively. The release date for this order is the 4th day of the month, whereas the order is expected to be produced till the end of the 10th day of the month while it takes 2.5 days to produce the order in addition to its set up time of 0.05 days.

Table 1.The Instance I in detail

Order	Fabric t.	Ear loop t.	Packaging t.	Order amount	Release t.	Due date	Processing t.	Set-up t.
1	meltblown	classical elastic	box	150000	4	10	2.5	0.05
2	spunbonded	elastic round shaped	box	112500	3	9	2	0.04
3	meltblown	classical elastic	bag	33750	3	12	2	0.04
4	meltblown	classical elastic	bag	101250	4	14	2	0.04
5	spunbonded	elastic round shaped	box	56250	6	20	2.5	0.05
6	meltblown	classical elastic	box	131250	10	15	0.5	0.01
7	spunbonded	elastic round shaped	box	168750	7	16	1	0.02
8	spunbonded	elastic round shaped	box	84375	10	25	1.5	0.03
9	spunbonded	elastic round shaped	box	225000	4	20	1.5	0.03
10	meltblown	classical elastic	box	75000	9	25	1.5	0.03
11	meltblown	elastic round shaped	box	67500	12	23	1	0.02
12	spunbonded	elastic round shaped	box	112500	10	25	1	0.02
13	meltblown	classical elastic	bag	67500	9	28	1.5	0.03
14	meltblown	classical elastic	box	112500	10	25	1	0.02
15	meltblown	classical elastic	box	112500	3	19	1	0.02
16	meltblown	classical elastic	box	225000	14	25	0.5	0.01
17	meltblown	classical elastic	box	37500	6	29	1	0.02
18	meltblown	elastic round shaped	bag	60000	9	22	0.5	0.01
19	meltblown	classical elastic	bag	135000	10	25	0.5	0.01
20	meltblown	elastic round shaped	box	150000	6	25	0.5	0.01

Results and Discussion

First, we applied the constructive heuristic, then the first improvement algorithm, and finally the SA algorithm with the parameters T=1,000 and cooling rate (α) as 0.5. We refer to the SA heuristic with this setting as SA1. The total tardiness of the orders, the objective function value, is summarized in Table 2. The computational time of all heuristics is less than a couple of seconds, hence respective computational times for each instance are not reported.

Table 2. Comparison of objective function values computed via constructive, first improvement (First imp.), and SA1 heuristics

# of runs	Run1			Run2			Run3		
Heuristic types	Constructive	First imp.	SA1	Constructive	First imp.	SA1	Constructive	First imp.	SA1
Instance1	29.83	24.82	21.73	29.83	28.81	21.15	29.83	23.32	24.82
Instance2	26.82	21.66	19.71	26.82	22.74	19.76	26.82	16.76	24.23
Instance3	33.65	31.61	27.47	33.65	21.54	17.48	33.65	32.62	24.94
Instance4	22.95	21.66	15.2	22.95	18.15	14.56	22.95	20.16	10.12
Instance5	28.74	17.86	22.45	28.74	21.51	20.51	28.74	27.7	20.51

Applying the first improvement algorithm to the constructive heuristic allows us to decrease the total tardiness. However, applying SA1 allows us to achieve better results than the first improvement algorithm. The most important reason for this is that while obtaining a better result in a single iteration with the first improvement, the order of the jobs in SA1 is checked with 14 iterations and the best objective function is selected among these iterations. In other words, more possible results are checked in SA1. In the next step, we calculate how the objective function changes by changing the parameters used in SA1. First, the T value is increased from 1,000 to 100,000 keeping the cooling rate constant (i.e., 0.5). The SA heuristic with the updated parameters is referred to as SA2. Second, the cooling rate is increased from 0.5 to 0.9 while keeping the temperature value constant (i.e., 1,000). The SA heuristic with the updated parameters is referred to as SA3. Table 3 summarizes the objective function values computed by SA1, SA2, and SA3. SA2 improves the objective function value within 18 iterations, whereas SA3 improves the objective value within 89 iterations.

Table 3. Comparison of objective function values computed via SA1, SA2, and SA3 heuristics

# of runs	Run1			Run2			Run3		
Heuristic types	SA1	SA2	SA3	SA1	SA2	SA3	SA1	SA2	SA3
Instance1	21.73	22.84	21.82	25.15	22.66	21.82	24.82	21.82	21.73
Instance2	19.71	19.71	17.18	19.76	17.18	16.76	24.23	17.69	16.76
Instance3	27.47	24.94	16	17.48	17.48	16	24.94	23	16
Instance4	15.2	5.61	1.13	14.56	14.56	4.68	10.12	4.68	1.13
Instance5	22.45	17.86	17.86	20.51	20.51	17.86	20.51	22.46	17.86

The smallest objective values are computed via SA3 heuristics. Especially, SA3 heuristics computes the total tardiness to 1.13 days, whereas others compute values more than 4.68 days.

Table 4 depicts the average results computed by constructive, first improvement, SA1, SA2, and SA3 heuristics.

Table 4. Average objective function values (μ) computed via constructive, first improvement (First Imp.), SA1, SA2, and SA3 heuristics

Heuristic types	μ of constructive	μ of first imp.	μ of SA1	μ of SA2	μ of SA3
Instance1	29.83	25.65	23.9	22.44	21.79
Instance2	26.82	20.38	21.23	18.19	16.9
Instance3	33.65	28.59	23.29	21.8	16
Instance4	22.96	19.99	13.29	8.28	2.31
Instance5	28.74	22.35	21.15	20.27	17.86

SA3 computes the smallest objective function values on average for all instances. This is expected because as the cooling rate increases in SA3, the number of iterations increases considerably allowing more possibilities to be examined. Hence, the objective function values may be improved by changing the parameters and increasing the number of iterations in all heuristic algorithms. According to these results, as the smallest objective function values (the total tardiness) are achieved via SA3 heuristic, we will use SA3 to compute the starting times for the medical mask manufacturer's setting.

5.1 Division of Order Amounts

The next question is to analyze the impact of the case and whether the manufacturer negotiates with the customers to post their large orders (with processing times 1-day or longer) by dividing them into two equal-sized, smaller orders. First, orders whose processing times are 1 and 2 days are divided equally into two, smaller orders. For instance, an order with a 1-day processing time is considered as two separate orders whose processing times are 0.5 days each. (Please note that decreasing processing time to half decreases the setup time to half). However, for these new small orders, their release times and due dates are not updated and kept as the same as the original order. Then, constructive, first improvement, SA1, SA2, and SA3 heuristics are applied, and Table 5 summarizes the objective function values computes by these heuristics.

Table 5. Comparison of objective function values computed via constructive, first improvement (First imp.), SA1, SA2, and SA3 heuristics

# of runs	Run1					Run2					Run3				
Heuristic types	Constructive	First imp.	SA1	SA2	SA3	Constructive	First imp.	SA1	SA2	SA3	Constructive	First imp.	SA1	SA2	SA3
Instance1	55.31	49.53	47.59	39.43	37.37	55.31	45.57	44.01	39.85	31.45	55.31	52.89	52.59	44.53	31.45
Instance2	45.38	40.87	37.26	36.22	35.24	45.38	36.84	37.28	36.22	36.2	45.38	40.28	35.22	36.84	36.2
Instance3	39.75	36.67	34.71	28.79	29.59	39.75	37.27	34.71	32.18	27.57	39.75	34.71	36.2	29.61	27.57
Instance4	24.18	20.19	19.11	15.51	15.51	24.18	22.14	22.13	19.09	17.09	24.18	23.63	17.55	19.09	17.55
Instance5	42.75	38.43	36.8	32.6	32.6	42.75	38.71	34.6	33.68	31.6	42.75	38.31	34.68	34.66	31.6

The tardiness values of orders change as the sorting is changed due to the rate order used during the constructive heuristic resulting in different sequences of orders. Dividing the order quantity into two results in increased total tardiness. (Please note that double counting of an order's tardiness is prevented by computing the largest ending time of the divided orders and comparing the largest value with the order's due date.) Since all heuristics' computations are based on the constructive heuristic result, all the proposed heuristics' objective function values increase. When the average objective function values are compared as seen in Table 6, SA3 outperforms the other heuristics as expected due to its increased number of iterations. To sum up, negotiating with the customers with large orders to post their orders as two smaller orders resultco in poor performance (with respect to the objective function values) compared to the original system.

Table 6. Average objective function values (μ) computed via constructive, first improvement (First Imp.), SA1, SA2, and SA3 heuristics for the case of divided orders

Heuristic types	μ of constructive	μ of first imp.	μ of SA1	μ of SA2	μ of SA3
Instance1	55.31	49.33	48.06	41.27	33.42
Instance2	45.38	39.33	36.58	36.42	35.88
Instance3	39.75	36.21	35.2	30.19	28.24
Instance4	24.18	21.98	19.59	17.89	16.71
Instance5	42.75	38.48	35.36	33.64	31.93

However, the manufacturer may prefer to send large orders of masks as if they are divided into smaller orders in real life as producing large orders lasting more than a couple of days means that the masks will be held as inventory. If this holding time is long, then the masks may become dusty and pose a risk of non-compliance with hygiene conditions. Hence, the manufacturer and the customer may negotiate to send partial orders as they are finished. However, this may also cause increasing logistics costs and box/packaging costs. Thus, a more detailed analysis should be performed in terms of both the objective function value (the total tardiness in our case), shipment, and sterile conditions during keeping inventory.

5.2 Robustness due to Due Date

The manufacturer may ask a due date delay due to their busy production plan or the customers may run out of masks hence they may need their orders earlier than they planned. Thus, the next question is to check the robustness of production planning with respect to due dates. The changes in the production plan due to the decreases (and the increases) in the due dates by 10% are analyzed. Table 7 shows the objective function values for the case when the due dates are decreased by 10%, whereas Table 8 shows the objective function values for the case when the due dates are increased by 10%. When the due dates are decreased by 10%, more orders become tardy contributing to the total tardiness objective function resulting in a higher increase of the objective function more than 10%. When the due dates are increased by 10%, some orders are not tardy anymore resulting in a higher decrease than 10%. It is recommended for the manufacturer to check the outcomes of such changes to define their robustness.

Table 7. Average objective function values (μ) computed via constructive, first improvement (First Imp.), SA1, SA2, and SA3 heuristics for the case when the due dates are decreased by 10 %

Heuristic types	μ of constructive	μ of first imp.	μ of SA1	μ of SA2	μ of SA3
Instance1	61.96	60.50	54.07	48.79	48.37
Instance2	77.02	75.93	53.53	45.6	41.57
Instance3	61	59.88	46.56	45.53	43.36
Instance4	53.87	52.06	29.85	30.98	26.43
Instance5	58.03	56.21	49.57	42.80	41.15

Table 8. Average objective function values (μ) computed via constructive, first improvement (First Imp.), SA1, SA2, and SA3 heuristics for the case when the due dates are increased by 10 %

Heuristic types	μ of constructive	μ of first imp.	μ of SA1	μ of SA2	μ of SA3
Instance1	20.45	20.15	19.37	18.35	15.54
Instance2	16.33	14.98	11.6	11.08	6.34
Instance3	16.74	16.91	8.66	8.12	7.31
Instance4	7.19	7.34	5.3	2.91	0
Instance5	8.78	8.78	6.37	6.50	2.6

Conclusion

In this paper, the production scheduling problem of disposable medical face masks is studied. The manufacturer receives many orders with varying release dates and due dates. We formulate a flow shop production scheduling problem with sequent two machines while minimizing the total tardiness This problem is motivated from a real-life mask manufacturer. A constructive heuristic, first improvement heuristic, and Simulated Annealing (SA) heuristics are proposed, and computational analysis is performed over real-life instances that are generated from the real medical face mask manufacturer.

According to our numerical results, SA outperformed other heuristic methods. We even try different parameters while applying SA and show a certain set of parameters results in better objective function values. The questions of whether negotiating with customers to divide their large orders into two equally sized, smaller orders are good or what happens when the due dates are decreased/increased are answered. Studying parallel machines during production, alternative objective functions, such as minimizing the makespan, and sequence-dependent setup times are possible future extensions.

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Biography

Yağmur Selcuk is an M.Sc. student in Industrial Engineering at Ozyeğin University. She received her B.Sc. degree in Industrial Engineering from Ozyeğin University. Her research interests include production scheduling, supply chain management and healthcare operations. She especially is interested in developing heuristic-based solutions and mathematical models to challenging real-life problems on these topics.

Elvin Coban is currently an Assistant Professor at Ozyegin University. She received her Ph.D. and M.Sc. in Operations Management and Manufacturing from Tepper School of Business, Carnegie Mellon University. Her research interests are optimization, data analytics, service centers, humanitarian operations, healthcare applications, and planning and scheduling problems.

Burcu Balcik is currently a Professor at Ozyegin University. She received her Ph.D. in Industrial Engineering from University of Washington. Her research expertise is in modeling and solution approaches for humanitarian supply chains and logistic systems.