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Procedia Computer Science 217 (2023) 1234–1242

Procedia Computer Science

www.elsevier.com/locate/procedia

4th International Conference on Industry 4.0 and Smart Manufacturing

Job-scheduling Model For an Autonomous Additive Manufacturing: a Case of 3D Food Printing

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Abstract

Three-dimensional food printing (3DFP) is an emerging application of additive manufacturing (AM) as it offers customized designs, personalized nutrition, simplified and efficient supply chain, and reduced waste. Grouping parts into jobs (batches) and sequencing these jobs (known as job-scheduling) is considered a key operational factor in additive manufacturing (AM). The task of job-scheduling is complex because the number of possible solutions grows exponentially with the number of parts and various constraints has to be considered (e.g., machine's capacity). In the case of 3DFP, scheduling presents a unique challenge since different 3D printed foods have different time constraints depending on material's shelf-life. In this paper, we propose a mathematical optimization model for job-scheduling in 3DFP that minimizes the makespan (total accumulative manufacturing time) and the deadline violation simultaneously. We reformulate the proposed optimization model to the form of mixed-integer linear programming (MILP) and solve in using MILP solver in MATLAB 2022. We demonstrate the effectiveness of the proposed model with a numerical case study. The obtained results show that our algorithm obtains scheduling that significantly reduces the deadline violation while achieving the same production time as the state-of-the-art baseline.

Keywords: Additive manufacturing; 3D food printing; job-scheduling; MILP

1. Introduction

Three-dimensional food printing (3DFP) is an emerging application of additive manufacturing (AM), owing to the increasing interest in the food industry [1]. 3D printing reduces many challenges in the food making process that currently face creators and inventors, for instance it lowers the need of sophisticated skills and expensive resources, to name few. Thus, food printers are becoming available commercially – for example, Foodini Printer by Natural Ma-

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10.1016/j.procs.2022.12.322

chines was built as a kitchen appliance for professional and home kitchen use. Chocolate printers were also designed for personal as well as professional food applications [2].

3DFP is a digitally controlled process of constructing food layer by layer based on pre-designed specifications [3]. 3DFP integrates AM technologies and digital gastronomy techniques to produce edible customized products in terms of nutrition, flavour, colour, shape, and texture [4]. Based on driving mechanisms, 3DFP technologies can be classified into four techniques as follows:

- Inkjet printing (IJP): in this technique, a liquid droplet (i.e., printing ink) is deposited repeatedly onto the substrate's surface to form the desired object. IJP can produce highly accurate products due to the fine droplet deposition (20-50 μm). However, the materials available are extremely limited [4].
- Binder jetting printing (BJP): the building material in BJP is deposited (sprayed) to a bed of powder located on the print bed, which moves down to allow a new layer of powder to be spread on the printing plate. One advantage of using BJP is that no support structure is needed since the powder bed supports the object being printed all the time [11].
- Laser sintering: similar to BJP technique, a powder bed is selectively targeted by a laser beam to fuse the particles of the building material to form the object [12].
- Extrusion-based techniques: the concept of extrusion-based relies on continuous material flow pushed through a nozzle by air pressure (air-based technique), a plunger (syringe-based technique), or an auger (screw- based technique). The extrusion-based type is the most widely used technique for 3DFP due to its flexibility and cost-effectiveness [3, 13]. Our work in this paper focuses on the application of extrusion-based techniques.

The selection of a specific technique plays an important role in the final product with respect to shape fidelity and material rheology [14]. Moreover, each technology is associated with different materials due to the difference in printability level, which is determined by the viscosity and the temperature required to print a given material. Figure 1 illustrates the correlation between viscosity and melting point with the four different 3DFP techniques.

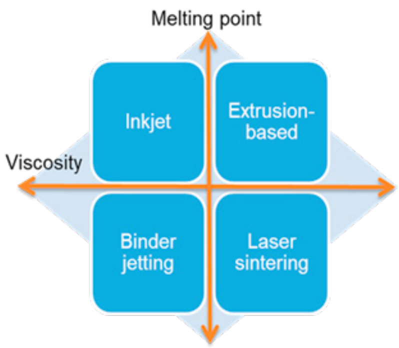

Fig. 1. The correlation between viscosity and melting point with the main 3DFP techniques.

3DFP promises great benefits including customized designs, personalized nutrition, simplified and efficient supply chain, broader sources of food materials, and reduced waste [5]. However, 3DFP faces some obstacles such as limited printable materials [6], low printing precision and accuracy [5], consumer acceptance [8, 9, 10], short shelf-life [7], and food safety concerns. We can circumvent the challenge of short shelf-life and food safety by finding an "optimal" job-scheduling that takes into account materials' deadline/expiration (this is the main contribution of our work in this paper).

Although job-scheduling methods for traditional flow-shop configurations have been well studied in the literature, the job-scheduling problem for single/multiple 3D printers is still under-investigated [14, 15, 16]. In traditional manufacturing, job-scheduling focuses on optimizing the operator-machine scheduling. On the other hand, scheduling in 3D printing needs to be an automated process that requires parts grouping, job sequencing, and delivery optimization, while taking into account uniform machine utilization [16]. This major difference is what makes job-scheduling in 3D printing present different sets of challenges than job-scheduling in traditional manufacturing.

In 3DFP (and general AM 3D printing), it is assumed that multiple parts (products) are grouped into one job to minimize the total production time and deliver multiple parts (food products). A job represent a set of parts that are produced in the same batch. More specifically, the main goal of the job-scheduling problem is to: i) group I parts into J jobs, where $J \leq I$, and ii) sequence the obtained jobs (which job starts first). The grouping and sequencing aims to optimize a certain objective, e.g., minimizing the production time.

Job-scheduling in 3DFP poses a unique challenge where the delivery time is crucial because it is tied to material expiration, which raises food safety concerns. We address this challenge by minimizing the deadline violation time simultaneously with the production time in the job-scheduling process. We define the deadline violation as the difference between the production time and the part's predetermined deadline. We reformulate the optimization problem to be in the form of mixed-integer linear programming (MILP), which is well-studied in the optimization literature and therefore can be solved by many off-the-Shelf algorithms. We verify the effectiveness of the proposed model with a numerical case study as will be shown later on.

2. Literature review

According to Oh et al. [16], there are three major types of systems for job scheduling in 3D printing as listed below:

- One-stage single-machine: where the parts are grouped into jobs (patches) that are produced by a single 3D printer. In this system, the jobs only undergo one stage (the 3D printer) where no additional machines are required for post-processing. The proposed model in this paper falls under this category.
- One-stage parallel-machines: where multiple machines are used to produce multiple jobs. These machines can be identical or non-identical with respect of their specifications as studied in [20]. Similar to the first type, this system has only one stage (the 3D printers).
- Multi-stage parallel-machines: similar to the second categories, this system has parallel-machines. In addition, the jobs need to go through multiple stages: 3D printers and additional machines (e.g., post-processing, inspection, packaging). Scheduling for this system is more complex since there are multiple different post-processing machines and possibly with different specifications.

Gushchin et al. [17] developed a FIFO (First-in-first-out) algorithm to manage multiple jobs served by multiple machines. Although the FIFO algorithm is fast and simple, it yields a high average waiting time. Moreover, the FIFO algorithm does not prioritize jobs based on other criteria such as the due date or most profitability. Kim et al. [18] developed an algorithm based on the shortest-job-first (SJF), which prioritizes jobs with the least printing time. Like FIFO, SJF does not prioritize jobs based on factors aside from the time required to perform the job. Li et al. [19] developed a mathematical model to reduce the production cost per unit volume for the Selective Laser Melting (SLM) technique in AM. This model examined allocating multiple parts to multiple machines with different specifications (i.e., operation cost, production efficiency, and maximum printing bed area and height). The results show significant cost reductions up to 29% at a total volume of 568003 m^3. However, this model does not account for any additional delivery priority requirement.

Closest to our work is the job-scheduling models presented in [20]. Kucukkoc [20] developed three models based on MILP to optimize the scheduling tasks in SLM of metal AM, where the objective is to minimize the makespan (production time). The first model is designed for scheduling jobs with a single machine, whereas the second and third models minimize the makespan with multiple identical and non-identical machines, respectively. In the third model, each machine may have different specifications (i.e., printing bed area, setup time, and machine height). Our work builds upon the single-machine model in [20] by adding a second objective to the optimization function that aims to minimize the deadline violation time. Unlike [20], our proposed model does not impose a job utilization constraint (jobs with less number of parts are scheduled first), instead it prioritizes scheduling jobs with smaller deadlines. To our knowledge, this work is the first in the literature to define a job-scheduling algorithm that minimizes the production time and deadline violation simultaneously.

3. Proposed job-scheduling: simultaneous makespan and deadline violation minimization

In this paper, we propose a multi-objective job-scheduling model that aims to group all parts into jobs (batches) and sequence these jobs such that: 1) the production time and, 2) the deadline violation time are minimized. Our proposed method is developed specifically for the extrusion-based 3DFP technology and it relies on MILP framework to solve the optimization problem. MILP has been effectively adopted in solving the scheduling problem in production lines, traditional food production [21, 22], and recently in AM production [20]. The data flow of the 3DFP ecosystem is illustrated in Figure 2 – this paper addresses the job-scheduling element. We assume that multiple parts ($i = 1, 2, \dots, I$) are grouped into jobs ($j = 1, 2, \dots, J$) that are scheduled on a *single* machine. Another assumption is that each part has a different design (height, area, and volume) as well as a deadline; the deadline represents the time constraint for part i. In the subsequent sub-sections, we introduce the mathematical formulation and the algorithmic solution of our model.

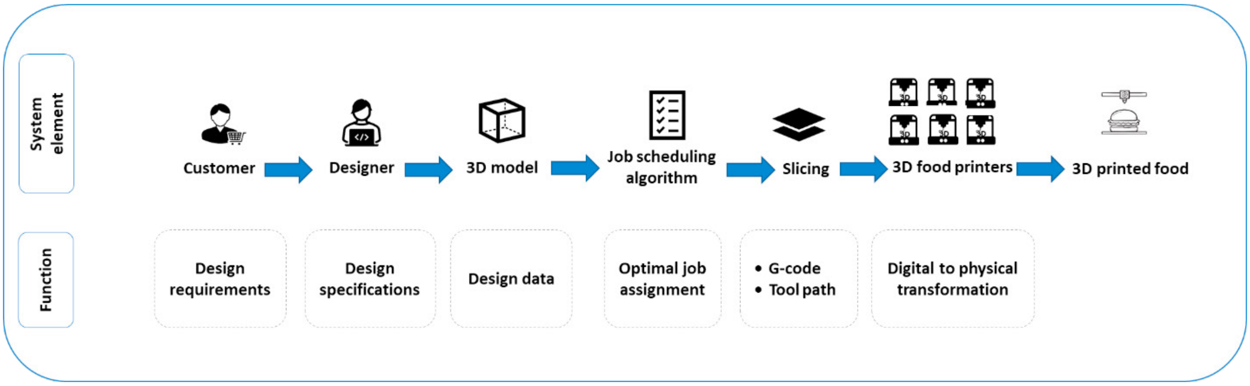

Fig. 2. The Data flow that includes the job-scheduling for 3D food printers.

3.1. Mathematical Formulation

In this section, we formally formulate the optimization problem, which consists of two main components: i) the objective function, and ii) the constraints that the solution has to follow. We assume that we have a total of I parts to be grouped to a total of J jobs. Before diving into the optimization equations, let us define the following design parameters:

- h_i: the height of part i.
- v_i: the volume of part i.
- a_i: the area of part i.
- d_i: the deadline of part i.
- MA: the productions area of the machine.
- HT: time required for vertical travel.
- VT: the required time per unit volume of material.
- SET: the machine's setup time.

The main constraints of the problem are listed as follows:

$$\sum_{j=1}^{J} X_{ji} = 1; \quad \forall i \in I \tag{1}$$

$$\sum_{i=1}^{I} a_i \cdot X_{ji} \leq MA; \quad \forall j \in J \tag{2}$$

where X_{ji} is a binary variable that is equal to 1 if part i is assigned to job j, and 0 otherwise. The first constraint in (1) ensures that each part is assigned to exactly one job, whereas (2) is to ensures that the total area of all the parts in job j does not exceed the machine's production area.

As we described earlier, we have two objectives: i) minimize the production time (PT), and ii) minimize the deadline violation (DV). We follow the work in [20] to formulate the production time of a job j as follows:

$$PT_j = SET \cdot Z_j + VT \cdot \sum_{i=1}^{I} v_i \cdot X_{ji} + HT \cdot \max(\{h_i \cdot X_{ji}\}_{i=1}^{I}); \quad \forall j \in J \tag{3}$$

where Z_j is a binary variable that is equal to 1 if $\max(\{X_{ji}\}_{i=1}^{J}) = 1$, and 0 otherwise (i.e., $Z_j = 1$ if job j has at least one part). Intuitively, the total production time can be obtained by the summation of all PT_j ($\sum_{j=1}^{I} PT_j$).

Next, we propose to formulate the deadline violation time of a job j (DV_j) as follows:

$$DV_j = \max(0, \sum_{k=1}^{j} PT_j - MD_j); \quad \forall j \in J \tag{4}$$

where MD_j is the minimum deadline of all parts in job j, e.g., if parts 3 and 4 are grouped into job 1, then $MD_1 = \min(d_3, d_4)$. The sum in $\sum_{k=1}^{j} PT_j$ is to obtain the cumulative production time from job 1 until the current job j. In other words, (4) aims to computes the difference between the cumulative production time of job j and the smallest deadline among the parts assigned to j. If $MD_j \geq \sum_{k=1}^{j} PT_j$, this means there is no deadline violation and we zero out the results using the max function. Since we do not know the parts assignment apriori, MD_j is a predetermined parameter that has to be set by the user. In our experimental results, we choose MD_j values based on intuitions from the parts deadlines d_i's.

Putting everything, the final proposed optimization formulation for the job-scheduling problem is as follows:

$$\min_{\{X_{ji}\}_{(i,j=1)}^{(I,J)}} \quad \sum_{j=1}^{J} PT_j + \lambda \sum_{j=1}^{J} DV_j \tag{5}$$

$$\text{s.t.} \quad \sum_{j=1}^{J} X_{ji} = 1; \ \forall i \in I \tag{6}$$

$$\sum_{i=1}^{I} a_i \cdot X_{ji} \leq MA; \ \forall j \in J \tag{7}$$

$$PT_j = SET \cdot Z_j + VT \cdot \sum_{i=1}^{I} v_i \cdot X_{ji} + HT \cdot \max(\{h_i \cdot X_{ji}\}_{i=1}^{I}); \ \forall j \in J \tag{8}$$

$$DV_j = \max(0, \sum_{k=1}^{j} PT_j - MD_j) \ \forall j \in J \tag{9}$$

$$Z_j = \max(\{X_{ji}\}_{i=1}^{I}); \ \forall j \in J \tag{10}$$

$$X_{ji}, Z_i \in \{0, 1\}; \ \forall j \in J, \ i \in I \tag{11}$$

where $\lambda \geq 0$ is a regularization parameter set by the user to balance the focus between minimizing the production time and the deadline violation time. The proposed formulation above has the advantage of solving the job-scheduling problem by minimizing the production time as well as the deadline violation time simultaneously. Moreover, the user can choose which one of these two objectives to focus on by means of λ (larger λ shifts the focus more on minimizing DV). Note that when we set $\lambda = 0$, then the algorithm will only minimize the production time. A general strategy to set the values of MD_j's is to run the algorithm with $\lambda = 0$ to obtain an initial scheduling solution, then use this solution to choose MD_j.

3.2. Algorithmic Solution

In this section, we briefly discuss how we obtain the solution to the proposed formulation in (5)-(11). The optimization problem is not linear due to the max functions in (8)-(10). In order to linearize these equations, we rely on the following common trick for linear programming. First, we add a variable that represents the maximum value. Then, we constrain this variable to be greater than or equal to all the terms inside the max function. For example, the equation

$$PT_j = SET \cdot Z_j + VT \cdot \sum_{i=1}^{I} v_i \cdot X_{ji} + HT \cdot \max(\{h_i \cdot X_{ji}\}_{i=1}^{I}) \tag{12}$$

is linearized by replacing it with the following equations

$$PT_j = SET \cdot Z_j + VT \cdot \sum_{i=1}^{I} v_i \cdot X_{ji} + HT \cdot \theta_j \tag{13}$$

$$\theta_j \geq h_i \cdot X_{ji};\ \forall i \in I \tag{14}$$

where θ_j is a dummy variable that represent the max function value. Once we linearize (8)-(10), the resulting formulation is a MILP problem. We use MILP solver in MATLAB R2022a software to obtain the solution[1].

4. Results and discussion

We validate the proposed model through the single-machine case study presented in [20] – we point out that we use this numerical example due to the unavailability of real dataset in the 3DFP domain. This case study includes 12 parts ($I = 12$), each with a different height (h_i), area (a_i), and volume (v_i) as shown in Table 1. In addition, we add a deadline (d_i) for each part in the case study to showcase the performance of the second objective (minimizing the deadline violation). The deadlines follow *hh*:*mm* format as shown in the last column of Table 1.

Table 1. Specifications of the parts in the case study (adapted from [20]).

Part (i)	Height (h_i) cm	Area (ai) cm^2	Volume (v_i) cm^3	Deadline (d_i) *hh*:*mm*
1	6.90	209.06	826.08	90:00
2	26.04	550.11	952.60	180:00
3	15.97	23.63	71.91	187:00
4	17.04	99.53	703.08	190:00
5	27.94	56.85	272.92	188:00
6	17.38	50.02	125.70	200:00
7	11.81	435.66	1142.25	92:00
8	2.67	84.27	121.82	96:00
9	17.13	48.27	315.00	189:00
10	4.27	122.62	102.83	08:00
11	2.18	178.34	214.79	10:00
12	6.48	134.08	124.66	98:00

[1] The code is available at: `https://github.com/Alghamdy/3D-food-printing-scheduling`.

We set the maximum number of jobs to $J = 3$ (the results stay the same when $J > 3$ as the added jobs stay empty with no parts allocated to them). The machine parameters are assumed to be $VT = 0.030864$ hr/cm^3, $HT = 0.7$ hr/cm, $MA = 900$ cm^2, and $SET = 1\ hr$.

Figure 3 shows the total production time PT (right y-axis) as well as the total deadline violation time DV (left y-axis) with varying values of λ (x-axis). Note that PT and DV are accumulated across all jobs in these results. We observe that the value of PT remains constant at 187.32 hr, which is similar to the total PT achieved by the work in [20]. On the other hand, the value of DV drops from 677.26 hr (with $\lambda = 0$) to 18.64 hr (with $\lambda = 0.001$ or larger).

In Figure 4 and 5, we show the part allocation, the production time for each job, and the total deadline violation with the scenarios when λ is set to 0 and 0.0001, respectively. One can observe that when $\lambda > 0$ (i.e., the DV minimization is enabled), our algorithm prioritizes scheduling parts with smaller deadlines, which significantly reduces the deadline violation time while achieving the same production time.

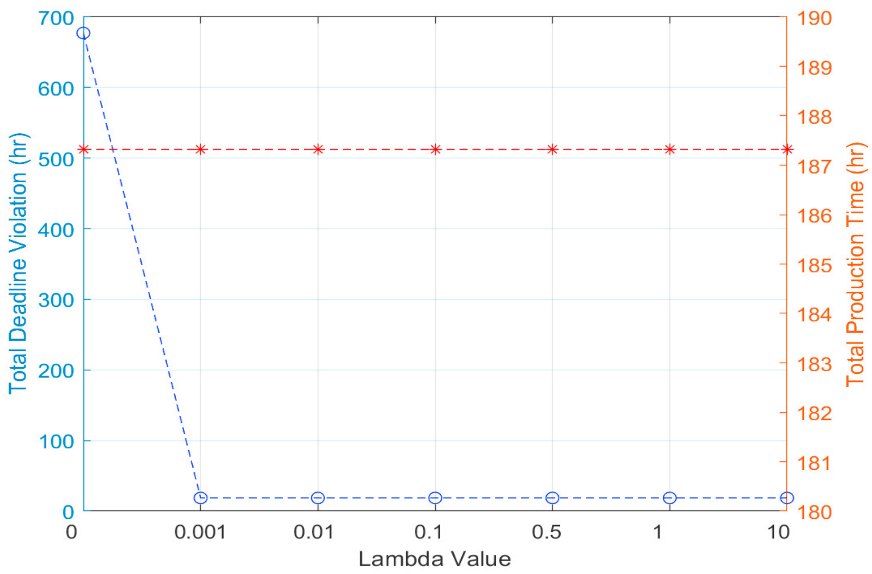

Fig. 3. Deadline violation and production time with varying values of λ

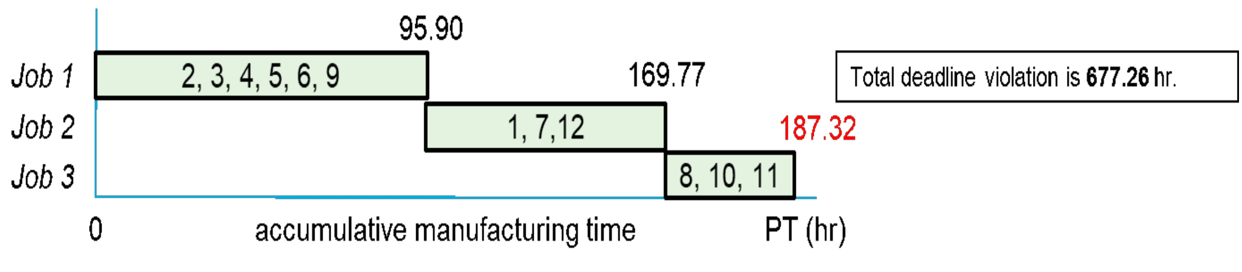

Fig. 4. Part allocation when $\lambda = 0$.

5. Conclusions and future work

Job scheduling is a key component in AM as it ensures a successful delivery and efficient use of resources. In the case of 3DFP, scheduling is more complex since different parts have different time constraints depending on material's

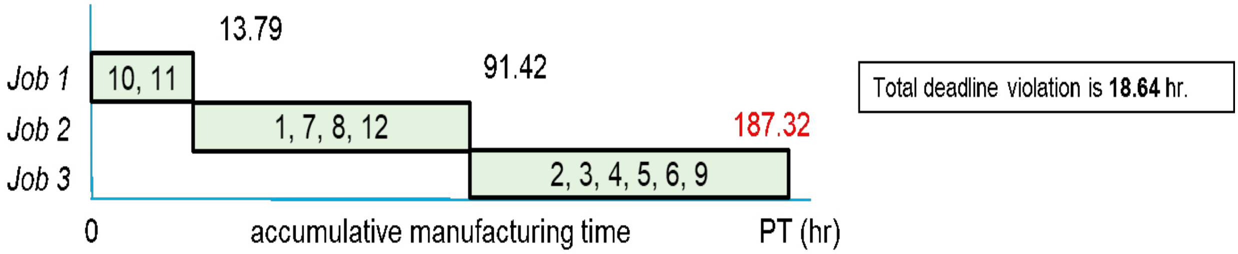

Fig. 5. Part allocation when $\lambda = 0.001$.

shelf-life. We proposed a job-scheduling algorithm that minimizes the production time and the deadline violation simultaneously. Our proposed model is the first in the literature that minimizes the makespan while being recognizant of parts' deadlines. Another main advantage of our model is that the user can control the focus between the two objectives by adjusting the weight using a regularization parameter. The experimental results show that our proposed model achieves scheduling that significantly reduces the deadline violation while obtaining the same production time as the state-of-the-art baseline method. The current model is designed to schedule parts in a single machine and our plan is to extend it to handle multiple parallel identical and non-identical machines.

Acknowledgements

M. Alghamdy and R. Ahmad acknowledge the financial support of the Natural Sciences and Engineering Research Council (NSERC) of Canada (Grant No. NSERC RGPIN-2017-04516 Ahmad) for supporting this project.

References

[1] Jayaprakash, S., Paasi, J., Pennanen, K., Flores Ituarte, I., Lille, M., Partanen, J., and Sozer, N. (2020). "Techno-economic prospects and desirability of 3D food printing: perspectives of industrial experts, researchers and consumers." *Foods*, **9** (12): 1725.
[2] Agunbiade, A. O., Song, L., Agunbiade, O. J., Ofoedu, C. E., Chacha, J. S., Duguma, H. T., ... and Guine, R. P. (2022). "Potentials of 3D extrusion-based printing in resolving food processing challenges: A perspective review." *Journal of Food Process Engineering*, **45** (4): e13996.
[3] Sun, J., Zhou, W., Huang, D., Fuh, J. Y., and Hong, G. S. (2015). "An overview of 3D printing technologies for food fabrication." *Food and bioprocess technology*, **8** (8): 1605-1615.
[4] Sun, J., Peng, Z., Zhou, W., Fuh, J. Y., Hong, G. S., and Chiu, A. (2015). "A review on 3D printing for customized food fabrication." *Procedia Manufacturing*, 1: 308-319.
[5] Liu, Z., Zhang, M., Bhandari, B., and Wang, Y. (2017). "3D printing: Printing precision and application in food sector." *Trends in Food Science & Technology*, 69: 83-94.
[6] Pulatsu, E., and Lin, M. (2021). "A review on customizing edible food materials into 3D printable inks: Approaches and strategies." *Trends in Food Science & Technology*, 107: 68-77.
[7] Lipton, J. I., Cutler, M., Nigl, F., Cohen, D., and Lipson, H. (2015). "Additive manufacturing for the food industry." *Trends in food science & technology*, **43** (1): 114-123.
[8] Lipson, H., and Kurman, M. (2013). "Fabricated: The new world of 3D printing." John Wiley & Sons.
[9] Manstan, T., and McSweeney, M. B. (2020). "Consumers' attitudes towards and acceptance of 3D printed foods in comparison with conventional food products." *International Journal of Food Science & Technology*, **55** (1), 323-331.
[10] Caulier, S., Doets, E., and Noort, M. (2020). "An exploratory consumer study of 3D printed food perception in a real-life military setting." *Food Quality and Preference*, 86: 104001.
[11] Holland, S., Foster, T., and Tuck, C. (2019). "Creation of food structures through binder jetting". *In Fundamentals of 3D food printing and applications*, (pp. 257-288). Academic Press.
[12] Sun, J., Zhou, W., Huang, D., Fuh, J. Y., and Hong, G. S. (2015). "An overview of 3D printing technologies for food fabrication". *Food and bioprocess technology*, **8** (8): 1605-1615.
[13] Tan, C., Toh, W. Y., Wong, G., and Li, L. (2018). "Extrusion-based 3D food printing–Materials and machines". *International Journal of Bioprinting*, **4**(2).
[14] Liu, S., Zhang, L., Zhang, W., and Shen, W. (2021). "Game theory based multi-task scheduling of decentralized 3D printing services in cloud manufacturing". *Neurocomputing*, 446: 74-85.

[15] Zhang, J., Yao, X., and Li, Y. (2020). "Improved evolutionary algorithm for parallel batch processing machine scheduling in additive manufacturing". *International Journal of Production Research*, **58** (8): 2263-2282.

[16] Oh, Y., Witherell, P., Lu, Y., and Sprock, T. (2020). "Nesting and scheduling problems for additive manufacturing: a taxonomy and review". *Additive Manufacturing*, 36: 101492.

[17] Gushchin, I. A., Martynovich, I. V., and Torubarov, I. S. (2019, March). "Automatic print job scheduling and management over multiple 3D printers". *In International Conference on Industrial Engineering* (pp. 477-487). Springer, Cham.

[18] Kim, S. C., Kim, M., and Ahn, N. (2019). "3D Printer Scheduling for Shortest Time Production of Weapon Parts." *Procedia Manufacturing*, 39: 439-446.

[19] Li, Q., Kucukkoc, I., and Zhang, D. Z. (2017). "Production planning in additive manufacturing and 3D printing." *Computers* & *Operations Research*, 83: 157-172.

[20] Kucukkoc, I. (2019). "MILP models to minimise makespan in additive manufacturing machine scheduling problems." *Computers* & *Operations Research*, 105: 58-67.

[21] Mahafzah, B. A., Alshraideh, M., Abu-Kabeer, T. M., Ahmad, E. F., and Hamad, N. A. (2012). "The optical chained-cubic tree interconnection network: topological structure and properties." *Computers* & *Electrical Engineering*, **38** (2): 330-345.

[22] Georgiadis, G. P., Pampín, B. M., Cabo, D. A., and Georgiadis, M. C. (2020). "Optimal production scheduling of food process industries." *Computers* & *Chemical Engineering*, 134, 106682.