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AN OPTIMAL QUANTITY OF SCHEDULING MODEL FOR MASS CUSTOMIZATION-BASED ADDITIVE MANUFACTURING

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ABSTRACT

The purpose of this study is to optimize production planning decisions in *additive manufacturing for mass customization (AMMC)* systems in which customer demands are highly variable. The main research question is to find the optimal quantity of products for scheduling, the *economic scheduling quantity (ESQ)*. If the scheduling quantity is too large, the time to collect customer orders increases and a penalty cost occurs due to the delay in responding to consumer demands. On the other hand, if the scheduling quantity is too small, the number of parts per jobs decreases and parts are not efficiently packed within a workspace and consequently the build process cost increases. An experiment is provided for the case of *stereolithography (SLA)* and *2D packing* to demonstrate how the build time per part increases as the scheduling quantity decreases. In addition, a mathematical framework based on ESQ is provided to evaluate the production capacity in satisfying the market demand.

Keywords: additive manufacturing, production planning, economic scheduling quantity, mass customization

NOMENCLATURE

λ	The arrival rate of customer demands (units / h)
P	The production rate of scheduled parts (units / h)
Q	The number of parts for scheduling (units)
T_c	Cycle time for scheduling (h)
T_p	Completion time for production (h)
T_b	Total build time (h)
c_t	Penalty cost per hour (\$/h)
c_p	Build process cost per hour (\$/h)
c_m	Unit material cost (\$/mm^3)
$\bar{v}$	The average volume per part (mm^3/unit)
M	The number of AM machines (units)

1. INTRODUCTION

Recently, on-demand production in 3D printing plants, or *3D printing farms,* has been developed as a promising business model [1]–[4]. In this newly developed business model, manufacturers install multiple 3D printers and run them simultaneously to produce hundreds and thousands of parts in a very short period of time. Customers place their orders through e-commerce websites by registering 3D models of what they need. Consumer orders are produced by multiple 3D printers and are shipped to consumers. In these types of business models, consumer orders are coming one by one and are highly variable in terms of features and characteristics. Products and design blueprints are personalized based on each customer order.

The current business models show that Additive Manufacturing (AM) is spotlighted for both mass production and customization. The focus of this study is on a production system for a 3D printing plant with mass customization capabilities named as *AM for Mass Customization (AMMC)*.

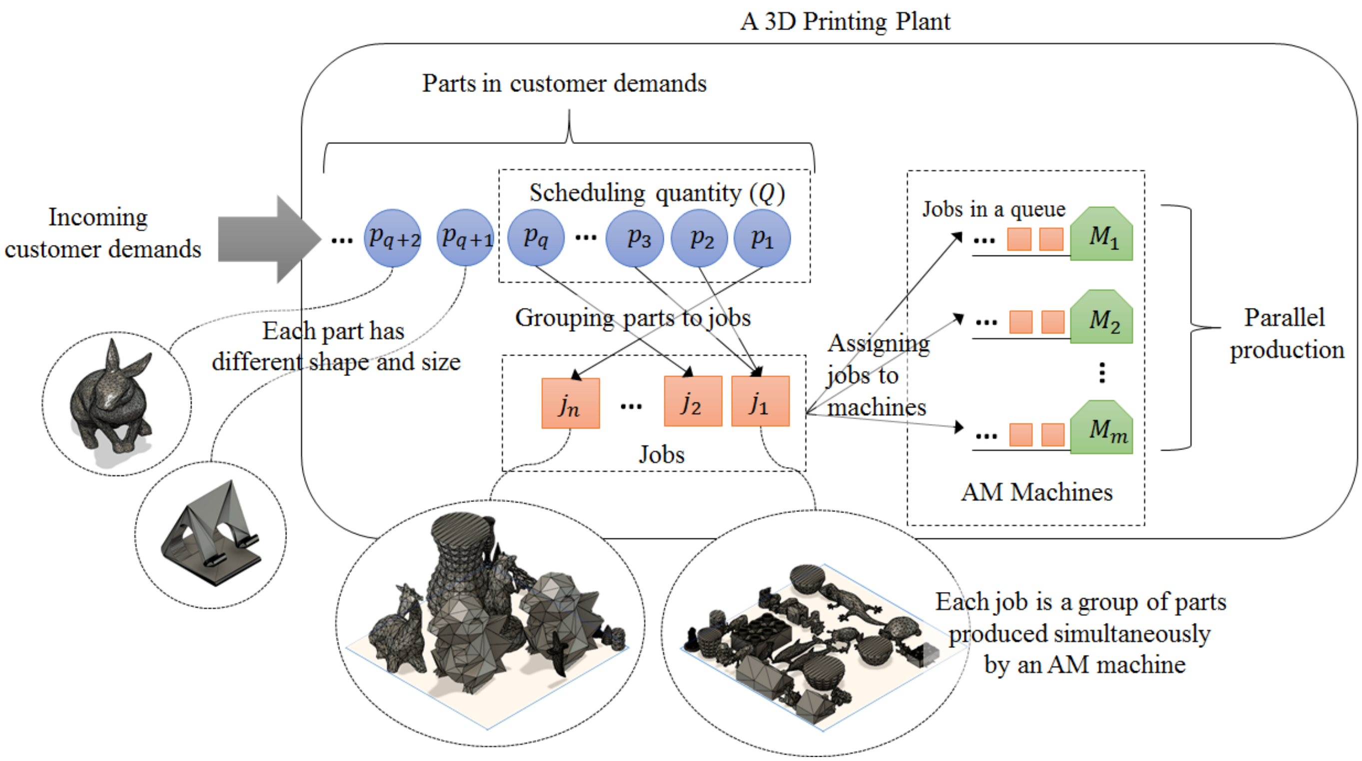

Figure 1: A production system in Additive Manufacturing for Mass Customization (AMMC)

AMMC adopts the *make-to-order (MTO)* production strategy [5]. Once a customer demand arrives, the plant begins the production. In MTO for AMMC, manufacturers have to deal with extremely customized parts, with different size, geometry and shape for individual customers.

Figure 1 represents how the AMMC system works. Customer demands arrive at a 3D printing plant. Each order has its own characteristics. Once the number of incoming orders reaches to Q, known as scheduling quantity, the manufacturer starts defining a production plan to take care of customer orders. Then, parts are grouped into jobs (or builds [6]). A job is a group of parts produced simultaneously by an AM machine (a 3D printer). Then, jobs are assigned to AM machines. Each AM machine has a queue and jobs in a queue are processed by their own AM machine. This is a type of parallel production in which multiple AM machines work on their assigned jobs independently.

The main question in this study is to decide about the scheduling quantity, Q. Defining a plan with a high number of parts (large Q) has a positive effect on minimizing the total build time, since it increases the number of parts per job and consequently improves the packing utilization. However, waiting to collect a high number of orders and then start the production may result in higher lead time and delay in responding to consumer demands. This study develops a method to find the optimal quantity of parts, the *economic scheduling quantity (ESQ)*, Q^*, with the aim of minimizing the production cost that also includes the penalty cost of delaying in addressing consumer orders.

2. LITERATURE REVIEW

2.1 Production planning for AM

Studies on production planning for AM have considered how to group parts into jobs and how to assign jobs to AM machines. Grouping parts into a single job has usually been focused on using different packing algorithms including 2D packing [7] and 3D packing [8]. In the case of grouping parts into multiple jobs, the approaches for the traditional bin packing problems are adopted for AM [6]. In addition to packing, build orientation determination is another aspect that should be addressed since the packing utilization depends on part orientations. Griffiths et al (2018) provided a heuristic method dealing with both bin packing problem and build orientation problem [9]. However, considering only the grouping issue is not sufficient for managing production systems at a higher level. This is where the planning and scheduling for AM with multiple 3D printers become important.

For assigning jobs or parts to AM machines, most of the previous studies have been based on classical scheduling problems. To name a few studies, Li et al. (2017) proposed heuristic algorithms and mathematical models to minimize the average production cost per volume of material [10]. Kim et al. (2017) suggested a *genetic algorithm (GA)* to match parts to 3D printers in order to minimize makespan [11]. Ransikarbum et al. (2018) solved a part-to-printer assignment problem by using multi-objective optimization [12]. However, previous studies have focused on planning and scheduling without considering the packing. To consider the details of the packing in the production planning level, mathematical models become too complicated and heuristic models result in computational inefficiencies. To overcome this issue, the current study considers the packing issue indirectly by using a result function extracted from a packing simulation experiment.

2.2 The economic order quantity model

Economic order quantity (EOQ) is the order inventory quantity to minimize the total holding and ordering costs proposed by Harris (1913) [13]. The EOQ model is one of the oldest classical production scheduling and inventory control models [14]. It has been extended in many ways including the *economic production quantity (EPQ)* model [15], the reorder point [16], and the stochastic EOQ [17]. EOQ has still being studied as a solid mathematical model for inventory lot sizing [18].

Although the classical EOQ model is based on inventory management [19], the current study focuses on a different production planning problem emphasizing more on customer demands. In order to find the optimal quantity of scheduling for AM, it only adopts the mathematical approach of the EOQ model for identifying the optimal quantity between the trade-off factors.

3. APPROACH

This section describes the proposed mathematical framework for calculating the total build time and the ESQ model. The following assumptions have been used:

- The customer demand arrival rate is known and is constant over time.
- Each customer demand has only one part.
- To make a production plan, Q is consistent for each cycle.
- All AM machines have the same process parameters. The size of the workspace and the model of AM machine are the same.
- Setup time for each job is not considered since it is negligible compared to its build time.

3.1 The relation between build time and scheduling quantity

Each job is completed through a build process by an AM machine, which means that each job has its own build time. The total build time of the jobs, T_b, is the sum of build time for all jobs that result from part grouping by using Q. Once T_b is divided by Q, the build time per part is obtained.

In the case of handling hundreds or thousands of parts using *stereolithography (SLA)* and *2D packing*, it is likely that the build time per part decreases as Q increases. This is mainly due to the increase in packing utilization.

To validate this, an experiment with the following conditions has been conducted. The build time estimation model and the 2D packing algorithm developed by Oh et al. (2017) are modified and adopted for this experiment [20]. 1000 input parts are randomly generated to simulate customer orders for AMMC. To generate random inputs, parts are arbitrarily chosen from a set of 100 different geometries from Thingiverse.com [21] and, after normalizing their size, the size is re-scaled by multiplying a value from a uniform distribution (1, 10). Without changing the build orientation of parts, the initial orientation is used for part placement. To avoid the undesired case that the shape and size of the generated 1000 parts are biased, the experiment is repeated three times. The width, length, and height of a workspace of an AM machine are 200×200×200 mm, respectively.

To produce 1000 parts based on AMMC, Q is set from 30 (representing a small number of parts) to 1000 (a large number). Table 1 shows T_b based on Q and its build time per part. Given the dataset of Q and the build time per part, the relation can be represented by a non-linear curve model as shown in Equation (1). In this equation, α is mostly affected by the size of workspace and the average volume of parts while β usually indicates the type of AM processes.

$$Build\ \ time\ \ per\ \ part = \alpha + \frac{\beta}{Q} \tag{1}$$

CurveExpert Professional 2.6.5 is used to identify two parameters, α and β, of the curve model, which are 0.3480 and 3.5095, respectively. Figure 2 represents the curve model fitting the dataset. As shown in the figure, the build time per part decreases and converges as Q increases.

Table 1: T_b to produce 1000 parts depending on Q

Q	T_b (hours)	Build time per part* (hours)
30	14.18	0.4727
100	35.96	0.3596
200	74.96	0.3748
300	110.62	0.3687
500	178.78	0.3576
1000	352.80	0.3528
Build time per part* $= T_b/Q$		

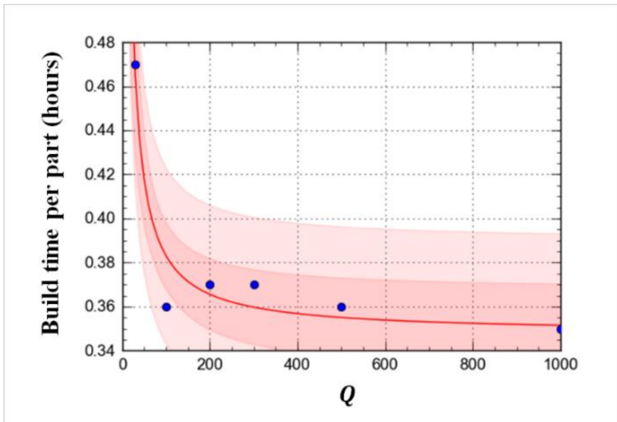

Figure 2: The build time per part depending on Q

3.2 The economic scheduling quantity (ESQ)

Equation (1) is used to estimate T_b based on Q by multiplying Q to both sides of the formula. It is shown as follow:

$$T_b = \alpha Q + \beta \tag{2}$$

In parallel production, jobs are assigned to multiple AM machines and the machines run simultaneously and independently. Therefore, if a manufacturer has more AM machines, the completion time, T_p of Q units will be smaller. Given this relation, T_p is calculated as follows:

$$T_p = \frac{T_b}{M} = \frac{\alpha Q + \beta}{M} \tag{3}$$

Figure 3 presents the number of scheduled and not scheduled customer demands over time. With T_c, the solid line that represents the not scheduled customer demands repeats with the same cycle. At the point of scheduling, Q units of customer demands are scheduled by grouping parts into jobs. Then, they are sent to queues of AM machines and the production begins. Therefore, at this point, while the number of not scheduled customer demands becomes zero, the number of scheduled orders goes to Q.

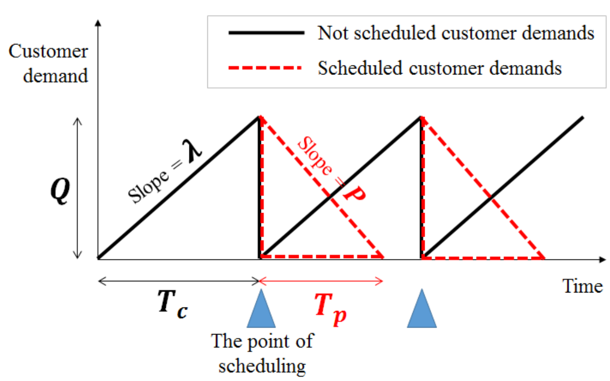

Figure 3: Customer demand level according to time

Since Q units are scheduled for each cycle, with the arrival rate of λ, the time T_c, can be calculated by Equation (4). T_c means the waiting time to make a production plan until Q units of consumer orders arrive.

$$T_c = \frac{Q}{\lambda} \tag{4}$$

In a similar way, Q units are produced during T_p, therefore, the production rate, P, is as follows:

$$P = \frac{Q}{T_p} \tag{5}$$

Since the customer demand level increases linearly or decreases between 0 and Q as shown in Figure 3, the average customer demand level can be calculated by Equation (6). Since the customer demand level is periodically repeated, this can be used as the average customer demand level over a time horizon.

$$\text{The average customer demand level} = \frac{Q(T_c + T_p)}{2T_c} \tag{6}$$

The average penalty cost, $C_t(Q)$, is obtained by multiplying the average customer demand level with the penalty cost per part, c_t. In addition, T_c and T_p are replaced by Equations (4) and (3), respectively.

$$C_t(Q) = \frac{c_t Q(T_c + T_p)}{2T_c} = \frac{c_t Q}{2} + \frac{\alpha\lambda c_t Q}{2M} + \frac{\beta\lambda c_t}{2M} \tag{7}$$

For each cycle, the cost of build processes is calculated by multiplying T_b with a unit build process cost per hour, c_p.

$$c_p T_b = \alpha c_p Q + \beta c_p \tag{8}$$

In addition, the material cost to produce Q units is computed as follows:

$$\text{Material cost} = Q\bar{v}c_m \tag{9}$$

The production cost for each cycle is the build process cost plus the material cost. In order to obtain the production cost per unit time, the cost is divided by the length of cycle time, T_c. Therefore, the annual cost, $G(Q)$, consists of the build process cost, the material cost, and the penalty cost as shown in Equation (10).

$$\begin{aligned} G(Q) &= \frac{(\alpha c_p Q + \beta c_p + Q\bar{v}c_m)}{T_c} + C_t(Q) \\ &= \alpha\lambda c_p + \frac{\beta\lambda c_p}{Q} + \lambda\bar{v}c_m + \frac{c_t Q}{2} + \frac{\alpha\lambda c_t Q}{2M} + \frac{\beta\lambda c_t}{2M} \end{aligned} \tag{10}$$

We wish to find Q^* to minimize $G(Q)$. The derivative of $G(Q)$ with respect to Q is obtained as follows:

$$G'(Q) = -\frac{\beta\lambda c_p}{Q^2} + \frac{c_t}{2} + \frac{\alpha\lambda c_t}{2M} \tag{11}$$

According to Equation (12), $G''(Q) > 0$. Therefore, $G(Q)$ is a convex function of Q and we can get the optimum (minimum) value.

$$G''(Q) = \frac{2\beta\lambda c_p}{Q^3} > 0 \tag{12}$$

The optimal value of Q, ESQ, is obtained from $G'(Q) = 0$.

$$Q^* = \sqrt{\frac{2\beta\lambda M c_p}{c_t(M + \alpha\lambda)}} \tag{13}$$

Some terms in Equation (10) are not functions of the scheduling size, Q, so we have put them in C, as shown in Equation (14). Therefore, the global average annual cost, $G(Q)$, is re-described by the partial average annual cost, $R(Q)$, and C as shown in Equation (15). $R(Q)$, is defined as the sum of $B(Q)$ and $E(Q)$, the buildup cost and penalty cost as functions of Q.

$$C = \alpha\lambda c_p + \lambda\bar{v}c_m + \frac{\beta\lambda c_t}{2M} \tag{14}$$

$$G(Q) = R(Q) + C \tag{15}$$

$$R(Q) = B(Q) + E(Q) \tag{16}$$

$$B(Q) = \frac{\beta\lambda c_p}{Q} \tag{17}$$

$$E(Q) = \left(\frac{c_t}{2} + \frac{\alpha\lambda c_t}{2M}\right)Q \tag{18}$$

In Figure 4, the curves represent $R(Q)$, $B(Q)$ and $E(Q)$. If $B(Q) = E(Q)$ is solved for Q, the ESQ formula, Equation (13), is obtained. This means the minimum $Q^*$is occurring at the intersection of the two curves, $B(Q)$ and $E(Q)$. This is the point of minimizing $R(Q)$ as well as $G(Q)$.

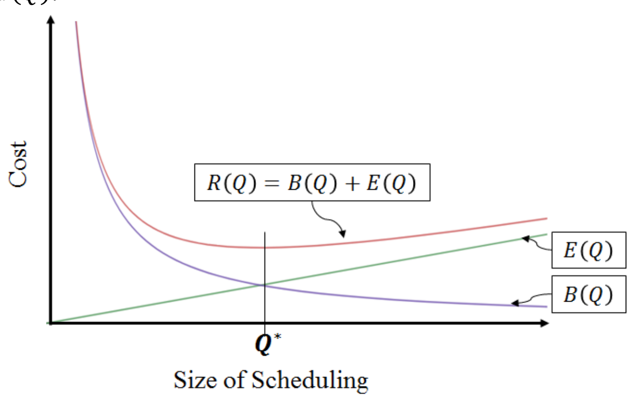

Figure 4: The partial average annual cost, $R(Q)$, consisting of the buildup and penalty costs with only the terms involved Q

3.3 Diagnosis for production status by ESQ

The production efficiency of a 3D printing plant can be analyzed by using ESQ. ESQ can help identify whether the current production capacity is sufficient to deal with the arrival rate of customer demands. This can be achieved by comparing T_c^* and T_p^*. Given Q^*, T_c^* and T_p^* are computed by Equations (4) and (3).

Figure 4 compares the two cases. In Case 1, if $T_c^* > T_p^*$, all scheduled parts are produced before the next cycle. In other words, the production capacity is sufficient to satisfy incoming orders. In Case 2, if $T_c^* < T_p^*$, all scheduled parts cannot be completed before the next cycle. Therefore, some parts that were scheduled in the previous cycle are still in production at the point of arrival of the new scheduled parts. In other words, production capacity is not sufficient to produce incoming parts. This could result in the stacking of customer demands and high penalty cost.

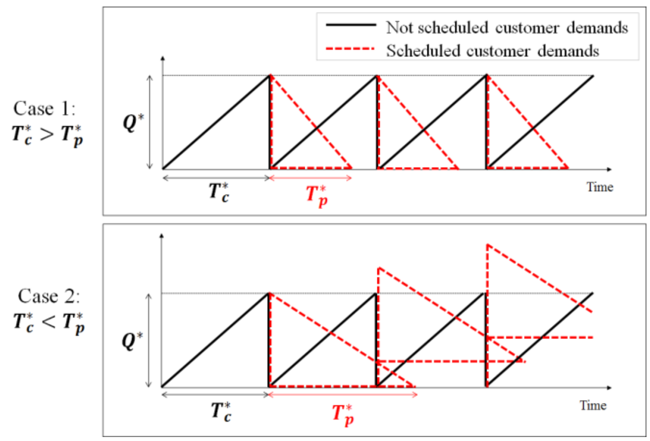

Figure 5: Diagnosis of production status

To fully handle incoming parts, a sufficient number of AM machines are needed. However, investing in too many AM machines may bring unnecessary costs to the system. Therefore, it is important to identify the minimum number of AM machines needed to satisfy consumer orders.

Equation (3) can be represented for M. T_p is replaced by T_c since the machine number is minimized when $T_p = T_c$. Then, T_c is substituted by Q/λ according to Equation (4). Given Q^*, the minimum number of AM machines is calculated by Equation (19). Since the machine number is a positive integer value, the equation has a ceiling function.

$$M^* = \left\lceil \frac{\alpha Q^* + \beta}{T_p} \right\rceil = \left\lceil \frac{\alpha Q^* + \beta}{T_c} \right\rceil = \left\lceil \lambda\left(\alpha + \frac{\beta}{Q^*}\right) \right\rceil \tag{19}$$

4. SENSITIVITY ANALYSIS

This section investigates the way that Q influences the average annual cost. The first sub-section describes the effect of Q on the global cost, $G(Q)$, and the second sub-section shows the impact of Q on the partial cost, $R(Q)$.

4.1 The impact of parameters λ and c_t on G(Q)

In this study, the decision variable Q is determined to minimize the total cost, $G(Q)$. Since $G(Q)$ consists of a variable part, $R(Q)$, and a constant part, C, determining Q is important if $R(Q)$ takes up the large part of $G(Q)$. To identify what conditions increase the effect of $R(Q)$ in $G(Q)$, two parameters, λ and c_t, are investigated. To do this, real estimates are used as shown in Table 2. α, β and $\bar{v}$ come from the experiment in Section 3.1. c_m is based on the material cost of SLA.

Table 2: Real values for major parameters

α	0.3480	β	3.5095
M	10 machines	c_p	10 \$/hour
$\bar{v}$	37928 mm^3	c_m	0.00009 \$/mm^3

Tables 3 and 4 represent $R(Q)$, C, and $G(Q)$ based on λ and c_t, respectively. Figure 6 shows the $R(Q)/G(Q)$ fraction based on λ and c_t. As λ decreases and c_t increases, $R(Q)$ is getting more portion in $G(Q)$, meaning that the global cost is getting more affected by Q. However, when λ is a large number, both $R(Q)$ and C increase to take care of many customer orders. In this case, even though $R(Q)$ is relatively small compared to C, it is sufficiently large that cannot be negligible.

Table 3: $R(Q)$, C and $G(Q)$ depending on λ ($c_t = 3$)

λ	$R(Q)$	C	$G(Q)$
1	14.76	7.42	22.18
5	35.16	37.10	72.26
10	53.28	74.20	127.48
20	84.51	148.40	232.91
30	113.63	222.60	336.23
60	197.52	445.20	642.72

Table 4: $R(Q)$, C and $G(Q)$ depending on c_t ($\lambda = 10$)

c_t	$R(Q)$	C	$G(Q)$
0.1	9.73	69.11	78.84
0.5	21.75	69.81	91.56
1	30.76	70.69	101.45
2	43.50	72.44	115.95
4	61.52	75.95	137.47
8	87.00	82.97	169.97

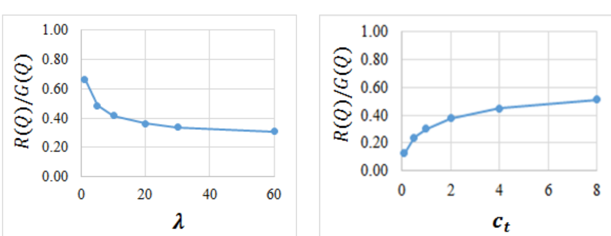

Figure 6: The $R(Q)$ portion of $G(Q)$ depending on λ and c_t

4.2 Sensitivity analysis of Q on R(Q)

Given $\lambda = 20$, $c_t = 1$ and the numbers in Table 2, ESQ is obtained as shown in Equation (20).

$$Q^* = \sqrt{\frac{2\beta\lambda M c_p}{c_t(M+\alpha\lambda)}} = 28.77 \tag{20}$$

Based on the Q^*, $R(Q^*)$ is calculated as follow:

$$R(Q^*) = \frac{\beta\lambda c_p}{Q^*} + \left(\frac{c_t}{2} + \frac{\alpha\lambda c_t}{2M}\right) Q^* = 48.79 \tag{21}$$

However, if a manufacturer does not follow ESQ, Q could be different from Q^*. For example, if $Q = 15$, then $R(Q)$ becomes \$59.51. The cost ratio of $R(Q)/R(Q^*)$ is 1.22.

The way that $R(Q)$ is sensitive to Q can be generally expressed by a formula. Suppose R^* is the partial cost at Q^* then it is expressed as Equation (22).

$$\begin{aligned} R^* &= B(Q^*) + C(Q^*) \\ &= \frac{\beta\lambda c_p}{Q^*} + \left(\frac{c_t}{2} + \frac{\alpha\lambda c_t}{2M}\right) Q^* \\ &= \beta\lambda c_p \sqrt{\frac{c_t(M+\alpha\lambda)}{2\beta\lambda M c_p}} \\ &\quad + \frac{c_t(M+\alpha\lambda c_t)}{2M} \sqrt{\frac{2\beta\lambda M c_p}{c_t(M+\alpha\lambda)}} \\ &= \sqrt{\frac{\beta\lambda c_p c_t(M+\alpha\lambda)}{2M}} + \sqrt{\frac{\beta\lambda c_p c_t(M+\alpha\lambda)}{2M}} \\ &= \sqrt{\frac{2\beta\lambda c_p c_t(M+\alpha\lambda)}{M}} \end{aligned} \tag{22}$$

It follows Equation (23) for any Q.

$$\begin{aligned} \frac{R(Q)}{R^*} &= \frac{1}{2Q}\sqrt{\frac{2\beta\lambda c_p M}{c_t(M+\alpha\lambda)}} + \frac{Q}{2}\sqrt{\frac{c_t(M+\alpha\lambda)}{2\beta\lambda c_p M}} \\ &= \frac{Q^*}{2Q} + \frac{Q}{2Q^*} = \frac{1}{2}\left(\frac{Q^*}{Q} + \frac{Q}{Q^*}\right) \end{aligned} \tag{23}$$

Therefore, if $Q = 15$ and $Q^* = 28.77$, $R(Q)/R^*$ is 1.22 from Equation (23) even though Q^*/Q is 1.92. This shows that the partial cost is relatively insensitive to errors of Q. This point is similar to the concept of EOQ models in the inventory planning literature.

5. CONCLUSION

This paper investigates the concept of production planning in mass customization-based additive manufacturing systems. Specifically, it provides a mathematical method for obtaining the optimal quantity for production planning, that is the *economic scheduling quantity (ESQ)*. In addition, a mathematical framework is provided to analyze the capacity planning in such production systems. Several sensitivity analyses have been conducted to show the impact of the model parameters on the total cost of the system.

The research can be extended in several ways. First, more accurate functions for calculating the build time per part can be extracted from practical experiments. Since the provided function is based on SLA and 2D packing, other conditions and AM processes can be studied to affect the function. Second, when estimating the build time per part other factors such as build orientation should be considered. In addition, the classical EOQ model could be combined with the ESQ model to simultaneously consider inventory control issues for parts as well as production planning. Lastly, the application of the model can be shown in practice for a real case study.

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