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Additive or Conventional Manufacturing for Spare Parts: Effect of Failure Rate Uncertainty on the Sourcing Option Decision

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Abstract: Additive manufacturing (AM) has recently been reported as enabler of digital spare parts supply. Thanks to its promise to produce spare parts with shorter lead times, AM may enable a make-to-order rather than a make-to-stock manufacturing process. Using AM, in fact, would allow to reduce the high inventory levels that are required by conventional manufacturing (CM) techniques to cope with spare parts' intermittent demand. However, AM is characterized by two main drawbacks, i.e. first high production costs and second uncertain failure rates (often these uncertainties are higher than those of CM counterparts since AM is a manufacturing technique that is still subjected to substantial technological developments, while CM techniques are very well-established). While the former limitation can be counterbalanced with lower inventory costs, the latter remains an open issue, so far barely investigated. To the best of our knowledge, although researchers have considered the impact of failure rate uncertainties on the inventory costs and the total costs of spare parts management, no one has investigated how the failure rate uncertainty would affect the final decision on whether to manufacture spare parts in AM or CM. In this work, we aim to do so. Specifically, to make the analysis accurate and reliable, we have used realistic values of the failure rate uncertainties of AM and CM parts, obtained through a material science approach. From our results, which represents just a preliminary analysis where we have considered 40 different scenarios characterized by different combinations of spare part demands and backorder costs, we have observed that the failure rate uncertainty limits the conveniency of AM as sourcing option to only 7.5% of the analyzed scenarios (when the failure rate was considered too be known precisely, AM was the most convenient option 42.5% of the analyzed scenarios). These preliminary results indicate the need to reduce AM failure rate uncertainties to leverage the potential of AM for spare parts supply chains.

Keywords: Additive Manufacturing (AM); Spare Parts; Failure Rate Uncertainty; Conventional Manufacturing (CM); Decision Tree; Decision Support System.

1. INTRODUCTION & BACKGROUND

Nowadays, the importance to manage spare parts correctly is well-know. It is only through a correct spare parts management, in fact, that a high availability of production systems can be achieved. However, it is not easy to manage spare parts correctly. Spare parts are often characterized by intermittent demands (difficult to forecast both in terms of quantity and frequency), strong dependency on suppliers, long procurement lead times, and high downtime costs (Huiskonen, 2001; Roda et al., 2019).

Recently, researchers and practitioners have identified additive manufacturing (AM) as potential opportunity to overcome these challenges. AM, often enables to manufacture spare parts (i) with shorter lead time (even on demand) and (ii) close to the point of use (Walter et al., 2004). This usually allows to decrease inventory levels without reducing spare parts availability. Moreover, when the production is in-house, the dependency on suppliers also decreases.

However, the use of AM for manufacturing spare parts is accompanied by two main disadvantages, i.e. first the production costs and second the mechanical properties. Dealing with the former, researchers and practitioners have started evaluating whether the high production costs can be counterbalanced by the decrease in inventory level (and hence costs). Interesting works in this perspective are those of (Westerweel et al., 2018), (Knofius et al., 2020), and (Sgarbossa et al., 2021). (Westerweel et al., 2018) adopted a life cycle cost analysis to identify the break-even point in terms of production costs between AM and conventional manufacturing (CM) techniques (e.g. casting, rolling, etc.). (Sgarbossa et al., 2021), then, used a decision tree algorithm to develop a decision support system (DSS) that supports managers in deciding when spare parts should be produced in AM and when in CM, showing that the lower inventory costs obtainable with AM can only partially counterbalance the high production costs. Finally, (Knofius et al., 2020) developed a mathematical model that helps to decide whether to manufacture parts in CM to supply part inventory in

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anticipation of demand, to manufacture them on demand using AM, or to use a dual sourcing approach. From their results it emerged that the dual sourcing approach is often the best option, and that the AM single source is often ruled out by the high unit cost of AM parts.
Moreover, all these works consider the second main disadvantage of AM, i.e. the mechanical properties of the parts. The mechanical properties are in fact important because they determine the Mean Time to Failure (MTTF) of parts: for example, the higher the mechanical properties, the longer the spare part can withstand the loading scenarios that it is subjected to, and hence the higher the MTTF. In the first studies dealing with AM for spare parts, researchers and practitioners considered the mechanical properties of AM parts equal to those of CM counterparts. This assumption, however, did not (and still does not) hold true. AM parts, in fact, were mostly characterized by lower mechanical properties than CM counterparts due to the poor technological developments of the first AM machines (Westerweel et al., 2018) and (Knofius et al., 2020). However, maturing AM technologies have led to parts characterized by higher mechanical properties than what is achievable through CM techniques. Furthermore, post-process operations are also used to further increase the mechanical properties of AM parts (Beretta and Romano, 2017; Liu and Shin, 2019; Peron et al., 2018). (Sgarbossa et al., 2021) were the first to adopt a multidisciplinary approach in which material science approach was used to determine the actual mechanical properties as compared to the CM counterparts.
Moreover, besides the mean value of the mechanical properties, also their uncertainties have an effect in the decision whether to produce in AM or CM. In fact, (Van Wingerden et al., 2017) showed that, with the acceptable number of backorders kept constant, an increase in the failure rate uncertainty[1] leads to an increase in the inventory costs. Similarly, we have preliminarily shown that the spare parts management costs increase exponentially as the failure rate uncertainty increases (Peron et al., 2021). However, to the best of our knowledge, no one has ever considered the impact of the failure rate uncertainties on sourcing decisions (i.e. whether to manufacture spare parts in AM or CM).
Due to the intrinsic nature of the AM manufacturing process[2] and due to the fact that AM is a manufacturing technique still subjected to substantial technological developments (contrarily to CM technologies which are very well-established manufacturing techniques), the failure rate uncertainty is often higher in AM parts, and this will hence penalize the economic profitability of AM. In this work, we will carry out a preliminary analysis trying to understand how the failure rate uncertainty affects the final decision on the sourcing option based on economic considerations. Specifically, to make the analysis accurate and reliable, we will use realistic values of the failure rate uncertainties derived from a material science approach. Furthermore, to generalize our analysis and draw general considerations on the impact of the failure rate uncertainty on the sourcing decision, we will carry out a parametrical analysis considering different scenarios characterized by different combinations of spare part demands and backorder costs.
More in details, aiming to investigate how failure rate uncertainty impacts on sourcing option decision, we will first consider a benchmark situation where the failure rate uncertainties of AM and CM parts are neglected (i.e. the failure rates of AM and CM are assumed to be known). For this benchmark situation, we will leverage the parametrical analysis to create a decision tree that will support the understanding of which sourcing option is to be preferred given a certain combination of spare part demands and backorder costs. Then, by developing a second decision tree for the situation where the failure rate uncertainties are considered, it will be possible to determine how the failure rate uncertainties influence the choice of the sourcing option.
It is worth mentioning that in this paper, we will consider selective laser melting (SLM) as AM manufacturing technique and casting (C) as CM manufacturing technique, both followed by polishing (P) as post-process operation. The choice of these two techniques over other AM and CM techniques are justified by the results obtained by (Sgarbossa et al., 2021).
The remaining of the paper will be divided as follows. Section 2 provides the methodology adopted in this study. Specifically, Section 2.1. provides the mathematical models used to determine the costs of the inventory management system in case of failure rate uncertainties considered or not considered; Section 2.2., then, provides the details of the procedure followed to develop the aforementioned decision trees, while Section 2.3. discusses the material science approach used to determine the realistic values of the failure rate uncertainties of AM and CM parts. Finally, Section 3 reports the results and discusses them, and Section 4 deals with the conclusions and future works.

2. METHODOLOGY

2.1 Mathematical models

This Section will provide the mathematical models used to determine the spare parts management costs for (i) the benchmark situation in which the failure rates of AM and CM are assumed to be known and for (ii) the situation in which the failure rate uncertainties are considered.
Dealing with the former situation, the authors adopt the periodic review model with Poisson distributed demand used by (Sgarbossa et al., 2021). The total costs C_{tot} (Equation 1) are defined as the sum of holding costs C_h (Equation 2), backorder costs C_b (Equation 3) and production costs C_p (Equation 4).

$$C_{tot} = C_h + C_b + C_p; \quad (1)$$
$$C_h = h \cdot c_p \cdot \sum_{y=0}^{S-1} (S-y) \cdot P_{\lambda,T+L,y}; \quad (2)$$
$$C_b = c_b \cdot \sum_{y=S+1}^{\infty} (y-S) \cdot P_{\lambda,T+L,y}; \quad (3)$$
$$C_p = C_p = \lambda \cdot c_p \quad (4)$$

[1] The failure rate is related to the MTTF
[2] Every change in the building routine affects the toolpath and ultimately the properties of the resulting component: even a small change in the toolpath can lead to big variations in the failure rate of the resulting part.

where S is the order-up-to-level, y is the stochastic demand (i.e., the number of failures in the period $T+L$), L is the lead time, T is the review period, h is the holding cost rate, c_p and c_b are the unitary production and backorder costs, respectively, λ is the failure rate and $P_{\lambda,T+L,y}$ is the probability of having y failures over the period $T+L$ given the failure rate λ. The order-up-to-level used in the above equations is the order-up-to-level that minimizes the total costs, that we will refer to as optimal inventory level S^*. Moreover, it is worth mentioning that AM and CM are considered to be characterized by different failure rates, and, based on (Sgarbossa et al., 2021), the failure rate of AM parts is considered 5.2 times lower than the failure rate of CM parts. In the following, the failure rates of CM would be considered as reference and indicated as λ.

Dealing with the second situation, the failure rates of AM and CM are unknown, and they are characterized by a certain uncertainty. As suggested by (Van Wingerden et al., 2017) and (Peron et al., 2021), the expectation of the failure rate is still λ, but its exact value follows a truncated normal distribution N (truncated such that $N \geq 0$), with standard deviation σ and probability density function f_n. The holding costs C_h, backorder costs C_b and production costs C_p are now described by Equations 5, 6 and 7, respectively.

$$C_h = h \cdot c_p \cdot \int_0^\infty f_n(x) \cdot \sum_{y=0}^{S-1}(S-y) \cdot P_{x,T+L,y}\, dx\,; \quad (5)$$

$$C_b = c_b \cdot \int_0^\infty f_n(x) \cdot \sum_{y=S+1}^{\infty}(y-S) \cdot P_{x,T+L,y} dx; \quad (6)$$

$$C_p = c_p \cdot \int_0^\infty f_n(x) \cdot x\, dx \quad (7)$$

where x is the realization of the normal distribution N.

2.2 Decision tree

A decision tree is a DSS that, given a set of attributes, suggests the optimal solution. In our case, the attributes are the spare parts demand and backorder costs, while the output is optimal sourcing option (i.e., AM or CM). Specifically, as mentioned above, we will develop two decision trees, one for the benchmark situation where the failure rates of AM and CM are assumed to be known and one for the situation where the failure rate uncertainties are considered. In this way, by comparing the two decision trees, it will be possible to understand how the failure rate uncertainty affects the final decision on the sourcing option.

To develop the decision trees, we have used a decision tree algorithm, which is a supervised machine learning technique (Nugroho et al., 2015). To create the dataset necessary to feed and train the decision tree algorithm, we have carried out two parametrical analyses, one per each situation.

Dealing with the benchmark situation (i.e. the situation in which the failure rates of AM and CM are assumed to be known), the total costs of spare parts management have been calculated according to Equations 1-4 considering different scenarios in which different combinations of unitary backorder costs c_b and failure rates λ are considered. The different values adopted in the parametrical analysis are reported in Table 1, together with the values of the other input parameters kept constant during the analysis.

Table 1. Parameters adopted in the parametrical analysis.

Parameters	Value(s)		Unit
Unitary backorder cost (c_b)	250; 500; 1,000; 2,000; 4,000; 8,000; 16,000; 32,000		€/week
	CM	**AM**	
λ	0.005; 0.01; 0.02; 0.04; 0.08	$\frac{\lambda}{5.21}$	1/weeks
L	4	0.1	Weeks
T	4	0.1	Weeks
Unitary production cost (c_p)	30	150	€

The values adopted for the parametrical analysis have been chosen to cover different spare parts scenarios. Specifically, we have considered five values of the unitary backorder cost c_b in order to cover scenarios of low, medium and high costs related to production losses, and five values of failure rate λ to consider different part consumptions. The values of the failure rate were chosen considering the suggestions of (Knofius et al., 2020), and they correspond to situations where the spare parts demand ranges from 4 parts per year to 1 part every 3 years. The values of the lead time L, of the review period T, and of the unitary production cost c_p have been considered constant but different between CM and AM, and they have been taken from (Sgarbossa et al., 2021). Another input parameter is the holding rate h which was assumed constant and equal to 0.58% of the production cost on a weekly basis (it is common practice to consider it equal 30% of the production cost on a yearly basis, which corresponds to 0.58% on a weekly basis (Azzi et al., 2014)).

Concerning the second situation where the failure rates of AM and CM are unknown, and they are characterized by a certain uncertainty, the total costs of spare parts management have been calculated according to Equations 1, 5-7 considering the same values of the unitary backorder cost c_b and of the failure rate λ used for the parametrical analysis of the benchmark situation (Table 1). Moreover, in this situation, the failure rate uncertainties of AM and CM parts are needed. Based on the assumption that the exact value of the failure rate follows a truncated normal distribution N, the failure rate uncertainty can be defined by the standard deviation σ, which in the following will be expressed as percentage of the expected value of the failure rate (λ). Based on the material science approach (see next Section for more details), the standard deviation σ has been found to be equal to 48% and 21% for AM and CM parts, respectively.

2.3 Failure rate uncertainty calculation

To determine the failure rate uncertainty, we have adopted a material science approach and examined fatigue curves obtained from laboratory specimens. Fatigue curves report the average fatigue strengths of laboratory specimens (i.e. the number of cycles to failure) for different applied loads F (i.e. the loading conditions). The fatigue strength of a laboratory specimen can be linked to the time to failure of a specific part subjected to the same loading condition (Lolli et al., 2022). We have hence exploited this relation to determine the failure rate uncertainty of AM and CM parts. More precisely, we have used the fatigue curves of laboratory specimens reported in the literature to determine the uncertainty in the MTTF, and from this we have obtained the uncertainty in the failure rate. Per each sourcing option, we have collected references reporting fatigue curves of that sourcing option. Per each reference, then, we have determined the fatigue strength corresponding to the same loading condition F^*. In this way, we were able to determine different values of fatigue strengths (one per each reference), which corresponded to an uncertainty in the expected value of the fatigue strengths, that, given the relationship between the fatigue strength and the MTTF (Lolli et al., 2022), we have then converted into an uncertainty in the expected value of the MTTF. Finally, from the uncertainty in the MTTF we were able to determine the failure rate uncertainty for each sourcing option, which leads to a standard deviation of the failure rate of 48% and 21% for AM and CM parts, respectively. Figure 1 shows schematically the adopted procedure, in which the diagonal lines are the fatigue curves.

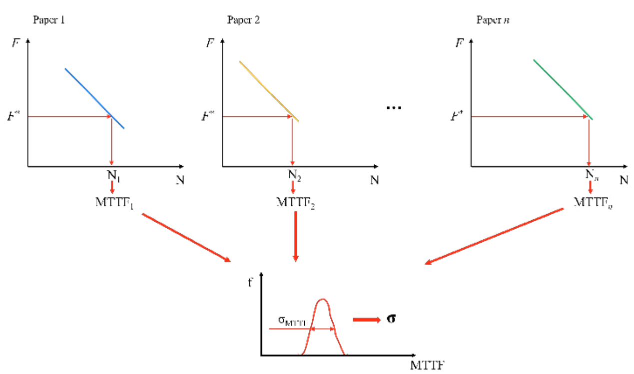

Figure 1. Determination of failure rate uncertainty: schematic representation.

3. RESULTS AND DISCUSSIONS

Figure 2 reports the decision tree for the benchmark situation (i.e. the situation in which the failure rates of AM and CM are assumed to be known). Per each leaf, we have calculated the percentage of items reaching that leaf (p), the accuracy (a) and the average percentage of the increased cost when the wrong sourcing option is selected (c).

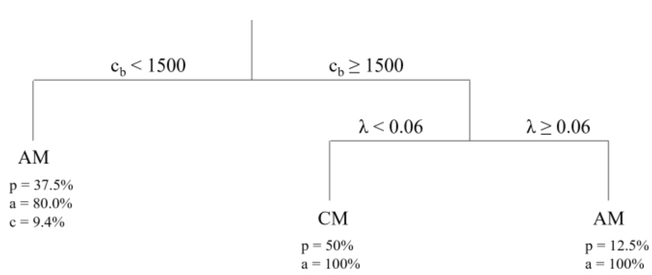

Figure 2. Decision tree for the benchmark situation.

From Figure 2, we can see that in 42.5% of cases the best sourcing option is AM. Specifically, AM results to be convenient for scenarios characterized by (i) low backorder costs and (ii) high backorder costs when the failure rates are high. This is due to the lower values of the optimal inventory level S^* achievable using AM (see Appendix A). When the backorder costs are low, the low criticality of the spare parts together with the low production time of AM renders the manufacturing of spare parts on demand a feasible option, hence allowing to fully exploit the benefits of AM. Instead, if backorder costs are high, spare parts cannot be produced on demand, but they need to be stored to secure against the risks of high backorder costs. However, when the failure rates are high, the request for spare parts is frequent, and again the short lead times of AM parts are beneficial and thus render AM preferable. CM parts are in fact characterized by long procurement lead times, and this leads to the necessity to have high inventory levels to be able to cope with the frequent demand of spare parts; however, when spare parts are manufactured via AM, this need for a high inventory level no longer exists: the short production lead time of AM, in fact, allows to highly reduce the stock level since spare parts can be replenished frequently.
However, things change if the failure rate uncertainties of AM and CM are considered, as it can be seen from the corresponding decision tree shown in Figure 3.

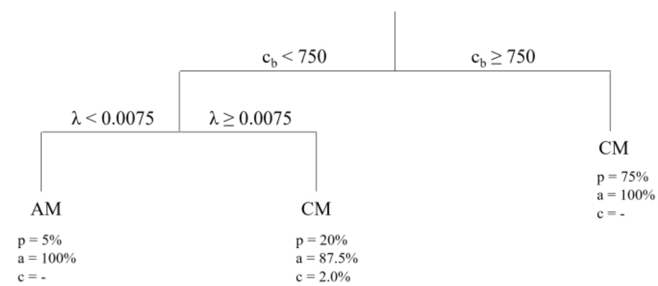

Figure 3. Decision tree for situation where the failure rates of AM and CM are characterized by a certain uncertainty.

In this case, AM is the most convenient sourcing option only in 7.5% of cases. That is only if both backorder costs and the expected values of the failure rate are very low. These are the scenarios in which manufacturing spare parts on demand is still the best approach. The high failure rate uncertainty of AM, in fact, limits the suitability of manufacturing spare parts on demand, and, more in general, increases the inventory levels of AM parts. This reduces the value of AM as sourcing option. The failure rate uncertainty has hence a great effect. The higher failure rate uncertainty of AM parts with respect to CM counterparts (48% vs. 21%), reduces the conveniency of using AM to manufacture spare parts from 42.5% of the scenarios analyzed to only 7.5%. In the future, hence, researchers and practitioners (especially in the material science field) need to reduce the failure rate uncertainties of AM parts and bring it closer to that of CM parts. In this perspective, Table 2 provides some insights on the benefits that reducing the failure rate uncertainties of AM parts to a value closer or equal to that of CM parts would have on the profitability of this technology.

Table 2. Profitability of AM as sourcing option depending on its failure rate uncertainty

σ (%)	**AM profitability (% of analyzed scenarios)**
48	7.5
45	7.5
40	15
35	15
30	32.5
25	47.5
21	52.5

As can be seen in Table 2, the profitability of AM increases with decreasing failure rate uncertainties. However, it is interesting that the profitability of AM can be higher than that obtained in the benchmark situation (i.e. 42.5% of the analyzed scenarios), and this happens not only when the failure rate uncertainty of AM parts equals that of CM parts, but also when it is slightly higher (e.g. $\sigma = 25\%$). As it can be seen from the optimal inventory level S^* reported in Appendix A, a failure rate uncertainty of 25% does not have any effect on the optimal inventory level of AM parts (the optimal inventory levels S^*, in fact, match those of the benchmark situation), while a failure rate uncertainty of 21% increases the optimal inventory levels of CM parts for certain scenarios).

These results, although not general since they are limited to the limited scenarios analyzed here, provide some useful insights, and stress the importance to decrease the failure rate uncertainty of AM parts for increasing its profitability as sourcing option. To do so, two different and concurrent approaches can be used. The first approach is to develop a mechanistic knowledge of the failure behavior of AM parts, which would allow a more precise determination of the mechanical properties (and hence of the failure rate) of AM parts thanks to a plethora of experimental data (data-driven approach) (Peron et al., 2018). The second approach is to improve the monitoring of the AM manufacturing processes; by monitoring the shape and heat distribution of the melt pool during the process, it is possible to estimate the mechanical properties (and hence the failure rate) of AM parts, leveraging also the knowledge developed in the discussed approach (Egan and Dowling, 2019).

6. CONCLUSIONS

In this work, for the first time, we have elaborated on the need to understand the effect of failure rate uncertainties on the sourcing option decision, i.e. whether to manufacture spare parts in AM or CM. Despite its importance, this topic has been completely overlooked in the literature.

To achieve our goal, we have adopted a material science approach to determine realistic values of the failure rate uncertainties of AM and CM parts, and we have determined the total costs of spare parts management for two situations, i.e. (i) a situation in which the failure rate uncertainties of AM and CM parts are neglected (i.e. the failure rates of AM and CM are assumed to be known), and (ii) a situation in which the failure rate uncertainties are considered. For each situation, we have determined under which combinations of spare part demands and backorder costs AM is convenient, and then we have compared the results. Specifically, we have considered 40 different scenarios (i.e. 40 different combinations of spare part demands and backorder costs), and we have seen that in the situation in which the failure rate of AM and CM are assumed to be known, AM is the best sourcing option 42.5% of the scenarios, while in the situation in which the failure rate uncertainties are considered, the suitability of AM is reduced to only 7.5% of the scenarios. However, if the failure rate uncertainty of AM parts can be reduced to the same value of that of CM counterparts, AM would be the best sourcing option 52.5% of the scenarios, even more than what would be achievable in the situation in which the failure rates of AM and CM are known. Although these numbers might vary if other scenarios are considered, they help to understanding the importance of failure rate uncertainties on the sourcing option decision, and they show the need to reduce the failure rate uncertainties of AM parts to allow this technology to become competitive for the manufacturing of spare parts.

As mentioned before, this work represents a preliminary study on understanding the impact of failure rate uncertainties on the sourcing option decision, and a wider scenario analysis needs to be deployed to obtain more general information. Moreover, it would be interesting to understand how much it is feasible to obtain in terms of failure rate uncertainty reduction of AM parts based on the solution adopted (process monitoring, mechanistic knowledge of the failure behavior of AM parts, …), and whether the savings obtainable from these reductions can cover the costs necessary to obtain them. This represents a topic of future research for the authors.

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Appendix A. OPTIMAL INVENTORY LEVEL

In this Appendix we report the optimal inventory levels of AM and CM for the benchmark situation (i.e. the situation where the failure rates of AM and CM are assumed to be known precisely) and for the situation where the failure rate uncertainties are considered. The comparison is reported in Table A.1.

Table A.1. Optimal inventory level of AM and CM for the benchmark situation (referred to as "no uncertainty") and for the situation where the failure rate uncertainties are considered (referred to as "uncertainty")

c_b (€/week)	λ (1/week)	S^*				
		No uncertainty		**Uncertainty**		
		CM	**AM**	**CM**	**AM (σ=48%)**	**AM (σ=25%)**
250	0.005	2	0	2	0	0
	0.01	2	0	2	0	0
	0.02	2	0	3	0	0
	0.04	3	0	3	0	0
	0.08	4	0	5	1	0
500	0.005	2	0	2	0	0
	0.01	2	0	2	0	0
	0.02	3	0	3	0	0
	0.04	3	0	4	1	0
	0.08	5	1	5	1	1
1,000	0.005	2	0	2	0	0
	0.01	2	0	2	0	0
	0.02	3	0	3	1	0
	0.04	4	1	4	1	1
	0.08	5	1	6	1	1
2,000	0.005	2	0	2	0	0
	0.01	2	0	2	1	0
	0.02	3	1	3	1	1
	0.04	4	1	4	1	1
	0.08	5	1	6	1	1
4,000	0.005	2	0	2	1	0
	0.01	3	1	3	1	1
	0.02	3	1	4	1	1
	0.04	4	1	5	1	1
	0.08	6	1	6	1	1
8,000	0.005	2	1	2	1	1
	0.01	3	1	3	1	1
	0.02	3	1	4	1	1
	0.04	4	1	5	1	1
	0.08	6	1	7	1	1
16,000	0.005	2	1	3	1	1
	0.01	3	1	3	1	1
	0.02	4	1	4	1	1
	0.04	5	1	5	1	1
	0.08	6	1	7	2	1
32,000	0.005	3	1	3	1	1
	0.01	3	1	3	1	1
	0.02	4	1	4	1	1
	0.04	5	1	5	1	1
	0.08	6	1	8	2	1