# Chapter 12
# Guidelines for Process Selection

## 12.1 Introduction

The initial purpose of rapid prototyping technology was to create parts as a means of visual and tactile communication. Since those early days of rapid prototyping, the applications of additive manufacturing processes have expanded considerably. According to Wohlers and Associates [21], parts from AM machines are used for a number of purposes, including:

- Visual aids
- Presentation models
- Functional models
- Fit and assembly
- Patterns for prototype tooling
- Patterns for metal castings
- Tooling components
- Direct digital/rapid manufacturing

AM processes, like all materials processing, are constrained by material properties, speed, cost, and accuracy. The performance capabilities of materials and machines lag behind conventional manufacturing technology (e.g., injection molding machinery), although the lag is decreasing. Speed and cost, in terms of time to market, are where AM technology contributes, particularly for complex or customized geometries.

With the growth of AM, there is going to be increasing demand for software that supports making decisions regarding which machines to use and their capabilities and limitations for a specific part design. In particular, software systems can help in the decision-making process for capital investment of new technology, providing accurate estimates of cost and time for quoting purposes, and assistance in process planning.

This chapter deals with three typical problems involving AM that may benefit from decision support:

I. Gibson, D.W. Rosen, and B. Stucker, *Additive Manufacturing Technologies*,
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1. Quotation support. Given a part, which machine and material should I use to build?
2. Capital investment support. Given a design and industrial profile, what is the best machine that I can buy to fulfill my requirements?
3. Process planning support. Given a part and a machine, how do I set it up to work in the most efficient manner alongside my other operations and existing tasks?

Examples of systems designed to fulfill the first two problems are described in detail. The third problem is much more difficult and is discussed briefly.

## 12.2 Selection Methods for a Part

### *12.2.1 Decision Theory*

Decision theory has a rich history, evolving in the 1940s and 1950s from the field of economics [9]. Although there are many approaches taken in the decision theory field, the focus in this chapter will be only on the utility theory approach. Broadly speaking, there are three elements of any decision [7]:

- Options – the items from which the decision maker is selecting,
- Expectations – of possible outcomes for each option, and
- Preferences – how the decision maker values each outcome.

Assume that the set of decision options is denoted as $A = \{A_1, A_2, \ldots, A_n\}$. In engineering applications, one can think of outcomes as the performance of the options as measured by a set of evaluation criteria. More specifically, in AM selection, an outcome might consist of the time, cost, and surface finish of a part built using a certain AM process, while the AM process itself is the option. Expectations of outcomes are modeled as functions of the options, $X = g(A)$, and may be modeled with associated uncertainties.

Preferences model the importance assigned to outcomes by the decision maker. For example, a designer may prefer low cost and short turn-around times for a concept model, while being willing to accept poor surface finish. In many ad hoc decision support methods, preferences are modeled as weights or importances, which are represented as scalars. Typically, weights are specified so that they sum to 1 (normalized). For simple problems, the decision maker may just choose weights, while for more complex decisions, more sophisticated methods are used, such as pair-wise comparison [13]. In utility theory, preferences are modeled as utility functions on the expectations. Expectations are then modeled as expected utility. The best alternative is the one with the greatest expected utility.

F. Mistree, J.K. Allen, and their co-workers have been developing the Decision Support Problem (DSP) Technique over the last 20 years. The advantages of selecting DSPs, compared with other decision formulations, are that they provide a means for mathematically modeling design decisions involving multiple objectives and supporting human judgment in designing systems [11, 12]. The formulation and solution of DSPs facilitate several types of decisions, including:

Selection – the indication of preference, based on multiple attributes, for one among several alternatives, [2].

Compromise – the improvement of an alternative through modification [12, 13].

Coupled and hierarchical – decisions that are linked together, such as selection–selection, compromise–compromise, or selection–compromise [12].

The selection problems being addressed in this chapter will be divided into two related sub-problems. First, it is necessary to generate feasible alternatives, which, in this case, include materials and processes. Second, given those feasible alternatives, a quantification process is applied that results in a rank-ordered list of alternatives. The first subproblem is referred to as "Determining Feasibility," while the second is simply called "Selection." Additional feasibility determination and selection methods will be discussed in this section as well.

### *12.2.2 Approaches to Determining Feasibility*

The problem of identifying suitable materials and AM machines with which to fabricate a part is surprisingly complex. As noted previously, there are many possible applications for an AM part. For each application, one should consider the suitability of available materials, fabrication cost and time, surface finish and accuracy requirements, part size, feature sizes, mechanical properties, resistance to chemicals, and other application-specific considerations. To complicate matters, the number and capability of commercial materials and machines continues to increase. So, in order to solve AM machine and process chain selection problems, one must navigate the wide variety of materials and machines, comparing one's needs to their capabilities, while ensuring that the most up-to-date information is available.

To date, most approaches to determining feasibility have taken a knowledge-based approach in order to deal with the qualitative information related to AM process capability. One of the better developed approaches was presented by Deglin and Bernard [3]. They presented a knowledge-based system for the generation, selection, and process planning of rapid manufacturing processes. The problem as they defined it was: "To propose, from a detailed functional specification, different alternatives of rapid manufacturing processes, which can be ordered and optimized when considering a combination of different specification criteria (cost, quality, delay, aspect, material, etc.)." Their approach utilized two reasoning methods, case-based and the bottom-up generation of processes; the strengths of each compensated for the other's weaknesses. Their system was developed on the KADVISER platform and utilized a relational database system with extensive material, machine, and application information.

A group at the National University of Singapore (NUS) developed an AM decision system that was integrated with a database system [6, 22]. Their selection system was capable of identifying feasible material/machine combinations, estimating manufacturing cost and time, and determining optimal part orientations. From the feasible material/machines, the user can then select the most suitable combination. Their approach to determining feasible materials and processes is broadly similar to the work of Deglin and Bernard. The NUS group utilized five databases, each organized in a hierarchical, object-oriented manner: three general databases (materials, machines, and applications) and two part-specific databases (geometric information and model specifications).

Several web-based AM selection systems are available. One was developed at the Helsinki University of Technology (*see* http://ltk.hut.fi/RP-Selector/). Through a series of questions, the selector acquires information about the part accuracy, layer thickness, geometric features, material, and application requirements. The user chooses one of 4–5 options for each question. Additionally, the user specifies preferences for each requirement using a 5-element scale from insignificant to average to important. When all 10–12 questions are answered, the user receives a set of recommended AM machines that best satisfy their requirements.

The problem of determining process and material feasibility can be represented by the Preliminary Selection Decision Support Problem (PS-DSP) [1]. The word formulation of the PS-DSP is given in Fig. 12.1. This is a structured decision formulation and corresponds to a formal decision method based on decision theory. Qualitative comparisons among processes and materials, with respect to decision criteria, are sufficient to identify feasible alternatives and eliminate infeasible ones. After more quantitative information is known, more detailed evaluations of alternatives can be made, as described in the next sub-section.

The key step in the ps-DSP is how to capture and apply experience-based knowledge. One chooses a datum concept against which all other concepts are compared. Qualitative comparisons are performed, where a concept is judged as better, worse, or about the same (+1, −1, 0, respectively) as the datum with respect to the principal criteria for the selection problem. Then, a weighted sum of comparisons with the datum is computed. Typically, this procedure is repeated for several additional choices of datums. In this manner, one gets a good understanding of the relative merits and deficiencies of each concept.

The ps-DSP has been applied to various engineering problems, most recently for a problem to design an AM process to fabricate metal lattice structures [19].

| | |
|---|---|
| **Given:** | a set of concepts |
| **Identify:** | The principal criteria influencing selection.<br>The relative importance of the criteria |
| **Capture:** | Experience-based knowledge about the concepts with respect to a datum and the established criteria. |
| **Rank:** | The concepts in order of preference based on multiple criteria and their relative importance. |

**Fig. 12.1** Preliminary selection decision support problem word formulation

### 12.2.3 Approaches to Selection

As stated earlier, there have been a number of approaches taken to support the selection of AM processes for a part. Most aid selection, but only in a qualitative manner, as described earlier. Several methods have been developed in academia that are based on the large literature on decision theory. For an excellent introduction to this topic, see the book by Keeney and Raiffa [9]. In this section, the selection DSP is covered in some detail and selection using utility theory is summarized.

While the basic advantages of using DSPs of any type lie in providing context and structure for engineering problems, regardless of complexity, they also facilitate the recording of viewpoints associated with these decisions, for completeness and future reference, and evaluation of results through post solution sensitivity analysis. The standard Selection Decision Support Problem (s-DSP) has been applied to many engineering problems and has recently been applied to AM selection [8]. The word formulation of the standard s-DSP is given in Fig. 12.2. Note that the decision options for AM selection are feasible material-process combinations. Expectations are determined by rating the options against the attributes. Preferences are modeled using simple importance values. Rank ordering of options is determined using a weighted-sum expression of importance and attribute ratings. An extension to include utility theory has recently been accomplished, as described next.

For the Identify step, evaluation attributes are to be specified. For example, accuracy, cost, build time, tensile strength, and feature detail (how small of a feature can be created) are typical attributes. Scales denote how the attribute is to be measured. For example, the cost scale is typically measured in dollars and is to be minimized. Tensile strength is measured in MPa and is to be maximized. These are examples of ratio scales, since they are measured using real numbers. Interval scales, on the other hand, are measured using integers. Complexity capability is an example attribute that could be measured using an interval scale from 1 to 10, where 10 represents the highest complexity. The decision maker should formulate interval scales carefully so that many of the integers in the scale have clear definitions. In addition to specifying scales, the decision maker should also specify minimum and maximum values for each attribute. Finally, the decision maker is to specify preferences using importance values or weights for each attribute.

For the Rate step of the s-DSP, each alternative AM process or machine should be evaluated against each attribute. From the Identify step, each attribute, $a_i$, has minimum and maximum values specified, $a_{i,\min}$ and $a_{i,\max}$, respectively. The decision maker specifies a rating value for attribute $a_{ij}$ for each alternative, $j$,

| | |
|---|---|
| **Given:** | Set of AM processes/machines and materials (alternatives) |
| **Identify:** | Set of evaluation attributes. Create scales and determine importances. |
| **Rate:** | Each alternative relative to each attribute. |
| **Rank:** | AM methods from most to least promising |

**Fig. 12.2** Word formulation of the selection decision support problem

that lies between $a_{i,\min}$ and $a_{i,\max}$. The final step is to normalize the ratings so that they always take on values between 0 and 1. For cases where the attribute is to be maximized, (12.1) is used to normalize each attribute rating, where $r_{ij}$ is the normalized rating for attribute $i$ and alternative $j$. (12.2) is used to normalize attribute ratings when the attribute is to be minimized.

$$r_{ij} = \frac{a_{ij} - a_{ij,\min}}{a_{ij,\max} - a_{ij,\min}} \tag{12.1}$$

$$r_{ij} = \frac{a_{ij,\max} - a_{ij}}{a_{ij,\max} - a_{ij,\min}} \tag{12.2}$$

After all attributes are rated, the total merit for each alternative is computed using a weighted sum formulation, as shown in (12.3). The $I_i$ are the importances, or weights. Note that the merit value $M_i$ is always normalized between 0 and 1.

$$M_j = \sum_{j=1} I_i r_{ij} \tag{12.3}$$

After computing the merit of each alternative, the alternatives can be rank ordered from the most favorable to the least. If two or more alternatives are close to the highest rank, additional investigation should be undertaken to understand under which conditions each alternative may be favored over the others. Additionally, the alternatives could be developed further so that more information about them is known. It is also helpful to run multiple sets of preferences (called scenarios) to understand how emphasis on certain attributes can lead to alternatives becoming favored.

Decision theory has a rich history, evolving in the 1940s and 1950s from the field of economics [9]. In order to provide a rigorous, preference-consistent alternative to the traditional merit function for considering alternatives with uncertain attribute values, the area of utility theory is often applied. This requires the satisfaction of a set of axioms such as those proposed by Von Neumann and Morgenstern [18], Luce and Raiffa [10], or Savage [16], describing the preferences of rational individuals. Once satisfied, there then exists a utility function with the desirable property of assigning numerical utilities to all possible consequences.

In utility theory, preferences are modeled as utility functions on the expectations. Mathematically, let alternative $A_i$ result in outcome $x_i \epsilon X$ with probability $p_i$, if outcomes are discrete. Otherwise, expectations on outcomes are modeled using probability density functions, $f_i = f_i(x_i)$. Utility is denoted $u(x)$. Expectations are then modeled as expected utility as shown in (12.4).

$$E[u(x)] = \sum p_i u(x_i) \quad \text{for discrete outcomes} \tag{12.4}$$

$$E[u(x)] = u(x)g(x) \quad \text{for continuous outcomes}$$

This leads to the primary decision rule of utility theory:

Select the alternative whose outcome has the largest expected utility.

Note that expected utility is a probabilistic quantity, not a certain quantity, so there is always risk inherent in these decisions.

Utility functions are constructed by determining points that represent the decision maker's preferences then fitting a utility curve to these points. The extreme points indicate ideal and unacceptable values. These points are labeled as $x_*$ and $x_0$, respectively, and are assigned utilities of 1 and 0, respectively, in Fig. 12.3. The remaining points are usually obtained by asking the decision-maker a series of questions (for more information, please consult a standard reference on utility theory, e.g., [9]) Specifically, a decision-maker is asked to identify his/her certainty equivalent for a few 50–50 lotteries. A lottery is a hypothetical situation in which the outcome of a decision is uncertain; it is used to assess a decision-maker's preferences. A certainty equivalent is the level of an attribute for which the decision-maker would be indifferent between receiving that attribute level for *certain* and receiving the results of a specified 50–50 lottery. For example, to obtain the value of $x_{0.5}$ in Fig. 12.3, the decision-maker is asked to identify his/her certainty equivalent to the lottery. Generally, at least five points are identified along the decision-maker's utility curve. This preference assessment procedure must be repeated for each of the attributes of interest. In the 5-point form, typical utility functions have the form

$$u(x) = c + b\,\mathrm{e}^{-ax}. \tag{12.5}$$

By complementing the standard selection DSP with utility theory, an axiomatic basis is provided for accurately reflecting the preferences of a designer for tradeoffs and uncertainty associated with multiple attributes. The utility selection DSP has been formulated and applied to several engineering problems, including AM selection [5, 11]. Quite a few other researchers have applied utility theory to engineering selection problems; one of the original works in this area is [17].

### 12.2.4 Selection Example

In this section, we present an example of a capital investment decision related to the application of metal AM processes to the production manufacture of steel caster

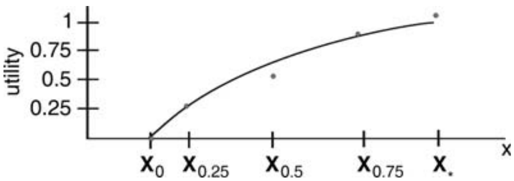


**Fig. 12.3** Utility curve from five data points

**Table 12.1** Caster wheel dimensions

| | Dimensions (mm) | |
|---|---|---|
| | Min | Max |
| Core outer diameter | 100 | 150 |
| Core inner diameter | 90 | 140 |
| Bore outer diameter | 38 | 58 |
| Bore inner diameter | 32 | 32 |
| Hub length | 64 | 64 |
| Core outer width | 38 | 125 |
| Core inner width | 12 | 32 |

wheels. This selection problem is very similar to a quotation problem, but includes a range of part dimensions, not single dimension values for one part. In this scenario, the caster wheel manufacturer is attempting to select an AM machine that can be used for production of its small custom orders. It is infeasible to stock all the combinations of wheels that they want to offer, thus they need to be able to produce these quickly, while also keeping the price down for the customer. The technologies under consideration are Direct Metal Deposition, Direct Metal Laser Sintering, Electron Beam Melting, Laser Engineered Net Shaping, Selective Laser Melting, and Selective Laser Sintering. A readily available stainless steel material (whatever was commercially available for the process) was used for this example. The processes will be numbered randomly (Processes 1–6) for the purposes of presentation, since this example was developed in early 2005 [20] and a significant improvement in technologies and materials renders the results irrelevant.

Before beginning the selection process, the uncertainty involved in the customization process was considered. Since these caster wheels will be customized, there is a degree of geometric uncertainty involved.

A model of a caster wheel is displayed in the Fig. 12.4a, while its main dimensions are shown in Fig. 12.4b. In this example, we have decided to only allow customization of certain features. Only standard 12 mm diameter $\times$ 100 mm length bolts will be used for the inner bore, therefore, these dimensions will be constrained. Customers will be allowed to customize all other features of the caster wheel within allowable ranges for this model wheel, as displayed in Table 12.1.

The alternative AM technologies will be evaluated based on 7 attributes that span a typical range of requirements, as shown in the following section. Scale type refers to the method used to quantify the attribute. For example, ultimate tensile strength is a ratio scale, meaning that it is represented by a real number, in this case with units of MPa. Geometric Complexity is an example of an interval scale, in this case with ratings between 1 and 10, with 1 meaning the lowest complexity and 10 meaning the greatest amount of complexity.

- Ultimate Tensile Strength (UTS): UTS is the maximum stress reached before a material fractures. Ratio scale [MPa].
- Rockwell Hardness C (Hard): Hardness is commonly defined as the resistance of a material to indentation. Ratio scale [HRc].

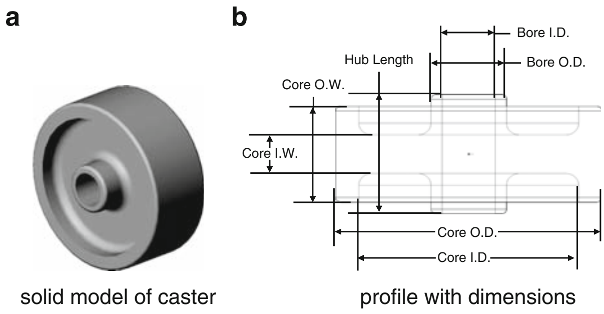


**Fig. 12.4** Model of steel caster wheel

- Density (Dens.): The density refers to the final density of the part after all processing steps. This density is proportional to the amount of voids found at the surface. These voids cause a rough surface finish. Ratio scale [%].
- Detail Capability (DC): The detail capability is the smallest feature size the technology can make. Ratio scale [mm].
- Geometric Complexity (GC): The geometric complexity is the ability of the technology to build complex parts. More specifically, in this case, it is used to refer to the ability to produce overhangs. Interval scale (1–10).
- Build Time (Time): The build time refers to the time required to fabricate a part, not including post processing steps. Ratio scale [h].
- Part Cost (Cost): The part cost is the cost it takes to build one part with all costs included. These costs include manufacturing cost, material cost, machine cost, operation cost, etc. Ratio scale [$].

In this example, we examine two weighting scenarios (relative importance ratings). In Scenario 1, geometric complexity was most heavily weighted because of the significant overhangs present in the build orientation of the casters. Build time and part cost were also heavily weighted because of their importance to the business structure surrounding customization of caster wheels. Because of the environment of use of the caster wheels, UTS was also given a high weighting. Detail capability was weighted least because of the lack of small, detailed features in the geometry of the caster wheels. In Scenario 2, all selection attributes were equally weighted.

Table 12.2 shows the results of the evaluation of the alternatives with respect to the attributes. Weights for the two scenarios, called Relative Importances, are included under the attribute names.

On the basis of these ratings, the overall merit for each alternative can be computed. Merit values for each scenario are given in Table 12.3, along with their rankings. Note that slightly different rankings are evident from the different scenarios. This indicates the importance of accurately capturing decision maker preferences. Process 4 is the top ranking process in both scenarios. However, the second choice could be Process 2, 3, or 6, depending upon preferences. In cases

**Table 12.2** Rating alternatives with respect to attributes

| | | Attributes | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | UTS | Hardness | Density | Detail cap. | Geom. compl. | | Build time | | Part cost | |
| | | | | | | mm | max | mm | max | mm | max |
| Rel. Imp. | Scen 1 | 0.167 | 0.143 | 0.071 | 0.024 | 0.214 | 0.214 | 0.19 | 0.19 | 0.19 | 0.19 |
| | Scen 2 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 | 0.143 |
| Alternatives | Proc 1 | 600 | 21 | 95 | 0.3 | 7 | 10 | 2.8 | 59 | 390 | 2050 |
| | Proc 2 | 1430 | 50 | 100 | 1.2 | 7 | 10 | 1.42 | 30 | 134 | 510 |
| | Proc 3 | 1700 | 53 | 100 | 0.762 | 4 | 6 | 0.26 | 5 | 64 | 310 |
| | Proc 4 | 2000 | 60 | 99.5 | 0.15 | 7 | 10 | 1.9 | 39 | 240 | 1340 |
| | Proc 5 | 600 | 15 | 100 | 0.6 | 7 | 10 | 1.4 | 24 | 180 | 890 |
| | Proc 6 | 1800 | 53 | 100 | 1 | 4 | 6 | 0.12 | 2 | 30 | 170 |
| Scales | Type | Ratio | Ratio | Ratio | Ratio | Interval | | Ratio | | Ratio | |
| | low | 500 | 10 | 95 | 0.1 | 1 | | 2 | | 25 | |
| | high | 2500 | 70 | 100 | 2 | 10 | | 120 | | 1000 | |
| | Pref. | high | high | high | low | high | | low | | low | |
| | Units | MPa | HRc | percent | mm | nmu | | h | | $ | |

**Table 12.3** Merit values and rankings

| | Scenario 1 | | Scenario 2 | |
|---|---|---|---|---|
| | Merit | Rank | Merit | Rank |
| Proc 1 | 0.254 | 6 | 0.284 | 6 |
| Proc 2 | 0.743 | 2 | 0.667 | 4 |
| Proc 3 | 0.689 | 4 | 0.703 | 2 |
| Proc 4 | 0.753 | 1 | 0.808 | 1 |
| Proc 5 | 0.528 | 5 | 0.539 | 5 |
| Proc 6 | 0.72 | 3 | 0.697 | 3 |

like this, it is a good idea to run additional scenarios in order to understand the trade-offs that are relevant.

This capital investment example illustrated the application of selection decision support methods. As mentioned, it is very important to explore several scenarios (sets of preferences) to understand the sensitivities of ratings and rankings to changes in preferences. Modifications to the method are straightforward to achieve target values, instead of minimizing or maximizing an attribute, and to incorporate other types of uncertainty.

## 12.3 Challenges of Selection

The example from the previous section illustrates some of the difficulties and limitations of straight forward application of decision methods to real decision making situations. The complex relationships among attributes, and the variations that can arise when building a wide range of parts make it difficult to decouple decision attributes and develop structured decision problems. Nonetheless, with a proper understanding of technologies and attributes, and how to relate them together, meaningful information can be gained. This section takes a brief look at these issues.

Different AM systems are focused on slightly different markets. For example, there are large, expensive machines that can fabricate parts using a variety of materials with relatively good accuracy and/or material properties and with the ability to fine-tune the systems to meet specific needs. In contrast, there are cheaper systems, which are designed to have minimal setup and to produce parts of acceptable quality in a predictable and reliable manner. In this latter case, parts may not have high accuracy, material strength or flexibility of use.

Different users will require different things from an AM machine. Machines vary in terms of cost, size, range of materials, accuracy of part, time of build, etc. It is not surprising to know that the more expensive machines provide the wider range of options and, therefore, it is important for someone looking to buy a new machine to be able to understand the costs vs. the benefits so that it is possible to choose the best machine to suit their needs.

Approaching a manufacturer or distributor of AM equipment is one way to get information concerning the specification of their machine. Such companies are obviously biased towards their own product and, therefore, it is going to be difficult to obtain truly objective opinions. Conventions and exhibitions are a good way to make comparisons, but it is not necessarily easy to identify the usability of machines. Contacting existing users is sometimes difficult and time consuming, but they can give very honest opinions. This approach works best if you are already equipped with background information concerning your proposed use of the technology.

When looking for advice about suitable selection methods or systems, it is useful to consider the following points. One web-based system was developed to meet these considerations [15]. An alternative approach will be presented in the next section.

- The information in the system should be unbiased wherever possible.
- The method/system should provide support and advice rather than just a quantified result.
- The method/system should provide an introduction to AM to equip the user with background knowledge as well as advice on different AM technologies.
- A range of options should be given to the user in order to adjust requirements and show how changes in requirements may affect the decision.
- The system should be linked to a comprehensive and up-to-date database of AM machines.
- Once the search process has completed, the system should give guidance on where to look next for additional information.

The process of accessing the system should be as beneficial to the user as the answers it gives. However, this is not as easy a task as one might first envisage. If it were possible to decouple the attributes of the system from the user specification, then it would be a relatively simple task to select one machine against another. To illustrate that this is not always possible, consider the following scenarios:

1. In an SLS machine, warm-up and cool down are important stages during the build cycle that do not directly involve parts being fabricated. This means that large parts do not take proportionally longer times to build compared with smaller ones. Large builds are more efficient than small ones. In SL and FDM machines, there is a much stronger correlation between part size and build time. Small parts would therefore take less time on an SL or FDM machine than when using SLS, if considered in isolation. Many users, however, batch process their builds and the ability to vertically stack parts in an SLS machine makes it generally possible to utilize the available space more efficiently. The warm-up and cool down overheads are less important for larger builds and the time per layer is generally quicker than most SL and FDM machines. As a result of this discussion, it is not easy to see which machine would be quicker without carefully analyzing the entire process plan for using a new machine.

2. Generally, it costs less to buy a Dimension or other low-end FDM machine compared to a ZCorp machine. There are technical differences between these machines that make them suitable for different potential applications. However, because they are in a similar price bracket, they are often compared for similar applications. Dimension FDM machines use a cartridge-based material delivery system that requires a complete replacement of the cartridge when empty. This makes material use much more expensive when compared with the ZCorp machine. For occasional use it is therefore perhaps better to use a Dimension machine when all factors are equal. On the other hand, the more parts you build, the more cost-effective the ZCorp machine becomes.
3. Identifying a new application or market can completely change the economics of a machine. For example, in the metals area, beam deposition machines (e.g., LENS, DMD) tend to be slower and have worse feature detail capability than powder bed metal machines (e.g., SLM, EBM, DMLS). This has led to many more machine sales for ARCAM, MTT, and EOS. However, some companies identified a market for repairing molds and metal parts, which is very difficult, if not impossible, with a powder bed machine.

These examples indicate that selection results depend to a large extent on the user's knowledge of AM capabilities and applications. Selection tools that include expert systems may have an advantage over tools based on straight forward decision methods alone. Expert systems attempt to embody the expertise resulting from extensive use of AM technology into a software package that can assist the user in overcoming at least some of the learning curve quickly and in a single stage. See [15] for a more complete coverage of this idea.

## 12.4 Example System for Preliminary Selection

A preliminary selection tool was developed for Direct Digital Manufacturing (DDM), called DDMS, applications that walks the user through a series of questions to identify feasible processes and machines [14]. Build times and costs are computed, but quantitative rating and rank-ordering is not performed. More specifically, the software enables designers, managers, and service bureau personnel to:

- Explore AM technologies for their application in a possible DDM project,
- Identify candidate materials and processes,
- Explore build times, build options, costs,
- Explore manufacturing and life-cycle benefits of AM,
- Select appropriate AM technologies for DDM applications.
- Explore case studies, anticipate benefits
- Support Quotation and Capital Investment decisions

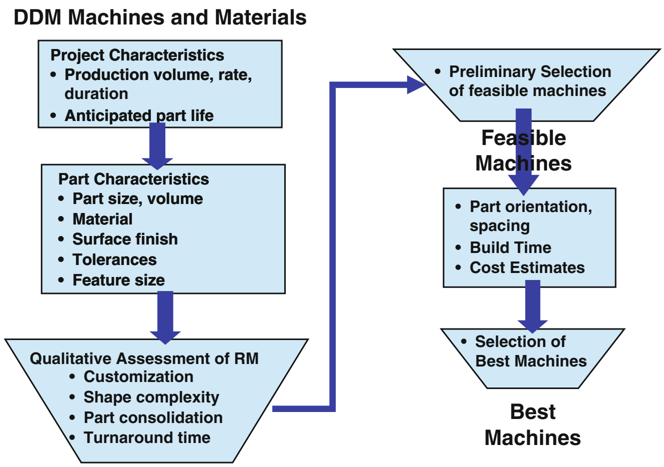


**Fig. 12.5** Flowchart of DDMS operation

Figure 12.5 illustrates the logic underlying DDMS. A database of machine types and capabilities is read, which represents the set of machines that the software will consider. The software supports a qualitative assessment of the suitability of DDM for the application, then enables the user to explore the performance of various AM machines. Build time and cost estimates are provided, which enable the user to make a selection decision.

To use DDMS, the user first enters information about the production project, including production rate (parts per week), target part cost, how long the part is expected to be in production, and the useful life of the part. After the user enters information about the part to be produced and its desired characteristics (Fig. 12.6), the user answers questions about how the application may take advantage of the unique capabilities of AM processes, as shown in Figs. 12.7 and 12.8. In this version of the software, the questions ask about part shape similarity across the production volume, part geometric complexity, the extent of part consolidation compared to a design for conventional manufacturing processes, and the part delivery time. Based on the responses, the software responds with general statements about the likelihood of AM processes being suitable for the user's application; for example, see the responses for the fictitious problem from Fig. 12.6. If the user is satisfied that his/her application is suitable for DDM, then they can proceed with a more quantitative exploration of AM machines.

The DDMS software enables the user to explore the capabilities of various AM machines for their application. As shown in Fig. 12.9, DDMS first segregates machines that appear to be feasible from those that are infeasible, based on material,

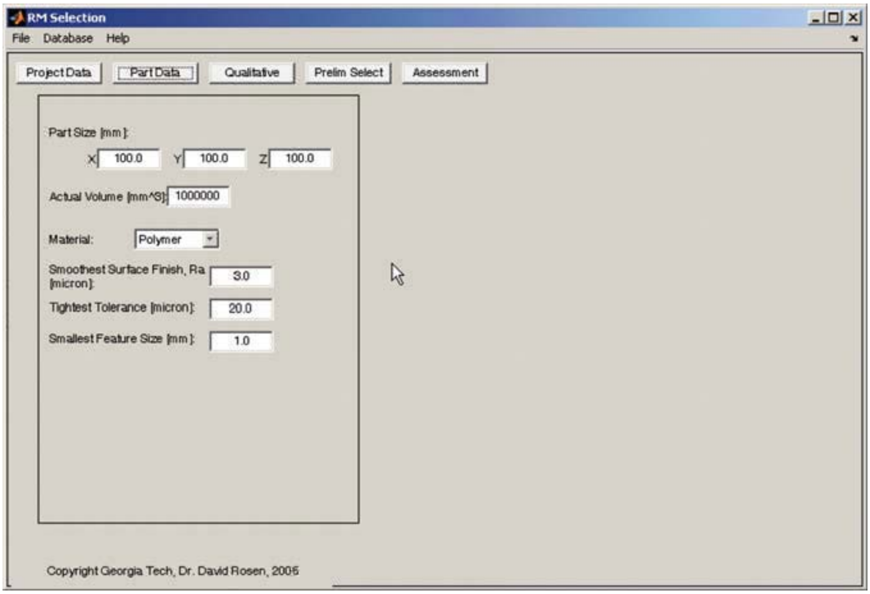


**Fig. 12.6** Part Data entry screen for DDMS

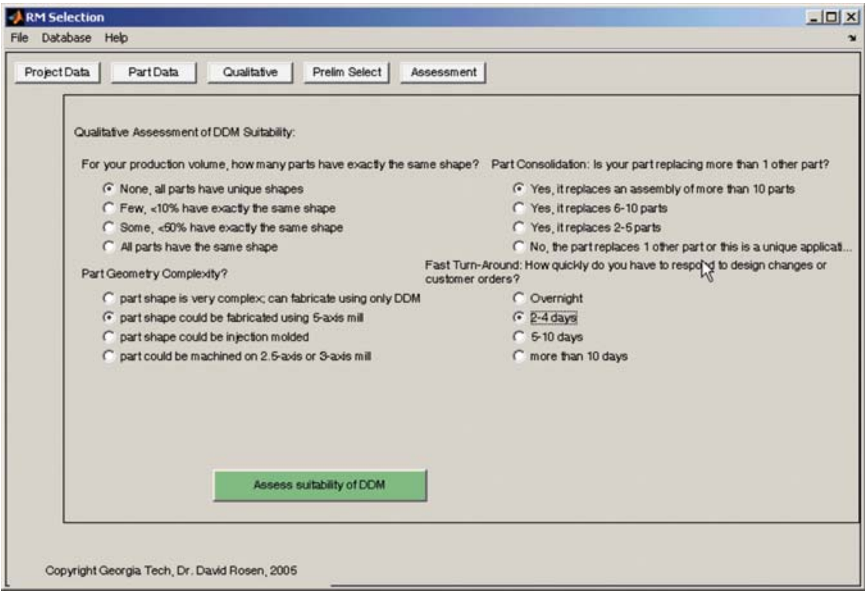


**Fig. 12.7** Qualitative assessment question screen

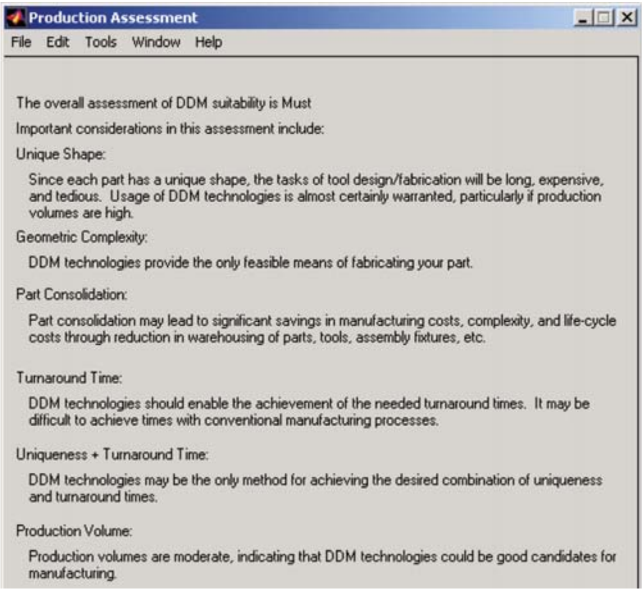


**Fig. 12.8** Qualitative assessment results for the entries in Fig. 12.7

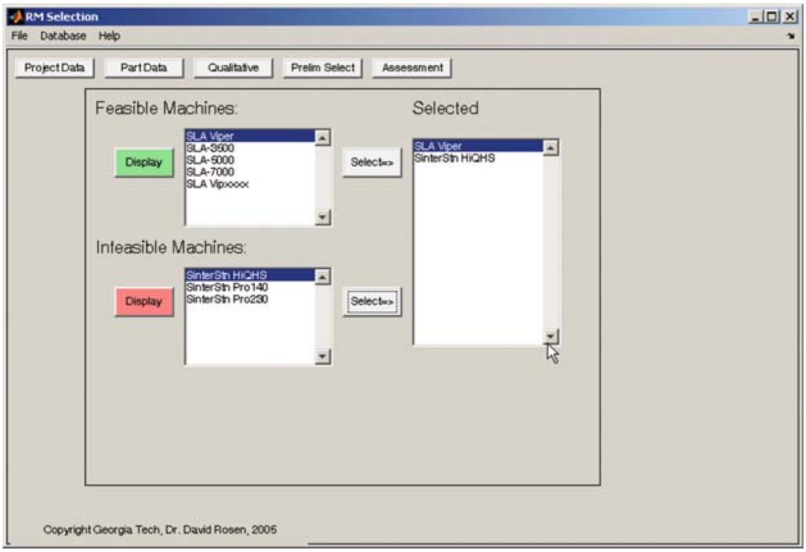


**Fig. 12.9** Preliminary selection of machines to consider further

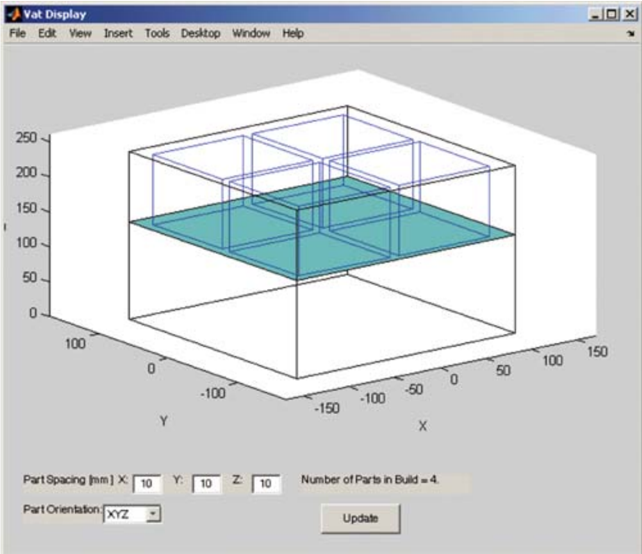


**Fig. 12.10** Layout of parts on the machine platform

surface finish, and accuracy requirements. The user can select from both the sets of feasible and infeasible machines, which can be useful for comparison purposes.

If the user wants to see the layout of parts in a machine's build chamber, they can hit the Display button, while the machine of interest is selected. For example, the build chamber of a SLA Viper Si2 machine is shown in Fig. 12.10 for parts with bounding box dimensions of 100 × 100 × 100 mm (part size from Fig. 12.6). Since the Viper Si2 has platform dimensions of about 250 × 250 mm, only four parts can fit on the platform, as shown. The user has control over the spacing between parts. Entering negative spacing values effectively "nests" parts within one another, which may be useful if parts are shaped like drinking cups, for example. Note that DDMS will stack parts vertically if that is a typical build mode for the technology; parts are often fabricated in stacked layers in SLS as one example. Also note that serial manufacturing of end-use products is assumed for the DDMS software. As such, the software assumes that a large quantity of parts must be produced and fills the platform or build chamber with only one type of part (part described in the Part Data screen, Fig. 12.6). The user can also change the part orientation in an attempt to fit additional parts into a build.

In the last major step in DDMS, the Assessment button (*see* Figs. 12.6, 12.7 and 12.9) can be selected to estimate the build time for the platform of parts, as well as the cost per part. These assessments can be particularly useful in comparing technologies and machines for an application. Considerable uncertainty exists regarding build speeds so ranges of build times are calculated based on typical ranges of scanning speeds, delay times, recoating speeds, etc. Part costs are broken

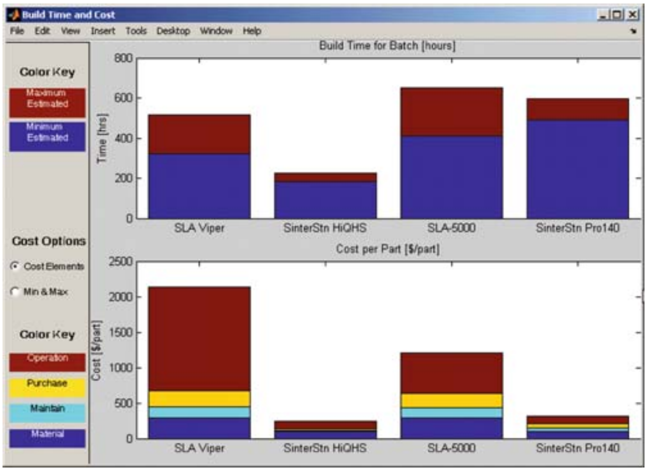


**Fig. 12.11** Build time and cost results for the example

down into machine, material, operation, and maintenance costs, similar to the cost model to be presented in Chap. 14.

As shown in Fig. 12.11, long build times do not necessarily translate to high part costs, particularly if many parts can be built at once. The SinterStation Pro 140 has a build time almost as long as the SLA-5000, but part costs are several times smaller since many more parts can be built in about the same amount of time. On the other hand, the SLA Viper Si2 takes almost as long for its platform, but parts are very expensive since the Viper is building in high-resolution mode (built-in assumption) and few parts can fit on its relatively small platform.

Maintenance of the database for DDMS can be problematic, since machine capabilities may be upgraded, costs may be reduced, and new machines developed. DDMS allows users to edit its database, either by modifying existing machines or by creating new ones. The screen that shows this capability is shown in Fig. 12.12.

Armed with these results, the user can make a selection of AM machines to explore further. The decision may be based on part cost. But, the user needs to take all relevant information into account. Recall that the SinterStation machines were not feasible for this application (due to feature size requirements, although this was not shown). This was why the SinterStation appeared in the infeasible column in Fig. 12.9. With these results, the user can determine whether or not s/he wants to relax the feature size requirement to reduce costs, or maintain requirements with a potential cost penalty. Hence, trade-off scenarios can be explored with DDMS.

In fact, DDMS can be used by machine vendors to explore new product development. They can "create" new machines by adding a machine to the database with the characteristics of interest. Then, they can test their new machine by quantitatively comparing it with existing machines based on build times and part costs.

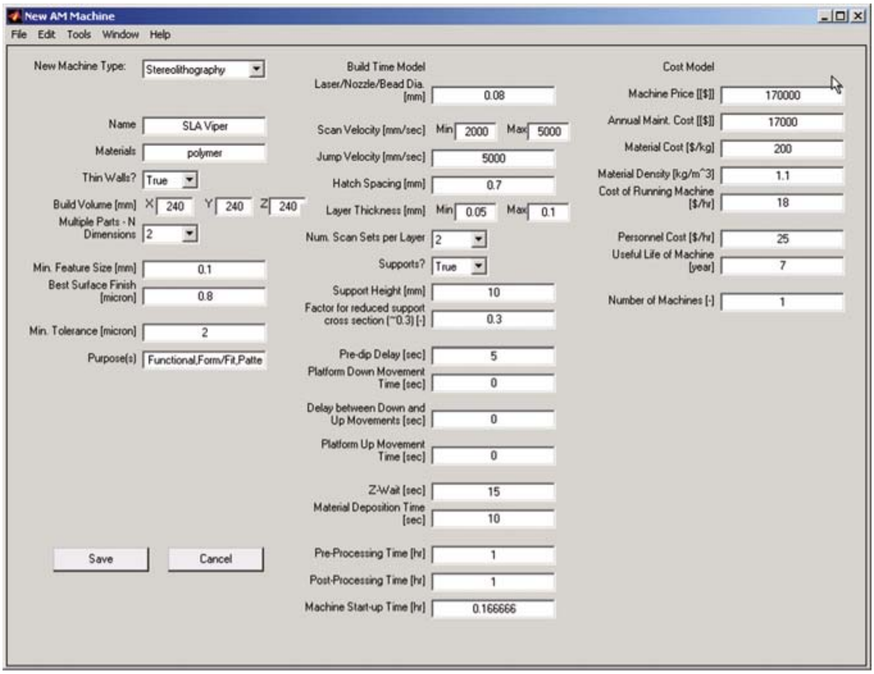


**Fig. 12.12** Screen for adding or editing an AM machine definition

## 12.5 Production Planning and Control

The material covered in this section addresses the third type of selection decision introduced in the Introduction, namely support for process planning. It is probably most relevant to the activities of service bureaus (SBs), including internal organization in manufacturing companies that operate one or more AM machines and processes. The SB may know which machine and material a part is to be made from, but in most circumstances, the part cannot be considered in isolation. When any new part is presented to the process planner at the SB, it is likely that he has already committed to build a number of parts. A decision support software system may be useful in keeping track and optimizing machine utilization.

Consider the process when a new part is presented to the SB for building. In general, the information presented to the process planner will include the following:

- Part geometry
- Number of parts
- Delivery date or schedule for batches of parts
- Processes other than AM to be carried out (pre-processing and post-processing)
- Expectations of the user (accuracy, degree of finish, etc.)

Furnished with this small amount of data, it is possible to start integrating the new job with the existing jobs and available resources. Four topics will be explored further, namely production planning, pre-processing, part build, and post-processing.

### 12.5.1 Production Planning

Several related decision are needed early in the process. A suitable AM process and machine must be identified from among those in the facility. This was probably done during the quoting stage before the customer selected the SB. After that is settled, AM machine availability must be considered. If the SB has more than one suitable machine, a choice must be made as to which machine to use. If the job is for a series of part batches, the SB may choose to run all batches on the same machine, or on multiple machines. If multiple machines, the SB must ensure that all selected machines can provide repeatable results, which is not always the case. Otherwise, potentially lengthy calibration builds may be needed to ensure consistent part quality from all machines used.

A job scheduling system should be used, particularly for production manufacturing applications, so that part batches can be produced to meet deadlines. If the SB has insufficient resources, it may need to invest in further capacity, necessitating a machine selection scenario. Alternatively, the SB could retain the services of other SBs if the economics of further machine investments is questionable.

### 12.5.2 Pre-processing

Preprocessing means software-based manipulation. This will be carried out on the file that describes the geometry of the part. Such manipulation can generally be divided into 2 areas, modification of the design and determination of build parameters.

Modification of the design may be required for two reasons. First, part details may need adjustment to accommodate process characteristics. For example, shaft or pin diameters may need to be reduced, to increase clearance for assembly, when building in many processes since most processes are material safe (i.e., features become oversized). Second, models may require repair if the STEP, IGES, or STL file has problems such as missing triangles, incorrectly oriented surfaces, or the like.

Determination of the build parameters is very specific to the AM process to be used. This includes selecting a part orientation, support generation, setting of build styles, layer thickness selection, temperature setting, etc. In general, this is either a very quick process or it takes a predictable length of time to set up. On occasion, and for some particular types of machine, this process can be very time consuming. This usually corresponds to instances when the user expectations closely meet the upper limits of the machine specification (high accuracy, build strength, early delivery date, etc.). Under such conditions, the user must devote more time and attention to parameter setting. The decision support software should make the process planner aware under which circumstances this may occur and allocate resources appropriately.

### 12.5.3 Part Build

For some processes, like FDM or LENS, it does not really matter in terms of time whether parts are built one after another (batches of 1) or parts are grouped together in batches. However, most processes will vary significantly regarding this factor. This may be due to significant preparation time before the build process takes place (such as powder bed heating in SLS), or because there is a significant delay between layers. In the latter case, it is obvious that the cumulative number of layers should be as low as possible to minimize the overall build time for many parts.

Another factor is part orientation. It is well known that because of anisotropic properties caused by most AM processes, parts will generally build more effectively in one orientation compared with another. This can cause difficulties when organizing the batch production of parts. Orientation of parts so that they fit efficiently within the work volume does not necessarily mean optimal build quality and vice versa. For those machines that need to use support structures during the build process, this represents an additional problem, both in terms of build time (allocation of time to build the support structures for different orientations) and post-processing time (removing the supports). Many researchers have discussed these dilemmas [4].

What this generally means to a process planner is compromise. Compromise is not unusual to a process planner, in fact it is a typical characteristic, but the degree of flexibility provided by many AM machines makes this a particularly interesting problem. Just because an AM machine is being used constantly does not mean it is being used efficiently.

### 12.5.4 Post-processing

All AM parts require a degree of post-processing. At the low end, this may require removal of support structures or excess powder for those who merely want quick, simple verification. At the high end, the AM process may be a very insignificant time overhead in the overall process. Parts may require a large amount of skilled manual work in terms of surface preparation and coating. Alternatively, the AM part may be one stage in a complex rapid tooling process that requires numerous manual and automated stages. All this can result from the same source machine.

It can even be an iterative process involving all of the above steps at different stages in the development cycle based on the same part CAD data.

### 12.5.5 Summary

It is clear that only process planners who have a very detailed understanding of all the roles that AM parts can play will be able to utilize the resources effectively and efficiently. Even then it may be difficult to perform this task reliably given the large number of variables involved. A software system to assist in this difficult task would be a very valuable tool.

## 12.6 Open Problems

Some summary statements and open problems that motivate continued research are presented here.

- Selection methods and systems are only as good as the information that is utilized to make suggestions. Maintaining up to date and accurate machine and material databases will likely be an ongoing problem. Centralized databases and standard database and benchmarking practices will help to mitigate this issue.
- Customers (people wanting parts made) have a wide range of intended applications and needs. A better representation of those needs is required in order to facilitate better selection decisions. Improved methods for capturing and modeling user preferences are also needed.
- Related to the wide range of applications is the wide range of manufacturing process chains that could be used to construct parts. Better, more complete methods of generating, evaluating, and selecting process chains are needed for cases where multiple parts or products are needed (10–100) or when complex prototypes need to be constructed. An example of the latter case is a functional prototype of a new product that consists of electronic and mechanical subsystems. Many options likely exist for fabricating individual parts or modules.
- More generally, integration of selection methods, with databases and process chain exploration methods would be very beneficial.
- Methods are needed that hide the complexity associated with the wide variety of process variables and nuances of AM technologies. This is particularly important for novice users of AM machines or even for knowledgeable users who work in production environments. Alternatively, knowledgeable users must have access to all process variables if necessary to deal with difficult builds.
- Better methods are needed that enable users to explore trade-offs (compromises) among build goals and to find machine settings that enable them to best meet

their goals. These methods should work across the many different types of AM machines and materials.

- It is not uncommon for AM customers to want parts that are at the boundaries of AM machine capabilities. Tools that recognize when capability limits are reached or exceeded would be very helpful. Furthermore, these tools should provide guidance that assists users in identifying process settings that are likely to yield the best results. Providing estimates of part qualities (e.g., part detail actual sizes vs. desired sizes, actual surface finish vs. desired surface finish, etc.) would also be helpful.

## 12.7 Exercises

1. You have been assigned to fabricate several prototypes of a cell phone housing for assembly and functional testing purposes. Discuss the advantages and disadvantages of commercial AM processes. Identify the most likely to succeed processes.
2. Repeat Exercise 1 for a laptop housing.
3. Repeat Exercise 1 for metal copings for dental restorations (e.g., crowns and bridges). Realize that accuracy requirements are approximately 10 μm. Titanium or cobalt-chrome materials are used typically.
4. For the selection example in Section 12.2.4,
   (a) update the information used using information sources at your disposal (web-sites, etc.).
   (b) repeat the selection process using your updated information. Develop your new versions of Tables 12.2 and 12.3.
5. Repeat Exercise 3 using the selection DSP method and the updated information that you found for Exercise 4.

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