12th International Research/Expert Conference
”Trends in the Development of Machinery and Associated Technology”
TMT 2008, Istanbul, Turkey, 26-30 August, 2008

AN EXPERT RULE-BASED SYSTEM FOR ADDITIVE MANUFACTURING SELECTION

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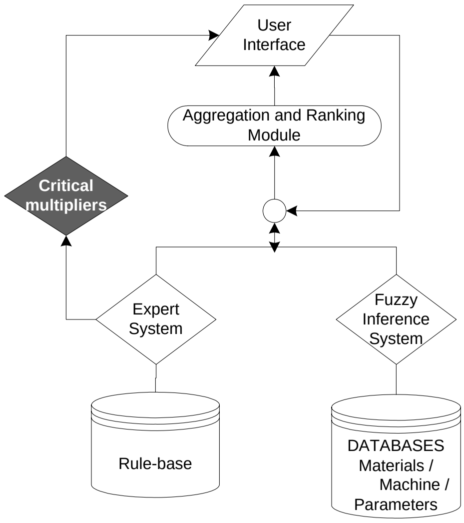
ABSTRACT
This paper assesses the possibility of using Rapid Manufacturing (RM) as a final manufacturing route through a comparison of RM processes capabilities vs. conventional manufacturing processes. This is done by means of a computer-aided system (RMADS) intended to guide the designer in the selection of optimum production parameters according to typical requirements of the first design stages. A number of Artificial Intelligence (AI) tools are applied namely: fuzzy inference, relational databases and rule-based decision making. A pilot application developed in Matlab® is presented to illustrate a case study for a real mechanical part.
Furthermore the proposed system makes use of two different costing approaches: Parametric and Empirical. An empirical cost model has been implemented for those widely studied RM processes whose parameters and their participation in the final cost can be clearly defined. On the other hand Empirical costing has been adapted trough the use of neural networks in order to get rough estimations of part cost for those RM processes whose parameters and their cost implications are not yet defined.
Keywords: Expert systems, Rapid manufacturing, Rule-based selection

1. INTRODUCTION
Rapid prototyping refers to those technologies capable of producing prototypes directly from a CAD source, via layer-wise deposition [1]. The selection of the most suitable RP process is dependent on factors such as build envelope, accuracy, material, build speed and other machine-related parameters. With around 22 manufacturers marketing between 40 and 60 models of RP machines [2], the development of computer-based selection systems has been a recurrent topic in RP related literature.
Knowledge-based expert systems for RP selection have been introduced by [1, 3, 4]. This software was partially based on data gathered from user’s surveys and proprietary info to construct their base of knowledge; however, they still lack of cost, materials properties and build time information for making manufacturing comparisons.
This paper proposes an integrated RM selection system to select the most appropriate RM process by integrating an expert system, a fuzzy inference engine and databases in order to support quantitative and qualitative data as well. The final goal is not the fabrication of a prototype but the identification of RM alternatives as feasible manufacturing options.

2. THE SYSTEM’S ARCHITECTURE
The RMADS architecture is comprised of 5 modules working together with data extracted from two main databases to support the decision making task (Figure 1). The model is based on an object-oriented methodology [5] i.e. it is capable of working with independent modulus performing event-driven calculations according to user selection.



2.1 The elements of the RMAD system

System interface*:* The user interface supports numerical values or linguistic terms to be chosen from a pre-defined list tailored to every qualitative design attribute. As a result of the modularity each activated option will lead to the development of a vector with values normalized to the range 0-1 depending on the parameter selection.

Expert system and its Rule-base: The expert's knowledge is represented as a series of IF-THEN –ELSE statements. A total of 500 rules are executed when all the options of the system are activated, however the number of rules is due to increase with every new material and process added to the database.

Figure 1. The elements of the RMAD system

Fuzzy inference system: This stage basically consists of representing all the goals and constraints as fuzzy sets [6] obtained by mapping the membership values based on the selection of linguistic variable by the user depending on the variable chosen (e.g. Surface Roughness, Tolerances, Mechanical properties, etc) the user will be presented a number of suitable options compatible with a triangular fuzzy membership (e.g. high/average/low, etc.),

IF Part X axis < Machine X axis
AND Part Y axis < Machine Y axis
AND art Z axis < Machine Z axis
THEN Machine = TRUE
ELSE IF Part Volume < (Machine build volume)
Machine (n) = True
Print ("Consider slicing or sectioning the part")
ELSE
Machine (n) = FALSE
END

Figure 2. Sample rule for the expert system

Table 1. Linguistic term converted to fuzzy numbers by means of a triangular membership

Corrosion resistance	Mech. properties	Fuzzy number (a,b,c)	Defuzzified value
Good	High	A1= (0.6, 1, 1)	0.867
Average	Average	A2= (0.1, 0.5 ,0.9)	0.5
None	Low	A3= (0,0, 0.5)	0.166

Database: Two different databases store data regarding 1) RM Process parameters and individual machine information. 2) Materials database. Data has been gathered from available vendor's info, related literature [7, 8] as well as from other electronic data [9, 10]. Data is stored in an MsAccess database and called from the system by the Matlab [11] database toolbox.

Aggregation and ranking module: This module performs the final decision based on the parameters and options selected. Since qualitative information is normalized to 1 and qualitative information is treated with fuzzy numbers this module's task is to perform a fuzzy-decision. Although there exist a number of different approaches for ranking fuzzy sets [12] each one with different advantages and drawbacks, for this paper the transformation method [13] is applied

Since not all the included parameters have the same importance for all design cases, the user is requested to grade from 1 to 4 the main categories according to the importance given for a specific task: Geometry, Appearance, Functionality, and Mechanical Properties where 1 corresponds to the most important factor and 4 for the least important. This leads to the creation of the weighting factor vector W, where

$$W = (w1, w2, w3\ w4) \quad (1)$$

According to [14] the numeric scale entered by the user from 1 to 4 can be converted to fuzzy numbers following the triangular membership for a 4 point scale to provide the following fuzzy values for the weights selected: 1=0.892, 2=0.666, 3=.333, 4= 0.108.

3. APLICATION OF THE MODEL

The part shown in Figure 3 belongs to a gym exercise machine, designed for a volume of 500 units per year. The original design however had to be modified in order to fulfil the restrictions imposed by sand casting (e.g. draft angles, constant wall thickness, avoid captured cavities, etc.). The part has two special aspects that suggest that RM should be explored as an option:

1- The part performs a non-critical function, i.e. it does not bear important mechanical forces.

2- The hollow cylinders need a low friction coefficient. A well known polyamide attribute

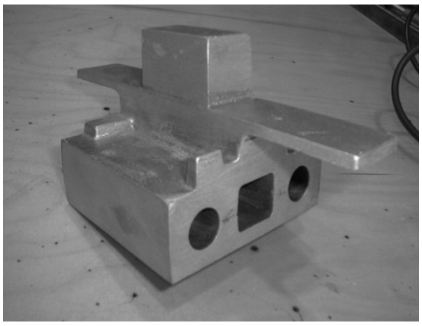
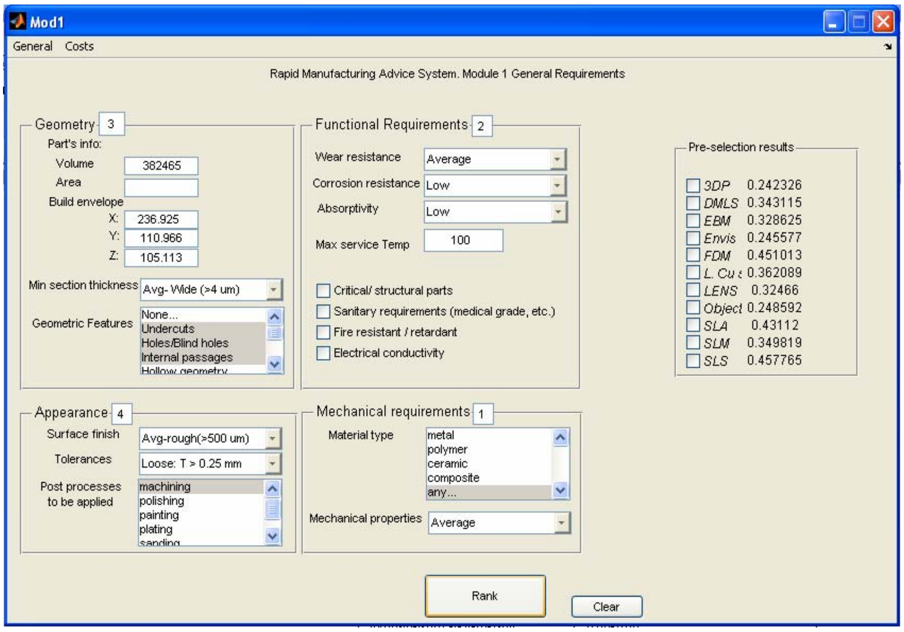


Figure 3. Sample mechanical part

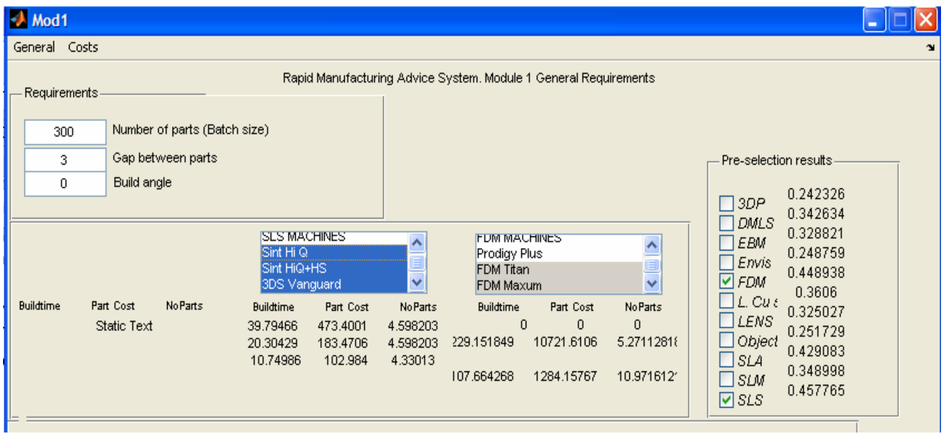
The RMADS interface was then used for entering the appropriate values according to the part requirements. It shows the iterative selection made by the designers in order to evaluate different options for the design and the result ranking.



According to design requirements and the designer's criteria, SLS and FDM would be possible alternatives to explore. Note that 3 important RP processes have been rule out, due to the critical requirement imposed for a Maximum Service temperature of 100^{oC} that is difficult to withstand by RM materials. On the other hand if we set Material type to "Metal" results would be screened and only metallic processes would be considered.

Figure 4.Graphical User interface for the RMADS system

3.1 Cost calculation



An embedded parametric cost calculation model is applied following [15] for a unified cost calculation tool. It relies on available information on machine parameters captured by datasheets and previous experience.

Figure 5.Cost estimation interface for the RMADS system

As shown in the previous Figure, the parametric costing method is applied since there's data available in the software's database for the two recommended processes (SLS, FDM). Should a different process be more appropriate without further cost information available, a neural network module would be deployed in order to get rough estimates of part cost.
The cost estimation module provides estimations for machine Build time, part cost and for the number of parts for each build. From the previous figure the following chart can be extracted.

Table 2. Estimated cost per part

Process /Machine	Cost per part
SLS / Sint Hi Q	118.25
SLS HiQ+HS	45.75
SLS/3DS Vanguard	25.5
FDM Titan	2934.35
FDM/ Maxum	116.72

In this way the user can make an informed decision based on technical feasibility, accurate cost estimation, besides parts and machine information. For example, although the FDM process is technically suitable for the part's application, it may not be the best economical solution, especially regarding the Titan machine. On the other hand, may the designer change the initial preferences such as production volume, design criteria and other specifications, the final results will be refreshed with every new entry. More effort is being done to provide the system with a more comprehensive machine and process database to be able to work with a wider range of RM alternatives.

4. CONCLUSIONS

The proposed method contributes in filling the gap between conventional manufacturing knowledge and the actual knowledge on Rapid Manufacturing. Although the real value of the system will depend on the ability to feed the databases and monitor upcoming materials and new technology developments, it contains an appropriate logic for the selection or recommendation of a suitable RP/RM alternative.
Since every design case is different, what is normally an inappropriate process for a certain task may be a quite good candidate for another, as long as the critical constraints imposed by the designer are fulfilled. Current work is being developed to integrate a cost model which is able to perform calculations on economic-batch and single part costs. It may be a hybrid between parametric models and neural networks which have not been extensively applied to this field but have already shown great potential in other areas of fabrication.

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