An Educational Tool for RM Feasibility Evaluation

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Abstract – **The use of computer aided systems is a common tool to solve the problem of process selection, cost and time estimation. Although many RM selection systems have appeared over time, none of them performs the selection task including concurrent factors such as cost, materials and technical feasibility. The RM evaluation method proposed herein splits the selection factors into: technical, economical and materials assessment. It makes use of matrix algebra and a number of Artificial Intelligence (AI) tools such as fuzzy logic, neural network modelling and expert systems, which are implemented in order to allow for more appropriate qualitative criteria for RM selection. A pilot application developed in MatLab is presented in order to illustrate the interaction between the different modules and to show the effect of the respective AI method on the final results according to the studied case.**

Keywords – **RM Process Selection, Cost Estimation**

I. INTRODUCTION

The Rapid Manufacturing Advice System (RAMDS) presented herein is intended to ‘recommend’ the most appropriate route for creating a final fully-functional part through additive manufacture. The main difference with previous selection systems consists in the concurrent evaluation of several manufacturing techniques from a set of initial user defined input parameters. The final goal is not the selection of prototyping processes, but the assessment of RM alternatives as feasible manufacturing options for end-use parts. This requires a series of steps in order to assure the feasibility of the system’s proposal.

II. THE SYSTEM’S ARCHITECTURE

The RMADS architecture is comprised of 3 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 [1] i.e. it is capable of working with independent modulus performing event-driven calculations according to user selection. The system is comprised of three main modules which can be executed independently to obtain separate results: General design requirements, Costs assessment and Materials selection module.

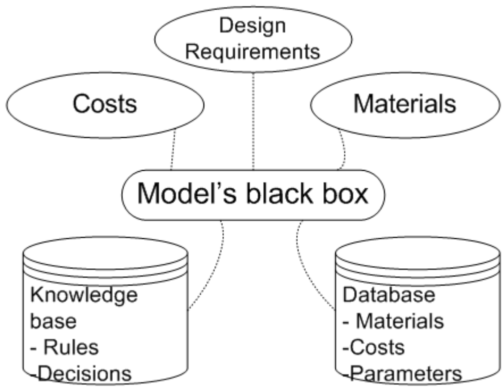


Figure 1. The RMADS system architecture

A. Module 1. General design requirements

Starting form a series of parameters divided in 4 groups: Geometry, Appearance, Functional and Mechanical requirements (Figure 2) each group contains a number of parameters which are processed differently according to their type:

- Quantitative data (Q): This data is processed by means of an expert rule base for each parameter. It is explicitly requested to the user in a numeric form or by the selection of precise preferences, for instance the maximum service temperature, which is then contrasted against the materials database for screening.

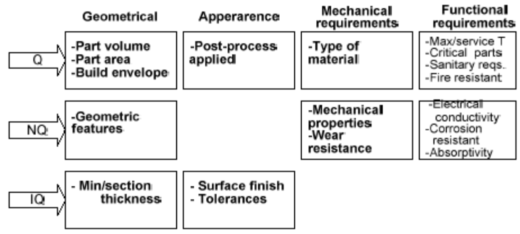


Figure 2. Grouping of the considered parameters

- Normalized qualitative criteria (NQ): For attributes of this type it is preferred to assign linguistic terms in order to generalize and appropriately represent this imprecise data for selection. These linguistic terms are then converted to fuzzy numbers following the procedures described on Table 1.

TABLE 1
LINGUISTIC VARIABLES AND CORRESPONDING FUZZY NUMBERS

Corrosion resistance	Wear resistance	Fuzzy number	Defuzz 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

- Individual qualitative data (IQ): This type of input information is called "individual" since it is not possible to apply uniform linguistic terms and the same membership function for each parameter as in the previous case. This criterion affects specifically to: Surface roughness, Tolerances, Min section Thickness and other qualitative parameters, therefore for each parameter a different fuzzy membership must be established.

B. Module 2. Economic assessment

Once a number of RM processes have successfully passed the previous stage, cost assessment is undertaken. This module exploits up to date knowledge on Artificial Neural Networks (ANN) for cost estimation, in addition to previously developed parametric models, [2, 3] to get an approximate part cost for each additive technology.

According to existing parametric time-estimation models, input data should correspond to simple geometrical variables (normally 3 to 5). Early studies on RP build-time estimation were based on the total scan length and laser speed, while more recent models calculate time as a function of part volume, height and surface area [4] or considering also the part bounding-box volume. For this system, in order to design a pilot application only two RM processes were modelled by ANNs: SLS and SLM. To identify the most useful input parameters for SLS and its derivate technologies, a series of correlation analysis were performed for a number of attributes. From this analysis three input parameters were selected namely: z height, part volume, and bounding box volume.

It is assumed that since the principle of additive fabrication of SLS is also used for SLM, the selection of the ANN architecture should be similar. The adopted learning algorithm is the Levenberg-Marquardt, as it is often a more efficient alternative to steepest ascent algorithm and also faster in converging [5]. A topology of 3 input nodes and one output node has been adopted, however in order to define the best performance, different configurations from 1 to 3 hidden layers were tested.

The maximum error found during the research is 15% which denotes a clear potential for the ANN-based method to be extrapolated to different RM processes. Figure 3 shows a general scheme of the calculations performed through the costing module.

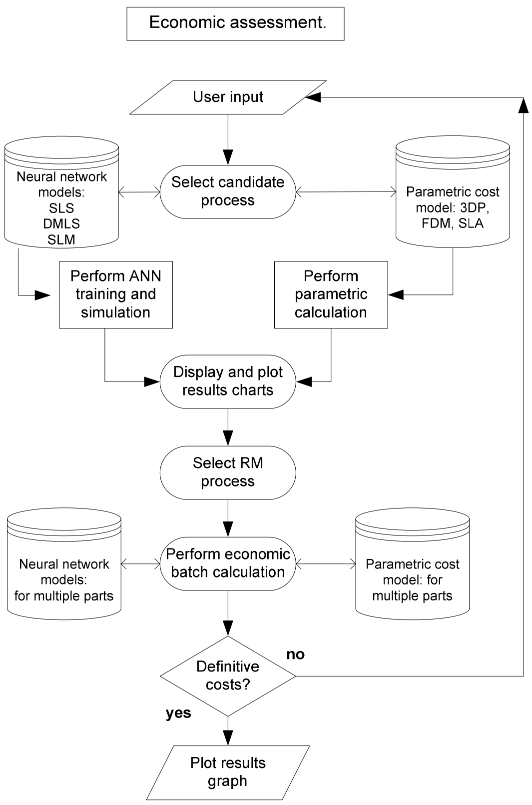


Figure 3. The Economic assessment scheme

C. Module 3.Materials properties

This module is comprised of an expert system linked to relational databases in order to show feasible materials for the intended application and depending on the properties selected by the user (Figure 4). The system also displays graphs based on material parameters so that the final selection is twofold: graphical and rule-based. In order to develop a pilot application for selecting materials within the RMADS system, a comprehensive compilation of sources was undertaken including manufacturers data, datasheets provided by specialized service bureaus and other specialized independent sources [6-10]. The RMADS system makes use of relational databases in order to perform the material selection task.

A MS Access database has been constructed to be used as a Materials repository due to the following advantages:

1) New materials registries can be added, automatically updated and retrieved by an ODBC database call from the RMADS system

2) New material properties can be added making it easier to add new constraints to the code

3) The data stored in Ms Access can be easily exported to other graphing software such as MS Excel.

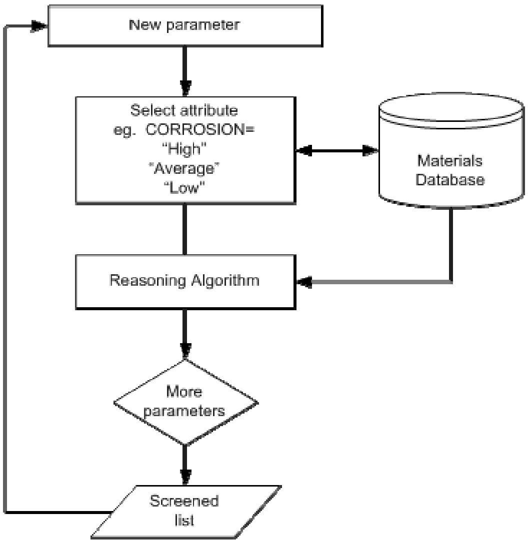


Figure 4. The materials selection scheme

III CASE STUDY

The Coin-Classifying Machine is a project developed at the CDEI Centre; the objective was to develop a universal and modular coin-classifying device by means of an electromagnetic principle (Figure 5).

The overall system is internally composed of a plastic transporting band which contains individual "links" (Figure 6). These are independently designed pldastic parts with the function of guiding individual coins along the path of the transport band. For this purpose the links incorporate a number of geometrical features to be highlighted such as undercuts, hidden channels and re-entrant elements.

According to the part specifications, the materials to be applied must fulfil the following conditions:

- High Dimensional precision
- Lightweight
- Slippery material preferred
- High impact resistance
- High repeatability
- Non conducting material
- High general mechanical properties
- High corrosion resistance

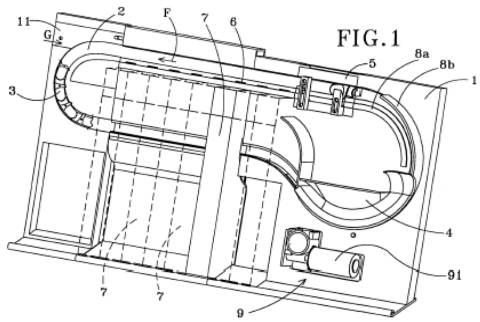


Figure 5 General scheme of the CCM machine. Source: Patent ES 2158803 [11]

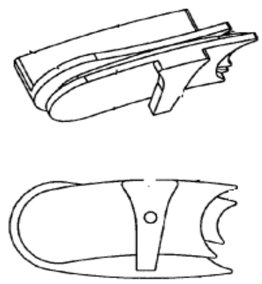


Figure 6. Perspectives of the 'link' polymer part

A. *Materials Module*

Since the main constraints applied to the part are material related, the Materials selection Module will be firstly executed. The RMADS system currently accepts parameters such as: Wear resistance, Corrosion resistance, Mechanical properties, and other critical conditions which are treated as fuzzy numbers as defined earlier in this text.

The preliminary selection includes a rough list of materials without applying more restrictive factors. For instance the materials Castform and Prime Cast which are intended for casting process are presented although they are not really suitable candidates. While an experienced user may know this, it will not be evident for or non experienced designers, therefore further analysis must be undertaken.

As the wear resistance and overall mechanical properties are important for the final design, the Graph display menu at the upper right cornet is activated by selecting the Wear-resistance/Tensile strength graph as shown on Figure 7. By analyzing this graph it is possible to observe how "in theory" the best propertie-relationship corresponds to the Windform series of materials followed by non reinforced PA polymers.

This however may open the debate on material properties: How does the SLS process behave with custom-made, fibre reinforced, carbon-filled tailored powders? This may be only responded through experimentation. The following chart (Table II) shows the theoretical values for the Tensile Strength (MPa) for the originally considered materials and the RM materials that resulted from the previous stage. It is evident that engineered thermoplastics still yield significant advantages versus laser sintering powders however the designer has the last word over the minimum-enough Tensile Strength necessary to perform the task.

TABLE II.
TENSILE STRENGTH VALUES FOR POWDER BASED AND ENGINEERING THERMOPLASTICS

RM material	Tensile strength (MPa)	Injection Moulding material	Tensile strength (MPa)
Windform XT	77	PA 66 (Filled)	117
PA 66	72	POM (25% glass filled)	110
Windform FX	48.9	PA 66 unfilled	62
PA 3200 GF	48	PE (20-30% glass filled)	55
Duraform PA	44	POM(30% carbon fibre)	51.54

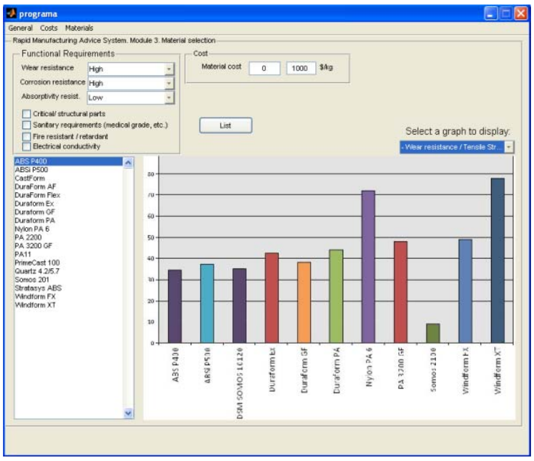


Figure 7 Materials selection module and the comparison graph being displayed

Being the reinforced Polyamides for Selective Laser Sintering the best theoretical option, it is interesting to apply additional factors to the screening process. Since cost is considered as a restricting factor, a maximum cost of 100 €/kg is applied, hence reducing the list to four alternatives. Also the parameter "critical" is activated since the mechanical response of the studied element would not result in catastrophic failure but would influence in the mal-functioning of the overall system.

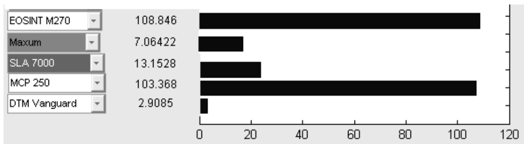
While mechanical properties seem to be superior for Windform XT, there is no available data regarding absorptivity levels. The same is true for some of the other RM materials, therefore it must be clarified that the results provided by the RMADS system will be on the basis on theoretical information available from materials manufacturers and by no means will they replace functional testing and user experience.

B. Costing module

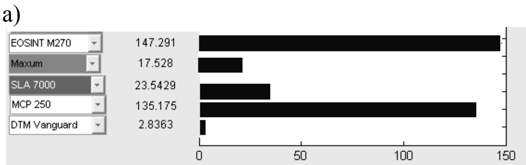
Once the most suitable material has been deteted it is propoer to proceed to the economic comparison among different RM technologies. This is done by activating the corresponding process on the RMADS costing interface. From there it is possible to see, how for different batch sizes the SLS remains the most competitive alternative (Figure 8).

After this analysis it is possible to foresee the economic alternative of this technology versus other processes such as Injection moulding. Consider an injection mould cost of 25,000€. This is a conservative cost since the intended mould would include movable ejector pins and a highly resistant base material to withstand the abrasion of fibre reinforced thermoplastics.

The following graph (Figure 9) show the cost comparison between the Injection moulding process and its SLS counterpart where the approximate break-even point is located around 20,000 parts, that is, from low to mid-volume batches.



a)



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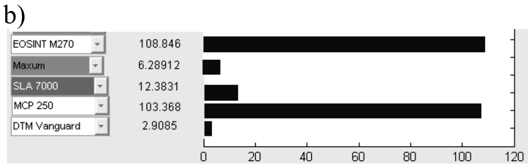

c)

Figure 8. Evolution of cost per part for different batch sizes: a) 100, b) 1000 c) 3000

C. General requirements module

The following figure (Figure 10) illustrates how the different queries on the General Design Requirements module have been selected, in order to assess the feasibility of RM technologies.

With this conclusion it can be established that from the competing processes SLS is technically feasible, cost effective and provides similar material properties to those provided by the injected polymers.

The next step should be a prototype test under functional conditions during repetitiveprolonged cycles in order to validate the viability of this solution.

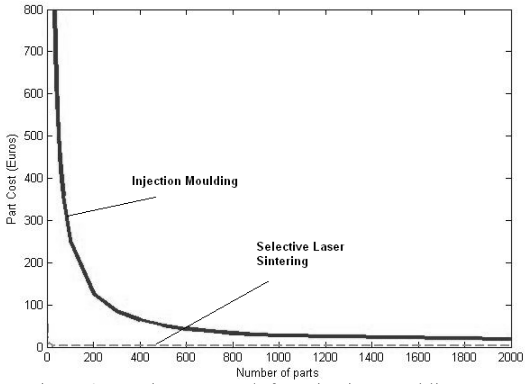

Figure 9. Break-even graph for Injection moulding vs. Selective Laser Sintering. (up to 20,000 units)

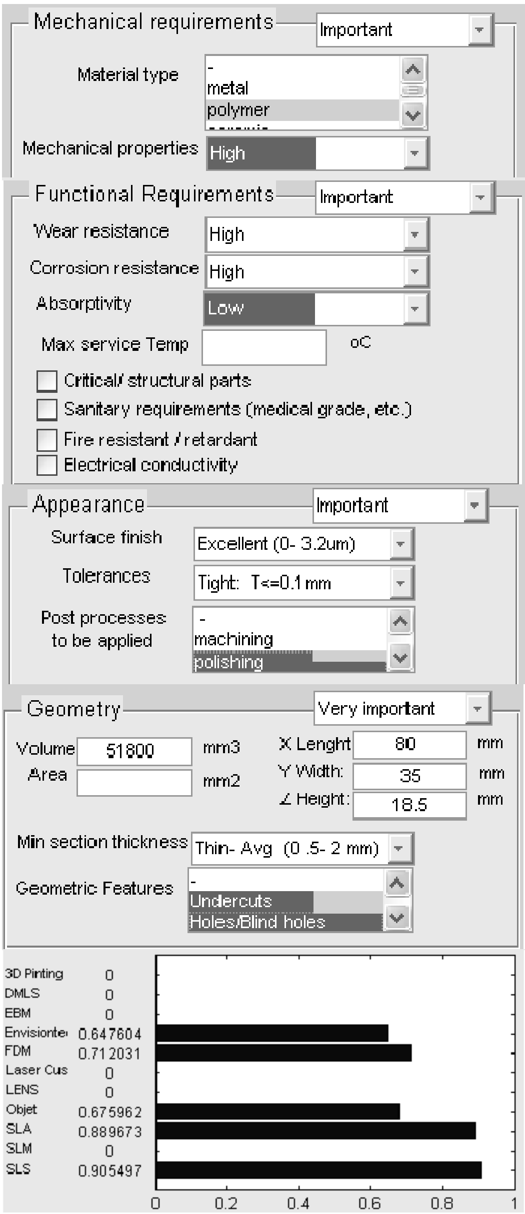

Figure 10. Design parameters requested by the RMADS system and the final process comparison chart.

IV. CONCLUSIONS

This research proposed an integrated RM selection system that includes an expert system, a fuzzy inference engine and Neural Network modelling as well as two databases: materials and process capabilities, in order to support quantitative and qualitative data to be entered by the user.

It was illustrated how with the interaction between those Artificial Intelligence techniques it is possible to build an intelligent environment for the assessment of RM methods as feasible or un-feasible manufacturing alternatives. This is a valuable aid specially for users with little or no previous knowledge of additive manufacturing methods.

This pilot application currently supports eight RM technologies and their respective machines and manufacturers; however the model can be easily modified and databases expanded in order to become a more comprehensive system, which is the objectiveof further research.

ACKNOWLEDGMENT

Special thanks to the CDEI centre of the Technical University of Catalonia for providing case studies and designing support. This research has been conducted with the support of the Spanish National Innovation and Science Council under project MAQMA: CIT-030000-2005-35

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