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Benchmarking for Decision Making in Rapid Prototyping Systems

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***Abstract* - This paper addresses an integrated rapid prototyping decision-making system (IRPDMS) based on fuzzy decision and benchmarking for selecting appropriate rapid prototyping and manufacturing (RP&M) processes. Data sets captured from benchmarking different RP&M processes are used in decision-making. The proposed IRPDMS provides decision support while interacting with an earlier developed benchmark database. Issues on standardizations and the purpose of using such standardized information datasets for offering decision support are discussed. Selection of five RP&M processes namely stereolithography (SLA), selective laser sintering (SLS), fused deposition modeling (FDM), laminated object manufacturing (LOM) and direct laser sintering (DLS) using the proposed IRPDMS is presented for the purpose of demonstration.**

Index Terms - Rapid prototyping, benchmarking, benchmarked database, fuzzy, decision support

I. BENCHMARKING

The practice of benchmarking is not new but the notion of quantitative benchmarking is relatively new. In quantitative benchmarking, standardized indices of performance are used to compare different processes. Several benchmarking and standardization approaches have been reported [1]. We categorize RP&M benchmarking into three types namely: geometric, mechanical and process benchmarks. There are many reasons for RP&M benchmarking, to mention a few: a tool for identification of best practices, a guide for improvement, to identify an optimal process, to determine an ideal approach, source of information, etc. Additional information on benchmarking could be referred from [2, 3].

The information gathered from RP&M benchmarking can be suitably stored in a RP&M database, to be used for information verification and decision support [4]. Integrated with an intelligent decision support system, it helps to select a suitable RP&M process to satisfy specific rapid prototyping requirements.

The geometric benchmark part earlier reported in [1] is used in this research to collect datasets through fabrication on various RP&M processes based on quality characteristics namely, geometric accuracy and surface finish. Fig.1 shows the geometric benchmark part. Standardized measurements were made using the Coordinate Measuring Machine. This research work primarily highlights the importance of benchmarking and how datasets captured from standardized

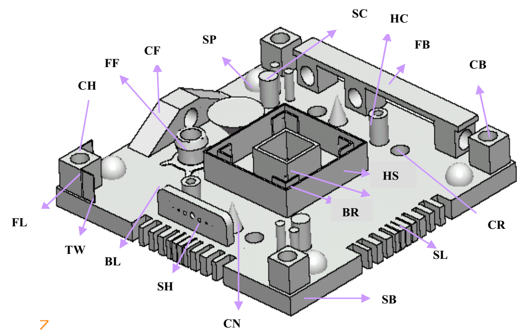

Fig. 1. Geometrical benchmark part

benchmarks can provide useful information to support decision-making, specifically addressing a developed methodology for selecting a suitable RP&M process based on the data captured through benchmarking.

The following section introduces the IRPDMS fuzzy decision making methodology, followed by the implementation and demonstration of the proposed approach.

II. IRPDMS METHDOLOGY

The proposed IRPDMS fuzzy decision methodology aims to find an optimal solution under imprecise or qualitative information based on the benchmark data. The challenge is to construct a model useful to handle precise, imprecise or vague data obtained from RP&M benchmarking and translate the data into a fuzzy quantitative method to arrive at a possible best solution.

The methodology is summarized in three stages namely:
Stage 1: Representation of the decision problem
Stage 2: Fuzzy set evaluation of goals/ constraints
Stage 3: Selection of the best solution

A. Stage 1: Representation of the decision problem

The starting point is to define the problem based on the user's requirements. In IRPDMS this stage consists of identifying the goals and constraints. According to Bellman and Zadeh [5] a fuzzy decision model accommodates certain constraints, C and goals, G. The constraints and goals are treated as fuzzy sets characterized by membership functions, $\mu_C : X \rightarrow [0,1], \mu_G : X \rightarrow [0,1]$, where X is the universe set of alternatives. The symmetry between the goals and constraints under this fuzzy model allows them to be treated in the same manner.

A hierarchical representation of the IRPDMS decision problem under consideration is presented in Fig. 2. Goals here include the overall geometric accuracy, surface roughness, etc. The constraints denote the desired geometric accuracy of individual geometric features. The processes (alternatives) denote the various RP&M processes. Each component of the structure can be further expanded if necessary (i.e. further goals, constraints or processes could be added on to be accommodated in future into the selection process. Example: cost-time criteria, orientation, etc.).

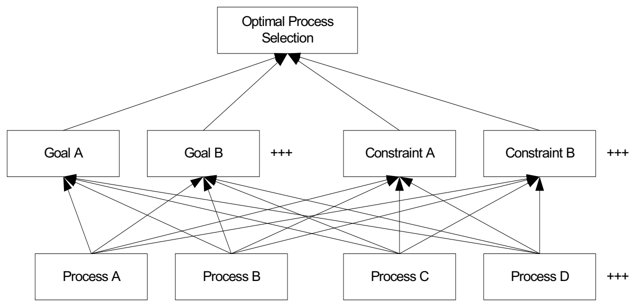

Fig. 2. Hierarchical structure of the IRPDMS decision problem

B. *Stage 2: Fuzzy set evaluation of goals and constraints*

This stage basically consists of representing all the goals and constraints as fuzzy sets [6, 7] obtained by mapping the membership values based on the selection of linguistic variable by the user. In the fuzzy IRPDMS two key concepts are employed: linguistic variables and fuzzy memberships. Linguistic variables are used to represent the decision criteria under consideration and the degrees of appropriateness of the processes perceived by a decision-maker (e.g. high, medium and low for geometric accuracy etc.). Then these linguistic variables are translated into the corresponding fuzzy numbers to facilitate quantitative decision operations.

As an example goal A and constraint A may be represented by: Goal A = FuzzySet [{A, 0.99}, {B, 0.96}, {C, 0.98}, {D, 0.99}, Universal Space --- {A, D}]; Constraint A = FuzzySet [{A, 1}, {B, 0.89}, {C, 0.99}, {D, 0.98}, Universal Space --- {A, D}], where Universal Space, U represents the processes: U= {Process A, Process B, Process C, Process D}. Also called as the Universe of Discourse, U is the range of all possible alternatives for an input to a fuzzy system. The numbers 0~1 are fuzzy numbers or membership grades.

1) Fuzzy membership: Different functions can be used for mapping the fuzzy membership, such as triangular, trapezoidal, bell curve, sigmoid and other user-defined functions to generate fuzzy memberships. We choose to use the triangular membership function because it is simple, effective and best suited for our case. Relative membership grades are assigned to linguistic variables for geometric features based on a triangular membership function derived from the measured results. Presently the main properties for the decision support include the accuracy details, geometric features, fine features and mechanical features.

2) Triangular Membership Function: The triangular membership functional involves a variable x, and depends on three scalar parameters a, b, and c as in (1). Fig. 3 illustrates a plot of the triangular membership function in relation to parameters a, b and c.

$$f(x;a,b,c)=\left\{\begin{array}{ll} 0, & x\le a \\ \frac{x-a}{b-a}, & a\le x\le b \\ \frac{c-x}{c-b}, & b\le x\le c \\ 0, & c\le x \end{array}\right\} \quad (1)$$

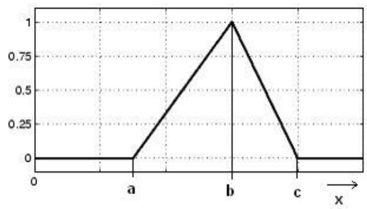

Fig. 3. Triangular membership function

C. *Stage 3: Selection of the optimal alternative*

This stage represents the decision-making stage. Decision can be made using basic fuzzy set operators like union, intersection, complement, product, etc. Following Bellman and Zadeh [5], the “optimal” decision is the point at which the intersection of fuzzy goal(s) and constraints take the maximum membership value. Also called the max-min approach [8], it is a confluence of goals and constraints. It considers that the best fuzzy decision is the union of the aggregated intersections of goal and constraints. A systematic description and classification of problem types, methods and approaches proposed in the literature can be seen in [9].

A fuzzy decision, D may be defined as the choice that satisfies both the goals, G and the constraints, C [7] represented by: $D=G\cap C$. D can be extended to any number of goals and constraints. We can represent the same using the classical fuzzy set intersection as

$$\mu_D(x) = \min\,[\mu_G(x),\, \mu_c(x)] \quad (2)$$

After this fuzzy decision set is obtained it is necessary to choose the ‘best’ single crisp alternative. For our case the straightforward way of doing this is to choose the alternative $x\in X$ that attains the maximum grade in D, represented by,

$$\mu_D(x_{\max}) = \max_x \min[\mu_G(x), \mu_C(x)] \quad (3)$$

We propose to use this max-min approach as shown in (3) since it is well known, acceptable and most importantly suits our case, where the decision, D is to select the best RP&M, given a set of goal and constraints. In our case the RP&M process that attains the maximum membership grade from the intersection of the goals and constraints is regarded as the best-solution choice.

III. IMPLEMENTATION

RP&M processes (such as SLA, SLS, FDM, LOM or DLS) are first benchmarked using a geometrical benchmark part. Vital information from the standardized benchmark part, standardized process benchmark, and results of the standardized measurements are appropriately stored in a benchmark database [1].

An earlier developed RP&M database is the source of information for different rapid prototyping machines, materials, processes, vendors, etc. The importance is the inter-relationship that exists between two databases: the benchmark database and the RP&M database. Based on a user's input, appropriate results could be generated. Fig. 4 illustrates the generation of the resultant output based on a set of conditional inputs by the end user. There could be more than one way of realizing a prototype using rapid prototyping technology. Thus, the results generated should be in the order of the best to the least desired method in realizing a prototype. The benchmarked database is specifically useful here to support decision-making.

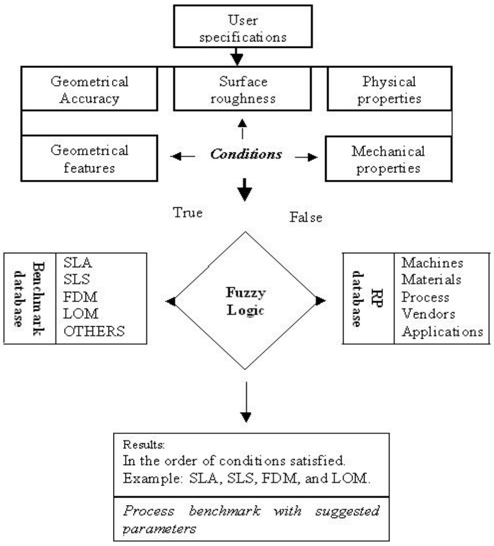

Fig. 4. Intelligent decision support of RP&M systems

Using the proposed method, more optimal results could be derived based on the input criteria. Note that benchmarks may be subjected to continuous improvement in accordance to the industrial best practices and technology. Therefore benchmarks and the corresponding databases could be continuously evolving based on the progress of the industry and technology.

Tables I-V presents benchmark datasets, in terms of varying membership grades of the properties for various RP&M processes. Presently the main criteria for decision support include accuracy details, mechanical properties, geometrical features, fine features and mechanical features based on triangular membership functions. Fig. 5 and Fig. 6 represent the triangular memberships for geometric accuracy and surface roughness. With reference to Fig. 5 we consider the geometric accuracy to be 'high' if the deviation in mm is 0, 'medium' if the deviation is 1mm and 'low' if the deviation is 5mm. The terms {high, medium, low} represent the linguistic variable set for geometric accuracy. 0, 1, 5 are basically the values of b as in (1), which locate the peaks in the triangular membership functions. The rationale behind choosing the scalar values is based on the experience gained from the various benchmarking studies pertaining to this research. Note that all the measurements were done without the actual post-processing generally required for any RP&M process and hence the values representing the linguistic variables such as high, medium and low representing the geometric accuracy should be chosen carefully.

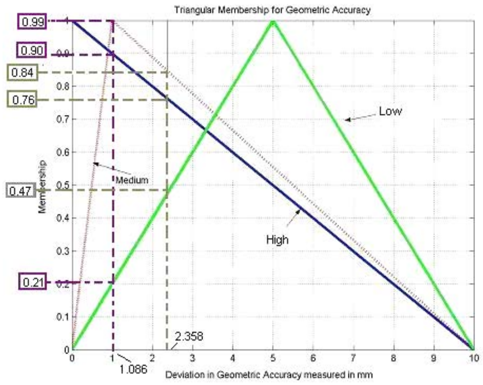

Fig. 5. Geometric accuracy in mm

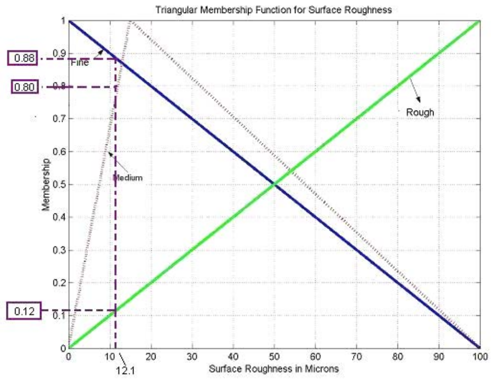

Fig. 6. Surface Roughness in μm

Table I presents membership values for various geometric features based on the benchmark part. The membership values were obtained from the triangular membership function as shown in Fig. 5. Considering the actual case of the circular holes (CR) built on the SLS process based on this study, the deviation in geometric accuracy, i.e., difference between actual and measured dimensions was 1.086 mm. Hence the corresponding membership values based on the triangular membership function (illustrated in Fig. 5) will be 0.21 for 'low', 0.99 for 'medium' and 0.90 for 'high' accuracy (shown as shaded cells in Table I). Likewise the membership values for low, medium and high accuracy for geometric features on the benchmark part for various RP&M processes have been computed using Matlab and recorded as can be seen from Table I. Fig. 6 illustrates the actual mapping of surface roughness for a measured value of 12.1 μm on the base of the benchmark part. SLS takes membership values of '0.12' for 'rough', '0.80' for 'medium' and '0.88' for 'fine'.

TABLE I
FUZZY MEMBERSHIPS FOR GEOMETRIC FEATURES

ProcessID	Deviation	GeoID	low	medium	high
1	0.0708	1	0.0142	0.0708	**0.9916**
2	1.0858	1	0.2172	0.9905	**0.9058**
3	0.0200	1	0.004	0.02	**0.9979**
4	0.1813	1	0.0363	0.1813	**0.9865**
5	1.0600	1	0.212	0.9933	**0.900**
1	0.8181	2	0.1636	0.8181	0.9182
2	1.1309	2	0.2262	0.9855	0.8869
3	1.7886	2	0.3577	0.9124	0.8211
4	1.5680	2	0.3136	0.9369	0.8432
5	2.0425	2	0.4085	0.8842	0.7957
1	0.2285	3	0.0457	0.2285	0.9771
2	0.6444	3	0.1289	0.6444	0.9356
3	0.9843	3	0.1969	0.9843	0.9016
4	0.7691	3	0.1538	0.7691	0.9231
5	0.6132	3	0.1226	0.6132	0.9387
1	1.0031	4	0.2006	0.9997	0.8997
2	0.6811	4	0.1362	0.6811	0.9319
3	0.9833	4	0.1967	0.9833	0.9017
4	1.3005	4	0.2601	0.9666	0.87
5	0.5721	4	0.1144	0.5721	0.9428
1	0.1188	5	0.0238	0.1188	0.9881
2	2.3576	5	0.4715	0.8492	0.7642
3	0.0943	5	0.0189	0.0943	0.9906
4	0.2055	5	0.0411	0.2055	0.9794
5	2.2372	5	0.4474	0.8625	0.7763
1	0.0492	6	0.0098	0.0492	**0.9951**
2	0.6225	6	0.1245	0.6225	**0.9377**
3	0.0450	6	0.009	0.045	**0.9955**
4	0.1487	6	0.0297	0.1487	**0.9851**
5	1.0535	6	0.2107	0.9941	**0.8947**
1	0.1166	7	0.0233	0.1166	0.9883
2	0.4200	7	0.084	0.42	0.958
3	0.0400	7	0.008	0.04	0.996
4	0.1533	7	0.0307	0.1533	0.9847
5	0.5790	7	0.1158	0.579	0.9421
1	0.1525	8	0.0305	0.1525	**0.9848**
2	0.4700	8	0.094	0.47	**0.953**
3	0.1431	8	0.0286	0.1431	**0.9857**
4	0.3183	8	0.0637	0.3183	**0.9682**
5	0.4160	8	0.0832	0.416	**0.9584**

GeoId	GeometricFeatures
1	Holes (CR)
2	Cylinders (SC)
3	Squares (CB)
4	Cones (CN)
5	Spheres (SP)
6	Slots (SL)
7	Brackets (BR)
8	Overhangs (FB)
9	Thinwalls (TW)
10	Thincylinders (TC)
11	Smallholes (SH)
12	Freeform (FF)
ProcessID	RP_process
1	SLA
2	SLS
3	FDM
4	LOM
5	DLS

Table II presents the degree of memberships for the overall geometric accuracy (based on the dimensional error in length on the X, Y and Z axes) irrespective of the geometric features. The memberships for overall geometric accuracy was obtained by mapping the average of the deviation values obtained from different dimensions in length on different axes.

TABLE II
OVERALL MEMBERSHIPS GRADES FOR GEOMETRIC ACCURACY

X-AXIS			
ProcessID	low	medium	high
1	0.1593	0.7963	**0.9204**
2	0.1183	0.5913	**0.9409**
3	0.0565	0.2825	**0.9717**
4	0.0622	0.3112	**0.9689**
5	0.1145	0.5723	**0.9428**
Y-AXIS			
ProcessID	low	medium	high
1	0.129	0.6448	**0.9355**
2	0.1363	0.6814	**0.9319**
3	0.0781	0.3904	**0.961**
4	0.0619	0.3097	**0.969**
5	0.1265	0.6324	**0.9368**
Z-AXIS			
ProcessID	low	medium	high
1	0.097	0.485	**0.9515**
2	0.107	0.535	**0.9465**
3	0.0791	0.3954	**0.9605**
4	0.0428	0.2142	**0.9786**
5	0.1226	0.6132	**0.9387**

TABLE III
MEMBERSHIPS GRADES FOR SURFACE ROUGHNESS

ProcessID	Actual SR	fine	medium	rough
1	0.4	**0.996**	0.026	0.004
2	12.1	**0.879**	0.806	0.121
3	18.4	**0.816**	0.960	0.184
4	2.6	**0.974**	0.173	0.026
5	10.1	**0.899**	0.673	0.101

Table III shows the membership degree for surface roughness. Table IV and V shows the degree of memberships for the some of the fine features and mechanical features on the benchmark part.

TABLE IV
FUZZY MEMBERSHIPS FOR FINE FEATURES

ProcessID	GeoID	CaseA	CaseB	CaseC
1	9	0.8	0.85	0.9
2	9	0.6	0.7	0.8
3	9	0.2	0.3	0.5
4	9	0.4	0.5	0.6
5	9	0.6	0.7	0.8
1	10	0.8	0.85	0.9
2	10	0.6	0.7	0.8
3	10	0.2	0.3	0.5
4	10	0.3	0.4	0.6
5	10	0.6	0.7	0.8
1	11	0.8	0.85	0.9
2	11	0.6	0.7	0.8
3	11	0.2	0.3	0.5
4	11	0.3	0.4	0.6
5	11	0.6	0.7	0.7
1	12	0.8	0.85	x
2	12	0.75	0.65	x
3	12	0.7	0.75	x
4	12	0.5	0.4	x
5	12	0.7	0.6	x
CaseA: GeoID= 0.5mm Case B: 0.5< GeoID<=1mm Case C: 2mm>=GeoID>1mm				

TABLE V
FUZZY MEMBERSHIPS FOR MECHANICAL FEATURES

ProcessID	Fillet	Chamfer	Blends
1	0.9	0.9	**1**
2	0.75	0.7	**0.7**
3	0.1	0.4	**0.5**
4	0.7	0.6	**0.55**
5	0.75	0.75	**0.65**

IV. ILLUSTRATION

Consider an example of the hand phone cover (shown in Fig. 7) as the user's part to be prototyped.

Fig. 7. A sample user's part

The hand phone cover basically consists of the following geometric features: 1mm thinwall, holes, overhangs, slots and blends. The model is used for *functional inspection* purpose and hence the goals are overall 'high' accuracy and 'fine' surface finish. The constraints are 'high' accuracy of individual geometric features namely holes, overhangs and slots, and capability to build thinwalls and blends. For the web-based system, the requirements will be input in the form of a questionnaire (shown in Fig. 9) from which the user makes appropriate selections. Based on this example the goals and constraints will be appropriately selected as: 'high' overall geometric accuracy, 'fine' surface roughness, 'high' accuracy for overhangs, 'high' accuracy for holes, 'high' accuracy for slots and additionally the condition when thinwalls '<= 1mm wall thickness' and blends 'yes'.

A. *Fuzzy Set Evaluation of goals/ constraints*

The corresponding fuzzy set for the first goal of overall geometric_accuracy on the X-axis is represented by the following set (4),

Xgeometric_accuracy = FuzzySet [{1, 0.920}, {2, 0.941}, {3, 0.970}, {4, 0.968}, {5, 0.942}, Universal Space - {1, 5}] (4)

where the Universal Space U, represents the set of RP&M processes: U= {SLA-1 , SLS- 2, FDM-3, LOM-4, DLS-5}. Since the user requirement is a 'high' overall geometric accuracy, the corresponding membership values are extracted from Table II (marked in bold) as 0.920 for SLA, 0.941 for SLS, 0.970 for FDM, 0.968 for LOM and 0.942 for DLS.

Fuzzy sets for geometric accuracy on the Y and Z-axis are represented as (5) and (6).

Ygeometric_accuracy = FuzzySet [{1, 0.935}, {2, 0.931}, {3, 0.961}, {4, 0.969}, {5, 0.936}, Universal Space- {1, 5}] (5)

Zgeometric_accuracy = FuzzySet [{1, 0.951}, {2, 0.946}, {3, 0.960}, {4, 0.978}, {5, 0.938},Universal Space - {1, 5}] (6)

The second goal of surface_roughness is represented by the following fuzzy set as shown in (7).

surface_roughness = FuzzySet [{1, 0.996}, {2, 0.879}, {3, 0.816}, {4, 0.974}, {5, 0.899},Universal Space -{1, 5}] (7)

Based on the user choice of a 'fine' overall surface roughness, the corresponding membership grades are extracted from Table III (marked in bold) as 0.996 for SLA, 0.879 for SLS, 0.816 for FDM, 0.974 for LOM and 0.899 for DLS.

Fuzzy set for the constraint 'high' accuracy of holes can be represented by the following set as in (8),

holes = FuzzySet [{1, 0.991}, {2, 0.905}, {3, 0.997}, {4, 0.986}, {5, 0.900},Universal Space - {1, 5}] (8)

From Table I the corresponding membership values for 'high' accuracy of holes are extracted as 0.991 for SLA, 0.905 for SLS, 0.997 for FDM, 0.986 for LOM and 0.9 for DLS. Similarly the fuzzy sets for constraints of 'high' accuracy for overhangs and slots (marked in bold, Table I) are summarized respectively in (9) and (10),

overhangs = FuzzySet [{1, 0.984}, {2, 0.953}, {3, 0.985}, {4, 0.968}, {5, 0.958}, Universal Space - {1, 5}] (9)

slots = FuzzySet [{1, 0.995}, {2, 0.937}, {3, 0.995}, {4, 0.985}, {5, 0.894},Universal Space - {1, 5}] (10)

Fuzzy set for constraint 'thinwalls' is represented in (11),

thinwalls = FuzzySet [{1, 0.85}, {2, 0.7}, {3, 0.3}, {4, 0.5}, {5, 0.7}, Universal Space --- {1, 5}] (11)

Based on the user requirement the corresponding membership grades based on Case B (i.e. 0.5 < thinwalls<= 1mm wall thickness) as shown in Table IV (marked in bold) will be chosen. The fuzzy set for inclusion of blends as a constraint is represented in (12),

blends=FuzzySet[{1,1},{2,0.7},{3,0.5},{4,0.55},{5,0.65}, Universal Space --- {1, 5}] (12)

The corresponding membership grades for blends are extracted from Table V (marked in bold).

Finally the Process_Selection (decision) is represented by,

process_selection = intersection [Xgeometric_accuracy, Ygeometric_accuracy, Zgeometric_accuracy surface_roughness, holes, overhangs, slots, thinwalls, blends]

i.e. process_selection = FuzzySet [{1, 0.85}, {2, 0.7}, {3, 0.3}, {4, 0.5}, {5, 0.65}] (13)

The values 0.85, 0.7, 0.3, 0.5 and 0.65 in (13) are the minimum of their respective individual membership grades of the five processes from (4) to (12). The final decision for the crisp alternate is given (14), *Optimal process_selection = max [{1, 0.85}, {2, 0.7}, {3, 0.3}, {4, 0.5}, {5, 0.65}]* (14)

The fuzzy plot in Fig. 8 shows the choice of the RP&M processes based on this example.

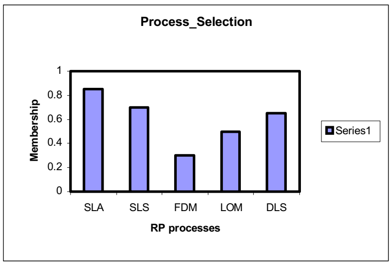

Fig. 8. Process selection based on the user's input

We now look for the maximum membership grade to decide which process best satisfies our goals and constraints. For the hand phone cover, we see that process 1, i.e. SLA (with μ= 0.85) appears to be the best choice, followed by SLS, DLS, LOM and FDM. Implemented as a web-based decision support system, the rules are in the form of *if-then* statements based on their membership grades. All these rules form part of the rule database. Fig. 9 and Fig. 10 are snapshots of the web-based questionnaire and decision support output respectively.

IV. CONCLUSION

An integrated rapid prototyping decision-making system is proposed based on benchmarking and fuzzy decision for selecting appropriate rapid prototyping processes. The web-accessible, IRPDMS can suggest to the RP&M users the most suitable system and process that can help him to realize his prototype according to his set of performance characteristics. The proposed methodology, supports decision making using datasets obtained through benchmarking and hence could be reliable to assist both novice and experts in RP&M process selections. Future works include investigation and experimentation for variations in the resultant output, based on different functional representations for decision-making.

REFERENCES

[1] Y.S. Wong, J.Y.H. Fuh, H.T. Loh and M. Mahesh, "Rapid prototyping and manufacturing (RP&M) benchmarking", Chapter 3, *Software Solutions for RP*, (Ed.) Gibson I, pp. 57- 94, PEP Ltd, UK, 2002.

[2] R.C. Camp, "Benchmarking: The search for industry best practices that lead to superior performance", ASQC Quality press, 1989.

[3] M. Zairi and P. Leonard, "Practical benchmarking: the complete guide", Chapman & Hall publications, Chapter 9,pp. 75-80, 1994.

[4] J.Y.H. Fuh, H.T. Loh, Y.S. Wong, D.P. Shi, M. Mahesh and T.S. Chong, , "A Web-based database system for RP machines, processes and materials selection", *Chapter2, Software Solutions for RP,* (Ed.) Gibson I, pp. 27-55, PEP Ltd, UK, 2002.

[5] R.E. Bellman and L.A. Zadeh, "Decision-Making in a Fuzzy Environment", *Management Science*,vol.17, no.4, pp. 141-164, 1970.

[6] L.A. Zadeh, "Fuzzy Sets. Information and Control", vol.8, pp. 338-353, 1965.

[7] G.J. Klir and T.A. Folger, "Fuzzy Sets, Uncertainty, and Information", Prentice Hall, Englewood Cliffs, NJ, 1988.

[8] H.J. Zimmermann, 'Fuzzy Sets, Decision Making and Expert Systems', International Series in Management Science/Operations Research, 1987.

[9] Y.J Lai and C.L. Hwang, 'Fuzzy Multiple Objective Decision Making', Lectures Notes in Economics and Mathematical Systems, Springer-Verlag, 1994.

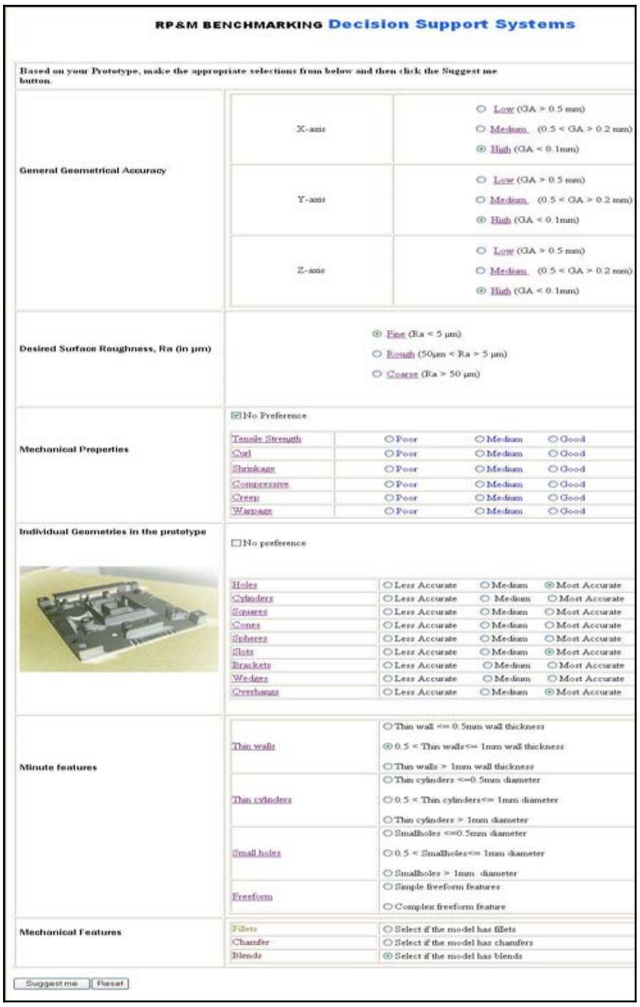

Fig. 9. Web-based questionnaire

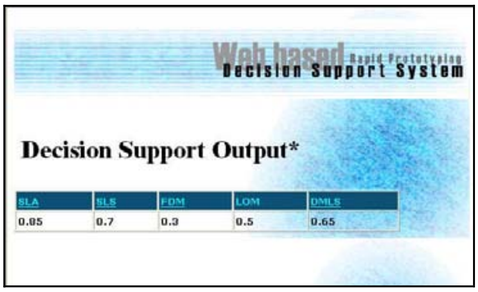

Fig. 10. Web-based decision support output