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Computer aided rapid tooling process selection and manufacturability evaluation for injection mold development

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Abstract

Injection mold development lead time has been reduced presently by over 50% by employing rapid prototyping based tooling methods. Rapid tooling methods however, have certain limitations in terms of mold material, accuracy, surface finish, and mold life. The relevant process knowledge, especially for newer routes, is not very well established, resulting inconsistent or inappropriate rapid tooling (RT) process selection and mold design incompatibility. This paper presents a computer aided rapid tooling process selection and manufacturability evaluation methodology for injection molding, supported by mold cost estimation models and RT process capability database. Rapid tooling process selection is based on process capability mapping in quality function deployment (QFD) against a set of tooling requirements that are prioritized through pairwise comparison using analytical hierarchal process (AHP). The mold manufacturability for the selected RT process is carried out using fuzzy-analytic hierarchy process (fuzzy-AHP) to identify problem features, if any. This is followed by estimating the cost of RT mold and comparing it with a conventional mold, using cost models developed based on the concept of cost drivers and cost modifiers. The entire methodology has been implemented in a software program using Visual C++ in Windows environment and demonstrated on an experimental mold as well as industrial cases. The proposed methodology enables selecting an appropriate rapid tooling process for a given injection mold requirement, and identifying critical features that could be modified to improve manufacturability, thereby achieving better quality and lower cost of molded parts along with shorter lead time.

Keywords: Rapid tooling; Process selection; Manufacturability evaluation; Injection molding; Decision methods

1. Introduction

In recent years product life cycles have reduced by half of those in 1980s that puts greater pressure on manufacturing lead time reduction, while maintaining quality and cost. One way to achieve this is by employing rapid prototyping based tooling methods in near net shape (NNS) manufacturing processes, such as injection molding and die-casting. Conventional mold making practice that depends on machining operations to generate the desired mold cavity is not found to be competitive any longer. This has led to a significant growth in rapid prototyping based tooling, referred to as *rapid tooling*. This meant developing core and cavity inserts using rapid prototyping based processes in one or more steps starting from their CAD models, reducing tooling development time by 50% or more [1]. These processes can be classified as *direct rapid tooling*, in which molds are fabricated in a rapid prototyping system, or *indirect rapid tooling*, in which a rapid prototype master is converted into a mold using a secondary process. Today, more than 25 rapid tooling processes are available, and these can also be classified based on their expected mold life (number of parts that can be produced in the mold), as *soft*, *bridge* and *hard* tooling. The most important RT processes useful for developing injection molds are listed in Table 1, indicating the related RP process, and their classification.

The soft and bridge tooling methods can produce either nonmetallic or softer metal (compared to conventional tool steels) molds and usually cannot withstand the pressures and temperatures involved in conventional injection molding. The hard tooling methods enable fabricating metal tooling that can be used in injection molding machines, and result in better quality and larger quantity of parts (compared to soft and bridge tooling).

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Table 1
Important rapid tooling processes and their parent RP processes

Sl.	Rapid tooling process	Parent RP process	Type of rapid tooling				
			Direct	Indirect	Soft	Bridge	Hard
1	SLA Direct-AIM	SLA	✓		✓		
2	SL EP 250 molds	SLA		✓		✓	
3	SLS-rapid steel	SLS	✓				✓
4	Direct metal laser sintering	DMLS/SLS	✓				✓
5	Direct shell production casting	3DP		✓			✓
6	Prometal RTS300	3DP	✓			✓	
7	Metal laminated tooling	LOM	✓				✓
8	Multi-metal layer tooling	SDM					✓
9	SDM mold	SDM		✓	✓		
10	Investment cast mold	SLA, FDM		✓		✓	✓
11	3D Keltool	SLA, Keltool		✓			✓
12	Spray metal tooling	SLA, SLS, m/c pattern		✓		✓	
13	Vacuum casting	SLA, SLS, m/c pattern		✓	✓		
14	RP Pattern based powder sintering	SLA, SLS		✓			✓

Injection molds are expected to produce parts very close to their final specifications. The accuracy, thermal conductivity and mechanical properties of the mold have a significant influence on molding cycle, part quality, geometric complexity and competitiveness [2]. Most of the materials (especially those introduced earlier) used in RP systems are soft, and cannot be used for directly producing dies and molds for use in conventional injection molding. Nevertheless, some progress has been made in this direction in recent years. Powder based sintering processes are now able to produce metal molds that can withstand a few thousand cycles of injection molding. A few researchers have reviewed various rapid tooling methods, their process capabilities, and recent progress. Over the years, researchers have attempted to improve the performance of RT molds in injection molding. This included metal filled SLA, metal coated (by electroforming) SLA molds, laser sintering of stainless steel mold [3], electroless nickel plating of DMLS [4], adaptive slicing [5], and layer machining [6] among others. However, effect of rapid tooling molds on part quality and mold failure has not been studied in depth. Few such studies include failure of SLA resin mold under the injection molding forces [7], effect of direct SL resin mold on part quality and shrinkage and coupled thermo mechanical FEM techniques [8] and optimization of injection molding parameters for low shrinkage and better soundness of part using grey relational analysis [9].

In summary, there is a growing body of research work on rapid development of molds and dies, leading to a range of rapid tooling processes, both direct and indirect. The choice of various secondary processes (such as investment casting, slip casting, sintering, and vacuum casting) multiplies the number of tooling routes. However, the use of RP based tooling with unconventional materials in injection molding give rise to a few issues of concern. These include: (1) accuracy, durability, surface finish and overall performance of the tooling, (2) cost, lead time, and RT process capability (such as geometric constraints), (3) mold life (quantity of parts produced), and (4) quality of final parts produced in the RT molds. Moreover, production of die steel molds using RP patterns or directly from layered manufacturing processes is however, still maturing, and process knowledge is not very well established. The selection of the most appropriate process route for a given application is therefore becoming a non-trivial task. This study aimed at developing a computer aided methodology for selecting rapid tooling process and perform manufacturability evaluation in terms of quality and cost, to develop injection molds for rapid manufacturing.

2. Previous and related work

Computer aided process selection, manufacturability evaluation, and cost estimation enable early prediction of manufacturing problems and minimizing design and tooling iterations. Most of the work in this direction is however, mainly applicable to material removal processes; very little work applies to rapid tooling processes. A few researchers have indeed highlighted the need for a 'rapid intelligent tooling system' for deciding the optimal process [10], though very few attempts appear to have been made in this direction. In one such attempt, a rule-based approach (with 180 rules) was used for selection and evaluation of four rapid tooling methods [11]. Establishing the rule base for each route made of a combination of various processes is however, a difficult task.

Manufacturability evaluation of a mold produced by a given RT process enables early identification of problem features that affect its quality and cost. A 'rapid tooling test bed for injection molding' has been recently developed to facilitate design for RT [12]. It employed compromise decision support to develop geometry based decision templates for SLA Direct-AIM tooling manufacturability [13]. Mold design guidelines for high manufacturability by SLA Direct-AIM process were evolved through studies and experimental validations related to mold expansion, percentage of crystallization and effect of direct SL resin mold on part quality and shrinkage [8]. In another work, manufacturability evaluation of parts fabricated by solid freeform fabrication processes involved identifying the optimal build direction to maximize flatness tolerance [14].

Process selection and manufacturability evaluation effectiveness are greatly influenced by process capability database and cost [15]. As mentioned earlier, the capabilities of RT processes are not established in a manner that is suitable for comparison with respect to a given requirement. While cost estimation of prototype models based on build time is reported for specific RP processes [16], there is very little work on cost estimation of RT molds.

In summary, the application of rapid tooling methods for fabrication of injection molds, which can be used in conventional injection molding machines to produce functional parts, is still maturing. The RT process capabilities and their effect on part quality are not fully understood, making their selection for a given requirement difficult. Continuous advances in RT processes, and competing processes such as high speed machining, have made it even more difficult for tool engineers to decide the most suitable process for rapid fabrication of molds. Moreover, most of the studies are specific to a particular RP/RT process, and do not provide any general framework for selection and manufacturability evaluation for a range of processes. Manufacturing process selection and manufacturability evaluation has been treated as a multi-criteria decision problem in machining and other domains. Major decision tools that have used in this regard include decision tables and trees, fuzzy logic, genetic algorithm, neural network, case based reasoning, multi-attribute utility theory, knowledge management, quality function deployment (QFD), and analytic hierarchy process (AHP). Many researchers have also developed hybrid decision-making methods by integrating one or more methods to overcome their individual limitations. This includes QFD integrated with AHP, QFD with fuzzy, and fuzzy with AHP. These hybrid methods, which are employed in the current framework, are reviewed in terms of special advantages and their applications in manufacturing domain.

While AHP is useful for analyzing multiple criteria in a structured hierarchal manner, it uses only relative priority values, not the actual performance of a specific tooling process. On the other hand, QFD uses direct performance values, but cannot consider multi-level criteria, unless a number of QFD charts are prepared, which is cumbersome. An integrated QFD-AHP approach has the advantages of both, and can be used in prioritizing customer requirements, enabling dealing with complex situations and order ranking [17]. Chuang suggested application of analytic hierarchy process (AHP) to calculate the relative weights of importance for customer requirements, and subsequently to determine the priority for the corresponding product attributes in QFD [18]. While, several fuzzy decision-making methods have been developed and applied in other domain, fuzzy-AHP is found to be better than other methods, when the problem is complex with a large number of attributes [19].

In an earlier investigation, authors explored hybrid decision methods to select a suitable RT process. This was based on prioritizing the tooling requirements using AHP and process capability mapping against each requirement using QFD [20]. However, capability mapping (weights calculation) was not automatic, since it was not linked to the process capability database. A fuzzy-AHP based rapid tooling manufacturability evaluation approach was also explored [21], which relied on interactive calculation of fuzzy weights, which depend on process capabilities. The process capability database was not exhaustive and did not considered form tolerance capabilities, which are critical in tool making. A cost model was also developed for conventional molds fabricated by machining, though rapid tooling estimation was not discussed [22]. A need was felt to fill the gaps in the above efforts, and to integrate them for providing a single user-friendly framework useful for rapid development of injection molded plastic parts, which has been taken up and presented in this paper.

3. Overall framework

The proposed methodology comprises three major steps: (1) rapid tooling process selection, (2) manufacturability evaluation, and (3) mold cost estimation. For RT process selection, an integrated QFD-AHP method has been developed in which tooling requirements are prioritized using AHP based pairwise comparison, and rapid tooling process capabilities are mapped using QFD. A fuzzy-AHP approach has been developed for manufacturability evaluation of functional elements of a mold, and secondary elements of a mold are evaluated in terms of their compatibility with the functional elements produced by a given RT process. The cost model developed in this work is driven by the mold geometry, process parameters and mold elements. RT process capabilities and their effect on part quality determined through experiments for a few important rapid tooling processes have been stored in database. The entire methodology has been implemented in a Visual C++ program running in Windows environment. Fig. 1 shows the information flow. This enables a toolmaker to select an appropriate rapid tooling process and evaluate the mold design for its manufacturability and cost effectiveness before investing in tooling development.

4. Rapid tooling process selection

The proposed QFD-AHP approach for RT process selection has three steps. The first step involves analyzing the customer (tooling) requirements and determining their relative importance considering attributes related to material, geometric features, mold material and production quantity by pairwise comparison using AHP. The second step involves selecting an appropriate tooling process using QFD, based on the process capability mapping and the importance values of requirements obtained in the first phase. In the third step, the effect of each process variable of the selected RT process is mapped and prioritized to identify critical process parameters that need special attention and have to be considered in manufacturability evaluation. Fig. 2 shows a pictorial representation of the proposed approach. Working of process selection module of the proposed system is discussed next.

4.1. Tooling requirements prioritization

While product manufacturers strive to produce functional prototypes cost effectively within a short time. The dimensional

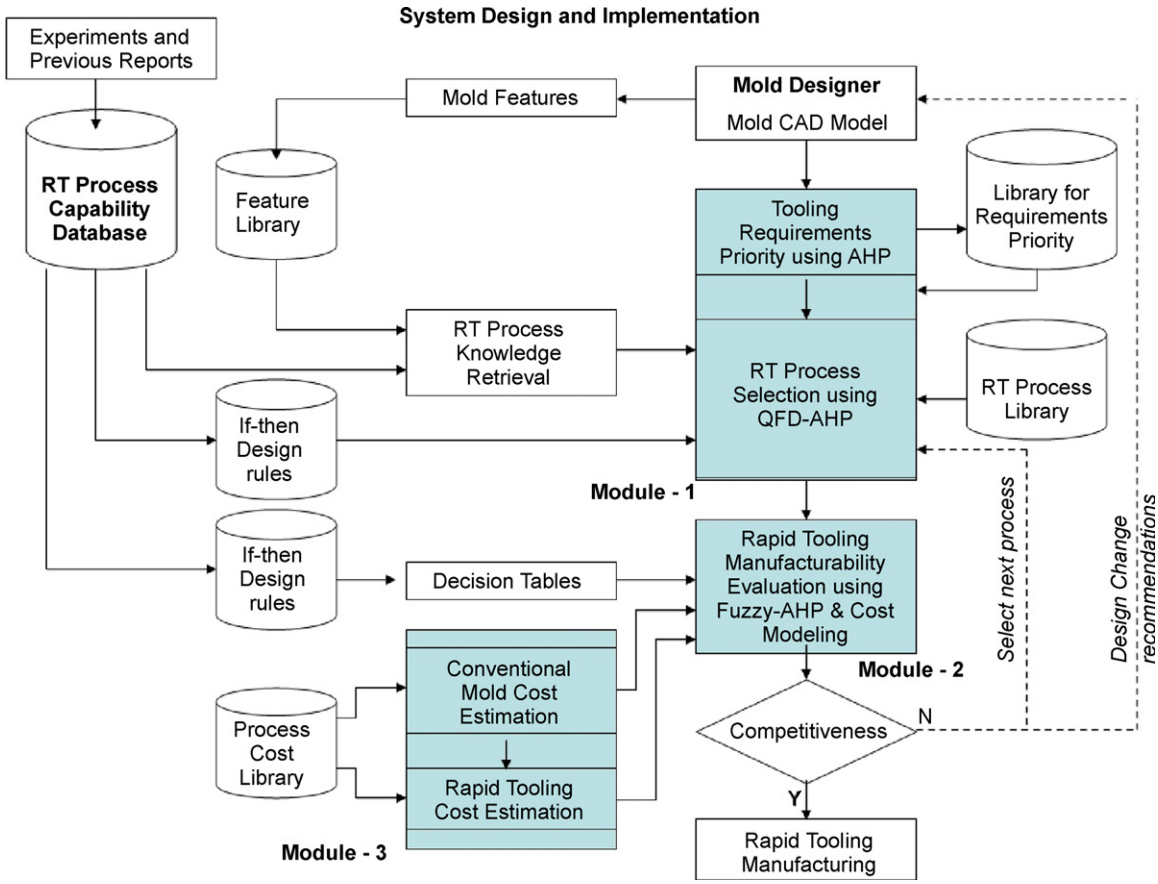

Fig. 1. System architecture and information flow.

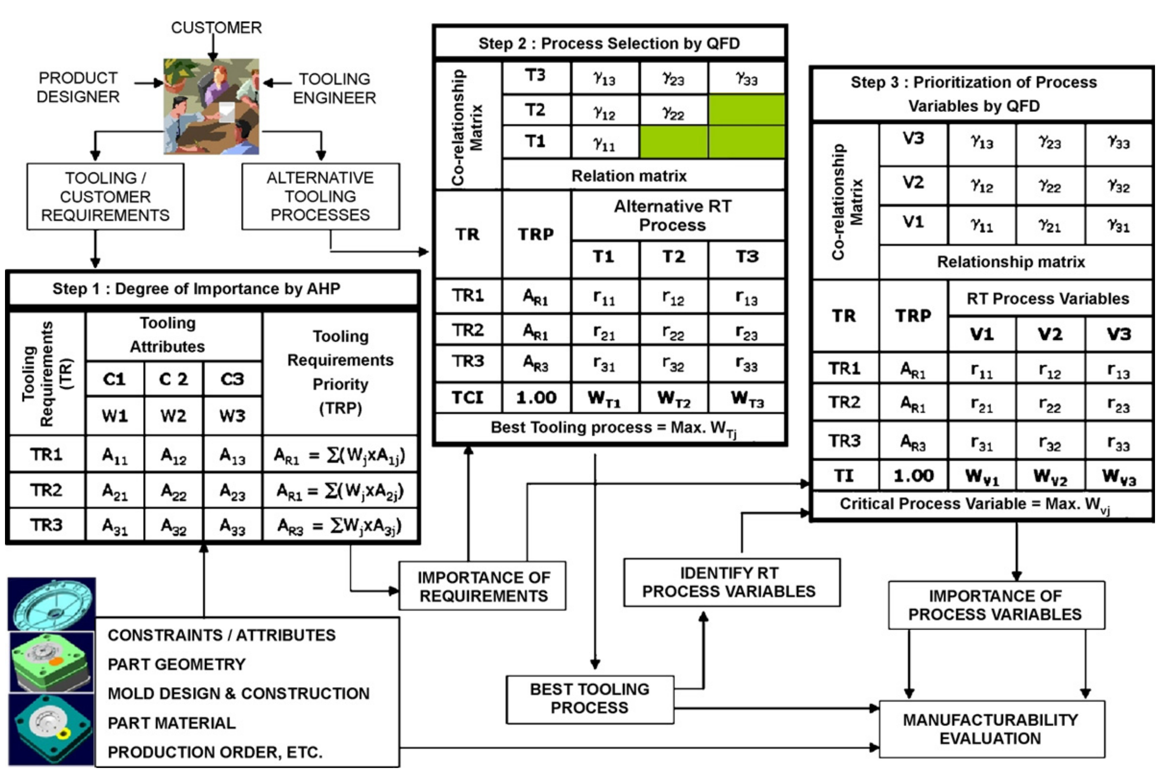

Fig. 2. QFD-AHP approach for RT process selection.

accuracy, surface finish, mold strength and flexibility to accommodate changes in feeding systems are becoming essential requirements of RT molds. Since rapid tooling processes may not completely fulfill all the requirements, and conventional mold making practice involves significant time and cost, it becomes necessary to compromise some of the requirements depending on the type of application. This leads to a debate between toolmaker and product manufacturers (tooling customer) related to tooling accuracy, life, material and cost expectations. This has been alleviated by developing AHP based requirements analysis that determines the importance of requirements by comparing the effects of the tooling attributes in a hierarchical manner (Fig. 3). Thus AHP based requirements prioritization methodology involves: (1) identification of tooling requirements and attributes, (2) developing a hierarchical structure of the decision problem, (3) determining the relative priorities of tooling requirements against each attributes by pairwise comparison, (4) checking the consistency of pairwise comparisons and (5) calculating the requirements priority weights.

4.2. Process selection

Rapid tooling process selection to meet the prioritized tooling requirements using QFD involves process capability mapping against each requirement, establishing the co-relationship coefficients between the processes, and normalizing the QFD relationship matrix to determine the technical capability index of different RT processes. In QFD relationship matrix, the process capabilities of rapid tooling processes against each tooling requirement ($r_{i,j}$) are mapped using a scale 1-3-5-7-9 representing poor, fair, good, very good and excellent, respectively. This is direct and one to one mapping. The process capability weights against a specific requirement are calculated using If-then rules, which are generated by considering the conventional mold making (CNC machined mold) capabilities as a reference capability. These weights are initially calculated at feature level and their average is used to map the net process capability of specific RT process in QFD relationship matrix.

While a number of rapid tooling processes have been developed, indirect RT processes originate from RP processes, which may also be capable of producing the RT mold also. Similarly, RT molds need finish machining for most of the applications. These interdependency needs to be estimated to a known scale 0.9-0.7-0.5-0.3-0.1 (representing very low, low, medium, high and very high dependencies respectively). These correlations between RT processes are represented by a co-relational coefficient ($\gamma_{j,k}$) in a co-relationship matrix of QFD, which in turn have the influence on calculation RT process capability index (TCI) for suitable RT process selection. High interdependency among processes is considered as undesirable because in such multi-stage RT processes, it is very difficult to establish the true process capabilities and co-relationship weights. The Wesserman method, which considers the coefficients of both relationship matrix and co-relationship matrix, is used for normalization [17]. The technical capability index (TCI) of each process is calculated by weighted sum of coefficients of normalized relationship matrix. The RT process that has highest TCI has been considered as best among others. While the suitability of each rapid tooling method against a set of tooling requirements (which are also prioritized based on functional and quality attributes of a mold) are assessed, the selected process is further studied in third step to identify the critical process variable for a same set of requirements, prior to mold manufacturability evaluation.

5. Rapid tooling manufacturability evaluation methodology

Manufacturability evaluation involves determining the technical and economical feasibility of a mold produced by

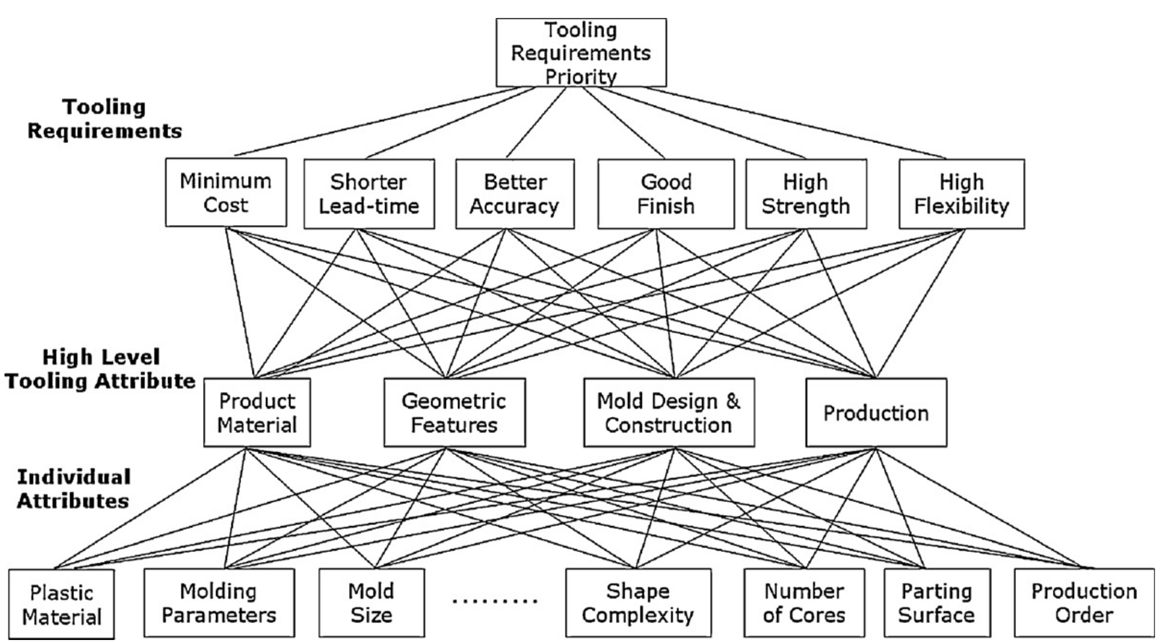

Fig. 3. Hierarchal structure of tooling requirements and attributes.

a selected rapid tooling process. The proposed RT manufacturability evaluation approach comprises three steps: (1) primary manufacturability evaluation of functional elements of tooling including cavity, cores and side cores, (2) compatibility of secondary elements of tooling (parting surface, ejectors, cooling lines, etc.) with RT mold properties, and (3) the cost effectiveness of RT mold. The steps are shown in Fig. 4. Manufacturability evaluation provides useful information to mold developers to take decisions regarding mold redesign and/ or process change.

5.1. Manufacturability evaluation of core and cavity

The primary manufacturability evaluation is carried out for the geometric features (hole, boss, slot, rib, etc.) of cavity, core and side cores, which are directly affected by RT process capabilities. This involves evaluating mold requirements with respect to RT process capabilities using fuzzy-AHP methodology. The quality criteria include geometric compatibility, accuracy and surface finish. The RT process capabilities are represented by triangular fuzzy numbers (lower, modal and upper limits). The decision tables use these data to ascertain the manufacturing difficulty of different mold features by a specific rapid tooling process in AHP pairwise comparison. In fuzzy-AHP the final relative weights are calculated as similar to typical AHP except that the principles triangular fuzzy number operations (reciprocal, addition, multiplication) are used. Finally, features with low manufacturability are identified through principle of comparison of fuzzy numbers in fuzzy-AHP [19], discussed here.

Let $\mu_i(x)$ denote the membership function for fuzzy number F_i,

$$e_{ij} = \max_{x \geq y}[\min(\mu_{m_i}(x), \mu_{m_j}(y))] \quad \text{for all } i,$$
$$j = (1, 2, 3, \ldots, m) \tag{1}$$

When a pair (x, y) exists such that $x \geq y$ and $\mu_{m_i}(x) = \mu_{m_j}(y) = 1$, then we have $e_{ij} = 1$. The probability of $F_j \geq F_i$ is given by

$$e_{ji} = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \tag{2}$$

The condition $F_i \geq F_j$ will be true if and only if $e_{ij} = 1$ and $e_{ji} < Q$, where Q is the sensitivity factor, less than one. A value of 0.8 or 0.9 for Q is considered appropriate

5.2. Secondary elements compatibility evaluation

The secondary elements of a mold such as parting surface and ejectors have to be compatible with the accuracy, machinability, strength and other characteristics of the functional elements produced by RT methods. This compatibility is evaluated by four criteria including parting surface design, multi-cavity mold, cooling design and ejector design. These are mapped to a 0–1 scale to facilitate overall evaluation based on process knowledge generated from experience and reported literature. The cost effectiveness of selected rapid tooling process is evaluated by comparing its cost with that of conventional mold. The cost models developed for both conventional and rapid tooling molds are briefly discussed next.

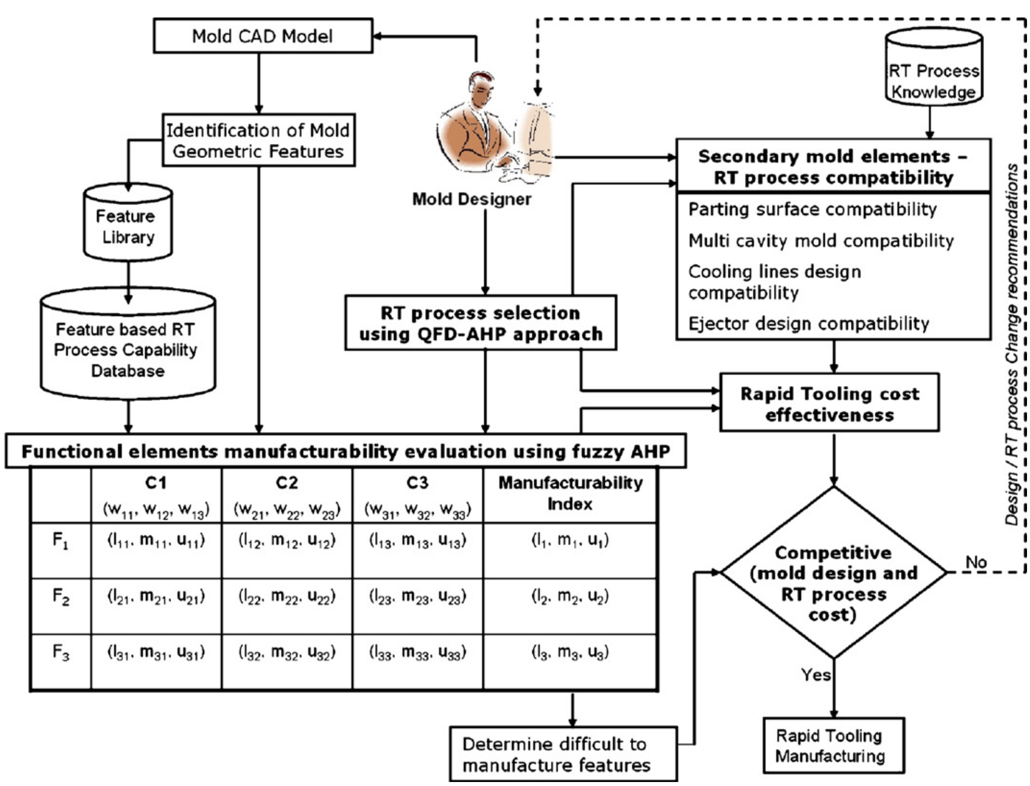

Fig. 4. Rapid tooling manufacturability evaluation approach.

5.3. RT mold cost effectiveness

The traditional cost estimation approaches are primarily based on cost similarity have limited capabilities for accurate estimation of mold cost. A generic cost estimation methodology, which is mainly driven by geometric features has been developed and can be used for any tool making practices after minor modifications. The basic concept involves cost drivers and cost modifiers. The cost drivers are driven by mold geometric features, and cost modifiers encompass mold complexity factors. Fig. 5 shows the overall cost estimation methodology.

For conventional tooling, the cost drivers are estimated by activity based costing by mapping mold features into machining features. The cost of machining features F_1, F_2 ... F_n is given by the following equation.

$$\text{Basic mold cost} \quad C_f = \sum_{f=1}^{n} I_f \left(\frac{L_f}{S} \right) (M_f) \tag{3}$$

For direct rapid tooling methods, the cost drivers are estimated using rapid prototype build process parameters. The basic cost of a mold manufactured by direct rapid tooling methods is given by:

$$\text{Basic mold cost} \quad C_f = \sum_{f=1}^{n} I_f \left[\left\{ \frac{X_i Y_i}{V_s p_s} \right\} \left\{ \frac{h_f}{l_t} \right\} + t_{dip} + t_{sweep} \right] (M_{RP}) + C_m + C_{comp} \tag{4}$$

where L_f: total cutting length of feature (f = 1–n), S: corresponding feed (mm/min), M_f: corresponding machine minute rate, I_f: machining complexity factor I, n: number of features, I_f: RP process complexity factor, X_i: maximum dimension of feature i along the scanning direction, Y_i: maximum dimension of feature i in the transverse direction of scanning, p_s: scanning pitch in mm, h_f: height of features F_1, F_2 ... F_n., l_t: layer thickness in mm, t_{dip}: material charging time in seconds, t_{sweep}: material coating time in seconds, M_{RP}: RP processing cost per minute, C_m: material cost, C_{comp}: data preparation/computation cost, V_s: scanning velocity (mm/min).

A number of complexity factors have a significant impact on the total cost of a mold, and are considered as cost modifiers in this work. These include parting surface complexity (γ_{ps}), presence of side cores (γ_c), surface finish/texture (γ_p), ejector mechanism (γ_e), die material machining (γ_m), and assembly preparation (γ_a). The cost implications of these factors were established from past data and experience. A QFD-based method has been proposed for customizing the cost modifiers for a specific mold after considering the complexity factors and associative secondary machining operations. The total cost of a mold is estimated from cost drivers, modifiers, tool design charge and standard items cost. The cost model has been evaluated using seventeen different molds, and implemented in the software program for RT process selection and manufacturability evaluation.

The indirect RT methods are multi-stage processes, in which the mold cost is given by the sum of the cost of RP model and cost of generating the mold geometry using RP patterns in other shape conversion processes (for example, forming, casting,

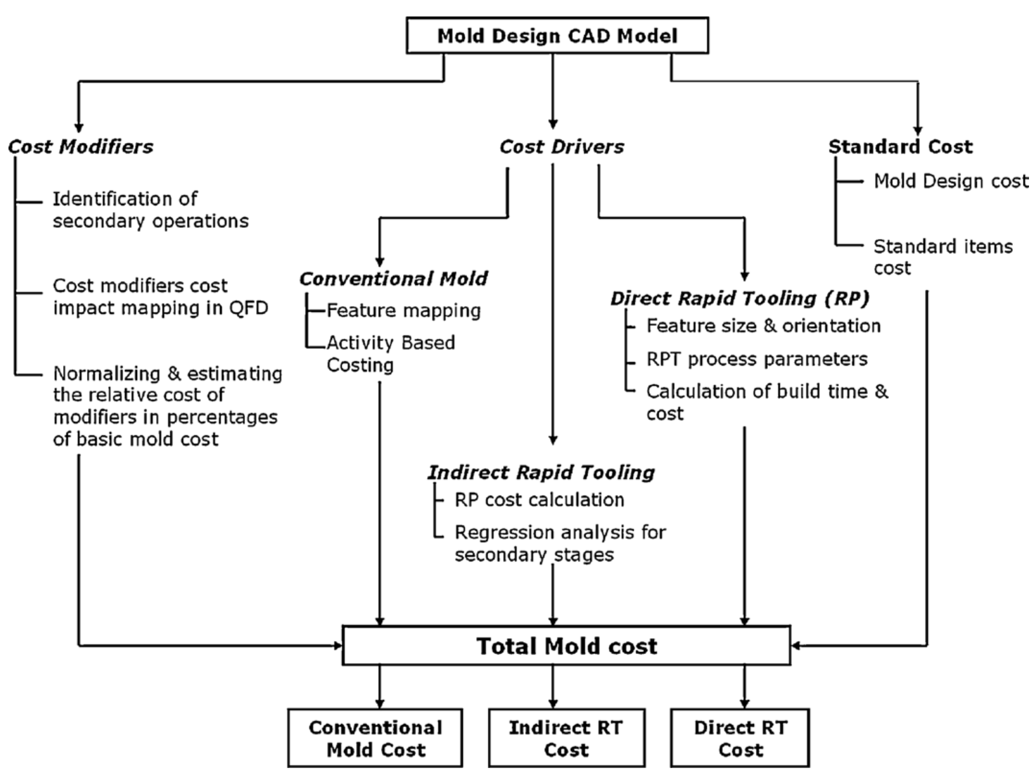

Fig. 5. Generic framework for injection mold cost estimation.

Table 2
Feature based RT process accuracy (in microns)

Features	Limit	Conventional mold	SLA direct mold	SLS direct mold	DMLS direct mold	Investment cast mold	Spray metal tooling
Round Hole Δd/*100 mm length*	l	5	80	100	100	100	300
	m	20	160	250	180	300	450
Round boss Δd/*100 mm length*	l	8	50	100	80	100	200
	m	20	120	160	120	260	450
Square Protrusion Δl/*100 mm length*	l	2	60	100	80	120	200
	m	20	125	200	130	280	450
Square Cavity Δl/*100 mm length*	l	5	80	100	100	120	300
	m	25	140	220	160	300	500
Thin Walls/ribs Δt/*100 mm length*	l	20	20	80	80	40	100
	m	40	160	120	120	80	160
Small gaps Δt/*100 mm length*	l	16	16	80	80	40	100
	m	25	80	120	150	80	160
Overall mold Δl/*250 mm length*	l	10	100	150	150	180	600
	m1	50	220	300	300	300	1200

sintering a green compact, etc.). The RP model cost is calculated using Eq. (4), and the shape conversion cost can be established based on previous projects and regression analysis. Cost estimation of indirect RT is however, not covered here, because the cost factors for each route have to be established through detailed experimentation or industry data, which was unavailable. Manufacturability evaluation of RT molds based on the above three aspects (mold feature manufacturability, secondary elements compatibility, and cost effectiveness) can minimize the tooling iterations and reduce the lead time.

6. RT process capability database

An accurate database of process capability is essential for rapid tooling process selection and manufacturability evaluation, which is not readily available. In the proposed system, this database has been developed from the experimental investigations, this database includes the following: dimensional accuracy of RT processes driven by geometric features (Table 2), surface roughness of different type of surfaces (Table 3), cost, lead time and form tolerances. The form tolerance capabilities of RT processes (Table 4) were generated using an adaptive sampling procedure proposed for machined components by Badar et al. [23]. Some of the data were taken from few benchmark studies reported by earlier researchers [24,25] to fill the gaps of present investigations. However, detail discussion on these investigations and database are beyond the scope of this paper, but this is available in reference [9].

7. System implementation

The methodology has been tested on two examples. The first example (Fig. 6) is an experimental mold for demonstrating the methodology, and was not actually fabricated. The assumed

Table 3
Rapid tooling surface finish database (Ra in microns)

Features	Limits	Conventional mold	SLA direct mold	SLS direct mold	DMLS direct mold	Investment cast mold	Spray metal tooling
Flat horizontal surface	l	0.2	1.0	8	8	0.8	1.4
	m	0.8	1.8	16	12	1.6	2.0
	u	1.6	3.2	26	26	3.2	6.3
Flat vertical surface	l	0.2	1.6	8	8	0.8	1.4
	m	0.8	3.2	18	12	1.6	2.6
	u	1.6	4.5	26	26	3.2	6.3
Inclined surface	l	0.4	2.0	10	8	1.0	1.6
	m	1.0	4.0	20	16	1.8	3.2
	u	1.6	4.8	32	32	6.3	6.3
Circular horizontal surface	l	0.4	1.2	10	8	1.0	1.6
	m	0.8	2.2	16	12	1.8	3.0
	u	1.6	3.2	32	24	4.8	4.8
Circular vertical surface	l	0.4	2.0	10	10	1.0	1.6
	m	0.8	3.2	18	14	2.0	3.2
	u	1.6	4.5	40	30	6.3	6.3

Table 4
Rapid tooling form tolerance database

Form tolerances	Conventional mold	SLA Direct-AIM	SLS direct mold	DMLS direct mold	RP-IC mold	Spray metal tooling
Straightness	10–20	58	45–65	37	146	>200
Flatness	20–50	123	100	86	360	>500
Circularity	40–50	1346	1532	1532	690	NA

requirement was to produce 2000 Nylon 66 functional parts, while meeting the requirements of low cost, shorter lead time, and accuracy. For better understanding of the methodology, the number of requirements, tooling attributes, RT process alternatives and parameters are kept to the minimum possible.

7.1. Tooling requirements prioritization

The necessary inputs, including mold geometric features, tooling requirements and attributes, were supplied to the program through the user interface shown in Fig. 7. The mold features including round boss, rectangular block, rectangular cavity, hollow circular cavity (with central core pin) and circular cavities are specified along with dimensions. Since the primary objective set for this analysis was to select the best RT process for small order production mold, the following four requirements were considered: better accuracy, shorter lead time, low cost and higher mold strength. The tooling attributes (constraints) considered for setting the tooling requirements priority were: minimum gap feature (mold consist of four ribs

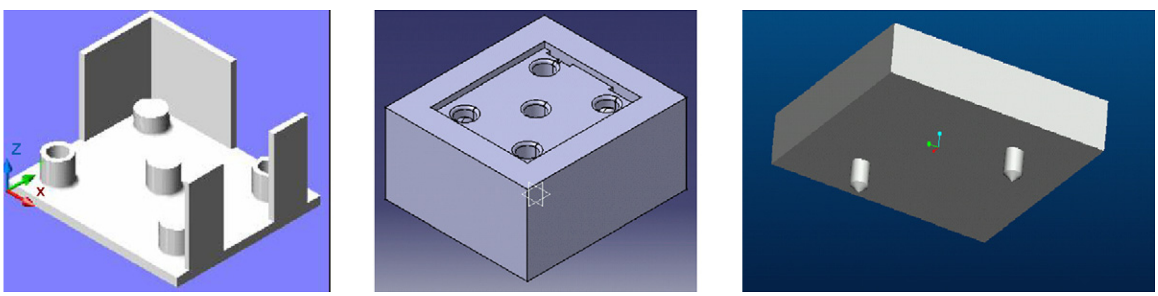

Fig. 6. CAD model of example part and corresponding mold inserts.

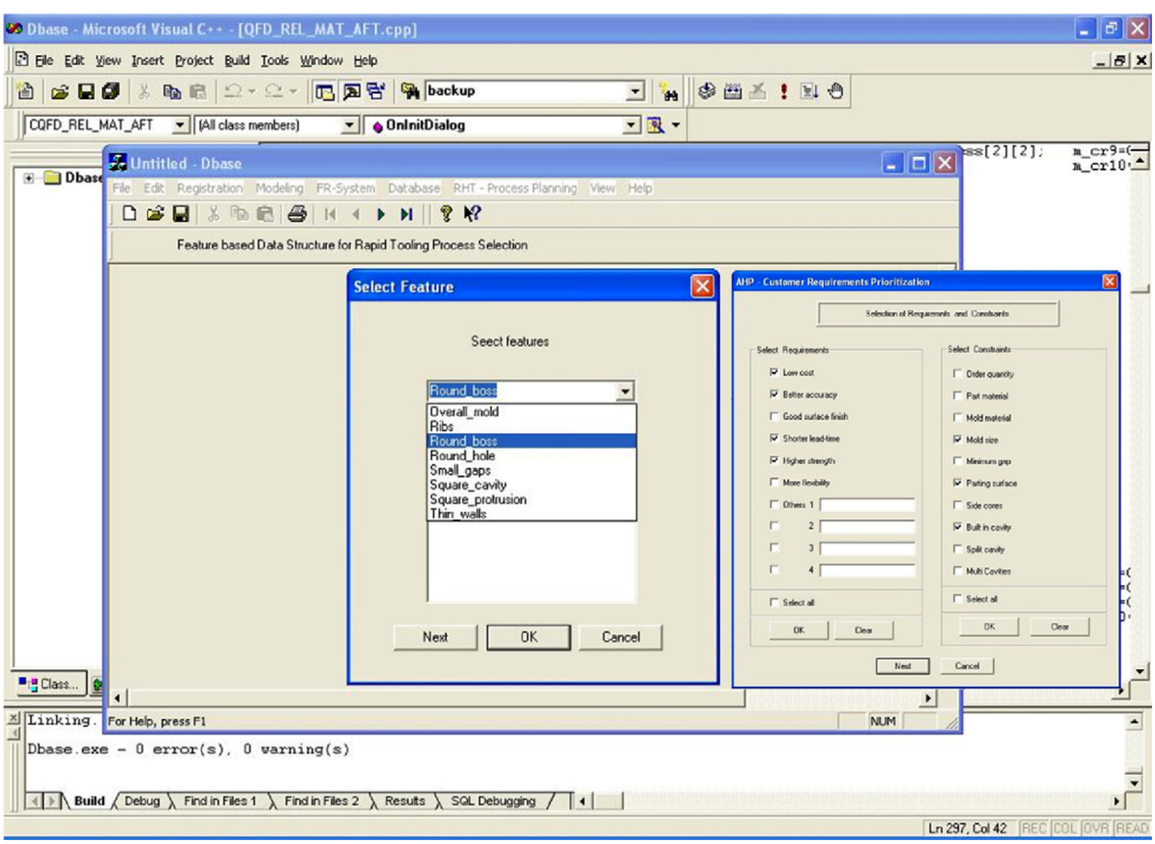

Fig. 7. User interface for specifying the inputs.

Table 5
Pairwise comparisons of requirements for geometric feature attribute

	Better accuracy	Shorter lead time	Low cost	Higher strength	Relative weights
Better accuracy	1	5	7	1	0.440
Shorter lead time	1/5	1	1	1/5	0.080
Low cost	1/7	1	1	1/5	0.074
Higher strength	1	5	5	1	0.404

cavities), built-in cavity, mold size, and parting surface. The relative importance weights derived for high level attributes are: geometric features (24%), mold material (14%), and finish machining (62%). These are used as constraints at next level to prioritize the tooling requirements. The calculations for pairwise comparison of requirements for the attributes (group) geometric features are given in Table 5.

In this case, the requirement ‘accuracy’ was assigned ‘very strong importance (7)’ weight while comparing with ‘cost’ (1 means equal importance, and 9 means extremely important compared to the other). Similarly, cost and lead time were assigned equal importance weight of 1. The final relative weights, after calculating the geometric mean and normalizing the matrix, indicated that accuracy is more important (44%) followed by mold strength (40%), for the attribute ‘geometric features’. Other requirements weights were relatively less.

7.1.1. Checking for consistency

The maximum eigen value $\lambda_{max} = 4.0142$, and for a matrix of order $n = 4$, random index (RI) = 0.90 (as suggested by Saaty). Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = (4.0142 - 4)/(4 - 1) = 0.00473$. Therefore, consistency ratio (CR) = CI/RI = 0.0053. Since CR < 0.10, pairwise comparison is quite consistent and it has been preformed for next attributes to calculate their relative weights.

7.1.2. Relative weights calculation

The relative weight for mold strength is calculated here. The geometric mean for the fourth row (relevant to the requirement ‘higher mold strength’) is given by

$$GM_4 = \left[\prod_{j=1}^{4} a_{4j}\right]^{1/4} \quad (5)$$

$$GM_4 = [5 \times 5 \times 1 \times 1]^{1/4} = 2.236$$

Similarly, $GM_1 = 2.432$, $GM_2 = 0.447$, and $GM_3 = 0.410$.
Therefore, $\sum_{i=1}^{4} GM_i = 5.526$

Relative weight for ‘higher strength’ $w_4 = GM_3/\sum_{i=1}^{4} GM_i = 2.236/5.526 = 0.404$

Similarly for other requirements $w_1 = 0.440$, $w_2 = 0.080$, and $w_3 = 0.074$.

7.1.3. Priorities of requirements

The pairwise comparison of requirements and attributes are performed as explained above, and the importance values for each requirement (R_1, R_2, R_3 and R_4) for this example are shown in the final AHP matrix (Fig. 8). These are used in quality function deployment (QFD) to represent the degree of importance of tooling requirements in rapid tooling process selection. This is discussed in detail next.

7.2. RT process selection

The tooling requirements and their importance weights are retrieved from the results of AHP based prioritization. These are: accuracy (22.10%), lead time (31.60%), cost (25.58%), and mold strength (20.72%). Shortlisting of rapid tooling processes

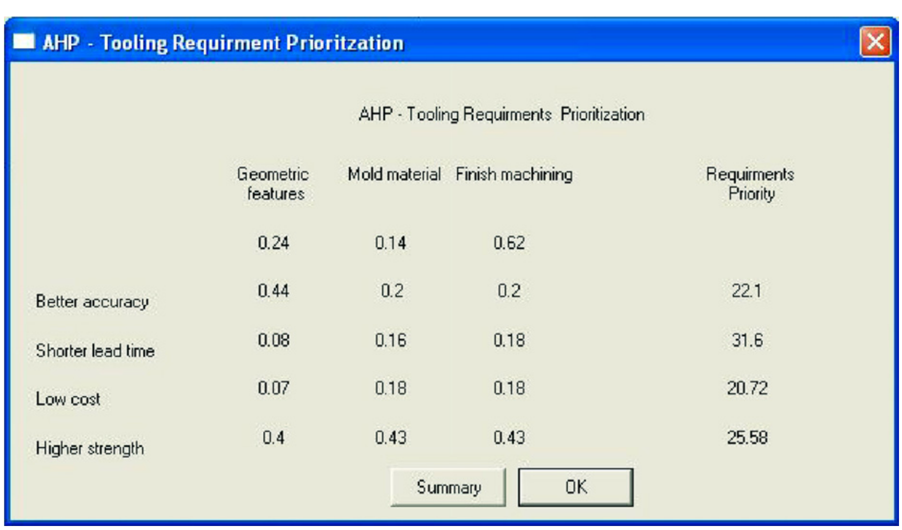

Fig. 8. Final priority ratings (degree of importance) of tooling requirements.

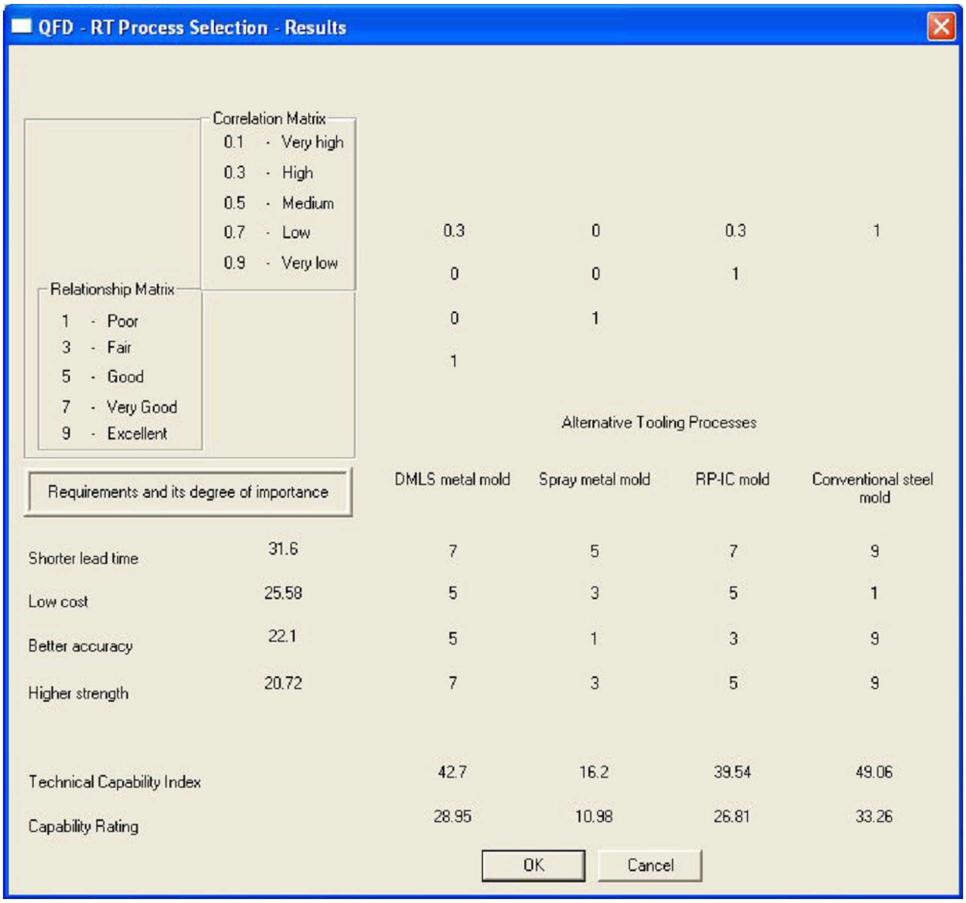

Fig. 9. QFD chart for tooling process selection for the experimental part.

for detailed analysis, and process capability mapping to select the best process are described here.

7.2.1. *Shortlisting of RT processes*

In this case, rapid tooling processes are shortlisted based on following aspects. The SLA Direct-AIM and EP 250 molds are soft materials for producing 2000 injection moldings. However, Cu–Ni bronze mold of DMLS, RP-IC aluminium mold, and MCP400 (Cu–Zn alloy) spray metal mold are capable of producing more than 2000 injection moldings. These are the primary factors considered in shortlisting the following three rapid tooling processes along with conventional mold for detailed analysis and selection: DMLS, RP-IC and Spray metal mold.

7.2.2. *Process capability mapping*

The process capability weights for accuracy, mold strength (life), cost and lead time, for the shortlisted rapid tooling processes are directly retrieved based on If-then rules linked to RT process capability database.

7.2.3. *Co-relationship weights*

In this example, DMLS, RP-IC and Spray metal mold are independent processes. However, DMLS and RP-IC mold need certain finish machining. These correlations were mapped based on the domain knowledge and experience of investigator.

7.2.4. *Normalization and process selection*

Wesserman normalization method is used to normalize the rows of the relationship matrix. For example, the coefficient of normalized matrix $r_{3,1}^{\text{norm}}$ is given by

$$r_{3,1}^{\text{norm}} = \frac{\sum_{k=1}^{5}(r_{3,k}\cdot\gamma_{k.1})}{\sum_{j=1}^{5}\sum_{k=1}^{5}(r_{3.j}\cdot\gamma_{j.k})} \tag{6}$$

The sample calculations for normalization and technical capability index (TCI) are given here.

In this example, QFD comprises four columns (RT processes), and $r_{3,1}^{\text{norm}}$ is given by

$$r_{3,1}^{\text{norm}} = \frac{r_{3,1}\cdot\gamma_{1,1} + r_{3,2}\cdot\gamma_{2,1} + r_{3,3}\cdot\gamma_{3,1} + r_{3,4}\cdot\gamma_{4,1}}{r_{3.1}(\gamma_{1,1}+\ldots+\gamma_{1,4}) + r_{3,2}(\gamma_{2,1}+\ldots+\gamma_{2,4}) + r_{3,3}(\gamma_{3,1}+\ldots+\gamma_{3,4}) + r_{3,4}(\gamma_{4,1}+\ldots+\gamma_{4,4})}$$

$$= \frac{7\times1+3\times0+5\times0+9\times0.3}{7(1+0+0+0.3)+3(0+1+0+0)+5(0+0+1+0.3)+9(0.3+0+0.3+1)}$$

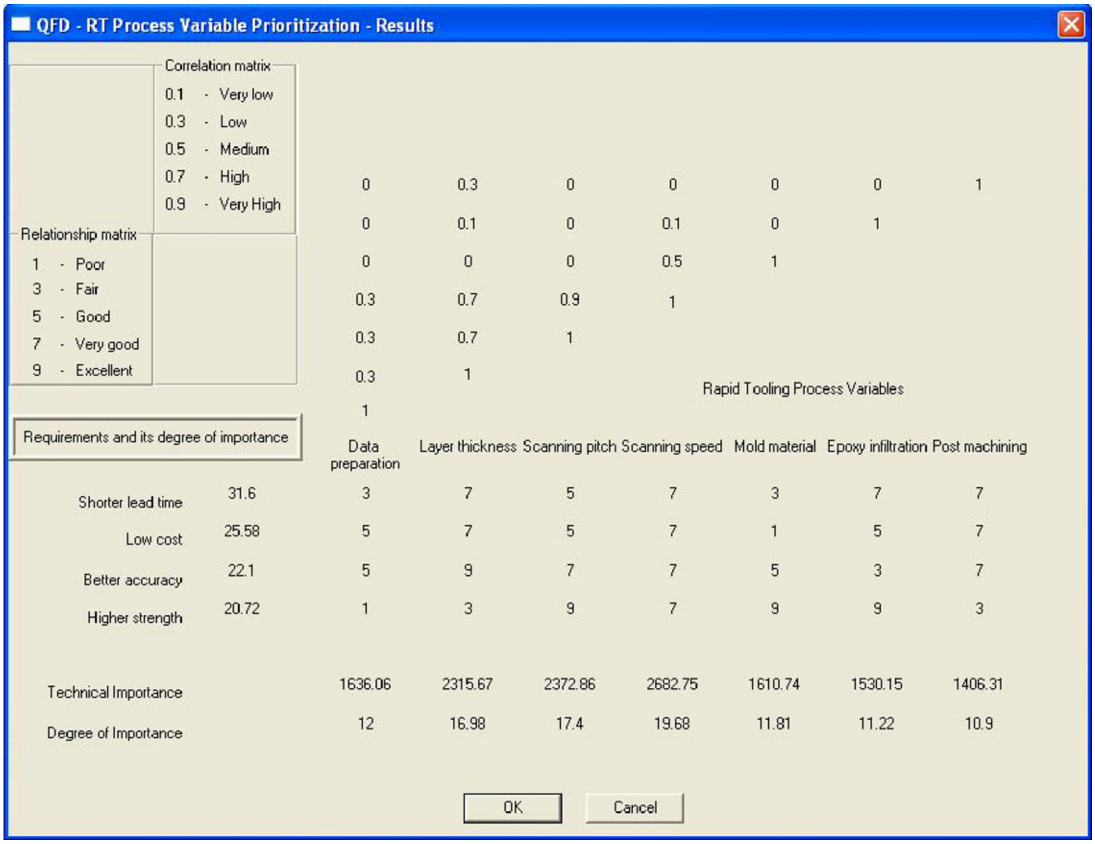

Fig. 10. QFD chart for DMLS process parameters prioritization.

For example, technical capability index (TCI) for DMLS process is given by

$$\mathrm{TCI}_{\mathrm{DMLS}} = \sum_{i=1}^{n} R_i \times r_{i1}^{\mathrm{norm}} = 42.76$$

Fig. 10 shows the final QFD chart along with the process capability weights, co-relationship weights, and technical capability index (TCI) values. The TCI for Spray metal tooling, RP-IC mold and conventional mold are 16.29, 39.54 and 49.06, respectively (Fig. 9). The DMLS rapid tooling process that has the highest technical capability index next to conventional mold emerged as best RT process.

7.2.5. Identification of critical process parameters

The effects of DMLS process parameters on each requirement were mapped to prioritize them in the order of their importance, while meeting a set of requirements. The process parameters (data preparation, base plate mounting accuracy, layer thickness, scanning pitch, scanning speed, mold material property (thermal, mechanical, microstructure) and postmachining), which are relevant to direct metal laser sintering (DMLS) mold were considered. In this analysis it was found that scanning speed is the most important parameter followed by scanning pitch and layer thickness (Fig. 10).

7.3. RT manufacturability evaluation

In the previous step DMLS process was selected for mold manufacturing. The feature based process capabilities related to this process are retrieved for manufacturability evaluation in the following steps. The evaluation methodology and the results are discussed. The core insert is simple and has two core pins and rectangular mold block, Hence manufacturability evaluation has been performed only for the cavity insert, which has a number of features, and is likely to be difficult to manufacture.

The fuzzy evaluation matrix $A = (a_{ij})_{nxm}$ was constructed using triangular fuzzy numbers through pairwise comparison as discussed in earlier sections. If feature F_i is relatively more difficult to manufacture compared to another feature F_j with respect to a given criterion (like accuracy), the corresponding coefficient of matrix a_{ij} is represented by triangular fuzzy scale (l, m, u), and its reciprocal scale is given by $a_{ij}^{-1} = (u^{-1}, m^{-1}, l^{-1})$. The final priority vectors calculated in fuzzy-AHP methodology are shown in Table 6. Based on the principle of triangular fuzzy numbers ranking (discussed in Section 5.2), difficult to manufacture features are identified for a selected RT process using these calculated fuzzy priority functions.

Fig. 12 shows the graphical representation of fuzzy priority numbers calculated from AHP pairwise comparison. Considering a sensitivity factor $Q = 0.9$, it is found that: $e_{21} = e_{31} = e_{41} = e_{51} = e_{32} = e_{42} = e_{52} = e_{43} = e_{53} = e_{54} = 1$, and $e_{12} = e_{13} = e_{14} = e_{15} = e_{23} = e_{24} = e_{25} = e_{34} = e_{35} = e_{45} \leq 0.9$. If

Table 6
Final priority vectors for feature manufacturability

	C_1	C_2	C_3	Priority vector
	0.793, 1.000, 1.144	***0.762, 1.000, 1.586***	***0.793, 1.000, 0.873***	
F_1	0.351, 0.556, 0.724	0.620, 0.755, 1.633	0.532, 0.801, 1.502	1.172, 2.112, 3.772
F_2	0.564, 0.757, 0.956	0.943, 1.319, 1.527	0.549, 0.802, 1.084	1.595, 2.878, 4.461
F_3	0.921, 1.210, 1.643	1.201, 1.622, 1.882	1.176, 1.584, 1.949	2.578, 4.326, 6.56
F_4	1.045, 1.319, 1.543	0.668, 0.786, 0.921	1.107, 1.465, 1.947	2.215, 3.570, 4.925
F_5	1.045, 1.496, 1.882	0.802, 0.921, 1.148	0.616, 0.802, 1.216	1.928, 3.219, 5.035

we consider the pair of features F_1 and F_3, as per the fuzzy ranking principles, $F_1 > F_3$ when $e_{13} = 1$ and $e_{31} < Q$. In this example $e_{31} = 1$, and $e_{13} = 0.37 < Q$ (0.9), hence $F_3 > F_1$, which indicates that feature F_3 is more difficult to manufacture than F_1. Using a similar approach, it was found that the feature F_3 is most difficult to manufacture followed by $F_{4.}$ In descending order of manufacturing difficulty, the features are ranked as: $F_3 > F_4 > F_5 > F_2 > F_1$. The program suggested conventional mold as the most suitable process, closely followed by DMLS method. This indicated F_3 (hollow cavity with central core) as difficult to manufacture feature by the selected process (Fig. 11).

In this example, the parting surface is straight and in a single plane, leading to a compatibility index for parting surface design of 0.9. The higher *l*/*d* ratio of rib may cause difficulty in ejection, and a lower value of compatibility index is assigned (0.30). The cooling design and multi-cavity mold design are not critical for this study.

The cost modifiers are nearly the same for both conventional and DMLS tooling routes, except for slight differences in final machining and assembly operations. The cost drivers include manufacturing cost of two inserts, which is calculated for both DMLS and conventional tooling process using the models developed in this thesis. The cost of DMLS tooling is INR 90,000/- and that of conventional mold is INR 142000/-. Thus, the cost of DMLS mold is found to be 36% lower than that of conventional tooling.

In this example, the manufacturability evaluation of mold features of cavity highlights the difficulty in manufacturing a hollow cavity with a central core, followed by a ribs cavity. The mold designer can check the process capability of DMLS process for these features and make suitable changes before mold manufacture. For example, the depth/thickness ratio of ribs (minimum gap) must be less than 3.5, and the gap between them must be more than 3 mm. In the present example, the depth to gap ratio of 16.66 (gap is 3 mm and depth is 50 mm) is far beyond the capability of DMLS process. The mold designer must either consider an alternative rapid tooling process, or explore other solutions such as incorporating a local insert at the outer wall of the main cavity or finish machining.

To test the methodology further, the production requirement was changed to 100 parts. This was reflected in the modified priorities: lead time (35.9%), low cost (25.9%), accuracy (19.5%) and mold strength (18.7%). The program now suggested SLA Direct-AIM as the most suitable process to fabricate the mold. Since it is an experimental mold, mold was not fabricated.

The second example was an industrial case of a hub gear mold required for producing 5000 Nylon 66 parts using

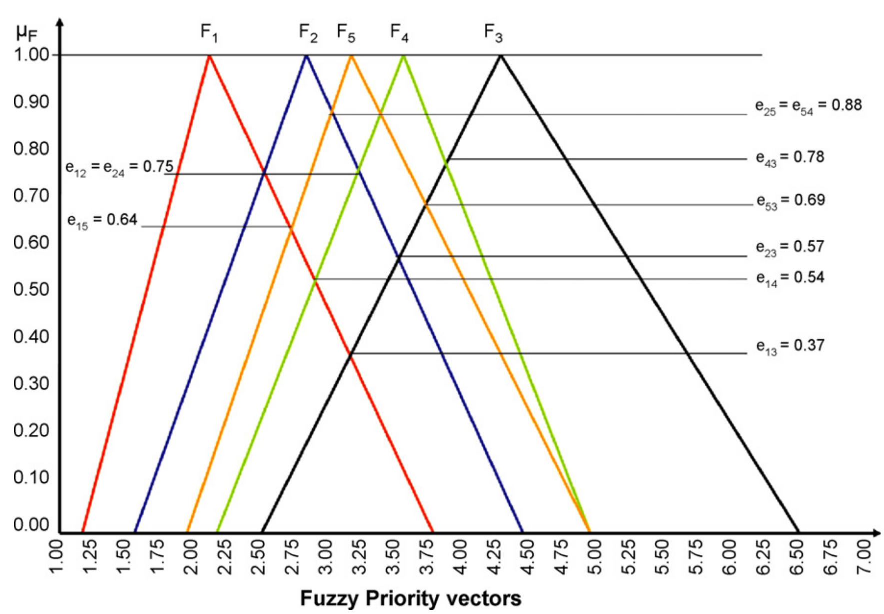

Fig. 11. Fuzzy membership functions for feature manufacturability.

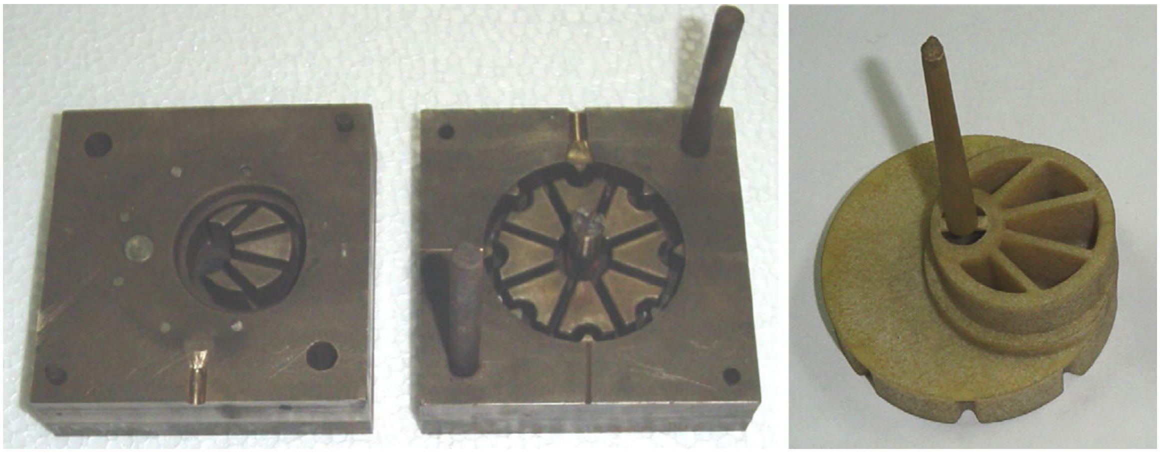

Fig. 12. DMLS mold and Nylon 66 hub gear part.

injection molding. The program suggested DMLS as the best. Accordingly, the mold was fabricated by this process, and successfully used to produce over 5000 nylon 66 parts (Fig. 12). The molding parameters were optimized using grey relational analysis and L_9 orthogonal array based experimental design, and set as follows: injection pressure (30 MPa), melt temperature (300 °C), injection speed (60 mm/s), and injection time (3 s). The melt temperature and injection speeds were found to significantly affect the response functions of low shrinkage and better soundness (strength) of molded parts. The mold was also manufactured by spray metal tooling method (not recommended by the program), and as expected it got damaged after only 70 shots.

8. Conclusion

An integrated framework has been developed for rapid tooling process selection and evaluation of mold design for its manufacturability and cost effectiveness. While QFD-AHP based RT process selection approach enables process capability mapping to meet a set of requirements, fuzzy-AHP based manufacturability evaluation approach assesses the mold design for a selected process that minimizes tooling iterations and ensures the cost benefit of the selected RT process. This decision framework not only helps in RT process selection, but also facilitates identifying difficult-to-manufacture features that could be modified to improve manufacturability before investing in tooling. The online mold cost estimation enables accurate comparison of cost effectiveness of different rapid tooling processes, which was offline and hard coded in previous attempts. The proposed methodology is driven by feature based process capability database that can be easily updated, unlike the rule-based approach used by previous researchers [11]. The software program developed in this work can be easily extended to emerging RT processes by adding respective process capabilities into the database. It fulfils an important gap in rapid tooling domain, and can help in increasing the penetration of RT methods for mold fabrication. In future, geometric feature recognition algorithms can be incorporated in it for automating manufacturability evaluation and cost estimation. It can also be linked to mold design software for seamless exchange of data between mold design, RT process selection, and manufacturability evaluation, an important step toward mold lifecycle engineering.

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