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Quantifying the Shape Complexity of Cast Parts

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ABSTRACT

Complex shaped metal parts with internal and external features and varying wall thickness are most economically produced by casting process. A higher shape complexity however, leads to lower manufacturability, implying sub-optimal quality, higher cost, and reduced productivity. Quantitative evaluation and comparison of shape complexity of alternative part designs can therefore be very useful in design for manufacturability. In this work, we define shape complexity factor using weighted criteria based on part geometry parameters such as number of cored features, volume and surface area of part, core volume, section thickness and draw distance. The coefficients of the criteria are computed by regression analysis using the actual shape complexity, which is defined as the additional cost of tooling manufacture compared to the machining of a simple shape like a cube, and computed using actual cost data from the tooling manufacturer. The regression was carried out using CAD models and cost data of 40 industrial castings of varying shapes. The equation thus obtained was successfully validated by applying it to a separate set of real life cast parts, yielding over 95% accuracy in shape complexity estimation.

Keywords: casting, shape complexity, tooling cost, design for manufacture.
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1 INTRODUCTION

Shape complexity of a part is usually described in qualitative terms like low, medium, high and very high. Geometric elements such as internal features (holes, pockets), external features (bosses, ribs) and wall thickness variation result in higher shape complexity. Here we focus on metal castings, which have the highest shape complexity among all manufactured parts, as well as a high variation in shape complexity.

It is well known that a high shape complexity affects manufacturability, leading to lower quality and productivity, and higher cost of tooling, materials, process, and overheads. The material, process and overhead costs depend on the part weight, overall production quantity and part shape complexity. In contrast, the tooling cost is driven more by its machining time, which in turn depends on its shape complexity. This becomes even more important during product development, when several design alternatives need to be prototyped and tested in functional materials, requiring manufacture of the respective tooling and castings. Thus a reduction in shape complexity of the part can result in improved manufacturability, including significant cost savings.

Several researchers have developed shape complexity factors to relate part geometry with tooling or process design in various domains of manufacturing. Shape complexity *S* of axi-symmetric forged parts can be determined by: $S = \alpha\beta$, $\alpha = X_f / X_c$ and $\beta = 2R_g / R_c$ [11]. Here α is the axial shape complexity factor and β is the lateral shape complexity factor, $X_f = P^2 / F$, and $Xc = P_c^2 / F_c$, where *P* and *F* are the perimeter and surface area of the axial cross section, P_c and F_c are the perimeter and area of axial cross section of a circumscribing cylinder, R_g is the distance from the axis of symmetry to the centre of gravity of the half axial cross section, and R_c is the radius of the circumscribing cylinder. Qamar et al. [8] established shape complexity for predicting the maximum pressure in extrusion. Here complexity *C* is a function of the ratio of perimeters of the actual profile section, P_s and an equivalent circular section of equal area P_o and is given by $C = \alpha + \beta\left(P_s / P_o\right)^{\gamma}$. The values of α=0.95, β=0.05 and γ=1.5 were obtained by regression analysis.

In machining domain, part feature driven cost estimation for DFM has been reported by several researchers [9],[12]. This depends on process planning for each retrieved feature type, followed by computation of machining time, and thereby cost estimation. This approach has been demonstrated for relatively simple machined shapes. The DFMA (Design for Manufacture and Assembly) software has a detailed casting cost estimation module aimed at product designers for early cost estimation, but this requires a large number of manual inputs about the process, such as the time and labour rates [1].

In casting and moulding domain, shapes are usually much more complex than extrusion or machined parts. Naganumiah et al [7] employed geometric features and mould complexity parameters for cost estimation of injection moulds and RP-based rapid tooling. The geometric features were related to core and cavity, and mould complexity factors were related to parting surface, presence of side cores, surface textures and other secondary mould design elements. Considerable efforts have also been made in injection mould and die cost estimation based on geometry and process parameters [3-5],[10]. Chougule and Ravi [2] developed an empirical equation for tooling cost estimation driven by shape complexity, given by: $X = \alpha_0 + \alpha_a C_a + \alpha_c C_c$ where, C_a is area complexity factor (1- (surface area of cube of equal volume / surface area of solid)), and C_c is the core complexity factor $(1-(1/(n_C+1)^{0.5}))$. Here n_c is number of cores. The coefficients α_i were obtained by regression analysis. However, several other important parameters related to tooling cost were left out, leading to fairly high percentage errors.

In summary, to enable design for manufacturability, there is a need for quantitative evaluation of part shape complexity. The tooling cost can be a good indicator of the shape complexity, but it requires a fairly accurate estimation at an early stage in product life cycle. This is not easy, since it depends on detailed process planning of tooling manufacture and comprehensive cost data, which are not feasible in early stages of product design. Traditional methods of cost estimation, such as history-based costing and activity based costing are therefore not suitable for part shape complexity estimation.

2 CRITERIA FOR SHAPE COMPLEXITY

Geometric features of part design, which influence the design of tooling, determine the complexity of tooling and therefore its cost. A cast part may require multiple pieces of tooling (separated by the parting surface), referred to as cope and drag patterns and core boxes (figure 1). The outer shape of the part is obtained by the sand mould prepared using cope and drag patterns placed in a flask. The inner features (holes and undercuts) are obtained by sand cores prepared in core boxes.

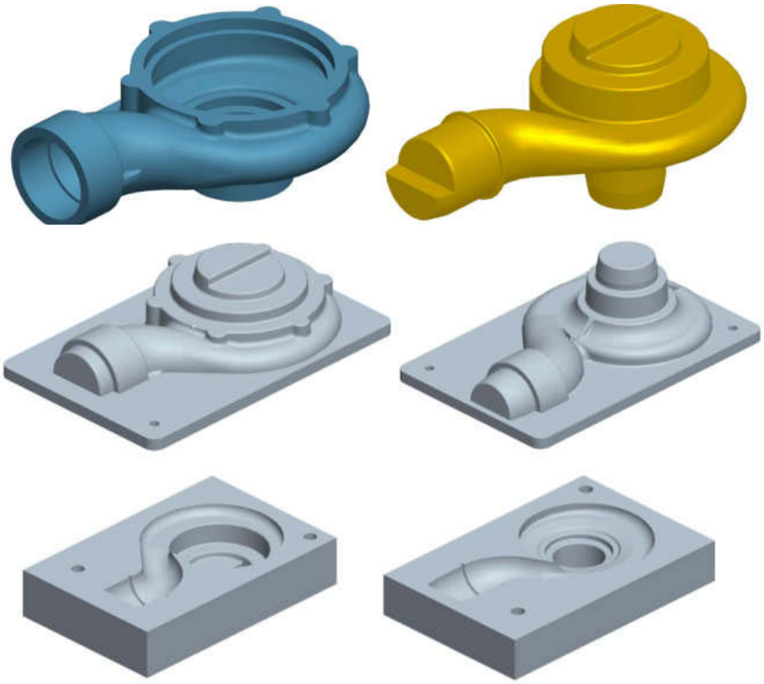

Fig. 1: Top: delivery casing and core, middle: cope and drag patterns, bottom: core box.

While interacting with part designers and tool makers, it was observed that the tool manufacturing cost depends on the number of cores, volume and surface area of part, core volume, draw distance and variation in section thickness, all of which can be determined from the part CAD model. Accordingly, we define the following six geometry-driven criteria for shape complexity evaluation. The criteria equations are set up to return a value between 0 and 1; higher values indicate a greater contribution to complexity.

Part volume ratio (C_{PR} **):** This is the ratio of volume of part to the volume of bounding box. The bounding box is given by the maximum length, width, and height of the part geometry. When the volume of part is close to its bounding box, less material removal is required, resulting in lower machining cost. Higher difference in these volumes leads to a higher manufacturing cost. This criterion is defined as:

$$C_{PR} = 1 - \frac{V_p}{V_b} \tag{1}$$

Where, V_p is the volume of part and V_b is the volume of its bounding box.

Area ratio (C_{AR} **):** This is the ratio of surface area of an equivalent sphere (with the same volume as that of the part) to the surface area of the part. This ratio is based on the fact that sphere has minimum surface area as compared to any other geometry. More features in tooling geometry increase the surface area of tooling. Higher this surface area more will be the cost of machining and hence higher the complexity. This criterion is defined as:

$$C_{AR} = 1 - \frac{A_s}{A_p} \tag{2}$$

Where A_s is the surface area of an imaginary sphere with volume equal to that of the part, given by: $A_s = (4\pi)^{1/3}(3V_p)^{2/3}$. Here A_p and V_p are the surface area and volume of part respectively.

Number of cores (C_{NC}): Cores are required for hollow portions of the part and regions that hinder pattern withdrawal during moulding. Each core requires a separate tooling; hence more the number of cored features, higher will be the tooling cost. The criterion for number of cores is defined as follows, considering that the rate of increase in shape complexity gradually decreases with an increase in the number of cored features:

$$C_{NC} = 1 - \frac{1}{\sqrt{(1+N_c)}} \tag{3}$$

Where, N_c is the number of cored features.

Core volume ratio (C_{CR}): Larger cores require larger size tooling and incur higher tooling cost. Hence the ratio of core volume to bounding box volume is included as another measure of complexity (figure 2).

$$C_{CR} = \frac{\sum_i Vc_i}{V_b} \tag{4}$$

Where, Vc_i is the volume of i^{th} core and V_b is the volume of part's bounding box.

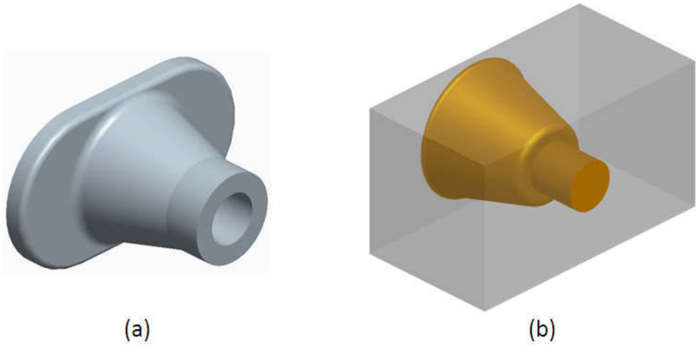

Fig. 2: (a) Part and (b) Core and part bounding box.

Thickness ratio (C_{TR}): This is the ratio of minimum and maximum thickness of the part. A tooling with thin sections will be more complex and is more difficult to machine as compared to one with thick sections. This criterion is defined as:

$$C_{TR} = 1 - \frac{T_{\min}}{T_{\max}} \tag{5}$$

Where, $T_{\min}$ and $T_{\max}$ are the minimum and maximum thickness of the part, respectively.

Depth ratio (C_{DR}): The draw distance, which is the maximum depth of the tooling, affects the tooling manufacturing time and hence its cost. The actual draw distance is compared to the minimum possible draw distance, which is half the minimum dimension of the part. The criterion is designed such that parts with higher depth ratio will indicate higher complexity (figure 3).

$$C_{DR} = 1 - \frac{0.5(\min(L,W,H))}{D_d} \tag{6}$$

Where, L, W, H are the length, width, and height of the part, respectively and D_d is the draw distance of the tooling.

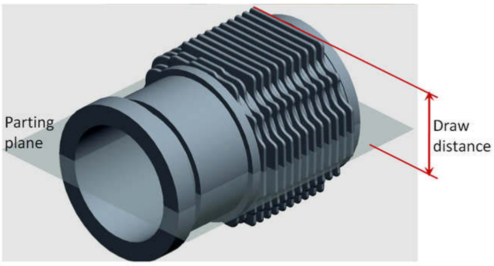

Fig. 3: Draw distance with respect to the parting plane.

The overall shape complexity factor can be estimated by the weighted sum of the individual criteria described above.

$$CF_{estimated} = w_0 + w_1 C_{PR} + w_2 C_{AR} + w_3 C_{NC} + w_4 C_{CR} + w_5 C_{TR} + w_6 C_{DR} \quad (7)$$

3 CORRELATION WITH TOOLING COST

The cost of machining a tooling element is usually higher for parts with greater complexity. For machining a simple shape such as a cube, the material can be removed by a single cutting tool by plane surface machining using traditional machines that incur low operating cost. If the same volume is to be removed for a complex shape, it may require 3D surface machining using CNC machines with multiple cutters, leading to a much higher cost.

In reality, shape complexity is not the only factor driving tooling cost. Other factors include tooling material and accuracy requirement. However, for a given set of tooling material and accuracy requirements, the tooling manufacturing cost is driven solely by its complexity, and becomes a quantitative indicator of relative part shape complexity.

The shape complexity of a part can be assessed in terms of the additional cost incurred for manufacturing its tooling, over the cost of machining a simple shape like a cube. This additional cost due to complexity is given by the difference in actual cost of tooling and the cost of machining a cube of 'differential volume'. The differential volume, which represents the volume to be machined, is obtained by subtracting the part volume from its bounding box volume (figure 4).

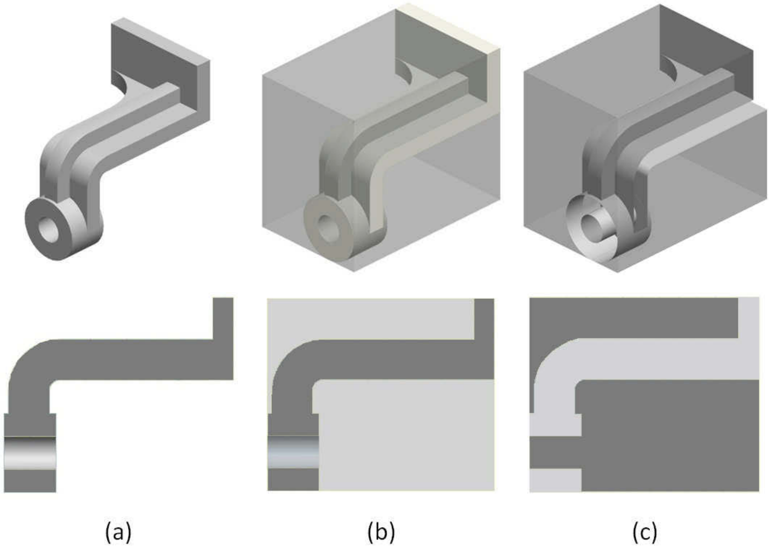

Fig. 4: (a) Part, (b) bounding box, and (c) differential volume.

We define CF_{actual} (actual shape complexity factor) as the ratio of additional cost of machining c_a (due to part shape complexity) to the cost of machining a cube of differential volume c_d. The additional cost of machining c_a is given by the difference of actual tool machining cost c_t and c_d. Hence the actual shape complexity of a part can be computed from its machining cost data, as follows.

$$CF_{actual} = \frac{c_a}{c_d} = \frac{c_t - c_d}{c_d} = \frac{c_t}{c_d} - 1 \tag{8}$$

Equation 8 is useful for correlating with the shape factor estimated from a part model using geometry based criteria described in the previous section (equation 7). A regression analysis can be carried out by equating the two relations for a number of benchmark parts with varying complexity, to obtain the coefficients of the geometry-based equation for shape complexity estimation.

4 COMPLEXITY FACTOR COMPUTATION

The proposed methodology for obtaining and validating the shape complexity equation comprises the following steps (figure 5).

1. Select existing benchmark parts of varying complexity and compile their actual cost of machining the tooling, to calculate CF_{actual} using equation 8.
2. Create the CAD models of these bench mark parts to compute the above six criteria $C_{PR}, C_{AR}, C_{NC}, C_{CR}, C_{TR}, C_{DR}$ using equations 1 to 6.
3. Perform multiple regression using CF_{actual} and the above six criteria to determine the coefficients (w_0 - w_6) of the proposed shape complexity equation 7.

$$CF_{actual} = w_0 + w_1 C_{PR} + w_2 C_{AR} + w_3 C_{NC} + w_4 C_{CR} + w_5 C_{TR} + w_6 C_{DR} \tag{9}$$

4. Interpret the results for the relative influence of various geometry criteria and validate the equation using parts not covered in regression analysis.

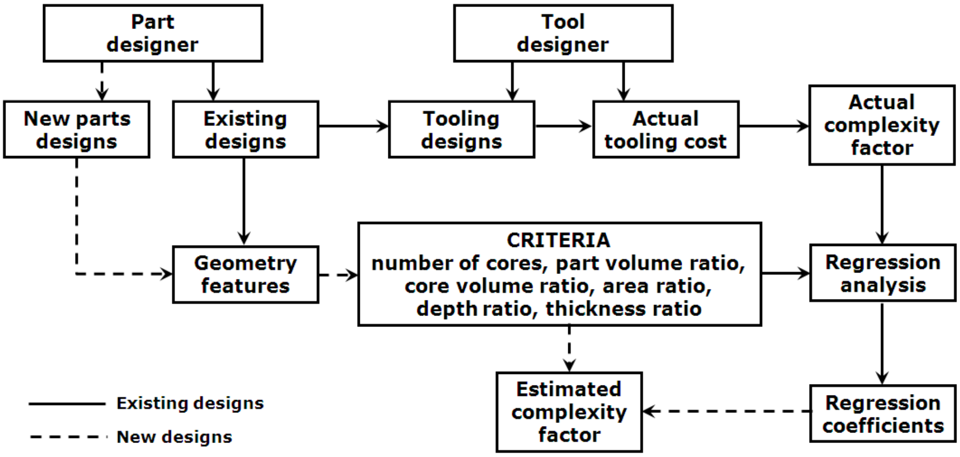

Fig. 5: Methodology for quantifying complexity.

The benchmark cases range from a simple cube to fairly complex castings (figure 6), and were obtained from a tooling manufacturing company.

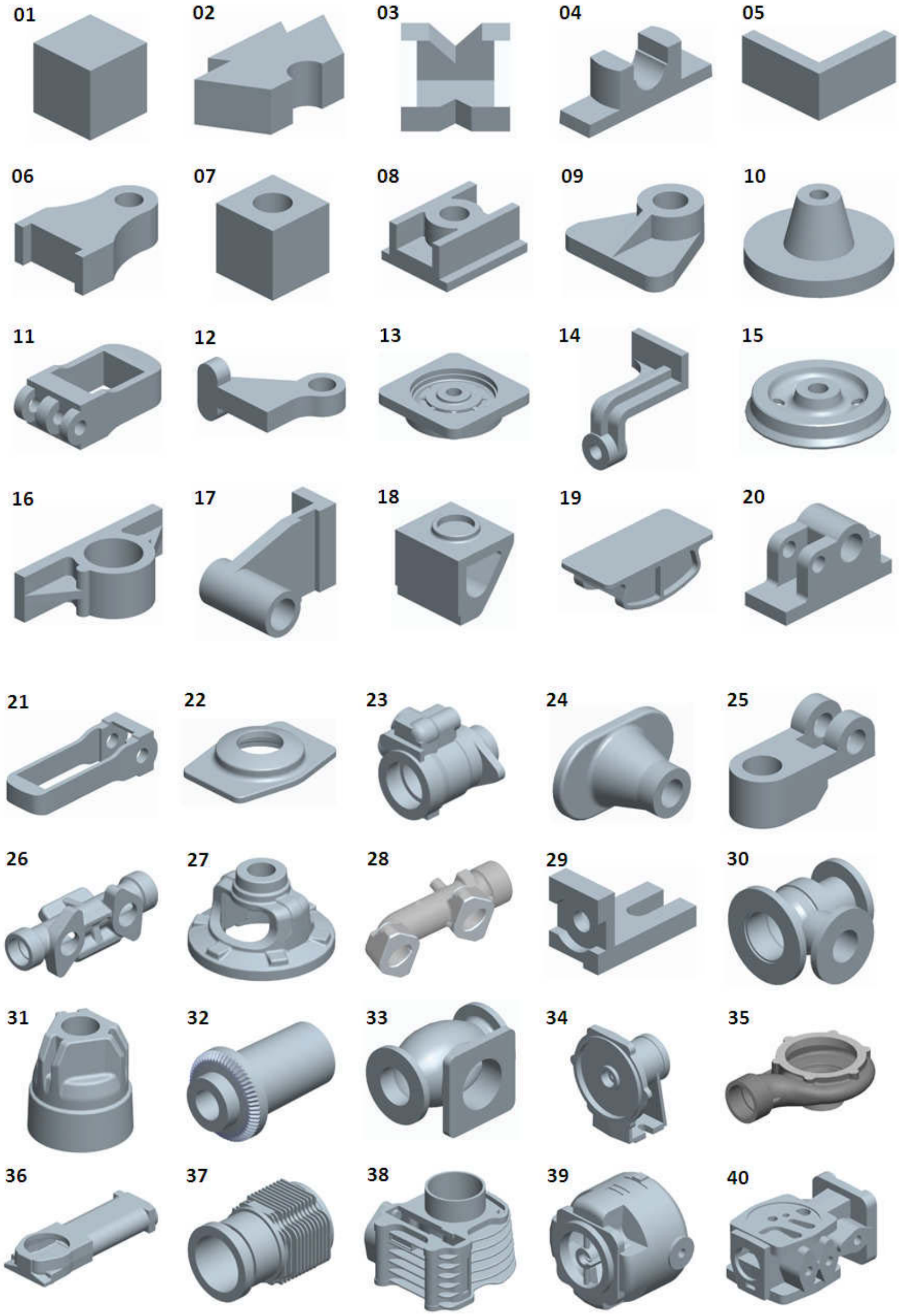

Fig. 6: Forty benchmark parts of varying complexity for regression analysis.

The tooling material is cast iron for all these parts. The tooling for these parts were developed in CAD as illustrated earlier in figure 1 considering shrinkage, machining, and draft allowances. The actual costs of tooling (c_t) for these parts were obtained from the records of the tool-maker. The cost of machining the cube of differential volume (c_d) were obtained from the senior tool maker in the same company, to provide a standard and consistent base. Since all parts were developed during a period of two years, the cost values are not corrected for the rate of inflation.

Data corresponding to geometry criteria (predictors) and actual complexity factor (response variable) were computed for the 40 benchmark cases. Sample computation for three parts (number 25, 33 and 38) is given here to explain the procedure.

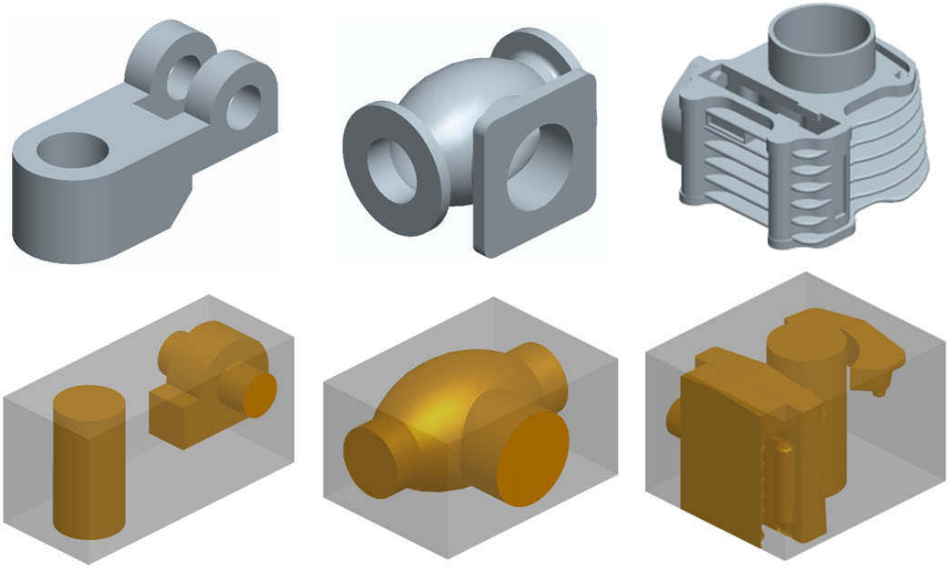

Fig. 7: Parts 25, 33 and 38 for sample calculation along with cores.

First, the length, width and height of a part are measured from its CAD model, and used to compute the bounding box volume. Part volume and surface area are obtained using mass property function; equating the volume of the part to the volume of an imaginary sphere, the radius of the sphere is obtained, from which the surface area of the equivalent sphere is computed. Next, the orientation of the part in the mould is determined by the selecting a parting surface that results in the least number of cored features. The cores are modeled and their volume is computed (figure 7). The actual complexity factor (response variable) is computed as the ratio of additional cost of machining (difference of actual machining cost and cost of machining the cube of same volume obtained from the tool maker) to the cost of machining the cube of same volume (table 1). In a similar manner, the geometry parameters and criteria (predictors) are computed for all 40 parts. These are presented in table 2 and table 3 respectively, ending with the actual complexity factor.

Parameter / Criteria	**Unit**	**Part 25**	**Part 33**	**Part 38**
L, Length	mm	240	375	135
W, Width	mm	100	270	85
H, Height	mm	120	282	110
V_b :Volume of bounding box	mm^3	2880000	28552500	1262250
V_p :Volume of part	mm^3	1089563	6361078	298882.8
Volume ratio	-	0.38	0.22	0.24
Criterion part volume ratio: C_{PR}	**-**	**0.62**	**0.78**	**0.76**
A_p :Surface area of part	mm^2	111352.3	719652.9	106798.7
Radius of imag. sphere of equal vol.	mm	63.8	114.87	41.45
A_s :Surface area of imag. Sphere	mm^2	51170.1	165888.9	21604.9
Area ratio	-	0.46	0.23	0.20
Criterion area ratio: C_{AR}	**-**	**0.54**	**0.77**	**0.80**
N_c :Number of cores	-	2	1	3
Criterion number of cores: C_{NC}	**-**	**0.42**	**0.29**	**0.50**
Total core volume	mm^3	582363.4	10039504.0	308805.4
Criterion core volume ratio: C_{CR}	-	**0.20**	**0.35**	**0.24**
T_{min} :Minimum thickness	mm	30	22	3
T_{max} :Maximum thickness	mm	120	270	135
Thickness ratio	-	0.25	0.08	0.02
Criterion thickness ratio: C_{TR}	-	**0.75**	**0.92**	**0.98**
D_d :Draw distance	mm	50	135	55
Minimum of L, W, H	mm	100	270	85
Criterion depth ratio: C_{DR}	-	**0.00**	**0.00**	**0.23**
c_d :Machining cost of cube	INR	224	1479	120
c_t :Actual tool machining cost	INR	10816	79179	7357
Actual complexity factor: CF_{actual}	-	**47.29**	**52.54**	**60.31**

Tab. 1: Sample computation of geometry parameters and criteria.

Part	Volume of part V_p (mm³)	Surface area of part A_p (mm²)	No. of cores. N_c	Total core volume (mm³)	Min. thick. $T_{\min}$ (mm)	Max. thick. $T_{\max}$ (mm)	Draw distance D_d (mm)
1	1000000	60000	0	0	100	100	50
2	14569317	433339.9	0	0	91	538	152.5
3	5316096	241126.4	0	0	36	250	168
4	723337.1	71004.05	0	0	5	260	31.5
5	8880000	408800	0	0	60	400	100
6	7828074	308170.9	1	621417.1	32	240	120
7	803650.5	71780.97	1	202284.2	25	100	50
8	484208.7	65260.62	1	60878.87	12	135	45
9	5227147	296220.4	1	894840.6	32	192	120
10	746882.8	81176.48	1	65394.5	14	107	85
11	14433010	695786.3	1	1032418	34.5	590	100
12	10550627	481438.2	1	1182634	32	420	135
13	8430326	573038.8	1	244683	13	420	50
14	6650513	409670	1	331422.4	40	332	200
15	22111748	910573.1	2	1147738	20	152	86
16	1399720	147993.6	1	712040.4	16	328	44
17	607812.4	98196.51	1	191111.6	12	140	60
18	2815344	210655.9	2	1179444	16	168	95
19	10249160	888864.4	1	1816271	20	641	101
20	2441142	183959	2	857509.8	31	290	56
21	14549792	967054.9	1	7303972	15	481	127
22	5485396	437847.7	1	4123771	20	508	92
23	577396.6	93358.44	1	377053.7	7	100	64
24	6995315	571463.4	1	7642707	15	300	146
25	1089563	111352.3	2	582363.4	30	120	50
26	629925	131605.3	1	544578.5	11	296	56
27	149233.2	35080.29	1	125533.1	4	24	56
28	412020	97929.03	1	390019.7	26	247	55
29	2192210	181821.2	3	727291.6	12	290	130
30	5955594	644121.1	1	6554878	25	145	145
31	429610.5	72878.95	1	365039.3	10	116	53.5
32	215801.8	35051.75	2	162376.5	10	112	37.5
33	6361078	719652.9	1	10039504	22	270	135
34	1062289	206302.5	2	812999.7	8	107	112.5
35	954664.8	264475.9	1	2529819	5	50	56.25
36	406001.5	113792.4	1	444576.4	7	131	21.5
37	699463.7	198449.1	1	1036978	3	178	60
38	298882.8	106798.7	3	308805.4	3	135	55
39	1432014	363415.8	2	3969743	10	215	97.5
40	2655620	447794.7	6	1911892	8	284	77.5

Tab. 2: Geometry parameters of 40 benchmark parts.

Part	C_{VR}	C_{AR}	C_{NC}	C_{CR}	C_{TR}	C_{DR}	**MC*cube** c_d **(INR)**	**MC tool** c_t **(INR)**	CF_{actual}
1	0.00	0.19	0.00	0.00	0.00	0.00	-	-	-
2	0.32	0.33	0.00	0.00	0.83	0.50	693	15690	21.64
3	0.37	0.39	0.00	0.00	0.86	0.50	308	7795	24.31
4	0.50	0.45	0.00	0.00	0.98	0.00	90	2511	26.90
5	0.72	0.49	0.00	0.00	0.85	0.00	1541	45567	28.57
6	0.37	0.38	0.29	0.05	0.87	0.50	459	15813	33.45
7	0.20	0.42	0.29	0.20	0.75	0.00	31	1105	34.64
8	0.43	0.54	0.29	0.07	0.91	0.37	57	2218	37.92
9	0.63	0.51	0.29	0.06	0.83	0.50	722	28483	38.45
10	0.76	0.51	0.29	0.02	0.87	0.37	235	9369	38.87
11	0.59	0.59	0.29	0.03	0.94	0.00	1414	56446	38.92
12	0.83	0.52	0.29	0.02	0.92	0.00	3321	132710	38.96
13	0.52	0.65	0.29	0.01	0.97	0.00	737	29974	39.67
14	0.85	0.58	0.29	0.01	0.88	0.31	2601	108948	40.89
15	0.63	0.58	0.42	0.02	0.87	0.12	2472	108971	43.08
16	0.66	0.59	0.29	0.17	0.95	0.00	270	11960	43.30
17	0.83	0.65	0.29	0.05	0.91	0.00	289	12820	43.36
18	0.50	0.54	0.42	0.21	0.90	0.12	280	12861	44.93
19	0.74	0.74	0.29	0.05	0.97	0.00	1906	88124	45.23
20	0.50	0.52	0.42	0.18	0.89	0.00	243	11323	45.60
21	0.80	0.70	0.29	0.10	0.97	0.00	1441	67529	45.86
22	0.70	0.66	0.29	0.23	0.96	0.50	1019	48443	46.54
23	0.76	0.64	0.29	0.16	0.93	0.00	230	10940	46.57
24	0.85	0.69	0.29	0.16	0.95	0.00	2641	127043	47.10
25	0.62	0.54	0.42	0.20	0.75	0.00	224	10816	47.29
26	0.82	0.73	0.29	0.16	0.96	0.00	504	24370	47.35
27	0.82	0.61	0.29	0.15	0.83	0.41	106	5135	47.45
28	0.83	0.73	0.29	0.16	0.89	0.21	244	12064	48.44
29	0.71	0.55	0.50	0.10	0.96	0.45	532	26536	48.88
30	0.82	0.75	0.29	0.20	0.83	0.00	1771	88416	48.92
31	0.68	0.62	0.29	0.27	0.91	0.00	114	5791	49.80
32	0.66	0.50	0.42	0.26	0.91	0.00	65	3447	52.03
33	0.78	0.77	0.29	0.35	0.92	0.00	1479	79179	52.54
34	0.86	0.76	0.42	0.11	0.93	0.40	635	34064	52.64
35	0.89	0.82	0.29	0.28	0.90	0.00	634	34693	53.72
36	0.62	0.77	0.29	0.42	0.95	0.00	102	5631	54.21
37	0.73	0.81	0.29	0.40	0.98	0.00	233	13318	56.16
38	0.76	0.80	0.50	0.24	0.98	0.23	120	7357	60.31
39	0.84	0.83	0.42	0.44	0.95	0.00	607	38260	62.03
40	0.69	0.79	0.62	0.22	0.97	0.00	602	38233	62.51

Tab. 3: Predictor and response variables for regression analysis.

5 REGRESSION ANALYSIS

The multiple regression analysis is performed using Minitab® statistical analysis software, [9] to compute the weights (w_0 - w_6) of equation 9. The regression equation for estimating shape complexity for new part designs using these weights is presented as equation 10. Analysis of Variance (ANOVA) is presented in table 4:

$$CF_{estimated} = 5.7 + 10.8C_{PR} + 18.0C_{AR} + 32.7C_{NC} + 29.0C_{CR} + 6.9C_{TR} + 0.7C_{DR} \quad (10)$$

S = 1.1758; R-Sq = 98.7%; R-Sq(adj) = 98.5%; R-Sq(pred.) = 97.9%

Overall				
DF	**SS**	**MS**	**F**	**P-value**
6	3393.44	565.57	409.08	0.000
Predictors				
Predictor	**Coef.**	**SE Coef.**	**T**	**P-value**
Constant	5.703	3.131	1.82	0.078
C_{PR}	10.809	1.746	6.19	0.000
C_{AR}	17.958	3.152	5.70	0.000
C_{NC}	32.750	1.691	19.37	0.000
C_{CR}	28.953	2.232	12.97	0.000
C_{TR}	6.898	3.927	1.76	0.089
C_{DR}	0.740	1.067	0.69	0.493

Tab. 4: Analysis of variance for data sets of 40 parts.

- The p-value in the ANOVA table (0.000) shows that the model obtained by regression procedure is significant at an α-level of 0.05 (table 4). The α -level, or the level of significance, is the maximum acceptable level of risk for rejecting a true hypothesis. Its low value indicates that the chance of finding an effect that does not exist, is very low.
- The p-values for the estimated coefficients of C_{PR},C_{AR}, C_{NC} and C_{CR} are 0.000, indicating that they are significantly related to $CF_{estimated}$. The p-value for C_{TR} and constant is 0.089 and 0.078, respectively, indicating that they are related to $CF_{estimated}$. The p-value for C_{DR} is 0.493, indicating that this parameter is not significant for $CF_{estimated}$ at an α -level of 0.05.
- The R^2 value indicates that the predictors explain 98.7% of the variance in $CF_{estimated}$. The adjusted R^2 is 98.5%, which accounts for the number of predictors in the model. Both values indicate that the model fits the data well.
- The predicted R^2 value is 97.9 %. Because the predicted R^2 value is close to R^2 and adjusted R^2 values, the model does not appear to be over-fit and has adequate predictive ability.

The histogram indicates that outliers may exist in the data, shown by one bar on the far right side of the plot (figure 8). The normal probability plot shows an approximately linear pattern consistent with a normal distribution. One point in the upper-right corner appears to be an outlier (figure 9). Since the predicted R^2 value is as high as 97.9%, this can be ignored. The plot of residuals versus the fitted values shows that the residuals are evenly distributed on both sides of reference line (figure 10).

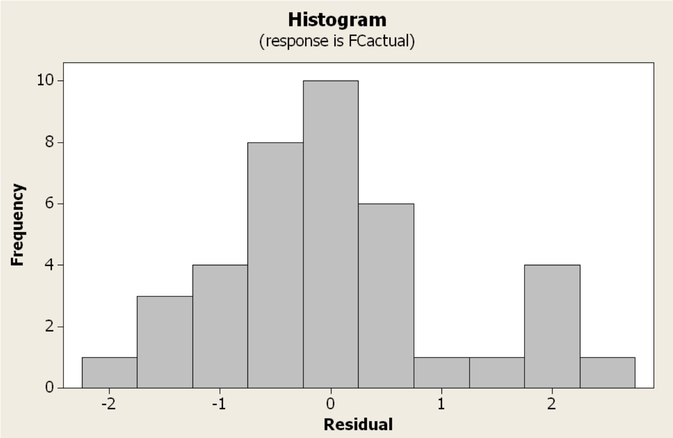

Fig. 8: Histogram of residuals for actual complexity factor.

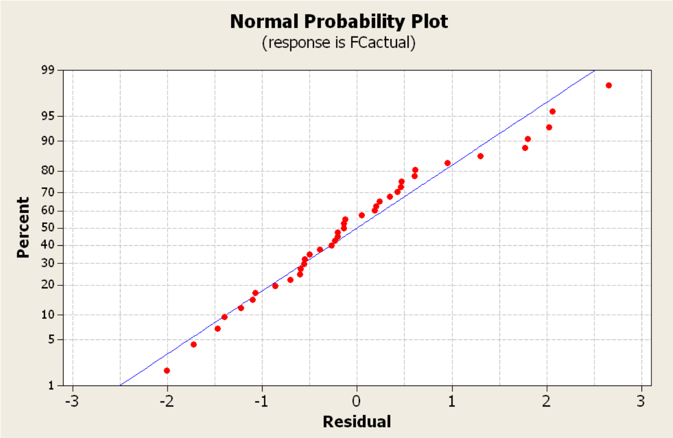

Fig. 9: Normal distribution plot for actual complexity factor.

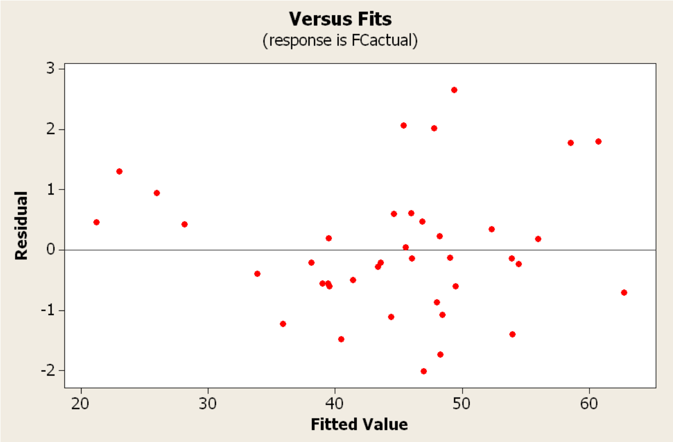

Fig. 10: Residual versus fit for actual complexity factor.

The coefficient for C_{NC} is the highest (32.7), followed by C_{CR} (29.0). This is in line with industrial experience, since every additional core requires a set of core boxes and both the number and volume of the core boxes increase the tooling cost. A part without cores requires only cope and drag patterns, and will have low complexity value. As the number of cores increases, the part complexity goes on increasing. Coefficients C_{AR} (18.0) and C_{PR} (10.8) are also quite high. This is also in line with industrial experience, since a larger surface area and volume of material removal increase the machining time. The coefficient C_{TR} is 6.9, signifying a lower relative importance of thickness in complexity. The coefficient C_{DR} is quite low (0.7); indicating that the depth ratio is relatively less important in complexity estimation and can be even dropped from the equation.

6 VALIDATION OF SHAPE COMPLEXITY EQUATION

To validate the shape complexity equation, it is tested on parts other than those used in the regression analysis. Three such parts are shown in figure 11. Geometry parameters for these parts are given in table 5. The computation of complexity criteria and the estimated shape complexity (using equation 10) are given in table 6. The estimated shape complexity factor is compared with actual shape complexity (obtained from the tooling company based on their actual cost data), and presented in table 7. It is observed that the absolute deviation is as low as 1.61%. Even the maximum deviation is 2.30%, which is well within generally acceptable limits of 5%. This establishes the validity of using the estimated complexity equation (equation 10) for a wide range of cast parts.

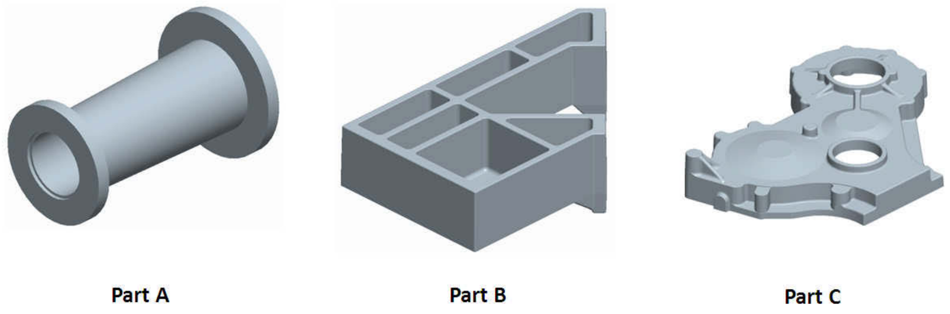

Fig. 11: Example parts for validation.

Part	Part	Volume of part V_p (mm³)	Surface area of part A_p (mm²)	No. of cores. N_c	Total core volume (mm³)	Min. thick. T_{min} (mm)	Max. thick. T_{max} (mm)
A	3872598.9	477892.3	1	4493711.8	24	71	127.5
B	20429753	1629391	0	0	14	875	166.0
C	1119275	285459.7	0	0	13	450	54.0

Tab. 5: Geometry parameters of example parts.

Part	C_{VR}	C_{AR}	C_{NC}	C_{CR}	C_{TR}	C_{DR}	***CF estimated***
A	0.85	0.75	0.29	0.17	0.66	0.00	47.35
B	0.79	0.78	0.00	0.00	0.98	0.31	35.25
C	0.90	0.82	0.00	0.00	0.97	0.50	37.22

Tab. 6: Criteria computation of example parts.

Part	Actual tooling cost (INR)	Cube machining cost (INR)	CF actual	CF estimated	% error
A	71420	1454	48.12	47.35	1.61
B	158480	4274	36.08	35.25	2.30
C	22476	576	38.02	37.22	2.10

Tab. 7: Comparison of estimated and actual complexity factors.

7 CONCLUSION

Quantitative evaluation of shape complexity of cast parts has been demonstrated, using geometry-driven criteria based on number of cores, part volume ratio, core volume ratio, area ratio, thickness ratio and depth ratio. Regression analysis using 40 industrial parts of varying complexity was successful in determining the coefficients of the shape complexity equation. The relation has been validated by parts not covered in regression analysis, proving its usefulness for estimation of shape complexity of new parts. The shape complexity equation can be employed in early phases of product life cycle, particularly in design for manufacturability, since it does not depend on process planning and detailed cost data. The part designer can quickly estimate the shape complexity of a cast part (from its CAD model), allowing comparison of alternate designs in terms of their influence on tooling and manufacturing cost.

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