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A part complexity measurement method supporting 3D Printing

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Abstract

The use of packing algorithms to fill build volumes in 3D printing promotes both more efficient processes and better utilisation of the available build space. There are various packing techniques, and the choice of an appropriate one is often highly dependent on the characteristics of the parts to be printed, among other factors. Part complexity, and particularly convexity, is an important factor. This paper presents metrics for quantitatively evaluating part complexity, extending a 2D metric to a 3D situation. These metrics are then available for classifying problems and identifying appropriate packing algorithms.

Introduction

Cutting and packing (C&P) is an important research area within Operations Research. It aims to develop solutions for problems of maximising the utilisation of available manufacturing capacity or material. It has been demonstrated that there is a relationship between the usage of the available build space and the efficiency of some 3D Printing processes in terms of resource consumption, including financial cost [1] and energy consumption [2]. Therefore, improving and applying automated packing methodologies to 3D Printing is likely to result in more sustainable and profitable production.

A large variety of C&P techniques have been developed in the last few decades. One particular approach that has shown promising results is the utilisation of basic information about the parts to be packed to evolve the method itself rather than to solve an individual case [3, 4]. The majority of papers that use this approach address regular packing problems by orthogonally placing cuboid elements of geometry within a large bin or container. To address more realistic cases, this research investigates whether additional characteristics, or features, present in irregular parts can be used to improve the performance of C&P methodologies.

Previous research on the evaluation of part complexity, sometimes referred to as shape complexity, has been applied to areas other than 3D Printing, e.g. architecture [5] and design [6]. This paper introduces a new part complexity measure for packing approaches supporting 3D Printing processes. By discussing the proposed complexity measure in the context of the existing measures which have already been identified in the literature, the authors expect to lay the groundwork for future research into irregular packing.

This paper is structured as follows: A brief presentation of packing methodologies applied to 3D Printing and an overview of existing shape complexity measures are presented in the next two sections. The next section introduces the new proposed metrics, along with a practical method for calculating the Spies Ratio. The experimental results are then presented and discussed, before the final section concludes the paper, summarising the work and discussing future work.

Background

A variety of packing methodologies has been applied to 3D Printing [7, 8, 9, 10] and they differ mainly in the way that they search for promising sequences of parts, i.e. in the order in which the items are positioned within the build volume. For example, Canellidis et al. [11] use a Genetic Algorithm (GA) to determine a good ordering of the parts. A GA is a metaheuristic, which is a high level algorithm that mimics the process of natural selection and reproduction of the fittest individuals [12]. An interesting aspect in [11] is that each part has its orientation previously optimised according to one of three criteria: height, volume of supporting structures and surface roughness. This method, therefore, uses basic information about the geometry of parts to improve the overall results of the algorithm.

There are metaheuristic optimization methods which make use of problem features for choosing and applying the best approach before or during the search process to solve a given problem instance [13, 4]. This line of studies on the application of data science techniques to exploit richer information (e.g., problem instance/solution features) improving the learning process leading to more effective solution methods in combinatorial optimization has been growing [14, 15]. For example, hyper-heuristics utilizing part characteristics have been successfully applied to regular packing [16, 17].

Existing Metrics

This section presents existing methodologies for evaluating part complexity. The first is the Spies Ratio (SR) [18], which is calculated by the dividing the volume of the geometry part by the volume of the primitive that contains it. An interesting aspect of the SR is the need to find the correct alignment of the part which will minimise the primitive volume.

The second part complexity that we consider was presented by Valentan et al. [19] and is a straightforward assessment of part complexity which depends entirely on the number of facets (f), the surface area (a) and the volume (v) of the used polygonal model of part geometry. Its method of calculation is presented in Table 1.

Finally, the mean connectivity value (MCV), proposed by Psarra and Grajewski [5], assesses the complexity of two-dimensional polygons (rather than three dimensional parts) by considering the ‘connectivity’ between areas on the perimeter. Additional supporting measures were introduced to evaluate the variation of connectivity amongst the perimeter locations and the fluctuation rate of connectivity values, which are the v-value and h-value respectively. 6 This measure is the basis for the proposed part complexity method in this paper, which extends the MCV and the v-value to the three-dimensional context leaving the h-value measure for future work. The MCV and the two part complexity methods previously mentioned are summarised in Table 1.

Measure	Formulation	Range	Interpretation
Spies Ratio[18]	$\frac{v_{part}}{v_{primitive}}$	(0,1]	Volume of the part divided by the volume of the primitive
Valentan et al.[19]	$\frac{f*a}{v}$	(0,∞)	Number of facets times the surface area divided by the volume
Psarra and Grajewski [5]	$\sum_{i=1}^{n} \frac{VC_i}{n}$	(0,1]	Mean of connectivity values of the n voxels on the surface

Table 1: Summary of the three part complexity in literature.

Proposed Metrics

This section proposes new metrics for measuring the characteristics of given 3D parts: a 3D version of MCV and v-value as well as a practical approach to calculating SR. The MCV measure, mentioned in the previous section, assesses two-dimensional geometries by evaluating the connectivity between *areas* on their perimeters [5]. This research extends [5] to a 3D situation, considers the way in which the voxelisation can affect the areas which are connected by the algorithm and the effects of the granularity of the voxelisation upon the value of the metric. Although not the main focus of this paper, an optimization method for calculating the minimum bounding box of a part is also proposed, to support the calculation of the Spies Ratio [18].

Calculation of MCV and v-value

The first step of the MCV calculation consists of the rasterization of the geometric model of the part into a 3D voxel grid with an appropriate resolution from the viewpoint of performance and execution time, a process called voxelization [20]. In contrast to the original approach [5], which calculates the connectivity between areas on the perimeter, this technique calculates the connectivity between voxels on the surface.

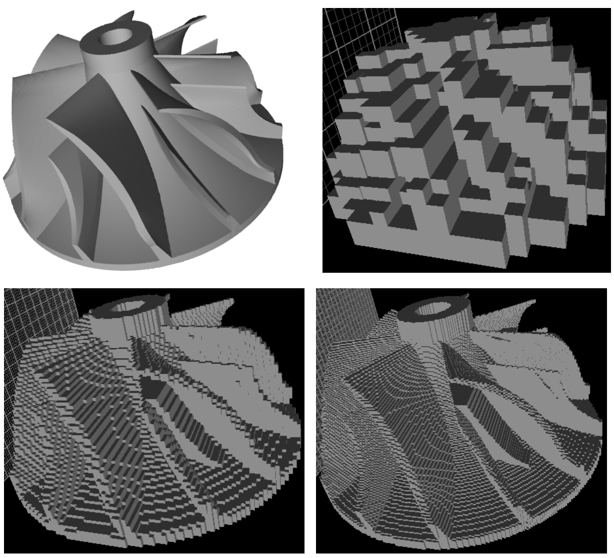


Figure 1. *An example from the Baumers et al. [9] rasterized in resolutions of 20, 100 and 200 voxels.*

Following the discretization process, the connectivity value (CV) of each voxel belonging to the surface of the part is calculated - which is the percentage of other surface voxels that can be connected to the former one through a Bresenham's line [21], such that all voxels on that line belong to the interior of the shape. The interpretation is that voxels with low CV have poor interconnectivity to other portions of the part.

The MCV of a part is then formed by calculating the mean of the CV values of all the surface voxels. For fully convex parts, the MCV is equal to 1. Entrant features will reduce the MCV value, so the more concave the shape, the closer MCV will be to 0.

The resolution of the voxelisation has a large effect upon performance, in terms of both runtime and accuracy. To visualise the differences, Figure 1 illustrates an example of part used by Baumers et al. [9] voxelized using a grid of 20, 100 and 200 parts, respectively. It was found that low resolutions lead to fast but imprecise MCV calculations, as perhaps expected from the visualisation, however high resolutions result in computationally expensive processing. For example, tests conducted on a 3.40GHz Intel PC with 8.00 GB RAM showed that resolutions above 100 voxels result in MCV calculations which take over five minutes per part.

The calculations of the CV and MCV metrics for voxel pairs and parts, respectively, allow the extension of the auxiliary metric v-value, which describes the variation of connectivity through the surface of the part. It is obtained by taking the standard deviation of the CV values of all of the voxels on the surface of the part.

Calculation of Spies Ratio

Algorithm 1: Pseudo-code of the Steepest Ascent Hill Climbing with Random Restart.

```
currentSolution = randomSolution();
bestSolution = currentSolution;
while not termination criterion do
    currentValue = evaluate(currentSolution);
    bestNeighbour = NULL;
    for each solution s in the neighbourhood of (currentSolution) do
        if evaluate(s) > evaluate(bestNeighbour) then
            bestNeighbour = s;
        end
    end
    if evaluate(bestNeighbour) <= evaluate(currentSolution) then
        if evaluate(currentSolution) > evaluate(bestSolution) then
            bestSolution = currentSolution;
        end
        currentSolution = randomSolution();
    end
    else
        currentSolution = bestNeighbour;
    end
end
return bestSolution;
```

Some non-trivial characteristics of a part, such as the volume of the minimum bounding box (MBB), the maximum and minimum dimension in any of the axis, the projected area on the building platform and the volume of supporting structures, depend upon its orientation. This paper presents a practical approach to determining an orientation for calculating the Spies Ratio (SR) [18], using the volume of MBB optimized by a local search algorithm.

This study uses the Steepest Ascending Hill Climbing with

Random Restart (SAHC) [22]. This is a local search metaheuristic that starts from a random solution, determines a neighbourhood around the solution (the set of solutions which can be reached with a single change) and iteratively changes the current solution to the best one in its current neighbourhood. Each solution in the SAHC implementation is represented by an array containing the rotation on x, y and z-axis. The neighbourhood of a solution corresponds to a small variation of the angles in all of the axes. The SAHC which is used is presented in Algorithm 1. The algorithm terminates after exceeding a certain number of tested solutions.

Results and discussion

The proposed metrics were evaluated on a collection of 3D datasets. The datasets which were used are discussed below, followed by an analyses of the results.

Experimental Design

The following datasets, which have all been used in previous 3D printing publications and have been named according to the publication which they appeared in, were evaluated: I97 from Ikonen et al. [7]; S05 from Stoyan et al.[23]; C06 from Canellidis et al. [11]; G08 from Gogate and Pande [8]; B13 from Baumers et al. [9]; and W14 from Wu et al. [10]. The parts are shown in the Figure 2. The calculated values of the MCV, the v-value, the Spies Ratio [18], the metric proposed by Valentan et al. [19], the volume and dimensions of the minimum bounding box achieved by the SAHC, the number of facets, the surface area and volume of the parts are all shown in Table 3 in the Appendix. The SAHC which was used in these experiments was terminated after it had visited 10,000 solutions, returning the best solution found so far at that time.

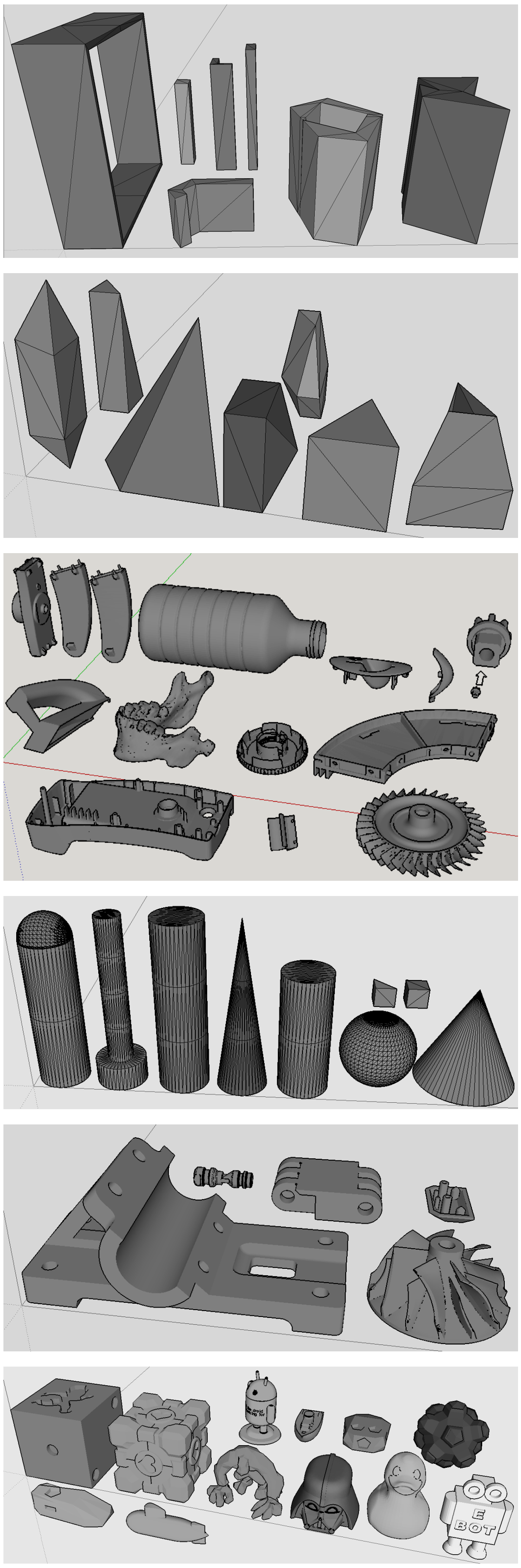


Figure 2. *Datasets I97[7], S05[23], C06[11], G08[8], B13[9] and W14[10].*

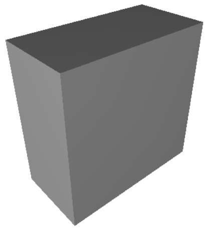
Results

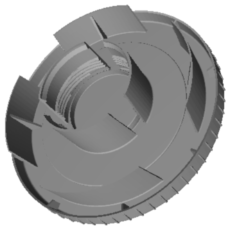
The results allowed for an improved understanding of the correlations between different part complexity metrics. For example, Figures 3(a) and 3(b) illustrate the relation between MCV and v-value of a simple and complex part. The simple convex part can be observed to have a high MCV and low v-value, while the second part has low MCV and comparatively high v-value. The other two pairs of figures (Figure 3(c) and 3(d), Figure 3(e) and 3(e)) show parts with the same MCV and different v-values. The part in Figure 3(c) has a lower v-value than the part in Figure 3(d), which means a smaller variation of connectivity over the surface of the part and, consequently, a perception of lower complexity. The same situation occurs for the parts shown in Figures 3(e) and 3(f), illustrating how the MCV and v-value metrics can cooperate to indicate a higher degree of part complexity.

The second observation from the data in Table 3 is with regard to the relationship between the MCV, the v-value, the additional part complexity measurement techniques and the basic characteristics of parts. The correlations between every pair of features can be seen in Figure 4. Positive correlations are shown as grey circles while negative correlations are represented by dashed circles. The circles have a radius proportional to the absolute value of the correlation.

It is possible to observe that the MCV measure presents a low negative correlation to the metric used in Valentan et al. [19] and a low negative correlation to the various more basic metrics, which present moderate to high positive correlations to each other. The correlation values between the MCV and all the other features are reported in the Table 2. The lack of a high (positive or negative) correlation with another metric, with the possible exception of the Spies Ratio, indicates that the usage of the MCV with this set of features does not result in data redundancy.

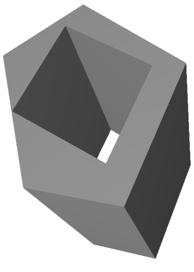
Despite the comparatively high correlation between the SR and the MCV, the MCV appears to be more successful in expressing non-convexity. For illustrative purposes, Figure 5 shows two pair of parts with similar values of SR but different MCV values.

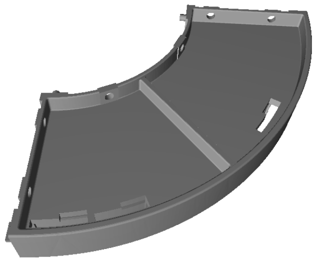




(a) I97-1-1; MCV = 1.00; V-Value = 0.00

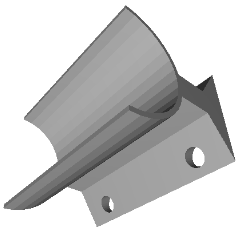
(b) C06-10. MCV = 0.22; V-Value = 0.20

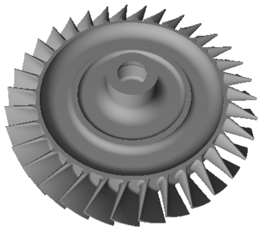




(c) I97-c2-4. **MCV = 0.32**; V-Value = 0.08

(d) C06-11. **MCV = 0.32**; V-Value = 0.23





(e) C06-13. **MCV = 0.32**; V-value = 0.09

(f) C06-14. **MCV = 0.32**; V-value = 0.20

Figure 3. *Comparison between a part with high MCV and low v-value to another with low MCV and comparatively high v-value; and comparisons between parts sharing the same values of MCV but different v-values.*

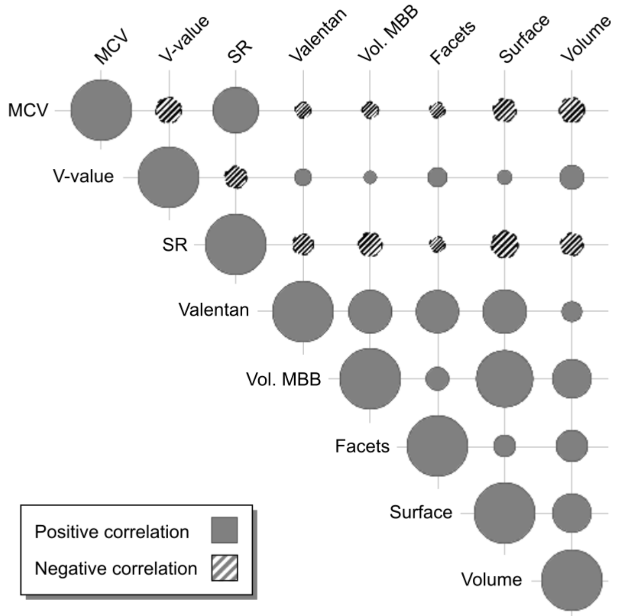
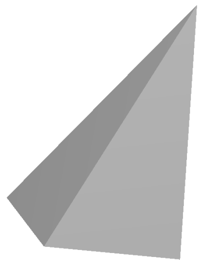


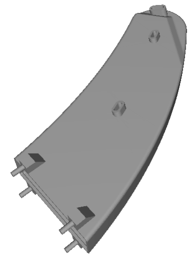
Figure 4. *Correlations between every pair of features.*

The parts in Figures 5(a) and 5(b) have a relatively low ratio between the volume and the minimum bounding box but the low mean of connectivity on the surface and shape convexity is better captured by the MCV, which is 1 for the convex part. The same applies to the second pair of parts, shown in Figures 5(c) and 5(d).

Feature	Correlation
Spies' Ratio	0.75
Number of facets	-0.25
Valentan	-0.26
Volume of the MBB	-0.27
Area of surface	-0.38
Volume of the part	-0.41
V-value	-0.42

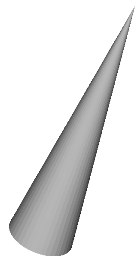
Table 2: The correlations between the MCV and the other features of parts.

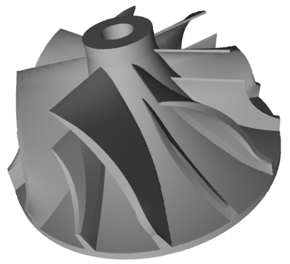




(a) S05-2. **SR = 0.17**; MCV = 1.00

(b) C06-2. **SR = 0.17**; MCV = 0.43





(c) G08-3. **SR = 0.26**; MCV = 1.00

(d) B13-4. **SR = 0.25**; MCV = 0.44

Figure 5. *Comparison between parts with the same Spies Ratio but different MCV values.*

Conclusions and future work

This paper presented the Mean Connectivity Value (MCV), a part complexity measure which was originally used for 2-dimensional shapes and has now been extended to assess three-dimensional geometries. It argues that the extended measure is more successful in detecting concavities and complexities in irregular parts than some previous measurement methods in the literature. A practical approach to detecting the Spies Ratio [18] was also presented.

These results show that the MCV and the extended v-value work well in capturing the perception of higher complexity and irregularity. Additionally, the results indicate that the combined usage of the MCV along with existing metrics does not result in data redundancy. This, therefore, provides new information which can be of potential advantage to heuristic and hyper-heuristic based packing methods that can potentially utilise information about the parts and state to improve the packing decisions. It is expected that such improvements would further enhance the efficiency and cost performance of 3D Printing technologies.

Future work will consider the development of packing approaches which will intelligently use these metrics, with the aim of improving the decision making during the packing. Other future work will consider the extension and interpretation of the h-value auxiliary metric which was presented for the 2-dimensional context in [19].

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Author Biography

Luiz Jonatã Pires de Araújo is a Ph.D. Student in the School of Computer Science at the University of Nottingham/UK since 2014, in the Automated Scheduling, Optimisation and Planning Research Group *(ASAP). His work has focused on the application of Cutting and Packing methodologies as Mathematical Modelling and Evolutionary Algorithms to Additive Manufacturing processes.*

Ender Özcan is an Assistant Professor in Operational Research and Computer Science with the Automated Scheduling, Optimisation and Planning (ASAP) research group in the School of Computer Science at the University of Nottingham. His research interests and activities lie at the interface of Computer Science, Artificial Intelligence and Operational Research, with a focus on intelligent decision support systems combining data science techniques and (hyper/meta)heuristics applied to real world problems, in particular, timetabling, scheduling, and cutting and packing.

Jason A.D. Atkin is an Assistant Professor in Operational Research and Computer Science in the Automated Scheduling, Optimisation and Planning (ASAP) research group in the School of Computer Science. He has a BSc in Mathematics with Computing, a PhD from the School of Computer Science and a decade of experience in industry. His research primarily involves modelling and solving real world optimisation and scheduling problems, particularly transportation and airport optimisation.

Martin Baumers is an Assistant Professor of Additive Manufacturing Management at the University of Nottingham with an interest in the financial cost and energy consumption of the various additive processes as well as the benefits that can be derived from adopting the technology. From 2010 on, Martin has written several academic and non-academic papers on the topic and contributed to Additive Manufacturing projects in aerospace, automotive, industrial machinery and the medical and retail sectors.

Appendix

Part	MCV	V-value	SR	Valentan	Vol. MBB	Dim. MBB	Facets	Surface	Volume
I97-1-1	1.00	0.00	1.00	48.00	4.00	1.00x2.00x2.00	12	16.00	4.00
I97-2-1	1.00	0.00	1.00	172.00	0.18	2.00x0.30x0.30	12	2.58	0.18
I97-2-2	0.75	0.10	0.56	148.35	5.19	1.20x1.73x2.50	24	17.81	2.88
I97-2-3	0.69	0.18	0.38	405.04	0.77	1.46x1.00x0.53	28	4.28	0.30
I97-2-4	0.36	0.08	0.39	489.01	5.73	2.00x1.86x1.54	52	20.88	2.22
I97-2-5	0.94	0.15	0.52	366.56	0.31	0.56x0.20x2.81	20	2.96	0.16
I97-2-6	0.74	0.15	0.42	411.10	0.58	0.45x0.51x2.50	20	5.00	0.24
I97-2-7	0.28	0.06	0.12	1061.21	10.50	1.00x3.00x3.50	48	27.71	1.25
S05-1	1.00	0.00	0.73	14.93	240.00	5.00x6.00x8.00	14	187.68	176.00
S05-2	1.00	0.01	0.17	10.33	429.63	2.64x9.83x16.55	4	192.88	74.67
S05-3	1.00	0.00	0.83	14.55	144.00	3.00x4.00x12.00	10	174.59	120.00
S05-4	1.00	0.00	0.65	21.83	192.00	3.00x4.00x16.00	16	170.11	124.67
S05-5	1.00	0.00	0.42	23.44	320.00	10.00x8.00x4.00	18	173.59	133.33
S05-6	1.00	0.00	0.50	10.42	294.00	6.00x7.00x7.00	8	191.40	147.00
S05-7	0.86	0.16	0.30	23.18	513.71	9.38x9.00x6.08	16	220.92	152.50
C06-1	0.19	0.08	0.14	18269.28	202730.78	35.50x46.96x121.60	17718	29440.74	28552.36
C06-2	0.43	0.11	0.17	10431.58	118113.17	44.84x127.62x20.64	10394	20624.27	20549.98
C06-3	0.43	0.11	0.17	10407.18	117966.54	127.46x44.84x20.64	10370	20624.30	20550.63
C06-4	0.56	0.11	0.02	297226.88	1945215.98	94.16x94.16x219.40	75432	131365.20	33338.64
C06-5	0.15	0.08	0.09	15633.79	131076.30	97.98x48.00x27.87	12498	14709.57	11759.15
C06-6	0.18	0.06	0.07	13990.58	27808.22	65.44x17.71x24.00	6552	4427.49	2073.46
C06-7	0.46	0.10	0.37	1733.93	1474.44	10.19x14.20x10.19	1420	659.05	539.73
C06-8	0.20	0.08	0.08	10245.34	345621.17	61.67x91.28x61.40	9698	29844.34	28249.97
C06-9	0.38	0.12	0.10	31920.49	666950.26	104.17x108.56x58.98	100948	20355.35	64373.44
C06-10	0.22	0.20	0.07	148936.88	82525.65	70.60x70.62x16.55	50910	16474.17	5631.24
C06-11	0.36	0.23	0.19	8323.79	486592.01	96.97x213.54x23.50	14353	52233.99	90068.93
C06-12	0.22	0.11	0.08	32060.56	640822.91	72.00x180.42x49.33	30004	57384.79	53703.78
C06-13	0.31	0.09	0.23	799.04	9953.23	30.00x18.48x17.95	620	2958.71	2295.75
C06-14	0.31	0.20	0.16	223892.84	490003.69	117.99x118.00x35.19	447578	40348.61	80659.79
G08-1	1.00	0.00	0.75	2454.55	27.91	2.00x1.99x7.00	1088	47.05	20.85
G08-2	0.66	0.16	0.28	2101.98	27.92	2.00x1.99x7.00	524	31.36	7.82
G08-3	1.00	0.00	0.26	866.84	27.62	7.06x1.98x1.98	250	25.32	7.30
G08-4	1.00	0.00	0.30	286.61	55.86	3.58x3.58x4.36	118	40.62	16.72
G08-5	1.00	0.00	1.00	72.00	1.00	1.00x1.00x1.00	12	6.00	1.00
G08-6	1.00	0.00	0.78	760.72	27.92	2.00x1.99x7.00	332	50.20	21.91
G08-7	1.00	0.00	0.78	596.59	19.94	2.00x1.99x5.00	248	37.65	15.65
G08-8	1.00	0.00	0.52	5215.85	26.79	3.00x2.99x2.99	2600	28.19	14.05
G08-9	1.00	0.00	0.50	70.63	1.00	1.00x1.00x1.00	8	4.41	0.50
B13-1	0.45	0.17	0.19	3806.47	504085.52	127.10x76.18x52.06	12712	28939.36	96645.28
B13-2	0.33	0.15	0.54	7768.05	30971.08	53.34x38.10x15.24	16000	8056.92	16594.99
B13-3	0.35	0.20	0.23	33761.81	7565.57	20.57x32.91x11.18	26892	2216.72	1765.66
B13-4	0.44	0.18	0.25	60785.56	81645.58	54.00x28.00x54.00	107806	11625.39	20618.17
B13-5	0.41	0.09	0.44	57649.74	3015.40	30.76x9.90x9.90	59294	1277.93	1314.38
W14-1	0.46	0.13	0.18	48919.81	11064.83	19.20x19.20x30.00	33520	2845.49	1949.74
W14-2	0.81	0.13	0.49	8162.00	13647.05	24.49x30.00x18.57	22776	2374.04	6624.74
W14-3	0.78	0.15	0.94	861.41	27000.00	30.00x30.00x30.00	3555	6148.68	25375.45
W14-4	0.91	0.15	0.41	4642.77	2876.30	30.00x7.99x12.00	7350	753.48	1192.83
W14-5	0.76	0.11	0.37	332.62	18124.40	26.23x26.37x26.20	706	3188.20	6767.17
W14-6	0.70	0.15	0.38	3582.17	17636.75	30.08x28.21x20.78	10960	2183.87	6681.77
W14-7	0.71	0.11	0.76	1255.94	26994.03	30.00x30.00x30.00	4730	5420.57	20414.48
W14-8	0.86	0.12	0.64	76.37	2814.30	12.51x30.00x7.50	124	1116.93	1813.62
W14-9	0.20	0.11	0.15	833.71	14272.39	24.91x22.73x25.21	892	1979.49	2117.90
W14-10	0.87	0.13	0.66	74.43	4724.65	21.00x30.00x7.50	144	1612.59	3119.68
W14-11	0.61	0.21	0.45	1973.88	5685.25	19.74x9.60x30.00	3172	1584.00	2545.48
W14-12	0.83	0.18	0.40	5474.86	3016.10	11.69x30.00x8.60	6966	951.77	1211.00

Table 3: Features of the parts from datasets I97[7], S05[23], C06[11], G08[8], B13[9] and W14[10].

