Laser Cutting Time Estimate for Sheet Metal Parts of Various Geometries by Machine Learning Approach

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Abstract

Manufacturing sheet metal parts with laser cutting machines involves placing several parts of various geometries from multiple customers on one sheet blank (e.g., 6' x 12'). While this practice is common, it can cause complications in accurately calculating fabrication time and subsequent cost of parts for each customer. The reason for this is that laser cutting machines display only the total cutting time per entire sheet blank, and the cutting order within and between parts on sheet blanks may not be sequential. To resolve this long-standing machine time distribution problem, this paper proposes a Machine Learning approach based on the geometric characteristics of parts. To test this approach, 348 sheet blanks with parts of various shapes and sizes were processed on a laser cut machine to collect the machine's cutting time for each sheet blank. The parts on the sheet blank were broken down into their component geometric characteristics (e.g., line length, number of vertices, arc length, number of piercing, etc.), which were used as features for the Machine Learning model. Data from 338 sheet blanks were used for training, and data from the remaining 10 were used to validate the trained model. Three Machine Learning algorithms—Linear Regression, Ridge Regression, and Lasso Regression—were selected and compared. The results show that the Machine Learning approach, based on parts' geometric characteristics, is a viable method for designating cutting time for parts on sheet blanks. With the real-time data collection of parts' geometry and shop floor machine run time in the era of Industry 4.0, this approach can be implemented on any laser cut machines to automatically determine the cutting time (and therefore manufacturing cost) of each part.

Keywords
Machine Learning, Laser Cutting Time Estimate, Sheet Metal Fabrication Cost, Automation, Industry 4.0

1. Introduction
Sheet metal parts are commonly manufactured by laser cut and turret punch machines by placing multiple parts of different geometries from various customers on a single sheet blank to improve material utilization. However, this practice makes it difficult to accurately calculate the machine run time and the subsequent manufacturing cost of each part on the sheet blank. Inaccurate machine run time estimation leads to challenges in determining operation profit or loss, as well as difficulties in quoting customer orders. Currently, the industry relies on subjective estimation or simple calculations based on part geometry to assign each part a machine run time, which lacks accuracy and consistency. When a different machine model is used, machine run times must be reset for each part, which can lead to confusion, accounting errors, and delays.

The main obstacle in resolving this issue is that laser cut and turret punch machines only display the total run time for the entire sheet blank, and there are infinite fabrication possibilities for each part. Although some machines may output time stamp data, it requires significant effort to analyze the log files and relate the data to individual parts.

A laser cutting work example is shown to illustrate the issue. On a 304-grade stainless sheet blank of 0.062" thickness and 48" by 48" size, two parts with 41 and 12 counts respectively are arranged as shown in Figure 1. Note that 24 small parts were placed inside the cut-offs ("holes") of large parts for better material utilization. The start position (piercing) and cutting sequence of geometric entities are shown by red lines. The cutting speed varied from geometry to geometry, and the fabrication was not in part-by-part order. There is not a viable way to know the correct machine run time for each part given the machine run time of the entire sheet.

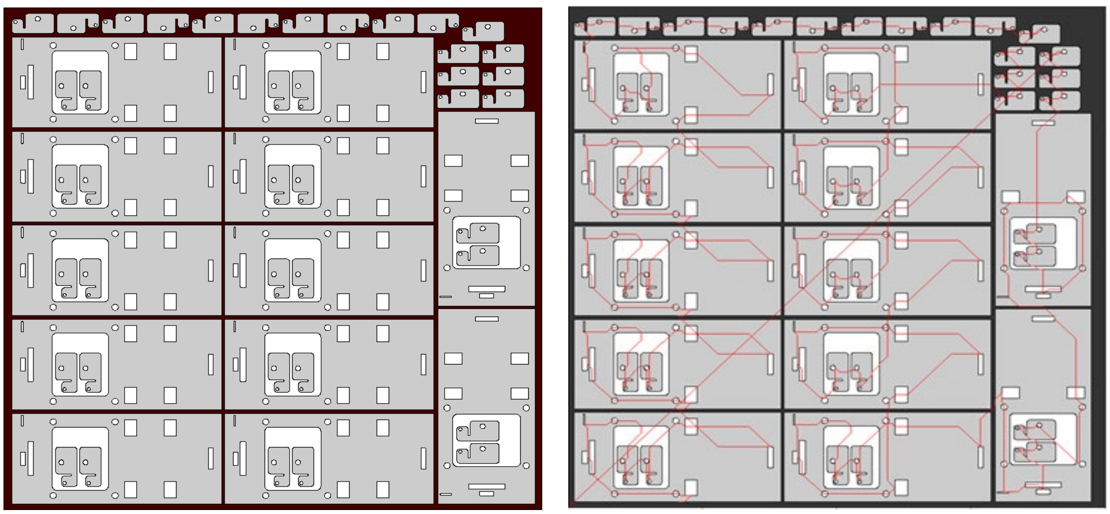

Figure 1. Cutting routes for 53 parts on a sheet blank

This paper proposes a Machine Learning approach to overcome this obstacle. We collected machine run time and geometric characteristics data for 348 sheet blanks with parts of various shapes and sizes. The approach also considers laser cutting actions such as piercing and fast move. By analyzing the cutting time of different shapes and establishing a relationship between cutting time and geometric characteristics, and through the training of three regression models, we can distribute the machine run time of a sheet blank to every part on the sheet blank with 92% or higher precision.

The proposed approach can be implemented on any laser cut machine, and will enable accurate machine run time of parts, regardless of the machine model used. Currently, the research is being expanded to encompass additional geometric characteristics of laser cut machines and to incorporate manufacturing features of turret punch machines, with the aim of developing a more comprehensive and versatile model.

1.1 Objectives

The objective of this paper is to provide a more precise and consistent approach to assign machine run time to each part on sheet blanks fabricated by laser cut machines. It is achieved by using Machine Learning method to distribute machine run time based on parts' geometric characteristics and associated laser cutting actions. 348 sheet blanks of parts with various geometries were executed to validate the approach. With real-time data collection in the era of Industry 4.0, our proposed approach can immediately and automatically calculate the parts' machine run time on any laser cut machines.

2. Laser Cutting Review

For laser cutting, a laser beam is emitted from the *laser head device* on the laser cut machine. Laser beam will penetrate (*piercing*) the sheet blank before actual cutting takes place. Unlike turret punch machines where the sheet blank moves during punching operations, it is the laser head device that moves during cutting. Due to the part's stability concern while cutting, a part's outer boundary is usually the last geometry to be processed by the laser beam. If a small part is placed inside a hole of a larger part, that small part will be cut before the cutting of its bounding hole. Based on parts' sizes, orientations, geometries and locations, cutting patterns and cutting routes may vary from part to part on sheet blanks regardless these parts are the same or not. As of today, shop owners rely on experienced workers to assign part's machine run time. However, this approach is seldom reliable nor consistent. Also, it is not uncommon to switch laser cut machines on the shop floor. Even though only small change in numerical control commands may be needed under such situation, the machine run time of parts, if ever re-assigned, becomes obsolete.

3. Model Formulation

The motion of laser head device on laser cut machines is dictated by two motors controlling the movements in X (length) and Y (width) directions respectively. It is assumed that these two motors are of the same characteristics. The geometric entities considered in this research are lines, circles, arcs, and composite curves. We first establish the relationship between laser's cutting time and polylines (piecewise continuous) characteristics, followed by extending the same concept towards circles, arcs, and composite curves. The piercing and fast moves actions are included in formulation. The geometric characteristics and cutting actions used in the model formulation are illustrated in the Figure 3 and explained in the sections below.

3.1 Polylines

For a rectangular part, the velocity-time and acceleration-time relations of cutting are shown in Figure 2 where **s** denotes the maximum speed and **a** denotes the acceleration of the laser head device. The cutting time t_1 and t_2 are derived by applying Newton's law of motion, as given in the Eq. 1 and Eq. 2 respectively. The total cutting time (t_p) for the rectangular part is subsequently calculated and shown in the Eq. 3. Note that the numerical value ***4*** in the Eq. 3 denotes the number of corners where the laser head device stops to make a turn.

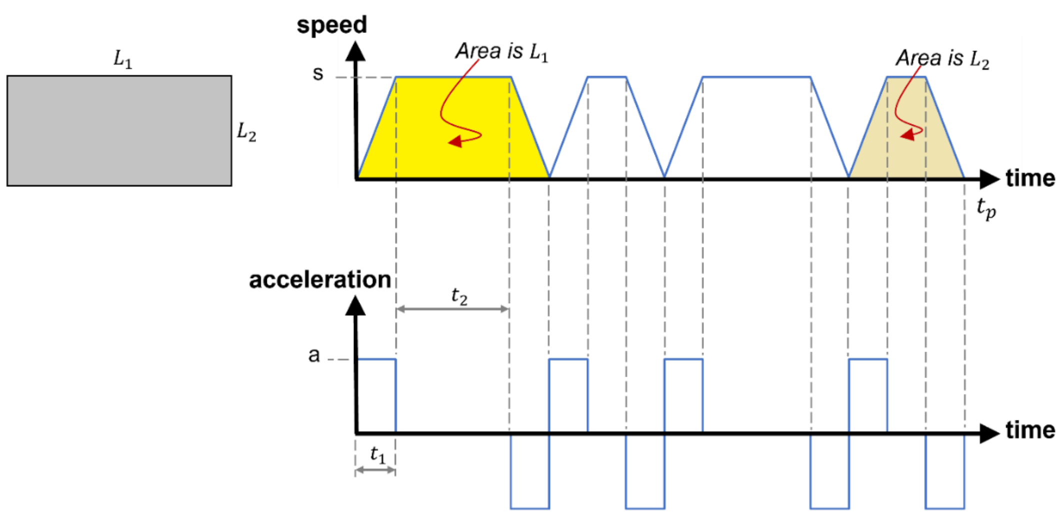

Figure 2. Velocity-time and acceleration-time charts of motors at cutting

$$t_1 = \frac{s}{a} \tag{1}$$

$$t_2 = \frac{L_1 - \frac{s^2}{a}}{s} \tag{2}$$

$$t_p = \frac{1}{s}(2L_1 + 2L_2) + \frac{s}{a} \times 4 \tag{3}$$

Similar induction is done for the cutting of polylines, and the corresponding cutting time is given in the Eq. 4 where *# of stops* is an integer number as long as the laser head device can reach its maximum speed **s** for every polyline segment.

$$t_{total} = \frac{1}{s}(total\ length) + \frac{s}{a} \times (\#\ of\ stops) \tag{4}$$

For cutting short lines, however, the laser head device cannot reach the maximum speed **s** before it must decelerate to stop. A scaling factor (less than 1.0) is therefore added to represent its highest speed when cutting each small line segment. The total cutting time for a polyline with arbitrary length of its segment is given in the Eq. 5 where the factor *k* reflects the collective effect of cutting time resulting from the stops between line segments (both long and short). In reality there can be time delay between cuttings, therefore the general form of the total cutting time for polylines can be expressed by the Eq. 6 where *travel* being the total length and the *# of stops* being the number of vertices of a polyline. The coefficients A_0, A_1, and A_2 are to be determined. As demonstrated in the Eq. 6, the cutting time of polylines is associated to two geometric characteristics – *travel* and *# of turns* (or *stops*).

$$t_{total} = \frac{1}{s}(total\ length) + \frac{s}{a} \times k(\#\ of\ stops) \tag{5}$$

$$t_{total} = A_0 + A_1(travel) + A_2(\#\ of\ turns) \tag{6}$$

3.2 Circle

Cutting time of a circle relates to its circumference and curvature (reciprocal of radius). The geometric characteristic of a circle can be its diameter or its circumference. We choose circumference because it is the actual cutting length. Note that the cutting time between small and large circles may not be proportional to its circumference. This is because of the highest speed that the laser head device can reach for small circles. Since we collected cutting time of various sizes of circles, the curvature of circle was skipped to be a geometric characteristic in this research.

3.3 Arc

Cutting time of an arc relates to its length and curvature (reciprocal of radius). The geometric characteristics of an arc can be the arc radius and arc angle, or the arc length and sector area of its corresponding circle. Since the arc length is the actual cutting length, the latter is used. By collecting cutting time of various sizes of arcs, the curvature of arc was skipped to be a geometric characteristic in this research.

3.4 Fast Move

The laser head device moves rapidly from the ending cut of one geometry to the start piercing of the next geometry. Depending on laser machine's setting, the laser head device may either lift up then move, stay low and move, or lift up and move simultaneously. Because the fast move in X and Y directions start at the same time, we chose the longer moving distance from either X or Y directions to be the geometric characteristic in every fast move action. The total fast move lengths in X and Y directions are two geometric characteristics.

3.5 Composite Curves

A part's geometries can use composite curves consisting of lines and arcs in this research. We treat lengths of line segments and arc segments of composite curves as two separate geometric characteristics. They should not be confused with lengths from the polylines and arcs.

3.6 Line-Arc Joint

Analogous to the *# of turns* for polylines, the *# of line-arc-joint* is identified as a geometric characteristic.

3.7 Piercing

Laser beam penetrates the material (*piercing*) before actual cutting takes place. The time of penetration differs among all laser cutting machines. Some machines use a fixed time interval for piercing while the others can detect actual occurrence of penetration and initiate cutting. However, the *# of piercing* as a feature in the model training is sufficient regardless of piercing type. Note that the model training is for one machine only.

3.8 Aspect Ratio

It is noticed that cutting time is longer for geometries with high aspect ratio such as a row of long and lean holes. The aspect ratio of geometry was chosen to be a geometric characteristic in our pursuit of machine run time model using Machine Learning method.

4. Data and Regression Model

4.1 Data

A low-power laser cutting machine, model *DC-13090* from the *Taiwan 3 Axle Technology Co*., was used to cut 34 sheets of rectangular parts of various sizes and quantities, 35 sheets of triangular parts with various sizes and quantities, 53 sheets of circular parts with various sizes and quantities, 25 sheets of obround-shaped parts with various sizes and quantities, 43 sheets of round-corner-shaped parts with various sizes and quantities, 57 sheets of cross-tip-shaped parts with various sizes and quantities, 64 sheets of teeth-shaped parts with various sizes and quantities, 28 sheets of composite-curve-shaped parts and 10 test sheets of real parts with various geometries.

Eleven (11) geometric characteristics data (polylines, circles, arcs, # of stops, # of piercing, fast move X length, fast move Y length, composite curve line length, composite curve arc length, # of line-arc joints, aspect ratio) from parts, and one shop floor data from machine (machine run time) were collected by running 348 sheet blanks. Examples of the training sheet blanks are shown in the Figure 4. The actual data collected from running 338 training sheet blanks and 10 test sheet blanks are given in Tables 1 and 2 respectively.

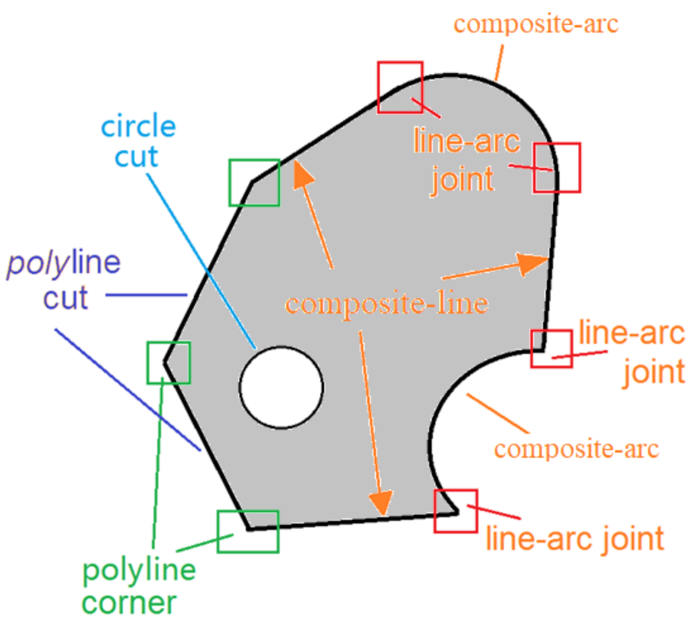

Figure 3. Geometric characteristics of a composite curve

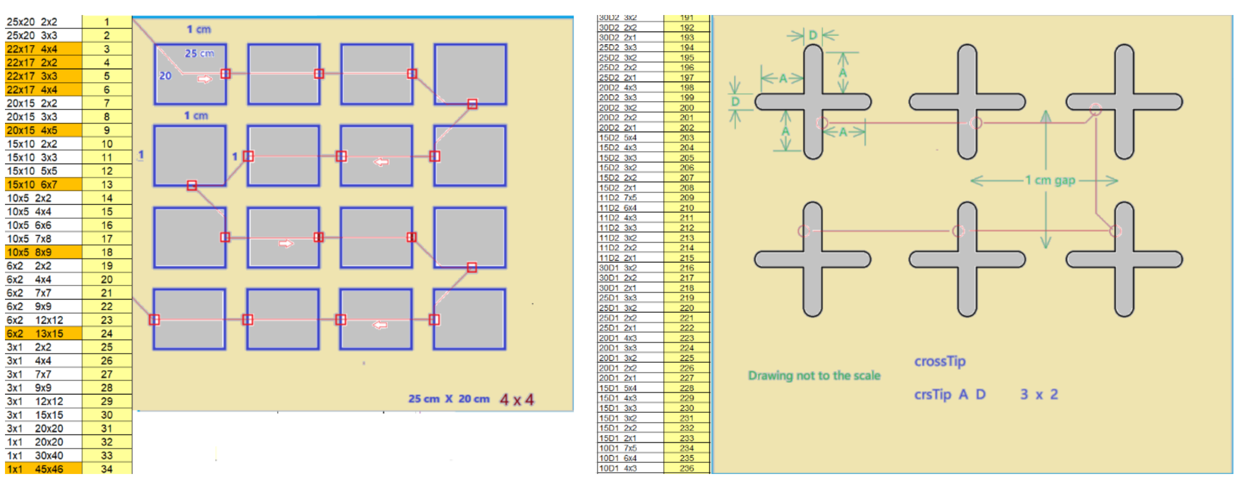

Figure 4. Examples from 338 training sheet blanks and parts

4.2 Regression Models

We chose three regression models—Linear Regression, Ridge Regression and Lasso Regression—to train with the machine run time of *DC-13090* model and the geometric characteristics of parts from 338 sheet blanks. The training goal was to minimize the error functions with the collected data. The error functions for the Linear Regression, Ridge Regression and Lasso Regression models are given in the Eq. 7, 8, and 9 respectively. A 5-fold cross validation training procedure was adopted in this research. In addition, permutation of data of 338 sheet blanks were performed before carrying out the 5-fold cross validation procedure. This process was repeated until it was determined that neither overfitting nor underfitting of the three models was found. The accuracy scores (93% and above) of the three regression models based on data of 338 sheet blanks are shown in Table 3. Note that the accuracy scores listed in Table 3 were the average value of scores of the 5-fold validation training procedure.

$$\boldsymbol{E}(\hat{\boldsymbol{y}}, \boldsymbol{y}) = \sum_i (\hat{y}_i - y_i)^2 = \sum_i (wx_i + b - y_i)^2 \tag{7}$$

$$\boldsymbol{E}(\hat{\boldsymbol{y}}, \boldsymbol{y}) = \sum_i (wx_i + b - y_i)^2 + \alpha \sum_i {w_i}^2 \tag{8}$$

$$\boldsymbol{E}(\hat{\boldsymbol{y}}, \boldsymbol{y}) = \sum_i (wx_i + b - y_i)^2 + \alpha \sum_i |w_i| \tag{9}$$

Table 1. Machine run time and geometric characteristics data of 338 training sheet blanks

	A	B	C	D	E	F	G	H	I	J	K	L
1	line cut length	circle cut length	arc-cut length	# of corner	# of piercing	fast move length X	fast move length Y	composite arc cut length	composite line cut length	# of line-arc joint	aspect ratio	machine time
2	360	0	0	16	4	52	21	0	0	0	1.25	77
3	810	0	0	36	9	130	42	0	0	0	1.25	174
4	1248	0	0	64	16	230	54	0	0	0	1.294	267
5	702	0	0	36	9	115	36	0	0	0	1.294	150
6	312	0	0	16	4	46	18	0	0	0	1.294	67
7	280	0	0	16	4	42	16	0	0	0	1.333	60
8	630	0	0	36	9	105	32	0	0	0	1.333	135
9	1400	0	0	80	20	252	64	0	0	0	1.333	299
• • •												
168	0	0	565.2	0	30	286	36	565.2	360	240	1.25	198
169	0	0	301.44	0	16	143	27	301.44	192	128	1.25	106
170	0	0	169.56	0	9	77	18	169.56	108	72	1.25	60
171	0	0	113.04	0	6	55	9	113.04	72	48	1.25	40
172	0	0	37.68	0	2	22	0	37.68	24	16	1.25	13
173	0	0	1507.2	0	120	777	54	1507.2	720	960	1.2	477
174	0	0	1004.8	0	80	511	42	1004.8	480	640	1.2	319
175	0	0	791.28	0	63	399	36	791.28	378	504	1.2	252
176	0	0	602.88	0	48	301	30	602.88	288	384	1.2	192
177	0	0	439.6	0	35	217	24	439.6	210	280	1.2	140
178	0	0	251.2	0	20	119	18	251.2	120	160	1.2	80
179	0	0	113.04	0	9	49	12	113.04	54	72	1.2	36
• • •												
332	192	0	0	64	16	40	12	0	0	0	1	38
333	588	0	0	196	49	148	12	0	0	0	1	156
334	972	0	0	324	81	260	32	0	0	0	1	192
335	1728	0	0	576	144	488	44	0	0	0	1	341
336	2700	0	0	900	225	788	56	0	0	0	1	528
337	4800	0	0	1600	400	1448	76	0	0	0	1	938
338	3200	0	0	1600	400	1086	57	0	0	0	1	634
339	174	0	0	4	1	49.5	0	0	0	0	1.3	38

5. Results and Discussion

With the same parameters found in the Linear Regression, Ridge Regression and Lasso Regression models in training, we generated three regression models using the total data of 338 sheet blanks. The three new regression models were applied to the 10 test sheet blanks (Figure 5). Because the 10 test sheet blanks were not used in training, the resulting scores were good indication of training outcome. The accuracy scores of 338 training sheets and that of 10 test sheets were given in Table 4. It shows that the Linear Regression, Ridge Regression and Lasso Regression models produced the same level of accuracy (91% and 92%). The accuracy confirmed that our proposed Machine Learning method is a reliable approach to predict the machine run time of sheet blanks running on the *DC-13090* laser cut machine.

Table 2. Machine run time and geometric characteristics data of 10 test sheet blanks

1	line cut length	circle cut length	arc-cut length	# of corner	# of piercing	fast move length X	fast move length Y	composite arc cut length	composite line cut length	# of line-arc joint	aspect ratio	machine time
2	1030	0	0	198	30	169	98	0	51	0	28	514
3	3454	45	670.6	630	50	348	91.2	270.26	2961	1196	56.2	1183
4	2513	153.6	452	80	28	362	153	315	19	36	46.5	727
5	376	26	0	124	18	179	125	0	64	0	15.7	514
6	553	249	317.8	56	18	359	42	257.48	468	184	83.25	453
7	696	241	0	64	15	288	95	0	160	0	46	641
8	1080	56	164.4	264	8	175	75.5	124.44	1044	184	13.3	345
9	988	120	102.4	299	15	112	52.9	62.46	758.8	260	36.83	401
10	1296	39	73	104	25	575	160	100	920	128	127	641
11	320	282.6	54.95	16	25	189	27	25.31	35	140	51	537

Because the accuracy level was almost identical among three models, Ridge Regression model was chosen to distribute the total machine run time of a sheet blank to each individual part on the sheet blank. Note that the machine run time for a sheet blank was calculated based on the sum values of geometric characteristics from every part on the sheet blank. Therefore, if we apply geometric characteristic values of a part in the same Ridge Regression model, it gives the machine run time of that part. It should be noted that the value of *fast move length* that precedes the first piercing of a part belongs to that part. The 27 parts on the 10 test sheet blanks were assigned their machine run time according to this calculation.

We further put each of the 27 parts on a new sheet blank to obtain the machine run time of cutting one part only. The actual machine run time of fabricating one part, and the calculated machine run time by Ridge Regression model were compared. It is found that the overall difference of machine run time for the 27 parts is 13% which is shown in Table 5. It should be noted that cutting only one part to see the machine run time was not a realistic way for this purpose, nor was it correct to simulate real cutting of many parts involving complicated routes and sequences.

In practice, the time difference of the actual machine run time (collected) and regression model time (calculated) is distributed among all parts on the sheet blank. A common way to divide this time difference is based on the ratio of the regression model time of a part and that of the sheet blank. The sum of machine run time of all parts will finally equate to the machine run time of sheet blank collected from the *DC-13090* laser cut machine.

Table 3. 5-fold validation training results

	5-fold training score	5-fold validation score
Linear Regression (default)	96%	94%
Ridge Regression (α = 1.0)	96%	93%
Ridge Regression (α = 10.0)	96%	93%
Ridge Regression (α = 0.1)	96%	93%
Lasso Regression (α = 1.0)	96%	94%
Lasso Regression (α = 0.01)	95%	95%
Lasso Regression (α = 0.001)	94%	94%

A part's manufacturing cost of laser cutting is proportional to its machine run time. All expenses associated with the manufacturing activities, including utilities, people's pecuniary compensation, equipment, finance, machine efficiency, etc. are directly or indirectly linked to the machine run time. The average machine run time of the same parts is therefore used for the manufacturing cost calculation.

Table 4. Test results of 10 test sheet vs. 383 training sheets

	383 sheets training score	10 sheets test score
Linear Regression (default)	96%	92%
Ridge Regression (α = 1.0)	96%	92%
Lasso Regression (α = 0.01)	95%	91%

5.1 Numerical Results

The comparison of actual run time of cutting one piece and the predicted run time from Ridge Regression model is listed in Table 5 for reference. The average difference is 13% for the 27 parts.

Table 5. Actual machine run time and the run time calculated based on geometric characteristics

Sheet - Part	Actual Run Time	Predicted Run Time	difference (ratio)		Sheet - Part	Actual Run Time	Predicted Run Time	difference (ratio)
1-A	7.0	8.5	0.21		4-E	38.0	40.5	0.07
1-B	22.1	23.6	0.07		4-F	20.0	22.5	0.13
1-C	17.7	19.2	0.08		5-A	25.2	27.4	0.09
2-A	6.6	8.7	0.32		6-A	42.2	45.9	0.09
2-B	6.3	8.4	0.33		6-B	43.8	47.5	0.08
2-C	7.6	9.7	0.28		7-A	44.3	48.1	0.09
2-D	90.7	92.8	0.02		7-B	39.5	43.3	0.10
3-A	5.6	7.9	0.41		8-A	47.2	49.5	0.05
3-B	64.5	66.8	0.04		8-B	15.3	17.6	0.15
3-C	62.1	64.4	0.04		8-C	11.4	13.7	0.20
4-A	36.0	38.5	0.07		9-A	41.1	43.3	0.05
4-B	21.0	23.5	0.12		9-B	11.4	13.6	0.19
4-C	12.8	15.3	0.20		10-A	21.5	23.4	0.09
4-D	33.0	35.5	0.08					

5.2 Proposed Improvements

The accuracy of three regression models can be improved if we include more features in the model formulation. Several features are considered for future improvements.

The true velocity-time and acceleration-time relationships of laser head device during laser cutting may be nonlinear. The higher order term(s), e.g. quadratic term, of the *polyline length* and *arc length* can be the additional features in order to capture the nonlinearity aspect of motion of the laser head device.

The curvature of circles and arcs is a geometric characteristic in addition to their length. The curvature of circles and arcs can be represented by the ratio of arc/circle's length divided by the arc/circle's sector area. Although we collected sufficient data from circles/arcs of various sizes in this research, curvature of circles/arcs could enhance the formulation of Machine Learning model.

Other curves such as B-Spline can be included in parts' geometry. The length of a curve can be computed in general. The curvature of a curve can be computed by the collective ratio of the curve's length versus the combined sector areas associated with the curve.

338 training sheet blanks were executed on *DC-13090* laser cut machine for the data collection. For other laser cut machines, it would require similar collection process for model training. This is not realistic in the real shops. Instead, we should automatically record the machine run time of sheet blanks, and retrieve geometric characteristics of parts on sheet blanks that run through laser cut machines. This is quite doable since almost all numerical control programs nowadays are generated by CAD/CAM software in which the geometric characteristics of parts are available. Sufficient amount of data can be accumulated for the application of the proposed approach.

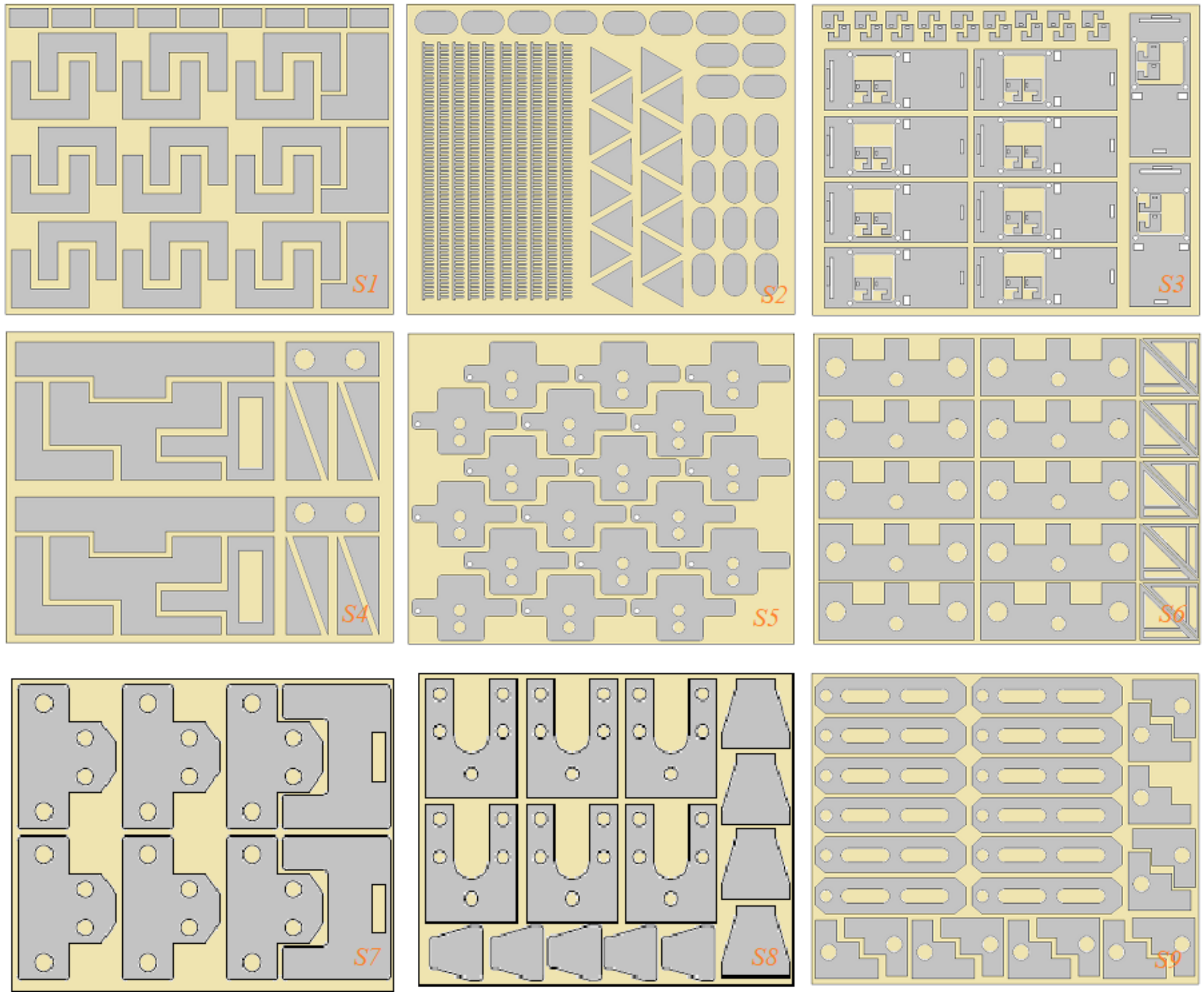

Figure 5. Parts on the test sheet blanks

6. Conclusion

A new approach is proposed to distribute the machine run time of a sheet blank to each part on the sheet blank for all laser cut machines. It adopts Machine Learning method and is based on parts' geometric characteristics and associated laser cutting actions. Through the training of Linear Regression, Ridge Regression, and Lasso Regression models, 338 training sheet blanks were executed with 93% to 95% accuracy result using 5-fold cross validation procedure, and 10 test sheet blanks with 91% to 92% accuracy result. Machine run time for the 27 parts on 10 test sheet blanks were accordingly assigned and verified. Additional geometric characteristics can be included for a broader geometry of sheet metal parts if needed.

Our results demonstrate that the proposed approach is viable to provide precise and consistent machine run time (hence manufacturing cost) for parts of various geometries on a sheet blank. It can replace the subjective estimation currently used in industry, and can be automated with real-time data collection in the era of Industry 4.0. The approach can be expanded to incorporate manufacturing features of turret punch machines to develop a more comprehensive and versatile model.

Acknowledgements

The authors would like to thank NSTC (National Science and Technology Council) of Taiwan for the financial support of this research.

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Biographies

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