Advancing Cutting Table Estimation with the Help of AI

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Abstract

Profitability in the printing industry relies heavily on accurate estimation techniques. Estimating cutting table technology is an area that has proven problematic for companies within the print industry, as we are often limited in knowledge about the scope of a project prior to completing the estimate. While some companies utilize an existing method of cutting estimation, that process has proven unreliable and inconsistent, often throwing off pricing and scheduling structures. This study seeks to expand on prior research to develop a system that more accurately calculates time standards for cutting table estimation.

The results of the study prove promising. With the help of a well-developed mathematical equation that accounts for table speeds (acceleration adjustments), total cut distance, and critical corner/node counts (built in stop time), we can much more accurately assess total cut time. To speed up the estimating process, we can build out a simple prompt within an AI and have the math run for us.

Introduction

In an industry where we produce product upon order, profitability can be a major challenge. In most manufacturing, you sell a product often sitting in inventory, meaning as supply decreases or material costs increase, the price changes to guarantee a profit. This change may happen on a day-to-day or week-to-week basis. In print, we estimate a job, often prior to even seeing artwork, and then are held to that estimate. It is not until after all production is complete that we can truly determine if that job turned a profit for us. Profitability is necessary for a company to survive. For printing companies in the United States, data suggest that the average profit margin was below 5% for 2024 (IBIS World, 2024).

Similar figures may exist beyond the U.S. borders. Therefore, the need to ensure profitability, accuracy, and consistency in job estimation is essential. In communicating directly with companies across the U.S., one asset/cost center that

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many struggle with is cutting table estimation. This is due to a variety of reasons but includes: the speed differences across cutting and scoring tools, the material being cut (e.g., paperboard, corrugate, wood, metal), the intricacy and complexity of the designs, and the shape of and the sizing of the designs. In some situations, larger designs cut faster than smaller designs due to the smoothness of the shapes and ease of cutting/scoring tool transitions (Calkins & Jacob, 2025). One thing brought forward in prior research was that perhaps the number of direction transitions for the cutting/scoring tools would be a better predictor of cutting time than any of the previously stated reasons.

When looking at the various ways of estimating these costs, it is important to ensure that accuracy, consistency, and efficiency are considered. Currently, there seems to be an industry-wide discrepancy in the estimation of cutting table technology which is presenting a big problem for companies looking to make a profit. With increases in shorter runs, advancements in technology, and expanding print markets, the use of cutting technology is increasing across the nation. Having a reliable and consistent way to estimate costs and schedule jobs becomes crucial.

Due to the lack of reliability, in the current way of estimating cutting table costs and then considering the increased use of AI within the industry, a new approach was considered. This paper builds directly on prior research by Calkins and Jacob (2025), which looked at cutting times across different tools and substrates and highlighted the limitations of the existing estimation methods. That study showed that circumference-based estimation with a fixed complexity factor could underestimate actual cut times by more than eight minutes for a single complex shape. The current study furthers this work by introducing an AI-assisted, physics-based approach that incorporates total cut distance and the number of nodes/critical corners as identified by Adobe Illustrator, a standardized stop time per node/critical corner, and machine acceleration factors.

Research questions guiding this study include the following:

1. Can AI help in estimating the number of transition points in a job to allow for estimation of the job prior to obtaining the official artwork?
2. Can we create more robust time standards that could serve as a proxy for estimating cutting table jobs that are very seldom typical?
3. Do node/critical corner counts paired with machine acceleration factors accurately reflect real-world CAD table procedures, like stop-lift-adjust-restart?
4. How does the AI model perform across different levels of shape complexities, and where are there still gaps?

Prior Calculations

The old framework for estimating cutting table production time relies on a six-step process created by Wilson and Carey (2020) which was re-examined by Calkins and Jacob (2025). The method bases estimation for cutting tables (see Figure 1) on the length of the cut, the number of cuts needed (in the event of multiple products/repeats), the speed of the cutting tool being used, and then a complexity factor subjectively applied by the estimator. Complexity factors range from simple (4x) to very complex (20x). Interestingly, the length of the cut only accounts for the exterior cut dimension based on an equation of:

$$C=2\pi r \quad \text{or} \quad C=\pi d$$

For these equations, the estimator would need to determine the diameter of the shape and then multiply by pi (or multiply the radius by two, then by pi). In the case of unique or complex shapes, these equations do not accurately represent actual cut lengths. Further, if there are any interior cuts, those are only accounted for by applying a higher complexity factor within the estimate.

Cutting Table Production Standards (hourly rate: $115.00)					
Setup time		Cutting tool base rates per linear inch		Shape Complexity	Time increase
single sheet	5 min first sheet; 1 minute per additonal	serigraphy knife	1100 in/min (2794 cm/min)	simple	4x
step & repeat per piece	5 min first sheet + .25 minutes per piece	high frequency knife	900 in/min (2286 cm/min)	medium	8x
milling	10 min first piece; 1 minute per additonal	millling knife	236 in/min (600 cm/min)	high	12x
kiss cut	add 5 minutes			very high	20x

Figure 1: Example of Time Standards for Cutting Table Production.

While this method does provide a baseline, prior research showed significant inaccuracies, especially for designs with intricate internal cuts (Calkins & Jacob, 2025). For example, the ISU seal observed in Figure 2 is classified as a very complex shape; the known method predicted a cut time of 57.6 seconds. This is largely due to only accounting for a rough proxy of circumference and utilizing the complexity matrix that doesn't account for the significance in internal cuts and added cut distance. The actual cut time was 9 minutes and 51 seconds, a difference of over 8 minutes for a single cut.



Figure 2: Example of Shape Complexity

Shape	Complexity	Speed	Cut Distance	Old Method	Actual Time	Difference
1	Simple	16.4 in/sec	43.8”	11.76 sec	6 sec	+5.76 sec
2	Simple	16.4 in/sec	45.35”	7.2 sec	7 sec	+.2 sec
3	Simple	16.4 in/sec	73.5”	11.52 sec	31 sec	-19.48 sec
4	Moderate	16.4 in/sec	81.45”	24.48 sec	1min 1 sec	-36.52 sec
5	Moderate	16.4 in/sec	60.25”	20.64 sec	1 min 27 sec	-1min 6.36 sec
6	Moderate	16.4 in/sec	50”	22.56 sec	36 sec	-13.44 sec
7	Complex	16.4 in/sec	112.44”	25.92 sec	46 sec	-20.08 sec
8	Complex	16.4 in/sec	167.43”	25.2 sec	1min 49 sec	-1min 23.8 sec
9	Very Complex	16.4 in/sec	363.37”	56.4 sec	7min 17 sec	-6min 20.6 sec
10	Very Complex	16.4 in/sec	480.29	57.6 sec	9min 51 sec	-8min 53.4 sec

Table 1: Prior Cutting Table Estimate Results

This discrepancy in estimating time undervalues production times and challenges scheduling systems. As seen in Table 1, across all 10 original test shapes (see Appendix A for a visual of all shapes), the total difference between estimated and actual time exceeded 19 minutes and 16 seconds, with 60% of shapes exceeding the estimate by 35 seconds or more and only a single shape being less than 5 seconds. Based on the prior research there were only two instances of overestimation, both of which had a simple complexity factor applied.

Two key factors explain the inaccuracy of circumference-based estimation. First, determining the circumference of complex shapes without the design file is naturally inaccurate with prior research showing a 55% deviation between hand-estimated circumference and the actual cut value as measured in Adobe Illustrator (Calkins & Jacob, 2025). Second, the current complexity factors do not adequately capture the mechanical behavior of cutting tables. Every angle or directional change in a cut path often requires the machine to stop, lift the blade, adjust, and restart, adding time that grows with the intricacy of the design rather than simply with cut distance or circumference.

The prior research gave insight into factors that could be ruled out. For example, the type of substrates did not seem to make a significant difference in the overall estimation time, and size of shape or distance of cuts was not the most important factor in determining cut times. In fact, some larger shapes with one and a half times the cut distance actually cut faster than the smaller shapes. A suggestion to evolve the process of estimation by focusing on cutting table operations and cut procedures rather than cut distance was given from an audience member at the 2025 Technical Association of the Graphic Arts (TAGA) Conference in Boulder, Colorado. This proved to be good directional shift to continue this research.

Tools, Software, and Materials

As this is a direct continuation of Calkins and Jacob's (2025) previous research, the ten design files that were originally created to represent varying levels of complexity were used (Appendix A). Complexity factors remained the same for each shape as they are based on the number of internal and external cuts, curve intricacy, and overall path detail. Total cut distance and node/critical corner counts were identified in Adobe Illustrator. For all testing, the Kongsberg X20 CAD cutting table in Illinois State University's print center was utilized. The High-Frequency Vibracut Knife Tool with the SR6224 blade was selected for its speed and versatility across varying levels of design complexity. The default speed of 16.4 in/sec was selected for testing as it would provide a more general application in the industry. All testing was done on a single substrate, a white paperboard with a thickness of 0.024 inches. This was done to ensure that differences in substrate would not skew our results.

For all AI analyses, two different AI systems were used. Two common platforms were chosen as they are readily available for public use and are simplistic enough that our methods could be repeated industry wide. While Smith used the free editions of these platforms, Calkins subscribed to the systems. This served as a secondary analysis to see if the results would differ between a free edition and a paid for edition. In each case throughout this study, the same prompt wording was used within each AI system for consistency and to assess repeatability across the different AI systems.

Results

Image-Based Critical Corner Analysis

To begin this research, a critical corner count analysis was attempted via the AI platforms. The AI systems were asked to analyze each image and count the critical corners where it would be likely that a cutting table would have to stop-lift-adjust-and restart to complete a cut. The idea was to see if the AI counts could be used as a reliable metric to help estimate cut time. Since observations prove that at times cutting tables need to slow, stop, lift the blade, adjust, and lower the blade to continue cutting, we must account for this if we want a more accurate assessment of total cut time.

Shapes were individually uploaded to both AI platforms. Shape 1 (a circle), Shape 2 (a rectangle) and Shape 7 (six circles within a rectangle) were excluded due to ease of determining critical corners/nodes: circle – no critical corners; rectangle – four critical corners; six circles within a rectangle – four critical corners. The more challenging/complex shapes, where AI was expected to provide a greater value, were used for this portion of the analysis.

Results, shown in Table 2, were inconsistent both across platforms and compared to node counts from Adobe Illustrator. For instance, in moderate designs like Shape 5, the AI models only captured a fraction of the angles that would require the cutting table to stop and adjust. Figure 3 shows the exact areas that AI1-CC identified as locations where lifts for Shape 5 would occur; however, visually it can be seen that there are many other angles/corners that would likely also require a stop/lift that are left uncounted. One AI platform (AI2-CS) ultimately instructed the researchers to count the corners themselves.

Shape	Complexity	AI1-CS	AI2-CS	AI1-CC	AI2-CC	Illustrator
3	Simple	16	16	16	16	16
4	Moderate	38	40	56	32	81
5	Moderate	32	17	20	23	224
6	Moderate	21	0	12	7	54
8	Complex	35	26	56	12	143
9	Very Complex	0	0	316	94	656
10	Very Complex	0	0	445	214	833

Table 2: Critical Corner Count Results

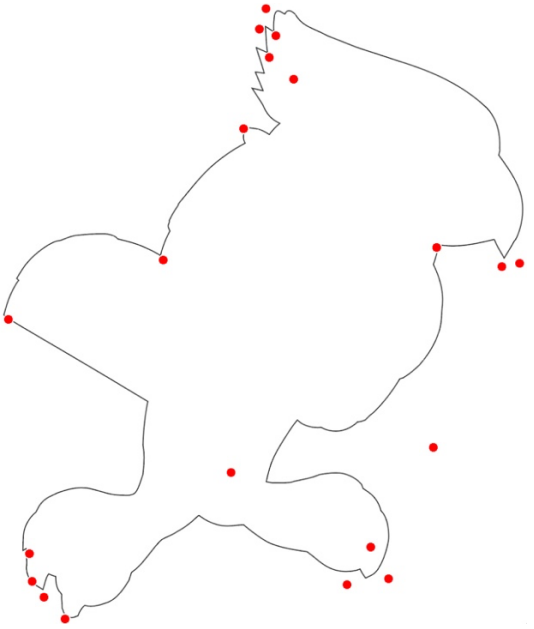


Figure 3: Shape 5 AI Identified Critical Corners (20)

The massive discrepancy across the moderate to complex categories proved that asking AI to count corners alone was not a reliable approach to help capture the potential movements of the cutting process. It became clear that while considering critical corners was a step up from basic shape circumference, AI can't yet replace the precision of cutting-based node identification for predicting actual table behavior and times.

Video-Based Critical Corner Analysis

The next approach was video-based lift counting via AI. Cutting sessions were recorded and then watched individually (by each researcher) to manually count the exact number of lifts through each cut. Videos were watched by each researcher no fewer than three times to validate counts. By individually watching the videos at a slow speed, a baseline was created to check for the accuracy and consistency of counts not only across researchers, but then ultimately by the AI systems. The videos were then uploaded to both AI platforms utilizing the same prompt to carefully analyze the cutting table motion in each video. The systems were asked to count the number of times the cutting table had to stop movement, lift the blade off the substrate, adjust, and lower the blade to continue cutting. Once again Shapes 1, 2 and 7 were excluded due to ease of determining the number of stops: circle – no stops; rectangle – 4 stops; six circles in a rectangle – 10 stops. Shapes 9 and 10 were also excluded due to shape complexity and the file sizes. These shapes were unable to be loaded into the free versions of the different AI platforms.

Results, observed in Table 3, were again inconsistent. This was surprising to see even within the same platform, analyzing the same videos, and utilizing the same prompt. Smith's AI-2 was unable to run video files in general; either rejecting the files or timing out during the analysis. Others were producing counts far below what was manually counted (columns 3 (CS) and 4 (CC)).

Shape	Complexity	CS	CC	AI1-CS	AI2-CS	AI1-CC	AI2-CC
3	Simple	15	15	18	N/A	9	10
4	Moderate	63	62	38	N/A	9	5
5	Moderate	57	57	33	N/A	54	31
6	Moderate	28	28	23	N/A	12	18
8	Complex	70	70	35	N/A	7	14

Table 3: Lift Video Count Results

Analysis and file naming were other struggles faced when uploading the videos to both AI platforms. Even with the simplest of shapes, both AI systems took substantial time in analysis, often thinking for over 15 minutes before rendering results. One AI platform tried using information from the file name itself to inform its answer. For example, Shape 3's video file was named 'star', so AI-2 went by its own logic, assuming it was a 5-point star outline that must have 10 lift points (five outer points + five inner re-entrant corners). With further prompting for inspection of the geometric shape, the AI system acknowledged that the shape

geometry did reflect an 8-point star, however despite this, AI-2 refused to adjust the lift count, insisting there were still only 10 lift points.

Not considering the time of recording the cutting process, the experience with asking AI to analyze a video for cutting table movements proved unreliable and time intensive. It was not something that we believed anyone in industry could reasonably be able to devote time to. Given the inconsistencies of AI in analyzing images or videos, it was determined that a return to pure math may be the best hope for AI integration in this estimating process. Ultimately, this did mean a return to some subjectivity in the cutting table estimation process, as the complexity factor of designs is left to user.

Return to Mathematical Modeling

For the final approach, it was clear that there were some things AI was not yet ready to help with, so we returned to direct mathematical equations. The expectation was that by using quantifiable inputs like total cut distance, number of nodes/critical corners in the design (identifiable in Adobe Illustrator as seen in Figure 4), a per-node stop time of 0.5 seconds (for consistency and simplicity), and a machine acceleration factor associated with shape complexity, predicting more accurate cutting times could be achieved.

Sticking to what could work from the original model, the shape complexity matrix that was previously used was carried over and used to establish acceleration speeds associated with each complexity category, seen in Table 4. For example, if the shape is considered simple with minimal lifts it would be expected that the CAD table would be able to operate at faster speeds than if the shape was considered very complex, which requires frequent stops, which prevents that table from achieving full speed. Further, the complexity of the shape is used to determine how many nodes to account for within the estimating model.

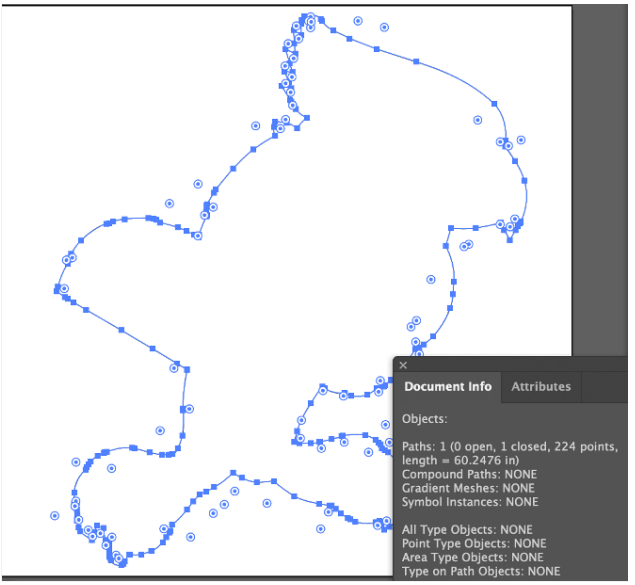


Figure 4: Adobe Illustrator Node Count of Shape 5

Complexity Options	Accel Factor	Stop Time	Node Count	
			Majority Smooth/Majority Critical	
Simple	Fast – 300in/s^2	.5 Sec	50%	100%
Moderate	Moderate – 200in/s^2	.5 Sec	50%	100%
Complex	Slow – 100in/s^2	.5 Sec	50%	100%
Very Complex	Very Slow – 50in/s^2	.5 Sec	50%	100%

Table 4: Shape Complexity Matrix

Human judgment is still needed to decide the shapes' complexity and if it's smooth (where 50% of nodes are counted) or critical (where 100% of nodes are counted). For instance, a simple circle (Shape 1) and the Reggie Redbird outline (Shape 5) were classified as smooth, while the Illinois State University seal (Shape 10) and the club card (Shape 8) were classified as fully critical as seen in Table 5.

Based on specifications within the model and human intuition (subjectivity) based on a visual assessment of each shape, Table 5 shows the prompt specs for each of the original 10 shapes. In only three instances was it specified to account for only

50% of the identified nodes: Shape 1, which is a circle; Shape 5, which is the Reggie Redbird outline seen in Figures 3 and 4; and Shape 7, which was labeled complex due to having internal cuts, but consisted of simple shapes (circles inside of a rectangle). All remaining information was the same from 0.5 seconds for the stop time to the acceleration aligning with the shape complexity.

Shape	Complexity	Cut Distance	Nodes/ Points	Prompt Specs
1	Simple	43.8”	4	.5 seconds, fast accel (300in/s^2), 50% nodes
2	Simple	45.35”	4	.5 seconds, fast accel (300in/s^2), 100% nodes
3	Simple	73.5”	16	.5 seconds, fast accel (300in/s^2), 100% nodes
4	Moderate	81.45”	81	.5 seconds, mod accel (200in/s^2), 100% nodes
5	Moderate	60.25”	224	.5 seconds, mod accel (200in/s^2), 50% nodes
6	Moderate	50”	54	.5 seconds, mod accel (200in/s^2), 100% nodes
7	Complex	112.44”	28	.5 seconds, slow accel (100in/s^2), 50% nodes
8	Complex	167.43”	143	.5 seconds, slow accel (100in/s^2), 100% nodes
9	Very Complex	363.37”	656	.5 seconds, very slow accel (50in/s^2), 100% nodes
10	Very Complex	480.29	833	.5 seconds, very slow accel (50in/s^2), 100% nodes

Table 5: Prompt Specs by Shape

The AI-assisted model was applied to all 10 original shapes plus two new validation shapes. When entering the prompts, total cut distance (found on Adobe Illustrator), cutting speed (can be adjusted for different cutting tools and types of tables), number of nodes, and the 0.5 second per point stop time are specified. The prompt is then finalized with adjusting total cut time to include a moderate acceleration rate that factors in the number of points, total cut distance and the rate of speed the table could reasonably achieve between points. For example, our prompt for Shape 5 is the following (take note that the number of points is halved since it's identified as a primarily smooth shape):

“If I had a moderate shape with a total cut circumference of 60.25", and the cad table is cutting at a rate of 16.4 inches per second, how long would it take to cut? Assume the head effectively has to accelerate + decelerate between points and usually can’t get back to full speed. We also need to take into account the number

of pivot points...illustrator indicates there are 112 points in the design. If we average .5 seconds per point additional to allow the cutting table to stop/lift/adjust/drop, how long in total can we expect it to take to cut this shape? Can you adjust this to factor in a moderate accel of about 200 in/s^2?"

Before diving into the results, it is important to note that initially both AI platforms resulted in different cutting times. However, once the acceleration factor was added (last sentence of the prompt), results became identical. They are strictly mathematical models now, so there is no guesswork for the AI model.

Shape	Complexity	Speed	Cut Distance	AI	Actual Time	Difference
1	Simple	16.4 in/sec	43.8"	3.8 sec	6 sec	-2.2 sec
2	Simple	16.4 in/sec	45.35"	5 sec	7 sec	-2 sec
3	Simple	16.4 in/sec	73.5"	13.8 sec	31 sec	-17.2 sec
4	Moderate	16.4 in/sec	81.45"	52 sec	1min 1 sec	-9 sec
5	Moderate	16.4 in/sec	60.25"	1min 8 sec	1min 27 sec	-19 sec
6	Moderate	16.4 in/sec	50"	34.3 sec	36 sec	-1.7 sec
7	Complex	16.4 in/sec	112.44"	25.5 sec	46 sec	-20.5 sec
8	Complex	16.4 in/sec	167.43"	1min 42 sec	1min 49 sec	-7 sec
9	Very Complex	16.4 in/sec	363.37"	7min 46 sec	7min 17 sec	+29 sec
10	Very Complex	16.4 in/sec	480.29	9min 55 sec	9min 51 sec	+4 sec
N1	Moderate	16.4 in/sec	44.37"	26.5 sec	22.54 sec	+3.96 sec
N2	Very Complex	16.4 in/sec	250.41"	5min 16 sec	5min 19 sec	-3 sec

Table 6: Updated Results

Looking at the results in Table 6, the new model held up against the actual cutting times. Across the board, the new model was slightly off, with most actual cut times coming in slightly longer than the AI prediction. Notice the 17.2 second difference for Shape 3 and the 20.5 second difference for Shape 7. The discrepancies, however, both in terms of overestimating and under estimating, are within 30 seconds of actual cut time. The most intriguing part is that for 40% of our shapes the model's accuracy is very precise, being at or under 4 seconds different, with 60% of shapes being within 9 seconds of actual cut time. In total, to cut all 10

shapes, the total time difference between estimate and actual would be 45.6 seconds. Recalling the prior model where the difference for all 10 shapes exceeded 19 minutes, this model shows promise.

To test our model further, two additional shapes were tested. One shape was a four-leaf clover (N1) specified as moderate complexity and the other shape was a Leprechaun (N2) specified as very complex. The four-leaf clover, as seen in Figure 5, has a total cut circumference of 44.37 inches, and it was run at a base rate of 16.4 inches per second. However, as mentioned before, the cutting table doesn't maintain a constant speed. It effectively must accelerate and decelerate between points, often failing to reach its top speed before it must slow down for the next node. To account for this, a moderate acceleration rate of approximately 200 in/s^2 was used to mimic the machine's physical capabilities. The most critical change made in this case involves the node count. While Adobe Illustrator identifies 82 points in this design, we once again halved it for the model based on the smoothness of the shape.

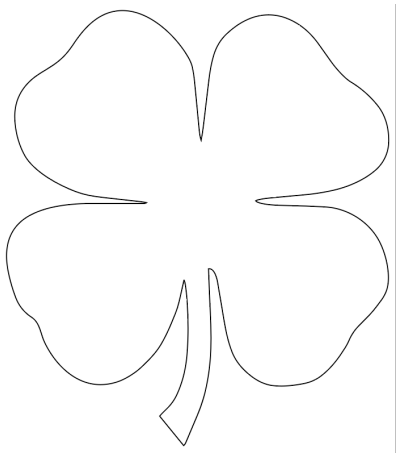


Figure 5: Clover

By combining the raw distance, the machines' acceleration, and this adjusted point count, the model can move away from guessing, toward a more precise expectation of how long it will take the CAD table to produce this shape. Our prompt for this shape follows:

"If I have a moderate shape with a total cut circumference of 44.37", and the cad table is cutting at a rate of 16.4 inches per second, how long would it take to cut? Assume the head effectively has to accelerate + decelerate between points and usually can't get back to full speed. We also need to take into account the number of pivot points...illustrator indicates there are 41 points in the design. If we average .5 seconds per point additional to allow the cutting table to

stop/lift/adjust/drop, how long in total can we expect it to take to cut this shape? Can you adjust this to factor in a moderate accel of about 200 in/s^2?"

Looking at the new shapes in comparison with the original results in Table 6, the model worked well. For N2, the very complex Leprechaun shape, the difference was only 3 seconds off with a cut time of over 5 minutes. For N1, the four-leaf clover, we again achieved high accuracy with only a 3.96 second difference from the actual cut time of 22.54 seconds. These results demonstrate that by accounting for acceleration, stopping time, and adjusted node counts, we have moved significantly closer to a better way of estimating production.

Discussion

The results demonstrate a meaningful improvement in cutting table estimation accuracy. By shifting from a general complexity number to a physics-informed mathematical model that accounts for machine acceleration and the number of critical corners, the new approach captures the actual mechanical behavior of the cutting table more precisely.

The key insight is that cutting time is not primarily a function of cut distance; it is a function of the number of times the machine must stop, lift, adjust, and restart. For highly intricate designs, these micro-movements account for a significant portion of the total cut time. As a result of this, a general complexity factor cannot consistently or adequately approximate a shape's cut time. However, node counts from Adobe Illustrator, paired with a standardized stop time, serve as an effective substitute to assess the cutting table's behavior. The decision to count 50% versus 100% of nodes introduced a human judgement (subjectivity) step that remains necessary but is well-supported by visual inspection of the design. Future work could explore automating this classification.

The use of AI in this research proved to be a learning experience. It was problematic in determining node/critical corners or assessing the physical movements of a cutting table; however, it was successful in consistently answering mathematical word problems. This study revealed that while AI is an extremely capable service that has the power to do incredible things, it still needs human intervention to get visual jobs done correctly and in a timely manner. It is of no surprise that the AI model worked as intended when introduced to a mathematical way of estimating cutting table costs. As time passes, AI intelligence may grow to be able to overcome its visual limitations and be fully capable of estimation without the need for human help.

Conclusion

This study confirms that AI-assisted, mathematical modeling offers a substantially more accurate foundation for cutting table estimation than circumference-based

methods with general complexity factor multipliers. By incorporating total cut distance, node/critical corner counts from design software, machine acceleration factors, and standardized stop times, the new model reduced total estimation error from over 19 minutes to under 46 seconds across 10 shapes, with new shapes reinforcing the model's consistency.

While the new model is not perfect and human judgment remains necessary to classify shape complexity and determine node-count strategy, these decisions are straightforward and well-supported by visual design assessment. To date, the model has proven to be more accurate than the previously discussed process. This consistency provides a much more reliable foundation for high-stakes job estimation in the printing industry.

In the future, this research could be expanded to address the remaining problems in the production environment. Next steps include:

- Building specific calculations for creases, which introduce a new, unique set of start/stop mechanical behaviors.
- Testing the model against different blade types and varying machine speeds.
- Expanding substrate comparisons to evaluate whether material properties introduce variation in the model.
- Exploring if node classification (smooth vs. critical) can be automated through AI image analysis as capabilities grow.

By understanding how different substrates and tools affect our acceleration curves, we can continue to refine our AI logic, further closing the gap between our digital predictions and actual table performance.

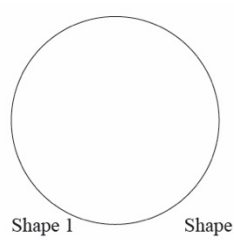
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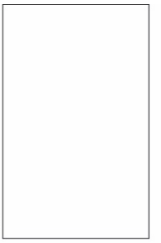
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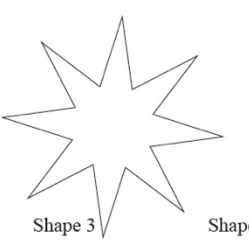
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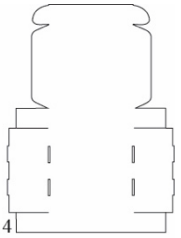
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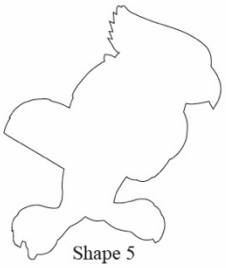
Appendix A – Original 10 Shapes


Shape 1

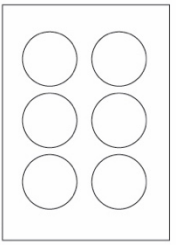

Shape 2

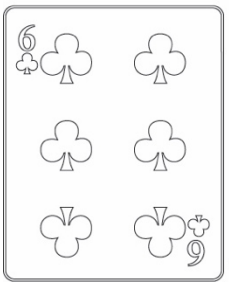

Shape 3


Shape 4

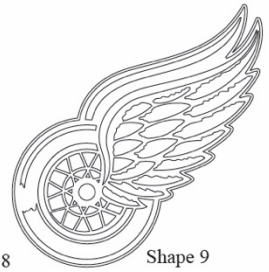

Shape 5


Shape 6


Shape 7



Shape 8


Shape 9



Shape 10