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Improving Cutting Tool Selection in Milling Processes Using Early Cost-Based Valuation

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Abstract

Selecting cutting tools for a milling process is crucial to determine the optimal cut. Minimizing milling process cost is one of the most common optimization objectives, and thus it determines the best cutting tool to be used. However, the chosen cutting tool might not bring the optimal result based on the tool's cost. Therefore, a valuation method based on the process and cutting-tool costs results were developed and analyzed to improve the cutting tool selection process. A specific rough-milling operation was entered to the quick cost-estimation and optimization application, and several cutting tools were compared based on the process cost by each tool. Using a weight-based analysis on both process-cost and tool-cost changes the cutting-tool options' initial rankings. This study showed that using different weight ratios altered the order of the most suitable cutting tools. The study found that using different weight ratios between each cost component results in different tool ranking results and changes the cutting tool selection. Another finding revealed in this study is how deflection constraint affected the rank of cutting tool selection. Thus, knowing the proper limit of deflection is crucial to validate the cutting tool selection outcome.

Keywords: *cutting tool selection, milling optimization, cutting tool valuation, cost estimation, cutting tool deflection*

Introduction

In machining, selecting a cutting tool is crucial in determining the workpiece's finished surface and the process cost and time. A cutting tool is a variable that determines the optimal cutting parameters for a machining process. In this case, optimality depends on the objectives. Optimization objectives could vary, and therefore the cutting parameters such as feed, cutting speed, depth of cut and other cutting parameters relied on that objectives. The most common optimization objective is production cost minimization (Lee et al., 2020). Apart from minimizing the overall costs, the optimization objective could also focus on minimizing production time (Chen et al., 2019), energy consumption (Ma et al., 2017), and even a combination between objectives (Wang et al., 2018). Moreover, optimization could use a lot of techniques other than simple linear modeling. Most modern techniques use probabilistic models to reduce process time while holding a high degree of accuracy. Several statistical methods could be implemented to optimize machining processes, such as the Taguchi model (Ribeiro et al., 2017) and response surface methodology (Badiger et al., 2018). Other probabilistic methods such as an artificial neural network (Abbas et al., 2019), genetic algorithm (Deepan Bharathi Kannan et al., 2019), Nelder-Mead simplex (Lee et al., 2020), and even fuzzy logic (Shankar et al., 2018). Other than probabilistic methods, deterministic methods could also determine optimality, such as the simplex method and combinatorial optimization (Blum et al., 2016; Dai et al., 2017; Hazimeh & Mazumder, 2020).

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However, optimization itself in the machining process is constrained by several aspects. The first factor that limits the optimization boundary is the cutting power needed for the cutting process. The spindle motor power mainly limits the cutting power of a machining process. The cutting power should not exceed the motor power with specific efficiency to prevent burnout and other damages (Groover, 2016; Stephenson & Agapiou, 2016; L. Zhou et al., 2017). Other than cutting power, a constraint for optimality also lies on the finished surface. A finished surface is determined by the cutting feed and the tool nose radius. That is why to reach specific surface roughness, a proper feed and cutting tool is needed. Besides surface roughness and cutting power, deflection remains the most significant constraint for the cutting tool. Since the cutting tool determines the cutting parameter possibility, the optimal result also changes if the cutting tool is different. Cutting tool deflection could damage the cutting tool itself, harm the workpiece, and make the cutting process inaccurate. These constraints heavily depend on the cutting tool specification, where it shows the range of the cutting parameters and determines the optimal parameters. Therefore, this optimization relies on how to choose the right cutting tool. The selection of a cutting tool is not only based on the desired specific process and materials but also on the cutting parameters and the constraints that result from the optimal cutting conditions it may provide. Choosing a cutting tool would not be complicated when only a few options of cutting tools are available. Still, when choosing from a plethora of available cutting tools, a more accurate method is needed to determine each cutting tool's final process result. A modern approach such as artificial intelligence (Saranya et al., 2018) and deep learning (G. Zhou et al., 2019) is implemented to choose the machining process's best cutting tool.

Optimization that leads to choosing the right cutting tools and setting the optimal cutting parameters might already be systemized for big and capital-intensive workshops, primarily when those big workshops use CNC machines to help optimize production. However, these competitive advantages do not arise in small to medium workshops with no CNC machines. Most of them still use conventional machines, which makes it harder to optimize the cutting process. These workshops need a proper cutting-tool selection system to determine the optimal cutting parameter (Ji et al., 2018). Therefore, such a problem has motivated the authors to develop a quick cost-estimator application that can help small to medium workshops to obtain optimized results, cutting parameters, and cutting tools to be used.

Specifically, the application's primary objective is to estimate the minimal production cost in a conventional milling machine and provide the detailed optimal cutting parameters and the most suitable cutting tool for the milling operation. This application also shows each appropriate cutting tool's results and cutting parameter so that operators could have options. However, even though the milling process cost determines the optimal cutting tool, some problem still lingers. The cutting tool that shows the minimal result sometimes has the highest initial and maintenance costs. Although each cost that incurs in overall tool cost is already considered in the process cost estimation, it seems that a more detailed study is needed to compare each cutting tool's cost component and the process cost.

Moreover, when a deflection constraint is applied, the optimal cutting tool might change to a different one. This study aims to improve this cutting tool selection by comparing each cutting tool using a weighted comparison and valuation. This work's findings should help small and medium workshops make better cutting tool selection decisions for milling.

Methods

This research method uses a cost estimation application to determine the minimal cost and cutting parameter for a facing milling process after entering all the base input for the program, including the deflection constraint. After having the optimal result of each cutting tool, the deflection limit is lifted to see the after result. Each cutting tool is then compared and valued to see whether the tool selection truly reflects the minimal cost. Thenceforth, the cutting tool with deflection limit is removed and finalizes the result. Figure 1 below briefly explains the research method.

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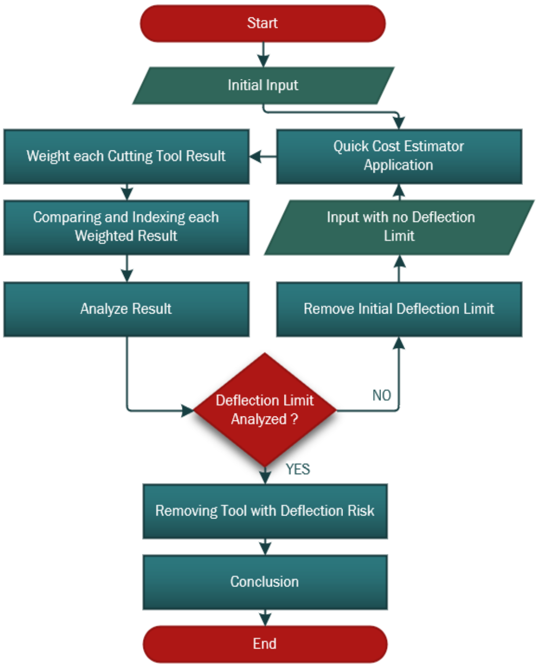

Figure 1. Research methodology

The initial input of the research is a roughing-only face milling operation. The process only cuts one workpiece dimension and does not include the finishing process since roughing and finishing cutting tools might differ. The input for the quick cost application is shown in Table 1 below.

Table 1. The initial input for the quick cost estimation application

Roughing Face Milling	Inputs
Material	C360 Brass
Initial Dimension	300 x 250 x 175 mm
Final Dimension	180 x 250 x 175 mm
Max. Deflection	0.1 mm
Operating Cost Rate	627.016 IDR / min.
Maximum Power	9 kW

Although the cost estimation method for machining processes might vary (Atia et al., 2017; Conradie et al., 2016; Kasim et al., 2016), the application uses a basic cost equation for milling processes. The algorithm uses Stephenson and Agapiou (2016) and Groover (2016) to split milling costs into three variables: machining cost, tooling cost, and non-productive cost.

$$C_p = C_o . T_m + \frac{T_m}{T}(C_o . T_L + C_t) + C_o . T_h \qquad \text{Eq. 1}$$

Where:

C_p : Milling Process Cost [IDR]

C_o : Operating Cost Rate [IDR / min.]

T_m : Machining Time [min.]

T : Cutting Tool's Life [min.]

T_L : Cutting Tool Loading/Unloading Time [min.]

C_t : Cutting Tool Cost [IDR]

T_h : Workpiece Handling Time [min.]

Equation 1 above calculates the cost incurred for a milling process. According to Masood et al. (2016), the cutting tool's life should be adjusted by how much the tool is used in the machining process, and it is shown in equation 1 that the cutting tool cost is multiplied by the usage of the tool's life. The tooling cost indicates the cutting tool's life used for a process and the cutting tool change time. There are nine face-mill (three cases with three different inserts) and three end-mill available for this roughing process. The cutting tool cost equation for both types of tools are shown below:

$$C_t = \frac{P_i}{n_e} . n_t \qquad \text{Eq. 2}$$

Where:

P_i : Insert Initial Cost [IDR]

n_e : Number of Insert's Edge

n_t : Number of Face-Mill Teeth

$$C_t = \frac{P_t}{n_g} + T_g . C_g \qquad \text{Eq. 3}$$

Where:

P_t : End-Mill Initial Cost [IDR]

n_g : Allowed Number of Grinding

T_g : Tool Grinding Time [min.]

C_g : Tool Grinding Cost [IDR / min.]

Equation 2 and equation 3 represents face-mill cost and end-mill cost, respectively. There is also a need for assumptions in grinding time and grinding cost since there is no specific data for the tools regarding the re-grinding time and cost. The grinding cost is assumed to be 10,000 IDR per minute, and the grinding time is considered to be around 3 minutes for all end-mill tools in this study. The grinding time is considered the same throughout all cutting tools since the workpiece is the same. Grinding itself have their own equations and to simplified the paper, it is assumed to have a grinding cost of IDR 30,000 in total. Even though grinding is allocated when the tool is dull due to multiple processes, in this case, we assume that the grinding cost is to be due immediately after this case. Another assumption is also needed in equation 1, where

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the part handling time for the workpiece and the tool change time is around 3 minutes.

Several studies, such as in Duan et al. (2016); Soori et al. (2017); and Moges et al. (2018), use specific equations to model the tool deflection and chatter based on several cutting forces. However, the tool deflection in this study uses a basic beam deflection equation shown below.

$$\delta = \frac{F_C.L_C{}^3}{3.E.I} \qquad \text{Eq. 4}$$

Where:
δ : Cutting Tool Deflection [mm]
F_c : Cutting Force [N]
L_c : Cutting Tool Length [mm]
E : Young's Modulus [GPa]
I : Area Moment of Inertia [mm^4]

Initially, the maximum cutting deflection limit is appointed in Table 1, where it is 0.1 mm. The young's modulus shows that the workpiece material also gives an effect on the deflection.

Deflection gives effect on the selection process by filtering result that has over the appointed maximum deflection. Moreover, the cutting force in the equation above consists of a vital cutting parameter such as depth of cut and width of cut. The equation for cutting force is shown below.

$$F_c = \tau.d.w \qquad \text{Eq. 5}$$

Where:
F_c : Cutting Force [N]
τ : Shear Strength [MPA]
d : depth of cut [mm]
w : width of cut [mm]

The shear strength depends on the workpiece material, which in this case is brass. Other than cutting force, the area moment of inertia is also one of the factors leading to deflection, and it is shown below.

$$I = \frac{\pi}{4}.R_C{}^4 \qquad \text{Eq. 6}$$

Where:
I : Area Moment of Inertia [mm^4]
R_C : Tool's Diameter [mm]

The area moment of inertia solely depends on the cutting tool's diameter even though deflection is used only for a limiter in the application, equation 5 and equation 6 show many essential variables that effects the selection process, such as the depth and width of cut that will determine the toolpath and eventually the process cost .

The quick cost estimation system uses combinatorial optimization, which iterates all possible combinations of cutting parameters (depth of cut, width of cut, feed, rotational speed). After gaining all structured data results, the program exhaustive the exploration (Durieux et al., 2018) find the optimal solution, which is the cheapest process cost. After having the optimal outcome for one cutting tool, the application does the same algorithm to the other available cutting tools. It determines the most suitable cutting tool for the process. Each tool's result will then be compared using a weighted ratio of cutting tool cost and the process cost. The reason is that the optimal cutting tool may result in a cheaper process cost but have an expensive initial cost without having a significant difference in quality. The equation used for the weight ratio is shown below.

$$R_W = W.C_t\left(\frac{T_m}{T}\right) + (1 - W).C_p \qquad \text{Eq. 7}$$

Where:
R_W : Weighted Result [IDR]
W : Weight [%]

The challenging part is on determining the weight for each variable. The weight helps to rationalize the value between tooling cost and the result (process cost). Different weight ratios will bring another solution to the equation. It is not clear whether which element of cost is the most important or impactful. Therefore, the weight ratio should be 70-30, heavier on the tooling cost, 50-50 for both variables, and 30-70 heavier on the process cost result. The first is that the weight for the tooling cost is heavier since each tool wants to be compared. So, the weight will be 70% of the machining tooling cost and 30% of the process cost. The second scenario is 50-50 between tooling cost and process cost to see each result's difference. The last scenario is somewhat eligible when a workshop wants to have the lowest possible process cost without worrying about the cutting tool cost.

After getting the weighted results, the equation below is used to rank each cutting tool. The range of index values from the equation is between 0 and 1, the rank for each tool is

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determined by subsequent order starting from the lowest value up to the highest.

$$T_v[i] = \frac{(R_W[i] - R_W[min])}{(R_W[max] - R_W[min])} \quad \text{Eq. 8}$$

Where:
T_v : Tool Value
i : Index
max, min: Maximum and Minimum Value of the Weighted Result

Equation 8 above shows the tool value index, and therefore the most compatible tool for the rough-facing milling process is known. The new findings will then be analyzed to see whether the cutting tool selection's initial result changes based only on the process cost. Other than that, the cause of these changes can be discussed as well.

Results and Discussion

Tool deflection is mainly caused by the cutting force directly applied to the cutting tool (Nghiep et al., 2018). The effect of tool deflection itself is creating a chatter that causes an unprecise machining process. Precision is a must in all machining since it should have the correct dimension and tolerances. Soori et al. (2017) and Huo et al. (2017) already prove and model that surface finish precision is affected by the presence of tool deflection. Apart from such precision issues, tool deflection also reduces tool life. Tool life is an essential aspect of a workshop's economy. If the cutting tool's initial cost is hefty but could have a long life with multiple-use, medium workshops might consider buying it. Therefore, the cutting tool's life and machining time are essential in deciding the tool selection. The operators have to consider the degrees of importance between the overall process cost and the cutting tool's perseverance. According to Sun et al. (2018), predicting a tool's life needs a better estimation approach than Taylor's constants. The articles used a combination or hybrid of data-driven model and physics-based model that shows a more accurate prediction. However, like mentioned above, this work only uses the available data retrieved from several books such as in Groover (2016) or the physics-based model, where each material's constant is stated. This paper does not focus on predicting the remaining useful life of a cutting tool but on selecting the cutting tool for a specific operation.

The tool used in this research comprises several milling cutting tools compatible with the milling roughing process. equation 2 and equation 3 above, each available tool's tooling cost is listed in Table 2 below. Each cutting tool provides a different range for feed, cutting speed, and other parameters due to the specifications. Therefore, after entering the initial input to the application, i.e., equation 7 and equation 8, the cutting tool optimality rank will change and show whether the priciest cutting tool would be the most optimal cutting tool in the milling process. Other than that, removing the deflection limit will show how it affects the cutting tool selection.

Table 2. Cutting tool cost and specifications**

Tool Number	**Tool Specification**				**C_t [IDR]**
	Type	**Diameter D_c [mm]**	**Length L_c [mm]**	**Max. Cutting Depth d_{max} [mm]**	
1	Face-Mill	32	39	9.75	219,000
2	Face-Mill	80	50	9.75	365,000
3	Face-Mill	152	63	9.75	657,000
4	Face-Mill	32	39	6.50	121,500
5	Face-Mill	80	50	6.50	202,500
6	Face-Mill	152	63	6.50	364,500
7	Face-Mill	32	39	6.50	156,000
8	Face-Mill	80	50	6.50	260,000
9	Face-Mill	152	63	6.50	468,000
10	End-Mill	8	19	18.00	475,000
11	End-Mill	12	50	16.00	904,333
12	End-Mill	20	38	37.00	1,457,500

***All cutting tool is taken from Sandvik Coromant and is compatible for cutting C360 Brass (ISO N). Cutting tools were all made by either coated carbide or cemented carbide.*
Catalogue: https://www.sandvik.coromant.com/en-gb/downloads/pages/default.aspx

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Result with Deflection Limit-Constraint

After entering the input in Table 1 above to the quick cost application, the result shows that the most suitable cutting tool for this specific milling operation is using tool 2. The application also removes tool 11 from consideration since it is the longest end-mill. The deflection caused by the minimum cutting parameter values shows that it is incompatible with this process and constraint. Figure 2 below shows the result of the application.

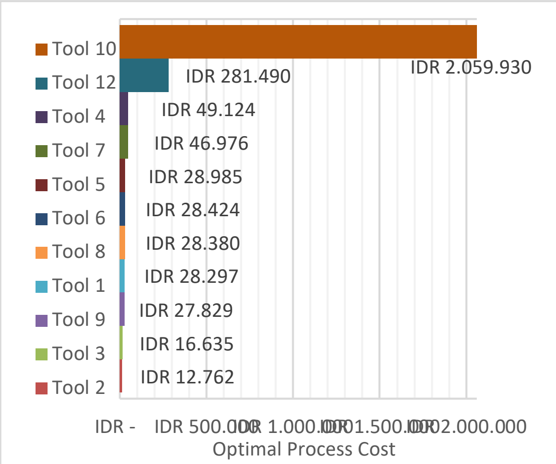

Figure 2. Optimal roughing process cost for each tool*

**The color for each bar differentiates each tool's result and provides better visualization. Each cutting tool have been assigned to a certain*

The figure above shows that each cutting tool's process cost might not be optimal because of the deflection constraint. The result stated in the figure results from the most cost-optimal calculation by the quick cost estimator. Take tool 4 for example, the application algorithm iterates all possible cutting parameter and decide the best combination of depth of cut, width of cut, feed, RPM, and cutting speed. Below is the optimal cost result of tool 4:

Width of Cut (w) *= 20 mm*
Depth of Cut (d) *= 6.5 mm*
Number of Cutting Pass = 19 times vertically (depth)
Deflection (δ) *= 0.09988 mm*
Cutting Speed (v) *= 150.796 m/s*
Rotational Speed (N) *= 1500 rpm*
Tool Life (T) *= 1,268.84 min*
Feed (f) *= 0.23 mm/tooth*
Feed Rate (f_r) *= 1035 mm/min*
Tool Path (mm) *= 67,512.8 mm*
Machining Time (T_m) *= 65.23 minutes*
Milling Process Cost (C_p) *= IDR 49,124*

The tool life parameter is calculated from the standard Taylor's tool life equation (Groover, 2016). The rotational speed depends on several gear steps as the machine used in this case is a conventional milling machine. The machining time is calculated from the feed rate and the tool path, with a specific algorithm to determine the optimal zig-zag pattern. The algorithm combines every possible cutting parameter (width and depth of cut, feed, rotational speed) with specific limitations and consideration from all the tools, resulting in different optimal results. Tool 10 and 12 have the highest process cost and significantly differ from the rest of the tools. This abnormality is because both tools 10 and 12 are end-mills and therefore have a typically longer cutting tool length. The cutting tool length itself carries the most significant role in determining deflection. From equation 4 it is shown that the cutting tool's length itself is powered by three and therefore possesses a heavier role than other variables. Cutting tool diameter also affects the deflection, and the wider the diameter of a tool, the smaller the deflection. Since tool 11 have the smallest diameter and a very long tool's length, it is expected to have the highest deflection among other tools, even though it has the same material amongst end-mill.

The next step is to use equation 1 to show how each tool has different machining times and tools' life due to each cutting tool's specifications. Table 3 below shows the cutting tool cost for the milling process

Table 3. Cutting tool cost used for the machining process

Tool Num.	Tool's Life T [min.]	Machining Time T_m [min.]	Tool's Machining Cost $C_t\left(\frac{T_m}{T}\right)$ [IDR]
1	1,268.8	33.0	5,691
2	2,631.1	14.2	1,969
3	7,886.4	20.8	1,730
4	1,268.8	65.2	6,246
5	816.1	30.9	7,665
6	2,052.9	33.0	5,851
7	1,268.9	60.0	7,378
8	1,453.1	32.8	5,874
9	2,052.9	30.3	6,911
10	324,822.0	3,274.6	4,789
11	-	-	-
12	8,315.5	348.4	61,069

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Table 3 above shows the similar calculation from the explanation on tool 4 results in Figure 2 before. The machining time on tool 4 can be seen as dividing the tool path by the feed rate. The tool's machining cost is a product of the milling process taking away the tool's life, which shows in the machining time and tool life ratio. The ratio is then multiplied by the tool's cost to represent the incurred tool process cost. Using equation 7 with three different ratios shows how each scenario will have different results after having the result. Table 4 below shows the weighted result for the process cost and the tool's machining cost.

Table 4. Weighted result for each scenario

Tool Num.	Weighted Result [IDR]		
	70-30 Weight	50-50 Weight	30-70 Weight
1	12,473	16,994	21,515
2	5,207	7,366	9,524
3	6,201	9,182	12,163
4	19,110	27,685	36,261
5	14,061	18,325	22,589
6	12,623	17,137	21,652
7	19,258	27,177	35,097
8	12,626	17,127	21,628
9	13,187	17,370	21,554
10	621,331	1,032,359	1,443,388
11	-	-	-
12	127,195	171,279	215,364

The first column of the weight result indicates the heavier weight on the tool's machining cost. The second indicates the same weight, and the last column shows the heavier side of the process cost result. Each scenario will have the minimum and maximum value using equation 8 and the index result is shown in Figure 3 below.

Figure 3 describes the smaller the tool index value means that the tool has more value or higher ranking in this particular cutting operation. The minimum and maximum valuations as expected are 0 and 1, accordingly. Therefore, the rank difference could be detected and be summarized in Table 5 below.

Table 5. Different ranking result

Rank	Tool Number			
	Initial by Process Cost Result	70-30 Weight	50-50 Weight	30-70 Weight
1	Tool 2	Tool 2	Tool 2	Tool 2
2	Tool 3	Tool 3	Tool 3	Tool 3
3	Tool 9	Tool 1	Tool 1	Tool 1
4	Tool 1	Tool 6	Tool 8	Tool 9
5	Tool 8	Tool 8	Tool 6	Tool 8
6	Tool 6	Tool 9	Tool 9	Tool 6
7	Tool 5	Tool 5	Tool 5	Tool 5
8	Tool 7	Tool 4	Tool 7	Tool 7
9	Tool 4	Tool 7	Tool 4	Tool 4
10	Tool 12	Tool 12	Tool 12	Tool 12
11	Tool 10	Tool 10	Tool 10	Tool 10
1	Tool 2	Tool 2	Tool 2	Tool 2

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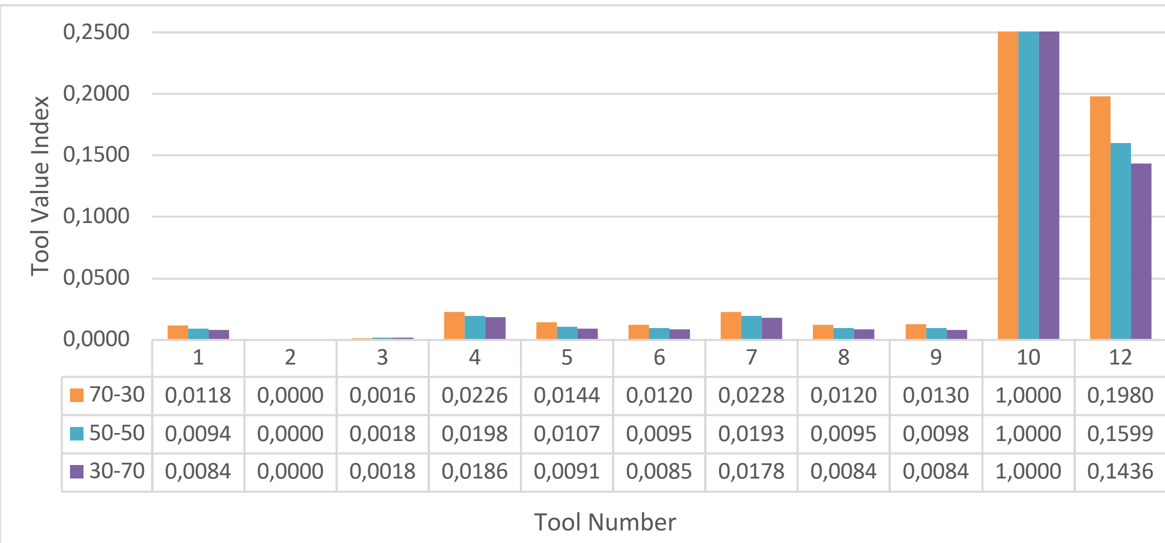

Figure 3. Cutting tool valuation result

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The weight ratios in Table 5 are based on the processing cost versus tool cost, as explained in the method section above. The first column states the original cutting tool ranking result-based process cost using equation 1, while the rest used the index value ranking result based on each ratio. According to Table 5, the first two ranks of the tool selection exactly stay the same. However, in the third rank, the result changes into tool 1 in every scenario, which means the cutting tool selection change based on the weight given to the tool's machining cost. The same goes with the rest of the rank, and the leading cause of this change is the weight ratio, not the initial process cost result.

Even though the first two ranks remain the same, it is still better to put weight ratios and valuation in the cutting tool selection. The main reason is the fact that not every tool is available all the time. All the tools above are shown capable of doing the process, but their availability is not known. The selected cutting tool might not be available for various reasons, such as it might be used in different machines by different operators. This opportunity leads to other tools to be picked as the ones that will support the operation. Other than these three scenarios, different ratios might also bring different results and ranks. This work only presents three weight composition scenarios representing a two-way tendency of the degree of importance between tooling cost and process cost.

Since the optimality objectives depend on the machine operator, including preserving the tool's life, minimizing the process cost, and balancing both is a challenge. Williams et al. (Williams & Patel, 2016) stated that the fundamental of cuttings lies in the cutting tool specifications. Different cutting tool specifications provide different cutting parameter range with different costs. Cutting tool specifications set all the cutting parameters and provide different process costs, deflection, and results. Therefore, depending on the tool selection operator, there is always a possibility of having a different outcome and different tool selection ranks.

The application user sets the maximum deflection limit. If it is different from the input inTable 1, the result of optimal process cost would be different and thus might change the overall selection tool. For example, tool 4 has the optimal cost of IDR 49,124 when the deflection limit is 0.1 mm. If the maximum deflection limit is 1 mm, the optimal cost will decrease to IDR 34,289. For sure, this is due to the increased allowance of cutting parameters and still making sure that the calculated deflection will not pass the limit.

Overall from this case, the cutting tool valuation technique using weight between process cost and the cutting tool's machining cost will have a different result from the original method to select cutting tool. Therefore, it shows that minimizing tool costing could also be an optimality objective and improve the tool selection.

Result without Deflection Limit-Constraint

This section provides the input without having deflection constraints to determine whether other factors could change the cutting tool selection. After removing the deflection, the initial process cost result change for almost every tool. Figure 4 below shows each tool's optimal process cost without having the deflection risk limit.

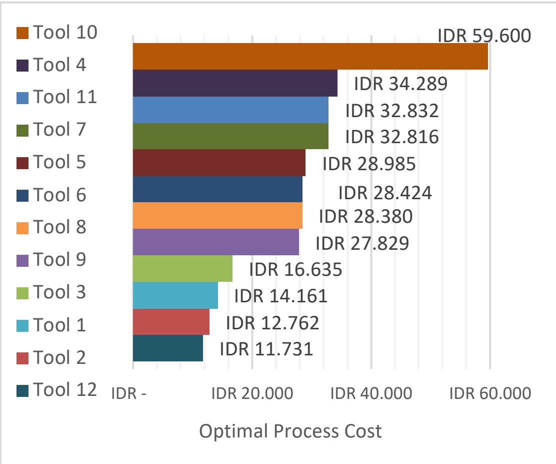

Figure 4. Optimal roughing process cost for each tool after removing deflection constraint

In contrast to the results presented in Figure 2 above, removing the deflection constraint proves that the optimal process cost can be better. In this case, tool 12 has the best value, and it is expected since Table 2 already shows that tool 12, although expensive, provides a suitable cutting parameter based on the specification. On the other hand, tool 10 has the most expensive process cost since it has the smallest diameter and provides a smaller cut width. The result shows that the most expensive cutting tool might provide a better tool life. The cost may come from having a better coating and material to prolong the cutting process. Other than that, the result also depends on the milling process.

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Some processes only require a slight volume reduction, and some require significant reduction. Therefore, not all acceptable tool suits the cutting process.

After having each result, the same valuation method is applied to this case. The results are shown in Figure 5 and Table 6.

Table 6. Different ranking results without deflection constraint

Rank	Tool Number			
	Initial by Process Cost Result	**70-30 Weight**	**50-50 Weight**	**30-70 Weight**
1	Tool 12	Tool 12	Tool 12	Tool 12
2	Tool 2	Tool 2	Tool 2	Tool 2
3	Tool 1	Tool 1	Tool 1	Tool 1
4	Tool 3	Tool 3	Tool 3	Tool 3
5	Tool 9	Tool 11	Tool 11	Tool 9
6	Tool 8	Tool 6	Tool 8	Tool 8
7	Tool 6	Tool 8	Tool 6	Tool 6
8	Tool 5	Tool 9	Tool 9	Tool 5
9	Tool 7	Tool 4	Tool 5	Tool 11
10	Tool 11	Tool 7	Tool 7	Tool 7
11	Tool 4	Tool 5	Tool 4	Tool 4
12	Tool 10	Tool 10	Tool 10	Tool 10

Table 6 above differs a lot from the result of Table 5 that has deflection as the selection limit. In this case, the tool has automatically had the cheapest process cost without deflection limit since it can take more extensive cutting parameters such as wider width of cut and deeper depth of cut. Therefore, making the toolpath shorter and, thus, in the end, reducing the process time and cost. This case shows that having a constraint such as deflection does alter the cutting tool selection.

Figure 5 below shows a different valuation range from before. In Figure 4, some valuation is too tiny compared to the highest value of one. In this case, however, the index valuation does not stand far from each other, and the rank result in Table 6 shows very little difference from the initial cutting tool selection. Compared to the initial rank, tool 7 and tool 11 swap in the third scenario of the 30-70 ratio. This change is because of the small difference in both optimal process costs and shows that if the weight is heavier on the process cost result, tool 11 is preferred. However, when the weight is heavier than the cutting tool's cost that calculates how much life is taken from the tool, tool 11 jumps into fifth place. This means that tool 11 has a more extended tool's life, and the method shows that having this valuation can improve tool selection by focusing on particular objectives. The small difference shows that putting weight will change the tool selection cost. Therefore, putting weight in this cost element is tricky since both tool cost and the result are important. Depending on the user, they might change whether to use any weights to select the tools.

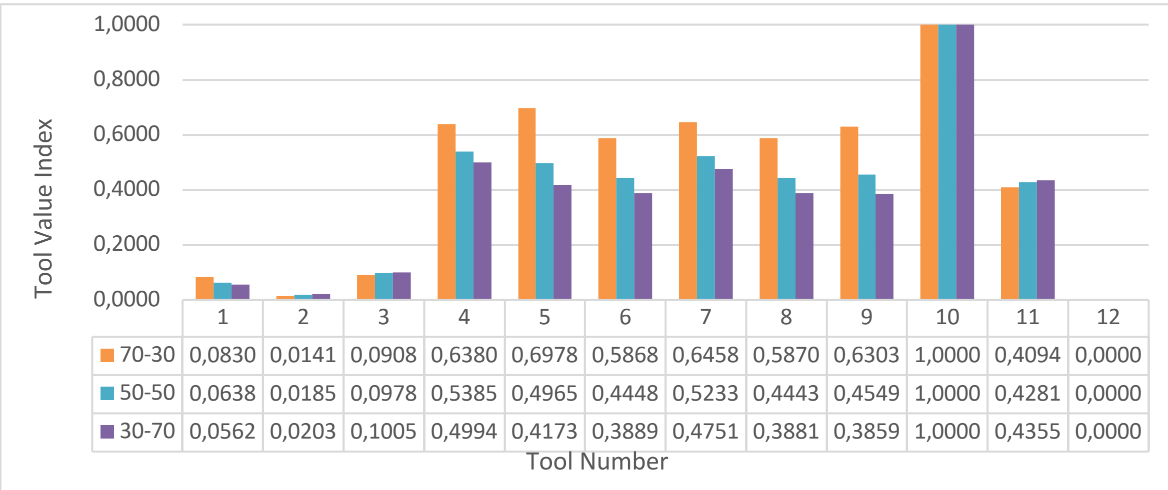

Figure 5. Cutting tool valuation result without deflection risk limit

The actual maximum deflection of a cutting tool has to be known by the operator to input the correct value in the optimization. Flöter & Denkena (2015) explained that tool deflection is a challenge in machining, and this study shows that the tool selection is also affected by it. All the end-mill tools have deflection risk if the deflection is more than 1 mm. Tool 10 and tool 12 result in having an approximate 3 mm deflection, and tool 11 has a 15 mm deflection. The rest of the tools have deflections less than 0.23 mm, not far from the initial limit. The exhaustive algorithm exploration finds the most optimal combination of cutting parameters and concluded that the most optimal results have a deflection of more than 1 mm. This shows that tools 10,11, and 12 (end-mills) have deflection risk when the limit is removed. Therefore, operators need to know the maximum deflection for each tool to validate the process. Deflection could be caused by the tool specification and the workpiece's materials, and the cutting tool. Overall, this case shows that using a weighted valuation could improve cutting tool selection for a milling process.

Conclusions

In conclusion, adding tool valuation improves the cutting tool selection for a milling process. Using a self-developed cost estimation tool, the authors can estimate each tool's optimal cost and find that the more expensive a tool is might not be the most suitable for a milling process. Tool valuation using weight between process cost estimation and tool's machining cost changes the index result of the applicable cutting tools. The conventional cutting tool selection method sorts the best cutting tool based only on the minimal process cost. However, when the process cost result and the tool's machining cost that shows the amount of tool's life taken for the process are added to the method as two weighted-average factors, the rank of preferable cutting tools are changed.

Furthermore, this study also shows that the deflection limit significantly influences the rank of preferable cutting tools. Changing the maximum deflection limit will create a different result for each tool and impact the cutting tool selection. Lifting the deflection constraint ensures that all cutting tools can have a depth of cut almost as deep as their maximum cutting length and, therefore, change the overall result. The three weight ratios in both cost components show that it changes the tool selection. If the user attends more into the tooling cost, they should use the 70-30 weight to select their tools, and it implies the other way around to other ratios. Therefore, choosing the best tool for a milling process might be based on the process cost incurred and the preservation and availability of the cutting tool that incurs the tooling cost. In small and medium workshops, real-world applications should be wary of choosing the maximum deflection limit and the proper ratio of tooling cost and process cost result.

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