Multi-Objective Optimization of Input Machining Parameters to Machined AISI D2 Tool Steel Material

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Abstract—**Poor surface finish on die and mould transfers the bad quality to processed parts. High surface roughness is an example of bad surface finish that is normally reduced by manual polishing after conventional milling machining process. Therefore, in order to avoid disadvantages by manual polishing and disadvantage by the machining, a sequence of two machining operations is proposed. The main operation is run by the machining and followed by Rotary Ultrasonic Machining Assisted Milling (RUMAM). However, this sequence operation requires optimum input parameters to generate the lowest surface roughness. Hence, this paper aims to optimize the input parameters for both machining operations by three soft-computing approaches – Genetic Algorithm, Tabu Search, and Particle Swarm Optimization. The method adopted in this paper begins with a fitness function development, optimization approach usage and ends up with result evaluation and validation. The soft-computing approaches result outperforms the experiment result in having minimum surface roughness. Based on the findings, the conclusion suggests that the lower surface roughness can be obtained by applying the input parameters at maximum for the cutting speed and vibration frequency, and at minimum for machining feed rate. This finding assists manufacturers to apply proper input values to obtain parts with minimum surface roughness.**

Keywords-Surface Roughness; Optimization; Rotary Ultrasonic Machining; Regression Analysis; Pareto-Front.

I. INTRODUCTION (HEADING 1)

The die and mould quality such as surface roughness will be transferred into processed parts [1], which influence its quality. Conventional machining alone cannot achieve the making of die and mould with good and permissible average surface roughness (R_a) [2]. The matter needs additional operation for surface refining that is workable for pocket and cut-through sections, not limited to flat surface only. However, manual polishing has resulted an inconsistent R_a due to the nature of human work such as inconsistent pressure and techniques of polishing that differ from one worker to another [3]; and required a huge number of working hours and cost [4] - the only operation workable for the need mentioned. Moreover, conventional machining also results in poor surface material integrity - another machining disadvantage. This is because while machining, it needs a high force and generates high heat, hence the change of the surface material behaviour. Alternatively, non-conventional machining such as Abrasive Water Jet (AWJ), Laser, Rotary Ultrasonic [5], and Electro Discharged machining (EDM) [6] has resulted in good R_a quality, without the need for manual polishing. Unfortunately, AWJ requires a great cost for slurry application and Laser machining needs high energy usage, making these machining uneconomical for manufacturers. Another disadvantage observed is both methods hole-making accuracy causes differences between hole entrance and exit in AWJ and heat effected zone by Laser machining [7]. As for EDM, it is a very slow method with complex mechanism and produces geometrical inaccuracies and inferior part surface [8, 9, 10]. In contrast, these disadvantages are not the issue for Rotary Ultrasonic machining (RUM). A study discovered that the use of RUM provides a good outcome in better surface roughness and fracture strength – both obtained by the reduction of cutting forces and tool wear [11].

Mold parts made of steel is polished manually, possibly the most important polishing industries today [12, 13] and could require up to a third of production time in some industries [14]. Manual polishing uses free abrasive cloth applied with lubricant and diamond paste [15]. The cloth is swiped back and forth between the center and the edge of the parts. This action releases abrasive particles in the lubricant. Also, a satisfactory application of hand pressure on the cloth to the parts surface is determined by the workers' experience, thus result varies among novice and experienced workers. Such operation leads to low operation efficiency and inconsistent surface quality. It also causes health problems among workers [16] especially those exposed to dusts and noises [14] may suffer from internal organ and hearing problem. Hence, the operation is cumbersome and time-consuming, and often the main cause of occupational injuries due to vibrating hand tools and monotonic operations [13, 17].

RUM is a hybrid non-traditional machining that combines conventional machining and static ultrasonic machining [18, 19]; such as RUM assisted milling (RUMAM). However, high amounts of power consumption are used by RUM's coolant pump, approximately 65% [20]. The high power consumption of the pump is not economical for a long running operation. Conversely, this is not the case for conventional machining such as milling. Previous researches show that power consumption for conventional milling machining (CM) is mainly used by milling operation [18, 21]. The fact is, the operation of die and mould making undergoes machining for roughing, semi-finishing, finishing, and super-finishing [3]. Interestingly, most of the operation can be done by CM and it resulted a high R_a. Hence, incorporating CM and RUMAM in sequence operation is the strategy that reduces the whole operation cost – the strategy proposed in this paper. It ends by listing similar input parameters for both machining operations to obtain a low R_a that can be practised in the production line.

Recent researches on machining common material for die and mould making are mostly interested in EDM. Optimization of the EDM input parameters based on R_a as the output is the main research study conducted through statistical approaches [11, 22, 23, 24, 25, 26, 27] and very few were done by soft-computing [28]. The rest of the researchers' interests in this line of study was conducted through other machining such as laser milling machining [29]; hard turning machining [30]; and micro-milling [31]. Based on the review (to the best of our knowledge), there is no similar kind of research in regards to this problem. No paper was found having the attempt to combine two machining operations in sequence in an optimization study. Despite the disadvantages of EDM aforementioned, the advantages of the proposed strategy justify this paper.

Manufacturing industry optimization in machining by soft-computing approach is the current trend study. Although the approach results more than one set of the best solutions, comparatively it is proven better than statistical approach. This is a dynamic approach that evolves drastically and multiple algorithms are available for the approach. For example, the use of Genetic Algorithm (GA) on machining optimization was carried out successfully by [32, 33, 34, 35]. In addition, other algorithms, also trending in manufacturing include Particle Swarm Optimization (PS) [36, 37, 38, 39]; and Tabu Search (TS) [40, 41]. This review approves these approaches being applicable in optimization study and defends its uses in this paper.

This paper acts as a sequel to [2] study, by conducting an optimization study to propose the use of proper input settings to economical manufacturing. The study finding i.e. system data and mathematical model are used in this paper for optimization study. The aim of this paper is to optimize input parameters of machining with R_a as the output on RUMAM and CM operations by three approaches, namely Genetic Algorithm GA, TS, and PS. In this study, the optimization is on both RUMAM and CM operations, which explains why multi-objective optimization study is required. Basically, the optimization study of soft-computing approach calculates repetitively the optimized input parameters. This is to search for the most efficient solutions to find global optima. Here, the repetitive calculation will find local optima values; which from these values the most efficient one is the global optima. In this case, more than one global optima may be calculated due to the consideration of multi objective problems in the study. The use of the three approaches in this paper enables performance comparison to be studied. The machining strategy in this paper indicates the use of CM up to the maximum amount of operation while RUMAM is used for the minimum operation. The planning is: CM begins from the roughing, up to semi-finishing, finishing, and the main portion of super-finishing. Then, the last few layers of milling operation are done by RUMAM. Notably, the incorporation of the portion of operations between RUMAM and CM should be decided by the technical persons on the production line. As for the remaining sections of this paper, the *Methodology* section elaborates the system's formulation and differentiates the optimization approaches proposed in this paper. The *result of the optimization* is presented and discussed in the third section and *conclusion* is drawn in the last section.

II. METHODOLOGY

A. Experimental Data

A study [2] has conducted experimental investigation to compare the input parameters performance for RUMAM and CM on surface finish machining. This study design of experiments is based on a Taguchi Orthogonal array with three levels for each machining input parameter. Cutting Speed (A), Feed Rate (B), Depth of Cut (C), Vibration Frequency (D), and Amplitude (E) are the input parameters with R_a being the quality indicator or the output. Comparatively, RUMAM outperforms CM by 89.5% of R_a improvement. Then, a Regression Analysis is used to design only on the RUMAM mathematical model or fitness function by the study. Later, this model Analysis of Variance (ANOVA) is conducted. Findings from this study, i.e. fitness function, data, and ANOVA will be used in this paper. [2] suggested that C and E input parameters are statistically insignificant as they show a weak effect on R_a. Based on this suggestion, this paper focuses on A, B, and D factors; and is less concerned on C and E. Besides, as both machining operations are targeted for surface finishing operation, the setting in this paper is applicable for surface finishing and super-finishing machining. As this paper acts as a sequel of [2] study, hence CM experimental data and RUMAM regression analysis is bringing up from [2].

B. Regression Analysis

TABLE 1. ANOVA FOR BOTH MODEL RESULTS

Machining	Overall ANOVA (α = 0.05)		Individual ANOVA (α = 0.05)		
	F-statistic	p-value	A p-value	B p-value	D p-value
RUMAM [2]	15.77	<0.0001	<0.0001	<0.0001	0.0053
CM	123.3066	<0.0001	<0.0001	<0.0001	-

Regression analysis was employed to develop a fitness function for predicting R_a of CM. This developed CM fitness function and the referred [2] RUMAM fitness function are required in a soft-computing optimization study. Initially, all of the considered inputs were applied to these fitness functions. The performance of the fitness functions analysed by ANOVA evaluates the variability between the function and the actual output, and determines the equations statistical acceptance [42]. For this case study, the selected significant level (α) of 0.05 with R_a is taken as the variability. By the selected α value, the p-value and F-statistic can be determined. Then the finding for all individual input parameters and general function p-value are examined by comparing them with the α value. The use of F-statistic should always be considered together with p-value: ideally both should be found statistically significant. Table I, shows ANOVA result which listed general p-value and individual p-values, i.e. A, B, and D. For the whole function examination, it is statistically significant if the finding of P-value is a value lower than α; and F-statistic is high value – numerically above than one. These findings in Table I, support that both functions are statistically significant. However, the ANOVA on individual input parameter for RUMAM finds that C and E input parameters are statistically insignificant [2]. Similar finding is seen on C parameter for individual input parameter ANOVA on CM. Thus, A, B, and D are the paper main parameters. The fitness function for RUMAM as in (1) and CM as in (2) are used in this paper.

$$\sqrt{R_a} = 3.09606-8.64343x10^{-4}A+0.015449B +0.010055C-0.057748D-0.13427E-1.63156x10^{-4}AC -9.48273x10^{-5}AD+7.54763x10^{-4}AE \quad (1)$$

$$R_a=3.844-0.0384A+0.1956B+0.0001A^2-0.0024B^2 \quad (2)$$

C. Optimization Algorithms

```
Population initial set and pre-setting
front = 1
While population is not classified Do
  Identified non-dominated chromosome
  Assign dummy fitness
  Sharing in current front
  front = front + 1
While stopping criteria is not reached Do
  For each chromosome is population Do
     Calculate fitness of chromosome
  Select chromosomes for Crossover as per dummy fitness
  Perform Crossover
  Perform Mutation
  Replace population with new
   chromosomes
Return Best fit chromosome
```

Figure 1. Non-Dominated Sorting GA

```
Particle initial Setting
Initialize an archive = 0
Repeat compute fitness value for each
 particle setting
  compute the best fitness value
  Begin perform PSO operation
     compute Speed
     compute Position
     perform Stored the best fitness value
  Update the content of the archive
  Calculate new position in archive after select Leader
     End
  Set n = n + 1
Until termination criteria satisfied
```

Figure 2. Dynamic Neighbourhood PS

```
Sbest = S0
bestSol = Sbest %%% Sol = Solution
TabuList ← [ ]
while (NOT StoppingSol ()) do
  Generate solutions in the neighborhood of Sbest
  set SSol as the first candidate in the Sbest Neighborhood
  for (SSol in Sbest Neighborhood) do
     if (SSol NOT in TabuList AND fitness SSol) > fitness(bestSol)
        then bestSol ← SSol
     end if
  end for
  if (fitness(bestSol) > fitness (Sbest) then
     Sbest ← bestSol
  end if
  Update Tabulist (switch the bestSol)
  if (tabuLength > maxTabuLength) then
    Remove the first element from TabuList
  end if
end while
return Sbest
```

Figure 3. TS with Modified Fitness Function

The designed and referred fitness functions will be used on optimization algorithms, i.e. GA, TS, and PS. The algorithms are well known in searching for solutions in high-level problems – these algorithms are classed as metaheuristic algorithm. The significance of this algorithm class is their development and usage are not depending on a system problem. This means a lot of time reduction compared to the exact method of optimization study that requires detailed study of the whole related system parameter and many repetitions of the experiment are needed. In addition, the exceptional solution quality of this approach can be achieved [43]. This algorithm class is also well adapted to various problems, and a system with multi-problem. Furthermore, this algorithm class is suitable for manufacturing system since it is a high-level problem compatible. Hence, this compatibility is relevant for this paper that runs multi-objective optimization – it runs the fitness functions optimization simultaneously. As resources and time are always limited in manufacturing industries, optimal utilization of these available resources is critical. These limitations, known as *optimization constraints* are also set in this paper. The setting of the constraints is applied based on the referred paper [2] and combined with the application in production line practice [43]. The constraints applied to input parameters include Cutting Speed 30-150 rpm, Feed Rate 5-45 mm/minute, and Vibration Frequency 10-

32 kHz. Following algorithms apply these constraints in their simulation.

- The initial variant of GA is based on a single objective optimization inspired by the genetic natural evolution theory [44]. It replicates the reproduction of new chromosomes derived from initial chromosomes and the amount of chromosomes is known as a population. The initial population undergoes crossover and mutation processes for new chromosome reproduction with high probability of escaping from local optima [45], thus global optima can be obtained. Furthermore, the processes resulted new chromosome inherited good genes from the initial population [46]. As aforementioned, the selected algorithm is applicable to a multi objective problem, hence the selected of GA is based on non-dominated sorting or ranking selection in remaining chromosomes being the most efficient solutions. This variant is called Non-Dominated Sorting Genetic Algorithm [47]. Here, the two machining models, i.e. RUMAM and CM that share non-dominated chromosomes are identified in their populations. These chromosomes are classed into Non-Dominated Front (NDF) and assigned to the dummy fitness value. They are allowed to reproduce new chromosomes by following the GA fundamental sequence. Later, the new NDF of chromosome will be re-identified after each new reproduction and re-shared in current NDF. By repeating the process of the reproduction and re-identification, the number of chromosomes is reduced using non-dominated ranking procedure. In addition, this procedure also ranks the new chromosomes. These chromosomes derive the efficient solutions for both models with R_a and optimized inputs are the information. The whole process involved in algorithm is shown in Fig. 1.

- The term *particles* in PS algorithm represents the inspired flocking of birds searching for food source. These particles carry dynamic information of speed and position that determines the fitness value. The advantages of PS algorithm include: its equipment with anti-local trap strategy, simple implementation, short computational time and efficient in finding solutions for complex model [39]. For multi objective application, the variant used for PS is based on Dynamic Neighbourhood [36] as shown in Fig. 2. In this approach, the non-dominated solutions are selected from among the best particles. Here, the use of two objectives may dominate one onto another, hence this can be avoided by this approach. From the selected particles, a leader is selected and stored in an archive. Leaders are selected from an archive using the neighbourhood information mechanism. This is done by adopting additional information from the neighbourhood in the archive. In this paper, the additional information is the particles distance between neighbourhoods in the archive that is calculated from the new position. At the end, based on this distance, the nearest distance from these leader particles are selected to be among the efficient solutions.

- TS algorithm uses the initial solution for searching the new improved solution within different neighbourhoods [41]. The new solution is compared to previous one to obtain the top solutions and kept them in an adaptive memory or a Tabu list in a descending order. Solution in the list is forbidden that defined the term of Tabu, for later reprocessing in the TS, which is also the mechanism of avoiding traps in local optima [40]. Iteratively, this process continues until the stopping criteria is satisfied to generate the efficient solutions. The usage of TS multi objective in this paper is still applying the standard algorithm shown in Fig. 3 to generate solution. However, the fitness functions, i.e. RUMAM (f(1)) and CM (f(2)) is modified in single fitness function. The model is normalized and turns the fitness function of f(1) and f(2) into f'(1) and f'(2). Then, the coefficient value is multiplied to f'(1) and f'(2), with the coefficient summation is equal to one, i.e. 0.3 + 0.7 = 1.0. This technique suggested by [48] is used in this paper with the new fitness function expressed in the following (3). Thus, the single solution resulted from this approach represents a set of two outputs and optimized inputs.

$$\text{Min}(f(3)) = 0.3f'(1) + 0.7f'(2) \quad (3)$$

From the result obtained through these algorithms, the R_a for RUMAM and CM generates many solutions. In order to select the most efficient solutions that combine these two machining, Pareto-Front will be applied for this purpose.

D. Evaluation and Validation

The concern of this study is the optimized input parameters by the three optimization approaches should be within the acceptance of machining value. Thus, the optimized inputs through the three approaches are evaluated on this basis with the following considerations:

- The prediction by the three soft-computing approaches minimum R_a values are expected to be lower than the minimum R_a obtained through the experiment. Here, the three optimization approaches namely GA, TS, and PS are used to generate the optimized input parameters and compared with experiment result.

- The optimized input parameters from both machining that lead to the best or lowest R_a is obtained when an algorithm reaches the convergence. Thus, the optimized input parameters of these approaches are expected to be within the range of values as the machining conditions applied in the experiment.

Optimization study validation can be classified into two approaches, using findings based on post and pre-experiments. While post-experiment is validated by conducting experiments based on the optimization results [46, 49], the pre-experiment gains validation via reusing the pre-experimentation finding.

Previous optimization studies show that the pre-experiment approach is much preferred. The pre-experiment includes the optimum findings which are: (i) matching with the developed model or fitness function either statistically or software aided based on pre-experiment data [45, 47, 50, 51]; (ii) parallel with the finding based on pre-experiment visual observation [42]; and (iii) matching with the data gathered from other sources of pre-experiment i.e. Non-Destructive, Destructive Test or other similar studies [52, 53, 54, 55]. This study validation is through the pre-experiment data: by using the fitness functions to generate the output based on the input parameter values generated through the used optimization approach. If the generated output value of the models matches the input parameter values obtained through the used optimization approach, the result is thus valid [48, 49].

III. RESULT AND DISCUSSION

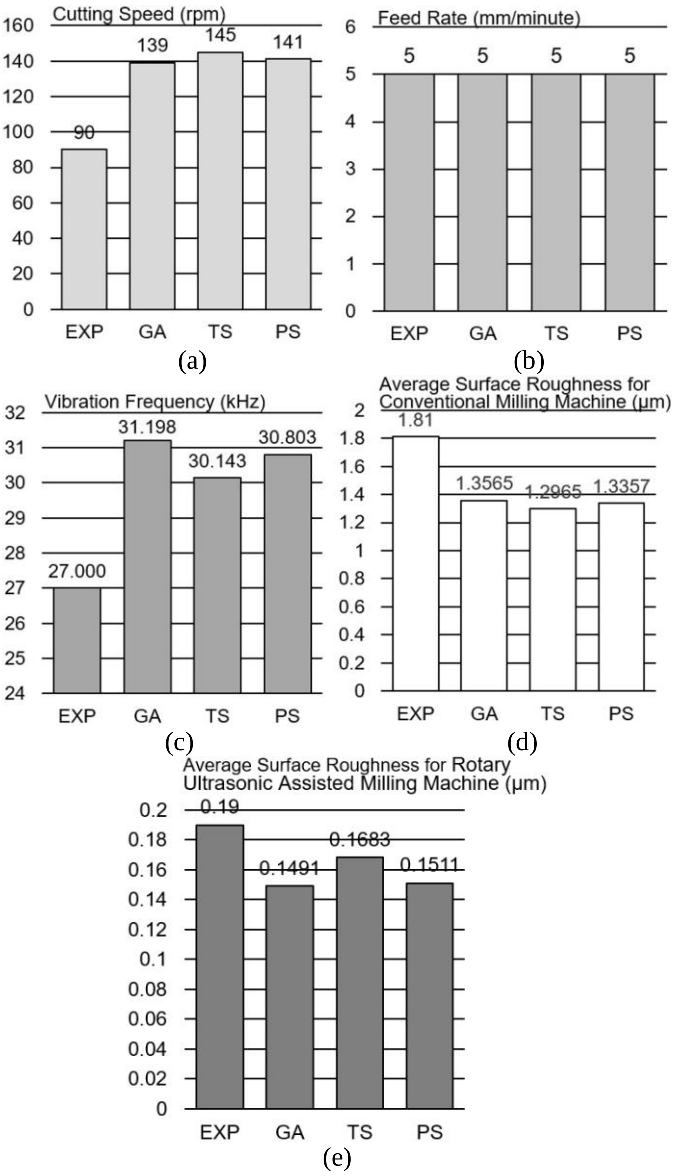

Figure 4. The Most Efficient Optimized Input and Outputs

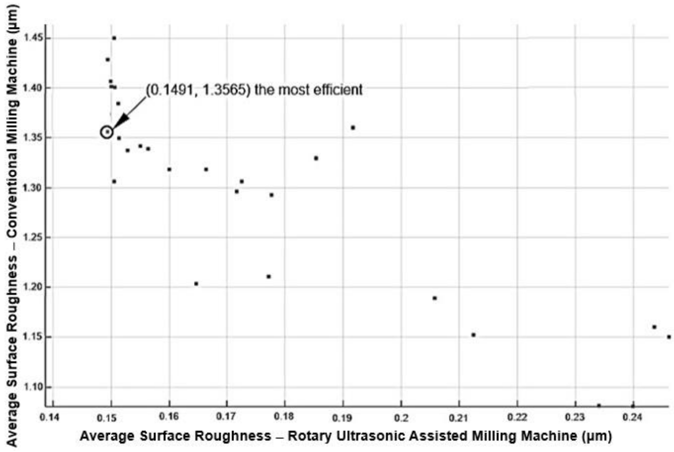

Figure 5. Pareto-Front for Non-Dominated Sorting GA

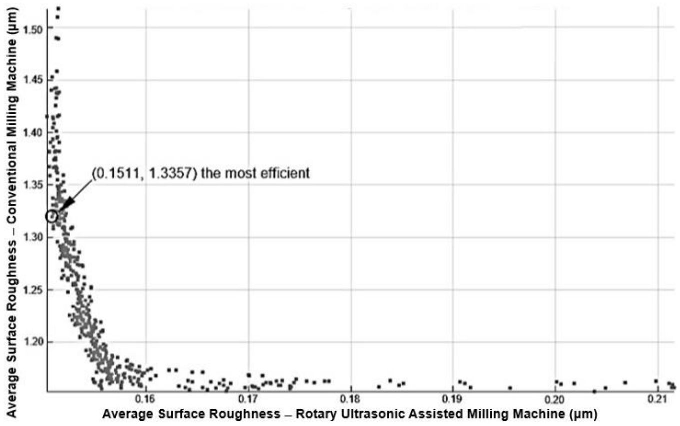

Figure 6. Pareto-Front for Dynamic Neighbourhood PS

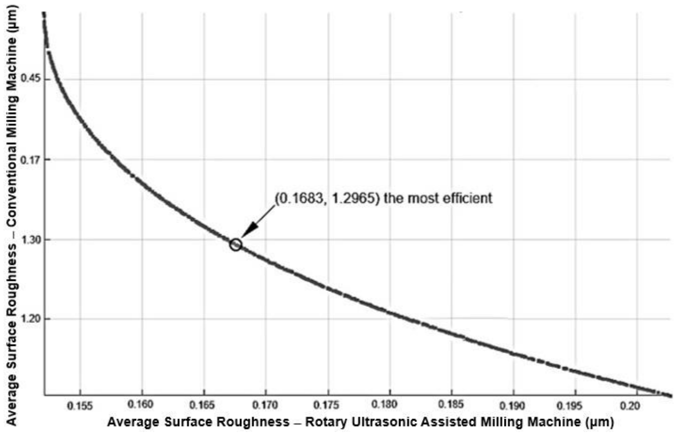

Figure 7. Pareto-Front for TS with Modified Fitness Function

The overall result is summarized in Fig. 4(a), Fig. 4(b), and Fig. 4(c) based on experiment result (EXP); and GA, TS, and PS optimization approach. Here, the multi objective is to achieve a minimum R_a on both RUMAM and CM operations. The best performance for minimum R_a by RUMAM is 0.1491 μm obtained by GA approach and the best performance for minimum R_a by CM is 1.2965 μm obtained by TS approach, shown in Fig. 4(d) and Fig. 4(e). These most efficient results are clustered at cutting speed about 140 rpm, feed rate at 5 mm/minute, and vibration frequency about 30 kHz. All these results were generated through 1673 generations by GA, 1274 generations by TS and 1897 generations by PS. By comparison, from these three approaches: the weakest performance is PS. The facts of output-input relations suggested that the lowest RUMAM R_a is influenced by the highest vibration value of 31.198 kHz and the lowest CM R_a is influenced by the highest cutting speed value of 145 rpm. As aforementioned on evaluation, the obtained outputs are found lower than R_a by experiment. Moreover, the inputs i.e. cutting speed, feed rate, and vibration frequency values are within the range of experiment value. This finding suggests that the obtained values are acceptable for production line usage.

The Pareto-Front for GA, PS, and TS results are shown in Fig. 5, Fig. 6, and Fig. 7 respectively. These figures also show the most efficient points. Based on the Pareto-front, it is clear that both objectives agreed with the selected most efficient point. The selected point is based on equal domination to both objectives.

IV. CONCLUSION

The result obtained suggests that GA, TS, and PS are effective to predict better result of the minimum R_a points compared to experiment result. Also, the minimum R_a value for RUMAM and CM through GA is decreased by 21.53% (RUMAM) and 25.06% (CM). The value by TS is decreased by 11.42% (RUMAM) and 28.37 % (CM); and by PS is decreased by 20.47% (RUMAM) and 26.20 % (CM). This shows the weakest performance out of the three approaches is through PS. Furthermore, a generalization can be made that in order to obtain the most efficient optimum point, the cutting speed and vibration frequency should be at the maximum value, and feed rate at the minimum value. This minimum and maximum values are based on the aforementioned constrain setting that is fixed to the input parameters.

This study suggests that the solution sets for optimum sequence process of RUMAM and CM will assist manufacturers to use proper input parameters in order to obtain optimum machining. Based on this finding, manufacturers can produce more economically particularly in testing time and resource usage.

Improvements for future works to discover a wider potential in this scope of study can be conducted under highly constrained cases for the inputs. Also, other sophisticated and more effective data model approaches should be applied such as Fuzzy Logic and Artificial Neural Network as these two models are the current trend approaches in research studies.

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