Applied Engineering Letters Vol.9, No.3, 132-145 (2024) e-ISSN: 2466-4847

OPTIMAL SELECTION FOR MACHINING PROCESSES USING THE PSI-R-PIV METHOD

UDC:621.91:519.816
Original scientific paper https://doi.org/10.46793/aeletters.2024.9.3.2

Tran Van Dua[*1]

[1]School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi City, 100000, Vietnam

Abstract:
Machining processes are crucial in the production of various products across different industries. The accuracy, lifespan, and cost of these products significantly depend on the machining processes. This research introduces a novel method for selecting the optimal solution for machining processes. The proposed method, named *PSI-R-PIV*, is a hybrid of three methods preference selection index (*PSI*), ranking of the attributes and alternatives (*R*), and proximity indexed value (*PIV*). *PSI*, *R*, and *PIV* are all techniques used to rank options to determine the best among the available choices. Moreover, *PSI* and *R* have an additional function of calculating weights for the criteria. Therefore, using *PSI-R-PIV* to rank options for each machining process results in four sets of rankings: one by *PSI*, one by *R*, and two by *PIV*. In the *PIV* method, the weights for the criteria are calculated using the *PSI* and *R* methods. The ranking method using *PIV* with weights calculated by the *PSI* and *R* methods is named the *PSI-PIV* and *R-PIV* methods respectively. The four methods in the *PSI-R-PIV* combination include *PSI*, *R*, *PSI-PIV*, and *R-PIV*, and have been utilized to rank options in various machining processes. The results indicate that the *PSI-PIV* method offers high accuracy and is recommended for selecting the best option among the available choices in machining processes.

ARTICLE HISTORY
Received: 9 July 2024
Revised: 26 August 2024
Accepted: 11 September 2024
Published: 30 September 2024

KEYWORDS
Multi-objective optimization, MCDM, PSI method, R method, PIV method, PSI-R-PIV method, machining processes

1. INTRODUCTION

Mechanical machining plays a pivotal role in modern industry, directly influencing the quality and efficiency of products across various sectors. Selecting the optimal machining method among numerous alternatives, such as turning, milling, drilling, grinding, etc., is critically important [1-3]. Each machining option impacts product accuracy, production cost, environmental effects, and equipment requirements differently [4]. Choosing the correct machining method not only ensures high product quality but also optimizes production costs, minimizes environmental impact, and makes efficient use of available equipment. This necessitates careful consideration and the application of precise evaluation and ranking methods to make the best decision [5-8].

In addition to using ranking methods for the options, it is also necessary to employ weighting methods for the criteria [9]. However, this can be quite challenging for users due to the wide variety of ranking methods and weighting methods available [10,11]. The choice of ranking method and weighting method significantly impacts the final decision regarding the best option among the many alternatives [12].

This research introduces a novel method for ranking machining options to determine the optimal choice. The proposed method, named *PSI-R-PIV*, is a hybridization of three distinct methods: *PSI*, *R*, and *PIV*. Each of these methods, *PSI*, *R*, and *PIV*, serves the purpose of ranking options to identify the best one. Additionally, *PSI* and *R* methods have the function of calculating weights for criteria. Thus, using the *PSI-R-PIV* hybrid model eliminates the

*CONTACT: Tran Van Dua, e-mail: duatv@haui.edu.vn

need for any additional method to compute criteria weights. This is the first novel aspect of this research. The weights of the criteria, calculated using *PSI* and *R* methods, will be used to rank the options via the *PIV* method. Consequently, integrating the three methods *PSI*, *R*, and *PIV* for option ranking generates four sets of rankings: one performed by *PSI*, one by *R*, one by *PIV* when the criteria weights are calculated by *PSI* (termed *PSI-PIV*), and one by *PIV* when the criteria weights are calculated by *R* (termed *R-PIV*). The ability to create four sets of option rankings by combining the three methods *PSI*, *R*, and *PIV* is a distinct feature of *PSI-R-PIV* compared to all existing methods and represents another significant novelty of this study compared to previous research. This research is driven by the urgent need to enhance the efficiency and quality of mechanical processing. The selection of the optimal processing option is currently limited by the diversity and complexity of evaluation methods. The proposed *PSI-R-PIV* method aims to provide a comprehensive solution, helping manufacturing enterprises make accurate and effective decisions, thereby reducing costs, increasing productivity, and enhancing market competitiveness.

Chapter 2 of this paper provides a concise review of recent literature on the application of option ranking methods in machining. A summary of the steps involved in applying the *PSI*, *R*, and *PIV* methods is presented in Chapter 3. The *PSI-R-PIV* hybrid model, combining the three independent methods, is detailed in Chapter 4. Chapter 5 describes the application of the *PSI-R-PIV* model to rank machining options in various machining methods. Recommendations on which method to use for ranking options in the field of cutting machining are provided in the conclusion, which is the final section of this paper.

2. LITERATURE REVIEW

Selecting the optimal option among various machining process alternatives significantly impacts both the economic and technical efficiency of these processes. Therefore, it is essential to apply mathematical models to ensure that the selection is not influenced by the subjectivity of the decision-maker. Numerous multi-criteria decision-making (*MCDM*) methods have been applied in this field in recent studies.

The ranking of alternatives through functional mapping of criterion sub-intervals into a single interval (*RAFSI*) method was utilized to select the milling parameters for SNCM439 material to simultaneously ensure minimal surface roughness and maximum cutting productivity, where the weights of these two criteria were calculated using three methods: equal weight, entropy weight, and method based on the removal effects of criteria (*MEREC*) weight [13]. The selection of metal milling parameters to ensure minimal surface roughness, minimal energy consumption, and maximum cutting productivity was conducted using the best-worst method (*BWM*) method, where criteria weights were calculated using the entropy method [14].

The technique for order preference by similarity to ideal solution (*TOPSIS*), multiobjective optimization on the basis of ratio analysis (*MOORA*), additive ratio assessment (*ARAS*), weighted aggregates sum product assessment (*WASPAS*), and multi-attributive border approximation area comparison (*MABAC*) methods were applied to optimize the photochemical milling process, aiming to maximize material removal rate while minimizing surface roughness, undercut, and etch factor. The optimal machining conditions were determined based on these methods. In this study, the weights of the four criteria were determined using four methods including criteria importance through inter-criteria correlation (*CRITIC*), *MEREC*, entropy, and equal weights [15]. The weighted sum method (*WSM*), weighted product model (*WPM*), *WASPAS*, *MOORA*, *TOPSIS*, evaluation based on distance from average solution (*EDAS*), *ARAS,* and complex proportional assessment (*COPRAS*) methods were all used to determine the milling method that ensures both minimal surface roughness and maximum cutting productivity. In this research, the weights for surface roughness and cutting productivity were calculated using two different methods: standard deviation weight method and entropy weight method [16], etc.

In [17], the *TOPSIS* and *WASPAS* methods were both employed to select the metal turning option that ensures the smallest surface roughness, the least energy consumption, and the highest cutting productivity, with the criteria weights determined by the analytic hierarchy process (*AHP*) method. The *ARAS* method has been employed to determine the optimal values of cutting speed, feed rate, depth of cut, and tool type to simultaneously ensure the minimum surface roughness, the highest surface hardness of the workpiece, and the maximum cutting productivity in turning operations, where the weights of these three parameters have been calculated using the equal weights method [18]. To find a metal turning solution that simultaneously ensures the minimum values of surface roughness, crater wear, flank wear, and the maximum tool life, the simple additive weighting (*SAW*), "visekriterijumska optimizacija i kompromisno resenje" (*VIKOR*), *TOPSIS*, and elimination and choice expressing reality (*ELECTRE*) methods were concurrently used to determine the optimal machining conditions. In this study, the weights of the four parameters: surface roughness, crater wear, flank wear, and tool life were also calculated using the equal weights method [19]. The *TOPSIS* method has been employed to determine the optimal values of various parameters including workpiece diameter, workpiece hardness, tool hardness, cutting tool length, end cutting angle, side clearance angle, number of revolutions, and setup system in the turning process. The weights of these parameters were determined using an artificial neural network (*ANN*) [20]. In another research, the *TOPSIS* method was also utilized to identify the optimal values of process parameters to minimize vibration in the turning process, where the weights of the process parameters were determined by developing a regression model [21], etc.

To find the optimal option for grinding SKD11 steel with CBN grinding wheels, ensuring both the smallest surface roughness and the highest cutting productivity, the *TOPSIS* method was used to rank the options, and the entropy method was employed to calculate the weights for the two criteria of surface roughness and cutting productivity [22]. To determine the grinding option for tooth surfaces that ensures the smallest values for surface roughness, surface hardness reduction, and the thickness of the surface layer with reduced hardness, the *TOPSIS* method was also used for ranking, and the *AHP* method was used to calculate the criteria weights [23]. The *TOPSIS* method was additionally utilized to choose the metal grinding solution that ensures both the smallest surface roughness and the longest grinding wheel life. Here, the weights for these two criteria were calculated using the entropy method [24]. In [25], the multi atributive ideal-real comparative analysis (*MAIRCA*) method was used to select the grinding option that ensures the smallest surface roughness and the highest cutting productivity, with the entropy method being used to calculate the weights for these two parameters. Four methods *TOPSIS,* measurement alternatives and ranking according to compromise solution (*MARCOS),* evaluation by an area-based method of ranking (*EAMR*), and *MAIRCA* were collectively employed to select the metal grinding option that ensures both the smallest surface roughness and the highest cutting productivity. In this case, the weights for these two parameters were calculated using both the entropy and *MEREC* methods [26], etc.

The *TOPSIS* method has been utilized to determine the optimal option for metal drilling, aiming to simultaneously achieve the smallest values for both surface roughness parameters (*Ra* and *Rz*) and the highest cutting productivity. In this research, the weights of the parameters were calculated using the entropy method [27]. To determine the optimal drilling option for carbon fiber reinforced plastic (*CFRP*) that ensures the smallest values for surface roughness, uncut carbon fibers, and delamination, the *TOPSIS* method was also used for ranking, and the entropy method was used to calculate the weights for the criteria [28]. To identify the optimal drilling option for Magnesium AZ91 alloy that ensures the smallest values for six parameters drilling time, entry burr height, exit burr height, entry burr thickness, exit burr thickness, and surface roughness, three methods, faire un choix adéquat (*FUCA*)*, TOPSIS*, and *COPRAS*, were used for ranking the options, with the criteria weights being assigned by the decision-maker [29]. Three methods, grey relational analysis (*GRA*)*, WASPAS*, and *VIKOR*, were employed to select the drilling option for glass-fiber-reinforced composite (*GFRP*) that ensures the smallest values for delamination, cracking, fiber tearing, ovality, and surface roughness. In this research, the criteria weights were calculated using the *AHP* method [30], etc.

Thus, it can be seen that *MCDM* methods have been extensively used to rank the options of machining processes. Some research uses a single *MCDM* method, while others use multiple *MCDM* methods simultaneously. However, in all the research mentioned above, in addition to using *MCDM* methods for ranking options, additional methods for calculating criteria weights are always required. This affects the user's confidence in the final chosen option because many studies have shown that the weight calculation method used significantly influences the ranking of options [10-12]. If *MCDM* methods could be used without the need for additional weight calculation methods for the criteria, users would have greater confidence in their final decision on the selected option. This research employs the *R, PSI*, and *PIV* methods to rank machining options. All three of these methods are used for ranking options. Notably, with *R* and *PSI*, users do not need to use additional weight calculation methods for the criteria because these two methods calculate the criteria weights themselves. This is why *PSI* and *R* are used in this research. Moreover, the criteria weights calculated by the *R* and *PSI* methods will be combined with the *PIV* method to rank the options. The *PIV* method is used because it is known for its ability to minimize rank reversal and to find the best option among multiple options without depending on the criteria weights [31,32]. Therefore, combining the three methods *PSI, R*, and *PIV,* to rank options will produce four different sets of results for each specific problem: one by applying *PSI*, one by applying *R*, one by applying *PIV* with criteria weights calculated by *PSI*, and one by applying *PIV* with criteria weights calculated by *R*. The combination of just three methods *PSI, R*, and *PIV* resulting in four outcomes for each problem is the most distinctive feature of this study compared to all previously published studies.

3. MATERIALS AND METHODS

The objective of this research problem is to identify the best option among the available alternatives. Therefore, it is essential to construct a matrix containing information about the options, including the number of options, the number of criteria for each option, and whether each criterion's value should be maximized or minimized.

Assuming we need to find the best option among *m* alternatives, each characterized by *n* criteria, the first step is to construct a matrix as shown in Eq. (1). Let x_{ij} be the value of criterion *j* for option *i*, with *j = 1* to *n*, and *i = 1* to *m*. The letters *B* and *C* are used to describe criteria that should be maximized (*B*) and minimized (*C*), respectively.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

This study proposes the *PSI-R-PIV* hybrid model, combining three component methods: *PSI, R*, and *PIV*. Therefore, it is necessary to first summarize the sequence of steps for applying each individual method.

Sequential optimization steps using *PSI* method [33]:

Step 1: Normalize the data according to (2) and (3).

$$n_{ij} = \frac{x_{ij}}{max(x_{ij})} \quad ij \quad j \in B \quad (2)$$

$$n_{ij} = \frac{min(x_{ij})}{x_{ij}} \quad ij \quad j \in C \quad (3)$$

Step 2: Calculate the normalized average value according to (4).

$$n = \frac{\sum_{i=1}^{m} n_{ij}}{m} \quad (4)$$

Step 3: Calculate priority values for each criterion according to (5).

$$\varphi_j = \sum_{i=1}^{m} \left(n_{ij} - n\right)^2 \quad (5)$$

Step 4: Calculate weights for each criterion according to (6). The weights of the criteria calculated in this step of the *PSI* method will be used to find the optimal solution using the *PIV* method. This linkage is referred to as the hybridization between *PSI* and *PIV*, named *PSI-PIV*.

$$w_j = \frac{1 - \varphi_j}{\sum_{j=1}^{n}(1 - \varphi_j)} \quad (6)$$

Step 5: Calculate the score for each option according to (7). The optimal solution is the option with the highest score.

$$\theta_i = \sum_{j=1}^{n} n_{ij} \cdot w_j \quad (7)$$

Ranking options using the *R* method [34]:

Step 1: Arrange the criteria in descending order of their importance.

Step 2: Calculate weights for the rankings of the criteria using Eq. (8), where r_j represents the ranking value of the j^{th} criterion.

$$w^{(j)} = \frac{1}{1 + \frac{1}{2} + \cdots + \frac{1}{r_j}}, j = 1 \div n \quad (8)$$

Step 3: Calculate weights for the criteria using Eq. (9). The weights of the criteria calculated in this step of the *R* method will be used to find the optimal solution using the *PIV* method. This linkage is referred to as the hybridization between *R* and *PIV*, named *R-PIV*.

$$w_j = \frac{w^{(j)}}{\sum_{j=1}^{n} w^{(j)}}, j = 1 \div n \quad (9)$$

Step 4: Rank the options for each criterion.

Step 5: Calculate weights for the rankings of the options using Eq. (10), where r_t is the ranking value of the t^{th} option.

$$\vartheta^{(t)} = \frac{1}{1 + \frac{1}{2} + \cdots + \frac{1}{r_t}}, t = 1 \div m \quad (10)$$

Step 6: Calculate weights for the rankings of the options using Eq. (11).

$$\vartheta_t = \frac{w^{(t)}}{\sum_{k=1}^{m} w^{(t)}}, t = 1 \div m \quad (11)$$

Step 7: Calculate scores for each option using Eq. (12). The solution with the highest score is the optimal solution.

$$S_i = \sum_{j=1}^{n} w_k^j * \vartheta_t^i , i = 1 \div m \tag{12}$$

Optimal solution procedure using the *PIV* method [31]:

Step 1: Calculate normalized values using Eq. (13).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{13}$$

Step 2: Calculate normalized values considering the weights of the criteria using Eq. (14), where w_j is the weight of criterion j. In this research, weights of the criteria will be calculated using both the *PSI* and *R* methods.

$$V_{ij} = w_j \times n_{ij} \tag{14}$$

Step 3: Calculate the weight proximity indices using Eq. (15) and (16).

$$u_i = v_{\max} - v_i \quad if \quad j \in B \tag{15}$$

$$u_i = v_i - v_{\min} \quad if \quad j \in C \tag{16}$$

Step 4: Calculate scores for the solutions using Eq. (17). The optimal solution is the solution with the smallest score.

$$d_i = \sum_{j=1}^{n} u_i \tag{17}$$

4. PSI-R-PIV HYBRID MODEL

Based on the application steps of the *PSI, R*, and *PIV* methods as discussed above, the hybrid model combining these three methods is illustrated in Fig. 1.

The application of the *PSI-R-PIV* hybrid model is summarized as follows:

- Sequentially apply the 5 steps of the *PSI* method to identify the best solution among the available options using the *PSI* method.

- Sequentially apply the 7 steps of the *R* method to identify the best solution among the available options using the *R* method.

- Apply the 4 steps of the *PIV* method and the first 4 steps of the *PSI* method (to calculate criteria weights using the *PSI* method) to find the best solution through the *PSI-PIV* hybridization.

- Apply the 4 steps of the *PIV* method and the first 3 steps of the *R* method (to calculate criteria weights using the *R* method) to find the best solution through the *R-PIV* hybridization.

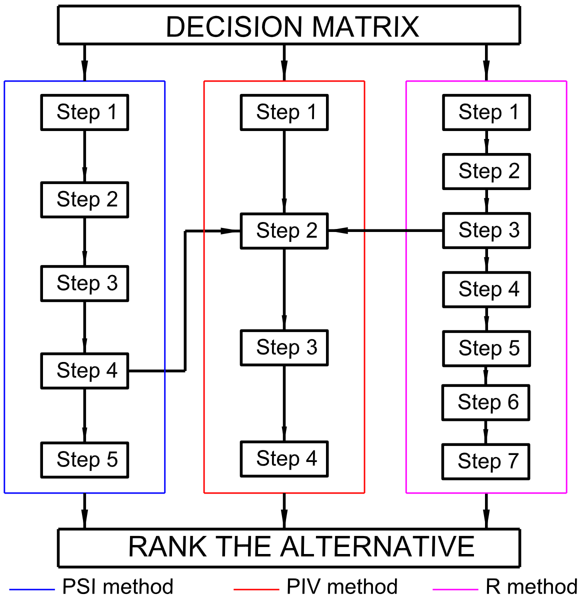

Fig. 1. PSI-R-PIV Hybrid Model

It is observed that implementing the *PSI-R-PIV* method is essentially the simultaneous implementation of three methods: *PSI*, *R*, and *PIV*. All three component methods are simple mathematical methods, easy to use, and have been applied in many researches, so it can be seen that the implementation of the *PSI-R-PIV* method does not encounter any difficulties. The novelty of *PSI-R-PIV* is simply the clever utilization of the weights of the criteria calculated by the *PSI* and *R* methods to serve the ranking of alternatives using the *PIV* method. When applying the *PSI-R-PIV* method, all calculations can be performed manually or using Excel.

5. RESULTS AND DISCUSSION

The accuracy evaluation of the *PSI-R-PIV* model is conducted in three different cases related to three common mechanical processing methods.

Case 1: Ranking of 9 milling process options, each comprising 1 criterion of type *B* and 1 criterion of type *C*.

Case 2: Ranking of 25 turning process options, each comprising 1 criterion of type *B* and 2 criteria of type *C*.

Case 3: Ranking of 17 drilling process options, each defined by six criteria, all of which are of type *C*.

Case 1

In this case, the task is to select the best milling process option. Table 1 summarizes the data from nine experiments of a milling process where four parameters were varied: cutting speed (v_c), feed rate (f), axial cutting depth (a_r), and radial cutting depth (a_p). Each experiment measured surface roughness (*Ra*) and material removal rate (*MRR*) [35]. The objective is to identify the best experiment among the nine, where *Ra* is minimized and *MRR* is maximized. This task has previously been performed using *VIKOR, MABAC,* combined compromise solution (*COCOSO*), *MAIRCA*, and range of value (*ROV*) methods [35]. The *PSI-R-PIV* hybrid model will be used to perform this task in this research.

Table 1. Experimental data for milling experiments [35]

Exp.	v_c (m/min)	f (mm/rev)	a_r (mm)	a_p (mm)	*Ra* (μm)	*MRR* (mm^3/min)
M1	80	0.05	4	0.1	0.97	25.465
M2	80	0.10	8	0.3	1.085	305.577
M3	80	0.15	12	0.5	2.032	1145.916
M4	100	0.05	8	0.5	0.746	318.31
M5	100	0.10	12	0.1	0.609	190.986
M6	100	0.15	4	0.3	1.001	286.479
M7	120	0.05	12	0.3	0.858	343.775
M8	120	0.10	4	0.5	0.326	381.972
M9	120	0.15	8	0.1	1.083	229.183

First, this task is performed using the *PSI* method. Step 1 of the *PSI* method calculates normalized values as shown in Table 2.

Steps 2, 3, and 4 are sequentially applied to calculate the values of n, φ_j, and weights w_j, which are summarized in Table 3. Note that the weights of the criteria calculated by the *PSI* method will be used to combine with the *PIV* method in the next part of this article.

Table 2. Normalized values in the PSI method

Exp.	Ra	MRR
M1	0.3361	0.0222
M2	0.3005	0.2667
M3	0.1604	1.0000
M4	0.4370	0.2778
M5	0.5353	0.1667
M6	0.3257	0.2500
M7	0.3800	0.3000
M8	1.0000	0.3333
M9	0.3010	0.2000

Table 3. Some parameters in PSI

	Ra	*MRR*
n	0.4195	0.3130
φ_j	0.4633	0.5986
w_j	0.5721	0.4279

The scores of the experiments are calculated in step 5, resulting in Table 4. The last column of this table also lists the rankings of the experiments based on their scores.

The ranking of milling experiments using the *R* method follows next. First, the criteria rankings are sorted, which means performing step 1. According to some researches, for milling processes evaluated by *Ra* and *MRR*, *Ra* should be given more importance [36,37]. This means *Ra* is ranked 1st and *MRR* is ranked 2nd.

Table 4. Scores and rankings of the experiments

Exp.	θi	rank
M1	0.2018	9
M2	0.2860	7
M3	0.5197	2
M4	0.3689	4
M5	0.3776	3
M6	0.2933	6
M7	0.3457	5
M8	0.7147	1
M9	0.2578	8

Steps 2 and 3 of the *R* method have been sequentially applied and the weights of *Ra* and *MRR*, corresponding to 0.6 and 0.4 respectively, have been calculated. Note that these weight values of *Ra* and *MRR*, besides determining the rankings of experiments using the *R* method, will also be used to combine with the *PIV* method in the next part of this article.

Step 4 has ranked the experiments for each criterion as shown in Table 5.

Table 5. Rankings of experiments for each criterion

Exp.	*Ra*	*MRR*
M1	5	9
M2	8	5
M3	9	1
M4	3	4
M5	2	8
M6	6	6
M7	4	3
M8	1	2
M9	7	7

Steps 5 and 6 have sequentially applied to calculate the weights of the rankings of experiments as shown in Table 6.

The scores of each experiment have been calculated in step 7, summarized in Table 7. The last column of this table also lists the rankings of the experiments based on their scores.

Table 6. Weights of rankings of experiments

Exp.	*Ra*	*MRR*
M1	0.0943	0.0761
M2	0.0792	0.0943
M3	0.0761	0.2153
M4	0.1174	0.1033
M5	0.1435	0.0792
M6	0.0879	0.0879
M7	0.1033	0.1174
M8	0.2153	0.1435
M9	0.0830	0.0830
SUM	1	1

So, the ranking of the milling experiments using the *R* method has concluded. Next, this task will be carried out using the *PIV* method in two scenarios: one where the criteria weights were calculated using the *PSI* method, and another where the criteria weights were calculated using the *R* method. First, the weight values of *Ra* and *MRR* calculated using the *PSI* method will be utilized.

Applying step 1 of the *PIV* method has normalized values as synthesized in Table 8.

Applying step 2 of *PIV* has computed V_{ij} values, ui values calculated in step 3, and scores of the experiments calculated in step 4. All these values have been synthesized in Table 9. The final column of this table also consolidates the ranking of the experiments based on their scores.

Table 7. Scores and rankings of milling experiments

Exp.	S_i	rank
M1	0.0870	7
M2	0.0852	8
M3	0.1318	2
M4	0.1118	4
M5	0.1178	3
M6	0.0879	6
M7	0.1090	5
M8	0.1866	1
M9	0.0830	9

Thus, the ranking of milling experiments using the *PIV* method with weights of *Ra* and *MRR* calculated by the *PSI* method has also been conducted similarly. Fig. 2 summarizes the rankings of milling experiments when ranked by methods in this research including *PSI, R, PSI-PIV, R-PIV, VIKOR, MABAC, COCOSO, MAIRCA*, and *ROV* [35].

Table 8. Normalized values in the PIV method

Exp.	*Ra*	*MRR*
M1	0.3038	0.0183
M2	0.3399	0.2192
M3	0.6365	0.8220
M4	0.2337	0.2283
M5	0.1908	0.1370
M6	0.3136	0.2055
M7	0.2688	0.2466
M8	0.1021	0.2740
M9	0.3392	0.1644

Table 9. Some parameters in PIV, scores, and rankings of milling experiments

Exp.	V_{ij}		u_i		d_i	rank
	Ra	*MRR*	*Ra*	*MRR*		
M1	0.1738	0.0078	0.1154	0.3439	0.4593	9
M2	0.1944	0.0938	0.1360	0.2579	0.3939	7
M3	0.3642	0.3517	0.3057	0.0000	0.3057	2
M4	0.1337	0.0977	0.0753	0.2540	0.3293	3
M5	0.1091	0.0586	0.0507	0.2931	0.3438	5
M6	0.1794	0.0879	0.1210	0.2638	0.3847	6
M7	0.1538	0.1055	0.0953	0.2462	0.3415	4
M8	0.0584	0.1172	0.0000	0.2345	0.2345	1
M9	0.1941	0.0703	0.1357	0.2814	0.4170	8

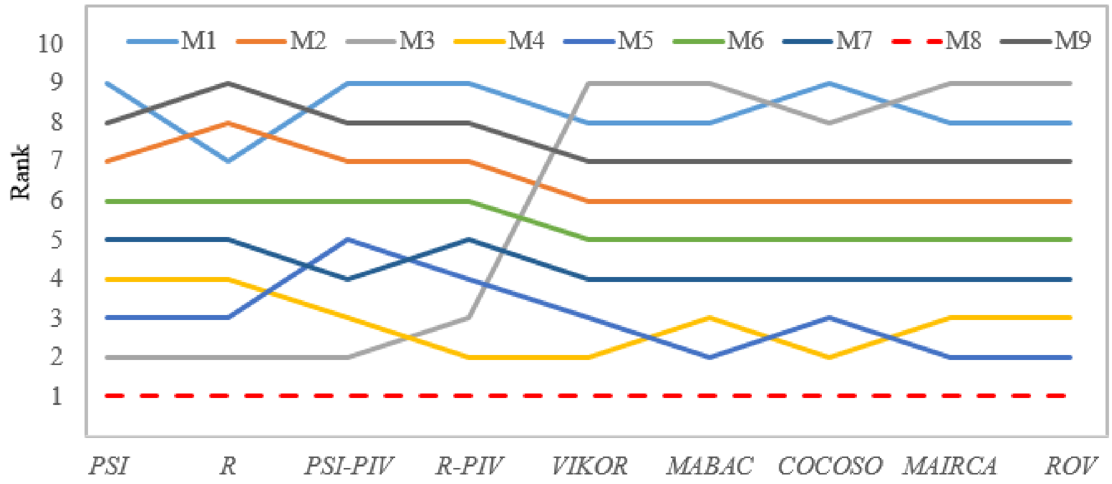

Fig. 2. Rankings of options in Case 1

It has been observed that the rankings of experiments are not entirely consistent when ranked using different methods. This has been reported in numerous studies as each *MCDM* method has been conducted with a different approach [32,38]. In this case, all nine methods, including *PSI, R, PSI-PIV, R-PIV, VIKOR, MABAC, COCOSO, MAIRCA*, and *ROV*, identified *M8* as the best experiment among the nine surveyed experiments. Thus, in terms of finding the best experiment, all nine methods are equally effective. It was also observed that the ranking of some experiments was consistently determined when evaluated by several different methods. *M3* was consistently ranked second when using the *PSI*, *R*, and *PSI-PIV* methods. M4 was consistently ranked 3rd when using the *PSI-PIV*, *MABAC*, *MAIRCA*, and *ROV* methods. *M6* was always ranked 6th when using the *PSI*, *R*, *PSI-PIV*, and *R-PIV* methods. *M2* was always ranked 7th, *M9* always ranked 8th, and *M1* always ranked 9th when ranked by the *PSI*, *PSI-PIV*, and *R-PIV* methods. However, as shown in Fig. 2, the rankings of some other experiments also showed significant differences when ranked by different methods in the *PSI-R-PIV* combination. To comprehensively evaluate the performance of the proposed methods, this research uses Spearman's rank correlation coefficient [32]. This coefficient is calculated according to Eq. (18), where D_i is the difference in the ranking of option i when ranked by different methods.

$$S = 1 - \frac{6D_i^2}{m(m^2-1)} \tag{18}$$

The application of (18) has calculated the Spearman correlation coefficient between *PSI-R-PIV* combination methods and other methods as shown in Table 10.

The average Spearman coefficient between *PSI, R, PSI-PIV, R-PIV* methods compared to *VIKOR, MABAC, COCOSO, MAIRCA*, and *ROV* methods respectively are 0.54998, 0.49332, 0.65002, and 0.51998. Thus, in this case, among the four methods in the *PSI-R-PIV* combination, the performance decreases in the order of *PSI-PIV* > *PSI* > *R-PIV* > *R.*

Table 10. Spearman correlation coefficient in Case 1

	VIKOR	*MABAC*	*COCOSO*	*MAIRCA*	*ROV*	Average
PSI	0.5167	0.5333	0.6333	0.5333	0.5333	0.54998
R	0.4667	0.4833	0.5500	0.4833	0.4833	0.49332
PSI-PIV	0.5167	0.4833	0.6333	0.4833	0.4833	0.65002
R-PIV	0.6500	0.6167	0.7500	0.6167	0.6167	0.51998

Case 2

In this case, the combination *PSI-R-PIV* is used to rank 25 experiments of the metal machining process denoted as *T1, T2,..., T25* in Table 11. Each experiment varied five parameters: tool nose radius ($r_ε$), tool shank length (L), spindle speed (n_w), feed rate (f_d), and cutting depth (a_p). Each experiment also measured two Type *C* criteria including surface roughness (*Ra*), roundness error (*RE*), and one Type *B* criterion, cutting efficiency (*Q*). The data from these 25 experiments were used in a published research where experiment rankings were determined using the *FUCA* method with four different sets of criterion weights. These combinations of the *FUCA* method with different criterion weights are denoted as *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4* [39].

Ranking of the experiments in this case using the *PSI-R-PIV* combination was performed similarly to Case 1. Fig. 3 illustrates the rankings of the turning experiments when ranked using *PSI-R-PIV* (including *PSI, R, PSI-PIV, R-PSI*) and the *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4* methods from [39].

Table 11. Data on the turning experiments [39]

Exp.	r_ε (mm)	L (mm)	n_w (rev/min)	f_d (mm/rev)	a_p (mm)	Ra (μm)	RE (μm)	Q (mm^3/s)
T1	0.25	25	421	0.08	0.2	0.823	8.333	10.581
T2	0.25	30	587	0.094	0.4	0.657	7.667	34.669
T3	0.25	35	659	0.112	0.6	0.459	9.333	69.562
T4	0.25	40	788	0.124	0.1	0.992	11.000	15.349
T5	0.25	45	926	0.316	1	0.817	13.667	459.640
T6	0.4	25	587	0.112	0.1	0.523	14.000	10.327
T7	0.4	30	659	0.124	1	0.449	13.333	128.359
T8	0.4	35	788	0.316	0.2	0.873	15.333	78.228
T9	0.4	40	926	0.08	0.4	0.645	11.667	46.546
T10	0.4	45	421	0.094	0.6	0.456	10.667	37.298
T11	0.6	25	659	0.316	0.4	0.992	16.667	130.844
T12	0.6	30	788	0.08	0.6	0.764	13.000	59.414
T13	0.6	35	926	0.094	0.1	0.654	8.333	13.673
T14	0.6	40	421	0.112	1	0.823	5.333	74.066
T15	0.6	45	587	0.124	0.2	0.446	11.333	22.867
T16	0.8	25	788	0.094	1	0.598	8.667	116.352
T17	0.8	30	926	0.112	0.2	0.777	11.333	32.582
T18	0.8	35	421	0.124	0.4	0.649	13.667	32.801
T19	0.8	40	587	0.316	0.6	0.568	8.333	174.822
T20	0.8	45	659	0.08	0.1	0.668	10.667	8.281
T21	0.85	25	926	0.124	0.6	0.786	17.333	108.219
T22	0.85	30	421	0.316	0.1	0.812	15.667	20.897
T23	0.85	35	587	0.08	1	0.452	12.667	73.765
T24	0.85	40	659	0.094	0.2	0.657	15.667	19.461
T25	0.85	45	788	0.112	0.4	0.678	16.333	55.453

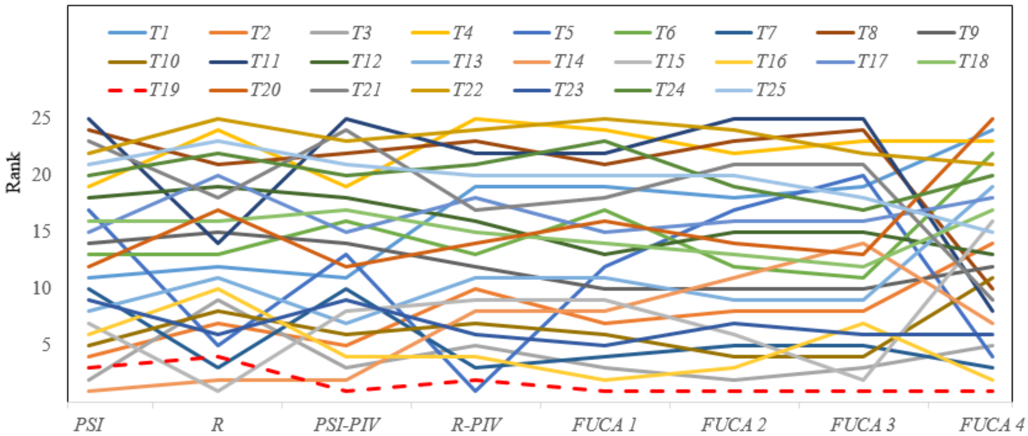

Fig. 3. Ranking of options for Case 2

In the *PSI-R-PIV* combination, among the four methods *PSI, R, PSI-PIV*, and *R-PSI*, only *PSI-PIV* identifies experiment *T19* as the best, similar to when using the *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4* methods. Thus, in terms of finding the best option, *PSI-PIV* has an advantage over the other three methods *PSI, R*, and *R-PSI* in this case. It was also observed that when using the *PSI-PIV* method to rank experiments, the rankings of some experiments were also consistently determined compared to when using other methods. For example, *T3* was consistently ranked 3rd when using both the *PSI-PIV* and *FUCA 3* methods, *T10* was consistently ranked 6th when using both the *PSI-PIV* and *FUCA 1* methods, *T11* was consistently ranked 25th when using all three methods *PSI-PIV*, *FUCA 2*, and *FUCA 3*, *T17* was consistently ranked 15th when using both the *PSI-PIV* and *FUCA 1* methods, *T18* was consistently ranked 17th, and *T24* was ranked 20th when using both the *PSI-PIV* and *FUCA 4* methods. Calculation of the Spearman correlation coefficient was also performed and the results are shown in Table 12.

Table 12. Spearman correlation coefficient for Case 2

	FUCA 1	*FUCA 2*	*FUCA 3*	*FUCA 4*	Average
PSI	0.8469	0.8962	0.8423	0.2992	0.7212
R	0.8100	0.7492	0.6962	0.5677	0.7058
PSI-PIV	0.8731	0.8915	0.8162	0.3800	0.7402
R-PIV	0.9246	0.8615	0.7854	0.6662	0.8094

The average value of the Spearman coefficient between *R* and the *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4* methods is 0.7058, the lowest among the methods in the *PSI-R-PIV* combination. Therefore, in this case, *R* shows the lowest efficiency. Although *R-PIV* has a higher average Spearman coefficient of 0.8094 compared to *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4*, it does not identify the best experiment similarly to the *FUC*A methods. Meanwhile, *PSI-PIV* has identified *T25* as the best experiment, similar to when using the *FUCA 1, FUCA 2, FUCA 3*, and *FUCA 4* methods. In conclusion, in this case, the performance of the options in the *PSI-R-PIV* combination decreases in the following order: *PSI-PIV > R-PIV > PSI > R*.

Case 3

Seventeen metal drilling options needing ranking have been synthesized in Table 13, denoted respectively as *D1, D2,..., D17*.

Table 13. Data on the drilling experiments [29]

Exp.	*n* (rpm)	*fd* (mm/rev)	*C1* (s)	*C2* (mm)	*C3* (mm)	*C4* (mm)	*C5* (mm)	*C6* (μm)
D1	1100	0.038	14.03	0.051	0.058	0.105	0.21	0.479
D2	1100	0.076	7.59	0.053	0.058	0.155	0.245	1.211
D3	1100	0.076	7.34	0.035	0.06	0.165	0.215	0.916
D4	1100	0.203	4.06	0.033	0.075	0.18	0.215	0.535
D5	2920	0.038	5.4	0.048	0.078	0.25	0.195	0.601
D6	2920	0.038	5.5	0.05	0.084	0.185	0.185	0.703
D7	2920	0.076	2.81	0.033	0.058	0.185	0.185	0.466
D8	2920	0.076	2.62	0.028	0.048	0.2	0.19	0.577
D9	2920	0.076	2.88	0.028	0.05	0.18	0.15	0.417
D10	2920	0.076	2.75	0.043	0.051	0.23	0.195	0.675
D11	2920	0.076	2.84	0.043	0.055	0.165	0.205	0.418
D12	2920	0.203	1.59	0.028	0.074	0.145	0.17	0.601
D13	2920	0.203	1.88	0.038	0.064	0.185	0.175	0.563
D14	4540	0.308	3.44	0.049	0.066	0.19	0.185	0.391
D15	4540	0.076	2.04	0.023	0.059	0.16	0.18	0.493
D16	4540	0.076	2.1	0.043	0.05	0.235	0.185	0.675
D17	4540	0.203	1.25	0.04	0.049	0.44	0.19	0.65

Each experiment varied two parameters: spindle speed (*n*) and feed rate (f_d). Six parameters were measured in each experiment, all Type *C* criteria including drilling time (*C1*), Entry burr height (*C2*), Exit burr height (*C3*), Entry burr thickness (*C4*), Exit burr thickness (*C5*), and surface roughness (*C6*). Previously, the *TOPSIS, COPRAS*, and *FUCA* methods were used to rank the experiments [27,28]. The *PSI-R-PIV* combination will also be used for this task in this research.

The application of the *PSI-R-PIV* combination to rank the drilling experiments in this case was carried out similarly to Case 1. Fig. 4 represents the ranking results of the experiments using four methods in the *PSI-R-PIV* combination (including *PSI, R, PSI-PIV*, and *R-PIV*) and three methods *TOPSIS, COPRAS*, and *FUCA* in [27,28].

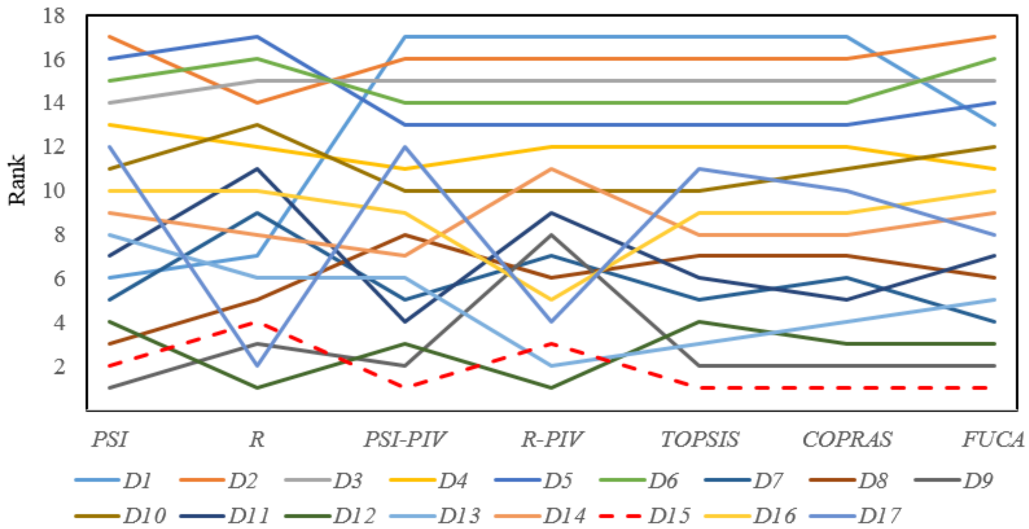

Fig. 4. Ranking of options for Case 3

All three methods used in previously published documents, including *TOPSIS, COPRAS*, and *FUCA*, identified *D15* as the best experiment among the 17 experiments conducted. *D15* was also found to be the best experiment when using the *PSI-PIV* method. However, when using the *PSI, R*, and *R-PIV* methods, *D15* was not identified as the best experiment. Therefore, in terms of identifying the best experiment, *PSI-PIV* also proves to be more effective than the *PSI, R*, and *R-PIV* methods in this case. Furthermore, it is easily observed that the rankings of the remaining experiments were also consistently determined when ranked using the PSI-PIV method compared to other methods. For instance, *D1* was ranked 17th, *D2* was ranked 16th, D5 was ranked 13th, *D6* was ranked 14th, and *D16* was ranked 9th, which was the same as when using *TOPSIS* and *COPRAS*. *D3* was ranked 15th, which was the same as when using all three methods *TOPSIS*, *COPRAS*, and *FUCA*, etc. The Spearman correlation coefficient ranking was also calculated in this case and summarized in Table 14.

Once again, we observe that the average value of the Spearman coefficient for *R* compared to *TOPSIS, COPRAS*, and *FUCA* is the lowest, while the average value of the Spearman coefficient for *PSI-PIV* compared to *TOPSIS, COPRAS*, and *FUCA* is the highest. This means that *R* is the least effective, whereas *PSI-PIV* is the most effective. In conclusion, the performance of the options in the *PSI-R-PIV* combination decreases in the following order across all three cases: *PSI-PIV* > *R-PIV* > *PSI* > *R*.

Table 15 summarizes the efficiency rankings of the four methods in the *PSI-R-PIV* combination after performing the three cases above.

Table 14. Spearman correlation coefficient for Case 3

	TOPSIS	*COPRAS*	*FUCA*	Average
PSI	0.7770	0.7794	0.8799	0.8121
R	0.6471	0.6814	0.8162	0.7149
PSI-PIV	0.9779	0.9828	0.9240	0.9616
R-PIV	0.8309	0.8431	0.8309	0.8350

Table 15. Efficiency ranking of methods

Method	Case 1	Case 2	Case 3
PSI	2	3	3
R	4	4	4
PSI-PIV	1	1	1
R-PIV	3	2	2

In all three cases conducted, *R* consistently shows the lowest efficiency among the four methods in the *PSI-R-PIV* combination. Conversely, *PSI-PIV* consistently demonstrates superior performance compared to the other methods. These results lead to a firm conclusion that *PSI-PIV* is the best-evaluated method in the *PSI-R-PIV* combination. Another notable point to mention is that in all cases conducted, the best option identified using *PSI-PIV* remains consistent compared to using other methods in the published documents. This is something that the *PSI, R*, and *R-PIV* methods fail to achieve. These findings demonstrate that *PSI-PIV* is a method that ensures high accuracy. This achievement is likely due to the use of the *PSI* method to calculate the weights of the criteria, which has taken advantage of the flexibility of this method, reducing subjectivity in weight calculation [40]. In addition, ranking alternatives using the *PIV* method has also taken advantage of the unique feature of this method, which is the determination of the degree of deviation of the weighted normalized value from the best value within its range for each criterion [31]. Using this method instills confidence in ensuring accuracy in finding the optimal solution in mechanical machining processes. Conversely, the R method is not recommended. This is not intended to criticize the R method or any other method but merely emphasizes that when seeking the best solution in mechanical machining processes, users should employ the PSI-PIV method.

CONCLUSION

Combining the three methods *PSI, R*, and *PIV* creates a new method named *PSI-R-PIV*. For each problem requiring ranking of options, using *PSI-R-PIV* always generates four sets of option rankings: one from *PSI*, one from *R*, one from *PSI-PIV*, and one from *R-PIV*. Examples conducted in the field of mechanical processing (milling, turning, drilling) demonstrate that *R* is not suitable for use, whereas *PSI-PIV* has affirmed the necessary accuracy and is recommended for use. This means using *PSI* to calculate weights for criteria and then using *PIV* to select the best option.

In the field of mechanical processing, users can confidently utilize *PSI-PIV* to find the best option among available alternatives without expending additional effort in searching for other methods to rank options or in determining weights for criteria.

Applying *PSI-PIV* to solve problems in other fields beyond machining operations to continue evaluating the effectiveness of this method when applied in other domains is a task for the near future to establish solid scientific foundations for this method.

In addition, some tasks to be implemented in the near future can be listed as follows: developing the *PSI-PIV* method to handle situations where the decision matrix contains fuzzy number sets or qualitative factors; or hybridizing *PSI* with other *MCDM* methods; or identifying alternative data normalization methods to combine with the PSI method in cases where the available data normalization method in the *PSI* method cannot be used (see Eqs. (2) and (3)), which is the case where in criteria of type B there is a criterion whose maximum value in the alternatives is 0 or in criteria of type C there is a value of 0.

Conflicts of Interest

The author declares no conflict of interest.

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