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Multi-Objective Optimization of Cutting Parameters for Polyethylene Thermoplastic Material by Integrating Data Envelopment Analysis and SWARA-Based CoCoSo Approach

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ABSTRACT

This paper presents a comprehensive study on the multi-objective optimization of cutting parameters for Polyethylene (PE) thermoplastic material utilizing a CO_2 laser. Recognizing the pivotal role of precise and efficient cutting in various sectors, from packaging to biomedical engineering, we integrate two potent analytical methodologies - Data Envelopment Analysis (DEA) and Step-Wise Weight Assessment Ratio Analysis (SWARA)-based Comprehensive Criteria Score Optimization (CoCoSo) approach. The cutting parameters chosen for the study were material thickness, power, and cutting speed. The experiments were conducted according to the Taguchi L_{18} orthogonal array. Surface roughness and kerf width measurements were performed to examine the cutting quality. Additionally, another response variable, material removal rate, was calculated. By integrating Data Envelopment Analysis and the SWARA-based CoCoSo approach, the experimental condition that yielded the lowest surface roughness, kerf width, and highest material removal rate was determined. The optimum experimental condition was found to be 4 mm material thickness, 80 W power, and 15 mm/s cutting speed. This work, therefore, paves the way for the innovative application of these combined methodologies in enhancing the production processes of PE and other thermoplastic materials, with clear implications for cost-effectiveness and sustainability in the manufacturing sector.

Veri Zarflama Analizi ve SWARA Tabanlı CoCoSo Yaklaşımını Entegre Ederek Polietilen Termoplastik Malzeme Kesme Parametrelerinin Çok Amaçlı Optimizasyonu

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ÖZ

Bu makale, Polietilen (PE) termoplastik malzeme için CO_2 lazer kullanarak kesme parametrelerinin çok amaçlı optimizasyonu üzerine kapsamlı bir çalışma sunmaktadır. Paketlemeden biyomedikal mühendisliğe kadar çeşitli sektörlerde kesme işleminin hassas ve verimli bir şekilde gerçekleştirilmesinin önemini göz önünde bulundurarak, Veri Zarflama Analizi (DEA) ve Adım Adım Ağırlık Değerlendirme Oranı Analizi (SWARA) temelinde Birleşik Uzlaşma Çözümü (CoCoSo) yaklaşımını entegre ediyoruz. Kesme parametreleri olarak malzeme kalınlığı, güç ve kesme hızı seçilmiştir. Deneyler Taguchi L_{18} ortogonal dizine göre uygulanmıştır. Kesim kalitesini incelemek için yüzey pürüzlülüğü ve kerf genişliği ölçümleri gerçekleştirilmiştir. Ayrıca, diğer bir yanıt olan malzeme kaldırma oranı hesaplanmıştır. Veri Zarflama Analizi ve SWARA Tabanlı CoCoSo yaklaşımı entegre edilerek en düşük yüzey pürüzlülüğü, kerf genişliği ve en yüksek malzeme kaldırma oranının elde edildiği deney koşulu tespit edilmiştir. Optimum deney koşulu; 4 mm malzeme kalınlığı, 80 W lazer gücü ve 15 mm/s kesme hızı olarak tespit edilmiştir. Bu çalışma, birleşik metodolojilerin PE ve diğer termoplastik malzemelerin üretim süreçlerini geliştirmede yenilikçi uygulamalarına yol açmaktadır. Bu durum, imalat sektöründe maliyet etkinliği ve sürdürülebilirlik açısından net etkileri olan bir perspektif sunmaktadır.

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1. Introduction

Thermoplastic materials are a class of polymers that possess unique properties, making them widely utilized in various industries, including automotive, aerospace, electronics, and packaging (Der et al., 2019a; Der et al., 2022). PE one of the most widely used thermoplastic materials, is characterized by its high resistance to impact, moisture, and chemical substances. This polymer, composed of ethylene monomers, offers distinct advantages such as low cost, ease of processing, and versatility, making it a critical material in diverse industries, including packaging, construction, and automotive engineering (Mierzwa-Hersztek et al., 2019). Thermoplastic materials, including polyethylene, exhibit the unique property of being mouldable and pliable at high temperatures and becoming hard upon cooling. This inherent plasticity facilitates their machining, moulding, and cutting, accommodating a spectrum of functional needs (Rastogi et al., 2011).

One significant procedure used to machine thermoplastic materials is carbon dioxide (CO_2) laser cutting (Der et al., 2019b). This non-contact, thermal-based process provides a high level of precision and operational control, which is ideal for processing thermoplastics like polyethylene. The principle of CO_2 laser cutting revolves around using the high-energy infrared light beam, which upon interaction with the material's surface, causes it to heat, melt, and vaporize, thereby effectuating a cut. This technique yields remarkable advantages, such as minimal heat-affected zones, low distortion, and the ability to handle intricate designs (Powell, 1993).

Optimizing the cutting parameters in the machining process is essential for ensuring the quality of the final product (Cus and Balic, 2003). In this context, three parameters play a crucial role in determining the cutting quality: Surface roughness, kerf width, and material removal rate. Surface roughness refers to the measure of the texture of the machined surface. A smoother surface denotes a higher-quality cut, minimizing post-processing efforts and costs (Liu et al., 2017). Kerf width, the width of material removed during the cutting process, directly impacts the precision of the cut and the total material usage. A smaller kerf width is generally desirable as it allows for more precise cuts and efficient material utilization (Llanto et al., 2021). The rate at which material is removed, which refers to the quantity of material eliminated in a given period, plays a vital role in determining the productivity of the cutting operation. Higher material removal rates indicate faster cutting speeds, leading to increased productivity and cost-effectiveness (Kini and Chincholkar, 2010). Therefore, a comprehensive and balanced optimization of these parameters is pivotal to achieving an efficient and high-quality machining process.

This study aimed to determine the optimal experimental parameter by using multi-objective optimization of the cutting parameters of thermoplastic materials with a CO_2 laser. For this, firstly, an experimental setup for the cutting experiment of Polyethylene thermoplastic material with a CO_2 laser was designed. Three different input parameters were selected: material thickness, power and cutting speed. Each input parameter was determined as a factor in the experimental design analysis and three levels of each factor were specified. In the experimental study, three different output parameters were measured: Surface roughness, kerf width, and material removal rate. Considering the approach developed in the study, first of all, efficient experiments were determined by data envelopment analysis. Then, the SWARA-based CoCoSo method was used to determine the ranking of the efficient experiments among themselves. In the second stage, the outputs of the experiment were used as criteria. The criteria weights were calculated by the SWARA method, and these criteria weights were used in the CoCoSo method. Parameter optimization of the efficient experiments was carried out by the SWARA-based CoCoSo method.

The rest of the study was organized as follows: Experimental setup and measurement were explained in greater detail. Then, the developed decision-making approach was explained step by step. Experimental results were given and the effects of cutting parameters on each output were analyzed. Multi-objective optimization was carried out by using the developed decision-making approach. Finally, the conclusion of the study was emphasized.

2. Literature Review

In the exploration of CO_2 laser cutting for thermoplastic polymers with thicknesses ranging from 2 to 10 mm, Caiazzo et al. (2005) evaluated an array of influential parameters such as laser power, cutting velocity, gas pressure, and the thickness of the work material. The study elucidated the superior laser-cutting efficacy of polycarbonate (PC), the moderate workability of polypropylene (PP), and the restrained suitability of polyethylene (PE) for laser cutting. Concurrently, Zhou and Mahdavian (2004) advocated for employing a 60W low-power CO_2 laser for slicing non-metallic substances and plastic boards, accentuating the efficacy of pulse mode cutting for medium-density fibreboards processing due to its narrowed kerf width and reduced burnout probability even amidst intricate angular profile cuts (Lum et al., 2000). In a related study, Mathew et al. (1999) executed parametric scrutiny on the laser cutting procedure of carbon fiber-reinforced plastic composites employing a pulsed Nd:YAG laser, utilizing response surface methodology for the establishment of predictive models. Their investigation examined variables including the heat-affected zone and the taper of the cut surface. Kurt et al. (2009) probed the implications of CO_2 laser cutting on engineering plastics, concluding the necessity of laser power and cutting speed regulation and optimization for the attainment of specified dimensions and optimal surface quality, characterized by satisfactory roughness values. The effect of gas pressure on achieving target dimensions was found negligible, and lower striation frequency was linked to an enhancement in surface quality. Contrarily, no linear correlation was observed between the cutting velocity and surface irregularity of the cut surface. In their assessment of laser power and cutting speed impacts on the quality of cuts across various polymeric materials, Davim et al. (2008a) identified the exceptional workability of Polymethyl Methacrylate (PMMA) for laser cutting, with Polycarbonate (PC) also showing high workability. Polypropylene (PP) displayed medium workability while reinforced thermoset plastic exhibited low workability in laser cutting operations. Davim et al. (2008b) also analyzed the cutting quality of PMMA utilizing a CO_2 laser, focusing on linear and complex 2D pattern surface quality. They reported a relatively small heat-affected zone and the absence of burr formation during the cutting procedure. Ilio et al. (1990) innovatively introduced a digital image processing technique for cut quality assessment in their study on laser cutting of aramid fiber-reinforced plastics. Furthermore, Rooks (2004) delineated the heterogeneous results stemming from different polymer-laser type combinations and discussed the use of robotics for specialized applications such as the dynamic scribing of packaging materials and pre-weakening car trims for integrated airbags. Der et al. (2021) exhibited the successful cutting of variable-thickness polypropylene plastics using a CO_2 laser. The cut pieces were subsequently joined via transmission laser welding, forming a flexible pulsating heat pipe, a process found to be notably efficient due to impeccable cutting.

Moreover, the potency of multi-objective optimization techniques in pinpointing the optimal blend of process parameters, which take into consideration a variety of evaluated cutting properties, has been exhibited. Tackling the shortcomings of the Taguchi method's unifocal optimization, Dubey and Yadava (2008) utilized principal component analysis alongside an orthogonal array to bring forth a multi-objective optimization for the Nd:YAG laser cutting of nickel-based superalloy sheets. Their method led to the discovery of optimized process parameters that resulted in a reduction of various cutting characteristics, encompassing kerf taper, kerf deviation along the length, and kerf width. The parameters could be defined to be optimal as a result of the decrease in oxygen pressure, the shortening of pulse duration, the intermediate pulse frequency, and the slower cutting speed. Through the execution of ANOVA analysis, the cutting speed was recognized as having the most profound impact (48%) on the outcome, subsequently followed by pulse width (33%). In another investigative study, Pandey and Dubey (2012) amalgamated the Taguchi method with fuzzy logic theory to enhance multiple results in the laser cutting procedure of Duralumin sheets, noted for their high reflectivity and thermal conductivity. The determination of the optimized parameter blend hinged on the appraisal of the maximum fuzzy multi-response performance index. This index emphasized beneficial outcomes in relation to augmented gas pressure, amplified cutting speed, attenuated pulse width, and mitigated pulse frequency. Remarkably, in this study, the paramount factor was oxygen gas pressure, which constituted 61.3% of the effect, with pulse frequency following at 34.5%. Chen et al. (2011) employed Grey relational analysis to fine-tune the CO_2 laser cutting process for 6 mm thick PMMA. The researchers honed their attention on two crucial performance features: acquiring a significant transmittance ratio and curtailing surface irregularities. Through rigorous examination, they discerned the optimal parameters to incorporate a moderate assisted-gas flow rate, a minimal defocussing distance, a low pulse frequency, and a higher cutting speed. Among these variables, the assisted gas flow rate and beam defocusing distance were found to exert the most substantial impact on the ultimate quality of the cut surface. Parameter optimization is instrumental in procuring the desired surface roughness for thermoplastic materials. Traditional optimization techniques typically concentrate on single-objective optimization, which contemplates a single criterion at a time (Nyiranzeyimana et al., 2021), for example, Basar et al. (2018) and Güvenç et al. (2019). Yet, in practical scenarios, multiple criteria necessitate concurrent consideration to attain optimal results. Multi-objective optimization methodologies, when united with multi-criteria decision-making (MCDM) approaches, are gaining recognition for addressing such intricate optimization problems (Kumar et al., 2017). AHP and TOPSIS are two of multi criteria decision making methods that are extensively used (Sasikumar and Ayyappan, 2019). AHP facilitates the determination of the comparative importance of different criteria, while TOPSIS assists in ranking the alternatives based on their performance relative to these criteria. The amalgamation of AHP and TOPSIS offers a holistic framework for decision-making, enabling effective parameter optimization and the realization of the desired surface roughness in thermoplastic materials (Roy et al., 2020). In fact, metaheuristic-based ANFIS applications have been implemented to accurately predict surface roughness, as demonstrated by Guvenc et al. (2022).

Numerous studies exist regarding laser cutting in the literature. For instance, Eksilmez et al. (2022) studied the laser processing of Hardox 500 steel and evaluated its processing parameters. Cebeci et al. (2022) processed AISI 304 stainless steel using a laser, focusing on the impact of cutting parameters on outputs such as surface roughness, kerf width, and burr height. The selection of materials suitable for laser cutting has also been a research topic, as explored by Ordu and Der (2023a). Moreover, Ordu and Der (2023b) concentrated on minimizing environmental impacts when selecting the most suitable plastic material for laser cutting.

Despite the extensive research on laser cutting of various materials, especially thermoplastic polymers, there remains a gap in understanding the integration of multi-objective optimization methodologies with multi-criteria decision-making techniques. The present study seeks to bridge this gap by combining the strengths of AHP and TOPSIS into a comprehensive framework for laser cutting applications. Such an approach not only enhances the predictability of outcomes, such as surface roughness but also highlights the study's novelty in addressing complex optimization challenges in laser cutting. Through this research, we aim to offer a pioneering pathway for stakeholders to achieve optimal results while considering multiple concurrent criteria, ensuring superior laser-cutting performance and quality.

3. Experimental Setups and Measurements

3.1. CO_2 Laser Machine and Thermoplastic

The preliminary experiments were carried out with a laser system, consisting of a 100 W continuous CO_2 laser (LazerFix LF7010 Laser Cutting Machine), and a three-axis CNC-controlled table with a working volume of 70 cm×100 cm×20 cm as shown in Figure 1.

Figure 1. LazerFix LF7010 laser cutting machine

The thermoplastic material selected for this research was PE. Its properties are given in Table 1. The selected material thicknesses were 2 and 4 mm.

Table 1. Average physical, thermal, and mechanical properties of PE

Thermoplastic	Density (kg/m^3)	Yield strength (MPa)	Tensile Strength (MPa)	Young's Modulus (GPa)	T_m (°C)	Service Temperature, min/max (°C)
PE	950	23.5	33.00	0.76	125	-70/80

PE, a widely used plastic material, is known for its lightweight, excellent insulation properties, and strong resistance to most acids, bases, and numerous organic solvents. Its flexibility and toughness combined with resistance to impact and abrasion make it mechanically reliable. Additionally, PE serves as an effective vibration damper. The material's melting point is approximately 125°C, emphasizing its substantial thermal properties. It also exhibits superior electrical characteristics, including commendable dielectric strength, volume resistivity, and high arc resistance, making it a popular choice for electrical insulation. Although the grade of polyethylene determines its opacity, it generally ranges from translucent to opaque.

3.2. Selection of Cutting Parameters

The cutting process is affected by various constant and varying parameters. The stand-off distance is the constant factor, while the variables encompass the power of the laser, the speed of the cut, the thickness of the material, and the pressure of the compressed air. The role of compressed air is twofold: to clear away molten material from the workpiece and to shield the focusing optics from any dust or smoke. Keeping the optics clean is crucial in guaranteeing that the workpiece is subjected to a beam of the highest quality. An optimum working distance of 7 mm has been established.

Once the polymer sheet was situated on the work surface, we examined its evenness with a spirit level. We did not employ compression pressure to secure the sheet to the table. For polymer sheets that are smaller and/or thinner, compression is generally essential to avoid unsteadiness induced by the effect of pressurized air on the sheet; however, with the minimum thickness of 2 mm in this study, it was not required. The thrust magnitude and the efficiency in eliminating molten material have correlations with the stand-off distance and nozzle diameter, to the contrary these correlations were not explored in this research.

In this study, material thickness, power and cutting speed were chosen as cutting parameters in cutting PE material with a CO_2 laser. Selected cutting parameters and levels are given in Table 2. Experiments were performed according to the Taguchi L_{18} orthogonal array.

Table 2. Cutting parameters and levels

Cutting parameters	Symbol	Level 1	Level 2	Level 3
Material thickness (mm)	t	2	4	-
Power (W)	P	80	90	100
Cutting speed (mm/s)	Vc	5	10	15

Figure 2 illustrates the geometric shapes employed in the laser-cutting process of polymeric materials. The results obtained from these cuts were used to determine surface roughness measurements. From a 130 mm x 130 mm square plate, nine pieces, each measuring 30 mm x 30 mm, were obtained. These pieces were cut at different cutting speeds and powers.

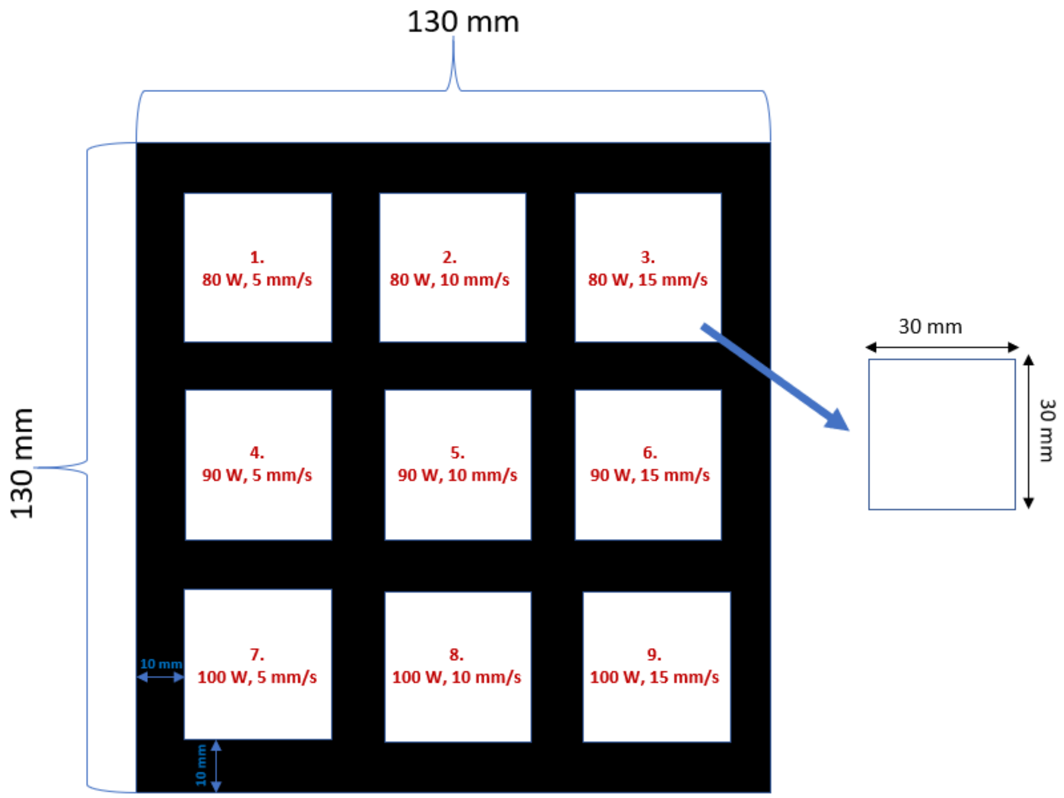

Figure 2. Geometric forms of the specimen for surface roughness measurements

In order to measure kerf width - an important cutting parameter - the part depicted in Figure 3 was cut. A straight cut was made on a 10 mm x 100 mm rectangular plate to measure the kerf widths associated with nine different parameters.

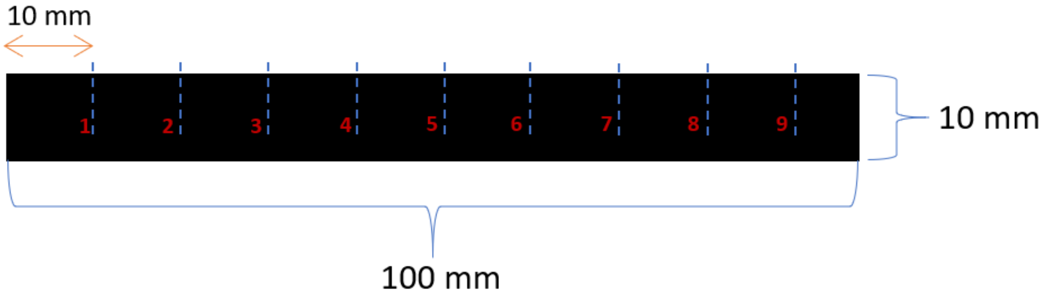

Figure 3. Geometric forms of the specimen for kerf width measurements

3.3. Measurement of Ra with Kerf Width and Calculation of Material Removal Rate

Surface roughness (Ra) and kerf width (KW) measurements were performed to examine the cutting quality of the PE material. Ra measurements were conducted using the DAILYAID brand and DR100 model surface roughness measurement device. The KW was measured using a computer-connected Dino-Lite AM4113T digital microscope. The measurements were taken from the captured images using Dino Capture 2.0 software. Ra and KW measurement pictures are shown in Figure 4.

Another response, material removal rate (MRR), is calculated by Eq. (1) (Madić et al., 2014).

$$MRR\ (mm^3/min) = t \cdot Vc \cdot KW \tag{1}$$

Here; t (mm) is material thickness, Vc (mm/s) means cutting speed and KW (mm) represents kerf width.

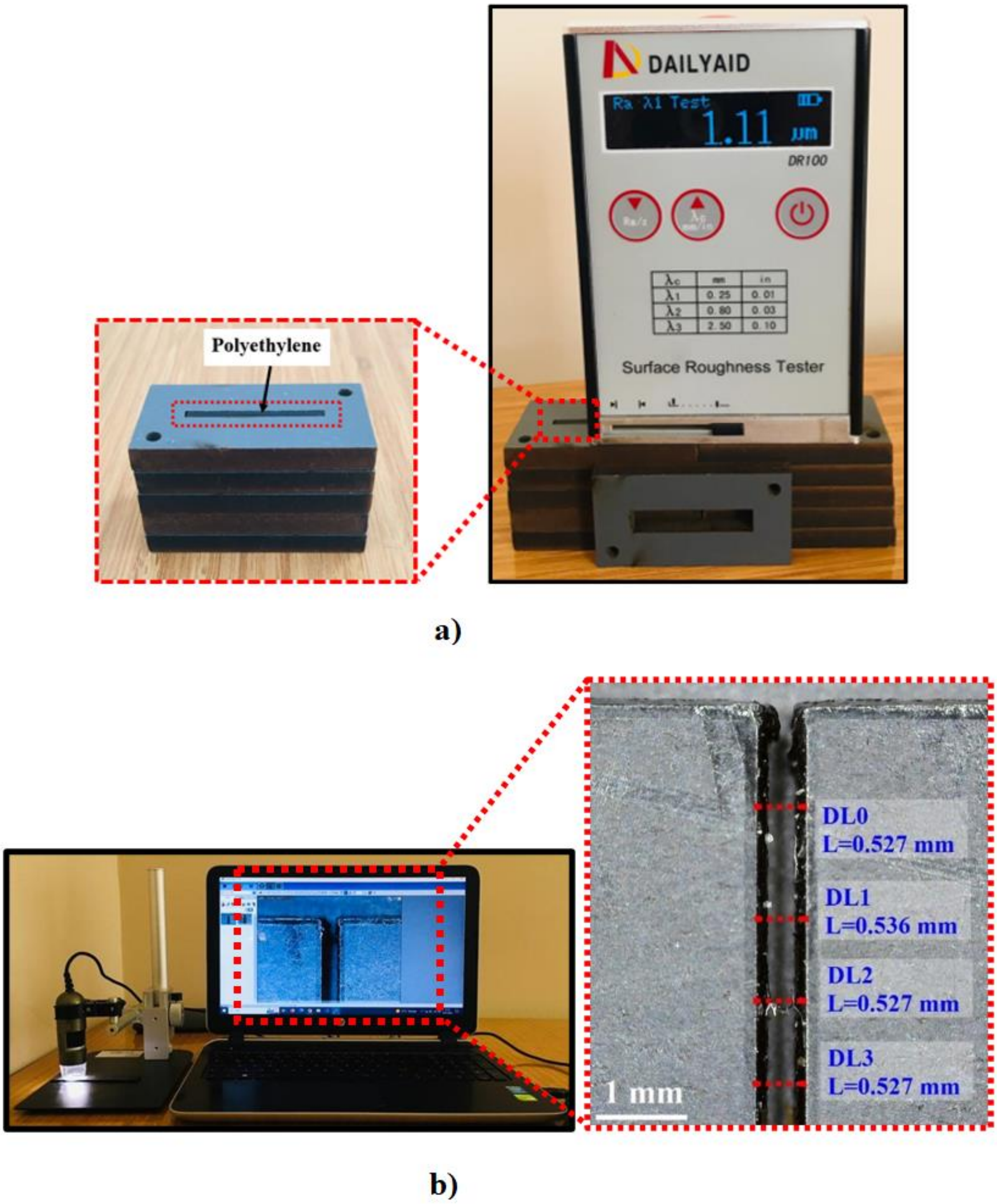

Figure 4. Measurement setup a) Surface roughness and b) Kerf width.

4. Data Envelopment Analysis Integrated with SWARA-Based CoCoSo Approach

4.1. Data Envelopment Analysis Modelling

Data Envelopment Analysis (DEA) is an approach used to evaluate the relative performance of alternatives and it has gained widespread use over the years (Po et al., 2009). Charnes et al. (1978) introduced the DEA method featuring the Charnes-Cooper-Rodes (CCR) model, while the DEA variant using the Banker-Charnes-Cooper (BCC) model was proposed by Banker et al. (1984). The core of the DEA model is a fractional programming process that optimizes a ratio obtained by dividing outputs by their corresponding inputs. The computation of weights involves the application of a mathematical programming method (Po et al., 2009). The transformation of fractional programming into a linear one was achieved by Charnes et al. (1981). We modified our DEA model for each Decision-Making Units (DMUs) following Cooper et al. (2000), incorporating 18 DMUs, three inputs, and three outputs.

The DEA model assigns efficiencies within the [0, 1] interval, with the highest possible efficiency score capped at 1. This restriction might induce uncertainty in comparing the relative efficiency scores of high-performing DMUs. That is, the DEA model does not facilitate a ranking system among the most efficient DMUs (Ordu et al., 2021).

4.2. Determination of the Criteria Weights by Using SWARA Method

The SWARA method is one of the multi-criteria decision-making methods and can be used to determine criterion weights. SWARA method was developed by Keršulienė et al. (2010). The steps of the method (Keršulienė et al., 2010) are given below:

Step 1: All criteria is sorted in descending order of their importance.

Step 2: For each criterion, the Comparative Significance of the Mean Value (s_j) is determined. For this, criterion j is compared with the criterion (j+1). The relative importance of the criterion j according to the criterion (j+1) is determined.

Step 3: The coefficient (k_j) is calculated using Eq. (2).

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{2}$$

Step 4: The importance vector (w_j) is calculated using Eq. (3).

$$w_j = \begin{cases} 1, & j = 1 \\ \dfrac{x_{j-1}}{k_j}, & j > 1 \end{cases} \tag{3}$$

Step 5: The criterion weights (q_j) is calculated using Eq. (4).

$$q_j = \frac{w_j}{\sum_{k=1}^{n} w_k} \tag{4}$$

4.3. CoCoSo Method

The CoCoSo method, proposed by Yazdani et al. (2020), integrates the principles of the following: Simple Additive Weighting (SAW), Multiplicative Exponential Weighting (MEW), and Weighted

Aggregated Sum Product Assessment (WASPAS). This method's unique capability is to fuse data support the development of more dependable models and facilitate highly accurate decision-making(Torkayesh et al., 2021). The process involved in the CoCoSo method is as follows (Yazdani et al., 2019):

Step 1: The decision matrix is initially established. Based on the compromise normalization equation, the criteria values are normalized by using Eq. (5) for maximization-oriented criteria and Eq. (6) for minimization-oriented criteria. x_{ij} was the value of the alternative *i* for the criterion *j*, r_{ij} meant the normalized value of the alternative *i* for the criterion *j*,

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{5}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{6}$$

Step 2: The sum of the weighted comparability (S_i) and power-weighted comparability sequences (P_i) for each alternative are calculated by utilizing Eq. (7) and (8). w_j is the weight of the criterion *j*.

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \tag{7}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{8}$$

Step 3: Construct three aggregated assessment scores to identify the corresponding weights of the alternatives by applying Eq. (9) - (11).

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{9}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{10}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i)} \tag{11}$$

Step 4: Broadly, Eq. (12) signifies the arithmetic average of the sum of the Weighted Sum Method and Weighted Product Method scores. On the other hand, Eq. (13) represents the sum of the relative Weighted Sum Method and Weighted Product Method scores in comparison to the optimal choice. Eq. (14) provides to determine the balanced compromise score of the WSM and WPM models. While the value from Eq. (14) may fluctuate between 0 and 1, the threshold value is generally set at 0.50.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{12}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{13}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i)} \tag{14}$$

Step 5: Ascertain based on the descending order of the total score the final ranking of the alternatives (k_i) calculated by Eq. (15).

$$k_i = (k_{ia}k_{ib}k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia}+k_{ib} + k_{ic}) \tag{15}$$

5. Results and Discussion

5.1. Experimental Results

The analysis of the data obtained from CO_2 laser cutting experiment, as represented in Table 2, has revealed interesting patterns and correlations between various factors such as power, cutting speed, and material thickness on parameters like surface roughness (Ra), kerf width (KW), and material removal rate (MRR). The Ra values have demonstrated that at a constant power and material thickness, an increase in cutting speed results in a reduction of surface roughness. For example, with a power of 80 W and thickness of 2 mm, an increase in cutting speed from 5 mm/s to 15 mm/s resulted in a decrease of Ra from 1.21µm to 0.67µm. This result was found to be compatible with the literature (Caiazzo et al., 2005; Choudhury and Shirley, 2010). However, at a fixed cutting speed and material thickness, an increase in power tended to increase the Ra value, presumably due to the larger amount of heat input causing more significant melting and potentially re-solidification phenomena, leading to a rougher surface. This outcome has aligned with what was previously published in the field (Anjum et al., 2022). Comparing the Ra values for a thickness of 2mm at 80 W power and 5mm/s cutting speed (Ra = 1.21µm), with those for a thickness of 4mm under the same power and cutting speed conditions (Ra = 1.28 µm), it can be seen that increased material thickness also tends to increase the Ra values.

For KW, the values also have tended to decrease as cutting speed increases, consistent with a reduction in the dwell time of the laser beam on the material resulting in narrower cuts. However, with increasing power and material thickness, the KW values increased, which was expected as a more powerful laser would deliver more energy to the cut zone, thus generating wider kerfs. The existing body of research also corroborates these findings (Moradi et al., 2017). For example, comparing the KW values for 2 mm thickness at 80W and 5mm/s cutting speed (KW = 0.466 mm), with the 4mm thickness under the same power and cutting speed conditions (KW = 0.709 mm), has demonstrated the effect of increased material thickness on the KW.

The MRR values ended up with a clear increase with both cutting speed and power, as expected. A faster, more powerful laser would be capable of removing material more quickly. For instance, with a material thickness of 2mm and power of 80 W, increasing the cutting speed from 5 mm/s to 15 mm/s results in the MRR increasing from 280 mm^3/min to 724 mm^3/min. Similarly, for a cutting speed of 5 mm/s and thickness of 2 mm, increasing the power from 80 W to 100 W increases the MRR from 280 mm^3/min to 341 mm^3/min. The results reported in the literature are also compatible with the ones found in this study (Varsi and Shaikh, 2019). Interestingly, MRR values also increase noticeably with material thickness, even though one might anticipate a thicker material would take longer to cut. This could be due to the calculation of MRR, which considers volume (mm^3/min), thus thicker materials result in a greater volume of material being removed per unit time. To sum up, this analysis implies a delicate balance and potential trade-off when choosing the parameters for laser cutting. Higher cutting speeds may lead to lower Ra and narrower KWs but at the cost of potentially reduced MMRs. Conversely, higher powers may boost the MMR but could result in rougher surface finishes and wider kerfs.

Table 3. Responses from CO_2 laser cutting experiment results

Experiment Number	Thickness (mm)	Power (W)	Cutting speed (mm/s)	Ra (μm)	KW (mm)	MRR (mm^3/min)
1	2	80	5	1.21	0.466	280
2	2	80	10	0.82	0.419	503
3	2	80	15	0.67	0.402	724
4	2	90	5	1.28	0.538	323
5	2	90	10	0.90	0.491	589
6	2	90	15	0.73	0.462	832
7	2	100	5	1.49	0.569	341
8	2	100	10	1.09	0.530	636
9	2	100	15	0.80	0.504	907
10	4	80	5	1.28	0.709	851
11	4	80	10	0.85	0.661	1586
12	4	80	15	0.70	0.623	2243
13	4	90	5	1.32	0.818	982
14	4	90	10	0.93	0.754	1810
15	4	90	15	0.75	0.702	2527
16	4	100	5	1.51	0.863	1036
17	4	100	10	1.12	0.793	1903
18	4	100	15	0.95	0.722	2599

5.2. The Effect of Cutting Parameters on Ra, KW and MRR

Three-dimensional graphs were generated to investigate the effects of CO_2 laser cutting parameters on Ra, KW, and MRR. The graphs for Ra were displayed in Figure 5 (a-c). It was established that an increase in cutting speed results in a decrease in Ra. Additionally, it was observed that the quality of the laser-cut surface improved with a reduction in both material thickness and power. A review of the figures suggested that cutting speed and power exerted a more significant influence on Ra than material thickness.

Three-dimensional graphs depicting KW are presented in Figure 6 (a-c). Observations showed that KW decreased as the cutting speed increased. Furthermore, it was determined that KW diminished with a reduction in material thickness and laser power. Material thickness and power significantly impact KW, whereas the influence of cutting speed was less pronounced. It was evident that the most crucial parameter was found to be the material thickness.

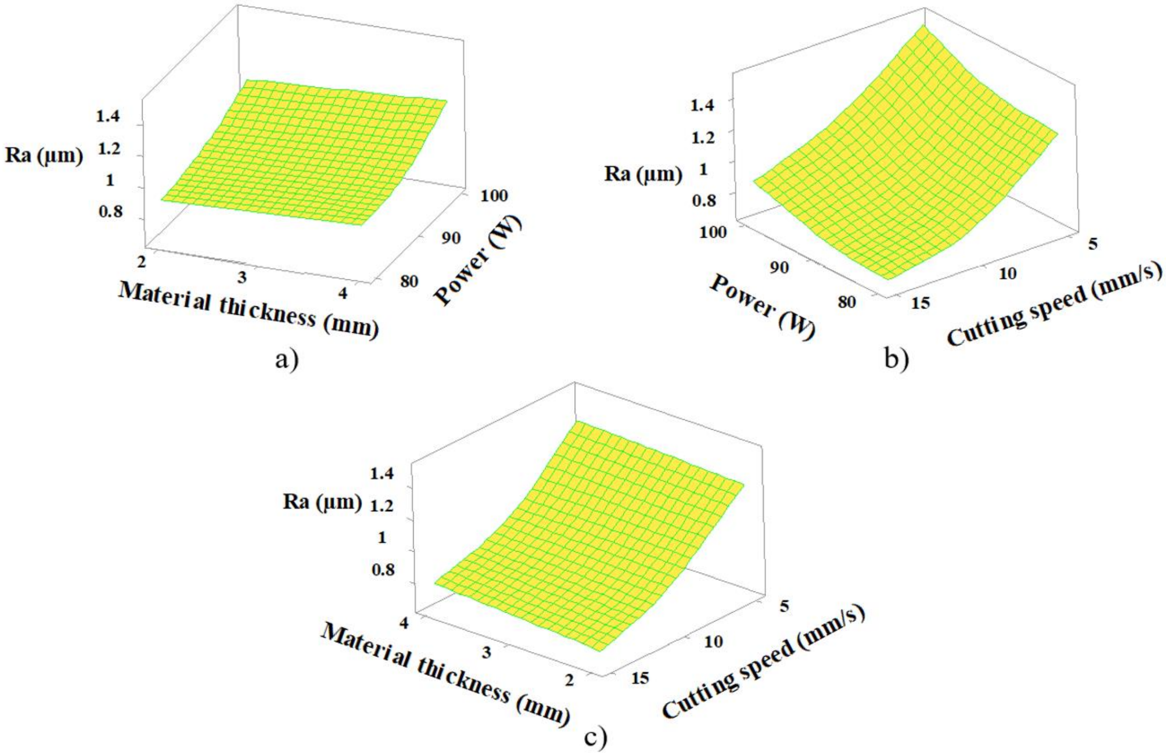

Figure 5. Three-dimensional graphics for Ra

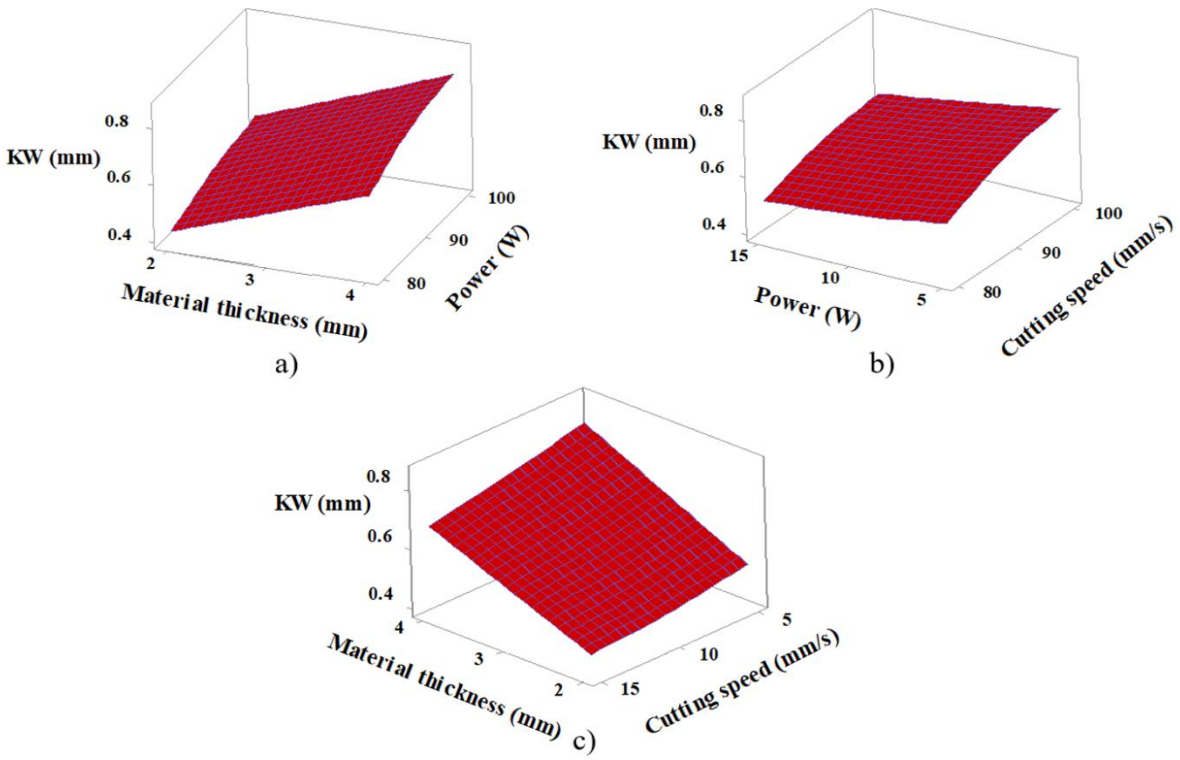

Figure 6. Three-dimensional graphics for KW

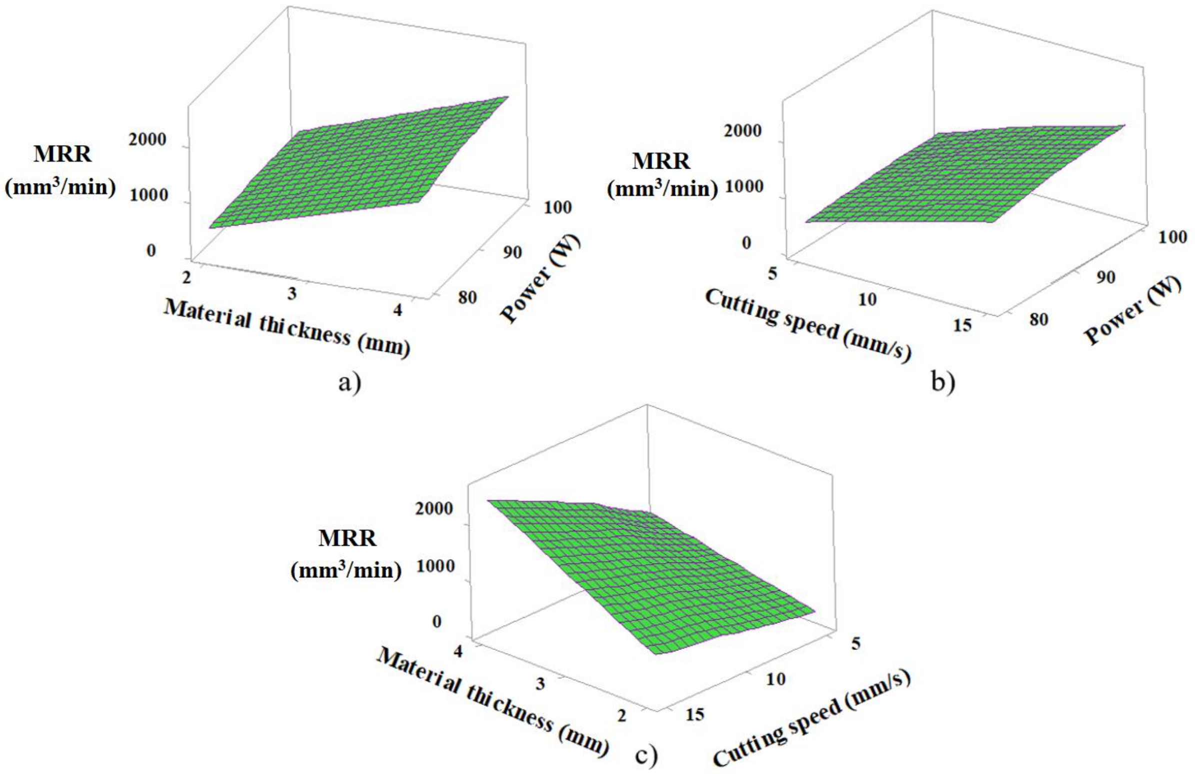

Figure 7. Three-dimensional graphics for MRR

Three-dimensional graphs illustrating the MRR are shown in Figure 7 (a-c). It was observed that the MRR increases as the cutting speed, power, and material thickness increase. The parameters of CO_2

laser cutting have a significant impact on the MRR. Since material thickness is a critical parameter influencing the KW, it also has the most significant effect on the MRR. As the material thickness increases, the KW and, consequently, the MRR also increase. This correlation is due to the use of the KW value in the calculation of the MRR.

5.3. Multi-Objective Optimization of Cutting Parameters

In the multi-objective optimization of cutting parameters, we have integrated three different methods: First, we determined the efficient experiments by using the data envelopment analysis method, then the weights of the criteria were calculated to evaluate the efficient experiments among themselves within the framework of a set of criteria, and lastly, the efficient experiments were ranked from the most optimal to the non-optimal. In the first stage, the efficiency scores of the experiments were calculated based on the input-output relationship by the data envelopment analysis. A total of 18 experiments were considered as decision-making units (DMUs). The factors considered in the experiment were taken into account as inputs and the measured parameters were selected as outputs. As can be seen in Table 4, 14 of the 18 experiments were found to be efficient, and all the efficiency scores are shown in Table 5.

Table 4. The summary of the DEA modeling

Maximum efficiency score	1.00
Minimum efficiency score	0.91
Number of efficient DMUs	14
Total number of DMUs	18
% of efficient DMUs	77.78

Table 5. The experiments and efficiency scores (%)

Experiments	Efficiency Scores (%)
E1	1.00
E2	1.00
E3	1.00
E4	0.97
E5	0.95
E6	1.00
E7	0.91
E8	0.92
E9	1.00
E10	1.00
E11	1.00
E12	1.00
E13	1.00
E14	1.00
E15	1.00
E16	1.00
E17	1.00
E18	1.00

In this multi-objective optimization study, we prioritized Ra, MRR, and KW, with the criteria weights of 50.4%, 28%, and 21.6%, respectively (see Table 6). These weights, signifying their importance, were derived using the SWARA method. Ra received the highest weight among the criteria, reflecting its crucial importance in the machining of polyethylene thermoplastic material. The quality of a finished product was primarily determined by the Ra, which was directly influenced by the cutting parameters. A superior surface finish could reduce the need for additional finishing processes, potentially saving time and cost. Moreover, a smoother surface was more resistant to wear and tear, leading to a longer product lifespan. Therefore, the weight of Ra, which reflected its dominant role in the machining process, was set at 50.4%.

Table 6. Criteria weights (%)

Criteria	s_j	k_j	q_j	w_j
Surface Roughness		1.00	1.000	0.504
Material Removal Rates	0.80	1.80	0.556	0.280
Kerf Width	0.30	1.30	0.427	0.216

On the other hand, the MRR also has played a significant role in machining, though its weight was less than Ra. This criterion was associated with the efficiency of the machining process, as a higher removal rate translates to faster job completion. However, a higher removal rate might have compromised the quality of the surface finish and the dimensional accuracy of the product. As a result, while it was important to maximize the MRR, this must be balanced with the need to achieve optimal Ra. Hence, the weight assigned to MRR was 28%. Lastly, the KW represented the width of the material that was removed during the cutting process. Although it had a lower weight of 21.6%, it still holded relevance in the optimization process. The KW had impacts on the amount of material wasted in the process and also affected the precision of the cut. A smaller KW often corresponds to a more precise cut, which is particularly critical in industries where high precision is required. However, due to the inherent resilience and relatively low cost of polyethylene thermoplastic material, the KW was deemed less important than Ra and MRRs in this specific context. In summary, criteria weights, derived from polyethylene material properties and machining implications, balance product quality (surface roughness), efficiency (material removal rates), and precision (kerf width) for optimal cutting parameter optimization.

The experimental results of the multi-objective optimization of cutting parameters for PE thermoplastic material are summarized in Table 7. This section has elucidated the findings, focusing primarily on the individual and combined effects of the key cutting parameters: thickness, power, and cutting speed. These parameters were optimized using the integrated Data Envelopment Analysis and SWARA-based CoCoSo approach, without delving into the specifics of the CoCoSo parameter values.

Table 7. Ranking experiments by CoCoSo Method

Experiments	Input Parameters			Parameter Values of CoCoSo Method				Rank
	Thickness (mm)	Power (W)	Cutting speed (mm/s)	k_a	k_b	k_c	k	
E1	2	80	5	0.0489	6.1531	0.5301	2.7863	11
E2	2	80	10	0.0777	10.4233	0.8423	4.6613	8
E3	2	80	15	0.0862	12.0807	0.9350	5.3585	3
E6	2	90	15	0.0842	11.4840	0.9136	5.1203	4
E9	2	100	15	0.0818	10.8488	0.8874	4.8628	6
E10	4	80	5	0.0574	5.7771	0.6221	2.7429	12
E11	4	80	10	0.0816	10.6322	0.8854	4.7823	7
E12	4	80	15	0.0922	12.9947	1.0000	5.7577	1
E13	4	90	5	0.0510	4.8655	0.5532	2.3391	13
E14	4	90	10	0.0769	9.7548	0.8341	4.4106	9
E15	4	90	15	0.0897	12.5468	0.9729	5.5672	2
E16	4	100	5	0.0208	2.0000	0.2258	0.9599	14
E17	4	100	10	0.0687	8.1533	0.7453	3.7366	10
E18	4	100	15	0.0829	11.0228	0.8989	4.9380	5

The thickness of the PE material seems to play a substantial role in the ranking. In particular, experiments conducted on materials with a thickness of 4mm (E10 - E18) predominantly ranked higher than those with a thickness of 2mm (E1 - E9). This suggests that, within the parameters tested, the cutting process efficiency tends to improve with increased thickness. The most important reason behind this is that the MRR value increases significantly when the material thickness increases. For example, while this value was 13.86 in E6, it increased to 43.34 in E18.

The power input used during the cutting process, however, did not show a straightforward correlation with the ranking. Considering experiments with constant thickness and cutting speed, we observed that an increase in power from 80W to 90W often improved the rank (as seen in E3 versus E6 and E12 versus E15), but a further power increase to 100W tended to result in a lower rank (as seen in E6 versus E9 and E15 versus E18). This could be indicative of a non-linear relationship between power input and performance, suggesting a need for more targeted optimization to identify the ideal power range. The most important factor that causes this situation is the increase in Ra and KW when the power reaches 100 W. These results are also supported by the existing literature (Eltawahni et al., 2010). For example, Ra was 0.73 at E6 and 0.8 at E9. Similarly, when the thickness reached 4 mm, KW was 0.623 at E12 and 0.863 at E16.

The cutting speed appeared to have the most consistent correlation with the performance rank. Higher cutting speeds generally yielded better ranks, particularly evident when other parameters remained constant (as shown in the set of experiments E1, E2, and E3). This pattern was also observed in experiments E10, E11, and E12, further emphasizing the positive correlation between the cutting speed and ranking. The most important factor behind this was that as the cutting speed increased, the Ra and KW values decreased and the MRR value increased. For example, in E10, Ra and KW were 1.28 and 0.709, respectively, while in E12, these values decreased to 0.7 and 0.623. Several scientists have examined the correlation between surface texture and parameters like cutting velocity, laser intensity, and the thickness of the material. The materials used for their experiments were polypropylene, polyethylene, and polycarbonate. Their research indicated that as the rate of cutting grew, the surface roughness diminished. This observation aligns well with the results of our latest study, which similarly has shown this pattern (Caiazzo et al., 2005; Choudhury and Shirley, 2010).

6. Conclusion

In this study, we explored the effects of material thickness, power, and cutting speed on surface roughness, KW, and MRR during CO_2 laser cutting of PE material. To optimize the cutting parameters for improving cutting quality, we integrated the use of Data Envelopment Analysis (DEA) and the SWARA-based CoCoSo (Combining Compromise Solution) approach. Our results are as follows:

- The surface roughness decreased with a decrease in material thickness and power, coupled with an increase in cutting speed. This means that using thinner materials, lowering power settings, and increasing cutting speeds can contribute to achieving smoother surfaces in the laser cutting process.
- Cutting speed emerged as the most influential parameter on surface roughness, suggesting its adjustment can significantly reduce surface roughness, even more so than varying material thickness.
- In terms of KW, we observed a decrease with an increase in cutting speed and a decrease in both material thickness and power.
- Material thickness stood out as the most influential parameter, implying that KW reduction was most effective when the material thickness was adjusted. For instance, when we doubled the material thickness while keeping the power and cutting speed constant, we saw a KW increase of 54.98%.
- We also determined that the MRR increases in line with increases in material thickness, power, and cutting speed. Given that the calculation of MRR takes into account KW, material thickness, and cutting speed, it is clear that material thickness significantly affects both KW and MRR. This is because of increasing the material thickness leading to a rise in KW and, subsequently, the MRR value.
- Applying the DEA model, we found that 77.78% of Decision-Making Units (DMUs) were efficient.
- Experimental conditions E4, E5, E7, and E8, which involved a material thickness of 2 mm, fell below efficiency with scores under 1.
- The SWARA method revealed that surface roughness, with a weight of 50.4%, was the most important criterion, followed by MRR with a weight of 28%, and KW with a weight of 21.6%.

- Using the DEA and SWARA-based CoCoSo approach, we determined that the best experimental condition was E12, where the material thickness was 4 mm, power is 80 W, and cutting speed was 15 mm/s.
- These findings on CO_2 laser cutting parameters, which have been obtained through multi-objective optimization, offer valuable insights for industry practitioners. By applying these optimized parameters, they can realize time and cost savings while ensuring a higher quality cutting process.

In conclusion, the results of the study underscore the importance of careful selection and optimization of cutting parameters when processing Polyethylene thermoplastic materials. It is suggested that while higher material thickness and cutting speed consistently enhance performance, the relationship between power input and performance would be more complex and non-linear. Future work should consider exploring this complexity further and might benefit from deploying additional experimental designs to comprehensively understand the interactions among these parameters and potentially discover optimal combinations. This study has underlined the power of an integrated approach to multi-objective optimization, combining data envelopment analysis with the SWARA-based CoCoSo method, to derive meaningful, real-world insights.

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Statement of Conflict of Interest

The authors have declared no conflict of interest.

Author's Contributions

The authors contributed equally to this study.

References

Anjum A., Shaikh AA., Tiwari N. Experimental investigations of channel profile and surface roughness on PMMA substrate for microfluidic devices with mathematical modelling. Optik 2022; 261: 169154.

Banker RD., Charnes A., Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 1984; 30(9): 1078–1092.

Basar G., Kirli Akin H., Kahraman F., Fedai Y. Modeling and optimization of face milling process parameters for AISI 4140 steel. Tehnički Glasnik 2018; 12(1): 5-10.

Caiazzo F., Curcio F., Daurelio G., Minutolo, FMC. Laser cutting of different polymeric plastics (PE, PP and PC) by a CO_2 laser beam. Journal of Materials Processing Technology 2005; 159(3): 279–285.

Cebeci İ., Özlü B., Demir H. AISI 304 paslanmaz sac malzemenin lazerle işlenmesinde kesme parametrelerinin yüzey pürüzlülüğü, kerf genişliği ve çapak yüksekliğine etkisinin araştırılması. Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi 2022; 11(2): 410-415.

Charnes A., Cooper WW., Rhodes E. Measuring the efficiency of decision making units. European Journal of Operational Research 1978; 2(6): 429–444.

Charnes A., Cooper WW., Rhodes E. Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow through. Management Science 1981; 27(6): 668–697.

Chen MF., Ho YS., Hsiao WT., Wu TH., Tseng SF., Huang KC. Optimized laser cutting on light guide plates using grey relational analysis. Optics and Lasers in Engineering 2011; 49(2): 222–228.

Choudhury IA., Shirley S. Laser cutting of polymeric materials: An experimental investigation. Optics & Laser Technology 2010; 42(3): 503–508.

Cooper WW., Seiford LM., Tone K. Data envelopment analysis. Springer: USA. 2000.

Cus F., Balic J. Optimization of cutting process by GA approach. Robotics and Computer-Integrated Manufacturing 2003; 19(1–2): 113–121.

Davim JP., Barricas N., Conceição M., Oliveira C. Some experimental studies on CO_2 laser cutting quality of polymeric materials. Journal of Materials Processing Technology 2008a; 198(1–3): 99–104.

Davim JP., Oliveira C., Barricas N., Conceição M. Evaluation of cutting quality of PMMA using CO_2 lasers. The International Journal of Advanced Manufacturing Technology 2008b; 35(9–10): 875–879.

Der O., Alqahtani AA., Marengo M., Bertola V. Characterization of polypropylene pulsating heat stripes: Effects of orientation, heat transfer fluid, and loop geometry. Applied Thermal Engineering 2021; 184: 116304.

Der O., Edwardson S., Bertola V. Manufacturing low-cost fluidic and heat transfer devices with polymer materials by selective transmission laser welding. In Encyclopedia of Materials: Plastics and Polymers 2022; 370-378.

Der O., Edwardson S., Marengo M., Bertola V. Engineered composite polymer sheets with enhanced thermal conductivity. IOP Conference Series: Materials Science and Engineering 2019b; 613(1): 012008.

Der O., Marengo M., Bertola V. Thermal performance of pulsating heat stripes built with plastic materials. Journal of Heat Transfer 2019a; 141(9): 091808.

Dubey AK., Yadava V. Multi-objective optimization of Nd:YAG laser cutting of nickel-based superalloy sheet using orthogonal array with principal component analysis. Optics and Lasers in Engineering 2008; 46(2): 124–132.

Eksilmez N., Özlü B., Demir H. Hardox 500 çeliğinin lazerle işlenmesinde kesme geometrisine ve işleme parametrelerine bağlı kesim kalitesinin değerlendirilmesi. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2022; 5(1): 301-314.

Eltawahni HA., Olabi AG., Benyounis KY. Effect of process parameters and optimization of CO_2 laser cutting of ultra high-performance polyethylene. Materials & Design 2010; 31(8): 4029–4038.

Guvenc MA., Bilgic HH., Cakir M., Mistikoglu S. The prediction of surface roughness and tool vibration by using metaheuristic-based ANFIS during dry turning of Al alloy (AA6013). Journal of the Brazilian Society of Mechanical Sciences and Engineering 2022; 44: 474.

Güvenç MA., Çakır M., Mıstıkoğlu S. Experimental study on optimization of cutting parameters by using Taguchi method for tool vibration and surface roughness in dry turning of AA6013. 10th International Symposium on Intelligent Manufacturing and Service Systems, 9-11 September 2019, Sakarya/Turkey, pp. 1032-1040.

Ilio A Di, Tagliaferri V., Veniali F. Machining parameters and cut quality in laser cutting of aramid fibre reinforced plastics. Materials and Manufacturing Processes 1990; 5(4): 591–608.

Keršulienė V., Zavadskas EK., Turskis Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of Business Economics and Management 2010; 11(2): 243–258.

Kini MV., Chincholkar AM. Effect of machining parameters on surface roughness and material removal rate in finish turning of ±30° glass fibre reinforced polymer pipes. Materials & Design 2010; 31(7): 3590–3598.

Kumar A., Sah B., Singh AR., Deng Y., He X., Kumar P., Bansal RC. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renewable and Sustainable Energy Reviews 2017; 69: 596–609.

Kurt M., Kaynak Y., Bagci E., Demirer H., Kurt M. Dimensional analyses and surface quality of the laser cutting process for engineering plastics. The International Journal of Advanced Manufacturing Technology 2009; 41(3–4): 259–267.

Liu J., Lu E., Yi H., Wang M., Ao P. A new surface roughness measurement method based on a color distribution statistical matrix. Measurement 2017; 103: 165–178.

Llanto JM., Tolouei-Rad M., Vafadar A., Aamir M. Impacts of traverse speed and material thickness on abrasive waterjet contour cutting of austenitic stainless steel AISI 304L. Applied Sciences 2021; 11(11): 4925.

Lum KCP., Ng SL., Black I. CO_2 laser cutting of MDF. Optics & Laser Technology 2000; 32(1): 67–76.

Madić M., Radovanović M., Slătineanu L., Dodun O. Optimization of laser cut quality characteristics considering material removal rate based on pareto concept. Applied Mechanics and Materials 2014; 657: 216–220.

Mathew J., Goswami GL., Ramakrishnan N., Naik NK. Parametric studies on pulsed Nd:YAG laser cutting of carbon fibre reinforced plastic composites. Journal of Materials Processing Technology 1999; 89–90: 198–203.

Mierzwa-Hersztek M., Gondek K., Kopeć M. Degradation of polyethylene and biocomponent-derived polymer materials: An overview. Journal of Polymers and the Environment 2019; 27(3): 600–611.

Moradi M., Mehrabi O., Azdast T., Benyounis KY. Enhancement of low power CO_2 laser cutting process for injection molded polycarbonate. Optics & Laser Technology 2017; 96: 208–218.

Nyiranzeyimana G., Mutua JM., Mose BR., Mbuya TO. Optimization of process parameters in fused deposition modelling of thermoplastics: A review. Materialwissenschaft Und Werkstofftechnik 2021; 52(6): 682–694.

Ordu M., Der O. Polymeric materials selection for flexible pulsating heat pipe manufacturing using a comparative hybrid MCDM approach. Polymers 2023a; 15(13): 2933.

Ordu M., Der. O. Yeşil üretim için çevresel etki temelli termoplastik malzeme seçimi: Karşılaştırmalı bir hibrid ÇKKV yaklaşımı. Erciyes Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2023b; 39(1): 100-115.

Ordu M., Kirli Akin H., Demir E. Healthcare systems and Covid19: Lessons to be learnt from efficient countries. The International Journal of Health Planning and Management 2021; 36(5): 1476–1485.

Pandey AK., Dubey AK. Taguchi based fuzzy logic optimization of multiple quality characteristics in laser cutting of Duralumin sheet. Optics and Lasers in Engineering 2012; 50(3): 328–335.

Po R-W., Guh Y-Y., Yang M-S. A new clustering approach using data envelopment analysis. European Journal of Operational Research 2009; 199(1): 276–284.

Powell J. CO2 Laser Cutting. Springer: London, 1993.

Rastogi S., Yao Y., Ronca S., Bos J., Van der Eem J. Unprecedented high-modulus high-strength tapes and films of ultrahigh molecular weight polyethylene via solvent-free route. Macromolecules 2011; 44(14): 5558–5568.

Rooks B. Laser processing of plastics. Industrial Robot: An International Journal 2004; 31(4): 338–342.

Roy MK., Shivakoti I., Phipon R. Sharma A. A holistic approach to polymeric material selection for laser beam machining using methods of DEA and TOPSIS. Foundations of Computing and Decision Sciences 2020; 45(4): 339–357.

Sasikumar G., Ayyappan S. Multi-criteria decision making for solar panel selection using fuzzy analytical hierarchy process and technique for order preference by similarity to ideal solution (TOPSIS): An empirical study. Journal of The Institution of Engineers (India): Series C 2019; 100(4): 707–715.

Torkayesh AE., Pamucar D., Ecer F., Chatterjee P. An integrated BWM-LBWA-CoCoSo framework for evaluation of healthcare sectors in Eastern Europe. Socio-Economic Planning Sciences 2021; 78: 101052.

Varsi AM., Shaikh AH. Experimental and statistical study on kerf taper angle during CO_2 laser cutting of thermoplastic material. Journal of Laser Applications 2019; 31(3): 032010.

Yazdani M., Torkayesh AE., Chatterjee P. An integrated decision-making model for supplier evaluation in public healthcare system: The case study of a Spanish hospital. Journal of Enterprise Information Management 2020; 33(5): 965–989.

Yazdani M., Zarate P., Kazimieras Zavadskas E., Turskis Z. A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. Management Decision 2019; 57(9): 2501–2519.

Zhou BH., Mahdavian SM. Experimental and theoretical analyses of cutting nonmetallic materials by low power CO_2-laser. Journal of Materials Processing Technology 2004; 146(2): 188–192.