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ORIGINAL ARTICLE

Energy Optimization for Milling 304L Steel using Artificial Intelligence Methods

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ABSTRACT – With increased production and productivity in modern industry, particularly in the automotive, aeronautical, agro-food, and other sectors, the consumption of manufacturing energy is rapidly increasing, posing additional precautions and large investments to industries to reduce energy consumption at the manufacturing system level. This research proposes a novel energy optimisation using a response surface methodology (RSM) with artificial neural network (ANN) for machining processes that saves energy while improving productivity.The feed rate was discovered to be the most influential factor in this study, accounting for 84.13 percent of total energy consumed. Furthermore, it has been established that as the material removal rate (MRR) increases, energy efficiency (EE) declines. This optimization of cutting conditions gives us the optimal values of cutting speed Vc = 129.37 m/min, feed rate f = 0.098 mm/rev and depth of cut ap = 0.5 mm. This approach will allow us to decrease the total energy consumed (Etc) by 49.74 % and increase the energy efficiency (EE) by 13.63 %.

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INTRODUCTION

The accelerated demand for energy in industrial sectors includes a significant impact not only on the business economy but also an introduction on the environment. The energy consumption of the world sector will increase by over half-hour from 2018 to 2050 [1]. Faced with this increase, it's necessary to figure more on the energy efficiency (EE) advice. Machining may be a process widely utilized in the manufacture of finished products, especially within the automotive, aeronautical, medical and other sectors. Machining may be a material removal technique that's wont to create a component from raw materials or to boost the surface quality of a previously produced part by eliminating excess material [2]. However, the sustainability of the manufacturing system is also increased by optimizing energy consumption [3]. Reducing machine power usage has the potential to considerably enhance both environmental performance and also the manufacturing process. In this context, this work deals with energy consumption and energy efficiency within the milling process. The link between input and output parameters is modeled using an empirical model determined using response surface methodology (RSM) by comparing it with a prediction made using the artificial neural network (ANN).

LITERATURE REVIEW

Research on the energy factor remains insufficient within the face of accelerating global energy consumption. Mori et al. [4] reported research with a replacement spindle acceleration control approach that reduced power usage. Increased cutting conditions for drilling and face/end milling, but within an affordable range of values that don't compromise tool life or surface finish, can help to cut back power consumption for these operations. Oda et al. [5] offer a study on a way to reduce the quantity of energy utilized in a mechanical system with multiple units. In keeping with the findings, an 8% reduction in energy use is feasible. The cycle time is additionally slashed by 20 %. Altıntaş et al. [6] present a prediction model to estimate the theoretical energy consumption involved in milling prismatic parts. The results show that the prediction model works with an accuracy of fifty. Blogun et al. [7] analyze the consequences of machine modules, auxiliary units, and machine codes on power and energy usage throughout the machining process. Velchev et al. [8] describe an approach for optimizing cutting parameters to cut back direct energy consumption during the turning process. The result shows that the insert, the feed rate, and also the depth of cut have influences on energy consumption. Thru in-line optimization of cutting conditions, the research conducted by Tapoglou et al. [9] demonstrates a completely unique approach to improving the energy efficiency of machine tools. Tebassi et al. [10] studied the consequences of Inconel 718 alloy cutting parameters on surface roughness, cutting force components, productivity, and energy consumption. Within the study, it had been discovered that surface finish was statistically sensitive to feed and cutting speed, with contributions of 43.58 % and 23.85 %, respectively, whereas the depth of cut had the best influence on the evolution of the cutting force further because of the consumption of energy. Camposeco-Negrete et al. [11] present the results of an experimental investigation on turning cutting parameter optimization. The goal is to lower the machine tool's energy consumption. The work of Bilga et al. [12] focuses on the optimization of the first response factors on energy consumption, like energy efficiency, machine active energy consumed and power factor. The energy efficiency (EE) is calculated using the subsequent formula:

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$$EE = \frac{ACE}{AECM} \quad (1)$$

with ACE - active cutting energy and ACE - machine active energy consumed. Li et al. [13] studied specific energy consumption to assess energy efficiency. The cutting parameters of energy efficiency and processing time objectives can be optimized using a combination of the Taguchi method, the multi-objective particle swarm optimization algorithm (PSO), and the response surface method (RSM).

$$SEC = \frac{E_{total}}{MRV} = \frac{\int p_{int}(t)dt}{MRV} \quad (2)$$

with SEC - specific energy consumption (J/mm^3), E_{total} - total electrical energy consumption (J), MRV- material removal volume (mm^3) and P_{int} (t) - input power (W). Research by Moreira et al. [14] presents an analysis of the impact of machining parameters on energy consumption within the milling process of BS EN24T alloy (AISI 4340). Zhang et al. [15] developed an energy-efficient machine control strategy. The results show that the reduction in energy consumption with this energy-efficient strategy may be up to 25 %.

Several researchers have used neural network to solve prediction and optimization problems in mechanical manufacturing. Girish and Kuldip [16] used the neural network to predict energy consumption and surface roughness. They performed machining experiments to verify the suitability of the proposed model for predicting energy consumption and surface roughness. The results predicted by the proposed model indicate a good synchronism between the predicted values and the values. The effects of cutting parameters on power, cutting force, surface quality, and material removal rate during turning operations were investigated by Zerti et al. [17]. AISI 420 stainless steel was utilized. To simulate the output responses, the scientists applied the response surface approach and neural networks. In comparison to the response surface approach, the findings demonstrate the high prediction accuracy of the neural network. Artificial intelligence was utilized by Imani et al. [18] to forecast cutting forces and surface roughness in milling. The findings demonstrate that the cutting force is significant and important influenced by the cutting speed and feed rate. For the modeling of surface roughness, two hidden layers containing 9 and 10 neurons allow for an accuracy of 97 percent.

This paper aims to present a replacement approach in milling cycles to attenuate energy consumption. We will study the cycles with and without tool change and with and without spindle speed variation taking into account the cutting conditions. To forecast and describe interactions between cutting factors, the response surface methodology (RSM) and neural networks (NN) were utilized and compared. Multi-objective optimization has been accustomed determine the optimal conditions which give us optimal energy consumption.

EXPERIMENTAL DATA

Materials

Austenitic 304L stainless steel is the material of choice for this investigation. It is a material very used in several fields, medicine and especially surgery, aerospace, and many other sectors. High corrosion resistance and toughness are the hallmarks of this material (174 HB). Table 1 summarizes the chemical properties.

Table 1. The material's chemical characteristics (*wt %*) [25].

C	*Mn*	*Si*	*P*	*Co*	*Ni*	*Cr*	*N*	*S*
0.014	1.56	0.43	0.035	0.2	8.01	18.06	0.092	0.027

Procedure and Measure

Energy efficiency within the manufacturing sector is becoming the most factor that reveals the company's ability to supply with less energy consumption. The work plan is shown in Figure 1. The part used is 41x42x34 mm in size. The workpiece is mounted directly within the vice of the machine. The machine used is a 4-axis Réalméca C300H machining center. The center generates power between 5.5 kW and 7.5 kW. The tool used is a 100 mm diameter milling cutter with five high-strength coated carbide inserts of the R290-90-T308 PPM-WL type (Figure 2). To evaluate the energy consumed during milling operations, a Chauvin Arnoux power analyzer was used. The axial cutting width for all tests equals the workpiece width of 34 mm. The tool is positioned symmetrically to the workpiece to ensure symmetrical face milling. The cutting parameters involved are the cutting speed (m/min), the feed rate (mm/rev), and also the depth of cut (mm). Each parameter has three levels (-1, 0, 1). The cutting parameters and levels are mentioned in Table 2. The facility consumed during a machining cycle is measured with an influence clamp that was attached to the machine power supply.

Table 2. The cutting parameters.

Factors	Parameters	Levels		
		-1	0	1
A	V_c (m/min)	64.68	91.10	129.37
B	f (mm/rev)	0.05	0.075	0.1
C	a_p (mm)	0.5	0.75	1

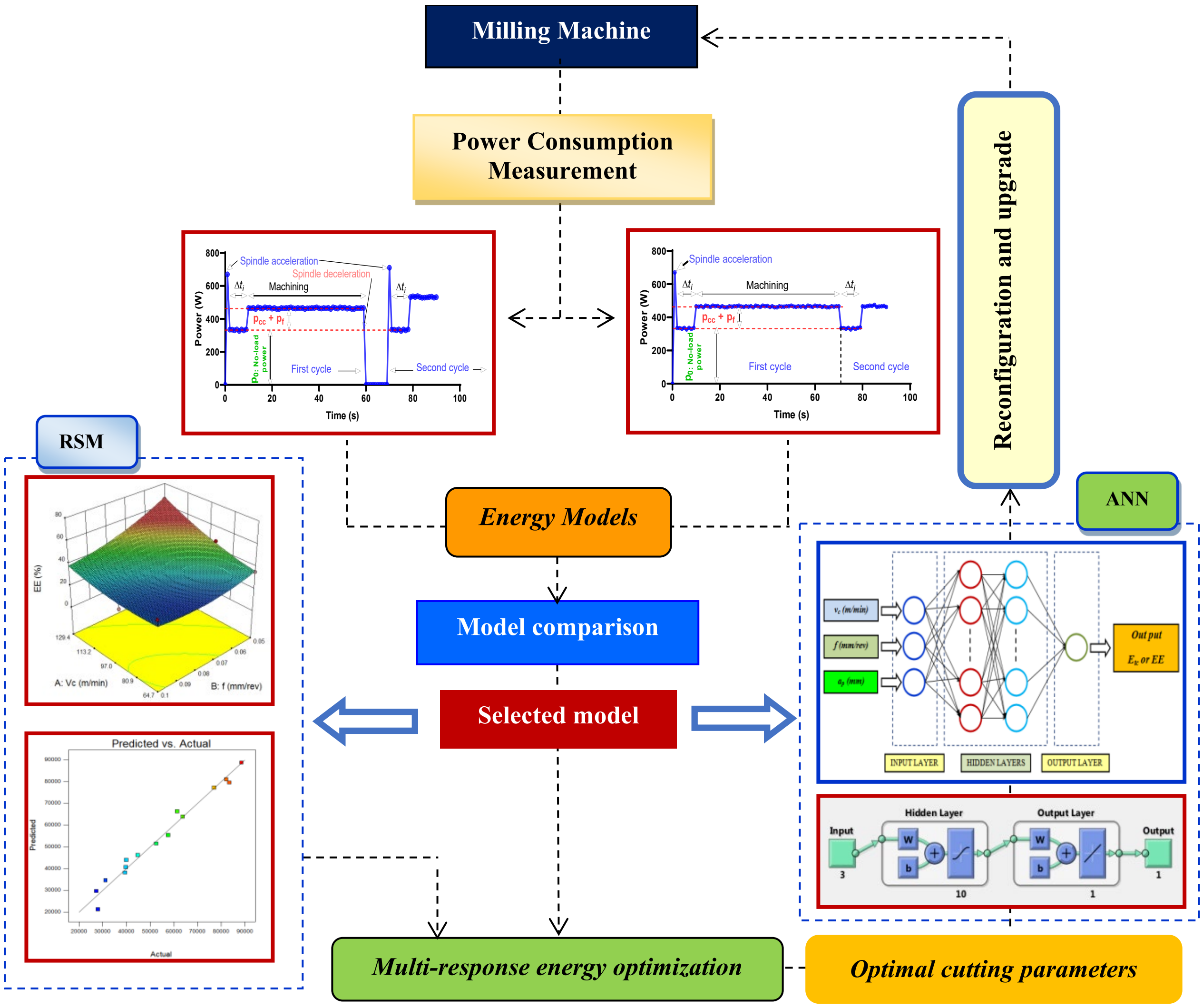

Figure 1. Energy plan.

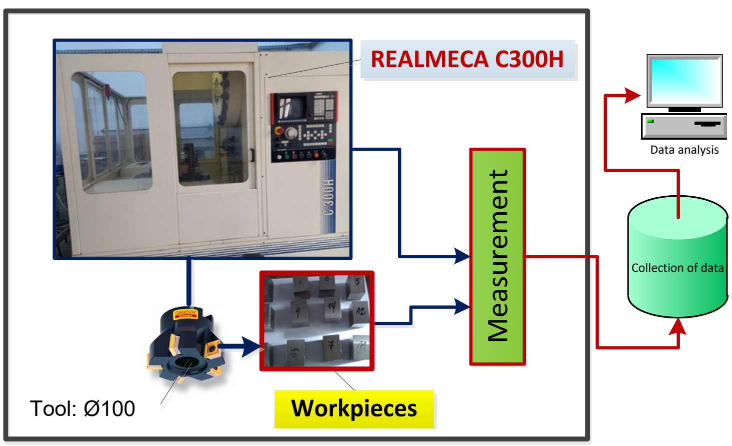

Figure 2. Measurement plane.

To determine the influences of cutting parameters on the energy consumption and energy efficiency of such a machine, response surface designs were used as an experimental design. The designs used to allow the screening of factors and sometimes lead to simple but sufficient models. However, there are numerous instances where accurate modeling of the phenomena under investigation is required, necessitating the use of second-degree mathematical models. These designs use quadratic polynomial models. The results obtained and the Response Surface Graphs are obtained with the Minitab 17.0 and Design Expert 10.0 software. The combinations between cutting parameters and the results of the experiments are mentioned in Table 3.

Table 3. Experimental results.

N°	A	B	C	p_{tc} (W)	p_{cc} (W)	E_{cc} (KJ)	E_{tc} (KJ)	SE_{tc} (J/mm^3)	SE_{cc} (J/mm^3)	$EE\%$
1	-1	-1	-1	486	148	25.01	82.13	18.19	5.54	30.45
2	-1	-1	0	524	186	31.43	88.55	13.25	4.70	35.50
3	-1	0	1	467	129	145.3	52.61	6.01	1.66	27.62
4	0	0	-1	493	155	124	39.44	9.09	2.86	31.44
5	0	1	0	455	117	7.02	27.30	4.25	1.09	25.71
6	0	1	1	468	130	7.80	28.08	3.34	0.93	27.78
7	1	-1	-1	755	417	35.23	63.79	15.33	8.47	55.23
8	1	-1	0	987	649	54.84	83.40	13.55	8.91	65.75
9	1	0	1	711	373	21.01	40.05	4.98	2.61	52.46
10	-1	0	-1	512	174	19.60	57.68	14.47	4.92	33.98
11	-1	1	0	531	193	16.30	44.86	7.62	2.77	36.35
12	-1	1	1	370	32	2.70	31.26	4.06	0.35	8.65
13	0	-1	-1	512	174	20.88	61.44	16.13	5.48	33.98
14	0	-1	0	642	304	36.48	77.04	13.70	6.48	47.35
15	0	0	1	497	159	12.72	39.76	5.41	1.73	31.99

ENERGY MODELING

In this part, the study consists of determining the energy model of the machining process with two different cases. The first case consists of carrying out n cycles without changing the spindle speed or changing the tool. The second case consists of carrying out cycles with the spindle speed change and with the tool change. Figure 3 represents the pattern of power consumption for the two cases.

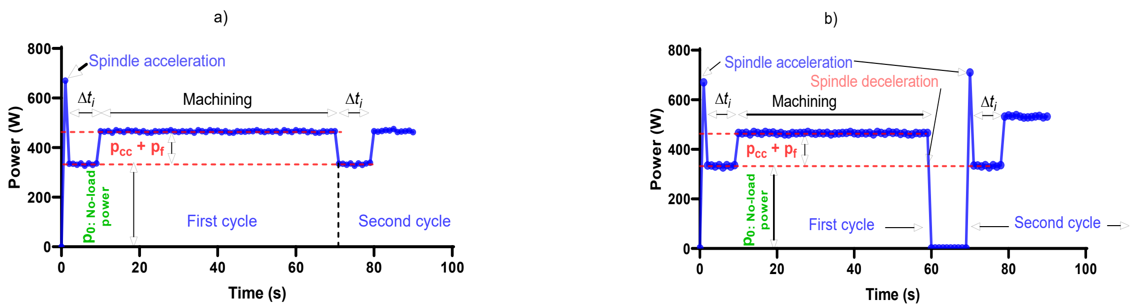

Figure 3. (a) Cycle without spindle speed change or tool change; (b) Cycle with spindle speed change and tool change.

First Case

The power measured is that of the total power consumed by the machine during a well-defined cycle. According to the proposed graph, this power is indeed the sum of the spindle acceleration power (p_{sa}), the no-load power (p_0) for a given speed, the cutting power consumed (p_{cc}), the feed power (p_f), and finally deceleration power (p_{sd}) (Eq. (3)).

$$p_{cycle}^{1} = p_{sa}(t) + p_0(t) + \sum_{i=1}^{n} \left(p_{cci}(t) + p_{fi}(t)\right) + p_{sd}(t) \tag{3}$$

Where n number of machining cycles and i increment per cycle. The cutting power consumed p_{cc} is the power supplied by the action of the tool on the part during machining time t_{ci}. The action of the tool on the part generates forces called cutting forces. The cutting power consumed can be estimated by Eq. (4) [17].

$$p_{cc}(t) = F_c(t) \times \frac{v_c(t)}{60} \tag{4}$$

The cutting speed is given by Eq. (5).

$$v_c(t) = \frac{\pi d}{1000} \times N(t) \tag{5}$$

The cutting force can be modeled by Eq. (6) [26].

$$F_c(t) = C_0 v_c{}^{\alpha}(t) f^{\beta}(t) a_p^{\gamma} \tag{6}$$

The total energy consumed for a cycle is the integration of power over time. The total energy is given by Eq. (7).

$$E^1_{cycle} = \int p_{sa}(t)dt + \int p_0(t)dt + \sum_{i=1}^{n} \int \left(p_{cci}(t) + p_{fi}(t)\right) dt + \int p_{sd}(t)\, dt \tag{7}$$

Second Case

Concerning the second case where there is a tool change with a change in the spindle speed at each new cycle, the total power consumed is estimated from Figure 3(b) by Eq. (8).

$$p^2_{cycle} = \sum_{i=1}^{n} p_{sai}(t) + \sum_{i=1}^{n} p_{0i}(t) + \sum_{i=1}^{n} (p_{cci}(t) + p_{fi}(t)) + \sum_{i=1}^{n} p_{sdi}(t) \tag{8}$$

The total energy consumed for a cycle is the integration of power over time. The total energy is given by Eq. (9).

$$E^2_{cycle} = \sum_{i=1}^{n} \int p_{sai}(t)dt + \sum_{i=1}^{n} \int p_{0i}(t)dt + \sum_{i=1}^{n} \int \left(p_{cci}(t) + p_{fi}(t)\right) dt + \sum_{i=1}^{n} \int p_{sdi}(t)dt \tag{9}$$

Comparative analysis

To make the comparison between the two models proposed for the two cases, we are going to make some assumptions to respect the same conditions of execution:

i. For both cases, we limit ourselves to 2 cycles;
ii. For the spindle speed of the first case is 500 *rev/min*;
iii. The two speeds of the second case are 500 and 700 *rev/min*;
iv. For both cases, we chose the same feed rate and depth of cut;
v. The power is assumed to be stable without disturbance;
vi. Δt = 10 s between two successive cycles.
vii. The acceleration and decoration of the spindle are done in a second.
viii. We will not consider the feed power in this calculation.

To determine the energy consumed for each case study, Table 4 contains the values of the various parameters presented in Eq. (7) and (9) that have been illustrated. These parameters are defined by the two graphs in Figure 3.

Table 4. Experimental values.

	p_{sa1} (W)	p_0 (W)	Δt_i (s)	t_{c1} (s)	t_{c2} (s)	p_{cc1} (W)	p_{sa2} (W)	p_{cc2} (W)
First case	670	338	10	80	60	155	-	117
Second case	670	338	10	120	84.5	174	710	417

$$E^1_{cycle} = p_{sa1}.t + 338.(\Delta_{t1} + t_{c1} + \Delta_{t2} + t_{c2}) + p_{cc1}.t_{c1} + p_{cc2}.(t_{c2} + 1) \tag{10}$$

$$E^1_{cycle} = 670 + 338 \times (10 + 80 + 60 + 10) + 155\ \times\ 80 + 117\ \times (60 + 1) = 74287J \tag{11}$$

According to Eq. (1) we obtain the energy efficiency:

$$EE^1 = \frac{155\ \times\ 80 + 117\ \times\ 60}{74287} = 0.2614 = 26.14\% \tag{12}$$

For the second case, and according to Eq. (9), we obtain:

$$E^2_{cycle} = p_{sa1}.t + 338.(\Delta_{t1} + t_{c1} + \Delta_{t2} + t_{c2}) + p_{cc1}.(t_{c1} + 1) + p_{sa2}.t + p_{cc2}.(t_{c2} + 1) \tag{13}$$

$$E^2_{cycle} = 670 + 338 \times (10 + 120 + 10 + 84.5) + 174 \times (120 + 1) + 710 + 417 \times (84.5 + 1) = 127208{,}5J \tag{14}$$

According to Eq. (1) we obtain the energy efficiency:

$$EE^1 = \frac{174\,.120 + 417\,.84.5}{127208{,}5} = 0.4411 = 44.11\% \tag{15}$$

We can conclude that the energy consumed in the first case $E^1_{cycle} = 74287\,J$ is lower than the second case $E^2_{cycle} = 127208.5\,J$. Changing spindle speeds requires more energy than without changing speeds. The energy efficiency of the second case is greater than that of the first case, with a value of 44.11%. For the second case, better energy efficiency but with high energy consumption, unlike the first case, low energy consumption but with poor energy efficiency compared to the second.

The objective of the second part is to do an energy study with optimization to minimize energy consumption and increase energy efficiency in a machining process. The total power consumed is obtained by summing the no-load power p_0, the cutting power p_c, and the feed power p_f, Eq. (16).

$$p_{tc} = p_0(t) + p_c(t) + p_f(t) \tag{16}$$

According to Eq. (16), the total energy consumed is equal:

$$E_{tc} = \int p_{tc} dt \tag{17}$$

The total specific cutting energy SE_{tc} is the ratio of the cutting power consumed p_{tc} by the material removal rate MRR.

$$SE_{tc} = \frac{p_{tc}}{MRR} \tag{18}$$

The energy efficiency (EE*)* is the ratio of the cutting energy consumed (E_{cc}) by the total energy consumed (E_{tc}). Over time, the material removal rate (MRR*)* during the milling process is primarily aimed at productivity. Indeed, maximizing this parameter can have positive effects on the machining process, especially in roughing operations. The material removal rate is calculated from Eq. (19) [17].

$$MRR = \frac{v_c \times f \times a_p \times 1000}{60} \tag{19}$$

RESULTS AND DISCUSSION

Energy study

Figure 4 represents the variation of the total power consumed as a function of the cutting speed for a feed speed of 0.05 mm/rev. This variation shows that the total power consumed increases with increasing cutting speed and also with cutting depth. The cutting parameter included in Eq. (4) is the cutting speed. So an increase in the cutting power consumed necessarily means an increase in the cutting speed.

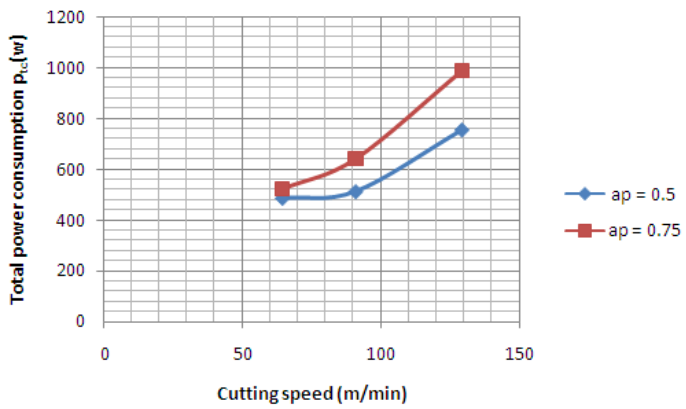

Figure 4. p_{tc} as a function of cutting speed (mm/min).

Table 5 presents the analysis of the variation of the responses of outputs p_{tc}, E_{tc}, SE_{tc}, and *EE*. It's the goal of ANOVA to spot the magnitude of every component of the target operation and to reduce the error [19]. ANOVA is to find the most effective components from lots of various options [20]. From this table, the total energy consumed model incorporates a value of p = 0.0002, which is less than 0.05. This verification allows us to conclude that this model is important, with a contribution of 97.89 %. We also note that the foremost influential parameter of the full energy consumed is the feed rate, with a contribution of 84.13 %. The factors and interactions that have a significant effect on the model of the total energy consumed are V_c, f, a_pxf, $V_c{}^2$, $a_p{}^2$, and f^2. The other parameters, a_p, V_cxf, and V_c*a_p, are insignificant. Figure 4 shows that when the feed speed decreases, the full energy consumed increases, this is often because of the rise within the cutting time *tc*. The results are validated by comparison with Guo et al. [21] and Velchev et al. [8]. The analysis of the variance of the whole specific energy consumed SE_{tc} (Table 5) shows that the model is important, with p-value < 0.0001 and a contribution of 98.93 %. Similarly for SE_{tc}, the foremost influential factor is the feed rate, with a contribution of 76.80 %. The second factor influencing SE_{tc} is that the depth of cut with a contribution of 16.75 %. From Figure 5, it may be noted that the minimum values of SE_{tc} and E_{tc} are obtained for the utmost values of feed rates and cutting speeds. The analysis of the variance of the energy efficiency *EE* (Table 5) shows that the model is critical (p-value = 0.0078 < 0.05), with a contribution of 92.25 %.The cutting speed is the most influential, with a contribution of 58.38 %, and then we discover the feed speed with a contribution of 15.57 %. Figure 6 depicts the change in energy efficiency *EE* and total specific energy consumption SE_{tc} as a function of the fabric removal rate *MRR*. It is shown that when the fabric removal rate *MRR* grows, so does the energy efficiency *EE*, but the full specific energy spent SE_{tc} declines. Comparisons with Camposeco-Negrete et al. [11] and Neugebauer [22, 23] corroborate the findings.

The correlation (R^2), which shows the efficiency of the chosen regression model, usually identifies the functional link between the input parameters and output parameters. The E_{tc} and EE results were analyzed employing a quadratic regression model.

$$E_{tc} = 168637 - 1797v_c - 1637478f + 193257a_p + 7.63v_c^2 + 6910983f^2 - 155181a_p^2 - 3852v_cf + 490v_ca_p \quad (20)$$

$R^2 = 97.89\%$; $R^2\ (adj) = 95.08\%$

$$EE = -70.1 - 0.89v_c + 1566f + 180a_p + 0.00355v_c^2 - 7987f^2 - 156.91a_p^2 - 7.37v_cf + 0.6v_ca_p \quad (21)$$

$R^2 = 92.25\%$; $R^2\ (adj) = 81.91\%$

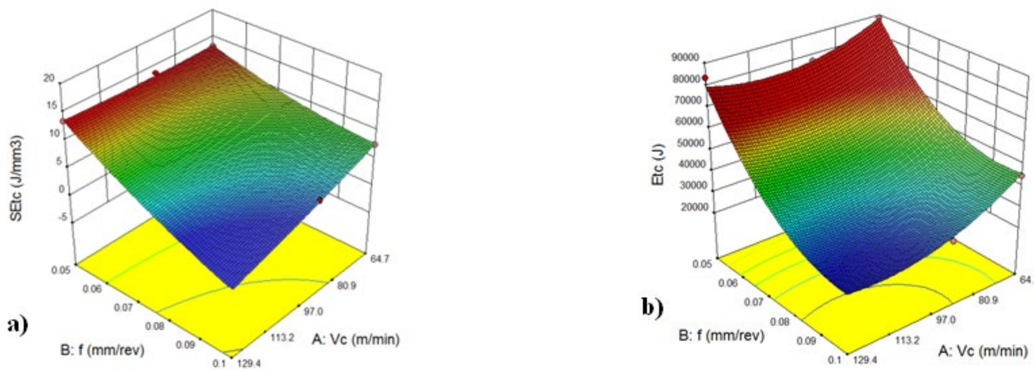

Figure 5. Surface plots of (a) SE_{tc} and (b) E_{tc}.

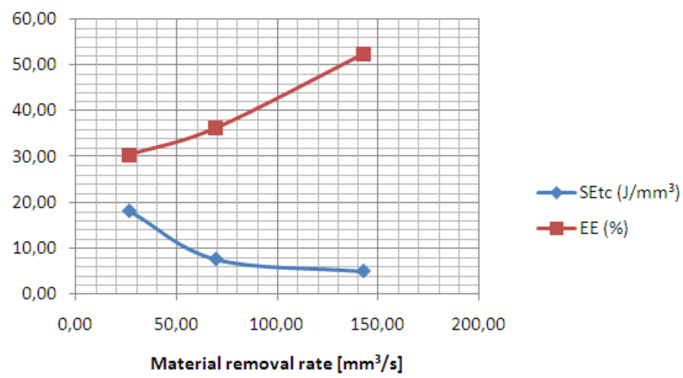

Figure 6. SE_{tc} and *EE* function of the material removal rate.

Table 5. Analysis of variance.

	p_{tc}		E_{tc}		SE_{tc}		EE	
Source	PC %	p-value	PC %	p-value	PC %	p-value	PC %	p-value
Model	96.15	0.0010	97.89	0.0002	98.93	< 0.0001	92.25	0.0078
V_c	62.41	0.0128	0.02	0.0301	0.08	*0.0053*	58.38	0.0325
f	10.16	0.0099	84.13	0.0002	76.80	*< 0.0001*	15.57	0.0588
a_p	0.17	0.2466	0.13	0.4002	16.75	*0.0019*	0.02	0.8127
$V_c \times f$	2.18	0.0343	0.01	0.4684	0.11	*0.0228*	0.18	0.2902
$V_c \times ap$	2.61	0.0899	0.64	0.2263	2.30	*0.0114*	2.16	0.2435
$a_p \times f$	-	0.0240	-	0.0197	-	*0.1455*	-	0.0468
V_c^2	8.91	0.1613	4.36	0.0441	1.29	*0.6137*	4.52	0.3898
f^2	0.75	0.0761	3.89	0.0039	1.51	*0.1082*	0.01	0.2665
a_p^2	8.96	0.0010	4.70	0.0002	0.09	< 0.0001	11.42	0.0078

Energy Study with ANN *Modeling*

ANNs are a category of statistical learning models inspired by biological neural networks that are wont to optimize input parameters. A system of feed-forward artificial neural networks with back-propagation is employed within the model. The training of the neural network was developed according to the Levenberg-Marquardt algorithm [24]. The dataset was divided into three distinct parts: training, testing, and validation. 70% of the total trials were used for the training phase, 15% for the testing phase, and finally, 15% of the total trials for validation. The ANN model was developed using the Neural Network Toolbox of the MATLAB software package. Cutting speed, feed rate, and depth of cut are the three input variables (Figure 7). The entire energy consumed (E_{tc}) and, therefore the energy efficiency (EE) are the outputs. At a minimum mean square error (MSE), the best number of neurons within the hidden layer is found. The square error is provided by Eq. (11).

$$MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{11}$$

The number of trials is n, and the difference between the actual and projected values is e_i.

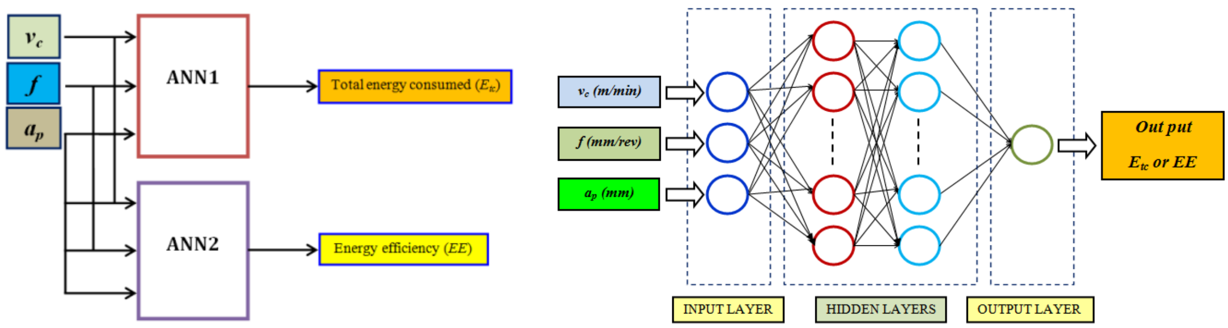

Figure 7. Output neural network design.

The neural structure used in this study is a 3-14-1 structure for E_{tc} output and a 3-10-1 structure for EE output (Figure 8). The minimum squared errors of the two outputs are presented in Table 6. On the other hand, for these structures, the total consumed energy has a total correlation coefficient of R = 0.99, and for the energy efficiency, R = 0 .97.

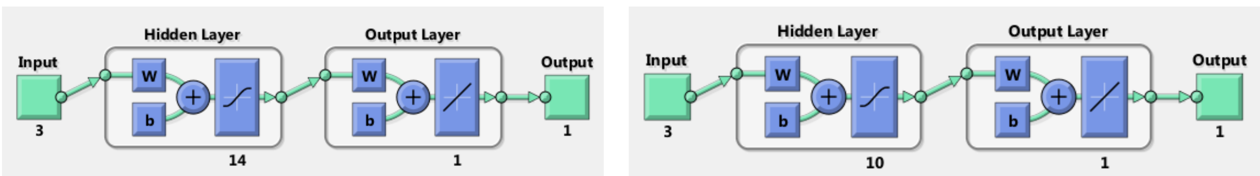

Figure 8. Output neural network design.

Table 6. The mean square error.

Structures NN	MSE	
	E_{tc}	EE
3 – 10 – 1	-	8.62526e-2
3 – 14 – 1	1.94041e-25	-

Tables 7 and 8 present the experimental and predicted values of E_{tc} ,and EE by the two methods (RSM and ANN). It can be found that errors from the ANN neural structure are less than those from the Response Surface Methodology (RSM). This shows us that the use of neural networks can give us more accurate results and can improve energy consumption and productivity in industrial sectors.

Table 7. Error between measured and predicted values (E_{tc}).

N°	E_{tc} (KJ)				
	Measured	ANN 3_14_1	MSR	Erreur ANN	Erreur MSR
1	82.134	82,134	80,938	-5,684e-14	1.196
2	88.550	88,550	88,676	-1,278e-13	-0.126
3	52.616	52,615	51,447	1,705e-13	1.169
4	39.440	39,440	38,125	-7,105e-15	1.315
5	27.300	27,859	29,622	-0,559	-2.322
6	28.080	28,079	21,196	1,140e-12	6.884
7	63.797	63,797	63,826	-9,947e-14	-0.029
8	83.401	83,401	79,481	-1,847e-13	3.92
9	40.050	32,821	43,941	7,228	-3.891
10	57.687	57,687	55,370	0	2.317
11	44.869	44,869	46,178	-4,689e-13	-1.309
12	31.265	31,264	34,517	7,105e-13	-3.252
13	61.440	67,011	66,237	-5,571	-4.797
14	77.040	73,290	77,208	3,749	-0.168
15	39.76	39,76	40,669	-1,278e-13	-0.909

Table 8. Error between measured and predicted values (*EE*).

N°	*EE (%)*				
	Exp	ANN 3_10_1	MSR	Erreur ANN	Erreur MSR
1	30.45	30,549	30.708	-0,099	-0.258
2	35.5	40,200	36.359	-4,700	-0.859
3	27.62	26,010	24.665	1,609	2.955
4	31.44	31,933	33.294	-0,493	-1.854
5	25.71	25,735	30.317	-0,025	-4.607
6	27.78	27,565	20.322	0,214	7.458
7	55.23	54,870	52.219	0,359	3.011
8	65.75	67,339	67.571	-1,589	-1.821
9	52.46	52,499	53.657	-0,039	-1.197
10	33.98	33,920	32.971	0,059	1.009
11	36.35	35,958	30.901	0,391	5.449
12	8.65	8,3779	16.944	0,272	-8.294
13	33.98	33,459	35.900	0,520	-1.92
14	47.35	47,223	45.513	0,126	1.837
15	31.99	41,965	32.912	-9,975	-0.922

Table 9. Constraints for machining parameter optimization.

Condition	Goal	Lower limit	Upper limit
V_c (m/min)	In range	64.68	129.37
f (mm/rev)	In range	0.05	0.1
a_p (mm)	In range	0.5	1
p_{tc} (W)		Minimize	
p_{cc} (W)		Minimize	
E_{tc} (J)		Minimize	
E_{cc} (J)		Minimize	
SE_{tc} (J/mm^3)		Minimize	
SE_{cc} (J/mm^3)		Minimize	
EE%		Minimize	

Table 10. Optimal values.

N°	Input			Output						
	v_c	f	a_p	p_{tc}	p_{cc}	E_{tc}	E_{cc}	SE_{tc}	SE_{cc}	EE	Des.
1	129.37	0.098	0.50	511.84	173.84	27389.21	8021.4	0.67	0.35	42.1	0.847
2	129.36	0.097	0.502	511.89	173.89	27350.25	7992.4	0.66	0.35	42.06	0.847
3	129.36	0.097	0.505	511.96	173.96	27305.57	7959.3	0.63	0.35	42.02	0.847
4	129.36	0.098	0.500	511.77	173.77	27461.71	8064.4	0.73	0.33	42.13	0.846
5	129.33	0.097	0.507	511.98	173.98	27263.60	7931.0	0.61	0.35	41.97	0.846
6	129.02	0.098	0.507	511.54	173.54	27301.27	7983.2	0.61	0.35	41.93	0.846

Multi-objective Optimization using the Desirability Function

Multi-objective optimization is that takes into account several factors at the same time [25]. Also, several iterations of cutting parameter combinations are performed to achieve multiple goals. In our case, the main objective is to maximize *EE* energy efficiency and minimize energies and powers using the desirability function. Table 9 summarizes these objectives. According to Table 10 the optimal solution is solution 1 with a cutting speed V_c = 129.37 m/min, a feed rate f = 0.098 mm/rev and a depth of cut a_p= 0.5 mm. These values give us an energy efficiency of 42.01 % and the total energy consumed by 27389.21 J. These values give us a reduction in total energy consumed E_{tc} of 49.74 % and an increase in energy efficiency *EE* of 13.63 % (Figure 9).

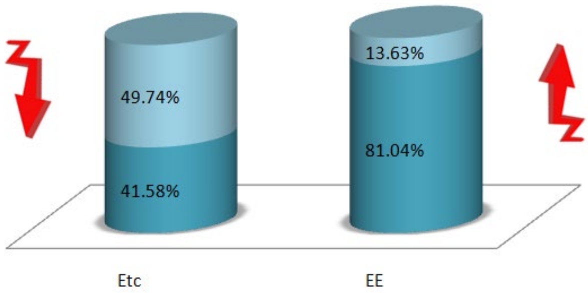

Figure 9. Energy optimization.

CONCLUSION

Product demand is increasing as a result of growth, which necessitates an enormous amount of energy. Industrial sectors are increasingly concerned with lowering their energy consumption. This text presents a replacement approach to machining energy consumption as a function of tool-part cutting power. Two cases are studied, the primary without tool change or spindle speed change, and therefore the second with tool change and spindle speed change. It can be deduced from this experimental study that, first of all, the cycles without spindle speed change consume less energy than with spindle speed change but with less energy efficiency. That the right choice of machining strategy, as well as the right choice of cutting tool to mitigate tool changes during a machining cycle, can minimize energy consumption. We also observe that the feeding rate, which represents 84.13% of the total energy consumed, proves to be the most influential element during this study. Energy efficiency decreases with increasing material removal rate MRR.

In our case study, the use of an artificial neural network (ANN) gives better results compared to the results given by the response surface methodology (RSM). The optimization of the cutting conditions gives us the optimal values of the cutting speed $Vc = 129.37$ m/min, the feed $f = 0.098$ mm/revolution; and therefore, the depth of cut $a_p = 0.5$ mm allows us to conclude that this approach will allow us to mitigate the total energy consumed E_{tc} by 49.74% and to increase the energy efficiency *EE* by 13.63%. The objective of the future work is to make a prediction and an optimization of the experimental results regarding the energy consumption, the machining cost, and the quality of an automotive part using an artificial neural network.

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