PREDICTION OF OPTIMUM CUTTING CONDITIONS IN DRY TURNING OPERATIONS OF S45C MILD STEEL USING AIS AND PSO INTELLIGENT ALGORITHMS

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ABSTRACT: *This study presents an approach for modeling and predicting the cutting zone temperature, surface roughness and cutting time when dry turning S45C mild steel is used with SPG 422 tungsten carbide tools. The suggested system is based on Particle Swarm Optimization (PSO) and Artificial Immune System (AIS) intelligent algorithms. S45C Mild steel bars are machined at different cutting conditions (cutting speeds, feed rates and depths of cut) without the use of cutting fluid. AIS and PSO results have been experimentally trained to find cutting zone temperature, surface roughness and cutting time by using the parameters directly on a CNC turning machine. The tests were conducted on a CNC turning machine type HAAS AUTOMATION SL 20. An infrared camera (Flir E60), a lathe tool dynamometer model USL-15 and a portable surface roughness device were respectively used to measure temperatures, cutting forces and surface roughness. The results predicted by AIS and PSO were compared with the experimental values derived from the testing data set. Testing results indicated that the predicted and experimental results are approximately similar and that suggested system can be used to estimate the cutting temperature, surface roughness and cutting time in the turning operation with high accuracy. Experimental results showed that the average accuracy of the AIS algorithm is 94.37 %, whereas that of the PSO algorithm is 92.84 % which indicated that the two percentages are convergent.*

KEYWORDS: AIS, PSO, Cutting zone temperature, Surface roughness, Cutting time, CNC turnin

1.0 INTRODUCTION

Selecting the ideal cutting parameters for every operating process is among the modern technological challenges in enhancing machining product quality, reducing operation costs, and increasing the effectiveness and productivity of cutting operations as in [1,5]..

Others [6] studied on the optimization of cutting parameters (which are cutting speed, feed rate and depth of cut as well) to aid in determining the optimal surface roughness and work piece surface temperature of AISI 1020 work material during the turning operation by using the Taguchi method. Temperature was measured by using the Stefan-Boltzmann law and an infrared thermometer was (OS534E) used to determine the emissivity of the radiation element. The results indicated that determining the work piece surface temperature by using a thermometer is an effective approach and is a good indicator for optimizing cutting parameters

Elsewhere [7] authors used the Taguchi method to minimize the tool-chip interface temperature with a tool-work thermocouple technique. A cutting tool was used for work piece Č1730 (EN C60) steel and cemented carbide is inserted to obtain the experimental results. The analysis indicated that cutting speed is the most significant parameter affecting cutting temperature.

Authors in [8] studied on using of the interface system ANFIS with PSO learning. This system can be used to calculate the cutting zone temperature and surface roughness of AISI304 austenitic stainless steel by using a multi-layer coated tungsten carbide cutting tool. The system is trained by using data on cutting parameters (cutting speed, feed rate and cutting force) collected during the experiment. The results showed that the use of this system can result in producing good quality product with raised productivity and minimal cost

2.0 Optimization and Analysis by AIS, and PSO

2.1 Objective Functions (O.F)

Three types of objective functions used in this study:-

2.1.1 Cutting area temperature objective Function

The first O.F is used to lessen the cutting zone temperature, which clearly shows the summation of shear and chip-tool zone temperatures, as SHOWN in Eq. (1) [9].:

$$\mathbf{T_{si} = [\,0.9 * Zs * w_1 * t_1 * Vc * \cos(j) / (\sin(\phi) * \cos(\phi - j) * w_1 * t_1 * Vc * M * L + N] + [0.6786 * Fc*\sin(j) + (Ft *\cos(j)] / (th * w) * sqrt((Vc * t_1 / t_2 * (th) / (M * L) / a]} \quad (1)$$

Where; T_{si} :- cutting zone temperature (C^o), Zs:-mean shear strength (N/m^2), w_1:-depth of cut (m), t_1:-feed (m),Vc:-cutting velocity (m/s), j:-cutting tool rake angle (Deg), ϕ:-shear plane angle (Deg), M:-work piece material density (Kg/m^3), L:-specific heat of work (J/Kg.C^o),N:-ambient temperature (C^o) equal to 25 C^o , Fc:-main cutting force (N), Ft :-feed force (N), th:-thermal conductivity of work (W/m.C^o), t_2:- chip thickness (m), a:-chip contact length (m). The shear plane angle can be calculated as shown in Eq. (2):

$$\mathbf{\phi = \tan^{-1} (r \cos (j) / 1 – r \sin (j))} \quad (2)$$

Where; r:- chip ratio ≤ 1, j:- cutting tool rake angle

2.1.2 Surface Roughness Objective Function

This O.F is used to minimize the work piece surface roughness (R_a) as SHOWN in Eq. (3) [10].:

$$\mathbf{R_a = 0.032 * f^{\,2} / r_1} \quad (3)$$

Where; Ra:- the transverse roughness (µm), f :- the feed rate between successive cuts (m),, r_1:- the cutting tool tip radius (m).

2.1.3 Cutting Time Objective Function

The third O.F is used to calculate the minimum operating cutting time (T_m) as shwon in Eq. (4)[11].:

$$\mathbf{T_m = L_f / f * N_w} \quad (4)$$

Where; T_m:- the machining cutting time (min), L_f:- length of the cutting surface (m), f:- feed rate (m), N_w:- the rotational speed of the work piece (rev/min).

2.2 Optimization by AIS

AIS used the clonal selection terminology such as antibody (cutting variable), antigen and clonal
for finding the optimum cutting parameters. This methodology is dependent on three principles; proliferation of cells, generation of diverse antibodies and antigenic receptors handling. Increasing the cell numbers (Nc), which represents the ideal solutions achieves is shown as Eq. (5) [12].:-

$$\mathbf{Nc = \Sigma\ round\ (\beta * N)} \qquad (5)$$

Where; β:- the multiplying factor equal to 1, N:- the total number of antibodies. The number of antibodies after mutation (Abi) which represents the cutting variables can be calculated as shown in Eq. 6:

$$\mathbf{Abi = Abi * [\ 1 + \alpha * Ni * (0\ ,1)} \qquad (6).$$

Where; α;- the step size equal to 1, Ni:- random variable. The AIS parameters for simulation operation are as follows; number of variables = 5, population size = 30, and number of iterations = 450. The optimum cutting temperature, surface roughness, and cutting time results of AIS are shown in Table 1:-

Table 1: Optimum results by AIS intelligent algorithm

Epo	w1 mm	t1 mm	Vc	T theo	Ra	ϕ theo	Th theo	t theo
50	0.6	0.15	100	229	2.50	27.3	55.3	2.07
100	0.3	0.15	100	186	2.50	53.4	56.3	2.09
150	0.6	0.1	100	202	1.06	29.6	54.6	2.51
200	0.3	0.06	60	110	0.49	72.2	51.5	7.25
250	0.6	0.15	60	175	2.50	53.4	53	2.82
300	0.3	0.1	60	165	1.45	53.4	52.3	4.20
350	0.8	0.1	40	166	1.06	31.6	53.4	6.41
400	0.6	0.15	40	153	2.50	47.5	51.5	4.22
450	0.6	0.05	40	150	0.26	47.5	50.2	13.3

Figures 1,2 and 3 show the ideal temperature, surface roughness and cutting time of AIS:-

Whereas those obtained equilibrium among all parameters are found in epoch 300 as shown in Table 2:-

Table 2: Optimal cutting parameters of AIS

Ep	w_1 mm	t_1 mm	Vc m/	T theor	Ra	ϕ theor	Th theor	t the
300	0.3	0.1	60	165	1.4	53.	52.	4.2

2.3 Optimization by PSO

In PSO algorithm, each particle (solution of the problem) flies through the multi-dimensional search space. The particle velocity and position are constantly updated according to the best, previous or neighbor's performance as well as the best performance of the particles in the entire population clustering large dataset [13]. The main procedure of this algorithm as shown in Eq. 7 [14]:-

$$\mathbf{Vi^{k+1} = w * vi^{k} + a_1 * rand_1 * (\ p_{besti} - xi^{k}) + a_2 * rand_2 * (\ g_{besti} - xi^{k})} \qquad (7)$$

Where; Vi^k:- velocity of particle i at iteration k, xi^k:- current position of particle i at iteration k, p_{besti} :- personal best of particle i, g_{besti} :- best position in the neighborhood, rand:- random number between 0 and 1, w:- weighting function, a_1, a_2:- learning rate. The PSO parameters for the simulation operation are as follows; number of variables = 5, population size = 30, number of iteration generations = 450, a_1= 0.01 and a_2= 0.01. The optimum cutting temperature, surface roughness, and cutting time obtained by the PSO are shown in Table 3:-

Table 3: Optimum results by PSO algorithm

Epo	w	t1	V	T theo	Ra	ϕ theo	Th theo	t theo
50	0.	0.15	100	218	2.	26.6	56.7	1.68
100	0.3	0.15	100	185	2.5	58.8	58.9	1.68
150	0.6	0.1	100	203	1	29.6	55.6	2.53
200	0.3	0.06	60	110	0.4	75	51.6	7.27
250	0.6	0.15	60	150	2.5	58.4	54.3	2.80
300	0.3	0.1	60	164	1.4	52	57.1	4.21
350	0.8	0.1	40	166	1.0	35.6	57.2	6.40
400	0.6	0.15	40	153	2.5	50	56.4	4.21
450	0.6	0.05	40	151	0.2	47.5	55.6	13.3

Table 4: Optimal cutting parameters of PSO

Epoc	w_1	t_1	Vc	T	Ra	ϕ	Th	t
300	0.3	0.1	60	16	1.4	52	57	4.2

Table 5: Chemical composition of the work piece material

Density (Kg/m^3)	**Young's Modulus (GPa)**	**Mean shear strength (N/m^2)**	**Specific heat of work ($J/Kg.C^o$)**	**Thermal conductivity of work ($W/m.C^o$)**
7800	200	340 $*10^6$	510	45- 65

Table 6: Mechanical properties of work piece material

Eleme	C	Si	Mn	P	S	Cr	Ni	Cu
Weig	0.42	0.17-	0.50-	0.0	0.0	0.	0.	0.2

Figures 4.5 and 6 show the ideal temperature, surface roughness and time of PSO Intelligent algorithm respectively:-

Whereas those obtained equilibrium among all parameters are found in epochs 300 as shown in Table 4:

3.0 Experimental Set Up

To verify the simulation results, the optimum parameters obtained by the AIS, and PSO were used as input for the CNC turning machine. After the completion of the turning operation, the actual and simulation results were compared. The tests were then conducted on the CNC turning machine type HAAS AUTOMATION SL 20. A mild steel work piece material (S45C) rod with a diameter of 50 mm and length of 160 mm, as well as a tungsten carbide insert cutting tool (WC) (SPG422) with a cutting tool rake angle equal to 15º

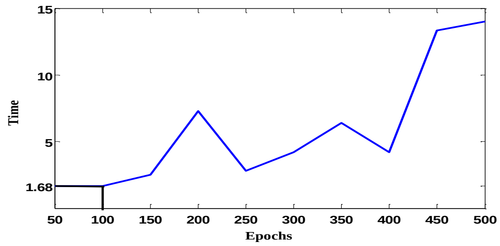

Figure: 1 Optimum cutting temperature

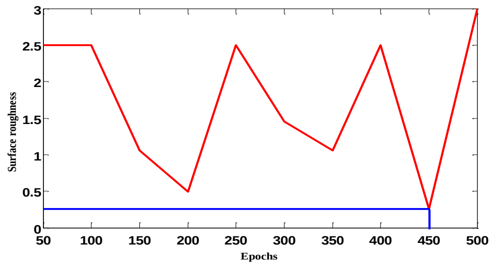

Figure 2: Optimum surface roughness

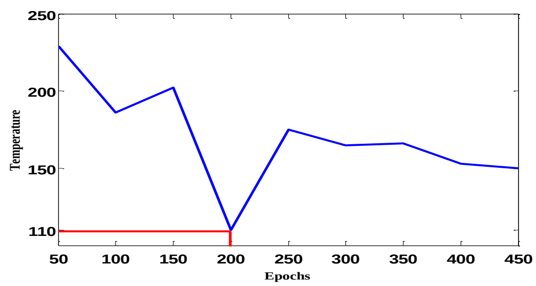

Figure 3: Optimum cutting time

was used in the experiment. The chemical composition and mechanical properties of the mild steel material are shown in Tables 5 and 6 respectively:-

A Flir E60 infrared thermal image camera and a dynamometer model USL-15 lathe tool with a capacity of 500Kg in the x , y, and z directions were used to measure the cutting temperature and cutting force as shown in Figure 7 , whereas a portable surface roughness device was used to work piece roughness measurement.

The experimental set up used in this study has been illustrated in Figure 8:-

4.0 RESULTS AND DISCUSSION

4.1 Comparison of experimental and simulation results

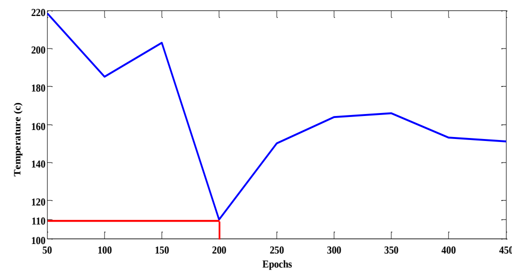

Figure 4: Optimum cutting temperature

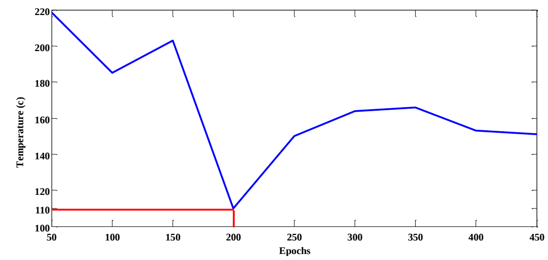

Figure 5: Optimum surface roughness

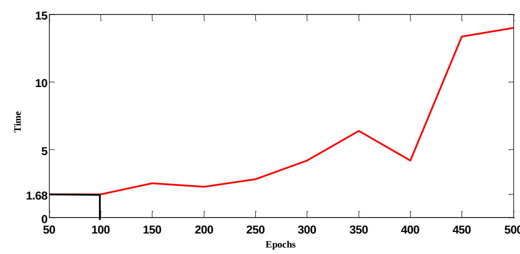

Figure 6: Optimum cutting time

The experimental and simulation results of AIS and PSO are compared, and the ideal algorithm that gives better results is obtained as shown in Tables 7 and 8 respectively:-

The average accuracy percentage between the simulation and actual results of PSO is (92.84%), AIS algorithm is (94.37 %), as shown in Figures 9, and 10 respectively:-

Figure: 7 Flir E60 Infrared Thermal Camera (left) and Force dynamometer (right)

Table7: Comparison between simulation and actual results of AIS

Epochs	w_1 (m)	t_1 (m)	V (m/min)	Fc actual (N)	F_f actual (N)	T theoretical (Co)	T actual (Co)	T accuracy% (Co)	Ra theoretical (µm)	Ra actual (µm)	Ra accuracy% (µm)	t theoretical (min)	t actual (min)	t accuracy % (min)
50	0.0006	0.00015	100	253	152	229	219	95.7	2.50	2.20	88	1.68	1.63	97
100	0.0003	0.00015	100	182	159	186	160.5	86.3	2.50	2.15	86	1.68	1.63	97
150	0.0006	0.0001	100	245	204	202	200	99.00	1.06	1.15	87	2.53	2.55	99.21
200	0.0003	0.00006	60	164	147	110	102.5	93.19	0.49	0.56	87.5	7.27	7.22	99.31
250	0.0006	0.00015	60	503	315	175	157	89.7	2.50	2.62	95.41	2.80	2.75	98.21
300	0.0003	0.0001	60	226	117	165	153.3	93.00	1.45	1.58	91.77	4.21	4.20	99.76
350	0.0008	0.0001	40	133	79	166	171	97.00	1.06	1.17	90.5	6.40	6.45	99.22
400	0.0006	0.00015	40	127	105	153	150	98.00	2.50	2.57	97.2	4.21	4.25	98.22
450	0.0006	0.00005	40	169	146	150	148	98.66	0.26	0.30	86.6	13.33	13.36	99.77
								94.5%			**90%**			**98.63%**

Table 8: Comparison between simulation and actual results of PSO

Epochs	w_1 (m)	t_1 (m)	V (m/min)	Fc	F_f	T theoretical (C^o)	T actual (C^o)	T accuracy% (C^o)	Ra theoretical (µm)	Ra actual (µm)	Ra accuracy% (µm)	t theoretical (min)	t actual (min)	t accuracy% (min)
50	0.0006	0.00015	100	251	150	218.4	219	99.72	2.50	2.20	88	1.68	1.64	97.60
100	0.0003	0.00015	100	181	160	185	160.5	86.75	2.50	2.15	86	1.68	1.43	85.11
150	0.0006	0.0001	100	240	200	203	200	98.5	1.06	1.25	85	2.53	2.55	99.21
200	0.0003	0.00006	60	161	143	110	102.5	93.18	0.38	0.56	82	7.27	7.42	98
250	0.0006	0.00015	60	500	311	150	157	95.5	2.50	2.62	95.4	2.80	2.55	91
300	0.0003	0.0001	60	223	110	164	153.3	93.48	1.46	1.58	92.4	4.21	4.40	95.68
350	0.0008	0.0001	40	131	71	166	171	97	1.10	1.17	94	6.40	7	91.14
400	0.0006	0.00015	40	120	100	153	150	98	2.50	2.87	87.9	4.21	4.05	96.17
450	0.0006	0.00005	40	165	144	151	148	98	0.24	0.30	86.38	13.33	13.36	99.77
								95.11%			**88.56%**			**94.85%**

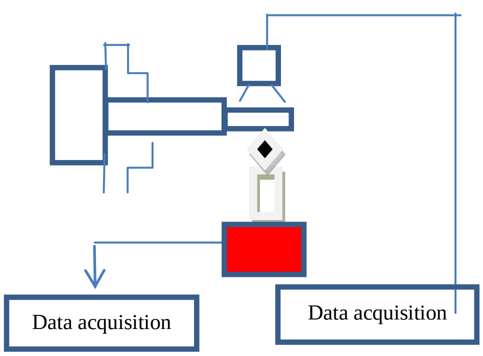

Figure 8: Experimental set up

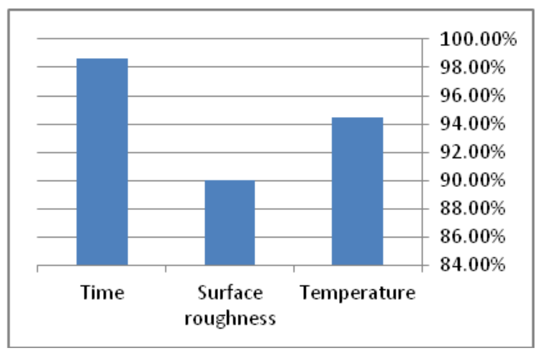

Figure 9: The accuracy percentage of PSO

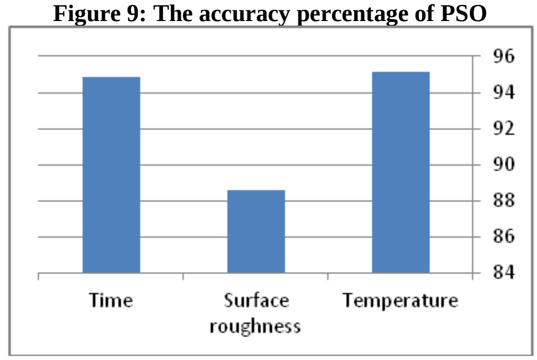

Figure 10: The accuracy percentage of PSO

The relationships among cutting parameters continually changed depending on the cutting operation conditions. The changes in the values of some parameters may cause changes in the values of other parameters.

The results show that an increase in cutting velocity causes an increase in cutting temperature and surface roughness, but a decrease in cutting time. Meanwhile, an increase in feed rate causes an increase in both temperature and surface roughness but a decrease in cutting time. The shear plane angle also affects the cutting operation, such that its increase results in a significant drop in cutting temperature and cutting forces. The change in thermal conductivity is simple and varies between (51 and 59 w/m.c).

5. CONCLUSIONS

The simultaneous optimization of many different parameters is a difficult problem in the manufacturing and optimization field. This study is presented to a PSO and AIS intelligent system to predict cutting zone temperature, surface roughness, and cutting time accurately in the dry turning of S45C mild steel with the use of SPG 422 tungsten carbide tools. PSO, and AIS were used to compute for the most suitable and ideal parameters. All the Cutting speed, feed rate, depth of cut, cutting force, and feed force data were used as model variables for PSO and AIS. The predicting capability of AIS was found to be 94.50% for cutting temperature, 90% for surface roughness, and 98.63% for cutting time. Meanwhile, the predicting capability of PSO was found to be 95.11% for cutting temperature, 88.56% for surface roughness, and 94.85% for cutting time. The results showed good agreement between the simulation results by AIS, and PSO and the actual results collected by the CNC turning machine. The average accuracy of the AIS algorithm was 94.37 %, whereas that of the PSO algorithm was 92.84 % which indicates that the two percentages are convergent. The proposed system was found to have shown satisfactory performance in predicting the ideal cutting temperature, surface roughness and cutting time. The results of AIS and PSO were found to be convergent, which confirms the robustness of the proposed system.

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