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Tool State Assessment for Reduction of Life Cycle Environmental Impacts of Aluminium Machining Processes via Infrared Temperature Monitoring

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Abstract

Modern industrial machining environments face new challenges in implementing process monitoring systems to improve energy efficiency whilst ensuring quality standards. A process monitoring methodology for tool state identification during milling of aluminium has been implemented through the utilisation of an infrared (IR) camera. A features extraction procedure, based on statistical parameters calculation, was applied to temperature data generated by the IR camera. The features were utilised to build a fuzzy c-means (FCM) based decision making support system utilising pattern recognition for tool state identification. The environmental benefits deriving from the application of the developed monitoring system, are discussed in terms of prevention of rework/rejected products and associated energy and material efficiency improvements.

Keywords: Process monitoring; Thermography ; End milling;

1. Introduction

In modern industries, the contemporaneous advancements in sensor monitoring systems, together with the understanding of environmental impacts flow analysis is leading to enhanced process performance for manufacturing activities.

In this context, improving energy efficiency has become increasingly vital. This rationalisation of energy consumption is not only a cost-effective way of cutting carbon emissions but can also improve productivity and energy security [1].

These improvements can be interpreted in terms of reduction of rejects and better machine utilisation, which are crucial factors to achieve a more energy efficient production.

Power consumption in machining processes increases with the tool wear [2], this highlights the importance of the development of Tool Condition Monitoring (TCM) systems, which operate in real time and employ indirect methods, representing the mainstream in today's automated manufacturing [3]. The measurement of temperature, as an indirect TCM, can be considered a particularly important "tool wear indicator" [4].

Since the work of Taylor in 1907, it has been recognised that machining temperature has a critical influence on tool wear and tool life [4][5], and Trigger and Chao [6] demonstrated that the growth of crater wear at the tool-chip interface was directly governed by the temperature distribution along the interface. Relatedly, Rivero et al. [7] showed the relationship between the tool temperature, the built-up layer and the large variability in those internal data that is sensitive to tool wear.

It has also been reported that high temperatures in machining can cause problems in the workpiece as well, including poor dimensional accuracy and surface finish, and residual stresses [5]. Current methodologies for temperature measurement in TCM of material removal processes comprise the use of resistance methods, thermocouples, thermo physical processes and "Spectral Radiation Thermometry" (infrared monitoring); this last method has shown to have the best spatial and temporal resolution [5][8].

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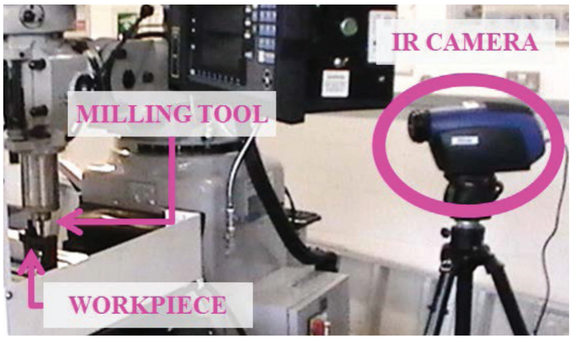

Fig. 1. Experimental setup

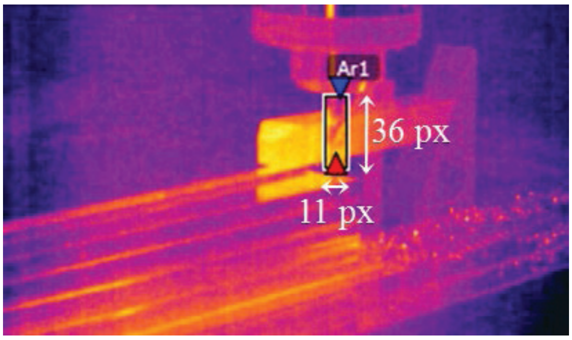

Fig.2. 11x36 pixel ROI within the IR video screenshot

This approach exploits the correlation between the temperature of an object and the wavelength of the electromagnetic radiation energy that it emits.

One of its major advantages for the monitoring of machining processes is the remote nature of the measurement method, meaning that no holes or sensors need to be incorporated into the cutting tool, which may impact the accuracy of reading [4][5]. Spectral radiation thermometry also looks at the local surface temperatures on the faces and edges of the cutting tool, which are more important than the average temperatures in the tool when considering tool wear [8]. In this work, a non-contact sensing approach based on infrared temperature data acquisition and processing, is proposed for tool wear state assessment during milling of aluminium. An experimental procedure is described, along with processing of collected data aimed at extracting statistical features [9] which are inputted into a fuzzy c-mean clustering (FCM) [10] decision making support system to assess tool wear state. The applicability of this procedure for industrial applications is discussed.

2. Experimental procedure

2.1. Milling tests

An experimental campaign of milling tests (see Fig. 1) under dry conditions was carried out on a XYZ SMX2000 CNC Three-axis vertical milling machining, with a 2.25 kW drive motor, and a maximum spindle speed of 4200 RPM.

The cutting tools used were two M2 High Speed Steel (HSS) Sherwood four-toothed, 12mm diameter end mills. The workpiece used for the cutting tests was a 51 x 51 x 610 mm square stock made of 6068 Aluminium, which has Temper Code T6, which means that aluminium is solution heat treated then artificially aged [11]. Milling operation was performed over the full stock length.

For the design of experiments (see Table 1) two cutting parameters were taken into account: spindle speed (RPM) and feed rate (mm/min). Three different values were adopted for both parameters, resulting in 9 different cutting combinations.

Each cutting test was performed under two tool state conditions: fresh tool and worn tool. Two repetitions for each test were carried out, i.e. 9 cutting conditions x 2 tool conditions x 2 repetitions, resulting in 36 total milling tests.

2.2. Infrared temperature measurement

Infrared temperature data acquisition was performed using a Cedip Infrared Systems Silver 450M InSb type infrared camera, and the sampling frequency was 383 frames per second; considering the rotational speeds involved (ranging from 15 to 25 rev/s) this results to be a suitable value according to Nyquist Sampling theorem [12]. An IR video was recorded for each milling test. Using FLIR's "ResearchIR" software, temperature data was generated by defining a rectangular 11 x 36 pixels Region Of Interest (ROI) within the IR video as shown in Fig. 2. The ROI shape and size were chosen in order to encompass the entire surface projection of the milling tool and its interface with the workpiece, which is equivalent to 12 mm x 40 mm = 480 mm^2 for this setup.

Table 1. Experimental Programme of milling tests

Feed Rate (mm / min)	Cutting Speed (RPM)	Test ID Fresh Tool	Test ID Worn Tool
254	900	T_1_F	T_1_W
		T_1_FR	T_1_WR
254	1200	T_2_F	T_2_W
		T_2_FR	T_2_WR
254	1500	T_3_F	T_3_W
		T_3_FR	T_3_WR
508	900	T_4_F	T_4_W
		T_4_FR	T_4_WR
508	1200	T_5_F	T_5_W
		T_5_FR	T_5_WR
508	1500	T_6_F	T_6_W
		T_6_FR	T_6_WR
762	900	T_7_F	T_7_W
		T_7_FR	T_7_WR
762	1200	T_8_F	T_8_W
		T_8_FR	T_8_WR
762	1500	T_9_F	T_9_W
		T_9_FR	T_9_WR

Table 2. IR thermography parameters and emissivity coefficient

IR thermography parameters	
Tool-camera distance	0.91 m
Atmospheric temperature	22˚C
Reflected temperature	22˚C
Tool emissivity coefficient	**0.393**

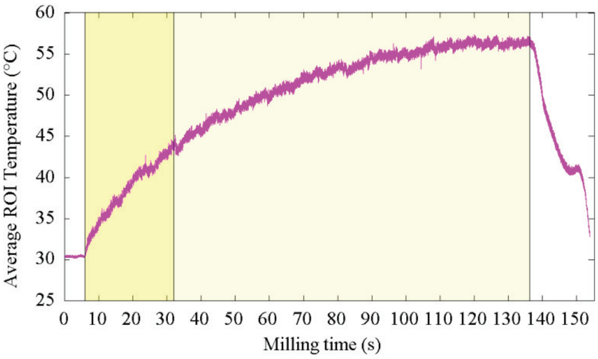

Fig. 3. Raw temperature data for test T2_F. The area within the patch indicates the actual milling time

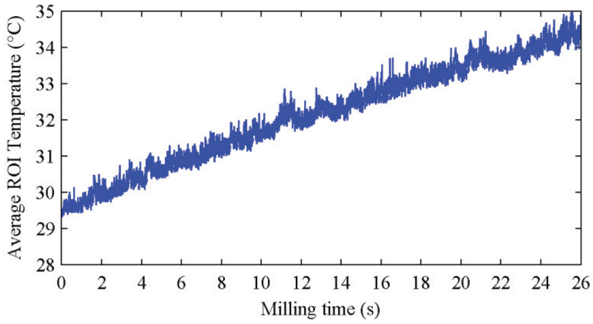

Fig. 4. Segmented temperature data for test T2_F (intense yellow patch in Fig. 3), the signal-to-noise ratio [13] for this signal instance is 7.65

In this way the temperature data recorded was an average over the ROI, avoiding temperature peaks due to the chip formation [7] and minimising dazzles at the tool chip interface [8][14] which could affect the results.

3. Data processing and features extraction

3.1. Pre-processing

A fundamental parameter in infrared temperature data acquisition is the emissivity. It depends on a several factors such as environment temperature, materials and surface finish of the workpiece [15]. Emissivity calibration procedure was carried out by matching the IR camera temperature data to the temperature data recorded using a k-type thermocouple mounted on the milling tool. A k-type was used taking into account the expected temperature range and the materials involved. The fitting was computed using linear regression analysis and the relevant parameters values are reported in Table 2. The raw data (Fig. 3) was pre-processed by implementing data segmentation [17] in order to get 10000 samplings comprised in tool-material contact phase (Fig. 4.).

In Fig. 3 the temperature reaches a steady state value towards the end of the test, this is due to the fact that the heat flux rate generated at the interface reaches a constant value [16]. This data segmentation procedure was applied to all the cutting tests. Hence, a dataset of segmented temperature data (36 tests x 10000 samplings) was obtained and reported in Table 3.

3.2. Features extraction

From the sensing unit data, signal features need to be derived that can describe the data adequately and maintain the relevant information about the process or tool conditions [17].

The technique used to extract features from temperature data provides for the calculation of four statistical parameters: Mean, Variance, Skewness and Kurtosis [18].

Table 3. Segmented data (36 x 10000)

Test #	Test ID	Samplings			
		1	2	…	10000
1	T1_F	29.3920	29.4689	…	34.5353
2	T2_F	29.1241	29.1734	…	32.7792
…	…	…	…	…	…
36	T9_WR	29.2139	30.4664	…	54.1582

Table 4. Statistical features

Test #	Test ID	Mean	Variance	Skewness	Kurtosis
1	T1_F	32.1536	1.9977	-0.1702	1.8806
2	T2_F	31.2110	1.0783	-0.1633	1.8825
…	…	…	…	…	…
36	T9_WR	52.5492	50.3544	-0.4070	2.1811

In this way, an input feature matrix, i.e. a dataset of 36 (milling tests) x 4 (features) was built as shown in Table 4.

4. Fuzzy c-means clustering algorithm

4.1. Theoretical background

Fuzzy clustering is a branch in clustering analysis and it is widely used in the pattern recognition field [19]. The aim in clustering is to determine the cluster centres, which are representative values of features corresponding to the classified categories [20]. Fuzzy clustering algorithms are partitioning methods that can be utilised to assign data points to their clusters. These algorithms can handle uncertainty in the data by providing a degree of membership when associating a data point to a cluster.

The fuzzy c-means (FCM) is the best known and most widely used algorithm. The FCM algorithm is used to find a fuzzy partition of the data set into fuzzy subsets. Each partition is described by a membership function [21].

Objective function approach is utilised for clustering n data points to c clusters. The main aim of the objective function is to minimise the Euclidian distance between each data point in the cluster i and its cluster centre, and maximise the Euclidian distance among cluster centres [22].

The algorithm is an iterative clustering method that produces an optimal c partition by minimising the weighted within group sum of squared error objective function J_{FCM}:

$$J_{FCM} = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^q d^2(x_k, v_i)$$

Where $X = \{x_1, x_2, \dots, x_n\} \subseteq R^p$ is the dataset in the p-dimensional vector space, n is the number of data items, c is the number of clusters with $2 \leq c < n$,u_{ik} k is the degree of membership of x_k in the i^{th} cluster, q is a weighting exponent on each fuzzy membership, $\mathrm{v_i}$ is the prototype of the centre of cluster i, $\mathrm{d^2(x_k, v_i)}$ is a distance measure between object $\mathrm{x_k}$ and cluster centre $\mathrm{v_i}$.

A solution of the objective function $\mathrm{J_{FCM}}$ can be obtained via an iterative process, which is carried out as follows [23]:

1. Set values for c, q, and ϵ.
2. Initialise the fuzzy partition matrix $U = [u_{ik}]$
3. Set the loop counter $b = 0$
4. Calculate the c cluster centres $\left\{v_i^{(b)}\right\}$ with $U^{(b)}$:

$$v_i^{(b)} = \frac{\sum_{k=1}^{n}\left(u_{ik}^{(b)}\right)^q x_k}{\sum_{k=1}^{n}\left(u_{ik}^{(b)}\right)^q}$$

5. Calculate the membership $U^{(b+1)}$. For $k = 1$ to n, calculate the following:
   $I_k = \{i | 1 \leq i \leq c, d_{ik} = \|x_k - v_i\| = 0\}, /I$; for the k^{th} column of the matrix, compute new membership values:
   a. If $I_k = \phi$, then $u_{ik}^{(b+1)} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{(q-1)}}}$,
   b. Else $u_{ik}^{(b+1)} = 0$ for all $i \notin I$ and $\sum_{i \in I_k} u_{ik}^{(b+1)} = 1$; next k
6. If $\left\|U^{(b)} - U^{(b+1)}\right\| < \epsilon$, stop; else, set $b = b + 1$ and go to step 4.

4.2. Fuzzy c-means clustering algorithm application

In this research work the following parameters were set up

- Number of clusters c = 2, representing fresh and worn tool state respectively;
- Maximum number of iterations: 100;
- Minimum improvement ϵ: $1\text{x}10^{-6}$;
- For the choice of weighting exponent q, several values of q, ranging from 1.4 to 2.4 were utilised [24][25] and compared as shown in Fig. 5.

The initial fuzzy partition matrix [10] is generated and the initial fuzzy cluster centres (light font numbers in Fig. 5) are calculated with the parameters described above. In each step of the iteration, the cluster centres and the membership grade point are updated and the objective function is minimised to find the best location for the clusters [26].

5. Results and discussion

5.1. Choice of exponent q

It has been chosen q = 1.6 because it minimises the objective function amongst the several configurations yielding to one single misclassification. Choosing a higher coefficient q appears to lead to a higher number of misclassification (Fig. 6), while choosing a lower one yields to a higher value of the objective function [24][25].

5.2. Membership and objective functions

A membership function describes the relationship between a variable and the degree of membership of the fuzzy set that correspond to particular values of that variable. This degree of membership is usually defined in terms of a number between 0 and 1, inclusive, where 0 implies total absence of membership, 1 implies complete membership, and any value in between implies partial membership of the fuzzy set [27].

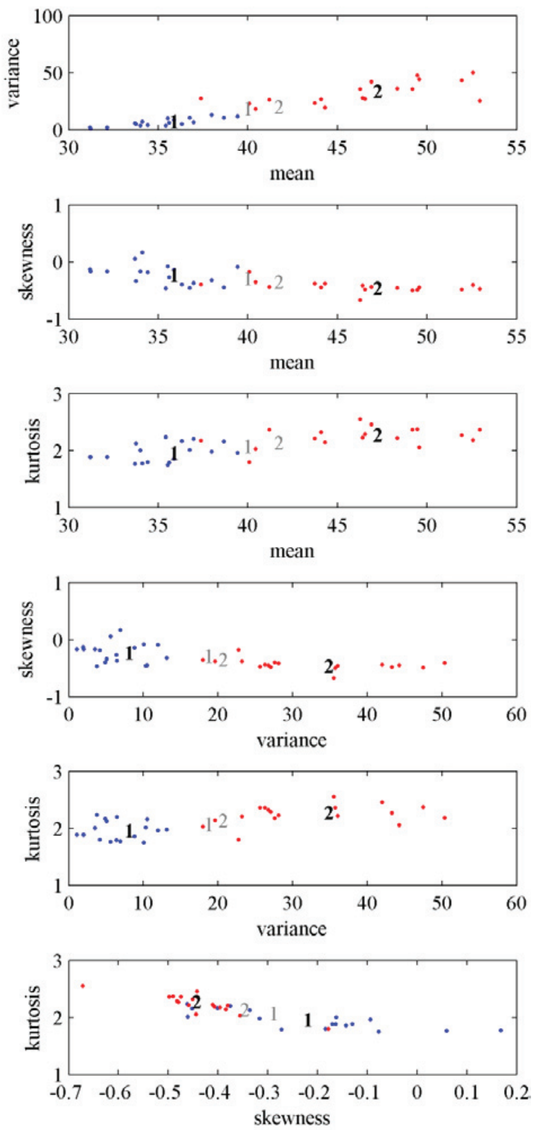

Fig. 5. Data features mutual influence plot. The figure shows the initial and final fuzzy cluster centres. The bold numbers represent the final fuzzy cluster centres obtained by updating them iteratively. Blue points represent fresh tool state tests (Cluster 1), red points represent worn tool state tests (Cluster 2).

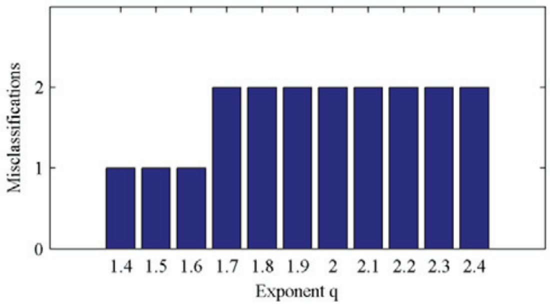

Fig. 6. Misclassifications vs exponent q

Table 5. Membership degrees and classification results

Test #	Membership degree		Classification	
	Fresh	**Worn**	Actual	Computed
1	0.9966	0.0034	Fresh	Fresh
2	0.9945	0.0055	Fresh	Fresh
3	0.9956	0.0044	Fresh	Fresh
4	0.9999	0.0001	Fresh	Fresh
5	0.9997	0.0003	Fresh	Fresh
6	0.9995	0.0005	Fresh	Fresh
7	0.9999	0.0001	Fresh	Fresh
8	0.9877	0.0123	Fresh	Fresh
9	0.9899	0.0101	Fresh	Fresh
10	0.9990	0.0010	Fresh	Fresh
11	0.9996	0.0004	Fresh	Fresh
12	0.9994	0.0006	Fresh	Fresh
13	0.9993	0.0007	Fresh	Fresh
14	0.9999	0.0001	Fresh	Fresh
15	0.9992	0.0008	Fresh	Fresh
16	0.9971	0.0029	Fresh	Fresh
17	1.0000	0.0000	Fresh	Fresh
18	0.9997	0.0003	Fresh	Fresh
19	**0.7955**	**0.2045**	**Worn**	**Fresh**
20	0.0375	0.9625	Worn	Worn
21	0.1874	0.8126	Worn	Worn
22	0.4912	0.5088	Worn	Worn
23	0.0115	0.9885	Worn	Worn
24	0.0002	0.9998	Worn	Worn
25	0.0211	0.9789	Worn	Worn
26	0.0505	0.9495	Worn	Worn
27	0.0116	0.9884	Worn	Worn
28	0.1363	0.8637	Worn	Worn
29	0.0883	0.9117	Worn	Worn
30	0.0059	0.9941	Worn	Worn
31	0.3584	0.6416	Worn	Worn
32	0.0000	1.0000	Worn	Worn
33	0.0217	0.9783	Worn	Worn
34	0.0003	0.9997	Worn	Worn
35	0.0118	0.9882	Worn	Worn
36	0.0354	0.9646	Worn	Worn

The membership function plot (Fig. 7) shows the membership degree of each milling test to the two clusters.

The first 18 tests, relative to fresh tool condition, are correctly classified presenting a degree membership very close to 1. A misclassification occurs for test #19, i.e. T1_W, which is erroneously classified as fresh tool with a quite high degree of membership (0.7955) (see Table 5.).

Test #22, i.e. T4_W can be considered ambiguous as its membership function degree to "worn" cluster is 0.5088, although it is still correctly classified.

No misclassifications occur for the rest of milling tests. One single misclassification over 36 tests results in a success rate (i.e. ratio of correct classification over the total number of tests) equal to 97.22%.

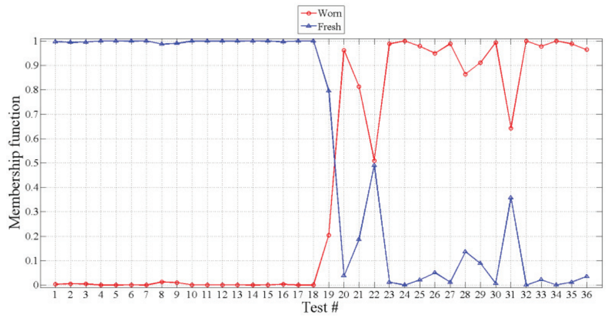

Fig. 7. Membership function for q = 1.6

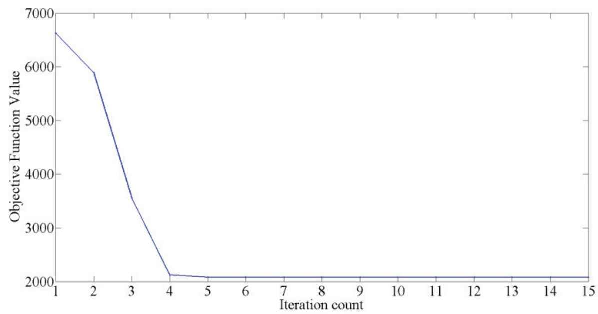

Fig. 8. Objective function value vs iteration count

The iterative algorithm converged to an objective function (Fig. 8) value equal to 2078.543 after 15 iterations; the elapsed time to reach the minimum is 0.0780 seconds, demonstrating a good suitability for real-time applications.

5.3. Mutual influence plot

Fig. 5 shows the centres clusters for the six combinations of features, both at the initialisation step (light font) and at the end of the clustering algorithm (bold). It is possible to notice how the algorithm iterations move the cluster centres from the centre of data to the final spots corresponding to the centres of the two data clusters. In the plot, some features present a clear distinction between the points belonging to the two clusters, this happens for *skewness vs variance* and *kurtosis vs variance*, indicating a better suitability of these features for the proposed clustering purpose.

A data overlapping occurs for other pairs of features (i.e. *mean vs variance*, *mean vs skewness* and *mean vs kurtosis*) visible by the presence of one red (worn tool) data point among the blue points, which correspond to the misclassified test. S*kewness vs kurtosis* plot present more overlapped points within both clusters. Finally, Fuzzy c-means algorithm has shown to successfully cluster data into two groups, representing fresh and worn tool states, utilising the statistical features calculated over a dataset made of 10000 samplings, corresponding to 26 seconds of milling time.

6. Conclusions

As sensing and processing monitoring techniques evolve, there is the potential to better managed production activities. One such example explored in this paper is tool condition monitoring, which has the potential to improve productivity and thus reduce the number of parts rejected and total energy used to machine a part. Reducing the number of defects by optimising tool life enhances process utilisation for 'good' parts. Since a large component of energy used by a facility is not directly consumed by the processes, such advancements increase overall energy efficiency per part.

In this work it has been demonstrated that the use of an IR camera in combination with fuzzy c-means clustering algorithm can accurately determine tool wear state and thus allow better maintenance scheduling, reduce the risks of catastrophic failure and maximise utilisation of individual tool bits. A comprehensive experimental programme of milling tests on aluminium was carried out, acquiring IR temperature data using an IR camera. This temperature data was then processed in order to extract statistical features, which were inputted in a fuzzy c-means decision making algorithm to assess the tool wear state in two clusters, namely fresh and worn tools. Future work will involve the utilisation of other low cost sensing techniques for temperature data acquisition in order to extend the scope and industrial applicability, in particular in cases with cutting fluid and high vibration rates.

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