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Optimization of Prediction Error in CO2 Laser Cutting process by Taguchi Artificial Neural Network Hybrid with Genetic algorithm

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Abstract: Simulation and prediction of CO_2 laser cutting of Perspex glass has been done by feed forward back propagation Artificial Neural Network (ANN). Experimental data of Taguchi orthogonal array L9 was used to train the ANN model. The simulation results were evaluated and verified with the experiment. In some cases, the prediction errors of Taguchi ANN model was larger than 10% even with Levenberg Marquardt training algorithm. To overcome such problem, a hybrid genetic algorithm-based Taguchi ANN (GA-Taguchi ANN) has been developed. The potential of genetic algorithm in optimization was utilized in the proposed hybrid model to minimize the error prediction for regions of cutting conditions away from the Taguchi based factor level points. The hybrid model was constructed in such a way to realize mutual input output between ANN and GA. The simulation results showed that the developed GA-Taguchi ANN model could reduce the maximum prediction error below 10%. The model has significant benefits in application to fabrication processes.

Keywords: Artificial Neural Network, Training algorithm, Genetic algorithm, Laser cutting, kerf width, Perspex Sheet.

1. Introduction

Laser cutting process has many advantages such as quick processing speed, high precision, induced small heat-affected zone and minimum distortion especially in the CO_2 laser cutting. In addition with the available computer technology, cutting process can be done even for complex shapes. Coherent [1] has used a 500-W CO_2 laser to cut nylon seat belts at 20mm/s cutting speed. He found that the nylon material was cut with no burn traces found and slit burn was minimized. Peters and Marshall [2] have used a gas injection supplemented 1 KW CO_2 laser to cut wood and cited that the water inside the timber significantly affected the cutting speed. Nuss [3] has used a 1 KW CO_2 laser to cut glass fiber. He compared his results to other cutting techniques such as water jet cutting, milling, punching, sawing, and ultrasonic excite knife and found that laser cutting was faster, cleaner, and timesaving. Rao et. al [4] has study about inert gas effect during the cutting processes of titanium sheet. He found that the used of Helium as a shear gas brought about significant reduction in dross formation. Todd [5] has used a 500-W CO_2 laser light to machine ceramic material at a removal rate of 5.3 mm/s. Zhou and Mahdavian [6] have used a low-power laser to cut non-metallic materials and analyzed the correlation between the cutting depth and speed. Recently, laser cutting is broadly adopted in industry; however, poor cutting quality may result from inappropriate process or controls parameters.

Many researches on prediction and simulation of CO_2 Laser cutting process have been addressed by traditional Artificial Neural Networks and Taguchi ANN as well. Traditional ANN method works well in [6–8] when sufficient number of traing data (real experimrnts) is avialabe. Because ANN use common error correction (back-propagation) algorithm for training [9,10], the increase in number of neuron and connection improve the networks model of the studied problem. The increase in neuron number gives the benefit up to some extent and start decreasing the ability

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of classification upon further increase, so a compromise between accuracy and computational efforts is needed. In general, the traditional ANN model has the inherent disadvantage of requiring a large number of training samples [11,12].

Lin ZC [13] and Ching-Been et. al [14] have proposed a combined Taguchi Artificial Neural Network model, which is different from the conventional ANN model, in order to reduce the number of training data. The method was used to construct a prediction model for a CO_2 laser cutting experiment. They claimed that Taguchi network has good predictive results for all regions and the prediction model of Taguchi artificial neural network serves as a reference for fabrication application and performance. However; the error prediction for regions (machining conditions) away from the Taguchi based factor level points is significantly high and model prediction was not tested under different training algorithms

Genetic algorithm GA has been successfully applied for prediction of surface finish in dry Turing[15]. GA has the quality to find a global solution but after a reasonable computation time. One of the most promising techniques in optimization problems is merging of Genetic algorithm with ANN to gain adaptability to environment and get significantly better intelligent model [16]. The optimization efficiency of machining parameters was significantly enhanced by using a GA-NN hybrid algorism [17].

In this paper the common training algorithms for feed forward back propagation are reviewed and explained in order to find out the best training algorithm for ANN model. ANN and Taguchi ANN prediction models for kerf width in CO_2 laser cutting of Perspex glass was established and trained by using L9 experimental data together with the best training algorithm. A genetic algorithm-based Taguchi ANN (GA-Taguchi ANN) model has been developed to have better simulation results and maintain the maximum prediction error below 10%. Ordinary ANN, Taguchi ANN and GA-Taguchi ANN models are compared for their predictions together with experimental ones and results are discussed and concluded.

2. Training Alghorithm

In ANN modeling and simulation process first create a network consisting of input, output with selection of training algorithm, number of hidden layers, number of neurons and selection of transfer function with the selection of feed forward back propagation. Create a network and export to workspace in case of Matlab. The network is prepared for training after initialization of network bias and weights. The network mapped the input and output examples to get the approximate transfer function on the basis of given datasets. The inputs and target output are iteratively minimizing the error. Some of the training algorithms for feed forward back propagation are explained in the following section. All the following training algorithms are utilizing the negative gradient of performance function to set the weights to minimize error in desired and actual output. The negative gradient is calculated by back propagation method.

2.1. Back Propagation Algorithms

The back propagation learning revises bias and weights of the network to reduce the mean square error. The iterations can be written mathematically

$$Y_{k+1} = Y_k - l_k g_k \tag{1}$$

Where Y_{k+1} is the current bias and weights vector, g_k is the current gradient, and l_k is the learning rate.

2.1.1. Batch Gradient Descent

Batch gradient descent algorithm [18] is not very effective because learning rate is adjusted manually. If it is very small, then there is the possibility of getting trapped in local minima, while a large learning rate may cause training to become unstable due to overshooting.

2.1.2. Gradient Descent with Momentum

This method resolves the issue of batch gradient descent in case of small learning rate. The convergence speed reduction and convergence trapped in the local minima is resolved by momentum. The gradient descent with momentum works as a low pass filter. The momentum feature ranges from 0 to 1. Zero means no momentum and 1 means high momentum [19].

2.2. Faster Training Algorithms

Gradient descent method (GDM) is slower than faster training algorithms like variable learning rate and resilient back propagation [20]. Both of the faster algorithms are also heuristic. It is difficult to adjust learning rate before the training. Advantage in these algorithms is that the optimal training rate is changing during the training process as the algorithm moves in the error space. Therefore, learning rate change during the training improves with the training process. The dynamic and adaptive change in learning rate increases the size of learning rate until the training process is stable. The algorithm of variable learning with the feature of momentum is the better choice.

Multilayer network normally uses sigmoid function in the range of [0 to 1] or [-1 to1]. Sigmoid function is normally used as a squashing function and makes an infinite function into finite one. In this type of problem Resilient back propagation algorithm can be used, but it is not the case for our data which is always finite.

2.2.1. Quasi Newton Algorithm

It is used as an alternate to conjugate gradient methods and is mostly faster because there is no need to calculate second derivatives. The modified Hessian matrix at every iteration is a function of gradient. It can be explained mathematically as follows

$$Y_{k+1} = Y_k - l_k^{-1} g_k \tag{2}$$

Where l_k^{-1} is a Second derivative Hessian matrix of MSE index at present values of bias and weights. Quasi Newtons algorithm is suitable for smaller networks and conjugate gradient algorithms are more suitable for large networks [21]. Therefore Quasi Newtons algorithm is better for the given case.

2.3. Levenberg-Marquardt Algorithm

Utilization of Levenberg-Marquardt Algorithm (LMA) eliminates the importance of Quasi-Newton, because it reaches to second order training pace without calculating Hessian matrix [22]. The Hessian matrix with MSE based performance is

$$H = J^T.J \tag{3}$$

Whereas gradient

$$g = J^T.e \tag{4}$$

Where J consists of first derivatives of network d(error) / d(biases and weights) and e is the error vector of the network. The LMA can be expressed as

$$Y_{k+1} = Y_k - [J^T J + \mu I]^{-1} J^T e \tag{5}$$

Where μ is a scale quantity. With reference to equation 5, if μ is zero then it becomes equation 2 i.e. Quasi Newtons or if μ is very large then it becomes equation 1 i.e. GDM with a smaller step size. As Newtons method performs faster convergence near error with more accuracy, therefore in LMA μ value reduces after each better iteration or increase in case of inferior iteration results on MSE point of view. The LMA is suitable for medium size datasets and fastest among the other training algorithms. This is the most suitable training algorithm with Matlab because Matlab by default supports matrix handling. In this algorithm for large datasets more memory is required to handle the matrices, but in the given case, LMA is the most suitable algorithm for training.

3. Design of Experiments and measurements

3.1. L9 orthogonal array

Taguchis design of experiments (DOE) is a robust, efficient statistical method for designing high quality systems at lesser expense for laser cutting process. It designs a systematic and efficient way to optimize controllable parameter. Dubey and Yadava [23] also mention the concept of OA experiment, and that it provides better quality and minimizes the design and development interval and a set of well-balanced experiments which consist of four variables with three levels Orthogonal design matrix. Its equivalent full factorial design $L3^4$ which equals 81 experiment, was reduced in L9 OA size of 9 experiment. It converts test range into factors and levels. Table 1 explains input factors three levels to cover the whole range of input data and also shows their units. The signal to noise (S/N) ratios of kerf width for smaller the better criteria was calculated and presented in Table 2. Table 3 lists the control factor S/N factor response of each parameter with its levels as calculated by the Taguchi method Analysis.

Table 1 Controllable input and factors levels

Input Factors	Level 1	Level 2	Level 3	Units
Laser Power: A	100	300	500	Watt
Cutting speed: B	0.2	0.7	1.2	m/min
Assist gas Pressure: C	0.5	2.5	4.5	Bars
Standoff Distance : D	1	5	10	mm

Table 2 L9 Experiment result for kerf width and signal to noise (S/N)

Run	A	B	C	D	Kerf Width, (mm)			S/N (dB)
1	1	1	1	1	0.55	0.56	0.57	5.04
2	1	2	2	2	0.55	0.58	0.55	5.03
3	1	3	3	3	1.38	1.39	1.38	-2.82
4	2	1	2	3	1.47	1.46	1.45	-3.29
5	2	2	3	1	0.6	0.6	0.59	4.49
6	2	3	1	2	0.7	0.7	0.7	3.1
7	3	1	3	2	0.99	0.99	0.99	0.09
8	3	2	1	3	1.23	1.23	1.23	-1.8
9	3	3	2	1	0.58	0.59	0.61	4.53

Table 3 Control factor S/N factor response table of the analysis of the Taguchi method Analysis

Level	Power (W)	Speed (m/s)	Pressure (Bar)	Stand of Distance (mm)
1	2.4167	0.6118	2.1118	4.6842
2	1.432	2.5735	2.0928	2.7396
3	0.9404	1.6039	0.5846	-2.6346
Delta	1.4763	1.9617	1.5272	7.3188
Rank	4	2	3	1

3.2. Kerf width measurement

Figure 1 shows a photograph of the laser cutting process. The experiment was conducted using a Zech Laser Austria system (CO_2 laser machine). It consists of laser cutting workstation ZL 1010 and Laser generation system is ZL X5 using AUTOCAD, C-Cut for Laser cutting and Zech Laser for Automatic machines mode software. Perspex sheets of 3 mm and 5 mm were used in experiments; the physical properties are listed in Table 4.

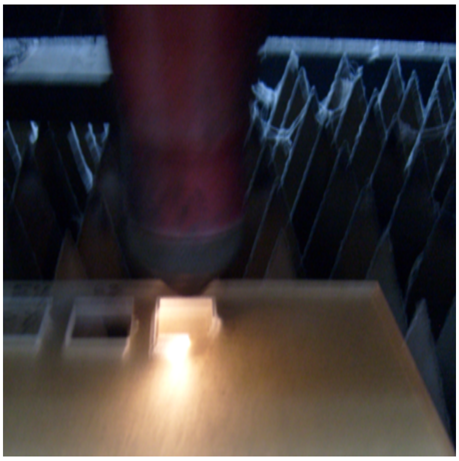

Figure 1 Laser cutting process

In this experiment cutting with is used to simulated and predict the laser cutting process. Digital caliper of resolution 0.01mm and range of 0 to 150 mm was used to measure side line lengths S1 and S2 as shown in Fig. 2. The outer grey field is the Perspex sheet while the inner grey filed represents the cut specimen as To calculate the kerf width, s1 and s2 are measured three times at different location and was calculated using Equation (6).

$$kerfwidth = \frac{(s1 - s2)}{2} \tag{6}$$

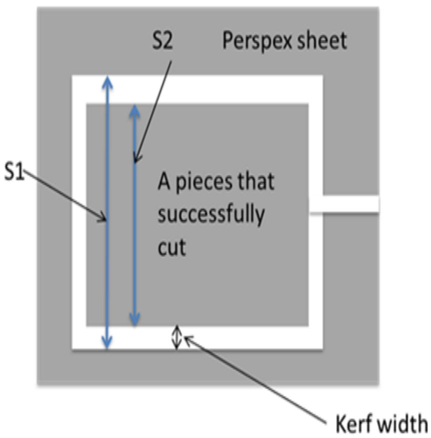

Figure 2 Schematic diagram for Kerf width measurements

Table 4 Physical properties of Perspex sheet

Property	Setting	Units	Value
Physical property	-	-	-
Relative Density	-	g/cm	1.19
Water Absorption	-	%	0.2b
Mechanical property	-	-	-
Tensile Strength at yield	5mm/min	MPa	75
Elongation at break	5mm/min	%	4
Flexural Modulus	2mm/min	MPa	3210
Flexural Strength at yield	2mm/min	MPa	116
Rockwell Hardness	-	M Scale	102
Thermal property	-	-	-
Vicat Softening Temperature	-	C	¿110
Coefficient of Thermal Expansion	-	mm/mC	0.077
Optical property	-	-	-
Light Transmission	3mm	%	¿92
Refractive Index	-	-	1.49
Electrical property	-	-	-
Dielectric Strength	-	kV/mm-1	15
Surface Resistivity	-	m-2	¿1014

4. Ordinary ANN and Taguchi ANN Model

Figure 3 shows a schema of general model of Laser cutting/Training and simulation process using ordinary ANN and Taguchi ANN models. Four controllable independent parameters and one dependent parameter (independent with each other which mean the source of parameter for the calculation of dependent parameters are different) has to be focused for the improvement of the quality of the Laser cutting process. The major issue of this ANN model is the estimation of error in predictions for of kerf width in CO_2 Laser cutting of Perspex. A well planned simulation (pseudo experiment) is a run or set of runs performed to identify the control variable effect on output response to investigate the reasons for changes in the output and its main contributors. In the design of ANN model there are a number of factors which affect the output quality. These factors are the number of inputs and input data, number of outputs in the output layer, the number of neurons in hidden layer and the number of hidden layers. The ANN is designed in such a way to estimate the error of training, testing and simulation. The variables U_1, U_2, U_3 ... U_i are uncontrollable parameters which may be controlled. The output variable (kerf width) variation is measured by the maximum, minimum, average percent errors of training, testing and simulation. The ANN model is based on feed forward back propagation uses Levenberg Marquardt for training, Mean Square Error for performance, tangent sigmoid functions for hidden layers, and the process training is taken as supervised learning. Taguchi L9 orthogonal is used for training, simulation and test of the ANN model, while L9 plus other three expedients were used to train Taguchi-ANN model.

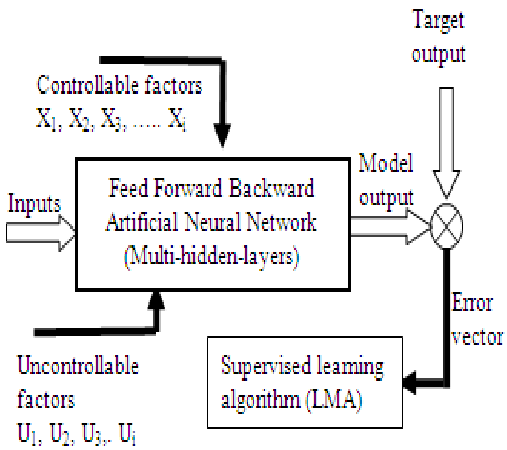

Figure 3 Computation style of ANN and Taguchi ANN-model for Laser cutting process (Training and simulation)

5. Hybrid Optimization model

A genetic algorithm-based Taguchi ANN (GA-Taguchi ANN) model for prediction and simulation of CO_2 laser cutting process has been developed. Figure 4 shows the layout of GA-Taguchi ANN model. As it is known, the GA provides a near-optimal solution for a complex problem having large number of variables and constrains. This potential is utilized in the proposed hybrid model to minimize the error prediction for regions of cutting conditions away from the Taguchi based factor level points. The model is constructed in such a way to realize mutual input output due to the hybrid of ANN and GA. Therefore, the experimental Taguchi L9 orthogonal array for Perspex laser cutting is normalized before it is used for training the ANN model. The GA generates normalized random inputs for the trained ANN and the output is again presented to the GA for error optimization. If the error level is less than 10% then the predicted results for kerf width (S/N) is confirmed.

6. Training and Simulation

6.1. Procedure

The problem statement for verification of Taguchi ANN Simulation was defined. The parameters have already been decided as controllable parameters and also non-controllable

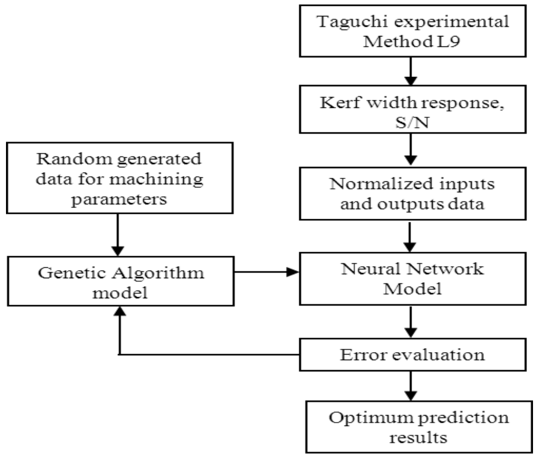

Figure 4 A flowchart of GA-Taguchi-neural network for optimum prediction of kerf width in CO_2 laser cutting of Perspex

parameters. The design of experiment was L9 orthogonal array and Perspex sheet was selected as material for this purpose. Nine planed experiment were performed and recorded in the designed tables of factorial design as shown in Tables 1, 2 and 3. After the completion of experiment kerf width was calculated and then its mean and signal-to-noise (S/N) ratio. Prepare training, test and Simulation datasets for training and simulation.

In the beginning the ANN training algorithm is selected based on the best technique that is fast and give minimum perdition errors. After the selection of algorithm, select the constant parameters for training environment. Start training and observe the changes in number of neurons and hidden layers. Levenberg Marquardt algorithm was selected since it is the best possible training algorithm as discussed in section 2. The training was performed with one output parameter (mean and signal to noise ratio of three replications) of kerf width on orthogonal array consisting of nine observations preprocessed data. The training set needs validation and test datasets in Matlab neural networks toolbox. Therefore only five datasets were used for training, two for validation and two for testing. The results were recorded and used for further analysis and discussion to conclude the effectiveness of Taguchi ANN with the given datasets.

6.2. Prediction results

Table 5 shows the best training datasets of Figure 5. The average percent error for test is 13% which is high because of very small datasets (even not all nine datasets are used for training) and the data is multi-variable nonlinear. Therefore, there is a need to increase the size of datasets to be trained. The early stopping of training provides a better generalization model. The simulation on average errors is 6.4% which is better. Hence this training technique is suf-

Table 5 Controllable input and factors levels

Fig. S.No.	No. of Neurons	Max.% error	Min.% error	Average % error	Results	Rem
9-7	20.20.20	61.063	0.000	5.778	Train	KW
	25.190	1.146	13.453	Test		
	61.063	0.000	6.441	Sim		

ficient for the training and further improvement was obtained by normalization of kerf width mean and input cutting parameters as shown in Table 6 shows the normalized input parameters and kerf width.

The orthogonal array represents approximately the properties of population (input-output variable). It loses knowledge due to less number of samples for representation of population, and conversion of fraction data into ordinal data also loses a lot of information that artificial neural network can be modeled by using real non reprocessed data. There is similar loss of information in factorial design due to usage of ordinal three level datasets. Off course full factorial design L81 is better than orthogonal design because of its larger size than L9. The training of ANN required data for training and testing therefore need some more data points to check the ability of OA and factorial design datasets.

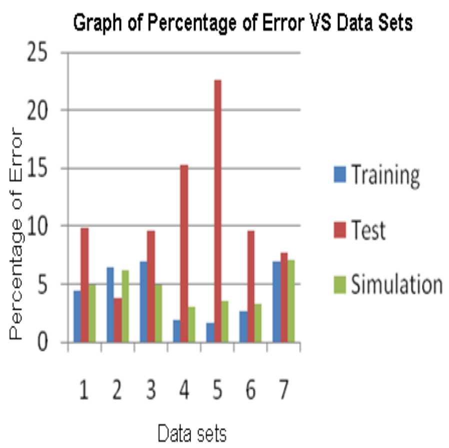

Figure 5 Kerf width mean training of factorial design

6.3. Verification of Simulated Data

Confirmation experiment was carried out with optimum factor level combination as predicted by Taguchi methods and values were 1.47 mm and 1.46 mm, respectively. Confirmation experiment is fundamental in order to prove that there are no additional significant factors. In case of ANN simulation predicted values must be verified by experimental values. Table 7 shows a comparison of the predicted results of the normal ANN, Taguchi ANN and hybrid model with experiments. It is seen that the GA-Taguchi ANN model can provide better prediction results that are more precise than those for Taguchi ANN model (as shown in Table 8). The GA-Taguchi ANN model has significant benefits in application to fabrication process

Table 6 Normalised L9 orthoganal array data for the training samples of ANN model

Run	Power	Speed	Pressure	Stand of Distance	S/N
1	0.2	0.2	0.2	0.2	0.8
2	0.2	0.5	0.5	0.47	0.8
3	0.2	0.8	0.8	0.8	0.23
4	0.5	0.2	0.5	0.8	0.2
5	0.5	0.5	0.8	0.2	0.76
6	0.5	0.8	0.2	0.47	0.66
7	0.8	0.2	0.8	0.47	0.44
8	0.8	0.5	0.2	0.8	0.31
9	0.8	0.8	0.5	0.2	0.76

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Table 7 : Comparison of the predicted S/N kerf width obtianed from ordinaryANN, Taguchi ANN and GA+ANN

7. Conclusion

In the process of laser cutting, L9 and L9 +3 orthogonal array based experimental data was trained by ANN, using Levenberg Marquardt algorithm and the model was used to predict kerf width. The prediction results show that L9 (nine experiments) is not sufficient for prediction of kerf width within the engineering acceptable error. The errors in ANN and Taguchi ANN model simulations are still above 10% for some cutting conditions even with using the best training algorithm of Levenberg Marquardt. To overcome such limitation, a hybrid GA-Taguchi-ANN optimization model has been developed. It is constructed in such a way to realize mutual input output through ANN and GA. The trained ANN takes random machining parameters from GA and the output of ANN is again presented to the GA for error optimization. If the error level is less than 10% then the predicted results for kerf width

Table 7 Comparison of the predicted S/N kerf width obtianed from ordinaryANN, Taguchi ANN and GA+ANN

Predicted check experiment	Network Input Model				Predicted Value			Check experiment values
	Power	Speed	Pressure	Stand of Distance	Normal ANN	Taguchi ANN	Taguchi ANN +GA	
1	0.2	0.2	0.8	0.2	0.83	0.82	0.97	0.90
2	0.2	0.5	0.2	0.47	0.77	0.76	0.81	0.81
3	0.5	0.5	0.5	0.2	0.83	0.82	0.72	0.76
4	0.8	0.2	0.5	0.47	0.52	0.46	0.36	0.38

Table 8 Comparison of error with experiments value

Predicted check experiment	Network Input Model				Predicted Value		
	Power	Speed	Pressure	Stand of Distance	Normal ANN	Taguchi ANN	Taguchi ANN +GA
1	0.2	0.2	0.8	0.2	7.78	8.89	-7.78
2	0.2	0.5	0.2	0.47	4.93	6.17	0
3	0.5	0.5	0.5	0.2	-9.21	-7.90	5.26
4	0.8	0.2	0.5	0.47	-36.84	-21.05	5.26

is confirmed. The results obtained from the hybrid model have confirmed that the GA-Taguchi ANN model can provide prediction results more precise than those for Taguchi ANN model.

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