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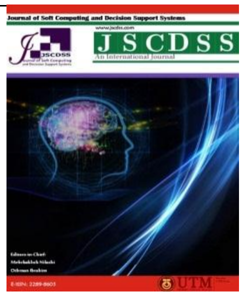

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Particle Swarm Optimization for Optimal Process Parameters in Injection Molding

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Abstract

Injection molding is a manufacturing process where the products or parts are made from plastic, glasses or other materials. In simple word, this process is involved with melting the required materials and injected it into the mold to produce a product or part. One of the biggest problems in manufacturing is to minimize the cost of producing a product without affecting their final product quality. To produce a high quality product using injection molding process, it is important to control efficiently the parameters involved in this manufacturing process. When one of these parameters has not been controlled efficiently, the quality of the final product can be affected. Soft computing technique can offer an option to evaluate this process efficiently at low cost before being applied by factory in creating and producing high quality product. This study focused on finding the optimal parameters' combination to produce high quality product using Particle Swarm Optimization (PSO). Based on the previous researches, PSO have been known as reliable soft computing techniques in optimization problems. The results found that PSO improved the minimum warpage value by 1.2111% compared to observed data.

Keywords: Optimization, Particle Swarm Optimization, Injection molding, Soft computing, Warpage

1. Introduction

The nature of market today is very competitive, in order to survive in this nature, manufacturers must produce high quality product. Without any doubt, quality has become a crucial competitive factor (Zaklouta, 2011). Product quality is the main factor in this competition, cost to manufacture this high quality product also become one of the factors involved in this competitive market nature. This statement has been introduced by Ishikawa (1982) and supported by Ryan (2011), there are four common causes lead to affect quality as shown in Fig. 1.

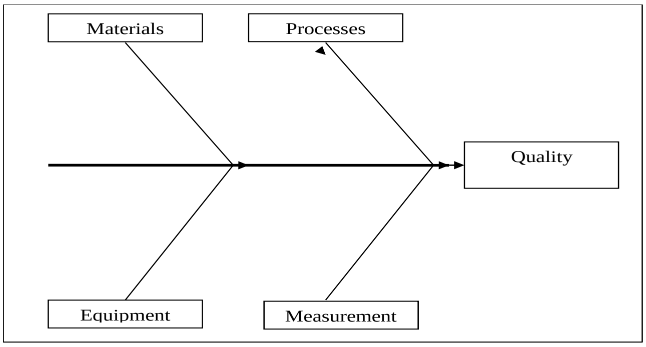

Fig. 1. : Cause-and-effect diagram (Ishikawa, 1982)

Fig. 1 shows there are four major factors affect the quality in manufacturing industry according to Ishikawa Diagram. These four factors are materials, processes, equipment and measurement.

There are many different types of industries in the manufacturing industry, which is fabricated metal industry, food and kindred industry, rubber and miscellaneous plastic industry and various other industries. Apart from a wide range of industries, manufacturing industries also have a variety of techniques to produce a variety of products, one popular technique is the injection molding.

Injection molding is a manufacturing process where the products or parts are made from plastic, glasses or other materials (Todd et al., 1994) . In simple word, this process is involved with melting the required materials and injected it into the mold to produce a product or part.

One of the main problems in manufacturing is to minimize the cost of producing a product without affecting their final product quality. To produce a high quality product using injection molding process, we have to control efficiently the parameters involved in this manufacturing process such as cooling temperature, mold temperature, injection time, Velocity/Pressure (V/P) switch over, cooling time and others. When one of these parameters has not been controlled efficiently, the quality of the final product can be affected.

To create or produce high quality product this process must be evaluated first before it being applied by factory, with soft computing technique this process can be evaluated efficiently at low cost.

One of the main issues in injection molding manufacturing is to determine the optimal combination value of control parameters to produce a high quality product. Until this day, there is no specific method to obtain the optimal combination values for injection molding control parameters without try-and-error method. This try-and-error method will increase the cost of manufacturing process undoubtedly (Lahoti et al., 2013) Based on nature offered by soft computing technique, this technique can be applied into this study.

In this study, the injection molding process has been evaluated using soft computing technique, PSO. This study focused on optimizing or minimizing the warpage value by finding the optimal combination values for involved parameters. Hence the objectives of this study are:

i. To estimate minimum warpage value in injection molding using PSO.
ii. To obtain the combination of parameters' value that contributes to minimum warpage value.

1.1 PSO

PSO is one of the artificial intelligence techniques that solve optimization problem with repeatedly update or modify the possible solution to obtain the optimum solution (Kennedy, 2010). In PSO the problem will optimize with populations of candidate solutions also known as particle, these candidate solutions moving in search space according to simple formula of mathematic based on their position and velocity. Each particles move according to locally best known location and the particles also are guided toward to the known best location in the search space. The particles also being updated frequently with the better locations found by other particles. With this method of optimization, the solution or particle expected to move toward the best solution.

PSO is inspired by the movement pattern of living organisms such in a fish school or bird flock. PSO the first intended is to simulate the social behaviour (Kennedy, 1997) and it originally attributed to Kennedy, Shi and Eberhart (Kennedy and Eberhart, 1995; Shi. and Eberhart, 1998).

As stated by Kennedy and Eberhart (1995), PSO has its advantages such as does not requires derivatives that makes this technique more stable compare to other technique, smaller time steps are possible with PSO, easily parallelizable, lower computational cost, fewer parameters to adjust and simple to understand.

In other hand, this techniques also suffers due to several disadvantages such as not able to solve non-coordinate system problem, easy to suffer from the effect of partial optimism and does not has mutation and overlapping operator.

1.2 Injection Molding

The injection molding process can be explained as follows. Material is fed into high temperature barrel to melt the material granules and mixed them. After these granules has been melted and mixed, the machine will force the material into a mold cavity (Todd et al., 1994). In this mold cavity the material will be harden to produce a product or part according to mold. Fig. 2 shows the basic injection molding machine.

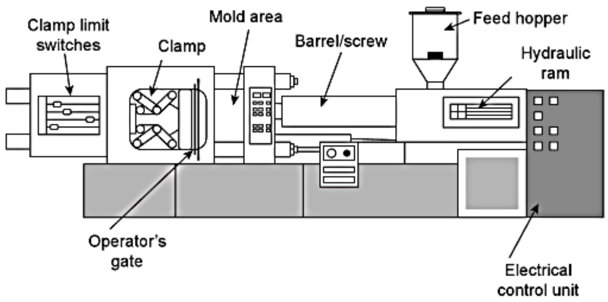

Fig. 2. Injection molding machine (Drobny, 2014).

Normally, engineer or industrial designer is the one who make the product's design. The moldmaker is the creator of the mold, the mold usually made from metal based on product designed earlier. Injection molding is very popular for producing a variety of parts and products.

There are six steps in injection molding manufacturing process. The steps as follows:

i. Beginning of plastication
In this step, screw transports the melted plastic to the barrel where the material is heated.
ii. End of plastication
The screw stops after the barrel is filled with the melted plastic.
iii. Mold closing
Clamping unit close the mold and ready to receive the melted material.
iv. Beginning of injection
The screw move in axial motion to push the melted plastic into the mold until it is filled.
v. End of injection and mold cooling
In this step, the mold begins to cool. Additional melted plastic is injected to fill the spaces produced by shrinkage.
vi. Ejection
The produced product or part is ejected and the screw retract ready for next cycle.

1.3 Initial Data

The initial data used in this study is based on experimental data by Guo et al. (2012). The data in that study was obtained by using Moldflow. The objective of the study is to find combination of the parameters' values that could lead to minimum warpage. Warpage can be described as dimensional distortion in a molded part or product that produced by injection molding (Rosato & Rosato, 2012). Fig. 3 shows the example of product affected by warpage.

Fig. 3. : Example of product affected by warpage.

The researchers has chosen automotive interior trim product as the case study. Fig. 4 shows the shape of the automotive interior trim product.

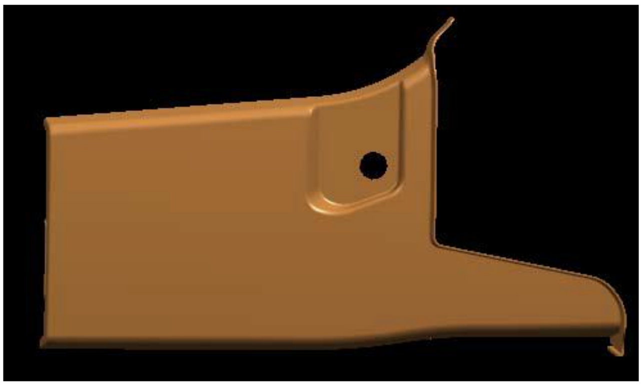

Fig. 4. : Shape of the automotive interior trim product.

The dimensions of this product are 260mm x 450mm x 70mm and the material of this product is polypropylene copolymer.

There are 4 parameters has been chosen in study by Guo et al. (2012), injection time (t_{inject}), cooling temperature (T_{cool}), mold temperature (T_{mold}) and V/P switch over (V/P). The cooling temperature is the temperature of coolant, injection time is the amount of time set to fill the mold, V/P switch over is switch-over from filling to packing/holding, or at the specified packing/holding pressure and mold temperature is mold temperature when the injection molding process takes place (Rosato & Rosato, 2012). The upper boundary, lower boundary and level for each parameter have been set as shown in Table 1.

Table 1
The upper boundary, lower boundary and level of parameters.

Code Level	Parameters			
	T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)
-1	20	1.8	97	20
-0.5	25	1.9	97.5	25
0	30	2.0	98	30
0.5	35	2.1	98.5	35
1	40	2.2	99	40

The researchers have conducted 25 trials and result from the trials shown in Table 2.

Table 2
Trial results.

No.	Parameters				Warpage (mm)
	T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)	
1	25/-0.5	2.1/0.5	98.5/0.5	25/-0.5	4.102
2	35/0.5	1.9/-0.5	98.5/0.5	35/0.5	4.101
3	35/0.5	2.1/0.5	98.5/0.5	25/-0.5	3.959
4	25/-0.5	1.9/-0.5	97.5/-0.5	25/-0.5	4.198
5	35/0.5	1.9/-0.5	97.5/-0.5	25/-0.5	4.103
6	35/0.5	1.9/-0.5	98.5/0.5	25/-0.5	4.115
7	25/-0.5	2.1/0.5	97.5/-0.5	35/0.5	4.098
8	30/0	2.0/0	98/0	30/0	4.097
9	35/0.5	1.9/-0.5	97.5/-0.5	35/0.5	4.091
10	25/-0.5	1.9/-0.5	97.5/-0.5	35/0.5	4.185
11	25/-0.5	1.9/-0.5	98.5/0.5	35/0.5	4.199
12	25/-0.5	2.1/0.5	98.5/0.5	35/0.5	4.088
13	25/-0.5	1.9/-0.5	98.5/0.5	25/-0.5	4.189
14	35/0.5	2.1/0.5	97.5/-0.5	25/-0.5	3.929
15	35/0.5	2.1/0.5	98.5/0.5	35/0.5	3.961
16	35/0.5	2.1/0.5	97.5/-0.5	35/0.5	3.952
17	25/-0.5	2.1/0.5	97.5/-0.5	25/-0.5	4.079
18	30/0	2.0/0	99/1	30/0	4.077
19	30/0	2.0/0	98/0	40/1	4.059
20	30/0	2.2/1	98/0	30/0	3.841
21	20/-1	2.0/0	98/0	30/0	4.229
22	30/0	2.0/0	97/-1	30/0	4.021
23	40/1	2.0/0	98/0	30/0	3.776
24	30/0	2.0/0	98/0	20/-1	4.083
25	30/0	1.8/-1	98/0	30/0	4.311
Min.					3.776

2. Development of Fitness Function

The mathematical equation is based on polynomial Eq. (1) obtained using Minitab software by Guo et al. (2012). This mathematical model simplified the relationship between involved parameters and warpage to describe and mimic the actual problem in this case study.

$$W = B_0 + \sum_{i=1}^{k} B_i X_i + \sum_{i<j}\sum B_{ij} X_i X_j + \sum_{i=1}^{k} B_{ij} X_i^2 \qquad (1)$$

where:

W = warpage value
B_0 , B_i , B_{ij} = coefficients
X_i , X_j = parameters

Based on obtained equation in Eq. (1), the regression model can be written as follows:

$$W = 4.09888 - (0.11621)\,T_{cool} - (0.12179)\,t_{inject} + (0.00587)V/P - (0.00387)\,T_{mold} - (0.02497)\,T_{cool}^2 - (0.00509)\,t_{inject}^2 - (0.01734)\,V/P^2 - (0.00772)\,T_{mold}^2 - (0.04706)\,T_{cool}\,t_{inject} + (0.00419)\,T_{cool}\,V/P - (0.00106)\,T_{cool}\,T_{mold} + (0.01294)\,t_{inject}\,V/P - (0.00106)\,t_{inject}\,T_{mold} - (0.00056)\,V/P\,T_{mold} \qquad (2)$$

where:

T_{cool} = cooling temperature
V/P = V/P switch over
t_{inject} = injection time
T_{mold} = mold temperature

2.1 Fitness Function Validation

Eq. (2) has been used to predict the warpage value to validate and verify this regression model to be use as simulation for the problem. Predicted warpage values shown in Table 3.

Table 3
Predicted warpage values using regression model.

No.	Parameters T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)	Predicted Warpage (mm)
1	-0.5	0.5	0.5	-0.5	4.1012725
2	0.5	-0.5	0.5	0.5	4.0983275
3	0.5	0.5	0.5	-0.5	3.9641575
4	-0.5	-0.5	-0.5	-0.5	4.1949475
5	0.5	-0.5	-0.5	-0.5	4.1007025
6	0.5	-0.5	0.5	-0.5	4.1024775
7	-0.5	0.5	-0.5	0.5	4.0871575
8	0	0	0	0	4.0988800
9	0.5	-0.5	-0.5	0.5	4.0971125
10	-0.5	-0.5	-0.5	0.5	4.1924175
11	-0.5	-0.5	0.5	0.5	4.1894425
12	-0.5	0.5	0.5	0.5	4.0971225
13	-0.5	-0.5	0.5	-0.5	4.1925325
14	0.5	0.5	-0.5	-0.5	3.9494425
15	0.5	0.5	0.5	0.5	3.9589475
16	0.5	0.5	-0.5	0.5	3.9447925
17	-0.5	0.5	-0.5	-0.5	4.0907475
18	0	0	1	0	4.0874100
19	0	0	0	1	4.0872900
20	0	1	0	0	3.9720000
21	-1	0	0	0	4.1901200
22	0	0	-1	0	4.0756700
23	1	0	0	0	3.9577000
24	0	0	0	-1	4.0950300
25	0	-1	0	0	4.2155800

Fig. 5 shows line graph of comparison between warpage values from experiment data and predicted warpage values using regression model in Eq. (2).

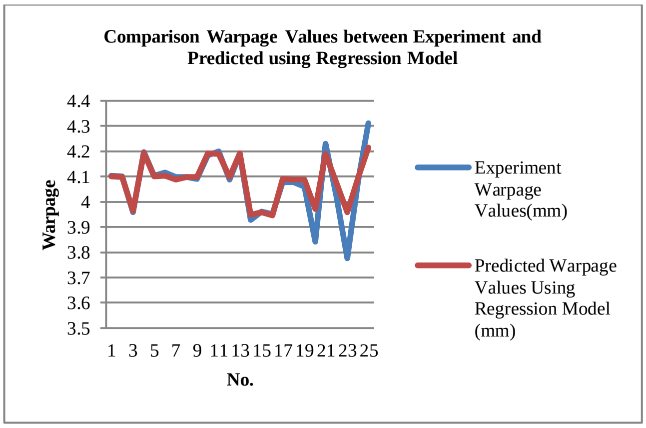

Fig. 5. Comparison warpage values between experiment and predicted using regression model.

The line pattern of warpage values between experiment and regression model are quite similar to each other as shown in Fig. 5. From this pattern, the regression model gives a close prediction to experiment warpage values. Therefore, the assumption could be withdrawn that the used regression model is good to predict the warpage value.

The assumption based on line pattern alone is not enough to verify and validate the regression model as a simulation to the problem. The paired *t*-test between experiment data and predicted regression model has been done to prove this assumption scientifically and indirectly verify and validate the regression model to be use as a picture of this problem.

Table 4, Table 5 and Table 6 show the result of paired *t*-test between experiment data and predicted regression model. This test has been done using SPSS software by IBM.

Table 4
Paired samples statistics between experiment data and predicted regression model.

Variable	Mean	N	Std. Deviation	Std. Error Mean
Experiment	4.073720	25	0.120849	0.024170
Regression	4.085651	25	0.0850016587	0.017000

Table 4 shows the mean, standard deviation and standard error mean for both variables is not significantly different from each other, all 25 data are valid to the test.

Table 5
Paired samples correlations between experiment data and predicted regression model.

Variable	N	Correlation	Sig.
Experiment	25	0.935805	0.000
Regression	25		

Table 5 shows that the variables are positively correlated to each other with high value, 0.935805 which is close to 1.0. This indicates the experiment data and predicted regression model are close to perfect correlation.

Table 6
Paired samples test between experiment data and predicted regression model.

Mean	Std Dev.	Std. Error Mean	95% Confidence Interval of the Diff. Lower	Upper	t	df	Sig.
-0.0119	0.05103	0.0102	-0.0330	0.0091	-1.1691	24	0. 2539

The mean difference, standard deviation difference and standard error mean difference are shown in Table 4.4 for these two variables. This table also shows the 95% confidence interval ranges from -0.032995 to 0.009132, t(24) equals to -1.169069 and significance or p equals to 0.253857.

In a nutshell, based on the similarity line pattern in line graph in Fig. 5 and supported scientifically by results shown in Table 3, Table 4, Table 5 and Table 6, the regression model is valid to be use to simulate the problem and suitable to be use as fitness function for this study.

3. PSO Optimization

The PSO optimization is conducted by using Matlab. The fitness function used in this optimization is based on regression model that obtained earlier as discussed in section 3. The lower and upper boundary for each parameter is set based on level in Table 1 and can be written as in Eq. (3), Eq. (4), Eq. (5) and Eq. (6). The default PSO operator setting has been set as shown in Table 7.

$$-1 \le T_{cool} \le 1 \tag{3}$$
$$-1 \le t_{inject} \le 1 \tag{4}$$
$$-1 \le V/P \le 1 \tag{5}$$
$$-1 \le T_{mold} \le 1 \tag{6}$$

Table 7
PSO operators setting.

Operators	Value
No. swarm population	50
Iteration	500
xMin	-100
xMax	100

Fig. 6 shows the snapshots of the PSO optimization using Matlab.

The PSO operators setting as shown in Table 7 have been used in finding the minimal warpage value. A total of 50 runs have been conducted using these setting. Table 9 shows the warpage values of PSO optimization.

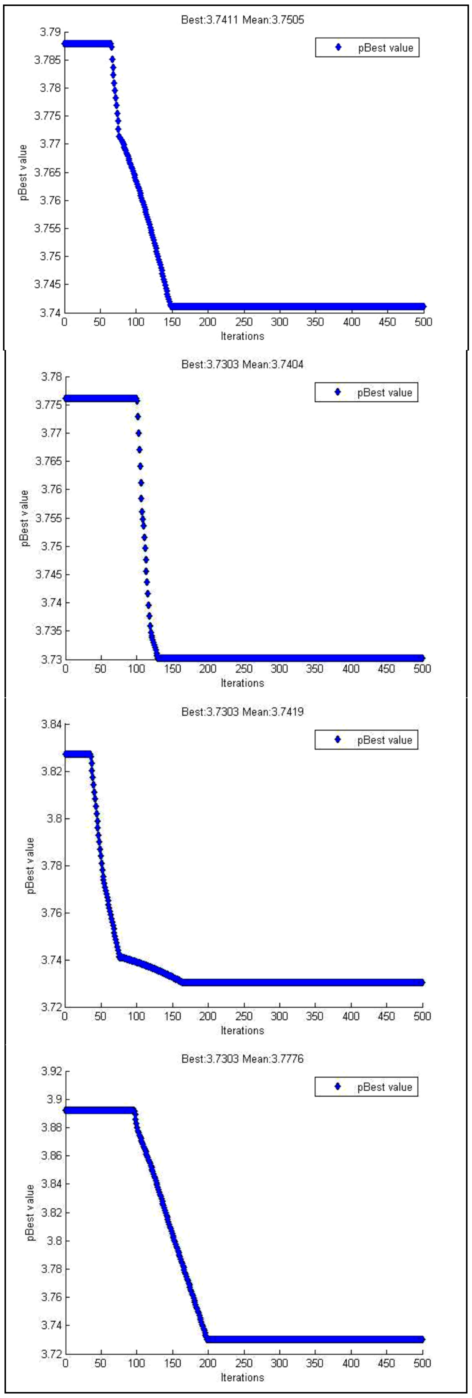

Fig. 6. : Snapshots of PSO optimization using Matlab.

Table 8
Warpage value of PSO optimization.

No.	Parameters				Warpage (mm)
	T_{cool} (°C)	t_{inject} (s)	V/P (%)	T_{mold} (°C)	
1	1	1	-1	1	3.73027
2	1	1	-1	-1	3.74113
3	1	1	-1	-1	3.74113
4	1	1	-1	1	3.73027
5	1	1	-1	1	3.73027
6	1	1	-1	-1	3.74113
7	1	1	-1	1	3.73027
8	1	1	-1	1	3.73027
9	1	1	-1	1	3.73027
10	1	1	-1	1	3.73027
11	1	1	-1	1	3.73027
12	1	1	-1	1	3.73027
13	1	1	-1	-1	3.74113
14	1	1	-1	1	3.73027
15	1	1	-1	1	3.73027
16	1	1	-1	-1	3.74113
17	1	1	-1	1	3.73027
18	1	1	-1	1	3.73027
19	1	1	-1	1	3.73027
20	1	1	-1	-1	3.74113
21	1	1	-1	1	3.73027
22	1	1	-1	1	3.73027
23	1	1	-1	1	3.73027
24	1	1	-1	-1	3.74113
25	1	1	-1	-1	3.74113
26	1	1	-1	-1	3.74113
27	1	1	-1	-1	3.74113
28	1	1	-1	-1	3.74113
29	1	1	-1	-1	3.74113
30	1	1	-1	-1	3.74113
31	1	1	-1	-1	3.74113
32	1	1	-1	-1	3.74113
33	1	1	-1	-1	3.74113
34	1	1	-1	-1	3.74113
35	1	1	-1	-1	3.74113
36	1	1	-1	-1	3.74113
37	1	1	-1	-1	3.74113
38	1	1	-1	-1	3.74113
39	1	1	-1	-1	3.74113
40	1	1	-1	-1	3.74113
41	1	1	-1	-1	3.74113
42	1	1	-1	-1	3.74113
43	1	1	-1	1	3.73027
44	1	1	-1	1	3.73027
45	1	1	-1	1	3.73027
46	1	1	-1	1	3.73027
47	1	1	-1	1	3.73027
48	1	1	-1	1	3.73027
49	1	1	-1	1	3.73027
50	1	1	-1	1	3.73027

As shown in Table 8 the minimum warpage value is 3.73027 and the range of minimum warpage value is 3.732027 to 3.74113.

As shown in Table 8, the optimal solution value obtained by PSO optimization is 3.732027 when using combination of parameters' value as shown in Table 9.

Table 9
PSO operators setting.

Parameter	Value
Coolant Temperature (°C)	40
Injection Time (s)	2.2
V/P Switch Over	97%
Mold Temperature (°C)	40
Warpage (mm)	3.73027

Based on Table 9, the minimum value of warpage is obtained when the coolant temperature is set at 40°C, injection time is set at 2.2s, V/P switch over is set at 97% and mold temperature is set at 40°C. The warpage value is 3.73027 when these parameters set as discussed earlier

4. Conclusion

The objective of the PSO optimization in this study is to determine the optimal process parameters in injection molding that could lead to the minimum warpage value. The minimum warpage value obtained from initial data is 3.776, while the minimum warpage value from PSO is 3.73027. Based on the facts and findings discussed earlier the PSO is capable of optimizing the warpage value, PSO has reduced the warpage value by 1.2111%. Therefore, PSO has been the effective technique in estimating the minimum warpage value compared to technique used by initial data.

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