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Dynamic PSO Algorithm Based In-Situ Induction Motor Efficiency Determination

V.P. Sakthivel[1], P.D. Sathya[2]
[1]Assistant Professor, Department of Electrical Engineering, FEAT, Annamalai University, Chidambaram- 608002, India.
[2]Assistant professor, Department of Electronics and Communication Engineering, FEAT, Annamalai University, Chidambaram – 608002, India
[1]vp.sakthivel@yahoo.com

Abstract: Three-phase cage induction motors consume almost two-thirds of the electricity generated. Replacing inefficient working induction motors with more effective ones leads to important energy savings. It is therefore necessary to develop a fresh effectiveness determination technique for in-situ induction motor (ISIM). IEEE standard 112 techniques that require no-load and locked rotor experiments can determine the efficiency of the induction engine. For the ISIM, these tests are not feasible. This article proposes a novel implementation of the Dynamic Particle Swarm Optimization (DPSO) algorithm to estimate the ISIM's effectiveness. In DPSO, the inertia weight is dynamically altered based on the particles ' highest fitness value to promote the worldwide particle exploration capacity at the start of the algorithm and provide the worldwide optima at the end point. The suggested technique utilizes the ISIM's measuring information of stator voltage, stator current, stator strength, power factor, input energy, and rotor velocity. The DPSO algorithm is used to assess the parameters of the engine equivalent circuit by minimizing the mistake between the determined and measured information instead of using no-load and blocked rotor tests. The effectiveness of the in-situ induction motor is then estimated using modified equivalent circuit model that involves stray load losses. The efficacy of the suggested algorithm has been tested on a 5 HP engine. The outcomes of the simulation acquired are contrasted with the equivalent circuit technique (ECM) and PSO algorithm. The findings show that the DPSO algorithm is better than the other comparative methods to determine the ISIM's effectiveness.

Keywords: Dynamic particle swarm optimization, Efficiency determination, In-situ motor, Modified equivalent circuit model, Particle swarm optimization.

1. INTRODUCTION

Determination of induction motor efficiency enhances energy savings in sector. The technique IEEE Std 112 does not apply to industrial processes. Non-intrusive motor efficiency determination techniques must be suggested for ISIM testing. The least intrusive categories of estimation techniques for induction motor effectiveness are equal circuit-based techniques. Over the years, techniques for determining effectiveness based on ECM have been implemented. The technique of IEEE Std-112 F is the typical circuit equivalent method [1]. Even if this technique is expected to be comparatively precise, the requirement for no-load, removal – rotor, varying voltage, and reverse rotation experiments render it impossible for in-situ testing.

The conventional 112-F technique is subsequently revised by abolishing the variable voltage test [2]. Nevertheless, rated no-load testing and complete load testing are required. In [3], the writers surveyed over twenty induction motor efficiency determination techniques and created the least intrusive efficiency determination method. The direct method for estimating the effectiveness of the induction motor is the technique of measuring shaft torque. But these techniques involve dynamometer measurement, which is not feasible in the field. A fresh approach [5] was suggested to determine the equivalent circuit parameters of the induction motor based on a single-phase experiment. Still, the requirement for no-load testing is a major problem in determining ISIM's effectiveness. No-load and blocked-rotor experiments estimate the corresponding circuit parameters. The no-load test is performed at ordinary no-load voltage and the locked rotor test is performed by mechanically locking the rotor and applying decreased voltage and frequency. Since no-load and blocked-rotor experiments are extremely intrusive, evolutionary algorithms are used to estimate equivalent circuit

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parameters by minimizing the mistake between the measured and determined information. Genetic algorithm (GA)[6][7], adaptive GA[8] evolutionary algorithm (EA)[9], PSO[10] bacterial foraging algorithm[11] were also used for ISIM parameter determination and effectiveness assessment. Thus, the evolutionary algorithms provide a non-intrusive technique of estimating effectiveness that uses engine input information. With ease, computational velocity and solution quality, these methods have many merits and demerits. This article presents a Dynamic Particle Swarm Optimization (DPSO) [12] algorithm for determining ISIM effectiveness. The simulation results using the DPSO algorithm are compared with the equivalent circuit method and standard PSO algorithm and prove the effectiveness of the proposed algorithm. The remainder of the document is categorized as follows. Section 2 explains the mathematical model of modified equivalent circuit. In Section 3, a fresh system using the DPSO algorithm is described. Section 4 shows the implementation of the DPSO algorithm for in-situ induction motor. Section 5 presents the recital of the DPSO algorithm with other algorithms and the simulation research. Section 6 illustrates the conclusion.

2. MODIFIED EQUALIENT CIRCUIT MODEL AND PROBLEM FORMULATION

The proposed method of in-situ efficiency estimation integrates the method of loss segregation, the ECM and the DPSO as an apprach to solve the non-linear ECM equations. The operation of the suggested ISIM technique is comparable to the technique of loss segregation. But no-load testing is not needed.

2.1 Stator winding resistance per phase

The stator resistance per phase is defined as

$$r_1 = \frac{r_{1\,line}}{2} \tag{1}$$

Where, $r_{1\ line}$ and r_1 are the line resistance and phase resistance of the stator winding respectively.

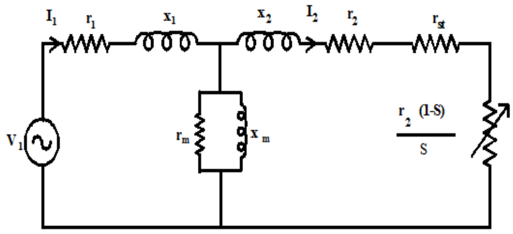

Figure 1. Modified equivalent circuit model of an induction motor

2.2 Input power factor

The input power factor is given as,

$$pf = \frac{P_{in}}{\sqrt{3}V_1 I_1} \tag{2}$$

Where, V_1 stator line voltage
I_1 stator current
P_{in} input power

2.3 Mutual impedance

The mutual impedance of Figure 1is given as

$$Z_m = r_m + jX_m \tag{3}$$

Where, r_m mutual resistance
The mutal resistance considers the core, windage and friction losses.

2.4 Stray loss

The stray loss of the rotor is determined as

$$P_{st} = \frac{P_{st\,fl} I_2^2}{I_{2\,fl}^2} \tag{4}$$

Where, $P_{st\ fl}$ full load stray load loss

I_2 rotor currents.

The stray resistance is defined as

$$r_{st} = \frac{0.018 r_2 (1 - S_{fl})}{S_{fl}} \tag{5}$$

Where, S_{fl} full load slip

2.5 Temperature rise

Temperature rise of stator winding and rotor winding of the ISIM are determined by

$$T_t = \left(\frac{I_1 - I_0}{I_{f1} - I_0}\right) \times \left(T_r - T_s\right) + T_s \tag{6}$$

2.6 Admittance functions

The stator, rotor and mutual admittances of Figure 1 are given as

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$$\overline{Y_1} = \frac{1.0}{r_{1c} + jx_1} \tag{7}$$

$$\overline{Y_2} = \frac{1}{r_{2c}/s + r_{st} + jx_2} \tag{8}$$

$$\overline{Y_m} = \frac{-j}{x_m} + \frac{1}{r_m} \tag{9}$$

2.7 Stator, rotor and magnetizing current determination

The stator current is given by

$$I_{1est} = \left|\bar{I1}\right| = \left|\frac{\overline{V_1 Y_1 (Y_2 + Y_m)}}{\overline{Y_1 + Y_2 + Y_m}}\right| \tag{10}$$

Rotor current is determined by

$$I_2 = \left|\frac{\overline{V_1 Y_1 Y_2}}{\overline{Y_1 + Y_2 + Y_m}}\right| \tag{11}$$

Magnetizing current is definedby

$$I_m = \left|\frac{\overline{V_1 Y_1}}{\overline{r_m (Y_1 + Y_2 + Y_m)}}\right| \tag{12}$$

2.8 Efficiency determination

The input power is given by

$$P_{inest} = 3\left(I_1^2 r_{1c} + I_2^2\left(\frac{r_{2c}}{s} + r_{st}\right) + I_m^2 r_m\right) \tag{13}$$

The output power is

$$P_{outest} = 3I_2^2 r_{2a}\frac{1-s}{s} \tag{14}$$

The efficiency of ISIM is determined by

$$\eta = \frac{P_{outest}}{P_{inest}} \times 100 \tag{15}$$

The objective of the DPSO optimization is to minimize the devations between the determined and measured parameters. The objective function is written as:

$$F(X) = \left[\frac{I_{1est} - I_{1m}}{I_{1m}}\right]^2 + \left[\frac{P_{inest} - P_{inm}}{P_{inm}}\right]^2 + \left[\frac{pf_{est} - pf_m}{pf_m}\right]^2 \quad 16)$$

3. REVIEW OF PSO AND DPSO

3.1 Particle swarm optimization

PSO is a population-based optimization paradigm that mimics the social behavior of birds flocking or fishing for food. It works with a population of possible solutions rather than a single individual and the solutions are flew through hyperspace and are moved in the direction of better or more optimal solutions. The population reacts to the accelerating variables of the best local individual values and the best worldwide community values. This method can be implemented to solve many multi-constrained issues of optimization such as GA. It doesn't have GA's drawbacks. It has also been shown to be energetic in solving non-linear, non-differential and high-dimensional issues.

PSO has a swarm of particles moving within the D-dimensional room of viable alternatives. Each particle implants the significant information considering the variables of the D decision and is related to a fitness that provides the indication of the recital in the objective space. Each particle i has a position $X_i = [X_{i,1}, X_{i,2} \ldots X_{i,D}]$ and a velocity $V_i = [V_{i,1}, V_{i,2} \ldots V_{i,D}]$. Besides, a swarm contains each particle i individual local best position $pbest_i = (pbest_{i,1}, pbest_{i,2}, \ldots, pbest_{i,D})$ found so far and a global best particle position $gbest = (gbest_i, gbest_i, \ldots, gbest_D)$ found among all the particles in the swarm so far. Basically, the flight of each particle is updated according to its individual flying experience and also the best particle in the swarm globally.The standard PSO algorithm can be defined as

$$V_{i,d}^{k+1} = W \times V_{i,d}^{k} + C_1 \times rand_1 \times (lbest_{i,d}^{k} - X_{i,d}^{k}) + C_2 \times rand_2 \times (gbest_d^{k} - X_{i,d}^{k}) \tag{17}$$

$$X_{i,d}^{k+1} = X_{i,d}^{k} + V_{i,d}^{k+1} \tag{18}$$

$i = 1, 2 \ldots, n;\ d = 1, 2 \ldots, D$

Where W is a factor of inertia weighting ; where C_1 is a factor of cognition acceleration ; where C_2 is a factor of social acceleration ; where $rand_1$ and $rand_2$ are two random numbers evenly distributed between 0 and 1 ;$V_{i,d\,k}$ is the velocity of particle i at iteration k; $X_{i,d\,k}$ is the dth dimension position of particle i at iteration k; $pbest_{i,d}^{k}$ is the dth dimension of the individual best position of

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particle i until iteration k; $gbest_d^k$ is the dth dimension of the global best particle in the swarm at iteration k.
The time varying weighting function is incorprated in PSO algorithm and is defined by

$$W = W_{max} - (W_{max} - W_{min}) \times t / t_{max} \qquad (19)$$

Where,
W_{max} and W_{min} initial and final weights respectively, t and t_{max} current and maximum generation numbers.
The model shown in Eq. (22) is called the inertia weights approach (IWA) which retains the swarm's worldwide and local exploration search capacities. A big weight of inertia assists exploration, while a tiny weight assists exploitation.

3.2 Dynamic PSO (DPSO)

A greedy strategy is used in this document to self-adopt the inertia weight factor in the PSO algorithm [12]. At each iteration, the inertia weight is updated to render the improvement in the best fitness. This technique imitates human behavior that "achievement in one's act improves one's self-possession, while failure reduces it." The inertia weight should be improved in this adaptation approach for better fit particles and vice versa. The powerful exploration behavior among swarms is accomplished when the algorithm begins with higher inertia weight values. By comparison, lower inertia weight at the algorithm's final generation causes the swarms to search for a better solution in the lower area. The inertia weight is taken as a function of generation number and is updated as follows:

$$\begin{aligned} W(t+1) &= 0.9 && \text{if } t = 0 \\ &= F(t-1) - F(t) && \text{if } t > 0 \end{aligned}$$

Where, $W(t+1)$ is inertia weight at $(t+1)^{th}$ iteration and $F(t)$ is the objective value at t^{th} iteration.

Using this greedy strategy, inertia weight oscillations are bigger at original generations of swarms that assist the swarm sustain diversity and lead to successful exploration. Thus, the particles rapidly travel through the entire search space. The inertia weight oscillations become lower towards the final generation, which facilitates the fine tuning of the solution. For much subsequent iteration, when the inertia weight is zero, the cognitive and social elements are stuck with the suboptimum alternatives and also decelerate the search process. If the swarm is trapped for successive iterations, some inertia is provided to boost variety. The inertia factor is thus altered as follows

$$\begin{aligned} W(t+1) &= 0.9 && \text{if } t = 0 \qquad (20) \\ &= F(t-1) - F(t) && \text{if } t > 0 \\ &= W_{max} - (W_{max} - W_{min}) \times \frac{t}{t_{max}} && \text{if } W = 0 \end{aligned}$$

4. SOLUTION OF IN-SITU EFFICIENCY DETERMINATION PROBLEMS WITH DPSO ALGORITHM

The DPSO algorithm method for solving the issues of determining in-situ induction motor efficiency can be explained as follows:

Step 1. Initialization of the swam
Since the decision variables are equivalent circuit parameters for the problems of determining in-situ efficiency, they are used to form the swarm. The in-situ motor's corresponding circuit parameters are depicted as the positions of the particle in the queue. Each swarm component is initialized by a periodic likelihood distribution function in the range [0 – 1] and situated between the reduced and upper limit of the corresponding circuit parameters.
Step 2. Evaluation of velocity
The velocities of the particles are generated randomly in the range $[-V_j^{max}, V_j^{max}]$
Step 3. Initialization of lbest and gbest
Eq's acquired objective values. (16) The original swarm particles are set as the original local best (lbest) particle values. The highest worldwide value among all the lbest values is ascertained as gbest.
Step 4. Updating of dynamic inertia weigh factor
The dynamic weight factor inspired by nature is calculated using Eq. (20)
Step 5. Updating of particles velocity
The velocities of each particle are updated using Eq in the DPSO algorithm. (17).
Step 6. Updating of particles' position
The fresh particle location is updated using Eq. (18) and then the lbest and best values are updated.
Step 7. Stopping criteria
Check the condition of termination. If the maximum generation of iteration is reached, the DPSO algorithm will be terminated and the optimal results will be produced. Otherwise, Step 4 repeats the operation.

5. SIMULATION RESULTS AND DISCUSSIONS

In this document, to assess the efficacy of the DPSO algorithm, it is used to assess the effectiveness of the in-situ induction motor considering the modified equivalent circuit model. MATLAB 7.1 Software is used to simulate

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the issue of in-situ efficiency determination and is tested on a personal computer with 2 GHz Pentium IV, 1 GB RAM. The amount of particles in a generation and the highest amount of generations are counted as 20 and 100 respectively.
The findings of the load test method are shown in Table 1. The two experimental techniques are performed on a 5 HP engine whose requirements are provided in the Appendix and the simulation outcomes of the suggested DPSO technique are compared with ECM and PSO.
Test Case 1: Initially, full load experimental data is considered for equivalent circuit parameter estimation.
Test Case 2: Secondly, each load experimental data is considered for equivalent circuit parameter estimation.

Table 1. Torque Gauge test data of three-phase induction motor

Motor Load	I_1 (A)	P_{in} (w)	pf	Efficiency (%)
25%	6.4	1600	0.63	57.2
50%	8.5	2500	0.74	67.05
75%	10.6	3300	0.78	77.01
100%	12.5	4100	0.82	63.81

Table 2. Comparison of ECM, PSO and DPSO results for Test case 1

Motor Load	ECM		PSO		EMA	
	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)
25%	73.57	16.37	66.08	8.88	64.7	7.5
50%	82.56	15.51	76.24	9.1	60.18	-6.87
75%	84.25	7.24	69.98	-7.03	71.69	-5.32
100%	82.65	18.84	58.32	-5.49	67.73	3.92

Table 3. Comparison of ECM, PSO and DPSO results for Test case 2

Motor Load	ECM		PSO		DPSO	
	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)	Efficiency (%)	Error (%)
25%	73.57	16.37	65.51	8.31	51.36	-5.84
50%	82.56	15.51	58.43	-8.62	71.98	4.93
75%	84.25	7.24	69.58	-7.43	80.73	3.72
100%	82.65	18.84	59.44	-4.37	60.60	-1.67

5.1 Test Case 1

In this test case, only complete load experimental information are used to estimate the parameters of the engine. DPSO technique randomly generates the equivalent circuit parameters, X_1, R_2, X_m, and R_m. Then these parameters are used at different load values to calculate the present stator line, power factor, stray-load losses, input energy, output power, and the respective efficiencies. The determined values are compared to the experimental values. The mistake is the distinction at each load between the effectiveness acquired from DPSO and the measured information.
Table 2 summarizes the comparison outcomes for Test case 1. Figs. 2, 3 and 4 demonstrate, respectively, the mistakes, efficiencies and average execution time acquired by different methods for this test case. The findings indicate that the DPSO mistake is less when compared to PSO, which demonstrates the better quality of the solution. Furthermore, it is inferred from Table 2 that the execution time of the suggested DPSO strategy is considerably less than that of PSO.

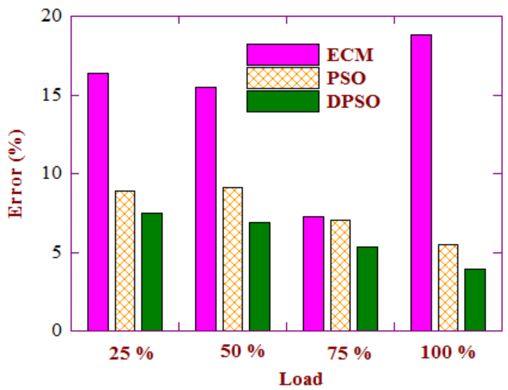

Figure 2. Magnitude of errors in percentage efficiency for Test case 1

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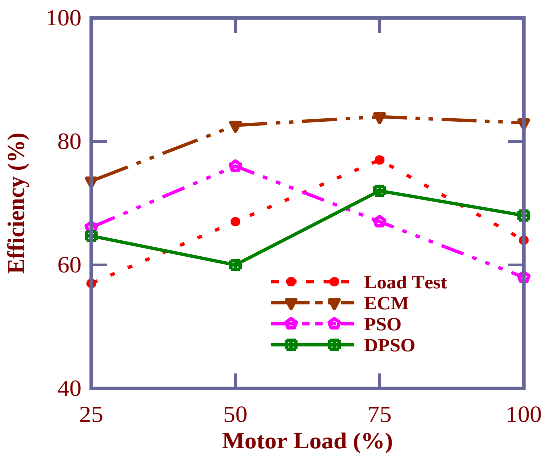

Figure 3. Efficiency of the in-situ induction motor using the load test, ECM, PSO and DPSO methods for Test

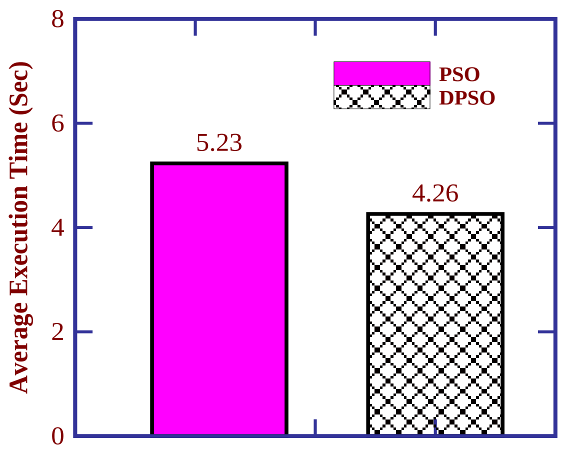

Figure 4. Average execution time for Test case1

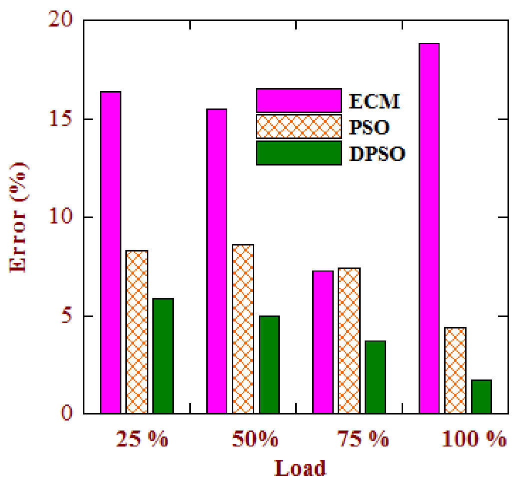

Figure 5. Magnitude of errors in percentage efficiency for Test case 2

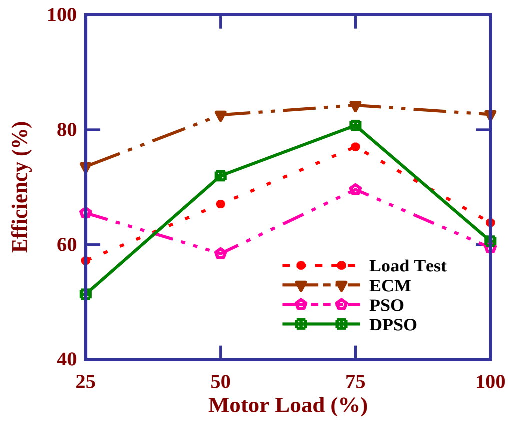

Figure 6. Efficiency of the in-situ induction motor using the load test, ECM, PSO and DPSO methods for Test case 2

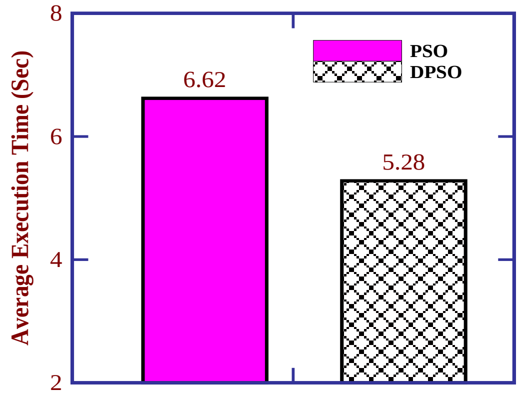

Figure 7. Average execution time for Test case 2

5.2 Test Case 2

In this test case, each experimental load point information is used to determine the engine parameter and the effectiveness. The comparison of the ISIM issue based on PSO and DPSO for Test case 2 is summarized in Table 3 and shown in Figs. 5, 6, 7.
From Table 3 and Figures, it can be concluded that the suggested method provides significantly better outcomes and computational effectiveness relative to the PSO method. Consequently, in terms of solution quality, it may be decided that the DPSO is better structured computationally than the PSO strategy. In addition, heuristic algorithms using Test case 2 provide better outcomes than the Test case1.

6. CONCLUSION

This article introduces a novel application of the dynamic PSO (DPSO) algorithm based on effectiveness

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determination of the in-situ induction motor. The suggested technique includes the ECM, the process of segregated losses, and the DPSO algorithm. Two test instances are used to determine the in-field effectiveness of 5 HP engine to demonstrate the applicability of the DPSO algorithm. Results of simulation show that the DPSO algorithm has superior elements, improvements over the ECM and PSO algorithm in terms of better solution quality and less computational effort. Although the suggested DPSO algorithm is used to address ISIM effectiveness determination issues in the current study job, it appears from its unique characteristic that DPSO has the capacity to solve other multi-constrained optimization problems in the field of electrical machine design, parameter identification and energy system issues.

APPENDIX

Specifications of 5 HP motor

Specifications	Value
Capacity	5 HP
Voltage	230 V
Current	12.5 A
Speed	1450 rpm

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