World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:8, No:1, 2014

Optimal Dynamic Economic Load Dispatch Using Artificial Immune System

I. A. Farhat

Abstract**—**The dynamic economic dispatch (DED) problem is one of the complex constrained optimization problems that have nonlinear, con-convex and non-smooth objective functions. The purpose of the DED is to determine the optimal economic operation of the committed units while meeting the load demand. Associated to this constrained problem there exist highly nonlinear and non-convex practical constraints to be satisfied. Therefore, classical and derivative-based methods are likely not to converge to an optimal or near optimal solution to such a dynamic and large-scale problem. In this paper, an Artificial Immune System technique (AIS) is implemented and applied to solve the DED problem considering the transmission power losses and the valve-point effects in addition to the other operational constraints. To demonstrate the effectiveness of the proposed technique, two case studies are considered. The results obtained using the AIS are compared to those obtained by other methods reported in the literature and found better.

Keywords**—**Artificial Immune System (AIS), Dynamic Economic Dispatch (DED).

I. Introduction

SYNAMIC economic load dispatch problem deals with deciding the optimal allocation of thermal electrical energy for the duration of a scheduling period of time. This is to determine, optimally, the output power of the running thermal units such that the load demand is met over a finite dispatch time and the total operating cost is minimized. In classical optimization methods, the input-output characteristics of the thermal units are approximated by a smooth differentiable quadratic or piecewise quadratic objective function. However, due to the valve-point effects, the real input-output characteristics contain higher order non-linearity and discontinuity which result in a non-convex, non-smooth fuel cost function. The valve-point effects are presented using two different approaches [1]. In the first model, the effects are formulated as inequality constraints that represent them as prohibited operating zones [2], [3]. The second model, which is considered in this paper, includes a rectified sinusoidal term in the original objective function to represent the effects [4]-[7]. Minimizing the total cost in this optimization problem is subject to many control and operational constraints. Reliability and security requirements are also accounted for when solving this problem. These constraints include load balance, generation limits [8]. As it is the case of most realistic operational optimization problems, there exist two types of constraints, equality and inequality constraints. The equality constraints of the DED problem are the load balance equation considering the active power transmission losses. Valve-point effects, prohibited operating zones, ramp-rates and capacity limits, are the inequality constraints of the problem. Additional constraints could also be accounted for in the DED problem [1], [9]-[12]. It is therefore evident that the DED is a large-scale nonlinear constrained optimization problem. To solve the problem, various optimization techniques have been applied and successfully implemented. According to the research on this topic, which was reported in the literature as early as the 1970s [13], [14], these techniques are mostly based on the principle of local search in the feasible region of solution [15]. Applied optimization methods can be calculus-based programming algorithms such as linear and nonlinear programming, dynamic programming and interior point methods [16], [17]. The other methods are the artificial intelligence techniques including neural networks [18], fuzzy systems [19] and the evolutionary methods such as genetic algorithms [20], the simulated annealing [21] and the particle swarm optimization technique [22]. These methods can be generally classified into two main groups: deterministic methods and heuristic methods. Deterministic methods include Lagrangian relaxation and Benders decomposition methods, mixed integer programming, dynamic programming and interior point methods. Genetic algorithms, particle swarm optimization and other evolutionary methods are heuristic. Most of the methods that have been used to solve the DED problem are deterministic in nature. However, modern methods are getting more attention in solving large-scale optimization problems. For the DED problem, a variety of approaches have been applied. Some of these are deterministic and calculus-based methods [23], [24] and others are heuristic such as Genetic Algorithms, Differential Evolution and Tabu Search Algorithms [25]-[27].

Artificial Immune System (AIS) has been proposed in the 1990s as a new branch in computational intelligence [28], [29]. AIS is inspired by immunology, immune function principles, observed in nature. This technique is getting more attention by many researchers and has been successfully applied to various power system optimization problems [30]-[33].

In this paper, an Artificial Immune System (AIS) technique is presented and applied to solve the DED problem considering the power transmission losses and valve-point effects. Two cases of test systems are utilized to validate the performance of the proposed AIS and to compare it to other well-known optimization techniques. The remainder of the

I. A. Farhat is with the Electrical and Computer Engineering Department, Al-Mergib University, Al-Khoms, Libya (phone:+218-53-2621488, PO Box: 40161, e-mail: iafarhat@elmergib.edu.ly).

paper is organized as follows: Section II provides the formulation of the DED problem. In Section III, the AIS is described. Simulation results are demonstrated in Section IV. The conclusion is drawn in Section V.

II. Dynamic Economic load Dispatch Problem Formulation

The DED problem is designed to determine the optimum loading of all committed generation units to minimize the cost function subject to the system constraints.

A. Objective Function

$$\min \quad F_T = \sum_{t=1}^{T}\sum_{j=1}^{N} F_j\left(P(j,t)\right) \tag{1}$$

where,
F_T: total production cost function
P (j,t): power generation of generating unit *j* at time interval *t*
$F_j(P(j,t))$: production cost for *P (j,t)*
N : number of generating units
T : number of time intervals

The cost function of the thermal power unit production is expressed as follows:

$$F_j\left(P(j,t)\right) = a_j + b_j P(j,t) + c_j P^2(j,t) \tag{2}$$

where a_j, b_j and c_j are the cost coefficients of the j^{th} thermal generating unit. To obtain an accurate cost function model, the valve-point effects are modeled in the fuel function as follows [6], [34]:

$$\begin{aligned} F_j\left(P(j,t)\right) &= a_j + b_j P(j,t) + c_j P^2(j,t) \\ &\quad + \left| e_j \sin\left(f_j\left(P(j)^{\min} - P(j,t)\right)\right)\right| \end{aligned} \tag{3}$$

where
e_j and f_j : Constant fuel cost coefficients for thermal unit *j* with valve-point effects.
$P(j)^{min}$: Minimum power generation for generating unit *j*

B. Constraints

The objective function represented by (1) is subject to a number of constraints including the following:

- Load Balance

$$\sum_{j=1}^{N} P(j,t) - P_D(t) - P_L(t) = 0 \tag{4}$$

where, $P_D(t)$: system load demand at time interval *t*
$P_L(t)$: system total losses at time interval *t*

The transmission power losses are given by the following loss formula:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{g_i} B_{ij} P_{g_j} \tag{5}$$

This formula is referred to as the loss formula and (5) represents its simplest form which is known as George's formula [35]. The parameters B_{ij} are called the loss coefficients or *B*-coefficients. In order to obtain a more accurate loss formula, a linear term and a constant is added to George's formula to outline the following expression [35]:

$$P_{L_k} = \sum_{i=1}^{N_g+M_H}\sum_{j=1}^{N_g+M_H} P_{i_k} B_{ij} P_{j_k} + \sum_{i=1}^{N_g} B_{0i} P_{i_k} + B_{00} \tag{6}$$

This formula, which is also referred to as Kron's loss formula, can be expressed in a vector notation as the following:

$$\begin{aligned} P_L &= \begin{bmatrix} P_{g1} & P_{g2} & \ldots & P_{gNg} \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1Ng} \\ B_{21} & B_{22} & \cdots & B_{2Ng} \\ \vdots & \vdots & \ddots & \vdots \\ B_{Ng1} & B_{Ng2} & \cdots & B_{NgNg} \end{bmatrix} \begin{bmatrix} P_{g1} \\ P_{g2} \\ \vdots \\ P_{gNg} \end{bmatrix} \\ &\quad + \begin{bmatrix} P_{g1} & P_{g2} & \ldots & P_{gNg} \end{bmatrix} \begin{bmatrix} B_{01} \\ B_{02} \\ \vdots \\ B_{0Ng} \end{bmatrix} + B_{00} \end{aligned} \tag{7}$$

The B-coefficients mainly depend on the operating condition of the system. They are usually assumed to be constant parameters, unless the system operating state of a new generation scheduling is significantly different from the base case.

- Generation Capacity

$$P(j)^{\min} \le P(j,t) \le P(j)^{\max} \tag{8}$$

where,
$P(j)^{min}$: minimum power generation for unit *j*
$P(j)^{max}$: maximum power generation for unit *j*

- Ramp Rate Limits

The upper (UR_j) and down (DR_j) ramp rate limits of the units are considered as follows:

$$\begin{aligned} P(j,t) - P(j,t-1) &\le UR_j \\ P(j,t-1) - P(j,t) &\le DR_j \end{aligned} \tag{9}$$

III. Artificial Immune System (AIS)

A. Biological Background

Immune systems of vertebrates, including humans, are composed of cells, molecules and organs that protect bodies from infectious diseases [36]. These infections are usually caused by foreign pathogens such as bacteria and viruses. To carry out this function, the immune system must have the ability to distinguish between the body's own cells as the self cells and foreign pathogens as the non-self cells or antigens. The immune system has to perform an immune response in order to eliminate non-self cell or antigen. Antigens are further categorized so that the proper defense mechanism is activated.

In addition, the immune system has to have a kind of memory to enable more efficient responses if further infection by similar antigens is experienced. The way that the immune system fights against an antigen is explained by the clonal selection theory. According to this theory, only those cells that recognize the antigen are selected for proliferation. These cells are subjected to an affinity maturation process in order to improve their affinity to the selected antigens. Clonal selection operates both on B-lymphocytes or B cells produced by the bone marrow and T-lymphocytes or T cells produced by the thymus. When the body is exposed to an antigen, B cells respond to secrete specific antibodies to the particular antigen. Thereafter, a second signal from the T-helper cells, a subclass of T cells, then stimulate the B cell to proliferate and mature into terminal (non-dividing) antibody secreting cells called plasma cells. In proliferation, clones are generated in order to achieve the state plasma cells as they are the most active secretors of the antibodies at a larger rate than rate of antibody secretion by the B cells. The proliferation rate is directly proportional to the affinity level i.e. higher the affinity level of B cells more clones is generated. Clones are mutated at a rate inversely proportional to the antigen affinity i.e. clones of higher affinity are subjected to less mutation compared to those which exhibit lower affinity. This process of selection and mutation of B cells is known as affinity maturation. T cells do not secrete antibodies but play a central role in the regulation of the B cell response and are the most excellent in cell mediated immune responses. Lymphocytes, in addition to proliferating into plasma cells, can differentiate into long-lived B memory cells. These memory cells circulate through the blood, lymph and tissues, so that when exposed to a second antigenic stimulus, they commence to differentiate into large lymphocytes which are capable of producing high affinity antibody, preselected for the specific antigen that had stimulated the primary response. Artificial immune system (AIS) mimics these biological principles of clone generation, proliferation and maturation. The main steps of AIS based on clonal selection principle are activation of antibodies, proliferation and differentiation on the encounter of cells with antigens, maturation by carrying out affinity maturation process, eliminating old antibodies to maintain the diversity of antibodies and to avoid premature convergence, selection of those antibodies whose affinities with the antigen are greater. In order to emulate AIS in optimization, the antibodies and affinity are taken as the feasible solutions and the objective function respectively. Real number is used to represent the attributes of the antibodies. Initially, a population of random solutions is generated which represent a pool of antibodies. These antibodies undergo proliferation and maturation. The proliferation of antibodies is realized by cloning each member of the initial pool depending on their affinity. In minimization problem, a pool member with lower objective value is considered to have higher affinity. The proliferation rate is directly proportional to the affinity of the antibodies. The maturation process is carried through hyper-mutation which is inversely proportional to the antigenic affinity of the antibodies. The next step is the application of the aging operator. This aging operator eliminates old antibodies in order to maintain the diversity of the population and to avoid the premature convergence. In this operator an antibody is allowed to remain in the population for at most generations. After this period, it is assumed that this antibody corresponds to local optima and must be eliminated from the current population, no matter what its affinity may be. During the cloning expansion, a clone inherits the age of its parent and is assigned an age equal to zero when it is successfully hyper-mutated i.e. when hyper-mutation improves its affinity [36].

B. Propose AIS-Based Algorithm

As an optimization technique, AIS mimics the biological process of clone generation, proliferation and maturation. The performance of the AIS is mainly based on the principle of clonal selection. In order to emulate AIS in optimization, the antibodies represent the solutions within the feasible region while the affinity is the objective function to be minimized. At the start, a population of random solution vector is generated as an initial pool of antibodies. The antibodies go through the operations of proliferation and maturation. The proliferation of antibodies is performed by cloning each element of the initial points depending on their affinity. In this minimization process, the lower the objective cost of an element in the solution vector the higher its affinity. In the same way, the proliferation rate is considered proportional to the affinity. The maturation process is performed by hyper-mutation which is inversely proportional to the antigenic affinity of these antibodies. The aging operator is then applied to eliminate old antibodies so as to maintain the diversity of the population and prevent the premature convergence. In this operator an antibody is allowed to remain in the population for a number of generations. After this time, this antibody is eliminated from the population as it is associated to local minima regardless of its affinity. The age of the parent is inherited by the clone through the cloning expansion. Furthermore, if the hyper-mutation process is successful and the clone's affinity is improved, it is assigned a zero age as a result.

An AIS-based algorithm for solving the DED problem is discussed and described in this section. Consider that the k^{th} individual (antibody) of a population is expressed by the following vector:

$$\begin{aligned} p_k = \Big[& \{P(1,1), P(2,1), ..., P(j,1), ..., P(N,1)\}, ..., \\ & \{P(1,t), P(2,t), ..., P(j,t), ..., P(N,t)\}, ..., \\ & \{P(1,T), P(2,T), ..., P(j,T), ..., P(N,T)\}\Big]^T \end{aligned} \tag{10}$$

where $k=1, 2, \ldots, N_p$ and the elements of the vector p_k are the output power of the running thermal units over the scheduling period of the T intervals.

The affinity of the antibodies is computed as an inverse of the objective function to be minimized and expresses as follows:

$$Affinity = \frac{1}{F_T} \tag{11}$$

Depending on their affinity, the antibodies are cloned proportionally. After this the maturation process takes place by exposing the clones to a specific hyper-mutation mechanism. After evaluating the affinities of the mutated clones, the ageing operator is applied to eliminate the old antibodies. The antibody is given the chance to exist in the population for a number of generations before it is eliminated regardless of how good its affinity is. The remaining mutated clones and antibodies are ranked in descending order and the first is selected for the next generation.

IV. Simulation Results

The proposed AIS algorithm is tested and validated using a case study of a 10-unit generation system. The algorithm was implemented in MATLAB 7.8 and executed on an Intel® core™ 2 Duo 3.0 GHz personal computer. In each test case 30 independent runs were conducted with different random initial solution for each run. Results obtained for each case are compared with those of other optimization techniques. The all-thermal generation system of this case study consists of 10 generating units [37]. The scheduling period for this system is divided into 24 intervals of 1 hour each. The characteristics of the ten generating units are given in Table I. The table also shows the upper and lower ramp rate limits for each of the units. The load demand for each time interval over the scheduling period is given in II. The system losses are taken into account using the loss formula of (5) with the loss coefficients matrices of (12). The AIS algorithm is successfully applied to solve this problem considering both the valve-point effects and the power losses.

The optimal power generation schedule as well as the hourly transmission power losses over the scheduling period is tabulated in Table III and illustrated in Fig. 1.

$$B_{ij} = 10^{-6}\begin{bmatrix} 49 & 14 & 15 & 15 & 16 & 17 & 17 & 18 & 19 & 20 \\ 14 & 45 & 16 & 16 & 17 & 15 & 15 & 16 & 18 & 18 \\ 15 & 16 & 39 & 10 & 12 & 12 & 14 & 14 & 16 & 16 \\ 15 & 16 & 10 & 40 & 14 & 10 & 11 & 12 & 14 & 15 \\ 16 & 17 & 12 & 14 & 35 & 11 & 13 & 13 & 15 & 16 \\ 17 & 15 & 12 & 10 & 11 & 36 & 12 & 12 & 14 & 15 \\ 17 & 15 & 14 & 11 & 13 & 12 & 38 & 16 & 16 & 18 \\ 18 & 16 & 14 & 12 & 13 & 12 & 16 & 40 & 15 & 16 \\ 19 & 18 & 16 & 14 & 15 & 14 & 16 & 15 & 42 & 19 \\ 20 & 18 & 16 & 15 & 16 & 15 & 18 & 16 & 19 & 44 \end{bmatrix} \tag{12}$$

TABLE I
CHARACTERISTICS OF CASE 1 GENERATION UNITS

Unit i	a_i	b_i	c_i	e_i	f_i	P_i^{min}	P_i^{max}	UR_i	DR_i
	$/MW^{2}h	$/MWh	$/h	$/h	rad/MW	MW	MW	MW/h	MW/h
1	0.1524	38.5397	786.7988	450	0.041	150	470	80	80
2	0.1058	46.1591	451.3251	600	0.036	135	470	80	80
3	0.0280	40.3965	1049.9977	320	0.028	73	340	80	80
4	0.0354	38.3055	1243.5311	260	0.052	60	300	50	50
5	0.0211	36.3278	1658.5692	280	0.063	73	243	50	50
6	0.0179	38.2704	1356.6592	310	0.048	57	160	50	50
7	0.0121	36.5104	1450.7045	300	0.086	20	130	30	30
8	0.0121	36.5104	1450.7045	340	0.082	47	120	30	30
9	0.1090	39.5804	1455.6056	270	0.098	20	80	30	30
10	0.1295	40.5407	1469.4026	380	0.094	10	55	30	30

TABLE II
LOAD DEMAND OVER THE SCHEDULING PERIOD

Hour	P_D(MW)	Hour	P_D(MW)	Hour	P_D(MW)	Hour	P_D(MW)
1	1036	7	1702	13	2072	19	1776
2	1110	8	1776	14	1924	20	1972
3	1258	9	1924	15	1776	21	1924
4	1406	10	2022	16	1554	22	1628
5	1480	11	2106	17	1480	23	1332
6	1628	12	2150	18	1628	24	1184

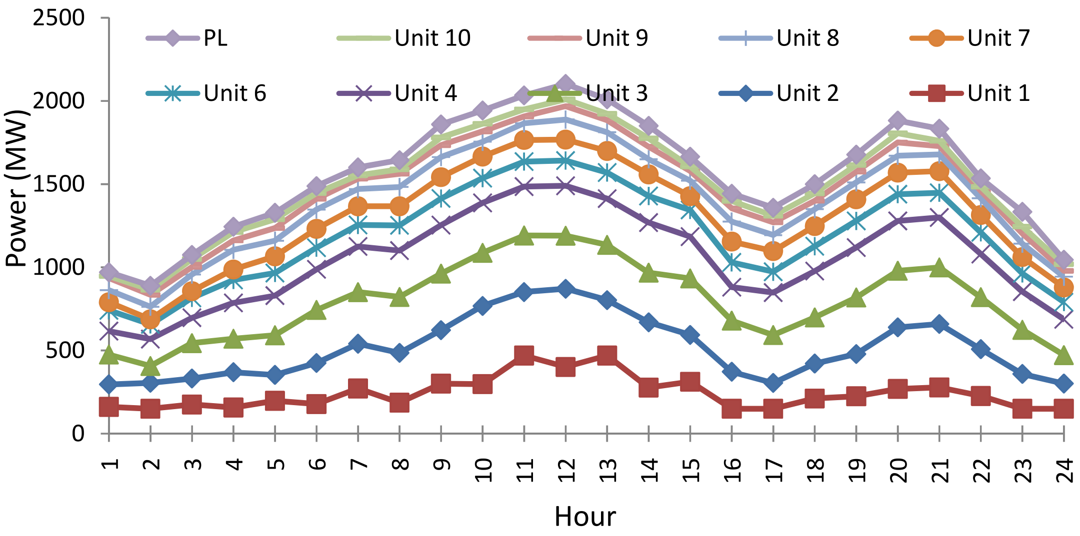

Fig. 1 Hourly power generation schedule

TABLE III
HOURLY GENERATION SCHEDULE AND POWER LOSSES (MW)

hr	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	P_L
1	161.1259	135.3240	179.2586	140.7457	111.2585	125.1249	49.1590	72.2488	71.8649	12.4790	22.5890
2	150.0000	155.5866	101.4257	161.4786	268.1255	88.1562	31.1458	75.1456	71.2556	31.2547	23.5742
3	175.5487	156.2747	212.5866	152.6549	232.8549	119.3655	40.5566	99.6985	46.0125	47.1424	24.6951
4	157.5316	212.1279	201.1268	215.2549	226.1424	138.2499	63.1257	117.2896	56.6366	50.5746	32.0599
5	198.1044	155.3269	238.4137	237.9785	231.0012	136.4138	100.2357	93.2747	76.4297	52.2067	39.3851
6	178.1383	246.7190	319.0410	243.9511	222.8359	130.1020	113.9272	114.8017	64.8462	35.0021	41.3646
7	271.4731	269.4602	310.1456	274.1486	197.2457	129.4799	112.4699	102.7463	62.3342	20.4789	47.9824
8	186.8206	299.0632	336.2252	278.7172	243.0000	151.4746	115.1456	115.2754	79.4536	26.5290	55.7044
9	301.1102	321.3148	340.0000	291.6232	221.8457	160.0033	128.3747	120.0000	70.9862	47.1326	78.3905
10	298.1476	470.0000	319.4613	300.0000	239.7896	148.5556	130.0000	88.2395	62.0185	46.0219	80.2339
11	470.0000	381.5699	340.0000	294.0875	242.0765	149.9148	130.0000	100.2256	40.2516	42.6365	84.7624
12	401.2569	470.0000	319.2457	300.0000	234.0256	151.2146	126.3658	120.0000	80.0000	41.1236	93.2322
13	470.0000	333.0248	332.0216	278.2155	235.5847	156.2365	130.0000	112.0056	72.3459	39.2557	86.6901
14	277.5648	392.0236	298.7590	300.2385	224.5424	160.0000	130.0000	91.0025	75.1463	50.0514	75.3285
15	312.4241	281.2546	340.0000	251.2135	231.2154	160.0000	83.1112	92.4586	58.3275	25.9987	60.0037
16	150.0000	222.2763	307.2469	200.8714	198.7896	149.2365	125.3845	120.0000	79.2713	44.4372	43.5136
17	150.0000	155.1042	288.1466	254.8956	218.4845	125.3746	124.5006	95.4658	75.6225	40.6414	48.2359
18	211.3267	210.4133	277.2547	278.5813	238.3216	149.4625	121.0236	101.1254	50.2879	45.1246	54.9214
19	225.1376	253.7468	340.0000	300.0000	222.4127	160.0000	130.0000	101.2357	64.2358	41.0216	61.7902
20	269.2326	370.1111	340.0000	300.0000	243.0000	160.0000	130.0000	101.1212	80.0000	55.0000	76.4649
21	278.2356	381.2326	340.0000	300.0000	237.1546	149.2224	129.3222	99.4659	50.5588	32.1005	73.2926
22	226.8546	281.4224	312.4586	259.4463	194.2790	130.2898	104.1988	99.9641	44.4113	25.2224	50.5472
23	150.0000	209.2146	265.3257	229.3356	174.4658	109.2366	98.8759	80.0003	61.2359	42.3251	88.0154
24	150.0000	151.2511	171.2102	214.3366	191.2334	104.0215	88.4569	64.1257	35.1246	40.4585	26.2184

The total operating cost is $ 2,500,684 which is shown in Table IV along with the mean and worse values obtained for the total cost. The table also shows the average CPU time.

TABLE IV
MINIMUM COST AND TIME OBTAINED

Cost ($)			Average time (sec)
Min	Max	Average	
2,500,684.3	2,511,958.4	2,507,442.3	49.8215

The results obtained by the proposed algorithm are compared with those obtained by other heuristic techniques implemented by the author. Namely; particle swarm optimization (PSO), genetic algorithm (GA) and modified bacterial foraging algorithm (MBFA). The comparison is shown in Table V.

TABLE V
COMPARISON OF COST AND CPU TIME

Method	Cost ($)	Average time (sec)
GA	2,596,847.38	71.24
PSO	2,580,148.25	69.88
MBFA	2,544,523.21	54.77
AIS	2,500,684.32	49.82

V. CONCLUSION

In this paper, an Artificial Immune System is proposed to solve the dynamic economic dispatch problem. The test systems used to validate the proposed algorithm considered most of the practical aspects of the all-thermal generation systems. The transmission power losses as well as the valve-point effect of the system are considered in the formulation of the problem. The upper and lower ramp rate limits of the generating units are also accounted for. Simulation results have demonstrated the good performance of the proposed algorithm. Comparison with other optimization methods has shown that the proposed algorithm achieved significantly better results in solving the problem.

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