Differential Evolution for Optimization of PID Gains in Automatic Generation Control

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Abstract:

Automatic generation control (AGC) of a multi area power system provides power demand signals for AGC power generators to control frequency and tie-line power flow due to the large load changes or other disturbances. Occurrence of large megawatt imbalance causes large frequency deviations from its nominal value which may be a threat to secure operation of power system. To avoid such situation, emergency control to maintain the system frequency using differential evolution (DE) based proportional-integral-derivative (PID) controller is proposed in this paper. DE is one of the most powerful stochastic real parameter optimization in current use. DE based optimum gains give better optimal transient response of frequency and tie line power changes compared to particle swarm optimization based gains.

***Keywords*: Automatic generation control, differential evolution algorithm, particle swarm optimization.**

NOMENCLATURE

Δf = Frequency deviation.
i = Subscript referring to area (i = 1,2,……).
$\Delta P_{tie\,(i,j)}$ = Change in tie line power.
ΔP_{di} = Load change of i^{th} area.
$D_i = \Delta P_{di} / \Delta f_i$
R_i = Governor speed regulation parameter for i^{th} area.
T_{hi} = Speed governor time constant for i^{th} area.
T_{ti} = Speed turbine time constant for i^{th} area.
T_{Pi} = Power system time constant for i^{th} area.
K_{Pi} = Power system gain for i^{th} area.
ACE_i = Area control error of i^{th} area.
H_i = Inertia constant of i^{th} area.
U_i = Control input to i^{th} area.
B_i = Frequency bias for i^{th} area.
US = Undershoot of ACE.
Mp = Overshoot of ACE.
ts = Settling time ACE.
tr = Rise time of ACE.
ess = Steady state error of ACE.

1. Introduction

AUTOMATIC generation control (AGC) maintains areas generation changes due to sudden change in load perturbations. The purpose of AGC is not only to maintain system frequency at nominal value but also to allocate generation between different areas at economical value and to keep the accurate value of tie line flows between different areas. The availability of an accurate model of the system is very crucial because it contains different uncertainties due to sudden change in load variation [1].

Over the past few decades, many researchers proposed different control strategy like proportional integral controller (PI), PID controller etc. Different state feedbacks controllers have been proposed and fixed gain controller of optimum conditions have been designed but they failed to provide better control performance. The PI controllers improve steady state error (ess) with small overshoot and conventional controller is simple to implement but very time consuming and gives high frequency deviation. PID controller has such capability to improve overshoot with minimum steady state error. Since the operating point of power system may change randomly during daily cycle and small load perturbations may occur simultaneously in all the areas, selection of optimum controller gain is to be explored to keep the system performance near to optimum, to track the operating conditions.

The main objective is to find optimum gain value of PID controller. The hit and trial method of finding the gains by indirect optimization with an appropriate performance index is not enough and convenient because of its space complexity. Yu et al. [17] have praised a linear quadratic regulation (LQR) method to tune PID gain, but it requires mathematical calculation and solving equations. Sinha et al. [1] introduced genetic algorithm (GA) based PID controller for AGC of two areas reheat thermal system. Ghoshal et al. [8] proposed PSO based PID controller for AGC. Some deficiencies in performance of GA method are identified by above paper.

New evolutionary algorithms (EA), DE (differential evolution) have similar structure as PSO in its search mechanism. Compared to most other EAs, DE is much more simple and straightforward to implement. The overall computational efficiency of DE is higher than other EAs. The space complexity of DE is low as compared to some of the most competitive real parameter optimization like PSO.

In view of the above, the following are the main objectives of the proposed work:

1. To obtain the optimize gain of PID controller by differential evolution algorithm for AGC of two area interconnected system.
2. To obtain dynamic response of AGC problem by using MATLAB.
3. To compare the performance of the differential evolution based PID controller to the PSO based PID controller.

The rest of the paper is organized as follows: In section 2 the two area system model is developed. Section 3 describes DE algorithm and implement DE based PID controller in section 4. Section 5 shows the result with detailed discussion and conclusion is drawn in section 6.

2. System Model

A large scale power system consists of interconnected control areas which are connected by tie-line. The areas are generally of different size and characteristics. A two area system of equal size is taken as a test system [18]. Fig.1 shows the AGC model. The task of controller is to generate a control signal that maintains system frequency and tie-line power.

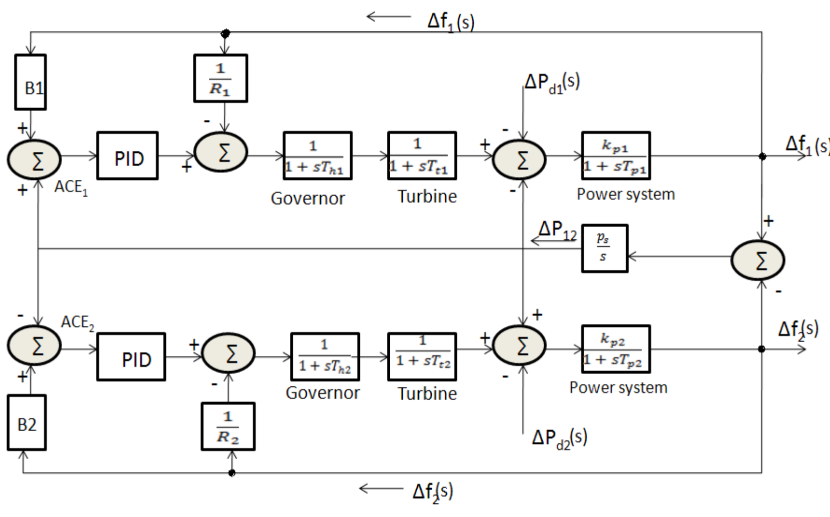

Fig.1: Linear model of two area system

In AGC control area is not only interconnected with one tie-line to one neighboring area but also with several tie-lines to neighboring control areas [18]. Tie-line power data are compared with the predetermined power, and the change in power is added with the biased frequency which is called area control error (ACE).

The ACE of each area is linear combination of biased frequency and tie-line error.

$$ACE_i = \sum_{j=1}^{n} (\Delta P_{tie(i,j)} + B_i \Delta f_i) \qquad (1)$$

Where ACE_i is area control error of i^{th} area, B_i is frequency bias coefficient of i^{th} area, Δf_i is frequency error, ΔP_{tie} is tie-line power flow error and 'n' is number of interconnected areas [18]. The area bias B_i determines the amount of interaction during load perturbation in neighboring area. To obtain better performance, bias B_i is selected as:

$$B_i = \frac{1}{Ri} + D_i \qquad (2)$$

Where Ri is regulation constant.
The block diagram of PID controller is shown in Fig.2. The control input to the system is as follows:

$$Ui = -(ki \int_0^t ACEi\, dt + kp * (ACEi) + kd \frac{d}{dt}(ACEi)) \qquad (3)$$

Where kp, ki, kd are proportional, integral and derivative gains respectively.

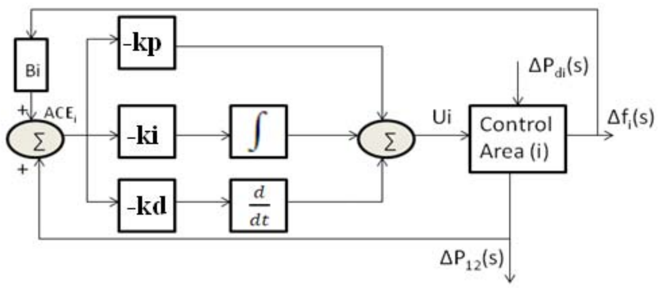

Fig.2: PID controller of i^{th} area

3. Overview of Differential Evolution Algorithm

Differential evolution (DE) was presented as heuristic optimization method which has been used to minimize nonlinear or non-differentiable functions [3]. While optimizing performance of a system, the objective is to find out such a set of values of the system parameters for which the overall performance of the system will be the best under some given conditions. It uses the differences of randomly sampled pair of object vector to provide mutation while other EA's use probability distribution functions. The main advantages of DE are its effective global optimization capability, efficient algorithm without sorting and easily handle non differentiable noisy time depended objective function. It works through a simple cycle of stages as:

Stage 1: Initial Population

The parameters governing the system are presented in a vector form as $x = [x_1, x_2, \text{----}\ x_N]^T$, each parameter x_i is a real number. DE searches a global optimum point in N-dimensional search space. It initializes the parameter vector randomly under uniform probability distribution within the search space constrained by the prescribed minimum and maximum bound as:

$$x_i^o = x_{i(min)} + rand.(x_{i(max)} - x_{i(min)}) \qquad \textbf{(4)}$$

Where $x_{i(min)}$ and $x_{i(max)}$ are lower and upper limit of object vectors respectively.

Stage 2: Mutation

The main characteristic of DE is the way it generates new population which is called mutation. A mutant vector is obtained through the weighted difference between two random vectors added to third random vector known as donor vector ($x_{new,i}^{k+1}$) [2]. These newly generated vectors are mixed with some predetermined trial vector (v_i^k). To create donor vector for each i^{th} target from the current (k^{th}) population, three distinct parameter vector x_{r1}, x_{r2} and x_{r3} are randomly generated. Difference of any two of these three vectors is scaled by constant *F* and this scaled difference is added to the third one as:

$$x_{new,i}^{k} = x_{r3}^{k} + F.(x_{r1}^{k} - x_{r2}^{k}) \qquad (5)$$

Where $r_1 \neq r_2 \neq r_3 \neq i$ are mutually exclusive. The scale factor *F* controls the scale of difference ($x_{r1}^k - x_{r2}^k$) as shown in Fig. 3.

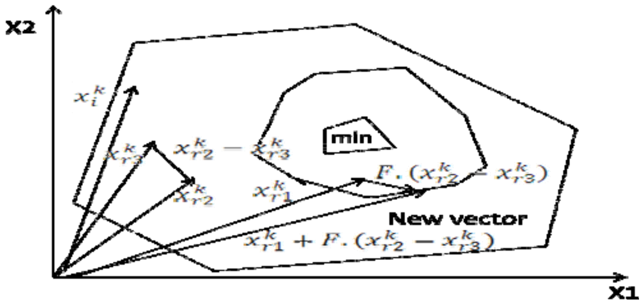

Fig.3: vector representation of new vector creation with DE.

Stage 3: Crossover:

After generating the donor vector through mutation, its components are exchanged with target vector which is parent vector from current generation. Binomial crossover is performed on each of N variable according to crossover probability. The number of parameters inherited from the donor has a binomial distribution. Crossover reinforcing prior successes by generating new vector out of existing object vector parameters. The crossover probability (CR) is used to determine that the new vector is to be recombined or not.

$$v_i^k = \begin{Bmatrix} x_{new,i}^k & if\ rand[0,1] \leq CR \\ x_i^k & otherwiswe \end{Bmatrix} \qquad (6)$$

Stage 4: Selection or Recombination:

The new generated vector is obtained by evaluating the fitness function. Selection determines that, whether the target vector is suitable for next iteration or not. The value of fitness function of current generation (f (v_i^k)) is compared with the previous fitness function (f (x_i^k)) of corresponding vectors. If the fitness functions to newly generated vector have lower value than previous one then former vector is replaced by new generated vector as:

$$x_i^{k+1} = \begin{Bmatrix} v_i^k & if\ f(v_i^k) \leq f(x_i^k) \\ x_i^k & if\ f(v_i^k) > f(x_i^k) \end{Bmatrix} \qquad (7)$$

The best parameters are evaluated for every generation to track the progress for minimization.
DE usually employs fixed population size throughout the operation. Selection of population size (Npop) is very important. To achieve fast computational result, Npop should be as small as possible, but such small size may lead to premature convergence. Therefore, in engineering application population size of 20*d* is usually generating better solution.

4. DE based Optimization of PID Gains

In a multi area system, the perturbation can occur anywhere, either in one area or in few area or all areas simultaneously. In PID tuning design, the most common performance criteria are Integral square error (ISE), integral absolute error (IAE) and integral of time weight square error (ITSE). These can be evaluated analytically in frequency domain, but in minimization using these criteria can result in a small overshot but long settling time because it weights all error equally independent of time [8]. In this paper following performance criterion for two area system is proposed:

$$J_1 = \int_0^t (ACE1^2 + ACE2^2) \tag{8}$$

Another performance criterion based on undershoots, steady state error, settling time and overshoot is also used for evaluating PID gains. The performance criterion is defined as:

$$J_2 = ((M_p + ess).\beta_1)^2 + (US.\beta_2)^2 + (ts)^2 \tag{9}$$

Where β_1, β_2 are weighting factors. The optimum selection of these factors depends on the designer's requirement and characteristics of the system. In this paper β_1 is set to 1000 and β_2 is set to 100 by trial and error.

4.1 Implementation of Algorithm

Step1: Select scale factor *F*, number of population, crossover probability (CR=0.98), number of maximum generation (gen_{max} =100).
Step2: Set the iteration count k=0 and randomly initialize population ($x_i = [x_1, x_2, --- x_{20}]$) for gains of PID using eq. (4).
Step3: Run AGC model and calculate performance parameter for each i^{th} vector.
Step4: Calculate fitness function (eq. 8 and eq. 9) and best fitness value.
Step5 (mutation): Generate donor vector ($x_{new,i}^k$) by using (eq. 5).
Step6 (crossover): Generate trial vector (v_i^k) for i^{th} vector through binomial crossover (eq. 6).
Step7 (selection): Evaluate trial vector (eq. 7) for each vector and set k = k+1.
Step7: If maximum number of generation is reached (k = gen_{max}) then stop otherwise go to step3.

The program flow chart of DE-PID controller is shown in fig 4.

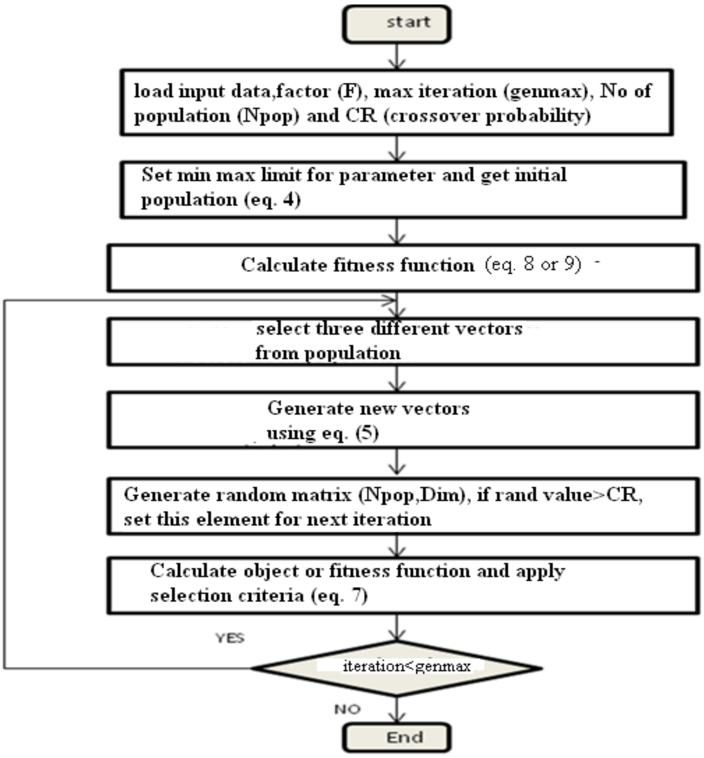

Fig.4: Flow chart of DE algorithm.

5. Result and Discussion

A DE based PID controller is designed using the above procedure. Figs 5-9 show system dynamic response of two areas interconnected power system with 1% step load perturbation in area two.

Fig 5 and fig. 6 present the comparative response of PID controller, with gains optimized from DE and PSO algorithm. From both performance index J_1 and J_2, DE-PID controller has shown better optimal performance of area control error (ACE_1 and ACE_2), in comparison to PSO-PID controller. Figures show that the DE based response using index J_1 have no such initial sharp undershoot and overshoot, in comparison to PSO based response.

Table I shows the PID gains, overshoot, undershoot, settling time and steady state error for two optimization algorithm. DE based PID gains result into less overshoot and significant reduction in settling time from 14.7199 to 10.7859 sec., steady state error for DE tuned PID gains is only $4.9496*10^{-11}$ compared to $11.7199*10^{-11}$as obtained for PSO based algorithm.

Table-II shows optimal gains value of DE and PSO based controller of performance index J_1 using algorithm parameters as given in appendix. DE based optimal PID gains results in to reduction in peak overshoot and settling time.

Figs 7-9 present a comparison of DE based performance index J_1 and J_2. The performance index J_1 have shown lesser undershoot, overshoot and settling time. Index J_2 based Δf_1 (t) have initial sharp undershoot but minimum settling time. The reason behind is the choice of weighting factors (β_1 and β_2) in the formulation of index J_2.

Table-I
Optimal PID gains and transient response parameter for DE and PSO algorithm for index J_2

Algorithms	Optimal PID gains			Transient response parameters				Fitness function
	Prop. Gain (k_p)	Inte. Gain (k_i)	Deri. Gain (k_d)	$Mp*10^{-4}$	$US*10^{-4}$	ts(sec)	$ess*10^{-11}$	
DE	1.2595	2.4396	0.4711	1.8436	-2.1542	10.7859	-4.9496	116.4479
PSO	0.8689	1.7375	0.3059	2.526	-3.3728	14.7199	-11.71	216.7414

Table-II
Optimal PID gains and transient response parameter for DE and PSO algorithm for index J_1

Algorithms	Optimal PID gains			Transient response parameters				Fitness function
	Prop. Gain (k_p)	Inte. Gain (k_i)	Deri. Gain (k_d)	$Mp*10^{-5}$	$US*10^{-5}$	ts(sec)	$ess*10^{-12}$	
DE	1.5897	1.3947	1.0893	3.196	-1.872	7.8959	-4.902	62.3459
PSO	1.4584	1.664	0.9847	3.229	-2.08	8.8805	1.1215	78.86

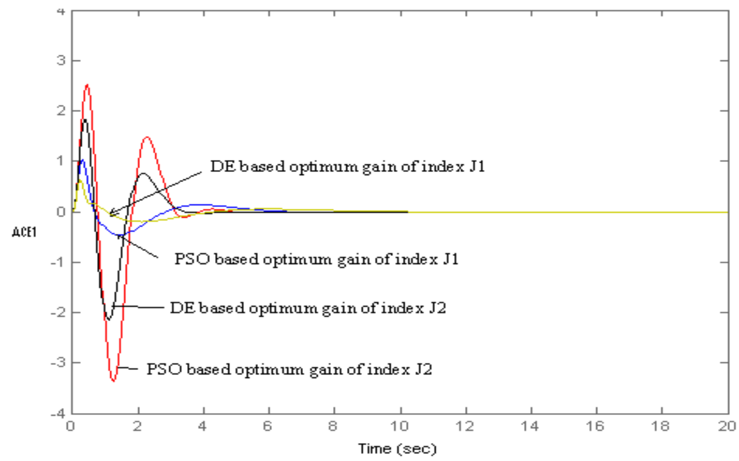

Fig.5: response of ACE1 with DE-PID and PSO-PID

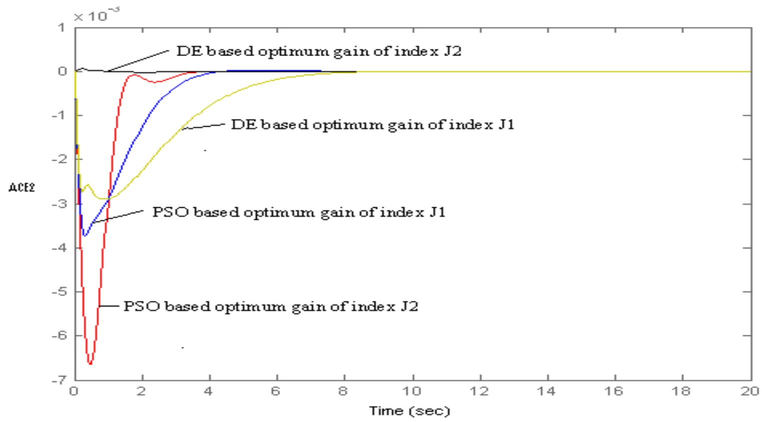

Fig.6: response of ACE2 with DE-PID and PSO-PID

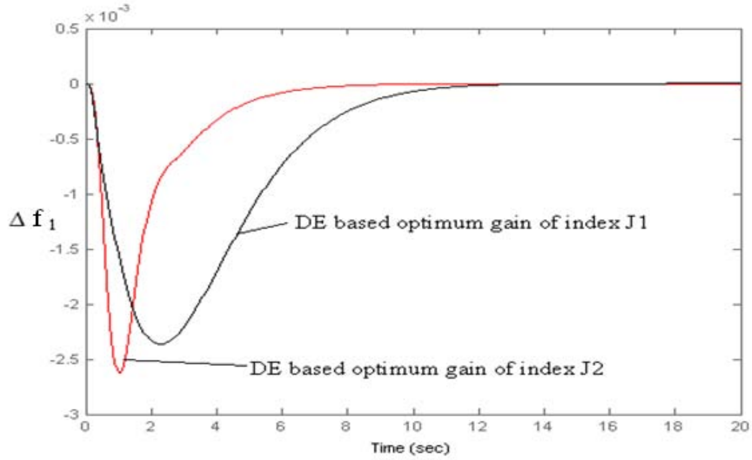

Fig.7: comparative transient response plot of frequency error Δf_1 .

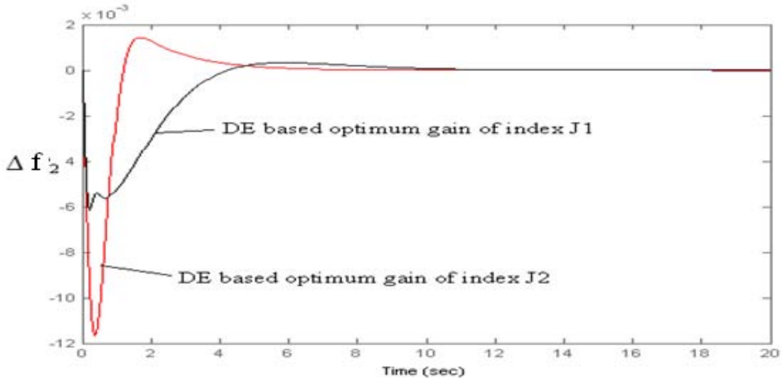

Fig.8: response of frequency error Δf_2.

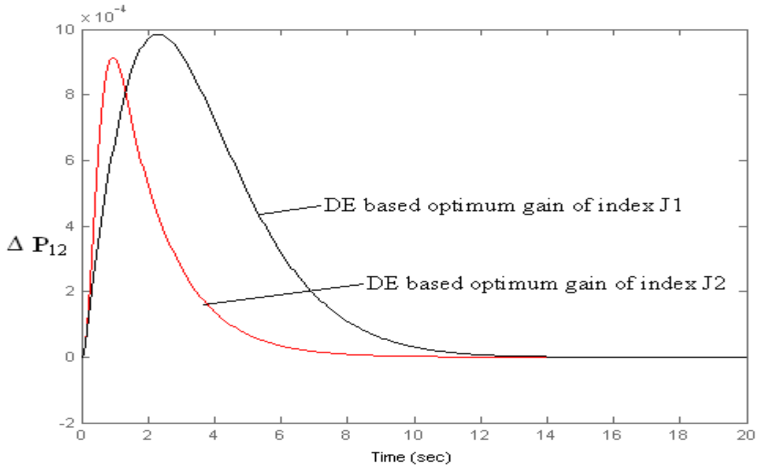

Fig.9: response plot of tie-line power error.

6. Conclusion

The advantage of a DE is simple and effective mutation process. This paper compared DE as an alternative with particle swarm optimization algorithm, to show the advantages of DE. Optimization of PID gains for automatic generation control is carried out using DE and PSO. Results presented in the above section clearly demonstrate the effectiveness and efficiency of DE algorithm. The proposed controller enhanced the performance of AGC systems.

Appendix

Nominal parameters of two area test system [17]:

H_1= H_1= 5 seconds

D_1= D_2= 8.33×10^{-3}P.U. MW/Hz

R_1= R_1=2.4 Hz/P.U. MW
Th_1= Th_2=80 ms
Tt_1= Tt_2=0.3 seconds
Kp_1= Kp_2=120HzP.U. MW
Tp_1= Tp_2=20 seconds
P_s=0.145P.U. MW/Radian
<u>Parameters for DE algorithm:</u>
Initial population= 20
Maximum iteration= 100
Scaling factor F= 0.5
Crossover probability (CR) = 0.98
<u>Parameters for PSO algorithm:</u>
Initial population= 20
Maximum iteration= 100
W_{max}= 0.6, W_{min}= 0.1
C_1= C_2= 1.5

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