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Tuning of PIDPSS employing Tidal Force Firefly Algorithm

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Abstract: *Power consumption is increasing day by day and it necessitates power grids to operate near peak transmission capacities. This leads to more serious transient stability issues caused by disturbances. When large disturbances occur in interconnected power systems the operating point of the system will change and may be displaced from the associated region of stability, if proper stabilization techniques are not employed. The stability of the synchronous generator in the electrical power system will be lost by a non-periodic deviation of the rotor angle, or due to speed deviation oscillatory. Proportional Integral plus Derivative Power System Stabilizers (PIDPSS) with fixed parameters are widely used in the power industry to provide damping to these oscillations, to keep the rate of deviation within limits, thus ensuring stability. When the power system state is close to the equilibrium, PIDPSS are effective. But, in general, they provide conservative regions of stability. To widen the region of stabilitythe parameters of the stabilizers are tuned according to the changes in the operating point. This work attempts to modify firefly algorithm for optimizing the parameters of PIDPSS. Tidal force formula derived from gravitational physics is incorporated for the modification, thus developing Tidal Force Firefly Algorithm (TFFA). Further the concept of Opposition based Reinforcement Learning is introduced ensuring global minimization. The effectiveness of this new modified firefly algorithm, TFFA, for tuning PIDPSS is investigated as applied to SMIB power systems compared to firefly algorithm in practice. TFFA was found more effective than conventional firefly algorithm and the stability limits enhanced substantially.*

Key Word*: Single Machine Infinite Bus; Power System Stabilizer, Firefly Algorithm; Tidal force; Opposition based Reinforcement Learning; Damping.*

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I. Introduction

Power consumption increases day by day and it necessitates power grids to operate near the transmission capacities. This leads to more serious transient stability issues caused by disturbances [1],[2]. When large disturbances occur in interconnected power systems the operating point of the system will change leaving the associated region of stability if proper stabilization techniques are not employed. The stability of the synchronous generator in the electrical power system will be lost by an aperiodic deviation of the rotor angle, or due to speed deviation oscillatory [3],[4]. To provide sufficient damping to these oscillations, to keep the rate of deviation within limits thus ensuring stability, Power System Stabilizers are employed [5],[6]. Proportional Integral Derivative Power System Stabilizers (PIDPSS) with fixed parameters are widely used in the power industry [7].

When the power system state is close to the equilibrium, PIDPSS with fixed parameters are highly effective [8]. But in general, they provide conservative regions of stability. To widen the region of stability, various techniques are employed and one such method is to tune the parameters the stabilizers according to the changes in operating point. This requires continuous monitoring of system parameters as well as tuning of parameters of PSS. Intelligent particle swarm algorithm [9], fuzzy logic tuning [10],[11],[12][13],[14], adaptive fuzzy [15],[16], fuzzy gravitational search algorithm [17], neuro-fuzzy [18],[19],[20], Artificial Bee Colony (ABC) algorithm [21] are some different techniques suggested for tuning PSS for optimized operation over changing operating conditions. ZakirhussainFarhad et al. [22] suggested Firefly algorithm as a better choice for tuning of parameters of PSS after comparing it with other algorithms already reported. ArefYelghi and CemalKose pointed out the limitation of fire fly algorithm based on the selection of initial population. They proposed a modification in firefly algorithm for global minimum optimization [23].

This paper attempts to customize the modification suggested by ArefYelghi and CemalKoseto employ the modified firefly algorithm for tuning PIDPSS. Here the firefly algorithm is modified using tidal force equation and Opposition-based reinforcement learning to ensure global minimum optimization. The new algorithm is tested with Single Machine Infinite Bus (SMIB) power system undergoing symmetrical line fault. Section 2 will give a brief account of modification of algorithm. Section 3 describes the system under study. The results and analysis are given in section 4. The paper is concluded in section 5.

II. Tidal Force Firefly Algorithm

Firefly algorithm (FA) is based on the flashing patterns and behavior of fireflies. The most distinctive features of the Firefly algorithm include discovering the mechanism, the social behavior of fireflies and communication. Following assumptions taken for the development of the algorithm [24],[25]

1. Fireflies are unisexual so that one firefly will be attracted to other fireflies regardless of their sex.
2. The attractiveness is proportional to the brightness and they both decrease as their distance increases. Thus, for any two flashing fireflies, the less bright one will move toward the brighter one. If there is no brighter one than a firefly, it will move randomly.
3. The brightness of a firefly is determined by the landscape of the objective function. The movement of a firefly is attracted to another, more attractive (brighter) firefly is determined via the function$exp^{-\gamma r}$

For updating the attractiveness following equation can be used

$$x_i^{t+1} = x_i^t + \beta exp^{-\gamma r_{ij}^2}\left(x_i^t - x_j^t\right) + \alpha_t \epsilon_t \tag{1}$$

In the above equation the second term gives the variation and third term is representing random move.α_t, is the parameter controlling the step size and $\epsilon_{t,}$ representing a vector drawn from some random distribution. β and γ represent firefly coefficients decided according toimplementation. The distance between any two fireflies x_i and x_j is given by Equation.

$$r_{ij} = \sqrt{\sum_{m=1}^{D}\left(x_{i,m} - x_{j,m}\right)^2} \tag{2}$$

When $\gamma \rightarrow 0$ the firefly algorithm can be viewed as same as standard particle swarm optimization algorithm. The pseudo code for the algorithm is given in shown in Figure 1.Various works are available in literature showing the effectiveness of firefly algorithm in optimization in power systems [26],[27],[28][29]. Here the algorithm is used for optimizing PID coefficients of power system stabilizer.

Tidal Force

The tidal force is a force that stretches a body towards and away from the center of mass of another body due to a gradient (difference in strength) in gravitational field from the other body. It arises because the gravitational field exerted on one body by another is not constant across its parts: the nearest side is attracted more strongly than the farthest side. It is this difference that causes a body to get stretched. The theory of tidal action can be derived from Newton's law of universal gravitation. According to Newtons law there will be attraction between bodies proportional to the product oftheir mass and inversely proportional to the square of the distance between them. The term tidal force is used to describe the forces due to tidal acceleration. By Newton's law of universal gravitation and laws of motion, a body of mass m at distance R from the center of a sphere of mass M feels a force$F_g$given by

$$F_g = -\hat{r}G\frac{Mm}{R^2} \tag{3}$$

here $\hat{r}$ is the unit vector pointing from the body *M* to body *m*. Now dividing by *m* gives the acceleration.

$$a_g = -\hat{r}G\frac{M}{(R\pm\Delta r)^2} = -\hat{r}G\frac{M}{R^2}\frac{1}{(1\pm\Delta r)^2} \tag{4}$$

Expanding

$$a_g = -\hat{r}G\frac{M}{R^2} \pm \hat{r}G\frac{2M}{R^2}\frac{\Delta r}{R} + \cdots \tag{6}$$

```
Begin
    Objective function : f(x), x = (x_1, x_2, x_3, ..., x_d)
    Generate an initial population of fireflies : x_i  (i = 1, 2, 3, ..., n)
    Formulate light intensity I so that it is associated with f(x); I ∝ f(x)
    Define absorption coefficient γ
    While t < MaxGeneration
      for i = 1 : n (all n fireflies)
        for j = 1 : i (n fireflies)
          if (I_j > I_i)
            Vary attractiveness with distance r via exp^{-γr}
            move firefly i towards j;
            Evaluate new solutions and update light intensity;
          end if
        end for j
      end for i
      Rank fireflies and find the current best;
    end while
    Post-processing the results and visualization;
End
```

Figure 1. The Pseudo code for Firefly Algorithm.

In Equation 6, the first term represents the acceleration of the whole-body m and to derive expression for tidal force that can be avoided. As Δr is small, higher order terms of this can be neglected. Hence the tidal acceleration can be given by

$$a_{gtidal} = \pm \hat{r} G \frac{M \Delta r}{R^3} \tag{7}$$

Multiplying the tidal acceleration with mass m will give tidal force. Hence the tidal force can be given by the derivative of gravitational force. It can also be taken as ΔF_g and can be represented as

$$F_{tidal} = \frac{GMm\Delta r}{R^3} = F_{near} - F_{far} \tag{8}$$

Generalizing as the tidal force due to a mass m_2 on the surface particle on m

$$F_{tidal} = \frac{Gm_2 m}{R_U^2} - \frac{Gm_2 m}{R_L^2} \tag{9}$$

where R_U and R_L are near and far distances. This concept of distances is illustrated in Figures 2 and 3.

Theabove concept Tidal Force can be incorporated in firefly optimization by viewing attraction between fireflies within the above framework. Fireflies are getting attracted by the brightness of the other. Decreasing the distance of one firefly with another can also be considered as increasing brightness.Let the population$x = (x_1, x_2, \dots, x_n)$ Each individual in the population $X = (x_{11}, x_{12}, \dots x_{1d})$ if d is the number of population (dimension) in each *x*. During iterations, fireflies are considered in pair and if one of the pair is less than the other it would be selected for new movement in all dimensions. Now the distance is computed between fireflies in pairwise.

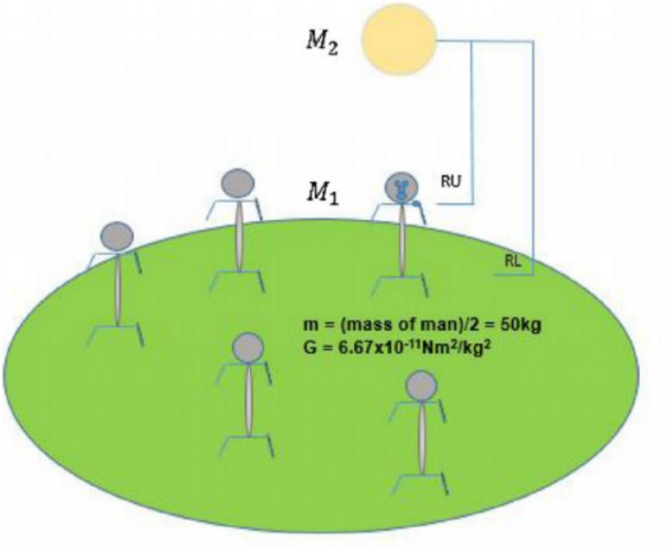

Figure 2. Tidal force on surface of earth: concept of R_U and R_L

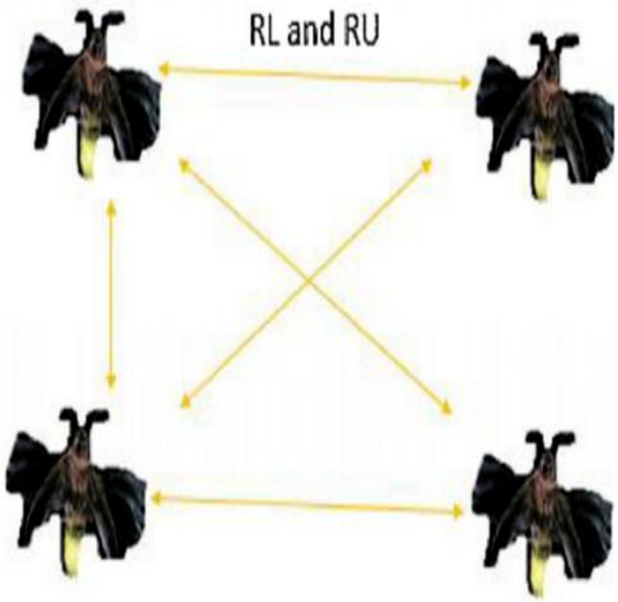

Figure 3. The concept of R_U and R_L in Firefly attraction.

Initially the pairwise vector *A* is taken and then it is converted to *B* in such a way by inverting each element since the attraction/brightness is inversely proportional to the distance.

$$\begin{bmatrix} x_{1,1} & x_{1,2} \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} \cdots & x_{2,n} \\ \vdots & \ddots & \vdots \ \vdots \\ x_{m,1} & x_{m,2} \cdots & x_{m,n} \end{bmatrix} \Rightarrow \begin{bmatrix} \frac{1}{x_{1,1}} & \frac{1}{x_{1,2}} & \cdots & \frac{1}{x_{1,n}} \\ \frac{1}{x_{2,1}} & \frac{1}{x_{2,2}} & & \frac{1}{x_{2,n}} \\ & \vdots & \ddots & \vdots \\ \frac{1}{x_{m,n}} & \frac{1}{x_{m,2}} & \cdots & \frac{1}{x_{m,n}} \end{bmatrix} \tag{10}$$

$$V_i = \begin{bmatrix} \frac{1}{x_{i,1}} & \frac{1}{x_{i,2}} \cdots & \frac{1}{x_{i,n}} \end{bmatrix} \quad (11)$$

Where V_i is the i[th]vector. Gaining the far and near distances in each dimension with two different vectors/fireflies,

$$R_L = w = Max(V) \quad (12)$$

and

$$R_U = z = Min(V) \quad (13)$$

Now the tidal force can be calculated using Equation 9. In Equations 12 and 13 the w and z are maximum and minimum distances and the deviation dw and dz are step movements in respective directions. Then the difference between this step movements will give dx.

$$dz = 2Gm_1m_2z \quad (14)$$

$$dw = 2Gm_1m_2w \quad (15)$$

$$dx = dz - dw = 2Gm_1m_2z - 2Gm_1m_2w \quad (16)$$

Here the movement of the firefly is depending on G, m_1 and m_2. Since R_U and R_L are coming denominator of the equations, the values of these variables should be kept nonzero. This is controlled by the equation $R_L \neq R_U$in the program and one (1) is added to R_L and R_U.

Opposition-based Reinforcement Learning

As in any optimization algorithm the initial population is a random guess. In absence of any prior knowledge on where the system must converge it is not possible to have the best initial guess. Hence the algorithm should look in all directions, including the opposite direction also. Hence the concept of Opposition-based reinforcement learning [30],[31],[32] is introduced in the algorithm. This can be explained as follows. Let x be a real number such that$x \in [m, n]$. Then the opposite number will be

$$\tilde{x} = m + n - x \quad (17)$$

In the D dimensional space, the same relationship can be generalized as

$$\tilde{x_i} = m_i + n_i - x_i \quad (18)$$

Where $i = 1, 2, \ldots, D$

After finding the Opposite of x_i the fitness function for this will be found, then if it is more optimum then the $x_i$will be replaced by the opposite. Hence the system will converge to the desired optimum even if the initial population is taken in the farthest end. Now the pseudo code for modified Firefly algorithm, Tidal Force Firefly Algorithm (TFFA) is given in Figure 4.

```
Begin
  Objective function f(x), x = (x_1, x_2, x_3, ..., x_n)^T
  Generate initial population of fireflies x_i (i = 1, 2, 3, ..., n)
  Calculate opposite of population in fireflies x̃_i ( Equations 5.18 and 5.19)
  Evaluate the fitness of both population x_i and x̃_i
  select the one of x_i and x̃_i based on finess function
  Define various variables G, m_1, m_2, α, MaxGeneration, nVar and β
  Tidal Force I_i at x_i is
  Define light absorption coefficient γ
     While (t < MaxGeneration)
        For i = 1 : n  all n fireflies
          For j = 1 : n  all n fireflies (inner loop)
            If (I_i ≠ I_j)
            If(I_i < I_j), Move firefly towards j; end if
            For k = 1 : nVar all n fireflies (innerloop)
            Vary attractiveness with distance r
            Evaluate new solutions and update Tidal Force
            End for k
            end if
          end for j
       end for i
    Rank the firefly and find the current global best g
    End While
  Post process results and visualization
End
```

Figure 4. Pseudo code for Tidal Force Firefly Algorithm.

III. System Under Study

In this study aSMIB power system model as shown in Figure 5, is used to evaluate the performance of powersystemstabilizer.Where R_e and X_e are in order the transmission line resistance and reactance. The V_B and V_G areinfinite bus voltage and terminal voltage of generator, respectively. The switches S_1, S_2 and S_3 arerepresenting switching between different algorithms for tuning of PIDPSS. The third order model synchronous generator [33] is taken for simulation. Also, IEEE's Type 1 exciter model is utilized for simulation. The system equations are given in Equations 19 to 22.

$$\dot{\omega} = \frac{1}{M}(T_m - T_e - T_e) \tag{19}$$

$$\dot{\delta} = \omega_b(\omega - 1) \tag{20}$$

$$\dot{e_q'} = \frac{1}{T_{d0}}\left[E_{FD} - e_q' - X_d - X_d'\right] \tag{21}$$

$$\dot{E_{FD}} = \frac{1}{T_A}\left[K_A\left(V_{ref} - V_t - U_{PSS}\right) - E_{FD}\right] \tag{22}$$

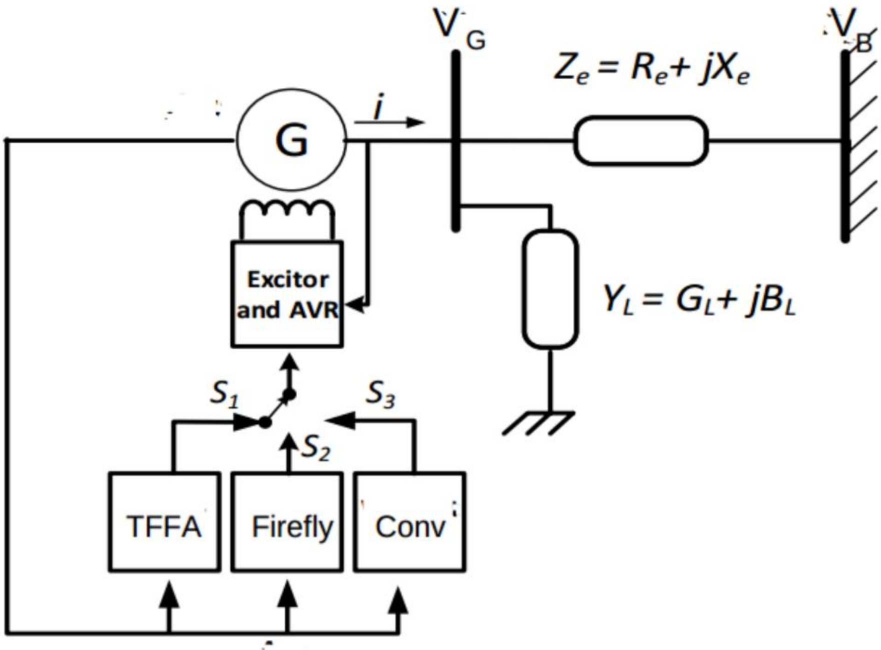

Figure 5. System under study. SMIB power system with PSS tuned with different algorithms.

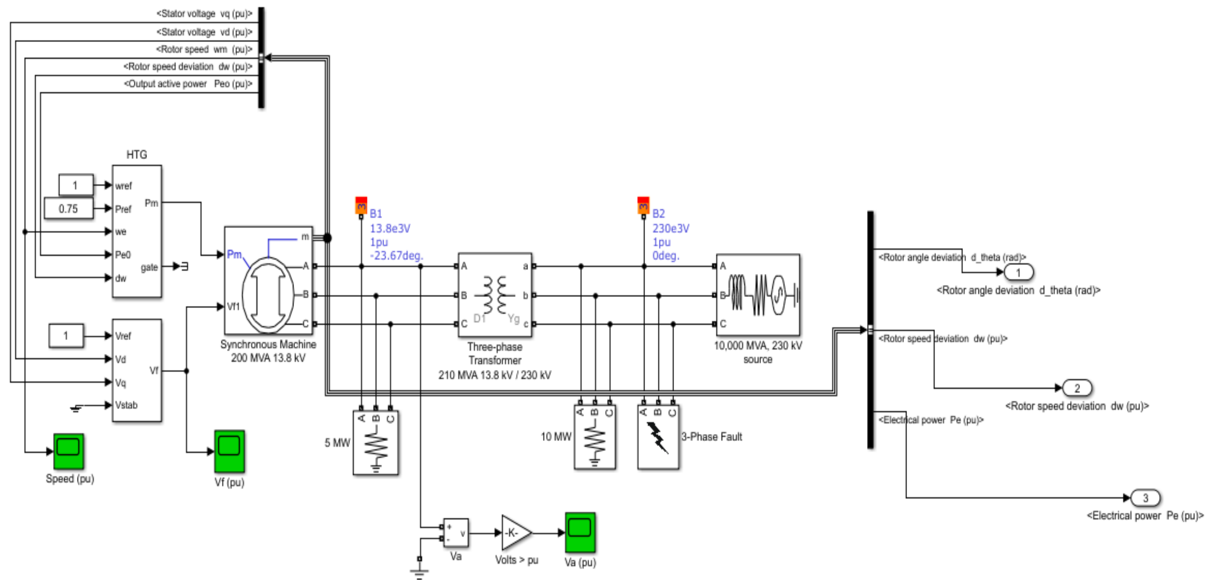

Figure 6. The SIMULINK block diagram of the SMIB system simulated for the study.

where δ is the rotor angle in rad, ω is the generator speed in rad/s, $eq\,'$ is the generator voltage in q-axis and E_{FD} is the output voltage of exciter. T_m, T_e and T_d are the mechanical, electrical, and damping torque respectively. X_d and $X_d^{'}$ is generator's synchronous reactance and transient reactance in d-axis, V_t,V_{ref} and U_{PSS} are the terminal, reference and power system stabilizer output voltages respectively. T_A and $T_{d0}^{'}$ are the time constants of the exciter and generator model. The system is simulated using MATLAB and SIMULINK package. The SIMULINK block diagram of the SMIB power system under study is given in Figure 6.

200 MW, 13.8 KV Synchronous machine connected to the infinite bus with 10,000MVA, 230KV capacity is simulated. 5MW symmetrical load is connected at generator terminal and 10MVA load after transformer with rating 210MVA and 13.8KV/230KV. 3phase symmetrical fault with fault resistance 1mOhm is utilized for study. SMIB system data given in Table 1, is same as in [47]

X_d = 1.97puX_q = 1.90 pu X_d' = 0.30 pu	T_{d0}' = 6.84 sK_A = 100 T_A = 0.02 s	$E_{FD}min$ = −5 pu $E_{FD}max$ = 5 pu ω_0 = 2π × 50 $radsec$.

Table 1. SMIB power system data used for simulation

Objective Function

PIDPSS is tuned to obtain optimized values of K_p, K_i and K_d the proportional, integral and derivative gains of the power system stabilizer. The purpose of power system stabilizer is to provide an additional input to the regulator to damp power system oscillations. Rotor angle deviations, rotor speed deviations, accelerating power, frequency deviation etc. are used as input for PSS singly or in combination. Here Δω the speed deviation is fed back as the single input. For tuning the parameters, a combination of rotor angle deviations, rotor speed deviations anddeviation in power is taken as objective function. The objectivecost function utilized here is given in Equation 23.

$$J = \int_0^t (G_1\Delta\delta + G_2\Delta\omega + G_3\Delta P)dt \quad (23)$$

Where the weighting factors are taken as G_1=1,G_2=100 andG_3= 10.

IV. Results and Analysis

The configuration of SMIB power system as in Figure 1 is used for the simulation. The reactance of the transmission line is 0.4 per unit. The power output is taken as 0.8per unit. The PIDPSS parameters with out tuning, tuned with Firefly algorithm and Tidal Force Firefly Algorithm are found out. Optimized values of objective cost function are also evaluated. The values obtained as per tuning is tabulated in Table 2. A Symmetrical earth fault with fault resistance of 1mΩ is simulated at 2 msec for the analysis. The time response of rotor angle, rotor speed and power delivered are plotted for PIDPSS with fixed parameter, tuned with firefly algorithm and tuned with TFFA. The responses are presented in Figures 7, 8 and 9.

From above responses it is evident that the rotor angle, speed as well as the power delivered are converging to the steady state values in a faster way for PIDPSS tuned with TFFA than tuned with firefly algorithm. Both firefly and TFFA tuned PSS's are giving faster convergence compared to fixed parameter PIDPSS. Overshoot and oscillations are also reduced in TFFA than firefly tuned PSS. The TFFA is improving the stability of the system to a great extent. As seen in Table 2 the objective cost function with TFFA is giving the minimum value and that also proves the effectiveness of the modified algorithm.

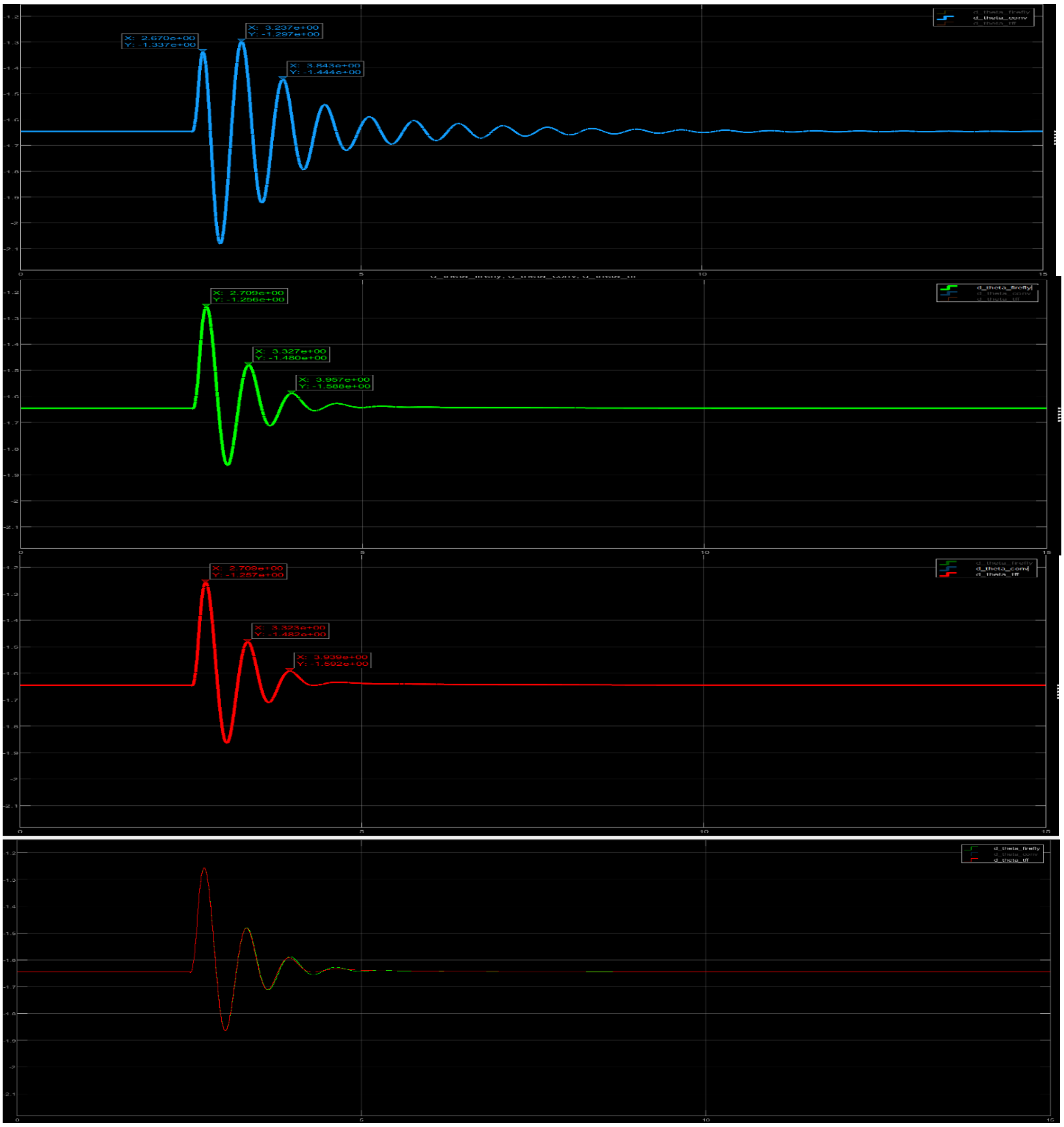

Figure 7. The time response plotted for Rotor angle with PIDPSS with fixed parameters, parameters tuned with firefly, parameters tuned with TFFA and combined plot (top to bottom respectively)

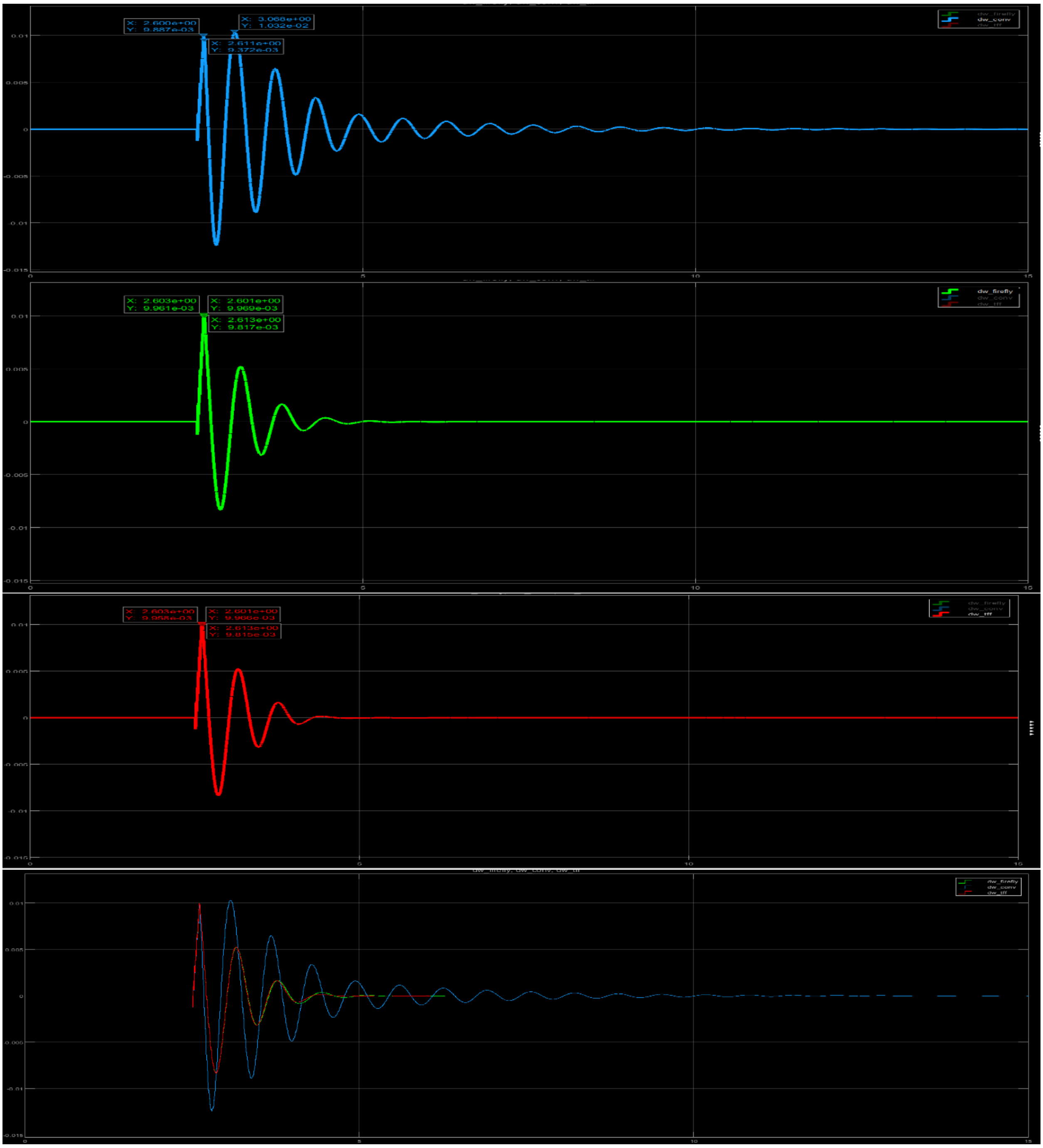

Figure 8. The time response plotted for Rotor speed with PIDPSS with fixed parameters, parameters tuned with firefly, parameters tuned with TFFA and combined plot (top to bottom respectively)

Figure 9. The time response plotted for Power delivered with PIDPSS with fixed parameters, parameters tuned with firefly, parameters tuned with TFFA and combined plot (top to bottom respectively)

	Fixed Parameter	Tuned with Firefly	Tuned with TFFA
K_p	1.163	1.6199	2.9345
K_i	0.105	0.8248	2.2415
K_d	0	0.0051	0
Objective Cost	37.78	30.12	29.54

Table 2. Parameters of PIDPSS with out Tuning and tuned with firefly algorithm and TFFA

V. Conclusion

This work presents a new modification of firefly algorithm employing Tidal Force function and Opposition-based reinforcement learning for tuning of PIDPSS. The effectiveness of the modified algorithm, TFFA is tested with SMIB power system undergoing symmetrical earth fault simulated using MATLAB and SIMULINK package. Time response of the system for rotor angle, rotor speed and power delivered are plotted and analyzed. The stability of the system gets improved with PIDPSS tuned with TFFA. The new algorithm gives a better minimum for the cost function.

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