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Design and performance analysis of a PID controller by using Differential Evolutionary Algorithm for an Autonomous Power System

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ABSTRACT- **In this paper we present the design and performance analysis of a Proportional Integral Derivate (PID) controller for the Autonomous Power system model using Differential Evolutionary Algorithm (DEA) for optimization of different parameter that can be tuned to improve the performance of the system studied. Differential evolutionary algorithm is a branch of evolutionary algorithm which is quiet capable of handling non-differentiable, non-linear and multi-modal objective function which indeed makes tuning of controller behavioral parameters easier. The optimization problem is formulated by considering the design problem of the proposed PID controller and DEA algorithm has been employed for the search of optimal controller parameters. A new objective function has been proposed in this paper for yet some improvement in the response for the tuned parameters generated. The model used to study here simulates the effect of change in terminal voltage on the main supply system and a diesel generator which act as a distributed generation and responds to the change in power demand. The study of this paper is based on deviation of terminal voltage for any input perturbation. The major objective of the paper is to tune the controller behavioral parameters such that the fluctuation of the terminal voltage can be controlled. It has been revealed by the analysis results that the proposed DEA based tuning of PID controller for the Autonomous Power system performs better than the algorithm used for the comparison which too is a population based optimization algorithm. SOA (Seeker Optimization Algorithm) is used for comparison.**

Keywords: Autonomous Power System, Differential Evolutionary Algorithm (DEA), PID controller, strategy adaptation, Adaptive parameter control, operating condition.

I. INTRODUCTION

Due to shortcomings of the conventional sources, research has hence been extended to these fields of non-conventional sources of energy, most of which are available very close to the consumer. These sources being quiet close to the point of demand makes them efficient sources for reliable and emergency power supply. These sources would supply power with minimum transmission loss. Thus better and better means are being developed to convert this energy from these non-conventional sources [1, 15] to usable electrical energy (i.e. electricity at a frequency of 50 Hz, sinusoidal in nature and with least harmonics). This conversion of energy from different sources to electrical energy can be termed as Distributed Generation.

These energy sources are naturally distributed over the earth, and can be harnessed are per the demand and need of electricity by the consumer. They act in a form of Autonomous Power System which has been represented in the figure 1. It is not much dependent on the main supply from the grid and can supply power for connected loads.

The PID controller is so taken that its parameter when optimized would improve the response of the Autonomous Power System [7, 14]. This optimization of the controller behavioral parameters such as K_P, K_D, K_I using Differential evolutionary algorithm would fulfill the above objective. The other parameter of the different blocks i.e. amplifier, exciter, sensor, generator, inertia and load blocks of the used model are summarized in table 1.

II. AUTONOMOUS POWER SYSTEM MODEL INTENDED FOR THE DESIGN

This power system model of a typical DEG, considering diesel generator as a DG source which respond to change in load demand, consists of a speed governor and an AVR with a PID controller [2, 9] is considered in the present work and is presented in Fig. 1. The upper half part of the blocks in the model shown in Fig. 1 represent the standard mechanical model for a DEG with a speed governor. The speed governor has Parameters such as the droop R and a K_{ii} the tunable integral control gain. The integral controller eliminates the steady-state frequency error of the studied model and this is the sole objective of this integral controller. The lower half part of the blocks in the model of Fig. 1 represent the electrical model for a DEG with an Automatic voltage regulator (AVR). The probable transfer function for the PID controller is as in (1) with the parameters K_P, K_D, K_I which are tunable.

$$G_{PID}(s) = K_P + \frac{K_i}{s} + sK_d \tag{1}$$

Table 1 summarizes the limits of the parameters in the transfer functions in (1) and the limits of other parameters for the different components of the blocks in the studied autonomous power system model [2,16].

IV. MATHEMATICAL PROBLEM FORMULATION

The major objective of the study of the autonomous power system represented by figure 1 is to improve the Degree of relative stability and damping of electromechanical oscillation. In this model studied parameters such as Kp, Ki, Kd, Kii are tuned and parameters like maximum peak overshoot, maximum undershoot and settling time are optimized(minimized). As minimizing peak overshoot and undershoot shows better damping of electromechanical oscillation and that of settling time provides better relative stability for a transient disturbance [5, 6].

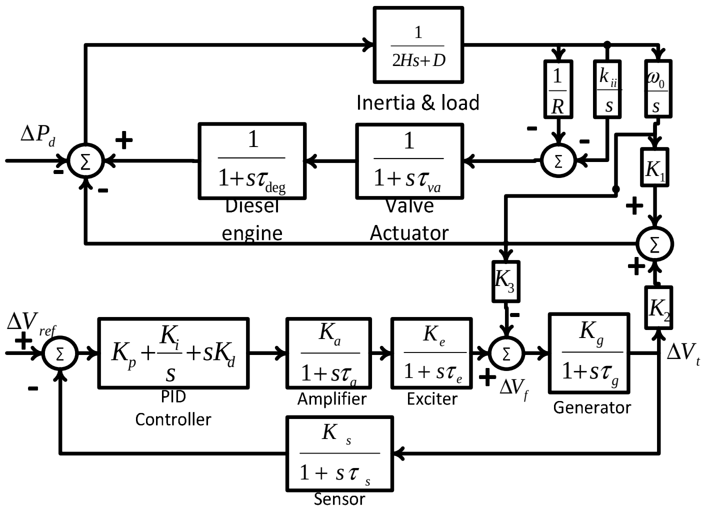

Figure 1: Block diagram of the studied autonomous power system.

III. CONSTRAINTS OF PROBLEM

The tunable behavioral parameter for the intended power system model can thus be tuned within limits which are given by the following equation.

$$\{K_p^{min}, K_i^{min}, K_d^{min}, K_{ii}^{min}\} \le \{K_p, K_i, K_d, K_{ii}\} \le \{K_p^{max}, K_i^{max}, K_d^{max}, K_{ii}^{max}\}$$

So the constrained optimization problem has been limited by the above equation. Where K_p^{min}, K_i^{min}, K_d^{min}, K_{ii}^{min} are the minimum value and the maximum value are K_p^{max}, K_i^{max}, K_d^{max}, K_{ii}^{max} for the parameters K_P, K_D, K_I, K_{ii}

which are to be tuned. So it can be concluded that the tunable parameter can be optimized by minimizing the 'M' value.
Transfer function and parameter limits of different parameters studied in this autonomous power system are given in Table 1[12, 16].

Table 1

Component	Transfer function	Parameter limits
PID controller	$G_{PID} = K_p + \frac{K_i}{s} + sK_d$	$0.0001 \le K_p, K_i, K_d \le 1.0$
I controller	$G_I(s) = \frac{K_{ii}}{s}$	$0.0001 \le K_{ii} \le 1.0$
Amplifier	$TF_{amplifier} = \frac{Kg}{(1+s\tau_a)}$	$10 \le K_a \le 40; 0.02s \le \tau_a \le 1.0s$
Exciter	$TF_{exciter} = \frac{K_e}{1+s\tau_e}$	$1 \le K_e \le 10; 0.4s \le 1.0s$
Sensor	$TF_{sensor} = \frac{K_s}{1+s\tau_s}$	$0.001s \le \tau_s \le 0.06s$
Generator	$TF_{generator} = \frac{K_g}{1+s\tau_g}$	K_g depends on load (0.7-1.0); $1.0s \le \tau_g \le 2.0s$
Diesel engine generator	$TF_{\deg} = \frac{1}{1+s\tau_{\deg}}$	$\tau_{\deg} = 2.31s$
Valve actuator	$TF_{valveactua\ tor} = \frac{1}{1+s\tau_{va}}$	$\tau_{va} = 0.82s$

IV. OBJECTIVE FUNCTION

A multi-objective objective function used in this paper has been formulated by considering the different parameters of the response produced by the studied autonomous power system model. It has been represented below in the following equations

Minimize $M = [T_R + T_P + OS + T_S + IAE - US] \times 10^{-3}$ **(2)**

$T_R = T_r \times 10^3$; where T_r is the rise time for the system response, it is the time required by the response to reach from 10% to 90% of steady state value. Reducing this value would reduce the time taken by the system to respond to any disturbance produced.

$T_P = T_p \times 10^3$; where T_p is the time taken by the response to reach the peak value i.e. peak time. This too reduces the response time. Hence improves the relative stability of the system.

$OS = OS_{max} \times 10^5$ is the maximum peak overshoot produced by the response in the first cycle. Minimization of this objective function will minimize the maximum peak overshoot.

$US = US_{max} \times 10^3$ is the maximum undershoot. Reducing this value reduces the mechanical oscillations.

$T_S = T_s \times 10^3$; where T_s is the settling time of the response after being subjected to any external disturbance.

IAE = iae $\times 10^3$ where iae is the integral average error.

Suitable weight has been multiplied to each of these parameters so as to make them mutually comparative. It can be observed that by optimizing the objective function M, the closed loop poles of the system would moved further left of the jω axis and also a reduction in the imaginary part of the poles can be observed as damping increases and there is increase in damping ratio. Thus it can be observed that there is enhancement of relative stability [5, 8]. The reduction of overshoot and undershoot reduces mechanical oscillation due to external disturbance to the system.

V. DIFFERENTIAL EVOLUTION AND ITS APPLICATION TO OPTIMIZATION PROBLEM IN THIS PAPER

Differential Evolution (DE) algorithm is one of the population-based stochastic optimization algorithm recently introduced [3, 4]. Advantages of DE are: simplicity, efficiency & real coding, easy use, local searching property and speediness. DE works with two populations; old generation and new generation of the same population. The size of the population is adjusted by the parameter N_P. The population consists of real valued vectors with dimension D that equals the number of design parameters/control variables. The population is randomly initialized within the initial parameter bounds. The optimization process is conducted by means of three main operations: mutation, crossover and selection. In each generation, individuals of the current population become target vectors. For each target vector, the mutation operation produces a mutant vector, by adding the weighted difference between two randomly chosen vectors to a third vector. The crossover operation generates a new vector, called trial vector, by mixing the parameters of the mutant vector with those of the target vector. If the trial vector obtains a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation. The evolutionary operators are described below [3, 4].

INITIALIZATION

For each parameter j with lower bound X_j^L and upper bound X_j^U, initial parameter values are usually randomly selected uniformly in the interval [X_j^L, X_j^U].

MUTATION

For a given parameter vector $X_{i,G}$, three vectors ($X_{r1,G}$ $X_{r2,G}$ $X_{r3,G}$) are randomly selected such that the indices i, $r1$, $r2$ and $r3$ are distinct. A donor vector $V_{i,G+1}$ is created by adding the weighted difference between the two vectors to the third vector as:

$$V_{i,G+1} = X_{r1,G} + F.(X_{r2,G} - X_{r3,G}) \tag{10}$$

Where F is a constant from (0, 2)

CROSSOVER

Three parents are selected for crossover and the child is a perturbation of one of them. The trial vector $U_{i,G+1}$ is developed from the elements of the target vector ($X_{i,G}$) and the elements of the donor vector ($X_{i,G}$).Elements of the donor vector enters the trial vector with probability CR as:

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} & \text{if} \quad rand_{j,i} \le CR \\ & \quad \text{or} \quad j = I_{rand} \\ X_{j,i,G+1} & \text{if} \quad rand_{j,i} > CR \\ & \quad \text{or} \quad j \ne I_{rand} \end{cases}$$

…….. (11)

With $rand_{j,i} \sim U(0,1)$, I_{rand} is a random integer from $(1,2,.....D)$ where D is the solution's dimension i.e. number of control variables. I_{rand} is to ensure that $V_{i,G+1} \ne X_{i,G}$.

SELECTION

The target vector $X_{i,G}$ is compared with the trial vector $V_{i,G+1}$ and the one with the better fitness value is admitted to the next generation. The selection operation in DE can be represented by the following equation:

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if } f(U_{i,G+1}) < f(X_{i,G}) \\ X_{i,G} & \text{otherwise.} \end{cases} \quad (12)$$

where $i \in [1, N_P]$.

VI.APPLICATION OF DIFFERENTIAL EVOLUTION TO STUDY THE AUTONOMOUS POWER SYSTEM

Implementation of DE would requires the determination of six fundamental issues: DE step size function also known to us scaling factor (*F*), crossover probability (*CR*), the number of population (N_P), initialization, termination and evaluation function. The scaling factor is a value within the range (0, 2) that would control the amount of perturbation in the mutation part of the algorithm. Crossover probability (*CR*) constants are generally chosen from the interval (0, 1) [10, 18]. DE offers several variants or strategies for optimization denoted by DE/x/y/z, where x=vector used to generate mutant vectors, y = number of difference vectors used in the mutation process and z = crossover scheme used in the crossover operation. In the present study, a population size of N_P = 50, generation number G = 100. The strategy employed is: - DE/best/1/bin. Optimization is terminated by the pre-specified number of generations for DE. In fact the strategy has been varied to predict the best possible strategy[11, 13]. One of the important factors that affect the optimal solution is the range for unknowns. For the initial step of execution for the program, a wider solution space can be considered and after getting the solution we can shorten the solution space near to the values obtained in the previous iteration. Here the upper and lower bounds of the gains were chosen as (1, -1). The optimization was repeated 100 times and the best final solution among the 100 runs has been chosen as proposed controller behavioral parameters.

VII. SIMULATION RESULT

The strategy of the algorithm has been varied at CR=0.8 and F=0.8 and the result has been summarized as in table 2 [13].

TABLE 2

STRATEGY	AVG	MIN	MAX	STDEV
1	1.2461	0.8794	4.8107	0.59043
2	1.2898	0.89451	6.0522	0.79517

3	**1.5158**	**0.86872**	**6.6908**	**1.199**
4	1.4495	0.94202	5.9924	1.0143
5	1.2898	0.89451	6.0522	0.79517
6	**1.5158**	**0.86872**	**6.6908**	**1.199**
7	1.4495	0.94202	5.9924	1.0143
8	1.2231	0.9208	7.4516	0.66353
9	1.3278	0.8688	6.0209	0.83234
10	1.3249	0.99437	5.5609	0.80657

From the above table it can be distinctly viewed that strategy 3 and 6 result in best values of the objective function and graphical comparison of some of the better results has been shown in the figure 2.

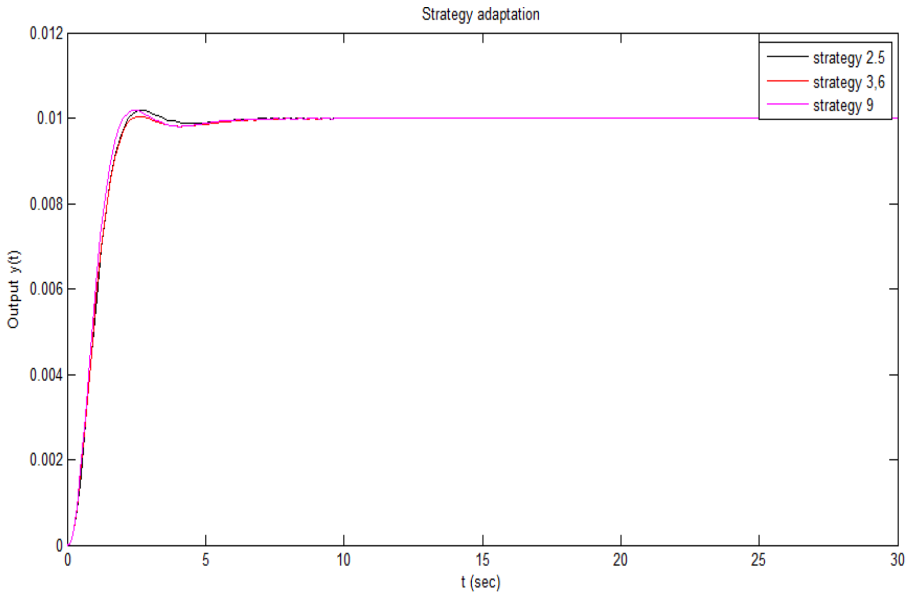

Figure 2: Variation of response as the Strategy changes

TABLE 3

Parameter		MIN	St.Dev	Other parameter
CR=0.1	F=0.8	0.009551	0.030422	F=0.1-1.0 NP=20 Ng=100
CR=0.2	F=0.8	0.009493	0.021979	
CR=0.3	F=0.2	0.009528	0.001158	
CR=0.4	F=0.4	0.009572	0.045994	
CR=0.5	F=0.8	0.009570	0.042119	
CR=0.6	F=0.8	0.009551	0.047353	
CR=0.7	F=0.7	0.009528	0.13676	
CR=0.8	F=0.6	0.009591	0.034636	
CR=0.9	F=0.6	0.009544	0.022649	
CR=1.0	F=0.7	0.009493	0.052084	

The data in table 3 represent the variation of the response with change in the cross over probability value (CR) and scaling factor (F). The controller parameters are thus optimized so as to get optimum working condition for the system. The best of the result is thus found with CR = 0.2 and F = 0.8. So the corresponding values of K_p , K_i , K_d , K_{ii} would be the optimum tuned parameter for the autonomous power system model studied.
The optimum values of K_p , K_i , K_d , K_{ii} obtained by SOA is 0.1000, 0.0947, 0.0050, 0.1000 respectively [12] and that obtained by DEA is 0.19996, 0.13559, 0.0086046, 0.14257 respectively.

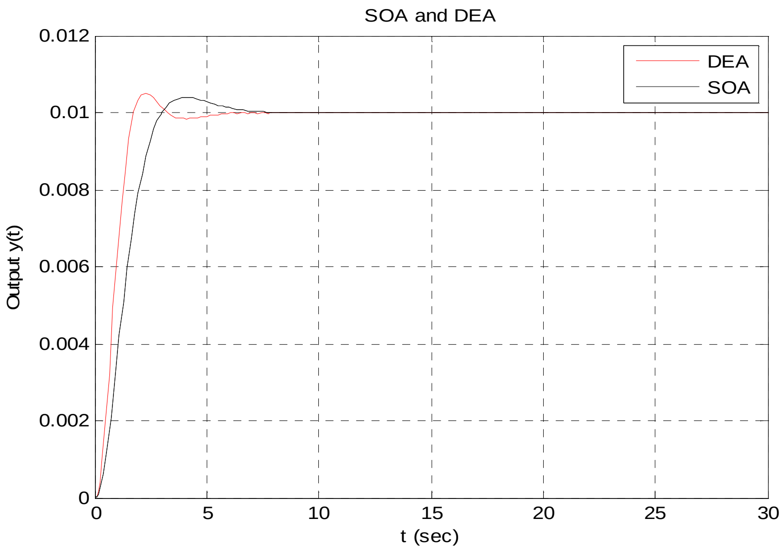

Figure 3: Comparative study of SOA and DEA

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The corresponding values of Rise time (T_r), Peak time (T_p), Maximum peak overshoot (OS), Peak undershoot (US), Settling time (T_s) for SOA and DEA respectively are:

TABLE 4

	DEA	SOA
T_r	0.12	0.22
T_p	0.38	0.60
OS	4.9968×10^{-4}	3.9331×10^{-4}
US	-1.7201×10^{-4}	-4.4949×10^{-6}
T_s	0.44	0.76

In the figure 3 and table 4 it can be easily observed that the graph and the values indicated by the DEA is better as compared to that of SOA. Thus it would be better optimization tool in this case study of autonomous power system. These set of data are obtained by substituting the values of K_p , K_i , K_d , K_{ii} in the power system model.

VIII. CONCLUSION

In this paper a analysis of performance and the effect of different perturbation in the autonomous power system model are done.

a. The strategy is so varied as the performance of the system can be optimized and this could be done with using strategy 3 or 6 as both provide similar results under similar operating condition.

b. Results provided in this paper by DEA are compared to SOA, so that a comparative study of performance of the model can be made.

c. Different tunable parameters were optimized by using DEA for the autonomous power system model which is used for studying the case.

Tunable parameters such as K_p , K_i , K_d , K_{ii} are tuned using DEA produced better result than that of the values obtained in SOA.

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