Model Order Reduction Using Hybrid Optimization Algorithm

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Abstract - In this paper presents a model order reduction technique for the reduction of linear higher-order continuous systems. Optimization technique used in development of reduced model is a combination of particle swarm optimization and differential evolutionary algorithm by minimizing the integral square error (ISE). Application and efficaciousness of the method is given by illustrating typical numerical examples.

Keywords - Particle Swarm Optimization(PSO),Differentially evaluation(DE) algorithm, impulse response energy(IRE), Error minimization, continuous Linear-time invariant systems, integral square error(ISE).

I. INTRODUCTION

Many modern mathematical models of real-life processes posses challenges when used in numerical simulations, due to complexity and large size dimension. Model Order Reduction aims to lower the computational complexity of such problems, for example, in simulations of large-scale dynamical systems and control systems. As more complex systems are modeled mathematically, it usually becomes necessary to use reduced-order modeling techniques that are sufficiently accurate and easy to implement. Consequently, interest has been shown recently in the development of optimal order reduction methods using a frequency domain approach. The complexity often makes it difficult to obtain a good understanding behavior of a system. So there is a requirement for effortless, reasonable cost, and faster simulation approach of large inter connected systems. This is attained by producing an lower order system that preserves the entire approximate properties of a given higher order model. Distinct methods of order reduction are existing in the literature [1-12] and each method is entirely unique in its individual approach. All these methods vary in terms of the system design features specifically matching steady-state conditions, stability, time response, and frequency response of reduced systems. To improve the mapping between original system and lower order model some of the combinational methods were developed, where the denominator polynomial obtained by retaining the stability of higher order system while the numerator polynomial is obtained using mixed method with easy numerical implementation.

Evolutionary algorithm namely particle swarm optimization (PSO) and genetic algorithm (GA) techniques are being prominent in area of research, optimization supposed as dominant techniques to obtain optimal solution to large number of problems as well as the order reduction of large-scale systems. These all methods are implemented based on the minimization of the integral square error (ISE). In spite of these optimization techniques, researchers are annoying to get a global optimization method that can be adaptable different problems and provide good results. The mutual combination of both PSO and DE gives very powerful global search algorithms. In PSO saves the limited computational source by restricting the particles from visiting the unused regions in the search space. The velocity scheme of PSO is updated by incorporates the differential vector operator barrowed from the DE. So this algorithm named as PSO-DV.

The main aim of the paper is to simplify the linear higher order continuous-time single input single output SISO system is to determine an optimal reduced-order model through minimizing of the integral square error(ISE), using the PSO-DV algorithm. In the process of this algorithm, the reduced order model numerator and denominator coefficients are taken as free parameters for ISE optimization. The ROM coefficients initialization/selection has to be done carefully so as to satisfy the R–H stability condition. The final ROM coefficients are obtained such that to optimize the ISE value. Due to this, the method has an inbuilt stability and accuracy preserving features. The application of this method is shown by illustrating one single area LFC & one typical numerical example taken from the literature.

II. PSO-DV Algorithm

The canonical PSO algorithm [13] updates the velocity of a particle using three steps. The first step contains past velocity term that contains the particle with the necessary momentum. Remaining two are the social and cognitive steps that are focused mainly on the cooperation of the particles. With memory size, each particle can track its own best performance and it is achieved in its surrounding throughout its lifespan. However, the particles in optimization are not terminated even though they have worst fitness and thus waste the limited computational resources. The velocity of the particles gets changes suddenly for small changes in weight 'W'. Hence, the benefit of the DE algorithm can compensate for the PSO's shortcoming. Then the motivation is to develop for a hybrid algorithm based on PSO and DE.

Based on the compound properties of PSO and DE, connect a differential operator with the velocity-updated PSO and proposed a new hybrid evolutionary algorithm named as a PSO-DV algorithm. The operator is invoked on the position vectors of two randomly chosen particles (population-members), not on their individual best positions. Further, unlike the PSO scheme, a particle is actually shifted to a new location only if the new location leads to a better fitness value, i.e. a selection process has been incorporated into the swarm dynamics.

III. APPLICATION OF PROPOSED METHOD

3.1 Model Order Reduction Method Using PSO-DV Algorithm

Consider a n^{th}-order linear dynamic system represented by:

$$Gn(s) = \frac{Y(s)}{U(s)} = \frac{a_{n-1}s^{n-1} + \cdot\cdot\cdot + a1s + a0}{b^n s^n + b_{n-1}s^{n-1} + \cdot\cdot\cdot + b1s + b0}$$

The aim is to find the r^{th}-order reduced model that has a transfer function *(n>r)*:

$$R(s) = \frac{Yr(s)}{U(s)} = \frac{c_{r-1}s^{r-1} + \cdot\cdot\cdot + c1s + c0}{s^n + d_{r-1}s^{r-1} + \cdot\cdot\cdot + d1s + d0}$$

The evaluation of successful reduced-order model (ROM) coefficients is done by reducing the integral square error (ISE) [10] between the step response of the actual system $G_n(s)$, and the reduced-order model *R(s)* using PSO-DV algorithm. The Integral square error is defined by

$$\text{ISE } (E) = \int_0^\infty [e(t)]^2 \, \text{dt.} = \int_0^\infty [\text{y(t)} - yr\ (t)]^{\,2} * dt = \sum_{i=1}^{n+r} \frac{\delta i^2}{2\gamma i}$$

Where y(t) and y_r (t) are the unit step responses of the actual system $G_n(s)$ and reduced model R(s)respectively.

The stability of the system steady state form the transaction state of initial state is given by the step response.

The main aim of this model order reduction method is to find an optimal reduced-order model for the given linear higher –order continuous-time varying system by keeping the stability of the system in the reduced-order model. The transfer function components in numerator and denominator of the reduced-order model are considered as free components in the optimization process. The PSO-DV optimization algorithm is used to search for accurate reduced-order model coefficients within the tolerable limits for which the ISE between the actual system and the reduced-order model step responses is reduced. The stability of the reduced-order model is maintained by choosing proper denominator polynomial coefficients within the tolerable limits of the search process, so that it satisfies the R–H stability condition.

To keep the steady-state response of the actual system in the reduced model, the following condition must be included when determination of the numerator coefficient (c_0) of the reduced-order model.

$$\boldsymbol{C_0} = \frac{a_0}{b_0} d_0$$

Step 1:

Initialize the parameters of PSO-DV algorithm i.e, swarm size *(N)*, number of components of a particle *(d)*, iteration count($g_{\max}$), acceptable limits of the particle positions ($X_{\max}$, $X_{\min}$)acceptable limits of the particle velocities ($v_{\max}$, $v_{\min}$). Every particle in the swarm impersonates the set of reduced-order model coefficients. The components of a particle *(d)* represent the number of unknown coefficients of numerator and denominator in the reduced-order model.

Step 2:

In iteration *(g)* = 1, the '*N'* reduced-order models in the swarm, every one of them is having *d* unknown coefficients. Initialize the coefficients such that it has to be satisfying the R–H criteria and particle velocities are to be selected randomly within the permissible limits.

Step 3:

Evaluate the ISO values of ROMs within the swarm limits.

Step 4:

The aimed velocities for the ROM coefficients are updated in the swarm.

Step 5:

The trail ROMs are created by summing the refreshed velocities to the past ROM's coefficients in the swarm.

Step 6:

Evaluate the ISE values of the trial ROMs and compare trail

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ISE values with the corresponding previous ISE values. Update the swarm with the ROM that give least ISE value for the next count.

Step 7:

Repeat the above Step 4 to Step 6 until the count reaches to maximum iteration $(g_{\max})$ (Or)the population reached up to global optimum ISE value. Finally, at the end of the problem the solution ROM coefficients that give the lowest ISE value in the swarm will be the optimum reduced-order model obtained by the PSO-DV algorithm. In addition to these ISE, another performance index such as impulse response energy(IRE) [5] with the original system it is also included to calculate the effectiveness of the ROM. The preserving of total IRE of the original system in the ROM leads to the matches of time moments of the impulse response and also coincidence the frequency response. The total impulse response energy of the given system/model is given by:

$$IRE(I) = \int_0^\infty [g(t)]^2 . dt$$

Where $g(t)$is the system/model impulse response.

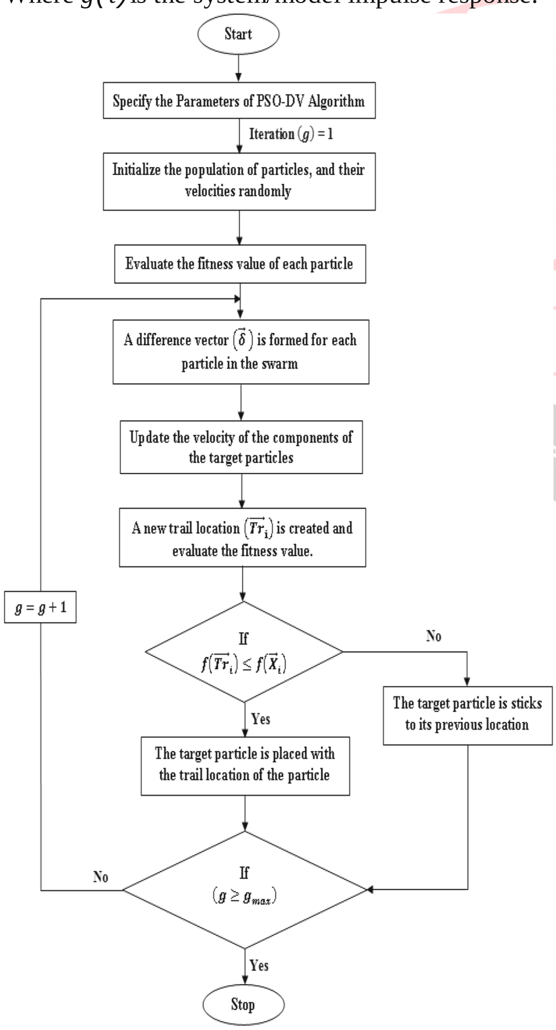


Fig. 1 **Flow diagram of the PSO-DV algorithm**

IV. NUMERICAL EXAMPLES

Numerical example for single area system

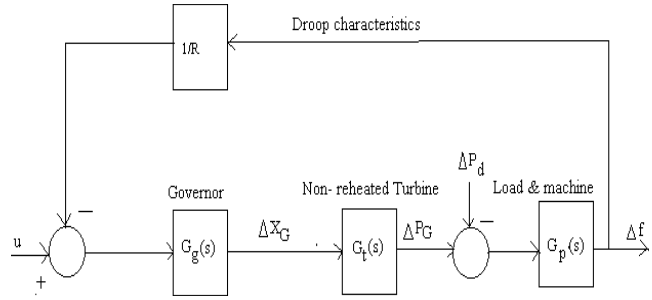


Fig 2 Basic block diagram of a single area power system

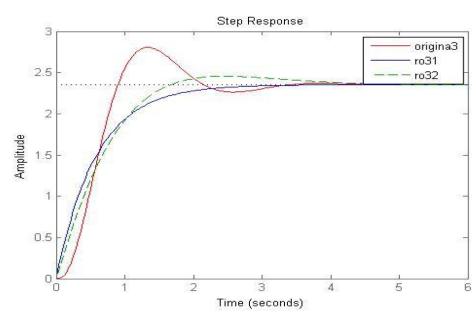
Considering a single-area power system supplying power from a single generator to a single Service-area. In general power systems(15)are non linear in nature hence linearized the characteristics at given operating a point. This single area power system

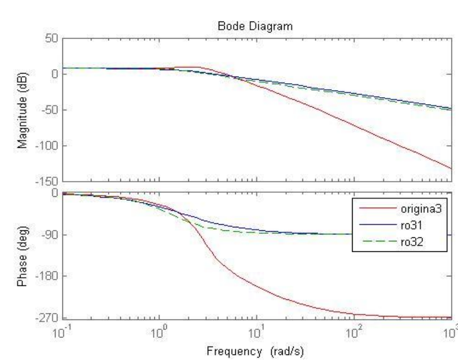
consists of governor Gg (s), turbine Gt (s), load Gp(s) and feedback represented as the droop characteristic(1/R),

$$G(s) = \frac{k_p[s^2T_tT_g + s(T_t + T_g) + 1]}{s^3T_tT_pT_g + s^2[T_t(T_p + T_g) + T_pT_g] + s(T_t + T_p + T_g) + \left(\frac{k_p}{R}\right) + 1}$$

$$G(S)_{original} = \frac{2.88S^2 + 45.6S + 120}{0.48S^3 + 7.624S^2 + 20.38S + 51}$$

$$G(S)_{reduced} = \frac{3.76S + 21.089}{S^2 + 1.8365S + 8.963}$$

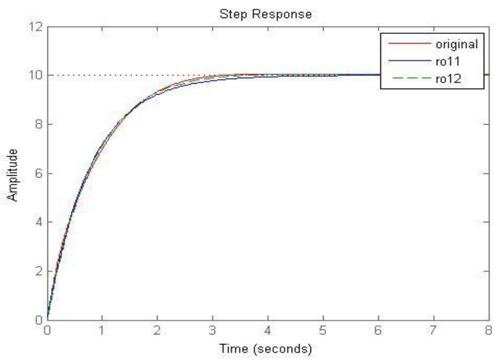


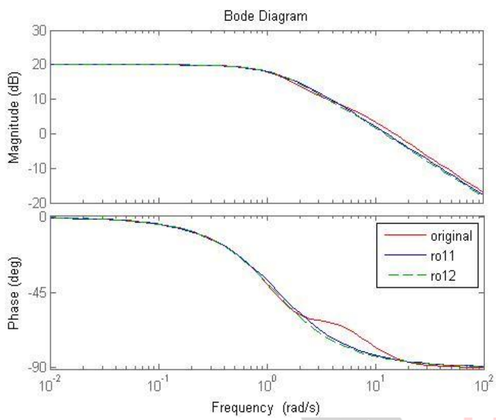


Numerical example:-2

$$G(S)_{original} = \frac{28S^3 + 496S^2 + 1800S + 2400}{2S^4 + 36S^3 + 204S^2 + 360S + 240}$$

$$G(S)_{reduced} = \frac{12.117S + 7.89}{S^2 + 1.806S + 0.789}$$





From the two numerical examples it was observed that the reduced order models are closely approximating the original system. The hybrid optimization model is resulting in optimal reduced model.

V. CONCLUSION

The Model Order Reduction Technique using PSODV algorithm for Single Area Power System has been designed. The reduced model order has been obtained and it can be observed with similar characteristics with the original model. The performance of the closed loop system has effectively improved with Second-order reduced system model instead of full order system. The Second-order reduced system model has proposed instead of full order system to effectively improved using this proposed model.

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