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A Combined Conventional and Differential Evolution Method for Model Order Reduction

J. S. Yadav, N. P. Patidar, J. Singhai, S. Panda, and C. Ardil

***Abstract*—**In this paper a mixed method by combining an evolutionary and a conventional technique is proposed for reduction of Single Input Single Output (SISO) continuous systems into Reduced Order Model (ROM). In the conventional technique, the mixed advantages of Mihailov stability criterion and continued Fraction Expansions (CFE) technique is employed where the reduced denominator polynomial is derived using Mihailov stability criterion and the numerator is obtained by matching the quotients of the Cauer second form of Continued fraction expansions. Then, retaining the numerator polynomial, the denominator polynomial is recalculated by an evolutionary technique. In the evolutionary method, the recently proposed Differential Evolution (DE) optimization technique is employed. DE method is based on the minimization of the Integral Squared Error (ISE) between the transient responses of original higher order model and the reduced order model pertaining to a unit step input. The proposed method is illustrated through a numerical example and compared with ROM where both numerator and denominator polynomials are obtained by conventional method to show its superiority.

***Keywords*—**Reduced Order Modeling, Stability, Mihailov Stability Criterion, Continued Fraction Expansions, Differential Evolution, Integral Squared Error.

I. INTRODUCTION

REDUCTION of high order systems to lower order models has been an important subject area in control engineering for many years. The mathematical procedure of system modeling often leads to detailed description of a process in the form of high order differential equations. These equations in the frequency domain lead to a high order transfer function. Therefore, it is desirable to reduce higher order transfer functions to lower order systems for analysis and design purposes.

Bosley and Lees [1] and others have proposed a method of reduction based on the fitting of the time moments of the system and its reduced model, but these methods have a serious disadvantage that the reduced order model may be unstable even though the original high order system is stable. To overcome the stability problem, Hutton and Friedland [2], Appiah [3] and Chen *et. al.* [4] gave different methods, called stability based reduction methods which make use of some stability criterion. Other approaches in this direction include the methods such as Shamash [5] and Gutman *et. al.* [6]. These methods do not make use of any stability criterion but always lead to the stable reduced order models for stable systems. Some combined methods are also given for example Shamash [7], Chen *et. al.* [8] and Wan [9]. In these methods the denominator of the reduced order model is derived by some stability criterion method while the numerator of the reduced model is obtained by some other methods [6, 8, 10].

In recent years, one of the most promising research fields has been "Evolutionary Techniques", an area utilizing analogies with nature or social systems. Evolutionary techniques are finding popularity within research community as design tools and problem solvers because of their versatility and ability to optimize in complex multimodal search spaces applied to non-differentiable objective functions. Differential Evolution (DE) is a branch of evolutionary algorithms developed by Rainer Stron and Kenneth Price in 1995 for optimization problems [11]. It is a population based direct search algorithm for global optimization capable of handling nondifferentiable, nonlinear and multi-modal objective functions, with few, easily chosen, control parameters. It has demonstrated its usefulness and robustness in a variety of applications such as, Neural network learning, Filter design and the optimization of aerodynamics shapes. DE differs from other Evolutionary Algorithms (EA) in the mutation and recombination phases. DE uses weighted differences between solution vectors to change the population whereas in other stochastic techniques such as Genetic Algorithm (GA) and Expert Systems (ES), perturbation occurs in accordance with a random quantity. DE employs a greedy selection process with inherent elitist features. Also it has a minimum number of EA control parameters, which can be tuned effectively [12, 13].

In the present paper, a mixed method is proposed for order reduction of Single Input Single Output (SISO) continuous systems is presented. The denominator polynomial of the reduced order model is obtained by Mihailov stability criterion [14] and the numerator polynomial is derived by employing DE optimization technique. The Mihailov stability criterion is to improve the Pade approximation method, to the general case. In this method, several reduced models can be obtained

J. S. Yadav is working as an Assistant Professor in Electronics and Communication Engg. Department, MANIT Bhopal, India (e-mail: jsy1@rediffmail.com).

N. P. Patidar is working as an Assistant professor in Electrical Engineering Department, MANIT, Bhopal, India. (e-mail: nppatidar@yahoo.com)

J. Singhai is working as Assistant Professor in Electronics and Communication Engineering Department, MANIT Bhopal, India.

S. Panda is working as a Professor in the Department of Electrical and Electronics Engineering, NIST, Berhampur, Orissa, India, Pin: 761008. (e-mail: panda_sidhartha@rediffmail.com).

C. Ardil is with National Academy of Aviation, AZ1045, Baku, Azerbaijan, Bina, 25th km, NAA (e-mail: cemalardil@gmail.com).

depending upon the different values of the constant λ_2 in the model and bring the Mihailov frequency characteristic of the reduced model to approximate that of the original system at the low frequency region.

The reminder of the paper is organized in five major sections. In Section II statement of the problem is given. Order reduction by Mihailov stability criterion is presented in Section III. In Section IV, a brief overview of DE optimization technique has been presented. In Section V, a numerical example is taken and both the proposed methods are applied to obtain the reduced order models for higher order models and results are shown. A comparison of both the proposed method with other well known order reduction techniques is presented in Section VI. Finally, in Section VII conclusions are given.

II. Statement of The Problem

Given an original system of order 'n' that is described by the transfer function $G(s)$ and its reduced model $R(s)$ of order 'r' be represented as:

$$G(s) = \sum_{j=1}^{n} b_{1,j} s^{j-1} \Big/ \Delta(s) \tag{1}$$

where

$$\Delta(s) = \sum_{j=1}^{n+1} a_{1,j} s^{j-1} \tag{2}$$

$$R(s) = \sum_{j=1}^{r} b_{2,j} s^{j-1} \Big/ D_r(s) \tag{3}$$

$$D_r(s) = \sum_{j=1}^{r+1} a_{2,j} s^{j-1} \tag{4}$$

Where a_1, b_1, a_2 and b_2 are constants. $D_r(s)$ is the reduced degree polynomial of order 'r', with ($r < n$).

The objective is to find a reduced r^{th} order reduced model $R(s)$ such that it retains the important properties of $G(s)$ for the same types of inputs.

III. Reduction by Conventional method

The reduction procedure by Mihailov stability criterion may be described in the following steps:

Step-1

Expand $G(s)$ into Cauer second form of continued fraction expansion:

$$G(s) = \cfrac{1}{h_1 + \cfrac{1}{h_2/s + \cfrac{1}{h_3 + \cfrac{1}{h_4/s + \cfrac{1}{\cdots}}}}} \tag{5}$$

Where the quotients h_i for $i = 1,2,3,...,r$ are determined using Routh algorithm [14] as:

$$a_{i,j} = a_{i-2,j+1} - h_{i-2} a_{i-1,j+1} \tag{6}$$

Where, $i = 3,4,.....,$ $j = 1,2,.....,$ and $h_i = a_{i,1} \big/ a_{i+1,1}$ provided $a_{i+1,1} \neq 0$

Step-2

Determine the reduced denominator $D_r(s)$ using Mihailov stability criterion as follows:

Substituting $s = j\omega$ in $\Delta(s)$, expanding and separating it into real and imaginary parts, gives:

$$\Delta(j\omega) = a_{11} + a_{12}(j\omega) + a_{13}(j\omega)^2 + ... + a_{1n+1}(j\omega)_n \tag{7}$$

$$= (a_{11} - a_{13}\omega^2 + ...) + j(a_{12}\omega - a_{14}\omega_3 + ...) \tag{8}$$

$$= \phi(\omega) + j\varphi(\omega)$$

Where 's' is angular frequency in rad/sec.

Setting $\phi(\omega) = 0$ and $\varphi(\omega) = 0$, the intersecting frequencies $\omega = 0, \pm\omega_1, \pm\omega_3, ...\pm\omega_{n-1}$ are obtained where $|\omega_1| < |\omega_2| < ... < |\omega_{n-1}|$.

Similarly substituting $s = j\omega$ in $D_r(s)$ gives

$$D_r(j\omega) = \xi(\omega) + j\eta(\omega) \tag{9}$$

Where

$$\xi(\omega) = e_0 - e_2\omega^2 + e_4\omega^4 - ..... \tag{10}$$

and

$$\eta(\omega) = e_1\omega - e_3\omega^3 + e_5\omega^5 - ..... \tag{11}$$

If the reduced model is stable, its Mihailov frequency characteristic must intersect 'r' times with abscissa and ordinate alternately in the same manner as that of the original system.

In other words, roots of $\xi(\omega) = 0$ and $\eta(\omega) = 0$ must be real and positive and alternately distributed along the ω-axis. So, the first 'r' intersecting frequencies $0, \omega_1, \omega_2, \ldots \omega_{r-1}$ are kept unchanged and are set to be the roots $\xi(\omega) = 0$ and $\eta(\omega) = 0$.

Therefore:

$$\xi(\omega) = \lambda_1(\omega^2 - \omega_1{}^2)(\omega^2 - \omega_3{}^2)(\omega^2 - \omega_5{}^2)\ldots \quad (12)$$

$$\eta(\omega) = \lambda_2 \omega(\omega^2 - \omega_2{}^2)(\omega^2 - \omega_4{}^2)\ldots \quad (13)$$

Where the values of the coefficients 'λ_1' and 'λ_2' are computed from $\phi(0) = \xi(0)$ and $\psi(\omega_1) = \eta(\omega_1)$ respectively, putting these values of 'λ_1' and 'λ_2' in (13) and (14) respectively, $\xi(\omega)$ and $\eta(\omega)$ are obtained and $D_r(j\omega)$ is found as given in equation (10).

Now replacing $j\omega$ by 's', the 'r^{th}' order reduced denominator $D_r(s)$ is obtained as given by equation (2).

Two other sets of 'λ_1' and 'λ_2' are also obtained resulting in reducing the denominator $\Delta(s)$ to different values of $D_r(s)$ to provide a range of different solutions. This is achieved as follows:

In the first criterion, 'λ_1' is determined by $\phi(0) = \xi(0)$ and 'λ_2' is determined by $(d\psi / d\phi)_{\omega_0}$ = $(d\eta / d\xi)_{\omega_0}$ in the reduced model to keep the initial slope of the Mihailov frequency characteristic unchanged.

In the second criterion, 'λ_1' is again unchanged but 'λ_2' is determined by keeping the ratio of the first two coefficients (a_{11} and a_{12}) of the characteristic equation (2) unchanged in the reduced model [14].

Step-3

Match the coefficients $a_{2,j}$ in (16) and h_i in (6) to determine reduced numerator polynomial $N_r(s)$ by applying the following reverse Routh algorithm:

$$a_{i+1} = a_{i,1} / h_i \quad (14)$$

For $i = 1,2,\ldots r$ with $r < n$

$$a_{i+1,j+1} = (a_{i,j+1} - a_{i+2,j}) \quad (15)$$

With $j = 1,2,\ldots(r-1)$ and $a_{1,r+1} = 1$

The reduced order model (ROM), $R(s)$ is obtained as:

$$R(s) = \frac{N_r(s)}{D_r(s)} \quad (16)$$

Step-4

There is a steady state error between the outputs of original and reduced systems. To avoid steady state error we match the steady state responses by following relationship, to obtain correction factor 'k' a constant as follows:

$$\frac{b_{11}}{a_{11}} = k \frac{b_{21}}{a_{21}} \quad (17)$$

The final reduced order model is obtained by multiplying 'k' with numerator of the reduced model obtained in step 3.

IV. Differential Evolution (DE)

In conventional mathematical optimization techniques, problem formulation must satisfy mathematical restrictions with advanced computer algorithm requirement, and may suffer from numerical problems. Further, in a complex system consisting of number of controllers, the optimization of several controller parameters using the conventional optimization is very complicated process and sometimes gets struck at local minima resulting in sub-optimal controller parameters. In recent years, one of the most promising research field has been "Heuristics from Nature", an area utilizing analogies with nature or social systems. Application of these heuristic optimization methods a) may find a global optimum, b) can produce a number of alternative solutions, c) no mathematical restrictions on the problem formulation, d) relatively easy to implement and e) numerically robust. Several modern heuristic tools have evolved in the last two decades that facilitates solving optimization problems that were previously difficult or impossible to solve. These tools include evolutionary computation, simulated annealing, tabu search, genetic algorithm, particle swarm optimization, etc. Among these heuristic techniques, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) techniques appeared as promising algorithms for handling the optimization problems. These techniques are finding popularity within research community as design tools and problem solvers because of their versatility and ability to optimize in complex multimodal search spaces applied to non-differentiable objective functions.

Differential evolution (DE) is a stochastic, population-based optimization algorithm introduced by Storn and Price in 1996 [11]. 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 [11-13, 15];

A. Initialization

In DE, a solution or an individual *i*, in generation *G* is a multidimensional vector given as:

$$X_i^G = \left(X_{i,1},...X_{i,D}\right) \tag{18}$$

$$X_{i,k}^G = X_{k\min} + rand(0,1)\times\left(X_{k\max} - X_{k\min}\right) \tag{19}$$

With $i \in [1, N_P]$, $k \in [1, D]$

where, N_P is the population size, D is the solution's dimension i.e number of control variables and *rand*(0,1) is a random number uniformly distributed between 0 and 1. Each variable k in a solution vector i in the generation G is initialized within its boundaries $X_{k\min}$ and $X_{k\max}$.

B. Mutation

DE does not use a predefined probability density function to generate perturbing fluctuations. It relies upon the population itself to perturb the vector parameter. Several population members are involved in creating a member of the subsequent population. For every $i \in [1, N_P]$ the weighted difference of two randomly chosen population vectors, X_{r2} and X_{r3}, is added to another randomly selected population member, X_{r1} , to build a mutated vector V_i.

$$V_i = X_{r1} + F\cdot(X_{r2} - X_{r3}) \tag{20}$$

with $r_1, r_2, r_3 \in [1, N_P]$ are integers and mutually different, and F > 0, is a real constant to control the differential variation $d_i = X_{r2} - X_{r3}$.

C. Crossover

The crossover function is very important in any evolutionary algorithm. It also should be noted that there are evolutionary algorithms that use mutation as their primary search tool as opposed to crossover operators. In DE, three parents are selected for crossover and the child is a perturbation of one of them whereas in GA, two parents are selected for crossover and the child is a recombination of the parents. The crossover operation in DE can be represented by the following equation:

$$U_i(j) = \begin{cases} V_i(j), & \text{if } U_i(0,1) < CR \\ X_i(j), & \text{otherwise.} \end{cases} \tag{21}$$

D. Selection

In DE algorithm, 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:

$$X_{i,G} = \begin{cases} U_{i,G+1} & \text{if } f(U_{i,G+1}) < f(X_{i,G}) \\ X_{i,G} & \text{otherwise.} \end{cases} \tag{22}$$

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

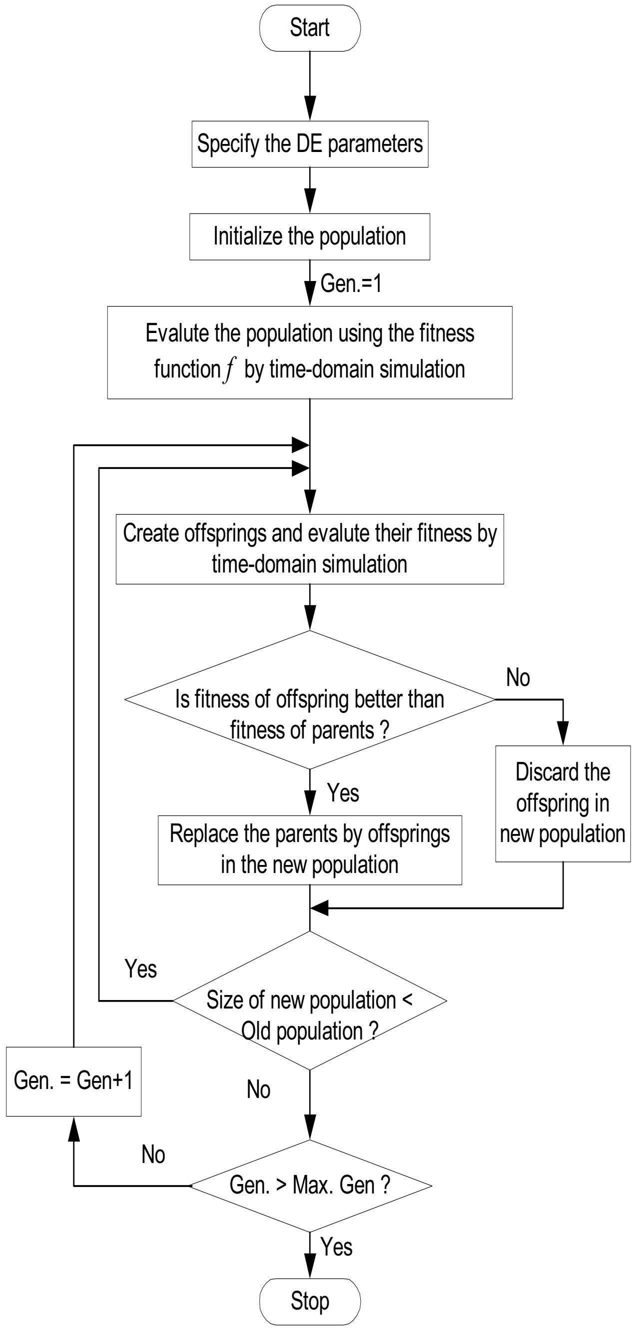

Fig. 1 Computational flow chart of Differential Evolution

The computational flow chart of the differential evolution algorithm is shown in Fig. 1. The vector addition and subtraction necessary to generate a new candidate solution in DE is shown in Fig. 2.

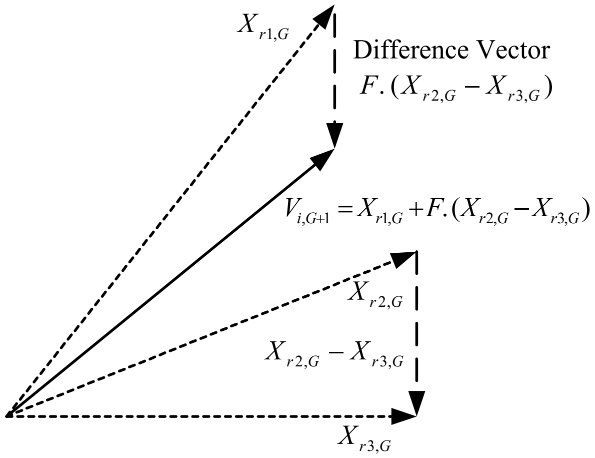

Fig. 1 Vector addition and subtraction to generate a new candidate solution in Differential Evolution

V. Numerical Examples

Let us consider the system described by the transfer function [14, 18]:

$$G(s) = \frac{10s^4 + 82s^3 + 264s^2 + 396s + 156}{2s^5 + 21s^4 + 84s^3 + 173s^2 + 148s + 40} \quad (23)$$

For which a second order reduced model $R_2(s)$ is desired.

A. Conventional Method for denominator polynomials

Step-1

The quotients h_i hi for $i = 1,2,3,...,r$ are determined using Routh algorithms as:

$$h_1 = 0.256, \quad h_2 = 2.92$$

$$h_3 = 0.872, \quad h_4 = 1.72 \quad (24)$$

Step-2

Determine the reduced denominator $D_r(s)$ using Mihailov stability criterion as follows:

$$\Delta(s) = 2s^5 + 21s^4 + 84s^3 + 173s^2 + 148s + 40 \quad (25)$$

Expanding and separating it into real and imaginary parts, gives:

$$\phi(\omega) = 40 - 173\omega^2 + 21\omega^4 \quad (26)$$

The roots are:

$\omega^2 = 0.238, 8$, and

$$\psi(\omega) = 148\omega - 84\omega^3 + 2\omega^4 \quad (27)$$

The roots are:

$$\omega^2 = 0, 0.167, 41.83$$

Now, reduced denominator polynomial is derived using the second criterion of Mihailov stability criterion method by calculating the values of 'λ_1' and 'λ_2' as given in (13) and (14) which come out to be 239.5 and 148 respectively, after putting $j\omega = s$ results into reduced denominator polynomial of a second order ROM as:

$$D_r(s) = 40 + 148 + 239.5s^2 \quad (28)$$

Step-3

The numerator is obtained by matching the quotients h_i of the Cauer second form of Continued fraction expansions with the coefficients of reduced denominator and using the reverse Routh algorithm as:

$$N_r(s) = 369s + 156 \quad (29)$$

The transfer function for the reduced order model (ROM) of second order can therefore be expressed as:

$$R_2(s) = \frac{369s + 156}{239.5s^2 + 148s + 40} \quad (30)$$

Step-4

In this particular example there is no steady state error between the step responses of the original system and the ROM, hence $k = 1$, and the final reduced model remains unchanged.

B. Differential Evolution Method

Implementation of DE requires the determination of six fundamental issues: DE step size function, crossover probability, the number of population, initialization, termination and evaluation function. Generally DE step size (F) varies in the interval [0, 2]. A good initial guess to F is to have the interval [0.5, 1]. Crossover probability (CR) constants are generally chosen from the interval [0.5, 1]. If the parameter is co-related, then high value of CR work better, the reverse is true for no correlation [19, 20]. In the present study, a population size of N_P=20, generation number *G*=50, step size F=0.8 and crossover probability of CR =0.8 has been used. Optimization is terminated by the prespecified number of generations for DE. One more important factor that affects the optimal solution more or less is the range for unknowns. For the very first execution of the program, a wider solution space can be given and after getting the solution one can shorten the solution space nearer to the values obtained in the previous iteration.

The objective function *J* is defined as an integral squared

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error of difference between the responses given by the expression:

$$J = \int_0^{t_\infty} [y(t) - y_r(t)]^2 \, dt \quad (31)$$

Where

$y(t)$ and $y_r(t)$ are the unit step responses of original and reduced order systems.

The convergence of objective function with the number of generations is shown in Fig. 3. The reduced 2nd order numerator is obtained by employing DE optimization technique by minimizing the objective function J as:

$$D_r(s) = 93.5606s^2 + 151.1163s + 39.8901 \quad (32)$$

So the final transfer function for the reduced order model (ROM) of second order can therefore be expressed as:

$$R_2(s) = \frac{369s + 156}{93.5606s^2 + 151.1163s + 39.8901} \quad (33)$$

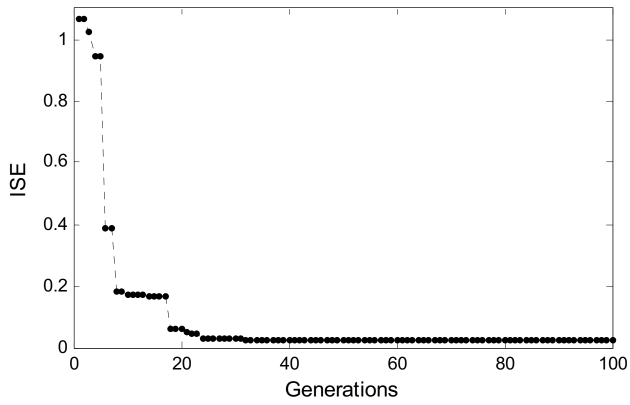

Fig.3. Convergence of objective function for example-1

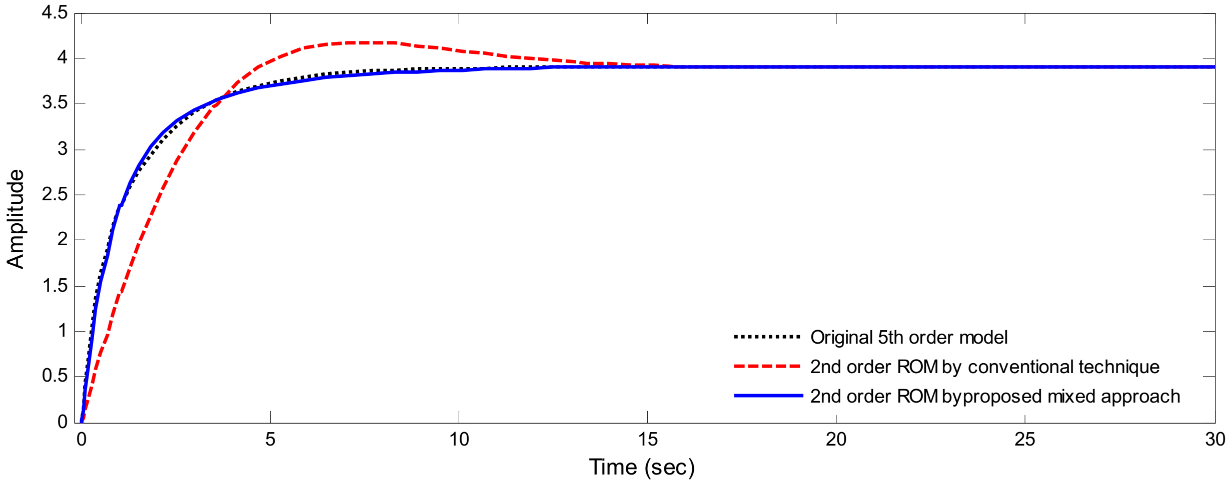

Fig. 4 Unit step response

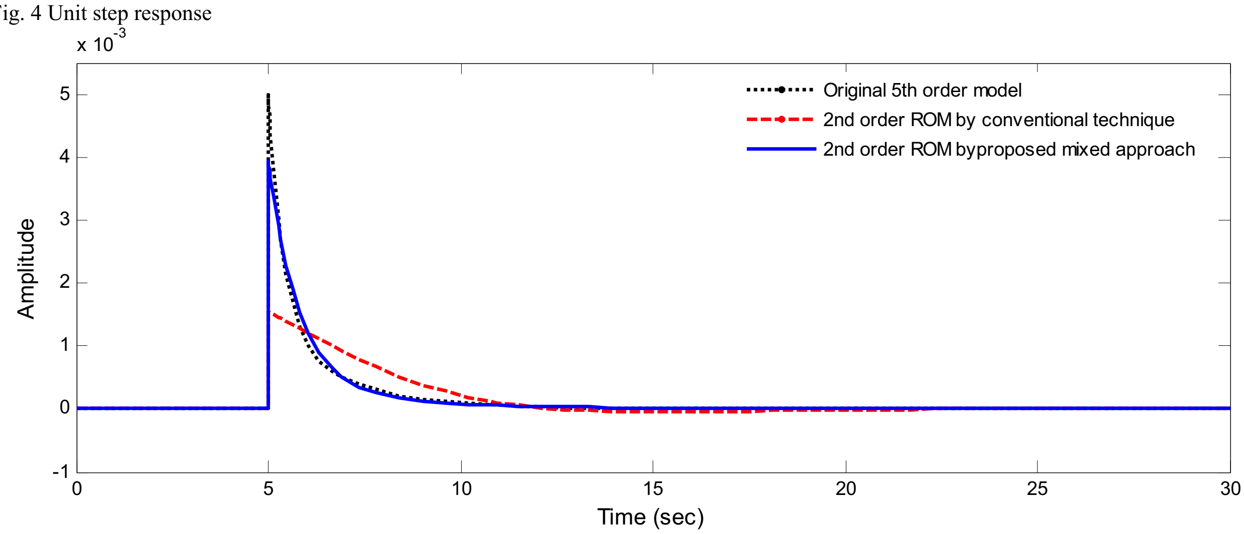

Fig. 5. Unit impulse response

The unit step responses of original and reduced systems are shown in Fig. 4. In Fig. 4, the unit step response of original 5^{th} order system is shown in dotted lines and the unit step response of reduced 2^{nd} order model by the proposed mixed approach is shown in solid lines. For comparison the unit step response of reduced 2^{nd} order model by conventional technique as given by equation (30) is also shown in dashed lines. It can be seen that the steady state responses of both the reduced order models are exactly matching with that of the original model. However, compared to conventional method of reduced models, the transient response of proposed mixed evolutionary and conventional reduced model is very close to that of original model.

The unit impulse responses of original and reduced systems are shown in Fig. 5 where the response of original 5^{th} order system is shown in dotted lines, response of reduced 2^{nd} order model by conventional technique is shown with dashed lines and response of reduced 2^{nd} order model by the proposed mixed approach is shown in solid lines. It can be seen from Fig. 5 that compared to conventional method of reduced models, the transient response of proposed mixed evolutionary and conventional reduced model is very close to that of original model.

VI. Comparison of Methods

The performance comparison of the proposed mixed conventional and evolutionary algorithm for order reduction techniques for a unit step input and an impulse input is given in Table I and Table II respectively. The comparison is made by computing the error index known as integral square error ISE [16, 17] in between the transient parts of the original and reduced order model pertaining to a certain type of input, is calculated to measure the goodness/quality of the [i.e. the smaller the ISE, the closer is $R(s)$ to $G(s)$, which is given by:

$$ISE = \int_{0}^{t_\infty} [y(t) - y_r(t)]^2 \, dt \qquad (32)$$

Table I: Comparison of methods for step input

Method	Reduced model	ISE
Proposed mixed method	$\frac{369s+156}{93.5606s^2+151.1163s+39.8901}$	0.0233
PSO [14]	$\frac{347.0245s+225.6039}{135.6805s^2+166.3810s+57.8472}$	0.0613
Conventional method	$\frac{369s+156}{239.5s^2+148s+40}$	1.0806

Table II: Comparison of methods for impulse input

Method	Reduced model	ISE
Proposed mixed method	$\frac{369s+156}{93.5606s^2+151.1163s+39.890}$	1.1852 x10^{-7}
PSO [14]	$\frac{347.0245s+225.6039}{135.6805s^2+166.3810s+57.847}$	8.6 x10^{-7}
Conventiona l method	$\frac{369s+156}{239.5s^2+148s+40}$	2.2709x10^{-6}

The frequency response of the original and reduced order model is shown in Bode diagram in Fig. 6, where the frequency response of ROM by conventional method is also shown for comparison. It can be seen fro Fig. 6 that the frequency response of proposed mixed evolutionary and conventional reduced model is very close to that of original model and better than the conventional method.

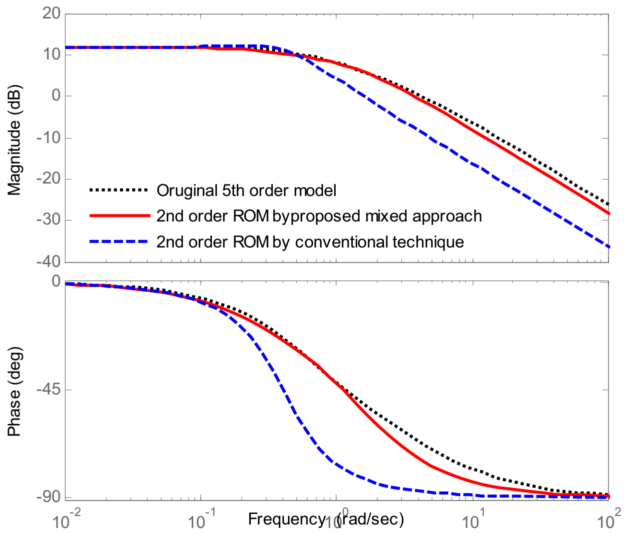

Fig. 6. Frequency response

VII. Conclusion

In this paper, a mixed method by combining an evolutionary and a conventional technique is proposed for reducing a high order system into a lower order system. First, the reduced denominator polynomial is derived using Mihailov stability criterion and the numerator is obtained by matching the quotients of the Cauer second form of Continued fraction expansions. Then retaining the numerator polynomial, the denominator polynomial is recalculated by an evolutionary technique. In the evolutionary technique method, the recently proposed Differential Evolution (DE) optimization technique is employed. DE method is based on the minimization of the Integral Squared Error (ISE) between the transient responses of original higher order model and the reduced order model pertaining to a unit step input. The proposed method is illustrated through a numerical example. Also, a comparison of the proposed method with recently published conventional and evolutionary methods has been presented. It is observed that the proposed mixed method preserve steady state value and stability in the reduced models and the error between the initial or final values of the responses of original and reduced order models is very less.

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Jigyendra Sen Yadav is working as Assistant Professor in Electronics and Communication Engineering Department, MANIT, Bhopal, India. He received the B.Tech.degree from GEC Jabalpur in Electronics and Communication Engineering in 1995 and M.Tech. degree from MANIT, Bhopal in Digital Communication in 2002. Presently he is persuing Ph.D. His area of interest includes Optimization techniques, Model Order Reduction, Digital Communication, Signal and System and Control System.

Narayana Prasad Patidar Narayan Prasad Patidar is working as Assistant Professor in Electrical Engineering Department, MANIT, Bhopal, India. He received his PhD. degree from Indian Institute of Technology, Roorkee, in 2008, M.Tech. degree from Visvesvaraya National Institute of Technology Nagpur in Integrated Power System in 1995 and B.Tech. degree from SGSITS Indore in Electrical Engineering in 1993. His area of research includes voltage stability, security analysis, power system stability and intelligent techniques. Optimization techniques, Model Order Reduction, and Control System.

Jyoti Singhai is working as Assistant Professor in Electronics and Communication Engineering Department, MANIT Bhopal, India. She received the PhD. degree from MANIT Bhopal in 2005, M.Tech. degree from MANIT, Bhopal in Digital Communication in 1997 and B.Tech. degree from MANIT Bhopal in Electronics and Communication Engineering in 1991. Her area of research includes Optimization techniques, Model Order Reduction, Digital Communication, Signal and System and Control System.

Sidhartha Panda is a Professor at National Institute of Science and Technology, Berhampur, Orissa, India. He received the Ph.D. degree from Indian Institute of Technology, Roorkee, India in 2008, M.E. degree in Power Systems Engineering in 2001 and B.E. degree in Electrical Engineering in 1991. Earlier he worked as Associate Professor in KIIT University, Bhubaneswar, India and VITAM College of Engineering, Andhra Pradesh, India and Lecturer in the Department of Electrical Engineering, SMIT, Orissa, India.His areas of research include power system transient stability, power system dynamic stability, FACTS, optimisation techniques, distributed generation and wind energy.

Cemal Ardil is with National Academy of Aviation, AZ1045, Baku, Azerbaijan, Bina, 25th km, NAA