Execution of bio-inspired IWO for the model order reduction in two area power system network

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Abstract

The use of bio-inspired invasive weed optimization (IWO) to lower a power system network's order is demonstrated in this article. The stability equation (SES) method has been used to evaluate the model order reduction performance analysis of a two-area power system. Additionally, the IWO estimates the parameters' coefficients. The steady state responses in terms of rise and settling times have been estimated using performance metrics such integral square error (E), integral absolute error (IAE), and integral time absolute error (ITAE). IWO is believed to have a quicker rising and settling time per unit step response than SES. Furthermore, compared to SES, IWO lowers E, IAE, and ITAE more. Additionally, a network of two-area power systems has been established to analyse the frequency deviation with 5% disruptions. IWO outperforms the SES approach in terms of frequency deviation for the 5% disturbances in the two-area model. These validations all show that IWO works better than the conventional model order reduction method.

Keywords—reduced order, SISO, IWO, power system

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Introduction

The mathematical description of real-time systems is a major problem for investigators. Both linear and non-linear systems make up the majority of real-time systems. Both linear & non-linear systems have an excessively high order. Higher degree differential systems are typically used to express real-time systems. Consequently, the order of the bigger order system—which is usually expressed using differential equations—must be decreased. If a reduced order is stable in its original form, it is presumed to be such. It has been proposed to minimize the order of bigger LTI systems using the stability equation strategy and the PSO technique.

A novel method for lowering the order of linear time-invariant (LTI) systems was presented by Sikander and Prasad [1]. The necessity to simplify higher-order transfer-function models while preserving the key elements of the original system is addressed by their work. When the original system has many poles and zeros that raise computational complexity, these methods are helpful. The research advances the creation of control-system analysis reduced-order representations. However, the correctness of the simplified model must be assessed across the pertinent frequency range and under various operating situations when applying such techniques to power systems, especially when multiple electromechanical modes affect system dynamics.

A soft-computing-based method for model order reduction of LTI systems was examined by Sikander and Prasad [2]. A foundation for finding reduced models that roughly mimic the behavior of higher-order systems is provided by the use of soft computing. Computational search strategies can provide more flexibility in choosing appropriate reduced-model parameters than traditional analytical reduction methods. However, the optimization process, objective function, and parameter choice all affect the final model's quality. To determine whether the reduced model maintains dominant modes, transient responses, and stability characteristics for power system applications, more validation is needed.

A unique order-reduction method that combines Routh approximation with Big Bang–Big Crunch (BB–BC) optimization was presented by Desai and Prasad [3]. While the Routh approximation offers a traditional analytical framework for streamlining system dynamics, the optimization method offers a search mechanism for identifying appropriate reduced-model parameters. The combination is an attempt to take advantage of the benefits of both conventional approximation methods and numerical optimization. However, the chosen error criterion, processing cost, and search parameters all affect how well the strategy works. Therefore, comparisons with other reduction techniques should be used to determine its efficacy for large interconnected power systems, especially with regard to dominant-mode preservation, transient-response accuracy, and computing economy.

An aggregation-based method for lowering system complexity was introduced by Naqvi, Nasiruddin, and Ali [4]. By using fewer equivalent components, aggregation aims to depict a complicated system. This idea applies to large-scale engineering models when several components have behaviors that are comparable or closely related. Aggregation can make groupings of generators, network elements, or dynamic subsystems in power networks easier to understand. However, because different dynamic responses and interactions between subsystems can result in errors, aggregating needs to be done carefully. More research is needed to see whether this method can be used to nonlinear power system models and whether it can maintain crucial oscillation modes.

Structure-preserving model order reduction for nonlinear differential-algebraic equation (DAE) models of power networks was studied by Nadeem and Taha [5]. Because power systems are described by differential equations that describe dynamic components and algebraic equations that define network limitations, this topic is very crucial. While lowering the number of states, a reduction technique that maintains this structure can preserve significant physical connections and network properties. However, with consideration for constraint consistency, numerical stability, and the accuracy of nonlinear responses, the practical efficacy of structure-preserving reduction should be assessed under various operating points, disturbances, and network configurations.

An adaptive nonlinear model reduction method was created by Osipov and Sun [6] to speed up power system simulations. Their study tackles the computational difficulties related to nonlinear power system dynamics, in which operating circumstances and disturbances may alter the system response. The approach offers a foundation for increasing simulation efficiency while taking nonlinear system behavior into consideration. However, evaluating reduction accuracy, processing overhead, and adaptability during major disruptions is necessary for its actual implementation. Because fluctuations in generation and operating circumstances can affect dynamic behavior, these factors are crucial for systems with a high penetration of renewable energy.

An effective computational technique for locating the prominent poles of multivariable transfer functions was presented by Rommes and Martins [7]. Because they control key elements of a system's dynamic response, such as damping and oscillatory behavior, dominant poles are significant. In big power systems, effective computation of these poles aids in determining the most important modes. Modal analysis and stability studies of interconnected networks benefit from this method. Nevertheless, a simplified model that is correct over the whole frequency range or in the presence of significant nonlinear disturbances is not always guarantyd by dominant-pole identification alone. To maintain input-output behavior and guaranty sufficient transient-response accuracy, additional actions could be necessary.

The computation of dominating zeros of transfer functions and their use in oscillation-damping management in large power systems were examined by Martins, Pellanda, and Rommes [8]. Zeros impact the relationship between inputs and outputs and may have an impact on controller performance, whereas poles characterize a system's inherent dynamic modes. The study creates a helpful link between power system control design and computer model analysis. However, maintaining pertinent poles, zeros, and input-output features is also necessary for a simplified model to be useful. Therefore, while creating reduced models for controller design and stability analysis, a combined pole–zero-based reduction framework can be helpful.

Levron and Belikov [9] presented a method for reducing power system dynamic models using sparse representations. Sparse representations seek to capture the essential information in a complex system using a smaller set of significant components. In power system applications, this approach can help identify the dominant variables or dynamic relationships that contribute most strongly to the system response. Such reduction is particularly relevant for large interconnected networks, in which the number of states and interactions can make detailed simulation computationally expensive. However, the reliability of sparse representations depends on the quality of the selected basis, the degree of sparsity, and the ability to retain weakly represented but dynamically important modes. Validation under different disturbances and operating conditions is therefore necessary before employing such models for control design.

An energy-based modal approximation technique for reduced-order modeling and analysis of power system models was presented by Ríos and Messina [10]. By identifying modes that significantly influence the system response, an energy-based approach can aid in the development of more straightforward dynamic models. This is essential to power system stability studies, since assessing oscillation characteristics and damping performance requires maintaining the prevailing electromechanical modes. However, the modes chosen and the operational conditions under which the system is examined determine how accurate the modal approximation is. Additional validation is needed to determine its appropriateness for nonlinear, time-varying, and renewable-rich networks.

Zimmerman, Murillo-Sánchez, and Thomas [11] developed MATPOWER, a widely used MATLAB-based package for power system steady-state operation, planning, and analysis. Unlike the preceding references, which primarily address model reduction, this work provides a computational foundation for power system studies through tools for power flow analysis and related steady-state calculations. MATPOWER is useful for establishing the operating point of a network, obtaining bus voltages

and phase angles, and calculating line flows before developing or validating a reduced-order dynamic model. It can therefore support the implementation and assessment of model reduction methods in standard test networks. However, steady-state power flow analysis alone does not establish the accuracy of a dynamic reduced-order model; additional time-domain simulation and modal analysis are required for that purpose.

I. PROBLEM STATEMENT

A.

The problem formulation for the LTI system's model order reduction will be assessed using SISO. The generic formulation of model can be stated as a component of the transfer function for the nth order, as shown in Eq. 1.[2]

$$G_n(s)=\frac{N_{n-1}(s)}{D_n(s)}=\frac{\sum_{i=0}^{n-1} m_i s^i}{\sum_{i=0}^{n} n_i s^i} \quad (1)$$

Conversely, mi and ni are the known constants that can be set in reference to the system's specific order, which falls inside the nth order. The simplified model of order "k" is represented by the transfer function as a function of Rk(s), as shown in Eq. 2. [2]

$$R_k(s)=\frac{N_{k-1}(s)}{D_k(s)}=\frac{\sum_{i=0}^{k-1} p_i s^i}{\sum_{i=0}^{k} q_i s^i} \quad (2)$$

In contrast, k<n for the reduced system's order and are the undefined and unknown constants. The 2nd order reduced transfer functional is expressed using Eq. 3 since 2nd order polynomials are generally considered in the literature that is currently available for numerical analysis.

$$R_2(s)=\frac{p_o+p_1 s}{q_o+q_1 s+q_2 s^2} \quad (3)$$

The PSO and system equation approach will be utilized to determine the unknown variables in Eq. 3 [2] in order to minimize the error as stated in Eq. 4.

$$E=\int_0^{\infty}[g(t)-r(t)]^2 \quad (4)$$

The unit response of orig. model & reduced order model are represented by $g(t), r(t)$

The standard terms that appear from Equations (5) to (6) will validate the use of the IWO and SES in the lower order model system. [2]

$$IAE=\int_0^{\infty} |g(t)-r(t)|\,dt \quad (5)$$

$$ITAE=\int_0^{\infty} t\,|g(t)-r(t)|\,dt \quad (6)$$

The parameters for evaluating the reduction model's performance are E, IAE, and ITAE, which stand for integral square error, integral absolute error, and integral time absolute error, respectively.

II. IMPLEMENTATION OF INTELLIGENT METHODS

Two approaches are used to evaluate reduced order transfer functions, and they are described as

A. Stability Equation (SES) method

The Stability Equation (SES) method is the conventional methodology. As shown in Eq. 3, the method of determining the coefficient of the lower order transfer function has been explained using the stability equation technique. The computation of the coefficient of denominator and numerator has been discussed in two ways. [1]

Step 1: The kth-order transfer function's coefficient of denominator will be determined first. Equation (7) illustrates the method's initial step, which is to split the denominator (Dk(s)) into even and odd parts.

$$D_k(s)=Q_{even}(s)+Q_{odd}(s) \quad (7)$$

$$Q_{even}(s)=\sum_{i=0,2,4,6}^{k} a_i s^i \quad (8)$$

$$D_{odd}(s)=\sum_{i=1,3,5,7}^{k} a_i s^i \quad (9)$$

The even and odd components of Dk(s) are described by equations (8) and (9). As shown analytically in Equations 10 and 11, let di and ei stand for the root values of the polynomial's even and odd components, respectively..

$$Q_{even}(s)=d_0\prod_{i=0,2,4,6}^{k}\left(1+\frac{s^2}{d_i^2}\right) \quad (10)$$

$$Q_{odd}(s)=e_1 s\prod_{i=1,3,5,7}^{k}\left(1+\frac{s^2}{e_i^2}\right) \quad (11)$$

The denominator of the transfer function can be expressed as Eq. (12) after the previously described process.

$$D_k(s)=\sum_{i=1}^{k-1} r_i s^i+s^k \quad (12)$$

Step 2: The numerator of the lower order transfer function (Nk-1(s)) will be illustrated using the factor division approach, as shown in Eq. 13.

$$N_{k-1}(s)=\frac{N_{n-1}(s)}{D_n(s)} * D_k(s) \quad (13)$$

Equation 14 illustrates how the series expansions can be used to estimate the numerator (Nk-1(s)) of the reduced order transfer function.

$$N_{k-1}(s) = \frac{N_{n-1}(s)}{D_n(s)} D_k(s) = \frac{\sum_{i=0}^{n-1} \gamma_i s^i}{\sum_{i=0}^{n-k} \chi_i s^i} \quad (14)$$

After accounting for the series expansion, the numerator can be stated in the generalized form as indicated in Eq. 15.

$$N_{k-1}(s) = \sum_{i=0}^{k-1} \alpha_i s^i \quad (15)$$

2. Invasive weed optimization (IWO)

The concept of IWO originated with A.R. Mehrabian. By mimicking the compatibility and randomness of weed colonies, the invasive weed meta-heuristic algorithm is a population-based optimization method that determines the general optimal solution of a mathematical function. Weeds are hardy plants that have a tendency to spread and pose a major risk to agriculture. These characteristics have made them incredibly resilient and flexible, leading to an efficient optimization technique. In a cannabis group survey, the program seeks to mimic tolerance, flexibility, and unpredictability.

The phenomenon of invasive weed colonies in agriculture is greatly influenced by this tactic. A typical definition of a weed is a plant that grows unintentionally. Weeds are classified as weeds because they grow in an area that interferes with human needs and activities, even if they may have many uses and advantages in other places. A straightforward numerical optimization approach based on colonized weeds has been introduced as the "Invasive Weed Optimization Technique." This approach is straightforward but effective in converging to optimal solutions using fundamental aspects like seeding, growth, and competition in a weed colony.

A flowchart illustrating the IWO procedure is presented in the Fig. 1. The following steps provide an explanation of the flowchart's concise design that illustrates the IWO algorithm:

1) A scattered quantity of seeds in the available space is known as population initialization.

2) The process by which each seed grows into a flowering plant and produces more seeds based on their fitness value is known as reproduction. The quantity of grass grains or seeds (s) decreases linearly from to and is expressed as,

$$S = \frac{f_i - f_{worst}}{f_{best} - f_{worst}} (S_{max} - S_{min}) + S_{min} \quad (16)$$

where are the f_{best} and f_{worst} are the greatest and worst objective function values, respectively, and S_{max} and S_{min} are the maximum and minimum number of seeds, respectively. is the fault current in this instance, which is the fitness function.

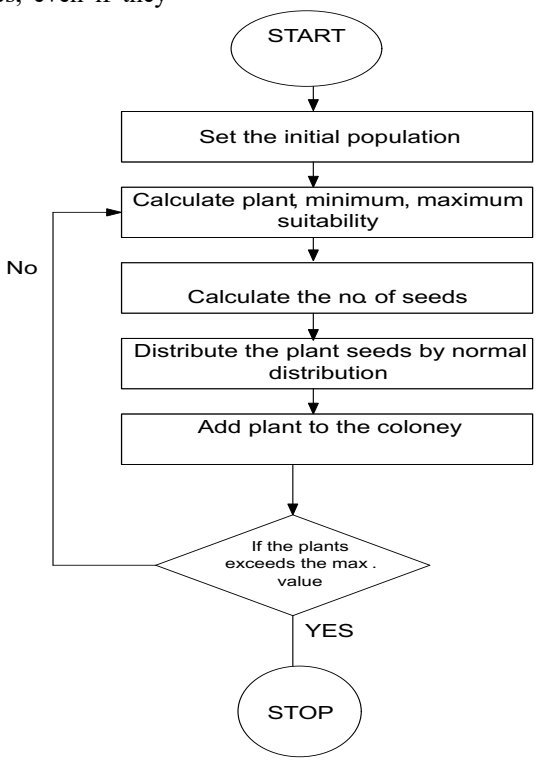


Fig.1. Flowchart illustrating the IWO mechanism.

Equation 17 illustrates how the group with the average planting site and standard deviation in a normal distribution produces seeds.

$$\sigma = \left(\frac{r_{max} - r}{r_{max}} \right)^{n} (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \qquad (17)$$

Where r_{max} is the maximum iterations no. , σ is the standard deviation, n is the non-linear modulation index, $\sigma_{initial}$ and σ_{final} are starting and steady values of standard deviation respectively.

III. MODELING OF TWO AREA POWER SYSTEM NETWORK

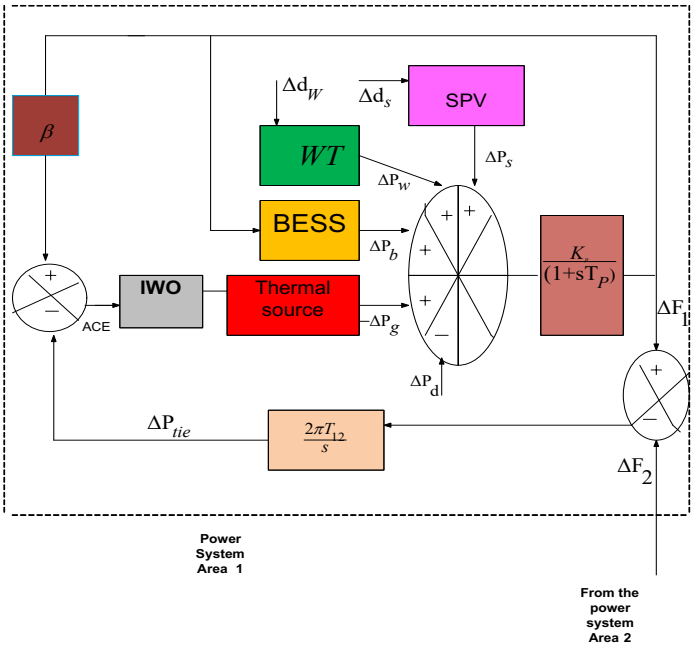


Fig.2 Transfer function model of the various generating units

The multi-area system transfer function design is shown in Figure 2. Equation 18 shows how the frequency fluctuations of the two area systems affect the line of tie power flow between two areas of a power system network(PSN).

$$\Delta P_{tie}(s) = \frac{2\pi T_{12}}{s} (\Delta F_1 - \Delta F_2) \qquad (18)$$

Equation 19 illustrates how the frequency in region 1 is altered by the variance of different generating units and load flows in the first order conventional generating system.

$$(\Delta P_s + \Delta P_w + \Delta P_b + \Delta P_g - \Delta P_d) \frac{K_p}{(1+sT_p)} = \Delta F_1 \qquad (19)$$

The disturbance that results in a steady shift in SPV production is estimated by equation 20.

$$\Delta P_{ss} = \Delta d_s \frac{1}{1+sT_s} \qquad (20)$$

Equation 20 states that the fluctuations in wind turbine power are determined by the input disruption. Equation 21 states that input disturbance determines the fluctuations in wind turbine output.

$$\Delta P_{ww} = \Delta d_w \frac{1}{1+sT_w} \qquad (21)$$

According to Eq. 22, the frequency deviations dictate how the BESS output varies.

$$\Delta P_b = \Delta F_1 \frac{1}{1+sT_b} \qquad (22)$$

Power deviations and frequency dev determine a change in area management for a certain region. Ideally, these power

dev. and frequency dev. should be near zero. As stated in Eq. 23, ACE usually depends on changes to frequency and power fluctuations as a linear combination.

$$ACE = \beta \Delta F_1 + \Delta P_{tie}$$

(23)

The power output of a conventional source changes as a result of this ACE traveling via IWO and transfer function gain, as shown by Eq. 24.

$$\Delta P_g = \frac{1}{(1+sT_g)(1+sT)}\left(k_{pd} + \frac{k_i}{s}\right)ACE$$

(24)

The two-area PSN design is being discussed. A detailed description is given for each standard variable required to build the two-area PSN . In the two-area PSN, ΔF1 shows the frequency dev. in area 1, and ΔF2 shows the frequency dev. in region 2.

IV. PERFORMANCE ANALYSIS OF POWER SYSTEM NETWORK

This section will evaluate the performance analysis of two area power system network. Two common analyses will be used to demonstrate the reduced order transfer function.

A) Unit step response of PSN reduced order transfer function

This section will look at the unit step response of the lower order transfer function and the original electrical system transfer function. According to [8], the initial transfer function of a fourth-order polynomial is represented by Eq. 25.

$$G_4(s) = \frac{s^3 + 8s^2 + 25s + 25}{s^4 + 11s^3 + 36s^2 + 51s + 25}$$

(25)

The initial 4th order transfer function model will be lowered to a 2nd order transfer function following the use of the SES. The two phases in section III already describe the process of reducing the order of the transfer function. Eq.26 displays the calculated value of the reduced second order transfer function [8].

$$R_2(s) = \frac{0.26s + 2.18}{3.19 + 4.98s + s^2}$$

(26)

IWO also estimates the reduced second order transfer function, as shown by Eq. 26. The process for calculating the transfer function coefficient using an IWO has already been discussed in Section III.

$$R_2(s) = \frac{0.72s + 0.77}{0.92 + 1.26s + s^2}$$

(27)

The unit step response of the second order power system lowered transfer function employing SES and IWO is shown in Fig.4 It is discovered that, in contrast to SES, the unit step response rapidly reaches its steady state value (unity) with IWO. A broad evaluation of performance metrics, including rise time (sec) and settling time (sec), using IWO & SES is shown in Table 1. The graphical analysis of this comparison is shown in Fig.3

Table.1 Comparative analysis of unit step response parameters with IWO & SES

Performance parameter	**SES**	**IWO**
Settling time(sec)	4.9	4.0
Rise time(sec)	2.8	1.5

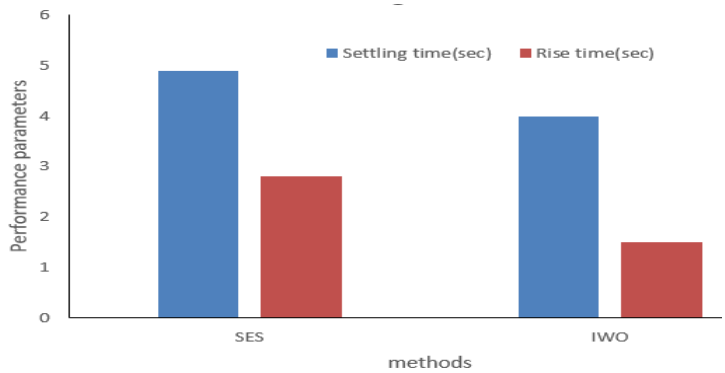


Fig.3 Graphical comparison of unit step response with IWO & SES

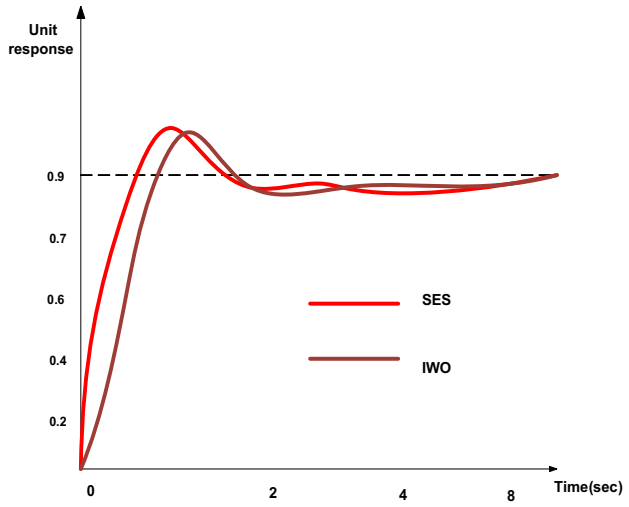


Fig.4 Unit step response of reduced second order transfer function with IWO & SES

B). Assessment of performance parameters

Performance measures like E, IAE, and ITAE have been calculated using IWO & SES; these parameters are already expressed in equations 4, 5, and 6. The performance characteristics are compared with IWO & SES in Table 3, and the graphical analysis of this comparison is shown in Fig.5

Table.3 Comparative analysis of performance parameter with conventional and PSO

Performance parameter	**SES*10^{-4}**	**IWO*10^{-4}**
E	3.61	1.02
IAE	4.89	1.32
IATE	5.32	1.46

Performance metrics such as E, IAE, and IATE are shown to be lower with IWO than with SES, indicating the system's stability.

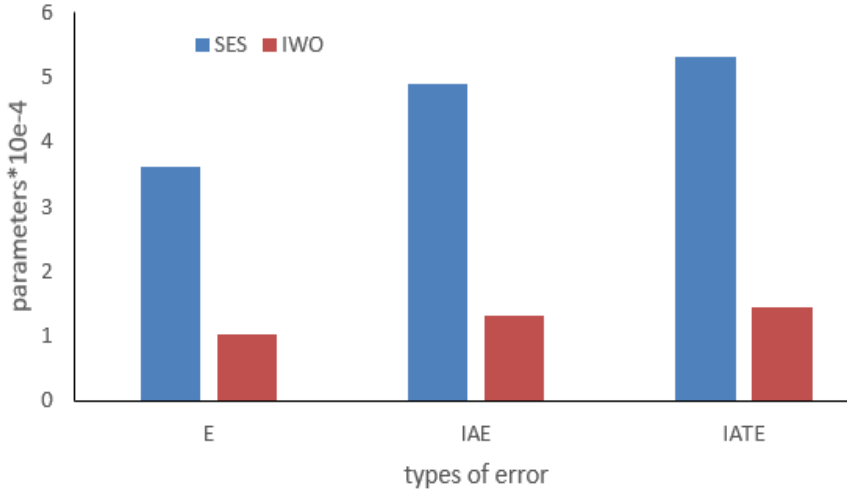


Fig.5 Graphical comparison of performance parameter with IWO & SES

C. **C). Estimation of frequency deviation of two area PSN for the 5% disturbances:**

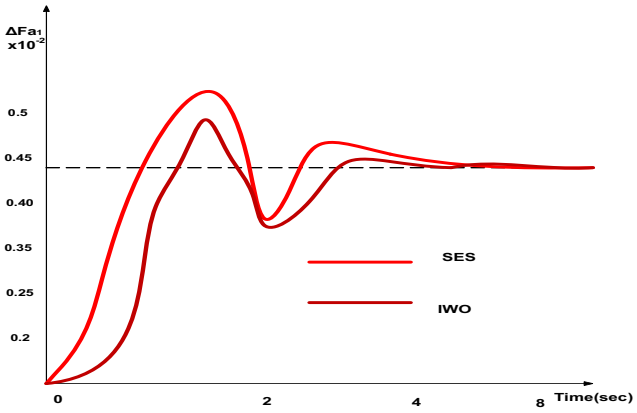


Fig.6 Change in frequency in area 1 due to the 5% disturbance in area 1

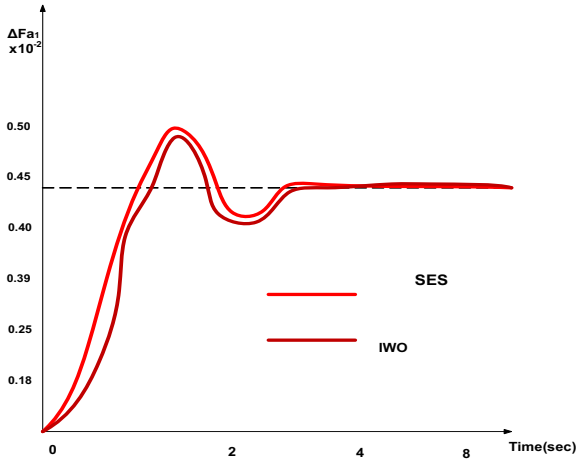


Fig.7 Change in frequency in area 1 due to the 5% disturbance in area 2

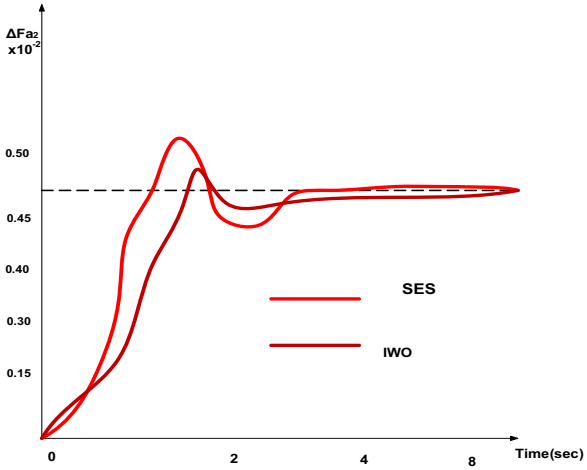


Fig.8 Change in frequency in area 2 due to the 5% disturbance in area 1

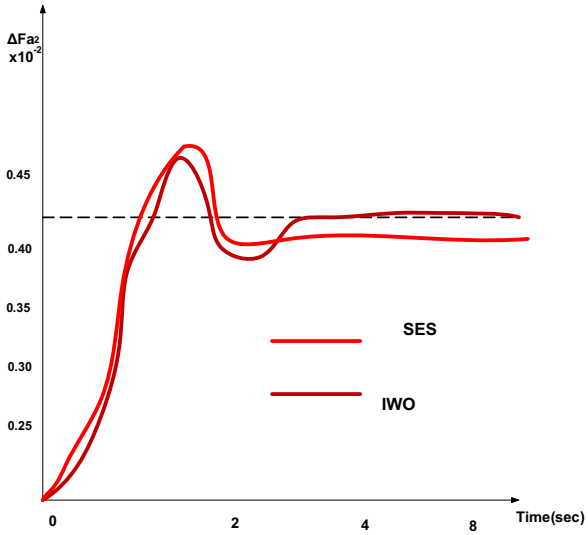


Fig.9 Change in frequency in area 2 due to the 5% disturbance in area 2

5% perturbations in regions 1 and 2 of the two-area system are responsible for the frequency fluctuation. The frequency shift in area 1 caused by a 5% disturbance is seen in Figure 6. Similarly, a 5% disturbance in area 2 causes a frequency shift in region 1, as shown in Fig. 7

A 5% disturbance in area 1 altered the frequency in region 2, as shown in Figure 8 The frequency variation in region 2 caused by a 5% disturbance is seen in Figure 9. It is commonly observed that IWO gives a quicker settling time than SES and produces a reduced peak overshoot of the frequency change in regions 1 and 2.

V. CONCLUSION

This article demonstrates the application of bio-inspired invasive weed optimization (IWO) to reduce the order of a power system network. The model order reduction performance study of a two-area power system has been assessed using the SES approach. The coefficients of the parameters are also estimated by the IWO. Performance measures like integral square error E, IAE, ITAE have been used to estimate the steady state responses in terms of rise and settling times. Compared to SES, IWO is thought to have a faster rising and settling time per unit step reaction. Additionally, IWO reduces E, IAE, and ITAE more than SES. In order to analyze the frequency variation with 5% disturbances, a network of two-area PSN has also been built. For the two-area model's 5% disturbances, IWO performs better than the SES method in terms of frequency deviation. All of these validations demonstrate that IWO outperforms the traditional model order reduction technique.

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