REDUCED ORDER MODELLING AND CONTROLLER DESIGN OF DIFFERENT POWER SYSTEM MODELS USING GREY WOLF OPTIMIZER

A Dissertation submitted in fulfillment of the requirements for the Degree
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Submitted by

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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, **"Reduced order modelling and controller design of different power system models using grey wolf optimizer"**, in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Power Systems, submitted to Electrical & Instrumentation Engineering Department of Thapar Institute of Engineering & Technology (Deemed to be University) is as authentic record of my own work carried under the supervision of Mr. Souvik Ganguli. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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ABSTRACT

This dissertation work deals with the order reduction and controller design of different power system models using grey wolf optimizer (GWO). The order reduction is carried out using a mixed method. The denominator polynomial of the reduced system is obtained through the stability equation method (SEM) while the numerator polynomial is determined using GWO, thus yielding a mixed technique GWO-SEM. The order reduction takes into account into dc gain matching, stability, and minimum phase as constraints. Test systems considered for model order reduction were load frequency control (LFC) two area power system, automatic voltage regulator (AVR) and single machine infinite bus (SMIB) system. Standard and latest heuristic algorithms were considered for comparison. The GWO-SEM method outperforms the techniques available in the literature on most occasions. Further, GWO is applied for the controller design of these power system models using approximate model matching (AMM) technique.

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LIST OF ACRONYMS

ACE	Area control error
AMM	Approximate model matching
AVR	Automatic voltage regulator
DA	Dragonfly algorithm
GWO	Grey wolf optimizer
SMIB	Single machine infinite bus
IAE	Integral of absolute error
ISE	Integral of square error
ITAE	Integral of time weighted absolute error
ITSE	Integral of time weighted square error
LTI	Linear time invariant
LFC	Load frequency control
MOR	Model order reduction
PID	Proportional integral derivative
SSA	Salp swarm algorithm
SCA	Sine cosine algorithm
SISO	Single input single output
SEM	Stability equation method
WOA	Whale optimization algorithm

CHAPTER 1
INTRODUCTION

1.1BACKGROUND OF WORK

With the quick evolution in electric power systems comprising of different technologies, the complete power system in today's world has become a complicated unit. While considering network of power systems interconnected to each other, both fluctuations of tie-line in power interchange often happen just because of parameter uncertainties of the system, inconsistent variations in power load demand, modeling errors, and hindrances occurring because of changing parameters of the environment as well [1]. Hence, the equilibrium in the power system is necessary in maintaining synchronism and prescribed levels of voltage, while any transient and sudden hindrances like overload, line trips, or other type of fault occur. The exact analysis of a higher order system is both too slow to perform and cost a good fortune. It is required always to replace such a higher order system of lower order. Engineers and many scientists are frequently faced against the analysis, design, and synthesis of real-life problem. The most necessary solution in such problems is the development and design of a 'mathematical model' that can act as an alternative for the real problem.

In the electric power industry, the need for effective and efficient load frequency control (LFC) methods to contradict the ever-rising complications of power systems of large-scale and their robustness against uncertainties of parameters and plant/model mismatch & change in external load, is rising day by day. In the past few decades, lot of research has been done for an effective and optimized answer to the load frequency control (LFC) problem of the power system which inturn signifies effect on generation, operation, power quality, and reliability [2-3]. This continued process of improvement of these schemes for increasing efficiency and effectiveness is seen through new applications and developing logic algorithms and process control approaches. If seen from a control perspective load frequency control (LFC) technology is considered as one of the first large scale, decentralized & optimal control issue in engg. practices [4-7]. AVR is a necessary parameter in operation of power system. Hence, for observing the nature and performance of Automatic Voltage Regulator (AVR), the study and research of its modeling is essential.

A lot of practitioners and researchers are involved in the design and formulation of the automatic voltage regulator (AVR); the primary aim involves maintainining steady terminal voltage at the point. Therefore, the basic requirements for designing the AVR are small overshoot, quick response, and zero steady-state error to the deviation of the operating reference voltage. The speed of the AVR triggers a great attention while studying stability. Since automatic voltage regulator (AVR) involves higher order transfer function making it a complex system, its model order reduction is required. Furthermore, single-machine infinite-bus (SMIB) power system poses yet another problem of model order reduction (MOR).

GWO (Grey Wolf Optimiser) developed by Mirjalili [8] corresponds to the hierarchy in leasdership and mechanism of hunting by grey wolves living in nature. There are four distinct kinds of grey wolves (alpha, beta, delta, and omega) which are utilized for simulation of the leadership hierarchy. Besides this, major sub-processes of hunting, namely searching, encircling, and finally pouncing upon the prey are implemented to carry out the desired optimization. The algorithm applies to diverse problems with unknown search spaces based on classical engineering design problems and real time applications.

MOR furnish an organized approach for modelling, analysis, design, and implementation of large scale system & extensively applied in various fields of engineering. Diminution of higher order systems has been investigated over the world for various times, and various technologies have been researched and developed to acquire reduced models in both frequency and time domain [1]. The difficulty in model matching control comprises of design of a controller which inturn compensates for a provided plant in a way that the resultant controlled system is provided with transfer function which is pre-specified (reference model). The benefit to this technique is that the specifications of the design (frequency and time domain) which are concluded with the help of the reference model can be covered by the controlled system. Design processes for model matching (exact and approximate) had been put furthur for the systems which are depicted by transfer function and state-space models [9].

1.2 LITERATURE REVIEW

1.2.1 Literature review on load frequency control

Saxena *et al.* [2] developed a model reduction technique which generates a stable control system required by a power system (single-area) comprising of a single generation unit, and satisfying optimal and robust performance. Load frequency control provided a reliable and effective power generation.

Mu *et al.* [3] proposed an adaptive supplementary control technique to regulate the frequency of the power system with the help of modeling the disturbances and uncertainties of parameters into the LFC model. Several control methods have been used like proportional-integration (PI) control, fuzzy logic control, internal model control, intelligent control. They showed the three control methods to show the more eficient performance of the approximate dynamic programming (ADP) supplementary control.

Guha et al. [4] solved the LFC problem involving a novel evolutionary algorithm. The author implemented the algorithm to the four-area hydrothermal power plant with a different proportional-integral-derivative (PID) controller and extended study to a five-area thermal power plant.

Yousef *et al.* [5] proposed the direct–indirect adaptive fuzzy control technique to LFC in multi-area power systems. A direct-indirect adaptive fuzzy control (DIAFLC) technique based controller was developed.

Sondhi *et al.* [6] proposed a fractional controller PID controller suitable for the Load Frequency Control & prevented a steady-state error, robustness of the system against gain changes and consisted of a good rejection of disturbances.

Ersdal *et al.* [7] proposed a model predictive controller (MPC) for load frequency control (LFC) in an interconnected power system. The writer presented some of the advantages of Model predictive controller, including flexibility and coordination in multiple inputs, considering limitations in the system, and utilizing knowledge about the hindrances acting on the system.

Philip *et al.* [10] proposed a reduced model order technique to search for the approximate dominant poles using reciprocal transformation and principal pseudo break frequency estimation technique. The author used the system having real dominant poles and complex poles in his technique.

Mu *et al.* [11] proposed a new adaptive LFC technique for single area as well as multi area power systems when prone to load disturbances and parameters of uncertainties. The algorithm was successfully improved sliding mode design for LFC method for single area and multi area power system for an integrated adaptive learning strategy.

Guha *et al.* [12] solved the load frequency control issue in an inter-connected power system network consisting of a classical PI or PID controller based on (GWO) grey wolf optimization method. An analysis for sensitivity was done for the ruggedness of the designed controller through variation of the parameters in the system and operating conditions during loading.

Guha *et al.* [13] developed an effective and optimal solution for Load Frequency Control problem of the power system using quasi-oppositional symbiotic organism search (QOSOS) technique. Furthermore, the sensitivity and ruggedness were tested and analysed for the considered power system for judging usefulness of the presented Quasi-Oppositional Symbiotic Organism Search (QOSOS) technique.

1.2.2 Literature review on automatic voltage control (AVR)

Biradar *et al.* [14] had imnplemented ten distinct model order reduction methods. An explained study of frequency & time domain analysis had been performed as well. The author pointed out that for observing the perfoemance and behaviour of automatic voltage control (AVR), a proper study of its modeling was essential.

Khedr *et al.* [15] developed a multi-objective approach applying the genetic algorithm (GA) for controller tuning of a non-linear automatic voltage regulator. The GA-tuned PID controller as compared to the GA-tuned ANN such as PID controller gave better response in linear as well as nonlinear models.

Anderson *et al.* [16] proposed a complicated scheme involving various entities of components considered in electrical power systems. The reduced order modeling concept relieved control practitioners and engineers by decreasing complications in the proposed models.

Zamani *et al.* [17] presented PID controller design of a fractional order for an Automatic Voltage Regulator through optimization of particle swarm. The proposed method included a new performance criterion in both the frequency and time domain. The method to a practical AVR when applied proved that the algorithm proposed could effectively investigate the optimal parameters of the FOPID controller.

1.2.3 Literature review on single machine infinite bus system (SMIB)

Sambariya *et al.* [18] made a conflate of stability equation technique and firefly algorithm to formulate reduced order modeling of Single Machine Infinite Bus power system model. The coefficients of the numerator of a required system of reduced order were made optimum through minimization of integral square error as an objective function pertaining to a unit-step as input. The denominator of the reduced order model was calculated through the stability equation technique.

Alsmadi *et al.* [19] developed a new method for reduction of model order of dynamical control MIMO (multi input multi output) systems through genetic algorithms (GA) with frequency selectivity, where it may be applied without frequency restrictions.

1.2.4 Literature review on model order reduction using soft computing techniques

Bansal *et al.* [20] addressed the complexity involved with the modeling of higher order practical system. The author used the Artificial Bee Colony optimization algorithm for solving system of higher order comprising of the SISO (single input single output) Systems. The conclusions acquired by Artificial Bee Colony were put in comparison with the two most deterministic methods and results reported were encouraging.

Mishra *et al.* [21] presented a hybrid algorithm integrating bacterial foraging along the genetic algorithm to solve the issue of MOR. The proposed technique outperformed other results which were reported so far, considering especially ISE (Integral Square Error) and IRE (Impulse response energy).

Alsmadi *et al.* [22] compared the artificial Intelligence methods for MOR with preservation of the substructure. The artificial intelligence (AI) methods had been beneficially implemented to the issue of MOR along with the benefit of stable and convergent steady state performance.

Sikander *et al.* [23] used the approach of minimizing the error or the ISE (integral square error) between reduced-order and original model for minimizing polynomial of the numerator of reduced -order model. The author analyzed two basic system approaches, transfer function approach in the frequency domain, and state space approach in the time domain.

Kumar *et al.* [24] proposed two bio-inspiring calculation techniques, namely particle swarm optimization (PSO) and Bacterial Foraging Optimization (BFO) for reducing order of the model of linear dynamic system model (LTI) that does not change over time. The algorithm minimized the integral square error to unit step and impulse inputs by PSO and BFO techniques.

Dia *et al.* [25] developed a MOR (model order reduction) approach to multivariable linear system based on invasive weed optimization (IWO). The algorithm had been implemented successfully to

10th order MIMO (Multiple-Input–Multiple-Output) linear model provided for a practical power system.

Sikander *et al.* [26] compared the results considering parameters of time response specifications, such as settling time, rise time and max. peak overshoot. The values of integral square error (ISE), integral of absolute error (IAE), integral of time multiplied absolute error (ITAE) obtained was found lesser than other pre-existing reduced order models.

Sikander *et al.* [27] proposed a cuckoo search algorithm to reduce the higher order system developed the most famous performance indices like integral square error, integral absolute error and integral time absolute error. The technique is further implemented for MIMO (multi input multi output) systems as well.

Sharma *et al.* [28] developed latest swarm intelligence based algorithm, like 'SMO' (Spider Monkey Optimisation) for solving the modeling problem of system of lower order.

1.2.5 Literature review on model order reduction using mixed methods

Desai *et al.* [29] proposed reduction of model order in SISO (single input single output) system of higher order and reduce them to a system of lower order. The Impulse response energy (IRE) and Integral Square Error (ISE) values obtained by the proposed reduced system indicate that there is an improvement in the consistency and computational efficiency.

Desai *et al.* [30] developed model order reduction inspired by nature called big bang big crunch (BBBC). Furthermore, the author proposes that BBBC has performed better over the genetic algorithm (GA) considering integral square error (ISE) and transient response parameter values.

Biradar *et al.* [31] proposed reduction of model order for Single Input Single Output , Multiple Input Multiple Ouput, and time delay systems. Further, Big-bang big-crunch (BBBC) algorithm was applied to calculate numerator of the reduced model while time moment method was utilized to .compute the denominator polynomial.

Narwal *et al.* [32] proposed an efficient algorithm for reducing both (SISO) and (MIMO) LTI systems. The author developed approach involving reducing the order which combined both CSO algorithm and stability equation method (SEM) developed recently.

Gupta *et al.* [33] presented a model order reduction method and validated it with the help of SISO and MIMO systems. The proposed approach guaranteed if the original higher order system remained stable, the reduced model would be stable as well.

Soloklo *et al.* [34], proposed a multi objective criterion based on the weighted sum approach. The author minimized the error between the singular values in the reduced-order system and the error between a set of subsequent time moments (markov parameters) and those of the original system were reduced to minimum.

1.3 RESEARCH GAPS

From the literature, it is found that although particle swarm optimization and cuckoo search algorithm have been employed with the stability equation method (SEM) for model order reduction, GWO stands a new candidate for estimating the variables of the reduced order system along with SEM. Further, unlike the conventional approach of response matching using step or impulse input, a pseudo random binary sequence (PRBS) is considered to match the responses of higher order and its corresponding reduced model to estimate the numerator polynomial coefficients. The denominator polynomial, on the other hand, is determined by SEM, thus proposing a new mixed method. Moreover, model order reduction techniques using composite approaches have only being applied to simple systems. Model order reduction of power sytem is rarely reprted and hence can be carried out.

In classical control literature, “Truxal” method is widely appreciated technique in control system synthesis, using principle of exact model matching in which the parameters of the reference model are computed to meet the given performance specifications of frequency and time domain and then the parameters of the controller are computed in a way that the overall closed loop controlled system closely resembles both frequency and time responses of the reference model. The prime demerit of exact model matching is that the controller so designed does not give ensure for its hardware implementation. To overcome the same, approximate model matching may be a viable alternative in which the model order reduction scheme can be employed to design the control scheme.

1.4 OBJECTIVES OF WORK

The primary objectives of the proposed work carried out of this dissertation are given as :

- To design GWO-SEM mixed approach to reduce different power system models like LFC, AVR, and SMIB.
- To develop a GWO based controller design for the above mentioned power system models applying approximate model matching (AMM) technique.

1.5 ORGANIZATION OF DISSERTATION

The rest of the dissertation is organized as follows:

Chapter 2 deals with the order reduction and controller design of two-area LFC model. The model order reduction is carried out using GWO-SEM mixed method while GWO is employed to design the controller parameter using AMM.

Chapter 3 deals with the order reduction and controller design of AVR model. The model order reduction is performed using GWO-SEM composite technique while GWO is utilized to tune the controller parameter using AMM.

Chapter 4 deals with the order reduction and controller design of SMIB model. The model order reduction employs GWO-SEM hybrid method while GWO is employed to estimate the controller parameter using AMM.

Chapter 5 summarizes the major results reported, inferences drawn and also gives some recommendations for future research.

CHAPTER 2

ORDER REDUCTION AND CONTROLLER DESIGN FOR LFC

2.1 INTRODUCTION

This chapter deals with the order reduction and controller design to control the frequency of the load in a two-area power system network. An order reduction has been carried out using a mixed method. The polynomial in the denominator is processed with the help of stability equation technique while the numerator polynomial coefficients are obtained through grey wolf optimization. The controller is developed using AMM applying GWO technique. The proposed technique is further correlated with some of the standard heuristic algorithms which were provided in the literature. The proposed method outperforms the existing algorithms on most of the occasions.

Due to the presence of structural variations, uncertainties in parameters and perturbations in sudden small load and various other factors, the power systems of large-scale are prone to decrease in their performance. Hence, modern control aspects are tremendously necessary in load frequency controller (LFC) design for power systems. The Load Frequency Control problem is typified as a rejection in disturbance and problem of control of large-scale system [2].

With the fast evolution of electric power industry, the total power system had developed into a complicated unit. Generation, transmission and distribution systems are built at different places that are normally interconnected along their neighboring areas through tie-lines. While considering the power systems interconnected to each other, both tie-line power interchange and area frequency variations often happen due to variation in power load demand, uncertainties in system parameters, modelling errors, and hindrances because of changing conditions of environment. Hence, the stability of the power system is highly required for retaining synchronisation and prescribed voltage levels, in any suuden transient disturbances such as line trips, faults, or an overload. So, LFC is solely accountable to provide an effective as well as dependable power generation of an electric energy system with tie-line power interchange [2].

By reduction of model order, we convey informally that the large-scale system is approximated by the small-scale system, in such a way that the intrinsic nature of the original method does not exploit. Till now, various model reduction methods have been researched and developed [35-36].

These techniques can be further exploited for SISO/MIMO systems for obtaining lower-order models or reduced models, which in turn could be utilized to develop the controller. The application of these methods to Load Frequency Control is further explained below.

The principal goals of LFC in power systems involves

- Preventing the sudden load disturbances
- Maintaining of negligible steady state errors in frequency variation
- Minimizing unscheduled tie-line power flows in nearby areas and sudden changes in area frequency
- Compensating with modelling uncertainties as well as nonlinearities in system within a tolerable region
- Performing well within prescribed limits of overshoots and settling time in tie-line power and frequency deviations.

With a minor variation in load power in a single area power system which is performing at a prescribed frequency, it builds a power mismatch both at generation as well as demand levels. Extracting kinetic energy from the system provides an initial solution for this mismatch problem; in result of which, declining of system, frequency occurs. With the gradually decreasing frequency, the power exploited by the old load reduces as well. However, the large power systems can acquire the equilibrium at a single point by distraction of the newly added load which is done by decreasing the power used by the old load and power corresponding to kinetic energy is depleted from the system. Definitely, at the cost of reduction of frequency, equilibrium is obtained. Under such condition, the frequency reduction is huge.

Few reduction techniques have been presented for a model order reduction (MOR) of continuous-time LTI systems in frequency and time domains. Moreover, various mixed methods are still being developed in which the coefficients of the numerator are acquired by a classical order reduction method or optimized method, and the polynomial of denominator of the reduced order model (ROM) is derived through a stability preservation technique for ensuring the stability of the ROM reduced order model [2]. In the present chapter, the polynomial in the numerator of the reduced order model is acquired by applying grey wolf optimization technique, while the polynomial of the denominator is derived through the stability equation technique to ensure the reduced order model stability.

2.2 LFC FOR SINGLE-AREA POWER PLANT

Generally, among complicated nonlinear dynamics, the power systems generally are large-scale systems [1]. However, when designed for relatively low load disturbance, these systems can prove to be constructive around the operating point. Consider power system model of a single area which supplies the power through single generator to single service-area. For load frequency control this power plant design includes the governor $G_g(s)$ on-reheated turbine $G_t(s)$, load & machine $G_p(s)$, with the droop characteristics as $\frac{1}{R}$, the type of feedback gain for improving the power system damping properties. The linear model of the proposed plant is provided in Fig. 2.1. The dynamic characteristics of these subsystems can be provided as

$$G_g(s) = (T_G s + 1)^{-1} \quad (2.1)$$

$$G_t(s) = (T_T s + 1)^{-1} \quad (2.2)$$

$$G_p(s) = K_P(T_P s + 1)^{-1} \quad (2.3)$$

The complete system model can be constructive by

$$\Delta f(s) = G(s)u(s) + G_d(s)\Delta P_d(s) \quad (2.4)$$

$$G_d(s) = \frac{G_g(s)G_t(s)G_p(s)}{\frac{1 + G_g(s)G_t(s)G_p(s)}{R}}$$

$$= \frac{K_P}{T_P T_T T_G s^3 + (T_P T_T + T_T T_G + T_G T_P)s^2 + (T_P + T_T + T_G)s + (1 + \frac{K_P}{R})} \quad (2.5)$$

$$G_d(s) = \frac{G_p(s)}{\frac{1 + G_g(s)G_t(s)G_p(s)}{R}} \quad (2.6)$$

Equation (2.4) suggest clearly that load frequency control is fundamentally a disturbance rejection (regulator) issue that involves the objective of

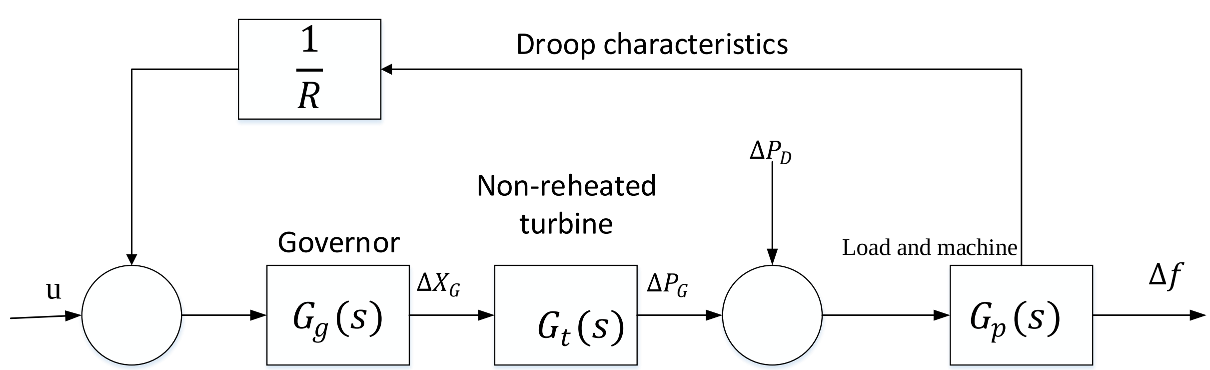

Fig. 2.1 Linear model of a single-area power system

evaluating the control rule: $u(s) = -K(s)\Delta f(s)$, where $K(s)$ is IMC based compensator employed for controlling the power plant $G(s)$ & reducing the effect on $\Delta f(s)$ in the surroundings of hindrance $\Delta P_d(s)$ in small loads[14].

2.3 LFC FOR TWO-AREA POWER PLANT

The model below explains the process for a thermal twp-area power system. The power system is shown by the block diagram of transfer function as represented in Fig.2.2. The system model comprises the transfer function as follows,

Governor: $G_g(s) = \frac{1}{(1+sT_g)}$, (2.7)

Non-reheat turbine: $G_t(s) = \frac{1}{(1+sT_t)}$ (2.8)

and collective inertia of load plus rotating mass: $G_p(s) = \frac{K_p}{(1+sT_p)}$ that area,

Droop characteristic: $\frac{1}{R}$ (2.9)

Load disturbance: ΔP_d (2.10)

The weedy link interconnecting between the two-areas is known as tie line. The system model tie line deviation and frequency is monitored by every control area in the system. The control area also attempts in restoring the normal operation state of the system. The difference between preferred and actual frequency of the system combined along variation from the scheduled net interchange in a control area is called ACE (area control error) which is provided by [37],

$$\mathrm{ACE}_i = \sum_{j=1}^{N}(\Delta P_{tie,i,j} \pm B_i \Delta f_i) \quad (2.11)$$

Where,

ACE_i- Area control error of ith area

N- Number of areas interconnected with ith area

$\Delta P_{tie,i,j}$- Tie-line power flow error between ith and jth area

Δf_i- Frequency error of ith area

B_i- Frequency bias coefficient of ith area which is given by,

$$B_i = \frac{1}{R_i} + D_i \quad (2.12)$$

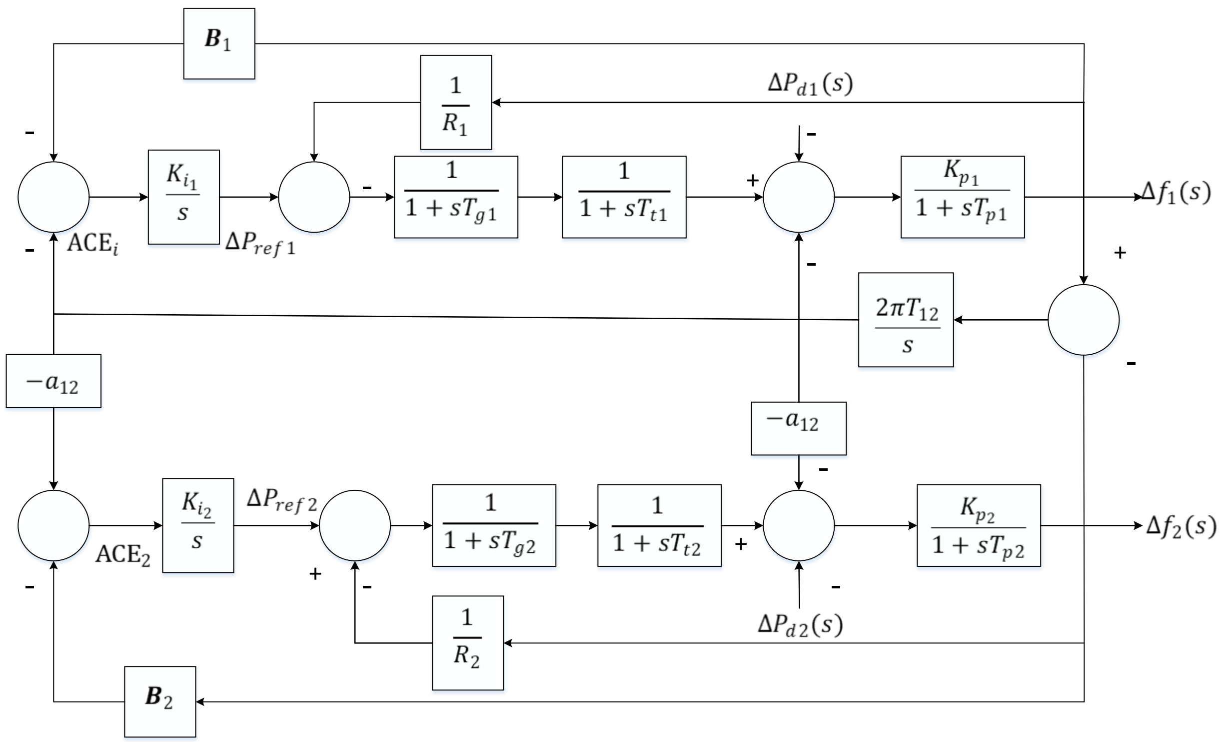

Fig: 2.2 Load frequency control model of two-area non-reheat thermal power system

2.4 PROBLEM FORMULATION

2.4.1 Statement of the problem

Assume general transfer function of n^{th} order continuous SISO system can be provided as

$$G(s) = \frac{N_{k-1}(s)}{D_k(s)} = \frac{\sum_{i=0}^{k-1} b_i s^i}{\sum_{i=0}^{k} a_i s^i} \tag{2.13}$$

where a_i and b_i are the denominator coefficients and the polynomials of the numerator of the n^{th} order system. Furthermore, it is assumed as well that $G_r(s)$ can't be reduced, i.e. $N_{k-1}(s)$ and $D_k(s)$ have zero similar factors. The aim is to find rth order reduced model which is shown by

$$G_r(s) = \frac{N_{r-1}(s)}{D_r(s)} = \frac{\sum_{i=0}^{r-1} d_i s^i}{\sum_{i=0}^{r} c_i s^i} \tag{2.14}$$

where c_i and d_i are the unknown coefficients and r is the order of the reduced system (r < n).

Similarly, for multi-input-multi-output system (p inputs and m outputs) shown in the delta domain by the following transfer matrix:

$$[G_n(s)] = \frac{1}{D_n(s)} \begin{bmatrix} H_{11}(s) & H_{12}(s) & \cdots & H_{1p}(s) \\ H_{21}(s) & H_{22}(s) & \cdots & H_{2p}(s) \\ \vdots & \vdots & \cdots & \vdots \\ H_{m1}(s) & H_{m2}(s) & \cdots & H_{mp}(s) \end{bmatrix} \tag{2.15}$$

where H_{ij} ; i=1,2……p and j=1, 2,.m are the polynomial matrix entries of the numerator of the nth order system. The primary aim is to calculate a reduced Multiple input multiple output system (p inputs and m outputs) of order $r(r < k)$ from the original multiple input multiple output system given by the following transfer matrix:

$$[G_r(s)] = \frac{1}{D_r(s)} \begin{bmatrix} D_{11}(s) & D_{12}(s) & \cdots & D_{1p}(s) \\ D_{21}(s) & D_{22}(s) & \cdots & D_{2p}(s) \\ \vdots & \vdots & \cdots & \vdots \\ D_{m1}(s) & D_{m2}(s) & \cdots & D_{mp}(s) \end{bmatrix} \tag{2.16}$$

where D_{ij} ; i=1,2……p and j=1,2,…….m are numerator polynomial matrix of the reduced order model.

2.4.2 Determining the polynomial of the denominator

Coefficients of the denominator of required reduced system can be acquired through the SEM (stability equation method) as provided by Chen et al. [38]. If the given original model is stable, then the reduced system must be stable model as well.

Step 1: A stable nth higher order system provided, the denominator $D_{os}(s)$ of the original system can be segregated into their odd and even parts in a way that $D_{os}(s) = D_{eos}(s) + D_{oos}(s)$, the denominator stability equations can be given as:

$$D_{eos}(s) = \sum_{k=0,2,4,\ldots\ldots}^{n} x_k s^k = x_o \prod_{k=1}^{a_1}\left(1+\frac{s^2}{z_k^2}\right) \tag{2.17}$$

$$D_{oos}(s) = \sum_{k=1,3,5,\ldots\ldots}^{n} x_k s^k = x_1 s \prod_{k=1}^{a_2}\left(1+\frac{s^2}{P_k^2}\right) \tag{2.18}$$

where a_1 and a_2 are integer parts of $\frac{n}{2}$ and $\frac{(n-1)}{2}$, and $z_1^2 < p_1^2 < z_2^2 < p_2^2 \ldots \ldots$

Step 2: The reduced stability equations can be provided by ignoring the factors with large magnitudes of z_k^2 and P_k^2 as,

$$D_{ers}(s) = x_o \prod_{k=1}^{a_3}\left(1+\frac{s^2}{z_k^2}\right) \tag{2.19}$$

$$D_{ors}(s) = x_1 s \prod_{k=1}^{a_4}\left(1+\frac{s^2}{P_k^2}\right) \tag{2.20}$$

where a_3 and a_4 are the integer parts of $\frac{r}{2}$ and $\frac{(r-1)}{2}$.

Step 3: The polynomial of the denominator of the reduced system can be provided by combination of the reduced stability equations given as:

$$D_r(s) = e_0 + e_1 s + e_2 s^2 + \cdots + e_{r-1} s^{r-1} + s^r \tag{2.21}$$

2.4.3 Determining the polynomial of the numerator

After computation of the polynomial of the denominator, the numerator polynomial coefficients are solved by applying GWO technique. The Grey wolf optimization technique is discussed below:

Grey wolf optimizer (GWO) is a population based meta-heuristic algorithm mimicking the hierarchy of leadership and mechanism of hunting in grey wolves found in environment [8]. Grey wolves are a-class predators, standing on the top of normal environmental food chain. They generally reside in packs (groups). On average, every group comprises of 5-12 members. The entire group maintains a strict social hierarchy, as given in Fig. 2.3.

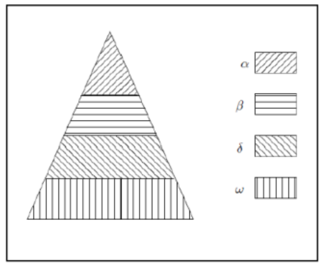

Fig. 2.3 Social hierarchy of grey wolves

From Fig. 2.3, it is evident that four kinds of grey wolves namely, alpha, beta, delta, and omega are utilized in simulation of the hierarchy of leadership. Alpha (α) is known to be the most dominant factor of the group. Furthermore, there are beta (β) and delta (δ) which act as subordinates to alpha, by helping to control the other wolves which are in majority in the hierarchy that are called omega (ω). In the social hierarchy, the ω wolves involves the least rank.

The GWO algorithm is explained in brief with the help of the following steps;

Step 1: Initialization of the GWO parameters like search agents (G_s) , size of variable for design (G_d), vectors a, A, C and maximum number of iterations $(iter_{max})$.

$$\vec{A}. = 2\vec{a}.\mathrm{rand}_1 - \vec{a} \tag{2.22}$$

$$\vec{C}. = 2.\mathrm{rand}_2 \tag{2.23}$$

The values of $\vec{a}$ are reduced linearly from 2 to 0 with the course of iterations.

Step 2: Generation of random wolves based on the size of the pack. Mathematically, these wolves can be shown as,

$$\text{Wolves} = \begin{bmatrix} G_1^1 & G_2^1 & G_3^1 & \cdots & G_{Gd-1}^1 & G_{Gd}^1 \\ G_1^2 & G_2^2 & G_3^2 & & G_{Gd-1}^2 & G_{Gd}^2 \\ & \vdots & & \ddots & \vdots & \\ G_1^{Gs} & G_2^{Gs} & G_3^{Gs} & \cdots & G_{Gd-1}^{Gs} & G_{Gd}^{Gs} \end{bmatrix} \tag{2.24}$$

where $G_j^i$is the initial value of the j^{th} pack of the i^{th} wolves.

Step 3: Estimation of the fitness value of every hunt agent utilizing equation (2.25) -(2.26).

$$\vec{D} = \left|\vec{C}.\vec{G}_p(t) - \vec{G}(t)\right| \tag{2.25}$$

$$\vec{G}(t+1) = \vec{G}_p(t) - \vec{A}.\vec{D} \tag{2.26}$$

Step 4: Identification of the best hunt agent(G_α), then second-best hunt agent (G_β) and then third best hunt agent (G_δ) using equation (2.27)-(2.32).

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\vec{G}_\alpha - \vec{G}| \quad (2.27)$$

$$\overrightarrow{D_\beta} = |\overrightarrow{C_2}.\vec{G}_\beta - \vec{G}| \quad (2.28)$$

$$\overrightarrow{D_\delta} = |\overrightarrow{C_3}.\vec{G}_\delta - \vec{G}| \quad (2.29)$$

$$\overrightarrow{G_1} = \vec{G}_\alpha(t) - \overrightarrow{A_1}.\overrightarrow{(D_\alpha)} \quad (2.30)$$

$$\overrightarrow{G_2} = \vec{G}_\beta(t) - \overrightarrow{A_2}.\overrightarrow{(D_\beta)} \quad (2.31)$$

$$\overrightarrow{G_3} = \vec{G}_\delta(t) - \overrightarrow{A_3}.\overrightarrow{(D_\delta)} \quad (2.32)$$

Step 5: Renewal of current hunt agent location by equation (2.33)

$$\vec{G}(t+1) = \frac{\overrightarrow{G_1+G_2+G_3}}{3} \quad (2.33)$$

Step 6: Estimation of the fitness value of all hunts.

Step 7: Update of the value of G_α G_β and G_δ.

Step 8: Checking of stopping conditions i.e., if the I_{ter} reaches $Iter_{max}$, display of the best value of the solution or back to step: 5.

2.4.4 Objective function

In this section, GWO is implemented to acquire the coefficients of the numerator of reduced order system through minimization of the following fitness function:

$$J = \int_0^\infty [y(t) - y_r(t)]^2 \times t \times dt \quad (2.34)$$

Where y_r and y(t) show, respectively the time responses of the reduced order and original systems corresponding to pseudo random binary sequence (PRBS). Equation (2.16) fulfils satisfying the constraints $x_i > 0$. Further DC gain is also matched with the help of the following equality constraint $\frac{x(2)}{x(4)} = \frac{b_0}{a_0}$.

2.4.5 Reference Model Selection

In the design of controller of model-matching type as shown in this thesis, this design aims involves defining the outset in the reference model transfer function. The difficulty and controller structure depends solely on the best selection of the transfer function for the reference model. The transfer function of reference model ought to be selected to possess a sufficient quick response;

Furthermore, it ought to keep the high frequency gain of the controller small in escaping saturation in the actuators. The reference model might require some more parameters to set some of the following design specifications [9].

- The time domain specification, for example, settling time, the overshoot, rise time, and steady state error.
- The frequency-domain specifications, for example, the cut-off rate, bandwidth, phase margin, and gain margin.
- The complex-domain specifications, for example, damping factor, damping ratio, and undamped natural frequency.
- Quadratic optimal criterion.

A few representative model selection procedure is described in brief.

Let a model transfer function be specified as

$$M(s) = \frac{b_0+b_1 s}{a_0+a_1+s^2} \quad (2.35)$$

For steady state matching, $b_0 = a_0$. Then

$$M(s) = \frac{a_0+b_1 s}{a_0+a_1+s^2} \quad (2.36)$$

Assume the required specifications for closed loop that $M(s)$ has to meet be

Velocity error constant: k_v

Cross-over frequency : ω_c

Damping ratio : ξ

The second-order model $M(s)$ of Eqn. (2.35) may be selected to meet these parameters. The parameters c_0, c_1, and d_1 are acquired by solving the following equations by Chen [9].

$$\omega_1^2 a_1^2 - \omega_c^2 a_1 b_1 - a_0^2 = -\omega_c^4 \quad (2.37)$$

$$a_1 - \left(\frac{a_0}{k_v}\right) - b_1 = 0 \quad (2.38)$$

$$a_1^2 - 4a_0\xi^2 = 0 \quad (2.39)$$

For example, when k_v =20, ω_c =5 and ξ=0.707, Eqn.(2.36) gives

$$M(s) = \frac{a_0+b_1 s}{a_0+a_1+s^2} \quad (2.40)$$

2.5 Results and discussions

Consider a transfer function for a closed-loop system [39]

$$G(s) = \frac{87.5s^2+59.2}{(s^4+16.12s^3+46.24s^2+48.65s^1+25.3)} \quad (2.41)$$

Denominator polynomial is divided into odd (D_o) and even (D_e) polynomial equations

$$D(s) = D_e(s) + D_o(s) \quad (2.42)$$

The denominator polynomial of G(s) as,

$$D(s) = s^4 + 16.12s^3 + 46.24s^2 + 48.65s^1 + 25.3 \quad (2.43)$$

$$D_e(s) = 25.3 + 46.24s^2 + s^4 \quad (2.44)$$

$$= 25.3\left(1 + \frac{s^2}{0.5471}\right)\left(1 + \frac{s^2}{46.24}\right) \quad (2.45)$$

$$D_o(s) = 48.65s + 16.12s^3 \quad (2.46)$$

$$= 48.65\left(1 + \frac{s^2}{3.0179}\right) \quad (2.47)$$

Neglecting factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order system equation will be

$$D(s) = D_e(s) + D_o(s) \quad (2.48)$$

$$D(s) = 25.3\left(1 + \frac{s^2}{0.5471}\right)48.65\left(1 + \frac{s^2}{3.0179}\right) \quad (2.49)$$

$$D(s) = 16.1204s^3 + 46.24s^2 + 48.65s + 25.3 \quad (2.50)$$

$$D_e(s) = 25.3 + 46.24s^2 \quad (2.51)$$

$$D_o(s) = 48.65s + 16.1204s^3 \quad (2.52)$$

$$D_o(s) = s(48.65 + 16.1204s^2) \quad (2.53)$$

Neglecting factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order system equation will be

$$D(s) = D_e(s) + D_o(s) \quad (2.54)$$

$$D(s) = 16.1204s^2 + 48.65s + 25.3 \quad (2.55)$$

$$D(s) = s^2 + 3.0179s + 1.5694 \quad (2.56)$$

Using GWO algorithm with a population size of 50 and the number of iterations is 200, the numerator polynomial is obtained as

$$N(s) = 0.10272s + 3.6923 \quad (2.57)$$

Thus, the reduced second-order system is given as

$$G_2(s) = \frac{N(s)}{D(s)} = \frac{0.10272s+3.6923}{s^2+3.0179s+1.5694} \tag{2.58}$$

The parameter values of GWO, as well as some standard algorithms with which comparison is carried out, is provided in Table 2.1.

Table 2.1 Algorithm parameters

Algorithm	Parameters	Values
GWO	Search agents	50
	Maximum iterations	200
	A	2→0 (linear decrease)
	A	$2 \times a \times rand_1 - a$
	C	$2 \times rand_2$
DA	Search agents	50
	Maximum iterations	200
	R	$\frac{(ub-lb)}{4} + (ub-lb) \times (\frac{t}{T})^2$
	W	$0.9 - \frac{t}{T} \times (0.9-0.4)$
	Enemy distraction weight (my_c)	$0.1 - \frac{t}{T} \times \left(\frac{0.1-0}{2}\right)$
	Separation weight (s)	$2 \times rand \times my\_c$
	Alignment weight (a)	$2 \times rand \times my\_c$
	Cohesion weight (c)	$2 \times rand \times my\_c$
	Food attraction weight (f)	$2 \times rand$
SCA	Search agents	50
	Maximum iterations	200
	A	2
	r_1	a→0 (linear decrease)
	r_2	$2 \times \pi \times rand$
	r_3	$2 \times rand$
SSA	Search agents	50
	Maximum iterations	200

	C_1	$2\times\exp((-4/T)^2)$
	C_2	*rand*
	C_3	*rand*
WOA	Search agents	20
	Maximum iterations	100
	A	2→0 (linear decrease)
	a_2	-1→-2
	A	$2 \times a \times rand_1 - a$
	C	$2 \times rand_2$

The reduced order model, along with the fitness value (J) acquired by the proposed method, is shown in Table 2.2. The models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are used for comparison.

Table 2.2 Reduced order models and their fitness function

Methods	Reduced systems	Fitness function (J)
Proposed method	$G(s) = \dfrac{0.10272s + 3.6923}{(s^2 + 3.0179s + 1.5694)}$	0.0067
DA-SEM	$G(s) = \dfrac{0.49071s + 3.6723}{(s^2 + 3.0179s + 1.5694)}$	0.0073
SCA-SEM	$G(s) = \dfrac{0.51594s + 3.6815}{(s^2 + 3.0179s + 1.5694)}$	0.0159
SSA-SEM	$G(s) = \dfrac{7.252s + 3.6723}{(s^2 + 3.0179s + 1.5694)}$	0.0745
WOA-SEM	$G(s) = \dfrac{3.7694s + 3.6722}{(s^2 + 3.0179s + 1.5694)}$	0.0265

The time and frequency response parameters are compared with that of the original system and provided in Table 2.3. The reduced models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are further used for comparison.

Table 2.3 Qualitative comparison of time and frequency response parameters for the test system

Parameters	Rise time	Settling time	Over Shoot	Gain Margin	Phase Margin
Original system	1.1435	5.5005	21.8343	5.9831	49.6143
Proposed system	3.5072	6.3307	0	Inf	93.0572
DA-SEM	6.2567	11.2526	0	Inf	69.1721
SCA-SEM	6.2557	11.2457	0	Inf	69.6537
SSA-SEM	3.4595	7.8774	0	Inf	101.4146
WOA-SEM	5.5299	10.1016	0	Inf	104.4828

Table 2.3 shows that the reduced model acquired by the presented technique provides nearly satisfactory outcomes. The step and bode responses of the original and the reduced order system acquired by the presented method are plotted in Fig. 2.4 and Fig. 2.5.

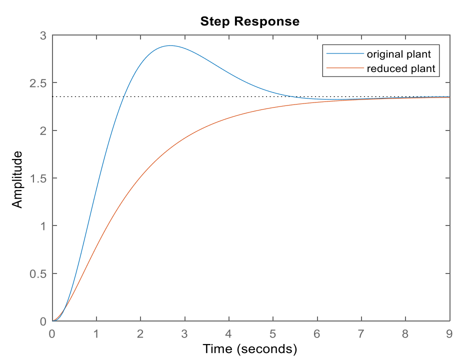

Fig: 2.4 Step response of original and reduced order model

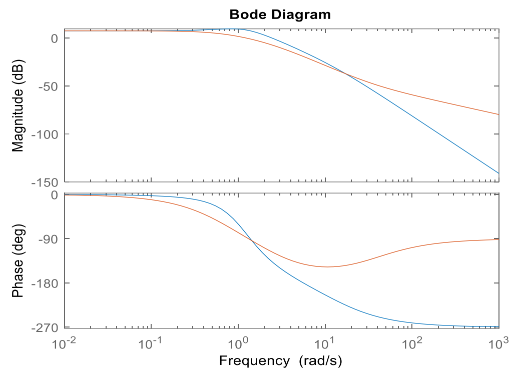

Fig: 2.5 Bode response of original and reduced order model

The responses, shown in Fig. 2.4 and Fig. 2.5 almost show a close match., various parameters indices like ISE, IAE, ITSE, ITAE & H_∞ norm is solved for the reduced model in Table 2.4.

Table 2.4 Comparison of error indices for the reduced order models of the test system

Methods	ISE	IAE	ITSE	ITAE	H_∞ norm
Proposed system	0.0070	0.0785	0.0067	0.0683	0.1166
DA-SEM	0.0074	0.0927	0.0073	0.0640	0.1092
SCA-SEM	0.0076	0.0941	0.0159	0.0647	0.1107
SSA-SEM	0.1891	0.4494	0.0745	0.2555	0.6876
WOA-SEM	0.0616	0.2591	0.0265	0.1491	0.3848

The proposed method gives better results on most occasions. Now, consider a reference model

$$M(s) = \frac{4.042465s+8.009}{(s^2+4.4431s^1+8.009)} \tag{2.59}$$

The reduced controller transfer function is given by

$$G_c(s) = \frac{M(s)}{G_2(s)} \tag{2.60}$$

$$= 4.4515s^2 + 0.0012s + 0.0474 \tag{2.61}$$

$$= \frac{4.4515s^2+0.0012s+0.0474}{s} \tag{2.62}$$

It is compared by PID controller transfer function as

$$G_c(s) = K_p + \frac{K_i}{s} + K_d s \qquad (2.63)$$

Applying GWO technique the value of K_p, K_i, and K_d are obtained as follows

$$K_p = 4.4515, \; K_i = 0.0012, K_d = 0.0474 \qquad (2.64)$$

Thus, the corresponding closed loop transfer function is represented as

$$G_{CL}(s) = \frac{G_c(s) \times G_2(s)}{1 + G_c(s) \times G_2(s)} \qquad (2.65)$$

Fig. 3.4 compares the step responses of the reference model and the plant model cascaded along the controller in closed loop fashion. This is noticeable through the step response that the controlled plant model matches nearly the reference model.

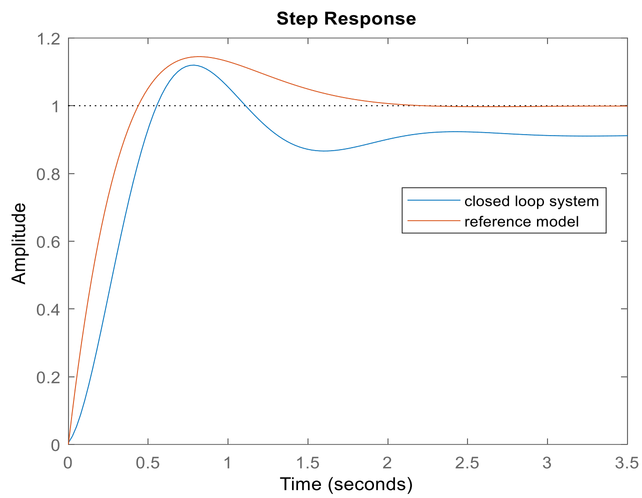

Fig: 2.6 Step response comparison of the reference model and closed loop system

2.6 CONCLUSIONS

The performance of the presented order reduction technique has been compared along four different nature inspired optimization algorithms (DA, SCA, SSA WOA) for load frequency control of a two-area power system network. The various methods have been evaluated using time domain (settling time, rise time, overshoot), frequency domain (phase margin, gain margin) and errors (IAE, ISE, ITAE, ITSE, H_∞ norm). The proposed order reduction method shows better performance over compared optimization algorithms (DA, SCA, SSA WOA) on most occasions. A Proportional-Integral-Differential controller has been developed for the reduced order model using reference model method and its step response has been compared with the closed loop model consisting of plant and controller. Reduction of order and controller design of automatic voltage regulator has been carried out similarly in the next chapter.

CHAPTER 3

ORDER REDUCTION AND CONTROLLER DESIGN OF AVR

3.1 INTRODUCTION

This chapter deals with the reduction in order and design of controller for an automatic voltage regulator. Reduced order modelling is performed using a mixed method. The polynomial of the denominator is determined by stability equation technique and while numerator polynomial coefficients are obtained through grey wolf optimization. The controller is designed using AMM applying GWO technique. The proposed method is correlated with some of the latest heuristic techniques provided in the literature. The proposed technique supercedes the standard algorithms on numerous occasions.

Automatic voltage regulation (AVR) is an utmost necessity for operation of power system. Hence, for analysing AVR, the study of its modelling is required. Since AVR comprises of complex system involving transfer function of higher order, reduction technique must be applied for controller design. A composite topology combining GWO with SEM has been adapted to reduce a higher order AVR model. Further, an approximate model matching technique is applied to design the controller of the reduced system. GWO estimated the controller parameters.

3.2 AVR SYSTEM DESCRIPTION

Usually, in case of power systems, more than one generator is connected to the same bus bar and each is provided by its own AVR. The design aim for an automatic voltage regulator is for controlling the voltage of the generator at the terminals , namely achieving control of primary voltage. For studying this system, the regulator plant is linearized and the linear components are provided in Fig. 3.1. [14]

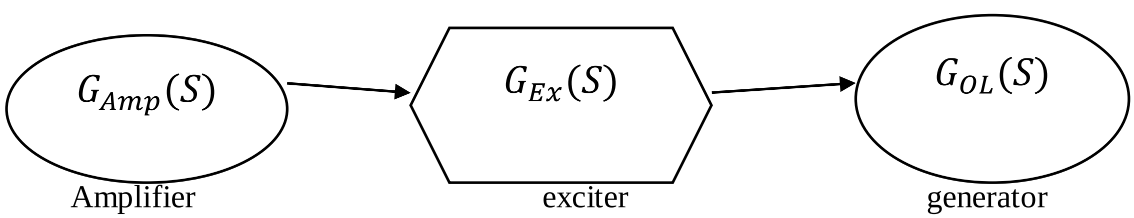

Fig 3.1 Linear model of AVR system

3.3 Results and discussions

Consider a transfer function for a closed-loop system [14]

$$G(s) = \frac{5.994s^2+825.2}{0.573s^5+7.176s^4+51.06s^3+451.1s^2+876.6s+260.8} \quad (3.1)$$

The denominator polynomial is divided into odd (D_o) and even (D_e) polynomial equations

$$D(s) = D_e(s) + D_o(s) \quad (3.2)$$

The denominator polynomial of G(s) as,

$$D_e(s) = 260.8 + 451.1s^2 + 7.176s^4 \quad (3.3)$$

$$D_e(s) = 260.8\left(1 + \frac{s^2}{0.5781}\right)\left(1 + \frac{s^2}{62.8623}\right) \quad (3.4)$$

$$D_o(s) = 876.6s + 51.06s^3 + 0.573s^5 \quad (3.5)$$

$$D_o(s) = 876.6\left(1 + \frac{s^2}{17.1680}\right)\left(1 + \frac{s^3}{89.1099}\right) \quad (3.6)$$

Neglecting factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order equation will be

$$D(s) = D_e(s) + D_o(s) \quad (3.7)$$

$$= 260.8\left(1 + \frac{s^2}{0.5781}\right)876.6\left(1 + \frac{s^2}{17.1680}\right) \quad (3.8)$$

$$D(s) = 51.0601s^3 + 451.1330s^2 + 876.6s + 260.8 \quad (3.9)$$

$$D_e(s) = 260.8 + 451.1330s^2 \quad (3.10)$$

$$D_o(s) = 876.6s + 51.06s^3 \quad (3.11)$$

$$D_o(s) = s(876.6 + 51.06s^2) \quad (3.12)$$

Neglecting the factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order equation will be

$$D(s) = D_e(s) + D_o(s) \quad (3.13)$$

$$D(s) = 451.1330s^2 + 876.6s + 260.8 \quad (3.14)$$

$$D(s) = s^2 + 1.9431s + 0.5781 \quad (3.15)$$

Using GWO algorithm the numerator coefficients are generated by minimizing the fitness function discussed already in chapter 2 with initial population size as 50, and the number of iterations is 200. Thus N(s) is given as

$$N(s) = 2.5867s + 1.8292 \quad (3.16)$$

Therefore, the reduced second-order system is shown as

$$G_2(s) = \frac{N(s)}{D(s)} = \frac{2.5867s+1.8292}{s^2+1.9431s+0.5781} \tag{3.17}$$

Same population size and iterations are considered for other algorithms which are used for comparison. The standard parameter values of all algorithms are thus provided in Table 3.1.

Table 3.1 Algorithm parameters

Algorithm	Parameters	Values
GWO	Search agents	50
	Maximum iterations	200
	a	2→0 (linear decrease)
	A	$2 \times a \times rand_1 - a$
	C	$2 \times rand_2$
DA	Search agents	50
	Maximum iterations	200
	r	$\frac{(ub-lb)}{4}+(ub-lb)\times(\frac{t}{T})^2$
	w	$0.9-\frac{t}{T}\times(0.9-0.4)$
	Enemy distraction weight (my_c)	$0.1-\frac{t}{T}\times\left(\frac{0.1-0}{2}\right)$
	Separation weight (s)	$2\times rand\times my\_c$
	Alignment weight (a)	$2\times rand\times my\_c$
	Cohesion weight (c)	$2\times rand\times my\_c$
	Food attraction weight (f)	$2\times rand$
SCA	Search agents	50
	Maximum iterations	200
	a	2
	r_1	a→0 (linear decrease)
	r_2	$2\times\pi\times rand$
	r_3	$2\times rand$

SSA	Search agents	50
	Maximum iterations	200
	C_1	$2\times\exp((-4/T)^2)$
	C_2	*rand*
	C_3	*rand*
WOA	Search agents	50
	Maximum iterations	200
	a	2→0 (linear decrease)
	a_2	-1→-2
	A	$2 \times a \times rand_1 - a$
	C	$2 \times rand_2$

The reduced order model, along with the fitness value (J) obtained by the proposed technique, is shown in Table 3.2. The models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are used to compare the proposed system.

Table 3.2 Reduced order models and their fitness function

Methods	Reduced system	J
Proposed method	$G(s) = \dfrac{2.5867s + 1.8292}{s^2 + 3.3125s + 3.3464}$	0.013251
DA-SEM	$G(s) = \dfrac{7.4451\text{s} + 1.8291}{s^2 + 1.9431s^1 + 0.5781}$	0.090062
SCA-SEM	$G(s) = \dfrac{2.6147\text{s} + 1.8338}{s^2 + 1.9431s^1 + 0.5781}$	0.013375
SSA-SEM	$G(s) = \dfrac{1.9855\text{s} + 1.8292}{s^2 + 1.9431s^1 + 0.5781}$	0.065371
WOA-SEM	$G(s) = \dfrac{6.5263\text{s} + 1.8288}{s^2 + 1.9431s^1 + 0.5781}$	0.069275

The frequency and time response parameters were calculated and correlated with that of original system and are depicted in Table 3.3. The reduced models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are then used for comparison.

Table 3.3 Qualitative comparison of frequency and time response parameters for the test system

Parameters	Rise time	Settling time	Over Shoot	Gain Margin	Phase Margin
Original system	6.2420	11.6452	0	9.2472	78.9266
Proposed system	4.8783	9.3961	0	Inf	117.5381
DA-SEM	0.5842	9.4593	23.8210	Inf	103.1848
SCA-SEM	4.8553	9.3717	0	Inf	117.4031
SSA-SEM	5.4439	10.0054	0	Inf	117.6834
WOA-SEM	0.7447	8.1841	13.5866	Inf	104.7687

Table 3.3 clearly shows that the reduced model acquired by the presented method provides outcomes almost satifactorily. The step and bode responses of the orginal and the reduced order system obtained by the presented method are plotted in Fig. 3.2 and Fig. 3.3 respectively.

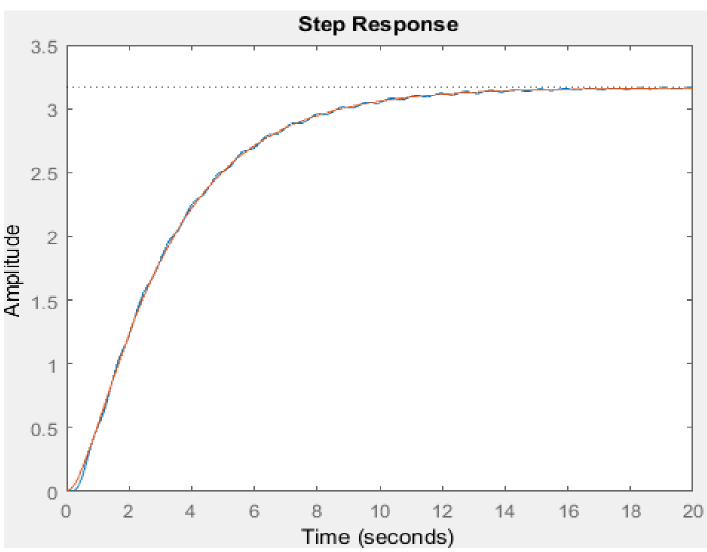

Fig 3.2 Step response of original and reduced order model

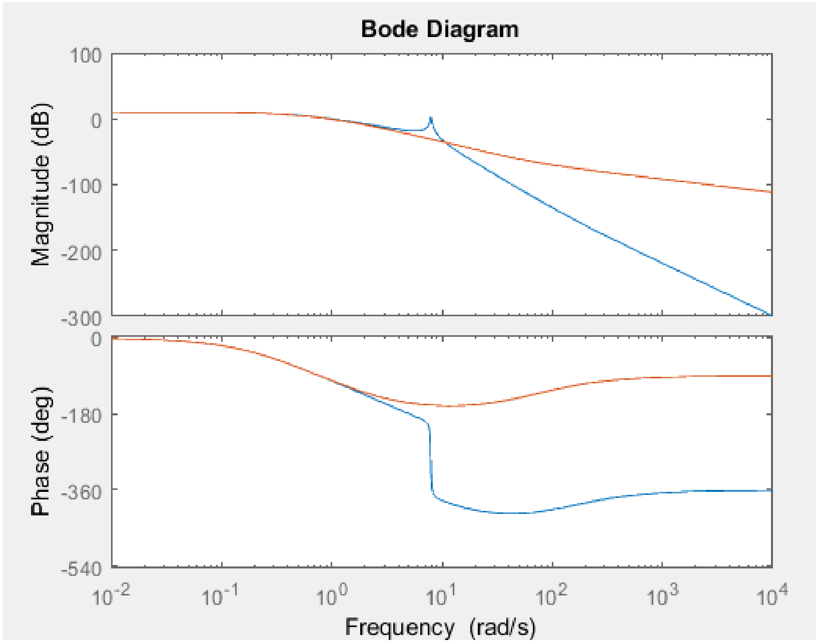

Fig 3.3 Bode response of original and reduced order model

The responses of the reduced order system, shown in Fig. 3.2 and Fig. 3.3 almost resemble the original system. Moreover, several parameters indices like ISE, IAE, ITSE, ITAE & H_∞ norm is computed for the reduced model in Table 3.4.

Table 3.4 Comparison of error indices for the reduced order models of the test system

Methods	ISE	IAE	ITSE	ITAE	H_∞norm
Proposed system	0.0211	0.1457	0.0110	0.0807	0.2372
DA-SEM	0.1679	0.4153	0.0901	0.2339	0.6587
SCA-SEM	0.0215	0.1473	0.0113	0.0817	0.2394
SSA-SEM	0.0126	0.1123	0.0065	0.0618	0.1851
WOA-SEM	0.1294	0.3643	0.0693	0.2050	0.5790

The proposed method gives better results on most occasions. Consider a reference model

$$M(s) = \frac{4.242s+25}{s^2+7.07s^1+25} \quad (3.18)$$

The reduced controller transfer function is given by

$$G_c(s) = \frac{M(s)}{G_2(s)} \quad (3.19)$$

$$= 4.4515s^2 + 0.0034506s + 0.047355 \tag{3.20}$$

$$= \frac{4.4515s^2+0.0034506s+0.047355}{s} \tag{3.21}$$

It is compared with a PID controller transfer function as

$$K_p + \frac{K_i}{s} + K_d s \tag{3.22}$$

Using GWO technique the value of K_p, K_i, and K_d are obtained as follows

$$K_p = 4.4515,\ K_i = 0.0034506, K_d = 0.047355 \tag{3.23}$$

Hence, the corresponding closed loop transfer function is provided as

$$G_{CL}(s) = \frac{G_c(s)\times G_2(s)}{1+G_c(s)\times G_2(s)} \tag{3.24}$$

Fig. 3.4 compares the step responses of the reference model and the plant model cascaded along the controller in closed loop form. This is seen from the step response that the controlled plant model follows approximately the reference model.

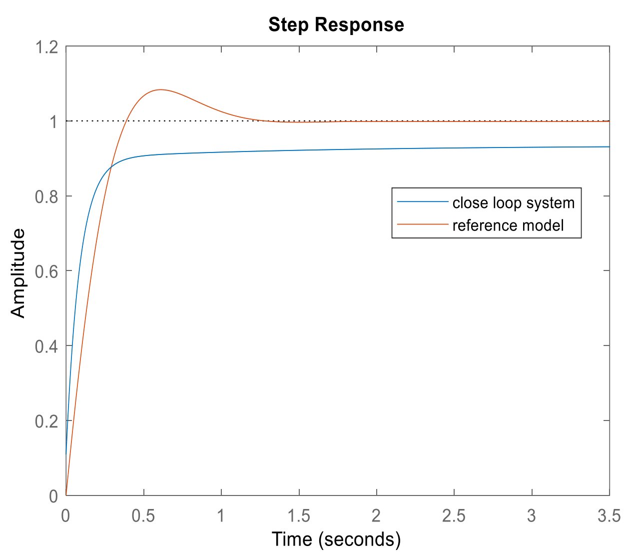

Fig: 3.4 Step response comparison of the reference model and closed loop system

3.4 CONCLUSIONS

The performance of the presented method are compared with four nature inspired metaheuristic algorithms (DA, SCA, SSA WOA) for an automatic voltage regulator. The various techniques have been assessed using time domain (settling time, rise time, overshoot), frequency domain (phase margin, gain margin) and errors (IAE, ISE, ITAE, ITSE, H_∞ norm). The proposed order reduction method shows better performance over compared optimization algorithms (DA, SCA, SSA WOA) on almost all occasions. A PID controller has been developed for the reduced order model using reference model method, and its step response has been used for comparison with the closed loop model consisting of plant and controller. Reduction in order of the model and controller design of single machine infinite bus (SMIB) system has been performed in the next chapter.

CHAPTER 4

ORDER REDUCTION AND CONTROLLER DESIGN OF SMIB

4.1 INTRODUCTION

This chapter deals with the order reduction and controller design of a single machine infinite bus system. Model order reduction of the higher order system is carried out using a mixed method. The polynomial of the denominator is determined by stability equation technique and while the numerator polynomial coefficients are obtained through grey wolf optimization. The controller of the reduced order model is then tuned applying AMM with the help of GWO. Further, the proposed method is correlated with some of the latest heuristic techniques present in the literature. The proposed technique performs better standard algorithms on numerous occasions.

4.2 SMIB SYSTEM DESCRIPTION

The stability analysis of power system is an essential aspect of the study. But most of the power system models are of a higher order. Hence to analyze the stability of the power system model, the system model is reduced to either a single machine connected to an infinite bus or two-machine equivalent system concluded corresponding transfer impedance. In the SMIB system, complete electric power system connected to the machine under study can be represented as Thevenin's equivalent. The advantages of a SMIB of power system involves helping in the tuning of the controllers at one machine without taking into consideration the effect of other electrical machines present in the power system. In an interconnected power system, there is a distribution of the corresponding effect among different machines [41].

The associated algebraic equations are given as

$$\Delta T_e = K_1 \Delta\delta + K_2 \Delta E_q' \tag{4.1}$$

$$\Delta V_t = K_5 \Delta\delta + K_6 \Delta E_q' \tag{4.2}$$

In the previous linear differential and algebraic equation, $\Delta\delta, \Delta E_q'$, ΔV_t and ΔT_e are the small signal deviations in rotor angle discussed in electrical radians, angular rotor speed expressed in rad/sec Fig 4.1.

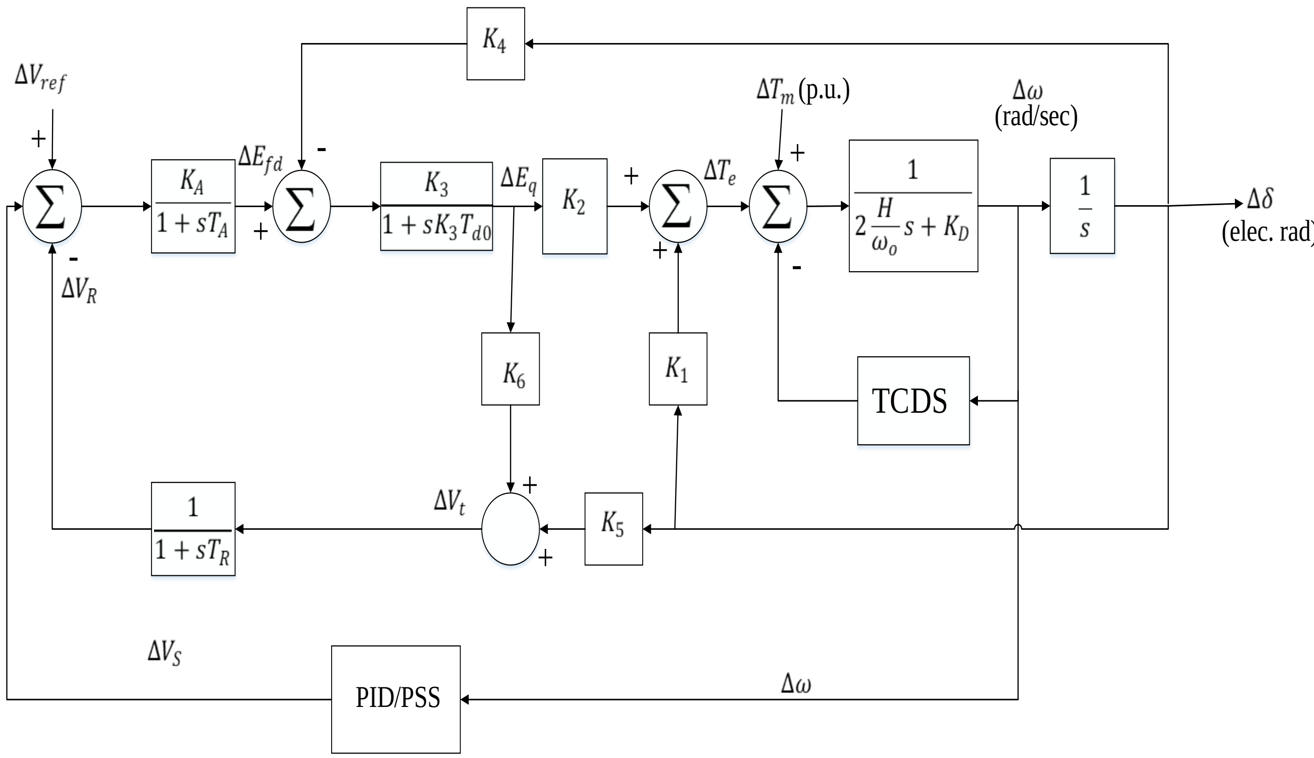

Fig. 4.1 Block Diagram of SMIB System with Controllers

4.3 RESULTS AND DISCUSSIONS

Consider a system with a closed-loop transfer function [40]

$$G(s) = \frac{33s^7+1086s^6+13285s^5+13285s^4+82402s^4+278376s^3+511812s^2+482964s+194480}{s^8+33s^7+437s^6+3017s^5+11870s^4+27470s^3+37429s^2+28880s^1+9600} \quad (4.3)$$

The denominator polynomial of G(s) is between into odd and even polynomial equations as,

$$D(s) = D_e(s) + D_o(s) \quad (4.4)$$

$$D_e(s) = 9600 + 37429s^2 + 11870s^4 + 437s^6 + s^8 \quad (4.5)$$

$$D_e(s) = 9600\left(1+\frac{s^2}{0.2564}\right)\left(1+\frac{s^2}{3.1532}\right)\left(1+\frac{s^2}{27.1624}\right)\left(1+\frac{s^2}{473}\right) \quad (4.6)$$

$$D_o(s) = 28880 + 27470s^3 + 3017s^5 + 33s^7 \quad (4.7)$$

$$D_o(s) = 28880\left(1+\frac{s^2}{1.0513}\right)\left(1+\frac{s^3}{9.10507}\right)\left(1+\frac{s^2}{91.4242}\right) \quad (4.8)$$

Neglecting factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order equation will be

$$D(s) = D_e(s) + D_o(s) \quad (4.9)$$

$$D_e(s) = 9600 + 37441.4977s^2 + 28880s + 27470.7505s^3 \quad (4.10)$$

$$D_e(s) = 9600 + 37441.4977s^2 \quad (4.11)$$

$$D_o(s) = 28880s + 27470.7505s^3 \quad (4.12)$$

$$D_o(s) = s(28880 + 27470.7505s^2) \quad (4.13)$$

Neglecting the factors with larger magnitudes of z_i^2 and p_i^2 in $D_e(s)$ and$D_o(s)$, respectively, the reduced second-order equation will be

$$D(s) = 27470.7505s^2 + 28880s + 9600 \quad (4.14)$$

$$D(s) = s^2 + 1.0513s + 0.3494 \quad (4.15)$$

Using GWO algorithm the numerator coefficients are generated by minimizing the fitness function described in chapter 2 for initial population size as 50, and the number of iterations as 200. Thus N(s) is represented as

$$N(s) = 20.825s + 7.07700 \quad (4.16)$$

Thus, the reduced second-order system is given as

$$G_2(s) = \frac{N(s)}{D(s)} = \frac{20.825s+7.07700}{s^2+1.0513s+0.3494} \quad (4.17)$$

The number of iterations is considered as 200, while the population size set practically as 50 for stable results. Same population size and number of iterations are used for comparison with other algorithms. The standard parameter values of all the algorithm are thus provided in Table 4.1.

Table 4.1 Algorithm parameters

Algorithm	Parameters	Values
GWO	Search agents	50
	Maximum iterations	200
	a	2→0 (linear decrease)
	A	$2 \times a \times rand_1 - a$
	C	$2 \times rand_2$
DA	Search agents	50
	Maximum iterations	200
	r	$\frac{(ub-lb)}{4} + (ub-lb) \times (\frac{t}{T})^2$
	w	$0.9 - \frac{t}{T} \times (0.9-0.4)$

	Enemy distraction weight (my_c)	$0.1-\frac{t}{T}\times\left(\frac{0.1-0}{2}\right)$
	Separation weight (s)	$2\times rand\times my\_c$
	Alignment weight (a)	$2\times rand\times my\_c$
	Cohesion weight (c)	$2\times rand\times my\_c$
	Food attraction weight (f)	$2\times rand$
SCA	Search agents	50
	Maximum iterations	200
	a	2
	r_1	a→0 (linear decrease)
	r_2	$2\times\pi\times rand$
	r_3	$2\times rand$
SSA	Search agents	50
	Maximum iterations	200
	C_1	$2\times\exp((-4/T)^2)$
	C_2	$rand$
	C_3	$rand$
WOA	Search agents	50
	Maximum iterations	200
	a	2→0 (linear decrease)
	a_2	-1→-2
	A	$2\times a\times rand_1-a$
	C	$2\times rand_2$

The reduced order model, along with the fitness value (J) obtained by the proposed technique, is shown in Table 4.2. The models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are used for comparison with the proposed system.

Table 4.2 Reduced order models and their fitness function

Methods	Reduced systems	J
Proposed	$G(s) = \frac{20.825s + 7.07700}{s^2 + 1.0513s^1 + 0.3494}$	0.18392
DA-SEM	$G(s) = \frac{26.0697s + 7.07808}{s^2 + 1.0513s^1 + 0.3494}$	0.18413
SCA-SEM	$G(s) = \frac{20.8258s + 7.0714}{s^2 + 1.0513s^1 + 0.3494}$	0.26503
SSA-SEM	$G(s) = \frac{23.8258s + 7.0753}{s^2 + 1.0513s^1 + 0.3494}$	0.20564
WOA-SEM	$G(s) = \frac{22.0012s + 7.0729}{s^2 + 1.0513s^1 + 0.3494}$	0.20101

The time and frequency response parameters are estimated and compared with that of the original system, the results of which are shown in Table 4.3. The reduced models developed by DA-SEM, SCA-SEM, SSA-SEM, and WOA-SEM methods are then used for comparison.

Table 4.3 Qualitative comparison of time and frequency response parameters for the test system

Parameters	Rise time	Settling time	Overshoot	Gain Margin	Phase Margin
Original system	1.0692	1.5686	0.7852	Inf	90.8510
Proposed system	1.3493	8.7723	14.6813	Inf	91.9581
DA-SEM	0.9673	9.1931	27.9351	Inf	91.7143
SCA-SEM	1.3477	8.7741	14.7207	Inf	91.9588

SSA-SEM	1.1036	9.0383	22.0219	Inf	91.8145
WOA-SEM	1.2413	8.8876	23.7818	Inf	91.9012

Table 4.3 shows that the reduced model acquired by the presented method provides outcomes which closely resemble the original system. The step and bode responses of the original and the reduced order system obtained by the presented method are plotted in Fig. 4.2 and Fig. 4.3 respectively.

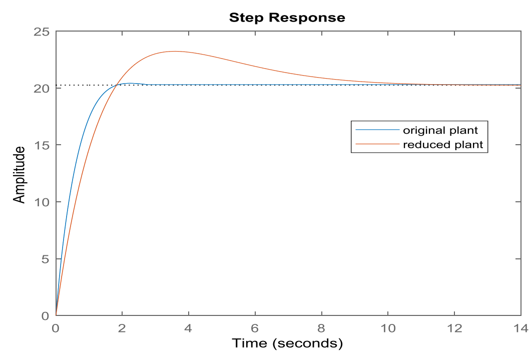

Fig. 4.2 Step response of original and reduced order model

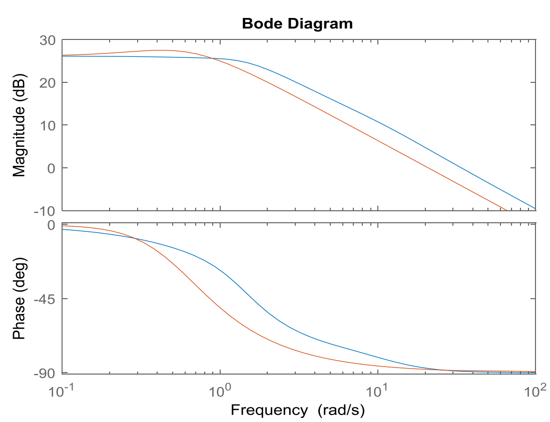

Fig. 4.3 Bode response of original and reduced order model

The responses of the reduced order system, as provided in Fig. 4.2 and Fig. 4.3 closely match the original system. Moreover, several error indices viz. ISE, IAE, ITSE, ITAE and H_∞ norm is computed for the reduced model in Table 4.4.

Table 4.4 Comparison of error indices for the reduced order models of the test system

Methods	ISE	IAE	ITSE	ITAE	H_∞ norm
Proposed system	0.1914	0.3967	0.1873	0.3240	1.0599
DA-SEM	0.1966	0.4073	0.1841	0.3145	1.1310
SCA-SEM	0.3861	0.5789	0.2603	0.3525	1.4891
SSA-SEM	0.2443	0.4500	0.1978	0.3061	1.2841
WOA-SEM	0.5202	0.3275	0.3199	0.2298	1.4088

The proposed method gives good results on most occasions. Consider a reference model

$$M(s) = \frac{4.242s+25}{s^2+7.07s^1+25} \tag{4.18}$$

The reduced controller transfer function is

$$G_c(s) = \frac{M(s)}{G_2(s)} \tag{4.19}$$

$$= 0.2409s^2 + 0.000206\text{s} + 1.7115\text{e} - 5 \tag{4.20}$$

$$= \frac{0.2409s^2+0.000206\text{s}+1.7115\text{e}-5}{s} \tag{4.21}$$

It is further compared by PID controller transfer function

$$K_p + \frac{K_i}{s} + K_d s \tag{4.22}$$

Using GWO technique the value of K_p, K_i, and K_d are obtained as follows

$$K_p = 0.2409,\ K_i = 0.000206, K_d = 1.7115\text{e} - 5 \tag{4.23}$$

Thus, the corresponding closed loop transfer function is given as

$$G_{CL}(s) = \frac{G_c(s)\times G_2(s)}{1+G_c(s)\times G_2(s)} \tag{4.24}$$

4.4 CONCLUSION

The proposed method is compared with the four latest metaheuristic algorithms viz. DA, SCA, SSA WOA for a SMIB system. The different techniques have been evaluated using time domain (settling time, rise time, overshoot), frequency domain (phase margin, gain margin) and errors (IAE, ISE, ITAE, ITSE, H_∞ norm). The proposed topology shows better performance over the compared metaheuristic algorithms on numerous occasions. A PID controller has been tuned for the reduced order model using reference model method, and its step response has been used for comparison with the closed loop model comprising of plant and controller. The controlled plant almost resembles the reference model.

CHAPTER 5
CONCLUSIONS AND FUTURE SCOPE OF WORK

5.1 CONCLUSIONS

A new mixed order reduction method based on grey wolf optimization of different power system models has been presented. The polynomial of denominator of the reduced system has been acquired by the stability equation technique, whereas the coefficients of the numerator are determined through grey wolf optimization. The three test systems chosen are load frequency control of two area power system network, automatic voltage regulator and single machine infinite bus system. The proposed reduction algorithm has been compared with four different nature-inspired optimization algorithms viz. DA, SCA, SSA, and WOA. The performance of various techniques has been assessed using time domain (settling time, rise time and overshoot), frequency domain (phase margin and gain margin) and some error indices (IAE, ISE, ITAE, ITSE, H_∞ norm). The proposed technique performs better over the standard metaheuristic algorithms as shown in figures and tables of the results section of chapters two, three, and four. A PID controller has been designed corresponding to the reduced order model using approximate model matching. The step response of the controlled plant has been compared with the reference model. The plant's closed-loop response cascaded along the controller nearly matches the response of the reference model.

5.2 FUTURE SCOPE OF WORK

The presented work utilized the advantages of both conventional as well as an optimization technique and proposed a hybrid method of model order reduction. The conventional method based on the stability equation has been used to decrease the order of denominator polynomial. Further to reduce the order of numerator polynomial, grey wolf optimization technique has been adopted. The proposed method of model order reduction has been validated for three power systems problems; load frequency control (LFC), automatic voltage regulation (AVR), and SMIB system. The performance of the method for all three test problems is highly encouraging. However, instead of single objective optimization, a combination of the objectives could have been considered yielding successful Pareto solution of multi-objective optimization. A hybrid metaheuristic algorithm could have given better results as compared to single algorithms discussed in this dissertation work. Other standard techniques like Routh approximation, Eigen spectrum method could have been applied to reduce the denominator coefficients instead of SEM.

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