Mohamed Khider University of Biskra
Faculty of Science and Technology
Department of Electrical Engineering

MASTER'S THESIS

Science and Technology
Electrotechnics
Power System
Réf :……….

Presented and defended by:
LAMAMARA RACHID / MOKRANI ABDERRAHIM

On: June , 2025

Power system stability enhancement using artificial intelligence algorithms

Jury :

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CLASS OF 2024/ 2025

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Supervisor's Approval:
Necira Abdelouahab

Signature Approval of the President of the Jury

Stamp and Signature

DEDICATIONS

To my beloved father and dear mother,

To my siblings, the dearest to my heart,

To my esteemed teacher, Mr. Necira Abdelouahab,

To my dear friends who stood by my side,

To everyone who supported us along the way,

Today, we receive our graduation certificate thank you for your support and trust in us.

Acknowledgements

Although the road was not easy, and despite all the obstacles and challenges we faced, we have finally reached the end. Today, we submit our final research project, carrying with us unforgettable experiences and invaluable lessons.

To those who supported us every step of the way, who were the light in moments of exhaustion, and who never withheld their prayers and encouragement...

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To these esteemed educators, we proudly dedicate this thesis. It is a fruit of your nurturing and a reflection of your effort.

To the one who planted ambition in my soul, and taught me that nothing is impossible with willpower...
To the one who stayed awake, tired, and sacrificed for me my beloved mother...
To the one who was my support and backing at every step my dear father...

To my siblings, a source of energy and constant motivation...
And to my loyal friends, companions of the journey, who were my support and my smile in difficult times:
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To my best friend Laroussi, thank you for always being there and supporting me, your presence means so much to me.

And to all those whose names were not mentioned, yet held a place in my heart and prayers... you have my deepest appreciation.

Rachid - Rahim – Class of 2025 – Power System

ملخص:

تُعدّ الاهتزازات الكهروميكانيكية منخفضة التردد من أهم التحديات التي تؤثر على استقرار أنظمة الطاقة الكهربائية. يهدف هذا العمل إلى تحسين تخميد هذه الاهتزازات باستخدام مثبتات أنظمة الطاقة. ولتحقيق ذلك، أُضيف مثبت تقليدي وثلاث تقنيات ذكاء اصطناعي حديثة:

خوارزمية سرب الجسيمات، وخوارزمية البحث عن الغراب، وخوارزمية الطائر الأزرق أحمر المنقار. تم تقييم أداء كل تقنية من خلال محاكاة للنموذج النموذج غير الخطي. أظهرت النتائج أن الخوارزميات الذكية تُوفر تخميدًا أفضل واستقرارًا أعلى مقارنةً بالنهج التقليدي..

Résumé

Les vibrations électromécaniques basse fréquence constituent l'un des défis majeurs pour la stabilité des réseaux électriques. Ce travail vise à améliorer l'amortissement de ces vibrations grâce à des stabilisateurs de réseaux. Pour ce faire, un stabilisateur conventionnel et trois techniques modernes d'intelligence artificielle ont été ajoutés : l'algorithme de l'essaim de particules, l'algorithme de recherche du corbeau et l'algorithme du merlebleu à bec rouge. Les performances de chaque technique ont été évaluées par simulation Simulink des modèles non linéaire. Les résultats ont montré que les algorithmes intelligents offrent un meilleur amortissement et une meilleure stabilité que l'approche conventionnelle.

Abstract

Low-frequency electromechanical vibrations are one of the most significant challenges affecting the stability of electrical power systems. This work aims to improve the damping of these vibrations using power system stabilizers. To achieve this, a conventional stabilizer and three modern artificial intelligence techniques were added: the particle swarm algorithm, the crow search algorithm, and the Red-billed Blue Magpie Optimizer. The performance of each technique was evaluated through by the Simulink simulation of the nonlinear model. The results showed that the intelligent algorithms provide better damping and higher stability compared to the conventional approach.

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List of Acronyms and Symbols

Acronyme	Signification
SMIB	Single Machine Infinite Bus
AVR	Automatic Voltage Regulator
PSS	Power System Stabilizer
OLTC	On-Load Tap Changer
AGC	Automatic Generation Control
LFC	Load Frequency Control
SVC	Static VAR Compensator
FACTS	Flexible AC Transmission Systems
PSO	Particle Swarm Optimization
CSA	Crow Search Algorithm
RBMO	Red-Billed Blue Magpie Optimizer
ADMM	Alternating Direction Method of Multipliers
GA	Genetic Algorithm
ST1A	IEEE Static Excitation System Model
AI	Artificial Intelligence
ML	Machine Learning

List of Acronyms and Symbols

Symbole	Description
δ	Rotor angle
ω	Angular speed
T_m	Mechanical torque
T_e	Electrical torque
P_m	Mechanical power
P_e	Electrical power
H	Inertia constant
D	Damping coefficient
V	Voltage
I	Current
E_fd	Excitation voltage
α	Learning rate
∇f	Gradient of the objective function
x	Decision variable
μ	Penalty parameter
λ	Lagrange multiplier
c_1, c_2	Acceleration coefficients in PSO
r_1, r_2	Random variables in PSO
v	Particle velocity in PSO

GENERAL INTRODUCTION

In light of the rapid advancements in the energy sector, the issue of power system stability has become one of the most pressing challenges faced by engineers and researchers especially with the increasing complexity of electrical networks and the growing reliance on renewable energy sources with intermittent nature. Maintaining grid stability is now a fundamental requirement to ensure continuous and high-quality power supply while minimizing the risks of outages and potential equipment damage.

Achieving this goal requires a precise understanding of the power system's behavior during and after disturbances, such as line faults or generator outages. In this context, analyzing the dynamic balance between generated and consumed power lies at the heart of stability studies. This necessitates accurate modeling of network components, particularly synchronous machines, which play a crucial role in maintaining system stability through their electrical and mechanical interactions with the grid.

The focus has been placed on the mathematical representation and modeling of these machines within simplified systems, such as the Single Machine Infinite Bus (SMIB) model, to assess system behavior under disturbances. This approach relies on voltage, torque, and time equations to describe operational dynamics.

To keep pace with advances in control technologies and to improve network performance, a set of modern strategies for tuning Power System Stabilizers (PSS) has been proposed. PSS are effective devices used to damp low-frequency electromechanical oscillations. This work includes a comparison between the conventional PSS (CPSS) and three intelligent optimization algorithms representing modern trends in artificial intelligence and optimization: Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), and Red-billed Blue Magpie Optimizer (RBMO).

The performance of these techniques was evaluated through by the Simulink simulation of the system nonlinear model, enabling an accurate comparison of each algorithm's effectiveness in enhancing stability and damping oscillations. Through this approach, the study aims to strengthen both the theoretical and practical understanding of power system stability, and to propose analytical and monitoring tools that align with the evolution of modern networks and support more effective and stable operational decisions.

CHAPTER I

I. 1. Introduction

Power system stability is a critical aspect of electrical network analysis, determining the system's ability to maintain or restore equilibrium after disturbances. The primary role of a power grid is to generate and transmit electrical power to loads while maintaining a continuous balance between generation and consumption. In deregulated environments, this balance must be achieved quickly and flexibly, as imbalances can lead to instability. Common disturbances, such as lightning strikes, generator failures, or short circuits, pose significant challenges to grid stability. Low-frequency electromechanical oscillations, particularly in weakly interconnected or radial networks, are a major cause of instability. These oscillations limit power transfer capacity and can lead to a loss of synchronism or even system-wide blackouts. To address these issues, Power System Stabilizers (PSS) are employed to enhance dynamic stability by introducing supplementary signals into the excitation system, generating torque in phase with generator speed variations to counteract phase delays caused by the excitation system. [1]

The reliable operation of a power system depends on its ability to meet load demands with satisfactory voltage and frequency levels at all times. Stability studies are among the most complex aspects of power system analysis, requiring detailed modeling and advanced solution methods. A stable system can return to equilibrium after a disturbance, while instability results from a significant imbalance between opposing forces. Factors contributing to instability vary, and identifying these factors is essential for developing methods to enhance system stability. The increasing complexity of modern power systems, driven by deregulation and interconnection, has heightened the importance of stability analysis. Major blackouts in recent decades have underscored the need for robust stability assessment and system security measures to prevent cascading failures. [2]

In conclusion, power system stability is vital for the reliable and secure operation of electrical networks. PSS plays a crucial role in enhancing dynamic stability by damping electromechanical oscillations. Power systems must withstand various disturbances and return to equilibrium efficiently. Advanced techniques, including Lyapunov's methods and optimized PSS tuning, are essential for ensuring stable and secure grid operation.[1]

The major components of a power system can be represented by a block diagram as shown in Figure (I.1). This representation does not depict all the dynamic interactions between elements and their controls, but it can serve as a general description of dynamic structures. Studying the dynamic performance of the power system is crucial for system operators (from an economic perspective) and for society in general (from a reliability perspective). An essential step in this type of study is to understand the physical and mathematical aspects of the dynamic phenomena of interest. Subsequently, the modeling and simulation of the system can reflect its critical behavior.[1]

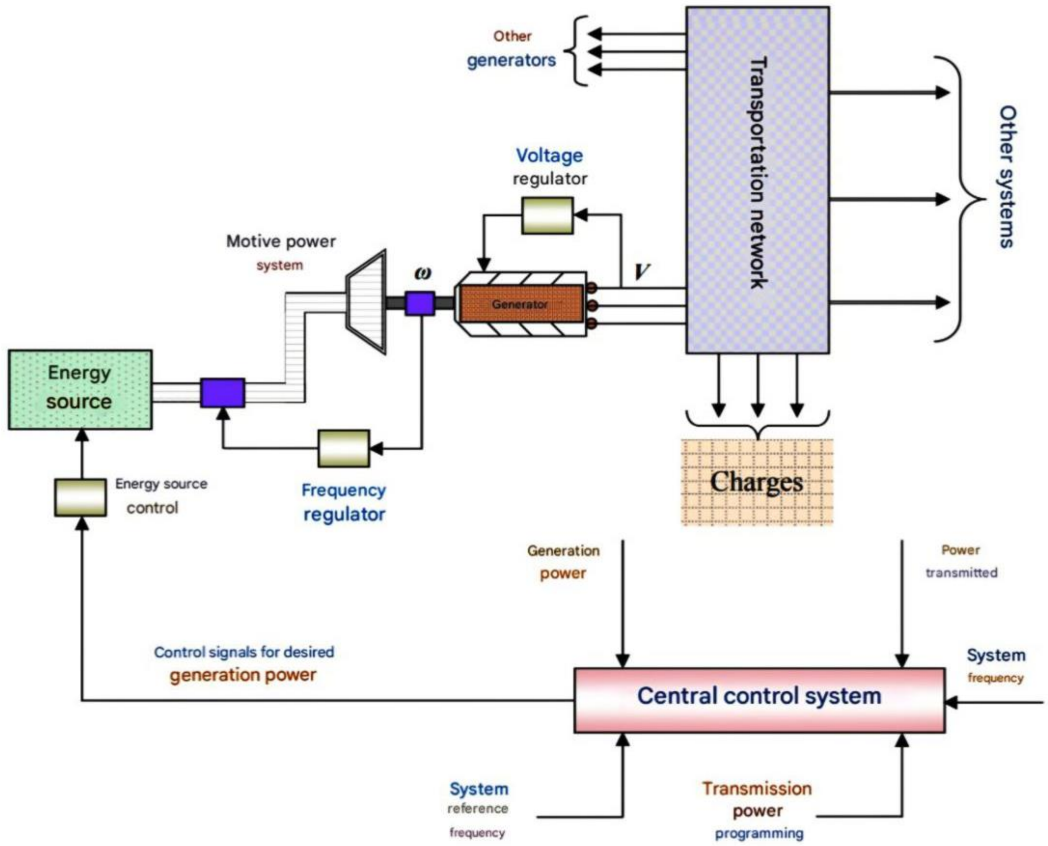


Figure I.1. General structure of power system

I. 2. Definition of power system stability

Power system stability is defined as the ability of the system to maintain an operational equilibrium under normal conditions or to restore an acceptable state of equilibrium after being subjected to disturbances, while keeping most system variables within their specified limits. In other words, stability is the property that enables the system to develop restoring forces equal to or greater than the disturbing forces, ensuring the system remains in a dynamic equilibrium. [2]

In power systems, stability primarily depends on the ability of synchronous generators to maintain synchronism during and after disturbances. When the system is subjected to a disturbance, such as the loss of a generator, a fault in transmission lines, or sudden load changes, the system undergoes a transitional period known as the transient period. During this period, the voltage angles of the synchronous generators are readjusted. If the system successfully achieves a new balance between generation and load, it reaches a new stable operating condition. [2]

The system is considered stable if its oscillatory response during the transient period is damped and it settles to a new operating condition within a finite time. If the system fails to achieve this, it is considered unstable. This practical definition of stability requires that oscillations in the system be damped, a condition known as asymptotic stability, where the network contains inherent forces that reduce oscillations. This property is desirable in power systems because continuous oscillations are unacceptable from a practical standpoint, both for power suppliers and consumers.

Stability problems can be divided into two main categories: steady-state stability and transient stability. Steady-state stability relates to the system's ability to maintain equilibrium under normal operating conditions, while transient stability focuses on the system's behavior after major disturbances such as faults or the loss of generators.

I. 3. Stability classification

stability of a power system is the basis safe and reliable operation of an energy system. Due to complexity of the service network and numerous influencing factors, Stability classified based on the nature of resulting system instability (voltage instability, frequency instability…), the size of the disturbance (small disturbance, large disturbance) and timeframe of stability (short term, longterm).

The most important categories include voltage stability, frequency stability, and rotor angle stability. Figure (I.2) clearly explains the problems of electrical grid stability by taking all these parameters into account.

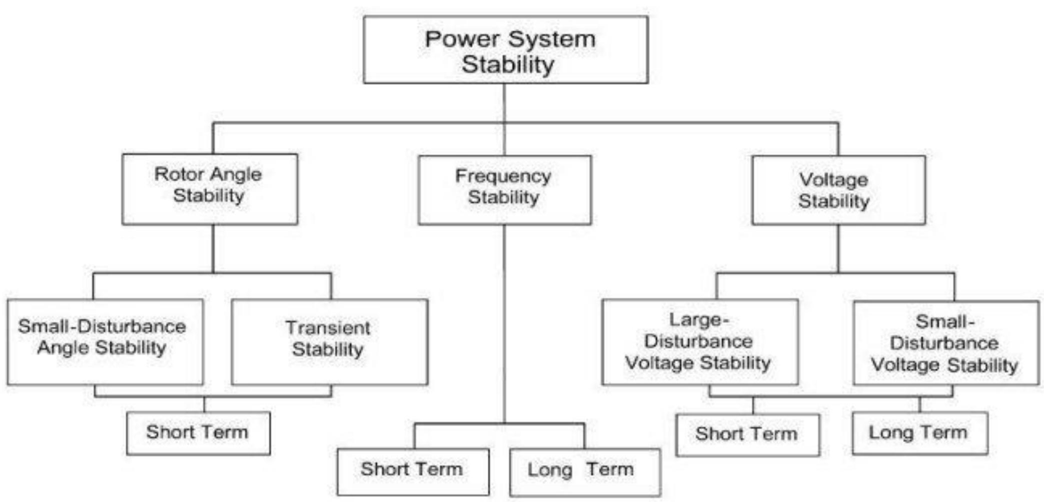


Figure I.2. Classification of power system stability

I. 3. 1. Rotor Angle Stability

Rotor angle stability refers to the ability to couple synchronized machines with a power system to maintain synchronization under normal operating conditions and to be exposed to faults. The stability of a synchronous machine depends on the ability to restore the balance between electromagnetic output torque and mechanical input torque, simultaneously synchronizing with other machines after major failures such as short circuits. there is a balance between the mechanical input torque and the electromagnetic output torque of each generator, ensuring a constant speed. However, if the system is disturbed, this balance can be disrupted, leading to instability in the form of increased or decreased angular fluctuations by some generators, resulting in loss of synchronization with other generators.

The change in electromagnetic torque (ΔT_e) of a synchronous machine following a perturbation can be divided into two main components

$$\Delta Te = \Delta T_{es} + \Delta T_{eo} \tag{I.1}$$

where

- $\Delta TS\delta$ is the torque change component in phase with the rotor angle perturbation ($\Delta\delta$), known as the synchronizing torque component.
- $\Delta TD\omega$ is the torque change component in phase with the speed deviation ($\Delta\omega$), known as the damping torque component.

Rotor angle stability is a critical aspect of power system operation and is classified into two main types small-disturbance rotor angle stability, which ensures the system's ability to maintain synchronism after minor disturbances, and large-disturbance rotor angle stability (or transient stability), which ensures that the system remains synchronized after significant disturbances such as faults or load losses . The stability of each machine in the system depends on the presence of both synchronous and damped torque. Insufficient synchronous torque leads to aperiodic or non-enzymaticin stability, leading to gradually drift, while insufficient damping torque leads to vibrational instability, leading to increased rotor vibration. Furthermore, rotor angle stability is influenced by initial operating conditions and the severity of affecting the synchronous machine.

I. 3. 1. 1. Large Disturbance Angular Stability (Transient Stability)

Transitory solidness alludes to the capacity of a control framework to preserve synchronism when subjected to a huge and sudden unsettling influence. These unsettling influences can emerge from different occasions, such as the sudden misfortune of a transmission line, the event of a serious brief circuit, or the unforeseen detachment of a critical producing unit. Such occasions lead to rapid and significant changes within the electrical and mechanical conditions of the framework, causing deviations in generator rotor points and changes in control streams over the network. This sort of soundness is on a very basic level affected by the nonlinear energetic behavior of the framework, as the interaction between the electrical and mechanical components decides whether synchronism can be maintained or not. Since transitory soundness marvels unfurl over an awfully brief time outline, ordinarily inside many seconds after the unsettling influence, the framework must rapidly react and reestablish harmony to dodge flimsiness. In the event that the reestablishing strengths inside the framework are inadequately to neutralize the unsettling influences, generators may lose synchronism, possibly driving to cascading disappointments or indeed system-wide blackouts. To assess transitory solidness, engineers utilize time-domain recreations, which include tackling the nonlinear swing conditions to track the energetic reaction of generators over time. Furthermore, coordinate energy-based strategies, such as the Basic Clearing Time (CCT) approach, are commonly utilized to decide the most extreme length inside which a blame must be cleared to avoid misfortune of synchronism. These expository procedures give fundamental experiences into framework behavior taking after major unsettling influences, empowering control framework administrators to plan defensive measures and actualize fitting control methodologies to improve generally framework strength.[6]

I. 3. 1. 2. Small-Signal Stability (Angular Stability for Small Disturbances)

Small-signal stability refers to the ability of a power system to maintain synchronism when subjected to small disturbances, such as minor variations in load demand or generation. These disturbances are not significant enough to cause major deviations from the system’s normal operating conditions. Instead, they result in gradual changes in power flow and rotor angles, which must be analyzed to ensure the long-term stability of the system.[2,7]

This type of stability is assessed using linearized system analysis, where the system's response is examined around a stable operating point. By analyzing the system’s small-signal behavior, engineers can determine whether the disturbances will decay over time or lead to sustained oscillations that may compromise stability.[2,7]

Small-signal stability is significantly influenced by the electrical and mechanical dynamics of synchronous machines, as well as the performance of various control systems, including

- Automatic Voltage Regulators (AVR): These controllers regulate voltage levels but can introduce oscillatory behavior if not properly tuned.
- Power System Stabilizers (PSS): These devices enhance damping to prevent undesirable oscillations and improve overall system stability. [1,2,10]

A key method for analyzing small-signal stability is eigenvalue analysis, where system stability is determined by examining the eigenvalues of its linearized state-space model. If any eigenvalue has a positive real part, it indicates an unstable mode, which may result in undamped or growing oscillations. In such cases, adjustments to control strategies are required to restore stability. [7]

Mathematically, this type of stability is analyzed using linear mathematical models that represent the system in the low-frequency range. This allows engineers to study the natural response of generators and their interactions. In some cases, insufficient damping may lead to low-frequency oscillations (LFOs) oscillations typically occurring in the range of 0.1 to 2.5 Hz which can negatively affect the system's long-term stability. If these oscillations are not properly damped, they may persist, reducing power transfer efficiency and increasing stress on system components. [2,8]

To mitigate the effects of poorly damped oscillations and ensure stable operation, system operators implement advanced control techniques, including:

- Optimized tuning of PSS controllers to enhance damping.
- Wide-Area Monitoring and Control (WAMC) to provide real-time stability assessment. [1,10]

I. 3. 2. Voltage Stability

Voltage stability refers to the ability of a power system to maintain steady acceptable voltage levels at all buses under normal operating conditions and after being subjected to disturbances. It ensures that voltage magnitudes remain within permissible limits to support the continuous and reliable operation of the electrical grid. [3]

A power system is considered voltage unstable when it fails to sustain voltage levels within acceptable limits due to excessive reactive power demand. This condition can lead to uncontrolled voltage drops, which, in severe cases, result in voltage collapse a phenomenon where voltages decline progressively,leading to wide-area blackouts or system failures. [3]

Voltage instability typically occurs due to the inability of the system to supply sufficient reactive power to maintain voltage levels. Several factors contribute to voltage instability, including

- High system loading conditions.
- Generator excitation limits.
- Network topology and transmission constraints.

- Load characteristics and their dynamic response to voltage variations.

If not properly managed, voltage instability can severely affect system reliability and security. Therefore, power system operators must implement effective voltage control mechanisms, reactive power compensation strategies, and system reinforcement measures to maintain a stable voltage profile across the network.

I. 3. 2. 1. Types of Voltage Stability

Voltage stability is classified based on the time frame of the system response to disturbances. The two main categories are

I. 3. 2. 1. 1. Short-Term Voltage Stability

Short-term voltage stability refers to the system's ability to maintain stable voltages following rapid disturbances that occur within a few milliseconds to several seconds. These disturbances include

- Transmission line faults.
- Sudden changes in load demand.
- Generator or transmission line outages.
- Rapid switching operations of power electronic devices.

Short-term voltage stability is primarily influenced by the dynamic response of fast-acting components in the power system. Automatic Voltage Regulators (AVRs) control the excitation of synchronous generators to maintain stable voltage levels, while excitation control systems rapidly adjust generator field currents to enhance voltage stability. Additionally, induction motors and power electronic devices respond instantaneously to voltage fluctuations, significantly affecting system stability. Failure to maintain short-term voltage stability can result in abrupt voltage drops, triggering relay operations and protective tripping, excessive reactive power demand that overloads generators and transmission lines, and cascading failures that propagate voltage instability, potentially leading to widespread power outages. To mitigate these issues, power system operators utilize high-speed reactive power support devices such as Static VAR Compensators (SVCs), synchronous condensers, and fast-acting generator excitation systems. [3,10]

I. 3. 1. 1. 2. Long-Term Voltage Stability

Long-term voltage stability pertains to the system's ability to maintain stable voltage levels over extended periods, ranging from several seconds to minutes or even hours. It is influenced by slower system dynamics, including:

- Gradual changes in power demand due to economic or seasonal factors.
- On-Load Tap Changer (OLTC) operations that adjust transformer voltage levels.
- Generator field current limitations affecting excitation capabilities.

- Delayed activation of reactive power compensation devices, such as capacitor banks and reactor switching.

Unlike short-term voltage stability, which is governed by fast control actions, long-term stability is influenced by

- Load dynamics, including the behavior of voltage-dependent loads and industrial motors.
- Generator reactive power capability, particularly in systems with high penetration of renewable energy.
- Transformer voltage control mechanisms, which adjust voltage levels gradually over time.

A failure to maintain long-term voltage stability can lead to a progressive voltage decline, eventually resulting in voltage collapse. It can also cause inefficient utilization of reactive power resources, reducing overall system efficiency, and lead to the overloading of network components, increasing the risk of equipment failure. To enhance long-term voltage stability, power system operators implement coordinated voltage regulation schemes to optimize reactive power distribution, upgrade transmission networks to minimize voltage drops over long distances, and employ optimized generator excitation control strategies to maintain adequate reactive power reserves. [3]

I. 3. 2. 2. Importance of Voltage Stability in Power Systems

Voltage stability is a critical aspect of power system security and reliability. With the increasing integration of renewable energy sources, dynamic loads, and power electronic-based devices, maintaining stable voltage levels has become more challenging. [8]

Modern power systems face challenges in voltage stability due to the high penetration of renewable energy with limited reactive power support, increased demand from electric vehicles and industrial loads, and the growing use of power electronics-based systems like HVDC and FACTS. To address these issues, operators enhance reactive power reserves using capacitor banks and synchronous condensers, implement real-time voltage control with Wide-Area Monitoring Systems (WAMS), and upgrade transmission networks to reduce voltage drops. Additionally, optimizing generator excitation systems and integrating AI and Machine Learning (ML) for predictive stability assessment help ensure a more resilient and efficient power system. [10]

I. 3. 3. Frequency Stability

Frequency stability refers to the ability of a power system to maintain its frequency within acceptable limits following a disturbance, such as a sudden loss of generation, a load change, or a system separation. A power system is considered frequency unstable when it fails to restore its frequency to a stable operating range, potentially leading to cascading failures or widespread blackouts. [9]

In a balanced power system, the total power generation must equal the total demand plus system losses at all times. Any imbalance between active power generation and consumption causes frequency deviations. If not controlled properly, these deviations can lead to system instability, equipment damage, and disconnection of critical loads.

I. 3. 3. 1. Causes of Frequency Instability

Frequency instability typically occurs due to mismatches between power generation and demand, which may result from

- Sudden loss of a large generating unit (e.g., generator tripping due to faults or mechanical failures).
- Unexpected load variations (e.g., rapid industrial load changes or unexpected disconnections).
- System islanding (i.e., separation of a portion of the grid due to faults or failures in transmission lines).
- Failure of frequency control mechanisms (e.g., malfunctioning governor systems in power plants).
- Increased penetration of renewable energy sources that lack inertia, leading to rapid frequency fluctuations.

If frequency deviations persist and exceed acceptable limits (e.g., ±0.5 Hz from the nominal 50 Hz or 60 Hz), protective relays may activate, disconnecting generation or loads and possibly leading to a complete system collapse. [9]

I. 3. 3. 2. Types of Frequency Stability

Frequency stability is categorized based on the time scale of system response into short-term frequency stability and long-term frequency stability

I. 3. 3. 2. 1. Short-Term Frequency Stability:

Short-term frequency stability, occurring within milliseconds to a few seconds, refers to the system's initial response to sudden power imbalances. It is influenced by

- Inertial response of rotating generators (acting within milliseconds to seconds).
- Primary frequency control via governor action (acting within a few seconds).
- Load response characteristics, where some loads naturally reduce power consumption when frequency drops.

I. 3. 3. 2. 2. Long-Term Frequency Stability

Long-term frequency stability, occurring over several minutes to hours, refers to the system's ability to maintain stable frequency over extended periods following slower variations in generation and load. It involves

- Secondary frequency control (Automatic Generation Control - AGC): Adjusting generator output to restore nominal frequency.
- Load restoration mechanisms: Reconnecting loads that were previously disconnected during instability.
- System re-synchronization after major disturbances: Ensuring power balance between different grid regions.

I. 3. 3. 3. Control Strategies for Frequency Stability

To maintain frequency stability, power system operators rely on several hierarchical control mechanisms Synchronous generators provide natural inertia, helping to slow frequency deviations, with high-inertia power plants like hydro and thermal playing a key role in stabilizing fluctuations. Primary frequency control occurs within seconds, where governors on synchronous generators adjust turbine output automatically, and droop control ensures a balanced response among generators. Secondary frequency control, taking minutes, relies on Automatic Generation Control (AGC) to fine-tune generation and Load Frequency Control (LFC) to balance power exchanges between interconnected areas. [9] Tertiary control, operating over minutes to hours, includes economic dispatch to optimize power generation costs and demand response programs that allow large consumers to adjust consumption based on frequency conditions. Additionally, advanced frequency support with renewable energy is achieved through Battery Energy Storage Systems (BESS) for fast frequency response, grid-forming inverters that mimic synchronous machines, and synthetic inertia, where wind turbines and solar inverters emulate rotational inertia.[10]

I. 3. 3. 4. Impact of Renewable Energy on Frequency Stability

With the increasing penetration of wind and solar energy, frequency stability faces new challenges because:

- Renewable energy sources lack natural inertia, making frequency fluctuations more severe.
- Inverter-based generation does not inherently provide frequency response.
- Variability in wind and solar output requires additional reserves for frequency regulation.[8]

I. 4. Single Machine Infinite Bus (SMIB) Model

The Single Machine Infinite Bus (SMIB) model is widely used to study power system stability and evaluate the performance of a Power System Stabilizer (PSS). It consists of a single generator connected to an infinite bus, which maintains constant voltage and frequency. To explain how the PSS parameters are set using the phase compensation method, this basic configuration is often considered. The linearized version of the SMIB system can be represented using the Heffron-Phillips block diagram, as shown in Fig. (I.3).[5]

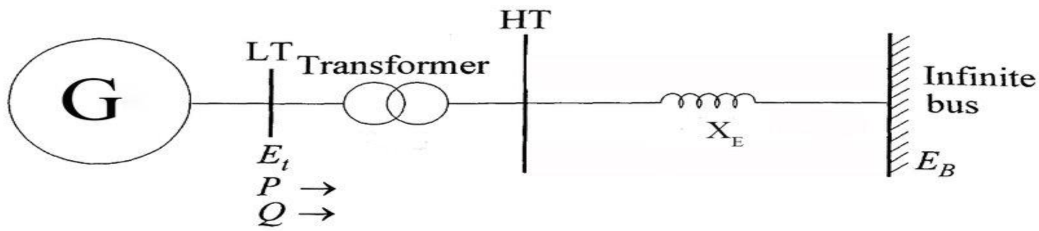


Figure I.3. Single Machine Infinite Bus System

I. 4. 1. Electrical Equations

In this section, the electrical equations for a synchronous machine within a multimachine power system are derived. The analysis focuses on the stator voltages along the **d** and **q** axes and the electric power.

Key points:

- The reference frame (**di, qi**) is specific to the i^{th} machine, while (**D, Q**) is common to all machines.
- The torque angle δi represents the position of the i^{th} machine's reference frame relative to the common frame and varies over time.

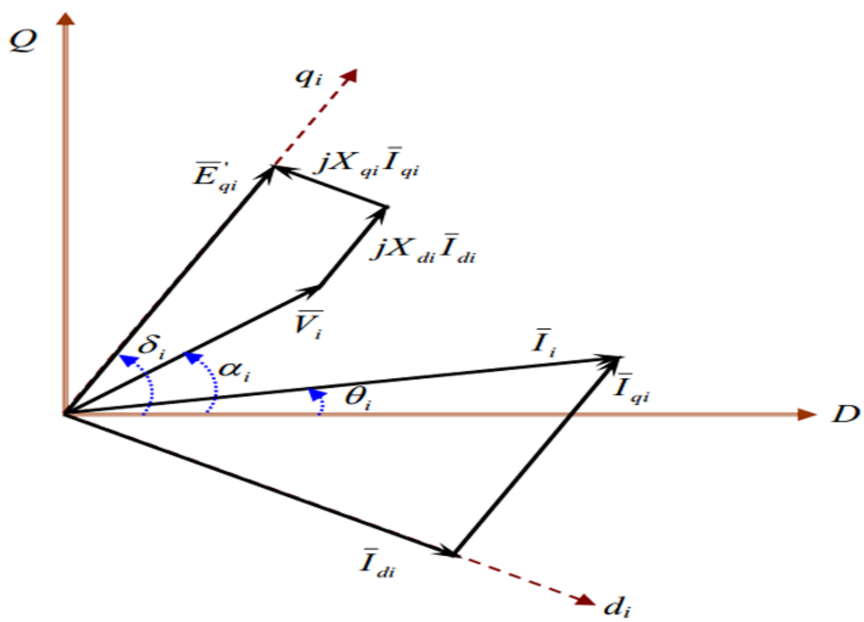


Figure I. 4. Phasors relating to the ith machine of a multi-machine system.

From fig(I. 4),the terminal voltage **Vi** of the i^{th}machine is given by

$$\bar{V_\iota} = \overline{E'_{q\iota}} - jX'_{di}\overline{I_{d\iota}} - jX_{qi}\overline{I_{q\iota}} \quad \text{(I. 2)}$$

Using transformations into the common reference frame (**D-Q**)

$$\overline{E'_{q\iota}} = E'_{qi}e^{j\delta_i}\ , \quad \overline{I_{q\iota}} = I_{qi}e^{j\delta_i}\ , \quad \overline{I_{d\iota}} = I_{di}e^{j(\delta_i - 90^\circ)} \quad \text{(I. 3)}$$

Substituting these into the voltage equation and separating real and imaginary parts, we obtain the V_e and V_q voltage components

$$V_{di=}X_{qi}I_{qi} \quad \text{(I. 4)}$$

$$V_{qi} = E'_{qi} - X'_{di}I_{di} \quad \text{(I. 5)}$$

The electrical equations of a synchronous machine in a multimachine power system are derived using the reference frames (d, q) for the individual machine and (D, Q) for the entire system. The terminal voltage V_i is expressed in terms of internal voltage E'_{qi} reactances and currents.

For an n machine in a multi-machine system, the voltage equation is written in matrix form

$$[\bar{V}] = [E'_q][e^{j\delta}] - j[X'_d][\bar{I}] + [X'_d - X_q][I_q][e^{j\delta}] \quad \text{(I. 6)}$$

where voltage, current, and internal voltage are column vectors, and reactances are diagonal matrices.

The electrical power components (apparent, active, and reactive) of the machine are given by

$$S_i = P_{ei} + jQ_{ei} = V_iI_i^* \quad \text{(I. 7)}$$

Expanding this, we obtain

$$P_{ei} = V_{di}I_{di} + V_{qi}I_{qi} \quad \text{(I. 8)}$$

$$Q_{ei} = V_{qi}I_{qi} - V_{di}I_{qi} \quad \text{(I. 9)}$$

Since stator transients are neglected, the electrical torque is equal to the active power

$$T_{ei} = P_{ei} \quad \text{(I. 10)}$$

I. 4. 2. Mechanical Equations

The rotor motion equation describes the mechanical behavior of synchronous machines and is essential for analyzing electromechanical oscillations. In steady-state operation, all machines rotate at the same angular speed, with the mechanical torque T_m acting in the direction of rotation and the electrical torque T_e opposing it. During disturbances, some generators may accelerate or decelerate, risking loss of synchronism, which can impact system stability. This interaction between mechanical and electrical torques is illustrated in Fig. I.5, which shows the forces acting on the rotor axis of a generator. [5]

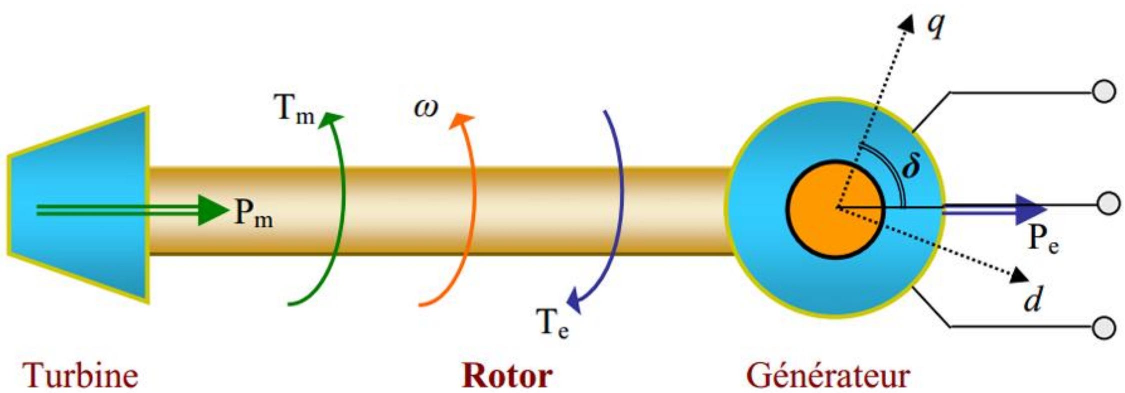


Figure I. 5. Mechanical and electrical couples acting on the axis of a generator.

For a multi-machinesystem, the motion equation for the $\boldsymbol{i^{th}}$machine is

$$\Delta\omega_i \frac{1}{2H_i}(T_{mi}T_{ei}) \tag{I. 11}$$

where H_i is the inertia constant representing the total rotating mass. At low frequencies, damping windings are neglected, and a damping coefficient D_i is introduced to model the system's natural damping. The modified motion equation becomes:

$$\Delta\omega_i = \frac{1}{2H_i}(T_{mi} - T_{ei} - D_i(\Delta\omega_i - 1)) \tag{I. 12}$$

The rotor angle equation is

$$\dot{\delta_\iota} = \omega_0(\Delta\omega_i - 1) \tag{I. 13}$$

where

- $\Delta\omega_i$is the angular speed deviation,
- ω_0 is the synchronous speed (2πf),
- T_{mi} is the mechanical torque,
- $T_{ei}$is the electromagnetic torque,
- D_i is the damping coefficient,
- $\delta_i$is the rotor angle.

I. 4. 3. Voltage regulator and model of the excitation system

The excitation system supplies power to the excitation windings of a synchronous machine to regulate reactive power. It provides steady-state DC voltage and current but must adjust excitation voltage rapidly during disturbances.

There are three main types of excitation systems (IEEE, 2005):

1. DC Excitation Systems – Use a DC generator with a collector.
2. AC Excitation Systems – Use an alternator with rectifiers (static or rotating) to generate DC excitation current.
3. Static Excitation Systems (ST Systems) – Use a controlled rectifier powered either directly from the generator (via a transformer) or from auxiliary windings.

Automatic Voltage Regulators (AVR) maintain system stability by controlling excitation current and regulating the generator's output voltage. AVRs ensure transient stability by adjusting the machine's magnetic flux.

The IEEE-ST1A static excitation model is widely used due to its speed and sensitivity, with

- A low time constant T_a (a few milliseconds).
- A high gain K_a(200–400 per-unit).

The voltage regulator compares the generator terminal voltage V_t with the reference voltage V_{ref}, generating an error signal that is amplified to produce the required excitation voltage E_{fd}. Additional control signals, such as Power System Stabilizers (PSS), can be included.

The voltage regulator function is described by

$$\dot{E}_{fd} = \frac{1}{T_a}(K_a(V_{vef} - V_t + V_s) - E_{fd}) \quad \text{(I. 14)}$$

And the relationship between excitation voltage E_{fd} and the generator's internal voltage E'_q is:

$$\dot{E}'_q = \frac{1}{T'_{d0}}(E_{fd} - (X_d - X'_d)I_d - E'_q) \quad \text{(I. 15)}$$

I. 4. 4. Transmission power system equations

The establishment of the transmission power system model involves formulating algebraic equations that describe the interconnections between generators, transformers, transmission lines, and loads. The system is represented in matrix form as

$$[\bar{I}] = [\bar{Y}].[\bar{V}] \quad \text{(I. 16)}$$

Where:

$[\bar{I}]$is the current vector.
$[\bar{V}]$ is the voltage vector.
$[\bar{Y}]$ is the power system admittance matrix.
The admittance matrix $[\bar{Y}]$ consists of

- Self-admittance terms $[\bar{Y}]_{ii}$, which represent the sum of all admittances connected to node i.
- Mutual admittance terms $[\bar{Y}]_{ij}$, which represent admittances between nodes i and j.

Applying the Kron reduction method, load buses are eliminated, leading to a reduced bus admittance matrix

$$[\bar{Y}_{bus}] = [\bar{Y}_{nn}] - [\bar{Y}_{nr}].[\bar{Y}_{rr}]^{-1}.[\bar{Y}_{rn}] \tag{I. 17}$$

which simplifies the system to

$$[\bar{I}_n] = [\bar{Y}_{bus}].[\bar{V}_n] \tag{I. 18}$$

Further incorporating generator equations, the total admittance matrix $[\bar{Y}_m]$is expressed as

$$[\bar{Y}_m] = \left[[\bar{Y}_{bus}]^{-1} + j[X'_d]\right]^{-1} \tag{I. 19}$$

In the DQ reference frame, the current for the i^{th} machine is

$$I_i = \sum_{j=1}^{n} Y_{mij} e^{j\beta_{ij}} \left(E_q j' e^{j\delta_j} + j\left(X_d j' - X_{dq} i\right) I_q j e^{j\delta_j}\right) \tag{I. 20}$$

Breaking it down into direct (d) and quadrature (q) components

$$I_{di} = \sum_{j=1}^{n} Y_{mij} \left(-S_{ij} E_q j' + \left(X_q j - X_d i'\right) C_{ij} I_q j\right) \tag{I. 21}$$

$$I_{qi} = \sum_{j=1}^{n} Y_{mij} \left(C_{ij} E_q j' + \left(X_q j - X_d i'\right) S_{ij} I_q j\right) \tag{I. 22}$$

Where:

$$C_{ij} = \cos(\beta_{ij} + \delta_{ij}) \tag{I. 23}$$
$$S_{ij} = \sin(\beta_{ij} + \delta_{ij}) \tag{I. 24}$$

These current equations, along with voltage equations, form the algebraic part of the general state model of the power system.

I. 4. 5. Swing Equation (Rotor Dynamics)

The rotor dynamics of the generator are governed by the swing equation, which describes the relationship between the mechanical and electrical torques

$$J\frac{d^2\delta}{d^2t} = T_m - T_e - D\frac{d\delta}{dt} \quad \text{(I. 25)}$$

Dividing both sides by the moment of inertia J , we obtain

$$\frac{d^2\delta}{dt^2} = \frac{T_m - T_e}{J} - \frac{D}{J}\frac{d\delta}{dt} \quad \text{(I. 26)}$$

Since power and torque are related as

$$P = T \times \omega_s \quad \text{(I. 27)}$$

The equation can be rewritten as

$$M\frac{d^2\delta}{dt^2} = P_m - P_e - D\frac{d\delta}{dt} \quad \text{(I. 28)}$$

where

- $\boldsymbol{\delta}$ is the rotor angle relative to the synchronous reference.
- P_m is the mechanical input power.
- P_e is the electrical output power.
- $M = \frac{J}{\omega_s}$ is the moment of inertia constant.
- $\boldsymbol{D}$ is the damping coefficient.

A power system is a nonlinear dynamic system that can be described by a set of first-order nonlinear differential equations and algebraic equations. The differential equations represent the dynamic behavior of generators, excitation systems, and other system components, while the algebraic equations describe the transmission system and generator stators. The combined solution of these equations determines the electromechanical state of the system at all times.

The system dynamics are governed by the following equations

$$\Delta\omega_i = \frac{1}{2H_i}(T_{mi} - T_{ei} - D_i(\Delta\omega_i - 1)) \quad \text{(I. 29)}$$

$$\dot{\delta_i} = \omega_0(\Delta\omega_i - 1) \quad \text{(I. 30)}$$

$$\dot{E}_{fd} = \frac{1}{T_a}(K_a(V_{vef} - V_t + V_s) - E_{fd}) \quad \text{(I. 31)}$$

$$\dot{E}'_q = \frac{1}{T'_{d0}}(E_{fd} - (X_d - X'_d)I_d - E'_q) \quad \text{(I. 32)}$$

$$T_{ei} = E'_{qi}I_{qi} + (X'_{qi} - X'_{di})I_{di}I_{qi} \quad \text{(I. 33)}$$

$$V_{di=}X_{qi}I_{qi} \quad \text{(I. 34)}$$

$$V_{qi} = E'_{qi} - X'_{di}I_{di} \quad \text{(I. 35)}$$

$$V_{ti} = \sqrt{V_{di}^2 + V_{qi}^2} \quad \text{(I. 36)}$$

$$I_{di} = \sum_{j=1}^{n} Y_{mij}\left(-S_{ij}E_qj' + \left(X_qj - X_di'\right)C_{ij}I_qj\right) \quad \text{(I. 37)}$$

$$I_{qi} = \sum_{j=1}^{n} Y_{mij}\left(C_{ij}E_qj' + \left(X_qj - X_di'\right)S_{ij}I_qj\right) \quad \text{(I. 38)}$$

At equilibrium, when the derivatives of the state variables are zero, $(i.e.\dot{x} = 0)$, the system reaches a steady-state where all state variables remain constant, and the system behavior around this point can be approximated as linear. Fig (I. 6) represents the elements of the power system model with their interactions.

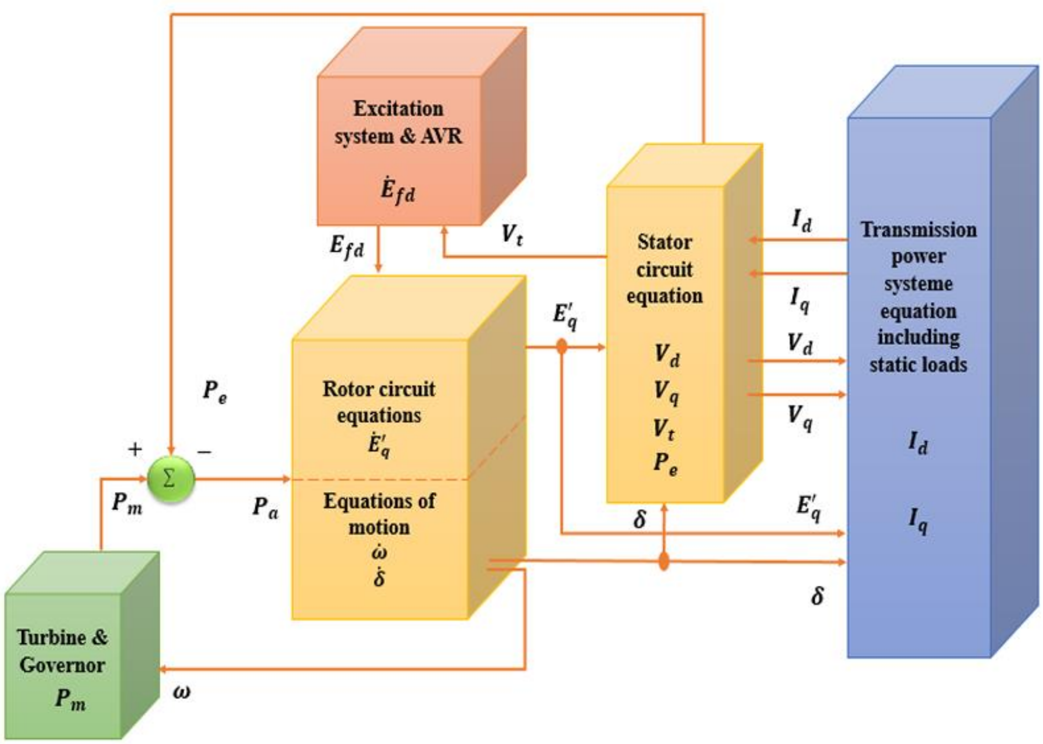


Figure I. 6. Diagram of all the blocks of the power system

I. 4. 6. State-Space Representation

By combining the equations, we can express the system in state-space form

$$\begin{bmatrix} \Delta\,\dot{\delta} \\ \Delta\,\dot{\omega} \\ \Delta\,\dot{E}'_q \\ \Delta\,\dot{E}_{fd} \end{bmatrix} = \begin{bmatrix} 0 & 2\pi f & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 \\ -\frac{K_4}{T'_{do}} & 0 & -\frac{1}{T'_{do}K_3} & \frac{1}{T'_{do}} \\ \frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \begin{bmatrix} \Delta\,\delta \\ \Delta\,\omega \\ \Delta\,E'_q \\ \Delta\,E_{fd} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{K_A}{T_A} \end{bmatrix} V_s(t) \qquad \text{(I. 44)}$$

Interpretation of the Coefficients

- $K_1, K_2, K_3, K_4, K_5, K_6$ are system-dependent coefficients.
- M is the moment of inertia constant.
- D is the damping coefficient.
- T'_{do} is the open-circuit time constant.
- T_A is the excitation time constant.
- K_A is the excitation system gain.

To illustrate the process of setting PSS parameters through the phase compensation method, a basic system is considered where a generator is connected to an infinite bus. This system can be modeled linearly and is typically represented using the Heffron-Phillips block diagram, as depicted in Fig. (I. 7). In this representation, the constants K1 to K6 correspond to the system's linearized parameters.

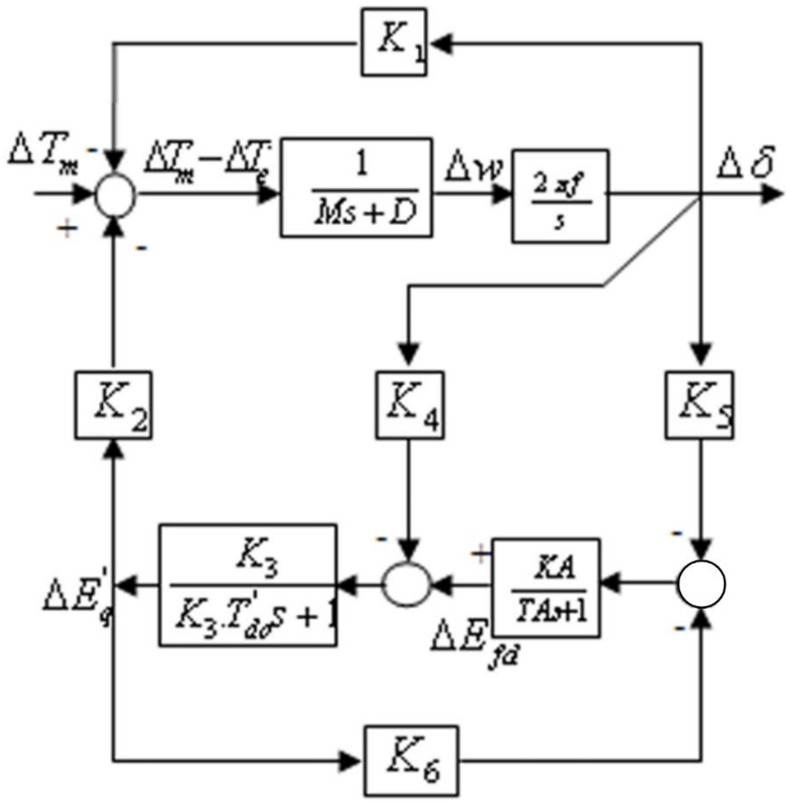


Figure I.7. Heffron-Phillips model (single-machine - infinite bus).

I. 5. Power System Stability Regulators

Power System Stabilizer (PSS) is a critical device designed to enhance the stability of electrical power systems by controlling the excitation of generators. Its primary objective is to dampen electromechanical oscillations, particularly those occurring at low frequencies (typically between 0.2 and 2 Hz), which can threaten the stability of the power grid. By adding an additional control signal to the generator's excitation system (AVR), PSS helps improve system stability and ensures smoother operation during small disturbances. Furthermore, PSS plays a key role in reducing resonance and oscillations between generators, enhancing the system's dynamic stability, and compensating for phase lag introduced by the excitation system. It also mitigates the negative effects of the Automatic Voltage Regulator (AVR), which, if left unchecked, could lead to system instability. Overall, PSS is an essential tool for maintaining the reliability and efficiency of modern power systems. Figure (I. 8) explains Automatic Voltage Regulator (AVR) and Power System Stabilizer (PSS) controllers.[10]

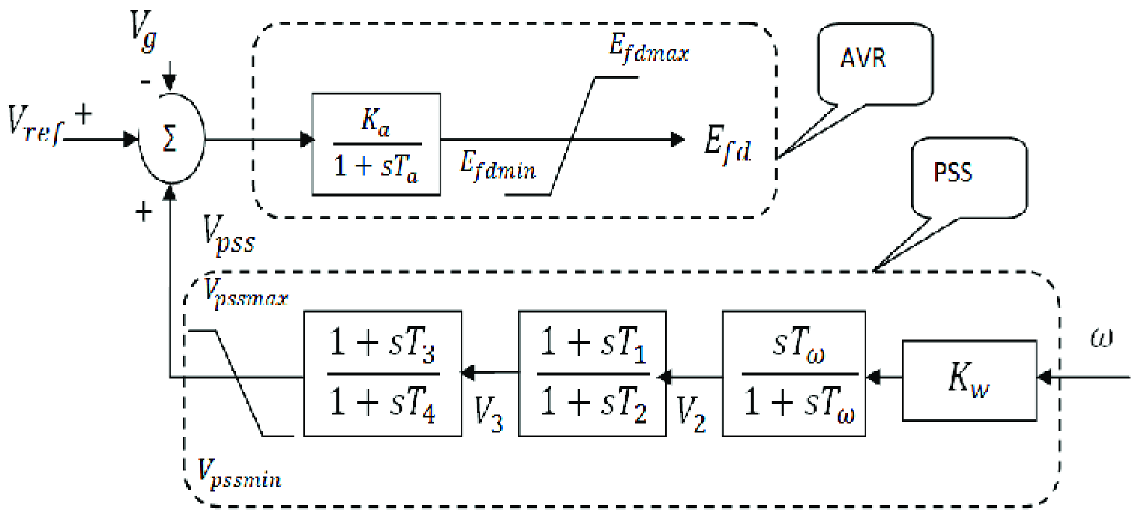


Figure I.8. Avr and pss regulator.

I. 5. 1. Components of PSS

A Power System Stabilizer (PSS) typically consists of four main components that work together to enhance the stability of electrical power systems.

The amplifier is responsible for amplifying the input signal, ensuring that the control signal is strong enough to influence the generator's excitation system.[10]

The washout filter removes very low frequencies that are not relevant to the damping process, allowing the PSS to focus on the critical oscillations that need to be controlled.

The phase compensation block compensates for the phase delay introduced by the excitation system, ensuring that the control signal is properly synchronized with the system's dynamics.

Finally, the limiter restricts the output signal of the PSS to prevent excessive control actions that could negatively impact the system. Together, these components enable the PSS to effectively dampen oscillations and improve the overall stability of the power system.

I. 5. 2. Methods for Tuning PSS

Proper tuning of the Power System Stabilizer (PSS) is essential to ensure its effectiveness in stabilizing power systems. Several methods are commonly used for tuning PSS parameters. The Phase Compensation Method adjusts PSS parameters based on phase and frequency analysis, ensuring that the control signal aligns properly with the system's dynamics.[10]

The Residue Method relies on eigenvalue analysis of the system to determine the optimal PSS parameters, focusing on damping values and system response delays.

Another approach is the Pole Placement Method, which involves specifying the desired pole locations in the complex plane to ensure system stability. Additionally, advanced techniques such as Genetic Algorithms and AI-based Optimization are increasingly used to fine-tune PSS parameters for optimal performance, leveraging computational intelligence to achieve the best possible damping and stability outcomes. These methods collectively ensure that the PSS operates efficiently under various system conditions, enhancing the overall reliability of the power system.

I. 5. 3. Comparison Between Conventional PSS and Optimized PSS

Conventional PSS (CPSS) relies on traditional methods for parameter tuning, which, while proven, may not be effective under all operating conditions. This limitation can result in suboptimal performance, especially in complex or dynamic power systems. On the other hand, Optimized PSS (GA-PSS and PSO-PSS) leverages intelligent algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), to fine-tune parameters. These advanced techniques enable the PSS to adapt more effectively to varying system conditions, ensuring improved damping of oscillations and enhanced system stability. As a result, optimized PSS solutions are more robust and reliable, making them better suited for modern power systems with diverse and dynamic operational requirements.[10]

Conclusion

Power system stability stands as a fundamental pillar for the secure and efficient operation of modern electrical networks. Through this study, we have explored the various dimensions of stability rotor angle, voltage, and frequency and their critical impact on system performance under both normal conditions and disturbances. The classification of stability types, supported by mathematical modeling and dynamic system analysis, provides a deep understanding of the complex interactions within power grids.

Furthermore, the implementation of Power System Stabilizers (PSS) and the advancement of control strategies, including AI-based optimization methods, underscore the continuous evolution of stability enhancement techniques. As power systems become more integrated and reliant on renewable energy sources, ensuring dynamic and robust stability remains a key challenge and a top priority for engineers and operators.

In conclusion, maintaining power system stability is not merely a technical requirement but a necessity for societal and economic resilience. Ongoing research and innovation in modeling, simulation, and control methods will be essential in navigating the complexities of future power networks.

CHAPTER II

2.1. Introduction

Optimization involves searching for the "best" element within a given set. Whether it is determining the most ergonomic design for a nuclear power plant, developing an optimal sales strategy, or finding the shortest path in a network, these are all classic examples of situations where we seek better solutions. [11]

Optimization translates such problems into mathematical objects, studies the properties of optimal solutions, and calculates these solutions precisely. This process forms the core of optimization objectives, a rich and broad field deeply connected to many other areas of mathematics. As can be imagined from the examples mentioned, optimization has diverse and numerous applications. [11]

Optimization is applied in physics, such as in the search for minimal energy states, in economics, where agents aim to maximize their utility or satisfaction, in logistics, where the goal is to minimize travel distances, in industry, and many other fields. These are just a few classic examples that illustrate the variety of optimization applications. [14]

2.2. Unconstrained Optimization

Unconstrained optimization involves minimizing or maximizing an objective function without imposing any restrictions on the decision variables. [12]

Commonly used methods include the Nelder-Mead method, a heuristic technique that does not require the computation of derivatives. [13]

2.2.1. Nelder-Mead Method

The Nelder-Mead method is a nonlinear optimization algorithm published by John Nelder and Roger Mead in 1965. It is a heuristic numerical method that seeks to minimize a continuous function in a multi-dimensional space. [13]

Also known as the downhill simplex method, the algorithm uses the concept of a simplex, which is a polytope with N+1 vertices in an N-dimensional space. Starting with an initial simplex, it undergoes transformations during iterations deforming, moving, and shrinking until its vertices converge to a point where the function is locally minimal.

The Nelder-Mead method with simulated annealing combines the original algorithm with the empirical mechanism of simulated annealing. [15]

2.2.2. Algorithm Steps

Let f be a function defined in an N-dimensional space. The algorithm starts by defining a non-degenerate simplex in this space. Through successive iterations, the process involves identifying the point in the simplex where the function is maximal and replacing it with its reflection with respect to the centroid of the remaining N points.

If the function value at the new point is less than all other values at the other points, the simplex is expanded in that direction. If the new value is better than the second-worst but worse than the best, the point is accepted and the process restarts. Otherwise, if the function behaves like a valley, the simplex contracts. If no improvement occurs, the simplex is reduced via a homothety centered at the minimum point. [16]

2.2.3. Advantages and Disadvantages of Unconstrained Optimization

Advantages

• Simplicity in implementation.
• Fewer parameters to manage.

Disadvantages

• Limited applicability to real-world problems with constraints.
• Risk of obtaining infeasible solutions.

2.3. Constrained Optimization

Constrained optimization aims to find the best solution while satisfying specific restrictions on the variables. Methods such as the augmented Lagrangian algorithm are used to manage these constraints by integrating penalty terms into the objective function.

Augmented Lagrangian algorithms replace a constrained problem with a series of unconstrained problems, adding both a penalty term and a Lagrange multiplier term to the objective function. Unlike simple penalty methods, the Lagrangian multiplier improves the convergence and conditioning. [16]

2.3.1. Augmented Lagrangian Method

We aim to solve the constrained problem:
Minimize $f(x)$, subject to $h\_i(x) = 0$ for i in E.

This can be transformed into an unconstrained problem using:

$$L(x, \lambda, \mu) = f(x) + \Sigma\lambda\_i\, h\_i(x) + (\mu/2)\, \Sigma h\_i(x)\text{^}2 \quad \text{(II. 1)}$$

After each iteration, update λ as:

$$\lambda^{k+1} = \lambda^k + \mu\, h(x^k) \qquad \text{(II. 2)}$$

The method avoids poor conditioning by keeping μ relatively small, improving numerical stability.

2.3.2. Alternating Direction Method of Multipliers (ADMM)

ADMM is a variant of the augmented Lagrangian method that uses partial updates of dual variables.

Often applied to problems of the form: Minimize $f(x) + g(y)$, subject to

$$Ax + By = c. \qquad \text{(II. 3)}$$

ADMM solves for x with y fixed, then for y with x fixed, and updates the dual variable. It does not require full convergence at each step but still ensures overall convergence under mild assumptions.

Alternating Direction Method of Multipliers is based on the Douglas-Rachford and proximal point algorithms and is widely used in optimization software like YALL1, SpaRSA, SALSA, and SNAPVX.

2.3.3. Stochastic Optimization:

Stochastic optimization involves minimizing a loss function using noisy gradient samples. The goal is to estimate the optimal parameter as new samples arrive.

Alternating Direction Method of Multipliers can be adapted for stochastic settings by using approximate Lagrangians and step-size adjustments. It is especially effective in high-dimensional regularized problems by promoting sparsity and structure in the solutions.

2.3.4. Advantages and Disadvantages of Constrained Optimization

Advantages

- Realistic solutions that respect practical limitations.
- Flexibility to model equality and inequality constraints.

Disadvantages

- Higher complexity and computation.
- Sensitivity to parameter choices (e.g., penalty coefficients).

2.4. Traditional Methods Based on Drift

Derivative-based methods are traditional optimization techniques that use the slope (derivative) of a function to find its minimum or maximum. These methods follow the direction where the function increases or decreases the fastest, using mathematical formulas based on calculus.

They work well when the function is smooth and differentiable but may not perform well on complex or noisy problems.

2.4.1. Gradient Descent

Gradient Descent is one of the most fundamental and widely used optimization algorithms in machine learning and numerical analysis. It is an iterative method for minimizing a differentiable function by moving in the direction of the negative **gradient** at the current point. The gradient vector indicates the direction of the steepest ascent, so by moving in the opposite direction, the algorithm gradually finds the function's local minimum. [17]

At each step of the algorithm, the current solution θ is updated using the rule

$$\alpha \nabla f(\theta) - \theta = \theta \quad \text{(II. 4)}$$

where α\alphaα is the learning rate (a small positive constant that determines the step size), and $\theta f(\theta)\nabla$ is the gradient of the function at point.

Gradient Descent can be used in several variations

- Batch Gradient Descent, which uses the full dataset to compute the gradient.
- Stochastic Gradient Descent (SGD), which uses only one data point at a time.
- Mini-Batch Gradient Descent, a balance between the two, using small batches.

This algorithm is especially powerful in training large models like deep neural networks, where analytical solutions are not practical. However, its performance is sensitive to the choice of the learning rate and can get stuck in local minima or saddle points if the optimization surface is complex.

2.4.2. Newton's Method

minima or maxima of a twice-differentiable function. Unlike first-order methods such as gradient descent that use only the gradient (first derivative), Newton's method also uses the Hessian matrix (the matrix of second derivatives), providing more precise information about the curvature of the function. [18]

The basic idea is to approximate the function locally by a second-order Taylor expansion and to jump directly to the minimum of that approximation. At each iteration, the parameter vector θ is updated as follows:

$$H^{-1} \nabla f(\theta) - \theta = \theta_{new} \quad \text{(II. 5)}$$

where

- $f(\theta)\nabla$ is the gradient of the objective function at θ.
- H is the Hessian matrix evaluated at θ.
- H^{-1} is the inverse of the Hessian.

This method converges very rapidly (quadratically) near a local minimum if the function is well-behaved and the Hessian is positive definite. However, it comes with challenges

- Computational cost: Calculating and inverting the Hessian can be expensive, especially in high-dimensional problems.
- Instability: If the Hessian is not invertible or poorly conditioned, the method may fail or diverge.
- Not suitable for non-convex problems: It can converge to saddle points or maxima unless properly adjusted.

Because of these issues, practical implementations often use Quasi-Newton methods (like BFGS), which approximate the Hessian rather than computing it directly.

2.4.3. Conjugate Gradient Method

The Conjugate Gradient Method (CG**)** is an efficient iterative algorithm designed for solving large systems of linear equations of the form

$$b = Ax \quad \text{(II. 6)}$$

where $\boldsymbol{A}$ is a symmetric positive-definite matrix. It can also be used to minimize a quadratic function of the form

$$c + b^T x - x^T A x \frac{1}{2} = f(x) \quad \text{(II. 7)}$$

This method is particularly useful in large-scale optimization problems where storing or inverting the matrix AAA is impractical. Unlike direct methods such as Gaussian elimination, CG avoids matrix factorization by generating a series of search directions that are A-conjugate (mutually orthogonal with respect to the matrix $\boldsymbol{A}$).

The algorithm starts with an initial guess x_0 and iteratively improves it by moving along conjugate directions instead of the steepest descent. Each iteration involves a matrix-vector multiplication, making it highly suitable for sparse systems where most elements of $\boldsymbol{A}$ are zero.

One of the key advantages of CG is that, in exact arithmetic, it converges in at most n steps (where $\boldsymbol{n}$ is the number of variables), though in practice, convergence may occur in far fewer steps.

2.5. Metaheuristic Methods

Metaheuristic methods are high-level optimization strategies designed to solve complex optimization problems where traditional methods may fail or be inefficient. They are typically inspired by natural processes and phenomena such as biological evolution, swarm behavior, or physical annealing. Metaheuristics are particularly useful for combinatorial, non-linear, and multi-modal optimization problems where the search space is vast or not well understood.

Unlike exact methods, metaheuristics do not guarantee finding the global optimum, but they often provide near-optimal solutions in reasonable computational time. They are flexible, problem-independent, and can be adapted to various types of optimization challenges.

Common metaheuristic algorithms include

2.5.1. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of birds flocking or fish schooling. It was first introduced in 1995 by James Kennedy (a social psychologist) and Russell Eberhart (an electrical engineer). [19]

PSO is used to find optimal or near-optimal solutions in complex, high-dimensional search spaces, especially where 2traditional optimization methods struggle.

In PSO, a swarm of candidate solutions called particles moves through the search space. Each particle represents a potential solution and has:

- A position (its current solution),
- A velocity (which determines how it moves),
- A memory of its personal best position (the best solution it has found so far),
- And access to the global best position found by any particle in the swarm.

At each iteration, a particle updates its velocity and position based on three key factors

- Inertia: its current motion,
- Cognitive component: its own best-known position,
- Social component: the best-known position of its neighbors (or the whole swarm).

The velocity and position are updated as follows:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad \text{(II. 8)}$$

$$x_i^{t+1} = x_i^t v_i^{t+1} \quad \text{(II. 9)}$$

Where

- $\boldsymbol{v_i}$: velocity of particle $\boldsymbol{i}$,
- $\boldsymbol{x_i}$: position of particle $\boldsymbol{i}$,
- $\boldsymbol{pbest_i}$: personal best position of particle $\boldsymbol{i}$,
- $\boldsymbol{gbest}$: global best position among all particles $\boldsymbol{i}$,
- $\boldsymbol{\omega}$: inertia weight,
- $\boldsymbol{c1}, \boldsymbol{c2}$: acceleration coefficients,
- $\boldsymbol{r1}, \boldsymbol{r2}$: random numbers in $[0, 1]$.

Over time, particles "swarm" toward promising areas of the search space by learning from their own experiences and those of their neighbors. This balance between exploration (searching new areas) and exploitation (refining good solutions) makes PSO both powerful and efficient.

PSO is widely applied in

- Neural network training,
- Function optimization,
- Control systems,
- Robotics,
- Scheduling, and more.

It's appreciated for its simplicity, ease of implementation, and fast convergence**.**

The following pseudocode presents the core steps of the Particle Swarm Optimization (PSO)

Initialize population
for $t = 1$: maximum generation
  for $i = 1$: population size
    if $f\left(x_{i,d}(t)\right) < f\left(p_i(t)\right)$ **then** $p_i(t) = x_{i,d}(t)$
      $f\left(p_g(t)\right) = \min_i\left(f\left(p_i(t)\right)\right)$
    end
    for $d = 1$: dimension
      $v_{i,d}(t+1) = wv_{i,d}(t) + c_1 r_1\left(p_i - x_{i,d}(t)\right) + c_2 r_2\left(p_g - x_{i,d}(t)\right)$
      $x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1)$
      if $v_{i,d}(t+1) > v_{\max}$ **then** $v_{i,d}(t+1) = v_{\max}$
      else if $v_{i,d}(t+1) < v_{\min}$ **then** $v_{i,d}(t+1) = v_{\min}$
      end
      if $x_{i,d}(t+1) > x_{\max}$ **then** $x_{i,d}(t+1) = x_{\max}$
      else if $x_{i,d}(t+1) < x_{\min}$ **then** $x_{i,d}(t+1) = x_{\min}$
      end
    end
  end
end

Figure II.1. Pseudocode for the Particle Swarm Optimization

2.5.2. Crow Search Algorithm (CSA)

One of the latest meta-heuristic optimization algorithms is inspired by the intelligent behavior of crows, birds known for their high mental abilities, such as storing food in secret locations for later retrieval. [20]

proposed by Askarzadeh, CSA has proven effective in tackling a wide range of complex, nonlinear optimization problems thanks to its reliance on a balance between exploration and exploitation within a search space. CSA mimics the behavior of crows following each other to reach hidden food locations.

Each crow in the algorithm represents a potential solution, and the environment is viewed as a d-dimensional search space. At each step, crow i attempts to approach the location of another crow j, which represents its best-known memory location (store). However, if the followed crow realizes it is being followed (controlled by the awareness probability (AP), it tricks the tracker into changing direction or moving to a new location. The crow's range of movement is controlled by its flight length (fl), allowing it to fine-tune the accuracy of approaching the target location. [21] [22]

This dynamic is controlled by two main parameters

- Flight Length (fl), which scales how far a crow moves toward the target cache
- Awareness Probability (AP), which determines the likelihood that the target crow notices it is being followed and thus forces the follower to explore a random new position instead.

The new position of crow i is calculated using the following update rule if the tracking is undetected (r≥AP)

$$x^{i,iter+1} = x^{i,iter} + r_i * fl^{i,tier} * (m^{j,iter} - x^{i,iter}) \quad \text{(II. 10)}$$

$x^{i,iter}$= is the current position of crow i

$x^{i,iter}$= is the memory position of crow j

r=is a uniformly distributed random number in [0,1]

fl= is the flight length.

If r<AP, crow i is forced to explore by jumping to a random position in the search space. After generating new positions, constraint validation is applied, and the fitness function is evaluated. Each crow updates its memory if the new position provides a better solution

Through this biologically inspired and probabilistic mechanism, CSA achieves a dynamic balance between intensifying the search around good solutions and diversifying the exploration across the search space. It has been effectively applied to various optimization problems including neural network training, engineering design, and resource scheduling, establishing itself as a competitive method in the field of swarm intelligence and evolutionary computation. [23] [24]

Figure (I) explains The image demonstrates how the crows (representing solutions) move within the search space to approach the optimal solution.

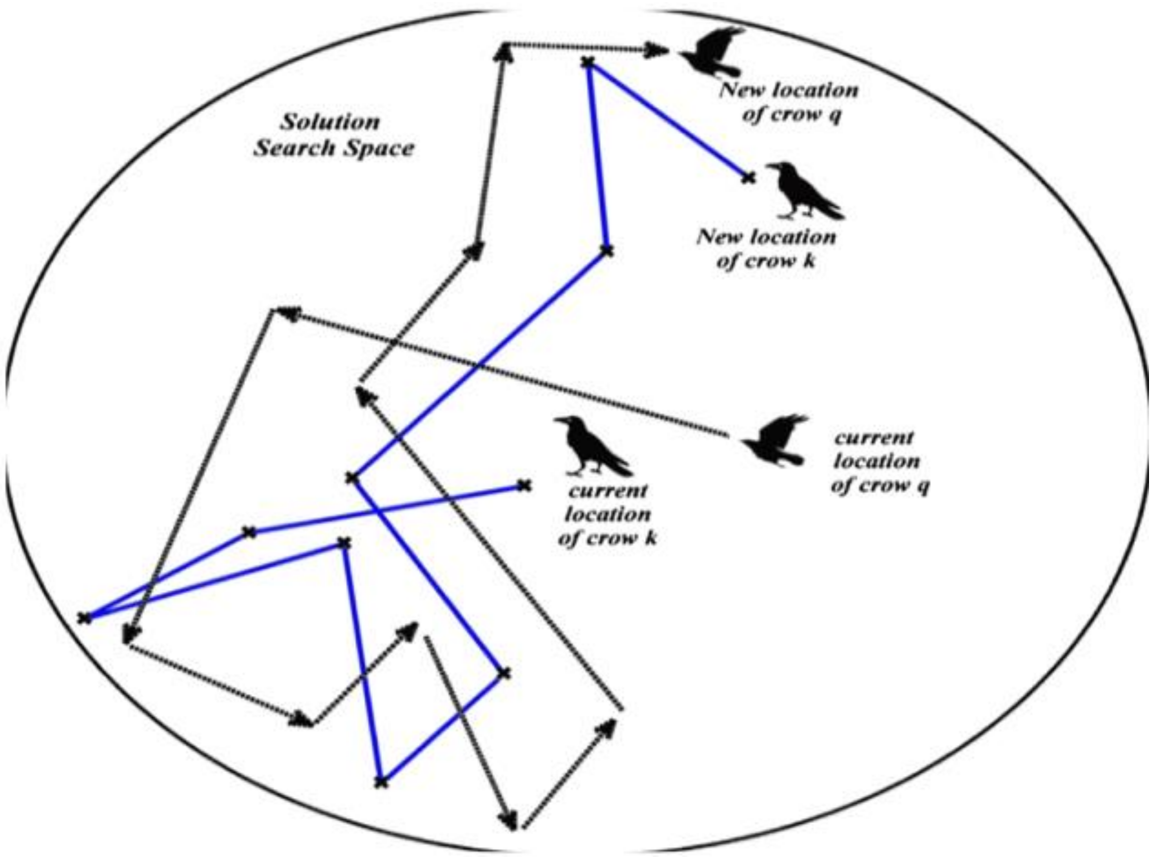


Figure II.2. Crow Search Algorithm

N ← Number of crows
t ← Iteration counter
T ← Total number of iterations
Set the initial values of $AP = 0.1$, $fl = 2.0$ and $t = 1$
x_i ← Crows positions; $i = 1, 2, \ldots, N$.
Initialize the positions of crows at random
Evaluate the fitness function of each crow $f(\cdot)$
Initialize the memory, m, of the crows
while $(t < T)$
  for $i = 1, 2, \ldots, N$
    Choose one of the crows at random, like crow j, and chase it.
    if $(r_j \geq AP)$
      $x_{t+1}^{i} = x_t^i + r_i fl(m_t^j - x_t^i)$
    else
      x_{t+1}^{i} = a random position in the search space
    end if
  end for
  Examine the viability of new positions (x_{t+1}^{i})
  Assess the crows' new position $f(x_{t+1}^{i})$
  Amend crows' memory m_{t+1}^{j}
  $t = t + 1$
end while

Figure II.3. Pseudocode for the Crow Search Algorithm

2.5.3. Red-billed Blue Magpie Optimizer

With the significant advances in artificial intelligence (AI) and intelligent systems, the importance of developing algorithms capable of solving complex optimization problems, such as unmanned aerial vehicle (UAV) path planning and engineering system design, has emerged. Swarm intelligence algorithms are among the most important techniques used in this field, given their ability to simulate the cooperative behavior of organisms in nature and provide effective solutions to nonlinear and multidimensional problems. [25]

This new algorithm, called the Red-billed Blue Magpie Optimizer (RBMO), is a metaheuristic algorithm inspired by the cooperative behavior of blue magpies during hunting and foraging.

The RBMO algorithm was inspired by the behavior of the red-billed blue magpie, a bird native to Asia that is known for its high adaptability and cooperative hunting abilities. [26] This bird is characterized by

Teamwork in small and large groups to efficiently search for food; a variety of hunting methods, such as hopping, flying, searching in trees and on the ground; and storing food in secret locations, such as tree cavities, for later use; and intelligent cooperative behavior that allows it to bypass animal defenses and overcome environmental challenges.

This complex and intelligent behavior inspired researchers to design a mathematical model that simulates these characteristics in an optimization algorithm. [27]

The RBMO algorithm is based on three main phases, mimicking the behavior of magpies during foraging

- Searching Phase

Represents collective exploration of the environment.

In this phase, the location of each "search agent" is updated based on the location of a subset of the flock or the entire flock.

When searching in a small group (2-5 items)

$$X^i(t+1) = X^i(t) + \left(\frac{1}{p} * \sum_{m=1}^{p} X^m(t) - X^{rs}(t)\right) * Rand_2 \quad \text{(II. 11)}$$

When searching in a large group (more than 10)

$$X^i(t+1) = X^i(t) + \left(\frac{1}{q} * \sum_{m=1}^{q} X^m(t) - X^{rs}(t)\right) * Rand_3 \quad \text{(II. 12)}$$

Explanation

- $X_i(t)$: Current position of agent iii at iteration ttt.
- $X_i(t+1)$: Updated position after search.
- p, q: Number of agents in small or large group (randomly selected).
- $X_m(t)$: Position of the mmm-th randomly selected agent.
- $X_{rs}(t)$: Randomly selected agent in the current iteration.
- $Rand2, Rand3$: Uniform random numbers in [0,1]
- **Attacking Phase:**

Mimics cooperative hunting tactics.

Locations are adjusted toward the best solution found (representing the "prey") using random parameters to ensure diversity.

Small group

$$X^i(t+1) = X^{food}(t) + CF * \left(\frac{1}{p} * \sum_{m=1}^{p} X^m(t) - X^i(t)\right) * Rand_1 \qquad \text{(II. 13)}$$

large group

$$X^i(t+1) = X^{food}(t) + CF * \left(\frac{1}{q} * \sum_{m=1}^{q} X^m(t) - X^i(t)\right) * Rand_2 \qquad \text{(II. 14)}$$

Explanation

- $X_{food}(t)$: Best position (optimal solution) found so far at iteration t.
- CF: Control factor calculated as

where $\boldsymbol{X}^{food}(T)$ represents the position of the food $CF = \left(1 - \frac{t}{T}\right)^2 . (\frac{t}{T})$
and $Randn$ represents a random number used to generate a standard normal distribution (mean 0, standard deviation 1).

- t: Current iteration.
- T: Maximum number of iterations.

- **Storage phase**

The quality of the old and new locations is compared, and if the new location is worse, the old location is retained.

This phase helps preserve the best solutions and prevent the loss of valuable information.

$$X^i\ (t+1) = \begin{cases} X^i(t) & if\ fitness_{old}^i > fitness_{new}^i \\ X^{\ i}(t+1) & else \end{cases} \qquad \text{(II. 15)}$$

Explanation

- $fitness_{old}^i$: Fitness value before position update.
- $fitness_{new}^i$: Fitness value after position update.

The algorithm is designed to combine global exploration with local exploitation, giving it a significant ability to avoid local solutions and achieve accurate results in complex search spaces.

The following pseudocode presents the core steps of the Red-billed Blue Magpie Optimizer (RBMO)

Algorithm 1 The RBMO

```
Begin
Initialize the relevant parameters (T, n, ε, etc.)
   while t<T
         Calculate the fitness of each search agent
         Update the best solution
         Exploration:
               if rand<ε
                     Update the position of red-billed blue magpie by Eq. (11)
               else
                     Update the position of red-billed blue magpie by Eq. (12)
               end if
         Exploitation:
               if rand<ε
                     Update the position of red-billed blue magpie by Eq. (13)
               else
                     Update the position of red-billed blue magpie by Eq. (14)
               end if
         Update the X^food(t) and accomplish food storage by Eq. (15)
   end while
   return best solution
end
```

Figure II.4. Pseudocode for the Red-billed Blue Magpie Optimizer

2.6. advantages and disadvantages of metaheuristic methods

Advantages

- **Flexibility**:
  Can be applied to a wide variety of optimization problems, whether linear, nonlinear, discrete, or continuous.
- **Global Search Ability**:
  Designed to escape local optima and search globally, increasing the chance of finding the best or near-best solution.
- **No Need for Problem-Specific Information**:
  They don't require gradient or second-order information, which makes them suitable for problems where such data is hard to compute.
- **Easy to Implement**:
  Most metaheuristics are simple to understand and implement (e.g., Genetic Algorithm, Simulated Annealing).
- **Parallelizable**:
  Many metaheuristics (like Genetic Algorithms or Particle Swarm Optimization) can be parallelized for faster performance.
- **Good for Complex Problems**
  Particularly effective for combinatorial and NP-hard problems where traditional methods fail.

Disadvantages

- **No Guarantee of Optimality**:
  They provide approximate solutions and cannot guarantee finding the global optimum.
- **Parameter Sensitivity**:
  Performance can heavily depend on the choice of parameters (e.g., mutation rate, temperature, population size), which may require tuning.
- **Computational Cost**:
  Can be computationally expensive, especially for large search spaces or problems requiring many iterations.
- **Problem-Dependent Performance**:
  Although they are general, their performance can vary significantly depending on the problem.
- **Lack of Theoretical Foundation**:
  Unlike traditional mathematical methods, they often lack strong theoretical guarantees for convergence.

2.7. conclusion

Metaheuristic methods have emerged as powerful tools for solving complex and high-dimensional optimization problems, especially where traditional methods fall short. Their strength lies in their flexibility, simplicity of implementation, and global search capabilities, which make them well-suited for real-world scenarios that involve nonlinearity, multiple constraints, or noisy data.

However, these methods also come with notable limitations. They often require careful tuning of parameters, offer no guarantee of reaching the global optimum, and can be computationally intensive. Despite these drawbacks, the empirical success and adaptability of metaheuristics like Particle Swarm Optimization, Crow Search Algorithm, and the Red-billed Blue Magpie Optimizer make them indispensable in modern optimization landscapes.

Ultimately, while metaheuristics may not replace traditional methods in every context, they complement them by offering robust, problem-independent solutions in situations where analytical approaches are not feasible.

CHAPTER III

3.1. Introduction

In this chapter is to determine the optimal parameters of the Power System Stabilizer (PSS) using metaheuristic methods, in order to ensure effective damping of rotor oscillations and maintain system stability regardless of any disturbances that may occur.

In this chapter, we will through which stability can be determined (whether the system is stable or unstable), for this purpose, a program was developed using MATLAB.

We will also validate, through simulations using MATLAB/Simulink, the effectiveness of a power system stabilizer (PSS) based on the RBMO algorithm and another stabilizer based on the Particle Swarm Optimization (PSO) algorithm and crow search algorithm (CSA), using the nonlinear model of the system.

In this study, a change in mechanical power is applied to the power system under different operating conditions, in order to evaluate the performance and robustness of the proposed stabilizers.

Finally, to demonstrate the robustness of the proposed PSSs, several operating points were considered.

3.2. Network Studies

The power system model considered in our study is illustrated in Figure (III. 1) The system consists of a single 220 MVA synchronous machine connected to an infinite bus through transmission lines and a voltage source with infinite capacity.

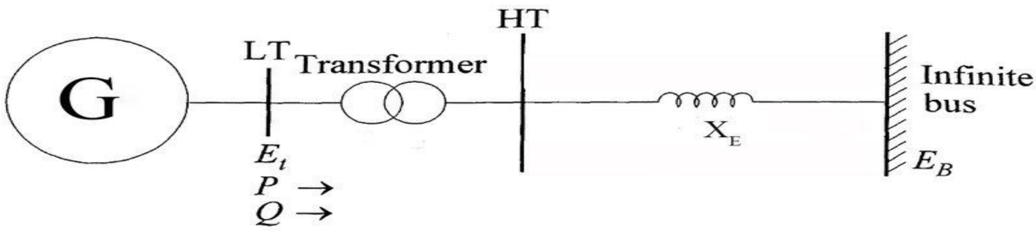


Figure III.1 Single Machine Infinite Bus System

Machine Parameters :

Parameter	Value	Description
D	0.3	Damping factor
M	3.214	Inertia constant
xd	0.973	Direct axis reactance
xq	0.55	Quadrature axis reactance
xdd	0.19	Transient reactance
Tdo	7.76	Open-circuit field time constant

Table.III.1 Machine Parameters

3.3. Results and discussion

In this study, a scenario is considered where a change in mechanical power is applied to the power system under different operating conditions.

This variation is evaluated under three different loading conditions:

Light Load: Active and reactive powers are P=0.5, Q=0.169.

Nominal Load: Active and reactive powers are P=0.8, Q=0.222.

Heavy Load: Active and reactive powers are P=1,1, Q=0.35.

The results obtained will be analyzed and discussed

- We begin with the analysis of the system without the use of PSS.
- Analysis of the system the use of PSS.
- We also present the results of the application of case intended to optimize the PSS parameters of the PSO particle swarm system.
- Present the results of the application of case intended to optimize the PSS parameters of the CSA particle swarm system.
- Present the results of the application of case intended to optimize the PSS parameters of the RBMO particle swarm system.

3.4. The system without PSS

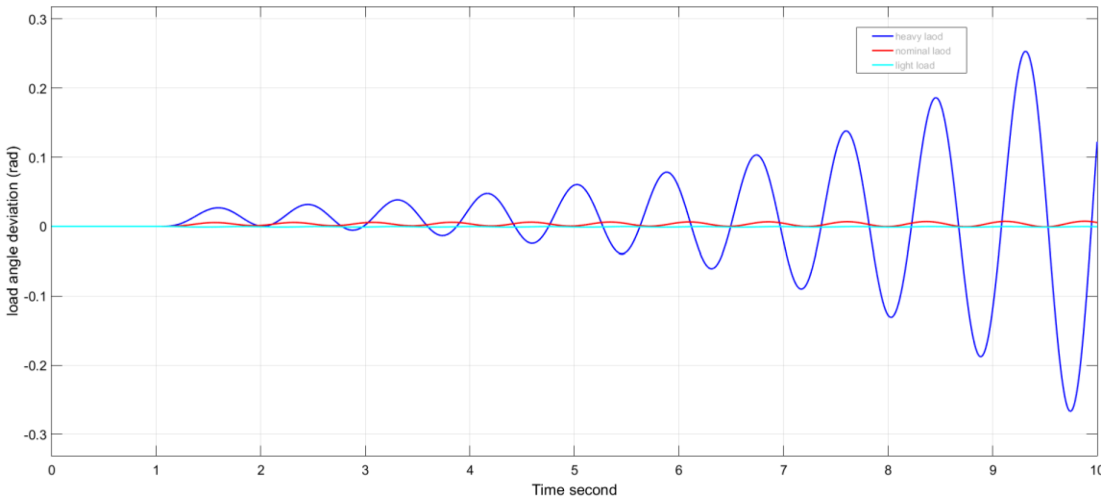
In this study, the system performance was evaluated using the Integral of Absolute Error (IAE) at light load and nominal load and heavy load. The IAE value represents the cumulative error over time, where lower values indicate better system stability and performance.

For the method without PSS, the IAE at heavy load was measured as 9.4, which is relatively high and indicates a significant accumulated error and poor system stability at this operating point. At nominal load, the IAE value decreased substantially to 1.553820, showing a marked improvement in system response and a reduction in cumulative error. Finally, at light load, the system recorded the lowest IAE value of 1.266603, indicating the best performance and improved stability compared to the other two points.

Therefore, it can be concluded that lowering the operating point value leads to better system performance in terms of stability and error minimization when using the method without PSS.

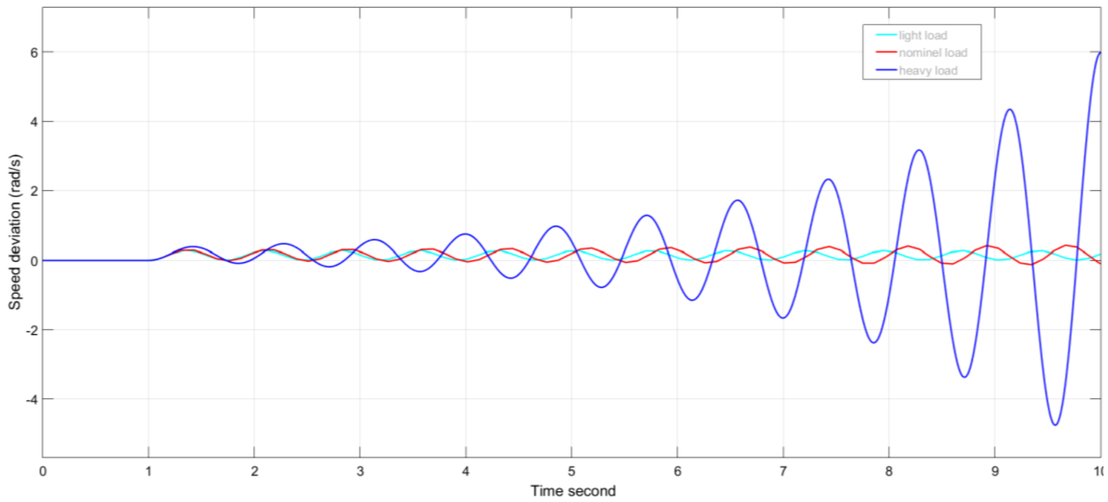
we analyze the performance of the power system without the use of a Power System Stabilizer (PSS), which is a key component used to enhance frequency and rotor angle stability, especially during disturbances.
The absence of the PSS makes the system more vulnerable to low-frequency oscillations and results in a slower recovery to steady-state conditions after disturbances. This can lead to degraded dynamic performance of the entire system.

The following figures present the simulation results that illustrate the behavior of the system without a PSS. Key variables such as rotor angle are affected significantly, as shown in the curves below



FigureIII.2. hange in Load Angle Deviation in a System without PSS

The graph shows the response of the Laod angel deviation (rad) without a PSS. It is observed that the oscillations increase significantly with increasing load. Under light load, the response is relatively stable, with small oscillations and good settling speed. Under medium load, the oscillations begin to increase and last longer before settling. Under heavy load, sharp, wide-amplitude oscillations appear with very slow damping, indicating poor dynamic stability of the system.



FigureIII.3. Change in Speed deviation in a System without PSS

The graph shows the response of the Speed deviation (rad/s) without a PSS.

The curves show that as the load increases, the angular oscillations increase significantly. Under light and medium loads, the oscillations remain relatively limited, while under heavy loads, the oscillations gradually amplify over time without damping, indicating a clear state of instability.

3.5. Conventional PSS (CPSS) performance

The classical method used to tune the parameters of the conventional Power System Stabilizer (PSS) is the phase compensation method.

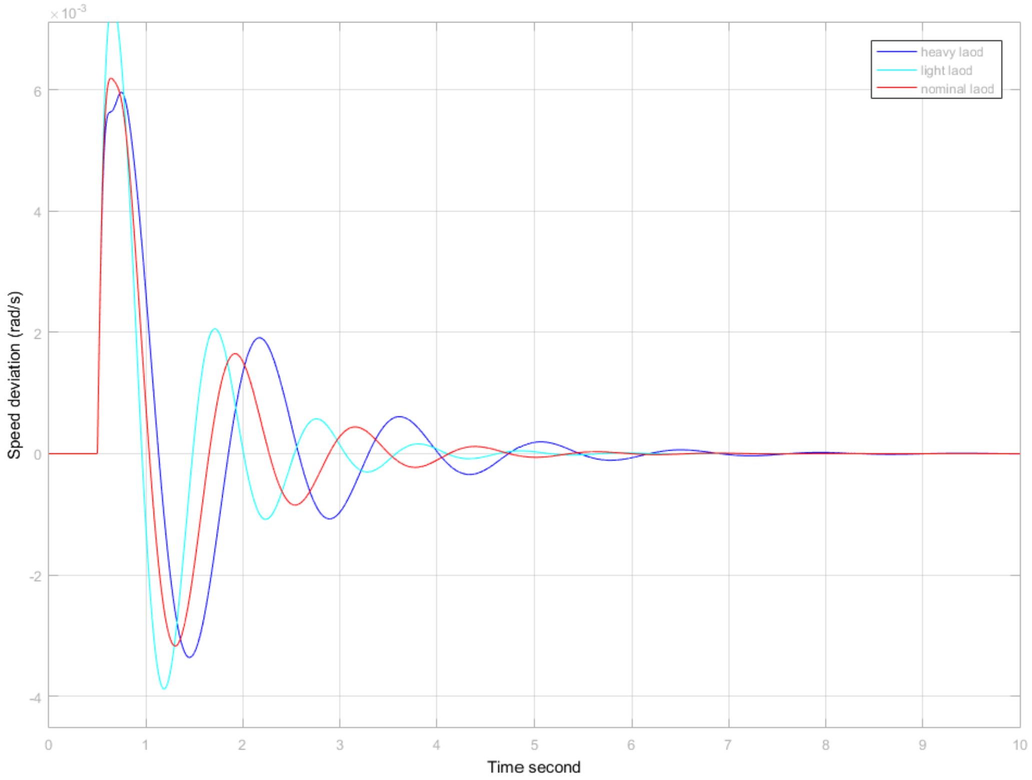
The conventional PSS was designed at the nominal operating point using this compensation technique, and its parameters are listed in Table

Ke	Tw	T1	T2	T3	T4
2.1783	10	1.4557	0.6143	1.0083	0.1005

Table.III.2 parameters PSS

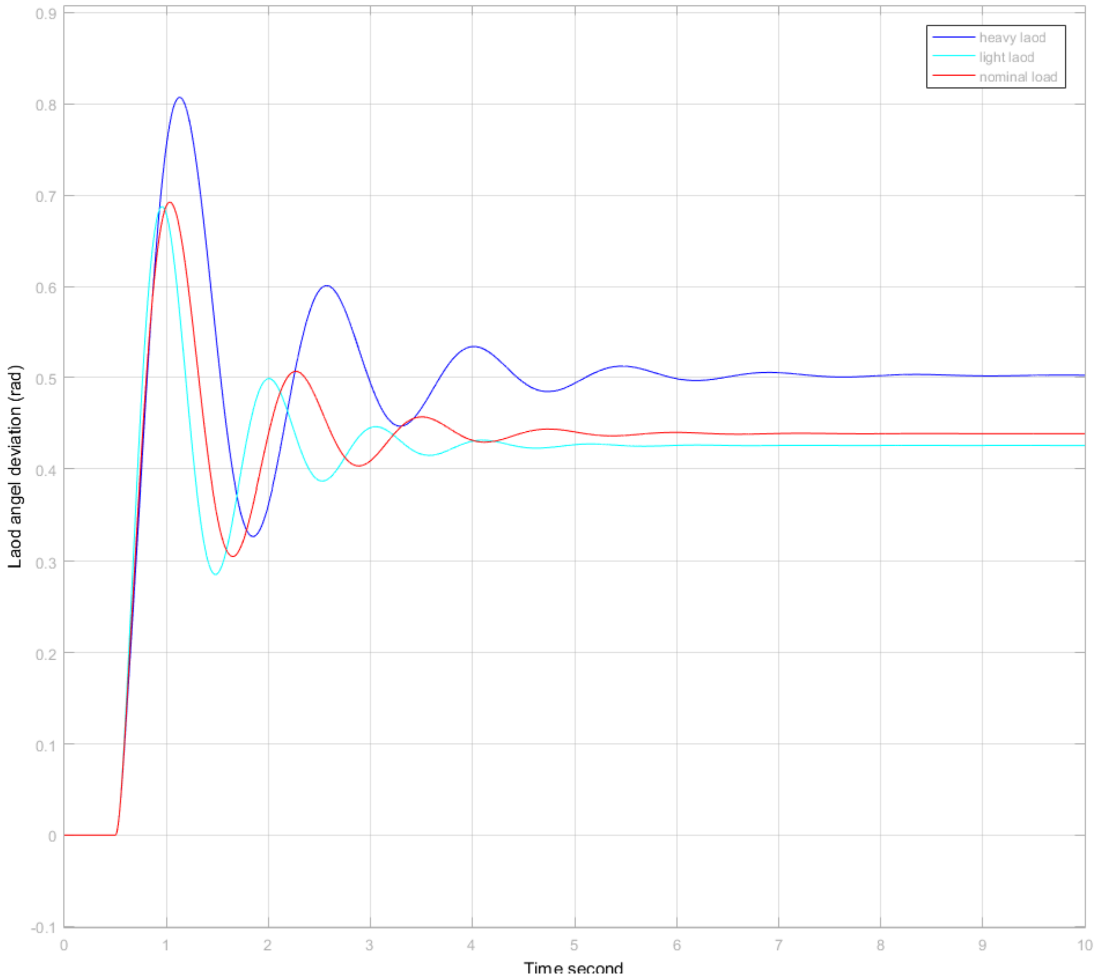
The selected conventional PSS parameters ensure system stability at the nominal operating point, as demonstrated by the Simulink simulation.

Curve analysis:



FigureIII.4. Change in Speed deviation in a CPSS

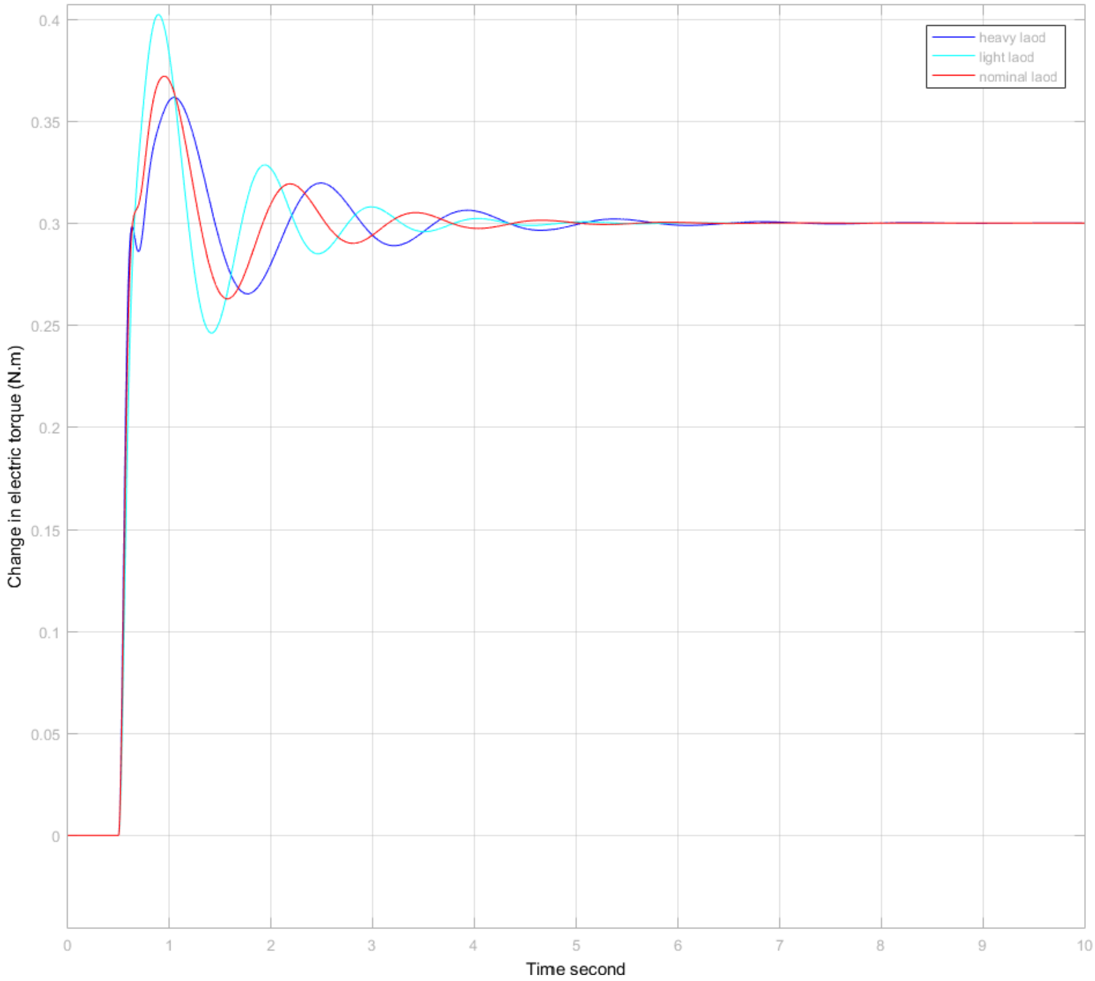
The graph illustrates the speed deviation response under three different load conditions using a CPSS. From the curves, it is observed that the light load results in fast but quickly damped oscillations, indicating good stabilizer performance. In the medium load , the oscillations are smoother but take longer to settle. Under the heavy load , the system exhibits more sustained oscillations and a longer settling time, reflecting a reduction in CPSS effectiveness as the load increases. This highlights the need to improve the performance of conventional stabilizers or consider advanced control techniques such as adaptive or intelligent PSS for better damping in high-load conditions.



FigureIII.5. Change in Laod angel deviation in a CPSS

The graph illustrates the Laod angel deviationin (rad) response under three different load conditions using a CPSS.

From the curves, it is evident that as the load increases, the rotor angle deviation becomes more pronounced. Under light and nominal loads, the system exhibits faster damping and a relatively quicker return to steady state. However, under heavy load conditions, the oscillations are larger and persist longer, indicating a slower damping response. This suggests that the CPSS performs adequately under low to moderate loading but struggles to effectively damp rotor angle deviations when the system is heavily loaded.



FigureIII.6. Change in electric torque in a CPSS

The graph illustrates the Change in electric torque (N.m) response under three different load conditions using a CPSS.

The curves show that as the load increases, the torque oscillations increase and last longer. Under light and medium load conditions, the system exhibits good damping capacity and a faster return to steady state. Under heavy load conditions, however, the oscillations are larger and more persistent, indicating poor damping response. This is due to the influence of low-frequency oscillation modes resulting from the interaction between the generator inertia and the voltage regulator (AVR) response.

3.6. PSS parameter optimization using a metaheuristic algorithm

In all the optimization algorithms studied, including CSA, RBMO, and PSO, a common set of parameters was employed to ensure a consistent optimization environment and allow for a fair comparison among the techniques. The sampling time step is set to $\Delta tm=0.25$, defining the resolution of the dynamic simulation. The population size N is fixed at 30, while the maximum number of iterations itermax is set to 100. Additionally, the problem dimension pd, representing the number of PSS parameters to be optimized, is defined as 5. These settings offer a practical compromise between computational efficiency and optimization performance.

In this study, the parameters of the Power System Stabilizer : the Integral of Absolute Error (IAE), defined as follows

- $IAE = \int_0^t |e(t)|dt$ (III.1)

Here, e(t) represents the error signal, and t is the simulation time. The speed deviation Δw, which occurs following a disturbance, is considered as the error signal. To evaluate the objective functions, a time-domain simulation of the nonlinear power system model is performed over the defined simulation period. The goal is to minimize these objective functions in order to enhance system stability. Therefore, the design task is formulated as an optimization problem.

Selected Parameter Ranges for PSS Tuning:

$0 \leq K_c \leq 50$

$0.01 \leq T_1 \leq 5$

$0.01 \leq T_2 \leq 5$

$0.01 \leq T_3 \leq 5$

$0.01 \leq T_4 \leq 5$

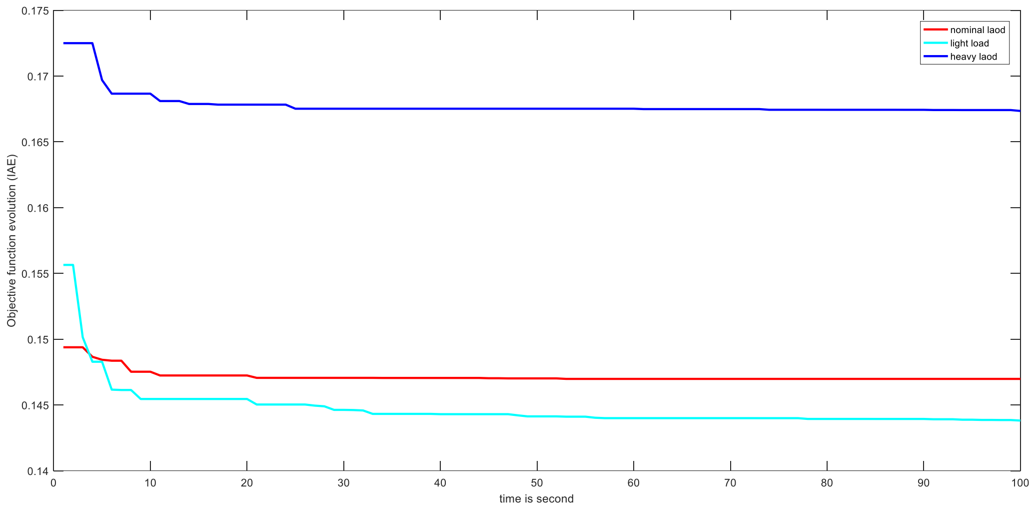
3.6.1. Optimization of PSS parameters by PSO

The parameter settings employed in the PSO technique for tuning the PSS parameters. The key parameters include the inertia weight (which controls the balance between exploration and exploitation), and the acceleration coefficients

C1 and C2 which guide the particles toward their personal best and the global best positions, respectively. In the present study, the inertia weight is fixed with

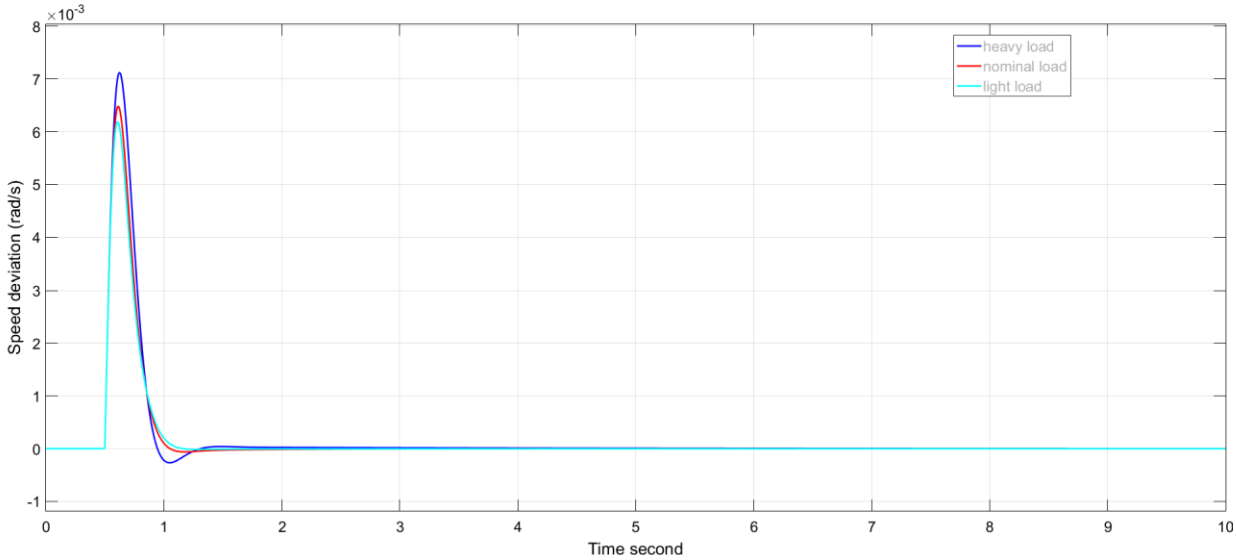
Wmax=0.1 and Wmin=0.1, while the acceleration coefficients are set at C1=5 and C 2=4

To achieve optimal performance of the PSS, artificial intelligence algorithms such as Particle Swarm Optimization (PSO) are employed to determine the optimal parameter settings. PSO simulates the behavior of a group of particles moving within the solution space in search of the best performance, thereby contributing to improved system stability and dynamic response.



FigureIII.7. Objective function evolution in a PSO

The figure illustrates the evolution of the objective function (IAE) using the PSO algorithm under three different loading conditions: light load, nominal load , and heavy . It is evident that the PSO algorithm performs best under the light load condition, where the IAE value decreases rapidly and stabilizes at the lowest level among the three cases. Under nominal load, the IAE also improves gradually and settles at a moderate value. However, under heavy load, the IAE remains significantly higher throughout the optimization process, indicating weaker performance. These results highlight the sensitivity of PSO's effectiveness to system loading, showing that its damping capability is more pronounced under lighter loads and diminishes as the load increases.



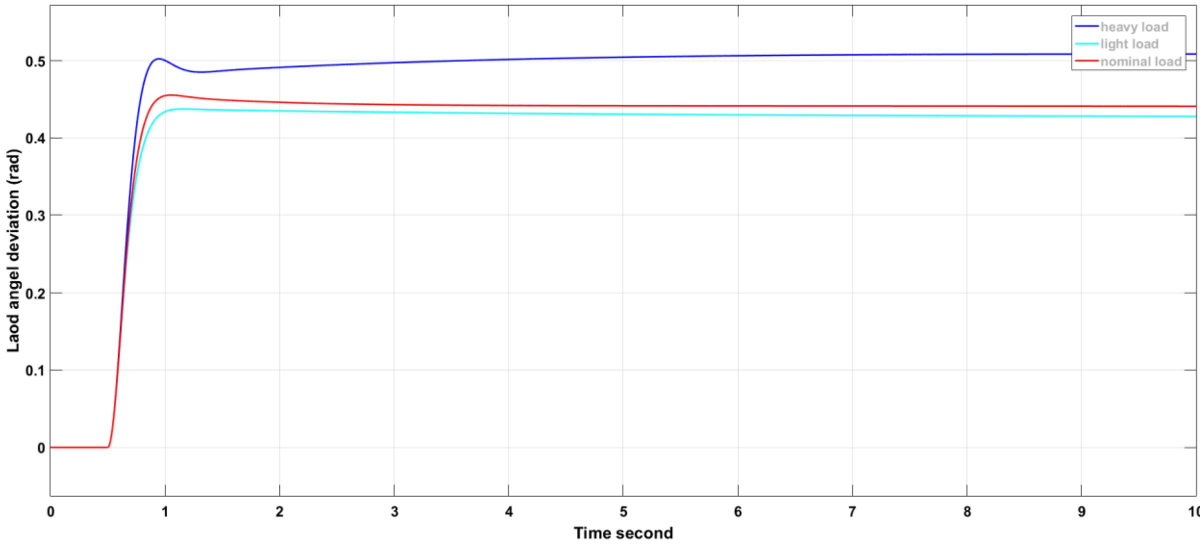
FigureIII.8. Change in Speed deviation in a PSO

This graph shows the system's response to the Speed deviation (rad/s) over time when using a PSS stabilizer tuned with the Particle Swarm Optimization (PSO) algorithm, under three different load conditions.

We observe that the response begins with high-amplitude oscillations immediately after the disturbance, then gradually decreases until it almost disappears after 6 seconds.

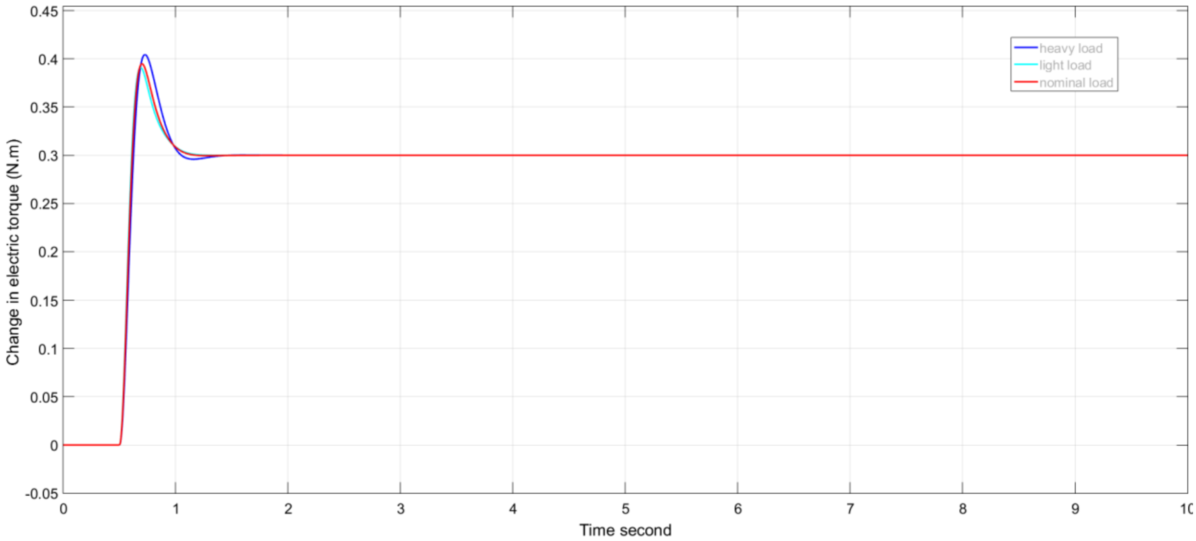
The results demonstrate the effectiveness of the PSO algorithm in reducing speed deviation and achieving dynamic stability of the system.

Although the initial oscillation amplitude was significant, the gradual damping indicates good performance under various loading conditions.



FigureIII.9. Change in Laod angel deviation in a PSO

The figure shows the load angle response (rad) using a power stabilization regulator (PSS) tuned with the PSO algorithm under three different load conditions. The heavy load results in larger oscillations and longer settling time due to higher inertia, while the light load exhibits faster settling and fewer oscillations due to lower inertia and faster system response. The nominal load lies between the two conditions and reflects balanced performance.



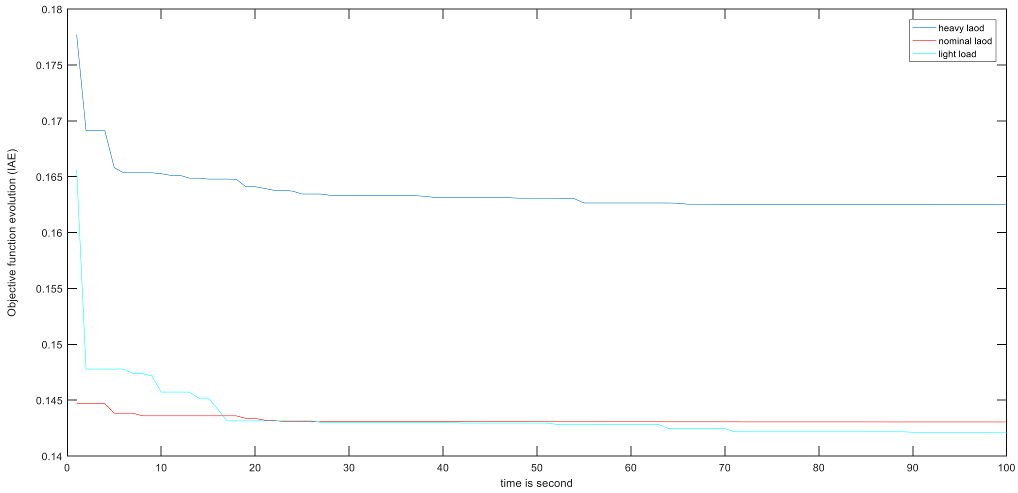
FigureIII.10. Change in electric torque in a PSO

The figure shows the Change in electric torque (N.m) when using a power stabilization regulator (PSS) tuned using the PSO algorithm under three load conditions. We notice that the oscillations are larger at the nominal load condition, while they are smaller at the light load condition, due to the different dynamic properties of the system at each load level. Over time, the oscillations gradually fade toward a steady state in all cases.

3.6.2. Optimization of PSS parameters by CSA

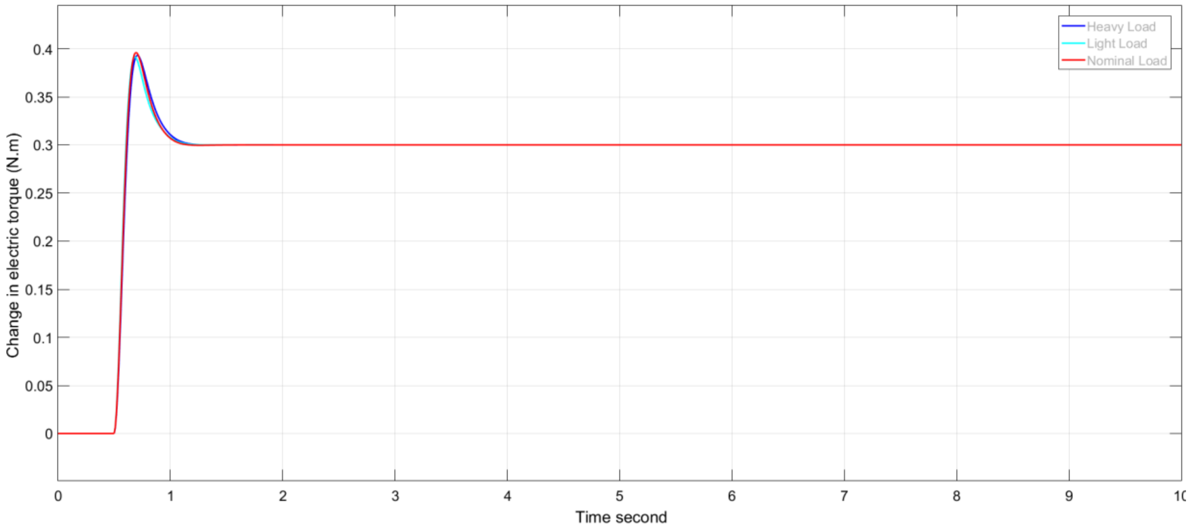
the parameter settings used in the implementation of the Crow Search Algorithm (CSA) for optimizing the PSS parameters. The main parameters include the Awareness probability (AP) and the Flight length (fl). In the present study, the values of AP and fl are set at 0.1 and 1.8 respectively. These parameters play a crucial role in balancing exploration and exploitation during the search process.

A simulation was carried out to evaluate the performance of the Power System Stabilizer (PSS) after tuning its parameters using the Crow Search Algorithm (CSA). The results demonstrated a significant improvement in system stability, with reduced frequency oscillations and settling time compared to the conventional PSS tuning.



FigureIII.11. Objective function evolution in a CSA

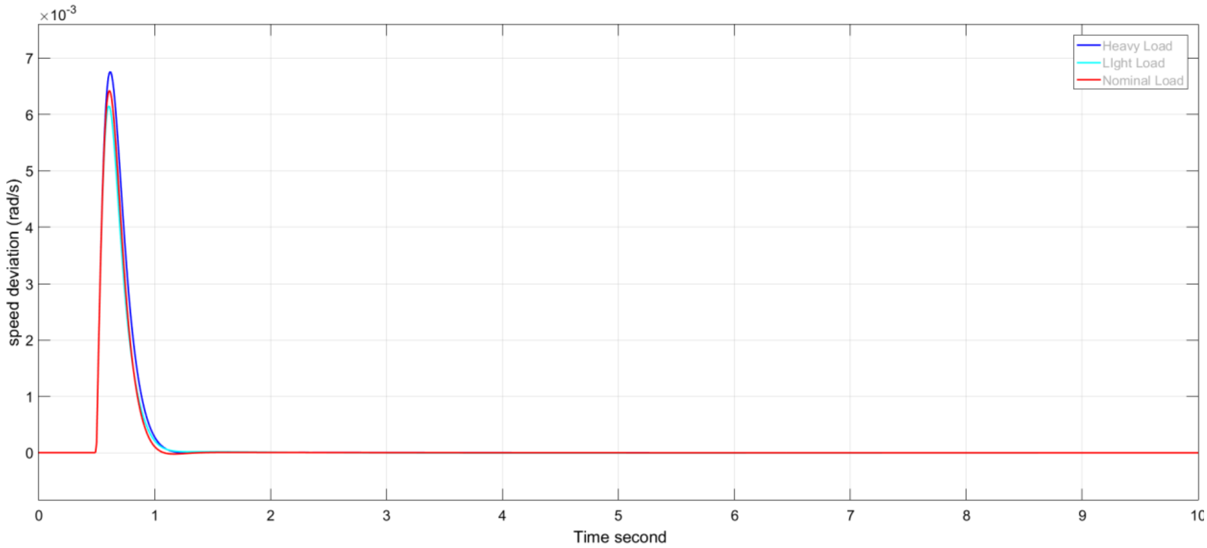
CSA for three different load scenarios: heavy, nominal, and light. The algorithm shows significant improvement in IAE reduction, especially under light and nominal load conditions. In the light load case, a rapid and noticeable drop in IAE is observed, with the curve stabilizing at the lowest value among the three cases. The nominal load scenario also demonstrates a consistent reduction in error over time, though slightly above the light load case. On the other hand, the heavy load condition results in the highest IAE values throughout the simulation, with only modest improvement.



FigureIII.12. Change in electric torque in a CSA

This graph represents the Change in electric torque (N.m) over time for three operating conditions. using a PSS stabilizer tuned with the CSA.

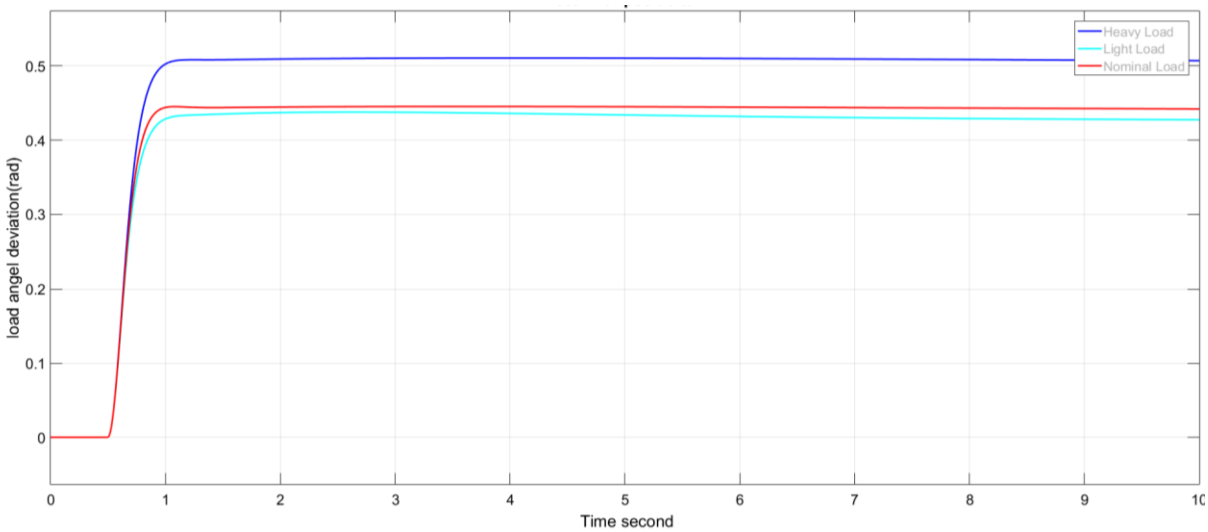
The curves show a rapid and stable response of the generating torque after a sudden disturbance. We note that all curves rise to a clear peak, then gradually decline, stabilizing around a constant value in less than two seconds. These results demonstrate the ability of the CSA algorithm to improve PSS performance by accelerating the stabilization of the generating torque and reducing oscillations.



FigureIII.13. Change in Speed deviation in a CSA

This graph represents the response of the Speed deviation (rad/s) over time under three load levels, using a power stabilizer optimized with the CSA.

The curves show that the system responds very effectively to all loads, with the maximum deviation in the angular velocity rate of change peaking within a very short time and then rapidly fading to a steady state in less than two seconds. It can be seen that the CSA algorithm contributes to accelerating the dynamic response and significantly improving the damping properties, as oscillations are almost nonexistent after the initial peak, even under heavy load conditions.



FigureIII.14. Change in Laod angel deviation in a CSA

This plot represents the response of the load angle deviation (rad) over time for three different operating conditions, using a power stabilization system (PSS) tuned via the CSA.

The curves show a stable and rapid response in all cases, with the load angle rising rapidly to a certain value and then stabilizing without any obvious oscillations or lag.

As the load increases, the peak value of the angle deviation increases, as in the heavy load case, indicating a direct influence of the loads on the angle behavior. However, it is noticeable that the curves converge rapidly toward a steady state, demonstrating high damping efficiency and achieving dynamic equilibrium of the system.

3.6.3. Optimization of PSS parameters by RBMO

This organizational chart the steps of the RBMO algorithm for tuning the parameters of a power system stabilizer (PSS). The process begins by initializing the algorithm parameters and generating a set of random solutions within specified bounds. The performance of each solution is then evaluated by simulating the SMIB system and calculating the performance index (IAE). The best solution is retained and updated through iterations, during which exploration and exploitation phases are applied to improve the solutions. Each time a better solution is found, the food location and the best known solution are updated. This process continues until the maximum number of iterations is reached, and the discovered optimal parameters are finally returned.

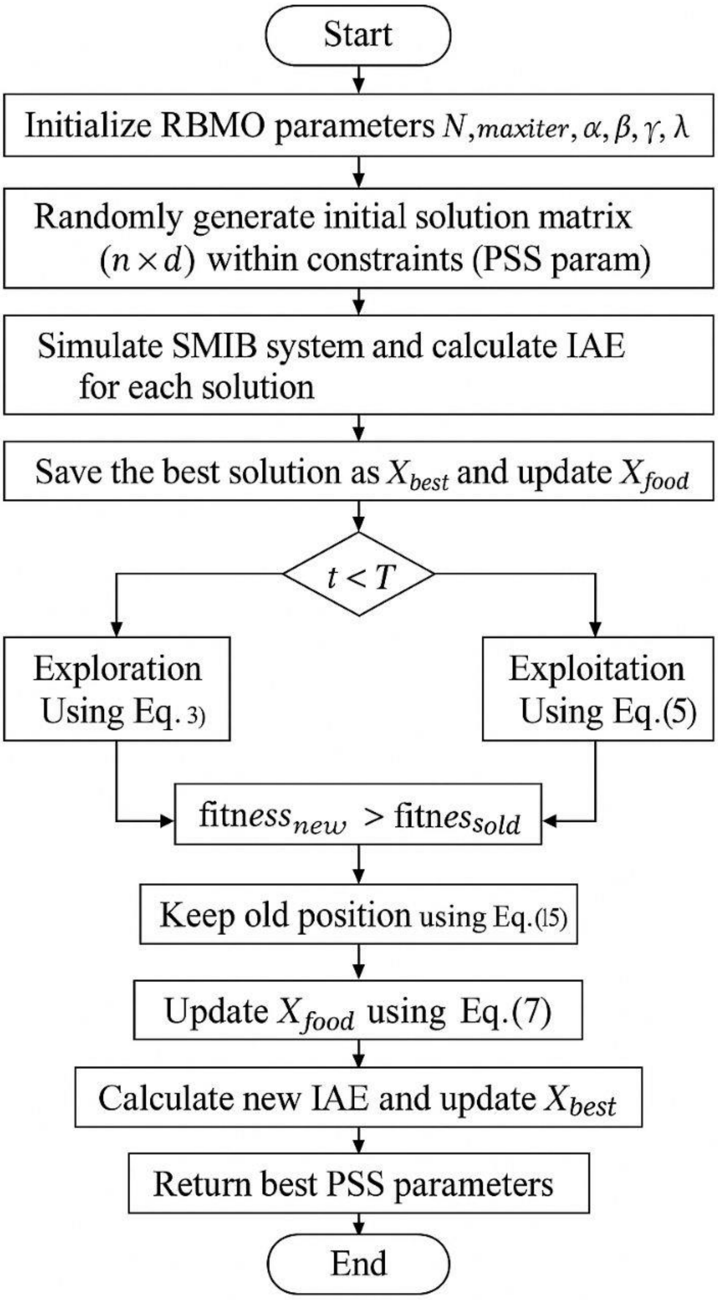


Figure III.15. Pseudocode for the Red-billed Blue Magpie Optimizer

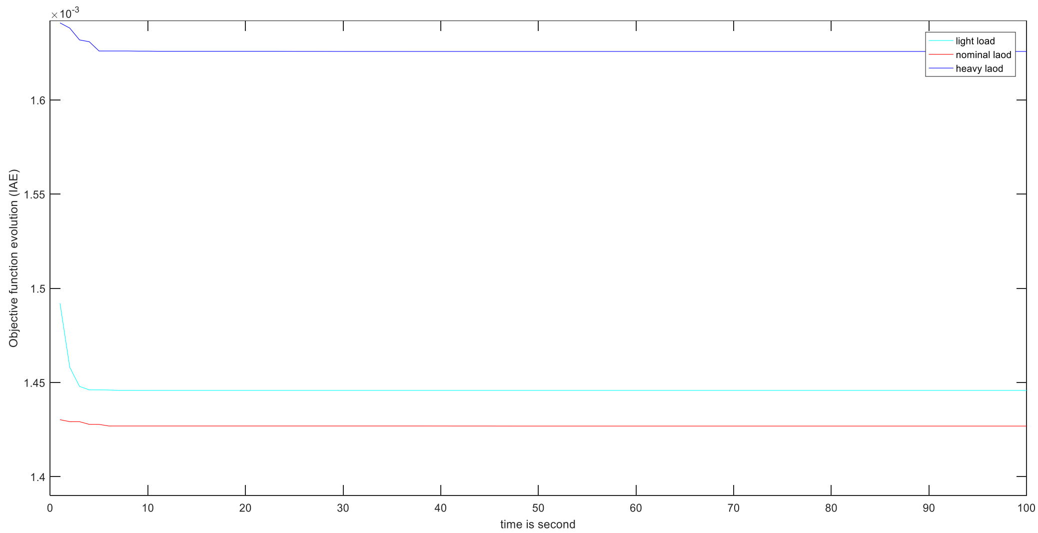
the parameter settings used in the RBMO method for tuning the PSS parameters. In this study, two key parameters are used: the ε value which governs the exploitation intensity, and the problem dimension (pd) which corresponds to the number of variables being optimized. The values of ε and pd are set at 0.5 and 5 respectively, ensuring a suitable trade-off between convergence speed and solution diversity.

enhance the damping of low-frequency electromechanical oscillations in power systems. Traditionally, fixed PSS parameters fail to ensure optimal performance under varying operating conditions. To address this limitation, the Red-billed Blue Magpie Optimizer (RBMO) is employed as a robust metaheuristic algorithm capable of adaptively fine-tuning the PSS parameters.

The Red-billed Blue Magpie Optimizer (RBMO), developed in 2024, is a cutting-edge AI technique inspired by the behavior of intelligent birds. RBMO is based on the intelligent cooperative hunting behavior of the red-billed blue magpie, giving it a unique ability to balance exploration and exploitation.

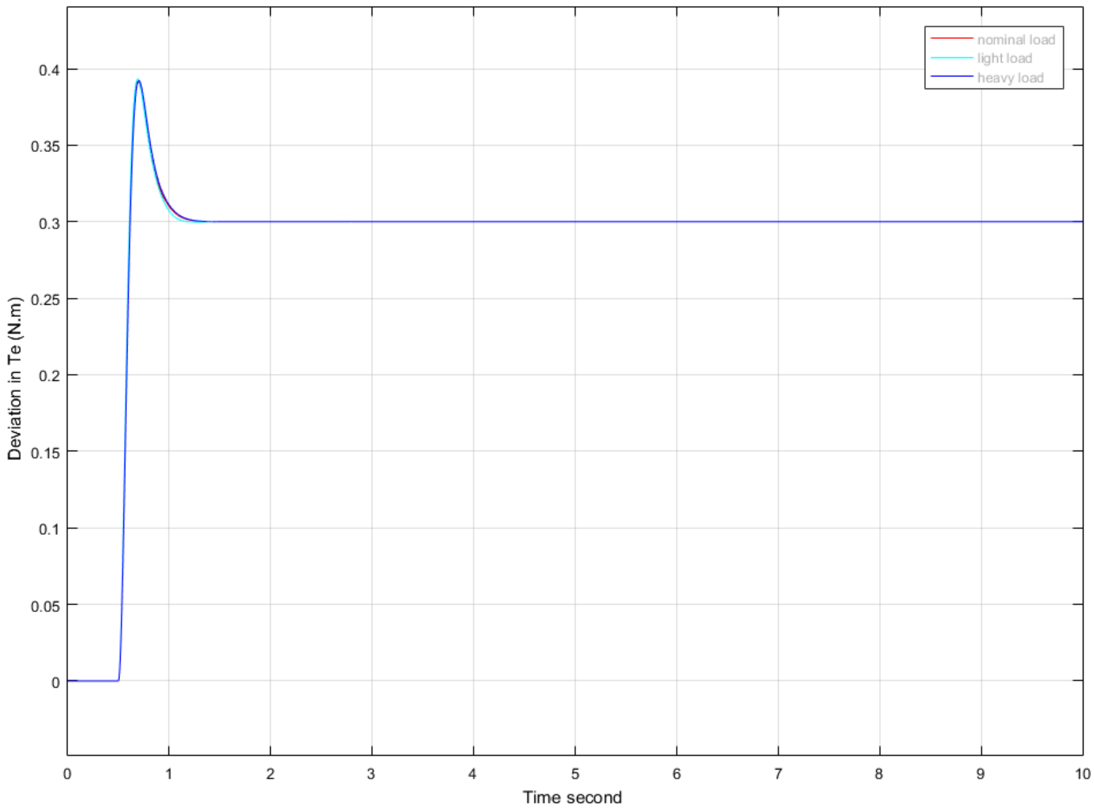
This algorithm was used to fine-tune the parameters of a Power System Stabilizer (PSS), and simulation results demonstrated excellent performance in reducing oscillations and accelerating stabilization, especially under high-load conditions. Thanks to its high adaptability and convergence speed, RBMO has proven its effectiveness compared to algorithms such as PSO and CSA.

RBMO is thus a revolutionary tool for enhancing the stability of modern electrical grids and opens up promising prospects for broader applications in smart energy systems.



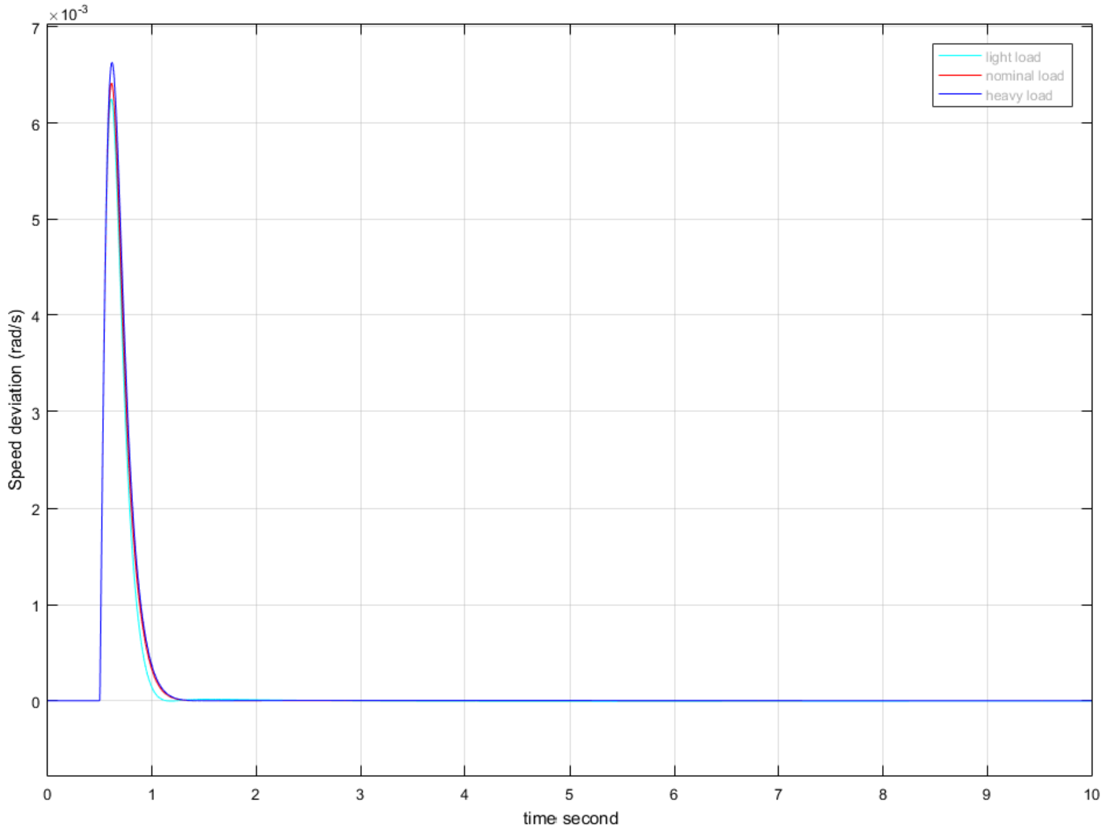
FigureIII.16. Objective function evolution in a RBMO

The figure shows the evolution of the objective function (IAE) when using the Red-billed Blue Magpie Optimizer (RBMO) algorithm. We note that the algorithm was able to rapidly reduce the IAE value in all cases, indicating its effectiveness in improving system stability. Under light load, the IAE decreased rapidly and stabilized at a low value. Under nominal load, the results were more impressive, maintaining a constant minimum IAE value. Under heavy load, despite significant challenges, RBMO was able to achieve a stable response and near-optimum performance. These results reflect the algorithm's ability to adapt to different operating conditions with high efficiency.



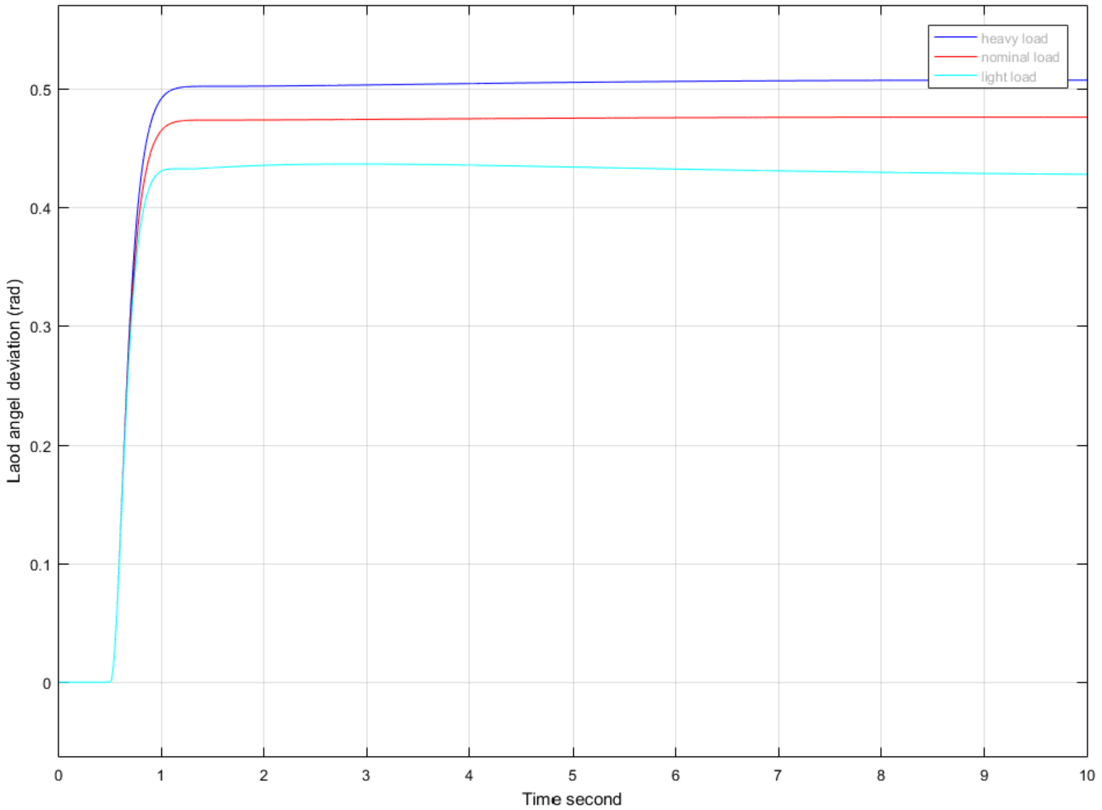
FigureIII.17. Change in electric torque in a RBMO

The curves show that all loads result in an instantaneous increase in torque immediately after the disturbance, with a peak near 0.4 Nm. Thereafter, the system gradually returns to a steady state. The light load exhibits the least overshoot and the fastest oscillation absorption, indicating a better dynamic response. The heavy load , although it exhibits the highest initial response, is successfully contained by the system thanks to the effectiveness of the RBMO algorithm.



FigureIII.18 Change in Speed deviation in a RBMO

The responses show that all cases experience an initial peak in velocity deviation immediately after the disturbance. However, the system stabilizes more quickly at light loads, with a lower peak and faster absorption of the oscillation. The curve heavy load shows the highest overshoot and takes slightly longer to stabilize, indicating that the system is under greater stress. This highlights the ability of the RBMO algorithm to maintain system stability despite changing loads.



FigureIII.19. Change in Laod angel deviation in a RBMO

From the curves, we notice that all conditions showed a rapid response towards a steady state with no oscillations, indicating the effectiveness of RBMO-PSS in improving damping and reducing transient effects. The difference between the final angle values also reflects the effect of the load on the settling point, with the settling angle increasing with increasing load.

Operating conditions	algorithms	IAE	Kc	T1	T2	T3	T4
Light load	PSO	0.01468	41.3405	4.7707	4.4702	4.2066	3.4195
P=0.5	CSA	0.00142	49.2803	1.0591	1.6011	3.8368	2.2825
Q=0.169	RBMO	1.4457 e-04	49.9999	4.9999	4.7810	4.9999	4.7831
Nominal load	PSO	0.01538	33.600	1.6356	3.9550	2.7346	1.16047
P=0.8	CSA	0.00143	49.0301	4.2106	4.7882	1.9615	2.5450
Q=0.222	RBMO	1.4297e-04	49.9998	4.6114	4.3164	2.1857	3.3931
Heavy load	PSO	0.0173	48.9304	1.4661	2.9657	2.8610	3.0831
P=1.1	CSA	0.00163	38.9762	3.0573	2.9590	2.2224	3.5057
Q=0.35	RBMO	1.6261e-04	49.5166	3.2827	4.2264	3.2976	4.9153

Table.III.3 PSS Parameter Values Obtained by CPSS, CSA, PSO, and RBMO under Three Loading Conditions

Light Load (P=0.5, Q=0.169):

- Best performance (lowest IAE): RBMO (1.4457e-04), followed by CSA (0.00142) and PSO (0.01468).
- RBMO achieves near-maximum gain (Kc ≈ 49.9999) and consistent time constants, indicating strong and stable damping.

2. Nominal Load (P=0.8, Q=0.222):

- Best IAE: RBMO (1.4297e-04), showing superior tuning precision compared to CSA (0.00143) and PSO (0.01538).

3. Heavy Load (P=1.1, Q=0.35):

- Best IAE: CSA (0.00163), slightly outperforming RBMO (1.6261e-04), but RBMO still maintains excellent time constants and high gain.

Conclusion:

Among the tested algorithms, the Red-Beaked Bluebird Optimization (RBMO) algorithm consistently delivers the most stable and accurate results under different load conditions.

- **Reasons for RBMO's superiority:**

1. Lowest IAE values under light and nominal load conditions, and nearly optimal under heavy load.
2. Stable and balanced tuning parameters (T1–T4), which reflect a consistent dynamic behavior.
3. High controller gain (Kc) in all scenarios, enhancing the system's damping capability.

- The comparative analysis of Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), and Red-Beaked Bluebird Optimization (RBMO) for PSS tuning demonstrates the superior effectiveness of RBMO. Inspired by the intelligent behavior of the red-beaked bluebird, RBMO outperforms the other techniques by minimizing the IAE and ensuring stable tuning parameters across all loading scenarios. Therefore, RBMO is recommended as a reliable and robust solution for enhancing the damping of electromechanical oscillations in power systems.

3.7. Comparison between the three stabilizers: CPSS, PSO-PSS, CSA-PSS, and RBMO PSS

In this section, we compare the performance of four different algorithms CPSS, PSO, CSA, and RBMO. The comparison is based under three different loading conditions. This evaluation aims to assess the effectiveness of each algorithm in enhancing the dynamic response and stability of the power system.

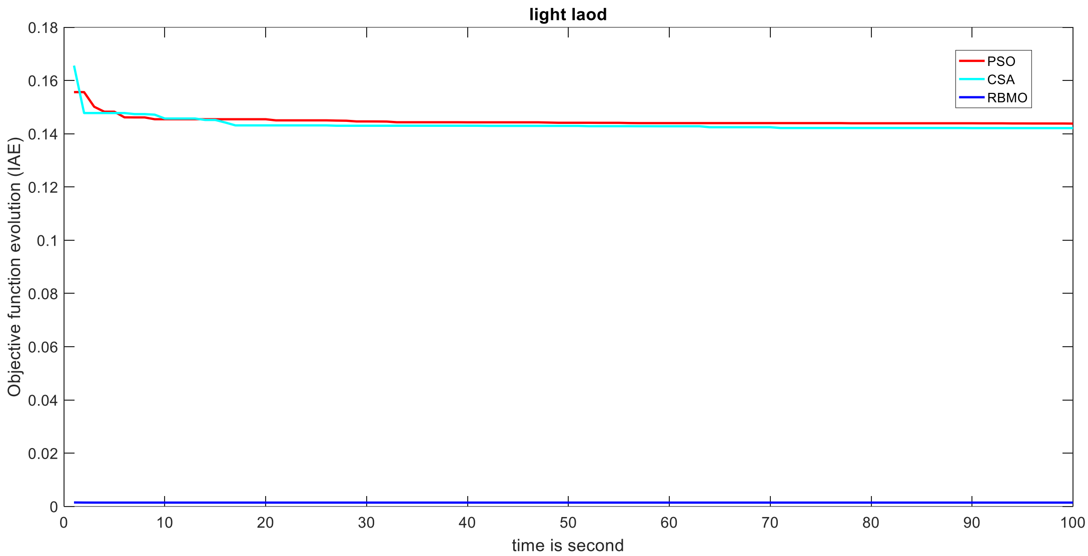


Figure III.20. Objective Function Evolution (AE) Over Time Under light Load Using PSO, RBMO, and CSA Algorithms

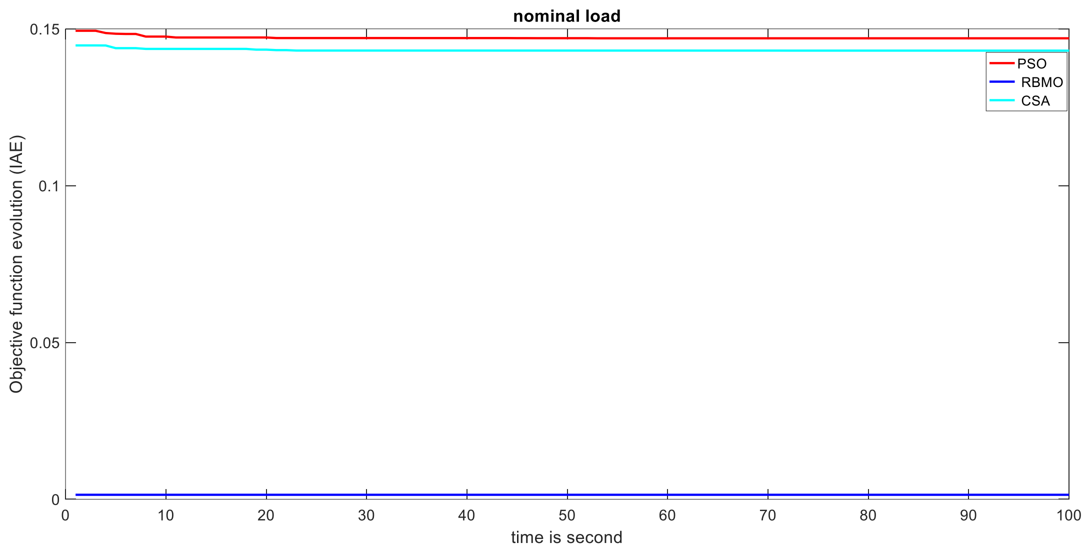


Figure III.21. Objective Function Evolution (AE) Over Time Under nominal Load Using PSO, RBMO, and CSA Algorithms

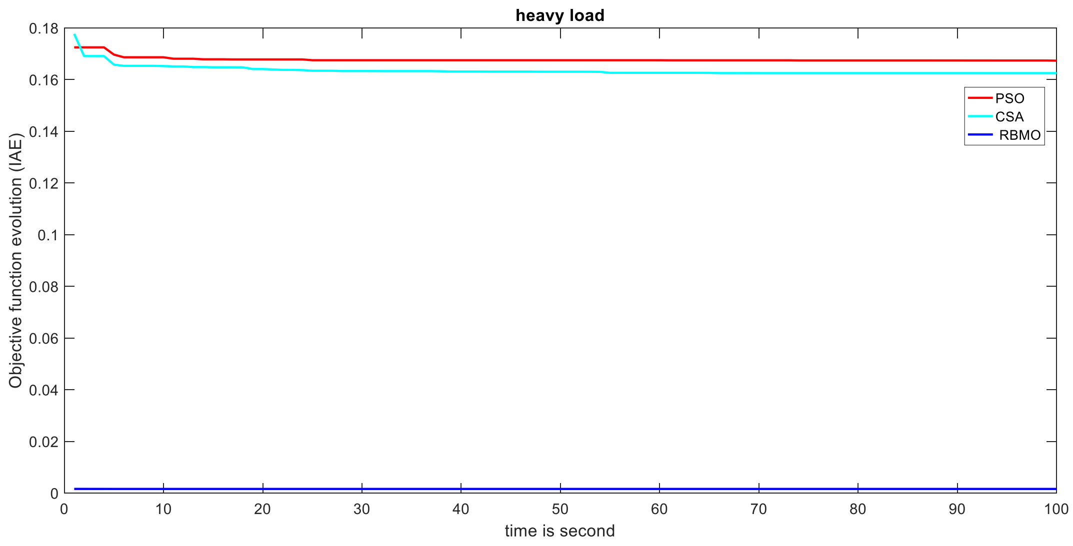


Figure III.22. Objective Function Evolution (AE) Over Time Under heavy Load Using PSO, RBMO, and CSA Algorithms

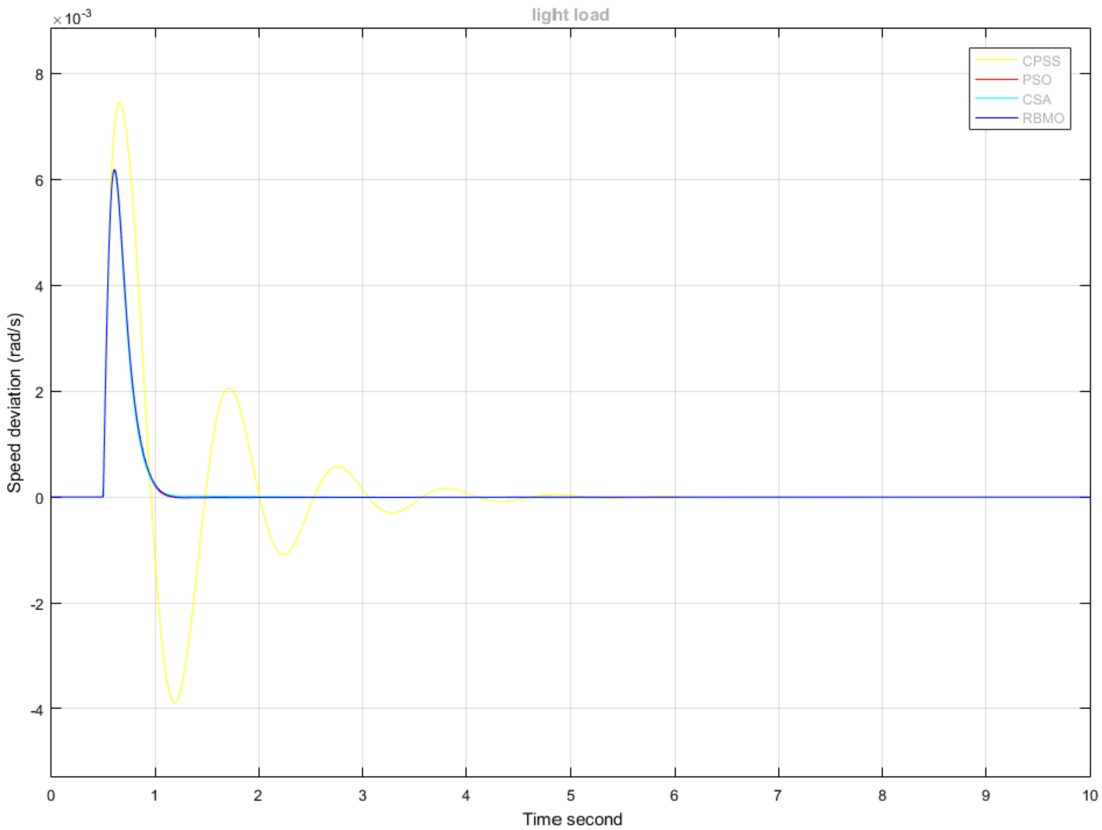


Figure III.23. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the speed deviation response of a power system under light load

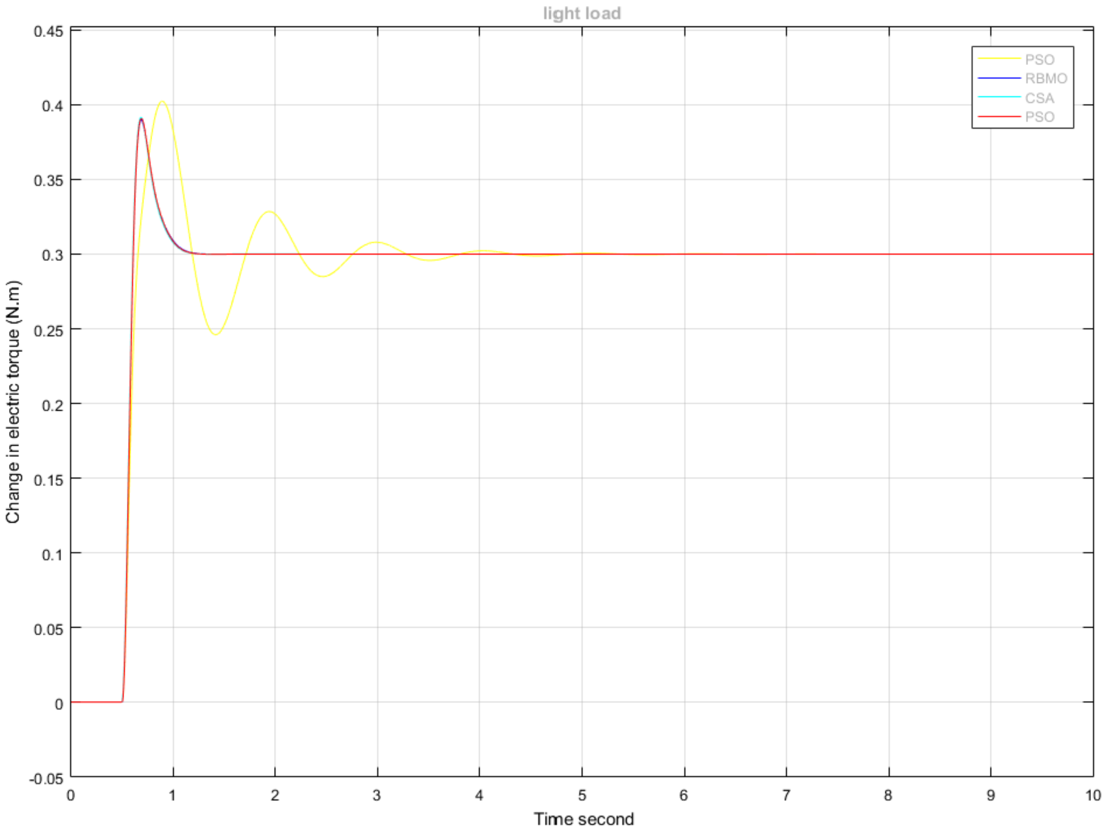


Figure III.24. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the Change in electric torque response of a power system under light load

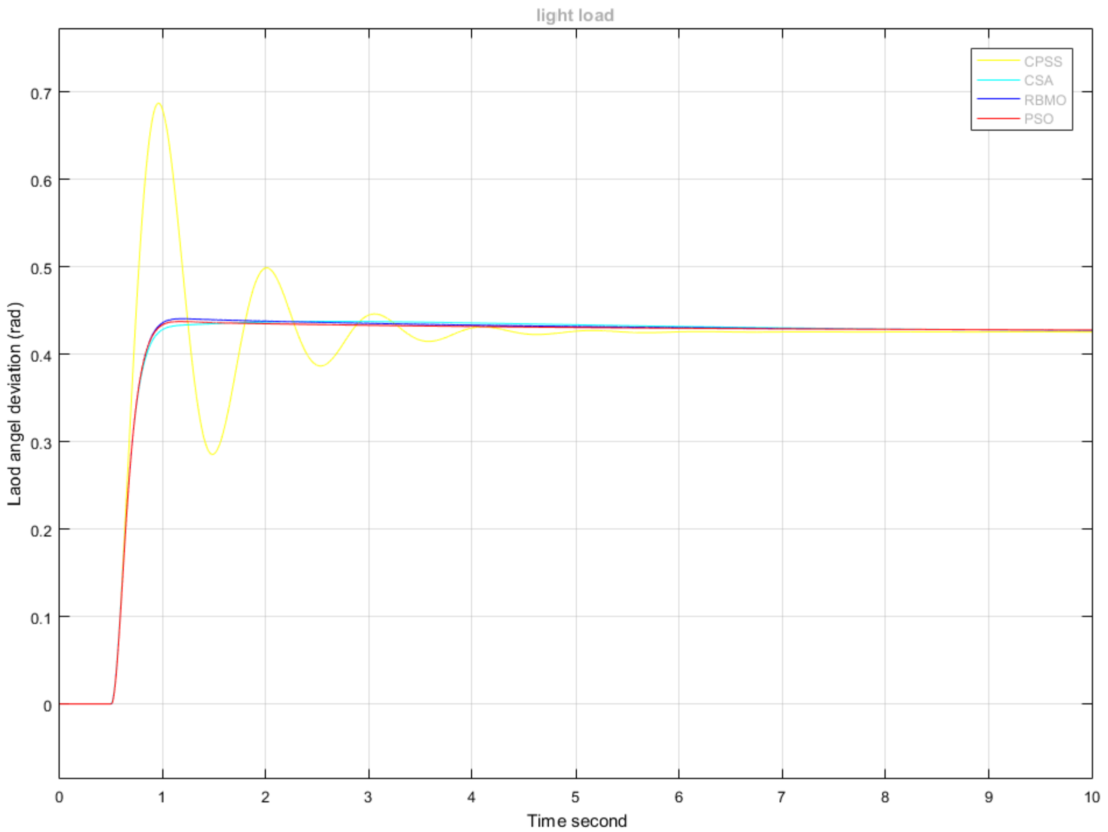


Figure III.25. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the load Angle deviation response of a power system under light load

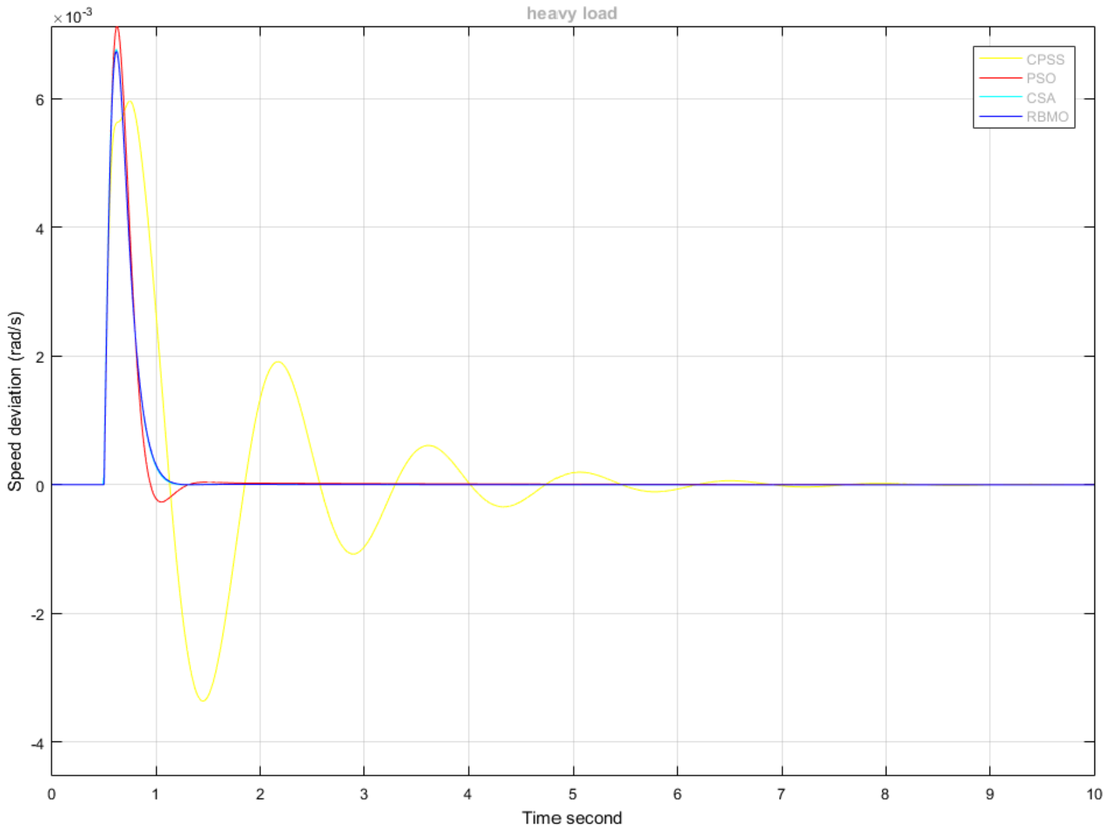


Figure III.26. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the speed deviation response of a power system under heavy load

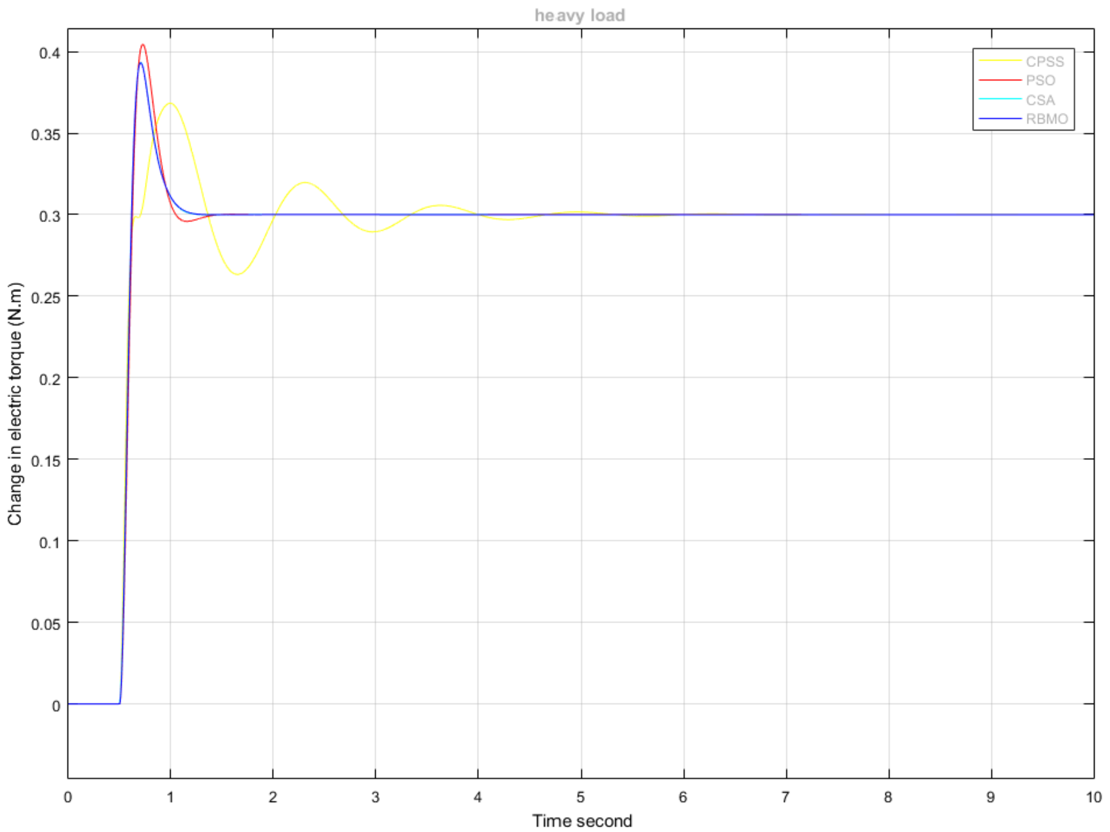


Figure III.27. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the Change in electric torque response of a power system under heavy load

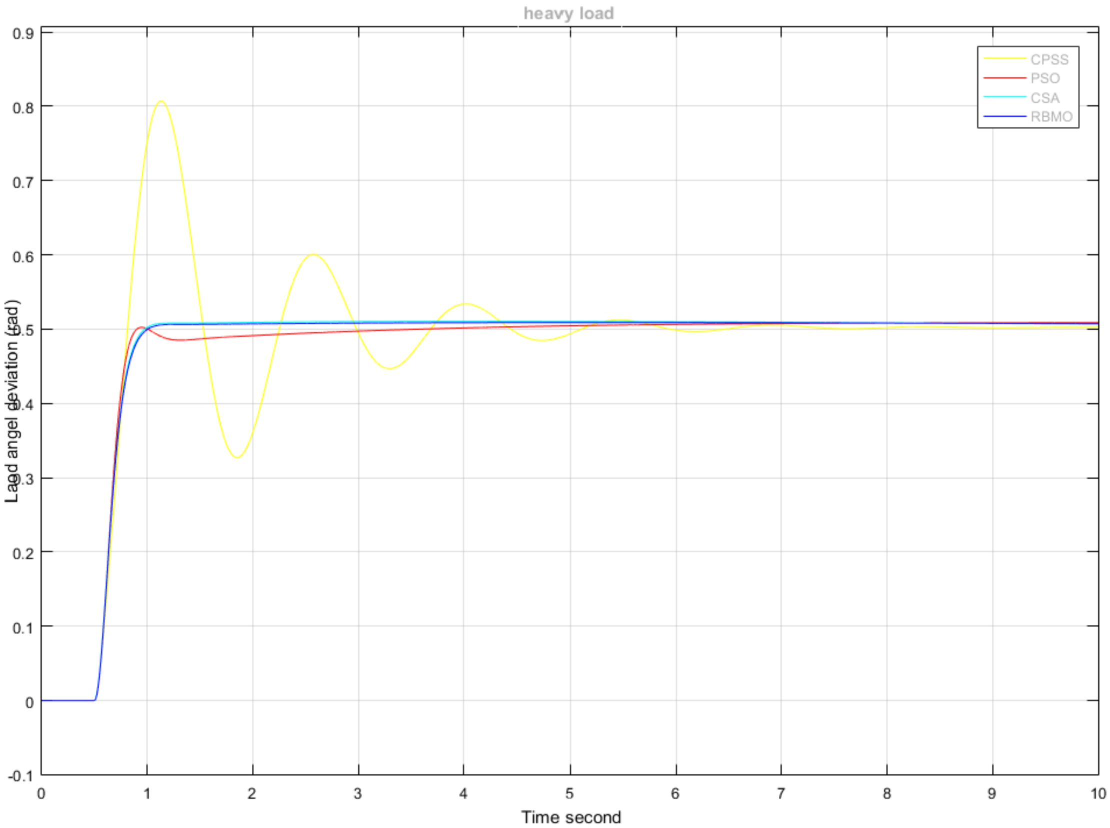


Figure III.28. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the load Angle deviation response of a power system under heavy load

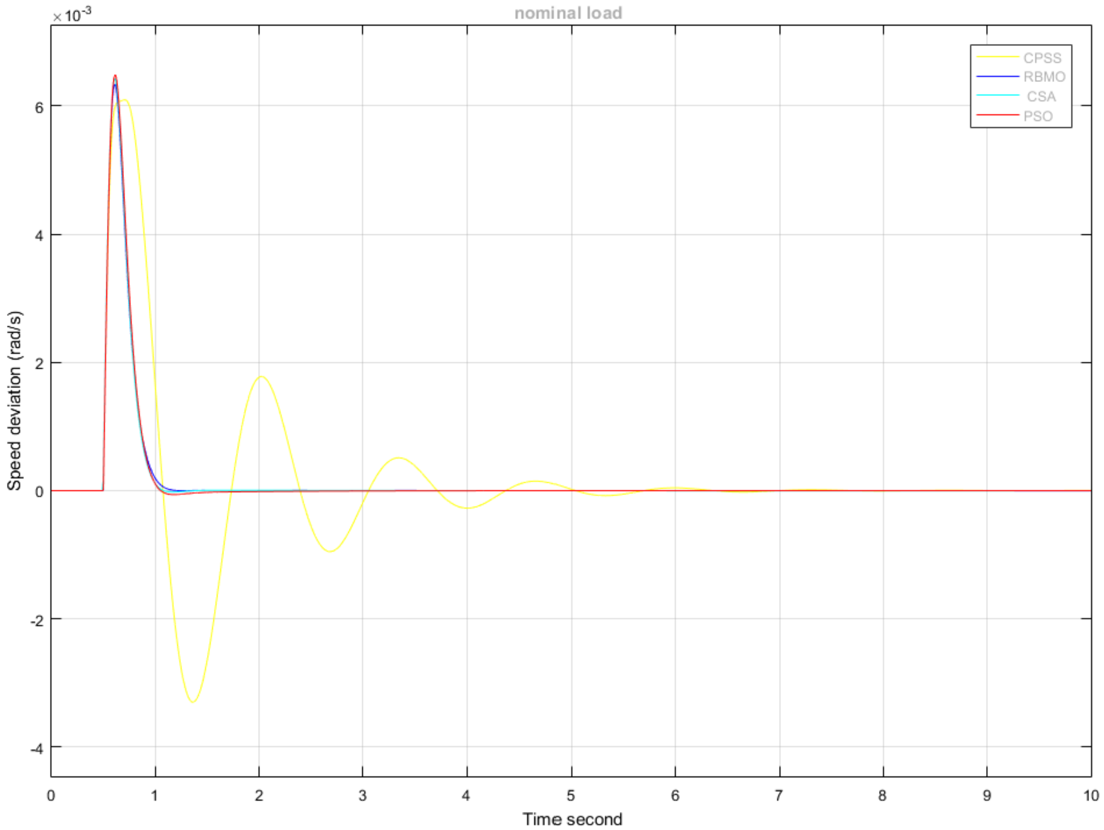


Figure III.29. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the speed deviation response of a power system under nominal load

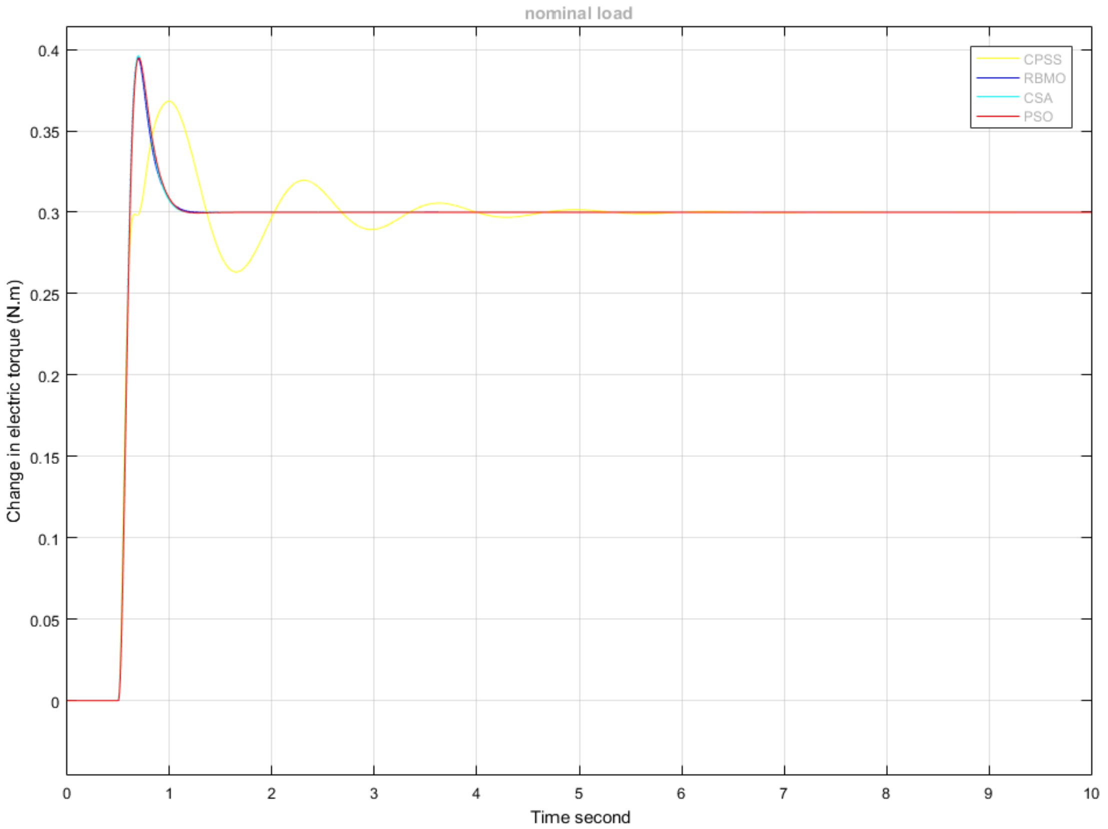


Figure III.30. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the Change in electric torque response of a power system under nominal load

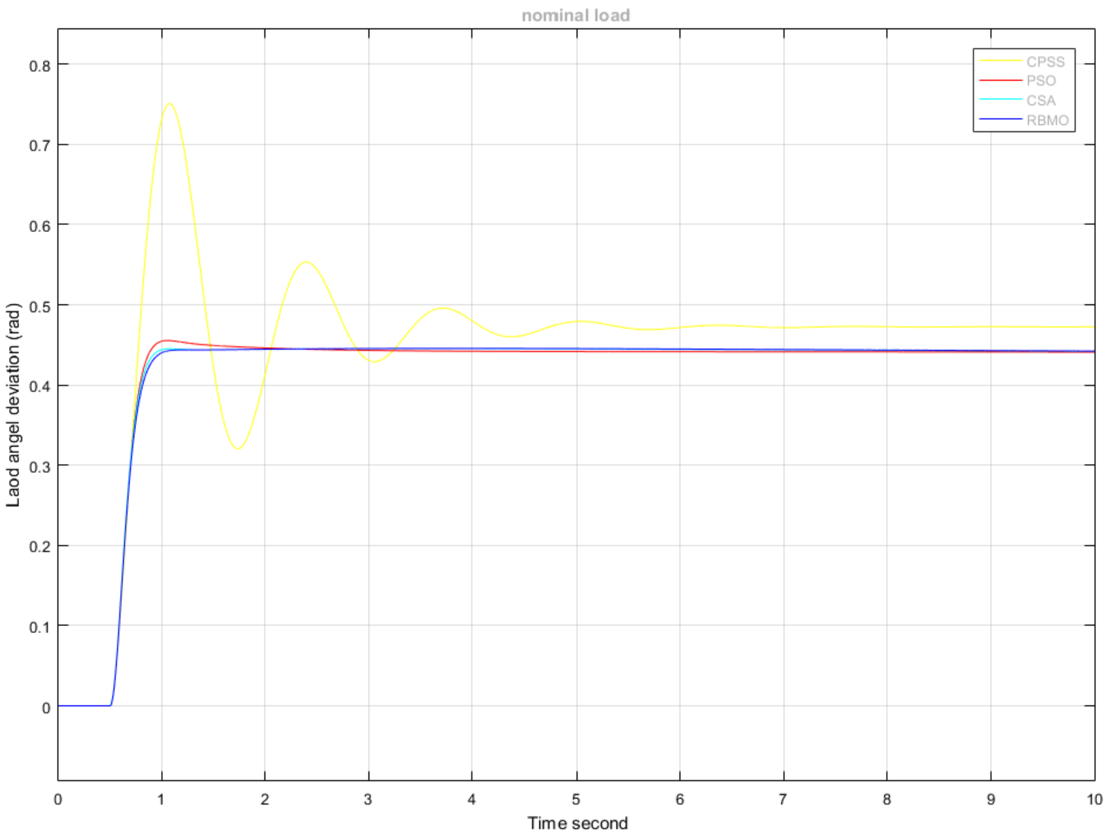


Figure III.31. Comparison of CPSS, PSO, CSA, and RBMO algorithms in improving the load Angle deviation response of a power system under nominal load

The plots of the variations in electrical torque (ΔTe), speed deviation (Δwr), and load angle deviation (Δδ) under light, medium, and heavy load conditions clearly highlight the differences in performance between the four algorithms: CPSS, PSO, CSA, and RBMO.

The conventional PSS shows high oscillations and slower settling time, indicating weaker damping performance. In contrast, the intelligent optimization algorithms demonstrate significantly improved responses. Both CSA and PSO reduce oscillations and enhance stability, but RBMO outperforms them by offering the smoothest response, the lowest overshoot, and the fastest settling in all three variables (ΔTe, Δω, Δδ).

Overall, RBMO consistently demonstrates the best performance in all load scenarios light, medium, and heavy by ensuring the fastest settling time, minimal oscillations, and superior dynamic response. This confirms that RBMO is the most effective and reliable among the tested algorithms, making it an excellent choice for improving power system stability under varying operational conditions.

conclusion

The dynamic system performance was improved by tuning the power stabilization regulator (PSS) parameters using three metaheuristic algorithms: PSO, CSA, and RBMO. Each of these algorithms was evaluated using linear and nonlinear system models under three different load levels: light, nominal, and heavy.

The results showed that the optimized regulators provided significantly better performance compared to the unstabilized condition, as well as to the conventional stabilizer (CPSS), especially at heavy loads. The RBMO regulator achieved the best damping of low-frequency vibrations and the lowest IAE value, followed by the CSA regulator and then the PSO.

The evaluation was based on applying mechanical power variations at different operating points, demonstrating the robustness of the smart regulators and their effective response to disturbances. These results demonstrate the ability of AI algorithms to improve the stability of power systems beyond conventional capabilities, making them a promising option in modern control system

General conclusion

This research addresses one of the most pressing challenges in modern power systems maintaining system stability in the presence of low-frequency electromechanical oscillations. The work begins by offering a comprehensive analysis of power system stability, including rotor angle, voltage, and frequency stability, while detailing the role of Power System Stabilizers (PSS) in mitigating instability.A key contribution of this study is the comparison between a Conventional Power System Stabilizer (CPSS) and three advanced metaheuristic algorithms Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), and Red-billed Blue Magpie Optimizer (RBMO) for tuning PSS parameters. These intelligent methods were assessed through by the Simulink simulation in nonlinear.The results clearly demonstrate that AI-based stabilizers outperform the conventional approach, especially under varying load conditions and disturbances. Among the methods tested, RBMO and PSO offered superior damping performance and robustness, effectively reducing oscillations and improving system recovery.

Ultimately, this study confirms that integrating intelligent optimization techniques into power system stabilizer design significantly enhances system stability. As electrical networks evolve with the integration of renewable energy and growing operational complexity, such advanced approaches will be vital for maintaining reliability and resilience in future power systems.

Perspectives

Based on the promising results obtained in this study particularly the superior performance of the Red-Billed Blue Magpie Optimizer (RBMO) in enhancing power system stability several future research directions can be proposed. One of the main perspectives is to extend the application of the RBMO algorithm to multi-machine systems, which better reflect the complexity of real-world power networks. Additionally, developing hybrid versions of the algorithm by combining RBMO with other intelligent techniques could further improve response speed and damping efficiency. Testing these algorithms in real-time simulation environments (RTDS) or through hardware-in-the-loop (HIL) systems would also be a crucial step toward validating their practical implementation. Moreover, adapting the RBMO algorithm to operate within networks with a high share of renewable energy sources represents a key research path to address challenges related to production variability and to ensure long-term grid stability. Therefore, continuing research in this direction could significantly contribute to the advancement of more reliable and efficient modern power systems.

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