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Power System Stabilizer Design for Multi-machine

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Abstract

This research aims to enhance the stability of multi-machine power systems by optimizing the design and parameterization of Power System Stabilizers (PSSs). These stabilizers are integrated into the excitation control system to counteract the limitations of Automatic Voltage Regulators (AVRs), which can negatively affect system damping and lead to oscillatory instability.

The study begins by highlighting the role of PSSs in damping electromechanical oscillations through the modulation of the excitation signal. The main objective is to ensure that the generated damping torque is in phase with the generator's rotor oscillations, thereby maintaining system frequency within acceptable limits and preventing widespread outages.

To achieve these objectives, the research investigates the application of advanced optimization algorithms for the design of PSSs. A comparative analysis is conducted between four optimization techniques: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Tabu Search (TS). The strengths and weaknesses of each method are assessed based on their ability to determine optimal parameters that improve system performance.

Moreover, the study explores hybridization between global and local search methods to combine the advantages of both approaches. Results show that hybrid algorithms provide superior performance in terms of damping oscillations and enhancing overall system stability.

Finally, the research identifies two key challenges: the variability of optimal PSS parameters depending on system operating conditions, and the high computational cost of metaheuristic techniques, which limits their application in real-time scenarios. These findings suggest that adaptive and computationally efficient solutions are necessary for practical implementation in modern power systems.

Key words: Multi-machine, Stabilizers, Optimization, Damping, Adaptivity

1. Introduction

A Power System Stabilizer (PSS) is a device used in electrical power systems to enhance the stability of the system by damping oscillations in the generator's rotor speed; it uses to improve the dynamic stability of power systems, particularly during disturbances such as faults or sudden changes in load. It helps to prevent oscillations that can lead to system instability, PSS works by providing additional control signals to the excitation system of synchronous generators. It measures the generator's speed or rotor angle and generates a control signal that is fed back to the excitation system to adjust the output voltage and damping characteristics, a typical PSS consists of a signal processing unit, which may include filters and gain settings, and a control unit that determines the appropriate response based on the measured parameters.

A power system needs a steady voltage level. Among the elements that set upper and lower limits on voltage levels are insulation, security, economy, and quality of service. There are several ways to regulate the voltage level in contemporary power systems across the generating, transmission, and distribution networks. The voltage profile at the generators' terminal following a significant disturbance is of concern in this work. Altering transformer taps and compensating for shunt/series capacitors are examples of additional voltage control strategies. In a power system, steady-state frequency is also required. One of the main causes of this is that the manufacturing line is synced with the power line at the location of some users. The parallel operation of generators and the correct operation of other devices, such as some protective relays, which have strict frequency requirements, also require a constant frequency. The constantly fluctuating active and reactive power demand is the main source of changes in voltage levels and operating frequency. As a result, in order to avoid unwanted frequency changes, generator power inputs must be adjusted to match demand. Additionally, the excitation of generators needs to be continuously controlled to balance the generation of reactive power with the demand for reactive power; otherwise, the voltages at different system buses can exceed the allowed limits. Numerous techniques have been put out for designing PSS blocks and for adjusting PID (Proportional, Integral, and Derivative) controllers in both sequential and simultaneous manners for multi-machine systems. The Ziegler-Nichols methods are arguably the most widely used techniques for PID controller tuning. However, using these techniques to get an optimal (or even nearoptimal) solution for a multi-machine system is still time-consuming. In (Abido 2002) and (Chen & Hsu 1987), some techniques for designing PSS in a multi-machine system were introduced. Because of the linearization and simplification required, these approaches have limitations. Additionally, they frequently only work with linear controls. Because PSO can be readily expanded to more intricate controllers and more thorough system models, this is what has spurred its adoption for this optimization problem. Recent methods for multi-machine AVR control and PSS designs have included fuzzy systems, neural and neuro-fuzzy systems, genetic algorithms, and, more recently, particle swarm optimization. For off-line PSS tuning in a multi-machine power system, the minimum phase control loop approach and genetic algorithm (GA) have been developed (Hongesombut et al. 2002). Using microGA, the PSS parameter problem was transformed into an optimization problem, and hierarchical GA was employed to automatically determine the PSS sites. Two local nonlinear optimum neuro-controllers on a realistic multi-machine power system were designed using the dual heuristic programming optimization approach (Park et al. 2005). One neuro-controller was created to take the place of the traditional linear controllers, such as a synchronous generator's speed-governor and automatic voltage regulator. The other was a flexible ac transmission systems device that used an external neuro-controller for the series capacitive reactance compensator.

A power system stabilizer based on adaptive fuzzy systems was proposed by Elshafei et al. (2005). A fuzzy-logic-based stabilizer with the capacity to adaptively adjust its rule-base online was the suggested controller. To accomplish the predetermined control objectives, a variable-structure direct adaptive control technique was used to modify the fuzzy rule basis. In order to reduce electromechanical oscillation modes and improve power system synchronous stability, a strong artificially intelligent adaptive neuro-fuzzy power system stabiliser (ANF PSS) design was introduced in (Barton 2004). The power system was divided into distinct subsystems, each of which had a single machine. The local ANF PSS was connected to each subsystem, and the local feedback controllers only used data specific to their subsystem, with the speed, power angle, and real power output serving as the input signals. El-Zonkoly (2006) examined the issue of simultaneously and cooperatively adjusting the automatic voltage regulator gains and stabilizer parameters in multi-machine power systems. The particle swarm optimization technique was used to tackle this challenge, which was formulated as an optimization problem. In order to describe the permitted range of the system parameters, the goal of the parameters optimization was formulated as a nonlinear problem with constraints. More recently, optimal PID improvements were achieved using a binary coded genetic algorithm and a craziness-based particle swarm optimization (Mukherjee & Ghoshal 2007). Sugeno fuzzy logic (SFL) was used to obtain the online terminal voltage response for the online off-nominal system parameters. To find off-nominal optimal gains, the nominal optimal gains were extrapolated using SFL. The design and control of power systems have recently benefited from the application of numerous artificial intelligence (AI) approaches. These techniques have shown great promise. Swarm intelligence is the foundation of PSO, one such technique (Chatterjee et al. 2009, Zamani et al. 2009). Eberhart R. and Kennedy J. introduced PSO in 1995 (Eberhart & Kennedy 1995). The method attempts to replicate the cognitive and social behavior of individuals in a flock, like locust swarms or fish schools. Because of its simplicity, the algorithm is computer-efficient. In order to determine the ideal proportional, integral, and differential gains as well as time constants for a PID controller mounted on the generators, this study applies the PSO technique.[1]

When designing power stabilizers, a number of aspects need to be taken into account. The excitation system typically controls the generated voltage, which aids in controlling the system voltage. In contrast to "governor controls" and "ammortisseur winding," automatic voltage regulators (AVR) are thought to be very appropriate for controlling generated voltage through excitation control. However, overuse of AVR has a negative impact on the power system's dynamic stability or steady state stability because low frequency oscillations (usually between 0.2 and 3 Hz) can linger in the system for a long time and occasionally impair its ability to transfer power. These organizations are required to adhere to the electrical system's operating conditions during the times when the mechanisms employed to control the electrical system should:

1. Maintain a consistent position during the first small swing after a significant system alteration by taking a certain amount of security into consideration[2] .
2. Provide a sufficient amount of steady-state damping following a significant disruption;
3. Minimize the risk of adverse effects that are unwanted.

Regarding the creation of flexible PSSSs. The rotors of the electrical machine are reduced as a result of these PSSs' propensity to realistically and automatically alter their parameters. the interplay of two phenomena—one mechanical with slow dynamics and the other electrical with relatively fast dynamics—those results in network generators, our next step in accomplishing this goal was to simulate every component of a multi-machine power system. [2]. The system model was then linearized around an operational point because we were interested in minor oscillations. The resulting equations were then converted into state form. The system's natural modes enabled us to conduct an investigation on its stability.

of the system via its natural modes and the determination of the number of PSSs and the location of their locations, through contributing factors. Two power networks were taken as test examples to validate the results, the first is a single machine system composed of an intermediate load norud and an infinite narud and the second is a system of nine neruds and three machines.

Although the generator's output power is primarily decided by the turbine's driving force, the generator's output power can also be altered by a temporary alteration of the excitation value. The PSS recognizes this alteration of power and controls the magnitude of this excitation, as a result, the power fluctuations are reduced quickly.

The selection of the local signal, which can be employed as the input to:

1- The chosen signal must be sensitive to the rotor oscillations of the machines.
In other words, it must detect the harmful oscillatory mode for the controller to provide an influential and stabilizing action.

2- We must minimize as much as possible the influence of the input signal on the other oscillation modes.

2- The influence on the input of the PSSs and on the outputs of the other controllers, in the absence of oscillations in the power system, must be low or zero.

These considerations have been taken into account in a number of designs in many real-world applications, requiring the mounting of a PSS on a generator's excitation systems. Several studies have looked at the effect of each entry. This made it possible to conclude that speed and/or frequency is the best-input signal for interzonal modes, on the other hand, the use of variation of power is convenient to [attenuate oscillations due to local modes [2].

The different types of PSSs proposed by the IEEE are identified by the input signal (to be detected). The simplest type is the one, which has as an input the variation of the electrical power (IP). Then, we have used as input the variation of the speed (Jo) and/or the variation of the frequency (J), These two signals were adopted in order to improve the stability of the inter-regional mode Figures 1, 2 and 3 respectively show the schematic of these PSSs for different inputs. From this point of view, there are several types of PSSs which we will briefly present below:

• PSO, or particle swarm optimization

The process of finding optimal values for the specific parameters of a given system to fulfill all design requirements Optimization is the process of taking into account the lowest possible cost. There are optimization issues in every scientific discipline.

The following are some drawbacks of traditional optimization methods, sometimes known as deterministic algorithms:

- Solutions that are solely based
- Reaching local optima
- Unknown problems with the search space

Numerous academics and researchers have created a number of metaheuristics to tackle challenging or unresolved optimization problems in order to get beyond these restrictions. Examples include the Cuckoo search algorithm, genetic algorithms, ant colony optimization, particle swarm optimization, and grey wolf optimization.

The fundamentals of stochastic optimization techniques and the reasoning behind particle swarm optimization (PSO) were covered in the Introduction to Particle Swarm Optimization (PSO) essay.

The algorithm's inspiration

Inspired by swarm behavior seen in nature, such as schooling fish and birds, Particle Swarm Optimization (PSO) is a potent meta-heuristic optimization technique. A simplified social system is simulated by PSO. The PSO algorithm was initially designed to visually mimic the elegant yet erratic dancing of a flock of birds.

In the natural world, the bird's visible range is restricted. But when there are multiple birds in a swarm, they can all recognize the bigger surface of a fitness function.

To help the swarm locate the global minima of a fitness function, let's theoretically represent the aforementioned ideas.

The mathematical model

- In particle swarm optimization, every particle has a position, velocity, and fitness value.
- The particle_bestFitness_value and particle_bestFitness_position are tracked by each particle.
- Global_bestFitness_value and global_bestFitness_position are tracked.

Algorithm

Problem parameters:

- Number of dimensions (d)
- Upper bound (maxx); lower bound (minx)

The algorithm's hyperparameters are as follows:

- Maximum number of iterations (max_iter)
- Number of particles (N)
- Inertia (w)
- Particle cognition (C1)
- Swarm's social impact (C2)

Algorithm:

Step1: Randomly initialize Swarm population of N particles Xi (i=1, 2, …, n)

Step2: Select hyperparameter values

w, c1 and c2

Step 3: For Iter in range(max_iter): # loop max_iter times

For i in range(N): # for each particle:

a. Compute new velocity of ith particle

```
swarm[i].velocity =
    w*swarm[i].velocity +
    r1*c1*(swarm[i].bestPos - swarm[i].position) +
    r2*c2*( best_pos_swarm - swarm[i].position)
```

b. Compute new position of ith particle using its new velocity

```
swarm[i].position += swarm[i].velocity
```

c. If position is not in range [minx, maxx] then clip it

```
            if swarm[i].position < minx:
               swarm[i].position = minx
            elif swarm[i].position > maxx:
               swarm[i].position = maxx
 d. Update new best of this particle and new best of Swarm
 if swaInsensitive to scaling of design variables.rm[i].fitness < swarm[i].bestFitness:
swarm[i].bestFitness = swarm[i].fitness
               swarm[i].bestPos = swarm[i]. position
            if swarm[i].fitness < best_fitness_swarm
               best_fitness_swarm = swarm[i].fitness
               best_pos_swarm = swarm[i].position
        End-for
     End -for
Step 4: Return best particle of Swarm
```

Advantages of PSO:

1. Insensitive to scaling of design variables.
2. Derivative free.
3. Very few algorithm parameters.
4. Very efficient global search algorithm.
5. Easily parallelized for concurrent processing.

Disadvantages of PSO:

Slow convergence in the refined search stage (Weak local search ability)

Figure 1 shows the diagram of the AVR system used for the generators (including a PSS block) (Anderson & Fouad 1993). The sensors' model is approximated to first order transfer functions as described in (Saadat 1999). The lead network block is, in fact, two lead

Compensators in cascade, as denoted by the following expression 1

$$\frac{1+\tau_1 s}{1+\tau_2 s}\frac{1+\tau_3 s}{1+\tau_4 s} \quad (1)$$

The reset block has the following transfer function (2):

$$\frac{K_0 s}{1+\tau_0 s} \quad (2)$$

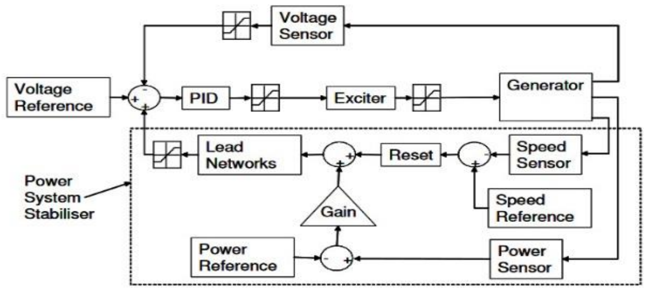

Figure 1: AVR system (Anderson & Fouad 1993)

In this section, we shall review the PSO method detailed in (Parsopoulos & Vrahatis 2002) And applied in section 3 for designing the PID controller of Fig.1.

PSO uses a population of particles that move through a search space, which is typically bounded. Each particle's movement is influenced by both its own (cognitive) and the flock's (social) experiences. A potential solution is represented as a particle and assessed using an objective function. The particle retains both the best solution of the entire flock (social) and the best solution (location in the search-space) it has encountered (cognition). A more comprehensive investigation of the search-space is made possible by the random fluctuations in each particle's velocity. According to recent studies (Eberhart & Shi, 1998), PSO performs better when it focuses on global search at the beginning of the search and local exploration at the conclusion (Petropoulos & Vrahatis 2002). PSO has numerous benefits over traditional optimization techniques.

a) An objective function is used to assess each particle. As a result, PSO can handle extremely complicated (and even non-differentiable) systems of equations with ease, where many traditional approaches, including gradient-based techniques, will not work. Furthermore, PSO allows for the removal of many of the approximations required by conventional approaches.

b) There is a form of parallel search because there is a population of particles floating around the workspace, each carrying out separate search, which reduces the possibility of becoming stuck in local optima.
c) Unlike many other conventional approaches, initialization is not crucial to PSO.

d) PSO improves search results by offering the option to balance local and global exploration. PSO can occasionally outperform other AI methods thanks to this property (such as genetic algorithms).

Particles traveling through the search space are the foundation of the PSO algorithm. The number of parameters that need to be optimized is m, and mathematically speaking, the particle is a vector of dimension.

One potential fix for the issue is this vector. Thus, particle I is represented as:

$P_i(t) = [P_{i,1}(t), P_{i,2}(t), \ldots, P_{i,m}(t)]$ *i=1,2..,n .. (3)*

Where, the p's are the optimized parameters,

t is the time index (iteration number), and, n is the number of particles

The velocity of a particle is defined as the change in position of the particle over iteration. It is thus a vector of dimension m, denoted as;

$V_i(t) = [V_{i,1}(t), V_{i,2}(t), \ldots, V_{i,m}(t)]$ *i=1,2..,m .. (4)*

The algorithm used for the implementation of PSO for this work is given in equations (5), (6) and (7) stated in (Parsopoulos & Vrahatis 2002).

$v_{i,j}{}^{(t+1)}$=($w^{(t)} \times v_{i,j}{}^{(t)}$)+($c_1 \times rand \times (pbest_{i,j}{}^{(t)} - p_{i,j}{}^{(t)})$)+($c_2 \times rand \times (gbest_j{}^{(t)} - p_{i,j}{}^{(t)})$).. (5)

$p_{i,j}{}^{(t+1)} = p_{i,j}{}^{(t)} + v_{i,j}{}^{(t)} \ldots (6)$

$w^{(t+1)} = w_{max} - a \times t \ldots (7)$

I=1,2,…,n

J=1,2…,m

where,

n number of particles in the swarm,

m number of optimized parameters,

t time index (iteration number),

$\mathbf{v_{i,j}}^{(\mathbf{t})}$ component of the velocity of the i^{th} particle with respect to the j^{th} dimension at iteration t,

$\mathbf{p_{i,j}}^{(\mathbf{t})}$position of the i^{th} particle in the j^{th} dimension at iteration t,

$\mathbf{w}^{(\mathbf{t})}$ inertia weight factor at iteration t,

$\boldsymbol{c_1}$ constant governing the cognitive behavior of each particle,

$\boldsymbol{c_2}$ constant governing the social behavior of the group

rand a random number from the standard uniform distribution,

$\boldsymbol{pbest_j}^{(\boldsymbol{t})}$ a vector of dimension m representing the best position visited by particle i

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as at iteration t,

$\boldsymbol{gbest_j}^{(t)}$ a vector of dimension m representing the global best position visited by the swarm as at iteration t,

a inertia weight's decrement

$\boldsymbol{w_{max}}$ maximum inertia weight's value.

The constants c_1 and c_2 determine the behavior of the individual particles in the swarm. A high value of c_1 (or small value of c_2) results in an "individualistic" behavior, which decreases the chances of finding the global optima. Nevertheless, a low value of c_1 (or large value of c_2) will result in all the particles behaving almost similarly, which diminishes the parallel search feature. Another constant known as the neighborhood constant is sometimes included. The neighborhood constant models the attraction to the best solution in the "neighborhood" of the particle

The velocity of each particle is bounded as,

$$V_{j\,min} \leq v_{i,j}{}^{(t)} \leq V_{j\,max}$$

By bounding the velocity, the resolution of the search is set. Usually,

$$V_{min} = -V_{max} \;\ldots.(8)$$

Thus the small value of Vmax gives high resolution. It, however, increases the convergence time and it can also cause the particles to stick to local optima.

- **Power stabilizer based on variation of electrical power**

stabilizer uses the electrical component (IP) as an input variable. Since of the variation of the mechanical power is limited by the dynamics of the turbine, these stabilizers prove their effectiveness for damping local modes. But this efficiency is limited when the electromechanical oscillations are slower (frequency less than 0.5 Hz) [3].

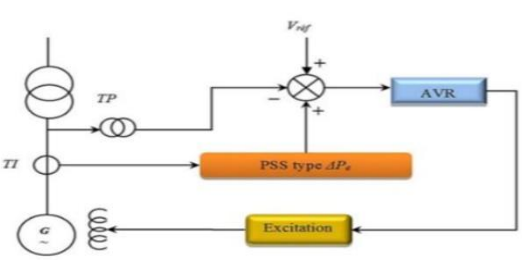


Figure (2) Implementation diagram of an AP-type PSS [4]

- **Power stabilizer based on acceleration power**

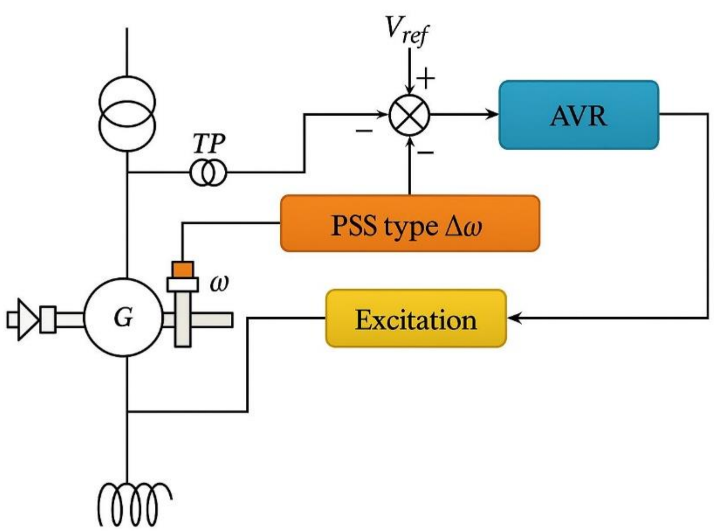
The acceleration power P is the difference between the mechanical power and the electrical power. This type of PSS uses at its input the measurement of mechanical power through a position sensor. This input improves dynamic response by slowing rotor oscillation modes. But these stabilizers could generate a strong reactive power oscillation whenever the power settings are changed. In such cases, a reduction in stabilization gains is often used to limit these detrimental effects [5].

- **Hybrid stabilizer based on acceleration power**

This PSS is based on the derivative of a speed measurement combined with the measurement of the electrical power Pe filtered to keep only the slow phenomena linked to the dynamics of the turbine. The two power components are then combined to produce the acceleration power, which is finally integrated to group a speed signal. Hence, this principle is used in most modern stabilizers although the high-order low-pass filter used to extract the mechanical power indirectly distorts the phase and gain of this signal in the cutoff zone, namely the range of intermediate frequencies (0.3 to 0.7 Hz) characterizing interzonal modes.

- **Stabilizer based on voltage frequency at machine terminals**

By using the external frequency measured at the machine terminals, the A/stabilizer offers good performance for slow interzonal modes. However, it is much less effective for local modes because the internal frequency differs from the external frequency for fast phenomena [6].



Figure(3) Implementation diagram of an Af-type PSS [6].

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- **tStabilizer based on mechanical speed measuremen**

These type la speed stabilizers are equipped with a mechanical sensor placed at the horizontal axis of the machine. In production units with a vertical axis, sensors must be installed separately, which increases installation costs. In addition, these sensors are sensitive to mechanical imperfections in the system, such as the lateral movements of the rod, which generate background noise during the measurement [7].

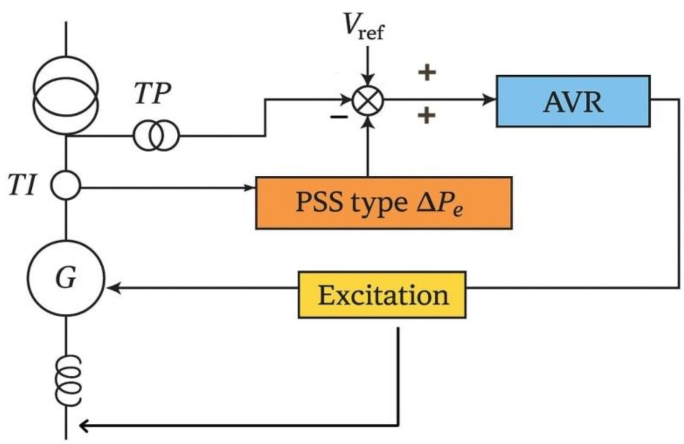

Figure (4) Implementation diagram of type A PSS [7].

- **Flow stabilizer based on indirect measurement of the internal frequency of the machine**

This type of stabilizer exclusively uses measurements of the electrical variables of the machine (voltage and current). The algorithm used to measure the rotor speed is based on the use of an internal voltage phasor. One of the major characteristics of this type of PSS is that it considers discontinuities generated by faults and transients. Thus, it is possible to take charge of high-frequency oscillations.

- **Definition of PSS**

High-gain and quick-reaction excitation devices can decrease small signal stability (damping torque) but also significantly improve transient stability (synchronizing torque). By reducing generator rotor angle swings throughout a wide frequency range in the power system, power system stabilizer (PSS) management makes a beneficial contribution. These include intra-plant modes (about 2–3 Hz), local modes (usually 1–2 Hz), and low frequency intertie modes (usually 0.1–1.0 Hz). Coherent groups of generators swinging against other groups in the interconnected system are the cause of the low frequency modes, also known as interarea or intertie modes. All interconnected systems include these modes, and the damping depends on the unit loading factors and tie line strength. Poorly damped intertie modes might result from weak ties brought on by line failures and high system loads. By adding stabilizers to the majority of units that engage in power swing modes, PSS control may typically result in notable increases in interrupt mode dampening.

The dampening of the "local mode," or the generator swinging against the rest of the power system, is frequently used to assess PSS performance. Typically, frequencies in this mode fall between 1 and 3 Hertz. Higher local mode frequencies are typically produced by stronger system ties and lighter loading, while lower local mode frequencies are typically produced by weaker ties and greater loading. PSS performance needs to be built to function well in a variety of system circumstances, which could arise from various operating circumstances (such lines going out of service or fluctuating load levels).

In order to assist clients in achieving optimal practical performance, GE Energy Consulting conducts PSS Tuning and Testing studies. These investigations have shown that small-signal frequency-domain techniques are highly effective, and for more than 30 years, GE Energy Consulting has been creating and refining simulation tools. It is well known that the PSS can cause undesired effects at the characteristic modes of the turbine-generator mechanical torsional system in addition to damping the low frequency modes, which are of major concern. GE's experience demonstrates that for GE turbine-generator configurations, this kind of contact must be severely regulated. GE PSS designs incorporate efficient techniques to lower torsional signal levels; Energy Consulting screening studies are used to determine the settings for these filters.

Theory of PSS

Though the turbine mechanical torque decides a generator output power, a generator output power also can be changed by changing excitation value transiently.

A PSS detects the changing of generator output power, controls the excitation value, and reduces the power swing rapidly.

Design of PSS Parameters

An appropriate parameter design is very important in order for a PSS to operate effectively. In general, these parameters are set with the single machine infinite bus model; however, on request, analysis using a multi-system model is also available.

3 Classification of PSSs according to their technological design

Several PSS models have been proposed with different transfer functions; here is a classification of these devices according to their technological design:

- **Analog PSSs**

They are also referred to as conventional PSSs (CPSS). This type of PSS is characterized by fixed parameters, and its disadvantage is the degradation of these performances with [the change of the operating point because it cannot adapt to all situations.[8]

- **Digital PSSs**

The basic transfer functions are the same as those of analog-type PSSs. The difference lies in the fact that the parameters of the transfer function and/or output are calculated by calculators. Many numerical methods are used to design the most efficient digital PSS possible. The best PSS is one that provides the best degree of stability to the power system and the best attenuation of rotor oscillations when the operating conditions change.

Classification of PSSs according to their internal structure [3]

Among the most commonly used classical structures, we distinguish three categories of PSS: The PSS a advances phase delay. Multi-band PSS.The PSS with PID action (proportional, integrating, derivative).These three types of PSS also have several variants, but their main role is to inject a voltage signal (proportional to the variation of the signal to be detected, representing the harmful mode) into the input of the voltage regulator (AVR). The PSS opposes weak oscillations by forcing the excitation system to respond in the most reliable way.[9] In this section, we

present the internal structures of the different types of PSSs, going through lead-delay PSSs (which are the most used PSSs given their simplicity), and then multi-band PSSs characterized by their possibilities of processing three fashion ranges separately. Finally, we present the PID, which are well-known classic regulators that are often used in industry and have proven their performance as power stabilizers.

● PSS model with phase advance and delay

The most commonly used type of PSS is lead-lag phase PSS. This type has proven its effectiveness in maintaining stability under small disturbances in a power system. It uses the rotor speed variation as input, and its transfer function provides a phase advance for the input signal in the frequency range of interest (0.1 to 3.0 Hz) [10].

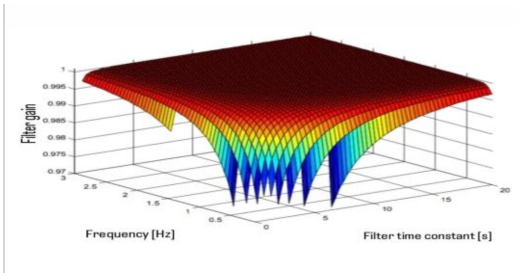

Figure (5) Evolution of the filter gain as a function of the time constant to and the frequency

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Phase compensation blocks

Phase compensation is a technique used in control systems and signal processing to adjust the phase of signals or system responses. We use it to improve the stability and performance of a system, particularly in feedback control systems.

In general, the ratio of the numerator to the first-order denominator represents the transfer function of the phase compensation block. In practice, obtaining the required phase compensation requires more than one phase advanced compensation block. Phase compensation must be performed in two steps, at least, to better ensure system stability. Each stage has a configurable delay, phase advance (T1, T3), and postzero as its transfer function [11]. The typical range of any time constant (is a measure of the time it takes for a system to reach approximately 63.2% of its final value after a step change in input) is between 0.01 and 2 seconds) this is a period of fixed time to clearly show the phase difference.(. Considering the several design variables of a PSS, T2=T4 € (0.01s, 2s) and T3 = T3 are the numbers commonly used in the literature [12].

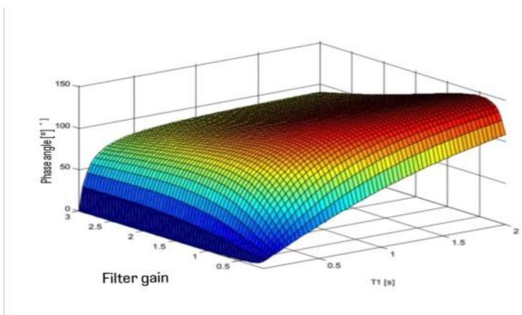

Figure (6) PSS phase variation for different values of (TT) and frequencies for T-T-0.05%

●Voltage limiter

The voltage limiter prevents the PSS from disturbing the AVR input. This can occur in the case of a sudden decrease in the load. In this case, the AVR reduces the voltage across the generator. At the same time, the PSS requires a higher voltage to increase the rotor speed. On the other hand, the negative limit of the PSS output is of great importance during the electromechanical mode feedback of the rotor. In this case, the AVR action is required to maintain the voltage to avoid loss of synchronism. The minimum and maximum limiter values range from ±0.02 to ±0.1 pu [13].

● Multi-band PSS

The idea behind the multi-band power system stabilizer (MB-PSS) was the requirement for efficient dampening of a broad variety of electromechanical oscillations. The MB-PSS structure is built on multiple working bands, as its name suggests. The MB-PSS's primary concept is the utilization of three distinct bands, each of which is devoted to the low, moderate, and high frequency oscillation modes. Generally speaking, the power system global mode is linked to the low band, the interarea modes to the intermediate band, and the local modes to the high band. A differential band-pass filter makes up each of the three bands. The stabilizer output Vstab is obtained by adding the outputs of the three bands and passing them through a

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final limiter. The generator voltage regulator's set point is subsequently modulated by this signal to enhance the electromechanical oscillations' damping. Typically, MB-PSS circuits should use a few lead-lag blocks.

The appearance of this new type of power stabilizer is supported by the appearance of other problems that affect the power network, such as low- and high-frequency oscillations simultaneously. This problem makes single-band stabilizers unable to cope with such oscillations.

Multi-band PSS (MB-PSS) was proposed in the 2000s by Hydro-Québec and the Institut de Recherche en Electricité du Québec (IREQ) to improve the two-band PSS denoted IEEE-PSS2B. In 2005, PIEEE presented and adopted a new PSS structure called PSS4B.[14]

The originality of the MB-PSS stabilizer is the fact that it uses speed measurements over the entire frequency range. In addition, it provides great flexibility through the provision of several compensation filters. Instead of relying on a single phase advance-lag compensation filter, the proposed filter subdivides the working area into three independently adjustable bands, each including a differential filter with characteristics that make it completely suitable for the frequency band in question [15].

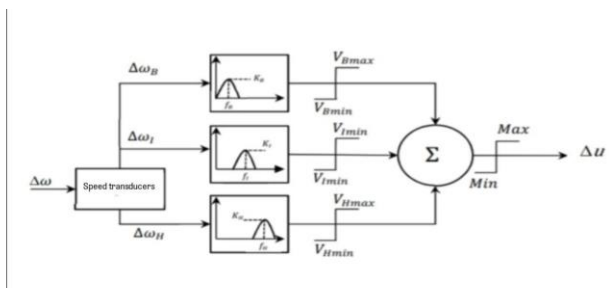
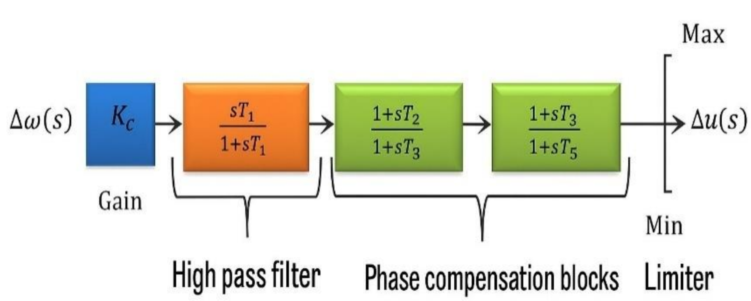


Figure (7) Block diagram of the multi-band PSS type IEEE PSS4B[15].

PSS4B has three distinct bands and is specifically designed to damp oscillations over a wide frequency range [16]. The proposed PSS has a more filtered frequency response and allows for better damping of several oscillatory modes. Its bandwidth (B) is designed for processing the frequency range spanning between 0.04 Hz and 0.1 Hz (these frequencies are due to the units constituting the system), the intermediate frequencies (1) ranging from 0.1 Hz to 1 Hz (they are generated by the inter-regional mode), and the high-frequency band between 1 Hz and 4 Hz, created by the local mode



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- **Internal structure of MB-PSS**

The low-frequency velocity deviation An, the intermediate-frequency velocity deviation A, and the high-frequency velocity deviation Δωμ serve as the basis for the three separate velocity deviations that feed the MB-PSS. The higher transducer receives its input signal directly from the speed variation of the rotor (40). The output signal of this block is then used to construct a signal that depicts the high oscillations by injecting it as an input into the low and middle parts of PSS4B. In addition, electrical power (P) serves as the lower transducer's input. An electrical power signal to be classified as a speed signal, it must travel through an integrated block [17]. The high-frequency part's input is then connected to its output. three factors are used as input to the MB-PSS.

● **MB-PSS transfer function**

The function of the transfer is illustrated in Figure 8. It is composed of three separate branches, each branch includes a bandpass filter, and each branch is composed of two other branches that represent filter stages that are Symmetrical in nature. These stages have three different elements with phase lead delay and individual gains. This simple and powerful filter design has a remarkable tuning capacity.

The low-frequency regime concerns phenomena that oscillate at a slow rate, such as the common modes present in isolated systems. For example, the natural frequency of Hydro-Québec is 0.05 Hz. The middle frequency is dedicated to internal modes that are typically between 0.2 and 0.8 Hz. The high-frequency band is concerned with local power plants in the frequency range between 0.8-4.0 Hz.

The output signal Au comprises the signals Va, V, and V from the three filters. In addition, the MB-PSS has limiters that correspond to each voltage output, as in the other devices. This attribute enhances the flexibility and efficiency of the MB PSS by allowing maximum control over each band while keeping the total dynamic range of the PSS constant.

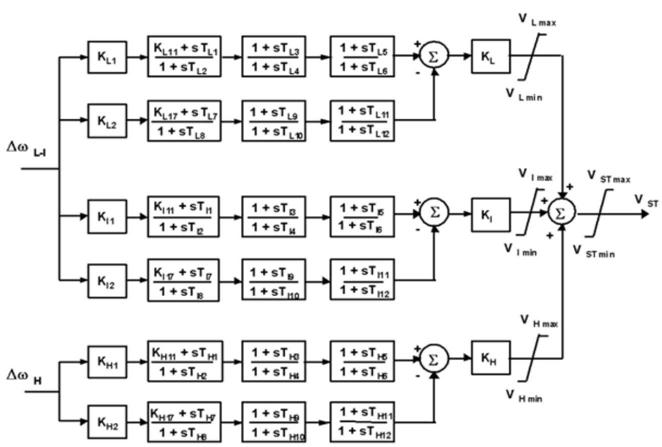

Figure (8) Internal structure of IEEE MB-PSS type PSS4B[19]

● MB-PSS parameterization methodology

Although the number of parameters constituting the MB-PSS is very high, their adjustment is simple In this section, we present the adjustment method proposed by the designers of this type of PSS, which was published in 2006 by CIGRE .

In the two articles from [19], there were different approaches to altering the parameters of MB-PSS based on the desired degree of optimization. However, the most common and simple strategy for filtering differential bands is the symmetric approach. This approach allows the definition of the PSS to involve only two types of high-level parameters: the three central frequencies FB, F, and Fa, and the gains Ka, K, and KH are all included. Although the parameters of PSS4B-type differential filters can be altered in different ways, a simple method based on three identical bandpass filters that are tuned to Fa, F, and Y is typically employed. For high frequencies, the time constants and branch gains are determined by the following equations [21]:

$$K_c\ (\mathrm{k+1}) = K_c\ (\mathrm{k}) - a\,\frac{\partial(\Delta W)}{\partial K_C}$$

$$T_1\ (\mathrm{k+1}) = T_1\ (\mathrm{k}) - \beta\,\frac{\partial(\Delta W)}{\partial T_1}$$

$$T_2\ (\mathrm{k+1}) = T_2\ (\mathrm{k}) - \acute{\Upsilon}\frac{\partial(\Delta W)}{\partial T_2}$$

The time constants T1 and Tha were computed using the values of TH_3 and Tuy in accordance with equations (3:2) and (3:3), with R = 1.2, the time constants T112 and Tu7y were directly obtained from the filter center frequency Fy. The KH1 and KH2 gains were determined using equation (3:4) to obtain a common gain for the differential filter. Thus, the band's total gain is equal to Ky. The remaining values are constants [22]. Similar words are also suitable for the other two bands. In any event, all 24 settings need to be changed.

In order to facilitate the utilization of this type of PSS and to provide fast and efficient calculations of the PSS parameters, Hydro Quebec and ABB designed a software tool for altering the parameters of these PSSs called "MB-PSS Tool" in 2006. The following searches are performed using metaheuristic methods to determine the parameters of the MB-PSSs. For this purpose, in 2007, Sumanbabu et al [24] used the BFA (Bacterial Foraging Algorithm) algorithm, in 2008, Castrillon and Colome [25] investigated the use of two EPSO (Evolutionary Particle Swarm optimization) algorithms.) and robust Ha. In 2013, Khodabakhshian relied on the PCEA (Preserving Contrast Enhancement Algorithm) 1931 algorithm. Note that all these methods are effective; however, they are also complicated and tedious.

● PID type PSS

In 1922, Nicholas Minorsky presented a command for application to position control systems. In fact, he described a control law called the controller (PID). He established this law of control by observing how to steer a ship. The first PID-type regulators used in the electricity field were dedicated to controlling the boilers, namely, the water level and steam pressure [26].

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The PID controller is currently used in all areas of control over the last century. In modern control processes, most control loops are PID-type [27]. Virtually all current PID controllers are digital and microprocessor-based. This has resulted in other features that make them most common in modern control systems. In this section, we describe the internal structure of a PSS-PID and present the classic methodology for determining these parameters.

The PID controller has three adjustable parameters, which are the proportional gain (k_p),integral gain (k_i) and derivative gain (k_d). The PSS has four parameters to be optimized: k_0,k_1 , τ_1 and τ_3. k_0 is the gain of the speed offset signal and k_1 is the gain of the power offset signal. Each individual are defined as a vector of dimension seven.

$$P = k_p, k_i, k_d, k_0, k_1, \tau_1, \tau_3$$

The search-space is, thus, of dimension seven. The boundaries of the search-space were defined as follows.

$$0 \le k_p \le 50$$

$$0 \le k_d \le 20$$

$$0 \le k_i \le 20$$

$$0 \le k_0 \le 150$$

$$0 \le k_1 \le 150$$

$$0 \le \tau_1 \le 2$$

$$0 \le \tau_3 \le 2$$

Next, the generator speeds are randomly selected from a normal distribution, where the variance is equal to ζ/(inertia constant) and the mean is equal to the synchronous speed. Then, for ten seconds, the power system and AVR systems' actions are emulated. The work of Kusic (1986), Stagg & El-Abiad (1968), and deMello & Concordia (1969) served as the foundation for the simulation algorithms. An objective function, which is described below, is used to evaluate the response in the temporal domain. For the New England power system, the constant ζ was set to 30..

$$\text{Performance} = \sum_{n=0}^{N} \int_{t=5}^{t=10} (change\ in\ speed\ \times (t-5))dt +$$
$$\beta \times \sum_{n=0}^{N} \int_{t=1.5}^{t=10} \big(change\ in\ voltage\ level\ \times (t-1.5)\big)dt$$

where N represents the total number of generators.

According to Chen and Hsu (1987), a balance between the frequency deviation and the voltage profile needs to be struck. Changing β, a weight constant, will do this. Beta was set to 0.0005 for the New England 10-generator 39-bus system. Additionally, a condition is added to the goal function that, if the voltage deviation surpasses 6% 1.5 seconds after the fault occurs, assigns a high performance value (a penalty). This situation mimics the voltage level constraints of the power systems. Therefore, in the optimization, every individual who provided fluctuations greater than 6% was disqualified.

Within the previously mentioned bounds, all PID controller and PSS parameters were initially set to random values (as in Anderson & Fouad 1993). Ten separate runs were conducted for both PSO and GA, and Table 1 displays the performance values (eqn. (9)) that were achieved.

Table 1: Performance of PSO and GA on ten independent runs.

Run Number	PSO	GA
1	**0.01113**	**0.01345**
2	**0.01358**	**0.01229**
3	**0.01259**	**0.01310**
4	**0.01482**	**0.01295**
5	**0.01588**	**0.01274**
6	**0.01287**	**0.01673**
7	**0.01246**	**0.01248**
8	**0.01299**	**0.01610**
9	**0.01301**	**0.01297**
10	**0.01256**	**0.01301**
Minimum	**0.01113**	**0.01229**
Maximum	**0.01588**	**0.01673**
Mean	**0.01319**	**0.01358**
Standard Deviation	**0.00132**	**0.00153**

By inspecting the values given by PSO and GA:

$$performance_{pso} = mean \pm standard\ diviation = 0.01319 \pm 0.00132$$

$$performance_{GA} = mean \pm standard\ diviation = 0.01358 \pm 0.00153$$

$\Delta performance_{max} = performance_{PSO,max} - performance_{GA.max}$=0.01511-0.01451=0.00060

And

$\Delta performance_{min} = performance_{PSO,min} - performance_{GA.min}$=0.01205-0.01287=-0.00082

These differences are very small to judge which one of PSO or GA is better. Hence, we can say that PSO and GA performance are very close on this particular problem.

Tables 2 and 3 give the best parameters obtained by PSO and GA respectively. It is to be noted that both PSO and GA converge to a value of zero for K_1 in all runs. These results may suggest that it is advisable to set the power offset signal gain to zero for a more stable

system. Moreover, only the PSO algorithm converges to a value of zero for k_d in all runs.The implication is that the system gives best performance when k_d is zero according to PSO.In practice, it is well established that k_d causes a system to be less stable.

Generator	1	2	3	4
k_p	0.1203	0.1548	0.11151	0.12321
k_i	0.1077	0.1357	0.001	0.001
k_d	0	0	0	0
K_0	34.276	45.809	23.4765	21.0603
K_1	0	0	0	0
T_1	0.9808	0.6963	0.787	0.9198
T_3	0.9756	0.6515	0.7618	0.6042

Table 2: Parameters obtained by PSO

Generator	1	2	3	4	5
k_p	0.5	5.9869	0.6314	0.6216	0.5807
k_i	0.4839	6.006	4.3181	0.3846	1.7606
k_d	0.2221	8.6838	6.1548	5.695	1.5485
K_0	0.1	150	149.9878	146.8611	0.1244
K_1	0	0	0	0	0
T_1	1.5573	1.6828	0.3233	1.3695	1.3747
T_3	1.2362	1.0328	0.9154	1.1624	0.5569

Table 3: Parameters obtained by GA

As observed from the responses, PSO and GA give comparable results for the particular set of disturbances considered. Oscillations are sustained for the classical machine representation whereas the PSO optimized AVR and GA optimized AVR achieve good damping characteristics in both generator speed and voltage profiles.

● Structure of a PSS-PID

The general structure of the PSS-PID is shown schematically in Figure 3:9 Similar to the PID regulator. a PSS-PID, is the combination of three control actions which are [28]:

A so-called proportional amplifier gain (Kp) that considerably affects the dynamic error. A larger gain reduces the static error (without canceling it) and makes the system faster; however, it affects the degree of stability of the system. The action of this proportional-type corrector is given by

P = Kρε(τ)

Here, (t) is the tuning error.

b. An integrator block is characterized by its gain Ky, which cancels the static error. Therefore, its primary objective is to correct and improve precision. Its action is expressed as :follows

K, de(t) dt, and = 1

vs. A diverting block characterized by the coefficient Kp that mainly allows degeneration of a derived correction with a stabilizing effect leading to limiting large variations in the error. This helps to dampen oscillations, stabilize the system, and improve the system response time. Its derivative action is expressed as follows:

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D = Kp de(t) dt, where

Since each parameter has its own influence on the dynamics and stability of the system, their combination in a PSS-type regulator is beneficial for improving the speed, precision, and stability of the system. Thus, the output of a PSS-PID is given by (see also figure 3:9):

u(t) = Kρε(t) + K de(t) dt + Kp de(t) dt.

It became the standard tool with the appearance of process control in the forties. In modern control processes, most control loops are PID-type [95]. Virtually all current PID controllers are digital and microprocessor-based. This has resulted in other features that make them most common in modern control systems.

In this section, we describe the internal structure of a PSS-PID and present the classic methodology for determining these parameters.

- **Structure of a PSS-PID**

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u(t) = Kρε(t) + K de(t) dt + Kp de(t) dt.

This gives the following transfer function: FPSS PID=Kp+ K_1/s + SKD

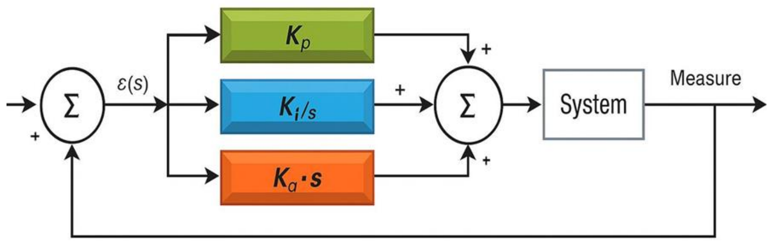

Figure (9) General structure of PSS-PID

● **Determination of PSS-PID parameters**

The design problem of PSS-PID lies in the determination of these parameters (Kp, K, and Kp). Several methods based on experimental tests on the behavior of systems have been developed for this purpose. We cite the Ziegler and Nichols method, which can only be used if the system studied supports overshoots (ratio between the first peak and the setpoint), figure 10.

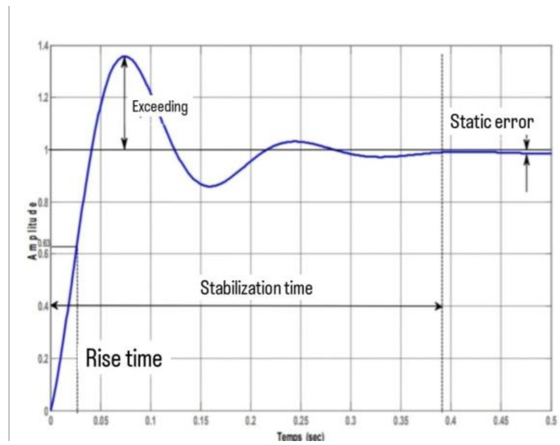

Figure (10) Response from a PSS-PID

This method consists of experimentally determining the critical gain Ke corresponding to a 2π oscillation Wer = 27/T and then calculating the parameters of the PSS-PID from the following table:

Other methods have been developed for the determination of the parameters of the PID regulator in general and of the PSS-PID in particular. We mainly cite analytical methods based on transfer functions; (pole placement, lambda method,...), heuristic methods (fuzzy logic neural networks,...etc.) [99, 100] frequency response methods, such as wavelets, and digital optimization methods. These are best suited to determining the tuned parameters of multiple regulators.

4_State of the art regarding self-adjusting PSSs

Member that the main objective of our work consists of proposing self-adjusting PSSs that adapt to any eventuality (load variation, appearance of short-circuit faults, etc.) to properly cushion the electromechanical oscillations of multimachine systems.

Typically, PSS design approaches are categorized into two groups [31]:

Linear methods, which are typically based on the analysis of eigenvalues or the placement of poles, are also used to control the system. Nonlinear methods, such as adaptive control, sliding mode, and artificial intelligence, are also employed. The primary purpose of adaptive control is to dynamically adjust the regulator parameters in response to the behavior of the system to ensure both good dynamic and static performance and a broad range of control authority. The adaptive control methods are partitioned into two classes [32]:

Optimal and direct estimation of the parameters of offline regulators for one or more reference scenarios and application of these regulators applied to the online system;

An adaptive control equipped with adaptation mechanisms and adjustment of the regulator parameters, which are mounted online in the actual state of the system.

In the sequel, we focus on and present a non-exhaustive state-of-the-art system corresponding to this type of self-adjusting PSS based on adaptive control techniques. The first PSSs using self-adjustment control were reported in 1989 [33]. In this case, the stabilizer employs a Clarke-Gawthrop generalized minimum variance [34]. In 1990, a PSS using a decentralized self-adjusting system was proposed by Lim, et al. [35]. It was followed by another study in which the suggested controller automatically adjusted its parameters by minimizing the integral of the input squared error [36]. In 1993, an adaptive PSS was proposed that uses a new control strategy that allows the self-optimization of pole displacement. The proposed method is based on an identified model of the system that is used to calculate the control using an algorithm that moves the closed-loop poles of the system to certain optimal locations [37].

The adaptive PSS is a system used in power networks to enhance the stability of electrical systems. It works by dynamically adjusting the system’s response based on changing conditions in the network, such as variations in load or changes in the network's state.

The main aim of Adaptive PSS is to reduce oscillations and improve frequency stability, which helps maintain reliable and safe operation of power plants. By using techniques like adaptive control, Adaptive PSS can optimize network performance more effectively than an implicit approach that allows direct identification of PSS parameters was presented in [38] in 1995. Furthermore, a new approach for bringing PSS parameters online using radial neural networks was established in [39] in 1999. Additionally, a methodical technique centered on the creation of an artificial neural network-based PSS autoturning process was introduced in (40) 2004. Real-time PSS parameter adaptation can be achieved using this intelligent network .

Another adaptive power stabilizer model was introduced in 2010 [41]. The components of an adaptive PSS use a traditional POWER SYSTEM STABILIZER to address the low frequency oscillation issue. As previously noted, these PSS offer an additional dampening signal to reduce the aforementioned oscillations and improve the system's overall stability. However, the transfer functions of highly linearized models around a certain operational point are used in these traditional PSS. Therefore, these systems cannot function satisfactorily under a variety of operational situations [22]. Artificial intelligence-based solutions have been developed to address this issue. These consist of genetic algorithms (GA), neural networks (NN), and fuzzy logic (FL). When made adaptive, fuzzy logic-based controllers have a great deal of potential for reducing local mode oscillations. Adaptability is attained by using neural network tuning[19].

Include a regulator that permits pole displacement and a linear element that identifies the third order average of the power system model (Autoregressive Moving Average, or ARMA). A new stabilizer that employs Nussbaum gain to enhance the angular stability of a power system was recently created (in 2013) and is based on a fuzzy adaptive sliding mode

In summary, the PSS self-adjustment techniques proposed in the specialized literature can be divided into two categories. One, based on an offline calculation of the appropriate PSS parameters, then adjusts the regulator parameters for each operating point and requires a complex and laborious mathematical calculation. And the other, based on an adaptation mechanism that adjusts the parameters of the PSS online. The real-time PSS parameter predictor is a simpler implementation and does not involve significant investment in hardware and software.

The main contribution of this part of the thesis is to propose a simple, but robust and effective stabilizer, dedicated to properly damping the electromechanical oscillations of the power system. This is a phase advance delay type PSS with self-tuned parameters (STPSS: self tuned PSS) based on the rotor speed gradient. The proposed self-regulation procedure is applied to automatically adjust the (PSS) parameters online to achieve the best performance. To validate and prove the effectiveness and robustness of this proposed STPSS, several simulations were carried out on a single machine system (SMIB) equipped with this kind of PSS, subjected to large disturbances and different operating conditions.

The second proposal consists of using a Mamdani fuzzy logic controller as a mechanism for self-adjusting the PSS parameters. The results obtained are tested on a system multimachine to prove the robustness and efficiency of the proposed PSS.

Include a regulator that permits pole displacement and a linear element that identifies the third-order average of the power system model (Autoregressive Moving Average, or ARMA). A new stabilizer that employs Nussbaum gain to enhance the angular stability of a power system was recently proposed (in 2013), and it is based on a fuzzy adaptive sliding mode

In summary, the PSS self-adjustment techniques proposed in the specialized literature can be divided into two categories. The second method, which is based on an offline calculation of the appropriate PSS parameters, adjusts the regulator parameters for each operating point and requires a complex and laborious mathematical calculation. The second method is based on an adaptation mechanism that adjusts the parameters of the PSS online. The real-time PSS parameter predictor is a simpler implementation and does not involve significant hardware and software investment.

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based on the rotor speed gradient. The proposed self-regulation procedure automatically adjusts the (PSS) parameters online to optimize the performance. To validate and prove the effectiveness and robustness of the proposed STPSS, several simulations were carried out on a single machine system (SMIB) equipped with this type of PSS and subjected to large disturbances and different operating conditions.

The second proposal uses a Mamdani fuzzy logic controller as a mechanism for self-adjusting PSS parameters. The obtained results were tested on a multimachine system to prove the robustness and efficiency of the proposed PSS.

5_ Self-adjustment of PSS parameters based on speed gradient

Different control strategies and optimization techniques have been used to design efficient and robust PSSs, and their applications have been found in this field. Several approaches have been applied and many useful results have been published. These include optimal control, adaptive control, variable structure control, and various optimization and artificial intelligence techniques [43].

The problem is that this type of PSS is not easy to implement, even if it is much more robust and efficient than a conventional PSS (CPSS). The main contribution of this study is the proposal of a robust, efficient, and simple stabilizer with self-adjusted parameters based on rotor acceleration. The proposed self-adjustment procedure involves the automatic online adaptation of the CPSS parameters to obtain the best performance.

The proposed PSS adjusts its parameters online at each sampling period based on the speed gradient to properly damp the protonic oscillations of the power generator. The basic concept of the adaptation mechanism proposed to adjust the CPSS parameters is illustrated in Figure 6:1 and the set of equations (11) to (12).

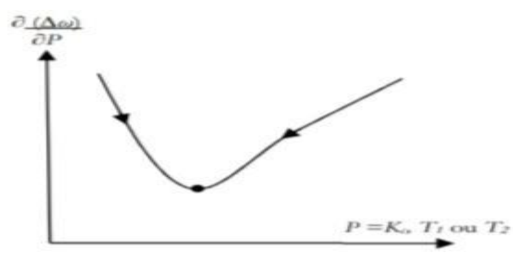

Figure (11) Principle of self-tuning of PSS parameters

The selection of the parameter to adjust depends on the sensitivity of the rotor speed to variations in these three parameters. Therefore, based on the speed variation with respect to each parameter and the sensitivity analysis, the PSS parameters were selected to be adjusted online.

From the parameters of a PSS initially and globally optimized by one of the metaheuristic techniques already observed, the proposed procedure updates and online the parameters as follows:

K(k + 1) = K.(k) - a 2(Δω)

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T(k+1)T(k)-B (Δω) aт

T2(k+1)=T2(k)-y- (Δω) aт

In practice, the PSS can be designed with the adjusted parameters based on the speed gradient by self-adjustment according to the following steps:

Determination of the globally optimized parameters of the initial CPSS based on the calculation of the eigenvalues for a set of restricted operating points and one of the optimization techniques studied;

Sensitivity analysis of the speed oscillations with respect to the three CPSS parameters at the neighborhood of their optimal values;

Delineation of the variation ranges of each PSS parameter; Setting the coefficients (a, ßor y are used to self-adjust the PSS parameters.

Design of a self-adjusted PSS for an SMIB based on the velocity gradient In this section, we implement the step-by-step procedure proposed in the previous section to design a PSS with self-adjusted parameters for an SMIB using the speed gradient.

- **Initialization of PSS parameters**

This step consists of determining the CPSS parameters globally optimized by the genetic algorithm over all three operating points table e: 2) in Appendix C. For the same parameterization of the GA, we also considered the maximization of the critical damping of these three operating points as an objective function. The results obtained from the globally optimized CPSS are as follows:

K-40, T = 0.20 s and T = 0.078 s

6_Self-adjustment by speed gradient of PSSs in a multimachine system

The infinite-bus single-machine system is generally used to test and evaluate the performance and robustness of the proposed PSS structure. However, the proposed solution must be generalized and then applied to a multi-machine system. This is closer to reality, where other phenomena appear, such as the interaction between machines and between regions. In this case, there are several parameters to self-adjust and many intervals to limit.

In this section, we apply the proposed self-adjustment method to a multi-machine system of 9 nodes and 3 machines (the WSCC system).[44]

The parameters of the PSSs are automatically adjusted according to the speed gradient of the generator equipped with this stabilizer in a manner similar to that of a single-machine system. Based on the results of the SMIB, we limited ourselves to the self-adjustment of the gains Kej given their great influence on the stability of the system and given the large number of parameters that can be self-adjusted in the case of a multi-machine system. We have already noted that the PSS gain is a key parameter for the damping of electromechanical oscillations.

The first step involves determining the optimized values of the two PSSs using the genetic algorithm.

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	K_{C0}	T_{10}=T_{30}	T_{20}=T_{40}
Pss2	47.06	0.2645	0.0264
Pss3	15.294	0.2625	0.0265

Table 3 of the optimized parameters of the two GAPSSs of the WSCC multimachine system.

7_Fuzzy self-adjustment of the PSS parameters of a multimachine system

Zadeh created fuzzy logic in 1964 to deal with the imprecision and uncertainty that are common in engineering difficulties. It was initially used in 1979 to solve power system issues. One could think of fuzzy set theory as an extension of classical set theory. An element of the cosmos can be classified as either belonging to or not belonging to the set in classical set theory. Thus, an element's degree of relationship is clear. An element's association may fluctuate over time in a fuzzy set theory. A fuzzy set is defined mathematically as a mapping (also called a membership function) from the discourse universe to the closed interval [0,1]. The requirements and limitations of the situation are typically taken into account when designing the membership function. Fuzzy logic uses fuzzy rules and membership functions to implement human preferences and experiences. A non-expert operator can understand the system because fuzzy variables are used. Fuzzy logic can be applied as a broad methodology to help controllers and decision makers assimilate knowledge, heuristics, or theories in this fashion.

Fuzzy theory has the following benefits: (i) it more closely reflects power systems' operational constraints; and (ii) fuzzyified constraints are softer than conventional constraints [118, 119]. In [120–122], a thorough overview of fuzzy logic and its uses in power systems is provided. The overview and literature review of fuzzy set theory's use in power systems was provided by Momoh et al. [123]. Fuzzy set theory has been used primarily in voltage and reactive power control, load forecasting, fault detection, power system protection/relaying, stability, and power system control, among other areas, according to a recent assessment published in [124].

The main goal of this section is to design a fuzzy self-adjustment mechanism for the PSS parameters of a multimachine system. We first briefly recall the concept of fuzzy logic and its application to control through the presentation of the Mamdani regulator. Next, we use this fuzzy concept to design a PSS with self-adjusting parameters.[45]

● Reminder on fuzzy logic and control

Let us recall that fuzzy logic appeared in 1965 with the publication of the first scientific article entitled “Fuzzy Sets,” in English by Professor Lotfi Askar Zadeh of the University of Berkeley (California, USA). This fuzzy logic is a generalization of classical Boolean logic (bivalent logic). In 1975, P Professor Mandani created the first experimental fuzzy controller for a steam boiler. This area has been quickly investigated by many researchers who are developing research. theoriques. Since then, most of the work on fuzzy logic and related applications has been conducted in Japan.

Fuzzy logic consists of submitting to the expertise of a human operator or a process engineer, the system to be controlled, which does not lend itself easily to modeling and/or parametric identification of the controller (the PSS in our case), and then to establish a set of rules in the rules of action.[46]

The fuzzy logic mode of reasoning is more intuitive than classical logic. It allows designers to better understand natural, imprecise, and difficult-to-model phenomena by relying on the definition of rules and functions belonging to sets called “fuzzy sets.” However, it adds a decisive functionality: the possibility of calculating a parameter by saying. simply how far it should be in this or that value zone.

Fuzzy Logic Systems (FLS) have been successfully applied to the control of complex or ill-defined processes whose mathematical models are difficult to design. The ability to transform linguistic descriptions into an automatic control strategy is indeed a practical and promising alternative for controlling classical or complex nonlinear systems. Conversely, fuzzy systems are inherently capable of modeling or controlling processes for which imprecise linguistic expertise exists. In general, a fuzzy system is based on the following three essential steps (4):

Fuzzifuation: This is the step of moving from the digital domain to the symbolic domain. It allows, among other things, determining the membership function of a variable to a fuzzy set. Inferesa: This involves processing information using fuzzy rules. It can be considered an interpolation procedure, as expressed by Zadeh. Defursification: This operation allows one to move from a representation in the form of a linguistic variable to a physically applicable numerical variable. It is the opposite phase of fuzzification.[46]

In general, a Fuzzy Logic Controller (FLC) has two inputs (setting error e and its variation Ae) and one output (control signal AP). For convenience, the two inputs and output of the CLF are scaled with three coefficient ke, kae ut cap (see figure 13)

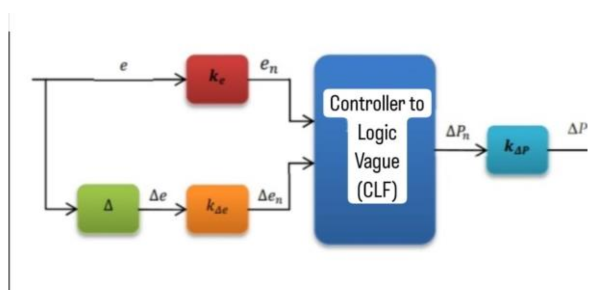

Figure (12) the output of the CLF

● Design methodology for fuzzy self-adjustment mechanism

In this section, we use the Mamdani CLF schematized by Figure 6:9 as a mechanism for self-adjusting the parameters of the PSSs of a multi-machine electric power system. The two inputs of this controller are the deviation of the speed of the generator equipped with a PSS and its variation, and its sorb is the variation of the parameter to be self-adjusted. All three are quizzified by five fuzzy subsets (NG: Negative Large, NP: Negative Small, EZ: Equals Zero, PP: Positive Small, PG: Positive Large), as shown in Figure 14.

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Figure 14 Fuzzification of the linguistic variables of the fuzzy self-adjustment mechanism. This CLF allows us to modulate the variation of the parameter to be adjusted by a proportional derivative action (PLD), whose inference matrix is summarized in table 6:10

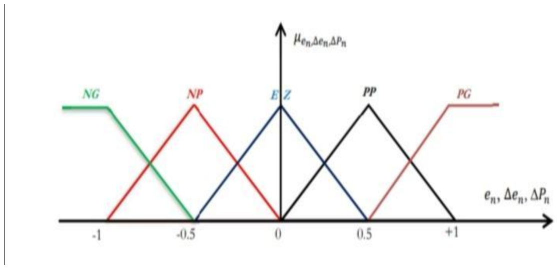

Figure (13) Fuzzy inference rules for parameters to be adjusted (P)

Similar to the PSS, this action occurs only in a transient state by modulating the variation of the parameter. The fuzzy inference results were evaluated using the centroid method. The control surface generated by this inference engine or on the standardized discussion universe is illustrated in figure 15.[47] [49]

Δe_n \ e_n	NG	NP	EZ	PP	PG
NG	NG	NG	NP	NP	EZ
NP	NG	NP	NP	EZ	PP
EZ	NP	NP	EZ	PP	PP
PP	NP	EZ	PP	PP	PG
PG	EZ	PP	PP	PG	PG

Figure (14) Control surface generated by the CLF

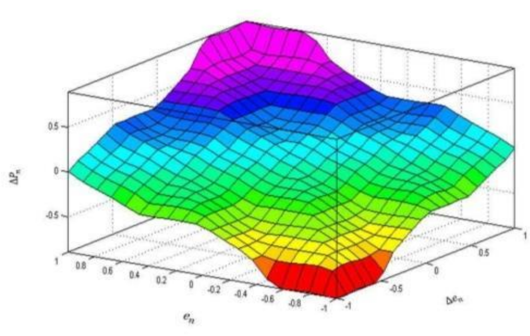

Figure (15) Control surface generated by the CLF

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Conclusion

In this study, strategies for employing AI techniques to optimize the AVR system of a multi-machine power system have been proposed. Successful applications of the suggested techniques have been made to traditional controllers (PID and lead networks). Some real-world limitations, like the limits placed on the voltage levels, are taken into consideration by the methods that are described. The system has been tested under various system setups and against a variety of disturbances.

It is seen that the optimized power system network performs satisfactorily. In contrast to classical approaches, which need more complex mathematics, the AI techniques employed offer a straightforward solution for a non-linear and discontinuous system. One of the upcoming tasks is to fine-tune the various PSO and GA optimization parameters.

The main advantage of this method is that it can be extended to more complex controllers and more comprehensive system models.

The demand for electrical energy is increasing daily because of industrial development. The power system must be flexible so that it can be operated at a wide variety of operating points and within its operating constraints. Low-frequency oscillations are operational constraints that limit the transmission of electrical energy. In such a scenario, the power system controls play a significant role and can help create either positive or negative damping. Negative damping refers to a phase in which a system experiences an increase in amplitude over time, rather than a decrease, when subjected to oscillations or vibrations. In typical damping scenarios, energy is dissipated from the system, leading to a gradual reduction in the oscillation amplitude. However, in negative damping, energy is added to the system, causing it to oscillate more vigorously.

We propose two techniques for self-adjusting the PSS gains of a multi-machine electrical system. These two self-adjustment strategies allow the generation of parameters (static gains) of PSSs in real time. They are simple to implement and greatly reduce the calculation time compared to adaptive PSSs using neural networks and neuro-fuzzy techniques. On the other hand, these self-adjustment techniques significantly improved the damping degree of the rotor oscillations. However, they only require a good adjustment of the self-adjustment parameters and a delimitation of the variation space of the parameters to be self-adjusted. These two elaborate techniques are very efficient, especially if the self-adjustment coefficients are chosen

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تصميم مُثبِّت نظام الطاقة لآلات متعددة

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الخلاصة

يهدف هذا البحث إلى تعزيز استقرار أنظمة الطاقة متعددة الآلات من خلال تحسين تصميم ومعلمات مثبتات أنظمة الطاقة .(PSS) تُدمج هذه المثبتات في نظام التحكم في الإثارة لتجاوز قيود منظمات الجهد الأوتوماتيكية(AVRs) ، والتي قد تؤثر سلبًا على تخميد النظام وتؤدي إلى عدم استقرار تذبذبي.

تبدأ الدراسة بتسليط الضوء على دور مثبتات أنظمة الطاقة في تخميد التذبذبات الكهروميكانيكية من خلال تعديل إشارة الإثارة. الهدف الرئيسي هو ضمان توافق عزم التخميد المُولّد مع تذبذبات دوار المولد، وبالتالي الحفاظ على تردد النظام ضمن الحدود المقبولة ومنع الانقطاعات واسعة النطاق.

ولتحقيق هذه الأهداف، يدرس البحث تطبيق خوارزميات تحسين متقدمة لتصميم مثبتات أنظمة الطاقة. يُجرى تحليل مقارن بين أربع تقنيات تحسين: الخوارزمية الجينية(GA) ، وتحسين سرب الجسيمات(PSO) ، والتلدين المُحاكي(SA) ، والبحث المحظور .(TS) يتم تقييم نقاط القوة والضعف لكل طريقة بناءً على قدرتها على تحديد المعلمات المثلى التي تُحسّن أداء النظام.

علاوة على ذلك، تستكشف الدراسة التهجين بين طريقتي البحث العالمية والمحلية للجمع بين مزايا كلا النهجين. تُظهر النتائج أن الخوارزميات الهجينة تُوفر أداءً متفوقًا من حيث تخميد التذبذبات وتعزيز الاستقرار العام للنظام.

وأخيرًا، يُحدد البحث تحديين رئيسيين: تباين معلمات نظام دعم الطاقة الأمثل (PSS) تبعًا لظروف تشغيل النظام، والتكلفة الحسابية العالية لتقنيات الاستدلال الفوقي، مما يحد من تطبيقها في سيناريوهات الوقت الفعلي. تشير هذه النتائج إلى ضرورة وجود حلول تكيفية وكفاءة حسابية للتطبيق العملي في أنظمة الطاقة الحديثة.

الكلمات الدالة: آلات متعددة، مثبتات، تحسين، تخميد، تكيف.