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Power System Steady State Stability Control - Lesotho Electricity Company Status Review

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Abstract: - Power systems are usually influenced by many factors under steady-state operating conditions. These impacts require control and optimization strategies that can alleviate or mitigate them. Some recent power systems control strategies are (artificial intelligence) AI-based and still require system modeling before their development. These control systems are considered superior to classical control systems techniques since the control can be executed in real-time or online. This is because high-speed computers are readily available to handle those tasks. One such method is the model reference adaptive control (MRAC). This control system can control large dynamic power systems under steady-state conditions and its development can entail practical imperfection for optimum control. The presented literature covers causes of instability under steady state operations and briefly covers system modeling, which is a prerequisite for developing and implementing control systems. Furthermore, recent power system steady-state control methods and algorithms are discussed to identify potential and appropriate control systems for Lesotho Electricity Company (LECs') power system steady-state control. Network planners and engineers at LEC can implement these advanced AI-based power system stabilizers (PSS) to optimize the performance of the power system under steady-state operating conditions.

Keywords: Steady-state stability control, power system stabilizers (PSSs), synchronous generator, control system, fuzzy logic, artificial intelligence, and neural networks.

I. INTRODUCTION

Large power systems of today are fundamentally dynamic systems that must meet stringent standards of high reliability to provide electricity to users continuously [1], [2]. The power system's capacity to operate steadily under steady-state conditions and after disturbances is a prerequisite for reliability [3]. Power system stability has been the focus of decades' worth of research. Recent decades have seen many innovations, which raise new issues and difficulties that require research and analysis [4]. It is vital to examine the power system's performance under various operating scenarios to guarantee steady system performance. Many researchers have studied power flow, steady-state stability control, and transient stability. It requires understanding the models used to describe the various parts of an integrated power system to carry out such research [5]. It is essential to implement controls that can guarantee a steady and constant supply of electricity in the event of an interruption when there is a risk of losing stability [6]. Thus, modeling, load flow computation in the transmission grid, stability analysis in both steady-state and disturbed circumstances, and adequate controls to improve stability are all included in the topic of stability. Many writers have suggested a variety of methods to improve stability [7], [8]. To enhance and control power system stability, both established and recently developed methodologies were investigated. Since their invention in the 1950s, power system stabilizers have been the most widely utilized technology in power systems to offer damping after disruptions [4], [9]. New algorithms for the power system stabilizer have been developed through the application of artificial intelligence (AI) and adaptive control approaches [10], [11].

The primary source of electricity generation in an interconnected power system is synchronous generators [12], [13]. All generators must rotate in synchronism, that is, their average electrical speed must be constant throughout the system, as this is a prerequisite for power transfer, distribution, and steady-state operation [14], [15]. Prime mover drives every generator. The generator receives mechanical power from the prime mover and uses it to produce electrical power, which is subsequently delivered to the coupled system [16]. The generator's input mechanical power and output electrical energy are regulated in a steady-state condition. When applied to the shaft, the mechanical input and the electrical output power produce mechanical and electrical torques. While the electrical torque is directed toward the opposite direction from the direction of rotation, the mechanical torque points in the direction of rotation of the shaft [17]. When a system fault occurs, the electrical power output varies more quickly than the mechanical power input. This is because the prime mover controller responds somewhat

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slowly while the generator's excitation system responds promptly [18]. As a result, a transient power imbalance modifies the torque applied to the shaft. Therefore, the rotor speed changes (increases or decreases), changing the relative rotor angle. The angle formed by the rotor magnetomotive force (MMF) and the product of the rotor and stator MMF is known as the rotor angle δ, sometimes referred to as the torque or power angle. Fig. 1 depicts the rotor angle of a synchronous generator [19]. The protective relaying mechanism disconnects the generator from the rest of the system if the rotor speed variation persists, possibly beyond the limits of generator synchronous operation [19]. The loss of generation then perturbs the remaining system. This disruption might cause other units to trip offline, leading to a cascading outage. As a result, the notion of power system stability is related to a system's generators' capacity to sustain synchronism and their propensity to resume steady-state functioning after a disturbance [20].

Authors in [21] suggest that it is possible to experience instability without losing synchronism. For instance, a system where a generator feeds an induction motor may become unstable if the load voltage collapses. This time, the problem is not with maintaining synchronism but rather with the stability and management of voltage. This type of instability can occur when loads in an enormous system are spread over a vast area. System controls, unique protections, and controls for the generator and prime mover become crucial when there is a large load/generation mismatch in a given location [22]. Inadequate coordination may cause the system frequency to become unstable, which could trip generating units, loads, or both, potentially resulting in a blackout [23]. This is another instance where the system becomes unstable even though the units may stay in synchronism (unless tripped by safeguards like under frequency).

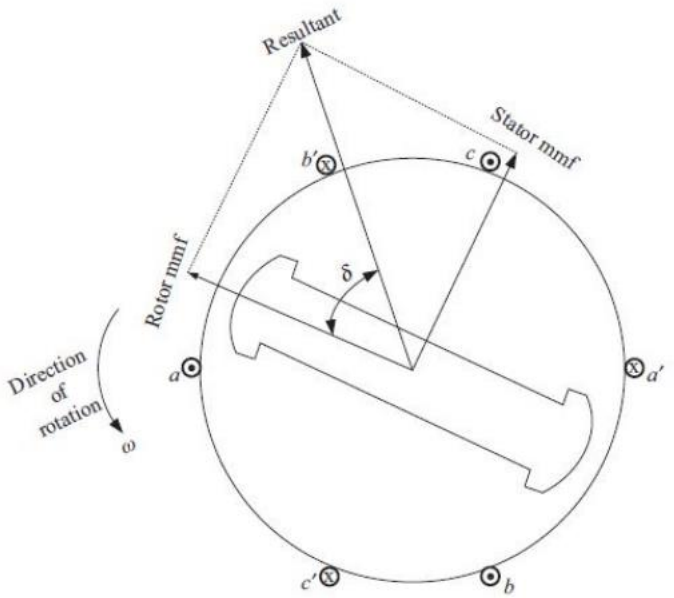

Fig. 1. Rotor angle and resultant of rotor magnetomotive force (mmf) and stator mmf [19]

Power system stability is generally classified according to the type of external disturbance. There are two categories of disturbances: small and large [7]. A little disruption causes the system to behave differently, such as tripping a line delivering negligible power, or causing slight variations in the load. Small signal analysis, also known as steady state analysis, is based on linearized equations and these equations can be used to examine the system's dynamics [24]. A significant disruption causes some of the system's properties to abruptly change dramatically. In this case, nonlinear equations are used to describe system dynamics. Large disturbances, also known as transient stability, include abrupt changes in load, a loss of generation, the replacement of overloaded transmission lines, symmetrical and unsymmetrical faults, and lightning strikes [25]. In an integrated power system, the synchronous generator can be described by an internal voltage source, E_g, behind the generator reactance, X_g, which, for steady-state analysis, equals the synchronous reactance, X_d. The output power, P_e, on a steady-state condition, is given by equation 1.

$$P_e = P_{max}\, sin(\delta) = \frac{E_g V_t}{X_g}\, sin(\delta) \quad (1)$$

where $P_{max} = \frac{E_g V_t}{X_g}, \delta\ and\ V_t$ are the maximum output power, power angle (phase shift between E_g and V_t) and the terminal voltage of the generator respectively. It is worth noting that the maximum power occurs when the power angle $\delta = 90^o$ and is generally called the steady state limit. Fig. 2 shows the relationship between the electrical output power and power angle under steady-state conditions. When operating normally, power systems often have effective oscillation damping [25]. In certain circumstances, their ability to dampen after disturbances may be significantly reduced, and in the worst case, damping could become negative. Consequently, the oscillations intensify until the synchronism vanishes. One or more of the oscillation types reported in large, interconnected power systems including rotor swings are caused by the loss of small signal stability [26]. The rotor swing might become uncontrollably enormous or dampen slowly. The stability analysis of small signals addresses three primary forms of oscillations. First, local mode oscillations occur when a power plant's synchronous generators swing in unison against a substantial power system or load center. They have a frequency between 0.7 and 2 Hz. Second, inter-unit oscillations occur when a power plant or a group of adjacent power plants' synchronous generators swing against one another at a frequency of 1.5–3 Hz. Third, inter-area oscillations of a power system often occur when a group of generators in one section of the system swings against another group in another area of the system. Usually, this kind of oscillation occurs at a frequency of less than 0.7 Hz [27].

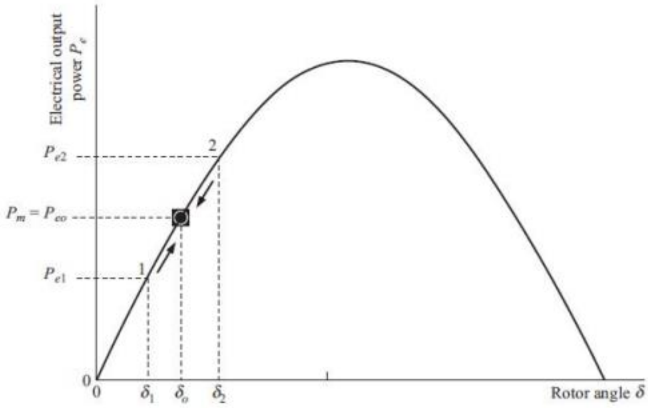

Fig. 2. Characteristic curve of the synchronous machine in steady state condition [19]

The general framework for power system stability evaluation and control development is depicted in Fig. 3. Most of the feedback controls at power stations are continuous, local controls [25]. At power plants and substations, the feedforward controls are discontinuous and may be local or broad area. Typically, disruptions like short circuits cause stability issues, which are resolved by removing faulty components. Frequency excursions and an imbalance in the generation and load may arise from either generation or load loss. These disturbances stimulate electromechanical dynamics in the power system. Negative damping torques produced by generator automatic voltage regulators are typical examples of how poorly designed or calibrated controls can lead to stability issues [27]. Some typical power system stability control and possibilities for advanced control algorithms are [1], [19], [21], [28], [29], [30]:

- Generator excitation controls;
- Prime mover controls (swift valving) ;
- Generator tripping • Swift fault clearing;
- High-speed reclosing and single-pole switching;
- Dynamic generator braking;
- Load modulation and tripping;
- Reactive power compensation switching or modulation (series and shunt) ;
- Fast phase shift control;
- HVDC link supplementary controls;
- Variable speed (doubly fed) synchronous machines;

- Controlled separation and under frequency load shedding;
- Artificial neural network (ANN) ;
- Adaptive neuro-fuzzy logic (ANFL) and
- Particle swarm optimization (PSO).

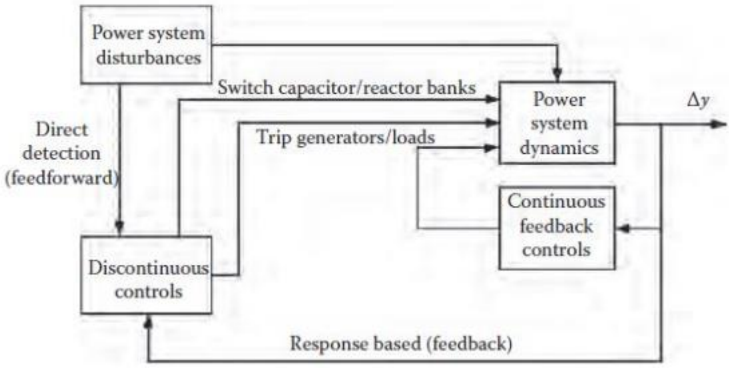

Fig. 3. General block diagram of a power system stability control [21]

This paper is structured as follows; section 1 is the introduction and discusses typical power system steady stability analysis, existing control techniques proposed by other researchers, and the importance of a stable steady-state operation of a power system. Section 2 covers the research objectives and formulates the mathematical model for the power system since modeling is a prerequisite for developing an appropriate classical control technique and advanced modern control algorithms for optimum control. Section 3 covers the benefits, research gaps, and challenges brought forth by power system stability control in the context of the already struggling LECs power system. Finally, section 5 concludes the paper.

II. LITERATURE REVIEW

A. System Modelling and Analysis

Since the notion of power system stability is related to generators' ability to sustain synchronism and their propensity to resume steady-state operation after disturbance as mentioned in the literature, the generator model will be presented and then followed by the proposed control method. Regarding steady state stability, the synchronous generator must maintain synchronism under small disturbances [31]. It is ultimately determined that the disturbances are sufficiently small to allow the study of the system equations using linearization. The dynamic behavior of a machine coupled to an infinite bus is taken into consideration to provide a mathematical model for the small signal stability problem. The synchronous machine's swing is given by equation 2, which describes its motion and is a non-linear second-order differential equation of the power angle δ [32].

$$\frac{2H}{\omega}\ddot{\delta} + D\dot{\delta} = P_m - P_{max}\,sin(\delta) \tag{2}$$

where $\omega = \dot{\delta}$ is the angular velocity of the rotor, D is the damping coefficient, H is the inertia constant of the machine, P_m is the input mechanical power. $\ddot{\delta}$ is the angular acceleration (second derivative of power angle δ with respect to time t in seconds) of the generator. The term on the right side of equation 2 is also referred to as the accelerating power $P_a = P_m - P_{max}\,sin(\delta)$. Since the prerequisite for all classical control techniques is the linearization of the nonlinear models of the plant, the linearized model is given by equation 3.

$$\frac{2H}{\omega_B}\frac{d^2}{dt^2} + D\frac{d\Delta\delta}{dt} + P_s\Delta\delta = 0 \tag{3}$$

where $\Delta\delta$ denotes a small change in power angle δ and P_s is the synchronizing power coefficient. This coefficient plays a prominent role in power system stability determination. For a multi-machine system, equation 3 can be extended and given by equation 4. This equation can be written as a state space model provided by equations 5 and 6 and the matrix form is provided by equation 7.

$$\frac{d^2\Delta\delta}{dt^2} + \frac{\omega_B}{2H}D\frac{d\Delta\delta}{dt} + \frac{\omega_B}{2H}P_s\Delta\delta = 0 \tag{4}$$

assuming the states space variables $x_1 = \Delta\delta$ and $x_2 = \Delta\omega = \Delta\dot{\delta}$ x2, therefore,

$$\dot{x_1} = x_2 \tag{5}$$

$$\dot{x}_2 = -\frac{\omega_B}{2H} P_s x_1 - \frac{\omega_B}{2H} D_{x_2} \tag{6}$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{-\omega_B}{2H} P_s & \frac{-\omega_B}{2H} D \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{7}$$

The system dynamics described above define the power system dynamics under unforced conditions and is a homogeneous equation. For forced conditions, the linearized forced dynamic equation is determined and is given by equation 8, and the state space representation is given by equations 9 and 10 [28].

$$\frac{d^2\Delta\delta}{dt^2} + \frac{\omega_B}{2H} D \frac{d\Delta\delta}{dt} + \frac{\omega_B}{2H} P_s \Delta\delta = \frac{\omega_B}{2H} \Delta P \tag{8}$$

$$\dot{x_1} = x_2 \tag{9}$$

$$\dot{x}_2 = -\frac{\omega_B}{2H} P_s x_1 - \frac{\omega_B}{2H} D_{x_2} + \frac{\omega_B}{2H} \Delta P \tag{10}$$

where ΔP is an increase in power input. The state space representation in matrix form is given by equation 11.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{-\omega_B}{2H} P_s & \frac{-\omega_B}{2H} D \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \Delta U \tag{11}$$

where $\Delta U = \frac{\omega_B}{2H} \Delta P$ is an incremental manipulated variable of the controller. In practice, a collection of interconnected synchronous machines operate in unison to meet the load demands [32]. Therefore, it is of utmost importance to consider that when dealing with stability. One way to conceptualize the multi-machine system is as a collection of synchronous generators connected to a transmission network at different places to feed different loads [33]. Therefore, it is necessary to obtain the desired mathematical relations defining interconnected machines to study the steady-state stability of such a system. The effect of additional system components is also involved and without the loss of generality, the load impedances are modeled as constant. For practical systems, stochastic equations can be utilized to describe the system as suggested by authors in [34]. The transmission network can be represented by an admittance or impedance matrix. A typical power system of interconnected generators is shown in Fig. 4 and an equivalent circuit for a simple power system is depicted in Fig. 5.

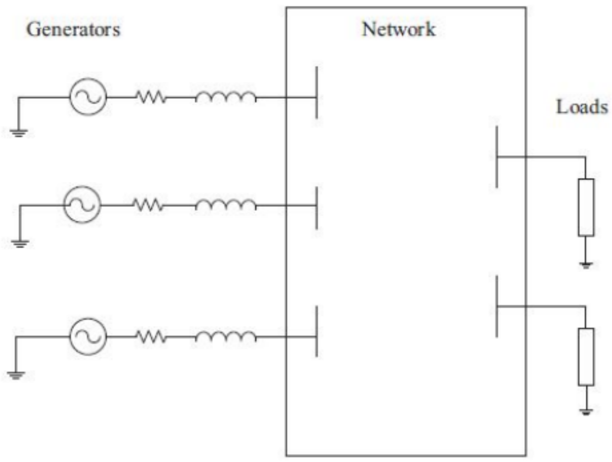

Fig. 4. Typical schematic of a power system

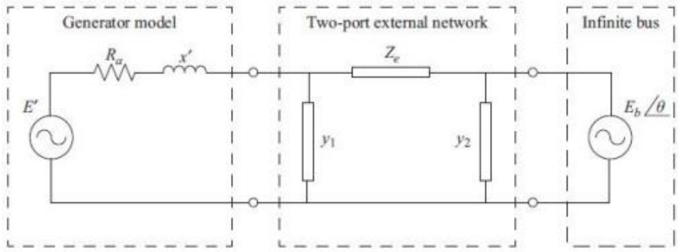

Fig. 5. Equivalent circuit diagram of a simple power system

B. Power System Stability Control Techniques and Algorithms

Now that the plant model is described, a suitable control method or algorithm can be derived to attain sufficient steady-state stability control. Due to computational time requirements, controlling large power systems using traditional analytical and time analysis methodologies for online real-time applications is very expensive [35]. Being non-linear and time-varying in particular, power systems are not appropriate for continuous tracking when conventional techniques are applied to determine their parameters, regulate their operation to preserve stability and dampen oscillations that occur after disturbances [3]. For offline design and research, they are more appropriate. Power system engineers, planners, and designers have been pushed to use artificial intelligence (AI) approaches based on logic mathematics to reduce computing time and design swift algorithms suitable for online power system applications [36], [37]. There are several AI and computational intelligence approaches, including genetic algorithms [38], fuzzy logic (FL) [39], neuro-fuzzy logic (NFL) [40], particle swarm optimization (PSO) [41], and artificial neural networks (ANN) [42]. ANNs are computer models inspired by biology, wherein the network structure comprises linked neurons, which serve as processing units [43]. In essence, they are estimates of non-linear functions that use inputs from the process to approximate outcomes [44]. The capacity of artificial neural networks (ANNs) to modify their connections through an adaptive learning process known as learning is a key characteristic [45]. A sequence of examples and patterns can be used to aid with learning. Information learned is stored and represented by connection weights within the neural network structure [46]. Fig. 6 depicts a typical model for an ANN system where the input signal or control variables are $x_{1,} x_2 \dots x_n$. These variables can be regarded as state variables as defined in the system modeling section. The set of input variables is weighted and summed together to feed it the activation function expressed by equation 12. Some of the commonly used activation functions for ANNs are hyperbolic tangent [47], Gaussian [48], Sigmoid [49], and hard-limit functions [50].

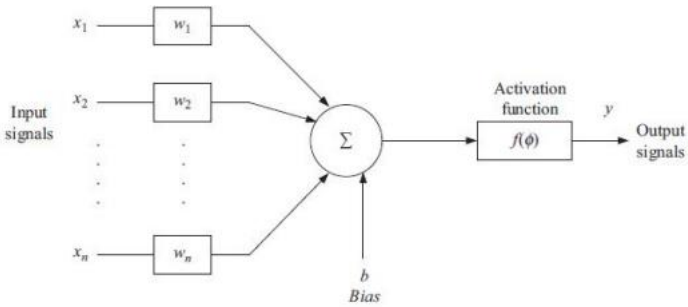

Fig. 6. A typical ANN system model

$$y = f\left(\sum_{0=1}^{n} w_i x_i + b\right) \tag{12}$$

where b is a bias variable that is used to increase or decrease the output signals. In terms of computing or representation, neurons are not incredibly powerful on their own [43]. Nonetheless, their interconnectedness provides strong processing capacities and enables the encoding of relationships between the variables [51]. Different network topologies are produced by the way neurons are linked inside a neural network and the kind of activation function that is used to build the network [43]. Basically, there are three categories of network designs namely; single-layer feed-forward architecture [52], multi-layer feed-forward architecture [53], recurrent neural network (RNN) [54], and back-propagation learning algorithm (BPL) [55].

Apart from that, Fuzzy Logic (FL) systems, formulated by L.A. Zadeh in the 1960s, is a field of mathematics concerned with ambiguous and linguistic data representations that approximate human comprehension or intuition [56]. Using analog values as inputs and outputs in logic calculations broadens the use of conventional binary logic [57]. Fuzzy set theory served as the foundation for the development of FL. When creating a mathematical model for a highly complicated problem proves to be too challenging or impossible, this important technique might be employed to address the challenge [58]. The basic block representation of the FL system is shown in Fig. 7.

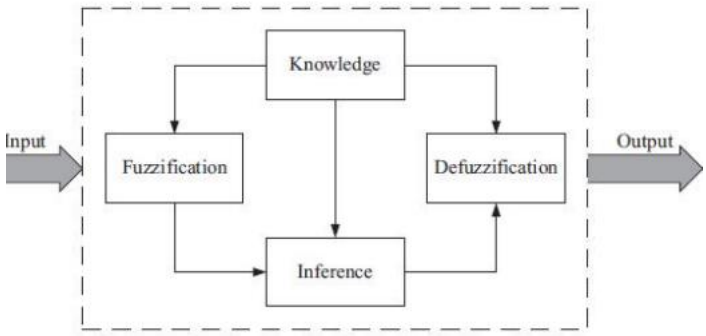

Fig. 7. The general block diagram of FL system

The fuzzification block entails mapping input variables into the corresponding linguistic values whilst the knowledge base defines control objectives through a set of linguistic control rules [56]. The inference, which is the core of the FL system, matches all rules in the fuzzy rule base with the input variables for every fuzzy variable in the precedent, resulting in the inferred value of a fuzzy set [59]. The defuzzification block translates the fuzzy set into the corresponding non-fuzzy output variables [60]. Typical defuzzification techniques are mean of maximum (MOM), smallest of maximum (SOM) [61], largest of maximum (LOM) [62], and center of gravity (COG) [63] defined by equation 13.

$$COG = \frac{\sum_{1=1}^{n} x_i \mu_A(x)}{\sum_{1=1}^{n} \mu_A(x)} \tag{13}$$

Moreover, when combining an FL system with an ANN system a new AI approach called neuro-fuzzy system emerges [64]. The fundamental concept of the integrated system is to use a neural network to simulate a fuzzy logic(FL) system and then utilize learning algorithms created in the neural network area to adjust the fuzzy system's parameters [65]. Merging FL with neutral networks serves the dual purpose of maximizing their benefits and mitigating their drawbacks [66]. Neural networks and FL might be seen as complementary technologies [67]. An automated tuning mechanism in a neuro-fuzzy system can provide the fuzzy system without changing its functioning. One of its advantages is that learning methods used in neural networks may be used to fine-tune the fuzzy system's rules [66]. In exchange, the neural network can increase transparency by building it with rule-based fuzzy reasoning taken into account.

Neuro-fuzzy control (NFC) is widely employed in many control system applications [68]. Some typical neuro-fuzzy systems are fuzzy net (FUN) [69], [70], Fuzzy adaptive learning control network (FALCN) [71], adaptive simplified neuro-fuzzy control (ASNFC), and adaptive neuro-fuzzy inference system (ANFIS) [72]. The block diagram of a discrete ASNFC control system is shown in Fig. 8. This architecture can control interconnected synchronous machines to optimize the power systems' performance in real time.

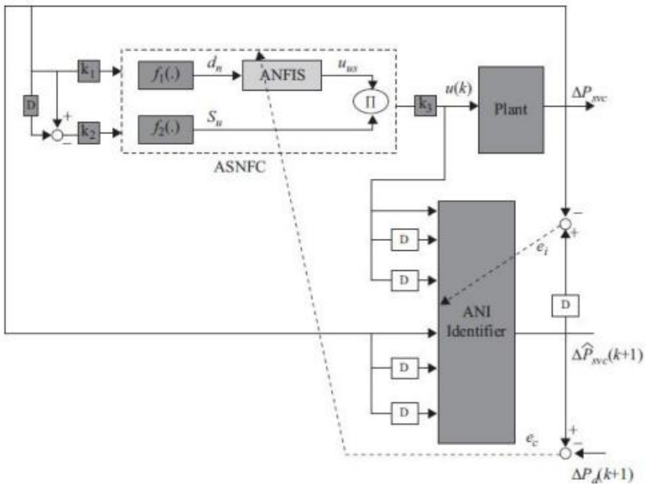

Fig. 8. The architecture of an ASNFC control system

Another typical control method that is suitable for steady-state stability control of interconnected machines is a power system stabilizer (PSS) [73]. To ensure that the synchronous generator operates properly, an automatic voltage control (AVR) is employed to ensure that the generator terminal voltage is stable and constant. However, AVRs can be problematic because high-gain fast-acting AVRs can potentially introduce negative damping in the excitation control system [74]. The PSS is essentially used to generate a supplementary signal to counter the undesirable effects of AVR. The system block diagram of the generator excitation with a dedicated PSS is depicted in Fig. 9.

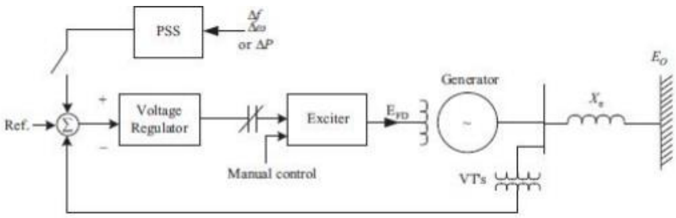

Fig. 9. System block diagram of generator excitation [75]

Fig. 10 depicts a deviation in rotor speed after a 0.1 p.u. step mechanical torque is imposed on the generator. In this arrangement, the system is operating under a normal load condition of real power = 0.70 p.u. and the power factor is 0.85 lagging, a 0.10 p.u. a step increase in the rotor input torque reference is initiated at 0.5 s. When the torque reference changes at 4.0 s, the system reverts to its initial operating conditions. Fig. 11 illustrates voltage deviation in the simulation. The system responds nearly identically to both SCPSS and ASNFC during the first half of the cycle. Nevertheless, -0.204 p.u. is the greatest value in the second half cycle when no control signal is given to the Static Var Compensation (SVC) device. This value decreases to -0.132 p.u. when the SVC receives the SCPSS control signal. By using the ANFC or ASNFC, the second-half oscillation cycle's peak value is further decreased to -0.0951 p.u. Additionally, it was discovered that when the SCPSS or adaptive controllers were utilized, the system disturbances were totally damped at t = 2.4 s. It is worth noting that the step response of an ASNFC control system is superior in terms of overshoot to Static Var Compensation conventional power system stabilizer (SCPSS). The performance of ANFC and ASFCN is the same. The LEC power system network is powered mainly by three 72MW hydro-power generator units and this novel control system can be utilized to improve the performance of the struggling LECs power system.

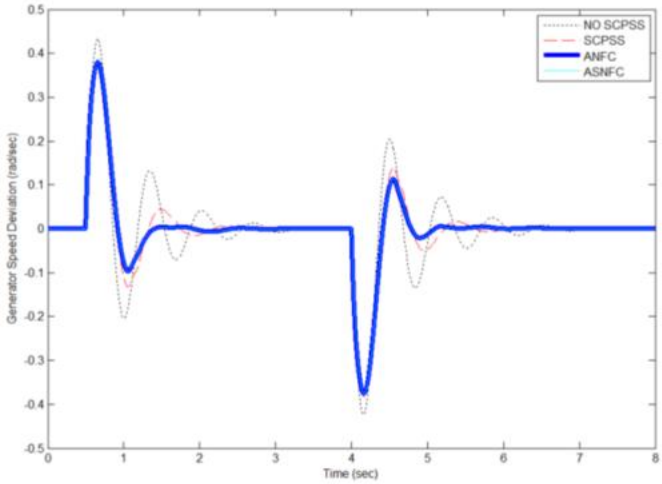

Fig. 10. Rotor speed deviation Δω due to a 0.1 p.u. STEP increase in input torque and return to normal operating condition. [76]

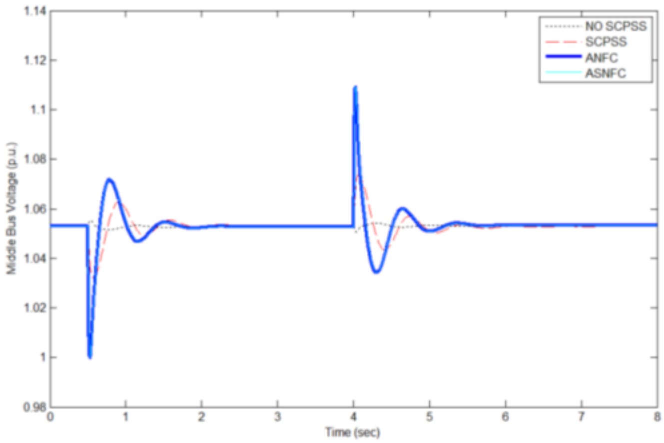

Fig. 11. Bus voltage deviation ΔV due to a 0.1 p.u. step increase in step input torque and return to normal operating condition. [76]

Another contemporary advanced control technique that is commonly used in an interconnected or multi-machine system is the model reference adaptive control (MRAC). An MRAC system's goal is to adjust the controller's settings such that the closed-loop system continues to operate at a level of performance that is predetermined by a reference model [77]. A controller, an adaptive mechanism, and an appropriate model are needed. The structure of MRAC-based PSS is shown in Fig. 12.

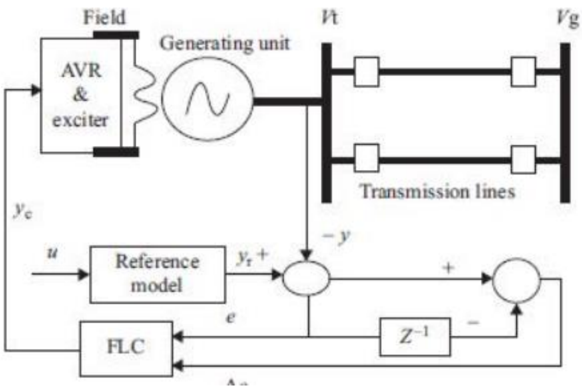

Fig. 12. The system structure of MRAC-based PSS [77]

The presented literature discussed several factors affecting the steady-state stability of the power system. These factors are important, particularly when identifying the root causes of small signal stability of LEC power system stability. To synthesize an optimum control technique for a single or multimachine power system, a dedicated plant model was derived as a prerequisite for formulating an appropriate control algorithm. The power system dynamic model was formulated, and relevant circuit diagrams were presented for better elaboration. Moreover, the literature covered advanced control algorithms that are currently being developed to overcome the limitations of classical control methods and pave a new avenue for the control of interconnected machines. The presented control techniques or algorithms in this literature are AI-based and are known to be the advent of modern control of power system stability control. Presented control algorithms are ANN, NFC, PSO, ANFIS, and ASNFC.

The presented literature discussed both contemporary power system steady-state control techniques and other advanced control algorithms that can potentially improve and optimize the steady-state stability of a multi-machine power system. The discussions were more based on identifying appropriate control methods for power system stability. Contemporary advances in control such as MRAC-based PSS incorporate the advantages of FLC and plant model to better control the system. The plant model described under the system modeling section can be used as a model reference or a more complex stochastic model for large interconnected systems can be utilized. For future work, a neural network-based algorithm like an ANFIS will be developed and incorporated with a stochastic model to realize a more novel PSS for a large power system.

III. Conclusion

The causes of the power system's steady-state stability problems were discussed in literature and contemporary control strategies were covered. The most recent applications of AI-based control strategies that are regarded as superior to classical techniques are MRAC and ASNFC control systems. They are preferred because they account for practical imperfections of the power system that were neglected in other classical control systems. This implies that to improve performance and optimize the power system under steady-state conditions, these algorithms should be applied and improved for better performance. In the context of LEC power system steady-state stability control, affiliated planners and network engineers can opt for these algorithms to improve and optimize systems performance. LEC planners and engineers can implement these novel AI-based PSS.

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