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Research Article

Tuning the Parameters of Power System Stabilizer Using Runge Kutta Algorithm[1]

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Abstract

Low-frequency oscillations due to unpredictable disturbances in an interconnected power grid are a serious threat to the stability of the power system. Reliable operation of a modern power system, when exposed to sudden disturbances, is crucial, and the safe operation of the system is directly related to success in damping oscillations. Power System Stabilizer (PSS) devices have been used to reduce fluctuations caused by short-time disturbances in power systems. These devices provide additional damping torque components to the generators as an auxiliary control device of the excitation system. Due to the non-linearity of electrical power systems, it is significant to design multi-machine power systems with optimum PSS parameters under critical conditions. In this paper, the PSS design problem was solved using the Runge Kutta Algorithm (RUN). The PSS design problem was considered an optimization problem in which an eigenvalue-based objective function has developed, and the proposed RUN method was tested in a WSCC 3-machine 9-bus test system using the linearized Heffron-Phillips model. In the linearized model, system stability has been enhanced by shifting the eigenvalues to the stability regions. When the results obtained from the test system are examined, it has seen that the proposed RUN is the most effective method in terms of system stability.

Keywords: *Power system stabilizer, Runge Kutta algorithm, Eigenvalue, Heffron-Phillips model.*

Runge Kutta Algoritması Kullanılarak Güç Sistemi Kararlı Kılıcısı Parametrelerinin Ayarlanması

Öz

Enterkonnekte bir güç şebekesindeki öngörülemeyen bozulmalardan kaynaklanan düşük frekanslı salınımlar, güç sisteminin kararlılığı için ciddi bir tehdittir. Modern bir güç sisteminin ani kesintilere maruz kaldığında güvenilir şekilde çalışması çok önemlidir ve sistemin güvenli çalışması, salınımların sönümlenmesindeki başarı ile doğrudan ilişkilidir. Güç Sistemi Kararlı Kılıcıları (GSKK), güç sistemlerinde kısa süreli kesintilerden kaynaklanan dalgalanmaları azaltmak amacıyla kullanılmaktadır. Bu cihazlar, uyarma sisteminin yardımcı bir kontrol cihazı olarak, generatörlere ilave sönümleme torku bileşenleri sağlar. Elektrik güç sistemlerinin doğrusal olmaması nedeniyle, kritik koşullar altında en uygun PSS parametrelerine sahip çok makineli güç sistemleri tasarlamak önemlidir. Bu çalışmada, GSKK tasarım problemi Runge Kutta Algoritması (RUN) kullanılarak çözülmüştür. GSKK tasarım problemi, öz değer tabanlı bir amaç fonksiyonunun geliştirildiği bir optimizasyon problemi olarak düşünülmüş ve önerilen RUN yöntemi, doğrusallaştırılmış Heffron-Phillips modeli kullanılarak WSCC 3-makineli 9-baralı sistemde test edilmiştir. Doğrusallaştırılmış modelde, öz değerler kararlılık bölgelerine kaydırılarak sistem kararlılığı arttırılmıştır. Test sisteminden elde edilen sonuçlar incelendiğinde önerilen RUN yönteminin sistem kararlılığı açısından en etkili yöntem olduğu görülmüştür.

Anahtar Kelimeler: *Güç Sistemi Kararlı Kılıcısı, Runge Kutta Algoritması, Öz değer, Heffron-Phillips modeli.*

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I. INTRODUCTION

In today's world, depending on technological and economic developments, electrical power systems are rapidly growing, and a significant increase in power demand is observed. Day by day, due to the ever-increasing power demand, the existing transmission lines are overloaded, and this causes various stability problems in the power system [1]. Stability problems cause adverse effects on the safe operating conditions of electrical power systems. Small Signal Stability (SSS) is the maintenance of synchronization of power systems under short-term disturbances due to small changes in load and generation [2-3]. In an interconnected power network, reasons such as weak connection lines, sudden fluctuations in load, line faults, control of the excitation system cause low-frequency electromechanical oscillations, which adversely affect the SSS [4-5]. In addition, poorly damped low-frequency electromechanical oscillations can cause some mechanical problems in synchronous machines and power failures.

Controllers are of great importance in damping low-frequency electromechanical oscillations occurring in an electrical power network [6]. The Power Sys-tem Stabilizer (PSS) is a conventional damping controller that generates an auxiliary control signal to the excitation system due to the speed deviation of the synchronous generator [7]. PSS design has attracted the attention of researchers for many years. In the past, a conventional power system stabilizer (CPSS) with constant parameters was generally preferred in power systems due to its basic structure. Firstly, De Mello and Concordia presented the main structure of the PSS [8]. In the study by Gibberd [9], constant-gain PSS tuning was discussed under different operating conditions. Kundur et al. [10] presented detailed analytical studies to determine the gain, output limits, and signal washout parameters of conventional lead-lag compensator PSSs to improve transient stability in local-area and inter-area oscillation modes. Depending on this situation, although classical optimization methods were used to tune the damping controller in the first years, more advanced methods were used for PSS design with the spread of PSS later on. Robust control [11-12], sliding mode control [13], linear-quadratic regulator [14, 15], H∞ techniques [16,17], fuzzy logic artificial intelligence techniques [18,19] are some of these methods. Although these methods are effective in terms of sys-tem stability, the use of traditional techniques in multi-machine systems is complex for PSS design and requires a lot of computation time [20-22].

Recently, various heuristic algorithms have been widely preferred by researchers, especially in engineering science, to overcome these disadvantages and solve complex optimization problems. These methods, which are divided into evolutionary and swarm intelligence algorithms, are generally inspired by natural phenomena. In any optimization problem, design parameters are optimized in minimum time by using heuristic algorithms compared to traditional methods. Another advantage of these algorithms is that they do not need to guess the initial solution. These methods are more flexible and effective methods when compared to traditional and deterministic methods for non-linear optimization problems. There are studies in which heuristic algorithms are used to optimize the control-gain parameters of PSS, the main task of which is to improve the low-frequency oscillation stability and implemented several different problems in electrical power systems. Optimum design of PSS parameters achieved by using heuristic methods such as Genetic Algorithm (GA) [23,24], Particle Swarm Optimization (PSO) [25,26], Tabu Search Algorithm (TSA) [27], Bat Algorithm (BA) [28,29], Cuckoo Search Algorithm (CSA) [30], Honey Bee Algorithm (HBA) [31], Firefly Algorithm (FA) [32], Whale Optimization Algorithm (WOA) [33], Chaotic Teaching–Learning Algorithm (CTLA) [34]. Although these methods are effective, it is seen that the application of different optimization techniques for the optimal design of PSS in multi-machine power systems has a significant contribution to the literature.

Runge Kutta Algorithm (RUN) is a novel swarm-based optimization algorithm developed by Ahmadianfar et al in 2017 [35]. In RUN, slope changes calculated by Runge Kutta (RK) method are used to solve a global optimization problem. Also, the enhanced solution quality (ESQ) used in RUN is important for balancing exploration and exploitation, and with this, solution quality is improved, and avoid from local optima is provided [35]. As a result of the literature studies, it has been observed that the PSS parameters are not tuned with the RUN method, which is a new heuristic algorithm. Therefore, in this study, the RUN algorithm was applied for the first time to obtain the optimum values of the parameters of the PSS device. The effect of RUN has been examined on a WSCC 3-machine 9-bus system based on eigenvalue analysis. The proposed RUN is compared with Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Hybrid PSO-ABC (HPA) [36], which are well-known in the literature, in terms of obtaining optimal PSS parameters to increase the dynamic stability of the system. The obtained results showed that RUN-PSS was more effective than other optimization methods in damping low-frequency oscillations and improving the system stability. Accordingly, the rest of the article continues in the following manner. The power system model, PSS model, and the objective function of the SSS problem are included in Section 2. The RUN method and its application in the PSS design problem are described in Section 3. The results obtained in solving the problem with RUN-PSS and other methods are presented in Section 4. The article ends with the conclusion in Section 5.

II. POWER SYSTEM MODEL

A. GENERATOR AND EXCITATION SYSTEMS

The mathematical model of a non-linear electrical power system has expressed by various differential and algebraic equations. In this study, the flux de-cay with the static exciter model is used for small signal stability and transient stability analysis. The dynamics of a synchronous machine with n-machines and m- buses with excitation system and PSS addition is expressed in Equation (1) - (7) [36]:

$$\dot{\delta}_i = \omega_s(\omega - 1) \tag{1}$$

$$\dot{\omega} = \frac{1}{M}(P_{gi} - P_{eo} - D(\omega - 1)) \tag{2}$$

where P_{gi} and P_{eo} are generator input and electrical power output. M is inertia constant, D is damping coefficient, ω_s is synchronous speed, δ is rotor angle, and ω is rotor speed, respectively. The generator output power can express as d-axis and q-axis components (i_d, i_q, v_d, v_q,) of the armature current I and the terminal voltage Vt as follows:

$$P_{eo} = v_d i_d + v_q i_q \tag{3}$$

The equation for internal voltage E'_q is as follows:

$$E'_q = \frac{1}{T'_{d0}}\left(E_{fd} - (x_d - x'_d)i_d - E'_q\right) \tag{4}$$

where, E_{fd} is the field voltage, T'_{d0} is represented open-circuit field time constant, x_d and x_d' expressions are the d-axis reactance and d-axis transient reactance of the generator.

The equation for the IEEE Type-STI excitation system is as follows:

$$\dot{E}_{fd} = \frac{K_A(v_{ref} - v_t + v_{pss}) - E_{fd}}{T_A} \tag{5}$$

where K_A , T_A, and v_{ref} are the gain constant, time constant and reference voltage of the excitation system, respectively. v_t terminal voltage is as given below:

$$v_t = \sqrt{(v_d^2 + v_q^2)} \tag{6}$$

$$v_d = x_q i_q \tag{7}$$

$$v_q = E_q^{'} - x_d i_d \tag{8}$$

where x_q is represented the q-axis reactance of the generator.

B. POWER SYSTEM STABILIZER (PSS)

The primary purpose of using PSS in a power system is to add damping to generator rotor oscillations utilizing an auxiliary stabilizing signal [37]. The IEEE Type-ST1 excitation system included PSS is given in Figure 1.

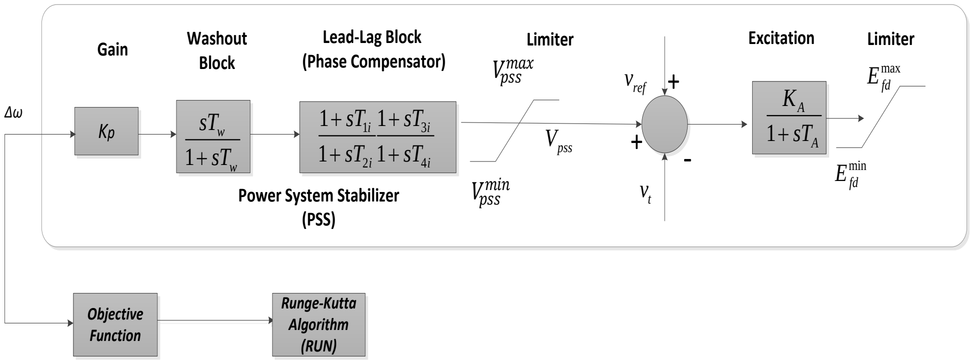

Figure 1. *IEEE Type-St1 excitation system with PSS.*

The transfer function of PSS with input signal $\Delta\omega$ and output v_{pss} is as follows:

$$v_{pss}(s) = K_p \frac{sT_w}{1+sT_w}\left[\frac{1+sT_1}{1+sT_2}\frac{1+sT_3}{1+sT_4}\right]\Delta\omega \tag{9}$$

The structure of the PSS comprises of a control gain K_p, a washing block with a time constant T_w, time constants T_1, T_2, T_3, and T_4, and the lead-lag block for phase compensation, and a limiter as shown in Figure 1. Here, the time constant T is usually in the range of 1-20 sec. The washing block with the high-pass filter is allow signals in the 0.2-2Hz range be passed unchanged. The phase lead-lag transfer function regulates the phase delay between PSS output and the electrical torque control.

C. LINEARIZED POWER SYSTEM MODEL

In design of PSS controller, the linearized incremental model is usually used for the nominal operating field. By linearizing the power system equations and adding the PSS equations, the state equation for the linearized power system model is as follows [3]:

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \Delta\dot{E}_q^{'} \\ \Delta E_{fd} \end{bmatrix} = \begin{bmatrix} 0 & \omega_b & 0 & 0 \\ -\dfrac{K_i}{M} & -\dfrac{D}{M} & -\dfrac{K_2}{M} & 0 \\ -\dfrac{K_A}{T_{d0}^{'}} & 0 & -\dfrac{K_3}{T_{d0}^{'}} & \dfrac{1}{T_{d0}^{'}} \\ -\dfrac{K_A K_5}{T_A} & 0 & -\dfrac{K_A K_6}{T_A} & -\dfrac{1}{T_A} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E_q^{'} \\ \Delta E_{fd} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \dfrac{K_A}{T_A} \end{bmatrix} \Delta v_{pss} \tag{10}$$

According to this, the linearized model of the power system is as Eq.(11):

$$\Delta\dot{x} = A\Delta x + B\Delta u \tag{11}$$

Here, A and B are the state variables and input matrices, Δx and Δu are vectors of state variables and input matrices, respectively. In this study, $\Delta x = [\Delta\delta \ \Delta\omega \ \Delta E_q^{'} \ \Delta E_{fd}]^T$ and Δu output signal of PSS. The primary objective in PSS design is to shift the eigenvalues of the A matrix to the left half of the complex plane. The eigenvalues are calculated from the A matrix.

$$\lambda_i = \sigma_i + j\omega_i \tag{12}$$

Here $i=1, 2, . . . , k$, and the k value represents the total number of eigenvalues The eigenvalue (λ) consists of real (σ) and imaginary (ω) parts. Then, the damping ratio (δ_i) of the i*'th* eigenvalue is defined by the Eq.(13):

$$\zeta_i = \frac{-\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \tag{13}$$

Figure 2 describes the block diagram of the linearized power system using the Heffron-Phillips model. The expressions of the constants *K1-K6* are given in [3].

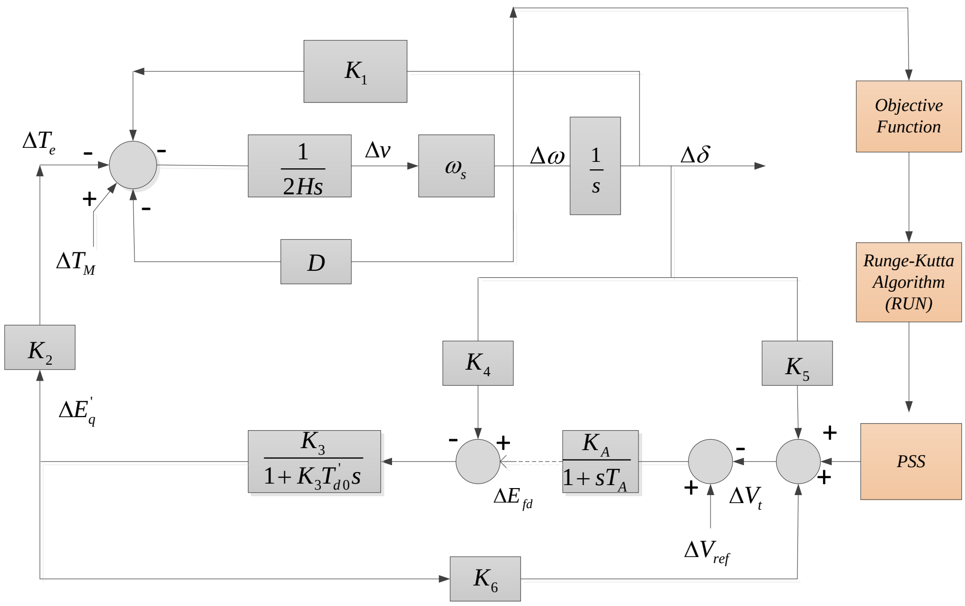

Figure 2. *Heffron-Phillips model with RUN-PSS.*

D. LINEARIZED POWER SYSTEM MODEL

The stability of a power system is determined by the eigenvalues of the linearized system. Eigenvalues with large negative real parts *(σ)* reduce the settling time of the system, and the system stabilizes faster. However, the maximum overshoot and oscillation values are determined from the damping ratios *(ζ)* of the system. Any increase in damping ratio causes the stability of the system to be improved. According to these two criteria, the objective function proposed in this study is considered as a combination of the damping ratio (*ζ*) and the real part of the eigenvalues *(σ)*. The proposed eigenvalue-based objective function is as follows and it is desired to be minimum [36].

$$J_1 = \sum_{i=1}^{k} (\sigma_i - \sigma_0)^2 \ and \ \sigma_i \le \sigma_0 \ \left(\sigma_0 = -1\right) \tag{14}$$

$$J_2 = \sum_{i=1}^{k} (\zeta_i - \zeta_0)^2 \ and \ \zeta_i \ge \zeta_0 \ \left(\zeta_0 = \%10\right) \tag{15}$$

$$J = J_1 + \alpha J_2 (\alpha = 10) \tag{16}$$

Our objective in minimizing the J objective function is to shift the eigenvalues of the system to the left of the s-plane and increase the damping ratio . The domain of the objective functions J_1, J_2 and $J=J_1+\alpha J_2$ is given in Figure 3. The expression J_1 in the objective function J controls the real part of the eigenvalues and generally shifts the system eigenvalues to the left of the imaginary axis in the region smaller than *σ0*. (Figure 3a). Similarly, the expression J_2 in the J objective function brings the damping ratio of the eigenvalues to the desired damping ratio (*ζ0*) and controls the overshoot of the system (Figure 3b). As a result of the tests, it was deemed appropriate to choose the value of the α coefficient as 10 [2,36]. For the design problem, it is necessary to determine the boundaries of the PSS system parameters and these restrictions are as follows:

$$\begin{gathered} 0.1 \le K_p \le 100 \\ 0.01 \le T_i \le 1; \ i = 1,2,3,4 \end{gathered} \tag{17}$$

The proposed design approach tries to find the optimal PSS system parameters *(K_P, T_1, T_2, T_3 and T_4)* by minimizing the $J=J_1+\alpha J_2$ objective function in the optimization problem by using the RUN technique.

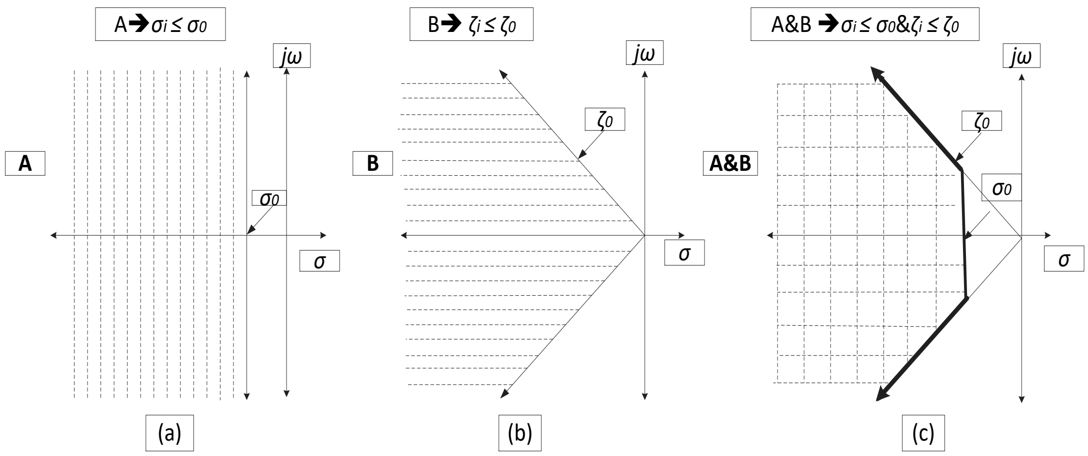

Figure 3. *The domain of the objective functions*

III. RUNGE KUTTA ALGORITHM

A. RUNGE KUTTA ALGORITHM (RUN)

A. 1. Inspiration of RUN

Runge Kutta Algorithm (RUN) is a novel swarm-based optimization algorithm developed by Ahmadianfar et al. in 2017 [35]. RUN is a population-based algorithm inspired by the Runge Kutta (RK) technique and describing the evolution of a group of agents. In RUN, the RK4 method is used to compute the slope and ordinary differential equations. In the proposed algorithm, with the slope calculated, efficient solution areas are explored in the search area, and a set of rules for the evolution of population members is created. The RUN consists of initialization, calculating the maximum or minimum fitness value, determining the minimum in three random individuals, exploring the search area, updating the parameter, and evaluating the fitness value. In RUN, *N* is the number of each member in the population, *D* is the problem size, and *MaxFES* is the maximum iteration number [35].

A. 2. Initialization

Firstly, it is created an initial population in the RUN. In the population of *N* size, *N* positions are chosen randomly. Each member *(n=1,2,3 ,... N)* is a solution for the optimization problem. In RUN, the starting positions are randomly calculated as follows [35]:

$$x_{n,1} = L_l + rand.(U_l - L_l) \tag{18}$$

where, U_i and L_i $l=(1,2,...,D)$ are the lower and upper limits, and *rand* is a random value in the range [0,1].

A. 3. Search Mechanism Root

In any optimization method, the exploration and exploitation models depend on the iteration mechanism. An efficient optimization method uses a set of random solutions in the search space to explore the area that yields the effective solution in the exploration mechanism [38]. According to these random solutions, a search mechanism is created with the RK4 method for global or local search.

In RUN, the coefficient k_1 has defined by the first-order derivative. According to the RK4 method, $x_n + \Delta x$ and $x_n - \Delta x$ are two neighboring positions of x_n . The positions $x_n + \Delta x$ and $x_n - \Delta x$ represent the best and worst positions, respectively, for a *y(x)* minimization problem. The expression $x_n - \Delta x$ equals the best position x_b around x_n , while the expression $x_n + \Delta x$ equals the worst position x_k around x_w . Accordingly, k_1 is defined as [35]:

$$k_1 = \frac{x_w - x_b}{2\Delta x} \tag{19}$$

Here, the x_w (worst) and x_b (best) solutions are determined in each iteration from three individuals selected from among the population members (x_{r1}, x_{r2}, x_{r3}), and $(r_1 \neq r_2 \neq r_3)$. To improve exploring and create random behavior, Eq. (20) is expressed as:

$$k_1 = \frac{1}{2\Delta x}(rand \times x_w - u \times x_b) \tag{20}$$

$$u = round(1+rand)\times(1-rand) \tag{21}$$

Here, *rand* is a random value in the range [0,1]. In general, the best solution (x_b) plays a key role in exploring good solution areas and obtaining the global best solution. Therefore, in RUN, *u* parameters have increased the importance of the best solution (x_b). In Eq. (22), Δx is given as follows [35]:

$$\Delta x = 2\times rand \times |Stp| \tag{22}$$

$$Stp = rand \times \left(\left(x_b - rand \times x_{avg} \right) + \gamma \right) \tag{23}$$

$$\gamma = rand \times (x_n - rand \times (u-l)) \times \exp(-4 \times \frac{i}{Maxi}) \tag{24}$$

Here, Δx *and Stp* are the position increment and step size, respectively. The parameter $\boldsymbol{\gamma}$ is a scale factor and decreases exponentially in the optimization. x_{avg} is the average solutions in each iteration. With the *rand* value, the RUN method can find more diverse search areas, and the other three coefficients (k_2, k_3, and k_4) can be written, respectively, as:

$$k_2 = \frac{1}{2\Delta x}(rand(x_w + rand_1 k_1 \Delta x) - (ux_b + rand_2 k_1 \Delta x)) \tag{25}$$

$$k_3 = \frac{1}{2\Delta x}(rand(x_w + rand_1 \left(\frac{1}{2}k_2\right)\Delta x) - (ux_b + rand_2 \left(\frac{1}{2}k_2\right)\Delta x)) \tag{26}$$

$$k_4 = \frac{1}{2\Delta x}(rand(x_w + rand_1 k_3 \Delta x) - (ux_b + rand_2 k_3 \Delta x)) \tag{27}$$

Here, $rand_1$ and $rand_2$ are two random numbers in the range [0,1]. In RUN, x_w and x_b are calculated by the following expressions [35]:

$$\begin{aligned}
&if\ f(x_n) < f(x_{bi}) \\
&\qquad x_b = x_n \\
&\qquad x_w = x_{bi} \\
&else \\
&\qquad x_b = x_{bi} \\
&\qquad x_w = x_n \\
&end
\end{aligned} \tag{28}$$

where, x_{bi} is the best random solution chosen from among the (x_{r1}, x_{r2}, x_{r3}) and $f(x_n)$ is the fitness value of the current solution. According to Eq. (28), if the $f(x_n)$ is better than x_{bi}, the x_b (best) and x_w (worst) solutions are equal to x_n and x_{bi}, respectively. Otherwise, these expressions are equal to x_{bi} and x_n, respectively. The Search Mechanism *(SM)* is given in Eq. (29) [35]:

$$SM = \frac{1}{6}(x_{RK})\Delta x \text{ and } x_{RK} = k_1 + 2\times k_2 + 2\times k_3 + k_4 \tag{29}$$

A. 4. Updating Solutions

In RUN, optimization starts with a group of random solutions, and these solutions are updated based on positions using the RK method [35].

$$
\begin{aligned}
&if\ \ rand < 0.5 \\
&\quad \textit{(exploration phase)} \\
&x_{n+1} = (x_c) + SF \times SM + \mu \times x_s \\
&else \\
&\quad \textit{(exploitation phase)} \\
&x_{n+1} = (x_m) + SF \times SM + \mu \times x_{s'} \\
&end
\end{aligned}
\tag{30}
$$

where,

$$\mu = 0.5 + 0.1 \times randn \tag{31}$$

where, $\boldsymbol{\mu}$ is a random value, and $randn$ is a random value using a normal distribution. The x_s and $x_{s'}$ are given as:

$$x_s = randn(x_m - x_c) \text{ and } x_{s'} = randn(x_{r1} - x_{r2}) \tag{32}$$

The x_m and x_c are given as:

$$x_m = \varphi \times x_{best} + (1-\varphi) \times x_{best} \text{ and } x_c = \varphi \times x_n + (1-\varphi) \times x_{r1} \tag{33}$$

where, φ is a random value in the range of (0,1), x_{best} is the best solution, and x_{lbest} is the best position for each iteration. The adaptive factor (*SF*) that balances exploration and exploitation is given in Eq. (34):

$$SF = 2(0.5 - rand) \times f \tag{34}$$

$$f = a \times \exp\left(-b \times rand \times \left(\frac{i}{Maxi} \right) \right) \tag{35}$$

Here, *a* and *b* are the constant values, *i* and *Maxi* are iteration and the maximum iteration numbers. Initially, a large SF value is set in the first iteration to improve exploration search; then, by increasing the iterations, the SF is decreased to improve the exploitation ability. According to Eq. (27), a case of $rand<0.5$ means a global search in the solution space and a local search around the solution x_c, while $rand>0.5$ means a local search around x_m. RUN can increase the convergence speed and providing effective solutions with this local search stage. Accordingly, Eq. (30) is restated in Eq. (36) to continue the local search around x_m and x_c and explore effective solution spaces:

$$
\begin{aligned}
& if \;\; rand < 0.5 \\
& \quad \textit{(exploration phase)} \\
& x_{n+1} = (x_c + r \times SF \times g \times x_c) + SF \times SM + \mu \times x_s \\
& else \\
& \quad \textit{(exploitation phase)} \\
& x_{n+1} = (x_m + r \times SF \times g \times x_m) + SF \times SM + \mu \times x_{s'} \\
& end
\end{aligned} \tag{36}
$$

where, r value can be 1 or -1, and it increases the variety by changing the search direction. g is a random value in the range of [0, 2]. According to Eq. (36), the smaller the number of iterations, the greater the local search.

A. 5. Enhanced Solution Quality (ESQ)

Enhanced Solution Quality (ESQ) is used in each iteration to improve solution quality and avoid local optima. With ESQ, each solution moves towards a better position calculating the mean of three random solutions, (x_{new1}) is created. The solution (x_{new2}) using ESQ is as follows [35]:

$$
\begin{aligned}
& if \;\; rand < 0.5 \\
& \quad if \;\; \mathrm{w} < 1 \\
& \quad x_{new2} = (x_{new1} + r.w.\left|\left(x_{new1} - x_{avg}\right) + randn\right| \\
& \quad else \\
& \quad x_{new2} = (x_{new1} - x_{avg}) + r.w.\left|u.x_{new1} - x_{avg}\right) + randn\right| \\
& \quad end \\
& end
\end{aligned} \tag{36}
$$

where,

$$
\begin{aligned}
& \mathrm{w}{=}rand\;\;(0{,}2)\;\exp\left(-c\left(\frac{i}{Maxi}\right)\right) \\
& x_{avg} = \frac{x_{r1} + x_{r2} + x_{r3}}{3} \\
& x_{new1} = \beta \times x_{avg}(1-\beta) \times x_{best}
\end{aligned} \tag{37}
$$

Here, β is the random value in the range [0,1]. c is expressed as $5 \times rand$. w is a random value that is inversely proportional to the iteration increase. r is an integer that can only be 1, 0, or -1. x_{best} is the best solution. For $w<1$ the x_{new2} solution tends to create exploitation search whereas in case of $w \geq 1$ x_{new2} tends to create exploration search. The u parameter is used to increase diversity. ESQ is used when $Rand<0.5$ condition. If the x_{new2} does not have a better fitness value than the existing solution (i.e. $f(x_n) \geq f(x_{new2})$), a new x_{new3} solution is created:

$$
\begin{aligned}
& if \;\; rand < w \\
& \quad \mathrm{x}_{new3} = (x_{new2} - rand.x_{new2}) + SF(rand.x_{RK} + (v.x_b - x_{new2})) \\
& end
\end{aligned} \tag{38}
$$

where, v is expressed as $2 \times rand$ and it is show the importance of x_b . The new solution (x_{new3}) is used for the $rand<w$ condition is fulfilled. The purpose of Eq. (39) is go to the x_{new2} solution for a better

position. It should be noted that the x_b and x_w solutions for calculating x_{RK} are x_k and x_{new2}, because the fitness value of x_n is less than x_{new2} (i.e. $f(x_{new2})>f(x_n)$). The pseudo code of RUN is given as:

The Pseudo-Code of RUN

```
Step 1. Initialization
Start a, b
Create the population. x_n (n=1,2,3…N)
Compute the objective function for all agents.
Compute the x_w, x_b, x_best solutions.
Step 2. RUN Operations
    for i=1:Maxi
        for n=1:N
            for l=1:D
                Compute the x_{n+1,l} position using Eq.(33).
            end for
            Application of the ESQ.
            if rand<0.5
                Calculate the x_new2 position using Eq.(34).
                if f(x_n)<f(x_new2 )
                    if rand<w
                        Calculate the x_new3 position using Eq.(36.)
                    end
                end
            end
            Update the position of x_w and x_b.
        end for
        Update the position of x_best.
        i=i+1
    end
Step 3. Return x_best.
```

B. IMPLEMENTATION OF THE RUN TO THE PSS DESIGN PROBLEM

Step 1: Collect the system uncertainties such as test system, line, generator, bus data, and define the location and parameters of PSS, fault location and duration, etc.

Step 2: Solve Newton Raphson's load flow problem for the test system and obtain the active-reactive powers, voltage, admittance matrix, and all required system sizes for each generator.

Step 3: Initialize the generator, excitation system, and mechanical system magnitudes from the obtained values.

Step 4: Using Eq. (1) - (13), obtain the test system linearized model with the system variable matrix.

Step 5: Start the RUN parameters (*N*, *MaxFES*, etc.). Create the initial population and calculate the objective function for each member of the population.

Step6: Obtain the x_w, x_b, x_{best} solutions and calculate $x_{n+1,l}$, x_{new2} and x_{new3} positions.

Step7: Update the x_w, and x_b, positions and accordingly update the x_{best} position.

Step8: Check parameter limitations for search agent positions and update the objective function if it violates.

Step 9: Check the *Maxi* condition. If the *Maxi* is violated, go to step 10, otherwise, go back to step 5.

Step 10: The best solution for parameter setting is obtained with RUN for the maximum iteration number.

IV. SIMULATION STUDY

In this study, a MATLAB m-file-based model is developed for PSS design with load flow analysis, small-signal stability analysis, and optimization problems. In addition, the results obtained were compared with PSO-based PSS (PSO-PSS), ABC-based PSS (ABC-PSS), and Hybrid-based PSS (HPA-PSS) [36] by analyzing the proposed RUN-based (RUN-PSS) method. The proposed RUN-PSS method has been tested in the WSCC 3-generator 9-bus system in Figure 4.

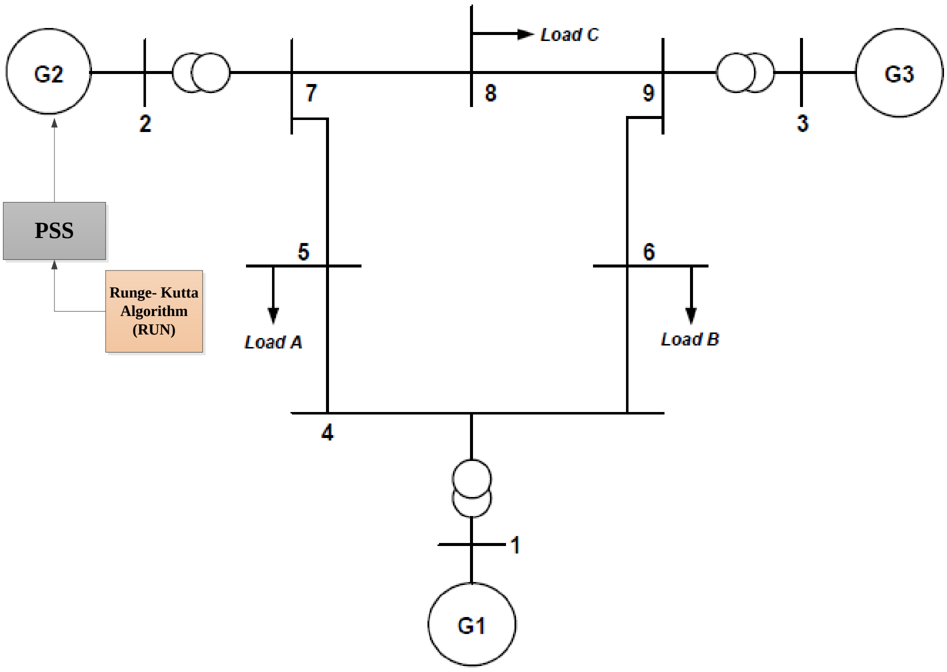

Figure 4. *WSCC 3 machine- 9 bus test system*

In the study, each generator is a fourth-order non-linear shown in the model. The optimum location of the PSS was determined using the participation factor method, and the PSS was placed in Generator 2 (G2) to dampen the local modes of oscillations. The load flow results, bus, line, generator, and excitation data of the power system are given in Table1-Table4 [36].

Table 1. *WSCC 3 machine- 9 bus test system load flow results*

Bus No	Type	Voltage	Angle (Degree)	$-P_L$	$-Q_L$	P_G	Q_G
1	Slack	1.0400	0	0	0	0.7164	0.2705
2	PV	1.0250	9.2800	0	0	1.6300	0.0665
3	PV	1.0250	4.6648	0	0	0.8500	-0.1086
4	PQ	1.0258	-2.2168	0	0	0	0
5	PQ	0.9956	-3.9888	1.2500	0.5000	0	0
6	PQ	1.0127	-3.6874	0.9000	0.3000	0	0
7	PQ	1.0258	3.7197	0	0	0	0
8	PQ	1.0159	0.7275	1.0000	0.3500	0	0
9	PQ	1.0324	1.9667	0	0	0	0

Table 2. *WSCC 3-machine 9-bus test system line data.*

Line No.	From Bus	To Bus	*R*	*X*	*B*	*Tap*
1	1	4	0	0.0576	0	1.0000
2	2	7	0	0.0625	0	1.0000
3	3	9	0	0.0586	0	1.0000
4	4	5	0.0100	0.0850	0.0880	1.0000
5	4	6	0.0170	0.0920	0.0790	1.0000
6	5	7	0.0320	0.1610	0.1530	1.0000
7	6	9	0.0390	0.1700	0.1790	1.0000
8	7	8	0.0085	0.0720	0.0745	1.0000
9	8	9	0.0119	0.1008	0.1045	1.0000

Table 3. *WSCC 3-machine 9-bus test system generator data.*

Gen. No	*H*	*D*	R_s	X_d	X'_d	X_q	X'_q	T'_{d0}	T'_{d0}
1	23.6400	0	0	0.1460	0.0608	0.0969	0.0969	8.9600	0.3100
2	6.4000	0	0	0.8958	0.1198	0.8645	0.1969	6.0000	0.5350
3	3.0100	0	0	1.3125	0.1813	1.2578	0.2500	5.8900	0.6000

Table 4. *WSCC 3-machine 9-bus test system excitation data*

Gen No.	K_A	T_A	E_{fd}^{max}	E_{fd}^{min}
1	100	0.05	7.3	-7.3
2	100	0.05	7.3	-7.3
3	100	0.05	7.3	-7.3

In this paper, PSS was designed only for G2 in the test system, and therefore five parameters were optimized. The RUN algorithm was run in the MATLAB program using the power system linearized model to determine the optimal values of the PSS parameters. In addition, the RUN algorithm for parameter optimization of the stabilizer is compared with the PSO-PSS, ABC-PSS, and HPA-PSS to show the dynamic stability performance and superiority. The optimum PSS parameters are given in Table 5.

Table 5. *Optimized PSS parameters*

Method	K_p	T_1	T_2	T_3	T_4
PSO-PSS [36]	13.9341	0.1072	0.9604	0.7490	0.0100
ABC-PSS [36]	26.8082	0.3341	0.2663	0.2566	0.0100
HPA-PSS [36]	5.0788	0.6887	0.0148	0.5806	0.5632
RUN-PSS	5.0799	0.6000	0.0199	0.5800	0.5699

In this study, to show the effectiveness of the RUN, eigenvalue analysis is realized for the WSCC 3-machine 9-bus test system, and the eigenvalues and damping ratios obtained depending on the optimized PSS parameters using the RUN algorithm are given in Table 6. Here, only lightly damped oscillation modes are analyzed, as they are accountable for the oscillating behavior of the system. These eigenvalues moved away from the imaginary axis using RUN-PSS compared with other methods. In addition, when compared in terms of damping rates, it is seen that RUN-PSS generally gives more effective results compared to other methods. According to these results, it can be stated that RUN-PSS gives a more effective dynamic performance than others.

Table 6. *Eigenvalues and damping ratios of electromechanical modes*

Method	**Eigenvalues**	**Damping ratios**
Without PSS [36]	-0.3831±8846i	0.0485
	–1.3738±11.7499i	0.1161
PSO-PSS [36]	–2.1240±13.0167i	0.1610
	–1.7668±8.1986i	0.2107
ABC-PSS [36]	–2.4971±10.2878i	0.2359
	–2.1924±6.2926i	0.3290
HPA-PSS [36]	–3.1273±10.6730i	0.2812
	–2.2671±5.5054i	0.3808
RUN-PSS	**-5.9335 + 18.864i**	**0.30005**
	-2.433 + 5.9188i	**0.38020**

V. CONCLUSIONS

In this paper, a new optimization approach based on a RUN algorithm with balanced exploration and exploitation capability, inspired by Runge Kutta (RK4) technique, is presented to increase power system stability through optimal tuning of the PSS controller. In the design problem of PSS parameters, a multi-objective function based on eigenvalue and damping ratio was used to improve the small-signal stability performances of the power system. Then, the RUN technique was successfully applied to find the optimum parameters of the power system stabilizer. The performance of the proposed power system stabilizer (RUN-PSS) was tested in the WSCC 3-machine 9-bus power system by comparisons with PSO-PSS, ABC-PSS, and HPA-PSS methods. Given that the results achieved from the test system, it is noticed that the proposed RUN method is the most effective one among all tested methods for the system stability according to the criteria of both eigenvalue analysis and damping ratio.The implementation of the proposed algorithm to larger-scale power systems and the use of different controllers are within the scope of further work to be done in the future.

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