A Novel PSO Based Fuzzy Controller for Robust Operation of Solid-State Transfer Switch and Fast Load Transfer in Power Systems

GLORRIA SEBASTIAN¹, M. A. HANNAN¹, ALI Q. AL-SHETWI², PIN JERN KER³, M. S. A. RAHMAN¹, M. MANSUR¹, AND K. M. MUTTAQI⁴, (Senior Member, IEEE)

¹Department of Electrical and Electronic Engineering, Universiti Tenaga Nasional, Kajang 43000, Malaysia
²Electrical Engineering Department, Fahad Bin Sultan University, Tabuk 71454, Saudi Arabia
³Institute of Sustainable Energy, Universiti Tenaga Nasional, Kajang 43000, Malaysia
⁴School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Wollongong, NSW 2522, Australia

Corresponding author: M. A. Hannan (hannan@uniten.edu.my)

This work was supported in part by the Tenaga Nasional Berhad under UNITEN Research and Development Sdn. Bhd., Universiti Tenaga Nasional, under Project U-TD-RD-19-20; and in part by the UNITEN Bold Refresh Publication Fund 2022 under Grant J510050002-IC-6 BOLDREFRESH2025-Centre of Excellence.

ABSTRACT This paper proposes a novel particle swarm optimization (PSO) algorithm based fuzzy logic controller (FLC) for improving the performance of automatic solid-state transfer switch (SSTS) with respect to transfer time. The proposed technique generates adaptive membership functions (MFs) of voltage error and rate of change of voltage error for input and output based on the fitness function formulated by the PSO. An optimal PSO-based FLC (PSOF) fitness function is further employed to tune and minimize the mean absolute error (MAE) to improve the performance of the load transfer in a short duration. Results obtained from the proposed PSOF are compared with those obtained with the conventional FLC to validate the developed controller. It is observed that the proposed PSOF optimized controller can transfer the load faster than the conventional FLC controller. The accuracy of the developed PSOF is illustrated and investigated via simulation tests for SSTS in the IEEE 9-bus system. It can be concluded that the PSOF controller is better than the only fuzzy controller in all tested cases in terms of transfer time.

INDEX TERMS Automatic solid-state transfer switch, fuzzy control, optimization algorithm, power transfer, load transfer, power system faults.

I. INTRODUCTION

Disturbances are spreading widely in the power sector, for example, voltage sags, surges, lightning strikes, and other interferences that contribute to power reliability issues. Thus, the SSTS of a distribution network is designed to transfer the power from an unhealthy feeder to a healthy feeder under a fault condition so as to keep the electricity feeding to the customers. The current switches in the power system are mostly mechanical/ electro-mechanical, or automatic switches, which take long cycles (longer time) to transfer power from one feeder to another feeder. Additionally, this conventional switching approach incorporates a number of power quality (PQ) problems. Moreover, it takes time for the mechanical switches to clear the fault in the system [1]. To solve the aforementioned concerns, this study will optimize control of the solid-state transfer switch (SSTS) in order to ensure fast load restoration with minimum time. Solid state circuit breakers provide no reliability or lifetime issues as opposed to electromechanical circuit breakers. In this context, scientists consider the SSTS as a potential move to solve the PQ issues [1], [2], in a wide range of low-, medium-, and large-scale industries [3]. The SSTS consists of a pair of anti-parallel thyristors to ensure two ways of the load current flow to ensure the negative and positive cycles in work [4]. Because of the flexible and adjustable configuration of SSTS system, it is commonly employed to improve existing power quality issues, particularly for sensitive loads [5]. The basic structure of SSTS configuration includes the preferred source, alternative source, control logic scheme comprising the voltage detection scheme, transfer signal, and the sensitive load as illustrated in Fig.1 [6].
To enhance the control performance of the SSTS, various controllers have been used. For instance, the fuzzy logic controller (FLC) has replaced other controllers owing to the former’s improved control of the speed and mechanical load, allowing such controllers to exhibit excellent performance in transient reduction and control. However, the performance of FLCs depends on the membership functions (MFs), the number of rules and the rule basis [7]. These variables are determined by a time-consuming trial-and-error approach [8].

![Figure 1: The basic structure of the SSTS system.](image)

There is a growing interest in developing diagnostic techniques based on fuzzy logic [9]. Fuzzy logic is, in reality, a very effective tool for converting uncertain and incorrect data. It is regarded as the finest approach for dealing with uncertainties and allowing the solution of some falseness [10]. The progressive nature of membership to a fuzzy set allows this technique to account for uncertainty. Thus, the FLC is used as an active solution in faulty detection systems, resulting in increased operational dependability in industrial and power systems while lowering operating and maintenance costs. However, multiple faults are becoming increasingly common as power systems industrial applications get more sophisticated [11]. In this regard, the FLC can detect the faults, but for accurate faults detection, the fuzzy membership function parameters need to be optimized using an optimization algorithm for better efficiency [12].

In the literature, various optimization techniques, such as ant colony optimization (ACO) [13], genetic algorithm (GA) [14], and differential evaluation (DE) [15], have been proposed to improve the FLC controller performance and regulate its parameters. However, because they have a single solution search area, the particle swarm optimization (PSO) algorithm can reach an optimal solution in a shorter amount of computing time than the GA technique. The advantages of PSO are that the particle changes its speed in accordance with its own flight experience and the flight experience of others in the swarm to speed up to highly objective (fitness) locations during the previous iterations. The technique does not need a differentiable or continuous objective function and may address a wide range of optimization challenges in nonlinear and non-continuous scenarios. In everyday use, a particle accelerates towards two sorts of positions. The first is termed \( P_{\text{best}} \), a particle’s best personal position up to the current iteration. The other is the best global position all particles have achieved so far, named \( G_{\text{best}} \) [16]. The PSO is available in many forms of literature. For better convergence speed, we picked the one with a constraint factor [17], [18].

Different optimization techniques have been applied to enhance the SSTS operation for fault detection and transfer time. For instance, fault diagnosis SSTS using based on GA optimized neural proposed in [19]. The results show that the neural network optimized by GA has higher diagnostic efficiency and accuracy than without GA. The transient state analysis and faults detection of SSTS using GA is proposed in [20]. The results demonstrated that the proposed optimized SSTS using GA has fair accuracy for fault detection. In [21], optimized FLC-based GA for fast transfer time in two areas of generation showed good performance. Fast time of fault isolation using optimized SSTS control is introduced by [22]. However, these optimization algorithms have drawbacks such as complex parameter calculation and formulation, coding complexities, and a longer computing time to obtain the best fitness value. In addition, the development of an FLC-based optimization method to overcome the complexity and high convergence rate is not sufficiently covered. Moreover, a fast and robust power transfer method using SSTS has not been discussed extensively in the literature.

Therefore, this paper focuses on studying the transfer time, fast fault detection, overall system improvement, and comparison with optimized FLC using PSO. This study proposes PSO to optimize the fuzzy membership function due to its advantages, such as its high robustness to control parameters, global convergence capabilities, speed, ease of implementation, and computational efficiency compared with mathematical algorithms and other heuristic optimization techniques. In addition, it can solve the limitations of FLC and enhance its performance. Furthermore, fuzzy-based structure strategy gives more flexibility, fast, and precise behavior in control action when optimized using PSO. For the better and fast operation of the SSTS, the FLC system will be in command for the transfer signals and rapid fault detection. The control circuit of the SSTS system contains the voltage detection scheme, the FLC approach optimized by the PSO to increase the efficiency and accuracy of fault detection and reduce the transfer time switching from the primary source to an alternative power source. As demonstrated in this study, FLC-based PSO optimization algorithm may play a significant role in achieving the fast and optimal fault detection and fast transfer of SSTS in the power system. This will decrease the impact caused by power disruption leading to power quality issues and financial losses. Thus, the proposed FLC-PSO control for SSTS has reduced the disruption and led to power system stability. The aims and contribution of this paper can be summarized as follows:

- The main aim of this paper is to optimize the SSTS system using FLC-PSO to attain better performance in detecting the faults precisely and consequently do fast power transfer from unhealthy feeder to healthy feeder. The novelty of this paper is in terms of the application of FLC-PSO in SSTS to yield accurate detection and speedy transformation between the power feeders.
- Propose novel PSO based FLC for robust operation of SSTS and fast load transfer in power systems. For this purpose, the FLC of the SSTS system is presented to overcome the shortcomings of conventional approaches, and the PSO is utilized to optimize the operation of FLC and reduce its inaccuracy for better SSTS operation.
- The fuzzy-based advance model of SSTS system has been simulated under different load conditions and real-time systems such as IEEE 9 BUS system to increase the SSTS effectiveness towards fast acting under different conditions.
- The fuzzy-based optimized controller in the SSTS system is designed and optimized based on PSO, which is responsible for parameterizing the membership function to reduce error more precisely than the non-optimized fuzzy logic controller. This AI method is an effective approach with less complexity and high accuracy as compared to conventional controllers towards the efficient and perfect operation of the SSTS system.
- To show the effectiveness of the proposed method, the simulation models are run under different voltage sag conditions and compared with non-optimized system and optimized system. The obtained results showed an accurate and good performance of the SSTS system as compared to other methods.

II. OPTIMIZED FUZZY CONTROLLER FOR SSTS

The SSTS fuzzy system allows the errors to be measured and recorded through a voltage detection scheme (voltage value - \( V_e \)). This scheme analyzes, detects, and evaluates it as an error or normal value through the FLC (\( V_e \) and \( dV_e \)). Accordingly, the controller can generate a pulse to the SSTS to turn ON or OFF. The rule-based method is used to investigate the control process. The interface engine subsystem is responsible for the execution of the fuzzy rules defined in the system. Defuzzification is the process of obtaining a single number from the output of the aggregated fuzzy set. It is used to transfer fuzzy inference results into a crisp output. The fuzzy membership function, constrained to be between zero and one (\( X \rightarrow [0,1] \)), reflects the degree of similarity between the data value at that location and the prototypical data value, or centroid, of its class. Due to the system’s ambiguity, it is difficult to determine whether the measured error is erroneous or typical. This is because the insensitive membership function affects the correctness and persistency of the membership function. Here, optimization is required to give parameterization for the membership functions’ parameters. Thus, the PSO is used to adjust the parameters of the fuzzy membership function on each iteration simulated. In this regard, the fitness value is calculated. Then, by using the parameters’ boundary range, swarm positions are randomly generated and the initial \( P_{\text{best}} \) is set. Next, each particle’s fitness value is calculated by using the objective function (MAE). During an iteration, the best fitness value is computed to obtain the best \( P_{\text{best}} \) among all the particle’s \( P_{\text{best}} \) and to assign it as \( G_{\text{best}} \). PWM, in brief, uses the relative width of pulses in a train of on-off pulses to adjust the level of FLC-PSO applied to the STSS. The controller is optimized offline because no online data is needed in the SSTS system. The optimized fuzzy approach is tested with the SSTS system, and the results were discussed. Then, the FLC-PSO is cooperated with the power system to evaluate its efficiency during fault occurrence. Fig. 2 below shows the single diagram of a power system incorporated with SSTS and the optimized controller (PSO-FLC) for the SSTS system.

Voltage errors extracted from the voltage detection scheme is run through the FLC system. Both errors, voltage error (\( V_{\text{error}} \)) and the rate of change of voltage error (\( dV_{\text{error}} \)) goes through PSO before defuzzification takes place. The output from the controller goes through the gating scheme containing the pulse generator (PWM) that outputs binary numbers as 1 and 0 for ON and OFF, respectively, directing to the SSTS switches. PWM generator outputs a pulse to fire the thyristor switch of the SSTS. The SSTS must receive the signal in binary output. Thus, the PWM play a vital role in the control system. The pulse generator uses a stimulator circuit which is dependent and sensitive. In this case, the stimulator circuit represents the generated output from the optimized fuzzy (FLC-PSO), which will be sent to the PWM to process and convert the obtained output from decimal to binary output synched in real-time and frequency. This is because the SSTS system must perform the switching action when the fault occurs.

A. FUZZY RULES AND MEMBERSHIP

In this section, the role of FLC is applied in the modelling of STSS systems. The rules established for the fuzzy system were 49 rules. For instance, as for Rule number 1, if \( V_{\text{error}} \) falls under NB, voltage range and \( dV_{\text{error}} \) under NB voltage range, the fuzzy logic output is a binary of 0 to stop conducting. As a result, the preferred switch will be switched OFF, and the alternative switch will be switched ON. As for Rule 2, when the obtained \( V_{\text{error}} \) falls under NM and the obtained \( dV_{\text{error}} \) under NB, the binary output will be 0, triggering the preferred switch to be switched OFF simultaneously triggering the alternative source’s switch to turn ON. Moving on Rule 7, when the \( V_{\text{error}} \) falls under range ZE and \( dV_{\text{error}} \) falls under ZE the binary output will be 1, signalling the preferred switch with a binary output of 1. Thus, the preferred switch will remain switched ON and the alternative switch will remain OFF. Here, both the errors in \( V_{\text{error}} \) and \( dV_{\text{error}} \) are in the normal range, remaining ON. The obtained information will pass through pulse generator which produces a signal to initiate the transfer process when a fault is detected. Finally, moving on to the final Rule, Rule 49, when the \( V_{\text{error}} \) falls under range PB and \( dV_{\text{error}} \) falls under PB, the binary output will be 0 signaling the preferred switch to be fuzzy logic outputs as a binary output of 0. Therefore, the preferred switch will be switched OFF and the alternative switch will be switched ON.
FIGURE 2. Block diagram of the PSO-FLC SSTS system.

TABLE 1. Fuzzy controller membership functions.

| \( V_{error} \) | NB | NM | NS | ZE | PS | PM | PB |
|----------------|----|----|----|----|----|----|----|
| \( dV_{error} \) | NB | NB | NB | NB | NM | NS | ZE |
| NB | NM | NB | NB | NM | NS | ZE | PS |
| NM | NS | ZE | PS | PM | PB | PB |
| NS | ZE | PS | PM | PB | PB | PB |
| ZE | PB | PB | PB | PB | PB | PB |

1) OPTIMAL MEMBERSHIP FUNCTIONS
The seven-membership function generates more rules, which may be able to capture more errors precisely. The more the number of fuzzy sets is formed, the more the number of rules that may be defined, increasing the complexity and processing required in implementations. Thus, a more accurate approximation can be obtained by defining more fuzzy sets for each input or output known as membership functions [30]. Table 1 shows the rule base (49 rules) for this system which carries seven sets of membership functions for each input and output.

2) RULE BASED SYSTEM
Fig. 3 and Fig. 4 show the membership function of inputs and output for FLC without PSO and with PSO, respectively. As illustrated in Figure 5, 21 membership functions were utilized in this system: seven for each input and output. The linguistic error variable is defined to have seven fuzzy sets, NB, NM, NS, ZE, PS, PM, and PB with associated membership functions as left trapezoidal, followed by five triangles, and right trapezoidal. The seven sets in the output demonstrate the severity of error that will pass through the threshold in the gating scheme producing binary output: 1 and 0 for ON and OFF, respectively.

B. FUZZY BASED PSO ALGORITHM
The basic PSO algorithm principle assumes the search space is D-dimensional and the population size is M. Swarm is a population of possible solutions found in PSO. In PSO, particles are known as a swarm of possible solutions. Every particle has a location in the optimization problem’s search space [31]. Using PSO to optimize the FLC for optimal detection and transfer of SSTS, the inputs’ parameters and the output’s membership functions parameters are optimized in this study.

1) INITIALIZATION
A total of 50 particles makes up the initial swarm population. Random values are used to produce the initial locations and
velocities of the particles. Each particle’s initial fitness value is set to a large positive constant. The current fitness value is set as the local best of each particle ($P_{besti}$). The best value of all ($P_{best}$) is assigned as the global best value of the position ($G_{best}$) [32].

2) FITNESS FUNCTION

The fitness function, often known as the objective function, is a population’s performance index. The Mean Absolute Error (MAE) is widely used as an objective function to get the optimal solution for the optimization process. It is a very good key performance indicator to measure accuracy. The lower the MAE, the higher the accuracy of a model [22], [33]. Based on [22], the MAE is a more natural measure of average error, and unlike root mean square error (RMSE) is unambiguous. The MAE is used as a metric for assessing the accuracy of an optimization technique and can be calculated as per power quality issues and financial losses. [33]. In this study, the PSO-based FLC fitness function is used to optimize and reduce the MAE (reduced to zero) to enhance the load transfer performance in a short period of time.

$$MAE = \frac{\sum_{n=1}^{N} |\hat{X}_n - X_n|}{N}$$  \hspace{1cm} (1)

where $\hat{X}_n$ represents prediction rating and $X_n$ is the real rating in the testing set of data. However, the number of rating prediction pairs between the testing data and the prediction outcomes is denoted by $N$. In terms of the problem in this study; the aim is to have proper fault detection decision. As a result, the fitness function applied fixes the rate of the fault detection error, which should be kept to a minimum. The PSO optimization constrains the overlap between the MFs. The variables or problem dimensions ($X_{ij1}$ to $X_{ij7}$), ($X_{ij8}$ − $X_{ij14}$) and ($X_{ij15}$ − $X_{ij21}$) shall not cross over between input and output. The following equation shows the restriction of this optimization:

$$X_{ij}^{f-1} < X_{ij}^f < X_{ij}^{f+1}$$  \hspace{1cm} (2)

Now the constraints for the fuzzy MF optimization can be expressed as follows:

$$e_{\min} \leq e(t_i) \leq e_{\max}$$  \hspace{1cm} (3)

$$e_{\min} \leq e_{opt-min} \leq e_{\max}$$  \hspace{1cm} (4)

$$e_{\min} \leq e_{opt-max} \leq e_{\max}$$  \hspace{1cm} (5)

$$\Delta e_{\min} \leq \Delta e(t_i) \leq \Delta e_{\max}$$  \hspace{1cm} (6)

$$\Delta e_{\min} \leq \Delta e_{opt-min} \leq \Delta e_{\max}$$  \hspace{1cm} (7)

$$\Delta e_{\min} \leq \Delta e_{opt-max} \leq \Delta e_{\max}$$  \hspace{1cm} (8)

where $e_{\min}$, $e_{\max}$, $e(t_i)$, and $e_{opt}$ represent the minimum, maximum, time, and optimization errors. The $\Delta e$ depicts the difference in errors obtained [34]–[37]. With the help of the proposed PSO optimization, the FLC can be improved further to reduce the power transfer time and perform fast power transfer.

3) PSO ALGORITHM

In PSO, a swarm of $N$ particles wanders across a confined search area to find the best solution for a given problem based...
on a specified fitness function. PSO consider two components to exploit and regulate cooperation inside the swarm: (a) the social attraction, which encourages particle collaboration; and (b) the cognitive attraction, which encourages a particle to depend on its own experience. The variables known as social \((c_{soc})\) and cognitive \((c_{cog})\). Furthermore, an inertia factor \((w)\) is used to weigh the inertia of particles. The magnitude of their velocities is clamped to a specified threshold \((v_{\text{max}})\) to explore the search space effectively. When distinct velocity values are assigned along the \(D\) dimensions of the search space, a vector \((v_{\text{max}} \ldots , v_{\text{max}})\) may be created. As many other optimization methods, PSO’s performance is highly dependent on the appropriate configuration of the key variable parameters [35].

The first location is the best point where the swarm finds the current iteration (local best). The second location is the best position found through all previous iterations (global best). For example, it is appeared below that the position \(X\) of \(D\) particle and speed \(V\) of \(D\)-particle are part of a space that has \(N\) parameter and \(D\) particle which means is \(N\) dimensional space. The following equations respectively represent the \(i^{th}\) Particle, \(G_{\text{best}}, v_{\text{best}},\) velocity and speed particles.

\[
P_{\text{best}} = p_{1}, p_{2}, p_{3}, \ldots, p_{i N} \quad (9)
\]

\[
G_{\text{best}} = g_{1}, g_{2}, g_{3}, \ldots, g_{i N} \quad (10)
\]

\[
X_{i} = x_{1}, x_{2}, x_{3}, \ldots, x_{i N} \quad (11)
\]

\[
V_{i} = v_{1}, v_{2}, v_{3}, \ldots, v_{i N} \quad (12)
\]

The velocity and position will be updated by using the following equations [27]:

\[
V_{i}^{k+1} = \omega V_{i}^{k} + c_{1} r_{1}(P_{\text{best},i}^{k} - X_{i}^{k}) + c_{2} r_{2}(G_{\text{best}} - X_{i}^{k})
\]

(13)

\[
X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1}
\]

(14)

where \(i = 1, 2, 3 \ldots, D\); and \(n = 1, 2, 3 \ldots, N\), \(w\) is inertia weight, the learning factors \(c_{1}\) and \(c_{2}\) are positive acceleration constants. The \(r_{1}\) and \(r_{2}\) stand for random numbers ranging from 0 to 1, while \(V_{i}^{k+1}\) and \(X_{i}^{k+1}\) represent the updated velocity vector and the updated location, respectively.

It is essential to mention that the \(P_{\text{best}}\) is the best previous experience of \(i^{th}\) particle that is recorded and \(G_{\text{best}}\) is the best particle (informant) among the entire population. A detailed description of the developed PSO used in this study is shown in Pseudo-Code below. A thorough description of the developed PSO used in this study is shown in Fig. 5. The first place is the ideal place where the swarm is present (local best). The best position discovered via all prior rounds is the second location (global best). Each particle’s velocity and location in the PSO is updated to the new value recorded for each iteration. This method is continued up to the maximum number of iterations or better than the target value until the algorithm gets the required fitness.

### III. RESULTS AND DISCUSSIONS

The simulation test of the SSTS system is carried out with the fuzzy approach and an optimized fuzzy approach (FLC based PSO) via MATLAB/Simulink. Four sets of different voltage sags are simulated as 100%, 50%, 25%, and 10% voltage sags. The total time of simulation is 0.2s and the fault is induced at 0.1s to 0.2s. The load used is a balanced load of \(R, L,\) and \(C\). The PSO optimizes the fuzzy approach. The first step is to determine the membership function parameters, which are important in detecting faults and non-faults errors. By adjusting the parameters of the membership functions, the system runs to determine the faulty feeder, which then proceeds to produce pulse through the gating scheme. The discussed results consist of various voltage sags with the fuzzy approach (FLC) and optimized fuzzy approach (FLC-PSO) of SSTS incorporated with the IEEE 9 BUS system. As many other optimization methods, the PSO parameters have been determined via the initialization process of the optimization. These parameters are determined based on the iteration, weight, input and output data of the problem, the dimension, and convergence speed [15], [33], [35]. Initialization is the process of locating and using the defined values for variable data that is used by the algorithm simulation. In the simulation, Table 2 shows the parameter data of initialization PSO parameters:

| Parameters | \(N\) | \(C_{1}\) | \(C_{2}\) | \(\omega\) |
|------------|------|------|------|------|
| Values     | 1mm  | 0.5  | 0.5  | 0.5  |

**FIGURE 6.** Convergence graph of particle swarm optimization.

The optimized fuzzy using PSO is applied to reduce the error. In this context, the MAE is computed and matched with the preceding values. Thus, as per Eq. (1), the PSO optimization process obtains the optimal values of FLC parameters at the 44th iteration, producing zero MAE, as shown in Fig.6. The gating scheme is necessary for the system. This is because the load transfer system is designed to transfer the load in the shortest time while avoiding source parallelising throughout the transfer process. When a defect is detected in the preferred feeder, a signal is delivered to the SSTS switches to ON the preferred side, causing the switches on the alternative side. The output (0)
indicates that the switch will be turned off when a defect is detected, hence commencing the transfer process. However, output (1) indicates that the switch will be turned on when the disturbance is cleared. The voltage detection input (the fault has occurred or not) is transferred to the FIS system for further analysis and produces a random value between 0 and 1. Next, the gating scheme will select the precise output, which will be a binary output. Accordingly, the gating scheme signal will be inverted and sent to the other feeder through a NOT gate. As a result, the signal will be transferred simultaneously from the malfunctioning feeder to the healthy feeder.

FIGURE 7. Fuzzy output from the optimized fuzzy logic controller.

FIGURE 8. Pulse generated based on optimized fuzzy output.

In this gating technique, the PWM serves as a time step. This is done to ensure that the resulting output is a binary output for the SSTS, regardless of the value received from the FIS output, as shown in Figs. 7 and 8. The intelligence works of analyzing and fast decision-making operation belong to the FLC. The absence of the pulse generator or the PWM will result in the SSTS failure to switch ON and OFF, or do power transfer, as illustrated in Fig. 9. It is worth mentioning that, as the NOT gate belongs to the logic family, the SSTS must receive the signal in binary output [38].

FIGURE 9. Transfer signal from the errored fuzzy output.

A. 100% FAULT CASE SCENARIO

The voltage and current profile of a 100% voltage sag fault (voltage dropped to zero) is shown in Fig. 10. Simulation time was 0.1 sec. The voltage has been reduced to near zero, while the current in the main feeder is extremely high. With constant power, when voltage depletes, the current shoots up. The fault parameters are set by adjusting the fault resistance to induce 100% voltage sag. The voltage and current profiles will be sampled through the voltage detection scheme. Fig. 11 shows the zoomed version of Fig. 10 in which the voltage and current values are not entirely zero per unit (pu). Thus, the voltage at normal conditions is 1 pu (normal value). The voltage value after the fault has occurred is approximately 0.2 pu due to a phenomenon known as voltage sag. The current value before the fault is approximately 0.1 pu, which is the healthy reading before the fault. When the fault occurs, the current increases up. The voltage and current profile are when the fault occurs, not after the circuit gets disconnected. The voltage and current profiles show a visual representation of the phenomenon and changes when the fault occurs, such as high surges, spikes, harmonic imbalance, transfer time is taken for power transfer, phase shift, phase jump, and delay in the detection time.

Receiving the sample of 100% voltage sag, the voltage detection scheme will extract the errors of \( V_{\text{error}} \) and \( dV_{\text{error}} \), as shown in Fig. 12. In direct-quadrature-zero (dq0) transformation, the zero component is neglected as it produces harmonics. The voltage vector is further transformed into a rotating dq-coordinate system. The amplitude of the vector supply is calculated and compared to the reference voltage to filter out the voltage error and the rate of change of the voltage error. These two signals obtained serve as inputs
to the FLC to be further analyzed for decision making. However, the NOT gate allows the alternative source to be simultaneously switched ON as soon as the preferred SSTS is turned OFF. The optimized fuzzy system with PSO (FLC-PSO) in Fig. 13(b) showed the error if the fault happens. The alternative source supplied from 0.1s to 0.2s. Thus, the total transfer time taken was less than approximately 0.5ms. Here, it can be concluded that FLC-PSO reached the optimum membership function to detect faults as fast as possible. Thus, the negative values of the voltage error and the rate of change of voltage error represent the voltage sag occurrence.

Figures 14(a) and (b) show the load voltage and current for 100% voltage sag when the fuzzy approach is used without PSO. The delayed detection time of the fault has an impact on the load voltage. In this regard, even if 100% of the voltage sag has been repaired with an alternative supply, the gap will occur when there is no voltage supply, and a very high spike of current occurs, as shown in Fig. 14(b) from 0.1 to around 0.103 s. This phenomenon is known as surge current and is caused by a voltage imbalance. The current profile can be easily influenced as the input current contains a power frequency component and harmonic components with frequencies equal to a multiple of the power frequency. This harmonic distortion of the current leads to harmonic components in the supply voltage [36].

Fig. 15 (a) below shows the voltage and current profile of a 100% voltage sag when the optimized fuzzy (PSO-FLC)
is applied. When the fault occurs at 0.1sec, the optimized FLC using PSO could detect the sag quicker than the FLC without the PSO implementation. This is because the main goal of PSO is to optimize the membership function and make the best decision, as shown in Fig. 15(b). It can be seen that phases A, B, and C are impacted differently. There is a different impact on each phase, as in Fig. 15 (a) and (b).

Moreover, the recovery is different for different types of faults, especially unbalanced faults. This is due to the imbalance faults that occurred. It also relies on whether transformers are present between the fault and the voltage sag, as well as the significant change between the jumping of the phase-angle [36], [39].

**B. 50% FAULT CASE SCENARIO**

The voltage and current profile for 50% voltage sag is shown in Fig. 16. The 50% voltage sag is induced by adjusting the fault resistance value, $R_{on}$. The fault is applied between 0.1sec and 0.2sec. The 50% voltage sag has caused a high fluctuation in the current as a result of the voltage drop.

**FIGURE 16. Voltage and current of 50% sag.**

The 50% voltage sag will be defined through the voltage detection scheme, producing two errors: voltage error and the rate of change of voltage error, as illustrated in Fig. 17. The non-faulty duration (normal operation) is between 0s and 0.1s, in which the acceptable error range will be $\pm 10\%$ for both voltage error and the rate of change of voltage error. The gating generated from the gating scheme will be sent as a pulse to the SSTS. The FLC without PSO delays the detection by about 4.25ms, as illustrated in Fig. 18 (a). This delay is caused by the un-tuned MF, which prevents or delays accurate error detection. The effectiveness of the optimized controller is shown in Fig. 18 (b); once PSO tunes the FLC, a negligible amount of detection time (almost 0s) leads to a total transfer time of 8.72ms, while the FLC without the implementation of PSO has a total transfer time of 13.07ms.

**FIGURE 17. $V_{error}$ and $dV_{error}$ signals.**

**FIGURE 18. (a) Transferred signals for SSTS without PSO. (b) Transferred signals for SSTS with PSO.**

The load profile for voltage and current in the case of 50% voltage sag without the implementation of PSO is
shown in Fig. 19(a). The recovery has differed following different faults, especially unbalanced faults, as illustrated in Fig. 19(b). The current profile has some noise in the recovery period. Noise can be generated by power electronic devices, control circuits, arc welders, switching power supplies, radio transmitters, etc. Moreover, poorly grounded sites make the system more susceptible to noise [40]. It also depends on whether there are transformers between the breakdown and the dip or even between phase-angle shifting. This is also due to the occurrence of imbalance faults. The measurement of both voltage and current for all the simulations is conducted in per unit. Because these systems rely on inaccurate data, inputs, and approximate membership functions set up by a trial-and-error method without using PSO tuning, there will be errors in the computational data because it is a simulation. This factor would add to the generated load voltage and current profiles based on the MF set.

C. PERFORMANCE OF IEEE 9-BUS SYSTEMS

The nine IEEE bus system simulations were simulated using two sets of SSTS at bus 3 to investigate the voltage and current profile during fault conditions. The controller follows the two feeders of the SSTS system, which consists of a voltage detection scheme, FLC, and gating scheme. Fig. 21 shows the 100% voltage sag induced by applying the fault block in MATLAB/Simulink via adjusting the $R_{on}$ value. It represents the unhealthy feeder. By inducing such a fault at 0.1s to 0.2s, the voltage profile shows a sag of almost zero, but there is still a small voltage supply available since two other generators are connected on bus 1 and bus 2.

The fault affected the voltage in terms of sags; however, the 100% voltage sag has caused a vertical shift, phase shift, and amplitude change as in the current profile. It also affects if the transformers are found between the breakdown and drop or even the phase angle is changes. The vertical shift for phase A can be known as the phenomenon of DC offset, which can get the transformers heated, ground fault current, nuisance tripping caused by faulty rectifiers, and power supplies. The DC offset happens when the fault is applied at 0$^\circ$ on the phase A voltage, and it implies that there is a minimal to almost negligible voltage value in the system. The current must be maximal in an inductive circuit when the voltage is almost zero. Since the voltages of the other two phases (B and C) are not at 0$^\circ$ as phase A, the phases restore differently to the same fault applied. DC current, typically owing to the lack of correctives within several AC to DC conversion technologies that have proliferated in modern facilities, might be induced into an AC distribution system. DC may pass through the AC power system and add undesired current to operating equipment at its rated level. Transformers can be overheated and saturated by flowing DC currents. When the transformer saturates, it is heated and unable to supply full load power. Thus further instability can be created in the load.

Fig. 22 depicts the behavior and response of nearby buses to Bus 3, which is Bus 9. The voltage rating of this bus is 230kV. Bus 9 has a total transfer time of 19ms, although the
minimal supply starts at 0.1ms. When the primary bus 3 is turned off, the alternative bus 3 is managed to supply as a backup source. Except for the spark between the load transfer, this bus has recovered well. In this regard, phase A recovered within 0.1ms, phase B recovered within 15ms, and phase C recovered within 19ms. Finally, it can be noticed that the recovery is different for various types of faults, especially unbalanced faults.

The voltage and current profile on bus 6 are illustrated in Fig. 23. This figure illustrates the impact of fault in bus 3 towards bus 6, which has a total transfer time of approximately 17ms. Phase A has the least impact compared to phases B, and C. Fault clearing does not always occur simultaneously for the three phases. The angle of the fault current will be different for different types of faults as generally circuit breakers clear a fault when the fault current has a zero crossing. The current profile has slight fluctuations and phase shifts as well. This is because of the fault, which caused the transmission and distribution systems to have the most frequent fluctuations in voltage and current. Any high load could cause this.

### D. PERFORMANCE COMPARISONS

1) COMPARISON BETWEEN FLC AND FLC BASED PSO

The FLC is applied to control the SSTS system to overcome the limitations of conventional methods. However, the FLC produces errors that cannot be avoided in this critical situation, especially in the sensitive load. Thus, the optimized FLC using the PSO algorithm has reduced the errors. Also, the MF would be optimized by PSO to obtain accurate and fast power transfer that is tested under different faults. Table 3 shows the data collection for the simulation of the SSTS system in MATLAB/Simulink. It can be seen that a 100% means the severed fault has a shorter transfer time compared to the lesser severed fault, e.g., 50%, 25%, 10%. Overall, the transfer time under different fault conditions such as 100%, 50%, 25%, 10% of voltage sags varies.

When 100% voltage sag happens, the frequency disruption is quite high, and the phase jump is high. Therefore, the response of voltage logic is very sensitive to the change occurring and causes difficulties in quick detection. This is because the voltage detection scheme used in this system is based on the d-q transform, which is highly influenced by frequencies. However, implementing the PSO shows a significant difference and a reduction in transfer time, which shows the proposed method’s effectiveness.

2) PERFORMANCE COMPARISON WITH EXISTING YLITERATURE

A comparison of the proposed technique with the recent techniques related to SSTS system control is conducted in Table 4 to validate and show the effectiveness and efficiency of the proposed technique. The comparison is made in terms of the preferred and alternate sources, configuration, control method, switching time, application, and load condition.

It can be noticed that the proposed method achieved less switching time. In addition, the proposed technique was not only tested with RLC load but also considered sensitive load with a real-time system such as the IEEE 9 bus, and showed better performance. It also tested under different voltage sags and was sensitive to the occurrence of faults and errors. Compared to the proposed technique, which provided rapid, efficient, and accurate fault detection and power transfer with zero error, the combination of traditional methods assessed in the table created inconvenient errors in terms of restoration and power transfer. However, the FLC has some constraints in detecting errors significantly. So, an optimization of the membership function of FLC is done using PSO to precisely capture errors and then reduce the detection time, which minimizes the total transfer time. The proposed model’s disadvantage is the complexity reduction compared to the existing configuration.

| Voltage Sags (%) | Transfer Time (ms) | Total Transfer Time reduced (ms) |
|------------------|--------------------|----------------------------------|
| 100              | ~ 2.00             | ~ <0.5                           | ~ 2.00                          |
| 50               | ~ 13.07            | ~ 8.72                           | ~ 4.35                          |
| 25               | ~ 11.56            | ~ 7.88                           | ~ 3.68                          |
| 10               | ~ 10.88            | ~ 7.32                           | ~ 3.56                          |
TABLE 4. Proposed SSTS controller performance comparison with existing systems.

| Refs. | Preferred & alternate source | Configuration | Control | Objective | Method | Switching time | Application | Load condition |
|-------|-----------------------------|---------------|---------|-----------|--------|----------------|-------------|----------------|
| [23]  | 10 kV | Thyristor-based transfer switch | Intelligent microprocessor control system | Fault isolation for ultra-fast protection system | Forced current commutation | 6.2 ms | Industrial | Sensitive Load-No detail |
| [24]  | 12.5 kV | Solid-State Distribution Switch | Phase locked loop | Transition of microgrid power sources | Park’s transformation | 8 ms | Induction motor | RL load |
| [25]  | 12 kV | Thyristor-based transfer switch | UPS | Fast isolation for protection in distribution systems | Thyristor base | 4.03 ms | Computers | RL load |
| [26]  | 12kV | Thyristor-based transfer switch | Synchronous Reference frame controller | Transfer sensitive load from one source to another with least time to protect industrial load | Thyristor base | 5.0 ms | Industrial | RL load |
| [27]  | 11 kV | Thyristor-based transfer switch | Voltage detection scheme and gating strategy | Provide connection to alternate sources | Thyristor base | 4 ms | Industrial customer | LC load for HV side and LV side |
| [28]  | 10 kV | Thyristor-based transfer switch | HATS | Reduce inrush current during the start-up process | Thyristor-based/ sag detection | 19.2 ms | Industrial | RL load |
| [29]  | 11kV | Thyristor-based transfer switch | SRF | Protect loads against power quality problems | Thyristor-based | 5 ms | Industrial/ grid Arrangement | RL load |
| Proposed method | 11kV | Thyristor-based transfer switch | PSO based FLC controller & Robust Power Transfer | Thyristor-Based | 2ms | Distribution Line | Sensitive load, IEEE 9 BUS system |

IV. CONCLUSION AND FUTURE WORK

This paper proposes a novel fuzzy logic controller (FLC) and an optimized fuzzy with particle swarm optimization (FLC-PSO) approach for fault detection and fast power transfer. The fuzzy system is efficient, accurate, and simple in computing fault and voltage regulation. However, the key concern with the fuzzy logic systems is poor analytical design (like parameterization of the membership functions). Therefore, the proposed method provides an enhancement to the controller by using the PSO technique to adjust the parameters of the fault detection system in terms of membership functions, resulting in more precise error detection. The detection inputs are adjusted perfectly through PSO. A three-phase simulation of the SSTS system illustrates that PSO implementation leads to more significant results (transfer time reduction) than without the implementation of PSO application. The optimized controller employed the fitness function in order to tune and minimize the MAE to almost zero, improving the performance of the load transfer in a short time. The zero MAE indicates the effectiveness of the optimization process. A comparison was made between FLC and FLC-PSO to demonstrate the optimised controller’s efficacy. Results obtained from the FLC-PSO are compared with those obtained with FLC to validate the developed controller. In this regard, the optimized controller (FLC-PSO) reduced the transfer time to 0.5 ms, 4.35 ms, 3.68 ms and 3.56 ms as compared to FLC without optimization, which was 2 ms, 13.07 ms, 11.56 ms, and 10.88 ms during 100%, 50%, 25% and 10% voltage sag, respectively. In sum, the simulation results show a good illustration of proper voltage detection as well as transfer time differences between FLC and FLC-PSO. However, there could be some suggestions for further research and development as follows:

- Optimize the FLC of SSTS systems using other optimization methods and compare them with the PSO proposed in this study for fast fault detection and fast load transfer.
- Test and improve the controller sensitivity by introducing several faults and loads conditions.
- The impact of SSTS controller on solving power quality issues such as harmonic distortion, voltage imbalance, voltage spike, voltage fluctuation, very short interruptions, and noise should be investigated.
- The fault current distribution system is rapidly growing, so faster protection is required. Therefore, SSTS needs a protection scheme to avoid equipment failure due to faults. Also, coordination and optimization techniques with respect to various integration controls should be investigated for ensuring efficient power system operation.
- The use of semiconductors in switching devices can also be developed in application areas such as high-voltage, high-frequency, and high power applications. Thus, SSTS will greatly impact the industry moving forward.
- In microgrids, to improve the utilization and reliability, and facilitate the integration of DC loads and sources such as PV or battery storage systems, etc. SSTs could be tested as key components acting as DC-DC or DC-AC converters in such hybrid grids.
- The optimized SSTS controller can be applied in the case of the renewable energy-connected grid as the penetration of these systems arises quickly.

REFERENCES

[1] M. Bajaj and A. K. Singh, “Grid integrated renewable DG systems: A review of power quality challenges and state-of-the-art mitigation techniques,” Int. J. Energy Res., vol. 44, no. 1, pp. 26–69, Jan. 2020.
[2] M.-J. Tsai, Y.-Y. Shen, J. Zhou, and P.-T. Cheng, “A forced commutation method of the solid-state transfer switch in the uninterrupted power supply applications,” IEEE Trans. Ind. Appl., vol. 56, no. 2, pp. 1609–1617, Mar. 2020.
[3] J. Yao, A. Abramovitz, Y. Wang, H. Weng, and J. Zhao, “Safe-triggering-region control scheme for suppressing cross current in static transfer switch,” Electr. Power Syst. Res., vol. 125, pp. 245–253, Aug. 2015.

[4] S. Agalar and Y. A. Kaplan, “Power quality improvement using STS and DVR in wind energy system,” Renew. Energy, vol. 118, pp. 1031–1040, Apr. 2018.

[5] S. A. M. Saleh, C. Richard, X. F. S. Onge, K. M. McDonald, E. Ozkop, L. Chang, and B. Alsaidy, “Solid-state transformers for distribution systems—Part I: Technology and construction,” IEEE Trans. Ind. Appl., vol. 55, no. 5, pp. 4524–4535, Sep. 2019.

[6] M. S. Molluk, M. A. Hannan, P. J. Ker, M. Faisal, M. S. A. Rahman, M. Mansur, and M. S. H. Lipu, “Review on solid-state transfer switch configurations and control methods: Applications, operations, issues, and future directions,” IEEE Access, vol. 8, pp. 182490–182520, 2020.

[7] T. Sutikno, A. C. Subrata, and A. Elkhateb, “Evaluation of fuzzy membership function effects for maximum power point tracking technique of photovoltaic system,” IEEE Access, vol. 9, pp. 109157–109165, 2021, doi: 10.1109/ACCESS.2021.3102050.

[8] M. A. Kacimi, O. Guenounou, L. Brikh, F. Yahiaoui, and N. Hadid, “New mixed-coding PSO algorithm for a self-adaptive and automatic learning of Mandani fuzzy rules,” Eng. Appl. Artif. Intell., vol. 89, Mar. 2020, Art. no. 103417.

[9] J. C. Bezekd, D. Dubois, and H. Prade, Fuzzy Sets in Approximate Reasoning and Information Systems: New York, NY, USA: Springer, 2012.

[10] D. Wu, H.-T. Zhang, and J. Huang, “A constrained representation theorem for well-shaped interval type-2 fuzzy sets, and the corresponding constrained uncertainty measures,” IEEE Trans. Fuzzy Syst., vol. 27, no. 6, pp. 1237–1251, Jun. 2019, doi: 10.1109/TFUZZ.2018.2874018.

[11] M. R. Zaidan, “Power system fault detection, classification and clearance by artificial neural network controller,” in Proc. Global Conf. Advancement Technol. (GCAT), Oct. 2019, pp. 1–5, doi: 10.1109/GCAT47503.2019.8978400.

[12] M. A. H. Sadi, A. AbuHussein, and M. A. Shoeb, “Transient performance improvement of power systems using fuzzy logic controlled capacitive-brige type fault current limiter,” IEEE Trans. Power Syst., vol. 36, no. 1, pp. 323–335, Jan. 2021.

[13] B. Liu, Y. Zha, and T. Zhang, “D-Q frame predictive current control methods for inverter stage of solid state transformer,” IET Power Electron., vol. 10, no. 6, pp. 687–696, May 2017.

[14] R. S. Mongrain, “On enhancing microgrid control and the optimal design of a modular solid-state transformer with grid-forming inverter,” Arizona State Univ., Tempe, AZ, USA, Tech. Rep. Mongrain_asu_0010E_19434, 2019.

[15] E. H. Houssein, A. G. Gad, K. Hussain, and P. N. Suganthan, “Major advances in particle swarm optimization: Theory, analysis, and application,” Swarm Evol. Comput., vol. 63, Jun. 2012, Art. no. 100868.

[16] Z. Shi, W. Yao, L. Zeng, J. Wen, J. Fang, X. Ai, and J. Wen, “Convolutional neural network-based power system transient stability assessment and instability mode prediction,” Appl. Energy, vol. 263, Apr. 2020, Art. no. 114586.

[17] H. Shi, H. Wen, Y. Hu, Y. Yang, and Y. Wang, “Efficiency optimization of DC solid-state transformer for photovoltaic power systems,” IEEE Trans. Ind. Electron., vol. 67, no. 5, pp. 3583–3595, May 2020.

[18] T. O. Olowu, H. Jafari, M. Moghaddami, and A. I. Sarwat, “Multiphysics and multiobjective design optimization of high-frequency transformers for solid-state transformer applications,” IEEE Trans. Ind. Appl., vol. 57, no. 1, pp. 1014–1023, Jan. 2021.

[19] L. Zhang and X. Zeng, “Research on transformer fault diagnosis based on genetic algorithm optimized neural network,” J. Phys., Conf. Ser., vol. 1848, no. 1, Apr. 2021, Art. no. 012004.

[20] M. Bigdeli and E. Rahimpour, “Optimized modeling of transformer in transient state with genetic algorithm,” Int. J. Energy Eng., vol. 2, no. 3, pp. 108–113, May 2012.

[21] V. Jain, E. Nsugbe, and S. Gupta, “A GA optimized fuzzy logic controller for two area automatic generation control under dynamic behavior of power system,” in Proc. 4th Int. Conf. Comput. Intell. Commun. Technol. (CCICT), Jul. 2021, pp. 9–13.

[22] C. J. Willmott and K. Matsumura, “Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance,” Climate Res., vol. 30, no. 1, pp. 79–82, 2005.

[23] C. Peng, X. Song, M. A. Rezaei, X. Huang, C. Widener, A. Q. Huang, and M. Steurer, “Development of medium voltage solid-state fault isolation devices for ultra-fast protection of distribution systems,” in Proc. 40th Annu. Conf. IEEE Ind. Electron. Soc. (IECON), Dallas, TX, USA, Oct. 2014, pp. 5169–5176.

[24] C. Li and T. Shengxue, “Solid-state AC breaker with parallel switched capacitor circuits for microgrid system,” J. Chin. Inst. Eng., vol. 42, no. 8, pp. 748–756, Nov. 2019.

[25] M. A. Hannan, A. Mohamed, and A. Hussain, “A simulation model of solid-state transfer switch for protection in distribution systems,” J. Appl. Sci., vol. 6, no. 9, pp. 1993–1999, Apr. 2006.

[26] M. R. Javed, T. Mahmood, and M. A. Choudhry, “Performance analysis of static transfer switch using MATLAB/simulink,” in Proc. Power Gener. Syst. Renew. Energy Technol. (PGSRET), Islamabad, Pakistan, 2015, pp. 1–5.

[27] H. Mokhtari, S. B. Dewan, and M. R. Iravani, “Analysis of a static transfer switch with respect to transfer time,” IEEE Trans. Power Del., vol. 17, no. 1, pp. 190–199, Jan. 2002.

[28] X. Zhang, Y. Xu, A. Siddique, Y. Long, and X. Xiao, “A microprocessor resource-saving dual active bridge control for startup and restart of three-stage modular solid-state transformer,” IEEE Trans. Power Del., vol. 35, no. 3, pp. 1443–1454, Jun. 2020.

[29] B. Tian, C. Mao, J. Lu, D. Wang, Y. He, Y. Duan, and J. Qiu, “400 V/1000 kVA hybrid automatic transfer switch,” IEEE Trans. Ind. Electron., vol. 60, no. 12, pp. 5422–5435, Dec. 2013.

[30] T. Mahmood and M. A. Choudhry, “Performance improvement of complementary feeders using static transfer switch system,” J. Zhejiang Univ.-Sci. A, vol. 10, no. 2, pp. 189–200, Feb. 2009.

[31] X. Li, K. Mao, F. Lin, and X. Zhang, “Particle swarm optimization with state-based adaptive velocity limit strategy,” Neurocomputing, vol. 447, pp. 64–79, Aug. 2021.

[32] J. A. Ali, M. A. Hannan, A. Mohamed, and M. G. M. Abdolrasol, “Fuzzy logic speed controller optimization approach for induction motor drive using backtracking search algorithm,” Measurement, vol. 78, pp. 49–62, Jan. 2016.

[33] M. Abdolrasol, R. Mohamed, M. Hannan, A. Al-Shtewi, M. Mansor, and F. Blaabjerg, “Artificial neural network based particle swarm optimization for microgrid optimal energy scheduling,” IEEE Trans. Power Electron., vol. 36, no. 11, pp. 12151–12157, Nov. 2021.

[34] M. S. Nobile, P. Cazzaniga, D. Besozzi, R. Colombo, G. Mauri, and G. Pasi, “Fuzzy self-tuning PSO: A settings-free algorithm for global optimization,” Swarm Evol. Comput., vol. 39, pp. 70–85, Apr. 2018.

[35] H. Wang, M.-J. Peng, A. Ayodeji, H. Xia, X.-K. Wang, and Z.-K. Li, “Advanced fault diagnosis method for nuclear power plant based on convolutional gated recurrent network and enhanced particle swarm optimization,” Ann. Nucl. Energy, vol. 151, Feb. 2021, Art. no. 107934.

[36] J. Li, Z. Teng, Q. Tang, and J. Song, “Detection and classification of power quality disturbances using double resolution S-transform and DAG-SVMs,” IEEE Trans. Instrum. Meas., vol. 78, pp. 2302–2312, Oct. 2016.

[37] S. D. Patil, R. A. Kachare, A. M. Mullla, and D. R. Patil, “Performance enhancement of modified SVC as a thyristor binary switched capacitor and reactor banks by using different adaptive controllers,” J. King Saud Univ.-Eng. Sci., vol. 5, no. 10, pp. 11–19, Jun. 2021.