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Determination of optimal control coefficients for Dynamic Voltage Restorer (DVR) based on Non-dominated Sorting Bird Swarm Algorithm (NSBSA)

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ABSTRACT

One of the useful solutions to improve power quality under fault conditions in power systems is the use of Dynamic Voltage Restorer (DVR), which has recently gained attention due to its high performance and easy implementation. The DVR structure uses a Proportional-Integral (PI) controller, which can help improve the performance of this device if optimally designed. In this paper, a novel hybrid optimization algorithm called Non-dominated Sorting Bird Swarm Algorithm (NSBSA) is proposed to determine the optimal control coefficients of the PI controller used in the DVR device. The optimization objectives are minimization of voltage sag and total harmonic distortion (THD) of the voltage signal. For simplicity of implementation, the objective function quantities are defined as fuzzy using fuzzy membership functions. Finally, by determining the optimal control coefficients of the DVR, the performance of this device is evaluated. Simulation results in MATLAB/Simulink environment show that the optimized controller designed using the proposed NSBSA algorithm is able to reduce the voltage sag and THD by about 15% and 13% respectively, compared to the best results reported in the literature.

KEYWORDS: Dynamic Voltage Restorer (DVR), Bird Swarm Algorithm (BSA), Non-dominated Sorting Genetic Algorithm (NSGA), Voltage Sag, Total Harmonic Distortion.

1. INTRODUCTION

Nowadays, with the increase in sensitive loads [1], the demand for stable and high-quality electrical power has increased significantly. In competitive industrial environments, the tendency of production units to use power electronics devices, computer processors, and non-linear loads is on the rise. On the other hand, any interruption or deviation in the quality of the delivered power can lead to economic losses. These economic losses can be examined from various aspects such as lost competitive opportunities for the producer, efficiency, production cost, product quality, equipment lifetime, repair costs, and production downtime. Therefore, achieving high-quality electricity can not only impact economic savings, but also the profitability of a production facility [1]. Disturbances in the power distribution system can cause problems such as outages, sags, swells, and voltage flicker. Among the above disturbances, the most important one is voltage sag, which is defined by the IEEE standard as a sudden decrease in voltage within the range of 10 to 90 percent for a duration of 0.5 cycles to 1 minute [2]. This problem occurs as a result of natural phenomena in the form of asymmetric system faults and electromagnetic phenomena in the form of inrush currents. 'Custom Power' devices have been introduced to compensate for the harmful effects of disturbances on sensitive loads. Among these devices, the Dynamic Voltage Restorer (DVR) is capable of compensating for voltage sags. The simple structure of the DVR consists of an energy storage source, a voltage source inverter, and a coupling transformer. The DVR, by detecting voltage sags in the feeder connected to the sensitive loads, generates an appropriate voltage signal using the coupling transformer, which is connected in series with the sensitive loads, and injects the proper voltage to the system, thus reducing the effect of the voltage sag. The control system of the DVR plays an important role in its response speed and performance. The main objective of the control system is to maintain a constant voltage at the point where the sensitive load is connected [3]. The analysis of the performance and control of the DVR, with different control strategies, has been studied and investigated by researchers. Most of the published works on the DVR have used a conventional Proportional-Integral (PI) controller in the synchronous frame [4]. The classical PI method has poor performance because it cannot achieve zero steady-state error. This problem is more evident when the reference voltage is a sinusoidal signal due to the bandwidth limitation [5]. Therefore, control strategies such as predictive control [6], sliding mode control [7], and robust control [8] have been employed to control the injected voltage of the DVR. In many studies, intelligent techniques have been focused on for the control of DVR-based compensators. Fuzzy logic control [9] has been investigated for DVR control, and the improvement of transient and steady-state performance of the controller using this control model has been evaluated. The performance of the fuzzy logic controller is very useful as it does not require an accurate mathematical model. An adaptive control model has been implemented in [10] with the capability of simple DVR control. In [11], a bi-objective optimization based on artificial neural networks has been used to determine the PI controller coefficients. This method has been proposed by combining the neural network and the classical Proportional-Integral controller to address the shortcomings of the classical PI. Although the control models presented in similar studies are capable of reducing the problems caused by voltage sags in sensitive loads, most of these approaches have not considered the reduction of voltage THD. In many sensitive loads such as medical equipment and adjustable-speed motors, this level of sensitivity can be very important. Most recent research has tried to use a stable controller in the system. These controllers must respond optimally to different fault conditions. To have proper performance against voltage sag of sensitive loads and voltage THD, a new control structure based on an optimal PI controller is proposed in this study. Voltage sag and voltage THD can be improved simultaneously using the proposed model. Previously, in [12], the standard bi-objective Particle Swarm Optimization (PSO) algorithm and the Chaotic Adaptive Particle Swarm Optimization (CAPSO) algorithm have been studied for tuning the PI controller in the DVR. Also, the optimization of PI coefficients using the Adaptive Gradient-based Least Mean Squares (LMS) algorithm has been proposed in [13] to improve the performance of the DVR.

In this paper, a hybrid metaheuristic algorithm called the Non-dominated Sorting Bird Swarm Algorithm (NSBSA) is proposed to determine the PI coefficients. It will be shown that the proposed method can be effective for DVR control. To evaluate the performance of the proposed controller, the results are compared with the results obtained from tuning the PI coefficients using the bi-objective PSO and CAPSO algorithms, as well as the classical PI controller.

2. DVR Topology and its Operation

The DVR is one of the 'Custom Power' devices in the distribution system that is connected in series with the transmission line. The load voltage is balanced by injecting controlled three-phase voltages during a disturbance in the power system. Therefore, the operation of the DVR is based on the injection of the appropriate voltage during the occurrence of a voltage sag in order to compensate for it. The operation of the DVR can be classified into two modes: standby mode and injection mode [14]. In the standby mode, a low magnitude voltage is injected into the system to cover the voltage drop due to the transformer reactance. In the second mode, the DVR injects the appropriate voltage into the three-phase lines in the event of a significant voltage sag. The DVR circuit consists of five main components as shown in Figure 1:

(1) Series transformer: The primary winding is connected to the inverter and the secondary winding is connected to the distribution system and the sensitive load.

(2) Voltage source inverter: The inverter is connected to the injection transformer. Energy storage devices are considered for the inverter. The inverter consists of Insulated Gate Bipolar Transistor (IGBT) switches that are switched using Pulse-Width Modulation (PWM) technique.

(3) Energy storage devices: Includes power storage sources such as batteries, capacitor banks, superconducting magnetic energy storage, and flywheels used to provide voltage and compensate for sags.

(4) Passive filter: Linear filters based on a combination of resistors, inductors, and capacitors. These filters are collectively known as passive filters and are usually connected towards the high-voltage side of the inverter to eliminate the harmonics generated by switching.

(5) Control system: The control system logic is based on detecting voltage sags and executing appropriate switching strategies for the inverter. The control system often uses the *abc-dq* transformation to calculate v_d and v_q. Under balanced conditions, v_d=1 and v_q=0, however, during fault conditions, these voltages change [14]. The variations in these signals can be controlled by comparing them with their reference values and applying the error signals to a PI controller.

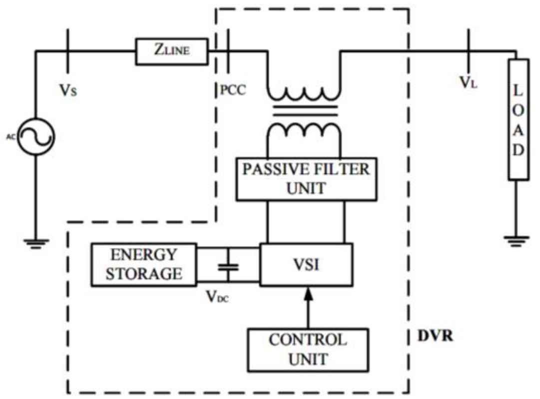

Figure 1: DVR Topology

3. PROPOSED CONTROL METHOD

3. 1. Fuzzy Formulation of Objective Functions

In most multi-objective optimization problems, the objective functions are not of the same nature, which creates challenges in solving such problems. One effective solution to overcome this issue is to use fuzzy membership functions to fuzzify the objective functions. With this method, despite the heterogeneity of the original functions, the equivalent fuzzy quantities are of the same nature, making the implementation of the optimization algorithm easier.

In this study, each objective is defined as a membership function in the fuzzy set environment, and then, using appropriate weighting factors, they are combined into a fuzzy objective function [15]. Therefore, this objective function is a linear combination of two objectives: voltage sag and *THD*. The corresponding membership functions for each objective function are shown in Figure 2. In this study, triangular membership functions are considered for voltage sag (VS) and total harmonic distortion (*THD*). The fuzzy quantity of each objective function is defined based on Equation (1):

$$\mu_x = \frac{A_l}{A_l + A_r} \tag{1}$$

In this equation, μ_x is the fuzzy quantity, A_l and A_r represent the allowable and unallowable areas corresponding to the objective function, respectively. By dividing the allowable area by the total area, the fuzzy quantity corresponding to each objective function is calculated, and the final linear combination is defined as Equation (2):

$$F = w_1\mu_{VS} + w_2\mu_{THD} \tag{2}$$

In this equation, w_1 and w_2 are the weighting factors. By determining these coefficients, the degree of importance of each objective function can be set. It should be noted that these coefficients are non-negative, and their sum is equal to 1. By minimizing the objective function (2), the performance of the DVR is improved, and therefore, the optimal PI controller coefficients can be determined in a way that minimizes the function _F_. It should be noted that the maximum values of _VS_ and THD in the fuzzy functions are set based on the requirements and topology of the power system.

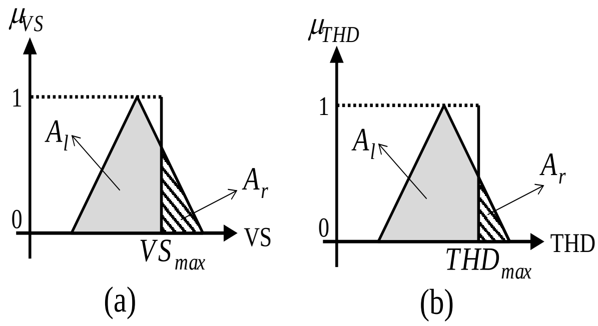

Figure 2. Membership functions corresponding to each objective function. (a) Average voltage drop, (b) Total harmonic distortion

3-2. Non-dominated Sorting Genetic Algorithm (NSGA)

The Genetic Algorithm (GA) is a common algorithm for solving optimization problems, inspired by the biological modeling of living organisms. In this algorithm, the characteristics of the organisms are modeled as an objective function, and using a set of operators called mutation and crossover, these characteristics are optimized over the subsequent generations. The Non-dominated Sorting Genetic Algorithm (NSGA) is essentially the multi-objective form of the classic GA. The steps of this algorithm are summarized as follows [16]:

1) Initialize the population.
2) Evaluate the fitness or objective function
3) Rank the population based on the dominance criterion
4) Calculate the crowding distance (CD)
5) Combine the initial population and the newly generated population through the mutation and crossover process
6) Replace the parents with the best individuals from the combined population. In the first step, the members with lower

fitness values are replaced with the previous parents, and then they are sorted based on CD. The initial population and the population resulting from the application of mutation and crossover operators are first ranked based on the fitness, and then those with lower fitness are eliminated. In the next step, the remaining population is re-ranked according to the crowding distance.

7) Repeat this process until the algorithm's termination condition is met. The termination condition can be based on the limit of the number of iterations or the fitness condition.

9) It should be noted that the CD factor is a parameter used to select the solutions from the set of possible solutions. The following assumptions hold regarding the CD:

- The crowding distance between the start and end points of the set of possible solutions is assumed to be infinity.
- For each assumed point on the set of possible solutions, the crowding distance is determined according to the following equation:

$$CD[i] = \frac{\left(f_m^{i+1} - f_m^{i-1}\right)}{\left(f_m^{max} - f_m^{min}\right)} \qquad (3)$$

In this equation, $CD[i]$ is the crowding distance of the i-th individual on the set of possible solutions F, f_m^i is the value of the m-th objective function for the i-th individual on the front F, and f_m^{min} and f_m^{max} are the minimum and maximum values of the m-th objective function on the front F, respectively. The solution with the highest CD among the set of possible solutions will be selected as the optimal solution. The flowchart of the NSGA algorithm is shown in Figure 3. In this figure, the "Offspring" refers to the population generated from the parent population.

3. 3. Bird Swarm Algorithm (BSA)

Birds typically fly in flocks and their search is carried out collectively. This behavior follows simple rules such as separation, alignment, and cohesion. Collective search allows birds to gather more information about the food path and improve the efficiency of the search process in the flock. Flocking is a natural response of birds to predator threats; this behavior, along with constantly raising their heads and scanning the surrounding environment, is called the "vigilance" phase. Therefore, birds in a flock have a better chance of identifying potential predator threats compared to individual birds. As the flock size increases, each bird spends more time foraging individually, as it has to choose between foraging and vigilance behavior at any given time. Birds on the edge of the group are more prone to being preyed upon than those in the center. Therefore, each bird tries to reach the center of the flock to reduce the risk of predator attacks. This movement is affected by the interference caused by competition among the bird groups. Therefore, birds may not directly move towards the center of the flock.

During the vigilance and foraging behaviors, birds may fly to a new location. After arriving at a new location, the search for food begins. Usually, there are two groups of birds in the flock: the producers and the scroungers. The producer birds are constantly searching for food, while the scrounger birds feed on the food found by the producers. Birds typically switch between these two groups periodically. Overall, these flocking behaviors increase the chances of each bird's survival and foraging success. All these behaviors originate from a swarming intelligence, which inspires a new optimization method that can be used to solve optimization problems. Considering the above behaviors, the following rules can be mentioned: Here is the continued translation of the section on the Bird Swarm Algorithm (BSA):

1) Each bird can periodically switch between vigilance and foraging behaviors. This choice can be modeled as a random decision variable.

2) During the foraging phase, each bird can quickly record the best result from its previous flight experience or update it if a better result is obtained. This social information is instantly exchanged among all the bird groups.

3) In the vigilance phase, each bird tends to move towards the center of the flock. This behavior is accompanied by a series of interferences resulting from the competitive behavior of the birds. Birds with more stored information who play the role of producers tend to move towards the center of the flock, while birds with less stored information remain on the periphery.

4) Birds may occasionally fly to other locations. The bird with the most stored information will be the producer, and the bird with the least stored information will be the scrounger. Other birds randomly switch between these two states.

5) Producer birds are constantly looking for food and going towards the center of the flock, while scrounger birds are always chasing the producer birds.

Considering the above rules, an accurate mathematical model for these social behaviors can be presented. Let's consider a flock of N birds, where the current position of each bird at time t is defined as x_i^t (i∈[1,...,N]). Rule (1) can be shown as a random decision variable. If the random number rand (0,1) is less than the foraging probability P∈(0,1), the bird will exhibit foraging behavior. Otherwise, the bird will exhibit vigilance behavior. Each bird searches for food based on its previous experience and the previous experience of the flock. Therefore, rule (2) can be written as:

$$x_{ij}^{(t+1)} = x_{ij}^{t} + C(p_{ij} - x_{ij}^{t})(rand(0,1)) + S(g_i - x_{ij}^{t})(rand(0,1)) \tag{4}$$

where j∈[1,...,D], D is the dimensions of the search space, C and S are two positive numbers called cognitive and social acceleration coefficients, p_{ij} is the previous best position of bird i, and g_i is the previous best position in the flock among all birds. According to rule (3), each bird tends to move towards the center of the flock, and in this movement, it inevitably has to compete with other birds. This rule is mathematically expressed as Equation (5):

$$x_{ij}^{(t+1)} = x_{ij}^{t} + A_1(mean_j - x_{ij}^{t})(rand(0,1) + A_2(p_{kj} - x_{ij}^{t})(rand(-1,1)) \tag{5}$$

where,

$$A_1 = a_1 e^{\left(-\frac{pFit_i}{sumFit+\varepsilon} \times N\right)} \tag{6}$$

$$A_2 = a_2 e^{\left(\left(\frac{pFit_i - pFit_k}{|pFit_i - pFit_k| + \varepsilon}\right)\left(\frac{pFit_k}{sunFit+\varepsilon} \times N\right)\right)} \tag{7}$$

where, k(k≠i) is a positive integer randomly selected between 1 and N, a_1 and a_2 are positive constant values in the range [0,2], p^{Fiti} represents the best fitness value of bird i, and *sumFit* is the sum of the best fitness values of the bird flock. ε is a very small number used to prevent division by zero. mean is also a D-dimensional vector whose elements are the average positions of all birds, and meanj is the j-th element of this vector. More details on these equations are provided in [17]. Rule (4) distinguishes between producer and scrounger birds. The behavior of these two groups can be mathematically modeled using the following equations:

$$x_{ij}^{(t+1)} = x_{ij}^{t} + x_{ij}^{t}(randn(0,1)) \tag{8}$$

$$x_{ij}^{(t+1)} = x_{ij}^{t} + FL(x_{kj}^{t} - x_{ij}^{t})(rand(0,1)) \tag{9}$$

where, rand (0,1) is a Gaussian random number with a mean of 0 and a standard deviation of 1. $FL \in [0,2]$ is a factor that determines the behavior of scrounger birds in chasing the producers to search for food. The pseudocode of the BSA algorithm is presented in "Algorithm 1".

Input:
N, the number of birds.
T, the maximum number of iterations (time steps).
P, the foraging probability for an individual bird.
FQ, the number of fighting behaviors for an individual bird.
C, *S*, a_1, a_2, *FL*, the constant parameters.
1. Evaluate the fitness of _N_ individuals and identify the best solution
2. While (_t < T_)
   If FQ ≠ 0
      For i = 1: N
         If rand(0,1)<P
Perform foraging behavior, otherwise,
Perform vigilance behavior,
Else
   For _i = 1: N_
      If individual i is a producer,
Perform producer behavior, otherwise
Perform scrounging behavior,
3. Compute the new fitness values.

4. If the new fitness values are better than the previous ones, update the solutions and re-identify the best solution.
5. t = t +1
Output: The best solution with the best objective function value in the population.

Finally, the flowchart of the proposed method for tuning the control parameters of the DVR based on the NSBSA algorithm can be depicted as shown in Figure 4. Based on this flowchart, the voltage sag and THD can be obtained from the MATLAB/Simulink software. These values are converted into fuzzy quantities using Equation (1). Then, the resulting fuzzy quantities are placed in the fitness function of the optimization algorithm defined in (2). This process is executed for each bird in the NSBSA algorithm and in each iteration of the optimization algorithm. This process continues until the termination condition of the algorithm is met. In this case, the final solution of the algorithm, i.e., the optimal values of the PI controller coefficients, is obtained and applied to the DVR controller.

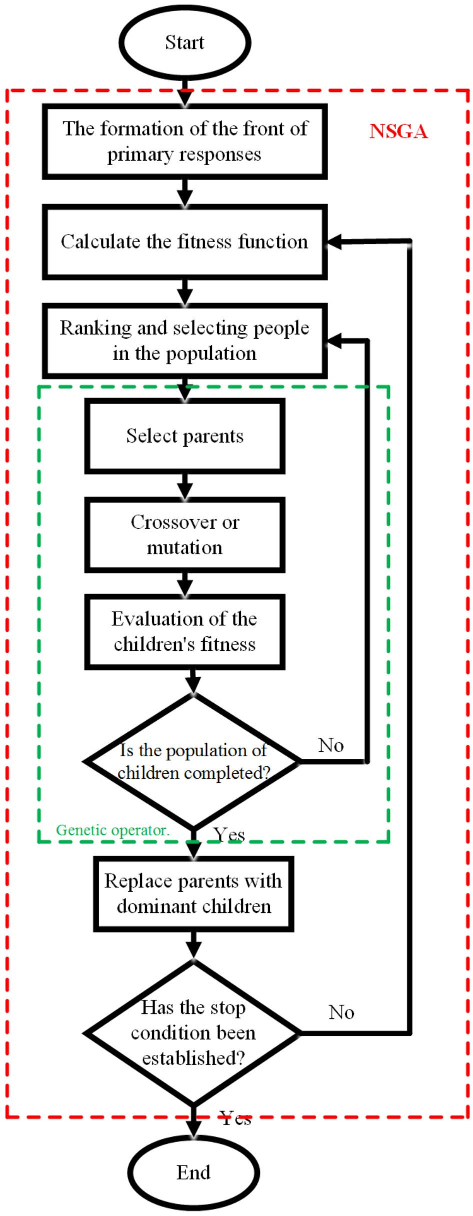

Figure 3: NSGA optimization algorithm flowchart

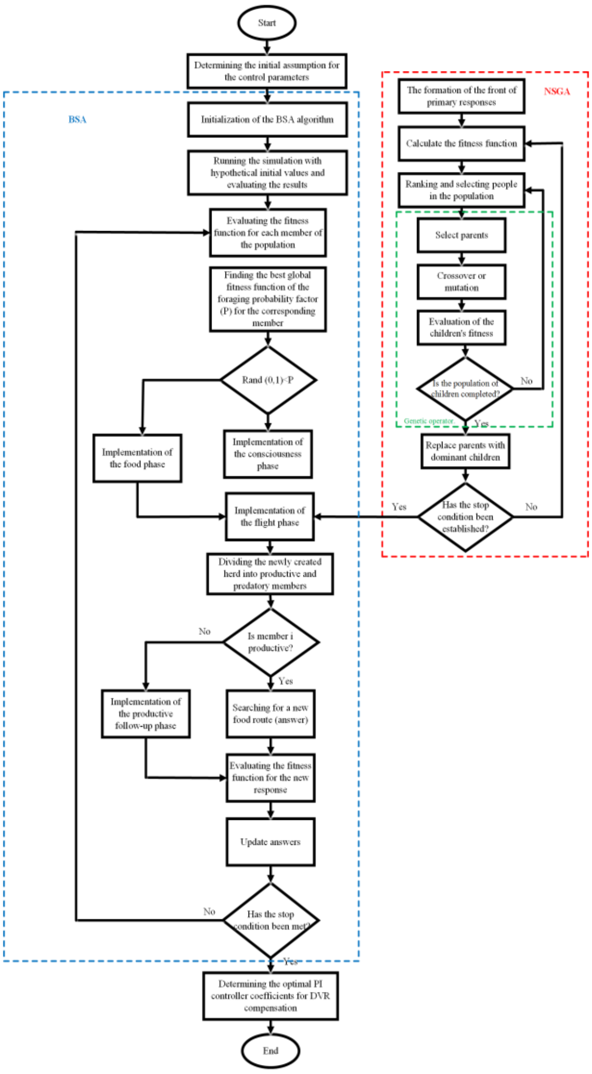

Figure 4: Flowchart of the proposed control method based on the NSBSA algorithm

3.4. DVR control

Figure 5 shows the block diagram of the DVR control model, and Figure 6 shows the model implemented in the MATLAB/Simulink environment. In this model, the rotating axis angle, θ, is the result of the Phase-Locked Loop (PLL). When a voltage sag occurs, the injected voltage vector $V_{inj}(t)$ provided by the DVR is used to restore the sensitive load voltage vector. At this time, the DVR must react as quickly as possible and inject the AC voltage into the grid. The control algorithm generates a three-phase reference voltage for the series converter, which tries to maintain the load voltage at its reference value. The voltage sag is measured by the error between the *d-q* load voltage components. The d-axis reference is set to the rated voltage, and the q-axis reference is set to zero. In Figure 5, the load voltage is connected to a transformation block that converts the fixed abc frame to the αβ frame. The output of this block is connected to a PLL and another transformation block that converts the *αβ* frame to the rotating (*dq*) frame. The variations in these signals can be easily controlled by comparing these voltages with their reference values and applying the error signals to a PI controller. The output of both PI controllers is converted back to the three-phase voltage. The injected voltage is applied to the voltage source converter using the three-phase voltage to produce the desired voltage using PWM.

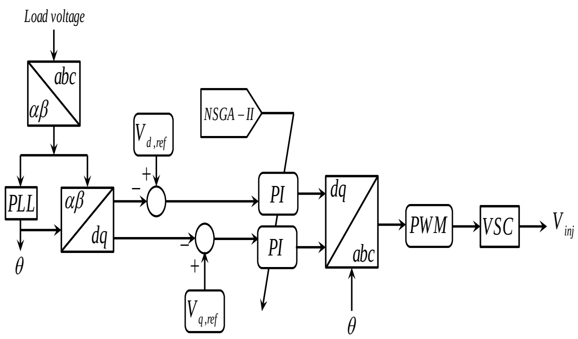

Figure 5: Block diagram of the DVR control model

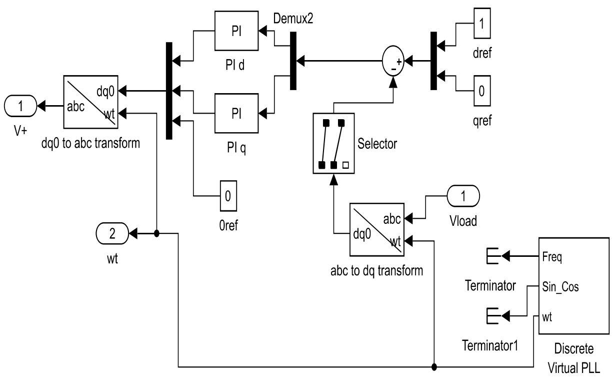

Figure 6: Control model implemented in MATLAB/Simulink

4. simulation results

Case Study: The power distribution system under study consists of two buses, one of which is connected to a sensitive load. The imulation model of this system is shown in Figure 7, and its parameters are given in Table 1. To simulate critical conditions, two faults are simulated on the series transformer side. The first fault is a two-phase-to-ground (*ac-g*) fault occurring in the time interval t=0.10s to t=0.15s, and the second fault is a three-phase-to-ground (*abc-g*) fault occurring in the time interval t=0.20s to t=0.22s. The resistance of the first fault R_{f1}=0.1Ω and the resistance of the second fault R_{f2}=0.04Ω are defined, and the ground resistance in both cases is assumed to be 0.01Ω. The parameters of the NSBSA optimization algorithm are also presented in Table 2. To compare the performance of the proposed control method, the results obtained from the implementation of the standard Particle Swarm Optimization (PSO) and Chaotic Adaptive Particle Swarm Optimization (CAPSO) algorithms, which were previously proposed in [12], are compared with the results of the proposed method. Figure 8 shows the simulation results using the proposed control method based on the controller optimized with the NSBSA algorithm. The results of the Fourier series analysis and the value of the load voltage THD using the proposed control method are shown in Figure 9. For better visualization, the voltage waveforms are per-unit based on the 400V base voltage. In addition, the optimization trends of the two objective functions, voltage sag and THD, using the NSBSA optimization algorithm over 5 consecutive iterations are shown in Figures 10 and 11.

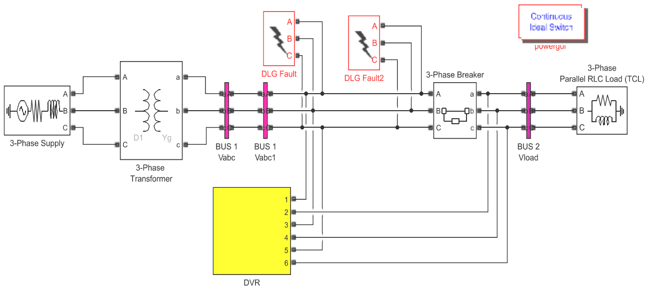

Figure 7: The study system, simulated in MATLAB/Simulink

Table 1. Parameters of the studied system.

Parametr	Symbol	Value
Power system frequency	f	50Hz
Power supply voltage	V_{rms}	11kV
Active power sensitive load	P_L	4.42kW
Reactive power sensitive load	Q_L	100var
Distribution transformer impedance	R_l, L_l , L_m	0.08,500, 0.002
Series transformer impedance	R_l, X , X_m	0.003, 200, 0.0001
DVR switching frequency	f_s	20kHz
DC supply voltage	V_{DC}	500V
Series filter impedance	R_s , L_s	10mH, 1Ω
Shunt filter impedance	R_p , C_p	20μf, 1Ω

Table 2: parameters of NSBSA optimization algorithm

Parametr	Symbol	Value
Initial population size	N	100
Maximum number of iteration	T	500
Number of war phase executions	FQ	3
Nonstant values a_1 and a_2	-	1
Constant values C and S	-	1.5
Probability of foraging for each individual bird	P	0.8
Constant value FL	-	0.5

The results shown in Figure 8 indicate that the proposed controller is capable of rapidly supplying the required load current in the event of a fault, such that the voltage across the load exhibits the minimal deviation from normal conditions. With the implementation of the proposed control model, the average voltage drop reaches 0.01353 p.u., which represents a reduction of approximately 15% compared to the best result obtained in the literature (0.0159 p.u. in [12]). Furthermore, the final value of the load voltage THD is found to be 0.5948%, which is around a 13% decrease compared to the best result reported in similar studies (0.69% in [12]). Table 3 presents the comparative study results.

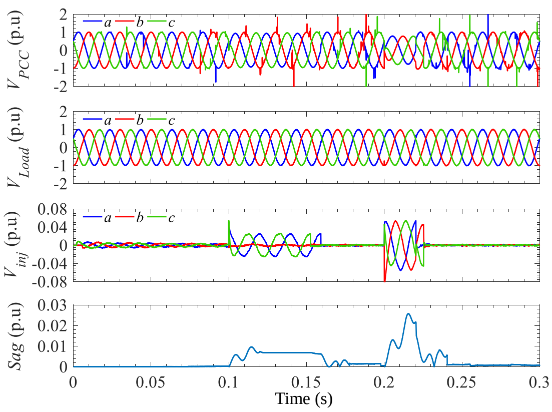

Figure 8: Simulation results using the proposed control method

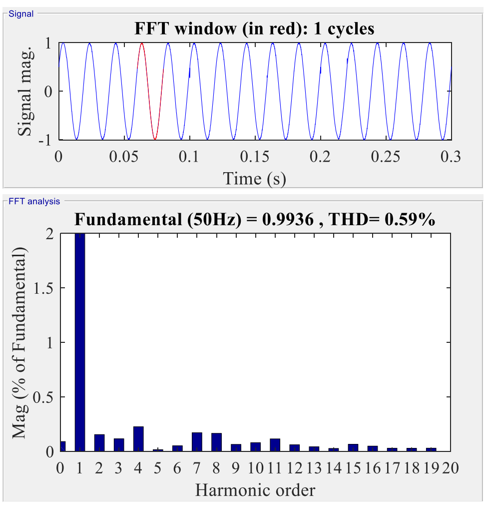

Figure 9: Results of Fourier series analysis and the value of load voltage THD

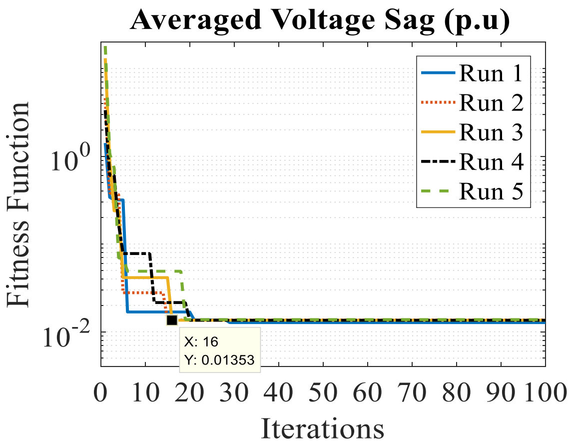

Figure 10: Convergence trend of the first objective function, average voltage drop

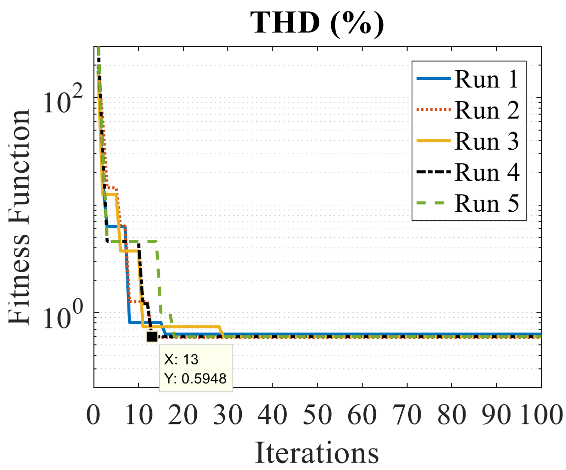

Figure 11: Convergence trend of the second objective function, voltage THD

Table 3: comparative study results

Controller	Average voltage drop (pu)	THD%
Classical PI controller [12]	0.0206	4.87
Optimal PI with PSO algorithm	0.0159	0.84
Optimal PI with CAPSO algorithm	0.0159	0.69
Optimal PI with NSBSA algorithm	**0.01353**	**0.5948**

3. Conclusion

In this paper, a novel control model based on an optimal PI controller optimized using the Non-dominated Sorting Bird Swarm

Optimization (NSBSA) algorithm was proposed for the control of a Dynamic Voltage Restorer (DVR). The optimal control coefficients of the conventional PI controller in the DVR control system were obtained using the proposed algorithm and applied to the PWM pattern. The objective function is composed of two independent functions, which for simplicity were defined as fuzzy quantities in the form of a single objective function. Finally, the proposed control model was implemented on a distribution system equipped with a DVR for sensitive load compensation under fault conditions. The simulation results show that by implementing the proposed control model, the load voltage under fault conditions will have the minimum deviation from the normal operating conditions. Additionally, by implementing the optimization algorithm, the optimal PI controller coefficients are selected in a way that simultaneously minimizes the average voltage drop and the total harmonic distortion (THD) of the load voltage. By implementing the proposed control model, the final values of the average voltage drop and THD are obtained as 0.01353 p.u. and 0.5948%, respectively, which represent a 15% and 13% reduction compared to the best results reported in similar studies. The proposed NSBSA algorithm, due to its ability to solve multi-objective problems and fast convergence, improves the response speed of the proposed control model in dealing with fault condition.

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