Hybrid Swarm Intelligence Approach Based PI Regulator for VSC-HVDC Optimal Parameters

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Abstract: The control of high voltage direct current system on voltage source converter VSC-HVDC by using the conventional techniques creates a number of challenges for the system operators, because it is a difficult operation and time consuming. In this paper, a new hybrid swarm intelligence optimization approach based PI regulator is proposed in order to improve the dynamic performance of the VSC-HVDC link. The synergy of Particle Swarm (PSO) and Bacterial Foraging (BFO) Optimization algorithms is investigated in order to determine the optimal PI regulator gains of VSC-HVDC link, which consequently improve the stability of the link after strict faults. The purpose of hybridization is to reduce the convergence time while keeping high precision. Different results are obtained to show the effectiveness of the proposed hybrid swarm implementation in optimal regulator design for VSC-HVDC. MATLAB/Similink simulations are provided to illustrate the performance of the proposed approach under serious perturbations.

Key words: BFO, Optimization, PSO, VSC-HVDC, PI regulators.

1. Introduction.

High-voltage DC (HVDC) transmission systems have several advantages compare to high-voltage AC (HVAC) transmission systems. These advantages are summarized as follow [1]:

- Enable power transmission over long distances with reduced power losses.
- Allows asynchronous connection between AC networks (connection of power networks with different frequencies).
- Active power flow is fully defined (magnitude and direction).
- Improves system stability as each system maintains its autonomy while real power.

There are two types of HVDC transmission systems: The first type uses current source converters, either line commutated converter (LCC) or capacitor commutated converter (CCC). The second type of HVDC transmission system uses voltage source converters known as VSC-HVDC [1]. For long distance, bulk

power transmission, conventional HVDC transmission is used due to some of its advantages, but with the development of semiconductors and control equipment, **HVDC** transmission with Voltage Sourced Converters (VSC-HVDC) based on IGBTs is today possible and many commercial projects are already in place [2]. HVDC power transmission system offers several advantages, one of which is to rapidly control the transmitted power [3]. It realizes the independent control of both active and reactive power, and has a good dynamic ability of reactive power support, which can improve the system's fault characteristic. Moreover, VSC-HVDC decouples the sending-end system and receiving-end system. If it is used in wind farm [2], it can improve its ability to resist interference from the power grid, and to a certain extent prevent the power grid from its voltage fluctuation. Therefore, VSC-HVDC is a better choice for integration of largescale wind farm [4]. These features make VSC transmission technology very attractive for connecting weak AC systems, island networks, and renewable sources into a main grid. However, VSC transmission does have high power loss and high cost compared to conventional HVDC system [5].

Control system and control strategy have notable effect on the characteristics of the VSC-HVDC system. A good control strategy depends on a precise mathematic model. The VSC-HVDC operating characteristics can be controlled through a closed loop composed of control units and the system. PI (i.e. proportional plus integration) controller, with its simple structure and strong robustness in a wide range of serving conditions, has been widely used in industry control. Therefore, it is important for the steady operation of VSC-HVDC system to choose proper PI parameters [6]. Authors in [7], [8], and [9] choose the control system of the VSC HVDC by using an inner current control loop and outer voltage control loop in rectifier and inverter side. This technology is mainly used in the recent years, but the selection of suitable PI parameters creates problems for network operators because the designing of optimal parameters for the PI regulators is a difficult calculating and time consuming.

In this paper, a synergy particle swarm optimization (PSO) with bacterial foraging optimization (BFO) is inserted in VSC-HVDC control block in order to contribute in solving the problem indicated above. In [10], transient stability performance of VSC-HVDC is improved by optimizing the gains of PI regulators for rectifier and inverter, using Particle swarm Optimization technique. The PSO approach presents the advantages of rapid convergence, less population size and reduced number of iterations [11]. These PSO advantages are taken in a synergy scheme with BFO Algorithm in order to direct bacteria convergence to the best solution. As presented, in [11] and [12], the hybridization of BFO and PSO Algorithms reduces the convergence time while maintaining high accuracy. This synergy approach has been applied to the outer voltage control and the inner current control in rectifier and inverter side. The work compares results of classical techniques and those obtained using this optimization hybrid approach. Some results illustrating the effectiveness of the proposed BFO-PSO- algorithm are found to be in good agreement.

2. System topology

The basic structure of the VSC based HVDC link, consists of two converters, DC-link capacitors, passive high-pass filters, phase reactors and DC cable. The VSCs as shown in Figure 1 are composed of six-Pulse Bridge equipped with self commutating switches (IGBTS) and diodes connected in anti parallel. The DC voltage is maintained constant and the complexity of control is increased compared to classical HVDC system. The two VSCs may be seen as the core of this transmission system topology. One of the VSCs works as rectifier, while the other one works as an inverter.

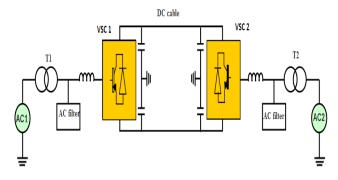


Fig. 1. The configuration of VSC-HVDC link.

3. VSC-HVDC model

The mostly used VSC-system is based on a two level topology which is shown in Figure 2 [13]:

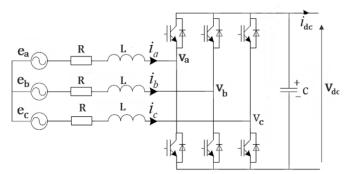


Fig. 2. Basic structure of VSC-HVDC converter.

In the analysis, all the AC voltages and AC currents have been transformed from a-b-c frame into d-q synchronous reference frame via Park transformation. Therefore, according to the Figure 2, the transient mathematical model of converter in synchronously rotating frame of reference can be obtained as following [14, 15]:

$$\begin{vmatrix} e_d \\ e_q \end{vmatrix} = R \begin{vmatrix} i_d \\ i_q \end{vmatrix} + L \frac{d}{dt} \begin{vmatrix} i_d \\ i_q \end{vmatrix} + L \begin{vmatrix} 0 & -\omega \\ \omega & 0 \end{vmatrix} \begin{vmatrix} i_d \\ i_q \end{vmatrix} + \begin{vmatrix} v_d \\ v_q \end{vmatrix}$$
 (1)

The voltage equations in d-q synchronous frame are,

$$v_d = -\frac{Ld (i_d)}{dt} - Ri_d + \omega Li_q + e_d$$
 (2)

$$v_{q} = -\frac{Ld \quad (i_{q})}{dt} - Ri_{q} - \omega Li_{d} + e_{q}$$
 (3)

Where the e_d , e_q are d-axis and q-axis component of the AC voltage of wind farm network or transmission network, the v_d , v_q are the d-axis and q-axis fundamental component of VSC AC voltage, the i_d , i_q are d-axis and q-axis component of the AC current of wind farm side or grid side, R and L are the equivalent resistance and inductance of T and ω is the angular frequency [13]. The power balance relationship between the AC input and the DC output is given by [14, 15]:

$$p = \frac{3}{2} \left(e_d . i_d + e_q . i_q \right) \tag{4}$$

$$Q = \frac{3}{2} \left(e_{q} . i_{d} - e_{d} . i_{q} \right)$$
 (5)

The grid voltage vector is defined to be along the daxis direction, and then a virtual grid flux vector can be assumed to be acting along the q-axis. With this alignment, $e_q = 0$ and the instantaneous real and reactive power injected into or absorbed from AC system is given by [15]:

$$p = \frac{3}{2}e_d.i_d \tag{6}$$

$$Q = -\frac{3}{2}e_d.i_q \tag{7}$$

4. VSC-HVDC control

4.1 VSC1 Control

A VSC controller employs a hierarchical control structure which consists of two loops: inner loop and Outer. The basic structure of the controller consists of an inner current control loop enabling effective decoupling of active and reactive power control, as it shown in Figure 3. As it shown, converter control is based upon the two-axis (d-q) reference frame [7]. The outer controller constitute of active/reactive power controller.

4.2 VSC2 Control

The VSC2 station controls the DC link voltage, so as to achieve automatic active power balance between the two terminals. Similar to VSC1, an outer DC voltage loop and an inner current loop are adopted in VSC2. The inner current controller of VSC2 is same with that of VSC1, but a conventional phase-locked-loop (PLL) is used to track the frequency and phase of the grid voltage [16]. Figure 4 shows the complete schematic of VSC1 and VSC2 controller.

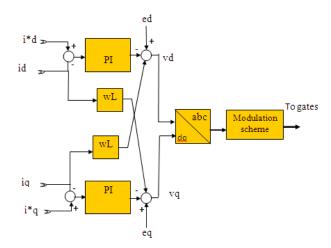


Fig. 3. Inner control loop.

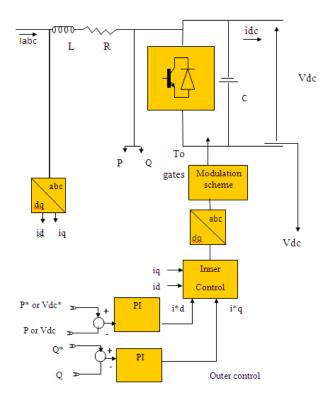


Fig. 4. The complete schematic control.

5. Swarm Intelligence approaches

5.1 Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm was first described by James Kennedy and R. C. Eberhart (1995). The technique has evolved greatly since then. PSO is a stochastic, population-based evolutionary computer algorithm for problem solving. In a PSO system, a swarm of individuals (called particles) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself (i.e., its own experience) and the position of the best particle in its neighborhood (i.e., the experience of neighboring particles). When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle, and the resulting algorithm is referred to a global best PSO. When smaller neighborhoods are used, the algorithm is generally referred to a local best PSO. The performance of each particle (i.e., how close the particle is from the global optimum) is measured using a fitness function that varies depending on the optimization problem.

Each particle in the swarm is represented by the following characteristics [17]:

- x_i : The current position of the particle;
- v_i : The current velocity of the particle;
- y_i : The personal best position of the particle.

 \hat{y} : The neighborhood best position of the particle.

The personal best position of particle i is the best position (i.e., the one resulting in the best fitness value) visited by particle i so far. Let F denotes the objective function. Then the personal best of a particle at time step t is updated as:

$$y_{i}(t+1) = \begin{cases} y_{i}(t) & \text{if } F(x_{i}(t+1)) \ge F(y_{i}(t)) \\ x_{i}(t+1) & \text{if } F(x_{i}(t+1)) < F(y_{i}(t)) \end{cases}$$
(8)

For the gbest model, the best particle is determined from the entire swarm by selecting the best personal position. If the position of the global best particle is denoted by the vector $\hat{\mathbf{v}}$, then:

$$\hat{y} \in \{y_0, y_1, y_2, \dots y_{s-1}, y_s\}$$
(9)

Where:

$$\hat{y} = \min\{F(y_0(t))...,F(y_s(t))\}$$
(10)

And: s denotes the size of the swarm.

The velocity update step is specified for each dimension $j: j \in \{1,....N_d\}$

Hence, $v_{i,j}$ represents the j^{th} element of the velocity vector of the i^{th} particle. Thus the velocity of particle i is updated using the following equation:

$$v_{i,j} = \omega \cdot v_{i,j}(t) + C_1 \cdot \Delta_1 + C_2 \cdot \Delta_2 \tag{11}$$

Where:

$$\Delta_1 = r_{1,j} \cdot (y_{i,j}(t) - x_{i,j}(t))$$
(12)

$$\Delta_2 = r_{2,j} \cdot (y^n{}_j(t) - x_{i,j}(t)) \tag{13}$$

 ω is the inertia weight, C_1 and C_2 are the acceleration constants, and $r_{1,j}$, $r_{2,j}$ are random coefficients distributed as: $r_{1,j}$ and $r_{2,j} \in [0,1]$

The position of particle i, x_i is then updated using the following equation:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$
 (14)

This process is repeated until a specified number of iterations is exceeded, or velocity updates are close to zero. The quality of particles is measured using a fitness function which reflects the optimality of a particular solution [18, 19].

5.2 Bacterial Foraging Optimization Algorithm

Foraging means locating, handling, and ingesting food. Animals that have successful foraging strategies are favored since they obtain enough food to enable them to reproduce, so they are more likely to enjoy reproductive success [20]. This has led scientists to model the activity of foraging as an optimization process. The foraging strategy of E. coli bacteria present in human intestine can be explained by four processes namely: Chemotaxis, Swarming,

Reproduction and Elimination/Dispersal [21].

- a) Chemotaxis: The characteristics of movement of bacteria in search of food can be defined in two ways, i.e., swimming and tumbling. A bacterium is said to be 'swimming' if it moves in a predefined direction; and 'tumbling' if it moves randomly in different directions. b) Swarming: For the bacteria to reach at the richest food location (i.e., for the algorithm to converge at the solution point), it is desired that the optimum bacterium should try to attract other bacteria so that together they converge at the desired location (solution point) more rapidly.
- c) Reproduction: The original set of bacteria, after getting evolved through several chemotactic stages reaches the reproduction stage. Here, the best set of bacteria (chosen out of all the chemotactic stages), get divided into two groups. The healthier half replaces the other half of bacteria, which gets eliminated, owing to their poorer foraging abilities.
- d) Elimination/Dispersal: In the evolution process a sudden unforeseen event can occur, which may drastically alter the smooth process of evolution and cause the elimination of the set of bacteria and/or disperse them to a new environment. In its application to optimization it helps in reducing the behavior of stagnation, (i.e., being trapped in a premature solution or local optima) [20].

5.3 Hybrid implementation: BFO-PSO

In the proposed hybrid approach, after undergoing a chemo-tactic step to perform a local search, each bacterium gets mutated by a PSO operator to accomplish a global search over the entire space. At this phase, the bacterium is stochastically attracted towards the globally best position found so far in the entire population at current time and also towards its previous heading direction. The PSO operator uses only the 'social' component and eliminates the 'cognitive' component as the local search in different regions of the search space [22]. BFO is changed by directing positions of bacteria and updating their velocities from the first chemotactic step using the power of PSO reaching the global solution in addition to its rapid convergence compared to BFO. This hybridization improved the convergence speed and accuracy of solutions obtained by the classical BFO, however, what is requested in image restoration is to attain a best approach to the original image by finding the best solution, which is accomplished by a hybrid implementation of BFO-PSO.

The following steps summarize the basic PSO algorithm and BFO algorithm [17]:

1-BFO Algorithm:

1.Initialization: We choose p, S, N_c , N_{re} , N_{ed} , P_{ed} and the C(i), i=1,2,...,S. for swarming, we choose also parameters of the cell-to-cell attractant functions. Initial values for θ^i , i=1,2,...S are also

chosen.

- 2. Elimination-dispersal loop: l=l+1
- 3. Reproduction loop: k=k+1
- 4. Chemotaxis loop: j=j+1

For i=1 to S take a chemotaxis step for bacterium Ias follows.

a) Compute f(i,j,k,l) and let:

$$f(i, j, k, l) = f(i, j, k, l) + f_{cc}(\theta^{i}(j, k, l), P(j, k, l)),$$

We add on the cell-to-cell attractant effect to the nutrient concentration.

- b) Let $f_{last} = f(i,j,k,l)$ to save this value since we may find a better cost via a run.
- c) Tumble: generate a random vector $(i) \in \Re^p with$ each element m(i), m=1,2,...P, a random number on [-1,1].
- d) Move: let:

$$\theta^{i}\left(j+1,k,l\right)=\theta^{i}\left(j,k,l\right)+C\left(i\right)\frac{\Delta\left(i\right)}{\sqrt{\Delta^{T}\left(i\right)\Delta\left(i\right)}}$$

this results in a step of size C(i) in the direction of the tumble for bacterium i.

e) Compute f(i,j+1,k,l), and then let:

$$f(i, j+1,k,l) = f(i, j+1,k,l) + f_{cc}(\theta^{i}(j+1,k,l), P(j+1,k,l))$$

f) Swim: let m=0 and While $m < N_s$ put m = m + 1, if $f(i,j+1,k,l) < f_{last}$ let $f_{last} = f(i,j+1,k,l)$ and let:

$$\theta(j+1,k,l) = \theta(j+1,k,l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta'(i)\Delta(i)}}$$

and use this position to calculate the new cost value. Else, let $m=N_s$ end while.

- g) Go to the next bacterium.
- 5. if $j < N_c$ then go to step 4.
- 6. Reproduction: For i=1,2,...,S.

$$f_{health}^{i} = \sum_{j=1}^{N_c+1} f(i, j, k, l)$$
 (health of bacterium)

Sort bacteria and chemotactic parameters C(i) in order of ascending cost f_{health} (higher cost means lower health). The S/2 bacteria of the highest cost will die and the healthiest are placed at the same location as their parent.

- 7. if $k < N_{re}$ go to step 4.
- 8. Elimination-dispersal: for i=1,2,...,S, with probability P_{ed} , eliminate and disperse each bacterium.
- 9. if l<Ned then go to step 1, otherwise end algorithm.

2-PSO Algorithm:

For each particle i=1,...,s do Randomly initialize xi

Randomly initialize vi (or just set vi to zero)

Set yi = xi

endfor

Repeat

For each particle i = 1,...,s do

Evaluate the fitness of particle i, f(xi)

Update yi using equation (8)

Update y[^] using equation (10)

For each dimension j = 1,...,Nd do

Apply velocity update using equation (11) endloop

Apply position update using equation (14) endloop

Until some convergence criteria is satisfied

In the previous BFO Algorithm, inside the Chemotaxis loop (step 4, point g), we introduce the PSO operator to update the global position of each bacterium, then calculating the cost function and subsequently we update both the global position and velocity of each bacterium before letting the bacteria swimming with the new speed on the way of the new updated direction:

- 3- hybrid PSO-BFO algorithm
- g) We introduce PSO operator (for each chemotactic step S):
- * Update the θ_{g_best} and $f_{best}(i, j, k, l)$
- * Update position and velocity of the d-th coordinate of the i-th bacterium to the following rule:

$$V_{id}^{new} = \alpha V_{id}^{new} + C_{i} Q_{i} Q_{g_be_{S}i} - Q_{d}^{ld}(i,j+1,k)$$

$$Q_{d}^{le}(i,j+1,k) = Q_{d}^{ld}(i,j+1,k) + V_{id}^{new}$$
(15)

To optimize the parameters of the control block, a Hybrid Swarm Intelligence (BFO-PSO) approach is inserted with the PI regulator, both in the inner and outer control in each station. The purpose of this new hybrid approach is to find the optimized gains of the PI regulators in order to improve the stability of the link after grave faults. All unknown gains of the PI regulators will be calculated using this hybrid approach as following:

In the outer control:

VSC1 side
$$x(1,i) = k_{p1}, x(2,i) = k_{i1}$$

VSC2 side $x(3,i) = k_{p1}, x(4,i) = k_{i1}$

VSC2 side
$$x(3,i) = k_{n1}, x(4,i) = k_{i1}$$

In the inner control:

VSC1 side
$$x(5,i) = k_{p_2},$$
 $x(6,i) = k_{i_2}$
VSC2 side $x(7,i) = k_{p_2},$ $x(8,i) = k_{i_2}$

Where: x is the obtained solution and i is the index of the temporary solution. Figure 5 shows the way of applying the BFO-PSO approach in the control block:

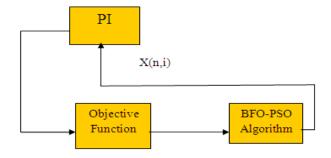


Fig. 5. Insertion of BFO-PSO approach with the PI regulator.

6. Simulation results

To demonstrate the effectiveness of the proposed BFO-PSO approach based PI regulator, a VSC-HVDC model 30 MW (60kV, 0.5 kA) was setup in MATLAB /Simulink. This model consists of two VSC-HVDC stations, two transformers and a DC cable. In this study, the objective is to determine the efficiency of this hybrid approach to minimize the effect of severe faults applied on our system. It is very important that all reasonable effective parameters of the algorithm are chosen so that the obtained results will be quite acceptable for use.

The selected PSO parameters are: C1=1.49; C2=1.49; r1=0.3; r2=0.95; Swarm Size=10; Maximum Iterations=10.

The selected BFO parameters are: s=4; Nc=4; Ns=4; Nre=4; Ned=1; Sr=s/2; Ped=0.25; c(i)=0.05.

After carrying out our simulation, the evolution of the objective function after 5 iterations is presented in figure 6. From this function some optimized gains are found. With the same way, all other gains are found.

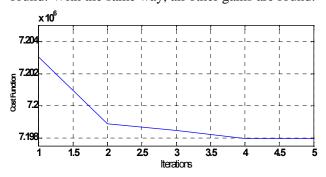


Fig. 6. Evolution of the objective function.

The calculated parameters are presented in table (1):

Table (1): Parameters of the PI gains using BFO-PSO approach.

	Outer control loop		Inner control loop	
Gains	K _{p1}	K _{i1}	K _{p2}	K _{i2}
VSC1	2.4625	0.8942	1.9033	0.7568
VSC2	0.1529	7.3191	0.1653	4.2276

6.1 Case 1

In order to verify the performance of PI regulators under this hybrid approach, in the sending station (VSC1), a negative step of 40% (from 30MW to 18MW) is applied at 1 s for duration of 0.2 s on reference active power $P_{\rm ref.}$

Initially, PI gains of a conventional method are used. The obtained results are shown in figure 7. It can be seen that the real power follows the reference active power but an observable overshoot of 6% is appearing. An effect in the DC voltage is visible because of the size of the DC used capacitor. During step application, the variation in active power does not affect the reactive powers, while there are some observed perturbations. Due to the inductance and capacitance of the system, it is clear that the transition is not instantaneous.

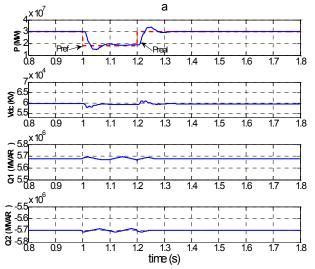


Fig. 7. Transient response of the regulator as a result of the reference active power step, using a conventional method (negative step of 40 %).

Secondly, the application of the hybrid algorithm presents perfect efficiency to remove the unsuitable overshoots of the real active power compared to the previous case, and limit, to some extent, the perturbations of direct voltage and reactive powers during step application as shown in figure 8:

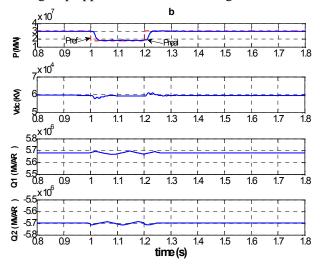


Fig. 8. Transient response of the regulator as a result of the reference active power step, using hybrid algorithm (negative step of 40 %).

In order to well distinguish between the use of PI regulator with and without hybrid algorithm, figure 9 presents the system improvement, in which the hybrid BFO-PSO approach has a perfect efficiency to reduce the overshoots.

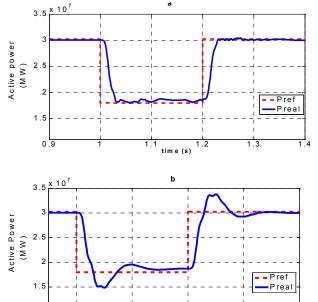


Fig. 9. Transition of active power: a) With optimization, b) Without optimization.

1.2 time (s)

6.2 Case 2

In order to show the performance of PI regulators under this hybrid approach, in the receiving station (VSC2), a negative step of 20 % (from 60KV to 48KV) is applied at 1 s for duration of 0.2 s in reference DC voltage.

Firstly, the used parameters of the regulators PI are obtained from a conventional method. In figure 10, it seems that the real DC voltage follows the reference DC voltage, while there is appearance of an unsuitable overshoot of 5%. At the starting and ending of the step, there are some large transients in active power and DC current. Of course, the size of the DC capacitor will be a major factor to limit this impact. It is clearly seen that the variation in DC voltage does not affect the reactive power on the same side.

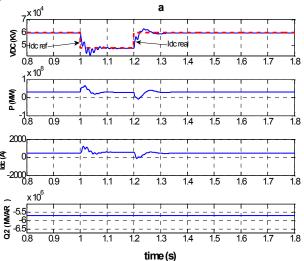


Fig. 10. Transient response of the regulator as a result of the reference DC voltage step, using a conventional method (negative step of 20 %).

Secondly, the used parameters of the regulators PI are obtained from our hybrid method. In this case, as it is shown in figure 11, the hybrid approach has a perfect effectiveness to decrease the DC voltage without overshoots compared to the previous case. Figure 12 shows clearly the deference between the use of PI regulator with and without hybrid approach.

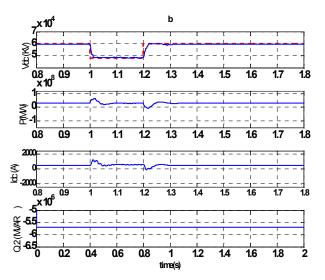


Fig. 11. Transient response of the regulator as a result of the reference DC voltage step, using hybrid algorithm (negative step of 20 %).

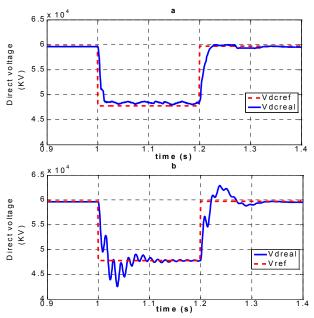


Fig. 12. Transition of DC voltage: a) With optimization, b) Without optimization.

7. Conclusion

In this paper, the validity of the proposed BFO-PSO optimization method is investigated. The gains optimization of all PI regulators for VSC1 and VSC2 by using this hybrid approach presents a perfect efficiency to limit the effect of the severe perturbations during transient conditions. This hybrid approach offers great flexibility for the permanent regime recovery and improves the stability of the VSC-HVDC link compared to conventional PI regulators. As advanced perspective, the robustness of our PI regulators optimized by BFO-PSO approach against

different short circuits at the input and output of VSC-HVDC link can be studied.

8. References

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