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Power Quality Improvement in Hybrid Power Micro Grid System Using Multiconverter UPQC with AWPA

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Abstract: Power quality analysis in hybrid power resources in a distributed generative system. Different power failures may cause huge damage for the end user the failures should be compensated as earliest. MC-UPQC is a new power quality conditioning system for multibus/multifeeder systems capable of simultaneous voltage and current compensation. Several series voltage source converters are used in this configuration, as well as one shunt voltage source converter (shunt VSC). As well as compensating for supply-voltage and load current imperfections on the main feeder, the system can also compensate for supply voltage imperfections on adjacent feeders. DC-link capacitors are shared among all converters in the proposed configuration. In this way, sag/swell and interruptions can be compensated by transferring power between feeders. Simulations are used to illustrate the performance of the MC-UPQC and the control algorithm named advanced wolf pack algorithm (AWPA). Results showing an accuracy of 98.8% of power quality compensation with the proposed work.

***Keywords**: Power quality analyssis, MC-UPQC, AWPA, Hybrid Power, Micro-grid.*

1. Introduction:

The increased use of nonlinear loads by both electric utilities and end users has adversely affected electric power quality by causing major power quality disturbances in distribution systems, including harmonics, imbalances, flickering voltages, sagging voltages, and interruptions. MC-UPQC is a new Unified Power Quality Conditioning system that eliminates these problems and improves power quality. A MC-UPQC has three VSCs connected by a dc link back to back to compensate voltage and current imperfections in one feeder and current imperfections in another feeder. The distribution system is gradually becoming active from a passive one due to the penetration of decentralized generation, distributed energy storage devices (ESD), control equipment, and advanced communication networks. A major challenge of smart grids is power quality [1]. Harmonic distortions have been on the rise as power electronic converters have been increasingly used.To compensate for power quality issues, active power filters (APFs) are preferred over passive filters. Power quality problems caused by sags, swells, and harmonics in the supply voltage are mainly compensated by series APFs. Conversely, shunt APF compensates for power quality issues caused by load currents, such as poor power factor, unbalance, and harmonics. An UPQC is a combination of shunt and series APFs sharing a common DC link. With UPQC, you can compensate for most power quality problems by combining the benefits of both series and shunt APFs [2]. In addition to providing better reliability, security, and efficiency, active distribution systems enable bi-directional power flow, allowing more energy to be shared among consumers. In addition, solar and wind energy can be integrated into the system. ADN's capacity to consume renewable energy (RES) is severely constrained by voltage fluctuations or overvoltages that may be caused by DG penetration. As a consequence, distribution network operators (DNOs) must dispatch dispatchable DGs' active and reactive power optimally. Therefore, active and reactive power coordinated optimization (ARPCO) has become a research area. Many researchers have also worked on optimal programming and operation in recent years. Reactive power dispatch (OPRD) can be optimized using a number of programming methods or intelligent techniques. C.-M. Huang[5], the hybrid differential evolution with ant system and particle swarm optimization (PSO) have all been applied to solving OPRD, as have artificial bee colonies (ABCs) [4, 5]. As an interface between combined generating and electric storage systems and the grid, Reference [6] proposes a new bidirectional converter on the compelling problem of ADNs control. [7-8] proposes a broadcast-based unified control algorithm for grid-based reactive power support using heterogeneous energy resources such as distributed storage systems and demand-response loads. The quasi-Newton method was applied by Marco Bronzini to solve the problem of centralized control in ADN [9-10]. Levron et al. [11] presented a dynamic search algorithm based on a load flow for the OPF

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problem in microgrids with ESDs and RESs. However, the method worked well only for systems with a small scale system. A solution for ARPCO in ADNs was presented in Reference [12], but the charging and discharging periods of ESS were fixed so that the solutions were low-quality. [13] proposes an optimal operation model for ADN based on mixed-integer second-order cone programming (MISOCP). This method can reach the optimal value by using existing optimization software, but the solution is not accurate enough. Graditi G. [14] models appliances' 24h behavior by means of a real-valued function and then extends the GSO algorithm to solve multi-objective energy management optimization problems for smart grids with direct control over shiftable loads. This method was found to be comparable to or even better than NSGA-II [15]. In [16], a comprehensive multi-objective optimum technique was proposed for efficient ADN operation. The present work proposes a multi converter UPQC to compensate both series and shunt compensators. An advanced wolf pack algorithm proposed for the power quality improvement.

2. Wolf pack algorithm

Based on the cooperative hunting characteristics of wolves, Wu Husheng, etc put forward a new intelligent algorithm-Wolf pack algorithm (WPA) [17]. It has been proven to has better global convergence and computational robustness, and especially suitable for solving high-dimension and multimodal function optimization problems with other classical intelligent algorithm such as PSO, fish swarm algorithm, genetic algorithm (GA) and Graasshopper optimization algorithm so on.

In nature, the wolf belongs to candidate family and lives in a pack consisting of 5-12 wolves on average. In general, the common wolf pack can be divided into three parts: a lead wolf, some scout wolves and ferocious wolves. The lead wolf, as a leader, is always the smartest and most ferocious one. Scout wolves hunt around for prey. Ferocious ones are responsible for rounding up the prey. WPA is different from previous swarm intelligence optimization algorithm. It has three different search abilities: hunting behavior, calling behavior, siege behavior, and two intelligent rules: a winner takes-all productive rule for lead wolf and a randomly renewable mechanism named survival of the stronger for the wolf pack.

The parameters such as Xi , N, $k$max , Tmax , S , Lnear , α, β and the objective function value Y have been defined explicitly and all the components have been discussed in detail in [8], so the main computation steps are only described below.

Step1: Initialization. For a D dimension of the search space, the follow parameters are initialized: Xi , N, $k$max , Tmax , S , Lnear, β.

Step2: The wolf with the maxium Y value (ie, Ylead) is selected as lead wolf, and the rest Nsw (an inter value between $N/(\alpha+1)$ and N/α) wolves with better Y value, as scount wolves, begin to scout in D dimension solution space according to equation (10) until Yi>Ylead or Tmax is reached, then go to

step3; The rest Nfw (=N-Nsw-1) wolves take calling behavior according to equation (11). If $Yi \geq Y$lead, go to step2; otherwise the wolf-i continue running until L (i, l) $\leq L$near, then go to

step 4; The position of siege wolves is updated

Step5: Update the lead wolf to the one with maximum objective function value, and then delete R wolves with worst objective function value from the wolf pack and meanwhile produce R wolves accordingly. Step6: If the program reaches the precision requirement or the maximum number of iterations, the position and Ylead of lead wolf, the problem optimal solution, will be outputted, otherwise go to step2 to continue iteration until termination condition is met. In the above steps, step 2 is fine search, reflecting the local optimal solution search precision; step 3 is a rough search, reflecting the local optimal solution search efficiency; step 4 is gradually refined search, which reflects the accuracy that the local optimal solution is also global one; step 5 produces a new generation of wolves, which not only retains the excellence of the local optimal solution founded by original wolves, but also increases the probability of reaching the optimal solution to guarantee the global optimal of the algorithm.

3. Adoption of AWPA to present work

Power quality issues of sag and swell after installing MC-UPQC the controlling algorithm after the load conditions from multi power inputs from wind and solar the 3 phase faults with critical load conditions. The nature of advanced wolf pack algorithm shown in the figure1.

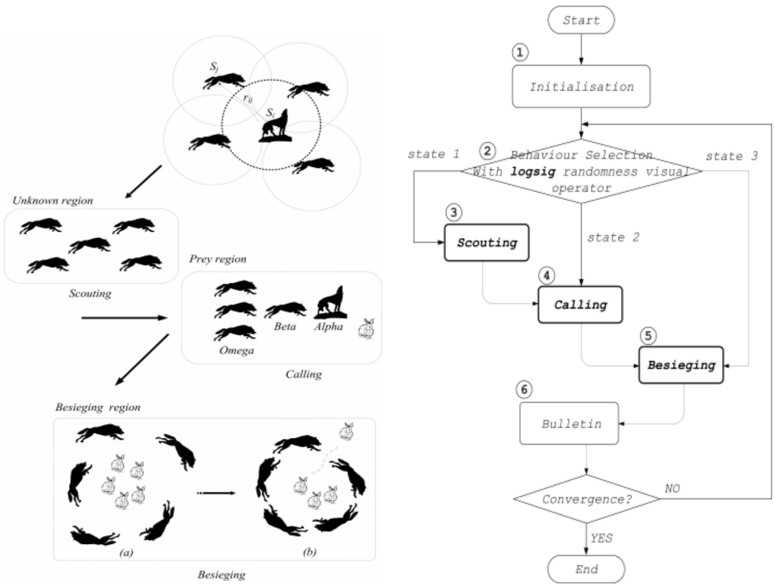

Fig: 1 work flow for AWPA algorithm

From the present work it has been observed that a set of combination wolfs checking the system at different iterative points. The communication between the wolfs can fix the hunting area like wise the searching area of faults will be updated for immediate compensation of sag and swell in the selected area. The simulation pseudo code shown in figure2.

```
Begin (1)

   t = 0 ;
   Initialise all parameters:
      xi with variable population P,  fitness(x0),
visual, try_number etc.

     While ( Not termination-condition) do
       Begin (2)

          t    =  t + 1;

         FOR i = 1: Population

             state = Behaviour Selection()
                 IF( state ==1)
                    Scouting();

                 Elseif (state ==2)
                    Calling();

                 Elseif (state ==3)
                    Besieging();

                 Else

                 End

          ENDi

        evaluation fitness(x) and best solutions

       End (2)

End (1)
```

Fig 2. AWPA Pseudo Code

(1) Initialization: in this step, all the variables and parameters are set to the per-defined values, in a case, population = 50, max generation = 200, etc., and the simulation program prepare for the subsequent steps. The wolf pack matrix updated in equation1.

$$WP_{M\times N}=\begin{bmatrix} S_{11} & S_{12} & \dots & S_{1q} & S_{1N} \\ S_{21} & S_{22} & \dots & S_{2q} & S_{2N} \\ & & \dots & & \\ S_{p1} & S_{p2} & \dots & S_{pq} & S_{pN} \\ & & \dots & & \\ S_{M1} & S_{M2} & \dots & S_{Mq} & S_{MN} \end{bmatrix} \quad (1)$$

(2) *Behavior Selection*: In the 'behavior selection', there are three types of 'states' to indicate three different types of behaviors of a WP, that is, 'scouting', 'calling' and 'besieging', in which, the 'scouting' state is set as the default state or initial behavior of each WP. Depending on the companion's number and the visual conditions, the prey density in the hunting region can be defined in Equation (2).

$$visual(t) = logsig\left(\frac{\frac{T}{2} - t}{k}\right) \times random(t)$$

• T is the maximum number of iterations;

• t is the current iteration number;

• k changes the slope of the *logsig*() function;

• *random*() is a random value within the range of (0,1).

(3) Scouting: For an AW individual k in a WP, let's define S as the finite state set, and there are states 1 to M that an AW can perform, as given in Equation (3).

$$S_{(*)k} = \{s_1, \ldots, s_M\} \tag{3}$$

Within the AW's visual field, let's define $S(*)i$ as the current state of an AW and $S(*)j$ as the next state. Specifically, an AW moves from its current state $S(*)i$ to the next state $S(*)j$ randomly, and keep checking the state updating conditions, as stated in Equations (5) and (4), where is a random movement factor, δ is the iteration step, and υ is the visual constant of the AW. For a given AW, the prey density is defined as z = $f(S)$, in which, z is the fitness function,z i and z j are the prey density in the state $S(*)i$ and $S(*)j$, respectively

$$S_{(*)j} = S_{(*)i} + \epsilon \cdot \upsilon \tag{4}$$

If $F_i \geq F_j$

$$S_{(*)i+1} = \begin{cases} S_{(*)i} + \epsilon \cdot \delta \\ S_{(*)i} + \epsilon \cdot \delta \cdot \dfrac{S_{(*)j} - S_{(*)i}}{\|S_{(*)j} - S_{(*)i}\|} \end{cases}$$

As defined in Equation (5), *rij* is the Euclidean distance of fault area between the AW*i th* and AW*j th*,also illustrated in the equation 6 and the AWF response shown in the figure 3.

$$r_{ij} = \|S_{(*)j} - S_{(*)i}\| \tag{6}$$

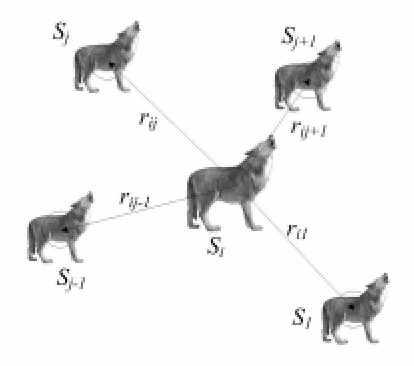

Fig 3: The Euclidean distance between the AW*i th* and AW*j th* and states updating.

Calling: Let's set $S(*)c$ as the the central state, η as the crowd factor, γ as the AW's neighbor number and z c as the prey density of the central state, as given in Equation (7) .

$$F_c = f(S_{(*)c}) \tag{7}$$

As given in Equation (8), when under the condition $C1$ as given in Equation (9): the AW performs the central statedriven 'Calling' behavior; Otherwise, the AW continues with 'Scouting' behavior, as defined in Equation (8), within the AW's visual field ($rij < \upsilon$).

$$S_{(*)i+1} = \begin{cases} S_{(*)i} + \dfrac{S_{(*)c} - S_{(*)i}}{\|S_{(*)c} - S_{(*)i}\|} \cdot \epsilon \cdot \delta & \text{if } C1 \\ (5) & otherwise \end{cases} \tag{8}$$

$$C1 == \left(\frac{F_c}{\gamma} > \eta F_i\right) \&\& \ (\eta \geq 1) \tag{9}$$

Besieging:

When a WP in its *Smax* states, that is, it is reaching to the "max" state, let's define z *max* as the max or highest prey density, and there are γ individuals in the neighborhood. As shown in Equation (10), when under the condition $C2$ as given in Equation (11): the AW performs the central statedriven 'Besieging' behavior, that is, the AW keeps updating the state in the z *max* region ; Otherwise, the AW continues

with 'Scouting' behavior, as defined in Equation (8).

$$S_{(*)i+1} = \begin{cases} S_{(*)i} + \dfrac{S_{max} - S_{(*)i}}{\|S_{max} - S_{(*)i}\|} \cdot \epsilon \cdot \delta & \text{if } C2 \\ \end{cases} \tag{10}$$

$$C2 == \left(\frac{F_{max}}{\gamma} > \eta F_i\right) \&\& (\eta \geq 1) \qquad (11)$$

Bulletin: The bulletin step compares the current state $S(*)i$ of each AW with the historical state data. The bulletin data are replaced and updated only when the current state is better than the previous state, as described by Equation (12). In the bulletin step, there is a data pool, to contain the 'bulletin data'. This step compares the current state $S(*)i$ of all the AW population with their historical data. As given in Equation (12): the bulletin data are replaced and updated only when the current state is better than the previous state; Otherwise, the bulletin data keep as they are. Then the bulletin data are moving to the next loop.

$$S_{(*)j+1} = \left\{ \quad S_{(*)i} \quad \text{if } F_i \geq F_j \right. \qquad (12)$$

The satisfied conditions will be re-check with compensated data

4. MC-UPQC adoption for power quality

As shown in Fig. , the MC-UPQC consists of two series VSCs and one shunt VSC which are controlled independently. The switching control strategy for series VSCs and the shunt VSC are selected to be sinusoidal Pulse width-modulation (SPWM) voltage control and hysteresis current control, respectively. Details of the control algorithm, which are based on the *d-q* method] are shown below in figure4.

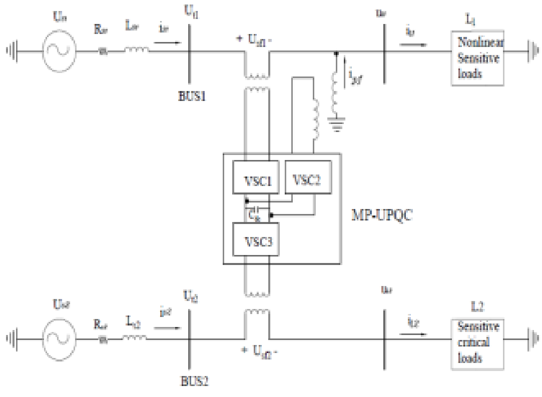

Fig :4 Typical MC-UPQC used in distriution system

Shunt-VSC: functions of the shunt-VSC are:

1) To compensate for the reactive component of the load L1 current;

2) To compensate for the harmonic components of the load current;

3) To regulate the voltage of the common dc-link capacitor.

The measured load current (i_{l_abc}) is transformed into the synchronous *dq0* reference frame by using the equation13.

$$i_{l\_dq0} = T_{abc}^{dq0}\, i_{l\_abc} \qquad (13)$$

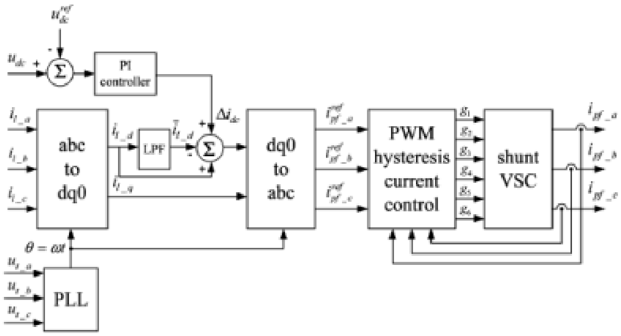

Fig 5: Shows the control block diagram for the shunt VSC

where the transformation matrix is shown in the equation 14

$$T_{abc}^{dq0} = \frac{2}{3}\begin{bmatrix} \cos(wt) & \cos(wt-120^0) & \cos(wt+120^0) \\ -\sin(wt) & -\sin(wt-120^0) & -\sin(wt+120^0) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \qquad (14)$$

Since the load current drawn by each phase is different due to different loads which may be present inside plant, therefore the instantaneous fundamental load reactive power and the instantaneous fundamental load active power demand for each phase may not be the same. In order to make this load unbalanced power demand to balanced fundamental three phase active power, the unbalanced load power should be properly redistributed between utility to get the linear and balanced loads calculated using quations 15 and 16.

$$p_{L,Total} = p_{La,1} + p_{Lb,1} + p_{Lc,1} \qquad (15)$$

$$p^*_{S/ph} = (p_{L,Total})/3 \qquad (16)$$

Equation gives the distributed per phase fundamental active power demand that each phase of utility supplies in order to obtain perfect balanced source currents. It is clear that under all the conditions the total fundamental active power demand by the loads would be equal to the total power drawn from the utility but with exactly balanced way even though the load currents are unbalanced. Thus the reference compensating currents representing a perfectly balanced 3-phase system can be extracted by taking the inverse of the formula 17

$$\begin{bmatrix} i^*_{Sa\_\alpha} \\ i^*_{Sa\_\beta} \end{bmatrix} = \begin{bmatrix} v_{La\_\alpha} & v_{La\_\beta} \\ -v_{La\_\beta} & v_{La\_\alpha} \end{bmatrix}^{-1} \cdot \begin{bmatrix} p^*_{S/ph} + p_{dc/ph} \\ 0 \end{bmatrix}$$

The source in order to maintain the dc-link voltage at a constant level and to over come the losses related with MC-UPQC. The following are the block diagrams of proposed circuits as shown in the figure 6 and the MC-UPQC simulation layout in figure7.

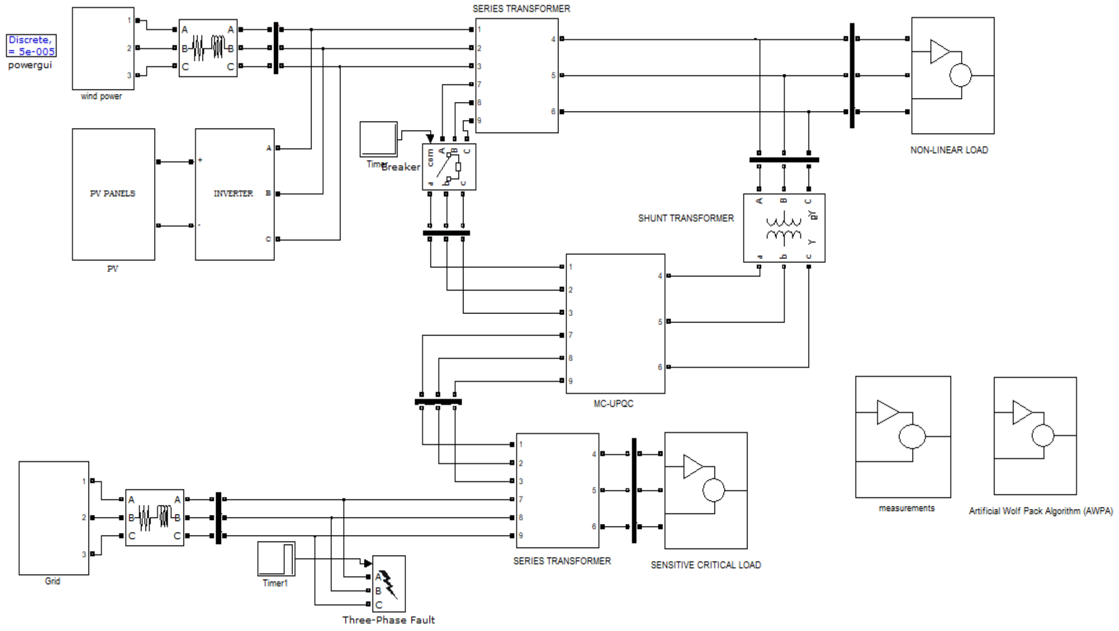

Fig:6 Main schematic diagram of proposed system

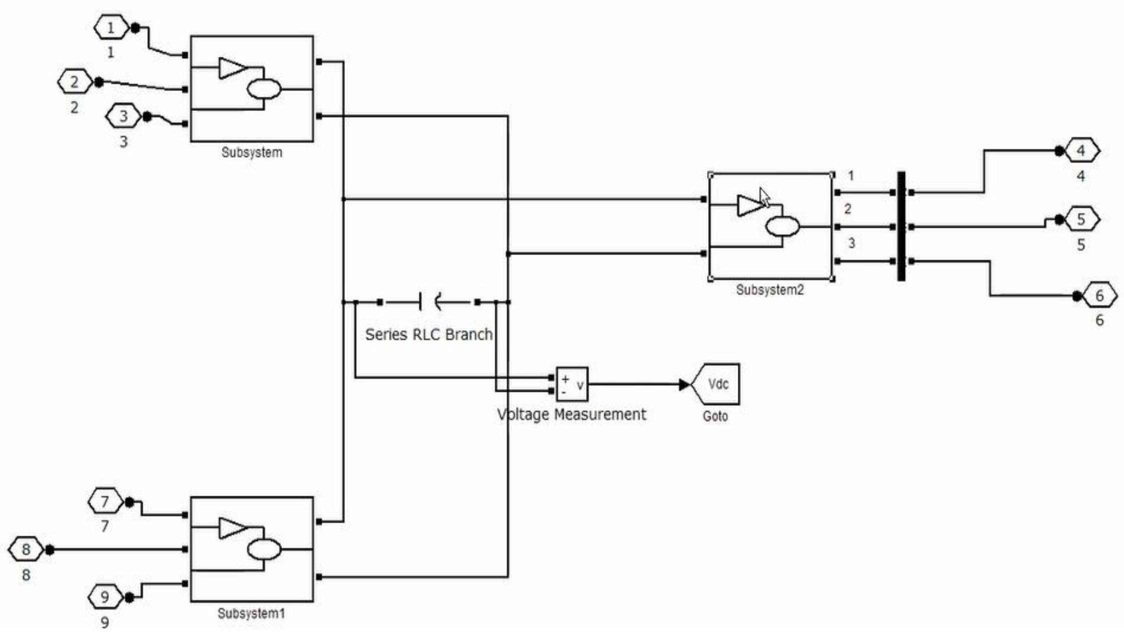

Fig:7 MC-UPQC schematic diagram of proposed system

The functioning of wolf pack algorithm with standard surchees at the series and shunt supplies shown in the figure8 and the POD circuit diagram in figure9.

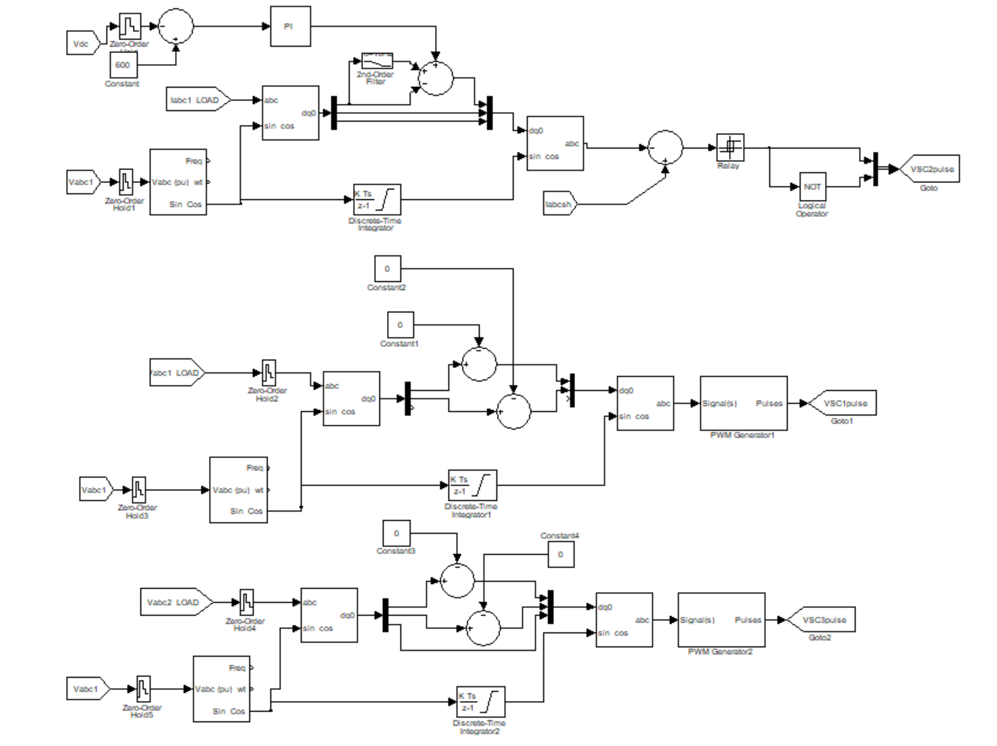

Fig:8 Functioning of Artificial wolf pack algorithm

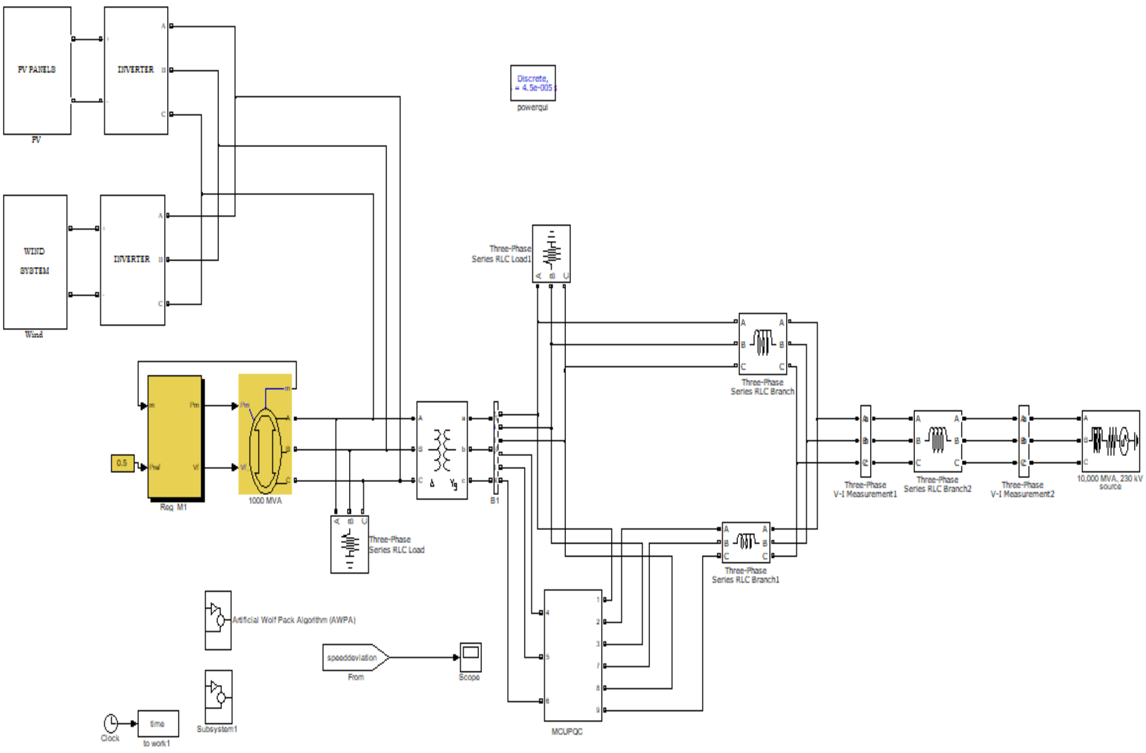

Fig:9POD main circuit diagram

The activation of AWPA control algorithm with multiple load conditions shown in the figure 10.

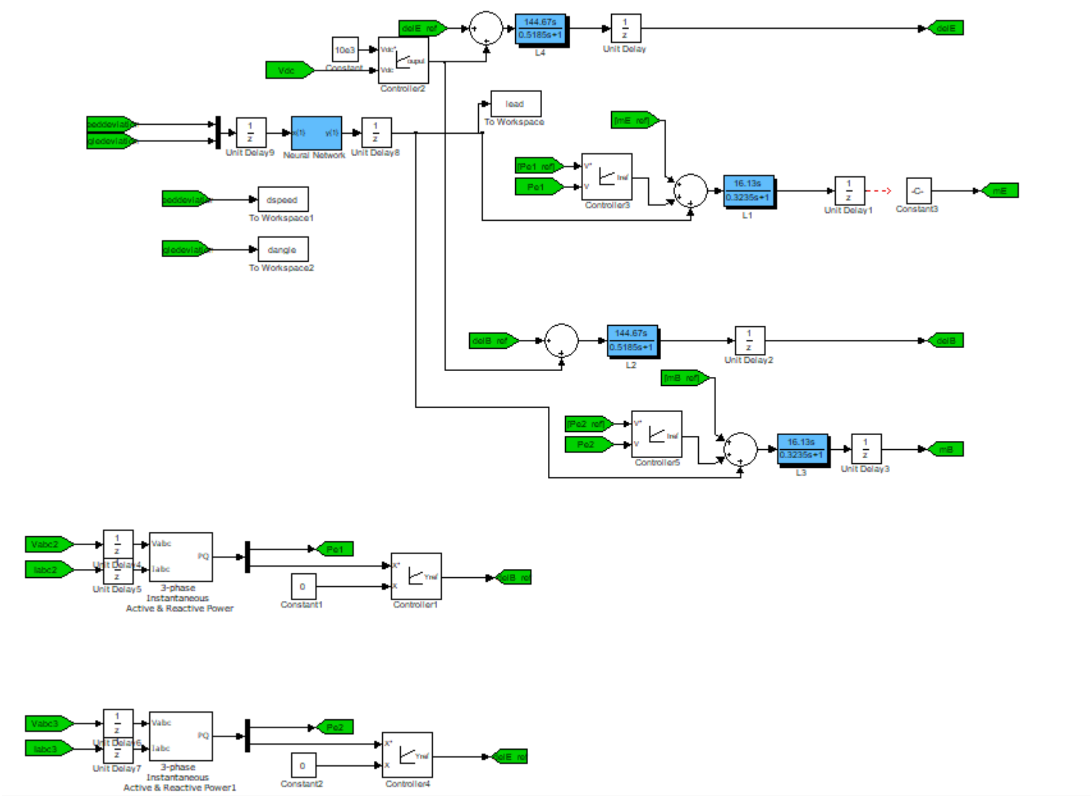

Fig:10 Active AWPA

5. Results and Discussions

The proposed MC-UPQC and its AWAP control schemes have been tested through extensive case study simulations using MATLAB/SIMULINK. In this section, simulation results are presented, and the performance of the proposed MC-UPQC system is shown. Simulation is carried out in this case study under distorted conditions of current and supply voltages in feeder1.The distorted nonlinear load currents are compensated very well. The input voltage harmonics and current harmonics caused by non-linear load, effectiveness of MCUPQC with different controllers is evident from Fiure.11, Figure 12 ,Figure13,14 and 15. As the source current becomes sinusoidal and balanced from 0.4s. The scheme is first simulated without MC-UPQC to find out the THD of the supply voltage and current. Then, it is simulated with MC-UPQC to observe the difference in THD of supply current and voltages for the proposed model MC-UPQC.

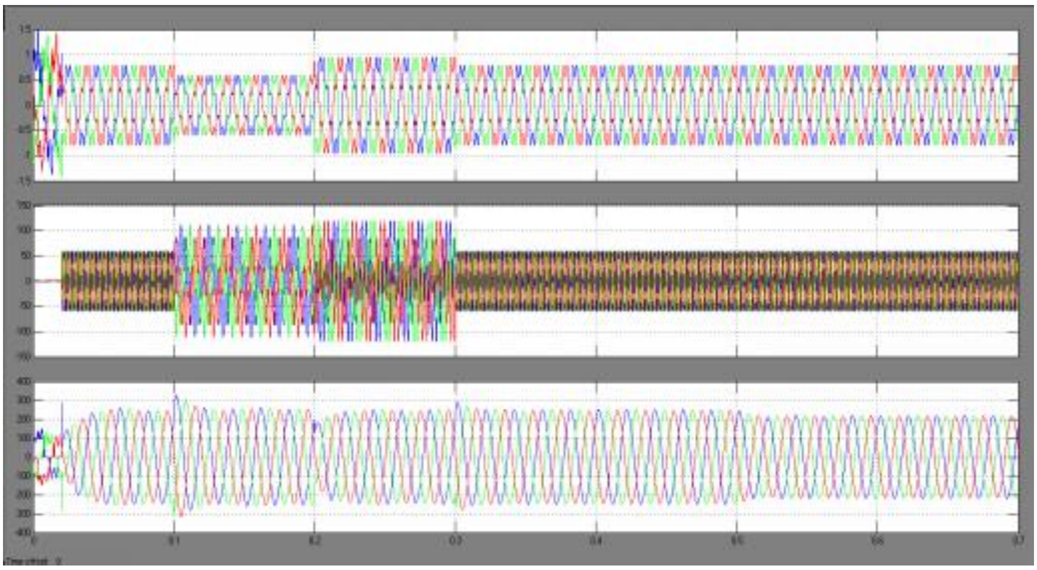

Fig :11 A. Sag & swell voltage B. compensation voltage (AWPA) C. Load voltage

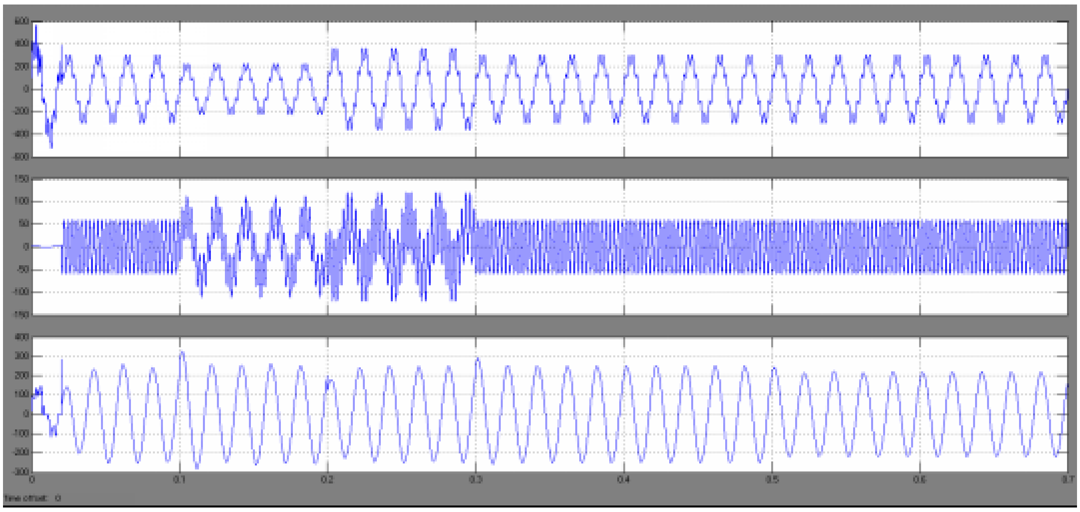

Fig 12: Single phase

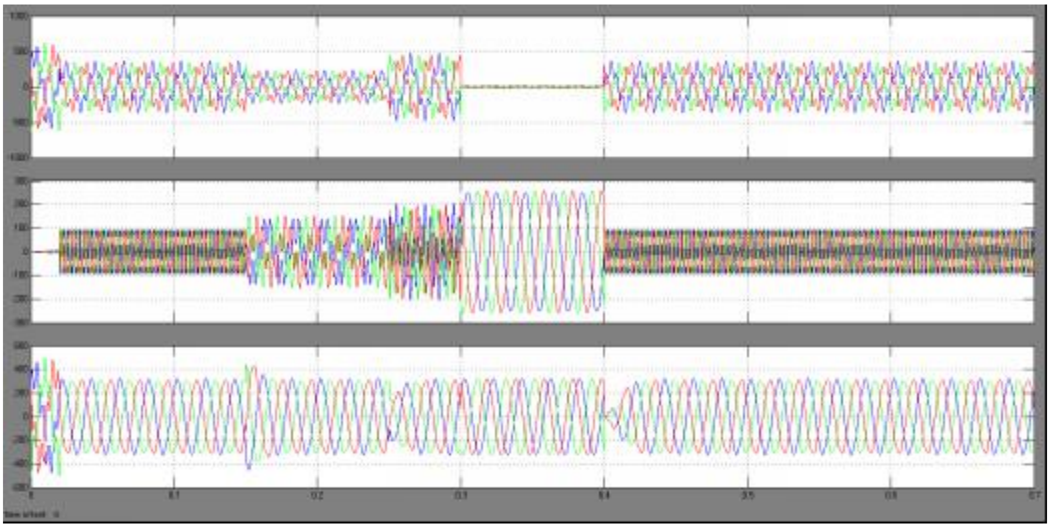

Fig13; Multiples faults compensation at a time

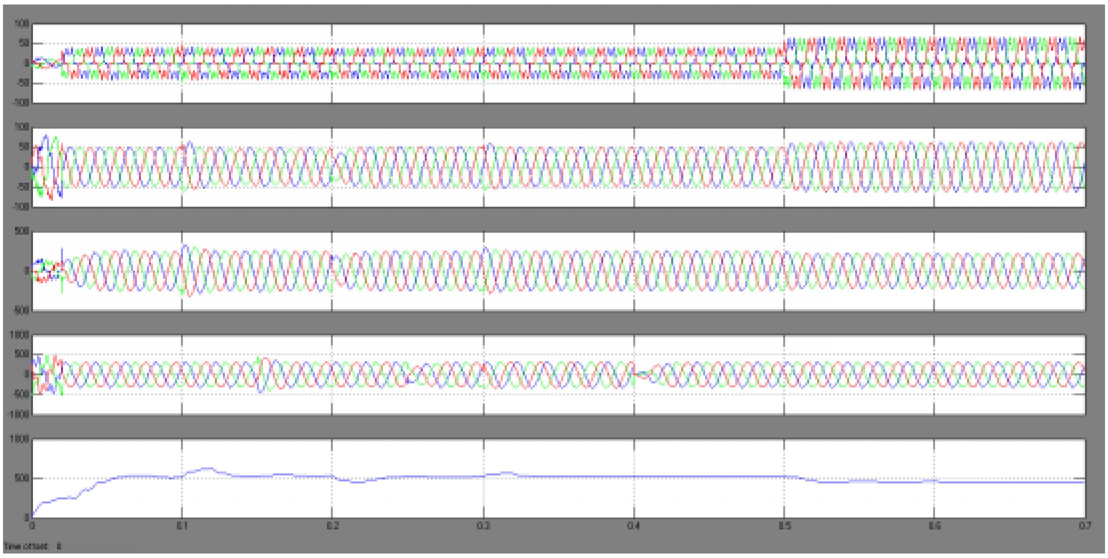

Fig14: Compensated voltages & currents & Vdc

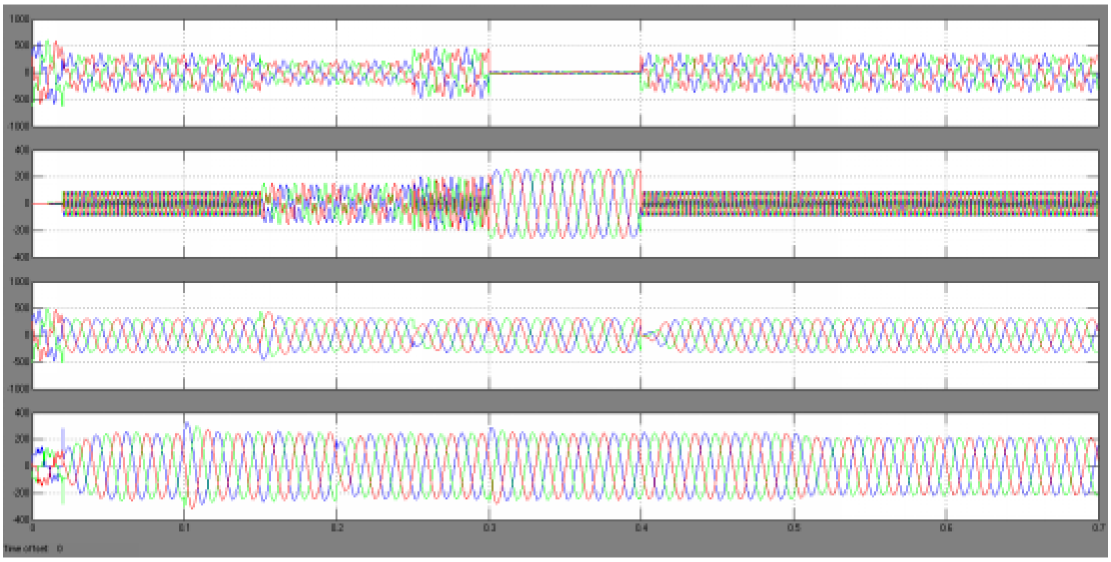

Fig 15:2 different load voltage balances

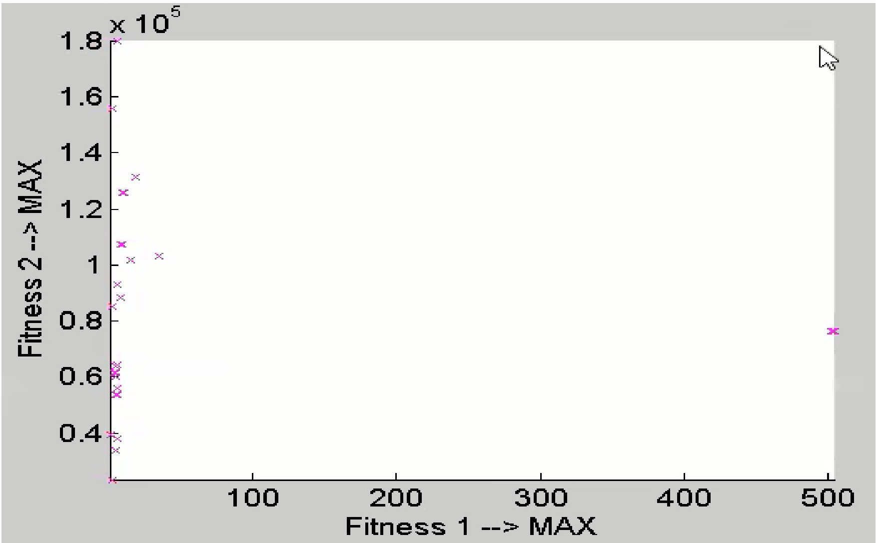

Fig 16: fitness iterations of finding fault distances in selected area of 500KM

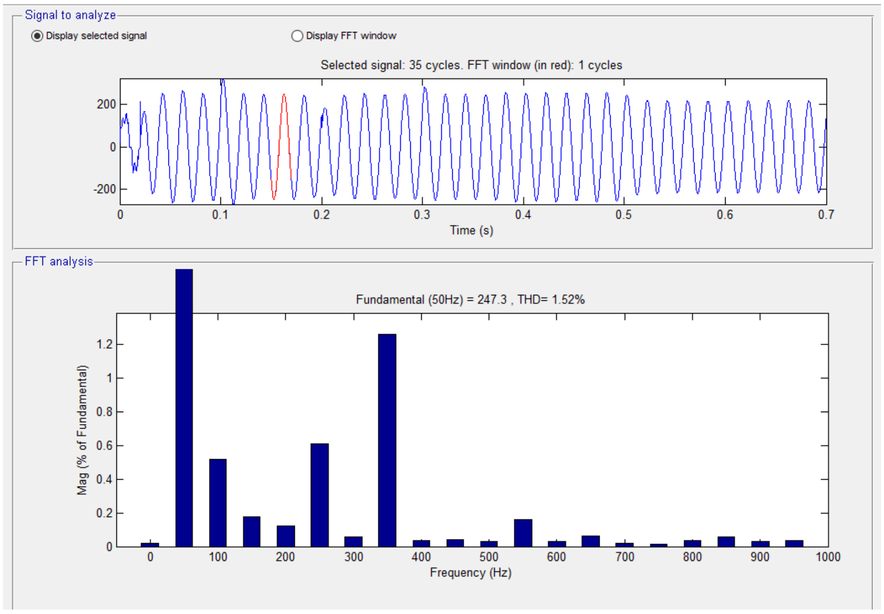

Fig 17: THD 1.52%

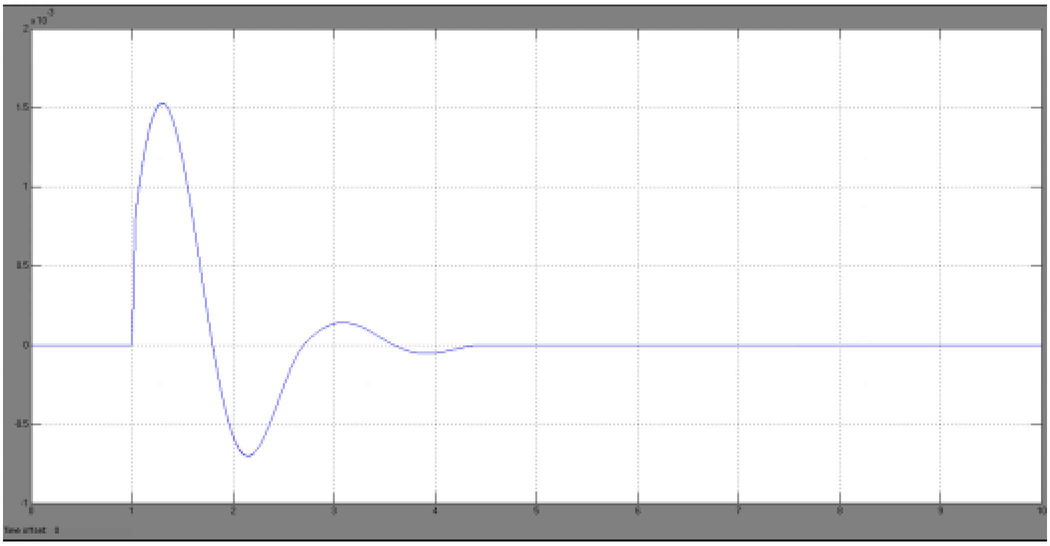

Fig 18: POD (power oscillation damping) compensation

The compensated areas after the installation of MC-UPQC the fitness observed in figure 16 and the oscillation damping in figure 18 and THD in figure 17. The dampings were compensated maximum of 3 seconds time in the proposed work.

Discussions: Multi sourced power input to the transformer with inverter based series transformer connected to the multi converter UPQC to verify non linear loads in the supply. Three different input powers from wind, Grid and PV connected to series transformer reconnects to UPQC controlled with AWPA.

6. Conclusions

A custom power device called MC-UPQC is used to mitigate voltage and current harmonics, to improve voltage regulation and to compensate reactive power. The simulation results on a two-feeder and multi bus distribution system are established by compensating execution of a novel series and shunt compensator. By increasing the number of VSCs, the advanced MC-UPQC can achieve various compensation functions. The work progressed for non- linear load conditions and the THD value is 1.52 only. The comparative analysis with GOA the accuracy increased up to 3-5% as simulated before. From POD graph its observed that the power compensation done at low time.

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