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Reconfiguration of Distribution Networks by the Presence of Distributed Generation with TLBO Algorithm

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Abstract

Distribution network optimization problem with objective such as minimizing the loss and service recovery in network, deviation of the voltage at the supply voltage profile improvement in the consumer be raised. There are Different methods for multi-unit losses in the distribution network there. They can include: capacitor, the use if distributed resources, load management transformers and network configurations mentioned. This article is distributed production on losses resulting from changes in network configurations are examined. Optimization algorithm used for solving optimization algorithm TLBO problems. To do so the optimal size and location of DG is first determined, then network reconfiguration for the 33 and 83 bus distribution systems. Loss minimization, voltage profile improvement and load balancing are considered as the objective functions for both the Placement and the Reconfiguration problem. Finally, the results obtained using the proposed method with the results of other methods on two test systems comparison and evaluation. The results of this simulation accuracy validate this matter.

Key words: reconfiguration, TLBO, loss reduction, load balancing

1. Introduction

The installation of distributed systems DG units is an important research priority in the last decades on that a lot of work has been done, and numerous techniques have been employed to solve this problem. Considerable research to find the optimal location and other DG parameters has been presented. The major drawback of this method is time-consuming analytical methods and major drawback of the method results in inefficiencies in network becomes large, as well as more rise of DGs, as well as more rise when calculations[1,2]. In recent years, with advances in smart search algorithms to solve this problem effectively is very good. The reference [3] of the genetic algorithm-based method is used to determine the location and capacity of distributed generation sources, some intelligent and evolutional method to find the optimum location of DGs have used. In reference [4] fuzzy genetic algorithms, in [5] of Tabu Search and reference [6] algorithm is used to Artificial bee colony or ant colony algorithm or PSO algorithm [7,8].

But it is used in most works performance, usually DGs installation is followed by a unit purpose. Typically, the goal of minimizing the amount of network losses are in reference [9], but the design of network parameters must also be considered. Reference [10] field with economic function definition, to determine number and location of sources DG is discussed. Reference [11], the placement DG to reduce voltage drop is done. Reference [12], scalability of the network has been used and reference [13], defines a target function based on increasing reliability and improving the voltage profile and set of parameters. Among the few studies to examine the simultaneous installation and focuses on units DG and reconfiguration has been done. At first, some studies have applied to deal with DG modeling and improving conditions of reconfiguration. Here, we tried in presence of distributed generation sources algorithm, teaching-learning-based optimization (TLBO) discuss the convergence and better time than evolutionary methods noted in reconfiguration of multi-objective distribution networks in order to reduce losses and improve the voltage profile of load balancing. Finally, the results obtained using the proposed method with results of the other methods on two test of the system IEEE has been compared and assessed.

2. Problem statement

Problem statement: The mathematical model can be expressed as follow:

$$Ft = min \begin{bmatrix} F1(X) \\ F2(X) \\ F3(X) \end{bmatrix} \quad (1)$$

The first term in the objective function (F1) to reduce the amount of network losses and is calculated using Eq.2

$$Ploss = \sum_{i=1}^{nf} ri \frac{Pi^2 + Qi^2}{Vi^2} \tag{2}$$

In which, the Pi, Qi active and reactive power balance pass from lines and and lines number nf,ri,vi respectively, and they are resistance and voltage range.

Second term represents the sum of deviations of the objective function value of the network buses voltage is pruned.

Finally, third term is the objective function that represents the load balancing feeders. Lines and distribution networks to meet increasing consumer power, often near or far from the thermal range, and response to increase unexpectedly balance. If the balance isn't controlled, some of the lines in certain directions may be overloaded. Thus, one of the best way to prevent this problem, is making load balancing amount. The function representing the loads balancing is considered, it is followed as (3):

$$FBI = \sum_{Fj} \left[\frac{I_{Fj}}{I_{Fj,avg}}\right]^2 \tag{3}$$

Where the IFJ current passesLine j and $I_{Fj,avg}$ the average pass load feeder is shown by Equation (4).

$$I_{Fj,avg} = \frac{1}{nf} \sum\nolimits_{j=1}^{nf} I_{Fj} \tag{4}$$

1-2. Normalization terms of the objective function.

Since the objective function are in different ranges, Using Equation (5) the values of about zero and a normalized are obtained.

$$\mu_{fi}(x) = \left\{ \begin{array}{c} 1\ ,f_i(x) < f_i^{min} \\ \dfrac{f_i(x) - f_i^{min}}{f_i^{max} - f_i^{min}}\ ,f_i^{min} \le\ f_i(x) \le\ f_i^{max} \\ 0\ ,\ f_i(x) >\ f_i^{max} \end{array} \right\} \tag{5}$$

Where fi denotes the objective function term iI and f_i^{min}, f_i^{max} are equal to the best and worse answers to the total of single-objective optimization in terms of the objective function can be seen.

3. Teaching–learning-based optimization

Assume two different teachers, T1 and T2, teaching a subject with the same content to the same merit level learners in two different classes. Fig. 1 shows the distribution of marks obtained by the learners of two different classes evaluated by the teachers. Curves 1 and 2 represent the marks obtained by the learners taught by teacher T1 and T2 respectively. A normal distribution is assumed for the obtained marks, but in actual practice it can have skewness. The normal distribution is defined as

$$F(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(Z-M)^2}{2\sigma^2}} \tag{6}$$

where σ^2 is the variance, μ is the mean and x is any value for which the normal distribution function is required.

It is seen from Fig 1 that curve-2 represents better results than curve-1 and so it can be said that teacher T2 is better than teacher T1 in terms of teaching. The main difference between both the results is their mean (M2 for Curve-2 and M1 for Curve-1), i.e. a good teacher produces a better mean for the results of the learners.Learners also learn from interaction between themselves, which also helps in their results.

Based on the above teaching process, a mathematical model is prepared and implemented for the optimization of a unconstrained non-linear continuous function, thereby developing a novel optimization technique called Teaching–Learning-Based Optimization (TLBO). Consider Fig 2, which shows a model for the marks obtained for learners in a class with curve-A having mean MA. The teacher is considered as the most knowledgeable person in the society, so the best learner is mimicked as a teacher, which is shown by TA in Fig 2 The teacher tries to disseminate.

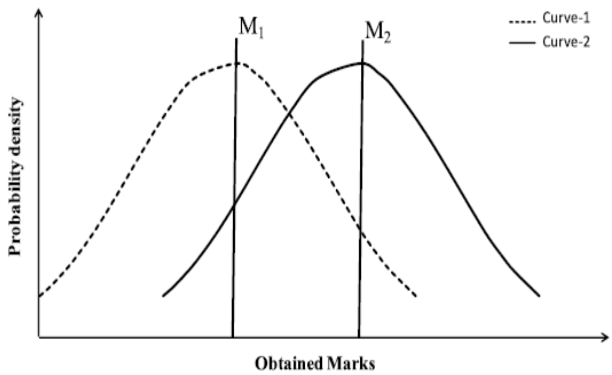

Figure 1: Distribution of marks obtained by learners taught by two different teachers

knowledge among learners, which will in turn increase the knowledge level of the whole class and help learners to get good marks or grades. So a teacher increases the mean of the class according to his or her capability. In Fig 2, teacher TA will try to move meanMA towards their own level according to his or her capability,thereby increasing the learners' level to a new meanMB.

Teacher TA will put maximum effort into teaching his or her students, but students will gain knowledge according to the quality of teaching delivered by a teacher and the quality of students present in the class. The quality of the students is judged from the mean value of the population. Teacher TA puts effort in so as to increase the quality of the students from MA to MB, at which stage the students require a new teacher, of superior quality than themselves, i.e. in this case the new teacher is TB.

Hence, there will be a new curve-B with new teacher TB. Like other nature-inspired algorithms, TLBO is also a population based method that uses a population of solutions to proceed to the global solution. For TLBO, the population is considered as a group of learners or a class of learners. In optimization algorithms, the population consists of different design variables. In TLBO, different design variables will be analogous to different subjects.

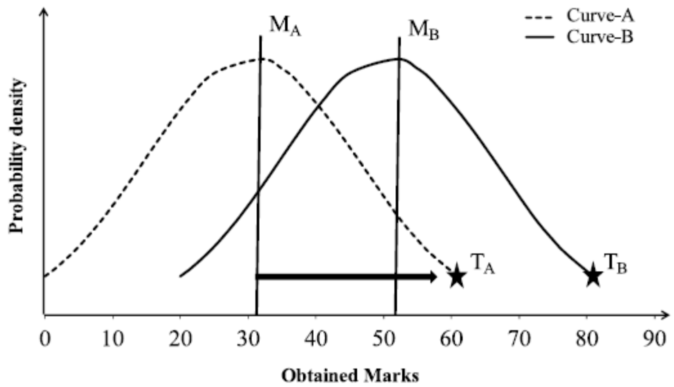

Figure 2:Model for the distribution of marks obtained for a group of learners

Offered to learners and the learners' result is analogous to the 'fitness', as in other population-based optimization techniques. The teacher is considered as the best solution obtained so far.

The process of TLBO is divided into two parts. The first part consists of the 'Teacher Phase' and the second part consists of the 'Learner Phase'. The 'Teacher Phase' means learning from the teacher and the 'Learner Phase' means learning through the interaction between learners Fig 3.[14]

1-3. Teacher phase

As shown in Fig 2, the mean of a class increases from MA to MB depending upon a good teacher. A good teacher is one who brings his or her learners up to his or her level in terms of knowledge. But in practice this is not possible and a teacher can only move the mean of a class up to some extent depending on the capability of the class. This follows a random process depending on many factors.

Let Mi be the mean and Ti be the teacher at any iteration i. Ti will try to move mean Mi towards its own level, so now the new mean will be Ti designated as Mnew. The solution is updated according to the difference between the existing and the new mean given by

$$Difference\_Mean_i = r_i\ (M_{new} - T_F M_i) \tag{7}$$

where TF is a teaching factor that decides the value of mean to be changed, and ri is a random number in the range [0, 1]. The value of TF can be either 1 or 2, which is again a heuristic step and decided randomly with equal probability as TF = round[1 + rand(0, 1) {2 − 1}].

This difference modifies the existing solution according to the following expression

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \tag{8}$$

2-3. Learner phase

Learners increase their knowledge by two different means: one through input from the teacher and the other through interaction between themselves. A learner interacts randomly with other learners with the help of group discussions, presentations, formal communications, etc. A learner learns something new if the other learner has more knowledge than him or her. Learner modification is expressed as

For i = 1 : Pn
Randomly select two learners Xi and Xj, where i≠j
If f (Xi) < f (Xj)
Xnew,i = Xold,i + ri(Xi − Xj)
Else
Xnew,i = Xold,i + ri(Xj − Xi)
End If
End For

Accept Xnew if it gives a better function value.

4. Simulation results

According to the model used in the past as well as the combination of the objective function has been defined, in this paper, two network simulation on practical tests conducted and analyzed the results of the simulations have been discussed.The results of optimization algorithm to evaluate algorithm TLBO are compared with the results of algorithms GA, PSO.

1-4. The first case study, a network of 33 bus IEEE

In order to evaluate the proposed method improves the objective function, the proposed algorithm has been implemented on network bus 33IEEE. The network is a standard with 32 Switch Sectionalizing and 5 number Tie Switch and voltage 12/66 kv. This network contains overall load 3/715MW, 2/3MVAr, and real lose power and reactive as normal operation are 201/87 MW and 153/5kVAr respectively,Fig3.

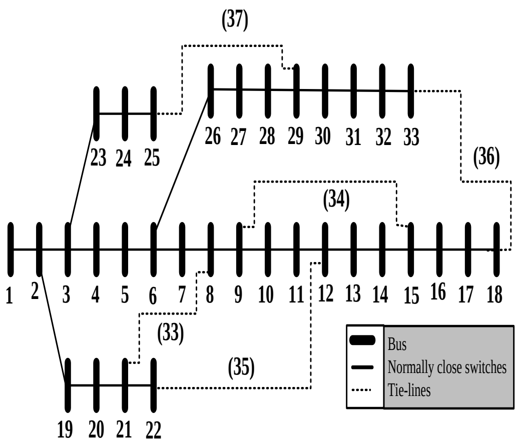

Figure 3: Single line diagram of network 33 bus IEEE

Simulation on above network at scenario 3 is done as follow:

- First scenario: Normal practical statement and reconfiguration in the network and no installation sources DG
- Second scenario: reconfiguration and no installation equipment's DG in network
- Third scenario: Installation equipment's DG and reconfiguration in the network

Results evaluations and showing operation of suggested algorithm, third scenario is that the most important and complicated simulation by algorithms GA, PSO. Simulation results in various scenarios will be discussed below,Table 1.

Table 1: Simulation results in various statements of operating

Third scenario	Second scenario	First scenario	
121/58	156/67	202/49	lose power (kW)
89/40	117/82	135/02	lose power (kVAr)
0/9406	0/9327	0/9131	Minimum voltage (p.u)

54/28	60/34	67/71	index Balance Congestion lines

Table 2: Location and Capacity of equipment DG and open Switches with different modes of operating of the network

installation sources DGand reconfiguration in the network							operating
33	34	35	36	37	open Switches		First scenario
28	21	17	14	7	open Switches		Second scenario
	30	25	7	4	Location	DG	Third scenario
	100/1	200 /0.9	100/0.9	50 /0.8	Capacity (kw)		
33	28	17	12	8	open Switches		

Table 2 Location and Capacity of installed DG equipment's of system and how Switching feeders are shown the different mode of its operations. At this stage, in addition to optimization processes of third scenario by third algorithm TLBO, this process will be done by GA, PSO.

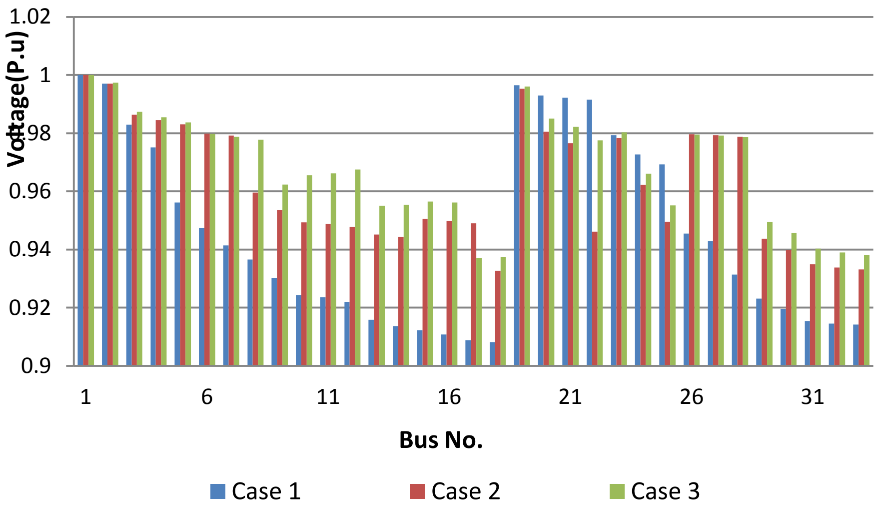

Figure 4: The profile of network voltage in various operation

The average convergence process of above algorithm as per 10 times on the same system is shown In Fig 5.As is clear, the results of algorithm TLBO insists on getting to the right answer.Based on figure. Algorithm TLBO after about 65 repeat the getting optimal answer, this is the state of after 85, 98 time repeat respectively, the algorithms GA and PSO have optimal answers. This advantage of logarithm TLBO causes great reduce in the simulation time.

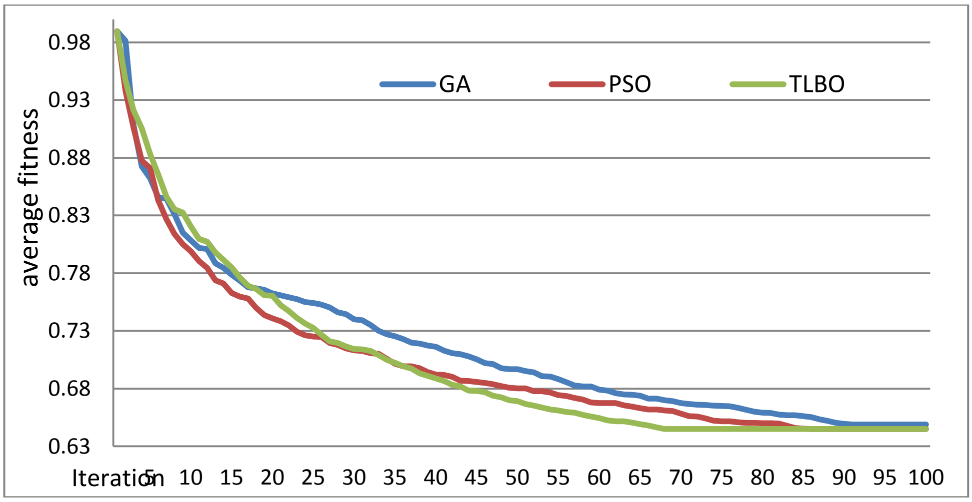

Figure 5: The average convergence process of algorithms TLBO, GA, PSO in third scenario as 10time performance

2-4. The Second case study: network Taiwan voltage 11/4KV

In order to evaluate and demonstrate the efficiency of suggested mode of practical networks, the great compare with network simulation bus 83, was implemented in Taiwan on 11/4KV. This network contains overall load 28/35kW, 20/7kVAr,13 number Tie Switch to and voltage 11/4kv. Fig 6 present the above network diagram [9].

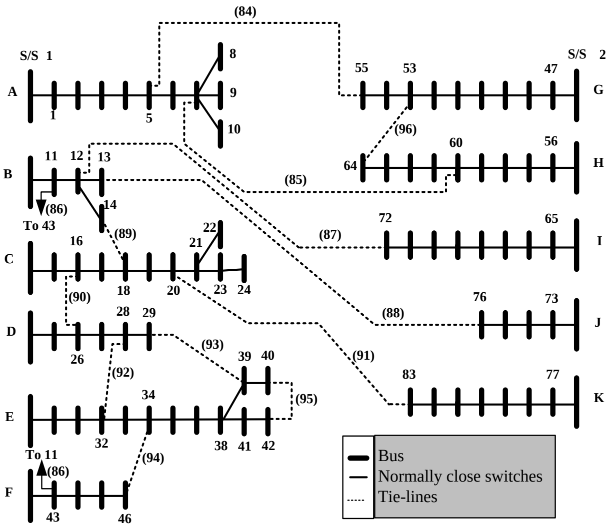

Figure 6: Network scheme of 83 bus (Taiwan power)

Table 3: The results of simulation in different scenarios of operation

Third scenario	Second scenario	First scenario	operating
432/73	487/61	531/812	lose power (kW)
1181/4	1282/1	1373/9	lose power (kVAr)
0/9522	0/9540	0/9286	Minimize voltage (p.u)
92/86	108/52	121/35	Balance index Congestion lines

Fig7 Network voltage profile is shown in different scenarios. And the third operational network of Taiwan is such as network 83 Bus to evaluate algorithm optimization TLBO, in comparison with results of algorithms GA, PSO.

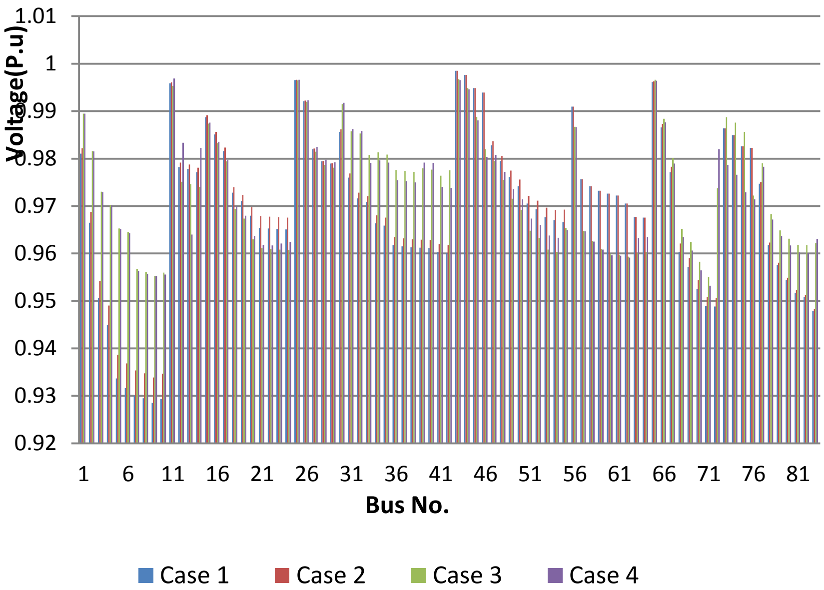

Figure 7: The profile of network voltage in different scenarios

Fig8 the average convergence process of above algorithm as per 10 time on the same system to program execution is shown. As is clear, algorithm TLBO has a higher speed and accuracy to get the optimal answer.

Table 4: The Location and Capacity of equipment DG and open Switches in different state of network operation

<table>
<tr><td colspan="7">installation sources DGand reconfiguration in the network</td><td>operating</td></tr>
<tr><td colspan="5">84 85 86 87 88 89 90 91 92</td><td colspan="2">open Switches</td><td>First scenario</td></tr>
<tr><td colspan="5">84 85 86 87 88 89 90 91 92</td><td colspan="2">open Switches</td><td>Second scenario</td></tr>
<tr><td>34</td><td>28</td><td>19</td><td>12</td><td>7</td><td>Location</td><td rowspan="4">DG</td><td rowspan="5">Third scenario</td></tr>
<tr><td>500/ 0.85</td><td>400 /0.9</td><td>500 /0.8</td><td>450/ 0.9</td><td>250 /0.8</td><td>Capacity (kw)</td></tr>
<tr><td></td><td></td><td>79</td><td>75</td><td>71</td><td>Location</td></tr>
<tr><td></td><td></td><td>400 /0.9</td><td>400/ 0.85</td><td>500 /1</td><td>Capacity (kw)</td></tr>
<tr><td colspan="5">7 33 39 42 55 63 72 76 82 86 89 90 92</td><td colspan="2">open Switches</td></tr>
</table>

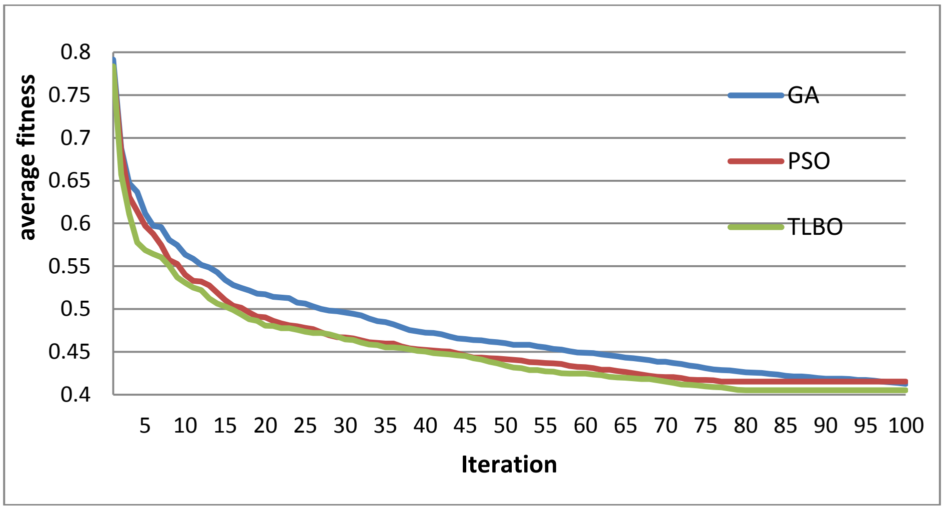

Figure 8: The average convergence process of third scenario is as per 10 time on the same system to execute the program

5. Conclusion

This paper provided a useful technique for reconfiguration. In order to improve the condition of network operation, a multi objective function to use the optimization of logarithm research TLBO. To select the best answer of the objective function, we used the phasic way. The proposed algorithm on a network 33 bus IEEE and 83-bus network has been implemented in practice in Taiwan. Continue to improve the network operation conditions have been used to reconfiguration. In this case we specified the first place of DGs and next step reconfiguration was performed and after that investment process and reconfiguration were done simultaneously. As results of this paper, reconfiguration and processing DG together, have important effect on network condition. In order to study the efficiency of proposed algorithm, the results obtained from this mode and algorithms PSO and GA, have been comprised with each other, and the results obtained from this study, have emphasized on algorithm ability.

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