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Evolutionary programming and multi-verse optimization based Technique for risk-based voltage stability control

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Abstract

Power system these days appears to work at high-stress load, which could trigger voltage security problems. This is due to the fact that the system will operate under low voltage conditions, which could be possibly below the allowable voltage limit. The voltage collapse phenomenon can become one of the remarkable issues in the power systems which can lead to severe consequences of voltage instability. This paper proposes a method for managing the voltage stability risk using two methods which are evolutionary programming (EP) and multiverse optimization (MVO). Consequently, EP and MVO were used to manage the risk in the power system due to load variations. The risk assessment is made in order to determine the risk of collapse for the system utilizing a pre-developed voltage stability index termed as Fast Voltage Stability Index (FVSI). It is used as the indicator of voltage stability conditions. Results obtained from the study revealed that the MVO technique is much more effective compared to EP.

Keywords: Voltage stability, Fast voltage stability index, Multiverse optimization (MVO) and Evolutionary programming (EP), Risk assessment

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1. Introduction

Voltage stability is not a new issue in power system operation and planning. It has been rigorously discussed; in particuar the voltage stability problems or any power system disturbances linked to power outage threat. This can potentially cause social and economic problems. In 1965 and 1996, over 50 incidences of voltage collapse or voltage instability were reported worldwide. In 1987, the nation's most severe voltage instability outages happened in Tokyo on 23 July 1987, which they had endured a shutdown in more than 3 hours, and more than 2.8 million users were impacted by the power outages [6]. A power failure in the North American Coordinating Council of Western Systems involving network on 2 July 1996 has resulted in interruptions of operation for more than 6 million people [1]. System voltage stability is defined as the capacity of the system to maintain tolerable voltages in all system buses even after being interrupted under normal condition. The voltage stability is also sometimes called as load balancing. The voltage stability state in an electrical system is identifiable with the voltage stability indices. Voltage stability indices can be used as the indicator for voltage stability assessment. It can be used online or offline to assist power system operators in running the power system in real-time, or in planning and designing operations [14]. Their values constantly change between 0 and 1 [6]. Such indices will be discussed to show how near a system can be worked to voltage instability and lead to failure in vast parts of the power system network [14]. A power system's ability to maintain voltage stability at all buses in any circumstances is necessary to avoid a collapse in voltage. The primary cause for voltage instability is that a system lacks adequate reactive power. The main factors of low reactive power are generator reactive power constraints and the reactive power demands in transmission lines [18]. The voltage will be unstable if the load generator is large. An analysis is done to locate the weakest bus, which would result in voltage instability and ways to manage the instability based on risk. Many techniques have been reported to manage voltage stability condition. Along with that, risk assessment has also been incorporated in managing this issue. Risk based voltage stability can be resulted from line outage, load variation and any possible disturbances. Some remarkable studies that be highlighted are work conducted in [13, 2, 15, 9, 20]. This paper presents evolutionary programming and multi-verse optimization-based technique for risk-based voltage stability control. In this study, two optimization algorithms were employed to manage the risk of voltage stability. Prior to that, FVSI was utilized to indicate the voltage stability with high risk. The risk-based voltage stability is observed by the impact of collapse and the probability of collapse. The impact of collapse is determined using the Fast Voltage Stability Index (FVSI). Validation process performed using evolutionary programming (EP) and multiverse optimization (MVO) was conducted on the IEEE 30 bus reliability test system (RTS). Results obtained from the study highlights the capability of FVSI in evaluating the risk condition. The implementation of EP and MVO also revealed the flexibility of both optimization techniques in managing the risk. MVO is superior than EP resulted from the study.

2. Risk based assessment

2.1. Voltage stability assessment

Voltage stability assessment is still significant issue in power system. It is measured using voltage stability index i.e. the Fast Voltage Stability Index (FVSI). FVSI is a voltage stability index; formulated from the voltage quadratic equation of the two-bus system which proposed by Ismail Musirin in [11]. FVSI is a static line voltage stability index. Although voltage stability is a complex problem, static indices played important role in evaluating voltage stability which will be beneficial to power system operators on how severe the actual operating point is to the limit of static stability

[12]. The application of voltage stability indices is the most often based on the notion that loads are modelled as stable power components where the voltage stability maximum is proportional to the nose of a PV curve [16]. It is used to locate critical areas in a large power system, capable of assessing the point of collapse of voltage, the allowable maximum load, the system's weak bus, as well as the most critical line in a linked system. The voltage stability can be analyzed at all lines in power system. Nevertheless, the overall maximum FVSI is already good enough to indicate the whole system stability. Several scenarios can be considered for this case [14]:

- If FVSI is close to 1, means that the line is near to its point of instability which can result in the failure of voltage in the entire system.
- If FVSI lower than 1, indicates a stable condition.
- If FVSI goes beyond 1, the bus voltage will suddenly drop and resulting in system collapse.

FVSI is based on the idea of power flow across the network line, which is based on a single line power flow concept. In FSVI formula, the power angle in the network between buses is assumed to be negligible and thus equated to 0. Hence, the FVSI formula becomes simpler and more analytical [11]. Thus, Fast Voltage Stability Index (FVSI) is written as follows:

$$FVSI = \frac{4 * Z^2 * Q_j}{V_i^2 * X_{ij}} \qquad (1)$$

Where, Z is the line impedance, X_{ij} is the line reactance, the reactive power at the receiving end is Q_j and V_i is sending end voltage [19]. From equation in (1), it implies that the FVSI value is proportional to the reactive power at the receiving end of a transmission line. As the reactive power increases, the FVSI value will increase accordingly.

2.2. Concept of risk

The risk is commonly defined as the product of the probability of uncertainty and the consequence of uncertainty. The uncertainty cam be due to the transmission line outage, generator outage, and fluctuation of load. The voltage collapse risk calculation is given as follows:

$$Risk(VC) = \sum_{i=1}^{M} Pr(Ei)xSev(Ei) \qquad (2)$$

In (1), i_1 comprises a group of M critical lines, where the probability of line outage and the consequence of voltage collapse are $P_r(E_i)$ and $Sev(E_i)$.

The risk index is known to be unit-less. In this study, the uncertainty considered is the line outage and load fluctuation. The probability of the collapse is generated randomly by using the Monte Carlo method and has the value from 0 to 1. The FVSI index is used to measure the impact of the voltage collapse. Subsequently, the risk is calculated using equation in (1). The flowchart of the risk-based assessment is shown in Figure 1.

3. Optimization techniques

3.1. Evolutionary programming

Evolutionary Programming (EP) is influenced by the evolutionary perspective. It is an Artificial Intelligence field of study.

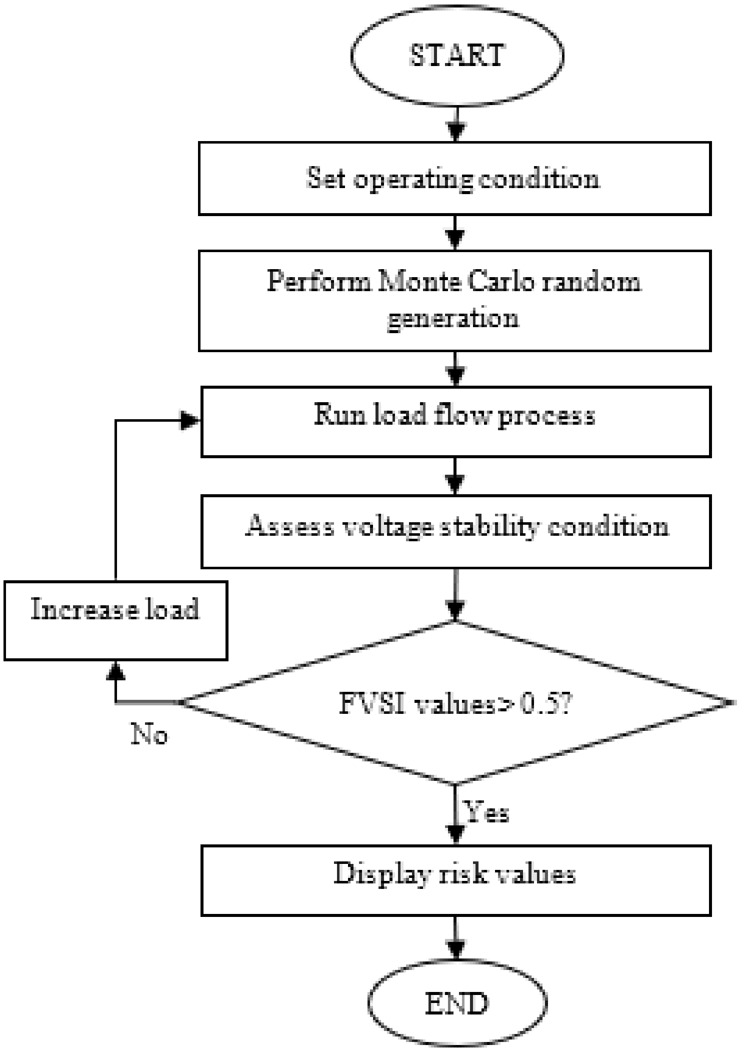

Figure 1: Flowchart for FVSI Based Risk Assessment

A solution is created in evolutionary programming and is modified repeatedly from an original group of candidates. Each generation is produced with less desired solution excluded. Then, small, spontaneous changes are made. The population will thus be developed over time to enhance the fitness which is the algorithm. The first basic step of evolutionary programming is by choosing a population randomly for initialization to generate parents. Then, find the initial population's fitness. Subsequently, mutate the population of the samples to generate offspring and recalculate of fitness value. Later, do the parents and offspring combination. Based on the lowest or maximum ratio, pick the new population and lastly the step is repeated until it converges. The population is initialized randomly and then subjected over many generations to the selection, recombination, and mutation process, so that the newly generated generations evolve into more favorable regions of the search space [7]. The new population of individuals is created in EP by mutating every individual from the parent generation. The mutation is based on the random disruption of the values of the mutated individual's specific genes. The newly formed populations and the parental populations are of the same size. Then, by using the ranking selection of the individuals from both parental and mutated populations, the new generation of the population is established in accordance with the fitness value [17]. By pointing to the evolutionary programming process flow displayed in Figure 2, these steps are

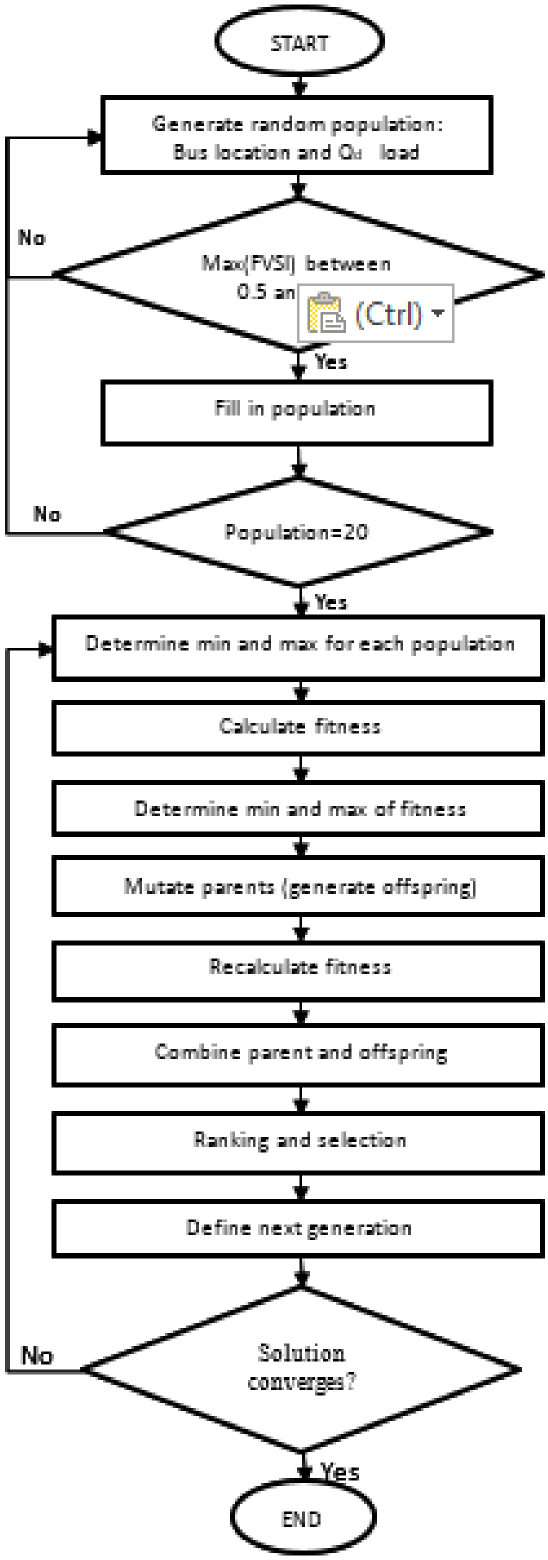

Figure 2: Flowchart for Evolutionary Programming

important to complete the evolutionary programming. From the flowchart, the random population created consists of 4 different populations, which are 2 bus locations and 2 values of reactive power. These population will generate 20 variables each. For the bus location, the variable value is between

2 and 30. As for the reactive power, the range is between 0MVar and 50MVar. The fitness stated is referring to the value of maximum FVSI. The FVSI value is considered between 0.5 and 0.9 to make the system laid down in condition where it does not reach the collapse point, as the focus for this paper is to control risk-based voltage stability.

3.2. Multi-Verse optimization technique

The MVO algorithm is a metaheuristic algorithm proposed by Seyedali Mirjalili in [10]. The MVO algorithm is a nature-inspired algorithm imitating a modern multi-versus theory popularly known by many physicists.

A. Basic concept of MVO

MVO is a stochastic population-based algorithm that was recently introduced. MVO was primarily influenced by the multiverse. The key to the multiverse theory is a black hole and a wormhole are among the components. a white void for the purpose of construction, these are mathematically modelled. MVO stands for m-theory. The evaluation process, called exploitation and exploration, is divided into two stages [5]. The three main principal theories in MVO are the white hole, black hole, and worm hole. Figure 3 shows the illustrations of white hole, black hole, and worm hole.

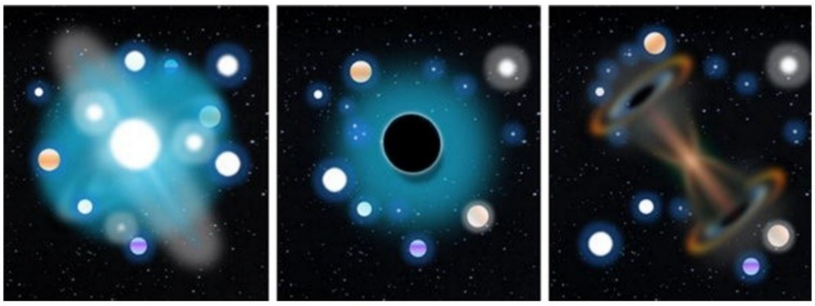

Figure 3: White hole, black hole and worm hole

White hole is regarded as a big bang that is not found in the universe and it is the principal universe source. The universe spots the black hole that will pull the objects inside of the universe. The wormhole is a passageway between two universes that function as time/space travel tunnels where objects can pass from one universe to another to any part of the universe. Each universe contains the rate of inflation which contributes to its growth. The fitness value is computed by the inflation rates.

During the entire optimization process, there are four rules.

a) Black holes: In a universe with a lower inflation rate, black holes appear to obtain more objects.

b) White holes: White holes, with a higher inflation rate, appear to send objects across the universe.

c) Wormholes: Also referred as " grey lanes " that linking black holes to white holes. Randomly, without being bound by the rate of inflation, objects from the universe can be sent to the best universe.

d) d) The expansion rate is the rate of universe inflation, which varies from universe to universe. In each iteration, the universe is ordered according to the level of the inflation rate and the white hole is located via the process of the roulette wheel.

Hence, objects will move from a universe with high inflation to a universe with low inflation by following these laws, thereby providing an improvement in average inflation, and achieving a stable state.

Mathematical equation

First, assuming that universe is equal to the universe's parameters with its solutions as in equation (3):

$$\begin{bmatrix} x_1^1 & \dots & x_1^d \\ \dots & \dots & \dots \\ x_n^1 & \dots & x_n^d \end{bmatrix} \qquad (3)$$

Where, the number of variables is d, and the number of solutions corresponding to the universe is n.

$$x_i^j = \begin{cases} x_i^k & r_1 < NI(U_i) \\ x_i^j & r_2 \geq NI(U_i) \end{cases} \qquad (4)$$

where x_i^j is the j^{th} variable of i^{th} universe, Ui is the ith universe, NI(U_i) indicates the standard inflation rate of the i^{th} universe and $x_k^j$is the j^{th} variable of k^{th} universe chosen by a roulette wheel selection mechanism [3]. To identify the white holes, the roulette wheel selection method is used according to a normalized rate of inflation as shown in (4).

Then, to ensure local modifications in each universe to manipulate the searching phase, wormhole tunnels are set up between the best universe and any created universe. Moving the mechanism into wormhole tunnels assures that each universe's inflation rate increases [4]. The mathematical formulation for the transfer of objects via a wormhole tunnel between a created universe and the best universe when r2 is lower than the probability of wormhole existence (WEP) is in equation (5) and when r2 is larger than WEP is in equation (6).

$$x_i^j = \begin{cases} x_j^{best} + TDR((ub_j - lb_j) \times r_4 + lb_j) & r_3 < 0.5 \\ x_j^{best} - TDR((ub_j - lb_j) \times r_4 + lb_j) & r_3 \geq 0.5 \end{cases} \qquad (5)$$

$$x_i^j = \{ \; x_j^{RouletteWheel} r_2 < WEP \qquad (6)$$

Where x_j^{best} represents the j^{th} parameter for the best generated universe to occur. Wormhole Existence Probability (WEP) and the travelling distance rate (TDR) are two coefficients modified using (7) and (8). Whereas, r_1, r_2, and r_3 are random numbers that between 0 and 1 interval. The universe location was modified with the following equations involving WEP and TDR as in equations (7) and (8).

$$WEP = min + l * (max - \frac{min}{L}) \qquad (7)$$

$$TDR = 1 - (iter^{\frac{1}{p}} \div L^{\frac{1}{p}}) \qquad (8)$$

Where, L is the highest iteration while iter is the current iteration, max and min are constants (typically, min=0.2, max=1) and p is the constant of exploitation accuracy (typically, p=6). Notice that more WEP values and less TDR values are found in the best universe [8]. Figure 4 shows the flowchart of MVO.

From the flowchart, the random universes created consists of 4 different universes, which are 2 bus locations and 2 values of reactive power. These universes will generate 20 individuals each. The upper and the lower boundaries are based on type of universes. For the bus location, the lower and upper boundary is 2 and 30 respectively. As for the reactive power, the lower and upper boundary is 10MVar and 100MVar respectively. The fitness stated is referring to the value of maximum FVSI. The FVSI value is considered between 0.5 and 0.9 to make the system in condition where it does not reach the collapse point, as the focus for this study is to control risk-based voltage stability.

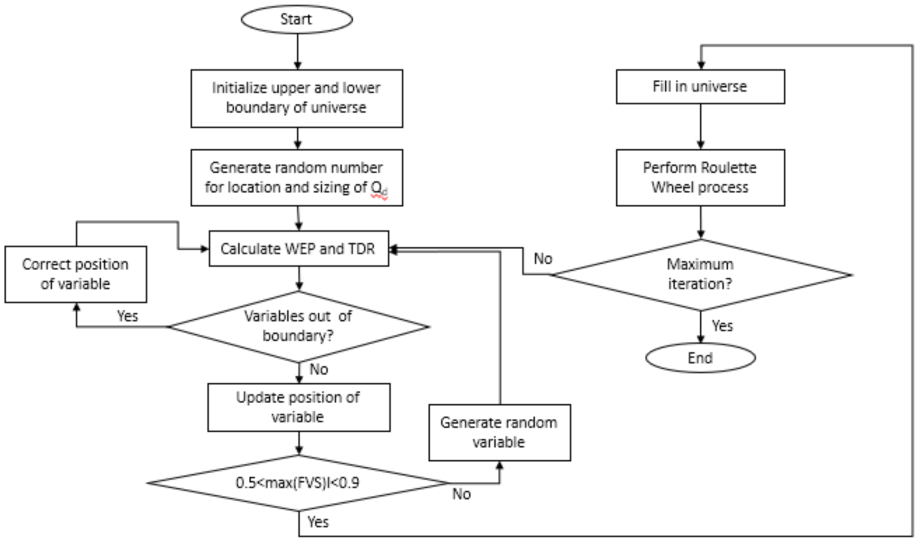

Figure 4: Flowchart for Multi-Verse Optimization Technique

Figure 5 shows the pseudo code for the MVO algorithm.

```
Input: Population size (N) and number of iterations (Iter_max)
Output: The best universe and its inflation rate
Define: SU=Sorted universes, NI=Normalized inflation rate,
Black_hole_index=I,r1,r2,r3,r4=rand([0,1])
Initialize all random universes, WEP, TDR and best universe
while (end condition is not met) do
Calculate fitness of universes
  for (each universe) do
      Update WEP and TDR
  for (each object) do
    if r1 < NI(each universe) then
      White_hole_index=RouletteWjeelSelection(-NI)
      U(Black_hole_index,j)=SU(White_hole_index,j)
    if r2 < WEP then
      if r3 < 0.5 then
        U(i,j)=Best_universe(j) + TDR x ((ub(j) –lb(j)) x r4 + lb(j))
      else
        U(i,j)=Best_universe(j) - TDR x ((ub(j) – lb(j)) x r4 + lb(j))
Return: The best universe and inflation rate
```

Figure 5: The pseudo code of MVO algorithm

4. Results and discussion

The simulation work was carried out on the IEEE bus test system, which is the IEEE 30 bus test system. The single line diagram for this system is illustrated in Figure 6. This system has 20 buses, 6 generators (including the swing bus) and 24 load buses. There are 40 transmission lines in the system. The bus data are tabulated in Table 1, while the line data are tabulated in Table 2. Table 1 tabulates the detailed data including the bus number, bus codes, active power demand P_d, reactive power demand Q_d, minimum reactive power limit, maximum reactive power limit and maximum reactive power compensation. In Table 1, it tabulates the sending bus, receiving bus, per unit resistance ($R_{p.u.}$), per unit reactance ($X_{p.u.}$), per unit susceptance ($G_{p.u.}$) and per unit transformer turns ratio. The primary objective of the simulation work is to evaluate the behavior of the tested bus system towards FVSI while the system is operated under variations of load. FVSI index is calculated for the entire system for different cases as the following:

a. Case I : Base Case Condition

b. Case II : Loaded Case

c. Case III : Optimal Load Management

4.1. Case I: Base Case Condition

Table 3 tabulates the result for FVSI computed for the base case condition. Base case condition refers to the initial loads set by the system planner, without adding any new loads to the system. Apparently, the computed FVSI is very small, demonstrating that the system is significantly stable. It can be shown that the maximum FVSI value is 0.2035 on the line connecting bus 4 and bus 12. The table shows the 5 lines with the top FVSI values. The system is stable indicated by low FVSI values, typically much lower than unity. So, there is no risk in the system. These values are expected to increase once load is increased as the load increment will affect the voltage level in the system. Since FVSI was formulated to be reactive power sensitive, small increment in Qd in the system will basically affect to the increment of FVSI value, which in turn may possibly cause the system to be unstable. In this case, no risk has been experienced by the system yet. This could be due to low FVSI values resulted from this condition.

In this case the FVSI values of the top five lines are recorded, with all the connecting buses at the sending and receiving ends are also tabulated. Lines 15, 11, 12, 13 and 8 are the lines which are responsible to exhibit high FVSI values at the base case. Amongst the five lines, line 15 experiences the highest FVS value worth 0.2035 p.u.. This is not exactly high, as compared to the limit being set, i.e. unity. What can be interpreted from this table is that line 15 cold be considered the most sensitive line among others due to its high FVSI value. This value may increase when reactive power loading is increased in the system. Nevertheless, the increment in reactive value should have direct or indirect connection with this line. Direct connection may reflect to sending or receiving buses connected to line 15. On the other hand, indirect connection may refer to next line closes to line 15.

4.2. Case II: Loaded Case

Table 4 shows the result for FVSI computed for the load increase case, where the load in the test system was set to 100Mvar at bus 20 and 28. These busses were selected, and the simulation was carried out to investigate the relationship between FVSI, reactive power demand and risk. The calculated FVSI is nearly 1, showing that the system is unstable. It can be shown that the highest FVSI value is 0.9945 for the line connecting bus 10 to bus 20, which makes this line critical as its

Table 1: Linedata for the IEEE 30-Bus Reliability Test Ssytem (RTS)

$\mathbf{Bus_{sending}}$	$\mathbf{Bus_{receiving}}$	$\mathbf{R_{p.u.}}$	$\mathbf{X_{p.u.}}$	$\mathbf{G_{p.u.}}$	**Trans**
1	2	0.0192	0.0575	0.02640	1
1	3	0.0452	0.1852	0.02040	1
2	4	0.0570	0.1737	0.01840	1
3	4	0.0132	0.0379	0.00420	1
2	5	0.0472	0.1983	0.02090	1
2	6	0.0581	0.1763	0.01870	1
4	6	0.0119	0.0414	0.00450	1
5	7	0.0460	0.1160	0.01020	1
6	7	0.0267	0.0820	0.00850	1
6	8	0.0120	0.0420	0.00450	1
6	9	0.0	0.2080	0.0	0.978
6	10	0	.5560	0	0.969
9	11	0	.2080	0 1	
9	10	0	.1100	0	1
4	12	0	.2560	0	0.932
12	13	0	.1400	0	1
12	14	.1231	.2559	0 1	
12	15	.0662	.1304	0	1
12	16	.0945	.1987	0	1
14	15	.2210	.1997	0	1
16	17	.0824	.1923	0	1
15	18	.1073	.2185	0	1
18	19	.0639	.1292	0	1
19	20	.0340	.0680	0 1	
10	20	.0936	.2090	0	1
10	17	.0324	.0845	0	1
10	21	.0348	.0749	0	1
10	22	.0727	.1499	0	1
21	22	.0116	.0236	0	1
15	23	.1000	.2020	0	1
22	24	.1150	.1790	0	1
23	24	.1320	.2700	0	1
24	25	.1885	.3292	0	1
25	26	.2544	.3800 0	1	
25	27	.1093	.2087	0	1
28	27	0	.3960	0	0.968
27	29	.2198	.4153	0	1
27	30	.3202	.6027	0	1
29	30	.2399	.4533	0	1
8	28	.0636	.2000	0.0214	1

value is close to unity. Meanwhile, the risk of the system to collapse is 0.6745 which is considered as a high risk. As a consequence of load increase, the FVSI value increases significantly for all the lines in the system. At this point, it can be summarized that extra power flows through the remaining

Table 2: Busdata for the IEEE 30-Bus Reliability Test System (RTS)

Bus No	Bus Code	V_m	d	P_d	Q_d	P_g	Q_g	Q_{gmin}	Q_{gmax}	Q_{gc}
[1	1	1.06	0.0	0.0	0.0	0.0	0.0	0	0	0
2	2	1.043	0.0	21.70	12.7	40.0	0.0	0	50	0
3	0	1.0	0.0	2.4	1.2	0.0	0.0	0	0	0
4	0	1.06	0.0	7.6	1.6	0.0	0.0	0	0	0
5	2	1.01	0.0	94.2	19.0	0.0	0.0	-40	40	0
6	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
7	0	1.0	0.0	22. 8	10.9	0.0	0.0	0	0	0
8	2	1.01	0.0	30.0	30.0	0.0	0.0	10	60	0
9	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
10	0	1.0	0.0	5.8	2.0	0.0	0.0	-6	24	19
11	2	1.082	0.0	0.0	0.0	0.0	0.0	0	0	0
12	0	1.0	0	11.2	7.5	0	0	0	0	0
13	2	1.071	0	0	0.0	0	0	-6	24	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9.0	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0.0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0.0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	0	1	0	0	0.0	0	0	0	0	0
28	0	1	0	0	0.0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0]

Table 3: Result for Base Case Voltage Stability

Line	Sending bus	Receiving bus	FVSI value
15	4	12	0.2035
11	6	9	0.1656
12	6	10	0.1450
13	9	11	0.1214
8	5	7	0.0587

lines in order to serve the load demand. Thus, making the remaining lines more heavily loaded and increase the risk of the system to collapse. This implies that high risk is very phenomenal to high FVSI value. Thus, the possibility of the system to experience voltage collapse is very prone. The risk was assessed for the whole system, when an event is subjected to the system. In this case, the

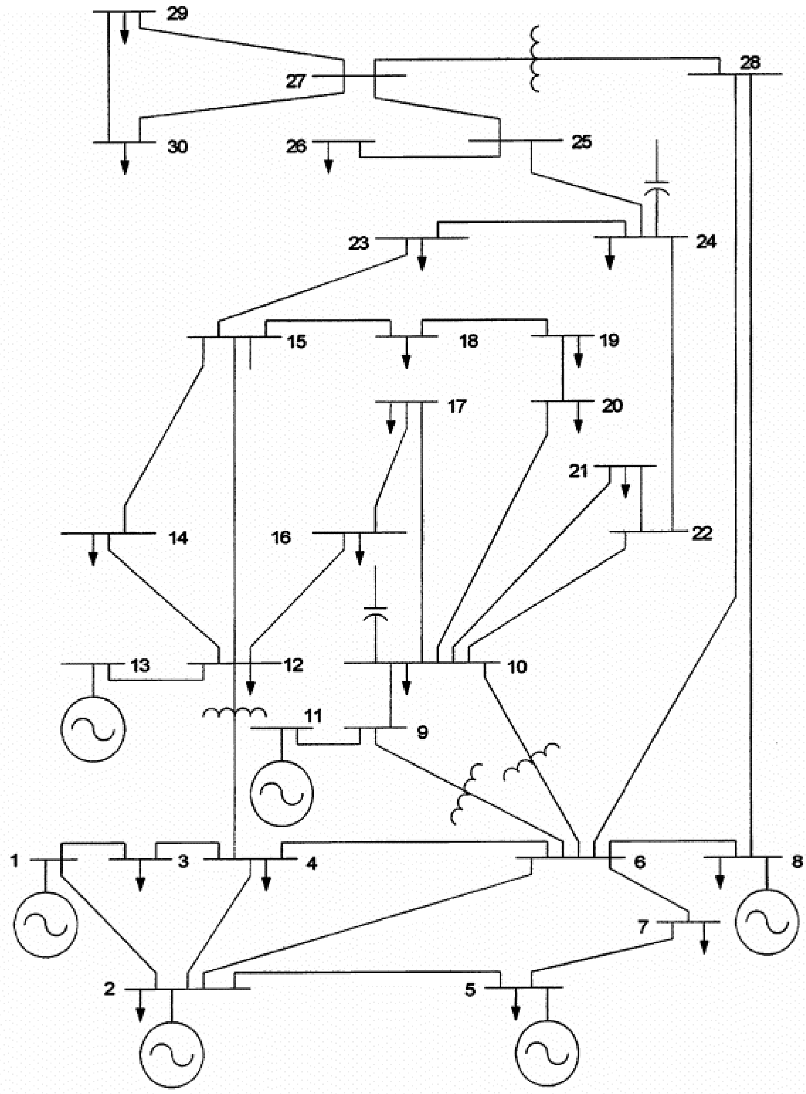

Figure 6: Single Line Diagram of IEEE-30 bus reliability test system (RTS)

increment of load at buses 20 and 28 worth 100 MVAR has led the system to experience high risk. The risky condition was due to acceptably high FVSI values involving lines 25, 13, 22 and 23. Even, only one-line experienced high FVSI value, closes to 1.00 worth 0.9945; it has led the whole system to experience risky condition.

Table 4: The Result for Risk under Load Increase

Line	**From Bus**	**To Bus**	**FVSI value**	**Risk**
25	10	20	0.9945	0.6745
13	9	11	0.7749	
22	15	18	0.6536	
23	18	19	0.5014	

4.3. Case III: Optimal load management

In this simulation, an optimization is done in order to get the best optimal FVSI value and reactive power to maximize or minimize the risk of collapse for the system when there is contingency exist. The optimization technique is using the Evolutionary Programming (EP) and the Multiverse Optimization (MVO). It is tested by generating 2 random loads. The contingency here represented by the load variation where the reactive power of two busses were randomly generated. Table 5 tabulates the result for power losses (P_{loss}), FVSI value and the risk index for the system before and after optimization technique to minimize and maximize the risk of collapse.

Table 5: The Result of Before and After Optimization

			$\mathbf{P_{loss}}$ **(MW)**	**FVSI**	**Risk**
Before			53.06	0.9945	0.6745
After	**Minimize**	EP	20.87	0.5069	0.3441
		MVO	19.98	0.5062	0.2886
	Maximize	EP	26.56	0.8865	0.6018
		MVO	30.85	0.8952	0.6221

In this case, two loads were managed to either minimize or maximize the risk in the whole system. In this study, apparently 2 objective functions were performed independently so that we can determine the optimal results to gain maximum and minimum risks. From Table 5, it can be concluded that Evolutionary Programming and Multiverse Optimization can be used to control the risk-based voltage stability, since it managed to minimize and maximize the Ploss,, FVSI value and the risk. Multiverse Optimization technique managed to achieve lower minimum risk and higher maximum risk, when the two objective functions were independently conducted to the system as compared to Evolutionary Programming. For minimization process, MVO managed to achieve 0.5062 as the FVSI value with its corresponding risk of 0.2886. This implies its capability to reach lower FVSI value as compared to EP, where it only managed to achieve 0.5069 with its corresponding risk of 0.3441. For maximization process, MVO managed to achieve high FVSI value, as high as 0.8952; while EP only managed to achieve only 0.8865. The corresponding risk resulted by MVO is 0.6221, while EP gives 0.6018. These results implied that MVO could search for the possible highest FVSI and risk values as compared to EP. This deduces the superiority of MVO over EP.

5. Conclusion

This paper has presented the risk-based voltage stability control using MVO and EP. In this study, FVSI, as a line-based voltage stability index was incorporated with risk analysis, optimized using MVO and EP. Three cases have been compared to assess the possibility of risky condition, which could also be due to load increment. By increasing the load at bus 20 and 28, it demonstrates that the FVSI value are affected. As the load is increased, the FVSI value is increased. The risk can be experienced by any subjected disturbances such as load increase, line outage or generator outage. Results obtained from the study revealed that MVO is superior to EP in achieving better results, such as gaining the possible minimum point or the possible maximum point for both FVSI and risk. Both, MVO and EP can be then utilized further problem problems in power system optimization issues.

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