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POWER SYSTEM LOAD LIMIT DETERMINATION USING THE PSO METHOD

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ABSTRACT

As electricity use rises, the electrical grid becomes more stressed. And if the electricity system is overloaded, it might fail. Overloading the system might cause a total shutdown. Power outages are never acceptable, but they are particularly dangerous in industrial settings. Therefore, the purpose of this research is to establish the safe carrying capacities of buses. The highest load amount is the maximum passenger capacity of the vehicle. While Fast Voltage Stability Index (FVSI) is often used to determine which bus is the most vital, in this case it will be used to find the weakest buses in the system. A low FVSI score indicates a bus with poor reliability. In addition, the maximum load ability limit of a bus system may be calculated using conventional techniques like the Newton-Raphson method, although doing so is difficult and time-consuming. As a consequence, we optimize the FVSI value using the Particles Swarm Optimization (PSO) Evolutionary Computation method to determine the load capacity of each bus. PSO and FVSI are evaluated with IEEE 6-bus and IEEE 30-bus systems, respectively. Both FVSI and PSO simulations are performed in MATLAB.

Keywords: IEEE, Particle swarm, voltage, FVSI, Bus system.

I. INTRODUCTION

The optimization technique known as Particle Swarm Optimization (PSO) takes its cues from the coordinated foraging methods of flocks of birds and schools of fish. Eberhart and Kennedy created and refined the method. Simple, robust to control factors, and computationally efficient, PSO stands out as a better heuristic solution in a continuous issue context, where the evolutionary algorithm is often applied. PSO may be used to efficiently provide superior outcomes for a broad variety of problems, including those that are not differentiable, non-linear, and/or have a large search space. Instead of utilizing conventional genetic operators, PSO has each particle modify its behavior based on what it and its neighbors have learned. PSO uses two sets of equations: one to update the location, and another to update the speed. By adjusting parameters at each iteration, the PSO algorithm is guaranteed to converge on the best possible answer.

The ith swarm particle in an n-dimensional search space is denoted by a vector of the same dimension, Xi = (xi1, xi2,...,Xin) T. An additional n-dimensional vector, Vi = (vi1, vi2,..., vin) T, represents the particle's velocity. The probability that a particle will visit a certain position, denoted by Pi, may be computed as follows: Mathematically, Pi equals (pi1, pi2,..., pin) T. For this swarm, 'g' is the best particle.

II. STRATEGIES FOR OPTIMIZING THE INERTIA OF A PARTICLE SWARM

The Inertia Weight plays a critical role in ensuring a satisfactory balance between the exploration and development stages. A particle's Inertia Weight defines the proportion of its present velocity that is owing to its past velocity. The idea of Inertia Weight was not included in Eberhart and Kennedy's initial PSO model from 1995. Shi and Eberhart introduced Constant Inertia Weight, the first public announcement of the notion of inertia weight, in 1998. They claim that a bigger Inertia Weight is better for a global search while a smaller one is preferable for a local one. Several academics have also proposed dynamically adjusting the Inertia Weight to improve PSO's efficiency. In this section, we provide a comprehensive overview of PSO's Inertia Weight methods.

Using a Random Inertia Weight method, as Eberhart and Shi did, has been shown to accelerate PSO convergence in the early stages of the algorithm. PSO's efficiency and effectiveness may be enhanced by using the Linearly Decreasing strategy. Experiments showed that the sweet spot for inertia weights was between 0.9% and 0.4%. As the problem of ever-increasing apices becomes more difficult to solve, however, it always converges to a local optimum rather than a global one.

The Inertia Weight in Global-Local Best is determined by averaging the particles' local best and global best for each generation. Either a fixed value over time or a linearly decreasing value over time is ruled out. The problem of early convergence to a local minimum is addressed by using the Adaptive Inertia Weight technique to improve the system's search capabilities. It regulates genetic variation by modifying the Inertia Weight of individuals in a population.

Particle Swarm Optimization with Simulated Annealing (PSOSA) is a technique for optimizing the inertia weight by use of a particle swarm. An effort was made to use the concept to solve a municipal planning issue. As the number of blocks in the urban planning problem to be fitted rises, the proposed solution improves in both convergence speed and long-term stability.

Gao et al. suggested a new PSO method using the Logarithm Decreasing Inertia Weight and the Chaos mutation operator. The Logarithm Decreasing Inertia Weight could improve convergence time, but the Chaos mutation might make it easier to break out of a rut and find a better solution. Gao et al. applied a stochastically produced mutation and an Exponent Decreasing Inertia Weight to the original PSO to fix the problems of premature convergence and later-period oscillatory occurrences. The current global optimum particle is subjected to stochastic piecewise mutation, and the Exponent Decreasing Inertia Weight allows this improved PSO to fast escape to a better partial optimal solution.

III. METHODOLGY

This endeavor makes use of the IEEE bus system. The IEEE bus system is used as a test bus due to the reliability of the power flow data it provides. Both a 6-bus and a 30-bus system are suggested by IEEE. Figures 1 and 2 show the IEEE 6-bus and IEEE 30-bus standards, respectively. The 30-bus system has 41 lines, whereas the 6-bus system has just 7.

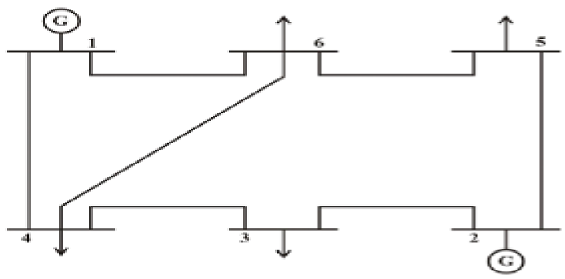

Figure 1. IEEE 6-bus system

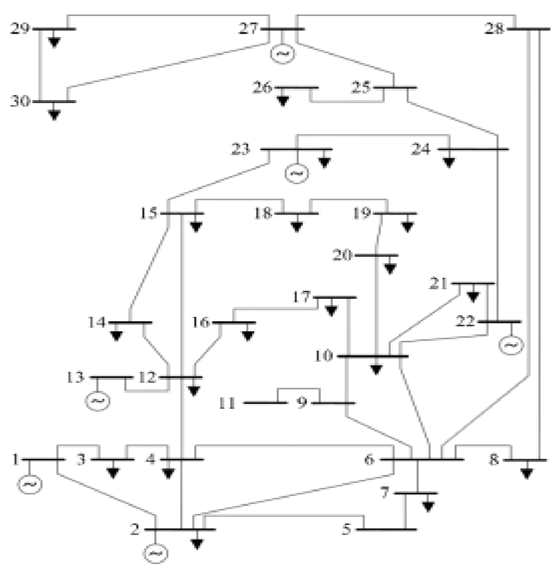

Figure 2. IEEE 30-bus system

- **Fast Voltage Stability Index (FVSI)**

In 2002, Ismail Musirin and TitikKhawa Abdul Rahman came up with the idea for FVSI. A bus or a line might be used to refer to this index. This allows it to identify problematic buses in the network. In this project, we utilize FVSI to calculate the maximum load for each bus using 100 iterations. The formula below is used to determine the load on each bus.

$$FVSI = \frac{4z^2 Qj}{V_i^2 x}$$

where,

Z = line impedance

X = line reactance

Q_j = reactive power flow at receiving end

V_i = sending end voltage

The level value of 1 shows that the line is approaching its stability point. As a result, if the FVSI value is close to 1, it indicates the bus's maximum load capacity.

- **Particles Swarm Optimization (PSO)**

Some examples of optimization methods are the Grey Wolf Optimizer and Evolutionary Programming. The PSO evolution computation method was developed by Russ Eberhart and James Kennedy, both PhDs. Evolutionary Computation is a meta-heuristic approach. Power system dependability, optimum flow power, and reactive power and voltage management are only few of the applications of PSO.

PSO is a method that uses an algorithm that finds solutions using a population. This method has been used to the study of the biology of foraging groups, including bird flocks and fish schools. But today, with the introduction of load caps, PSO may be applied in practical problem analysis.

PSO's general behavior is outlined in the following scenario. The birds had flown a short distance from their nest to forage for food. The flocks of birds are subsequently divided into smaller groups where they forage for food. If one group finds the best restaurant, the others will use their brains to go there. Therefore, the birds may discover the ideal feeding place after repeating the procedure.

In order to calculate the absolute maximum load that each bus can handle, PSO is used to optimize the load value in FVSI.

$PSO = \omega v + c1r\,(xbest - x) + c2r\,(xglobal - x)$

Where,

c1, c2 = acceleration coefficients

ω = inertia weight

r = random function

The FVSI value is calculated over 100 iterations and then ordered from highest to lowest. The highest possible FVSI value on a bus. The greatest FVSI value for that bus is considered the best possible value in that area; we'll call it xbest. This held true for every single bus. The xbest for each bus is again rearranged, this time from best to worst. The maximum value of xbest is maintained as the global best value, xglobal. After PSO optimization, the largest load factor in the FVSI value became the bus's capacity.

Figure 3 depicts particle optimization using the PSO approach. In the meantime, see Figure 4 for a flowchart of how the PSO approach works.

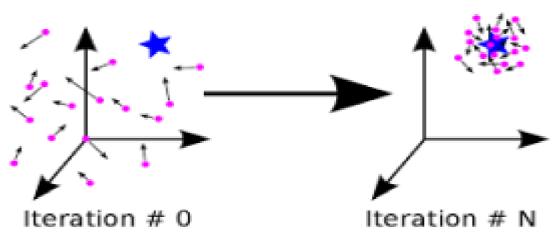

Figure 3. Optimization of particles using PSO

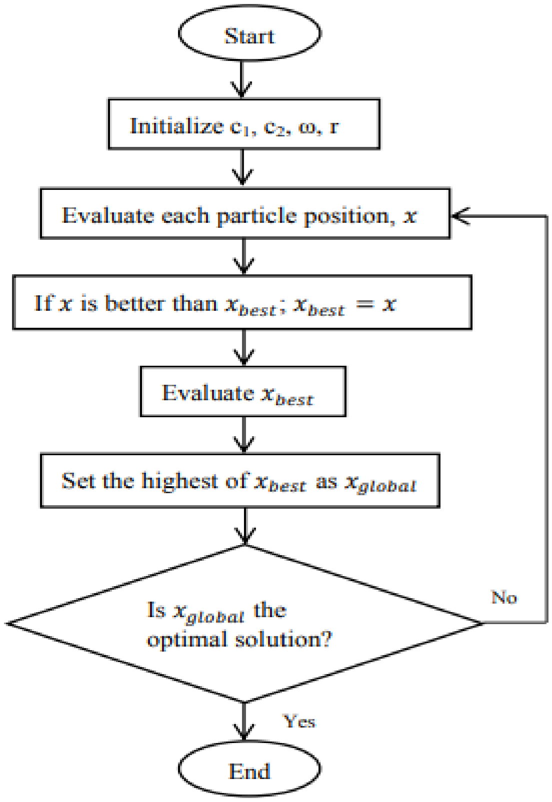

Figure 4. PSO flowchart

IV. RESULTS AND DISCUSSION

Because Bus 1 is a reference bus, it is not included. As a result, it has no load. Table 1 lists the load limit and FVSI value for buses 2 through 6 in a 6-bus system.

Table 1. Load limit and FVSI value of 6-bus system

Bus Number	**Load (MW)**	**FVSI Value**
2	76.7791	0.7760
3	136.5282	0.8969
4	108.6728	0.7968
5	50.9830	0.3671
6	136.8691	0.8491

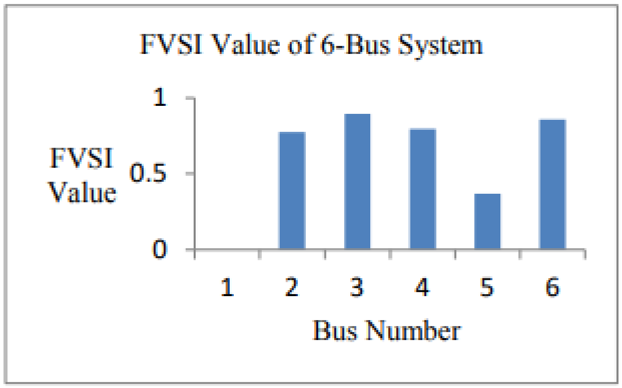

Figure 5. Bar graph of FVSI value of 6-bus system

Figure 5 shows that the greatest FVSI value for a 6-bus system is 0.8969 at bus 3. The maximum load that the system can support is 136.8691 MW at bus 6. If the load exceeds that threshold, bus 6 will collapse, potentially affecting the entire system. At bus 5, the lowest FVSI value in the system is 0.3671. With a load value of 50.9830 MW, bus 5 has the lowest load.Table 2 is the load limit and FVSI value of bus 2 until bus 30 for 30-bus system.**Table 2. Load limit and FVSI value of 30-bus system**

Bus Number	Load (MW)	FVSI Value
2	710.4557	0.3354
3	533.7875	0.8739
4	592.7608	0.9821
5	593.6774	0.4701
6	650.2154	0.8923
7	518.2250	0.8182
8	598.3411	0.8147
9	199.2537	0.5257
10	249.5796	0.8163
11	278.1556	0.5606
12	198.1350	0.3795

13	263.5991	0.8658
14	134.5042	0.5358
15	212.6415	0.9858
16	188.1913	0.7965
17	198.9395	0.7159
18	129.4750	0.6014
19	134.8540	0.6480
20	141.1894	0.8065
21	199.8094	0.6915
22	199.9142	0.8324
23	131.3240	0.6094
24	152.5138	0.7051
25	96.7191	0.4805
26	40.8337	0.2694
27	114.7917	0.3864
28	486.8339	0.8918
29	48.8702	0.2888
30	49.3991	0.2748

Figure 6 shows that the bus 15 has the greatest FVSI value of 0.9858. Meanwhile, according to Table 2, the bus system's highest load limit is bus 2, which has a load value of 710.4557 MW.

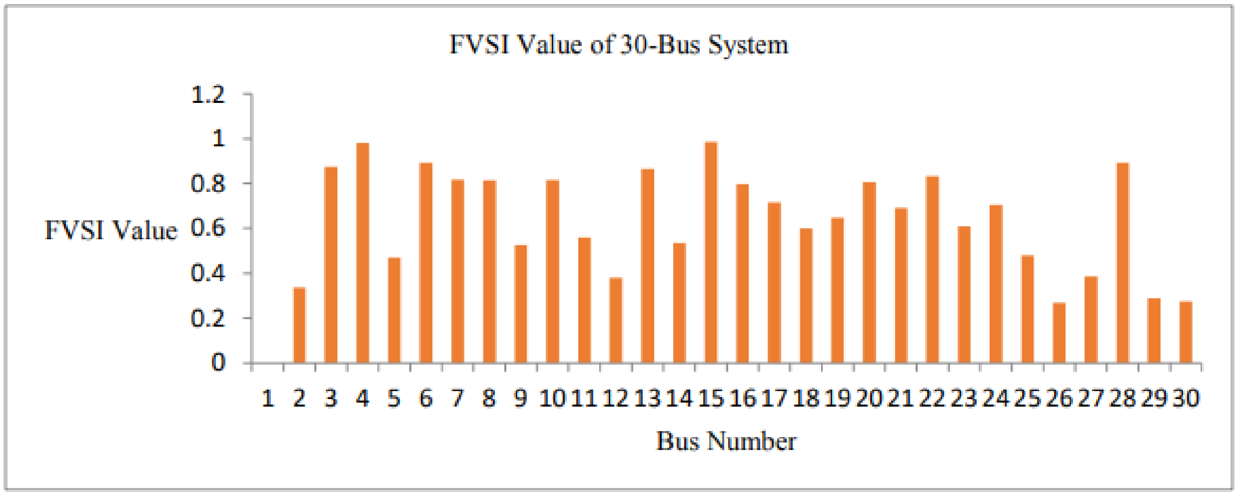

Figure 6. Bar graph of FVSI value of 30-bus system

V. CONCLUSION

Despite being part of the same system, each bus has its own load restriction. The FVSI value is the same way. The maximum load limit is not always determined by the greatest FVSI value. Buses with an FVSI rating close to one are considered weak. With FVSI values of 0.8969 and 0.9858, respectively, bus 3 and bus 15 are the weakest buses in the 6-bus and 30-bus systems. The maximum limits for 6-bus and 30-bus are 136.8691 MW and 710.4557 MW, respectively, as shown in Tables 1 and 2.

REFERENCES: -

1. Acharjee, P., Indira, A., Mandal, S. & Thakur, S. S. 2009. Maximum loadability limit of power systems using different particle swarm optimization techniques. Industrial Engineering and Engineering Management 2009 IEEM 2009 IEEE International Conference on (December): 1573–1577.

2. Mehdi, O. H., Izzri, N. &Abd, M. K. 2011. Fast prediction of voltage stability index based on radial basis function neural network: Iraqi super grid network, 400-kV. Modern Applied Science 5(4): 190–199.

3. Acharjee, P. 2011. Identification of maximum loadability limit under security constraints using genetic algorithm. Proceedings 2011 International Conference on System Science and Engineering, ICSSE 2011 (June 2011):234–238.

4. Kamari, N. A. M., Musirin, I. & Othman, M. M. 2013. PSS-LL Based Power System Stability Enhancement Using IPSO Approach (June): 658–663.

5. Uri, D. 2014. a Particle Swarm Optimization for 2(6): 2588–2595.

6. Kumar, R., Ahmed, M., Ahmed, R., Engineer, J. & Dispatch, E. L. 2015. OPTIMAL POWER SYSTEM USING I(Ii): 159–165.