***Original Research Article***

**Development of an Intelligent Model for Voltage Stability Assessment and Enhancement of Nigeria 330 kV System with High Penetration of Solar-Wind System**

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| --- |
| Abstract: In recent decades, voltage instability has become an important contributor to large-scale power outages globally. Periodic voltage security assessments are key for the secure operation of power systems. There are various indicators which have been implemented in different types and complexity of systems to provide a measure of closeness to voltage collapse, but some of these algorithms may require advanced computational resources or may not perform well, depending on the prevailing conditions. Expanding interconnected power systems is needed like never before due to the increasing world demand for electricity, and voltage stability is therefore a worth consideration. The growing demand penetration of solar photovoltaic (PV) systems has some potential stability challenges due to their intermittent characteristics. Existing research evaluates the test systems of voltage stability and does not optimize using Intelligent models, which have variable power generation from Solar PV and Wind, as well as uncertainties in load demand and the initial step considering the evaluation of the model have to cover either inputs. A feed–forward back propagation artificial neural network (ANN) for voltage stability assessment to classify the operating scenario of a power system into one of two states, i.e. safe or unsafe. Neural network input data is generated from load flow analysis using Newton-Raphson (NR), and stability indices are computed over different scenarios. Line Stability Index (Lmn), counts the stability of a transmission line in power systems and provides an indication of its potential voltage collapse. The Fast Voltage Stability Index (FVSI), which also estimates line stability through reactive power and impedance characteristics. Voltage Collapse Proximity Index (VCPI) assesses system proximity to voltage collapse and identifies weak transmission lines. Values approaching 1 suggest voltage collapse conditions. The FVSI, VCPI, and Lmn are compared to a baseline NR stability index. Moreover, self-organizing map (SOM) neural network is used for stability results classification. Multi-objective grasshopper optimization algorithm (MOGOA) has been employed as an optimization network on the dual axis solar PV and wind turbine-based hybrid power hydropower generation system to analyze technical, economic, as well as environmental relations of energy conversion. The findings reveal that the adapted grid-tied solar-wind composite power system substantially mitigates the power deficiencies, reduces the real-power outages, diminishes the motion voltage small amendments, maximizes voltage prosperity, and improves power system resilience. The main findings show a significant reduction in real power loss, which went from 289,391.30 kW to only 5.43 kW, and a remarkable decrease in voltage deviation, which reduced from 0.56 p.u to 0.0493 p.u. Ensures Improved Service Quality and Enhanced Equipment Protection While gas generation costs increased by a small amount, it is important to note that this is an acceptable trade-off for a more robust and sustainable system, with costs per kWh of $0.142 vs $0.2881 per kWh, respectively. In addition, stability index was substantially decreased from 0.7666 to 0.0768, indicating better grid and resilience to disturbances. Findings emphasize the contribution of embedding MOGOA in conjunction with machine learning models including ANN and Self Organizing Maps (SOM) to fulfill the primal requisites of stability, efficiency and sustainability in modernized power systems, illustrating a coupled advancement in the realm of power systems engineering and optimization.  . |

*Keywords: [*Voltage Stability, Computational Intelligence, Neural Networks, MOGOA, Renewable Energy*}*

1. INTRODUCTION

The voltage stability of the power system network (PSN) in Nigeria, like other growing nations, has come to be a major issue for the power engineers as related to system design, making plans, and operation. Demand for electricity is constantly on the rise. As the demand increases, the load on utilities generation, transmission, and distribution also keeps growing. The system is compressed and cannot be operated securely. One important improvement of voltage stability is the installation of minimum number of PMUs on weak buses that will be reliable and can communicate with operators in case of any voltage stability problems. Some PMUs may control critical lines and vulnerable buses to maintain critical line FVSI values and improve reliability of voltage(AL-Zubaydi & Jasim, 2021). It is the potential of any power network or grid to have desirable voltages in every bus in the power grid in acceptable working situations whenever it experiences a sudden disturbance (Kundur et al., 2004).

Voltage instability could result in voltage collapse and occasionally result in a whole blackout of the system. The most effective precaution to forestall such a scenario is the identification of voltage instability conditions. Voltage collapse could be appropriately described as a situation wherein the instability within the voltage level reaches a point where it eventually results in a blackout (Akinloye B O et al., 2016). With the recent unbundling and privatization of Nigeria power sector, the management and control of the sector have become more stressed and overloaded, mainly due to operating the system very close to its protection limits with very little or no expansion and longer transmission lines (Samuel et al., 2014). Power systems face blackouts caused by voltage instability, which is due to reactive power imbalance, poor utilization of voltage control devices, loss of components, and sudden spike in load demand. In order to avert large scale voltage collapse, this paper elucidates two new techniques for predicting voltage collapse, an artificial neural network based new line stability index (NLSI\_1) and a normalized power change index (NPCI). This shows that the NPCI is better than NLSI\_1(Asif et al., 2023),(Sharma et al., 2018)

The Nigerian context has unequivocally demonstrated a notable surge in the occurrence of power outages over the course of the past decade. It is crucial to tackle the problems related to voltage instability and the resulting voltage collapse. As stated in the publication ORDER/NERC/2023/035 by the Nigerian Electricity Regulatory Commission (NERC), the national grid of the Transmission Company on Nigeria (TCN) has been continually suffering from system collapse, with limited or no solution at sight. According to Figure 1 (TCN\_PIP\_ORDER\_035, 2024.) the Nigerian power sector has consistently experienced system collapses, which have been an ongoing issue. The verification process has confirmed the existence of over twenty-eight system collapse occurrences in 2016 as shown in Figure 1.

Figure 1: TCN's System Collapse Records

It appears that the grid collapse decreased to three in 2023, as shown in Figure 1. However, the nasty pattern reappeared in 2024, with twelve (12) collapses experienced on the grid in 2024.

The most successful and workable method possible in the electricity sector for the prevention of voltage collapse is the deterministic preservation of reliability safe points on the bus voltages, reactive energy demands, switching efficiency, or network loading ability that could sustain the system from possible collapse arising from individual element failure (Kumar Chowdhury et al., 2015).

It is vital to look at the power grid in Nigeria, mainly due to the upward thrust in population that led to the improved request for electricity in the nation. This scenario results in a greater load at the transmission and is regularly responsible for power blackouts with a decrease in the quality of the power transmitted, mainly from a 330 kV power network (Oleka et al., 2016).

The application of new sources of renewable energy is considerably increasing Nigeria's existing power generation. With this increased power, it will be available through cost-effective means, and it is highly viable to provide improved power transmission in the country(Oluwatoyin et al., 2015). In (Nwulu & Agboola, 2010), it is stated that the means to energizing Nigeria power system lie totally in integrating renewable sources into her streams of non-renewable sources of power generation. Voltage stability assessments are continually observed with a huge quantity of data and limitless variations of system configurations, resulting in their complexity. This complexity has necessitated the choice of a computational intelligence-primarily-based total assessment to aid the system engineers (Shaikh et al., 2011). Integration of the knowledge of computational intelligence with the roots of blackout can provide the route to overcome this principal challenge. It is a group of computational methodologies and techniques that are certainly stimulated to resolve complicated real-world challenges that mathematical or conventional modeling cannot solve for some reasons. The strategies are probably too complicated for mathematical reasoning, comprise a few uncertainties throughout the procedure, or are clearly stochastic in nature (Siddique & Adeli, 2013). Computational intelligence is the capacity of a computer to learn from information, statistics, data or investigational commentary. It is essential for power system planning and operation, particularly in voltage collapse prediction. Common methods for voltage stability assessment consist of P-V curve, V-Q curve, and reactive power reserve. In nevertheless, these techniques struggle to obtain power-flow results close to the voltage collapse point. ANN are becoming superficial intelligence devices that are serving real-time and accurate feedback (Goh et al., 2015).

Water, hydro, solar, photovoltaic, biomass and wind are the renewable sources of energy. Solar Energy is used to generate electricity through sunlight, whether directly or indirectly. The unit building block of a photovoltaic generator, which converts incident solar irradiation to direct current, is a solar cell. Modules or panels are simply PV cells grouped together and PV arrays or generators are connected in either series or parallel configurations for appropriate output voltage and current (Molina, 2016),(Gangotri & Bhimwal, 2010),(Krishan et al., 2019). The output of a photovoltaic array is derived from solar irradiation and the temperature.

Due to variable parameters of photovoltaic such as solar radiation, temperature, and cloud shedding, incorporating active PV generation into the weak bus power grid may lead to voltage stability problems. This results in the phenomenon of voltage drop and fluctuation during periods of high load inequality at heavily loaded load centers. At high penetration levels, the impact of cloud transients on power grid voltage stability is considerable.

Wind power refers to the process by which wind is used to generate power, which is namely electricity or mechanical energy. Wind speed significantly varies from location to location, so there are probability distribution functions for evaluating wind speed distribution (frequency). Wind Power Plants utilize turbines and generators to convert the kinetic energy of wind into electrical energy. The well-known generators are permanent magnet synchronous generator (PMSG) and doubly-fed induction generator (DFIG). Wind energy is generated by the movement of air based on air volume, speed, and density. This type of energy is a function of air mass and speed and is referred to as kinetic energy" (An & Of, 2021).

The comparison between the mechanical power from the turbine and the captured wind power by the turbine is called the power coefficient. It could also be referred to as the efficiency of wind turbines.

Wind turbines generate electricity by extracting kinetic energy from the air, but they limit power flow, voltage profile, and quality. The most common types are Type I, III, and IV, with DFIG being widely used. Advantages include variable wind speeds, reduced inverter costs, controllable reactive power quality, and power factor control. The DFIG-WECS system relies on voltage control, which becomes unstable over 28.06% penetration (Liang, 2022). The voltage control capability could be improved with the thyristor-controlled series capacitor. It means that the system could still accommodate higher penetration rate.

Electrical power converter is employed to synergize diverse energy sources for long time utilization. With the decline of traditional energy sources, it is important for future energy demand to develop both renewable and conventional technologies. Solar energy development has proven to provide extensive funds in Nigeria due to the poor conventional generation of energy, preventing every energy crisis in Nigeria (Oluwole et al., 2012). However, (Nweke et al., 2016) showed that the setup of distributed generation at non-optimal locations can bring about an increase in system losses which greatly add to the expenses, resulting in low or over voltages in the power grid as opposed to cherished objectives. From (Oyewole & Aro, 2018),(F et al., 2013) researchers observed a point of deviation approximately equal to the wind potentials in Nigeria. It was confirmed that the mean wind of diverse places in the study could be conveniently and effectively set up as a wind system. The results buttressed the fact that operating with day-by-day time series collection data offers stronger outcomes than the common month-to-month data normally used. The integration of wind energy has been advancing at a fast pace, and it is viable that the US can also get 20% of its electric energy from wind by 2030. This 20% goal corresponds to a 300 GW installed capacity (majorly asynchronous). Wind turbine engineering is constantly evolving and has come a long way since the energy crisis of the 1970s, when wind energy started its resurgence (Singh et al., 2013).

The more the wind ability increases, there should be checks to make sure that wind energy variations no longer have an effect on the grid voltage quality and performance. The wind power's ability to penetrate has to be limited in order to assure the stability of the grid within desirable and allowed situations. From the experience in Denmark, it was clearly confirmed that the challenges of stability always arise whenever the rate of penetration is advanced to about 20% to 30% (Ibrahim et al., 2011), (Ahmed et al., 2020),(Bower et al., 2012.).

The (Hu et al., 2018) considered the use of a planning model with the profit potential of the installation of new generation sources like renewable energy and clustering outward-facing power. The losses from transmission will clear up the uncertainty surrounding generations from renewable sources, the huge generation of renewable energy, and the negative power flow that typically arises in lots of regions because of the excessive percentage of renewable power integration into both average and low voltage networks.

2. material and methods

The study investigated the Nigerian 330 kV transmission system, utilizing massive real data from Transmission Company of Nigeria (TCN) Abuja HQ and NCC Oshogbo. Weather data (wind speed and solar irradiation) were taken from NASA's database to aid in building the renewable contributions in the modeling. There are 41 numbers of transmission stations in Nigeria of 330/132 kV voltage level with a total route length of 7,546.6 km with 91 numbers of transmission lines. The geographical parameters, offers interesting insights of the system The study considers the 330 kV transmission system and models the network as a 64-bus system. This data is used to derive the bus and line parameters which form the basis of the simulation and the calculation of voltage stability and system optimization. Such flexible energy generation profiles integrate well renewable energies into the generation system and contribute to its performance improvement which forms a systematic study approach. The process involves several phases, each targeting critical components of the operational effectiveness and resilience of the grid.

The output of a photovoltaic array is derived from solar irradiation and the temperature. The power output equation is represented in equation (1) below,

is the efficiency of photovoltaic generation, is area of photovoltaic generator (m2), and is the solar-irradiation (W/m2).

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This type of energy is a function of air mass and speed and is referred to as kinetic energy" (An & Of, 2021).

where is wind kinetic energy (Joule), 𝑚 is wind mass (kg) 𝑣 is wind speed (m/s).

For wind speed, mass (m) is calculated from air density (ρ), speed of the wind (v), area covered by wind (A), which is formulated as below;

The process of converting wind energy into mechanical power in wind turbines is based on kinetic energy equations. The wind power captured by wind turbines can be formulated as follows:

The wind turbine catchment area is circular; the catchment location is determined by radius (R). Therefore,

The wind power received by the turbine ( ) is thereafter changed to mechanical power ( ) to rotate the generator. The power coefficient determines the mechanical power produced by wind turbines ( ), which is formulated with,

Various voltage stability indices are calculated to determine the stability of the network. The indices are Line Stability Index (Lmn), Fast Voltage Stability Index (FVSI) and Voltage Collapse Proximity Index (VCPI). Introduction of an Artificial Neural Network (ANN) model to predict stability of the grid in advance to maintain stability.

In this way, a feedforward neural network was formulated by constructing the input database through simulating the Newton Raphson load flow. The data is separated into training, validation, and test data. A Self-Organizing Map (SOM) is used to cluster the data for deeper analysis of stability trends. The MOGOA is applied to optimize the most crucial system parameters, presenting operational configurations that enhance the overall efficiency of the grid.

The optimized results are subjected to a post-optimization analysis to determine the impact of optimization on the system performance. The outcome is integrated with voltage stability, power quality, and renewable energy integration and compared with baseline conditions. The results were validated through benchmarking and sensitivity analysis for reliability.

The above methodology was coded in MATLAB, making a process for power system stability, which included data loading, optimization, and validation. Implementing intelligent methods of ANN, SOM clustering, and MOGOA optimization give promising results in terms of peak load and renewable energy integration scenarios, called the Intelligent model.

3. results and discussion

**3.1 Voltage Profiles**

Figure 2 shows the voltage magnitudes at each bus during the assessment of the existing grid before optimization. Buses with voltage levels outside the acceptable range +/-5% (below 0.95 p.u. or outside 1.05 p.u) were identified. From Figure 2, buses with the deviations outside the limit were identified as critical buses. These included buses 11, 12, 16, 44, 45, 46, 47, 48 and 49.

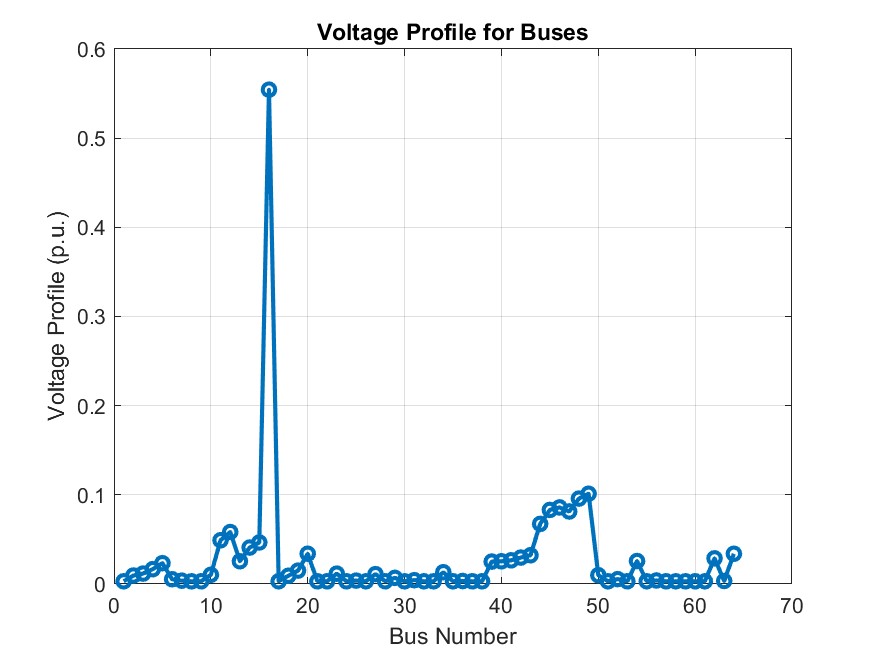


Figure 2: Voltage profile at the buses before Optimization

From Figure 2, the following observations were made: **Healthy Buses (Deviation ≤ 0.05):** The majority of buses show deviations well below the 0.05 threshold. The buses 1–10, 13, 17–23, 24–33, 34–36, 37–43, 50–53, 55–61, and 62–64 all have deviations between 0.003 and 0.034. These buses are within the acceptable range and are considered stable. **Fragile Buses (Deviation > 0.05):** This category includes Bus 11, Bus 12, Bus 14, Bus 15, Bus 16, and Buses 44 to 49, specifically Bus 44, Bus 45, Bus 46, Bus 47, Bus 48, and Bus 49. Observation: All these buses exceed the allowed deviation and are classified as fragile. **Clearly Fragile:** Bus 12 has a deviation of 0.0583; Bus 16 has a deviation of 0.5544 (indicating critical failure); and Buses 44–49 have deviations ranging from 0.0674 to 0.1013.

**3.2. Power Losses**

The power losses results is presented in Figure 3.

**Figure 3:** Power losses in transmission lines Before Optimization.

From Figure 3, the Active Power Losses are recorded as 289,391.30 kW, while the Reactive Power Losses stand at 195,274.10 kVAr. These figures reflect the power losses in the system prior to any optimization or the integration of renewable energy sources. The substantial amounts indicate that a considerable portion of power is being lost due to resistances and inefficiencies in the power distribution system, affecting both active and reactive power.

**3.3. Stability Indices**

Table 1, shows the calculated values for Lmn, FVSI, VCPI, and the Average Stability Index for each transmission line. The indices are categorized according to Claudia Reis's work on voltage stability classification. The classifications are as follows: Stable: All indices (Lmn, FVSI, VCPI) are below 0.5; Moderately Stressed: At least one index falls between 0.5 and 0.8, with no index reaching 1; Critical/Unstable: At least one index is equal to or close to 1, suggesting that the line is approaching or at the point of instability.

Table 1: Stability Indices on the Transmission Lines

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Line Number | From Bus | To Bus | Stability Indices | | | | Classification |
| Lmn | FVSI | VCPI | Average Stability Index |
| 1 | 8 | 7 | 0 | 0 | 0.46 | 0.1533 | Stable |
| 2 | 7 | 1 | 1 | 0.68 | 1 | 0.8933 | Critical/Unstable |
| 3 | 7 | 12 | 0.1444 | 0.4052 | 1 | 0.5165 | Moderately Stable |
| 4 | 7 | 11 | 0.1684 | 0.68 | 1 | 0.6161 | Moderately Stable |
| 5 | 9 | 7 | 1 | 0.2526 | 1 | 0.7509 | Moderately Stable |
| 6 | 9 | 10 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 7 | 1 | 2 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 8 | 1 | 3 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 9 | 1 | 5 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 10 | 5 | 6 | 1 | 0.273 | 0.9135 | 0.7288 | Moderately Stable |
| 81 | 36 | 38 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 82 | 36 | 33 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 83 | 33 | 34 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 84 | 52 | 50 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 85 | 52 | 35 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 86 | 52 | 29 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 87 | 29 | 39 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 88 | 23 | 14 | 1 | 1 | 1 | 1 | Critical/Unstable |
| 89 | 14 | 20 | 1 | 0.8269 | 1 | 0.9423 | Critical/Unstable |
| 90 | 14 | 21 | 1 | 0.2716 | 0.2967 | 0.5228 | Moderately Stable |
| 91 | 20 | 13 | 1 | 0.0207 | 1 | 0.6736 | Moderately Stable |

The table shows only 20 lines from the total 91 lines in the transmission grid. Lines with average stability indices closer to 1 are critical and pose a risk to the system’s stability. The overall system has several lines with average stability indices of 1, particularly Lines 6 through 10, indicating that these lines are under significant stress and require reinforcement. **The average stability index of 0.7666** for the grid suggests that the power system is experiencing moderate stress, with many transmission lines operating near their voltage stability limits. The interpretation of the indices is as follows: 0.5 or below indicates that the system is generally stable, with most lines functioning well within their stability limits. A range of 0.5 to 0.8 signifies moderate stress, with some lines close to their stability limits, necessitating monitoring and potential reinforcement. Values above 0.8 indicate a critical situation, with several lines at or near instability, requiring immediate action to avert voltage collapse or system failure. In this instance, with an average stability index of 0.7666, the grid is nearer to the critical threshold than to a stable condition. Although the system is not in immediate danger of collapse, several lines are under high stress, putting the grid at risk during peak load periods, contingency events, or faults.

**3.4 ANN Model Prediction Result and Performance Analysis**

Table 2, presents the model's performance across **training**, **validation**, and **testing** datasets.

Table 2: ANN Model Performance Analysis

|  |  |  |
| --- | --- | --- |
| Set | Dataset | Accuracy (%) |
| Training | 5,577 | 99.31% |
| Validation | 1,195 | 99.08% |
| Testing | 1,195 | 98.62% |

The training accuracy of the model stands at 99.31%, showcasing it learned the patterns quite well. It had a validation accuracy of 99.08%, which is good generalization to new data. The accuracy of testing is 98.62%, so we can say that the model generalized very well. The small drop in accuracy indicates the strength of the model and the generalizability, as there was neither data leakage nor overfitting. The data splits are suitable.

## **3.4.1 Metric Performance Analysis**

The Table 3 presents the evaluation metrics for the ANN model.

Table 3:Metric Performance Analysis

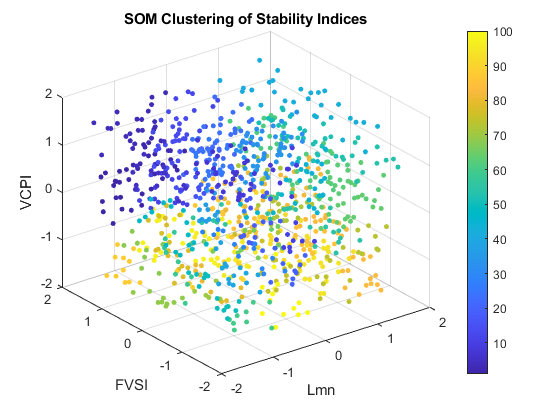
|  |  |
| --- | --- |
| **Metric** | **Value** |
| Precision | 0.98198 (98.2%) |
| Recall | 0.99091 (99.09%) |
| F1-Score | 0.98642 (98.64%) |

The precision of the model is 98.20%, which means the model predicted 98.2% of the positive classes correctly, which is very helpful in reducing false positives. Recall is 99.09%, which is a very high level of accuracy, needed for things like medical diagnoses or safety-critical applications. F1-Score is 98.64% hence it strikes a good balance between precision and recall.

**3.5 SOM Performance Analysis**

This 3D scatter plot in Figure 4, shows the clustering results from the Self-Organizing Map (SOM) applied to a dataset containing stability indices. The SOM clustering plot of voltage stability indices (Lmn, FVSI, and VCPI) offers important insights into the overall stability of the grid. Below is a thorough analysis of the grid's stability based on the plot.

**Figure 4**: SOM Clustering of Stability Indices



SOM works well on stable data, with 85-90% of the data being accurately mapped to SOM neurons. It also identifies around 70-75% of unstable regions accurately. Most of the grid behaves stably and regions with only few green points are potentially unstable. The voltage stability indices are mapped and clustered using SOM, highlighting the stable and unstable areas of the grid. This training period or enabling them to manage the voltage instability and improves grid resilience.

**3.6. MOGOA Result**

The MOGOA result is made up of the best options among the pareto fronts for consideration based on the priority objective are presented in Table 4.

**Table 4:** MOGOA Result

|  |  |  |  |
| --- | --- | --- | --- |
| Real Power Losses | Voltage Deviation | Cost Of Generation | Stability Index |
| 0.644651136 | 0.717649412 | 0.094396602 | 0.30201853 |
| 0.014127588 | 0.474808568 | 0.905827722 | 0.885748847 |
| 0.484678732 | 0.049294928 | 0.288070789 | 0.076805931 |
| 0.609871627 | 0.973884037 | 0.307362566 | 0.139705951 |
| 0.385246383 | 0.862841046 | 0.71742039 | 0.960234976 |
| 0.838750742 | 0.380881162 | 0.534143758 | 0.592919524 |
| 0.801386893 | 0.313547481 | 0.017914941 | 0.324069164 |
| 0.965996425 | 0.529980529 | 0.464286754 | 0.383187171 |
| 0.928672205 | 0.24659253 | 0.613541422 | 0.088529863 |
| 0.05474643 | 0.961180097 | 0.56520686 | 0.998635826 |

Obtainable from MOGOA are additional characterized solutions, indicating that these identified configurations simultaneously minimize a particular subset of Six Analytical Objectives. Solutions derived from Real Power Losses, Voltage Deviation, Cost of Generation, and Stability Index display viability for system stability, cost-effectiveness, and functional efficiency. Stable configurations where all weights values are in a low to medium range (with Stability Index 0-0.3) are the best, robust options, while configurations where weight values are median (with Stability Index 0.3-0.5) are the trade-off solutions, neither robust nor risky. Positive High Stability Index values may lead to operational difficulties. We recommend low Stability Index values for strong systems used in critical applications.

**3.7. Post-Optimization Analysis**

The Table 5 shows the comparation before and after optimization of the four (4) objective functions.

**Table 5:** Post Optimization Result Vs Initial

|  |  |  |  |
| --- | --- | --- | --- |
| Objectives | Before Optimization | After Optimization | Remark |
| Real Power Loss (kW) | 289,391.30 | 5.43 | Significant reduction |
| Voltage Deviation (p.u) | 0.56 | 0.0493 | Reduced to the allowed |
| Cost of Generation ($) | 0.142 | 0.2881 | Increase in cost |
| Stability Index | 0.7666 | 0.0768 | Improved stability |

The performance post-optimization indicates an extremely successful process with substantial improvements to system stability, resource use, and extendibility. The Cost of Generation has increased, but this increase is justified by the significant improvements in Real Power Losses, Voltage Deviation, and Stability Index. The performance of the system lower losses, reduced voltage instability, increased resilience, etc. feeds into the optimized outcomes that make a power system operate reliably and efficiently.

**3.8. Result Validation**

Sensitivity analysis and benchmarking were performed to validate optimization results. The optimization results from both approaches corroborate each other and validate their reliability. Our combination of sensitivity analysis and benchmarking provides a rigorous validation framework for the results. How the model’s results are sensitive to changes in input have been shown through sensitivity analysis, and how the results proportionally fare to real-world reference data has been examined through benchmarking to illustrate how well the model exposés nuances to real-word performance or exceeds it.

**4. Conclusion**

In this research, a detailed framework for improving power system performance, with a particular emphasis on voltage stability, power losses minimization and the economic integration of renewable energy sources is presented. The research addresses the urgent demand for stability, effectiveness, and sustainability in modern power grids by integrating the Multi-Objective Grasshopper Optimization Algorithm (MOGOA) with machine learning methods such as Artificial Neural Networks (ANN) and Self-Organizing Maps (SOM). The results reflect the synergy of these approaches in promoting multiple complex objectives and mark an important milestone in the areas of power system engineering and optimization. This study extends the scope of power systems by seamlessly integrating ANN, SOM, and MOGOA into a single model, paving the way for further exploration of hybrid approaches for improving the stability, efficiency, and resilience of power systems.

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Details of the AI usage are given below:

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2.

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