IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE FOR EARLY DETECTION OF GENERATOR FAULTS IN POWER PLANTS

Maickel Tuegeh *, Markus Karamoy Umboh , Febrina P. Y. Sumanti
Faculty of Engineering, Sam Ratulangi University, Manado, North Sulawesi
Email: maickel_tuegeh@unsrat.ac.id, markus_umboh@unsrat.ac.id, febrina.sumanti@unsrat.ac.id*

Article Info

Article history:
Received Jan 23, 2025
Revised Mar 03, 2025
Accepted Apr 29, 2025

ABSTRACT

In addition to achieving optimal generator scheduling, ensuring the safe operation of the generator itself is equally important. This paper proposes the implementation of artificial intelligence for early detection of generator faults in power plants. A neural network (NN) approach is employed to construct the virtual simulation of the generator capability curve. The developed visualization model enables simulation of generator operating behavior while accounting for various operational constraints and component limitations. Furthermore, the visualization of the capability curve can effectively illustrate different potential operating scenarios that may occur in real-world generator operations. It also allows simulations under special or specific conditions, providing an accurate and flexible representation of generator performance.

Keywords: *Generator, Artificial intelligence, Early detection, Capability curve,*

ABSTRAK

Selain mencapai penjadwalan generator yang optimal, memastikan operasi yang aman dari generator itu sendiri juga sangat penting. Makalah ini mengusulkan penerapan kecerdasan buatan untuk deteksi dini kerusakan generator di pembangkit listrik. Pendekatan jaringan saraf (neural network/NNA) digunakan untuk membangun simulasi virtual dari kurva kapabilitas generator. Model visualisasi yang dikembangkan memungkinkan simulasi perilaku operasi generator dengan mempertimbangkan berbagai batasan operasional dan keterbatasan komponen. Selain itu, visualisasi kurva kapabilitas dapat secara efektif menggambarkan berbagai skenario operasi potensial yang mungkin terjadi dalam operasi generator di dunia nyata. Model ini juga memungkinkan simulasi dalam kondisi khusus atau tertentu, memberikan representasi yang akurat dan fleksibel tentang kinerja generator.

Keywords: *Generator, Kecerdasan Buatan, Deteksi Dini, Kurva Kapabilitas*

Corresponding Author:
Maickel Tuegeh,
Electrical Engineering, Faculty of Engineering,
Sam ratulangi university,
Kampus UNSRAT, bahu, malalayang, Manado.North Sulawesi
maickel_tuegeh@unsrat.ac.id

1. INTRODUCTION

Optimization of generator scheduling is primarily aimed at minimizing the total operating cost of power plants. Numerous methods have been developed to achieve cost-efficient operation by optimizing generator scheduling under various cases and constraints [1-4]. However, despite achieving optimal scheduling solutions, it remains essential to ensure the operational safety of generators. In power plant operations, generator safety can be monitored using the Generator Capability Curve (GCC), which visualizes the generator's operating point. A typical synchronous generator capability curve is presented in [5]. This curve defines the generator's operational boundaries. The capability curve is commonly used on the generation side to track power variations resulting from load fluctuations. It provides information regarding the generator's operational limits in supplying power, including restrictions related to active and reactive power, rotor current, stator current, stator end-core heating, and steady-state stability. Each generator possesses a distinct capability curve that reflects its specific power capacity. Several studies have examined generator capability curves [6-9]. For example, [10] proposed an adaptive analytical approach to analyze synchronous generator capability curves. In [11], three different AC optimal power flow formulations incorporating generator capability curves represented by D-curves were explored. The study in [12] analyzed generator operating limits using the capability curve to determine whether load shedding is necessary. Meanwhile, [13] utilized the GCC to improve active power pricing by considering reactive power. The integration of active and reactive power components in wind farm operation through capability curves is discussed in [14]. Furthermore, [15] presented an efficient approximation algorithm for capability curves within the virtual power plant framework. The use of capability curves in designing distributed control for permanent magnet synchronous generators based on distributed consensus demand response is examined in [15]. Finally, [15] developed a GCC for low-voltage ride-through (LVRT) generators connected to the grid. Although the aforementioned studies address GCC analysis, protection coordination, and stability assessment, none have focused on simulating the capability curve to enable real-time virtual monitoring of generator conditions. Monitoring a generator's operation through its GCC can be challenging without direct access to the plant. Therefore, this study proposes an alternative approach by simulating the GCC using a neural network (NN) model to visualize generator operating conditions virtually. In this research, the GCC is utilized to monitor the generator's operating point and ensure safe operation. Unlike previous works, the proposed GCC model is capable of virtually representing generator operations similar to real conditions. The GCC is developed using a neural network with constructive backpropagation. The main contribution of this study is the development of a virtual visualization tool for simulating the generator capability curve, enabling monitoring and visualization of the generator's operational state. Moreover, the simulation provides insights into various possible operating scenarios that may occur in real power plant operations.

2. RESEARCH METHODS

The generator capability curve is developed using a neural network (NN) model with a constructive backpropagation method. The formation process consists of two stages:

1. Plotting the capability curve to obtain the P–Q data pairs.
2. Training the neural network using these data points.

The flowchart of the GCC formation process is shown in Figure 1. Capability curve plot is done to get P and Q data pairs from capability curve. How to plot the generator capability curve is shown in Figure 2 with three steps of line drawing, the first is by drawing a line from point O to reach the boundary of the curve line. Then from the end of the line pull (the point at the curve line), the next line is drawn, the first one in the direction of the X axis so that the length of Q is obtained, the second one is along the Y axis to obtain the length P. that is, from the Q_{min} limit to the curve Q_{max} limit so that as many P and Q data pairs as possible are obtained. In this case, 81 data pairs are generated consisting of P and $-Q$ data pairs for the leading region and P and Q data pairs for the lagging region.

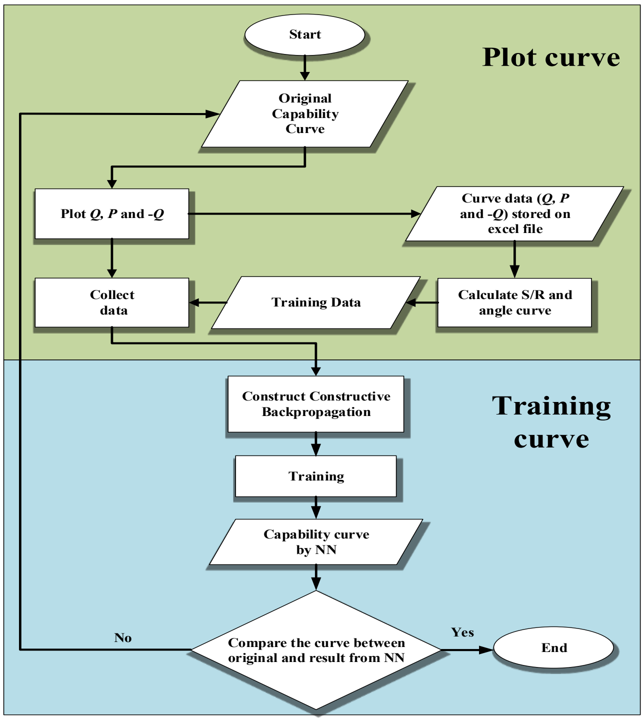

Figure 1. Flowchart of generator capability curve formation.

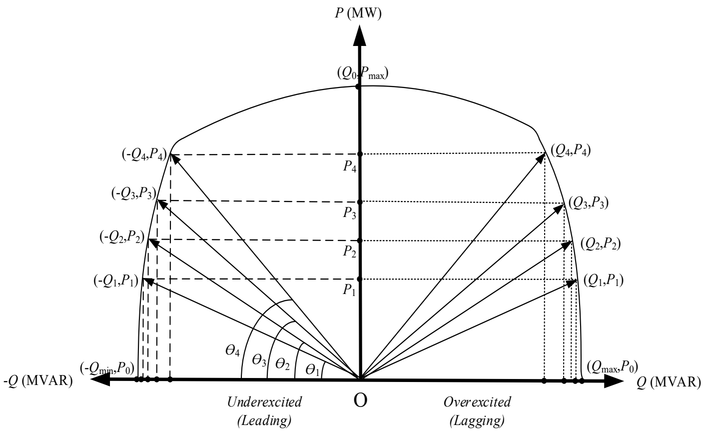

Figure 2. How to plot the capability curve.

To ensure that the generator capability curve produced by the neural network (NN) closely resembles the actual capability curve, training is performed using the PQ curve data. The training process employs a Neural Network based on the Constructive Backpropagation (CBP) method. The training procedure is carried out through the following stages:

1. **Data Loading,** the PQ data obtained from the plotted generator capability curve is stored in Microsoft Excel and subsequently imported into MATLAB for processing.
2. **Calculation of Complex Power and Power Angle (θ),** using MATLAB, the complex power magnitude and the corresponding angle are calculated according to the following equations:

$$S_{curve} = \sqrt{P^2 + Q^2} \tag{4}$$

$$\theta_{curve} = \tan^{-1}\frac{Q}{P} \tag{5}$$

To ensure that the generator capability curve produced by the neural network (NN) closely resembles the actual capability curve, training is performed using the PQ curve data. The training process employs a Neural Network based on the Constructive Backpropagation (CBP) method. The

training procedure is carried out through the following stages:

1. Data Loading**,** the PQ data obtained from the plotted generator capability curve is stored in Microsoft Excel and subsequently imported into MATLAB for processing.
2. Calculation of Complex Power and Power Angle (θ), using MATLAB, the complex power magnitude and the corresponding angle are calculated according to the following equations:

$$S_{curve} = \sqrt{P^2 + Q^2} \quad (4)$$

$$\theta_{curve} = \tan^{-1}\frac{Q}{P} \quad (5)$$

3. Defining Input and Target Data
Input: angle θ curve
Target: complex power curve (S) or distance between center point and curve line (R).
4. Constructing the Hidden Layer. The hidden layer is developed incrementally using the CBP method. Neurons are added one by one, starting from the smallest number, until the network achieves an acceptably low error rate.
5. Building the Constructive Backpropagation Network. The training begins with weight initialization, followed by the feedforward process implemented using MATLAB's `newff` function. This function creates a feedforward neural network that transmits weighted input signals to both hidden and output layers.
6. Setting Training Parameters. Prior to training, several parameters—such as learning rate, number of epochs, and error tolerance—are configured to achieve optimal network performance.

Testing of the generator capability curve from NN training is carried out to test the safety of the generator. The algorithm for testing the generator capability curve of the NN training results is as follows:

1. Entering the active power (P) and reactive power (Q) of the original capability curve as input to the capability curve of the NN training results.
2. From the P and Q data of original capability curve, the θ value and the magnitude of the R_{gen} are calculated (the power of the generator complex or the radius of the load curve)
3. By entering the angle data θ as input to the NN yield curve that has been previously generated, the output of the NN yield capability curve will be obtained in the form of R_{ref} (the radius of the NN yield curve)
4. Generator safety testing is done by comparing the R_{gen} and R_{ref} values. If $R_{gen} \leq R_{ref}$, where the difference between R_{gen} and R_{ref} (difference R) is positive, the generator status is safe. Conversely, if $R_{gen} > R_{ref}$ where the difference between R_{gen} and R_{ref} (difference R) is negative, the generator status is not safe.

Figure 3 shows the relationship between the generator operating point (P, Q), angle θ, R_{gen} and R_{ref}. Where line OA is the length of the radius of the load (R_{gen}), line OB is the length of the radius of the curve (R_{ref}) and line AB is the difference between Rgen and R_{ref}.

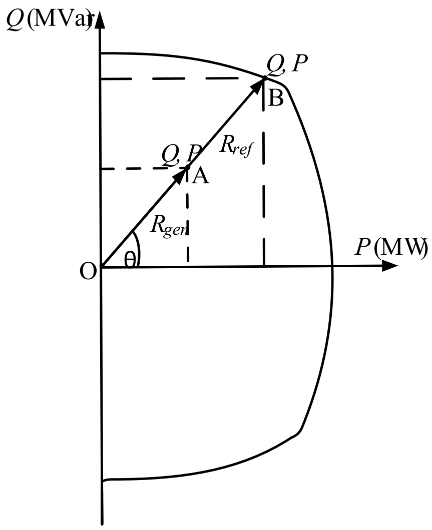

Figure 3. Relationship between P, Q, θ, R_{gen} and R_{ref}.

The algorithm for testing the generator capability curve is shown in Figure 4.

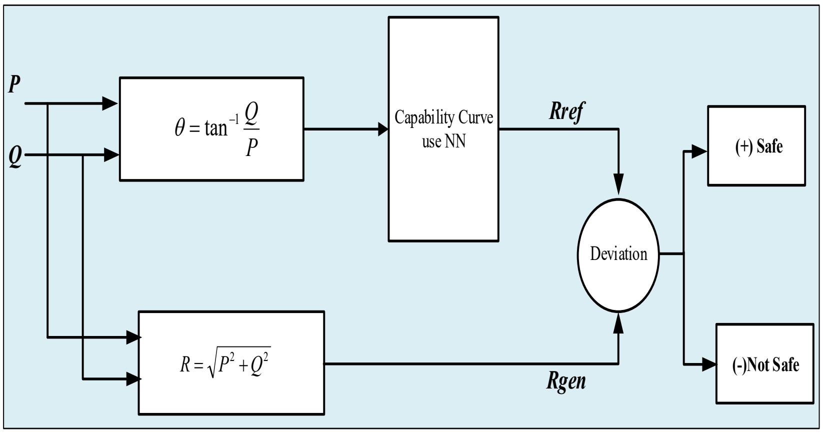

Figure 4. Generator Capability Curve Testing Algorithm.

The GCC is limited by some constraints. The limit of the generator operating capability in sending power to the system is illustrated in Figure 5.

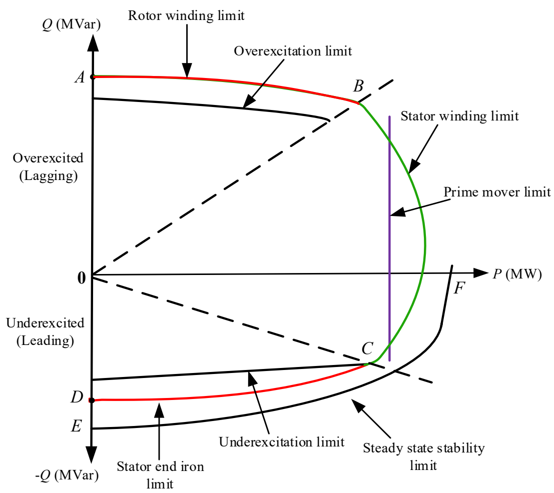

Figure 5. Limitations on generator capability curve.

3. RESULTS AND DISCUSSION

To validate the proposed method, the original generator capability curve from the Lahendong IV Geothermal Power Plant is used as a reference. The Lahendong IV plant is located in Minahasa, North Sulawesi, Indonesia, and operates a generator unit with a capacity of 20 MW. The technical specifications of this generator are presented in Table 1.

Table 1. Generator specification

Generator Name	LH4
Type	GTLRI494 /45 – 2
Output [MVA]	25
Output [MW]	20
Voltage [kV]	11
Current [A]	1312
Excitation voltage [V]	160
Excitation current [A]	808
Phase	3
Power factor	0,8
Frequency [Hz]	50
Number of Poles	2
Speed [rpm]	3000
Production year	2010
Producer	*Fuji Electric*

The simulated capability curve display with the original ***PQ*** curve data of generator in the Lahendong IV geothermal power plant is shown in Figure 6.

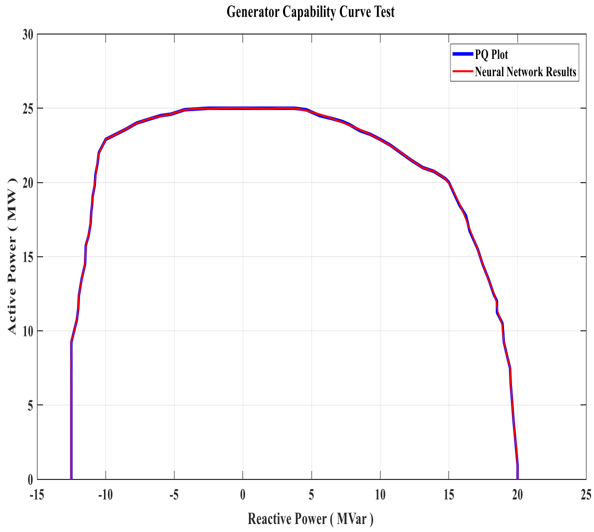

Figure 6. The developed capability curve of a generator of NN training

The capability curve from the NN training results already recognizes the target as the initial capability curve which is the $\boldsymbol{PQ}$ curve data. This is proven that the capability curve of the NN training results (red line) similar to the $\boldsymbol{PQ}$ curve data target (blue line). A trial of the capability curve of the NN training results was carried out to obtain the work point of the generator so that it could be determined whether the generator worked at safe limits or not. Generator work point is declared safe if it meets the requirements of $\boldsymbol{R_{gen}} \leq \boldsymbol{R_{ref}}$. The testing of the generator capability curve is carried out on several loading conditions, namely by entering the $\boldsymbol{P}$ and $\boldsymbol{Q}$ values as input to the capability curve of the results of the NN training, as shown in Figure 7.

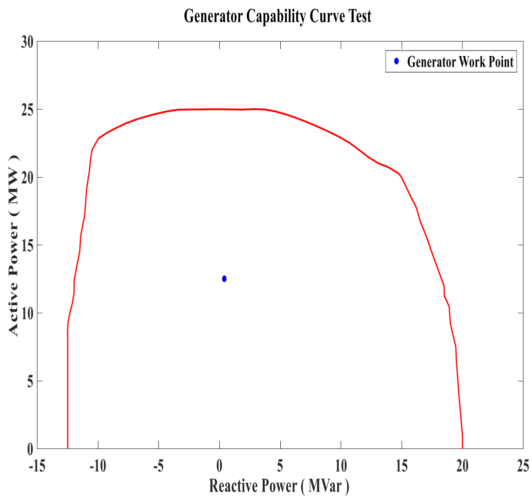

Figure 7. The developed capability curve of a generator of NN training.

To further validate the effectiveness of the proposed method, another test case was performed using the original generator capability curve from the Lahendong IV Geothermal Power Plant, with operating data of operation $\boldsymbol{P}$ = 19.9 MW, $\boldsymbol{Q}$ = 2,236 MVAr as shown in Figure 8 is used to verify the effectiveness of the method.

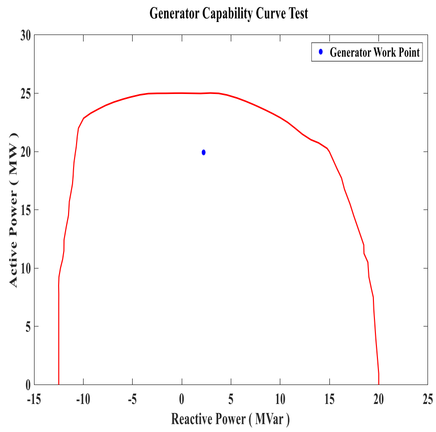

Figure 8 Simulation results.

Refers to Figure 8, when the generator supplies a load with P = 19.9 MW, Q = 2,236 MVAr, resulting in the generator working point. From the Figures 17 (a) and (b) show the location of the generator working point (P, Q) from the original capability curve of Lahendong IV geothermal power plant generator and the simulation result capability curve at the loading point (19.9 MW, 2,236 MVAr) is the same. At this loading condition the generator operates in over-excitation conditions, that is, the generator works in the lagging area or sends reactive power to the system. The working point of the generator is within the limits of the capability curve, besides that the reactive power to the system is quite small, namely 2,236 MVAr, resulting in a large generator power factor value of 0.99 lagging which indicates that the generator is still in a normal excitation condition. Therefore, in this condition the generator works in safe conditions.

4. CONCLUSIONS

This study successfully developed a virtual visualization system for generator capability curve simulation, enabling effective representation of generator operating conditions. The proposed method demonstrated excellent accuracy, as the generated capability curve closely matches the original one. Although a simple neural network (NN) model was employed, its performance proved to be highly effective, providing clear visualization of the generator's operating point to ensure operational safety. Moreover, the developed virtual visualization model can simulate various potential operating scenarios, replicating real-world generator behavior under different conditions, including special or extreme operating cases.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to LPPM Universitas Sam Ratulangi for providing the funding and support that made this research possible.

REFERENCES

[1] C. Y. Lee and M. Tuegeh, "Optimal optimisation-based microgrid scheduling considering impacts of unexpected forecast errors due to the uncertainty of renewable generation and loads fluctuation," *IET Renewable Power Generation,* vol. 14, no. 2, pp. 321-331, 2020, doi: https://doi.org/10.1049/iet-rpg.2019.0635.

[2] C. Fu, S. Zhang, and K.-H. Chao, "Energy management of a power system for economic load dispatch using the artificial intelligent algorithm," *Electronics,* vol. 9, no. 1, p. 108, 2020, doi: https://doi.org/10.3390/electronics9010108.

[3] X. Shen, G. Wu, R. Wang, H. Chen, H. Li, and J. Shi, "A self-adapted across neighborhood search algorithm with variable reduction strategy for solving non-convex static and dynamic economic dispatch problems," *IEEE Access,* vol. 6, pp. 41314-41324, 2018, doi: https://doi.org/10.1109/ACCESS.2018.2858554.

[4] Y. Yang, B. Wei, H. Liu, Y. Zhang, J. Zhao, and E. Manla, "Chaos firefly algorithm with self-adaptation mutation mechanism for solving large-scale economic dispatch with valve-point effects and multiple fuel options," *IEEE Access,* vol. 6, pp. 45907-45922, 2018, doi: https://doi.org/10.1109/ACCESS.2018.2865960.

[5] N. Nilsson and J. Mercurio, "Synchronous generator capability curve testing and evaluation," *IEEE Transactions on Power Delivery,* vol. 9, no. 1, pp. 414-424, 2002, doi: https://doi.org/10.1109/61.277713.

[6] H. Pulgar-Painemal, "Enforcement of current limits in DFIG-based wind turbine dynamic models through capability curve," *IEEE Transactions on Sustainable Energy,* vol. 10, no. 1, pp. 318-320, 2018, doi: https://doi.org/10.1109/TSTE.2018.2831451.

[7] S. Thakar, A. Vijay, and S. Doolla, "Effect of PQ limits on microgrid reconfiguration: A capability curve perspective," *IEEE Transactions on Sustainable Energy,* vol. 11, no. 3, pp. 2040-2048, 2019, doi: https://doi.org/10.1109/TSTE.2019.2952043.

[8] G. Sangeetha, S. Sherine, K. Arputharaju, and S. Prakash, "On line monitoring of higher rated alternator using automated generator capability curve administer," in *2018 International Conference on Recent Trends in Electrical, Control and Communication (RTECC)*, 2018: IEEE, pp. 176-181, doi: https://doi.org/10.1109/RTECC.2018.8625687.

[9] H. Zhong, X. Wang, and Z. Tan, "An efficient method for estimating the capability curve of a virtual power plant [J]," *Csee Journal of Power and Energy Systems,* pp. 1-2, 2020.

[10] J. Khazaei, D. H. Nguyen, and A. Asrari, "Consensus-based demand response of PMSG wind turbines with distributed energy storage considering capability curves," *IEEE Transactions on Sustainable Energy,* vol. 11, no. 4, pp. 2315-2325, 2019, doi: https://doi.org/10.1109/TSTE.2019.2954796.

[11] J. J. Grainger and W. D. Stevenson, *Power system analysis*. McGraw-Hill, 1994.

[12] H. W. Beaty and D. G. Fink, *Standard handbook for electrical engineers*. McGraw-Hill New York, 2013.

[13] B. Park, L. Tang, M. C. Ferris, and C. L. DeMarco, "Examination of three different ACOPF formulations with generator capability curves," *IEEE Transactions on Power Systems,* vol. 32, no. 4, pp. 2913-

2923, 2016, doi: https://doi.org/10.1109/TPWRS.2016.2626142.

[14] I. G. Fernandes, V. L. Paucar, and O. R. Saavedra, "Impacts of synchronous generator capability curve in power system analyses trough a convex optimal power flow," in *2019 IEEE PES Innovative Smart Grid Technologies Conference-Latin America (ISGT Latin America)*, 2019: IEEE, pp. 1-6, doi: https://doi.org/10.1109/ISGT-LA.2019.8895455.

[15] P. E. Sutherland, "Safe Operating Limits," *IEEE Industry Applications Magazine,* vol. 17, no. 5, pp. 14-19, 2011, doi: https://doi.org/10.1109/MIAS.2010.939648.