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Voltage profile enhancement in grid system using expert system

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ABSTRACT

Frequent and severe blackouts are been attributed to insufficient voltage stability, resulting in voltage collapse. To mitigate this issue and ensure adequate voltage stability and damping in power systems, this study explores smart grid solutions. The proposed control strategies are applied to a distribution static synchronous compensator (DSTATCOM) within a multi-machine system. The recommended approach, radial basis function neural network (RBFNN)-DSTATCOM with support vector machine (SVM), incorporates a PI controller to minimize system deviations. The damping performance of the RBFNN-DSTATCOM controller is analyzed against a fixed-parameter proportional-integral (PI)-DSTATCOM controller. Simulation analysis indicates that the proposed RBFNN-DSTATCOM controller effectively enhances power system stability under various disturbances and operating conditions. Critical bus graphs are provided for scenarios both with and without the DSTATCOM. A parametric evaluation is conducted using the 'powergui' toolbox based on the system's standard ratings. Finally, a comparative analysis is presented, utilizing the results from both systems, with all graphs plotted against time using the power system analysis toolbox (PSAT) in MATLAB.

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1. INTRODUCTION

In recent years, power systems have encountered challenges such as harmonics, substantial reactive power fluctuations, and instability in voltage, primarily because of the increasing adoption of non-linear loads in heavy industries. These loads inject harmonics and non-sinusoidal currents, leading to inefficiencies in system operation. A highly effective solution for dynamically managing reactive power in such environments is the distribution static synchronous compensator (DSTATCOM), which, when equipped with an appropriate control strategy, can also mitigate harmonics [1]-[5]. Although DSTATCOM is widely utilized, other controllers, such as synchronous boiling compensators and fixed-gain proportional-integral (PI) controllers, have also been developed. However, nonlinear controllers often outperform their linear counterparts, as they are better suited to manage the complexities introduced by non-linear loads [6]. To maintain stable and controlled power system operations, dispatch center operators require real-time solutions. Artificial neural networks (ANNs) are particularly well-suited for this task, given their ability to rapidly and accurately synthesize complex system representations.

In this study, multi-layer feedforward neural networks are employed to predict the control and operational parameters of a DSTATCOM, optimizing the voltage profile across varying load conditions. The proposed technique is evaluated on the IEEE 14-bus system, with results demonstrating its superior performance in both speed and accuracy [7], [8]. A comprehensive review of the smart grid and the potential role of AI research in supporting its vision was presented in [9]. To highlight AI's technological contributions toward achieving the smart grid’s prolonged objectives, we focus on two key areas: adaptive dynamic programming (ADP)-based smart control and wide situation-dependent awareness. To develop an intelligent power grid capable of meeting the rising demand for a sustainable global energy system, advanced time optimization techniques, distributed intelligence, and neural networks have been explored to address complex and stochastic challenges. A study based on 3rd and 4th generation power systems research was proposed in [10] to further this vision. Building on these research efforts, our work integrates artificial neural networks, an established computational intelligence technique for energy system control. Specifically, we employ an RBFNN-based DSTATCOM to regulate the voltage profile. To further enhance system stability, we optimize the response speed to instabilities by fine-tuning the gain factor and several other critical parameters. This approach contributes to the development of a smarter, more resilient power grid.

2. METHOD

The IEEE 14-bus transmission system has been used to represent the ‘American Electric Power System’ in the Midwest region of the USA since 1962. However, the data originally used for validation lacked real power. In this study, we employ the IEEE 14-bus transmission system to evaluate the efficiency of the introduced technique by analyzing network gains or losses through the integration of distributed generators (DGs) of extendable sizes and places. Unlike power systems of the 1990s, the 14-bus test scenario does not impose line limitations and features a reduced voltage with wide-ranging voltage administration abilities. Voltage stability, a critical aspect of power system reliability, refers to the grid's ability to maintain constant desired voltage magnitudes at all bus locations, even in the presence of disturbances [11].

All proposed bus specifications, including voltage amplitude and angle of the phase, were taken into account. Voltage drop issues often arise in power networks because of lengthy feeder lines, high rating loads at the nodes, and a reduced reactance-to-resistance X/R ratio, which weakens system links and necessitates continuous observation. To address this, a ‘power flow’ assessment is conducted to identify vulnerable points in the network. Once these weak points are detected, a load forecast analysis is executed to track power consumption trends. This process involves manually adjusting the active and reactive power (P&Q) values of the loads in the feeder system for analysis. The data extracted is then fed into the radial basis function neural network (RBFNN) unit, which is trained to recognize and predict power consumption patterns based on these trends [12].

Next, a traditional DSTATCOM is integrated to the determined weak buses, and its impact on the voltage magnitudes of each bus is analyzed. By comparing voltage magnitudes with and without the DSTATCOM, we assess network performance under both normal and fault conditions. Voltage trends across buses and weak linkages are closely monitored. The DSTATCOM is then placed at the bus with the lowest voltage magnitude, followed by the next round of voltage magnitude analysis.

Subsequently, the RBFNN is trained using observed voltage variations and corresponding network gains [13]. Once trained, the RBFNN is integrated into the DSTATCOM to enhance its control capabilities through predictive forecasting. The obtained results are analyzed, and a comparative study is conducted between the traditional DSTATCOM and the RBFNN controller-based DSTATCOM. The findings demonstrate that the RBFNN controller-based DSTATCOM offers superior control, rapid response times, and enhanced stability, ultimately contributing to a more intelligent and efficient power system network.

2.1. Distribution static compensation (DSTATCOM)

For STATCOM modules deployed across various locations, a distributed approach to reactive power (Q) compensation and voltage enhancement can effectively address reactive power challenges at both the feeder and distribution levels. In distribution networks, this method is known as distribution static compensation (DSTATCOM). In the event of a primary reactive power source failure, DSTATCOM helps maintain system stability by mitigating the loss of reactive support [14]. DSTATCOM enhances power system efficiency and improves distribution network reliability through its parallel-connected voltage source converter. By providing voltage support and managing power dissipation under both dynamic and steady-state conditions, DSTATCOMs play a crucial role in maintaining system performance [15]. Key benefits of DSTATCOM include enhanced reactive power support, improved voltage regulation, rapid voltage recovery, strengthened transient stability, and increased overall system reliability. Additionally, its adaptability contributes to higher line capacity and reduced system losses, making it an essential component of modern power distribution networks [16].

Integrating DSTATCOM with an energy storage system (ESS) further enhances its flexibility and voltage support capabilities, leveraging the benefits of flexible AC transmission systems (FACTS) devices. Additionally, superconducting magnetic energy storage (SMES) in combination with DSTATCOM can improve transmission capacity. With the capability to both absorb and supply P&Q, DSTATCOM operates in four quadrants. Beyond voltage regulation, it can modify system phase angles and series impedance, enabling transmission lines to function closer to thermal limits while minimizing line losses [17]. DSTATCOM technology is applicable across ultra-high-voltage (UHV), extra-high-voltage (EHV), and high-voltage (HV) feeder systems. Fundamentally, DSTATCOM and other FACTS devices share similar design principles and functionalities, making them essential components for modern power system stability and efficiency.

2.2. Support vector machine (SVM)

SVMs objective to increase the margin across the dividing hyperplane and the data points while reducing the upper bound of simplification errors. In most of cases, the hyperplane for data cataloging is determined by selecting a subset of support vectors from the training set of input. By employing the structural risk minimization (SRM) principle, SVMs decrease simplification errors on test datasets. SRM enhances class separation by mapping data non-linearly into a high-dimensional space, where a simpler model is chosen for a given training model, ensuring that the decision limit in the transformed space remains linear [18]. Alternatively, SVM kernels can non-linearly adjust the 'input space' to a 'higher-dimensional space', enabling more effective classification. A kernel function, K(yi,y) is proposed using support vectors 'yi' from the test data and an input vector 'y'. The primary objective of SVMs is to minimize sorting errors by constructing optimal finalized functions that accurately predict and categorize hidden inputs into separate groups. In our approach, we utilize SVMs to achieve this goal. The resulting SVM function exhibits strong generalization capabilities, reducing overshoot while identifying a well-oriented, maximized-margin hyperplane. The mathematical expression for the optimal separating hyperplane is formulated and solved using MATLAB SVM tools (1).

$$Q^{*T}.y + a^* = 0 \tag{1}$$

It minimizes misclassification errors while maximizing the margin. The (2) defines the optimal weight vector Q^*.

$$Q^* = \sum_{k=1}^{N} \gamma j^* \, yj^* \tag{2}$$

Where $\gamma 1^* = (\gamma 1^*, \gamma 2^*, \gamma 3^* \ldots\ldots\ldots\ldots \gamma N^*)$, yi with $\gamma^* > 0$ are the points of support vector. The (3) can be utilized to separate a novel data vector y.

$$z = sign(f(y)) \tag{3}$$

Here, *f(y)* is the optimum determined boundary which need from samples of the training variable set expressed in (4).

$$f(y) = Q^{*T}.y + a^* \tag{4}$$

Here is another way to state the above equation:

$$f(y) = (\sum_{k=1}^{N} \gamma j * yj)y + a^* \tag{5}$$

next, the sets of training is utilized to determine the class z∈{−1,1} of 'y' by computing the dot product amid the trained data and the support vector [19]. For linearly separable data, a dividing hyperplane can be utilized for classification. Though, in real-world scenarios, data is often non-separable and non-linear, requiring kernel functions for effective mapping. This architecture allows for various types of data separation.

3. RADIAL BASIS FUNCTION NEURAL NETWORK

Figure 1 illustrates a backpropagation network structure with a single hidden layer, which forms the core of a RBFNN. Conferring to survey findings in [20], RBFNN is the utmost effective and reliable network for organization tasks. Each hidden layer consists of centroids and a smoothing factor. Typically, neurons calculate the distance between the input and the centroids, producing results that survey a distance-dependent, radially balanced pattern. As the input approaches the centroid value, the output becomes more robust.

The mapping function, U_{map} can be generally given as (6).

$$U_{map}(y) = \sum_{k=1}^{Z} v_k \, p[\,(y_k - c_k\,)/\rho_k] \tag{6}$$

Here ‘p’ is radial symmetrical kernel function which is calculated using Z kernel units. Fundamental exponential functions of one of RBF's is given as (7).

$$U_{map}(y) = \beta \exp\left(-\sum_k [\ (x_k - c_k\ )/\sigma_k]^2\ \right) \tag{7}$$

The spread parameter (ρ_k), constant (β), and centroid (c_k) must be chosen dependent on the training dataset [21]. The effectiveness of DSTATCOMs in the power grid depends on their number, placement, and capacity, whether deployed independently or in aggregation with a dynamic source. DSTATCOM plays a critical role in enhancing grid performance. Numerous studies have explored optimal placement strategies for FACTS devices, including DSTATCOM, to maximize power system efficiency. Potential installation sites include both the consumer side distribution and the feeder side levels. DSTATCOMs can be deployed either centrally in a single location or distributed across multiple sites for improved performance.

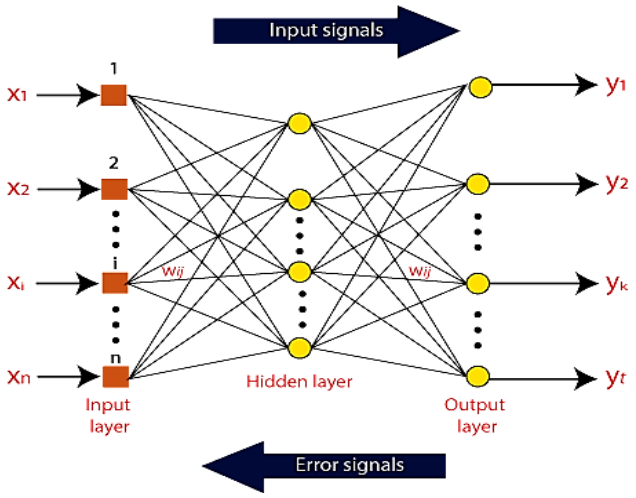


Figure 1. Architecture of NN

3.1. PSAT modelling of IEEE 14 bus system

Variable loads were introduced to examine the system's response. Capacitor banks are incorporated to counteract the initial voltage drop triggered by the variable heavy loads. PSAT tools were employed to facilitate to present of waveform plotting in graphical format and for analysis. By choosing appropriate choices, responses from the lowest and highest voltage buses, among others, were obtained [22]. The toolbar’s library functions enabled the creation of disturbances within the system, allowing for modifications to individual fault parameters as needed. To further assess system performance and enhance its intelligence, a fault condition—specifically a ‘line-to-ground (L-G)’ fault on bus 1 was introduced. The fault is occurred at t = 0 seconds and was removed at 2 seconds. The bus system was then redesigned and simulated using PSAT software [23]. Voltage profiles across all buses was analyzed to evaluate system stability. Figures 2 and 3 present the IEEE 14-bus system’s single-line diagram and PSAT model, respectively.

Figure 3 presents the introduced DSTATCOM topology, which is based on the RBFNN technique. The voltage profile variations and response gains obtained from a traditional controller serve as inputs to the RBFNN. During data analysis, the RBFNN module allocates 85% of the input data for processing and 15% for tuning and testing. The system adopts the back-propagation algorithm for the training, enabling it to adapt effectively to new or unknown voltage profiles and gain variations [24].

The RBFNN controller-based DSTATCOM is designed in MATLAB to simulate an L-G fault disturbance at bus 12. The fault occurs at t = 0 seconds and is cleared after 2 seconds. Results indicate that the power system incorporating the RBFNN controller-based DSTATCOM restores the voltage profile more rapidly than a traditionally controlled bus system. Additionally, system stability is efficiently sustained even during multiple disturbances to the system. To demonstrate the enhanced performance of the intelligent system, the voltage magnitudes of the 3 low-voltage buses during the fault are compared for both the traditionally controlled DSTATCOM and the RBFNN controller-based DSTATCOM. This comparison highlights the improved efficiency and adaptability of the bus system achieved through artificial intelligence integration [25].

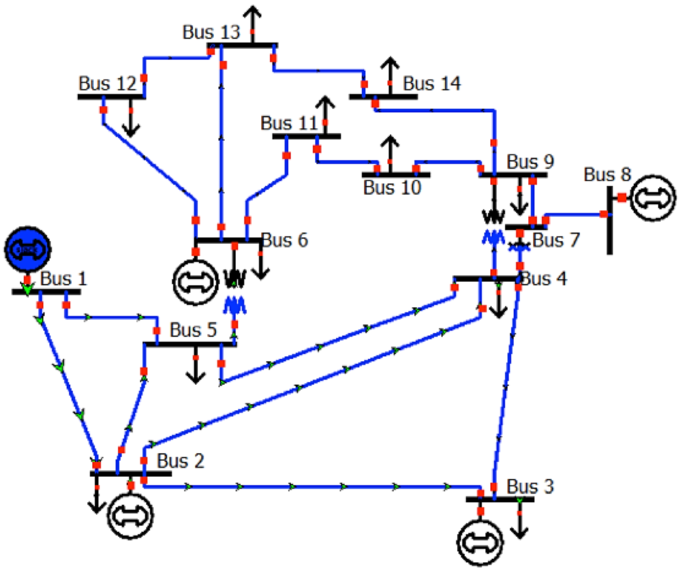


Figure 2. IEEE 14 bus system

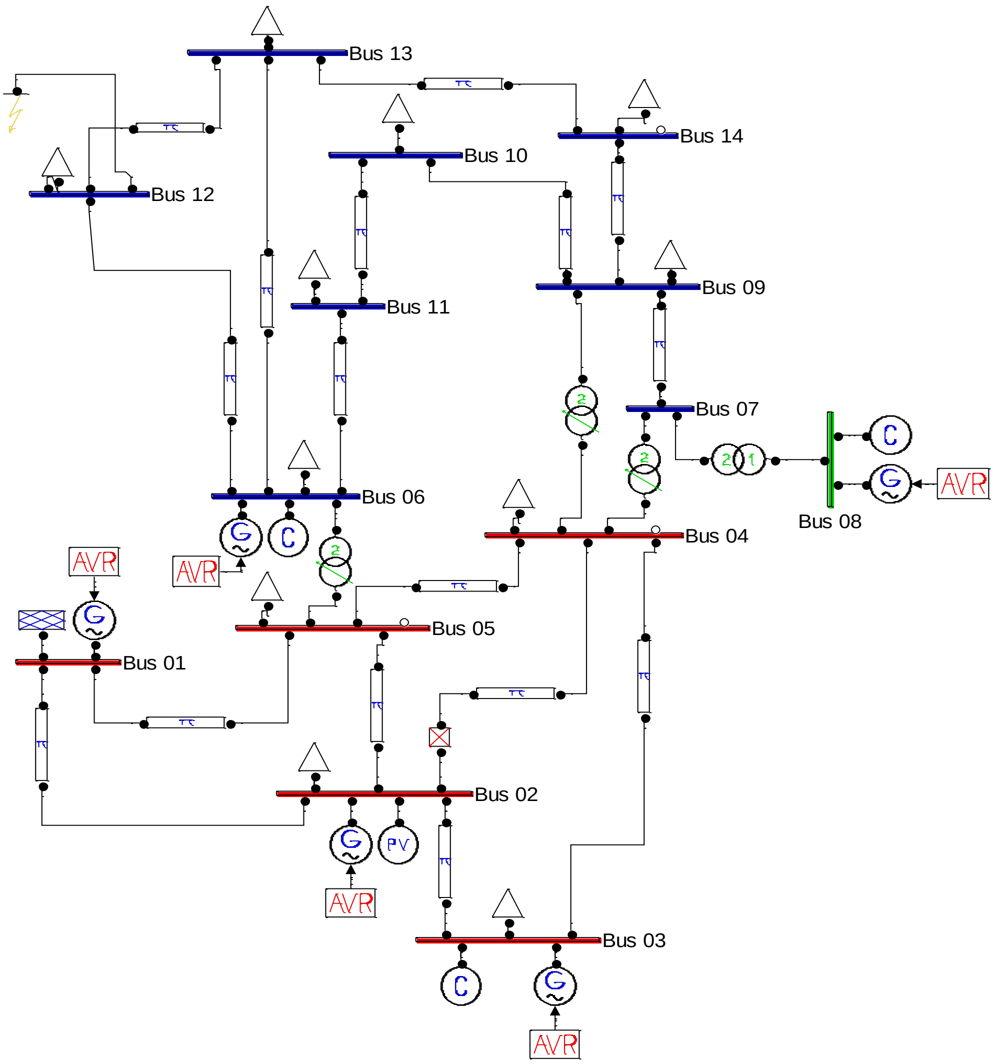


Figure 3. IEEE 14 bus system PSAT model

4. RESULT AND DISCUSSION

The observed oscillations are a result of the variable loading characteristics. Initial decline in the voltage magnitude is attributed to the inherent nature of dynamic loading. As presented, the voltage magnitude has fallen below 1 per unit (p.u.), classifying them as weaker cells. These weaker cells are highly sensitive to disturbances, and any disruption can lead to system instability.

Figure 4 illustrates the magnitude of bus voltages for buses 4, 5, and 14, showing values dropping below 1 p.u. Identifying weak links in the network is vital for maintaining the system stability in these conditions. These vulnerable points are continuously monitored to ensure they remain under control, thereby preventing potential network-wide malfunctions or outages.

The PI regulator has a significant part in determining the proportional gain (Kp), integral gain (Ki), gains of AC and DC controllers, and the damping controller. As per the simulation results, it is observed that there is an improvement in the voltage magnitudes of 3 low voltages buses. Notably, the 3 buses voltage magnitudes were maintained near to 1 p.u. The voltage goes low in these buses are effectively increased by integrating the DSTATCOM, as illustrated in Figures 5 through 11.

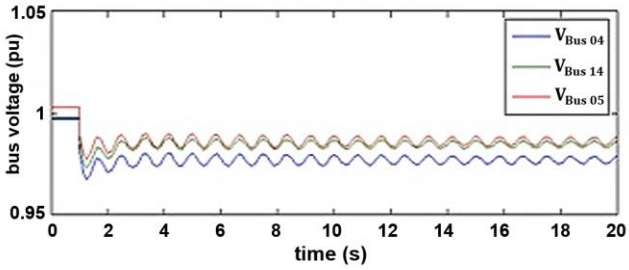
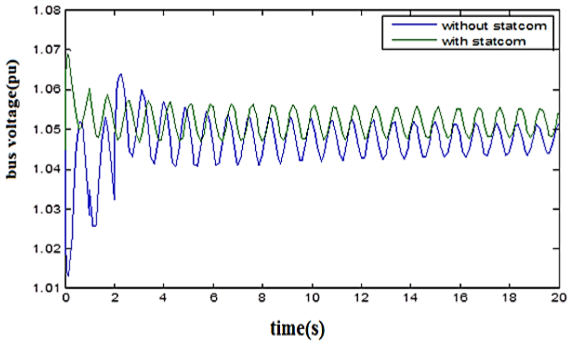
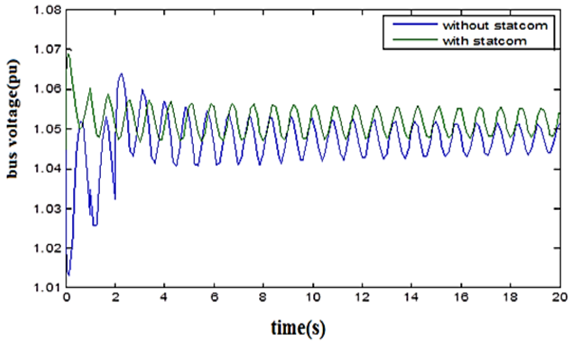


Figure 4. Buses with lowest voltage

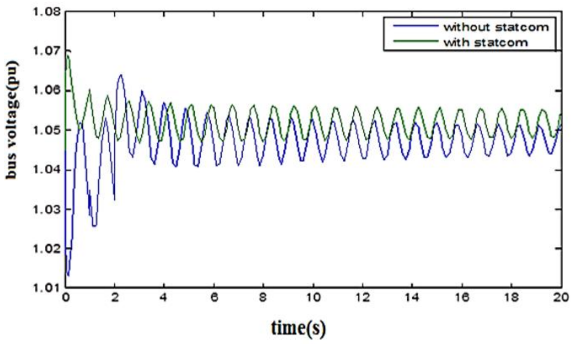


(a)

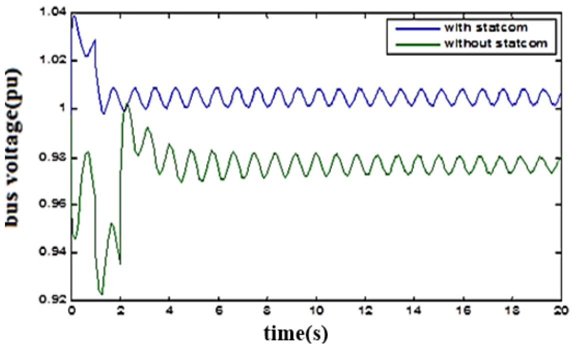


(b)

Figure 5. Voltage magnitude comparison with and without D-STATCOM in per unit at (a) bus 1 and (b) bus 2

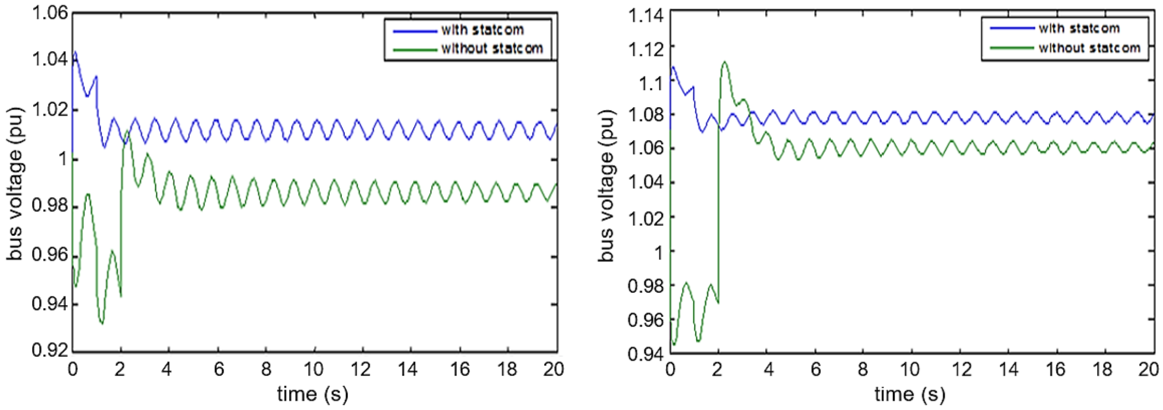


(a)



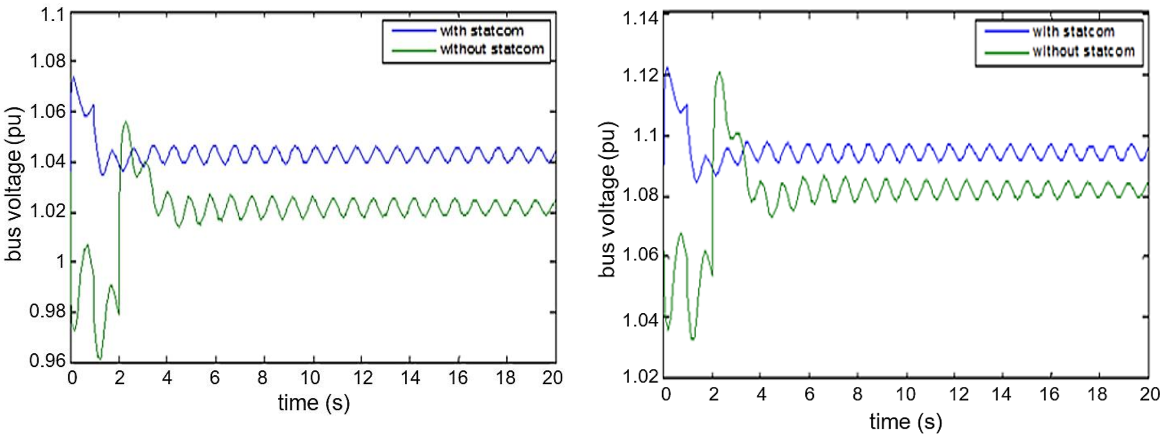
(b)

Figure 6. Voltage magnitude comparison with and without D-STATCOM in per unit at (a) bus 3 and (b) bus 4



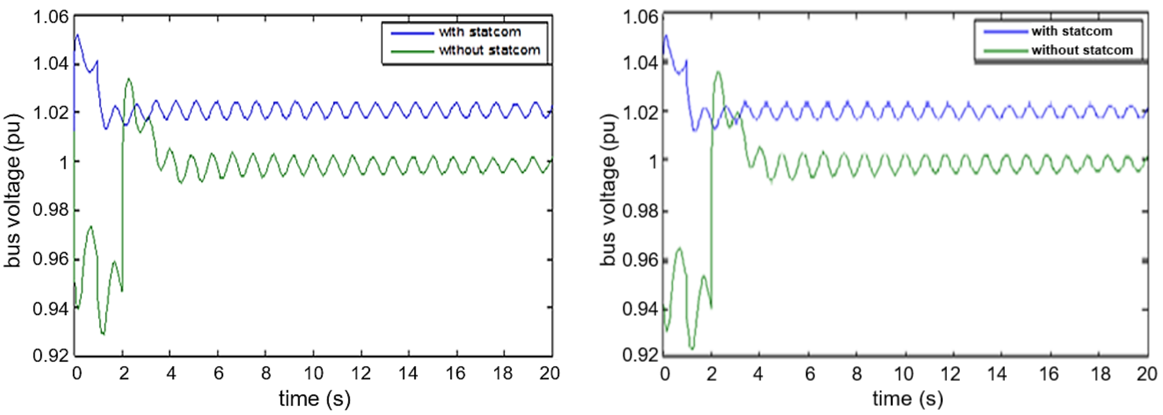
(a) (b)

Figure 7. Voltage magnitude comparison with and without D-STATCOM in per unit at
(a) bus 5 and (b) bus 6



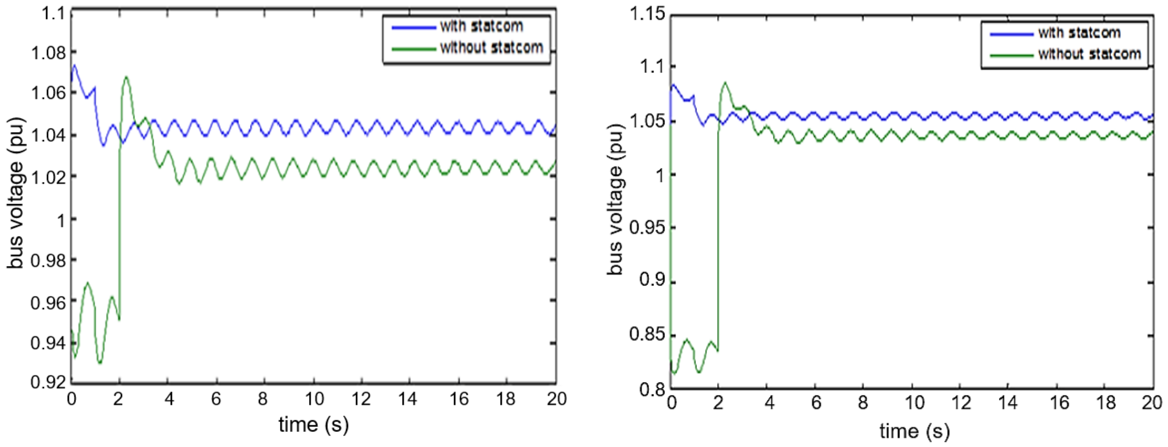
(a) (b)

Figure 8. Voltage magnitude comparison with and without D-STATCOM in per unit at
(a) bus 7 and (b) bus 8



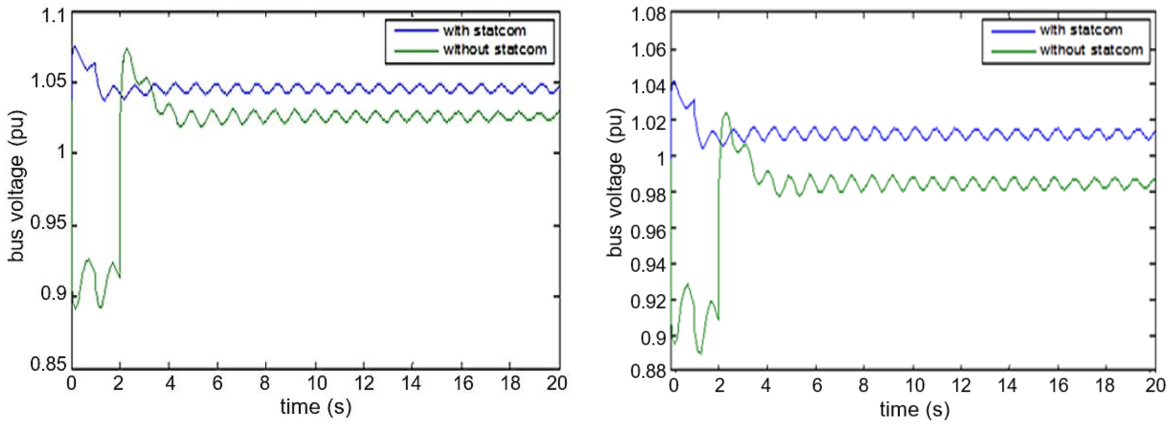
(a) (b)

Figure 9. Voltage magnitude comparison with and without D-STATCOM in per unit at
(a) bus 9 and (b) bus 10



(a) (b)

Figure 10. Voltage magnitude comparison with and without D-STATCOM in per unit at (a) bus 11 and (b) bus 12



(a) (b)

Figure 11. Voltage magnitude comparison with and without D-STATCOM in per unit at (a) bus 13 and (b) bus 14

5. CONCLUSION

This study emphasized the importance of maintaining a constant voltage profile and explored various aspects related to voltage stability. It delved into topics surrounding flexible AC transmission systems (FACTS) technology, highlighting the crucial features of several FACTS devices. To address power flow challenges in systems utilizing DSTATCOM, the Newton-Raphson method was employed. By modeling and analyzing the DSTATCOM integrated to the bus, a stable voltage magnitude was maintained through the entire operational range whenever necessary. Reactive power (Q) compensation was successfully executed in a large feeder system, demonstrating consistent effectiveness. To improve the system performance, load flow analysis is implemented using MATLAB software, providing valuable power flow analysis data between the buses, voltage profiles, and optimal position for DSTATCOM in the considered bus system. The integration of a proficient system with the DSTATCOM ensured stable and constant voltages, further improving system reliability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
G. Sathish Goud	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
R. Senthil Kumar		✓			✓	✓			✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors listed below hereby certify that they do not have any affiliations with or involvement in any organization or entity with any financial interest, such as honoraria, educational grants, participation in speakers' bureaus, membership, employment, consultancies, stock ownership, or other equity interest, and expert testimony or patent-licensing arrangements, related to the subject matter or materials discussed in this manuscript. Furthermore, they declare no non-financial interests, such as personal or professional relationships, affiliations, knowledge, or beliefs, that could potentially bias the content presented in this manuscript.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article. The data that support the findings of this study are available from the corresponding author [GSG], upon reasonable request.

REFERENCES

[1] P. Kanirajan and V. S. Kumar, "Power quality disturbance detection and classification using wavelet and RBFNN," *Applied Soft Computing Journal*, vol. 35, pp. 470–481, 2015, doi: 10.1016/j.asoc.2015.05.048.

[2] P. Kanirajan and V. S. Kumar, "Wavelet-based power quality disturbances detection and classification using RBFNN and fuzzy logic," *International Journal of Fuzzy Systems*, vol. 17, no. 4, pp. 623–634, 2015, doi: 10.1007/s40815-015-0045-0.

[3] P. Kanirajan and V. S. Kumar, "A wavelet based data compression technique for power quality events classification," *WSEAS Transactions on Power Systems*, vol. 10, pp. 82–88, 2015.

[4] P. Kanirajan and M. Joly, "An integrated data compression using wavelet and neural networks for power quality disturbances," *WSEAS Transactions on Computer Research*, vol. 7, pp. 9–22, 2019.

[5] P. Kanirajan, M. Joly, and T. Eswaran, "A comparison of back propagation and PSO for training RBF neural network for wavelet based detection and classification of power quality disturbances," *International Journal of Signal Processing*, vol. 6, pp. 33–38, 2021.

[6] Y. Zhang, G. P. Chen, O. P. Malik, and G. S. Hope, "An artificial neural network based adaptive power system stabilizer," *IEEE Transactions on Energy Conversion*, vol. 8, no. 1, pp. 71–77, Mar. 1993, doi: 10.1109/60.207408.

[7] J. M. Ramirez and R. Tapia O., "Neural network control of the STATCOM in multimachine power systems," *WSEAS Transactions on Power Systems Manuscript*, vol. 2, no. 9, pp. 209–214, 2007.

[8] A. M. Gole and V. K. Sood, "Static VAR compensator models for power flow and dynamic performance simulation," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 229–240, 1994, doi: 10.1109/59.317606.

[9] P. Rao, M. L. Crow, and Z. Yang, "STATCOM control for power system voltage control applications," *IEEE Transactions on Power Delivery*, vol. 15, no. 4, pp. 1311–1317, 2000, doi: 10.1109/61.891520.

[10] L. Gyugyi, C. D. Schauder, and K. K. Sen, "Static synchronous series compensator: A solid-state approach to the series compensation of transmission lines," *IEEE Power Engineering Review*, vol. 17, no. 1, p. 62, 1997, doi: 10.1109/MPER.1997.560708.

[11] X. Xu, M. Bishop, E. Camm, and M. J. S. Edmonds, "Transmission voltage support using distributed static compensation," in *IEEE Power and Energy Society General Meeting*, 2014, doi: 10.1109/PESGM.2014.6938785.

[12] A. Jain, A. R. Gupta, and A. Kumar, "An efficient method for D-STATCOM placement in radial distribution system," in *India International Conference on Power Electronics, IICPE*, 2015, doi: 10.1109/IICPE.2014.7115746.

[13] E. Ghahremani and I. Kamwa, "Optimal allocation of STATCOM with energy storage to improve power system performance," in *Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference*, 2014, doi: 10.1109/tdc.2014.6863431.

[14] Y. Li and Y. W. Li, "Power management of inverter interfaced autonomous microgrid based on virtual frequency-voltage frame," *IEEE Transactions on Smart Grid*, vol. 2, no. 1, pp. 30–40, 2011, doi: 10.1109/TSG.2010.2095046.

[15] R. Hasan, S. Mekhilef, M. Seyedmahmoudian, and B. Horan, "Grid-connected isolated PV microinverters: A review," *Renewable and Sustainable Energy Reviews*, vol. 67, pp. 1065–1080, 2017, doi: 10.1016/j.rser.2016.09.082.

[16] Maneesh, "Frequency control of a microgrid by using PI controller," in *2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth, ICEPE 2015*, 2016, doi: 10.1109/EPETSG.2015.7510081.

[17] A. Raj and A. Gopinath, "Proportional plus integral (PI) control for maximum power point tracking in photovoltaic systems," *International Research Journal of Engineering and Technology*, vol. 2, no. 6, pp. 408–412, 2015, [Online]. Available: www.irjet.net

[18] M. F. N. Zolkifli, M. S. Robian, S. Saon, and A. K. Mahamad, "FPGA based maximum power point tracking of photovoltaic system using ANFIS controller," *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 8, pp. 5094–5097, 2016.

[19] T. H. Kwan and X. Wu, "An adaptive scale factor based MPPT algorithm for changing solar irradiation levels in outer space," *Acta Astronautica*, vol. 132, pp. 33–42, 2017, doi: 10.1016/j.actaastro.2016.12.010.

[20] M. Mehrasa, E. Pouresmaeil, H. Mehrjerdi, B. N. Jørgensen, and J. P. S. Catalão, "Control technique for enhancing the stable operation of distributed generation units within a microgrid," *Energy Conversion and Management*, vol. 97, pp. 362–373, 2015, doi: 10.1016/j.enconman.2015.03.078.

[21] K. Prabaakaran, N. Chitra, and A. S. Kumar, "Power quality enhancement in microgrid - A survey," in *2013 International Conference on Circuits, Power and Computing Technologies (ICCPCT)*, IEEE, Mar. 2013, pp. 126–131, doi: 10.1109/ICCPCT.2013.6528830.

[22] N. Mahdian Dehkordi, N. Sadati, and M. Hamzeh, "A backstepping high-order sliding mode voltage control strategy for an islanded microgrid with harmonic/interharmonic loads," *Control Engineering Practice*, vol. 58, pp. 150–160, 2017, doi: 10.1016/j.conengprac.2016.10.008.

[23] E. E. Aker, M. L. Othman, I. Aris, N. I. A. Wahab, H. Hizam, and O. Emmanuel, "Transmission line fault identification and classification with integrated facts device using multiresolution analysis and naïve bayes classifier," *International Journal of Power Electronics and Drive Systems*, vol. 11, no. 2, pp. 907–913, 2020, doi: 10.11591/ijpeds.v11.i2.pp907-913.

[24] A. Karami and S. Z. Esmaili, "Transient stability assessment of power systems described with detailed models using neural networks," *International Journal of Electrical Power and Energy Systems*, vol. 45, no. 1, pp. 279–292, 2013, doi: 10.1016/j.ijepes.2012.08.071.

[25] F. Aydin and B. Gümüş, "Comparative analysis of multi-criteria decision making methods for the assessment of optimal SVC location," *Bulletin of the Polish Academy of Sciences: Technical Sciences*, vol. 70, no. 2, 2022, doi: 10.24425/bpasts.2022.140555.

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