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Original Article

Predictive Modeling of Power System Contingencies with SVMs and FACTS Devices for Enhanced Stability

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Abstract *- In modern power systems, ensuring stability and reliability is paramount. This study proposes a novel approach to the predictive modelling of power system contingencies using Support Vector Machines (SVMs) in conjunction with Flexible A.C. Transmission System (FACTS) devices. The integration of SVMs aids in accurately forecasting potential contingencies by analyzing historical data and identifying patterns. Additionally, FACTS devices can dynamically control power flow and enhance system stability. The proposed methodology involves two main phases: training the SVM model using historical data and simulating the impact of various contingencies with and without FACTS intervention. Comparative analysis demonstrates the effectiveness of the SVM-based predictive model in identifying critical contingencies. Moreover, incorporating FACTS devices showcases their potential to mitigate stability issues through real-time control actions. This combined approach offers an advanced tool for power system operators to anticipate and minimize contingencies effectively, ultimately leading to an enhanced and resilient power grid.*

Keywords *- Enhanced stability, Grid resilience, Machine learning, Predictive modeling, Support Vector Machine.*

1. Introduction

In modern society, power systems' reliable and efficient operation is paramount. The growing demand for electricity and the integration of renewable energy sources underscores the need for robust and stable power systems. However, these systems' inherent complexity and interconnected nature expose them to various contingencies, such as line failures, generator outages, and sudden load changes, leading to instability and even blackouts.

To address these challenges, advanced predictive modelling techniques have emerged as crucial tools for enhancing the stability and reliability of power systems. Support Vector Machines (SVMs), a class of machine learning algorithms, have gained prominence due to their ability to handle complex and nonlinear relationships within power system data effectively. By learning from historical data, SVMs can predict system behaviour under different contingencies, aiding operators in making informed decisions to mitigate potential issues. Moreover, FACTS devices have proven indispensable in maintaining power system stability. These devices, which include controllable elements like phase shifters and voltage regulators, offer real-time adjustments to power flow and voltage levels. Incorporating FACTS devices into predictive models can significantly enhance the accuracy of contingency predictions, as they provide additional degrees of control to counteract disruptions [1-4].

Predictive modelling of power system contingencies has emerged as a critical area of research and application within the field of electrical engineering. This practice involves using advanced algorithms and techniques to forecast potential disturbances and failures in power systems, allowing operators to take preemptive actions to maintain grid stability and prevent cascading failures. This investigation explores the key concepts, methodologies, and advancements in the predictive modelling of power system contingencies [5-9].

The evolution of predictive modelling has also seen a shift towards more advanced techniques, such as deep learning and hybrid models. Deep neural networks, especially convolution and recurrent architectures, have demonstrated promising results in capturing complex spatial and temporal relationships within power systems. Hybrid models that combine multiple machine learning approaches offer the advantage of exploiting the strengths of different methods, yielding more robust and accurate predictions [10 - 14].

The power systems are subject to various sources of uncertainty, such as fluctuations in renewable energy generation and sudden changes in load. Probabilistic forecasting, a technique that provides a range of potential outcomes along with associated probabilities, has gained traction as a way to account for uncertainty. This approach equips system operators with valuable information about the likelihood of different contingency scenarios, aiding decision-making processes [15-19].

The practical implementation of predictive modelling in power systems requires seamless integration with operational processes and decision support systems. Several studies have highlighted the importance of real-time data processing, model updating, and effective communication between predictive tools and control centres. Using predictive insights can enhance the overall resilience of power systems, enabling more efficient utilization of resources and reducing the likelihood of widespread outages [20-26].

SVM is a powerful machine learning technique that has gained prominence in various fields due to its ability to classify and predict complex data effectively. In power systems, SVMs have found utility in conjunction with FACTS devices, which are advanced technologies used to enhance the controllability and efficiency of power transmission. One primary application of SVMs in FACTS device power systems is fault detection and classification. Power system faults can lead to disruptions and even blackouts, and swift and accurate fault detection is crucial.

SVMs can analyze data from FACTS devices such as Phasor Measurement Units (PMUs) to quickly identify the location and type of fault. This aids in promptly implementing corrective measures, thereby enhancing power system reliability. Another significant application is in load forecasting with FACTS devices. SVMs can utilize historical load data and input from FACTS devices to build accurate load forecasting models.

This assists power utilities in optimizing generation and scheduling, leading to economic benefits and reduced environmental impact. SVMs have also demonstrated prowess in the optimal placement and sizing of FACTS devices. Determining these devices' best locations and capacities traditionally involves complex optimization problems. SVMs can aid in streamlining this process by learning from historical data and suggesting optimal configurations that enhance power system efficiency and stability [27-31]. The synergy between SVMs and FACTS devices presents a promising power system stability enhancement solution. SVMs can assist in predicting potential contingencies, while FACTS devices can respond rapidly to mitigate voltage and transient instability when these contingencies occur. This combined approach enables proactive and reactive stability control.

Numerous case studies have validated the effectiveness of integrating SVMs and FACTS devices for enhanced stability. These studies often simulate various contingencies and evaluate the system's response with and without SVM-guided FACTS control. The results consistently show improved stability margins and reduced voltage deviations. Despite the promise of this approach, challenges such as accurate data availability, model generalization, and real-time implementation need to be addressed. Future research could focus on refining SVM algorithms for more precise contingency prediction and optimizing FACTS control strategies for rapid response [32-35].

Analyzing potential outcomes is very beneficial for giving the power system static security. The machine learning algorithm k nearest Neighbor is introduced to classify the failure patterns. In this case, the KNN strategy is used with the pattern recognition technique. The K Nearest Neighbor (KNN) modelling algorithm has been discussed. Fuzzy logic was also suggested in the classification of line outages in addition to KNN. Finally, the outcomes of these two applications were compared. IEEE 118 bus systems have adopted the Support Vector Machine Based Pattern Classification (SVMBPC) method. Concepts like feature extraction and feature selection were introduced to help reduce the amount of input data needed to get results faster.

Here, the pattern classification of SVM is introduced to give the power system online security. The classifier received the input data generated offline using the A.C. load flow technique. The SVM is a good choice for an online security monitoring system since there is less misclassification. Higher expectations for dependability and a rise in degrees of freedom for functional improvement of integrated energy systems are brought about by the ongoing growth of energy systems.

Modern energy system improvement can be seen from fresh angles thanks to mathematical modelling. Data-driven models based on machine learning have a remarkable potential to play a significant role in boosting the overall utilization rate of various forms of energy, including renewable sources. Accurate P.V. and wind power forecasts are also crucial for competitive strategic bidding in the renewable energy markets. The prediction accuracy of time series energy data is predicted to increase with the use of deep learning techniques such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and

Convolution Neural Networks (CNN) [36] and [37]. This paper aims to enhance the stability of power systems by combining SVMs with FACTS devices to mitigate contingencies effectively. The study aims to develop a predictive SVM-based framework for identifying potential system vulnerabilities and determining optimal FACTS device settings.

By integrating advanced machine learning techniques and FACTS devices, the research seeks to improve power system resilience against contingencies, reduce the risk of instability, and enhance overall grid performance. Through this approach, the study aims to contribute to developing more reliable and secure power systems in the face of operational challenges.

2. Contingency Analysis

2.1. Contingency Ranking

A crucial stage in contingency analysis is contingency rating, which ranks each scenario according to how it could affect the stability and security of the power system. Each contingency scenario's severity and chance of occurrence are evaluated as part of the ranking process. The ranking procedure often considers several factors, including the severity of the effect on the power system, the importance of the affected equipment, and the availability of resources for contingency planning. Following the ranking of the scenarios, mitigation measures may be created and put into action, with an emphasis on initially addressing the most severe and likely situations. Power system operators may allocate resources more effectively and prioritize their efforts to maintain the stability and security of the power system in challenging circumstances by ranking the scenarios. Active Power Performance Index (APPI) and Line Voltage Stability Index (LVSI) are considered for contingency ranking; this can be illustrated in equation (1),

$$PI_{MW} = \sum_{i=1}^{N_L} \left(\frac{W}{2z} \right) \left\{ \frac{P_l}{P_l^{\max}} \right\}^{2z} \tag{1}$$

Where, P_l : Power flow through line

$P_l^{\max}$: Maximum capacity of power flow through the line l

N_L : Number of transmission lines

W : Real non negative weighting factor

z : Exponent of penalty function

$P_l^{\max}$: $\dfrac{V_i * V_j}{X}$

V_i : Voltage at bus i

V_j : Voltage at bus j

X : Reactance

2.2. Line Voltage Stability Index

The relationship between the line active power and the line of the bus voltage is the subject of the line voltage stability index. The index will fail if the transmission line's resistance in the power system equals 0. LVSI of bus voltage can be expressed in the following equation (2),

$$LVSI = \frac{P_R r}{[V_S \cos(\theta - \delta)]^2} \leq 1.0 \tag{2}$$

Where, P_R : Receiving end power

r : Resistance

V_S : Voltage at the sending end

θ : Line impedance angle

δ : The angle difference between the supply voltage and the receiving voltage. Its range is from 0 to 1, where 0 indicates a stable system and 1 indicates an unstable system.

2.3. Stability Improvement

The FACTS is categorized based on its connection with the electricity system. They are listed as series-connected controllers, shunt-connected controllers, combined series–series controllers and combined shunt–series controllers.

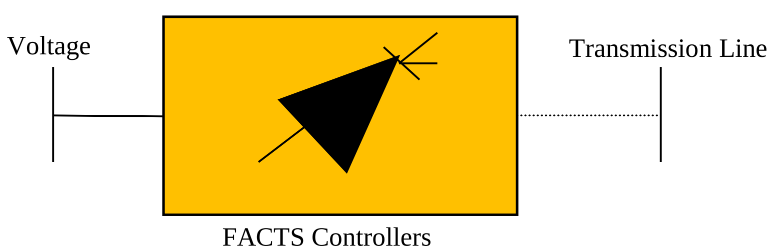

Fig. 1 Series connected controller

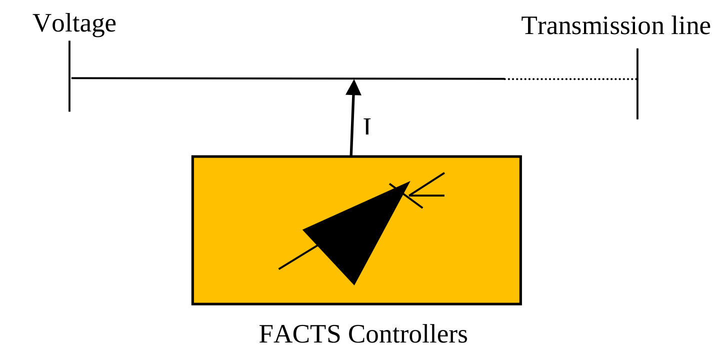

Fig. 2 Shunt-connected controller

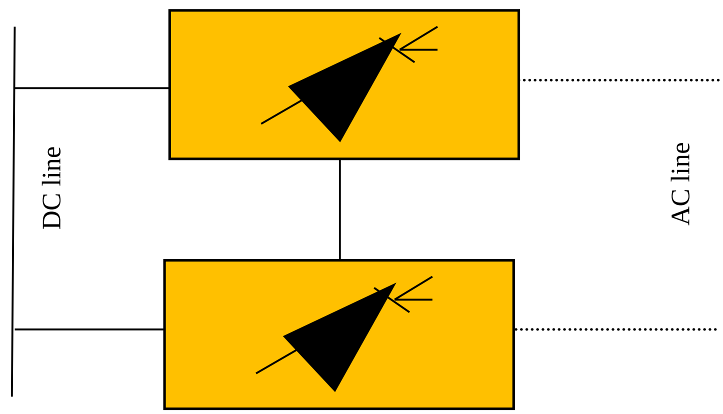

Fig. 3 Combined series-series controller

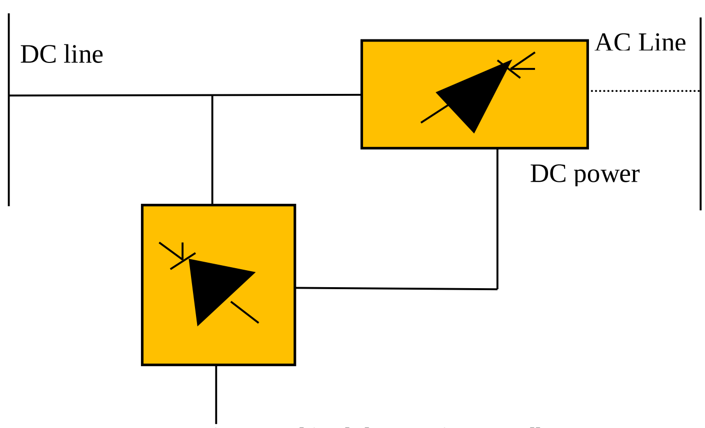

Fig. 4 Combined shunt-series controller

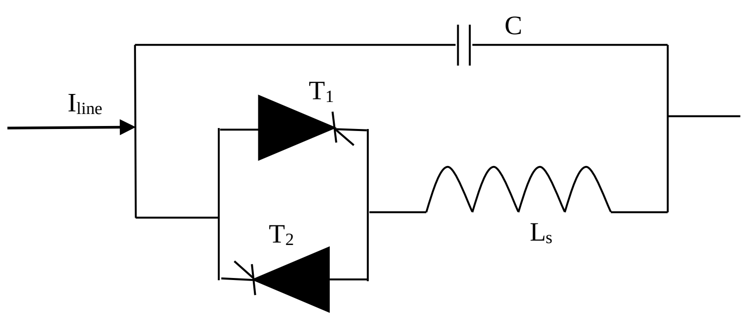

Fig. 5 Thyristor controlled series capacitor

2.3.1. Series Connected Controller

This device is inserted in series with the transmission line, allowing control over the line's impedance. Adjusting the controller's parameters can enhance voltage stability by regulating the line's reactance, thereby minimizing voltage deviations during transient events. Figure 1 illustrates the series-connected controller.

2.3.2. Shunt Connected Controller

Installed parallel with the transmission line, it can regulate voltage levels by controlling reactive power flow. This aids in voltage stability during normal and fault conditions by maintaining acceptable voltage profiles. Figure 2 illustrates the shunt-connected controller.

2.3.3. Combined Series-Series Controller

Figure 3 illustrates the integrated series-series controller. This configuration involves series controllers placed at multiple points along the transmission line. These controllers work collaboratively to fine-tune the line's impedance and enhance transient stability by mitigating voltage fluctuations.

2.3.4. Combined Shunt-Series Controller

This arrangement combines the benefits of shunt and series controllers. The shunt controller maintains voltage levels, while the series controller manages line impedance, jointly bolstering transient stability. Figure 4 illustrates the combined shunt-series controller.

2.3.5. Thyristor Controlled Series Capacitor (TCSC)

TCSC is a device that employs thyristors to control the capacitive reactance in series with the transmission line. By adjusting the thyristor firing angle, TCSC can swiftly modify the line's impedance, aiding in power flow control and transient stability enhancement. Figure 5 illustrates the thyristor-controlled series capacitor.

3. Proposed algorithm

3.1. Contingency Ranking Using APPI

Contingency ranking is crucial in power system analysis to identify vulnerable components that might lead to system instability or disruptions. The APPI is a technique used for this purpose. Figure 6 illustrates the flowchart of contingency ranking using APPI.

Step 1 : The process starts with gathering essential data about the power system. This includes bus and line information. Additionally, system parameters like angles, loads (both M.W. and MVAR), and generator details (M.W., MVAR, Qmin, Qmax) are assumed to remain constant throughout the analysis.

Step 2 : An initial load flow analysis is conducted without considering line outage contingencies. The results of this analysis serve as the base case for comparison in subsequent steps.

Step 3 : To evaluate the impact of line outages, N-1line contingency scenarios are simulated. For each scenario, one line is intentionally disconnected at a time while keeping the rest of the system intact.

Step 4 : APPI calculation is performed for each N-1 contingency scenario. APPI measures the angular displacement at critical buses due to the line outage. It's defined as the product of the change in system voltage magnitude and the angular removal of the voltage vectors. APPI quantifies the shift in power transfer and system stability due to the contingency.

Step 5 : After calculating APPI values for each contingency scenario, lines are ranked based on their sensitivity to the system's stability. Lines with higher APPI values are more critical, indicating that their outage significantly impacts the system's strength and power flow.

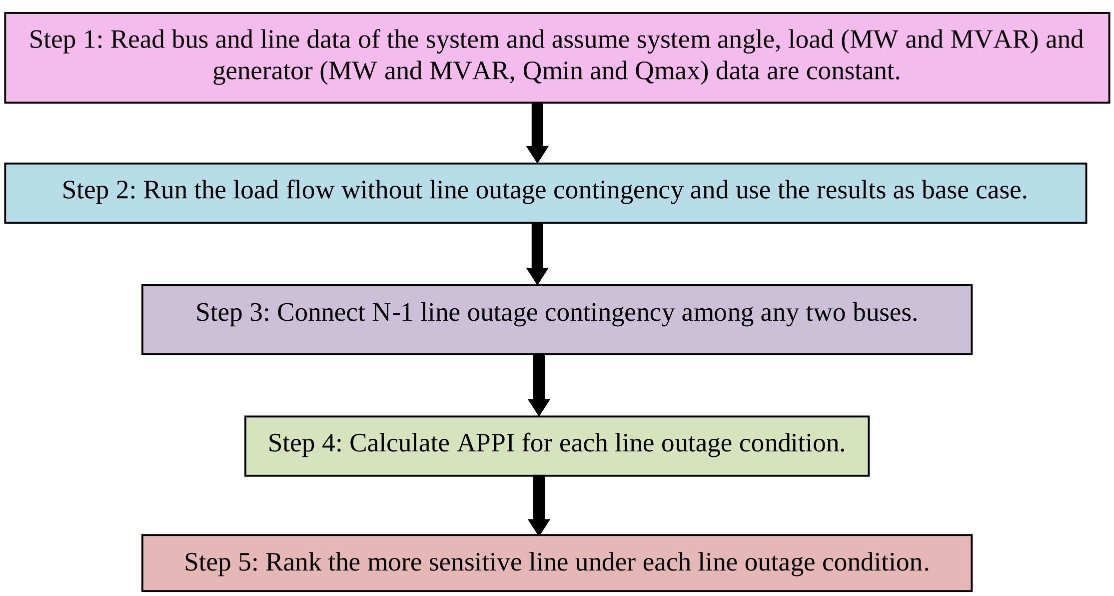

Fig. 6 Flowchart of contingency ranking using APPI

3.2. Contingency Ranking Using LVSI

The process involves evaluating the impact of potential line outages on system stability. The method detailed below utilizes the Line Voltage Stability Index (LVSI) to determine the critical lines.

Figure 7 illustrates the flowchart of contingency ranking using LVSI.

Step 1 involves gathering essential data, including bus and line information, generator characteristics, and system loads. This analysis assumes constant values for system angle, loads (M.W. and MVAR), and generator parameters (M.W., MVAR, Qmin, and Qmax).

Step 2's load flow analysis is executed under normal conditions without line outage. This initial state serves as the base case for subsequent comparisons.

Proceeding to Step 3, N-1 line outage contingencies are introduced. This means temporarily disconnecting one line at a time while keeping the rest of the system operational. Each line outage is simulated separately.

Step 4 involves calculating the LVSI for each line outage condition. LVSI is a quantitative measure to assess voltage stability and potential collapse scenarios in a power system. It typically involves evaluating parameters like bus voltages, reactive power flows, and line impedances.

In Step 5, the calculated LVSI values are examined to identify the lines that display greater sensitivity to outages. A higher LVSI indicates reduced voltage stability and, thus, higher susceptibility to instability when the line is compromised. These more sensitive lines are ranked based on their LVSI values, allowing for a prioritized list of critical lines.

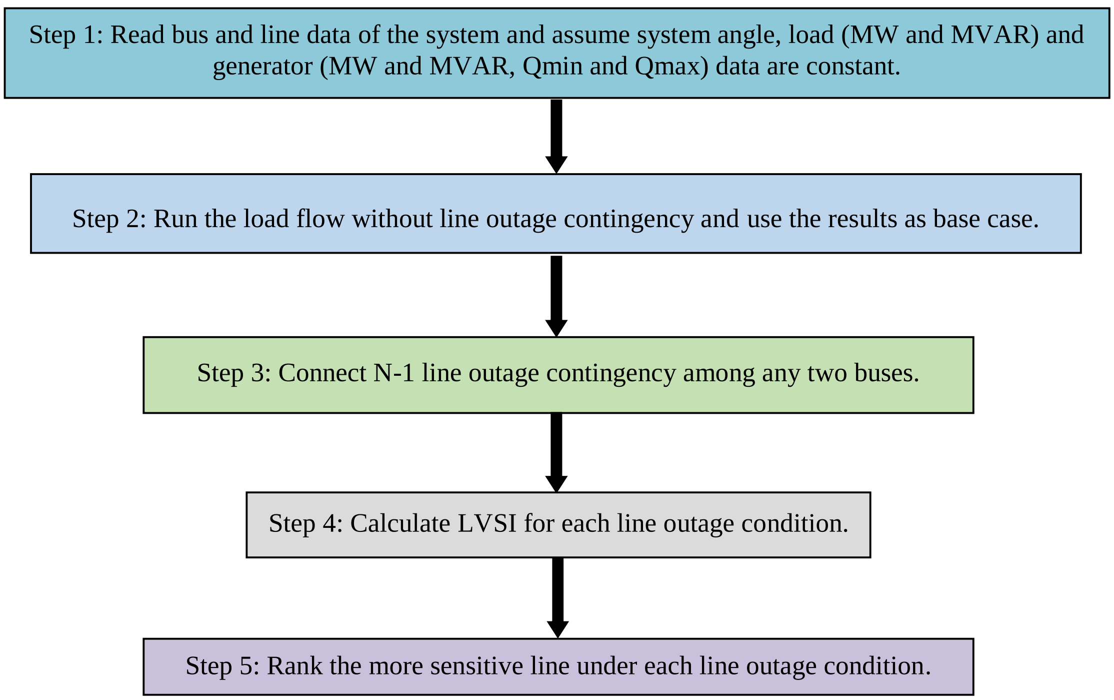

Fig. 7 Flowchart of contingency ranking using LVSI

4. Results and Discussion

The tables below represent the bus and line data of the UPSEB-75 bus system. The data provided in Table 1 is the bus data of 20 buses out of 75 buses, and Table 2 consists of 20-line data out of 97 transmission lines.

The voltage magnitude of 75 buses is provided in Figure 8 to Figure 10. Similarly, the voltage angle for 75-buses is provided in Figure 11 to Figure 13. The three cases are when Active Power (P_d) and Reactive Power (Q_d) system loading are done under 50%, 100% and 150% loading without single line transmission contingency. The following graphs show that the voltage angle is decreasing when both Pd and Qd loading increase. Figure 14 and Figure 15 show the voltage magnitude and the angles for the buses up to 45. With TCSC in the system, the voltage magnitude has increased compared to without TCSC. The APPI values for 86 transmission lines are given in Table 3.

Table 1. Bus data of Indian utility 50-bus system (UPSEB-data)

Bus No.	Bus Code	Voltage		Load		Generator		Qmin	Qmax	Injected Bus (Mvar)
		Magnitude	Angle	Pd (MW)	Qd (Mvar)	Pd (MW)	Qd (Mvar)			
1	1	1.03	0	1300	160	725	0	2500	-10	0
2	2	1.03	0	500	50	260	0	1500	-100	0
3	2	1.05	0	0	500	180	0	1500	-100	0
4	2	1.03	0	400	400	200	0	1500	-100	0
5	2	1.05	0	50	100	500	0	1500	-100	0
6	2	1.05	0	0	0	400	0	1900	-10	0
7	2	1.05	0	0	500	212	0	1900	-10	0
8	2	1.05	0	0	60	80	0	1500	-100	0
9	2	1.05	0	0	0	550	0	1800	-10	0
10	2	1.02	0	0	700	80	0	1900	-10	0
11	2	1.02	0	0	0	109	0	1900	-10	0
12	2	1.05	0	0	87	500	0	1944	-10	0
13	2	1.05	0	0	0	900	0	1580	-10	0
14	2	1.03	0	0	50	150	0	1800	-10	0
15	2	1.01	0	0	55	454	0	500	-30	0
16	0	1.00	0	25	75	0	0	0	0	0
17	0	1.00	0	0	0	0	0	0	0	0.907
18	0	1.00	0	0	0	0	0	0	0	0
19	0	1.00	0	0	50	0	0	0	0	0.453
20	0	1.00	0	75	33	0	0	0	0	0

Table 2. Line data of Indian utility 75-bus system (UPSEB-data)

Line No.	Bus Nr.	Bus Nr.	Line Impedance		1/2 B (p.u)	Tap Changing Transformer (B=1)
			R (p.u)	X (p.u)		
1	19	20	0.00065	0.00260	0	1.00
2	17	16	999990	0.00260	0	1.00
3	22	25	0.00065	0.00260	0	0.98
4	23	24	0.00065	0.00260	0	0.95
5	26	27	0.00065	0.00260	0	0.89
6	29	30	0.00043	0.00174	0	1.00
7	36	37	0.00065	0.00604	0	0.97
8	38	39	0.00130	0.00521	0	0.98
9	45	44	0.00130	0.00222	0	0.87
10	16	2	0.00123	0.00247	0	0.89
11	18	3	0.00001	0.00292	0	0.98
12	17	1	0.00073	0.00146	0	0.85
13	28	4	0.00306	0.00614	0	0.89
14	31	5	0.00235	0.00471	0	0.88
15	32	6	0.00514	0.00285	0	0.98
16	33	7	0.00549	0.01098	0	0.88
17	34	8	0.00001	0.00486	0	0.89
18	35	9	0.00049	0.00194	0	0.95
19	24	10	0.00243	0.00486	0	0.94
20	40	11	0.00770	0.00272	0	0.99

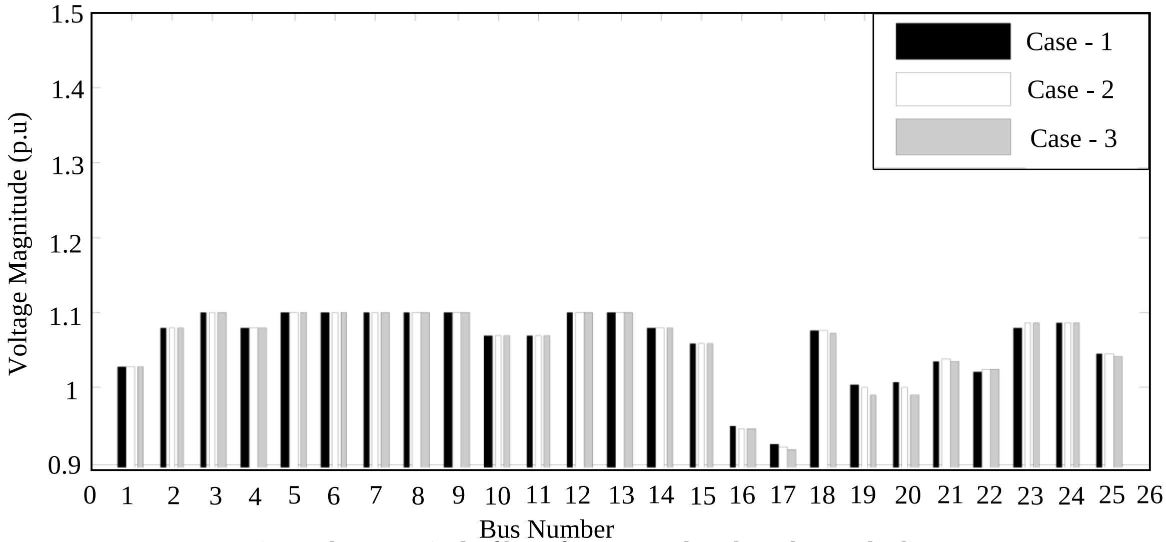

Fig. 8 Voltage magnitude of buses from 1-25 under Pd & Qd system loading

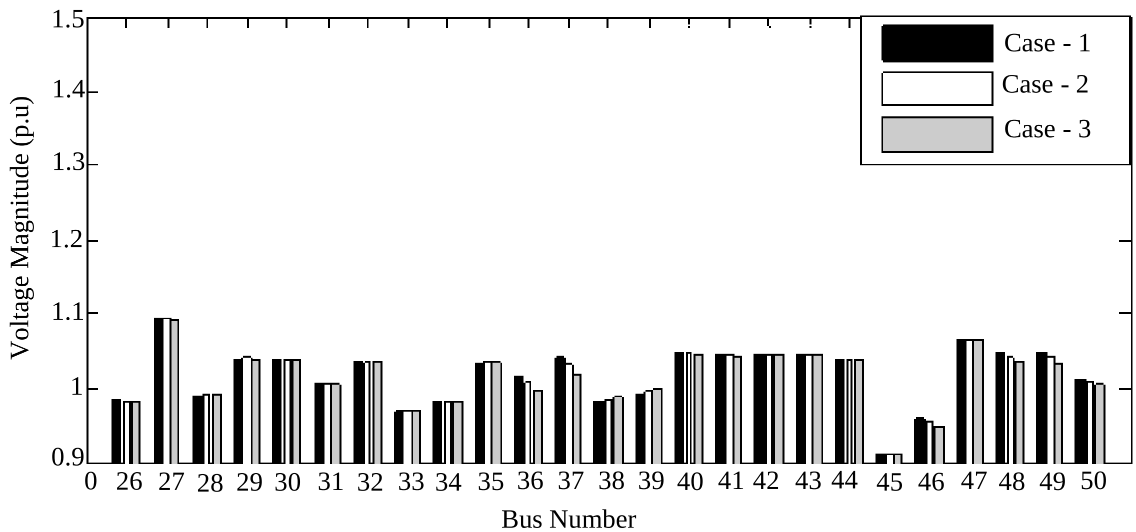

Fig. 9 Voltage magnitude of buses from 26-50 under Pd & Qd system loading

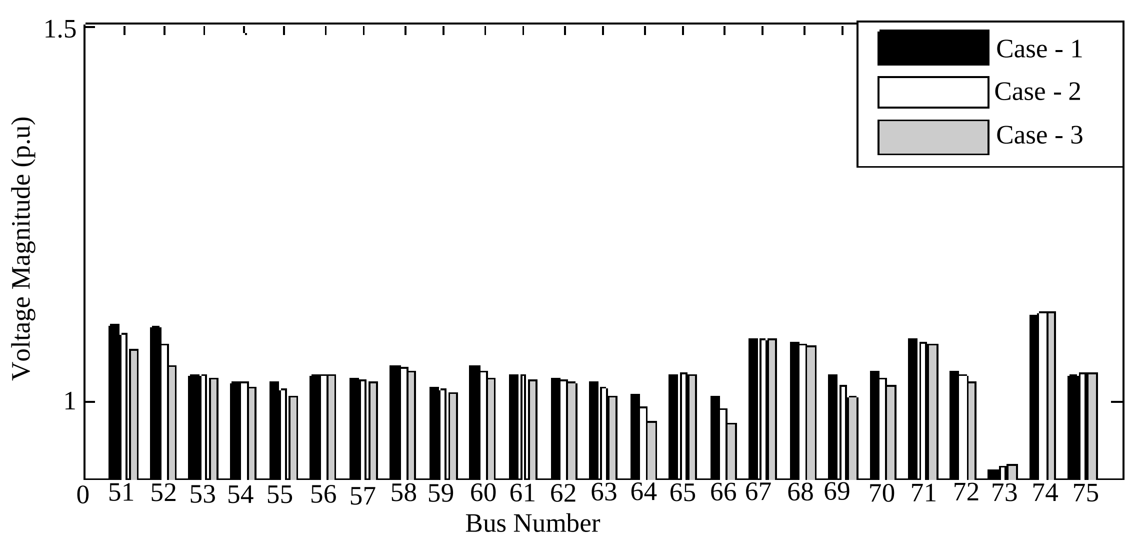

Fig. 10 Voltage magnitude of buses from 51-75 under Pd & Qd system loading

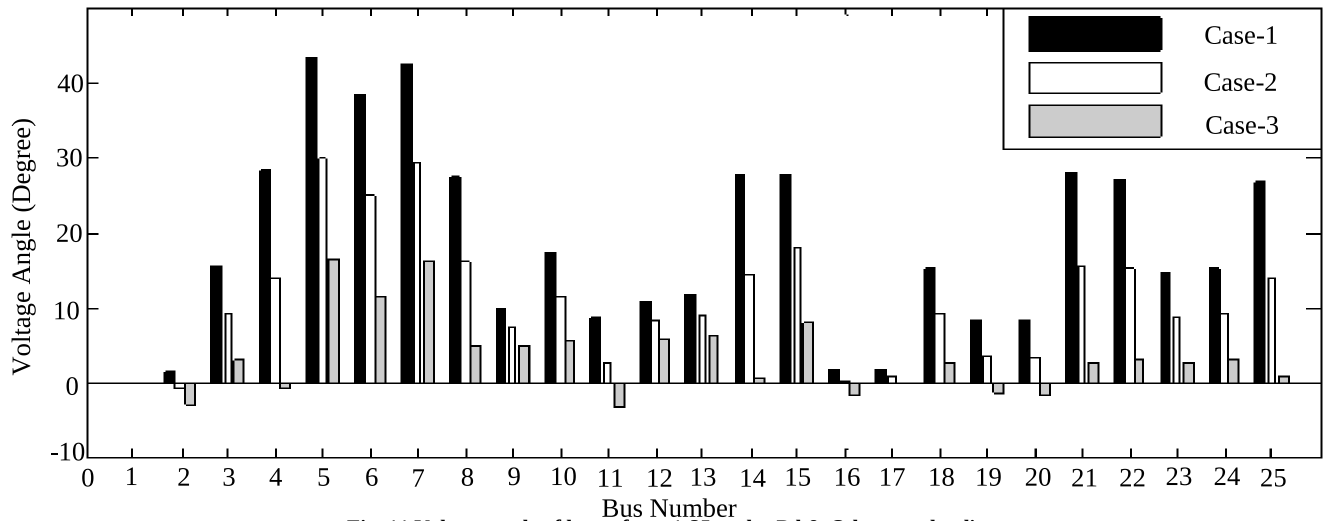

Fig. 11 Voltage angle of buses from 1-25 under Pd & Qd system loading

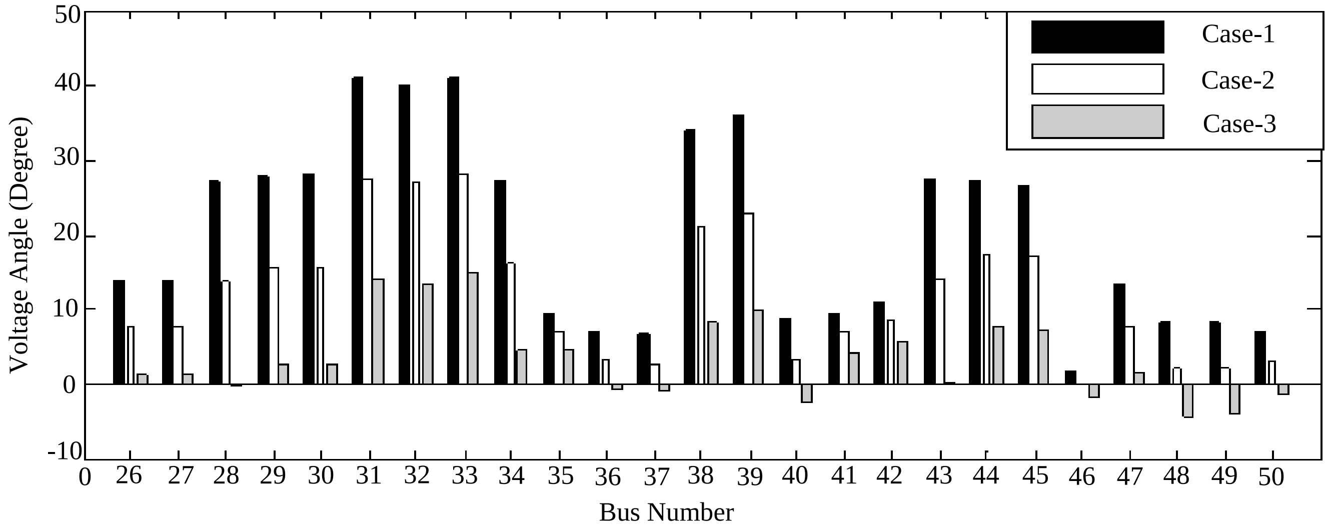

Fig. 12 Voltage angle of buses from 26-50 under Pd & Qd system loading

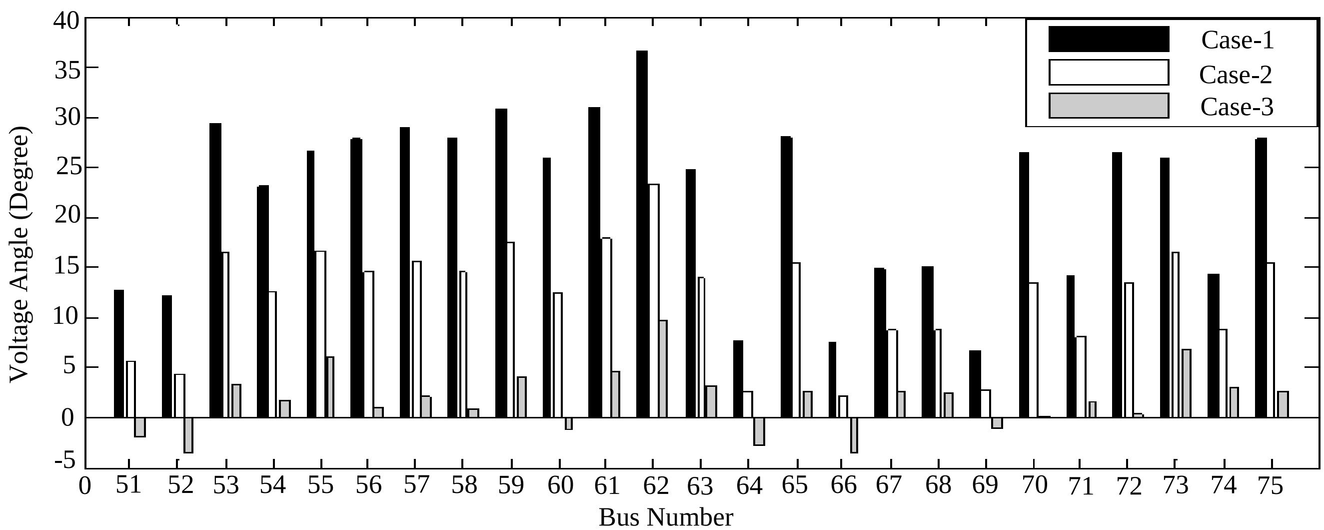

Fig. 13 Voltage angle of buses from 51-75 under Pd & Qd system loading

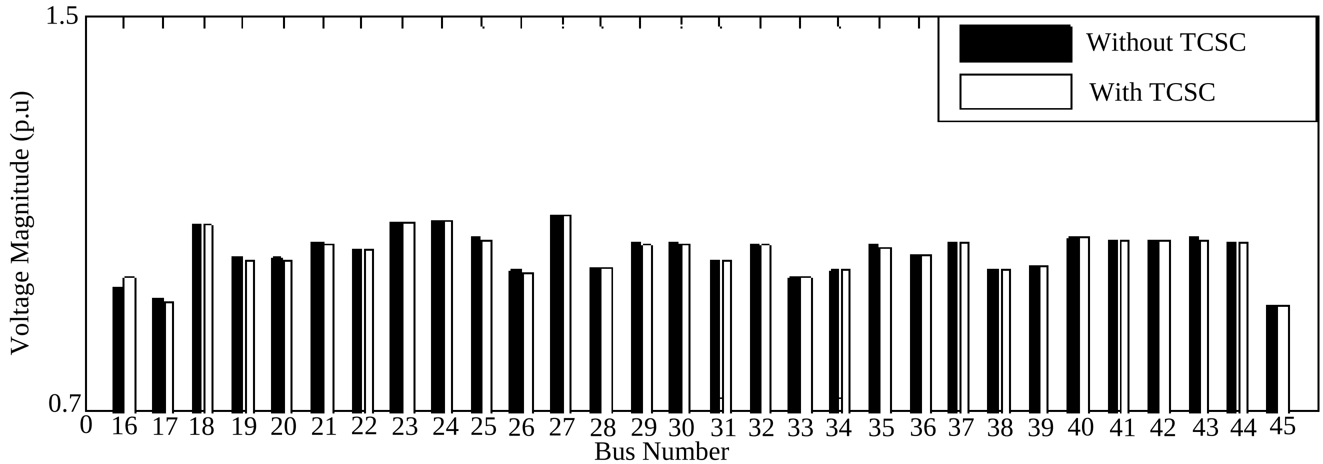

Fig. 14 Voltage magnitude of buses from 1-45 under Pd & Qd system loading

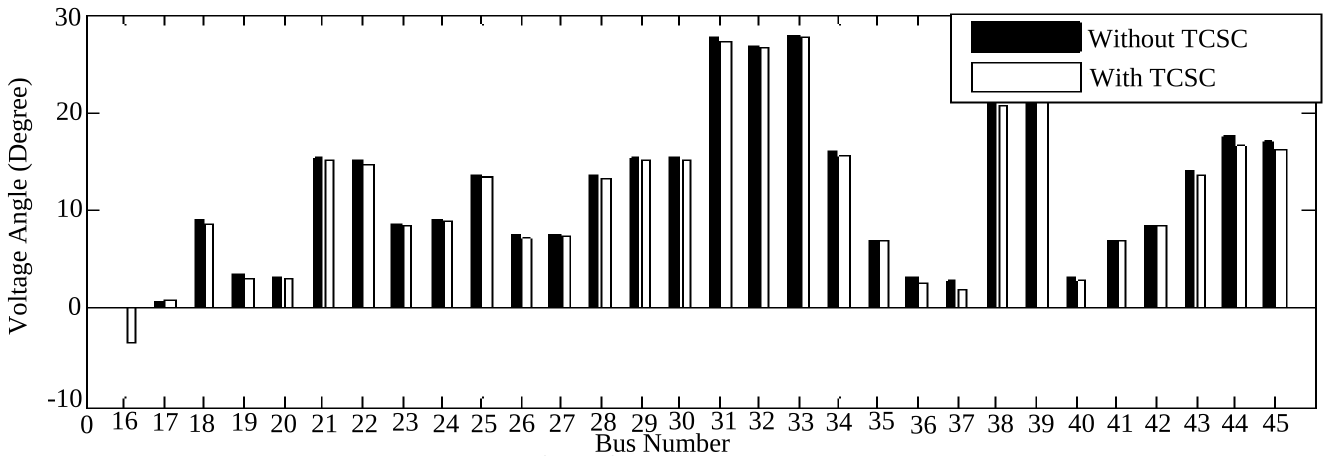

Fig. 15 Voltage angle of buses from 1-45 under Pd & Qd system loading

Table 3. Contingency ranking based on APPI under 150% of both Pd and Qd loading with and without TCSC

Line No.	Without TCSC	With TCSC	Line No.	Without TCSC	With TCSC	Line No.	Without TCSC	With TCSC
1	5.0205535	5.021	34	0.7593	0.761	67	5.0000	5.000
2	0.0162493	0.016	35	0.8373	0.837	68	8.1626	8.164
3	0.4254466	0.423	36	0.3188	0.313	69	9.0000	9.000
4	5.0806465	5.084	37	0.0259	0.026	70	0.5161	0.514
5	12.382718	12.38	38	4.0880	4.088	71	1.5000	1.500
6	0.2112549	0.212	39	0.8193	0.823	72	0.1269	0.129
7	0.8822254	0.881	40	1.7384	1.746	73	0.8821	0.883
8	17.192957	17.20	41	1.1211	1.110	74	4.5400	4.540
9	1.8000000	1.800	42	1.6499	1.658	75	1.2527	1.278
10	0.9148535	0.911	43	0.0139	0.015	76	0.3298	0.330
11	0.3786796	0.383	44	0.7503	0.750	77	1.1976	1.195
12	0.5063533	0.506	45	0.3161	0.317	78	0.7404	0.741
13	2.0052317	2.005	46	0.4611	0.461	79	0.0144	0.014
14	1.3612532	1.359	47	0.1740	0.174	80	0.4671	0.467
15	0.4531849	0.454	48	4.2500	4.250	81	0.4529	0.453
16	0.2260124	0.226	49	2.9188	2.920	82	0.3054	0.305
17	0.1711831	0.171	50	4.0000	4.000	83	0.6836	0.683
18	0.479314	0.479	51	2.1283	2.128	84	0.7908	0.790
19	0.2761368	0.276	52	0.8000	0.800	85	0.4318	0.420
20	0.2766843	0.277	53	0.5000	0.500	86	1.3157	1.303

5. Conclusion

The application of SVMs in the predictive modelling of power system contingencies, coupled with FACTS devices, has shown promising results in enhancing power system stability. The SVM-based approach has demonstrated its effectiveness in accurately predicting contingencies and identifying critical system vulnerabilities.

FACTS devices have been instrumental in mitigating the impact of contingencies and improving overall system stability. For future scope, further research can focus on optimizing the integration of FACTS devices into power systems to enhance their response during contingencies, such as developing advanced control strategies. Exploring more advanced machine learning techniques, such as deep learning and reinforcement learning, could provide even more accurate predictive models for power system stability. Moreover, extending the research to address real-time control and coordination of FACTS devices to respond dynamically to changing system conditions and contingencies is a promising avenue for improving power grid resilience and reliability in the face of evolving challenges.

References

[1] Hossein Parastvand et al., "Cyber-Security Constrained Placement of FACTS Devices in Power Networks from a Novel Topological Perspective," *IEEE Access*, vol. 8, pp. 108201-108215, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mehrdad Ahmadi Kamarposhti et al., "Optimal Location of FACTS Devices in Order to Simultaneously Improving Transmission Losses and Stability Margin Using Artificial Bee Colony Algorithm," *IEEE Access*, vol. 9, pp. 125920-125929, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Beibei Li et al., "On Feasibility and Limitations of Detecting False Data Injection Attacks on Power Grid State Estimation Using D-FACTS Devices," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 854-864, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Mohammad Amin Chitsazan, M. Sami Fadali, and Andrzej M. Trzynadlowski, "State Estimation for Large-Scale Power Systems and FACTS Devices Based on Spanning Tree Maximum Exponential Absolute Value," *IEEE Transactions on Power Systems*, vol. 35, no. 1, pp. 238-248, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] K. Suresh, and E. Parimalasundar, "ITBC Controlled IPWM for Solar Based Wide Range Voltage Conversion System," *IETE Journal of Research*, pp. 1-9, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Luis A. Paredes, Marcelo G. Molina, and Benjamín R. Serrano, "Enhancing Dynamic Voltage Stability in Resilient Microgrids Using FACTS Devices," *IEEE Access*, vol. 11, pp. 66150-66176, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Sindhuja R. et al., "A Reconfigurable Multilevel Inverters with Minimal Switches for Battery Charging and Renewable Energy Applications," *2022 6th International Conference on Electronics, Communication and Aerospace Technology*, Coimbatore, India, pp. 422-427, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Noor Habib Khan et al., "A Novel Modified Lightning Attachment Procedure Optimization Technique for Optimal Allocation of the FACTS Devices in Power Systems," *IEEE Access*, vol. 9, pp. 47976-47997, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ayda Faraji, Ali Hesami Naghshbandy, and Arman Ghaderi Baayeh, "A Hybrid Coordinated Design Method for Power System Stabilizer and FACTS Device Based on Synchro squeezed Wavelet Transform and Stochastic Subspace Identification," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 4, pp. 910-918, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] Yu Yang, Hen-Geul Yeh, and Son H. Doan, "Model Predictive Control via PV-Based VAR Scheme for Power Distribution Systems with Regular and Unexpected Abnormal Loads," *IEEE Systems Journal*, vol. 14, no. 1, pp. 689-698, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] E. Parimalasundar et al., "Investigation of Efficient Multilevel Inverter for Photovoltaic Energy System and Electric Vehicle Applications," *Electrical Engineering & Electromechanics*, no. 4, pp. 47-51, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Wenjie Han, and Aleksandar M. Stanković, "Model-Predictive Control Design for Power System Oscillation Damping via Excitation - A Data-Driven Approach," *IEEE Transactions on Power Systems*, vol. 38, no. 2, pp. 1176-1188, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Dongran Song et al., "Adaptive Model Predictive Control for Yaw System of Variable-Speed Wind Turbines," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 1, pp. 219-224, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Krishnan Suresh, and Ezhilvannan Parimalasundar, "Design and Implementation of Dual-Leg Generic Converter for DC/AC Grid Integration," *International Journal of Circuit Theory and Applications*, vol. 51, no. 8, pp. 3865-3879, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Omar Abdel-Rahim, and Haoyu Wang, "A New High Gain DC-DC Converter with Model-Predictive-Control Based MPPT Technique for Photovoltaic Systems," *CPSS Transactions on Power Electronics and Applications*, vol. 5, no. 2, pp. 191-200, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Parimalasundar Ezhilvannan, and Suresh Krishnan, "Fault Analysis and Compensation in a Five Level Multilevel DC-AC Converter," *El-Cezeri*, vol. 10, no. 1, pp. 99-108, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Akshay Kumar et al., "Load Frequency Control of Distributed Generators Assisted Hybrid Power System Using QOHSA Tuned Model Predictive Control," *IEEE Access*, vol. 10, pp. 109311-109325, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohammad Ebrahim Zarei et al., "Multivector Model Predictive Power Control for Grid Connected Converters in Renewable Power Plants," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 10, no. 2, pp. 1466-1478, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Suresh K. et al., "Encapsulated 3Ø Converter for Power Loss Minimization in a Grid-Connected System," *Automatika Journal for Control, Measurement, Electronics, Computing and Communications*, vol. 64, no. 1, pp. 189-197, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Kai Ni et al., "Power-Compensated Triple-Vector Model Predictive Direct Power Control Strategy for Nonredundant Fault-Tolerant Rectifiers," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 11, no. 4, pp. 3803-3814, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] K. Suresh et al., "Design and Implementation Bidirectional DC-AC Converter for Energy Storage System," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 2, pp. 130-136, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Liang Zhong et al., "Research on Model Predictive Controlled HESS for Seamless Mode Switching of DC Microgrid," *IEEE Transactions on Applied Superconductivity*, vol. 31, no. 8, pp. 1-5, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Mishkat Ullah Jan et al., "Frequency Regulation of an Isolated Microgrid with Electric Vehicles and Energy Storage System Integration Using Adaptive and Model Predictive Controllers," *IEEE Access*, vol. 9, pp. 14958-14970, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] K. Suresh, and E. Parimalasundar, "Fault Analysis and Clearance in FL-APC DC–AC Converter," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 1, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] E. Parimalasundar et al., "Efficient Integration of Photovoltaic Cells with Multiport Converter for Enhanced Energy Harvesting," *2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, pp. 1590-1595, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Cedrick Lupangu, Jackson J. Justo, and Ramesh C. Bansal, "Model Predictive for Reactive Power Scheduling Control Strategy for PV-Battery Hybrid System in Competitive Energy Market," *IEEE Systems Journal*, vol. 14, no. 3, pp. 4071-4078, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[27] Parimalasundar Ezhilvannan et al., "Analysis of the Effectiveness of a Two-Stage Three-Phase Grid Connected Inverter for Photovoltaic Applications," *Journal of Solar Energy Research*, vol. 8, no. 2, pp. 1471-1483, 2023. [Google Scholar] [Publisher Link]

[28] Qiuye Sun et al., "Model Predictive Direct Power Control of Three-Port Solid-State Transformer for Hybrid AC/DC Zonal Microgrid Applications," *IEEE Transactions on Power Delivery*, vol. 37, no. 1, pp. 528-538, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] M.G. Manjula, and S. Surendra, "Integration of Multi-Terminal Unified Power Quality Conditioner in Microgrid System," *International Journal of Recent Engineering Science*, vol. 10, no. 4, pp. 7-13, 2023. [Google Scholar] [Publisher Link]

[30] Mahmoud Mehrabankhomartash, Maryam Saeedifard, and Santiago Grijalva, "Model Predictive Control Based AC Line Overload Alleviation by Using Multi-Terminal DC Grids," *IEEE Transactions on Power Systems*, vol. 35, no. 1, pp. 177-187, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[31] B. Perumal, K. Suresh, and E. Parimalasundar, "Fault Analysis in the 5-Level Multilevel NCA DC–AC Converter," *Automatika Journal for Control, Measurement, Electronics, Computing and Communications*, vol. 64, no. 3, pp. 606-612, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[32] P. Manohar, and Chandrasekhar Reddy Atla, "Development of Predictive Reliability Model of Solar Photovoltaic System Using Stochastic Diffusion Process for Distribution System," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 12, no. 1, pp. 279-289, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] Sindhuja R. et al., "Comparison between Symmetrical and Asymmetrical 13 Level MLI with Minimal Switches," *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, pp. 187-191, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[34] Krishnan Suresh, and Ezhilvannan Parimalasundar, "Newly Designed Single-Stage Dual Leg DC-DC/AC Buck-Boost Converter for Grid Connected Solar System," *International Journal of Circuit Theory and Applications*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[35] Weipeng Liu, Yutian Liu, and Lei Wu, "Model Predictive Control Based Voltage Regulation Strategy Using Wind Farm as Black-Start Source," *IEEE Transactions on Sustainable Energy*, vol. 14, no. 2, pp. 1122-1134, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[36] E. Parimalasundar et al., "Performance Analysis of DC-DC Converter for Electric Vehicle Charging Applications," *2023 7th International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, pp. 1543-1546, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[37] Dae-Jin Kim et al., "Disturbance Observer-Based Model Predictive Voltage Control for Electric-Vehicle Charging Station in Distribution Networks," *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 545-558, 2023. [CrossRef] [Google Scholar] [Publisher Link]