Advancements in Load Forecasting and Contingency Analysis for Modern Power Systems: A Case Study on the IEEE 39 Bus System

[1]Mitin Kumar Digarse,[2]Prof. Sachindra Kumar Verma

[1]Department of Electrical Engineering, NRI Institute of Research and Technology Bhopal (M.P.)

[2]HOD, Department of Electrical Engineering, NRI Institute of Research and Technology Bhopal (M.P.)

[1]mitinkmr@gmail.com

* Corresponding Author: Mitin Kumar Digarse

Abstract: *In modern power systems, ensuring uninterrupted electricity supply demands accurate load forecasting and effective contingency analysis. This research delves into the development and validation of advanced load prediction techniques, focusing on the IEEE 39 bus system as a representative testbed. The study reviews existing short-term load prediction models, emphasizing the significance of accurate forecasts in decision-making for power utilities. Through the integration of fuzzy logic with neural networks, a novel load distribution approach is proposed and evaluated for its accuracy and reliability. Additionally, the paper explores contingency analysis using load flow solutions, highlighting the importance of identifying critical contingencies for system security. The results demonstrate the effectiveness of the proposed methodologies in handling irregularities and uncertainties, thus enhancing the resilience and efficiency of modern power systems.*

Keywords: *Load forecasting, Contingency analysis, IEEE 39 bus system, Fuzzy logic, Neural networks, Power system resilience.*

I. INTRODUCTION

Modern power system demands an uninterrupted supply of electricity to the load side. This requires a proper idea of predicting present and future load demand with the least amount of error. For achieving this goal, scientists and scholars have been trying to develop the most efficient and optimal state-of-the-art method for predicting the future demand for electricity consumption by a method known as load forecasting. Load forecasting is used to control several operations and decisions such as dispatch, unit commitment, fuel allocation, and off-line network analysis. This gives the power utility company an idea about the future demand of the consumers and an ample amount of time to mitigate the difference between the generation capacity and load demand. Demand prediction minimizes the power generation cost and helps to establish an organized power system utility, especially because of the large expense pertaining to power generation [1]. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. The subject of load forecasting has been in existence for decades to forecast the future demand. This involves the accurate prediction of both the magnitudes and geographical locations of electric load over the different periods of the planning horizon [2].

A. The Load Forecast Levels

Decision-making in management involves distinct levels for predicting energy consumption, each employing various methodologies. The process of load forecasting is influenced by the size and consumption patterns of a region, leading to two primary categorizations: micro and macro forecasting. Micro-level forecasting focuses on estimating the energy use of smaller sections within a larger area, aggregating these to determine the total consumption for the entire region. This approach is typically applied to low voltage demands due to the extensive computations involved. Conversely, macro-level forecasting estimates the energy needs of larger areas, such as cities, provinces, or entire countries, without delving into finer, smaller-scale consumption details. These forecasting levels are further classified into different time frames, each with its own set of approaches [3].

- Short-Term Load Forecast
- The Mid-Term Load Forecast
- The Long-Term Forecast

B. Contingency Analysis Using Load Flow Solution

Load flow analysis serves as a static security assessment method for a given power system, ensuring its defensive operation. However, in the event of a contingency, the system can transition into an emergency state, prompting rapid actions by operators to restore normalcy. During this phase, all elements identified as contingency cases in the contingency analysis section are assessed, and outage studies are conducted. The program's output provides alerts to the user regarding potential overloads or voltage deviations beyond permissible limits.
Contingency analysis involves predicting the impact of individual contingency cases, which can become arduous and time-consuming, especially when dealing with large power system networks. To address this challenge, the contingency

screening or selection process comes into play. In practice, it is observed that not all potential outages lead to overloads or voltage issues in other power system components. Identifying the specific contingencies that result in operational limit violations is known as contingency selection. This selection process relies on calculating severity indices known as Performance Indices (PI) to pinpoint the critical contingencies [4]. Transmission line congestion can arise from either overloading or underloading within the overall transmission network. Such imbalances can lead to failures of power system components. To address these challenges and ensure effective power system operation and security, contingency analysis is employed. This security measure involves determining and assessing the operational limits of the system both before and after potential contingencies at an operation control center. The aim is to minimize the likelihood of power system failures caused by component loss or failure [5].
Conducting contingency analysis involves performing Alternating Current (AC) load flow calculations to assess the impact of possible failures across generators and transmission lines. The extensive array of possible scenarios renders this evaluation process both time-consuming and cumbersome. To address these difficulties, the implementation of automated contingency screening techniques is being embraced. These techniques are designed to detect and sequence outages that result in breaches of power flow or voltage thresholds on the network. Contingencies are assessed and ordered according to their severity or performance metrics, where higher scores signify more critical issues [6]. The transmission network of Ethiopian electric power is notably intricate, attributed to its unified grid interconnection architecture. As a result, a single transmission line failure can precipitate widespread disturbances throughout the grid. This effect is particularly pronounced in the North-West region of Ethiopia, which is frequently challenged by security issues.

II. LITERATURE REVIEW

Li, C., et al. (2022) [7] emphasize the significance of precise short-term electrical demand forecasting for ensuring power grid safety and stability. They propose a novel approach, the Sparrow Algorithm-based SSA-GRU model, to address challenges posed by nonlinear load patterns. This model improves load forecasting accuracy by integrating complementary sets with Empirical Mode Decomposition and employing an integrated SSA-GRU model. Experimental validation using real-world data confirms the superiority of the proposed model over other forecasting methods, underscoring its effectiveness in enhancing short-term load forecasting.

Pollen Barua et al. (2022) [8] discuss the increasing global demand for renewable energy integration into power systems, focusing on Bangladesh's transition toward sustainability. They propose the installation of wind and solar generators in the Western grid of Bangladesh and employ machine learning techniques to predict contingency analysis outcomes. Additionally, they propose integrating a Static Synchronous Compensator (STATCOM) to mitigate voltage fluctuations, enhancing the power system's stability and security.

Van Hoa Nguyen et al. (2022) [9] introduce a self-updating and self-evaluating building load forecasting system to address challenges in accurately forecasting building loads. This dynamic system integrates the Prophet model with building SCADA systems, ensuring continuous learning and periodic retraining to adapt to changing building conditions. Evaluation results demonstrate improved load consumption forecasting accuracy over time, offering a solution for efficient building energy management in dynamic environments.

S. B. Daram et al. (2022) [10] discuss the prediction of single transmission line failures using Big Data Analytics. They employ the LVSI and machine learning methods to predict the severity of line failures based on simulation data, providing valuable insights for power system maintenance and reliability.

ML Woldesemayat et al. (2022) [11] address the challenge of bus voltage infractions in the Ethiopian Electric Power network due to increasing contingency events. They propose a methodology for conducting static security assessment and optimizing the deployment of interline power flow controllers (IPFCs) using the Grey Wolf Optimization algorithm. Integration of IPFCs significantly improves system performance and stability under severe contingency scenarios.

Patel, Ravindu & Nimje et al. (2022) [12] highlight the importance of contingency analysis in anticipating potential equipment failures in electrical networks. They discuss the effectiveness of contingency ranking selection in conducting safety assessments, demonstrating a reduction in violations and restoration of parameters within safe operational ranges.

Kumar, P., et al. (2022) [13] focus on contingency analysis in power systems during transmission line outages. They propose integrating load buses with solar power plants to enhance system resilience and minimize vulnerability using particle swarm optimization. The study employs Newton-Raphson load flow method and MATPOWER tool for comprehensive contingency analysis.

N. Ahmad et al. (2022) [14] review load forecasting technologies in electric utility companies, emphasizing the importance of accurate predictions for ensuring reliable power supply. They evaluate various machine learning, deep learning, and artificial intelligence algorithms, comparing single and hybrid forecasting models to identify optimal solutions for accurate load predictions.

H. Yuan et al. (2022) [15] propose a robust optimization framework for addressing transient stability challenges in power systems integrating wind power generators. Their two-stage robust optimization model effectively synchronizes generation dispatch and emergency load shedding, demonstrating significant improvements in system stability under variable wind power conditions.

Han, H., et al. (2021) [16] propose a two-stage dispatch model for optimizing power system operations considering renewable energy integration. The model incorporates system security indices and active demand response behavior, offering a comprehensive approach for balancing system security and economic efficiency.

Groß, A., et al. (2021) [17] evaluate eight approaches for day-ahead load forecasts in individual buildings, highlighting advancements in load forecasting methods. They demonstrate significant reductions in forecast errors using machine learning and statistical techniques, emphasizing the importance of tailored forecasting approaches based on specific requirements.

III. OBJECTIVES

The work is aimed at achieving the following key objectives from the work:

- To develop a comprehensive understanding of the IEEE 39 bus system, including its topology, load characteristics, and voltage contingency scenarios.
- To review and analyze existing short-term load prediction models and techniques in power systems.by collecting and preprocess historical load data for the IEEE 39 bus system, ensuring data quality and consistency.
- To validate the proposed load prediction and assess its accuracy and reliability in predicting load for various loading condition and comparing it with fourier series model

.

IV. METHODOLOGY

Ensuring the continuous fulfillment of power system demands and supporting sustained economic advancement necessitates accurate load forecasting as a critical function for electric power utilities. The precision of load forecasts is increasingly vital for utility management, the formulation of power supply strategies, financial planning, and the management of electricity market prices. Generally, load forecasting can be segmented into three distinct durations: short, medium, and long term. Short-term load forecasting, ranging from half an hour to one week, is crucial for the secure and efficient operation of power systems. Medium-term forecasting, spanning from a week to several months, facilitates the planning of fuel supply and maintenance activities. Meanwhile, long-term forecasts, extending beyond a year, play a key role in strategic planning and operational expansion efforts. The work has described using fuzzy logic with neural network interference for load distribution in the IEEE 39 bus system.

The reliable and efficient operation of modern power systems relies heavily on accurate load forecasting and contingency assessment. Load forecasting aids in the optimal scheduling of generation and resources, while contingency assessment ensures the system's resilience in the face of unexpected events. In this context, the IEEE 39 bus system serves as a valuable testbed for research and development due to its complexity and resemblance to real-world power systems.

A. IEEE 39 bus system description

Researchers frequently utilize IEEE bus systems as experimental platforms to test and implement novel concepts and innovations. This Technical Note provides an in-depth overview of the IEEE 39-bus system, delineating its intricate components which encompass loads, capacitor banks, transmission lines, and generators. It serves as a representative model of a medium-sized power system, making it an ideal platform for the development and testing of new algorithms, control strategies, and optimization techniques. It is used to validate their ideas before applying them to larger and more complex real-world power grids.

B. Adaptive_neuro_interval_fuzzy (ANIF) algorithm

The use of Artificial Intelligence (AI) in forecasting is of paramount importance due to the manifold advantages it brings to various domains. One of the primary benefits is the marked improvement in accuracy. AI, employing machine learning algorithms and neural networks, excels in analyzing extensive historical data, discerning intricate patterns, and yielding forecasts of exceptional precision. Furthermore, AI models adeptly handle complexity, accommodating complex relationships and non-linear patterns in data, making them suitable for forecasting tasks that involve multiple variables or intricate interactions.

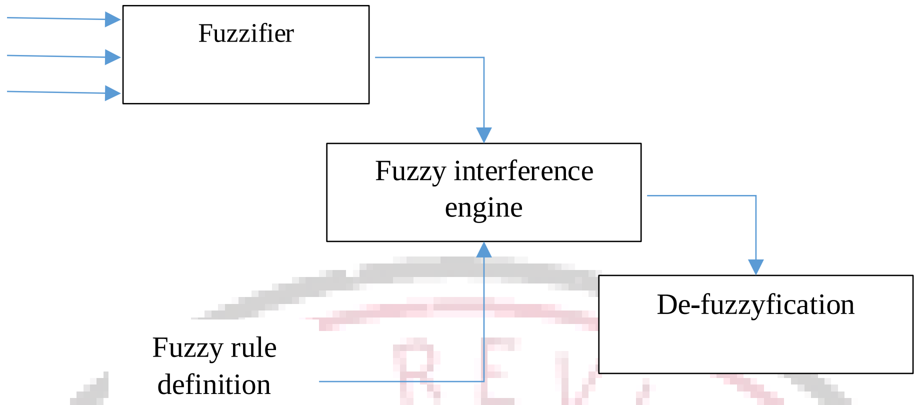

Figure 4.1: fuzzy system working flow chart

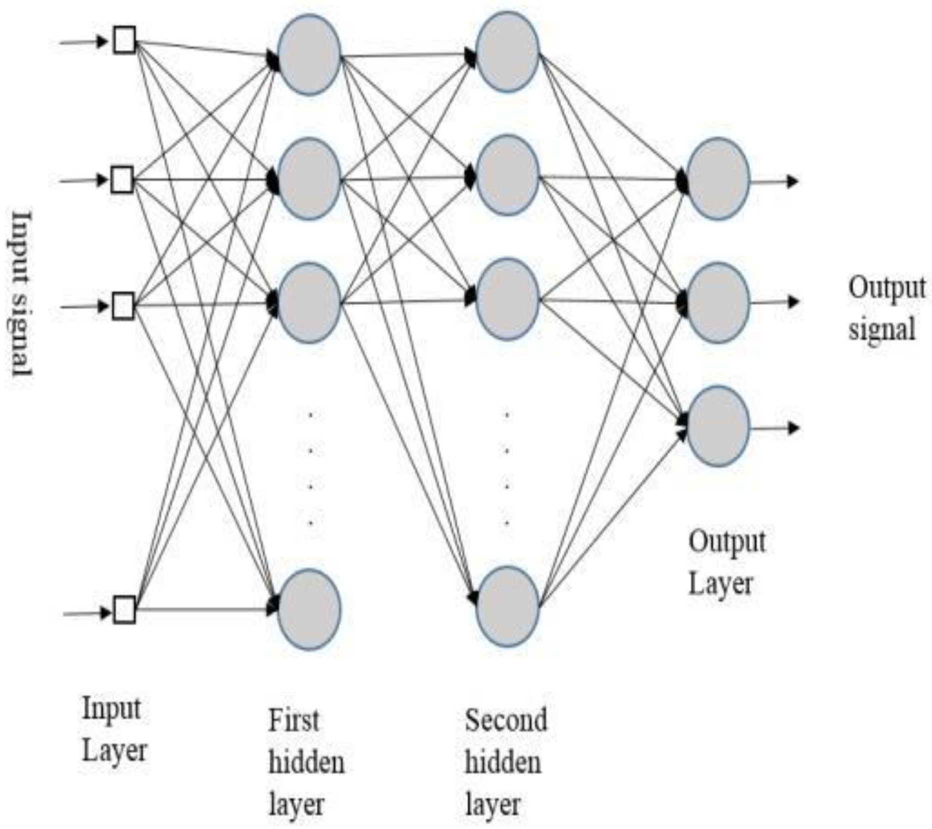

Figure 4.2: Architectural Diagram of a Multi-Layer Perceptron (MLP) Network Featuring Two Hidden Layers.

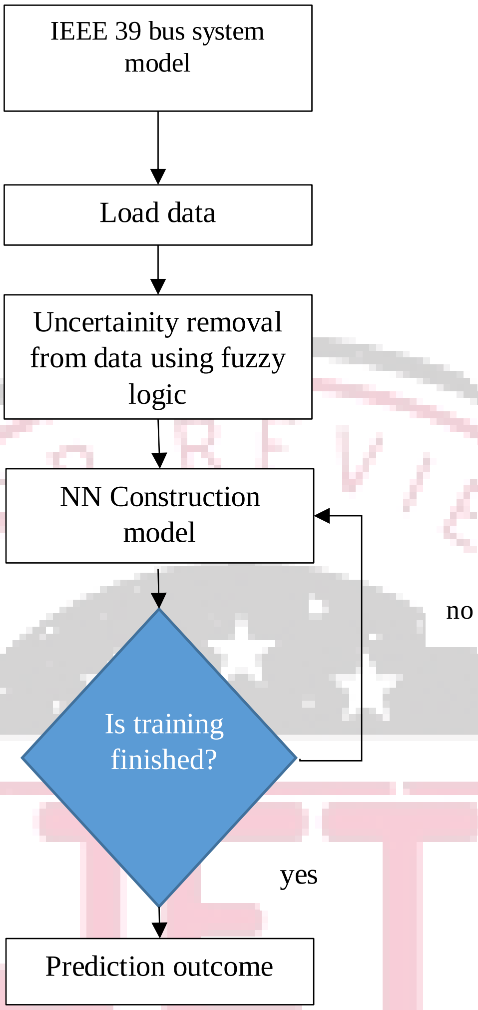

Figure 4.3: Flow chart for Adaptive_neuro_interval_fuzzy (ANIF) algorithm for prediction

A general outline of how you can implement load forecasting using these techniques:

- Data Collection and Preprocessing: Gather historical load data for the IEEE 39 bus system, including factors that can influence load (e.g., weather data, day of the week, time of day, holidays). Clean and preprocess the data, handling missing values, outliers, and scaling the features appropriately.
- Data Splitting: Splitting the dataset into training, validation, and test sets. The training set is used to train the neural network, the validation set helps with hyper parameter tuning, and the test set is used for final evaluation.
- Neural Network Model: Designing and building a neural network model for load forecasting. Configuring the input layer to accept the engineered features and the output layer to predict the load. Experimenting with different architectures, activation functions, and layers to optimize performance.
- Fuzzy Logic: Utilize fuzzy logic to capture and incorporate expert knowledge or rules into your load forecasting model. Fuzzy logic can help model the uncertainty and imprecision in the system. Define linguistic variables and membership functions that describe input and output variables. Create fuzzy rules that capture the relationships between inputs and outputs. These rules can be derived from domain knowledge or data-driven learning.
- Training and Validation: Training of the neural network using the training dataset and validate its performance on the validation dataset. Fine-tune hyper parameters, such as learning rate, batch size, and the number of hidden layers and neurons, to optimize the model's performance.
- Testing and Evaluation: Evaluating the neural network and fuzzy logic model on the test dataset using appropriate metrics, such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE). Compare the model's performance against benchmarks or other forecasting methods.

In the recall phase, novel input data is applied to the neural network, and its outputs are computed and evaluated for testing purposes. The Short-Term Load Forecasting (STLF) model, which relies on Artificial Neural Networks (ANNs), employs a layered ANN architecture consisting of an Input layer, Hidden layer, and Output layer. The computation of neural network weights is accomplished through a learning process that incorporates error propagation within a parallel distributed processing framework.

Neural networks and fuzzy systems have gained substantial traction in various engineering and scientific domains. Their applications span a wide range, from consumer products to decision analysis. Neural networks are fundamentally parallel distributed processors known for their inductive learning capability from numerical data. They optimize their performance by adjusting synaptic weights. Feed-forward neural networks, particularly multilayer perceptrons (MLP's), have proven their ability to accurately approximate any continuous real function within a compact set. Consequently, feed-forward neural networks are valuable for system modeling and identification. However, they exhibit three primary limitations. First, there is a lack of a systematic approach for defining the neural network's architecture. Second, training neural networks is often time-intensive. Lastly, once trained, neural networks lack the ability to provide explicit explanations for their responses, resulting in non-transparent inference processes. Hence, when attempting to represent a complex system using a trained neural network, the information contained within the network's parameter values lacks human interpretability, which is crucial for informed decision-making. Consequently, there is a significant need to develop methods for obtaining a relevant and interpretable system description from observed data or experiential knowledge.

V. RESULTS AND DISCUSSION

A. Implementation Details

In this chapter, we present a comprehensive exposition of the algorithm we have developed for conducting sentiment analysis specifically tailored to evaluate the performance buffer. The performance buffer is simulated as a crucial component within our algorithm, serving the purpose of optimizing its overall effectiveness and efficiency. We provide both analytical and numerical insights into the inner workings of this algorithm, offering a detailed examination of its functionality and performance characteristics in the context of sentiment analysis. To evaluate the performance of the proposed algorithm scheme, the proposed algorithm is simulated in the following configuration:
Pentium Core I5-2430M CPU @ 2.40 GHz
4GB RAM
64-bit Operating System
Matlab Platform

B. Simulation Environment

MATLAB, an acronym for MATrix LABoratory, is a specialized software package designed for efficient and rapid computation of logical operations and input/output tasks. It encompasses an extensive library of pre-built functions tailored to a diverse range of calculations, complemented by a multitude of toolkits catering to specific analytical domains such as statistics, optimization, partial differential equation solving, and data analysis. In the context of this research, we leverage the capabilities of the MATLAB platform to facilitate the implementation and performance simulation of our algorithm. We harness measurement toolkits and a selection of built-in functions to generate graphical representations of data. Furthermore, MATLAB functions are instrumental in deriving the simulation results for the performance assessment of the bus system under the influence of specific algorithms.

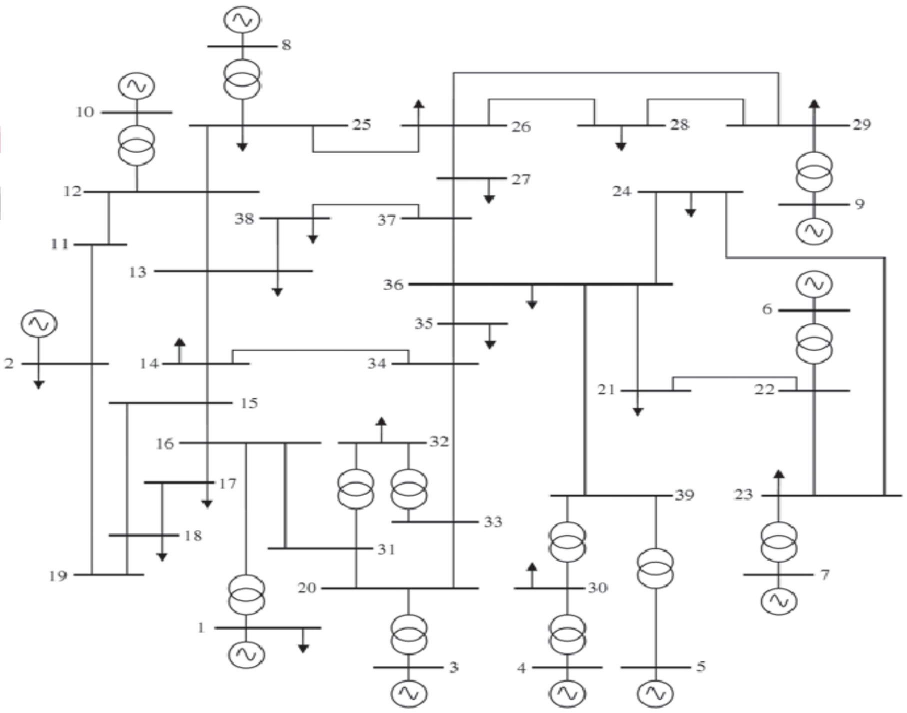

Figure 5.1: IEEE 39 single line bus diagram

Table 5.1 Calculation of Line data for IEEE 39 Bus system

From Bus	To Bus	Line impedance (*p.u.*)		Half line charging susceptance (*p.u.*)	MVA of line	Voltage in KV
		Resistance	Reactance			
1	2	0.0035	0.0411	0.6987	100	345
1	39	0.001	0.025	0.75	100	345
2	3	0.0013	0.0151	0.2572	100	345
2	25	0.007	0.0086	0.146	100	345
2	30	0	0.0181	0	100	22
3	4	0.0013	0.0213	0.2214	100	345
3	18	0.0011	0.0133	0.2138	100	345
4	5	0.0008	0.0128	0.1342	100	345
4	14	0.0008	0.0129	0.1382	100	345
5	8	0.0008	0.0112	0.1476	100	345
6	5	0.0002	0.0026	0.0434	100	345
6	7	0.0006	0.0092	0.113	100	345
6	11	0.0007	0.0082	0.1389	100	345
7	8	0.0004	0.0046	0.078	100	345
8	9	0.0023	0.0363	0.3804	100	345
9	39	0.001	0.025	1.2	100	345
10	11	0.0004	0.0043	0.0729	100	345
10	13	0.0004	0.0043	0.0729	100	345
10	32	0	0.02	0	100	22
12	11	0.0016	0.0435	0	100	345
12	13	0.0016	0.0435	0	100	345
13	14	0.0009	0.0101	0.1723	100	345
14	15	0.0018	0.0217	0.366	100	345
15	16	0.0009	0.0094	0.171	100	345
16	17	0.0007	0.0089	0.1342	100	345
16	19	0.0016	0.0195	0.304	100	345
16	21	0.0008	0.0135	0.2548	100	345
16	24	0.0003	0.0059	0.068	100	345
17	18	0.0007	0.0082	0.1319	100	345
17	27	0.0013	0.0173	0.3216	100	345
19	33	0.0007	0.0142	0	100	22
19	20	0.0007	0.0138	0	100	345
20	34	0.0009	0.018	0	100	22
21	22	0.0008	0.014	0.2565	100	345
22	23	0.0006	0.0096	0.1846	100	345
22	35	0	0.0143	0	100	22
23	24	0.0022	0.035	0.361	100	345
23	36	0.0005	0.0272	0	100	22
25	26	0.0032	0.0323	0.513	100	345
25	37	0.0006	0.0232	0	100	22
26	27	0.0014	0.0147	0.2396	100	345
26	28	0.0043	0.0474	0.7802	100	345

26	29	0.0057	0.0625	1.029	100	345
28	29	0.0014	0.0151	0.249	100	345
29	38	0.0008	0.0156	0	100	22
31	6	0	0.025	0	100	22

The system comprises a total of 46 transmission lines and 39 buses. The performance indices are summarized in Table 5.2. Analysis of Table 5.2 reveals that the vulnerability of bus 16 is the most significant, with its fault having a major impact on the entire system. The elevated PI score associated with this fault highlights its critical importance in system operation, indicating that it receives substantial attention during operational procedures.

Table 5.2 Bus Voltages in the Pre and Post Contingency State

Bus Number	Pre-contingency voltage (pu)	Post-contingency voltage (pu)	Performance index (PI)
1	1.0086	0.9823	0.0263
2	0.9971	0.828	0.1691
3	0.9855	0.9851	0.0004
4	0.9826	0.9826	0
5	1.1363	1.1363	0
6	0.9797	0.9796	0.0001
7	0.9884	0.9814	0.007
8	0.9913	0.9788	0.0125
9	1.0086	1.0086	0
10	0.9942	0.8253	0.1689
11	0.9826	0.8126	0.17
12	0.9768	0.807	0.1698
13	1.0115	0.8414	0.1701
14	1.0173	0.8462	0.1711
15	0.9913	0.8188	0.1725
16	0.9855	0.8123	0.1732
17	0.9913	0.8912	0.1001
18	0.9768	0.8956	0.0812
19	1.2272	1.1227	0.1045
20	0.9913	0.9901	0.0012
21	0.9971	0.995	0.0021
22	0.9826	0.9825	0.0001
23	1.0086	1.0063	0.0023
24	0.9797	0.9796	0.0001
25	0.9971	0.9962	0.0009
26	0.9913	0.9910	0.0003
27	0.9942	0.9939	0.0003
28	1.0144	1.0142	0.0002
29	1.0115	1.0113	0.0002
30	0.9768	0.9765	0.0003
31	1.1818	1.1816	0.0002
32	0.9884	0.987	0.0014
33	0.9545	0.9543	0.0002
34	0.9768	0.9724	0.0044
35	1.0115	1.010	0.0015

36	0.8636	0.8532	0.0104
37	0.9913	0.9902	0.0011
38	0.8181	0.8056	0.0125
39	0.9855	0.9855	0

C. Fore casting load in IEEE 39 bus system

Forecasting the load in a power system, such as the IEEE 39 bus system, using Fourier series is a mathematical technique that can help you approximate and predict load patterns. Fourier series decomposition can represent a periodic load curve as a sum of sinusoidal components with different frequencies and amplitudes. Forecasting load in the IEEE 39 bus system using neural networks and fuzzy logic is a more advanced and data-driven approach compared to Fourier series decomposition. The analysis results are being described with outcomes evaluated as RMSE error in the predicted and actual load values.

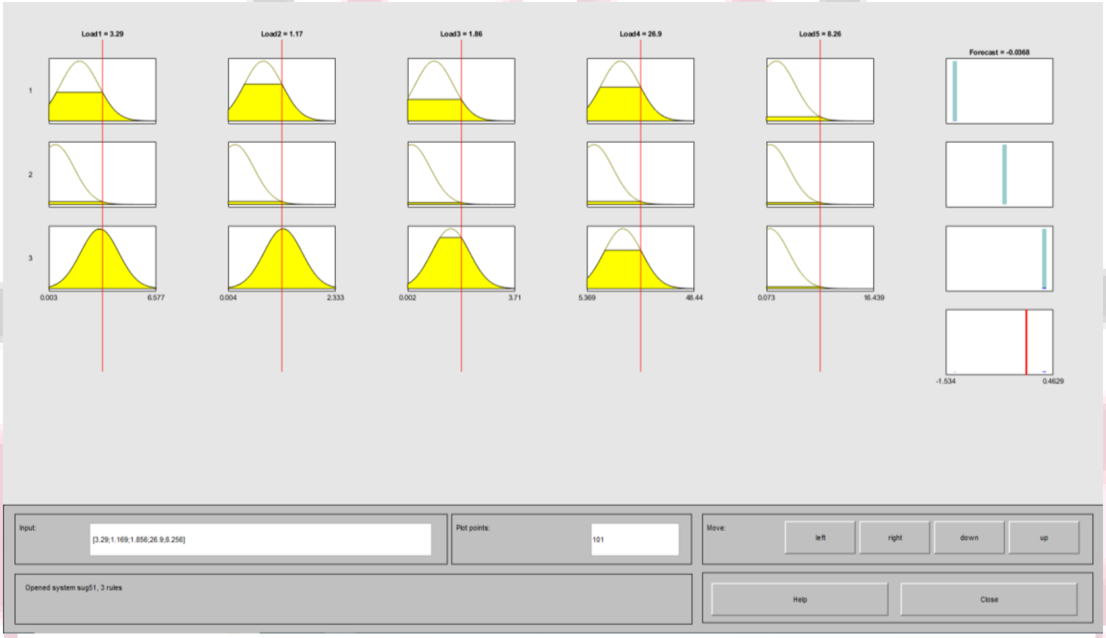

Figure 5.2: Fuzzy rule definition tool box in MATLAB for different loading points

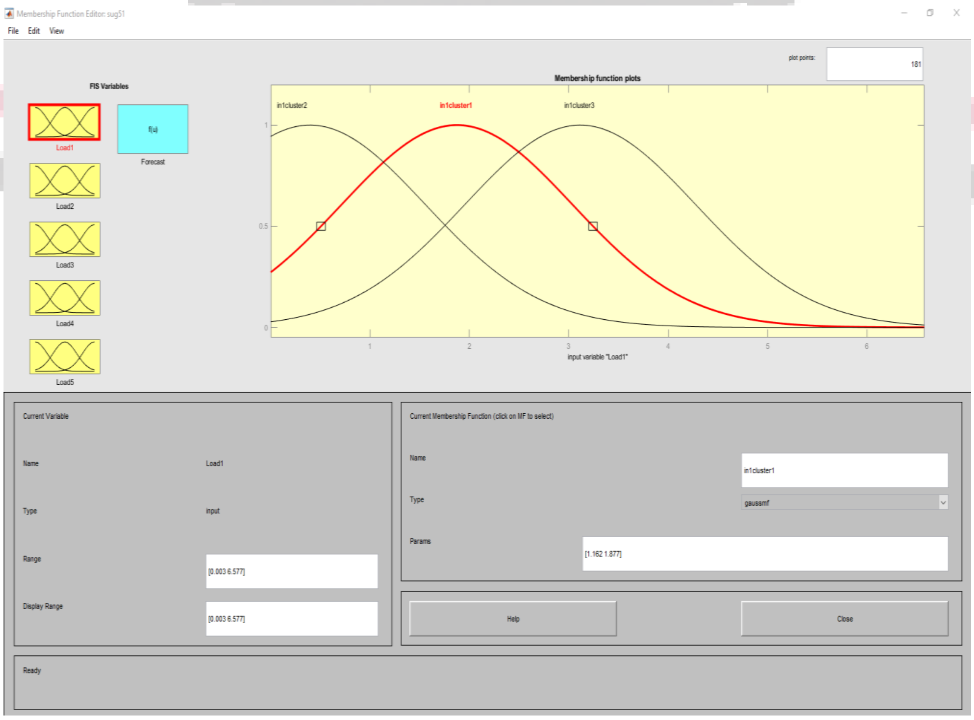

Figure 5.3: Madami functions of fuzzy system

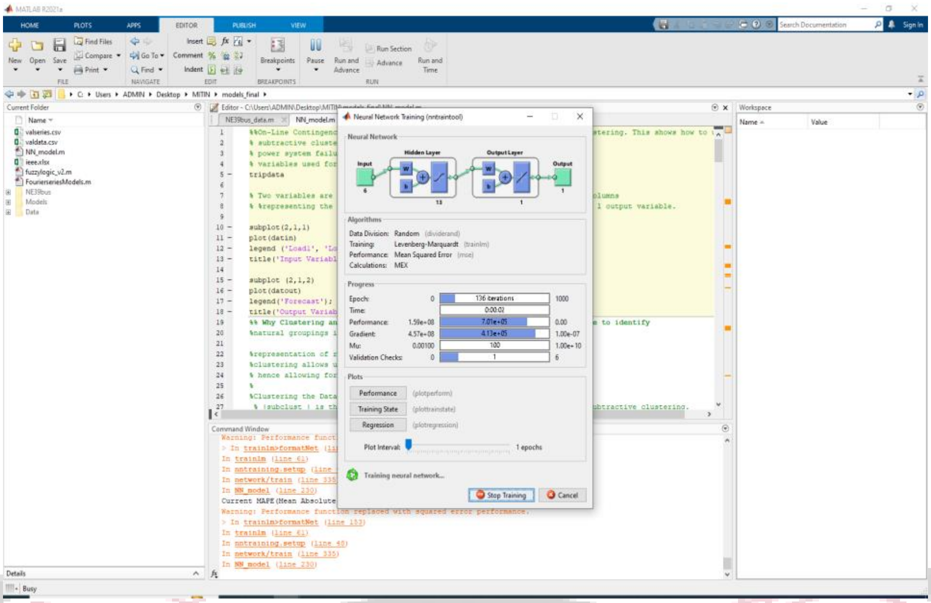

Figure 5.4: Adaptive_neuro_interval_fuzzy (ANIF) algorithm evaluation in MATLAB for load prediction

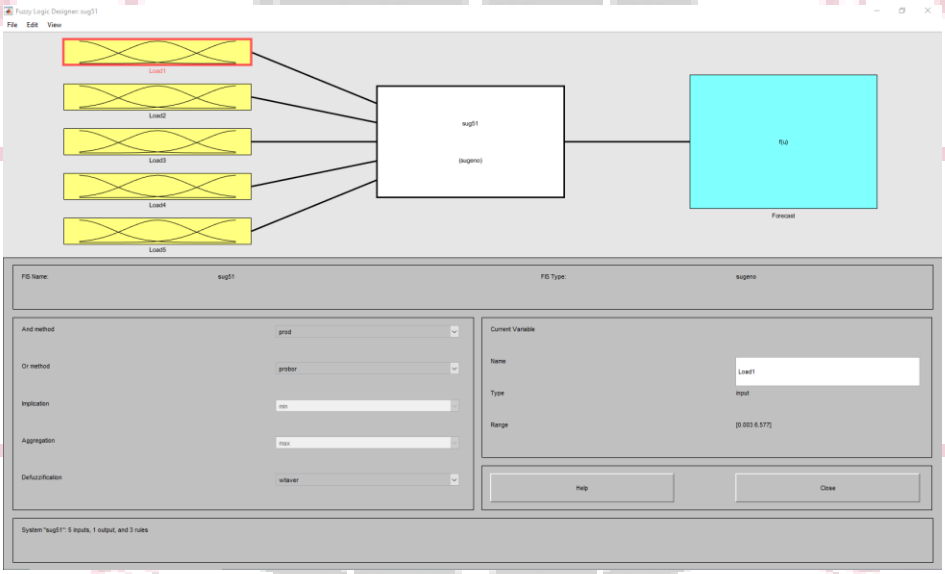

Figure 5.5: Multi input system in fuzzy algorithm

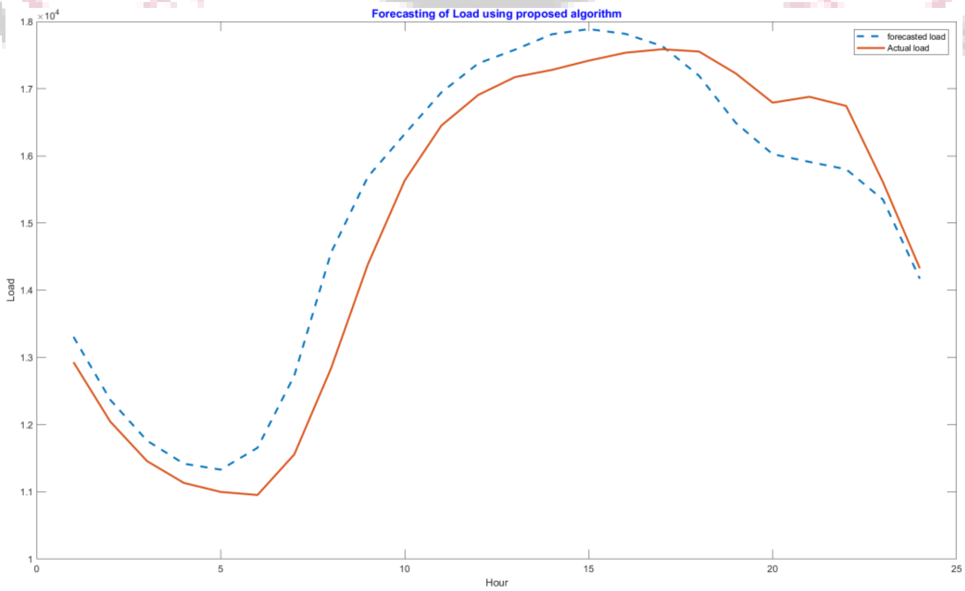

Figure 5.6: Actual load vs predicted load using proposed algorithm

The figure 5.6 provides a visual representation of how well a load forecasting model based on the Adaptive_neuro_interval_fuzzy (ANIF) algorithm performs in predicting actual load values. In an ideal scenario, the predicted load values should closely follow the actual load values. The red line in the graph represents the actual load whereas the blue line represents the forecasted loading condition of IEEE 39 bus system

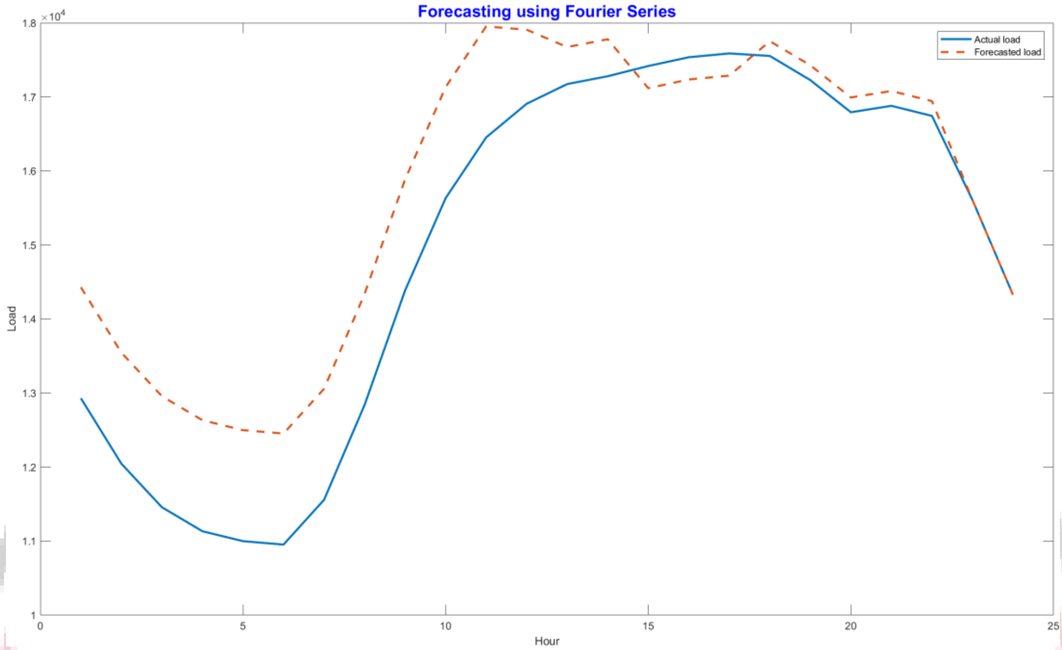

Figure 5.7: Actual load vs predicted load using fourier series method

The figure 5.7 provides a visual representation of how well a load forecasting model based on the Fourier series mathematical model performs in predicting actual load values. In an ideal scenario, the predicted load values should closely follow the actual load values. The red line in the graph represents the forecasted load whereas the blue line represents the actual loading condition of IEEE 39 bus system

Table 5.4: Comparative analysis of error in prediction in IEEE 39 Bus system using two algorithms

Algorithm of Prediction adopted	**MSE %**
Fourier Series	6.437
Adaptive_neuro_interval_fuzzy (ANIF) algorithm	4.086

The "Fourier Series" algorithm was used to make load predictions. The MSE percentage associated with this algorithm is 6.437%. This means that, on average, the squared difference between the predicted load values and the actual load values was 6.437% of the total variance in the data. Adaptive_neuro_interval_fuzzy (ANIF) algorithm" was used as an alternative prediction method. The MSE percentage associated with this algorithm is 4.086%. Compared to the Fourier series model, the ANIF algorithm achieved a lower MSE percentage, indicating that it provided more accurate load predictions

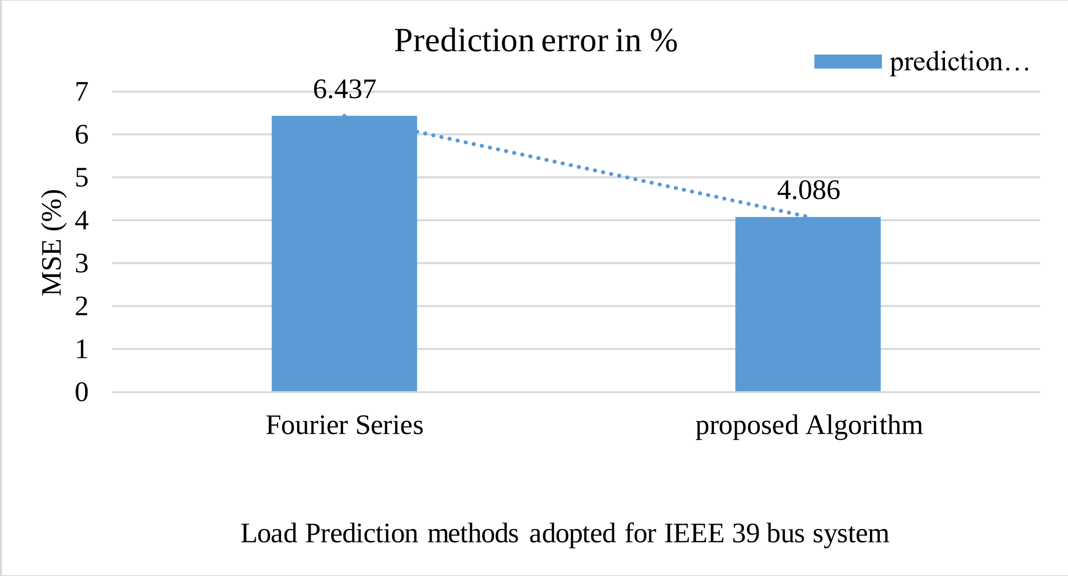

Figure 5.8: Comparative analysis of Prediction performance of two algorithms

It has been found that the proposed model with adaptive_neuro_interval_fuzzy load forecasting model is better at Handling Irregularities. In scenarios where the load data is highly irregular or where there are a lot of uncertainties (such as in rapidly changing urban environments or with the increasing use of renewable energy sources), adaptive_neuro_interval_fuzzy logic performs better. The controller can adapt to changing scenarios without requiring a complete restructuring of the forecasting model. It allows the incorporation of expert knowledge through user-defined rules, making it more versatile in handling various scenarios.

VI. CONCLUSION

The research presented in this paper underscores the critical role of accurate load forecasting and contingency analysis in modern power systems. By leveraging advanced techniques such as fuzzy logic and neural networks, significant improvements in load prediction accuracy and system resilience are achieved. The integration of these methodologies into the IEEE 39 bus system provides valuable insights into their practical applicability and effectiveness. The results highlight the importance of adaptive approaches in handling irregularities and uncertainties, ensuring robust performance even in dynamically changing environments. Moving forward, the findings of this study pave the way for further advancements in load forecasting and contingency analysis, contributing to the optimization and sustainability of power system operations..

REFERENCES

[1] A. A. Mamun, M. Sohel, N. Mohammad, M. S. Haque Sunny, D. R. Dipta and E. Hossain, "A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models," in IEEE Access, vol. 8, pp. 134911-134939, 2020, doi: 10.1109/ACCESS.2020.3010702.

[2] A. K. Singh, Ibraheem, S. Khatoon, M. Muazzam and D. K. Chaturvedi, "Load forecasting techniques and methodologies: A review," *2012 2nd International Conference on Power, Control and Embedded Systems*, Allahabad, India, 2012, pp. 1-10, doi: 10.1109/ICPCES.2012.6508132.

[3] Haihong Bian, Qian Wang, Guozheng Xu, Xiu Zhao, Load forecasting of hybrid deep learning model considering accumulated temperature effect, Energy Reports, Volume 8, Supplement 1, 2022, Pages 205-215, ISSN 2352-4847, https://doi.org/10.1016/j.egyr.2021.11.082.

[4] Lakshmiswarupa, M., & Ramesh, M. D. (2016). Load Flow, Contingency Analysis, State Estimation And Optimal Operation For Ieee 14-Bus System. *power*, *2*(15), 247-253.

[5] Agajie T.F., Salau A.O., Hailu E.A., Sood M., Jain S., Optimal sizing and siting of distributed generators for minimization of power losses and voltage deviation, 5th IEEE International Conference on Signal Processing, Computing and Control (ISPCC), pp. 292–297 (2019), DOI: 10.1109/ispcc48220.2019.8988401.

[6] Aeggegn, D. B., Salau, A. O., & Gebru, Y. (2020). Load flow and contingency analysis for transmission line outage. *Archives of Electrical Engineering*, 581-594, DOI 10.24425/aee.2020.133919.

[7] Li, C., Guo, Q., Shao, L., Li, J., & Wu, H. (2022). Research on Short-Term Load Forecasting Based on Optimized GRU Neural Network. *Electronics*, *11*(22), 3834. MDPI AG. Retrieved from http://dx.doi.org/10.3390/electronics11223834

[8] Pollen Barua, Ratul Barua, Vineet Shekher, Muhammad Quamruzzaman & M.G Rabbani | Qingsong Ai (Reviewing editor) (2022) Contingency analysis and adoption of STATCOM in highly renewable energy penetrated Western Grid of Bangladesh, Cogent Engineering, 9:1, DOI: 10.1080/23311916.2022.2076550

[9] Van Hoa Nguyen, Yvon Besanger, Quoc Tuan Tran, Self-updating machine learning system for building load forecasting - method, implementation and case-study on COVID-19 impact, Sustainable Energy, Grids and Networks, Volume 32, 2022, 100873, ISSN 2352-4677, https://doi.org/10.1016/j.segan.2022.100873.

[10] S. B. Daram, V. Ak, R. V. Angadi and K. Sesiprabha, "An approach to Contingency Severity Prediction using Data Analytic Techniques in a Power System," 2022 International Conference on Smart and Sustainable Technologies in Energy and Power Sectors (SSTEPS), Mahendragarh, India, 2022, pp. 63-67, doi: 10.1109/SSTEPS57475.2022.00028.

[11] Muluneh Lemma Woldesemayat, Ashenafi Tesfaye Tantu, "Security Enhancement of Power Systems through Interline Power Flow Controller (IPFC) under Contingency Condition: A Case Study and Analysis-EEP 400 kV System", *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 5897285, 12 pages, 2022. https://doi.org/10.1155/2022/5897285

[12] Patel, Ravindu & Nimje, Akhilesh & Godwal, Shanker & Kanojia, Sarika. (2022). Contingency Analysis: A Tool to Improve Power System Security. 10.1007/978-981-19-2764-5_7.

[13] Kumar, P., Bohre, A.K. (2022). Contingency Analysis and Improving Overall Performance of Power System with Optimal Sizing of Solar-PV Using PSO. In: Gupta, O.H., Sood, V.K., Malik, O.P. (eds) Recent Advances in Power Systems. Lecture Notes in Electrical Engineering, vol 812. Springer, Singapore. https://doi.org/10.1007/978-981-16-6970-5_21

[14] N. Ahmad, Y. Ghadi, M. Adnan and M. Ali, "Load Forecasting Techniques for Power System: Research Challenges and Survey," in *IEEE Access*, vol. 10, pp. 71054-71090, 2022, doi: 10.1109/ACCESS.2022.3187839.

[15] [43] H. Yuan, Y. Xu and C. Zhang, "Robustly Coordinated Generation Dispatch and Load Shedding for Power Systems Against Transient Instability Under Uncertain Wind Power," in IEEE Transactions on Power Systems, vol. 37, no. 2, pp. 1032-1043, March 2022, doi: 10.1109/TPWRS.2021.3104590.

[16] Han, H., Wu, C., Wei, Z., Zang, H., Sun, G., Sun, K., & Wei, T. (2021). A Two-Stage Cooperative Dispatch Model for Power Systems Considering Security and Source-Load Interaction. Sustainability, 13(23), 13350. MDPI AG. Retrieved from http://dx.doi.org/10.3390/su132313350

[17] Groß, A., Lenders, A., Schwenker, Daniel A. Braun & David Fischer, Comparison of short-term electrical load forecasting methods for different building types. *Energy Inform* 4 (Suppl 3), 13 (2021). https://doi.org/10.1186/s42162-021-00172-6