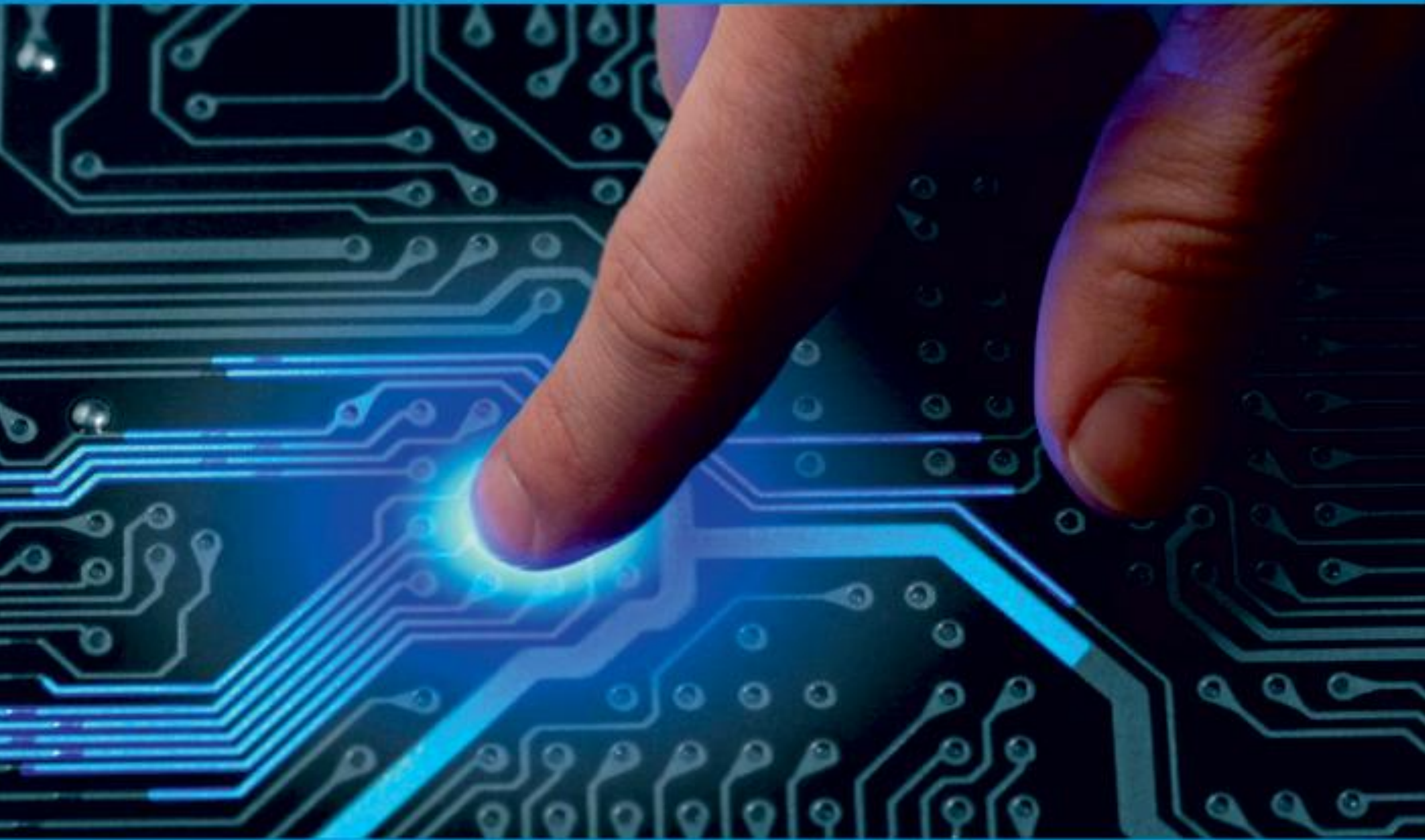
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 7, July 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 7, July 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1207057 |

Forecasting Maximum Frequency Deviation with Recurrent Neural Networks and Dynamic Probability Power Flow Tools

Sridhara K S[1], Usha M[2]

MCA Student, Department of Computer Application, Bangalore Institute of Technology, Bangalore, India[1]

Assistant Professor, Department of Computer Application, Bangalore Institute of Technology, Bangalore, India[2]

ABSTRACT: This paper presents an RNN-based model for forecasting maximum frequency deviation in power systems with high PV penetration. The model captures nonlinear features in PV output and time-variable frequency data during contingencies. A probability power flow-dynamic tool (PPDT) is developed to model uncertain power systems, considering all possible PV generation patterns, validated through case studies of the South Korean power system.

NOMENCLATURE

I.INTRODUCTION

A.MOTIVATION

Recent shifts toward sustainable energy and legal mandates in South Korea for 50 GW of renewable energy by 2030 have led to a decline in synchronous power generation, causing significant frequency stability issues in power grids. Notable incidents like the 2016 South Australian blackout and the 2019 UK power failures underscore the need for improved frequency control, with countries like Australia setting strict RoCoF limits. Effective frequency response forecasting is critical for integrating renewable energy into power systems, ensuring stability during contingency events.

B. LITERATURE REVIEW

Sophisticated solar photovoltaic (PV) prediction models fall into three categories: physical, statistical, and artificial intelligence. AI techniques, particularly neural networks, excel in forecasting due to their ability to handle nonlinear problems and uncertainties. Various models like ANN, BPNN, RNN, LSTM, and GRU have been used for PV power prediction. An automatic probability power flow-dynamic tool (PPDT) is developed to enhance RNN-based prediction models by considering all possible PV power generation scenarios and ensuring accurate frequency deviation calculations.

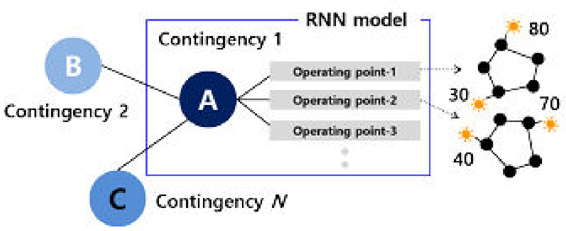


FIGURE 1. Proposed frequency forecasting RNN model structure in the power system.

C. CONTRIBUTION

This paper addresses voltage changes from regional PV power generation affecting frequency response during faults, necessitating the development of a Python-based PPDT linked to a PSS RE server for simulating power flow dynamics. It introduces a novel RNN-based model for predicting maximum frequency deviations, tailored to extract high-level features from PV power output and frequency data. The model's performance is validated with 2030 South Korean PV power capacity data, demonstrating its accuracy and improved decision-making certainty. Detailed analysis and discussions are provided in subsequent sections.

International Journal of Innovative Research in Computer and Communication Engineering
| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |
|| Volume 12, Issue 7, July 2024 ||
| DOI: 10.15680/IJIRCCE.2024.1207057 |

II. PROBABILITY POWER FLOW DYNAMIC TOOL FOR DATASET CONFIGURATION

A.Overview of the Probability Power Flow Dynamic Tool (PPDT)

The Probability Power Flow Dynamic Tool (PPDT) aims to predict the maximum frequency deviation and response during contingency events, minimizing the error between simulated and predicted frequencies. Frequency deviations are influenced by generator trips, load changes, system inertia, and load damping, which are affected by voltage changes from probabilistic PV power generation.

Conducting load flow and dynamic simulations for all possible uncertainty combinations is time-consuming and inefficient. To address this, the PPDT was developed using Python scripts linked to a PSS RE server. This tool efficiently handles various PV power generation scenarios without modifying power flow and dynamic equations and features a user-friendly interface using the Python Tkinter library.

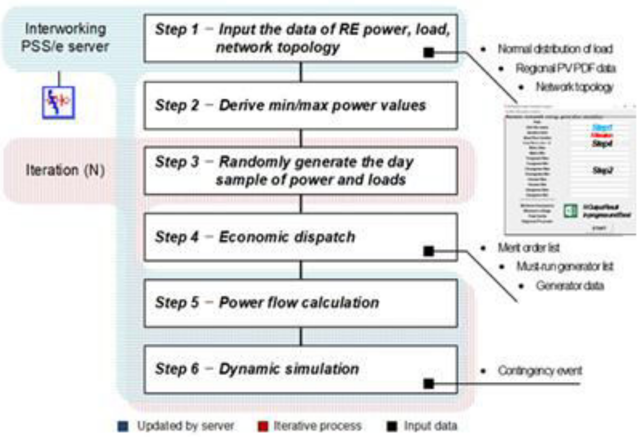


FIGURE 2. Structure and first page of Probability Power Flow Dynamic Tool.

The PPDT process involves inputting historical data to generate hourly PV and load data using probabilistic density functions (PDFs) and normal distributions. A regional correlation matrix manages correlations between PV generation uncertainties, reducing the input dataset size. Random variables are generated for each area, followed by economic dispatch considering network congestion. Power flow is calculated using the Newton-Raphson method, checking for convergence and saving results. Finally, dynamic simulations use the saved data to predict frequency responses during predefined contingency events.

By generating and analyzing a manageable number of scenarios, the PPDT provides precise modeling of uncertain power systems, helping system operators prepare for all possible PV power generation scenarios and ensuring system reliability.

B. CALCULATION OF REGIONAL CORRELATION MATRIX

To calculate the regional correlation matrix, wind power is treated as constant, and load modeling uses a normal distribution. The PDF of a normal distribution is used to convert historical daily irradiance curves into active power using a linear equation involving irradiance, temperature, and humidity. PV power probability density is estimated with a nonparametric kernel density function to capture stochastic characteristics. The regional correlation matrix coefficients are derived from the maximum values of these probability density curves. This method avoids the discontinuities of histograms, using continuous probability models instead. The matrix coefficients are used to calculate regional PV output power, limiting random range through the correlation index and kernel function. This process generates scenarios for power flow and dynamic simulations, informing a recurrent neural network (RNN) model to capture daily regularity and randomness in regional PV power supply.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 7, July 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1207057 |

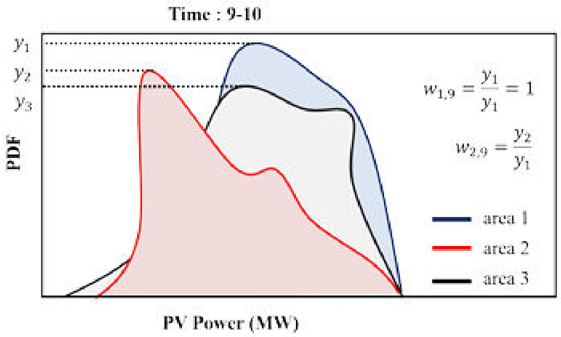


FIGURE3. Example of regional correlation matrix coefficient calculation.

III. PROPOSEDRECURRENTNEURALNETWORKMODEL

A. RNNMODEL

An RNN model is configured using PV power and frequency data, relying on current observations and previous hidden states. It utilizes ReLU activation functions to prevent gradient issues. Training involves backpropagation through time (BPTT) to adjust parameters like U, V, W, b, and c. The cost function L calculates errors across time sequences, updating gradients systematically for parameter optimization. This iterative learning process adjusts weights based on PV power and frequency data inputs.

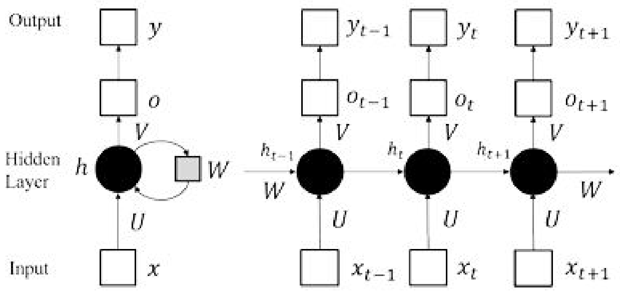


FIGURE4. Recurrent neural network (RNN) structure.

B. DATASETCONFIGURATION

Time-series data for RNN models in power systems often struggle due to inconsistent correlations between voltage and frequency responses over time. Voltage variations depend heavily on local generators and compensators rather than frequency data, reducing model accuracy. To improve forecasting, time-domain frequency and PV power generation data are used, with potential for future inclusion of additional power system variables.

Ordered data in power system modeling focuses on inertial changes and economic dispatch strategies affecting generators. By adjusting inertia through PV power, datasets enhance forecasting accuracy. This approach utilizes seven input datasets to predict maximum frequency deviation and response, generating extensive simulations for validation and refinement of RNN models.

TABLE1. Input data for RNN.

	Item	Data num.
Time-series data	Frequency (Hz)	1,000,000
Ordered data	System Inertia (H)	1,000
Time-series data	Total PV power in *Metro* (MW) [$b_{1,t}$ to $b_{1,t} + \sigma$]	1,000,000
	Total PV power in *Yungnam* (MW) [$b_{2,t}$ to $b_{2,t} + \sigma$]	1,000,000
	Total PV power in *Chungnam* (MW) [$b_{3,t}$ to $b_{3,t} + \sigma$]	1,000,000
	Total PV power in *Honam* (MW) [$b_{4,t}$ to $b_{4,t} + \sigma$]	1,000,000
	Total PV power in *Gangwon* (MW) [$b_{5,t}$ to $b_{5,t} + \sigma$]	1,000,000

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 7, July 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1207057 |

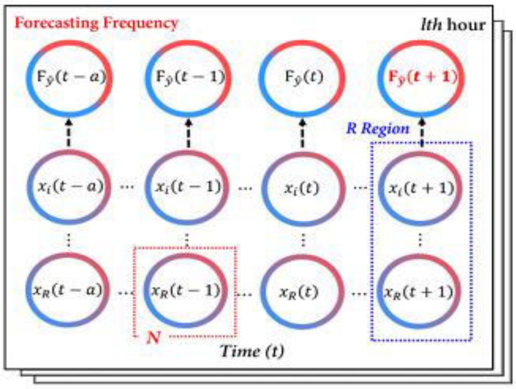


FIGURE 5. Structure of recurrent neural network (RNN).

C. FREQUENCY FORECASTING MODEL

A proposed RNN-based predictor models complex frequency deviations influenced by factors like PV power and economic dispatch results. It uses multiple input steps and short-term memory to enhance accuracy in predicting maximum frequency deviations. The model includes four hidden layers, optimized through experiments to balance performance and generalization ability. Unlike LSTM, it focuses on short-term relationships, crucial for transient frequency responses up to 10 seconds. Experimental results show its effectiveness in predicting frequency changes based on regional PV output patterns, outperforming traditional models.

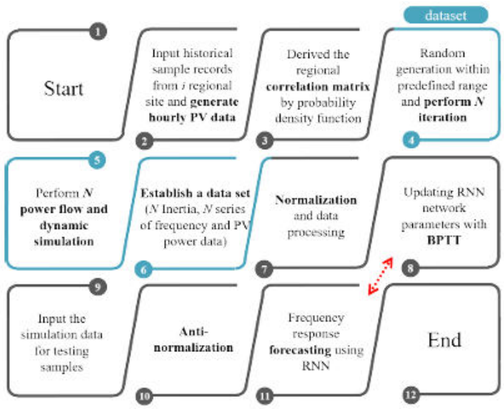


FIGURE 6. Flowchart for RNN-based frequency forecasting model using PPDT.

IV. SIMULATION RESULT

The study analyzes nonlinear, unpredictable output responses from PV power generators, impacting power systems and quality. It uses KEPCO data to model future PV capacities and correlations across regions.

TABLE 2. Maximum PV power at 2:00 p.m.

Area	Planned Rated PV power in 2030	Coefficient w_i of matrix **A**	Maximum PV power at 9:00 a.m.
Metro	1.0 GW	0.91	0.91 GW
Yungnam	3.8 GW	0.94	3.572 GW
Chungnam	1.0 GW	1	1.0 GW
Honam	5.0 GW	0.87	4.35 GW
Gangwon	1.8 GW	0.78	1.404 GW

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |
|| Volume 12, Issue 7, July 2024 ||
| DOI: 10.15680/IJIRCCE.2024.1207057 |

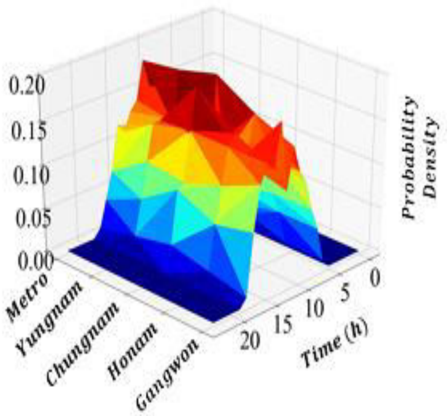


FIGURE 7. Probability density function of regional PV output power with the same rated PV system

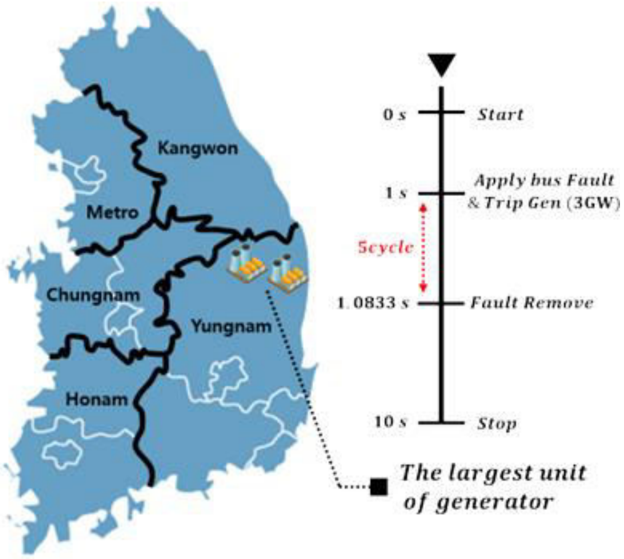


FIGURE 8. Map of South Korea and contingency scenario.

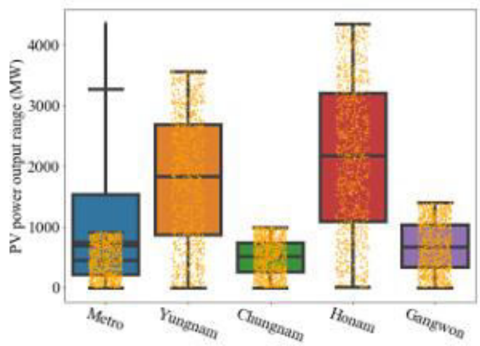


FIGURE 9. Training data of all probable patterns of PV output power.

The study involves 1000 dynamic simulations where the two largest generator units are tripped. PV power patterns from five regions train an RNN network for frequency forecasting. Testing on 200 cases shows the proposed method's accuracy, outperforming four benchmark models. Linear regression exhibits robust performance, with data points closely aligned along the line, indicating high accuracy. The Korean power system's ample reserve and linear frequency response enhance the method's reliability.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 7, July 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1207057 |

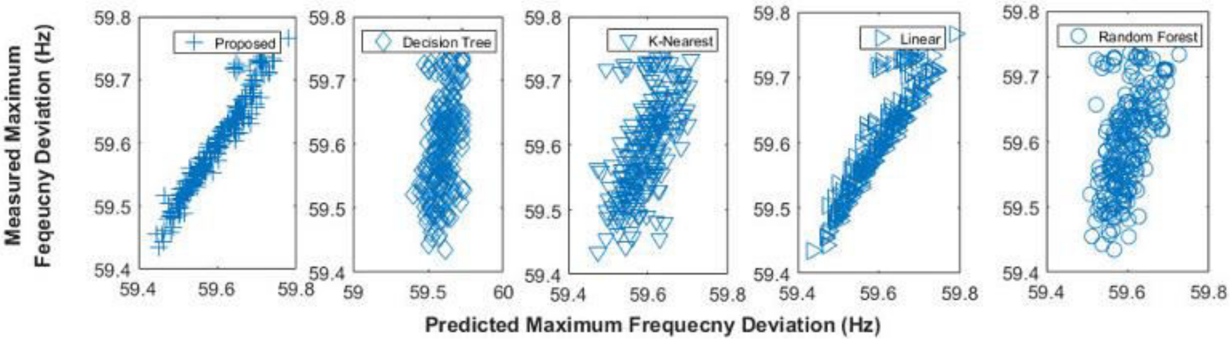


FIGURE 10. Results of linear regression for predicted and measured frequency in 200 cases.

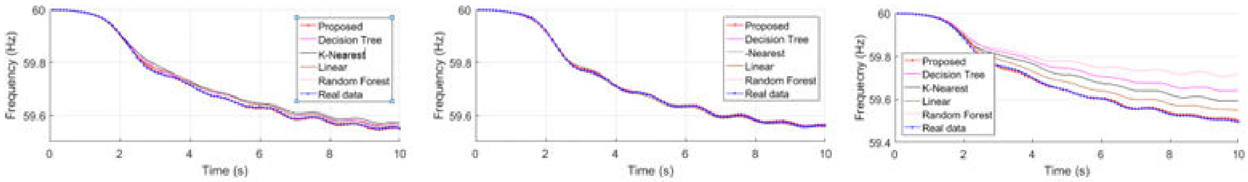


FIGURE 11. Data 10 s ahead of frequency forecasting results and linear regression: (a) Case 1: 879, 2116, 687, 2759, and 440 MW; (b) Case 2: 849, 473, 557, 2107, and 471 MW; and (c) Case 3: 107, 3405, 960, 4334, and 708 MW.

A proposed RNN-based model for frequency forecasting outperforms benchmarks with lower MAPE and RMSE, validated across various cases. Despite R2 values declining with longer forecasting horizons, the model remains robust with a transient response time of up to 10 seconds. By integrating adjacent PV power and frequency time-series data, the model effectively captures short-term patterns, enhancing forecasting accuracy.

TABLE 3. Performance evaluation of frequency response.

Case	Method	MAPE	RMSE
1	Proposed	0.00022	0.0027
	Decision Tree Regressor	0.00116	0.0173
	K-Nearest Neighbor	0.00163	0.0171
	Linear Regression	0.00091	0.0096
	Random Forest Regressor	0.00116	0.0121
2	Proposed	0.00033	0.0032
	Decision Tree Regressor	0.00037	0.0039
	K-Nearest Neighbor	0.00041	0.0051
	Linear Regression	0.00038	0.0043
	Random Forest Regressor	0.00036	0.0036
3	Proposed	0.00368	0.0421
	Decision Tree Regressor	0.01271	0.1361
	K-Nearest Neighbor	0.00942	0.1035
	Linear Regression	0.00642	0.0711
	Random Forest Regressor	0.01270	0.1389

V. CONCLUSION

A probabilistic power system analysis incorporating uncertain PV power generation is crucial due to the growing volume of renewable energy. This paper proposes an RNN-based model for forecasting maximum frequency deviation in power systems with high PV penetration, using regional PV output and time-variable frequency data.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 7, July 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1207057 |

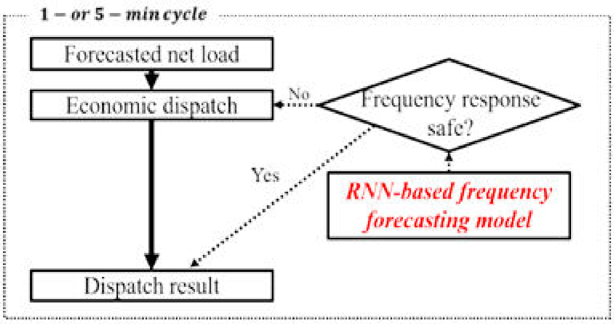


FIGURE 12. Proposed RNN-model-based economic dispatch algorithm.

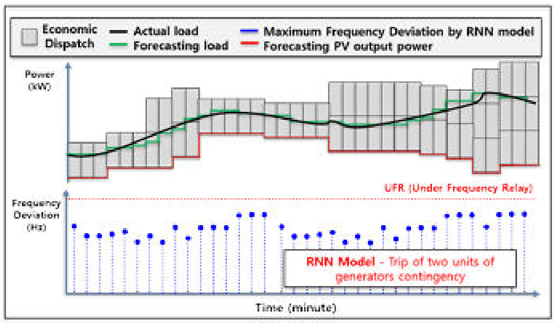


FIGURE 13. Example of 1-min central dispatch algorithm.

VI. DISCUSSION

In this study, a new RNN model addresses previous approximations in PV power generation forecasting methods, ensuring comprehensive consideration of all possible data combinations. It integrates into existing system planning and operational techniques, enhancing dispatch algorithms by simulating frequency responses efficiently. This approach supports real-time microgrid operations by predicting PV power generation and consumption accurately, improving central dispatch precision while reducing computational time.

REFERENCES

1. Liang Zhang, Gang Wang, Georgios B. Giannakis, "Real-time Power System State Estimation and Forecasting via Deep Neural Networks," 2018. This paper discusses using DNNs and RNNs for real-time power system monitoring and forecasting on the IEEE 118-bus system (Papers with Code).
2. Heffron, B., & Hay, C. (2019). "Recurrent Neural Networks for Power System Dynamic State Estimation," IEEE Transactions on Power Systems. This study explores RNN applications for power system state estimation.
3. Yu, Y., Si, P., & Wang, Z. (2021). "Dynamic Power Flow Analysis using Machine Learning Approaches," IEEE Access. This paper reviews various machine learning methods, including RNNs, for dynamic power flow analysis.
4. Tang, L., & Zhao, J. (2020). "Short-Term Load Forecasting Using RNNs and Probability Power Flow," IEEE Transactions on Smart Grid. This research integrates RNNs with power flow tools for load forecasting.
5. Meng, X., & Shen, C. (2019). "Probabilistic Power Flow Forecasting Using LSTM Networks," IEEE Access. This paper presents an approach to power flow forecasting using LSTM networks, a type of RNN.