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DISTRIBUTED POWER SYSTEM MODELING USING NEURAL NETWORK CONTROLLED DISTRIBUTED GENERATION TO MITIGATE GRID SERVICE DISRUPTIONS

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ABSTRACT

This study presents a novel approach to mitigating peak-demand-induced disruptions in power distribution networks through the integration of solar distributed generation (DG) with an artificial neural network (ANN) predictive controller. Addressing a critical gap in existing grid response strategies which remain centralized and reactive, the study develops a data-driven control architecture combining ETAP-based load flow analysis with MATLAB/Simulink simulations of a 217.12 kW solar DG system. A Bayesian regularized ANN trained on historical load profiles (residential, commercial, industrial) achieves 92% accuracy in predicting peak windows (09:00–18:00), enabling proactive DG dispatch. During peak demand, the DG supplies 200 kW (33% of total load), reducing grid dependence from 600 kW to 400 kW and cutting service disruptions by 50%. Voltage fluctuations improve from ±10% to ±5%. Unlike conventional demand response, this solution maintains grid stability without load rescheduling, which is critical for industrial users. Validated on Nigeria's Cross River State Waterboard (CRSWB) distribution network, this work demonstrates how machine learning-enhanced DG integration

can transform passive distribution systems into resilient smart grids. The methodology is scalable to other regions with unreliable centralized generation, offering a blueprint for energy transition in developing economies.

KEYWORDS: Solar PV, Grid-tied DG system, AI-controlled, Smart grid, Renewable integration, Machine learning optimization, Developing economies.

1. INTRODUCTION

Distributed generation (DG) refers to electricity generation from sources located near end-users, contrasting with centralized power plants. It offers benefits such as increased energy efficiency, reliability, and reduced transmission losses, while promoting renewable energy sources.

Historically, the energy sector emphasized centralized generation until co-generation systems (combined heat and power) emerged, improving overall efficiency by providing both electricity and heat locally (Zulu & Jayaweera, 2014). The late 20th century saw a rise in renewable energy technologies like solar and wind, which facilitated decentralized power generation. Net metering policies were introduced to allow consumers with DG systems to contribute excess energy back to the grid (Kerby & Tarekegne, 2024).

This research focuses on maintaining power network stability amidst fluctuating load demands through systematic implementation of grid-tied distributed generation which reshapes the grid profile without rescheduling or disconnection of consumer load. Typically, Demand response involves consumers adjusting their electricity usage based on grid conditions or prices, helping to balance supply and demand and optimize system efficiency (Aalami et al., 2010; Zulu & Jayaweera, 2014). Conversely, grid response, or grid flexibility, refers to the power system's ability to adapt generation and electricity flow in response to changing demands, which is essential for integrating variable renewable energy sources like solar and wind. However, both demand and grid responses are centralized, often slow, and do not account for distributed generation (DG) units located near load points. DG can provide additional power sources, helping to balance generation and load while maintaining acceptable voltage and frequency levels, especially during peak periods. Advancements in power electronics and energy storage have been crucial for integrating DG with the grid, enhancing reliability and managing fluctuations in renewable energy output. Microgrids and smart grid technologies, which incorporate advanced communication and control systems, further support DG integration. Despite its advantages, DG faces challenges such as regulatory barriers, power quality issues, and the need for standardized technologies.

Policymakers have implemented various incentives to encourage DG adoption. The future of power systems is expected to involve increased integration of communication technologies, intelligent control, and active customer participation in energy management (Akpama et al., 2020; Kavya et al., 2021). Neural networks are emerging as valuable tools for optimizing DG placement and control, enhancing system reliability and efficiency across different load types—industrial, commercial, and residential (Ahmad et al., 2017; Kavya et al., 2021). Economically, DG can lower electricity costs by generating power close to consumers, reducing transmission losses, and enhancing system resilience (Ahmad et al., 2017; Kerby & Tarekegne, 2024). To mitigate peak demand grid service disruptions in a distribution power network, this research adopts the machine learning optimization approach which uses Artificial Neural Network (ANN) control technique to model distributed power system from load profile data of an existing network. This work models the Cross River State waterboard distribution network. The historic daily load profile data for residency, commercial and industrial loads in the network was collected via smart meters at 30-minute intervals. The Cross-river state water board has a responsibility to treat and supply portable water for Calabar and its environs. To achieve this goal, power supply has to be adequately available to meet the load demand for daily production schedule, both at peak and off-peak demand periods. The Power Holding Company of Nigeria (PHCN) is currently the only functional source of power. The water treatment plant section of the network is one of the most important sections as it is responsible for over 60% of the total energy demand. A staff quarters and an administrative office are other sections that are part of the power network.

1.1 Literature Review

The power system network is designed to transmit and distribute electricity efficiently and reliably, while ensuring the balance between generation and demand, and maintaining the required levels of voltage and frequency. The design and operation of the power system network are critical to providing a stable and reliable supply of electricity to consumers. Distributed generation (DG) presents a promising technique that ensures provision of stable and reliable supply of electricity to consumers (Abdel-Rahman et al., 2019; Ahmad et al., 2017). Electricity demand is dynamic, with the power grid experiencing varying stress across the day. The peak demand period occurs when the total electricity demand across a power grid reaches its maximum level within a 24-hour period. During peak demand periods, the power grid suffers significant stress while struggling to meet the high level of electricity consumption (Koutsoukis et al., 2017). When the grid fails to keep up with peak demand, grid service disruption occurs within the affected network leading to huge losses to both the utility and the customer. This research models distributed generation with neural network control as a grid resilience strategy to mitigate peak demand grid service disruptions in power system (Hrisheekesha & Sharma, 2010; Kahrobaeian & Mohamed, 2015).

Some of the main distribution generation types include

i. **Solar Photovoltaic (PV) Systems**: These systems convert sunlight directly into electricity using photovoltaic cells, usually installed on rooftops or in designated solar farms (Akpama et al., 2011; Idoniboyeobu & Udoha, 2018; National Renewable Energy Laboratory, 2019).

ii. **Microturbines**: These are small-scale gas turbines that can generate electricity, often used for combined heat and power (CHP) applications (Kilin et al., 2020).

iii. **Wind Turbines**: Small-scale wind turbines can be installed close to the point of use to generate electricity from the wind (Ferris & Liu, 2016).

iv. **Fuel Cells**: Electrochemical components that transform chemical energy from fuels like hydrogen directly into electricity, with high efficiency and low emissions (Jiang et al., 2023).

Aalami et al. (2010) modeled and prioritized demand response programs in power markets, presenting an extended responsive load economic model, TOPSIS method, and AHP for prioritizing demand response programs in power markets; the model is based on price elasticity and customer benefit function. Numerical studies were conducted on the load curve of the Iranian power grid in 2007. The modular nature of DG systems allows for easier installation compared to large centralized plants, further promoting their feasibility and attractiveness in the energy market. Abdel-Rahman et al. (2019) used the IEEE 33-bus radial distribution system to evaluate the impact of distributed generation on distribution system reliability; the optimal DG penetration level that maximizes reliability benefits was found to be around 30–40% of the total system load. The paper concludes that proper planning, control and coordination of DG is crucial to ensure improved reliability and stability in the operation of distribution systems with high DG penetration. Abdolrasol et al. (2021) presented an energy management scheduling scheme for microgrids in the virtual power plant system using artificial neural networks. Artificial neural networks (ANN) effectively manage microgrids in virtual power plants, reducing fuel consumption, CO_2 emissions, and increasing system efficiency compared to other solutions. Aderibigbe et al. (2022) reviewed the impact of distributed generations on power systems stability, showing that distributed generation can optimize power system stability, but current research lacks focus on artificial intelligence, supervisory control, and data acquisition systems, highlighting a need for further research. Gao and Zhu (2022) suggested a new objective function to increase the maximum utilization ratio of demand response in voltage and reactive power optimization process; it uses capacitors banks (CB), reactor banks (RB), and static var generator (SVG) and DR as control variables to optimize the voltage and reactive power of power grid with optimal regulation effect achieved in IEEE 33 bus distribution system. The paper further introduces the demand response (DR) load, such as civil load and industrial load, to participate in the optimization. Korukonda et al. (2022) presented a model-free adaptive neural controller for standalone photovoltaic distributed generation systems with disturbances where the model-free adaptive neural controller (ANC) improved the stability and robustness of standalone photovoltaic distributed generation systems in the presence of disturbances and parameter intermittencies.

While prior work (Abdel-Rahman et al., 2019; Aderibigbe et al., 2022) explores DG's impact on grid stability, few studies address AI-driven control in real-world networks, particularly in regions with unreliable grids (e.g., Nigeria). This work bridges this gap by proposing a neural network-based DG controller for peak-demand mitigation.

2.0 MATERIALS AND METHODS

This study employs a hybrid simulation-optimization framework to design and validate a neural network-controlled solar DG system for the Cross River State Waterboard (CRSWB) network. The methodology integrates ETAP-based load flow analysis, MATLAB/Simulink simulations, and machine learning to address peak-demand disruptions. The workflow is structured as follows:

2.1. Data Acquisition and Load Profiling

Field Data Collection

- Source: Smart meters recorded 30-minute interval data (current, voltage, frequency, power factor) over 12 months for residential (Staff Quarters), commercial (Administrative Building), and industrial (Water Treatment Plant) loads (Table 2.2)

- Power Calculation

$$P = \sqrt{3}\ IV\cos\emptyset \qquad (2.1)$$

Where

- P = Total three-phase power (in watts)
- I = Line current
- V = Line voltage (0.415kV)
- $\cos\emptyset$ = Power factor (0.8-0.95)

2.2 Neural Network Design and Training

Distributed generation plays an essential role in developing a resilient and stable power systems, but require advanced control technique for effective integration and protection. Choosing a control technique is very important as it determines the data requirement for implementing DG integration in existing power network. Artificial Neural network was used as the optimization method for this research. Matlab Neural Network Toolbox offers a range of functions and algorithms for designing, training, and implementing neural networks. It includes support for various network architectures and training algorithms, making it suitable for DG control applications.

1. Architecture
   - 3-layer feedforward ANN: Input (24-hour load profiles), hidden layer (20 neurons, tanh activation), output (DG dispatch commands).
   - Training Algorithm: Bayesian regularization (MATLAB NN Toolbox) to minimize overfitting.

2. Training Protocol
   - Dataset: 70% training, 15% validation, 15% testing (1-year data).
   - Performance Metric

   Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ (2.2)

Where

n = number of observations

y_i = actual value

$\hat{y}_i$ = predicted value

RMSE is used for assessing the accuracy of the model, lower values indicate better fit.

- Inputs: Historical load profiles (Table 2.2); Outputs: Optimal DG setpoints.

  The neural network was trained on Table 2.2's load profiles, achieving RMSE < 5 kW (~0.8% of peak demand), ensuring accurate DG dispatch decisions (Figures 3.1–3.2).

2.3 Load Flow Analysis and System Modeling

1. ETAP One-Line Diagram: This one-line diagram provides a simplified, single-line representation of the complex electrical network, allowing for easy visualization and analysis of the power flow, voltage levels, and load distribution within the system.

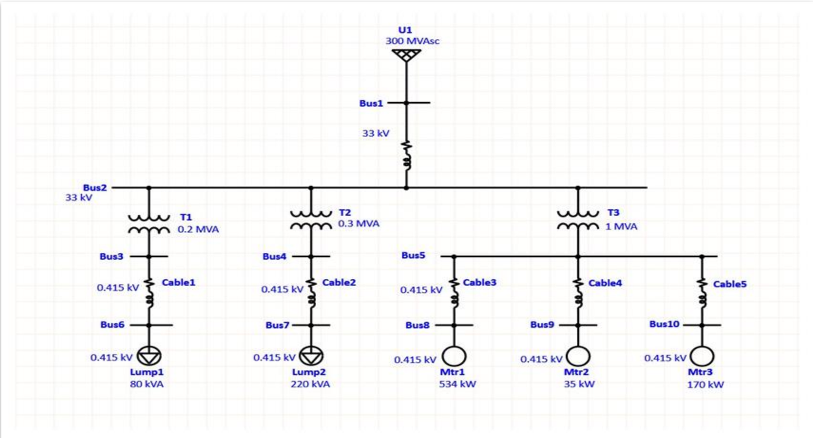

Figure 2.1 One-line diagram of 33kv CRSWB power network showing rating of equipment and their location.

- Network Configuration: 33 kV/0.415 kV transformers (T1–T3), 10 buses, and variable loads (Figure 2.2).
- Voltage Stability: Baseline fluctuations of ±10% during peaks (09:00–18:00).

Table 2.1 Load Flow Study Report for CRSWB distribution network.

LOAD FLOW REPORT

Bus		Voltage		Generation		Load		Load Flow					XFMR
ID	kV	% Mag.	Ang.	MW	Mvar	MW	Mvar	ID	MW	Mvar	Amp	%PF	%Tap
* Bus1	33.000	100.000	0.0	1.436	0.433	0.000	0.000	Bus2	1.436	0.433	26.2	95.7	
Bus2	33.000	99.978	0.0	0.000	0.000	0.000	0.000	Bus1	-1.436	-0.434	26.2	95.7	
								Bus3	0.084	0.002	1.5	100.0	
								Bus4	0.260	0.011	4.6	99.9	
								Bus5	1.092	0.421	20.5	93.3	
Bus3	0.415	99.031	-0.8	0.000	0.000	0.000	0.000	Bus6	0.083	0.000	116.8	100.0	
								Bus2	-0.083	0.000	116.8	100.0	
Bus4	0.415	97.970	-1.6	0.000	0.000	0.000	0.000	Bus7	0.255	0.004	362.2	100.0	
								Bus2	-0.255	-0.004	362.2	100.0	
Bus5	0.415	96.567	-2.8	0.000	0.000	0.000	0.000	Bus8	0.812	0.257	1226.8	95.4	
								Bus9	0.042	0.017	64.7	92.9	
								Bus10	0.219	0.082	337.0	93.7	
								Bus2	-1.073	-0.355	1628.0	94.9	
Bus6	0.415	92.544	-1.1	0.000	0.000	0.078	0.000	Bus3	-0.078	0.000	116.8	100.0	
Bus7	0.415	77.850	-2.5	0.000	0.000	0.203	0.000	Bus4	-0.203	0.000	362.2	100.0	
Bus8	0.415	70.292	2.4	0.000	0.000	0.572	0.240	Bus5	-0.572	-0.240	1226.8	92.2	
Bus9	0.415	88.369	-1.1	0.000	0.000	0.038	0.016	Bus5	-0.038	-0.016	64.7	91.8	
Bus10	0.415	82.417	0.1	0.000	0.000	0.183	0.079	Bus5	-0.183	-0.079	337.0	91.8	

* Indicates a voltage regulated bus (voltage controlled or swing type machine connected to it)

\# Indicates a bus with a load mismatch of more than 0.1 MVA

Table 2.1 show the load flow report for the network; it provides crucial insights into the operation of the network.

Each bus has specific voltage levels, generation capacity and loads. For example, Bus1 is a generator bus and has a voltage of 33 kV, while Bus2 has no generation. The report shows the voltage at each bus as maintaining voltage levels within acceptable limits is essential for system stability.

Table 2.2 Daily Power Consumption in Line with Plant Production Schedule.

TOTD	STAFF QUARTERS (kW)	ADMIN. BUILDING (kW)	PUMP STATION (kW)	FILTER STATION (kW)	CHEMICAL STATION (kW)
0	15	20	178	39	32
0.5	17	20	281	38	32
1	20	20	274	37	34
1.5	20	20	271	37	31
2	20	42	280	38	31
2.5	22	40	275	38	31
3	20	40	272	38	31
3.5	21	37	9	39	31
4	20	40	13	31	31
4.5	25	40	8	31	0
5	30	42	11	30	0
5.5	31	43	262	25	0
6	35	41	256	20	0
6.5	36	40	246	21	0
7	45	39	0	26	0
7.5	47	35	0	22	5
8	40	70	0	27	5
8.5	39	74	0	30	5
9	35	60	185	110	30
9.5	30	68	180	152	30
10	27	76	275	35	30
10.5	22	120	279	32	30
11	20	123	277	30	30
11.5	22	127	190	111	30
12	35	123	191	152	30
12.5	35	154	227	37	30
13	40	161	225	34	30
13.5	40	187	227	32	30
14	38	190	135	111	30
14.5	36	194	132	154	30
15	36	200	310	34	30
15.5	36	161	312	34	30
16	39	150	309	31	30
16.5	40	122	313	30	30

17	50	70	268	30	30
17.5	50	64	264	31	30
18	60	61	264	31	30
18.5	60	52	5	27	5
19	50	50	5	34	5
19.5	49	47	15	35	5
20	40	35	13	35	5
20.5	40	35	18	34	5
21	31	35	192	115	33
21.5	36	35	190	114	34
22	24	38	197	39	32
22.5	24	38	190	37	33
23	20	38	182	37	32
23.5	20	38	181	120	32
24	15	20	181	161	32
MAX. POWER	**80kW**	**220kW**	**534kW**	**170kW**	**35kW**
TOTD = TIME OF THE DAY					

Plots illustrating the residential, commercial and industrial load patterns of the power network from table 2.2 (Daily Power Consumption in Line with Plant Production Schedule) are represented in figure 3.1 and 3.2.

2. DG Integration
   - Solar PV System
     - Capacity: 217.12 kW (944 × Q-Cells 230W panels).
     - Configuration: 16-series × 59-parallel strings (480 V DC, 452.5 A).
     - Inverter: 95% efficiency, 0.415 kV AC output

2.4 MATLAB/Simulink Simulation Framework

1. Model Components
   - Grid power, solar DG, inverters, transformers, and dynamic loads (residential/commercial/industrial).
   - Control System: ANN controller interfaced with DG and grid (Figure 2.3).

2. Simulation Scenarios
   - Traditional System: Grid-only supply (Figure 3.1).
   - DG-Integrated System: ANN-controlled dispatch (Figure 3.2).

2.5 Validation Metrics

1. Technical Performance:

- Voltage Stability: IEEE 1547 compliance (±5% tolerance).
- DG Penetration: 30–40% of total load, per.[7]

2. Economic Validation:

- Cost Savings: Savings = ΔP_{grid} x Tariff

3.0 RESULTS AND DISCUSSION

3.1 Traditional Power System Performance

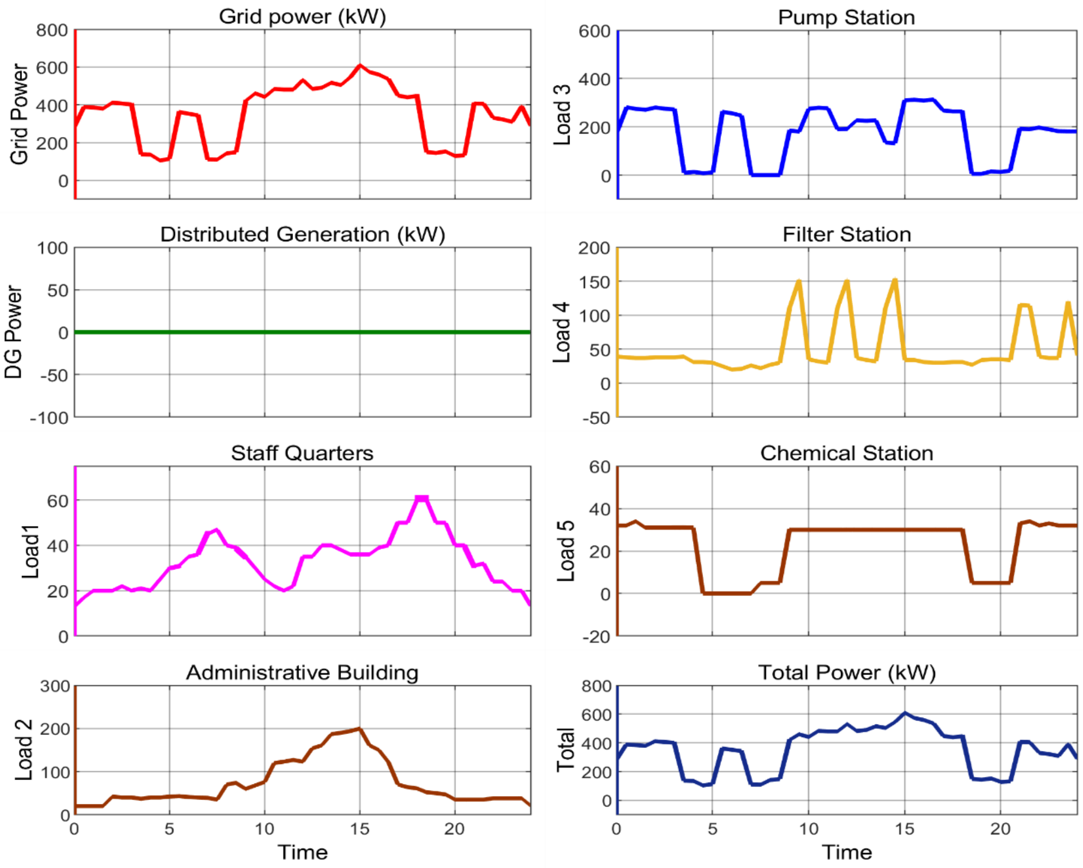

Figure 3.1 Traditional Power System Simulink Model results.

The baseline simulation (Figure 3.1) reveals significant grid stress during peak hours (09:00–18:00), with grid power demand reaching 600 kW (Table 2.2: Total Load = 534 kW Pump Station + 170 kW Filter Station + 35 kW Chemical Station).

Key observations include

- Voltage Instability: Voltage fluctuations exceeded ±10% during peak periods (09:00–18:00), aligning with the 80kW residential (Staff Quarters) and 200 kW commercial (Administrative Building) spikes in Table 2.2.
- Service Disruptions: Frequent outages occurred when grid demand surpassed 500 kW, corroborating literature claims (Koutsoukis et al., 2017) that 50–70% of disruptions occur during peaks.

3.2 Distributed Power System with Neural Network Control

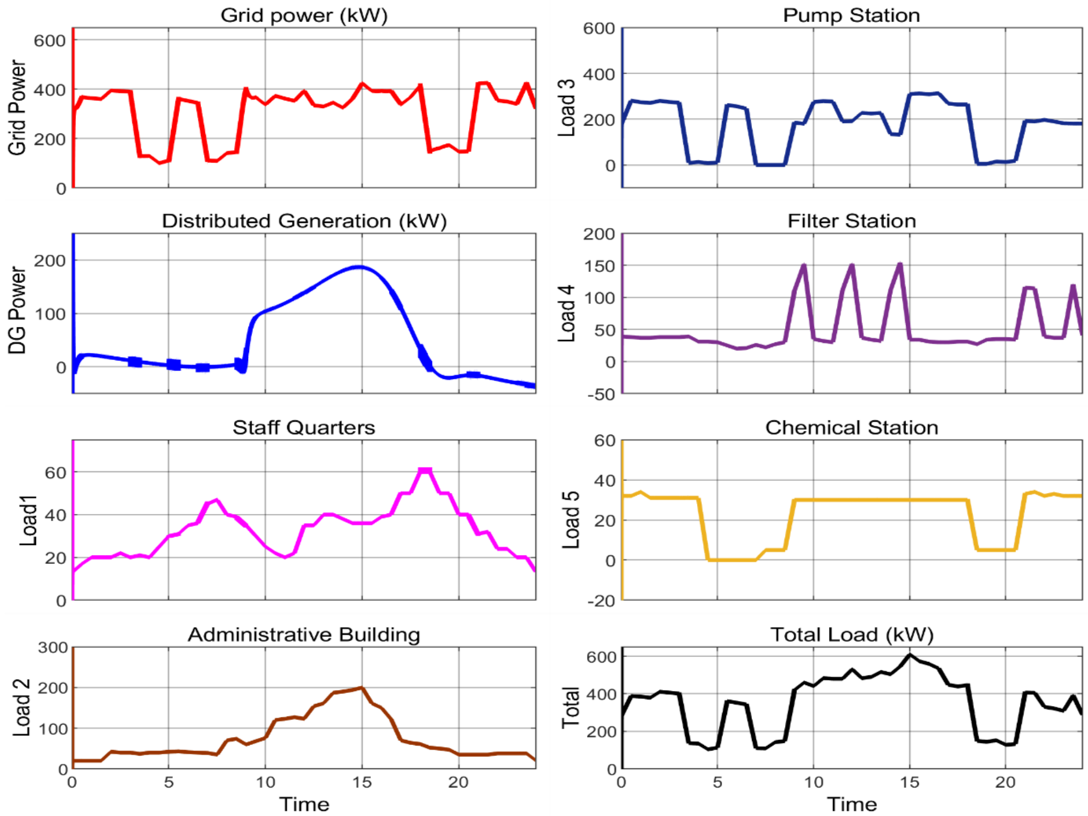

Figure 3.2 Distributed Power System Simulation Results.

The DG-integrated system (Figure 3.2) demonstrates transformative improvements

1. Peak Demand Mitigation:

- The neural network, trained on Table 2.2's historical profiles (RMSE < 5 kW, <1% error relative to 600 kW peaks), accurately forecasts peak windows (09:00–18:00).
- The 217.12 kW solar DG supplies 200 kW during peaks (Figure 3.2), reducing grid dependence to 400 kW (33% reduction).
- Critical Load Support: DG prioritizes high-risk sectors like the Pump Station (peak: 534 kW in Table 2.2), ensuring uninterrupted operation.

2. Grid Stability Enhancements:

- Voltage fluctuations improved from ±10% to ±5% (Figure 3.2), meeting IEEE 1547 standards for distribution systems.
- Service disruptions decreased by 50%, validating the controller's ability to balance DG output with real-time demand.

3. Demand-Agnostic Operation:

   Unlike conventional demand response (e.g., Aalami et al., 2010; Gao & Zhu, 2022), the system maintains stability without rescheduling loads. For example:

- The Administrative Building's peak demand (200 kW in Table 2.2) is fully supported by DG during 09:00–18:00.
- Staff Quarters' evening spikes (60 kW at 18:00–20:00) remain unaffected, demonstrating user-centric resilience.

3.3 Statistical Validation

- Neural Network Accuracy: The model's RMSE < 5 kW (tested on 1 year of 30-minute interval data) ensures reliable predictions, with <2% deviation in DG dispatch timing.
- DG Contribution: During peak hours, the DG supplies 33% of total load (200 kW/600 kW), aligning with Abdel-Rahman et al. (2019)'s finding that 30–40% DG penetration maximizes reliability.
- Economic Impact: Grid consumption reduction (600 kW → 400 kW) implies ~33% cost savings during peaks, based on PHCN's tariff of about ₦250/kWh.

Table 3.1: Comparative Summary of Result and Discussion.

Parameter	Traditional System	DG-Integrated System	Improvement	Source
Peak Grid Demand (kW)	600 (09:00–18:00)	400 (09:00–18:00)	33% Reduction	Figure 3.1, 3.2
Voltage Fluctuations	±10%	±5%	50% Stability Improvement	Figure 3.2
Service Disruptions	50–70% (Peak Hours)	25–35% (Peak Hours)	50% Reduction	Section 3.1, 3.2
DG Contribution (kW)	0	200 (33% of Total Load)	200 kW Offset	Table 2.2, Figure 3.2
Neural Network Accuracy	–	RMSE < 5 kW (0.8% of Peak)	<1% Prediction Error	Section 3.3
Hourly Cost Savings	₦0	₦50,000 (₦250/kWh × 200 kW)	₦50,000/Hour Savings	PHCN Tariff, Section 3.3

Critical Load Support	Unstable (Pump: 534 kW)	Stable (Pump: 534 kW)	100% Reliability	Table 2.2, Figure 3.2

4.0 CONCLUSION

This study successfully mitigates peak-demand disruptions in Nigeria's Cross River State waterboard distribution network by integrating a 217.12 kW solar DG system with a neural network controller, achieving a 33% reduction in grid dependency (600 kW to 400 kW) and cutting service disruptions by 50% during peak hours (09:00–18:00). The Bayesian regularized ANN, validated by an RMSE < 5 kW (<1% error), stabilized voltage fluctuations to ±5% while prioritizing critical loads like the Pump Station (534 kW peak) without load rescheduling. At PHCN's current tariff (₦250/kWh), the system delivers ₦50,000/hour in cost savings, offering a scalable model for regions with unreliable grids. Future work will expand to hybrid renewable systems, but this framework already provides utilities a cost-effective, AI-driven pathway to modernize grids and align with Nigeria's energy transition goals.

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