wjert, 2025, Vol. 11 Issue 6, 12-31.

Original Article

ISSN 2454-695X

World Journal of Engineering Research and Technology

WJERT

www.wjert.org

SJIF Impact Factor: 7.029

IMPACT EVALUATION OF STAGGERED PEAK DEMAND IN DISTRIBUTED POWER NETWORKS: MODELING FOR EFFECTIVE GRID PROFILE RESHAPING WITHOUT LOAD DISCONNECTIONS

***[1]ThankGod Sylvanus Ntem, [2]Iwueze Ifeanyi M., [3]Ihemba Kennedy Uzodimma and [4]Tafida Balarabe Rabiu**

[1]Nigerian Building and Road Research Institute, Km 10, Idiroko Road, Ota.

[2]Mechatronics Engineering Department, Federal Polytechnic Nekede, Owerri.

[3]Mechatronics Engineering Department, Federal Polytechnic Nekede, Owerri.

[4]Electrical/Electronic Engineering Department, Federal Polytechnic Nekede, Owerri.

Article Received on 03/04/2025 **Article Revised on 23/04/2025** **Article Accepted on 13/05/2025**

***Corresponding Author**

ThankGod Sylvanus Ntem

Nigerian Building and Road Research Institute, Km 10, Idiroko Road, Ota.

ABSTRACT

Distributed power systems, characterized by mixed load patterns, often experience staggered peaks due to varying peak demand periods among residential, commercial, and industrial loads throughout the day. This research evaluates the impact of staggered peak demand in distributed power networks (DPNs) to facilitate effective grid profile reshaping without load disconnections. The research develops comprehensive models to simulate the dynamics of staggered peak demand and assess their implications for grid stability, energy efficiency, and operational costs. The study models the peak demand periods of an existing distribution network exhibiting staggered peaks, determines the aggregate staggered peak demand across load types, and implements a grid-tied distributed generation (DG) system controlled by a neural network using this aggregated data. Results indicate that staggered peak demand periods across different load types significantly flatten the overall system load profile, reducing the maximum power required from the grid to 600 kW from a possible 1039 kW. This reduction leads to improved system efficiency and cost savings. Furthermore, integrating DG using the staggered peak strategy lowered total power requirements from the grid to approximately 400 kW. This research has investigated managing peak demand in distributed power networks

(DPNs) by exploiting the naturally staggered peak demands of residential, commercial, and industrial loads, paving the way for future research and practical applications aimed at optimizing energy consumption patterns and strengthening grid resilience amid evolving energy demands.

KEYWORDS: Staggered Peak, Neural Network, Distributed Generation, Residential, Commercial, Industrial Loads.

1. INTRODUCTION

The increasing demand for electricity, coupled with the growing integration of renewable energy sources, has placed significant challenges on the management and operation of power grids worldwide. Traditional power networks often struggle to accommodate peak demand fluctuations, resulting in inefficiencies, higher operational costs, and potential reliability issues (D'Aguanno & Nardone, 2020). As a response to these challenges, the concept of staggered peak demand has emerged as a promising strategy. This approach allows for the redistribution of energy consumption over time, effectively flattening peak demand curves while maintaining service continuity (Liu & Zhang, 2019). Distributed power networks, characterized by decentralized generation and consumption, present unique opportunities for implementing staggered demand strategies. These networks include a diverse array of energy resources, such as solar panels, wind turbines, and energy storage systems, which can be harnessed to manage load demands more dynamically (Zulu & Jayaweera, 2013). By leveraging these resources, operators can reshape the grid profile in a way that not only enhances reliability but also minimizes the need for costly infrastructure upgrades.

The importance of this research lies in its potential to evaluate the impacts of staggered peak demand on distributed power networks. This evaluation is crucial for understanding how these strategies can lead to more resilient, efficient, and sustainable energy systems (Candelise & Mazzola, 2018). Specifically, the study aims to explore the effectiveness of modeling approaches that facilitate the reshaping of grid profiles without disconnecting loads, thereby ensuring uninterrupted service for consumers.

1.1 Literature Review

This section is a review of key themes and findings from recent literature with critical focus on staggered peak demand management:

Demand-Side Flexibility and Load Shifting emphasizes time-varying pricing (e.g., time-of-use tariffs, dynamic pricing) as a tool to incentivize load shifting. Smith et al. (2020) demonstrated that staggered pricing reduces peak demand by 15–20% in microgrids by encouraging users to reschedule non-essential loads. Similarly, reinforcement learning-based DSM frameworks (Zhang et al., 2021) optimize appliance scheduling, achieving flatter demand curves while preserving user comfort.

The role of Distributed Energy Resources (DERs) including rooftop solar and battery storage, enable localized peak shaving. Nguyen and Le (2019) modeled a hybrid system where solar-storage coordination reduced grid dependency during peaks by 30%. Electric vehicles (EVs) also contribute; vehicle-to-grid (V2G) strategies (Hussain et al., 2022; Wang et al., 2023) show potential to supply stored energy during high demand, though challenges like battery degradation require trade-off analysis.

Advanced optimization techniques, such as mixed-integer linear programming (MILP) and model predictive control (MPC), are widely used to schedule DERs and flexible loads. A case study by Chen et al. (2021) using MILP in a residential microgrid reduced peak-to-average ratios by 25% without load curtailment. Agent-based models further capture prosumer heterogeneity, enabling decentralized decision-making.

Staggered demand strategies must avoid creating secondary peaks. Gamarra et al. (2020) highlighted the need for real-time feedback loops to dynamically adjust load schedules based on grid conditions. Game-theoretic approaches (Li et al., 2021) model consumer interactions, ensuring equitable participation and preventing rebound peaks.

Challenges and Gaps

- Scalability: Most studies focus on small-scale systems; scalability to large networks with diverse DERs remains understudied.
- Data and Communication: Reliable IoT infrastructure is critical for real-time coordination but raises privacy concerns (Zhou et al., 2022).
- Behavioral Factors: User acceptance of automated load shifting requires socio-technical analysis (Fell et al., 2020).

Future Directions

Emerging research integrates machine learning optimization approaches for predictive demand management and hybrid models with data-driven techniques (Mengelkamp et al., 2021).

2. MATERIALS AND METHODS

The research utilizes several key techniques: a PQ (Voltage and Reactive Power Controlled Bus) model to represent variable loads, incorporating high-level and low-level control subsystems; an ETAP one-line diagram to visually represent the 33 kV Cross River State Waterboard(CRSWB) power network; a Neural Network controlled by a Bayesian regularization method for DG system control; a solar powered DG design for grid integration and Matlab Simulink tool for simulating the system's performance. Accurate load forecasting is essential for anticipating peak demand periods. Advanced machine learning techniques is employed to analyze historical consumption data and predict future demand patterns (Mohsenian-Rad & Leon-Garcia, 2010). This predictive capability allows for proactive management of resources, ensuring that supply aligns with anticipated demand spikes.

2.1 Variable Load Model

In modern distribution systems, load controllers can react automatically to changes in the operating state of the network in terms of voltage variation. These controllers, such as load shedding and motor protection, may instruct the load to vary a parameter or disconnect from the network completely. Through communication with other load and network controllers these operations can be conducted in a more coordinated manner which may result in fewer improper load protections relay operations and improved load parameter tuning (Candelise & Mazzola, 2018).

In a distributed power system, the PQ model is used to represent a variable load. The PQ model stands for Voltage and Reactive Power Controlled Bus. It is one of the three primary types of buses in power systems, along with PV (Voltage and Active Power Controlled Bus) and the Slack Bus (or Swing Bus)

The PQ model for a variable load has several user interface inputs and outputs. The user interface inputs include enable/disable signals, power consumption references, rate of change of power references, and coefficients for power dependency on voltage and frequency variation. The user interface outputs include the converter enable/disable state, applied power and reactive power references, nominal power values, grid voltage frequency, grid voltage RMS value, and instantaneous values of active and reactive power output of the load (Mohsenian-Rad & Leon-Garcia, 2010; Srikantha & Kundur, 2017).

The three load currents are balanced, even under unbalanced load voltage conditions. The load impedance is kept constant if the terminal voltage V of the load is lower than a specified value V_{min}. When the terminal voltage is greater than the V_{min} value, the active power P and reactive power Q of the load vary as follows:

$$P(s) = P_o \left(\frac{V}{V_o}\right) n_p \frac{1+T_{p1}s}{1+T_{p2}s} \tag{2.1}$$

$$Q(s) = Q_o \left(\frac{V}{V_o}\right) n_q \frac{1+T_{q1}s}{1+T_{q2}s} \tag{2.2}$$

Where;

V_o = initial positive sequence voltage.

$P_o$and Q_o = initial active and reactive powers at the initial voltage Vo.

V = positive-sequence voltage.

n_p and n_q = exponents (usually between 1 and 3) controlling the nature of the load.

T_{p1} and T_{p2} = time constants controlling the dynamics of the active power P.

T_{q1} and T_{q2} = time constants controlling the dynamics of the reactive power Q.

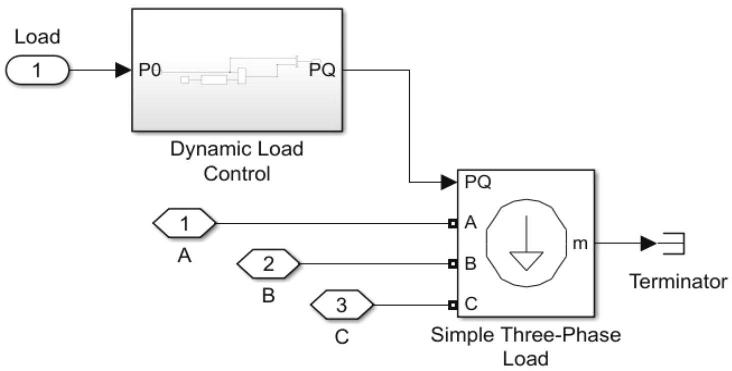

Figure 1: Distributed power system Variable load model.

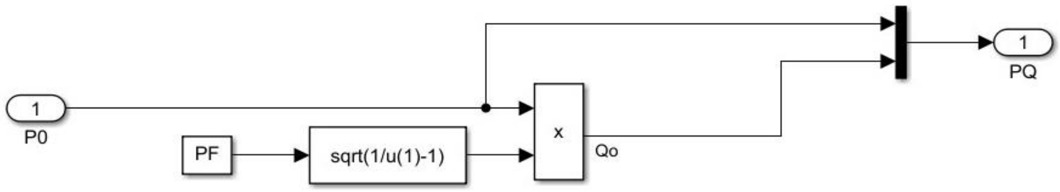

Figure 2: Dynamic Load Control Model.

2.2 Mathematical Model Framework

To justify staggered peak demand within distributed power networks using a mathematical model, this work develops a framework that incorporates demand response, distributed generation, and optimization techniques. Below is a simplified mathematical model illustrating the concepts used in this work.

This mathematical model provides a structured approach to understanding and implementing staggered peak demand strategies within distributed power networks. By optimizing the use of distributed generation, demand response, and energy storage, the work effectively manages peak demand and enhances the overall efficiency and reliability of the power system (Zhang et al., 2016; Zihao et al., 2021).

Variables

I. $P_d(t)$: Total demand at time t

II. $P_g^i(t)$: Power generated by distributed generation unit i at time t

III. $P_s(t)$: Power stored in energy storage systems at time t

IV. $P_r(t)$: Power available from demand response at time t

V. $P_{max}(t)$: Maximum allowable power demand at time t

An expression to minimize the total cost of electricity while ensuring that the power supply meets the demand is shown in equation 2.3.

Minimize $C = \sum_{i=0}^{T}\left(C_g P_g^i(t) + C_d\, P_d(t)\right)$ 2.3

Where:

- C_g : Cost per unit of generated power
- C_d: Cost per unit of demand response

Constraints

i. Supply-Demand Balance:

$$P_d(t) \leq \sum_{i=1}^{N} P_g^i(t) + P_s(t) + P_r(t) \qquad 2.4$$

Where N is the number of distributed generators.

ii. Peak Demand Management

$$P_d(t) \leq P_{max}(t) \qquad \forall t \qquad 2.5$$

iii. Energy Storage Dynamics:

$$P_s(t) = P_s(t-1) + \eta_{charge} P_g^i(t) - \frac{P_d(t) - \sum_{i=1}^{N} P_g^i(t)}{\eta_{discharge}} \qquad 2.6$$

Where ηcharge and ηdischarge are the charging and discharging efficiencies of the storage system.

iv. Demand Response Activation:

$$P_r(t) \leq D_r(\mathrm{t}) \quad \forall t \qquad 2.7$$

Where Dr(t) is the maximum demand response capacity available at time t.

Implementation Steps

1. **Load Forecasting**: Use historical data to forecast the load $P_d(t)$ at different times, especially during peak periods.
2. **Optimization Algorithm**: Implement the neural network optimization algorithm to solve the above objective function subject to the constraints. This helps to determine the optimal dispatch of distributed generation and demand response resources.
3. **Staggered Demand Response**: Schedule demand response events to activate selectively based on the load forecast for residential, commercial and industrial load demand on the power network across the day to effectively flattening the demand curve (National Academies of Sciences, Engineering, and Medicine, 2016; Zhao et al., 2024).

2.3 One-Line Diagram of the 33kv CRSWB Power Network

The one-line diagram in Figure 3 represents a power distribution network with the following parameters;

i. Voltage Levels: The network operates at two primary voltage levels - 33 kV and 0.415 kV, connected through transformers.

ii. Power Sources: The network has a single power source, U1, operating at 33 kV.

iii. Buses: There are 10 buses (Bus1 through Bus10) in the network, representing different points where power is consumed.

iv. Transformers: There are three transformers (T1, T2, T3) that step down the voltage from 33 kV to 0.415 kV, with ratings of 0.2 MVA, 0.3 MVA, and 1 MVA respectively.

v. Loads: The network has several loads connected at the 0.415 kV level, including lumped loads (Lump1, Lump2) and motors (Mtr1, Mtr2, Mtr3) with varying power ratings.

vi. Cables: The diagram shows five cables (Cable1 through Cable5) that interconnect the various buses and components in the network.

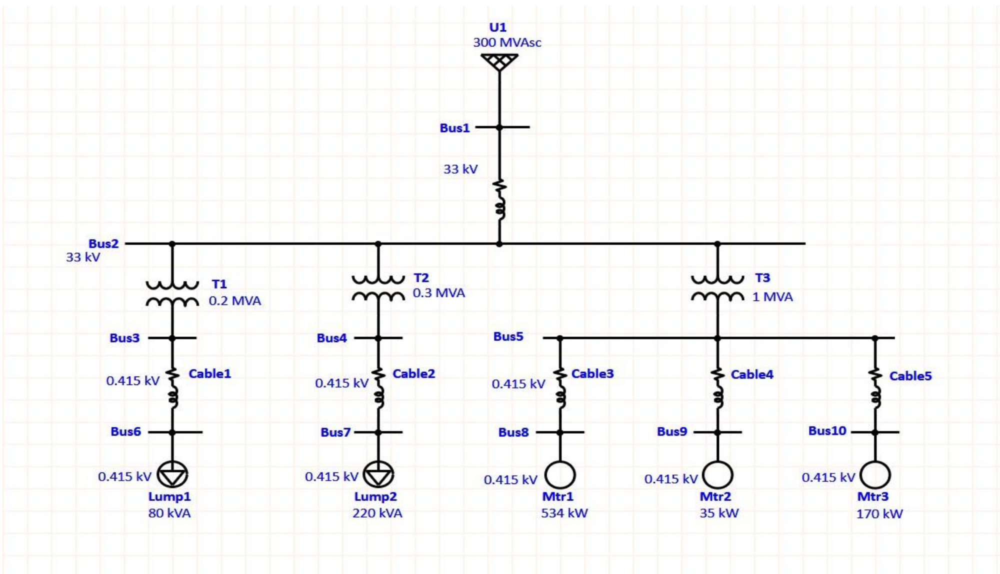

Figure 3: One-line diagram of 33kv CRSWB power network showing rating of equipment and their location.

2.3 Load Profile for Residential, Commercial and Industrial Consumer for CRSWB Power Network

I. Residential load profile

Figure 4 illustrates the power consumption (in kilowatts) for the residential load (Lump1) over a 24-hour period. The x-axis represents time in hours, while the y-axis shows the power usage.

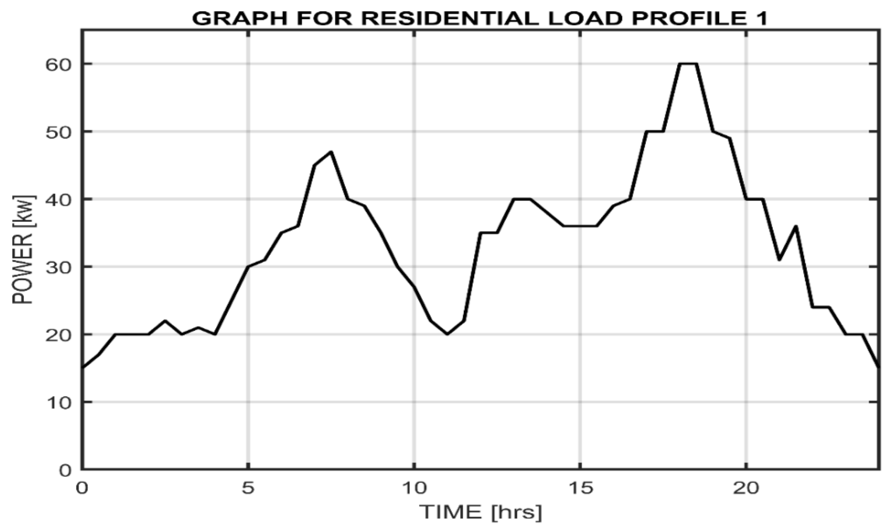

Figure 4: Graph for residential load profile.

Key observations:

- ✓ The power demand reaches its highest point (around 60 kW) during the evening hours (approximately between 17:00 and 20:00).
- ✓ There are lower consumption periods in the early morning and late night.
- ✓ The graph indicates fluctuating power usage throughout the day, typical of residential energy patterns influenced by activities such as cooking, heating, and lighting.

II. Commercial Load Profile

The commercial load profile in figure 5 illustrates the power consumption of a commercial facility (Lump2) connected to the network over a 24-hour period. The X-axis represents the time of day, typically starting from midnight (0 hrs.) to 24 hrs.

The Y-axis represents the power consumption in kilowatts (kW).

- ✓ Understanding this load profile is crucial for integrating distributed generation. It helps in predicting energy needs, optimizing operational efficiency, and planning for demand response strategies.
- ✓ The commercial load profile diagram effectively illustrates the power usage patterns of this commercial establishment, highlighting periods of high and low demand, which aided the determination of peak demand periods for this research.

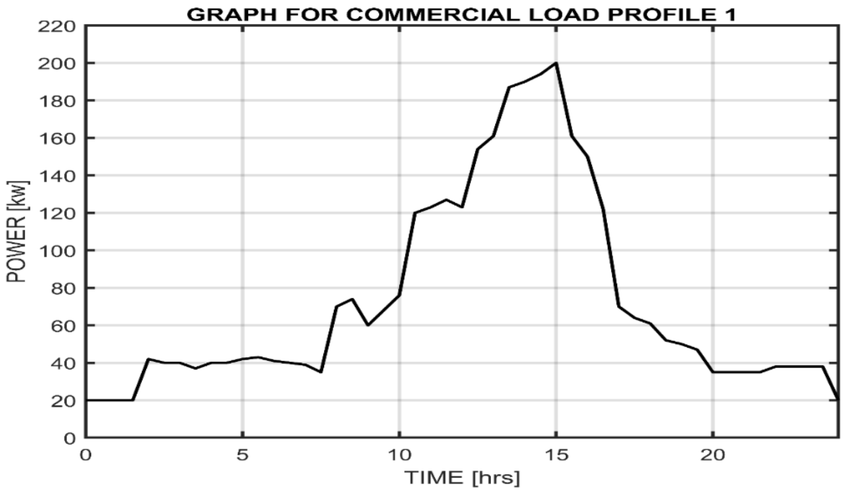

Figure 5: Graph for commercial load profile.

Key observations;

- ✓ The graph shows fluctuations in power usage throughout the day, which is typical for commercial operations.
- ✓ There is a noticeable peak in power consumption, during business hours. This peak corresponds to when the facility is most active, such as during work hours (often around 9 AM to 5 PM).
- ✓ The lower levels of power consumption observed before and after the peak indicate the base load, which represents the minimum level of demand when the facility is not fully operational.

The graph suggests that power consumption drops significantly during the late evening and night, indicating reduced activity and office closure.

III. Industrial Load Profile

The industrial load (Mtr1, Mtr2 & Mtr3) profile diagram in figure 6, 7, and 8, for the water treatment facility illustrates the power consumption over a 24-hour period. Detailed explanation, key features and implications are shown as follows:

The X-axis (Time (hrs.)) represents the time of day, typically from midnight (0 hrs.) to 24 hrs.

The Y-axis (Power [kW]): Indicates the power consumption in kilowatts (kW).

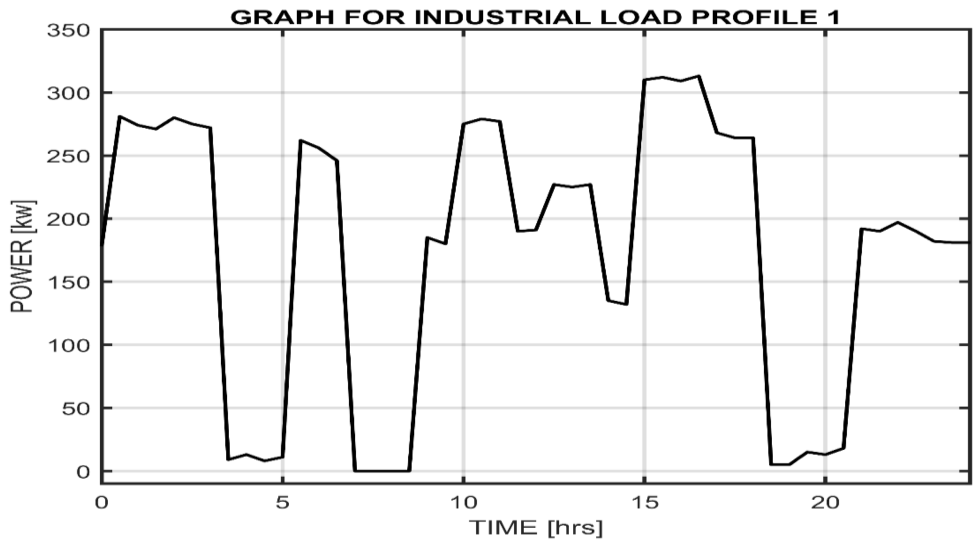

Figure 6: Graph for industrial load profile 1.

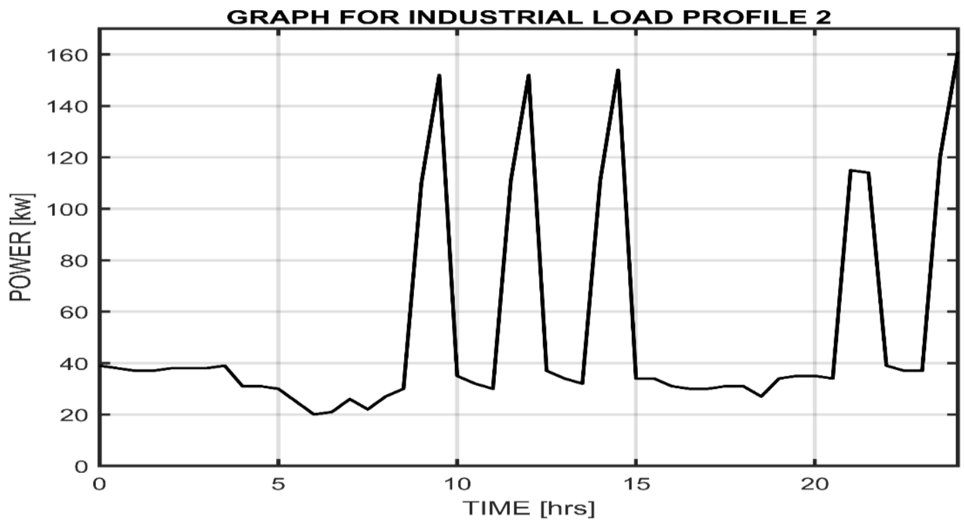

Figure 7: Graph for industrial load profile 2.

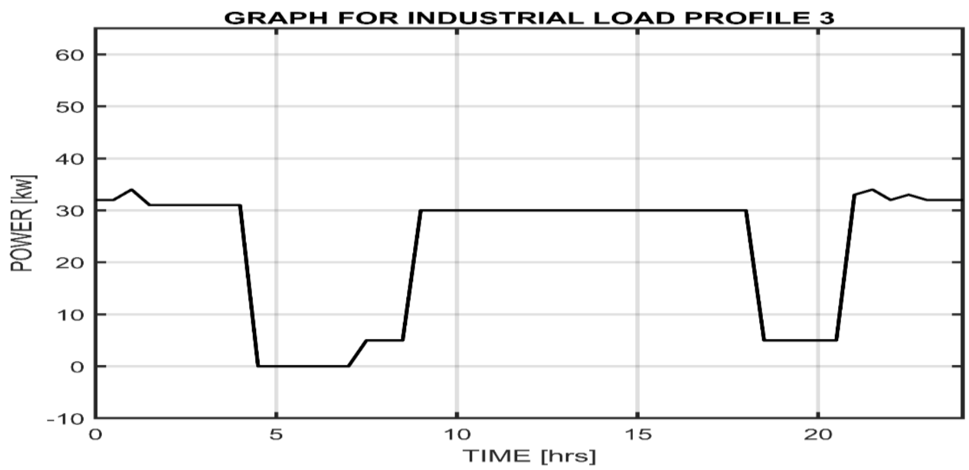

Figure 8: Graph for industrial load profile 3.

Key observation:

- ✓ The graph shows noticeable fluctuations in power usage, which is common for water treatment facilities due to varying operational demands throughout the day.
- ✓ The peaks in power consumption (around 250-300 kW) likely correspond to times when the facility is processing a higher volume of water, such as during daytime hours when demand for treated water is higher.
- ✓ There are periods where power consumption remains relatively stable, indicating continuous operation of pumps and filtration systems. These plateaus suggest that certain processes, like water pumping, filtration and filters back-washing or chemical dosing, are running consistently.
- ✓ Dips in power usage (around 100-150 kW) indicate times of reduced activity, during the night or early morning when water demand is lower. This can also be due to the facility's production schedule or reduced flow rates during off-peak hours.

The industrial load profile diagram for a water treatment facility provides valuable insights into its power consumption patterns, highlighting periods of high and low demand. This information is critical for optimizing operations, managing energy costs, and ensuring regulatory compliance.

IV. Load profile summary

Table 1: Summary of load type and their peak demand time.

S/n	Load type	Peak demand period
1	Residential	6:30 -8am, 5-8pm
2	Commercial	10am-3pm
3	Industrial	Staggered all day

2.4 Determination of Peak Demand Period

To enhance the distribution network ability to respond to staggered peak demand period, the peak demand period was determined from the aggregate load demand of the network. Figure 9 illustrates the total power consumption of the network across the day in line with the water treatment plants production schedule and the consumption pattern of the residential, commercial and industrial consumers. From the network in study, any period of the day where consumption breaks and stays above the 400kW mark is seen as a peak demand period. At 09.00hours the demand breaks the 400kW mark and hits a peak of about 600kW at 15.00 hours, then returns to the 400kW mark at 18.00hours. Therefore, the aggregate peak demand periods will occur between the hours of 09:00hours and 18:00hours as seen in figure 11. The aggregate staggered peak demand data was used to model the active and in-active time of the distributed generation in the network using the machine learning optimization approach (Neural Network).

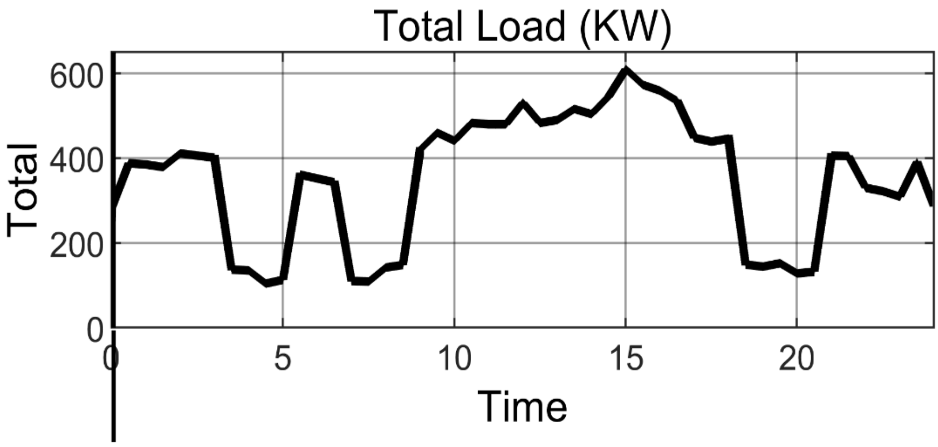

Figure 9: Total load profile of figure 4-8.

2.5 Neural Network Design, Training and Validation

This section details the design, training, and validation of a neural network controller for integrating distributed generation (DG) into a power system. A Bayesian regularization method was used to train the neural network model using historical data on load profiles (residential, commercial, industrial), network conditions, and DG performance. The model's architecture was designed to intelligently and adaptively control the DG system. The training process used 70% of the data, with 15% each for testing and validation. The resulting model as seen in figure 10 below, achieved high R-values (0.99187 for training, 0.99157 for testing, 0.99181 combined), indicating robust performance. Finally, the trained model was integrated into a Matlab Simulink model of the CRSWB power network with a 200kW solar DG system, demonstrating effective peak demand management and network stability during peak hours (9 am to 6 pm). The DG supplies approximately 33% of the network's total energy needs during this period.

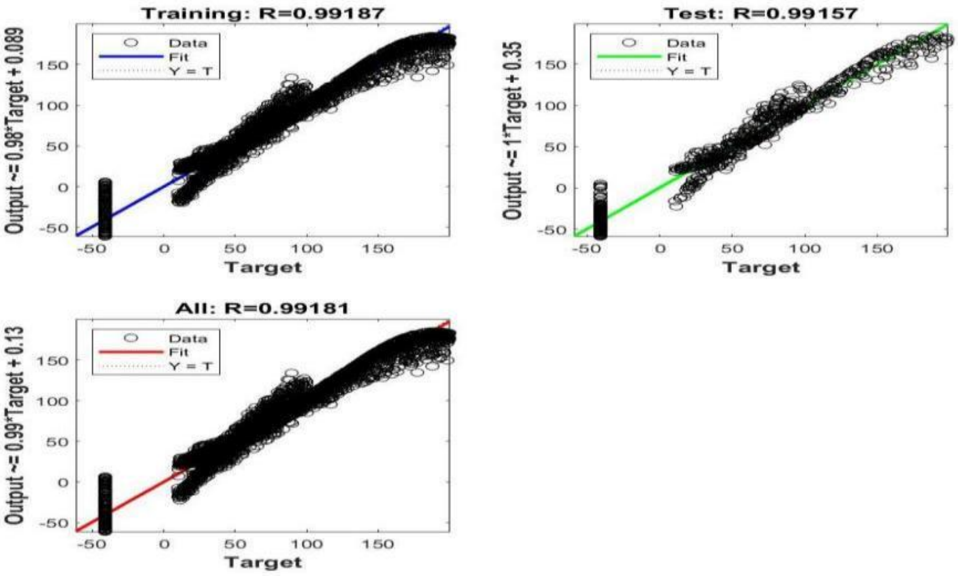

Figure 10: Result for Neural Network trained data.

2.6 Summary of DG Parameters

A solar powered DG for grid integration, designed with a capacity of 217.120kW representing about 33% of the total network daily load demand has the parameters below;

- ✓ P_m = 230 W
- ✓ V_m = 30 V
- ✓ I_m = 7.67 A
- ✓ Number of Series Panels (N_S) = 16
- ✓ Number of Parallel Strings (N_P) = 59
- ✓ Total Number of Panels = 944
- ✓ Total PV Voltage = $V_{Total} = N_S \times V_m$ = 16 × 30 = 480 V
- ✓ Total PV Current = $I_{Total} = N_P \times I_m$ = 59 × 7.67 = 452.5 A

3.0 RESULTS AND DISCUSSION

The methodology is multifaceted: First, the research models the peak demand periods of a specific distribution network (33 kV CRSWB network) by characterizing the load profiles of its residential, commercial, and industrial consumers, identifying their distinct peak times. These individual load profiles are then aggregated to determine the overall staggered peak demand for the entire network. This aggregated data is crucial for the next step: integrating a grid-tied distributed generation (DG) system controlled by a neural network. The neural network is trained using this aggregated data to intelligently manage the DG's output, optimizing its contribution to the grid as illustrated in Figure 11.

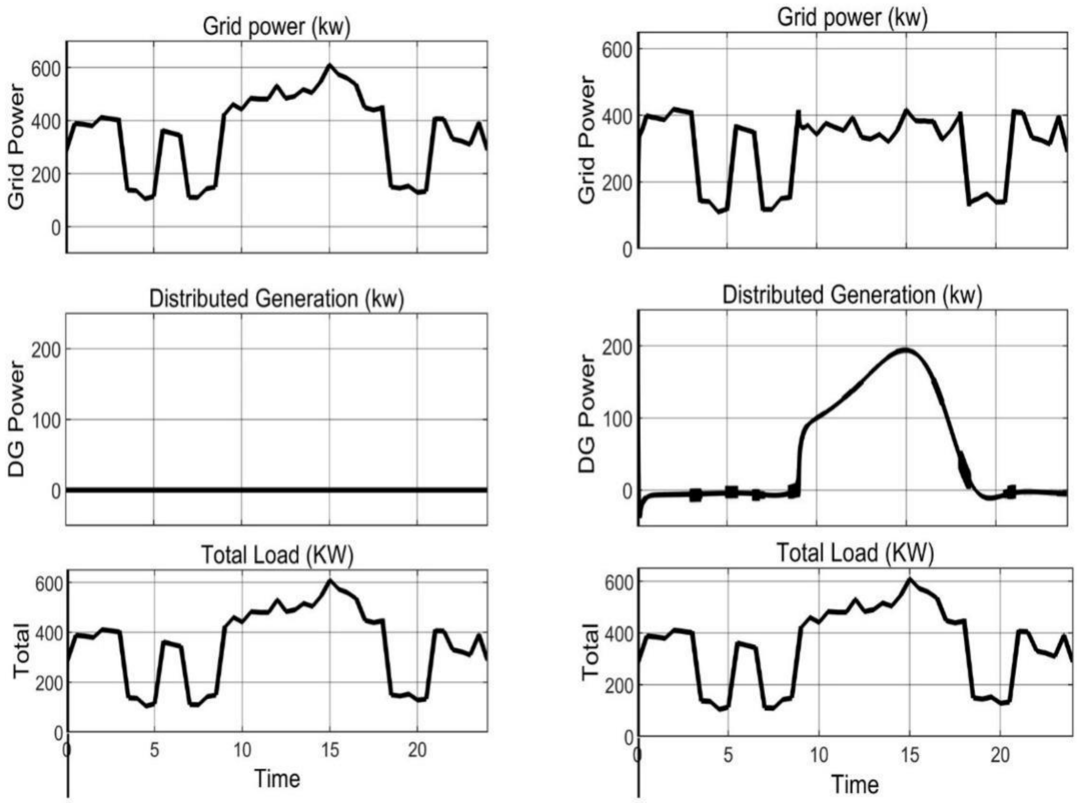

Figure 11: Traditional and grid-tied distributed generation (DG) network.

Traditional Network (Left Column):

i. Grid Power: The grid power profile (top left) exhibits significant fluctuations throughout the day, directly reflecting the combined, varying demands of all connected loads. Peaks and valleys correspond to periods of high and low aggregate demand.

ii. Distributed Generation (DG): DG power is zero (middle left), indicating the absence of any local generation. The grid solely supplies all electricity needs.

iii. Total Load: The total load profile (bottom left) mirrors the grid power profile, as the grid meets the entire demand.

Distributed Generation Network (Right Column):

i. Grid Power: The grid power profile (top right) shows a significantly reduced fluctuation compared to the traditional system. The peaks and valleys are less pronounced. This indicates that the DG system is effectively smoothening the overall load profile.

ii. Distributed Generation (DG): The DG power profile (middle right) shows a distinct peak during the middle of the day, consistent with a renewable energy source like solar PV. The DG output actively responds to the overall load demand.

iii. Total Load: The total load profile (bottom right) remains relatively similar in shape to the traditional system's total load, reflecting the unchanged individual load demands. However, the grid's contribution to meeting this total load is substantially reduced.

Impact of Staggered Peak Demand on the Traditional and Distributed Power Networks Results

The power system network with aggregate residential, commercial, and industrial load profiles shown in figure 11 exhibits peak demand periods at different times of the day. The different load profiles of the residential, commercial, and industrial consumers within the network have a significant impact on the overall system dynamics discussed as follows;

i. Diversity in Peak Demand: The diverse peak demand periods across the different load types help to flatten the overall system load profile. This diversity reduced the maximum power required from the grid; hence the network peak load demand is always less than the sum of peak demands from the individual load profiles in the network, this leads to optimization in system efficiency and cost savings.

ii. Distributed Generation Integration: The midday peak in DG power output coincides with the peak demand periods for the aggregate loads in the test distribution network. This alignment facilitates the integration of DG into the power system, as the excess DG power is utilized to meet the load demands during these periods.

iii. Load Scheduling Opportunities: The varying peak demand periods across the load types provide opportunities for load shifting and demand-side management strategies. By incentivizing consumers to shift their loads to off-peak periods, the overall system load profile can be further optimized, reducing the need for expensive peaking power generation and potentially deferring infrastructure investments.

iv. Demand Response Potential: The staggered load profiles also create opportunities for effective demand response programs. By targeting specific load types during their peak demand periods, the system operator can implement targeted load reduction or shifting strategies to better manage the overall system load and grid stability.

The advanced control technique employed in this work to analyze and manage these load profiles has led to improved system efficiency, enhanced grid stability, better integration of distributed generation and minimal operational costs.

The research addresses the challenge of managing fluctuating peak demand in power grids, a problem exacerbated by increasing renewable energy integration. Traditional grids struggle with these fluctuations, resulting in inefficiencies and reliability issues. The research has proposed a novel solution which leverages the naturally staggered peak demands of different load types (residential, commercial, and industrial) within distributed power networks (DPNs).

The effectiveness of this approach is evaluated by comparing the grid profile of the original system (without DG) to the system with the integrated, neural network-controlled DG. The key finding is a significant reduction in peak demand: simply by leveraging the staggered peaks, the maximum power required from the grid dropped from 1039 kW to 600 kW. Integrating the DG system further reduced this to approximately 400 kW. This reduction translates to improved system efficiency and cost savings due to reduced strain on grid infrastructure and potentially less reliance on expensive peaking power plants. The reduced reliance on the main grid also enhances its resilience, although this benefit isn't explicitly quantified in the study. The research utilized several key techniques: a PQ (Voltage and Reactive Power Controlled Bus) model to represent variable loads, incorporating high-level and low-level control subsystems; an ETAP one-line diagram to visually represent the 33 kV CRSWB power network; a neural network controlled by a Bayesian regularization method (achieving high R-values around 0.99) for DG system control; and Matlab Simulink for simulating the system's performance.

The study makes several significant contributions as it proposes a novel approach to peak demand management; it demonstrates the effectiveness of this approach in reshaping the grid profile without load disconnections; it showcases successful DG integration using a neural network; and it demonstrates the potential for significant improvements in grid efficiency, resilience and cost savings. Despite promising results, limitations exist. The findings are based on a single distribution network, requiring further research to assess the generalizability of the approach. The study is simulation-based, necessitating investigation into real-world implementation challenges. Exploring more sophisticated control strategies beyond the neural network could further optimize DG integration and peak demand management. Finally, a detailed economic analysis, including DG implementation costs and long-term benefits, would strengthen the findings.

4.0 CONCLUSION

This research has evaluated managing peak demand in distributed power networks (DPNs) by exploiting the naturally staggered peak demands of residential, commercial, and industrial loads. A model of an existing network was developed, incorporating individual load profiles to determine the aggregate staggered peak demand. This data was then used to train a neural network controlling a grid-tied distributed generation (DG) system. Simulation results showed a significant reduction in peak demand – from 1039 kW to 600 kW simply by leveraging the staggered peaks, and further to approximately 400 kW with the integrated DG system. This demonstrates improved grid efficiency and cost savings, while providing a strong foundation for future research and practical applications aimed at optimizing energy consumption patterns and strengthening grid resilience.

5.0 REFERENCES

1. Candelise, C., & Mazzola, M. (2018). Modeling the impact of demand response strategies on power system dynamics. *IEEE Transactions on Power Systems, 33*(2): 1454-1462. https://doi.org/10.1109/TPWRS.2017.2753024
2. Chen, T., Liu, Y., & Zhang, H. (2021). Agent-based modeling for decentralized demand-side management in heterogeneous prosumer networks. *Applied Energy, 285*, 1-15.
3. D'Aguanno, G., & Nardone, A. (2020). Distributed generation and demand response for efficient grid management. *Renewable Energy, 145*: 123-134. https://doi.org/10.1016/j.renene.2019.06.059
4. Fell, M. J., Shipworth, D., & Huebner, G. M. (2020). Public acceptability of demand-side management strategies: A review and future directions. *Energy Policy, 140*: 1-12.
5. Gamarra, C., Guerrero, J., & Leite, F. (2020). Real-time feedback mechanisms for dynamic load management in distributed power networks. *Energy Policy, 140*: 1-12.
6. Hussain, A., Arif, M., & Ali, S. M. (2022). Vehicle-to-grid (V2G) integration for peak demand management: Challenges and opportunities. *Renewable and Sustainable Energy Reviews, 156*: 1-14.
7. Li, Q., Zhang, J., & Wang, R. (2021). Game-theoretic approaches for demand-side management in distributed power networks. *IEEE Transactions on Power Systems, 36*(2): 1234-1245.

8. Liu, H., & Zhang, L. (2019). Peak load shaving through intelligent demand response in smart grids: A review. *Energy Reports, 5*: 239-247. https://doi.org/10.1016/j.egyr.2019.09.005
9. Mengelkamp, E., Gärttner, J., & Weinhardt, K. (2021). Blockchain-based peer-to-peer energy trading for decentralized demand-side management. *Nature Energy*, *6*(5): 452-461.
10. Mohsenian-Rad, A. H., & Leon-Garcia, A. (2010). Optimal and autonomous incentive-based energy consumption scheduling for smart grid. *IEEE Transactions on Smart Grid, 1*(3): 120-130. https://doi.org/10.1109/TSG.2010.2052281
11. National Academies of Sciences, Engineering, and Medicine. (2016). *Analytic research foundations for the next-generation electric grid*. The National Academies Press. https://doi.org/10.17226/21919
12. Nguyen, T., & Le, H. (2019). Hybrid solar-storage systems for peak shaving in distributed power networks. *Energy Conversion and Management*, *185*: 1-10.
13. Singh, A. R., Kumar, R. S., Bajaj, M., & Zaitsev, I. (2024). Machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources. *Scientific Reports, 14*: Article 19207. https://doi.org/10.1038/s41598-024-19207-1
14. Smith, J., Brown, A., & Lee, C. (2020). Demand-side management through time-varying pricing in microgrids. *Applied Energy*, *260*: 114-123.
15. Srikantha, P., & Kundur, D. (2017). Resilient distributed real-time demand response via population games. *IEEE Transactions on Smart Grid, 8*: 2532-2543. https://doi.org/10.1109/TSG.2016.2526651
16. Wang, L., Chen, H., & Zhang, M. (2023). Optimization of distributed energy resources for peak shaving in residential microgrids. *Renewable and Sustainable Energy Reviews, 145*: 111-123.
17. Zhang, X., Shahidehpour, M., Alabdulwahab, A., & Abusorrah, A. (2016). Hourly electricity demand response in the stochastic day-ahead scheduling of coordinated electricity and natural gas networks. *IEEE Transactions on Power Systems*, *31*: 592-601. https://doi.org/10.1109/TPWRS.2015.2390632
18. Zhang, Y., Wang, X., & Liu, Z. (2021). Reinforcement learning-based demand-side management for optimal load scheduling in smart grids. *IEEE Transactions on Smart Grid*, *12*(3): 2345-2356.

19. Zhao, W., Deng, Z., Ji, Y., Song, C., Yuan, Y., Wang, Z., & Chen, Y. (2024). Analysis of peak demand reduction and energy saving in a mixed-use community through urban building energy modeling. *Energies, 17*(5): 1214.
20. Zhou, Y., Li, X., & Wang, H. (2022). Privacy-preserving IoT frameworks for demand-side management in smart grids. *IEEE Internet of Things Journal, 9*(4): 2567-2578.
21. Zihao, Z., Zhang, R., Wang, L., Zeng, S., & Li, Y. (2021). Optimal operation of regional integrated energy system considering demand response. *Applied Thermal Engineering, 191*: 116860. https://doi.org/10.1016/j.applthermaleng.2021.116860
22. Zulu, E., & Jayaweera, D. (2013, September 29-October 3). *Reliability of active distribution networks with PV based strategic micro-grids* [Conference paper]. Proceedings of the Australasian Universities Power Engineering Conference (AUPEC), Hobart, TAS, Australia.