ML-Driven Distribution Network Aggregation Considering Load and IBR Voltage-Dependency

2nd
Department of
Habib University
Karachi, Pakistan
email

3rd
Department of
Habib University
Karachi, Pakistan
email

Rubab Shah
Department of Computer Science
Habib University
Karachi, Pakistan
rs08104@st.habib.edu.pk

Dr. S. M. Hur Rizvi
Department of Electrical & Computer Engineering
Habib University
Karachi, Pakistan
hur.rizvi@sse.habib.edu.pk

***Abstract*—The integration of distributed generation sources, such as photovoltaic (PV) systems and battery energy storage systems (BESS), is revolutionizing traditional power distribution networks, presenting new challenges in grid management due to the dynamic and bidirectional flow of electricity. Accurate estimation of power system parameters is essential for optimizing performance and maintaining grid stability; however, existing methods often suffer from inadequate datasets that fail to reflect the complexities introduced by these advanced technologies. This research addresses this gap by leveraging modern machine learning (ML) techniques to enhance the accuracy of parameter estimation for network aggregation in active distribution networks.Using the IEEE 33-bus system and incorporating control modes as defined under the IEEE 1547 standard, we developed a robust data generation framework. This framework utilizes OpenDSS simulations and automated data extraction methods to create comprehensive and diverse datasets, represented as rank-3 tensors of inhomogeneous shape. These datasets were employed to train ML models capable of predicting key parameters, including voltage per unit, active power loss, reactive power loss, new ZIPV parameters, and power bases across various operational scenarios. Our findings demonstrate that the ML models achieved a mean squared error (MSE) as low as 0.015 for the loads-only model and 0.014 for the PV-BESS system, highlighting the potential for high prediction accuracy in real-world applications.**

***Index Terms*—Machine Learning, Distributed Energy Resources (DERs), Network Aggregation, IEEE 33-Bus System, Parameter Estimation**

I. INTRODUCTION

The evolution of power systems from the early to the late twentieth century was largely characterized by a centralized structure, where electricity was generated at large scale and then transmitted to major load centers. This approach was efficient for the technology and energy needs of the time. However, as we entered the 21st century, the energy landscape began to shift significantly due to a growing emphasis on renewable energy resources. This shift led to a fundamental transformation in the architecture of power systems, moving away from centralized generation towards a more distributed and decentralized model [1]. This change was driven by the integration of various renewable energy sources, such as wind and solar power, which are inherently distributed. The increasing adoption of renewable energy sources, especially photovoltaic (PV) systems, has introduced both challenges and opportunities for the power grid [2]. Distributed generation, where electricity is produced closer to consumption points, has transformed grid management by requiring new strategies to handle complex and dynamic power loads [3].

Digital advancements, such as Phasor Measurement Units (PMUs) and smart meters, have revolutionized how power systems are monitored and controlled [4]. These devices provide real-time data, giving grid operators detailed insight into network power flow. PMUs monitor electrical waves to assess grid health, while smart meters offer precise consumption data, enabling operators to manage grid operations in real-time better [5]. Real-time visibility enables more accurate grid monitoring and quicker responses to anomalies, enhancing efficiency and reliability in power system operations [4]. With the growing integration of renewable energy sources and smart loads, such as PV systems and Electric Vehicles (EVs), grid management has become more unpredictable, requiring advanced strategies to address the fluctuating nature of modern energy systems [3].

Power system loads are often modeled to tackle these challenges based on their dependence on voltage and frequency [3]. The ZIP load model, which represents loads as a combination of constant impedance (Z), current (I), and power (P), is widely used for forecasting load behavior under varying conditions [5]. The coefficients for each load type in the ZIP model; az (constant impedance), ai (constant current), and ap (constant power) are essential for understanding how loads respond to voltage and frequency changes. Moreover, the IEEE 1547 standard outlines control modes like Volt-VAR and Volt-WATT, crucial for integrating distributed energy resources [2].

Traditional power systems, primarily designed for unidirectional energy flows, struggle to manage the dynamic, bidirectional power exchanges introduced by DERs. The variability in energy production and consumption adds further challenges to grid stability, making accurate estimation of key parameters like voltage and power loss essential for efficient grid operations [4]. Despite the advancements in digital monitoring technologies, existing estimation methods often fall short in capturing the complexities of these modern, distributed networks. Machine learning (ML) techniques present a promising solution to this problem by enabling more precise and scalable parameter estimation, which can significantly improve grid resilience and operational efficiency [6].

In this research, we present a machine learning framework designed to determine the reduced aggregate of distribution network or a critical sub-network. Using extensive simulations and data-driven techniques, we tackle the challenge of aggregating networks using machine learning. Our key contributions include:

1) **Enhanced Parameter Estimation:** We propose a machine learning approach that improves the accuracy of grid parameter estimations, such as voltage per unit and power losses, using the IEEE 33-bus system.
2) **Data Generation Framework:** A novel method utilizing OpenDSS simulations generates diverse datasets reflecting realistic grid conditions, including load-only and PV-BESS systems.
3) **Integration of IEEE 1547 Control Modes:** By incorporating control modes like Volt-VAR and Volt-WATT, our model ensures effective management of distributed energy resources.
4) **High Prediction Accuracy:** Our models achieve mean squared errors of 0.015 (load-only) and 0.014 (PV-BESS), demonstrating potential for real-world application.
5) **Network Aggregation Techniques:** We explore methods to simplify distribution network modeling while maintaining accuracy in predicting operational parameters.

II. Background

Accurate modeling of load behavior is crucial for maintaining stability and efficiency in modern power distribution networks, particularly with the shift from centralized to decentralized structures. This shift, driven by renewable sources like photovoltaic (PV) systems and battery energy storage systems (BESS), has transformed traditional operations. The unidirectional flow of energy has now evolved into complex bidirectional flows, introducing new challenges for control and management.

A popular approach to model these loads is the ZIP load model, which combines constant impedance (Z), constant current (I), and constant power (P) components. This model effectively captures the behavior of loads under fluctuating voltage conditions, which is especially critical in networks with distributed energy resources (DERs). By adjusting the proportions of Z, I, and P, the model allows for precise estimations of how loads will respond to voltage fluctuations, facilitating dynamic voltage and power management.

The IEEE 1547 standard further enhances grid management by offering control modes such as Volt-VAR and Volt-Watt, which optimize grid performance by regulating reactive and real power based on voltage levels. However, traditional methods of parameter estimation struggle to capture the dynamic behavior of DERs and load variability, necessitating more advanced solutions.

This is where machine learning (ML) techniques, particularly Long Short-Term Memory (LSTM) networks, offer a promising alternative. LSTM networks are well-suited for time-series prediction, capturing the temporal dependencies that are essential for forecasting operational metrics like voltage and power loss. Integrating these techniques with the ZIP load model and IEEE 1547 control modes presents an opportunity to enhance parameter estimation, improving grid resilience and operational efficiency.

III. Methodology

A. *Research Design*

This research explores the potential of machine learning for distribution network aggregation considering load, PV, and BESS systems by following the design specified in *Fig.1*.

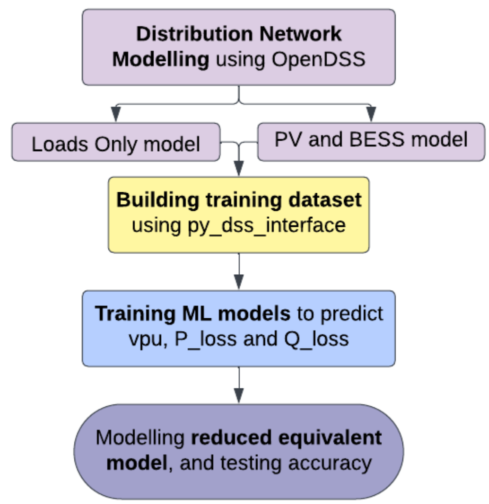

Fig. 1. Summary of Methodology

A reduced equivalent model is simulated for the loads-only system, as shown in *Fig.2*. The IEEE 33-bus system

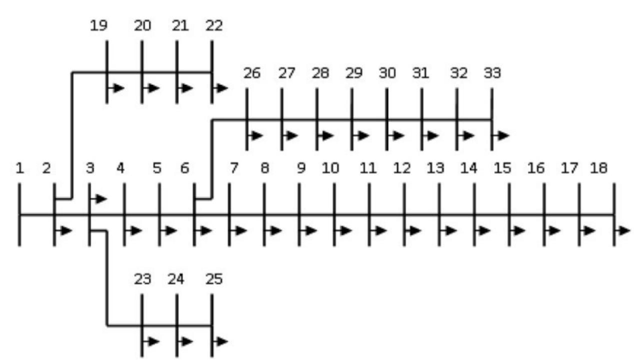

Fig. 2. IEEE 33 Bus System with loads only

was considered as the test network. OpenDSS was chosen for its ability to handle diverse power system configurations, renewable resources, and its compatibility with Python for automation. By simulating the distribution system, operational parameters like power, current, and voltage are generated and used as features in the ML model to predict parameters for a reduced aggregated network model, as illustrated in *Fig.3*, for each branch in *Fig.2*. Only magnitudes of the parameters are considered for simplicity, as phase angle differences can be ignored in a balanced system.

Mean Squared Error (MSE) will serve as the error metric to evaluate the accuracy of the ML model. MSE will also validate the reduced model's parameters by comparing them with those from the original simulated model. A low MSE score would indicate the effectiveness of ML in estimating operational parameters. This research design allows for systematic data generation and analysis, essential for training accurate ML models. The automation process facilitates efficient data generation while the simulations cover various real-world conditions.

For detailed analysis, branch with loads 6-18, the longest branch in the IEEE 33-bus system in *Fig.2*, were selected. This choice provides a representative dataset covering a significant portion of the network and captures a broad range of operational conditions and parameters.

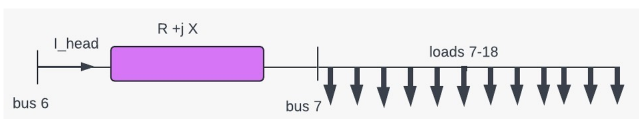

Fig. 3. Reduced Equivalent of branch 6-18 by Network Aggregation

B. Data Generation & Collection

1) Data Generation in OpenDSS: Data for this study was generated by simulating two modified IEEE 33-bus distribution systems in OpenDSS, forming the basis for a simulation-based approach.

The loads-only system operated at a base frequency of 50 Hz and included transformers, lines, and loads. The network, consisting of 33 buses interconnected by lines and transformers, featured a new circuit initialized with a base voltage of 150 kV in a three-phase system, with the source bus as the main power source. A step-down transformer (T1) reduced the voltage from 150 kV to 12.66 kV at bus 1, with a wye connection on the primary side and a delta connection on the secondary side. Transformer parameters included a 0.05% winding resistance and 6% reactance.

Lines with varying resistance and reactance connected the buses, facilitating power flow across the network. Loads, modeled using the ZIPV model, were placed at various buses and characterized by active power (kW), reactive power (kVAR), and voltage. The control mode was set to static, and the simulation ran in snap mode.

The PV and BESS system followed a similar configuration but included distributed energy resources (DERs), such as photovoltaic systems and battery energy storage systems (BESS). The DERs were strategically placed in the network as follows:

- **Wind turbines** Connected at buses 7, 10, and 18 with power ratings of 150 kW, 60 kW, and 70 kW, respectively, operating with a power factor of 0.85.
- **Battery Energy Storage Systems** Placed at buses 15 and 13, with a rated power of 50 kW, 1000 kWh energy storage capacity, and a maximum reactive power support of 600 kVAR, operating under Volt-VAR control to manage voltage levels.
- **PV System** Connected at bus 9, with a power rating of 500 kW, also operating under Volt-VAR control for voltage stability.

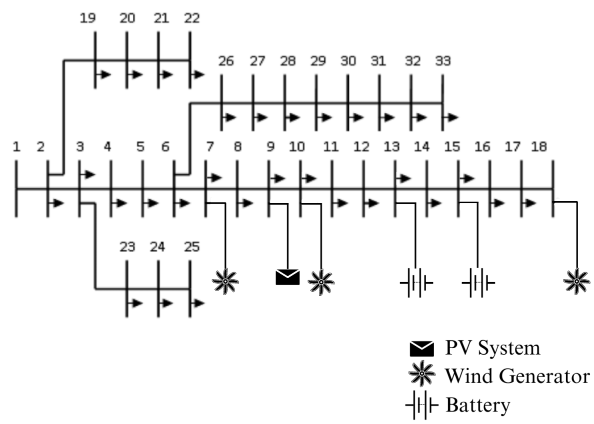

Fig. 4. IEEE 33 Bus System with PV & BESS system

The voltage levels were set to 12.66 kV and 150 kV to maintain consistency with IEEE 33-bus standards. Simulations were conducted in daily mode with a one-hour time step over 12 hours, allowing detailed monitoring of battery charge and discharge cycles. Data from these simulations were collected for further analysis.

2) Data Extraction: Data extraction was automated using a Python script with the libraries py_dss_interface, pathlib, numpy, and pandas. Pathlib facilitated access to the modeled .dss files, while py_dss_interface provided control over OpenDSS commands within Python.

For the load-only model, the extracted parameters included ZIPV, active power (P_b in kW), reactive power (Q_b in kVar), voltage per unit (vpu) for each load, and active power loss (P_{loss}), reactive power loss (Q_{loss}) of each line section, and current at the head (*I_head*) of the branch. P_{loss}, and Q_{loss} were calculated by subtracting the power at the receiving end (bus2) from the sending end (bus1) of each line section. Voltage per unit (vpu) was derived by dividing the load voltage magnitude by the base voltage.

In the PV and BESS model, additional parameters included stored efficiency, state (charging = 1, discharging = 0), active power output of the batteries, and PV irradiance. These parameters were crucial for capturing the interactions between distributed energy resources (DERs) and the

distribution network.
The extracted features (ZIPV, P_b, Q_b, vpu, P_{loss}, Q_{loss}, *I_head*) provided essential insights into load dynamics, power flow, and losses, while the additional DER-related parameters enhanced understanding of energy storage and generation behavior.

3) Building Training Dataset: To create the training dataset for the loads-only model, `numpy` was used to generate unique random magnitudes for the ZIPV parameters, active power (P_b), and reactive power (Q_b). Both P_b and Q_b were varied between 50-150% of their original values, while the ZIPV parameters were adjusted to ensure that the sums of active and reactive components ($a_z + a_I + a_P = 1$ and $r_z + r_I + r_P = 1$) remained valid. These modifications affected parameters like voltage per unit (vpu), power losses ($P_{\text{loss}}, Q_{\text{loss}}$), and current at the head of the branch (*I_head*).
For the PV and BESS models, additional parameters such as stored efficiency (0-100%), battery state (0 or 1), power output (up to battery capacity), and irradiance (0-1) were varied.
The datasets were stored as 3D tensors with 5000 entries to ensure sufficient data for training and testing the ML models. These arrays were later converted to `pandas` dataframes and saved as Excel files for further processing.

C. Data Analysis:

1) Preparing Tensors For Analysis: In this research, the TensorFlow library is utilized for machine learning. The dataset is first read from Excel into numpy arrays due to its inhomogeneous shape and then split into input and output features for training the ML model, which predicts voltage per unit (vpu), active power loss (P_{loss}), and reactive power loss (Q_{loss}).
For the loads-only model, the X_features for predicting vpu, P_loss, and Q_loss, are ZIPV, active power kW, reactive power kVar as shown in *Table.1*

The ZIPV parameters, active power (P_b), and reactive power (Q_b) were chosen because they capture essential aspects of load dynamics, voltage stability, and power quality, which directly affect vpu, P_{loss}, and Q_{loss}. These predictions facilitate network aggregation, allowing the calculation of equivalent resistance (R) and reactance (X), and simplified modeling of the distribution network.

For the PV and BESS models, additional features like battery efficiency, state of charge, active power output, and irradiance were included. The tensor format is similar to the loads-only model but with these additional parameters to account for the variability introduced by distributed energy resources as shown in *Table.1*

2) Training and Validation Data Split: The dataset was split into training and validation sets using `sklearn`'s `train_test_split` library, with 80% of the data used for training and 20% reserved for testing.

3) Machine Learning Model: For predicting v_{pu}, P_{loss}, and Q_{loss} in both the loads-only and PV/BESS models, a

Features	Loads Model X/Y	PV BESS X/Y
load ZIPV	X	X
load kW	X	X
load kVar	X	X
load VPU	Y	Y
line P_{loss}	Y	Y
line Q_{loss}	Y	Y
I_{head}	✓	✓
battery eff%	-	X
battery state	-	X
battery kW	-	X
PV Irradiance	-	X

TABLE I
X AND Y FEATURES INCLUDED IN LOADS-ONLY AND PV BESS MODELS

sequential neural network was built using TensorFlow's Keras library. The model architecture, illustrated in *Fig.5* and *Fig.6*, is specifically designed for time-series prediction tasks and consists of the following layers:

1) **Input Layer**: This layer is shaped to match the training data (x_{train}), ensuring proper input format.
2) **LSTM Layers**: The model incorporates two Long Short-Term Memory (LSTM) layers, each with 64 units to effectively capture temporal dependencies in the data:
   - The first LSTM layer processes input sequences and returns the full sequence to the next LSTM layer.
   - The second LSTM layer continues processing the sequence output.
3) **Time-Distributed Dense Layers**: Following the LSTM layers, the model includes two TimeDistributed dense layers:
   - The first layer contains 32 neurons and uses the ReLU activation function to capture complex patterns.
   - The second layer outputs a shape matching the target data (y_{train}).

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 12, 64)	18,944
lstm_1 (LSTM)	(None, 12, 64)	33,024
time_distributed (TimeDistributed)	(None, 12, 32)	2,080
time_distributed_1 (TimeDistributed)	(None, 12, 3)	99

Total params: 54,147 (211.51 KB)
Trainable params: 54,147 (211.51 KB)

Fig. 5. Loads only ML Model Summary

The model is compiled using the Adam optimizer with a learning rate of 0.001 and mean squared error (MSE) as both the loss function and performance metric to assess prediction accuracy. Early stopping is applied to prevent overfitting, halting training when validation loss no longer improves, with patience of 10 epochs. Overfitting occurs when the model starts to memorize training data rather than generalize to unseen data, so early stopping helps prevent this. The best

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 12, 64)	20,736
lstm_1 (LSTM)	(None, 12, 64)	33,024
time_distributed (TimeDistributed)	(None, 12, 32)	2,080
time_distributed_1 (TimeDistributed)	(None, 12, 3)	99

Total params: 55,939 (218.51 KB)
Trainable params: 55,939 (218.51 KB)
Non-trainable params: 0 (0.00 B)

Fig. 6. PV & BESS ML Model Summary

weights are restored to retain optimal parameters for validation performance.

Hyperparameters such as 50 epochs and a batch size of 32 were chosen to balance model complexity, efficiency, and accuracy after iterative tuning.

4) Network Aggregation: For the loads-only model, the predicted values of vpu, P_{loss}, and Q_{loss} were further utilized to calculate the overall active and reactive power losses, resistance (R), reactance (X), as well as the new base powers P_b, Q_b, and updated ZIPV parameters for the loads in the branch 6-18.

According to Joules Law it is known that power dissipated (P) from a circuit is $P = I^2R$, where I and R are current and resistance, respectively.

To calculate the resistance R, we utilized the active power losses in the formula.

$$R = \frac{P_{\text{loss}}}{I^2} \tag{1}$$

For calculating the reactance X, we utilized the reactive power loss in the formula:

$$X = \frac{Q_{\text{loss}}}{I^2} \tag{2}$$

Since the entire branch 6-18 is reduced to lines 6-7, the line-to-line voltage at the receiving end of lines 6-7 in the reduced network model needs to be calculated using the predicted parameters.

For the line-to-line voltage (V_{LL}) at the sending end (bus 6), we used the following formula:

$$V_{\text{LL}}(S) = V_{\text{base}} \times VPU_{\text{bus6}} \tag{3}$$

$$V_{\text{LL}}(S) = 12.66 \times VPU_{\text{bus6}} \tag{4}$$

Since the model is a balanced 3-phase system, the line-to-neutral voltage at the sending end, $V_{\text{LN}}(S)$ is given by:

$$V_{\text{LN}}(S) = \frac{V_{\text{LL}}(S)}{\sqrt{3}} \tag{5}$$

Now, the line-to-neutral voltage at the receiving end $V_{\text{LN}}(R)$ can be calculated using $V = IR$:

$$V_{\text{LN}}(R) = V_{\text{LN}}(S) - I(R + jX) \tag{6}$$

The per-unit voltage at the receiving end is then given by:

$$V_{\text{LN}}(R)pu = \frac{V_{\text{LN}}(R)}{V_{\text{base}}/\sqrt{3}} \tag{7}$$

Once the new per-unit V_{LN} is predicted, the new ZIPV parameters, along with the new active and reactive power bases (P_b and Q_b), needs to be predicted for each branch. Base power at the load can be calculated by:

$$P = P_b \left(a_z V^2 + a_i V + a_p\right) \tag{8}$$

Since we aim to achieve the reduced equivalent model:

$$\begin{aligned} P'_b \left(a'_z (V_{\text{LN}}(R)_{\text{pu}})^2 + a'_i (V_{\text{LN}}(R)_{\text{pu}})\right) \\ = P_b \left(a_z V^2 + a_i V + a_p\right) \end{aligned} \tag{9}$$

To predict P'_b (predicted active power base), we use the fact that:

$$a'_z + a'_i + a_p \quad = 1 \tag{10}$$

From Equation (9), we can equate:

$$a'_i = \frac{P_b \times a_i \times V}{P'_b \times V_{\text{LN}}(R)} \tag{11}$$

$$a'_z = \frac{P_b \times a_z \times V^2}{P'_b \times (V_{\text{LN}}(R))^2} \tag{12}$$

$$a'_p = \frac{P_b \times a_p}{P'_b} \tag{13}$$

Substituting these into Equation (10):

$$P'_b = \frac{P_b \times a_z \times V^2}{(V_{\text{LN}}(R))^2} + \frac{P_b \times a_i \times V}{V_{\text{LN}}(R)} + (P_b \times a_p) \tag{14}$$

Similarly, the same approach can be applied to find the predicted reactive power base Q'_b:

$$Q'_b = Q_b \times \left(\frac{a_z \times V^2}{(V_{\text{LN}}(R))^2} + \frac{r_i \times V}{V_{\text{LN}}(R)} + a_p\right) \tag{15}$$

Now the predicted P'_b will be substituted in Equations(11), (12), and (13) to find new active ZIPV factors, and Q_b' will be used to predict reactive ZIPV factors (r'_Z, r'_I, r'_P).

5) Reduced Equivalent Model Validation: The predicted parameters—resistance (R), reactance (X), new active (P_b) and reactive (Q_b) power components, along with new ZIPV model coefficients—were used to create a reduced equivalent model. This model aggregated the system to replicate network behavior with simplified parameters. The performance of the reduced model was validated by comparing it with the original, detailed loads-only model to assess its accuracy in reflecting the actual system dynamics.

The original model simulated the IEEE 33-bus system (buses 6-18 with a load at each bus), while the reduced model condensed branch 6-18 to 6-7 by placing loads 7-18 with predicted parameters at bus 7. This simplification aimed to replicate key performance metrics—power, voltage, and current—of the original system.

To validate the reduced model's accuracy of the predictions, we compared the total active and reactive power losses, the current at the head of the branch (lines 6-7), and the voltages of each load with the original model using Mean Squared Error (MSE) as the error metric.

IV. Results and Discussion

A. *Research Results*

The findings are based on the longest branch (bus 6-18) in *Fig.2*.

1) Training Accuracy of Machine Learning Model: The model predicted the voltage LN per unit (vpu), active power loss (P_{loss}), and reactive power loss (Q_{loss}) during training. It achieved a mean squared error (MSE) of 0.015 for the loads-only model (*Fig.7*) and 0.014 for the PV BESS network (*Fig.8*).

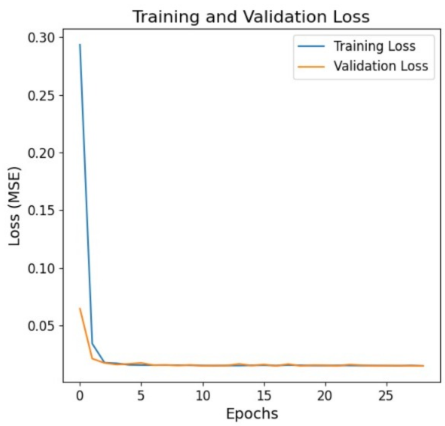

Fig. 7. Training vs. Validation loss of loads-only Model

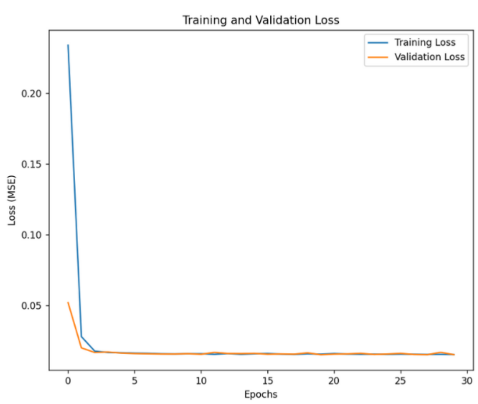

Fig. 8. Training vs. Validation loss of PV BESS model

2) Test Performance of the Model: The model continued to predict vpu, P_{loss}, and Q_{loss} with strong accuracy as visible in *Fig.9* and *Fig.10*.The predicted total P_{loss} for the loads-only model was 8.3107, and Q_{loss} was 7.0382. In comparison, the manually calculated values were 8.0719 for P_{loss} and 6.976 for Q_{loss}.

3) Comparison of Orginal and Reduced Network Models: For loads-only models the MSE for voltage LN per unit was 0.04, while for total active and reactive power it was 0.0008 and 0.00059, respectively. *Table.2* summarizes the circuit values from the original and reduced models.

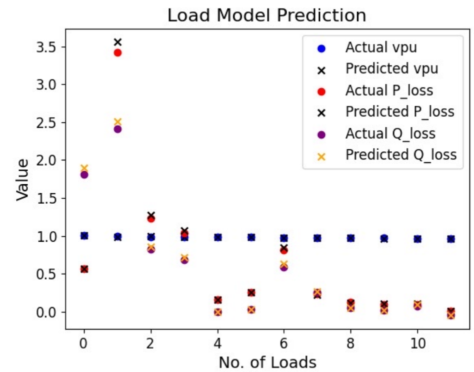

Fig. 9. ML Accuracy in parameter prediction of loads-only Model

Parameter	Original	Reduced
Max p.u Voltage	1.0488	1.0488
Min p.u Voltage	0.96825	0.99753
Total Active Power	3.5926 MW	3.58002 MW
Total Reactive Power	1.70019 Mvar	1.68095 Mvar
Total Active Losses	0.1192 MW (3.319%)	0.0966 MW (2.699%)
Total Reactive Losses	0.0782786 Mvar	0.0589674 Mvar

TABLE II
Circuit Summary of Original and Reduced Load Models on OpenDSS

B. *Discussion*

1) Accuracy of ML model: The ML model demonstrated strong accuracy in predicting power network parameters, with a mean squared error (MSE) of approximately 0.015 and 0.014 for voltage line to neutral per unit (vpu), active power loss (P_{loss}), and reactive power loss (Q_{loss}). This indicates that the model effectively learned the complex interactions within the system. The small deviation between predicted and manually calculated P_{loss} (8.3107 vs. 8.0719) and Q_{loss} (7.0382 vs. 6.9976) of loads-only modelunderscores the model's precision, with discrepancies around 0.025. These results reflect the dataset's quality and the model's capability in capturing power network dynamics.

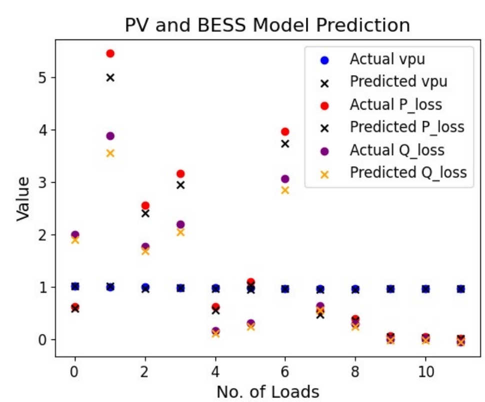

Fig. 10. ML Accuracy in parameter prediction of PV BESS Model

2) Error analysis of reduced equivalent simulation: The reduced load model, compared to the original, showed an MSE of 0.04 for voltage line to neutral per unit, indicating minimal discrepancy. The MSE for total active and reactive power was 0.0008 and 0.00059, respectively, highlighting the model's precision in capturing power dynamics. However, the higher error score of approximately 2.1009 for I_{head} suggests that the reduced model may not fully capture complex interactions in head current calculations.

Table.2 shows that while the reduced model accurately reflects the original in most aspects, minor discrepancies are acceptable given the difference could account for the lines that are now removed from the reduced network. Overall, the reduced model maintains high fidelity to the original, making it a viable option for efficient simulations with minimal accuracy loss.

V. Conclusion

This research underscores the transformative potential of artificial intelligence (AI) and machine learning (ML) in modernizing power distribution networks. By integrating distributed energy resources (DERs) such as photovoltaic (PV) systems and battery energy storage systems (BESS) with traditional load models in the IEEE 33-bus system, a robust framework for data generation and analysis has been developed using OpenDSS and ML techniques.

Our findings reveal that ML models are proficient in estimating key parameters such as voltage, current, and power across various operational scenarios. The incorporation of ZIPV parameters significantly enhances the models' ability to capture the complex dynamics of DERs, which is crucial for maintaining grid stability and reliability.

The advancements highlighted in this study demonstrate ML's potential to revolutionize grid management and operational efficiency. Future research should focus on improving data quality and developing advanced models to better address the complexities of modern power systems. Additionally, efforts can be directed towards creating a reduced model of PV and BESS systems, integrated with loads. By applying ML algorithms to these reduced models, the accuracy of parameter estimations in real-world scenarios can be further enhanced. This study offers valuable insights for advancing power system management and supports the transition towards more resilient and adaptable energy networks.

References

[1] Z. K. Pecenak, H. V. Haghi, C. Li, M. J. Reno, V. R. Disfani, and J. Kleissl, "Aggregation of voltage-controlled devices during distribution network reduction," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 33–42, 2021.

[2] "Ieee standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces," *IEEE Std 1547-2018 (Revision of IEEE Std 1547-2003)*, pp. 1–138, 2018.

[3] S. M. H. Rizvi, S. K. Sadanandan, and A. K. Srivastava, "Real-time parameter tracking of power-electronics interfaced composite zip load model," *IEEE Transactions on Smart Grid*, vol. 13, no. 5, pp. 3891–3902, 2022.

[4] D. Stokes, "Analysis of volt/var optimization in a radial distribution network with der penetration." June 2021.

[5] S. M. H. Rizvi, S. K. Sadanandan, and A. K. Srivastava, "Real-time zip load parameter tracking using sensitivity-based adaptive window and variable elimination with realistic synchrophasor data," *IEEE Transactions on Industry Applications*, vol. 57, no. 6, pp. 6525–6536, 2021.

[6] S. M. H. Rizvi, K. S. Sajan, and A. K. Srivastava, "Synchrophasor based zip parameters tracking using ml with adaptive window and data anomalies," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 3–13, 2022.