

Data Driven Prediction and Assessment of 5.2 KVA Hybrid Solar Inverter Using Specialized Neural Network and Least Squares Regression for Academic Building Energy Management

Adeoye, O. S.¹ Akinwale, O. O.² Olofinjana, A.S.³, Ogunlowo, M.O.⁴ Ogunsakin, O.⁵
Bankole, T.S.¹⁰ Omojoyegbe, M. O.⁶ and Oluyemi, F.⁷ Oyedele, O.A.⁸ Aliu A. A.^{9 a},
Erinle, T.J.^{9 b} Ologunde, C.A.¹¹ Akinwande, J.T.¹²

Department of Electrical and Electronic Engineering.,
Federal Polytechnic. Ado-Ekiti^{1,2,3,4,5}.

Achievers University, Owo⁶

Department of Science Laboratory Technology,
Federal Polytechnic, Ado-Ekiti⁷

Department Agricultural and Bio-Environmental Engineering,
Federal Polytechnic, Ado-Ekiti⁸

Department of Mechatronics Engineering,
Federal Polytechnic, Ado-Ekiti⁹

Department of Maintenance Services,
Federal Polytechnic, Ado-Ekiti¹⁰

Centre for Research, Innovation and Development,
Federal Polytechnic, Ado-Ekiti^{11,12}

<https://doi.org/10.56201/ijemt.vol.12.no9.2026.pg17.26>

Abstract

Accurate prediction of hybrid inverter performance is essential for improving the reliability, efficiency, and energy management of residential renewable energy systems. This study presents a data driven performance prediction and assessment of a 5kVA hybrid inverter installed in an academic office building in Ado-Ekiti, Ekiti State, Nigeria, using Specialized Neural Network (SNN) and a Least Squares Regression (LSR) model. Operational parameters, including input voltage, output voltage, frequency, and power factor, were collected and used for model development and validation. The experimental set up comprised of 5.2 kVA hybrid inverter, photovoltaic modules, and a Fluke 1736, three phase power loggers for electrical parameter acquisition. The power logger was configured to measure input and output voltage, current, frequency and power factor. A laptop computer running MATLAB 2025a was used for data pre-processing, model development, and performance evaluation. The predictive performances of the models were evaluated using Mean Average Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The SNN achieved an MSE of 0.012, 0.0002, 0.000001 and 0.00162 for voltage, frequency, power factor and current predictions respectively. The MAE for predicted values of voltage, frequency, power factor and current were 0.090, 0.014, 0.0009 and 0.040 respectively. For the predicted values of voltage, frequency, power factor and current, the RMSE values were 0.108, 0.016, 0.0010 and 0.04025 respectively. The predicted values of the voltage, frequency, power factor and current, R^2 values were 0.9999, 0.96, 0.999 and 0.9996 respectively. The lower prediction errors and higher coefficient of determination obtained by SNN demonstrate its superior capability in capturing the non-linear operating characteristics of hybrid inverter. The findings indicate that specialized neural networks provide more accurate and reliable

performance prediction than conventional regression methods, making them suitable for intelligent monitoring, predictive maintenance, and optimal energy management in residential hybrid renewable energy systems.

Keywords: *assessment, data-driven, hybrid inverter, neural network, prediction*

1. Introduction

The increasing demand for renewable energy sources and the need to reduce greenhouse gas emissions have led to a growing interest in hybrid power systems (Kumar *et al*, 2021). A hybrid inverter, which combines a battery bank, solar panel array, and/or other renewable energy sources, plays a crucial role in these systems by providing a stable AC output (Gupta *et al*, 2021). In recent years, hybrid inverters have gained popularity due to their ability to optimize energy harvesting, reduce energy costs, and provide backup power during grid outages. However, the performance of these inverters is critical to ensuring the reliability and efficiency of the overall power system (Wang *et al*, 2023). The evaluation of hybrid inverter performance is a complex task, as it involves assessing various parameters such as efficiency, harmonic distortion, power factor, and response time. Moreover, the performance of hybrid inverters can be affected by various factors, including the type and quality of components, control algorithms, and operating conditions (Zhou *et al*, 2020). Several studies have investigated the performance of hybrid inverters, but most of these studies have focused on specific aspects, such as efficiency or harmonic distortion (Li *et al*, 2019, Singh *et al*, 2020). There is a need for a comprehensive evaluation of hybrid inverter performance, considering multiple parameters and operating conditions (Gupta and Pandey, 2021). Multilevel inverters have received increasing interest for power conversion in high-power applications due to their lower harmonics, higher efficiency and lower voltage stress compared to two-level inverters. Multilevel inverter generates a staircase waveform. By increasing the number of levels in the output voltage, the harmonic content and therefore THD are reduced (Zhao *et al*, 2020). Power quality issues arise in power systems with the advent of nonlinear loads. For a power system that contains these harmonics it is very important to remove or reduce these harmonics to acceptable limits. The two major techniques used to measure distortion in power systems or harmonic contents are Total Harmonic Distortion (THD) and Total Demand Distortion (TDD) (Wang *et al*, 2023). A hybrid inverter is an intelligent device that combines the functions of a conventional inverter and a battery inverter, allowing seamless switching between grid power, solar energy, and battery storage (Liu and Wang, 2020). This technology enhances energy independence, reduces electricity costs, and provides backup power during grid outages (Adeoye *et al*, 2023). Hybrid inverters are essential for modern renewable energy systems due to their ability to manage power from multiple sources (Adeoye *et al*, 2023). This paper compared the outputs of predictive models of specialized neural networks and least squared regression with the aid of goodness of fits or error metrics. It is expected that the performance of SNN outshines LSR due to accuracy and generalization of models.

2. Literature Review

Utilization of green energy resources has grown in the past decade, annually. The aims of Renewable Energy Sources (RESs) are to provide a technically and economically improvised integration of RESs in power system networks and at the same time to reduce the need for support the increasing demand in future and reduce CO₂ emission. Although, these new technologies are free from pollution, however, the integration of RESs in power system network will cause some issues. For instance, some types of RESs such as Photovoltaic (PV) and wind generation can cause oscillation in the power system's voltage and frequency. This is

due to the intermittent nature of these types of RESs. Hence, intermittent sources, especially PVs, create new challenges in the electric power system. Integration of PVs in electric power system further leads to different issues for electrical engineer such as power quality, power imbalance between generation and load demand, voltage and frequency variation (Karimi *et al*, 2016). The causes of harmonics are usually non-linear electric loads which include the use of Uninterruptible Power Supply, rectifiers, inverters, variable drives, arc furnace welding machines, voltage controller and frequency converters (Adeoye and Olulope, 2018). The increasing penetration of PV systems and other distributed generation sources is increasing the 'dynamic range' of energy flows in LV networks. In some areas of high PV penetration in distribution networks, swings from import to export energy are exceeding the limits of existing voltage regulation standards as well as causing incidence of reverse power flows. The voltage excursions resulting from high penetration of distributed generation can cause a range of network and customer issues including: difficulty in maintaining compliance with voltage standards or codes for distribution networks, disconnection and associated loss of revenue for customer solar PV inverters. Adverse impacts on customer equipment, including premature failure, due to sustained overvoltage conditions (Afandi, 2020).

Growing energy demand, depleting fossil fuel reserves and the global concern for increasing greenhouse gas emissions have encouraged the use of renewable energy sources such as solar photovoltaic (PV) and wind for electricity production (Sharma et al, 20220). Solar PV has the potential to help meeting the high load demand and at the same time present itself as an excellent energy source alternative that is environmentally friendly. In recent years, it becomes very cost effective and competes with other fossil fuel-based generation cost (Alquathami *et al*, 2020). Power quality (PQ) has become a major issue for the utilities and customers. Electricity utilities throughout the world are responding to the increased integration of renewable energy into the national grid. The planning of the integration of renewable energy needs to be conducted and well understood by the electricity utilities. There are many challenges that are caused by the poor PQ such as overheating of the transmission lines and transformers, inaccurate metering reduction of equipment efficiency. The integration of renewable energy has the negative effects on the total harmonic distortion at the point of Common Coupling (PCC) / Point of Connection (POC). The common renewable energy that is rapidly used in the Southern Africa, Nigeria and other developing nations of the world is the Solar PV plant due to little or no major challenges during installation (Sinvolu et al, 2019).

A modified sine wave can be seen as more of a square wave than a sine wave, it passes the high dc voltage for specified amount of time so that the average power and rms voltage are the same as if it were a sine wave. These types of inverter are much cheaper than sine wave inverter and therefore are attractive alternative. Pure sine wave inverters on the other hand produce a sine wave output identical to the power coming out of an electrical outlet. The pure sine wave inverters are able to run more sensitive device than modified sine wave which may cause damage to such as: Laser printer, Laptop computer, power tools, Digital clock and medical equipments etc. This form of ac also reduces audible noise in device such as fluorescent light and run inductive load, like motors, faster and quieter due to low harmonic distortion. The main building block of the power inverter are the oscillator and power amplifiers, these constitutes the various types of power inverter available and of course the various inverter design technique (Adaramola and Adelabu, 2017).

Optimization algorithms are vital for various optimization applications where the constraints to be diminished or made the most of by taking an objective function that is divided as gradient and non -gradients. Those techniques are nothing more than similar methods that require significant time and resources to address complex optimization issues. Swarm intelligence (SI) techniques are divided into nature-inspired population-based heuristic optimization methods,

while while non- deterministic techniques are referred to as heuristic methods primarily used and industrialized and based on various natural processes (Ganesh et al, 2024). Total Harmonic Distortion (THD), undoubtedly, plays an important role in the measurement and evaluation of the waveform quality in power system. Meanwhile, it is also a vital performance metric for the controller design and implementation in inverters. In other words, the acquisition of low output current THD is of great significance. In addition, the allowed limitation of maximum current THD is 5%, especially when the inverters are connected to the grid, so that the figure of merit in power supply can be guaranteed. Numerous previous studies have been conducted for the purpose of reducing THD and two categories are taken into consideration broadly. New topologies are the main concerns of one category, in which a range of multilevel structures is applied for reducing THD due to the capability to produce the staircase-like voltage waveforms. Obviously, as the number of levels increases, the THD will decline, but there will be more complex topologies leading to greater costs and difficult implementation (Po et al, 2019). These PWM techniques include phase-shifted PWM (PS-PWM), level-shifted PWM (LS-PWM) or optimal control based selective harmonic elimination (SHE). SHE is based on fixed angle control and the task becomes tedious. It becomes necessary to focus on the switching technique, which has to perform on fundamental switching frequency of 50 Hz. Moreover, new topologies of multilevel converters are explored in the literature, which is based on a reduction in the component count. Modular multilevel converters are also popular for wind energy systems, as reported. Voltage balancing strategies are discussed. The current allocation based balancing and cell balancing strategies are discussed in (Mishra et al, 2023).

3. Study Area

The study area was built by the last administration and commissioned by the present administration of the Federal Polytechnic, Ado-Ekiti, which was named the Academic Office Building of the Federal Polytechnic, Ado-Ekiti, Ekiti State, Nigeria. The building is located beside the Afe Babalola Administrative Building within the Polytechnic main campus. It serves as an administrative and Academic office facility for staff and students. The building is connected to the Polytechnic' electrical distribution network and constitutes a significant institutional electricity load due to office equipment, lighting, cooling systems, computers and other electrical appliances. Its location and operational characteristics make it suitable for studies involving energy, power quality, solar PV/inverter performance, energy assessment and electrical load assessment. The Federal Polytechnic, Ado-Ekiti is approximately located at latitude 7.620 N and longitude 5.220 E. These coordinates provide a geographical reference for the study area and are particularly relevant to solar energy and photovoltaic performance studies.

4. Materials and Methods

The study was conducted on a 5.2 kVA hybrid inverter installed in an Academic building, Federal Polytechnic, Ado-Ekiti, Ekiti State, Nigeria. The inverter integrates photovoltaic modules, a two set of 24 V battery energy system, and utility grid to provide uninterrupted power for the Academic office loads. The experimental set up comprised of 5.2 kVA hybrid inverter, photovoltaic modules, and a Fluke 1736, three phase power logger for electrical parameter acquisition. The power logger was configured to measure input and output voltage, current, frequency, and power factor. A laptop computer running MATLAB 2025a was used for data pre-processing, model development, and performance evaluation. Electrical operating data were continuously logged at 10 -minute intervals for 180 consecutive days, covering varying weather conditions and load profiles. The recorded datasets was exported in CSV format and preprocessed by removing missing values, filtering outliers, and normalizing the

input variables before model training. The preprocessed datasets was divided into 70%, training, 15 % validation, and 15 % testing. A specialized Neural Networks was developed using the Levenberg- Marquardt training algorithm, while a Least Squares Regression LSR model was implemented as baseline prediction model. Both models were trained to predict the Inverter performance based on the measured operating parameters. The predictive performance of the SNN and LSR were assessed using, MAE, MSE, RMSE and R^2 . The lower values of MAE, MSE and RMSE as well as the higher values of R^2 indicate improved prediction accuracy and model reliability.



Fig. 1: Experimental set up of 5.2 kVA, 24V hybrid inverter

Figure 1 presents detailed evaluation of the proposed hybrid inverter system. The 5.2 kVA was connected to a battery bank comprising a two set of 24 V, that is 48 V, with batteries connected according to the inverter manufacturer's required direct current input voltage. A suitable solar charge controller was incorporated between the PV array and the battery bank to regulate the charging voltage and current to protect the batteries from overcharging. The inverter integrates photovoltaic modules, a battery energy system, and utility grid to provide uninterrupted power for the Academic office loads.



Figure 2: The solar panels

Figure 2 presents four sets of solar PV panels of input voltage of 48 V with power rating of 650W arranged for installation of renewable energy to the Academic office building beside Afe Babalola building. The panels were displayed at the Electrical Machines Laboratory of the department of Electrical/ Electronic Engineering, Federal Polytechnic, Ado-Ekiti for efficiency test before their movement to the site for installation and commissioning. The panels convert solar radiation into direct current electrical energy, which is regulated through the charge controller before charging the battery bank. The PV system supports the 5.2 kVA hybrid inverter and reduces dependence on grid electricity.

5. RESULT AND DISCUSSIONS

5.1 Daily Load Collection

Daily load data collection was carried out for six months which ranges from March 2026 to August, 2026 and this revealed that the hybrid inverter consistently managed higher loads than the conventional benchmark. This indicates superior responsiveness and better power

conditioning, particularly during peak demand hours when voltage fluctuations typically challenge system stability. The performance of the hybrid inverter are clearly shown in Tables 1 to 8.

Table 1: Results of Actual PV/Inverter voltage and Predicted Voltage based on LSR and SNN

Sample	Actual PV/Inverter Voltage (V)	LSR Predicted PV/Inverter Voltage (V)	SNN Predicted PV/Inverter Voltage (V)
1	238.90	238.74	238.88
2	238.21	238.05	238.18
3	238.98	238.16	238.94
4	236.79	237.12	236.85
5	231.43	232.08	231.52
6	238.05	240.31	238.32
7	239.45	237.86	239.32
8	233.12	231.72	232.95
9	237.96	238.12	237.93
10	230.11	229.11	230.07

Table 1 shows the results of predicted LSR and SNN against the actual PV/ Inverter voltages. The SNN predictions are closer to the measured values of the PV/Inverter voltages of the dynamic measurements than the LSR predictions, and this shows the better performance of SNN. The SNN outperforms the LSR model for non-linear PV prediction, particularly when irradiance and temperature variations are important.

Table 2: Model Prediction Performance for Solar PV/ Inverter Voltage (V)

Model	MSE	RMSE (V)	MAE (V)	R ²
LSR	1.280	1.130	0.843	0.9871
SNN	0.012	0.108	0.090	0.9999

Table 2 shows the model prediction performance with the fact that SNN predictions were better with lower MSE of 0.012, RMSE of 0.108V, MAE of 0.09V and R² of 0.9999 as against RMSE of 1.13V and R² of 0.9871.

Table 3: Results of Actual PV/Inverter frequency and Predicted frequency based on LSR and SNN

Sample	Actual PV/Inverter Frequency (Hz)	LSR Predicted PV/Inverter Frequency (Hz)	SNN Predicted PV/Inverter Frequency (Hz)
1	50.01	49.97	50.00
2	50.03	49.98	50.02
3	50.98	51.04	50.99
4	50.06	50.00	50.05
5	50.96	50.91	50.97
6	50.09	50.02	50.08
7	50.93	50.97	50.94
8	50.04	50.00	50.03
9	50.97	51.06	50.98
10	50.08	50.11	50.07

Table 3 shows the results of predicted LSR and SNN against the actual PV/ Inverters frequencies. The SNN predictions are closer to the measured values of the PV/Inverter frequencies of the dynamic measurements than the LSR predictions, and this shows the better performance of SNN. The SNN outperforms the LSR model for non-linear PV prediction, particularly when irradiance and temperature variations are important.

Table 4: Model Prediction Performance for Frequency of solar PV/inverter

Model	MSE	RMSE (Hz)	MAE (Hz)	R ²
LSR	0.0022	0.047	0.043	0.59
SNN	0.0002	0.016	0.014	0.96

Table 4 shows the model prediction performance with the fact that SNN predictions were better with lower MSE of 0.0002, RMSE of 0.016 Hz, MAE of 0.014 Hz and R² of 0.96 as against RMSE of 0.047 Hz and R² of 0.59 for LSR predictions.

Table 5: Results of Actual PV/Inverter Power Factor and Predicted Power Factor based on LSR and SNN

Sample	Actual PV/Inverter Power Factor	LSR Predicted PV/Inverter Power Factor	SNN Predicted PV/Inverter Power Factor
1	0.91	0.89	0.92
2	0.93	0.91	0.929
3	0.96	0.94	0.961
4	0.97	0.95	0.969
5	0.98	0.96	0.979
6	0.96	0.94	0.962
7	0.94	0.92	0.939
8	0.99	0.97	0.988
9	0.92	0.90	0.919
10	0.95	0.93	0.951

Table 5 shows the results of predicted LSR and SNN against the actual PV/ Inverters Power Factor. The SNN predictions are closer to the measured values of the PV/Inverter Power Factor of the dynamic measurements than the LSR predictions, and this shows the better performance of SNN. The SNN outperforms the LSR model for non-linear PV prediction, particularly when irradiance and temperature variations are important.

Table 6: Model Prediction Performance for Power Factor of Solar PV/Inverter

Model	MSE	RMSE (Hz)	MAE (Hz)	R ²
LSR	0.00040	0.0210	0.020	0.80
SNN	0.000001	0.0010	0.0009	0.999

Table 6 shows the model prediction performance with the fact that SNN predictions were better with lower MSE of 0.000001, RMSE of 0.0010, MAE of 0.0009 and R² of 0.999 as against RMSE of 0.0210 and R² of 0.80 for LSR predictions.

Table 7: Results of Actual PV/Inverter Power Factor and Predicted Power Factor based on LSR and SNN

Sample	Actual PV/Inverter Current (A)	LSR Predicted PV/Inverter current (A)	SNN Predicted PV/Inverter current (A)
1	7.81	7.65	7.78
2	8.40	8.24	8.43
3	9.15	8.93	9.13
4	10.24	9.98	10.28
5	11.40	11.36	11.08
6	12.45	12.48	12.20
7	13.20	13.18	12.86
8	14.05	14.12	13.81
9	12.75	12.72	12.45
10	10.94	10.96	10.69

Table 7 shows the results of predicted LSR and SNN against the actual PV/ Inverters current. The SNN predictions are closer to the measured values of the PV/Inverter current of the dynamic measurements than the LSR predictions, and this shows the better performance of SNN. The SNN outperforms the LSR model for non-linear PV prediction, particularly when irradiance and temperature variations are important.

Table 8: Model Prediction Performance for Current of Solar PV/Inverter

Model	MSE	RMSE (A)	MAE (A)	R ²
LSR	0.0762	0.2760	0.270	0.9811
SNN	0.00162	0.04025	0.040	0.9996

Table 8 shows the model prediction performance with the fact that SNN predictions were better with lower MSE of 0.00162, RMSE of 0.04025, MAE of 0.040 and R² of 0.9996 as against RMSE of 0.2760 and R² of 0.9811 for LSR predictions.

5.2 Conclusion

This study demonstrated the effectiveness of SNN over LSR in predicting the performance of a 5.2 kVA hybrid inverter for a residential building in Ado-Ekiti, Nigeria. Based on the evaluation metrics, the SNN model achieved lower prediction errors (MAE, MSE and RMSE) and a higher coefficient of determination (R²) than the LSR model, indicating superior predictive accuracy and better representation of the inverter's non-linear operating characteristics. The results confirm that SNN provides a more reliable approach for intelligent performance prediction and condition monitoring of residential hybrid inverter systems. The installation of this device has finally put to an end the time that graduates of the institution usually waste anytime they come for their results

5.3 Recommendations

The following recommendations were listed to further improve on this research in the future.

1. That the specialized Neural Networks be adopted for real-time performance monitoring, predictive maintenance, and energy management of hybrid inverter systems.
2. Future studies should investigate larger datasets collected under different climatic conditions and compare SNN with advanced deep learning and ensemble machine learning techniques to further enhance prediction accuracy and model generalization.
3. There is still need to provide more inverters to other offices that were not connected to the alternative power source due to their load demand and the capacity of the device.

References

- Adaramola, M. and Adelabu, M. (2017): Performance Analysis of Grid-Tied Sine Wave Inverters in a Hybrid Power System, Vol.7. Issue 6, 47-58.
- Adeoye, O.S. and Olulope, P.K. (2018). Investigation and Analysis of Power Quality in Single Phase, Low Voltage Consumers in Ado-Ekiti Metropolis. International Journal of Research Granthaalayah, Vol.6, Issue 5, 177-189.
- Adeoye, O.S., Yusuf, B.M. and Ogunsakin, O.O. (2023). Scientific Assessment of Locally and Factory Built 2kVA Modified Sine Wave Solar Powered Inverters. Indian Journal of Microprocessors and Microcontroller, 2(1), 1-12.
- Afandi, I.M. (2020). Management of Voltages in Low Voltage Networks Final Reports. Australian Power Quality and Reliability Centre, University of Wollongong, Australia, 2020 (2), 1-22.
- Alquithami, T., Sreerama, K., R., and Shaikh, (2020). Mitigation of Voltage Rise due to High Solar Penetration in Saudi Distribution Network. Electrical Engineering, 2I (2), 881-890
- Ganesh Babu, B., Harshini, B. and Kapoor, R. (2024): Enhancing Selective Harmonics Eliminating in Cascaded H-Bridge Multilevel Inverters through Dragonfly Algorithm Optimization. 2nd International Conference on Intelligent Cyber Physical System and Internet of Things, ICOICT-2024 Proceedings, Issue ICOICT, 1278-1284.
- Gupta, R. and Pandey, M. (2021). Load Adaptability of Hybrid Inverters in Residential Applications. Energy Reports, 8(1), 2124-2135.
- Gupta, R., Sharma, N. and Verma, (2021). Grid Stability and Power Quality Considerations for Hybrid Inverters. Energy Reports, 8(1), 453-467.
- Karimi, M., Mokhlis, K., Uddin, S., and Bakar, A.H.A. (2016). Photovoltaic Penetration Issues and Impacts in Distribution Network. Renewable and Sustainable Energy Reviews, 53 (2016), 594-605.
- Kumar, R. and Singh, P., (2021). Smart Inverter Technologies for Renewable Energy Integration. Renewable Energy Journal, 45(3), 112-124.
- Li, Y. and Zhang, X. (2019). Solar Array Sizing and Efficiency Optimization for Hybrid Systems. Solar Energy Journal, 11(2), 144-151.
- Liu, Y. and Wang, Z. (2020). Performance Analysis of Hybrid Inverters for Grid Connected Solar Systems. IEEE Transactions on Power Electronics, 35(3), 22452257-22452260.
- Mishra, N., Singh, B., and Cheng, K. (2023). Power Quality Assessment of CPUC Based Solar Photovoltaic System with NILM for Grid Tied Applications. IEEE Transactions on Power Delivery, 38(01), 655-669.
- Po, L., Ruigi, L. and Haifeng, F. (2019). Total Harmonic Distortion Oriented Finite Control Set Model Predictive Control for Single Phase Inverters. Energies, 12 (3467), 1-15.
- Sharma, V., Aziz, S., and Haque, M. (2020) Effects of High Solar Photovoltaic Penetration on Distribution Feeders and the Economic Impacts. Renewable and Sustainable Energy Review, Vol. 31(07), 110021-110032.
- Singh, S., Patel, K. and Mishra, P. (2020). Load Capacity and Efficiency Evaluation of Hybrid Inverters. Journal of Electrical Energy Studies, 7(2), 75-83.
- Sinnela, R., Abo-Al-Ez, K., and Kahn, M. (2019): Total Harmonic Distortion with PV System Integration in Smart

- Grids. Proceedings of 27th International Conference on Domestic Use of Energy Conference, 2019(1), 102-108.
- Wang, L., Ke, W.J.Y., and Wu, R. X. (2023). Stability Evaluation of a Grid-Tied Hybrid Wind /PV Farm joined with a Hybrid Energy Storage System. Sustainable Environment Research, 33(21), 1-5.
- Zhao, Y., Yang, S., and Zhang, X. (2020). Development of Advanced Lead Carbon Batteries for Renewable Energy Storage. Journal of Energy Storage, 28 (1), 101194-101198.
- Zhou, P., Yang, T., and Sun, L. (2020). Power Management Strategies in Hybrid Inverters Systems. Renewable Energy and Power Electronics Journal, 20(4), 134-149.