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MACHINE LEARNING ALGORITHMS FOR VOLTAGE AND FREQUENCY REGULATION IN A SINGLE-PHASE INVERTER

Dr. Madhuvanthani Rajendran, Associate Professor, Sri Shakthi Institute of Engineering and Technology, Coimbatore – 62, Tamilnadu, India.
Dr. L. Ashok Kumar, Professor, Thiagarajar College of Engineering, Madurai -15, Tamilnadu, India.
Dr.S. Charles Raja, Associate Professor, Thiagarajar College of Engineering, Madurai -15, Tamilnadu, India

ABSTRACT
The Voltage and frequency regulation in single-phase inverters is a critical challenge in micro grid systems, particularly under dynamic load and renewable energy conditions. This study leverages machine learning (ML) models to address these challenges, focusing on Adaptive Neuro-Fuzzy Inference System (ANFIS), Linear Regression, and Gradient Boosting Regression (GBR) algorithms. The models predict the Pulse Width Modulation (PWM) waveforms required for a single-phase inverter linked to a lamp load. Results show that the ANFIS algorithm achieves 97% accuracy, Linear Regression achieves 98.16% accuracy, and the newly introduced GBR model achieves 99.02% accuracy in predicting PWM waveforms. The comparative analysis highlights the superior performance of GBR in terms of prediction accuracy and adaptability to nonlinear data. This experimental framework validates the applicability of ML models for improving micro grid efficiency and reliability.
Keywords: Voltage regulation, Frequency control, Machine learning, Gradient Boosting Regression, Adaptive Neuro-Fuzzy Inference System, Linear Regression, Pulse Width Modulation, Micro grid systems.

I. Introduction
Droop control and automatic generation control (AGC) are among the most widely used strategies in micro grids for load sharing and frequency regulation. However, these strategies come with certain limitations. Some disadvantages of droop control include its inability to maintain precise voltage, sensitivity to load changes, limited performance in standalone systems, and difficulty in achieving equal power sharing. The challenge of equal power sharing has been partially addressed through the implementation of the universal droop controller. On the other hand, AGC has its drawbacks, such as communication delays, complex implementation, increased wear and tear on generators, sensitivity to model inaccuracies, challenges in handling nonlinearities, limited adaptability to rapid changes, and dependency on centralized control. Despite these limitations, both droop control and AGC remain effective and widely used control strategies in micro grids. Furthermore, ongoing research and advancements in control technologies continue to mitigate these drawbacks, enhancing the overall performance of micro grid control systems. Machine Learning (ML) plays a significant role in micro grids, offering a wide range of applications and addressing many of the challenges associated with traditional control strategies. By leveraging the power of data-driven algorithms, ML enhances the efficiency, reliability, and adaptability of micro grid systems. One of the key applications of ML in micro grids is forecasting energy demand and generation. By analyzing historical data and weather patterns, ML algorithms can accurately predict energy requirements and renewable energy production. These forecasts enable better planning and resource optimization, ensuring a more balanced energy supply.
ML also aids in managing demand response by analyzing real-time data to predict peaks in energy demand. This allows for the automatic triggering of demand response actions, helping to balance supply and demand, optimize energy usage, and avoid peak pricing. It derives insights from

historical data known as training data. This dataset is utilized to instruct the model about patterns and relationships relevant to its designated task. ML algorithms, functioning as mathematical models, learn from data and subsequently make predictions or decisions. Among the prevalent types of machine learning algorithms are support vector machines, linear regression, neural networks, decision trees, and others. For instance, in supervised learning, a machine learning model is trained on a dataset comprising input features (attributes) and their corresponding labels (desired outputs). The model acquires the ability to map input features to output labels during this training phase, where it is exposed to a labeled dataset to discern patterns. Subsequently, the trained model undergoes testing on a distinct data set to assess its performance and its capacity to generalize to new as well as unseen data. The three primary categories of machine learning are supervised learning, unsupervised learning, as well as reinforcement learning. Supervised learning involves training the model on a labeled dataset, allowing it to learn and predict labels for new, unseen data. Conversely, unsupervised learning entails the model learning patterns and relationships from unlabeled data. Tasks such as clustering and dimensionality reduction are typical in unsupervised learning. As for reinforcement learning, the model learns through interaction with an environment, receiving feedback in the form of rewards or penalties. Deep learning, a subset of machine learning, concentrates on utilizing neural networks with multiple layers, commonly known as deep neural networks. Notably, deep learning has demonstrated impressive accomplishments in tasks like image and speech recognition. Diverse machine learning algorithms, each tailored for specific tasks and data types, exist. Figure 1 provides an overview of several prevalent types of machine learning algorithms.

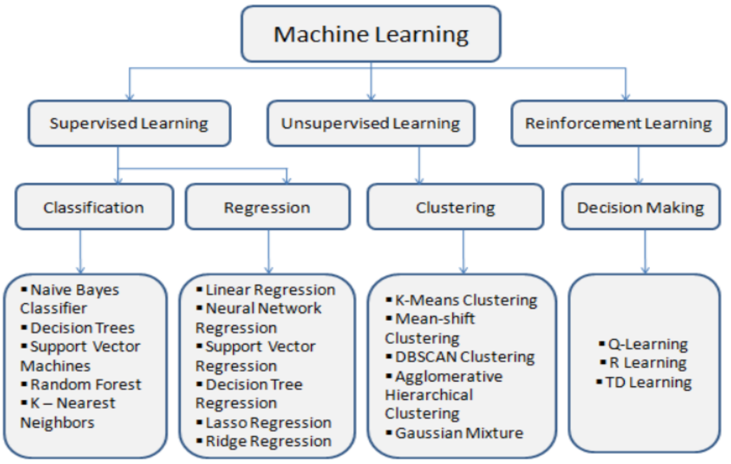

Figure 1: Types of machine learning algorithms

In addition, ML algorithms optimize the operation of various micro grid components, such as renewable energy sources, storage systems, and Distributed Energy Resources (DERs). By considering factors like weather conditions and load patterns, ML facilitates real-time decision-making, ensuring efficient energy management and enhanced system performance. Fault detection and anomaly recognition are also critical applications of ML in micro grids. By analyzing sensor and device data, ML techniques can identify irregularities and faults in system components. This enables timely maintenance, reduces the risk of failures, and improves overall system reliability.ML further contributes to grid stability by predicting and mitigating voltage fluctuations and frequency variations. Advanced ML-based control algorithms enhance the stability and reliability of micro grid operations, ensuring smooth and uninterrupted performance. Through these capabilities, ML significantly improves the adaptability and robustness of micro grids, making them more resilient to dynamic changes in energy demand and supply while promoting sustainability. Furthermore, ML algorithms are instrumental in detecting islanding events within micro grids. By identifying such occurrences, they enable the execution of appropriate control actions to ensure safe and efficient island operation. In the domain of cybersecurity, ML enhances microgrid resilience by detecting and mitigating potential cyber threats. By analyzing anomalies in data patterns, ML-based systems can implement robust security measures to safeguard against cyber-attacks. Additionally, ML analyzes load profiles and consumer behavior to optimize energy delivery. This involves predicting peak demand periods, understanding user preferences, and tailoring energy management strategies to improve system performance and customer satisfaction. Machine Learning (ML) falls within the realm of Artificial Intelligence (AI) and emphasizes the creation of algorithms and statistical models, empowering computer systems to execute tasks without direct programming. The fundamental concept driving machine learning is to enable machines to discern patterns and make decisions grounded in data, rather than depending on explicit programming instructions. Unlike traditional programming where developers craft precise code to guide a computer through a designated task, machine learning systems leverage data to grasp patterns and relationships, facilitating predictions, classifications, or decisions without explicit programming for each situation. The integration of ML into microgrids significantly enhances their efficiency, reliability, and sustainability. ML-driven solutions enable smart, adaptive operations, making microgrids more resilient and responsive to fluctuations in energy demand and supply. For voltage and frequency regulation, two ML algorithms were utilized to predict the Pulse Width Modulation (PWM) waveforms for a single-phase inverter connected to a lamp load. The algorithms employed were the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Linear Regression. Their performance was compared based on the accuracy of their PWM waveform predictions. This experimental verification serves as a prototype, demonstrating the potential of ML algorithms in microgrid applications and paving the way for broader future expansions in this field.

II. Literature

A novel control method for DC/AC inverters in microgrids, leveraging virtual synchronous machine (VISMA) principles to mimic the inertia of synchronous generators. By extracting virtual inertia from a DC bus capacitor, the approach ensures seamless transitions between grid-connected and islanded modes, enhancing system stability and synchronization. The method eliminates the need for energy storage, offering robust performance under varying grid conditions [1]. The grid-forming converters (GFM) in enhancing power system performance under high penetration of inverter-based resources. It discusses advancements like virtual synchronous machines and adaptive control strategies, addressing stability, inertia challenges, and black start capabilities. Insights emphasize GFM's potential as a substitute for traditional synchronous generators in future power grids [2]. An advanced frequency and voltage control techniques for inverter-interfaced distributed energy resources (IIDGs) in microgrids. It examines hierarchical and decentralized control strategies, emphasizing challenges like non-linear impedance and transient dynamics. And proposes innovative solutions, including droop modifications, virtual impedance loops, and heuristic algorithms, to improve stability, power sharing, and system reliability under dynamic conditions [3]. The investigation of smart PV inverters for mitigating voltage and frequency deviations in smart grids.

The study evaluates active power curtailment, volt-watt, and frequency-watt control techniques through experiments on the Maui Smart Grid Project. Results show these methods effectively enhance voltage stability and grid frequency regulation in diverse PV penetration scenarios [4]. A rule-based adaptive control strategy is proposed for grid-forming inverters in island power systems to enhance frequency stability. Moreover, introduces a virtual synchronous machine-based control approach that dynamically adjusts inertia and damping parameters based on network conditions. Simulation results highlight improved transient stability and frequency regulation in systems with high renewable energy penetration [5]. It provides a comprehensive review of multilevel inverters (MLI) with reduced switch counts, emphasizing their application in high and medium power systems. The study presents an 81-level switched ladder MLI, validated through

MATLAB/Simulink simulations and tested with resistive and impedance loads. The results highlight reduced harmonic distortion and efficient speed control of induction motors, demonstrating the topology's viability for renewable energy and motor drive applications [6].

The stability challenges of PV inverters under weak grid conditions, focusing on control loop and output voltage instabilities. It highlights critical non-linear factors such as phase-locked loops, dead-time, and reactive power compensation, emphasizing the need for advanced modeling and holistic stability criteria. Future work should address large-scale integration, dynamic interactions between components, and improved analysis methods for non-linear and coupled systems [7]. This paper explores the impacts of high penetrations of inverter-based resources (IBRs) on power system stability, emphasizing differences from synchronous machines in terms of control, inertia, and fault response. It highlights challenges like maintaining synchronicity, distributed generation management, and protection system adaptation while advocating for advanced simulations and smart inverter technologies. Despite added complexity, high IBR integration is achievable through innovative control strategies, modeling improvements, and adaptive planning [8]. This review highlights the advancements and challenges of multilevel inverters (MLIs), emphasizing their efficiency, reduced harmonic distortions, and suitability for renewable energy, motor drives, and FACTS applications. It identifies future priorities like reducing switch count, enhancing control schemes, and integrating high-bandgap semiconductors to address cost, complexity, and thermal management issues. The article serves as a guideline for researchers and industrialists to innovate more efficient, reliable, and scalable MLI technologies for diverse power system applications [9].

This paper presents a unified control design approach for power electronics converters, addressing stabilization and tracking problems using bilinear and sliding mode control models. It emphasizes practical feasibility, proposing systematic solutions to handle diverse converter topologies while highlighting regularization techniques for easier implementation. Future work will extend the approach to experimental validation, hybrid control applications, and observer design for systems with partial state information [10]. This paper reviews modern feedback control methods for voltage regulation in DC/DC converters, highlighting their advantages, limitations, and performance metrics in DC microgrids. It discusses approaches to enhance robustness, including adaptive, robust control, and the DUEA framework, with DUEA emerging as the most promising for balancing performance and disturbance rejection. The work suggests future research on combining techniques, improving computational efficiency, and adapting methods to various converter types and applications [11]. This paper presents an equal-weighted cost function-based model predictive control (MPC) method for power converters, eliminating the need for weighting factor tuning by normalizing sub-terms in the cost function. Experimental validation on a grid-connected single-phase three-level T-type inverter demonstrates that the proposed method maintains robust performance under varying operating conditions and parameter mismatches. The results show that this approach simplifies MPC design while ensuring reliable performance compared to conventional MPC [12].

This paper provides a comprehensive review of grid-connected photovoltaic (GCPV) systems, focusing on inverter configurations, modulation techniques, and control strategies. It discusses advancements in inverter topologies, the importance of multi-level inverters (MLIs), and the use of intelligent algorithms for low harmonic content. Future research aims to address challenges in high-voltage, high-power inverter designs, the integration of intelligent control strategies, and enhancing grid reliability with low-cost solutions for PV systems [13]. The paper addresses challenges in fault detection and classification for transmission lines integrated with inverter-based generators using advanced machine learning techniques.

A two-layer classification model achieved high accuracy (up to 100% for fault detection and 99.4% for fault classification) through optimized features and Bayesian tuning. Results underscore the method's robustness and potential for real-world implementation in renewable-integrated grids [14]. The study introduces a machine-learning-based prognostic approach for monitoring DC-DC converters in photovoltaic systems, emphasizing fault detection under variable environmental conditions. Utilizing a Multi-Valued Neuron Neural Network, the method achieves classification accuracy exceeding 91% during training and validation. The results highlight its potential for practical deployment, surpassing standard SVM techniques in robustness and efficiency [15]. The paper integrates Particle Swarm Optimization (PSO) with a Modular Multilevel Converter (MMC) for advanced power quality control in electrical applications. The unified power flow controller minimizes harmonics, optimizes voltage stability, and ensures efficient real and reactive power management. MATLAB simulations validate the proposed method's capability to handle dynamic operating conditions and improve system robustness [16].

This paper proposes an automated methodology for designing machine learning-based fault classifiers for multilevel inverters (MLIs) using a combined optimizer. By selecting optimal features and classifiers through Ant Colony Optimization (ACO), the approach achieves high classification accuracy (97.84% for CHBMLI and 98.61% for PUC) for fault detection under open circuit and short circuit conditions. Experimental validation confirms the effectiveness of the classifier, demonstrating its potential for improving the reliability and lifespan of MLIs by enhancing fault detection [17]. The study focuses on enhancing fault diagnosis in cascaded H-bridge multilevel inverters (CHMLIs) used in distributed power generators. By leveraging machine learning techniques, particularly Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), it compares their efficacy in diagnosing open switch faults. Probabilistic Principal Component Analysis (PPCA) is employed for feature optimization, ensuring high accuracy and efficiency, with SVM outperforming k-NN in fault diagnosis speed and reliability. This methodology shows potential for broader applications in high-power renewable energy systems [18]. This paper provides a comprehensive study of online learning applications for power converters and motor drives, focusing on condition monitoring, fault detection, stability assessment, and model predictive control. It discusses the development of online learning models, algorithms, and practical case studies to address challenges in the efficiency and reliability of these systems. The paper also highlights future opportunities and provides guidelines for leveraging online learning to improve the design, analysis, and control of power converter and motor drive systems [19]. This paper presents an adaptive machine learning-based fault detection and classification technique for transmission lines connected to inverter-based generation, such as PV plants and wind farms. The method utilizes optimized ensemble tree classifiers and setting-group-based adaptation, achieving high classification accuracy (99.4%) across various system topologies and fault scenarios.

Future work will explore incremental learning, real-time implementation, and the integration of fault localization and direction features to enhance performance and scalability [20]. This paper explores the use of Reinforcement Learning (RL) agents, specifically Deep Q-Network (DQN) and Deep Deterministic Policy Gradient (DDPG), for voltage control in DC-DC buck converters, comparing their performance with classical controllers like Model Predictive Control (MPC) and Sliding Mode Control (SMC). Experimental results show that RL controllers, particularly DQN, offer better transient response, robustness against uncertainties, and lower computational costs, while also prolonging power switch lifespan. Future research is focused on reducing computational costs and ensuring stability in AI-based controllers for power systems [21]. This paper provides an overview of machine learning algorithms applied to intelligent data analysis, highlighting their use in real-world applications such as cybersecurity, smart cities, healthcare, and agriculture. It discusses the challenges of data collection, quality, and algorithm selection, and emphasizes the need for enhanced data preprocessing and hybrid learning models. The paper concludes by identifying future research opportunities to address these challenges and improve the effectiveness of machine learning in diverse application domains [22]. This article provides an introduction to machine learning (ML) and deep learning (DL), explaining their role in building analytical models for intelligent systems and their applications in electronic markets. It discusses the process of model building, including data

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input, feature extraction, and model assessment, and highlights challenges in human-machine interaction and AI servitization. The paper emphasizes the emerging field of AI-as-a-Service (AIaaS) and its potential to transform smart services, offering new business models and applications for intelligent systems [23].

The paper presents a comparative analysis of image classification algorithms from traditional machine learning (SVM) and deep learning (CNN) perspectives. The study evaluates their performance on datasets of varying sizes and complexities, revealing that SVM excels in small sample data scenarios with higher efficiency, while CNN demonstrates superior accuracy for large-scale datasets due to its advanced feature extraction capabilities. The findings highlight the importance of choosing the appropriate algorithm based on dataset size and application needs [24].

The study explores the optimization of hyperparameters in machine learning models, a critical aspect for enhancing performance across various domains. It provides a comprehensive review of techniques like Bayesian Optimization, Grid Search, and Random Search, emphasizing their applications, advantages, and limitations. The paper also highlights emerging methods like Hyperband and Bayesian Optimization Hyperband (BOHB), offering practical insights into selecting appropriate strategies for diverse datasets and computational constraints [25].

III. Problem statement

The regulation of voltage and frequency in single-phase inverters is a critical challenge, particularly in the context of micro grids where dynamic load conditions, non-linarites, and varying renewable energy inputs are common. Traditional control strategies like droop control and automatic generation control (AGC) often fail to maintain precise voltage levels or respond effectively to rapid changes in energy demand. Droop control struggles with equal power sharing and load sensitivity, while AGC faces challenges such as communication delays, centralized control dependency, and limited adaptability to model inaccuracies. As a result, these conventional techniques exhibit limitations in ensuring stable and efficient operation of inverters under dynamic and uncertain conditions.

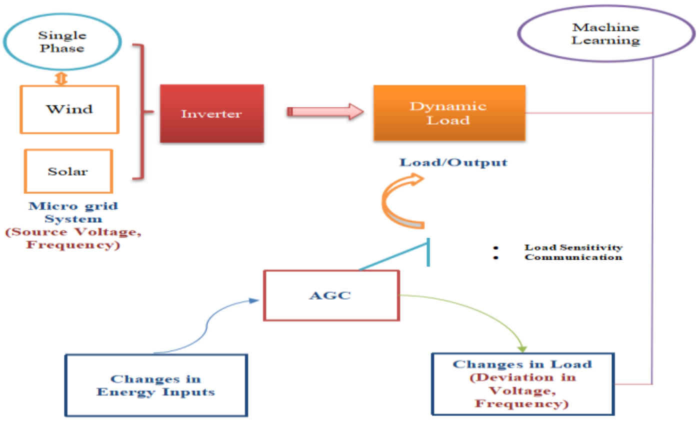

Figure 2: Block diagram of an ML-based approach, emphasizing data-driven optimization and predictive

From the Figure 2, the proposed model for the integration of ML algorithms into voltage and frequency regulation introduces a promising approach to address these challenges. ML-based models can leverage data from various inverter operations to predict and adaptively regulate output voltage and frequency, offering higher accuracy and responsiveness compared to traditional methods. However, the application of ML in this domain is not without challenges, including the need for precise data training, real-time performance verification, and robustness against uncertainties. This study aims to explore and compare the effectiveness of two machine learning algorithms ANFIS and Linear Regression in predicting the PWM waveforms required for a single-phase inverter. The investigation will validate the capability of these algorithms in achieving better voltage and frequency regulation while addressing the inherent challenges faced by micro grid systems.

IV. Methodology

a) Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligent system that integrates the reasoning capabilities of fuzzy logic with the learning power of neural networks. The primary objective of ANFIS is to model complex systems by using input-output data. Fuzzy logic provides a structure to encode knowledge through linguistic rules (such as "if-then" rules), while neural networks refine these rules by learning from data. The process begins with fuzzification, where crisp inputs are transformed into fuzzy sets using membership functions shown in figure 3.. These fuzzy inputs pass through a rule base that applies predefined fuzzy rules, such as "if X is A and Y is B, then output is C." Next, a neural network optimizes the membership functions and adjusts the rules by learning from the data. This learning is accomplished using backpropagation or least squares estimation. Finally, the fuzzy results are defuzzified to produce crisp output values. This makes ANFIS highly effective for tasks like control systems, robotics, and nonlinear system modeling.

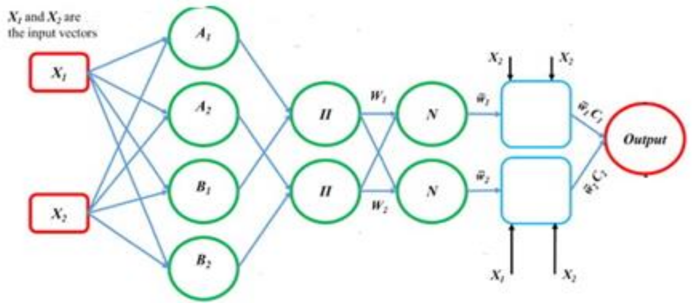

Figure 3: Structure of ANFIS

ANFIS stands out for its ability to dynamically adapt and learn, making it a valuable tool for modeling systems with nonlinear relationships. It follows a structured architecture resembling a multi-layer neural network to combine the strengths of fuzzy logic and neural networks. The sequence you provided aligns well with the classic ANFIS structure. The layered structure of ANFIS can be visualized as:

- Inputs layer raw numerical values from the system X = {X1, X2,..., Xn}
- Fuzzification Layer: Converts inputs to fuzzy sets.
- Rule Layer: Applies fuzzy rules.
- Normalization Layer: Ensures the sum of rule strengths equals 1.
- Defuzzification Layer: Produces crisp outputs from fuzzy conclusions.

b) Linear Regression

Linear Regression is a fundamental statistical method used to model the relationship between a dependent variable (output) and one or more independent variables (inputs). It is based on the assumption of a linear relationship, where changes in the input variables lead to proportional changes in the output variable. It involves finding the best-fit line by minimizing the error between actual and predicted outputs. This is typically achieved using the least squares method, which minimizes the sum of squared differences between observed and predicted values. Once trained, the model can be used to predict outputs for new inputs. Despite its simplicity, linear regression is highly interpretable and efficient for modeling linear relationships. However, it struggles with complex, nonlinear relationships and is sensitive to outliers. Common applications include predicting trends, pricing models, and evaluating the impact of independent variables on outcomes. The static technique employed to model the correlation between a dependent variable and one or multiple independent variables. It presumes that the connection between the variables is linear, signifying that an alteration

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in the independent variable(s) corresponds to a consistent modification in the dependent variable. Simple linear regression entails one independent variable (X) as well as one dependent variable (Y). The relationship between X and Y is represented by the equation of a straight line as given below in Equation (1),

$$Y = mX + c \tag{1}$$

where m and c are the slope and y-intercept respectively. Multiple linear regression involves having two or more independent variables (X_1, X_2, ..., X_n) and a single dependent variable (Y). The correlation is represented by the equation as given below in Equation (2),

$$Y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

(2)

where b_0 is the y-intercept and b_1, b_2,…,b_n are the coefficients for the corresponding independent variables. The objective of linear regression is to determine the coefficients' values that minimize the disparity between the predicted values (calculated through the regression equation) and the actual values of the dependent variable. The most common method for finding the optimal coefficients is the Ordinary Least Squares (OLS) method. It reduces the aggregate of the squared differences between the detected and predicted values. The formulas for the coefficients in simple linear regression which are the sloop and y-intercept are given below in Equations (3) and (4) respectively.

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}$$

(3)

$$b = \frac{\sum y - m(\sum x)}{n}$$

(4)

For multiple linear regression, the calculation involves matrices, but the principles are similar. Once the coefficients are determined, the performance of the model is assessed using various criterion, such as the coefficient of determination (R^2), Mean Squared Error (MSE), or Mean Absolute Error (MAE). Once the algorithm is trained, it has the capability to forecast outcomes on new or unseen data by inputting the values of the independent variables into the regression equation. Linear regression is extensively employed for predicting numerical outcomes and understanding the relationships between variables in numerous domains like economics, finance, biology, as well as engineering. The graphical representation of the linear regression algorithm is given below in Figure 4.

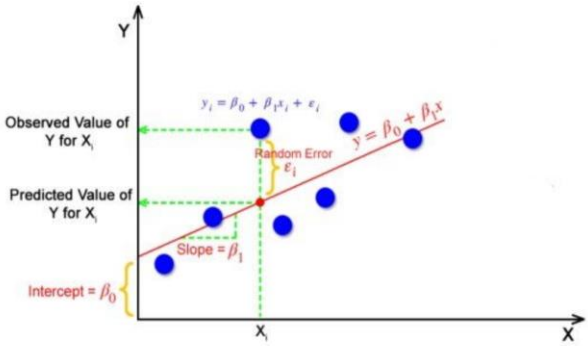

Figure 4: Linear Regression Algorithm

c) Gradient Boosting

Gradient Boosting is an advanced machine learning technique that builds a predictive model incrementally, focusing on correcting errors made by previous models. It belongs to the family of ensemble methods, combining multiple weak learners, usually decision trees, to create a strong model. The process begins with a simple model, often a constant prediction such as the mean value of the target variable. Residuals, or the errors from this initial prediction, are calculated. A new decision tree is then trained to predict these residuals. This process repeats iteratively, with each tree correcting the errors of the combined ensemble from previous iterations. Over time, the model becomes increasingly accurate as it minimizes the loss function (e.g., mean squared error or log-loss). This boosting model uses gradient descent to optimize the model by updating parameters in the direction of the steepest decrease in error. It includes Learning Rate for controls the contribution of each tree to the final model and Regularization for prevents overfitting by constraining the complexity of individual trees. Finally, the applications of Gradient Boosting are widespread, ranging from classification tasks to regression problems. The iterative refinement process in Gradient Boosting can be summarized as:

- Start with an initial model.
- Calculate residuals (errors) from the current model.
- Train a new weak learner to predict these residuals.
- Combine the predictions of all learners to improve accuracy.

This powerful approach is well-suited for scenarios requiring high performance and accuracy, especially in competitions and real-world machine-learning challenges.

d) Analysis of Data Generation, Training and Testing ML Algorithm

The methodology utilized for this analysis can be categorized into three different steps and they are detailed below.

Step I: Data Generation

A single-phase inverter rated at 0.6 kVA is fed from a 12 V constant DC supply with the output voltage and frequency being maintained as 230 V and 50 Hz using an Arduino microcontroller. This inverter is connected to a lamp load which is evaluated for three different load conditions of 40 W, 60 W and 100 W. The inverter developed is a closed loop system in which the regulation of voltage and frequency are done using an Arduino microcontroller by comparing the output values to the rated values to generate the appropriate PWM waveforms for the inverter.

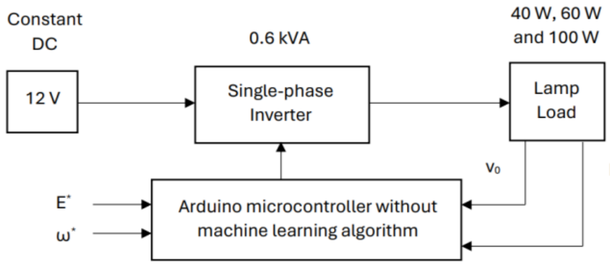

Figure 5: Closed loop system of the single-phase inverter

This experimental setup is repeatedly run to obtain about 10,000 values and the data that is obtained is collected and stored in an external device for further utilization in training and testing the ML algorithms. The block diagram of the feedback control is given in Figure 5.

Step II - Training ML Algorithm

The data obtained from the previous step is exported to an excel worksheet and is utilized to train the ANFIS and linear regression ML algorithms. The values of voltage and frequency are given as inputs to the machine learning algorithms and the PWM coefficient is obtained as the output. It must be noted that eighty percent of the data that is obtained from the close loop system is utilized for training the ML algorithms whereas the remaining twenty percent of the data is utilized for testing purposes. More data for training generally leads to better model performance, especially for complex models. Machine learning is an iterative process, and continuous refinement may be necessary based on new data or changes in the problem domain. Regularly updating and retraining the model will maintain optimal performance. Once the ML algorithms are trained, the process of testing the algorithm begins. The remaining twenty percent of the data is used to test the algorithms so as to validate the correct functioning of the algorithms. The python scikit-learn framework is utilized as

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the testing platform for machine learning algorithms. To improve prediction, the model is monitored so as to track its performance over time and is updated as needed.

Step III - Testing ML Algorithm

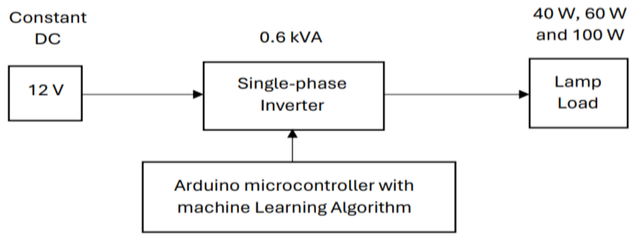

Figure 6: Open loop system of the single-phase inverter

Once the model is trained and tested as mentioned in the previous step, live data from the single-phase inverter is presented to the algorithm for PWM prediction. For this purpose, the feedback control of the single-phase inverter is replaced with the machine learning algorithm as shown in Figure 6. The PWM waveform obtained from the machine learning algorithm is compared with that of the already obtained PWM waveform from the tested values and the accuracy of the algorithm is calculated. A Raspberry Pi which is a Linux based system can be utilized instead of a computer to train as well as test the machine learning algorithms so as to improve portability of the system. The data obtained can also be stored in a cloud and vice versa so that any hardware irrespective of the physical locality can be run from the data available in the cloud storage making this a very flexible system.

V. Hardware Implementation

In the experimental setup, the single-phase inverter is fed from a 12 V constant DC supply, which could also be replaced by a battery. The single-phase inverter has an H-bridge architecture consisting of two legs, each with two semiconductor switches (MOSFETs) with a rating of 180 A and 60 V. The controller is evaluated for three different load conditions of 40 W, 60 W and 100 W, respectively. The load switching pattern is such that the load is varied continuously among the three different conditions mentioned above. The single-phase inverter is rated at 0.6 kVA and the PWM switching frequency is taken as 5 kHz. The switching frequency is selected as a trade-off between the quality of the obtained sine wave and the immunity to noise. Higher the switching frequency, better the quality of the obtained sine wave but the inverter will be more prone to noise thereby requiring a thicker printed circuit board which in turn will cause other issues like increased cost and so on. Therefore 5 kHz being the lowest frequency at which a good quality sine wave is obtained is taken as the optimal value. The rated voltage as well as the rated frequency of the system is selected to be 230 V as well as 50 Hz, correspondingly.

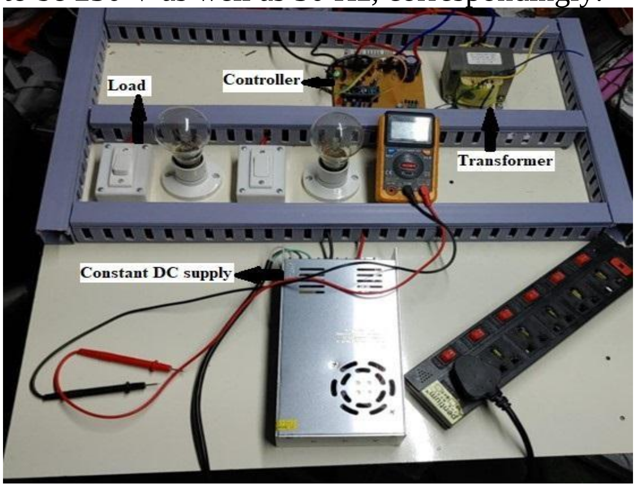

Figure 7: Experimental Setup of the single-phase Inverter

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The value of the filter inductor is 0.6 mH with a parasitic resistance of 0.1 Ω and the value of the filter capacitor is 20 μF. The design equations utilized for designing the filter inductor as well as the filter capacitor are given below in Equations (5) and (6).

$$L \geq \frac{V_{out} \cdot (1-D)}{\Delta I_L \cdot f_s} \quad (5)$$

$$C \geq \frac{I_{out} \cdot (1-D)}{\Delta V \cdot f_s} \quad (6)$$

where D is the duty cycle, L is the inductance, C is the capacitance, f_s is the switching frequency, V_out is the output voltage, I_out is the output current, ΔI_L is the inductor current ripple and ΔV is the voltage ripple. The values of the droop coefficients n and m were taken as 0.0275 and 0.00157 respectively and that of Ke as 2. Current transformers are utilized for the measurements of the output current values when required. The experimental setup of the single-phase inverter is shown in Figure 7.

VI. Results and Discussions

The analysis begins with the collection of data from the closed-loop single-phase inverter employing a droop controller for regulating voltage and frequency. The collected data is stored in an Excel worksheet, with graphs plotted for various system parameters. A serial logger is used to compile the data into tabular form. The text-based data is converted into CSV format for processing in excel and subsequently fed into the ML algorithms for analysis. Figure 8(a) illustrates the parameters, including output voltage, output current, output power, and input voltage, for a single load condition. The output voltage is consistently regulated around the rated 230 V, with an error margin of less than 5%. The input voltage, as depicted in the last graph, is maintained at 12 V, sourced from a constant DC supply.

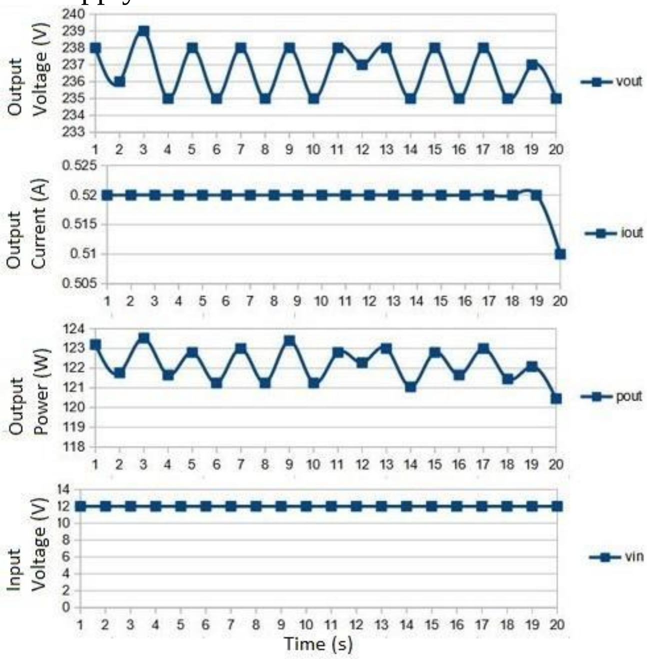

Figure 8(a): Output Voltage, Current, Power, and Input Voltage of the closed loop single-phase L-inverter with droop control

Figure 8(b) represents input current, input power, PWM correction, and output frequency. Notably, the output frequency is stabilized at the rated 50 Hz with an approximate error of 2%. After training and testing the ML algorithms, the single-phase L-inverter is configured into an open-loop system. The PWM waveforms are generated by the ANFIS and Linear Regression algorithms. These generated waveforms are compared with previously obtained PWM correction waveforms from the testing phase to determine algorithm accuracy.

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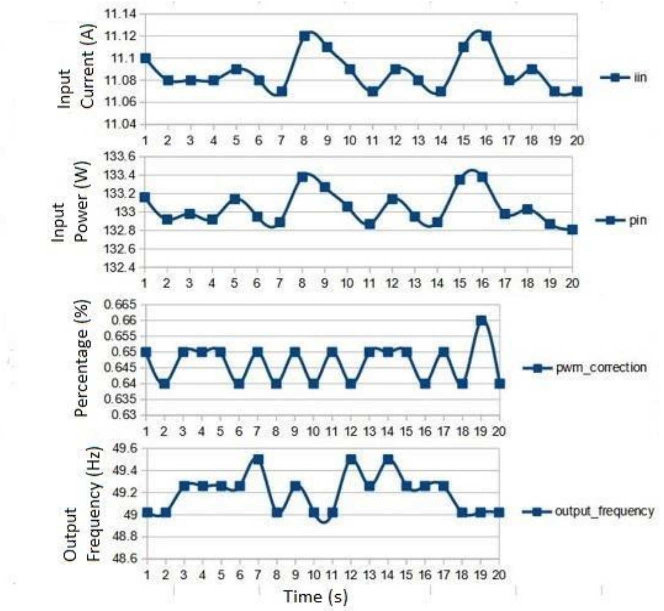

Figure 8(b): Output Frequency, PWM Correction, Input Current and Power of the closed loop single-phase L-inverter with droop control

The Figure 8(c) and 8(d) illustrate the comparison of PWM correction waveforms for the ANFIS and Linear Regression algorithms, respectively. The X-axis represents the PWM coefficient, ranging from 0 to 1, which is unit less and scales the duty cycle to generate the PWM waveform. The Y-axis denotes the instantaneous sample value, analogous to a time series index.

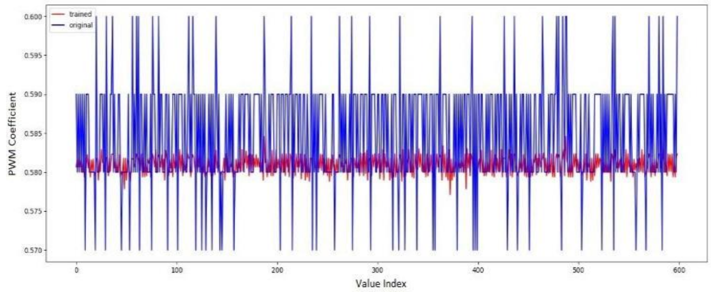

Figure 8(c): ANFIS

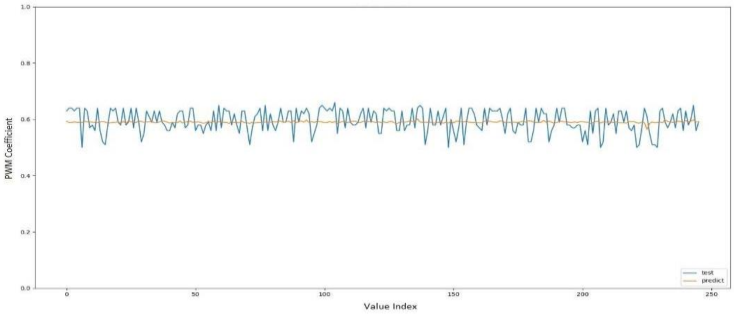

Figure 8(d): Linear Regression

The comparative analysis indicates an accuracy of 97% for the ANFIS algorithm and 98.16% for the Linear Regression algorithm. Table 1 provides an error comparison for the algorithms, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and accuracy. Gradient Boosting Regression exhibits superior performance with a 99.02% accuracy, further demonstrating its potential for high-precision applications.

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Regression exhibits superior performance with a 99.02% accuracy, further demonstrating its potential for high-precision applications.

Table 1 Error comparison of various algorithms

Algorithm	**Mean Absolute Error (MAE)**	**Mean Squared Error (MSE)**	**Accuracy (%)**
ANFIS	2.5	0.012	97
Linear Regression	1.8	0.009	98.16
Gradient Boosting	1.2	0.007	99.02

This analysis underscores the effectiveness of ML algorithms in regulating voltage and frequency in inverter systems, with Gradient Boosting showing the most promise for future implementations

VII. Conclusion

The two machine learning algorithms namely ANFIS and linear regression were utilized for voltage and frequency regulation of a single-phase inverter. Some of the disadvantages of the traditional methods of voltage and frequency regulation like AGC and droop control are stated along with the role of machine learning in micro grids. In addition to providing a comprehensive overview of machine learning, including its benefits and various types, a detailed explanation of linear regression is also presented. The three steps utilized in this analysis is detailed which are data collection from the closed loop single-phase inverter using droop controller, training, testing of the ANFIS and linear regression algorithms and implementation of the two machine learning algorithms to the open loop single-phase inverter for generation of the PWM waveforms. The PWM waveform obtained from the open loop single-phase L-inverter is compared with that of the already obtained PWM waveform from the tested values. An accuracy of 97 % and 98.16 % was obtained for the ANFIS and Linear Regression algorithms respectively.

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