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Development of Machine Learning based Hybrid Power Generation System for Rural Electrification

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Abstract:

Introduction: Electrifying rural areas in developing countries presents numerous challenges, including the limited reach of conventional power grids, high upfront infrastructure costs, and insufficient maintenance capabilities. Additionally, regulatory restrictions and logistical obstacles, such as difficulties in transportation and security concerns, further complicate efforts to expand electricity access. Overcoming these barriers necessitates the implementation of a dependable and economically viable solution that can provide a consistent and sustainable power supply, ensuring long-term benefits for rural communities.

Objectives: This study is dedicated to the development of a Hybrid Power Generation (HPG) system that combines multiple renewable energy sources to improve both reliability and efficiency. The research emphasizes the use of a machine learning-based approach to optimize power generation by implementing a real-time Maximum Power Point Tracking (MPPT) technique. This ensures optimal energy conversion, even under dynamic environmental conditions such as fluctuations in sunlight and wind speed, ultimately enhancing the system's overall performance and sustainability.

Methods: The proposed Hybrid Power Generation (HPG) system integrates solar and wind energy sources using a dual-input DC-DC buck-boost converter, which allows both sources to function independently while maintaining simultaneous operation. This integration enhances the system's reliability and ensures a stable power supply. To optimize the Maximum Power Point Tracking (MPPT) process, a Linear Regression-based Machine Learning Algorithm is employed, which dynamically adjusts the duty cycle of the converter through a microcontroller-driven data storage unit. This algorithm effectively predicts the optimal duty cycle, even in the presence of Partial Shading Conditions (PSC) and rapidly changing atmospheric factors. The system's efficiency and adaptability are assessed under three different shading scenarios: zero shading, weak shading, and strong shading, demonstrating its capability to maintain consistent performance across varying environmental conditions.

Results: The developed Hybrid Power Generation (HPG) system exhibits exceptional efficiency across different shading scenarios, with recorded efficiencies of 99.91% in zero shading, 99.38% in weak shading, and 99.78% in strong shading conditions. Furthermore, the system demonstrates rapid response times, achieving convergence within 0.4 seconds under zero shading, 0.8 seconds under weak shading, and 1.4 seconds under strong shading. A comparative assessment against traditional Maximum Power Point Tracking (MPPT) algorithms underscores the enhanced performance of the Linear Regression-based Machine Learning Algorithm. By effectively optimizing power extraction, the proposed system ensures stable and efficient energy generation, making it a reliable solution for sustainable power supply.

Conclusions: The findings of this study validate that the proposed Hybrid Power Generation (HPG) system, enhanced through a Linear Regression-based Machine Learning Algorithm, provides a highly efficient and dependable solution for rural electrification. By maintaining consistently high efficiency across diverse environmental conditions, the system proves to be a practical and sustainable alternative for power generation in developing regions. Its ability to adapt to variations in solar and wind energy availability ensures reliable energy access, making it a promising approach to addressing the challenges of rural electrification.

Keywords: Hybrid Power Generation, Linear Regression, Machine Learning, Maximum Power Point Tracking, Partial Shaded Condition, Renewable Energy Sources, Solar Energy, Wind Energy.

1. Introduction

Rural electrification play significant role in the socio-economic development of rural village which converter the important services like education, health care and communication. Many of the rural village in the globe are facing the issues of electrification due to the difficulty to extend the conventional grid [1]. The notable barriers of rural electrifications are limited infrastructure, nature of geographical location, lower income level, and lack of awareness. In globally, many rural villages are located at south east Asia and Africa where they are facing unavailability of electricity. In India, initiatives like the Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY) are introduced, but still many villages are yet to be electrified. To address these challenges, a decentralised power generation is essential for uplifting the socio-economic development. The proposed research focuses on an efficient decentralised approach.

Hybrid Power Generation (HPG) [2] is a decentralised power generation approach which combines two independent sources of energy to meet the load demand by ensuring reliability. HPG system can be either using conventional sources of energy or RES, however, using RES is more sustainable approach. The HPG system overcomes the setbacks of using single energy source to meet the load demand. The proposed HPG utilising both solar and wind energy to meet the load demand of rural areas where traditional grid is not admissible. The HPG ensures energy security by providing the utilisation of diversifying energy sources minimizes the emission of greenhouse gases and reduces dependencies of single source of energy. At present, the trend in energy sector moving towards RES, and the role of HPG is highly essential for modern energy infrastructure. Therefore, the proposed HPG is treated as one of the feasible solution for rural electrification.

In order to operate the RES in maximum efficiency an optimising algorithms are desirable. There are traditional and Artificial Intelligence (AI) [3] based optimizing algorithms are available to adopt in RES. Machine Learning (ML) [4] based algorithms are most commonly used in the modern RES applications. The proposed HPG consists of solar and wind energy sources, it is essential to operate the solar energy in the Maximum Power Point condition, so that maximum efficiency can be ensured. ML based algorithms are can predict energy demand, optimise resource allocation, and improves the decision making. In addition to that, ML based algorithms are suitable for Partial Shaded Condition (PSC) [5], prevent equipment failure, reduce maintenance time, and saves the money. In general, ML based algorithms works based on prediction. In this research, the weather data of Mavinahunda site, Raybagh Taluk, Belagavi district, Karnataka is collected using the open source data of Karnataka Renewable Energy Development Limited (KREDL), India. In this research, regression based ML algorithm helps to operate the Solar Photovoltaic Panel (SPV) at its maximum efficiency. The complexity of HPG is minimized using regression based ML algorithm. The block diagram of proposed HPG is shown in Figure 1.

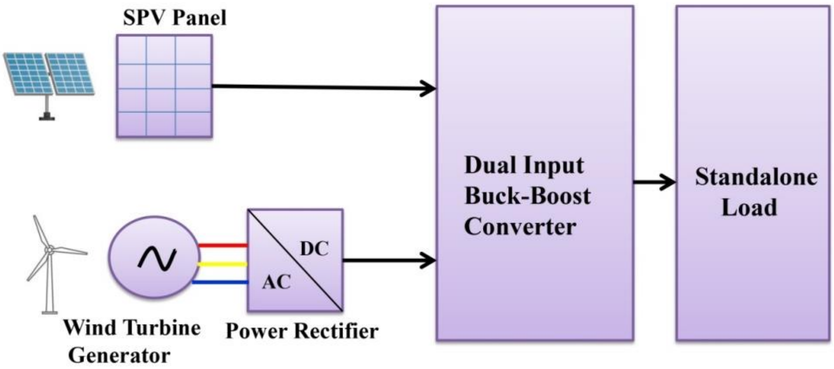

Figure.1. Block diagram of proposed solar-wind HPG

The dual input dc-dc buck –boost converter [6] integrates two independent RES such as solar and wind energy simultaneously or independently as mentioned in Figure 1. The regression based Machine learning algorithm is added in the form of feed forward control to make the SPV panel at maximum efficiency. Also, it helps to predict the optimum value of duty cycle to operate the dual input dc-dc buck boost converter/ the regulated output of power converter is supplied to the standalone load. Since the system is standalone, an efficient battery unit is added in HPG.

In the growing field of energy systems, various researches have been done on HPG and the use of machine learning (ML) to optimize energy production and distribution. Nevertheless, there is still a remarkable gap when it comes to integrating ML-driven optimization into HPG designed specifically for rural electrification [7]. While some studies have focused at how ML can improve the efficiency of individual RES like solar or wind, there is limited research on how these technologies can be combined in rural areas. These regions face unique challenges, such as unreliable power supply, limited infrastructure, and fluctuating energy demand.

Most existing research concentrates on urban or industrial settings, where the power grid is reliable and energy needs are more predictable. Rural areas, on the opposite hand, have different needs due to their isolation, lower population density, and socio-economic factors, which have not been thoroughly studied. Additionally, there is a slackness of practical, real-world studies showing how ML-based hybrid power systems can be effectively implemented in rural electrification beyond just theoretical models or small pilot projects. Addressing these research gaps would greatly enhance the development of more reliable, efficient, and sustainable energy solutions for rural communities that are currently underserved. The main objectives of the proposed research are to develop a software model of HPG added with regression based ML algorithm for improving the efficiency. Also, to validate the superior performance of regression based ML algorithm, comparison with other popular algorithm is also carried out in this work. The entire research article is segmented as follows: section 2 presents extensive literature review, section 3 explains materials and methods, section 4 presents detailed results and discussion and section 5 concludes the paper.

2. Objectives

The primary objective of this research is to develop a Hybrid Power Generation (HPG) system that integrates multiple renewable energy sources to provide a sustainable and efficient solution for rural electrification in developing countries. The study aims to address key challenges such as limited grid accessibility, high initial costs, poor infrastructure maintenance, and regulatory barriers by utilizing a combination of solar and wind energy. A key goal is to design and implement a double input DC-DC buck-boost converter that enables simultaneous and independent operation of both energy sources, thereby improving system reliability and efficiency. Furthermore, this research seeks to optimize the Maximum Power Point Tracking (MPPT) process through the implementation of a Linear Regression-based Machine Learning Algorithm. The objective is to enhance energy extraction efficiency by accurately predicting and adjusting the duty cycle of the converter in real-time, even under dynamic environmental conditions such as Partial Shading Conditions (PSC) and fluctuating atmospheric parameters. Another major objective is to evaluate the system’s performance under various shading conditions, including zero shading, weak shading, and strong shading, to analyse efficiency and convergence time. The study also aims to conduct a comparative analysis between the proposed algorithm and conventional MPPT techniques to validate its superiority in terms of power optimization, response time, and overall system performance. Additionally, the research aims to explore the feasibility of deploying the proposed system in off-grid rural areas, ensuring its scalability and adaptability to different climatic and geographical conditions. By achieving these objectives, the study aspires to contribute towards developing a cost-effective and reliable renewable energy solution that can enhance energy accessibility, support socio-economic growth, and promote sustainability in underdeveloped and remote regions. Future directions of this research include integrating additional renewable energy sources, incorporating predictive maintenance strategies, and implementing real-time monitoring to further enhance the efficiency and resilience of the HPG system.

3. Literature Review

The literature review include the review of existing HPG, the significance of ML algorithm in HPG, overview of HPG projects and the gap identification of existing research work. The comprehensive literature review of various articles is presented here.

A. **The review of existing optimizing algorithms used in HPG**

There are conventional and AI based optimizing algorithms are used in HPG. Since, the main focus is solar based HPG; the optimizing algorithm is referred as Maximum Power Point Tracking (MPPT) algorithms. The reviews of popular MPPT algorithms are presented here.

A. Chellakhi *et al*., developed a Perturb & Observe (P&O) based MPPT algorithm for Hybrid Power Generation (HPG) systems. The P&O method is easy to implement, requires minimal computational resources, and is straightforward to understand. However, it exhibits oscillations around the Maximum Power Point (MPP) under rapidly changing atmospheric conditions, resulting in power loss and making it unsuitable for Partial Shading Conditions (PSC). The authors also highlighted its slower response time in dynamic conditions. The Hill Climbing algorithm, which shares similarities with P&O but accounts for temperature, also demonstrates poor performance in fluctuating environments.

H. Abouobaida *et al*., developed the Incremental Conductance (INC) algorithm for Hybrid Power Generation (HPG) systems, noting its superior performance over P&O in rapidly changing atmospheric conditions, with fewer oscillations around the Maximum Power Point (MPP). However, INC has drawbacks, including higher memory requirements, slower response time, and the need for precise current and voltage measurements. B. Gu *et al.*, proposed a Fuzzy-based optimizing algorithm for HPG systems, which effectively handles non-linear and dynamic conditions. Despite its ability to manage environmental uncertainties, the design complexity and membership function formation require significant computational resources.

O. S. Alemdar *et al*,. highlighted that Artificial Neural Network (ANN)-based algorithms offer high tracking accuracy for optimizing Hybrid Power Generation (HPG) systems, with the ability to learn, adapt, and reduce oscillations around the Maximum Power Point (MPP). However, ANN requires extensive data training, significant computational resources, memory, and involves complex design and implementation. P. Manasa *et al.*, suggested that Particle Swarm Optimization (PSO) is well-suited for Partial Shading Conditions (PSC) due to its fast convergence to MPP and suitability for rapidly changing environments. However, it requires high-speed computing devices and precise tuning to achieve optimal performance.

A. Awad *et al.*, discussed the use of a Genetic Algorithm (GA) for real-time MPPT in Hybrid Power Generation (HPG) systems. GA is effective for Partial Shading Conditions (PSC) and rapidly changing environments, capable of optimizing multiple parameters and finding global maxima in complex non-linear conditions. However, GA has slower convergence compared to PSO and requires fine-tuning for optimal performance. A. Ostadrahimi *et al.*, explored Ant Colony Optimization (ACO) for HPG, which accurately identifies the Maximum Power Point (MPP) in PSC but also has slower convergence and requires precise tuning. N. Priyadarshi *et al.*, examined Differential

Evolution (DE) in solar-based HPG, noting its high accuracy in finding global MPP and faster convergence compared to traditional algorithms. DE is flexible in handling various optimization problems but requires tuning, high-speed computing, and extensive experimentation.

B **The review of existing HPG systems**

The HPG includes more than one combination of energy sources. The combination can be either RES or conventional source, and combination of both the sources. The detailed review of possible combinations of HPG is presented here.

A. Chellakhi *et al*., highlighted the practical feasibility of a solar-biomass Hybrid Power Generation (HPG) system, emphasizing sustainability, the complementary nature of solar and biomass, and waste utilization. However, challenges include biomass availability, storage space, reactor design, and gas emissions. P. Kuntal *et al*,. discussed the wind-diesel combination, noting its reliability, feasibility, and suitability for remote applications, but pointed out fuel dependency, CO_2 emissions, and wind power intermittency as key drawbacks. S. Jha *et al*., explored the solar-diesel HPG system, finding it provides reliable backup, peak shaving, and is suitable for versatile applications due to the complementary nature of both energy sources.

S. El Idrissi Essebtey *et al.*, explored the feasibility of a wind-biomass combination, citing continuous power supply, reduced fuel use, and environmental benefits as advantages. However, real-time implementation faces challenges like complex operations, biomass availability, and high infrastructure costs. S. Tyagi *et al*., reviewed the solar-hydro hybrid system, highlighting its complementary nature and effective energy storage. The primary obstacles include geographical limitations, ecological impacts from dam construction, and high initial investment.

S. Puchalapalli *et al.*, presented a solar-wind-diesel combination, highlighting its high reliability but noting the need for complex control systems. A. El-Ayoubi *et al*., proposed solar-wind-biomass as a viable HPG option due to its complementary energy mix, sustainability, and waste utilization, though complex integration, high maintenance, and resource dependency pose challenges. W. Zuo *et al*, studied the wind-diesel-biomass combination, finding it reliable, flexible, and with reduced greenhouse emissions, but environmental impact, complexity, and fuel logistics remain obstacles. A. B. d. Oliveira Neto *et al.*, explored the solar-wind HPG system for rural and isolated areas, citing complementary energy production and scalability, though challenges like high capital costs, space requirements, and intermittency need to be addressed with optimization techniques. The proposed research uses the solar-wind combination for rural electrification.

C **The role of Machine Learning Algorithm in Hybrid Power Generation**

Machine learning (ML) algorithms play a crucial role in optimizing Hybrid Power Generation (HPG) systems by predicting energy demand, renewable energy output, and enabling dynamic load balancing, real-time decision-making, and predictive maintenance to enhance energy efficiency. G. Senthilkumar *et al.* noted that ML improves predictive accuracy for HPG systems, but requires high-quality datasets and memory. W. Ahmed *et al*., highlighted ML's potential to optimize operational costs, though implementation is expensive due to the need for advanced hardware and software. R. Colucci *et al*., emphasized the scalability of HPG systems, but noted infrastructure challenges in rural areas. ML excels at handling non-linearities, making it effective during Partial Shading Conditions (PSC) and rapidly changing weather. A. Djellad *et al*., suggested that ML offers advantages in prediction, adaptability, and real-time decision-making over traditional methods. K.-H. Chao *et al*., recommended regression-based ML for its simplicity, ease of implementation, quick training, and low computational demands, making it suitable for smaller datasets. The proposed research incorporates a linear regression-based ML algorithm for optimizing the solar-wind HPG system.

4. Materials and Methods

The proposed HPG system consisting of two independent RES such as solar and wind energy sources, double input dc-dc buck-boost converter, ML based MPPT controller, and the electrical load. In order to adopt regression based ML algorithm in the HPG, data set is required. Regarding the data collection, the temperature and solar irradiance Mavinahunda site, Raybagh Taluk, Belagavi district, Karnataka, India is collected using the open source data of Karnataka Renewable Energy Development Limited (KREDL).The steps involved for the implementation of proposed HPG is illustrated in Figure 2

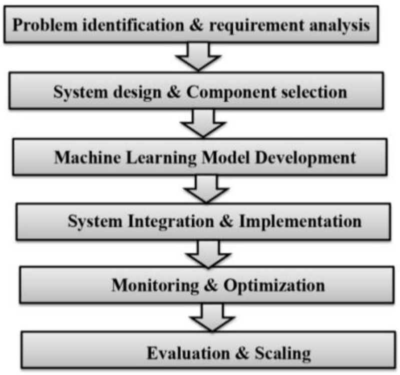

Figure. 2. Steps for the implementation of HPG

A. Components details of proposed HPG

In order to familiar the HPG, the components details are necessary. The components are selected for the implementation of hardware prototype. Once the prototype is tested, HPG can be implemented for the large scale.

a. Solar Panel

The SPV panel converts sunlight directly into electrical energy using photovoltaic cells. It serves as one of the primary RES in the HPG system. The output from the SPV panel is in the form of direct current (DC), which is then fed into the dual input buck-boost converter. The efficiency of the SPV panel is maximized using a machine learning-based feed-forward control, which predicts and adjusts the operating conditions to ensure optimal performance. The efficiency of solar panel is calculated using the equation (1)

$$\eta_{spv} = \frac{P_{\max}}{P_{\text{in}}} = \frac{V_{mp} \times I_{mp}}{G \times A} \tag{1}$$

Here η_{spv} indicates efficiency of solar panel, $P_{\max}$ is the output of solar panel, P_{in} is the incident solar power, V_{mp} is the voltage corresponding to the maximum power, Imp is the current corresponding to the maximum power, G indicates solar Irradiance (W/m^2), and A is the area of SPV panel in m^2.

b. Wind turbine generator

The wind turbine generator [30] captures kinetic energy from the wind and converts it into mechanical energy, which is then transformed into electrical energy via an AC Generator. The output from the wind turbine is typically in the form of alternating current (AC), which is rectified into DC using a power rectifier. This DC output is then supplied to the dual input buck-boost converter for further processing.

c. Power Rectifier

The power rectifier is a crucial component that converts the AC output from the wind turbine generator into DC. This conversion is necessary for integrating the wind energy source with the DC-DC converter and ensuring compatibility with the other components of the HPG system. In this proposed HPG system, the power rectifier is uncontrolled rectifier using power diode.

d. Dual input buck-boost converter

The dual input buck-boost converter [31] is a versatile DC-DC converter that can step up or step down the voltage from the two independent RES (solar and wind). This converter can operate with inputs from either one or both sources simultaneously. The converter is controlled by a regression-based machine learning algorithm, which optimizes the duty cycle (D) to maintain a regulated output voltage despite variations in input power or load conditions.

e. Standalone load

The standalone load represents the electrical devices or systems that consume the power generated by the HPG system. The load is isolated from the main grid, meaning it relies solely on the HPG system for its energy needs. The dual input buck-boost converter ensures that the load receives a stable and regulated power supply. In the proposed research, light load is considered as standalone load.

f. Battery unit

Given that the HPG system is standalone, a battery unit is integrated to store excess energy generated by the solar and wind sources. This stored energy can be used during periods of low energy generation or high demand, ensuring continuous power availability. The battery unit enhances the reliability and efficiency of the overall system, especially during fluctuating weather conditions.

g. ML based optimizing algorithm

The ML plays an important role in the proposed HPG system by optimizing the operation of the SPV panel and the dual input buck-boost converter. By analyzing data and predicting the optimal duty cycle, the algorithm ensures maximum efficiency in energy conversion and regulation, adapting to changing environmental conditions and load demands.

B **Implementation of Machine Learning Algorithm**

Machine learning algorithms use mathematical techniques and logical rules to process data and adjust to achieve desired outcomes, whether quantitative or logical. They are crucial for decision-making, forecasting, optimization, logistics, and data analysis, relying on precise data for effectiveness. Based on input, they generate outputs such as quantities, classifications, or logical conclusions. The three main types of machine learning algorithms are Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

Linear regression is a simple yet accurate prediction model in supervised learning. In solar photovoltaic (SPV) systems, it predicts the duty cycle for a boost converter, enabling voltage and current tracking. This ensures maximum power output under varying conditions like shading and microclimates. The use of a regression algorithm for this purpose is called a regression controller, effectively implementing maximum power point tracking (MPPT) in SPV systems.

The regression controller distinguishes itself from traditional MPPT algorithms by predicting the boost converter's duty cycle using a best-fit approach. In this controller, the solar PV panel's voltage (independent variable) and the PWM of the DC-DC boost converter (dependent variable) are used to predict the optimal duty cycle. This method ensures maximum power output under partial shading conditions with high accuracy and minimal computational effort. Linear regression, a machine learning algorithm, is employed to predict the PWM value based on variables such as voltage and current, analyzing the relationship between dependent and independent variables.

$$y=mx+c \tag{2}$$

In the general equation (2), x stands for input training data, y indicates labels to the data, m is the intercept, and c is the coefficient of x. During model training, the algorithm accurately predicts the optimal value of y by precisely determining the tuning parameters m and c. The flow chart of optimal duty cycle prediction using voltage and solar irradiation is shown in Figure 3. In the proposed regression controller, the microcontroller's memory stores the voltage and current values obtained from the respective sensors. These stored values are then utilized to calculate the duty cycle using the Gradient Descent regression technique [33].The equation (2) can be modified and presented in the equation (3)

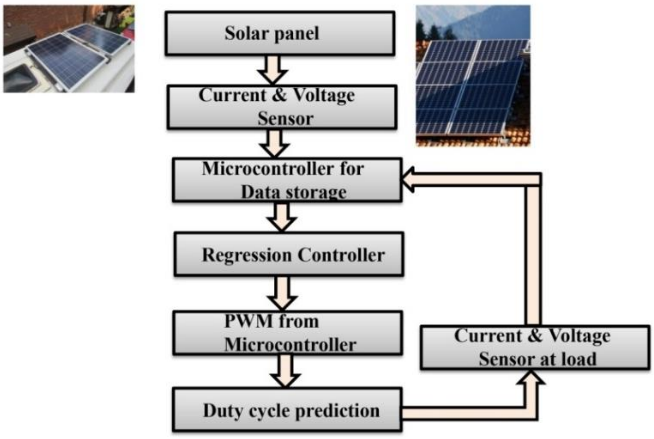

Figure. 3. Optimal duty cycle prediction using regression controller

$$y(D)=m\times(\text{voltage from x axis of PV curve})+c \tag{3}$$

In the equation (3) D stands for duty ratio of double input dc-dc buck-boost converter, m represents the slope , and c is the constant factor. A gradient descent algorithm is involved in the regression controller. While analysing the gradient descent algorithm, the cost function needs to be considered. The cost function can be computed using the formulae (4)

$$J=\frac{1}{n}\sum_{j=1}^{n}\left(D_j-y_j\right)^2 \tag{4}$$

In the equation (4), J represents cost function, n is the total number of samples, D_j is the predicted value of duty ratio, y_j is the actual value of duty ratio. The steps of linear regression model are presented Figure 4. The overall process involves continuously acquiring accurate current and voltage values from a solar SPV panel using sensors, then utilizing a linear regression model to determine the relationship between the duty cycle of double input buck-boost converter and the measured variables.

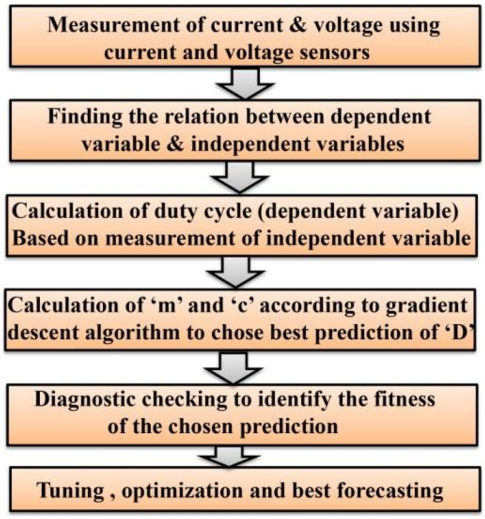

Figure. 4. Steps involved in the linear regression model

Through the gradient descent algorithm, the best-fitting model parameters are optimized, and diagnostic checks are performed to ensure model accuracy. If the model is not accurate, fine turnings are made by changing the learning rate to improve predictions.

C **Data collection method**

To implement the linear regression model, solar and wind data from the Mavinahunda site in Raybagh Taluk, Belagavi district, Karnataka, was obtained from KREDL. This dataset is used to train the model, with the duty cycle as the dependent variable and environmental factors as independent variables. Figure 5 illustrates the data collection process.

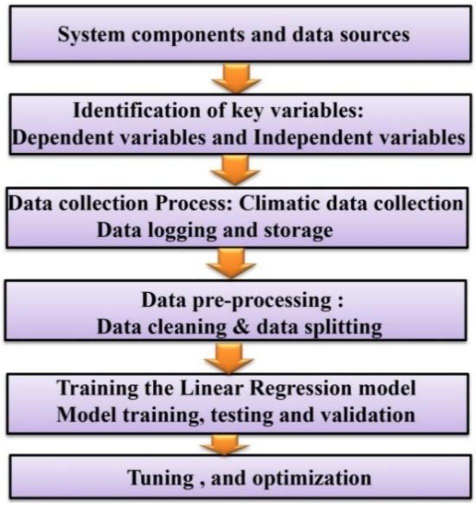

Figure. 5. Overview of data collection method

The proposed HPG system integrates solar and wind energy sources, requiring data from these sources for training the machine learning model. Current and voltage sensors monitor real-time outputs from solar panels and wind turbines, while light intensity sensors capture partial shading effects. Climatic variables such as temperature, humidity, wind speed, and solar irradiance are monitored by weather stations or system sensors and serve as independent variables.

The data collection process starts with installing current and voltage sensors at key points in the system, including solar panels, wind turbines, and the load side. These sensors continuously monitor and record electrical parameters, with data stored in a microcontroller or a dedicated storage system for analysis. Concurrently, climatic data—such as temperature, humidity, wind speed, solar irradiance, and shading—is collected using weather stations and environmental sensors near the hybrid system. The microcontroller acts as the central hub, logging and processing data at regular intervals to capture all operating conditions.

For data pre-processing, clean the dataset by removing outliers, missing values, and noise to enhance accuracy. Generate new features if necessary, such as normalized current and voltage values or combined indices for shading and climate conditions. Split the dataset into training (70%) and testing (30%) sets. Train the linear regression model with the training data to learn the relationship between independent variables (e.g., shading and climate changes) and the dependent variable (duty cycle). Evaluate the model's performance using testing data and metrics like mean squared error (MSE) [34]. Finally, fine-tune the model's parameters to improve predictions, adjusting aspects such as learning rate or applying regularization techniques.

D. **Implementation details**

MATLAB 2024a is used to develop the HPG system, utilizing toolboxes for data analysis, simulation, and machine learning. Simulink models and analyzes the HPG system, while the Statistics and Machine Learning Toolbox implements the Linear Regression model. The Optimization Toolbox is employed for fine-tuning and optimizing model parameters. Linear Regression, a supervised learning algorithm, models the relationship between independent variables (e.g., partial shading, climatic conditions) and the dependent variable (duty cycle) to predict the duty cycle that maximizes power output. Gradient Descent is applied to reduce model error by iteratively adjusting coefficients.

The process begins with collecting real-time data on current, voltage, partial shading, and climatic conditions such as temperature and irradiance. Next, pre-process the data to remove noise and clean it. Split the dataset into 70% for training and 30% for testing. Use the Statistics and Machine Learning Toolbox [35] to create the linear regression model, with the duty cycle as the dependent variable and micro-climatic conditions as independent variables. Train the model with the training dataset and refine coefficients using gradient descent to minimize prediction error. Model the SPV panel, Wind Turbine Generator (WTG), and partial shading conditions using resistances. Validate the model by calculating the Mean Squared Error (MSE) and adjust parameters using the Optimization Toolbox to enhance accuracy. Finally, predict the optimal duty cycle using linear regression [35], with hardware implementation as the next research phase.

5. System Design

The system design consists of design of SPV panel, design of wind turbine generator, design of double input buck-boost converter, and controller design. The proposed HPG is designed for a small scale for the purpose of prototype development. The same design can be followed for the large scale implementation.

A. **Design of SPV Panel**

Designing a 500W solar panel system to power a 250W lighting load requires determining the necessary components and evaluating the energy balance between production and consumption. Assume that system efficiency is considered as 85% by considering losses of components. The power requirement is calculated using the equation (5)

$$P_{required=}\frac{P_{load}}{\eta}=\frac{250W}{0.85}\approx 294W \tag{5}$$

In the equation (5), η denotes the system efficiency. SPV panel is supposed to produce 294 W to meet the load demand. The operating voltage of SPV panel (V_{panel}) is 18 V. Therefore, current required for 500 W SPV panel is given by the equation (6)

$$I_{panel}=\frac{P_{panel}}{V_{panel}}=\frac{500W}{18V}\approx 27.8A \tag{6}$$

The energy storage is desirable for standalone applications. In general effective sun hours are available 4 to 5 hours in a day. Therefore energy generated can be calculated using the equation (7)

$$E_{generated}=P_{panel}\times T_{sun} \tag{7}$$

The energy consumed by the load can be calculated using (8)

$$E_{consumed}=P_{load}\times T_{load}=250\times T_{load}\,Wh/day \tag{8}$$

Suppose, the load is operating 4 hours in a day. Therefore, battery size can be computed using (9). The estimated battery size is 83.33 Ah.

$$C_{battery}=\frac{E_{consumed}}{V_{battery}}=\frac{250W\times T_{load}}{12V} \tag{9}$$

Panels are required to connect series-parallel for meeting the current and voltage in the large scale implementation.

B. **Design of Wind Turbine Generator**

The wind turbine generator used in the proposed HPG is 250 VA. The rating of the lighting load is 250 W. The following steps are used to design wind turbine generator for the proposed HPG. The required power can be computed using the equation (5). The power generated by the wind turbine is estimated using the equation (10)

$$P_{wind}=\frac{1}{2}\rho AV^3C_p \tag{10}$$

In the equation (10), P_{wind} is the power generated by wind turbine, ρ is the air density, A is the swept area of turbine blade in m^2, v is the wind speed in ms^{-1}, C_p is the power coefficient of turbine. Suppose, turbine blade has radious r, swept area can be calculated using equation (11)

$$A = \pi r^2 \tag{11}$$

The energy generated by the wind turbine ($E_{wind-energy}$) is given by the equation (12)

$$E_{wind-energy} = P_{wind} \times T_{wind} \tag{12}$$

The sizing of battery can be estimated using the equation (9).

C. **Design of double input buck-boost converter**

The double input dc-dc buck-boost converter is used to integrate two RES independently or simultaneously depending on the load demand. The circuit diagram of double input dc-dc buck boost converter is shown in the Figure 6. The topology includes back to back connection of two buck boost converter supplied to dc load. The predicted duty cycle is generated using linear regression controller and supplied to the SW_1. The sizing of the double input dc-dc buck boost converter, mode of operation, design computation is presented in the article [36]. In case, power from Wind Turbine is not available, the entire HPG works purely on power from SPV panel and vice versa.

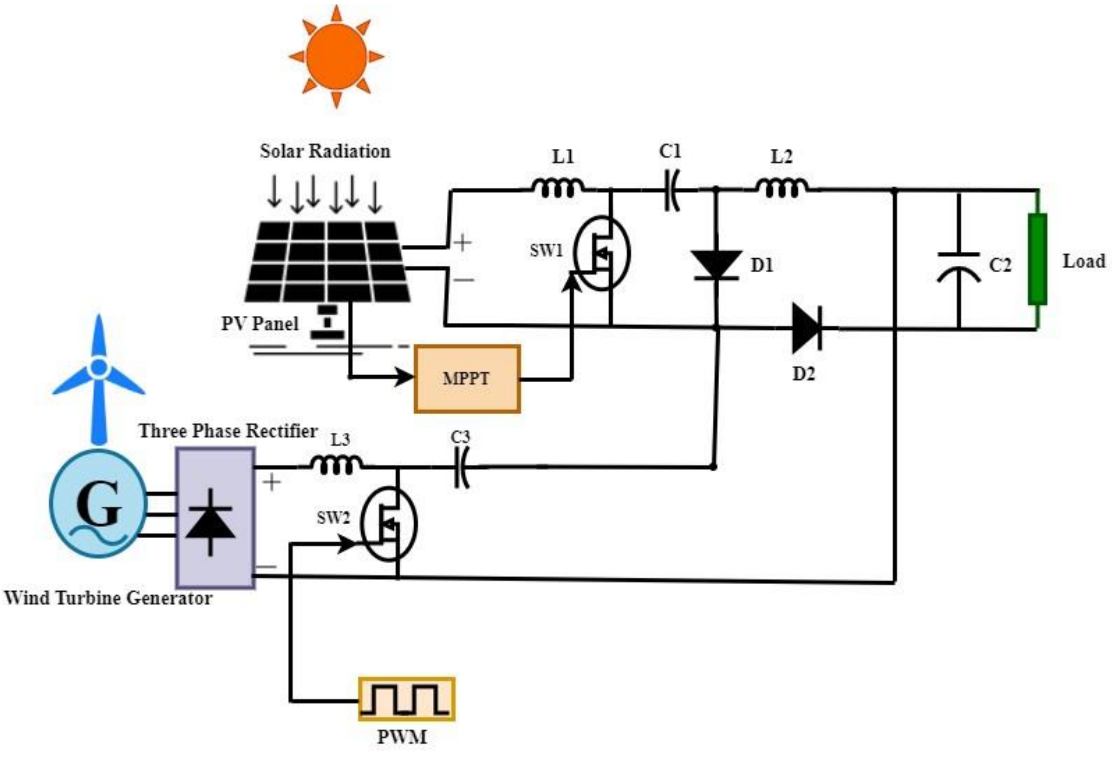

Figure. 6. Double input dc-dc buck boost converter

D. **Development of linear regression model**

To implement a Linear Regression model for Maximum Power Point Tracking (MPPT) of a Solar Photovoltaic (SPV) system, the mathematical equation (13) is considered.

$$P = \theta_0 + \theta_1 \times Irradiance + \theta_2 \times Temperature \tag{13}$$

In the equation (13), θ_0, θ_1, and θ_2 are the model parameters to be learned. Training the model involves finding the optimal value of θ_0, θ_1, and θ_2 that minimizes the actual and predicted power. Calculate performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared to assess the accuracy of the model.

6. Results and Discussions

The proposed hybrid power generation (HPG) system is implemented using MATLAB/Simulink with the machine learning toolbox [37]. Initially, a 250 W solar photovoltaic (SPV) panel, a 250 W wind turbine generator, and a double input buck-boost DC-DC converter are modeled. The effects of partial shading are analyzed, and performance under various microclimatic conditions is evaluated. A machine learning algorithm is integrated into the HPG system, and its performance is tested under zero, weak, and strong shading conditions. Conventional algorithms are also compared to assess the machine learning algorithm's performance across different conditions. Results are presented accordingly.

A. Performance of SPV and WTG during rapidly changing environment

The solar and wind energy sources are intermittent. In order to verify the performance of Solar Photovoltaic Panel (SPV) and Wind Turbine Generator (WTG), MATLAB simulation carried out at different temperature and irradiance.

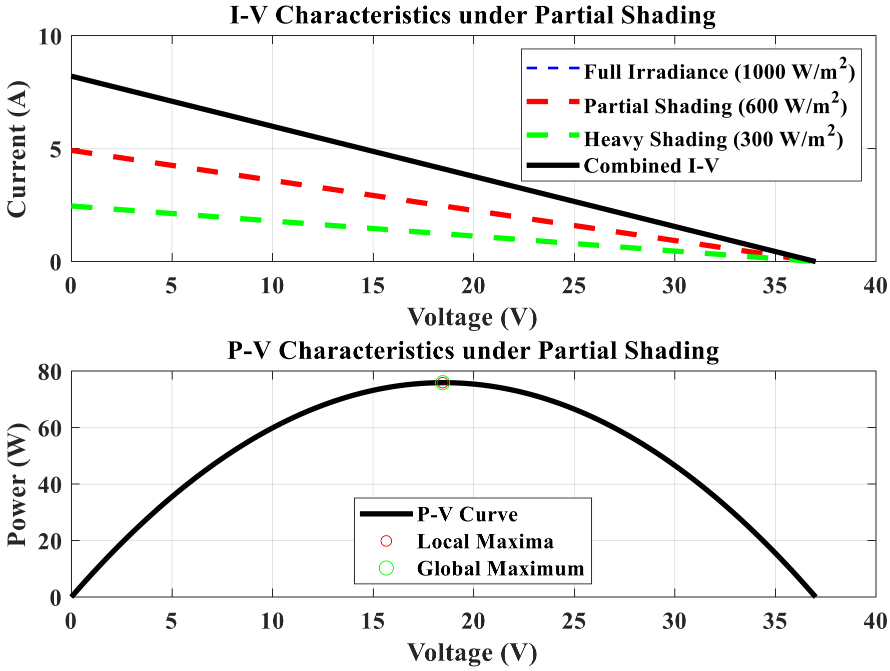

Figure 7. I-V and P-V characteristics under partial shading conditions

It can be observed that partial shading effect reduces maximum current produced by the SPV panel, and results reducing overall current. The I-V curve of SPV panel is shifted to lower level at the same voltage level. While considering P-V curve, multiple peaks are observed. The shaded cell draws power from illuminated cell and the phenomenon is known as hotspot effect. Also, shaded cell contribute reduction in overall power generation. In view of the Figure 7, an efficient control algorithm is necessary to operate SPV panel at its Global Maximum Power Point (GMPP) [38]. The impact of external parameters to the performance of wind turbine generator is presented in the Figure 8.It is observed that wind turbine output increases with increase in wind speed and once the optimal speed is reached, output power remains constant. However, the aerodynamic effect influences on the wind turbine effect and due to this impact, power can slightly reduce. In the Figure 8 (b), as the air density increases more kinetic energy to the turbine blades and results in higher output power.

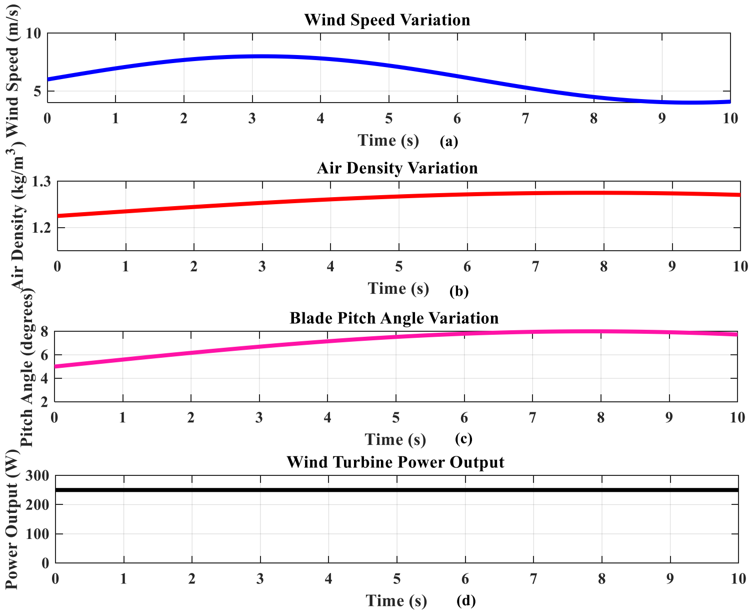

Figure 8. Variation of WTG output with respect to external parameters

The blade angle plays important role to regulate the power output of wind turbine generator. A small pitch angle allows more capturing of energy, whereas high pitch angle doesn't support capturing of more energy. The impact of blade pitch angle variation and wind turbine output power is illustrated in Figure 8 (c) and 8(d).

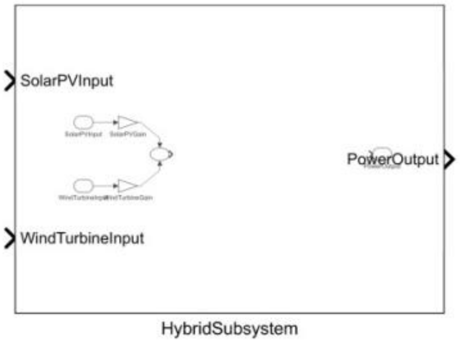

Figure. 9. Subsystem of proposed HPG in MATLAB/Simulink

The SPV model, WTG model, model of double input buck-boost converter and load are integrated in MATLAB/Simulink environment. The subsystem of entire HPG is illustrated in Figure 9. The linear regression algorithm is added in the HPG system and obtained the performance parameters during Zero Shading Condition (ZSC), Weak Shading Condition (WSC), and Strong Shading Condition (SSC) [39]. To validate the performance of linear regression based controllers, popularly used MPPT controllers are added in HPG and evaluated the performance in ZSC, WSC, and SSC.

B. **Performance of Controllers in Partial Shading Condition**

Whenever a small portion of SPV panel is shaded due to trees, clouds, shadows, or dust which affects overall performance of SPV panel is known as partial shading. Initially, the performance of HPG under ZSC is evaluated by considering linear regression and conventional MPPT algorithms. ZSC is an ideal condition at which SPV panel receives full sunlight without partial shading. In ZSC SPV panel is exposed to 1000 W/m^2 and the temperature of 25^0 Celsius. The Figure 10 depicts variation of power output of HPG using linear regression controller at ZSC. Linear regression controller play relatively better regulated output power. The linear regression controllers takes 0.4 to 2.5 s to reach the global power of 118 W.

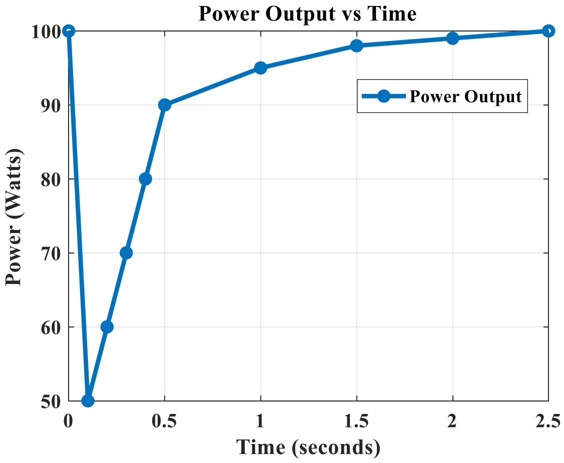

Figure. 10. Output power of HPG with linear regression controller under ZSC

The Figure 11 indicates the variation of duty cycle of dual input dc-dc buck-boost converter. There is a sharp increase in the duty cycle, show cases rapid response from the linear regression controller. It can be observed that, duty cycle has been reduced after 0.5 s due to the reduction in switching action.

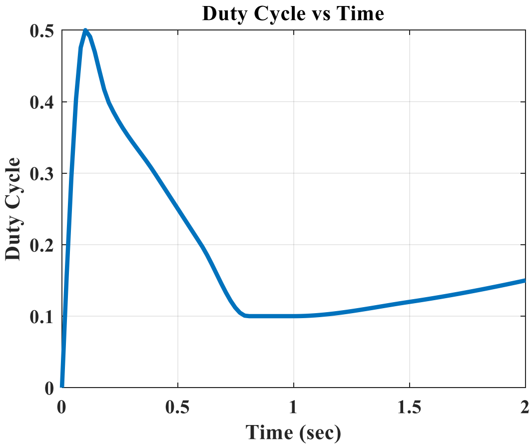

Figure 11. Variation of duty cycle of dual input dc-dc buck-boost converter using regression controller under ZSC

It is found that duty cycle becomes stable after 1s. In the same way, evaluated the performance of linear regression controller in the WSC and the panels are exposed to 800 W/m^2 in WSC.

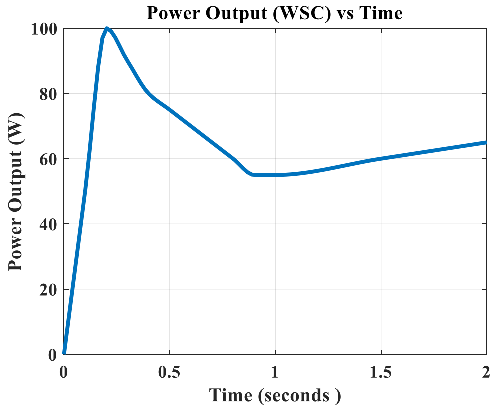

Figure 12. Power ouput of HPG using regression controller under WSC

The Figure 12 depicts regression controller likely plays a significant role in shaping the system's response to the WSC. The rapid initial increase and the subsequent stabilization recommend that the controller is effectively managing the power output to maintain system stability.

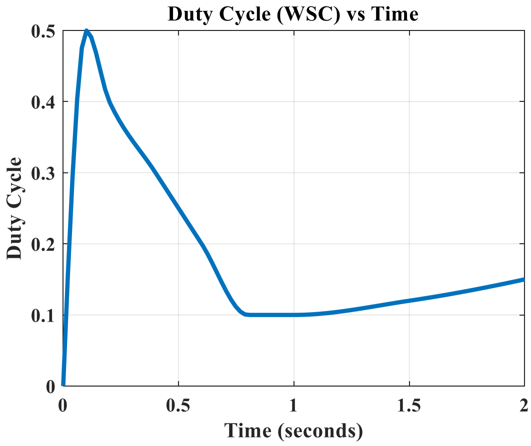

Figure 13. Duty cycle of HPG using regression controller under WSC

In the Figure 13, the duty cycle rapidly increases and became stable after certain time. The linear regression controller helps to maintain the HPG stable. The analysis during the SSC is illustrated here. In the case of SSC, the solar irradiance is considered as 400 to 200 W/m^2.

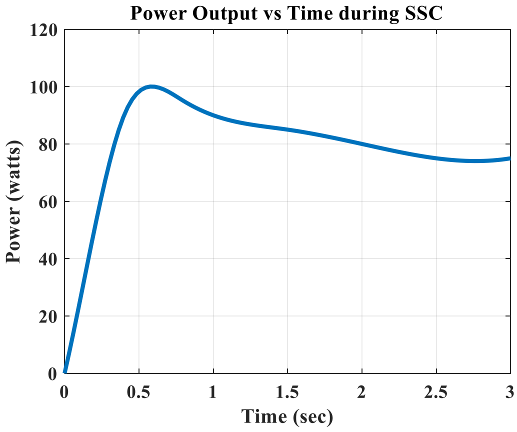

Figure 14. Power output of HPG using regression controller under SSC

It can be observed from the Figure 14, linear regression controller effectively manages power output to ensure system stability. The SSC impacts the performance of entire system compared to ZSC and WSC.

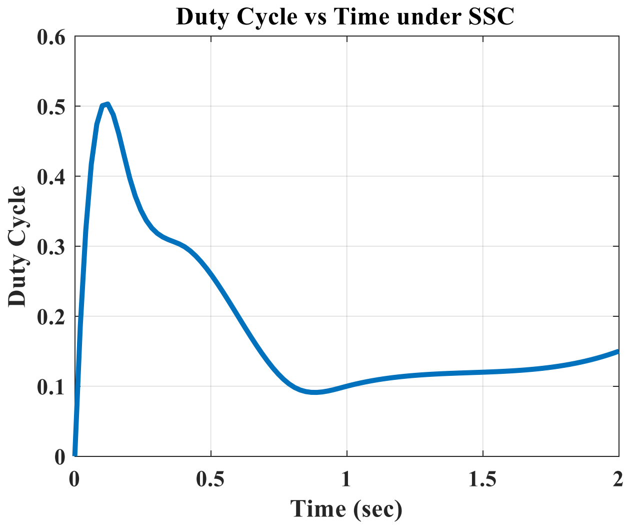

Figure 15. Duty cycle of HPG using regression controller under SSC

The Figure 15 indicates initial increase of duty cycle, gradual decrease and stabilizes after 1s. The regression controller is effective to regulate the duty cycle under SSC.

C. **Comparative Analysis of regression controllers with popularly used MPPT controllers**

In order to validate the performance of regression controller, a comparative analysis with popular MPPT controllers such as Perturb & Observe (P&O), Particle Swam Optimization Algorithm (PSO), and Firefly Algorithm (FA). The parameters such as voltage at maximum power point (VMPP), current at maximum power point (IMPP), Power at MPP, and Efficiency are considered. The Figure 16 illustrates voltage at maximum power point of different control algorithm. It is observed that linear regression controller shows highest voltage at MPP whereas P&O exhibit least voltage at MPP. While observing PSO, and FA algorithm, voltage at MPP remains same. The performance comparison of various control algorithms are shown in Table 1. The Figure 17 presents the comparison of current at MPP. It is found that PSO & P&O exhibit high value of current at MPP. Linear regression controller shows moderate value current at MPP.

Table 1: Performance comparison of control algorithms during ZSC.

Method	Voltage at Maximum Power Point (V)	Current at Maximum Power Point (A)	Power at MPP (W)	Efficiency (%)
Linear Regression (Method 1)	66.38	1.8	118.78	99.91
FA (Method 2)	65.25	1.68	109.15	99.79
PSO (Method 3)	62.46	2.39	105.25	97.32
P&O (Method 4)	60.97	2.28	95.52	93.27

The Figure 18 presents the comparison of maximum power at MPP. The linear gression algorithm shows superior performance where P&O exhibit poor performance. Also, FA and PSO show cases similar performance.

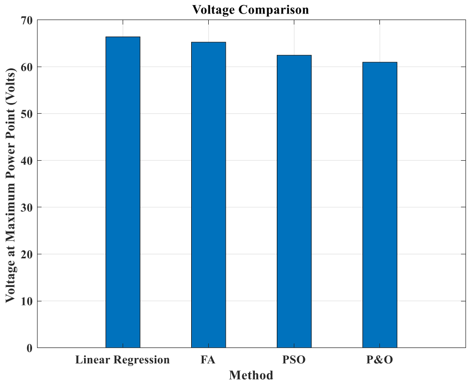

Figure 16. Comparison of control algorithm based on voltage

The Figure 19 illustrates comparison of efficiency of various control algorithms. It is observed that FA and Linear regression show cases highest efficiency. PSO indicates moderate efficiency and P&O exhibit least efficiency among four control algorithm.

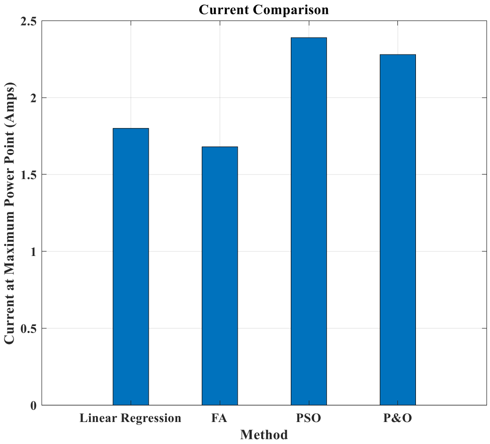

Figure. 17. Comparison of control algorithm based on current

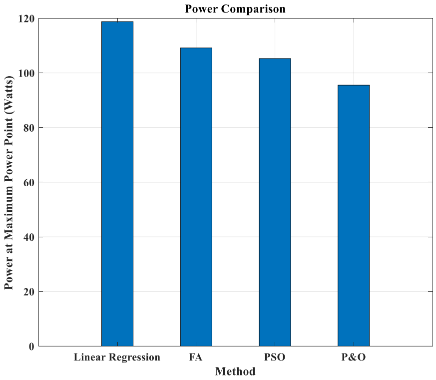

Figure. 18. Comparison of available power at MPP

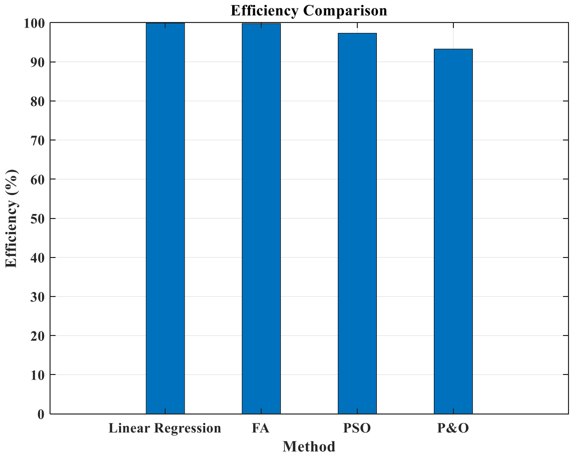

Figure. 19. Comparison of Efficiency

The Table 2 presnts the comparative analysis of control algorithms during WSC. The four methods are compared with respect to four important performance parameters. The graphical analysis is presented in the Figure 20.

Table 2: Performance comparison of control algorithms during WSC

Method	Voltage at Maximum Power Point (V)	Current at Maximum Power Point (A)	Power at MPP (W)	Efficiency (%)
Linear Regression (Method 1)	40.39	2.73	110.23	99.38
FA (Method 2)	36.54	2.35	85.48	96.22
PSO (Method 3)	34.58	2.34	80.23	93.32
P&O (Method 4)	33.69	2.07	70.45	90.27

Method 1 (Linear Regression) recorded the highest voltage at the maximum power point, followed by Method 2 (FA), Method 3 (PSO), and Method 4 (P&O). Both Method 1 and Method 3 produced similar current values, while Method 2 and Method 4 had slightly lower values. Method 1 also delivered the highest power output, with the other methods ranked in the same order. Efficiency was high across all methods, with Method 1 leading. Based on these results, Method 1 is the most effective overall, but the choice of algorithm may vary depending on specific application needs and performance priorities.

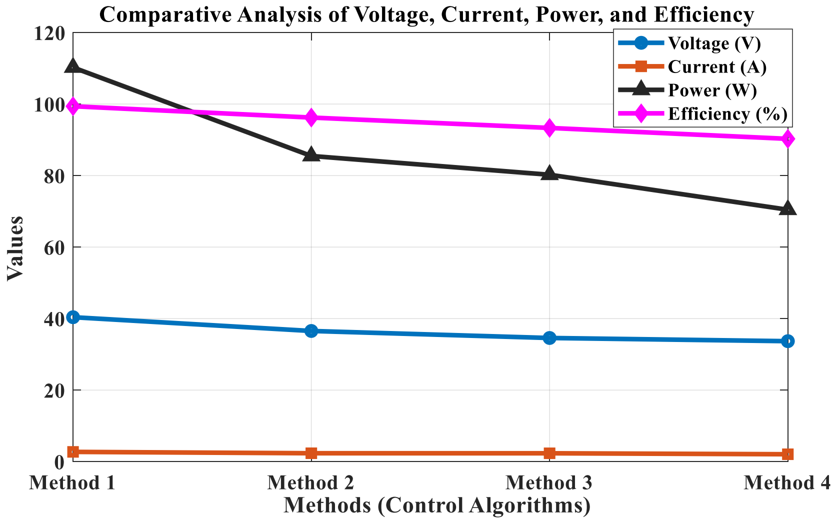

Figure. 20. Comparative Analysis of control algorithm during WSC

The SSC severely impacts on the performance of HPG system. In view of this fact, the performance parameters are computed and presented in Table 3.

Table 3: Performance comparison of control algorithms during SSC

Method	Voltage at Maximum Power Point (V)	Current at Maximum Power Point (A)	Power at MPP (W)	Efficiency (%)
Linear Regression (Method 1)	54.84	1.79	98.16	99.78
FA (Method 2)	56.28	1.54	86.67	98.72
PSO (Method 3)	57.24	1.49	85.29	96.32
P&O (Method 4)	22.47	1.35	30.36	95.27

Method 1 (Linear Regression) yielded the highest voltage, followed by Method 2 (FA) and Method 3 (PSO), while Method 4 (P&O) produced a notably lower voltage. In terms of current, Methods 1 and 2 displayed similar levels, with Methods 3 and 4 having slightly reduced values. Method 1 also delivered the greatest power output, followed by Methods 2 and 3, with Method 4 generating the lowest. Efficiency was high across all methods, with Methods 1 and 2 leading, and Method 4 slightly lagging behind.

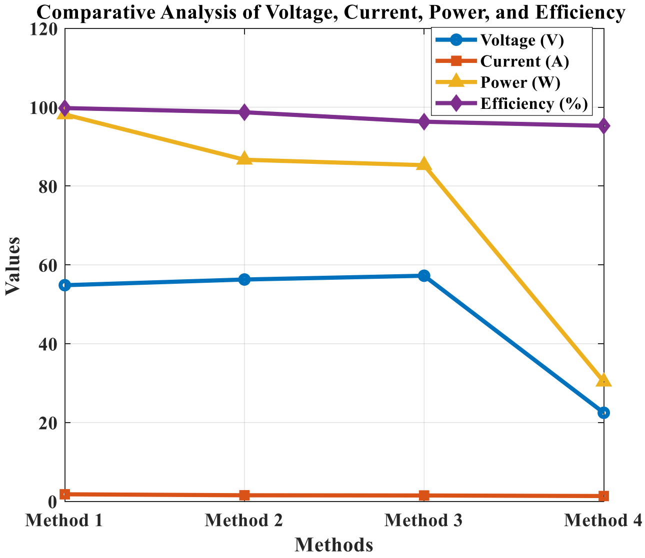

Figure. 21. Comparative Analysis of control algorithm during SSC

Overall, Method 1 proved to be the most effective control algorithm, though the optimal choice may depend on the specific application's performance requirements. The Figure 21 depicts comparative analysis of control algorithms during SSC.

7. Conclusions

In conclusion, the proposed Hybrid Power Generation (HPG) system, integrating solar and wind energy through a double input DC-DC buck-boost converter, effectively addresses the challenges of rural electrification in developing countries. The use of a Linear Regression-based Machine Learning Algorithm for Maximum Power Point Tracking (MPPT) significantly enhances system performance under varying atmospheric and shading conditions. The algorithm's accuracy in duty cycle prediction ensures optimal power output, as demonstrated by the high efficiency levels of 99.91%, 99.38%, and 99.78% under zero, weak, and strong shading conditions, respectively. Moreover, the system exhibited fast convergence times, validating its robustness and reliability. Comparative analysis with existing MPPT algorithms further highlights the superior performance of the proposed approach. Thus, the HPG system offers a promising and feasible solution for reliable rural electrification in developing regions. Future research could explore the integration of additional renewable energy sources or advanced storage solutions to further improve system resilience and scalability. Additionally, expanding the optimization algorithm to include predictive maintenance and real-time monitoring could enhance system reliability in remote areas.

References

[1] Y. Wang et al., "Enhancing Power Grid Resilience With Blockchain-Enabled Vehicle-to-Vehicle Energy Trading in Renewable Energy Integration," in *IEEE Transactions on Industry Applications*, vol. 60, no. 2, pp. 2037-2052, March-April 2024, doi: 10.1109/TIA.2023.3312639.

[2] M. Mahdavi, F. Jurado, K. Schmitt and M. Chamana, "Electricity Generation From Cow Manure Compared to Wind and Photovoltaic Electric Power Considering Load Uncertainty and

Renewable Generation Variability," in *IEEE Transactions on Industry Applications*, vol. 60, no. 2, pp. 3543-3553, March-April 2024, doi: 10.1109/TIA.2023.3330457.

[3] L. Xie, X. Zheng, Y. Sun, T. Huang and T. Bruton, "Massively Digitized Power Grid: Opportunities and Challenges of Use-Inspired AI," in Proceedings of the IEEE, vol. 111, no. 7, pp. 762-787, July 2023, doi: 10.1109/JPROC.2022.3175070.

[4] S. Roy, S. Tufail, M. Tariq and A. Sarwat, "Photovoltaic Inverter Failure Mechanism Estimation Using Unsupervised Machine Learning and Reliability Assessment," in IEEE Transactions on Reliability, vol. 73, no. 3, pp. 1418-1432, Sept. 2024, doi: 10.1109/TR.2024.3359540.

[5] K. Baranwal, P. Prakash and V. K. Yadav, "A Modified Bypass Circuit for Improved Reliability of PV Module Validated With Real-Time Data," in IEEE Transactions on Device and Materials Reliability, vol. 23, no. 2, pp. 187-197, June 2023, doi: 10.1109/TDMR.2023.3247809.

[6] M. Oun, A. Amin, M. A. Qureshi, A. R. Bhatti, and M. M. Ali, "Deep learning based buck-boost converter for PV modules," Heliyon, vol. 10, no. 5, 2024, Art. no. e27405. [Online]. Available: https://doi.org/10.1016/j.heliyon.2024.e27405.

[7] Y. Liu, G. Zhao, X. Tian and W. Li, "Exploration and Practice of Typical Models of Rural Electrification Under the Background of Energy Intelligence," 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS), Bangalore, India, 2024, pp. 1-5, doi: 10.1109/ICITEICS61368.2024.10625152.

[8] A. Chellakhi, S. El Beid, and Y. Abouelmahjoub, "An improved adaptable step-size P&O MPPT approach for standalone photovoltaic systems with battery station," Simulation Modelling Practice and Theory, vol. 121, 2022, Art. no. 102655. [Online]. Available: https://doi.org/10.1016/j.simpat.2022.102655.

[9] H. Abouobaida, Y. Mchaouar, Y. Abouelmahjoub, H. Mahmoudi, A. Abbou, and M. Jamil, "Performance optimization of the INC-COND fuzzy MPPT based on a variable step for photovoltaic systems," Optik, vol. 278, 2023, Art. no. 170657. [Online]. Available: https://doi.org/10.1016/j.ijleo.2023.170657.

[10] B. Gu et al., "Optimal Charge/Discharge Scheduling for Batteries in Energy Router-Based Microgrids of Prosumers via Peer-to-Peer Trading," in IEEE Transactions on Sustainable Energy, vol. 13, no. 3, pp. 1315-1328, July 2022, doi: 10.1109/TSTE.2022.3154145.

[11] O. S. Alemdar, M. U. Oner, O. Altun and O. Keysan, "Ripple Minimization in Asymmetric Interleaved DC–DC Converters Using Neural Networks," in IEEE Transactions on Power Electronics, vol. 39, no. 3, pp. 3411-3421, March 2024, doi: 10.1109/TPEL.2023.3339699.

[12] P. Manasa et al., "Tweet Spam Detection Using Machine Learning and Swarm Optimization Techniques," in IEEE Transactions on Computational Social Systems, vol. 11, no. 4, pp. 4870-4877, Aug. 2024, doi: 10.1109/TCSS.2022.3230823.

[13] A. Awad, A. Hawash and B. Abdalhaq, "A Genetic Algorithm (GA) and Swarm-Based Binary Decision Diagram (BDD) Reordering Optimizer Reinforced With Recent Operators," in IEEE Transactions on Evolutionary Computation, vol. 27, no. 3, pp. 535-549, June 2023, doi: 10.1109/TEVC.2022.3170212.

[14] A. Ostadrahimi and Y. Mahmoud, "Novel Spline-MPPT Technique for Photovoltaic Systems Under Uniform Irradiance and Partial Shading Conditions," in IEEE Transactions on Sustainable Energy, vol. 12, no. 1, pp. 524-532, Jan. 2021, doi: 10.1109/TSTE.2020.3009054.

[15] N. Priyadarshi, M. S. Bhaskar and D. Almakhles, "A Novel Hybrid Whale Optimization Algorithm Differential Evolution Algorithm-Based Maximum Power Point Tracking Employed Wind Energy Conversion Systems for Water Pumping Applications: Practical Realization," in IEEE Transactions on Industrial Electronics, vol. 71, no. 2, pp. 1641-1652, Feb. 2024, doi: 10.1109/TIE.2023.3260345.

[16] A. Mohammad-Alikhani, A. Mahmoudi, R. Khezri and S. Kahourzade, "Multiobjective Optimization of System Configuration and Component Capacity in an AC Minigrid Hybrid Power System," in IEEE Transactions on Industry Applications, vol. 58, no. 3, pp. 4158-4170, May-June 2022, doi: 10.1109/TIA.2022.3160411.

[17] P. Kuntal, A. Mathur and M. N. Alam, "Optimal Power Scheduling of Hybrid Power System," 2021 IEEE 2nd International Conference on Smart Technologies for Power, Energy and Control (STPEC), Bilaspur, Chhattisgarh, India, 2021, pp. 1-6, doi: 10.1109/STPEC52385.2021.9718620.

[18] S. Jha, B. Singh and S. Mishra, "Control of ILC in an Autonomous AC–DC Hybrid Microgrid With Unbalanced Nonlinear AC Loads," in IEEE Transactions on Industrial Electronics, vol. 70, no. 1, pp. 544-554, Jan. 2023, doi: 10.1109/TIE.2022.3148754.

[19] S. El Idrissi Essebtey, L. Villard, P. Borderies, T. Koleck, B. Burban and T. Le Toan, "Long-Term Trends of P-Band Temporal Decorrelation Over a Tropical Dense Forest-Experimental Results for the BIOMASS Mission," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5102415, doi: 10.1109/TGRS.2021.3082395.

[20] S. Tyagi, B. Singh and S. Das, "Small Hydro Based Grid Forming Converter Having Power Sharing and Synchronization Capability With DFIG Based WECS," in IEEE Transactions on Industry Applications, vol. 59, no. 4, pp. 5048-5058, July-Aug. 2023, doi: 10.1109/TIA.2023.3261863.

[21] S. Puchalapalli, B. Singh and S. Das, "Grid-Interactive Smooth Transition Control of Wind-Solar-DG Based Microgrid at Unpredictable Weather Conditions," in IEEE Transactions on Industry Applications, vol. 60, no. 1, pp. 1519-1529, Jan.-Feb. 2024, doi: 10.1109/TIA.2023.3322396.

[22] A. El-Ayoubi and N. Moubayed, "Economic optimization of sources of energies using Wind/PV hybrid system," 2012 International Conference on Renewable Energies for Developing Countries (REDEC), Beirut, Lebanon, 2012, pp. 1-6, doi: 10.1109/REDEC.2012.6416686.

[23] W. Zuo, X. Qin, J. Yi and Y. Xu, "Analysis of Carbon Emission Flow in Hybrid Power Market Based on Cooperative Game Theory," 2024 7th International Conference on Energy, Electrical and Power Engineering (CEEPE), Yangzhou, China, 2024, pp. 1625-1631, doi: 10.1109/CEEPE62022.2024.10586446.

[24] A. B. d. Oliveira Neto, E. G. d. Costa, T. V. Ferreira, B. V. S. Araujo, L. N. T. Alves and K. -E. B. Brito, "Multiparametric Identification of Favorable Regions for Wind or Solar Generation in

the State of Pernambuco," in IEEE Latin America Transactions, vol. 20, no. 6, pp. 891-900, June 2022, doi: 10.1109/TLA.2022.9757371.

[25] G. Senthilkumar, B. Mallala, S. Sivarajan, C. Harish, D. Harsha and N. L, "Maximizing Power Utilization through Machine Learning and IoT based Power Flow Strategies in DC Micro Grids with Renewable Energy Resources," 2024 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 2024, pp. 1166-1171, doi: 10.1109/ICICT60155.2024.10544791.

[26] W. Ahmed et al., "Machine Learning Based Energy Management Model for Smart Grid and Renewable Energy Districts," in IEEE Access, vol. 8, pp. 185059-185078, 2020, doi: 10.1109/ACCESS.2020.3029943.

[27] R. Colucci and I. Mahgoub, "Solar Irradiance Prediction with Ensemble Learning Method as Input for Battery Operation Optimization," 2024 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 2024, pp. 1-6, doi: 10.1109/TPEC60005.2024.10472247.

[28] A. Djellad, N. Bouderres, B. A. Hamdi, S. Chiheb and P. O. Logerais, "A Comprehensive Comparative Study and Optimization of MPPT Algorithms in a Standalone Photovoltaic Plant using Classical and Machine Learning Techniques," 2023 2nd International Conference on Electronics, Energy and Measurement (IC2EM), Medea, Algeria, 2023, pp. 1-6, doi: 10.1109/IC2EM59347.2023.10419644.

[29] K. -H. Chao, M. -H. Wang and Y. -H. Lee, "An extension neural network based incremental MPPT method for a PV system," 2011 International Conference on Machine Learning and Cybernetics, Guilin, China, 2011, pp. 654-660, doi: 10.1109/ICMLC.2011.6016761.

[30] Y. Xu, L. An, B. Jia and N. Maki, "Study on Electrical Design of Large-Capacity Fully Superconducting Offshore Wind Turbine Generators," in IEEE Transactions on Applied Superconductivity, vol. 31, no. 5, pp. 1-5, Aug. 2021, Art no. 5201305, doi: 10.1109/TASC.2021.3061903.

[31] Z. Lu, G. Xu, W. Xiong, Y. Sun and M. Su, "A Quasi-Two-Stage Isolated Bidirectional Buck-DAB Converter for Wide Input Voltage Range," in *IEEE Transactions on Power Electronics*, vol. 38, no. 2, pp. 1384-1390, Feb. 2023, doi: 10.1109/TPEL.2022.3208105.

[32] X. Wang, D. Wang, S. Zhu, Y. Liu and H. Zhao, "Research on Maximum Power Tracking Control Method of 10MW MVSPMSG Based on Neutral Point Potential Balance," in *IEEE Transactions on Applied Superconductivity*, vol. 31, no. 8, pp. 1-4, Nov. 2021, Art no. 0604704, doi: 10.1109/TASC.2021.3117751.

[33] A. N. Ahmed and R. Saini, "Detection of Credit Card Fraudulent Transactions Utilizing Machine Learning Algorithms," 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-5, doi: 10.1109/INOCON57975.2023.10101137.

[34] K. Pundir, N. Kaur, A. Kumar, N. Kumar and C. Das, "Detect Legitimate and Illicit Transactions Using Machine Learning," 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India, 2024, pp. 418-423, doi: 10.1109/IC3SE62002.2024.10592946.

[35] M. M. Badr, M. S. Hamad, A. S. Abdel-Khalik, R. A. Hamdy, S. Ahmed and E. Hamdan, "Fault Identification of Photovoltaic Array Based on Machine Learning Classifiers," in IEEE Access, vol. 9, pp. 159113-159132, 2021, doi: 10.1109/ACCESS.2021.3130889.

[36] M. M. Badr, M. S. Hamad, A. S. Abdel-Khalik, R. A. Hamdy, S. Ahmed and E. Hamdan, "Fault Identification of Photovoltaic Array Based on Machine Learning Classifiers," in IEEE Access, vol. 9, pp. 159113-159132, 2021, doi: 10.1109/ACCESS.2021.3130889.

[37] M. Z. Ali, M. N. S. K. Shabbir, S. M. K. Zaman and X. Liang, "Single- and Multi-Fault Diagnosis Using Machine Learning for Variable Frequency Drive-Fed Induction Motors," in IEEE Transactions on Industry Applications, vol. 56, no. 3, pp. 2324-2337, May-June 2020, doi: 10.1109/TIA.2020.2974151.

[38] M. Kermadi, Z. Salam, J. Ahmed and E. M. Berkouk, "A High-Performance Global Maximum Power Point Tracker of PV System for Rapidly Changing Partial Shading Conditions," in IEEE Transactions on Industrial Electronics, vol. 68, no. 3, pp. 2236-2245, March 2021, doi: 10.1109/TIE.2020.2972456.

[39] R. Rao P, V. K. Vethanayagam, B. Venkatesaperumal and V. V. Ramana, "Modified Current Control for Tracking Global Peak Under Fast Changing Partial Shading Conditions," in IEEE Transactions on Energy Conversion, vol. 37, no. 2, pp. 1211-1222, June 2022, doi: 10.1109/TEC.2021.3122550.