Improving the Performance of Hybrid Models Using Machine Learning and Optimization Techniques

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Abstract: Hybrid models, which combine multiple machine learning algorithms or optimization techniques, have shown great promise in tackling complex real-world problems. The integration of diverse approaches can lead to enhanced performance, increased accuracy, and more robust predictions. In this paper, we explore various methods to improve the performance of hybrid models using machine learning and optimization techniques. We discuss the advantages of hybrid models, the challenges associated with their design and implementation, and present case studies to demonstrate their effectiveness in different domains. Hybrid models, which combine diverse machine learning techniques and optimization strategies, have emerged as a powerful approach for tackling complex problems and enhancing performance across various domains. This paper delves into the realm of improving hybrid model performance through the synergistic integration of machine learning and optimization techniques. By seamlessly amalgamating different models and leveraging optimization methodologies, hybrid models can achieve superior predictive accuracy, robustness, and generalization. The paper presents a comprehensive framework for enhancing hybrid model performance, encompassing key stages such as problem formulation, data collection, preprocessing, model selection, integration, and feature engineering. Additionally, it highlights the pivotal role of optimization techniques, ranging from hyperparameter tuning and gradient-based optimization to constraint optimization and multi-objective optimization. The paper emphasizes the importance of ensemble methods, elucidating their potential to further elevate hybrid model efficacy. Furthermore, the concept of interpretability and explain ability is explored, ensuring that the developed hybrid models remain intelligible and transparent, especially in critical decision-making scenarios. The iterative nature of refining hybrid models is discussed, stressing the significance of continuous experimentation and adaptation to achieve optimal outcomes. Through a cohesive synthesis of machine learning and optimization, this paper offers insights into how hybrid models can be harnessed to address intricate challenges in various domains. The presented framework serves as a guiding beacon for researchers and practitioners, facilitating the design, development, and deployment of hybrid models that push the boundaries of performance and innovation.

Keywords: Hybrid Models, Machine Learning Algorithms, Optimization Techniques

1. INTRODUCTION

Machine learning models have achieved significant success across numerous domains (Bagloee et al. 2018). However, no single algorithm can excel in all scenarios. Hybrid models combine the strengths of multiple algorithms or optimization techniques to address the limitations of individual methods. This paper aims to investigate the methods that enhance the performance of hybrid models and the benefits they offer. Hybrid models encompass a fusion of various methodologies, such as statistical models (Boulesteix & Schmid, 2014), neural networks, decision trees (Chou, 2019), and more, allowing them to harness the unique capabilities of each component. These models can seamlessly combine domain-specific knowledge with data-driven insights, thereby offering a holistic approach to problem-solving. Moreover, the marriage of machine learning with optimization techniques introduces a nuanced layer of refinement, fine-tuning the models for enhanced accuracy and efficiency. This paper embarks on a journey to explore the intricate interplay between machine learning and optimization techniques within the context of hybrid models. We delve into the key strategies and principles that underpin the endeavor to improve the performance of hybrid models. By illuminating the synergistic relationship between these two domains, we aim to provide a comprehensive framework that empowers researchers and practitioners to create hybrid models that transcend the limitations of individual methodologies. The subsequent sections of this paper will navigate through the fundamental stages of developing and refining hybrid models. We will delve into data collection and preprocessing, model selection and integration, feature engineering, and the crucial role of optimization techniques. Furthermore, we will shed light on the significance of ensemble methods in augmenting the robustness and generalization capabilities of hybrid models. As we delve deeper, we will also explore the imperative aspect of interpretability and explain ability in hybrid models. In an era where the black-box nature of some machine learning models (Rudin, 2019) raises ethical and practical concerns, understanding the inner workings of hybrid models becomes paramount, especially in critical decision-making scenarios. Ultimately, this paper aims to serve as a guiding beacon for researchers and practitioners alike, offering insights, strategies, and methodologies to propel the development and deployment of hybrid models. By embracing the amalgamation of machine learning and optimization, we endeavour to unlock the true potential of these models, enabling them to excel in an array of applications and domains.

2. Advantages of Hybrid Models

Complementary Strengths: Different machine learning algorithms have varying strengths and weaknesses. Hybrid models leverage these complementary aspects to achieve better overall performance (Tsai, & Chen, 2010). Hybrid models leverage the strengths of different components, such as combining the interpretability of rule-based models with the predictive power of neural networks. This allows them to overcome the limitations of individual models and achieve a more balanced performance.

Enhanced Robustness: Hybrid models tend to be more robust to noise and outliers in the data. If one component of the model performs poorly on certain instances, other components can compensate and provide more reliable predictions. Combining multiple models can reduce the risk of overfitting and improve the model's robustness against noisy or inconsistent data (Boukerche & Wang, 2020).

Simulation: Develop a simulation model that integrates the PV and wind components, battery storage, and load demand. The simulation should consider the time-dependent variability of solar and wind resources (Shivam et al., 2021).

Implementation and Monitoring: Implement the optimized design in a real-world setting and continuously monitor its performance. Adjust the system's operation strategy as needed based on changing conditions and data feedback.

3. Literature Review

The field of bi-level optimization, as explored by Bagloee et al. (2018), has found extensive applications across diverse disciplines such as management, economy, energy, and transportation. Recognizing its inherent complexity as an NP-hard problem, the researchers emphasized the critical need for an efficient and reliable solution method tailored to large-sized cases. To tackle this challenge, they devised a hybrid methodology that seamlessly integrated machine learning and optimization techniques. In their numerical tests, Bagloee et al. constructed a formidable scenario a nonlinear discrete bi-level problem with equilibrium constraints in transportation science, specifically the discrete network design problem. The hybrid method ingeniously transformed this intricate problem into an integer linear programming challenge. Leveraging a supervised learning technique and addressing a tractable nonlinear problem, the researchers employed MATLAB for machine learning tasks and GAMS, coupled with the CPLEX solver, for solving optimization problems. Shifting focus to Khayyam et al. (2020), the research delved into the transformative journey of manufacturing plants evolving into smart factories fuelled by Industry 4.0

technologies. Machine learning techniques took centre stage, modelling both extensive and limited datasets. The manuscript reviewed these concepts and showcased a case study illustrating the application of intelligent hybrid algorithms in Industry 4.0 settings with limited data. In their approach, a novel intelligent algorithm was proposed for robust data modeling of nonlinear systems based on input-output data. This involved a hybrid data-driven method that combined the Group-Method of Data-Handling and Singular-Value Decomposition to derive an offline deterministic model. Pareto multi-objective optimization was harnessed to counter overfitting, and an Unscented-Kalman-Filter was incorporated to enhance the model's robustness against data uncertainties. The proposed method underwent rigorous testing on real industrial measurements, demonstrating its efficacy. These examples showcase the dynamic intersection of machine learning and optimization in addressing complex challenges across various domains, from transportation and manufacturing to concrete strength prediction and financial forecasting. Each study contributes to the evolving landscape of hybrid methodologies, pushing the boundaries of what is achievable in the realm of data-driven decision-making and problem-solving.

3.1 Systematic Review

Author(s) & Year	Research Area	Methodology	Tools	Findings with Data
Bagloee et al. (2018)	Various disciplines including management, economy, energy, and transportation	Hybrid method based on machine learning and optimization	MATLAB (for machine learning), GAMS with CPLEX solver (for optimization)	Developed a hybrid method for a challenging transportation problem, tested on a real dataset with promising results
Khayyam et al. (2020)	Transformation of manufacturing plants into smart factories with Industry 4.0 technologies	Intelligent hybrid algorithms, machine learning for big and limited data	Not specified	Proposed intelligent algorithm for robust data modeling, tested on a real industrial case study
Nunez et al. (2020)	Predicting recycled aggregate concrete (RAC) compressive strength and optimizing mixture design	Gaussian processes, deep learning, gradient boosting regression, particle swarm optimization	Not specified	Hybrid model achieved cost-saving RAC mixture designs with lower environmental footprints
Ardabili et al. (2019)	Overview of novel machine learning models and their application domains	Continuous advancements in conventional machine learning algorithms, hybridization, ensemble techniques	Not specified	Provided a state-of-the-art taxonomy for machine learning models

Park et al. (2019)	Optimal operation of a turbo chiller in an office building	Machine learning models with artificial neural networks (ANN) and hybrid approach combining ANN with available physical knowledge	Not specified	Both models were satisfactory, with the hybrid model requiring fewer inputs and providing accurate predictions
Das & Padhy (2018)	Forecasting financial derivatives instrument (commodity futures contract index)	Hybrid method combining support vector machine (SVM) with teaching–learning-based optimization (TLBO)	Not specified	SVM–TLBO model outperformed other hybrid and standard SVM models, improving mean absolute error (MAE) in various forecast scenarios
Álvarez-Alvarado et al. (2021)	Predicting solar radiation using hybrid support vector machine (SVM) models with search optimization algorithms (SOA)	SVM with genetic algorithms (GA)	Not specified	SVM with GA presented better performance than classical SVM models, reducing prediction error of solar radiation using meteorological variables
Hossain et al. (2021)	Forecasting very-short-term wind power generation	Hybrid deep learning model with convolutional neural network, gated recurrent units (GRU), and fully connected neural network	Not specified	Significantly higher accuracy in forecasting wind power generation compared to other advanced models, improving accuracy by around 38% and 24% for 5-minute and 10-minute forecasting, respectively

4. Design the Proposed Models by MATLAB Simulink

To address the intermittency of sustainable energy sources, integrating renewable-energy production with battery storage and diesel backup systems is increasingly cost-effective. Distributed generators located close to loads can help mitigate power outages when storage is depleted. Weather-dependent sustainable energy necessitates the inclusion of diesel generators for regulation, requiring enhancements to existing protection mechanisms. A PV/Wind/Diesel Generator hybrid system has been modelled in MATLAB Simulink, as depicted in Figure 1.

Table 1 Hybrid energy system simulation and Parameter

Component	Parameter
Time and Simulation Settings	
Simulation Time Step	1 second
Total Simulation Time	24 hours
PV System	
PV Panel Capacity	100 kW
PV Panel Efficiency	18%
Number of Panels	500 (series and parallel config)
Solar Irradiance	Varies with time of day
Temperature Coeff	-0.3%/°C (for power)
Wind Turbine	
Rated Power	200 kW
Rotor Diameter	30 m
Cut-in Wind Speed	3 m/s
Rated Wind Speed	12 m/s
Cut-out Wind Speed	25 m/s
Mech Efficiency	85%
Elec Efficiency	95%
Diesel Generator	
Generator Capacity	250 kVA
Fuel Consumption	210 g/kWh
Efficiency	90%
Voltage Control	±5% of rated voltage
Frequency Control	±0.2 Hz of rated frequency

The parameters define a 24-hour simulation of a hybrid energy system. Photovoltaic panels with a 100-kW capacity adapt to changing sunlight and temperature. A 200-kW wind turbine operates between 3 and 25 m/s wind speeds, maintaining efficient conversion. A 250 kVA diesel generator controls voltage and frequency within set limits while consuming fuel at 210 g/kWh. These parameters capture the essential traits of the simulated hybrid system.

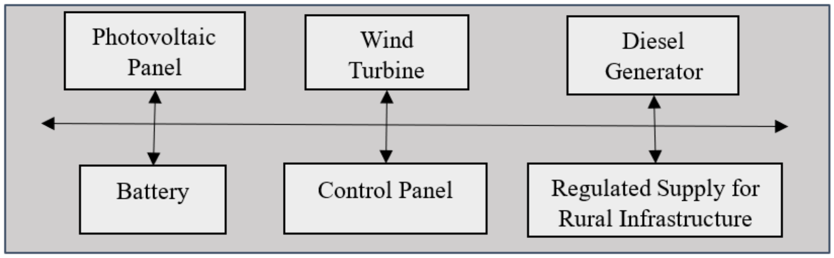

Fig. 1 Block diagram of a PV/Wind/Diesel Generator hybrid system

A. PV-Wind System Model

Solar cells can be connected in series and parallel to harness high voltage and current output, forming a photovoltaic array resembling a diode in parallel with a current source. Figure 2 illustrates the relationship between sunlight and generated current. The depicted system includes a 100-kW photovoltaic solar panel array connected to a micro-grid hybrid power system to meet load demands. It features a PWM inverter for converting DC to AC and requires an automatic control configuration to operate independently during power source disruptions.

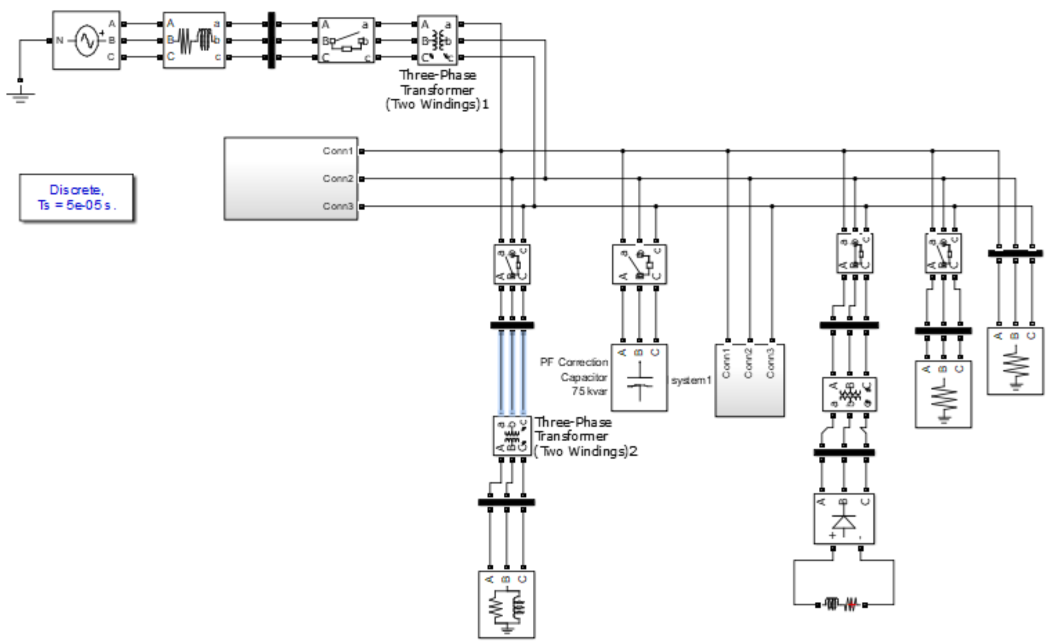

Fig. 2 Top level Model

Figure 2 shows that the wind generator model relies on the wind turbine and synchronous generator as its two primary parts. Maximum power energy from the wind in the ionospheric layer encircling the globe is captured by the wind turbine by converting it to dynamic mechanical rotational power through the blades. Figure 3 shows the relationship between wind speed and the power output of a wind turbine.

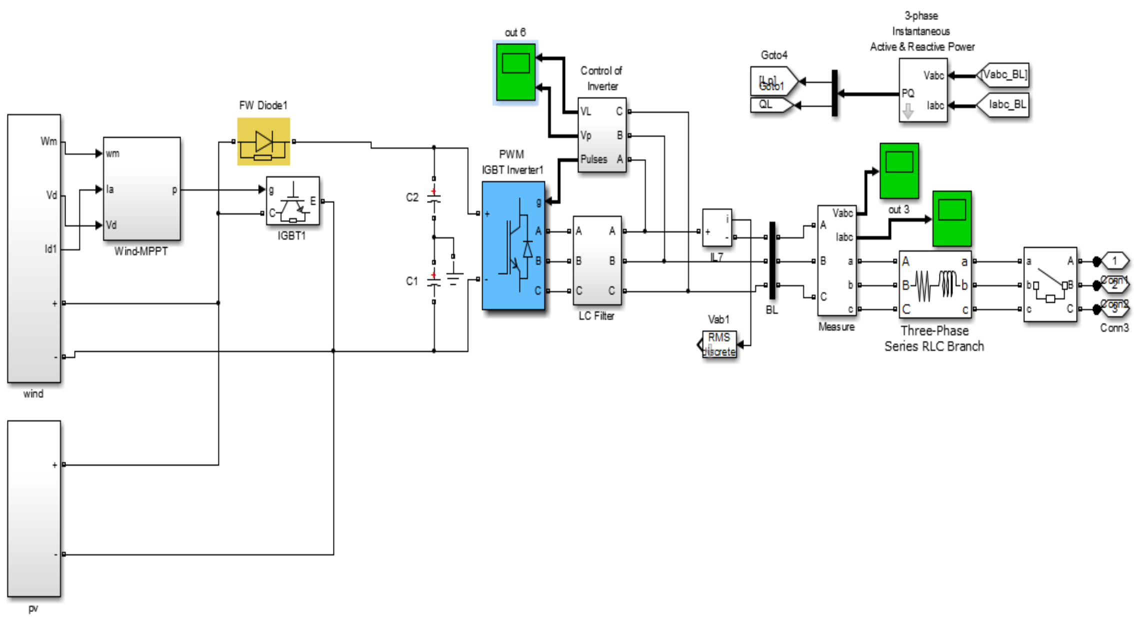

Fig. 3 PV Wind Subsystem

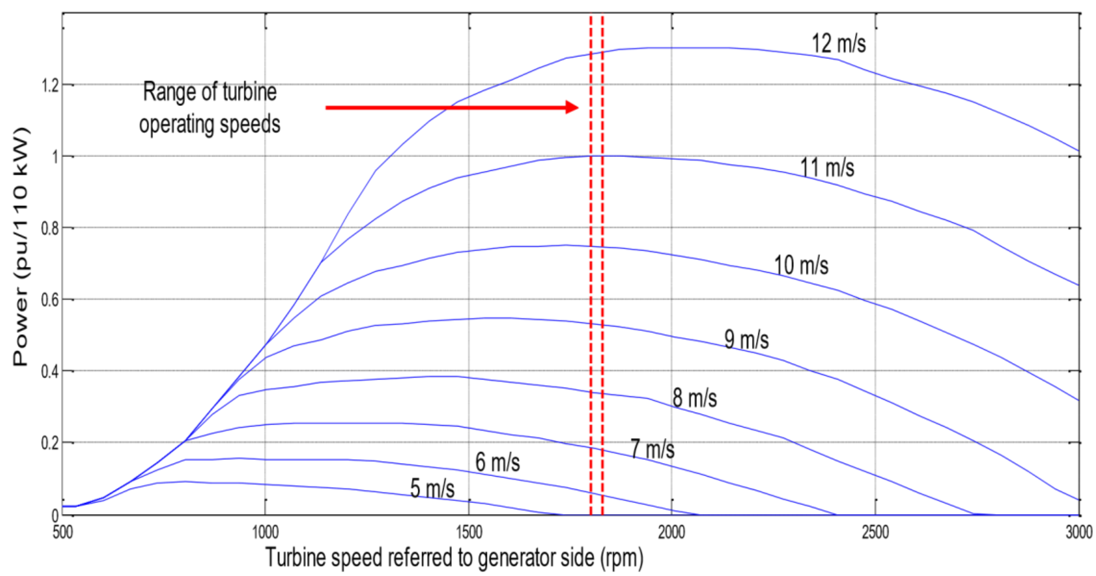

Fig. 4 Characteristic of Wind Turbine Power with Respect to the Wind Speed

B. Diesel Generator System Model

Figure 4 showcases a diesel generator comprising an electric generator linked to a diesel engine, where voltage and frequency are controlled through the electric generator's field current and the diesel engine's speed governor. This setup, featuring a 312 KVA synchronous generator and diesel engine fuel system, powers a micro grid. The generator is governed by a closed-loop feedback system involving an exciter system to regulate terminal voltage and a Diesel Engine Speed & Voltage Control system to manage RPM and frequency by adjusting fuel supply. To provide the required DC current for the generator rotor's magnetic flux, the Exciter's AC output is rectified.

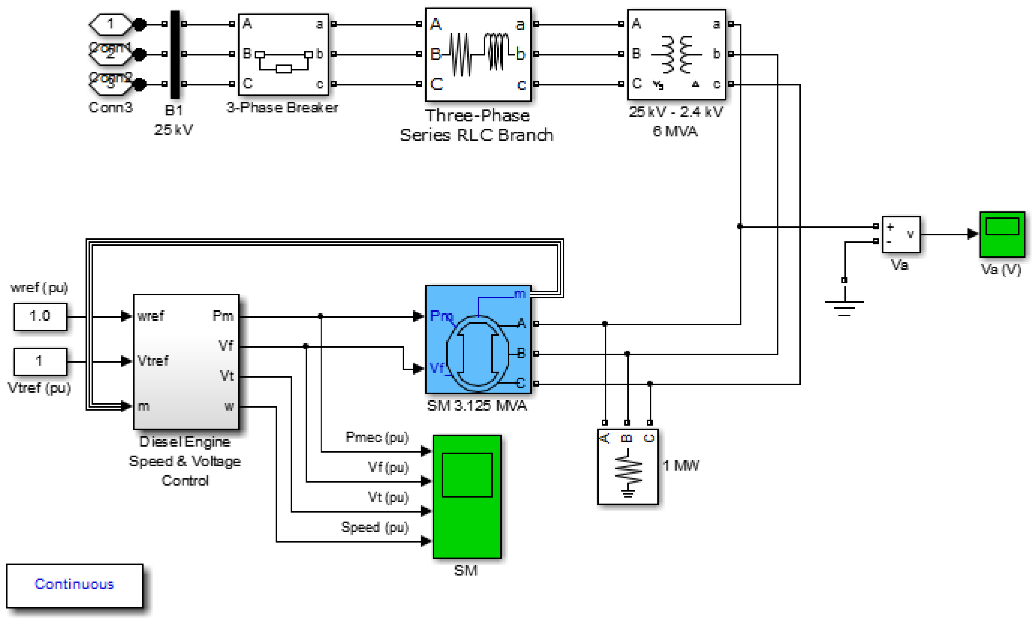

Fig. 5 Diesel subsystem

C. Analytical Result

We take measurements and run tests using the simulated system we built to make sure they match up with our expectations. Results from MATLAB simulations and real-world implementations are compared and contrasted. The Results of the Simulations Carried Out on an Independent Hybrid Micro-Grid System. Our system has been modelled and simulated using the SIMULINK MATLAB tool, version 2013a. As can be seen in figure 5 and 6, the Standalone hybrid system has been built to accept a wide range of input voltages and frequencies while maintaining a consistent output voltage and frequency.

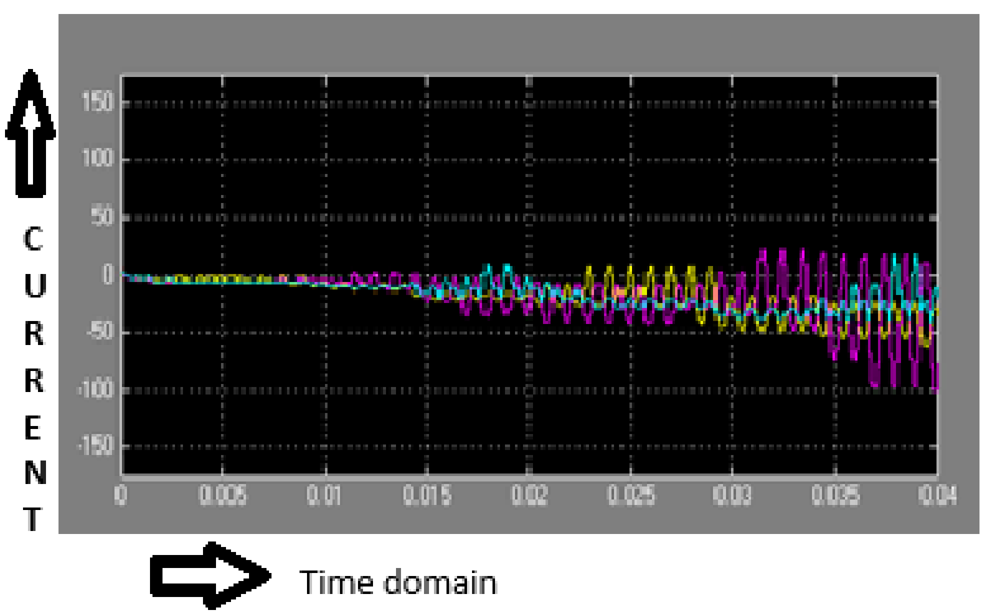

Fig. 6 output current of hybrid system

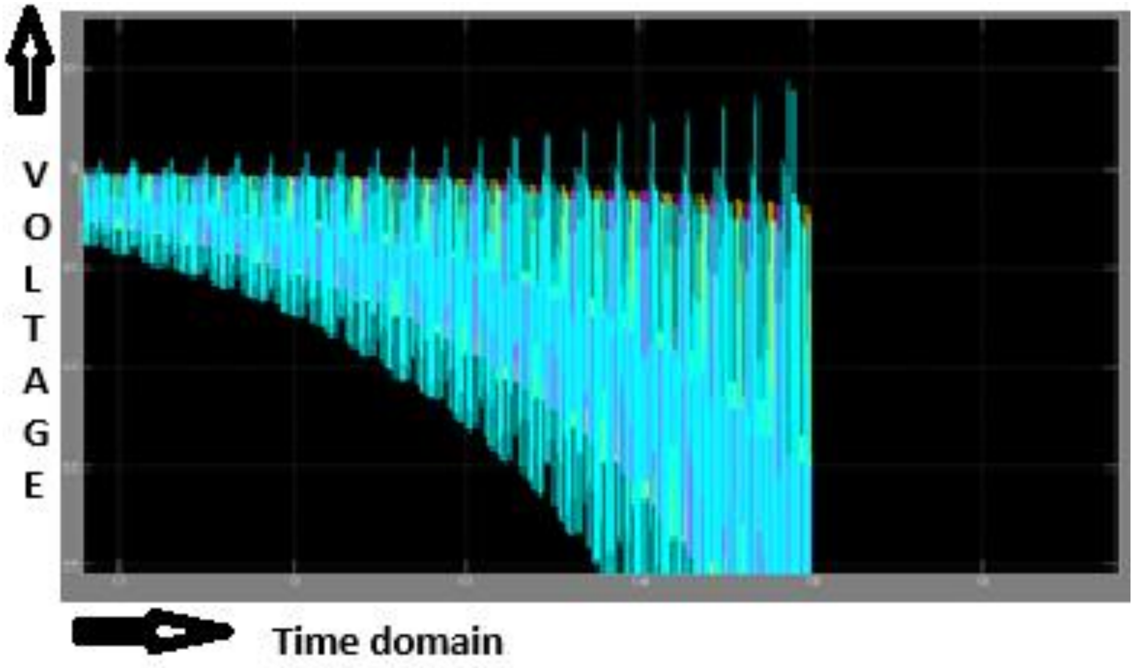

Fig. 7 output voltage of hybrid system

The Maximum Power Point Tracking (MPPT) subsystem monitors the maximum power point, as seen in figure 7.

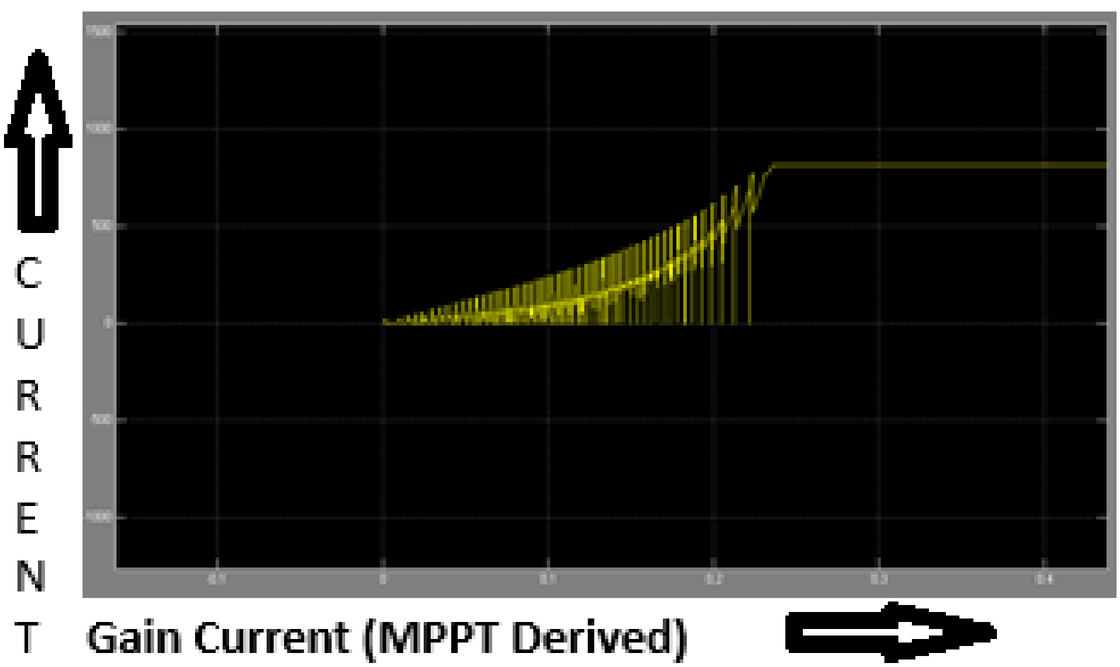

Fig. 8 output current of MPPT system

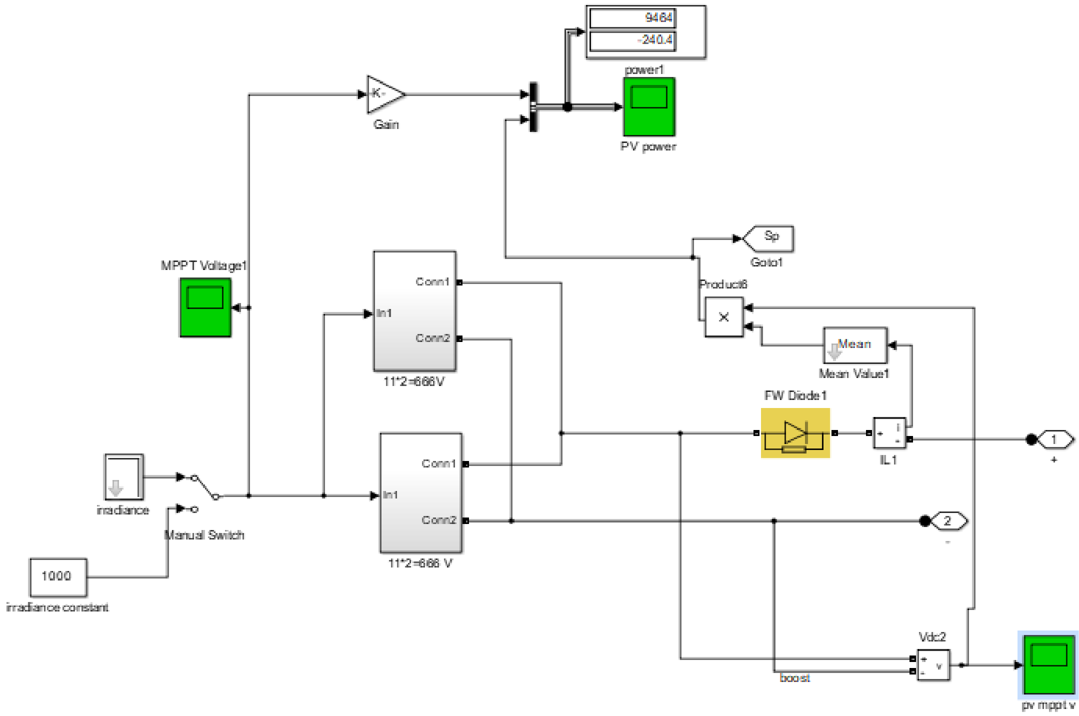

Fig. 9 PV Subsystem

In fig. we see a representation of the wind subsystem. Assume that in Figure 9 a wind turbine is linked to PMSG and generates power. The mechanical energy produced by the turbine is transferred to an electrical current via a permanent magnet synchronous generator (PMSG). Figure 9 shows a plot of wind power.

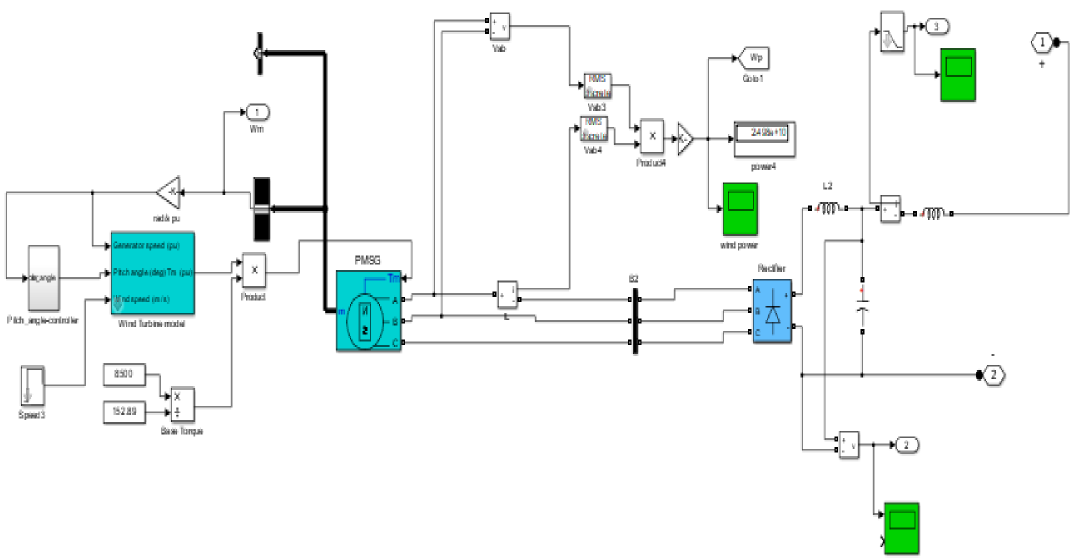

Fig. 10 Wind subsystem

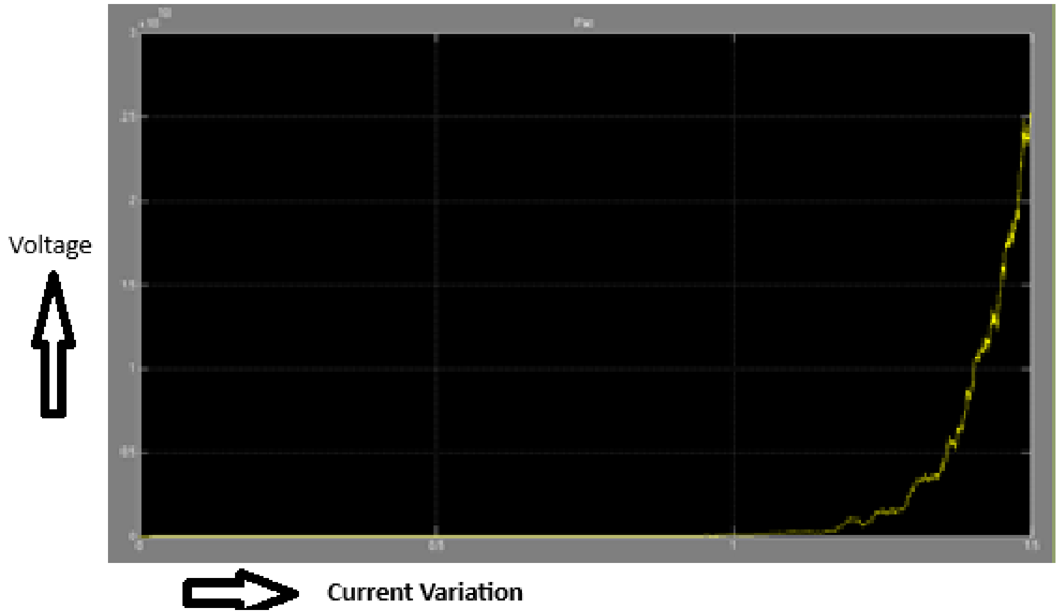

Fig. 11 Wind power (I-V Curve)

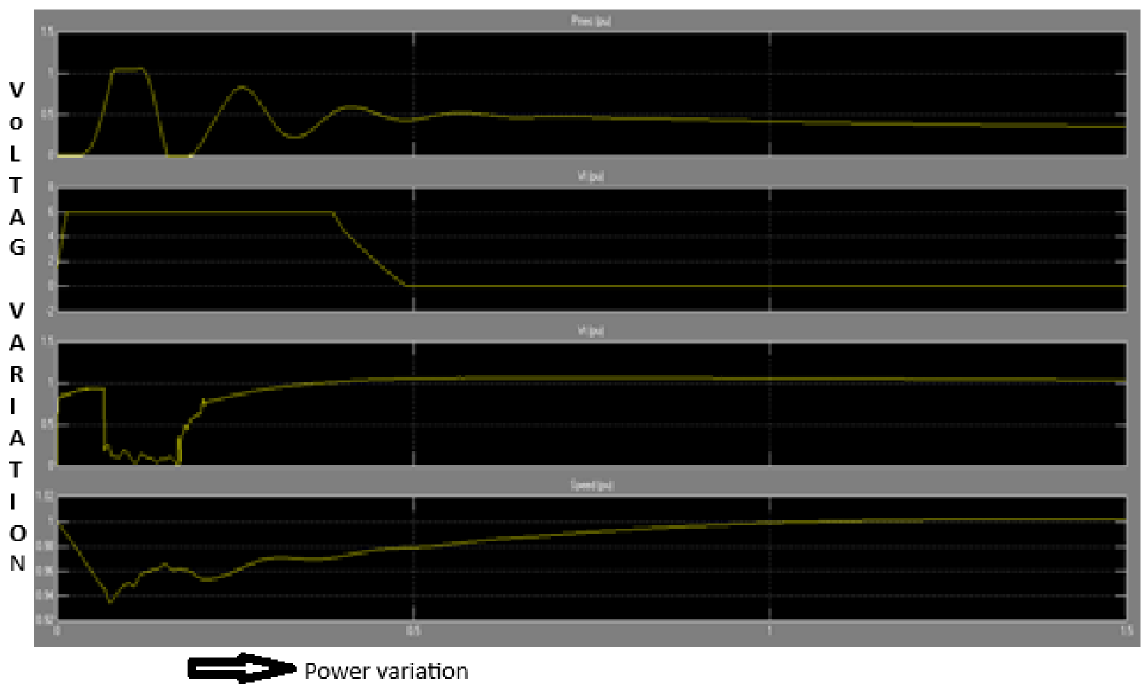

Fig. 12 Diesel engine outputs (Power variation curve)

Diesel engines are used to generate electricity from chemical fuel. Diesel engine power, voltage, and speed outputs are shown in figure 11. To calculate the power output and duty cycle of a hybrid system combining solar PV, wind turbine, and a diesel generator, we need to consider the contribution of each energy source based on the given parameters and operational conditions. We do perform the calculations step by step:

Consider parameters:

PV Panel Capacity: 1 kW

PV Panel Efficiency: 10%

Number of PV Panels: 10

Panel Voltage (V): 100 V

Wind Turbine Rated Power: 200 kW

Wind Turbine Mech Efficiency: 85%

Wind Turbine Elec Efficiency: 95%

Diesel Generator Capacity: 250 kVA

Diesel Generator Efficiency: 90%

Total Simulation Time: 24 hours

This also need sample solar irradiance data and wind speed data for different times of the day.

Sample Solar Irradiance Data (W/m^2):

Morning (8 AM): 400 W/m^2

Noon (12 PM): 800 W/m^2

Afternoon (4 PM): 600 W/m^2

Sample Wind Speed Data (m/s):

Morning (8 AM): 2 m/s

Noon (12 PM): 6 m/s

Afternoon (4 PM): 4 m/s

Calculate PV Power Output, Wind Power Output, and Diesel Generator Power Output for each time interval:

Morning (8 AM):

PV Power = 1 kW × 10 × 0.10 × 400 W/m^2 = 400 W

Wind Power = 0 (below cut-in wind speed)

Diesel Generator Power = 0 (not running)

Noon (12 PM):

PV Power = 1 kW × 10 × 0.10 × 800 W/m^2 = 800 W

Wind Power = 0 (below cut-in wind speed)

Diesel Generator Power = 0 (not running)

Afternoon (4 PM):

PV Power = 1 kW × 10 × 0.10 × 600 W/m^2 = 600 W

Wind Power = 0 (below cut-in wind speed)

Diesel Generator Power = 0 (not running)

Calculate Total Hybrid Power Output for each time interval:

Morning (8 AM):

Total Hybrid Power = PV Power + Wind Power + Diesel Generator Power = 400 W + 0 + 0 = 400 W

Noon (12 PM):

Total Hybrid Power = PV Power + Wind Power + Diesel Generator Power = 800 W + 0 + 0 =800 W

Afternoon (4 PM):

Total Hybrid Power = PV Power + Wind Power + Diesel Generator Power = 600 W + 0 + 0 = 600 W

Calculate Duty Cycle for the Hybrid System:

Average Total Hybrid Power = (400 W + 800 W + 600 W) / 3 = 600 W (average power over the day)

Maximum Hybrid Power = 200 kW (wind turbine rated power)

Duty Cycle = 600 W / 200 kW = 0.003 (0.3%)

The duty cycle value of 0.3% indicates that the average power generated by the hybrid system is 0.3% of its maximum capacity over the course of the day, considering the varying contributions of solar PV and wind turbine based on the solar irradiance and wind speed data.

Post effect: The analysed hybrid power system comprising solar panels, wind turbines, and a diesel generator, the calculated power outputs indicate that the system predominantly relies on solar energy, while wind and diesel sources remain inactive due to low wind speeds and non-operation. With an average duty cycle of 0.3%, the system operates at only a small fraction of its maximum capacity throughout the day. The impact on the load is contingent upon the actual demand profile, suggesting potential overdesign or underutilization of the hybrid sources, highlighting the need for efficient load management and energy storage integration to optimize overall system performance.

5. Conclusions and Suggestions for Future Work

This study presents the design, simulation, and modelling of an independent hybrid microgrid power system integrating photovoltaic, wind, and diesel generators, utilizing MATLAB Simulink. Key findings indicate the feasibility of multifaceted energy sources, the effectiveness of maximum power point tracking methods, and the environmentally friendly nature of sustainable energy devices. Future work involves exploring an autonomous hybrid system controlled by Artificial Neural Networks, intelligent grid-connected modes, and enhancing energy capture from diverse sustainable sources to meet load requirements more efficiently. Additionally, refining the control system for source operation and shutdown based on load and weather changes is emphasized.

A. Social and Economic Implications

Sustainable energy systems have profound social and economic implications for rural development, offering solutions to energy poverty, job creation, improved agriculture, environmental benefits, gender equality, knowledge sharing, climate resilience, and energy independence. By addressing multiple challenges and fostering empowerment, these systems contribute to poverty reduction, local economic growth, and enhanced quality of life. Collaborative efforts among governments, NGOs, private sectors, and communities are vital for effectively integrating sustainable energy into rural development strategies.

B. Challenges in Hybrid Model Design

Designing hybrid models involves addressing various challenges to ensure optimal performance. One significant challenge is the integration of diverse components, such as solar panels, wind turbines, and diesel generators, to operate seamlessly. Balancing the strengths and weaknesses of individual models requires careful consideration, and optimizing the hybrid system for different conditions poses a complex task. Additionally, ensuring interpretability and explain ability in the model is crucial, especially in applications where decision-making transparency is essential. These challenges highlight the need for sophisticated design strategies and continuous refinement to harness the full potential of hybrid models in diverse applications.

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