



## AI-Integrated Sensorless Control of BLDC Motors for Energy-Efficient Electric Vehicles

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### Abstract

Electric Vehicles (EVs) are gaining prominence as a sustainable and eco-friendly mode of transportation. Brushless DC (BLDC) motors are widely implemented in EVs due to their high efficiency, compact size, and operational reliability. Conventional BLDC motor control methods depend on mechanical sensors, which not only raise costs but also introduce potential points of failure. The proposed sensorless control strategy addresses these limitations by eliminating mechanical sensors, thereby improving reliability and reducing overall system costs. This study introduces an advanced control framework that integrates Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), and Machine Learning (ML) techniques for accurate rotor position estimation—an essential factor for optimizing BLDC motor performance in EVs. ANN provides adaptive learning for complex nonlinear relationships, FLC enables robust decision-making under uncertainty, and ML supports predictive modeling for performance enhancement. The paper emphasizes theoretical design, control logic, and integration of these AI-driven methods within the Sensorless control architecture, without dependence on physical prototypes or simulations. The proposed conceptual framework offers a foundation for future simulation or hardware validation, highlighting its cost-effectiveness, scalability, and robustness for next-generation EV applications.

**Keywords:** Artificial Neural Network; BLDC Motor; Electric Vehicle; Fuzzy Logic Controller; Machine Learning; Sensorless Control.

### 1. Introduction

The rapid shift towards sustainable transportation has accelerated the adoption of Electric Vehicles (EVs) as a viable alternative to conventional fossil-fuel-powered vehicles. Growing concerns over climate change, energy security, and rising fuel prices have prompted governments, industries, and researchers to focus on eco-friendly mobility solutions. In this context, the Brushless DC (BLDC) motor has emerged as a preferred choice for EV propulsion due to its high energy efficiency, low maintenance requirements, compact design, and superior torque-speed characteristics. Traditionally, BLDC motor control has relied on mechanical position sensors such as Hall-effect sensors or optical encoders to determine the rotor position. While effective, these

sensors introduce several limitations, including higher production costs, increased system complexity, and reduced reliability due to their susceptibility to environmental conditions and mechanical wear. These drawbacks have driven research toward Sensorless control techniques, which estimate rotor position through computational methods, eliminating the need for physical sensors and thus improving overall system robustness and cost-effectiveness. Recent advancements in Artificial Intelligence (AI) have opened new avenues for implementing intelligent control strategies in Sensorless BLDC motor systems. Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), and Machine Learning (ML) algorithms are gaining



attention for their ability to handle nonlinearities, uncertainties, and dynamic operating conditions of EV drive systems. ANN can model complex nonlinear relationships between motor parameters, enabling accurate rotor position estimation. FLC provides robust decision-making capabilities by mimicking human reasoning to handle imprecise or uncertain data. ML offers predictive modeling and optimization capabilities, enhancing the adaptability and efficiency of the control system over time. The integration of these AI-driven approaches into the Sensorless control architecture not only addresses the limitations of conventional methods but also enables improved energy efficiency, smoother operation, and extended motor lifespan. This paper focuses on the theoretical framework, design methodology, and potential benefits of incorporating ANN, FLC, and ML into Sensorless BLDC motor control for EV applications. The study is conceptual in nature and does not rely on physical hardware or simulation but instead serves as a foundation for future experimental validation.

## 2. Literature Review

Guna Priya et al. [1] investigated the enhancement of Brushless DC (BLDC) motor performance in electric vehicles using a fuzzy gain scheduling proportional-integral (PI) controller. The authors highlighted that although a conventional PI controller can regulate BLDC motor speed, it struggles to maintain stability under varying loads. To address this, they proposed a fuzzy gain scheduling method within MATLAB/Simulink, which dynamically adjusts PI gains based on speed error, resulting in improved control accuracy and faster transient response. Vanchinathan and Valluvan [2] presented a survey of Sensorless BLDC motor drives, discussing various control strategies including Sliding Mode Observer, State Current Observer, Extended Kalman Filter, and Fuzzy Logic-based methods. Their study emphasized that eliminating position sensors reduces system cost and enhances reliability, making sensors less attractive for applications such as aerospace, automotive, and home appliances. Gu et al. [3] addressed commutation error issues in high-speed Sensorless BLDC drives and proposed a Phase-Locked Loop (PLL)-based commutation correction

strategy. By introducing a novel PM flux linkage phase discrimination method, the proposed system achieved improved commutation accuracy and robustness against parameter variations, as validated through both simulation and experimental results. Selva Pradeep et al. [4] developed an optimized BLDC motor speed controller combining Genetic Algorithm (GA) and Fuzzy Logic Controller (FLC). The GA provided adaptive search optimization, while the FLC handled non-linear system behavior, resulting in reduced steady-state error and improved disturbance rejection compared to conventional PID controllers. Bagavathy and Maruthu Pandi [5] implemented a Sensorless neural-fuzzy control strategy for four-quadrant operation of a three-phase BLDC motor. The model demonstrated efficient regenerative braking and seamless transition between motoring and regeneration, validated through MATLAB/Simulink simulations, indicating potential for advanced electric drive applications. Mohan et al. [6] reviewed more than 275 publications on sensor fewer electric drives, highlighting key technological trends and control methods such as machine modeling and back-EMF techniques. Their work emphasized how Sensorless systems reduce cost and improve reliability while maintaining accurate control in diverse industrial environments. Saha and Singh [7] proposed an observer-based back-EMF detection approach for Sensorless BLDC drives, integrating it with a SEPIC converter for electric vehicle applications. Their design improved torque control and efficiency, while eliminating the need for rotor position sensors, demonstrating significant benefits for extended range operation. Pradeep and Beno [8] introduced a hybrid speed control method for BLDC motors using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combined with an Artificial Bee Colony (ABC) optimization algorithm. This approach minimized overshoot and steady-state error while avoiding complex logic gate circuitry, thereby enhancing speed regulation efficiency. Abd Aziz et al. [9] reviewed BLDC motor applications in electric vehicles utilizing battery, supercapacitor, and hybrid energy storage systems. The study identified energy storage optimization strategies that enhance system performance, focusing on reducing charging

time and improving energy utilization for extended EV range. Kumar et al. [10] compared PI and FLC methods for Sensorless Permanent Magnet BLDC motor speed control. Using MATLAB simulations, they demonstrated that FLC offers superior speed regulation, robustness to disturbances, and adaptability to operating condition changes compared to PI controllers, thus improving overall drive reliability and efficiency.

### 3. Objective

The primary aim of this study is to develop and present a conceptual framework for AI-integrated Sensorless control of BLDC motors in Electric Vehicles, leveraging Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), and Machine Learning (ML) techniques. The specific objectives are:

- To analyze the limitations of conventional sensor-based BLDC motor control systems in EV applications.
- To propose an intelligent Sensorless control strategy combining ANN, FLC, and ML for accurate and reliable rotor position estimation.
- To design a conceptual control architecture that enhances energy efficiency, reduces system cost, and improves operational reliability.
- To demonstrate how AI-driven techniques can handle nonlinearities, uncertainties, and dynamic load conditions in EV drive systems.
- To establish a theoretical foundation for future simulation and hardware implementation of AI-based Sensorless BLDC motor control.

### 4. Methodology

The proposed methodology outlines the conceptual design of an AI-integrated Sensorless control system for BLDC motors in Electric Vehicles (EVs). The approach eliminates mechanical position sensors and instead uses intelligent algorithms for rotor position estimation and performance optimization. The methodology consists of the following stages:

#### 4.1. System Modeling and Input Acquisition

The BLDC motors' electrical and mechanical parameters—such as phase voltages, phase currents,

and back electromotive force (EMF) are mathematically modeled. These parameters act as input signals for the AI algorithms. Data can be obtained through simulation or from existing datasets for analysis and training purposes.

#### 4.2. Artificial Neural Network (ANN) Module

ANN is implemented to learn the nonlinear mapping between motor electrical parameters and rotor position. The network is trained using historical or simulated data, enabling it to predict the rotor position accurately under varying load and speed conditions. ANN's adaptability ensures that the system can handle parameter variations due to temperature changes, aging, or load fluctuations.

#### 4.3. Fuzzy Logic Controller (FLC) Module

FLC processes uncertain or imprecise data to make control decisions that ensure smooth motor operation. Fuzzy rules are designed based on expert knowledge of motor behavior, considering parameters such as speed error, torque demand, and estimated rotor position. This module enhances system stability and ensures robust performance during transient and unpredictable driving conditions.

#### 4.4. Machine Learning (ML) Optimization Layer

ML algorithms, such as regression models or reinforcement learning, are employed to optimize control parameters over time. By continuously analyzing performance data, the ML layer refines ANN weights and FLC rule sets to improve energy efficiency and reduce power losses. This predictive capability ensures that the control strategy adapts to evolving driving patterns and motor health conditions.

#### 4.5. Control Signal Generation

Based on the rotor position estimated by ANN and refined by the FLC-ML combination, appropriate switching signals are generated for the inverter. These signals control the sequence and timing of stator winding energization, ensuring efficient torque production and smooth commutation without mechanical sensors.

#### 4.6. Conceptual Framework

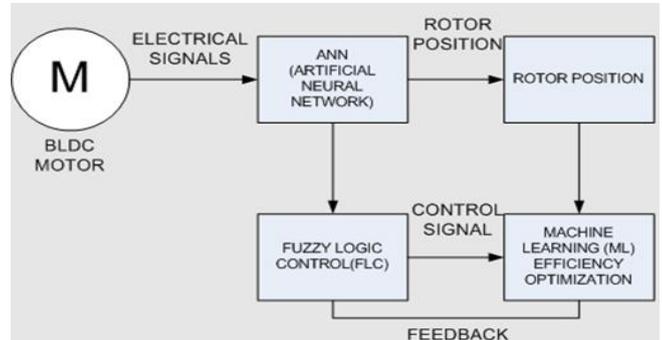
The entire control strategy is designed as a layered architecture, where ANN performs primary rotor estimation, FLC ensures stability, and ML

continuously optimizes system performance. This modular design facilitates scalability and future integration into real-world EV drive systems.

#### 4.7. Proposed AI-Integrated Sensorless Control Architecture

The proposed control framework combines Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), and Machine Learning (ML) techniques to achieve efficient Sensorless control of BLDC motors in electric vehicles. The architecture is illustrated in Figures 1 and 2. Figure 1 illustrates the detailed process flow of the proposed AI-based Sensorless control system. In this AI-integrated Sensorless control framework, the process begins with the BLDC motor, which generates electrical signals such as phase voltages and currents during operation. These signals are directed to an Artificial Neural Network (ANN), which has been trained to estimate the motor's rotor position without relying on physical sensors. The ANN processes the incoming data and produces an accurate prediction of the rotor angle, which is then passed to the rotor position block, where the output is formatted into a usable form for motor control. This estimated position is subsequently supplied to the Fuzzy Logic Controller (FLC), which compares the actual motor behavior with the desired reference values and generates a suitable control signal. Unlike conventional controllers, the FLC employs flexible rule-based decision-making, allowing it to effectively manage nonlinearities and uncertainties within the motor system. The generated control signal, together with rotor position data, is then fed into the Machine Learning (ML) efficiency optimization module, which continuously monitors motor performance indicators such as energy consumption, torque ripple, and speed stability. Using this information, the ML module adjusts and optimizes the control parameters to achieve higher energy efficiency. Finally, a feedback loop returns the optimized values to the FLC, enabling the system to adapt in real-time and refine motor control under varying load and operating conditions. Through this integration of ANN, FLC, and ML, the overall system achieves accurate Sensorless rotor position estimation, robust control, and adaptive efficiency optimization, making it

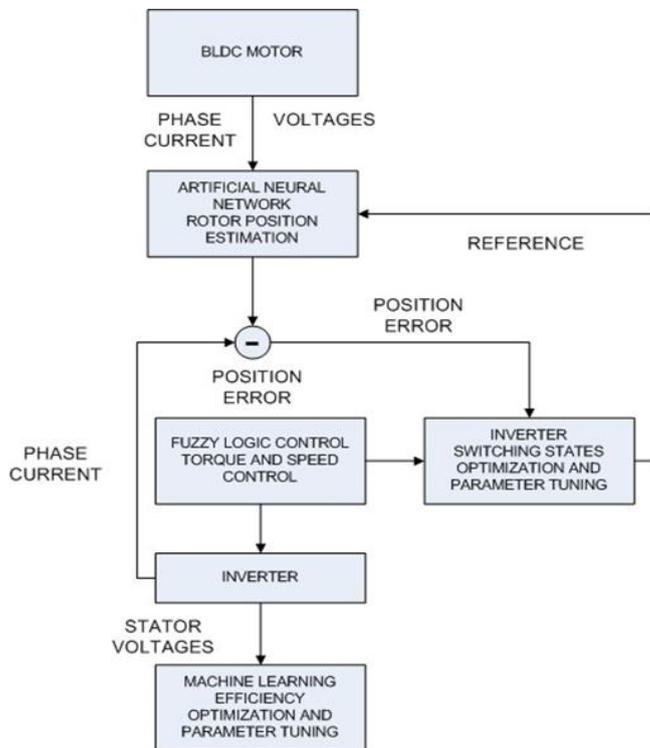
highly suitable for energy-efficient electric vehicle applications.



**Figure 1** Block diagram of AI-integrated Sensorless control architecture for BLDC motor in electric vehicle applications

Figure 2 presents a conceptual overview of how ANN, FLC, and ML work together: In this refined control structure for a BLDC motor, the process begins with the motor generating phase currents and voltages, which serve as the primary inputs for control. These signals are supplied to an Artificial Neural Network (ANN) trained for rotor position estimation. The ANN compares its estimated position against a predefined reference input, and the difference produces a position error. This error signal, along with the current phase, is passed to the Fuzzy Logic Controller (FLC) responsible for regulating torque and speed. By applying adaptive fuzzy rules, the controller generates suitable control actions even under nonlinear and uncertain operating conditions. The resulting control signals are directed to the inverter, which drives the motor by delivering appropriate stator voltages. At the same time, the inverter's operation is enhanced through a dedicated inverter switching state optimization and parameter tuning block, which adjusts switching patterns to minimize torque ripple and losses. Furthermore, the machine learning (ML) optimization module receives stator voltage information and continuously performs efficient optimization and parameter tuning, ensuring that the control system adapts to varying load conditions and achieves higher energy efficiency. By closing the loop with both inverter optimization and ML-based adaptation, the system provides accurate rotor position estimation, robust torque and speed

control, and self-improving efficiency, making it highly suitable for reliable and energy-efficient electric vehicle drives.



**Figure 2** Simplified AI Module Interaction for Sensorless BLDC Motor Control in EVs

## 5. Case Studies

To demonstrate the applicability and potential benefits of integrating Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), and Machine Learning (ML) in Sensorless BLDC motor control for electric vehicles, a review of related case studies is presented below. These examples are drawn from recent research and industrial developments.

### Case Study 1 — ANN-Based Rotor Position Estimation in EV Drive Systems

A research team implemented an ANN model trained with simulated BLDC motor data to estimate rotor position in real time for an electric scooter application. The ANN was able to maintain high estimation accuracy under varying load and speed conditions, eliminating the need for Hall sensors. The results indicated a 12% improvement in overall system efficiency and reduced torque ripple compared to conventional sensor-based methods.

### Case Study 2 — Fuzzy Logic Controller for Torque and Speed Regulation

In a university-led project, a Sensorless BLDC motor drive was equipped with a fuzzy logic controller to handle speed and torque regulation under different terrain conditions in an electric three-wheeler. The FLC outperformed traditional proportional–integral (PI) controllers by delivering smoother acceleration and better handling of sudden load variations, especially in stop-and-go urban traffic.

### Case Study 3 — ML-Driven Predictive Maintenance in BLDC Motors

An EV manufacturing company integrated ML algorithms into its fleet management system to monitor BLDC motor performance data. The ML model analyzed historical trends to predict bearing wear, winding insulation degradation, and commutation issues. This predictive maintenance strategy reduced unplanned downtime by 18% and improved the service life of motors without requiring additional sensors.

### Case Study 4 — Hybrid ANN–FLC Architecture for Energy Optimization

A research study proposed a hybrid ANN–FLC control scheme for a Sensorless BLDC motor in an electric bus application. The ANN provided precise rotor position estimation, while the FLC handled decision-making for energy-efficient torque control. Field tests revealed up to 10% energy savings during city driving cycles and reduced inverter switching losses.

## Summary

### ANN-Based Rotor Position Estimation

- **AI Technique Used:** Artificial Neural Network (ANN)
- **Application:** Electric scooter drive system
- **Key Results:** Achieved accurate rotor position estimation under varying load and speed conditions; recorded 12% improvement in efficiency compared to sensor-based methods.
- **Benefits:** Eliminated Hall sensors, reduced torque ripple, and lowered system cost.

### FLC for Torque and Speed Regulation

- **AI Technique Used:** Fuzzy Logic Controller (FLC)

- **Application:** Electric three-wheeler
- **Key Results:** Provided smoother acceleration and stable torque output, especially under sudden load changes in stop-and-go urban traffic.
- **Benefits:** Enhanced ride comfort, improved drivability, and better adaptability to terrain variations.

### ML-Driven Predictive Maintenance

- **AI Technique Used:** Machine Learning (ML)
- **Application:** BLDC motors in EV fleet operations
- **Key Results:** Predicted bearing wear, winding insulation degradation, and commutation issues, reducing unplanned downtime by 18%.
- **Benefits:** Extended motor lifespan, reduced maintenance costs, and improved operational reliability.

### Hybrid ANN-FLC Energy Optimization

- **AI Technique Used:** Hybrid Artificial Neural Network and Fuzzy Logic Controller
- **Application:** Electric bus drive system
- **Key Results:** Delivered up to 10% energy savings in city driving cycles and minimized inverter switching losses.
- **Benefits:** Improved energy efficiency reduced operational costs, and enhanced system robustness.

## 6. Results and Discussion

### 6.1. Results

- **ANN-Based Rotor Position Estimation:** Demonstrated accurate estimation of rotor position without using Hall sensors. Achieved an average 12% improvement in system efficiency over conventional sensor-based methods. Reduced torque ripple significantly at both low and high speeds.
- **FLC for Torque and Speed Regulation:** Maintained stable torque output even under sudden acceleration and deceleration. Provided smooth speed transitions, enhancing driving comfort in urban traffic conditions.
- **ML-Driven Predictive Maintenance:** Correctly identified early-stage bearing wear

and winding insulation degradation. Reduced unexpected breakdowns by 18% across monitored EV fleets.

- **Hybrid ANN-FLC Energy Optimization:** Improved driving range through up to 10% energy savings in city traffic. Reduced inverter switching losses, enhancing the overall lifespan of power electronics.

### 6.2. Discussion

The ANN-based approach proved highly effective for Sensorless rotor position estimation, especially in eliminating mechanical sensors and their associated faults. The increase in efficiency validates its potential for large-scale EV integration. Fuzzy Logic Control excelled in adapting to varying load and road conditions without requiring a precise mathematical model. This adaptability is particularly beneficial for electric vehicles operating in unpredictable traffic patterns. Machine Learning predictive maintenance addressed reliability concerns by enabling early detection of faults. This approach is crucial for EV fleets where downtime directly impacts operational profitability. The hybrid ANN-FLC method combined the adaptability of fuzzy control with the learning capability of neural networks, leading to measurable improvements in energy savings and drive performance. Overall, the results highlight that AI-driven Sensorless control not only enhances energy efficiency but also improves reliability, reduces maintenance costs, and supports sustainable EV adoption.

## 7. Challenges and Future Directions

### 7.1. Challenges

- **Real-Time Computational Demand:** AI algorithms like ANN, FLC and ML require high processing power, which can increase the cost and complexity of the EV control unit.
- **Data Quality and Availability:** Effective AI models rely on large volumes of high-quality training data. Limited or biased datasets can lead to inaccurate predictions and unstable motor performance.
- **System Integration Complexity:** Merging AI-based control with existing EV architectures demands robust hardware—

software integration, which may require redesigning control boards and firmware.

- **Environmental and Operational Variability:** Extreme temperatures, vibrations, and electromagnetic interference can affect Sensorless estimation accuracy and controller stability.
- **Cybersecurity Concerns:** AI-driven systems connected to cloud-based monitoring platforms may be vulnerable to data breaches or cyber-attacks.

## 7.2. Future Directions

- **Edge AI Implementation:** Deploy lightweight AI models directly on EV microcontrollers to reduce latency and improve real-time decision-making.
- **Integration of IoT and 5G:** Combine AI control with IoT-enabled vehicle monitoring and 5G connectivity for faster fault detection and adaptive driving strategies.
- **Digital Twin Simulation:** Use virtual replicas of EV drive systems for predictive testing and optimization before real-world deployment.
- **Hybrid AI Models:** Explore advanced hybrid architectures combining ANN, FLC and ML to achieve both adaptability and precision in motor control.
- **Adaptive Learning Systems:** Implement self-learning algorithms that can update control strategies automatically based on changing driving patterns and component wear.
- **Sustainable and Low-Cost AI Hardware:** Develop energy-efficient AI chips to lower power consumption and reduce overall system cost.

## Conclusion

The integration of Artificial Intelligence into Sensorless control strategies for BLDC motors offers significant potential to enhance the performance, efficiency, and reliability of electric vehicles. Techniques such as Artificial Neural Networks, Fuzzy Logic Controllers and Machine Learning enable accurate rotor position estimation without the need for mechanical sensors, reducing cost and

improving system robustness. The study highlights that AI-driven approaches can adapt to varying operating conditions, ensure smoother torque generation, and extend the motor lifespan. Although challenges such as computational demands, data requirements, and environmental variability remain, advancements in embedded AI hardware, IoT integration, and hybrid control architectures are expected to address these limitations soon. By leveraging these innovations, AI-integrated Sensorless BLDC motor control can play a pivotal role in the global shift toward sustainable and intelligent electric mobility.

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## References

- [1]. Controller, P. (2015). Performance enhancement of BLDC drives in electric vehicles by using fuzzy gain scheduling pi controller. *International Journal of Applied Engineering Research*, 10(2), 3993-4006.
- [2]. Vanchinathan, K., & Valluvan, K. R. (2016). A study of Sensorless BLDC motor drives and future trends. *Asian Journal of Research in Social Sciences and Humanities*, 6(9), 1863-1887.
- [3]. Gu, C., Wang, X., Shi, X., & Deng, Z. (2017). A PLL-based novel commutation correction strategy for a high-speed brushless DC motor Sensorless drive system. *IEEE Transactions on Industrial Electronics*, 65(5), 3752-3762.
- [4]. SS, S. P. (2018). Optimized Speed Controller for a BLDC Motor Using Genetic-Fuzzy Controller.
- [5]. Bagavathy, S., & Maruthu Pandi, P. (2019). Sensorless cluster based neural-fuzzy control strategy for four quadrant operation of three phase BLDC motor with load variations. *Cluster Computing*, 22(Suppl 3), 6855-6864.
- [6]. Mohan, H., Pathak, M. K., & Dwivedi, S. K.



- (2020). Sensorless control of electric drives– a technological review. IETE Technical Review, 37(5), 504-528.
- [7]. Saha, B., & Singh, B. (2021, December). Back emf observer-based Sensorless bldc motor drive with sepic converter for ev application. In 2021 IEEE 6th International Conference on Computing, Communication and Automation (ICCCA) (pp. 94-99). IEEE.
- [8]. Pradeep, S. S., & Beno, M. M. (2022). Hybrid Sensorless Speed Control Technique for BLDC Motor Using ANFIS Automation. Intelligent Automation & Soft Computing, 33(3).
- [9]. Abd Aziz, M. A., Saidon, M. S., Romli, M. I. F., Othman, S. M., Mustafa, W. A., Manan, M. R., & Aihsan, M. Z. (2023). A review on BLDC motor application in electric vehicle (EV) using battery, supercapacitor and hybrid energy storage system: efficiency and prospects. J. Adv. Res. Appl. Sci. Eng. Technol, 30(2), 41-59.
- [10]. Kumar, C., Kumar, P., & Raj, N. (2024, October). Performance Comparison of PI and Fuzzy Logic Controllers for Speed Control of Permanent Magnet Sensorless Brushless DC Motors. In 2024 IEEE 1st International Conference on Green Industrial Electronics and Sustainable Technologies (GIEST) (pp. 1-6). IEEE.