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Implementation of Type-2 Fuzzy Logic Control in an Internet of Things-Based Solar-Wind Hybrid Power Generation System to Improve Stability and Energy Efficiency

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ABSTRACT

The increasing demand for electricity has accelerated the development of sustainable and environmentally friendly renewable energy systems. Hybrid solar-wind power generation systems offer a promising solution because solar and wind resources exhibit complementary generation characteristics. However, these systems remain vulnerable to intermittency and output uncertainty caused by variations in solar irradiance, wind speed, and weather conditions. These fluctuations may result in battery voltage instability, reduced energy management efficiency, and relay chattering during power distribution. This study presents the implementation of Type-2 Fuzzy Logic Control (T2-FLC) in an Internet of Things (IoT)-based hybrid solar-wind power generation system to improve voltage stability and energy management performance. The proposed prototype consists of a 200 W photovoltaic (PV) panel, a Savonius wind turbine, a PZEM-017 direct current power sensor, an Arduino Mega, an ESP32 communication module, and a 24 V battery bank. The proposed T2-FLC utilizes the Footprint of Uncertainty (FOU) to effectively accommodate sensor noise and input uncertainty during the decision-making process. Experimental evaluation was conducted over seven consecutive days under real operating conditions with continuous real-time monitoring. The results demonstrate that the proposed system successfully maintained the battery voltage within the range of 23.9-24.5 V while reducing relay switching frequency by approximately 40%, thereby mitigating relay chattering. Furthermore, the IoT-based monitoring platform enabled real-time data acquisition, remote supervision, and historical data logging, supporting more reliable operation of the Hybrid Renewable Energy System (HRES). These findings demonstrate that integrating T2-FLC with IoT technology enhances the stability, reliability, and operational efficiency of small-scale HRES for smart grid applications.

1. INTRODUCTION

Global electricity demand continues to increase because of rapid population growth, industrial expansion, and digital transformation across various sectors. At the same time, concerns regarding greenhouse gas emissions and climate change have accelerated the transition from conventional fossil fuel-based power generation to renewable energy systems. Among the available renewable energy technologies, photovoltaic (PV) and wind energy have attracted considerable attention because of their environmental sustainability and complementary generation characteristics. Consequently, hybrid solar-wind renewable energy systems have become a promising solution for improving power availability and reliability, particularly in remote areas and small-scale smart grid applications [1-4]. Despite these advantages, hybrid solar-wind systems remain vulnerable to the intermittent nature of renewable energy sources. Variations in solar irradiance and wind speed continuously affect electrical power generation, resulting in unstable battery charging, inefficient energy distribution, and frequent relay switching. One of the most critical operational issues is relay chattering, where repeated relay activation occurs because of rapid fluctuations in measured electrical parameters. Relay chattering increases switching losses, accelerates relay wear, reduces battery lifetime, and decreases the overall reliability of the energy management system [5-7]. The problem becomes more significant in laboratory-scale renewable energy systems that employ low-cost sensors. Measurement noise, sensor uncertainty, and environmental disturbances may generate fluctuating input signals that trigger unnecessary switching decisions. Therefore, intelligent control strategies capable of handling uncertainty are required to ensure stable energy management under practical operating conditions [8, 9]. In addition to intelligent control strategies, Internet of Things (IoT) technologies have become an essential component of modern Hybrid Renewable Energy Systems (HRES). HRES combining PV generation, wind turbines, and battery energy storage have been extensively investigated to improve power reliability, complementarity of renewable resources, optimal system sizing, and intelligent energy management in distributed power systems [10-13]. IoT enables real-time monitoring, wireless communication, historical data logging, predictive maintenance, and remote supervision, thereby improving the operational reliability and management efficiency of distributed renewable energy systems. Recent studies have demonstrated that IoT technologies significantly enhance monitoring, communication, predictive maintenance, and distributed energy management in modern renewable energy systems [14-18]. Fuzzy Logic Control (FLC) has been widely applied in renewable energy systems because of its capability to control nonlinear systems without requiring accurate mathematical models. However, conventional Type-1 FLC represents membership functions using precise numerical values and therefore has limited capability to accommodate measurement uncertainty. Type-2 Fuzzy Logic Control (T2-FLC) overcomes this limitation by introducing the Footprint of Uncertainty (FOU), enabling the controller to model sensor noise, environmental disturbances, and uncertain operating conditions more effectively [19-28]. Several studies have demonstrated the effectiveness of T2-FLC in renewable energy applications. Aljohani [28] proposed a T2-FLC-based hybrid microgrid energy management strategy and reported improved energy distribution efficiency. Moghadam et al. [29] applied T2-FLC for battery-supported microgrid power regulation, while Bayrak and Kaya [30] demonstrated smoother energy management decisions than conventional Type-1 fuzzy logic in hybrid energy systems. Shakibjoo et al. [31] further reported that optimized T2-FLC improved frequency stability in multi-area power systems under uncertain operating conditions. Similarly, Kumari et al. [32] developed an optimized dual-degree Type-2 fuzzy controller for frequency regulation in renewable-energy-integrated power systems, demonstrating the robustness of T2-FLC under dynamic operating conditions. Although these studies have demonstrated the effectiveness of T2-FLC, most existing research has been validated through simulation environments rather than practical hardware implementation. Furthermore, only a limited number of studies have investigated relay chattering in laboratory-scale hybrid solar-wind systems, particularly those integrating low-cost sensing devices, battery energy storage, and Internet of Things (IoT)-based real-time monitoring. Consequently, the practical capability of T2-FLC to improve voltage stability and reduce unnecessary relay switching under actual operating conditions remains insufficiently investigated. This limitation constitutes the primary research gap addressed in this study.

To address these limitations, this study presents the implementation of T2-FLC in a laboratory-scale hybrid solar-wind power generation system integrated with an IoT-based monitoring platform. The proposed prototype consists of a 200 W PV panel, a Savonius wind turbine, a 24 V battery bank, an Arduino Mega controller, an ESP32 communication module, and a PZEM-017 direct current power sensor. Experimental evaluation was conducted over seven consecutive days under actual operating conditions to assess voltage stability, relay switching performance, and real-time monitoring capability. The main contributions of this study are summarized as follows.

1. Implementation of a laboratory-scale hybrid solar-wind renewable energy system using T2-FLC under actual operating conditions.
2. Integration of an IoT-based monitoring platform for real-time data acquisition, remote supervision, and historical data logging.
3. Experimental validation demonstrating that the proposed controller maintained battery voltage within 23.9-24.5 V while reducing relay switching frequency by approximately 40%.
4. Demonstration of intelligent energy management using low-cost sensing and communication hardware suitable for practical small-scale smart grid applications.

2. METHODOLOGY

2.1 System design

This study proposes a HRES that integrates solar PV generation, wind power generation, battery energy storage, an intelligent control system, and IoT-based monitoring. The proposed system is designed to manage the distribution of electrical energy generated by the solar PV panel and the Savonius wind turbine to the battery bank and electrical loads using T2-FLC. The primary objectives of the proposed system are to ensure continuous power supply, improve battery charging performance, reduce relay chattering, and provide real-time system monitoring. The main hardware components consist of a 200 W PV panel, a Savonius Vertical Axis Wind Turbine (VAWT), a 24 V battery bank, a Maximum Power Point Tracking (MPPT) hybrid charge controller, a Direct Current-Alternating Current (DC-AC) inverter, a PZEM-017 direct current power sensor, a Direct Current Solid-State Relay (DC-SSR), an Arduino Mega microcontroller, and an ESP32 communication module. The PV panel and the wind turbine function as renewable energy sources, whereas the battery bank stores surplus electrical energy for subsequent use when renewable energy generation decreases. The Arduino Mega executes the T2-FLC algorithm to determine the optimal energy distribution strategy, while the ESP32 transmits monitoring data to the IoT platform for remote observation. The operating principle of the proposed system begins with electricity generation from the PV panel and the Savonius wind turbine. The generated electrical parameters, including voltage, current, and power, are measured by the PZEM-017 sensor and transmitted to the Arduino Mega. These measurements are processed as input variables for the T2-FLC algorithm. Based on the fuzzy inference results, the controller determines whether the available energy should be directed to charge the battery bank, supply the electrical load, or activate the backup power source. Finally, the ESP32 continuously transmits the operating data to the IoT monitoring platform, enabling real-time monitoring, data logging, and remote system supervision. The overall architecture of the proposed hybrid solar-wind energy management system is illustrated in Figure 1.

2.2 Hardware implementation

The hardware implementation integrates renewable energy generation, energy storage, sensing, control, actuation, and communication components into a single laboratory-scale HRES. A 200 W PV panel serves as the primary energy source during daytime operation. Under standard operating conditions, the PV panel provides an operating voltage of approximately 18-20 V and a maximum output current of 10-11 A, as shown in Figure 2(ii). The electrical output of the PV panel is influenced by several environmental factors, including solar irradiance, ambient temperature, panel orientation, tilt angle, and PV conversion efficiency. The performance of PV systems is strongly influenced by several environmental and operational factors, including solar irradiance, ambient temperature, PV module technology, and surface soiling, all of which directly affect conversion efficiency and electrical power output [33-36]. These factors should therefore be considered when evaluating the performance of PV-based HRES. A Savonius VAWT, shown in Figure 2(i), is employed as the secondary renewable energy source. The Savonius turbine was selected because of its simple mechanical structure, high starting torque, ability to operate at low wind speeds, and suitability for environments with multidirectional wind conditions. The turbine converts the kinetic energy of the wind into mechanical energy, which is subsequently converted into electrical energy by a permanent magnet generator. The generated electrical power varies according to wind speed, turbulence intensity, and wind direction. Savonius vertical-axis wind turbines have been widely investigated for small-scale renewable energy applications because of their high starting torque, simple mechanical construction, and reliable operation under low and multidirectional wind conditions. These characteristics make Savonius turbines particularly suitable for HRES intended for distributed generation and smart grid applications [37, 38]. A 24 V battery bank functions as the energy storage unit by storing surplus electrical energy generated from the PV panel and the wind turbine. During periods of low renewable energy generation, the battery bank supplies electrical power to maintain continuous operation of the load. Battery voltage is used as one of the principal input variables in the control system because it serves as a practical indicator of the battery operating condition and supports energy management decision-making.

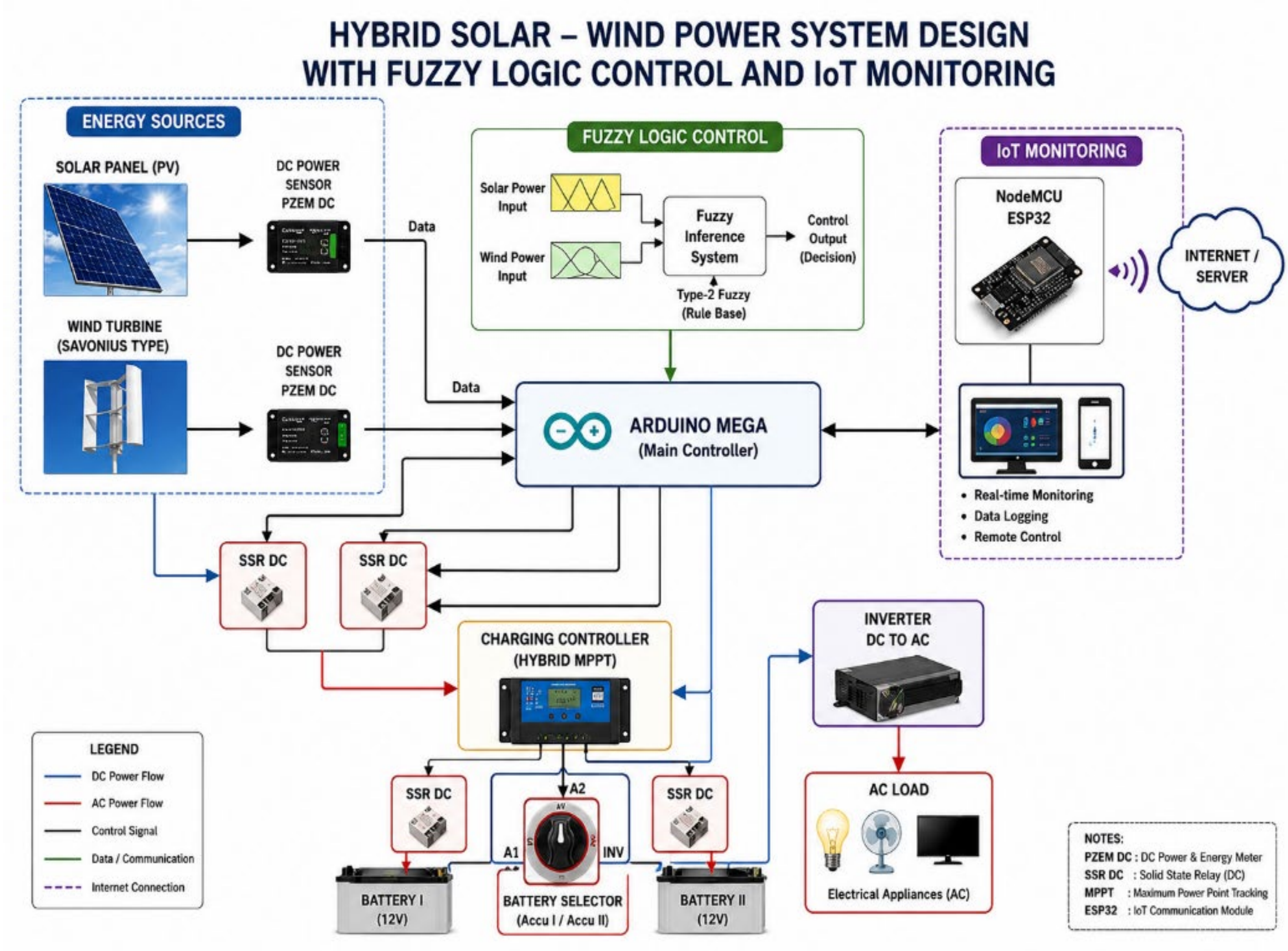

Figure 1. Design of a hybrid solar-wind system with Fuzzy Logic Control (FLC) and Internet of Things (IoT) monitoring

Battery Energy Storage Systems (BESS) play a crucial role in HRES by balancing the intermittent output of renewable energy sources, improving supply reliability, and supporting intelligent energy management. Effective battery monitoring and charging management are therefore essential to maintain battery performance, operational safety, and long-term system reliability. Various battery management and state estimation techniques have been developed to improve the efficiency and reliability of renewable energy storage systems [39-41].

Electrical parameters, including voltage, current, power, and accumulated energy, are measured using a PZEM-017 direct current power sensor. These measurements are transmitted to the Arduino Mega as input variables for the proposed T2-FLC algorithm. Load switching is performed using a DC Solid-State Relay (SSR-40DD), which is controlled by the Arduino Mega according to the control decisions generated by the T2-FLC. The SSR-40DD operates with a control input voltage of 3-32 VDC, an output operating voltage of 5-60 VDC, and a rated switching current of 40 A, making it suitable for low-voltage DC switching applications in HRES. The control algorithm is executed every 5 s, and the relay switching state is updated at the same interval. Compared with conventional electromechanical relays, the SSR provides high-speed electronic switching without mechanical contacts, thereby eliminating contact bouncing, reducing mechanical wear, and improving switching reliability under frequent operating conditions. In this study, relay chattering is defined as repeated and unnecessary switching events occurring within a short operating interval due to rapid fluctuations in PV power generation, wind turbine output, and measurement uncertainty. The proposed T2-FLC suppresses these unnecessary switching operations, thereby improving battery voltage stability and reducing stress on the switching device. Battery charging is managed using a hybrid MPPT charge controller, which maximizes energy harvesting from both renewable energy sources while providing built-in battery protection against overcharging and excessive discharge through its charging management algorithm. The MPPT controller also incorporates reverse-polarity and overcurrent protection to ensure safe operation of the laboratory-scale prototype throughout the experimental period. A DC-AC inverter converts the stored direct current electrical energy into alternating current electricity suitable for supplying conventional electrical loads. The complete hardware implementation, including the PV panel, Savonius wind turbine, battery bank, sensing devices, control unit, switching actuator, and power conversion components, is presented in Figure 2(iii).

(i) (ii) (iii)

Figure 2. Hardware implementation of the proposed hybrid solar–wind power generation system: (i) Savonius wind turbine, (ii) photovoltaic (PV) panel, and (iii) laboratory-scale prototype

2.3 Internet of Things monitoring system

The proposed monitoring system employs an Arduino Mega as the primary controller for data acquisition and execution of the T2-FLC algorithm. The Arduino Mega was selected because it provides a sufficient number of input-output pins, supports multiple communication interfaces, and is compatible with various sensors and actuators used in the proposed HRES. The controller continuously receives electrical measurements from the PZEM-017 direct current power sensor, including voltage, current, and power generated by the PV panel and the Savonius wind turbine, as well as the battery voltage. The acquired sensor data are processed by the Arduino Mega to determine the operating conditions of the HRES. These measurements are used as input variables for the T2-FLC algorithm, which determines the appropriate energy distribution strategy according to the available renewable energy and the battery charging condition. Based on the fuzzy inference results, the controller regulates the DC SSR to control energy flow between the renewable energy sources, the battery bank, and the electrical load. This adaptive control strategy minimizes unnecessary relay switching caused by small variations in sensor measurements, thereby improving system stability and reducing relay chattering.

To support remote monitoring, an ESP32 microcontroller is employed as the IoT communication module. The ESP32 transmits operational data to the IoT monitoring platform through a wireless network in real time. The transmitted parameters include PV panel voltage, PV panel current, PV panel power, wind turbine voltage, wind turbine current, wind turbine power, battery voltage, battery power, relay status, and system operating mode. The IoT monitoring platform provides continuous visualization of the operating conditions of the HRES and enables real-time data logging, remote supervision, and historical performance analysis. These capabilities allow system operators to evaluate energy generation, battery charging performance, relay operation, and overall system efficiency without requiring direct physical access to the experimental prototype. The developed monitoring interface is presented in Figure 2(iii).

2.4 Type-2 Fuzzy Logic Control design

The proposed T2-FLC algorithm is designed to determine the optimal energy distribution strategy based on the operating conditions of the renewable energy sources and the battery bank. The controller receives three input variables, namely PV power, wind turbine power, and battery voltage. PV power represents the electrical power generated by the PV panel, wind turbine power represents the electrical power generated by the Savonius wind turbine, whereas battery voltage is used as a practical control variable to represent the battery operating condition during charging and discharging. Each input variable is represented by three linguistic terms: Low, Medium, and High. The Low membership function represents insufficient power generation or a low battery voltage, the Medium membership function represents normal operating conditions, and the High membership function represents abundant renewable energy generation or a high battery voltage.

In this study, battery voltage was used as an indicator of the battery operating condition for control purposes rather than as a direct State of Charge (SOC) measurement. The proposed controller utilizes battery terminal voltage to determine the charging and discharging operating mode because voltage can be measured continuously using the installed DC sensor. However, battery terminal voltage is affected by charging current, load variations, and temperature; therefore, it does not represent the actual SOC under all operating conditions. More accurate SOC estimation methods, such as coulomb counting or model-based estimation, are beyond the scope of this study and will be considered in future work.

Unlike conventional Type-1 FLC, the proposed T2-FLC represents each membership function as an interval bounded by the Upper Membership Function (UMF) and the Lower Membership Function (LMF). The region enclosed between the UMF and LMF is referred to as the FOU, which enables the controller to model uncertainties arising from sensor noise, measurement errors, and environmental disturbances. Consequently, the controller is capable of producing smoother and more robust control actions under dynamic operating conditions. The T2-FLC algorithm consists of four sequential stages: fuzzification, rule inference, type reduction, and defuzzification.

The theoretical foundation of fuzzy set theory was first introduced by Zadeh [42]. Subsequent developments in Interval Type-2 Fuzzy Logic Systems (IT2FLS) have demonstrated improved capability for representing uncertainties arising from measurement noise, parameter variations, and nonlinear system behavior. Recent studies have shown that IT2FLS-based controllers provide enhanced robustness and more reliable decision-making than conventional Type-1 fuzzy systems, particularly in renewable energy and intelligent control applications [43-47]. During the fuzzification stage, the measured input variables are transformed into interval-valued fuzzy sets according to their corresponding membership functions. Subsequently, the inference engine evaluates a predefined rule base to determine the appropriate operating mode of the HRES. Examples of the fuzzy rules employed in this study are presented in Table 1.

Table 1. Representative fuzzy rules

Photovoltaic (PV) Power	Wind Turbine Power	Battery Voltage	Operating Mode
Low	Low	Low	Grid
High	High	High	Battery
Medium	Low	Medium	Balanced
High	Low	Low	Solar Priority
Low	High	Medium	Wind Priority

The proposed T2-FLC employs a complete fuzzy rule base consisting of 27 rules generated from three input variables (solar power, wind power, and battery voltage), each having three linguistic states (Low, Medium, and High). Owing to space limitations, only representative rules are presented in Table 1. All 27 rules were fully implemented in the Arduino Mega controller during experimental testing. The fuzzy inference process generates one of several operating modes, including Grid, Battery, Balanced, Solar Priority, and Wind Priority. The Grid mode is activated when renewable energy generation is insufficient and the battery voltage is low.

The battery mode is selected when renewable energy generation is adequate and stored energy is sufficient to supply the electrical load. The Balanced mode distributes power proportionally between the renewable energy sources and the battery bank. The Solar Priority and Wind Priority modes prioritize the dominant renewable energy source according to the available generation. Following the inference stage, the type reduction process converts the interval Type-2 fuzzy output into an equivalent Type-1 fuzzy set. In this study, the Karnik-Mendel algorithm is employed to calculate the left and right endpoints of the type-reduced set, denoted by y_l and y_r, respectively. The final crisp control output is then obtained through the defuzzification process using:

$$y = \frac{y_l + y_r}{2} \tag{1}$$

where, y is the crisp control output obtained after defuzzification; y_l is the left endpoint produced by the type-reduction process; y_r is the right endpoint produced by the type-reduction process.

The resulting crisp output is subsequently used to control the DC SSR and determine the charging priority, energy distribution strategy, and operating mode of the HRES. By incorporating the FOU into the decision-making process, the proposed T2-FLC provides greater robustness against measurement uncertainty, sensor noise, and rapid fluctuations in renewable energy generation. The overall control algorithm is illustrated in Figure 3.

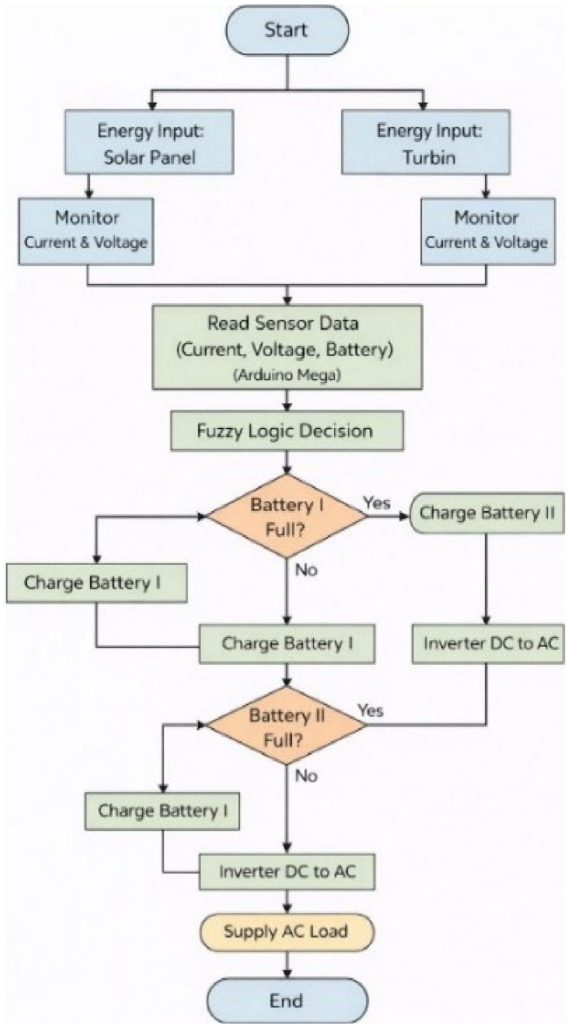

Figure 3. Flowchart of the proposed energy distribution algorithm based on Type-2 Fuzzy Logic Control (T2-FLC)

2.5 Testing scenario

The experimental evaluation was conducted to assess the performance of the proposed hybrid solar-wind power generation system in terms of renewable energy generation, battery charging performance, intelligent energy management, relay switching behavior, and IoT-based monitoring. The experiments were performed under actual operating conditions using the laboratory-scale prototype described in the previous section. The first testing scenario evaluated the performance of the PV panel. Electrical parameters, including voltage, current, and output power, were measured under different levels of solar irradiance to investigate the relationship between environmental conditions and PV power generation. The second testing scenario focused on the performance of the Savonius VAWT. The output voltage, current, and electrical power generated by the wind turbine were measured under various wind speed conditions. This experiment was conducted to evaluate the capability of the turbine to generate electrical energy under low and fluctuating wind conditions. The third testing scenario evaluated the charging and discharging performance of the 24 V battery bank. Battery voltage was continuously monitored during charging and energy supply processes to verify charging stability and to ensure that the proposed energy management strategy effectively prevented overcharging and deep-discharge conditions. The fourth testing scenario assessed the performance of the T2-FLC algorithm. The controller was evaluated by applying different combinations of PV power, wind turbine power, and battery voltage as input variables. The resulting operating modes and energy distribution decisions were analyzed to verify their consistency with the predefined fuzzy rule base. The fifth testing scenario investigated relay switching performance and relay chattering reduction. The number of relay switching operations before and after implementing the T2-FLC algorithm was recorded and compared. The observed parameters included switching frequency, relay operating stability, and controller response under fluctuating renewable energy conditions. The final testing scenario evaluated the performance of the IoT monitoring system. Operational data transmitted by the ESP32 communication module, including voltage, current, power, battery voltage, relay status, and system operating mode, were monitored to verify the reliability of real-time data transmission, remote monitoring capability, and data logging performance. The IoT monitoring system was considered successful when the transmitted data accurately represented the actual operating conditions of the hardware prototype throughout the experimental period.

3. RESULTS AND DISCUSSION

3.1 Seven-day system testing

The proposed hybrid solar-wind power generation system was experimentally evaluated over seven consecutive days under actual operating conditions to assess its electrical performance, battery charging behavior, and energy management capability. During the testing period, the system continuously recorded battery voltage, PV power output, wind turbine power output, and operating status using the developed monitoring platform. The summarized experimental results are presented in Table 2, while the corresponding battery voltage and renewable energy generation profiles are illustrated in Figures 4 and 5, respectively.

Based on the experimental results presented in Table 2, the battery voltage remained relatively stable throughout the testing period. The average battery voltage ranged from 23.96 V to 24.08 V, indicating that the proposed energy management system successfully maintained stable battery charging and discharging conditions despite fluctuations in renewable energy generation. The average output power generated by the PV panel varied between 62.94 W and 88.88 W, depending primarily on solar irradiance and weather conditions. As expected, PV generation exhibited a relatively smooth daily profile because solar radiation changes gradually throughout the daytime. In contrast, the average power generated by the Savonius wind turbine ranged from 77.73 W to 88.89 W. The wind turbine output exhibited greater fluctuations than the PV panel because wind speed is strongly influenced by turbulence, wind direction, and atmospheric conditions. Consequently, variations in wind speed produced more dynamic changes in electrical power generation. Although the renewable energy sources exhibited different generation characteristics, the proposed energy management strategy effectively balanced energy distribution between the renewable energy sources and the battery bank. Throughout the seven-day testing period, no significant voltage instability was observed, demonstrating that the proposed T2-FLC algorithm successfully maintained stable system operation under varying environmental conditions.

Table 2. Experimental results of the seven-day system testing

Date	V_Batt_min	V_Batt_avg	V_Batt_max	P_Solar_avg	P_Solar_max	P_Wind_avg	P_Wind_max
2026-03-26	22.79	23.98	25.51	88.88	222.26	77.73	200
2026-03-27	22.4	23.96	26.04	62.94	211.67	80.76	200
2026-03-28	22.96	24.08	25.78	64.05	228.81	79.58	200
2026-03-29	22.69	23.99	25.36	63.77	217.33	84.53	200
2026-03-30	22.78	24.01	25.59	63.1	219.02	88.89	200
2026-03-31	22.29	23.98	25.35	63.36	215.61	82.42	200
2026-04-01	22.81	24	25.25	64.02	215.85	80.69	200

Note: = Battery Voltage; P_Solar = Solar Power; P_Wind = Wind Power

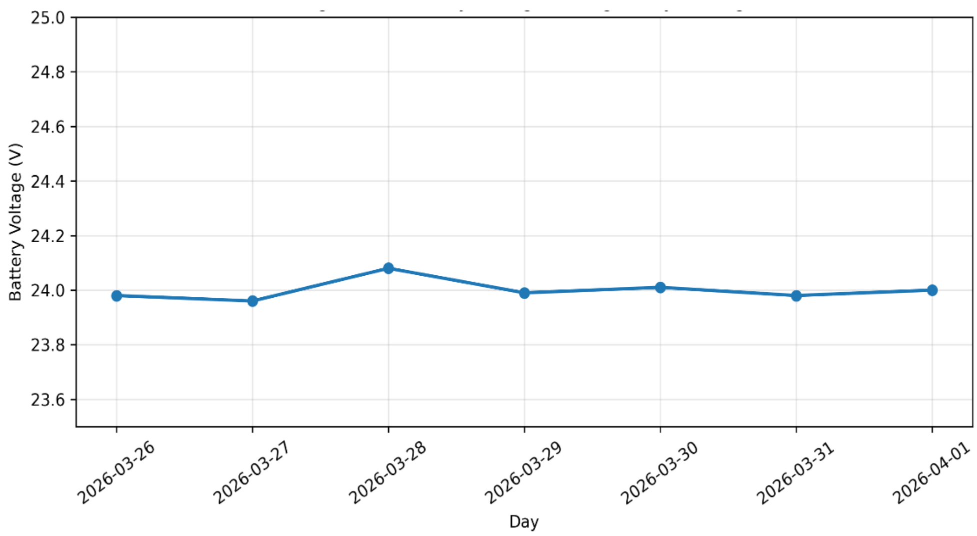

Figure 4. Battery voltage profile during the seven-day experimental testing

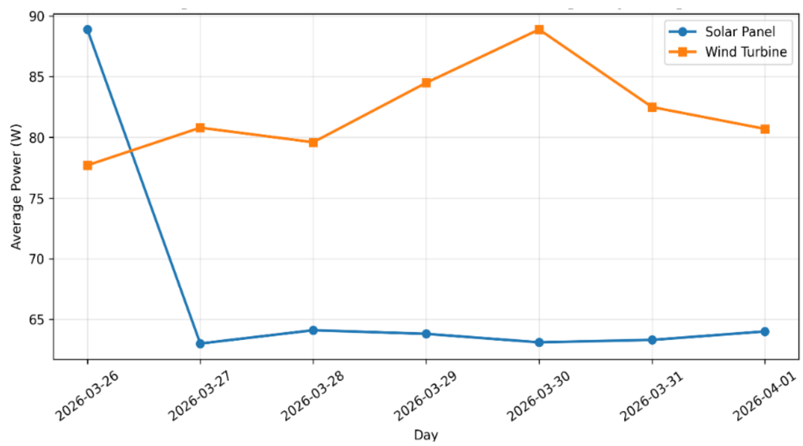

Figure 5. Average photovoltaic (PV) panel and wind turbine power output during the seven-day experimental testing

Overall, the experimental results demonstrate that the developed HRES is capable of maintaining stable battery operation while efficiently utilizing complementary PV and wind energy sources. These findings confirm that the proposed control strategy provides reliable energy management under practical operating conditions.

3.2 Voltage stability analysis

Voltage stability analysis was conducted to evaluate the effectiveness of the proposed T2-FLC algorithm in maintaining stable battery voltage under fluctuating renewable energy generation. Before implementing the proposed T2-FLC, the HRES operated using a conventional threshold-based relay switching strategy, in which relay operation was determined solely by predefined battery voltage thresholds without considering measurement uncertainty. Both the baseline and the proposed T2-FLC experiments were performed using the same laboratory prototype, battery bank, electrical load, sampling interval, and comparable environmental conditions to ensure a fair comparison. The battery voltage responses before and after implementing T2-FLC are presented in Figure 6, while the corresponding relay switching performance is illustrated in Figure 7.

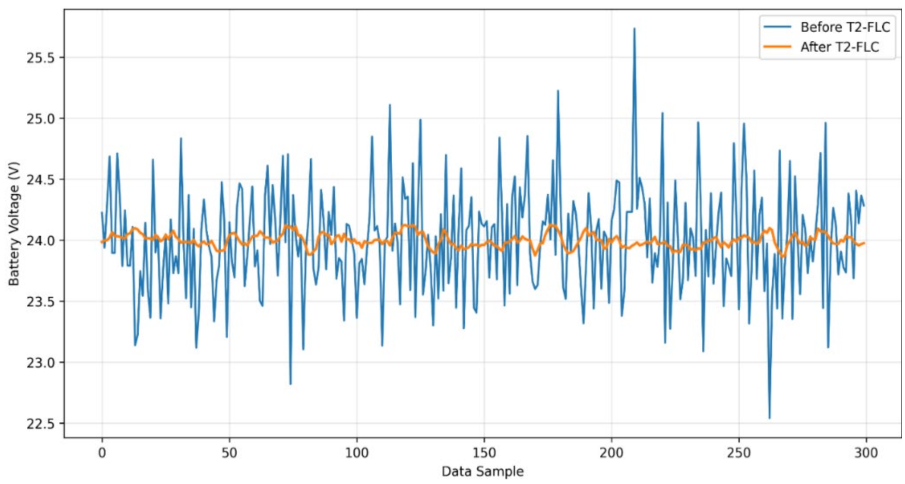

Figure 6. Comparison of battery voltage stability before and after implementing Type-2 Fuzzy Logic Control (T2-FLC)

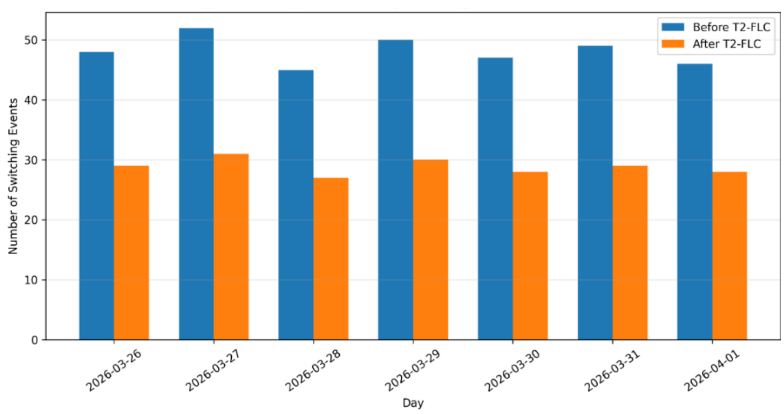

Figure 7. Comparison of relay switching before and after implementing Type-2 Fuzzy Logic Control (T2-FLC)

Based on the observations, the battery voltage during testing averaged approximately 24 V. This indicates that the system is capable of maintaining stability in the charging process and energy distribution. The implementation of T2-FLC helps the system make more adaptive switching decisions, so that voltage fluctuations do not immediately trigger repeated relay switching. Research by Shakibjoo et al. [31] reported an approximately 20% improvement in stability in a multi-area power system using T2-FLC. In this study, the proposed implementation demonstrated a reduction in relay switching based on the results of system testing.

3.3 Relay chattering analysis

Relay chattering was analyzed by comparing the number of relay switching operations before and after the implementation of the proposed T2-FLC. The results indicate that relay switching decreased by approximately 39.13% to 40.82% over the seven-day experimental period, with an average reduction of approximately 40%, demonstrating the effectiveness of the proposed controller in mitigating relay chattering. Representative electrical parameters recorded during the experimental testing are presented in Table 3, whereas the reduction in relay switching is illustrated in Figure 8. The experimental results demonstrate that the implementation of the proposed T2-FLC algorithm substantially reduced unnecessary relay switching throughout the experimental period. The number of relay switching operations decreased by approximately 39.13% to 40.82%, with an average reduction of approximately 40% compared with the conventional switching strategy. This improvement was achieved because the proposed T2-FLC incorporates the FOU into its fuzzy membership functions. The FOU enables the controller to tolerate measurement uncertainty, sensor noise, and minor fluctuations in PV power, wind turbine output, and battery voltage. Consequently, insignificant variations in the input variables do not immediately trigger changes in the relay operating state. By reducing excessive relay switching, the proposed controller minimizes switching losses and decreases the mechanical and electrical stress imposed on the relay. This operating characteristic is expected to extend relay service life while improving the reliability and operational stability of the HRES. The experimental findings are consistent with previous studies. Bayrak and Kaya [30] reported that T2-FLC produces smoother energy management decisions than conventional Type-1 fuzzy logic in hybrid power systems. Likewise, Moghadam et al. [29] demonstrated that T2-FLC effectively reduces system oscillations and improves power regulation under uncertain operating conditions. The relay switching reduction observed in this study further confirms that the proposed controller provides robust decision-making under practical operating conditions. Overall, the results indicate that integrating T2-FLC into the hybrid solar-wind energy management system effectively suppresses relay chattering while improving the operational reliability and long-term durability of the switching system.

3.4 Monitoring performance

The monitoring performance of the proposed system was evaluated to verify the reliability of the IoT-based monitoring platform in acquiring, transmitting, and displaying operational data in real time. The monitoring system employs an ESP32 communication module to transmit electrical measurements from the HRES to the remote monitoring platform through a wireless network. The transmitted monitoring data include PV panel voltage, PV panel current, PV panel power, wind turbine voltage, wind turbine current, wind turbine power, battery voltage, battery power, relay status, and system operating mode. These parameters enable continuous observation of the operating conditions of the HRES during the experimental period. The real-time monitoring dashboard is presented in Figure 9, which visualizes the operating conditions of the proposed hybrid solar–wind system, including PV power, wind power, battery voltage, relay status, and system operating mode. The experimental results demonstrate that the ESP32 communication module successfully transmitted monitoring data to the IoT platform in real time without significant communication interruptions. The displayed electrical parameters accurately represented the operating conditions of the laboratory-scale prototype, allowing continuous supervision of renewable energy generation, battery charging status, and relay operation.

Table 3. Representative electrical parameters recorded during the seven-day experimental testing

Date	Solar Voltage (V_Solar)	Solar Current (I_Solar)	Solar Power (P_Solar)	Wind Voltage (V_Wind)	Wind Current (I_Wind)	Wind Power (P_Wind)	Battery Voltage (V_Batt)	Battery Current (I_Batt)	Battery Power (P_Batt)
2026-04-01 23:09	28.6	0	0	24.92	0.25	6.17	24.01	4.68	112.35
2026-04-01 23:14	29.79	0	0	23.9	5.84	139.5	23.42	-3.65	-85.52
2026-04-01 23:19	28.86	0	0	28.1	1.67	46.99	23.93	1.03	24.64
2026-04-01 23:24	31.55	0	0	22.09	3.14	69.41	23.52	1.34	31.46
2026-04-01 23:29	29.29	0	0	20.13	9.63	193.83	23.12	-4.6	-106.47
2026-04-01 23:34	30.66	0	0	19.69	3.42	67.44	23.91	2.96	70.84
2026-04-01 23:39	29.62	0	0	23.63	1.69	39.84	24.59	2.52	62.05
2026-04-01 23:44	31.47	0	0	26.13	1.16	30.43	23.9	4.81	115.03
2026-04-01 23:49	30.21	0	0	22.02	3.22	70.88	23.1	1.82	41.99

2026-04-01 23:54	29.92	0	0	23.19	2.19	50.75	23.94	1.94	46.4

Note: V = Voltage; I = Current; P = Power; Batt = Battery

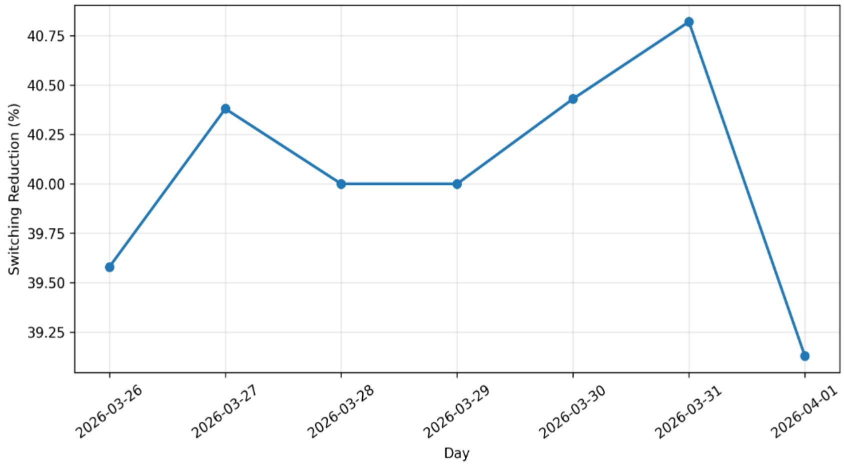

Figure 8. Reduction in relay switching after implementing Type-2 Fuzzy Logic Control (T2-FLC)

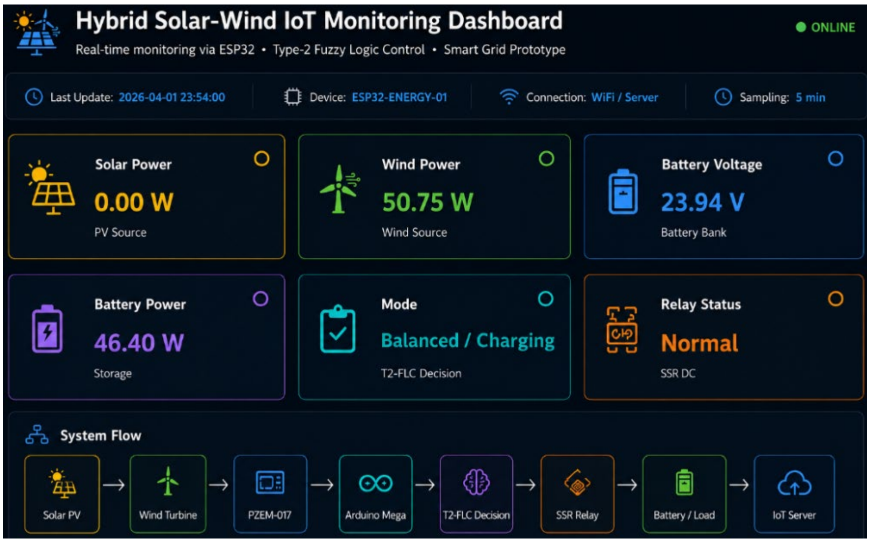

Figure 9. Real-time monitoring interface of the Internet of Things (IoT)-based hybrid solar–wind power generation system

Figure 10. Data logging results obtained from the Internet of Things (IoT)-based monitoring system

The monitoring platform also provides automatic data logging. Figure 10 presents an example of the historical data logging interface generated by the IoT platform. The recorded data provide detailed information on voltage, current, power, battery condition, and relay operation, supporting performance evaluation and system diagnostics. This capability enables historical operating data to be stored and analyzed for system performance evaluation. This feature facilitates the identification of voltage variations, renewable energy generation patterns, battery charging behavior, and relay operating conditions over extended periods. The integration of IoT technology significantly improves the operational flexibility of the proposed HRES by enabling remote monitoring without requiring direct physical access to the hardware prototype. Such capability supports predictive maintenance, rapid fault identification, and more efficient system management, which are essential characteristics of modern smart grid applications. Overall, the experimental results confirm that the developed IoT monitoring system provides reliable real-time communication, continuous data acquisition, and effective remote supervision, thereby enhancing the practical applicability of the proposed hybrid solar-wind energy management system.

3.5 Comparison with previous studies

To further evaluate the contribution of the proposed system, the experimental results obtained in this study were compared with those reported in previous research on T2-FLC for renewable energy applications. The comparison focuses on implementation approach, system configuration, IoT integration, and experimental outcomes. The comparison is summarized in Table 4.

Table 4. A comparison of this study with previous studies

Study	Control Method	Validation	Internet of Things (IoT) Integration	Main Contribution	Experimental Result
Aljohani [28]	T2-FLC	Simulation	No	Hybrid microgrid energy management	Hybrid microgrid optimization
Shakibjoo et al. [31]	T2-FLC	Simulation	No	Multi-area frequency control	Frequency stability has improved by 20%
Bayrak and Kaya [30]	T2-FLC	Simulation	No	Hybrid energy management	EMS is more stable
This study	T2-FLC + IoT	Yes	Yes	Hybrid solar–wind energy management with IoT	Relay switching reduced by approximately 40%

Previous studies have consistently demonstrated that T2-FLC improves the performance of renewable energy systems under uncertain operating conditions. For example, Maqekeni [20] implemented T2-FLC for hybrid microgrid energy management and reported improvements in energy distribution efficiency through simulation. Similarly, Shakibjoo et al. [31] achieved approximately 20% improvement in frequency stability using an optimized T2-FLC strategy for a multi-area power system. Bayrak and Kaya [30] also demonstrated that T2-FLC provides smoother energy management decisions than conventional Type-1 fuzzy logic in hybrid energy systems. Unlike these previous studies, the proposed approach was validated through experimental implementation using a laboratory-scale hardware prototype rather than simulation alone. The developed system integrates a PV panel, a Savonius wind turbine, a battery bank, an Arduino Mega controller, an ESP32 communication module, and an IoT-based monitoring platform into a complete HRES.

The experimental evaluation demonstrated that the proposed controller successfully maintained the battery voltage within the operating range of 23.9-24.5 V, while reducing relay switching frequency by approximately 40%. In addition, the IoT monitoring platform enabled real-time data acquisition, historical data logging, and remote supervision of system operation. These capabilities provide practical advantages for smart grid applications by improving operational reliability and simplifying system monitoring. Overall, the comparison indicates that the primary contribution of this research lies not only in the application of the T2-FLC algorithm but also in its successful integration with real hardware and IoT technology. This combination demonstrates the practical feasibility of implementing intelligent energy management in small-scale HRES operating under real environmental conditions.

4. CONCLUSIONS

This study successfully implemented a T2-FLC algorithm in a laboratory-scale hybrid solar-wind power generation system integrated with an IoT-based monitoring platform. The proposed system combines a PV panel, a Savonius wind turbine, a battery bank, an Arduino Mega controller, an ESP32 communication module, and a PZEM-017 direct current power sensor to perform intelligent energy management under actual operating conditions. The experimental results demonstrated that the proposed controller effectively maintained the battery voltage within the operating range of 23.9-24.5 V throughout the seven-day testing period, indicating stable battery charging and energy distribution despite fluctuations in renewable energy generation. Furthermore, the implementation of the T2-FLC algorithm reduced relay switching frequency by approximately 40%, thereby mitigating relay chattering and improving the operational reliability of the HRES. The developed IoT monitoring platform successfully provided real-time data acquisition, remote supervision, and historical data logging, enabling continuous observation of system performance and supporting more efficient operation and maintenance. These capabilities improve the practical applicability of the proposed system for small-scale smart grid and distributed renewable energy applications.

Overall, the experimental findings confirm that integrating T2-FLC with IoT technology provides an effective solution for improving voltage stability, reducing unnecessary relay switching, and enhancing intelligent energy management in hybrid solar-wind renewable energy systems. Future research will focus on implementing adaptive optimization techniques for automatic fuzzy rule tuning, integrating additional renewable energy sources and battery management strategies, and evaluating the proposed system under larger-scale microgrid operating conditions.

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REFERENCES

[1] World Energy Outlook 2023. (2023). IEA. https://www.iea.org/reports/world-energy-outlook-2023.

[2] Mostafaeipour, A., Sedaghat, A., Dehghan-Niri, A.A., Kalantar, V. (2011). Wind energy feasibility study for city of Shahrbabak in Iran. Renewable and Sustainable Energy Reviews, 15(6): 2545-2556. https://doi.org/10.1016/j.rser.2011.02.030

[3] Roy, P., He, J.B., Zhao, T.F., Singh, Y.V. (2022). Recent advances of wind-solar hybrid renewable energy systems for power generation: A review. IEEE Open Journal of Industrial Electronics Society, 3: 81-104. https://doi.org/10.1109/OJIES.2022.3144093

[4] Wang, Z.L., Zhang, X.Q., Rezazadeh, A. (2021). Hydrogen fuel and electricity generation from a new hybrid energy system based on wind and solar energies and alkaline fuel cell. Energy Reports, 7: 2594-2604. https://doi.org/10.1016/j.egyr.2021.04.060

[5] Hassan, Q., Algburi, S., Sameen, A.Z., Salman, H.M., Jaszczur, M. (2023). A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications. Results in Engineering, 20: 101621. https://doi.org/10.1016/j.rineng.2023.101621

[6] Asiaban, S., Kayedpour, N., Samani, A.E., Bozalakov, D., De Kooning, J.D.M., Crevecoeur, G., Vandevelde, L. (2021). Wind and solar intermittency and the associated integration challenges: A comprehensive review including the status in the belgian power system. Energies, 14(9): 2630. https://doi.org/10.3390/en14092630.

[7] Bihari, S.P., Sadhu, P.K., Sarita, K., Khan, B., Arya, L. D., Saket, R.K. (2021). A comprehensive review of microgrid control mechanism and impact assessment for hybrid renewable energy integration. IEEE Access, 9: 88942-88958. https://doi.org/10.1109/ACCESS.2021.3090266

[8] Islam, Md.S., Bushra, I.J., Roy, T.K., Oo, A.M.T. (2025). Enhanced transient stability in hybrid DC/AC microgrids: Robust composite control strategy with virtual capacitors integration using ANFIS-optimized control gain parameters. IET Renewable Power Generation, 19(1): e70066. https://doi.org/10.1049/rpg2.70066

[9] Hernández-Mayoral, E., Madrigal-Martínez, M., Mina-Antonio, J.D., Iracheta-Cortez, R., Enríquez-Santiago, J.A., Rodríguez-Rivera, O., Martínez-Reyes, G., Mendoza-Santos, E. (2023). A comprehensive review on power-quality issues, optimization techniques, and control strategies of microgrid based on renewable energy sources. Sustainability, 15(12): 9847. https://doi.org/10.3390/su15129847

[10] Jurasz, J., Canales, F.A., Kies, A., Guezgouz, M., Beluco, A. (2020). A review on the complementarity of renewable energy sources: Concept, metrics, application and future research directions. Solar Energy, 195: 703-724. https://doi.org/10.1016/j.solener.2019.11.087

[11] Babatunde, O.M., Munda, J.L., Hamam, Y. (2020). A comprehensive state-of-the-art survey on hybrid renewable energy system operations and planning. IEEE Access, 8: 75313-75346. https://doi.org/10.1109/ACCESS.2020.2988397

[12] Agajie, T.F., Ali, A., Fopah-Lele, A., Amoussou, I., Khan, B., Rodríguez Velasco, C.L., Tanyi, E. (2023). A comprehensive review on techno-economic analysis and optimal sizing of hybrid renewable energy sources with energy storage systems. Energies, 16(2): 642. https://doi.org/10.3390/en16020642

[13] Eyimaya, S.E., Altin, N. (2024). Review of energy management systems in microgrids. Applied Sciences, 14(3): 1249. https://doi.org/10.3390/app14031249

[14] Motlagh, N.H., Mohammadrezaei, M., Hunt, J., Zakeri, B. (2020). Internet of Things (IoT) and the energy sector. Energies, 13(2): 494. https://doi.org/10.3390/en13020494

[15] Albarakati, A.J., Boujoudar, Y., Azeroual, M., Eliysaouy, L., Kotb, H., Aljarbouh, A., Alkahtani, H.K., Mostafa, S.M., Tassaddiq, A., Pupkov, A. (2022). Microgrid energy management and monitoring systems: A comprehensive review. Frontiers in Energy Research, 10: 1097858. https://doi.org/10.3389/fenrg.2022.1097858

[16] Jia, L., Li, Z., Hu, Z.J. (2024). Applications of the Internet of Things in renewable power systems: A survey. Energies, 17(16): 4160. https://doi.org/10.3390/en17164160

[17] Xu, L.D., He, W., Li, S.C. (2014). Internet of Things in Industries: A survey. IEEE Transactions on Industrial Informatics, 10(4): 2233-2243. https://doi.org/10.1109/TII.2014.2300753

[18] Abir, S.M.A.A., Anwar, A., Choi, J., Kayes, A.S.M. (2021). IoT-enabled smart energy grid: Applications and challenges. IEEE Access, 9: 50961-50981. https://doi.org/10.1109/ACCESS.2021.3067331

[19] Almihat, M.G.M., Munda, J.L. (2024). Review on recent control system strategies in Microgrid. Edelweiss Applied Science and Technology, 8(6): 5089-5111. https://doi.org/10.55214/25768484.v8i6.3116

[20] Maqekeni, S., Obileke, K., Ndiweni, O., Mukumba, P. (2025). Application of fuzzy logic techniques in solar energy systems: A review. Applied System Innovation, 8(5): 144. https://doi.org/10.3390/asi8050144

[21] Sridharan, M. (2022). Short review on various applications of fuzzy logic-based expert systems in the field of solar energy. International Journal of Ambient Energy, 43(1): 5112-5128. https://doi.org/10.1080/01430750.2021.1927839

[22] Nagaiah, M., Sekhar, K.C. (2020). Analysis of fuzzy

logic controller based bi-directional DC-DC converter for battery energy management in hybrid solar/wind micro grid system. International Journal of Electrical and Computer Engineering, 10(3): 2271-2284. https://doi.org/10.11591/ijece.v10i3.pp2271-2284

[23] Khairi, N.N.M., Ahmad, S.S.S. (2014). A comparison of type-1 and type-2 fuzzy logic controllers in robotics: A review. International Journal of Numerical Analysis and Methods in Engineering, 2(5): 155-161. https://www.praiseworthyprize.org/jsm/index.php?journal=irena&page=article&op=view&path%5B%5D=16187.

[24] Tai, K., El-Sayed, A.R., Biglarbegian, M., Gonzalez, C., Castillo, O., Mahmud, S. (2016). Review of recent type-2 fuzzy controller applications. Algorithms, 9(2): 39. https://doi.org/10.3390/a9020039

[25] Vidal-Martínez, R., García-Martínez, J.R., Rojas-Galván, R., Álvarez-Alvarado, J.M., Gozález-Lee, M., Rodríguez-Reséndiz, J. (2025). A review of mamdani, takagi-sugeno, and type-2 fuzzy controllers for mppt and power management in photovoltaic systems. Technologies, 13(9): 422. https://doi.org/10.3390/technologies13090422

[26] Castillo, O., Sanchez, M.A., Gonzalez, C.I., Martinez, G.E. (2017). Review of recent type-2 fuzzy image processing applications. Information, 8(3): 97. https://doi.org/10.3390/info8030097

[27] Castillo, O., Melin, P. (2012). A review on the design and optimization of interval type-2 fuzzy controllers. Applied Soft Computing, 12(4): 1267-1278. https://doi.org/10.1016/j.asoc.2011.12.010

[28] Aljohani, T. (2024). Intelligent type-2 fuzzy logic controller for hybrid microgrid energy management with different modes of EVs integration. Energies, 17(12): 2949. https://doi.org/10.3390/en17122949

[29] Mohammadi Moghadam, H., Mohammadzadeh, A., Hadjiaghaie Vafaie, R., Tavoosi, J., Khooban, M.H. (2022). A type-2 fuzzy control for active/reactive power control and energy storage management. Transactions of the Institute of Measurement and Control, 44(5): 1014-1028. https://doi.org/10.1177/01423312211048038

[30] Bayrak, Z.U., Kaya, M.N. (2024). Modeling and detailed analysis of rule based, conventional fuzzy and type-ii fuzzy logic energy management systems of fuel cell-battery hybrid powered unmanned aerial vehicles. IEEE Access, 12: 110655-110670. https://doi.org/10.1109/ACCESS.2024.3441107

[31] Shakibjoo, A.D., Moradzadeh, M., Din, S.U., Mohammadzadeh, A., Mosavi, A.H., Vandevelde, L. (2022). Optimized type-2 fuzzy frequency control for multi-area power systems. IEEE Access, 10: 6989-7002. https://doi.org/10.1109/ACCESS.2021.3139259

[32] Kumari, N., Aryan, P., Raja, G.L., Arya, Y. (2023). Dual degree branched type-2 fuzzy controller optimized with a hybrid algorithm for frequency regulation in a triple-area power system integrated with renewable sources. Protection and Control of Modern Power Systems, 8(1): 48. https://doi.org/10.1186/s41601-023-00317-7

[33] Marques Lameirinhas, R.A., Torres, J.P.N., De Melo Cunha, J.P. (2022). A photovoltaic technology review: History, fundamentals and applications. Energies, 15(5): 1823. https://doi.org/10.3390/en15051823

[34] Bamisile, O., Acen, C., Cai, D.S., Huang, Q., Staffell, I. (2025). The environmental factors affecting solar photovoltaic output. Renewable and Sustainable Energy Reviews, 208: 115073. https://doi.org/10.1016/j.rser.2024.115073

[35] Vodapally, S.N., Ali, M.H. (2022). A comprehensive review of solar photovoltaic (PV) technologies, architecture, and its applications to improved efficiency. Energies, 16(1): 319. https://doi.org/10.3390/en16010319

[36] Maghami, M.R., Hizam, H., Gomes, C., Radzi, M.A., Rezadad, M.I., Hajighorbani, S. (2016). Power loss due to soiling on solar panel: A review. Renewable and Sustainable Energy Reviews, 59: 1307-1316. https://doi.org/10.1016/j.rser.2016.01.044

[37] Mohamed, M.H., Janiga, G., Pap, E., Thévenin, D. (2011). Optimal blade shape of a modified Savonius turbine using an obstacle shielding the returning blade. Energy Conversion and Management, 52(1): 236-242. https://doi.org/10.1016/j.enconman.2010.06.070

[38] Roy, S., Saha, U.K. (2013). Review on the numerical investigations into the design and development of Savonius wind rotors. Renewable and Sustainable Energy Reviews, 24: 73-83. https://doi.org/10.1016/j.rser.2013.03.060

[39] Datta, U., Kalam, A., Shi, J. (2020). A review of key functionalities of battery energy storage system in renewable energy integrated power systems. Energy Storage, 2(4): e224. https://doi.org/10.1002/est2.224

[40] Sutikno, T., Arsadiando, W., Wangsupphaphol, A., Yudhana, A., Facta, M. (2022). A review of recent advances on hybrid energy storage system for solar photovoltaics power generation. IEEE Access, 10: 42346-42364. https://doi.org/10.1109/ACCESS.2022.3165798

[41] Hannan, M.A., Lipu, M.S.H., Hussain, A., Mohamed, A. (2017). A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. Renewable and Sustainable Energy Reviews, 78: 834-854. https://doi.org/10.1016/j.rser.2017.05.001

[42] Zadeh, L.A. (1965). Fuzzy sets. Information and Control, 8(3): 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X

[43] Hannan, M.A., Ghani, Z.A., Hoque, M.M., Ker, P.J., Hussain, A., Mohamed, A. (2019). Fuzzy logic inverter controller in photovoltaic applications: Issues and recommendations. IEEE Access, 7: 24934-24955. https://doi.org/10.1109/ACCESS.2019.2899610

[44] De, A.K., Chakraborty, D., Biswas, A. (2022). Literature review on type-2 fuzzy set theory. Soft Computing, 26(18): 9049-9068. https://doi.org/10.1007/s00500-022-07304-4

[45] Mendel, J.M. (2007). Type-2 fuzzy sets and systems. IEEE Computational Intelligence Magazine, 2(1): 20-29. https://doi.org/10.1109/MCI.2007.380672

[46] Mendel, J.M. (2024). Sources of uncertainty and membership functions. In Explainable Uncertain Rule-Based Fuzzy Systems, pp. 219-235. https://doi.org/10.1007/978-3-031-35378-9_5

[47] Karnik, N.N., Mendel, J.M. (2001). Centroid of a type-2 fuzzy set. Information Sciences, 132(1): 195-220. https://doi.org/10.1016/S0020-0255(01)00069-X