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Electric Spring-based Voltage Regulation with Adaptive IoT-Tuned Type-2 Fuzzy Control for Critical Loads in Microgrids

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Abstract: This paper presents a wind power generation system for grid-isolation mode operation, controlled by an electric spring. The electric spring is efficiently controlled by a smart and adaptive Internet-of-Things (IoT) platform combined with an interval type-2 fuzzy logic controller (IT2FLC) to provide voltage stability for isolated critical loads. The proposed system is particularly designed to work in grid-secluded mode, feeding power to critical loads with stable voltage and frequency irrespective of variations in wind speeds and fluctuating load demands. The load voltage regulation is kept within +3% and voltage THD is also low for the proposed controller. The novelty of this work lies in the integration of real-time IoT-based adaptive tuning with IT2FLC for Electric Spring operation, enabling dynamic voltage stabilization in off-grid wind systems under fluctuating source and load conditions. The performance of the proposed scheme and its control is verified by different simulation studies and experimental findings gathered from a laboratory-scale test prototype.

Keywords: *Induction generator, Internet-of-things, Electric Spring, Interval Type-2 Fuzzy control, Wind power.*

1. Introduction

With constant increase in penetration of renewable energy sources and need for decentralized power generation, grid isolated renewable systems have become significant in modern energy infrastructures. Wind energy has become an ideal source of renewable powering isolated, off-grid locations. This is because wind is clean, inexhaustible source with significant output in selected locations [1]. However, wind is intermittent and variable and thus pose substantial challenge for maintaining stable voltage especially for delivering critical loads such as a health center. Wind generation in most cases have used induction generators for electricity generation owing to the obvious advantages [2]. Before the advent of power electronic devices, mostly, wind energy was utilized to serve grid-connected loads [3]-[5]. Use of wind energy to supply microgrids is now a well-researched domain although in microgrids, the voltage regulation is still a developing area of research [6]-[8]. The voltage fluctuations and load variations still impose challenges for supplying grid-isolated loads and can be a serious concern for supplying

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critical loads [9, 10]. To address this problem, often researchers resort to hybrid generation systems employing any other generation along with wind power [11]-[13]. Hybrid generation often also uses better storage facilities during low wind conditions enabling supply of critical loads effectively [14]. However, sizing of such storage is also a concern. Hybrid system control has recently focussed on optimal management of energy [15]. The reliability of generation is bettered using voltage variation strategy in [16]. Numerous strategies are also adopted to stabilize such hybrid generations [17]-[19]. In recent studies, artificial intelligence (AI) techniques such as deep learning framework is employed for load forecasting and real time control [20]. Isolated generation intelligent energy management with artificial neural network is proposed in [21]. Machine learning techniques are also in progress for such control systems [22]. Regardless of the generation and control strategies, maintaining stable power is a serious concern. A hybrid source of generation is thus always favoured. Electric springs (ES) are a unique power electronic device known for its ability to provide better voltage regulation in renewable energy systems [23]. It typically consists of a switched capacitor connected with non-critical load in series. This circuit is linked in parallel to the generation system typically stabilizing power across a critical load. The capacitor is switched electronically using an inverter system and thus it requires proper control [24]. ES are used in grids to mitigate voltage swings [25]. It has also been used to supress harmonics in power systems [26]. Voltage and frequency peaks are also successfully reduced using ES control in [27] and to alleviate blackouts [28]. In ES control, the main aim is to get power system stability and better voltage regulation while using renewable sources. It can inject voltage to non-critical load in accordance to generation source. The crucial load voltage is sustained at a stable value. Load voltage balancing is shown to be a good control strategy for such ES systems [29]. Synchronized voltage and reactive power control is also adopted in [30]. Recently, multiple ES coordination-based control is also shown to be beneficial for small grids [31]. Direct power control is also a simplistic control approach for such a system as shown in [32].

This work proposes a novel real-time, IoT-enabled electric spring (ES) control architecture enhanced with an interval type-2 fuzzy logic controller (IT2FLC) for voltage stabilization in grid-isolated wind power systems. IT2FLC is utilized in the proposed scheme as it is better than type-1 fuzzy as it can easily handle imprecise and uncertain data which suits the proposed control better which uses wind power as a primary source [33], [34]. Most importantly,

- The combination of IoT-based sensing and control with IT2FLC is chosen to address the dual challenge of real-time responsiveness and uncertainty handling in voltage regulation, where IoT enables dynamic monitoring and remote adaptability, while IT2FLC provides robust decision-making under fluctuating wind and load conditions.

Power System Technology
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- Unlike previous studies, the proposed method integrates novel cloud-based adaptive tuning of fuzzy control parameters using live field data, allowing dynamic adjustment to varying wind speeds and loads.
- The combination of real-time IoT data acquisition with uncertainty-aware fuzzy inference enhances system resilience, leading to improved voltage regulation (±2%), reduced harmonic distortion (<3.5%), and faster transient recovery (<80ms).

The paper further provides a unique comparison across multiple control schemes, parameter optimization cases, and hardware experiments, establishing the proposed system as a scalable solution for critical load management in standalone microgrids.

2. System Configuration

The proposed generation system consists of a wind turbine driving a three-phase induction machine as induction generator. An electric spring (ES) is configured in series-ES mode is connected across the generator. The ES is used mainly for voltage stabilization of a critical load which in this case is a medical facility connected in isolation from the grid. A non-critical heating load is connected in series with the ES. IoT-based control platform integrated with an interval type-2 fuzzy logic controller (IT2FLC) is employed for control of the ES. A considerable degree of imprecision modelling can be achieved with IT2FLC, which is an expanded form of type-1 fuzzy logic and thus it is more suitable for decision making with desired level of performance. The IoT platform used with the control logic collects data from voltage, current, and wind speed sensors and communicates this information to a centralized controller, which adjusts the control parameters in real time. The proposed generation system is depicted in Fig.1.

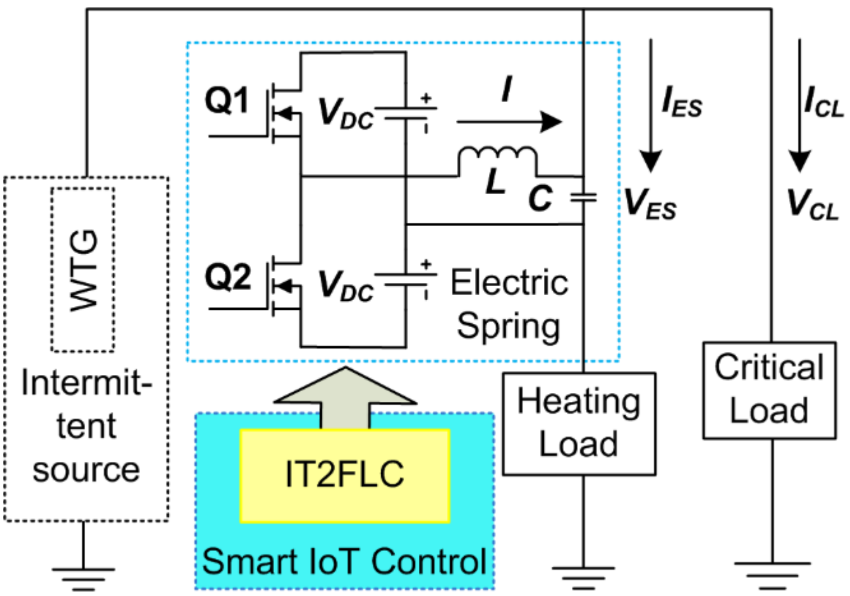

Fig. 1. Proposed generation system.

Power System Technology
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3. Proposed Electric Spring Operation and Control

The electric spring (ES) acts as an active compensator to regulate voltage across the critical loads. It injects or absorbs voltage in response to fluctuations in supply and load mandate. The ES comprises of a bidirectional half-bridge inverter and a series compensator interfaced with the supply line. The ES is envisioned to control voltage across essential loads by dynamically injecting a compensating voltage in series with non-essential loads. In the system presented, the ES is in series-ES mode and is regulated through a PWM voltage source inverter (VSI) in half-bridge mode that is powered by an interval type-2 fuzzy logic controller (IT2FLC). It is supported by an IoT-enabled platform that allows real-time monitoring and remote parameter tuning, which increases the adaptability of the system in conditions of variable winds and loads. The block diagram of the control scheme employed is shown in Fig.2.

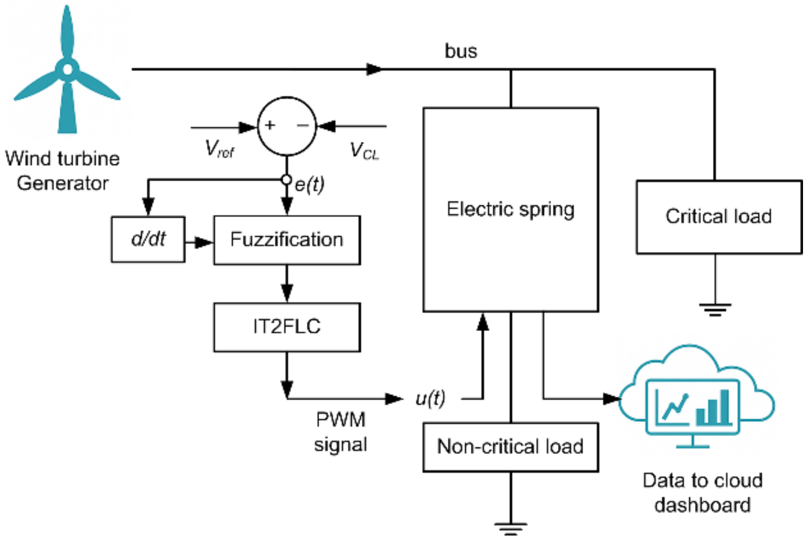

Fig. 2. The block diagram of the proposed control.

3.1. Control Principle of Electric Spring

In the suggested scheme, the electric spring (ES) is in Series-ES mode and is employed as a dynamic voltage compensator to inject a controllable voltage in series with the non-critical loads to regulate the voltage fed to the critical loads. The ES control is enabled by a pulse-width modulation (PWM) inverter, which is controlled using an interval type-2 fuzzy logic controller (IT2FLC) integrated with internet-of-things (IoT). The ES constantly samples the voltage at the point of common coupling (PCC) using IoT-powered voltage sensors and sends real-time information to a cloud-based central control system. The IT2FLC accepts two main inputs: the voltage error (deviation of real load voltage from the reference voltage) and rate of change in error over time. These inputs are converted to fuzzy sets by fuzzification using interval type-2 fuzzy sets, which comprise a footprint of uncertainty (FOU) for dealing with

Power System Technology
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the imprecision and noise in measurements caused by fluctuating wind speed and nonlinear load behavior. The rule base of the fuzzy controller takes the input information and computes a control output that decides the magnitude and sign of the compensating voltage supplied by the ES. This output is consequently transformed into PWM signals to drive the inverter. The IoT interface also aids in real-time and adaptive tuning of the fuzzy rules and membership functions based on load and generation. This hierarchical, intelligent control approach enables the ES to adapt to disturbances, keeping the voltage across critical loads within a stable limit.

The total voltage at the supply point is given by,

$$V_{total}(t) = V_{CL}(t) + V_{ES}(t) \tag{1}$$

where, $V_{total}(t)$ is the total supply voltage, $V_{CL}(t)$ is the voltage across the critical load and $V_{ES}(t)$ is the voltage across the electric spring. The goal is to maintain the critical load voltage at a stable value V_{ref}irrespective of fluctuations in the total voltage. This total voltage is referred to as the generated voltage at a certain time slot and the fluctuations if any are caused by wind variability. Also, dynamic loads can cause a change in voltage across the critical load. The voltage error $e(t)$ and its derivative $\Delta e(t)$ are calculated as,

$$e(t) = V_{ref} - V_{CL}(t) \tag{2}$$

$$\Delta e(t) = \frac{de(t)}{dt} \tag{3}$$

These are fed into the IT2FLC to produce the control output, which further modulates the ES inverter output.

3.2. Interval Type-2 Fuzzy Logic Controller

The IT2FLC offers improved robustness over conventional Type-1 and Type-2 FLCs by representing membership functions as intervals. This provides better management of uncertainties and imprecise data [33]. The controller inputs are:

- Error (e): Difference between reference and measured voltage.
- Change of error (Δe): Rate of change of error.

The output is the control signal to the PWM inverter for controlling the ES. The fuzzy rule base is created to handle a wide range of operating conditions. The IT2 fuzzy sets with footprint of uncertainty (FOU) significantly improve the system's capability to report noise and modelling uncertainties [33].

Power System Technology
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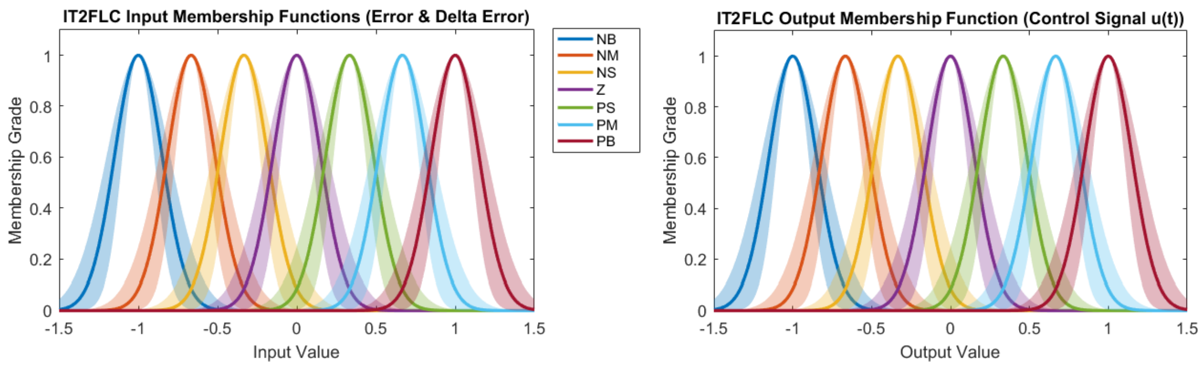

Fig. 3. The membership functions (μ) of the inputs and the output for IT2FLC for the proposed control.

Contrasting to type-1 fuzzy logic, where the membership grades are crisp (e.g., $\mu \in [0, 1]$), an IT2FLS defines the membership function as a fuzzy set of fuzzy sets. This means, the output membership is itself an interval, which captures a range of possible values for each input. Mathematically, the membership function $\tilde{\mu}_A(x)$ of an IT2FLC is given by:

$$\tilde{\mu}_A(x) = \left[\underline{\mu}_A(x), \overline{\mu}_A(x)\right] \quad \forall\, x = X \tag{4}$$

where, $\underline{\mu}_A(x)$ and $\overline{\mu}_A(x)$ are the lower and upper membership functions, correspondingly. The design of input membership functions is vital for effective IT2FLC performance. For this application, the error $e(t)$ and change in error $\Delta e(t)$ are each mapped to seven interval-valued Gaussian membership functions. These are labelled as: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), and Positive Big (PB). Each Gaussian function is defined by a center value (mean) and an uncertainty band (standard deviation ± delta), which together define the FOU. For example, the NB function has a center at -1.0 with a spread of 0.4 and FOU width of ±0.2. This structure allows the controller to handle sensor noise and fluctuating conditions, especially prevalent in wind-based systems. The output variable — inverter duty cycle adjustment — is also defined using similar interval-valued functions. The fuzzification and defuzzification processes are adjusted using the Karnik-Mendel algorithm for type-reduction, confirming real-time usability. This structure provides both robustness and adaptiveness, which are key for critical voltage regulation.

The membership functions of input and output are shown in Fig.3. The shaded areas are the FOU as explained. Proposed IT2FLC follows the steps:

- Fuzzification: Input error, and change of error are converted into IT2 fuzzy values using interval-valued membership functions.
- Rule Evaluation: Rules are fired using an interval t-norm as,

Power System Technology
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$$w_i = \left[\min\left(\underline{\mu}_e(x), \underline{\mu}_{\Delta e}(x)\right), \min\left(\overline{\mu}_e(x), \overline{\mu}_{\Delta e}(x)\right)\right] \quad (5)$$

where, the min operator is logical AND representation of fuzzy set and lower and upper membership functions of error denoted as $\underline{\mu}_e(x)$ and $\overline{\mu}_e(x)$respectively. Similarly change in error memberships are shown. This evaluation ensures the output of the operation is not a singular value within the unit interval.

- Type-Reduction: The fuzzy output set is converted to a crisp interval using the Karnik-Mendel (KM) algorithm [35].
- Defuzzification: A single crisp control output is obtained as the average of the left and right limits.

$$u(t) = \frac{y_L + y_R}{2} \quad (6)$$

where, y_L and y_R are the left and right limits of the membership function. The $u(t) \in [-1, +1]$ represents the required control action where positive is for voltage injection and negative indicates absorption. The duty cycle $D(t)$ for the inverter of ES is adjusted in MATLAB/Simulink and then transmitted to IoT system via necessary communication protocols for PWM,

$$D(t) = \frac{u(t)+1}{2}.(D_{max} - D_{min}) + D_{min} \quad (7)$$

Where, D_{min} and D_{max} are minimum and maximum allowable values of duty cycle. Equation (7) is obtained following fuzzy output of (6) after linear scaling and normalization. This also enables real-time voltage compensation via the ES.

In the proposed scheme, the IT2FLC is designed to regulate the voltage across the critical load by dynamically adjusting the output of the PWM inverter driving the ES. As mentioned, the IT2FLC receives two time-varying input signals: (i) the voltage error $e(t)$, and (ii) the rate of change of error $\Delta e(t)$. These inputs are fuzzified using interval-valued Gaussian membership functions that include uncertainty through FOU. The controller then processes these fuzzy inputs through a rule base developed explicitly for voltage regulation in the proposed system. The fuzzy output is a control action signal $u(t)$, which modulates the duty cycle of the inverter to inject or absorb voltage through the ES. This adaptive control enables the system to suppress voltage sags and sustain regulation even under rapid changes in wind speed and dynamic load switching. The IT2FLC implementation is developed in MATLAB/Simulink, and real-time tuning of membership functions was integrated via IoT using the ESP32 dashboard to enhance robustness under field conditions.

Received: 06-06-2025 Revised: 15-07-2025 Accepted: 10-08-2025

3.3. IoT-based Monitoring and Control

The IoT platform utilizes microcontrollers (e.g., ESP32) and sensors for real-time data collection, transmission, and control. Data is sent to a cloud-based dashboard where analytics are performed to dynamically tune the FLC parameters. This adaptive tuning allows the ES to respond effectively to varying wind conditions and load demands. In grid-isolated renewable energy systems, remote control and real-time data acquisition play a crucial role in providing reliable and intelligent operation. With the incorporation of internet-of-things (IoT) technology for the ES system, remote monitoring, adaptive voltage stabilization according to real environmental and load conditions, and dynamic control are possible.

In this application, ESP32 microcontrollers are used at the hardware level to obtain real-time measurements like, wind speed, supply voltage, load current and ambient temperatures using dedicated sensors. These measurements are sent over Wi-Fi to a cloud server or central processor (with message queuing telemetry transport (MQTT) brokers). MQTT is used as it is lightweight with publish-subscribe communication practice, suitable for proposed IoT system control [34]. A dashboard interface displays these parameters and enables system operators to view critical load performance and remotely diagnose problems. Control parameters (for example, weights on fuzzy rules) are revised in real time, from previous patterns of operation or sometimes faults. Such closed-loop control over IoT devices permits anticipatory regulation — that is, for example, a decline in wind speed is observed and, automatically, the ES can proactively increase the voltage support. The ESP32 runs a PWM generator for 20kHz frequency with duty cycle $D(t)$, controlling the half-bridge inverter output voltage $V_{ES}(t)$ as in (1). The loop then restarts with new sensed values — making it a real-time, closed-loop IoT control system. The control algorithm (Algorithm 1) is shown below:

Algorithm 1. Real-time ESP32 PWM for IoT-based fuzzy control for Electric Spring operation

```
Initialize:
    Set PWM frequency = 20 kHz
    Set PWM resolution = 10-bit (0 to 1023)
    Set MQTT broker address and topic names
    Set ADC pin for V_CL sensing
    Set DAC/PWM output pin to inverter gate
Loop (Every T = 5ms):
    1. Read voltage sensor (V_CL) using ADC pin
    2. Send V_CL to cloud (MQTT publish to topic "sensor/v_cl")
    3. Receive control signal u(t) from MATLAB (via MQTT subscribe topic "control/u")
    4. Map u(t) ∈ [−1, 1] to duty cycle D(t):
         D(t) = ((u(t) + 1)/2) × (D_max − D_min) + D_min
         D_out = floor(D(t) × 1023)   // for 10-bit PWM resolution
    5. Generate PWM:
         analogWrite(PWM_pin, D_out)
    6. Wait for next 5ms
```

Power System Technology
ISSN:1000-3673
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End Loop

4. Results

The simulations are accomplished using MATLAB/Simulink and further, experiments are conducted on a laboratory setup. A three-phase induction machine is utilized for generation with four-stator-pole, rated at 1.5 kW, 400 V, and 50 Hz. The important load is the combined health clinic load, which is rated at 500W at its maximum and consumes roughly 7.5 kWh of energy daily. A non-critical load of a 300W water heater is used which is frequently run below its rated capacity. For the simulation, the wind speed profile, along with the critical load voltage and ES PWM output is shown in Fig.4. As detected from the figure, the system critical voltage is maintained at a stable value with changing wind speeds. The ES output provides the necessary support during bus voltage dips.

Fig.5 depicts the simulated critical load voltage with a sag event at 3s. The voltage is restored after about 200ms which shows the fast recovery dynamics and ES controller agility with the proposed control. Moreover, the control voltage output is also shown in the figure.

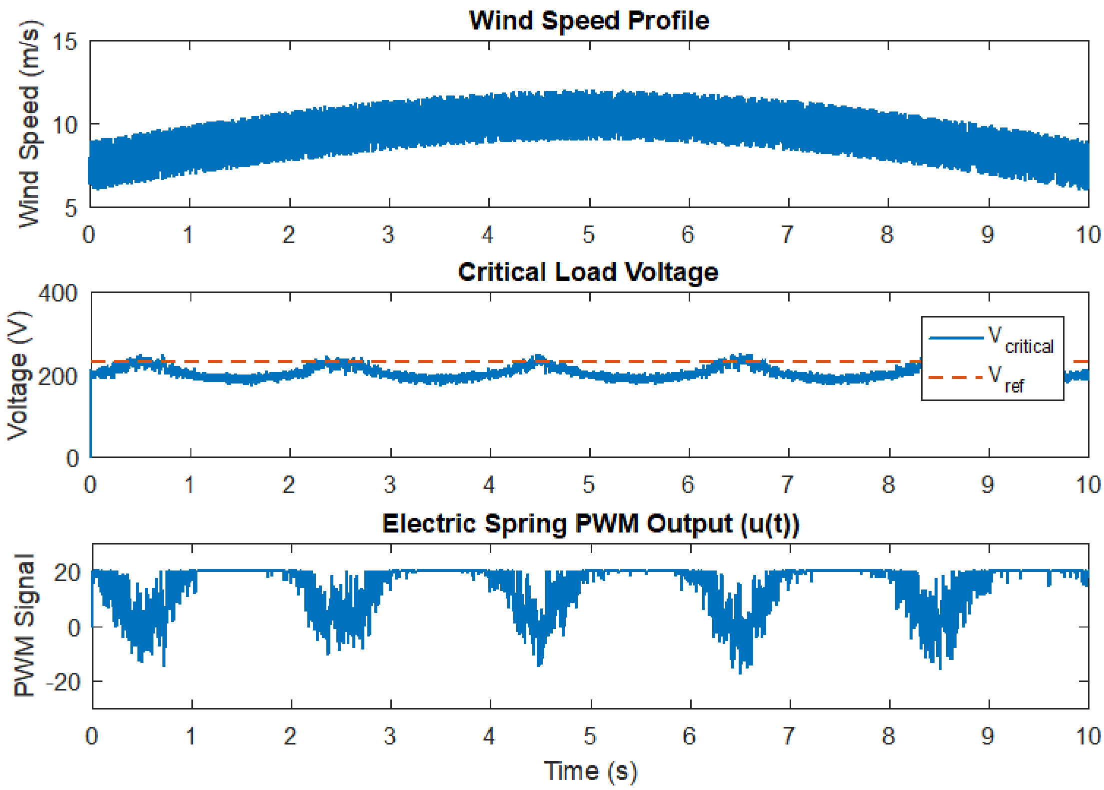

Fig. 4. Simulated wind speed profile, critical load voltage and electric spring PWM output waveforms.

Power System Technology
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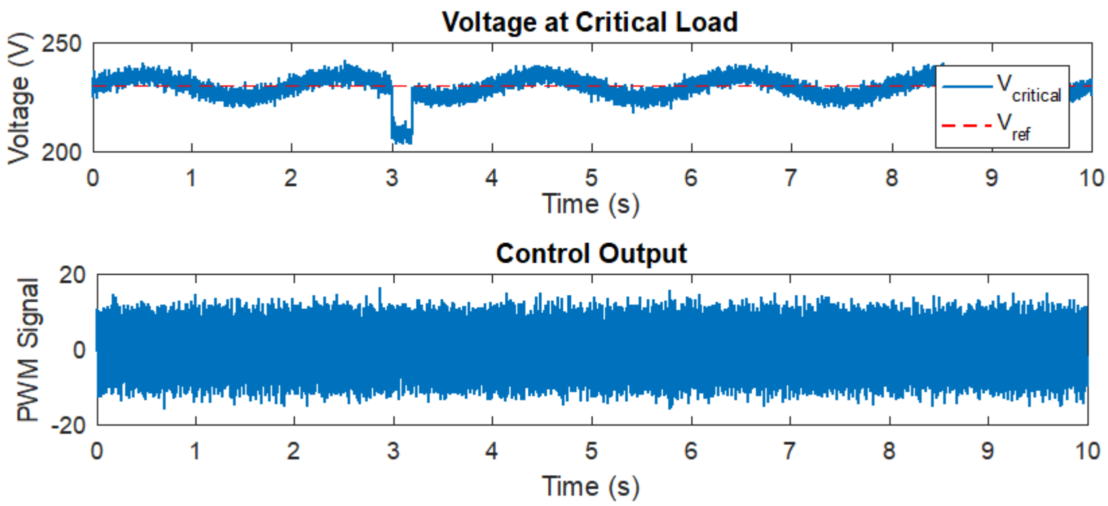

Fig. 5. Simulated critical load voltage with a sag and control voltage waveforms.

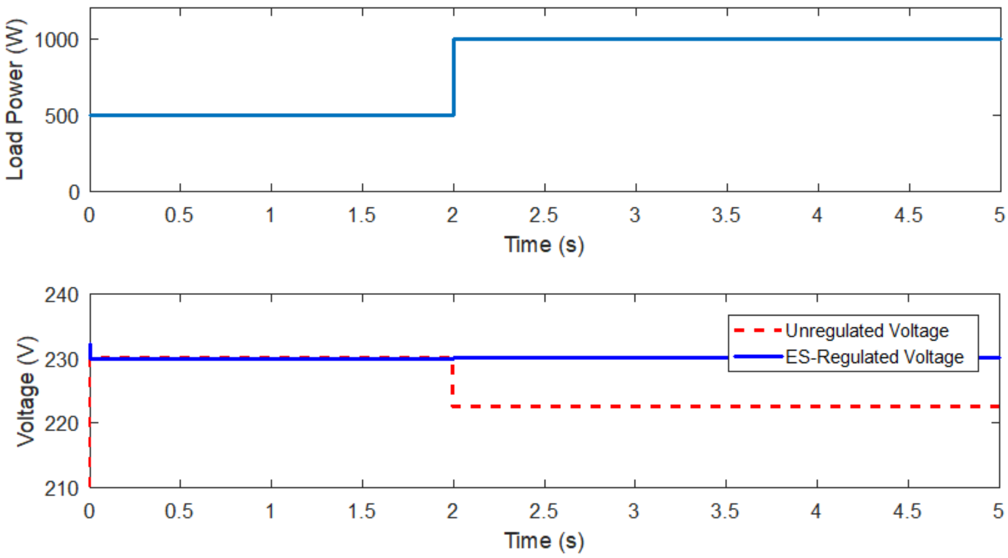

Fig. 6. Simulated step change in load power and ES regulated voltage output.

Fig.6 shows the simulated step change in load power from half-rated to full-rated load and corresponding regulated voltage waveform of the load. The load voltage remains at a persistent value with the ES regulation while if remain unregulated, the voltage is shown to be dipping when load is increased suddenly.

The experimental laboratory prototype uses the same parameters as the simulated system. The details of the ES and the IoT system are tabulated in Table-1.

Power System Technology
ISSN:1000-3673

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Table 1. System hardware component details.

Component	Parameters	Description
System and electric spring	Nominal phase voltage	230V
	Voltage at source	400V
	Active power	500W
	Reactive power	220VAr
	Circuit of ES	MOSFET based single-phase half bridge, K2611 MOSFET
	MOSFET driver	MC33153PG
	Switching frequency	20kHz
IoT control system	Controller	ESP32
	Network router	IPv6
	Broker	MQTT
	Dashboard	NodeRED
	Relay	Optically isolated, 5V, 4-channel
	Sensors used	voltage ZMPT101B, current ACS712, temperature LM35

The experimental setup is similar with the proposed control. The data from the ESP system is used and then it is logged into a computer system. The data are separated into individual signals: wind speed, load power, and voltage. The control logic of IT2FLC is used to generate appropriate control actions. The ES behavior is modelled using hardware setup and finally NodeRED dashboard blocks such as gauge, scope, and display to visualize real-time signal values. The experimental setup block is depicted in Fig.7.

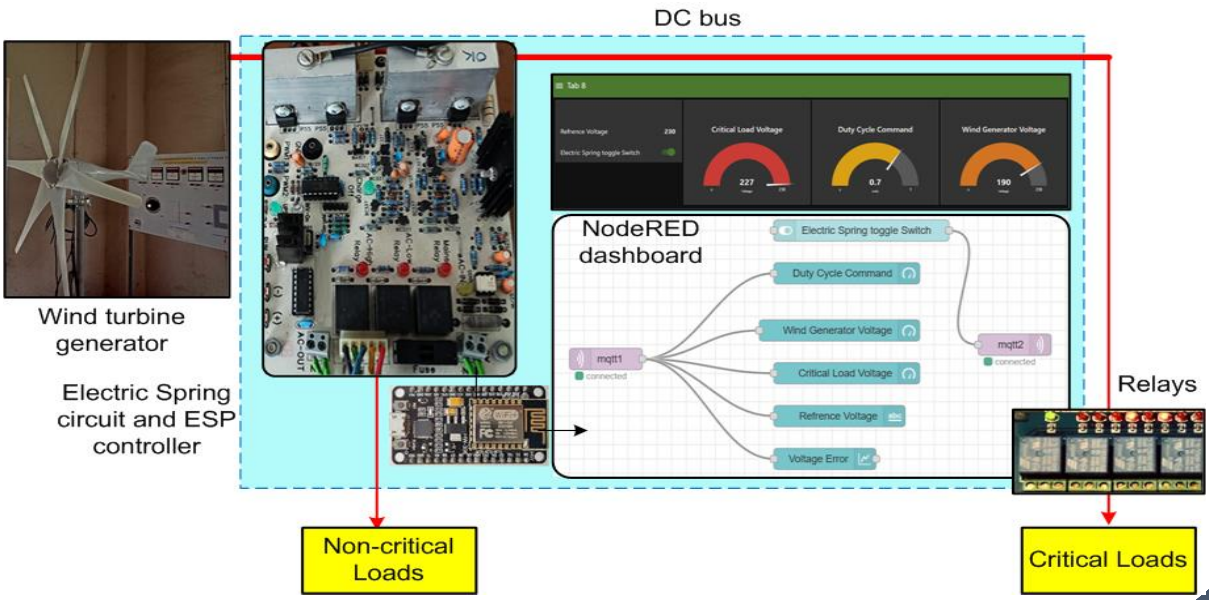

Fig. 7. Experimental setup block diagram.

Power System Technology
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In the laboratory setup the relays are connected for the non-critical load connection in the ES setup. Critical loads are also connected via relays. A 20µF filter capacitor and a 1mH filter inductor are connected. ESP32 microcontroller is used to program the control logic. The IG is coupled to a wind turbine in the setup driven in lab using wind gust emulating a wind-turbine characteristics. The generated output is sent to the bus. The ES is connected in the bus for sustaining voltage across the critical load as observed from the figure. The ES is implemented employing a single-phase half-bridge PWM inverter which is controlled by the ESP microcontroller. The controller runs the IT2FLC for control. Sensors measure the voltage, current and temperature which are processed in real-time. ESP32 transmits key parameters to a cloud-connected Node-RED dashboard via MQTT for monitoring and remote-control purpose. The system is tested under varying wind conditions and dynamic loading to evaluate the system performance in these scenarios. Additionally, the controller can be interfaced for data logging for local readout. Load variations are made using programmable relays and voltage sags are simulated to evaluate controller performance. The IT2FLC parameters are tuned offline and finally updated dynamically via the IoT interface.

The experimental wind speed, load power (step increase from half-rated to rated value) and critical load voltage is shown in Fig.8. As observed, the critical load voltage is maintained at a stable value with changing loads and wind speeds. However, the effect of changing load is shown to be creating more degenerating effect on the critical load voltage.

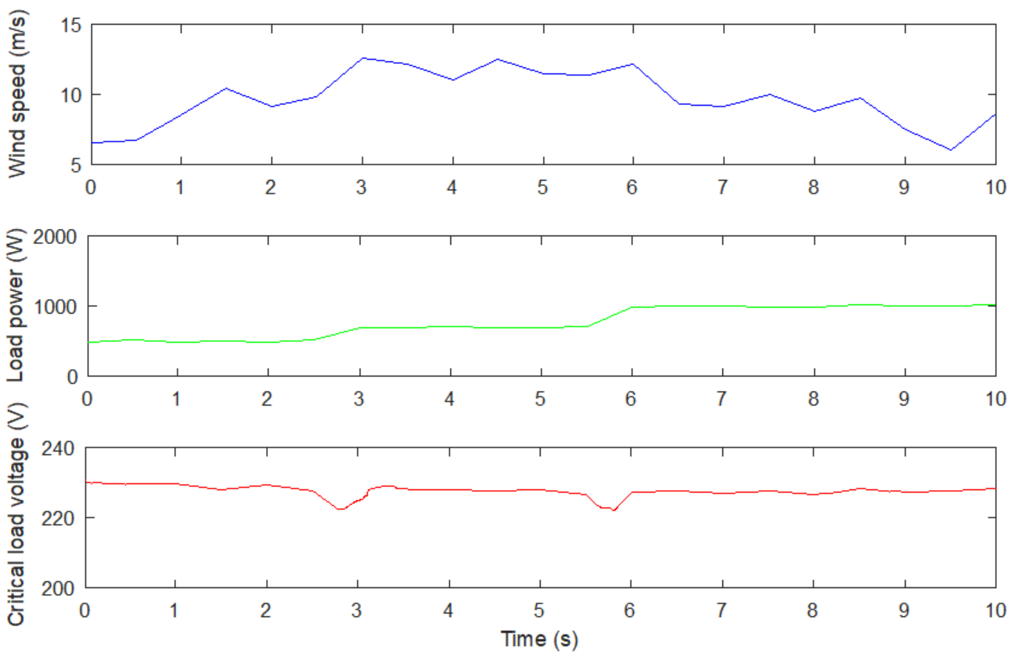

Fig. 8. Experimental wind speed profile, load power and critical load voltage waveforms.

Power System Technology
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Fig.9 shows the experimental variation of generated voltage from wind, critical load voltage and duty cycle variation or the control signal voltage.

In this figure, the generated voltage from wind increases from 180V to 210V indicating that the wind is fluctuating in nature and the generated voltage is not constant. The critical load voltage however remains at a constant value with the control. Consequently, the duty cycle varies dynamically in response to the error between the reference and the load voltage. It reaches a constant value as the load voltage reaches steady value.

Fig.10 shows the experimental real input power drawn from the supply and output power delivered to load. The different powers are calculated experimentally from the voltage and current sensor data obtained over time from ESP log. For reactive power calculation, voltage and current waveforms are taken and power factor angle is computed. The losses are calculated from calculated power data and measured temperature and voltage across the passive elements in the circuit.

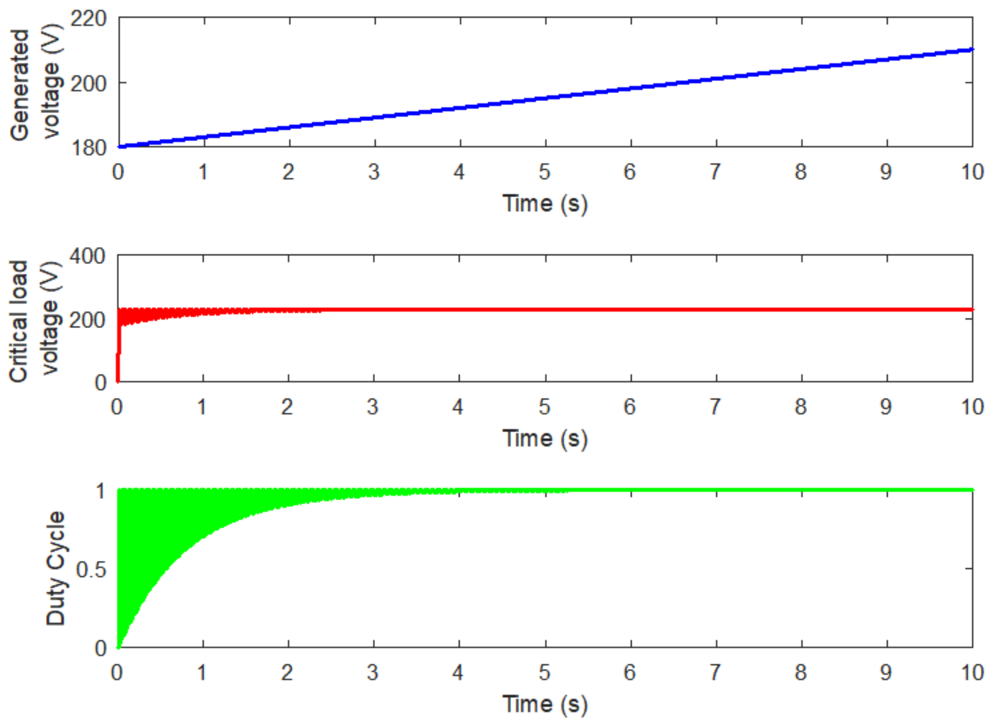

Fig. 9. Experimental generated voltage, critical load voltage and duty cycle waveforms.

The input power varies slightly due to input voltage fluctuations and load oscillations. The output power is smoother, indicating the ES is maintaining constant load power delivery. The difference between the two powers is due to losses and ES activity. It also indicates that the ES is buffering power fluctuations. The figure also shows the reactive power inserted or absorbed by the ES. The graph shows the adaptive nature of the ES in maintaining voltage stability under

Power System Technology
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varying loads and it is actively working for reactive power compensation, which supports voltage regulation. The composite losses are also shown. There is conversion loss and some additional system losses. The losses are minimal indicating the system is efficient. The losses are slightly higher during high reactive power swings, which is normal.

A performance comparison is drawn between the different types of controllers for ES control. These controllers are adopted for the proposed control from the researches [36]-[38]. The case study is shown below as Table-2.

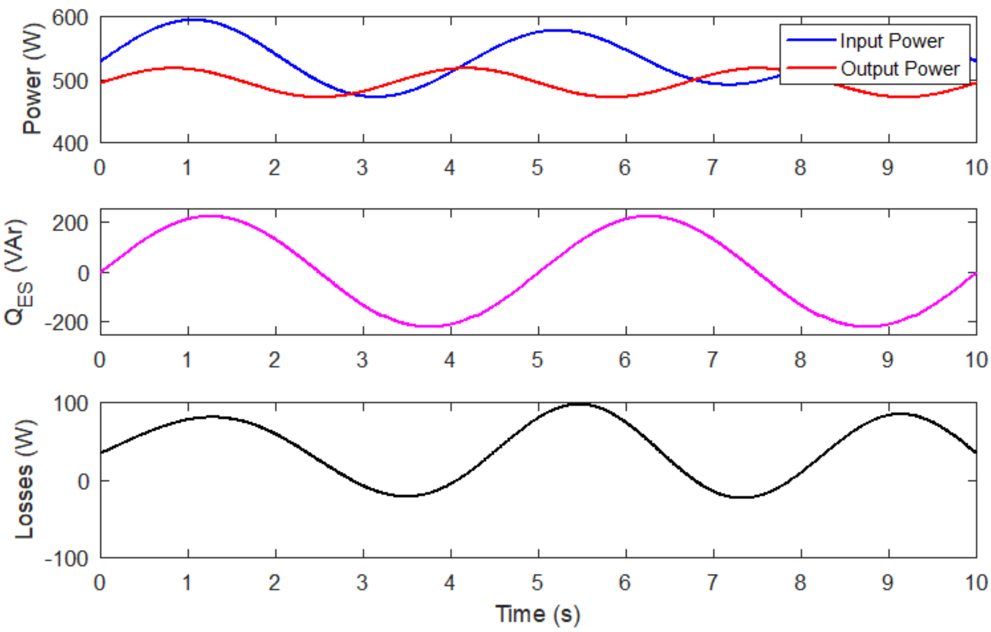

Fig. 10. Experimental wind speed profile, load power and critical load voltage waveforms.

Table 2. Case study related to different type of controllers for ES.

Controller type	Voltage regulation (±%)	THD (%)	Response time (ms)	Robustness to load and wind variations
PI [36]	7	6.5	140	Moderate
PR [37]	5	5.2	100	Good
Type-1 fuzzy [38]	3	4.1	80	Very good
Proposed control (IT2FLC+IoT)	2	3.4	70	Excellent

Compared to PI and PR controllers, the proposed IT2FLC maintained voltage within ±2% under most of load and wind speed conditions tested. The controller responded within 70ms and kept voltage THD under 3.5%, outclassing others in both transient and steady-state performance. The proposed control has better voltage regulation, lower THD of voltage and lower response time. Thus, the proposed control is robust concerning ES control for wind based

Power System Technology
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renewable systems. Also, to check the robustness of the IT2FLC, a comparative analysis is done involving the different fuzzy controllers with varying parameters set for control evaluation. The proposed system has Gaussian membership function shape with FOU width of 0.2-0.3 with sampling period of 5ms. The comparative analysis is shown in Table-3 below.

From the case study showing effect of control parameters on performance, it can be concluded that although the proposed system controller is more robust to uncertainty of load and speed variations. It is also stable with minimal voltage regulation and better voltage THD. Only the proposed controller parameter makes it a bit slower for real-time performance. However, with the sampling time of 5ms, the controller performance is good with real-time compatibility. Also, it is more suitable for real-time embedded simulation using ESP and MATLAB.

Table 3. Case study showing effect of control parameters on performance.

Parameter	Variation	Voltage regulation (±%)	THD (%)	Response time (ms)	Observation
Membership Function Shape	Triangular (Type-1 FLC)	6.2	7.8	95	Faster computation but less accurate under dynamic load
	Gaussian (Type-1 FLC)	5.3	6.4	92	Smoother control; better for noisy signals
	Gaussian (IT2FLC, FOU = 0.1)	3.1	4.7	78	Good balance of response and stability
	Gaussian (IT2FLC, FOU = 0.3)	2.6	3.6	82	More robust to uncertainty, most stable, but slightly slower

A case study is conducted to validate the adaptive tuning with the proposed controller. For the same, a comparative study is performed with proposed adaptive IoT-integrated IT2FLC and offline IT2FLC. For the proposed technique, FOU and rules can be updated according to the generation and load demand and thus provides better voltage regulation. Also, the proposed control has better THD and recovery time. The results are shown in Table 4.

Table 4. Comparative Case Study showing performance for Real-Time IoT vs Offline IT2FLC.

Mode	FOU update	Rule update	Voltage Regulation (%)	THD (%)	Recovery time (ms)
Offline IT2FLC	Static	Fixed	±4	4.5	110
IoT-Integrated IT2FLC (Proposed)	Real-time	Adaptive	±2	3.4	70

Table 5 shows the parameters for the proposed control which also validates its use in remote and grid isolated conditions as it is lightweight and easy to implement and use.

Power System Technology
ISSN:1000-3673
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Table 5. Parameters of the proposed control.

Parameters	Average value	Peak value	System impact
MQTT Latency (ms)	120	180	Minimal
Control Update Rate (Hz)	5	10	Stable
Bandwidth Usage (kbps)	22	35	Efficient

5. Conclusion

This paper presents an effective solution for voltage stabilization in grid-isolated wind systems using an IoT-enabled electric spring controlled by an interval type-2 fuzzy logic controller. The adaptive controller is suitable for controlling the ES maintaining stable voltage across a critical load. Intelligent control in combination with real-time data analytics ensures resilient and durable performance under changing wind and load conditions. The load voltage regulation is within +3% and THD is also quite low ensuring decent control. Simulation and experimental findings confirm the viability and dependability of the suggested system, therefore validating it for use in rural or remote areas relying on wind energy. The system although having numerous advantages is a bit sluggish due to real-time computation and modification of fuzzy rules but is accurate as shown from the results.

The future studies with the proposed control will include expanding the system with hybrid sources and its deployment in real-world microgrid scenarios. Similarly, blockchain will be used for better and secure IoT data handling.

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