OPTOELECTRONICS AND ADVANCED MATERIALS – RAPID COMMUNICATIONS Vol. 20, Iss. 3-4, March-April 2026, p. 169 - 178

AI controlled drivers for reducing energy consumption and lumen depreciation in LED lighting systems

M. S. KALYANA SUNDARAM[1], J. GNANAVADIVEL[2,*], K. S. KRISHNA VENI[2]
[1]Department of EEE, AAA College of Engineering and Technology, Tamil Nadu, India
[2]Department of EEE, Mepco Schenk Engineering College, Tamil Nadu, India

LED light performance is significantly affected by driver performance. This article investigates how different driver topologies and controllers affect the lumen depreciation and energy efficiency of LED lamps. Brightness control, power consumption and long-term dependability under various working situations are all taken into account for investigations. With the help of AI controlled drivers efficiency is optimized and the degradation rate of luminous is minimized. Both simulation and hardware results verify that the SCGANN governed Bridgeless Buck-Boost topology enhances efficiency considerably and increase LED light lifespan. Also, these investigations showcase the potential of AI driven driver which results in smart power management system for LED lighting systems.

(Received December 17, 2025; accepted April 8, 2026)

Keywords: LED driver topology, AI based control, Energy efficiency, Lumen depreciation, Bridgeless Buck-Boost converter

1. Introduction

Light emitting diode (LED) lighting is popular because of its long life, low power consumption. Also, it is eco-friendly. The type of driver used plays a major role in the performance of LED light because LED light performance can be improved by controlling the current flow and proper driver design. These improvements will lead to reduce energy loss and prevent thermal damage. Pulse width modulation based (PWM) dimming is another widely used method to regulate brightness, though its influence on power consumption and light degradation and these parameters can differ based on the driver configuration. As a result, many researchers have examined how various LED driver topologies affect the overall lifetime and efficiency of LED systems.

Buck and Boost converters are the most often used, of these because of their power handling efficiency and ease of control. According to published research, boost converters improve voltage control but impose additional strain on the LED components, whereas buck converters provide consistent output but lose efficiency at high dimming levels. The effectiveness of Bridge Buck-Boost (BBB) and Bridgeless Buck-Boost topologies (BLBB) in regulating voltage and current in LED lighting systems, capability of enhancing energy efficiency and dependability has also been thoroughly investigated [1–9].

Tran et al. offered more upgrades to Bridgeless Buck-Boost converters for LED lights with a focus on efficiency improvements, although it was still constrained by the absence of learning control techniques [10]. Gnanavadivel et al. presented high-performance LED driver solutions by implementing a single-phase positive output super-lift Luo converter with unity power factor and reduced input current harmonics [11] and FPGA-based three-level converter to enhance power quality, efficiency and controllability in high-power LED lighting applications [12]. When compared to conventional lighting, LED systems significantly lower energy usage and carbon emissions, according to environmental lifecycle evaluations; these benefits could be further enhanced with sophisticated control techniques [13]. Although energy efficiency has improved, till now most LED driver systems operate in open-loop condition. Even though regulations such as the EU Eco design Directive encourage sustainable and energy efficient designs, they didn’t force the industries to adopt advanced Artificial Intelligence (AI) based control strategies for dynamic lighting operation [14]. In smart building environments, networked lighting is vital to achieve energy efficient management. Bhatti et al. also showed that networked lighting can greatly lower energy consumption, but its dynamic capability remained limited due to the absence of AI enabled adaptability [15].

PWM and continuous current reduction (CCR) based dimming methods have led to a better color stability and improvement in overall LED light behavior. However, these methods rely on fixed steady-state inputs since they lack real-time feedback responsiveness [16], [17]. Kumar and Dwivedi stressed that effective driver design and suitable control approaches are necessary for improving LED energy efficiency, but their analysis did not incorporate intelligent or self-optimizing control strategies [18].

Thermal aging in LED lights is a serious issue because it affects both LED performance and long-term reliability. Wang et al. highlighted the importance of thermal aware modeling, they observed that these considerations are rarely integrated with advanced dimming methods or intelligent control systems [19]. In smart city applications, adaptive street lighting that uses ambient sensing has proven effective in raising energy efficiency [20]. The use of AI in lighting is expanding beyond conventional energy saving purposes. Yu et al. illustrated this concern by applying deep learning to control color temperature, which improved both visual comfort and system efficiency [21].

Despite serving as the foundation for communication in smart lighting systems, network protocols like Zigbee and Bluetooth Low Energy (BLE) do not provide adaptive or self-tuning control [22]. Novel research has investigated cutting-edge techniques including smart grid based integration and reinforcement learning to get over this restriction. Although Zhang et al. and Song & Li demonstrated the feasibility of these techniques, their application in LED specific applications is still in its early stages [23], [24]. There is little study on AI based adaptive dimming techniques, whereas conventional studies focus on static driver performance.

One major research gap is the lack of an effective, intelligent control system to dynamically regulate PWM dimming as a function of real-time LED light circumstances. Furthermore, previous studies have not thoroughly investigated how driver topologies affect the long-term deterioration of LED lights and energy efficiency under different dimming circumstances. These voids are filled in this work by comparing various driver topologies' performance. The article aims to optimize PWM dimming for improved LED light life and energy efficiency by utilizing AI driven control. The paper demonstrates how the Scaled Conjugate Artificial Neural Networks (SCGANN) controlled Bridgeless Buck-Boost architecture significantly lowers energy loss and increases brightness stability. This research supports the creation of LED driver systems that deliver better performance, reduced power usage and higher reliability in real-world conditions. To further enhance energy efficiency and limit luminous flux degradation, the present work introduces a system that employs bridgeless buck-boost converters controlled through SCGANN based approach.

2. Proposed system

The proposed system's work flow diagram is shown in Fig. 1. To maximize LED lamp performance, in the proposed system AI controller is used and it operate based on the voltage, current, light intensity and temperature parameters. The system architecture consists of a photodiode to monitor luminous LED light intensity and evaluate lumen deterioration rate over a period of operation. The current and voltage sensors are used to monitor supply stability and temperature sensor to monitor overheating of LED light. To effectively control LED light brightness, traditional and AI based controller analyzes sensor data and produces optimum pulse width modulation signals. The proposed system continuously gathers data on temperature swings, light intensity degradation, voltage fluctuations and current variations.

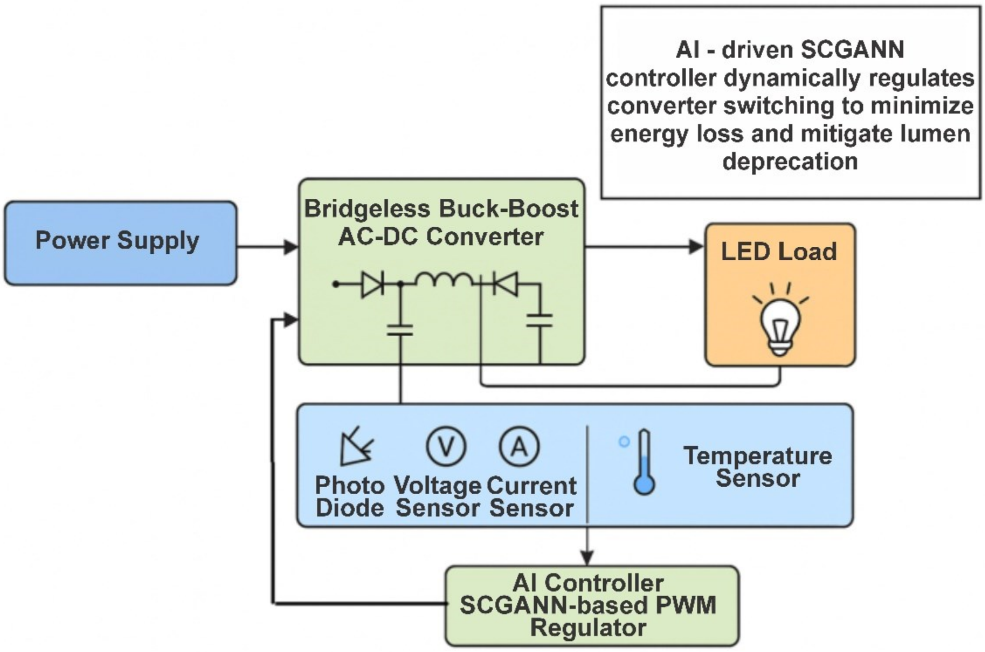
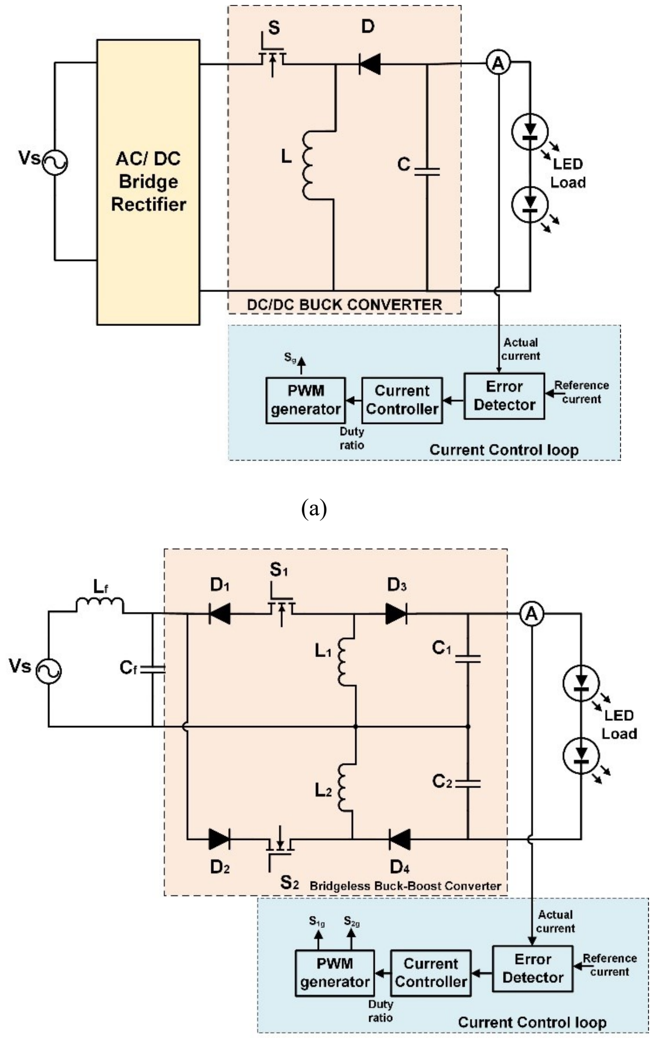


Fig. 1. Proposed system work flow diagram (colour online)

The controller receives this data, evaluates it and modifies PWM duty cycles if necessary. The maximum brightness is guaranteed without wasting power with the help of AI controlled PWM management. Additionally, this configuration helps LED lights to survive longer by lowering thermal stress and it adjusts effectively to changes in the environment and the aging process of LED lights. The main advantages of this are its boosting energy efficiency and it can be achieved by reducing power losses with smart control methods. LED lifespan also gets increased because of drop in lumen depreciation and adaptive performance is achieved through PWM approach.

A. AC – DC converter:

Topologies for LED lights that use AC-DC converters are available in bridge and bridgeless configurations. Four diodes are used in a typical bridge rectifier. By managing both half cycles, it converts AC input into DC. However, diode voltage decreases cause conduction losses. Following rectification, the DC is fed to a boost / buck / buck boost (BB) type converter for step up/down regulation. Good power conversion efficiency is achieved with this type of configuration. The main drawback is its losses due to diode switching and conduction. Whereas in bridgeless (BL) topology, the diode bridge rectifier is replaced by active switches which handle rectification and regulation of the AC input directly. Conduction losses drop because fewer semiconductor devices work at the same time. Efficiency improves due to the direct conversion that reduces power loss. Thermal management gets better since heat build-up stays lower than in traditional rectifiers. The BL topology ensures improved stability and efficiency under different AC mains conditions



(a)

(b)

Fig. 2. (a) BB Converter and (b) BLBB converter topology (colour online)

Fig. 2 showcase the bridge and bridgeless AC-DC converter topologies for Buck Boost configurations. The BB converter presented in Fig. 2(a) integrates the buck and the boost converter functions such that it can both increase and decrease the input voltage depending on the load demand. The circuit operates by charging energy in an inductor and discharging it to the load via switching with control. The primary limitation of the standard BB converter is that it reverses the output polarity. The bridgeless buck boost (BLBB) converter shown in Fig. 2(b). It merges buck and boost capabilities. At the same time, the absence of input bridge rectifier results in better efficiency, low thermal losses and wide operating ranges. This will be helpful in areas that are sensitive to energy, such as LED lighting.

B. Intelligent controller:

LED light driver performance can be improved by integrating intelligent control mechanism. To assess power supply stability, voltage and current sensors are used. Temperature sensor helps prevent overheating and a photodiode for measuring luminous intensity. The sensor inputs are processed by the controller and generate optimized PWM signals for regulating the brightness efficiently. The LED light lifespan is extended by the AI managed PWM regulation. It adapts to changes in the surroundings and the effects of LED aging. The traditional and AI converter investigated in this article and it is given below.

B.1. PI controller

The most widely used controller in industries are the PI controller. This controller is renowned for its ease of use and effectiveness in linear systems. The error between a setpoint and measurable process variables is continuously calculated. The current inaccuracy is addressed in the proportionate section. The integral term increases system stability by adding up previous errors to correct steady state offsets. Under stable conditions, PI controllers are simple to set up and adjust. However, they have trouble with nonlinear time-varying systems. LED lighting essentially fits into that group. Control is challenging because of degradation due to thermal drift and fluctuating loads. Furthermore, PI has poor real-time adaptability, lacks learning capacity and requires manual calibration.

B.2. Hysteresis controller

Hysteresis control is a nonlinear method and gives fast dynamic response. Hysteresis control works by maintaining the output variable current or voltage within a defined lower and upper threshold. When the output rises above the upper limit, the controller switches the power device OFF and turns it back ON once the value falls below the lower limit. This process enables accurate regulation without relying on complex mathematical modelling, keeping the output continuously oscillating within the set band. In LED light driver circuits, hysteresis current controller ensures a steady current through the LED lights, which directly affects both brightness and overall lifespan. The main drawback is its switching frequency, which varies depending on changes in supply or load conditions.

B.3. SCGANN controller

SCGANN uses the scaled conjugate gradient optimization method, a second-order algorithm that achieves a practical balance between fast learning and numerical stability. SCGANN offers improved convergence speed and better training efficiency compared to many conventional approaches. Also, this method allows the network to reach an optimal set of weights more effectively than traditional gradient-descent-based training techniques.The algorithmic flow chart of the SCGANN architecture is shown in Fig. 3. The SCGANN controller uses real-time data from sensors that measure temperature, voltage, current and luminous intensity to regulate LEDs. In order to adaptively modify the PWM duty cycle and achieve ideal brightness levels while minimizing power consumption and thermal stress, it computes this multi-dimensional input. Because of its high control output, intelligent learning capability and adaptability, SCGANN is a flexible solution. The block diagram of the SCGANN control based bridgeless converter is shown in Fig. 4. Compared to Fuzzy Logic Control (FLC), which relies on predefined rule sets and expert knowledge, the proposed SCGANN eliminates the need for manual rule design and can learn system behaviour directly from data, resulting in improved adaptability and precision. Also, when compared to conventional ANN variants trained using standard backpropagation, SCGANN utilizes the Scaled Conjugate Gradient optimization technique, which avoids iterative line search, provides better numerical stability and achieves faster convergence with improved generalization. As a result, SCGANN demonstrates superior performance in terms of energy efficiency, reduced lumen depreciation, faster dynamic response and robustness under varying operating conditions, thereby establishing its effectiveness over existing AI based control strategies.

The SCGANN model employed in this article is trained offline using a dataset generated from closed-loop simulations based on a PI-controlled system. To ensure real-time adaptability to LED aging and environmental variations, continuous feedback from sensors measuring voltage, current, temperature and luminance is utilized, enabling the controller to dynamically adjust PWM duty cycles within the trained operating range.

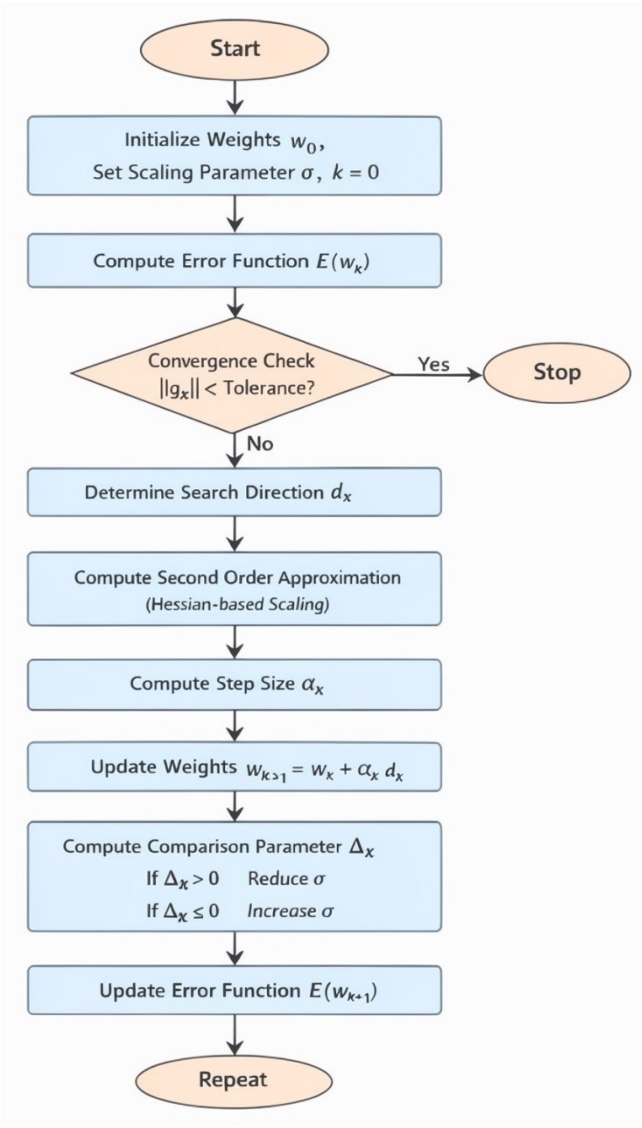


Fig. 3. SCGANN controller based Bridgeless Buck-Boost AC-DC converter (colour online)

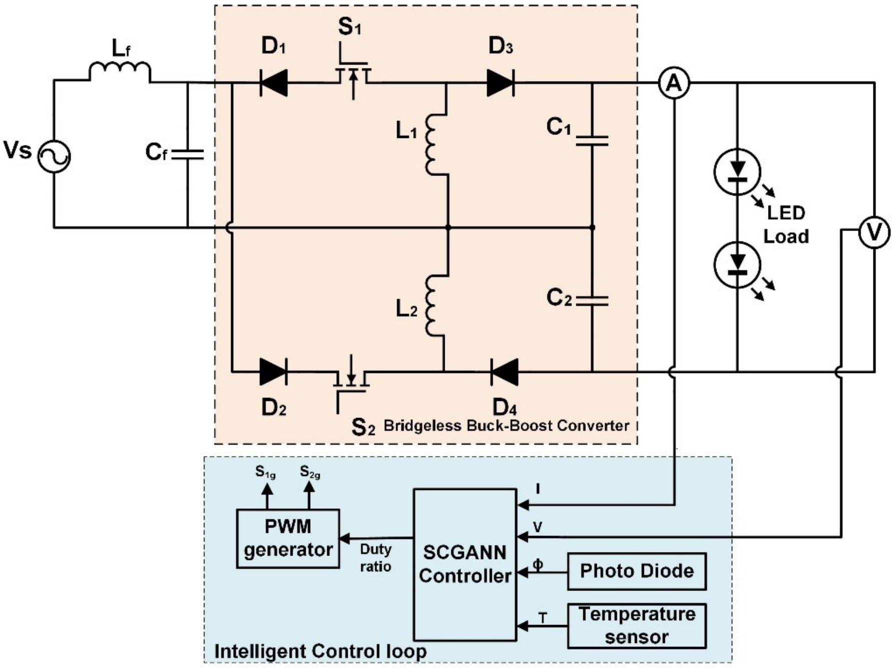


Fig. 4. SCGANN controller based Bridgeless Buck-Boost AC-DC converter (colour online)

The SCGANN approach differs from conventional ANN based controllers by utilizing the Scaled Conjugate Gradient optimization algorithm instead of standard backpropagation, thereby eliminating the need for manual learning rate tuning and ensuring faster convergence, improved numerical stability and better generalization performance. The system operates with a sampling time of 2 μs, ensuring accurate and responsive control. The SCGANN network is designed with a multi-layer architecture consisting of an input layer (error and change in error along with sensor parameters), one or two hidden layers with an optimized number of 30 neurons and an output layer that generates the control signal for PWM regulation. The training dataset consists of input-output pairs obtained under varying operating conditions, capturing nonlinear system behaviour. In this study, the dataset includes 8000 samples and the network is trained using the SCG algorithm with Mean Square Error (MSE) as the performance metric, achieving convergence at an MSE of 5.87 at the 88th epoch.

3. Results and discussion

The performance of various converter topologies was simulated by MATLAB/Simulink to ensure that they functioned optimally under set conditions. To test the regulation ability, supply voltage is varied from $90V_{rms}$ to $230V_{rms}$, with the output voltage kept constant at 60 V to supply a constant load of 120 W. All simulations were conducted using a switching frequency of 20 kHz and the same values are used in hardware implementation to enable proper comparison between different configuration, their values are $C_1 = C_2 = 4600$ μF and $L_1 = L_2 = 4.5$ mH.

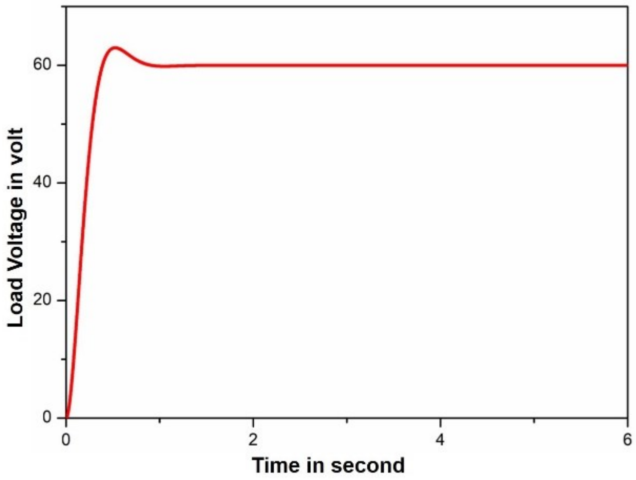
Table 1. Energy consumption comparison

Converter	**Input Voltage (V)**					
	90V	**120V**	**150V**	**180V**	**210V**	**230V**
BBB (Wh)	15.8	15.0	14.4	13.9	13.5	13.2
BLBB(Wh)	14.0	13.3	12.8	12.4	12.0	11.5
Energy Savings (%)	11.39	11.33	11.11	10.79	11.11	12.88

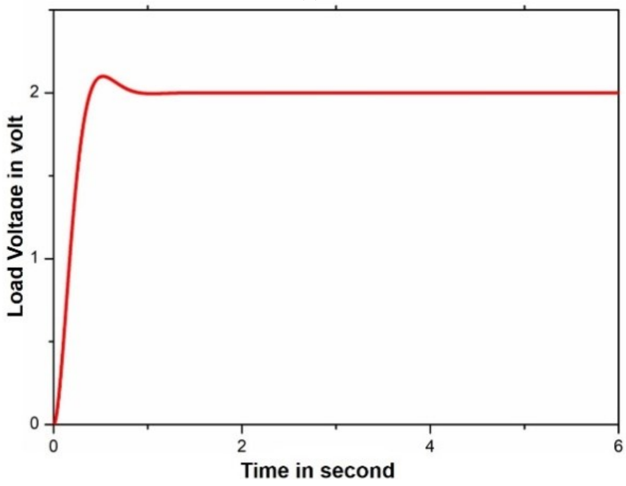
The simulation was conducted for open loop configuration and energy saving value calculated is tabulated in Table 1. Equation (1) is used for calculating energy saving and it represents the relationship between input power and LED output luminance.

$$\text{Energy Savings (\%)} = \frac{(\text{BBB Energy} - \text{BLBB Energy})}{\text{BBB Energy}} \times 100\% \quad (1)$$

Table 1 indicates that, in terms of energy efficiency, the BLBB Converter performs better than the bridge design at all voltage levels. Due to a significant decrease in conduction losses brought about by the bridgeless topology, the greatest energy savings of 12.88% is achieved at 230V. The BLBB converter shows high efficiency for LED driver applications because it typically reduces energy consumption by 11% to 13%. The BBB and BLBB converters performance with various controllers under rated working circumstances is shown in Figs. 5 and 6, Figs. 7 and 8 shows the transient response of the BBB and BLBB converter respectively.

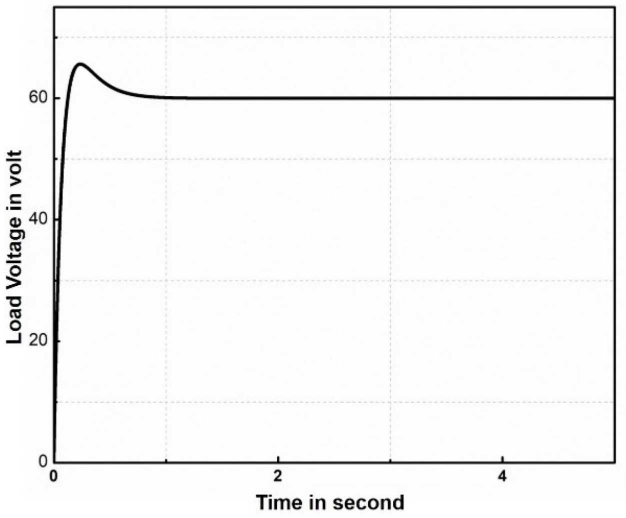


(a)

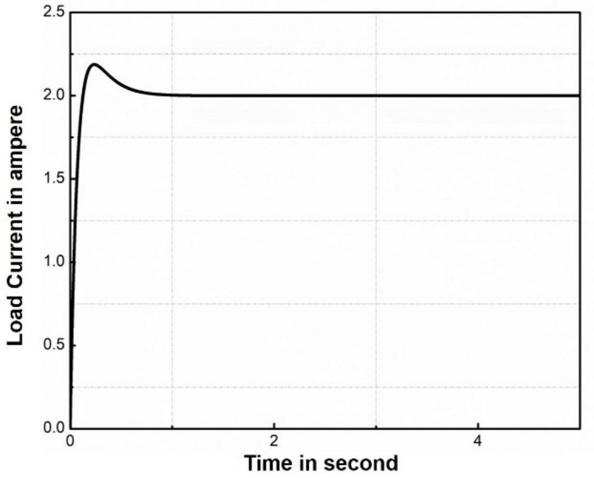


(b)

Fig. 5. Simulation results of BBB converter under rated operating conditions a) load voltage b) load current waveform



(a)



(b)

Fig. 6. Simulation results of BBLB converter a) load voltage b) load current waveform under rated operating conditions

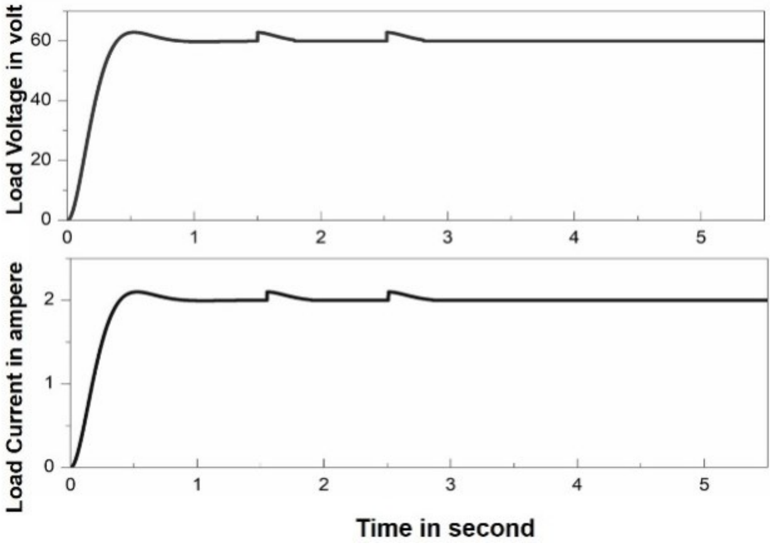


Fig. 7. Transient response of BBB converter for sudden change in a) input voltage b) load current

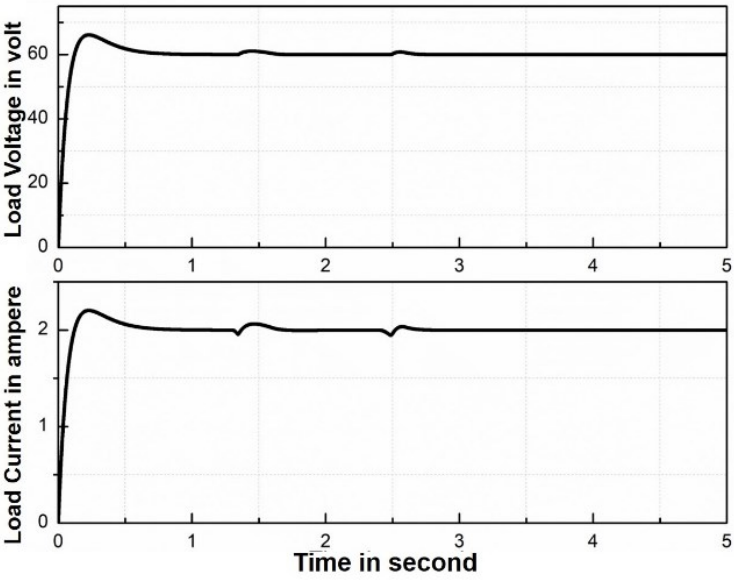


Fig. 8. Transient response of BLBB converter for sudden change in a) input voltage b) load current

Table 2. Observation of various converter parameters during simulation

Topology with Controller	**V_s(V)**	**R_L(Ω)**	**P_s (W)**	**V_L (V)**	**I_L (A)**	**P_o (W)**	**PF**	**η (%)**	**THD (%)**	**I_p(A)**	**t_r (s)**	**O_{shoot}(%)**	**t_s (s)**
BBB - PI	90	30	161.5	60	2	120	0.8	74.3	2.36	2.74	0.017	37.23	0.03
	180	30	159.43	60	2	120	0.8	75.27	2.23	2.79	0.0205	39.31	0.038
	270	30	156.1	60	2	120	0.77	76.88	2.27	2.65	0.0145	32.43	0.032
	220	30	151.47	60	2	120	0.81	79.22	1.76	2.42	0.0215	21.22	0.039
	220	40	117.88	60	1.5	90	0.73	76.35	1.91	1.99	0.0195	32.42	0.037
	220	60	79.69	60	1	60	0.73	75.29	2.11	1.31	0.0205	30.63	0.038
BBB -Hysteresis	90	30	157.85	60	2	120	0.83	76.02	2.32	2.33	0.0265	16.32	0.044
	180	30	156.06	60	2	120	0.83	76.89	2.07	2.3	0.0265	14.8	0.044
	270	30	149.36	60	2	120	0.82	80.34	2.11	2.27	0.0395	13.42	0.057
	220	30	149.08	60	2	120	0.82	80.49	1.72	2.21	0.0375	10.51	0.055
	220	40	113.31	60	1.5	90	0.75	79.43	1.83	1.64	0.0375	9.46	0.055
	220	60	76.68	60	1	60	0.71	78.24	2.14	1.12	0.0295	11.81	0.047
BBB -SCGANN	90	30	150.03	60	2	120	**0.9**	79.98	**2.13**	2.14	0.005	6.94	0.006
	180	30	147.61	60	2	120	**0.91**	81.3	**1.67**	2.14	0.005	6.82	0.006
	270	30	145.52	60	2	120	**0.91**	82.46	**1.64**	2.12	0.005	6	0.006
	220	30	143.63	60	2	120	**0.91**	83.55	**1.62**	2.1	0.005	4.98	0.006
	220	40	109.69	60	1.5	90	**0.91**	82.05	**1.76**	1.56	0.005	3.74	0.006
	220	60	75.26	60	1	60	**0.9**	79.73	**2.29**	1.05	0.005	5.39	0.006
BLBB - PI	90	30	142.52	60	2	120	0.877	84.2	1.88	2.65	0.015	32.32	0.043
	180	30	140.68	60	2	120	0.876	85.3	1.78	2.68	0.018	34.12	0.046
	270	30	137.74	60	2	120	0.85	87.12	1.81	2.56	0.012	28.15	0.04
	220	30	133.66	60	2	120	0.89	89.78	1.4	2.37	0.019	18.42	0.047
	220	40	104.02	60	1.5	90	0.8	86.52	1.52	1.92	0.017	28.14	0.045
	220	60	70.32	60	1	60	0.8	85.32	1.68	1.27	0.018	26.59	0.046
BLBB - Hysteresis	90	30	139.29	60	2	120	0.916	86.15	1.85	2.28	0.024	14.17	0.054
	180	30	137.71	60	2	120	0.913	87.14	1.65	2.26	0.024	12.85	0.054
	270	30	131.8	60	2	120	0.9	91.05	1.68	2.23	0.037	11.65	0.067
	220	30	131.55	60	2	120	0.9	91.22	1.37	2.18	0.035	9.12	0.065
	220	40	99.99	60	1.5	90	0.82	90.01	1.46	1.62	0.035	8.21	0.065
	220	60	67.67	60	1	60	0.78	88.67	1.71	1.1	0.027	10.25	0.057
BLBB - SCGANN	90	30	132.39	60	2	120	**0.992**	90.64	**1.7**	2.12	0.005	6.02	0.006
	180	30	130.25	60	2	120	**0.997**	92.13	**1.33**	2.12	0.005	5.92	0.006
	270	30	128.41	60	2	120	**0.998**	93.45	**1.31**	2.1	0.005	5.21	0.006
	220	30	126.74	60	2	120	**0.998**	94.68	**1.29**	2.09	0.005	4.32	0.006
	220	40	96.8	60	1.5	90	**0.995**	92.98	**1.4**	1.55	0.005	3.25	0.006
	220	60	66.41	60	1	60	**0.99**	90.35	**1.83**	1.05	0.005	4.68	0.006

By performing simulation, the performance of several LED driver topologies was examined. Table 2 shows the three control techniques that were used to test all topologies. The parameters observed for validating the proposed system performance are input power (P_s), load current (I_L), load voltage (V_L), output power (P_o), efficiency (ɳ), setting time (t_s), rise time(t_r), Overshoot (O_{shoot}) and peak current (I_p). The results show that in every evaluated case, the SCGANN controller performed better than the PI and Hysteresis controllers. Among all tested conditions, the SCGANN based system showed the lowest input power consumption, resulting in noticeably higher efficiency. The SCGANN based BLBB converter achieves an efficiency of 94.68% at a 220 V supply voltage (V_s) and 30 Ω load resistor (R_L) which is 15.46% higher than BBB converter using PI control. SCGANN also achieved an almost unity power factor of 0.99 and maintained the lowest Total Harmonic Distortion, ranging from 1.29% to 1.7%. Further, SCGANN based BLBB converter limits the peak current below 2.14 A, which leads to lower thermal stress and enhanced the overall reliability of the circuit. SCGANN showcased constant performance during change in supply voltage between 90V to 270V, which signifies its tolerance to variations. The same performance was observed in different load resistances (30Ω, 40Ω and 60Ω) as well, where it continuously provided rated output power and high efficiency. On the whole, the combination of BLBB topology with SCGANN control proved to be the best configuration, showcasing better efficiency, improved power quality and better dynamic behaviour. These features make it a most appropriate solution for contemporary LED lighting systems for improved energy savings and long lifespan. The real-time hardware of the AC-DC converter circuit used to power a 60V, 120W LED bulb is depicted in Fig. 9. The system makes use of an8-bit controller PIC18F45J10 with firmware supplied using PIC kit and developed using the MPLAB IDE. For accurate real-time current feedback, a WCS2705 Hall effect sensor for current measurement is incorporated. A voltage sensor (ZMPT101B) is used to measure voltage, a LM35 temperature sensor to measure temperature changes surrounding the LED panel and 15 photodiodes (BPW34) evenly distributed on the LED lights surface to measure brightness deterioration and lighting conditions.

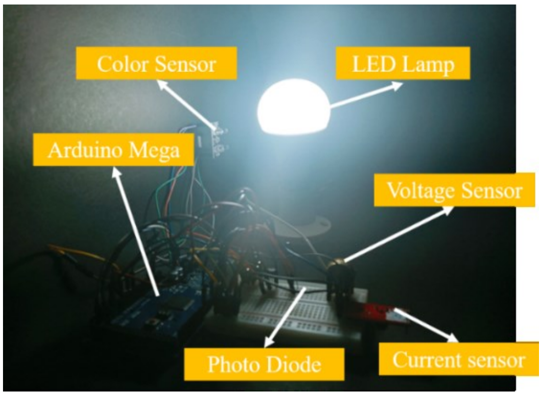


Fig. 9. Hardware implementation of the BLBB converter controlled by SCGANN (colour online)

Table 3. Observation of various converter parameters during hardware implementation

Topology with Controller	V_s (V)	R_L (Ω)	P_s (W)	V_L (V)	I_L (A)	P_o (W)	PF	ɳ (%)	THD (%)
BBB - PI	90	163.65	60	2	120	90	0.8	73.33	2.32
	180	159.8	60	2	120	180	0.75	75.09	2.22
	270	153.9	60	2	120	270	0.74	77.97	2.33
	220	153.47	60	2	120	220	0.8	78.19	1.65
	220	120.27	60	1.5	90	220	0.72	74.83	2.03
	220	78.94	60	1	60	220	0.73	76.01	2.49
BBB - Hysteresis	90	159.59	60	2	120	90	0.84	75.19	2.27
	180	157.87	60	2	120	180	0.82	76.01	2.03
	270	148.87	60	2	120	270	0.81	80.61	2.02
	220	147.66	60	2	120	220	0.82	81.27	1.73
	220	112.06	60	1.5	90	220	0.76	80.32	1.84
	220	77.18	60	1	60	220	0.71	77.74	2.44
BBB - SCGANN	90	148.43	60	2	120	90	**0.91**	80.85	**2.02**
	180	148.39	60	2	120	180	**0.91**	80.87	**1.68**
	270	144.86	60	2	120	270	**0.91**	82.84	**1.62**
	220	142.83	60	2	120	220	**0.91**	84.01	**1.62**
	220	109.54	60	1.5	90	220	**0.91**	82.16	**1.74**
	220	75.35	60	1	60	220	**0.9**	79.63	**2.34**
BLBB - PI	90	144.4	60	2	120	90	0.88	83.1	1.85
	180	141.01	60	2	120	180	0.82	85.1	1.77
	270	135.81	60	2	120	270	0.814	88.36	1.86
	220	135.42	60	2	120	220	0.877	88.61	1.32
	220	106.13	60	1.5	90	220	0.7888	84.8	1.62
	220	69.65	60	1	60	220	0.8	86.14	1.99
BLBB - Hysteresis	90	140.83	60	2	120	90	0.926	85.21	1.81
	180	139.31	60	2	120	180	0.9	86.14	1.62
	270	131.36	60	2	120	270	0.889	91.35	1.61
	220	130.29	60	2	120	220	0.899	92.1	1.38
	220	98.88	60	1.5	90	220	0.8325	91.02	1.47
	220	68.1	60	1	60	220	0.78	88.1	1.95
BLBB - SCGANN	90	130.98	60	2	120	90	**0.999**	91.62	**1.61**
	180	130.93	60	2	120	180	**0.998**	91.65	**1.34**
	270	127.82	60	2	120	270	**0.998**	93.88	**1.29**
	220	126.04	60	2	120	220	**0.996**	95.21	**1.29**
	220	96.66	60	1.5	90	220	**0.995**	93.11	**1.39**
	220	66.49	60	1	60	220	**0.991**	90.24	**1.87**

The microcontroller can effectively monitor the LED light operating state and make the required system modifications to improve performance and longevity. From Table 3, it is evident that the SCGANN controller outperformed the PI and hysteresis controllers. For the BBB topology, SCGANN recorded higher efficiency up to 84.01% and lower THD down to 1.62% than PI and Hysteresis, which reported relatively lower efficiencies in the range of 73 to 78% and high THD values. Using SCGANN, the BLBB topology demonstrated noticeably greater performance benefits. SCGANN based drivers achieved efficiency above 95% with THD as low as 1.29% and near-unity power factor. However, despite having a lower PF and a larger THD, BLBB's PI and Hysteresis controllers had an average efficiency of 83%–88%. With improved output power delivery of quality and energy efficiency, SCGANN showed exceptional performance even in the face of fluctuating load resistance. These results suggest that SCGANN controlled drivers offer sophisticated LED lightning systems, highly effective and power-quality improving alternative. Equation (2) is used to determine lumen depreciation (LD), which represents how light output decreases over time.

$$\mathrm{LD}(\%) = \frac{\text{Initial luminous flux} - \text{Luminous flux at time t}}{\text{Initial luminous flux (lumens)}} \times 100 \quad (2)$$

where the initial luminous flux (in lumens) is the light output at the beginning of operation and the luminous flux at time t (in lumens) is the measured output after a certain operating duration. This metric indicates the aging effect of the LED, where a higher LD (%) signifies greater degradation in brightness over time.

The efficacy measures how efficiently electrical power is converted into visible light and it is computed using equation (3).

$$\text{Efficacy (lumen/W)} = \frac{\text{Luminous Flux}}{\text{Input Power}} \quad (3)$$

where luminous flux is measured in lumens (lm) and input power in watts (W). A higher efficacy value indicates better energy efficiency, meaning the LED produces more light output per unit of electrical power consumed.

The voltage ripple is the peak-to-peak variation in the output voltage of a driver and it is computed using equation (4).

$$\text{Ripple voltage } (V_{rpp}) = V_{mx} - V_{mn} \quad (4)$$

where V_{mx} and V_{mn} are the maximum and minimum output voltages, respectively.

In order to assess the BBB and BLBB SCGANN converters' long-term ability to maintain luminous flux, a comparison of lumen depreciation over 4320 hours was conducted and the results are showcased in Table 4. The BBB and BLBB converters performance was observed at regular time intervals, where the initial Luminous Flux (LF) of the LED used is 5345. After 4320 hours, the BLBB converter controlled by SCGANN showed lumen degradation (LD) of only 4.9%, while the SCGANN based BBB converter exhibited a 6.9% reduction. These observations clearly state that the BLBB based SCGANN configuration maintains light output more effectively and performs better in long-term operation, making it a suitable choice for applications where low lumen loss and extended reliability are essential.

Table 4. Lumen depreciation rate comparison

Time (Hours)	SCGANN based BBB Configuration		SCGANN based BLBB Configuration	
	LF (Lumen)	LD (%)	LF (Lumen)	LD (%)
0	5345	0	5345	0
720	5297	0.90	5321	0.45
1440	5240	1.96	5302	0.80
2160	5124	4.13	5231	2.13
2880	5068	5.18	5289	1.05
3600	5000	6.45	5102	4.55
4320	4976	6.90	5084	4.88

Table 5. Experimental observations of various configurations after specified operating period

Topology with Controller	Rise in temperature of LED panel (°C)	Ripple Voltage (V_{pp})	LD specified working period (%)
BB with PI	27	2.4	18.2
BB with Hysteresis	24	1.87	12.31
BB with SCGANN	20	0.7	6.9
BBLB with PI	19	1.5	10.9
BBLB with Hysteresis	17	1.12	8.41
BBLB with SCGANN	**11**	**0.005**	**4.88**

Table 5 shows the comparison of various LED driver configurations that were operated continuously and assessed after 4320 hours. Key parameters such as temperature rise, output voltage ripple and lumen depreciation were used to evaluate its performance. The results highlight the reliability of each setup during prolonged operation. Among all configurations, the PI controller-based BBB shows the most significant reduction in light output, with a lumen depreciation of 18.2%. The BBB with Hysteresis controller performed better, reducing lumen degradation to 12.31% and increasing efficacy to 92 lm/W with a reduced heat rise (24 °C) and ripple of 1.87 Vpp. The BBB with SCGANN setup showed improved performance. The advantage of AI based control was demonstrated by the configuration's low lumen depreciation, better efficacy and decreased ripple. Performance was further improved by switching to BLBB architecture. The BLBB with SCGANN combination demonstrated the best performance across all metrics. Table 6 shows the overall comparative performance of various driver topologies and control strategies for LED systems. It is observed that in every parameter, the recommended setup performs better than the alternative option. With improved power regulation and optical stability, it offers maximum energy savings of 21.8%, lumen depreciation reduction of 12.5% and ripple reduction of 70.8%. The efficiency of the SCGANN regulated BLBB converter is also supported by the increase in efficacy. BBB and Hysteresis arrangements provide slight gains over conventional BB with PI and BBB with Hysteresis configurations.

Table 6. Overall comparison of proposed topology

Parameters	**Energy Savings (%)**	**Lumen Depreciation Reduction (%)**	**Ripple Reduction (%)**	**Efficacy Gain (lm/W)**
BB with PI	5.1	2.7	16.6	+3.1
BB with Hysteresis	8.6	4.3	32.6	+5.2
BB with SCGANN	10.2	5.7	45.8	+7.8
BBLB with PI	12.9	7.3	37.5	+12
BBLB with Hysteresis	14.2	9.6	42.3	+18
BBLB with SCGANN	21.8	12.5	70.8	+25

4. Conclusion

This article analyzes the various LED light driver topologies combined with different control algorithms, with a focus on energy efficiency and long-term light output stability. The findings confirm that AI driven control strategies can significantly reduce both energy usage and illumination degradation in LED lighting systems. Under all input voltage and load conditions, the BLBB design consistently outperformed the conventional BBB converter. When integrated with SCGANN control, the BLBB setup achieved a peak efficiency of 95.21% at a 220 V supply while drawing less input power, highlighting better thermal behaviour and reduced power consumption. SCGANN continually outperformed traditional PI and hysteresis controllers, delivering the highest efficiency of 95.21%, THD of 1.29% and nearly unity power factor of approximately unity which indicates excellent power quality and minimal losses. Moreover, implementing intelligent SCGANN control with the BLBB topology was found to extend LED light lifespan by supporting more stable and thermally efficient operation. In future work, the proposed system can be extended by integrating IoT-based monitoring and control for remote operation and smart lighting applications. Additionally, incorporating adaptive or online learning algorithms can further enhance real-time responsiveness to LED aging and environmental variations. The integration of edge computing and smart grid compatibility can also improve scalability and energy management in large-scale lighting systems.

References

[1] M. Esteki, S. A. Khajehoddin, A. Safaee, Y. Li, IEEE Access **11**, 38324 (2023).
[2] O. Akalp, H. Ozbay, S. B. Efe, Light & Engineering **29**(2), 96 (2021).
[3] J. Hegedüs, G. Hantos, A. Poppe, Microelectronics Reliability **79**, 448 (2017).
[4] M. Sikora, K. Różycka, D. Borecki, Scientific Reports **13**(1), 1 (2023).
[5]M. S. K. Sundaram, J. Gnanavadivel, K. S. K. Veni, Optoelectron. Adv. Mat. **19**(3-4), 179 (2025).
[6] F. Abbasinejad, S. P. Corgnati, S. Sahab, Energy and Buildings **297**, 113432 (2024).
[7] T. Chew, A. S. M. Supangat, M. S. M. Aras, Energy and Buildings **133**, 752 (2016).
[8] M. P. Royer, Leukos **10**(2), 69 (2014).
[9] O. F. Farsakoglu, H. Y. Hasirci, J. Optoelectron. Adv. M. **17**(5-6), 816 (2015).
[10] T. T. Tran, A. M. Rahmani, J. W. Park, IEEE Transactions on Power Electronics **35**(7), 7231 (2020).
[11] J. Gnanavadivel, N. Senthil Kumar, C. N. Naga Priya, S. T. J. Christa, K. S. K. Veni, J. Optoelectron. Adv. M. **18**(11-12), 1007 (2016).
[12] J. Gnanavadivel, N. Senthil Kumar, P. Yogalakshmi, J. Optoelectron. Adv. M. **18**(5-6), 459 (2016).
[13] M. Hossain, R. Saidur, M. Mekhilef, Renewable and Sustainable Energy Reviews **52**, 1075 (2015).
[14] European Commission, EU Ecodesign Directive, (2019).
[15] S. S. Bhatti, S. H. Zahir, T. A. Khan, Sustainable Cities and Society **38**, 341 (2018).
[16] X. Li, J. Lu, K. Wang, IEEE Transactions on Industrial Electronics **68**(6), 5032 (2021).
[17] Y. Sun, D. Chen, L. Zhang, IEEE Access **10**, 45490 (2022).
[18] R. Kumar, G. Dwivedi, Energy Reports **6**, 708 (2020).
[19] J. Wang, Y. Liu, Z. Wu, Applied Energy **261**, 114426 (2020).
[20] K. Pandharipande, D. Caicedo, IEEE Sensors Journal **11**(9), 1909 (2011).
[21] Y. Yu, Y. He, X. Zhang, Opt. Express **31**(5), 6012 (2023).
[22] F. Jiang, R. Li, X. Tan, Sensors **21**(6), 2027 (2021).
[23] Y. Zhang, L. Chen, M. Zhou, IEEE Transactions on Smart Grid **11**(3), 2020 (2020).
[24] J. Song, X. Li, IEEE Transactions on Industrial Informatics **18**(2), 1395 (2022).

---

[*] Corresponding author: gvadivel@mepcoeng.ac.in