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Design and Implementation of Deep Learning-Driven Sensorless Controller for DC LED Street Lights

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Research Article

Keywords: DC-DC converter, Boost LED driver, Street light, Deep-Learning, Sensorless control

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Design and Implementation of Deep Learning-Driven Sensorless Controller for DC LED Street Lights

Krishna Perumallapalli[1], Devendra Potnuru[2]

Abstract

The adoption of energy-efficient and intelligent control systems is critical for modern LED-based street lighting solutions. Traditional control methods, while effective, often struggle to adapt to non-linearities and dynamic changes in system parameters. This paper presents the design and implementation of a novel sensorless controller for boost converter driven DC LED Street lights, leveraging deep learning to achieve accurate and robust voltage regulation without a physical voltage sensor. A Deep Neural Network (DNN) is trained to estimate the output voltage of the system using measurable parameters such as input voltage, load current, and duty cycle. This estimated voltage is then utilized in a control loop to maintain stable operation under varying load and environmental conditions. The DNN model is trained on simulated and experimental data representing a wide range of operating conditions, including load variations. The controller is implemented on DSP controller platform and validated on a laboratory prototype of 500W DC boost converter-based LED driver. Performance evaluation is demonstrated using simulation and experimental results. This work provides a scalable and cost-effective solution for modern street lighting systems, paving the way for smarter and more sustainable urban lighting infrastructure.

Keywords DC-DC converter · Boost LED driver ·Street light. Deep-Learning. Sensorless control

1 Introduction

The LED (Light Emitting Diode) street lighting has emerged as a superior alternative to conventional lighting systems, such as high-pressure sodium (HPS), metal halide, and fluorescent lights, due to its numerous advantages in energy efficiency, environmental sustainability, cost savings, and performance. LED driver circuits are critical components in LED-based systems as they regulate the power supplied to LEDs to ensure optimal performance and longevity. The types of LED driver circuits can be broadly classified based on the input power source, output control, and topology. They are classified as AC input driver and DC input driver based on the type of the input supply.

Traditionally, there are two primary methods to power high-brightness LED strings using an AC power supply: (a) employing a linear regulator with relatively low efficiency, or (b) utilizing a more complex yet highly efficient switching regulator, also referred to as a switch-mode power converter or switch-mode power supply (SMPS) (Chou, 2023, Zhou et al., 2008 and Wu et al., 2011) as depicted in Fig. 1. While the linear regulator approach offers the benefit of lower cost, it comes with two major drawbacks. First, its efficiency is generally low, and second, the efficiency of a linear driver is influenced by the number of LED segments. Typically, having more LED segments results in improved efficiency (Esteki et al., 2023. C. H. Wu & Chen, 2009, Gacio et al., 2015, Abdelmessih et al., 2022 Kim et al., 2014 and Dasohari et al., 2024), However, the AC drivers involve the conversion of AC-DC, Power Factor Correction (PFC) equipment and switching mode power converter (SMPC) in addition to the control equipment (Dasohari et al., 2024). On the other hand, LED street lighting systems with DC drivers have gained popularity due to their compatibility with renewable energy sources, high efficiency, and ability to provide stable operation under variable load conditions. Unlike AC-driven systems, DC drivers eliminate the need for AC-DC conversion, reducing energy losses and simplifying the circuit design as shown in Fig.2. The most common circuit configurations are buck, boost and buck-boost converters (Liu et al., 2018, Li, 2015, Hsieh & Chen, 2009; Seo et al., 2015).

Further, the control approaches for this driver circuits are basically constant current drivers,

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constant voltage driver and hybrid driver which combine features of both constant current and constant voltage drivers(Qiao et al., 2021). Nevertheless, these control schemes for DC-DC converter-based driver, such as proportional-integral-derivative (PID) or proportional-integral controllers and model predictive control (MPC), have been widely used due to their simplicity and effectiveness (Pallapati & Chinthamalla, 2023) and(Shagerdmootaab & Moallem, 2016). However, these conventional approaches often face challenges in dealing with the inherent non-linearities and dynamic changes present in practical power conversion systems. Moreover, designing robust controllers to handle the aforementioned challenges depends on voltage or current sensor data. The failure of these sensors will create big problem to the overall

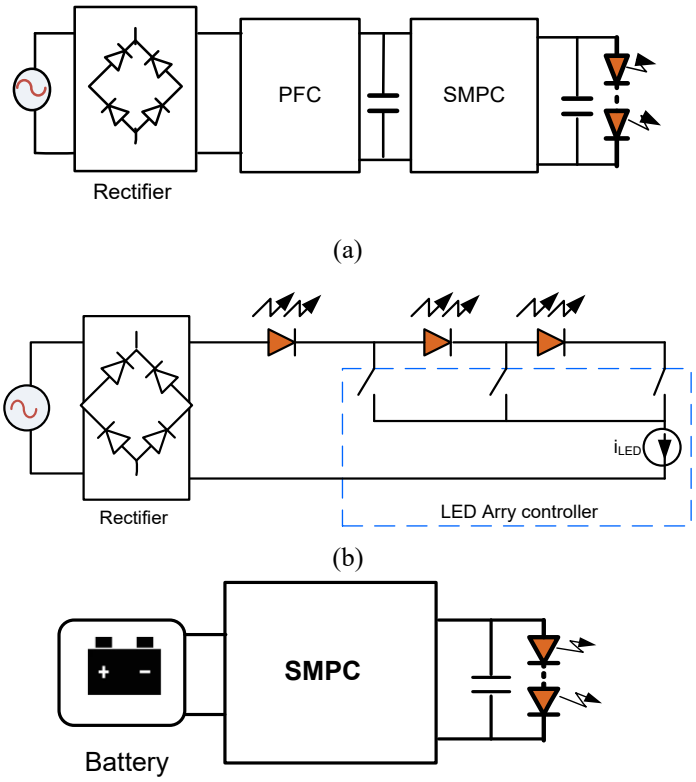


Fig.1 Block diagram (a) Typical AC LED driver configuration (b) Linear Driver (c) DC LED Driver

system. Hence, sensorless control, coupled with modern computation methods like deep learning, is emerging as a promising alternative. In recent years; advancements in artificial intelligence and machine learning have opened new avenues for control system design. Deep neural networks (DNNs), in particular, have shown remarkable success in various complex and non-linear control tasks, ability to learn and generalize from large datasets. By leveraging the power of DNNs, it is possible to develop sophisticated control strategies that can dynamically adapt to changing system parameters and non-linear behaviours more effectively than traditional methods. There are many electrical engineering applications in the existing literature using deep learning (Mustafa et al., 2024),.(Fetanat et al., 2021) (Attestog et al., 2023; MacHina et al., 2023; Wilamowski & Yu, 2010)The increasing demand for efficient and reliable power conversion systems has driven significant advancements in the design and control of LED drivers.

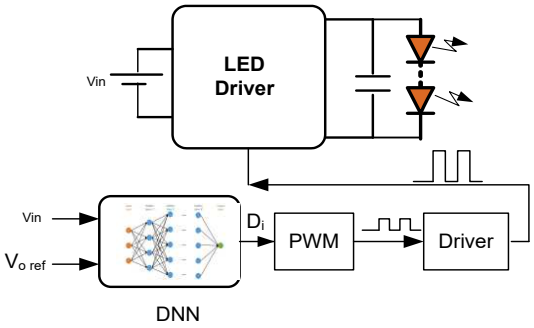


Fig. 2 Deep Neural Network Implementation block diagram for DC-DC converter

In this paper, deep learning technique integration into the control design of DC-DC Boot converter-based LED driver for street light application. The following are the contributions of this paper.

- Deep Learning based controller is designed for LED driver for Street Light application.
- It is sensorless voltage control approach and hence voltage sensing is not required.
- The LED driver gives constant output voltage across the load irrespective sudden variations in load
- Reduced device count and control complexity

2 Methodology for implementation of deep learning

(a). DNN controller for LED driver:

The DNN controller is implemented to boost converter-based DC driver for LED Street light. The schematic diagram of implementation is shown in Fig.2. It involves one DNN with input data of dc input and reference output voltage. The trained deep neural network will generate the magnitude of duty ratio (i.e. control variable) which in turn used to generate the PWM signals. Later, gate driver is used control the power semiconductor switches of the boost converter.

(b). Data set preparation, Training and Testing of DNN

Data sets are commonly built using historical information, but this method has a notable drawback: it frequently overlooks potential anomalies that could occur within the system. To improve the resilience of controller design, it is crucial for data sets to encompass all potential values and uncertainties that may arise during system operation [22]. In this approach, data sets are created by simulating the LED driver within the MATLAB environment. Although this process can be computationally demanding, it ensures the inclusion of all possible data with abnormalities.

Choosing appropriate hyper such as activation function, number of epochs, weight update strategy, and network architecture, play a significant role in determining the model's performance. The activation function, specifically, introduces non-linearity into the training process, allowing the model to manage non-linear systems efficiently. Among the commonly used activation functions, sigmoid, tanh, and ReLU are the most fundamental and widely adopted.

The weight update mechanism plays a critical role in reducing error and improving the training effectiveness. After feeding all the training data set into the network, the predicted value is compared with the actual value to calculate the corresponding error. This error is then further reduced by adjusting the weights across the network's layers. Optimizers serve as tools for updating weights, in the present work, the Levenberg-Marquardt training algorithm is used for training neural networks. This method is embedded with advantages of both gradient descent and Gauss-Newton resulting it highly efficient for problems involving least-squares errors. This algorithm is particularly well-suited small network and medium size networks and provides faster convergence compared to standard backpropagation. It adjusts the weight updates dynamically by balancing between gradient descent (for larger error regions) and Gauss-Newton approximation (for fine-tuning near the solution), ensuring robust and accurate model training. The Levenberg-Marquardt (LM) training algorithm is an optimization technique used for minimizing the sum of squared errors in non-linear functions, particularly for neural network training.

Table. 1 Deep Learning Model parameters

S. No.	**Parameter**	**Description & Value**
1	Training Algorithm	Levenberg-Marquardt
2	Predictor's size: input	[2 x 100000 double]
3	Responses: output	[1x100000 double]
4	Number of input nodes	02
5	Number of hidden layers	10
6	Number of output nodes	01
7	Performance:	Mean Squared Error (MSE)
8	Data division	Random

The key mathematical equations in the LM algorithm [23] are as follows:

Levenberg-Marquardt (LM) training algorithm

1. *Initialization:*

   Initialize the weights w of the neural network randomly.

   Set the damping parameter μ>0, typically a small positive value (μ=0.01).

   Define convergence criteria, such as a maximum number of iterations or an acceptable error threshold.

2. *Compute the Output and Error:*

   Feed forward the input data through the neural network to compute the predicted output $y_{predicted}$.

   Compute the error vector: $e=y_{actual}-y_{predicted}$

3. *Calculate the Jacobian Matrix:*

   Determine the Jacobian matrix J, where each element is the partial derivative of the error with respect to the network weights:

$$J_{ij} = \frac{\partial e_i}{\partial w_j}$$

   The Jacobian can be computed efficiently using backpropagation.

4. *Approximate the Hessian Matrix:*

   Use the Gauss-Newton approximation to estimate the Hessian matrix:

$$H \approx J^T J$$

5. *Compute the Weight Update:*

   Update the weights using the LM update formula:

$$w_{new} = w_{old} - (J^T J + \mu I)^{-1} J^T e$$

   Here, μ is the damping parameter, and I is the identity matrix.

6. *Evaluate the Error:*

   Calculate the total error after updating the weights. Compare it with the previous error:

$$E = \frac{1}{2}\|e\|^2$$

7. *Adjust the Damping Parameter (μ):*

   If the error decreases, reduce μ (e.g., μ=μ/β, where β>1), making the algorithm behave more like the Gauss-Newton method.

   If the error increases, increase μ (e.g., μ=μ·β), making the algorithm rely more on gradient descent.

8. *Check Convergence:*

   Stop if one of the following criteria is met:

   The error e is below a predefined threshold.

   The change in weights $\|w_{new} - w_{old}\|$ is below a tolerance value.

   The maximum number of iterations is reached.

9. *Repeat:*

   If convergence criteria are not met, repeat steps 2 to 8.

The flowchart for training implementation of DNN is presented in Fig.3

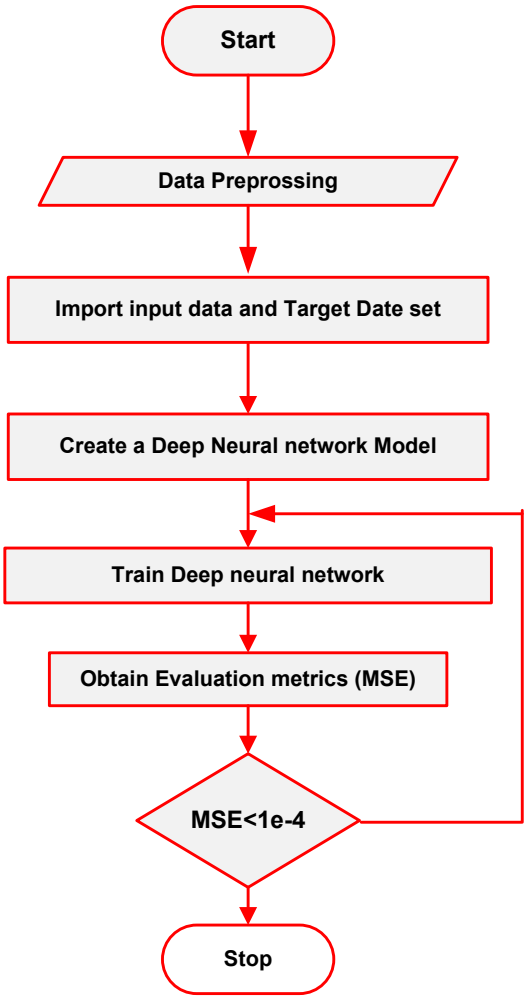


Fig.3 Flowchart for designing DNN controller [22]

(c). DNN Model for proposed work

The DNNs are a type of machine learning algorithm designed to mimic the brain's ability to process information. The Fig.4 illustrates the structure of the DNN-based model employed in this study They are distinguished by their structure, which includes multiple hidden layers positioned between the input and output layers, as illustrated in Fig.5. Each layer comprises several units (neurons), each of which applies a specific functional transformation to its input. A typical DNN model with 2 input, 2-hidden layers with -4 nodes and 2 output nodes is shown in Fig.5.

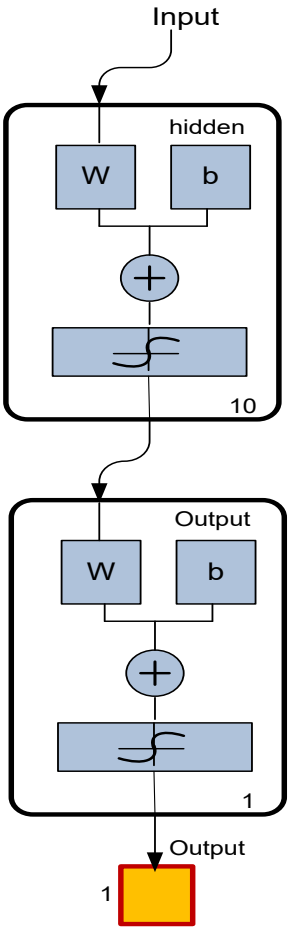


Fig. 4 The proposed DNN for DC-DC converter

According to the universal approximation theorem, these models are capable of approximating the behaviour of any function. The output (y) of a unit (i) in layer (1) is derived from the output (x) of the previous layer (k),

which has J outputs, through a set of weights ($w_{i,k}$), a bias (b_i), and a non-linear activation function f.

$$y_i^t = f\sum_{j=1}^{j} w_{i,k}x_k + b_i$$

. The model includes input layer with 02- nodes, 10- hidden layers, and output layer-01 node and other details described in Table. I. In this setup, the input consists of two nodes for input dc voltage and target or reference voltage, whereas the output layer with one node is dedicated for duty ratio (control variable) generation for given reference voltage to the converter.

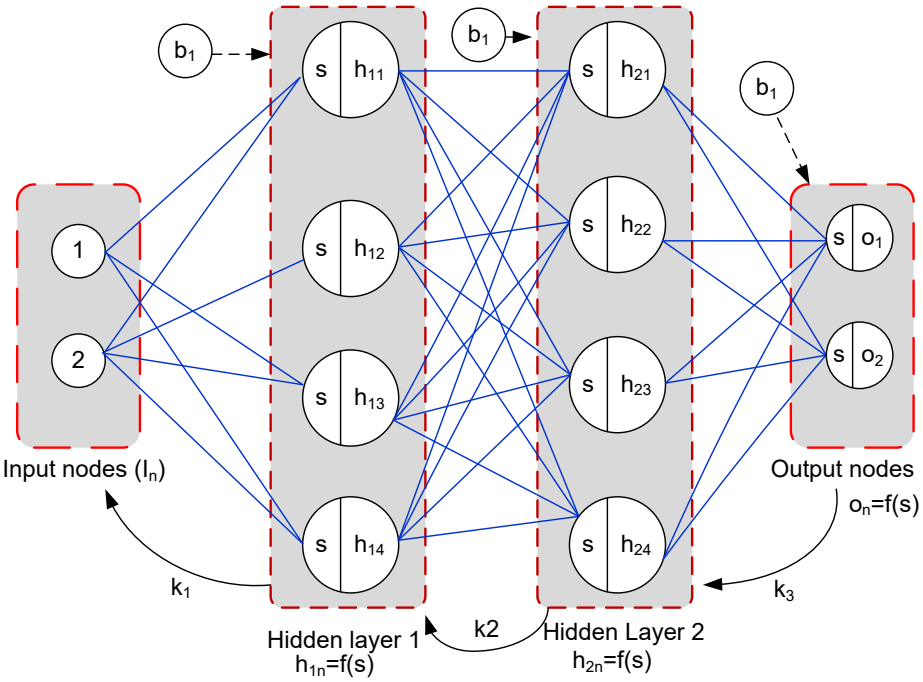


Fig. 5 A generalized DNN model with 2 input, 4 hidden-1, 4 hidden-2 and 1 output nodes [14]

The training performance of the DNN is shown in Fig.6. After several epochs, the model parameters are trained and then tested. It is observed that Mean Square Error (MSE) is 4.7391e-5 at epoch 1000. The training, testing and validation performance characteristics for shown in Fig.7 and the correlation coefficient is 0.99998 and also shown in Table. II.

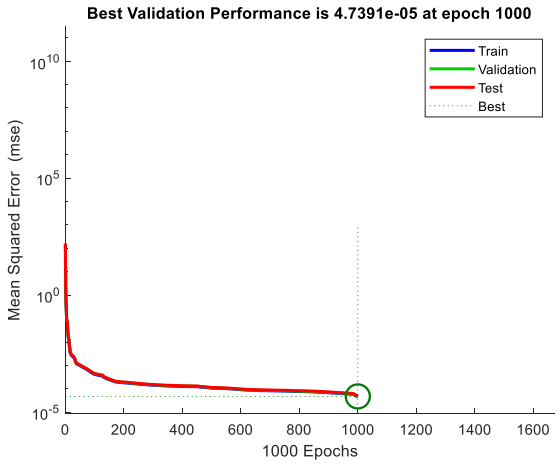


Fig. 6 Mean Square Error convergence plot (best is 4.739e-5 at epoch 1000

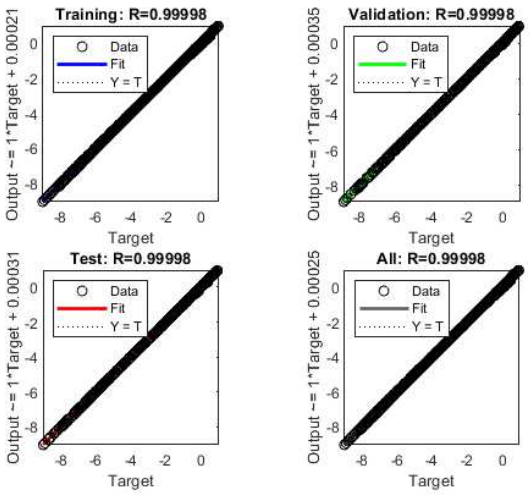


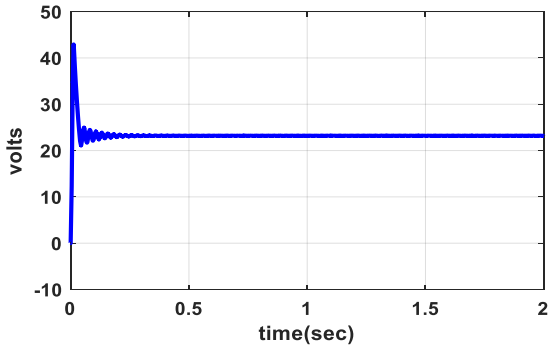
Fig.7 Performance characteristics of training, testing and validation of dataset

Table. 2 Training performance of Deep Neural Network (DNN)

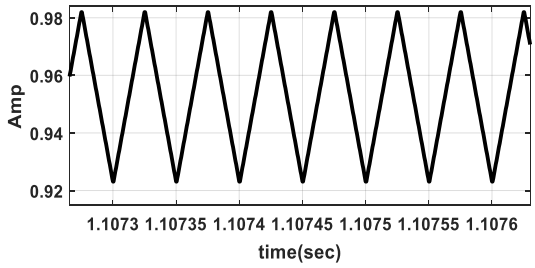
	Observations	**MSE**	**R**
Training	70000	4.5277e-5	1.000
Validation	15000	4.7391e-5	1.000
Test	15000	4.9509e-5	1.000

3 Simulation Results

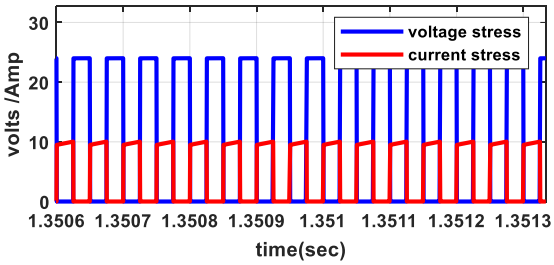
The DNN controller is implemented to DC-DC Boost converter in MATLAB/ Simulink environment with the converter specifications are shown in Table. III. Various case studies are implemented to test their performance and accuracy. The 12V Input voltage for the converter is considered and is tested for reference voltage of 24 V (two times of the input voltage) and also with 50V (i.e. two times of the input voltage). It is observed that the converter delivered exactly 24 voltage for given reference input with DNN controller as shown in Fig.8(a).The corresponding load current is displayed in Fig.8(b). Similarly, DNN is validated for 50V reference voltage, the converter is generated the expected output voltage as shown in Fig.9 (a), moreover the corresponding load current is shown respectively in Fig.9 (b). The effectiveness of the converter is also validated for designed DNN with different reference voltages. It is observed that the converter performance is superior for closed loop control without any voltage sensing.



(a)

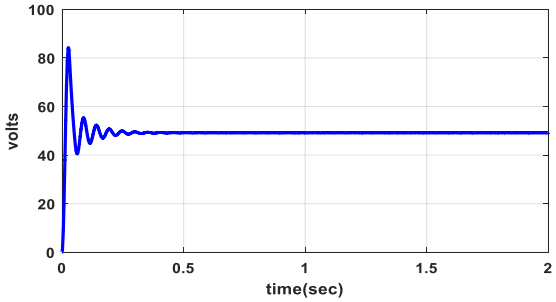


(b)

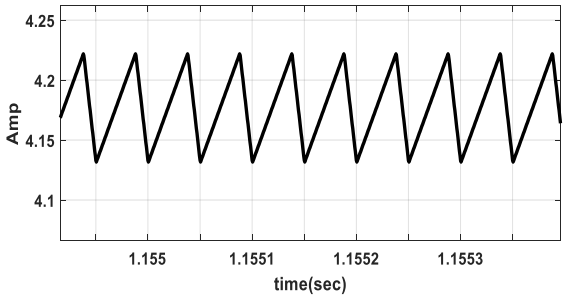


(c)

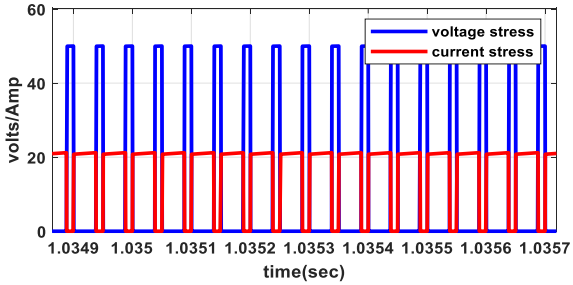
Fig.8 Simulation Results: (a) output voltage (V_o) for reference voltage of 24V (b) inductor current (c) voltage and current Stress (10x zoomed) of switch



(a)



(b)



(c)

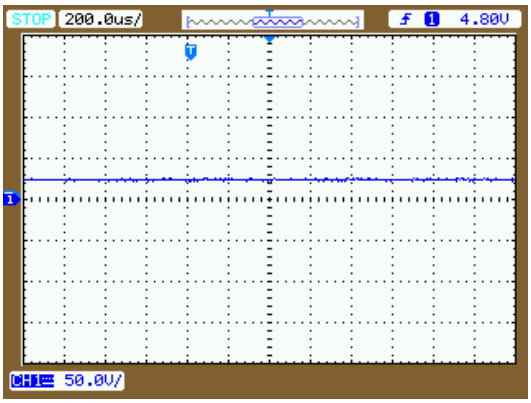
Fig.9 Simulation Results: (a) output voltage (V_o) for reference voltage of 50V (b) inductor current (c) voltage and current Stress (5x zoomed) of switch

Table. 3 DC-DC converter parameters

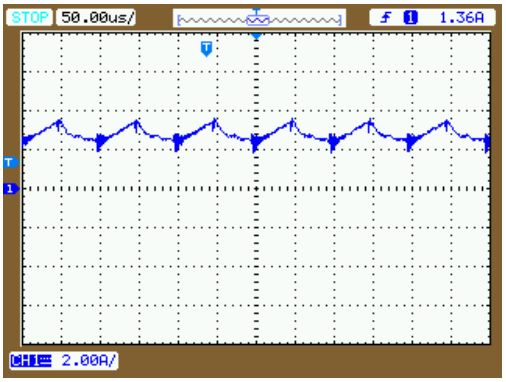
Parameter	Value
Input voltage	24V
Output voltage (V_0)	50V
Output current (I_0)	2 A
Inductor (L)	8 mH
Capacitor (C)	470 µF
Switching frequency	10kHz

4 Experimental Results

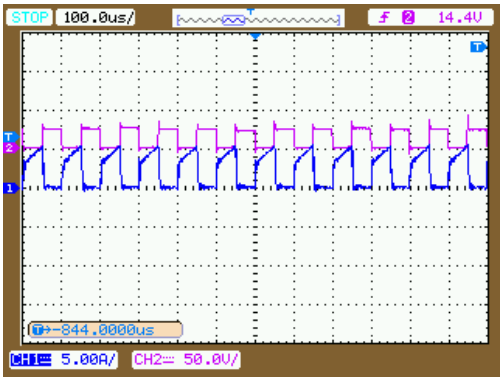
The proposed method is tested using parameters specified for the experimental prototype, as listed in Table III. In this hardware setup, a DSP controller generates gate pulses to control the IGBTs through appropriate gate driver circuits. The converter is evaluated at an input reference voltage of 12V, a duty ratio of 50%, and a switching frequency of 10kHz. The corresponding results are presented in Fig. 11, where the converter's output voltage is observed to be 24V, aligning with the theoretical expression of a boost converter. The inductor current, shown in Fig. 11(b), exhibits a 50% charging and 50% discharging cycle, with the inductor ripple maintained within the considered value. Fig. 11(c) illustrates the device stress, including voltage and current stress, with the maximum voltage stress corresponding to the output voltage. Additionally, tests conducted at Vin=24V yield results displayed in Fig. 12. Fig. 12 presents the prototype of a Boost converter-based LED driver, developed to validate the effectiveness of the proposed DNN for street lighting applications.



(a)

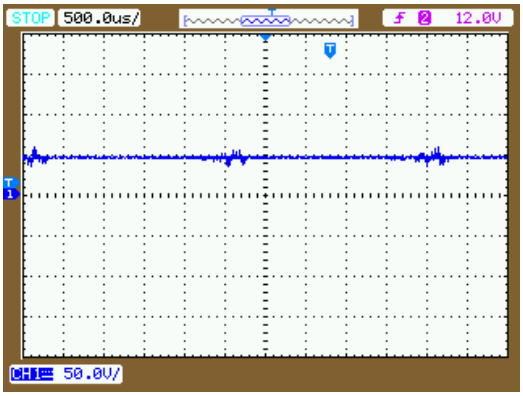


(b)

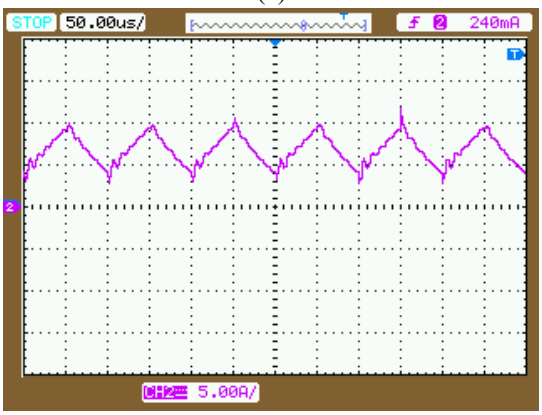


(c)

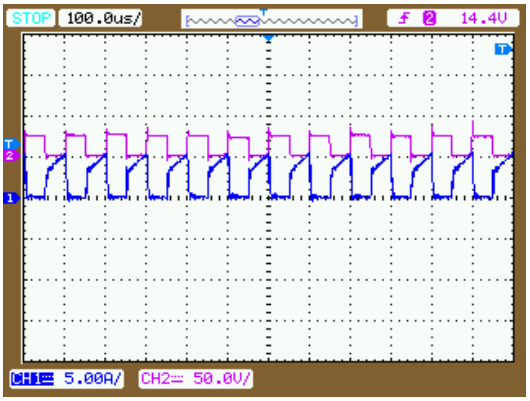
Fig.10 Experimental Results: (a) output voltage (V_o) for reference voltage of 24V (b) Inductor current (c) Voltage stress across device



(a)

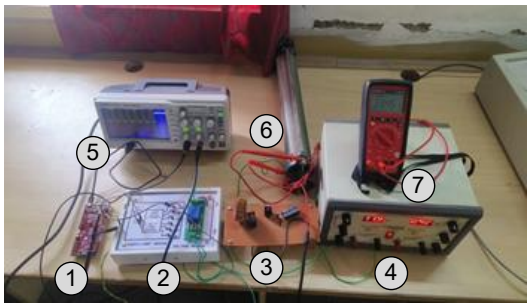


(b)

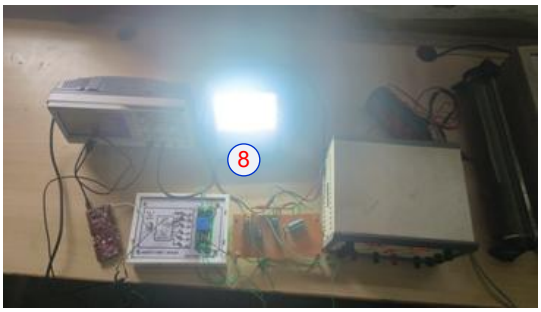


(c)

Fig.11 Experimental Results: (a) output voltage (V_o) for reference voltage of 50V (b) Inductor current (c) Voltage stress across device



(a) DNN controller-based LED driver for Resistive Load



(b) DNN controller-based driver for LED DC Street lamp (24V, 1A)

Fig.12 Experimental test bed on laboratory prototype ((1) TMS320F28379D Microcontroller, (2) PWM driver (3) Boost converter (4) regulated DC input (5) DSO (6) Rheostat (7) Multimeter (8) LED Street Lamp).

5 Conclusion:

This paper introduces A NEW method that leverages deep neural networks (DNNs) to develop a controller for a DC-DC power converter. The proposed DNN-based controller is trained to determine optimal control actions based on the converter's state variables, improving stability, response time, and adaptability to changing load conditions. This work comprehensively presents the neural network architecture, the training process using simulation data, and its successful implementation in a Boost converter.

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Data availability: The authors are willing to provide the data upon request, as long as the request is deemed reasonable.

Declarations Conflict of interest: The authors state that there are no financial or personal connections that could have influenced the research presented in this paper.

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