Modelling of a Boost Converter Using Bayesian Regularized Artificial Neural Network

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Abstract. In this work, a Boost converter is modeled using Machine Learning Algorithm. Bayesian Regularized ANN is used in this work for reducing the lengthy cross-validation and the usage of neural networks to fit the data appropriately. First the boost converter is modeled using state space analysis. The stability of the system is observed using frequency response characteristics. It is observed that the system is well stable with the outer voltage control and inner current control. Inductor current and output voltage are taken as state variables. To obtain less steady state error, for different values of duty cycle, appropriate PI controller parameters are tuned and tabulated. It is found that the controller works effectively and tracks the reference voltage of 15 V with a steady state error of 4.459%. Secondly using BR-ANN method the modeling of the boost converter is performed. The steps involved in the process are (i) using the simulated model of the converter, collect data of different system parameters such as the system variables, (ii) classify into input and output parameters, (iii) use BR-ANN in ANN tool box in MATLAB to validate the models with training and testing data sets, (iv) to model the converter for steady state response (v) obtaining Mean Squared Error and Regression plots for analyzing the convergence. It is found the boost converter is modeled with efficacy (i.e. the response obtained is in close to the simulation results) and the obtained results can still be used for optimal performance and to predict fault conditions. MATLAB simulink and ANN tool box set is used for the work.

Keywords: Artificial Neural Network · Boost Converter · PI controller · Steady state error · Stability

1 Introduction

Machine learning was developed by Arthur Samuel in the year 1959. With less programming, the developer introduces machine learning as a subfield of computer science with the ability to learn the systems. It is realized as a self-learning process. Self learning means application of statistical modelling to detect the flow and increase the efficiency based on the data set and the available empirical information. It doesn't mean that it requires enormous programming but it requires an input data instead of an input command. There are many reasons why machine learning is important. It enables us to

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learn how humans and animals learn to adapt. But engineering applications are predominant using the machine learning concepts. A concise relationship between the input and desired output is very much essential for obtaining a well stable system. The machine learning algorithms are required to adjust their internal structure to deliver a desired output for a large number of input samples. Many confidential and hidden data can well be recovered by using the machine learning algorithms and it is necessary to extract these relationships often known as data mining. Machines due to continuous learning would be able to learn and acquire knowledge more than the humans. Hence even though full information of the working environment is ot known at the design time, these algorithms would use the existing design data and explore to give optimal solution. Therefore machines which can adapt to changes in environment or the working functionality would reduce the need for redesigning the system. The main applications of machine learning include image recognition, product recommendation, speech recognition, smart vehicles, virtual personal assistant, power systems, waveform magnitude estimation, control etc.

Due to the development of electric vehicles and the scenario towards self driving cars are the future trends. The use of machine learning has been a great area of interest to the researchers in the power electronics industry. Since power converters play an important role in the power conversion, their modelling is of utmost importance. Many classical methods have been developed for the last 4 decades. Few methods include are PWM, transformer models, state space average models etc. for DC-DC converters [1]. The stability, efficiency, transfer functions etc. are estimated before the actual prototype is built. Due to the development of power converters which are fast, modular and low cost, the research also focussing on their resiliency, reliability and their overall performance [2]. Many model based approaches and predictive control mechanisms are being developed for converter circuits. All these methods and with large data collection and processing, immense opportunities are opened in the area of power electronic systems [3]. Hence developments in analysis and modelling of power converters are the need of the hour in the industry.

Many authors have presented their work in these areas starting with the power electronic device (MOSFET) interpretation and their aging. Few have proposed on the condition monitoring of high frequency GaN converters with adaptive prognostics. They used bayesian algorithm for data exploitation. Digital twins are developed by few authors for obtaining better performance and reliability meaning co-simulations of power semiconductor converters hardware and simulations on a system. These works are attractive provided low cost or open source software's are available. Hence ANN (Artificial Neural Networks) came into existence which provide not only precise modelling of power converters with their transient and steady state characteristics and also less expensive. Deep feed forward neural networks for GaN modelling and Automated design for reliability of power electronics systems have been already proposed in the recent works. Hence there is a widespread adoption of machine learning in the power electronics industry as well.

In this work, a Baseyian Regularization Artificial Neural Network is used to model a boost converter for obtaining a desired output voltage. The main advantages of the work are (i) Based on the data and resolution, the model can be précised and can be controlled,

(ii) no advanced mathematical methods required, (iii) Power converters can be implemented using open source software, (iv) a digital twin can be developed since the model can be adapted with the real time data available, (v) simulation results obtained through the model and algorithms can be compared and analysed, (vi) control mechanisms can be modelled together with the converters.

This paper presents a classical control mechanism of outer voltage and inner current control mechanism for a boost converter for obtaining a desired output DC voltage. A state space model is developed and the stability is studied using frequency response plots. Simulation results are obtained for the closed loop system. A Bayesian regularised ANN algorithm is used to model the boost converter. The methodology is understood. It is implemented to synthesize the response of the boost converter. Finally the output voltage response is obtained from the output of the ANN algorithm and simulated. It is observed that the response obtained from MATLAB SIMULINK MODEL and BAYESIAN REGULARISED BASED MODEL are compared. Both the responses closely match realizing the application of these algorithms to power converters.

2 Bayesian Regularized-ANN Based Model Development of a Boost Converter

The model development process consists of data collection, data processing, machine learning algorithm, model verification and model implementation [4]. A boost converter consists of different converter parameters like the inductance, capacitance, resistance, input voltage, duty cycle, frequency etc. A desired output voltage response plot has to be obtained.

(i) Data Collection
This step involves the collection of data either from the hardware prototype of the boost converter or from the simulation representation. The output voltage depends upon several parameters like the input voltage, load resistance, inductance, capacitance, on-state resistances, parasitic capacitances of the power electronics switches. The computational time increases if large amount of data is considered. But at the same time, more precise can be obtained from a large data. In this work, parasitic components are kept constant while the remaining parameters mentioned are varied over a small range to understand the operation of this algorithm for modelling. A resolution of 1 μs is considered in the work.

(ii) Data processing
As the data set may overfit many a times in ANN, the data has to be down sampled before training the network. The output voltage requires less data in this work and hence the disparity does not arise in this case.

(iii) Machine Learning Algorithm
BR-ANN is used to model the boost converter for output voltage regulation. MATLAB neural network tool box is used instead of the open source software python and R. Figure 1 represents the BR-ANN model used in this work. It consists of a hidden layer and an output layer. The hidden layer consists of twice the number of nodes in a given input signal. The output layer consists of the same number of nodes as the output signal.

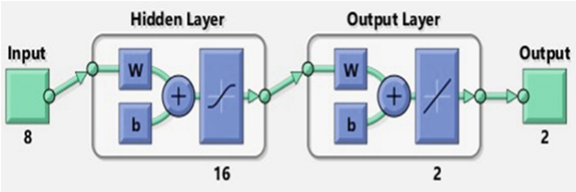


Fig. 1. BR-ANN model representation

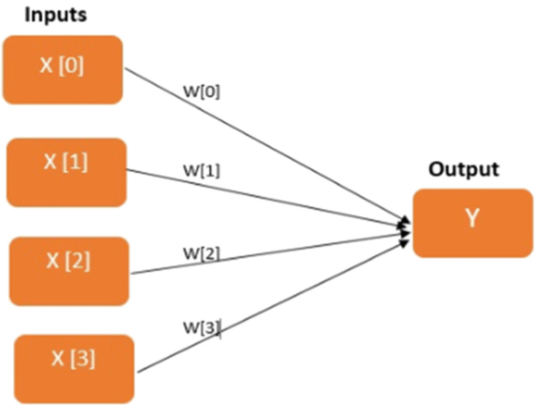


Fig. 2. Simple Bayesian neural network

To reduce the mean squared error [4], a minimization of cost function is taken as the objective function as (1)

$$C(f) = b\sum\nolimits_{n=1}^{D}\left[Output_n - f(input_n)\right]^2 + a\sum_{m=1}^{W}[W_m]^2 \tag{1}$$

a and b are the hyper parameters. D and W are the no. of data rows and weights. Output and Input are the converters output and input data tables. In this work output voltage is the output and the system parameters along with the input voltage form the input. f (input) is the predicted output table from the model which is used to find the mean squared error.

A simple linear model of Bayesian algorithm is shown in Fig. 2. To predict the output by the weighted sum of a series of input features is shown. Bayesian theory is being used in lots of fields: from game development to drug discovery. These when used with neural networks offer advantages of regularization and model selection without the need for cross validation. It allow us to estimate uncertainty in predictions, which is a great feature for fields like medicine. BNNs allow you to automatically calculate an error associated with your predictions when dealing with data of unknown targets.

(iv) Model Verification
Training involves 70% and testing involves 30% of data rows for the model. It forms the first layer of verification. These are analysed using error histograms and regression plots.

The model is said to be verified only if it passes this first layer verification, otherwise it is retrained.

(v) Model Implementation
If the model gives good results with the testing data, it is worked with new values of test inputs within the data range taken. For each set of inputs, the model gives an output which is compared with the simulation result already obtained for accuracy [7]. The work flow for the model development is given below

Collection of developed converter results

$\Downarrow$

Selection of Input & Target data

$\Downarrow$

ANN Tool-Box

$\Downarrow$

Importing the Input & Target data

$\Downarrow$

BR-ANN Network Formulation

$\Downarrow$

Training the Loaded Data

$\Downarrow$

Output Results

$\Downarrow$

Exporting the BR-ANN Results

$\Downarrow$

Developing New Model

3 State Space Model of the Boost Converter and Stability

The state space model is derived for the boost converter using state space analysis. The inductor current i_L and output voltage V_o are taken as state variables [5]. The model so obtained is given in Eq. (2) and Eq. (3) represents the output matrix. Figure 3 shows boost converter circuit.

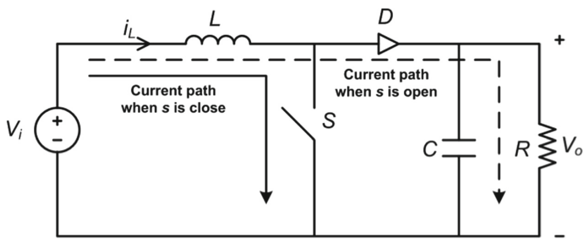
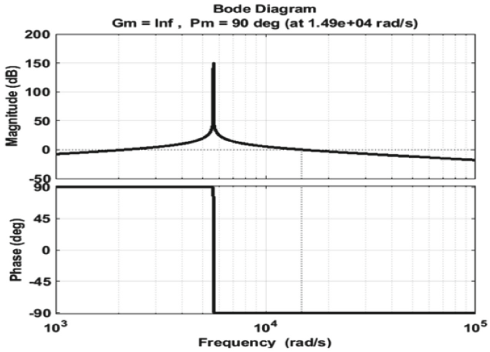
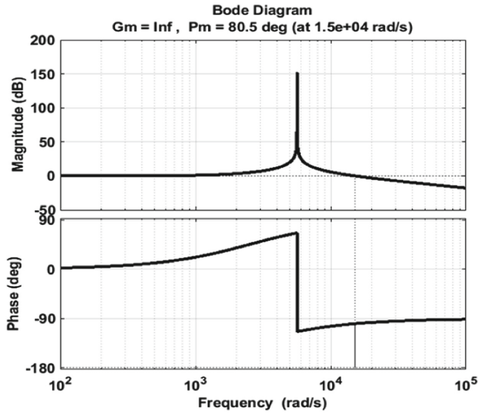


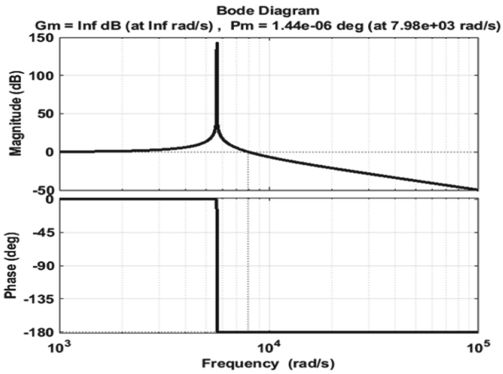
Fig. 3. Boost Converter Circuit



(a)



(b)



(c)

Fig. 4. Frequency response characteristics for (a) inductor current control, (b) output voltage control, (c) outer voltage and inner current control

Table 1. System Parameters

S. No.	Parameter	Value
1	Input DC Voltage	12 V
2	Input inductor	78.6 mH
3	Output capacitor	400 µF
4	Resistance	4 Ω
5	Power	50 W
6	Switching frequency	20 kHz

$$\begin{bmatrix} \dot{i}_L \\ \dot{V}_o \end{bmatrix} = \begin{bmatrix} 0 & -1/L \\ 1/C & -1/RC \end{bmatrix} \begin{bmatrix} i_L \\ V_o \end{bmatrix} + \begin{bmatrix} V_{dc}/L \\ 0 \end{bmatrix} u \tag{2}$$

$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} \left[\frac{i_L}{V_o} \right] \tag{3}$$

Now using state feedback approach [6], the frequency response characteristics can be obtained as shown in Fig. 4. It is observed that the need of inner current control is very much essential to obtain a well stable output and hence the system stability improves during inner current and outer voltage control. Table 1 shows the boost converter configuration parameters.

4 Simulation Results

(i) Figure 5 shows the simulink diagram of a boost converter voltage control in MATLAB. Table 2 shows the data samples used for the boost converter modelling using BRR-ANN algorithm [8]. For a reference voltage of 15 V, the simulation is carried out at an operating frequency of 20 kHz. One can find K_{p} and K_{i} values by trial and error method, here we used Ziegler Nichols method. The Ziegler Nichols method in which K_{p} value will be changed until we obtain good stable system. By changing K_p and K_i values we can change the output response and then we can select the response with less ripple. Table 3 is presented for different values of K_p and K_i the output voltage ripple is obtained along with the inductor current, duty ratio.

Figure 6 shows the tracking of output voltage with the reference voltage along with the inductor current. It is observed that using the classical closed voltage control, the output voltage of 15 V is well tracked with less steady state error. It was found through Table 2 that the voltage ripple is lowest at a duty ratio of 0.25 with an inductor current of 4.49 A.

(ii) Bayesian ANN based results
Figure 7 and Figure 8 shows the performance of the model development process and results from training/test data. It can be seen that the Mean Squared Error (MSE) [9, 10]

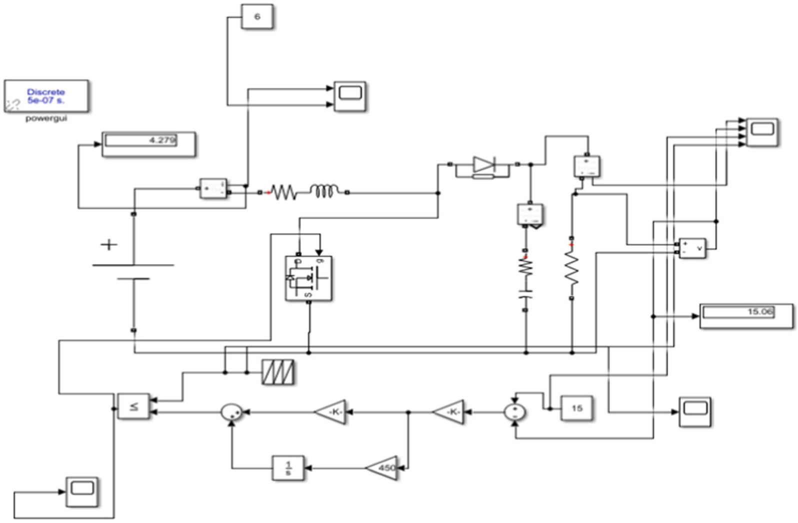


Fig. 5. Simulink diagram of Boost converter with closed loop outer voltage and inner inductor current control.

Table 2. Data Samples of the developed simulation based Boost converter for BR-ANN algorithm

Vs	L	C	Rl	Kp	Ki	Vo theoretical	%Duty cycle	%Vol. Ripple	il	Kp
11	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	15.27	0.28	6.49	4.89	0.45
11.25	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	15.625	0.28	4.56	4.989	0.45
11.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	15.97	0.28	4.56	4.7	0.45
12	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.01	0.28	4.56	3.88	0.45
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.23	0.23	4.56	4.395	0.45
13	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.66	0.22	4.56	3.452	0.45
13.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.875	0.2	4.56	2.94	0.45
14	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	17.03	0.18	4.56	3.468	0.45
14.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	17.05	0.15	4.56	3.267	0.45
15	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	17.24	0.13	4.56	3.2	0.45
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.23	0.23	4.56	4.395	0.45
12.5	$80 * 10^{-6}$	$410 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	4.832	0.45
12.5	$90 * 10^{-6}$	$430 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	4.17	0.45
12.5	$100 * 10^{-6}$	$450 * 10^{-6}$	4	0.45	450	16.66	0.25	4.56	4.316	0.45
12.5	$120 * 10^{-6}$	$470 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	5.662	0.45
12.5	$70 * 10^{-6}$	$400 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	3.829	0.45
12.5	$60 * 10^{-6}$	$380 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	3.374	0.45

(*continued*)

Table 2. (*continued*)

Vs	L	C	Rl	Kp	Ki	Vo theoretical	%Duty cycle	%Vol. Ripple	il	Kp
12.5	$75 * 10^{-6}$	$390 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	3.374	0.45
12.5	$70 * 10^{-6}$	$405 * 10^{-6}$	4	0.45	450	16.44	0.24	4.56	3.898	0.45
12.5	$75 * 10^{-6}$	$395 * 10^{-6}$	4	0.45	450	16.44	0.25	4.56	3.811	0.45
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4	0.5	400	16.23	0.23	4.56	4.455	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	4.5	0.5	400	16.23	0.23	4.56	3.157	0.5
12.5	$76.8 * 10^{-6}$F	$400 * 10^{-6}$	5	0.5	400	16.23	0.23	4.56	3.426	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.5	0.5	400	16.23	0.23	4.56	2.982	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.75	0.5	400	16.23	0.23	4.56	2.692	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.25	0.5	400	16.23	0.23	4.56	3.259	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.6	0.5	400	16.23	0.23	4.56	2.784	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.7	0.5	400	16.23	0.23	4.56	3.171	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.4	0.5	400	16.23	0.23	4.56	2.838	0.5
12.5	$76.8 * 10^{-6}$	$400 * 10^{-6}$	5.45	0.5	400	16.23	0.23	4.56	2.951	0.5

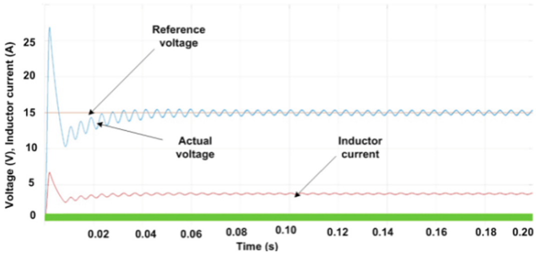


Fig. 6. Actual and reference output voltage tracking

came down from about 40,000 to 6.28 and the minimization has converged. Figure 7 shows the regression plot from both training and testing set, with a good R-value of about 0.9982. The data curve distribution seen about the mean can be further improved by taking more data points in the training set. Next step is the implementation and validation with new parameter values. The response using BR_ANN is obtained using the trained model as shown in Fig. 9. The output voltage response shown in Fig. 10 is found to be same as the response of MATLAB simulink model. More data samples if taken would result in obtaining close to 15 V of reference. Hence the modelling of power electronic converters can well be developed using machine learning methods [11]. More data samples if taken would result in obtaining close to 15 V of reference.

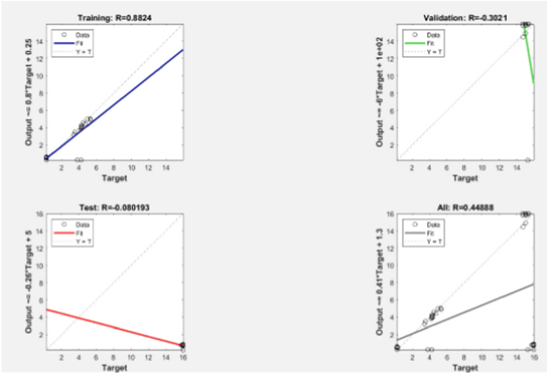


Fig. 7. Regression plots

Table 3. Varying K_p and K_i for voltage ripple

K_p	K_i	Voltage ripple	Duty cycle	V_{out} (Sim)	V_{out} (ex.)	I_L
0.45	450	5.019	0.25	15.31	16	3.78
0.45	500	5.19	0.25	15.03	16	5.31
0.45	550	6.452	0.25	15.33	16	3.40
0.45	380	3.289	0.25	15.06	16	4.72
0.40	400	5.161	0.21	15.17	15.78	4.27
0.50	400	6.189	0.24	14.73	15.88	5.27
0.55	**400**	**3.088**	**0.25**	**15.06**	**16**	**4.49**

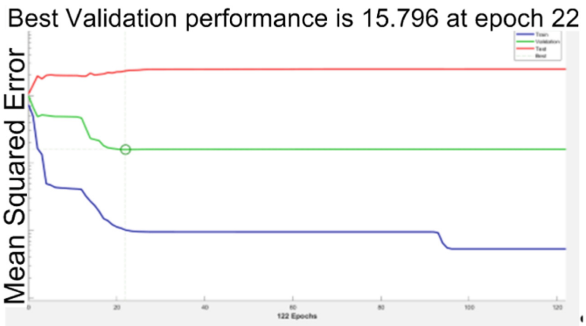


Fig. 8. Mean Squared Error

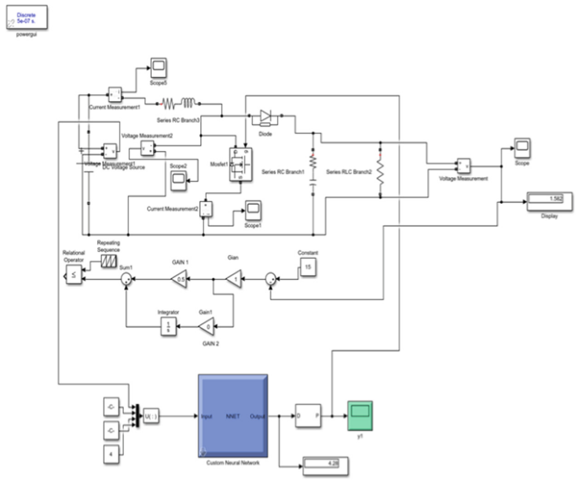


Fig. 9. Matlab Simulink using the trained BRR-ANN model

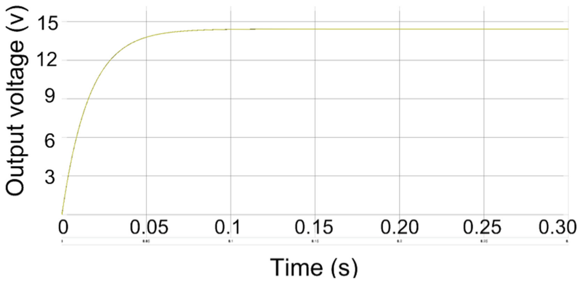


Fig. 10. Output voltage response using BR-ANN Algorithm

5 Conclusions

This work presents a BR-ANN based modelling of a boost converter. The classical method of inner inductor current and outer voltage is presented to obtain a well regulated output voltage of 15 V. Stability of the converter circuit is presented using frequency response plots. The PI controller parameters are tuned properly for obtaining low output voltage ripple content. BR-ANN algorithm flow chart and procedure is implemented for modelling the boost converter with different data set values and mean squared error and regression plots are obtained. From the Mean Squared error graph we the error value is obtained and observed the approximate values to be taken into account for tuning the Boost Converter for obtaining the desired output response. From the Regression Graphs it is observed that the errors in the prediction and target values and the noted them. It is seen that the machine learning based models were able to provide very close responses to the simulation results.

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