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Application of machine learning controller in matrix converter based on model predictive control algorithm

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ABSTRACT

Finite control set model predictive control (FCS-MPC) algorithms are famous in power converter for its easy implementation of constraints with cost function than classical control algortihms. However computation complexity increases when swicthing state is high for converters such as matrix converter, multilevel converters and this impose a serious drawback to compute multi-step prediction horizon MPC algorithm which further increases the computation. To overcome the above said difficulty, machine learning based artificial neural network (ANN) controller for matrix converter is proposed. The training data for ANN controller is derived from MPC algorithm and trained offline with an accuracy of 70.3%. The proposed ANN controller shows a similar and better performance than MPC controller in terms of total harmonic distortion (THD), peak overshoot during dynamic change in reference current and dynamic change in load parameter and less computation with less execution time. Further, ANN controller for matrix converter is tested in OPAL-RT using hardware in-loop (HIL) simulation and showed that it outperforms MPC controller.

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1. INTRODUCTION

Model predictive control of matrix converter have gained a lot of interest in past years as it is simple with good and fast dynamic response with inherent reactive power control. Mir *et al.* [1] proposed improvised multi-objective finite control set model predictive control which relatively results in reduced total harmonic distortion (THD) of source current by 5%. Model predictive control (MPC) at each step selects an optimal switching state in accordance with pre-defined cost function. Though MPC offers several advantages such as fast transient response, easy and straightforward constraints with implementation, it suffers when the number of switching state is high. One such is matrix converter, as the valid switching state of three phase matrix converter is 27. In each sampling time, the cost function is calculated for the 27 possible switching state and one optimal switching state is selected to be applied in the next sampling time. This will increase the computation burden of controller and the case would be worser if multi-horizon predictions are employed.

Supervised machine learning techniques is very popular in the application of power electronic converters as it reduces the complexity and process the results in a very short time [2]-[4]. ANN is aided in real time modeling apprach for power electronic converters to model thermal stress, and switching loss, and reported a unique performance in computation burden and resource utilisation of FPGA [5]. Khan *et al.* [6] applied artificial neural network (ANN) to control voltage in DC-DC converter in DC microgrid applications and found

ANN's performance is better in terms of accuracy and computational burden. ANN has also been applied to optimise the parameters of permanent magnet synchornous motor based model predictive control [7]. Akpolat *et al.* [8] proved that ANN has also found application in reducing the number of sensor in the control of DC microgrid and thus makes the system more reliable. Simonetti *et al.* [9] applied machine learning techniques to reduce the computational burden for a cascaded H-bridge inverter instead of MPC control.

In recent years, supervised imitation learning of model predictive control is very popular which results in less computation burden, improved total harmonic distortion in most of the test cases and same dynamic performance as that of MPC. Supervised imitation learning is applied to three phase inverter with an output LC filter which results in less harmonic distortion of output voltage in most of the test cases [10]. Time delayed ANN is proposed and used as controller in grid-tied three level neutral point clamped transformerless inverter [11]. Novak and Dragicevic [12] tested neural network controller for 2 step prediction horizon of three phase inverter and proves that neural network controller outperforms MPC controller. Wang *et al.* [13] applied ANN in place of MPC for power converters which results in less resource utilization of FPGA comparatively. Zaid *et al.* [14] used ANN controller as end-to-end learning policy to control transformerless grid connected neutral pointed clamped inverter and stated that ANN controller results with low harmonic distortion with enhanced power quality and minimized leakage current than MPC. Abu-Ali *et al.* [15] tested deep learning controller for permanent magnet synchronous motor drives and results with better torque transient response than conventional MPC. Ahmed *et al.* [16] proposed recurrent neural network based predictive current control with better dynamics, excellent control and tracking error. Akpolat *et al.* [17] ANN-MPC instead of proportional integral (PI) controller for stabilization of DC microgrid and noted that ANN-MPC resulted in less instability issue and oscillations in DC microgrid. Sabzevari *et al.* [18] proposed state-space recurrent neural network controller for three phase power converter and showed that the control scheme is more robust compared to conventional MPC. Sahu *et al.* [19] developed neural network based dicrete model predictive controller for induction motor drive based on direct torque and flux and reported reduction of ripples in flux, torque and current compared with conventional PI direct torque and flux control. Further, the authors used various intelligence techniques in power converters [20]-[24]. The above literature motivated to train ANN controller for a matrix converter which has higher switching possibilities and to test the performance of ANN controller for a matrix converter.

In this paper, a supervised machine learning based controller is developed and trained for matrix converter of 27 valid switching states with the data collected from model predictive control. The main contributions of the paper are as follows:

- Model free ANN based controller is tested for matrix converter in MATLAB simulation and hardware in-loop (HIL) using RT-LAB.
- ANN based controller results in low THD in most of the test cases and dynamic performance is improved.
- Computation time and average switching frequency are compared which results in less computation burden.

2. MATRIX CONVERTER AND ITS SWITCHING STATE

Power circuit of matrix converter as shown in Figure 1 has a set of bidirectional switch with two power transistor and anti-parallel diodes (S) which are connected to input supply through LC filter. To avoid abrupt interruption of load current atleast one switch in the load phase must always be on as mentioned in (1).

$$S_{xu} + S_{yu} + S_{zu} = 1 \qquad \forall u \in a, b, c \tag{1}$$

Based on the above restriction, 27 switching combinations are possible. Input and load voltages are related as (2).

$$\begin{bmatrix} v_{a(t)} \\ v_{b(t)} \\ v_{c(t)} \end{bmatrix} = \begin{bmatrix} S_{xa} & S_{ya} & S_{za} \\ S_{xb} & S_{yb} & S_{zb} \\ S_{xc} & S_{yc} & S_{zc} \end{bmatrix} \cdot \begin{bmatrix} v_{ex(t)} \\ v_{ey(t)} \\ v_{ez(t)} \end{bmatrix} \tag{2}$$

Where $v_a(t), v_b(t)$, and $v_c(t)$ forms the load voltage vector and $v_{ex}(t), v_{ey}(t)$, and $v_{ez}(t)$ forms the input voltage vector. By KCL, input and load current are relates as (3).

$$\begin{bmatrix} i_{ex(t)} \\ i_{ey(t)} \\ i_{ez(t)} \end{bmatrix} = \begin{bmatrix} S_{xa} & S_{ya} & S_{za} \\ S_{xb} & S_{yb} & S_{zb} \\ S_{xc} & S_{yc} & S_{zc} \end{bmatrix} \cdot \begin{bmatrix} i_{a(t)} \\ i_{b(t)} \\ i_{c(t)} \end{bmatrix} \tag{3}$$

Where $i_a(t), i_b(t)$, and $i_c(t)$ forms the output current vector and $i_{ex}(t), i_{ey}(t)$, and $i_{ez}(t)$ forms the input current vector.

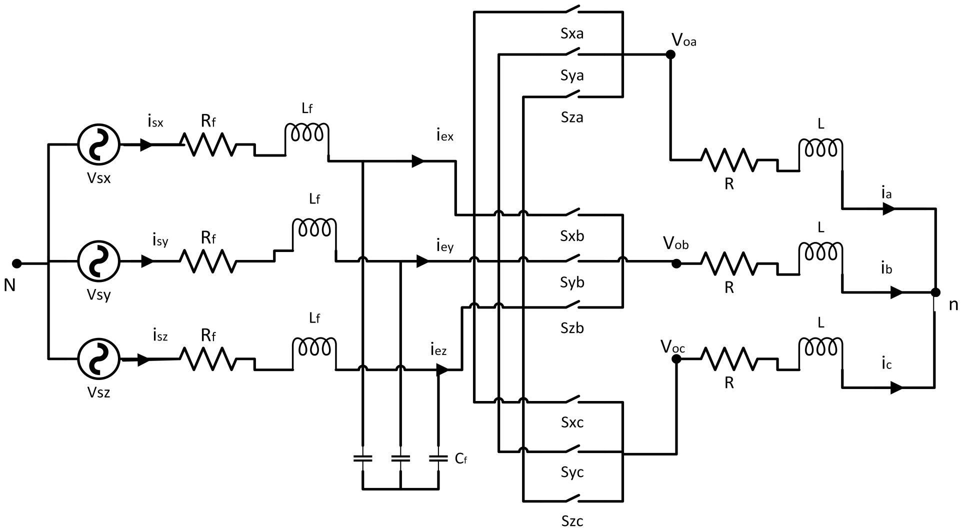


Figure 1. Power circuit of matrix converter

3. CONVENTIONAL FINITE CONTROL SET MODEL PREDICTIVE CONTROL OF MATRIX CONVERTER

Model predictive control uses discretized system model to predict the future behaviour of the variables for a certain time horizon. The predicted variables are used in all possible 27 switching state and one switching state is selected to be applied at the next sampling time based on the minimisation of cost function. The objectives of finite control set-model predictive control (FCS-MPC) are to control output current, control of input current with less harmonics and unity power factor.

Filter current and capacitor voltage differential equations are used to predict the future behaviour of source current $i_s(k+1)$.

$$\begin{bmatrix} \frac{dv_f(t)}{dt} \\ \frac{di_s(t)}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{C_f} \\ \frac{-1}{L_f} & \frac{-R_f}{L_f} \end{bmatrix} \begin{bmatrix} v_f(t) \\ i_s(t) \end{bmatrix} + \begin{bmatrix} 0 & \frac{-1}{C_f} \\ \frac{1}{L_f} & 0 \end{bmatrix} \begin{bmatrix} v_s(t) \\ i_i(t) \end{bmatrix} \tag{4}$$

The (4) is discretized using euler forward disctretization method and source current $i_s(k+1)$ is predicted. Reactive power $Q(k+1)$ is predicted with (5).

$$Q(k+1) = v_{s\beta}(k+1)i_{s\alpha}(k+1) - v_{s\alpha}(k+1)i_{s\beta}(k+1) \tag{5}$$

Where α and β are the real and imaginary parts of the vector. The source current $i_s(k+1)$ is predicted from (4) using the discretised model and the source voltage $v_s(k+1) = v_s$, as source voltages are low frequency components. The load current is predicted in (6).

$$i_o(k+1) = (1 - \frac{RT_s}{L})i_o(k) + \frac{T_s}{L}(v_o(k) - e(k)) \tag{6}$$

Where T_s is the sampling time. The FCS-MPC algorithm of matrix converter are detailed below in steps.

- The controlled variables such as filter capacitor voltage $v_f(k)$, source current $i_s(k)$, source voltage $v_s(k)$, and output current $i_o(k)$ are measured at an instant k.
- The system model is discretized from (4) to predict $i_s(k+1)$ and $Q(k+1)$.
- Load current $i_o(k+1)$ is predicted as in (6).

– Cost function C to track the reference load current and to maintain unity power factor at source side is:

$$C = (i^*_{o\alpha} - i^p_{o\alpha}) + (i^*_{o\beta} - i^p_{o\beta}) + \lambda(Q^* - Q^p) \quad (7)$$

where the superscript p represents the predicted quantity, λ is the weighing factor. Q^* is maintained at zero to achieve unity power factor.

– Cost function is evaluated for all 27 possible switching state and the optimum switching state that minimises the cost function is selected to be applied at next sampling instant.

4. NEURAL NETWORK BASED MODEL PREDICTIVE CONTROLLER

4.1. ANN based controller

In general, ANN controller can be trained and tested with a given set of data. Model predictive control scheme uses this feature of ANN to imitate as that of MPC controller. Initially model is made to run under model predictive control scheme and the training datas are generated. With the generated data, ANN is trained to predict next optimal switching state. Input data generated from MPC scheme to train ANN are desired output reference current i^*_o, filter voltage v_f, filter current i_f, source voltage v_s, source current i_s, output voltage v_o, output current i_o, and the previous optimum switching state $S_{opt-prev}$. Output data from MPC scheme to train ANN is optimum switching state at next instant k+1 $S_{opt(k+1)}$. Training conditions for ANN based controller are listed in Table 1 with a total of 100001 samples. Of this 80% and 20% samples are used for training and testing phases respectively. Samples are trained until it reaches an accuracy of 70.3% with 50.03 epochs. Even with minimal samples, ANN is trained perfectly to achieve the performance of MPC controller.

ANN is trained to work with shallow layer (i.e only one hidden layer) initially. But the performance is poor as compared with MPC controller as the number of possible output states are 27. Hence two hidden layers are used in this paper with 45 and 15 units respectively. Input and output layer has 15 and 27 units respectively.

Table 1. Training parameters for ANN controller

$i^*_o(A)$	R (Ω)	L (mH)	$T_s(\mu s)$
14	3.33	10	10
12	5	15	10
10	5	15	10
8	5	15	10
8	10	30	10
7	10	30	10

5. RESULTS AND DISCUSSION

ANN controller is trained with input and output parameters for conditions mentioned in Table 1. The controller is tested for the following cases.

– Dynamic performance analysis with respect to change in load and reference current.
– Harmonic analysis for different loads.
– Computational burden of ANN and MPC controller

The nominal parameters used in simulation are source voltage: 230 V, T_s of predictive algorithm: 10 μs, L_f: 400 μH, R_f: 0.5 Ω, C_f: 61 μF, R: 0.5 Ω, and L: 30 mH. The weighing factor λ as in (7) that results in reduction of input current THD and load current THD is $0.0045V^-1$ [25].

5.1. Harmonic analysis for different loads

Performance of ANN controller and MPC controller are listed in Table 2 for different load conditions. ANN controller is trained with only 6 conditions as in Table 1 and is able to achieve similar performance as that of MPC controller for the un-trained cases. Normally in model predictive control method, higher step prediction horizon increases computation burden but results with good performance. Hence data from MPC 2-step prediction horizon is used as training data to train ANN controller. Total harmonic distortion of MPC and ANN controller are almost similar and in most of the cases, ANN controller's source current harmonic is less on compared with MPC controller. The disadvantage of ANN controller is a slight increase in average switching frequency than MPC controller.

Table 2. Performance comparison of MPC and ANN controller

i_o^*	R	L	MPC-1 Step		MPC-2 Step		ANN	
			THD	$f_{sw(avg)}$	THD	$f_{sw(avg)}$	THD	$f_{sw(avg)}$
A	Ω	mH	%	kHz	%	kHz	%	kHz
12	5	18	2.23	12.2	2.09	12.4	1.85	12.4
9.5	8	25	1.91	12.8	1.98	13.02	1.58	13.05
11	5	20	2.49	13.2	2.52	13.6	2.06	13.6
9	5	20	4.24	12.19	3.27	12.58	3.05	12.9
8	7	23	3.75	12.04	2.47	12.3	2.28	12.1
9	7	23	2.44	12.5	2.24	12.9	2.12	12.7
10	6	20	2.40	12.8	2.33	13.2	2.21	13.2
6	12	25	33.28	10.5	3.31	9.6	2.42	9.7

5.2. Dynamic performance comparison of ANN and MPC controller

Performance of MPC and ANN controller are compared for sudden change in reference load current and for sudden change in load parameters. Figures 2 and 3 shows the dynamic performance in source and load current of ANN and MPC controller for sudden change in reference load current from 14 A to 9 A at 0.06 seconds. Similar performance is noted in both controller in terms of its dynamic response. ANN controller's peak overshoot at 0.06 seconds is quite less when compared with MPC controller as in Figure 2. Also in terms of harmonic analysis for source current, THD of MPC controller is 2.17% and ANN controller is 1.47% when reference load current is 14 A and 3.28% for MPC controller and 3.12% for ANN controller when reference load current is 9 A. In most of the cases, ANN controller outperforms MPC controller in harmonic performance of source current. Figures 4 and 5 shows the dynamic performance in source and load current of ANN and MPC controller for sudden change in R=5 Ω and L=20e^{-3} H to R=2.5 Ω and L=10e^{-3} H at 0.06 seconds. Similar performance is noted in both controller in terms of its dynamic response. Also in terms of harmonic analysis for source current, THD of MPC controller is 2.17% and ANN controller is 1.47% when reference R=5 Ω and L=20e^{-3} H and 3.35% for MPC controller and 3.13% for ANN controller when R=2.5 Ω and L=10e^{-3} H. The above results confirms that ANN controller can be a good alternative for MPC controller as the performance is similar and comparable. ANN controller is trained with $Q^* = 0$ as in (7) to maintain unity power factor. Source voltage and source current in Figure 6 are in-phase with the trained ANN controller.

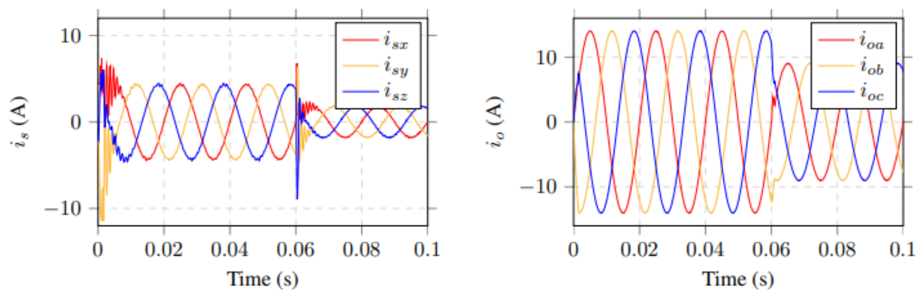


Figure 2. Source and load current for sudden change in reference load current from 14 A to 9 A at 0.06 seconds for R=5 Ω and L=20e^{-3} H in ANN controller

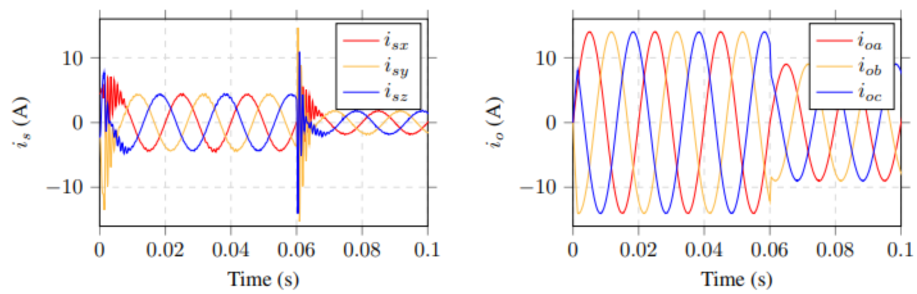


Figure 3. Source and load current for sudden change in reference load current from 14 A to 9 A at 0.06 seconds for R=5 Ω and L=20e^{-3} H in MPC controller

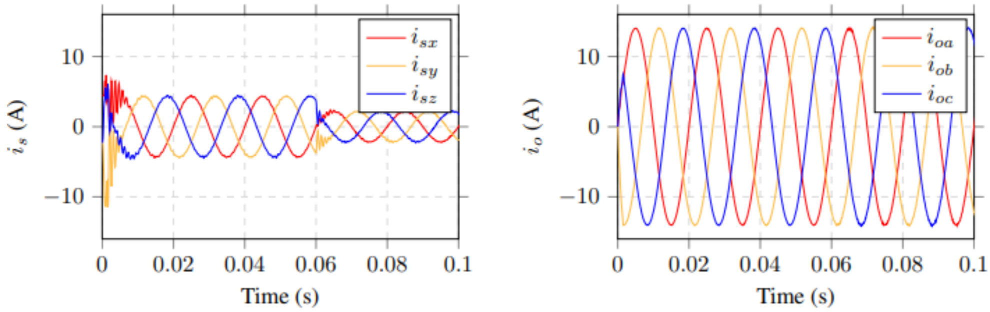


Figure 4. Source and load current for sudden change in R=5 Ω and L=20e^{-3} H to R=2.5 Ω and L = 10e^{-3} H in ANN controller

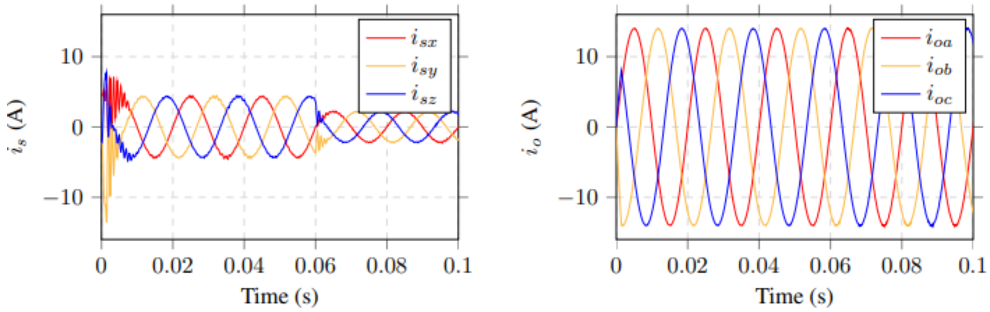


Figure 5. Source and load current for sudden change in R=5 Ω and L=20e^{-3} H to R=2.5 Ω and L=10e^{-3} H in MPC controller

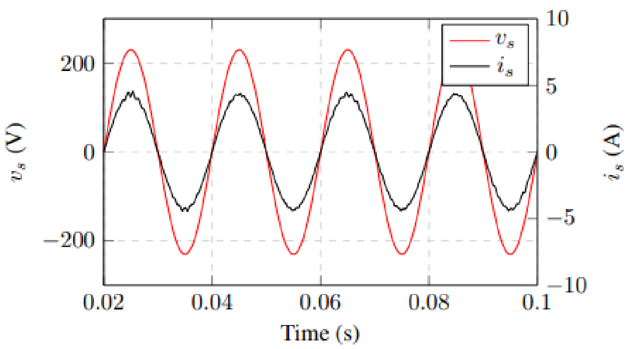


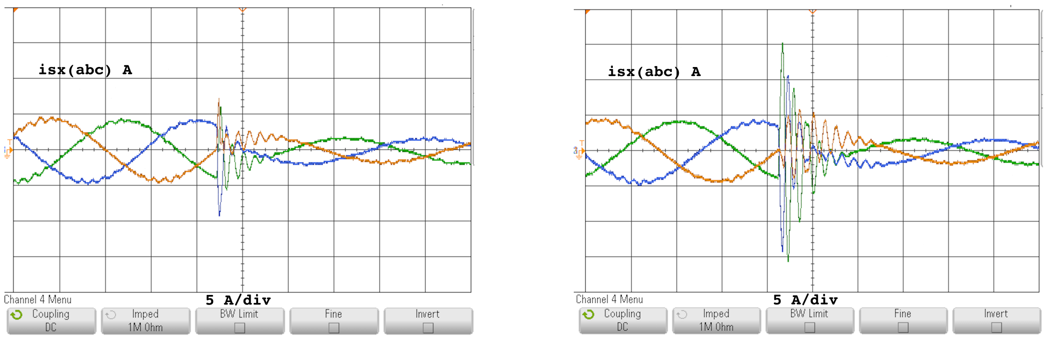
Figure 6. Source and load current in ANN controller for $Q^* = 0$

5.3. Computational burden of ANN and MPC controller

MPC controller calculates (5)-(7) for all possible 27 switching states and selects an optimal switching state for every instant. For a two step prediction horizon, MPC controller calculates (5)-(7) for 27*27 times. Whereas ANN controller has 45 units and 15 units in two hidden layers in which computational burden is quite lesser than MPC controller and shows a similar performance as that of MPC controller. To calculate computational burden, MATLAB profiling tools are used. ANN and MPC controller is simulated for 0.5 seconds in simulation time. The simulation execution time of whole MPC 2-step prediction horizon, MPC 1-step prediction horizon and ANN model are 24.27 seconds, 8.98 seconds, and 6.16 seconds respectively, of which the execution time of MPC 2-step controller, MPC 1-step controller and ANN are 14.62 seconds, 3.98 seconds, and 0.99 seconds respectively. This proves that ANN controller's computation burden is comparitively less when compared to MPC controller.

5.4. HIL validation of the proposed model

Further the model has been validated in hardware in-loop (HIL) simulation through OPAL-RT and presented in Figure 7. δI in source current for sudden change in reference load current as in Figure 7(a) is 10.6 A for ANN controller whereas δI in source current for sudden change in reference load current as in Figure 7(b) is 30.2 A for MPC controller. Dynamic performance of ANN controller is best in terms of peak overshoot.



(a) (b)

Figure 7. Results from HIL simulation - source current for sudden change in reference load current from 14 A to 9 A for R=5 Ω and L=20e^{-3} H in (a) ANN controller and (b) MPC controller

6. CONCLUSION AND FUTURE SCOPE

This paper evaluates the performance of machine learning based controller for matrix converter using model predictive control algorithm. A similar dynamic performance with sudden change in reference load current and with sudden change in load parameters are noted for ANN controller. The main advantage of ANN controller is reduction in harmonics in most of the tested cases, reduced peak overshoot during dynamic performance assessment and less computation burden. But ANN controllers suffers from slight increment in average switching frequency which may increase swicthing loss comparatively. The future improvement can be made by testing other advanced machine learning techniques in power converters.

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