NEURAL SWITCHING TABLES FOR A FOUR-LEVEL MULTICELLULAR INVERTER TO ENHANCE DIRECT TORQUE CONTROL OF A PMSM

BACHIR MOKHTARI[1], MOHAMED ALI MOUSSA[2]

This paper proposes neural switching tables (NCST, NRST) to improve direct torque control (DTC) of a permanent magnet synchronous motor (PMSM) driven by a four-level multicellular inverter (4LMI). Classical DTC suffers from high torque and flux ripples, which can cause mechanical stress and reduce reliability. The neural approach replaces conventional and reduced lookup tables with compact neural network models, allowing seamless integration in Simulink without large precomputed datasets. Simulation results confirm identical control behavior to that in classical tables, while reducing torque ripple by approximately 50% and maintaining flux within hysteresis limits. This solution enhances modularity, simplicity, and scalability, making it a promising step toward AI-based DTC strategies.

1. INTRODUCTION

Among control strategies for electric drives, Direct Torque Control (DTC) stands out for its fast dynamic response and structural simplicity, especially compared to Field-Oriented Control (FOC) [1–3]. However, a well-known drawback of classical DTC is the significant ripple in torque and flux, leading to adverse effects such as mechanical stress, magnet demagnetization, and acoustic noise [4–7].

To mitigate these drawbacks, three major improvement avenues have emerged: the use of multilevel inverters, the optimization of switching tables, and the introduction of advanced control techniques such as sliding mode control, predictive models, and adaptive methods [7–26]. While multilevel inverters are effective, they involve increased hardware complexity and cost.

Alternatively, a reduced switching table (RST) offers improved performance with lower computational demands. However, it often relies on large, precomputed tables stored externally to the control loop [8–13]. Recently, artificial intelligence (AI) techniques, including fuzzy logic, neural networks, and genetic algorithms, have been increasingly used to enhance DTC performance [20, 26–32]. Building upon this trend, we propose a novel neural-based approach to switching signal generation in a DTC scheme applied to a permanent magnet synchronous motor (PMSM) supplied by a four-level multicellular inverter.

This approach simplifies the control architecture, reduces dependency on lookup tables, and enhances integration within the control block.

2. SYSTEM MODELING AND CONTROL STRUCTURE

In the literature, several references can be found regarding the modelling of the PMSM. This motor has the same stator structure as an induction motor. However, it differs in its rotor, which consists of a permanent magnet that provides the main magnetic field. As a result, the equations describing the stator behaviour are similar for both machines, but in the case of the PMSM, there is no electrical coupling between the stator and the rotor; only magnetic coupling exists. The permanent magnet attached to the rotor generates a constant magnetic field [1,8,14,18–19,21,29].

DTC is a high-performance control strategy for AC machines, particularly effective in applications requiring fast torque and flux responses. The principle of DTC was initially introduced by Takahashi and Noguchi in the 1980s. Unlike traditional field-oriented control (FOC), which relies on coordinate transformations and current regulators, DTC achieves direct control of torque and stator flux without the need for a modulation block or inner current loops. The torque is controlled based on the stator magnetic flux and the instantaneous stator current drawn from the supply. This method offers a fast dynamic response, reduced complexity, and is widely used in industrial drives for induction and permanent magnet synchronous motors [2,3].

In this study, we use standard formulations for flux and torque estimation.

- *Stator Flux Components:*

$$\begin{cases} \psi_{s\alpha} = \int (v_{s\alpha} - R_s i_{s\alpha})\mathrm{d}t \\ \psi_{s\beta} = \int (v_{s\beta} - R_s i_{s\beta})\mathrm{d}t \\ |\psi_s| = \sqrt{\psi_{s\alpha}^2 + \psi_{s\beta}^2} \end{cases} \qquad (1)$$

- *Flux Angle:*

$$\theta = \arctan \frac{\psi_{s\beta}}{\psi_{s\alpha}} \qquad (2)$$

- *Sector Number (for 1 to 9):*

$$\text{sect} = \frac{\theta}{\left(\frac{2\pi}{9}\right)} \qquad (3)$$

- *Electromagnetic Torque:*

$$T_e = \frac{3}{2}p(\psi_{s\alpha}i_{s\beta} - \psi_{s\beta}i_{s\alpha}) \qquad (4)$$

The structure of the 4LMI and its delivered voltage vectors are presented in Fig. 1. The two switching tables CST and RST are used and detailed in [8]. The CST is based on the switching table initially used by [2] for a two-level inverter.
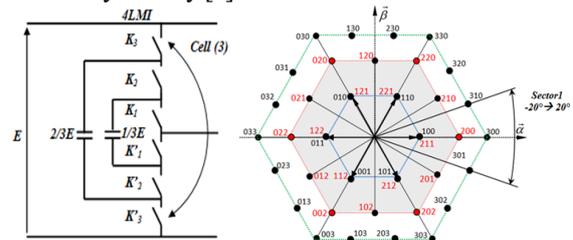
Fig. 1 – 4LMI structure and its space vector diagram [8].

The overall DTC control block diagram is illustrated in Fig. 2, and features estimators and a switching table that form the core decision-making mechanism for inverter signal generation.

[1]Faculty of Technology, University of Laghouat, Algeria. E-mail: ba.mokhtari@lagh-univ.dz / mokhtari71@yahoo.fr
[2]LGEER Laboratory, University of Chlef, Algeria. E-mail: m.alimoussa@univ-chlef.dz

Fig. 2 – Block diagram of the DTC control of PMSM under Simulink/Matlab.

3. NEURAL SWITCHING TABLE DESIGN

Artificial Neural Networks (ANNs), known for their pattern recognition and classification capabilities, are used to emulate both conventional and reduced switching tables. Using MATLAB's NNTOOL, we trained two networks: one for the conventional switching table, named here NCST, and one for the reduced switching table, named NRST.

A) DATA PREPARATION

The input vectors for both neural networks:
- For NCST: [flux deviation, torque deviation, sector];
- For NRST: [speed sign, flux deviation, torque deviation, sector].

The output vector encodes the states of the inverter's upper switches. Figures 3 and 4 depict sample input-output datasets.

Fig. 3 – Learning vectors for a CST.

Fig. 4 – Learning vectors for an RST.

B) NETWORK CONFIGURATION AND TRAINING

Each neural network comprises two layers:
1) *A hidden layer with a predefined number of neurons.*
2) *An output layer using linear activation for classification.*

We employed Generalized Regression Neural Networks (GRNN), suitable for this application due to the linear mapping between inputs and outputs.

Fig. 5 – Validation of the neural switching table.

The networks were trained using supervised learning. After training, the outputs were compared to those of the original switching tables. A rounding step was applied to the neural network outputs to ensure compatibility with binary switching states. Validation confirmed that the trained networks exactly replicate the original table outputs. Figure 5 shows that the gap between the target vector and the produced neural vector is zero, which confirms that the designed neural block is working correctly.

The final structure of the proposed neural network features two hidden layers, as depicted in the following figure:

Fig. 6 – Structure of the neural CST.

The method chosen to design this structure is very simple, comparable to that used by [13], who chose the *Levenberg–Marquardt backpropagation learning algorithm.*

Although this method is fast, GRNN is simpler and faster and does not require any adjustment or change in the number of neurons and/or hidden layers.

C) INTEGRATION INTO CONTROL SCHEME

Using MATLAB's "genism" function, trained networks were converted into Simulink blocks.

Figure 7 shows the control architecture, enabling toggling between neural switching tables (4LMI_NRST and 4LMI_NCST) at the top of the diagram and the classical tables (4LMI_RST and 4LMI_CST) at the bottom.

Fig. 7 – Block diagram for generating switching signals.

4. STUDY RESULTS AND DISCUSSION

To validate the proposed method, we use the PMSM whose parameters are given in Table 1.

The motor was subjected to a test scenario:

- t = 0–0.1 s   : No load.
- t = 0.1 s   : Load of 6 Nm applied.
- t = 0.15 s   : Motor reversal.
- t = 0.2 s   : Switching from CST to RST and from NCST to NRST.

Table 1

PMSM Parameters

Pole pairs	4
Stator resistance (Ω)	1.09
Stator inductances (L_d; L_q) (H)	0.0124
Permanent magnet flux (Wb)	0.1821
Inertia (Kg.m²)	4.15×10^{-4}
Viscous friction coefficient (Pa.s)	9×10^{-4}

The simulation parameters are listed in Table 2.

Table 2

Control Parameters

The speed PI controller gains	Kp =0.53, Ki=52
Speed references (rad/s)	+200, -200
DC bus Voltage (V)	700
The torque hysteresis bands	$6 \times 10^{-3}, 3 \times 10^{-3}, 15 \times 10^{-4}$
The flux hysteresis band	10^{-3}
Sample time (s)	10^{-5}

In future simulations involving a different motor, these parameters must be adjusted, particularly the speed PI controller gains, the DC bus voltage, and the flux and speed reference values to be achieved by the motor. To know the effectiveness of the proposed neural system, the performance is compared with that of the conventional and the reduced switching tables. Results (Fig. 8 to 10) compare the system behaviour under classical and neural control.

1) Flux Control: Magnetic flux remains within hysteresis bounds around its reference 0.3Wb in Fig. 8; this result shows the decoupling between the magnetic flux and the electromagnetic torque that the DTC imposes.

2) Torque Response: The CST and RST switching tables and the neural-based NCST and NRST switching tables result in the production of the same electromagnetic torque; in Fig. 9, RST and NRST both significantly reduce torque ripple by approximately 50% compared to CST/NCST.

3) Speed Response: Stable dynamics observed, particularly during reversal. Although a step reference is not representative of real-world scenarios, the system demonstrates in Fig. 10 excellent tracking performance and dynamic stability during speed reversals.

These results confirm those obtained by [8–9] where the RST considerably reduces the magnetic torque ripples but very little those of the stator magnetic flux of different motors.
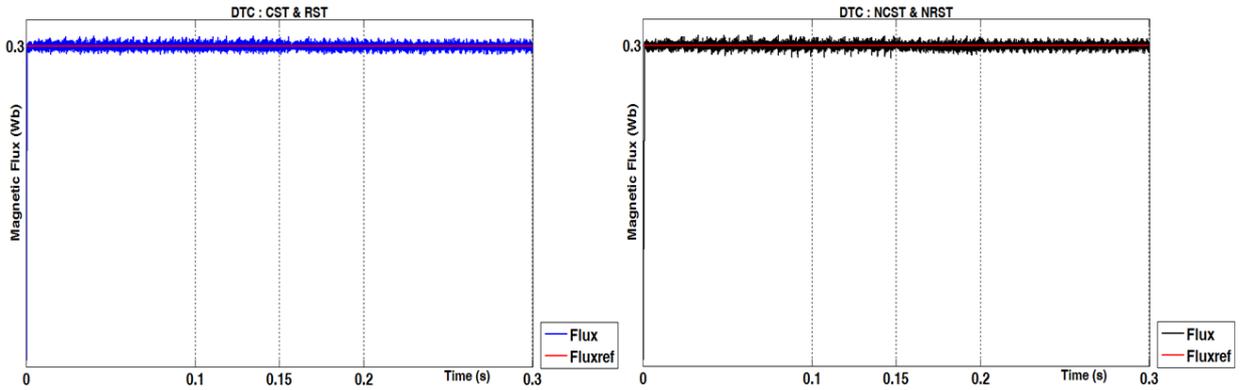
Fig. 8 – Evolution of the stator magnetic flux.
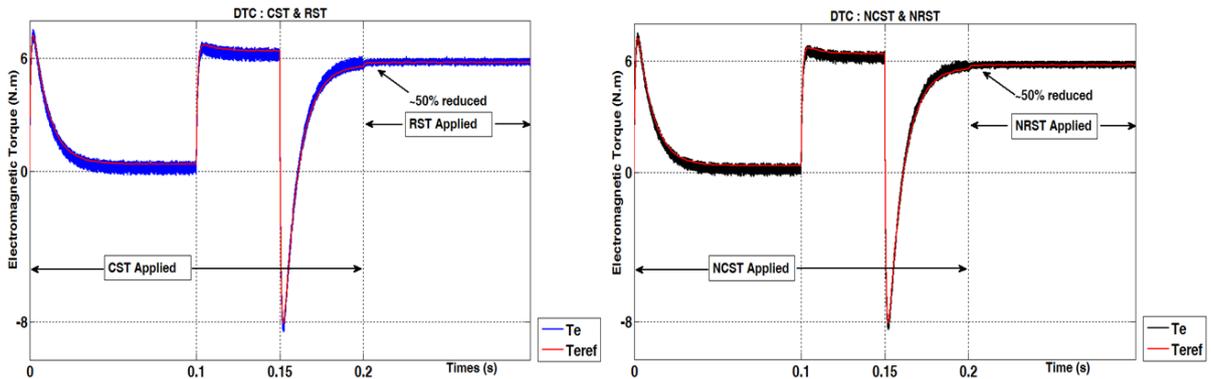
Fig. 9 – Evolution of the electromagnetic torque.
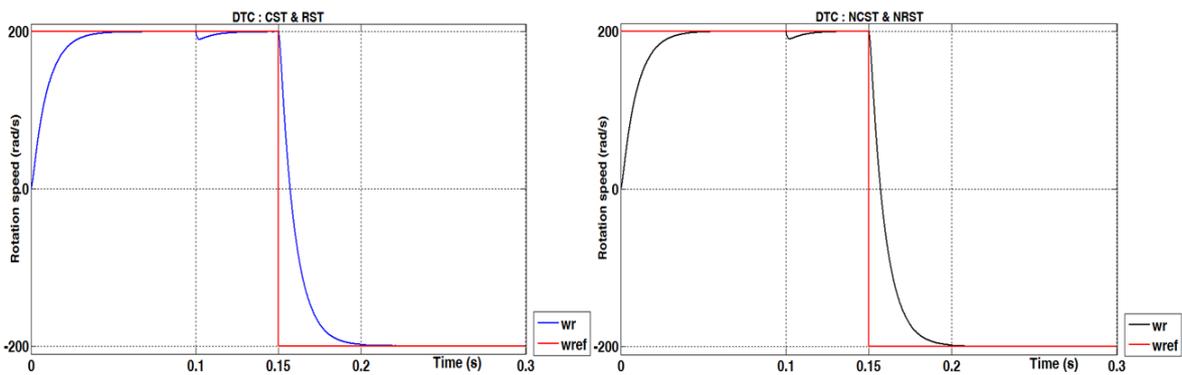
Fig. 10 – Evolution of the rotation speed of the PMSM.

These results confirm that neural tables are functionally equivalent to their classical counterparts, with added advantages of reduced complexity and seamless block-level integration. We can therefore conclude that the objective of this proposal has been achieved and that the neural blocks of the CST and the RST can be used for any DTC implementation associated with a four-level multicellular inverter.

5. CONCLUSION

This study presented a modular and computationally efficient neural-network-based replacement for conventional and reduced switching tables in a four-level multicellular

inverter DTC scheme applied to a PMSM. The proposed neural CST and RST architectures demonstrated identical control performance to their table-based counterparts, with torque ripple reductions of around 50% and flux ripple reductions consistent with classical RST performance.

Beyond preserving control quality, the neural approach offers significant architectural advantages: compact Simulink integration, elimination of large external lookup files, and simplified adaptation to system changes. These benefits directly address the scalability and maintainability challenges of traditional DTC implementations, particularly in complex multilevel inverter systems.

Future work will focus on experimental validation, extending the neural approach to flux, torque, and position estimation, and benchmarking against other AI-driven DTC enhancements, including deep learning and reinforcement learning frameworks. This will pave the way toward a fully AI-based DTC platform, combining high-performance motor control with adaptive intelligence for diverse industrial and transportation applications.

CREDIT AUTHORSHIP CONTRIBUTION

B. Mokhtari: Original draft, Methodology, Writing, Simulation, Result Analysis, Review, Editing.
M. Ali Moussa: Methodology, Result Analysis, Review, Editing.

REFERENCES

1. S. Taa, B. Mokhtari, *Proposal of an optimal control of an electric vehicle by combined FOC and DTC techniques*, Electrica, **24**, *3*, pp. 660–669 (2024).
2. I. Takahashi, T. Noguchi, *A new quick-response and high-efficiency control strategy of an induction motor*, IEEE Trans. Ind. Appl., **IA-22**, *5*, pp. 820–827 (1986).
3. M. Depenbrock, *Direct self-control (DSC) of inverter-fed induction machine*, IEEE Trans. Power Electron., **3**, *4*, pp. 420–429 (1988).
4. A.T. Siti Azura, J. Auzani, M.J. Mohd Luqman, A.K. Kasrul, S. Tole, *A review of direct torque control development in various multilevel inverter applications*, International Journal of Power Electronics and Drive System (IJPEDS), **11**, *3*, pp. 1675–1688 (2020).
5. J.K. Kang, D.W. Chung, S.K. Sul, *Direct torque control of induction machine with variable amplitude control of flux and torque hysteresis bands*, IEEE International Electric Machines and Drives Conference (IEMDC), Seattle, WA, USA, pp. 640–642 (1999).
6. S.S. Hakami, K.B. Lee, *Four-level hysteresis-based DTC for torque capability improvement of IPMSM fed by three-level NPC inverter*, Electronics, **9**, *10*, 1558 (2020).
7. B. Mokhtari, M.F. Benkhoris, *High ripples reduction in DTC of induction motor by using a new reduced switching table*, Journal of Electrical Engineering, **67**, *3*, pp. 206–211 (2016).
8. B. Mokhtari, *Enhancement ripples of a direct torque control applied to a permanent magnet synchronous motor by using a four-level multicellular inverter and a new reduced switching table*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **69**, *2*, pp. 207–212 (2024).
9. K. Lv, Z. Xie, M. Zhou, J. Bu, *A comparative study of three starting strategies for an aero flywheel motor using the modified DTC method*, IEEE Access, **7**, pp. 59548–59558 (2019).
10. R.E. Kodumur Meesala, V.K. Thippiripati, *An improved direct torque control of three-level dual inverter fed open-ended winding induction motor drive based on modified look-up table*, IEEE Trans. Power Electron., **35**, *4*, pp. 3906–3917 (2020).
11. F. Yashar, M. Alzayed, H. Chaoui, S. Kelouwani, *A novel switching table for a modified three-level inverter-fed DTC drive with torque and flux ripple minimization*, Energies, **13**, *18*, pp. 4646 (2020).
12. C.A. Martins, X. Roboam, T.A. Meynard, A.S. Carvalho, *Switching frequency imposition and ripple reduction in DTC drives by using a multilevel converter*, IEEE Trans. Power Electron., **17**, *2*, pp. 286–297 (2002).
13. B. Mokhtari, *Intelligent DTC applied to the control of the asynchronous machine*, Dissertation, University of Batna2, Algeria (2014).
14. B.D. Lemma, S. Pradabane, *Control of PMSM drive using lookup table-based compensated duty ratio optimized direct torque control (DTC)*, IEEE Access, **11**, pp. 19863–19875 (2023).
15. J. Zhang, L. Li, D. Dorrell, Y. Guo, *Direct torque control with a modified switching table for a direct matrix converter-based AC motor drive system*, 20th International Conference on Electrical Machines and Systems (ICEMS), Sydney, NSW, Australia, pp. 1–6 (2017).
16. S.V. Bhangale, R. Kumar, K. Bhangale, *18-sector direct torque controlled strategy with improved stator flux estimator for induction motor drive*, 8th IEEE India International Conference on Power Electronics (IICPE), Jaipur, India, pp. 1–6 (2018).
17. M.M. Alshbib, I.M. Alsofyani, M.M. Elgbaily, *Enhancement and performance analysis for modified 12 sector-based direct torque control of AC motors: experimental validation*, Electronics, **12**, *3*, pp. 549 (2023).
18. T.L. Le, M.F. Hsieh, *An enhanced direct torque control strategy with composite controller for permanent magnet synchronous motor*, Asian Journal Control, **26**, *4*, pp. 1683–1702 (2024).
19. A. Adam, A. Elnady, *Adaptive steering-based HDTC algorithm for PMSM*, Asian Journal Control, **23**, *1*, pp. 209–227 (2021).
20. A. Ammar, B. Talbi, T. Ameid, Y. Azzoug, A. Kerrache, *Predictive direct torque control with reduced ripples for induction motor drive based on T-S fuzzy speed controller*, Asian Journal Control, **21**, *4*, pp. 2155–2166 (2019).
21. C. Ortega, A. Arias, J. Espina, *Predictive direct torque control of matrix converter fed permanent magnet synchronous machines*, Asian Journal Control, **16**, *1*, pp. 70–79 (2014).
22. O. Moussa, L. Hellali, S. Belhamdi, *Direct torque control with space vector modulation using interval type 2 fuzzy logic regulators of dual star induction machine fed by two three-level neutral point clamped inverter*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **69**, *2*, pp. 159–164 (2024).
23. V.B.R., S. G, *Direct torque control scheme for a four-level-inverter-fed open-end-winding induction motor*, IEEE Trans. Energy Convers., **34**, *4*, pp. 2209–2217 (2019).
24. F. Khoucha, S.M. Lagoun, K. Marouani, A. Kheloui, M.E.H. Benbouzid, *Hybrid cascaded H-bridge multilevel-inverter induction-motor-drive direct torque control for automotive applications*, IEEE Trans. Ind. Electron., **57**, *3*, pp. 892–899 (2010).
25. M.F. Escalante, J.C. Vannier, A. Arzande, *Flying capacitor multilevel inverters and DTC motor drive applications*, IEEE Trans. Ind. Electron., **49**, *4*, pp. 809–815 (2002
26. O. Moussa, L. Hellali, S. Belhamdi, *Direct torque control with space vector modulation using interval type 2 fuzzy logic regulators of dual star induction machine fed by two three-level neutral point clamped inverter*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **69**, *2*, pp. 159–164 (2024).
27. A.E. Idrissi, A. Derouich, S. Mahfoud, N. El Ouanjli, A. Chantoufi, M.I. Mosaad, *Asynchronous motor bearing fault diagnosis and speed control using fuzzy logic-based direct torque controller*, Electrica, **25**, 0121 (2025).
28. R. Belal, M. Flitti, M.L. Zegai, *Tuning of PI speed controller in direct torque control of dual star induction motor based on genetic algorithms and neuro-fuzzy schemes*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **69**, *1*, pp. 9–14 (2024).
29. A. Tlemçani, *Contribution to the application of adaptive controls by fuzzy systems to a synchronous machine with permanent magnets fed by a serial multicellular converter*, Dissertation, National Polytechnic School, Algeria (2007), available online, last accessed August 2025.
30. H. Sudheer, S.F. Kodad, B. Sarvesh, *Improvements in direct torque control of induction motor for wide range of speed operation using fuzzy logic*, Journal of Electrical Systems and Information Technology, **5**, *3*, pp. 813–828 (2018).
31. D. Boudana, L. Nezli, A. Tlemçani, M. Mahmoudi, M. Tadjine, *Robust DTC based on adaptive fuzzy control of double star synchronous machine drive with fixed switching frequency*, Journal of Electrical Engineering, **63**, *3*, pp. 133–143 (2012).
32. A. Chikhi, K. Chikhi, B. Sebti, *Induction motor direct torque control – fuzzy logic contribution*, Electrica, **10**, *2*, pp. 1207–1212 (2010).