GENERALIZED SWITCHING TABLE OF THE DTC OF AN INDUCTION MOTOR DETERMINED BY REINFORCEMENT LEARNING

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This paper proposes a new method of reinforcement learning. (RL) method based on Q learning algorithm applied to the direct torque control (DTC) of an induction machine powered by a multilevel inverter. The Q-learning algorithm is used in direct torque control with multilevel inverters to find optimal actions at data states off-line among several available discrete actions, updating the action (voltage vector) awards received. The results obtained by the reinforcement learning (RL) method are validated by simulation using Matlab/Simulink. The generalization of this approach to N levels without any difficulty (increase of the level of inverter and therefore of the number of voltage vectors to be selected) gives the reinforcement learning method an appreciable advantage. It makes it possible to determine the switching table automatically regardless of the number of voltage levels of the inverter used.

Keywords: Direct torque control, multi-level inverter, voltage balancing, control of switching frequency, reinforcement learning, Q-learning.

1. Introduction

The direct control techniques were originally based on a qualitative and simplified knowledge of the behavior of the machine. Their characteristics are based on the elimination of the modulation block in Pulse Width, the definition of switchboards from which are chosen "directly" the voltage vectors and the hysteresis adjustment of the torque and the stator flux [1]. The implementation of these algorithms was therefore simpler, at a time when the computer resources continued to grow in power and speed.

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Simultaneously, new and promising static multilevel conversion topologies have been proposed and increasingly used in high power variable speed drive applications. Compared to conventional 2-level structures, in which the output voltage can be modulated only by varying the duration of use of the high and low state, Pulses Width Modulation (PWM). Multilevel structures indeed open a new dimension to the amplitude modulation. So, in the present study, our main objective is to propose new strategies of the direct control type, compatible with multilevel voltage inverters more particularly the Neutral Point Clamped (NPC) having any number of levels.

The development of the switching table consists of formulating linguistic rules in which the process will be controlled. However, there is no general principle to determine them systematically determining them. This problem can be addressed into two ways. The first is called natural extraction, is done through a human expert familiar within the system. As part of this study, the formulation of the rules is thus based on a qualitative analysis of the vector diagram of the (DTC).

However, this analysis becomes rapidly imprecise and complex as the number of voltage levels increases and the problem of the optimized choice of inverter voltage vectors must therefore be studied more precisely and deeply.

The second approach is used when natural extraction is not feasible in its entirety. It consists of using learning methods. In our research paper, we have focused on reinforcement learning methods that actively explore all states and receive criticism in the form of rewards and punishments. Reinforcement learning means routing from situation to action in a way that the numerical reward of the action is in the maximum. In this method the learner is not told what to do, but he tries to discover the action with maximum reward [2]. Therefore, reinforcement learning methods is signified by Q-Learning algorithm [3]. This algorithm is used by the agent to learn through experience or training.

Every repetition equals a training course. Its aim is to create the brain of the agent, which is displayed by Q matrix. More training will lead to a better Q matrix that can be used by the agent to move in the optimal direction. In this way, by having a Q matrix, the agent can choose the best state by referring to the state matrix and selecting the maximum choice, rather than doing a lot of exploration and searching [4].

To designate this system, the study will deal with controlling induction motor drive. It is assumed that the agent has no information about the drive system. It means the agent can collect states and actions of the system during the real behavior of the motor.

The structure of the presented work is organized as follow: the description of the proposed approach is set in section 2. The physical modeling and control of different part of our system with their equations model is set in section 3, 4, 5, 6, 7 and 8. The simulation results of the studied are presented in section 9. Section 10 summarizes the work done in the conclusion.

2. Proposed approach

In any generalization of direct control strategies, the problem of the optimized choice of inverter voltage vectors must therefore be studied more precisely and more thoroughly.

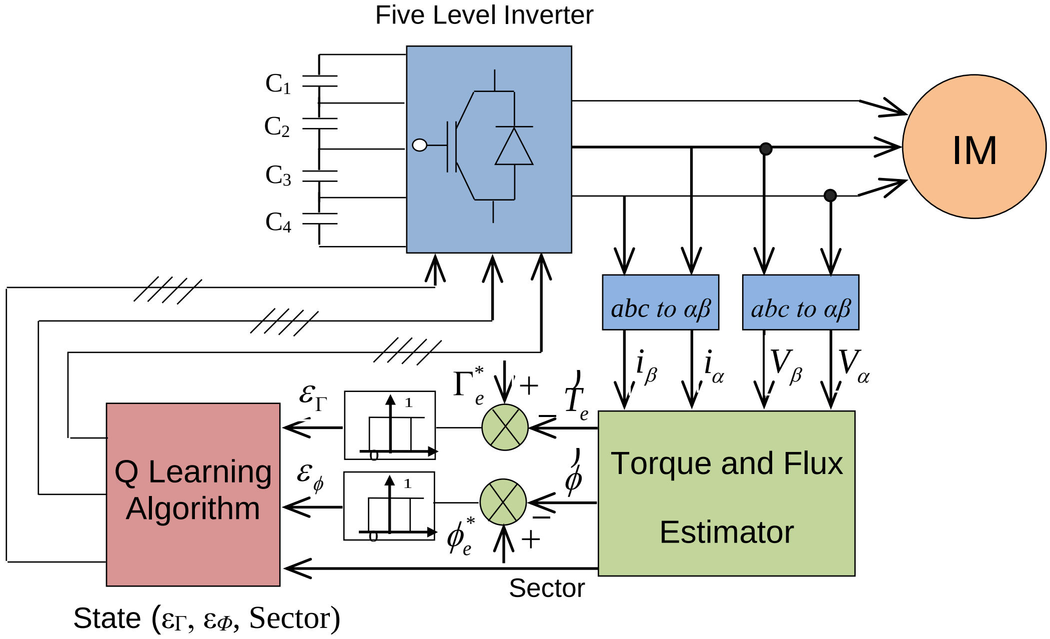

Fig. 1. Schematic diagram of the proposed Q learning approach

We propose in this study, a method of learning based on the method of reinforcement which makes it possible to determine the optimal vector of tension for the tables of commutation used in the direct control of the torque of an asynchronous machine fed by a multilevel inverter. We will show the interest of this approach for a five-level inverter as show in Fig. 1.

3. Dynamic Model of IM

The state space representation of the induction motor with the stator currents and the rotor flux linkages components as state variables can be written as [5]:

$$\begin{bmatrix} \frac{d}{dt}i_{sd} \\ \frac{d}{dt}i_{sq} \\ \frac{d}{dt}\phi_{rd} \\ \frac{d}{dt}\phi_{rq} \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma T_r}\right) & 0 & \frac{L_m}{\sigma L_s L_r T_r} & \left(\frac{L_m}{\sigma L_s L_r}\right).\omega_r \\ 0 & -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma T_r}\right) & -\left(\frac{L_m}{\sigma L_s L_r}\right).\omega_r & \frac{L_m}{\sigma L_s L_r T_r} \\ \frac{L_m}{T_r} & 0 & \frac{-1}{T_r} & p\omega_r \\ 0 & \frac{L_m}{T_r} & -p\omega_r & \frac{-1}{T_r} \end{bmatrix} \begin{bmatrix} i_{sd} \\ i_{sq} \\ \phi_{rd} \\ \phi_{rq} \end{bmatrix}$$
$$+\begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{sd} \\ v_{sq} \end{bmatrix} \tag{1}$$

where:

T_r : is the rotor time constant;

σ : is the leakage coefficient.

The electromagnetic torque and the rotor speed are given by:

$$\Gamma_{em} = \frac{3}{2} p \frac{L_m}{JL_r} (\phi_{rd} i_{sq} - \phi_{rq} i_{sd}) \tag{2}$$

$$\frac{d\omega_r}{dt} = \frac{p}{J}\Gamma_{em} - \frac{B}{J}\omega_r - \frac{p}{J}\Gamma_l \tag{3}$$

where:

R_s, R_r : are the stator and rotor winding resistances (Ω);

L, L_s, L_r : are the mutual, stator and rotor inductance (H);

p : is the number of pole pairs;

ω_e, ω_r, ω_{sl} : are the synchronous, rotor and slip speed in electrical (rad/s);

v_{sd}, v_{sq} : are the stator voltage (*d*-*q*) components in the rotor flux oriented reference frame (V) ;

i_{sd}, i_{sq} : are the stator current (*d*-*q*) components in the rotor flux-oriented reference frame (A);

ϕ_{rd}, ϕ_{rq} : are the rotor flux (*d*-*q*) components in the rotor flux-oriented reference frame (Wb);

Γ_{em} : is the electromagnetic torque (N.m);

Γ_l : is the load torque (N.m);
J : is the motor inertia (Kg.m^2);
B: is the viscous friction coefficient respectively (N.m/rad/sec).
The induction machine parameters used in this system is shown in table 1.

Table 1

Induction Motor Parameters

Components	Rating values
Voltage V	400 V
Sample period *Te*	50 µs
Rated power	7.5 kW
Rated voltage	460 V
Rated speed	1760 rpm
Rated frequency	60 Hz
Rotor resistance	0.451 Ω
Stator resistance	0.6837 Ω
Stator inductance	0.004152 H
Rotor inductance	0.004152 H
Magnetizing Inductance	0.1486 H
Number of poles	2
Rotor inertia	0.05 Kg.m^2
Friction Coefficient	0.008141 N.m.s/rd

4. Modeling of Five Level Inverter

The Q-Learning algorithm is used to determine the optimal actions for each state, it is then determined deterministically and non-randomly (difference with the previous flowchart) according to an exploitation term (the quality of the action) and an exploration term based on a counter measuring the frequency of application of actions in the states and the apprentice then favors actions little tested.

A two-level inverter is only able to produce six non-zero voltage vectors and two zero vectors [6, 7]. The representation of the space voltage vectors of a five-level inverter for all switching states forming a four-layer hexagon centered at the origin of the (d, q) plane and a zero-voltage vector at the origin of the plane, as depicted in Fig. 2. According to the magnitude of the voltage vectors, we divide them into nine groups:

(V_0); (V_1, V_{11}, V_{21}, V_{31}, V_{41}, V_{51}); (V_7, V_{17}, V_{27}, V_{37}, V_{47}, V_{57}) ; (V_2, V_{12}, V_{22}, V_{32}, V_{42}, V_{52}); (V_6, V_9, V_{16}, V_{19}, V_{26}, V_{29}, V_{36}, V_{39}, V_{46}, V_{49}, V_{56}, V_{59}); (V_3, V_{13}, V_{23}, V_{33}, V_{43}, V_{53}); (V_8, V_{18}, V_{28}, V_{38}, V_{48}, V_{58}); (V_5, V_{10}, V_{15}, V_{120}, V_{25}, V_{30}, V_{35}, V_{40}, V_{45}, V_{50}, V_{55}, V_{60}); (V_4, V_{14}, V_{24}, V_{34}, V_{44}, V_{54}).

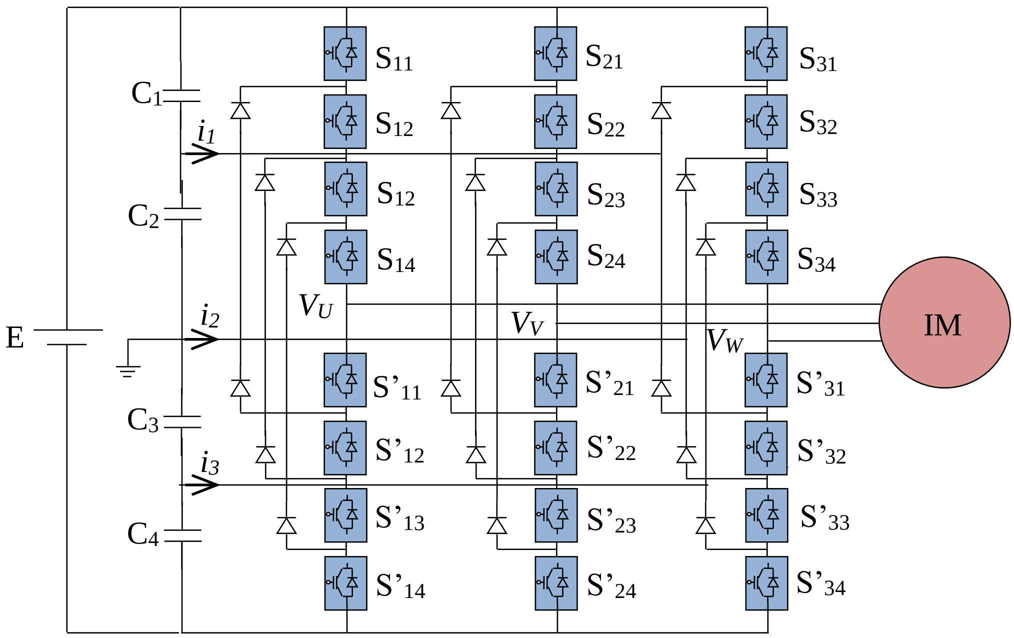

Fig. 2. Five level inverter

The Zero Voltage Vector (ZVV) has five switching states, the Large Voltage Vector (LVV) have only one [8].

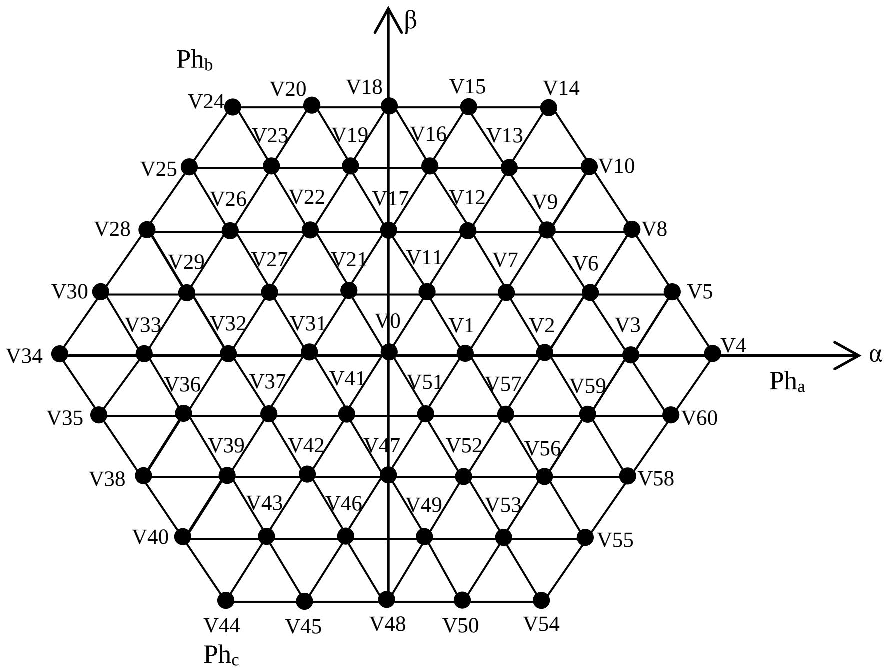

Fig. 3. Topology of the 61 vectors generated by a NPC structured five level inverter

Table 2

Switch states of the five levels NPC inverter

State	S_{11}	S	S	S	S	S	S	S	V
2	ON	ON	ON	ON	OFF	OFF	OFF	OFF	$\frac{E_d}{4}$
1	OFF	ON	ON	ON	ON	OFF	OFF	OFF	$\frac{E_d}{2}$
0	OFF	OFF	ON	ON	ON	ON	OFF	OFF	0

5. Flux and torque Estimator

The (*d-q*) axes stator flux linkage is estimated by computing the integral of difference between the respective (*d-q*) input voltage and the voltage drop across the stator resistance.

$$\phi_{sd} = \int\left(-R_s i_{sd} + v_{sd}\right)dt \tag{4}$$

$$\phi_{sq} = \int\left(-R_s i_{sq} + v_{sq}\right)dt \tag{5}$$

The resultant stator flux linkage can be expressed as:

$$\phi = \sqrt{\phi_{sd}^2 + \phi_{sq}^2} \tag{6}$$

The location of the stator flux linkage should be known so that the appropriate voltage vector is selected depending upon the flux location.

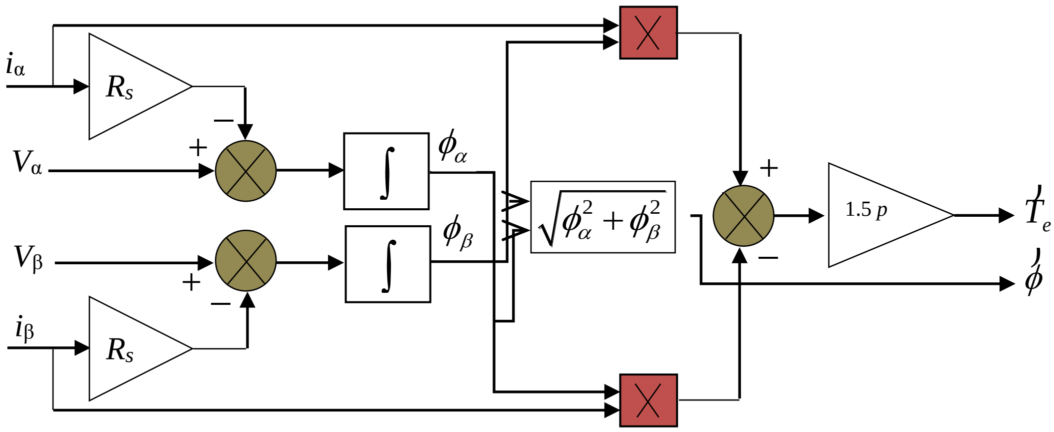

Fig. 4. Torque and flux estimation

6. Torque and flux control

The main objective is to define optimal selection rules for voltage vectors based on the torque and flux error defined as follows:

$$\varepsilon_\phi = \phi_{sref} - \phi_s \tag{7}$$

$$\varepsilon_{\Gamma} = \Gamma_{ref} - \Gamma_{em} \tag{8}$$

For the control of the flux, the error (ε_{ϕ}) is localized in one of the three associated intervals and which are fixed by the constraints:

$$\begin{aligned}
&\varepsilon_{\phi} < \varepsilon_{\phi\max} \\
&\varepsilon_{\phi\min} \le \varepsilon_{\phi} \le \varepsilon_{\phi\max} \\
&\varepsilon_{\phi} > \varepsilon_{\phi\min}
\end{aligned} \tag{9}$$

The level of the suitable flux is bounded between ($\varepsilon_{\phi\min}$) and ($\varepsilon_{\phi\max}$), is therefore controlled by a two-level hysteresis comparator. The electromagnetic torque is equal to the load torque in the steady state. It is then the most important variable for the electromagnetic considerations of training. Therefore, high performance for torque control is required. To improve the control of the torque, we associate with the error of the pair (ε_{Γ}) five regions defined by the following constraints:

$$\begin{aligned}
&\varepsilon_{\Gamma} > \varepsilon_{\Gamma\min 2} \\
&\varepsilon_{\Gamma\min 2} \le \varepsilon_{\Gamma} \le \varepsilon_{\Gamma\min 1} \\
&\varepsilon_{\Gamma\min 1} \le \varepsilon_{\Gamma} \le \varepsilon_{\Gamma\max 1} \\
&\varepsilon_{\Gamma\max 1} \le \varepsilon_{\Gamma} \le \varepsilon_{\Gamma\max 2} \\
&\varepsilon_{\Gamma\max 2} < \varepsilon_{\Gamma}
\end{aligned} \tag{10}$$

The torque control is here ensured by a hysteresis comparator with two upper bands $(\varepsilon_{\Gamma\max 1}, \varepsilon_{\Gamma\max 2})$ and two lower bands $(\varepsilon_{\Gamma\min 1}, \varepsilon_{\Gamma\min 2})$ illustrated by the Fig. 5.

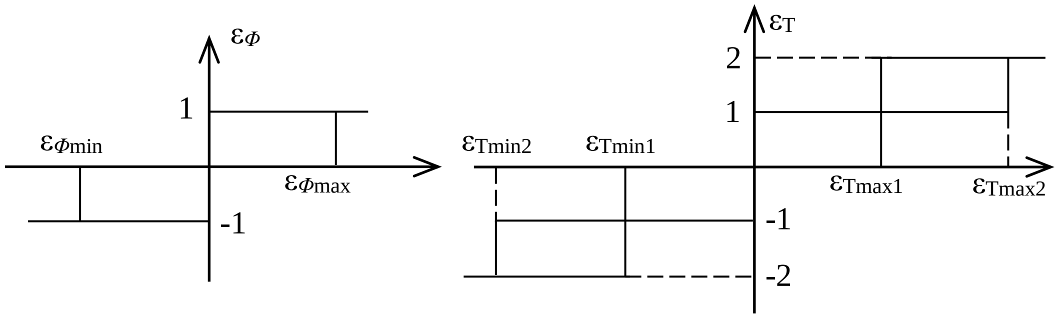

Fig. 5. Hysteresis blocks of the DTC with NPC inverter

The best margin of the control of the pair is that localized by $\left(\varepsilon_{\Gamma\min 1}, \varepsilon_{\Gamma\max 1}\right)$ and the region bounded by $\left(\varepsilon_{\Gamma\min 2}, \varepsilon_{\Gamma\max 2}\right)$ should give useful values of the couple.

7. Proposed Q Learning Algorithm

Q-Learning is the most used reinforcement learning algorithm. Three main functions participate in Q-Learning: an evaluation function, a reinforcement function and an update function (Fig. 6). From the current situation as it is perceived by the system, the "evaluation function" proposes an action based on the knowledge available within the internal memory. This knowledge is stored as an utility value associated with a pair (situation, action). The selected action is the one with the best probability of positive reinforcement (reward). This proposal action proposal is however altered to allow the exploration of the space of the situation-action pairs [9, 10].

Here the flux and torque estimators are used to determine the actual value of torque and flux linkages. In this block, the VSI voltage vector is entered in and it is transformed to the d-q stationary reference frame. The three variable phases are transformed into the (*d*-*q*) axes variables [11].

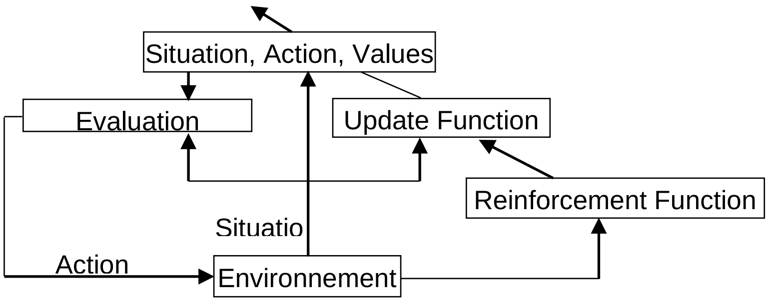

Fig. 6. Principle of the Q-Learning method

8. Application Q Learning Algorithm

The Q-Learning algorithm is used to determine the optimal actions for each state, it is determined deterministically and non-randomly (difference with conventional methods) according to an exploitation term (quality of the action) and an exploration term based on a counter measuring the frequency of application of the actions in the states and the apprentice then favors the actions little tested. We use three inputs (torque error, flux error and sector) each input having respectively nine, three and six states, the output contains 61 vector voltages (actions) and initially the switching table is empty and the objective of the learning method to fill the states where we must find the actions are as follows:

If (ccpl is A_i) et (cflx is B_j) and (N is C_k) So (The output is V_{ii})

where:

Ai : is the state of the torque error (4,3,2, 1, 0, -1, -2,-3,-4)(i=1 :9)
Bj : is the state of the flux error (1,0,-1) (j=1 :3)
Ck : is the sector where the flux vector is (k=1 : 6)
Vii is the action elected in each rule from a set A of available actions (distinct vectors) (ii=1 :61)

- **Possible states**

There are totally 162 possible states (9 × 3 × 6), whose learning method should find their optimal actions. In this case it has a new switching table that has not yet studied in our work.

- **The reinforcement function**

The first reinforcement function used is defined as follows:

if (error_flux<=0.1) & (error_flux>=-0.1) & (error_torque<=3) & (error_torque>=-3)
    Reward= 10;
else
    Reward= -1;
End

9. Simulation Results

9.1. The switching table found

The tables (θ1 to θ6) give the actions chosen for each state after the learning has been completed. The policy consists in choosing only the actions with the maximum qualities (t-optimal actions).

Table 3

Switching table found by the Q Learning method

$\theta 1$

ε_T \ ε_ψ	1	0	-1
4	V14	V14	V22
3	V51	V51	V12
2	V51	V2	V51
1	V12	V	V22
0	V4	V28	40
-1	V1	V2	V
-	V11	V21	V3
-3	V11	V41	V12
-4	V4	V 4	V40

$\theta 2$

ε_T \ ε_ψ	1	0	-1
4	24	V29	V39
3	13	V42	V52
2	V42	V21	V42
1	V3	V51	V43
0	V20	V29	V43
-1	V51	V11	V13
-2	V21	V21	V22
-3	V21	V41	V2
-4	V8	V37	V60

$\theta 3$

ε_T \ ε_ψ	1	0	-1
4	26	V32	43
3	V 1	31	V52
2	V1	V21	V52
1	V12	V31	V53
0	V24	V22	V54
-1	V1	V48	V33
-2	V11	V1	V51
-3	V11	V1	V51
-4	V53	V23	V2

$\theta 4$

ε_T \ ε_ψ	1	0	-1
4	V37	V5	V3
3	V11	V3	51
2	V 1	V33	V 1
1	V31	V11	V5
0	V34	V33	V14
-1	V 1	V1	V31
-2	V59	V11	V11
-3	V1	V11	V8
-4	V33	V21	V0

$\theta 5$

ε_T \ ε_ψ	1	0	-1
4	V54	V50	V4
3	V53	V52	V3
2	V52	V22	V2
1	V51	V51	V1
0	V49	V46	V17
-1	V31	V31	V21
-2	V32	V1	V22
3	V33	V32	V23
-4	V34	44	V2

$\theta 6$

ε_T \ ε_ψ	1	0	-1
4	V54	V8	18
3	V57	V23	V52
2	V51	V53	V3
1	V1	V 1	V26
0	V42	V 2	V24
-1	V1	V41	V21
-2	V1	V11	V1
-3	V1	V1	V1
-4	V41	V4	V21

9.2. Validation of obtained switching table and discussions

To verify the technique proposed in this paper, digital simulations based on Matlab/Simulink have been implemented.

A step change of reference torque was applied between different times 0.2 s, 0.4 s, 0.6 s and 0.8 s. Motor started up by no-load then after 0.1 s, a different values of torque are applied respectively 35 N.m, 65 N.m, 50 N.m, -35 N.m and 50 N.m. Torque, flux amplitude, three phase currents and stator voltage according to time are showed in Fig. 7 and Fig. 8. Fig. 7 shows that switching states has become more regular and also torque ripple is less using Q learning algorithm.

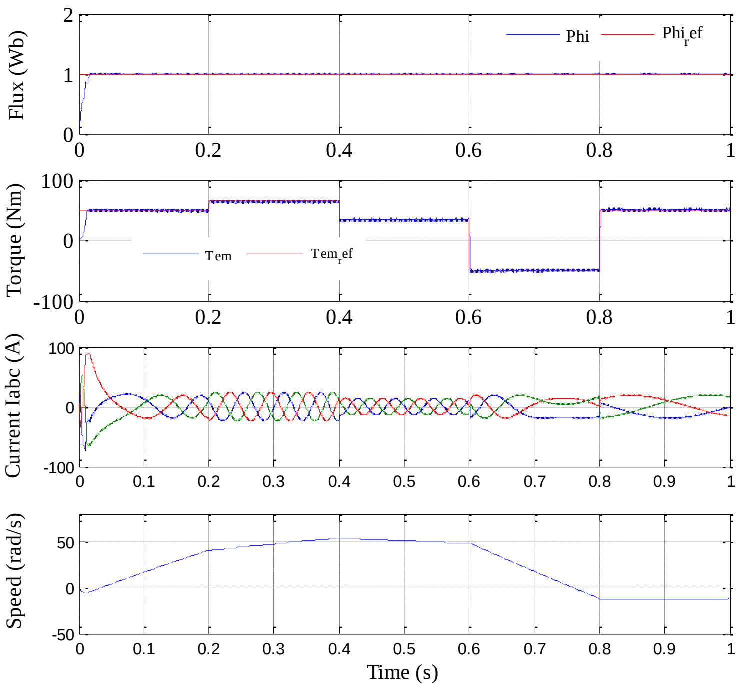

Fig. 7. Simulations results of DTC based Q learning algorithm

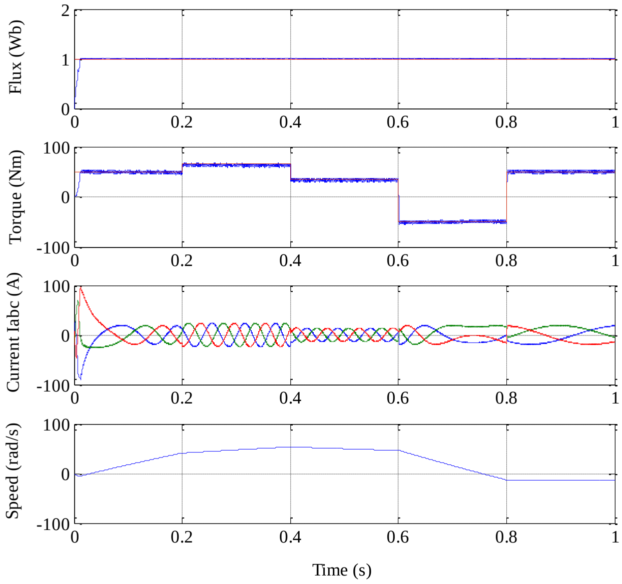

Fig. 8. Simulations results of conventional DTC

The simulation results in Fig .8 shows that the current's stator ripples obtained with Q learning method is significantly reduced compared to (DTC) conventional Fig.10. The ripple of torque with Q learning strategy is significantly reduced.

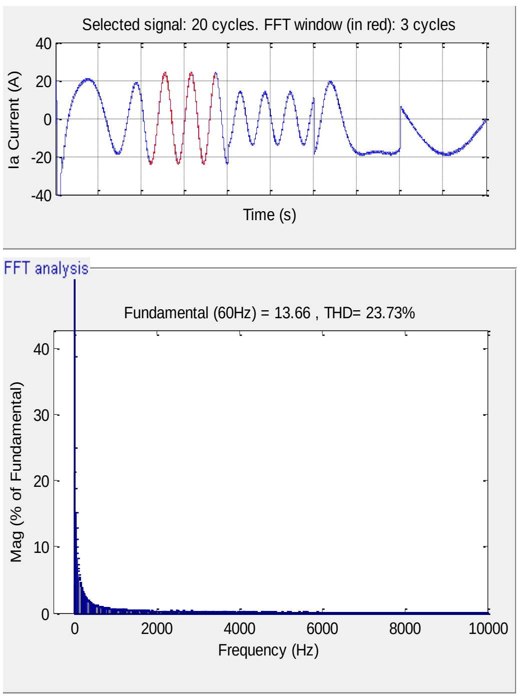

Fig. 9. Spectrum of current (DTC based Q learning)

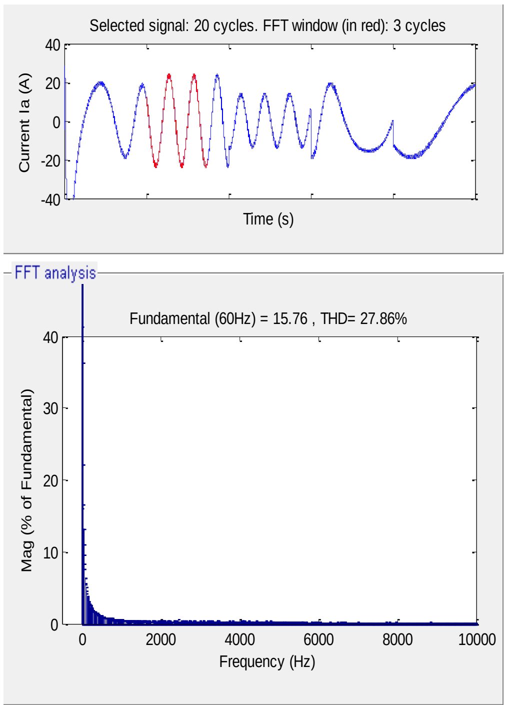

Fig. 10. Spectrum of current (DTC conventional

It's noticed that the statorique currents obtained with Q learning method presented a good THD 23.73% in fig. 9 compared with the results obtained with (DTC) conventional Fig.10. The behavior of induction motor fed by a five-level inverter, using the switching table found by the reinforcement learning method (Q-Learning) reduces advantage the harmonics of currents and the ripple of torque and flux.

10. Conclusions

Reinforcement Learning is a type of Machine Learning. It allows machines and software agents to automatically determine the ideal behaviour within a specific context, in order to maximize its performance. The reinforcement learning method (RL) trains algorithms using a system of reward and punishment. By interacting with its environment, the agent receives a delayed reward in the next time step to evaluate its previous action. Indeed, its effectiveness has been shown in the context of (DTC) with multilevel inverters to find their switching tables. So the Q-Learning algorithm applied to (DTCs) makes it possible to make the optimal choice for each situation of one of several discrete actions available. The results obtained by the reinforcement learning method in case of 5 levels of inverter show the excellent dynamic performance of torque and flux control compared to conventional approaches. The generalization of this approach to N levels without any difficulty (increase in the level of inverter). Therefore, the number of voltage vectors to be selected gives the reinforcement learning method an appreciable advantage. In other words, it determines the switching table automatically regardless to the number of voltage levels of the inverter used. Contrary to the methods presented previously, when this number of levels increases; all of them are based on a qualitative analysis with the whole inaccuracies.

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