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PAPERS

A new control strategy for harmonic reduction in photovoltaic inverters inspired by the autonomous nervous system

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This paper proposes a new inverter control strategy whose main purpose is to reduce the current harmonic distortion resulting from unnecessary control actions without sacrificing the system's dynamic response. The brain's capabilities to learn and react to stress are mimicked to generate control actions based on emotional cues. The model is based on the brain emotional learning based intelligent controller, to which an autonomous nervous system was added. The modified controller aims at separating the strategy during transient states from the one during steady states. The proposed method was compared to the PI controller, the PR controller, and a neural network-based controller on Matlab Simulink. It shows major improvements in terms of harmonic distortion and a complete removal of the inter-harmonics. It provides a good dynamic response in transient states and an immunity to irrelevant signal variations during the steady state, which results in an improvement in the harmonic production.

K e y w o r d s: photovoltaic system control, harmonic spectrum, THD, BELBIC, grid integration, transient state detection

1 Introduction

In recent years, environmental concern has led to an increase in the scale and penetration of clean and renewable energy sources. One of the most favorable resources is solar energy, which has experienced rapid development, leading to decreased production costs. The number of installed systems is increasing remarkably, with most of these systems being grid-connected [1].

Unlike conventional synchronous generators, photovoltaic (PV) arrays are interacted with the AC grid through power electronics. It provides clean energy to the network but deteriorates the power quality through the injection of current harmonics.

The research on the topic has been increasing and the literature is largely focused on the discussion about power inverter topologies and their control [2]. Multilevel inverters offer an improvement in terms of harmonics [3]. Another solution is to improve the control of the power electronic converters involved in the grid integration of photovoltaic systems [4]. Most of the measured signals are affected by switching noises and other disturbances, which can generate undesired control activity. The performances and the harmonics are worsened [5].

In the literature, various types of classical and modern control schemes have been studied and proposed to improve the converters performances [6]. A widely used controller for three-phase inverters is the proportional integral (PI) controller [7]. It has seen a lot of improvements in the recent years, most often focusing on their tuning [8]. Several different strategies have also been investigated [9]. Alongside the PI controllers, the most used controllers for this application are the proportional resonant (PR) controllers, repetitive controllers (RC) and deadbeat controllers (DB). These have been compared in [10]. Although all the controllers demonstrated satisfactory performance, DB was found superior during single phase faults. In [11], PR and RC have been found to perform better than the PI controller in terms of harmonic distortion.

Other controllers have been explored in the literature, namely, fuzzy logic controllers [12], neural networks [13], sliding mode control [14] and fractional order notch filter [15]. Overall, neural networks and fuzzy logic controllers are found to be superior to classic ones.

The current scenario in control systems witnesses the success of intelligent and bio-inspired approaches similar to neural networks (NN) [16]. These approaches, where intelligence is not given to the system from outside but is acquired through learning, have proven to be successful [17]. Intelligent controllers borrow the troubleshooting techniques of biological systems to solve the control problem. The brain emotional learning based intelligent controller (BELBIC) is the latest development in bio-inspired controllers. It is based on the emotional learning computational model proposed in [18]. BELBIC mimics the parts of the limbic system thought responsible for emotional learning.

The controller first appeared in [17]. It has since seen numerous applications in different fields, one of which is power systems. BELBIC has successfully been used for

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maximum power point tracking in PV systems and dc-dc converter control in [19] and [20], respectively. In [21], it was used for voltage regulation through D-STATCOM control. In [22], a fractional-order BELBIC was also developed to improve small signal stability in hybrid power systems through automatic generation control (AGC).

The proposed control algorithm adds to BELBIC a hippocampus and a hypothalamus. The hippocampus capacities for contextual processing improve the controller's performance [23]. The hypothalamus node serves as a switch between a sympathetic control strategy (SNS) and a parasympathetic control strategy (PNS). The SNS takes advantage of the learning capabilities of BELBIC in transient states, while the PNS controls the system in open loop during steady states. The open loop strategy is meant to reduce any undesired control action by maintaining the system at an optimal output while dismissing the irrelevant variations in the signal.

We describe the studied photovoltaic system and the control strategies adopted, present the simulation studies of a simplified 1 MW grid-connected photovoltaic system in Simulink/Matlab, and the proposed algorithm is assessed in terms of dynamic and harmonic performances in steady state.

2 System description

In a two-stage photovoltaic system, a DC/DC converter extracts the maximum power from the PV array through an MPPT algorithm. A widely used approach is the perturb and observe (P&O) algorithm for its simplicity and its high tracking capabilities. A three-phase voltage source inverter (VSI) transfers the DC power to the AC grid. The output current from the VSI is filtered to attenuate high switching frequencies using an LCL filter and synchronized to the grid frequency using a phase-locked loop (PLL).

2.1 Traditional photovoltaic system control

The control strategy used for the grid-side converter consists mainly of two cascaded loops. Usually, there is an internal current loop that regulates the grid current and an external voltage loop that controls the DC-link voltage. In most cases, the active power current component is regulated through a DC-link voltage control aimed at balancing the active power flow in the system. The outer PI controller loop is used to regulate the DC-voltage to match the reference one U^*_{DC} [24].

2.2 PI controller

A proportional integral (PI) controller is generally used in the synchronous reference frame as it is superior with DC variables. The active and reactive powers are determined independently by the active current reference i^*_d and the reactive current reference i^*_q [25].

2.3 PR controller

Unlike PI controllers, a proportional resonant (PR) controller can track a sinusoidal current reference without steady-state magnitude and phase error. It is most used in the stationary reference frame ($\alpha\beta$ frame).

2.4 Predictive neural network

A neural network is an interconnection of several artificial neurons that simulates a biological brain system. It can approximate an arbitrary function mapping. Matlab's deep learning toolbox offers a powerful tool to create a neural network model of a nonlinear plant to predict its future performance. The controller then calculates the input that will optimize plant response. The controller is trained offline using simulated data, considering different scenarios of active and reactive set-points randomly generated.

2.5 BELBIC

Is essentially an action generation mechanism inspired by the computational model of the limbic system for emotional learning. The fundamental idea behind decision-making based on this model is to generate an action (output) that minimizes emotional stress (or maximizes emotional reward [26]. The controller is described in [17,16].

In a synchronous reference frame, the BELBIC implementation for PV inverter control has the same basic layout as PI controllers. Two parallel controllers are needed to independently control the direct current i_d and quadratic current i_q.

3 Modified BELBIC strategy

Effective response to a threat is crucial to survival. The mammalian brain has developed an excellent fear detection network capable of tracking and monitoring threats and determining suitable responses. Detecting a threat activates the sympathetic nervous system (SNS), which leads to the "fight or flight" response. The parasympathetic nervous system (PNS), on the other hand, maintains homeostasis in the absence of a treat. It is the body's maintenance of a steady state function of the autonomic nervous system (ANS). The SNS and PNS typically have opposing effects. A simple attempt to mimic this process is proposed in this work by the addition of a hippocampus and a hypothalamus to the BELBIC Controller. The implemented model is presented in Fig. 1.

3.1 Hippocampus module

The hippocampus is an important part of the limbic system for the formation of associative memories, such as the acquisition of information about the context, especially contextual fear learning. It is based on the concept of situation awareness in the sense of being aware of an entity's variations during a period of time [27].

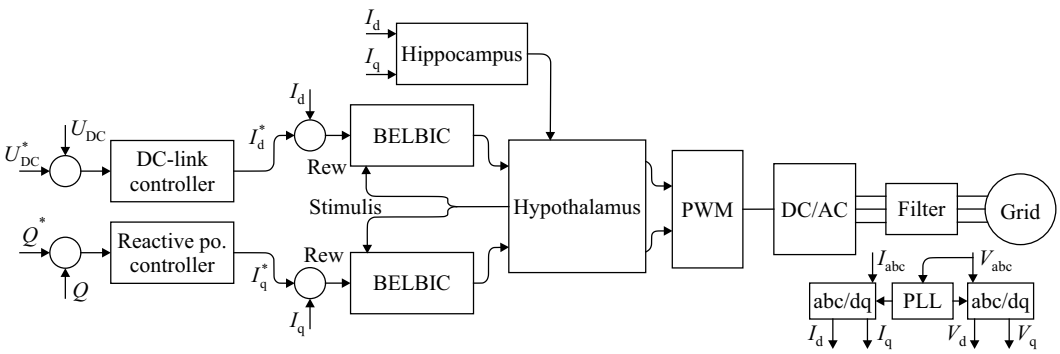

Fig. 1. Block diagram of the proposed control strategy

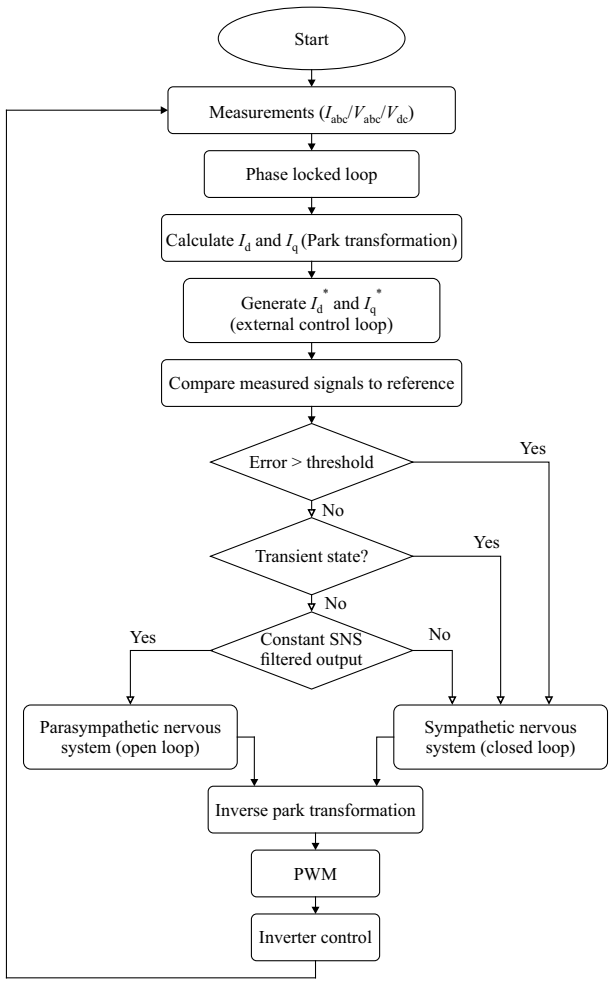

Fig. 2. Flow chart of the proposed m-belbic algorithm

The process as explored in this work relies on detecting transient and steady states. Thus, the proposed hippocampus module is a state detection algorithm based on the filtered value of a signal calculated as

$$X_{f,i} = \lambda X_i + (1-\lambda) X_{f,i-1}, \tag{1}$$

where X is the process variable, X_f is the filtered value of X, λ is the filter factor, and i represents the time sampling index. If a process is at steady state, the filtered signal X_f is almost in the middle of the data [28]. The method adopted uses the difference D_i between X_i and $X_{f,i}$.

$$D_i = X_i - X_{f,i}. \tag{2}$$

In steady states, D constantly changes sign. For every step the sign does not vary, a probable transient state index is incremented T_i. If this index reaches a predefined limit, the system is considered in a transient state. If not, the system is in a steady state. T_i is reset to 0 for every sign change in D.

3.2 Hypothalamus module

The hypothalamus is in charge of regulating the endocrine system, the autonomic nervous system (ANS), and primary behavioral surviving states [29]. The sympathetic nervous system (SNS), a division of the ANS, activates the "fight or flight" response, which is a feedforward mechanism that prepares the body to react to an imminent threat. The parasympathetic nervous system (PNS) maintains a steady state. The proposed SNS strategy is BELBIC's learning algorithm in close loop control. It refers to a configuration that maintains a prescribed relationship between the output and the reference input [30]. The PNS strategy is an open-loop control in which the system output does not influence the control actions. It is chosen to lessen the impact of switching noises, grid harmonics, and other disturbances. The implemented PNS algorithm uses the filtered SNS control value when its variation is minimal. This strategy ignores any irrelevant signal variations. During this phase, the SNS learning process is stopped using the stimuli signals.

While the error has no direct effect on the output, it is still monitored to re-engage the SNS strategy if the error exceeds a specified margin. A flowchart of the hypothalamus node proposed is provided in Fig. 2.

4 Results and discussion

In this section, grid-tied photovoltaic system control using the proposed control strategy is assessed through simulations of a Matlab/Simulink model. The system is designed to supply 1 MW to the grid at unity power factor. To reduce the model complexity, it is simplified by

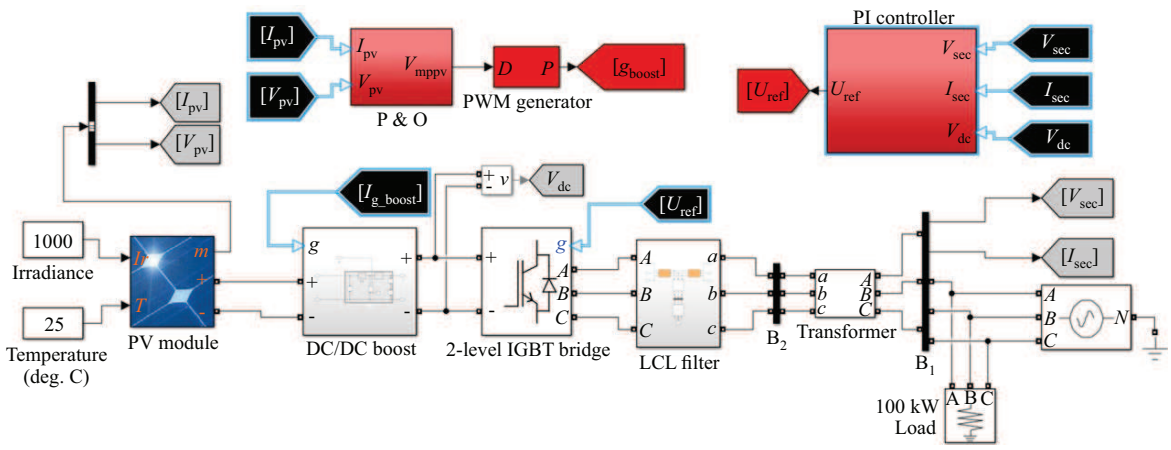

Fig. 3. Matlab model of the sudied system

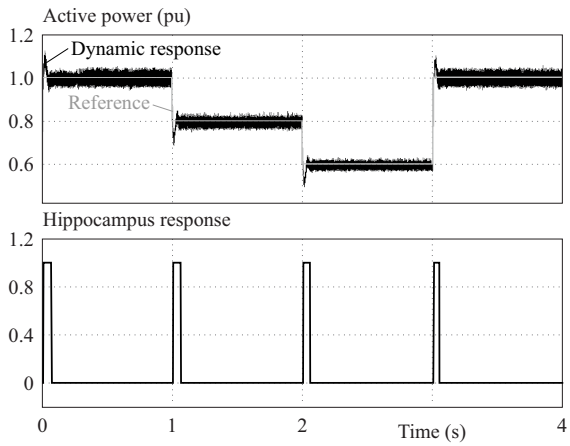

Fig. 4. Hippocampus response under a varying irradiance scneario

an equivalent PV module, a dc-dc boost converter, and a dc-ac converter as shown in Fig. 3. The photovoltaic array is a SunPower SPR-315E-WHT-D. One module has 96 cells in series and provides 315 W of nominal maximum power. The grid is represented as a three-phase voltage source acting as an infinite bus.

First, the hippocampus and hypothalamus nodes are tested in different irradiance scenarios. Then, the dynamic performances of the proposed controller are assessed through the evolution of the active power, reactive power at the inverter output and the DC-link voltage. The results are compared to the most widely used controllers for this application, namely the PI and PR controllers [10]. A third controller based on neural networks is also used for the comparison. The network was trained by a dataset of 500 000 samples considering different combinations of active and reactive power variations. It consists of 5 hidden layers with the Bayesian regression algorithm [31]. The harmonic performances of the controllers are examined through the current harmonic spectrums and harmonic distortion. The active and reactive power results are shown in p.u with the nominal power of the photovoltaic system (1 MW) as a reference.

4.1 Hippocampus and hypothalamus validation

The main objective of the hippocampus node is to determine a context from the measured signals, the context being either a transient state or a steady state. The information is then sent to the hypothalamus node. Figure 4 shows the system response to different variations in the irradiance. These variations alter the maximum attainable power and cause the system to transition to a new power point. The hippocampus node correctly detects each transient state resulting from these changes.

Following the detection of a steady state, a 1 s delay is introduced by the hypothalamus node before switching to the PNS-control strategy. The transition is shown in Fig. 5. Slightly after $t = 2$s, the learning process of the SNS strategy is turned off and the command signal is fixed to a specific value. The system keeps monitoring the error and the system state. At $t = 3$ s, the active power set-point is changed by changing the irradiance, which causes the system to transition back to the SNS strategy. The active power response is smoother when the PNS is active.

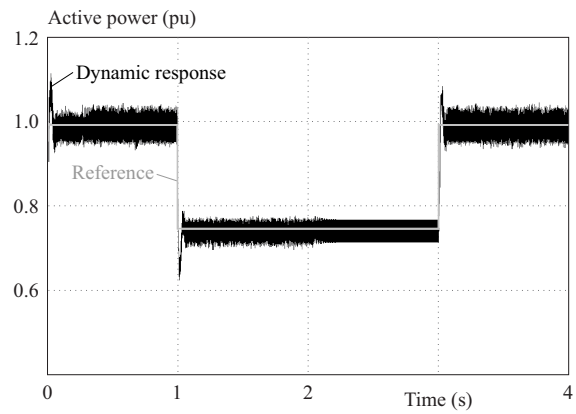

Fig. 5. Hypothalamus response under a varying irradiance scneario

4.2 Dynamic performance comparison

The PI and PR controllers, which are the most widely used for photovoltaic systems, serve as a comparison point

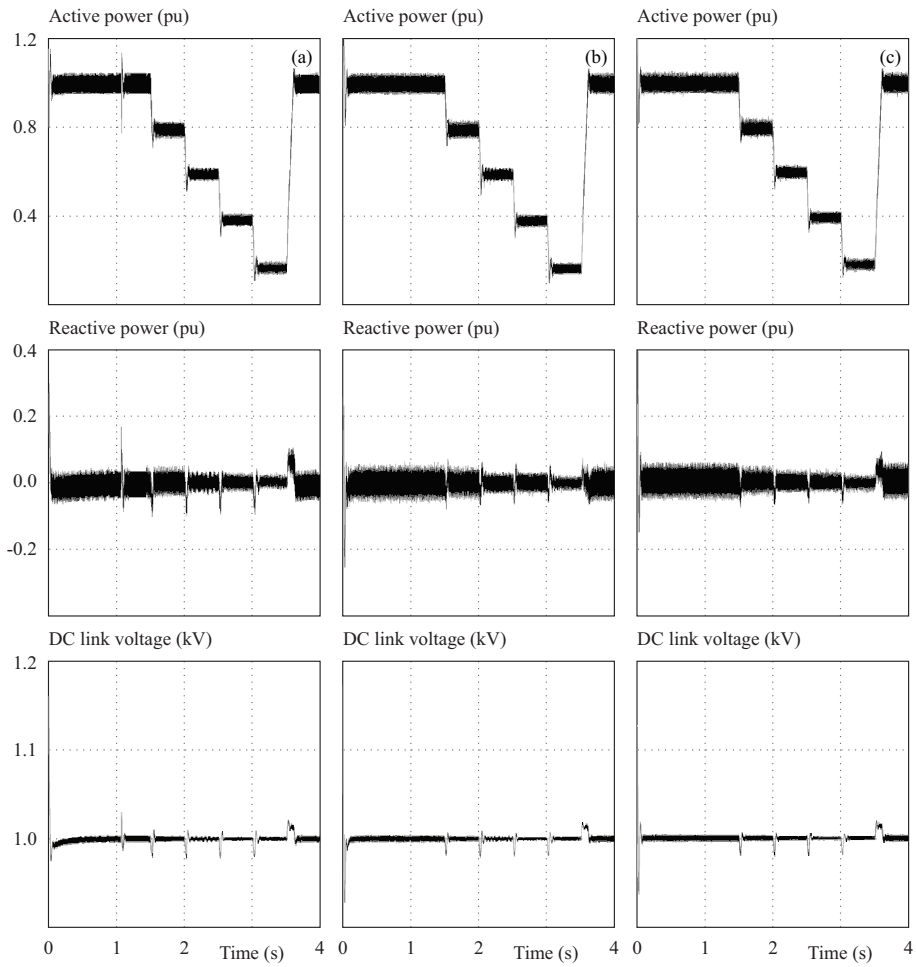

Fig. 6. System response in terms of active and reactive power output and in terms of dc-link voltage variations for: (a) – proposed strategy, (b) – PI controller, (c) – PR controller

Table 1. Complementary results of the comparison between the proposed controller, the PI, PR, and NN controllers

	Proposed	PI	PR	NN
		Settling time (ms)		
Active power	73	102	92	100
Reactive power	109	139	79	119
DC-link voltage	152	141	96	125
		Overshoot (pu)		
Active power	1.18	1.24	1.29	2.11
Reactive power	2.91	0.25	5.17	2.11
DC-link voltage	10	17.2	11.9	27
Simulation time (s)	39	18	25	312

for the proposed strategy in terms of active power, reactive power, and DC-link voltage responses under multiple step changes in the irradiance starting at 1000w/m. Fig. 6, shows the dynamic response of the proposed strategy next to the PI and PR controllers.

A similar response is noticed. All three correctly track the irradiance changes and follow the set-points in terms of active power, reactive power, and DC-link voltage. The activation of the PNS strategy in the proposed controller (at $t = 1.1$s) causes a brief oscillation visible in the three measured signals.

Additional comparison with the neural network, Fig. 7, shows good reference tracking for this technique when considering active and reactive power. The DC-link voltage suffers from a deviation from the predetermined setpoint. Moreover, the response time is noticeably higher. Further investigations of the overshoot and response time help discriminate between the controllers, as shown in Tab. 1. The tracking performance of the controllers is similar except for the DC-link voltage when using the neural network. The differences in terms of overshoot and settling time are not huge; nonetheless, the PR controller is found to be the fastest in the overall system response but has the highest overshoot in reactive power.

An indication of the system complexity is obtained through the execution time needed to run a 1s simulation. It was run using a 4th generation i7 with 8 GB of RAM. The PI and PR controllers show the fastest time, followed by the proposed strategy, which is coherent in terms of complexity. The proposed strategy is more complex, resulting in a longer execution time. The highest time is seen for the neural network control, showing a major difference compared to the other controllers.

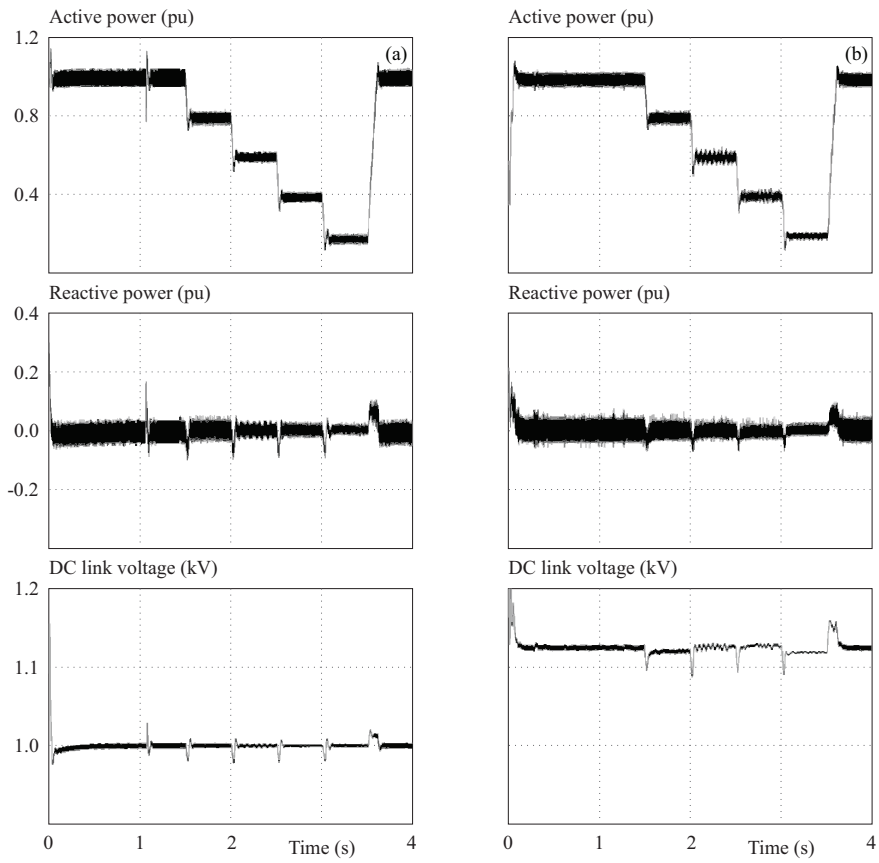

Fig. 7. System response in terms of active and reactive power output and in terms of dc-link voltage variations for: (a) – proposed strategy, (b) – neural network

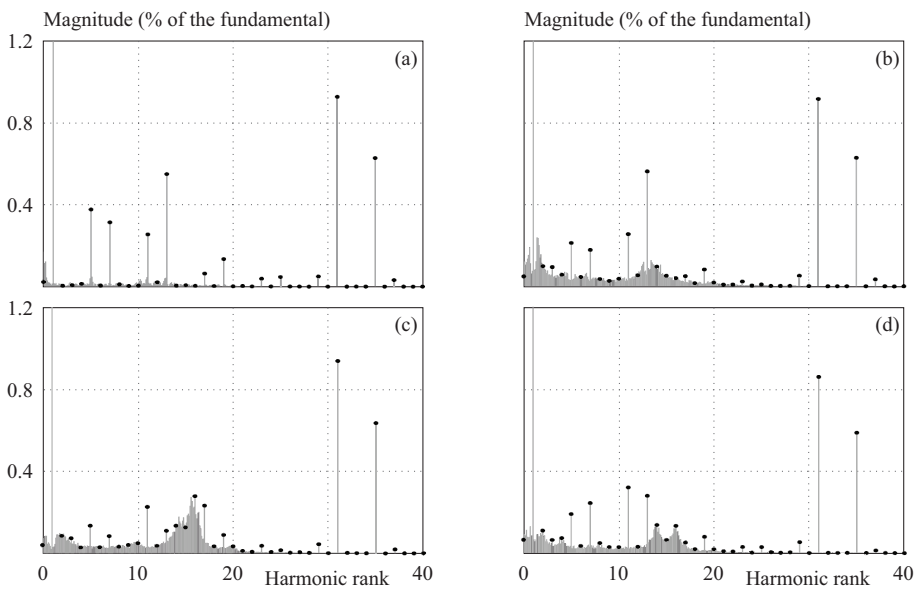

Fig. 8. Harmonic spectrum at: (a) – 1000 w/m^2, (b) – 800 w/m^2, (c) – 600 w/m^2, and (d) – 400 w/m^2

4.3 Harmonic performances comparison

The harmonic performances of the proposed strategy were investigated using fast fourier transform (FFT) according to the IEEE-519-2004 standards for a very short period (3 s). The calculations are performed in standard test conditions at 1000w/m. Figure 8 presents the harmonic spectrum of each controller tested.

The THD shows an advantage for the proposed strategy and for neural networks. The PR controller performs the worst in this matter. It is noteworthy to mention that the tuning of the PR controller's parameters was focused on obtaining good dynamic performances. When focusing the tuning on the harmonic performances the THD was lowered to 1. 43 % but at the cost of worse transient

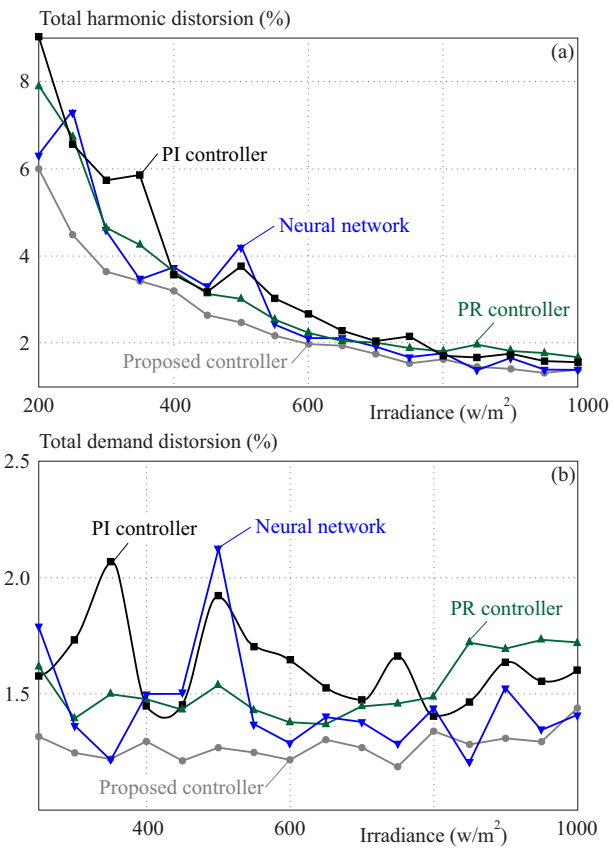

Fig. 9. Evolution of the THD with irradiance

response. In that case, the system's response time was considerably higher, which is why that scenario was not considered.

The harmonic spectrum shows low amplitudes of the 5th, 7th, 11th, and 13th harmonics when using the PR controller. The inter-harmonics, on the other hand, are the worse for this controller, showing more undesired control actions. These inter-harmonics are the result of random fluctuations of the power on the DC side. The proposed strategy displays an increase in the 5th and 7th harmonics and similar results with the PI controller in terms of the 11th and 13th harmonic order. Due to the PNS strategy, the inter-harmonics are considerably lower when using it.

The evolution of the THD (total harmonic distortion) and TDD (total demand distortion) in respect to the irradiance is shown in Fig. 9.

With lower irradiance values, the THD tends to increase, mainly due to the lower fundamental current. This correlation is absent when considering the TDD, which is calculated regarding the nominal current. Nonetheless, the different operating points influence harmonic distortion. Overall, the PI controller offers the highest THDs and TDDs, followed by the PR controller, which performs better, nonetheless. The neural network performance is influenced by the operating point. The controller performs better than both the PI and the PR controllers but significantly worse in some cases (500w/m). The proposed controller has the best THD and TDD in almost all the scenarios tested.

5 Conclusion

A bio-inspired controller for photovoltaic systems is presented in this paper. The strategy is based on BELBIC, which mimics the mammalian emotional learning process. The proposed method adds a hippocampus node and a hypothalamus node. The hippocampus, responsible for context evaluation, is modeled using a simple transient state detection method. The hypothalamus serves as an autonomous nervous system (ANS). It handles the switching between a sympathetic strategy (closed-loop state) and a parasympathetic strategy (open-loop state). The proposed algorithm offers a new approach to PV system control through an ANS-inspired algorithm with dual control.

The proposed algorithm is an attempt to reduce the impact of irrelevant signal variations by ignoring them in steady state. Its dynamic performances are satisfactory. Due to its strong learning algorithm, the SNS strategy based on BELBIC acts adequately during transient states. The PNS strategy eliminates any undesired control action, which results in reduced harmonic distortion, mainly due to the suppression of inter-harmonics. It outperforms all the other controllers tested while still performing satisfyingly in terms of set-point tracking and response time. Nonetheless, the controller adds to the complexity of the controller but remains less complex than the neural networks used.

Moreover, the simplified system tested neglects the effects of multiple MPPTs and controller interactions. A more realistic system would have a higher distortion level. In addition, inverters are known to have worse harmonic performances in practical scenarios compared to laboratory tests and simulations. Further testing, especially for a real photovoltaic system, is necessary to determine the strengths and weaknesses of the proposed strategy. In this scenario, the improvements in harmonic distortion should be significantly higher.

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