Utilizing Artificial Neural Network For the Regulation Of Electric Springs In Renewable Systems

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Abstract. Now a days the research work is going on to improve the performance of electric springs (ESs) by integrating a current source inverter (CSI) and a neural network controller. A new ES configuration that includes CSIs is introduced to enhance ES functionality. This configuration is accompanied by a control strategy that involves direct current control and mitigation of harmonic distortion, like the methods used in active power filters (APFs). By transitioning from voltage source inverters (VSIs) to CSIs and integrating a neural network controller, a significant reduction in total harmonic distortion (THD) can be achieved. The paper presents two distinct control loops, each equipped with proportional-integral (PI) controllers. One loop is focused on regulating the Critical load voltage (CL voltage), while the other is specifically designed for reactive power compensation.

1 Introduction

The escalating environmental crisis highlights the increasing importance of power grid stability, particularly due to the growing variability of non-conventional energy sources. Sustainable energy sources like solar and wind power are expected to replace traditional petroleum-based fuels. Electric springs has been put forward to make sure uninterrupted operation of essential loads (CLs) within specific regions while diverting oscillations to non-critical loads (NCLs). The foundational concept and primary adaptation of ESs are outlined in a reference, which also elaborates on their eight compensation capabilities. A subsequent iteration integrates the active suspension concept into bi-directional grid-connected converters, addressing control strategies and equipment performance. ESs find application in various fields.

The advantages of power inverter over voltage fed inverter are explained in another reference. CSIs offer features such as direct current control and the ability to function as boost inverters. Control techniques for ESs are discussed in multiple sources, where two separate control loops are introduced, each equipped with PI controller. One loop is dedicated to regulating the critical load voltage, while other focuses solely on reactive power compensation. It

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is crucial to emphasize the control tactics described may have harmonics, as discussed in another source. A control methodology presented achieves dual objectives using a single parameter applied to a predetermined sinusoidal target value for a corresponding proportional resonant regulator.

Integrating Energy Storage Systems (ESs) into distributed control systems requires identifying their practical operating ranges. The control objectives for ESs revolve around stabilizing the CL voltage, with changes in input voltage primarily affecting line impedance rather than the ES itself. Voltage control for ESs presents a complex challenge. This paper elaborates on the performance of electric springs equipped with CSIs and describes a control system that employs a new ES variant alongside CSIs and a neural network controller to achieve a pure and sinusoidal waveform for CLs.

2 The operational principles and control techniques of the Electric Spring (ES) are described as follows

Changing the control approach requires a transition from voltage regulation to current regulation, requiring the use of a controlled current source. To accomplish this, an Electric Spring with a Current Source Inverter is introduced, labelled as a current-controlled current source, as shown in Figure 1(a). A fundamental alteration in this ES design involves integrating a solitary capacitor (Cf) as the filtering element.

The control framework for regulating current, illustrated in fig. 1.b, replaces the Electric Spring with Controlled Current Source labelled 'ic,' while the line impedance in a specific branch, is represented as an electric current generator labelled 'i.' As i1 varies with changes in the input voltage 'vg,' the ES must generate alternating current variations, ensuring a steady, secure, reliable, unchanging, Critical Load voltage.

Total Harmonic Distortion (THD) reduction is achieved through hysteresis control, demonstrated In Figure 1(c), which consists of two functional components. In the lower section, like the control mechanism strategy outlined in [11], the aim is to attain the intended CL voltage and offer purely reactive power compensation. This control block significantly reduces the THD of the CL voltage.

The upper segment in Figure 1(c) is inspired by the Active Power Filter (APF) concept. It is engineered to alleviate the Total Harmonic components in the input current, thereby improving the reduction of Total Harmonic Distortion (THD).

In summary, the proposed control strategy for the Electric Spring involves a shift from transitioning from voltage control to current control involves the use of a Current Source Inverter and a Controlled Current Source (CCCS). Additionally, hysteresis control is employed to reduce Total Harmonic Distortion (THD), with one block ensuring CL voltage and reactive power compensation and another block derived from the Active Power Filter (APF) concept to further enhance THD reduction in the input current.

3 Analysis of Control Methods
The mobile and web-based application for IoT based smart parking system is named as Park Quick. Fig.5 shows schematic representation of the parking system Park Quick using the circuitry elements as well as the web application and mobile application implementation

3.1 Control Block employing δ Control Strategy
In this section, primary emphasis will be on the control schematics situated in the lower portions of Figures 1(c) and (d). These schematics incorporate the hysteresis controller and the Proportional Resonant in addition to P controllers, as mentioned earlier. These control strategies operate in a manner like existing control methods and static var generators (SVG).
Hysteresis Control: Figure 1(c) depicts the signal 'i2,' representing the electric current passing through the Critical Load. The control system generates a reference signal 'i2ref.' A hysteresis controller processes the error signal 'error,' where 'iH' indicates the hysteresis width. As illustrated in Figure 1(a), the 'iH' and 'iL' limits are compared with the output current of the Electric Spring, represented as 'ic,' to generate four drive signals. This direct current control approach facilitates the adjustment of the Critical Load (CL) voltage, allowing it to be set to a specific level (such as 220V). Guided by the control system's reference, the Electric Spring can effectively operate in capacitive, resistive, and inductive modes, adapting to fluctuations in the grid voltage. This adaptability leads to a reduction in Total Harmonic Distortion (THD), a benefit we will examine in more detail later. However, it is important to consider switching losses and costs associated with the high switching frequency inherent in hysteresis current control in practical applications. Additionally, knowledge of the CL parameters is necessary to obtain the reference value.

**Alternative Control Methodology:** To tackle the challenges associated with hysteresis control, an alternative control approach is presented in Figure 1(d). In this method, a Proportional Resonant (PR) controller is responsible for regulating the Critical Load (CL) voltage, and a Proportional (P) controller supervises the output current of the system. The internal loop of this control system handles both inductor current and inductor voltage. In summary, this section offers an in-depth examination of control techniques, specifically emphasizing direct current control. It explores the hysteresis controller and the PR in addition to P controllers are analysed for their similarity to established methods. The discussion delineates their potential benefits and constraints in the regulation of both voltage and current for the Critical Load in the Electric Spring.
Figure 1. Illustrates a common application of the Electric Spring with Current Source Inverter and its corresponding regulatory techniques. (a) Depicts the ES with CSI setup. (b) Represents the circuit diagram with the same functionality of (a). (c) Displays the control schematic for regulation of hysteresis. (d) Shows the control diagram for Proportional Resonant (PR) plus Proportional (P) controllers.

3.2 Single-Phase d-q Transformation and its Role in Harmonics Suppression

The diagrams illustrating the control methods displayed in the upper sections of Figures 1(c) and 1(d) illustrate the functioning of the harmonic suppression feature, with Figure 1(d) specifically showcasing an enhancement in Part A. Although direct control has led to performance enhancements, there remains room for further reduction in the Total Harmonic Distortion (THD) in the voltage of the Critical Load (CL).

To address this issue, the solution lies in transitioning to the dq coordinate system, where a signal that is imaginary and orthogonal to the measured current is created. In Figure 1(c), 'i1' signifies a theoretical signal derived from the actual 'i1' signal, but delayed by 5 milliseconds. Below, we outline the process of transforming from the single-phase Real-Imaginary (ReIm) representation to the dq coordinate system. Utilizing Fourier analysis on 'i1' yields the following outcomes:

\[
i_{1}(t) = i_{1\infty}(t) = \sum_{n=1}^{\infty} I_n \cos(n\omega_1 t + \varphi_n) \]

\[
= I_1 \cos\varphi_1 \cos\omega_1 t - I_1 \sin\varphi_1 \sin\omega_1 t + \sum_{n=2}^{\infty} I_n \cos(n\omega_1 t + \varphi_n) \]

\[
= I_{p1} \cos\omega_1 - I_{q1} \sin\omega_1 + \sum_{n=2}^{\infty} I_n \cos(n\omega_1 t + \varphi_n) \]

(1)

‘Corresponds to the harmonic order. ‘In’ indicates the magnitude of the harmonic current at each particular order. ‘1’ represents the fundamental angular frequency. ‘\varphi_n’ denotes the initial phase of the harmonic current relative to the phase of the reference signal.
'Ip1' and 'Iq1' represent the maximum values of active and reactive powers at the fundamental frequency '1' and are expressed as follows:

'Ip1' represents the maximum active power and is measured as 'Ip1' = 'Ip1 cos(φ1).

'Iq1' shows the maximum reactive power attained as 'Iq1' = 'Iq1 sin(ω1).

\[ I_{p1} = \text{Ip}_1 \cos(\phi_1) \]  \hspace{1cm} (2)

\[ I_{q1} = \text{Iq}_1 \sin(\omega_1) \]  \hspace{1cm} (3)

The imaginary signal perpendicular to i1(t) can be represented as

\[ i_{1\beta}(t) = \sum_{n=1}^{\infty} I_n \cos(n \omega_1 t + \varphi_n - \frac{\pi}{2}) \]

\[ = \text{Ip}_1 \cos(\varphi_1) + \text{Iq}_1 \sin(\varphi_1) + \sum_{n=2}^{\infty} I_n \sin(n \omega_1 t + \varphi_n) \]  \hspace{1cm} (4)

Then together 1 and 4 for the differential form in d-q coordinated as

\[ \begin{bmatrix} \text{i}_{d} \\ \text{i}_{q} \end{bmatrix} = [C] \begin{bmatrix} \text{i}_{1\alpha} \\ \text{i}_{1\beta} \end{bmatrix} \]  \hspace{1cm} (5)

Where \( C = \begin{bmatrix} \cos(\theta_0) & \sin(\theta_0) \\ -\sin(\theta_0) & \cos(\theta_0) \end{bmatrix} \), \( \theta_0 = \omega_1 t \) is the immediate phase angle of the reference signal. Substituting the matrix C into (5) gives.

\[ \begin{bmatrix} \text{i}_{d} \\ \text{i}_{q} \end{bmatrix} = \begin{bmatrix} \cos(\theta_0) & \sin(\theta_0) \\ -\sin(\theta_0) & \cos(\theta_0) \end{bmatrix} \begin{bmatrix} \text{i}_{1\alpha} \\ \text{i}_{1\beta} \end{bmatrix} \]  \hspace{1cm} (6)

4 Neural Network Controller and Artificial Neural Network Model

ANN is a measurable model and information processing mechanisms of Organismal nervous systems, such as the human brain. ANNs are characterized by their intricate structure, comprising numerous interconnected processing elements, or "neurons," which collaborate to solve specific tasks. Like human brains, ANNs learn through a tailored training process designed for specific applications such as pattern recognition and data classification involve identifying patterns and categorizing data into specific groups. During this Process of learning, synaptic connections are adjusted, analogous to how biological brains modify connections between neurons.

In natural brains, a biological neuron, illustrated in Figure 2, serves as a fundamental processing unit. Each neuron operates as a compact computational unit, and the brain consists of billions of interconnected neurons working in harmony. Within this complex network, neurons receive input signals from other neurons, apply a transfer function to these inputs, and transmit the results to subsequent layers of neurons. This cascading process continues through the layers of the brain.

Typically, Artificial neural networks (ANNs) are composed of numerous basic processing units interconnected in parallel across multiple layers. In biological neural networks, memory is thought to be stored in the intensity of connections between layers of neurons. The term "weight" in neural network terminology indicates the strength or influence of these connections. Artificial neural networks (ANNs) employ adjustable connection weights between layers of simulated neurons. Despite being introduced in the 1960s, ANNs attracted substantial interest in the mid-1980s. Before this period, training networks with more than two layers posed difficulties, and early networks could only represent linear relationships between binary input and output data. However, the development of the backpropagation method marked a breakthrough in ANN research.
The widespread availability of fast and affordable personal computers has led to a surge in interest in ANNs. The primary goal is to enable computers to perform tasks beyond human capabilities. Consequently, ANNs attempt to mimic the operation of the human brain, closely mirroring its architecture.

Figure 3 presents a model of artificial neural network consists of an input layer, a hidden layer, and an output layer. The input layer includes, artificial neurons responsible for receiving and processing external input. The output layer comprises units that react to information acquired during the learning process. Situated between the input and output layers are hidden layers, which convert input data into a format that can be utilized by the output layer. Most neural networks are fully connected, meaning that each hidden neuron establishes connections with every neuron in the previous input and following output layers.

**Key components in a neuron include:**

**Neuron:** Neurons, also called cells or units, function as self-contained processing elements. Each neuron's task involves receiving information from other neurons, conducting simple computations on the received data, and then transmitting the results to one or more other neurons.

**Layers:** Layers consist of neurons assumed to collectively carry out specific functions. Neurons within a layer are typically numbered, with the convention that there are no connections between neurons within the same layer.

**Synapses:** Synapses serve as communication links between cells and can be either one-way or two-way connections. In a feed-forward network, information flows unidirectionally from input cells to output neurons, whereas recurrent networks allow for bidirectional communication.

**Weights:** Weights, represented as 'wij,' are real numbers indicating the influence of one neuron ('ni') on another neuron ('nj'). Positive weights signify strengthening, negative weights indicate inhibition, and a weight of zero or the absence of weight implies the absence of a direct connection.

**Propagation Rule:** Propagation rule is a network-wide guideline applicable to all neurons, determining how the outputs of cells are combined into a net input for neuron 'n'.

In essence, Artificial Neural Networks (ANNs) strive to emulate the neural processing observed in biological systems and have emerged as potent tools for various computational tasks.
5 Simulation Results
Case 1

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<thead>
<tr>
<th>TABLE I</th>
<th>SIMULATION PARAMETERS</th>
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<tr>
<td>Items</td>
<td>Values</td>
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<tr>
<td>Reference Voltage for Critical Load (Vcl)</td>
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<tr>
<td>Direct Current (Idc)</td>
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<td>Inductance of the Line (L1)</td>
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<td>Critical Load Resistance (R2)</td>
<td>2000Ω</td>
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<td>Non-Critical Load resistance (R3)</td>
<td>101.4Ω</td>
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<td>Low Pass Filter capacitance (Cf)</td>
<td>50µF</td>
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<td>Hysteresis current (ith)</td>
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<tr>
<td>LPF cut-off frequency</td>
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(a)

(b)
Fig. 3. Illustrates the MATLAB/SIMULINK diagram representing the proposed system. (a) Simulink model (b) Neuron model 1 (c) Neuron model 2 (d) Neuron model 3

Fig. 4. Illustrates the simulation outcomes, showing the Total THD of Critical Load (CL) voltage using a hysteresis controller for an Electric Spring (ES) integrated along CSI. The subfigures include: (a) The
Simulink results of CL voltage and (b) Fast Fourier Transform critical load voltage, indicating a THD of 0.32%.

**Fig.5:** Displays the simulation outcomes for Critical Load voltage using P and PR controllers along with Current Source Inverter (CSI).

**Fig.6.** Exhibits the simulation outcomes for Critical Load voltage utilizing the Suggested control approach in an Electric Spring (ES) integrated with a Current Source Inverter (CSI).
Fig. 7. Represents the simulation findings for Critical Load voltage using an extended Controller based on neural networks in an Electric Spring (ES) integrated with a Current Source Inverter (CSI).

### TABLE II
SIMULATION PARAMETERS

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<th>Items</th>
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<td>Direct Current (Idc)</td>
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<tr>
<td>Inductance of the Line (L₁)</td>
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<td>Critical Load load resistance(R₂)</td>
<td>43.5Ω</td>
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<tr>
<td>Non-Critical Load resistance (R₃)</td>
<td>2.2Ω</td>
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</table>
Fig. 8. Displays the simulated outcomes for total THD of critical load voltage using P and PR controllers for an Electric Spring with CSI at higher power ratings. (a) Illustrates the results without an additional harmonics suppression function. (b) Shows the results with an additional harmonics suppression function.

Fig. 9. Presents the extended simulation results for Critical Load voltage utilizing neural network controllers in an Electric Spring integrated with a Current Source Inverter.
6 Conclusion

To address total harmonic distortion, a control strategy is employed, replacing the conventional voltage control for the Electric Spring (ES) with Voltage Source Inverter (VSI) with current control for the ES integrated with a Current Source Inverter (CSI). This approach also involves the use of a neural network controller and comprises two fundamental blocks: one focused on control strategies and the other dedicated to harmonics suppression. By employing the effectiveness of the proposed control technique, involving a single-stage d-q transformation and harmonics suppression function, is evaluated for its ability to decrease Total Harmonic Distortion estimates in Critical Load voltage. The findings reveal that coordinating current control markedly decreases THD values in comparison to traditional voltage control. Additionally, it is highlighted that implementing immediate current control and additional efforts in harmonic suppression can further reduce the harmonic components in CL voltages, especially advantageous for high-power systems.

The simplicity and rapid design and implementation of the neural network control scheme are praised when compared to traditional integral control methods. Simulation outcomes underscore the superior performance of the neural network controller in stabilizing voltage fluctuations under various disturbance conditions, accomplishing this task within a relatively short timeframe.

Previously, the control of CL voltage and ES output current relied on Proportional Resonant (PR) and Proportional (P) controllers, which have now been replaced with neural network controllers in the proposed method. The shift has resulted in reduced THD percentages in comparison to the traditional approach.

References