ADAPTIVE CRITIC-BASED CONTROL OF VOLTAGE SOURCE
CONVERTERS IN MICROGRID SYSTEMS

by

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Abstract

Control of microgrids, as the main building blocks of the future smart power grid, is an important problem which has initiated many research activities in recent years. The microgrid should appear to the power grid as a single united entity, in which the majority of distributed energy resources are interfaced through voltage source converters (VSCs). In dynamic situations, specific structure, natural nonlinearity, and low physical inertia of VSCs may lead to higher sensitivity to network disturbances and power oscillations and in occasions result in violation of overall stability; hence the need for fast and flexible control techniques in the microgrid is evident.

The design simplicity and easy implementation of PI controllers have resulted in their popularity in controlling VSCs; however their application is associated with a number of drawbacks such as poor harmonics attenuation and unsatisfactory operation in case of load changes and high penetration of distributed generators.

In this Ph.D. thesis, three different control algorithms are proposed for VSCs in microgrid systems. The control systems are based on the adaptive critic-based control concept and employ an element called critic whose task is to evaluate the credibility of the performance and compare it with the desired goals. The critic’s evaluations are then used in an on-line procedure to update the controller parameters during dynamic transients. The critic-based control idea is used in conjunction with PI and neuro-fuzzy controllers.

With the proposed approach, the need for precise design of the controller is removed, and because of the supervisory role of the critic, no complicated mathematical calculations are required for its design. This fact increases the degree of intelligence and adaptivity against changes such as high penetration of distributed generators and dynamically demanding situations like presence of motor loads and results in a self-tuning and non-model-based control system with high computational speed.
The simulation results verify that the application of the proposed approach significantly improves the dynamic performance by reducing the convergence time, output oscillations, tracking error, and unwanted current harmonics and confirm the effective control in case of high penetration of distributed generators.
Acknowledgements

I would like to express my deepest and sincere gratitude to my supervisor Prof. Alireza Bakhshai, for his invaluable assistance, ideas and encouragement throughout this research.

I am thankful to the defense session chair and the committee members, and my thanks to Prof. Mehrdad Moallem (Simon Fraser University) for accepting to be the external examiner of the defense session.

A special gratitude and love goes to my family for their unfailing support during my studies.
I wish to dedicate this dissertation

to my devoted mother,

and to the memory of my beloved father.
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<tr>
<td>VSC</td>
<td>Voltage Sourced Converter</td>
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<tr>
<td>CHP</td>
<td>Combined Heat and Power</td>
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<tr>
<td>DG</td>
<td>Distributed Generator</td>
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<tr>
<td>DER</td>
<td>Distributed Energy Resource</td>
</tr>
<tr>
<td>$dq$ reference frame</td>
<td>Synchronous reference frame</td>
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<tr>
<td>$a\beta$ reference frame</td>
<td>Stationary reference frame</td>
</tr>
<tr>
<td>$abc$ reference frame</td>
<td>Natural reference frame</td>
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<tr>
<td>PI</td>
<td>Proportional Integral</td>
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<tr>
<td>PR</td>
<td>Proportional Resonant</td>
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<tr>
<td>THD</td>
<td>Total Harmonic Distortion</td>
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<tr>
<td>DS</td>
<td>Distributed Storage</td>
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<tr>
<td>PV</td>
<td>Photo Voltaic</td>
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<tr>
<td>PCC</td>
<td>Point of Common Coupling</td>
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<tr>
<td>RL filter</td>
<td>Resistive-inductive filter</td>
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<tr>
<td>LCL filter</td>
<td>Inductive-capacitive-inductive filter</td>
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<tr>
<td>$d$ axis</td>
<td>Direct axis</td>
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<tr>
<td>$q$ axis</td>
<td>Quadrature axis</td>
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<td>PLL</td>
<td>Phase Locked Loop</td>
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<tr>
<td>PWM</td>
<td>Pulse Width Modulation</td>
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<td>$m$</td>
<td>Modulation Index</td>
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<tr>
<td>SPWM</td>
<td>Sinusoidal Pulse Width Modulation</td>
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<td>MPPT</td>
<td>Maximum Power Point Tracking</td>
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<tr>
<td>Term</td>
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<tr>
<td>$f$-$P$ droop</td>
<td>Frequency-Real Power droop</td>
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<td>$V$-$Q$ droop</td>
<td>Voltage-Reactive Power droop</td>
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<td>TSK</td>
<td>Takagi-Sugeno-Kang</td>
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<td>ANN</td>
<td>Artificial Neural Network</td>
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<td>MLP</td>
<td>Multi-Layer Perceptron</td>
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<tr>
<td>N</td>
<td>Negative</td>
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<td>Z</td>
<td>Zero</td>
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<td>P</td>
<td>Positive</td>
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<td>SP</td>
<td>Small Positive</td>
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<tr>
<td>LP</td>
<td>Large Positive</td>
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<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
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<tr>
<td>NB</td>
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<tr>
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<td>Negative Medium</td>
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<td>Positive Medium</td>
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<td>MB</td>
<td>Medium Big</td>
</tr>
<tr>
<td>VB</td>
<td>Very Big</td>
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<td>CSPI</td>
<td>Critic-based Self-tuning PI</td>
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Electric power grid is a highly complex and interdependent infrastructure which is geographically distributed and closely connected to other infrastructures. Many research activities in recent years have been dedicated to solve the problematic issues associated with the existing power grid. These issues mainly include: high level of complexity, dependency to other infrastructures, effect of possible cascading events on the grid, and insufficient spare capacity as a result of deregulation [1]-[3].

Nowadays, in different areas of the power grid higher levels of power quality and reliability, self-healing, efficiency and cost reduction are desired [4], [5]. Various ongoing efforts aim to meet these demands by improving the performance of the utility grid to increase the quality of service that customers receive.

Due to the growing number of electronic loads and interconnection of emerging sensitive data networks such as internet, higher levels of power quality, reliability and availability are required from the utility grid [6].

On the other hand, the complexity and geographic extension of the grid and its interconnection to other infrastructures raises several concerns on its security in response to natural events, human error and intentional threats. The power grid is expected to survive these accidents and/or attacks, and should keep the desired standard levels of stability and reliability at any time even when one or more components are disabled. In other words, the future power grid must be a self-healing infrastructure [2], [3].
Introduction

Other important issues are the system efficiency and the cost of electricity for customers. Traditionally, high security, quality, reliability and availability factors have been achieved by increasing the energy price, and customers have had no choice but to pay more for such service improvements. Nowadays, with the deregulation process that is growing rapidly within European and North American power grids, power companies are competing to provide energy to the customers at a lower price. In addition, the governments’ initiative programs encourage private sector to reduce the government’s part in providing electric energy as a traditional energy provider.

How are the objectives met?

To cope with the aforementioned objectives, the smart grid concept has been proposed. In the future smart grid, each grid node has a degree of computational power and decision making capability. These single nodes will operate separately but have the ability to communicate, co-operate and even compete with each other to form the distribution system. In this approach, the power grid provides every node with smart sensing and measurement devices, and gives them the capability to locally decide to buy or sell energy (based on the offered prices and the unit specific requirements) and react to the unwanted events and damages without the need for sending huge amounts of data to the central controllers. This will make the power grid an adaptive and fast, self-healing intelligent network with plug-and-play capability.

The smart grid is therefore an integration of various subsystems and functions under the operation of an advanced and intelligent distributed control system and a two-way communication network.

The current centralized form of the power grid is degrading in its capability to fulfill these technical and economic scopes and the arisen concerns are causing the power network to gradually re-shape to a distributed form. Distributed renewable energy resources with their exciting benefits such as renewable energy application, reduced transmission line length and loss, reduced carbon footprint, increased power quality and reliability and grid expansion capability
are one of the key drivers to this change [7]-[13]. An important benefit of the distributed renewable energy resources is the viability of local power generation and consumption which results in reduced carbon emission and line losses, increased power quality and reliability, and grid expansion deferral. Also with the application of Combined Heat and Power (CHP) cycles increased efficiencies are achievable [11]. Despite these interesting merits indiscriminate nature of distributed renewable energy resources which is due to their unpredictability and dependency on the natural and climate conditions requires the utility planners to think of additional means to meet the consumers’ demand for high reliability and power quality.

The newly proposed concept of microgrids suggests that instead of indiscriminate aggregation of Distributed Generator (DG) units in the grid, multiple units should be integrated in a single united system to form the so-called “microgrid” [12]. A microgrid therefore is an integration of multiple Distributed Energy Resources (DERs) such as generation, storage and load units at the distribution level in a united system. This single united system should be capable of operating in both grid-connected and stand-alone or islanded modes.

The aggregation of multiple distributed energy resources into one microgrid system allows for local control of distributed generation, thereby reduces the need for central dispatch. During disturbances, the generation and corresponding loads can separate from the distribution system to isolate the microgrid’s sensitive loads from the disturbance and consequently maintaining high level of service without affecting the transmission grid’s integrity. The size of distributed generation technologies permits generators to be placed optimally in relation to heat loads, allowing the use of waste heat in combined heat and power systems. Such applications can significantly increase the overall efficiencies of the system and help to improve the operation of power system [12], [13].

Considering the numerous benefits of microgrid application, it is evident that the realization of smart grid concept is only possible with the integration and evolution of smart or intelligent
microgrids as the main building blocks of the future power grid. Application of smart microgrids will enable the integration of distributed intelligence in the grid.

The nature of most distributed energy resources in the microgrid requires power electronic-based converters to re-shape their generated energy to a form compatible with the utility grid’s voltage and frequency. The majority of distributed generators are hence interfaced to the microgrid through voltage source converters. Application of power electronic converters yields to more operation and control flexibility for the microgrid sources, compared to traditional electric machines. Nevertheless, it should be noted that specific nonlinearities, interdependencies, and lower physical inertia of power electronic converters requires advanced fast and flexible control techniques to maintain their integrity within the microgrid.

While connected to the grid, the microgrid should appear to the power grid as a single united entity. In a grid-connected mode, voltage and frequency are enforced by the power grid, and DG units typically supply pre-determined active and reactive power to the loads.

If the situations on the grid-side dictate so, the microgrid must be able to seamlessly disconnect or island itself from the grid and remain functional in the autonomous or islanded mode. In the islanded mode, power sharing algorithms such as droop control are often used to regulate the base voltage and frequency in the microgrid system. In case of an imbalance between the supplied and demanded power in this mode, a number of non-critical loads are shed.

Power control of voltage source converters has been traditionally implemented in synchronous (dq), stationary (αβ) or natural (abc) reference frames and depending on the reference frame used the adopted control structures can be chosen from linear or nonlinear algorithms such as Proportional Integral (PI), Proportional Resonant (PR), vector control, hysteresis control etc. [14]-[31]. The design simplicity and easier implementation of linear control algorithms used in synchronous or stationary reference frames have resulted in their relative popularity compared to non-linear approaches. The synchronous reference frame which has received more attention, uses a Park transformation to convert three-phase rotating quantities to
direct and quadrature dc variables. These dc quantities can be regulated by using simple and linear PI controllers. Despite good performance in controlling dc variables, PI controllers fail to operate well in case of load changes and high penetration of distributed generators in microgrids. Poor compensation capability for low order harmonics has also been reported [14]-[19]. PI controllers have the well-known drawback of a non-zero steady state error if used in natural or stationary reference frames, i.e. if regulating sinusoidal variables. Application of Proportional Resonant (PR) controllers in the stationary reference frame eliminates the steady state error, however is accompanied with other drawbacks such as sensitivity to grid frequency variations, poor transient response during step changes and low stability margins [20]-[22]. The use of natural reference frames on the other hand, requires more complex control structures such as hysteresis control. Application of such nonlinear structures will itself result in variable switching frequencies, which requires complex adaptive band hysteresis control [23].

In addition to classic control approaches, intelligent control algorithms such as fuzzy logic and artificial neural networks have been also used in recent years with the purpose of improving the dynamic performance and adaptivity; however in some cases these algorithms increase the control system complexity [32]-[37].

It is also worth mentioning that previous research on voltage source converters control in microgrids have been mostly conducted over simplified microgrid models that are not good approximations of real microgrids [16], [18], [19].

1.1 Objectives of This Thesis

The objective of this PhD thesis is to develop control algorithms for voltage source converters in a microgrid system to cope with the poor adaptation of traditional PI regulators to load changes, disturbances and high DG penetrations. The control system is intended to manage
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reliable and high quality energy supply to local loads, and to ensure appropriate power tracking and power sharing among microgrid sources in grid-connected and islanded modes.

The proposed control algorithms are based on the adaptive critics design concept [38], [39]; and employ a so-called critic element to evaluate the credibility of the control system performance. The critic’s evaluations are then used to dynamically update the controller parameters until the desired performance is achieved.

1.2 Thesis Contributions

The developed adaptive critic-based controller, controls active and reactive power of DGs in the grid-connected microgrid and voltage and frequency at grid nodes in the islanded mode. It is assumed that reference values are provided by external sources.

The critic-based control idea is used in conjunction with traditional PI controllers (critic-based PI control and critic-based self-tuning PI control), as well as neuro-fuzzy controllers (critic-based neuro-fuzzy control). The following are the contributions of this thesis:

• In contrary to previous studies, which have been mostly conducted on simple microgrid models, the microgrid model used in this thesis considers high penetrations of DG units (3-DGs and 5-DGs) and different load types such as constant power and dynamic motor loads. Furthermore, multiple operational scenarios are considered to ensure the effectiveness of the proposed controls in different conditions.

• Using the critic-based control approach, the need for precise design of the controllers is removed and more value is given to the design of the critic agent. It should be noted that the critic is only responsible for providing linguistic evaluations of the performance; hence no complicated mathematical calculations is needed for its design. Designing the critic instead of the controller increases the degree of intelligence and adaptivity against changes such as high penetration of DGs and dynamically demanding situations like
Introduction

presence of motor loads and results in a self-tuning control system with the ability of on-line learning and independency from system model. Simple learning rules increase the computational speed.

- Application of the critic-based neuro-fuzzy controller is associated with the removal of de-coupling and feed-forward terms in $dq$ reference frame which results in the simplification of the control system.

- The proposed control algorithms successfully reduce the initial transient time of the controller $\sim$%80 with the critic-based neuro-fuzzy control and critic-based self-tuning PI control, and $\sim$%66 with the critic-based PI controller compared to traditional PI control.

- The initial overshoot associated with PI control is completely removed for real power and reduced considerably for reactive power. Also output oscillations are significantly reduced.

- A comparison between the tracking errors shows that the average error over the transient time is reduced $\sim$%50 for real and reactive power in the critic-based neuro-fuzzy control compared to PI control. This parameter is increased $\sim$%30 for real power and decreased $\sim$%30 for reactive power in the critic-based PI control, and reduced $\sim$%60 for real power and $\sim$%50 for reactive power for the proposed critic-based self-tuning approach.

- A comparison between the current waveforms shows that the proposed critic-based neuro-fuzzy and critic-based self-tuning PI controllers reduce the Total Harmonic Distortion (THD) factor of phase current $\sim$%50. This parameter is however increased in the critic-based PI control and is almost doubled.

1.3 Thesis Outline

This thesis is structured as follows:
Introduction

In Chapter 2 the microgrid structure, operation and control principals are discussed, and the previous classical and non-classical control algorithms for voltage source converters are reviewed and compared. An introduction to the principals of fuzzy systems and neural networks is provided at the end of this chapter.

Chapter 3 presents the Critic-based Neuro-fuzzy Control concept and its application to the under-study microgrid system. The simulation results are provided and compared to those of conventional PI control.

In Chapter 4 and Chapter 5 the proposed Critic-based PI Control and Critic-based Self-Tuning PI Control algorithms are discussed and the simulation results over the under-study microgrid system are presented and compared to traditional PI control.

In Chapter 6 the contributions of the thesis are summarized and concluded and possible areas for future works are suggested.

A list of the publications from this thesis is provided in Appendix A.
Chapter 2

Literature Review

2.1 Microgrids Structure, Operation and Control

2.1.1 Microgrid Structure

The term microgrid refers to a set of low (≈≤1 kV) or medium voltage (usually ≈ 1-69 kV) distributed energy resources including distributed generators, storage and loads that work together and are connected to the main grid from a single point of connection. From the grid’s perspective, the microgrid must appear as a single generation or load unit. In addition to operating in the grid-connected mode, the microgrid should be able to smoothly disconnect or island from the grid and stay operational in case of abnormal conditions occurring on the grid-side. Hence, in the absence of the utility grid microgrid must supply full or a portion of total loads in the system.

Figure 2.1 illustrates a typical microgrid architecture in which the key parts are: distributed generators (DGs), distributed storage systems (DSs), loads, and interconnecting and control systems.

The electrical system is usually assumed to be radial, and could have multiple feeders. Distributed energy resources can be selected among various technologies, such as wind turbines, fuel cells, Photo Voltaic (PV) units etc. among which renewable energy resources have received greater attention.
The electric energy form produced by most renewable energy sources is not compatible with the main grid; therefore power electronics interfaces are used to change the produced power to an ac form compatible with the grid voltage and frequency. Voltage source converters are the most popular type of power electronic interfaces that are used for this purpose. In addition to their major interfacing role, power electronic converters can provide efficient and advanced control means to ensure that the microgrid appears as a single united system to the power grid.

The microgrid is interfaced to the utility grid through an interconnection switch located at the primary side of a transformer at the end of distribution feeder from the grid which is called the
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Point of Common Coupling (PCC). Each microgrid feeder can have several interconnection switches and control systems.

In case a disturbance occurs on the main grid the entire or a part of the microgrid can separate from the network to minimize disturbance to the local loads. These can be industrial or sensitive loads which require a high level of power quality and reliability. Islanded operation is possible only when there is enough local generation to meet the demands of loads, otherwise a number of non-critical loads must be shed after the islanding.

2.1.2 Microgrid Operation

A microgrid normally operates in the grid-connected mode. However, it is also expected to provide sufficient generation capacity, controls, and operational strategies to supply at least a portion of the load after disconnecting from the grid and remain operational as an autonomous system. The high amount of penetration of DER units requires provisions for both islanded and grid-connected modes of operation and smooth transitions between them, i.e. islanding transients. The required control systems can be studied at two levels: the microgrid management, and DERs local control.

2.1.3 Microgrid Supervisory Control and Management

Sound operation of a microgrid with more than two DER units, especially in an autonomous mode, requires a power and energy management strategy [40]. Fast response of the management system is more critical for a microgrid compared to a conventional power system, because of the presence of various DER units of different technologies, lack of a dominant energy source and fast response of electronically coupled DER units that can have negative impacts on voltage/angle stability.
The management system of a microgrid must guarantee all or a subset of functions such as: supply of electrical and/or thermal energy, interacting with the energy market, providing the desired power quality and reliability for sensitive loads etc. [41].

In the technical literature, the management system has been implemented in fully or partially (hybrid) centralized or decentralized forms [42]-[44]. In a fully centralized management system, a central controller is responsible for the maximization of the microgrid value and the optimization of its operation based on different interests of the microgrid and energy market [44]. On the contrary, in a fully decentralized approach, local DER controllers have major responsibilities and must take all appropriate decisions to ensure safe and seamless operation of the under control units [45].

In a fully centralized approach [43], the supervisory controller has a hierarchical structure at three control levels:

- Distribution network operator and market operator
- Microgrid central controller
- Local controllers which could be either DG controllers or load controllers

The distribution system operator is responsible for the operation of areas in which more than one microgrid exist. In addition, one or more market operators are responsible for the market function of the area. The main interface between the distribution system and market operators and the microgrid is the microgrid central controller. The microgrid central controller may accept different roles ranging from the responsibility for the maximization of the microgrid value and optimization of its operation to simply coordinating local controllers [43].

At the lowest level of control, the local DER controllers use the power electronic interfaces and control the production and storage units and some of the local loads. Depending on the control approach, each controller may have a certain level of intelligence.

In decentralized control, the main function of each controller is to enhance the overall performance of the microgrid rather than maximizing the revenue of the corresponding unit.
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Thus, the architecture must be able to include economic functions and environmental issues, as well as technical requirements. This organization of the microgrid can be conducted based on distributed control approaches such as multi-agent system concept, which is an evolved form of the classical distributed technology with some specific features that provide new capabilities in controlling complex systems [45]-[52].

In a centralized control, local controllers receive set points from the microgrid central controller, while in a decentralized strategy they can take actions locally. In either method, there are some decisions that are only made locally; that is, the local controllers do not need the coordination of a central controller and all necessary calculations are performed locally. Voltage control is an example of such decisions [43], [44].

The main difference between the two approaches lies in the amount of information that needs to be processed in each case. In a decentralized method, local controllers do not need direct access to the information of the neighboring controllers. In the centralized approach on the other hand, the microgrid central controller needs the access and the ability to process all the information of the local controllers. In practice however, it is very difficult for the microgrid central controller to have access to the all available data of local controllers and it might be very hard to implement such a centralized system at a reasonable cost with access to this amount of data and the required processing and operational power [45].

2.1.4 DERs Local Control

Voltage source converters are the most popular type of power electronics based interfaces used to connect renewable energy resources within microgrids. Figure 2.2 shows a representation of a DG unit within a microgrid, along with the required control and monitoring systems. The distributed generation unit consists of a primary energy source which could be any of the different technologies such as wind, solar etc. The energy source is interfaced to the rest of the
microgrid through a power electronic converter, which is a voltage source converter here. The monitoring and control systems measure and control the current and voltage of the output filter and the primary energy source.

**Figure 2.2. Representation of a DG unit in a microgrid.**

Because of the different structural nonlinearities and interdependencies of voltage source converter mediums, the control concepts, strategies, and characteristics of electronically coupled DERs are significantly different from the rotating machine generators. As a result, the dynamic behavior and control of a microgrid, particularly in an autonomous mode of operation, is noticeably different from a conventional power system.

**Grid-connected Mode Control**

In the grid-connected mode, voltage and frequency in the microgrid are enforced by the power grid which is a dominant energy source and therefore direct control of voltage and/or frequency at the point of connection is not required; hence, in this mode the microgrid can
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exchange active or reactive power with the grid and DG units typically supply pre-determined active and reactive power to the loads [14]-[16].

In this mode of operation, the overall power produced by DG units supplies all or a portion of microgrid loads and the utility grid provides/absorbs the required/excessive power. Consequently, each DG will follow its active and reactive power references. These reference values may be calculated locally or come from a higher level controller.

Figure 2.3 shows a grid-connected voltage source converter connected in a microgrid. A series resistive-inductive (RL) filter is used to connect the converter to the rest of the system. VSCs can also be connected to the grid using inductive-capacitive-inductive (LCL) filters which provide higher harmonics attenuation; however they require more complicated control system designs to damp LCL resonance, which can cause poor damped oscillations and even instability and therefore have not been used here.

The inverter in the circuit is treated as an ideal, lossless power transformer and the dynamics of dc side are neglected.

![Diagram of a grid-connected voltage source converter](image)

**Figure 2.3. Grid-connected voltage source converter.**

The governing equations of ac-side circuit are given by (2.1):
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\[
\begin{bmatrix}
e_a \\
e_b \\
e_c
\end{bmatrix} = R \begin{bmatrix}
i_a \\
i_b \\
i_c
\end{bmatrix} + L \begin{bmatrix}
\frac{di_a}{dt} \\
\frac{di_b}{dt} \\
\frac{di_c}{dt}
\end{bmatrix} + \begin{bmatrix}
v_a \\
v_b \\
v_c
\end{bmatrix} \tag{2.1}
\]

In which \(e_a, e_b, e_c\) and \(v_a, v_b\) and \(v_c\) represent the converter and grid voltages, respectively, and \(i_a, i_b\) and \(i_c\) denote for three-phase line currents.

The instantaneous active power at a point on line is:

\[P = v_a \cdot i_a + v_b \cdot i_b + v_c \cdot i_c \tag{2.2}\]

Different control schemes have been proposed to control grid-connected voltage sourced converters. In the technical literature classic control algorithms have received greater attention; however non-classic algorithms using fuzzy logic and neural networks are also reported.

**Classic Control Approaches**

These controllers have been designed and implemented in one of the three reference frames, i.e., synchronous reference frame, stationary reference frame, and natural reference frame [14]-[16].

**A. Synchronous reference frame control**

This reference frame also called \(dq\) reference frame uses an \(abc\) to \(dq\) transformation to convert three phase voltage and currents to their dc projections onto two perpendicular axes rotating synchronously with the grid voltage. This will make filtering and controlling easier.

Using the Park transform in [17] the Park transform matrix \(K\) is as follows:

\[
K = \frac{2}{3} \begin{bmatrix}
\cos(\theta) & \cos(\theta - \frac{2\pi}{3}) & \cos(\theta + \frac{2\pi}{3}) \\
\sin(\theta) & \sin(\theta - \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}, \theta = \omega \cdot t + \theta_0 \tag{2.3}
\]

Using the above transform matrix, three phase quantities can be transformed to \(dq\) quantities and vice versa as follows:
Using (2.4), equation (2.1) is transformed to the synchronous reference frame as follows:

\[ e_{dq} = R_i_{dq} + L \frac{d}{dt} i_d + jωL_i_q + v_{dq} \]  

(2.5)

The dynamics of direct (d) and quadrature (q) axes are derived by separating the real and imaginary terms:

\[ R_i_d + L \frac{d}{dt} i_d = e_d - ωL_i_q - v_d \]  

(2.6)

\[ R_i_q + L \frac{d}{dt} i_q = e_q + ωL_i_d - v_q \]  

(2.7)

And (2.2) is transformed as follows:

\[ P = \frac{3}{2} (v_d \cdot i_d + v_q \cdot i_q) \]  

(2.8)

\[ Q = \frac{3}{2} (v_d \cdot i_q - v_q \cdot i_d) \]  

(2.9)

And finally, (2.6) and (2.7) can be re-written in the Laplace form as:

\[
\begin{bmatrix}
E_d - V_d \\
E_q - V_q
\end{bmatrix}
= \begin{bmatrix}
R + Ls & ωL \\
-ωL & R + Ls
\end{bmatrix}
\begin{bmatrix}
i_d \\
i_q
\end{bmatrix}
\]  

(2.10)

A block diagram representation of (2.10) is depicted in Figure 2.4. As seen, undesired cross-coupling between the d and q axes parameters, and interfering grid voltages are major issues that must be addressed in the control system design.
Figure 2.4. Output filter block-diagram in the grid-connected VSC.

If the synchronous reference frame is controlled in such a way that the \(d\) axes is always locked to the voltage vector \(v\), then \(v_q = 0\); consequently in equations (2.8) and (2.9) \(P\) would be directly proportional to \(i_d\) and \(Q\) would be proportional to \(i_q\). This way, to control the active power we need to control \(i_d\) and to control the reactive power it is required to control \(i_q\). The task of bringing the \(d\) axis in phase to the grid voltage is usually done using a so-called Phase Locked Loop (PLL) system. Using the PLL block the synchronization to the grid voltage is achieved. A block diagram of a very popular PLL system is shown in Figure 2.5.

Figure 2.5. Phase Locked Loop (PLL) system block diagram.
Voltage source converters are often working in the current mode within a microgrid; in other words to control the active and reactive power it is required to control the inverter’s output voltage using the inverter current.

Based on the previous modeling of the VSC system, a schematic diagram of a traditional control system in $dq$ reference frame is shown in Figure 2.6.

![Figure 2.6. Synchronous reference frame control in a grid-connected VSC.](image)

The $dq$ control structure is normally associated with PI controllers as they have a good performance in controlling dc variables. To bring the controlled current in phase with the grid voltage, the angle $\theta$ for $abc \rightarrow dq$ and $dq \rightarrow abc$ transformations is derived from the grid voltage using a PLL block. To remove the cross-coupling effect between $d$ and $q$ axis equations and disturbance behavior of grid voltage terms on the operation of controllers (as seen in Figure 2.4), decoupling and feed-forward terms are typically used. The control system’s output signals are used to generate Pulse Width Modulation (PWM) gate signals of the VSC after being transformed to the $abc$ reference frame.

**B. Stationary reference frame control**

In this control scheme, three phase quantities are transformed into the stationary or $\alpha\beta$ reference frame using $abc \rightarrow \alpha\beta$ transformation. This way, three phase variables are transformed
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to their projections onto two perpendicular axes, i.e. axis $\alpha$ and axis $\beta$. The $\alpha\beta$ reference frames axes are not rotating but stationary as compared to the synchronous reference frame. As a result $\alpha\beta$ variables are sinusoidal. For sinusoidal variables, with the application of PI controllers zero steady state error is not achievable, therefore, PR controllers are typically used [23]. Figure 2.7 shows a typical structure for this control scheme.

![Diagram](image)

**Figure 2.7. Stationary reference frame control in a grid-connected VSC.**

C. Natural reference frame control

In natural or $abc$ reference frame, the three phase currents are controlled by three controllers. Different structures such as PI, PR and hysteresis control have been implemented in this reference frame [23]. A block diagram representation of the natural reference frame control is shown in Figure 2.8.
Each of these control structures have some merits and disadvantages. Application of \( dq \) reference frame results in dc variables that can be easily regulated using simple and linear PI controllers; however the necessity of de-coupling and feed-forward terms increases the complexity of control system. Furthermore, the required \( abc \rightarrow dq \) and \( dq \rightarrow abc \) transformations and the need for calculating the phase angle of grid voltage are other added complexities in the structure. Despite good performance in controlling dc variables, PI regulators fail to operate well in case of load changes and high penetration of distributed generators in microgrid systems. Also poor compensation capability for low order harmonics has been reported [14]-[19].

PI controllers have the well-known drawback of a non-zero steady state error in regulating sinusoidal variables. Application of PR controllers in the stationary reference frame removes the non-zero steady state error, however it is accompanied with drawbacks such as sensitivity to grid frequency variations, poor transient response during step changes and low stability margins [20]-[22]. Also if PR controllers are used, the controller complexity will decrease, but it is still required to include \( abc \rightarrow a\beta \) and \( a\beta \rightarrow abc \) transformations and even \( abc \rightarrow dq \) transform if the control system is implemented in conjunction with \( dq \) reference frame.
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And finally if natural reference frame is adopted, PI controllers can be used in conjunction with $dq$ reference frame which results in more complexity, while the application of PR controllers will somehow reduce the complexity. Application of nonlinear structures such as hysteresis control will itself result in variable switching frequencies, which requires more complex adaptive band hysteresis control [23].

Non-classic Control Approaches

In addition to classic control approaches, intelligent control algorithms such as fuzzy logic and artificial neural networks have been also used in recent years to cope with the control system complexity while improving the transient performance [32]-[37]. Neural network technology with its learning and interpolation capabilities shows great promise for addressing such control problems. Fuzzy controllers on the other hand, work well as supervisory controllers in conditions such as plant nonlinearity and uncertainty.

Regardless of the control method, these controllers are mostly implemented in natural reference frame [34], [35], [36], [53]; but application of fuzzy systems in a $dq$ reference frame is also reported in [33], [37].

In [34] and [35] two separate fuzzy and neural controllers are implemented to control active and reactive power of a VSC using instantaneous parameters and by means of controlling angle and amplitude (modulation index, $m$) of Sinusoidal Pulse Width Modulation (SPWM) reference signal. In [37] fuzzy logic is used for the purpose of current regulation of $d$ and $q$ axis currents in a grid connected VSC with LCL filter.

In [53] a neuro-fuzzy structure is used to control the output of a PV-based DG using Maximum Power Point Tracking (MPPT) concept on dc-side. The neuro-fuzzy system is used to estimate the reference voltage that guaranties optimal power transfer between DG and microgrid.

A block diagram representation of the proposed controller in [34] is seen in Figure 2.9.
Islanded Mode Control

During the islanded mode, the utility grid is absent; therefore if none of the DG units enforces the base frequency and regulates the voltage, voltage and frequency will change freely within the microgrid. Droop control is a popularly adopted control strategy in this mode, in which by defining frequency-real power \((f-P)\) and voltage-reactive power \((V-Q)\) droop characteristics the frequency and voltage deviations are limited within a maximum allowed range. This range of changes is calculated based on the DGs ratings to ensure that proper active and reactive power sharing among DGs takes place [17], [54], [55], [56].

The typical droop characteristics for a DG unit in a microgrid are:

\[
\omega = \omega_{\text{max}} - m_P P \quad (2.11)
\]

\[
V = V_{\text{max}} - m_Q Q \quad (2.12)
\]

where \(m_P\) and \(m_Q\) gains are the slopes of droop characteristics. The droop gains must satisfy design margins of frequency, voltage and power of each DG.

Droop control strategy enables decentralized control of multiple DG units, as it is only dependent on locally collected data.
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In [17] droop-based control strategy in \(dq\) reference frame is used to control the islanded microgrid and droop control systems have been implemented in natural reference frame in [54], and [56].

Figure 2.10 shows the structure of a sample droop control system. With the droop control, a change in load will result in a steady-state frequency and voltage deviation that requires supplementary provisions to restore the frequency and voltage to their normal values [55]. Another drawback of the droop control system is its transient performance which is dependent on the droop coefficients that are usually calculated based on steady state conditions. Also these calculations are typically based on the assumption of a highly inductive system, which is not always the case in distribution networks [57].

![Droop control system block diagram.](image)

2.2 Mathematics of Fuzzy Systems

In English literature the word “fuzzy” refers to a blurred, indistinctive or imprecisely defined object; however in technical context fuzzy systems are systems to be precisely defined and fuzzy control is a special kind of nonlinear control with exact definitions. In other words, although fuzzy systems may be used to define fuzzy phenomena but fuzzy logic is a precise theory itself.
Fuzzy logic is a generalized form of classical logic where the truth values of propositions can be any number in the $[-1,1]$ interval, instead of two values of 0 and 1. This generalization enables approximate reasoning which is in other words the ability to deduce imprecise or fuzzy conclusions from imprecise or fuzzy propositions [58].

### 2.2.1 Fuzzy Sets

Let $U$ be the *universe of discourse*, or universal set, which contains all possible elements of concern in the application. A classical or *crisp* set $A$, in the universe of discourse $U$ can be defined by listing all of its members (the list method) or by specifying the properties that must be satisfied by the members of the set (the rule method). The third method to define a set is the membership method which introduces a zero-one membership or characteristic function for $A$ denoted by $\mu_A(x)$ such that,

$$
\mu_A(x) = \begin{cases} 
1, & \text{if } x \in A \\
0, & \text{if } x \notin A
\end{cases}
$$

This way the set $A$ is mathematically equivalent to its membership function $\mu_A(x)$.

By definition, a fuzzy set in a universe of discourse $U$ is characterized by a membership function $\mu_A(x)$ that takes values in the interval $[0,1]$. Hence a fuzzy set is a general form of a classical set where the membership function can take any value between 0 and 1.

The fuzzy set $A$ in $U$ can be represented as a set of pairs of element $x$ and its membership value:

$$
A = \{(x, \mu_A(x)|x \in U\}
$$

When $U$ is continuous such as $R$, $A$ is commonly written as,

$$
A = \int_U \mu_A(x)/x
$$
where the integral sign denotes the collection of all points \( x \in U \) with the associated membership function \( \mu_A(x) \) not the arithmetic integration. When \( U \) is discrete, \( A \) is commonly written as,

\[
A = \sum_u \mu_A(x)/x
\]  \hspace{1cm} (2.16)

Where the summation sign denotes the collection of all points \( x \in U \) with the associated membership function \( \mu_A(x) \) not the arithmetic summation.

There are a variety of choice of membership functions depending on the application; however in each context the membership function should meet the following criteria:

1. The membership function should be a good representative of linguistic statements or human knowledge.
2. It must be easily specified by mathematical equations to minimize the computational load and maximize the speed.

Two of the most popular membership functions are Gaussian and sigmoid membership functions:

- **Sigmoid Membership Function**: the sigmoid membership function has the following form:

\[
\mu_{sgm}(x: a, b) = \frac{1}{1+\exp(-(a(x-b)))}
\]  \hspace{1cm} (2.17)

with center \( b \) and curve inflection parameter \( a \).

- **Gaussian Membership Function**: the Gaussian membership function has the general form as,

\[
\mu_{gsn}(x: c, \sigma) = \exp\left(-\left(\frac{x-c}{\sigma}\right)^2\right)
\]  \hspace{1cm} (2.18)

where \( \sigma \) is the variance and \( c \) the center of Gaussian function.

Figure 2.11 shows the Gaussian and sigmoid membership functions for \( a = 11, b = 0.3, c = 0, \sigma = 1/\sqrt{8} \)
2.2.2 Fuzzy Operators

Although fuzzy sets and membership functions are tools to represent the fuzzy membership concept in a set, but in addition to the ability of assigning data to fuzzy membership functions we need operators to combine these data and make deductions. Fuzzy logic operations have this ability and are basically similar to the famous Boolean operations such as AND, OR, NOT, etc. Assuming that $A$ and $B$ are fuzzy sets defined in the universe of discourse $U$, some of these operators are defined as follows:

- **Fuzzy Complement**: let $c: [0,1] \rightarrow [0,1]$ be a mapping that transforms the membership functions of fuzzy set $A$ into the membership function of the complement of $A$, that is,

$$c(\mu_A(x)) = \mu_{\overline{A}}(x) \quad (2.19)$$

In order for any function $c$ to be considered as a fuzzy compliment it must meet the following:

1. $c(0) = 1, c(1) = 0 \quad (2.20)$

2. For all $a, b \in [0,1]$, if $a < b$, then $c(a) \leq c(b)$ where $a$ and $b$ denote membership functions of some fuzzy sets, i.e. $a = \mu_A(x)$ and $b = \mu_B(x) \quad (2.21)$
A basic fuzzy complement of fuzzy set $A$ is defined as follows:

$$\mu_A^C(x) = 1 - \mu_A(x) \quad (2.22)$$

- **Fuzzy Union- The S-Norms**: let $s: [0,1] \times [0,1] \rightarrow [0,1]$ be a mapping that transforms the membership functions of fuzzy sets $A$ and $B$ into the membership function of the union of $A$ and $B$, that is,

$$s(\mu_A(x), \mu_B(x)) = \mu_{A\cup B}(x) \quad (2.23)$$

Any function $s$ that satisfies the following is called an $s$-norm:

1. $s(1,1) = 1, s(0, a) = s(a, 0) = a \quad (2.24)$
2. $s(a, b) = s(b, a) \quad (2.25)$
3. If $a \leq a'$ and $b \leq b'$, then $s(a, b) \leq s(a', b') \quad (2.26)$
4. $s(s(a, b), c) = s(a, s(b, c)) \quad (2.27)$

There are various types of fuzzy $s$-norms; but the basic union of fuzzy sets $A$ and $B$ in $U$ denoted by $A \cup B$ which is defined as follows is easy to prove as an $s$-norm:

$$\mu_{A\cup B}(x) = \max\{\mu_A(x), \mu_B(x)\} \quad (2.28)$$

- **Fuzzy Intersection- The T-Norms**: let $t: [0,1] \times [0,1] \rightarrow [0,1]$ be a mapping that transforms the membership functions of fuzzy sets $A$ and $B$ into the membership function of the intersection of $A$ and $B$, that is,

$$t(\mu_A(x), \mu_B(x)) = \mu_{A\cap B}(x) \quad (2.29)$$

Any function $t$ that satisfies the following is called a $t$-norm:

1. $t(0,0) = 0, t(1, a) = t(a, 1) = a \quad (2.30)$
2. $t(a, b) = t(b, a) \quad (2.31)$
3. If $a \leq a'$ and $b \leq b'$, then $t(a, b) \leq t(a', b') \quad (2.32)$
4. $t(t(a, b), c) = t(a, t(b, c)) \quad (2.33)$

Various types of $t$-norms have been defined but the basic intersection of fuzzy sets $A$ and $B$ in $U$ denoted by $A \cap B$ which is defined as follows is easily proved to be a $t$-norm:
\[ \mu_{A \cap B}(x) = \min\{\mu_A(x), \mu_B(x)\} \] (2.34)

2.2.3 Linguistic Variables

A linguistic variable is a variable that can take words in natural languages as its values. These words are characterized by fuzzy sets in the universe of discourse in which the variable is defined.

A linguistic variable is characterized by \((X, T, U, M)\), where:

- \(X\) is the name of linguistic variables such as error.
- \(T\) is the set of linguistic values that \(X\) can take such as \{small, medium, big\}.
- \(U\) is the actual physical domain in which the linguistic variable \(X\) takes its quantitative (crisp) values for example \([0, 0.05]\).
- \(M\) is a rule that relates the linguistic values in \(T\) to fuzzy sets in \(U\).

2.3 Fuzzy Systems

Fuzzy systems are knowledge-based decision making systems. They receive several types of information, process them, and develop control strategies that cannot be done by conventional analytical control laws. A typical fuzzy system comprises of a fuzzifier, a rule-base, an inference engine and a defuzzifier. The fuzzy system can be interpreted as a nonlinear mapping from an input vector \(X \in R^n\) to an output vector \(y \in R^m\) (where \(n\) and \(m\) are input and output vectors dimensions, respectively). The fuzzifier receives linguistic input variables and calculates their degree of membership to fuzzy sets (e.g. Small, Medium, Big, etc.). The antecedent parts of the rules in the rule-base are then calculated by the inference engine and the defuzzifier finally maps the fuzzy output variables to their corresponding real values.

Figure 2.12 shows a block diagram representation of a fuzzy system and its components.
2.3.1 Fuzzy Rule-base

A fuzzy rule-base consists of a set of fuzzy rules. The rule-base is the heart of fuzzy system as all other parts of the fuzzy system are supposed to implement these rules. There are two general types of fuzzy rule-base: Mamdani [59] and Takagi-Sugeno-Kang (TSK) [60] fuzzy rule-base.

- **Mamdani Fuzzy Rule-base**: A fuzzy rule in the Mamdani rule-base has the following general form:

\[
R_q: \text{If } (x_1 \text{ is } A_{1q}^{q} \text{ and } \ldots \text{ and } x_n \text{ is } A_{nq}^{q}), \text{ Then } y \text{ is } B^{q} \quad (2.35)
\]

where \( A_{i}^{q} \) and \( B^{q} \) are fuzzy sets in \( U_i \subset \mathbb{R} \) and \( V \subset \mathbb{R} \), respectively and \( x = (x_1, x_2, \ldots, x_n)^T \in U \) and \( y \in V \) are the input and output linguistic variables of the fuzzy system, respectively. Let \( M \) be the number of rules in the fuzzy rule-base, that is \( q = 1, 2, 3, \ldots, M \). The fuzzy rule-base will be as follows:

\[
R_1: \text{If } (x_1 \text{ is } A_{11}^{1} \text{ and } \ldots \text{ and } x_n \text{ is } A_{n1}^{1}), \text{ Then } y \text{ is } B^{1} \\
R_2: \text{If } (x_1 \text{ is } A_{12}^{2} \text{ and } \ldots \text{ and } x_n \text{ is } A_{n2}^{2}), \text{ Then } y \text{ is } B^{2} \\
\vdots
\]
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\[ R_M: \text{If } (x_1 \text{ is } A_{1M} \text{ and } \ldots \text{ and } x_n \text{ is } A_{nM}), \text{ Then } y \text{ is } B^M \]

- **TSK Fuzzy Rule-base**: in the TSK rule-base, the If part of the rule is similar to a Mamdani rule, however the consequence part is a function of input variable. The TSK fuzzy rule-base is hence in the following form:

\[ R_1: \text{If } (x_1 \text{ is } A_{11} \text{ and } \ldots \text{ and } x_n \text{ is } A_{n1}), \text{ Then } y_1 = g_1(x) \]

\[ R_2: \text{If } (x_1 \text{ is } A_{12} \text{ and } \ldots \text{ and } x_n \text{ is } A_{n2}), \text{ Then } y_2 = f_2(x) \]

\[ \vdots \]

\[ R_M: \text{If } (x_1 \text{ is } A_{1M} \text{ and } \ldots \text{ and } x_n \text{ is } A_{nM}), \text{ Then } y_M = f_M(x) \]

where \( A_{qi} \) is a fuzzy set in \( U_i \subset R \) associated with the linguistic variable \( x_i \), and \( y_i = f_i(x_i) \) is the consequence of the \( q \)th rule.

Sugeno considered a linear combination of input variables as the function \( y \):

\[ f(x) = \frac{\sum_{l=1}^{M} y_l \omega^l}{\sum_{l=1}^{M} \omega^l} \quad (2.36) \]

where \( \omega^l \) weights can be calculated as follows:

\[ \omega^l = \prod_{i=1}^{n} \mu_{A_{li}}(x_i) \quad (2.37) \]

where \( A_{li} \) are the input fuzzy sets assigned to rule \( l \).

### 2.3.2 Fuzzy Inference Engine

In the fuzzy inference engine, by combining the rules in the fuzzy rule-base a mapping from fuzzy set \( A' \in U \) to the fuzzy set \( B' \in V \) happens. There are two general types of fuzzy inference methods: individual rule-base inference and composition based inference. In composition based inference all rules in the fuzzy rule-base are combined into a single fuzzy relation in \( U \times V \) which will be considered then as a single fuzzy If-Then rule. In individual rule-based inference each rule in the fuzzy rule-base produces an output fuzzy set and the output of the inference engine is the combination of these fuzzy sets which can be done either by union or intersection. There are a
variety of choices in selecting fuzzy inference engines among these two categories, such as Mamdani inference, Dienes-Rescher, product inference engine, minimum inference engine etc. The product and minimum inference engines that are the most commonly used inference engines in fuzzy systems and fuzzy control are as follows:

- **Product Inference Engine**: the product inference engine is obtained as
  \[
  \mu_{B'}(y) = \max_{i=1}^{M} [\sup_{x \in U} (\mu_{A'}(x) \prod_{i=1}^{n} \mu_{A_i}(x_i), \mu_{B'}(y))] 
  \]
  That is, given the fuzzy set \(A'\) in \(U\), the product inference engine returns the fuzzy set \(B'\) in \(V\) according to (2.38).

- **Minimum Inference Engine**: the minimum inference engine is obtained as
  \[
  \mu_{B'}(y) = \max_{i=1}^{M} [\sup_{x \in U} \left(\mu_{A'}(x), \mu_{A_1}(x_1), ..., \mu_{A_n}(x_n), \mu_{B'}(y)\right)] 
  \]
  That is, given the fuzzy set \(A'\) in \(U\), the minimum inference engine returns the fuzzy set \(B'\) in \(V\) according to (2.39).

The main advantage of the product and minimum inference engines are their computational simplicity which is specifically true for the product inference engine.

**2.3.3 Fuzzifier and Defuzzifier**

As discussed before, the fuzzy inference engine combines the rules in the fuzzy rule-base into a mapping from fuzzy set \(A'\) in \(U\) to fuzzy set \(B'\) in \(V\). In most practical and specially control applications input and outputs of the fuzzy system are real numbers; hence there must be interfaces between these input and output values and the fuzzy inference engine. These interfaces are called fuzzifier and defuzzifiers. A fuzzifier is therefore a mapping from the real-valued crisp \(x^* \in U \subset R^n\) to a fuzzy set \(A' \subset U\) and a defuzzifier is a mapping from fuzzy set \(B'\) in \(V \subset R\) to a crisp output \(y^* \in V\). In other words the fuzzifier is responsible for finding a fuzzy set such as \(A'\) that best represents the crisp input \(x^*\) and a defuzzifier is supposed to specify a crisp point \(y^*\) that
best represents fuzzy set $B'$. Some of the most popularly used fuzzifiers are Singleton fuzzifier, Gaussian fuzzifier and Triangular fuzzifier.

- **Singleton Fuzzifier**: the singleton fuzzifier maps the crisp input $x^* \in U$ into a fuzzy singleton $A' \in U$ which has membership value 1 at $x^*$ and 0 elsewhere. i.e.

$$\mu_{A'}(x) = \begin{cases} 1, & \text{if } x = x^* \\ 0, & \text{elsewhere} \end{cases} \quad (2.40)$$

- **Gaussian Fuzzifier**: the Gaussian fuzzifier maps the crisp input $x^* \in U$ into a fuzzy singleton $A' \in U$ with the following Gaussian membership function:

$$\mu_{A'}(x) = e^{-\frac{(x_1-x_1^*)^2}{a_1^2}} \times \ldots \times e^{-\frac{(x_n-x_n^*)^2}{a_n^2}} \quad (2.41)$$

where $a_i$ are positive parameters and the algebraic products can be replaced with $\min$ operator.

Some of the most popular defuzzifiers are the center of gravity defuzzifier, center of average defuzzifier and maximum defuzzifier.

- **Centre of Gravity Defuzzifier**: the center of gravity defuzzifier specifies the center of the area covered by the membership function $B'$ as the crisp output, i.e.:

$$y^* = \frac{\int y \mu_{B'}(y)dy}{\int \mu_{B'}(y)dy} \quad (2.42)$$

Figure 2.13 shows a graphic sample of this defuzzifier.

The drawback of the center of gravity defuzzifier is that it requires a high computational level.

- **Center Average Defuzzifier**: the fuzzy set $B'$ is the union of $M$ fuzzy sets in the $M$ rules and therefore to reduce the computational level of center of gravity defuzzifier, it can be approximated with the weighted average of the centers of $M$ fuzzy sets, with the weights equal to the height of the corresponding fuzzy set. Accordingly the center average defuzzifier can be defined as:
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\[ y^* = \frac{\sum_{l=1}^{M} y^l \omega_l}{\sum_{l=1}^{M} \omega_l} \quad (2.43) \]

where \( y^l \) is the center of the \( l \)'th fuzzy set and \( \omega_l \) is its height.

Figure 2.14 shows a sample for this defuzzifier for a simple case with \( M = 2 \), hence

\[ y^* = \frac{y^1 \omega_1 + y^2 \omega_2}{\omega_1 + \omega_2} \quad (2.44) \]

![Figure 2.13. Center of gravity defuzzifier.](image)

The center average defuzzifier is the most popular defuzzifier in fuzzy systems and fuzzy control.

![Figure 2.14. Center of average defuzzifier.](image)


2.3.4 Fuzzy System Types

From the previous sections it is clear that there are a large number of choices for fuzzy inference engine, fuzzification and defuzzification methods in a fuzzy system. By combining these different types of inference engines, fuzzifiers and defuzzifiers we can have different fuzzy systems. Some of these classes of fuzzy systems are very useful in control systems applications.

- For a normal fuzzy system $B^l$ with center $\vec{y}^l$, the fuzzy systems with Mamdani fuzzy rule-base (2.35), product inference engine (2.38), singleton fuzzifier (2.40), and center average defuzzifier (2.43) can be described as:

$$f(x) = \frac{\sum_{l=1}^{M} \vec{y}^l \prod_{i=1}^{n} \mu_{A_i}^l(x_i)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \mu_{A_i}^l(x_i)} \quad (2.45)$$

where $x \in U \subset \mathbb{R}^n$ is the fuzzy system input and $f(x) \in V \subset \mathbb{R}$ is the output.

As seen, these fuzzy systems are nonlinear mappings from $x \in U \subset \mathbb{R}^n$ to $f(x) \in V \subset \mathbb{R}$. This type of fuzzy systems is the most commonly used in technical literature, because of their computational simplicity and intuitive appeal.

From (2.45) it is seen that the output of this fuzzy system is a weighted average of centers of output membership functions in the fuzzy rule-base where the weights are the values of membership functions in the If parts of the rule at the input point.

The fuzzy system that has been used for the proposed fuzzy critics in this thesis have this form.

- Another class of fuzzy systems can be obtained by replacing the product inference engine with the minimum inference engine (2.39) in the previous class as:

$$f(x) = \frac{\sum_{l=1}^{M} \vec{y}^l \min_{i=1}^{n} \mu_{A_i}^l(x_i)}{\sum_{l=1}^{M} \min_{i=1}^{n} \mu_{A_i}^l(x_i)} \quad (2.46)$$

where $x \in U \subset \mathbb{R}^n$ is the fuzzy system input and $f(x) \in V \subset \mathbb{R}$ is the output.
For a normal fuzzy set $B^l$ with center $\bar{y}^l$, the fuzzy systems with Mamdani fuzzy rule-base (2.35), product inference engine (2.38), singleton fuzzifier (2.40), and maximum defuzzifier can be described as follows:

$$f(x) = \bar{y}^{l*}$$

(2.47)

where $l* \in \{1, 2, ..., M\}$ meets the condition below:

$$\prod_{i=1}^n \mu_{A_i^{l*}}(x_i) \geq \prod_{i=1}^n \mu_{A_i^l}(x_i), \quad l = 1, 2, ..., M$$

(2.48)

In this case it is seen that fuzzy systems are piece-wise constant functions where theses constants are the centers of the output membership functions in the fuzzy rule-base. Because of the discrete nature of changes in $f(x)$, these fuzzy systems are not appropriate for closed-loop control.

By changing the product inference engine to minimum inference engine another class of theses fuzzy systems are build that are simple functions.

### 2.4 Artificial Neural Networks

Artificial Neural Networks (ANNs) have been developed with the objective of understanding the human brain’s problem solving mechanism and emulate its capabilities to improve digital computing. An artificial neural network is hence an information-processing machine designed to mimic the operation of biological neural networks. Neural networks use a large amount of data transfer between simple arithmetic units called “Neurons”. Therefore an artificial neural network is a parallel data processing system that its basic data processing blocks store and access practical knowledge and is build based on the mathematical model of human brain and biological neural systems [61], [62]. This mathematical model is build based the following assumptions:

- Information processing is executed in simple elements called *neurons*.
- Signals are transferred between the neurons using connection links.
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- Each connection link in a neural network contains a weight which multiplies the transmitted signals.
- The sum of weighted input signals (net input) is sent to an activation function (usually nonlinear) to produce the neuron’s output signal.

Therefore each neural network is characterized with three factors: (1) the pattern of connection of neurons or the architecture of the net, (2) the method of determining the connecting weights (training or learning algorithm), and (3) the network’s activation function.

The weights of an artificial neural network are representatives of the information that is used to solve a problem. Neural networks are used in a variety of applications such as storing or recalling data or patterns, classifying patterns, performing mapping from input patterns to output patterns, pattern recognition, optimization problems, etc.

Each neuron has an internal state called its activation or activation level which is a function of its inputs. Typically the output of the neuron is sent as a signal to other neurons. It should be noted that each neuron can only send one signal at a time, although the signal might be sent over to multiple neurons.

Figure 2.15 shows a sample neuron in a neural net. The neuron receives its inputs from the neurons $X_1, X_2, X_3$ and $X_4$ and sends its output to neurons $Z_1$ and $Z_2$. The connection weights from $X_1, X_2, X_3$ and $X_4$ to neuron $Y$ are $w_1, w_2, w_3$ and $w_4$ and from neuron $Y$ to $Z_1$ and $Z_2$ are $v_1$ and $v_2$. The input of the neuron is the sum of weighted signals from input neurons,

$$y_{\text{in}} = x_1 \cdot w_1 + x_2 \cdot w_2 + x_3 \cdot w_3 + x_4 \cdot w_4 \quad (2.49)$$

The final output or activation of neuron $Y$ is a function of $y_{\text{in}}$ as follows:

$$y = f(y_{\text{in}}) \quad (2.50)$$

In case of a sigmoid activation function the neuron’s output is calculated as,

$$y = \frac{1}{1 + \exp(y_{\text{in}})} \quad (2.51)$$
The activation signal $y$ is transmitted to neurons $Z_1$ and $Z_2$ after being scaled by $v_1$ and $v_2$. weights.

![Diagram of a neuron in a neural network](image)

**Figure 2.15. Connections of a neuron in a neural network.**

### 2.4.1 Multi-Layer Perceptron (MLP) Neural Networks

The neurons in neural nets are often considered as arranged in layers. Neurons in the same layer typically behave in the same manner; that is, within each layer, the neurons have the same activation functions and the pattern of weighted connections over which the signals are transmitted. The units that receive the input signals are called *input units* and those that produce the outputs are called *output units*. The input units are not usually counted as a separate layer as they typically receive the inputs and activation of each unit is equal to the output signal.

A neural network that includes one or more layers of connection between input and output units is called a neural network with hidden layers or a Multi-Layer Perceptron (MLP) neural network. Multi-layer networks are capable of solving more difficult problems as compared to single-layer networks. Figure 2.16 shows a sample MLP network.
Most MLP neural nets have these characteristics:

- Each neuron consists of a nonlinear, continuous and differentiable activation function.
- The network includes at least one hidden layer which helps the network in learning nonlinear and complicated mappings.
- The network has a high level of connectivity between neurons. This high level of connection and continuity together with nonlinear activation functions enable the network to learn complicated and nonlinear problems.

2.4.2 Training in Neural Networks

In addition to the architecture of neural net, the method of determining the weights or training is another important characteristic of neural networks. Training algorithms in neural networks fall within three main categories [61].

- **Supervised Training**: The first category includes *supervised training* algorithms. In these methods a supervisor or teacher oversees the learner’s actions and reminds of correct behavior. In most common neural network applications, supervised training is accomplished by presenting a set of training vectors or patterns, each associated with a
corresponding target output vector. The weights are then tuned according to a learning algorithm.

- **Unsupervised Training**: The second category includes *unsupervised learning* algorithms. In these methods, contrary to the supervised learning algorithms, there is no supervisor and the learner must learn from the similarities between its actions and observations. In this method of training the neural net groups similar input vectors together without the use of training data to specify what a typical member of each group looks like or to which group each vector belongs. Here, a sequence of input vectors is provided, but no target vectors are specified. The net modifies its weights in a way that most similar input vectors are assigned to the same output unit. The neural net produces a representative vector for each cluster formed.

- **Reinforcement Training**: The third class of training algorithms are somehow in between the previous two and called *reinforcement training* methods. In this approach a supervisor observes the training process; but it only makes qualitative assessments of the behavior. In other words, the supervisor criticizes the system; but does not give an exact solution to improve the performance. The critic’s main role is hence to evaluate the behavior of the learner using linguistic variables such as “good”, “bad” etc.

Our proposed adaptive critic-based control concept is based on the idea of reinforcement learning; and an in depth discussion on this training method and the proposed structures will be provided in the next chapters.
Chapter 3

Critic-based Neuro-fuzzy Control of Microgrids

As discussed in the previous chapter, among different control strategies for voltage source converters the design simplicity and easy implementation of linear control algorithms used in synchronous or stationary reference frames have resulted in their relative popularity compared to non-linear approaches. Traditionally, PI controllers are used to regulate direct and quadrature quantities in the popular synchronous reference frame control. Despite good performance in controlling dc variables, PI regulators fail to operate well in case of load changes and high penetration of distributed generators in microgrids. Poor compensation capability for low order harmonics has also been reported [14]-[19].

To cope with the aforementioned deficiencies of PI controllers in power electronic-based microgrid systems, an adaptive critic-based neuro-fuzzy control structure is presented in this chapter.

Neuro-fuzzy systems are well-grounded hybrid intelligent systems that combine the human-like reasoning of fuzzy systems with learning and connectionist structure of neural networks [38]. Among different learning methods of neuro-fuzzy controllers, critic-based or reinforcement learning approaches are a class of learning algorithms that facilitate online tuning of controllers even in case of highly nonlinear and noisy systems without the need for a mathematical model of the system [39].

The proposed critic-based neuro-fuzzy control system includes a TSK neuro-fuzzy controller and a critic agent and operates by optimizing a satisfaction signal produced by the critic
Critic-based Neuro-fuzzy Control of Microgrids

representing the credibility of the system performance. The proposed control algorithm is of a non-model-based and adaptive structure; hence, the traditional de-coupling and feed-forward terms are eliminated. Multiple operational scenarios are simulated to validate the performance of the control system. Simulation results prove the superiority of the proposed scheme and show its adaptivity and fast dynamics due to the self-tuning feature.

3.1 Critic-based Neuro-fuzzy Control

As rule-based expert systems built to emulate the human beings’ approximate reasoning, supervisory fuzzy controllers work well in conditions such as plant nonlinearity, uncertainty and time varying parameters. However, manual extraction of the rules based on expert’s prior knowledge is not always an easy task to accomplish. To cope with this concern, researchers have developed different structures that enable automatic tuning of fuzzy controllers. Neuro-fuzzy systems are one of the well-grounded hybrid intelligent systems that have been proposed so far to address this issue. Neuro-fuzzy systems combine the human-like reasoning characteristics of fuzzy systems with learning and connectionist structure of neural networks. A neuro-fuzzy network is therefore a fuzzy inference system which is implemented in the framework of an adaptive neural network, hence has the ability of automatic learning.

The critic-based neuro-fuzzy control system, Figure 3.1, consists of a control agent (neuro-fuzzy controller) and a critic agent. The control agent receives the states and produces a control action through its actuator. The system feedback, interpreted as the controller’s action in the previous state, is being applied to the critic agent’s input. The evaluation or reinforcement signal generated by the critic agent is then used alongside the back-propagation of error to update the output layer weights of the neuro-fuzzy controller in an online learning process. The final objective of learning is to minimize the reinforcement signal.
Critic-based Neuro-fuzzy Control of Microgrids

![Control system structure in the critic-based methodology.](image)

**Figure 3.1.** Control system structure in the critic-based methodology.

### 3.1.1 TSK Neuro-fuzzy Controller

A fuzzy system can be interpreted as a nonlinear mapping from an input vector $X \in \mathbb{R}^n$ to an output vector $y \in \mathbb{R}^m$ (where $n$ and $m$ are input and output vectors dimensions, respectively).

Using the TSK definition, the fuzzy system is defined by the following rule-base:

- $R_i$: If ($x_1$ is $A_{1i}$ and … and $x_n$ is $A_{ni}$), Then $c_i = f_i(X)$
- $: :$
- $R_p$: If ($x_1$ is $A_{1p}$ and ... and $x_n$ is $A_{np}$), Then $c_p = f_p(X)$

where $A_{bi}$ is the linguistic value associated with the linguistic variable $x_b$ in the $a$th rule, and $c_p = f_p(X)$ is the consequence of the $p$th rule. The membership function $\mu_{A_{bi}} \in [0,1]$ quantifies the degree of membership of input variable $x_b$ to the fuzzy set $A_{bi}$.

The antecedent part of each rule is quantified by the fuzzy $t$-norm which has been defined by the product operator here:

$$\mu_{A_1 \times A_2 \times ... \times A_n}(x_1, ..., x_n) = \mu_{A_1}(x_1) \times \mu_{A_2}(x_2) \times ... \times \mu_{A_n}(x_n)$$  \hspace{1cm} (3.1)

And according to the TSK model, the consequent part of each rule is a linear combination of input variables, or in other words a crisp function of the rule inputs:

$$c_i = K_{0,i} + \sum_{j=1}^n K_{j,i} \cdot x_j$$  \hspace{1cm} (3.2)
The final output of the fuzzy system is a weighted average of each rule’s output:

\[ y = f(X) = \frac{\sum_{i=1}^{p} c_i \mu_i}{\sum_{i=1}^{p} \mu_i} \quad (3.3) \]

where \( \mu_i \) is the firing level of the antecedent part of the \( i \)th rule.

A TSK Neuro-fuzzy System is a TSK fuzzy system realized in the form of an adaptive neural network which consists of 4 layers and each layer represents a part of its equivalent fuzzy system i.e., fuzzifier, defuzzifier, inference engine and the rule-base [38], [39]:

- **First layer**: This layer’s task is to map input variables to \([-1,1]\) interval; hence in each neuron we have:

  \[ f = k.u_1^1, w_j = 1 \quad (3.4) \]

  where \( u_1^1 \) is the \( i \)th input of the neuron placed in the first layer, \( f(.) \) is the activation function of the neuron and \( w_j \)'s are the first layer’s weights.

- **Second layer**: In this layer, the input’s degree of membership to fuzzy sets are calculated through the neuron’s activation function \( f \). Each neuron indicates a fuzzy set and the outputs of these neurons show the degree of membership. For instance for Gaussian membership function we have:

  \[ f = \exp\left(-\frac{(u_1^2 - m_{ij})^2}{\sigma_{ij}^2}\right) \quad (3.5) \]

  where \( m_{ij} \) is the center of \( j \)th fuzzy set and \( \sigma_{ij} \) is the width of Gaussian function for \( i \)th input of second layer, \( u_1^2 \).

- **Third layer**: In this layer each neuron is representative of a rule, and the antecedent part of each rule is calculated using the product operator as the neuron’s activation function:

  \[ f = u_1^3 \times u_2^3 \times ... \times u_n^3 \quad (3.6) \]

  where \( u_i^3 \) is the \( i \)th input of a neuron placed in the third layer. This layer’s weights are equal to unit.

- **Fourth layer**: Using Sugeno defuzzification rule, we have:
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\[ R_i: \text{If } (x_1 \text{ is } C_1^i \text{ and } \ldots \text{ and } x_n \text{ is } C_n^i), \text{ Then } y^i = c_0^i + c_1^i x_1 + \ldots + c_n^i x_n \]  
(3.7)

where \(C_j^i\) is a fuzzy set, \(c_j^i\) is a constant and \(i = 1,2,\ldots,n\).

The final output \(y \in V \subset R\) of the TSK system is a weighted average of \(y^i\)’s; i.e.:

\[ y = \frac{\sum_{i=1}^{n} y^i u_4^i}{\sum_{i=1}^{n} u_4^i} \]  
(3.8)

where \(n\) is the number of rules and \(u_4^i\) is the input of the \(i\)th neuron placed in the 4th layer.

The \(c_j^i\)’s are the output layer weights of the TSK neuro-fuzzy system to be determined via learning.

### 3.1.2 Adaptive Critic-based Learning

Four main categories of automatic learning algorithms have been proposed for neuro-fuzzy systems, including “direct teacher”, “distal teacher”, “performance measure” and “critic” [39]. Among different learning methods, critic-based approaches also known as reinforcement learning, adaptive critic designs, approximate dynamic programming or neuro-dynamic programming, address the online tuning of controllers even in case of highly nonlinear and noisy systems without the need for a mathematical model of the system [63]-[65]. This class of learning algorithms was originally proposed in [66] and developed more in [67]. In these algorithmic problem solving methods, a set of actions (decisions) are applied to a system over a period of time, in order to achieve a desired goal. The critic-based algorithms are based on providing rewards and punishments to the learner depending on the system states, without defining the correct actions or trajectories, in other words these methods allow the system to learn how to make good decisions by observing its own behavior and improve its actions through a reinforcement mechanism [64], [68], [69]. The adaptive critic-based control optimizes a satisfaction signal representing the credibility of the system performance and because of its low
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informative nature provides the control system with a very flexible tool for online tuning of controllers.

In [38] and [65], neuro-fuzzy networks were used to replace the neuron-like adaptive elements in the earlier structures, so that the neuro-fuzzy network could represent expert knowledge to speed up its learning [70].

In the classical reinforcement learning [65], the reinforcement signal \( R \) which evaluates the failure/success in the system, is a binary signal. For example, if \( R = +1 \), the control system has failed and should modify itself so that a reinforcement signal \( R = 0 \) is achieved, i.e., the learning has successfully been achieved when the critic is fully satisfied in subsequent trials. In the modern approaches however [71], [72], the reinforcement signal is continuous and the learning element tunes the controller’s parameters to minimize the reinforcement signal. In these methods, the reinforcement signal \( r \) is continuous and accepts any value between -1 and +1; with \( r = +1 \) (or -1) indicating total failure, and therefore the closer the reinforcement signal gets to zero, the better the control action deemed to have been. Here the system does not wait for a total failure. Instead, at each time period, it continues its learning process at the same time as it applies the control action.

In the critic-based learning algorithm in this thesis, which is in a way a cognitive restatement of reinforcement learning [63], the critic agent evaluates the present operation of controller and compares it with the desired goals. A reinforcement signal is produced based on these assessments and the main goal of the control system is to minimize the critic’s reinforcement signal. The learning algorithm emulates the behavioral learning process of human beings in real world whom as biological intelligent systems always search for a way to lower their stress with respect to the environment based on the rewards and punishments received from the teacher during the learning process [73]-[75].

Therefore in the critic-based algorithm, the critic and the reinforcement signal have crucial roles in the online learning process. Critic’s performance can be better understood if we
investigate the different states of a sample dynamic system. The critic’s inputs can be any signals that are representative of system states, for instance error and error derivative. If the output error is positive but its derivative is negative, the performance is not bad but a better performance is expected in future. In this case, the system is modifying itself because error is decreasing; hence the reinforcement signal should be close to zero. In another case, if error and its derivative are both negative, the controller behavior is unsatisfactory because the error is increasing. In this case, the critic produces a large negative reinforcement signal. The ideal situation is when error and error derivative are both zero that is when the reinforcement signal produced by the critic is zero.

3.1.3 Learning Element

The reinforcement signal, \( r \), contributes collaboratively to updating output layer weights of the neuro-fuzzy controller. Reward and punishment are judged and applied to the system based on \( r \) which in general can be defined as an online cost function \( f(\cdot) \) of the signals that represent the system states, such as control action, \( u \), the error signal, \( e \), the output, \( y \), and their derivatives:

\[
r = f(e, u, y)
\]  
(3.9)

Let us define the cost function \( E \) as:

\[
E = \frac{1}{2} r^2
\]  
(3.10)

The control system goal is to minimize the cost function \( E \); and the controller’s parameters are updated based on the steepest descent optimization rule; therefore in the opposite direction of \( \nabla E \) (\( \nabla \) is the gradient operator):

\[
\Delta w \propto -\nabla E \propto -\frac{\partial E}{\partial w} = -\eta \cdot \frac{\partial E}{\partial w}
\]  
(3.11)

where \( \eta \) is the learning rate of the controller and \( w \)s are the neural network weights. It should be noted that the steepest descent rule is used because of its simplicity, which results in faster control, and initial weights are selected randomly. More advanced optimization methods can be
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used in case the change in initial conditions cause local minima problems, however this will increase the computational load of the controller.

Using the chain rule we have:

\[ \frac{\partial E}{\partial w} = \frac{\partial E}{\partial r} \cdot \frac{\partial r}{\partial y} \cdot \frac{\partial y}{\partial u} \cdot \frac{\partial u}{\partial w} \]  
(3.12)

The output error, \( e \) is defined by;

\[ e = y_{ref} - y \]  
(3.13)

From (3.12) and (3.13) we have:

\[ \frac{\partial E}{\partial w} = \frac{\partial E}{\partial r} \cdot (-\frac{\partial r}{\partial e}) \cdot \frac{\partial y}{\partial u} \cdot \frac{\partial u}{\partial w} \]  
(3.14)

To simplify the rule and without losing the generality \( \frac{\partial r}{\partial e} \) in (3.14) is replaced by its sign. The critic is designed in a way that with an increase in the error signal the reinforcement signal also increases and therefore this term is replaced with "+1",

\[ \frac{\partial E}{\partial w} = -\frac{\partial E}{\partial r} \cdot (+1) \cdot \frac{\partial y}{\partial u} \cdot \frac{\partial u}{\partial w} \]  
(3.15)

The term \( \frac{\partial y}{\partial u} \) in (3.15) is the gradient of the system, and as in a proper linear system after the transient response is damped \( y \) is directly proportional to \( u \) with a positive constant; without losing the generality \( \frac{\partial y}{\partial u} \) can be replaced by its sign "+1" for the adaptation rule, and the constant will be included in the learning rate, \( \eta \),

\[ \frac{\partial E}{\partial w} = -\frac{\partial E}{\partial r} \cdot (+1) \cdot (+1) \cdot \frac{\partial u}{\partial w} \]  
(3.16)

From (3.10) we have:

\[ \frac{\partial E}{\partial r} = r \]  
(3.17)

And finally using (3.11) to (3.17), \( \frac{\partial E}{\partial w} \) and \( \Delta w \) are calculated as follows:

\[ \frac{\partial E}{\partial w} = -r \cdot \frac{\partial u}{\partial w} \]  
(3.18)

\[ \Delta w = \eta \cdot r \cdot \frac{\partial u}{\partial w} \]  
(3.19)
3.2 Under-study Microgrid System

Previous investigations have mostly been conducted on simplified microgrid models [16], [18], [19]. The microgrid model used here, however, more realistically considers higher penetration of DGs and different load types. Figure 3.2 shows a single line diagram of the under-study microgrid system. This microgrid has five power electronic-based DG units; each rated at 15 kVA, three constant impedance loads each rated at 15 kW and 3 kVAR and a three-phase 5 hp induction motor. Each DG uses a VSC as an interface to the rest of the microgrid, and can be of different types such as a fuel cell unit, a micro turbine, etc.

![Diagram of the under-study microgrid system](image)

Figure 3.2. Single-line diagram of the under-study microgrid system.

To investigate the performance of the control system different operational scenarios are studied. At first the switch S2 is OFF, hence a 3-DG microgrid is yielded. Afterwards, to study the effect of an induction motor load, switch S1 is turned ON and the induction motor is placed in circuit. Finally, to investigate the adaptivity of the proposed controller in case of higher DG
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penetrations, S2 is turned ON and the performance of the proposed controller is studied in presence of all 5 DGs.

3.3 Critic-based Neuro-fuzzy Control of Microgrid

In this section, the proposed critic-based neuro-fuzzy control structure is adapted to control the voltage source converters interfacing the 5 DGs to the microgrid system shown in Figure 3.2. Each individual control system is implemented in $dq$ reference frame, and consists of a TSK neuro-fuzzy controller and a fuzzy critic. The control system is used in the grid-connected and islanded modes.

Figure 3.3 shows a block-diagram representation of the critic-based neuro-fuzzy control system in the microgrid. The details of the monitoring and control systems for each VSC in the grid-connected and islanded modes will be discussed in the remaining parts of this section.

3.3.1 Grid-connected Mode Control

In the grid-connected mode, DGs are under PQ control; hence the references of active and reactive power directly contribute to the $d$-axis and $q$-axis current references. The proposed critic-based neuro-fuzzy controller controls the DGs active and reactive power by directly controlling $d$ and $q$ components of DG’s current. In this mode, the power generation of DG units is directly determined based on the assigned power references. A block diagram representation of the grid-connected control system for each DG is seen in Figure 3.4.

The inputs to the TSK controller are $d$ and $q$ axes currents error and its derivative; and output reference voltages are used to generate PWM signals, after being transferred to the $abc$ frame.

The design procedure for TSK controller and fuzzy critics will be discussed later in this section.
Figure 3.3. Block-diagram representation of the critic-based neuro-fuzzy control in the microgrid system.
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Figure 3.4. Critic-based neuro-fuzzy control structure for a VSC in the microgrid system.

3.3.2 Islanded Mode Control

Figure 3.5 shows the control system in the islanded mode. During this mode, the critic-based neuro-fuzzy current control (as seen in Figure 3.4) is used in conjunction with $\omega$-$P$ and $V$-$Q$ droop characteristics and an outer voltage control loop to adjust the frequency and voltage in each DG.

Figure 3.5. Critic-based neuro-fuzzy control structure for a VSC in the islanded microgrid.
The droop characteristics are in the form of (2.11) and (2.12) and frequency and voltage droop gains, i.e. \( m_P \) and \( m_Q \) are 1.33 and 13.3 respectively.

### 3.3.3 TSK Neuro-fuzzy Controller Design

A two-input/one-output TSK controller is used in our VSC control system. The \( i_d \) and \( i_q \) TSK controllers shown in Figure 3.4 receive \( d \) and \( q \) axes currents error and their derivatives as inputs and each have three linguistic labels for each input and therefore \( 3^2 = 9 \) rules in their rule base. Figure 3.6 shows a representation of this neuro-fuzzy controller.

![TSK neuro-fuzzy controller for a VSC in the microgrid.](image)

The input variables, i.e. error and error derivative, are normalized in the first layer. The inputs’ degrees of membership to the linguistic labels of the rule-base are then calculated in the second layer, in which each neuron represents one fuzzy set. The linguistic labels include Negative (N), Zero (Z), and Positive (P) for both error and error derivative. In the third layer,
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each neuron represents a rule and the antecedent part of the rules is calculated using the product law.

The TSK fuzzy rule-base is as follows:

\( R_1 \): If \((e\) is Negative and \(\dot{e}\) is Negative), Then \(y_1 = K_{0.1} + K_{1.1} \cdot e + K_{2.1} \cdot \dot{e} \).

\( R_2 \): If \((e\) is Negative and \(\dot{e}\) is Zero), Then \(y_2 = K_{0.2} + K_{1.2} \cdot e + K_{2.2} \cdot \dot{e} \).

\( R_3 \): If \((e\) is Negative and \(\dot{e}\) is Positive), Then \(y_3 = K_{0.3} + K_{1.3} \cdot e + K_{2.3} \cdot \dot{e} \).

\( R_4 \): If \((e\) is Zero and \(\dot{e}\) is Negative), Then \(y_4 = K_{0.4} + K_{1.4} \cdot e + K_{2.4} \cdot \dot{e} \).

\( R_5 \): If \((e\) is Zero and \(\dot{e}\) is Zero), Then \(y_5 = K_{0.5} + K_{1.5} \cdot e + K_{2.5} \cdot \dot{e} \).

\( R_6 \): If \((e\) is Zero and \(\dot{e}\) is Positive), Then \(y_6 = K_{0.6} + K_{1.6} \cdot e + K_{2.6} \cdot \dot{e} \).

\( R_7 \): If \((e\) is Positive and \(\dot{e}\) is Negative), Then \(y_7 = K_{0.7} + K_{1.7} \cdot e + K_{2.7} \cdot \dot{e} \).

\( R_8 \): If \((e\) is Positive and \(\dot{e}\) is Zero), Then \(y_8 = K_{0.8} + K_{1.8} \cdot e + K_{2.8} \cdot \dot{e} \).

\( R_9 \): If \((e\) is Positive and \(\dot{e}\) is Positive), Then \(y_9 = K_{0.9} + K_{1.9} \cdot e + K_{2.9} \cdot \dot{e} \).

Where the antecedent part of each rule is calculated as follows:

\[ \mu_i = \mu_{e,R_i} \mu_{\dot{e},R_i} \quad (3.20) \]

where \(\mu_i\) is the antecedent of \(R_i\), \(\mu_{e,R_i}\) is the degree of membership of \(e\) to the corresponding membership function in \(R_i\), and \(\mu_{\dot{e},R_i}\) is the degree of membership of \(\dot{e}\) to the corresponding membership function. For example in the first rule:

\[ \mu_1 = \mu_{Ne} \mu_{N\dot{e}} \quad (3.21) \]

Finally, the defuzzification occurs in the fourth layer and using the TSK formula the crisp output of neuro-fuzzy system is calculated. The output of the system is a weighted average of the inputs as calculated in (3.22):

\[ y = \frac{\sum_{i=1}^{9}(K_{0.i} + K_{1.i} \cdot e + K_{2.i} \cdot \dot{e}) \mu_i}{\sum_{i=1}^{9} \mu_i} \quad (3.22) \]
where $e$ and $\dot{e}$ are the error and its derivative, and $i$, $u_i$, and $y$ are the rule index, $i$th input of the last layer, and output of the controller, respectively. $K_{0,i}$, $K_{1,i}$ and $K_{2,i}$ are the neuro-fuzzy controller weights that are to be determined via learning.

The selected membership function forms for the linguistic variable, $Z$, is Gaussian, and that of $N$ and $P$ linguistic variables are in the form of sigmoid function. Figure 3.7 and Figure 3.8 show these membership functions for the TSK controllers designed for $d$-axis and $q$-axis currents.

![Membership functions of the TSK controller for d-axis.](image)

![Membership functions of the TSK controller for q-axis.](image)
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3.3.4 Fuzzy Critics Design

The linguistic evaluations discussed in subsection 3.1.2 show the nature of the critic agent and its supervisory duties. Accordingly, a fuzzy system with an appropriate rule-base is proposed in our microgrid system.

The proposed fuzzy critic includes a singleton fuzzifier, a product inference engine and a center average defuzzifier. This fuzzy system can be best described by (2.45) provided that normal fuzzy membership functions are chosen.

The \( i_d \) and \( i_q \) control critics receive \( d \) and \( q \) axes currents error and their derivatives as inputs and have 3 linguistic labels for each input; hence 9 rules in their rule-base. The fuzzy critic rule-base is as follows:

\[
R_1: \text{If} (e \text{ is Negative and } \dot{e} \text{ is Negative}), \text{Then } r \text{ is Large Negative.}
\]

\[
R_2: \text{If} (e \text{ is Negative and } \dot{e} \text{ is Zero}), \text{Then } r \text{ is Small Negative.}
\]

\[
R_3: \text{If} (e \text{ is Negative and } \dot{e} \text{ is Positive}), \text{Then } r \text{ is Zero.}
\]

\[
R_4: \text{If} (e \text{ is Zero and } \dot{e} \text{ is Negative}), \text{Then } r \text{ is Small Negative.}
\]

\[
R_5: \text{If} (e \text{ is Zero and } \dot{e} \text{ is Zero}), \text{Then } r \text{ is Zero.}
\]

\[
R_6: \text{If} (e \text{ is Zero and } \dot{e} \text{ is Positive}), \text{Then } r \text{ is Small Positive.}
\]

\[
R_7: \text{If} (e \text{ is Positive and } \dot{e} \text{ is Negative}), \text{Then } r \text{ is Zero.}
\]

\[
R_8: \text{If} (e \text{ is Positive and } \dot{e} \text{ is Zero}), \text{Then } r \text{ is Small Positive.}
\]

\[
R_9: \text{If} (e \text{ is Positive and } \dot{e} \text{ is Positive}), \text{Then } r \text{ is Large Positive.}
\]

The fuzzy rules shown in Table 3.1 cover all possible states of the system.

From (2.45), the proposed fuzzy critic system can be described as a non-linear mapping from input vector \( x = [e, \dot{e}] \) to the output signal \( r \) as follows:

\[
r = \frac{\sum_{l=1}^{p} \gamma^l (\prod_{i=1}^{2} \mu_{A_i}^l(x_i))}{\sum_{l=1}^{q} (\prod_{i=1}^{2} \mu_{A_i}^l(x_i))} \quad (3.23)
\]
where $\mu_{A_i}$ are the selected input membership functions associated with rule $l$ the $i$th input, and $\bar{y}^l$ is center of normal output membership function in rule $l$.

Table 3.1. Fuzzy critic rule-base.

<table>
<thead>
<tr>
<th>$e_{idq}$</th>
<th>$\hat{e}_{idq}$</th>
<th>$\dot{e}_{idq}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_{idq}$</td>
<td>$N$</td>
<td>$Z$</td>
</tr>
<tr>
<td>$\hat{e}_{idq}$</td>
<td>LN</td>
<td>SN</td>
</tr>
<tr>
<td>$\dot{e}_{idq}$</td>
<td>SN</td>
<td>Z</td>
</tr>
<tr>
<td>P</td>
<td>Z</td>
<td>SP</td>
</tr>
</tbody>
</table>

The critic’s input membership functions are Negative (N), Zero (Z) and Positive (P). The Zero membership function is Gaussian and Negative and Positive functions are sigmoid functions. The output membership functions are Large Negative (LN), Small Negative (SN), Zero (Z), Small Positive (SP) and Large Positive (LP), and all are in the form of sigmoid function. These membership functions are shown in Figure 3.9.

Because of the fuzzy nature of the controller and the critic, the membership functions can be chosen from different shapes such as sigmoidal or triangular form, however in this case the selected forms show a better response. The mean value and the variance are chosen in a linguistic procedure considering the fact that the critic and the controller both receive normalized inputs. In this procedure a set of initial parameters are selected in a way that the membership functions smoothly cover the $[-1,1]$ interval and then a fine tuning is performed to achieve the best performance. It should be mentioned that the learning algorithm can also be used to tune these parameters based on the back-propagation of the error signal; however there would be some disadvantages such as high computational load, the possibility of local optiums, higher
sensitivity and most importantly departing from the linguistic nature of the fuzzy system itself which is the main reason that fuzzy logic is implemented. Therefore, the parameters of the membership functions were chosen based on the linguistic knowledge of the system.

![Fuzzy critic membership functions](image)

**Figure 3.9. Fuzzy critic membership functions (a) input (b) output membership functions.**

It is worth mentioning that the shape of the critic’s output membership functions LP, and LN limit the critic’s output from increasing indefinitely and remove the possible noise issues that the term $\dot{e}$ may cause.
3.3.5 Learning Algorithm

Equation (3.19) gives the updated weights for a TSK neuro-fuzzy controller in general form. In our microgrid control system, for the 2-input 1-output neuro-fuzzy system in Figure 3.6 with 9 rules, the control action \( u \) in (3.22) can be written as:

\[
u = \frac{\sum_{i=1}^{9}(K_{0i}+K_{1i}\theta+K_{2i}\dot{\theta})\mu_i}{\sum_{i=1}^{9}\mu_i} \tag{3.24}
\]

Accordingly, from (3.19) the update rules for the parameters of neuro-fuzzy controller are given in (3.25)-(3.27):

\[
\Delta K_{1,i} = \eta \cdot r \cdot e \cdot \frac{\mu_i}{\sum_{j=1}^{9}\mu_j} \tag{3.25}
\]

\[
\Delta K_{2,i} = \eta \cdot r \cdot \dot{e} \cdot \frac{\mu_i}{\sum_{j=1}^{9}\mu_j} \tag{3.26}
\]

\[
\Delta K_{0,i} = \eta \cdot r \cdot \frac{\mu_i}{\sum_{j=1}^{9}\mu_j} \tag{3.27}
\]

3.4 Simulation Results

Simulations were conducted on the microgrid system shown in Figure 3.2, and were carried out in MATLAB/SIMULINK. To verify the feasibility of the proposed control system, seven operational scenarios are considered for the microgrid and the results from the critic-based neuro-fuzzy control are compared to those of a conventional PI control in the first four cases. The PI coefficients are the best of the two sets of gains obtained from the Root Locus and Ziegler Nichols algorithms. The gains obtained from Root Locus algorithm resulted in a better response and then a manual tuning was employed to achieve to the best response.

Six cases in the grid-connected mode and one in the islanded mode are considered. In the first five cases a 3-DG microgrid is studied. The induction motor is only in circuit in Case-D and in Case-F higher penetration of DGs in the 5-DG microgrid is studied. In the grid-connected mode, P and Q references are assumed to be generated by a higher level controller which distributes the power among the DGs based on their ratings.
3.4.1 Grid-connected Control

A) Real and Reactive Power Tracking

The steady state performance of the controller and its real and reactive power tracking capability in the grid-connected microgrid is studied. Three constant impedance loads each of 15 kW and 3 kVAr are present in the microgrid and the reference values of real and reactive power are set to 10 kW and 3 kVAr, 9 kW and 2 kVAr, and 8 kW and 1 kVAr for DG1, DG2 and DG3 respectively. Figure 3.10 to Figure 3.13 show the real and reactive power tracking and the three-phase current and voltage in DG1 for conventional PI control and the proposed critic-based neuro-fuzzy control.

As seen, the PI controller experiences large amplitude oscillations and large transient time (~0.12 s), but the proposed critic-based scheme goes through minimal transient and reaches its steady state within 0.02 s. The initial power transient in DGs active and reactive power is due to the simulation start-up and as seen in case of the critic-based control this overshoot is completely removed for real power and reduced significantly for reactive power.

Unlike the proposed critic-based control, after the initial transients are damped, the PI controller shows steady state oscillations. It is worth mentioning that in practical microgrids large power oscillations can lead to the unwanted activation of protection systems, and in such cases the microgrid DGs might fail to maintain the desired supply to loads. This can violate the overall system reliability and stability.

By comparing Figure 3.11 and Figure 3.13, it is evident that the proposed algorithm contributes significantly to preserving the desired shape of phase currents and removing unwanted harmonics.
Figure 3.10. Case-A: Real and reactive power tracking under PI control, a) Real power, b) Reactive power.

Figure 3.11. Case-A: Three-phase current and terminal voltage in DG1 over the transient period under PI control.
Figure 3.12. Case-A: Real and reactive power tracking under critic-based neuro-fuzzy control, a) Real power, b) Reactive power.

Figure 3.13. Case-A: Three-phase current and terminal voltage in DG1 under critic-based neuro-fuzzy control.
B) Step Change in DGs’ Real Power

To study the behavior of the control system in case of power transients, a 2kW step increase occurs in each DG’s active power reference at t=0.25 s in the grid-connected microgrid. Figure 3.14 to Figure 3.17 show the real and reactive power tracking and the three-phase current and voltage of DG1 over the transient period. After the transient is applied, the behavior of the PI controller is greatly affected causing unwanted power oscillations. Application of the proposed critic-based neuro-fuzzy control however removes real power initial transient and reduces the magnitude of reactive power start-up overshoot. After the step power increase, the critic-based control shows a smooth transient to the new state and follows the reference power with negligible tracking error. It can be observed that with the proposed critic-based control, the step change in the real power has a slight disturbing effect on the reactive power over the transient period. This phenomenon can be explained with respect to the intrinsic dependency between P and Q equations in the system model (as discussed in previous chapter) and the fact that despite the traditional PI control, no decoupling term has been employed in our proposed algorithm. This effect has been neglected because of its small magnitude.

As seen in Figure 3.15 and Figure 3.17, it is obvious that, the proposed critic-based algorithm preserves the desired current shape by removing unwanted harmonics.
Figure 3.14. Case-B: Real and reactive power tracking under PI control, a) Real power, b) Reactive power.

Figure 3.15. Case-B: Three-phase current and terminal voltage in DG1 over the transient period under PI control.
Figure 3.16. Case-B: Real and reactive power tracking under critic-based neuro-fuzzy control, a) Real power, b) Reactive power.

Figure 3.17. Case-B: Three-phase current and terminal voltage in DG1 over the transient period under critic-based neuro-fuzzy control.
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C) Step Change in DGs’ Reactive Power

To investigate the control system behavior in case of reactive power transients, a step change of the magnitude of 1kVAr is applied to the DGs’ reactive power reference at t=0.25 s in the grid-connected microgrid. Figure 3.18 to Figure 3.21 show the real and reactive powers of DGs and the three-phase current and voltage of DG1 under conventional PI control and our proposed approach over the transient period.

Figure 3.18. Case-C: Real and reactive power tracking under PI control, a) Real power, b) Reactive power.
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Figure 3.19. Case-C: Three-phase current and terminal voltage in DG1 over the transient period under PI control.

![Three Phase Current (A)](image)

![Three Phase Voltage (V)](image)

Figure 3.20. Case-C: Real and reactive power tracking under neuro-fuzzy critic-based control, a) Real power, b) Reactive power.
As seen, the proposed control system is well capable of injecting the desired power into the microgrid and smooth transition between the two states. At the transient moment, despite the fact that real power reference remains unchanged, a disturbing effect appears on the output power. This effect can be explained with respect to the natural dependency of P and Q equations and has been neglected because of its small magnitude.

**D) Operation in Presence of Motor Load**

Unlike conventional impedance loads, inertial loads such as induction motors are not capable of absorbing instantaneous changes in active and reactive powers during power system transients. Therefore, the dynamic behavior of motor loads may have negative impacts on the control system behavior during the transients. In this section, power tracking in the grid-connected microgrid in presence of a three-phase 5hp induction motor is investigated. In this case, the switch S1 is closed at t=0.3 s and the induction motor starts up with no start-up controller. After the motor output reaches the steady state, a 2kW step change occurs in real power set points at t=1 s. Figure 3.22 to Figure 3.25 show the power tracking and three-phase current and voltage of DG1. The results show that dynamic behavior of the motor load has no effect on the behavior of the control system in the microgrid.
Figure 3.22. Case-D: Real and reactive power tracking with motor load under PI control.

Figure 3.23. Case-D: Three-phase current and voltage in DG1 under PI control.
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Figure 3.24. Case-D: Real and reactive power tracking in critic-based neuro-fuzzy control.

Figure 3.25. Case-D: Three-phase current and voltage in DG1 under critic-based neuro-fuzzy control.
E) Large Step Change in DGs’ Real Power

To study the stability of the control system in case of large power transients, a 5kW step increase (%50 of nominal power) occurs in each DG’s active power reference at t=0.25 s in the grid-connected mode, while the initial set points are 5 kW and 3 kVar for DG1, 4.5 kW and 2 kVar for DG2, and 5.5 kW and 1kVar for DG3 respectively. Figure 3.26 and Figure 3.27 show the real and reactive power tracking in the microgrid and three phase current and voltage of DG1.

Figure 3.26. Case-E: Real and reactive power tracking under critic-based neuro-fuzzy control.
As seen, the large transient does not affect the stability of the microgrid and the controller smoothly follows the new set points. It is however observed that the large step change causes a large effect on Q at the transient time. Figure 3.27 shows that the desired current shape is maintained in the microgrid.

**F) High DG Penetration**

Traditional PI controllers fail to operate well in case of load changes and microgrids with high penetration of distributed generators. In a desired microgrid however, the control system should be designed in a plug and play manner in which an increase in the number of system elements such as DGs does not jeopardize the controller design and performance.

To prove the effectiveness of our proposed control system in case of higher DG penetrations in the grid-connected microgrid, switch S2 in Figure 3.2 is closed and a 5-DG microgrid is studied. Different step changes occur in the active power references of DGs (except for DG5) at t=0.25 s, and the microgrid behavior is studied.

Figure 3.28 and Figure 3.29 show the real and reactive power tracking in the microgrid and three-phase current and voltage in DG1.
Figure 3.28. Case-F: Real and reactive power tracking in the 5-DG microgrid under critic-based neuro-fuzzy control, a) Real power, b) Reactive power.

Figure 3.29. Case-F: Three-phase current and terminal voltage in DG1 over the transient period in the 5-DG microgrid under critic-based neuro-fuzzy control.
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As seen in the results, high penetration of DGs does not counteract the response of the proposed controller and the transient response is well damped and smooth power injection is yielded.

3.4.2 Islanded Mode Control

To create the islanded microgrid during the simulations, switch S2, S1 and the PCC switch are OFF, therefore an islanded 3-DG microgrid with two constant impedance loads is studied. The droop characteristics are the same, therefore equal power sharing between DGs is expected. Figure 3.30 and Figure 3.31 show the three-phase current and voltage in DG1 and real and reactive power sharing between the DGs in the islanded microgrid.

The frequency in DG1 is shown in Figure 3.32.

Figure 3.30. Real and reactive power sharing in the 3-DG islanded microgrid under critic-based neuro-fuzzy control.
Figure 3.31. Three-phase current and terminal voltage in DG1 in the 3-DG islanded microgrid under critic-based neuro-fuzzy control.
Figure 3.32. Frequency in the islanded 3-DG microgrid in DG1 under critic-based neuro-fuzzy control.

As the total load present in the system is 30kW and 6kVAr, therefore each DG receives 10kW active power and 2kVAr reactive power, however the controller shows a better response in regulating the active power.

As seen, with the proposed critic-based approach, not only the initial transient time is decreased, but also the initial overshoot is completely removed for P and reduced considerably for Q and a faster and more accurate control is yielded. Also comparing the MAE and THD factors shows the superior performance of the controller, in removing the unwanted harmonics and steady stated oscillations with respect to the PI control.

Table 3.2 and Table 3.3 show a quantitative comparison between the results of the conventional PI control and the proposed approach. For the purpose of analogy, only the results for DG1 are presented here; but a similar trend can be observed for other DGs.

To obtain a precise correspondence between the two methods, initial overshoot, Mean Absolute Error (MAE) and the settling time for power and Total Harmonic Distortion (THD) for current are observed and listed. The MAE factor is calculated after $t=0.1$ s when the initial transients are damped and a steady state response is reached.
Critic-based Neuro-fuzzy Control of Microgrids

As seen, with the proposed critic-based approach, not only the initial transient time is decreased, but also the initial overshoot is completely removed for P and reduced considerably for Q and a faster and more accurate control is yielded. Also comparing the MAE and THD factors shows the superior performance of the controller, in removing the unwanted harmonics and steady state oscillations with respect to the PI control.

<table>
<thead>
<tr>
<th>Case</th>
<th>Quantity</th>
<th>Overshoot</th>
<th>MAE</th>
<th>Settling Time</th>
<th>THD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case1</td>
<td>P1</td>
<td>15.25kW</td>
<td>0.56%</td>
<td>0.12 s</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>16.63kVAr</td>
<td>5.47%</td>
<td>0.12 s</td>
<td></td>
</tr>
<tr>
<td>Case2</td>
<td>P1</td>
<td>12.47kW</td>
<td>1.2%</td>
<td>0.12 s</td>
<td>0.106</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>16.02kVAr</td>
<td>6.63%</td>
<td>0.12 s</td>
<td></td>
</tr>
<tr>
<td>Case3</td>
<td>P1</td>
<td>15.25kW</td>
<td>0.7%</td>
<td>0.12 s</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>16.63kVAr</td>
<td>5.34%</td>
<td>0.12 s</td>
<td></td>
</tr>
<tr>
<td>Case4</td>
<td>P1</td>
<td>12.47kW</td>
<td>1.31%</td>
<td>0.12 s</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>16.02kVAr</td>
<td>4.38%</td>
<td>0.12 s</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Case</th>
<th>Quantity</th>
<th>Overshoot</th>
<th>MAE</th>
<th>Settling Time</th>
<th>THD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case1</td>
<td>P1</td>
<td>10.00kW</td>
<td>0.49%</td>
<td>0.02 s</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>4.50kVAr</td>
<td>2.48%</td>
<td>0.02 s</td>
<td></td>
</tr>
<tr>
<td>Case2</td>
<td>P1</td>
<td>10.03kW</td>
<td>0.89%</td>
<td>0.02s</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>3.90kVAr</td>
<td>2.57%</td>
<td>0.02s</td>
<td></td>
</tr>
<tr>
<td>Case3</td>
<td>P1</td>
<td>10.11kW</td>
<td>0.28%</td>
<td>0.02s</td>
<td>0.048</td>
</tr>
</tbody>
</table>
3.5 Conclusions

In this chapter an adaptive critic-based neuro-fuzzy control structure for power control of grid-connected microgrids was presented and studied. The control system consists of a neuro-fuzzy controller and an element called critic whose task is to evaluate the performance of the control system and compare it with the desired goals. The controller then modifies its behavior so that the critic’s satisfaction is insured. This critic-based learning method which is based on the neuro-dynamic programming is similar to the learning process in human beings which is often associated with a supervisor providing reinforcements and punishments to facilitate learning.

In multiple operational scenarios the performance of the critic-based controlled microgrid was studied and in four cases compared to the response of traditional PI control. The results verify that application of the adaptive critic-based neuro-fuzzy controller has significantly improved the performance of the microgrid by reducing the convergence time, output oscillations and tracking error. The intelligent nature of the proposed controller ensures robust performance against changes such as high penetration of DGs and dynamically demanding situations like presence of motor loads in the system; and the evaluation results confirm the stable and adaptive power control of multiple DG units in the microgrid. The proposed controller shows fewer harmonic in the output current in the present configuration with the selected output filter, converter topology and the modulation scheme.
Chapter 4

Critic-based PI Control of Microgrids

In this chapter a critic-based PI control system is proposed to cope with the deficiencies of traditional PI control by increasing the control system adaptivity while simplifying the control system compared to the critic-based neuro-fuzzy controller developed in the previous chapter. One approach to cope with the slow adaptation of traditional fixed-gain PI regulators to power changes, disturbances and parameters variations is to implement a continuous scheme to adjust the controller gains over time. The traditional solution is to tune the gains manually by observing the output of the system. However, to avoid unknown number of trial and error tasks in manual control and increase the reliability, an on-line and automatic tuning approach must be adapted [76]. An online gain tuning method based on the adaptive critic-based control concept is proposed here to improve the behavior of PI controllers. In this approach fuzzy critics are used to automatically tune the proportional and integral gains; that is using the reasoning capability of the fuzzy critics the desired updated gains are estimated and used in the PI controller. The proposed gain tuning algorithm is used to control the active and reactive power of voltage source converters within a power electronic based microgrid. Simulation results prove the effectiveness of the scheme to consolidate adaptivity and intelligence in the system and show the improved dynamics compared to traditional PI control.
4.1 Critic-based PI Control

The critic-based control concept discussed in the previous chapter is adapted in conjunction with traditional PI control. Here, a critic agent is added to the traditional PI control system whose task is to evaluate present operation of the PI controller, compare it with the desired goals and produce the desired PI gains. In other words, the controller gains are modified so that the critic’s satisfaction is ensured.

With the implementation of critic-based control idea, the superior capabilities of supervisory control are employed to improve the performance of the microgrid control system over load transients and high DG penetrations.

Figure 4.1 shows a block diagram representation of the proposed control scheme.

![Block diagram of critic-based PI control system](image)

Figure 4.1. Critic-based PI control system structure.

4.1.1 Fuzzy Critics

To adapt intelligence in the control system and increase its degree of adaptivity, the critic-based PI control system design focuses on the critic instead of precise design of the PI controller. Each critic is responsible for supervising the system performance and providing the changes according to which the controllers update their gains.
Critic-based PI Control of Microgrids

The critics are designed based on the qualitative descriptions of the system in different operation modes. Inputs of the critic are error and error derivative, and outputs contribute to update PI controllers’ weights, i.e. proportional gain ($K_p$) and integral gain ($K_i$).

To understand the critics’ performance, let’s consider different states of a dynamic system under PI control and investigate them. For example, if at a time error and error derivative are positive, the performance is not satisfactory and integral gain should be increased. In another case, if the error is positive and its derivative is negative integral gain should be decreased as the system is correcting its behavior. The critics are designed based on such linguistic evaluations of the control system.

4.2 Under-study Microgrid System

A microgrid model similar to the previous chapter is also used here. As seen in the single line diagram shown in Figure 3.2, the understudy microgrid has five power electronic-based DG units; each rated at 15 kVA, three constant impedance loads each rated at 15 kW and 3 kVAr and a three-phase 5 hp induction motor. The control system performance is studied in the grid-connected and islanded modes, in the 3-DG and 5-DG modes, and with and without the motor load.

4.3 Critic-based PI Control of Microgrid

The critic-based PI control concept is used to control the VSCs in the microgrid system in Figure 3.2. Figure 4.2 shows a block-diagram representation of the critic-based PI control system in the microgrid. The details of the monitoring and control systems for each VSC in the grid-connected and islanded modes will be discussed in the remaining parts of this section.
Figure 4.2. Block-diagram representation of the critic-based PI control in the microgrid system.
Critic-based PI Control of Microgrids

4.3.1 Grid-connected Mode Control

Each individual control system is implemented in $dq$ reference frame, and consists of a PI controller and a fuzzy critic. The control system and the output reference voltages are used to generate PWM signals, after being transferred to the $abc$ reference frame.

The control system controls the DGs active and reactive power by directly controlling $d$ and $q$ components of current. In the grid-connected mode, DGs are under PQ control and therefore the references of active and reactive power directly contribute to the $d$-axis and $q$-axis current references. In this mode, the power generation of DG units is directly determined based on the assigned power references. A block diagram representation of the grid-connected control system is shown in Figure 4.3.

Figure 4.3. Critic-based PI control system block diagram for a VSC in the grid-connected microgrid.

4.3.2 Islanded Mode Control

Figure 4.4 shows the control system in the islanded mode. In the islanded mode, $\omega$-P and V-Q droop characteristics are used in conjunction with the critic-based PI current control (as seen in
Critic-based PI Control of Microgrids

Figure 4.3) and an outer voltage control loop to adjust the nominal frequency and voltage. The droop characteristics are in the form of (2.11) and (2.12) and frequency and voltage droop gains are set to 1.33 and 13.3, respectively.

![Critic-based PI control system for VSCs in the islanded microgrid.](image)

4.3.3 Fuzzy Critics Design

Based on the linguistic rules used for the critic design, a fuzzy system with a corresponding rule-base represents the supervisory roles of the critic in our VSC control system. Each critic is a fuzzy system with singleton fuzzifier, product inference engine, and center average defuzzifier and can be described by (2.45).

The fuzzy critic rule-base is then designed to tune the $i_d$ and $i_q$ PI controller parameters. Each critic has 5 linguistic labels for each input signal, i.e. $d$ and $q$ axes current error and their derivatives, and therefore $5^2=25$ rules in its rule-base. The advantage of this tuning method is that it does not depend on complex measurements and calculations.

The rule-base for $K_p$ critic is as follows:
Critic-based PI Control of Microgrids

\[ R_1: \text{If } (e \text{ is Negative Big and } \dot{e} \text{ is Negative Big}), \text{Then } K_P \text{ is Very Big.} \]

\[ R_2: \text{If } (e \text{ is Negative Medium and } \dot{e} \text{ is Negative Big}), \text{Then } K_P \text{ is Big.} \]

\[ R_3: \text{If } (e \text{ is Zero and } \dot{e} \text{ is Negative Big}), \text{Then } K_P \text{ is Medium.} \]

\[ R_4: \text{If } (e \text{ is Positive Medium and } \dot{e} \text{ is Negative Big}), \text{Then } K_P \text{ is Small.} \]

\[ R_5: \text{If } (e \text{ is Positive Big and } \dot{e} \text{ is Negative Big}), \text{Then } K_P \text{ is Zero.} \]

\[ R_6: \text{If } (e \text{ is Negative Big and } \dot{e} \text{ is Negative Medium}), \text{Then } K_P \text{ is Big.} \]

\[ R_7: \text{If } (e \text{ is Negative Medium and } \dot{e} \text{ is Negative Medium}), \text{Then } K_P \text{ is Medium.} \]

\[ R_8: \text{If } (e \text{ is Zero and } \dot{e} \text{ is Negative Medium}), \text{Then } K_P \text{ is Small.} \]

\[ R_9: \text{If } (e \text{ is Positive Medium and } \dot{e} \text{ is Negative Medium}), \text{Then } K_P \text{ is Zero.} \]

\[ R_{10}: \text{If } (e \text{ is Positive Big and } \dot{e} \text{ is Negative Medium}), \text{Then } K_P \text{ is Small.} \]

\[ \vdots \]

\[ R_{25}: \text{If } (e \text{ is Positive Big and } \dot{e} \text{ is Positive Big}), \text{Then } K_P \text{ is Very Big.} \]

Table 4.1 shows the rule-base for \( K_P \) critic. Here, input membership functions are Negative Big (NB), Negative Medium (NM), Zero (Z), Positive Medium (PM) and Positive Big (PB) and the output membership functions are Zero (Z), Small (S), Medium (M), Big (B), and Very Big (VB).

**Table 4.1: Fuzzy critic rule-base for \( K_P \) tuning.**

<table>
<thead>
<tr>
<th>( e_{idq} )</th>
<th>NB</th>
<th>NM</th>
<th>Z</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>VB</td>
<td>B</td>
<td>M</td>
<td>S</td>
<td>Z</td>
</tr>
<tr>
<td>NM</td>
<td>B</td>
<td>M</td>
<td>S</td>
<td>Z</td>
<td>S</td>
</tr>
<tr>
<td>Z</td>
<td>M</td>
<td>S</td>
<td>Z</td>
<td>S</td>
<td>M</td>
</tr>
<tr>
<td>PM</td>
<td>S</td>
<td>Z</td>
<td>S</td>
<td>M</td>
<td>B</td>
</tr>
<tr>
<td>PB</td>
<td>Z</td>
<td>S</td>
<td>M</td>
<td>B</td>
<td>VB</td>
</tr>
</tbody>
</table>
Critic-based PI Control of Microgrids

From (2.45), the proposed fuzzy critic system with the rule-base shown in Table 4.1 can be described as a non-linear mapping from input vector \( x = [e, \dot{e}] \) to the output signal \( K_p \) as follows:

\[
K_p = \frac{\Sigma_{l=1}^{25} \overline{y}_l (\prod_{i=1}^{2} \mu_{A_i}(x_i))}{\Sigma_{l=1}^{25} (\prod_{i=1}^{2} \mu_{A_i}(x_i))} \tag{4.1}
\]

where \( \mu_{A_i} \) are the selected input membership functions associated with rule \( l \) and the \( i \)th input, and \( \overline{y}_l \) is center of normal output membership function in rule \( l \).

Figure 4.5 shows the input and output membership functions for the \( K_p \) critic.

![Input membership functions](image1)

![Output membership functions](image2)

(a)

(b)

Figure 4.5. Kp critic membership functions, a) Input, b) Output membership functions.

The rule-base for \( K_I \) critic is as follows:
Critic-based PI Control of Microgrids

$R_1$: If ($e$ is Negative Big and $\dot{e}$ is Negative Big), Then $K_I$ is Medium.

$R_2$: If ($e$ is Negative Medium and $\dot{e}$ is Negative Big), Then $K_I$ is Small.

$R_3$: If ($e$ is Zero and $\dot{e}$ is Negative Big), Then $K_I$ is Small.

$R_4$: If ($e$ is Positive Medium and $\dot{e}$ is Negative Big), Then $K_I$ is Small.

$R_5$: If ($e$ is Positive Big and $\dot{e}$ is Negative Big), Then $K_I$ is Medium.

$R_6$: If ($e$ is Negative Big and $\dot{e}$ is Negative Medium), Then $K_I$ is Big.

$R_7$: If ($e$ is Negative Medium and $\dot{e}$ is Negative Medium), Then $K_I$ is Medium Big.

$R_8$: If ($e$ is Zero and $\dot{e}$ is Negative Medium), Then $K_I$ is Small.

$R_9$: If ($e$ is Positive Medium and $\dot{e}$ is Negative Medium), Then $K_I$ is Medium Big.

$R_{10}$: If ($e$ is Positive Big and $\dot{e}$ is Negative Medium), Then $K_I$ is Big.

\vdots

$R_{25}$: If ($e$ is Positive Big and $\dot{e}$ is Positive Big), Then $K_I$ is Medium.

Table 4.2 shows the rule-base for $K_I$ critic. Here, input membership functions are Negative Big (NB), Negative Medium (NM), Zero (Z), Positive Medium (PM) and Positive Big (PB) and the output membership functions are Small (S), Medium (M), Big (B), Medium Big (MB) and Very Big (VB).

<table>
<thead>
<tr>
<th>$e_{idq}$</th>
<th>NB</th>
<th>NM</th>
<th>Z</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
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<td>S</td>
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<td>S</td>
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<td>NM</td>
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<td>B</td>
</tr>
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<td>PB</td>
<td>M</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>M</td>
</tr>
</tbody>
</table>
From (2.45), the proposed fuzzy critic system with the rule-base shown in Table 4.2 can be described as a non-linear mapping from input vector \( x = [e, \dot{e}] \) to the output signal \( K_I \) as follows:

\[
K_I = \frac{\sum_{l=1}^{25} \psi l \left( \prod_{i=1}^{2} \mu_{A_i}^l(x_i) \right)}{\sum_{l=1}^{25} \left( \prod_{i=1}^{2} \mu_{A_i}^l(x_i) \right)} 
\]

(4.2)

where \( \mu_{A_i}^l \) are the selected input membership functions associated with rule \( l \) and the \( i \)th input, and \( \bar{y}^l \) is center of normal output membership function in rule \( l \).

Figure 4.6 shows the input and output membership functions for the \( K_I \) critic. It is worth mentioning that the shape of the critic’s output membership functions \( S \) and \( VB \) limit the critic’s output from increasing indefinitely and remove the possible noise issues that the term \( \dot{e} \) may cause.

![Figure 4.6. Ki critic membership functions, a) Input, b) Output membership functions.](image)
4.4 Simulation Results

The critic-based PI controller is applied to the microgrid system shown in Figure 3.2. Different operational scenarios have been simulated to verify the feasibility of the proposed controller and simulations are carried out in MATLAB/SIMULINK.

Also to show the advantages of the critic-based PI controller, the results from the proposed controller are compared to conventional PI control results provided in the previous chapter. The simulation results show the performance improvements with the application of the critic-based PI control and its drawbacks.

4.4.1 Grid-connected Microgrid

A) Real and Reactive Power Tracking

In this case switch S2 is open and therefore a 3-DG microgrid is studied. Two constant impedance loads each at 15 kW and 3 kVAr are present in the microgrid and the reference values of real and reactive power are set to 10kW and 3kVAr, 9kW and 2 kVAr, and 8 kW and 1kVAr for DG1, DG2 and DG3 respectively. The motor load switch is open and therefore no motor load in circuit.

Figure 4.7 and Figure 4.8 show the real and reactive power and the three-phase current and terminal voltage in DG1. As seen, the proposed critic-based PI control scheme removes the initial transients of PI control (Figure 3.10) and reaches its steady state within almost 0.04 s. Unlike the neuro-fuzzy critic-based controller that was proposed in the previous chapter, after the initial transients are damped, the critic-based PI controller shows steady state oscillations, which are still not comparable to the those of the traditional PI control.
Figure 4.7. Case-A: Real power tracking under critic-based PI control

Figure 4.8. Case-A: Three-phase current and voltage under critic-based PI control.
By comparing Figure 4.8 and Figure 3.11, it is seen that the proposed algorithm results in an increase in the harmonic content of the phase currents. This effect is discussed later with comparing the THD numbers.

**B) Step Change in DGs’ Real Power**

In the 3-DG microgrid, P and Q reference values are set to 8kW and 3kVAr, 7.5kW and 2 kVAr, and 8.5 kW and 1kVAr for DG1, DG2 and DG3 respectively and a 2kW step change occurs in each DG’s real power reference at t=0.25 s. Figure 4.9 and Figure 4.10 show the real and reactive power and the three-phase current and voltage in DG1 over the transient period.

![Graph of real power tracking under critic-based PI control](image)

**Figure 4.9.** Case-B. Real power tracking under critic-based PI control.
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Figure 4.10. Case-B. Three-phase current and voltage under critic-based PI control.

As seen the critic-based PI controller is capable of smooth transition between the two states, however higher current harmonics appear in the output.

C) Step Change in DGs’ Reactive Power

In this case, to investigate the control system reactive power tracking performance, a 1kVAR step change is applied to each DG’s reactive power reference at $t=0.25$ s while the initial set points are 10 kW and 3 kVAR for DG1, 9 kW and 2 kVAR for DG2, and 8 kW and 1kVAR for DG3. The motor load switch is open and therefore no motor load in circuit. Figure 4.11 and Figure 4.12 show the real and reactive power and the three-phase current and terminal voltage in DG1 over the transient period.
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Figure 4.11. Case-C. Real and reactive power tracking under critic-based PI control.

Figure 4.12. Case-C. Three-phase current and voltage under critic-based PI control.
D) Operation in Presence of Motor Load

In this section, power tracking in the grid-connected microgrid in presence of a motor load is investigated to study the behavior of the controller in case of a dynamic load. The switch S1 is closed at $t=0.3$ s and the induction motor starts up with no start-up controller. This change occurs after the DGs have reached their initial power set points. Figure 4.13 and Figure 4.14 show the power tracking and three-phase current and terminal voltage of DG1. The results show that dynamic behavior of the motor load has no effect on the behavior of the control system in the microgrid.

![Real Power Tracking](image)

![Reactive Power Tracking](image)

Figure 4.13. Case-D. Real and Reactive power tracking under critic-based PI control.
Critic-based PI Control of Microgrids

Figure 4.14. Case-D. Three phase current and voltage in DG1 under critic-based PI control.

**E) Large Step Change in DGs’ Real Power**

To study the stability of the control system in case of large power transients, a 5kW step increase (%50 of nominal power) occurs in each DG’s active power reference at t=0.25 s in the grid-connected microgrid, while the initial set points are 5 kW and 3 kVAr for DG1, 4.5 kW and 2 kVAr for DG2, and 5.5 kW and 1kVAr for DG3 respectively.

Figure 4.15 and Figure 4.16 show the real and reactive power tracking in the microgrid and three-phase current and voltage in DG1. As seen, the control system smoothly follows the reference power, and large amplitude of the power transient does not jeopardize the stability. It is however observed that this large transient in P causes a relatively big disturbing effect on Q at the transient time.

Figure 4.16 shows the harmonic attenuation performance of the controller which is not affected by the transient.
Figure 4.15. Case-E. Real and Reactive power tracking under critic-based PI control.

Figure 4.16. Case-E. Three phase current and voltage in DG1 under critic-based PI control.
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F) High DG Penetration

To prove the effectiveness of our proposed control system in case of higher DG penetrations in the grid-connected microgrid of Figure 3.2, switch S2 is closed and a 5-DG microgrid is studied. Different step changes occur in the active power references of DGs (except for DG5) at t=0.25 s and the control system behavior is studied. Figure 4.17 and Figure 4.18 show the real and reactive power tracking in the microgrid and three-phase current and voltage in DG1.

As seen high penetration of DGs does not affect the response of the control system and the transient response is well damped and smooth power injection is yielded.

Figure 4.17. Case-F: Power tracking under critic-based PI control in the 5-DG microgrid.
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Figure 4.18. Case-F: Three-phase current and voltage in DG1 in the 5-DG microgrid.

4.4.2 Islanded Microgrid

During the simulations switch S1, S2 and the PCC switch are open and therefore an islanded 3-DG microgrid with two constant impedance loads rated at 15 kW and 3 kVAr is studied. As the DGs droop characteristics are the same an equal power sharing is expected. Figure 4.19 and Figure 4.20 show the three-phase current and voltage of DG1 and the real and reactive power sharing between the DGs, and Figure 4.21 shows frequency in DG1.

Figure 4.19. Three phase current and terminal voltage in DG1 in islanded microgrid under critic-based PI control.
Figure 4.20. Active and reactive power sharing in islanded mode under critic-based PI control.
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![Graph showing frequency in islanded microgrid in DG1 under critic-based PI control.](image)

**Figure 4.21. Frequency in islanded microgrid in DG1 under critic-based PI control.**

As seen the total load present in the system is 30kW and 6kVAr therefore each DG receives 10kW active power and 2kVAr reactive power, however the controller shows a better response in regulating the active power.

Table 4.3 shows a quantitative evaluation of the results of the critic-based PI control structure. For the purpose of analogy, only the results for DG1 are presented here; but a similar trend can be observed for other DGs.

To obtain a precise correspondence, initial overshoot, Mean Absolute Error (MAE) and the settling time for power and Total Harmonic Distortion (THD) for current are observed and listed. The MAE factor is calculated after t=0.1 s when the initial transients are damped and a steady state response is reached.

As seen, when compared to traditional PI control in Table 3.2, with the proposed critic-based PI approach, the initial transient time and the initial power overshoot are significantly reduced and a faster and more accurate power control is yielded. Comparing the MAE factors shows the improved performance of the controller in reducing the convergence error for reactive power, but an increase for real power. Also it is observed that with the proposed algorithm the THD factor is increased compared to traditional PI control.
Critic-based PI Control of Microgrids

It is worth mentioning that despite the increase in THD, the proposed control method still enables the microgrid system to work with high penetrations of DG units. Also the simple structure is another merit of the critic-based PI method.

Table 4.3. Quantitative evaluation of results for critic-based PI control.

<table>
<thead>
<tr>
<th>Case</th>
<th>Quantity</th>
<th>Overshoot</th>
<th>MAE</th>
<th>Settling Time</th>
<th>THD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P1</td>
<td>11.45kW</td>
<td>1.2%</td>
<td>0.04s</td>
<td>0.217</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>6.03kVAr</td>
<td>3.98%</td>
<td>0.04s</td>
<td></td>
</tr>
<tr>
<td>Case2</td>
<td>P1</td>
<td>10.25kW</td>
<td>1.48%</td>
<td>0.04s</td>
<td>0.217</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>5.55kVAr</td>
<td>4.6%</td>
<td>0.04s</td>
<td></td>
</tr>
<tr>
<td>Case3</td>
<td>P1</td>
<td>11.45kW</td>
<td>1.12%</td>
<td>0.04s</td>
<td>0.211</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>6.03kVAr</td>
<td>3.44%</td>
<td>0.04s</td>
<td></td>
</tr>
<tr>
<td>Case4</td>
<td>P1</td>
<td>10.22kW</td>
<td>1.39%</td>
<td>0.04s</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>5.55kVAr</td>
<td>4.76%</td>
<td>0.04s</td>
<td></td>
</tr>
<tr>
<td>Case5</td>
<td>P1</td>
<td>10.46kW</td>
<td>1.56%</td>
<td>0.04s</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>6.44kVAr</td>
<td>2.97%</td>
<td>0.04s</td>
<td></td>
</tr>
</tbody>
</table>

4.5 Conclusions

In this chapter a critic-based PI control structure was presented to cope with the deficiencies of traditional PI control by increasing the control system adaptivity while simplifying the control system compared to the critic-based neuro-fuzzy controller developed in the 3rd chapter. Based on the critic-based control concept, an online gain tuning method was proposed in which fuzzy critics are used to automatically tune the proportional and integral gains of PI controller. In this
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structure, no learning formula is used in the weight updating process, instead using the reasoning capability of the fuzzy system the desired gains are estimated by the critic and the updated gains are used in the PI controller.

The proposed gain tuning algorithm was used to control the active and reactive power of voltage source converters within a power electronic based microgrid. In multiple operational scenarios the performance of the critic-based PI controlled microgrid was studied and compared to the response of the PI control in previous chapter. The results verify the improved dynamics compared to traditional PI control via reduced convergence time, output oscillations and tracking error; however the proposed approach shows an increase in the amount of unwanted harmonics in the phase current. Furthermore, the intelligent nature of the proposed controller ensures adaptive performance against changes such as high penetration of DGs and dynamically demanding situations like presence of motor loads in the system.

When compared to the critic-based neuro-fuzzy control system, the critic-based PI control shows more convergence time and current harmonics content; however it should be noted that the control system structure is significantly simple.
Chapter 5

Critic-based Self-tuning PI Control of Microgrids

In the previous chapter, fuzzy critics were implemented to automatically tune the gains of PI controllers to cope with the slow adaptation of traditional fixed-gain PI regulators to power changes, disturbances and parameters variations in microgrids. In this method, based on the reasoning capability of the fuzzy system, the change in integral and proportional gains were estimated and used to tune the PI controller. In the current chapter, a novel gain tuning algorithm is developed in which on-line tuning of PI gains is achieved by combining the reasoning capability of a fuzzy critic and a mathematical learning algorithm.

The proposed control system contains a PI controller and a critic agent whose task is to continuously assess the performance and generate an evaluation signal. The PI controller gains are updated using a learning formula with the objective of optimizing critic’s evaluation signal, which represents the credibility of the system performance. The proposed approach is a non-model-based adaptive structure and is named the Critic-based Self-tuning PI (CSPI) controller hereafter. Application of this algorithm increases the control system adaptivity while avoiding unnecessary complexity.

5.1 Critic-based Self-tuning PI Control

PI controllers have been widely used in controlling voltage source converters and this popularity can be attributed to their simple and well established design methods and good performance in a wide range of operating conditions. As simple as a PI controller’s design may
Critic-based Self-tuning PI Control of Microgrids

be, they are associated with the main drawback of poor adaptivity in case of dynamically demanding situations and plant changes. Self-tuned or auto-tuned PI controllers have been proposed to overcome these technical problems.

The critic-based self-tuning PI control is inspired from adaptive critic-based learning algorithms and uses a critic agent for the purpose of online tuning of the PI controller. The system feedback, interpreted as the control action in the previous state, is being applied to the critic agent’s input. An evaluation signal is then generated by the critic and is used alongside the back-propagation of error to update the weights of PI controller in an online learning process. Final goal in the learning process is to optimize the critic’s output signal. The mathematical concept and explicit details of the self-tuning algorithm are discussed in this section.

5.1.1 CSPI Control System Structure

Figure 5.1 shows a block diagram of the proposed CSPI control system and its components. The PI controller receives the states and produces a control action through its actuator and the evaluation signal provided by the critic agent contributes in updating the parameters of the controller through the self-tuning scheme.

![Figure 5.1. CSPI control system structure.](Image)
This way, instead of precise design of the PI controller more effort is dedicated to the design of the critic. As a result, a level of intelligence is incorporated into the control system and an adaptive design is yielded. Simple and on-line learning rules result in a self-tuning system with a fast dynamic response.

5.1.2 Critic Agent

Inputs of the critic are error and error derivative, two signals that indicate the performance of the system; and the output signal contributes to update PI controllers’ gains, i.e. $K_p$ and $K_i$. The final goal of the self-tuning procedure is to minimize a cost function which is related to the critic’s output signal, $r$.

The critic agent is continuously evaluating the performance of the control system and comparing it with the desired behavior and is designed based on qualitative assessments of the system in different modes of operation. These linguistic criticisms are obtained by investigating different states of the system. If at a time interval error and error derivative are both positive, it means that the output is smaller than the reference and because the error derivate is positive too, this decreasing trend is continuous, i.e. the error is still increasing. In this case the system behavior is not satisfactory at all and therefore the critic produces a large evaluation signal. In another example, if at a time interval the error is positive, which means the output is smaller than reference, but error derivative is negative it means that the performance is not at its best right now but an improving trend is observed as the error is decreasing (because error derivative is negative). In this case the critic produces a very small evaluation signal.

These linguistic evaluations show the supervisory nature of the critic system and accordingly a fuzzy critic with an appropriate rule-base which represents these evaluations is chosen. This fuzzy critic is similar to the critic system used in Chapter 3.
5.1.3 Gain Tuning

The evaluation signal $r$ which is generated by the critic is a feedback of system’s behavior and in its general form is an online cost function, $f(.)$, of the error signal $e = y_{ref} - y$, the control action $u$, and the output $y$,

$$ r = f(e, y, u) \quad (5.1) $$

Let us define the cost function $E$ as:

$$ E = \frac{1}{2} r^2 \quad (5.2) $$

The cost function $E$ must be minimized and the controller’s parameters are updated based on the steepest descent optimization rule, i.e. in the opposite direction of $\nabla E$ ($\nabla$ is the gradient operator):

$$ \Delta K_{P,I} \propto -\nabla E \propto -\frac{\partial E}{\partial K_{P,I}} = -\eta \frac{\partial E}{\partial K_{P,I}} \quad (5.3) $$

where $\eta$ is the learning rate and $K_{P,I}$ denotes for the PI controller gains; i.e. $K_p$ and $K_i$.

Using the chain rule:

$$ \frac{\partial E}{\partial K_{P,I}} = \frac{\partial E}{\partial r} \frac{\partial r}{\partial y} \frac{\partial y}{\partial u} \frac{\partial u}{\partial K_{P,I}} \quad (5.4) $$

From (5.2) and (5.4) and the definitions of $e$ and $E$ we have:

$$ \frac{\partial E}{\partial K_{P,I}} = r. (-\frac{\partial r}{\partial e}) \frac{\partial y}{\partial u} \frac{\partial u}{\partial K_{P,I}} \quad (5.5) $$

To simplify the rule without losing the generality the term $\frac{\partial r}{\partial e}$ is replaced by its sign, i.e. “+1”.

Also the controller is designed in such a way that term $\frac{\partial y}{\partial u}$ is always a positive constant; therefore it can be replaced by its sign "+1" for the adaptation rule, and the constant will be included in the learning rate, $\eta$,

$$ \frac{\partial E}{\partial K_{P,I}} = -r. (+1). (+1). \frac{\partial u}{\partial K_{P,I}} \quad (5.6) $$

And finally using (5.2) to (5.6), $\frac{\partial E}{\partial K_{P,I}}$ and $\Delta K_{P,I}$ are calculated as follows:
Critic-based Self-tuning PI Control of Microgrids

\[ \frac{\partial E}{\partial K_{P,J}} = -r \cdot \frac{\partial u}{\partial K_{P,J}} \]  \hspace{1cm} (5.7)

\[ \Delta K_{P,J} = \eta \cdot r \cdot \frac{\partial u}{\partial K_{P,J}} \]  \hspace{1cm} (5.8)

For the PI control system in Figure 5.1, the control signal \( u \) can be written as:

\[ u = K_p \cdot e + K_i \cdot \int e \cdot dt \] \hspace{1cm} (5.9)

Accordingly, the final update rules for the proportional and integral gains of the PI controller, \( K_p \) and \( K_i \) which will be used in the self-tuning element are given in (5.10) and (5.11):

\[ \Delta K_p = \eta \cdot r \cdot e \] \hspace{1cm} (5.10)

\[ \Delta K_i = \eta \cdot r \cdot \int e \cdot dt \] \hspace{1cm} (5.11)

5.2 CSPI Control of Microgrids

In this section, the proposed CSPI control concept is used to control the VSCs in the microgrid shown in Figure 3.2. Figure 5.2 shows a block-diagram representation of the CSPI control system in the microgrid. The details of the monitoring and control systems for each VSC in the grid-connected and islanded modes will be discussed in the remaining parts of this section.

5.2.1 Grid-connected Mode Control

Each individual controller is implemented in \( dq \) reference frame, and consists of a PI controller and a fuzzy critic. The control system controls the DGs active and reactive power by directly controlling \( d \) and \( q \) components of current and output reference voltages are used to generate PWM signals, after being transferred to the \( abc \) frame.

In the grid-connected mode DGs are under PQ control and the control system is implemented in \( dq \) reference frame, hence the references of real and reactive power contribute directly to the \( d \) and \( q \) reference currents. Decoupling and feed-forward terms are added to minimize the effect of the undesired cross-coupling between \( d \) and \( q \) axes equations and interfering grid voltages. The control system block diagram in each DG is shown in Figure 5.3.
Figure 5.2. Block-diagram representation of the CSPI control in the microgrid system.
5.2.2 Islanded Mode Control

In the islanded microgrid, the CSPI current control (as seen in Figure 5.3) is used in conjunction with frequency and voltage droops and an outer voltage control loop to control VSCs. Figure 5.4 shows a block diagram of the control system in this mode.
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As in this mode the utility grid is not present, the major control tasks are voltage and frequency control. The droop characteristics are in the form of (2.11) and (2.12) and the droop gains $m_p$ and $m_q$ are equal to 1.33 and 13.3 respectively.

5.2.3 Fuzzy Critics Design

In the proposed CSPI control algorithm for VSCs, each critic is a fuzzy system with singleton fuzzifier, product inference engine, and center average defuzzifier which is best described by (2.45). The $i_d$ and $i_q$ critics receive $d$ and $q$ axes currents error and their derivatives as inputs and each have 3 linguistic labels for each input signal; hence 9 rules in their rule-base. These fuzzy rules are as follows:

$R_1$: If ($e$ is Negative and $\dot{e}$ is Negative), Then $r$ is Large Negative.

$R_2$: If ($e$ is Zero and $\dot{e}$ is Negative), Then $r$ is Small Negative.

$R_3$: If ($e$ is Positive and $\dot{e}$ is Negative), Then $r$ is Zero.

$R_4$: If ($e$ is Negative and $\dot{e}$ is Zero), Then $r$ is Small Negative.

$R_5$: If ($e$ is Zero and $\dot{e}$ is Zero), Then $r$ is Zero.

$R_6$: If ($e$ is Positive and $\dot{e}$ is Zero), Then $r$ is Small Positive.

$R_7$: If ($e$ is Negative and $\dot{e}$ is Positive), Then $r$ is Zero.

$R_8$: If ($e$ is Zero and $\dot{e}$ is Positive), Then $r$ is Small Positive.

$R_9$: If ($e$ is Positive and $\dot{e}$ is Positive), Then $r$ is Large Positive.

These rules that cover all possible states in the system are shown in Table 5.1. The input membership functions are Negative (N), Zero (Z) and Positive (P) and output membership functions are Large Negative (LN), Small Negative (SN), Zero (Z), Small Positive (SP) and Large Positive (LP).
Table 5.1. Fuzzy critic rule-base.

<table>
<thead>
<tr>
<th>$e_{ldq}$</th>
<th>N</th>
<th>Z</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>LN</td>
<td>SN</td>
<td>Z</td>
</tr>
<tr>
<td>$Z$</td>
<td>SN</td>
<td>Z</td>
<td>SP</td>
</tr>
<tr>
<td>$P$</td>
<td>Z</td>
<td>SP</td>
<td>LP</td>
</tr>
</tbody>
</table>

From (2.45), the proposed fuzzy critic system with the rule-base shown in Table 5.1 can be described as a non-linear mapping from input vector $x = [e, \dot{e}]$ to the output signal $r$ as follows:

$$r = \frac{\sum_{l=1}^{9} \sum_{i=1}^{9} \mu_{A_l}^i(x_i)}{\sum_{l=1}^{9} \sum_{i=1}^{9} \mu_{A_l}^i(x_i)} \quad (5.12)$$

where $\mu_{A_l}^i$ are the selected input membership functions associated with rule $l$ and $i$th input, and $\tilde{y}_l^i$ is center of normal output membership function in rule $l$.

Figure 5.5 shows the input and output membership functions of each critic. The membership function of the linguistic variable Z is Gaussian and that of N and P linguistic variables are of the Sigmoid form.

The most important part of the CSPI control system design is the critic design. Because of the fuzzy nature of the critic, the membership functions can be chosen from different shapes such as sigmoidal or triangular form, however in our case the selected forms show a better response. In should be emphasized that for (2.45) to hold, the membership functions must be normal functions. The mean value and the variance are chosen in a linguistic procedure considering the fact that the critic receives normalized inputs, which means that a set of initial parameters are selected in a way that Negative, Zero, and Positive membership functions smoothly cover the $[-1,1]$ interval and then a fine tuning is performed to achieve the best performance. A similar approach is used to tune the critic’s output membership functions.
The critic’s output signal, \( r \), is used in the gain tuning algorithm to adjust the integral and proportional gains. The shape of the critic’s output membership functions LP and LN limit the critic’s output from increasing indefinitely and remove the possible noise issues that the term \( \dot{e} \) may cause.

### 5.2.4 Gain-tuning Algorithm

The updated proportional and integral gains of \( i_d \) and \( i_q \) PI controllers are calculated from the extracted gain-tuning formulas in (5.10) and (5.11).
The learning rate parameter embeds the proportionality constant of (5.3). Because of the nature of the gain tuning algorithm and its dependency on the fuzzy critic, this parameter is determined via trial and error; that is an initial value is chosen for the learning rate and then through trial and error process a fine tuning is achieved. This parameter can be constant or a function of time. In our particular microgrid control system multiple simulations showed that a constant learning rate does not result in a satisfactory performance, however an exponential function in which the learning rate changes over time creates the best results; therefore the learning rate was chosen as an exponential function of time for all DGs,

$$\eta = 0.09 + \frac{0.25}{(1+\exp(-20t))}$$  \hspace{1cm} (5.13)

It is worth mentioning that the learning algorithm can also be used to tune the learning rate based on the back-propagation of the error signal; however because of possible disadvantages such as high computational load, the possibility of local optimums and increased sensitivity due to the selected initial values, this parameter was chosen based on the linguistic knowledge of the system.

### 5.3 Simulation Results

The CSPI controller is applied to the microgrid system shown in Figure 3.2. Simulations are carried out in MATLAB/SIMULINK and to verify the feasibility of the proposed controller different operational scenarios in the grid-connected mode and a case in the islanded mode are studied. The simulation results verify the considerable performance improvements as compared to PI control and the critic-based PI control of Chapter 4.
5.3.1 Grid-connected Microgrid

A) Real and Reactive Power Tracking

To evaluate the power tracking capability of the proposed controller in the steady state mode, in the microgrid system of Figure 3.2 (switch S2 is OFF and therefore a 3-DG microgrid is studied) constant real and reactive power references are assigned to each DG and the control system performance is studied. The reference values of DGs are set to 10 kW and 3 kVAr, 9 kW and 2 kVAr, and 8 kW and 1 kVAr for DG1, DG2 and DG3 respectively. Figure 5.6 and Figure 5.7 show the real and reactive power tracking in DGs and three-phase current of DG1 under the CSPI control.

![Real Power Tracking](image1)

![Reactive Power Tracking](image2)

Figure 5.6. Case A- Real and reactive power tracking under CSPI control.
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As seen, with the CSPI control a smooth transient response is achieved and the output reaches its steady state within \(\sim 0.02\) s which is almost one sixth of the transient time of \(\sim 0.12\) s in PI control which was observed in Chapter 3. Also the initial power oscillations of PI control are completely removed for real power and significantly reduced for reactive power; hence unwanted activation of protection systems, in which case the desired supply to loads might fail, is averted and therefore the overall system reliability and stability is increased.

From Figure 5.7 it is evident that the proposed CSPI control achieves to a high level of harmonics attenuation compared to traditional PI and the critic-based PI control and the desired current shape is maintained.

![Graph](image-url)

**Figure 5.7. Case A- Three phase current and terminal voltage in DG1 under CSPI control.**

B) **Real Power Change**

In this case in the 3-DG microgrid, the reference values of \(P\) and \(Q\) are set to 8kW and 3kVAr, 7.5kW and 2 kVAr, and 8.5 kW and 1kVAr for DG1, DG2 and DG3 respectively, and a 2kW step change occurs in each DG’s real power reference at \(t=0.25\) s. Figure 5.8 and Figure 5.9 show the real and reactive power tracking and the three-phase current and voltage in DG1 over the transient period.
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As seen, at the transient time the CSPI control system smoothly follows the change to the new state and the new real power reference is traced with negligible tracking error. Also it is observed that with the proposed CSPI control the step change in the real power has a slight disturbing effect on the reactive power at the transient time. This phenomenon can be explained with respect to the intrinsic dependency between P and Q equations; however because of the small magnitude of the effect it has been neglected.

As seen in Figure 5.9, the proposed algorithm significantly improves the harmonics attenuation capability of the controller and preserves the desired current shape in the microgrid.

![Graphs of real and reactive power tracking](image)

*Figure 5.8. Case B- Real and reactive power tracking under CSPI control.*
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Figure 5.9. Case B- Three phase current and terminal voltage in DG1.

C) Reactive Power Change

In this case, to investigate the behavior of the control system in case of reactive power transients, a 1kVAR step change is applied to each DG’s reference at t=0.25 s. The motor load switch is OFF and therefore no motor load in circuit. Figure 5.10 and Figure 5.11 show the real and reactive power and the three-phase current and voltage of DG1 over the transient period.

Similar to the previous scenarios, the CSPI control system smoothly tracks the reference values and supplies the desired active and reactive power in the microgrid.

From Figure 5.11 it is seen that the desired current shape is maintained in the microgrid.
Figure 5.10. Case C- Real and reactive power tracking under CSPI control, a) Real power tracking b) Reactive power tracking.

Figure 5.11. Case C- Three phase current and terminal voltage in DG1.
D) Motor Load Effect

To study the behavior of the control system in presence of a dynamic load, a three-phase 5hp induction motor is added to the microgrid. The switch S1 is ON and hence the induction motor is in circuit and starting up at $t=0$ s (with no start-up control) and a 2kW step change occurs in real power at $t=0.4$ s. Figure 5.12 and Figure 5.13 show the power tracking in the microgrid and three-phase current and terminal voltage of DG1.

![Real Power Tracking](image)

![Reactive Power Tracking](image)

**Figure 5.12.** Case D- Real and reactive power tracking with motor load under CSPI control.
The simulation results indicate that the good performance of the control system is not affected by motor load’s dynamic behavior.

**E) Large Step Change in DGs’ Real Power**

To study the stability of the control system in case of large power transients, a 5kW step increase (%50 of nominal power) occurs in each DG’s active power reference at t=0.25 s in the grid-connected microgrid, while the initial set points are 5 kW and 3 kVAr for DG1, 4.5 kW and 2 kVAr for DG2, and 5.5 kW and 1kVAr for DG3 respectively.

Figure 5.14 and Figure 5.15 show the real and reactive power tracking in microgrid and three phase current and voltage in DG1. As seen, the large amplitude of step transient does not affect the stability of the microgrid and the controller is well capable of injecting the desired P and Q in the microgrid; however the coupling effect of P change on Q at the transient time is increased.

Figure 5.15 shows that the desired current shape is maintained in the system.
Figure 5.14. Case E- Real and reactive power tracking under CSPI control, a) Real power tracking b) Reactive power tracking.

Figure 5.15. Case E- Three phase current and terminal voltage in DG1.
F) High DG Penetration

To prove the effectiveness of our proposed control system in case of higher DG penetrations in the microgrid, switch S2 is closed and the resulted 5-DG microgrid is studied. Different step change occur in the active power reference of DGs at $t=0.25$ s (except for DG5) and the values of load-1, load-2 and load-3 are 15kW and 3kVAr each. Figure 5.16 and Figure 5.17 show the real and reactive power tracking in the microgrid and the three-phase current and voltage in DG1 for the proposed CSPI control algorithm over the transient period.

![Diagram showing real and reactive power tracking in the microgrid](image)

Figure 5.16. Case F- Real and reactive power tracking in the 5-DG microgrid under CSPI control.
It is seen that higher DG penetration does not counteract the response of the proposed controller and the transient response is well damped and smooth power injection is yielded.

5.3.2 Islanded Microgrid

In this case, switch S1, S2 and the PCC switch are open, therefore an islanded 3-DG microgrid with two constant impedance loads is studied. As the DGs droop characteristics are the same, equal power sharing is expected. Figure 5.18 and Figure 5.19 show the three-phase current and voltage of DG1 and real and reactive power sharing between the DGs and Figure 5.20 shows the frequency in DG1.

Figure 5.17. Case F- Three-phase current and voltage in DG1 in the 5-DG microgrid under CSPI control.

Figure 5.18. Three-phase current and voltage in DG1 in the islanded mode in CSPI control.
Figure 5.19. Real and reactive power sharing in the 3-DG islanded microgrid under CSPI control.
As the total load present in the system is 30kW and 6kVar, therefore each DG receives 10kW active power and 2kVar reactive power, however the controller shows a better response in regulating the active power.

A quantitative assessment of the previous operational scenarios is provided in Table 5.2. In this table, initial overshoot and Mean Absolute Error (MAE) of active and reactive power in DG1 and Total Harmonic Distortion (THD) of its current are calculated. The results can be compared with those of the traditional PI control in As seen, with the proposed critic-based approach, not only the initial transient time is decreased, but also the initial overshoot is completely removed for P and reduced considerably for Q and a faster and more accurate control is yielded. Also comparing the MAE and THD factors shows the superior performance of the controller, in removing the unwanted harmonics and steady stated oscillations with respect to the PI control.

Table 3.2.

To obtain a more precise comparison, the MAE factor is calculated for the times after t=0.1 s when all the initial transients are damped.
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As seen, the proposed CSPI controller results in significant reduction of initial power overshoot and average error when compared to traditional PI control; hence a faster and more accurate control is yielded.

Also by comparing the THD factors between the traditional PI and CSPI controls, it is evident that the proposed gain tuning algorithm is more efficient in removing the unwanted harmonics in the phase current waveform within the microgrid system.

<table>
<thead>
<tr>
<th>Case</th>
<th>Quantity</th>
<th>Overshoot</th>
<th>MAE</th>
<th>Settling time</th>
<th>THD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case1</td>
<td>P1</td>
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<td>0.16%</td>
<td>0.02 s</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
<td>5.31kVar</td>
<td>4.72%</td>
<td>0.02 s</td>
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<tr>
<td>Case2</td>
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</tr>
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<td></td>
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<tr>
<td>Case3</td>
<td>P1</td>
<td>10.59kW</td>
<td>0.22%</td>
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</tr>
<tr>
<td></td>
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<td>5.31kVar</td>
<td>2.54%</td>
<td>0.02 s</td>
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</tr>
<tr>
<td>Case4</td>
<td>P1</td>
<td>10.02kW</td>
<td>0.56%</td>
<td>0.02 s</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
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<td>4.11kVar</td>
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<td>0.02 s</td>
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</tr>
<tr>
<td>Case5</td>
<td>P1</td>
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<td>0.44%</td>
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<td>0.053</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
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</tr>
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</table>

5.4 Conclusions

In this chapter a novel control method called the Critic-based Self-tuning PI (CSPI) control was proposed and applied to control voltage source converters within a microgrid system. To cope with the limited adaptivity of conventional fixed-gain PI controllers in case of power
Critic-based Self-tuning PI Control of Microgrids

changes, disturbances and high DG penetrations, an on-line gain-tuning algorithm was developed in which linguistic evaluations of a fuzzy critic are used and the PI controller gains are updated by optimizing the evaluation signal produced by the critic.

The performance of the control system was studied in multiple operational scenarios and the response was compared to that of a traditional PI control in the first four cases. The results verify the effectiveness of the proposed algorithm and prove that the CSPI controller has significantly improved the microgrid performance by reducing the convergence time, power oscillations and tracking error especially in case of higher DG penetrations. Also with the CSPI control algorithm, the controlled DGs’ currents show a significant reduction in the amount of undesired harmonics. Furthermore, the intelligent nature of the proposed approach ensures adaptive control of DG units in high DG microgrids.
Chapter 6

Summary, Conclusions, and Future Work

6.1 Summary

Control of microgrids, as the main building blocks of the future smart power grid, is an important problem which has initiated many research activities in recent years. As the majority of distributed energy resources are interfaced to microgrids through voltage source converters, their specific structure, natural nonlinearity, and low physical inertia may lead to higher sensitivity to network disturbances and power oscillations and in occasions result in violation of overall stability; hence the need for fast and flexible control techniques for VSCs in microgrid systems is evident.

The design simplicity and easy implementation of linear PI controllers have resulted in their relative popularity compared to non-linear approaches in controlling voltage source converters; however despite good performance in controlling dc variables, their application in microgrid systems is associated with a number of drawbacks such as poor harmonics attenuation capability and unsatisfactory operation in case of load changes and high penetration of distributed generators.

In this thesis, to cope with the problems associated with the conventional PI control, three different control algorithms for voltage source converters in microgrid systems were proposed. The control systems are based on the adaptive critic-based control concept and employ an element called critic whose task is to evaluate the credibility of the performance and compare it with the desired goals. The critic’s evaluations are then used in an on-line procedure to update the
controller parameters during dynamic transients. The critic-based control idea was implemented in three structures in a microgrid system. The accomplishments of this thesis can be summarized as follows:

- In contrary to previous studies which have been mostly conducted on simple microgrid models, in this thesis a microgrid model was developed with high penetrations of DG units (3-DGs and 5-DGs) and different load types such as constant power and dynamic motor loads. Furthermore, multiple operational scenarios in grid-connected and islanded modes were considered to ensure the effectiveness of the proposed controls in different conditions.

- An adaptive critic-based neuro-fuzzy control system for power control of microgrids was presented in Chapter 3. This control system consists of a TSK neuro-fuzzy controller and a critic agent whose task is to evaluate the performance of the control system and compare it with the desired goals. The controller then modifies its weights so that the critic’s satisfaction is insured. The control system was adapted to control VSCs in the developed microgrid model and appropriate rule-bases of the TSK controller and fuzzy critics were designed for our microgrid system. With the proposed approach, not only the initial transient time of PI control was decreased, but also the initial power overshoot was completely removed for P and significantly reduced for Q, and a faster and more accurate control was yielded. Also a comparison between the MAE (a representative of the tracking error) and THD (representative of current harmonics content) factors shows the superior performance of the controller, in removing the unwanted harmonics, output oscillations and the average error. Also the proposed method enables the microgrid to work in high penetration of DGs.

- In Chapter 4, a critic-based PI control structure was developed to cope with the deficiencies of traditional PI control by increasing the control system adaptivity while simplifying the control system compared to the critic-based neuro-fuzzy controller.
of Chapter 3. In this approach, using the reasoning capability of the fuzzy systems, the desired PI gains are estimated by a fuzzy critic with no need for a mathematical gain optimization algorithm. The control system was adapted to control VSCs in the developed microgrid model and appropriate rule-bases of the fuzzy critics for proportional and integral gains tuning were designed for our microgrid system. With the proposed critic-based PI approach, the initial transient time and the initial power overshoot of PI control were significantly reduced and a faster control was yielded. Comparing the MAE factors showed the improved performance of the controller in reducing the average error for Q and an increase in MAE for P. Also it was observed that with the proposed algorithm the THD factor is increased compared to the traditional PI control. The proposed method enables the microgrid to work in high penetration of DGs and simple structure of the proposed method compared to the critic-based neuro-fuzzy control is another advantage.

- In Chapter 5, a novel control system called the critic-based self-tuning PI or CSPI control was proposed to cope with the limited adaptivity of conventional fixed-gain PI controllers. The control system is based on an on-line learning algorithm in which the PI controller gains are updated by optimizing the evaluation signal produced by the fuzzy critic. The control system was adapted to control VSCs in the developed microgrid model and appropriate rule-bases of the fuzzy critics and the gain-tuning formula were designed for our microgrid system. By comparing the initial power overshoot, transient time and MAE factors, it is observed that the proposed CSPI controller results in significant reduction of initial power transients and steady state oscillations compared to the traditional PI control. Also by comparing the THD factors, it is evident that the proposed gain tuning algorithm is efficient in removing the unwanted harmonics from the phase current waveform. It is worth mentioning that being an adaptive non-model-based
controller, the proposed approach can be applied to any other controllable system. Also the proposed method enables the microgrid to work in high penetration of DGs.

### 6.2 Conclusions

The following conclusions are drawn:

- Using the critic-based control approach, the need for precise design of the controllers is removed and more value is given to the design of the critic agent. As the critic is only responsible for providing qualitative evaluations of the performance, no complicated mathematical calculations is needed for its design. Designing the critic instead of the controller increases the degree of intelligence and adaptivity against changes such as high penetration of DGs and dynamically demanding situations like presence of motor loads and results in a self-tuning control system with the ability of on-line learning and independency from system model. Simple learning rules increase the computational speed.

- With the critic-based neuro-fuzzy control compared to PI, the convergence time is reduced ~%80, and the MAE and THD factors are reduced ~%50. The initial overshoot in P and Q are almost removed completely. The decoupling and feed-forward terms are also removed.

- With the CSPI controller, the convergence time is reduced ~%80, the MAE factor is reduced ~%60 for real power and ~%50 for reactive power, and the THD is reduced ~%50. The initial overshoot in P and Q are removed almost completely.

- With the critic-based PI control, the convergence time is reduced ~%66, the MAE factor is increased ~%30 for real power and decreased ~%30 for reactive power, and the THD factor is almost doubled. The initial overshoot in P and Q are almost removed completely.
Summary, Conclusions, and Future Work

- These numbers show that the critic-based PI control is less effective compared to the other two algorithms in reducing the average error and convergence time, and also results in an increase in harmonic content of the phase current. Also, it is obvious that the critic-based neuro-fuzzy control and the critic-based self-tuning PI (CSPI) control are the most successful approaches in improving the dynamic behavior of the microgrid system; however the simpler structure of CSPI controller must not be neglected.

6.3 Future Work

The following areas are suggested for future work:

- Investigation of control system performance under different load types such as other non-linear and un-balanced load conditions.
- Study of the control system performance in case of grid disturbances such as voltage sag, harmonics, etc.
- Investigation of the control system performance in case of unbalanced grid conditions such as fault scenarios.
- Stability analysis in the grid-connected and islanded modes.


Bibliography


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Bibliography


Appendix A

Publications from Thesis


