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AI-BASED CONTROLLER FOR GRID-FORMING INVERTER-BASED GENERATORS UNDER EXTREME DYNAMICS

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ABSTRACT

This paper presents two artificial intelligence (AI)-based controllers for grid-forming inverter-based generators in a simplified microgrid. The supervised learning approach was considered for the AI-based controls. The training datasets were collected from an experimentally validated virtual synchronous generator controller. The first AI model is a convolutional neural network (CNN), and the second is a gated recurrent unit (GRU). These two neural network types are chosen as they handle short-term temporal sequence data, provided as a sliding window of measurements. The proposed controllers are tested under a black start, load variations, and a three-phase-to-ground short circuit at the inverter's output. Both controllers manage to achieve the black start of the inverter, supply the power demanded by the load, damp the short circuit current during a fault occurrence and recover afterward.

I. INTRODUCTION

To reduce greenhouse gas emissions, sources of electricity production are diversified, which introduces a high penetration of distributed renewable energy resources (RES) in electrical grids [1] [2]. The use of such distributed generation brings new challenges regarding grid stability due to the intermittent nature of RES [3]. Furthermore, distributed generation units are mostly inverter-based generators (IBG). As they do not provide inertia by default, their operation could weaken the stability of distribution grids. Thus, new control methods are indispensable for guaranteeing the stability of the power system under these new conditions. We are referring here notably to grid-forming controllers. In that category, the main solutions are either based on model-based controllers or data-driven controllers.

Concerning model-based approaches, virtual synchronous generator (VSG) controllers represent a traditional solution [4]. Simplified approaches exist, like virtual inertia, for instance, most of the time implementing a droop control [5], [6]. Less-traditional forms of controls are investigated in the literature as well, like virtual oscillators [7] or matching control [8]. Model-based controllers are usually restricted to operating in a predefined environment and require precise tuning.

Regarding data-driven approaches, numerous methods can be found in the literature. Neural networks can be used to control a grid-connected inverter under disturbances, considering dynamic and power converter switching conditions [9]. The virtual inertia of grid-connected inverters can be controlled via an adaptive critic design-

based reinforcement approach [10]. Moreover, the inertia of a VSG can be controlled with a neural network [11]. For instance, reinforcement learning was also considered, to achieve a data-driven optimal control strategy of a VSG [12]. The aforementioned solutions are either applied to the whole grid-following inverters or just to some parameters.

In a previous study [13], we proposed a feedforward neural network (FFNN) to control a grid-forming inverter-based generator in a microgrid (MG). Although the FFNN has demonstrated promising capabilities of conserving the frequency and voltage at their nominal values in typical load variations, it has also shown weaknesses in capturing the extreme dynamics of the controlled system like, for instance, damping the short circuit current and recovering afterward. This is because the FFNN operates instantaneously, meaning that predictions are based on the state of the system per time step, without considering historical states. The dynamics of the system are thus lost. To avoid the complexity of model-based controllers, cover the ensemble of the grid-forming unit, and overcome the limitations of the instantaneous operation of FFNN, a short-term temporal sequence approach is considered in this work. The features are represented as short-term temporal sequences of measurements, provided via a sliding window. As a result, two data-driven models, a convolutional neural network (CNN) and a gated recurrent unit (GRU) are tested in this paper, as they both can handle short-term temporal sequence features, thus can capture the dynamics of the system during harsh events like a short-circuit. The proposed controllers have thus to achieve voltage and frequency control as a grid-forming unit, as well as be capable of damping the short circuit current in dedicated situations by capturing the temporal sequence of the controlled system.

The paper is organized as follows: the second section covers the electrical models. The electrical environment, the model-based controller used for data generation, and the AI-based controllers' testing scenarios are described. The third section elaborates on the AI-related part. The CNN and GRU implementation are described as well as their interaction with the electrical environment. The obtained results and observations are presented in the fourth section. Finally, the paper is concluded and future developments are listed in the last section.

II. ELECTRICAL MODELS

The electrical aspect of the case study is elaborated in this section by explaining the electrical environment, the model-based controller used for data collection, and the testing scenarios of the proposed AI-based controllers.

A. Electrical Environment

The considered case study, from the electrical point of view, is a simplified isolated microgrid (MG), illustrated in Figure 1. It is represented by one inverter-based generator (IBG) and three loads connected one at a time during the simulation. The three loads are located at a single point of connection, downstream of the line linking them to the IBG.

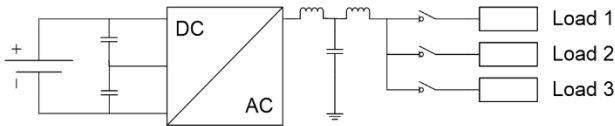


Figure 1. Simplified Isolated Microgrid

The MG operates in a balanced three-phase mode at the low voltage distribution level, i.e., the nominal phase voltage is 230 V and the nominal frequency is 50 Hz. The dc bus voltage is assumed to be constant.

B. Data Generation

Knowing that the adopted data-driven approach is relying on supervised learning, the availability of labeled training data is key. Thus, data were collected by simulating the virtual synchronous generator (VSG), from [4], under numerous scenarios. This VSG consists of a linear quadratic regulator including an integrator and a state observer. This controller is developed to provide high robustness during harsh events such as short circuits. Each simulated scenario includes the black start of the IBG and the occurrence of a three-phase short circuit at its output during the supply of the load. The power demand, i.e., rating in kW and kVAR, and type of the load, i.e., resistive inductive and capacitive, vary from one scenario to the other, ensuring the balance of the dataset, yet the black start and the short circuit are always present. The generated dataset includes the measurements describing the state of the inverter and the MG, such as the voltages and currents of the MG and the inverter, the active and reactive powers, the frequency, and the errors between the RMS phase voltage and the nominal value. These measurements represent the features (inputs) of the AI-based controllers. Furthermore, the generated dataset also includes the control signals, meaning that the duty ratios. These control signals represent the labels (outputs) of the AI-based controllers.

C. Testing Scenarios

The AI-based controllers' capabilities are tested with the loads and the events defined in Table 1 and Table 2 respectively. The proposed controllers are expected to start the IBGs, conserve the stability of the simplified MG (i.e., fulfill the demand of the connected loads concerning their power ratings and types) by maintaining the voltage and frequency at their nominal values, and damp the short circuit current during the occurrence of a three-phase short circuit at the output of the IBG.

Table 1 describes the three designed loads by including their power ratings and types. Load 1 is set to be highly capacitive, Load 2 is resistive with small rated power, and Load 3 is designed to be highly inductive.

Load	Active Power (kW)	Inductive Reactive Power (kVAR)	Capacitive Reactive Power (kVAR)
Load 1	15	0	7
Load 2	1	0	0
Load 3	15	7	0

Table 1 Characteristics of the Connected Loads

The events in Table 2 are chosen to ensure the capability of the proposed AI-based controllers in terms of black start and load variations, similar to the FFNN in [13].

Time (s)	Event
0	Black start and connection of Load 1 (A)
0.5	Occurrence of a three-phase short circuit on the output of the IBG (B)
0.7	End of the short circuit faulty event (C)
1	Disconnection of Load 1 and connection of Load 2 (D)
2	Disconnection of Load 2 and connection of Load 3 (E)

Table 2 List of Occurring Events

The three-phase short circuit event at the output of the IBG is considered to challenge the controllers' capabilities of damping the short circuit current and recovering afterward, which is not the case with the FFNN [13]. In the end, the aforementioned events are designed to test the controllers' abilities to ensure the stability of the MG, by maintaining the voltage and frequency at their nominal values, during the black start and load variations. Moreover, these events are designed to test whether the controllers can physically protect the inverter, by damping the short circuit current, during the occurrence of the fault.

III. AI MODELS IMPLEMENTATION

The integrations of the proposed AI models in the electrical environment are identical. Both models communicate with the electrical environment via the same set of parameters that represent the inputs and outputs of the AI-based controllers. The outputs or the control signals provided by the AI-based controllers are the duty ratios (in the dq -frame).

The inputs expected by both AI-based controllers are the following: voltages and currents of the grid and the inverter (in the dq -frame), measured active and reactive powers, frequency of the grid, and the RMS voltage errors (difference between measured rms voltages and 230 V for the three phases).

In addition to what was implemented in [13], a buffer memory is added upstream of the input layer of each AI model. The purpose of this buffer is to provide short-term temporal sequences of measurements at the inputs of the

AI-based controllers. This temporal sequence of measurements adds extra stability to the controller, during operation, by compensating for any faulty instantaneous measurement by the other instants present in the sequence. Moreover, the memory buffer acts as a fixed range sliding window of inputs, such that at every time step, the oldest instantaneous measurement is dropped and the latest is added.

Figure 2 illustrates schematically the implemented control policy and the interaction with the electrical environment.

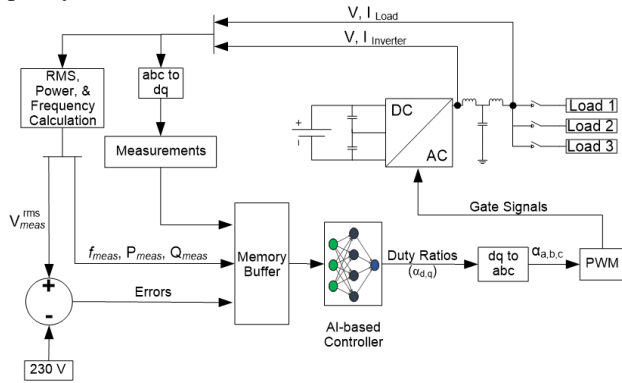


Figure 2. Implemented Control Policy

A. Convolutional Neural Network

Convolutional neural networks (CNN) are part of the various types of deep learning methods. CNNs are used in numerous fields, e.g., image classification, object tracking, and speech and natural language processing [14].

The CNN provides the capacity of mapping inputs in the form of batches, i.e., a batch including a set of instantaneous measurements per feature. In our case study, the memory buffer provides batches of inputs in the following shape: {Batch, number of historical instantaneous measurements, number of features}.

The proposed sequential CNN model consists of 11 layers. The first layer represents the input layer, then is followed by a normalization layer. The third layer is a convolutional one-dimensional layer including 128 filters and followed by a one-dimensional max pooling layer. The fifth layer is also a 1-D convolutional layer, yet including 64 filters, that is followed by a 1-D max pooling layer. The seventh layer is the last 1-D convolutional layer. It consists of 32 filters. The eighth layer is a flattened layer that prepares the outputs of the previous 1-D convolutional layer to fit in the ninth layer representing a 64-units dense layer. The tenth and eleventh are as well dense layers, including 32 units and representing the outputs layer respectively.

B. Gated Recurrent Unit

The gated recurrent neural networks have proven favorable outcomes in numerous applications including sequential or temporal data [15]. As a result, the gated recurrent unit (GRU) is the second chosen approach in our case study. The addition of the memory buffer upstream of the input layer provides the temporal sequences of measurements required by the GRU.

The proposed sequential GRU model includes six layers. The first layer corresponds to the input layer. The second layer is the normalization layer. The third layer is a GRU layer that includes 160 units and returns the sequence to the following layer. The fourth layer is also a GRU layer including 64 units returning the sequence to the following layer. Finally, the fifth layer is a GRU layer with 96 units followed by the outputs layer, represented in the form of a dense layer.

IV. RESULTS AND OBSERVATIONS

The results following the testing of the CNN and the GRU models are presented in this section by considering the MG's frequency, MG's voltage, and IBG's current respectively.

A. Microgrid Frequency Profiles

The MG's frequency profiles of both the CNN and GRU-based models are illustrated in Figure 3. As shown, both controllers are capable of restoring the frequency at its nominal value (50 Hz) following the designed events. Although both plots are close, the GRU's frequency reaches a slightly higher peak than the CNN, during the black start of the IBG and following the elimination of the short circuit fault.

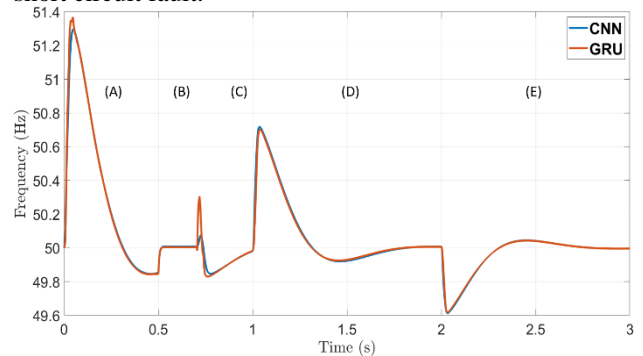


Figure 3 Frequency Profiles of CNN vs. GRU

B. Microgrid Voltage Profiles

The MG's voltage profiles of both the CNN and GRU-based models are illustrated in Figure 4. Since the considered simplified MG is a balanced three-phase system, only one phase voltage is presented. As shown, both controllers are capable of keeping the RMS voltage within the acceptable range following the designed events. However, the CNN requires extra time to stabilize the voltage at the beginning of the event (D).

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