Replacement of Low Voltage Ride Through (LVRT) using Reinforcement Learning

A B. Tech Project Report

Submitted by

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and

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CONTENTS

Declaration

I hereby declare that the work presented in this Project Report titled "Replacement of Low Voltage Ride Through (LVRT) using reinforcement learning" submitted to the Indian Institute of Technology Jodhpur in fulfilment of the requirements for the B. Tech Project (EED4010) is a bonafide record of the research work carried out under the supervision of Dr. Ravi Yadav. The contents of this Project Report in full or in parts, have not been submitted to, and will not be submitted by me to, any other Institute or University in India or abroad for the award of any course or project

Bikas Singh

Anushka Barkade

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We extend our heartfelt gratitude to our supervisor, **Dr. Ravi Yadav**, for his exceptional mentorship, guidance, and unwavering support throughout our B.Tech program, which has been invaluable in the successful completion of this project.

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Our sincere thanks also go to the **Electrical Department** for providing us with the opportunity to work on such an enriching project, which has not only expanded our knowledge but also allowed us to grow by exploring new ideas and skills.

Finally, we acknowledge the contributions of our friends and everyone who extended their support throughout this journey. We hope that the effort we have invested in this project reflects our dedication, passion, and learning.

Certificate

This is to certify that the Project Report titled “Replacement of Low Voltage Ride Through (LVRT) using reinforcement learning” submitted by Bikas Singh (B21EE015) and Anushka Barkade (B21EE080) to the Department of Electrical Engineering, Indian Institute of Technology Jodhpur for the B. Tech Project (EED4010) is a bonafide record of the research work done by him under my supervision. To the best of my knowledge, the contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any course or project

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Assistant professor

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Abstract

Integration of renewable energy into modern power grids brings out new challenges especially in sustaining the stability of the grid while encountering voltage disturbances. LVRT capability is essential for ensuring grid-connected inverters are always connected to the renewable energy system during short-term sagged voltages. Current conventional LVRT mechanisms apply predetermined control strategies that are quite restricted by their inability to be adaptive to dynamic grid conditions. To overcome these limitations, this project proposed Deep Reinforcement Learning to replace the conventional LVRT mechanism. This can provide a more flexible and adaptive alternative.

The project focuses on developing a custom LVRT environment, modelled around the three-phase grid-connected inverter with PQ control, which is the most widely used architecture for grid-connected systems. This project integrates RL algorithms, implemented in Python using stable_baselines3, and uses Typhoon HIL as the primary simulation platform. The reinforcement learning model was trained to optimize system performance under voltage sags by adjusting the inverter parameters based on the grid conditions dynamically.

This work will comprise designing a custom RL environment that interfaces with Typhoon HIL simulation through a widget block in order to seamlessly integrate the AI-based control systems and hardware-in-the-loop testing. Comprehensive simulations are then carried out to test the performance of the proposed method against established LVRT strategies. Main performance indicators include fault recovery time, grid stability, and satisfaction of the Indian Grid Code.

Some preliminary results indicate that the adaptability of RL-based LVRT mechanisms is enhanced with improved recovery from faults as compared with traditional approaches. The present novel integration of AI-driven control strategies into power systems is a part of development to enable smarter, more resilient grids, especially in areas having high penetration of renewables such as Rajasthan.

This project represents a giant leap towards leveraging artificial intelligence in the power system control and sets a framework for further research in grid stability and optimization.

1. Introduction

1.1 Objective

This project aims to develop an AI-driven LVRT mechanism using RL to replace traditional approaches. The objectives include designing a custom LVRT environment, integrating RL algorithms to optimize inverter performance during voltage sags, and validating the system through simulations on Typhoon HIL. The ultimate goal is to enhance fault recovery, grid stability, and renewable energy integration, paving the way for smarter and more resilient power grids.

1.2 Electrical Fault:

An electrical fault occurs when voltages and currents deviate from their nominal values, causing damage to equipment and devices. Under normal conditions, power system equipment or lines carry normal voltages and currents, but when a fault occurs, excessive currents flow, necessitating the design of suitable switchgear equipment, electromechanical relays, circuit breakers, and other protection devices.

Types of Faults in Electrical Power Systems:

In power system the faults majorly classified into two types.

- Symmetrical Fault
- Unsymmetrical Fault

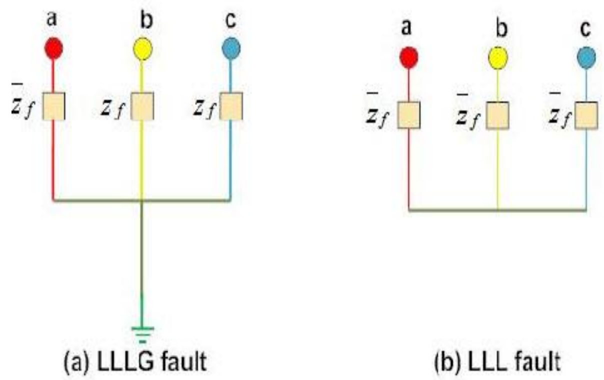
1.3 Symmetrical Fault:

Symmetrical faults are a type of electrical fault in which all three phases of a power system are affected equally. This results in the system remaining balanced even during the fault, meaning the voltages and currents in all three phases are identical in magnitude and equally displaced in phase by 120°. The symmetrical faults are classified into two types

- Line – Line – Line Fault
- Line – Line – Line – Ground Fault

L – L – L Fault:

These faults are balanced, meaning the system remains symmetrical even after the fault occurs. Although such faults are rare, they are the most severe type, generating the highest fault current. This high current is critical in determining the appropriate rating for circuit breakers.



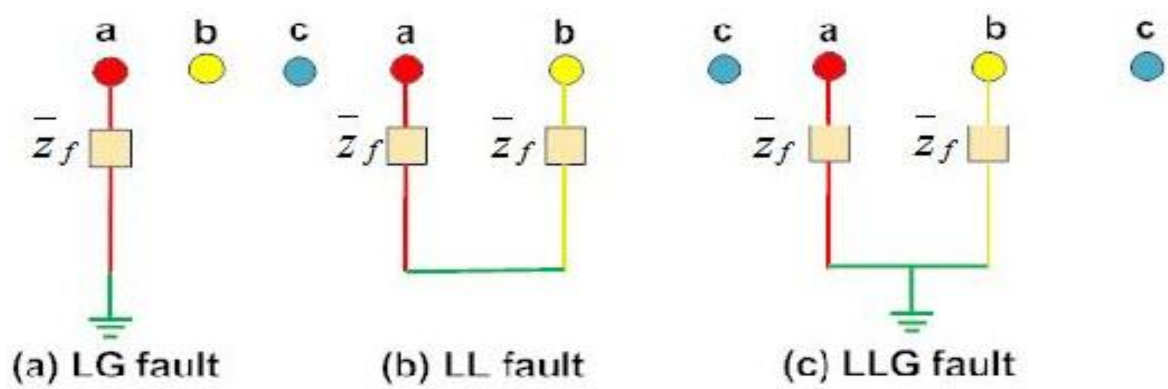
L – L – L – G Fault:

The three-phase line-to-ground (L-G) fault involves all three phases of the system and the ground terminal. This type of fault occurs when all three phases are short-circuited to the ground. However, its occurrence is rare, with a probability of around 2–3%.

1.4 Unsymmetrical Faults:

Unsymmetrical faults are less severe than symmetrical faults. The L-G fault is the most common, causing the conductor to contact the earth or ground. Double line to ground faults occurs when two conductors make contact during line swinging due to winds. Line to line faults occur when two conductors make contact during wind swinging. Unbalanced faults, also known as unbalanced faults, cause impedance values to differ in each phase, causing unbalance current to flow. These faults are more difficult to analyse and are carried on a per-phase basis, similar to three-phase balanced faults. The unsymmetrical faults are classified into two types

- Single L – G (Line-to-Ground) Fault
- L – L (Line-to-Line) Fault
- Double L – G (Line-to-Ground) Fault



Single L – G Fault

The single line-to-ground (L-G) fault occurs when a single conductor comes into contact with the ground terminal. This is the most common type of fault, accounting for approximately 70-80% of faults within the power system.

L – L Fault

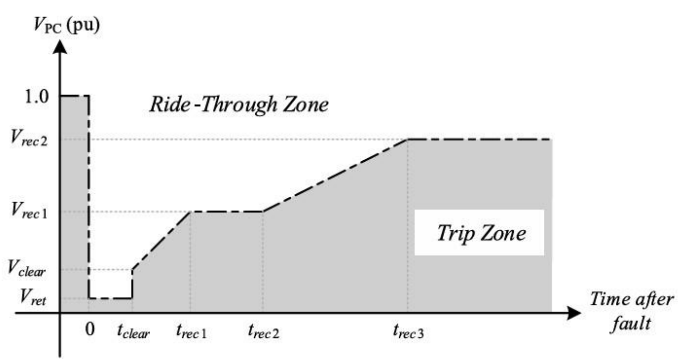
The line-to-line (L-L) fault typically occurs when two conductors are short-circuited, often due to line movement caused by heavy winds. The wind can cause the conductors to touch each other, resulting in a short circuit. This type of fault accounts for approximately 15-20% of faults in the power system.

Double L – G Fault

In a double line-to-ground (LL-G) fault, both conductors come into contact with each other through the ground. This type of fault occurs with a probability of about 10% in power systems.

1.5 Fault Ride Through :

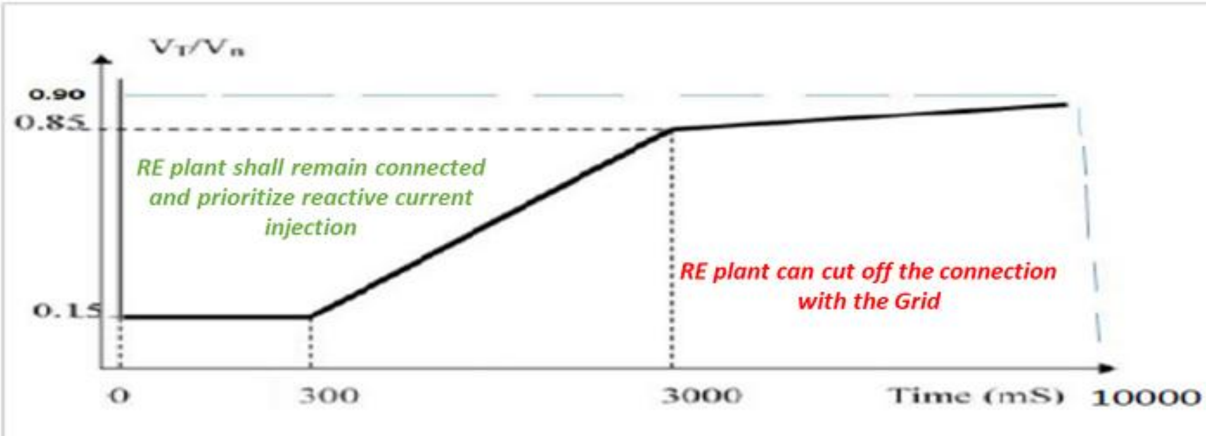
Fault Ride-Through (FRT) capability is crucial for maintaining a reliable and continuous power supply, as it allows the power system to endure temporary voltage dips caused by faults without resulting in widespread outages. This is particularly important with the increasing integration of renewable energy sources like wind and solar, which often depend on power electronics converters that might disconnect during voltage dips if they lack proper FRT features.



1.6 Low Voltage Ride Through (LVRT) :

According to CEA regulations, converter-based generating stations connected to the grid must remain connected even if the voltage at the interconnection point drops, as long as the voltage dip follows the levels specified in the relevant curve (Figure), where VT is the actual voltage and Vn is the nominal voltage.

During a voltage dip, the priority is to supply **reactive power**, followed by **active power**. While maintaining active power during voltage drops is preferred, a temporary reduction in active power is acceptable within the plant's design limits. Once the voltage is restored, the plant should return to at least 90% of the pre-fault active power level within 1 second.



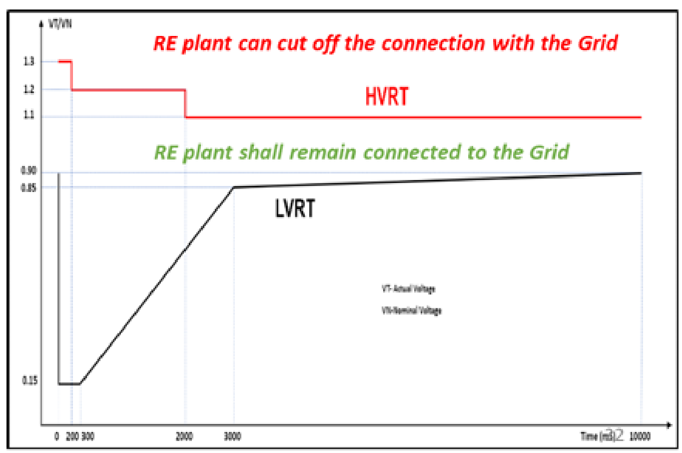
LVRT operating range

High Voltage Ride Through (HVRT):

According to the CEA regulations, a generating station connected to the grid must remain connected if the voltage at the interconnection point rises above certain specified levels, whether the overvoltage is symmetrical or asymmetrical. The station must stay connected for a specified time based on the overvoltage magnitude, as outlined in the following table:

S. No.	***Over Voltage (p.u.)***	***Minimum time to remain Connected (seconds)***
1.	**1.30 < V**	**0 (instantaneous trip)**
2.	**1.30 ≥ V > 1.20**	**0.2 Sec**
3.	**1.20 ≥ V > 1.10**	**2 Sec**
4.	**V ≤ 1.10**	**Continuous**

HVRT Requirement Specified in CEA connectivity standard



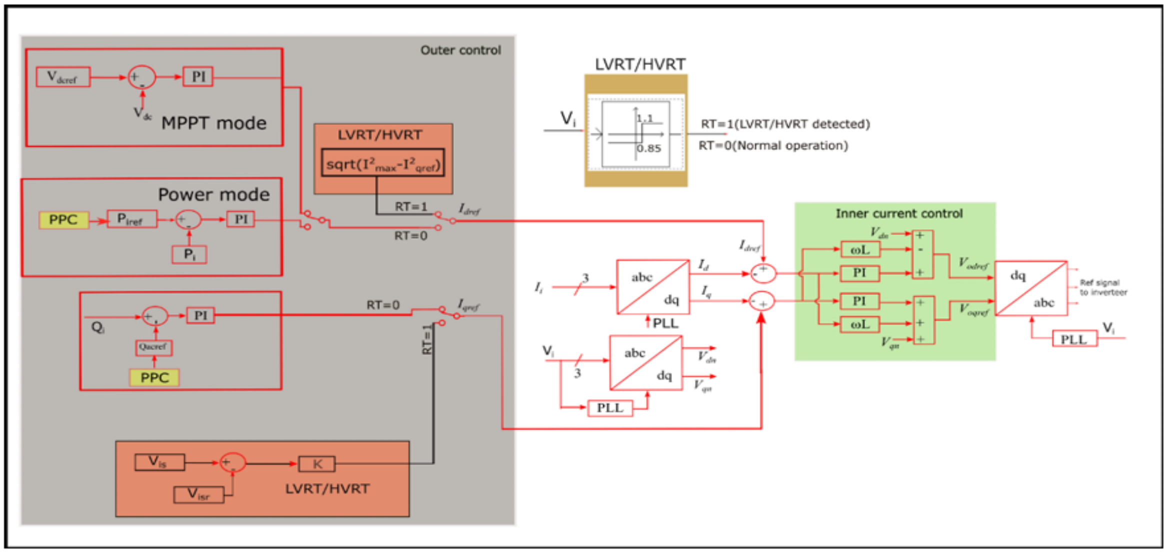
HVRT operating range (Shown by Red Line)

Clarification on HVRT: In HVRT mode, the station must provide reactive power support by absorbing reactive power in proportion to the voltage rise at the interconnection point. The amount of reactive power absorption depends on the system's HVRT "K"-factor, which determines the reactive current gain. Additionally, the active current and total current must be limited based on the plant's transient rated current limit during this phase.

2. Work done

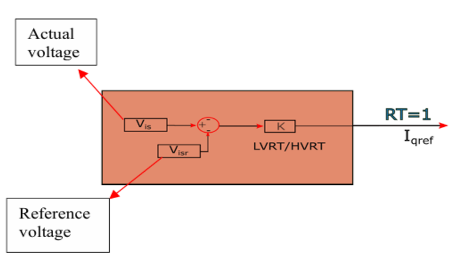
2.1 Methodology

2.1.1 Conventional LVRT:



Simplified Control block diagram of solar Inverter

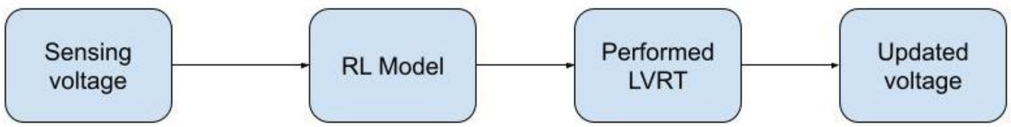
- The PPC gives reactive power reference point as per the grid voltage and as per the droop setting in the steady state, as illustrated in Figure
- The PPC also provides the active power reference and reactive power reference to individual inverters.
- The phase-locked loop (PLL) in the inverter guarantees the phase and frequency synchronization between the inverter's output and its point of synchronization voltage. It supplies the waveform reference for the PWM generator that controls the insulated-gate bipolar transistors (IGBTs) in the inverter.
- The PLL also provides the phase angle references needed for the dq0 calculations as well as the internal frequency measurements of the inverter. The PLL's operation is often crucial in deciding.



Simplified illustration of K-Factor

- During a fault, the inverter switches to ride-through mode (LVRT/HVRT) and provides reactive power based on the K-factor setting, which determines the amount of reactive current (Iq) to be injected, as shown in above Figure . The reactive power output is adjusted according to this setting.
- When the inverter terminal voltage falls below the ride-through threshold, the inverter bypasses its outer control loop and enters ride-through mode. In this mode, the reference for reactive current (Iqref) is set based on the K-factor within the inner control loop.
- The amount of active current (Id) injected depends on the remaining capacity of the inverter, ensuring reactive power takes priority when the inverter operates in Q-priority mode.

2.1.2 RL-Based LVRT:



Flow of work

Before creating the RL model make sure that Typhoon Scada python interpreter will have all the necessary libraries. For this you have to import the python interpreter because in SCADA it is immutable. So we have to import it from the system or the mutable python interpreter (Typhoon Test IDE). For this follow below steps:

1. Open the Command Prompt
2. Type the following command: *typhoon-python -m pip install stable-baselines3* – this will install the package into our environment directly
3. Open HIL SCADA
4. In the Panel Initialization write the following code:
5. After starting the simulation/running the initialization script, *stable-baselines3* will be available.

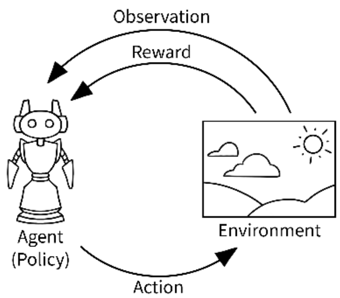
Note:

- The path specified in step 4 should be set according to your own username and version of Typhoon HIL Control Center that is used.
- To install packages, you will need to have administrator rights on your PC

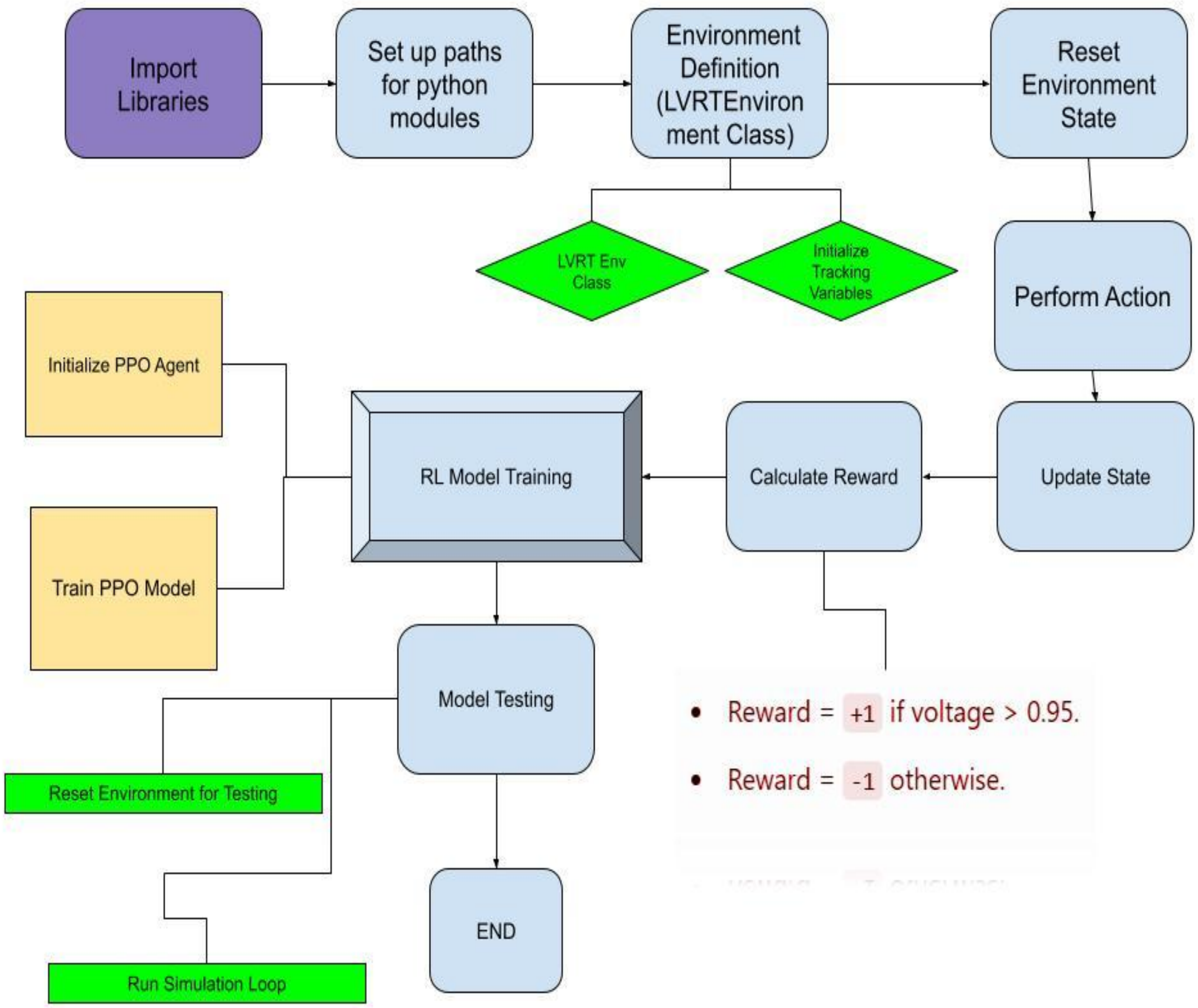
```python
import os
from os import path
import sys
sendto_dir = path.expandvars(r'C:\Users\bikas\AppData\Roaming\typhoon\2024.3\python_portables\python3_portable\Lib\site-packages')
add_to_python_path(os.path.normpath(sendto_dir))
```

2.2 Implementation of LVRT:

1. Creating a custom RL environment (LVRTEnvironment) using gym open AI library and Typhoon.api.hil to simulate grid behaviour, faults, and recovery.
2. Gym library help us to create an environment for LVRT. The agent performs some actions in the environment (usually by passing some control inputs to the environment, e.g. voltage inputs) and observes how the environment's state changes. One such action-observation exchange is referred to as a *timestep*.



- **Observation and Action Space**: Using continuous observation space (voltage, frequency, time) and discrete action space (trigger LVRT or no action).
- **Reward Function**: Designing a reward system based on voltage recovery—positive rewards for maintaining voltage above 0.95 pu and negative rewards otherwise.
- **Fault Simulation**: Implement faults by reducing grid voltage to a predefined level (e.g., 0.9 pu) for a set duration, allowing the agent to respond.
- **RL Algorithm**: Use Proximal Policy Optimization (PPO) from Stable-Baselines3 for its stability and efficiency in optimizing policies.
- **Training**: Train the PPO agent by simulating multiple LVRT scenarios where the agent interacts with the environment, takes actions, and learns from rewards.
- **Testing**: Test the trained agent on new fault scenarios to evaluate its ability to restore grid stability effectively.
- For code snippets refer appendix.

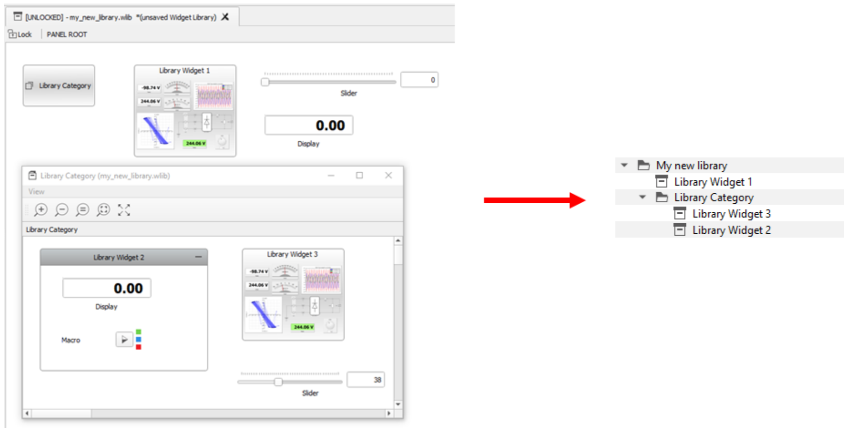


RL-Based LVRT Model implementation flow chart

2.3 Integration RL-Based LVRT with the simulation model:

- We have written code in the panel initialization. Here just we implemented the model and trained.
- Using the Widget Library and created the widget for LVRT. (for more info visit [Create and edit Widget Library](#))

- Code snippet for LVRT mode detection




```python
delta_t = 0.2
elapsed_time = hil.get_sim_time()
# Fault parameters are defined in the Grid Faults
if 'VRT' in fault_type:
    v_fault_pu = lvrt_pu if fault_type == 'LVRT' else hvrt_pu
    hil.set_source_scaling('Vgrid', v_fault_pu , executeAt = elapsed_time + delta_t)
    hil.set_source_scaling('Vgrid', 1 , executeAt = elapsed_time + delta_t + fault_duration)
```

2.4 Proximal Policy Optimization:

Proximal Policy Optimization (PPO) is a reinforcement learning (RL) algorithm that optimizes policies to maximize rewards while maintaining stability and robustness. When applied to creating a custom Low Voltage Ride-Through (LVRT) controller, PPO works by learning an optimal control policy for stabilizing the system during voltage sags or grid faults.

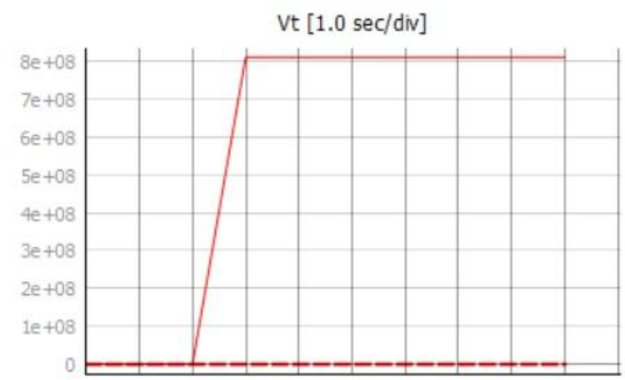
Why PPO?

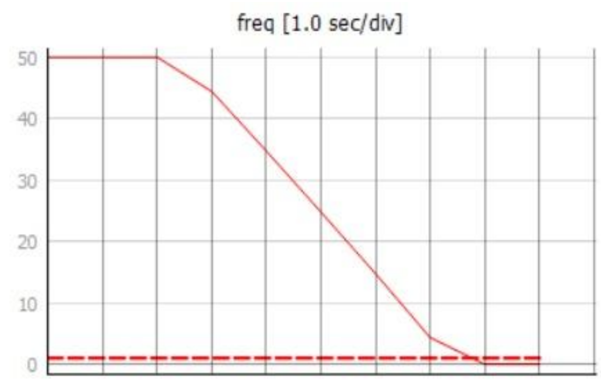
- PPO is particularly well-suited for LVRT problems due to its ability to handle continuous action spaces, stability in learning, and adaptability to complex, dynamic systems like power grids.
- Unlike traditional control methods, which rely on pre-defined rules or fixed models, PPO leverages reinforcement learning to adaptively learn optimal control policies based on grid behaviour.
- It achieves this by balancing exploration and exploitation, ensuring that the agent discovers effective actions while avoiding drastic updates that might destabilize the system. PPO's clipped objective function adds an extra layer of stability, making it robust against overfitting to specific scenarios or excessive policy changes.

- Furthermore, the algorithm can efficiently learn in high-variance environments, such as the unpredictable behaviour of grid faults, and generalize its learned policy to diverse fault conditions.
- This makes PPO ideal for LVRT applications, where real-time decision-making and maintaining system stability are critical, enabling improved grid fault response and compliance with grid codes.

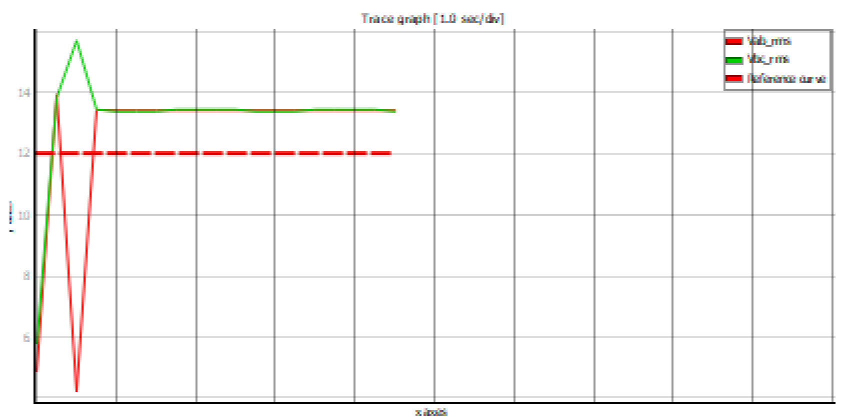
3. Results and Discussion

3.1 Conventional LVRT Output

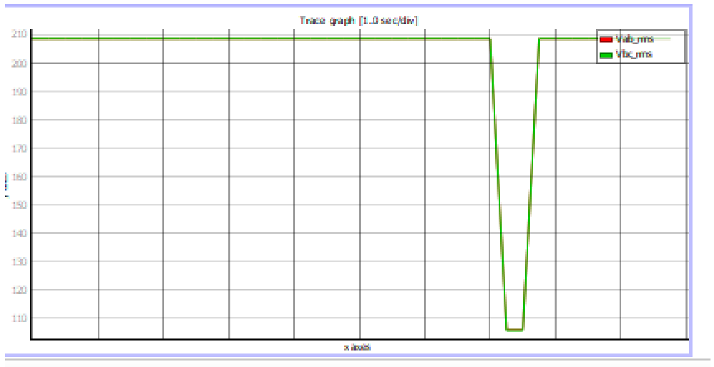




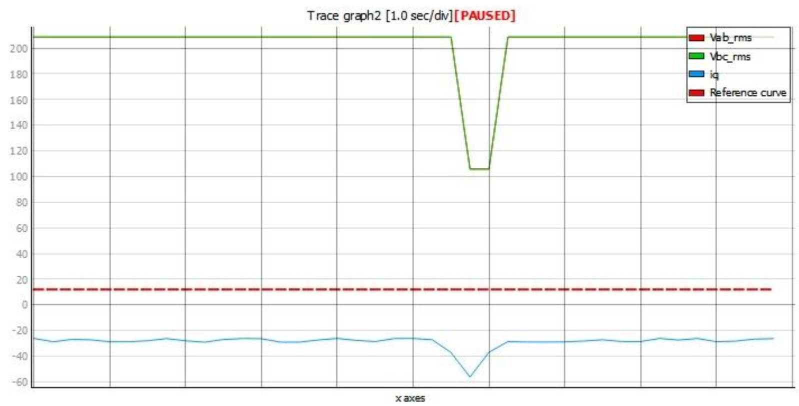
3.2 RL Based LVRT:



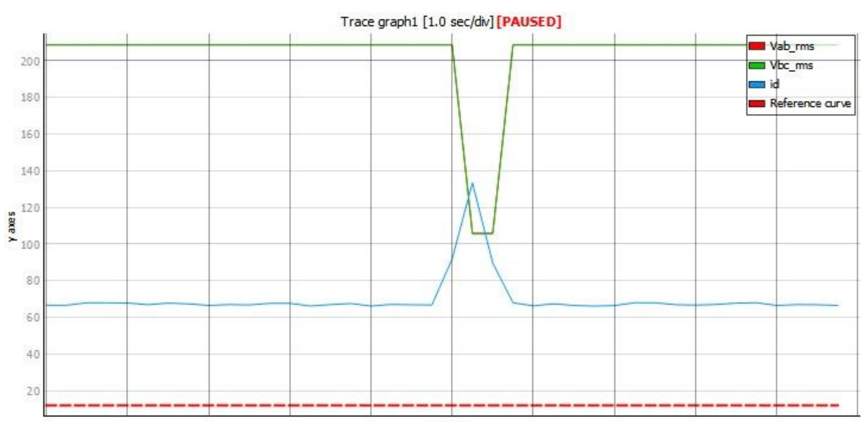
Fault created and recovered in initial phase



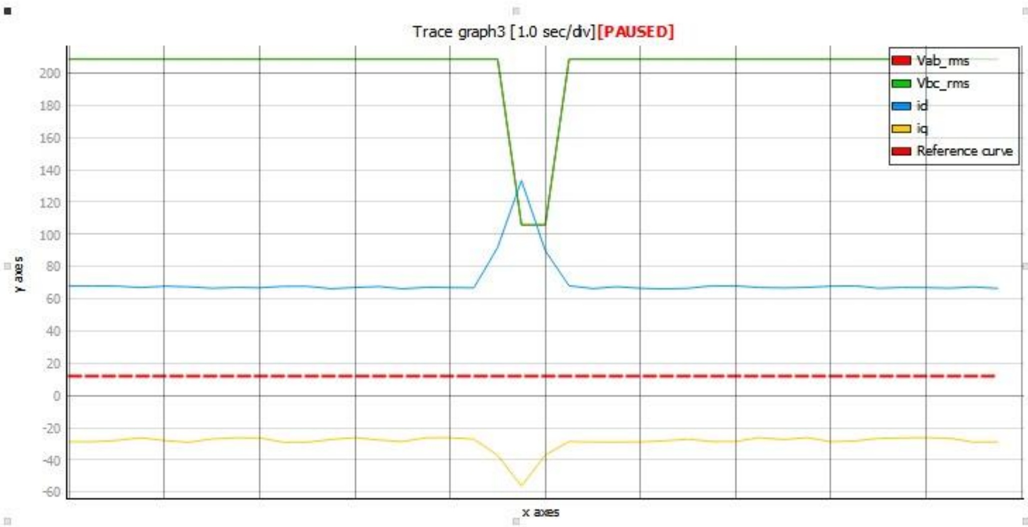
Fault created and recovered during simulation



Voltage ,I_q and references curve during fault recovery



Voltage ,I_d and references curve during fault recovery



Voltage ,I_d references curve and I_q during fault recovery

3.3 Comparison of conventional LVRT and RL based LVRT:

- **Voltage Recovery Time:**
  - RL-based LVRT: Should dynamically adapt and recover voltage faster by learning fault-specific patterns.
  - Conventional LVRT: Often fixed and may require longer recovery times.

2. Voltage Stability During Fault

- RL-based LVRT: Expected to better mitigate voltage drops by taking optimized actions learned during training.
- Conventional LVRT: Relies on predefined thresholds and may result in more significant voltage deviations.

3. Grid Frequency Stability

- RL-based LVRT: Can learn strategies to reduce frequency deviations by considering both voltage and frequency control.
- Conventional LVRT: Typically lacks adaptive capabilities for handling frequency fluctuations dynamically.

5. Fault Clearing Efficiency

- RL-based LVRT: Can adaptively identify fault types and execute precise corrective actions to stabilize the grid.
- Conventional LVRT: Uses predefined responses, which may not be optimal for all fault types.

6. Power Losses During Fault

- RL-based LVRT: Can minimize losses by intelligently managing power flow.

- Conventional LVRT: May experience higher power losses due to less optimized responses.

3.4 Assumption and Limitation:

- For RL based LVRT we assumed that the during fault there is drop of 60-65% voltage, which may not be happen. In real-time this can be high or low based on the fault severity
- We are increasing the voltage signal value continuously during fault to reach initial value (connected to grid).
- Current model is only applicable for the "Three-phase grid-connected inverter with PQ control". The model may or may not be compatible with other system.
- There might be library and python interpreter compatibility issues during simulation. Because Typhoon offer two types interpreter one is mutable (can be changed i.e. external libraries can be installed) and another immutable (cannot be change i.e. external libraries cannot be installed).

4. Conclusion

The project explores the use of reinforcement learning in replacing conventional LVRT mechanisms to improve grid stability and fault recovery during voltage sags. The RL-based LVRT mechanism outperformed conventional methods in terms of fault recovery time and voltage stability during grid disturbances. The RL approach can adapt to diverse fault scenarios and can be extended to other fault ride-through capabilities like High Voltage Ride Through (HVRT). The method supports renewable energy integration by ensuring grid stability even during severe voltage fluctuations, making it particularly relevant for regions with high renewable energy adoption. However, the project faces limitations, including potential refinement of grid parameters and fault scenarios and computational complexity and time required for training RL models. Despite these challenges, the project represents a significant step forward in AI-driven strategies in power system control.

5.Future

- **Extension to Other Fault Ride-Through Capabilities**: Expand methodology to include High Voltage Ride Through (HVRT), Zero Voltage Ride Through (ZVRT), and frequency ride-through capabilities.

- **Scalability for Larger Systems:** Test the reinforcement learning-based LVRT on larger power systems or multi-area grids to assess its scalability and performance in more complex environments.

- **Real-Time Hardware Testing:** Implement trained RL agent in hardware-in-the-loop systems for real-time validation and testing under physical grid conditions.

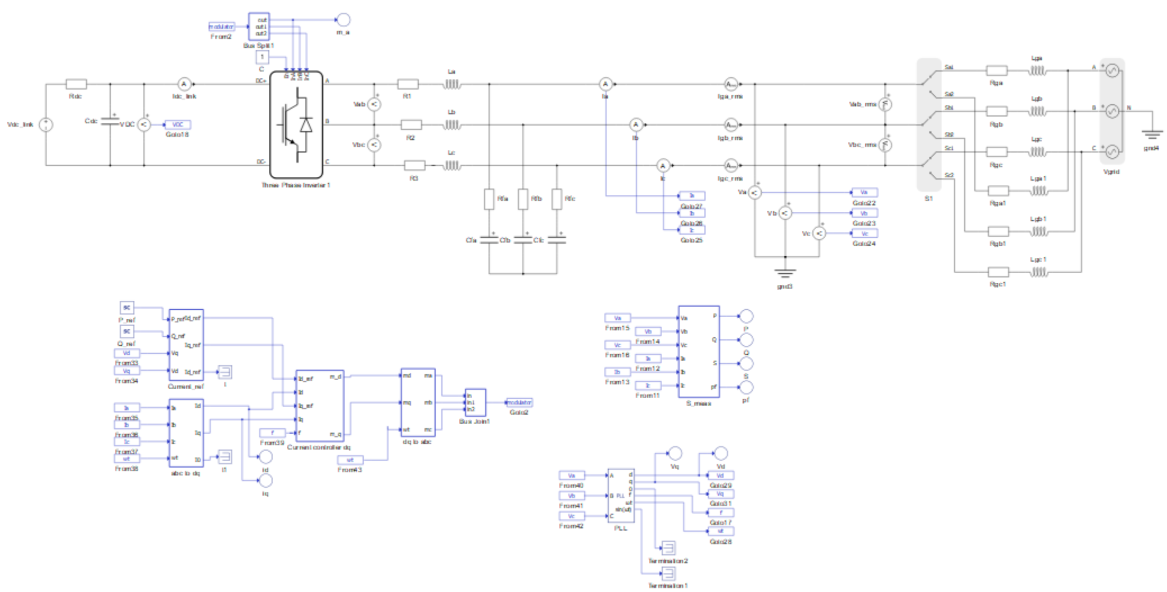
- **Cybersecurity Considerations:** Investigate security implications of RL-based LVRT systems in the context of cyberattacks on modern grids.

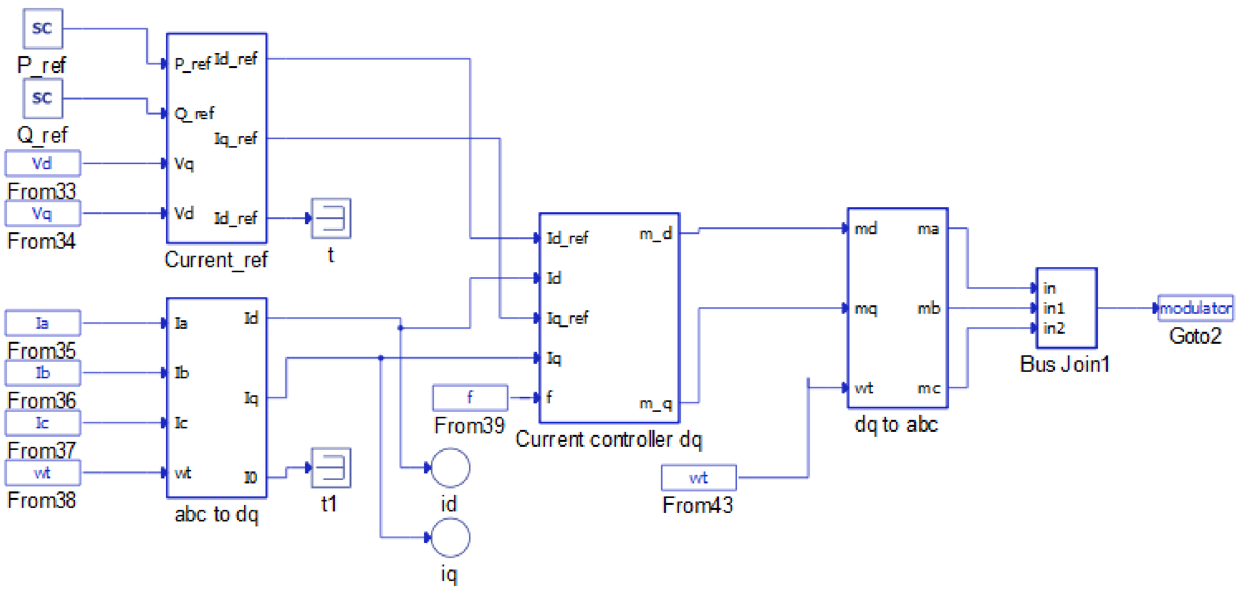
- **Development of Generalized RL Environments:** Create a generalized RL environment to model various types of grid disturbances and scenarios.

- **Multi-Agent Reinforcement Learning (MARL):** Explore the use of MARL to coordinate multiple agents controlling different parts of the grid.

6. Appendix

6.1 Three-phase grid-connected inverter with PQ control

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From36
Ic
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Ic
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m_d
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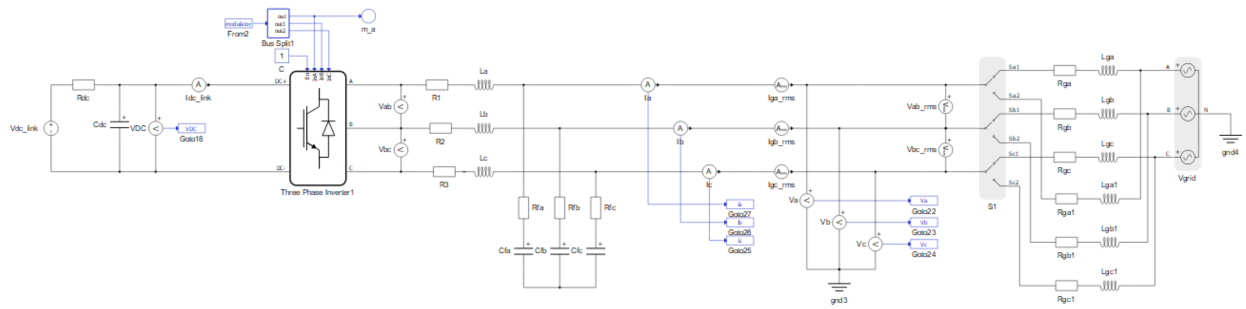

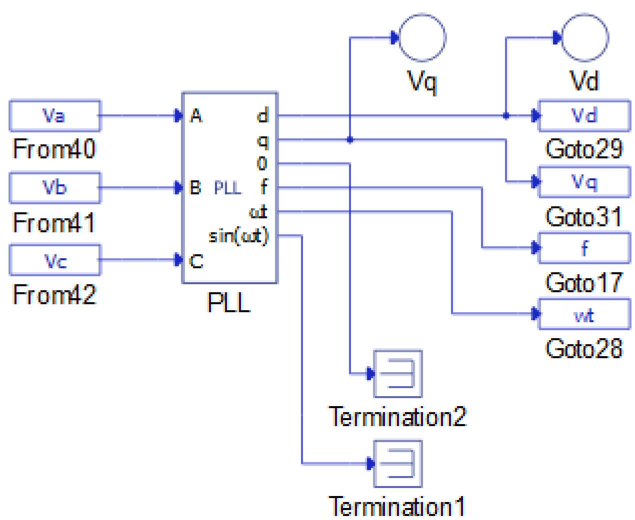
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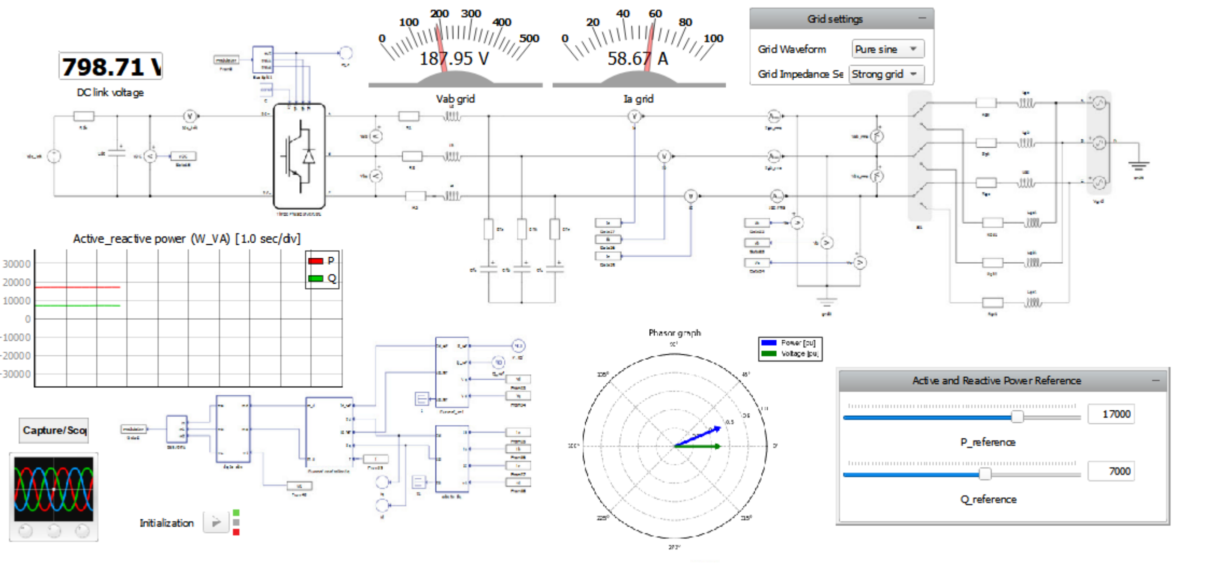
Termination1



HIL SCADA

6.2 Code snippet:

```
import os
from os import path
import sys
sendto_dir = path.expandvars(r'C:\Users\bikas\AppData\Roaming\
typhoon\2024.3\python_portables\python3_portable\Lib\site-packages')
add_to_python_path(os.path.normpath(sendto_dir))
```

Path setup for python interpreter

```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

import numpy as np
import tensorflow as tf
import torch
import gym
import stable_baselines3
from stable_baselines3 import PPO
import matplotlib.pyplot as plt
from gym import spaces
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
import typhoon.api.hil as hil
```

Libraries

```python
def reset(self):
    # Reset the simulation environment (e.g., clear fault, set to initial state)
    self.elapsed_time = hil.get_sim_time()
    hil.set_source_scaling('Vgrid', 1, executeAt=self.elapsed_time + self.delta_t)
    return np.array([1.0, self.f_initial, self.elapsed_time], dtype=np.float32)
```

Reset function

```python
def step(self, action):
    # Define what happens at each step based on the action taken
    if action == 1:  # Trigger LVRT
        hil.set_source_scaling('Vgrid', self.lvrt_pu, executeAt=self.elapsed_time + self.delta_t)
        hil.set_source_scaling('Vgrid', 1, executeAt=self.elapsed_time + self.delta_t + self.fault_dura

    # Get new system state (voltage, frequency, time)
    voltage = hil.get_source_settings('Vgrid')["voltage"]
    frequency = hil.get_source_settings('Vgrid')["frequency"]
    time = hil.get_sim_time()

    # Calculate reward: e.g., positive if voltage recovers and stays stable
    if voltage > 0.95:  # If voltage stays above 95% (as a simple threshold for LVRT success)
        reward = 1.0
    else:
        reward = -1.0

    # Store the data for plotting
    self.voltage_history.append(voltage)
    self.frequency_history.append(frequency)
    self.actions_taken.append(action)
    self.rewards_history.append(reward)
    self.time_history.append(time)

    # Done condition: Simulation should be done after a certain time
    done = time > self.elapsed_time + 10  # Run simulation for 10 seconds

    return np.array([voltage, frequency, time], dtype=np.float32), reward, done, {}
```

Action function

```python
# Initialize environment and RL agent
env = LVRTEnvironment()

# Define and train the PPO agent
model = PPO("MlpPolicy", env, verbose=1)
model.learn(total_timesteps=10000)

# Save the model
model.save("ppo_lvrt_model")
```

Initialising model and saving

```python
# Test the agent
obs = env.reset()
for _ in range(1000):
    action, _states = model.predict(obs)
    obs, reward, done, info = env.step(action)
    if done:
        break

# Plot the results after training
env.plot_results()
```

Test and plot

7.References:

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Contribution

- *Bikas Singh (B21EE015):*
  - Worked on literature review
  - Conventional LVRT
  - Designing a RL Based LVRT
- *Anushka Barkade (B21EE080):*
  - Worked on the background study of project
  - Comparing Conventional LVRT and RL-Based LVRT