

# **Power system stability improvement and digital protection/control using synchrophasor measurements**

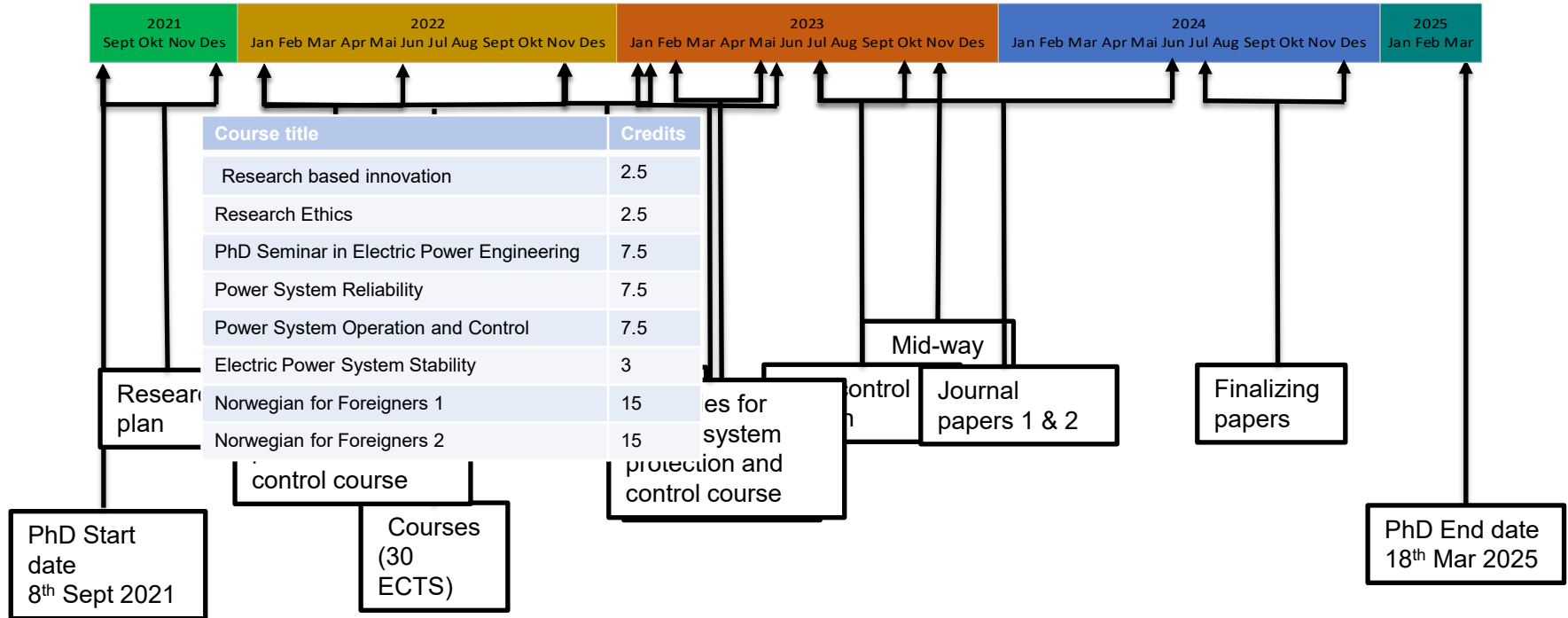
PhD mid-term evaluation

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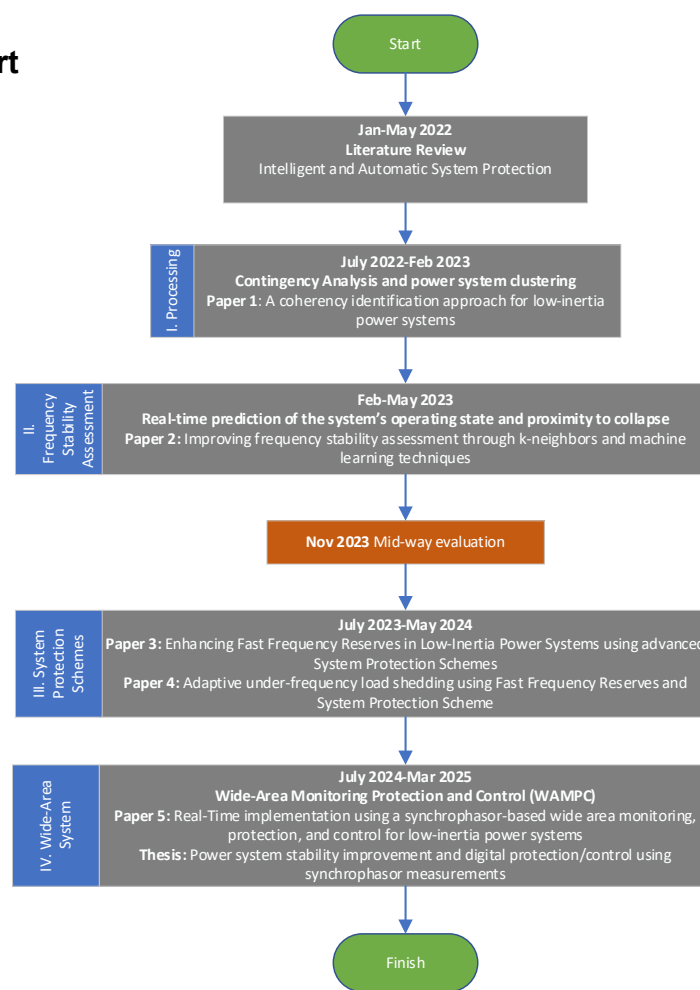
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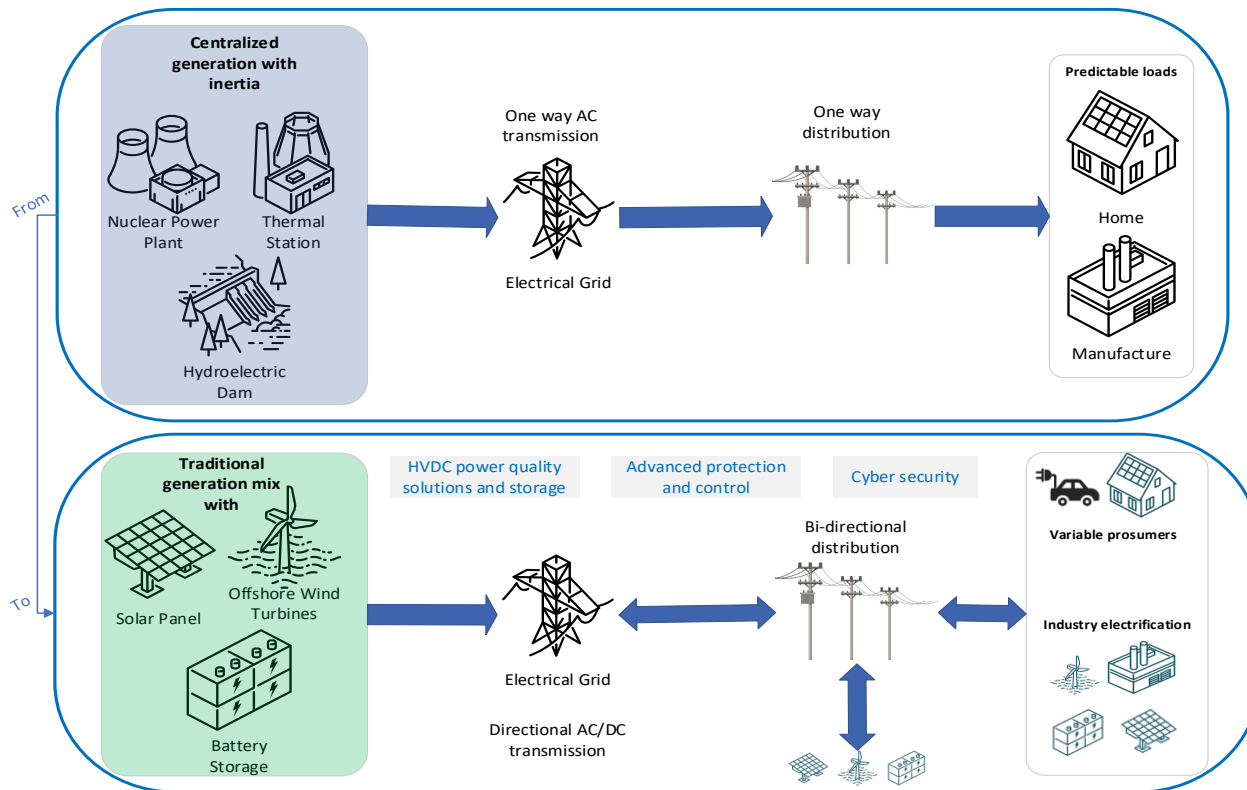
# PhD Timeline



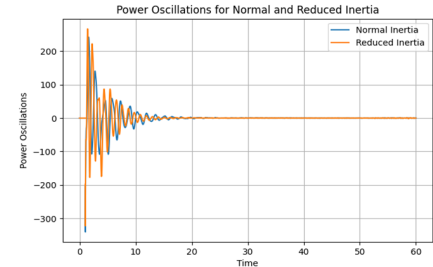
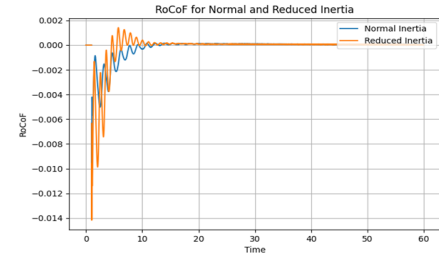
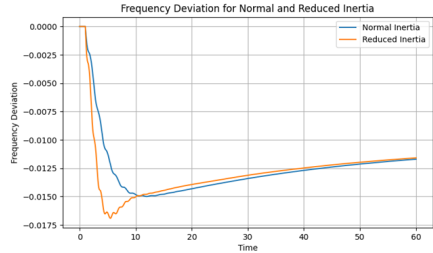
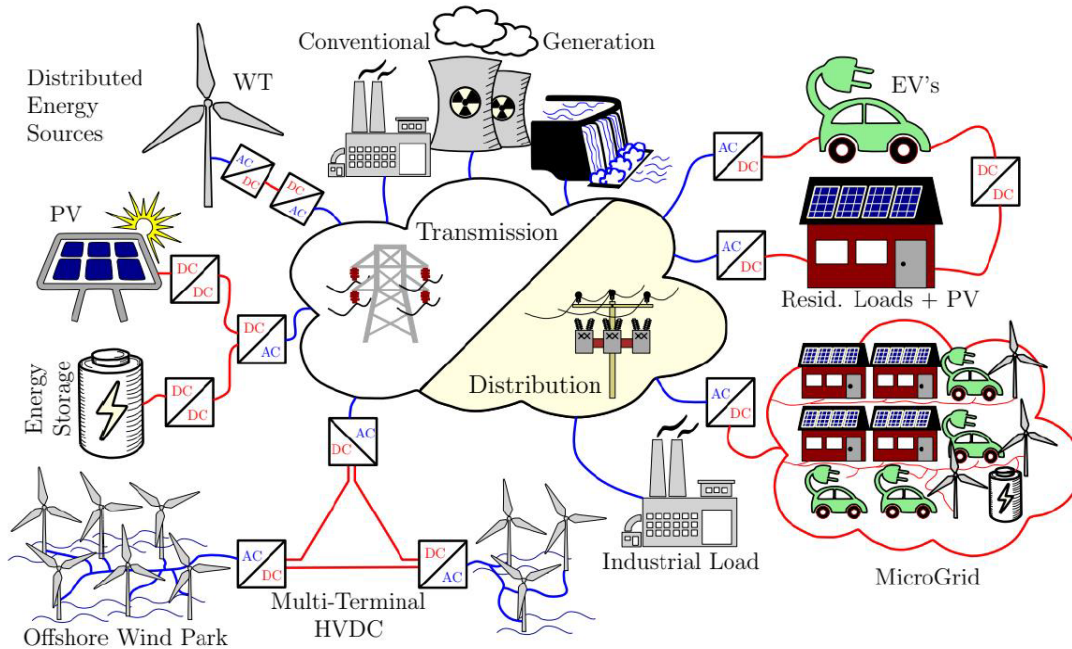
## Scientific PhD work time flow chart



# Energy transition



# Impact of reduced inertia power system



Gilbert Bergna-Diaz "The role of power electronics in the digital power grid"

# Background and motivation

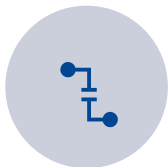
## ❖ Background



Low-inertia due to large-scale integration of inverter-based renewable sources



Large RoCoF and frequency nadir

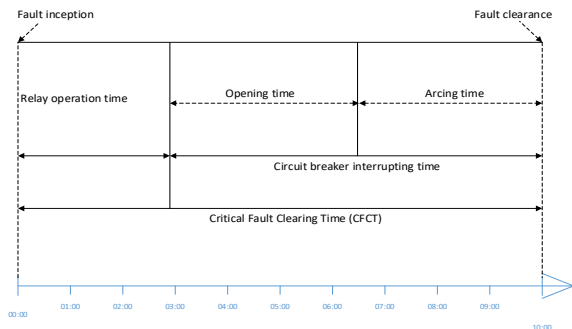


Mal-operation of under-frequency relays and SPS's

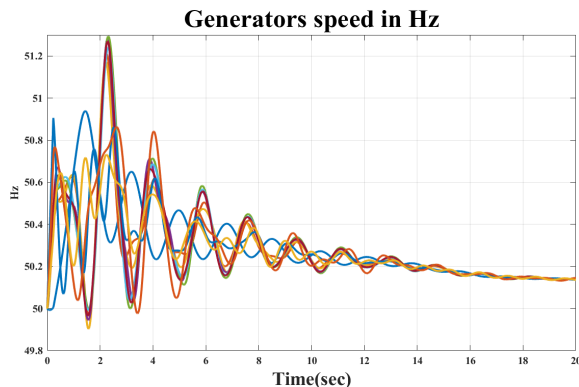
## ❖ Motivation

- Explore the development of advanced, robust and flexible SPS control algorithms specifically tailored for low-inertia power systems with the application of real-time measurements
- Optimization of the Fast Frequency Reserves (FFR) performance by dynamically adjusting reserve capacity and response times

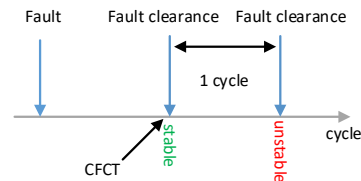
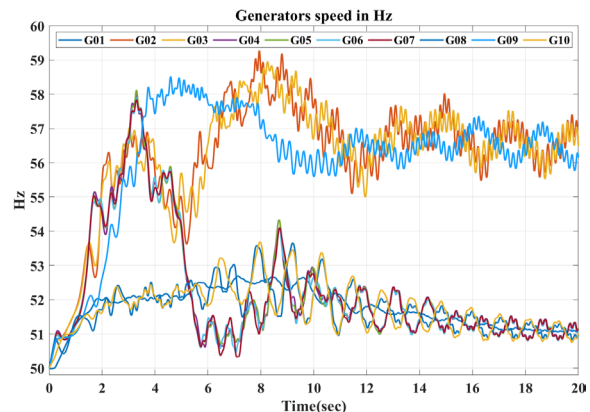
# Analysis of the impact of low-inertia



- ❑ Transmission line short-circuit at instant 0 sec
- ❑ Fault cleared at 0.23 sec following a relay trip
- ❑ The system remains stable



- ❑ Same fault incident with reduced inertia simulated at instant 0 sec
- ❑ Low value of system inertia drives the generators into instability and not able to trip in a timely way
- ❑ CFCT is reduced below 200 ms





# Paper 1: A coherency identification approach for low-inertia power systems

## ❖ Motivation

- Explore the development of simplified approach to assess frequency stability for low-inertia power systems
- Improve the accuracy of the Centre of Inertia (COI) by optimally partitioning the number of coherent group of generators with maximum electrical connectivity into network clusters

B. Elenga Baningobera and I. Oleinikova, "A Coherency Identification Approach for Low-Inertia Power Systems," 2023 58th International Universities Power Engineering Conference (UPEC), Dublin, Ireland, 2023, pp. 1-6

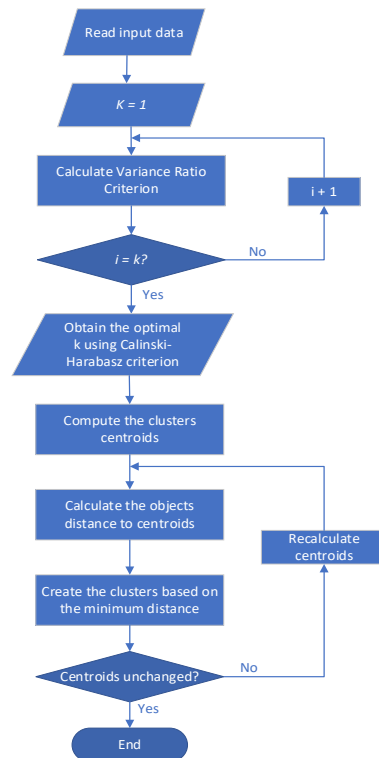
# Methodology

❑ The proposed clustering algorithm process is as follows:

1. Select the number of clusters  $k$
2. Read the input data
3. Create the clusters
4. Compute new centroid of each cluster
5. Assess the quality of each cluster
6. Repeat steps 3-5 until the stopping criteria is satisfied

❑ The following are the stopping criteria of the clustering algorithm:

- Centroids of newly formed clusters do not change
- Points remain in the same cluster
- Maximum number of iterations are reached



➤ **K-means**

$$d(x, c) = \sum_{j=1}^p |x_j - c_j|$$

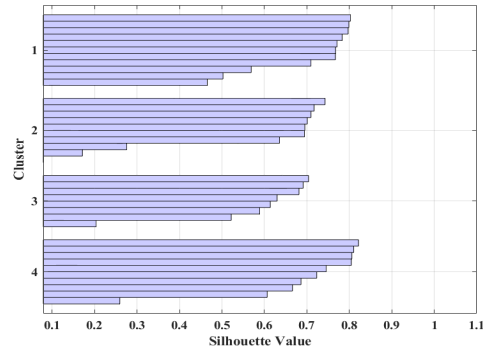
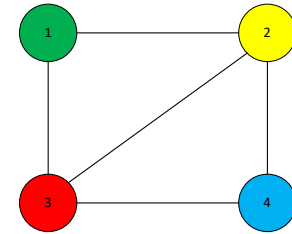
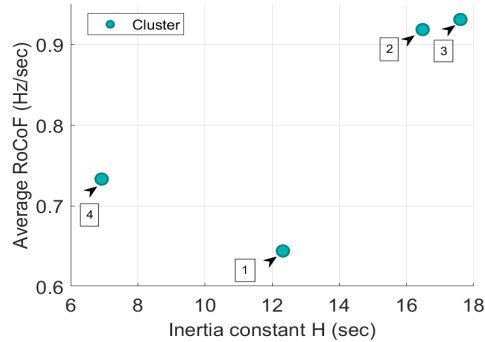
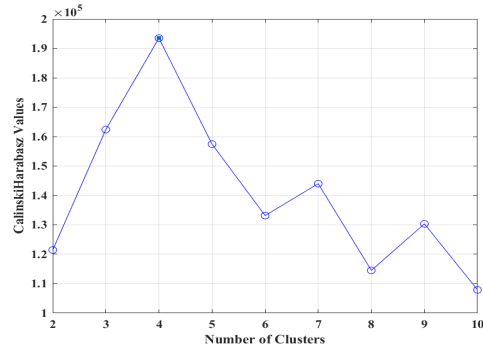
➤ **Calinski-Harabasz criterion**

$$VRC_k = \frac{SS_B}{SS_W} \times \frac{(N - k)}{(k - 1)}$$

$$SS_B = \sum_{i=1}^k n_i \|m_i - m\|^2$$

$$SS_W = \sum_{i=1}^k \sum_{x \in c_i} \|x - m_i\|^2$$

# Simulation results



Cluster number	Bus cluster	Generator cluster
1	2, 19, 22, 23, 25, 26, 28, 29, 30, 35, 36	G06, G07, G10
2	6, 9, 10, 11, 13, 14, 15, 33, 34, 39	G01, G04, G05
3	4, 5, 7, 8, 12, 20, 31, 32	G02, G03
4	1, 3, 16, 17, 18, 21, 24, 27, 37, 38	G08, G09

- ❑ The reduced IEEE-39 bus networks. The clusters are modelled as single-machine models
- ❑ Instead of evaluating a power system's frequency stability with a single COI metric for the whole network, a more granular approach is proposed

# Paper 1 summary

This study proposes a new approach for the frequency stability assessment using machine learning techniques and offers two benefits:

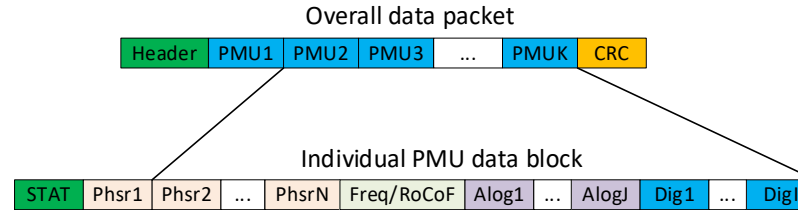
- ❑ The Frequency Control Areas (FCA) from the coherent group of generators is formed by selecting the optimal number of partitions with maximum electrical connectivity and minimum number of network clusters.
- ❑ The increase of the COI metric accuracy when applied in each cluster compared to the entire power system. In addition, it helps the TSOs with the optimal placement of technology such as virtual inertia, battery storage and System Protection Schemes (SPS) in order to ensure safe and reliable operation of low-inertia power systems with large-scale integration of RES.

# Paper 2: Improving frequency stability assessment through k-neighbors and machine learning techniques

## ❖ Motivation

- Explore the development of machine learning models to assess the frequency stability that can be used to design advanced control schemes for low-inertia power systems
- Improve the performance of power system models in the presence of missing data from PMU measurements

# Phasor Measurement Units (PMU)



## ❑ Latency

- Measurement delay ( $t_{meas}$ )
- Measurement uplink delay ( $t_{up}$ )
- Computation delay ( $t_{comp}$ )
- Control action downlink delay ( $t_{down}$ )
- Control action delay ( $t_{con}$ )

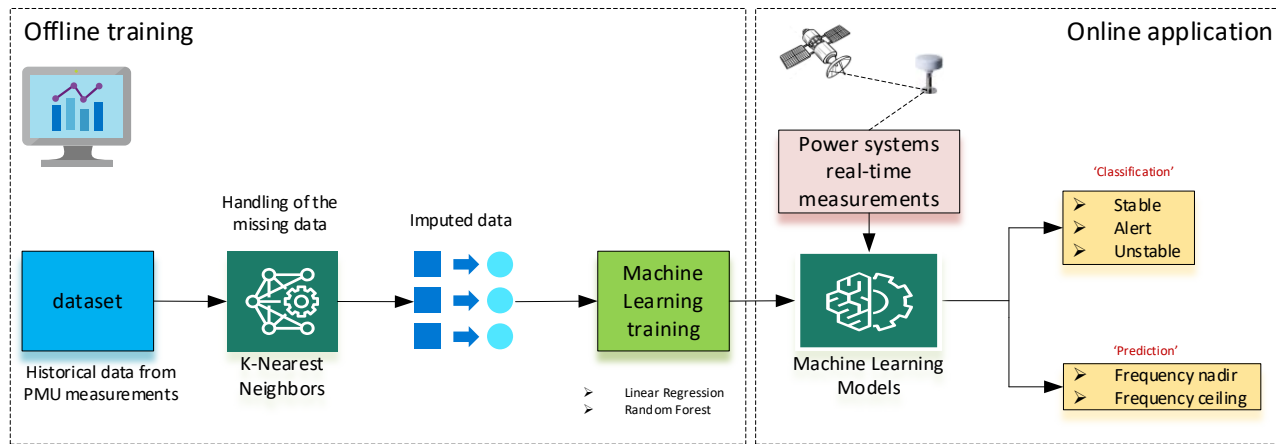
## ❑ Packet loss

- Congestion
- Routing instability
- Signal loss in the com network

## ❑ Network corruption

- Data transmission errors
- Noise in the com channel
- Signal attenuation

# Framework



## ❖ Stability margins

if  $f \geq 49.9$ , the system is stable

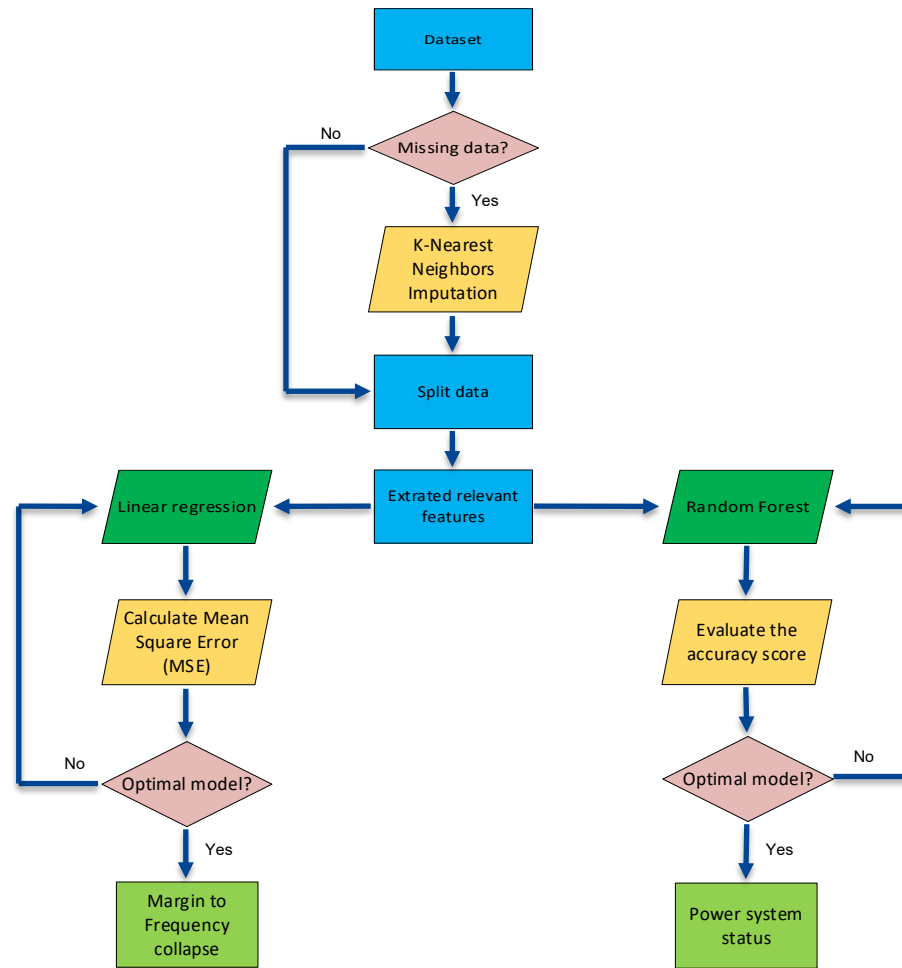
if  $49.3 \leq f < 49.9$ , the system is in alert state

if  $f < 49.3$  OR  $f \geq 50.1$ , the system is unstable

## ❖ Frequency prediction

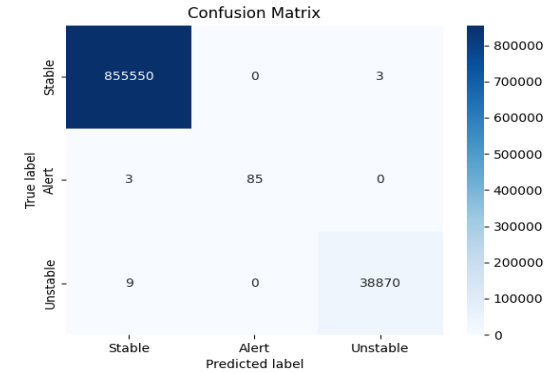
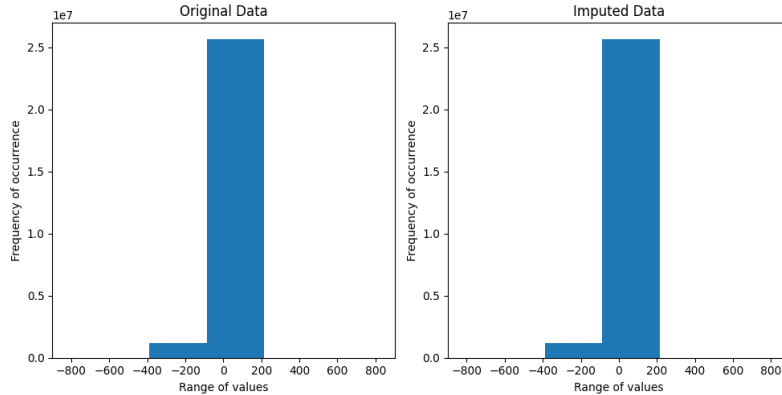
Frequency nadir:  $f < 49.3$

Frequency ceiling:  $f \geq 50.1$





# Results



**Table 1:** Performance evaluation of the models

Missing data	KNN	KNN	Simple	Simple
%	MSE	Accuracy	MSE	Accuracy
10	0.022	0.995	0.031	0.995
20	0.066	0.991	0.088	0.990
30	0.112	0.989	0.347	0.986
40	0.064	0.987	0.073	0.987
50	0.086	0.987	0.115	0.984

# Results

**Table 2:** Misclassifications of Frequency Stability Classification

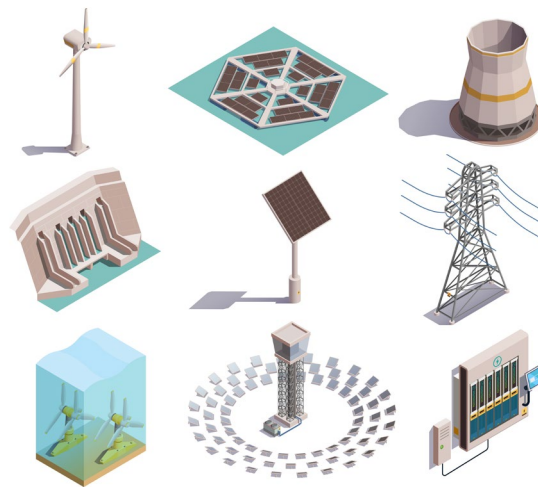
Missing Data	Method	Stable	Alert	Unstable
10%	KNN Imputation	2 128	7	2 022
	Simple Imputation	2 253	12	2 054
20%	KNN Imputation	4 025	25	3 102
	Simple Imputation	4 448	26	3 844
30%	KNN Imputation	5 098	35	4 163
	Simple Imputation	5 853	38	4 606
40%	KNN Imputation	7 003	24	4 083
	Simple Imputation	7 475	45	4 459
50%	KNN Imputation	8 163	36	3 329
	Simple Imputation	8 530	42	3 610

# Paper 2 summary

- This study proposes a method that is able to impute the missing measurements data from PMUs by using a combination of machine learning and physical constraints
- The approach effectively imputed the missing values in the dataset, as evidenced by the low Mean Square Error (MSE) values and the distribution analysis revealed a strong correlation between the imputed values and the original values
- The models performance, as measures by accuracy, demonstrated that the imputed data performed well in the frequency stability classification task
- The performance predictions of both frequency nadir and frequency ceiling were also promising as shown by the low MSE values

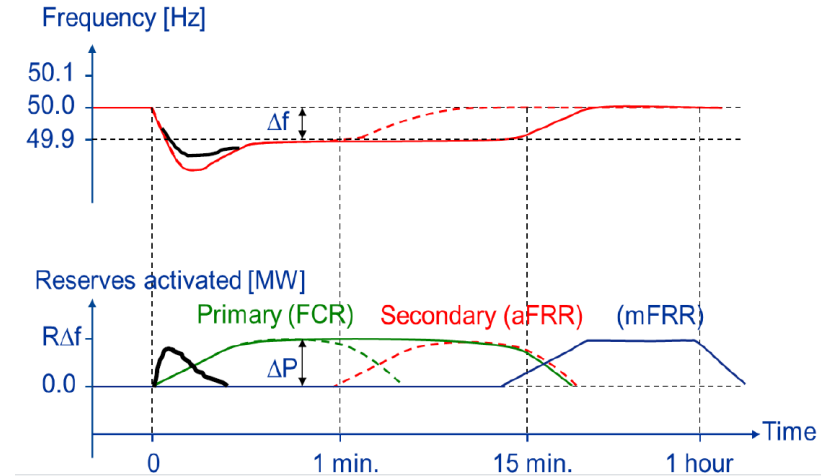
# Papers 3 & 4: Advanced system protection schemes design

- Started with case studies and simulations to analyze the impact of reduced low-inertia power systems provided a solid foundation for **understanding the challenges and dynamics of such systems**
- Subsequently, proposing advanced SPS control algorithms both for power generation adjustment and load shedding to optimize Fast Frequency Reserves (FFR) which will **demonstrate how innovative solutions can be developed to address the identified issues**



# New service: Fast Frequency Reserves - FFR

- **Aim of FFR** is to get contributions from fast controllable units (generators and demand) to mitigate adverse consequences of low system inertia
- Once the FFR has been activated, it can be controlled to respond in many ways. The control scheme can rely totally on feedback



System frequency response and services (Kjetil Uhlen)

# FFR implementation

- Activation

Alternative	Activation level [Hz]	Maximum full activation time [sec]
A	49.7	1.30
B	49.6	1.00
C	49.5	0.70



$$FFR_{\text{capacity}} = \min \left( \text{abs}(P(t) - P(0)) \right) [\text{MW}]$$

Where,

$FFR_{\text{capacity}}$  is the prequalified FFR capacity [MW]

$P(t)$  is the active power exchange between the grid and the providing entity [MW]

$P(0)$  is the baseline power exchange over the specified time interval [MW]

$t$  is time such that  $t \in [t_{\text{FullAct}}, t_{\text{FullAct}} + t_{\text{MinDur}}]$

$t_{\text{FullAct}}$  is the maximum full activation time (specified for each providing entity to 0.70, 1.00, or 1.30 s)

$t_{\text{MinDur}}$  is the minimum support duration (specified for each providing entity to 5.0 or 30 s)

# FFR implementation

- **Deactivation**

- ❖ Support duration of the FFR

Type of support	Duration [sec]
Long term	30
Short term	5

$$FFR_{DeAct, rate, max} = 0.20 \cdot FFR_{capacity} \text{ [MW/s]}$$

$$\Delta FFR_{DeAct, step, max} = 0.20 \cdot FFR_{capacity} \text{ [MW]}$$

where,

$FFR_{DeAct, rate, max}$  is the maximum FFR reduction rate during the deactivation [MW/s]

$\Delta FFR_{DeAct, step, max}$  is the maximum FFR deactivation step during the deactivation [MW]

- **Recovery**

$$FFR_{ReCov, max} = 0.25 \cdot FFR_{capacity} \text{ [MW]}$$

where,

$FFR_{ReCov, max}$  is the maximum FFR recovery ("undershoot") [MW]



# FFR control

## ❑ Power generation adjustment and load shedding

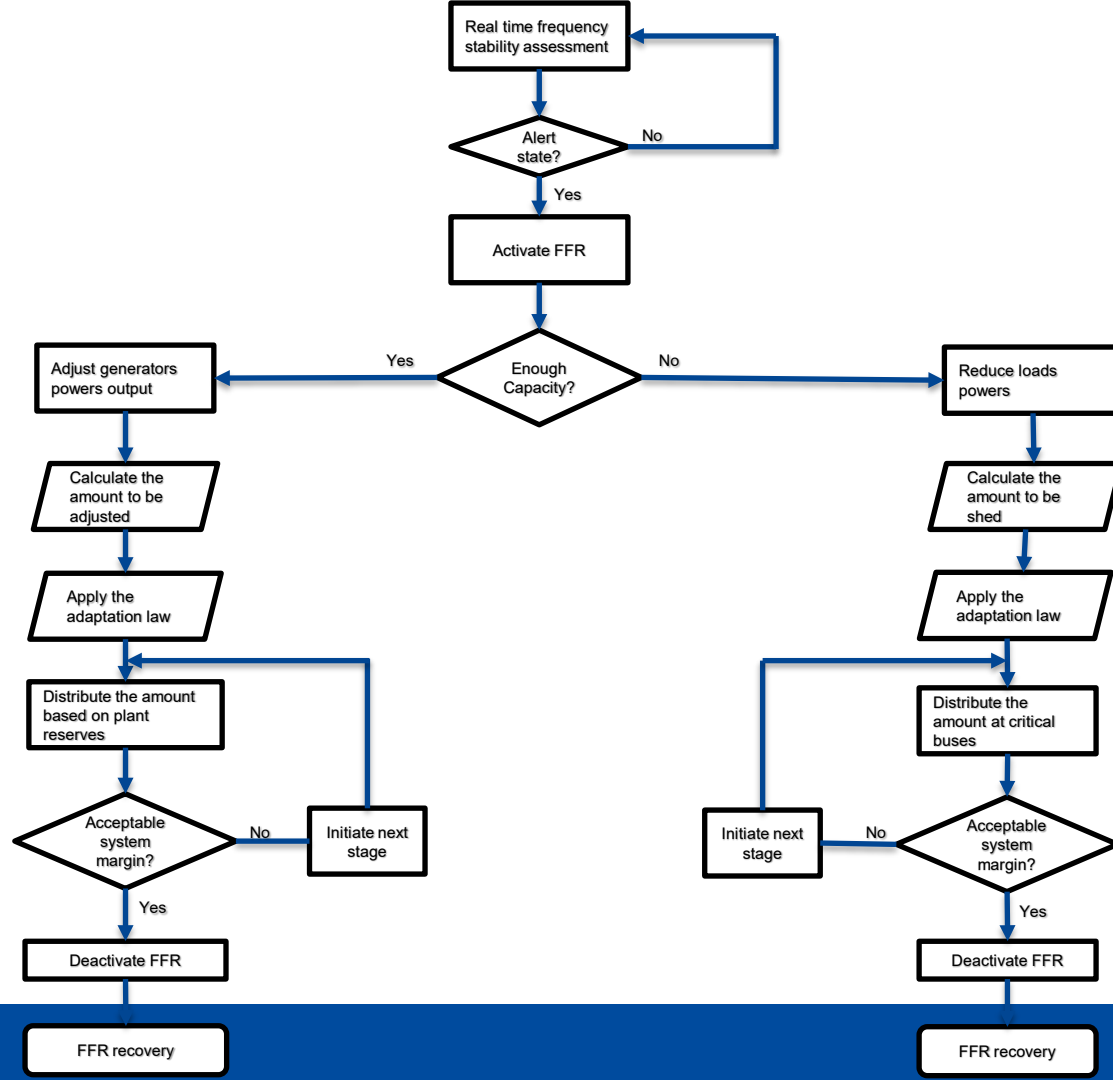
$$\Delta P_e = -K_p * \Delta f * (\text{reserve} / \text{total\_reserve}) * \text{Power}[j][i] / \text{generator\_max\_powers}[j])$$

$$\Delta P_e = -K_p * \Delta f * (\text{reserve} / \text{total\_reserve}) * (\text{Load}[i] / \text{total\_load})$$

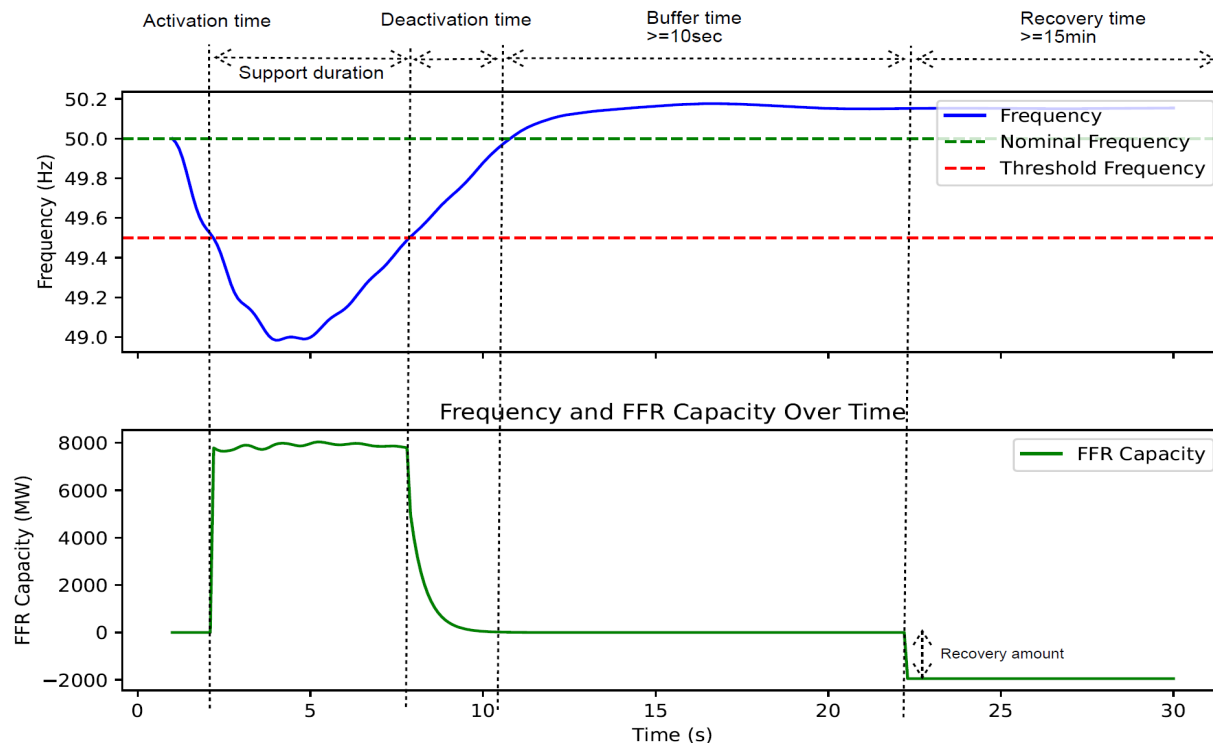
Where:

- **$\Delta P_e$**  : This represents the change in power output due to the FFR control action
- **$K_p$**  : The proportionality constant that scales the control action based on the frequency deviation
- **reserve** : This refers to the available FFR reserve
- **total\_reserve** : The total available FFR reserve in the system
- **Power [j][i]** : The power output of the  $j$ -th generator at the  $i$ -th time step
- **generator\_max\_powers [j]** : The maximum power capacity of the  $j$ -th generator
- **Load[i]** : the power demand at the  $i$ -th time step
- **total\_load** : the total power demand in the system



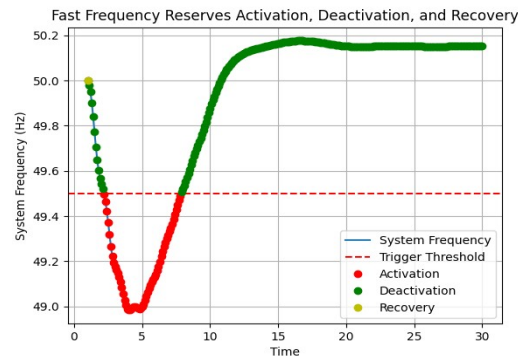
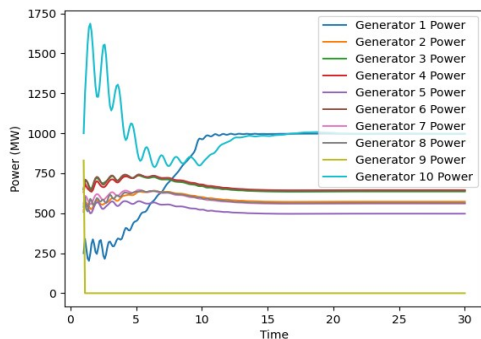


# FFR simulation results



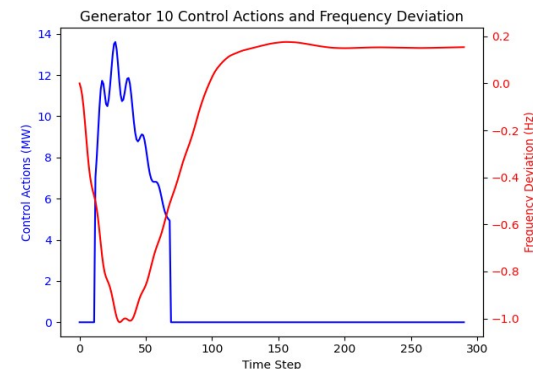
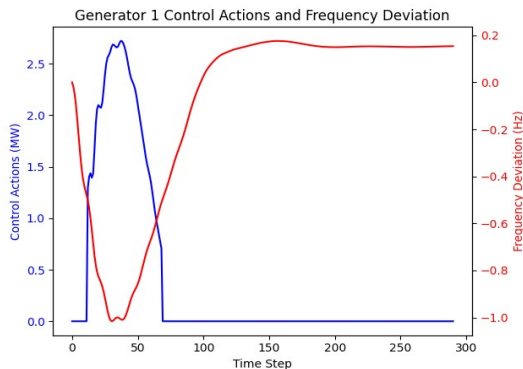
# FFR simulation results

- ✓ Generators powers adjustments due to FFR activation and control actions



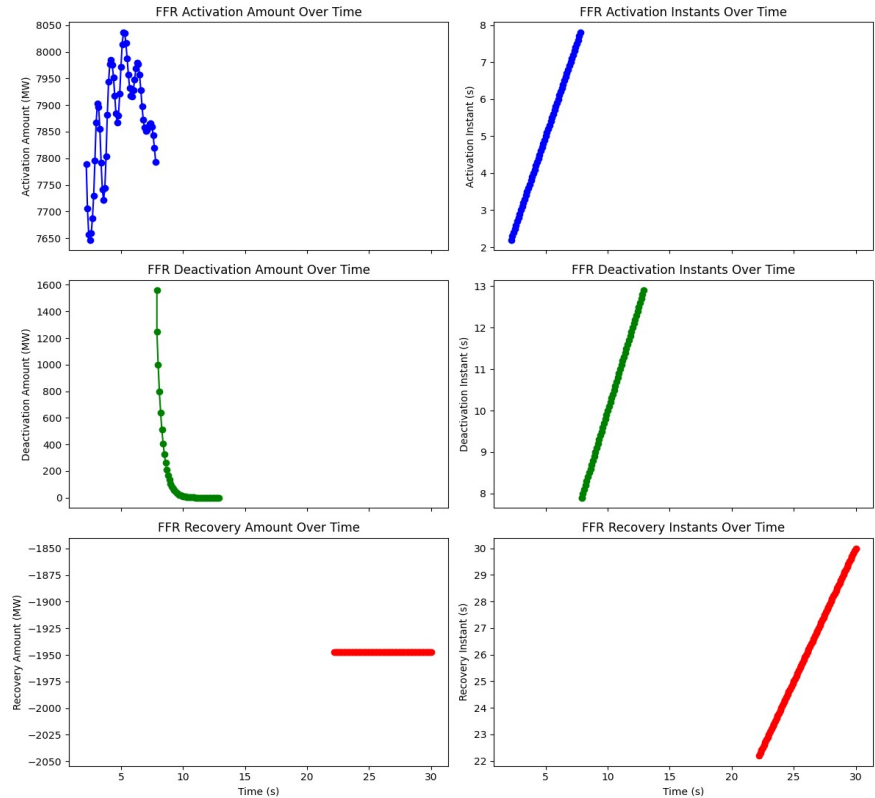
- ✓ FFR activation, deactivation and recovery

- ✓ FFR control actions inversely proportional to frequency deviation



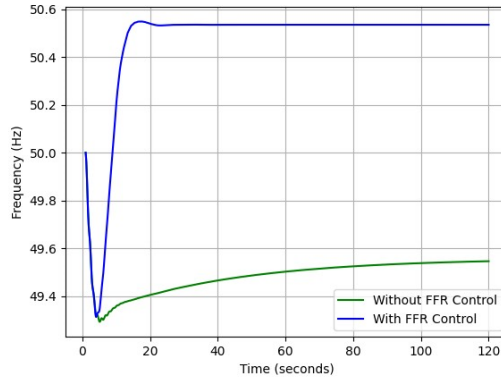
- ✓ FFR control actions inversely proportional to frequency deviation

# FFR activation, deactivation and recovery

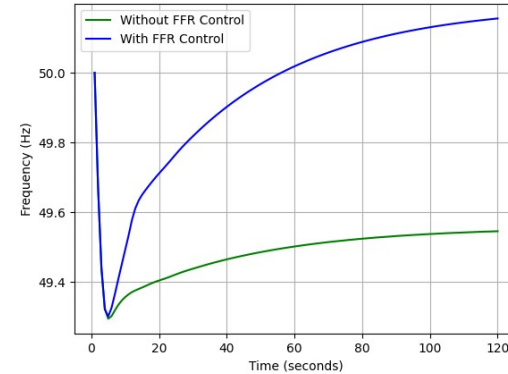


# FFR control challenges

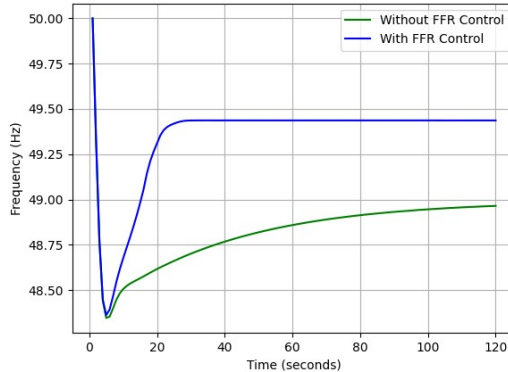
- ✓ **Case 1:**  
disconnection of  
one machine  
with fast FFR  
parameters and  
response times



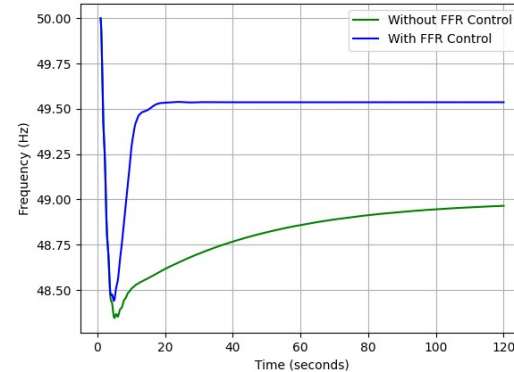
- ✓ **Case 2:**  
disconnection of  
one machine  
with slow FFR  
parameters and  
response times



- ✓ **Case 3:**  
disconnection of  
two machines  
with slow FFR  
parameters and  
response times



- ✓ **Case 4:**  
disconnection of  
two machines  
with fast FFR  
parameters and  
response times



# Papers contributions

- **Adaptive Control Algorithm for Power Generation Adjustment (FFR Power Control) and Load shedding (FFR Load Shedding):**

## Step 1 Modeling:

- Let  $\Delta f$  be the frequency deviation and  $\Delta Pe$  be the change in power output due to FFR.
- We can use the equation  $\Delta Pe = -Kp * \Delta f$ , as provided earlier.

## Step 2 Adaptive parameter:

- Let  $Kp$  be the control gain that we want to adapt.

## Step 3 Error calculation:

- We calculate the error between the actual frequency deviation and the desired frequency deviation:

$$\text{error} = \Delta f - \text{desired\_}\Delta f$$

## Step 4 Adaptation Law:

- Design of an adaptation law that updates the adaptive parameter based on the error and other relevant data:

$$Kp_{\text{new}} = Kp_{\text{old}} + \mu * \text{error}$$

where  $\mu$  is the adaptation rate.

## Step 5 Implementation of the Adaptive Mechanism:

- Update the control gain ( $Kp$ ) at each control iteration based on the adaptation law:

$$Kp = Kp_{\text{new}}$$

## Step 6 Validation and Tuning:

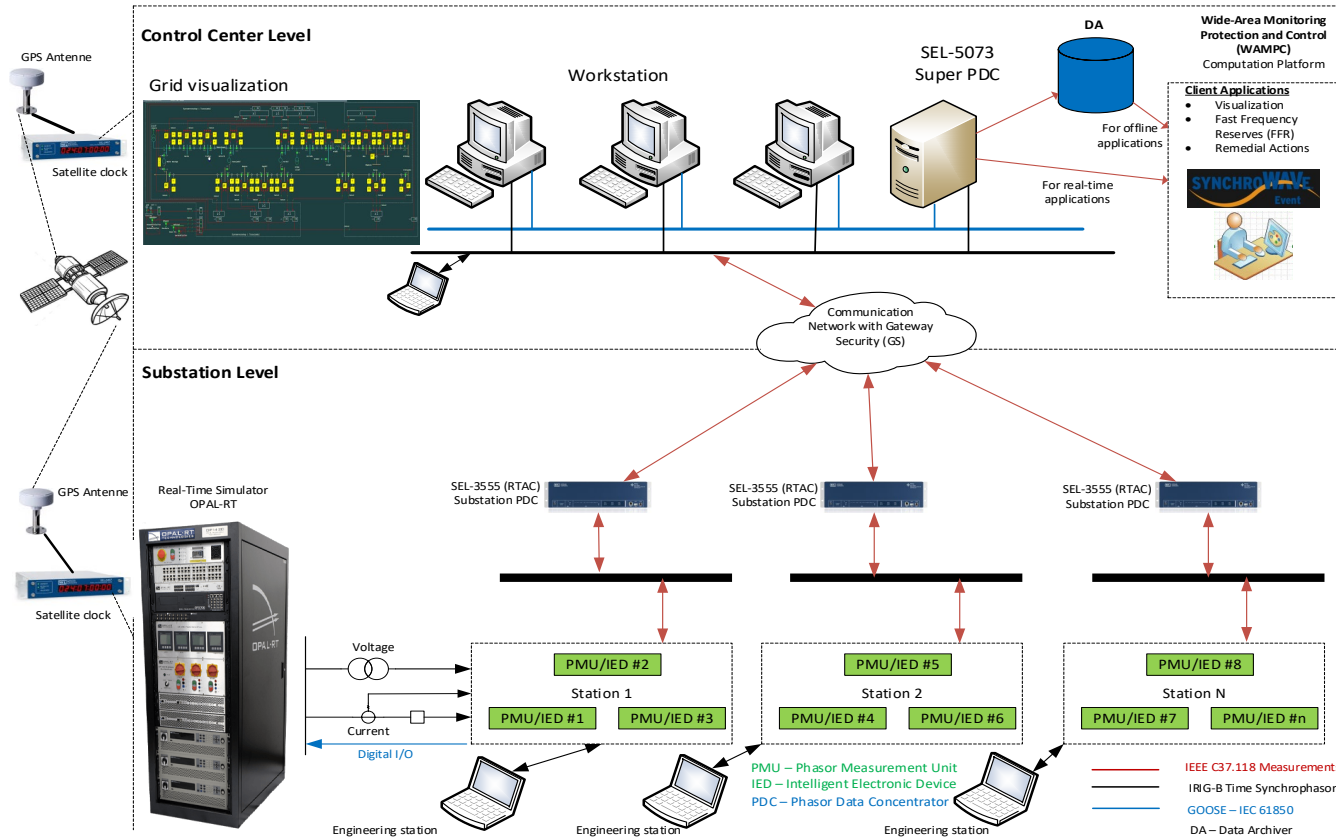
- Test the adaptive control system through simulations and real-time tests.
- Fine-tune the adaptation rate ( $\mu$ ) to achieve desired control behavior.

# Possible advanced techniques for adapting control parameters in an adaptive control algorithm

- **Weighted Summation of Adaptation Rate ( $\mu$ )**
- **Curve Fitting Model using Least Squares for Adaptive Control**
- **Model Reference Adaptive Control (MRAC)**
- **Self-Tuning Regulators (STR)**
- **Neural Networks and Machine Learning**
- **Reinforcement Learning (RL)**
- **Fuzzy Logic Control**
- **Particle Swarm Optimization (PSO) and Genetic Algorithms (GA)**
- **Kalman Filtering and Estimation Techniques**

- MathWorks et al., "Optimization toolbox user's guide," 2021.
- Mahdi, M.M., Thajeel, E.M. and Ahmad, A.Z., 2018, December. Load frequency control for hybrid micro-grid using MRAC with ANN under-sudden load changes. In *2018 Third Scientific Conference of Electrical Engineering (SCEE)* (pp. 220-225). IEEE.
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- Hasan, N., Alsaidan, I., Sajid, M., Khatoon, S. and Farooq, S., 2022. Robust self tuned AGC controller for wind energy penetrated power system. *Ain Shams Engineering Journal*, 13(4), p.101663.
- Wang, W., Yorino, N., Sasaki, Y., Zoka, Y., Bedawy, A. and Kawauchi, S., 2022. A novel adaptive model predictive frequency control using unscented Kalman filter. *Electric Power Systems Research*, 213, p.108721.

# Future work





# Thank you!

Questions?