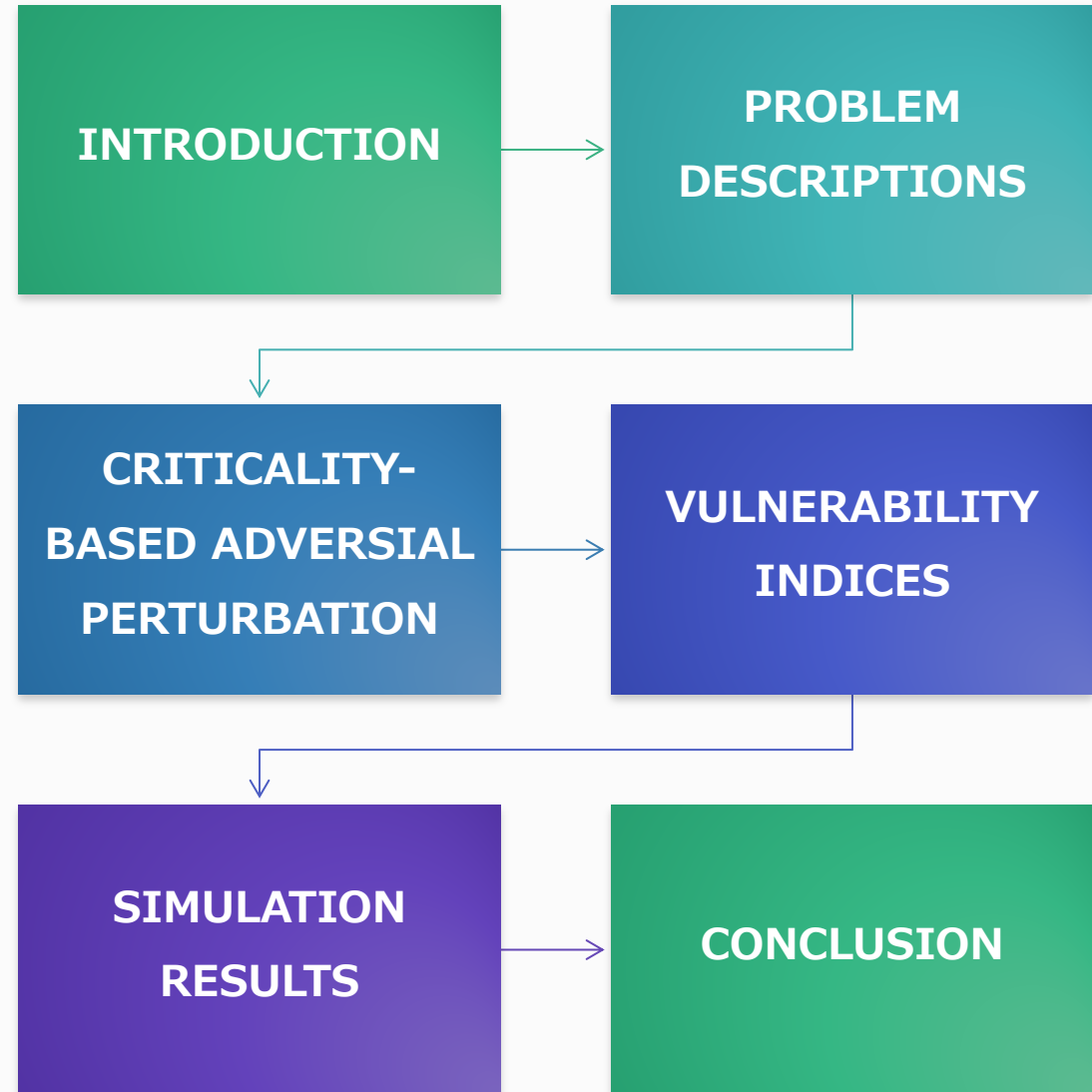


VULNERABILITY ASSESSMENT OF DEEP REINFORCED LEARNING MODELS FOR POWER SYSTEM TOPOLOGY OPTIMIZATION

Paper Authors: Yan Zheng, Ziming Yan, Kangjie Chen,
Jianwen Sun, Yan Xu and Yang Liu

CONTENTS



SECTION I: INTRODUCTION

Motivation

- Complex Power Grids
- Insufficiency of Traditional Methods
- DRL Vulnerable to cyber attacks and data perturbations

Problem

- Limited research on DRL Vulnerability assessment in Power systems

Proposed Solution

- Criticality-Based Perturbations
- Vulnerability Indices

Targeted users

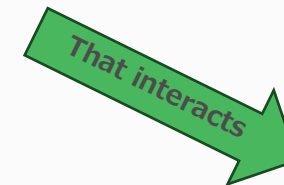
- Grid operators - Safe grid operations

SECTION II: PROBLEM DESCRIPTIONS

1. DRL for Network Topology Optimization

Focus on Optimizing Power flow by switching transmission lines or disconnecting loads

Achieved using DRL agents



Power System
Agent

SECTION II: PROBLEM DESCRIPTIONS

2. Technical Details

- *Describes objective function*

Maximizes

Remaining Transfer
Capabilities

- Power flow solution using power flow equations
- Markov Decision Process (MDP) is used to formulate the decision-making process

- Reward function

Penalizes

Power Flow divergence
and satisfies
transmission line limits

- Deep Q Neural Network (DQN)

Train

DRL Agent to find
Optimal Policy

SECTION II: PROBLEM DESCRIPTIONS

Perturbation-Based DRL Vulnerability Assessment

Highlight of potential vulnerability of DRL Models to potential small data perturbations

Pointers on existing research on adversarial attacks against DRL Models

Intro. of the concept of perturbation-based assessment

Formulates equations for adding perturbations and the DRL's response

SECTION III: CRITICALITY- BASED ADVERSARIAL PERTURBATION

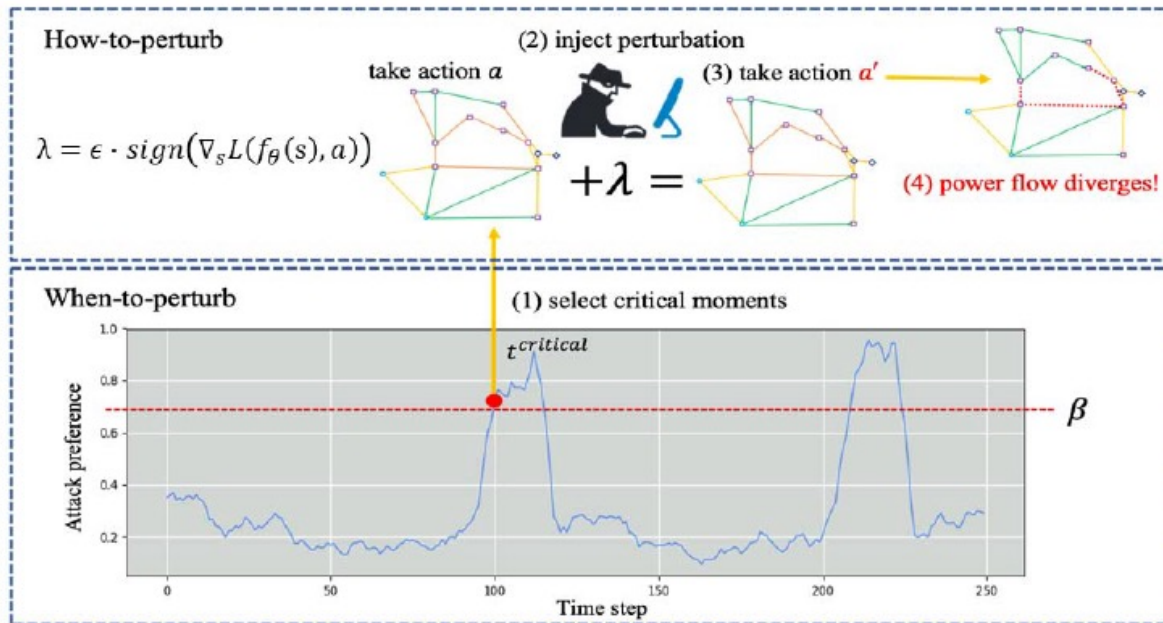


Fig. 2. Illustration of criticality-based adversarial perturbation.

WHEN TO PERTURB

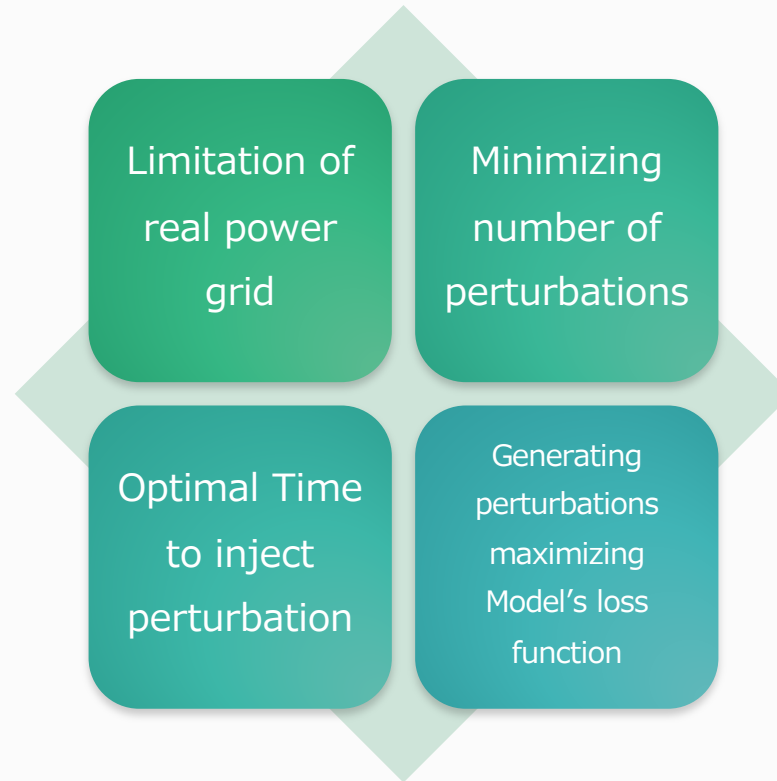
- Critical moment identification
- Model -> Calculating attacker-preference value
- Higher preference values

HOW TO PERTURB

- Focus on crafting effective perturbations
- Model leverages Fast Gradient Sign Method (FGSM)

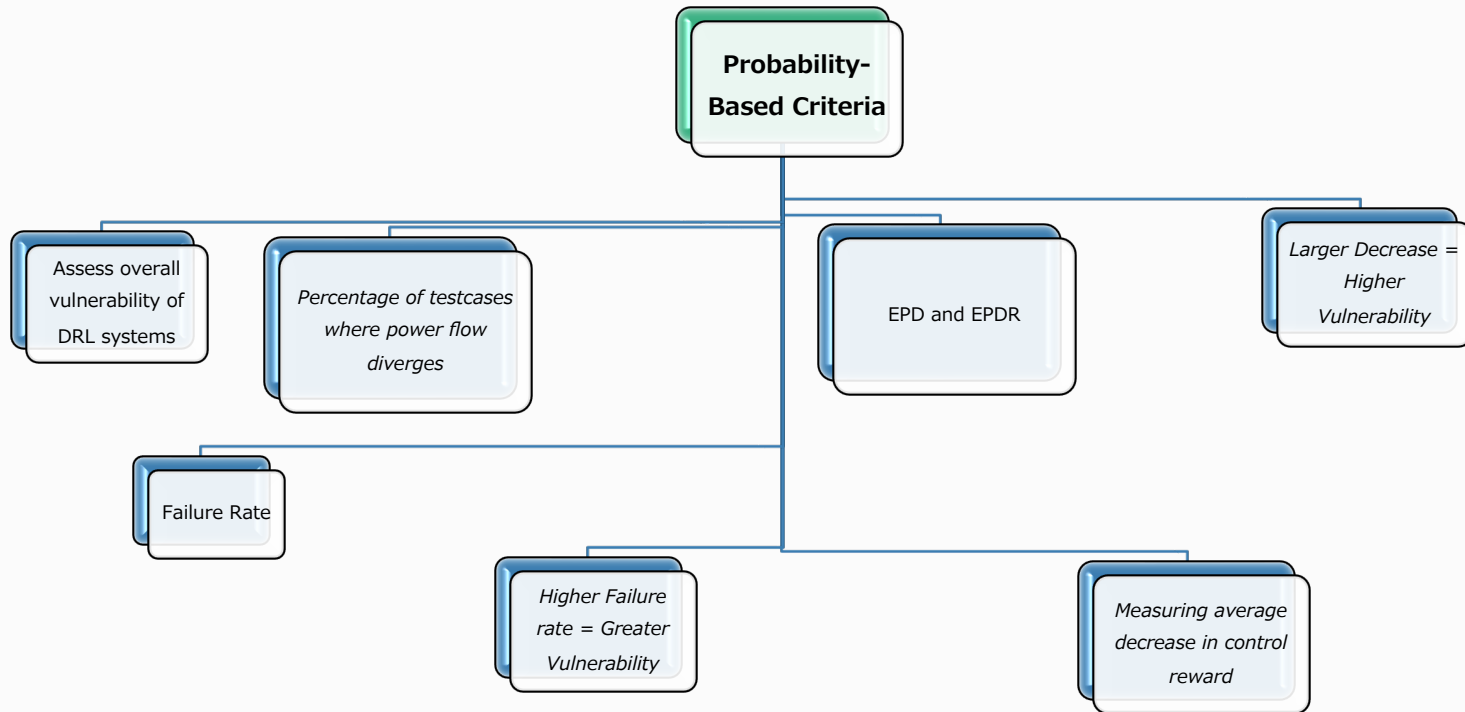
SECTION III: CRITICALITY-BASED ADVERSARIAL PERTURBATION

KEY POINTS

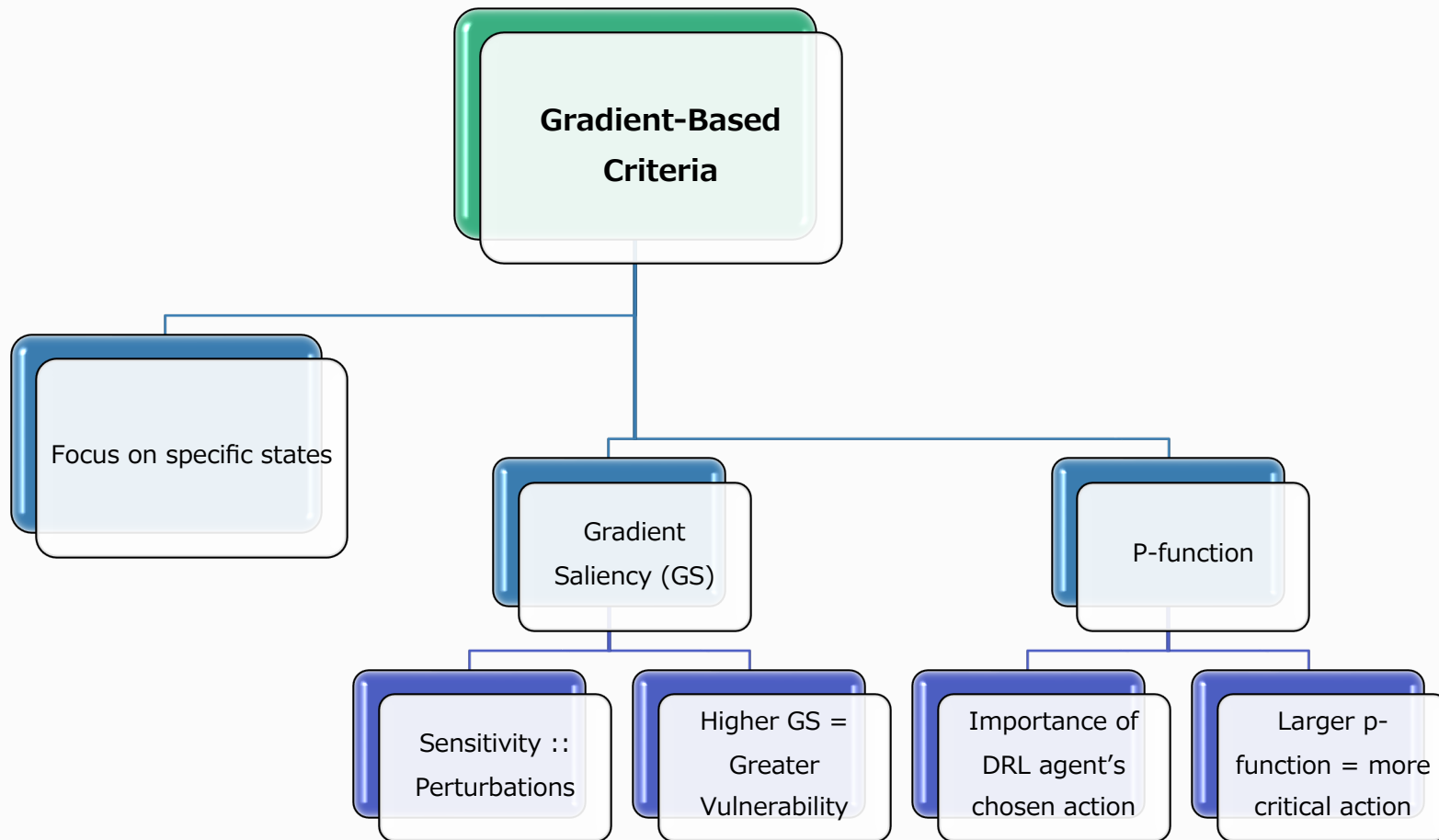


SECTION III: CRITICALITY-BASED ADVERSARIAL PERTURBATION

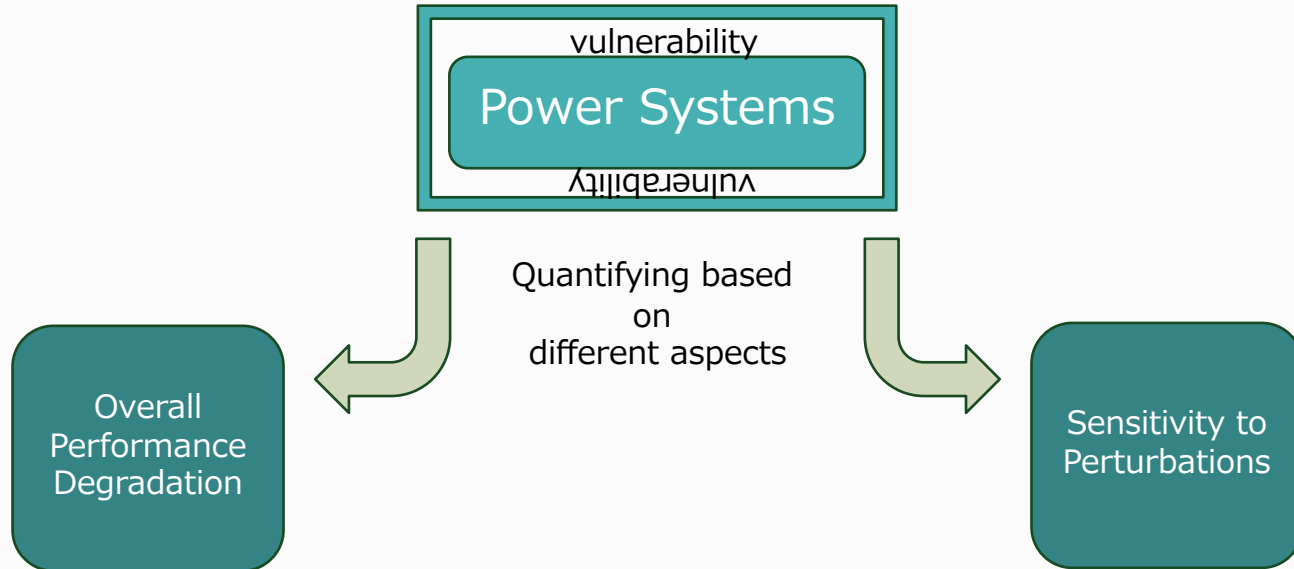
SECTION IV: VULNERABILITY INDICES



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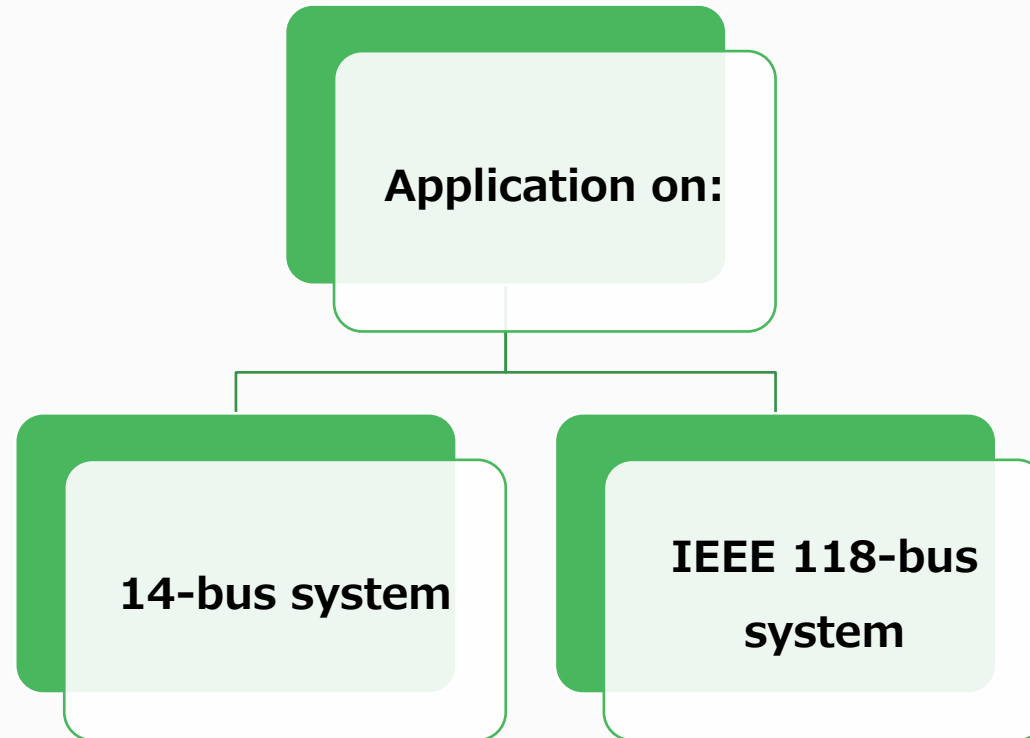


In Summary



SECTION IV: VULNERABILITY INDICES

SECTION V: SIMULATION RESULTS



SECTION V: SIMULATION RESULTS

Evaluation Method

DRL Controller Performance

- No Perturbations
- Random Noise Perturbations
- Targeted Attacks (FGSM and Criticality-based)

Metrics - Accessing Vulnerabilities

- Critical Attack Rate (CAR)
- EPD and EPDR
- Action Preference (p-function)
- Gradient Saliency (GS)

SECTION V: SIMULATION RESULTS

DRL CONTROLLER PERFORMANCE

- Degrades with FGSM and Criticality based attacks
- No degrade with no perturbations and random noise

PROPOSED METHOD

- Higher efficiency over FGSM
- Since, fewer attacks achieve similar performance

KEY FINDINGS

CRITICALITY-BASED APPROACH

- Higher Critical Attack Rate compared to FGSM

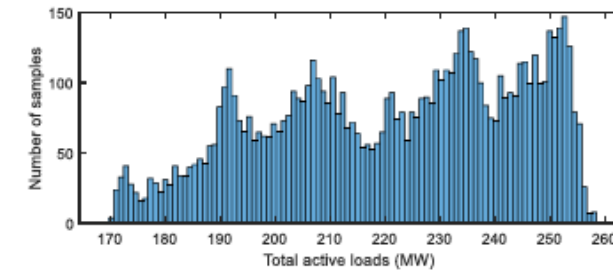
P-FUNCTION > GS

- Prediction of potential DRL malfunction before they occur
- GS - not effective

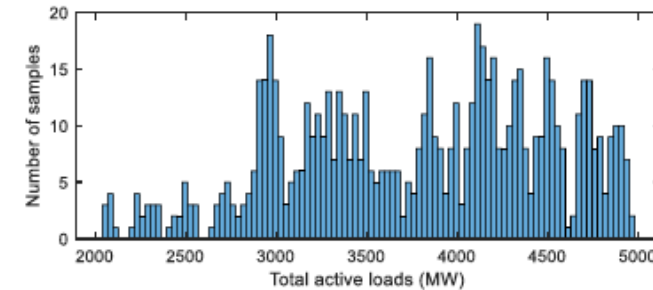
Impact of attacks is more severe with the 14-bus system vs 118-bus system

SECTION V: SIMULATION RESULTS

Impact of attacks is more severe with the 14-bus system vs 118-bus system



(a) Histogram of the employed 14-bus system total load



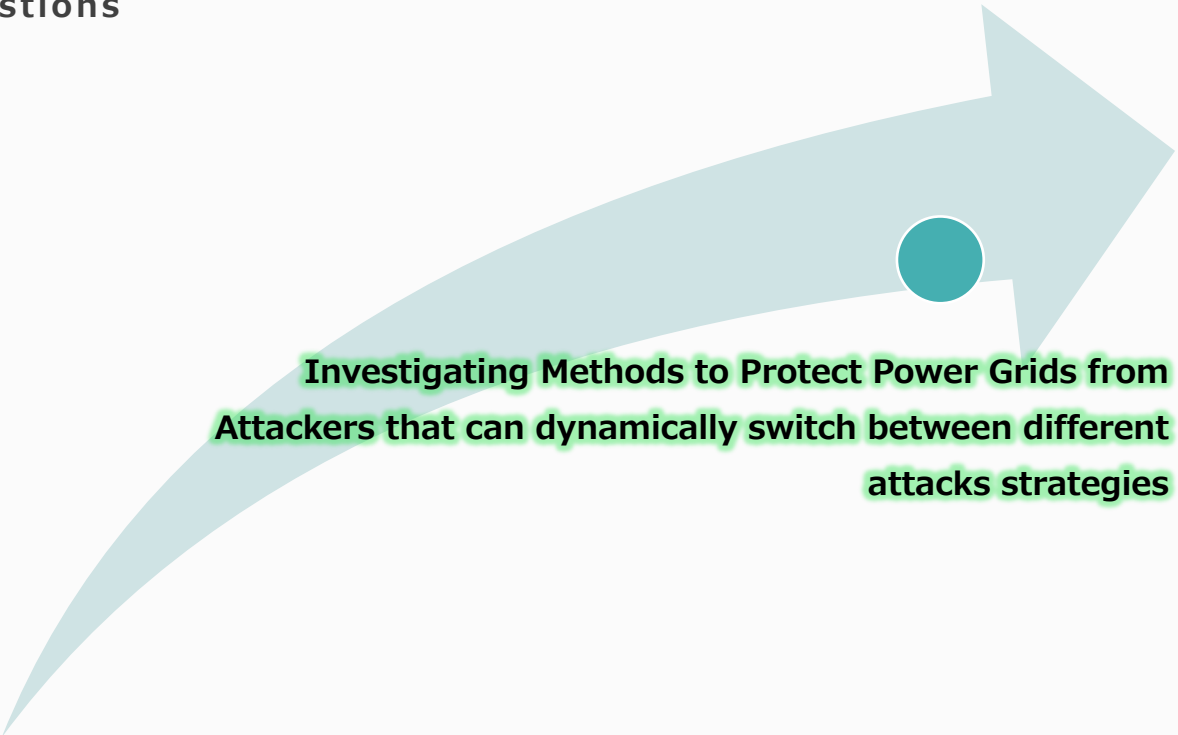
(b) Histogram of the employed IEEE 118-bus system total load

SECTION VI: CONCLUSION



SECTION VI: CONCLUSION

Future Work suggestions



Investigating Methods to Protect Power Grids from
Attackers that can dynamically switch between different
attacks strategies

THANK YOU
FOR YOUR
PATIENCE 😊

