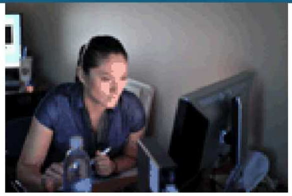
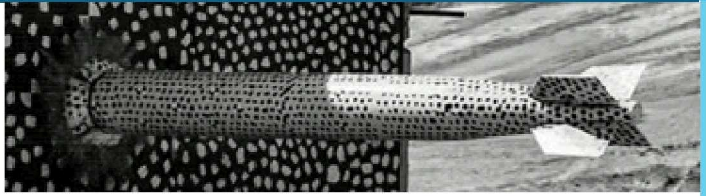
SAND2019-7862PE

Grid Stability Using Machine Learning State Space Navigation





Co-PIs – Ross Guttromson
Stephen J. Verzi

Sandia National Laboratories

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Outline

- Project Purpose
- Significance & Impact
- Technical Approach
- Technical Accomplishments
- Conclusions/Summary
- Future Effort
- Acknowledgments and Contacts

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Project Objective and Purpose

During near blackout conditions, grid operators may have an opportunity to restore the system to a safe condition if a real-time decision support tool is available.

This project investigates the development of a real-time decision support tool for that purpose.

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Existing Planning and Operations

1. In the infrequent occurrence when grid operations depart from planned criteria, how do we move to a 'good' operating point?
2. Where are we? Where do we want to go? What path do we take?

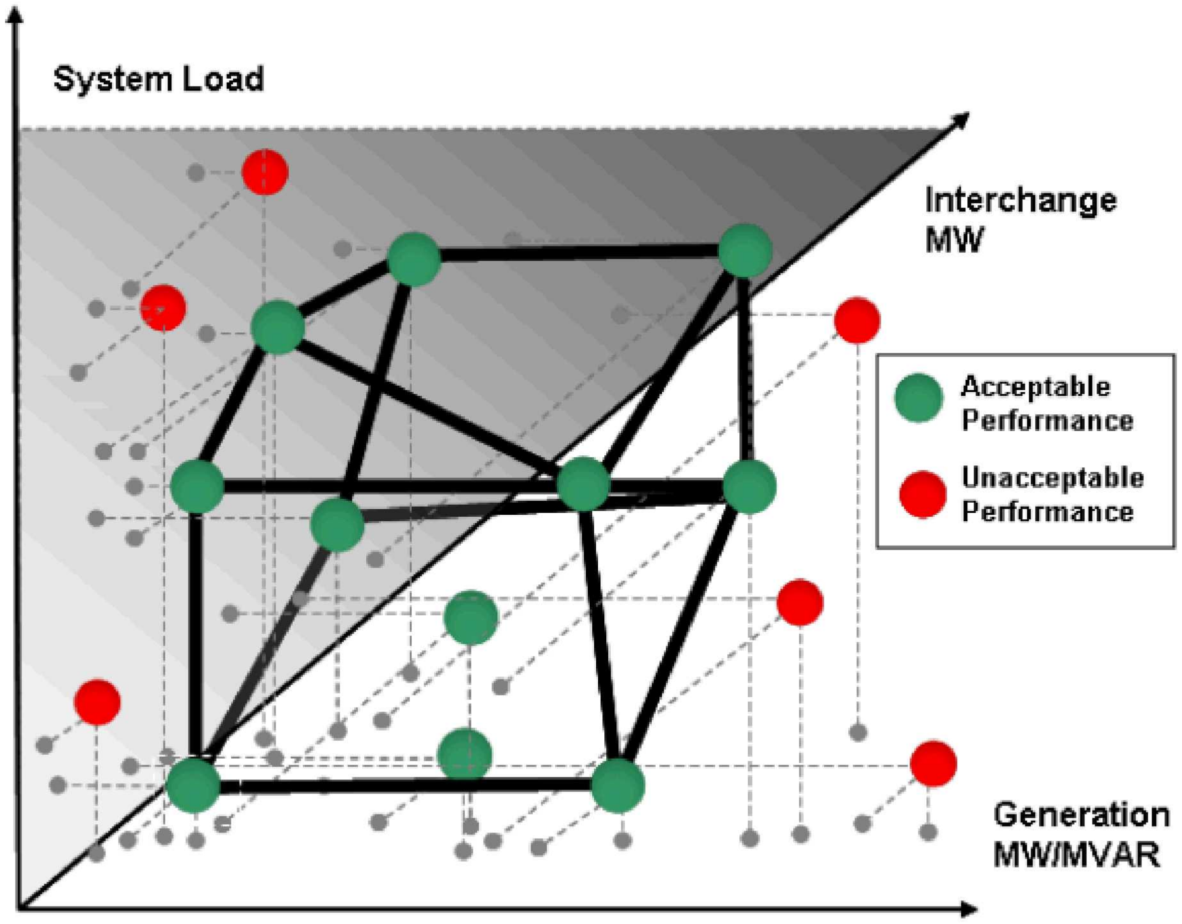

Figure 9 - "Scatter" plot of planning scenarios.

Metaphor For Stability Margin

Require "Stability" Margins of Interest

Voltage Stability Margin

Transient Stability Margin

Non-Linear/Eigen-analysis Stability Margin

System Voltage Margins

Power Line Transfer Margins

System Droop Margin

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General Method

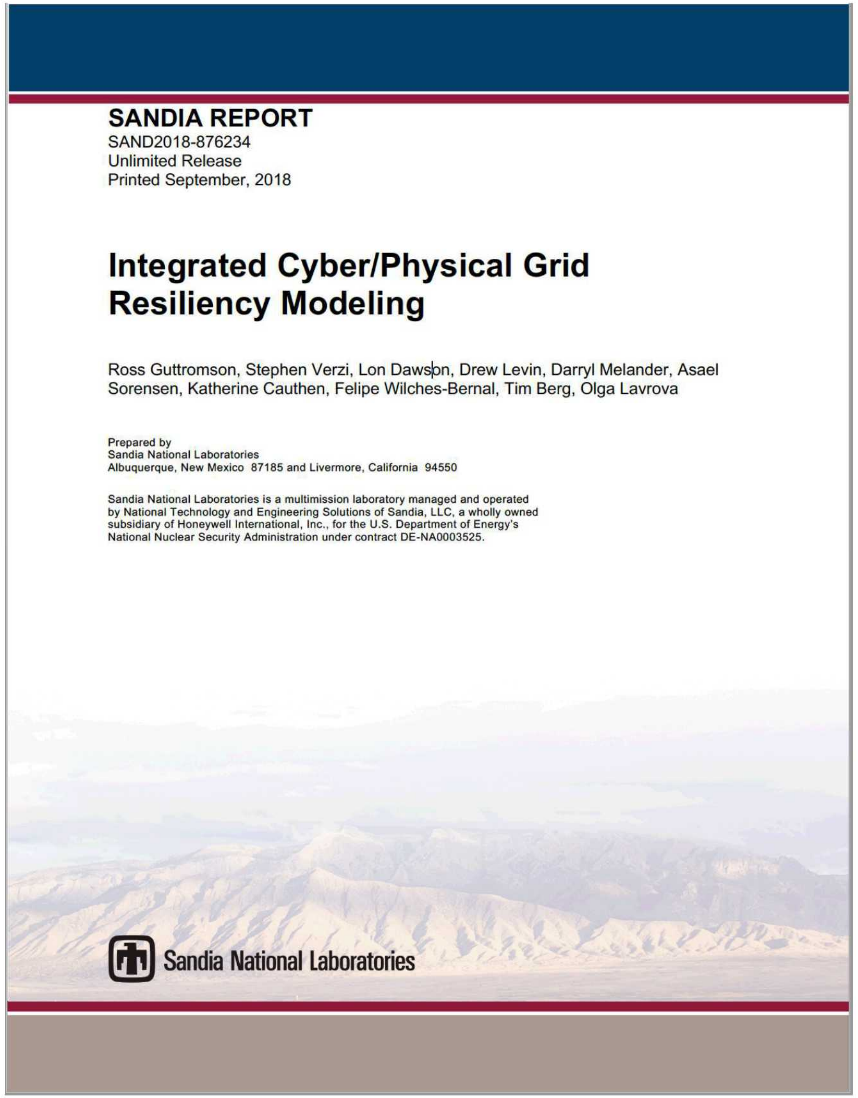
The solution method uses Deep Neural Networks combined with Monte Carlo Decision Trees to represent the sequence of control actions and dispatches needed for the grid to increase its stability margins.

Our approach offers the potential of a speedy solution to this problem, with a low risk of non-convergence. The solution will not be proven optimal, although it will be demonstrated to be feasible and ‘good’ during off-line testing.

Based on recent work conducted at Sandia

Recent Work We Are Building Upon

- Slides 10-19 describe Previous LDRD work
  - Uses Simplified Grid Model
  - Demonstrates the Feasibility of the Approach
  - Clarifies Areas for Needed Research



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Integrated Cyber/Physical Grid Resiliency Modeling

Ross Guttromson, Stephen Verzi, Lon Dawson, Drew Levin, Darryl Melander, Asael Sorensen, Katherine Cauthen, Felipe Wilches-Bernal, Tim Berg, Olga Lavrova

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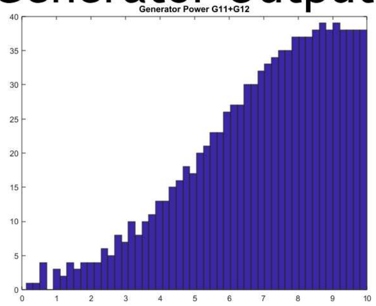
Defining the State Space

Generator Outputs



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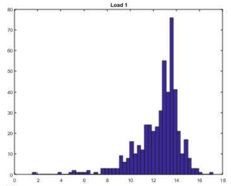
L1 Load



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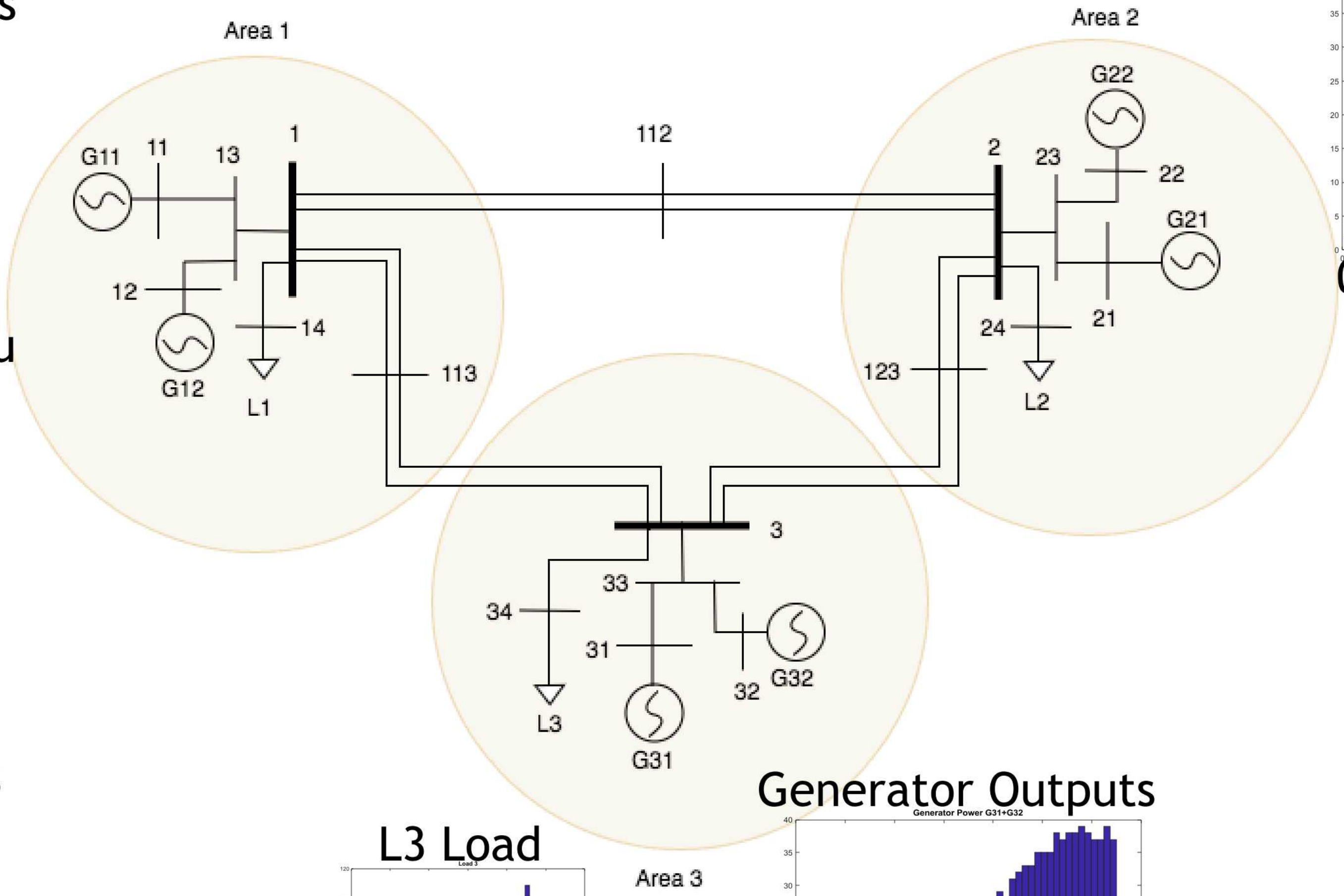
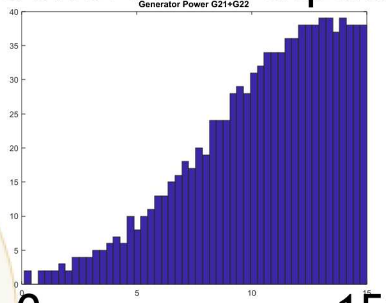


Generator Outputs



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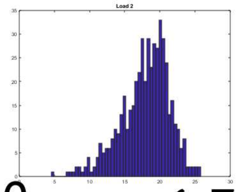
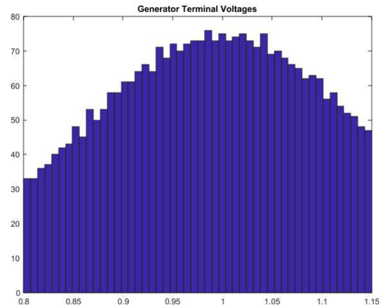
L2 Load



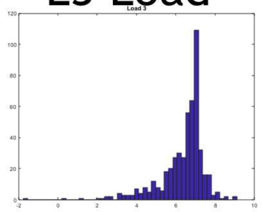
0 6.7pu

Generator Terminal Voltages



0.8pu 1.15pu

L3 Load



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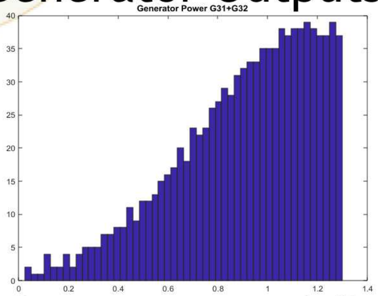
Generator Outputs



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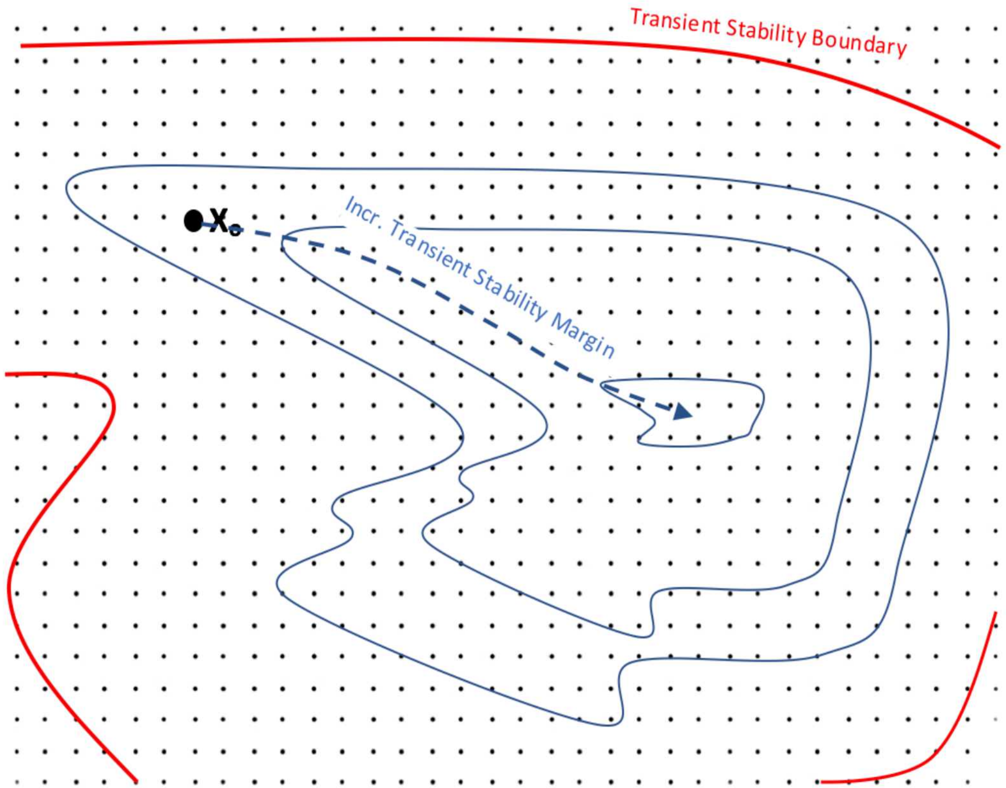
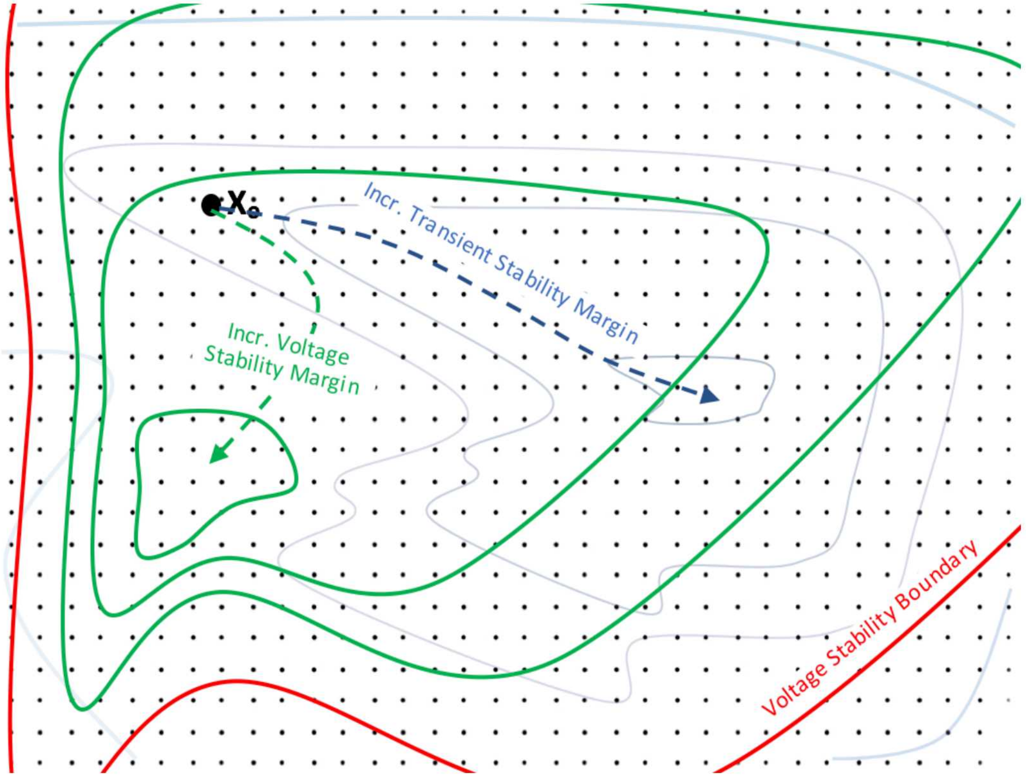
Stability Margins

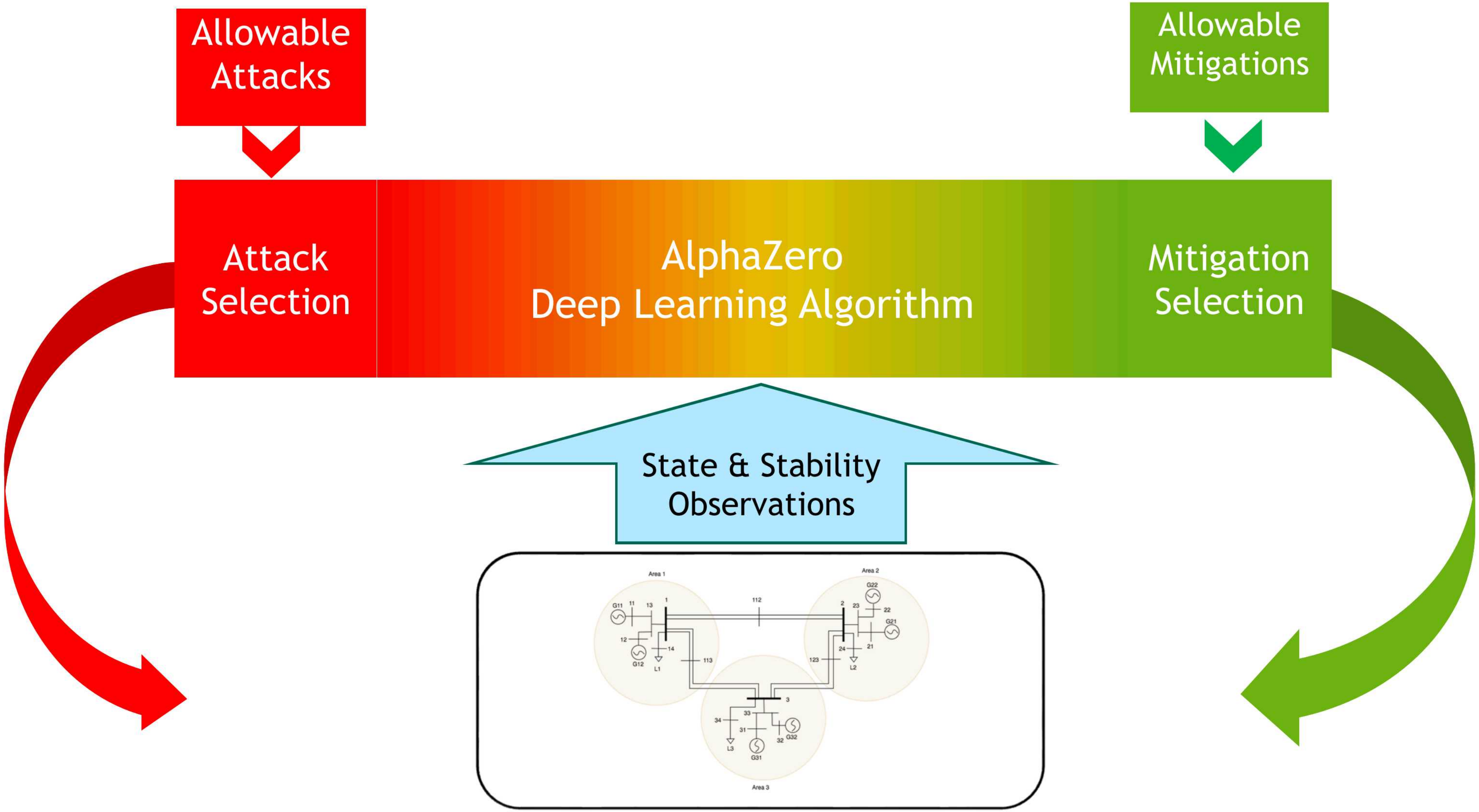


Transient Stability Level Curves



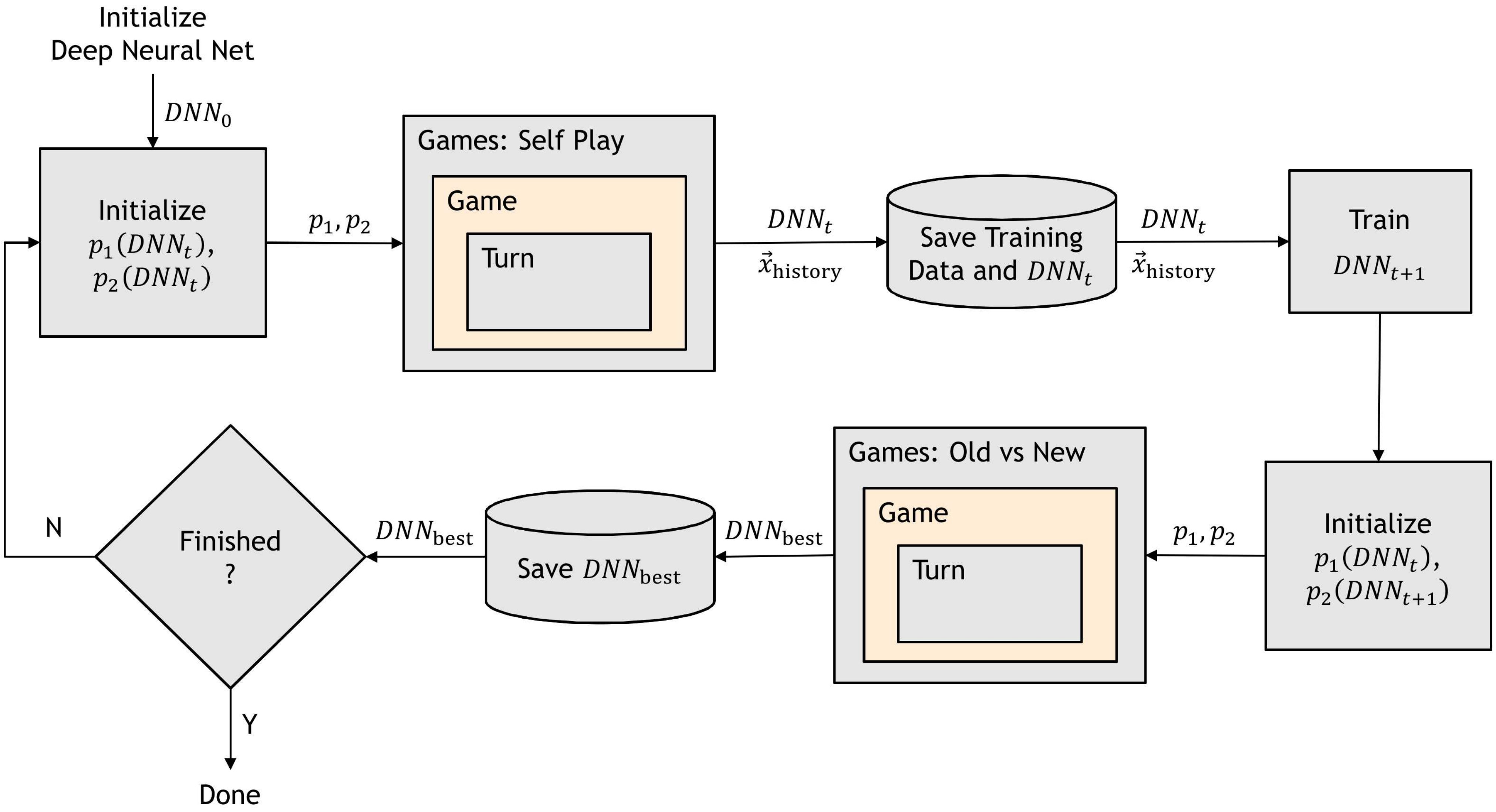
Transient Stability and Voltage Stability Level Curves

Approach: Machine Learning

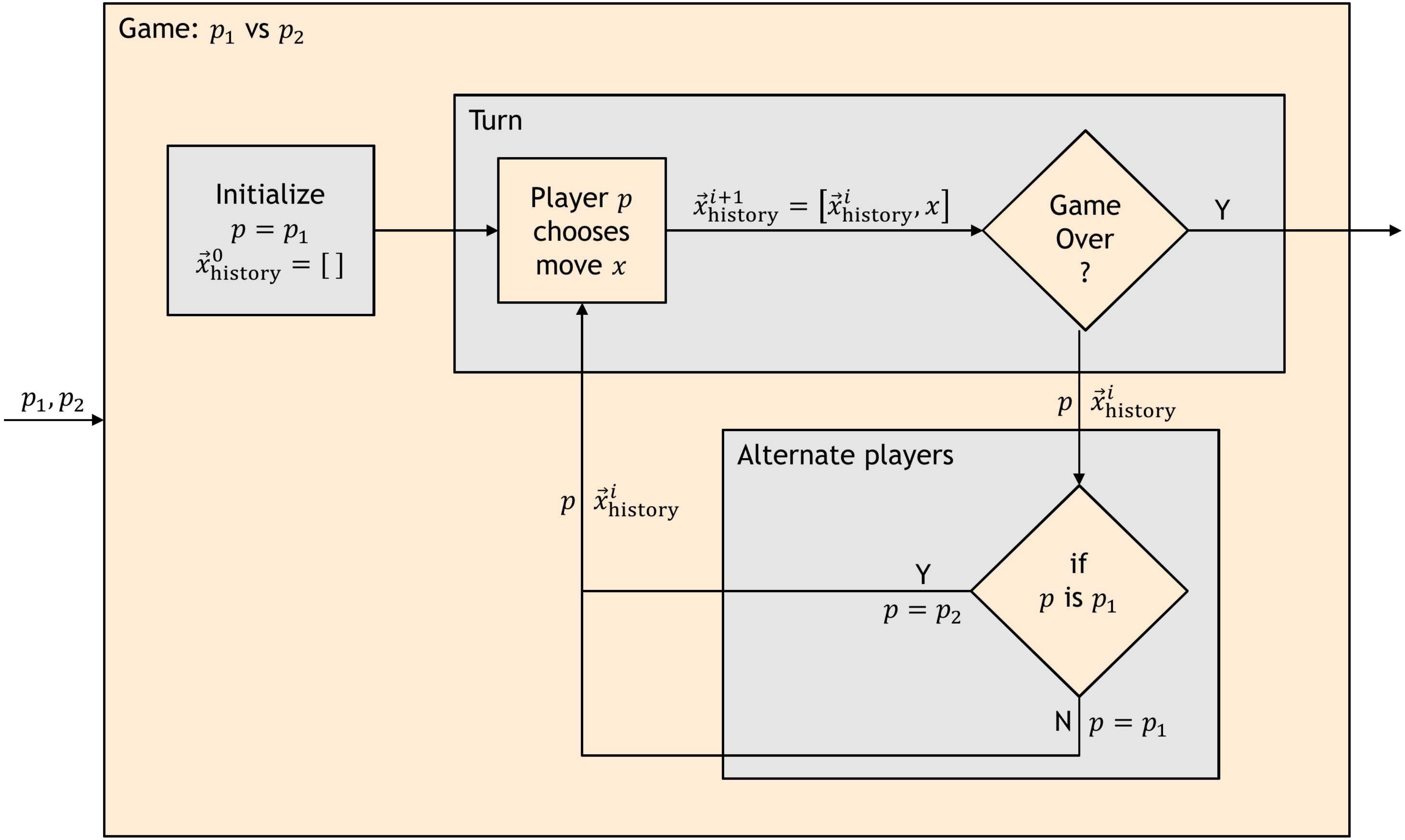


Small Grid Model

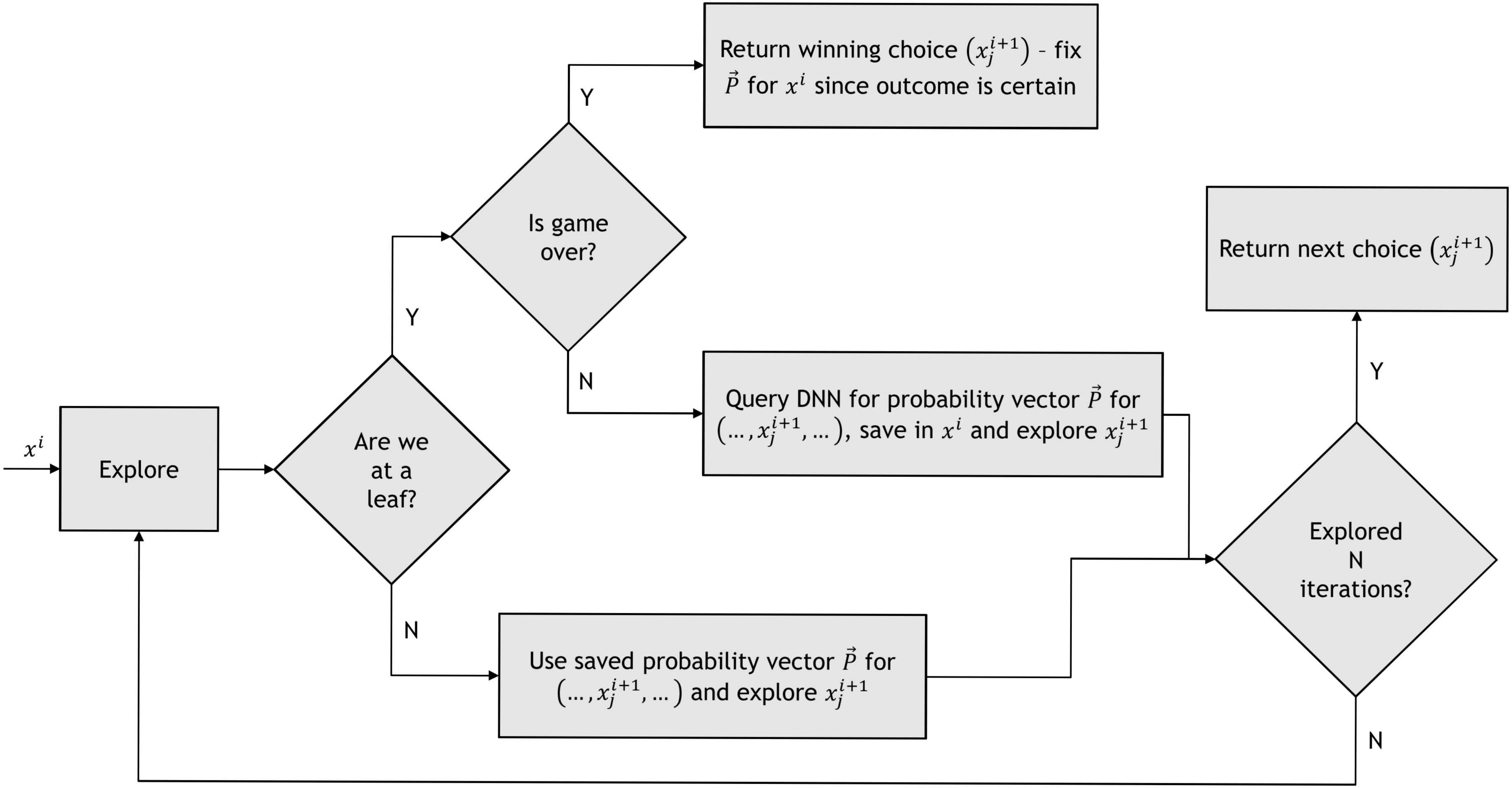
AlphaGrid Deep Neural Network Block Diagram



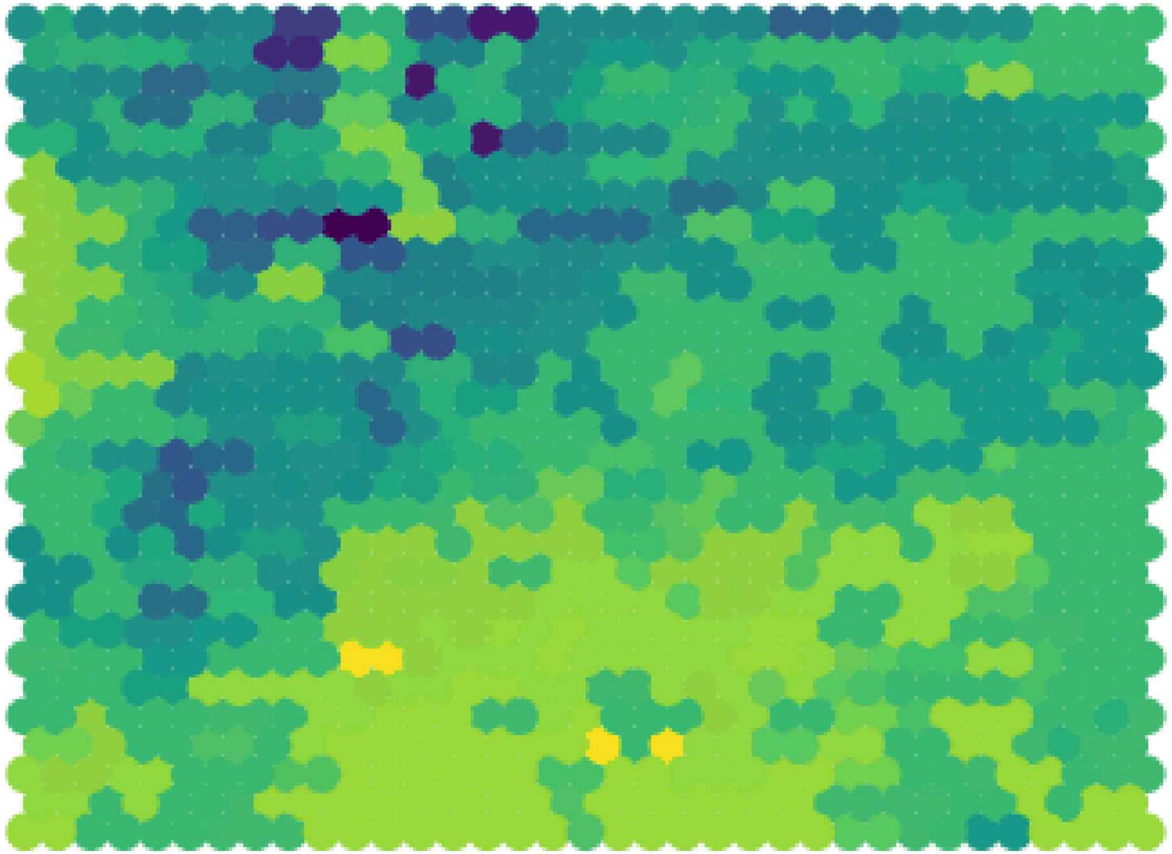
Game Play Block Diagram



Monte Carlo Tree Search (MCTS) Block Diagram (Game Play Turn)



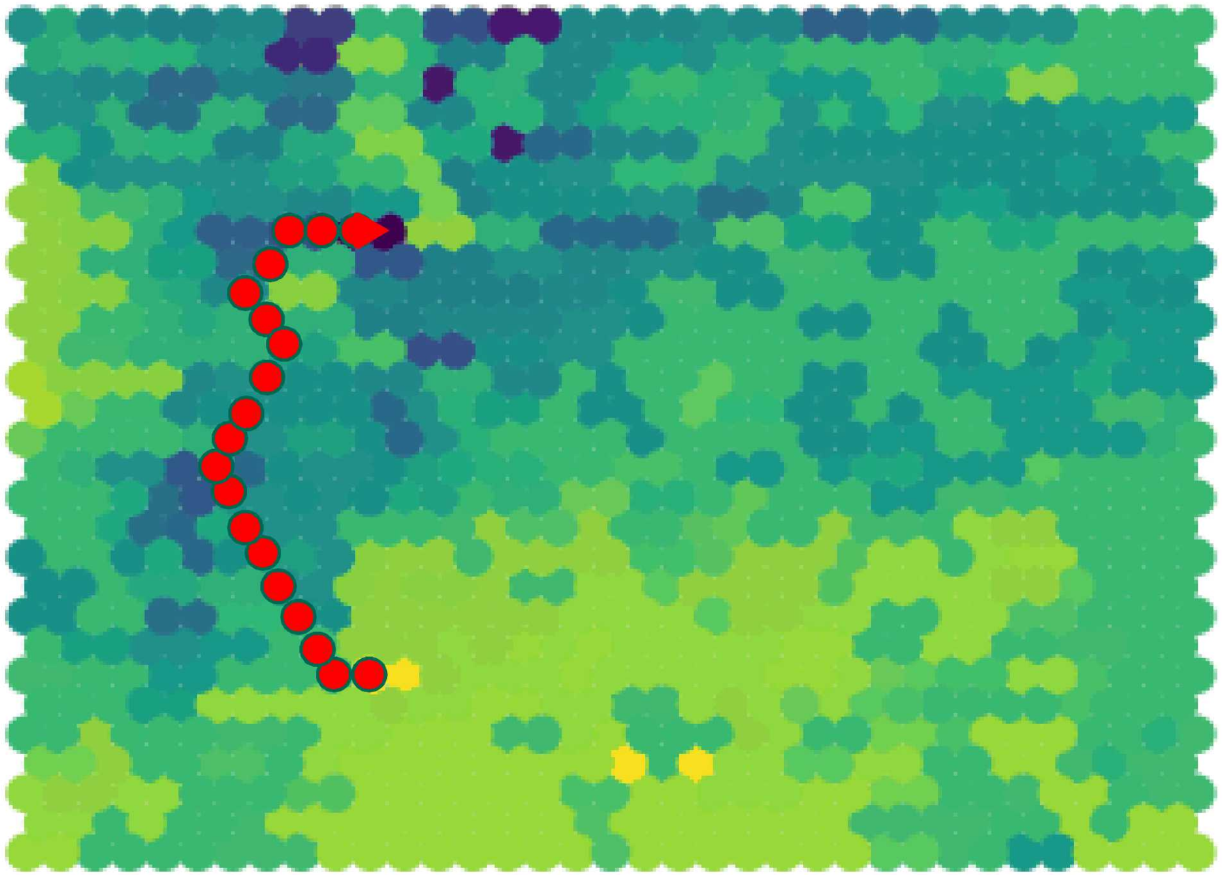
Structure (of Grid State Data) infers validity of Machine Learning Approach



15-dimensional grid state data of 1,001 precomputed points flattened onto a 2D hex grid for visualization. Light yellow represents high stability scores, dark blue represents low stability. The plot shows spatial correlation and bounded stability regions, validating a machine learning approach!

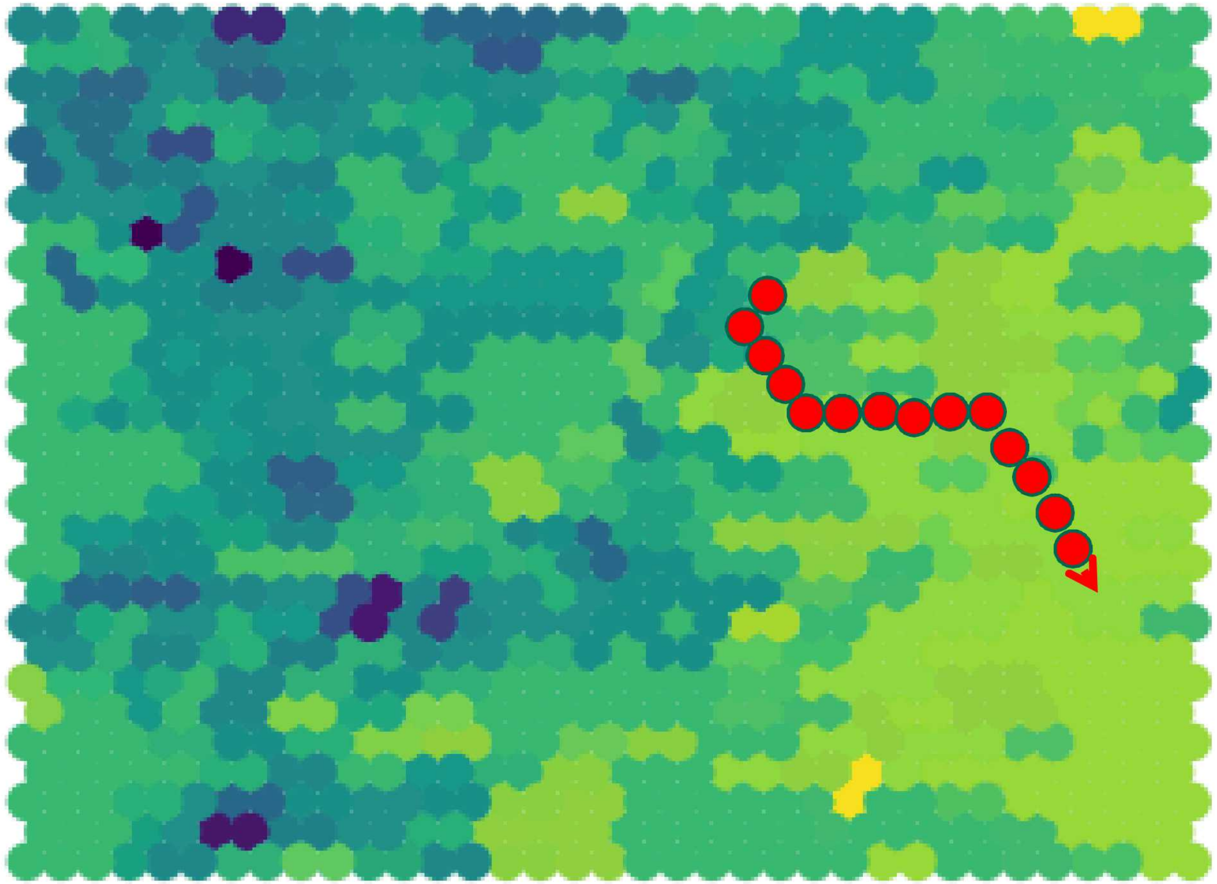
AlphaGrid – playing the game (attacker)

On its own an attacker would play a trajectory from good (yellow) to bad (blue)



AlphaGrid – playing the game (defender)

On its own a defender would not necessarily play a trajectory from bad (blue) to the nearest good (light yellow) but rather would choose good within a group of other good (yellow within a sea of yellow)



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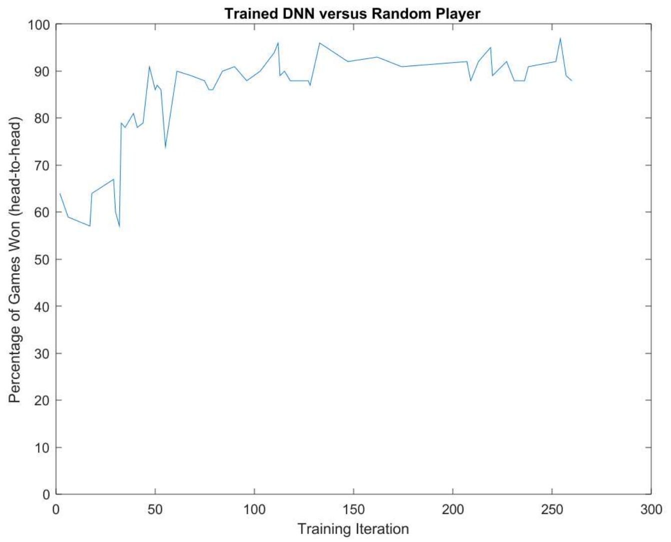
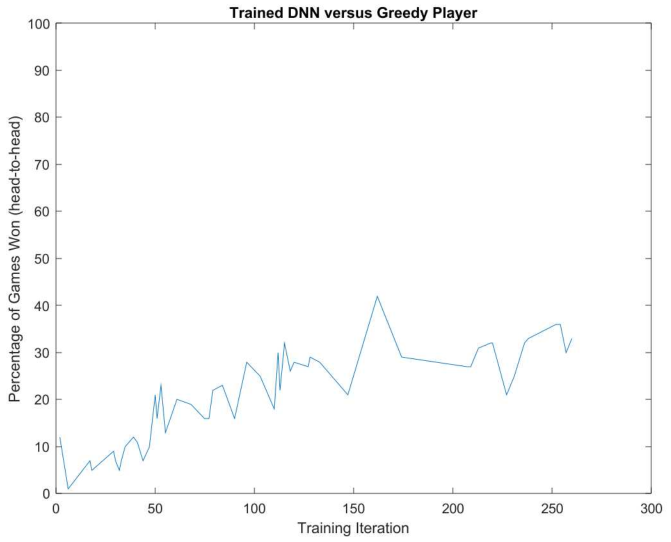
AlphaGrid Learning Results

Grid model operator comparison

- Trained vs Random – average 89.6% of the time Trained out-performs Random (in last half of training iterations)
- Trained vs Greedy – average 26.6% of the time Trained out-performs Greedy (in last half of training iterations)





Random here refers to choice of next state from current, where a random choice (without repeat) reachable from the current state is chosen

Greedy here refers to choice of next state from current, where the most stable next state reachable from the current state is always chosen

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Conclusions

- Demonstrated feasibility of approach
- Verified learning shows improvement in comparison to
  - Random state walk
  - Greedy state transition
- Just getting started

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Key Research Challenges

- Scalability of State Space Dimensions- Map reduction without losing fidelity
- DNN partitioning – Provides metadata, allowing insights into each solution (geography, type of constraint, etc)
- Modify solution from discrete space to continuous space
- Use of Transfer Learning- Allows a DNN to be trained for a specific system without starting from a blank DNN
- Management of cyclical state transitions
- Evaluation of tool across multiple scenarios- checking solution accuracy against many constraints

Project Goals for 2019

Each year a demo will be conducted, and a paper will be submitted for publication

Year 1 (2019)

- Construction and validation of a state space map at approximate control dimensionality of $\mathbb{R}^{20}$
- Demonstrate operation of the ML decision process using the reduced WECC system and perform solution verification using dynamic power system analysis.
- Start the development of state space compression methods.

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Our Team – Sandia

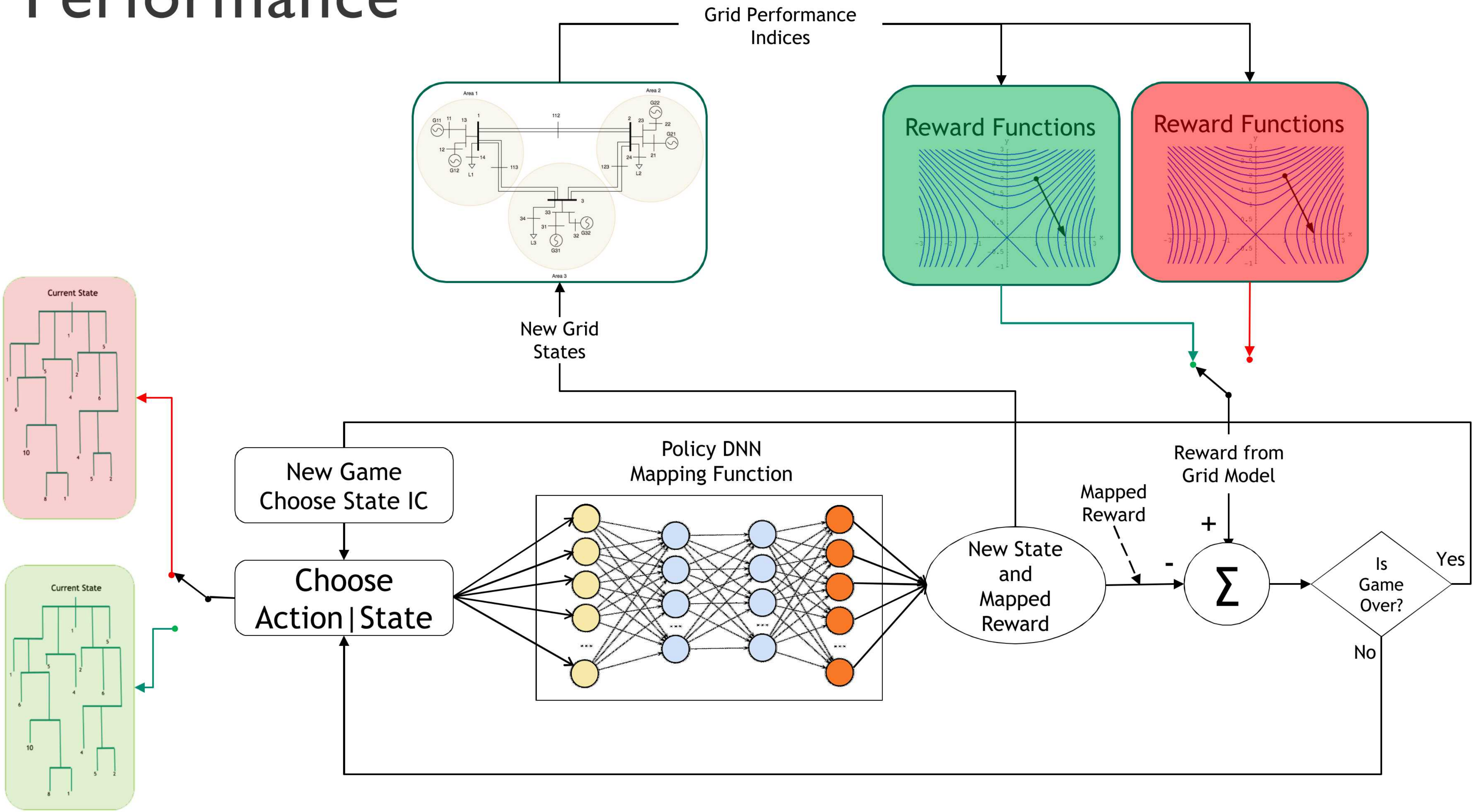
- Ross Guttromson (co-PI)
- Stephen J. Verzi (co-PI)
- Christian "Birk" Jones (grid modeling)
- Asael "Ace" Sorensen (deep reinforcement machine learning)
- Raymond "Ray" Byrne (PM)
- Charles "Charlie" Hanley (Senior Manager)

Thank You

Questions?

Backup Slides

Performance



Proposal Details (Deliverables to be Reduced by 2/3)

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Year 1

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Year 2

- Develop and apply state space compression methods.
- Exercise the tool for multiple scenarios, each requiring a sequence of stable state space transition solutions, demonstrating feasibility at approximate control dimensionality of $\mathbb{R}^{40}$
- Start investigation to increase scalability using transfer learning methods.
- Start the development of methods to implement this process in continuous space.

Year 3

- Improve scalability to approximate control dimensionality of $\mathbb{R}^{60}$
- Implement the development of continuous-space solutions
- Utilize transfer learning to train the SoCo DNN.
- Implement the DNN as partitioned blocks to yield meta-information about the solution.
- Identify the steps necessary for the deployment of a real-time operational tool.