University of Houston

Department of Electrical and Computer Engineering

PhD Dissertation Defense

System Flexibility and AI Computational Enhancement for Power System Day-Ahead Operations

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Chapter 1

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Introduction

Power Systems

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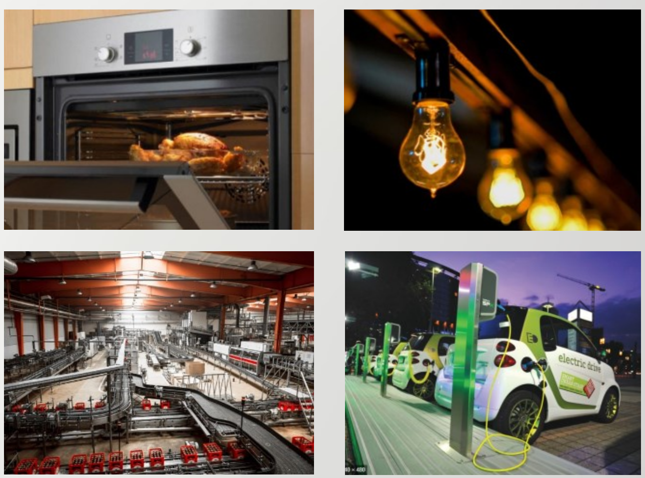
A power system is an electrical network of interconnected elements that are used to generate, transmit, and consume electric power. It contains various types of elements:

- Generators
- Loads
- Transmission lines
- Transformers
- Phase shifters
- Circuit breakers
- Shunts
- HVDC
- … …

Generation

Transmission & Distribution



Consumption

Power System Management

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- Power system management problems can be divided into a few groups based on time-scale:
  - 5-40 years: power system expansion planning
  - 1-3 years: maintenance scheduling for large equipment, long-term bilateral contracts, generation capacity commitment
  - 1 day - 1 week: maintenance scheduling for medium and small equipment; power system operational planning
  - 1 day: day-ahead scheduling (through SCUC)
  - 5-30 minutes: contingency analysis, look-ahead dispatching
  - < 1 minute: system control, frequency regulation, stability

Source: Li, Xingpeng (2022): ECE6327_SmartGrid. figshare. Online resource. https://doi.org/10.6084/m9.figshare.19761268.v1

Day-Ahead Scheduling

- Day-ahead scheduling is to determine the ON/OFF status of generators for different hourly intervals in the next operating day to meet the forecasted loads and other constraints such that the total cost is minimized.
- To efficiently operate the power system, we want least-cost solutions that maintain system security.
- In day-ahead scheduling, we solve the optimization problem: security-constrained unit commitment (SCUC).
- SCUC: MIP, MILP.
  - Binary variables are required to represent the on/off status of each unit in each time interval.

Source: Li, Xingpeng (2022): ECE6327_SmartGrid. figshare. Online resource. https://doi.org/10.6084/m9.figshare.19761268.v1

Contingency

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What is a "Contingency"?

- The loss/failure of a single element or several elements in the power system.

- Failure of a single element (*N*-1):
  - A generator contingency.
  - A branch contingency.

- In the U.S., North American Electric Reliability Corporation (NERC) requires "*N*-1".
  - *N*-1 refers to a system with *N* components, and *N*-1 is the system state with a single component out.
  - This rule states that no single outage will result in other components experiencing flow or voltage limit violations.
  - ensure the reliability of the North American bulk power systems

Preventive and Corrective Actions

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- Preventive actions are implemented in a prior sense to avoid a disturbance or contingency in the system.
  - De-rate transmission line ratings to leave excess capacity
  - Keep generators from producing at their max output
  - Reserves to handle uncertainty.

- Corrective actions are implemented after a disturbance or contingency in the system.
  - Generation re-dispatch
  - FACTS
  - Network Reconfigurations (CNR)
  - Demand Response (CDR).

Can be used both as preventive and corrective action.

Chapter 2

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System Flexibility Benefits

Overview

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Traditional approach:

- System flexibility is one-way (top-down)
- Commit more generators.

What are other forms of flexibility in the system?

- Network topology built with redundancy (Meshed structure)
- Demand flexibility through Demand response

Power System Diagram

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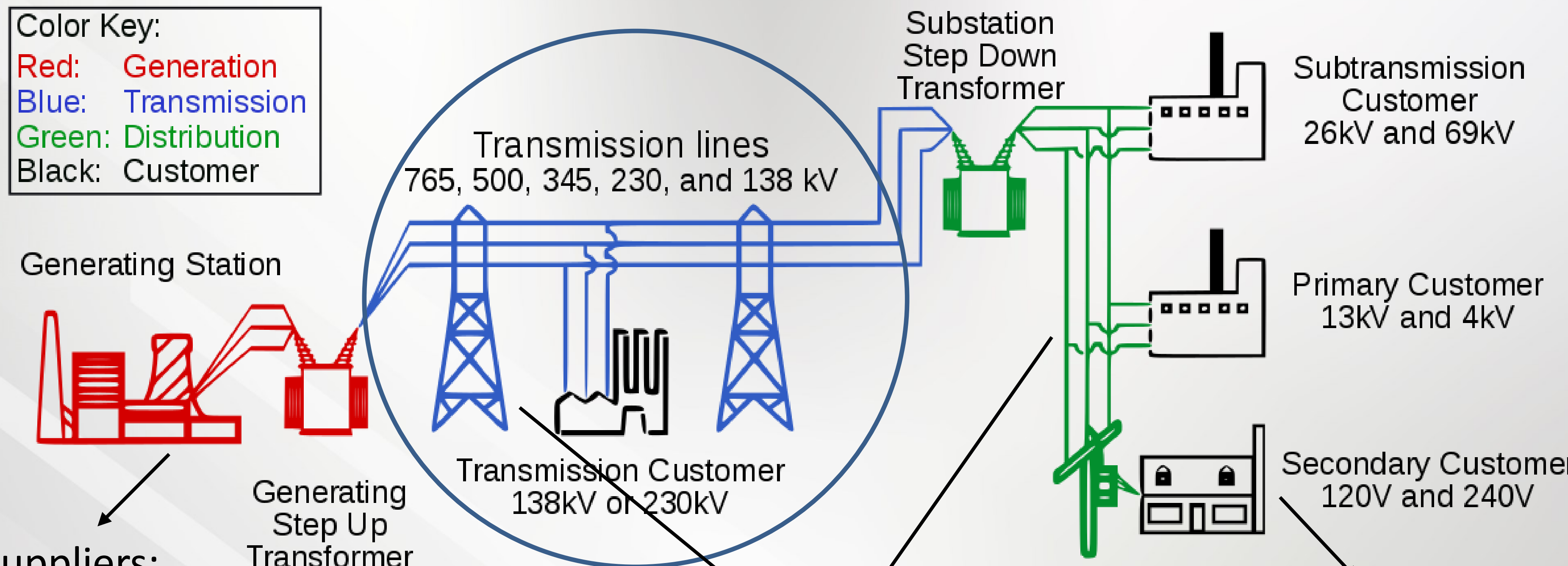

Suppliers: generators (units)

Electrical network

Customers: demands (loads)

- High-voltage transmission subsystem

Meshed network

Source: Li, Xingpeng (2022): ECE6327_SmartGrid. figshare. Online resource. https://doi.org/10.6084/m9.figshare.19761268.v1

Industrial Practice: PJM (CNR)

pjm | about pjm | training | committees & groups | planning | markets & operations | documents

- Operational Data
- Data Dictionary
- Interregional Data Map
- PJM Tools
  - Tools Information
  - System Requirements
  - PJM Security
  - Bulletin Board
  - Data Miner
  - eCredit
  - eDART
  - eData
  - eDataFeed
  - eFTR
  - eGADS
  - eLRS
  - Emergency Procedures
  - eMKT

Home ▸ Markets & Operations ▸ PJM Tools ▸ OASIS ▸ System Information ▸ Switching Solutions

Switching Solutions

The following is a list of potential transmission switching procedures identified by PJM that may assist to reduce or eliminate transmission system congestion. These identified potential transmission switching procedures may or may not be implemented by PJM based upon system conditions, either projected or actual, and ultimately are implemented solely at the discretion of PJM and its Transmission Owners. This posting is for informational purposes only. Consequently, PJM does not guarantee that any of these identified switching procedures will be included in any market-based auctions or in the real time analysis. Accordingly, PJM expressly disclaims any liability for financial consequences that a Member may incur in taking action in reliance on these informational postings.

Procedure Title	Company 1	Company 2	Action
Darrah-Tristate switching option	AEP		To control overloads on the Darrah-Tristate 138kV line, study opening the Darrah 'A' 138kV CB. If this cannot be done precontingency, issue a PCLLRW with the post contingency switching plan.
Ruth-Turner overload control	AEP		To control loading on the Ruth-Turner 138kV line, study opening the Turner "D" 138kV CB precontingency. Studies show this provides approximately 40MVA of relief. If additional relief is required, the following post contingency switching option may be available and provides ~60MVA additional relief: - @ Bradley, open the "B" CB. OR - @ Cabin Creek open "A" & "B" CB's AND @ Kanawha River open "G" CB - A PCLLRW will be required if the switching option is only available post contingency.
Ohio Central-Powelson 138kV l/o Ohio Central-Coshocton 138kV	AEP		Study opening the Philo 'D' 138kV CB. This will open end the Philo-LR Bladen 138kV line.

Source: http://www.pjm.com/markets-and-operations/etools/oasis/system-information/switching-solutions.aspx

Proposed method

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Obj: $Min \sum_{g,t} (c_g P_{gt} + c_g^{NL} u_{gt} + c_g^{SU} v_{gt})$

s.t.:

Base-case constraints

$Gen\ limits$
$Reserve\ Requirement$
$Powerflow\ constraints$
$Node\ balance$
$Hourly\ ramp\text{-}up\ and\ ramp\text{-}down\ constraints$
$Start\text{-}Up\ Constraints$
$Min\text{-}Up/Min\text{-}Down\ Constraints$

$\rightarrow d_n,\ P_{gt},\ P_{kt},\ u_{gt}, v_{gt}, r_{gt}$

Extensive formulation: Co-optimize Base-case constraints and Post-contingency constraints

Post-contingency constraints

$10\text{-}Min\ Gen\ Ramping\ for\ contingency$
$Post\text{-}contingency\ modelling\ of\ line\ flow$
$Switching\ Restriction\ (reduce\ disturbance)$
$Post\text{-}contingency\ node\ balance$

$\rightarrow P_{gct},\ r_{gct},\ P_{kct},\ z_{kct}$

Detailed formulation in appendix

IEEE 24-Bus system

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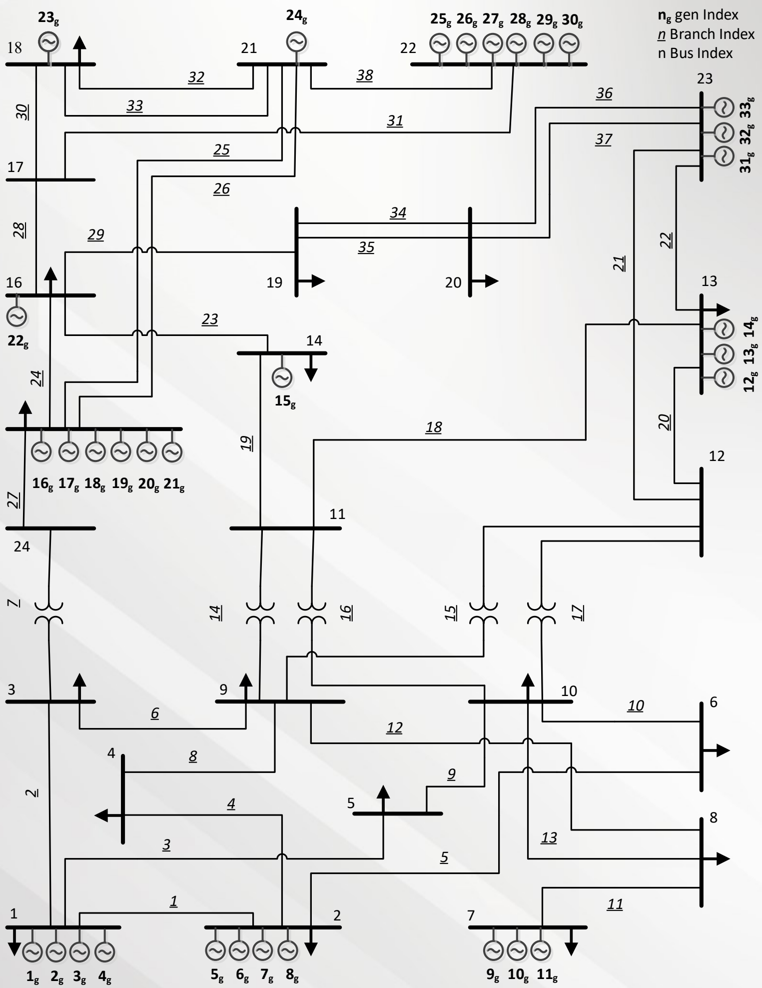

- Number of buses: 24
- Number of Lines: 38
- Number of generators: 33
- 24-hour (Day-Ahead) load period

Source: Arun Venkatesh Ramesh and Xingpeng Li, “Security-constrained Unit Commitment with Corrective Transmission Switching,” North American Power Symposium (NAPS), Wichita, KS, USA, Oct. 2019.

Results

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Total Cost benefits

	N-1 SCUC without CNR		*N*-1 SCUC with CNR	
Scenario	I	II	I	II
Cost ($)	932,911	921,812	923,995	921,812
***CC* ($)**	11,099		2,183	

$$CC = TC_{Scenario\ I} - TC_{Scenario\ II}$$

- Scenario I: regular transmission emergency rating
- Scenario II: infinite transmission emergency rating (benchmark)

- CNR results in **reduction of congestion cost by 80.33%**
- Flexibility in the network is utilized

Sample CNR actions

Outage Line	Switched OFF Line
4	31
7	34
8	5
12	37
17	31
…	…

Results

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Transmission congestion reduction

Post-contingency congested line (line number [from-bus – to-bus])	Post-contingency line outage	
	N-1 SCUC without CNR	N-1 SCUC with CNR
10 [6-10]	1 [1-2],2 [1-3],7 [3-24],8 [4-9],9 [5-10],27 [5-24]	2 [1-3]
23 [14-16]	7 [3-24], 18 [11-13],21 [12-13],22 [13-23],27 [5-24]	7 [3-24]

- Line 10 and Line 23 are susceptible to post-contingency congestion
- 6 contingencies lead to Line 10 congestion and 5 Contingencies lead to Line 23 congestion when CNR was not implemented.
- **With CNR:**
  - Scenarios leading to post-contingency congestion were reduced.
  - **Line overload reduction of 4% and 24%** in Line 10 and Line 23 respectively.

Chapter 2: Summary

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- SCUC-CNR utilizes the available system flexibility to meet high demand profiles.
- CNR resulted in fewer line congestion and substantially reduces congestion cost.
- CNR offers total cost savings due to alleviation of system congestion.

List of Publications:

1. **Arun Venkatesh Ramesh** and Xingpeng Li, "Security-constrained Unit Commitment with Corrective Transmission Switching," *North American Power Symposium (NAPS)*, Wichita, KS, USA, Oct. 2019.
2. **Arun Venkatesh Ramesh** and Xingpeng Li, "Enhancing System Flexibility through Corrective Demand Response in Security-Constrained Unit Commitment" *North American Power Symposium*, Tempe, AZ, USA, April 2021.

Chapter 3

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Multi-Scenario Stochastic Approach to facilitate Renewable Energy Sources

Part a: Renewable Energy Integration (RES)

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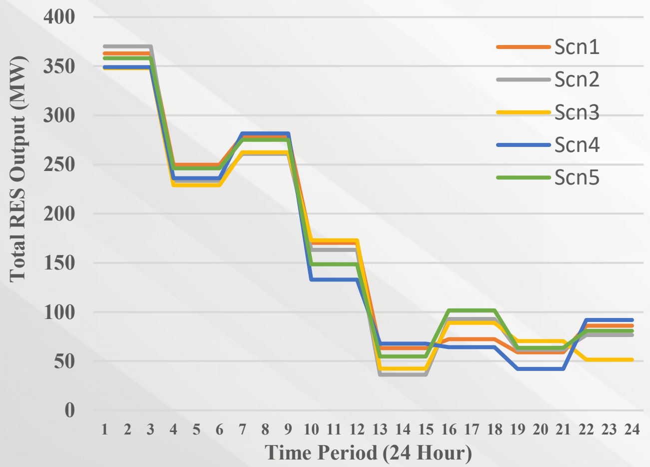
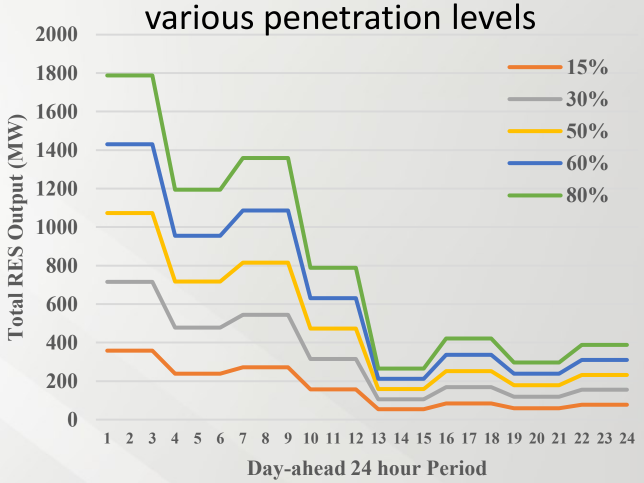
$$Min: \sum_{g,t}\left(c_g^{NL} u_{g,t} + c_g^{SU} v_{g,t} + \sum_s\left(\pi_s c_g P_{g,t,s}\right)\right) + \sum_{w,c,t,s}\left(\pi_s c_w^{pen}\left(P_w^{max} - P_{w,c,t,s}\right)\right)$$

- Increased participation of RES to address climate issues requires better algorithm for integration in the system.
- Stochastic approach for multi-scenario Renewable Energy Sources (RES): SSCUC-CNR(C)
  - Commitment is common for all scenarios but dispatch can vary.

Total renewable generation for each scenario



Average system-wide RES generation for various penetration levels



Part a: Results

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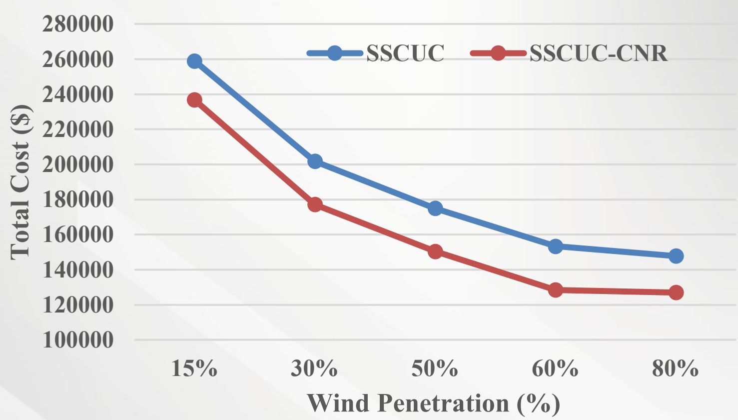
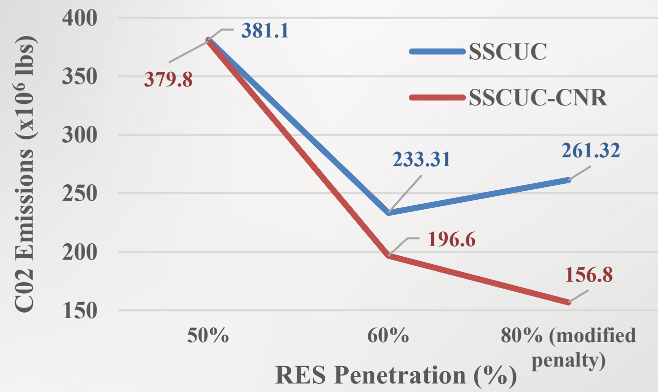
Total cost benefits



CO_2 emission benefits



- SSCUC-CNR utilizes transmission flexibility to attain lower total cost for varying RES penetration.
- Higher penetration reduces cost.

- Increasing RES penetration results in lower CO_2 emissions.
- Congestion-induced RES curtailment in SSCUC leads to increased emissions.
- SSCUC-CNR leads to lower emissions compared to SSCUC.

Part b: Background

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- Energy storage system (ESS) are utilized to address the intermittent nature of RES. But ESS may also be distributed in the system.
- Due to favorable location for RES, limited transmission availability and transmission congestion can lead to the free RES output curtailment, or it cannot be stored in ESS.
- Network Flexibility through topology reconfiguration can alleviate these issues.
- Technology: We propose a multi-scenario *N*-1 Stochastic-SCUC (SSCUC) solution integrating RES supported by ESS while considering Preventive Network Reconfiguration (P) and/or Corrective Network Reconfiguration (C) to achieve significant system flexibility.
- Study: Four models were compared; SSCUC, SSCUC-P, SSCUC-C, SSCUC-PC

Part b: Results – Cost studies

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System Cost Studies

	SSCUC	SSCUC-PNR(P)	SSCUC-CNR(C)	SSCUC-PNR+CNR(PC)
Total Cost ($)	161,340	154,835	158,400	148,231
Solve time (s)	82.09	260.36	561.67	2500 (Timeout)
Avg. RES Curtailed (MW)	208	68.25	172.25	45.5

- The transmission flexibility through Preventive and/or Corrective Network reconfiguration results in significant economic benefits over Traditional SSCUC.
- SSCUC-P results in greater transmission flexibility than SSCUC-C. However, SSCUC-PC leads to maximum system flexibility benefits due to increase in total feasibility region.
- Mainly, SSCUC-P, SSCUC-C and SSCUC-PC results in alleviation of congestion cost of $ 6,505, $ 2,940 and $ 13,109 over SSCUC, respectively.

Chapter 3: Summary

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- Network congestion can still lead to RES curtailment and inefficient use of ESS.
- The cost studies demonstrate substantial cost saving by reducing network congestion and utilizing additional free RES output through NR.
- NR strategies, particularly CNR, leads to lower carbon emissions.
- Few reconfiguration strategies are key to addressing system congestion => leveraged for scalability to large power systems.

List of Publications:

1. **Arun Venkatesh Ramesh** and Xingpeng Li, "Reducing Congestion-Induced Renewable Curtailment with Corrective Network Reconfiguration in Day-Ahead Scheduling," *IEEE PES General Meeting*, Montreal, Canada, Aug. 2020.
2. **Arun Venkatesh Ramesh** and Xingpeng Li, "Network Reconfiguration Impact on Renewable Energy System and Energy Storage System in Day-Ahead Scheduling" *IEEE PES General Meeting*, Washington, DC, USA, July 2021.

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Computational Improvement: Decomposition of SCUC and SCUC-CNR

Issues: Scalability

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IEEE 73-Bus system solution

MIPGAP=0.01	SCUC	SCUC	SCUC-CNR
Total cost ($)	3,224,459	3,224,459	NA
Solve time (s)	12,856	7,743	100,000
Feasibility	Feasible	Feasible	TimeOut
Starting point	No	Yes	Yes

- Original SCUC problem is too complex.
- Addition of N-1 contingency makes the solution more constrained.
- No feasible solution for SCUC-CNR.

Computational Challenges

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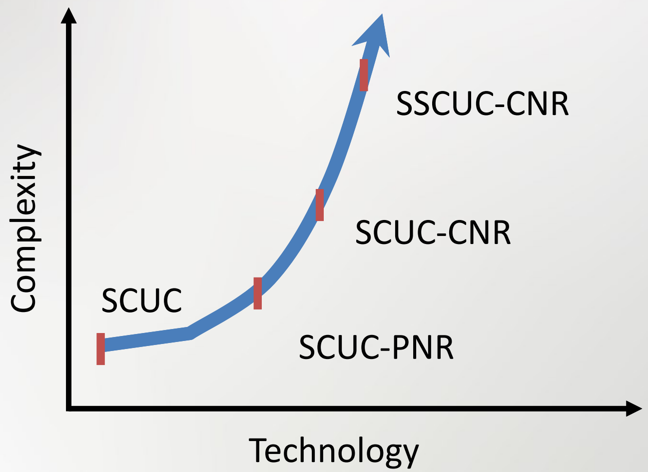
- Day-ahead scheduling is performed daily.
- SCUC is a large-scale MILP problem for practical systems.
- Challenges:
  - Computational complex
  - Hard to solve
  - Limited computing time



- How to speed up the MILP problems?
- Decompose the MILP problem in two types (or sets) of smaller problems

Remedy 1: Accelerated Benders' Decomposition (A-SCUC-CNR)

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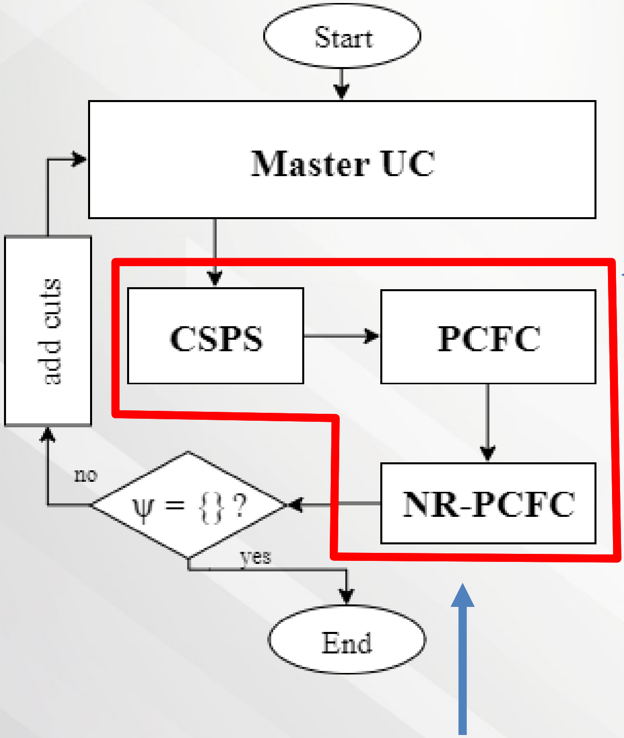

A-SCUC-CNR:

- Accelerated Benders' decomposition algorithm considering three different types of system feasibility check sub-problems.

Steps for checking whether system is feasible under a given contingency:

- Check CSPS: if system is infeasible, go to PCFC;
- Check PCFC: if system is infeasible, go to NR-PCFC;
- Check NR-PCFC: if system is infeasible, add a feasibility cut per PCFC to Master-UC and move on to the next contingency.

Sub-problem (contingency scenario) feasibility check:

- **CSPS:** check system feasibility **with NO adjustment**.
- **PCFC:** Check system feasibility **using unit dispatch only**.
- **NR-PCFC:** Check system feasibility **using unit dispatch and CNR**.

Results

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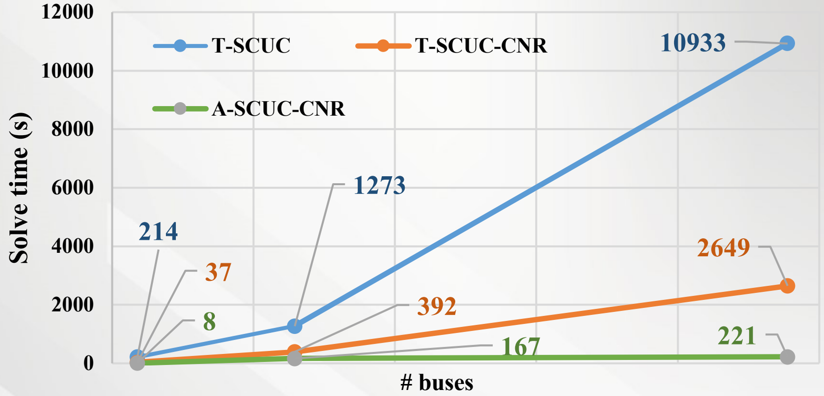
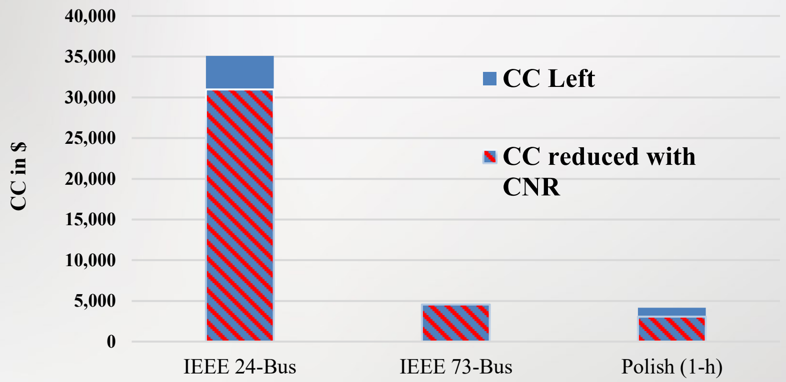
Algorithm solve time for various systems (24-bus, 73-Bus and Polish 1-h)



Congestion cost (CC) elimination



- Previously *N*-1 SCUC for IEEE 73-Bus system required ~7000 secs with warm start now takes only 1273 secs using T-SCUC.
- Addition of technologies such as CNR increases computational efficiency. T-SCUC-CNR is faster than T-SCUC.
- Heuristics bring additional time savings and is more significant in larger systems. (around 90%).

Results: Scalability

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Advantages:

- Scalability to large Power systems networks.
- Significant solve time reduction while maintaining same solution quality.
- Accelerations through CSPS achieves 90% reduction in solve time and increases problem scalability.
- A good starting solution can speed up the algorithm further.

Results of Polish system for 24-hour period

Parameters	T-SCUC-CNR	A-SCUC-CNR
Total Cost ($)	5,335,330	5,335,330
Time (s)	59,473.1	6,257.32
MIPGAP	0.1175%	0.1175%
Iterations	2	2
# of cuts	192	192

- Number of buses: 2383
- Number of Lines: 2895
- Number of generators: 327
- Number of periods: 24 (day-ahead)

Chapter 4: Summary

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- System flexibility can bring cost savings and increase system reliability.
- Additional complexities when introducing new constraints associated with transmission flexibility.
- Optimization based computational enhancement techniques with heuristics can address scalability for larger power systems.
- Proposed method performs better as complexity of the system and outperforms decomposed SCUC.

List of Publications:

1. **Arun Venkatesh Ramesh**, Xingpeng Li and Kory Hedman, "An Accelerated-Decomposition Approach for Security-Constrained Unit Commitment with Corrective Network Reconfiguration", in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2021.3098771.

Chapter 5

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Computational Benefit: Machine Learning aided approach to SCUC

Remedy 2: Machine Learning Approach

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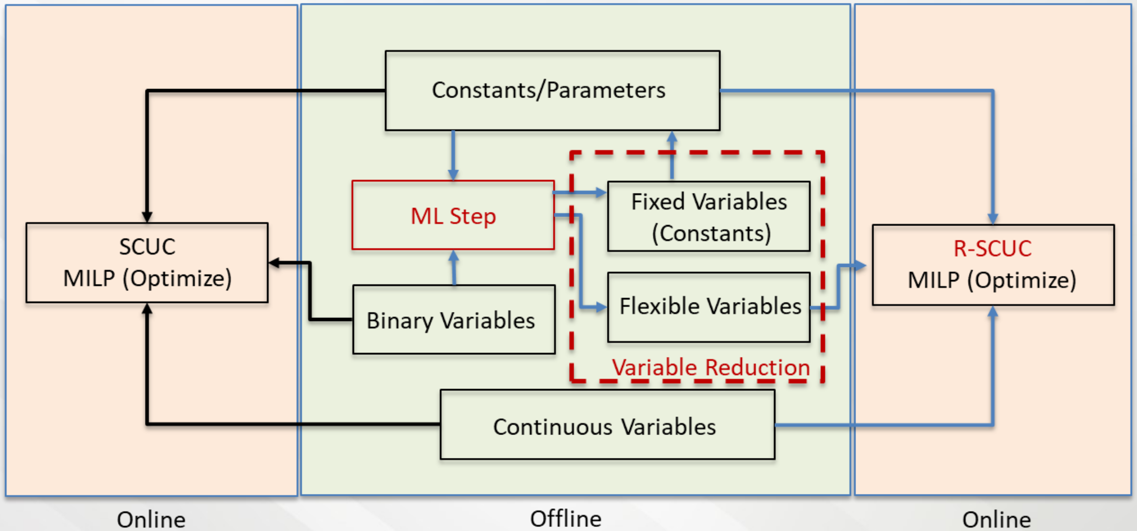
- One solution: machine learning-assisted SCUC.
  - Provide the **partial solution**.
  - Pre-determine a **subset of binary variables**.
  - **Reduce** the problem size of SCUC.



Remedy 2: Machine Learning

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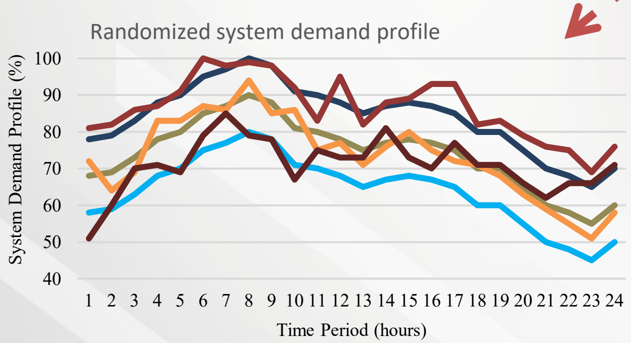
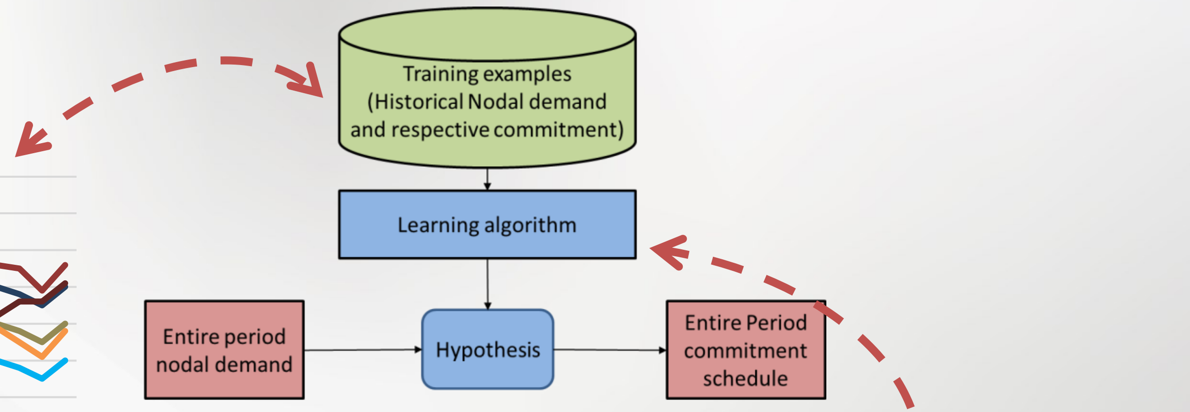
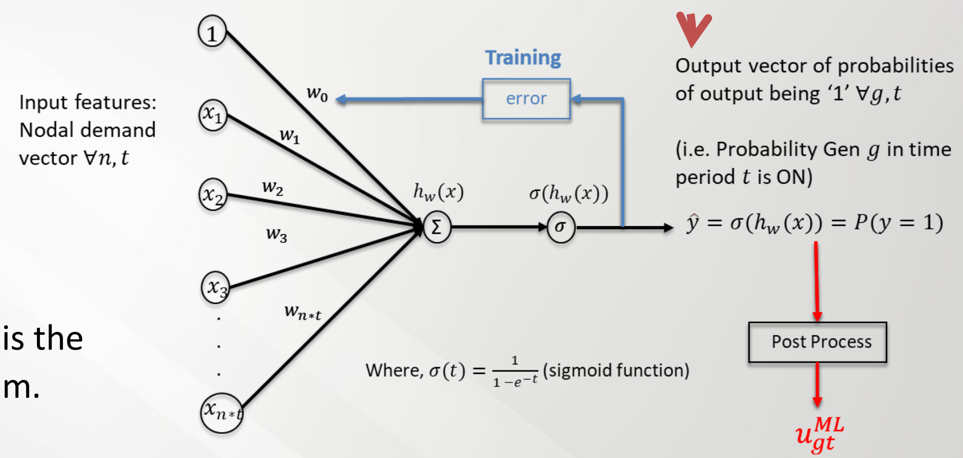
How?

- A supervised learning algorithm trained using historical commitment schedules and provide a predicted commitment schedule.







How is accuracy calculated?

Accuracy = 100 - np.mean(np.abs($u_{gt} - \widetilde{u_{gt}}$)) * 100)

where, u_{gt} is the actual optimum solutions and $\widetilde{u_{gt}}$ is the predicted values from the machine learning algorithm.

Part a:
Basic SCUC Model

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Objective function

$$min \sum_{g\in G} \sum_{t\in T} (c_g P_{gt} + c_g^{NL} u_{gt} + c_g^{SU} v_{gt})$$

Constraints

Gen supply limits:

$$P_g^{min} u_{gt} \le P_{gt} \le P_g^{max} u_{gt} \quad \forall g, t$$

Powerflow constraints:

$$P_{kt} = \theta_{kt}/x_k \quad \forall k, t$$

$$-P_k^{max} \le P_{kt} \le P_k^{max} \quad \forall k, t$$

Gen Hr requiremen:

$$-R_g^{hr} \le P_{gt} - P_{g,t-1} \le R_g^{hr} \quad \forall g, t$$

Node balance:

$$\sum_{g\in G(n)} P_{gt} + \sum_{k\in K(n-)} P_{kt} - \sum_{k\in K(n+)} P_{kt} = d_{nt} \quad \forall n, t$$

Binary Constraints:

$$v_{gt} \in \{0,1\} \quad \forall g, t$$

$$u_{gt} \in \{0,1\} \quad \forall g, t$$

$$v_{gt} \ge u_{gt} - u_{g,t-1} \quad \forall g, t$$

Minimum on/off Constraints: **(Ignored)**

$$\cancel{\sum_{w=t+1}^{t+DT_g} v_{gw} \le 1 - u_{gt} \quad \forall g, t \le nT - DT_g}$$

$$\cancel{\sum_{w=t-UT_g+1}^{t} v_{gw} \le u_{gt} \quad \forall g, t \ge UT_g}$$

Part a: Case Studies and Results

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- 5 Test systems of various sizes were considered.
- Data was generated for all models using the SCUC model.
- ML model was trained for each system separately.

Test Systems

System	Gen Capacity (MW)	# bus	#gen	# branch
IEEE 24-Bus System	3,393	24	33	38
IEEE 73-Bus System	10,215	73	99	117
IEEE 118-Bus System	5,859	118	54	186
Synthetic South Carolina Grid 500 Bus	12,189	500	90	597
Polish System-2383 Bus	30,053	2,383	327	2,895

Summary of ML Results

# Buses	Number of Samples			Accuracy (%)		Training time (min)
	Total	Train	Test	Train	Test	
24	1,446	1,157	289	98.97	98.96	<1
73	1,391	1,113	278	96.89	96.88	~8
118	1,500	1,200	300	93.61	93.53	~5
500	1,499	1,200	299	98.56	98.51	~17
2383	1,200	960	240	95.94	95.86	~85

How is accuracy calculated?

$$\text{Acc} = 1 - \frac{1}{m*N_g*N_t}\sum_{i=1}^{m}\left(\sum_{g\in G}\sum_{t\in T}\left|u_{i,g,t} - u_{i,g,t}^{ML}\right|\right)$$

*where, $u_{i,g,t}$ is the actual optimum solutions and $u_{i,g,t}^{ML}$ is the predicted values from the machine learning algorithm.

Part a: Solution Procedures

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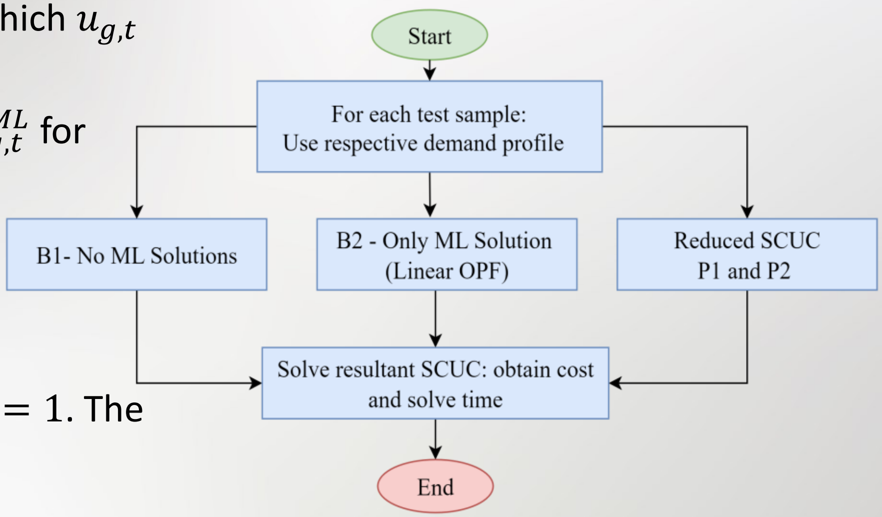
Benchmark methods:

- **B1: SCUC** that **does not utilize any ML outputs** $u_{g,t}^{ML}$, in which $u_{g,t}$ is solved only through MILP
- **B2: R-SCUC (Linear problem – OPF),** where Fix $u_{g,t} = u_{g,t}^{ML}$ for each g and t in R-SCUC.

Verification



Proposed Methods:

- **P1: R-SCUC (fix On units only),** where fix $u_{g,t} = 1$ if $u_{g,t}^{ML} = 1$. The warm-start uses $u_{g,t} = 0$ if $u_{g,t}^{ML} = 0$.
- **P2: R-SCUC (fix always-on/off units only),** where "always ON/OFF" generators are identified and fix their status in R-SCUC.

For each testing sample (grid profile), if a generator g is predicted to be always ON in 24-hour period then fix $u_{g,t} = 1$ for the entire 24-hour period for the corresponding generator. Similarly, if generator g is always OFF in 24-hour period, then fix $u_{g,t} = 0$ for all periods for the corresponding generator. For all other generators, use warm-start $u_{g,t} = u_{g,t}^{ML}$.

Part a: Verification Results

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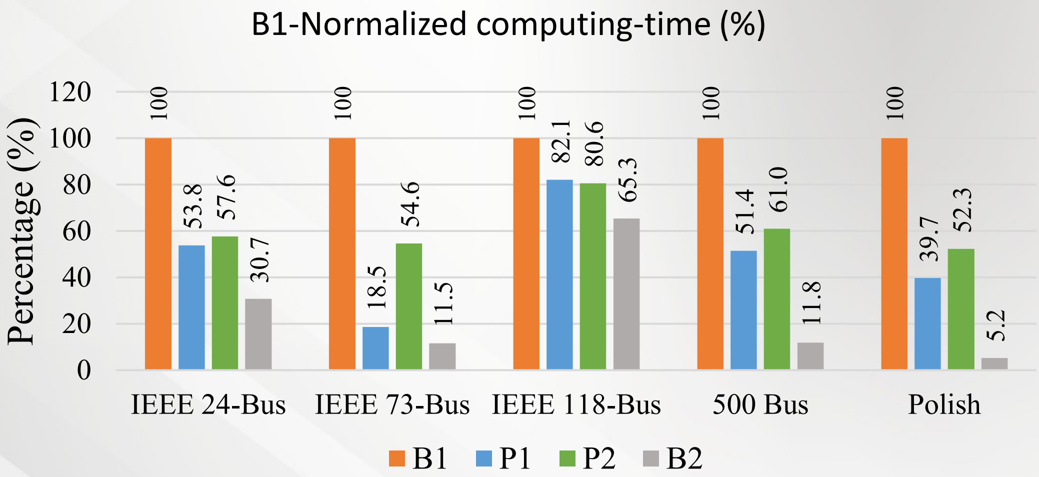

- B1: SCUC (No ML)
- B2: R-SCUC (OPF)
- P1: R-SCUC (fix On-unit only)
- P2: R-SCUC (always ON/OFF)

- Not all samples of B2 are feasible even though the accuracy is >93%.
- On average the infeasibility of test samples is ~30% for B2 across all test systems.

- Procedure can be utilized for any type of formulations (deterministic/stochastic/heuristic ect).
- ML cannot directly replace the optimization procedure from *B2* since this lead to infeasible problems. B2 results in 95% computational time saved.
- The proposed post-processing techniques, *P1* (fix On-unit only) and *P2* (Always ON/OFF), effectively utilize the ML predicted outputs without infeasibility.
- Selective use of ML solutions that are high confidence are used to reduce the variables in SCUC.
- *P1* and *P2* result in time savings of 50.9% and 38.8%, respectively, on average across all the test systems while also resulting in high-quality solutions.

Part b: Generator Minimum On/Off Time Limits

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- Generator minimum on/off time limits are ignored so far.

Temporal Constraints

$$\sum_{w=t+1}^{t+DT_g} v_{gw} \leq 1 - u_{gt} \quad \forall g, t \leq nT - DT_g$$

$$\sum_{w=t-UT_g+1}^{t} v_{gw} \leq u_{gt} \quad \forall g, t \geq UT_g$$

- Note: Regenerate data for the new SCUC model.

- Now, consider such practical constraints.
  - More infeasible cases for R-SCUC even for *P1* (fix On-unit only) and *P2* (Always ON/OFF).
  - Develop a Feasibility Layer (FL)
    - A small optimization model: minimize change in $u_{g,t}^{ML}$.
    - Adjust $u_{g,t}^{ML}$ if minimum on/off time limits are violated.

Updated Machine Learning Procedure

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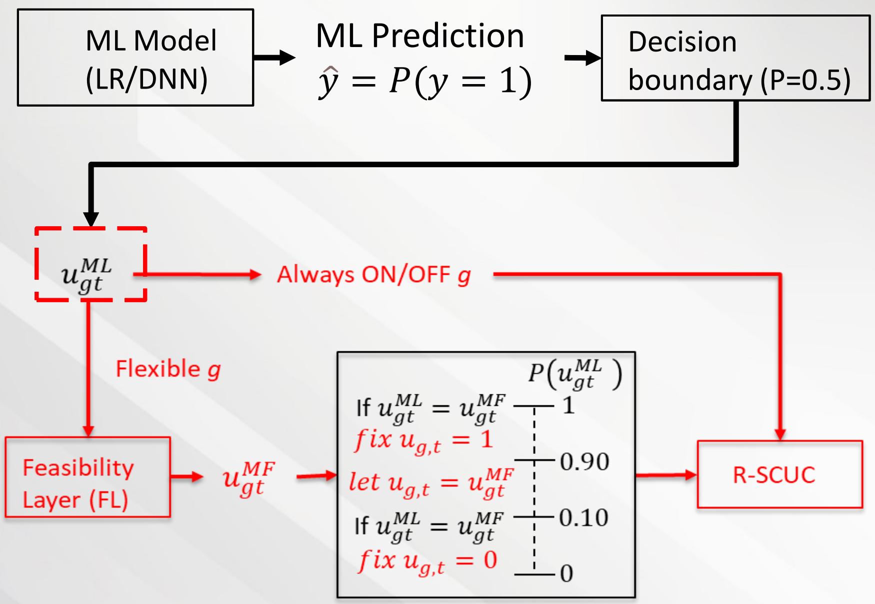

- Identify two sets of generators for each sample of 24 Hour period:
    - Always ON/OFF: generators that show only one pattern.
    - Flexible: genertors that have turn on and off.
- Introduce a Feasibility layer (FL) to verify temporal constraints.
- Only reduce variables that confirm with FL, otherwise let optimization figure solution online.

Part b: Verification Results

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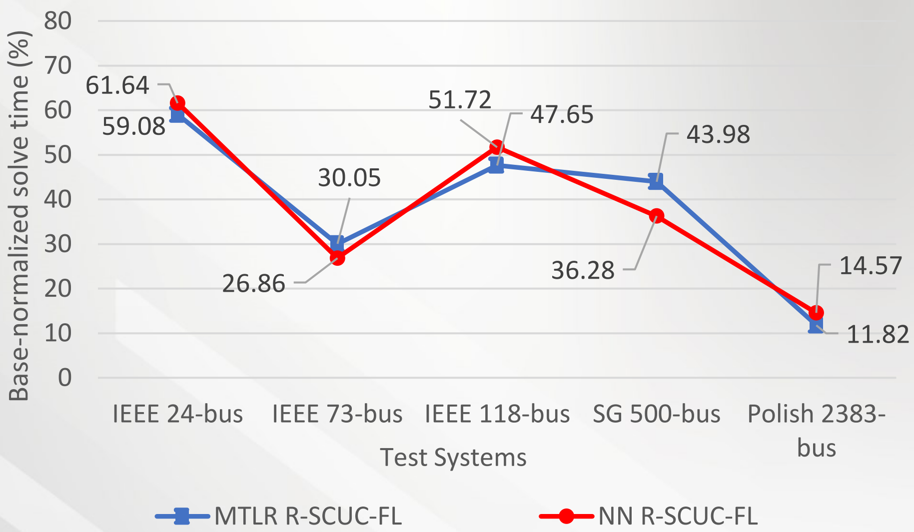

- On average across all test systems, model reductions with the proposed MTLR R-SCUC FL and NN R-SCUC-FL resulted in a speed-up 3.6x and 3.4x, respectively, when compared with SCUC.
- All test problems were feasible due to FL.
- Solution quality maintained well within MIPGAP.

Elimination of infeasible problems/percentage by FL

System	IEEE 24-Bus	IEEE 73-Bus	IEEE 118-Bus	SG 500-Bus	Polish 2383-Bus
NN	28 (100%)	18 (100%)	4 (100%)	32 (100%)	6 (100%)
LR	4 (100%)	6 (100%)	0 (N/A)	8 (100%)	4 (100%)

Chapter 5: Summary

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- Machine Learning with historical information and post-processing techniques can provide high quality solutions while ensuring problem size reduction.
- Procedure can be utilized for any type of formulations (deterministic/stochastic/heuristic ect).
- Problem-size reduction results in significant computational time-savings.
- Feasibility layer eliminates all infeasible problems.

List of Publications:

1. **Arun Venkatesh Ramesh** and Xingpeng Li, “Machine Learning Assisted Model Reduction for Security-Constrained Unit Commitment”, *North American Power Symposium,* Salt Lake, UT.
2. **Arun Venkatesh Ramesh** and Xingpeng Li, ““Feasibility Layer Aided Machine Learning Approach for Day-Ahead Operations”, *IEEE Transactions in Power Systems.* (Under 2nd Review).

List of Publications

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1. **Arun Venkatesh Ramesh** and Xingpeng Li, "Machine Learning Assisted Model Reduction for Security-Constrained Unit Commitment", *North American Power Symposium,* Salt Lake, UT.
2. **Arun Venkatesh Ramesh** and Xingpeng Li, ""Feasibility Layer Aided Machine Learning Approach for Day-Ahead Operations", *IEEE Transactions in Power Systems.* (Under 2nd Review).
3. **Arun Venkatesh Ramesh** and Xingpend Li, "Spatio-Temporal AI Approach for Variable and Constraint Reduction in Security-Constrained Unit Commitment ", *IEEE Transactions in Power Systems.* (Journal manuscript under preparation).

Chapter 6

Conclusions and Future Work

Advanced ML models (Spatio-temporal)

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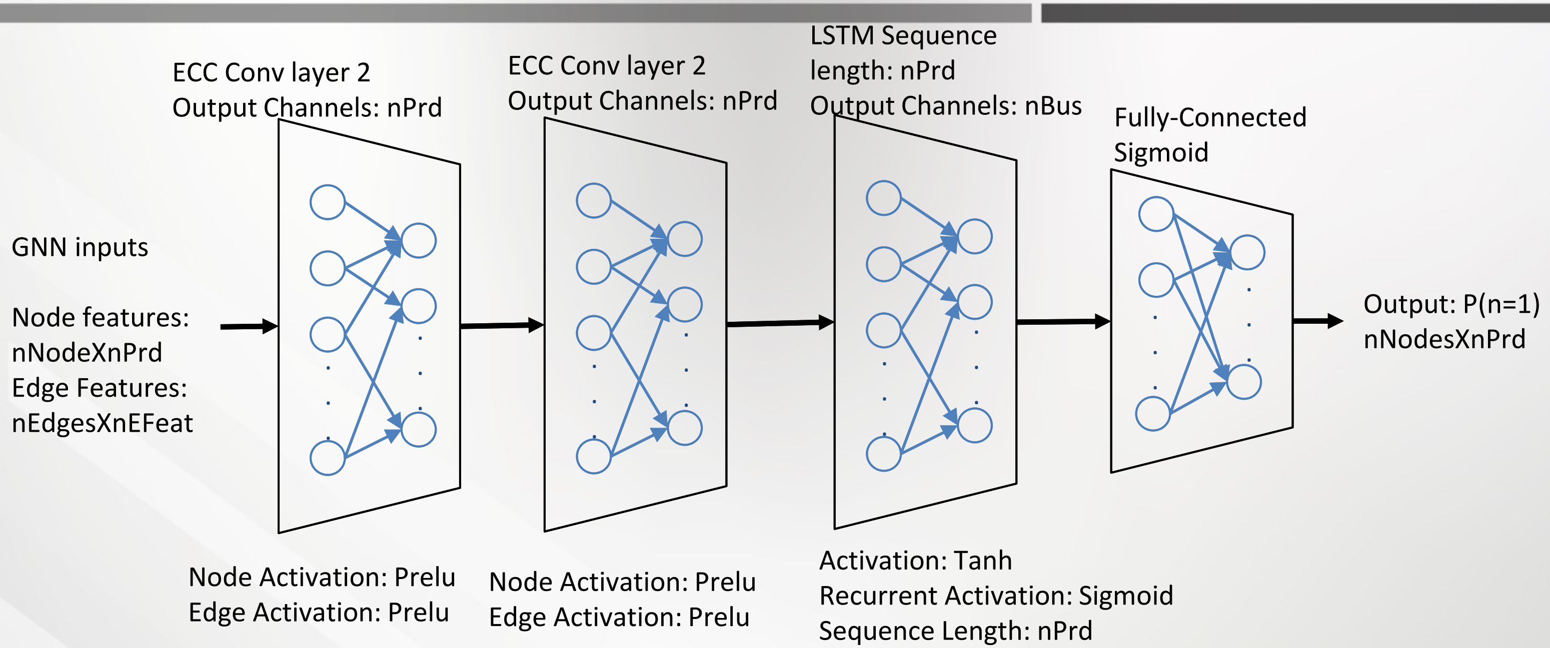

- Graph neural networks (GNN) for a spatial understanding of data.
- A dynamic Edge conditioned convolution (ECC) layer is utilized as the GNN layer.
- Each GNN layer provides a node embedding w.r.t adjacent nodes and edges.
- Output of node embedding is fed to Long Short-Term Memory (LSTM) layer for 24 Periods.

Preliminary Results

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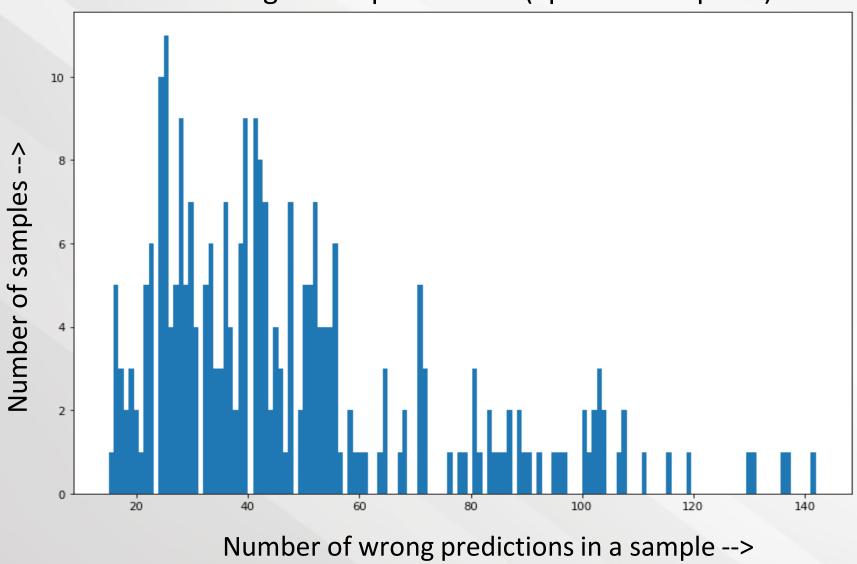
Training Summary

Model	System	Train Acc	Val Acc	Test Acc
Spatio-Temporal	IEEE 24-Bus	98.31 % (↑ 1.15%)	99.50 %	98.40 % (↑ 1.39%)
Deep-NN	IEEE 24-Bus	97.16 %	NA	97.01 %
Spatio-Temporal	IEEE 73-Bus	97.04 % (↑ 1.22%)	97.34 %	97.24 % (↑ 1.59%)
Deep-NN	IEEE 73-Bus	95.82 %	NA	95.65 %
Spatio-Temporal	IEEE 118-Bus	98.96 % (↑ 1.13%)	99.44 %	98.99 % (↑ 1.37%)
Deep-NN	IEEE 118-Bus	97.83 %	NA	97.62 %
Spatio-Temporal	SG 500-Bus	99.80 % (↑ 0.74%)	99.81 %	99.79 % (↑ 0.75%)
Deep-NN	SG 500-Bus	99.06 %	NA	99.04 %

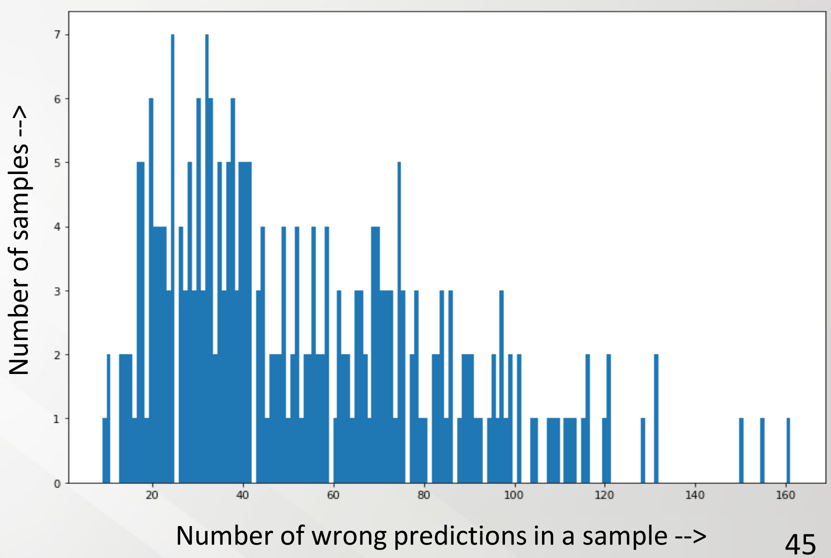
- Spatio-Temporal model learns the relationship better compared to Deep-NN (DNN).
- Accuracy 0.75-1.6% increase means that many flexible generators that were hard to identify in NN are realized well by a spatio-temporal approach.

IEEE 73-Bus system

Histogram of predictions (Spatio-Temoporal)



Histogram of predictions (Deep-NN)



Verification

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System/Model	Infeasible cases	Avg Base Norm Cost (%)	Avg Base Norm Time saved (%)
IEEE 24-Bus/DNN R-SCUC	0	0	3.92
IEEE 24-Bus/ST R-SCUC	0	0.024	34.29
IEEE 73-Bus/DNN R-SCUC	7	0.12	50.83
IEEE 73-Bus/ST R-SCUC	0	0.034	44.23
IEEE 118-Bus/DNN R-SCUC	4	0.28	38.72
IEEE 118-Bus/ST-SCUC	0	0.001	36.29
SC 500-Bus/DNN R-SCUC	13	0.13	63.72
SC 500-Bus/ST R-SCUC	0	0.062	77.40

- Advanced Spatio-Temporal (ST) model eliminates any infeasibilities in prediction without FL.
- Time saved is better for larger systems.
- Solution quality is higher with ST R-SCUC when compared with Deep-NN R-SCUC.

Preliminary Summary

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- Spatio-Temporal AI models can learn the geographical and time temporal relationship in data leading to better predictions.
- No infeasibilities and therefore does not require a FL.
- Superior computational-efficiency due to better predictions compared to rudimentary ML models.

Future Work

- Spatio-temporal ML model to predict critical lines/highly loaded lines in the system to be monitored.
- Reduce redundant constraints in the SCUC.
- Try with other formulations of SCUC.

List of Publications

1. **Arun Venkatesh Ramesh** and Xingpend Li, "Spatio-Temporal AI Approach for Variable and Constraint Reduction in Security-Constrained Unit Commitment ", *IEEE Transactions in Power Systems.* (manuscript under preparation).

Thesis Conclusion

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- System flexibility can bring cost savings and increase system reliability.
- Additional complexities when introducing new constraints associated with transmission flexibility.
- Proposed optimization based computational enhancement techniques with heuristics utilizing Benders Decomposition can address system flexibility scalability for larger power systems.
- ML with historical information and post-processing techniques can provide high quality solutions while ensuring problem size reduction and computational efficiency.
- Feasibility Layer can be introduced to verify/modify ML predictions to eliminate infeasible solutions in SCUC.
- Proposed ML based procedures can be utilized with any deterministic/ stochastic/ decomposition based SCUC algorithms.
- Advanced ML models can learn the geographical and time temporal relationship in data leading to better predictions and superior computational-efficiency

Comprehensive List of Publications:

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1. **Arun Venkatesh Ramesh** and Xingpeng Li, "Security-constrained Unit Commitment with Corrective Transmission Switching," *North American Power Symposium (NAPS)*, Wichita, KS, USA, Oct. 2019.
2. **Arun Venkatesh Ramesh** and Xingpeng Li, "Enhancing System Flexibility through Corrective Demand Response in Security-Constrained Unit Commitment" *North American Power Symposium*, Tempe, AZ, USA, April 2021.
3. Mingjian Tuo, **Arun Venkatesh Ramesh** and Xingpeng Li, "Benefits and Cyber-Vulnerability of Demand Response System in Real-Time Grid Operations", *2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 2020
4. **Arun Venkatesh Ramesh** and Xingpeng Li, "Reducing Congestion-Induced Renewable Curtailment with Corrective Network Reconfiguration in Day-Ahead Scheduling," *IEEE PES General Meeting*, Montreal, Canada, Aug. 2020.
5. **Arun Venkatesh Ramesh** and Xingpeng Li, "Network Reconfiguration Impact on Renewable Energy System and Energy Storage System in Day-Ahead Scheduling" *IEEE PES General Meeting*, Washington, DC, USA, July 2021.
6. **Arun Venkatesh Ramesh**, Xingpeng Li and Kory Hedman, "An Accelerated-Decomposition Approach for Security-Constrained Unit Commitment with Corrective Network Reconfiguration", in *IEEE Transactions on Power Systems*, doi: 10.1109/TPWRS.2021.3098771
7. **Arun Venkatesh Ramesh** and Xingpeng Li, "Machine Learning Assisted Model Reduction for Security-Constrained Unit Commitment", *North American Power Symposium,* Salt Lake, UT.
8. **Arun Venkatesh Ramesh** and Xingpeng Li, ""Feasibility Layer Aided Machine Learning Approach for Day-Ahead Operations", *IEEE Transactions in Power Systems.* (Under 2nd Review).
9. **Arun Venkatesh Ramesh** and Xingpend Li, "Spatio-Temporal AI Approach for Variable and Constraint Reduction in Security-Constrained Unit Commitment ", *IEEE Transactions in Power Systems.* (Journal manuscript under preparation).

Thank you