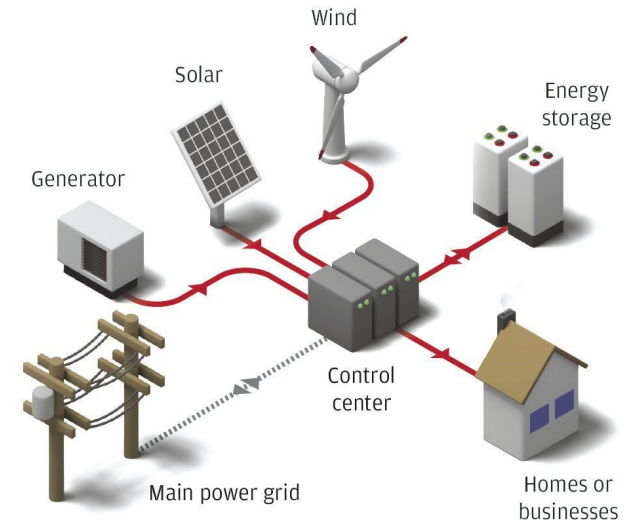


Microgrid Grid Planners need Simulation Tools

- Major research on microgrids with distributed energy resources (DER) and energy storage systems (ESS)
- Planning Engineers must optimize system with realistic battery and renewable behavior
- Problem: Commercial OPF tools don't work for distribution networks or microgrids with batteries and renewables (MATLAB PowerWorld, ETAP, PSSE, PSLF)

Utilizing a microgrid

Microgrids are self-contained energy systems that can be connected to the larger grid or function as an "island."



Design requirements

	ML Forecasting	Optimization	Web App
Functional	Take location as input Pull hourly forecast from weather API Predict generation and loads for 24hr horizon	Multi-Period Convergence Battery Constraints met < 0.2% Single Period Error	Take user input - location Visualize Gridlab-D Model files and power flows Visualize forecast, load, and dispatch
Performance	NRMSE < 20% Train time ~ minutes Predict time ~ seconds	Local Optimum at Convergence < 30 min run time for all test cases	Response time < 1sec

Solution Approach

Prediction Models:

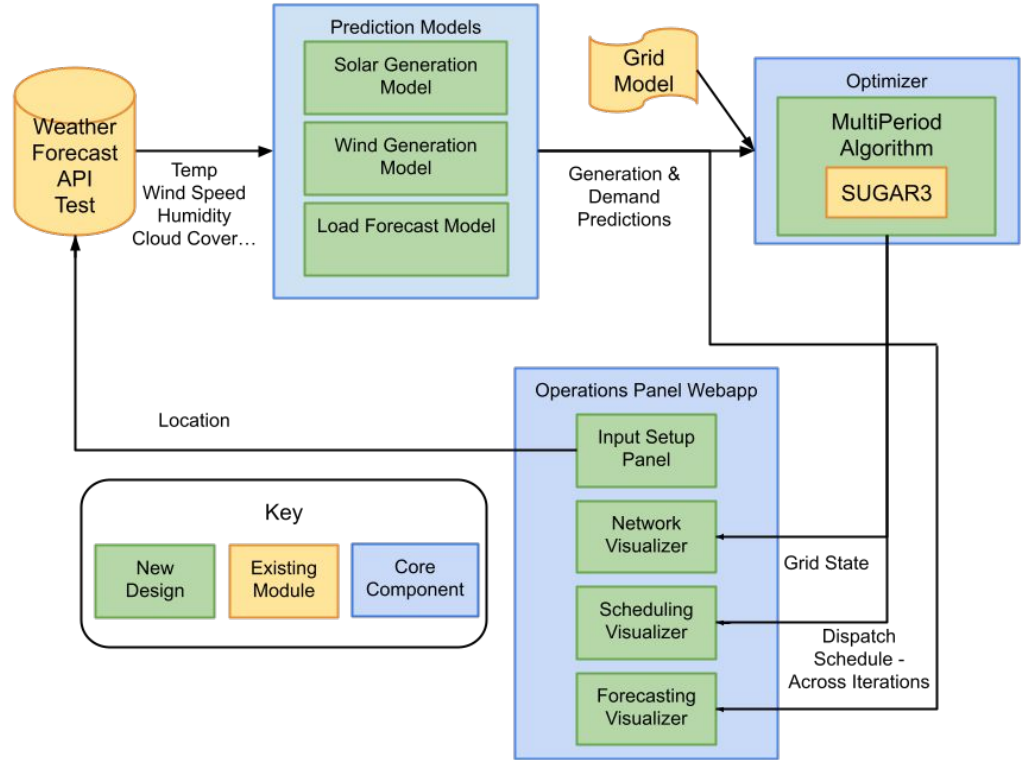
- Trained 3 Sklearn RF regressors on historical power and weather data

Optimizer:

- Adapted SUGAR AC-OPF to a multi-period solver with DDP
- Incorporated ESS behaviors and forecasts to optimize costs across time

Operations Panel Webapp:

- Built a Django website deployed on EC2
- Used Vis.js for grid and data visualizations



Upload Your GridLab -D File

State: City:

Upload a GLM File: No file chosen

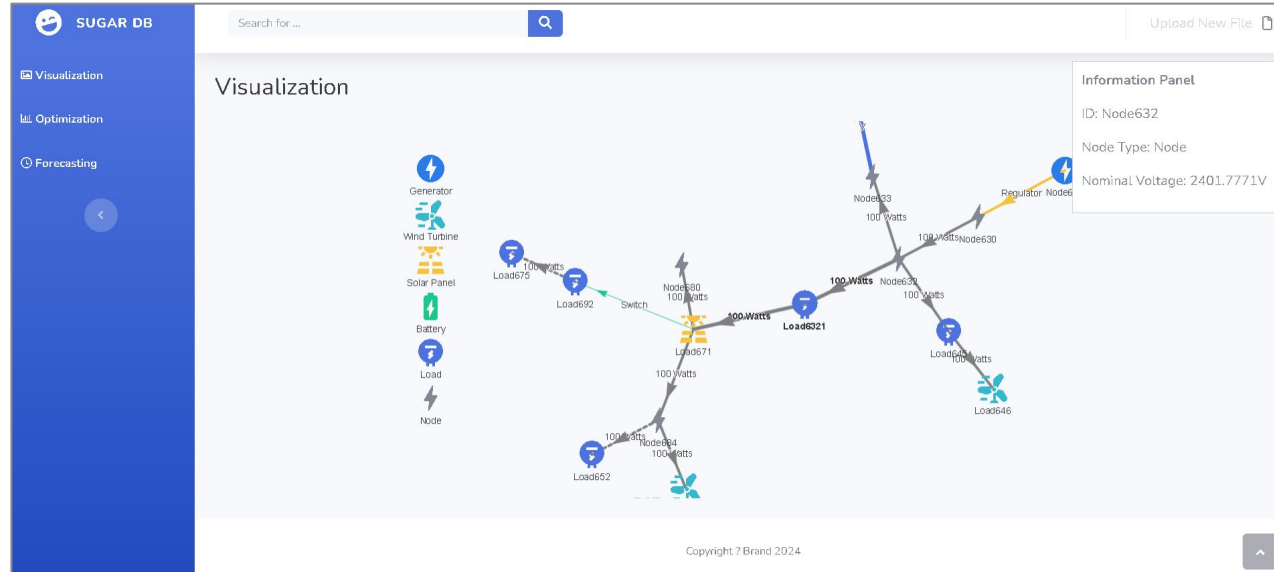
Solution - Grid Visualization

User inputs location and GLM file describing their grid

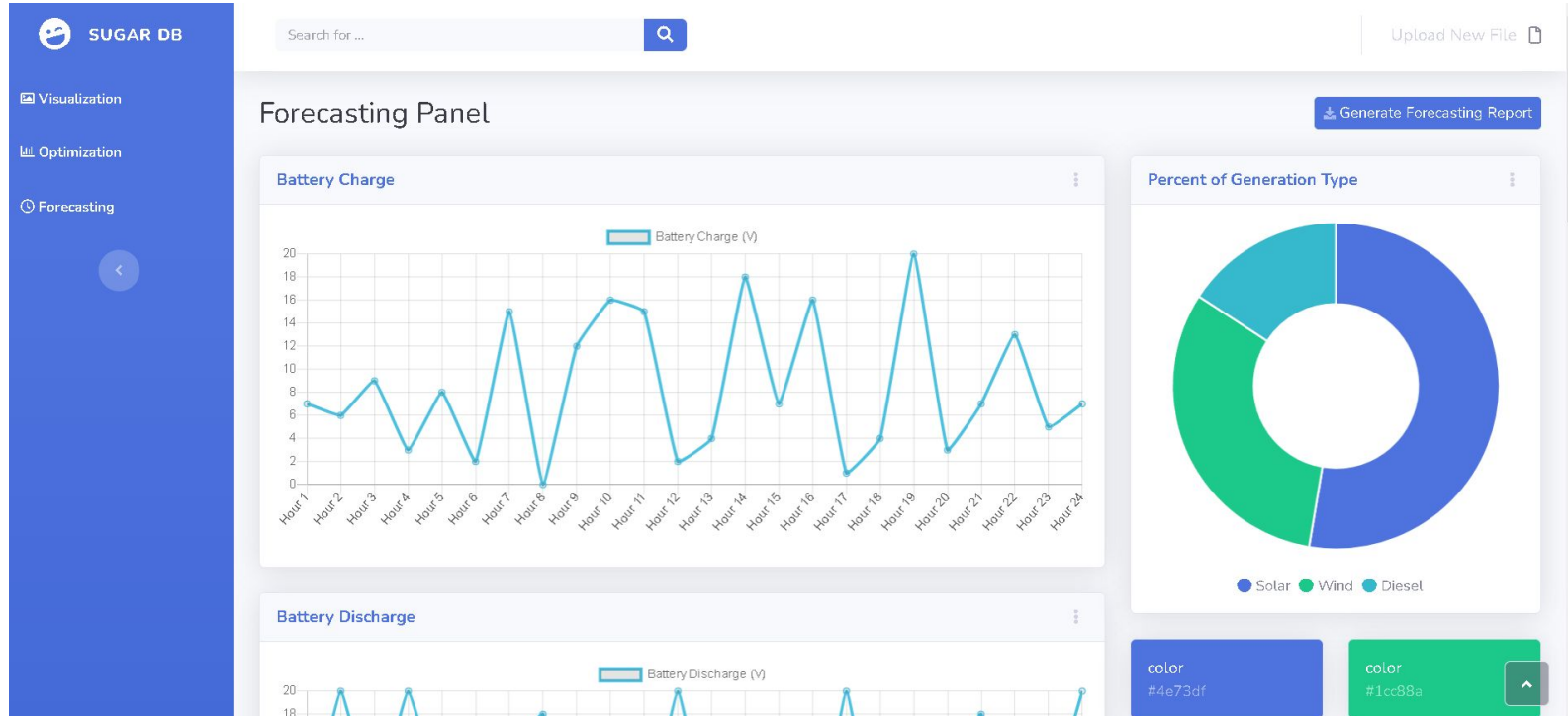
Web app displays Real-time grid visualization:

- Shapes = nodes
- Lines = power flows

Clicking nodes gives info



Solution - Statistics Dashboard



Test, Verification and Validation - ML

Timing	Goal	Actual
Train Time	minutes	< 10 seconds
Predict Time	seconds	< 5 seconds

Performance Metrics	Goal	Actual
Wind Power	< 20% NRMSE	9.9% NRMSE
Solar Power	< 20% NRMSE	8.6% NRMSE
Load	< 20% NRMSE	11.8% NRMSE

ML Verification - Plots

For time-dependent variables:
(pictured right)

- Predictions follow same hourly trend as test data

For weather-dependent variables:
(not pictured)

- Predictions show correlation with change in weather
(i.e. wind speed \sim wind power)

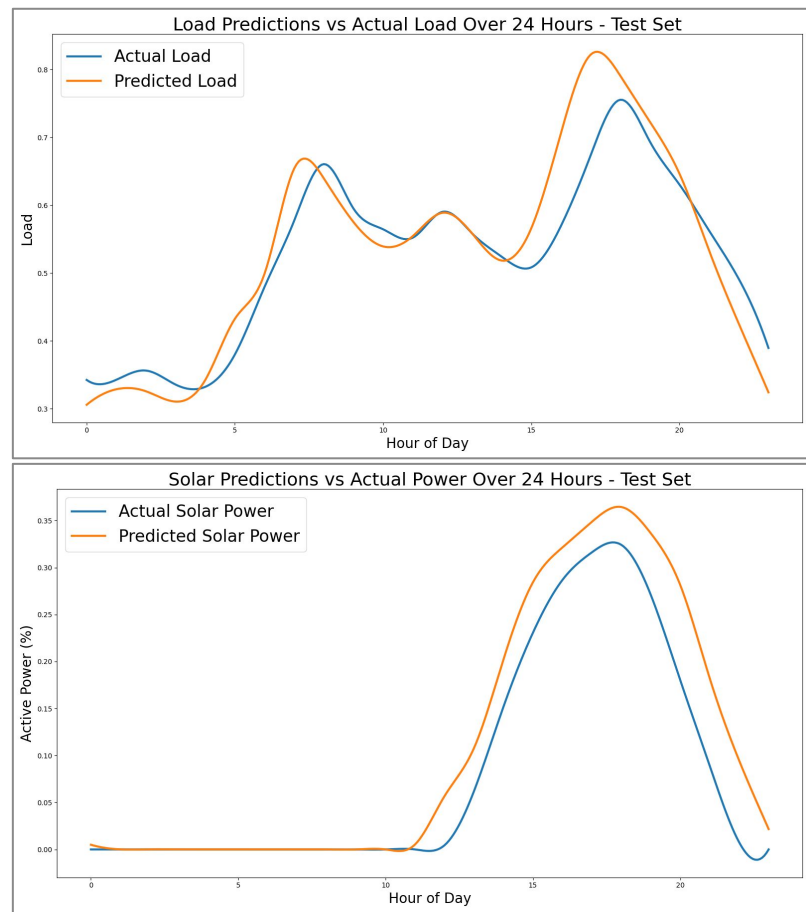


Fig 1. Daily Solar Power and Load Prediction

Test, Verification and Validation - Optimization

Functional Testing Results:

- Multi-period Convergence within 10 epochs (for partial discharge cases)
- Battery constraints satisfied at each period
- <0.2% error in single-period solution of modified SUGAR3 compared to GridLab-D

Performance Testing Results:

- All 24 period test cases converge in < 1min running on intel i5 8th gen CPU

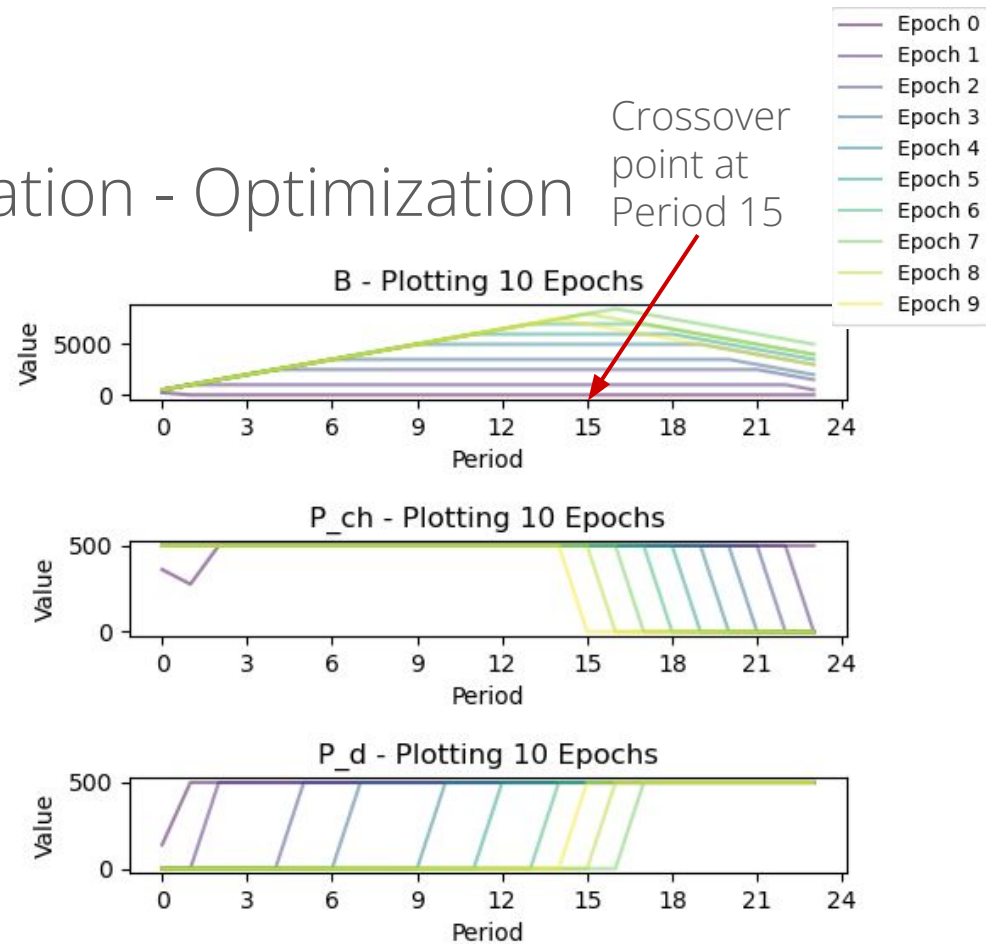
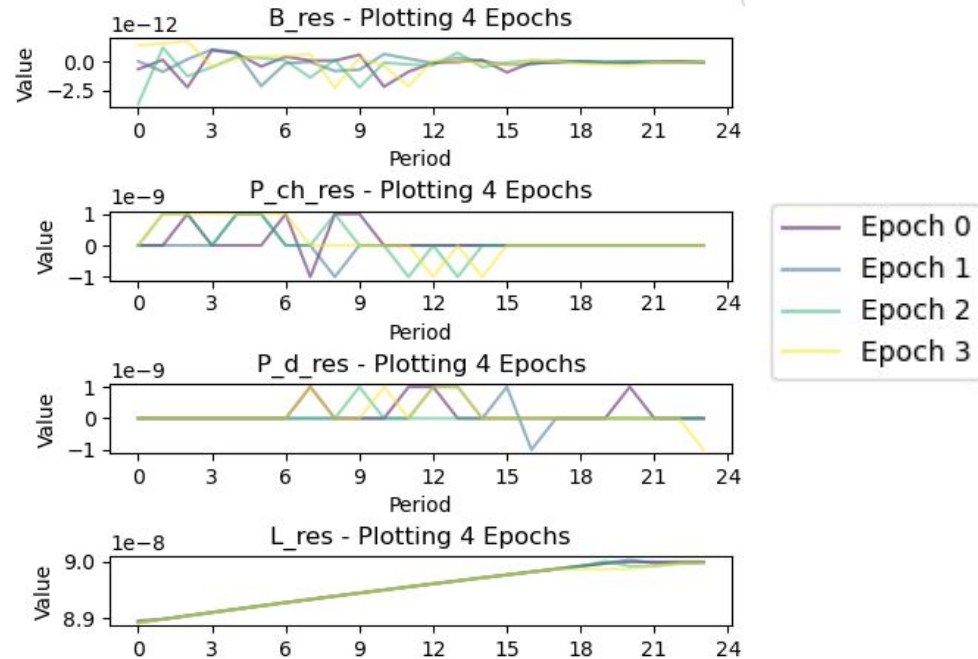


Fig 2. Example Battery Dispatch Optimization Trajectory
Carnegie Mellon University

Residuals Show Battery Constraints Met

Residuals are the error in the battery constraint functions

They are plotted over all 24 periods for 4 epochs of DDP and are all **near zero**, indicating that battery is behaving as expected within allowable tolerances.

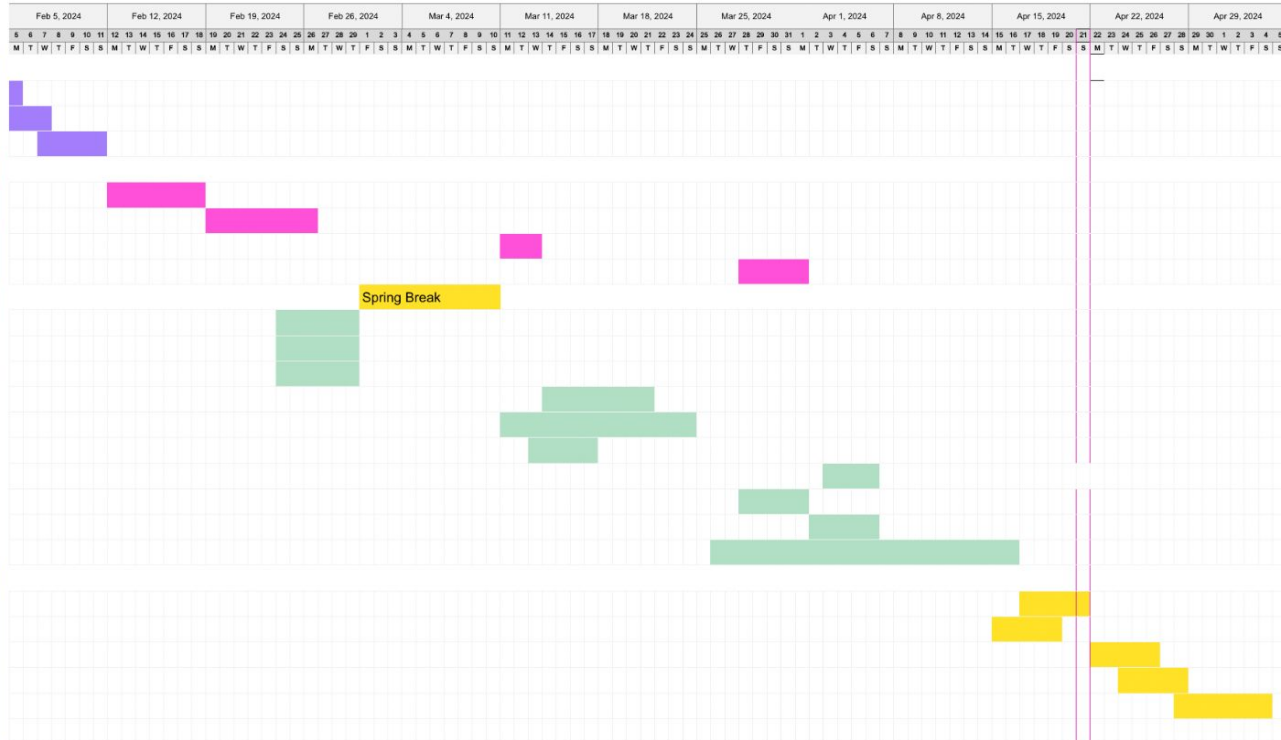


Test, Verification and Validation - Web Apps

Category	Details
Test Inputs	Sample GridLab-D files, user interaction scenarios
Performance Metrics	Response time, accuracy, interaction responsiveness
Verification Criteria	100% success in data parsing and visualization, responsive UI controls
Validation Criteria	Response \leq 2s, Interaction \leq 500ms
Results	Avg. Response: 1.8s, Interaction: 480ms, 100% visualization accuracy
Quantitative Trade-offs	Balance between performance (1.8s load time) and functionality (enhanced UI controls, high accuracy)

Project Management

TASK	ASSIGNED TO	START	END
Planning			
Proposal slides	Alby	1/29/24	2/5/24
Setup wordpress	Yuchen	1/29/24	2/7/24
Collect data for training	Carter	2/7/24	2/11/24
Design			
Design slides	Yuchen	2/12/24	2/18/24
Design review doc	Alby	2/19/24	2/26/24
Ethics assignment	Carter	3/11/24	3/13/24
Interim demo prep	All	3/28/24	4/1/24
Execution			
Create wind forecast ML model	Carter	2/24/24	2/29/24
Optimization python wrapper	Alby	2/24/24	2/29/24
Web app backend	Yuchen (Carter)	2/24/24	2/29/24
Fine-tune wind forecast model	Carter	3/14/24	3/21/24
Create solar/load forecast ML models	Carter (Yuchen)	3/11/24	3/24/24
Setup web app frontend	Yuchen	3/13/24	3/17/24
Deploy solar forecast in optimization	Alby	4/3/24	4/6/24
Fine-tune solar/load forecast models	Carter (Yuchen)	3/28/24	4/1/24
Deploy wind forecast in optimization	Alby	4/2/24	4/6/24
Customize web app frontend	Yuchen	3/26/24	4/16/24
Closure			
Final slides (optimization)	Alby	4/17/24	4/21/24
Final slides (ML)	Carter	4/15/24	4/19/24
Final Poster	Alby	4/22/24	4/26/24
Final Video	All	4/24/24	4/28/24
Final Report	All	4/28/24	5/4/24



Conclusions

Lessons Learned

- Preliminary data analysis helps inform forecasting methods
- Simple models can be effective even for complex problems
- Start testing earlier - for optimization to find convergence issues

Future Work

- Validate optimization on real-world microgrid with physical hardware
- Optimize for battery size and placement
- Ensure the application can scale to handle larger and more complex microgrid models
- Allow users to customize their microgrids directly from the interface