Smart Energy: Applying Machine Learning to Renewable Energy Challenges

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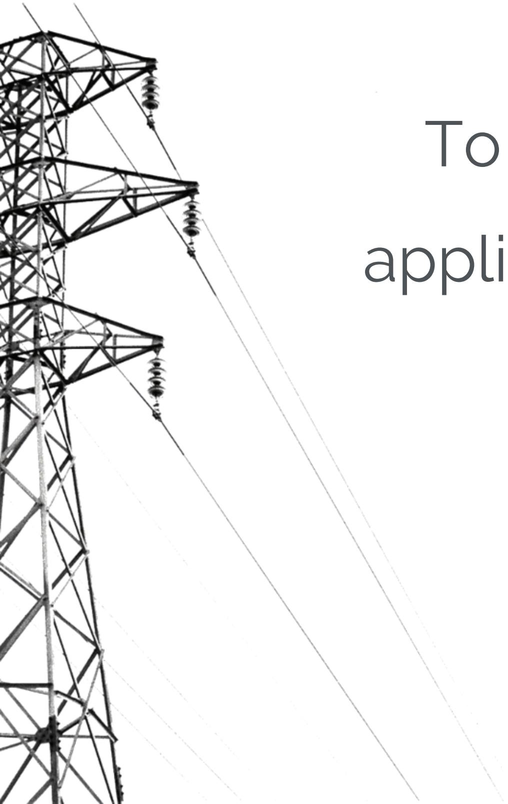
Faculty of Engineering

Industry Showcase 2025

Goal of this presentation = application



To show how researchers at Stellenbosch University have applied machine learning in the context of renewable energy?

…hopefully spark some ideas

Applying Machine Learning to Renewable Energy Challenges

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Renewable Energy (solar, wind) = intermittent and stochastic power source

- More renewables = More uncertainty & stress onto the electrical grid
- Biases power utilities against dominant grid connection of renewables

Applying Machine Learning to Renewable Energy Challenges

Solution: Reduce uncertainty with Forecasting

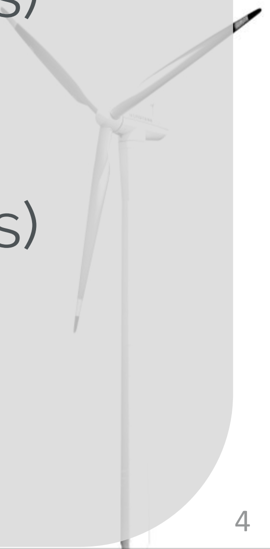
- Aids both grid operators and power producers

Transmission Operator

- Aids with balancing supply & demand
- Maintaining grid stability (power quality)
- Lowers standby costs of operating reserves

Power Producers

- Aids with accurate unit commitment (avoid penalties)
- Optimised energy trading (enhanced bidding strategies)
- Performance monitoring



Commercial Solar PV forecasting

- First group in South Africa to deliver a state-of-the-art forecast model
- 75MW PV system
  - 84x 880 kVA inverters
  - 13000+ strings
- Successfully delivered 1h – 6h ahead forecasts

Commercial Solar PV forecasting

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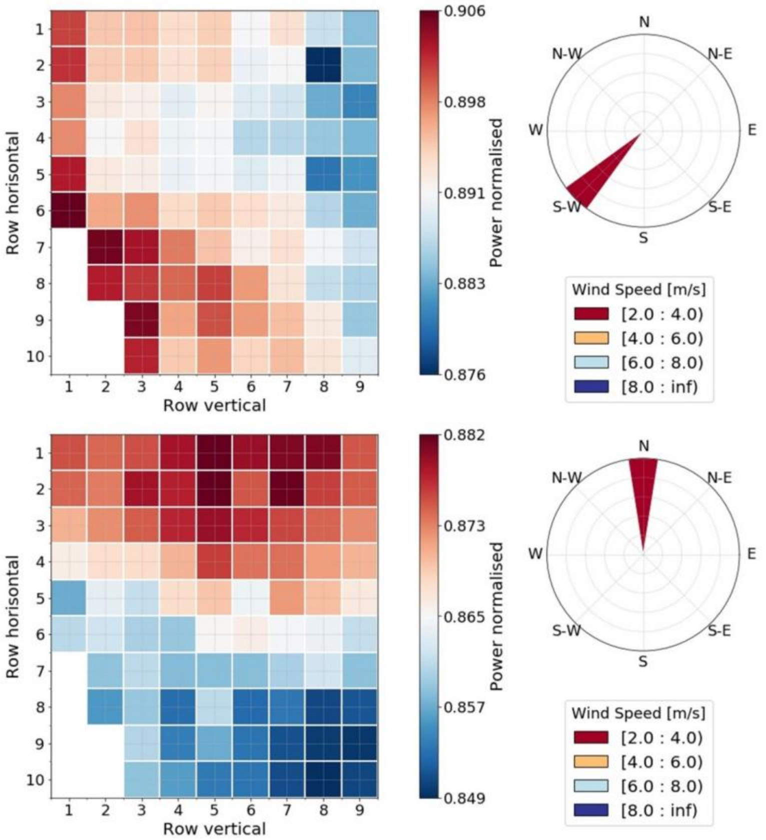
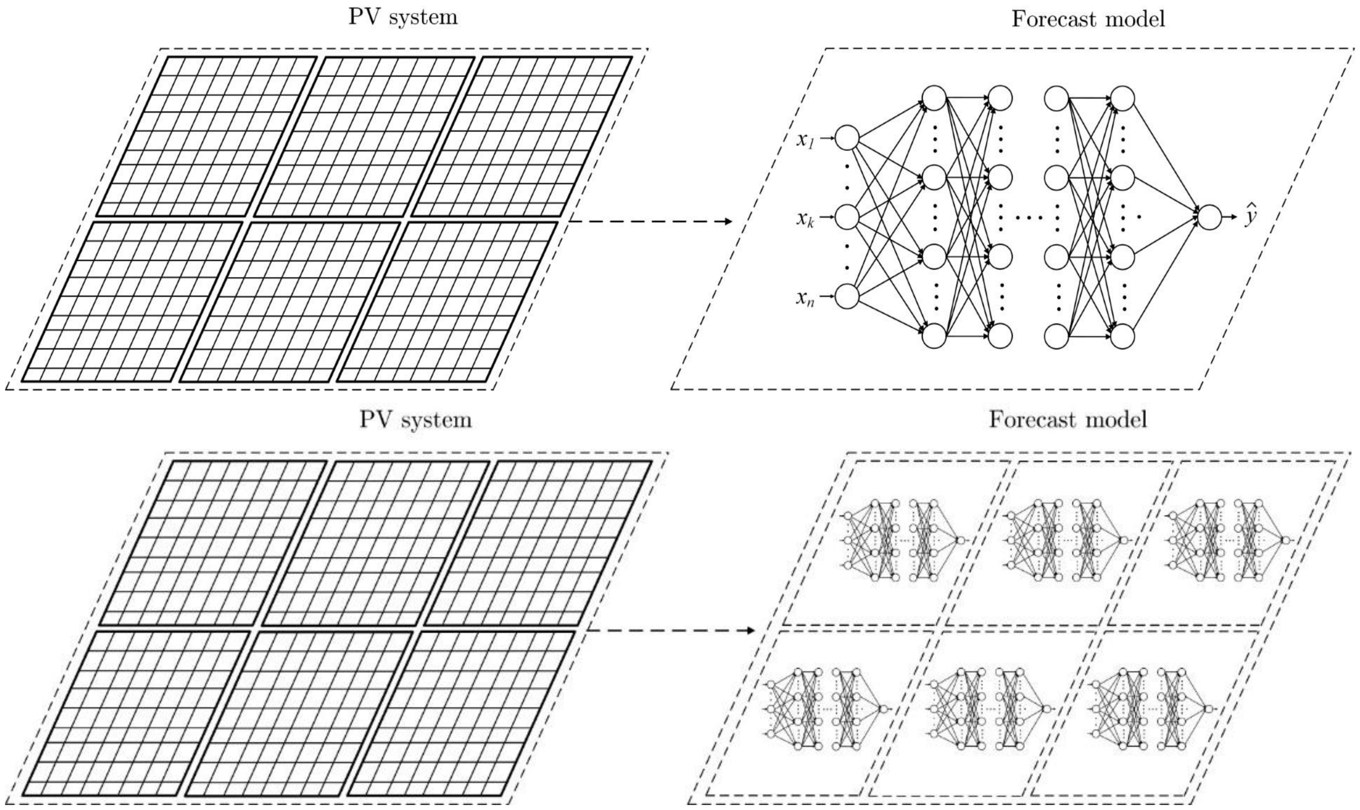
Discovery: Proof of non-uniform low-level power output dynamics

Big question: Macro-level vs Inverter-level forecasting

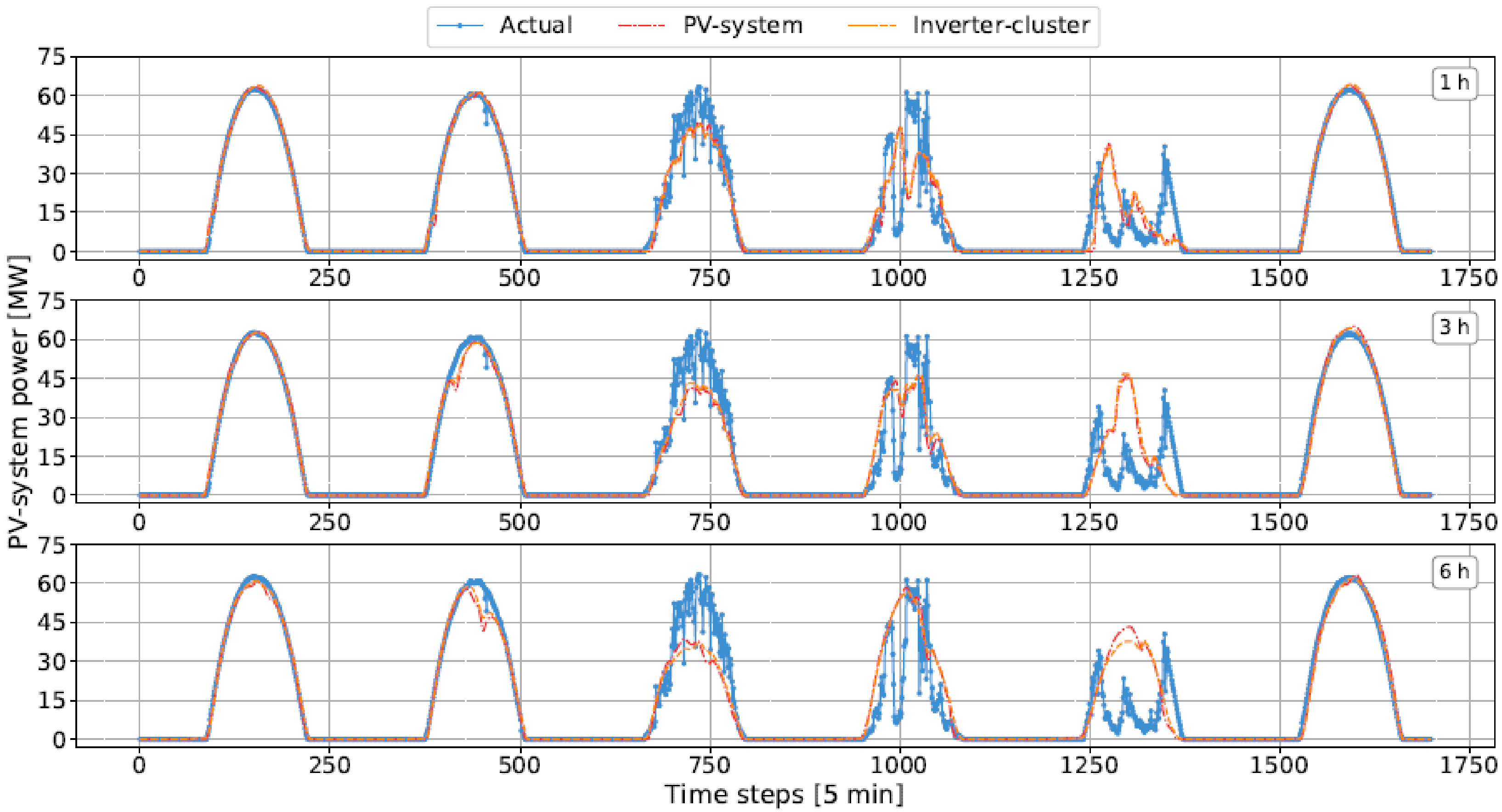
- Is one ML model enough to capture PV system dynamics?
- Or should we divide PV system into sections and forecast each section's behaviour?





Project: Solar PV Forecasting

Answer: With machine learning – we can divide large PV systems into smaller sections (correlation) & create a forecast model for each section.



Results:

- Solution proven to reduce computational expense without sacrificing accuracy

Industry need to know:

- Machine Learning is powerful enough to capture all PV system dynamics.

"One model to rule them all"

Hydro-Power forecasting

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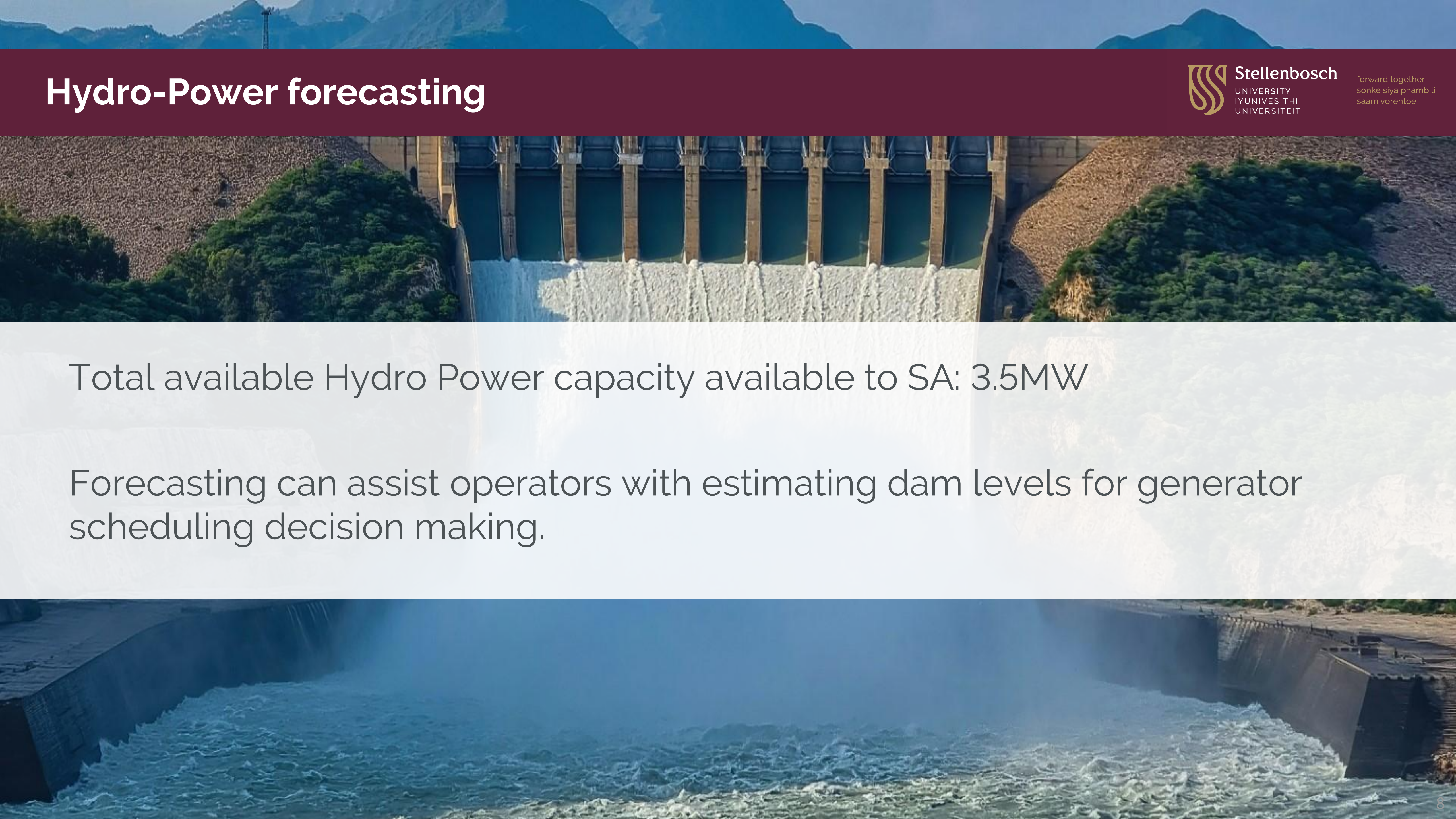


Total available Hydro Power capacity available to SA: 3.5MW

Forecasting can assist operators with estimating dam levels for generator scheduling decision making.

Hydro-Power forecasting

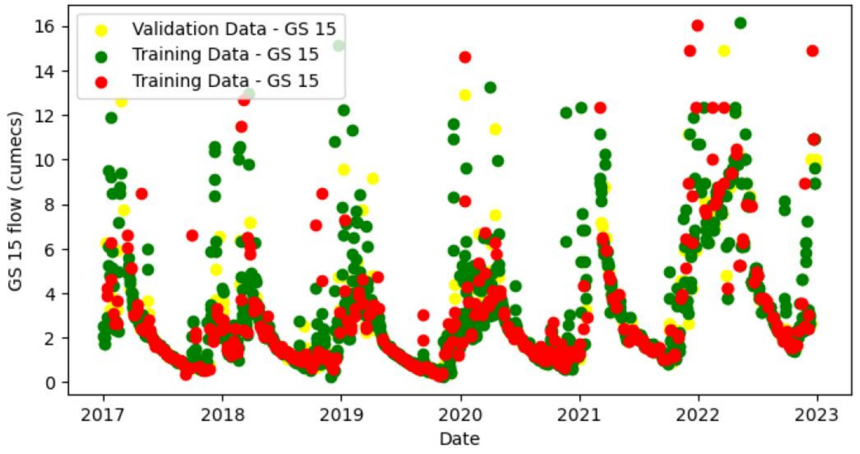
Project: Eswatini Electricity Company (EEC)

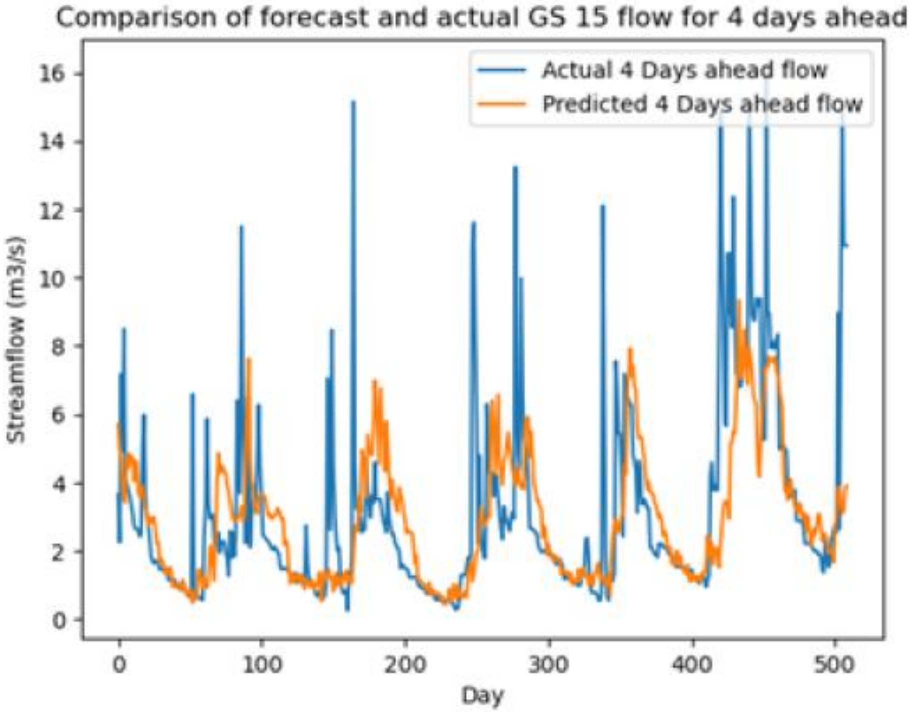
- Hydroelectric scheme: 20 MW + 40 MW cascaded scheme
- EEC exploits arbitrage opportunities for electricity sales, during high TOU (time-of-use tariffs)
- These conditions require an optimum dispatch strategy
- 4-day ahead forecasts = great value

Hydro-Power forecasting

Data & Results

- Forecast model delivered for 4-day ahead forecasts.
- Deep learning networks outperformed linear regression by a factor of 3.
- **Outcome**: Ultimately, power plant managers can further optimise their dispatch strategy.





Wind-Power forecasting

Question: We can forecast the wind, but how can we further eliminate the forecast model uncertainty?

Answer: Local-Area Weather Forecasts; Battery Storage

Wind-Power forecasting

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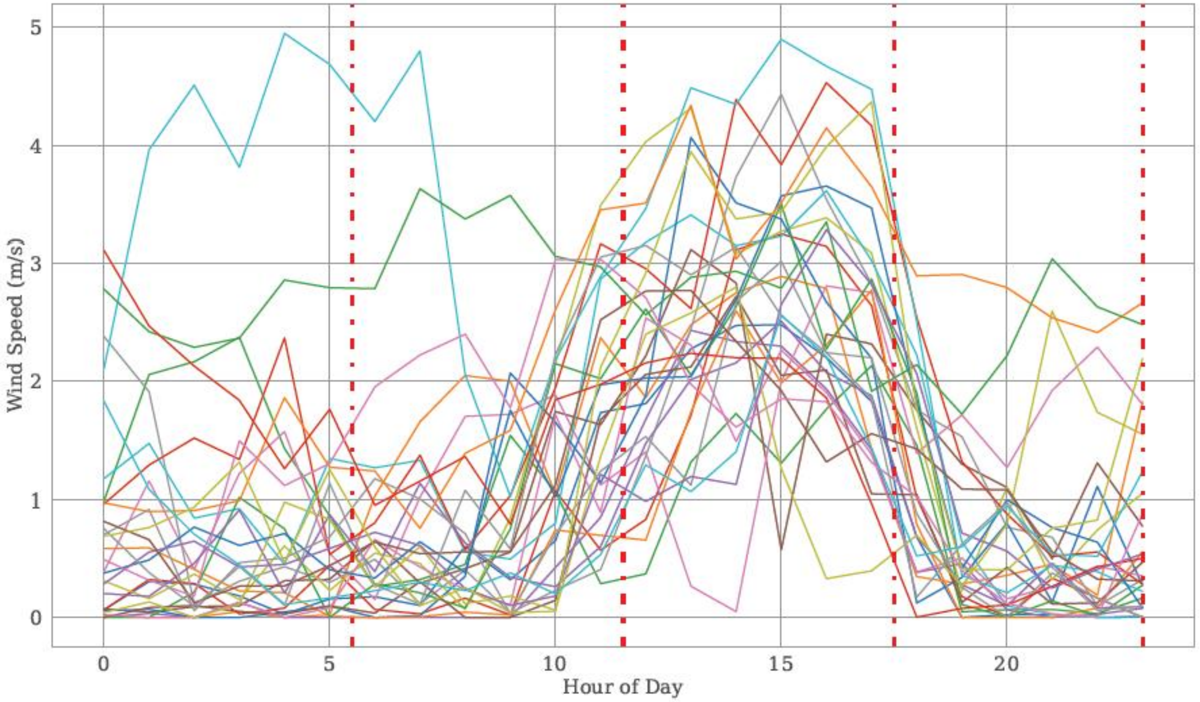
Data:

- Stellenbosch daily wind speed data set



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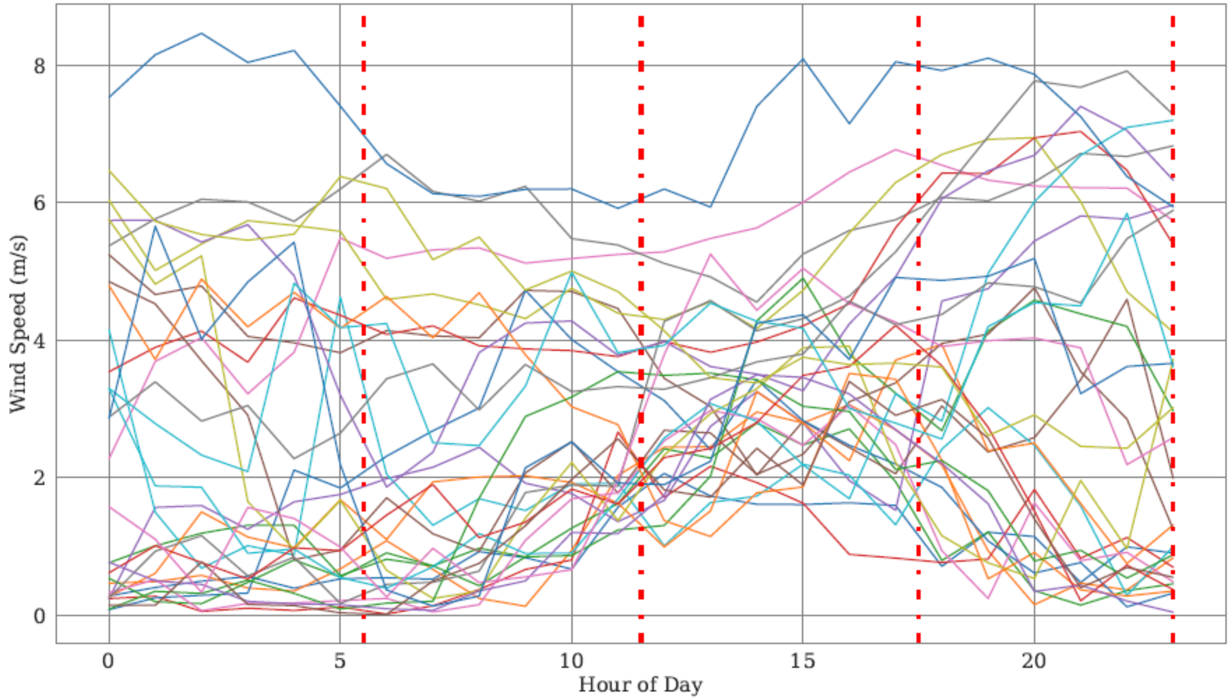

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Wind-Power forecasting

Challenge: Wind speed forecasting

- Average user or company cannot create or operate a custom weather forecasting model
- Reason: don't posses the necessary computational power
- Forced to subscribe to weather forecasting companies

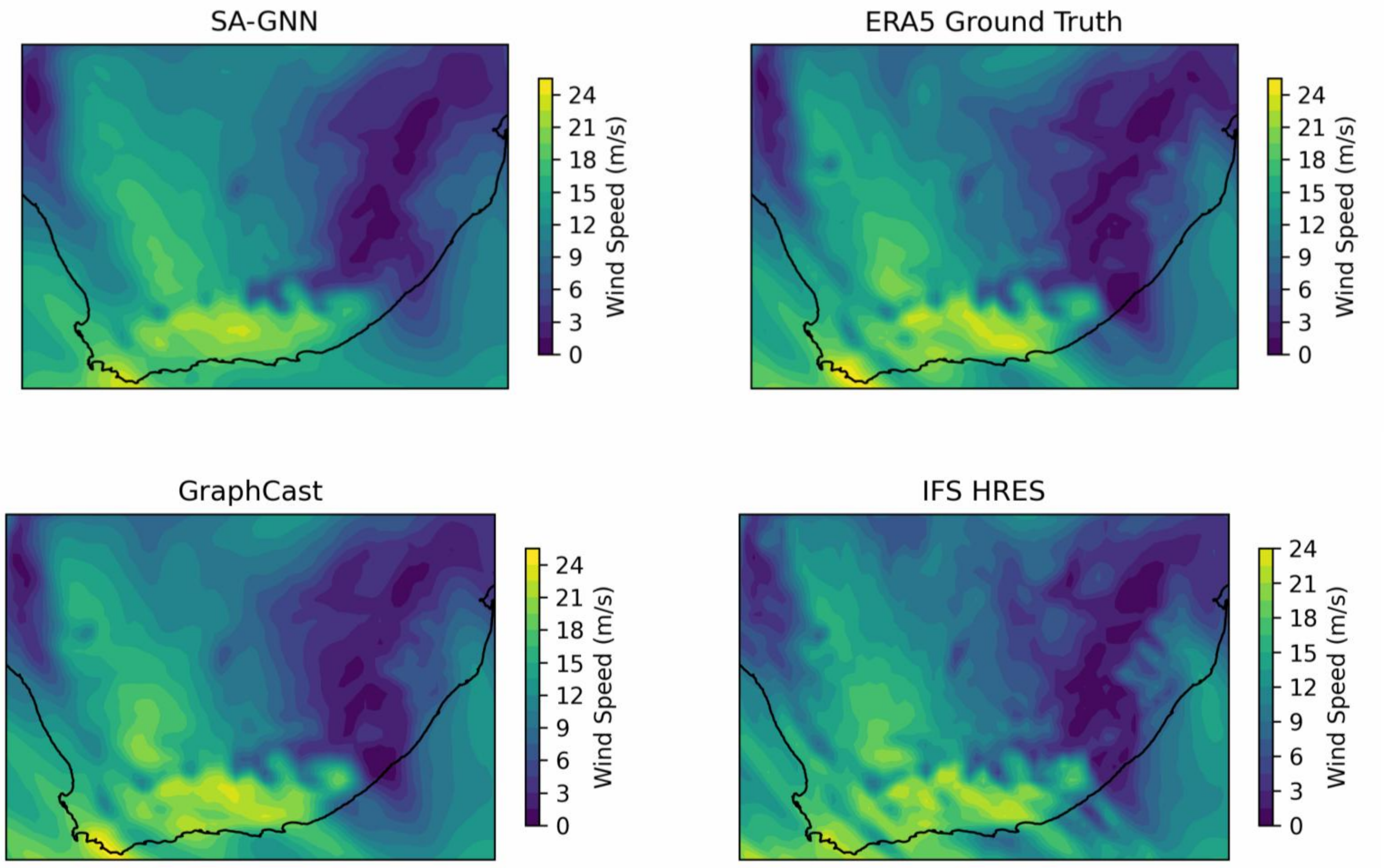
Solution:

- To develop a local-area weather forecast model
- Computationally less expensive alternative to current weather forecasting models.

Wind-Power forecasting

AI-based Weather Prediction (AIWP)

- Identified AIWP as a computationally efficient alternative to NWP models
- Proved that AIWP can contend with NWP
- Current results: 18% less accurate than NWP
- **Amazing result**: Near future, we will generate forecasts at a fraction of the computational requirements of NWP models.



Wind-Power forecasting

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Challenge:

- Unit commitments are required in day-ahead energy markets.
- If forecasts under-predict, there is a loss of sales.
- If forecasts over-predict, there is a penalty/fine imposed.

Solution:

- Use energy storage (battery) as power supplement for over-predicted power forecast errors.
- But how big should this battery be?

Wind-Power forecasting

Question: How can energy storage be used to assist with forecast deviations?

Over-prediction

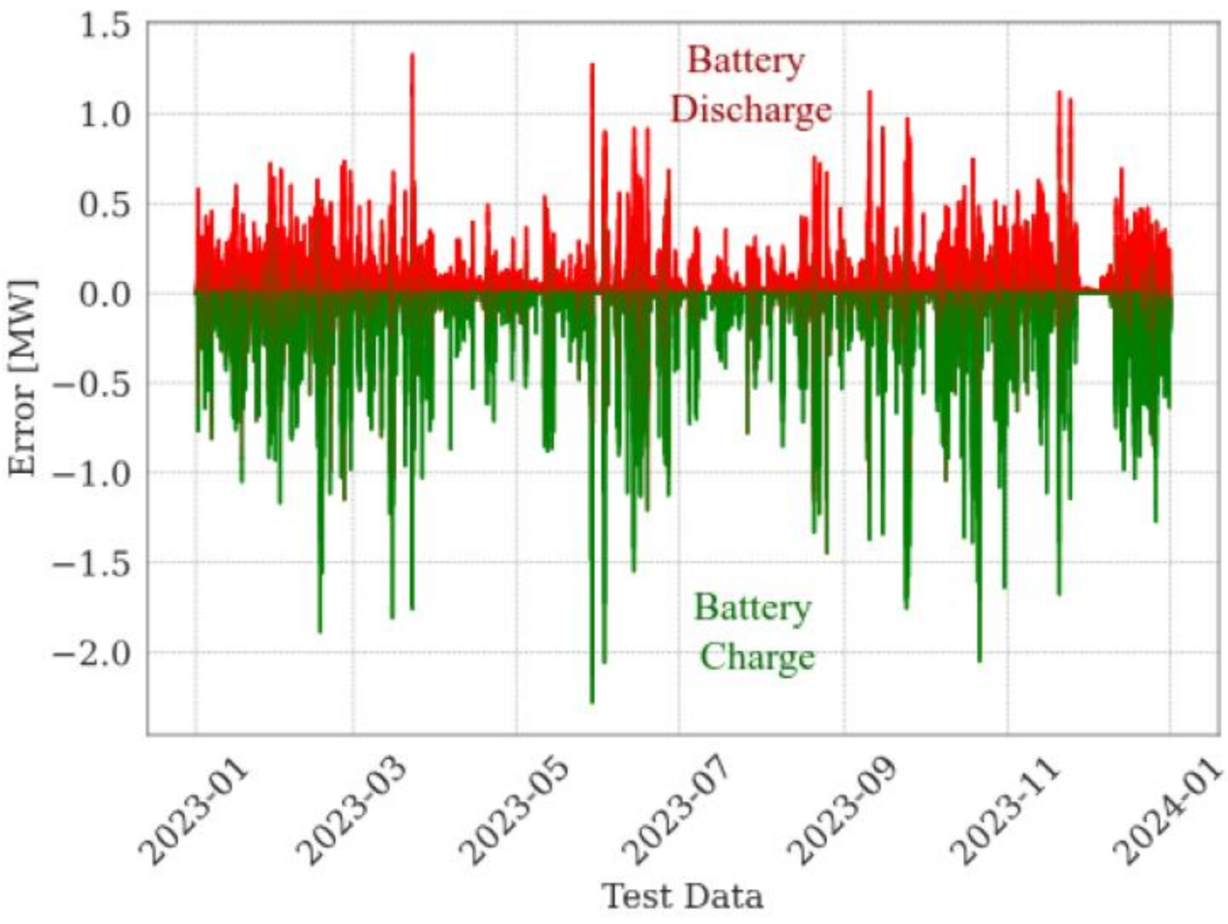
(i.e. less power produced than predicted)

- Energy shortage is supplemented from batteries
- Avoids energy market penalties

Under-prediction

(i.e. surplus power available)

- Surplus wind power is stored into batteries
- Avoids self-imposed curtailment

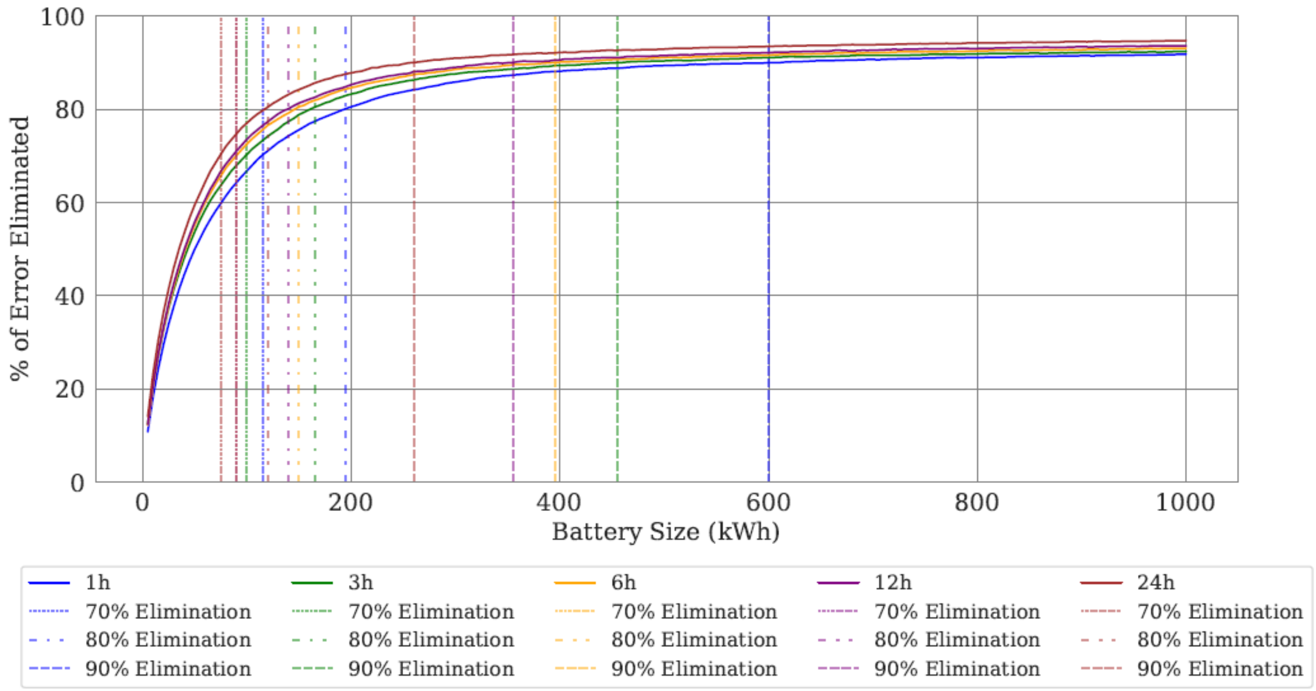


Wind-Power forecasting

Case Study Results (1h – 24h forecast)

- Eliminate 70 % of forecast errors with battery ≈ 3-7 % of rated capacity x h
- Eliminate 80 % of forecast errors with battery ≈ 5-12 % of rated capacity x h
- Elimination of 80% < Errors Battery size becomes increasingly impractical

Typical wind forecast error?



Performance monitoring

Real-time performance monitoring

Challenge

- Large SA company installed a 3MW PV system
- Experienced issues with system monitoring

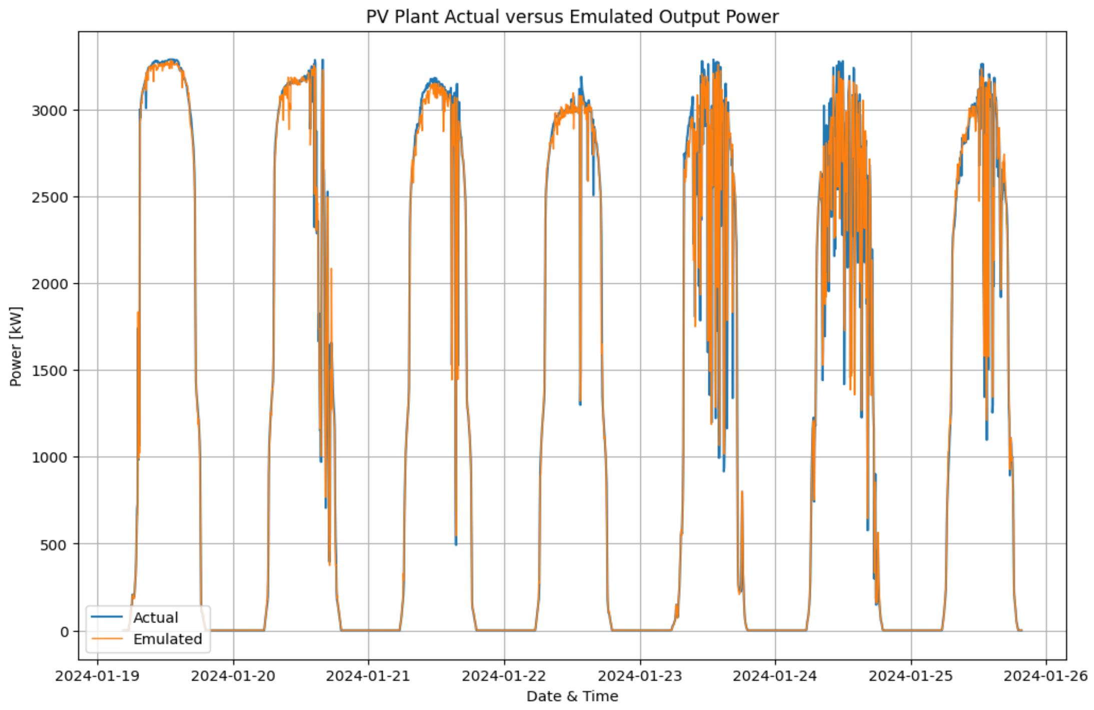
Objective:

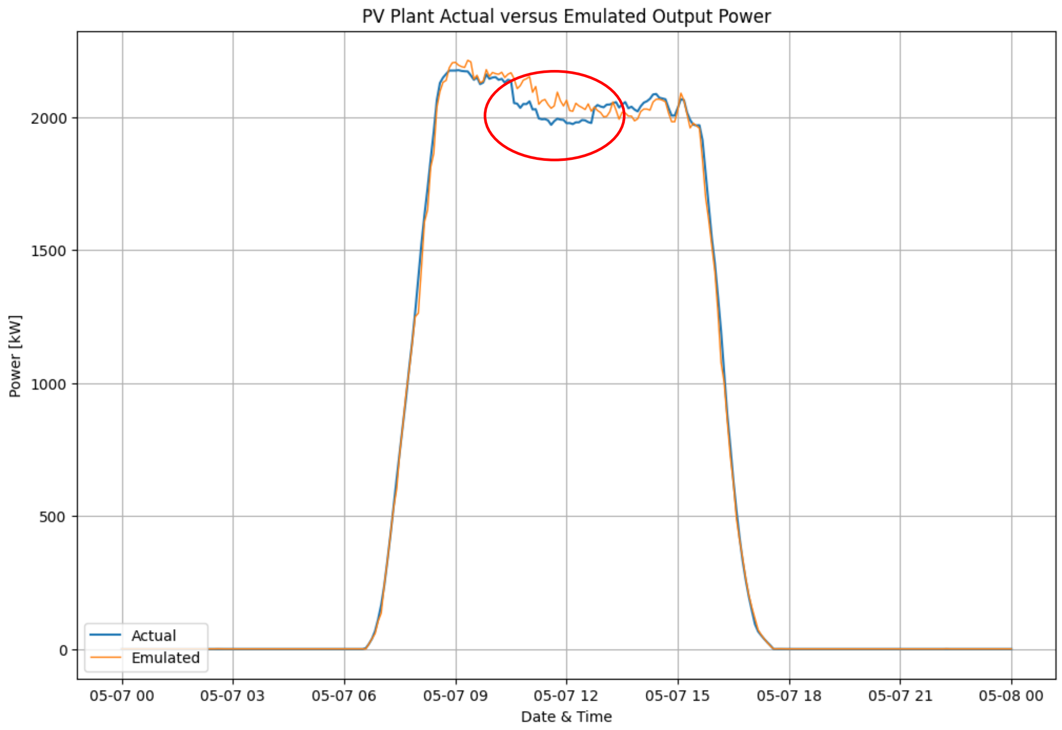
- Develop a highly sensitive monitoring tool with machine learning

Real-time performance monitoring

Result

- Real-time system performance executed with little to no dependence on human observation





System deviation identified

Battery energy management

Objective:

- How can we utilise battery banks as an asset for owners?

Solution

- Use of Reinforcement-Learning to “gamify” real-time battery deployment strategies.
    - Peak shaving
    - Time-of-use arbitrage, (Load shifting)
    - Ancillary services (power quality)
    - Energy storage (loadshedding)

Renewables, Batteries, Electric Vehicles & Machine Learning

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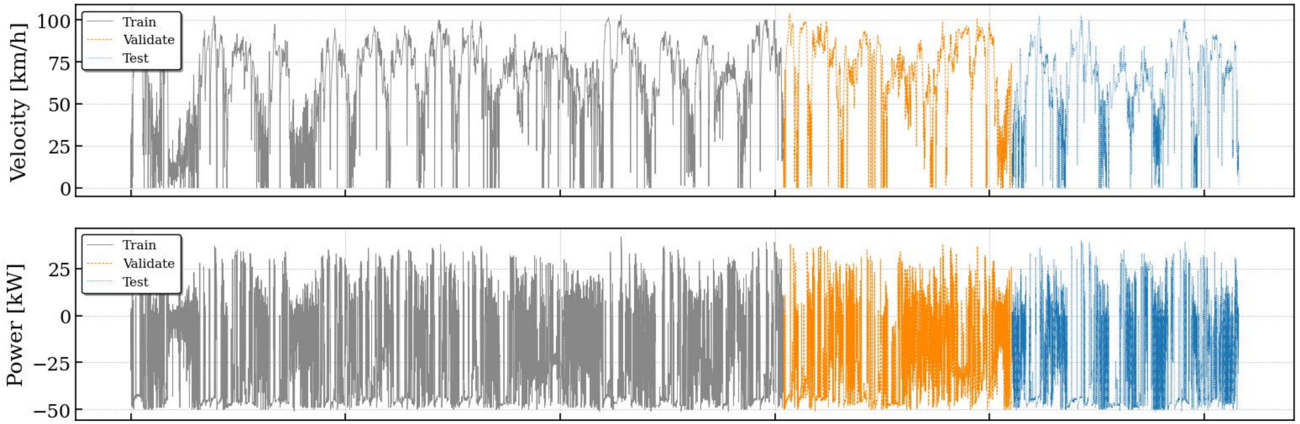
Perspective:

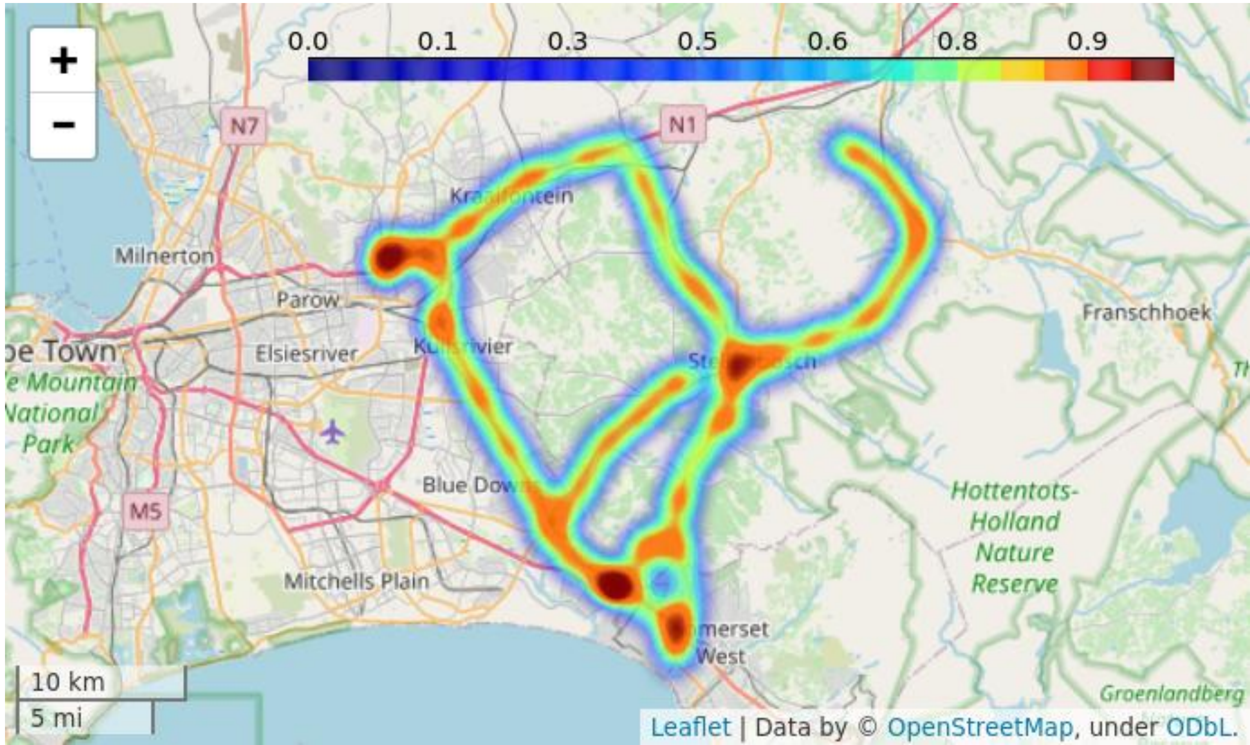
- Common belief that an effective deployment of Renewable Energy is a catalyst for the mass adoption of EV's
- But....the opposite is also true:
  More EV's = more Renewable Energy
- Machine Learning serves as a second catalyst for mass adoption (of both EVs & Renewable Energy)

Renewables, Batteries, Electric vehicles & Machine Learning

Application:

- Machine learning has proven to be an effective tool to assess EVs efficiency.
- Provided the data of any existing EV, we can emulate any route, anywhere.
- With kWh/km identified, financial feasibility can be determined





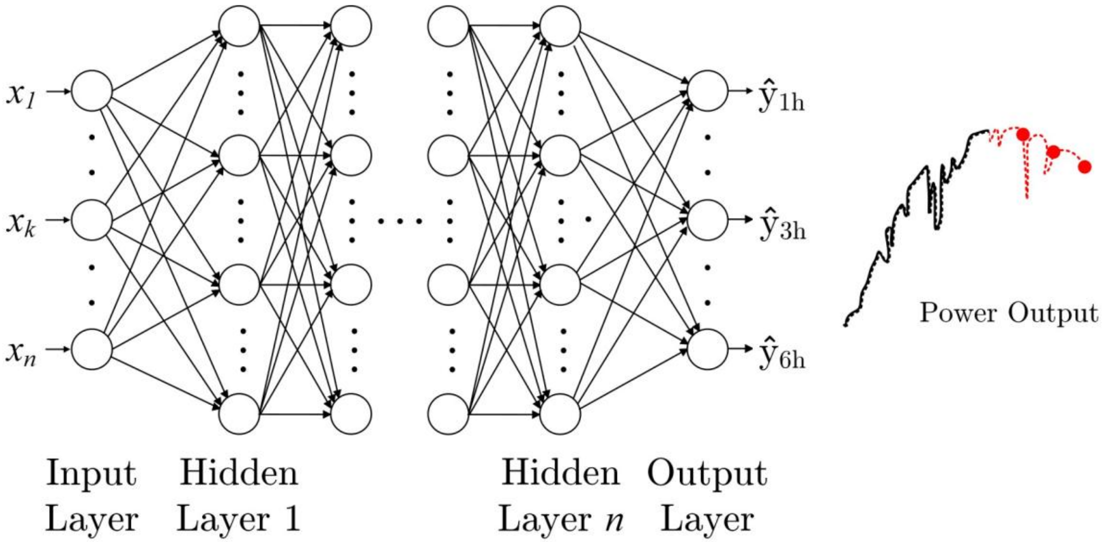
Some advice to industry engineers

Machine Learning models

- Don't be a hero – you can achieve a lot with Linear Regression, Feed-Forward-Neural-Networks, XGBoost (LSTM, GRUs, Transformers – extreme)

Forecasting:

- Multi-step forecasting vs. Single-step forecasts
- Multi-step saves time, dev. cost & is accurate enough



Key take-aways

Some advice to industry engineers

What's Next?

- Energy markets and bidding strategies
    - Forecasting, trading, arbitrage
    - Machine Learning can solve it all

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Thank you
Enkosi
Dankie