# EGAT Renewable Energy Forecast Center (REFC)

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Advanced Power System Technology Division

Electricity Generating Authority of Thailand

17 November 2026

# Agenda

- ❖ Introduction & Current Status of VRE in Thailand
- ❖ Background & Overview of EGAT REFC
- ❖ VRE Forecasting Methodology
- ❖ EGAT REFC Infrastructure
- ❖ Conclusion & Key Takeaways



# Agenda

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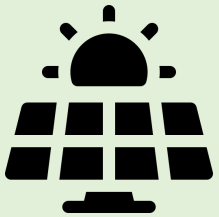
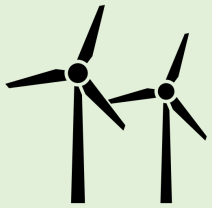
# Types of Renewable Energy

## Solar Energy



Captures sunlight using photovoltaic (PV) panels for electricity or thermal collectors for heat.

## Wind Energy



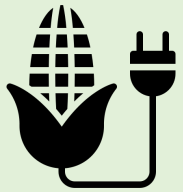
Uses wind turbines (onshore or offshore) to convert wind's kinetic energy into electricity.

## Hydropower



Generates power from flowing water, often using dams or run-of-river systems.

## Biomass



Burns organic materials (wood, crops, waste) or converts them into biofuels.

## Geothermal



Taps into the Earth's heat, providing constant power.

## Ocean Energy

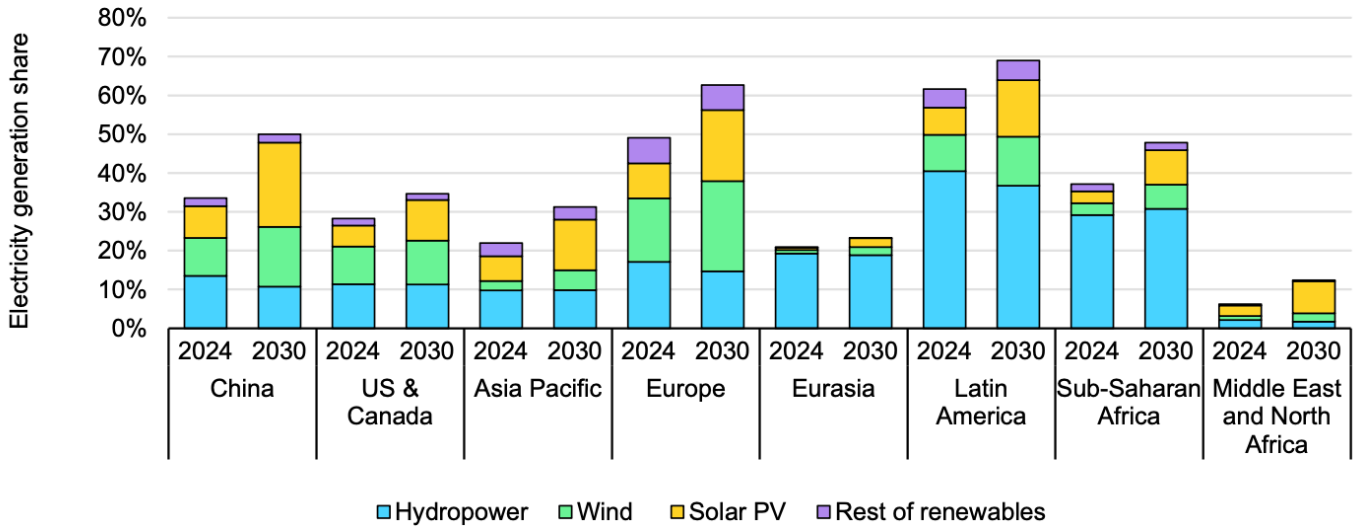


Harnesses power from the ocean's tides and waves.

# Global Solar PV & Wind Energy

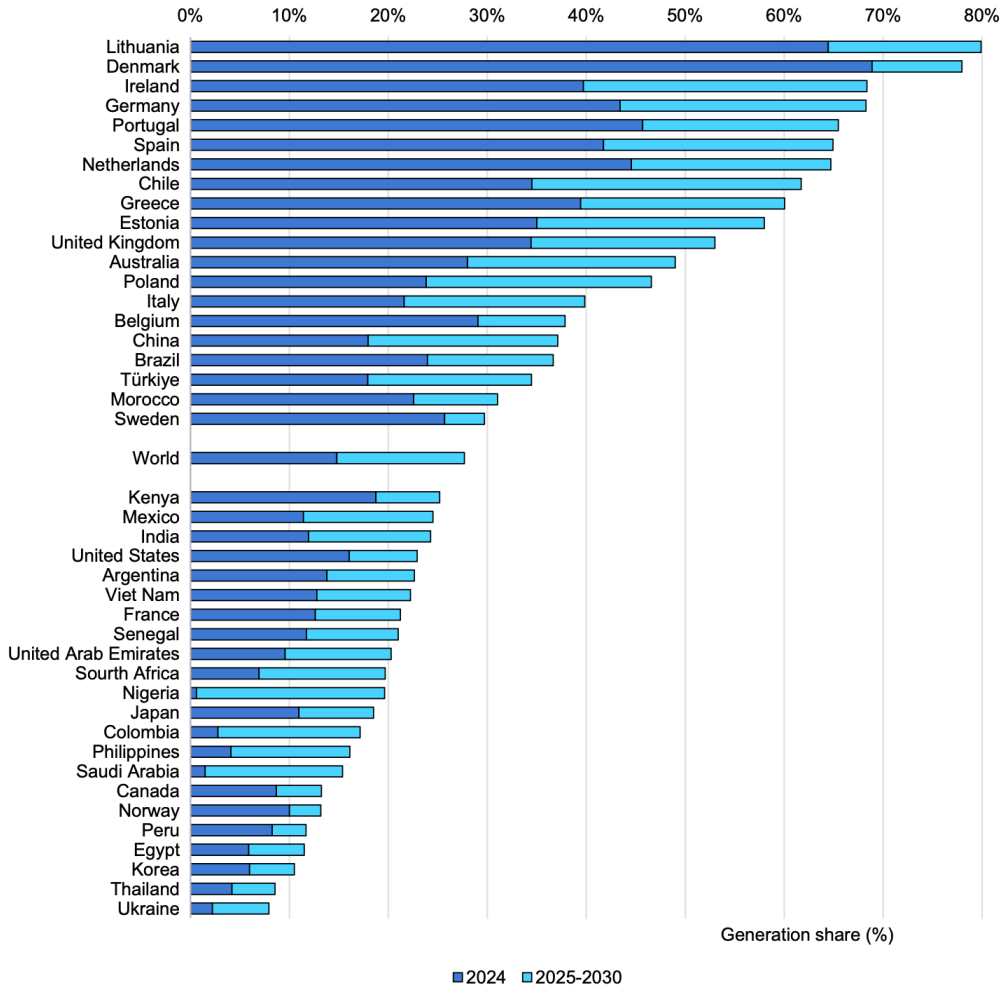
- Solar PV + Wind share in electricity rises from 13% (2023) → 30% (2030)
- Europe: Leads globally, reaching ~45% from wind & solar by 2030. Wind overtakes nuclear, solar reaches 20%.
- China: Nearly 40% from wind & solar by 2030, solar surpasses wind to become top renewable.

## Shares of renewable energy technologies in power generation by region




IEA. CC BY 4.0.

## VRE generation shares in 2024 and 2030 for selected countries

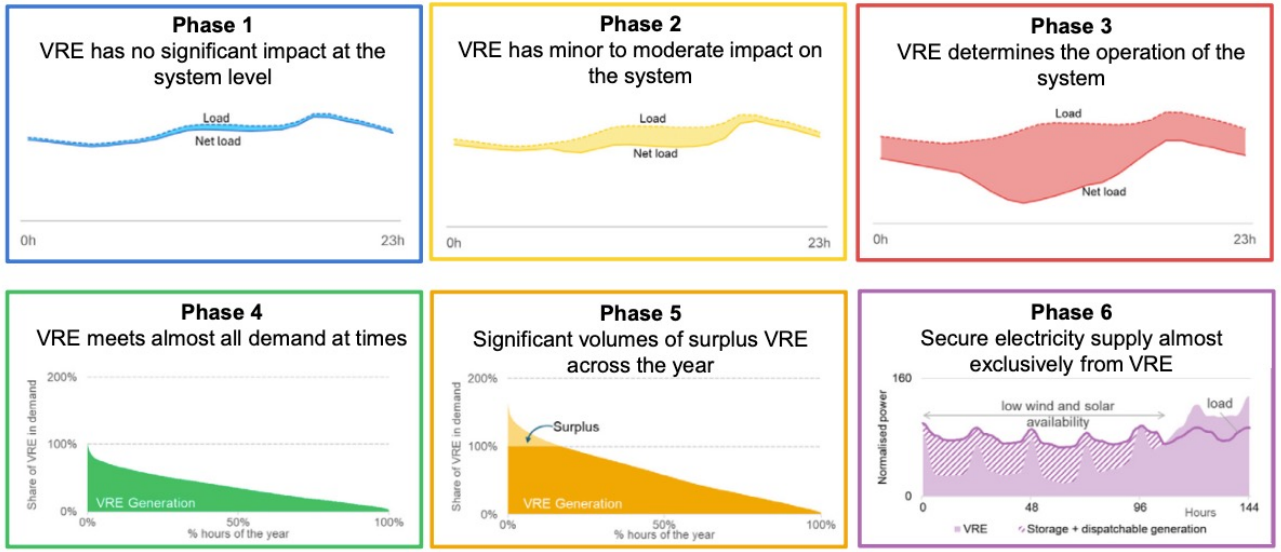



IEA. CC BY 4.0.



Source: IEA Renewables 2025

# EGAT IEA VRE integration framework phases




IEA. CC BY 4.0.

## LOW PENETRATION (Phases 1–2)

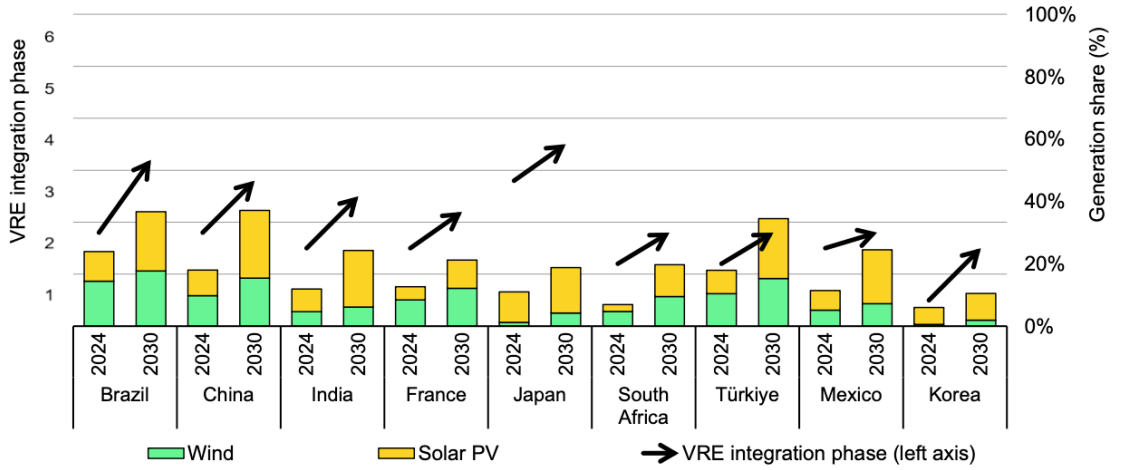
- **System Impact**: Minimal to moderate. Renewable generation initially acts as a basic load reduction.
- **Operational Shift:** Requires increased ramping of conventional power plants and enhanced forecasting.

## GROWING ROLE (Phase 3)

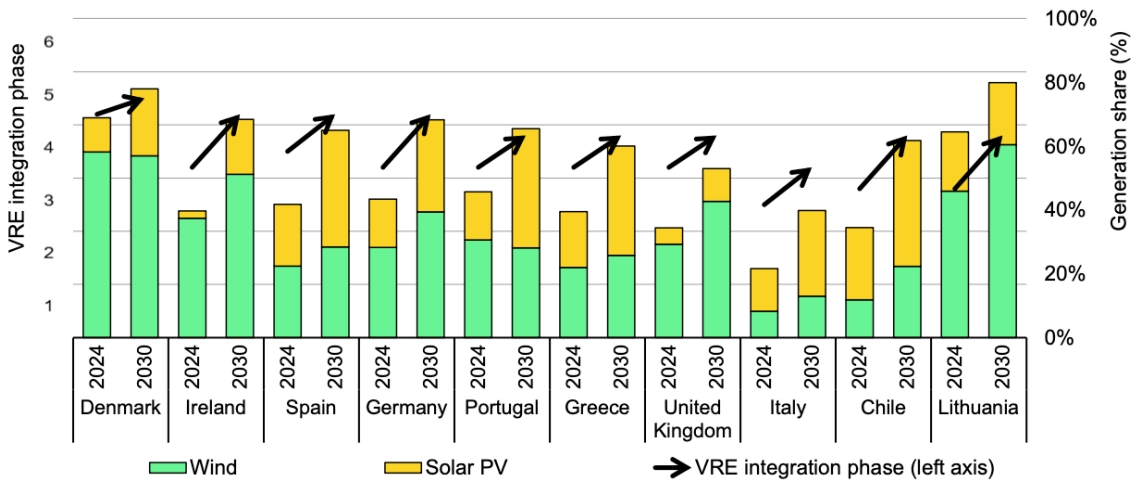
- **System Impact:** VRE begins to actively determine daily operation patterns.
- **Operational Shift:** Grid experiences stronger net load variability and sharper power swings.

## HIGH PENETRATION (Phases 4–6)

- **System Impact:** VRE regularly meets total demand; massive power surpluses begin to appear.
- **Operational Shift:** System flips to relying almost exclusively on VRE, pushing thermal plants to backup status.




IEA. CC BY 4.0.




IEA. CC BY 4.0.



Source: IEA Renewables 2025

# VRE Integration Measures

| Measure to integrate VRE | Phase of VRE integration | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| **Enhance power plant capability** | | | | | |
| Retrofit conventional power plants | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| Flexible offtake and upstream fuel contracts | 🔴 | 🔴 | 🟡 | 🟢 | 🟢 |
| Increase VRE technical requirements | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| **Forecasting** | | | | | |
| VRE generation | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| Net load | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| Power flows | 🔴 | 🟡 | 🟡 | 🟡 | 🟡 |
| **Demand-side measures** | | | | | |
| Industrial demand response | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| Commercial demand response | 🔴 | 🟡 | 🟢 | 🟢 | 🟢 |
| Residential demand response | 🔴 | 🔴 | 🟡 | 🟡 | 🟢 |
| Steer location of new demand | 🔴 | 🔴 | 🔴 | 🟡 | 🟡 |
| **Modify system operation rules** | | | | | |
| Allow VRE curtailment | 🔴 | 🟡 | 🟡 | 🟡 | 🟢 |
| High granularity/closer to real time | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| Least-cost dispatch | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| Capacity mechanism | 🔴 | 🟡 | 🟡 | 🟡 | 🟡 |
| Establish balancing market | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| Establish ancillary service market | 🔴 | 🟡 | 🟡 | 🟡 | 🟢 |
| Enhance use of interconnection | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| **Enhance grid capacity and use** | | | | | |
| Install stability support devices (STATCOMs, SYNCONs) | 🟡 | 🟡 | 🟡 | 🟡 | 🟢 |
| Interconnection/redundancy/mesh | 🟢 | 🟢 | 🟢 | 🟢 | 🟢 |
| Reinforcement | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| Allow VRE curtailment | 🟡 | 🟢 | 🟢 | 🟢 | 🟢 |
| Power flow control | 🔴 | 🟡 | 🟢 | 🟢 | 🟢 |
| Steer location of new VRE | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| **Storage** | | | | | |
| Pumped hydro | 🟡 | 🟢 | 🟡 | 🟡 | 🟢 |
| Battery energy storage | 🔴 | 🟡 | 🟡 | 🟢 | 🟢 |
| Long-duration storage | 🔴 | 🔴 | 🔴 | 🔴 | 🟡 |

🟢 **> 80% of systems**

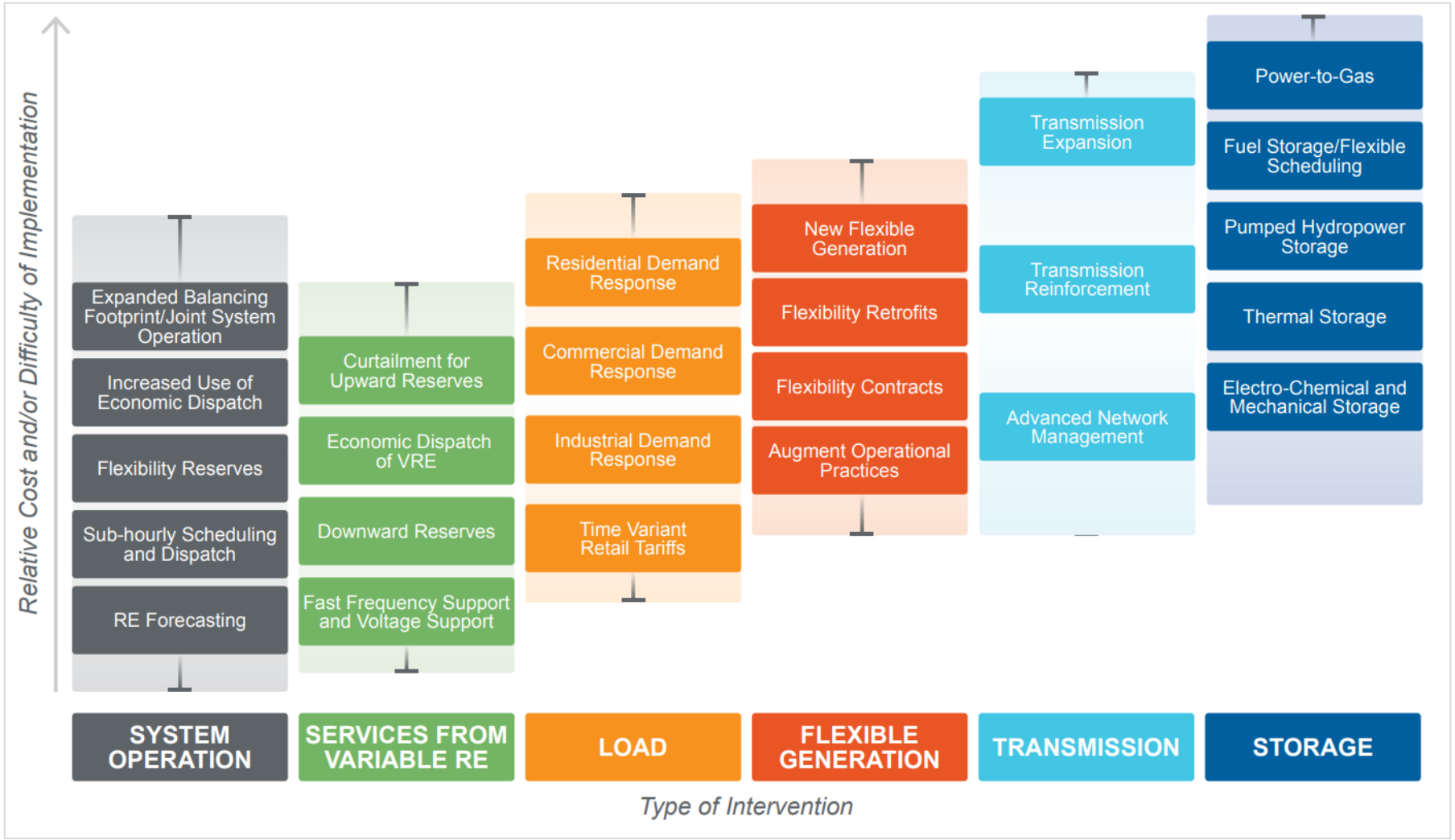
🟡 **50–80% of systems**

🔴 **< 50% of systems**



Source: IEA Integrating Solar and Wind 2024

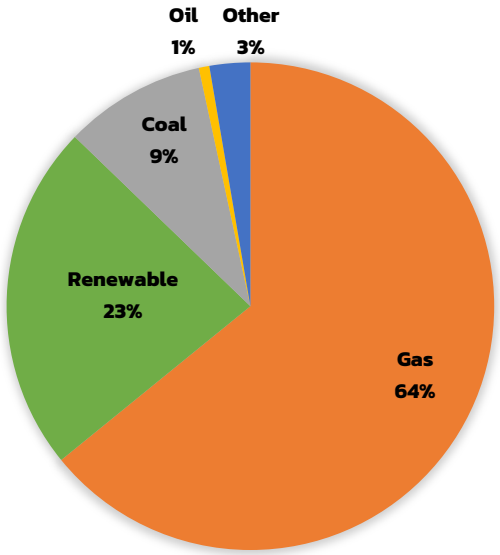
# EGAT Integrating Variable Renewables: A Cost-Benefit Roadmap




*Source: NREL, Renewable Energy Grid Integration – System, Load, Generation, Transmission & Storage measures*

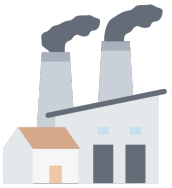
# Overview of Thailand's Electricity Industry Structure

## Enhanced Single Buyer (ESB)

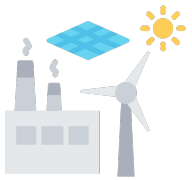



**Generation**

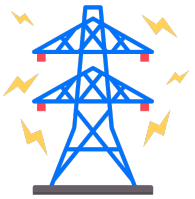
Electricity Generating Authority of Thailand (**EGAT**)



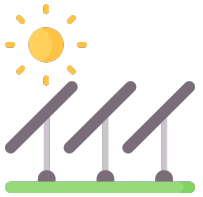
Independent Power Producers (**IPP**) > 90 MW



Small Power Producers (**SPP**) 10 – 90 MW



Cross-border Power Purchase



Very Small Power Producers (**VSPP**) < 10 MW

**Transmission**

**Transmission System and National Control center**

Electricity Generating Authority of Thailand (**EGAT**)

**Distribution**

Provincial Electricity Authority (**PEA**)

Metropolitan Electricity Authority (**MEA**)

**End User**



EGAT Direct Customers

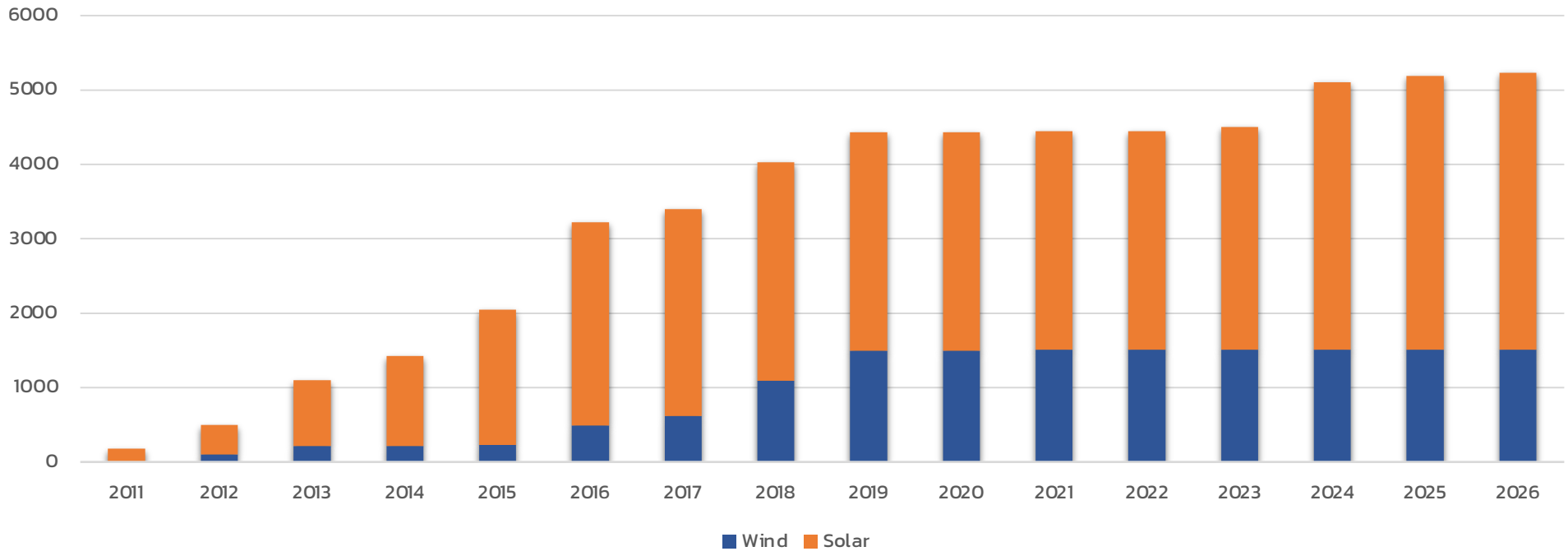


Power Users

As of 15/11/2026.

# Thailand's VRE Current Status

- Total installed electricity capacity : ~55 GW
- Renewables: ~30% of generation mix
- Solar PV: ~3.7 GW installed, fastest-growing source
- Wind: ~1.5 GW installed, mainly Northeast of Thailand

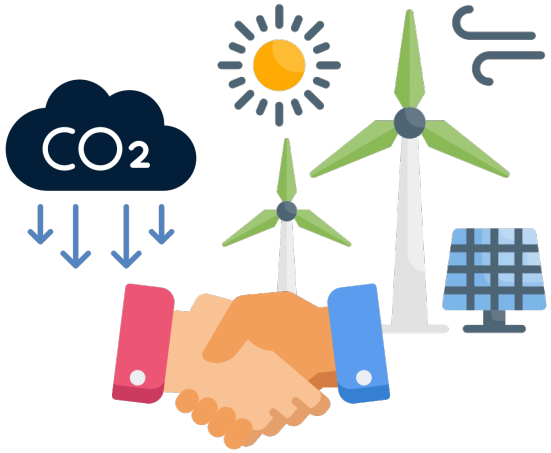


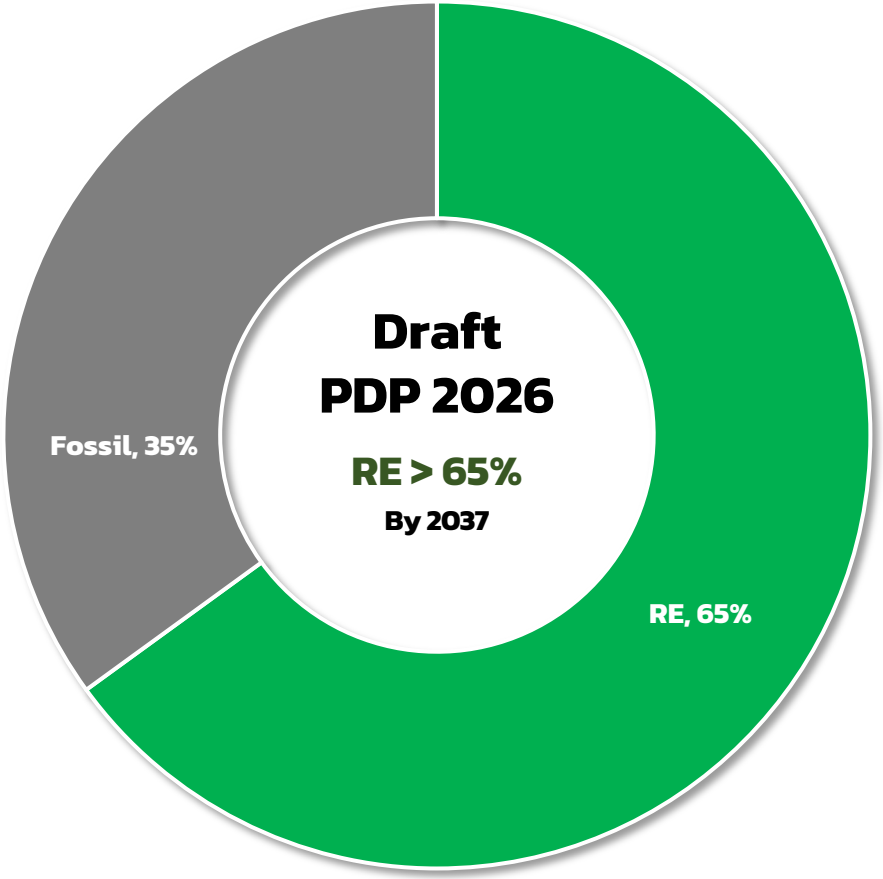



Source: ERC (as of Oct 2026)

**NDC 3.0 (COP30)**

Thailand aims to reduce its net GHG emissions to 152 million tCO2eq by 2035, representing a 47% reduction (135.2 MtCO2eq) compared to 2019 levels. This target aligns with the 1.5-degree pathways and **a goal of net-zero emissions by 2050.**



# EGAT Thailand's Smart Grid Master Plan



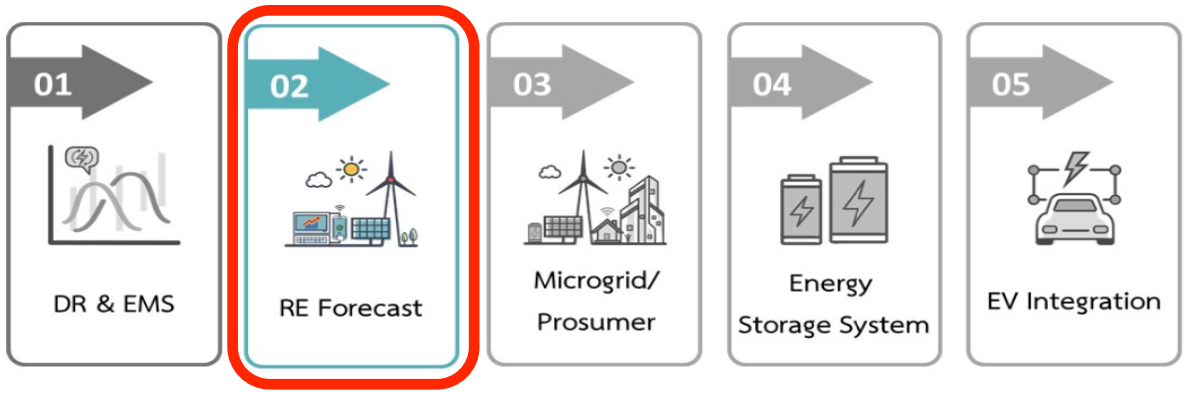

**Thailand Smart Grid Development Master Plan (2025 – 2036)**




**Thailand Smart Grid Action Plan Short-term (2017 – 2021)**




**Thailand Smart Grid Action Plan Medium-term (2022 – 2031)**




## Key Objectives of Developing RE Forecasting Systems

- RE forecast is a key pillar in developing a smarter power system. **It supports power plant scheduling and grid operation to accommodate increasing shares of renewable energy in the future** without compromising system stability.
- **It enables effective control and balancing between demand and supply**, thereby enhancing the reliability of renewable power generation.
- To enable the implementation of renewable energy power forecasting systems **covering Independent Power Producers (SPP), Very Small Power Producers (VSPP), as well as aggregators.**

# Key Challenges of Integrating VRE into the Grid



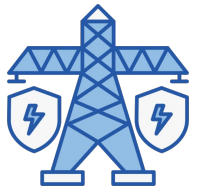
## Intermittency & Variability

VRE output fluctuates constantly with weather patterns (e.g., wind speed, cloud cover), which makes it difficult to match real-time supply with demand, leading to potential surpluses or shortfalls.



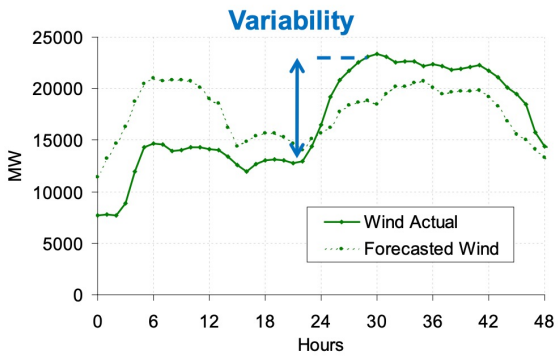
## Uncertainty

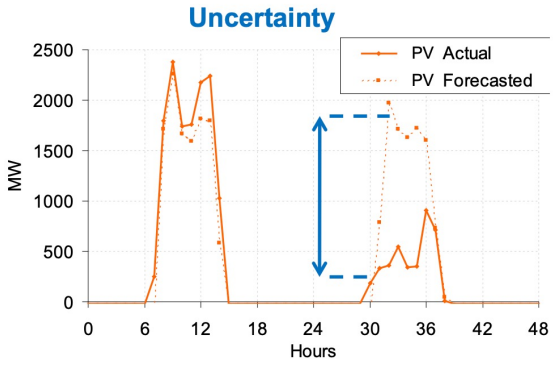
Even with advanced forecasting, predicting exact renewable output remains challenging.



## Lack of System Inertia & Grid Stability

The grid becomes more susceptible to rapid frequency deviations, increasing the risk of instability and blackouts.






Source: Ela, E., Diakov, V., Ibanez, E., & Heaney, M. (2013). Impacts of variability and uncertainty in solar photovoltaic generation at multiple timescales. National Renewable Energy Laboratory. NREL/TP-5500-58274. https://www.nrel.gov/docs/fy13osti/58274.pdf

# Benefits of VRE Forecasting for Power System Operations



## Economic Dispatch

Accurate day-ahead and hour-ahead forecasting informs optimal unit commitment and economic dispatch decisions.



## Reduced Spinning Reserves

Improved forecasting reduces the need for expensive spinning reserves by minimizing operational uncertainty.



## Curtailment Avoidance

Better forecasting minimizes renewable energy curtailment by allowing operators to manage expected grid congestion and oversupply.

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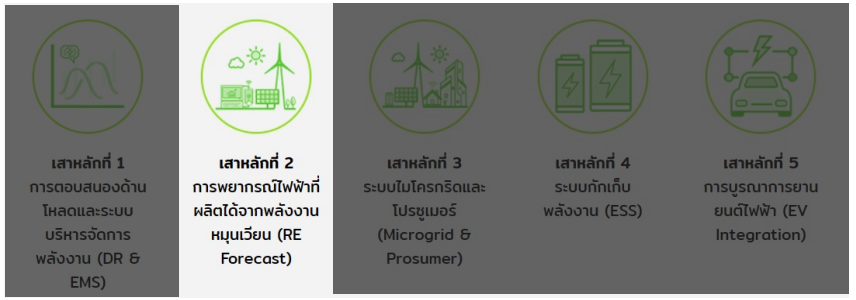
# EGAT Thailand Smart Grid Action Plan

## Short-term 2017 – 2021 and Medium-term 2022 – 2031




Pilot testing of technology for forecasting electricity production from renewable energy sources.

**EGAT-03**

A feasibility study and implementation of electricity forecasting technology for renewable energy production.

**EGAT-02**

Pilot project for forecasting electricity production from renewable energy sources at the VSPP power plant.

**EGAT-2-01**

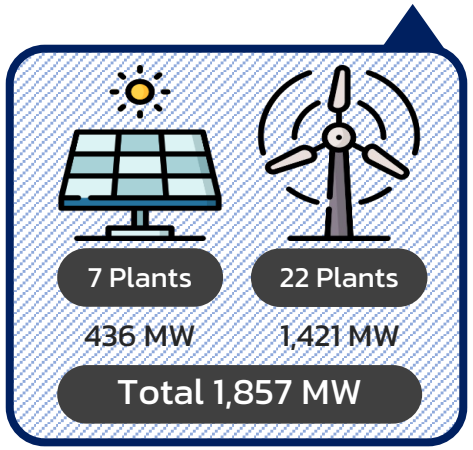
Renewable Energy Generation Forecasting Project using the Ensemble Method for SPP Power Plants

**EGAT-2-02**

Renewable Energy Generation Forecasting Project using the Ensemble Method for VSPP Power Plants

**EGAT-2-03**

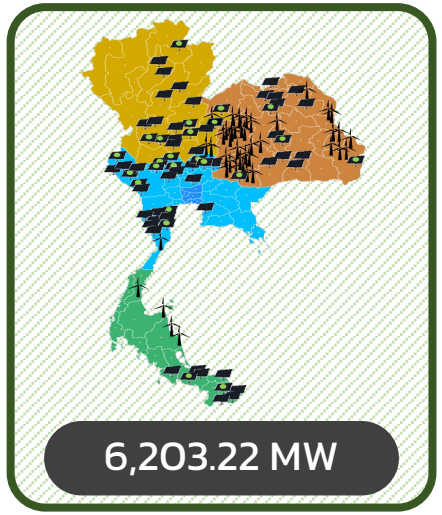
2017 2018 2019 2020 2021 2022 2023 2024 2025 We're Here 2026 2027 2028 2029 2030 2031









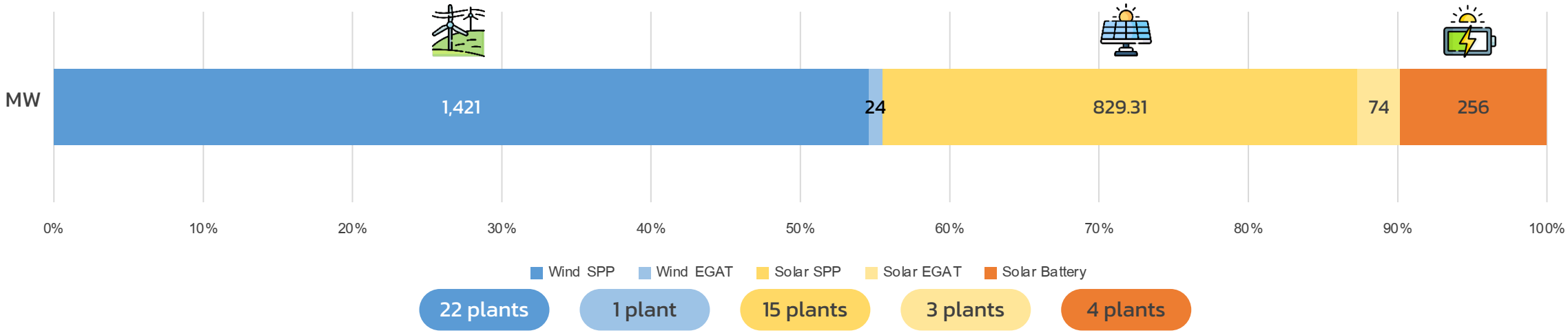



# EGAT REFC Achievements

Solar and Wind forecasting now successfully covers the entire system

Total 45 plants **2,604.31** MW

Average error of
**Solar below 8%**
**Wind below 12%**
across multiple model types




## Multiple Models per Plant

Accommodates diverse weather conditions and the unique characteristics of each power plant, improving forecast stability.

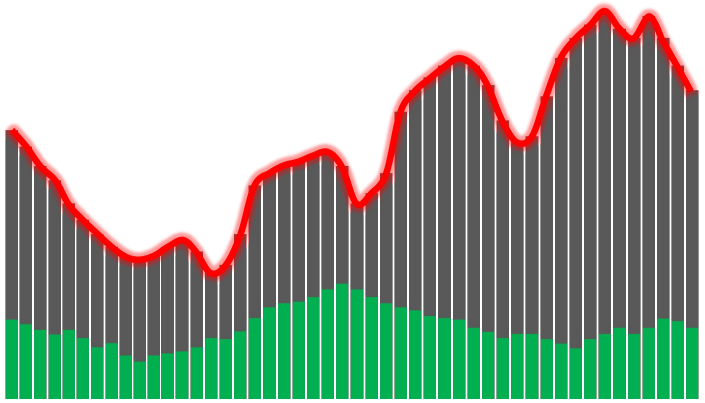
## Ensemble Method

Combines multiple forecasting models to deliver more accurate and reliable forecasts.

## Ready for All RE Plants

Includes RE Big Lots over 263 plants, 9,722 MW

# EGAT RE Forecast Center : Role



Forecast time : Daily (13:00)
Time horizon : 10 days
Resolution : 30 minutes

- Load Forecast
- Dispatchable Gen.
- Day-ahead Forecast
- Intraday Forecast

Workflow

REFC

**Day-ahead**

**10 Day**-ahead Forecast

**Intraday**

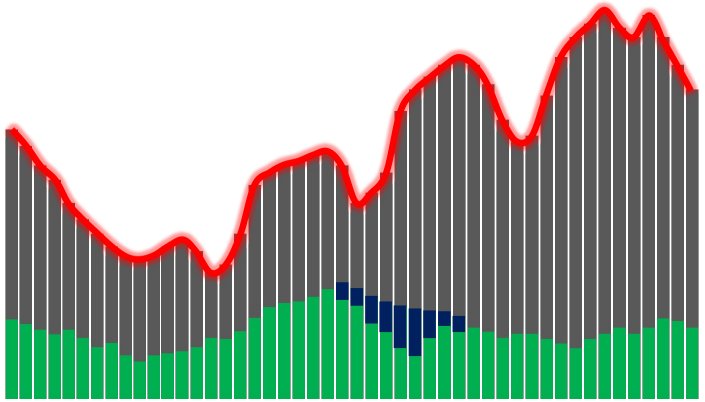
**6 Hour**-ahead Forecast

**Scheduler**

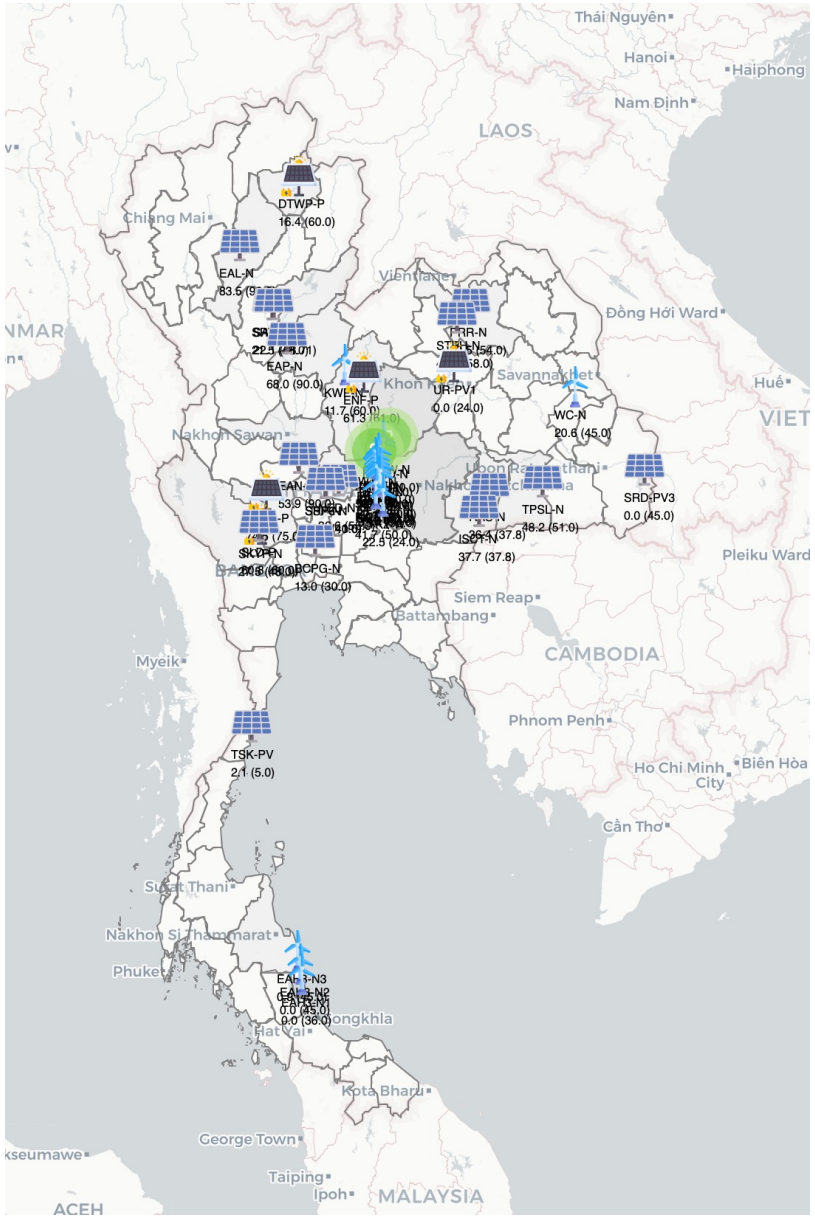
Medium-term & Short-term

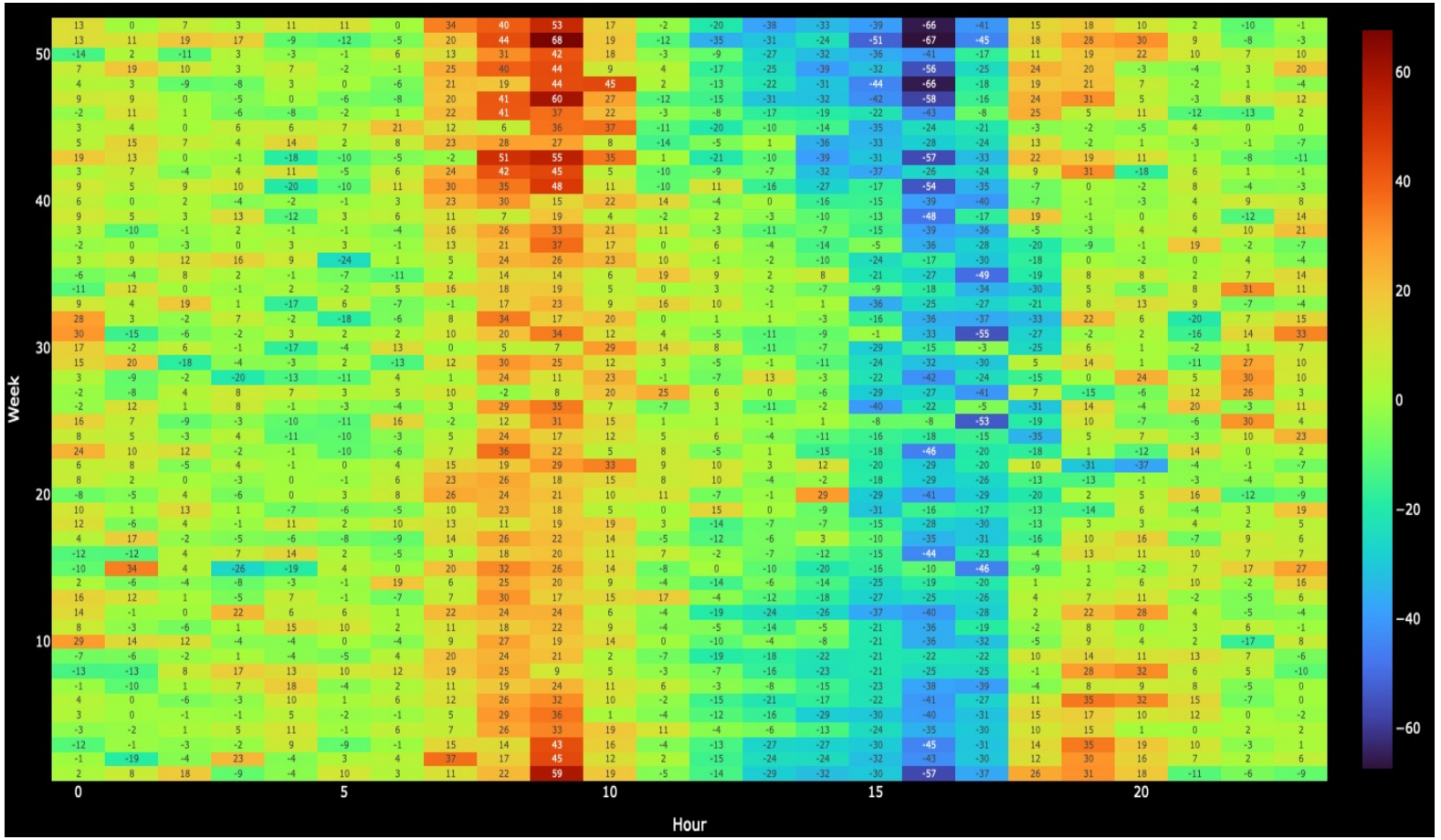
**NCC**

National Control Center



Forecast time : Hourly
Time horizon : 6 hours
Resolution : 30 minutes



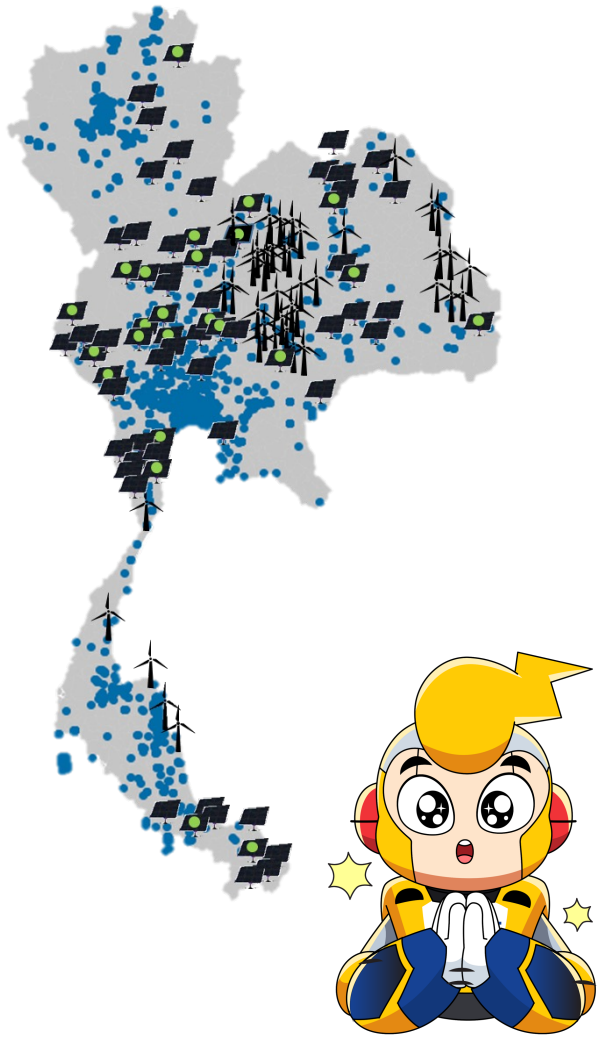




# Variation (MW) in 2025

# REFC Coverage Roadmap

## Roadmap of SPP capacity, REFC will forecast by 2030

| | |
|---|---|
| **Solar SPPs** | 2,313.96 MW<br>46 plants |
| **Wind SPPs** | 2,895.20 MW<br>42 plants |
| **Solar BESS** | 994.06 MW<br>24 plants |
| **Total SPP** | 6,203.22 MW<br>112 plants |



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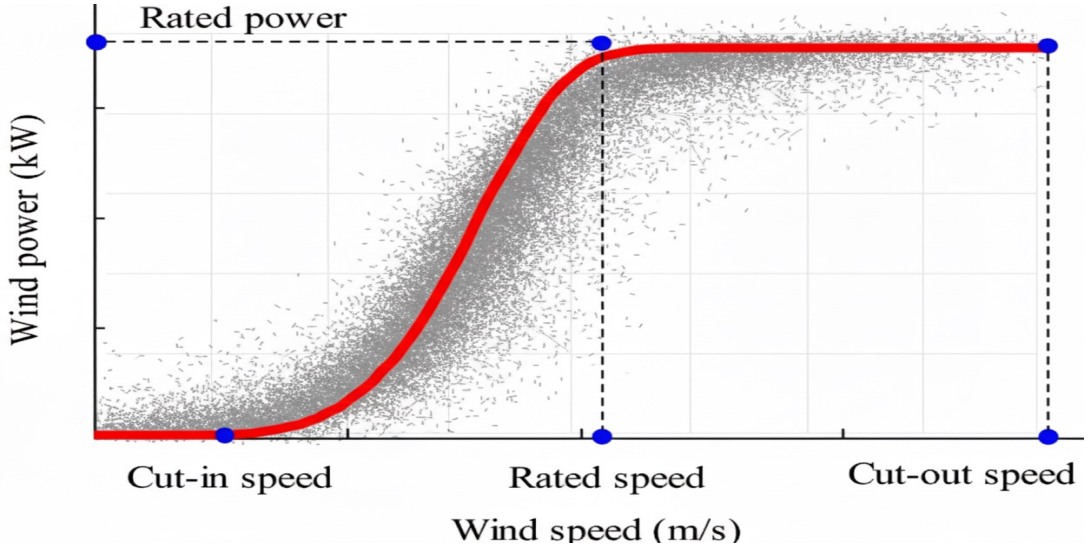
# Wind Turbine Power Curve

The power output of a wind turbine is highly dependent on wind speed. The relationship is not linear; it is described by **the Power Cube Law**, which means **a small increase in wind speed results in a much larger increase in power**.

$$P = \frac{1}{2}\rho A v^3, P \propto v^3$$

Where:

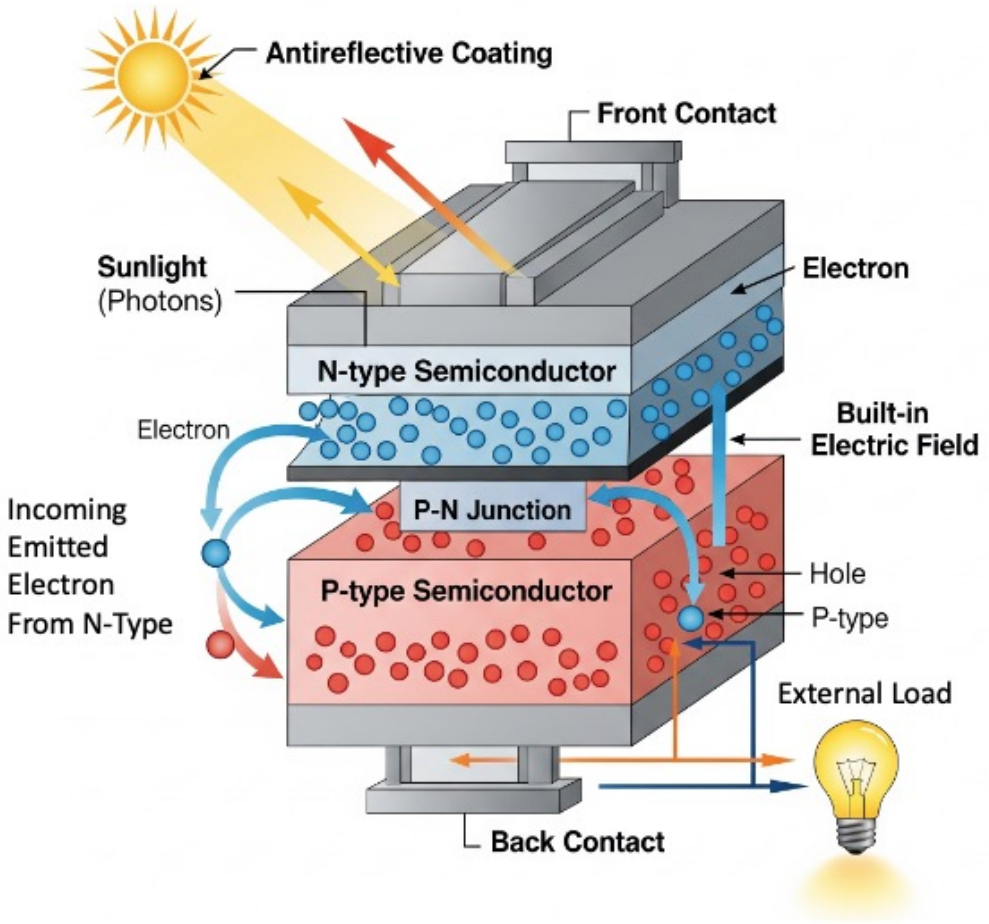
- P = Power
- ρ (rho) = Air density
- A = Swept area of the blades
- v = Wind speed

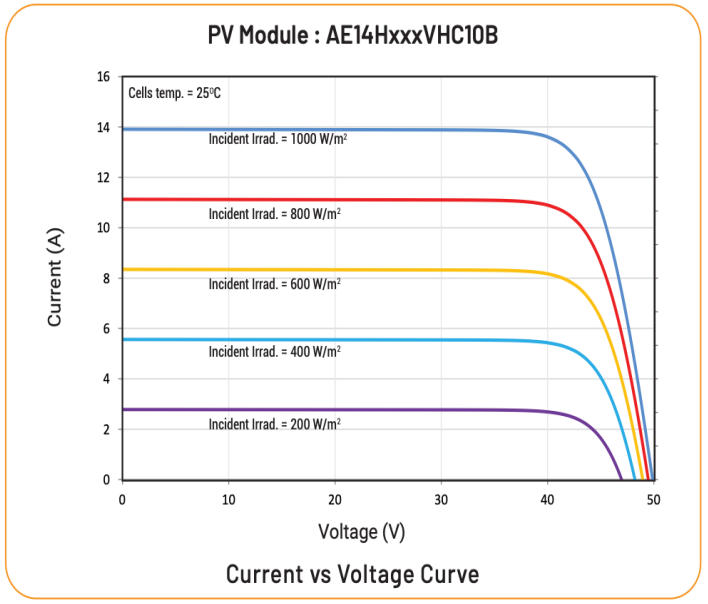


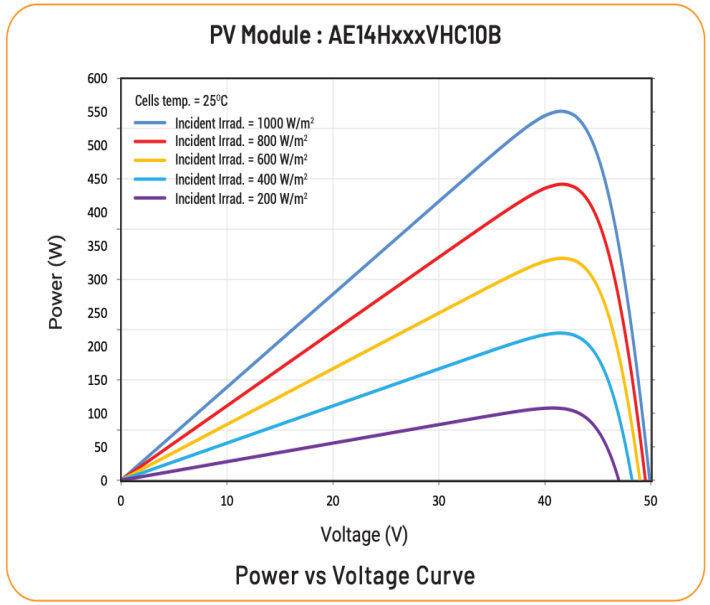

**Key operating speeds:**

- **Cut-in Speed**: The minimum wind speed required for the turbine to start generating power.
- **Rated Speed**: The wind speed at which the turbine reaches its maximum, or "rated," power output.
- **Cut-out Speed**: The wind speed at which the turbine automatically shuts down to prevent damage from high winds.

# Solar PV Power Generation




## Temperature Characteristics

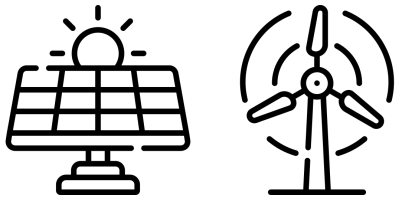
| | |
|---|---|
| Temperature Coefficient of Pmax(γ) | -0.36 %/°C |
| Temperature Coefficient of Voc(β) | -0.304 %/°C |
| Temperature Coefficient of Isc(α) | +0.050 %/°C |
| Nominal Operating Cell Temperature (NOCT) | 42±2°C |



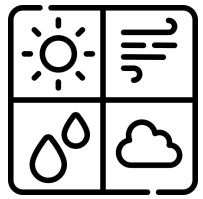
Source: https://lssth.panasonic.com/products/energy/product_finder/img/solar002.pdf

# How to Forecast VRE?

## Input



Generation



Numerical Weather Prediction



Satellite / Sky Image

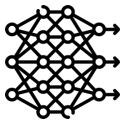
## Model



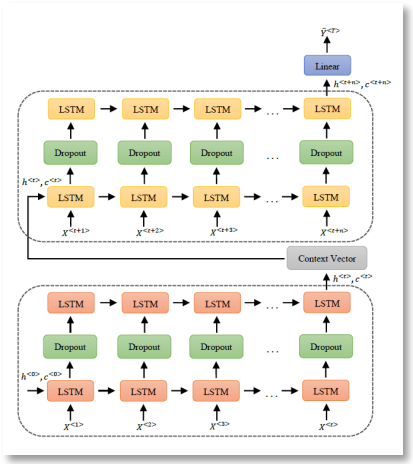
Physics-based

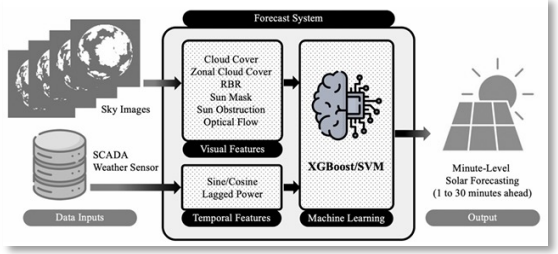


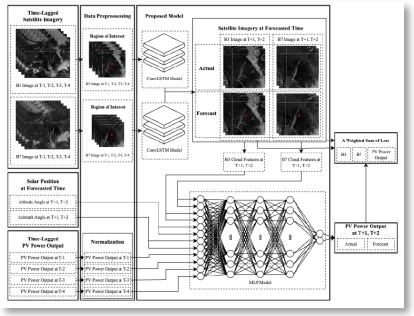
Machine Learning



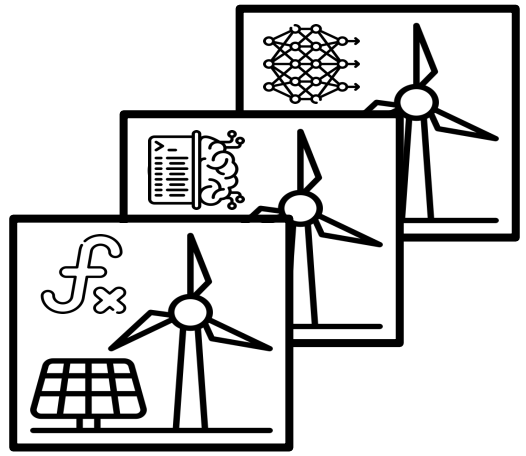
Deep Learning



## Output



Forecasted Generation





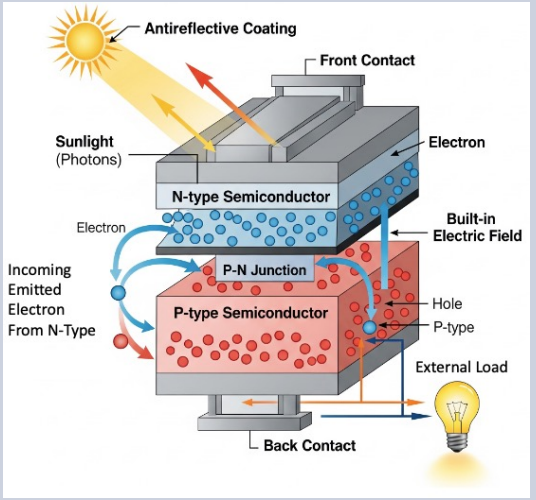


# EGAT Forecasting Methodology : Physical-based

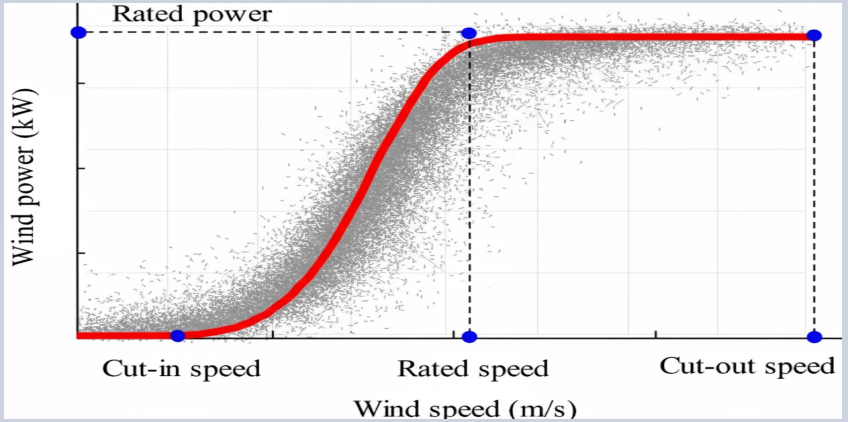
## Main Concepts

- Calculation of electricity generation from renewable energy is based on **laws of physics, equipment engineering specifications, and mathematical equations** to directly describe natural phenomena, rather than relying solely on historical statistical data.
- **Physical models work sequentially**, taking real environmental data to calculate through the physical properties of the power system.

| Pros | Cons |
|---|---|
| **Does not require massive historical data:** Can instantly forecast for a newly completed power plant from day one because it references calculation formulas from the plant's technical specifications. | **Highly dependent on the accuracy of weather models:** If raw data from the Meteorological Department is inaccurate, the power system output will immediately deviate. |
| **High logical soundness:** Explains the underlying scientific principles (Interpretability) of why power generation increases or decreases. | **Complex calculation and resource-intensive:** Requires significant computer processing power to simulate the local terrain and physical structure. |




**PV Conversion Model**



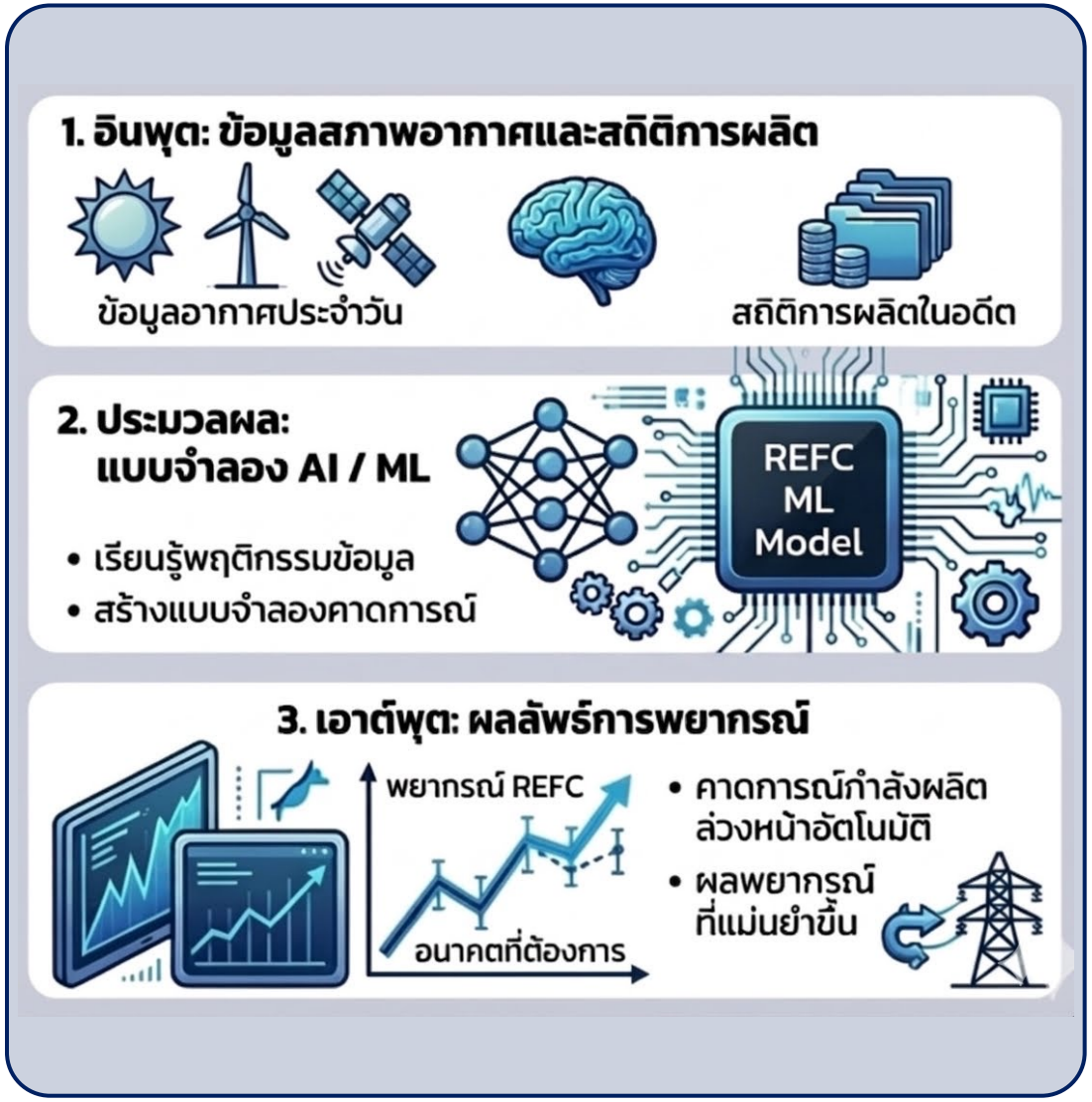

**Turbine Conversion Model**

# EGAT Forecasting Methodology : Machine Learning

## Main Concept

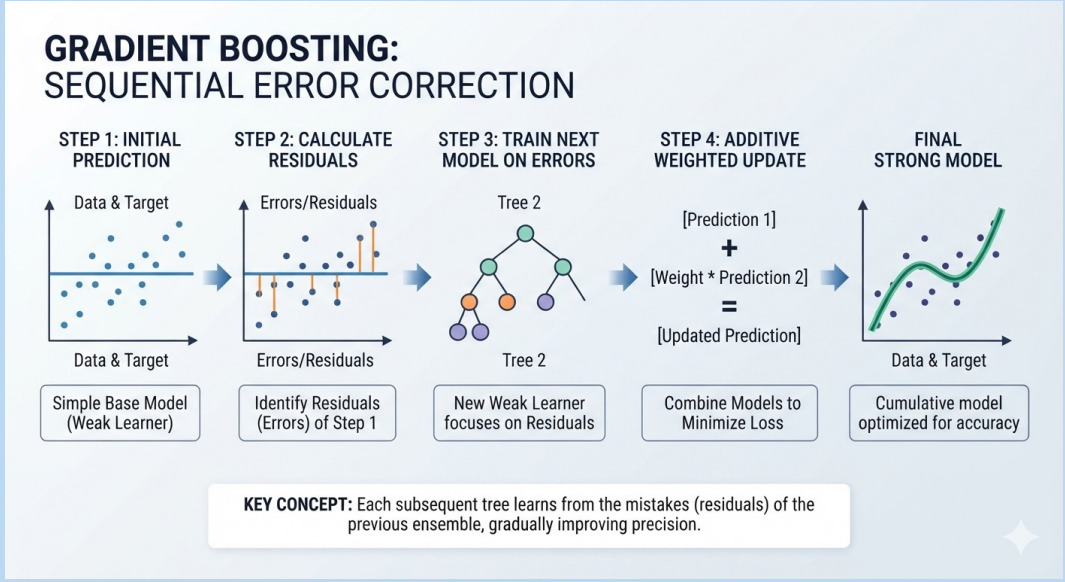
- Applying AI technology and machine learning algorithms to **discover deep correlations between daily weather data and historical power generation records** in order to automatically build solar and wind power forecasting models. The system does not primarily rely on the physical calculation formulas of the equipment but instead uses methods to learn and memorize from the "behavior of actual data" that occurred in the past.

| Pros | Cons |
|---|---|
| **Excellent at capturing complex patterns:** Can detect relationships that are difficult for physics formulas to calculate. | **Requires a massive amount of data:** Cannot be used to forecast for power plants that do not have historical generation data. |
| **Highly adaptable and continuous learning (Self-learning):** The longer it is used and the more new data is fed in, the more accurate the model becomes over time. | **Functions as a Black Box:** It is quite difficult to scientifically explain the reasoning behind why the AI generated those specific forecast figures. |




"Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed." –Arthur Samuel (1959)

# Forecasting Methodology : Machine Learning



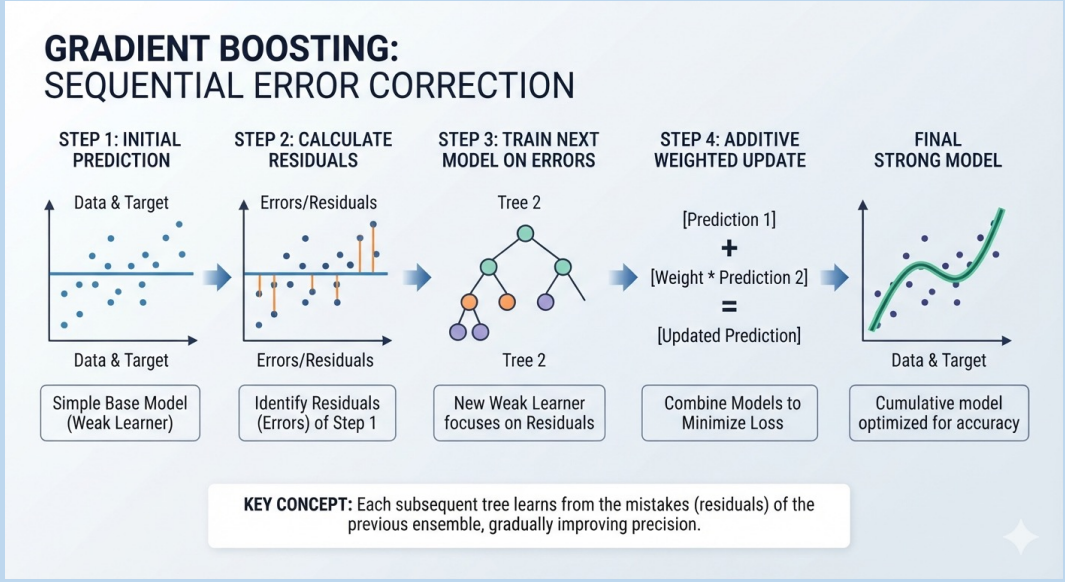

**Core Concept:**

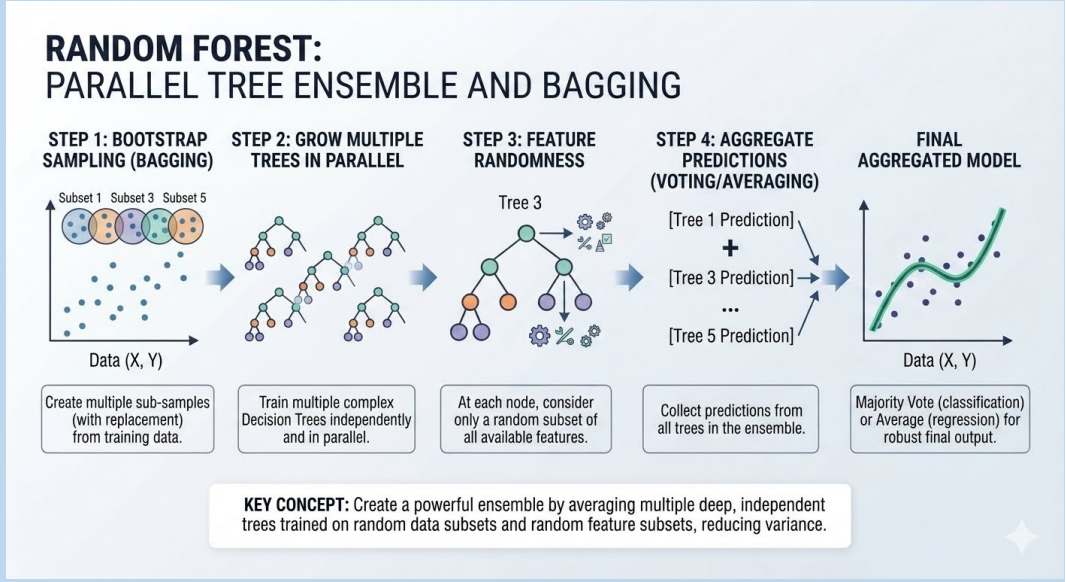
- Trains trees sequentially.
- Fixes errors of past trees.
- High accuracy, needs tuning.

**Mechanism**: Every new tree corrects the errors made by the previous one.

**Strength**: Exceptional accuracy for complex, non-linear trends.

# EGAT Forecasting Methodology : Machine Learning

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- Fixes errors of past trees.
- High accuracy, needs tuning.

**Mechanism**: Every new tree corrects the errors made by the previous one.

**Strength**: Exceptional accuracy for complex, non-linear trends.

**Core Concept:**

- Trains trees in parallel.
- Averages out individual votes.
- Stable, resistant to noise.

**Mechanism**: Creates an ensemble of independent trees and averages their votes.

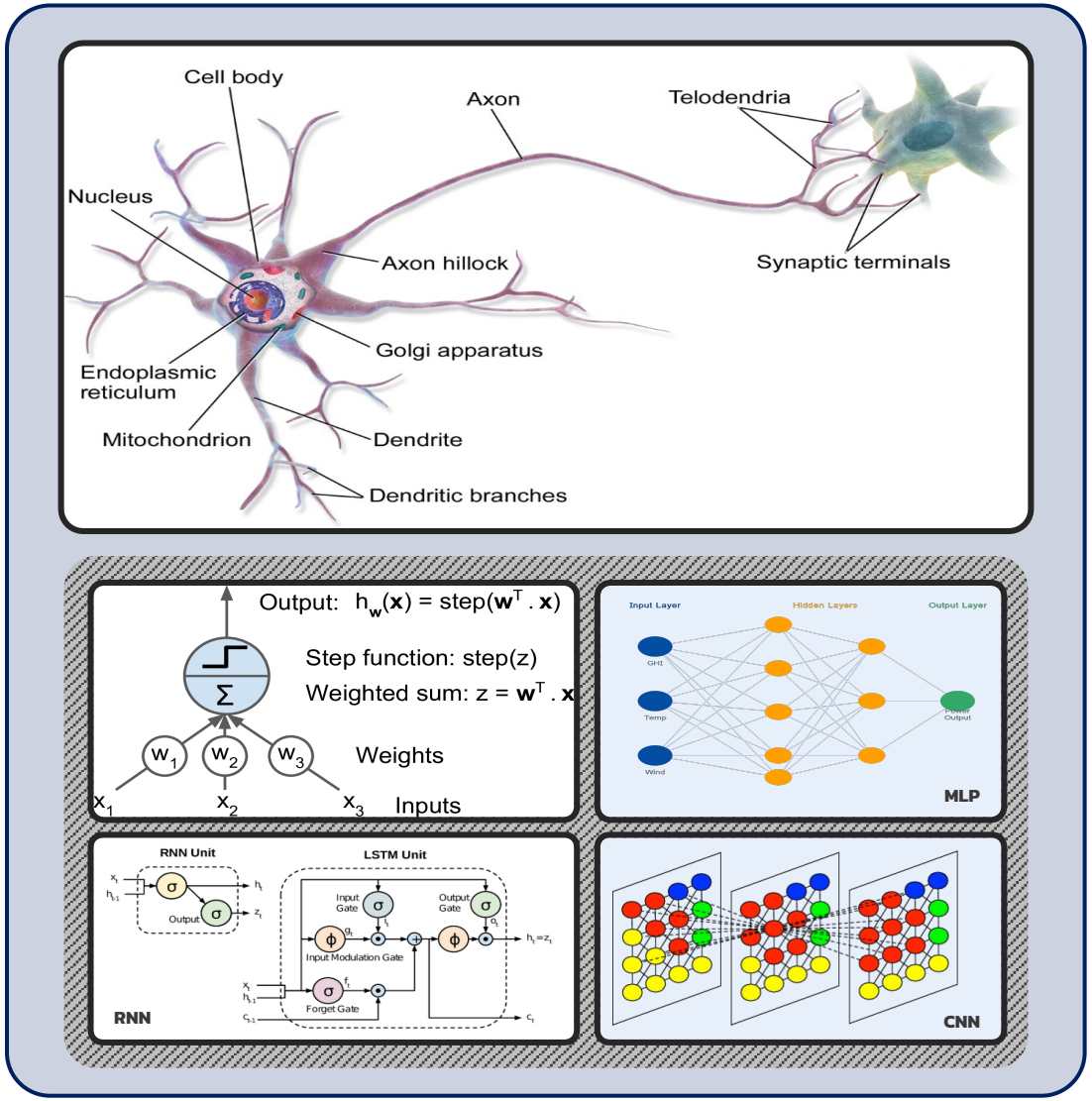
**Strength**: Highly stable, robust against data noise, and hard to overfit.

# EGAT Forecasting Methodology : Deep Learning

## Main Concept

- Applying artificial neural networks with complex, multi-layered architectures such as LSTM or Transformers to learn and forecast solar and wind power generation. The system can automatically extract key features from raw data with highly complex dimensions on its own.
- Because renewable energy varies across time and space, Deep Learning can process satellite imagery (Spatial) and real-time time series (Temporal) simultaneously to forecast sudden fluctuations with high accuracy.

| Pros | Cons |
|---|---|
| **Top Accuracy with Big Data:** Automatically extracts features from satellite/radar data; accurately predicts sudden cloud and wind changes. | **Ultimate Black Box:** The structure is so complex that it is impossible to explain the reasoning or origin behind the forecast figures based on principles of physics. |
| **Superb Complex Data Handling:** Processes real-time satellite imagery and weather radar directly to track immediate solar and wind shifts. | **High Cost & Error Risk:** Requires expensive GPU hardware and risks severe errors when facing unseen, extreme weather. |

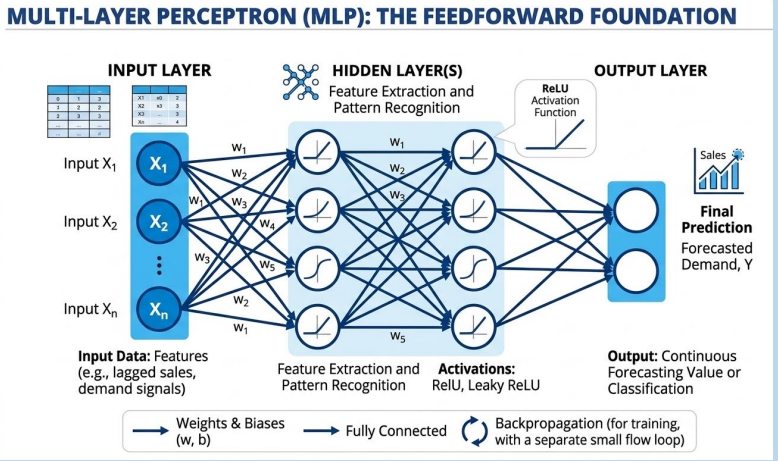



Source: https://www.oreilly.com/library/view/neural-networks-and/9781492037354/ch01.html


*Goodfellow, Bengio & Courville, Deep Learning (MIT Press, 2016)*

*Donahue, J., Hendricks, L. A., Rohrbach, M., Venugopalan, S., Guadarrama, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. In *Proceedings of the IEEE conference on computer vision and pattern*

# EGAT Forecasting Methodology : Deep Learning



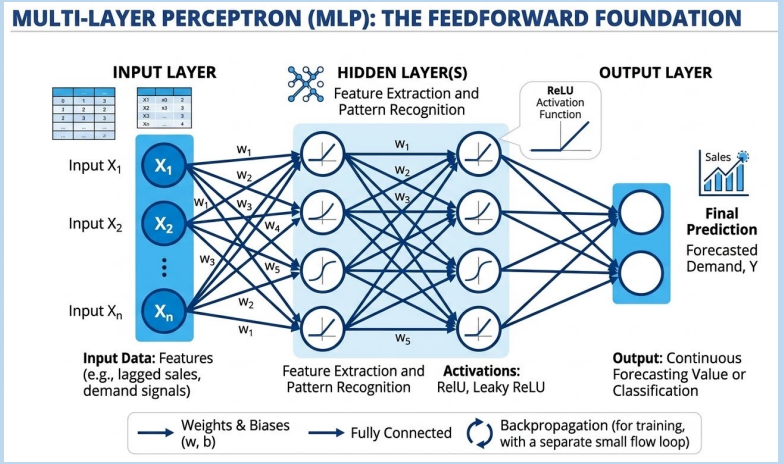

**Core Concept:**
Fully connected feedforward neural network architecture.

**Mechanism:**

- Passes data forward through input, hidden, and output layers of interconnected neurons.
- Uses Backpropagation and optimization functions to tweak network weights based on error rates.

**Strength:**
Excellent baseline for tabular data classification and capturing complex, non-linear relationships.

# EGAT Forecasting Methodology : Deep Learning

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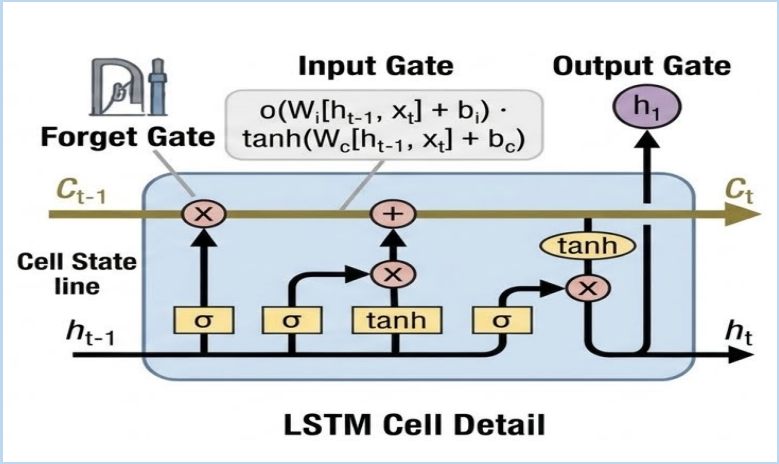


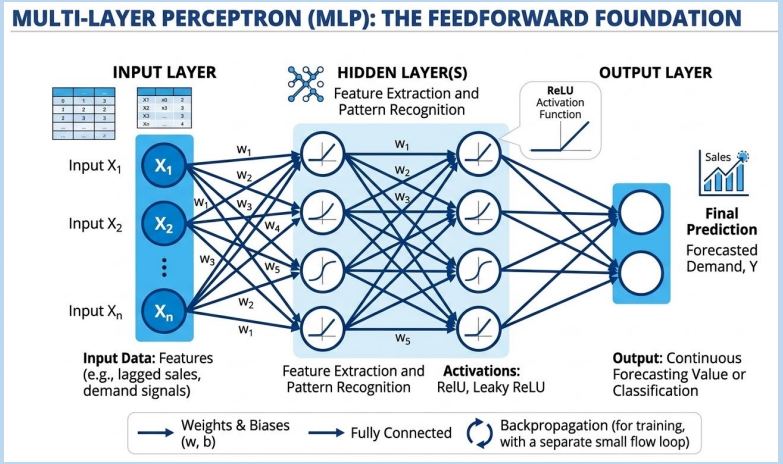

**Core Concept:**
Recurrent Neural Network (RNN) designed for sequential data processing.

**Mechanism:**

- Tracks historical context across sequences using an internal **Cell State** memory line.
- Regulates information flow dynamically using three mathematical filters: **Forget, Input, and Output gates**.

**Strength:**
Prevents vanishing gradients, allowing the network to remember critical information across long-term dependencies (e.g., text generation, time-series forecasting).

# EGAT Forecasting Methodology : Deep Learning

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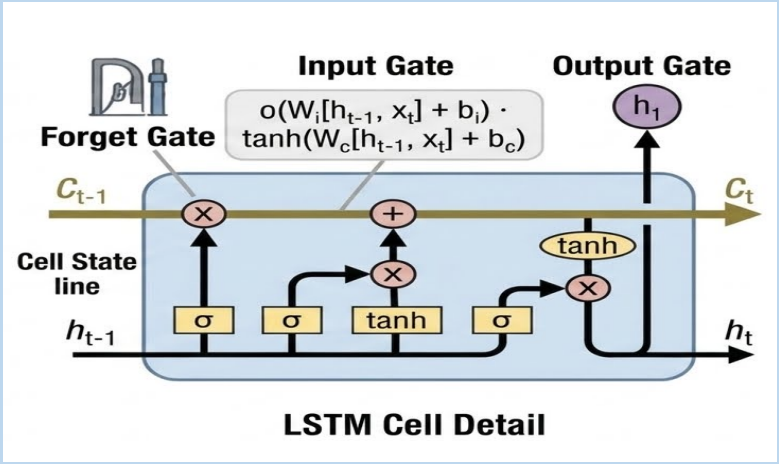


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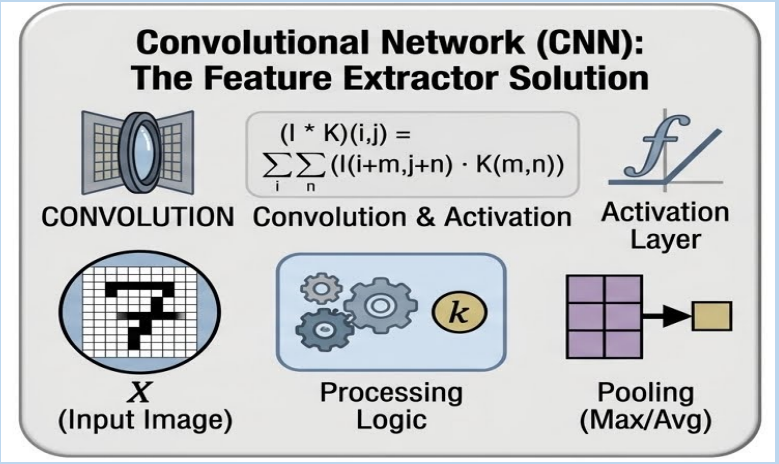



**Core Concept:**
Grid-based neural network architecture optimized for spatial pattern recognition.

**Mechanism:**

- Uses moving mathematical matrix filters (**Convolutions**) to extract features.
- Drops feature matrix dimensions dynamically via Pooling layers.

**Strength:**
Drastically cuts total parameters for elite image recognition.

# Forecasting Configurations



## Type of Forecast

- Deterministic Approach : Single best estimate of output, Simple to use, fast decisions
- Probabilistic Approach: Range + likelihood of outcomes (probability distribution, quantiles, or prediction intervals), Captures uncertainty for robust planning



## Time Horizon & Application

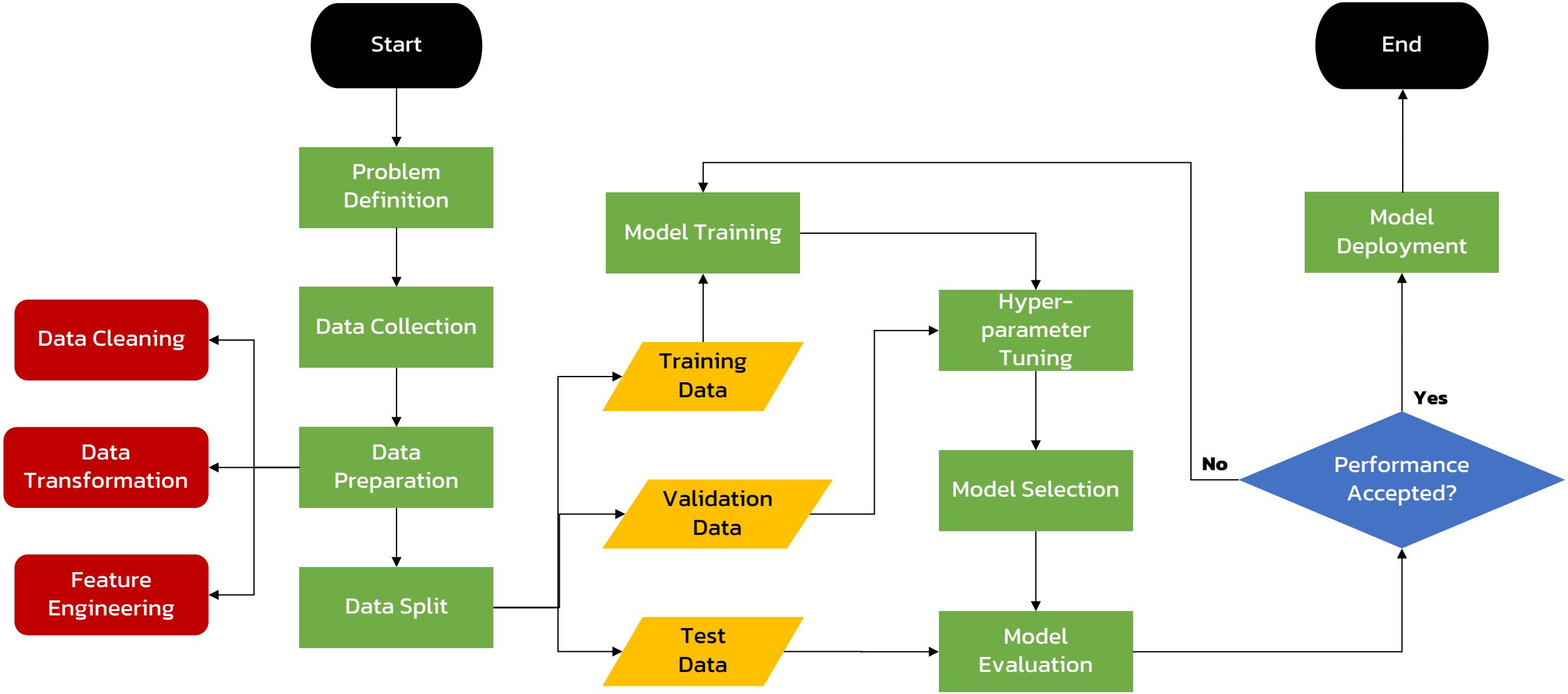
- Very Short-Term (nowcasting, minutes–1hour): Grid balancing, frequency control
- Short-Term (1hour–1day): Unit commitment, market scheduling
- Medium-Term (1day–1month): Maintenance planning, reserves allocation
- Long-Term (>1month–years): Investment, capacity expansion, policy planning



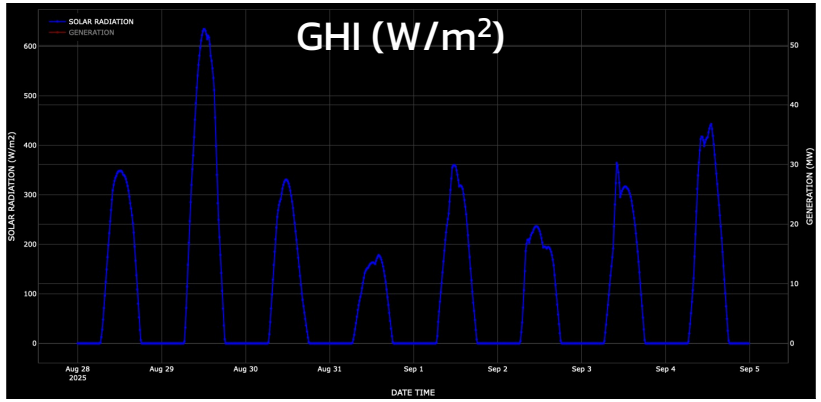
## Granularity

- Resolution: 1 / 5 / 15 / 30 minutes
- Time Step: Hourly, Daily

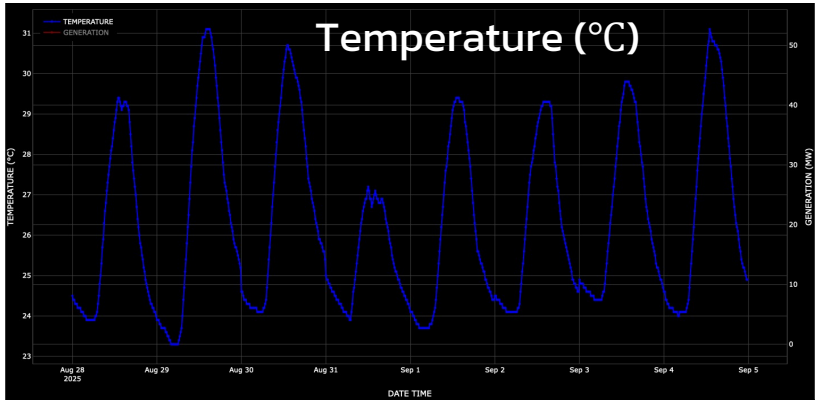
# AI Model Development Cycle



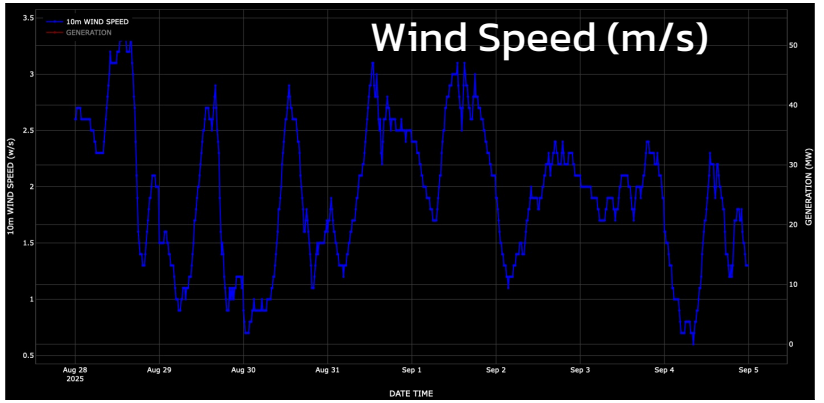
# Meteorological Time Series Example



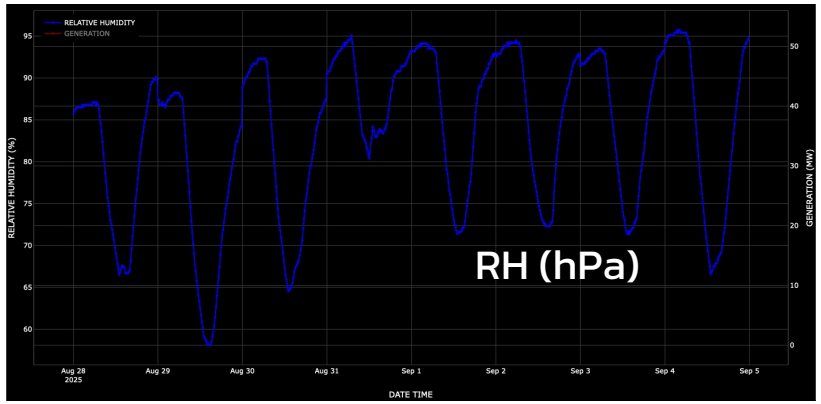

GHI (W/m$^2$)




Temperature (°C)



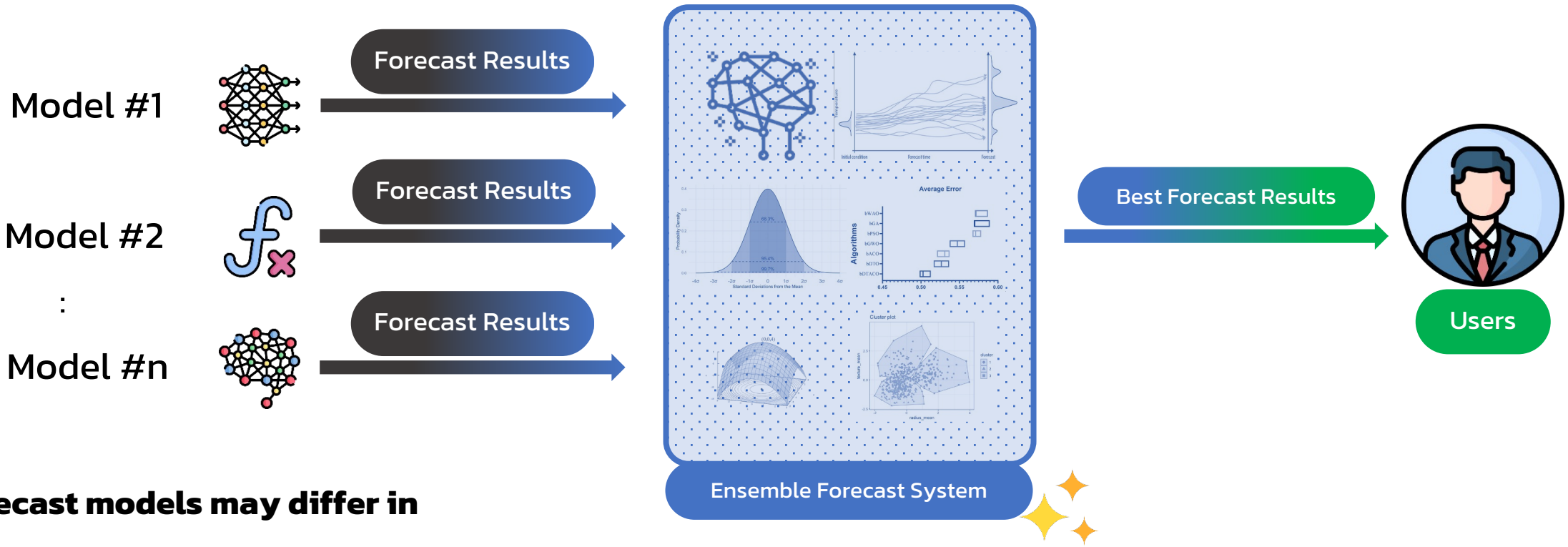

Wind Speed (m/s)




RH (hPa)

| | MW | cloudlow | dwpt | prec | prss | rh | swdown | tc | wg | ws10m | wshub |
|---|---|---|---|---|---|---|---|---|---|---|---|
| wshub | 0.36 | 0.28 | 0.41 | 0.02 | -0.37 | -0.68 | 0.43 | 0.72 | 0.88 | 0.79 | 1.00 |
| ws10m | 0.63 | 0.47 | 0.27 | -0.13 | -0.18 | -0.75 | 0.71 | 0.77 | 0.96 | 1.00 | 0.79 |
| wg | 0.63 | 0.47 | 0.35 | -0.14 | -0.28 | -0.84 | 0.70 | 0.87 | 1.00 | 0.96 | 0.88 |
| tc | 0.76 | 0.41 | 0.42 | -0.16 | -0.33 | -0.98 | 0.81 | 1.00 | 0.87 | 0.77 | 0.72 |
| swdown | 0.95 | 0.45 | 0.38 | -0.16 | 0.01 | -0.78 | 1.00 | 0.81 | 0.70 | 0.71 | 0.43 |
| rh | -0.72 | -0.34 | -0.27 | 0.20 | 0.31 | 1.00 | -0.78 | -0.98 | -0.84 | -0.75 | -0.68 |
| prss | 0.00 | -0.01 | -0.17 | -0.21 | 1.00 | 0.31 | 0.01 | -0.33 | -0.28 | -0.18 | -0.37 |
| prec | -0.19 | -0.10 | 0.16 | 1.00 | -0.21 | 0.20 | -0.16 | -0.16 | -0.14 | -0.13 | 0.02 |
| dwpt | 0.41 | 0.47 | 1.00 | 0.16 | -0.17 | -0.27 | 0.38 | 0.42 | 0.35 | 0.27 | 0.41 |
| cloudlow | 0.49 | 1.00 | 0.47 | -0.10 | -0.01 | -0.34 | 0.45 | 0.41 | 0.47 | 0.47 | 0.28 |
| MW | 1.00 | 0.49 | 0.41 | -0.19 | 0.00 | -0.72 | 0.95 | 0.76 | 0.63 | 0.63 | 0.36 |

# EGAT Ensemble Forecast



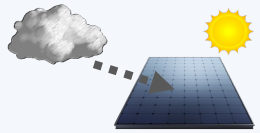

**Forecast models may differ in**

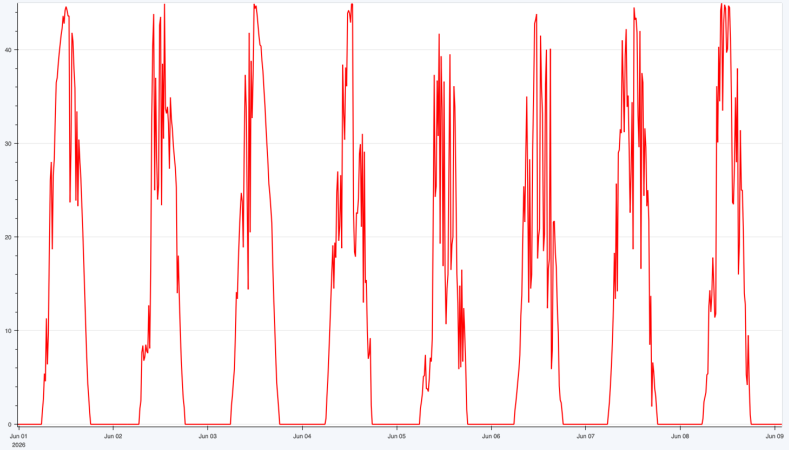
- Model Structure
- Hyperparameters used for training
- Training data
- Other assumptions used in modeling

# Intrahour Forecasting

## Why?

- **Solar Intermittency:** Rapid cloud movements cause sudden, massive drops in solar power output called ramp events.
- **Weather Models (NWP):** Designed for hourly or daily regional forecasts, not rapid local sky changes.
- **Ground Sensors:** Pyranometers record current sunlight but cannot look ahead to see oncoming clouds.



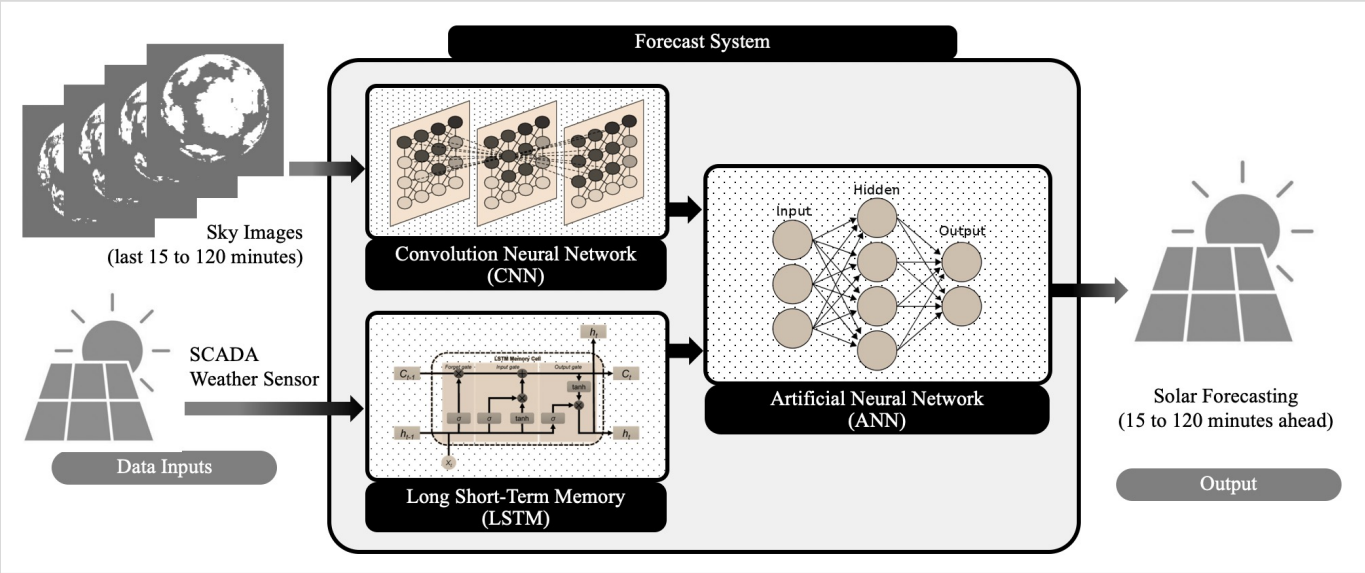


## Solution : All-Sky Imager (ASI)

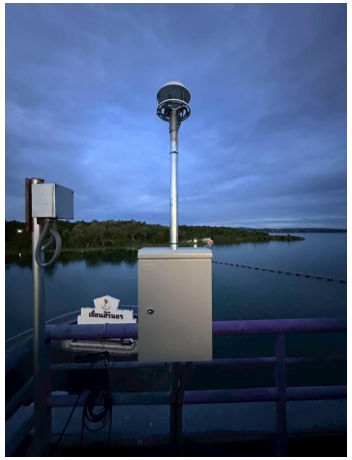
- **High Resolution:** Capture continuous, 360-degree ground-sky imagery in real-time (15 seconds).
- **Cloud Motion Vectors:** Calculate the exact speed, trajectory, and arrival time of cloud shadows.
- **Cloud Optical Depth:** Differentiate between thin, transparent clouds and thick, heavy blockages.
- **Ramp Event Detection:** Anticipates sudden drops or spikes in solar generation caused by fast-moving clouds.

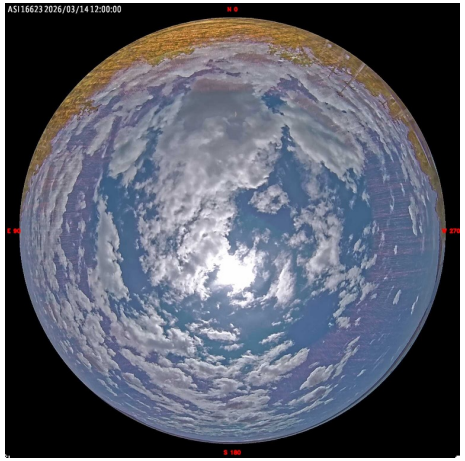


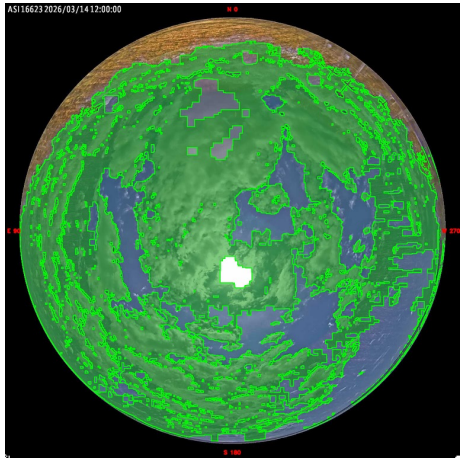
# EGAT REFC Sky Image




**1 Hour Ahead, 15 minutes resolution**
**15, 30, 45, 60 minute ahead**

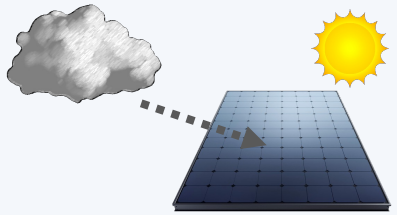






## Pilot Project: Sky Imager

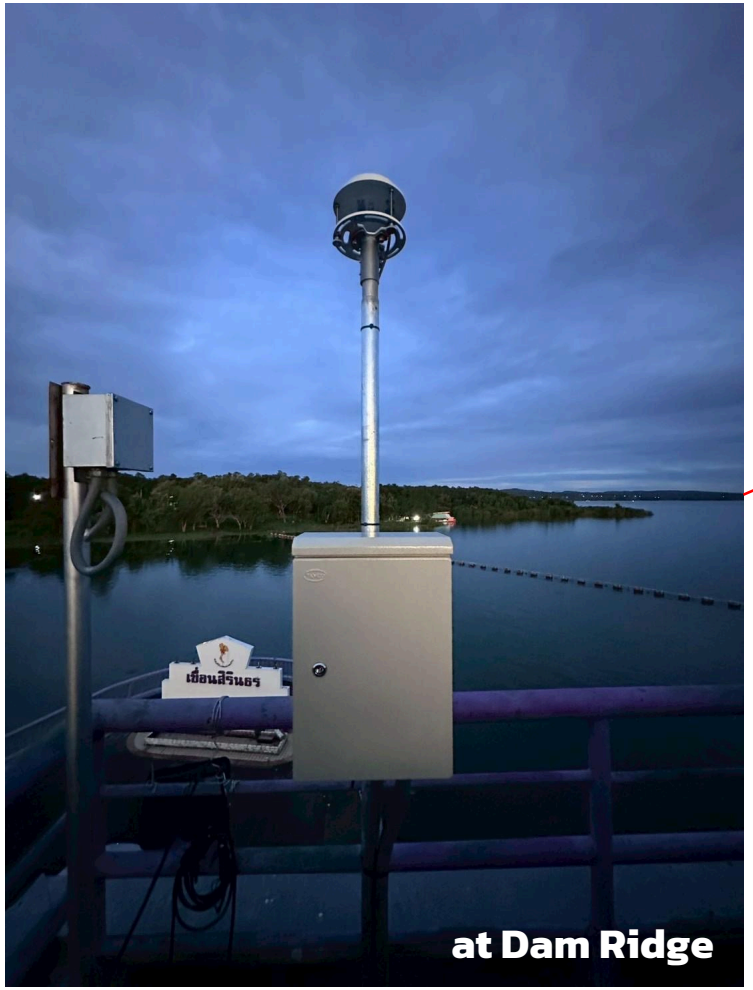
- Deploys 180° **Sky Cameras capturing data every 10–30 seconds**, synchronized in real time with PV output and irradiance sensors.
- Combines **CNN for spatial cloud features** with **LSTM for tracking temporal motion** to predict power generation 1–60 minutes ahead.
- Acts as a **dynamic filter during high cloud volatility**, outperforming slow weather updates and providing early ramp-rate warnings for grid control.
- Establishes **a pilot base model** then maps regional cloud risks to rapidly scale deployment.





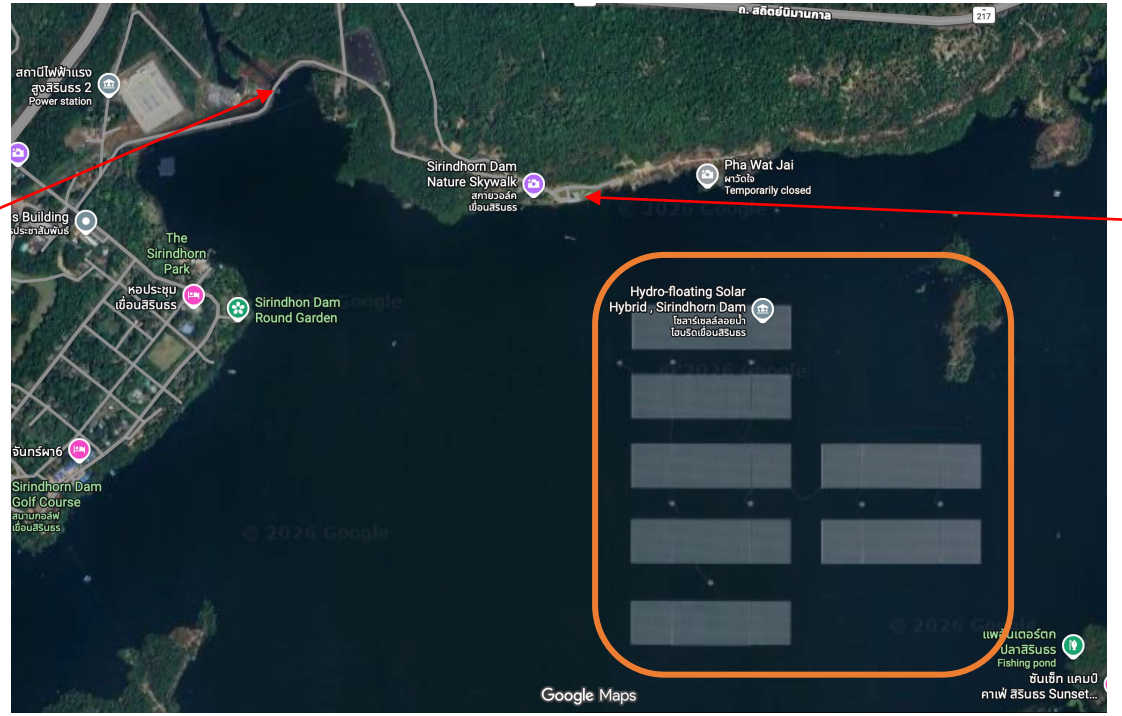
EGAT

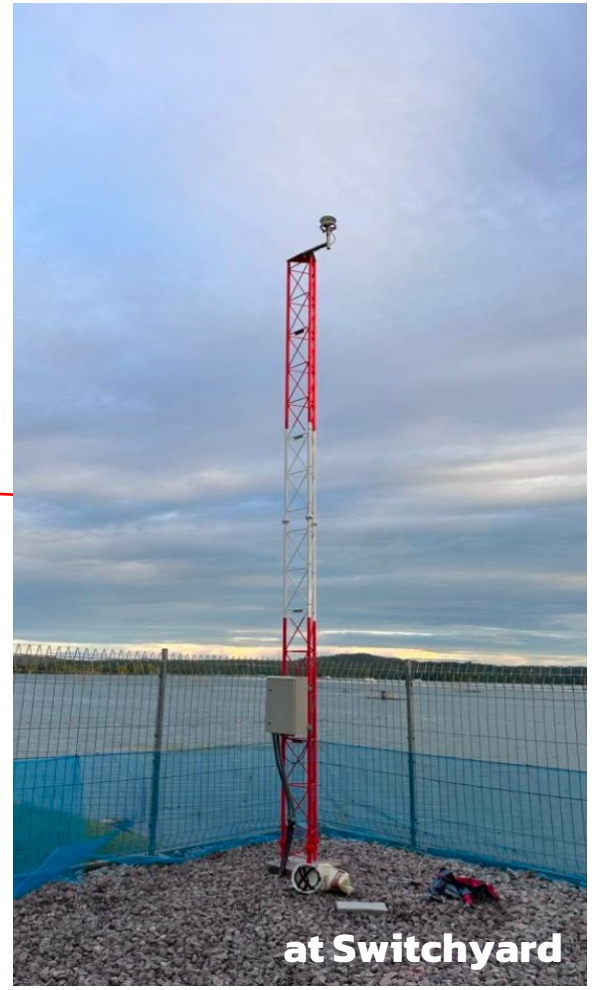
# Pilot Project : Sky Imager at Sirindhorn Dam




**Location :** Sirindhorn Dam Hydro-Floating Solar Hybrid.

**Capacity :** 45 MW flagship project pairing floating solar with traditional hydropower.



# Agenda

- Introduction & Current Status of VRE in Thailand
- Background & Overview of EGAT REFC
- VRE Forecasting Methodology
- **EGAT REFC Infrastructure**
- Conclusion & Key Takeaways



# EGAT RE Forecast Center : Components

Power Plants

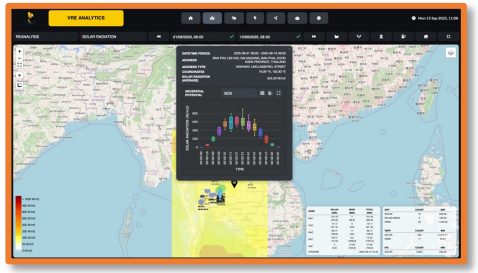
Weather

Satellite / Sky Image

Data Sources



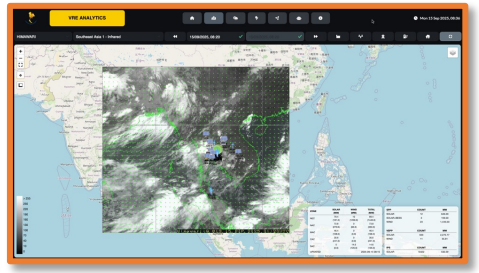
RE Forecast System





VRE Analytics








PyTorch

XGBoost

AI

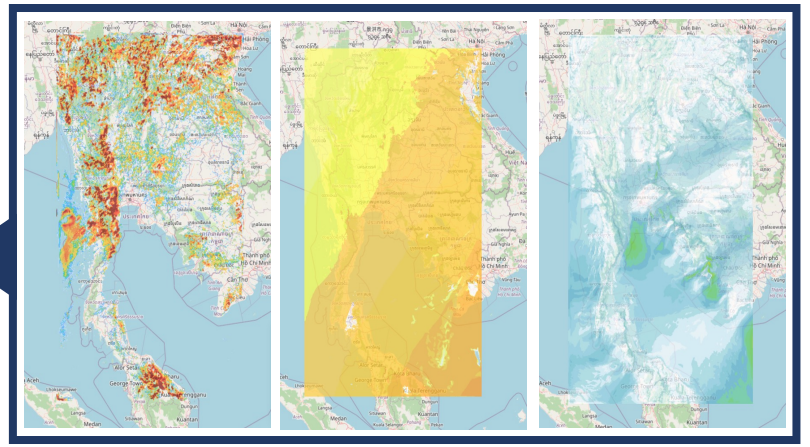
scikit learn

TensorFlow

Generation Forecast

WRF Weather Research & Forecasting

Weather Forecast



# Agenda

- Introduction & Current Status of VRE in Thailand
- Background & Overview of EGAT REFC
- VRE Forecasting Methodology
- EGAT REFC Infrastructure
- **Conclusion & Key Takeaways**



# EGAT RE Forecast Center: Solar Forecast

**No. Plants : 22**

**Contract Capacity : 1,159 MW**

Day-ahead MAPE (2025) : 6.76%

10 Day-ahead MAPE (2025) : 7.25%




**Day-ahead Forecast**




**Intraday Forecast**

# EGAT RE Forecast Center: Wind Forecast



**No. Plants : 23**

**Contract Capacity : 1,445 MW**

Day-ahead MAPE (2025) : 8.19%

10 Day-ahead MAPE (2025) : 10.96%

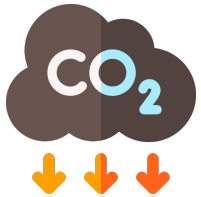



**Day-ahead Forecast**




**Intraday Forecast**

# Conclusion & Key Takeaways



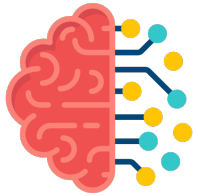

**Decarbonization** : Draft PDP 2024 targets >50% RE by 2037 to support the 2050 Net-Zero goal.



**VRE Impact** : Intermittency and uncertainty from solar/wind require sophisticated mitigation strategies.



**Forecasting Accuracy** : Precise Day-Ahead and Hour-Ahead forecasts reduce the need for expensive reserves and prevent energy curtailment.



**Tech-Driven Stability**: Leveraging AI, Machine Learning, and Deep Learning is the key to modern grid reliability.

# EGAT

# Q&A

## Thank You

