IEEE PES Big Data & Analytics Webinar Series

2-3pm, Wednesday, EDT, June 28th

An energy IoT platform for real-time production and delivery of wind power generation forecasts

Le Xie, Subcommittee Chair, Texas A&M University
Bo Yang, Webinar TF Chair, Hitachi America, Ltd.
Yang Weng, Webinar TF co-Chair, Arizona State University

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BDA and Webinar Taskforce

BDA Mission

- A professional society hub for information and collaboration
- A forum bringing together academy, regulatory and industry leaders
- Topics of interest:
  - Standards, Data management, Analytics
  - Big multi-domain multi-resolution data (PMUs, SCADA, Weather, GIS, etc.) for power grid operations
- http://sites.ieee.org/pes-bdaps/

Webinar* Taskforce Objective

- State-of-arts from researchers
- Strategy and solutions from BDA vendors
- Regulatory push from policy makers

*Every month or two, speaker by invitation only

Upcoming events

- July 20, BDA subcommittee meeting @ Chicago, IL

How to join BDA?

- Please contact subcommittee chair:
  - le.xie@tamu.edu

Would like to be a speaker?

- Please contact taskforce chairs:
  - Bo.yang@hal.hitachi.com
  - Yang.Weng@asu.edu

Active members

NREL, pjm, Dominion Energy, ATM, Edison, CenterPoint Energy, ASU, HITACHI Inspire the Next, pjm, UC Riverside, Binghamton University, EPRI

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An energy IoT platform for real-time production and delivery of wind power generation forecasts

Chandrasekar (Chandra) Venkatraman is Principal Research Scientist at Hitachi America Big Data Laboratory focusing on Industrial IoT Architectures and Analytics for Energy. Prior to joining, he was Chief Scientist at FogHorn Systems – Palo Alto based start-up focusing on Big Data Analytics and applications platform for Industrial Internet of Things (IoT). Chandra was with Hewlett Packard Labs, Palo Alto for almost two decades working on Information architectures, distributed computing, in-home network, ePrint architecture, sensor networks and Internet of Things. He has authored over 15 patents and a number of research papers and talks.

Pierre Huyn has over 30 years of research and advanced development experience in data management, big data analytics, and software engineering. His current interest is in big data architectures for IoT and deep learning for time series data in the domain of renewable energy.

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IEEE PES Technical Webinar Series

HITACHI Inspire the Next

An Energy IoT Platform for Real-time Production and Delivery of Wind Power Generation Forecasts

Chandrasekar Venkatraman & Pierre Huyn
Hitachi America, Ltd. R&D, Big Data Laboratory, Santa Clara, CA, USA

IEEE PES Webinar on June 28, 2017

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Topics Covered:

Introduction

Energy IoT Platform - *Chandra*

Wind Power Forecasting - *Pierre*

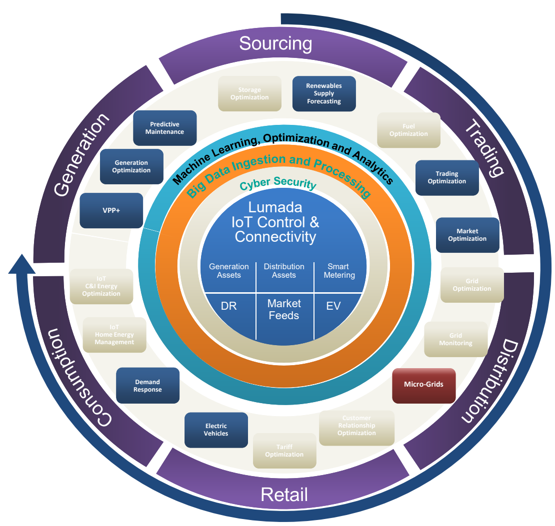
Q & A

Introduction

- Hitachi – Global Center for Social Innovation
  - Based in Santa Clara, California
  - Research through Co-creation with customers
  - **Big Data Lab**
    - Power and Energy Research
      - **Energy IoT Platform**
      - **Renewable Energy Forecasting**
      - Microgrid
      - Distributed Energy Resource Management Systems (DERMS)
      - Distribution Operations and Maintenance Optimization (DOMO)

Part 1: Energy IoT Platform and Real-time Wind Turbine data collection system

Energy IoT Platform



https://www.hitachiinsightgroup.com/en-us/lumada.html

Energy Forecast

- Increasingly Utilities purchasing power from Independent Power Producers (IPP) have been demanding accurate estimate of power they can supply in 15-minute intervals.
- Renewable Energy Forecasting is becoming increasing important topic – both in research, engineering, and business community
  - Meteorological wind speed forecasting techniques
  - New IoT and machine-learning based techniques
- Focus of this webinar:
  - An Energy IoT platform for wind turbine farm power forecasting
  - Novel machine learning techniques for forecasting and results

Need for an Energy IoT Platform

- Wind Turbines systems are
  - Complex and are highly instrumented for optimal operations and maintenance
  - Typically they have a SCADA (Supervisory Control And Data Acquisition) system
  - Wind mast in the vicinity
  - Multiple turbines in a Farm
    - e.g. 16 turbines, 1.6MW each
      - 'test site'
  - In Remote locations

Need for a robust data acquisition system (IoT)

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Energy IoT Platform Requirements

Key Requirements
- Access to all sensor data from Wind Turbines
  - Accommodate multiple manufacturers
  - Typically 2000+ sensors
    - Volume and Velocity
- Sensor data from wind masts
  - Usually they are not in the same SCADA system
- Handle network and connectivity failures
- Security
- Remote management

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Data acquisition: Challenges and approach

- Large amount of data
  - Close to 1GB per day from test site (10sec sampling rate)
  - Need for sensor selection
  - Adaptive sampling rate
- Latencies
  - 260 – 300 msec round trip delays
- 24x7 data
  - Handle network failures
- Access to site is not convenient
  - Architecture to accommodate remote configuration and management
- Process automation
  - Customer requires update every 90 minutes

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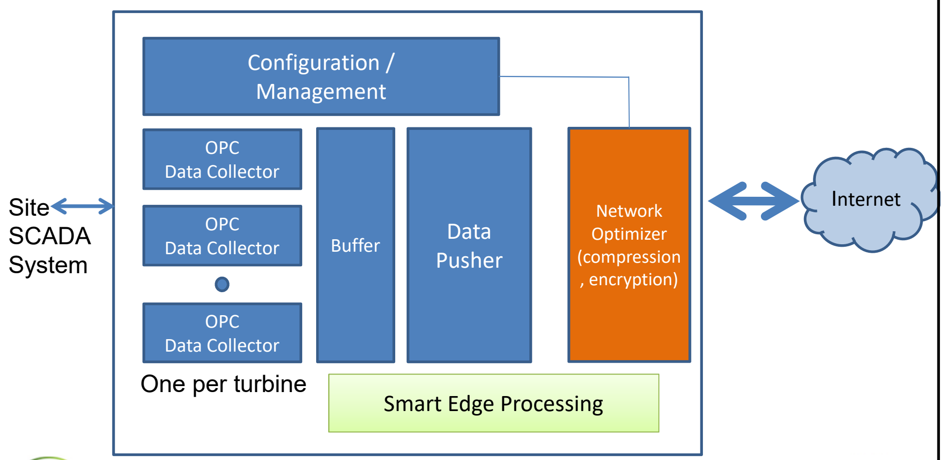
Wind Turbine – Edge System (at the Wind Farm site)

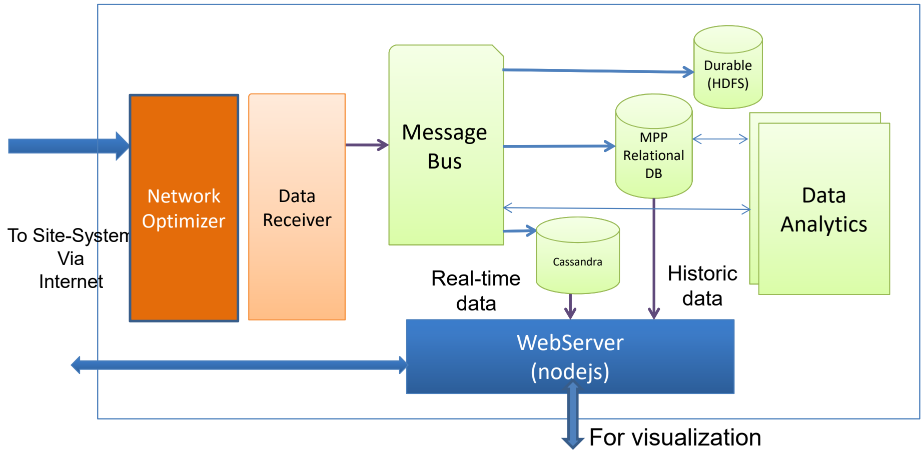


Edge System blocks

- Data Collector
  - Software module to retrieve data from site SCADA systems
    - Support OPC DA and OPC UA systems
    - Java based – multi-threaded
    - Instantiate one per turbine
- Buffer system
    - To accommodate network failures, congestion
    - Memory and file-system based – configurable
- Data Pusher
    - Socket based data transfer
    - Restart fast_sync on reconnection
- Network Optimizer
    - Adaptive compression
    - Encryption option
- Configuration and Management
- Smart Edge Processing
    - Microservices – sensor data processing and model processing

Server Side

- Addressing Scale, Open source, Security



Wind Turbine (test) site

GE Wind Turbine – 1.6MW
Tower height - 80m, Rotor diameter – 82.5m
Average wind speed – 8.5 m/s
SCADA system – OPC-DA

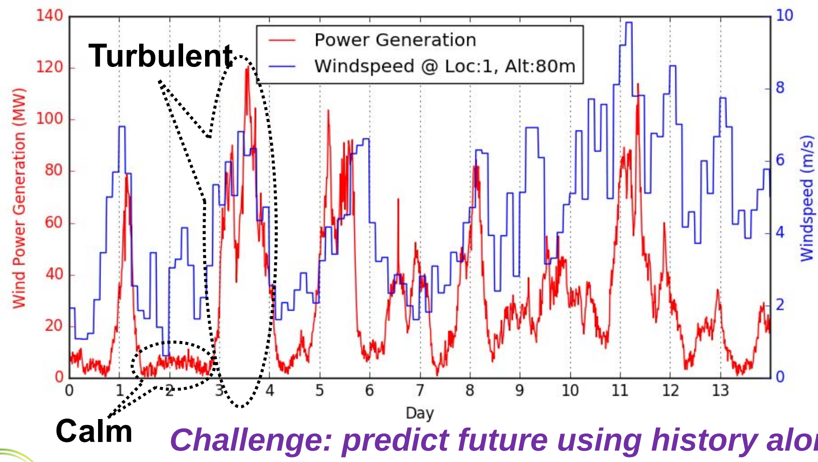
Part 2: Day-Ahead Wind Power Generation Forecasting Using Support Vector Machines

Pierre Huyn

1. Day-Ahead Wind Power Generation Forecast

- Forecast wind power generation
  - Every 90 minutes, produce 96 forecast values
  - For the next 24 hours, in 15-minute periods, starting in the next 90 minutes
- Forecasting is an important core problem because
  - When feeding renewable energy to the grid, this is mandated
  - When trading renewable energy in the spot market, this is used to determine electricity pricing
- Accurate forecast is very important
- Accurate forecast is difficult due to weather unpredictability

2. Observations From a Historical Data Sample



Challenge: predict future using history alone

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3. Challenges and Opportunities

- ☹ Capturing sudden and wild swings in weather is difficult when prediction produces average and not extreme behaviors
- ☹ Mismatch between Weather data and Power data resolution:
  - Spatial: location and elevation
  - Temporal
- ☹ Weather forecast data available at low resolution
- ☹ Limited availability of historical data
- ☺ Leverage day-to-day seasonality
- ☺ Leverage year-to-year seasonality

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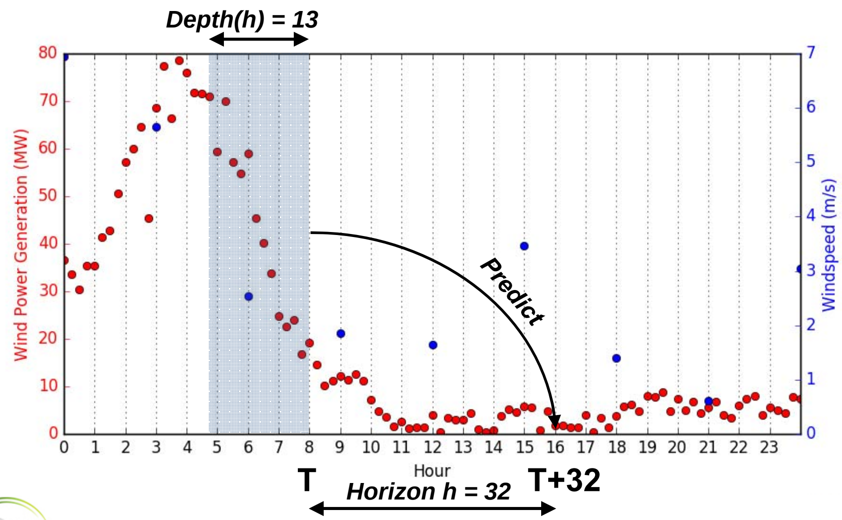
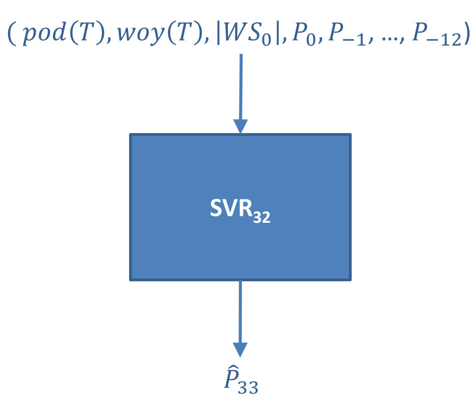
4. Forecast Solution Approach Defined



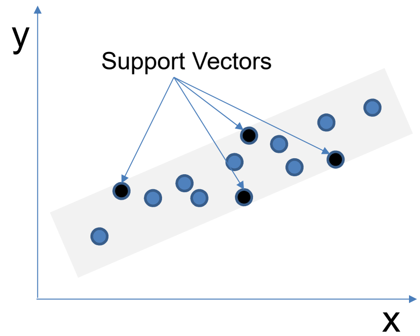
5. Forecasting Framed as SVM Regression



- Model for horizon h = 32
- Depth = 13 for power history
- Depth = 1 for windspeed history
- pod(T): indexes period-of-day
- woy(T): indexes week-of-year
- 96 models independently built, minimize error propagation for long horizons

6. What is and Why SVM Regression?

- Supervised learning technique
- Success in NL and biotech in the 90's, high-dimensional data
- Unlike deep learning techniques, optimal solution unique: convex
- Efficient QP algorithms.
- Support large number of predictors with minimal overfitting: built-in regularization
- Tunable: adjustable non-linearity and regularization (C, Gamma)

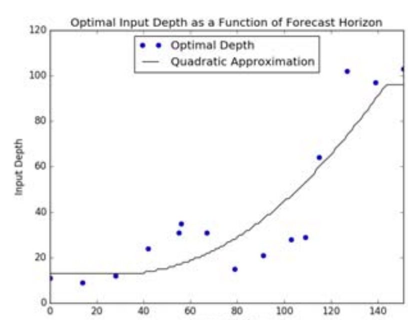


Linear SVR: $y = w.x + b$
Minimize $|w|_2^2$ subject to containment constraint

7. Features Selection, Hyper-parameters Tuning

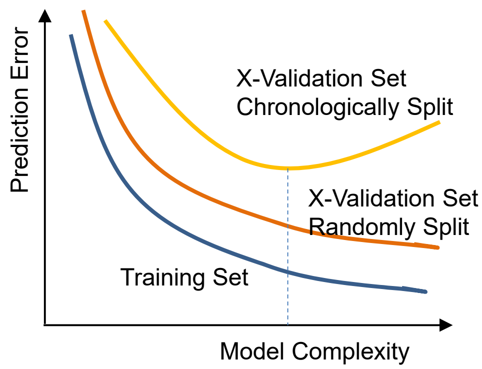
Models: $\hat{P}_h = SVR_h(woy, pod, |WS_0|, P_0, \ldots, P_{depth(h)-1})$

- Power input depth varies with horizon (tuning C only)
- Period-of-Day
- Week-of-Year
- Use RBF Kernel in SVR Regression
- Tuning Hyper-parameters C and Gamma using log grid search

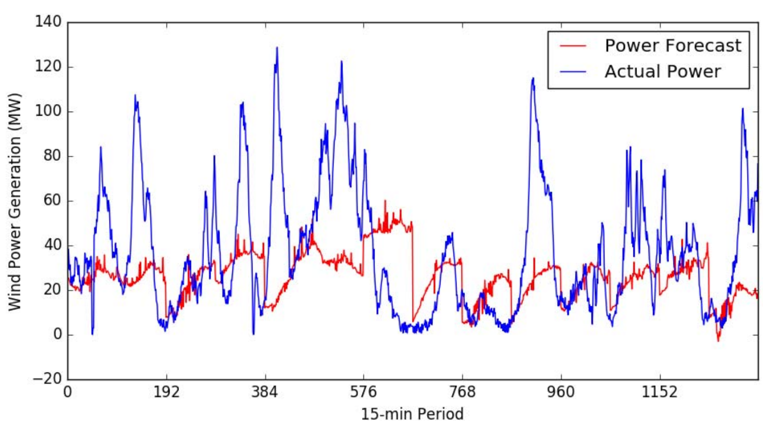


8. Model Evaluation and Optimization

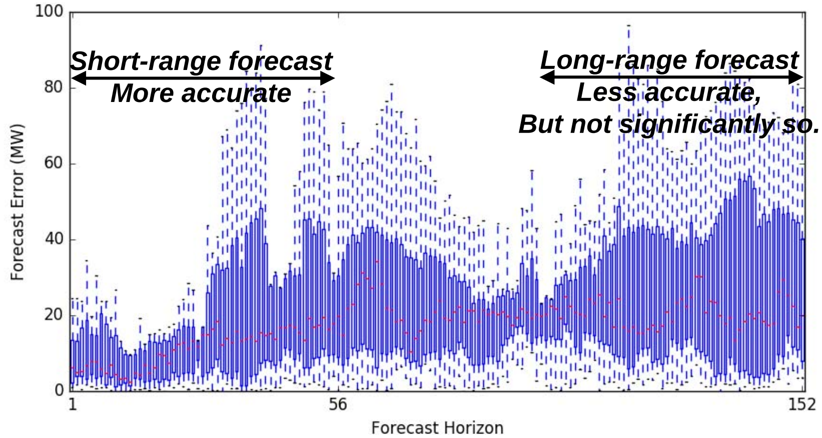
- Evaluation metrics: MAE error
- Model trained on training dataset and evaluated on cross-validation dataset
- Error as a function of model complexity: input depth, hyper-parameters
- Split data set for cross-validation: random vs. chronological



9. Forecast vs. Actual During a 14-Day Test Period



10. Forecast Error as a Function of Horizon



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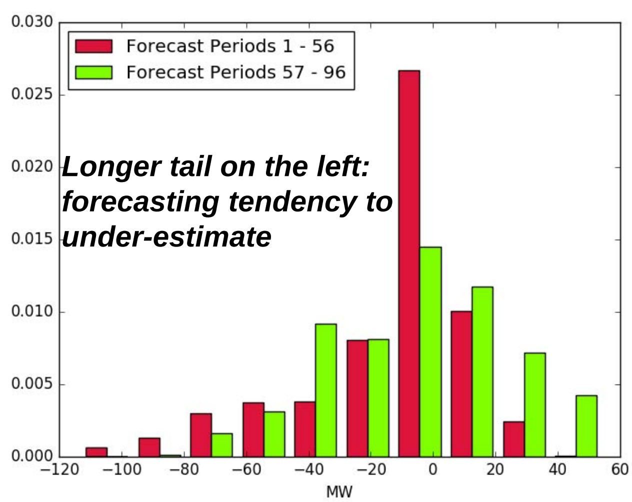
11. Error Distribution for Short/Long Horizons



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12. Leveraging External Weather Forecast Data

- Limitations of history-only-based forecasting:
  - Accuracy suffers under turbulent weather conditions
  - Long-horizon data weakly correlated with history data
- Estimate power generation as a function of weather forecast. Accuracy hinges on:
  - Accuracy of weather forecast
  - Proximity of external weather forecast location to turbines
  - Spatial resolution
  - Temporal resolution

13. Simplest Model: Weather Forecast Data Only

$$(\,pod(T), woy(T), \widehat{WSx}_{33}, \widehat{WSy}_{33})$$

$$\downarrow$$

$$\boxed{SVR_{32}}$$

$$\downarrow$$

$$\hat{P}_{33}$$

Wind Speed
Vector Forecast

14. Combining History with External Weather Forecast Data – Accommodate New Data Easily

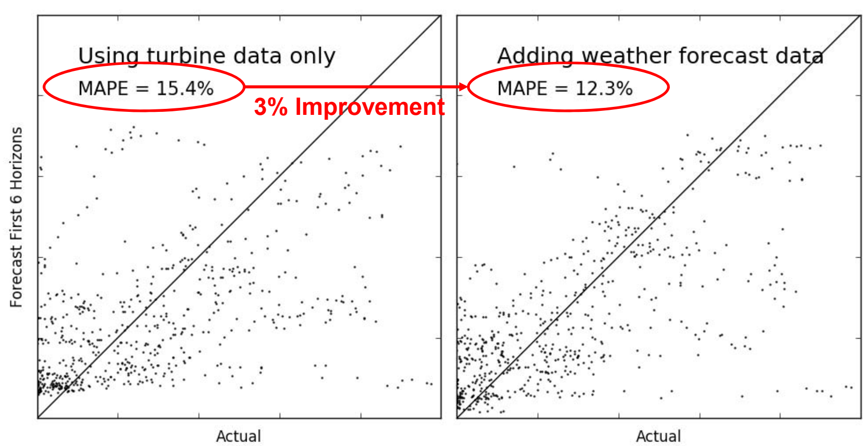
$$(pod(T), woy(T), |WS_0|, P_0, P_{-1}, \ldots, P_{-12}, \widehat{WSx}_{33}, \widehat{WSy}_{33})$$

SVR_{32}

Wind Speed
Vector Forecast

$$\hat{P}_{33}$$

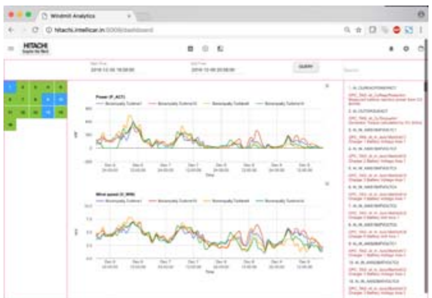
15. Enhancing Forecast Accuracy With Weather Forecast Data



Even low quality weather forecast data can enhance history-based power forecast

16. Dashboard

Historic Data



Forecasting Result

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17. Forecasting Competition

- EEM 17 14 INTERNATIONAL CONFERENCE ON THE EUROPEAN ENERGY MARKET 6-9 June 2017, Dresden, Germany
- Technical Sponsor IEEE IEEE PES Power & Energy Society®
- Day-Ahead Forecast Competition using only historical data
- Team Hitachi 3rd-Place Competition Winner

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Conclusion

- Hitachi R&D – Big Data and Analytics based Applications for emerging digital energy
- Renewable Energy is key and forecasting is a must
- A scalable, secure, flexible platform to retrieve, store, and process real-time data – Energy IoT
- Novel machine learning based Wind Turbine power forecasting approach and results
- Validation of the approach and performance in a Wind Turbine Farm

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