Topic 5: Renewable Power

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Carbon Footprint

- Carbon Footprint is usually defined as:

> A measure of the total amount of carbon dioxide (CO_2) and methane (CH_4) emissions of a defined population, system, or activity, considering all relevant sources, sinks, and storage within the spatial and temporal boundaries of that population, system, or activity of interest.

- Usually the measure is presented in carbon dioxide equivalent.

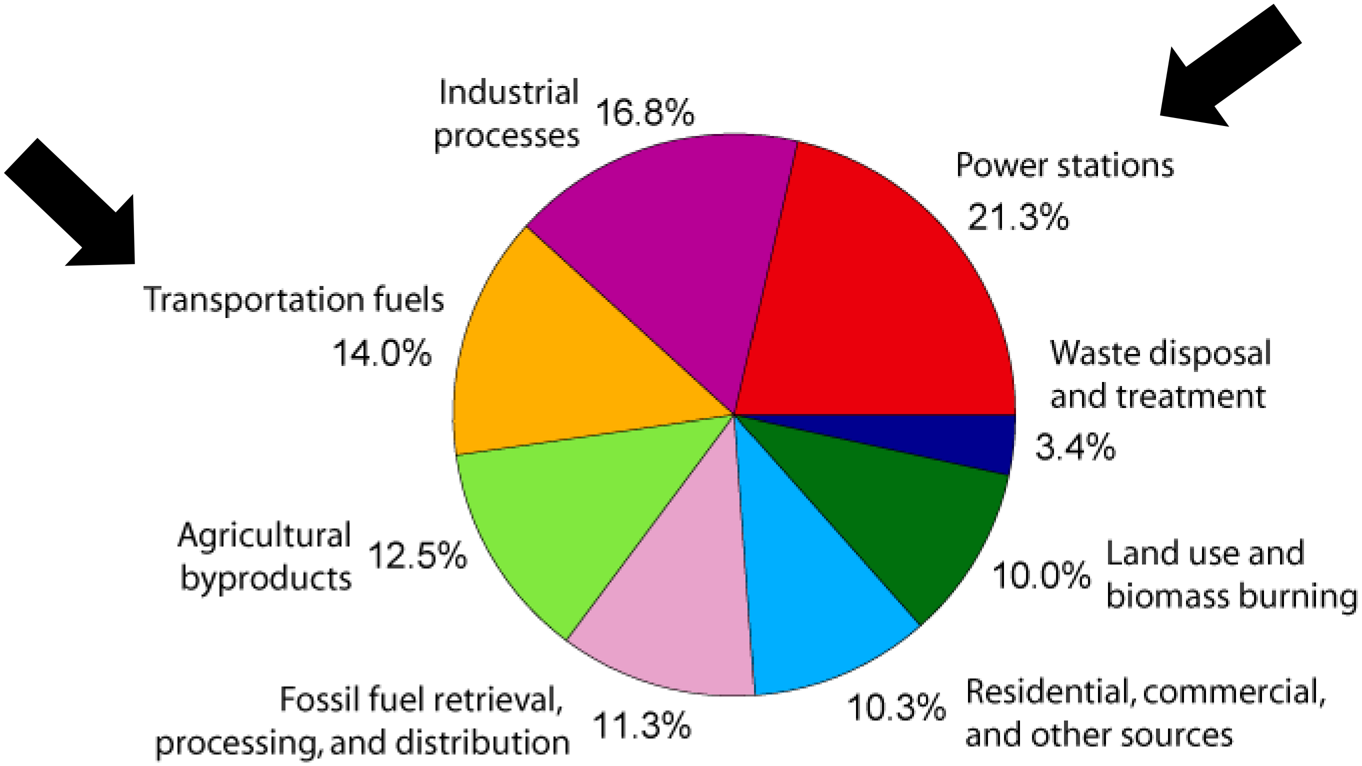
Carbon Footprint

- We are interested in power plants with low carbon footprint:
  - Both CO_2 and CH_4 are greenhouse gases.
  - Potential for "Global Warming"
  - They can also be toxic at high concentrations

- It is desired to reduce carbon footprint of different sectors.

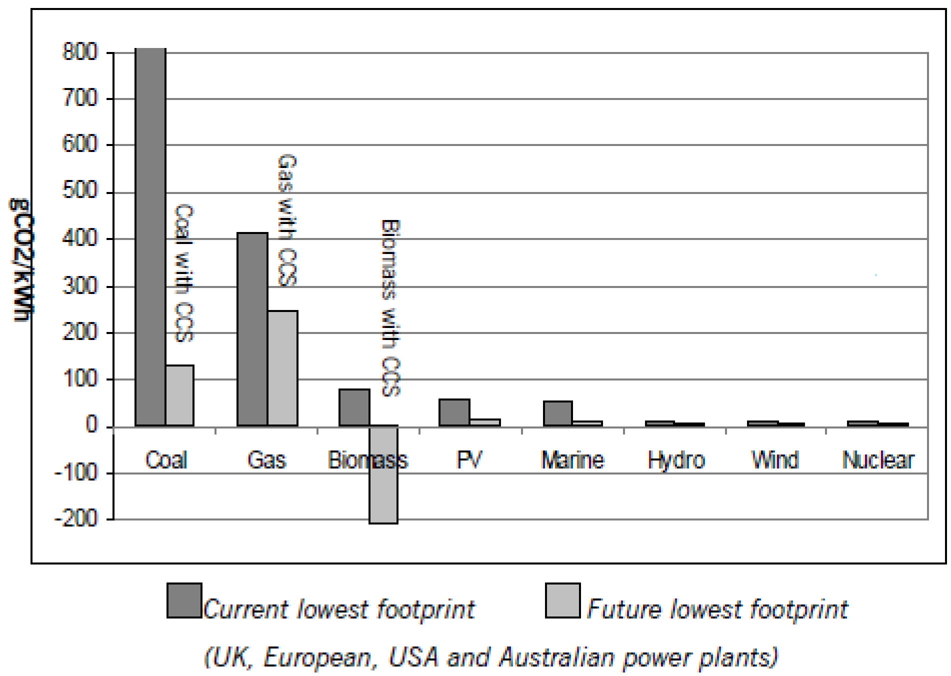
Carbon Footprint

- Annual greenhouse gas emissions by sector:



Carbon Footprint

- Carbon footprint is also defined for power plants:

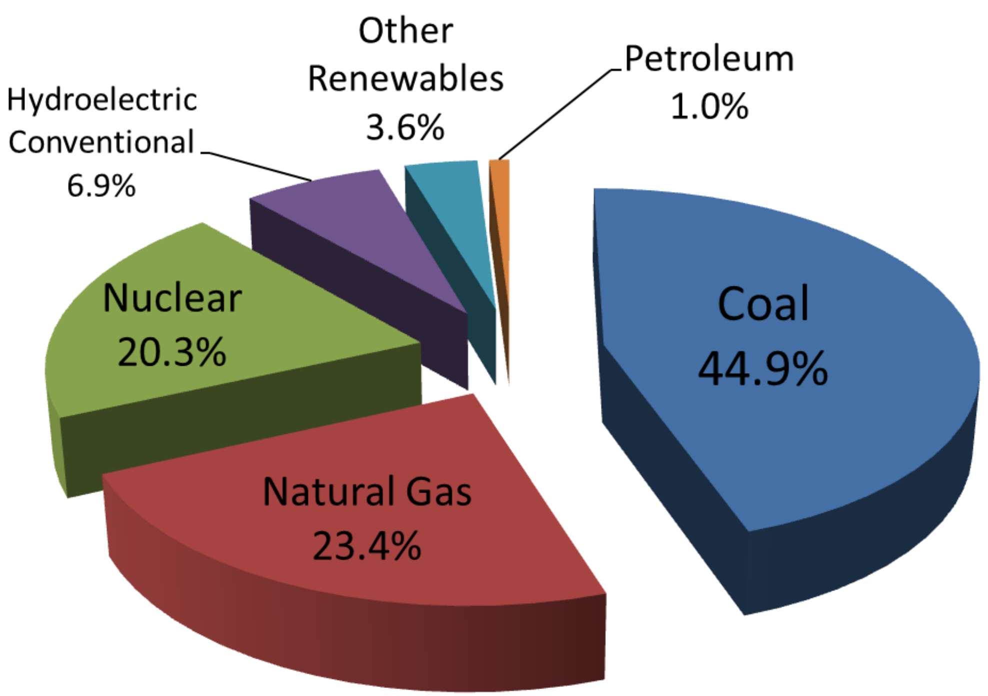


Ref: www.parliament.uk

- Conventional coal combustion has highest carbon footprint.

Carbon Footprint

- U.S. Electricity Generation by Source:



- The top sources are those with top carbon footprints.

Carbon Footprint

- Percentage contributions of CO_2 emissions in 2008:

Carbon Footprint

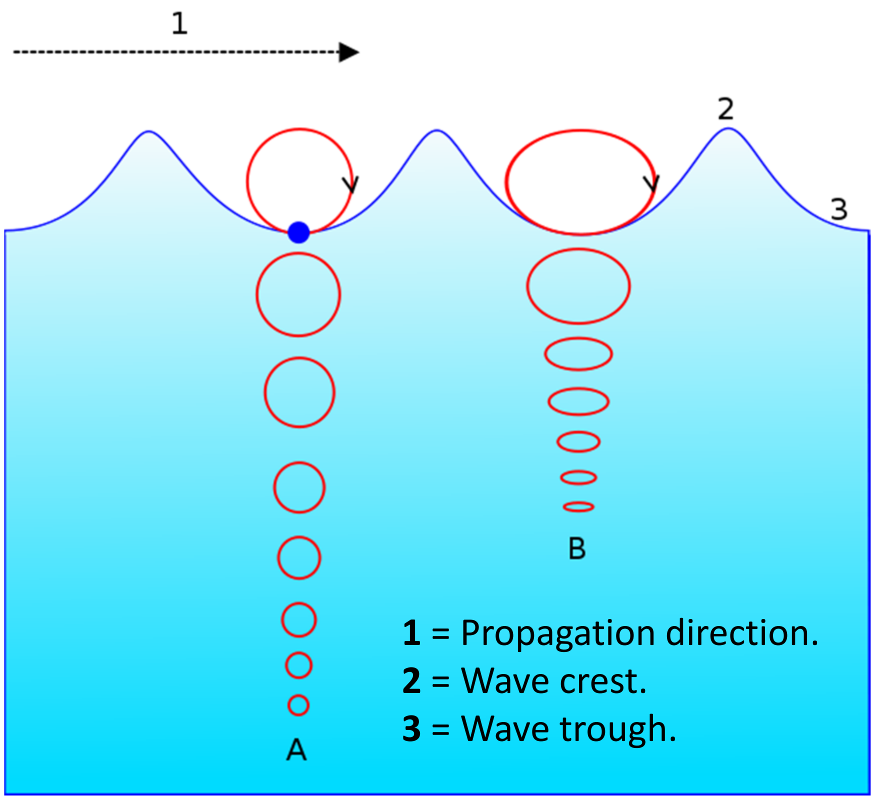
- Nuclear energy has low carbon footprint.
  - But it does have issues with respect to nuclear wastes.
- Desired choices (Renewable Sources):
  - Marine: Wave and Tidal
  - PV: Solar
  - Wind
  - Hydro

Carbon Tax

- Tax applied based on carbon footprint.
  - It is to encourage moving towards renewable generation.
- Example:
  - Natural Gas: 181 g CO_2 / kWh (0.66 cents / kWh)
  - Coal: 215 g CO_2 / kWh (1.21 cents / kWh)
- Boulder, CO applied the first carbon tax in the U.S. in 2006.

Wave Energy

- Wave power is the energy from ocean surface waves.



- Orbital motion of particles decreases with increasing depth.

Wave Energy Converter

- Wave Snakes as wave energy converter

- They are floating on the ocean surface waves.

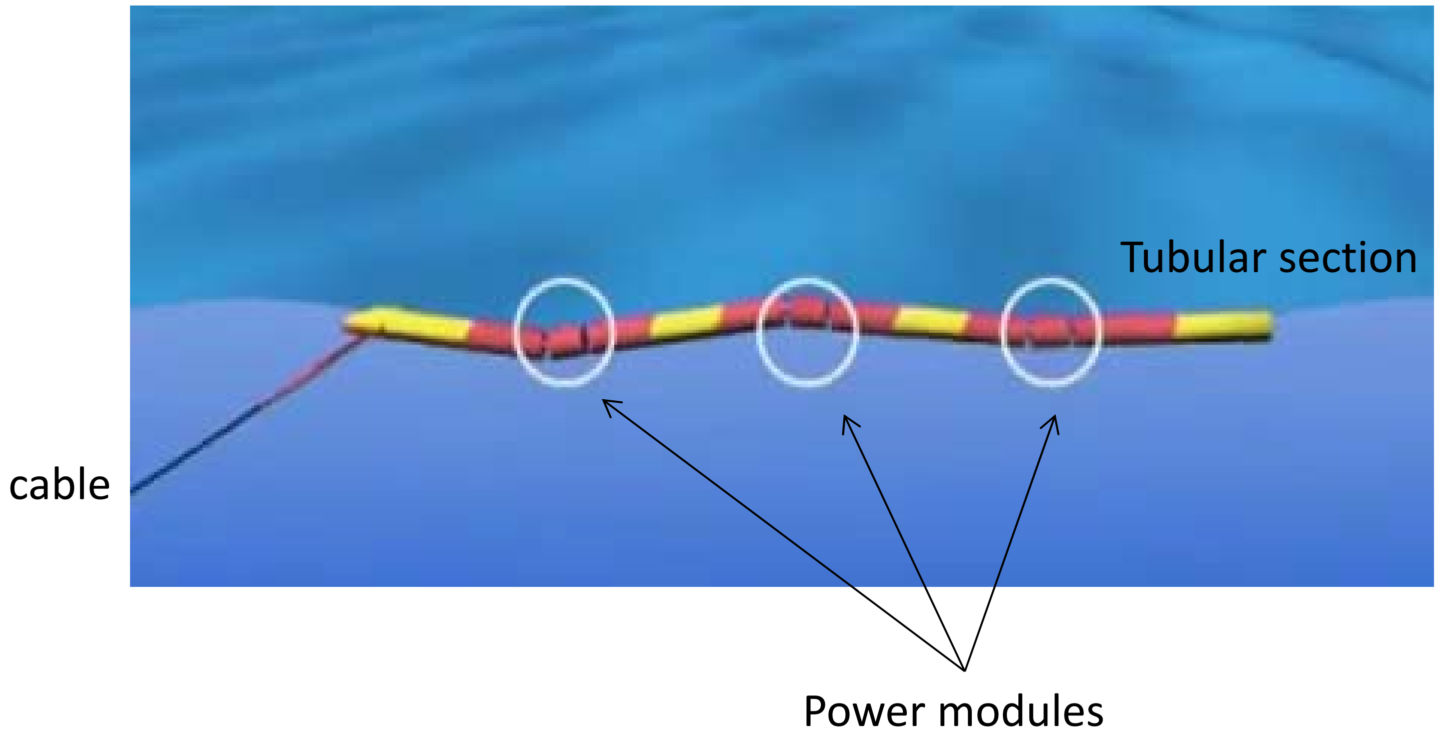
Wave Energy Converter

- Generation capacity for each device is around 750 kW-1MW.

- They come as wave farms with up to 10 MW capacity or so.

Wave Energy Converter

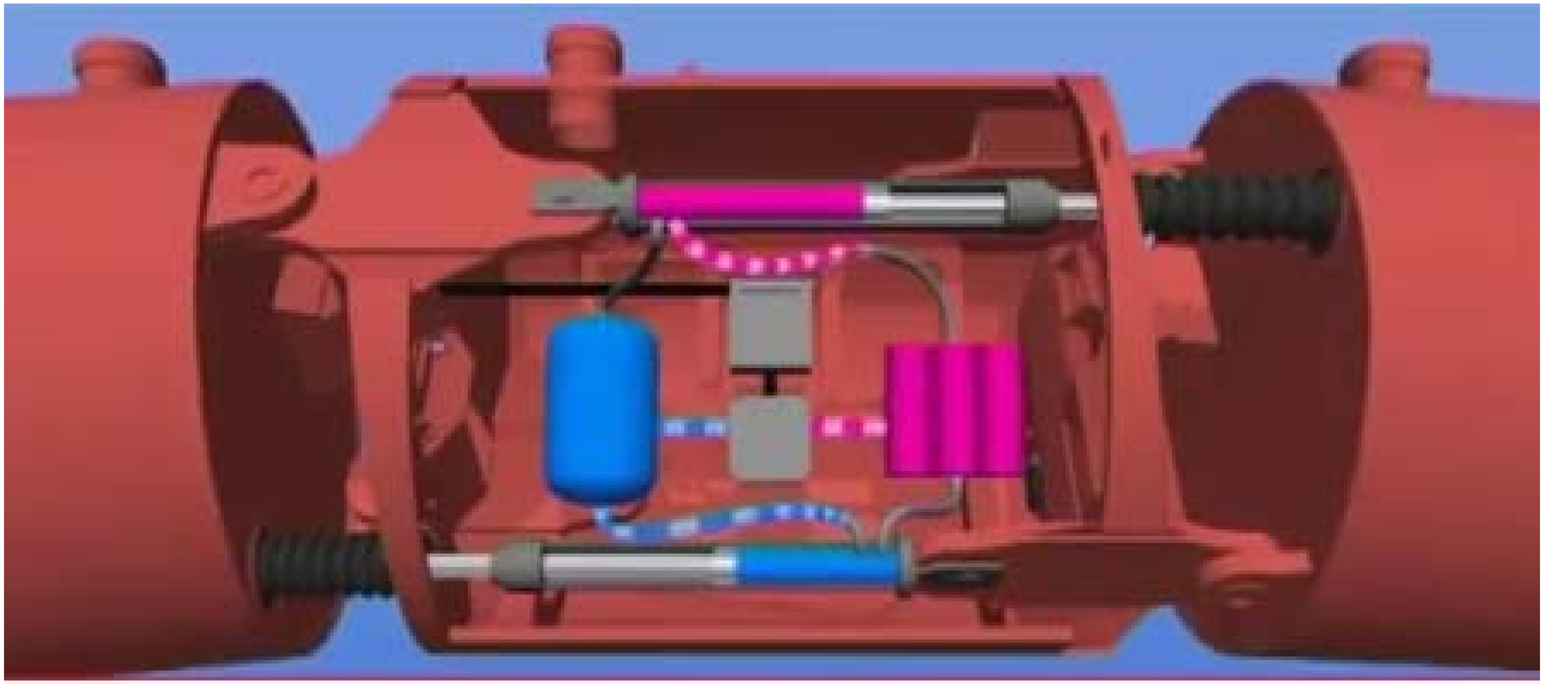
- Each device has 3 power modules joined by tubular sections:



- A cable connects the device to the ocean floor to hold it.

Wave Energy Converter

- Inside each power module:



- Motion is resisted by hydraulic arms in each tubular joints.

Tidal Energy

- Tides are the rise and fall of sea levels:
  - Caused by moon and sun's gravitational forces.
- Most places in the ocean usually experience
  - One or two high tides / low tides every day.
- The times and amplitude of the tides at the coast:
  - Are influenced by the alignment of the sun and moon.

Tidal Energy

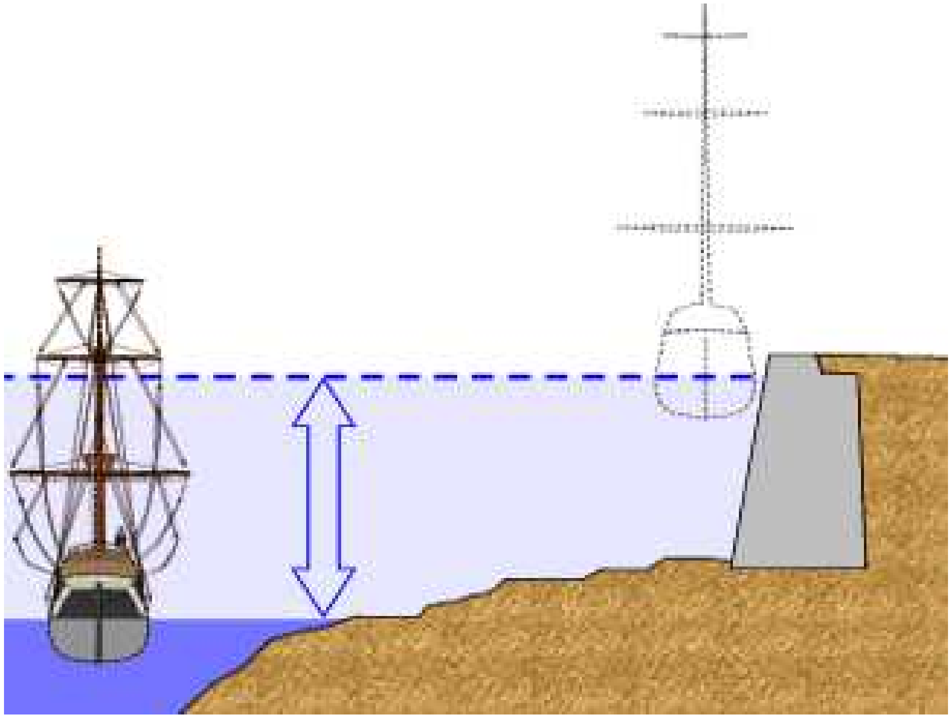
- Example:

High Tide

Low Tide

Tidal Energy

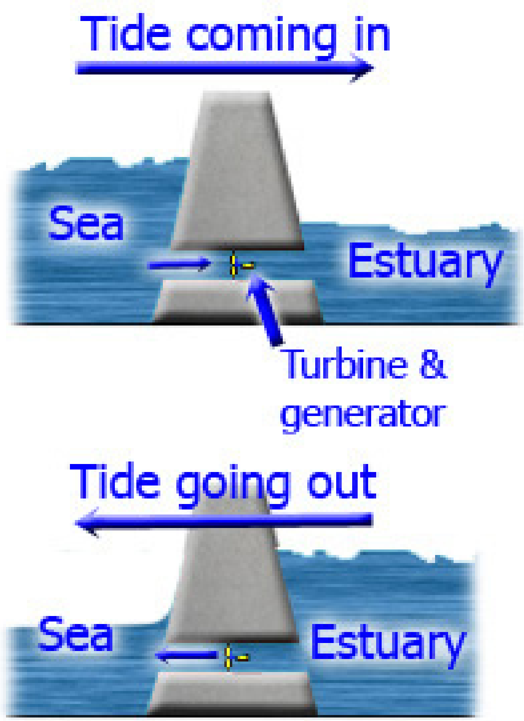
- Tides are major sources of energy:

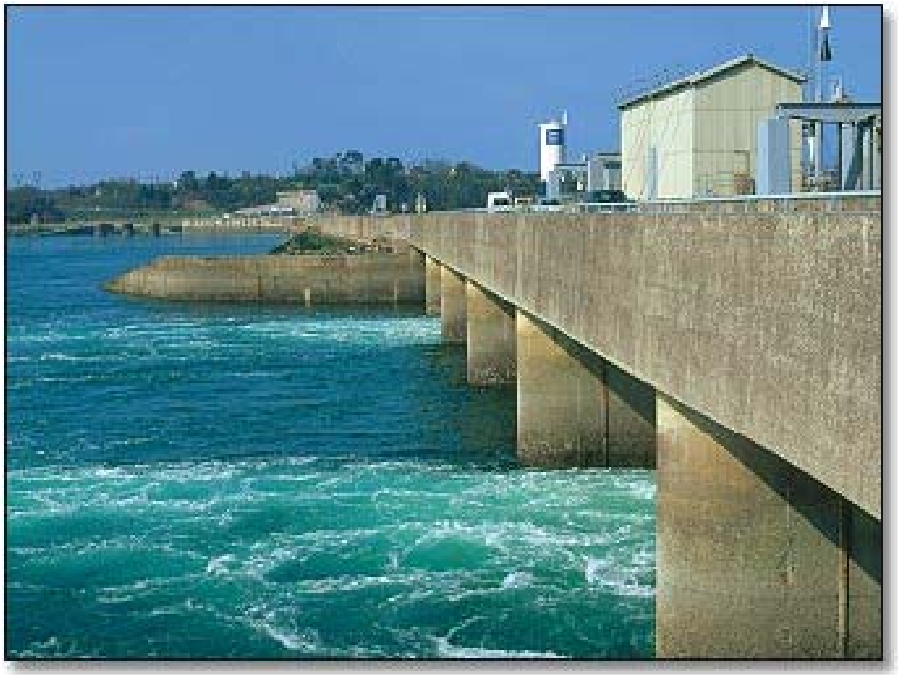


- Q: How can we use the tidal energy in this figure?

Tidal Barrage

- Tides are major sources of energy:





- The operation is somehow similar to a dam! (Q: Why?)

Tidal Barrage

- Rance Tidal Power Station in France (world's first tidal station):

- Turbines: 24, Peak: 240 MW, Annual generation: 600 GWh
- Video: http://www.youtube.com/watch?v=tSBACzRE3Gw

Hydro Dam Energy

- Hydro dams are built on big rivers.

- In the U.S. the largest dams are on the Columbia River.

Hydro Dam Energy

- There are 6 dams with more than 2000 MW capacity in U.S.

Name	Capacity (MW)	State
Grand Coulee Dam	6800	WA
Chief Joseph Dam	2600	WA
John Day Dam	2200	OR
Bath County Dam	2100	VA
Hoover Dam	2000	AZ
The Dalles Dam	2000	WA

- The world's largest dam is in China: 18000 MW

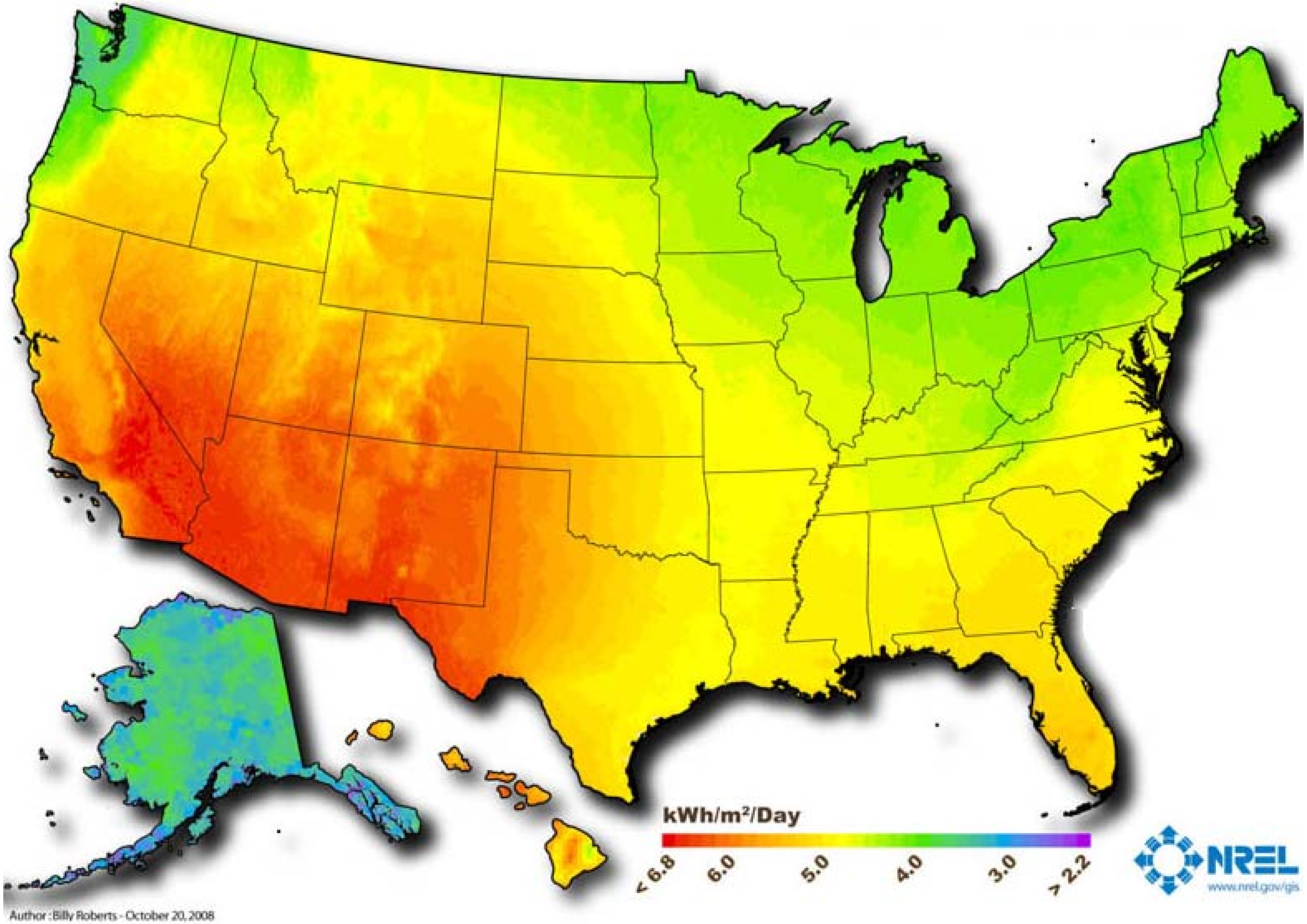
- Canada has 8 dams with more than 2000 MW capacity.

Solar Energy

- Solar panels are used to convert solar energy to DC power.

- 14 MW solar farm in Nevada.

Solar Energy Capacity in the U.S.



Solar Energy

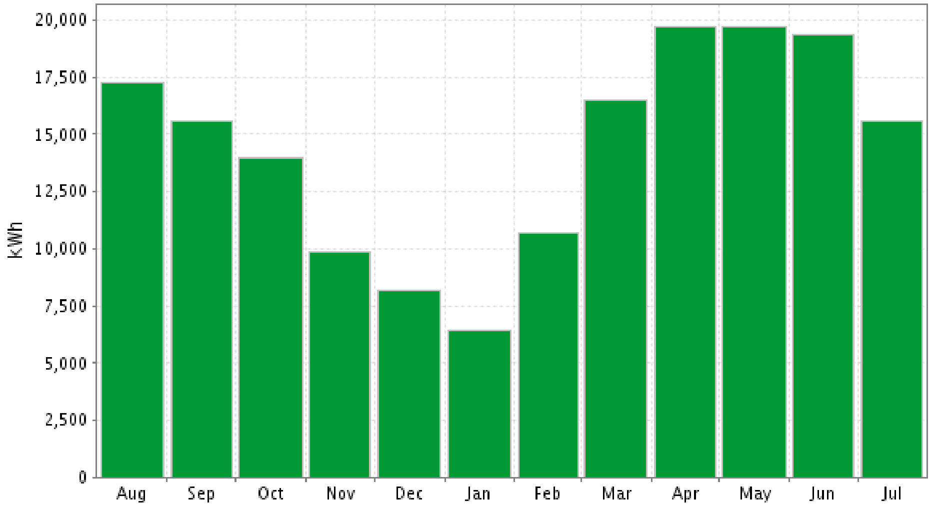
- States with highest grid-connected solar generation capacity:

State	Capacity (MW)
California	1022
New Jersey	260
Colorado	121
Arizona	110
Nevada	104

- Total U.S. solar generation capacity: 2152 MW
- World's largest photovoltaic power station is in China: 200 MW

Solar Energy

- Seasonal variation of average generation level in San Fransico:



- The generation level may also change during the day:
    - A cloudy sky means lower generation.

Concentrated Solar Power

- CSP systems use mirrors or lenses to concentrate:
  - A large area of sunlight onto a small area
- In many cases, the mirrors follow the sun.
- The sun light could be concentrated on
  - PV cells
  - Pipes of hot liquid

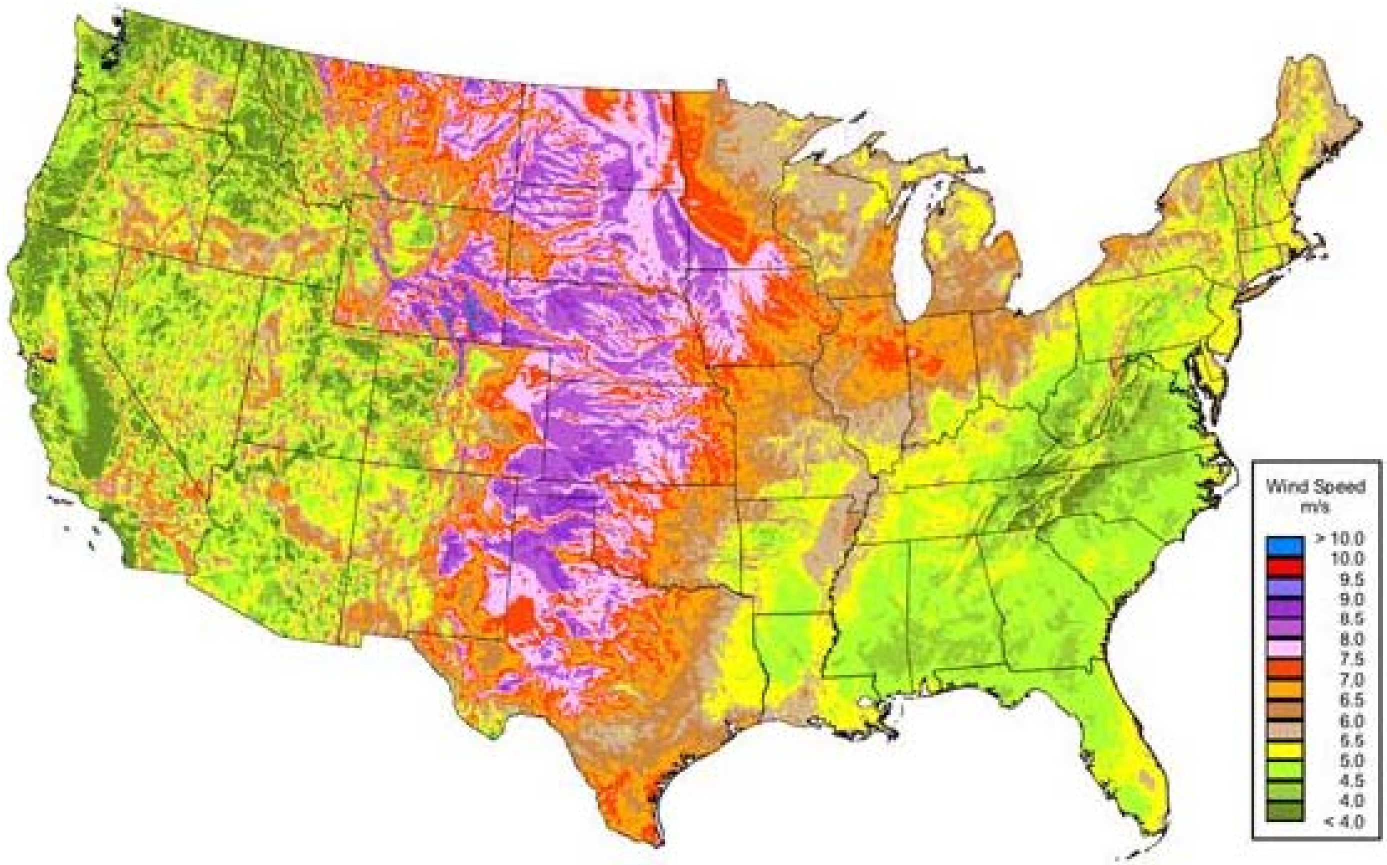
Solar Thermal Energy

- The concentrated sun light is used to:
  - Boil some liquid
  - Generated steam is used to create power in a generator

- Video: http://www.youtube.com/watch?v=rO5rUqeCFY4

Wind Energy Potential in the U.S.

- Wind power depends on the wind speed.



Wind Energy Potential in the U.S.

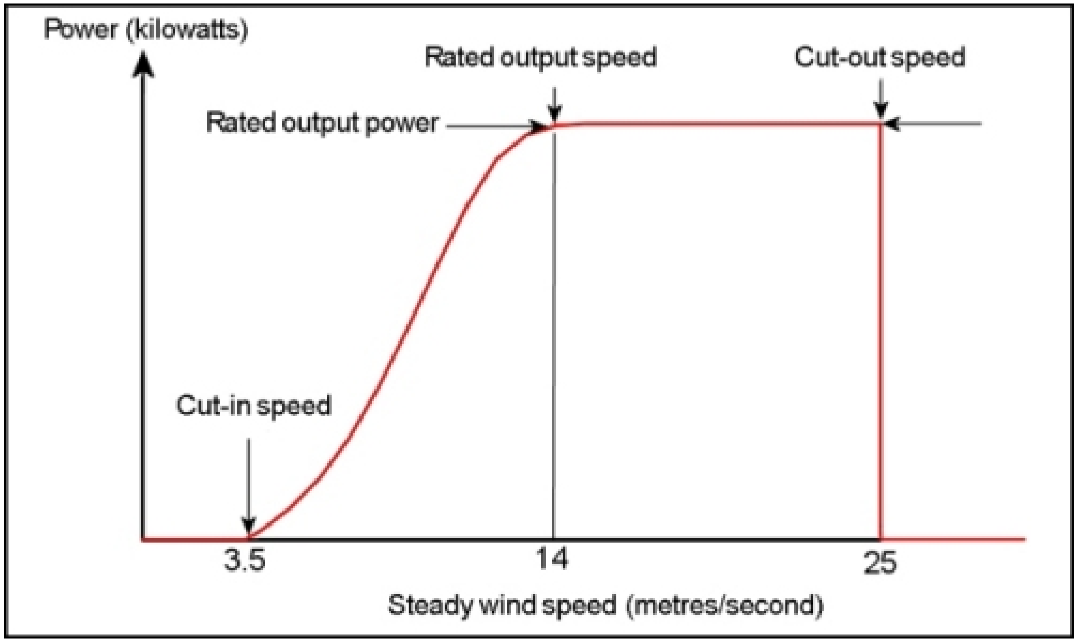
- States with highest wind power generation potential:

State	Capacity (MW)
Texas	1022
Kansas	260
Montana	121
Nebraska	110
South Dakota	104

- Total U.S. Wind Power Capacity in 2011: 43,461 MW
- U.S. DoE target: 20% Wind Power by 2030.

Wind Power vs. Wind Speed

- A typical wind speed – wind power curve:



- A minimum cut-in speed is needed to start generation.
- Video: http://www.youtube.com/watch?v=tsZITSeQFR0

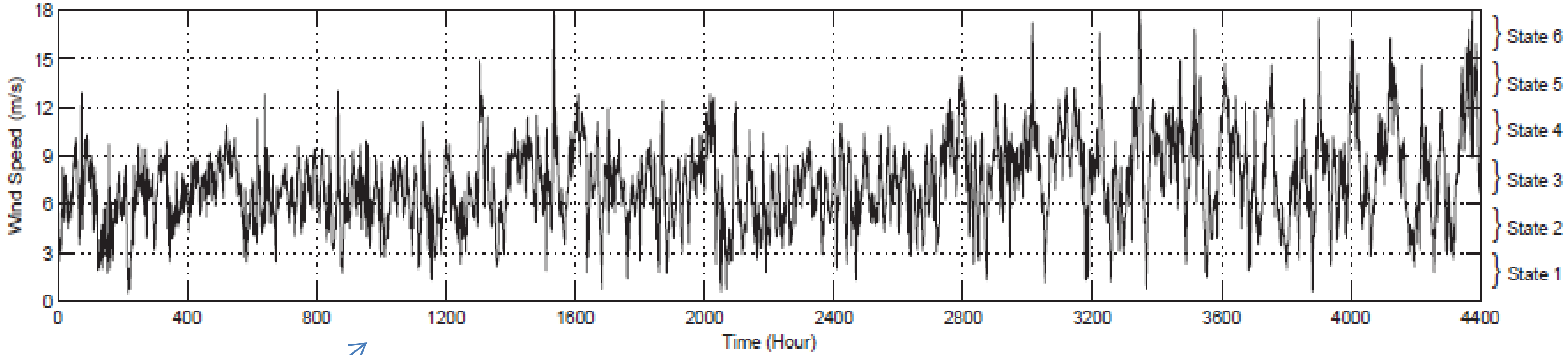
Onshore vs. Offshore

- Wind turbines can be installed:
  - Onshore: on land
    - Cheaper Installation
    - Cheaper Integration
    - Cheaper Maintenance
  - Offshore: on sea
    - Less Obstruction
    - Higher and More Steady Wind Speed (Q: what is the advantage?)

An Offshore wind farm

Challenges with Renewable Energy

- The key problem is the intermittency:

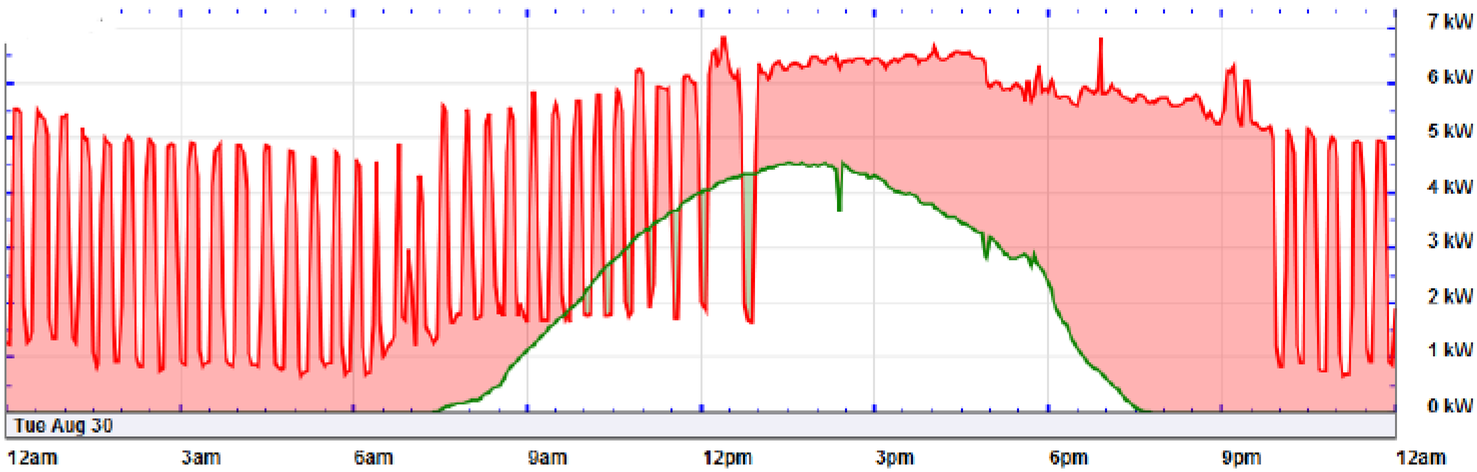


Wind Speed in Lubbock, TX

- Changes in wind speed will result in changes in wind power.

Challenges with Renewable Energy

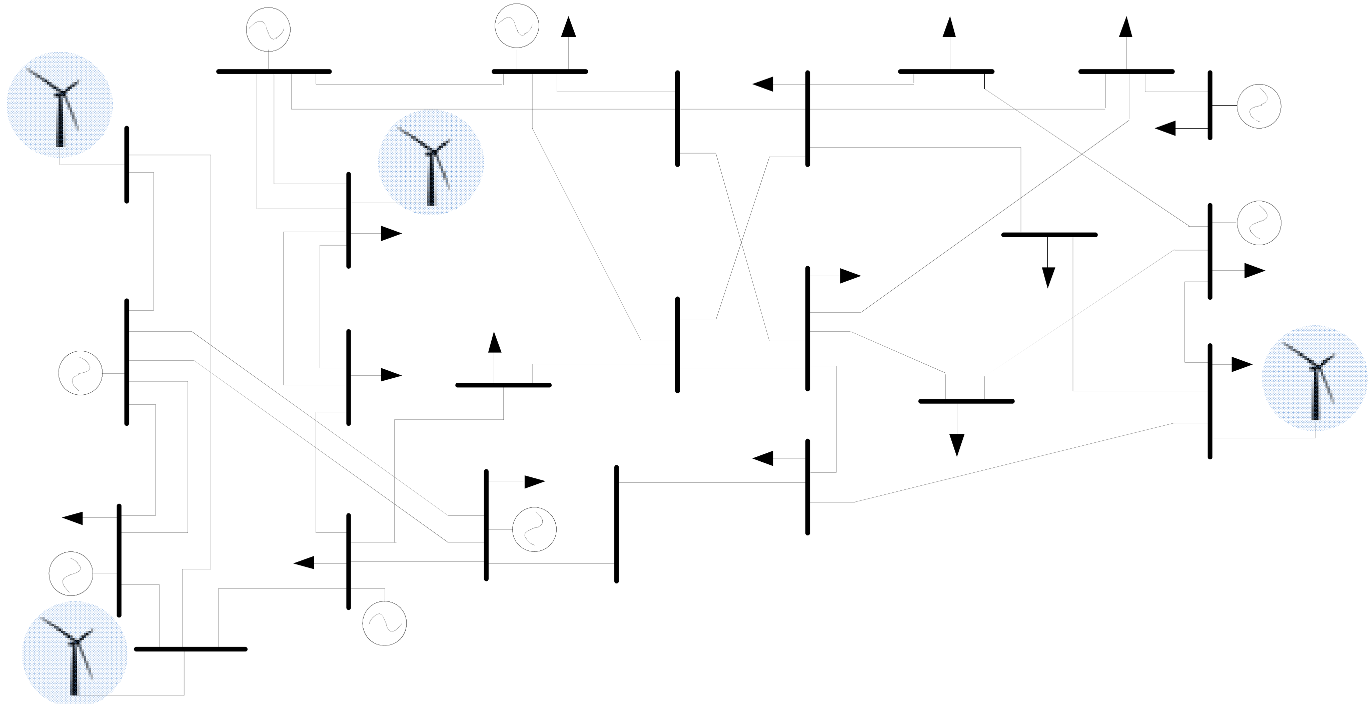
- The key problem is the intermittency:



- Actual power consumption (red) and solar power generation (green) on Aug. 30, 2011 for a home at the Mueller Smart Grid Demonstration Project of Pecan Street Inc. in Austin, TX.

Challenges with Renewable Energy

- Consider a power grid connected to multiple wind farms.



Challenges: Constantly Matching Supply and Demand

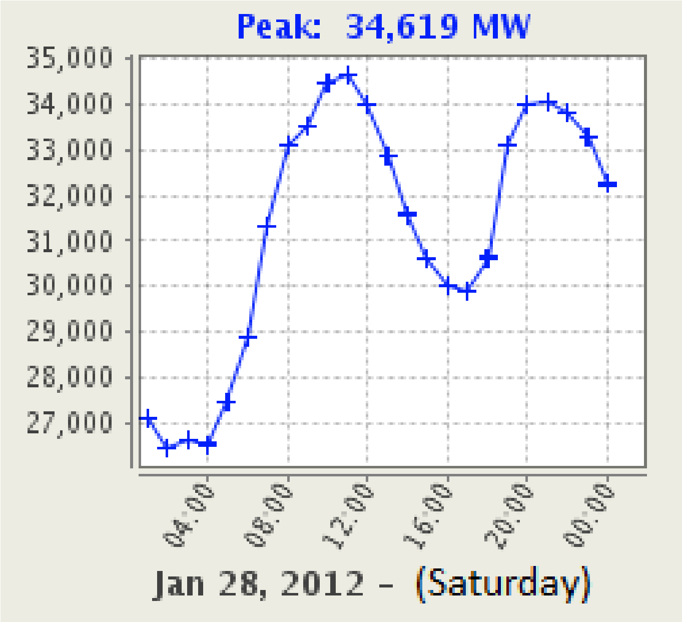
Fluctuations Can Destabilize the Grid

Renewable Power Integration

- Some options to make integration easier:
  - Limit Renewable Generation
  - Curtailing
  - Using Fast Responding Generators
  - Using Storage Devices
  - Demand Response
  - Q: What else?

Limited Renewable Generation

- Consider a typical daily load in Texas:



- Total load demand is always more than 25,000 MW.

- In general, we can assume a base load of at least 10,000 MW.

Limited Renewable Generation

- If total renewable generation is much less than the base load:
  - Renewable generation can never exceed the demand.
  - We can define net load as

Net Load = Load – Renewable Generation ≥ 0

- Fluctuation in renewable generation:
  - Will be treated just like fluctuations in load demand.

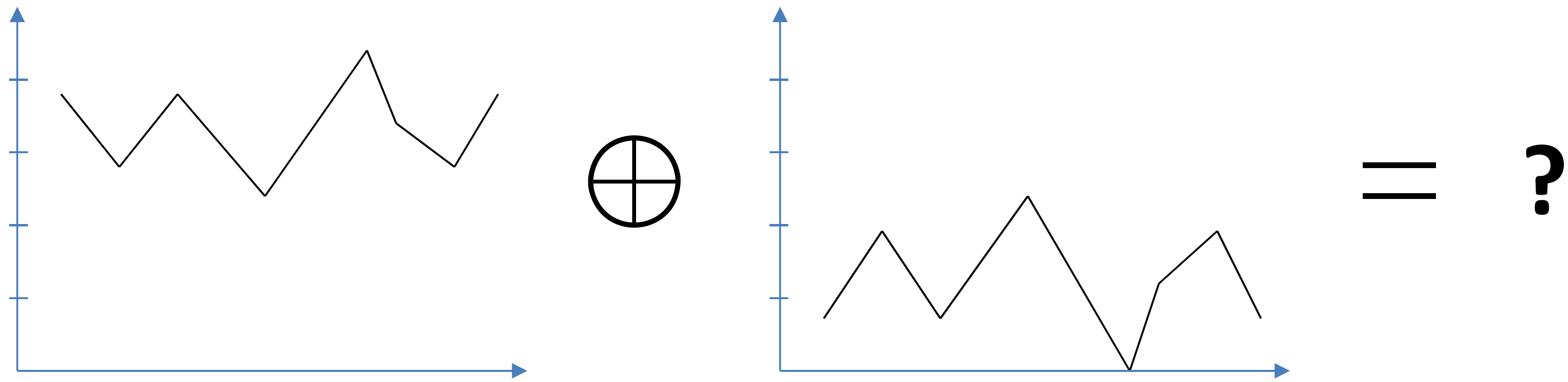
Curtailing

- As we increase the installed capacity of renewable generation:
    - It may happen that generation exceeds load demand
- The key problem:
    - Peak generation may not match peak demand.
- An easy option is to curtail excessive generation
    - Shut down some wind turbine, solar panels, etc…

Using Fast Responding Generators

- Natural gas and coal units can quickly change generation level.

- They can compensate fluctuations in renewable power.



Renewable Generation

Fast Responding Generation

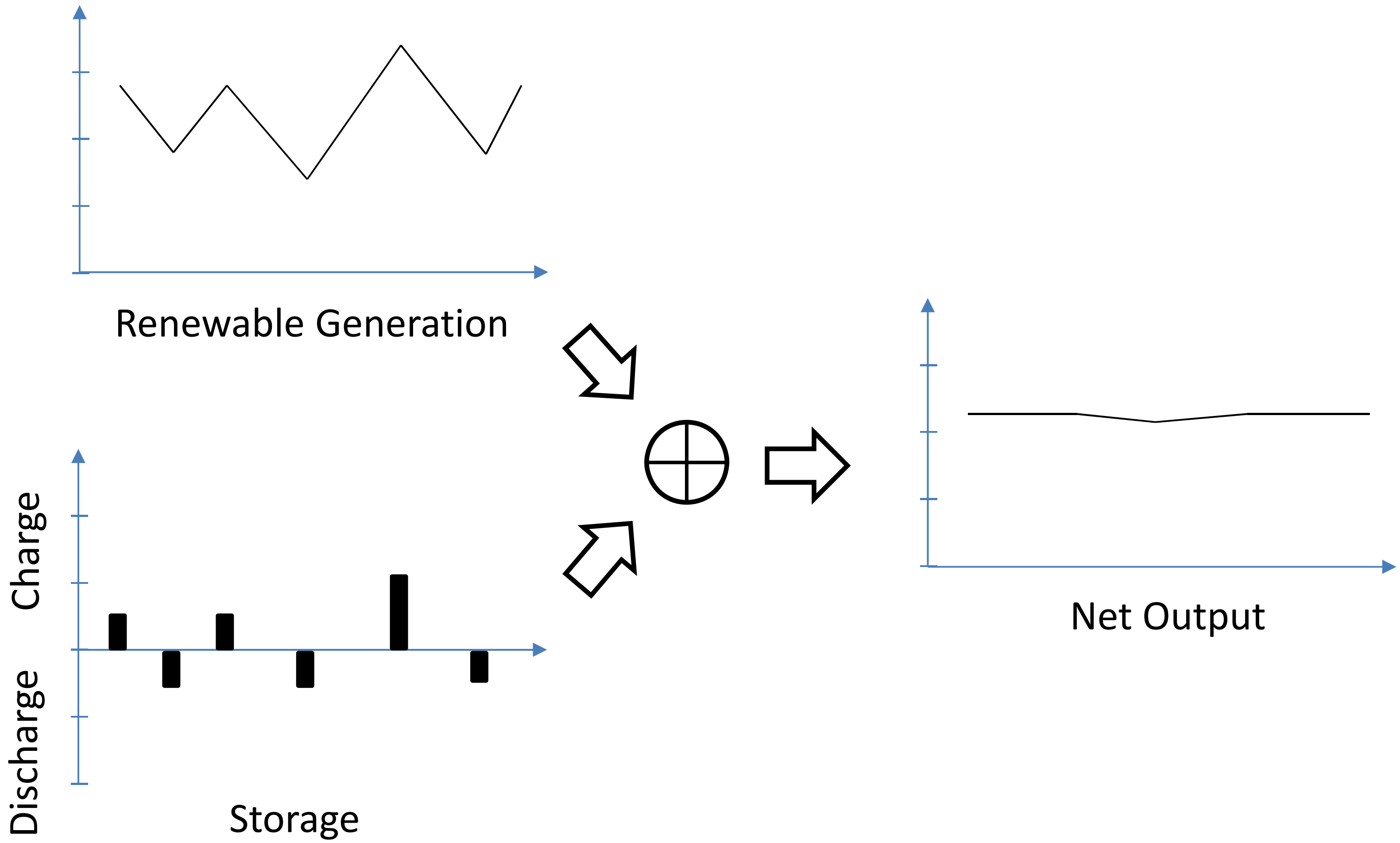
Using Fast Responding Generators

- Q: Do you see any disadvantage in this solution?

- Q: What are the carbon footprints for natural gas and coal?

Using Storage Devices

- Charge at higher generation levels. Discharge otherwise.

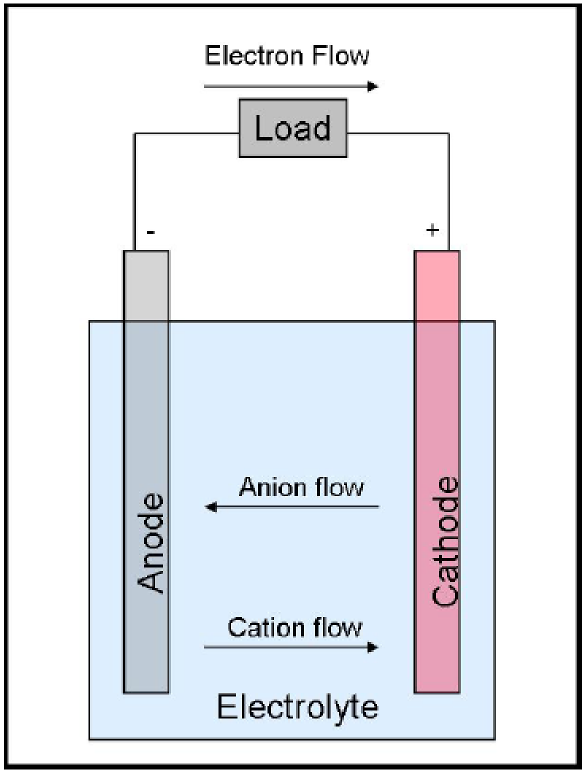


Using Storage Devices

- Some existing storage technologies:
  - Batteries
  - Flywheels
  - Ultra Capacitors
  - Hydrogen Fuel Cell
  - Compressed Air
  - Pumping Hydro
  - Liquid Heating

Storage Technologies: Batteries

- Common Options:
  - Lead-acid Battery
    - Electrochemical Reactions
    - Mature Technology
    - Inexpensive
    - Low energy / power densities
    - Poor life cycle
    - Often Requires maintenance.



- Common Options:
  - Lithium-ion Battery
    - Lithium-ion Electrochemical Cells

A Lithium-ion Battery of a Laptop Computer

Storage Technologies: Batteries

- Industrial / Commercial Products (Order of Megawatts):

One MW pilot storage projects by PJM in Pennsylvania

Storage Technologies: Batteries

- AES Battery Storage Projects in the U.S.:
  - A two-MW project in Huntington Beach, CA
  - A one-MW project in Houston, TX
  - An eight-MW project in New York that is scaling to 20 MW.
  - A 32 MW Project in West Virginia to connect to PJM.
- Applications:
  - Frequency Regulation / Renewable Energy Integration

Storage Technologies: Batteries

- AES Battery Storage Projects in the U.S.:

These containers hold 1.3 million batteries: AES WV Project

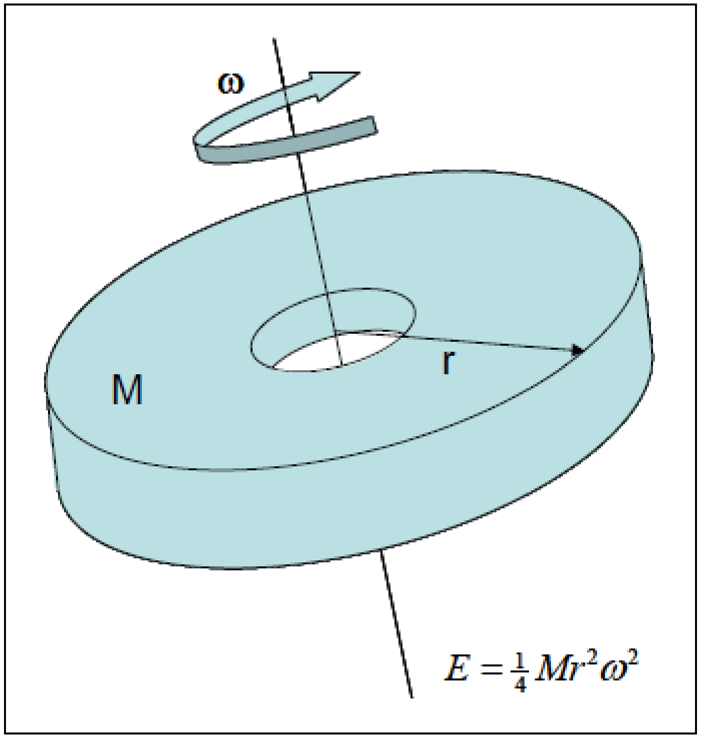
- Video: http://vimeo.com/32170739 (Watch From Min 3:20)

Storage Technologies: Flywheels

- Flywheels Energy Storage (FES) Operation:
  - Accelerating a rotor (flywheel) to a very high speed
  - Maintaining energy in the system as rotational energy
  - Once we disconnect energy source:
    - Rotor will continue rotating
    - Acting as a source of energy
- Video: http://www.youtube.com/watch?v=mV_b5oMqc2M

Storage Technologies: Flywheels

- Energy storage is calculated given:
  - Mass *M*
  - Cylinder radius *r*
  - Angular velocity *ω*



- Two approaches:
  - Big heavy wheels spinning slowly
  - Small light wheels spinning quickly

Storage Technologies: Flywheels

- Commercial FES:
  - Rotors are suspended by magnetic bearings
  - Maintaining energy in the system as rotational energy
  - Spinning at 20,000 - 50,000 rpm in a vacuum enclosure
  - Efficiency: Can be up to 90%.
  - Capacity: hundreds of kwh per flywheel.

Storage Technologies: Flywheels

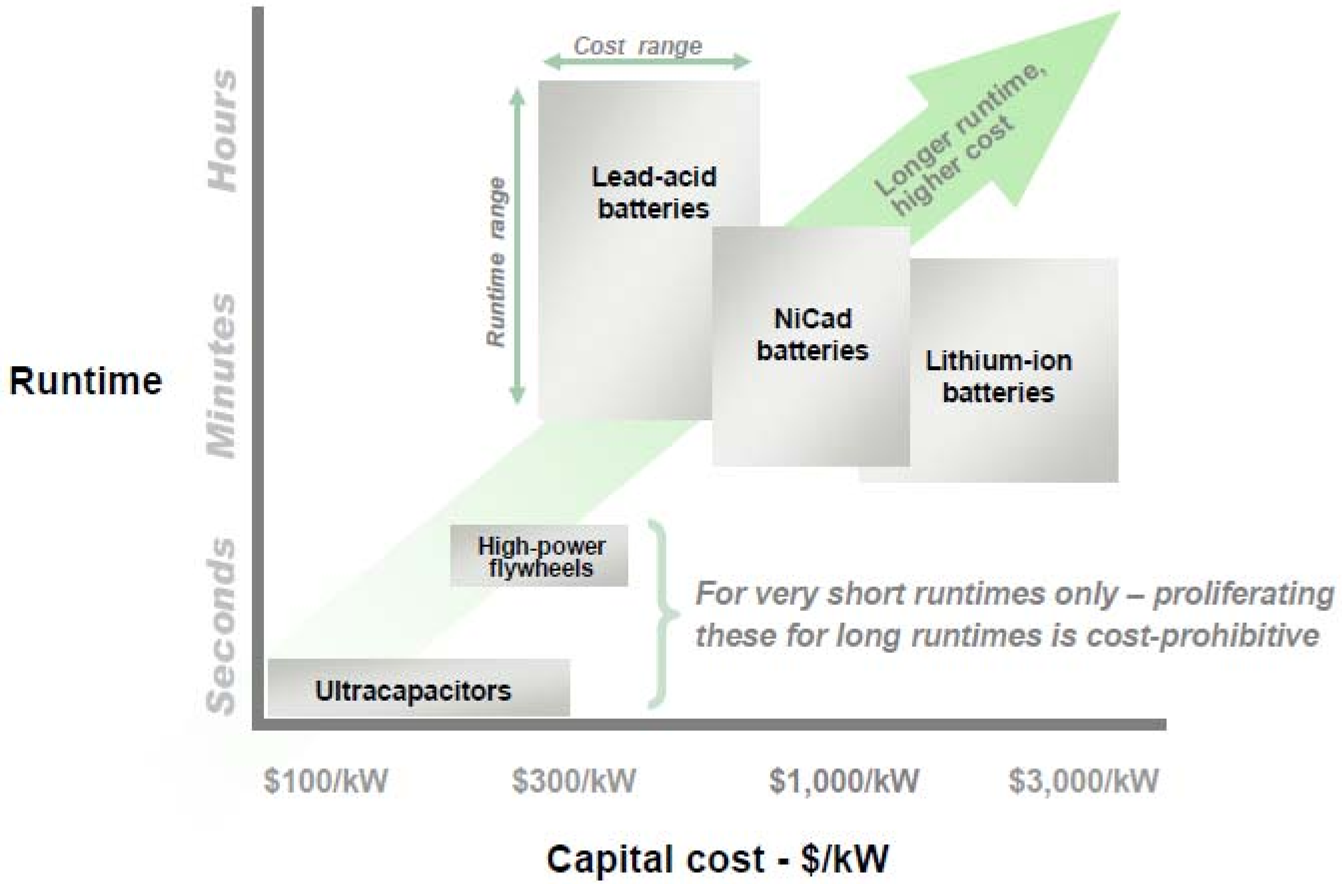
- Commercial FES:

A Flywheel storage technology in New York by Beacon Power

- Video: http://www.youtube.com/watch?v=ay_NiGu7mis

Storage Technologies: Flywheels

- Comparison Between Batteries and Flywheels:



Ref: S. McCluer and J.-F. Christin

Storage Technologies: Ultra Capacitors

- Also known as Electric Double-Layer Capacitor:

An example for what you would see in an Ultra Capacitor Box

- Video: http://www.youtube.com/watch?v=aO4qIGo6x_Y

Storage Technologies: Ultra Capacitors

- Advantages:
  - Very long life time
    - Millions of Charge and Discharge Cycles
  - Low cost per cycle.
  - Very high rate of charge and discharge
  - Very high cycle efficiency: 95% or more.
    - Low internal resistance

Storage Technologies: Ultra Capacitors

- Disadvantages:
  - High weights
    - The amount of energy stored per unit weight is low
  - High Self-discharge rate
    - Short runtime (recall the comparison diagram)
  - Low maximum voltage

Storage Technologies: Hydrogen Fuel

- Hydrogen is not a primary energy source.

- Rather we should use some other type of energy
  - To manufacture hydrogen

- Hydrogen is an eco-friendly fuel
  - Can be used as a transportation fuel
  - Can be used to generate electricity

Storage Technologies: Hydrogen Fuel

- Hydrogen as a transportation fuel:

Hydrogen Vehicle

Hydrogen Airplane

- We can use extra renewable power to manufacture hydrogen!

Storage Technologies: Hydrogen Fuel

- Hydrogen as electricity storage:
  - Charge: Use excessive power to manufacture hydrogen
  - Storage: Storage Hydrogen in tanks / underground caves
  - Discharge: Use hydrogen to generate electricity
    - Hydrogen is eco-friendly fuel.
- Of course, the extra hydrogen can be used for transportation.
- Related Video: www.youtube.com/watch?v=meDgY98EuMw

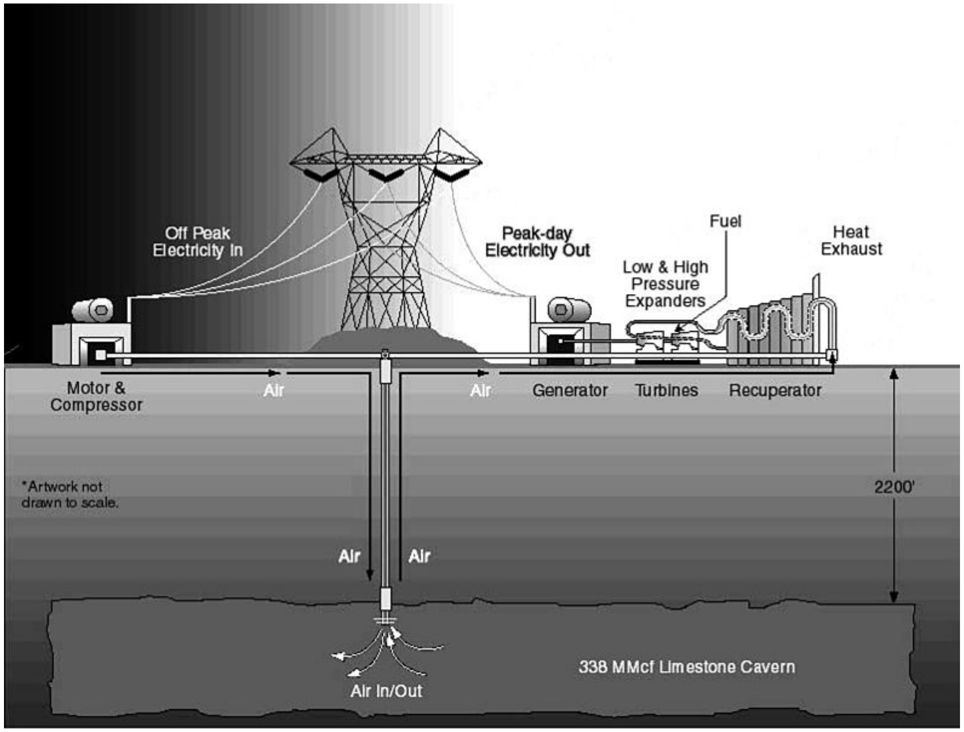
Storage Technologies: Compressed Air

- Compressed Air Energy Storage (CAES):
  - Charge: Use excessive power to compress air
  - Storage: Storage compressed air in underground caves
  - Discharge: Use compressed air to generate electricity
    - Through a compressed air engine / turibne
      - Using expansion of compressed air

- Video: www.youtube.com/watch?v=dGd7PIC09AM (from 1:00)

Storage Technologies: Compressed Air

- Compressed Air Energy Storage (CAES):
- Pros:
  - Huge power capacity
- Cons:
  - Special Locations
  - Slow Responding
  - Relatively Expensive

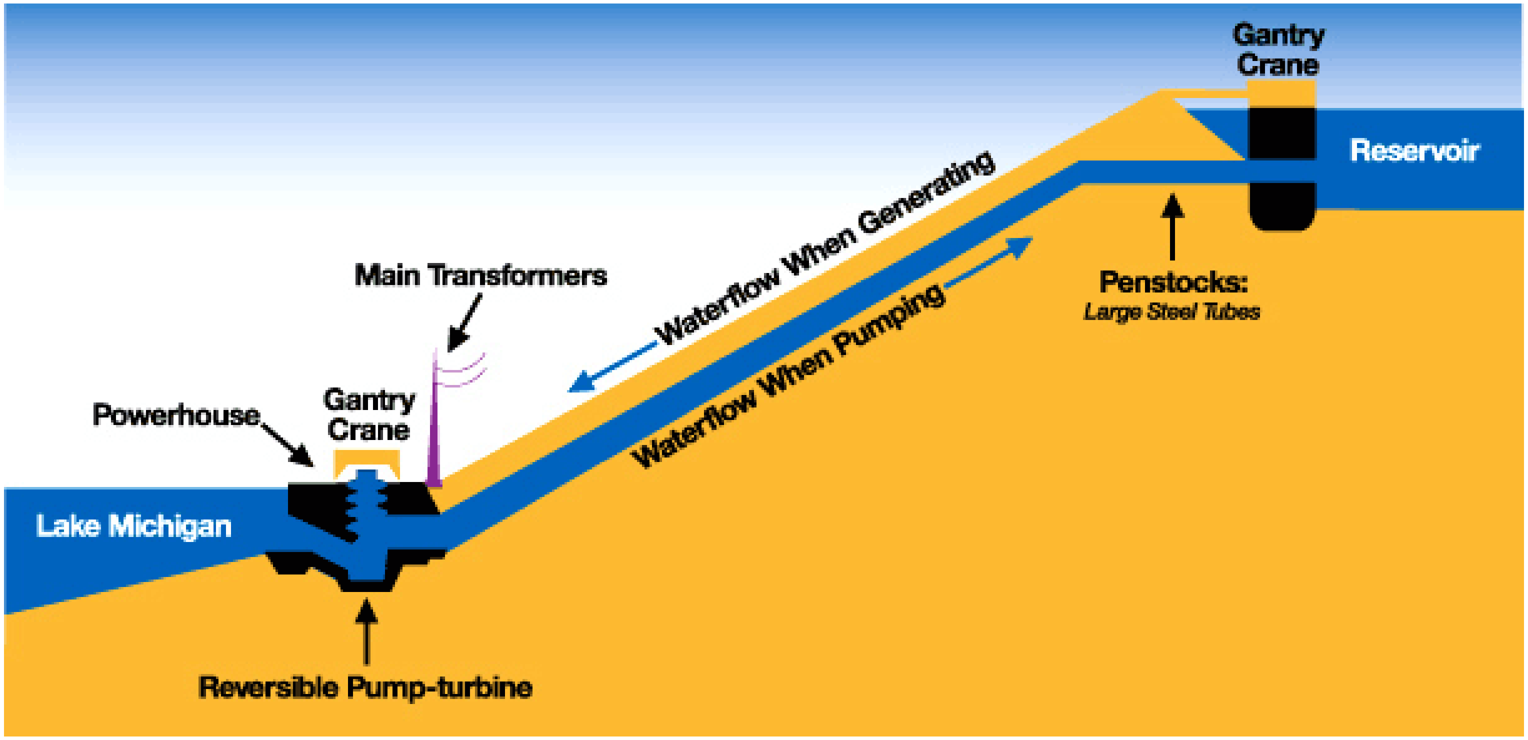


Storage Technologies: Pumping Hydro

- Pumped Storage Hydroelectricity (PSH):
  - A type of hydroelectric power generation (Q: other exmp?)
  - Charge: Mump water to a reservoir in high altitude
  - Storage: Store water in the reservoir until needed
  - Discharge: Release water to a hydro turbine
  - Charge at off-peak hours and discharge at peak hours!

Storage Technologies: Pumping Hydro

- Pumped Storage Hydroelectricity (PSH):



An example for the operation of PSH

Storage Technologies: Pumping Hydro

- PSH requires building big reservoirs:

A PSH reservoir in Michigan

A PSH reservoir in Japan

- Video: www.youtube.com/watch?v=mMvOZSVXlzI (up to 4:30)

Storage Technologies: Liquid Heating

- Renewable power is used to heat / boil a liquid.
- Boiled liquid is stored in tanks.
- It is later used to generate electricity.
- We already saw an example:
  - Solar Thermal Energy
  - See Slide #27

Storage Technologies: Optimal Choices

- Renewable Integration May Require Various Storage Options.

- They may not be a single best option

  - Different Cost and Availability

  - Different Capacity and Runtime

  - Different Response Time

Q: What is the difference?

- Optimal resource management is needed to utilize them all!

Demand Response

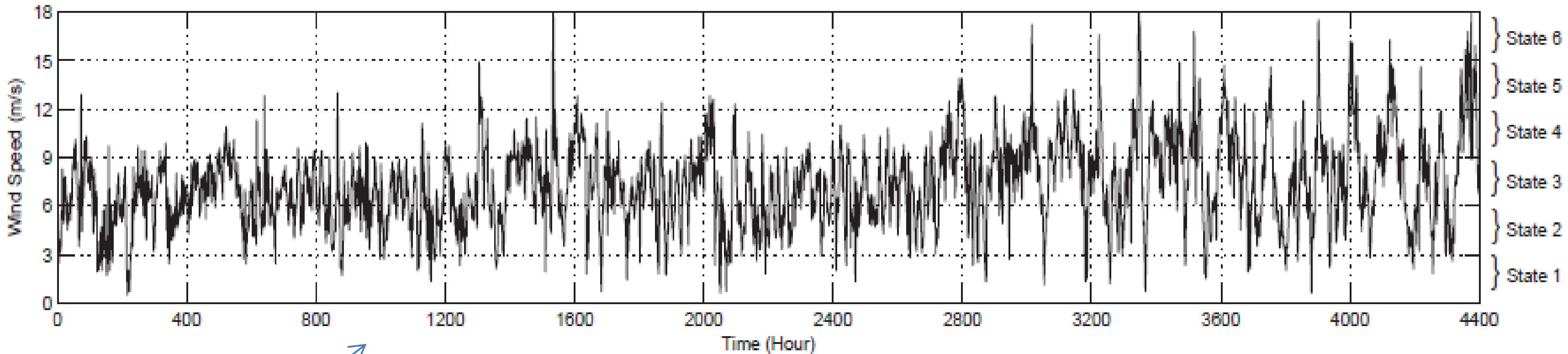
- Main Idea:
  - Increase load when more renewable power is available.
  - Decrease load when less renewable power is available.
- Pricing (e.g., Real-time Pricing) can help:
  - Lower (even negative) prices when generation increases.
  - Higher prices when generation level drops.

Demand Response

- Challenges:
  - Demand Response is Usually Slow Responding
    - Requires Notification to Users
    - ECS Devices May Help to Some Extent
  - Required Response Time: 10 Minutes or Less
  - Otherwise, we may need excellent wind forecasting.
- Existing Project: Bonneville Power Admin (NW) and EnerNOC

Renewable Energy Prediction

- So far, we saw multiple ways to integrate renewable power.
- However, efficient decision making still requires
  - Accurate renewable (specially wind) power forecasting.



Wind Speed in Lubbock, TX

Q: When should we charge or discharge a battery?

Renewable Energy Prediction

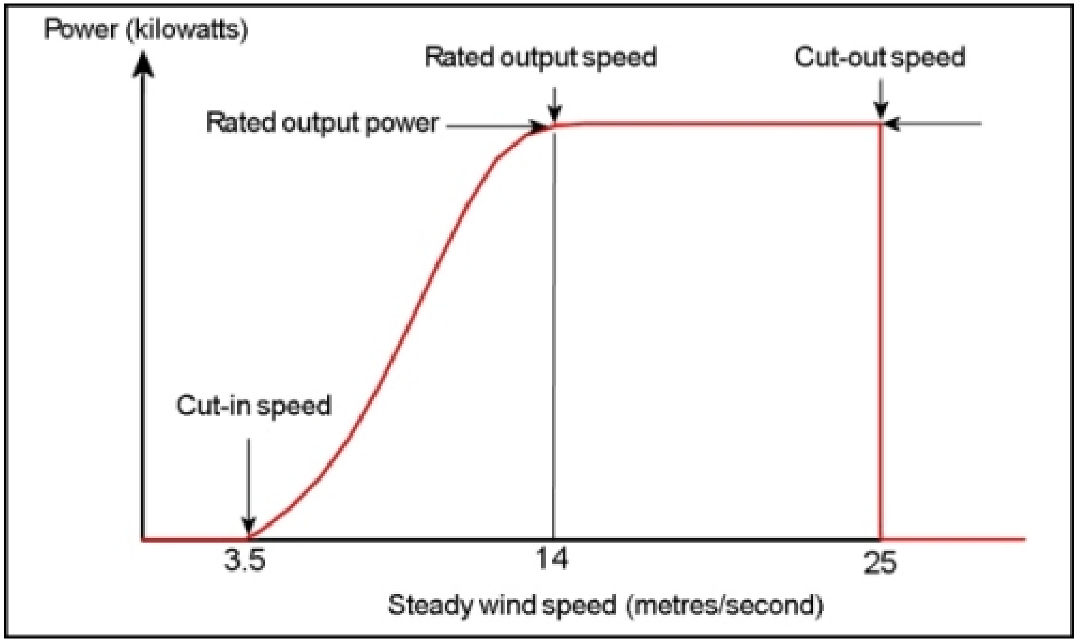
- Our focus is on wind power forecasting.
  - In particular, short-term forecasting.

- But some techniques are general to any energy source.

- We may also differentiate:
  - Forecasting the Power Output of a Single Wind Turbine
  - Forecasting the Power Output of a Wind Farm

Single Wind Turbine

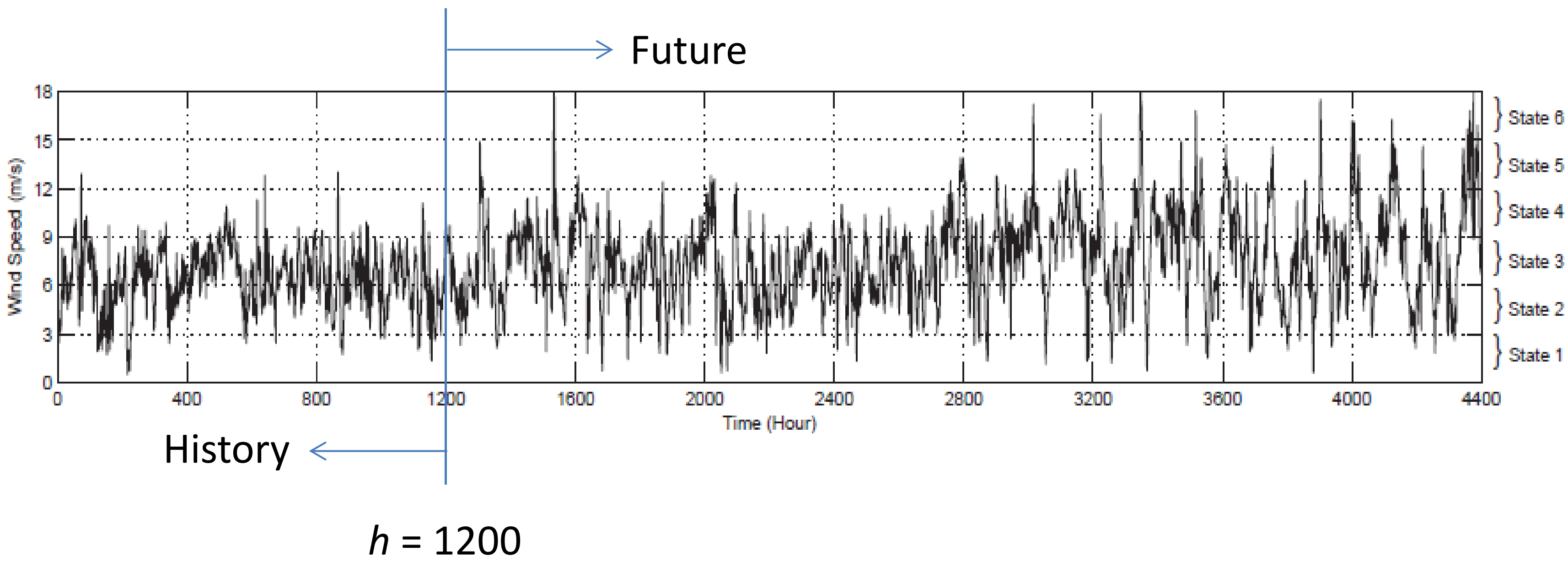
- Assume that we know the wind speed vs. wind power curve.



- Predicting wind speed can help us predict wind power.

Single Wind Turbine

- Consider the following set of measurements



- Let $W(h)$ denote the wind speed measured at hour h.
  - Prediction of W(1200) can be a function of W(1)…W(1199).

Single Wind Turbine

- Assuming a linear prediction model, we can write:

$$W(h) = a_1 W(h-1) + a_2 W(h-2) + a_3 W(h-3) + \cdots + a_{h-2} W(2) + a_{h-1} W(1)$$
$$= \sum_{i=1}^{h-1} a_i W(h-i)$$

- Sampling resolution can be anything: 5 min, 10 min, …, 1 hour.

- Furthermore, we may not use the entire history:

$$W(h) = \sum_{i=1}^{N} a_i W(h-i), \qquad N \leq h-1$$

Single Wind Turbine

- Q: How can we obtain the right choice of
  - Parameters $a_1, a_2, \ldots, a_N$?
- This can be done:
  - Offline: Using a training sequence
  - Online: A new model is derived / updated every time slot.
- Q: What is the difference between online and offline cases?

Single Wind Turbine: Online Model Prediction

- At time h = 1000, if N = 5, we expect to see:

$$\text{Unknown} \left\{ W(1000) = \sum_{i=1}^{5} a_i W(1000-i) = \right.$$

$$\text{Known} \left\{ \begin{aligned} W(999) &= \sum_{i=1}^{5} a_i W(999-i) = \\ W(998) &= \sum_{i=1}^{5} a_i W(998-i) = \\ W(997) &= \sum_{i=1}^{5} a_i W(997-i) = \\ W(996) &= \sum_{i=1}^{5} a_i W(996-i) = \\ &\vdots \qquad\qquad \vdots \end{aligned} \right.$$

Single Wind Turbine: Online Model Prediction

- Prediction Error:

$$\left\{ e(1000) = W(1000) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(999) \;\; W(998) \;\; W(997) \;\; W(996) \;\; W(995)]^T \right.$$

$$\left\{ \begin{array}{l} e(999) = W(999) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(998) \;\; W(997) \;\; W(996) \;\; W(995) \;\; W(994)]^T \\ e(998) = W(998) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(997) \;\; W(996) \;\; W(995) \;\; W(994) \;\; W(993)]^T \\ e(997) = W(997) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(996) \;\; W(995) \;\; W(994) \;\; W(993) \;\; W(992)]^T \\ e(996) = W(996) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(995) \;\; W(994) \;\; W(993) \;\; W(992) \;\; W(991)]^T \\ e(995) = W(995) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(994) \;\; W(993) \;\; W(992) \;\; W(991) \;\; W(990)]^T \\ \quad \vdots \qquad\qquad\qquad \vdots \end{array} \right.$$

- Q: Can we choose a_1, …, a_N to minimize mean prediction error?

Single Wind Turbine: Online Model Prediction

- Least Square Error Parameter Estimation:

$$\begin{aligned}
\underset{a_1,\cdots,a_5}{\text{minimize}} \; & \left(W(999) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(998) \;\; W(997) \;\; W(996) \;\; W(995) \;\; W(994)]^T\right)^2 + \\
& \left(W(998) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(997) \;\; W(996) \;\; W(995) \;\; W(994) \;\; W(993)]^T\right)^2 + \\
& \left(W(997) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(996) \;\; W(995) \;\; W(994) \;\; W(993) \;\; W(992)]^T\right)^2 + \\
& \left(W(996) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(995) \;\; W(994) \;\; W(993) \;\; W(992) \;\; W(991)]^T\right)^2 + \\
& \left(W(995) - [a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5][W(994) \;\; W(993) \;\; W(992) \;\; W(991) \;\; W(990)]^T\right)^2 + \\
& \cdots
\end{aligned}$$

- Q: Can you rewrite the above problem in matrix form?
  - Q: Can you solve the formulated optimization problem?

Single Wind Turbine: Online Model Prediction

- Q: Do we always want to look at the whole history
  - When we calculate the Least Square Error criteria?
- Q: What if we want to care less about older errors?

Single Wind Turbine: Online Model Prediction

- Once we calculate a_1, a_2, …, a_N , we use them to predict:

$$\hat{W}(1000) = \underbrace{[a_1 \;\; a_2 \;\; a_3 \;\; a_4 \;\; a_5]}\underbrace{[W(999) \;\; W(998) \;\; W(997) \;\; W(996) \;\; W(995)]^T}$$

- Q: Should we use the same a_1, a_2, …, a_N at time h = 1001?

- Q: What if we want to update the prediction model?

- Q: What is the difference between online and offline models?

Single Wind Turbine: Online Model Prediction

- So far, our predictions have been one-step ahead.

- Q: How can we make multiple step (e.g., 3) ahead prediction?

$$\hat{W}(1000) = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix} \begin{bmatrix} W(999) & W(998) & W(997) & W(996) & W(995) \end{bmatrix}^T$$

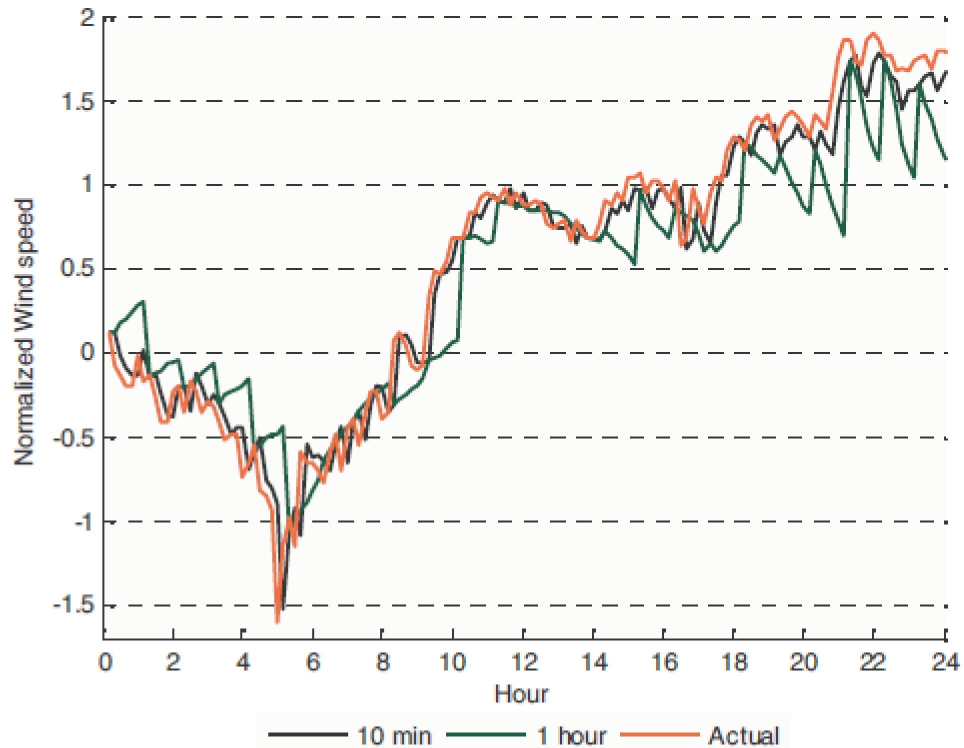
$$\hat{W}(1001) = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix} \begin{bmatrix} \hat{W}(1000) & W(999) & W(998) & W(997) & W(996) \end{bmatrix}^T$$

$$\hat{W}(1002) = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \end{bmatrix} \begin{bmatrix} \hat{W}(1001) & \hat{W}(1000) & W(999) & W(998) & W(997) \end{bmatrix}^T$$

- Accuracy degrades as we move forward in time for prediction.

Single Wind Turbine

- Abdel-Karim et al. applied offline training to Dunkirk, NY data:
  - Measurement resolution: 10 minutes

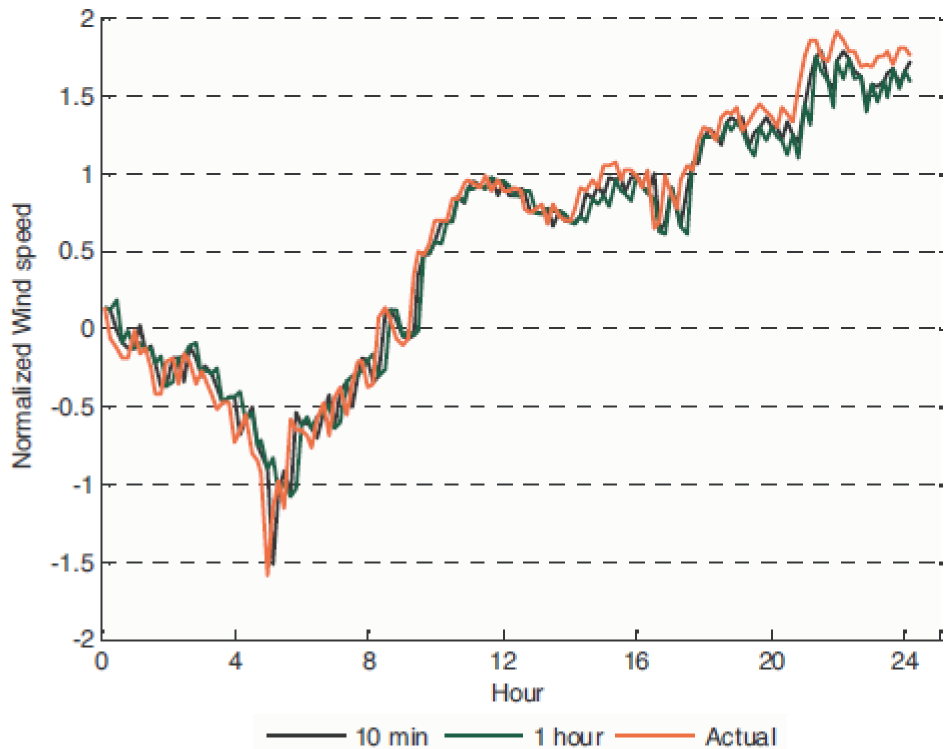


Q: What is N?

Ten min and one hour prediction using one hour past values

Single Wind Turbine

- Abdel-Karim et al. applied offline training to Dunkirk, NY data:
  - Measurement resolution: 10 minutes



Q: What is N?

Ten min and one hour prediction using 10 min past value

Single Wind Turbine

- It seems $N = 1$ works better.

- Similar results are reported in other papers.

- Q: How do you interpret these results?

- Q: What are the other prediction models when
  - We only use the one past data to make the prediction?

Single Wind Turbine: Markov Chain Prediction

- A Markov chain (MC) is a mathematical system that
  - Undergoes transitions from one state to another
  - Between a finite or countable number of possible states
- MC is a memoryless random process:
  - The next state depends only on the current state
  - Not on the sequence of events that preceded it.

Single Wind Turbine: Markov Chain Prediction

- The memoryless property:

$$\Pr\left\{W(h) = w \,\middle|\, w(h-1) = w_1, w(h-2) = w_2, \cdots, w(1) = w_{h-1}\right\}$$
$$= \Pr\left\{W(h) = w \,\middle|\, w(h-1) = w_1\right\}$$

- For stationary Markov Chains:

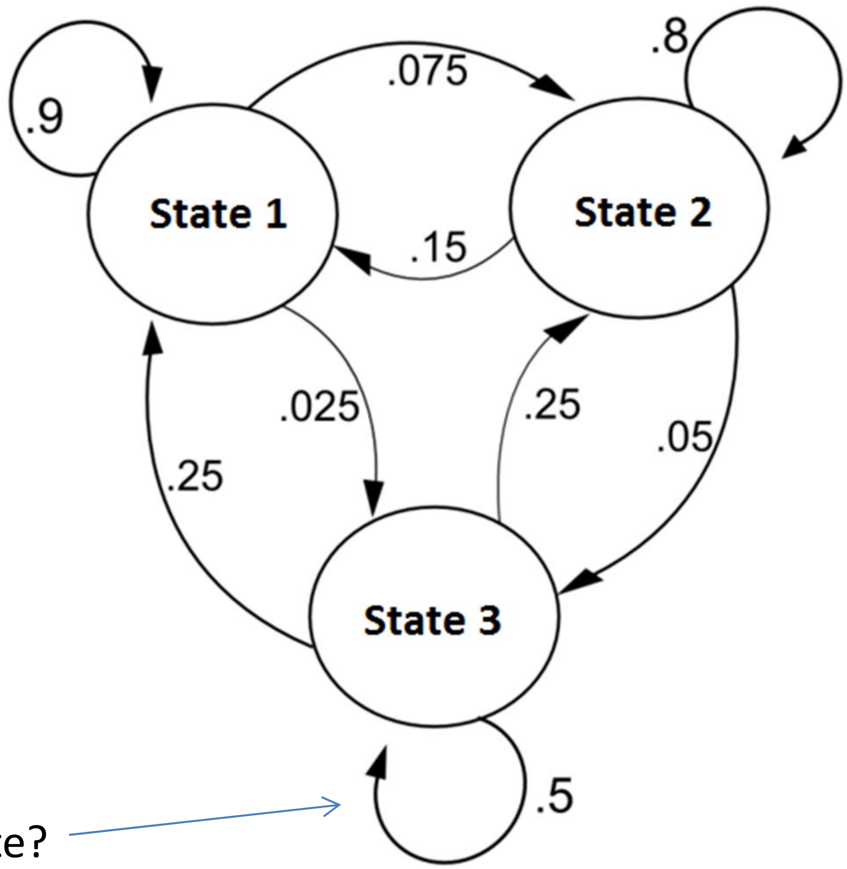
$$\Pr\left\{W(h) = w \,\middle|\, w(h-1) = w_1\right\} = \Pr\left\{W(h-1) = w \,\middle|\, w(h-2) = w_1\right\}$$

Single Wind Turbine: Markov Chain Prediction

- Example: A Stationary Markov Chain with Three States

- Q: What is the sum of
    - Incoming probabilities
    - Outgoing probabilities

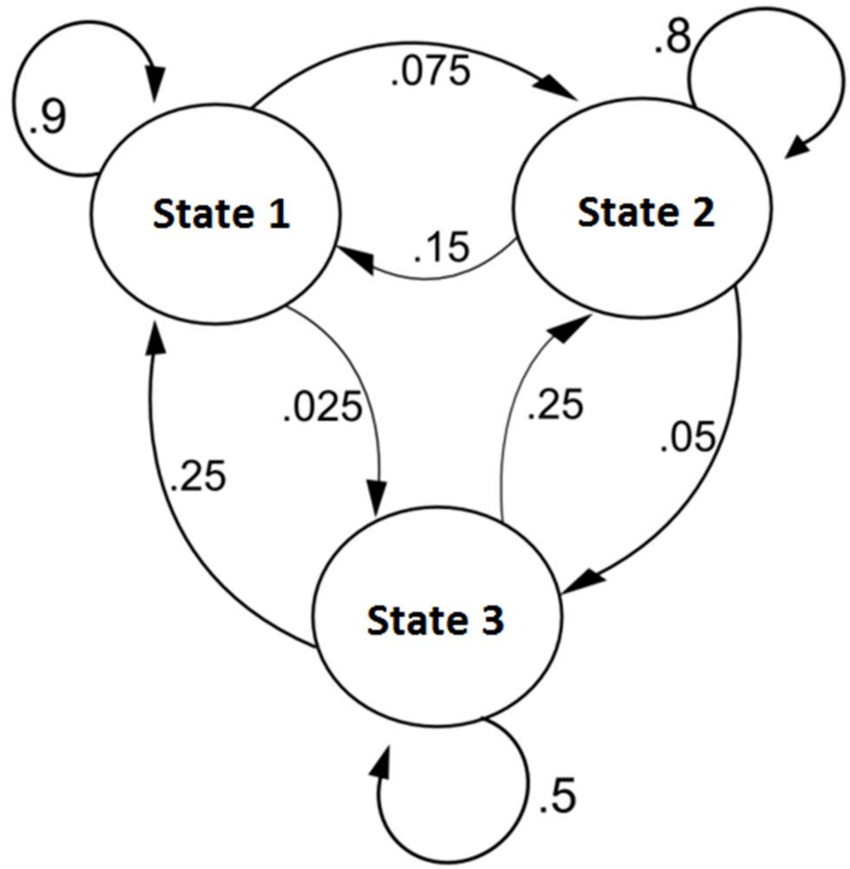
to and from each state?



Q: What does it indicate?

Single Wind Turbine: Markov Chain Prediction

- Example: Obtain the transition probability matrix for this MC:



Single Wind Turbine: Markov Chain Prediction

- Obtain the transition probability matrix from measurements:

1, 3, 2, 2, 3, 1, 2, 1, 3, 3, 2, 1, 1, 2, 3, 3, 2, 3, 1, 2, 3, 1, 2, 3, 3, 2, 2, 1, 1, 3, 2, 1, 2, 2, 3

- If we are in state 1:
  - Probability of staying in State 1:
  - Probability of going to State 2:
  - Probability of going to State 3:

Single Wind Turbine: Markov Chain Prediction

- Obtain the transition probability matrix from measurements:

1, 3, 2, 2, 3, 1, 2, 1, 3, 3, 2, 1, 1, 2, 3, 3, 2, 3, 1, 2, 3, 1, 2, 3, 3, 2, 2, 1, 1, 3, 2, 1, 2, 2, 3

- If we are in state 2:
  - Probability of going to State 1:
  - Probability of staying in State 2:
  - Probability of going to State 3:

Single Wind Turbine: Markov Chain Prediction

- Obtain the transition probability matrix from measurements:

1, 3, 2, 2, 3, 1, 2, 1, 3, 3, 2, 1, 1, 2, 3, 3, 2, 3, 1, 2, 3, 1, 2, 3, 3, 2, 2, 1, 1, 3, 2, 1, 2, 2, 3

- If we are in state 3:
  - Probability of going to State 1:
  - Probability of going to State 2:
  - Probability of staying in State 3:

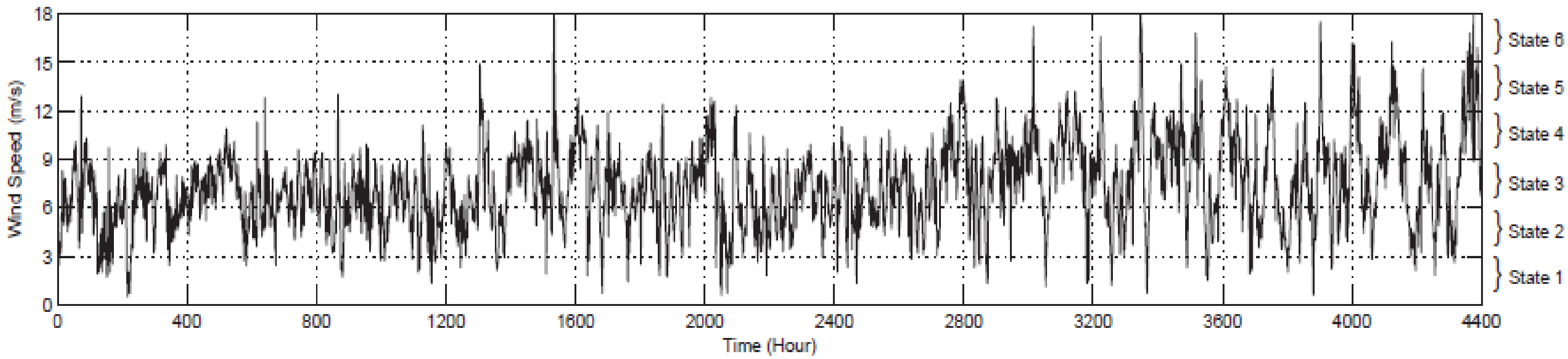
Single Wind Turbine: Markov Chain Prediction

- Obtain the transition probability matrix from measurements:

1, 3, 2, 2, 3, 1, 2, 1, 3, 3, 2, 1, 1, 2, 3, 3, 2, 3, 1, 2, 3, 1, 2, 3, 3, 2, 2, 1, 1, 3, 2, 1, 2, 2, 3

Single Wind Turbine: Markov Chain Prediction

- Q: How can you choose states if the data is continuous?

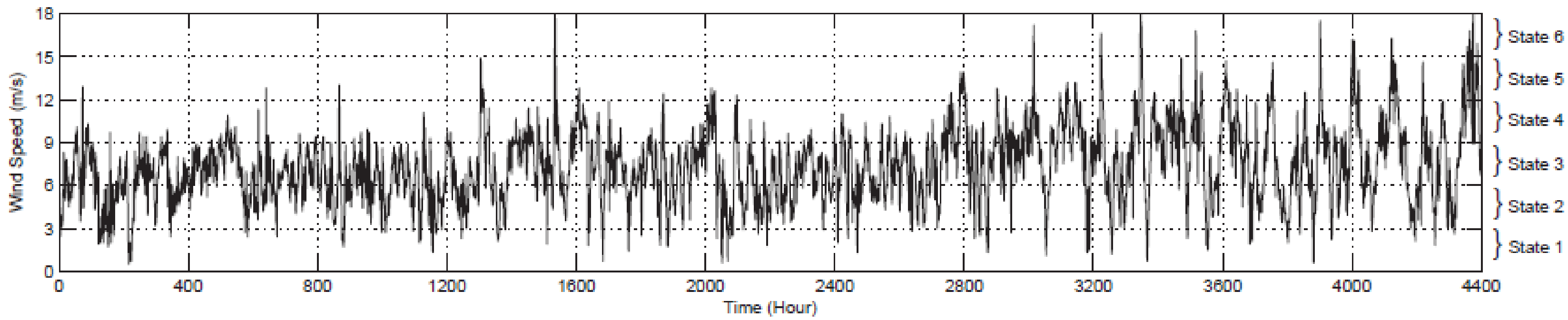


- Q: How many states did we choose in the above figure?

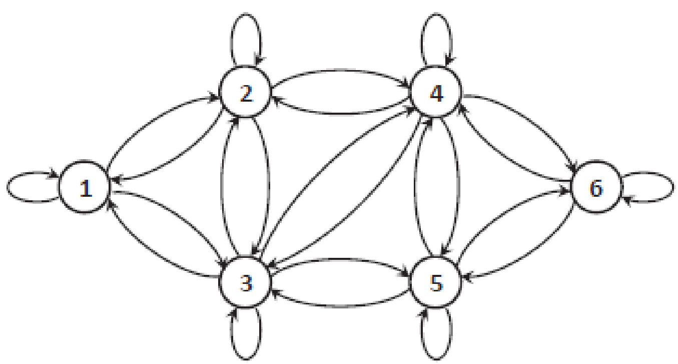
- More states → Higher Computational Complexity

Single Wind Turbine: Markov Chain Prediction

- For wind power, transition probability matrix is usually sparse.



(a) Wind Speed Measurements over Six Months



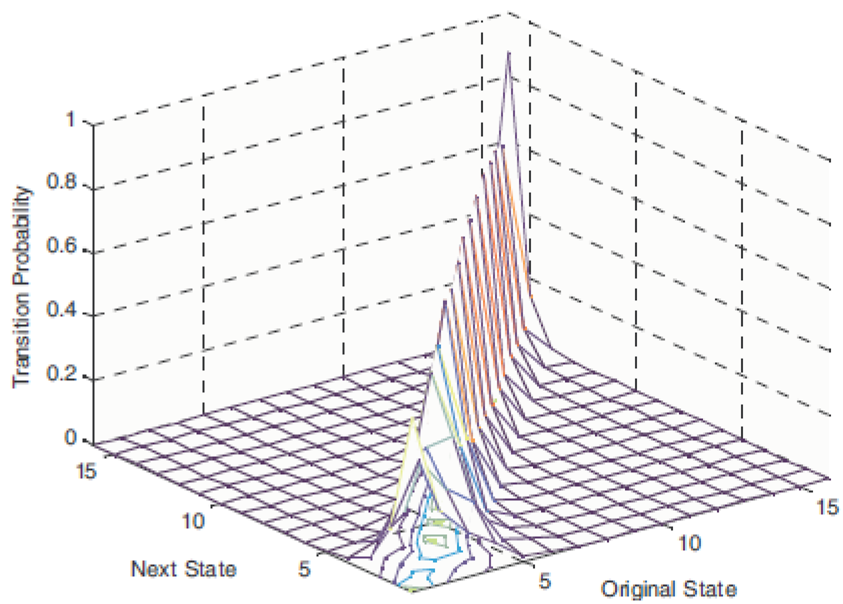
(a) Corresponding Markov Chain Model

State	1	2	3	4	5	6
1	0.60	0.38	0.02	0.00	0.00	0.00
2	0.06	0.74	0.20	0.01	0.00	0.00
3	0.00	0.13	0.76	0.11	0.00	0.00
4	0.00	0.01	0.25	0.68	0.06	0.00
5	0.00	0.00	0.02	0.28	0.66	0.05
6	0.00	0.00	0.00	0.09	0.31	0.60

(c) State Transition Probabilities

Single Wind Turbine

- Abdel-Karim et al. also used MC models for wind speed

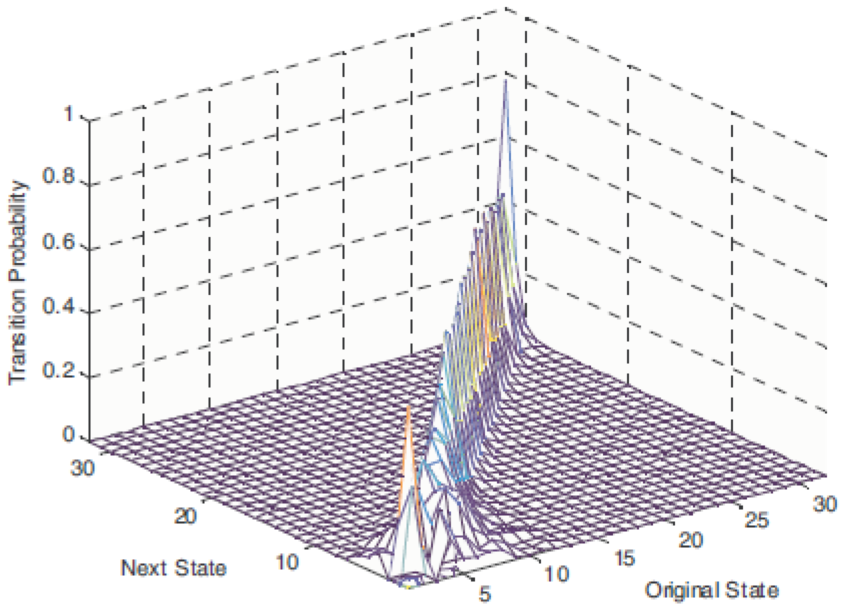


Transition Probabilities with 16 States

Q: Is the corresponding transition probability matrix sparse?

Single Wind Turbine

- Abdel-Karim et al. also used MC models for wind speed

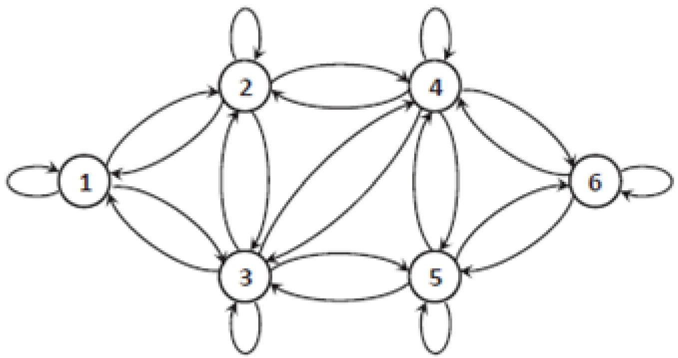


Transition Probabilities with 32 States

Q: Does increasing the number of states help in modeling?

Single Wind Turbine

- Q: Given a Markov Chain model, how can we make prediction?
- Q: What does prediction depend on?



(a) Corresponding Markov Chain Model

State	1	2	3	4	5	6
1	0.60	0.38	0.02	0.00	0.00	0.00
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4	0.00	0.01	0.25	0.68	0.06	0.00
5	0.00	0.00	0.02	0.28	0.66	0.05
6	0.00	0.00	0.00	0.09	0.31	0.60

(b) State Transition Probabilities

- Q: Assume the current wind speed is 7 m/s:
  - What do you predict wind speed to be in the next hour?

Single Wind Turbine

- As an alternative model for linear wind speed predictors:
  - We may use certain probability distribution functions.
- They too need training to obtain optimal parameters.
- Training can be done offline or online:
  - But the common approach is offline parameter selection.

Single Wind Turbine

- A common model is Weibull Distribution:
  - PDF:

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} \exp -\left(\frac{x}{\lambda}\right)^{k} & \text{if } x \geq 0, \\ 0 & \text{if } x < 0. \end{cases}$$

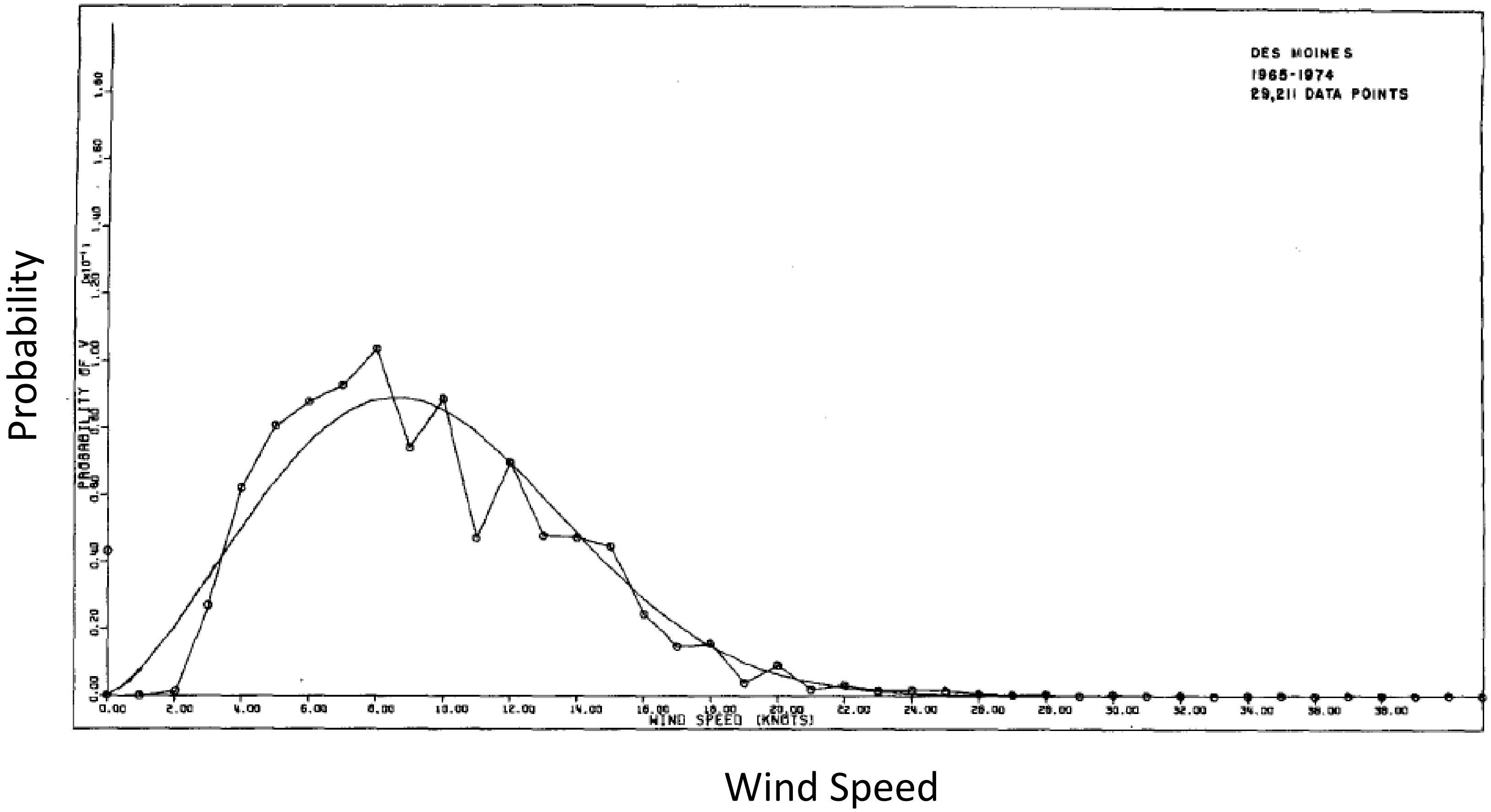
- Parameters to be estimated:

λ and k

- We may use seasonal parameter estimation.

Single Wind Turbine

- A common model is Weibull Distribution:



Single Wind Turbine

- A common model is Weibull Distribution:
  - Different parameter estimation methods can be used.

	Graphical			Weighted LL SQ			Maximum likelihood			Calculated mean
	c (m s^{-1})	k	$\bar{x}_H$ (m s^{-1})	c (m s^{-1})	k	$\bar{x}_H$ (m s^{-1})	c (m s^{-1})	k	$\bar{x}_H$ (m s^{-1})	$\bar{x}$ (m s^{-1})
Ames (1963–70)	5.40	2.24	4.76	5.50	2.33	4.85	5.49	2.24	4.84	4.89
Des Moines (1965–74)	5.20	2.22	4.41	5.21	2.42	4.42	5.54	2.38	4.71	4.69

- The PDF can particularly be used for stochastic optimization.

Wind Farm

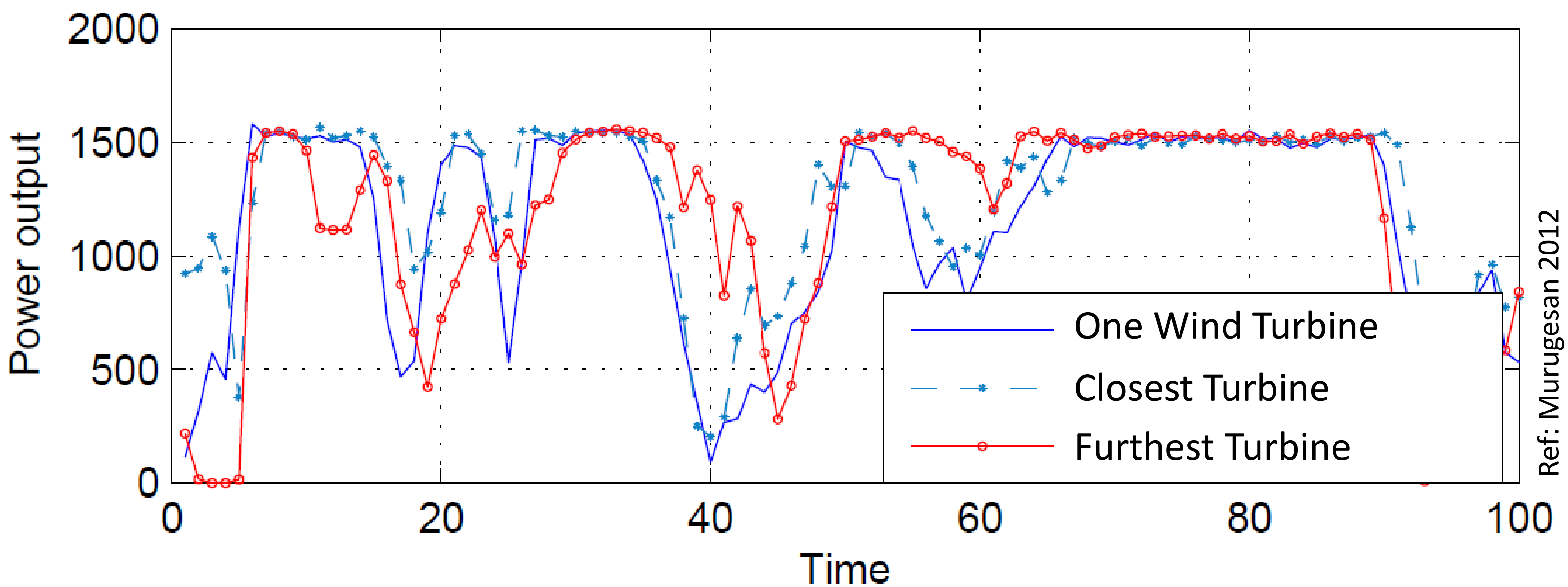
- Q: Why is wind power prediction different for wind farms?

Wind Farm

- Key Challenges:
  - Wind speed can vary within a wind farm.
    - In particular, in non-flat/mountain areas.
    - One single wind speed measurement is not enough.
  - A wind farm may include different types of turbines.
    - Each type has a distinct wind-speed wind-power curve.
    - We cannot scale up wind power prediction.

Wind Farm

- Wind speed (generated power) can vary within a wind farm:

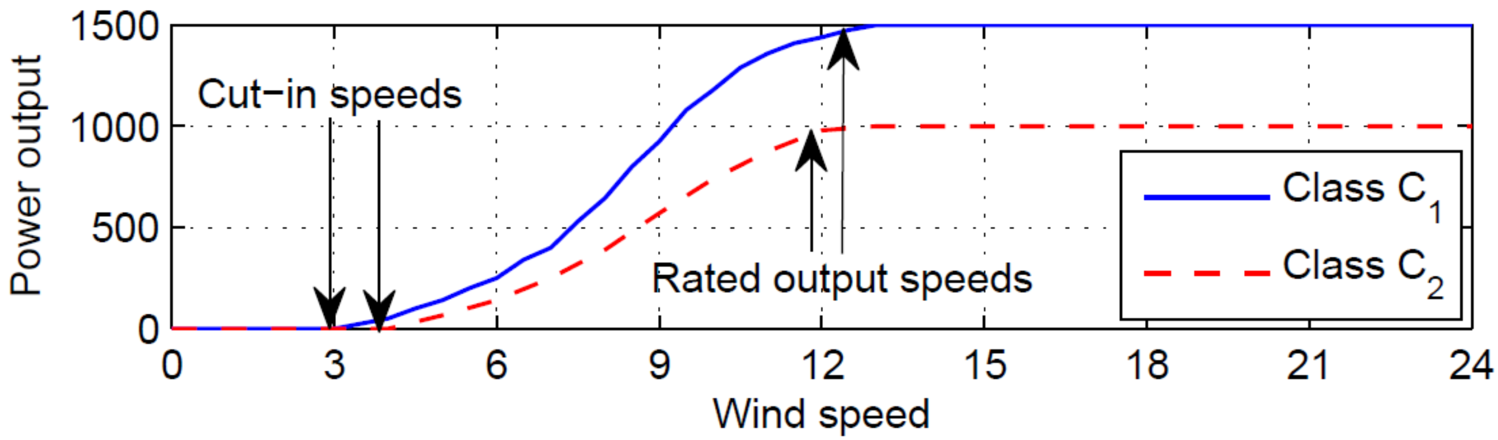


Ref: Murugesan 2012

- Three identical turbines within same farm have different outputs.

Wind Farm

- A wind farm may include different types/classes of turbines:



Ref: Murugesan 2012

- Different classes can have different wind speed / power curves.

Wind Farm

- Q: How can we tackle these two challenges?

  - Option 1: We measure wind speed for each turbine.

    - Perform individual forecasting for each single turbine.

    - Aggregate the results to predict the farm’s output.

- This is a reasonable option:

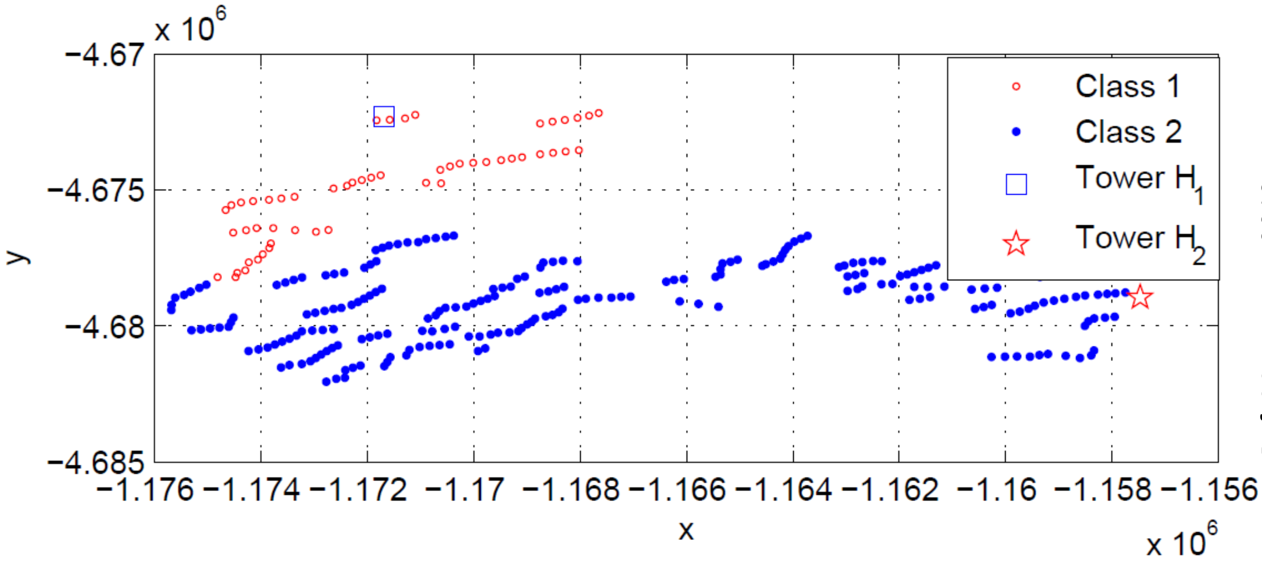
  - It can be computationally complex and requires resources.

Wind Farm

- Q: How can we tackle these two challenges?
  - Option 2: Wind-form specific prediction with limited data.
    - Separate wind speed measurement for each class.
    - Could be challenging.
    - Still an ongoing research.
- Here, we briefly review the 2012 work by Murugesan *et al*.

Wind Farm

- Consider a wind farm with two types/classes of turbines.



Ref: Murugesan 2012

- For each class, one turbine is linked with a meteorological tower.
  - Such turbine is called the root of that turbine class.

Wind Farm

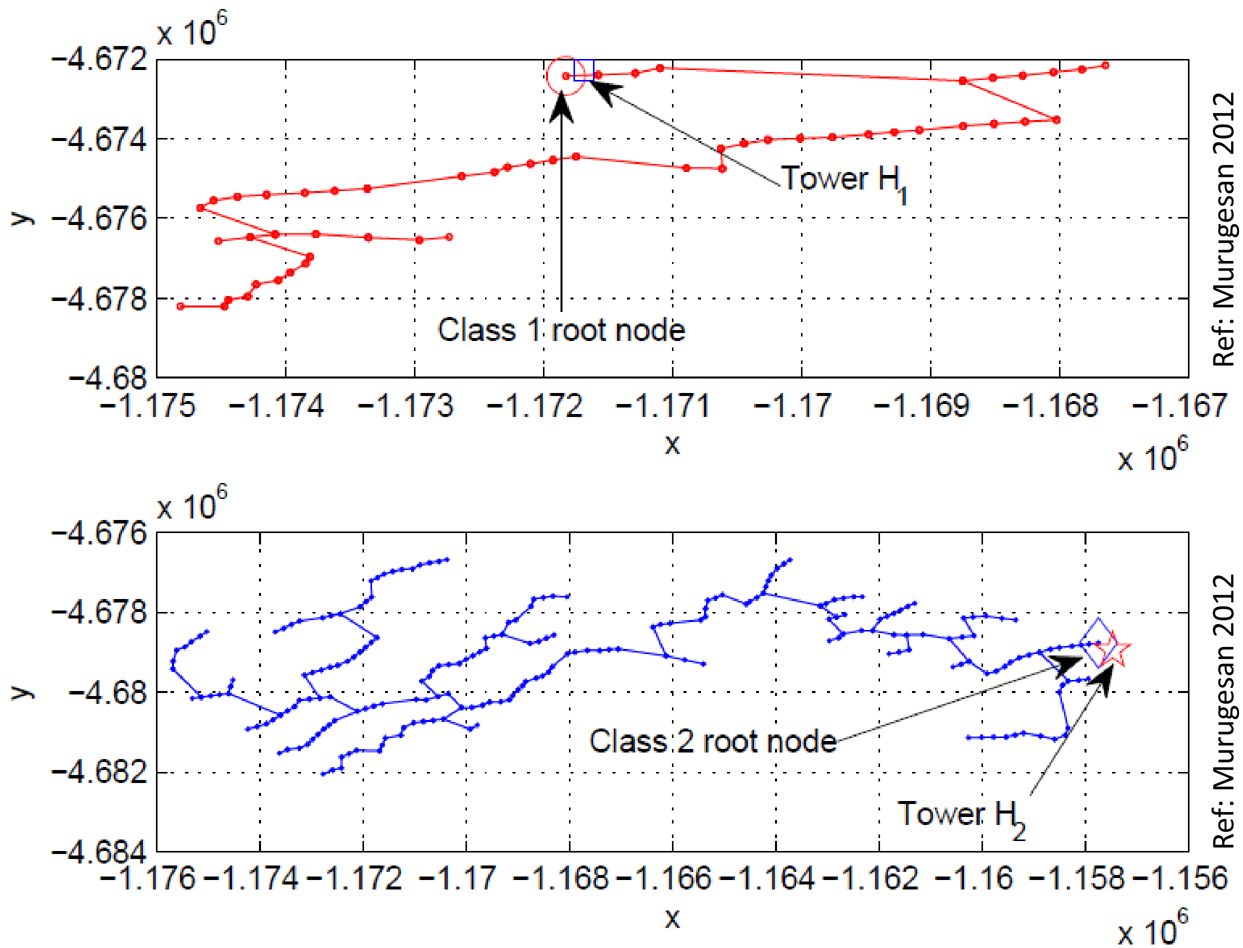
- Using one of the methods described before:
  - We can predict wind speed and power output for the root.
  - Example: Using Markov Chain or Weibull Distribution

- Q: How can we extend the prediction to turbines in same class?

- Q: Can we simply multiple it by number of turbines? Why?

Wind Farm

- Let us define the minimum spanning tree (MST) for each class.

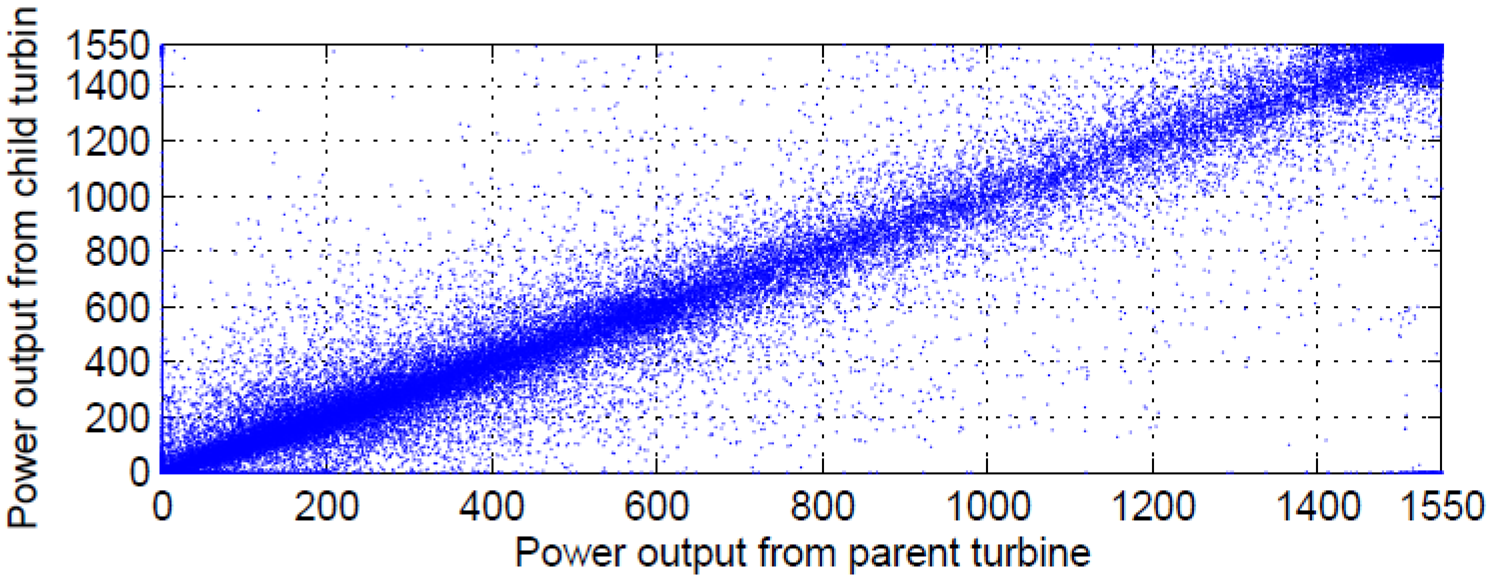


Wind Farm

- We want to answer this question:
  - Q: Given the prediction of wind power for a parent turbine:
    - How can we predict the wind power for the child turbine?
- Starting from the root:
  - We can predict wind power for all turbines in same class.
- Again, we will use a linear predictor: $P_{Child} = \alpha \, P_{Parent}$

Wind Farm

- We should estimate α using experimental data:



- For each turbine at MST depth level *d* (Q: Why?):

$$P_{Turibe} = \alpha^{d} \, P_{Root}$$

Wind Farm

- For each class *m*, we estimate α_m as:

$$\alpha_m = \arg\min \frac{1}{N} \sum_{t=1}^{N} \left(P_{Class\,m} - \hat{P}_{Class\,m} \right)^2$$

$$= \arg\min \frac{1}{N} \sum_{t=1}^{N} \left(\sum_{i=1}^{C_m} P_i - P_{Root\,m} \times \left(\sum_{i=1}^{C_m} (\alpha_m)^{d_i} \right) \right)^2$$

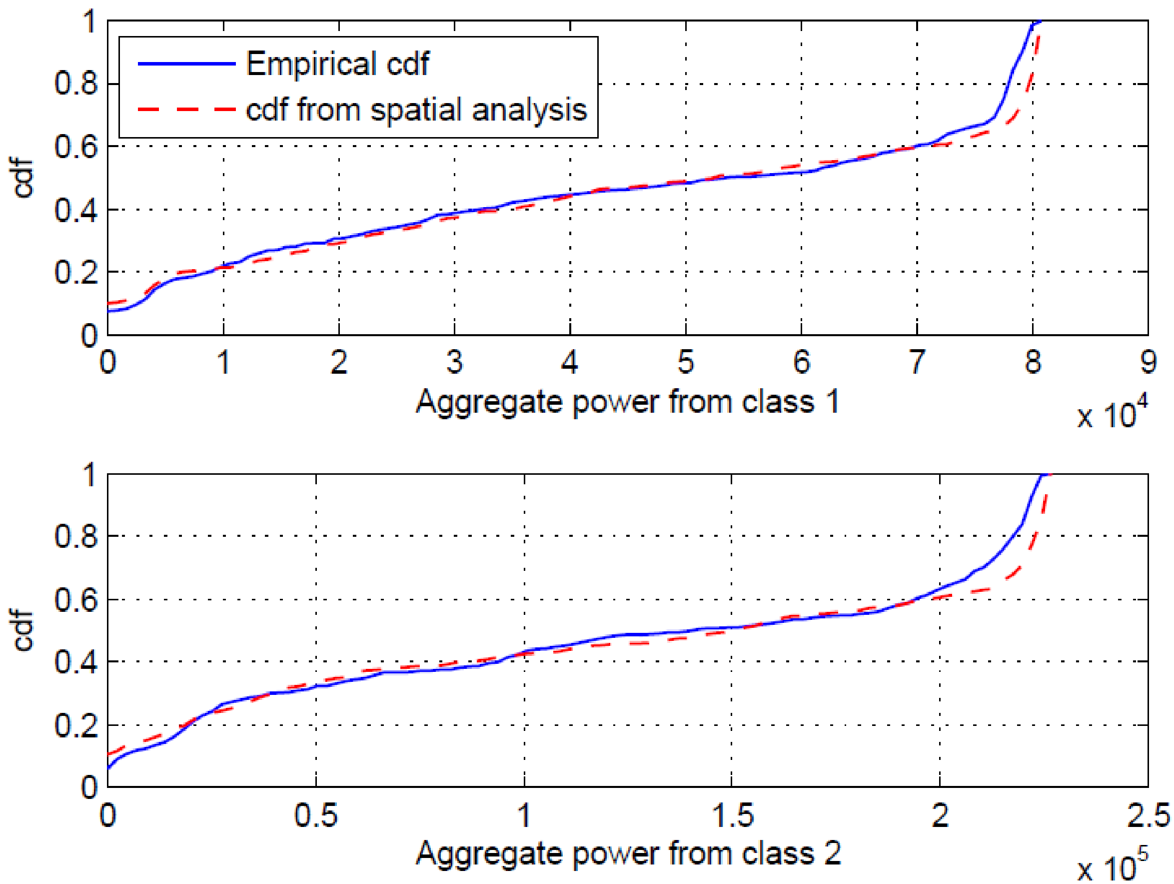
where

$$N : \text{Number of Data Samples}$$

$$C_m : \text{Number of Turbines in Class } m$$

Wind Farm

- This results in predictions with reasonable accuracy:



Microgrid

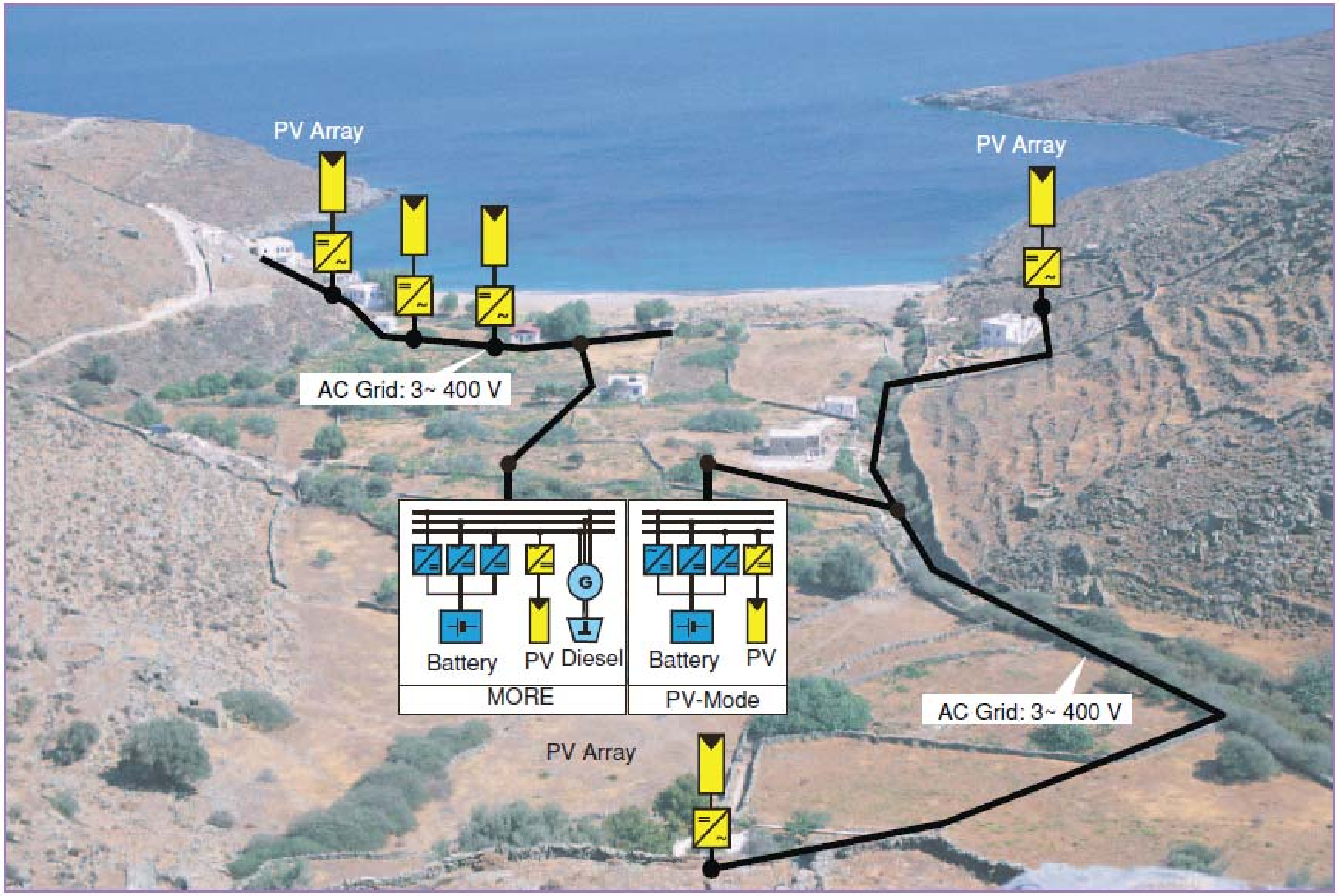
- A microgrid is a localized grouping of:
  - Electricity generation
  - Energy storage
  - Controllable and Non-controllable Load

Distributed Energy Resources (DERs)

- It can operate in two modes:
  - Grid-Connected
  - Islanded

Microgrid

- An isolated microgrid in Kythnos Island – Greece:



Microgrid

- An microgrid facility: can operate in both modes:

It could be a zero-net energy building with behind-the-meter generator

Microgrid

- A microgrid can operate autonomously:
  - Connected to grid when needed
  - Disconnected otherwise

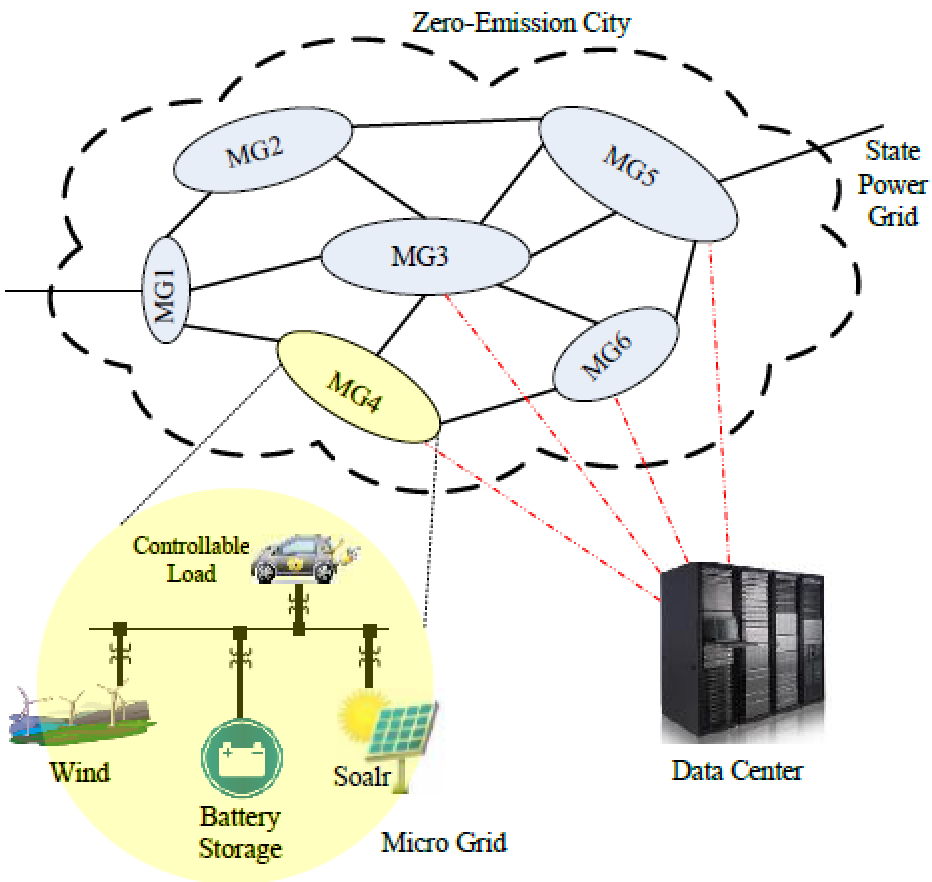
Challenge: Having Smooth Transitions

- From the point of view of the grid operator:
  - A connected microgrid can be controlled as if it was one entity.

- Microgrids allow distributed generation and control.

Microgrid

- Microgrid as a building block for smart grid:



Inter-connecting Several Micro-grids to Build a Zero-Emission City

Microgrid

- Microgrid as a building block for smart grid:
  - Inter-connection options:
    - DC and AC Lines.
- Coordination can be done through a data center and SCADA.
- Just like the Internet, each micro-grid will be:
  - An Autonomous System (AS)

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