How to Design Energy Systems with Renewables and Storage?

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The Renewables Challenge

Renewable energy sources are

- Variable
- Very difficult to predict
- With high ramp rates

Wind Power

- Highly variable
- No-seasonality in daily profile
- Point-wise Weibull distribution
- The forecast error increases quickly with time
Solar Power

- Multiple time-scale variations:
  - Daily (sun position)
  - 9h-10min (Long-term cloud effect)
  - Less than 10 min (Short-term cloud effect)

- Can be more accurately modeled (compared to wind) by separately characterizing each of the above three time scales
Variability

Need

• Generation reshaping
• Load control

1. *Load profile* projected by the California Independent System Operator for January 2020 (high-load case) illustrates the challenge facing generators in the state.
Difficult to Predict

- Difficult to control
- Need forecasting or modeling

High ramp rate

- Need to have another generator with a high ramp rate to compensate
  - If natural gas or coal, increases carbon footprint
Goal: Generation Reshaping

Unpredictable, variable, and with high ramp rates

Renewable Source (S(t)) \[\rightarrow\] Energy Matching System \[\rightarrow\] Energy Demand (D(t))

- **Given**
  - Energy demand (D(t))
  - Renewable generator traces (S(t))

- **Find the ‘best’ energy matching system that**
  - Reshapes renewable to match the demand
  - Guarantees that the matching occurs most of the time
The Matching System

Composed of:
- Storage elements
- Local generators
- Grid
- ...

Energy matching system
Storage: An Integral Element in Matching

Storage is the most important element in matching system

- It is green
  - Local generators have large carbon footprints
  - Grid causes large carbon emissions to capture the fluctuations of renewables

- It is different in the matching system
  - It reshapes the renewable energy profile
  - Reduces the need for fast ramping generators

- Perhaps the ONLY feasible solution for bulk integration
Taxonomy of Storage Technologies

- **Mechanical**: e.g., Flywheel, pumped hydro
- **Thermo-dynamic**: e.g., Compressed Air
- **Electro-chemical**: e.g., battery
- **Electro-magnetic**: e.g., Coil
- **Electro-static**: e.g., Capacitors
- ...
Modelling Storage

- Many energy storage systems can be modelled in this way (e.g., batteries)
Three Issues with Reshaping

- **Offline Design**
  - **Choice of elements**: Choose the elements of the matching systems
  - **Sizing**: Size each element

- **Operation**: control rules
  - \((S_1(t), S_2(t), S_3(t)), (D_1(t), D_2(t), D_3(t)), (D_i(t), D_d(t))\)

- **Examples of objectives**
  - Satisfying a target loss of power probability
  - Satisfying a target waste of power probability
  - Maximizing the overall revenue, cost
  - Minimizing carbon footprint
The Troublesome Coupling

- Optimal sizing depends on the design and control
- Optimal control depends on the sizing and design
- Optimal design depends on the sizing and control
Problem 1: Design

■ Given
  • D(t)
  • A trace for S(t)
  • A control strategy
  • Sizes of energy elements

■ Find
  • Choice of energy elements

■ Such that
  • The target performance metric is satisfied
Problem 2: Sizing

■ Given
  • $D(t)$
  • A trace for $S(t)$
  • A control strategy
  • Choice of energy elements

■ Find
  • Size of energy elements

■ Such that
  • The target performance metric is satisfied

![Diagram](Image)
Problem 3: Control

- **Given**
  - $D(t)$
  - A trace for $S(t)$
  - Size and choice of energy elements

- **Find**
  - $S_1(t), S_2(t), S_3(t)$,
  - $D_1(t), D_2(t), D_3(t)$,
  - $D_i(t), D_d(t)$

- **Such that**
  - The target performance metric is satisfied
Approaches

- Three approaches:
  - Simulation
  - Optimization
  - Analysis

- These approaches differ in
  - Characterizing renewable energy generation
    - Traces
    - Model
  - Characterizing the operation of energy matching system
  - Evaluating the performance metric
Method 1: Trace-based Simulation

- Characterizing renewables
  - Use large real or synthetic data traces

- Storage characterization: Recursive description of SoC
  \[ b(t) = \min(B \times \text{DoD}, [\min(S_1(t), \alpha_c)\eta_c T_u - \min(D_1(t), \alpha_d)T_u/\eta_d - \gamma + b(t - 1)]_+) \]

- How performance metrics are computed?
  - Control strategy is implemented in the simulator
  - Try all possible combinations of the free parameters
  - Compute statistics over output variables to find best choice of free parameters
Simulation: Pros and Cons

**Pros:**
- Simple
- Can study any control strategy
- Can model storage effects accurately

**Cons:**
- Requires representative real or synthetic traces
- Only useful when control strategy is known
- Computationally expensive
Method 2: Optimization

- **Characterizing renewables**
  - Use large real or synthetic date traces

- **Storage characterization**: Linear constraints
  \[ b(t) = \eta_c S_1(t)T_u - D_1(t)T_u/\eta_d \]
  \[ 0 \leq b(t) \leq B \times \text{DoD} \]
  \[ 0 \leq D_1(t) \leq \alpha_d \]
  \[ 0 \leq S_1(t) \leq \alpha_c \]

- **How performance metrics are computed?**
  - Design is a free parameter
  - Sizing is a free parameter
  - Control strategy is a free parameter
  - Optimizer returns the best choice of design, sizing and control for a given input trace \((S(t))\) and a given target output power \(D(t))\)
Optimization: Pros and Cons

■ Pros:
  • Optimal in sizing, design, and (non-causal) control
  • Insightful to obtain a good causal control strategy
  • Provide a benchmark

■ Cons:
  • Requires representative traces
  • Computationally very expensive
  • Non-causal control strategy
Method 3: Analysis

- **Characterizing renewables**
  - Using envelopes (next slides)

- **Storage characterization**
  - Using the analogy between smart grids and computer networks (next slides)

- **How performance metrics are computed?**
  - Control strategy is formulated
  - Using results from computer networks
  - Computing upper or lower bounds for evaluation metrics
Analysis: SoC Characterization

\[ q(t) = \min (Q, [A(t) - C(t) + q(t-1)])_+ \]

\[ b(t) = \min (B \times \text{DoD}, [\min(S_1(t), \alpha_c)\eta_c T_u - \min(D_1(t), \alpha_d)T_u/\eta_d - \gamma + b(t-1)])_+ \]

\[ \equiv q(t) \quad \equiv Q \quad \equiv A(t) \quad \equiv C(t) \quad \equiv q(t-1) \]

Loss of power \( \equiv \) Empty queue

Waste of power \( \equiv \) Queue overflow
Computing Loss of Traffic

\[ L(t) \approx \min \left( A(s, t) - C(s, t), \max_{0 \leq s \leq t} (A(s, t) - C(s, t) - Q) \right) \]

If

\[ A(s, t) - C(s, t) < l \]

or

\[ \max_{0 \leq s \leq t} (A(s, t) - C(s, t) - Q) < l \]

Then

\[ L(t) < l \]
Buffer Sizing

- Suppose: $C(s,t) = C.(t-s)$ for all $s,t$
- What is the minimum $Q$ which guarantees $L(t) < l$?

$$A(t) - C < l \quad \Rightarrow \quad L(t) < l$$

In this case $Q=0$;

Or
The Need for an Envelope

\[
\max_{0 \leq s \leq t} \left( A(s, t) - C(t - s) - Q - l \right) - E(t-s) < 0 \quad \forall t \Rightarrow L(t) < I
\]

In this case, \( Q+l \) is the y-intercept of a deterministic envelope for \( A \).
From Deterministic to Probabilistic Setting

- Deterministic analysis considers worst-case scenarios ➔ oversizing
- A probabilistic setting instead allows violation in rare occasions.
- Loss metric in a probabilistic setting:

\[
P(L(t) > l) < \varepsilon \quad \forall t
\]

\[
P(L(t) > l) \leq \min \left( \frac{P(A(t) - C(t) > l)}, \frac{\max_{0 \leq s < t} \left( [A(s, t) - C(s, t) - Q]_+ > l \right)} \right)
\]

Point-wise

Envelope
Sample Path Envelope
Characterizing Energy Processes

- A power source $A$ is represented by $(\mathcal{G}, \varepsilon)$

$$P\left( \sup_{0 \leq s \leq t} (\mathcal{G}(s, t) - A(t - s)) > \sigma \right) \leq \varepsilon(\sigma)$$

- Example: For wind power, we can use

$$\varepsilon(\sigma) = ue^{-w\sigma}$$
$$\mathcal{G}(t) = at + b$$

- Note: Solar power needs more complicated functions.
Obtaining Parameters

- Step 1: Construct a set with the following elements for any time $t$ and any sample path $i$

$$Y_{i,t} = \sup_{0 < s < t} \{ [G(t - s) - A^i(s, t)]_+ \}$$

- Step 2: Compute $u$ to be

$$u = P(Y_{i,t} > 0)$$

- Step 3: Remove zero elements from the set

- Step 4: Fit an exponential distribution to the set

- Step 5: $w$ is the exponent

$$\varepsilon(\sigma) = ue^{-w\sigma}$$

$$G(t) = at + b$$
Analysis: Pros and Cons

- **Pros**
  - Fast, once the set is computed
  - Tractable for any control strategy
  - Easy for what-if analysis

- **Cons**
  - Only useful when control strategy is known
  - Modelling a control strategy is complex
  - Less accurate
Case Study 1: Battery Sizing for a Target Loss

\[ S(t) \quad \xrightarrow{\text{min}(S(t), D(t))} \quad D(t) \]

\[ [S(t) - D(t)]_+ \xrightarrow{\text{Battery}} \quad [D(t) - S(t)]_+ \]
Example Setup

- Wind power trace from NREL (10-min resolution)
- $D(t) = 0.1$ MW
- Li-ion battery
- (Optimal) control strategy is trivial: Optimization and simulation are equivalent
- Compare simulation with analysis
Loss of Power vs. Battery Size

![Graph showing the relationship between Li-ion (Analysis) and Li-ion (Simulation) for different ESD sizes (MWh). The y-axis represents the loss probability, and the x-axis represents the ESD size in MWh. The graph includes data points for ideal (Analysis) and ideal (Simulation).]
Case Study 2: Battery Sizing for Energy Harvesting Maximization
Example Setup

- Solar power trace from ARM (1-min resolution)
- $D(t) = \text{Hourly average with a vertical offset}$
- $P(L(t)>0)<0.01$
- Li-ion battery
- (Optimal) control strategy is trivial: Optimization and simulation are equivalent
- What is the optimal size of battery which maximizes the output power?
Output Power vs. Battery Size
Open Problems

- How to both optimize for design and control?
  - Plausible solutions:
    1. Reverse Engineering the optimization solution
    2. Iterating

- What is the optimal time and spatial scale for aggregation and control?

- What are the optimal causal control rules?

- How can we extend analysis to a hybrid energy backup system?
Conclusions

- There are three methods to design and analyze an energy system: Optimization, simulation, and analysis.

- Each of them has its own cons and pros.

- There is an inherent inter-correlation among optimal design, optimal sizing, and optimal control which complicates the problem.
Publications


