On the Design of Standalone Renewable Energy Systems: Accounting for Inter-year Variability in Systems Sizing

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Overview

Motivation

Standalone energy systems

- Off-grid, continuous operations in remote locations e.g. mines.
- Previous works: Seasonal (inter-year) variability, PV/Wind/Diesel/Battery systems

Research Objective

Develop models for the design of renewables-based systems which

1. integrate thermal and electrical generation and storage options;
2. account for renewables variability between years at design stage; quantify risk of failure.

Assessing Risk In Energy Systems Sizing

"*Evaluate risk of power system failure* based on *design performance* over a *large number of renewable input conditions*"

- Scenario-based reliability measure
- Energy system model: Generation and storage options
- Chronological renewables data generation: solar, wind

Scenario-based Reliability Evaluation

Loss of Power Supply Probability (LPSP)

Typical LPSP definition

Accounts inter-year variability

$$LPSP = \frac{\text{Number of hours with power failure (h)}}{\text{Total hours of operation (Typically 8760h)}}$$

Modified LPSP

Accounts for intra-year variability instead:

$$\overline{LPSP}_m = \frac{\text{Number of scenarios with unsatisfactory performance}}{\text{Total years (scenarios) of operation, } N_{year}}$$

$$\overline{LPSP}_m = \frac{N_{year} \mid_{R_i < R'}}{N_{year}}$$

Scenario-based Reliability Evaluation

Example

- Required performance $R' = 90\%$ demand satisfaction.
- Actual performance R_i from 5 scenarios: [92%, 91% , 87%, 90%, 89%]

$$\overline{LPSP}_m = \frac{N_{year}\,|_{R_i<90\%}}{N_{year}} = \frac{2}{5} = 0.4$$

- *40% probability of failure*

- Require performance information from energy system model
- Large renewables data requirement. Availability problems?

Energy System Model

Differential Algebraic Equation (DAE) system

Generation technologies: Algebraic models

1. Photovoltaics (PV): Global horizontal irradiance information
2. Wind generation: Windspeed information
3. Solar thermal: Direct Normal Irradiance (DNI) information

Storage technologies: Dynamic models

$$ACC = IN - OUT - LOSSES$$

$$\frac{\mathrm{d}}{\mathrm{d}t}E(t) = \eta_C \dot{E}_{in}(t) - \frac{\dot{E}_{out}(t)}{\eta_D} - \text{storage losses}(t)$$

Renewables Modelling

Global Horizontal Irradiance (GHI)

- Fit historical data to Pearson family of distributions
- Input: Moments {Mean, std. deviation, skewness, kurtosis}.

Windspeed Data

- Fit historical data to Weibull distribution
- Input: Scale parameter, shape parameter

Direct Normal Irradiance (DNI) Data

- GHI = DHI + DNI$\cdot \cos \theta_z$
- Louche decomposition model

Generation of Monthly Data: Methodology

Model Input: Historical data (GHI,Wind), Location information.

1. Group into monthly data→12 datasets. Calculate monthly statistical properties.
2. Generate random data from distributions for each day, e.g.

$$\hat{R}_k \leftarrow \texttt{Pearson}\left(S_j\right) \qquad j = 1, \ldots, 12; k = 1, \ldots, n_{days}$$

3. Add trend to predicted data, e.g.

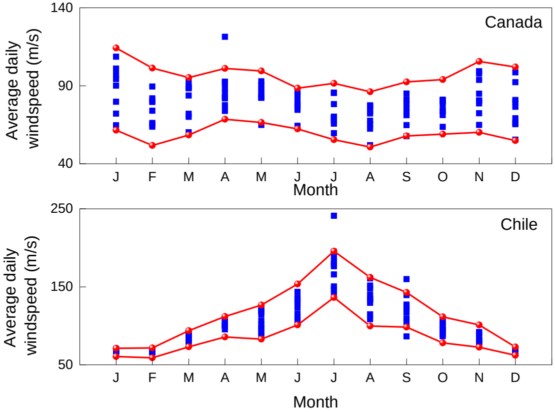
$$R_k = \omega_d \cdot \hat{R}_1 + (1 - \omega_d) \cdot \hat{R}_k \qquad \omega_d \epsilon \left[0, 1\right]$$

4. For each GHI dataset, calculate corresponding DNI using location information (Day of year, latitude, time zone).

Windspeed data: Historical Data vs Synthetic predictions

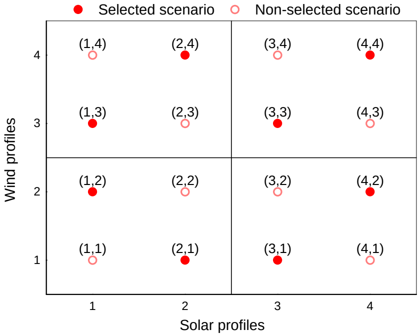
Blue squares = historical data monthly averages

Red lines = range covered by simulated data: 500 sample profiles.

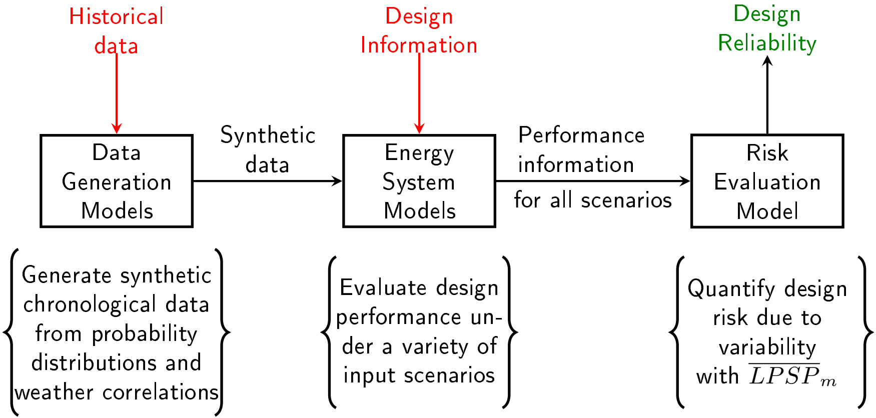


Selection of Scenarios: Stratified sampling

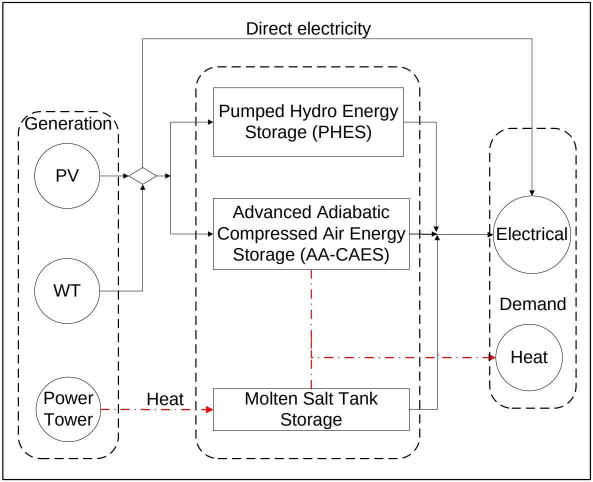
- N_s solar profiles, N_w wind profiles, $N_s \times N_w$ space
- Stratified sampling concept: divide into d strata, random selection, $N^2 \rightarrow N \cdot d$ space
- Example: 4 solar profiles, 4 wind profiles, 2 strata



To Summarize...



Integrated Energy System



Problem Definition

Given

Energy requirements of the plant, historical data for the plant location, unit cost data, efficiencies for mechanical units

determine the Pareto-optimal set of designs $\bar{X} = \{\bar{x}_1, \bar{x}_2 \ldots \bar{x}_n\}$ which minimize the capital cost and maximize reliability:

$$\min_{\bar{x} \in \bar{X}} z = (F_1, F_2) \begin{cases} F_1(\bar{x}) = CC(\bar{x}) \\ F_2(\bar{x}) = 1 - R(\bar{x}) \end{cases}$$

subject to design (generation, storage, capacity) and operational constraints.

Case Studies

- Case 1: Collahuasi mine - Atacama, Chile
  - Receives one of the highest levels of solar radiation annually
  - $D_\tau^{el} = [164MWh, 178MWh]$; $D_\tau^{th} = 0.1 \cdot D_\tau^{el}$
  - Required performance R': 100% demand satisfaction
- Case 2: Collahuasi mine relocation to Alberta, Canada
  - Lower solar and wind resource (GHI about 1/3rd of Chile's)

Solution strategy

- Discretization: MIDO→MINLP, MATLAB implementation
- Initial conditions: storage level = 60%
- 300 solar and wind profiles, 4 strata: $N_{year} = 1200$
- Solved with NSGA-II : $N_{pop} = 100$, $N_{gen} = 200$
- Parallel computing: 12 cores → Comp. time ≈ 87 h

Case 1: Optimal Energy System Configuration

Characteristics

- Power tower (PT) and molten salt tank storage (MTS) selected
- Extremely high solar resource; more attractive than wind
- PT uses sun-tracking technology; less seasonal variability

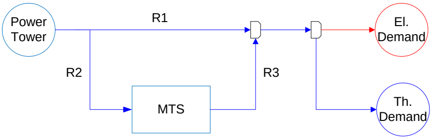


Figure 1: Energy system design

Case 2: Cost Profile

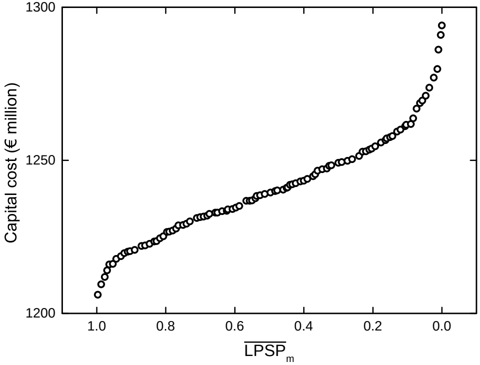


Figure 2: Cost-reliability trade-off profile

- 7.3% cost variation: Low cost variation
- Variability most significant at high reliabilities

Least reliable design, Worst input conditions: Performance

PT capacity	MTS capacity	MTS peak output	LPSP	Capital cost
1208 MW_{th}	6358 MWh	178 MW_e	0.9967	€ 1206.06M

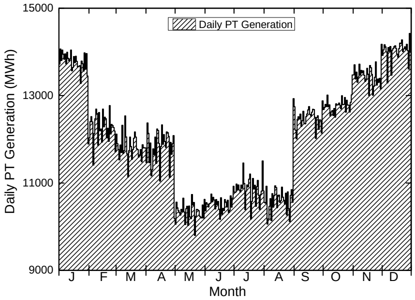


Figure 3: Power tower generation

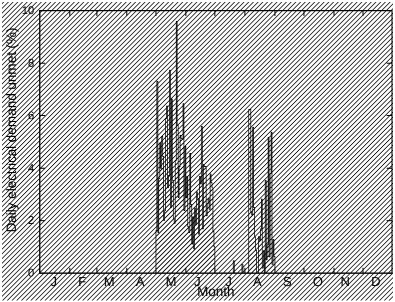


Figure 4: External requirement

- Design fails for 161h (2% of year) over 4 months
- $>$ 90% (21h) daily demand satisfaction.

Case 2: Optimal Energy system Configuration

Characteristics

- Power tower integrated with salt storage, wind generation integrated with pumped hydro
- Exploits solar/wind seasonal anti-correlation
- Discharge order: R1>R4>R3>R6

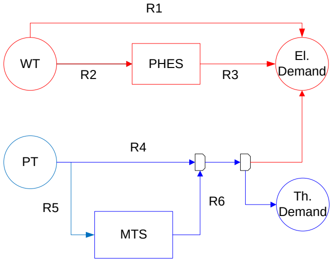


Figure 5: Energy system design

Case 2: Cost Profile

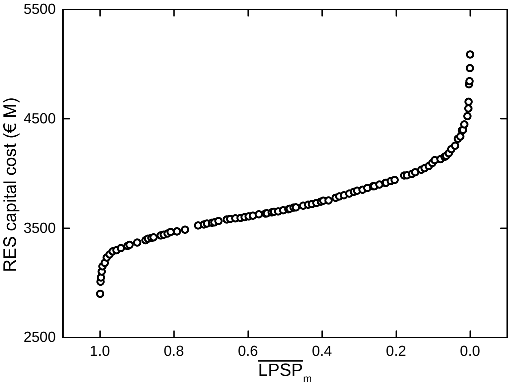
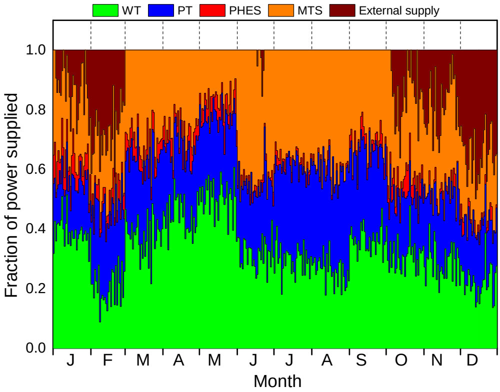


Figure 6: Cost-reliability trade-off profile

- 76% cost variation: Higher variability, higher cost variation

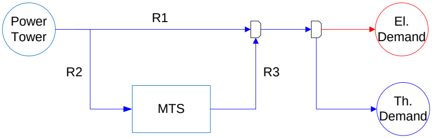
Least reliable design, Worst input conditions: Performance



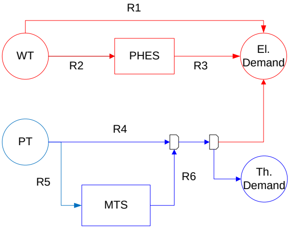
- Design fails for 1193h (13% of year) over 6 months
- Guaranteed demand satisfaction per day ≈ 50%

Conclusion

- Model for bi-criteria design of integrated energy systems
- Stochastic generation of renewables input data
- Year-based reliability measure for risk assessment
- Methodology easily applicable to other geographies and technologies



Chile



Canada