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Optimal Design of Hybrid Renewable Energy Systems

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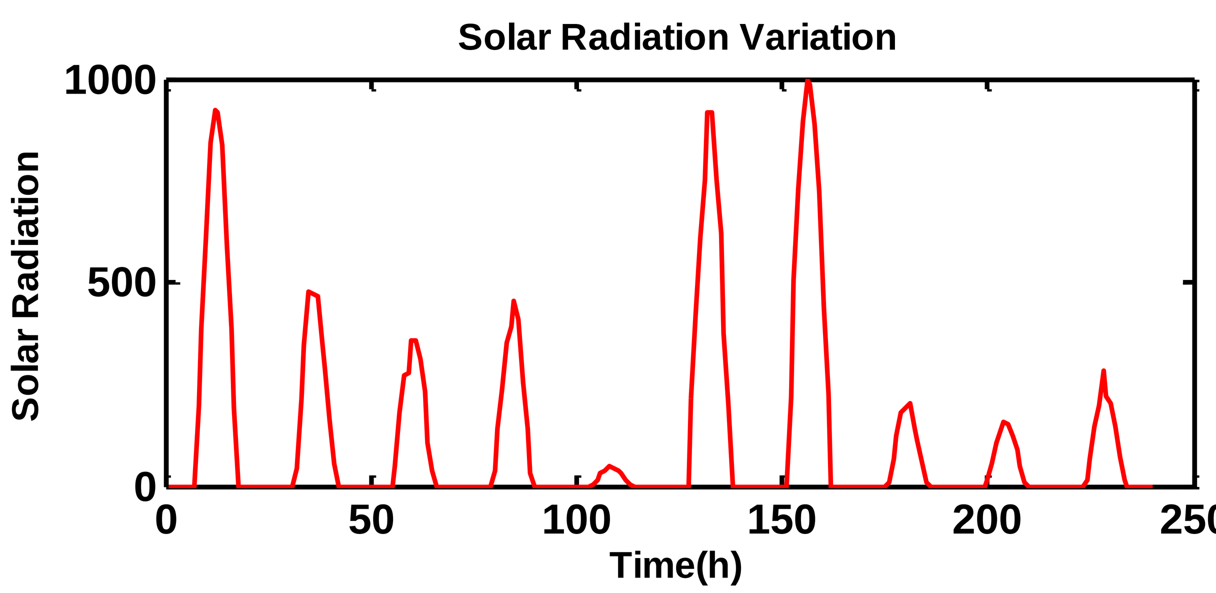
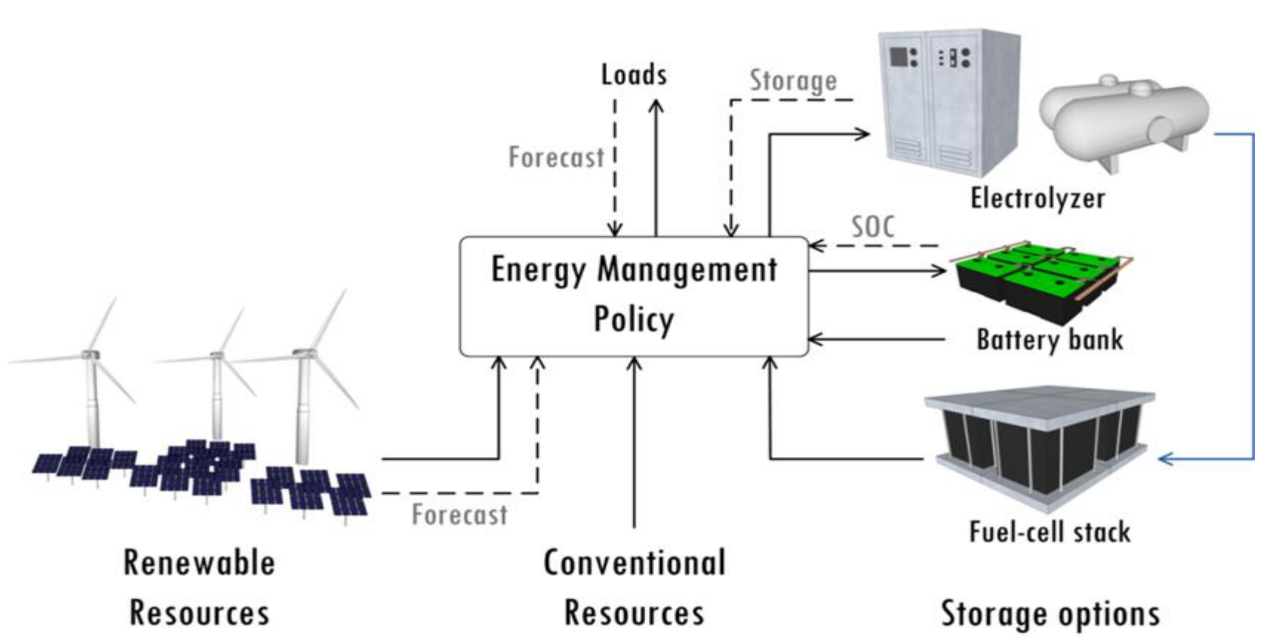
Introduction

Utilization of renewable energy sources such as wind and solar can overcome environmental threats associated with fossil fuels. But expensive power producing and storage components are required to harness and store renewable energy. In addition renewable sources are intermittent, thus unreliable when used independently.



Hybrid Renewable Energy Systems (HRES) combine different renewable sources, storage components and/or conventional sources to improve reliability and decrease capital and operational costs.



Energy Management Policy (EMP):
Logical set of rules used to decide when and how each component should be used.

Applications of HRES:
HRES are used on a small scale to power off-grid commercial or residential buildings, remote areas such as islands, remote villages, and telecommunication sites. They are also used on large scale.

Design Challenges and Design Methods in Literature

Design challenges:

- Weather forecasting
- Optimal component selection and operational strategies

Literature design methods

- A Typical Meteorological Year (TMY) ignores weather variability
- Metaheuristic optimization methods are slow and do not guarantee an optimal solution. Additionally, the optimal solution cannot be formally verified via gradient information.

Ignoring weather variability and using unreliable optimization methods during designs stages may result in sub-optimal designs which can lead to underperformance of the systems during real operating conditions.

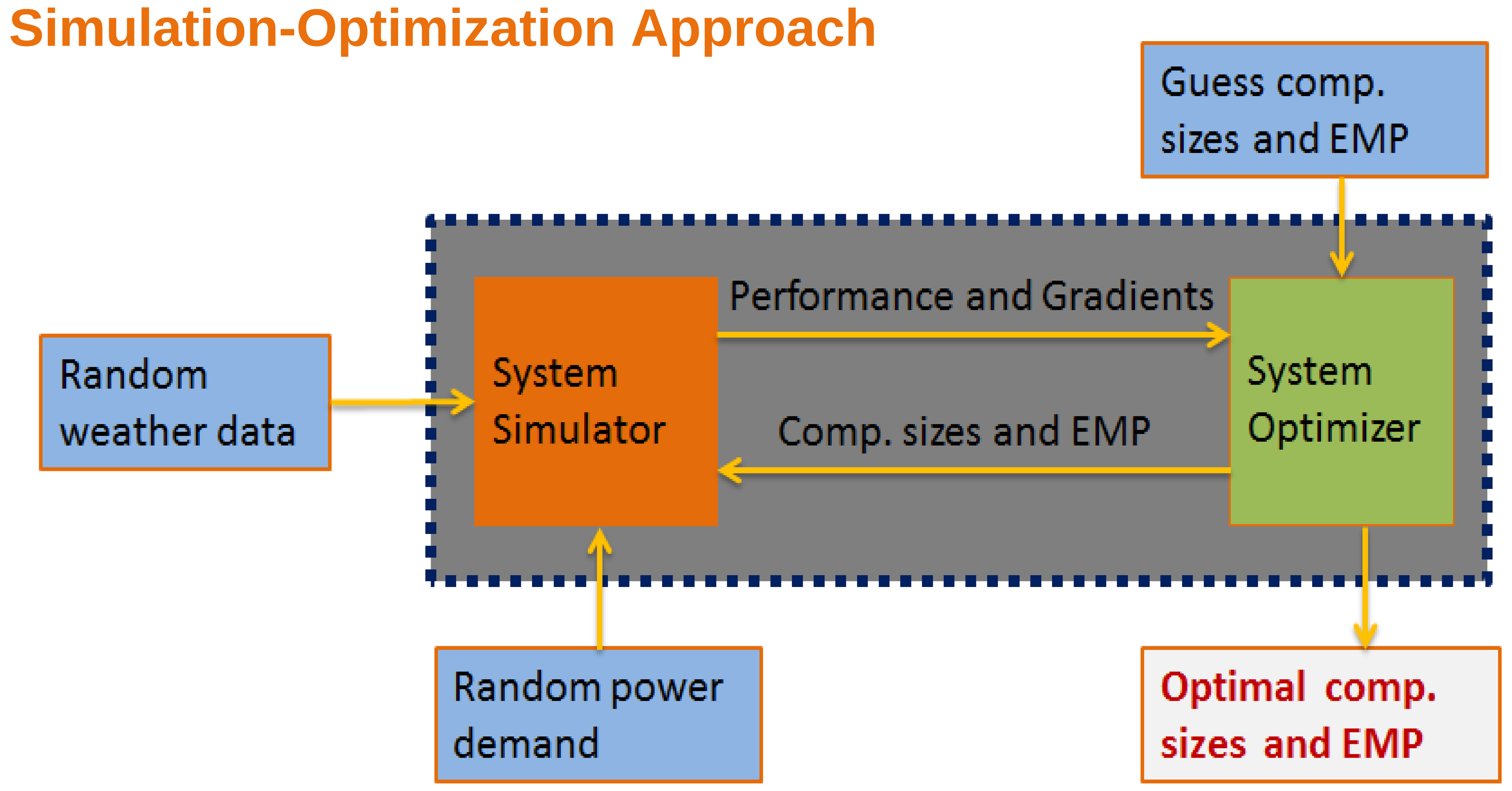
Research Objective & Problem Approach

Gradient optimization of HRES considering weather variability

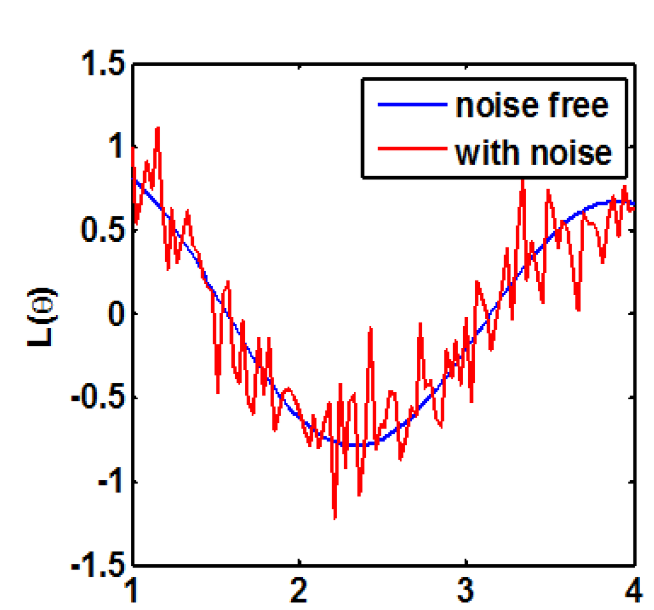
- Weather data= TMY+ Randomness
- Gradient optimization method: Stochastic Approximation

Find **Optimal Component Size** and **Energy Management Policy** (EMP) that minimize the expected capital and operational costs while simultaneously satisfying the power demand reliably.

Simulation-Optimization Approach



Stochastic Approximation (SA)

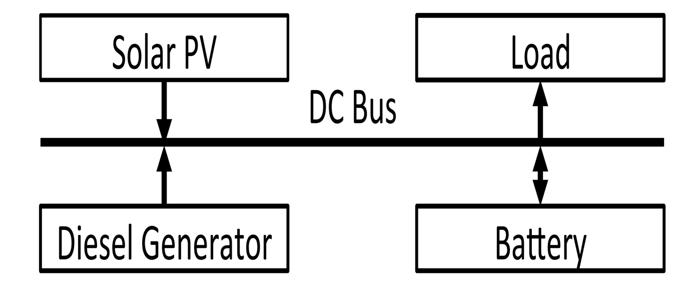


As opposed to deterministic gradient optimization, SA accepts stochastic (i.e. random/noisy) gradient values, and finds an optimal solution of the corresponding differentiable expected value function.

$$\theta_{k+1} = \theta_k - a_k Y_k(\theta_k)$$

Step-size   Noisy gradient

A Simple Test Example of HRES

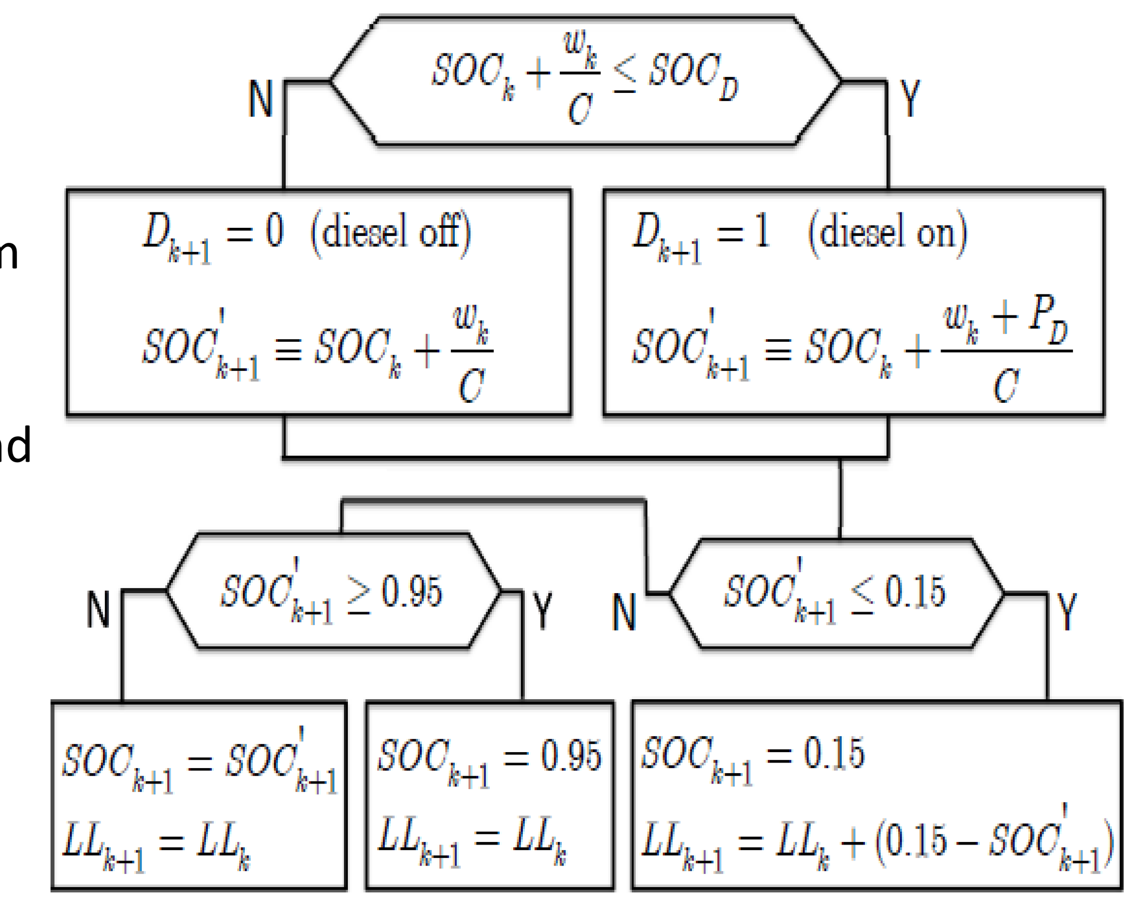


- Random inputs in each hour: Power from solar panel and power demand.
- Evaluate the system on hourly basis
- Update the state of the system at the end of each hour

EMP decisions in each hour

- Decide diesel generator status: ON/OFF based on threshold SOC_D
- Keep the battery's state of charge in the pre-specified limits SOC=[15%, 95%]

Energy Management Policy (EMP) Decision Tree



Total cost at the end of hour N

$$L(\mathrm{C}, \mathrm{SOC_D}, \mathrm{w}) = \mathrm{J}(\mathrm{C}, \mathrm{SOC_D}) + \varepsilon \text{ (noise)}$$

$$L(\theta, \mathbf{w}) = \beta_1 C + \beta_2 \sum_{k=0}^{N} D_k + \beta_3 LL_N$$

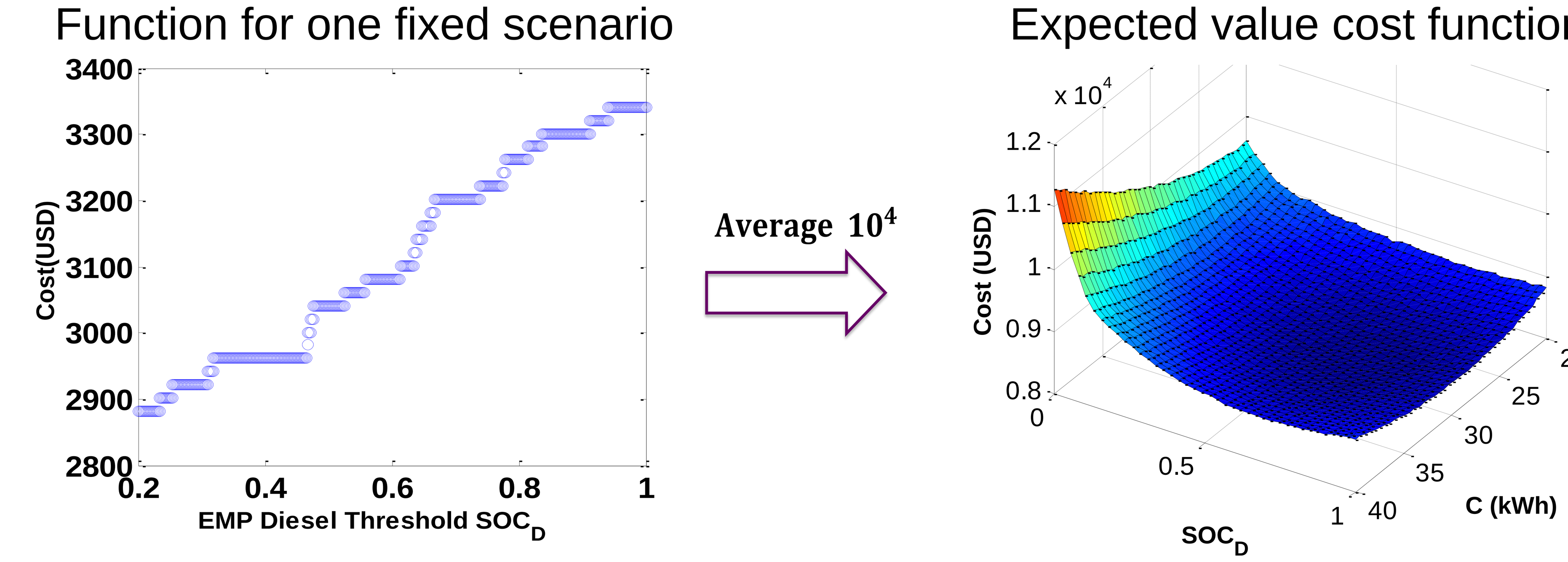
$$\mathrm{J}(\mathrm{C}, \mathrm{SOC_D}) = \mathbb{E}[L(\mathrm{C}, \mathrm{SOC_D}, \mathrm{w})]$$

$$\min_{C, SOC_D} \mathbb{E}\left(\beta_1 C + \beta_2 \sum_{k=0}^{N} D_k + \beta_3 LL_N\right)$$

Observation on differentiability of the expected value cost function:

. Discontinuities are introduced by EMP decisions
. Discontinuities may disappear under expectation

Function for one fixed scenario   Expected value cost function



Preliminary Results: SA vs Metaheuristics

Method	Optimal Solution [C(kWh), SOC_D]	Time (min)
GA	(30.0, 0.77)	15 min
PSO	(30.0, 0.85)	6 min
SA	(29.4, 0.82)	1.5 min

Stochastic Approximation outperformed Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)

Future Work

- Mathematically understand and determine necessary conditions to ensure differentiability of the expected value cost function
- Improvements on stochastic approximation, application to a more complex systems and more comparisons with metaheuristics