Data-driven Generator Maintenance and Operations Scheduling under Decision-dependent Uncertainty

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Motivation

Effectively model and solve the condition-based maintenance and operations scheduling problem of a fleet of generators with explicit consideration of decision-dependent degradation and uncertainty of generator failures

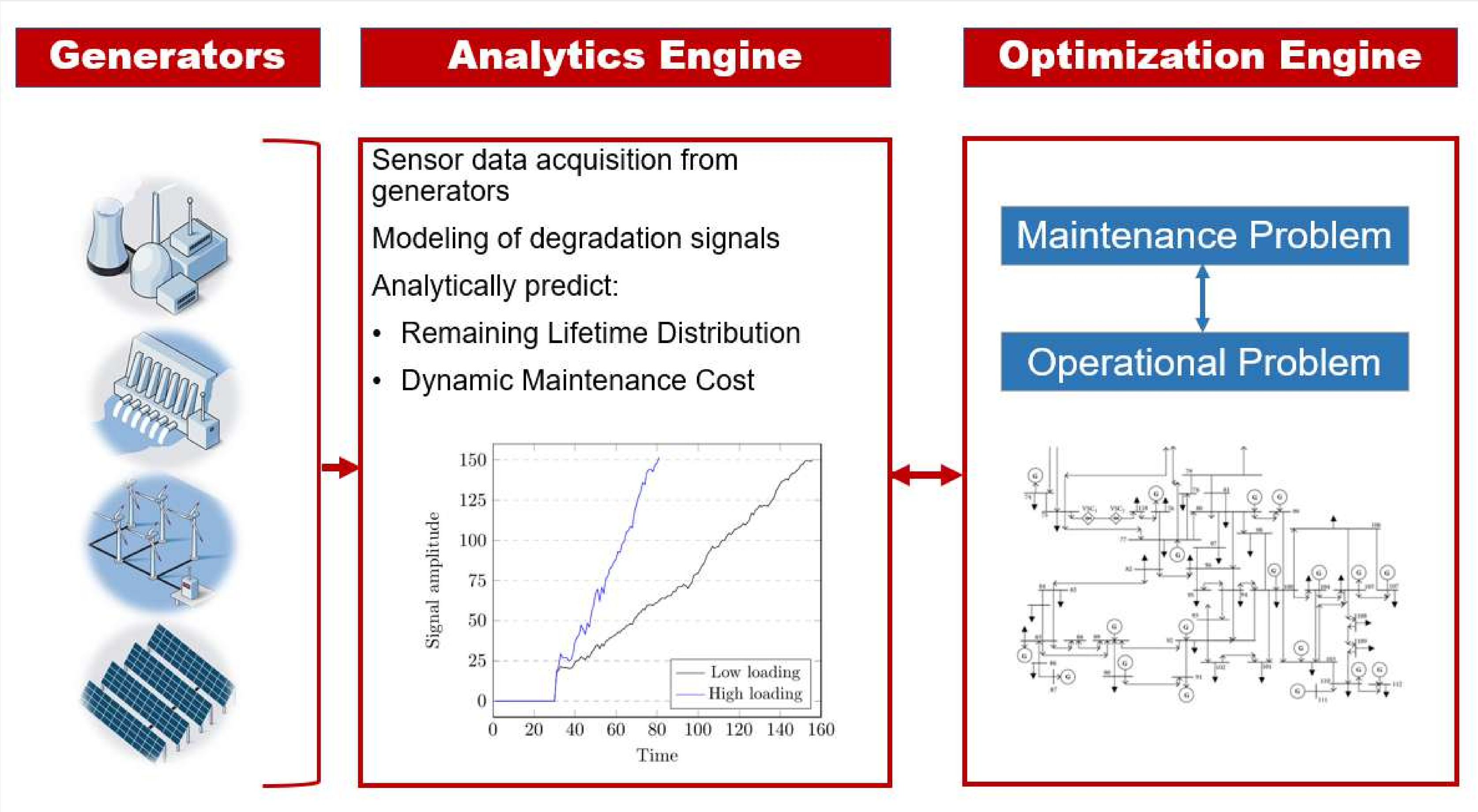

Figure: Decision-dependent Maintenance and Operations Planning Framework

Analytics Framework

How to model generator conditions?

- Model generator signals as a linear model with Brownian motion
- Estimate **remaining lifetime distributions** of generators using sensor observations and posterior distributions through Bayesian updates

- Maintenance cost function of generator i at time t with initial age t_i^o:

⇒ Represents the trade-off between preventive and corrective maintenance
⇒ **Nonlinear** in its argument!

$$C_{i,t}(w) = \frac{C^p \Pr(R_i > w) + C^c \Pr(R_i \leq w)}{\int_0^w \Pr(R_i > z)dz + t_i^o}$$

⇒ For a **load-independent** model, w simply equals to age of generator, t
→ Existing approach in literature for maintenance scheduling [1]

⇒ For a **load-dependent** model, w equals to degradation equivalent age of generator, namely d, depending on operational decisions
→ Proposed approach!
→ Remaining lifetime distribution and maintenance cost function involve **decision-dependent uncertainty**!
→ Model degradation amount d as an affine function of the operational decisions x and y

$$d = \alpha^\top x + \beta^\top y$$

→ Integrate signal variability to the model by learning from the data set to estimate α, β

Optimization Framework

Load-dependent generator maintenance and operations scheduling problem can be formulated as a stochastic program as follows:

$$\begin{aligned}
\min_{z,x,y,d}\ & \lambda C(d)^\top z + V^\top x + W^\top y && \textit{Total cost via weighted sum}\\
\text{s.t. } & \Pr(\zeta(d)^\top z \leq \rho) \geq 1-\epsilon && \textit{Chance-constraint}\\
& Az \leq l && \textit{Maintenance}\\
& Bz + Ex \leq m && \textit{Coupling}\\
& Fx + Hy + Gd \leq n && \textit{Operation}\\
& z \in \{0,1\}^{|T|\times|G|}, x \in \{0,1\}^{|T|\times|G|\times|S|}, y, d \geq 0.
\end{aligned}$$

Decision variables:
z: maintenance start time
x, y: commitment decision and dispatch amount
d: degradation amount in terms of operational variables

Random variables:
R_i: remaining lifetime of generator i

$$\zeta_{i,t}(d) = \begin{cases} 1, \text{ if generator } i \text{ fails until time } t \text{ under decision } d, \text{ i.e. } \Pr(R_i \leq d) \\ 0, \text{ otherwise} \end{cases}$$

Chance-constraint: For ensuring a reliable maintenance plan restricting the number of generators that enter maintenance due to a failure with a threshold ρ with high probability $1-\epsilon$

Maintenance Constraints: One maintenance per year, capacity constraint on maintenance schedules
Coupling Constraints: Generators are off under maintenance
Operational Constraints: Coupling between degradation amount and operational decisions, production capacity limits, demand satisfaction constraint, transmission line limits

⇒ Resulting optimization model is mixed-integer nonlinear due to the structure of the objective and the chance-constraint!

Proposition (extended [1] to decision-dependent setting):

$$\mathbf{E}[\zeta(d)]^\top z \leq \max\left(\rho\,\epsilon, \max_{\alpha>0}\left[\frac{((\epsilon\, e^{\alpha\rho})^{1/|\mathcal{G}|}-1)|\mathcal{G}|}{e^\alpha - 1}\right]\right)$$ is a safe approximation of the chance constraint.

How to linearize the optimization problem?

1. Piecewise linearization: Map continuous degradation amount d to the maintenance cost C(d) and the probability distribution of $\zeta(d)$
   - Identify break points in terms of d and evaluate functions at these points
   - As the functions are not convex, we need SOS2 constraints
   - Adopt log formulation with logarithmically many extra binary variables [2]
   - Improve formulation by conducting a polyhedral study and integrating into piecewise linearization
2. McCormick envelopes: Use for bilinear terms where one of the variables is the binary variable z
   - Results in an exact formulation
   - Improve upper bounds of the formulation by examining maintenance cost function and remaining lifetime distribution by considering the definition of variable d

Note: In load-independent models, $C(d)$ and $\zeta(d)$ values only change with respect to the time a generator enters maintenance, irrespective of the operational decisions and variable d.

Computational Results

- Computational efficiency of the proposed approach on sample hard instances:
  - Priority branching: prioritize branching decisions of maintenance over commitment

	39-bus	118-bus
Linear formulation	>10000.00	>10000.00
Log formulation	437.62	1704.73
Log formulation with enhancements	233.74	1014.94
Log formulation with enhancements + priority branching	193.04	908.88

Table: Run time (seconds) comparison on sample instances.

How to evaluate solutions?

- Develop a decision-dependent simulation framework for evaluating a solution considering the underlying signal variability
- Check generator's signal at the end of each period by generating signal degradation based on d level:
  - If scheduled maintenance is at current period, generator enters maintenance as planned.
  - If signal amplitude exceeds the failure threshold, failure occurs and generator enters corrective maintenance. Incur demand curtailment for production loss.
  - Otherwise, continue to the next period.
- Repeat decision-based simulation procedure 1000 times for each generator
- Solve optimization model with 5 different set of initial signals assigned to generators, and repeat the overall simulation procedure for evaluating solutions

- Sample evaluation of **load-dependent (LD)** and **load-independent (LI)** solutions under high system congestion:

	ϵ	Type	# of failures	Maintenance cost ($M)	Gain (%)	Total cost ($M)	Gain (%)
9-bus	0.05	LD	0.27	0.38	44.06	11.72	37.49
		LI	1.27	0.68		18.75	
	0.10	LD	0.27	0.38	43.78	11.99	36.26
		LI	1.27	0.68		18.81	
39-bus	0.05	LD	0.53	1.16	46.79	113.64	36.01
		LI	3.93	2.18		177.60	
	0.10	LD	0.60	1.18	46.00	115.46	35.49
		LI	3.96	2.19		178.97	
118-bus	0.05	LD	0.54	2.06	36.56	70.23	29.69
		LI	4.51	3.25		99.88	
	0.10	LD	0.41	2.02	37.19	69.88	29.11
		LI	4.41	3.22		98.57	

- Significant reductions in cost and failure under different λ, ϵ, and system congestion levels

References

[1] B. Basciftci, S. Ahmed, N.Z. Gebraeel, M.Yildirim. "Stochastic Optimization of Maintenance and Operations Schedules under Unexpected Failures," *IEEE Transactions on Power Systems*, 2018.
[2] J. P. Vielma, S. Ahmed, G. Nemhauser, "Mixed-integer models for nonseparable piecewise-linear optimization: Unifying framework and extensions," *Operations Research*, 2010.