Uncertainty-aware Day-ahead Datacenter Workload Planning with Load-following Small Modular Reactors

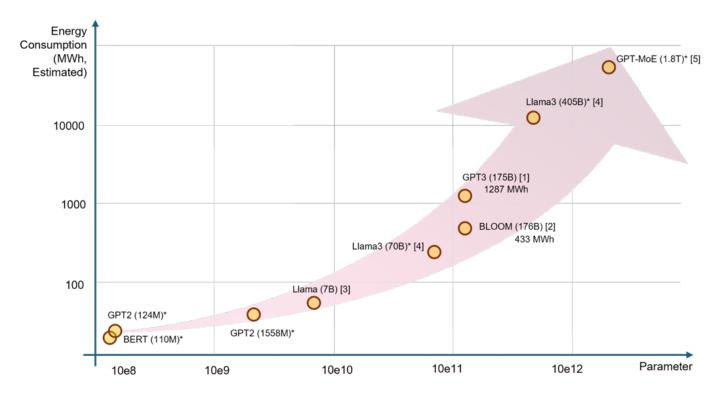
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AI Growth Drives Datacenter Energy Demand



- The increase in AI applications leads to increasing energy demands in AI datacenters.
- Training a GPT-3 model needs 1287 MWh.



(Source: [2409.11416] The Unseen Al Disruptions for Power Grids: LLM-Induced Transients)

24/7 Carbon-Free Energy



24/7 Carbon-Free Energy:

- Goal: Matching the consumption with carbon-free energy every hour, every day
- Measurement: Requires real-time (hourly) matching

Net-Zero:

- Goal: Balance all greenhouse gas emissions (Scope 1, 2, & 3)
- Measurement: Focuses on annual accounting

Nuclear Power as a Solution



- Nuclear energy is carbon-free, and safe
 - Death per Terawatt-hour, Nuclear 0.07 vs. Lignite 32.72 (accidents and air pollution)
- Big tech companies are pursuing nuclear power solutions.
 - Google: Partnered with Kairos Power to launch by 2030.
 - Microsoft: Restart the Three Mile Island energy plant.
 - Amazon: Purchased a nuclear-powered datacenter facility in Pennsylvania.
 - Meta: Seeking proposals for 4GW of new nuclear capacity, early 2030s.

^{[2].} Data center owners turn to nuclear as potential electricity source https://www.eia.gov/todayinenergy/detail.php?id=63304#

Load-following Small Modular Reactors (LF-SMRs)



- Load-following Small Modular Reactors (LF-SMRs):
 - 20-300 MW
 - Capable to adjust its power output dynamically in response to real-time demands
- Standard Nuclear Power Plants:
 - □ > 1000 MW
 - 1+ square mile and massive infrastructure (e.g., cooling towers)
 - Greater human intervention

LF-SMR is very suitable for co-location with datacenters

^{[1].} Going Nuclear: A Guide to SMRs and Nuclear-Powered Data Centers: https://www.datacenterknowledge.com/energy-power-supply/going-nuclear-a-guide-to-smrs-and-nuclear-powered-data-centers

^{[2].} Do SMRs and Microreactors embody a nuclear renaissance? https://www.aquaswitch.co.uk/blog/smrs-and-microreactors/

Related work



- SMRs as energy sources
 - SMR for electricity market [1]
 - SMR for electricity-hydrogen integrated systems [2]
 - SMR for electricity-heating multi-energy systems [3]
 - SMR for datacenters [4]

SMRs are more cost-effective than stardard NPPs for DCs in minimizing capital and operations costs

 Emphasis on investment level, i.e., SMRs can increase the revenue of energy systems and minimize energy generation costs

There is a lack of study on operation level for collocated datacenter & LF-SMR

^{[1].} Jubeyer Rahma, et al., "Optimization of nuclear-renewable hybrid energy system operation in forward electricity market," IEEE GreenTech 2021

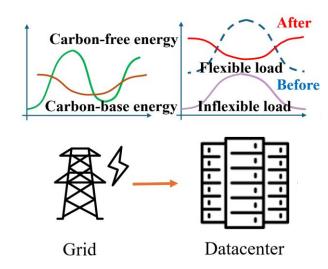
^{[2].} Jubeyer Rahman, et al., "Multi-timescale power system operations for electrolytic hydrogen generation in integrated nuclear-renewable energy systems," Applied Energy 2025

^{[3].} Jubeyer Rahman et al., "Multi-timescale operations of nuclear-renewable hybrid energy systems for reserve and thermal product provision," Journal of Renewable and Sustainable Energy 2023

Carbon-aware datacenter operations



- Day-ahead datacenter operations
 - Step 1: Day-ahead renewable energy forecasting (through PPAs)
 - Step 2: Day-ahead workload planning: shifting the flexible workloads (e.g., Al training)



^{[1].} Bostandoost, Roozbeh, et al., "Data-driven Algorithm Selection for Carbon-Aware Scheduling," ACM SIGENERGY Energy Informatics Review 2024

^{[2].} Diandian Gu, et al., "GreenFlow: A Carbon-Efficient Scheduler for Deep Learning Workloads," IEEE Transactionson Parallel and Distributed Systems 2024

^{[3].} Yejia Liu, et al., "Geographical Server Relocation: Opportunities and Challenges," ACM SIGENERGY Energy Informatics Review 2024

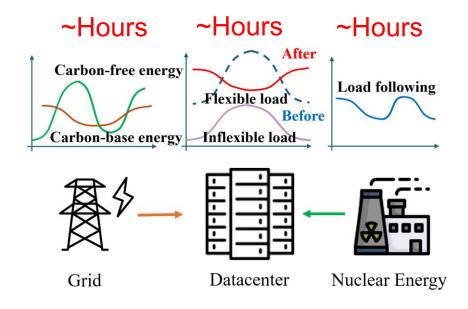
^{[4].} Ana Radovanović, et al., "Carbon-aware computing for datacenters," IEEE Transactions on Power Systems 2022

Carbon-aware datacenter operations



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 Day-ahead workload planning with LM-SMRs: to adapt to the renewable energy dynamics, and co-planning the datacenter workload planning and SMR energy generation



^{[1].} Bostandoost, Roozbeh, et al., "Data-driven Algorithm Selection for Carbon-Aware Scheduling," ACM SIGENERGY Energy Informatics Review 2024

^{[2].} Diandian Gu, et al., "GreenFlow: A Carbon-Efficient Scheduler for Deep Learning Workloads," IEEE Transactionson Parallel and Distributed Systems 2024

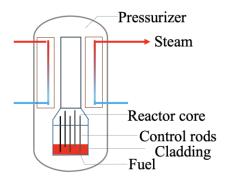
^{[3].} Yejia Liu, et al., "Geographical Server Relocation: Opportunities and Challenges," ACM SIGENERGY Energy Informatics Review 2024

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Challenges



- LF-SMR is not an extra energy source immediately dispatchable
 - SMR in a nut shell



- Nuclear fission generates heat, producing steam to drive a turbine to generate electricity.
- Control rods regulate the fission rate and power output.

- Ramping limit: Rapid changes cause mechanical stress on fuel cladding, leading to damage.
- Stable power period: After a reactor reduces its power generation, the xenon buildup rate still exceeds decay, causing the Xe-135 to increase for hours before decline to a new equilibrium
- Excess energy cost: if the generation is too much, unused energy affects grid stability and introduces economic penalties

System Models and Problem Formulation



The LF-SMR Model Ramp-down limit and ramp-up limit

$$\begin{aligned} p_{t-1} - p_t &\leqslant \overline{P}_{RD} \times Rd_t & \delta \times Up_t, & \forall t, \\ p_t - p_{t-1} &\leqslant \overline{P}_{RU} \times Up_t - \delta \times Rd_t, & \forall t, \\ Rd_t + Up_t + St_t &= 1, & \forall t, \\ Rd_t, Up_t, St_t &\in \{0,1\}, & \forall t & \text{Minimum stable period hour} \\ (Up_t - Up_{t-1}) &\times T_h &\leqslant \sum_{t=t-T_h}^{t-1} \left(St_t + Up_t\right), & \forall t, \end{aligned}$$

The Datacenter Power Supply Model

$$w_t = (1 + \epsilon_t)W_t$$
, $g_{grid,t} = q_t + w_t$.

The Datacenter Power Demand Model

$$\begin{split} z_t &= \sum\nolimits_{c \in C} \sum\nolimits_{k \in \mathcal{H}} Y_{k,c,t} \cdot s_{k,c}, \qquad v_t = e(z_t), \\ \sum\nolimits_{t \in \mathcal{T}} Y_{k,c,t} &\geq 1, \quad \forall k \in \mathcal{H}, c \in C, \\ Y_{k,c,t} &= 0, \quad \forall k \in \mathcal{H}, c \in C, t \notin \mathbb{Z}_{\left[k:k+h_c\right]}. \end{split}$$

The Datacenter Power Cost Model

$$EPC = \sum_{t=1}^{T} \alpha q_t + p_{co_2} q_t I_t + \kappa w_t, \longrightarrow \text{Energy Purchased Cost}$$
 $NGC = \sum_{t=1}^{T} \gamma p_t, \longrightarrow \text{Nuclear Generation Cost}$
 $EEC = \sum_{t=1}^{T} \beta(p_t - d_t), \longrightarrow \text{Excess Energy Cost}$

Problem Formulation



- Given Datacenter workload profile $s_{c,k}$, SMR operation parameters T_h , \bar{P}_{RU} , \bar{P}_{RD} , Renewable energy of the grid
- Minimize Total Cost (Energy Purchase Cost + Nuclear Generation Cost + Energy Excess Cost)

$$\min EPC + NGC + EEC$$
s.t. $(1) - (11),$

$$p_t \ge d_t, \quad \forall t,$$

$$g_{grid,t} + d_t = v_t, \quad \forall t,$$

$$w_t + d_t \ge \eta v_t, \quad \forall t,$$

Methodology



- Uncertainty-aware Day-ahead Datacenter Workload Planning with LF-SMR
 - A robust chance-constraint optimization
- A Two-Stage Approach:
 - Stage 1 (Renewable Energy Prediction): Forecast the availability of the renewable energy and quantify the uncertainty
 - Stage 2 (Co-optimization): Optimize the SMR energy generation under the physicsconstraints and datacenter workload scheduling based on the forecast with uncertainty

Stage 1: Uncertainty-aware Renewable Forecast



- Method: Conformal Prediction (CP)
 - What CP Does: Uses historical data to construct prediction intervals [L, U] for future renewable energy availability.
- Given a statistical confidence level ε , find the prediction intervals in history with confidence ε .

$$P(Actual \ w_t \in Predicted \ Interval) \geq \varepsilon$$

- For example, ε = 90%, we carry out renewable energy prediction in history and find the interval that can cover 90% of the predictions, which can be ± 25 .
- We use this uncertainty set for stage 2 robust optimization problem.

Stage 2: Co-optimization



- Reformulation: Robust Optimization (RO) Problem
 - Use the prediction intervals from Stage 1 to reformulate the problem as a robust optimization (RO) problem with a traditional box uncertainty set
- Method: Mixed Integer Linear Programming (MILP)
 - The RO problem can be transformed into a MILP problem, solved by commercial MILP solvers such as CPLEX and Gurobi.

Algorithm Analysis



Corollary 4.1 (**Green Energy Coverage Guarantee**). If w_t is obtained using conformal prediction to determine the interval $Y_{w_t} \in \hat{C}(X_{w_t})$, the green energy coverage constraint Eq. (20) can be guaranteed with the probability of ϵ , namely,

$$\mathbb{P}(Y_{w_t} + d_t \geqslant \eta v_t) \ge \epsilon$$

Explanation: If the datacenter requires a green energy coverage of 80% (η =0.8), and employing a 95% confidence level (ϵ =0.95), our operational strategy (workload and SMR) guarantees: the 80% coverage target is achieved with the probability of 95%.

Evaluation Setup



- Datacenter Workloads: Google datacenter trace (May 2019)
 - Peak capacity: 20MW
 - Job types: Inflexible (No delay), Flexible (5h maximum delay)

SMR:

- Capacity: 20MW
- Ramp-rate: 10%, stable power time: 3 hours

Power Grid:

- Renewable energy: Wind/solar based on historical weather data
- Brown energy: All other energy (demand renewable nuclear)

Baselines and Metrics:



Baselines:

- DC-Plan: Grid only (No nuclear energy)
- DCNPP-PA: SMR fixed output (Physics-Agnostic, no load-following)
- DCNPP-Plan: DC-SMR with deterministic renewable forecast (No uncertainty)

Metrics:

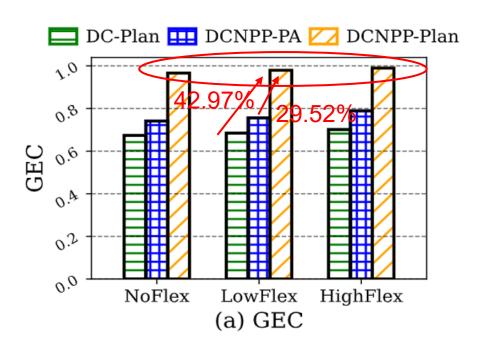
- Green Energy Coverage (GEC): proportion of carbon-free energy (renewable + nuclear) in the total datacenter energy consumption
- Nuclear Energy Utilization (NEU): proportion of nuclear energy consumed to total nuclear energy produced

Scenarios:

- Varying Workload Flexibility: (NoFlex 0%, LowFlex 10%, HighFlex 30%)
- Varying Renewable Penetration levels: (LowRP: 14 MW solar capacity, MedRP: 28 MW solar capacity, and HighRP: 42 MW solar capacity)

Results

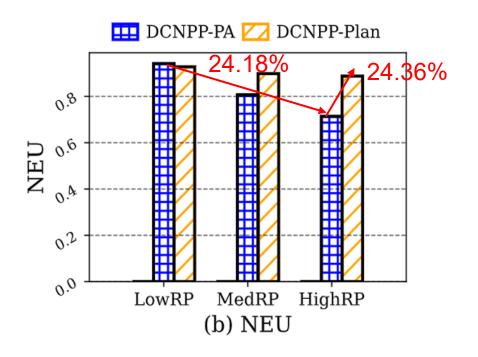




- DCSMR-Plan can achieve almost 100% GEC
- DCSMR-Plan outperforms DC-Plan (no nuclear) in GEC 42.97% and DCNPP-PA (fixed SMR) by 29.52%

Results: Impact of Renewable Penetration

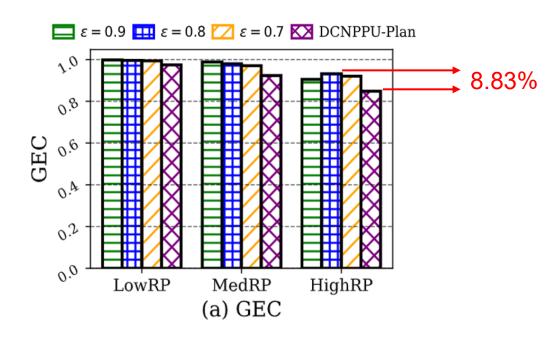




- With more renewable (solar, wind), the NEU (nuclear utilization) of DCNPP-PA (fixed SMR) decreases
 - DCNPP-PA has no model of the physical constraints & no load following
- We maintains high NEU in HighRP with 24.36% greater NEU than DCNPP-PA

Results: Impact of Uncertainty Handling





- Handling uncertainty is important when there is High Renewable Penetration
- We (ε =0.8) outperform DCNPP-Plan (without uncertainty handling) by 8.83% under HighRP

Conclusion



- We studied co-located datacenters and SMR at the operation level.
- We formulated a problem of uncertainty-aware day-ahead datacenter workload planning with LF-SMR; where we explicitly incorporated the physics and operational constraints of LF-SMRs.
- We employed predict and optimize approach where we use conformal prediction to handle grid renewable uncertainty.

Future Work



- One SMR can support multiple datacenters and one datacenter can use multiple SMR supplies
 - The mathematical tools will be different, Game theory.
- Multi-output LF-SMRs (co-generation of thermal energy, hydrogen)
 - Absorption chiller, a type of chiller that uses heat to produce chilled water.



Thank you! Q&A