

Enabling Adaptive Power Control through HPC Job Power Prediction

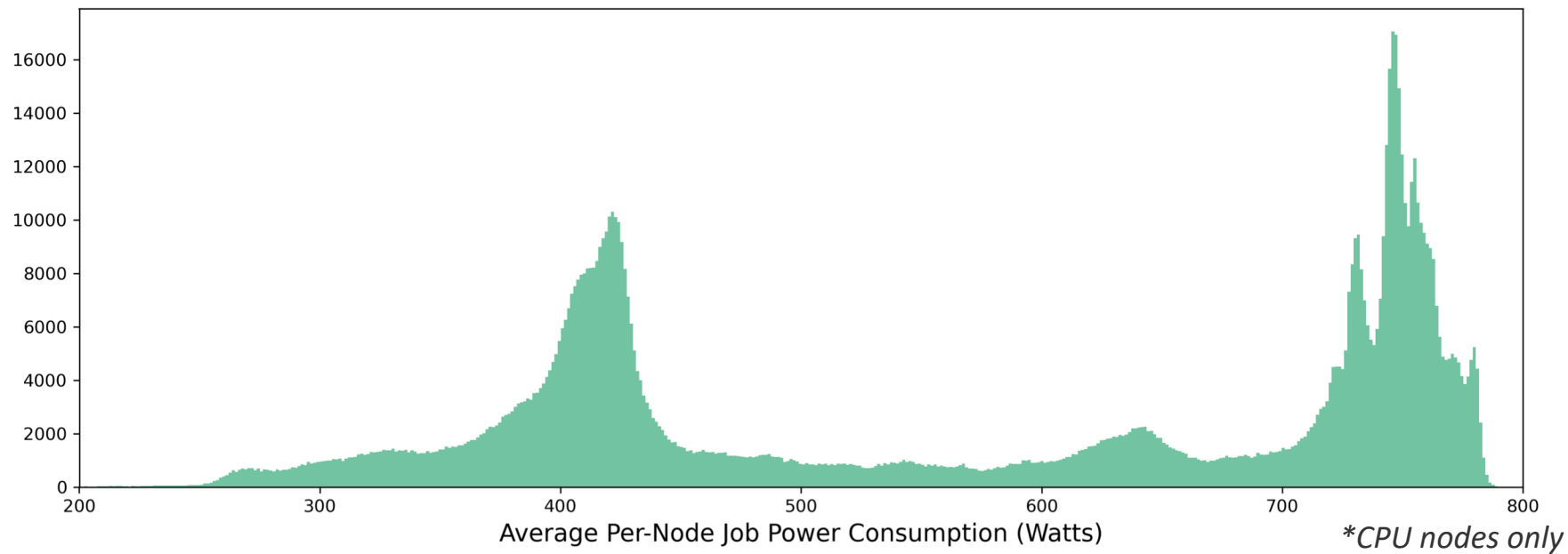
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MODA25
06/13/2025

Load Flexibility

AI and large-scale simulations are **driving up datacenter power use**, straining the grid

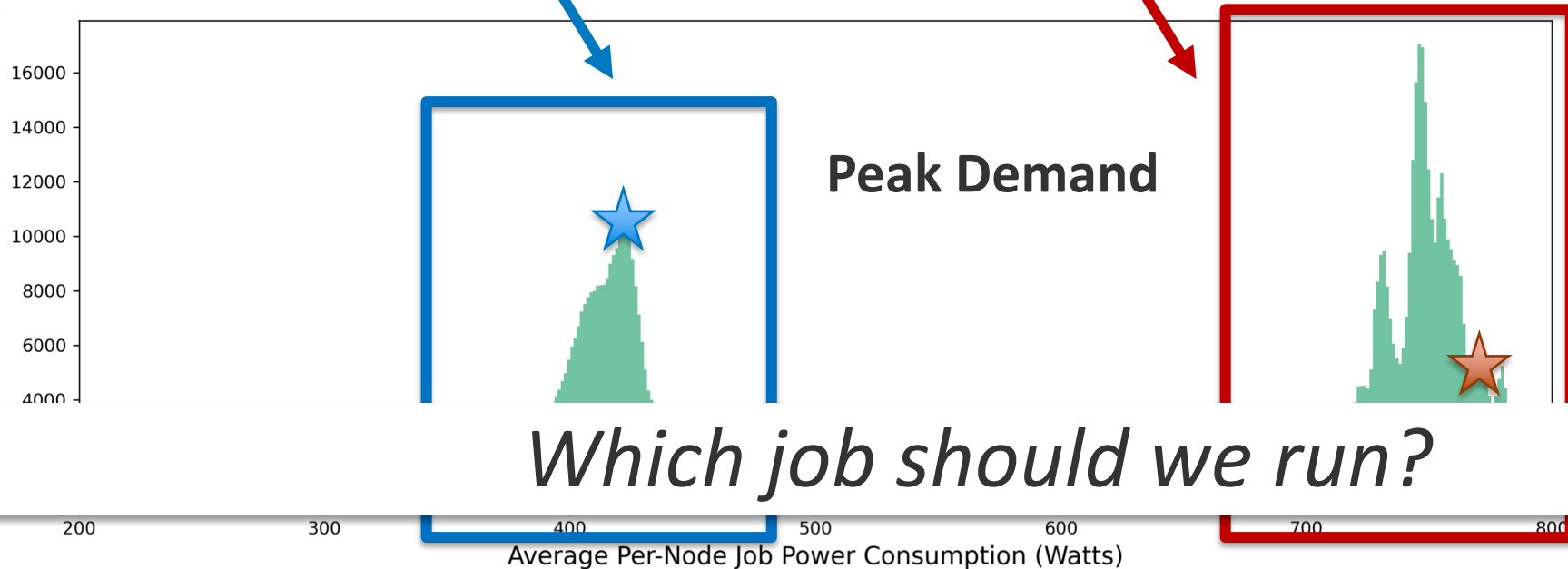
Just 1% load curtailment could enable **126 GW of new datacenter load *without grid expansion****

Load flexibility can **expedite new datacenter construction and decrease costs**



Low CPU Utilization

High CPU Utilization



...but we need to know job power consumption *in advance*.

How can we predict per-job power consumption?

Available Data

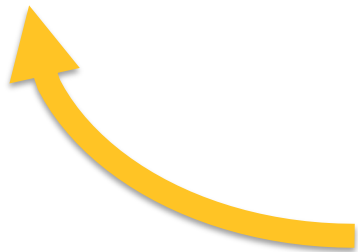
- Only data available at job submission time (*before the job runs*)
- **Metadata**
 - Submit time, user name, account
- **User-provided information**
 - Resources requested, modules to load, commands to execute
 - Single line (*potentially multiple commands*) → Submit line
 - Shell script → Job script

State of the Art (Traditional Approach)

- **Extract meaningful information** from the job script/submit line
 - Feature extraction
- **Preprocess data**
 - Feature engineering
 - Categorical features must be encoded (transformed to numerical)
 - Label encoding, one-hot encoding, target encoding...
 - More recently, encoding with language models!
- **Train a machine learning model/kNN with job features**

State of the Art (Traditional Approach)

- **Extract meaningful information** from the job script/submit line
 - Feature extraction



This is the problematic step!

- Domain expert decides what to keep and what to discard
- Drops most task-specific tokens (e.g. descriptive job names, software flags, Python code)

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```
User: [SCRUBBED_USER]
Account: [SCRUBBED_ACCOUNT]
Partition: standard
Job Type: python
Job Name: [SCRUBBED_JOB_NAME]
QOS: normal
Submit Line: sbatch [SCRUBBED_LAUNCH_SCRIPT]

Script:
#!/bin/bash
#SBATCH --account=[SCRUBBED_ACCOUNT]
#SBATCH --time=40:00:00
#SBATCH --job-name=[SCRUBBED_JOB_NAME]
#SBATCH --nodes=1 # number of nodes
#SBATCH --output=[SCRUBBED_PATH]/stdout/[SCRUBBED_JOB_NAME]_%j.o
#SBATCH --error=[SCRUBBED_PATH]/stdout/[SCRUBBED_JOB_NAME]_%j.e
#SBATCH --qos=normal # extra feature

echo "Running on: $HOSTNAME, Machine Type: $MACHTYPE"

python -c '
from nsrdb.nsrdb import NSRDB
NSRDB.run_data_model(
    "[SCRUBBED_PATH_ROOT]/", # root data directory
    "20201014", # target date
    "[SCRUBBED_PATH]/surfrad_meta.csv",
    freq="5min",
    var_list=None,
    dist_lim=2.0,
    max_workers=1,
    max_workers_regrid=1,
    log_level="INFO",
    log_file="data_model/data_model.log",
    job_name="[SCRUBBED_JOB_NAME]",
    factory_kwargs={
        "cld_opd_dcomp": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "cld_press_acha": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "cld_reff_dcomp": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "cloud_fraction": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "cloud_probability": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "cloud_type": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "refl_0_65um_nom": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "refl_0_65um_nom_stddev_3x3": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "refl_3_75um_nom": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
        "surface_albedo": {"source_dir": "[SCRUBBED_PATH]"},
        "temp_11_0um_nom": {"pattern": "[SCRUBBED_PATH_PATTERN]"},
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    },
    mlclouds=True
)'
```

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...but that's exactly the kind of input LLMs are designed to understand.

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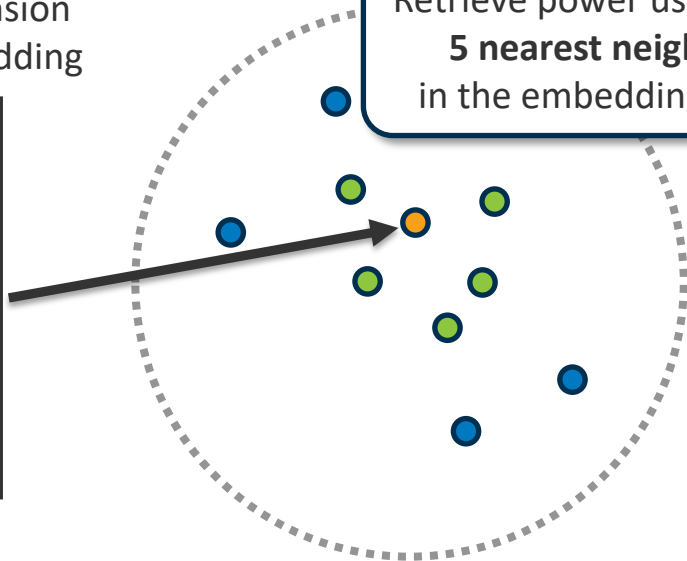
HPC Job Script & Metadata

```
User: jdoe
Account: science
Partition: standard
Job Type: vasp
Job Name: example_job
QOS: normal
Submit Line: sbatch job.sh
Script: #!/bin/bash --login
#SBATCH --nodes=2
#SBATCH --ntasks-per-node=36
#SBATCH --time=12:00:00
#SBATCH --job-name=example_job
#SBATCH --partition=standard
module load vasp
srun vasp_std
```



**Linq-Embed-Mistral*

4,096 Dimension
Vector Embedding

$$\begin{bmatrix} 0.342 \\ -0.209 \\ \vdots \\ 0.893 \\ 0.416 \end{bmatrix}$$


Retrieve power usage from
5 nearest neighbors
in the embedding space

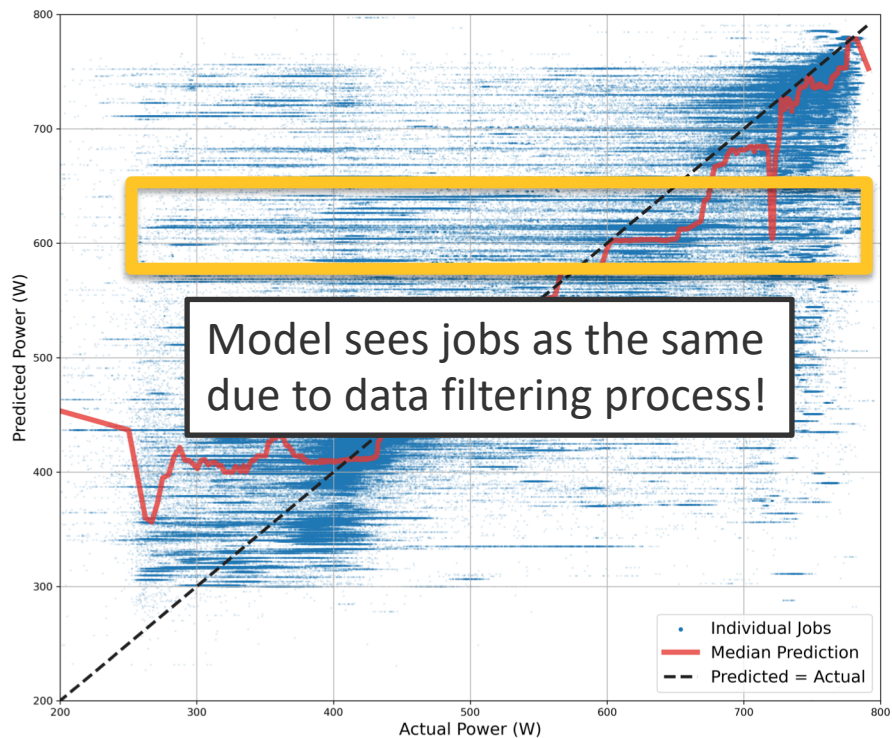
Predicted power is
weighted average of
nearest neighbor
power usage

$$\hat{P}_{\text{job}} = \frac{\sum_{i=1}^5 \cos(\theta_i) \cdot P_i}{\sum_{i=1}^5 \cos(\theta_i)}$$

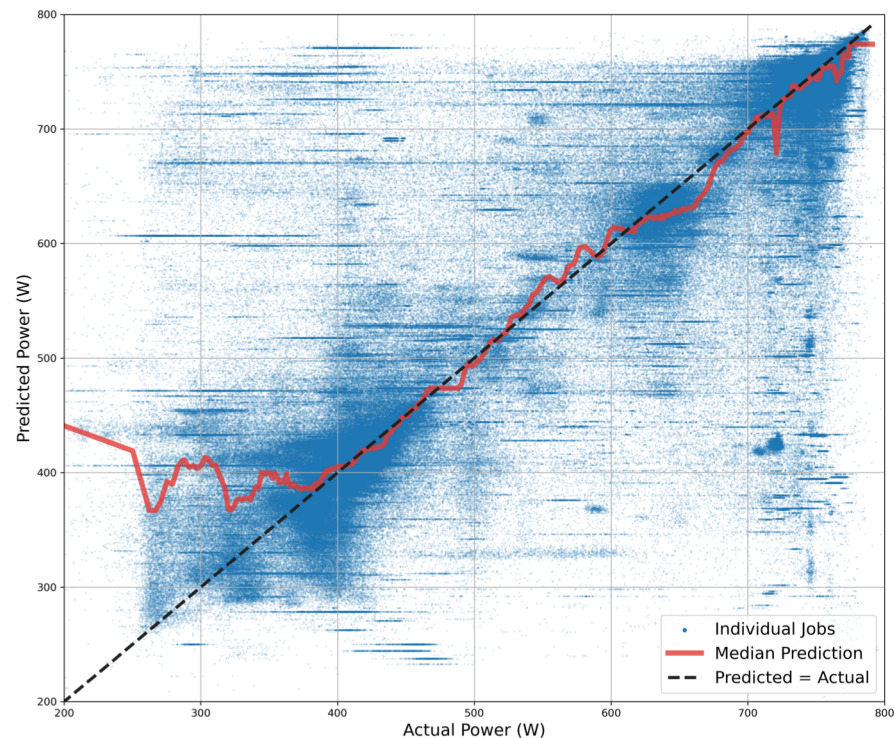
$\hat{P}_{\text{job}}$:= new job predicted power
 i := completed job (neighbor)
 $\cos(\theta_i)$:= cosine similarity
 P_i := neighbor power usage

Results

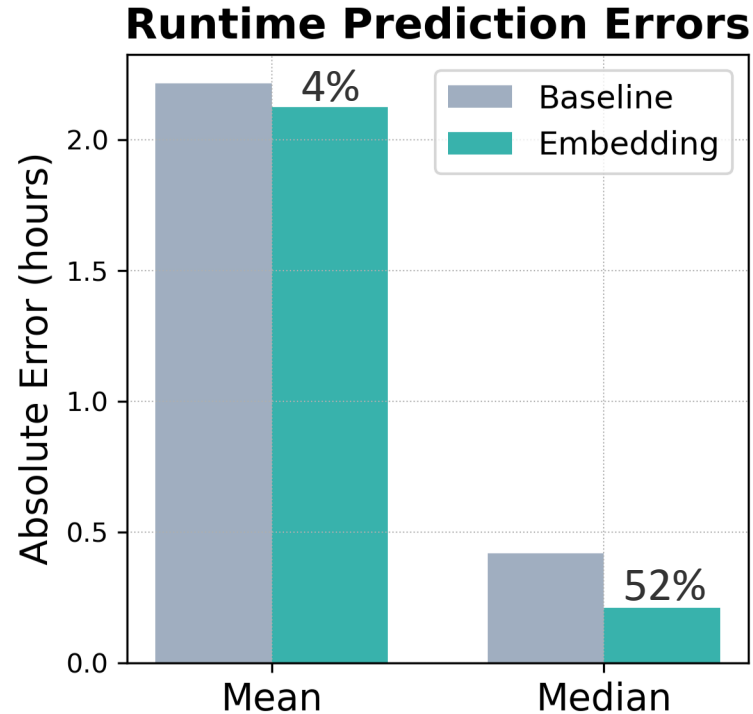
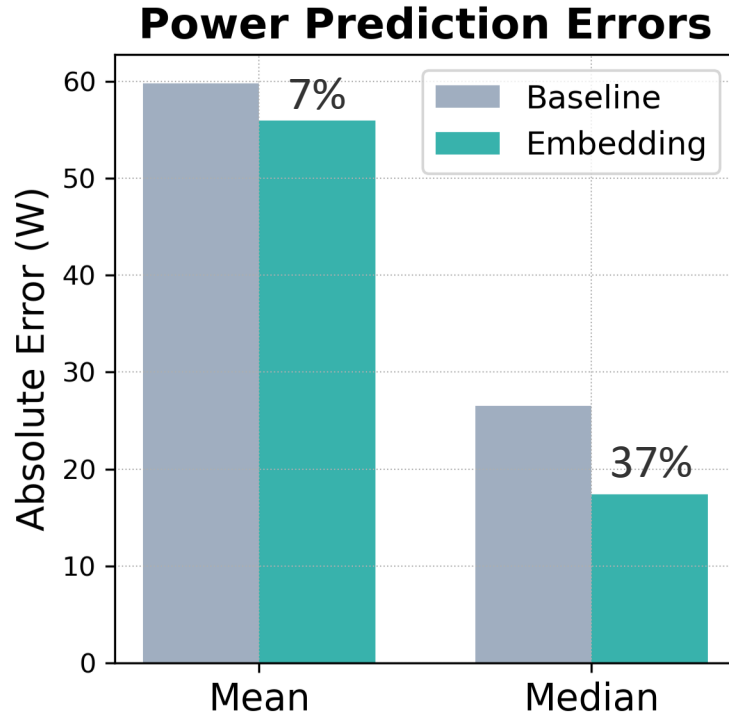
Baseline (Machine Learning Model)



New Approach (Semantic Search)



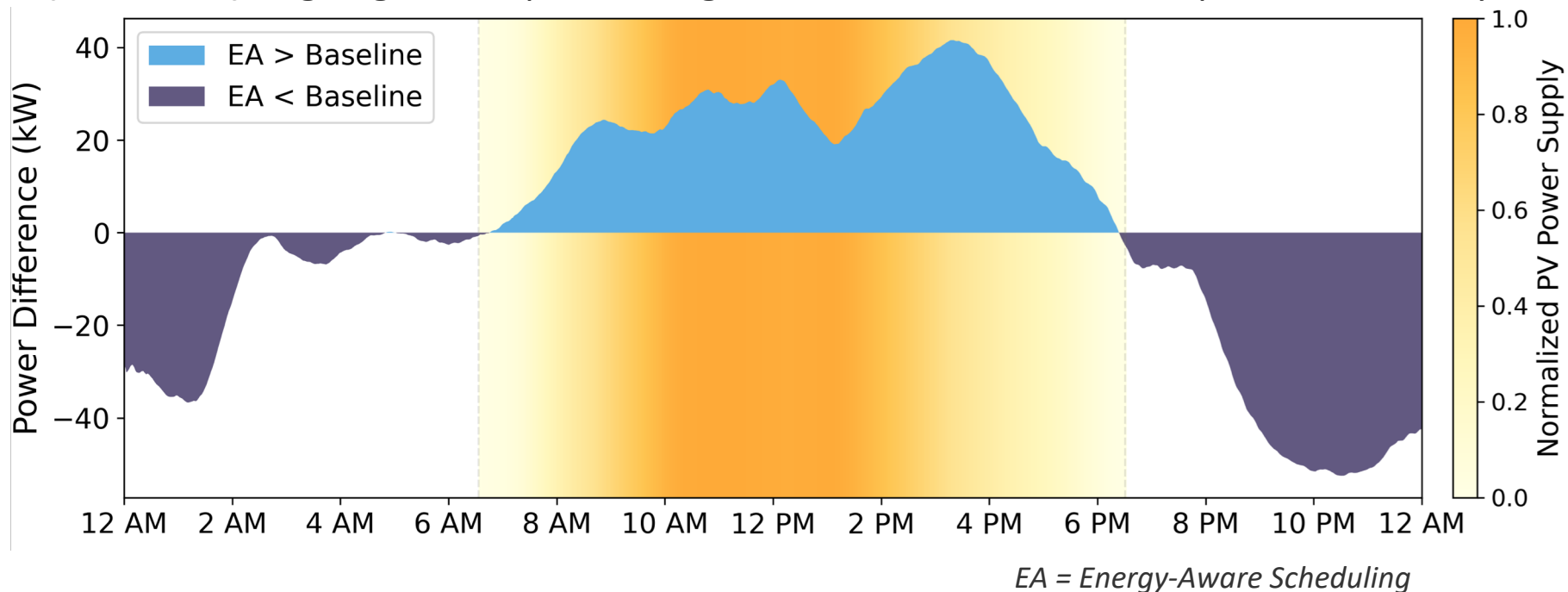
Results



Can predict
other metrics
**without any
additional
overhead**

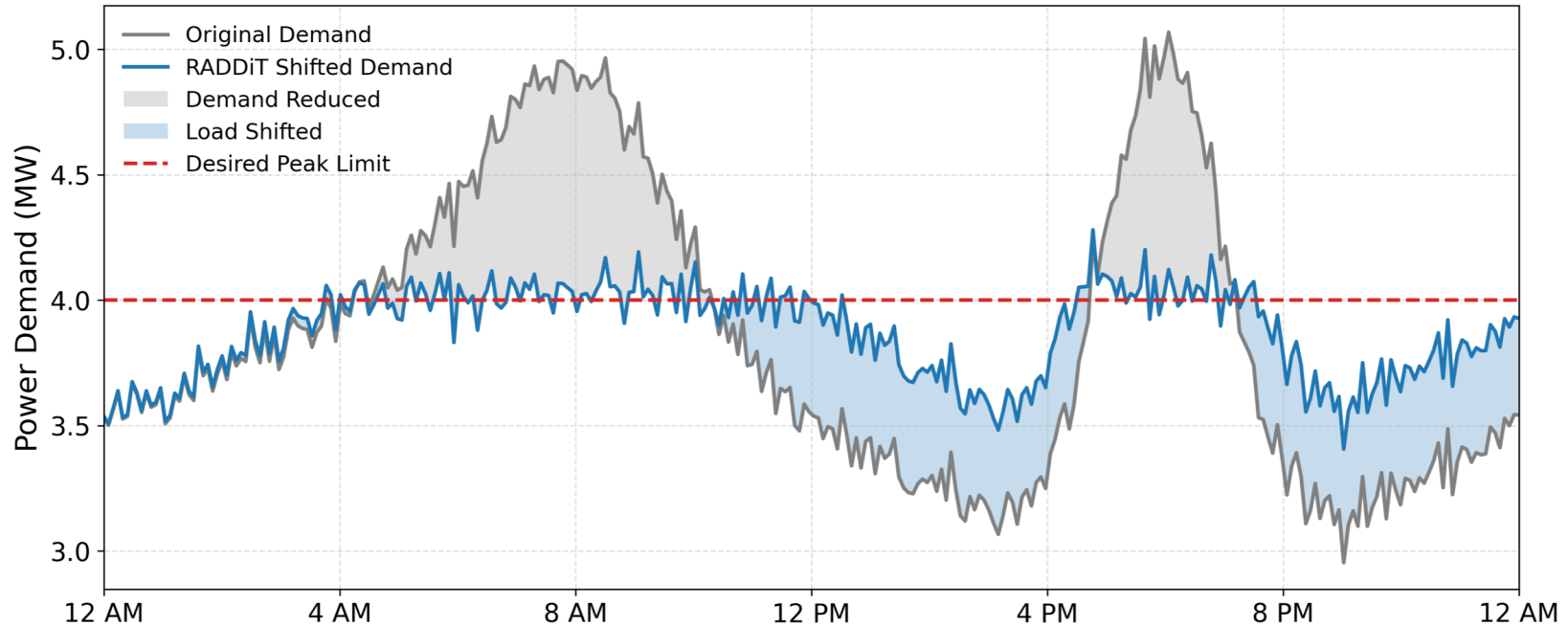
Current Application

(Simulated) Aligning Kestrel power usage with behind-the-meter PV power availability



Future Objective

(Mockup) Shifting load to reduce peak power demand





Thank you!

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