GRACE

a grid that is risk aware for clean electricity

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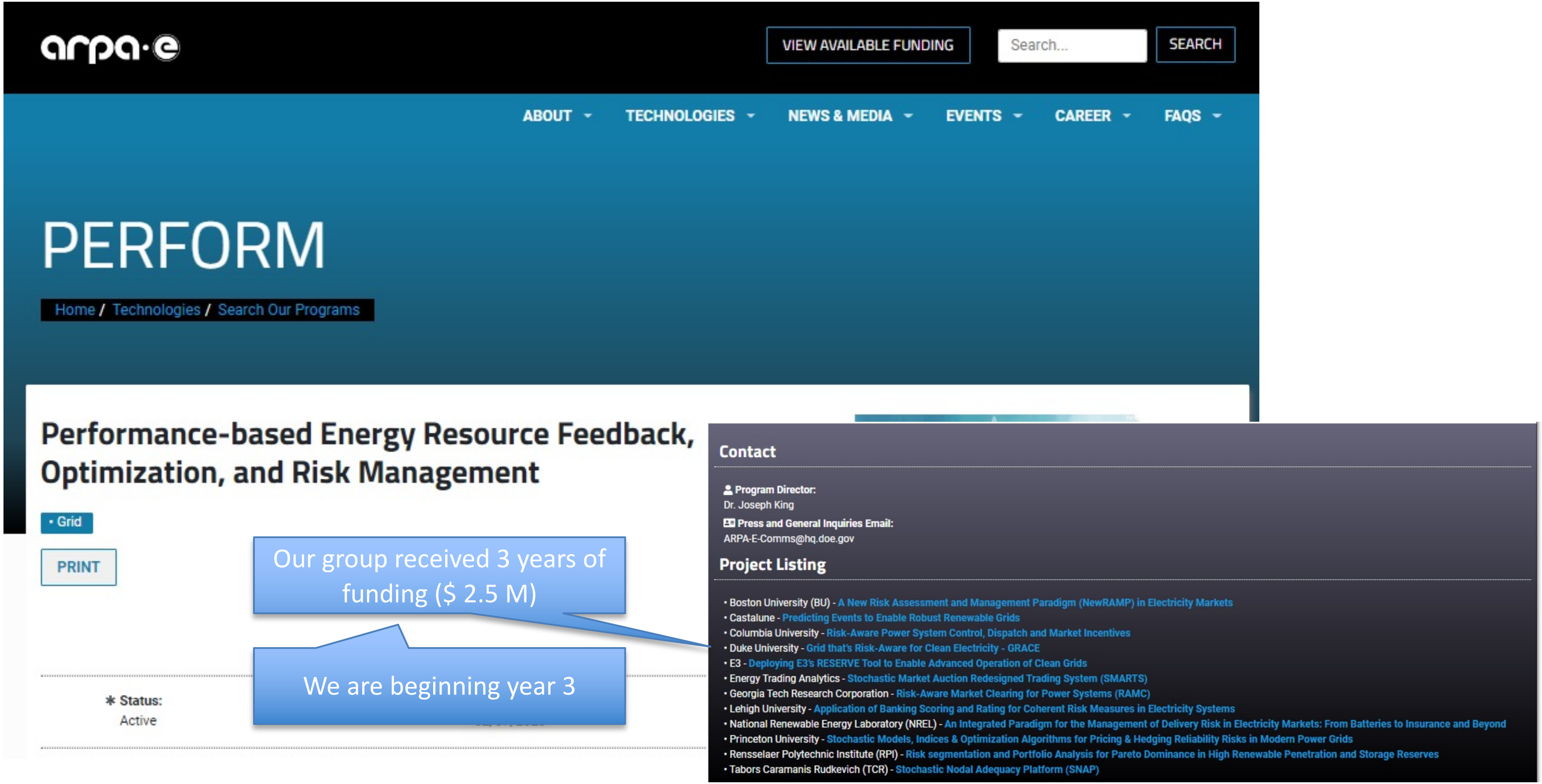
Duke University

ESIG Meteorology and Market Design for Grid Services Workshop
Denver, CO, June 15, 2023

Duke | NICHOLAS SCHOOL OF THE ENVIRONMENT
forging a sustainable future



PERFORM

Performance-based Energy Resource Feedback, Optimization, and Risk Management

- Grid

✱ Status:
Active

Contact

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Dr. Joseph King

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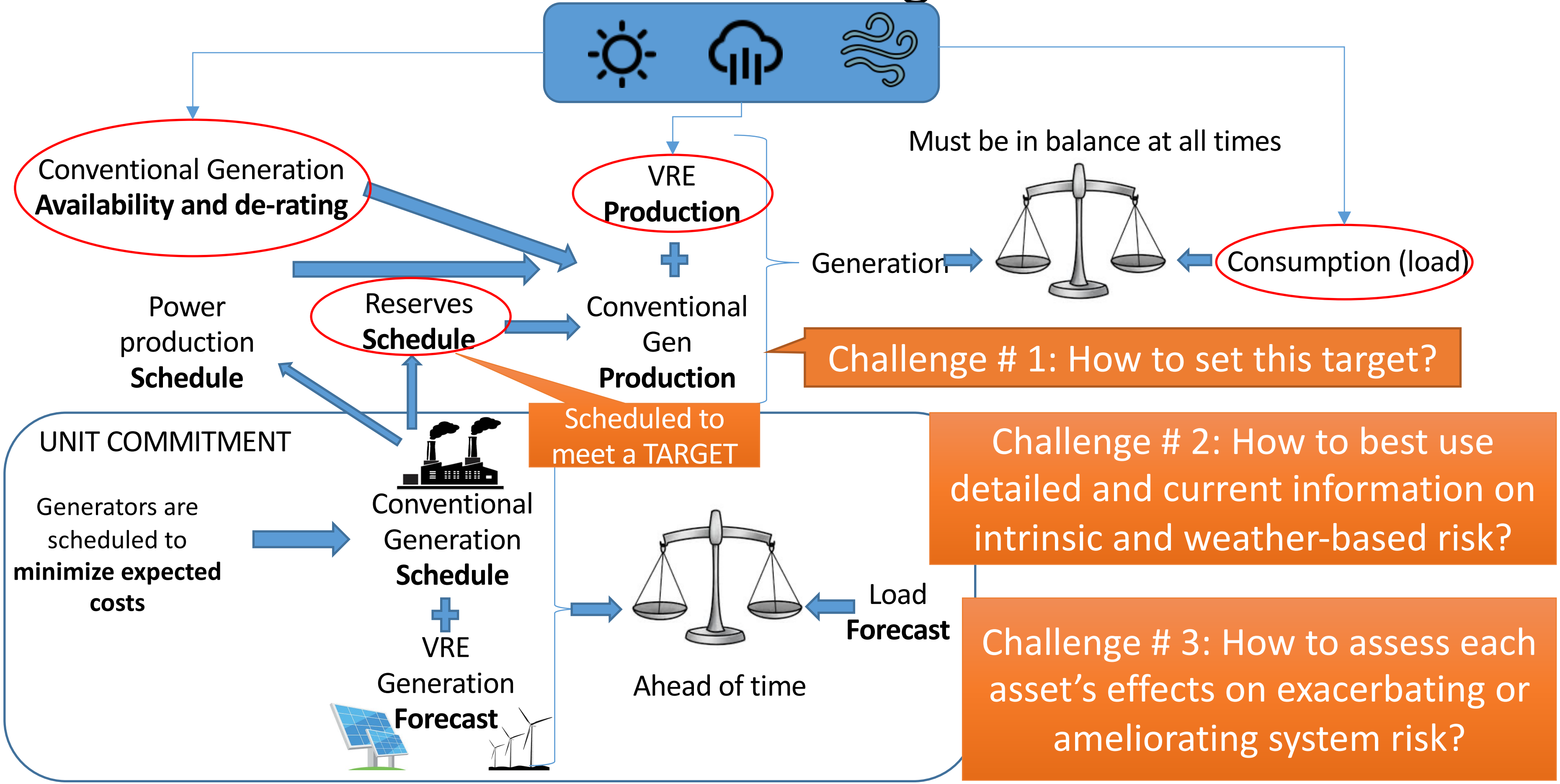
Project Listing

- Boston University (BU) - A New Risk Assessment and Management Paradigm (NewRAMP) in Electricity Markets
- Castalune - Predicting Events to Enable Robust Renewable Grids
- Columbia University - Risk-Aware Power System Control, Dispatch and Market Incentives
- Duke University - Grid that's Risk-Aware for Clean Electricity - GRACE
- E3 - Deploying E3's RESERVE Tool to Enable Advanced Operation of Clean Grids
- Energy Trading Analytics - Stochastic Market Auction Redesigned Trading System (SMARTS)
- Georgia Tech Research Corporation - Risk-Aware Market Clearing for Power Systems (RAMC)
- Lehigh University - Application of Banking Scoring and Rating for Coherent Risk Measures in Electricity Systems
- National Renewable Energy Laboratory (NREL) - An Integrated Paradigm for the Management of Delivery Risk in Electricity Markets: From Batteries to Insurance and Beyond
- Princeton University - Stochastic Models, Indices & Optimization Algorithms for Pricing & Hedging Reliability Risks in Modern Power Grids
- Rensselaer Polytechnic Institute (RPI) - Risk segmentation and Portfolio Analysis for Pareto Dominance in High Renewable Penetration and Storage Reserves
- Tabors Caramanis Rudkevich (TCR) - Stochastic Nodal Adequacy Platform (SNAP)

Our group received 3 years of funding ($ 2.5 M)

We are beginning year 3

Three Challenges



Conventional Generation
Availability and de-rating

VRE
Production

Must be in balance at all times

Generation

Consumption (load)

Power
production
Schedule

Reserves
Schedule

Conventional
Gen
Production

Challenge # 1: How to set this target?

Scheduled to
meet a TARGET

UNIT COMMITMENT

Generators are
scheduled to
minimize expected
costs

Conventional
Generation
Schedule

VRE
Generation
Forecast

Challenge # 2: How to best use detailed and current information on intrinsic and weather-based risk?

Load
Forecast

Ahead of time

Challenge # 3: How to assess each asset’s effects on exacerbating or ameliorating system risk?

GRACE

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Objective

To develop a scheduling & dispatch approach that effectively considers the risk posed by weather-based and intrinsic uncertainty, and is computationally tractable so it can be implemented now.

GRACE will

- -minimize operating **costs**,
- -maintain or improve **reliability**,
- -maintain or improve utilization of **low-carbon** resources
- -quantify the impacts of grid resources on **system risk**

Duke
UNIVERSITY

THE OHIO STATE
UNIVERSITY

GRACE
a grid that is risk aware for clean electricity

NC STATE
UNIVERSITY

Pacific Northwest
NATIONAL LABORATORY

DARTMOUTH

Risk measures – Risk Scores

James Smith

- Distinguished Professor in Decision Science
- Tuck School of Business

DARTMOUTH

Risk-adjusted stochastic UC model libraries & Integration of all modules

Duke UNIVERSITY

Kyle Bradbury

- Assistant Research Professor
- Electrical & Computer Engineering

David Brown

- Profesvsor
- Fuqua School of Business

Dimitrios Floros

- Postdoctoral Fellow
- NSOE

Mauricio Hernandez

- Ph.D. Student
- NSOE

Dalia Patino-Echeverri

- Associate Professor
- NSOE

Xiaodong Zhang

- Ph.D. Student
- NSOE

Uncertainty Characterization

NC STATE UNIVERSITY

Jordan Kern

- Assistant Professor
- Department of Forestry and Environmental - Civil, Construction and Environmental Engineering and Operations Research

Luis Prieto

- Ph.D. Student
- Civil, Construction and Environmental Engineering

Henry Ssembatya

- Ph.D. Student
- Forestry and Environmental Resources

Stochastic Model

Antonio Conejo

- Professor
- Integrated Systems Engineering and Electrical and Computer Engineering

Gonzalo Constante

- Ph.D. Student
- Electrical and Computer Engineering

Xuan Liu

- Ph.D. Student
- Electrical and Computer Engineering

Uncertainty Characterization

Veronica Adetola

- Chief Research Scientist in the Electricity Infrastructure and Buildings Division

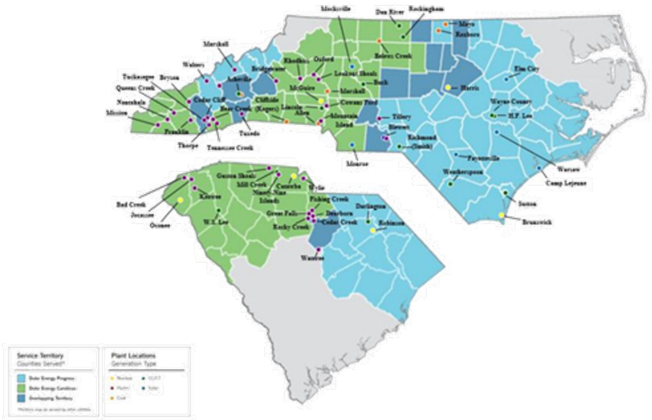
Arnab Bhattacharya

- Operations Research Scientist

Wei Wang

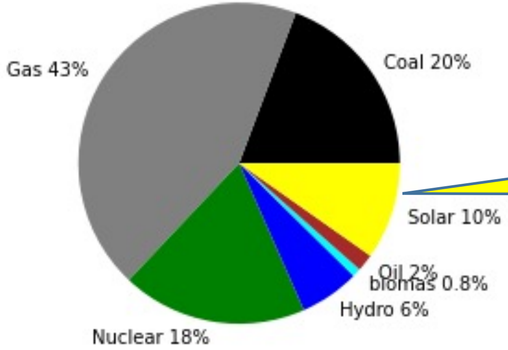
- Postdoctoral Fellow

Industry Partner :



Duke Energy Carolinas + Duke Energy Progress East + Duke Energy Progress

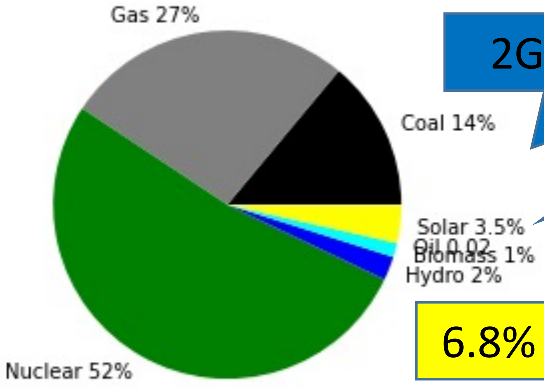
Capacity: DEC+DEP in 2020 = 62.6 GW (eGRID 2020)



6 GW

6.6% of US Solar Capacity

Generation: DEC+DEP in 2020 = 171 TWh (eGRID 2020)

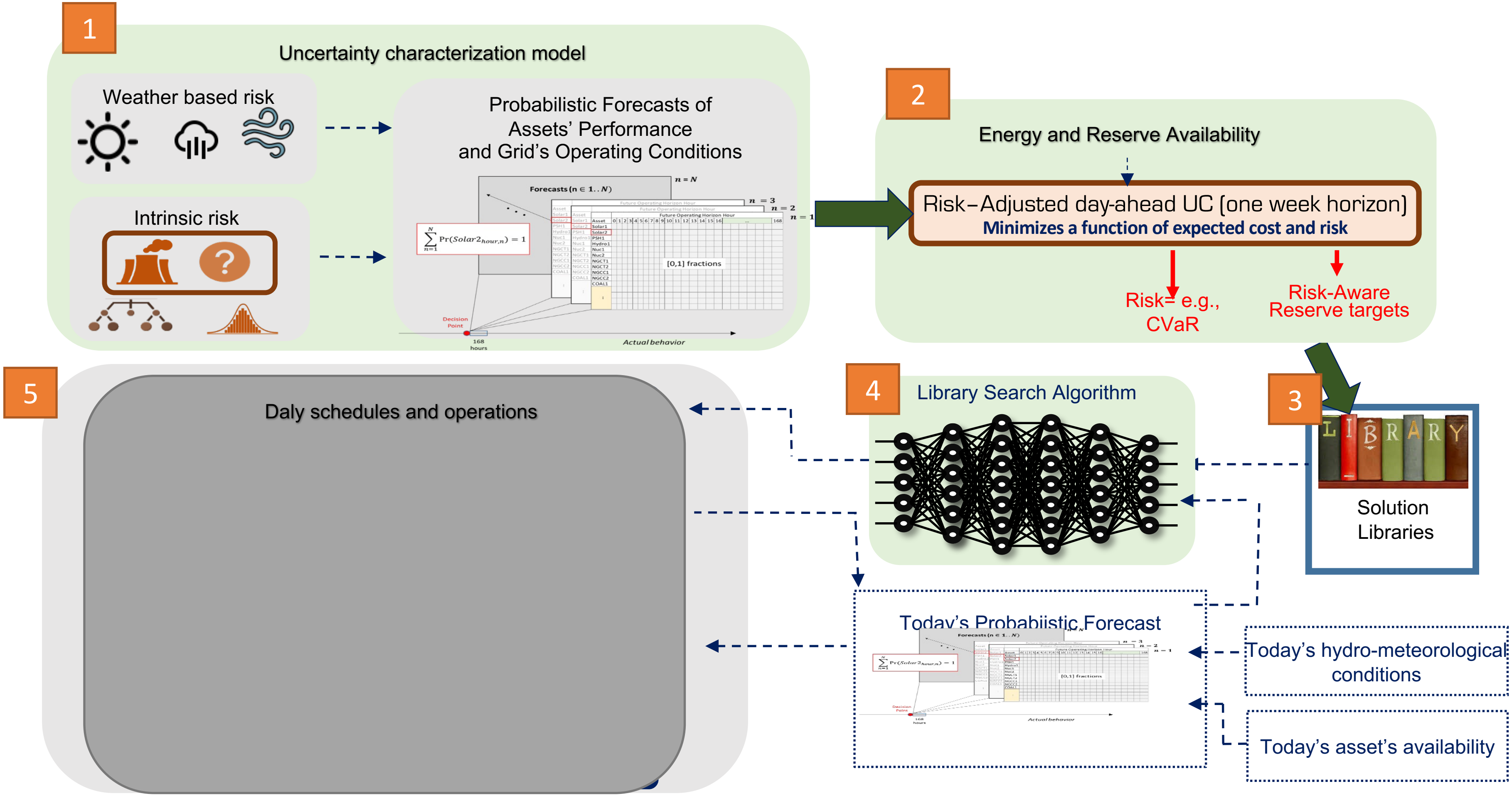


2GW or Pumped Hydro ES

6 TWh

6.8% of US Solar Generation

GRACE’s Improved Scheduling and Dispatch System



1

Uncertainty characterization model

Weather based risk

Intrinsic risk

Probabilistic Forecasts of
Assets’ Performance
and Grid’s Operating Conditions

2

Energy and Reserve Availability

Risk−Adjusted day-ahead UC (one week horizon)

Minimizes a function of expected cost and risk

Risk= e.g., CVaR

Risk-Aware Reserve targets

3

Solution Libraries

4

Library Search Algorithm

5

Daly schedules and operations

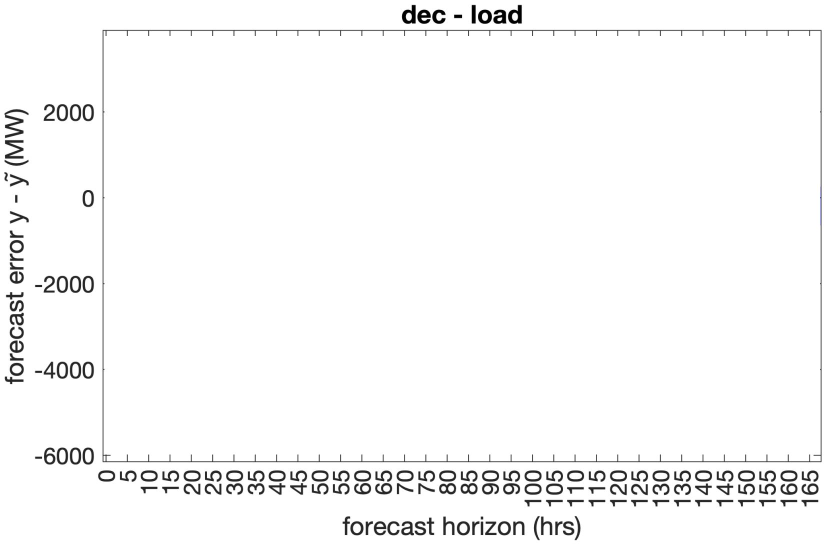
Today’s Probabilistic Forecast

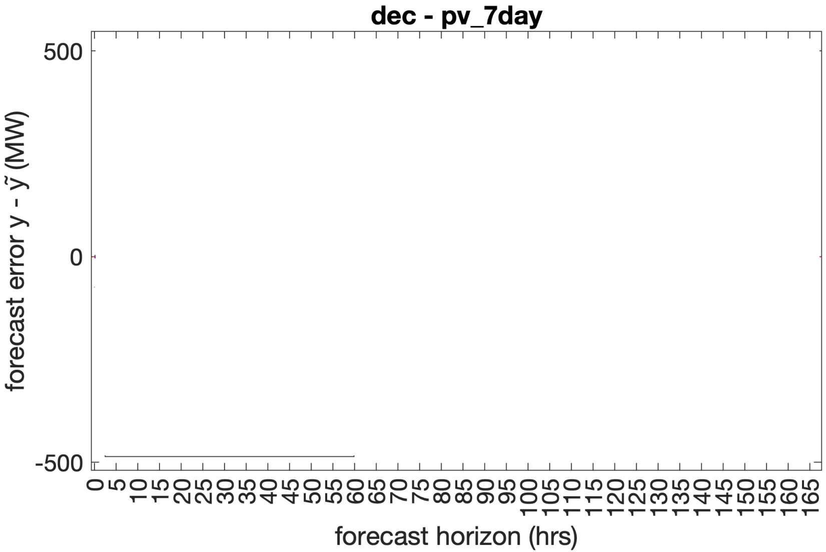
Today’s hydro-meteorological conditions

Today’s asset’s availability

Uncertainty Characterization

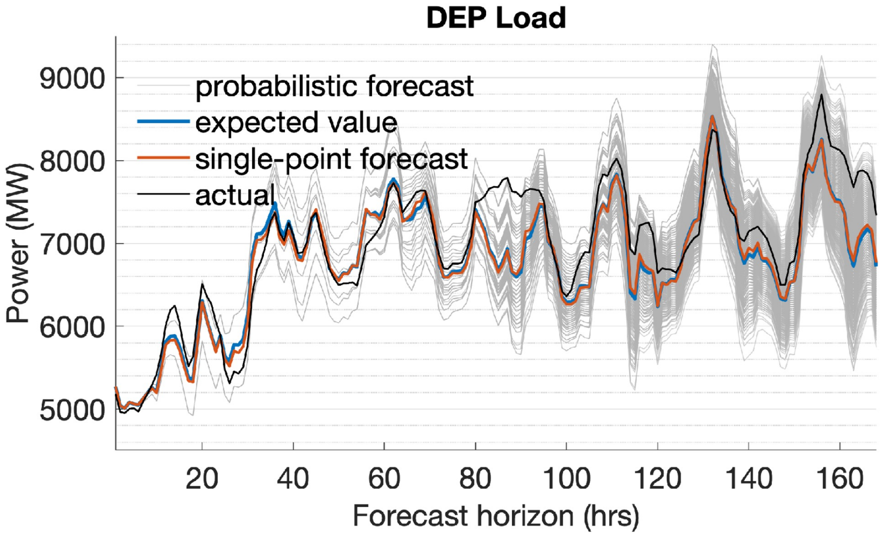
Forecast errors of load and solar





Probabilistic forecasts

- 3 components to investigate the GRACE benefits
    - Actual time series (observations)
    - Single-point (deterministic) forecast
    - Probabilistic forecast
- E[Probabilistic] = deterministic
- Actual can be historical or synthetic



The DEP load for the first 7 days of 2019

Generation of probabilistic forecasts

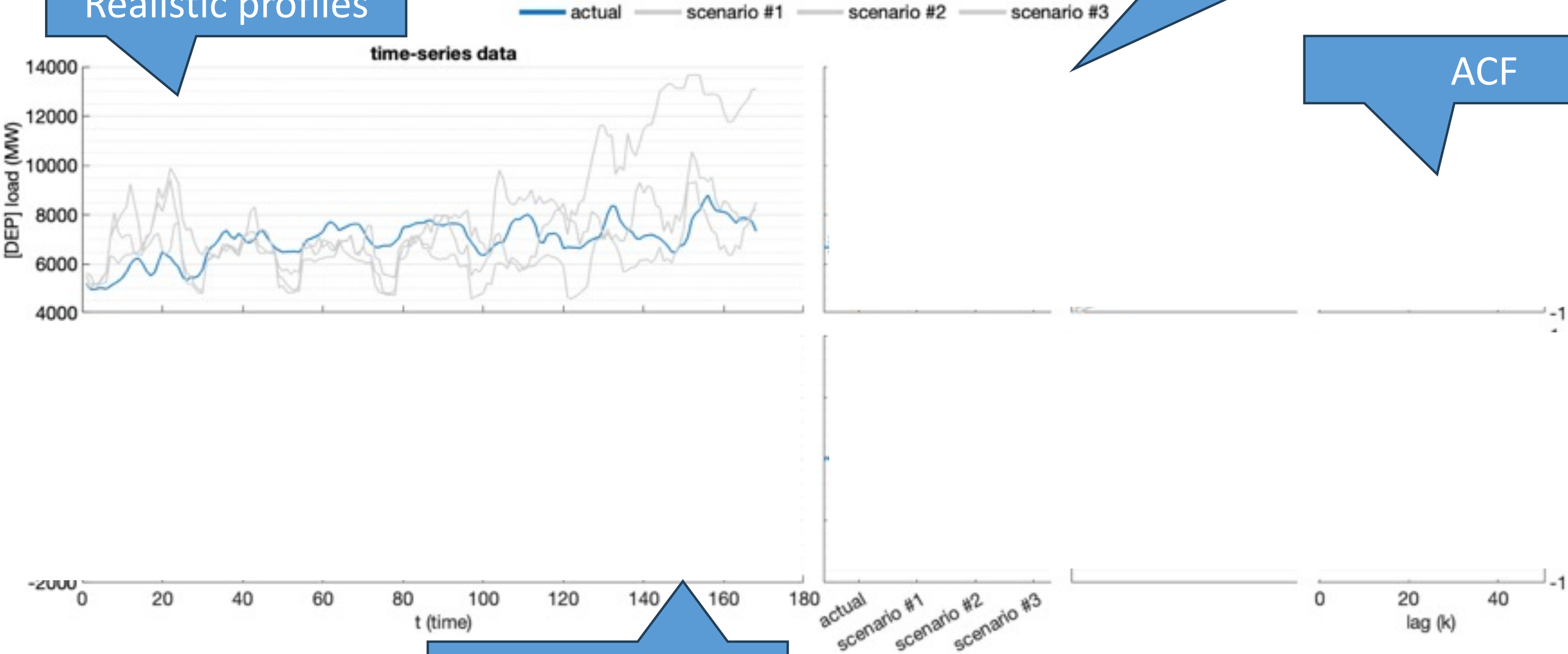
Methods

- Historical sampling
- Monte-Carlo approaches
- Lattice scenarios (baseline)

Quality assessment

- Are the scenarios realistic?
- How do the different methods compare in realism and forecast accuracy?

Quality assessment of synthetic data



Realistic profiles

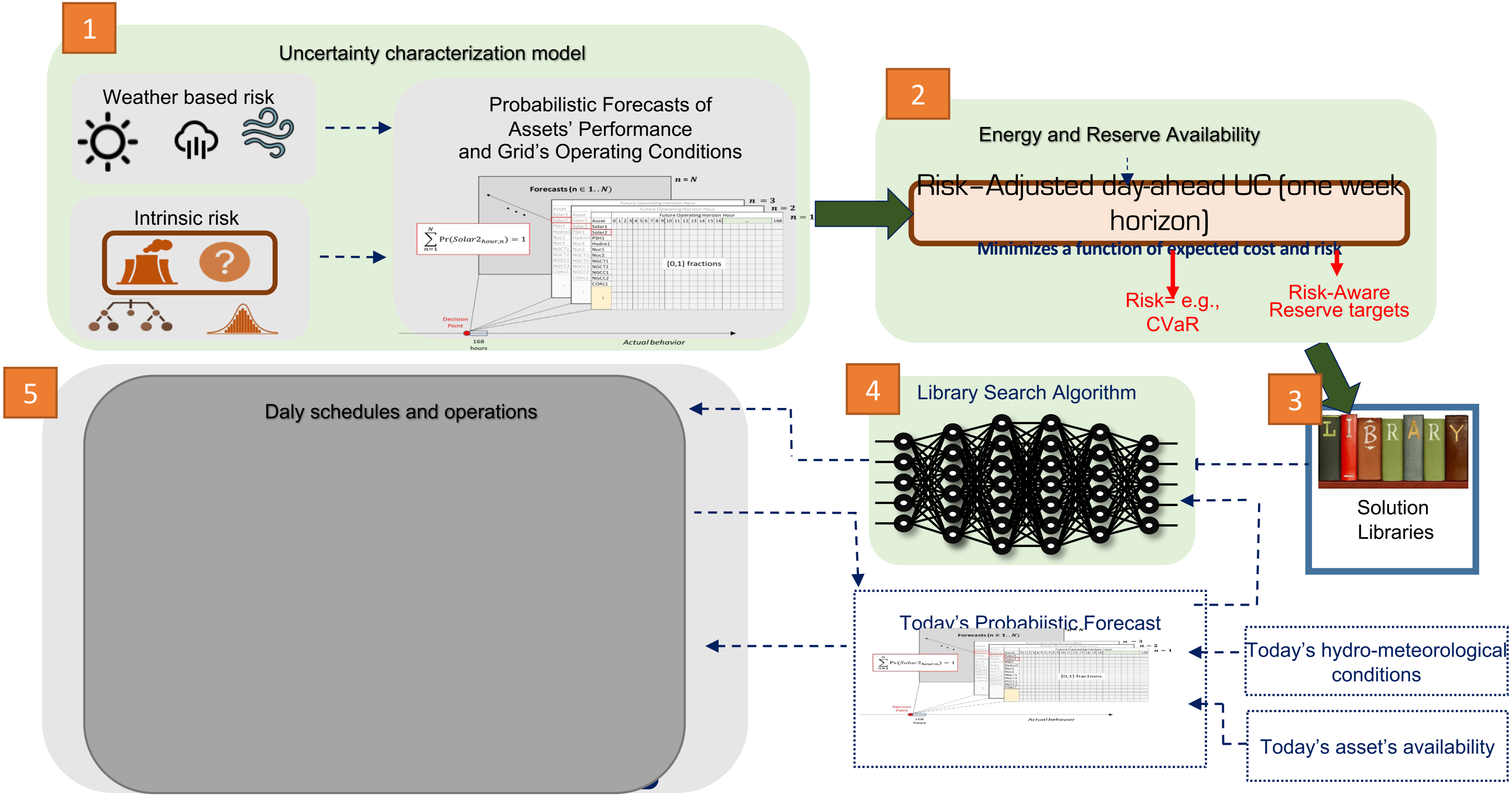
PDF & CDF

ACF

Step changes

Comparison between historical observation and probablistic forecasts of DEP demand load on January 1st, 2019.

GRACE’s Improved Scheduling and Dispatch System



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$$\sum_{n=1}^{N} \Pr(Solar2_{hour,n}) = 1$$

2

Energy and Reserve Availability

Risk–Adjusted day-ahead UC (one week horizon)

Minimizes a function of expected cost and risk

Risk= e.g., CVaR

Risk-Aware Reserve targets

3

Solution Libraries

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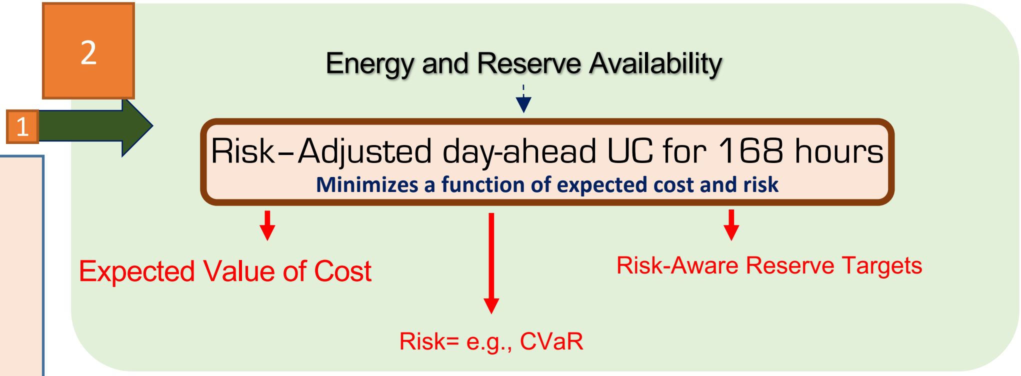
Daly schedules and operations

Today’s Probabiistic Forecast

Today’s hydro-meteorological conditions

Today’s asset’s availability

Risk-adjusted stochastic UC model



1st stage: No load, start-up and shut-down costs

2nd stage: start-up of peakers, production costs, cost of load shedding

Minimize
(1-β)Expected Cost + βCVaR of Cost

Subject to:

First Stage:

- Start-up/shut-down logic
- Min up/down time
- Power generation limits
- Pumped-hydro storage constraints
- Production = Expected net demand

For all units and time periods

Second Stage:

- Ramping up/down limits
- Min / max generation limits
- power balance constraints per area
- transmission capacity limits
- VRE curtailment limits
- Unserved demand limits
- (CVaR constraints)

For all scenarios and time periods

$$\min_{\Xi}$$

$$(1-\beta)\ \text{Expected Cost} + \beta\ \text{CVaR of Cost:}$$

$$(1-\beta)\Bigg[\sum_{t\in T}\Bigg(\sum_{j\in J^{\mathrm{coal}}\cup J^{\mathrm{gas}}}\left(c_j(p_j(t)) + c_j^{\mathrm{U}} y_j(t) + c_j^{\mathrm{D}} z_j(t)\right) +$$

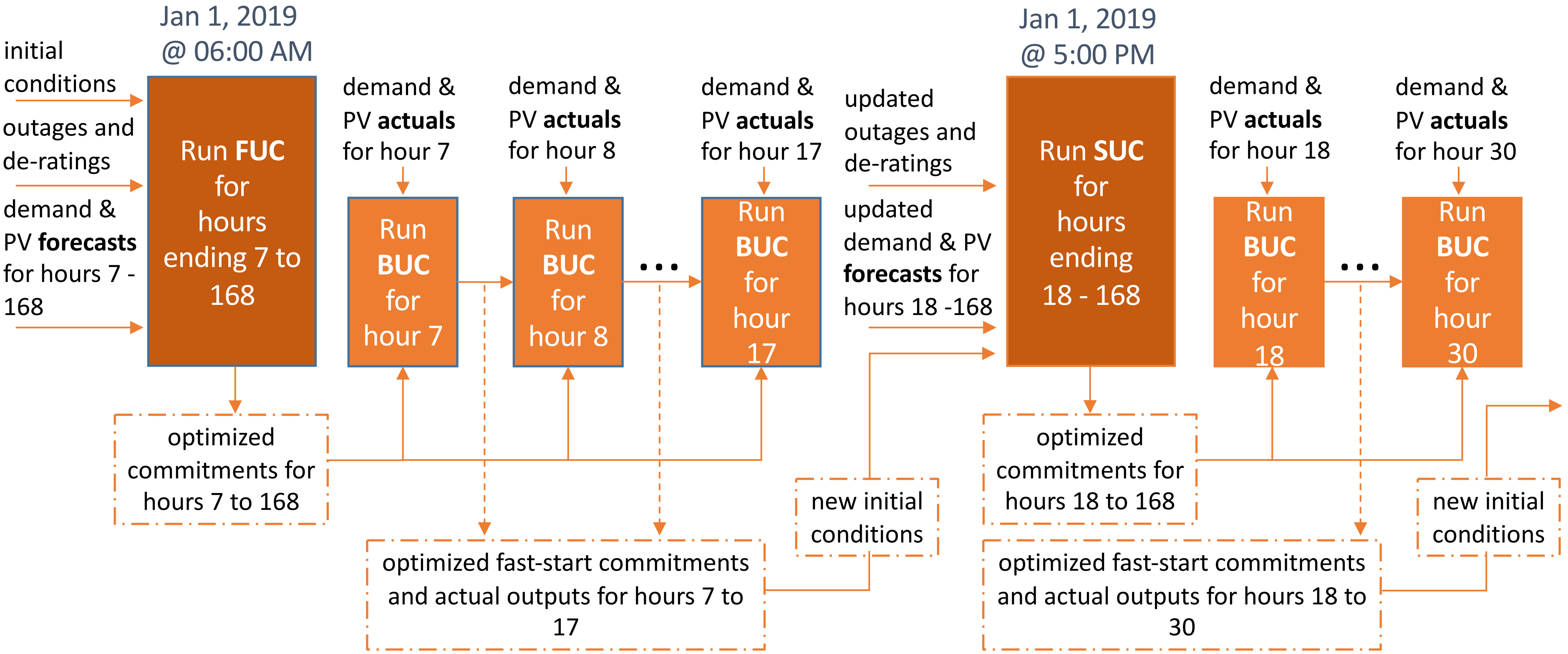
$$\sum_{j\in J^{\mathrm{ng}}} c_j(p_j(t)) + \sum_{j\in J^{\mathrm{w}}} c_j(p_j^{\mathrm{W}}(t))\Bigg) +$$

$$\sum_{\omega\in\Omega}\pi_\omega \sum_{t\in T}\Bigg(\sum_{j\in J}\left(c_j^{\mathrm{RU}} r_{j\omega}^{\mathrm{U}}(t) - c_j^{\mathrm{RD}} r_{j\omega}^{\mathrm{D}}(t)\right) + \sum_{i\in\Lambda^D} c_i^{\mathrm{LOL}} D_{i\omega}^{\mathrm{shed}}(t)\Bigg)\Bigg] +$$

$$\beta\left(\zeta + \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi_\omega\eta_\omega\right)$$

Optimization of conditional value-at-risk,
Rockafellar & Uryasev, 2001

Duke Energy's Energy Management System (CP-EMS)



Jan 1, 2019
@ 06:00 AM

initial conditions

outages and de-ratings

demand & PV **forecasts** for hours 7 - 168

Run **FUC** for hours ending 7 to 168

optimized commitments for hours 7 to 168

demand & PV **actuals** for hour 7

Run **BUC** for hour 7

demand & PV **actuals** for hour 8

Run **BUC** for hour 8

...

demand & PV **actuals** for hour 17

Run **BUC** for hour 17

optimized fast-start commitments and actual outputs for hours 7 to 17

new initial conditions

updated outages and de-ratings

updated demand & PV **forecasts** for hours 18 -168

Jan 1, 2019
@ 5:00 PM

Run **SUC** for hours ending 18 - 168

optimized commitments for hours 18 to 168

demand & PV **actuals** for hour 18

Run **BUC** for hour 18

...

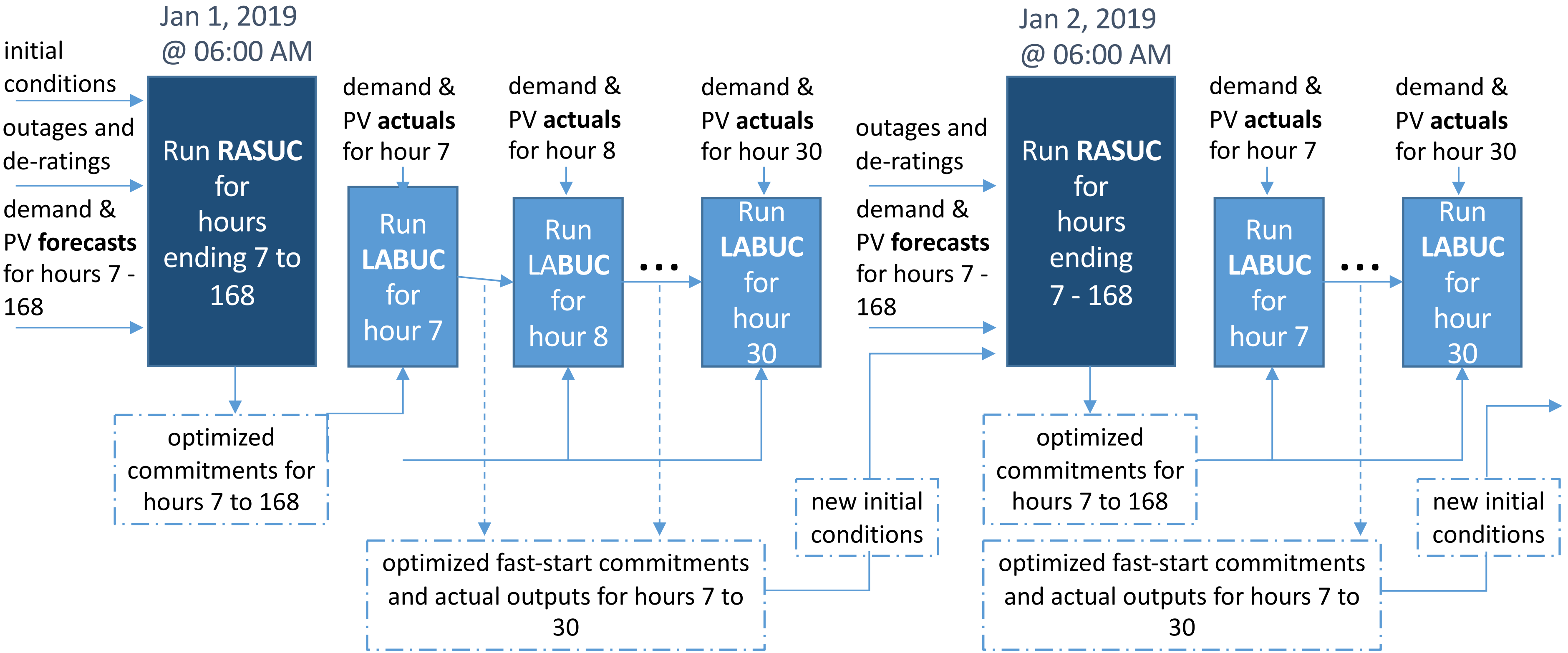
demand & PV **actuals** for hour 30

Run **BUC** for hour 30

optimized fast-start commitments and actual outputs for hours 18 to 30

new initial conditions

Overview of the RA-EMS



Jan 1, 2019
@ 06:00 AM

initial conditions

outages and de-ratings

demand & PV **forecasts** for hours 7 - 168

Run **RASUC** for hours ending 7 to 168

optimized commitments for hours 7 to 168

demand & PV **actuals** for hour 7

Run **LABUC** for hour 7

demand & PV **actuals** for hour 8

Run LABUC for hour 8

…

demand & PV **actuals** for hour 30

Run **LABUC** for hour 30

optimized fast-start commitments and actual outputs for hours 7 to 30

new initial conditions

Jan 2, 2019
@ 06:00 AM

outages and de-ratings

demand & PV **forecasts** for hours 7 - 168

Run **RASUC** for hours ending 7 - 168

optimized commitments for hours 7 to 168

demand & PV **actuals** for hour 7

Run **LABUC** for hour 7

…

demand & PV **actuals** for hour 30

Run **LABUC** for hour 30

optimized fast-start commitments and actual outputs for hours 7 to 30

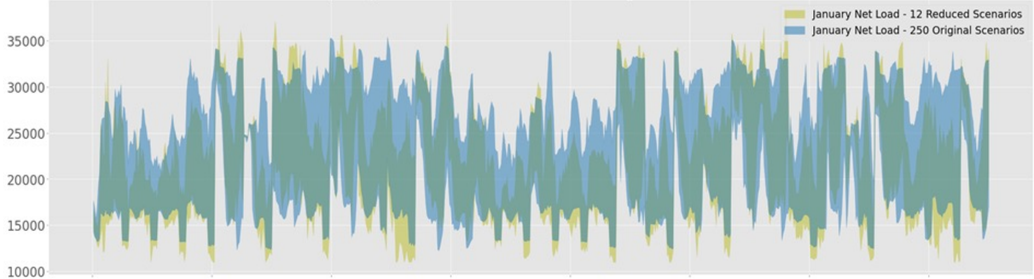
new initial conditions

Risk-adjusted stochastic UC model vs CP-deterministic

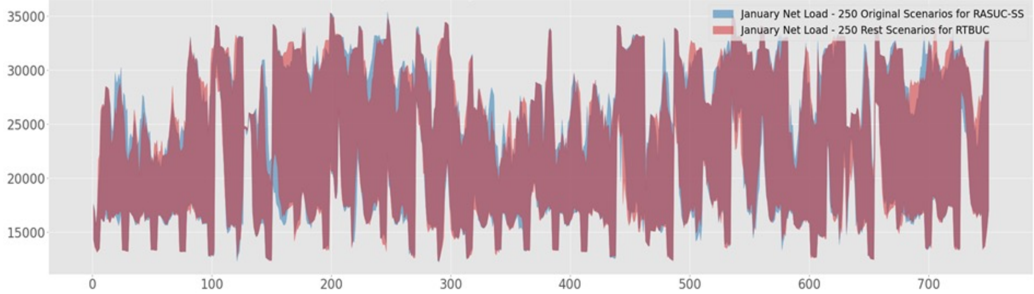
Probabilistic da- forecasts taken from 250 scenarios

Real time 250 actuals

a) Compare 12 reduced scenarios to the original 250 scenarios

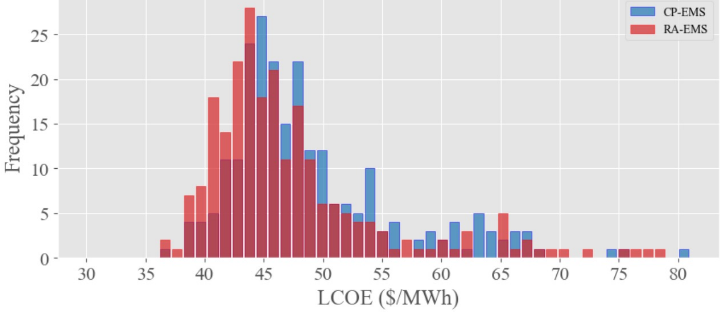


b) Compare 250 original scenarios to the rest 250 scenarios

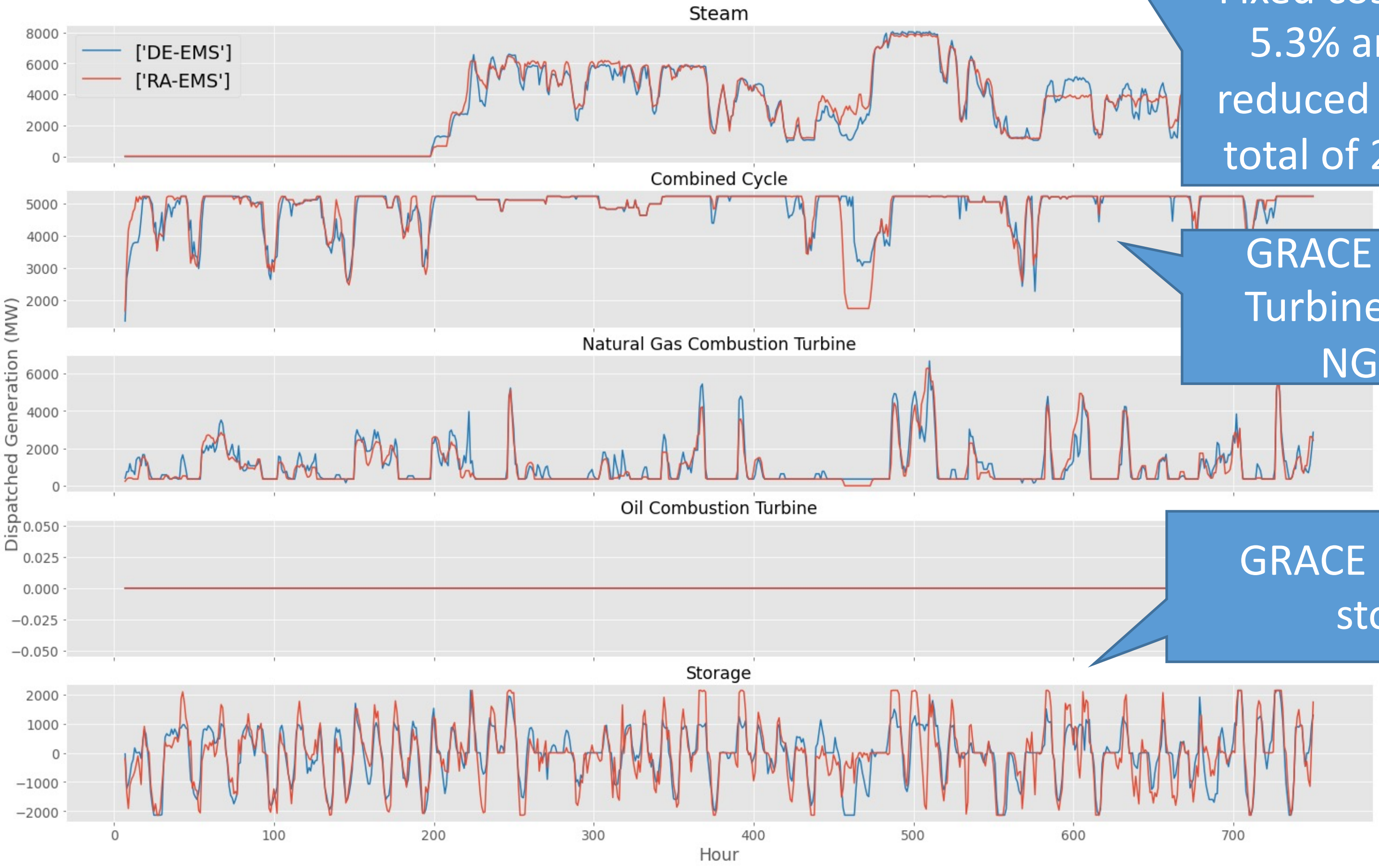


System costs are on average 2% lower than current practice for 2019 fleet

Cost reductions vary from 0% to 5%



Differences in operations

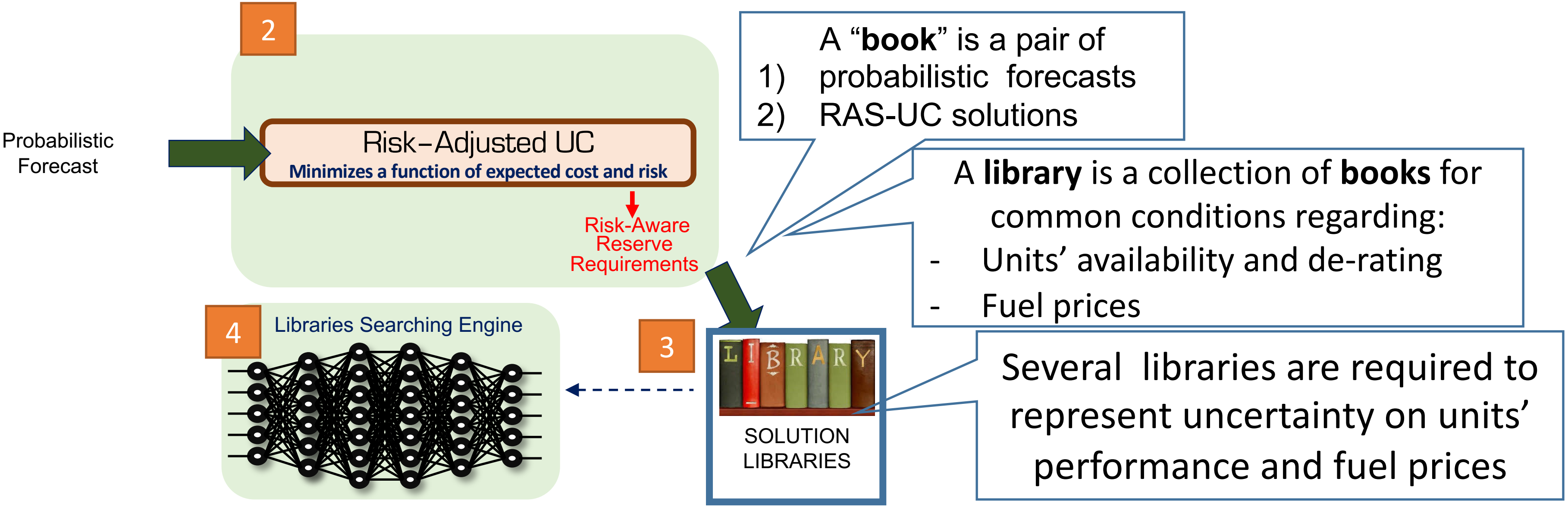


Fixed cost reduced by 5.3% and fuel cost reduced by 1.3% for a total of 2% reduction

GRACE uses Steam Turbines more and NGCTs less

GRACE uses more storage

GRACE's Improved Energy Management System



A "**book**" is a pair of
1) probabilistic forecasts
2) RAS-UC solutions

A **library** is a collection of **books** for common conditions regarding:
- Units' availability and de-rating
- Fuel prices

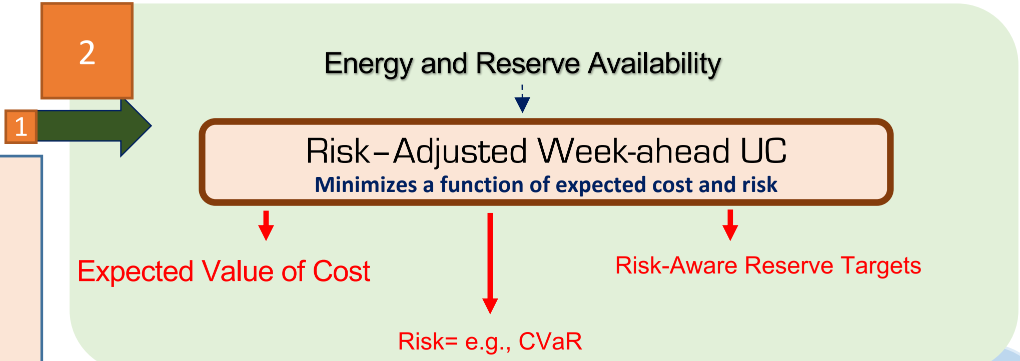
Several libraries are required to represent uncertainty on units' performance and fuel prices

FOUR USES OF THE LIBRARIES & SEARCHING ENGINE

1. To select starting solutions for the RAS-UC
2. To identify scenarios to enforce in the first-stage
3. To identify binary variables to fix and constraints to relax
4. To avoid running the RAS-UC → Extracting Reserve Targets for CP-UC

Learning from solutions libraries

Uncertainty characterization from 1


2

Energy and Reserve Availability

Risk–Adjusted Week-ahead UC

Minimizes a function of expected cost and risk

Expected Value of Cost

Risk= e.g., CVaR

Risk-Aware Reserve Targets

1st stage: No load, start-up and shut-down costs

2nd stage: start-up of peakers, production costs, cost of load shedding

Minimize
(1-β)Expected Cost + βCVaR of Cost

Subject to:

First Stage:
- Start-up/shut-down logic
- Min up/down time
- Pumped-hydro storage constraints

For all units and time periods

Second Stage:
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- Ramping up/down limits
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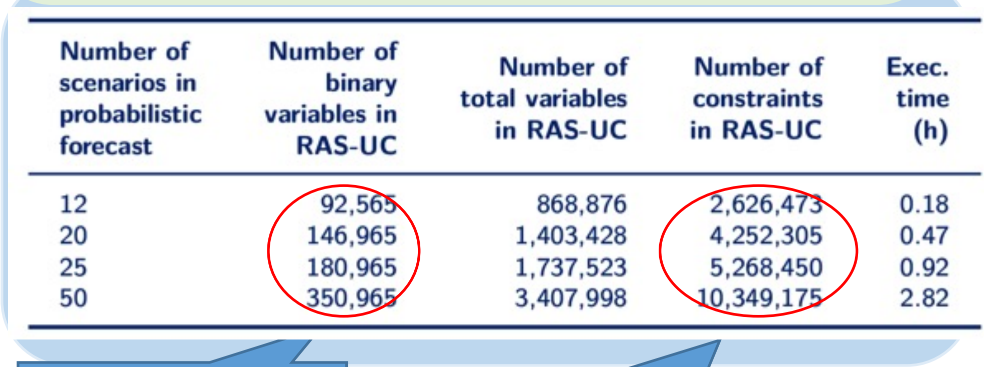
- VRE curtailment limits
- Unserved demand limits
- (CVaR constraints)

For all scenarios and time periods



Number of scenarios in probabilistic forecast	Number of binary variables in RAS-UC	Number of total variables in RAS-UC	Number of constraints in RAS-UC	Exec. time (h)
12	92,565	868,876	2,626,473	0.18
20	146,965	1,403,428	4,252,305	0.47
25	180,965	1,737,523	5,268,450	0.92
50	350,965	3,407,998	10,349,175	2.82

Some binary variables are always 1 or zero

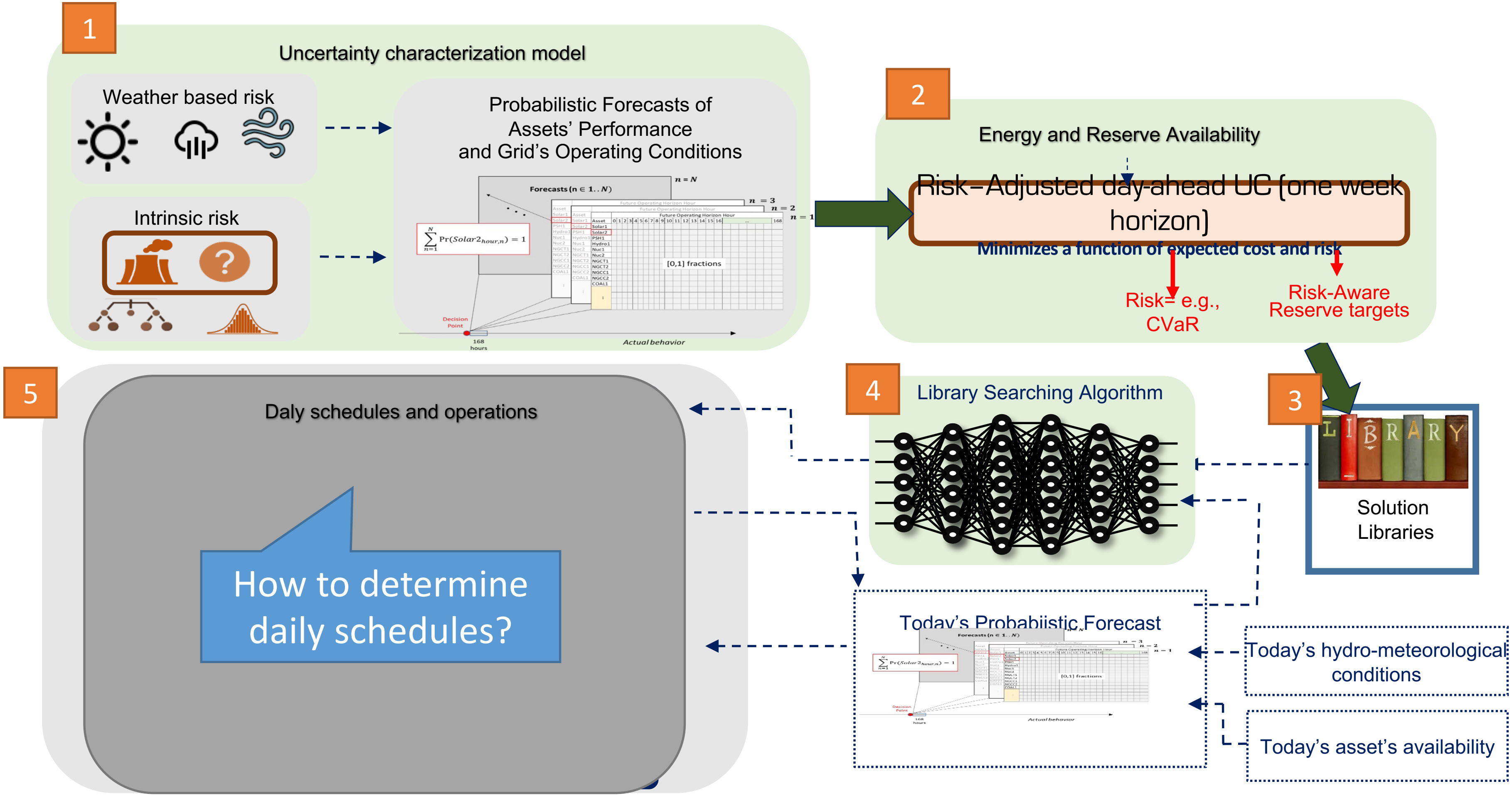
Some constraints are never binding

We could set the commitment variables of those power generators as inputs

Use ML to identify variables and constraints

We could eliminate those constraints

GRACE’s Improved Scheduling and Dispatch System



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Risk= e.g., CVaR

Risk-Aware Reserve targets

3

Solution Libraries

4

Library Searching Algorithm

5

Daly schedules and operations

How to determine daily schedules?

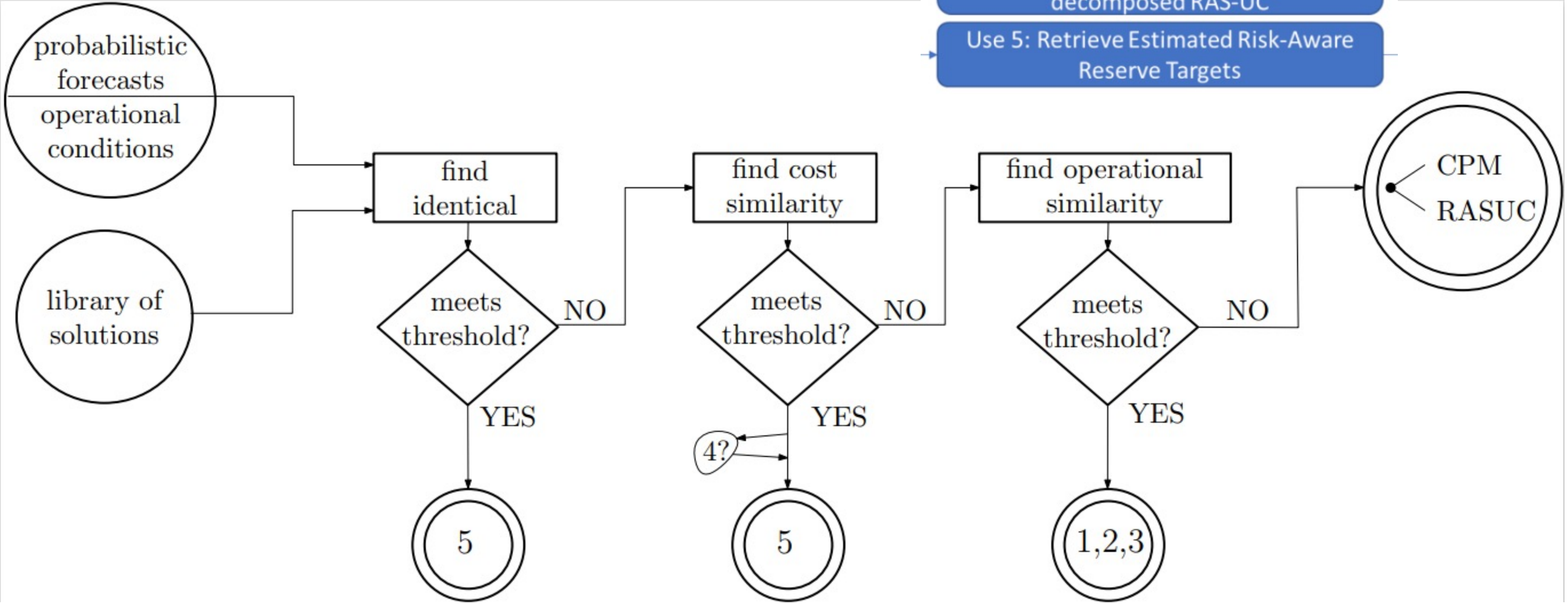
Today’s Probabilistic Forecast

Today’s hydro-meteorological conditions

Today’s asset’s availability

How to use the libraries?

- Use 1: Retrieve RAS-UC initial solution
- Use 2: Determine which RAS-UC binary variables can be eliminated
- Use 3: Determine which RAS-UC constraints can be eliminated
- Use 4: Determine which scenarios must be enforced in the first-stage of a decomposed RAS-UC
- Use 5: Retrieve Estimated Risk-Aware Reserve Targets



Conclusions

GRACE

a grid that is risk aware for clean electricity

- GRACE's approach is promising
  - A risk-adjusted stochastic unit commitment plus a look-ahead balancing UC reduce expected value of costs and increase reserves availability
  - We expect better results with the 2030 fleet
- The libraries search system is promising
  - More work needed to develop the four different uses of the libraries of solutions

- We seek collaborators with access to
  - weather measurements & forecasts
  - power-plants operations

Thank you!

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