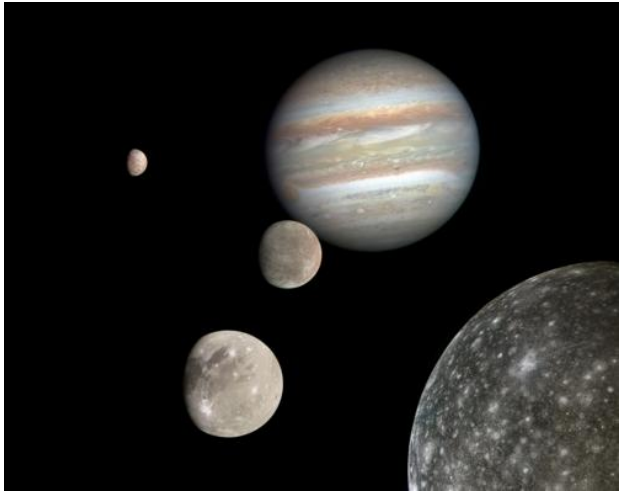




Beyond Jupyter: Energy Modeling with MOSEK



Jens Schulz
COO – Mosek ApS

Jupyter and marimo in numbers

JUPYTER

- ~10 million notebooks on GitHub by 2021
- Growth numbers:
 - 2011: First IPython Notebook released.
 - 2014: Project Jupyter created.
 - 2015: 200k on GitHub
 - 2018: 2.5M on GitHub
 - 2021: ~10M on GitHub
(source: Wikipedia)
- VS code (July 2026): 106.6M downloads
(July 2022): 40M downloads
second most popular extension!

MARIMO

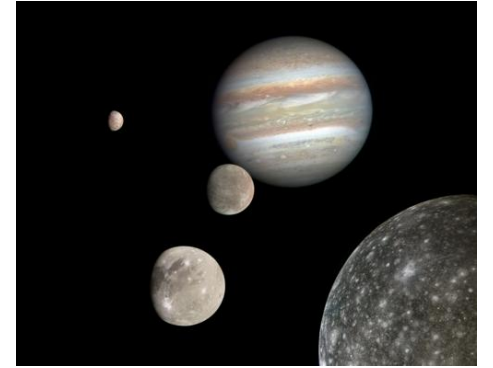
- 10k's of users
- Growth numbers
 - Created in 2023
 - Today: Marimo Github repo has 21k+ stars (exceptionally fast!)
 - 180k+ weekly downloads
- VS code (July 2026): 58k downloads

Jupyter Notebooks - The pain points

- Inconvenient:
 - Change value in a cell -> need to ensure you re-run the correct cells
 - Creates hidden states (internally inconsistent)
- Large JSON files
 - Terrible GIT diffs
 - Cannot execute easily standalone (CI, command line)
 - Limited re-usability (import functions,...)

Advantages of Jupyter

- Huge community
- Many extensions
- Support in virtually every scientific library
- Widespread familiarity in universities
- Frontend interface for cloud users, Amazon Sagemaker Notebook, Google Colab, MS Azure Notebook, GitHub Codespaces
- Interactivity:
 - ipywidgets for interactive components
 - e.g., streamlit for app deployment



Jupyter versus marimo notebooks – A star for optimization use cases

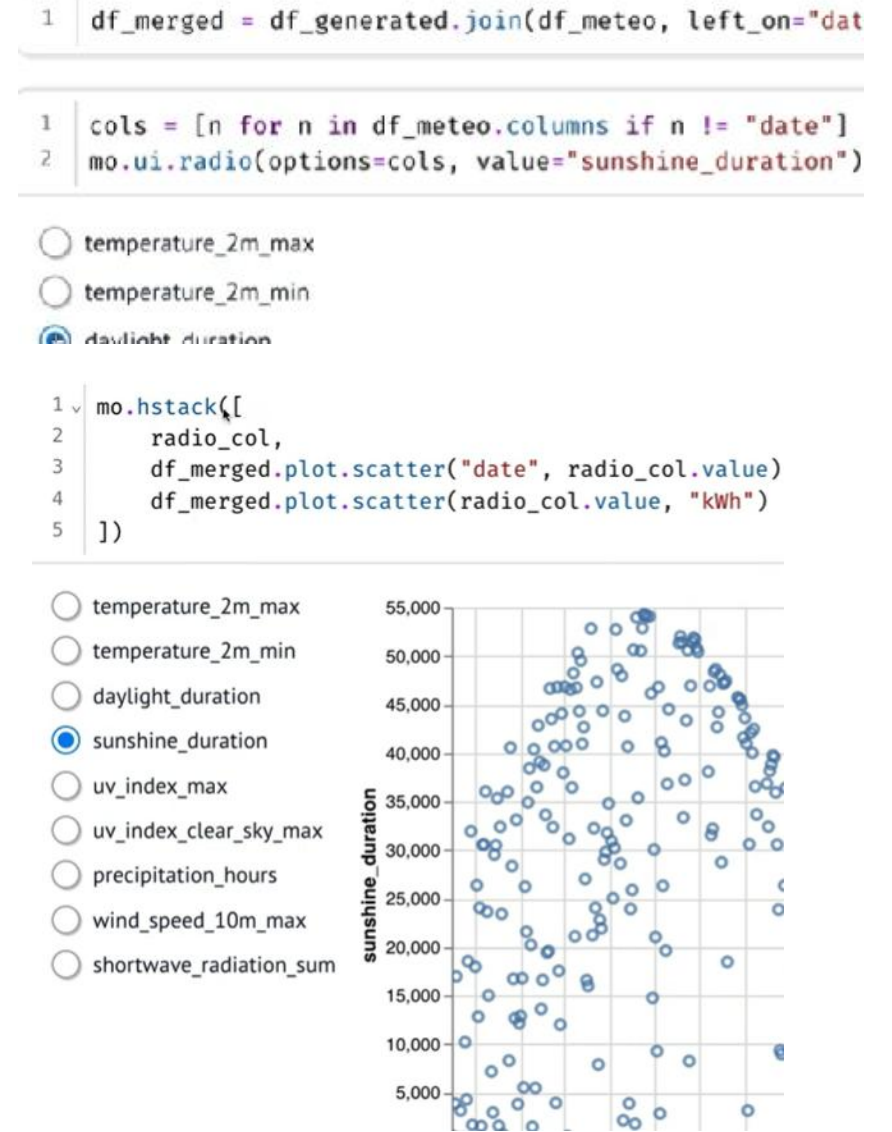
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- Interactivity:
 - ipywidgets for interactive components
 - e.g., streamlit for app deployment

Marimo notebooks

- Halfway between notebook, dashboard, and web app
- Reactive dependency graph
- Reproducible execution
- Stored as Python code
- Clean version control
- Testing of single functions
- Reactive user interfaces
- Deploy as interactive web app w/o additional packages

Advantages of marimo for optimization use cases

- Marimo notebooks are pure Python scripts
 - Run notebooks as if they were scripts
 - Run notebooks as if they were apps
 - Supports CI/CD workflows
 - Easy to integrate with GIT
 - Ability to re-use function definitions
- Reactive Python environment
 - Dependency graph to re-run only dependent cells
- Ability to deploy as web app
 - Mix UI elements with code
 - No Python backend, fully local browser
 - “Pydite” helps to run on WASM
 - Partly limited, not all Python packages
- Allows to: “re-think the way we are working with data”



Main concepts

- App:
 - Instantiates the marimo application, serving as the container for all reactive cells and their dependency graph
- Cells:
 - Implement reactive computations that automatically update when their dependencies change
- Setup cells:
 - Executed once to define imports, constants, and configuration shared across the notebook
- Functions:
 - Encapsulate reusable Python logic
 - Easy to test

- At top of marimo notebook write:

```
import marimo
app = marimo.App()
```

- `@app.cell()`
`def _(dependencies):`
 your code
 return *values for other cells*

- Setup cells:
with `app.setup:`
 import xyz
 global values

- `@app.function`
`def compute():`
 x = 2
 y = 3
 return x + y

Testing / Continuous Integration: marimo apps support pytest

- Define “test_” functions within app cells
- Use assert condition based on specific values in notebook; or call a function from this marimo app
- Run “pytest solar_battery.py”

Callstack of pytest

- import solar_battery.py
↓
marimo builds notebook
(register app cells)
↓
marimo executes required cells
(test_* dependency graph)
↓
pytest executes test_* functions

Example:

- `@app.function`
`def test_compute():`
 `print("Testing compute function...")`
 `assert compute() == 5`

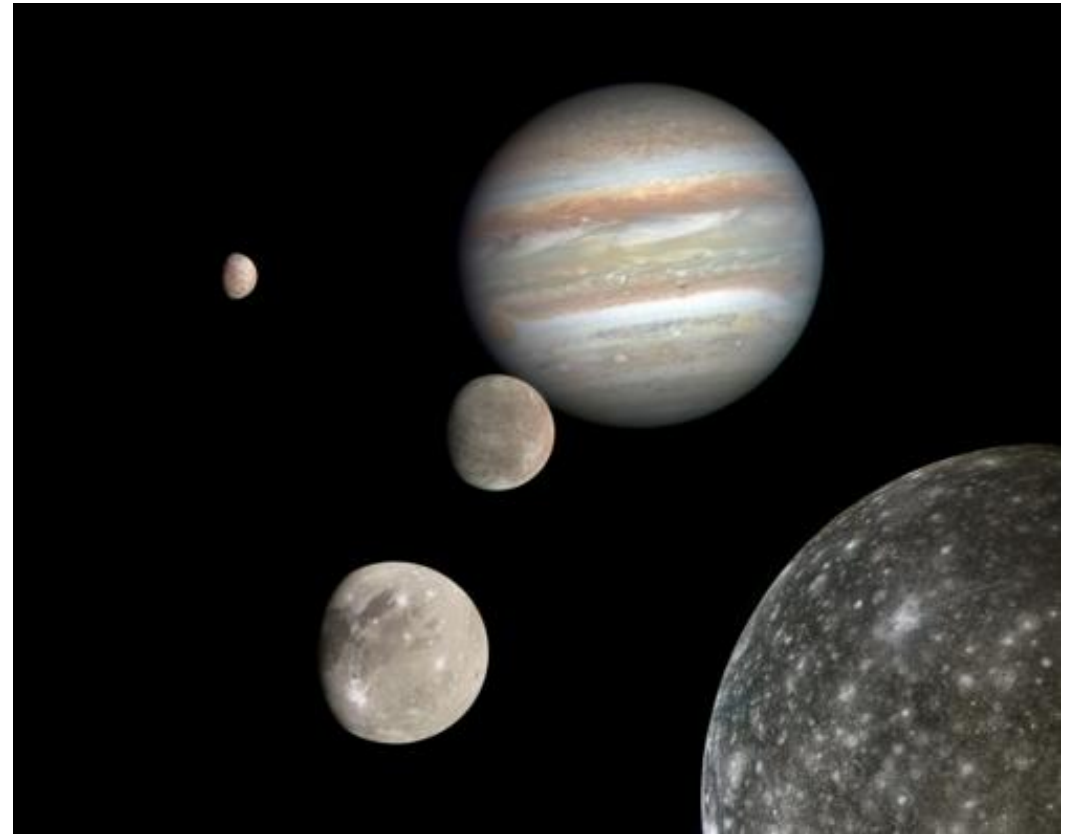
- Command line:
 Pytest solar_battery.py

Learnings along the way

- **Avoid Variable/Function Redefinition Errors**
 - Currently, marimo is too conservative!
- Make Functions Reusable/Exportable via “Reusable Cells” = app functions
- Separation of concerns
 - Business logic (load data, solve, generate solution, etc.)
 - app functions
 - unit/smoke tested with pytest
 - Marimo UI
 - Reactive cells
 - manually verified or tested with browser automation if desired.
E.g., playwright library to test that app starts, widgets exist, optimization completes
 - test that app starts successfully (`marimo run xxx.py`)

Beyond Jupyter: Marimo notebooks

- Marimo in early stage v0.23.x
- Promising to cover optimization use cases
- Pure Python:
 - Much better for version control
 - Fulfills CI and testing requirements
- Reactive components that avoid hidden states



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GOR

PMO111

Optimization in the era of Generative AI

ENERGY OPTIMIZATION

- Unit Commitment
- Economic Dispatch
- Energy Storage
- Grid Optimization

PORTFOLIO OPTIMIZATION

- Mean-Variance Optimization
- Risk Management
- Asset Allocation
- Trust Optimization

How can I help you optimize your energy system or investment portfolio?

Optimize energy system minimizing cost and emissions while balancing supply and demand.

Optimize portfolio to maximize return for a given level of risk.

OPTIMIZATION MODEL

Objective: Maximize return / Minimize cost

Subject to:

- Resource limits
- Risk tolerance
- Demand balance

$$\min c^T x$$
$$\text{s.t. } Ax \leq b, x \geq 0$$

You: Find the optimal solution with lower risk and include renewable energy.

Munich, Germany
November 26 & 27 2026
Hosted by Flix SE

Source: AI-generated image

PMO112

Shaping the Mobility of the Future: A Mathematical Optimization Perspective

Ingolstadt, Germany
March 11 & 12, 2027

Organized with TH Ingolstadt

Source: <https://unsplash.com/de/fotos/luftaufnahmen-von-betonstrassen-7nrsVjvALnA>

<https://www.gor-ev.de/arbeitsgruppen/praxis-der-mathematischen-optimierung>

Jupyter Notebook- inconsistent (hidden) state

▶ ▼ 1 x = 3 [1]	▶ ▼ 1 x = 3 [2] ✓ 0.0s
▶ ▼ 1 y = 3 2 print(x+y) [2]	▶ ▼ 1 y = 4 2 print(x+y) [5] ✓ 0.0s
... 6	... 7
[3] 1 z = x + y 2 print(z) 3	[4] ✓ 0.0s 1 z = x + y 2 print(z) 3
... 6	... 6

Marimo – reactive execution model
dependency graph will execute dependent cells

▶ 1 x = 3 ✓ 0.0s
▶ 1 y = 4 2 print(x+y) ✓ 0.0s
... 7
1 print(x) ✓ 0.0s
... 3
1 z=x+y 2 print(z) ✓ 0.0s
... 7



```
1 def compute():
2     x = 3
3     y = 5
4     return x + y
```

✓ 0.0s [e] compute

```
1 z = compute()
2 print(f"z: {z}")
```

✓ 0.0s

... z: 8

```
1 def test_compute():
2     print("Testing compute function...")
3     assert compute() == 8
```

✓ 0.0s [e] test_compute

```
(.venv) PS C:\Users\jenss\gitprojects\ifors-energy> pytest .\B_compute_test.py
```

```
===== test session starts =====
```

```
platform win32 -- Python 3.13.12, pytest-9.1.1, pluggy-1.6.0
```

```
rootdir: C:\Users\jenss\gitprojects\ifors-energy
```

```
plugins: anyio-4.14.1
```

```
collected 1 item
```

```
B_compute_test.py .
```

[100%]

```
===== 1 passed in 0.88s =====
```

```

1 def compute():
2     x = 3
3     y = 5
4     return x + y

```

✓ 0.0s [⌂] compute

```

1 z = compute()
2 print(f"z: {z}")

```

✓ 0.0s

... z: 8

```

1 def test_compute():
2     print("Testing compute function...")
3     assert compute() == 8

```

✓ 0.0s [⌂] test_compute

```
import marimo
```

```
__generated_with = "0.23.9"
```

```
Open as notebook
```

```
app = marimo.App()
```

```
@app.function
```

```
def compute():
```

```
    x = 3
```

```
    y = 5
```

```
    return x + y
```

```
@app.cell
```

```
def _():
```

```
    z = compute()
```

```
    print(f"z: {z}")
```

```
    return
```

```
@app.function
```

```
def test_compute():
```

```
    print("Testing compute function...")
```

```
    assert compute() == 8
```

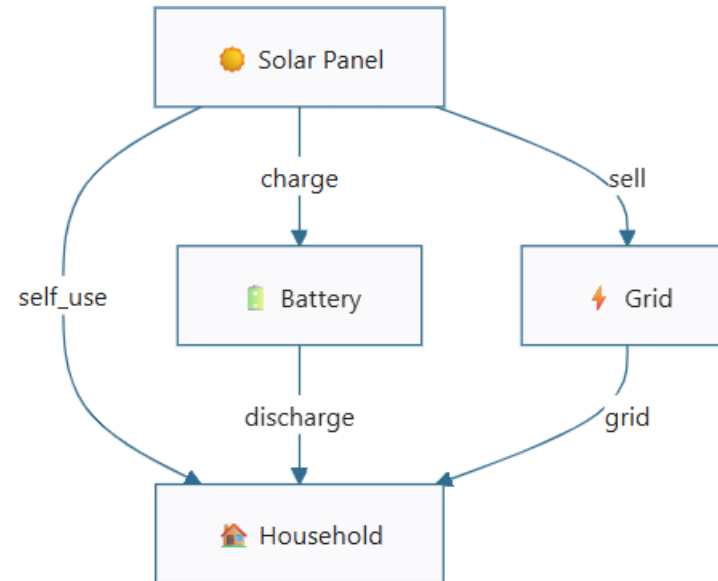
Import and use functions from other notebooks

```
1 from B_compute_test import compute
```

```
1 print(compute())
```

Household - Solar Energy Optimization with Battery

Optimizing the operation of a battery attached to a solar PV installation over a certain time horizon, e.g., 24-hours.



Input Data / Parameters

```
\begin{aligned}
&\text{PV generation:} \quad g_t \\
&\text{Household demand:} \quad d_t \\
&\text{Selling price:} \quad p_t^{sell} \\
&\text{Grid purchase price:} \quad p_t^{grid} \\
&\text{Initial battery state of charge:} \quad E_0 \\
&\text{Battery capacity:} \quad E_{max} \\
&\text{Charging/discharging efficiency:} \quad \eta_c, \eta_d
\end{aligned}
```

Model : Variables, Objective and Constraints

Maximize profit: gain for sold energy less cost to grid

$$\max \sum_{t=1}^T (p_t^{sell} \text{sell}_t - p_t^{grid} \text{grid}_t)$$

Subject to:

Demand balance: my demand can be fulfilled from grid, pv production or battery

$$\text{selfuse}_t + \text{discharge}_t + \text{grid}_t = d_t, \forall t$$

PV allocation: hourly solar energy produced is either used, sold or charged

$$\text{selfuse}_t + \text{sell}_t + \text{charge}_t = pv_t, \forall t$$

Battery dynamics: Charging and discharging a battery following standard model with round trip efficiency

$$\text{SoC}_{t+1} = \text{SoC}_t + \eta_c P_t^{\text{charge}} - \frac{1}{\eta_d} P_t^{\text{discharge}}, \quad \forall t = 1, \dots, T-1$$

Battery initial state:

$$\text{SoC}_1 = E_0$$

Battery capacity:

$$0 \leq \text{SoC}_t \leq E_{max} \quad \forall t$$

Input Data / Parameters

PV generation: g_t

Household demand: d_t

Selling price: p_t^{sell}

Grid purchase price: p_t^{grid}

Initial battery state of charge: E_0

Battery capacity: E_{max}

Model : Variables, Objective and Constraints

Maximize profit: gain for sold energy less cost to grid

$$\max \sum_{t=1}^T (p_t^{sell} \text{sell}_t - p_t^{grid} \text{grid}_t)$$

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Battery initial state:

$$\text{SoC}_1 = E_0$$

Battery capacity:

$$0 \leq \text{SoC}_t \leq E_{max} \quad \forall t$$

Mathematical Model in Python

```
1 M = mf.Model("HouseholdEnergy")
2 #M.setSolverParam("cacheLicense", "off")
3
4 # Decision Variables:
5 self_use = M.variable("self_use", n, mf.Domain.greaterThan(0.0))
6 sell = M.variable("sell", n, mf.Domain.greaterThan(0.0))
7 charge = M.variable("charge", n, mf.Domain.greaterThan(0.0))
8 discharge = M.variable("discharge", n, mf.Domain.greaterThan(0.0))
9 grid = M.variable("grid", n, mf.Domain.greaterThan(0.0))
10
11 soc = M.variable("soc", n, mf.Domain.inRange(0.0, battery_capacity))
```

PV allocation: hourly solar energy produced is either used, sold or charged

$$self_use_t + sell_t + charge_t = pv_t, \forall t$$

```
1 # PV allocation: hourly solar energy produced is either used, sold or charged
2 cons_pv = M.constraint(
3     ...mf.Expr.add([self_use, sell, charge]),
4     ...mf.Domain.equalsTo(pv.tolist()),
5 )
```

Household - Solar Energy Optimization with Battery

Optimizing the operation of a battery attached to a solar PV installation over a certain time horizon, e.g., 24-hours.

Data Input:

toy

Verbosity Threshold ($\leq$)

Pick demand file

Pick solar production file

Battery Capacity (kWh)

Initial State of Charge (kWh)

Hour

Demand at 0	Solar production at 0	Battery start state at 0		
0.4 kWh	0.0 kWh	2.0 kWh		
Grid Purchase	PV Sold	Battery Charge	Battery Discharge	
-0.0 kWh	0.0 kWh	0.0 kWh	0.4 kWh	

