OFFICE in Larnaca

ICT IN BUILDING DESIGN

Master Degree in ICT4SS
A.Y. 2024 - 2025

Team Members:
Arezou Shadkam
S.Kiyana M.Sabet
Ali Abdollahzadeh
M.Mahdi Azizian

Professors:
Giacomo Chiesa
Lorenzo Bottaccioli

Politecnico di Torino

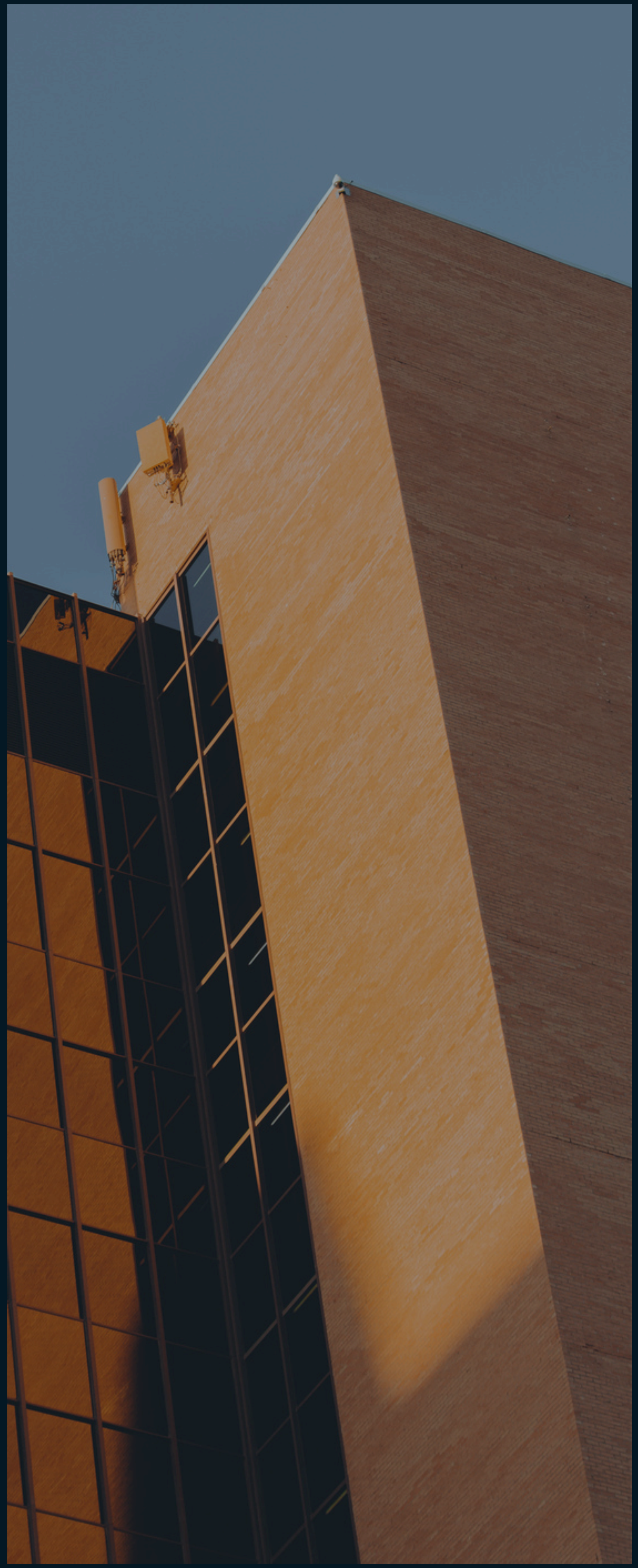
INTRODUCTION

The Challenge

- Building sector consumes over one-third of global final energy.
- Traditional simulations are time-consuming and computationally intensive.
- Difficult to explore and optimize thousands of design options.

Our Approach

- ICT-Driven Workflow: Integrated simulation with machine learning.
- Used Deep Neural Network (DNN) surrogate models to rapidly predict energy use.
- Achieved fast multi-objective optimization to find an energy-optimal design.

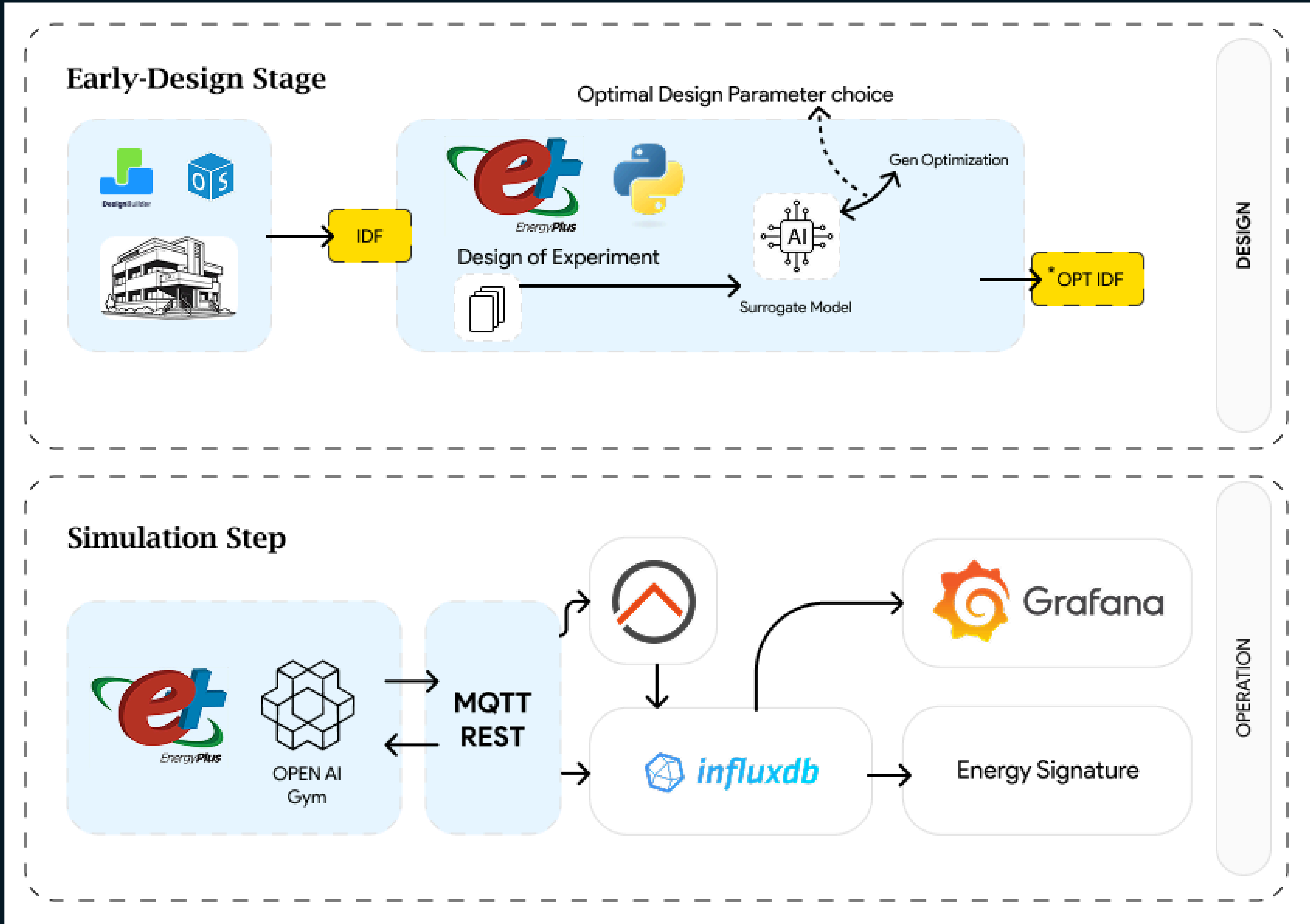


Objectives

What we aimed to achieve through ICT integration

1. **Design & Optimization**
   Optimize an office building model for maximum energy efficiency.
2. **Simulation Acceleration**
   Reduce simulation cost and time using surrogate models.
3. **Real-Time Analysis**
   Convert the final optimized design into a FMU for dynamic co-simulation.
4. **Monitoring Pipeline**
   Build a full data pipeline: MQTT → InfluxDB → Grafana for live monitoring.
5. **Performance Assessment**
   Analyze building performance trends using energy signature modeling.

Project Workflow



TOOLS & TECHNOLOGIES

🐳 **Docker**- Full containerized environment

Design & Simulation

🧱 **EnergyPlus**
Building energy simulation

🐍 **Eppy / BESOS**
Python libraries to automate IDF edits

🧪 **EnergyPlusToFMU**
Export building model as FMU

Machine Learning & Optimization

🤖 **TensorFlow / Keras**
Deep Neural Network (DNN)

📈 **Scikit-learn**
GP, MLP models

🧬 **PyGMO**
NSGA-II multi-objective optimization

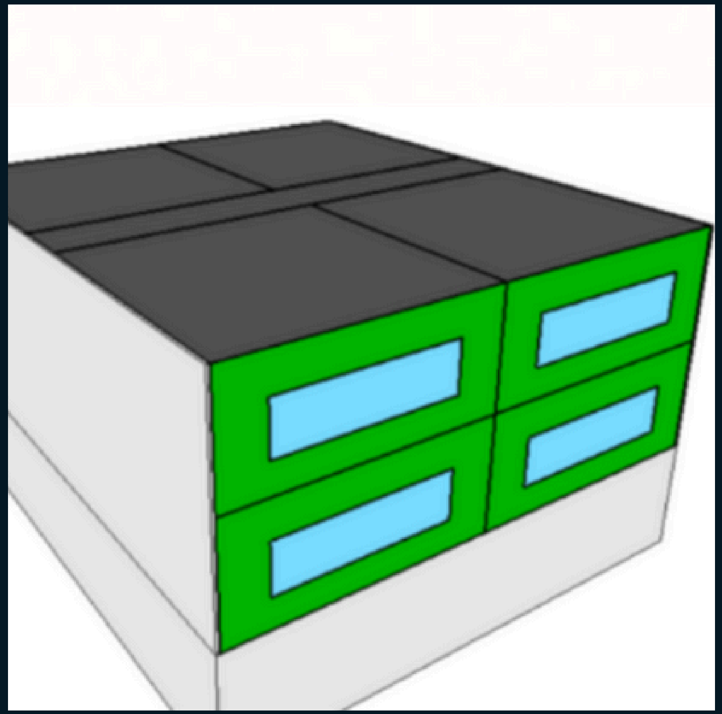
Data Streaming & Visualization

🔄 **MQTT**
Publish/subscribe messaging

📦 **InfluxDB**
Time series data storage

📊 **Grafana**
Real-time dashboards

BUILDING MODEL



Base Model: Office

- Represents an 8-zone office block with standard geometry
- Contains zones for workspaces, corridors

Climate & Location

- Simulated in Larnaca, Cyprus
- Hot summer Mediterranean climate (Csa)

SIMULATION RESULTS

30 Design Variants Simulated

- Each with a different combination of design parameters
- Simulated using EnergyPlus

Design parameters:

- Wall Insulation Thickness
- Roof Insulation Thickness
- Window Glazing Type
- Ventilation Rate (ACH)
- RadShadingRange
- TempShadingRange

Optimization objectives:

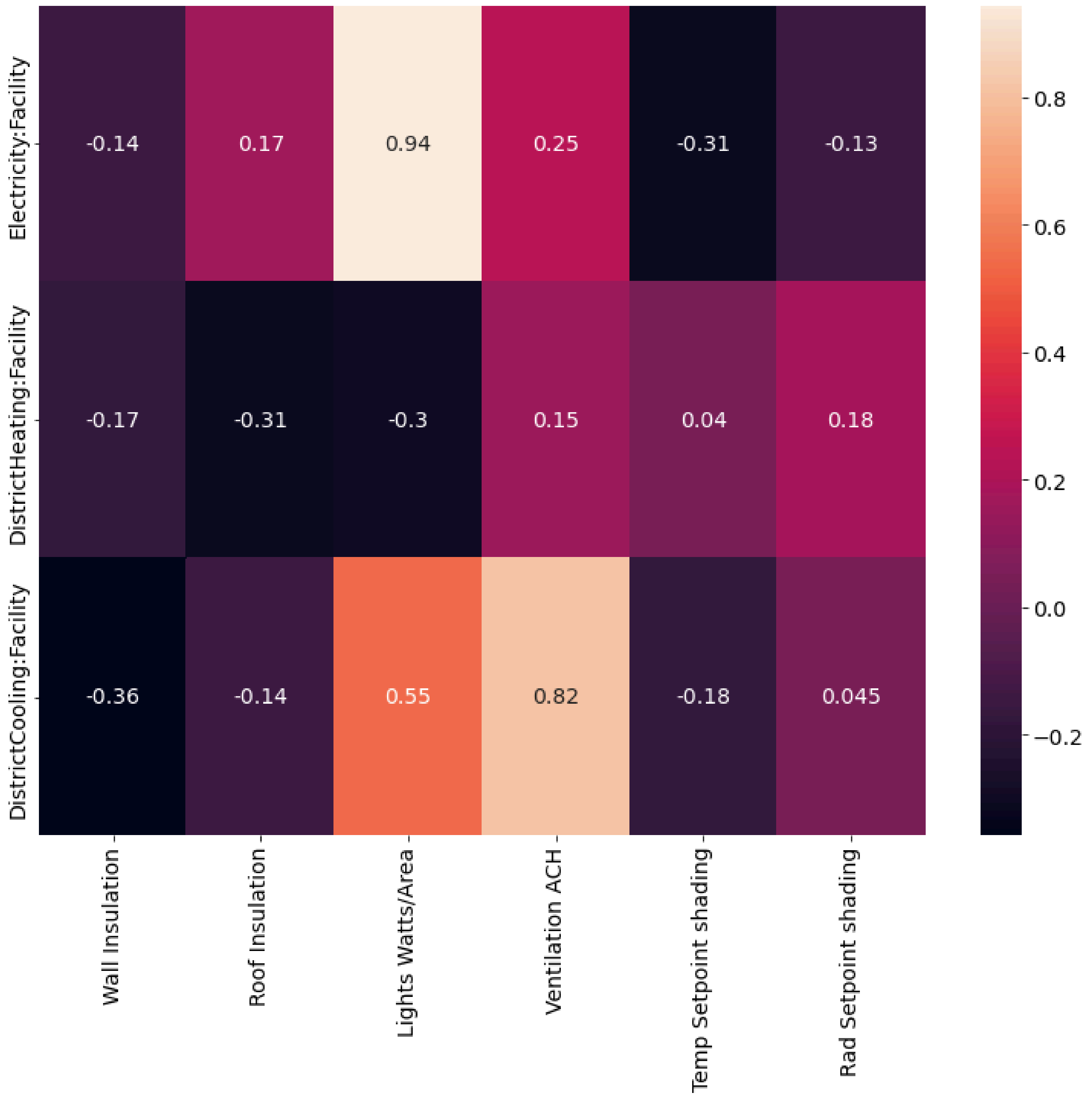
Electricity | **Heating** | **Cooling**

SIMULATION RESULTS

Calculated Pearson correlation coefficients between each design parameter and the three energy outputs.

- Lighting Power Density → strong positive correlation with electricity consumption
- Wall Insulation → weak correlation with cooling demand

This analysis reveals which design choices have the strongest impact on energy use, guiding both optimization and model training.



SURROGATE MODEL SELECTION

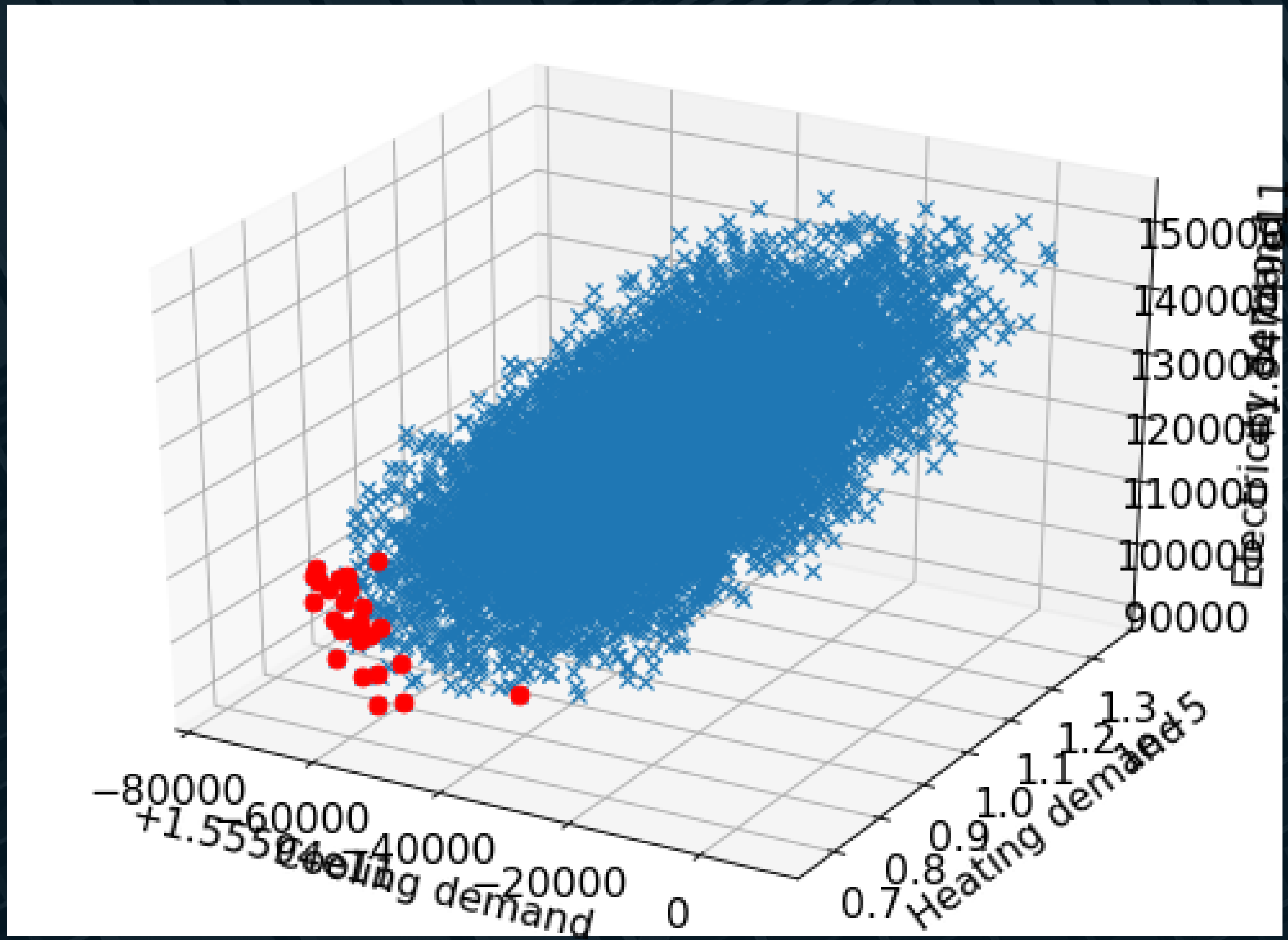
EnergyPlus simulations are slow for large design spaces
Surrogate models give fast energy predictions once trained

Models Tested:
GP (Gaussian Process)
MLP (Multi-layer Perceptron)
DNN (Deep Neural Network)

Outcome:
DNN performed best → lowest RMSE for electricity & cooling
GP was unstable, especially for low-variance heating data
MLP underperformed on nonlinear relationships

Best Model: Deep Neural Network (DNN)
Electricity RMSE: ~3.5%
Cooling RMSE: ~3.9%
Heating: Very low demand → harder to model accurately

OPTIMIZATION WITH NSGA-II



How We Used It:

- Used a trained DNN as a fast surrogate model
- Evaluated 500 new building design configurations
- Optimized for Electricity, Heating, and Cooling simultaneously

Why NSGA-II?

- Multi-objective algorithm — perfect for balancing trade-offs
- Finds a set of pareto optimal solution
- Not just one answer, but a range of “best trade-offs”

Result:

- Generated a diverse Pareto front of high-performing solutions
- Selected the design with the lowest total energy use and best overall balance

OPTIMAL DESIGN

Parameter	Selected Value
Wall Insulation	0.49 m
Roof Insulation	0.67 m
Glazing Type	Triple
Lighting Power Density	8.6 W/m²
Ventilation Rate	0.27 ACH
Temp Setpoint shading	27.84 °C
Rad Setpoint shading	120.4

Performance Outcome:
Electricity ↓, Cooling ↓, Heating very low
Outperforms most baseline designs

IDF TO FMU CONVERSION

To transform the selected IDF model into an FMU for co-simulation and data streaming.

Key Steps:

- **01** Added sensors to IDF
- **02** Added actuators for control
- **03** Added the program for our sensors
- **04** Added the FUNCTIONALMOCKUPUNITEXPORTs
- **05** Exported model using EnergyPlusToFMU tool

Outcome:
A fully functional FMU ready to be simulated in Python-based environments

CO-SIMULATION & REAL-TIME STREAMING

Simulation Setup

The FMU was simulated using fmi-gym in Python
Included real-time control logic

Data Logging & Streaming

Environmental variables were logged locally to CSV files
Data was also published via MQTT protocol
Streamed into InfluxDB (a time-series database)

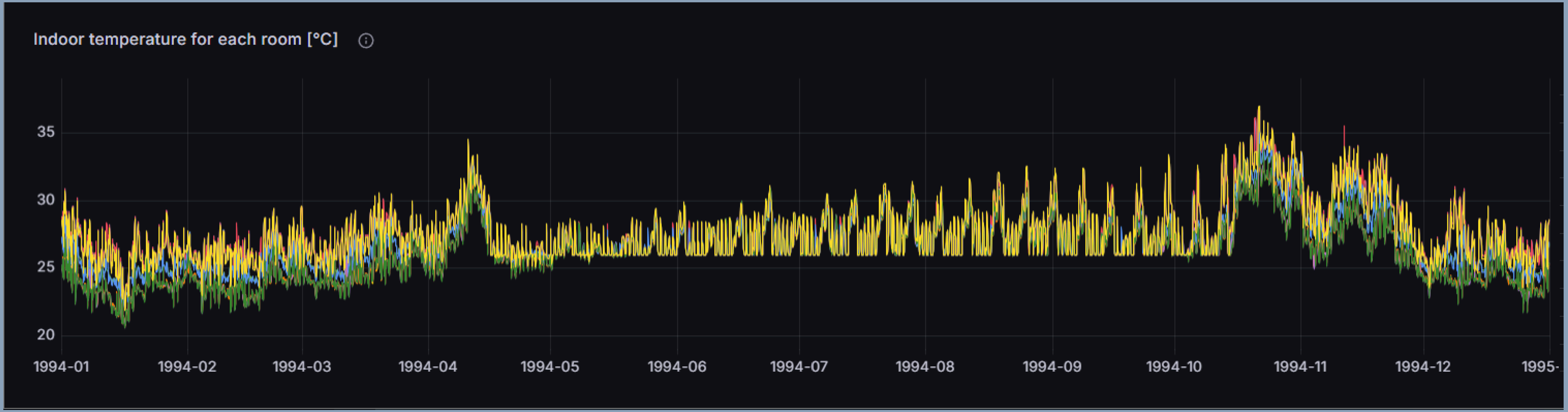
Why This Architecture?

Supports both offline analysis (via CSV) and real-time monitoring (via MQTT + InfluxDB)
Makes the system ready for future feedback control and data-driven decision making

Grafana Dashboards

INDOOR TEMPERATURE PER ROOM

Real-time data streamed via MQTT → InfluxDB → Grafana



Most rooms maintained average temperatures between 26.3°C - 27.6°C

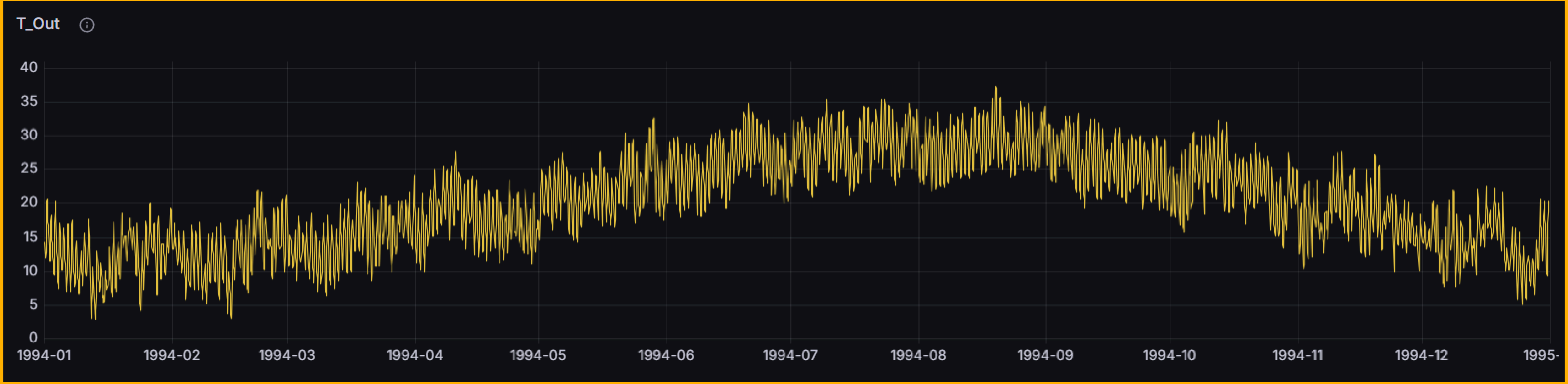
Corridors stayed cooler (~26.9°C), while South-facing offices (e.g., South West Block 1) had slightly higher peaks

Short spikes above 30°C during summer months, but generally well-controlled climate

Grafana Dashboards

OUTDOOR TEMPERATURE

Real-time data streamed via MQTT → InfluxDB → Grafana



Typical Mediterranean climate profile: mild winters, hot dry summers

High fluctuation range during summer days (25°C to 38°C)

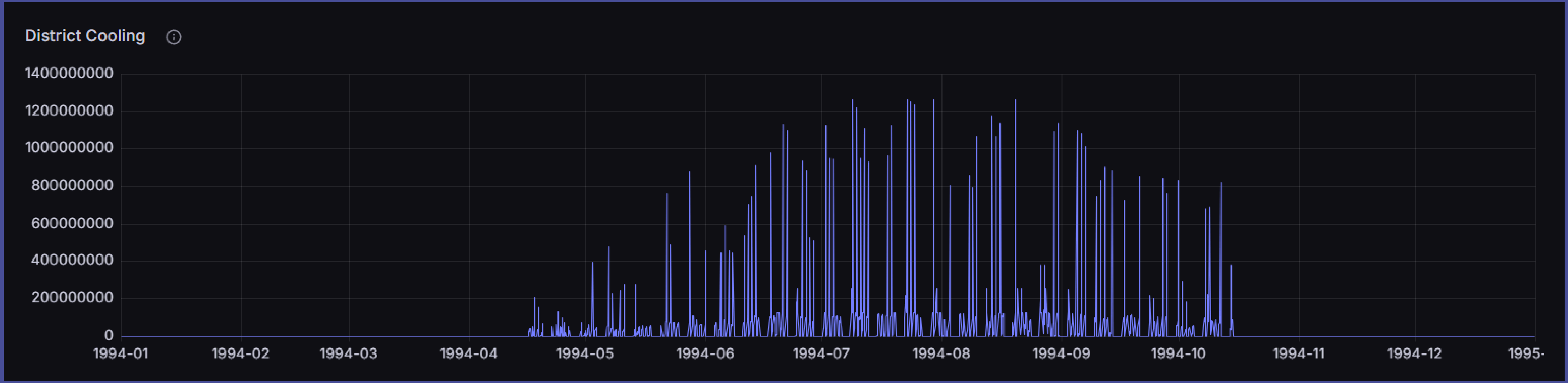
This external condition drives the cooling demand in indoor zones

Peak values exceed 38°C in July and August

Grafana Dashboards

DISTRICT COOLING

Real-time data streamed via MQTT → InfluxDB → Grafana

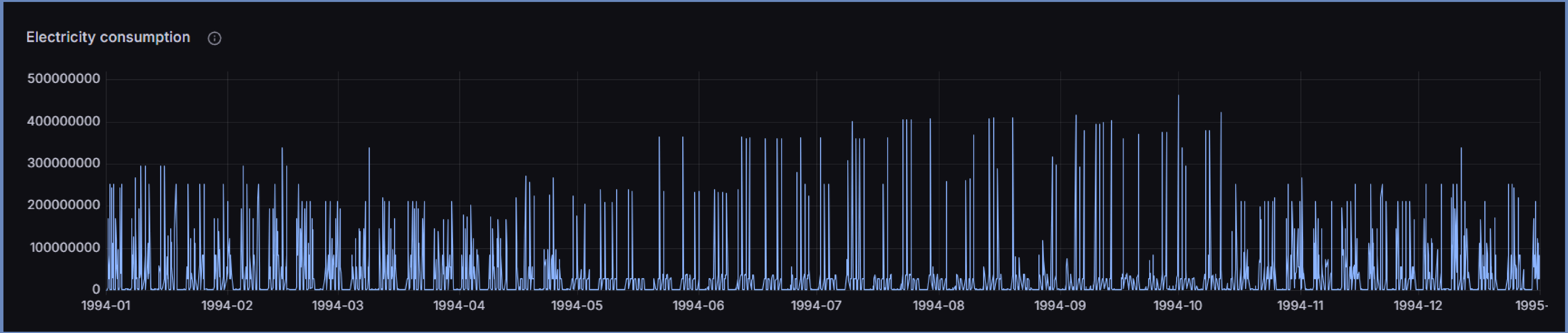


- Zero demand from November to March
- Cooling starts increasing in late spring (April/May)
- Highest demand occurs in July and August, aligned with outdoor temperature and solar radiation
- Sudden drop after October due to milder external conditions

Grafana Dashboards

ELECTRICITY CONSUMPTION

Real-time data streamed via MQTT → InfluxDB → Grafana



Peaks reach up to 50 million J/hour

Winter months (Jan–Mar): lower and more stable electricity use

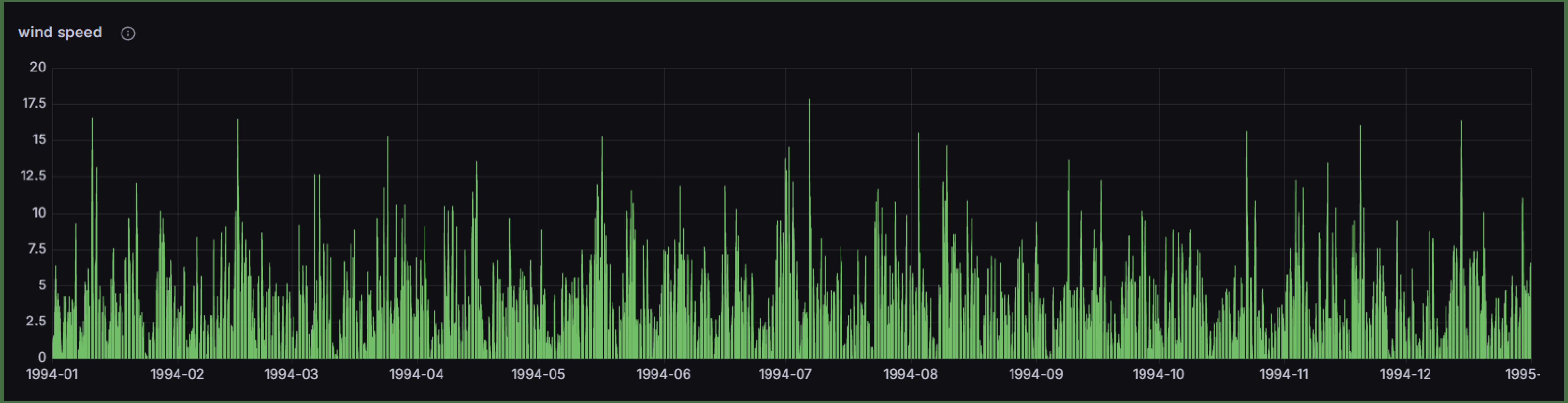
Summer & early autumn (May–Oct): frequent high peaks

These peaks are mainly due to increased cooling and ventilation fan activity

Grafana Dashboards

WIND SPEED

Real-time data streamed via MQTT → InfluxDB → Grafana



Natural ventilation was activated when windows opened based on temperature and airflow thresholds

Wind speed affects air exchange rates between indoor and outdoor zones

Higher wind events enhance passive cooling, especially during shoulder seasons (spring/fall)

Energy Signature

How energy use responds to temperature differences (ΔT) represent Energy behaviour of Building

Hourly insight:

- Sensitive to fast environmental changes

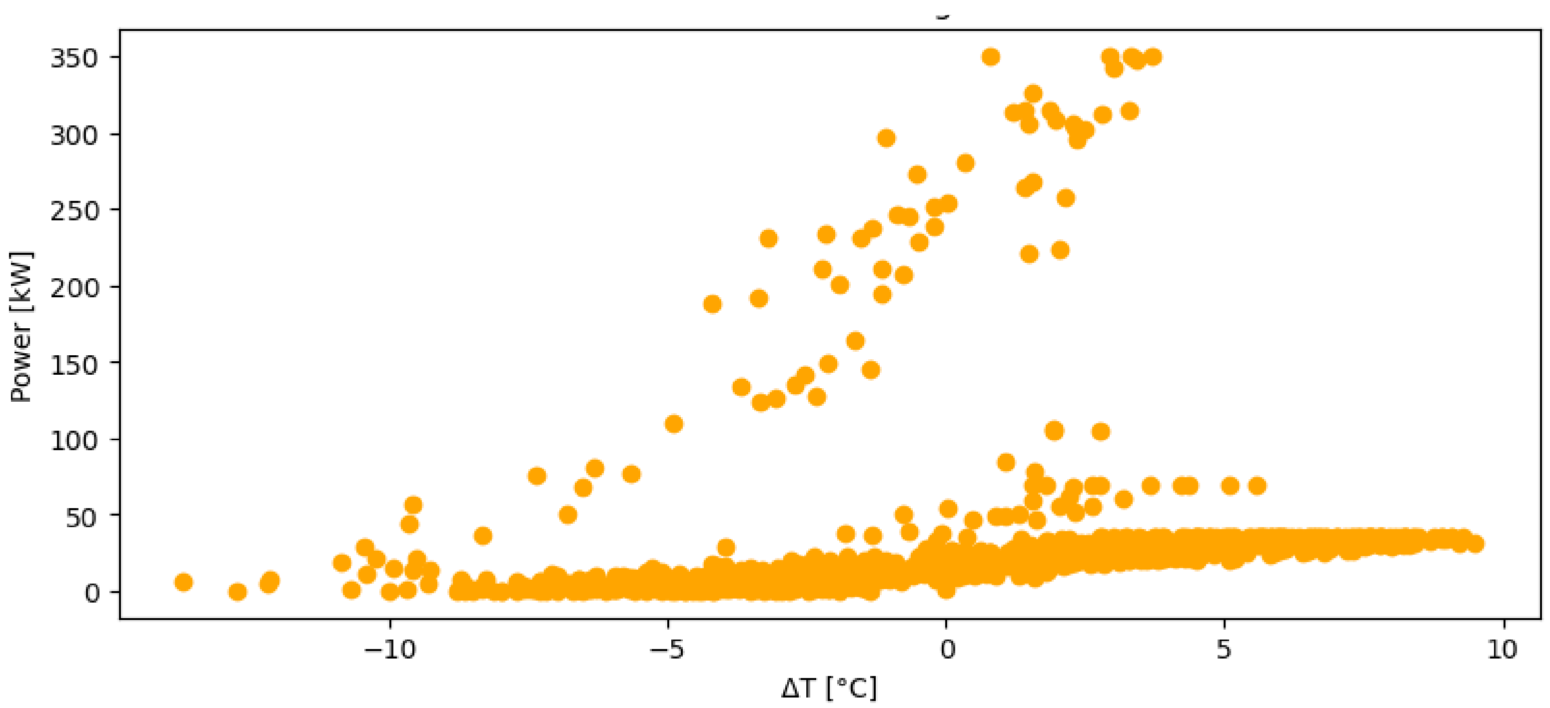
Daily Insight:

- Provides detailed performance trends

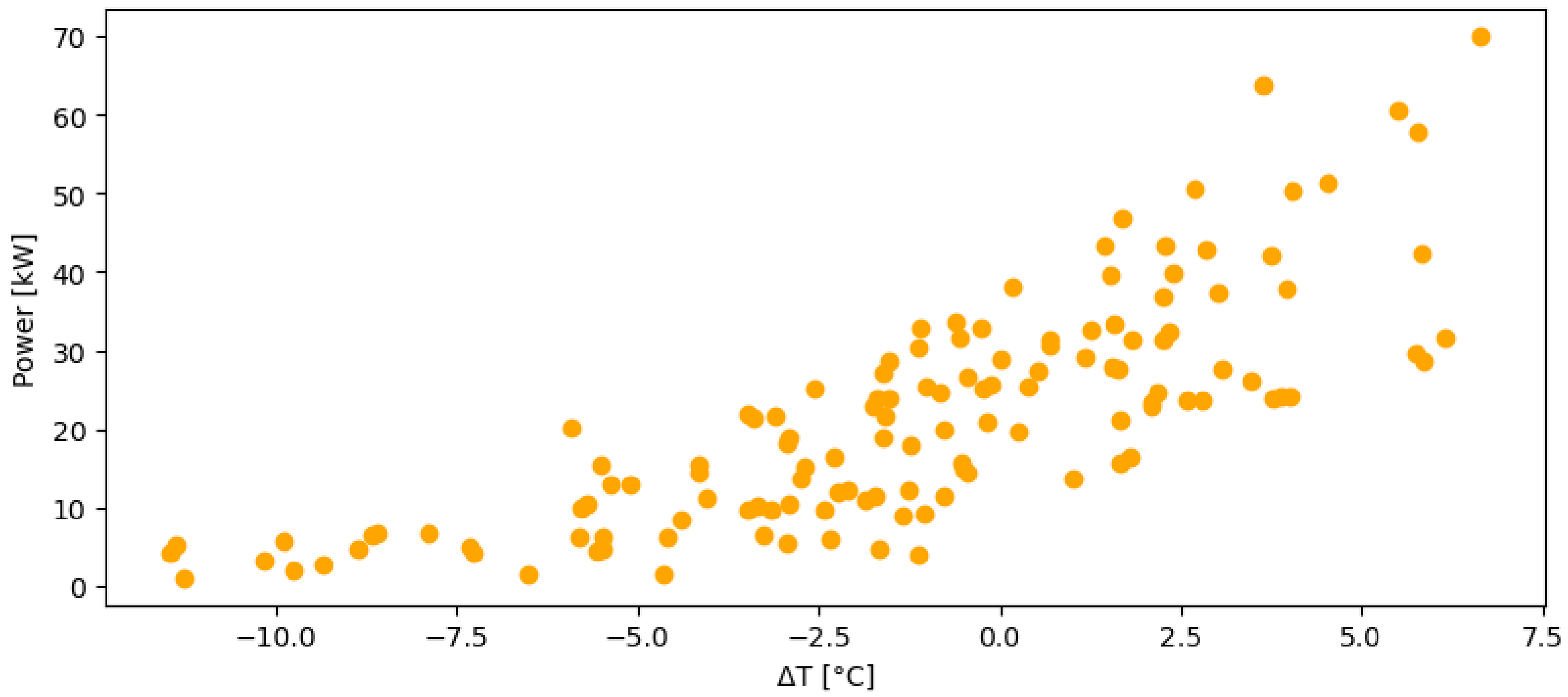
Weekly Insight:

- Gives a stable overview of building behavior
- Best suited for trend analysis and automation logic

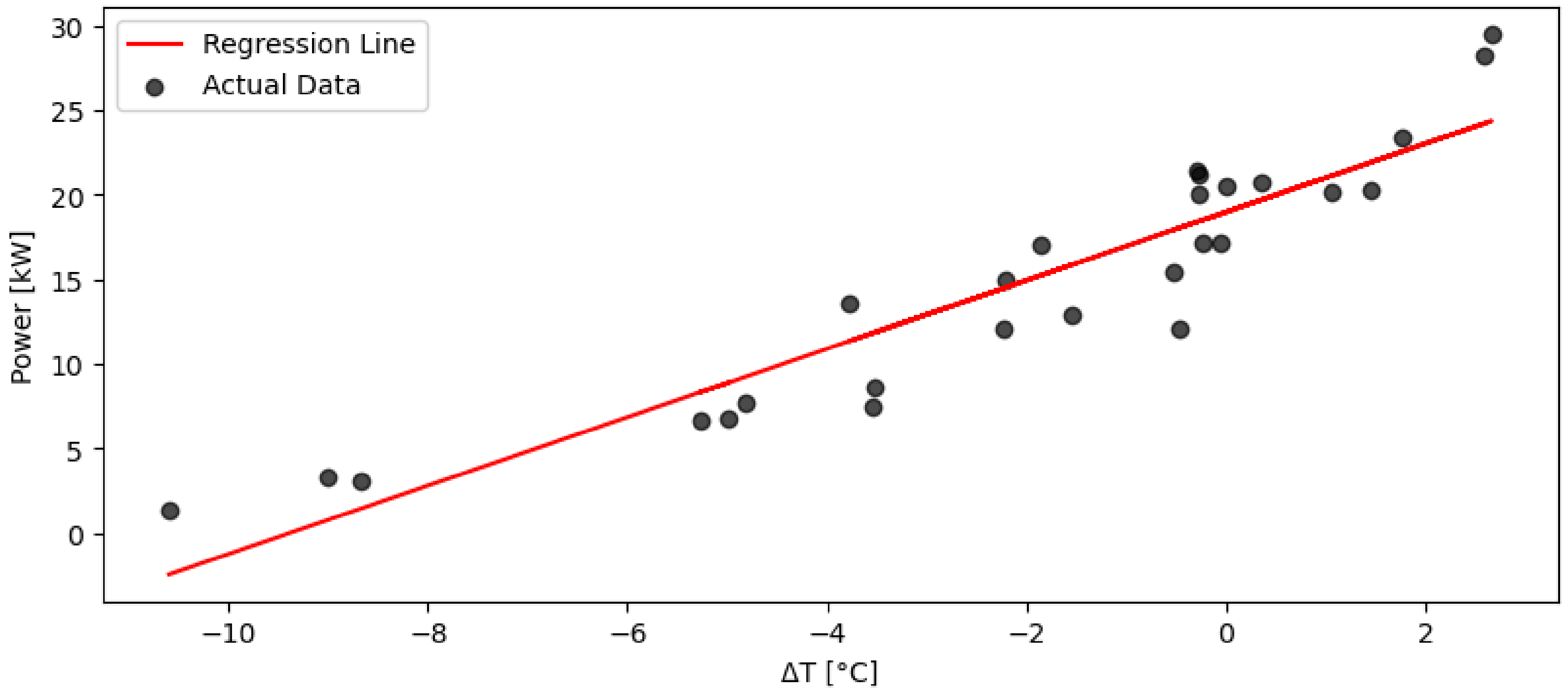
Weekly regression: R^2 = 0.86, stable trend



Hourly



Daily



weekly

Conclusion

- Design & Optimization
  - Achieved an optimal building design.
  - Used multi-objective optimization.

- Core Methodology
  - Deployed DNN surrogate models.
  - Accelerated the design evaluation process.
  - Created a Functional Mock-up Unit (FMU) for co-simulation.

- Analysis & Impact
  - Visualized real-time performance data.
  - Quantified the building's energy signature.

Politecnico di Torino

Thanks for your attention

Any Questions?