# A Framework for Strategy Selection of Atomic Entities in the Holonic Smart Grid

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# Presenter Introduction

**Alexander Wallis, M.Sc.**

- *since 2018:* Research Assistant of Sascha Hauke
  Research: Machine Learning for Smart Grids.
- *2016-2018:* Software Developer for BMW Group and MENTZ GmbH.
- *2008-2016:* B.Sc and M.Sc. in Computer Science at UAS Landshut.

**University of Applied Sciences Landshut**

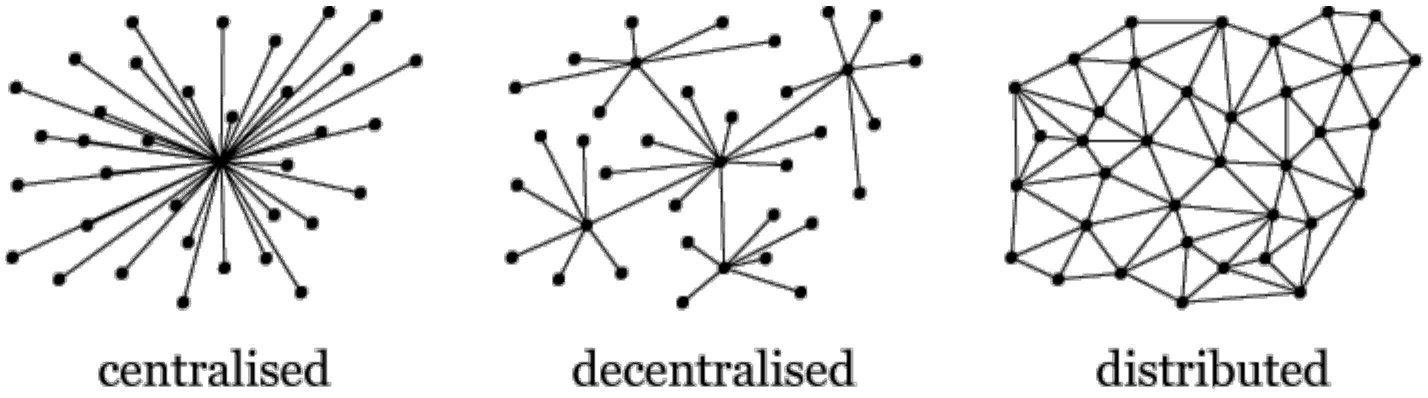
# Energy Research at UAS Landshut


- **Energy Technology Centre (TZE)**
  - Located in Ruhstorf a.d. Rott, BY
  - ~25 Employees
  - ~13 Projects parallel
  - Main research areas:
    - Energy Storage
    - Energy Systems
    - Energy Efficiency
    - Smart Grids

www.haw-landshut.de/kooperationen/technologiezentren/energie-tz-energie.html

# Motivation

- Electrical grids are evolving from **centrally managed** critical infrastructure to **distributedly managed** Smart Grids.
- This is driven by the need to incorporate local production capabilities of **renewable energy resources**.




Source: 1983~enwiki, https://commons.wikimedia.org/wiki/File:Centralised-decentralised-distributed.png, CC-BY-SA-3.0

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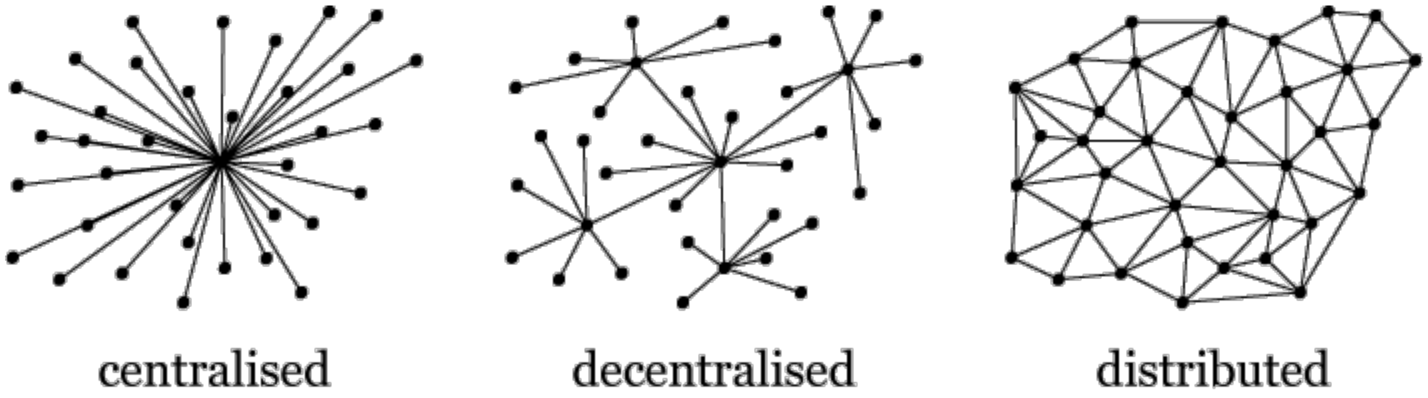


- **Problem:** This paradigm shift leads to a considerable increase in the complexity of network management tasks.
- **Approach:** Cellular network segmentation, especially **holar structures**.

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# Holarchies and Holons

**Holar Structures:**

- These systems seek to leverage formation and segmentation by enabling the reuse of mechanisms on different hierarchical levels.
- Entities in such a system are called Holons.
- Holons are simultaneously a „whole“ and a „part“ of something bigger.
- The emerging system-of-systems structure is referred to as a holarchy.

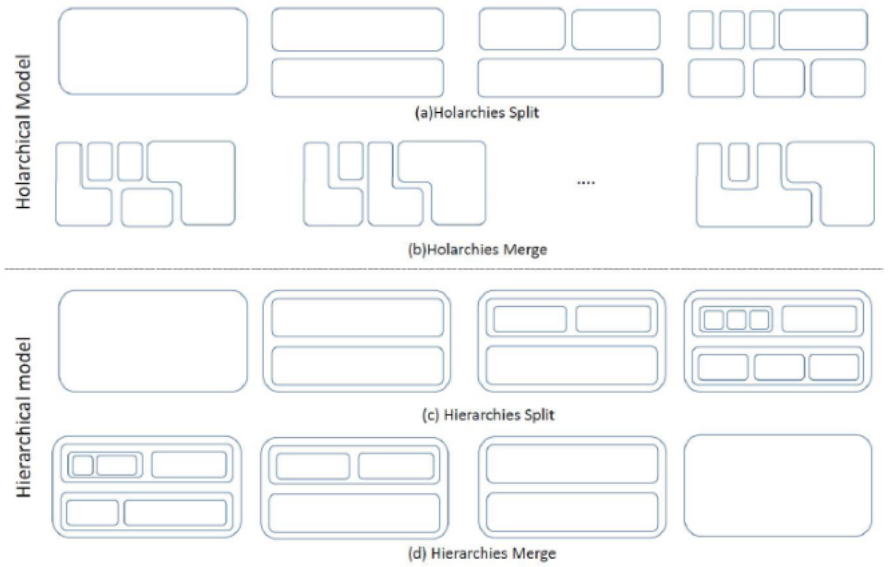


**Fig. 1:** Holarchical model versus Hierarchical model

Source: R. Egert, C. G. Cordero, A. Tundis, and M. Mu¨hlha¨user, “HOLEG: A simulator for evaluating resilient energy networks based on the Holon analogy,”

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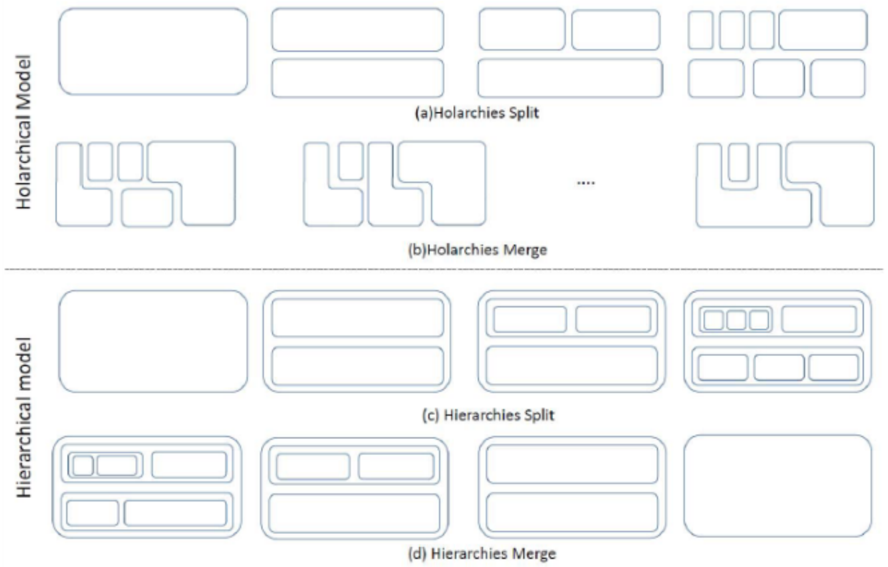
**Holons:**

- Are dynamic cells, which can merge with other holons or seperate into individual smaller ones, see Figure 1.
- Under optimal conditions, holons tend to form larger holons.
- Holarchies are mainly based on the concepts of isolation and containment.

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# Contributions

- **We consider single buildings to be atomic building blocks of holons.**

- They may be both producer and consumer, so-called prosumer.
  - To facilitate holon creation and stable operation, accurate models for bahavior of these prosumers are necessary.
  - This entails the need for a framework that is capable of forecasting both electrical load and production behaviors.

- The main contributions of the proposed framework are:
  - Dynamic control via smart strategy selection for holonic smart microgrids.
  - Advancement of current smart microgrid capabilities by enabling forecasting and operation optimization on the level of atomic holons.
  - Showcasing the applicability of the current deployment by deploying it at a real-world prosumer site.

# Atomic Unit of Holons

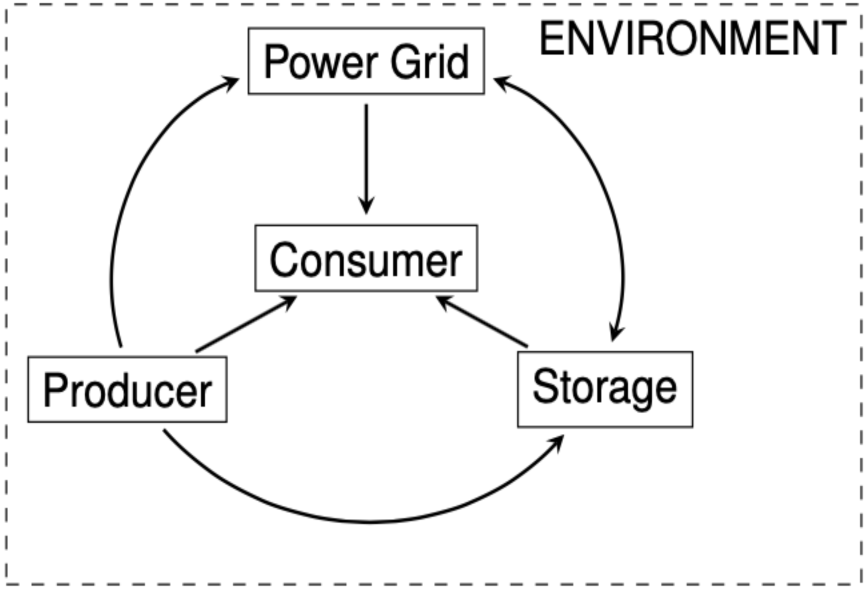


Figure 1. Energy flow between the four different holon components.

**The four components of an atomic holon:**
(can but does not need to implement all)

1. **Consumer:** The holons' total aggregated energy consumption.
2. **Producer:** The holons' total aggregated production capacity, e.g., from solar photovoltaic or wind turbines.
3. **Power Grid:** The grid-connected power supply of the building.
4. **Storage:** The daily production and consumption variations can be mitigated by energy storage systems, e.g., batteries or electric vehicles.

# Framework Description

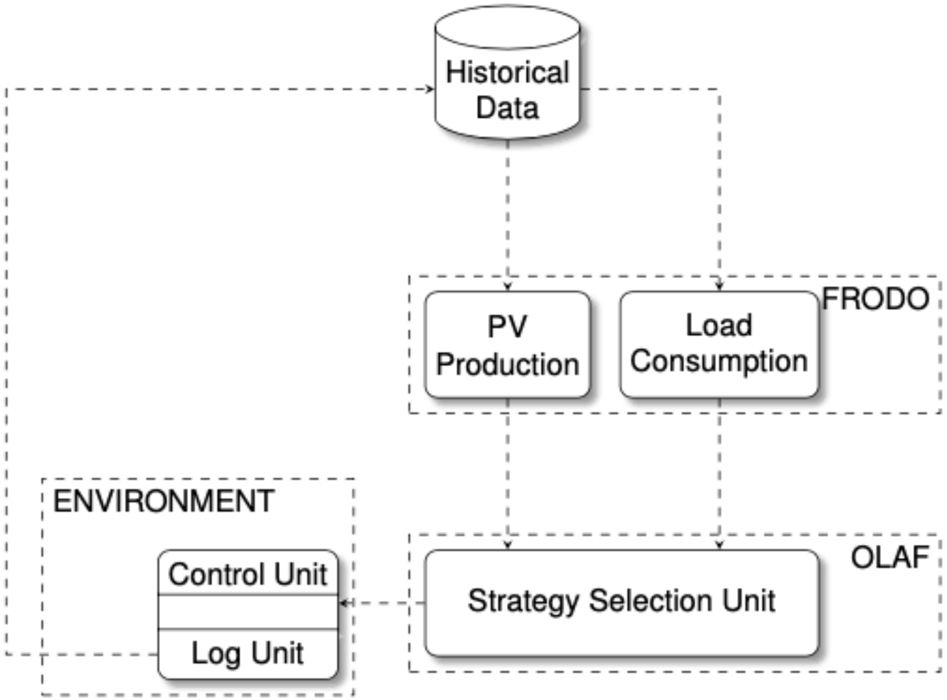


Figure 2. Structure and information flow within the Framework.

- **The framework aims to optimize control strategies in holarchy systems.**
- A bottom-up approach is chosen.
- Regulates the strategic operation within an atomic holon.
- **Future work:** expand the framework to non-atomic holons.

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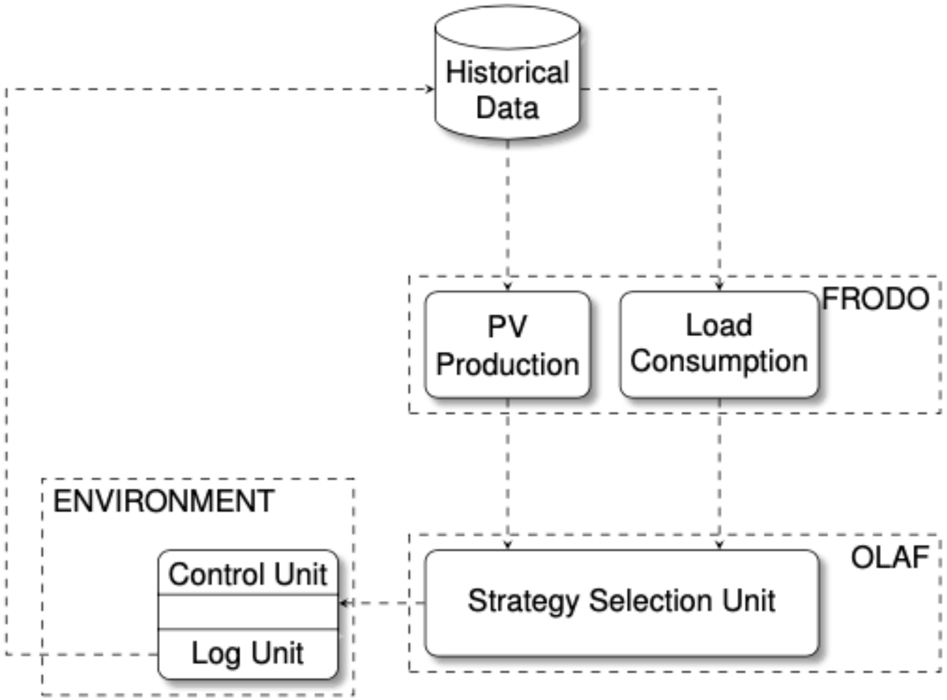


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**The three main parts:**

- Historical Data: Records of power production and consumption within the holon.
- FRODO (*Forecasting of Resources for Dynamic Optimization*): Forecasting of the next days' production and consumption.
- OLAF (*Optimal Load and Energy Flow*): Select the next days' battery charge and discharge strategy based on the forecast values.

# Methods

## Historical Data:

- Load consumption and photovoltaic production data are provided by the TZE.
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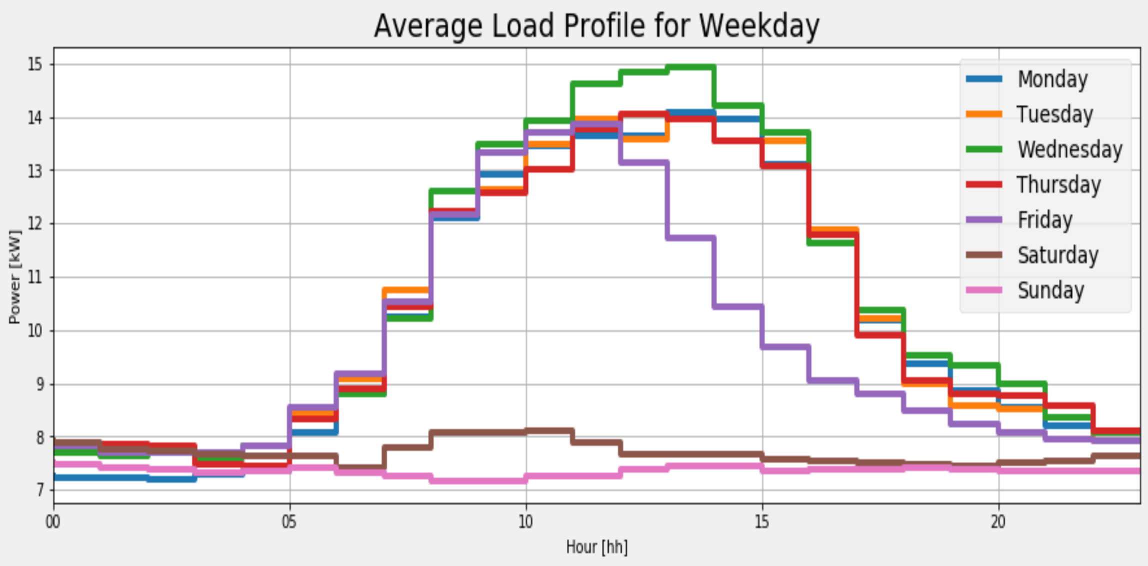


**Average consumption per weekday:**

- Difference between workday and weekend.
- Clear decrease after friday lunchtime due to worktime.


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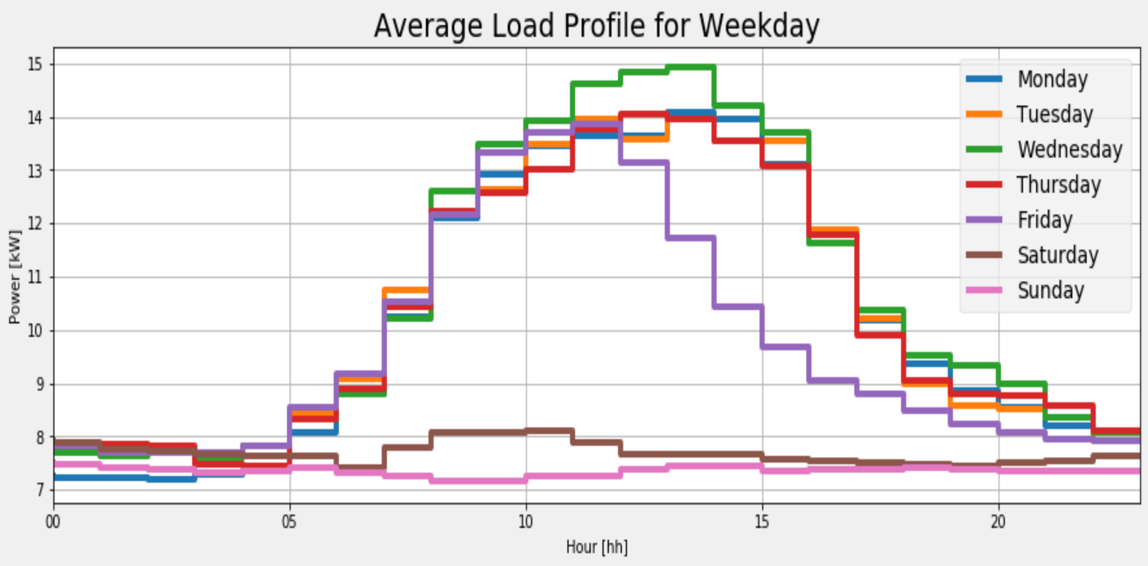


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This data provides the basis for the forecasting module FRODO.


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# Methods

FRODO:

- A precise load consumption and PV production forecast is essential.
- Different approaches are classified by forecast horizont: here Short-Term Load Forecasting (STLF) is used.
- **Workflow:** (1) Data-preprocessing; (2) model training; (3) model evaluation.
- **Used machine leanring models:** (1) Random Forest; (2) Long-Short Term Memory Neural Network.
- As well as **three persistance models**: (1) previous day; (2) last week; (3) weekday average.

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TABLE I. Results of the measurements for the different conducted forecasts

| Model | MSE | RMSE | MAE | MPE |
|---|---|---|---|---|
| *Previous Day* | 15.82 | 3.98 | 2.46 | -6.51 |
| *Last Week* | 9.27 | 3.04 | 2.16 | *1.45* |
| *Weekday Average* | 5.42 | 2.33 | 1.77 | -3.39 |
| *RF* | *4.86* | *2.20* | *1.43* | -1.57 |
| *LSTM* | 6.23 | 2.45 | 1.67 | -4.29 |

**Forecast results:**

- Random Forest has an increased accuracy compared to the other models.
- Worth mentioning: Random Forest errors remain mostly the same regardless of the different training splits
- The Neural Network depends highly on the segmentation of training and test data.

# Methods

OLAF:

- Based on the forecast values a charge and discharge strategy is chosen.
- The strategies can roughly be divided into three categories*: customer-, market- and grid-oriented*.
- Some strategy definitions with the primary beneficiary:
  - *Maximized consumption of self-generated power* (grid)
  - *Limited power grid feed-in* (grid/customer)
  - *Time-scheduled (dis-)charging* (grid)
  - *(Dis-)charging depending on energy pricing* (market/customer)
  - *Incremental grid relief* (grid)
  - *State-of-Charge dependent charging* (customer)

# Conclusions & Future Work

- We introduced a framework to provide **dynamic control for the holonic smart grid**.
- Based on the **bottom-up approach**, the framework enables holarchical organization.
- The presented approach is designed to **improve current smart grid capabilities**.
  - By providing a **modular structure for *forecasting* and *optimization***.
- The **machine learning models** are practicable methods for forecasting consumption and production.
- The framework is **able to handle uncertain behavior** and divergent forecasts through feedback-loop.


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- The **machine learning models** are practicable methods for forecasting consumption and production.
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- **In future research**, we are improving the forecast models with different machine learning techniques.
- Defining more strategies to optimize holarchical operation


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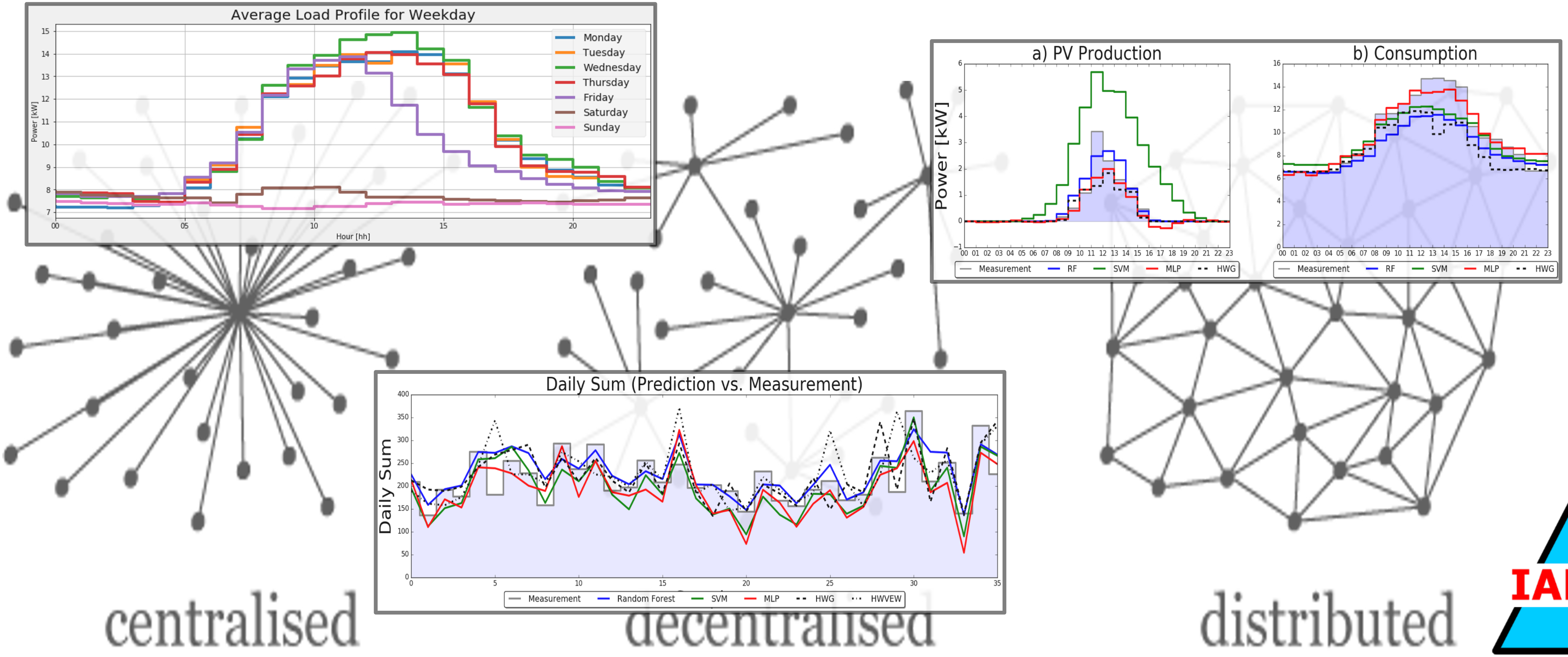
# Thank you for your Attention



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