INTERNATIONAL HELLENIC UNIVERSITY

CERTH
CENTRE FOR RESEARCH & TECHNOLOGY HELLAS

Smart Grids & Artificial Intelligence

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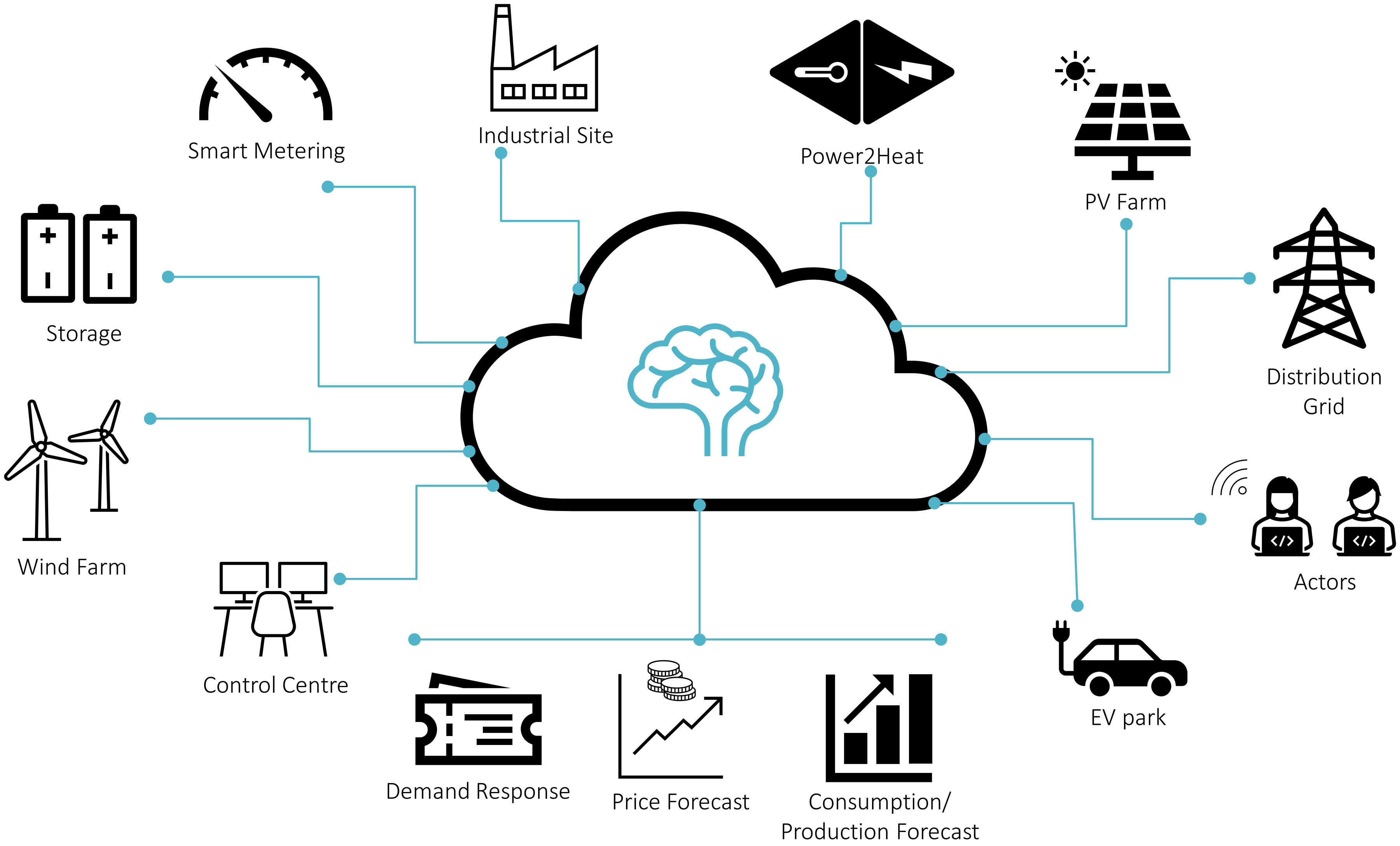
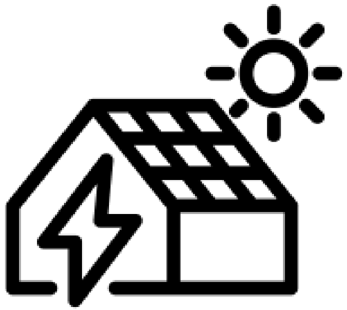
Academic Researcher at CERTH

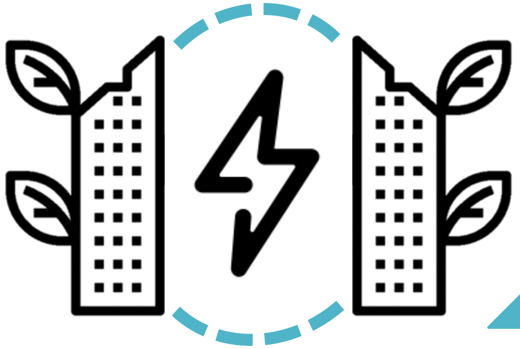
Smart Grid, VPPs & Microgrids Ecosystem



Solutions at 3 Different Levels

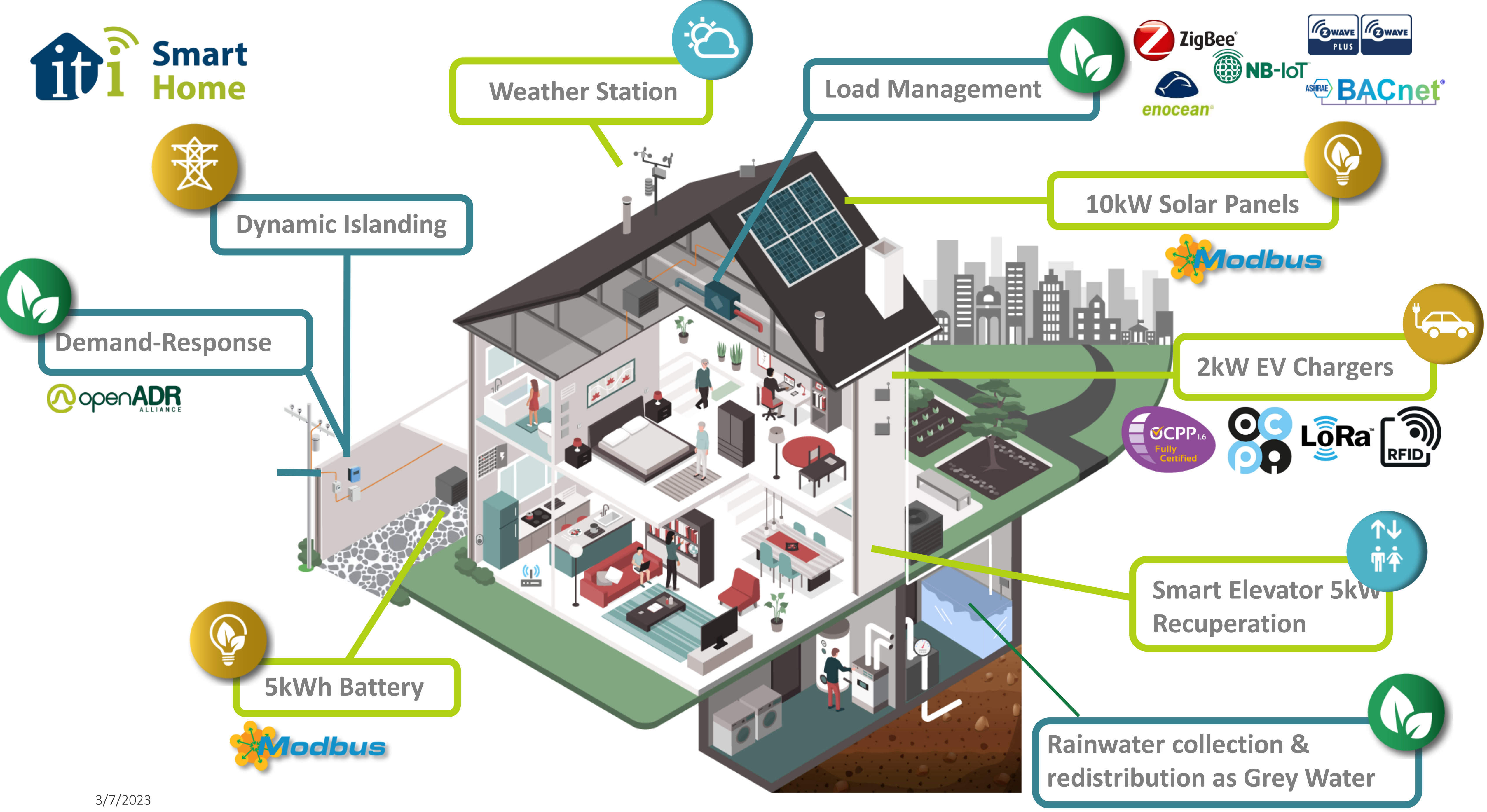


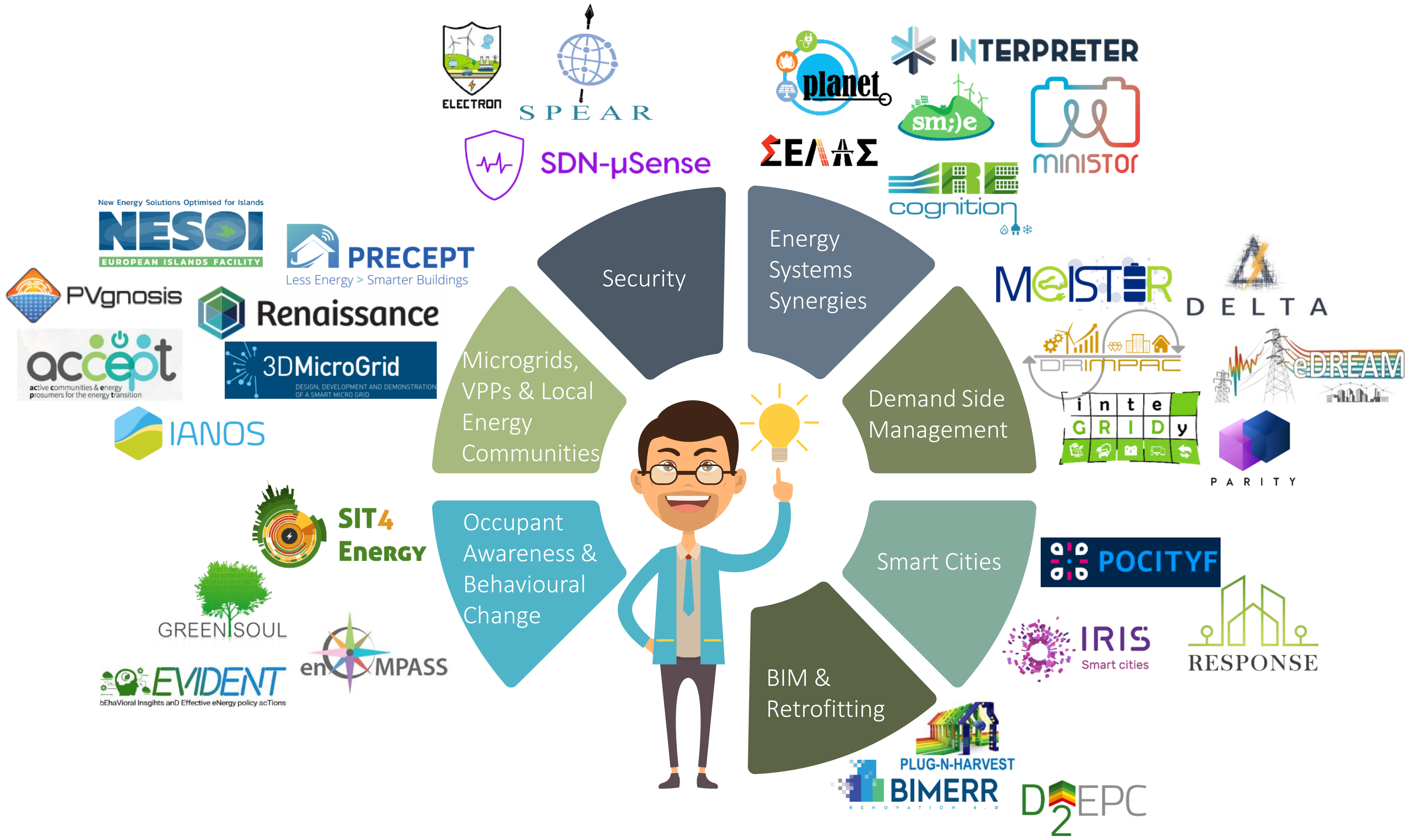
Building Level / Microgrids



Virtual Power Plants

Smart Grid


Smart
Home
Weather Station
Load Management
ZigBee
NB-IoT
enocean
BACnet
Dynamic Islanding
10kW Solar Panels
Modbus
Demand-Response
openADR
ALLIANCE
2kW EV Chargers
OCPP 1.6
Fully Certified
LoRa
RFID
Smart Elevator 5kW
Recuperation
5kWh Battery
Modbus
Rainwater collection &
redistribution as Grey Water


Security
Energy Systems Synergies
Demand Side Management
Smart Cities
BIM & Retrofitting
Occupant Awareness & Behavioural Change
Microgrids, VPPs & Local Energy Communities
ELECTRON
SPEAR
SDN-μSense
planet
INTERPRETER
sm;)e
ΣΕΛΛΑΣ
MINISTOR
cognition
New Energy Solutions Optimised for Islands
NESOI
EUROPEAN ISLANDS FACILITY
PRECEPT
Less Energy > Smarter Buildings
PVgnosis
Renaissance
accept
active communities & energy prosumers for the energy transition
3DMicroGrid
DESIGN, DEVELOPMENT AND DEMONSTRATION OF A SMART MICRO GRID
IANOS
MEISTER
DELTA
DRIMPAC
eDREAM
inteGRIDy
PARITY
SIT4 Energy
GREENSOUL
EVIDENT
bEhaVioral Insgihts anD Effective eNergy policy acTions
enCOMPASS
POCITYF
IRIS
Smart cities
RESPONSE
PLUG-N-HARVEST
BIMERR
RENOVATION 4.0
D2EPC

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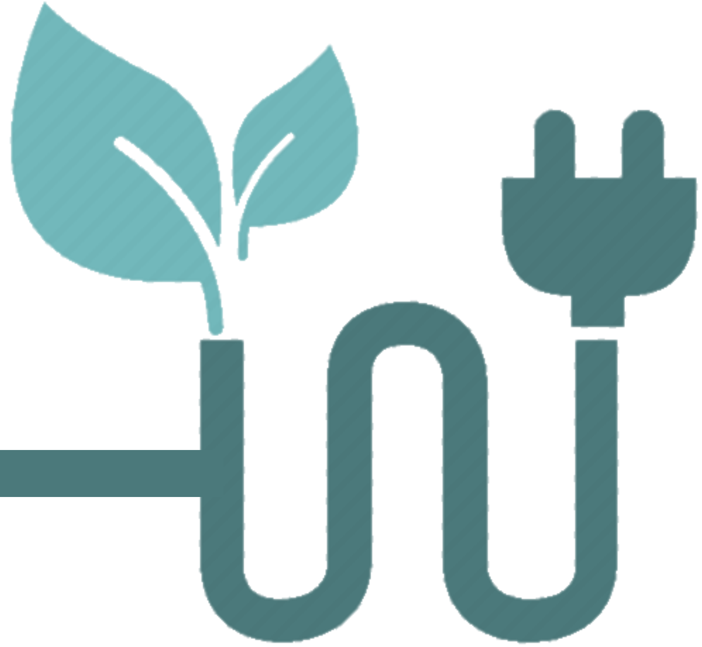
Building Energy Efficiency / Microgrids



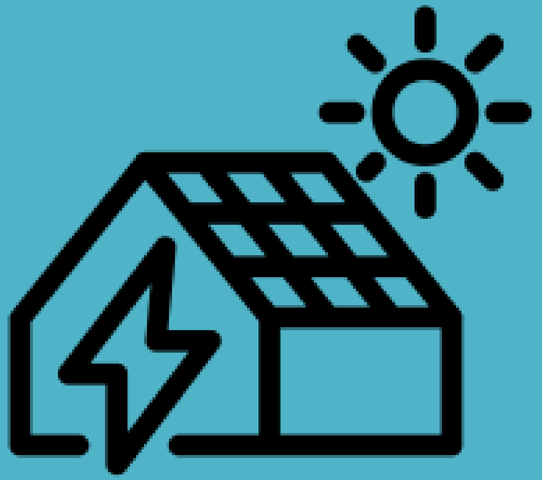
Technology & Innovation

- Implementation of **Demand Response** (DR) schemes based on available local **Flexibility**

- Optimal **energy management** of building's **distributed energy resources**
  - Dynamic Islanding
  - Optimized Load Sharing & Power Management

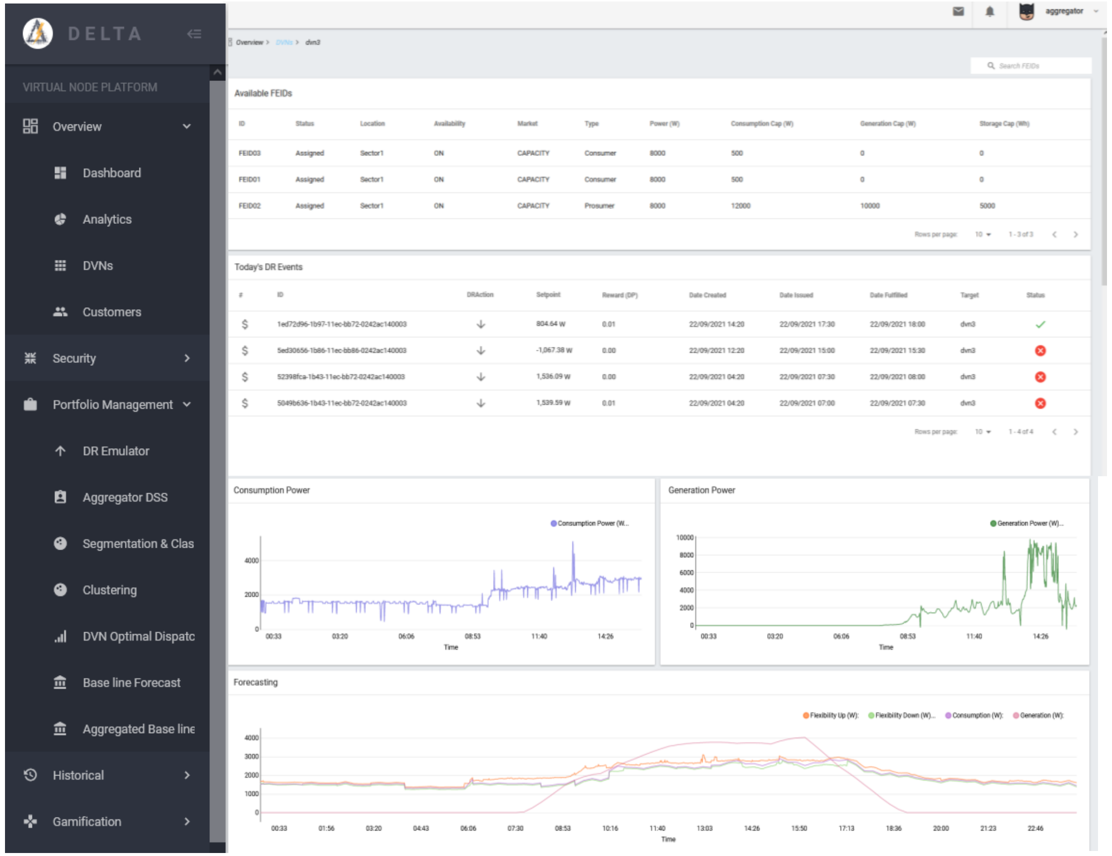
- Seamless inclusion of EVs (V1G & V2G) and novel schemes for **EV Profiling**

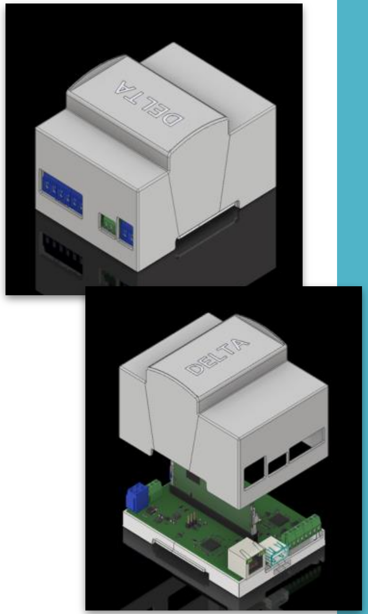
Building Energy Efficiency / Microgrids



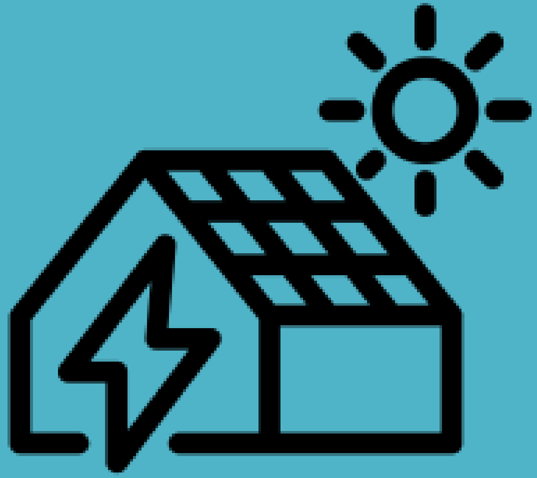
Edge Intelligence for Demand Response Applications

- Fog-enabled monitoring and control of customers
- Fault-tolerant architecture and DR application
- Lightweight flexibility & load forecasting



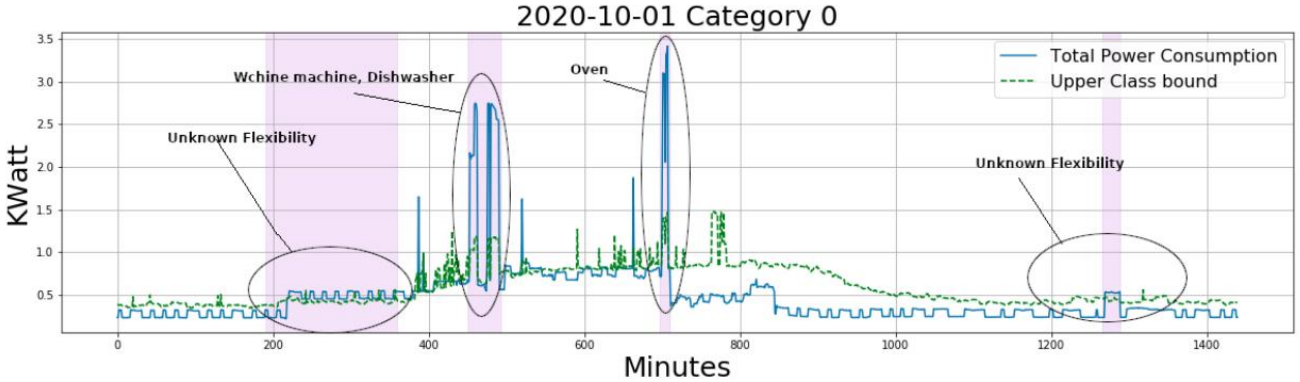


Building Energy Efficiency



Adaptive Flexibility Estimation System (AFeS)

Energy flexibility in residential demand is as an indicator of how much load can be shifted or reduced within user-specified limits



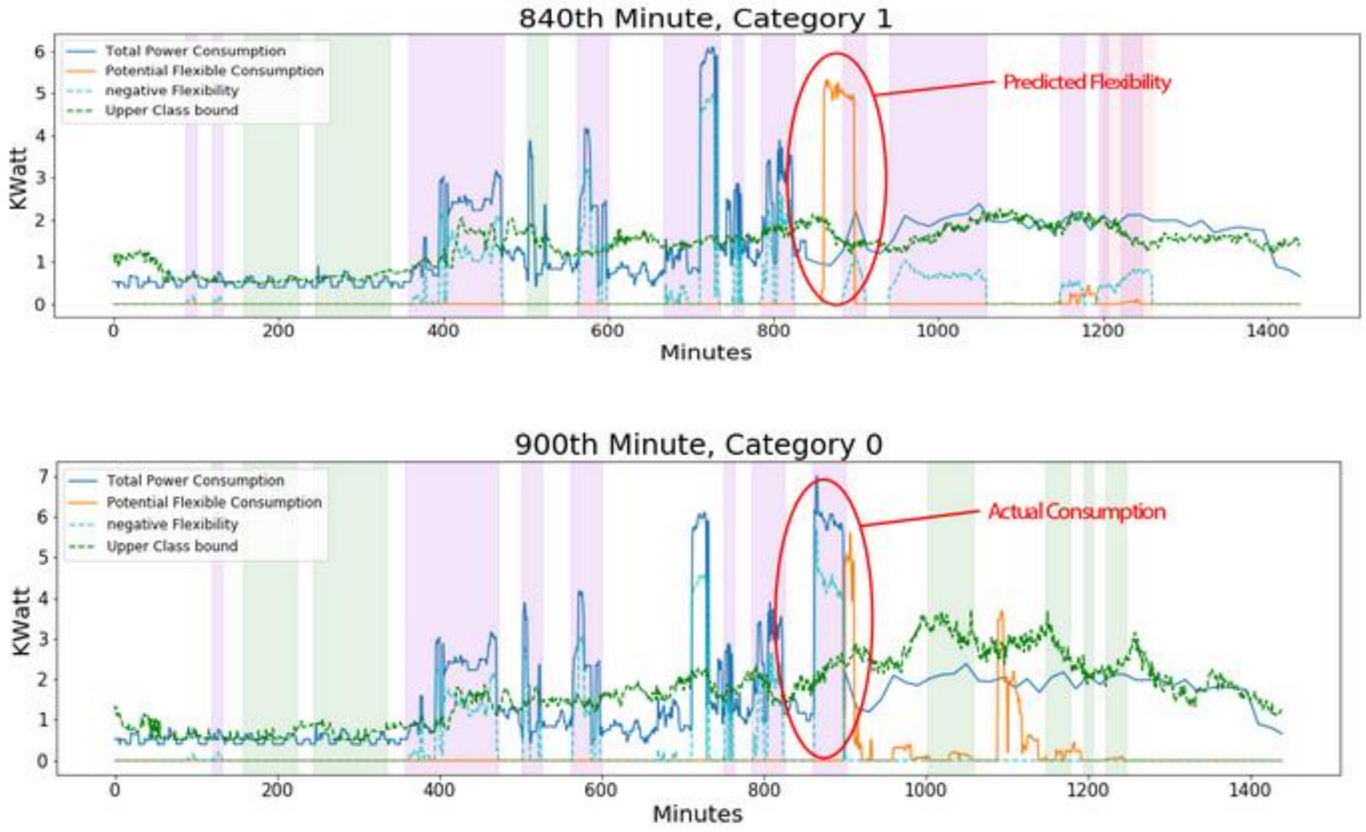
The main key features of the AfeS:

- Ability to estimate with high precision the future flexibility with the help of technologies such as Deep Learning
- Ability to adapt to any new client without prior knowledge of him by analyzing his daily electricity usage patterns
- Provide flexibility for demand response without compromising the comfort of residents

Building Demand Flexibility

Adaptive Flexibility Estimation System (AFeS)

Not only AFeS detects the available flexibility but also whether the customer is willing to dispose it

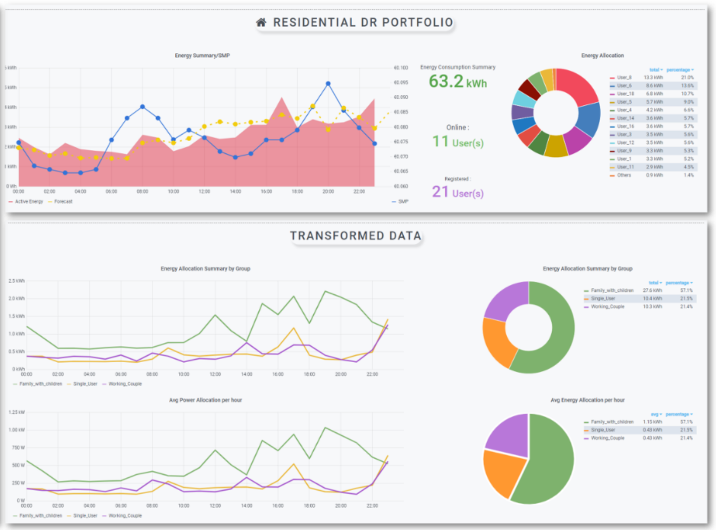


Building Demand Flexibility

Customer Engagement in DR schemes

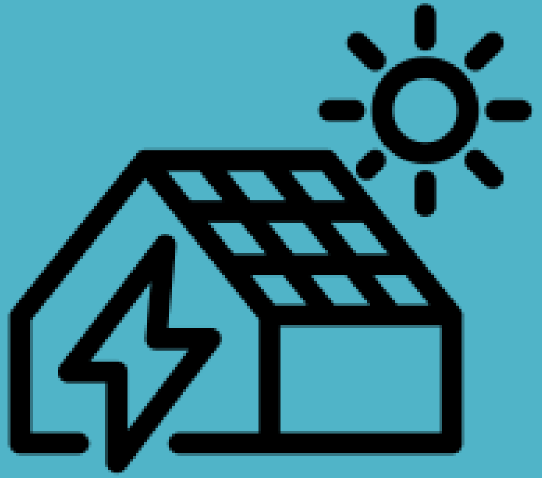
- Engage the end-user to participate in DR, using gamification.
- Visualization for the Aggregator for improved DR portfolio management.

User Dashboard View



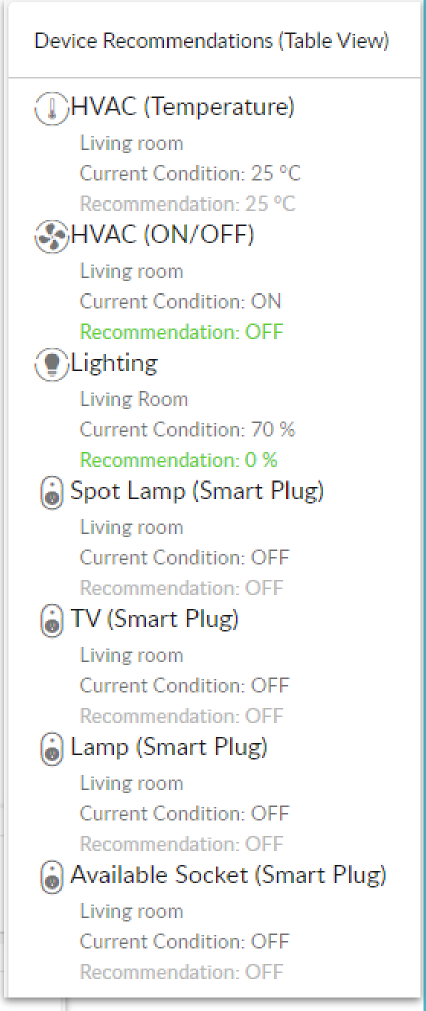
Aggregator Dashboard View

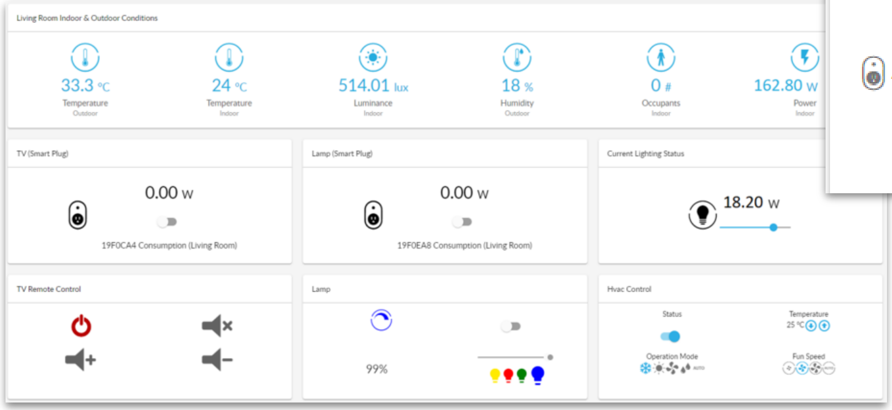
Building Energy Efficiency



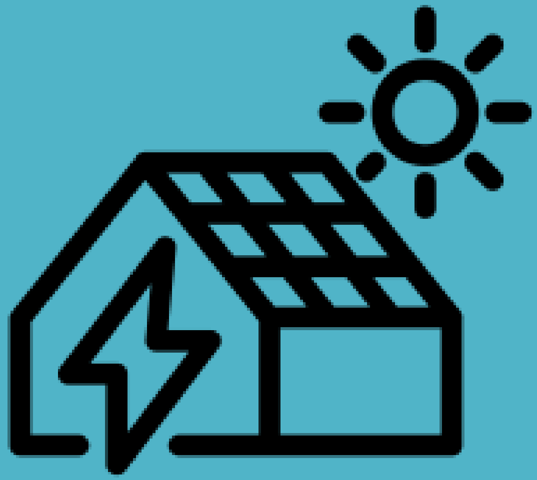
Recommendation Engine for Building Performance Optimization

- Real-time **users' recommendations**
- Buildings performance optimization
- **Energy savings**
- **Users' comfort preservation**
  - Thermal & visual comfort
- **Two operation modes**:
  - Recommendations forms
  - Immediate implementation of the recommendations/ commands



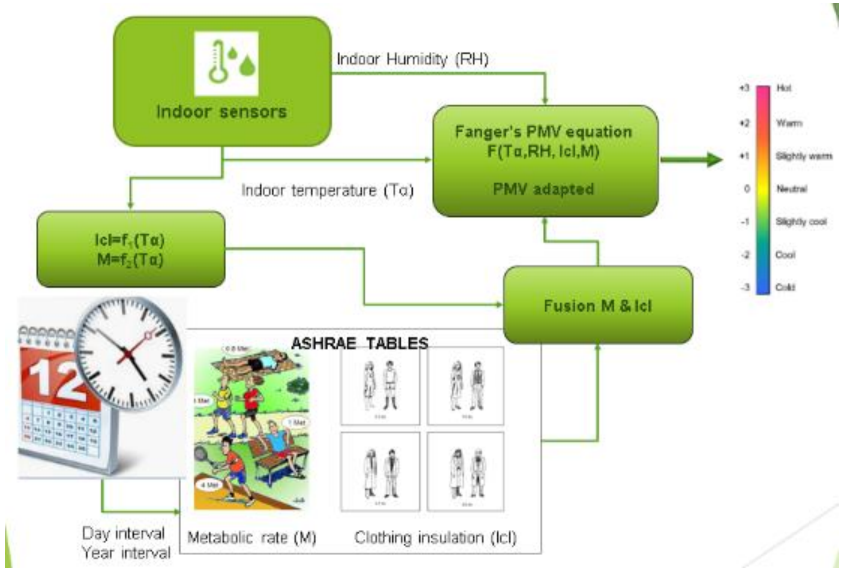


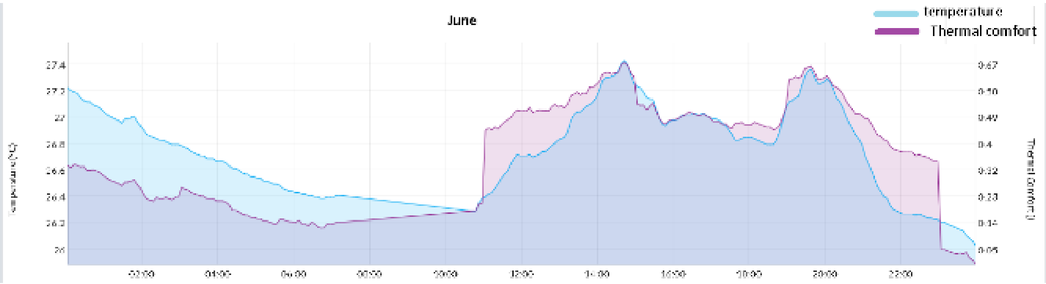
Building Energy Efficiency



Thermal Comfort

- Non-intrusive and low-cost estimation of thermal comfort levels
- Exploit the least possible data
- Estimate thermal comfort by exploiting the most accurate method (ANSI ASHRAE Standard, Fanger's PMV) eliminating the subjectivity of personal factors

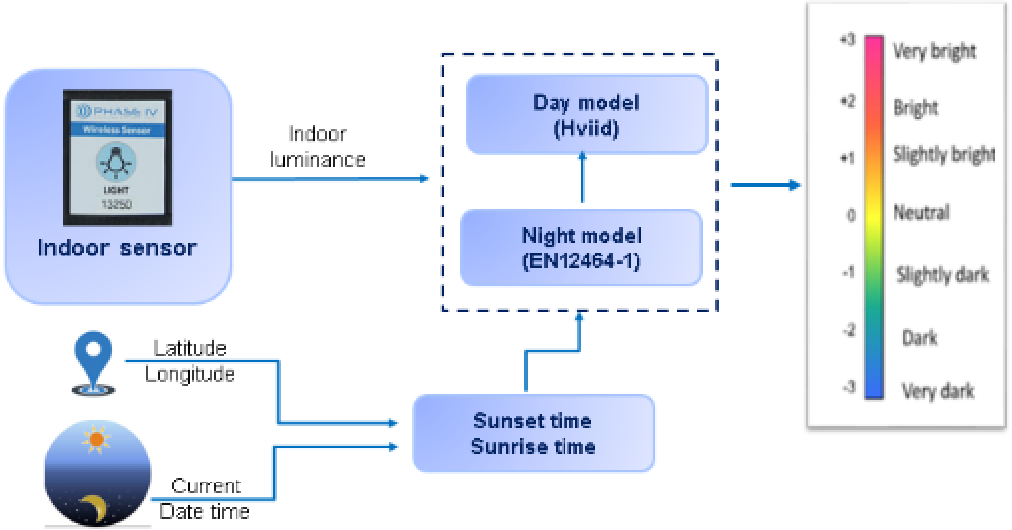


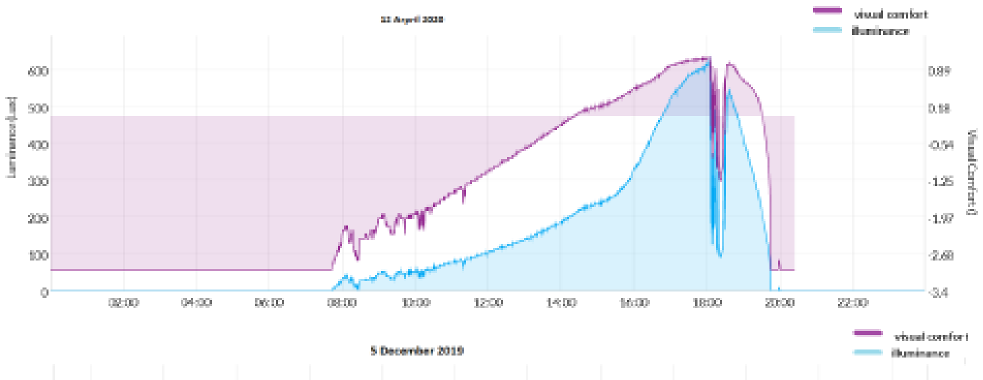


Thermal comfort

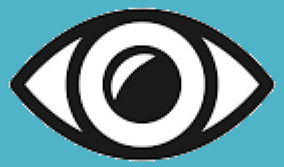
Visual Comfort

- Non-intrusive and low-cost estimation of visual comfort levels using the least possible data
- Access accurately visual comfort only with indoor illuminance



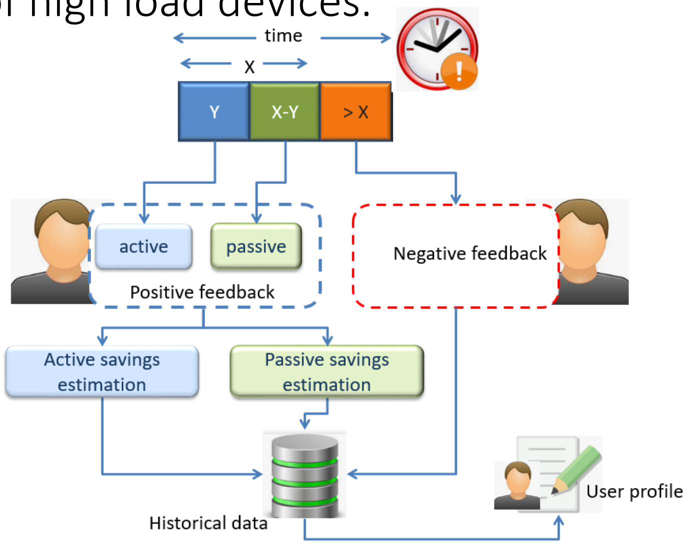


Visual comfort



Personalized energy recommendations

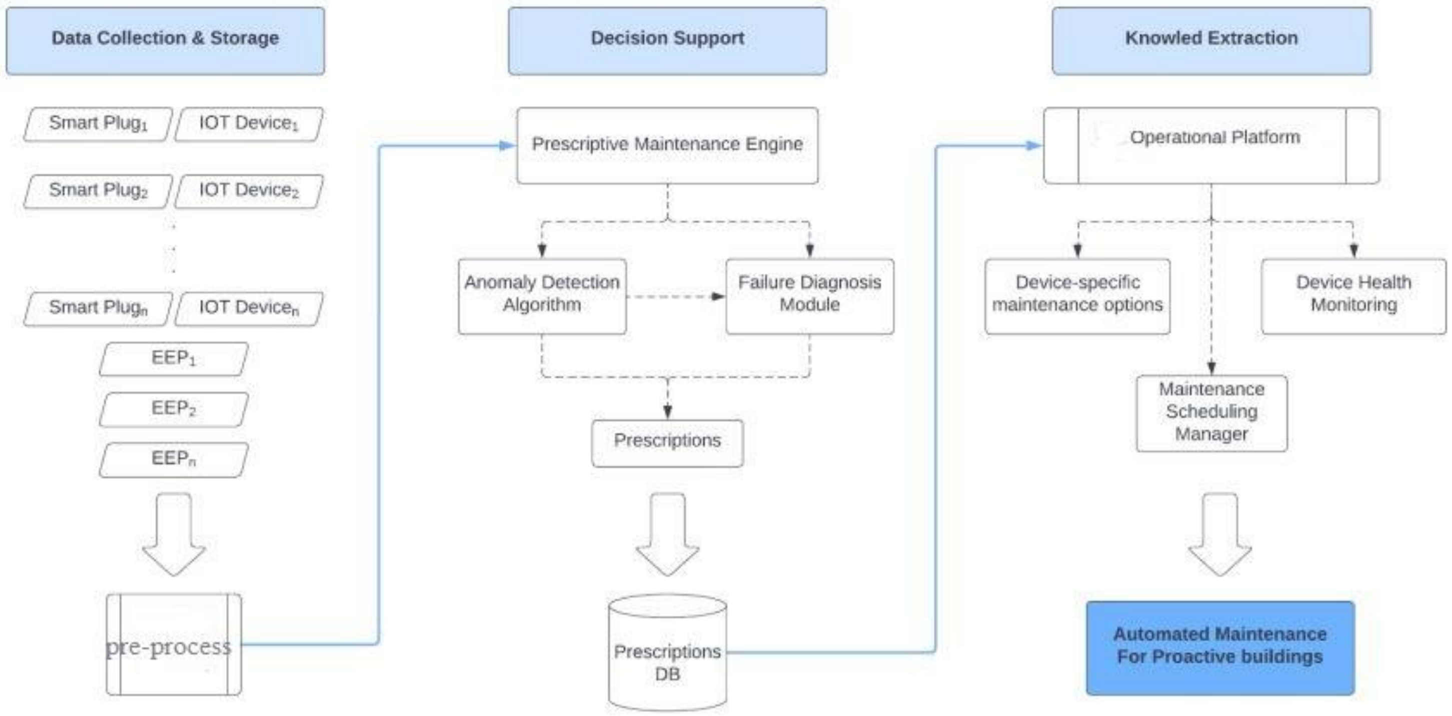
- General recommendations based on indoor conditions
- User-based recommendations based on reported consumption values
- Estimation of energy actual and potential savings
- Production of automatic recommendations specific feedback to adapt each recommendation to the user profile.
- Energy awareness enhancement by utilizing a simple sensor infrastructure and the least building information
- Personalized recommendations based on user preferences adjusting to user's feedback
- Event-based recommendations triggered either by abnormal sensor data or unusually long usage of high load devices.



Recommendations

Prescriptive maintenance

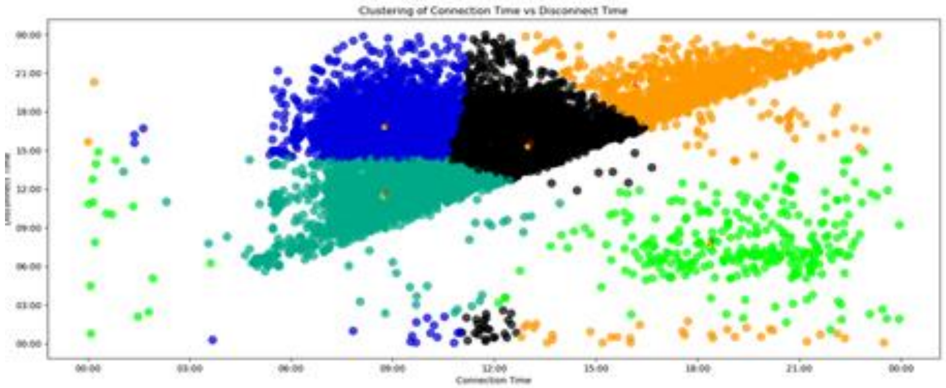
1. Data Collection & Storage
2. Decision Support
3. Knowledge Extraction
4. General prescriptions



Prescriptive maintenance residential framework

Dynamic EV Profiling in Smart Districts for Local Flexibility

- Non-parametric algorithm for clustering EV users based on their EV charging behavior
  - Set of clusters describing common behaviors found amongst total EV user population
  - Distribution of the total sessions of a single user



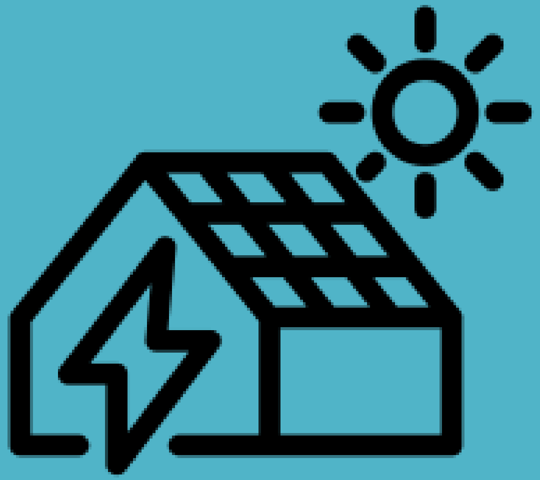
Non-parametric Clustering results

- Use of tree-based machine learning model XGBoost implementation for predicting user's departure time based on historical data

Connection time	Estimated departure	Actual departure
25/07 16:48:59	25/07 18:59:02	25/07 19:00:40
31/07 07:39:55	31/07 16:24:03	31/07 15:57:30
08/06 07:49:16	08/06 09:48:19	08/06 09:20:14
13/05 17:07:27	13/05 18:54:12	13/05 18:44:03
02/04 07:51:23	02/04 16:42:05	02/04 18:08:19

Estimated versus actual departure times for five sessions

Building Energy Efficiency



Business Cases & Challenges

- Optimal exploitation of RES generation combined with storage units for residential or industrial prosumers

- Balancing of energy generation and consumption by grid operators and optimization of the way that controllable units are dispatched

- Addressing the challenges introduced by the integration of RES into the electricity grid (e.g. grid stability issues)

RES Power Generation Forecasting

Hybrid approach for robust RES forecasting

Analytical Modelling

- Derives from physics laws
- Domain specific
- May introduce errors due to imprecise modelling of complex systems

Data-driven modelling

- Flexible
- Problem agnostic
- Low interpretability, requires large volume of data that cover all possible configurations

+

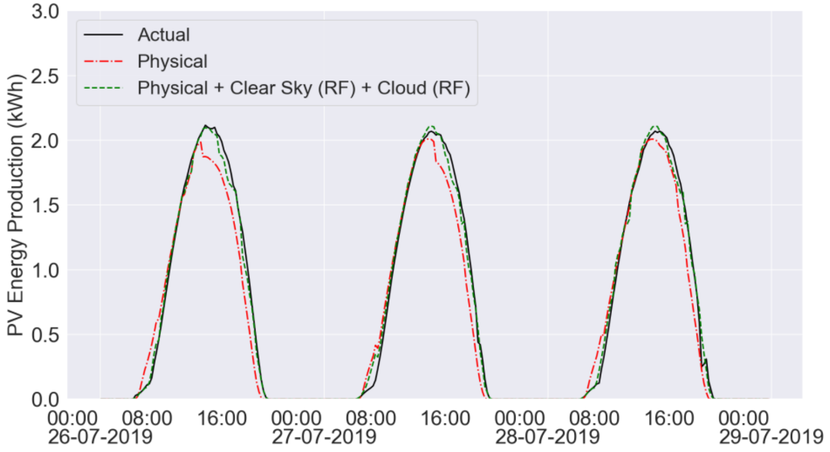
Hybrid model

Combines the best from both worlds

Analytical calculations fine-tuned with machine learning models

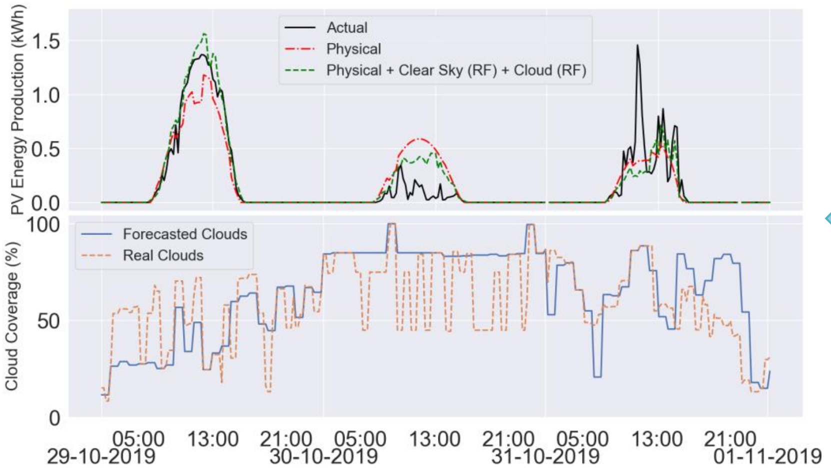
RES Power Generation Forecasting

PV forecast



Clear sky evaluation

Hybrid solution based on neural networks increases accuracy by 22.8%

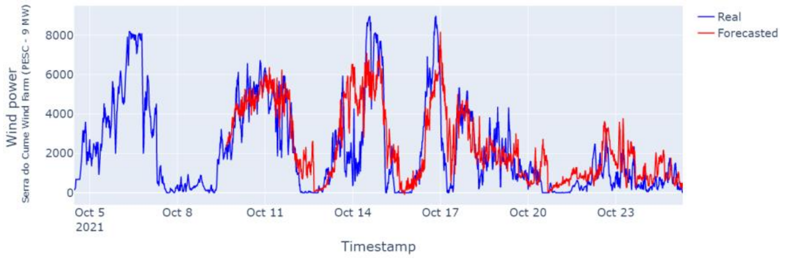


Cloudy days evaluation

RES Power Generation Forecasting

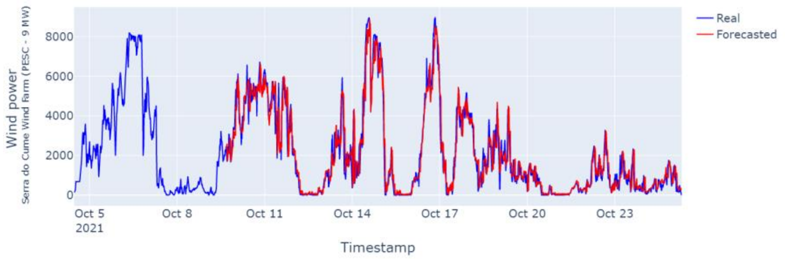
Wind forecast

Day-ahead scenario



Prediction Model	MAE	RMSE	MMR (%)	sMAPE (%)	Time (s)
Random Forest (RF)	0.14	0.18	36.37	29.27	273.12
Gradient Boosting Regressor (GBR)	0.14	0.18	35.87	29.29	368.7
eXtreme Gradient Boosting (XGBoost)	0.14	0.19	36.95	30.59	110.43
Light Gradient Boosting Machine (LightGBM)	**0.13**	**0.18**	**34.75**	**28.53**	**93.64**
Support Vector Regressor with RBF kernel (RBF SVR)	0.2	0.26	53.22	37.64	314.19
Multilayer Perceptron (MLP)	0.19	0.26	55.8	41.4	225.95
Long short-term memory RNN (LSTM RNN)	0.16	0.23	47.2	39.31	448.59

Short-term scenario



Prediction Model	MAE	RMSE	MMR (%)	sMAPE (%)	Time (s)
Random Forest (RF)	0.07	0.11	18.49	20.35	11.29
Gradient Boosting Regressor (GBR)	0.07	0.11	18.85	20.28	15.49
eXtreme Gradient Boosting (XGBoost)	0.07	0.11	19.65	21.17	4.58
Light Gradient Boosting Machine (LightGBM)	**0.07**	**0.1**	**18.38**	**20.16**	**3.92**
Support Vector Regressor with RBF kernel (RBF SVR)	0.07	0.11	19.77	21.12	11.73
Multilayer Perceptron (MLP)	0.14	0.19	40.66	33.87	8.73
Long short-term memory RNN (LSTM RNN)	0.07	0.11	20.53	24.54	13.55

RES Power Generation Forecasting

RES forecasting tested in ITI Smarthome facilities and in numerous research projects

RES Power Generation Forecasting

Business scenarios

- Participation in DR schemes
- Optimal planning of the production line operations
- Detection of abnormal patterns in energy consumption – predictive maintenance
- Efficient handling of the most energy-intensive loads

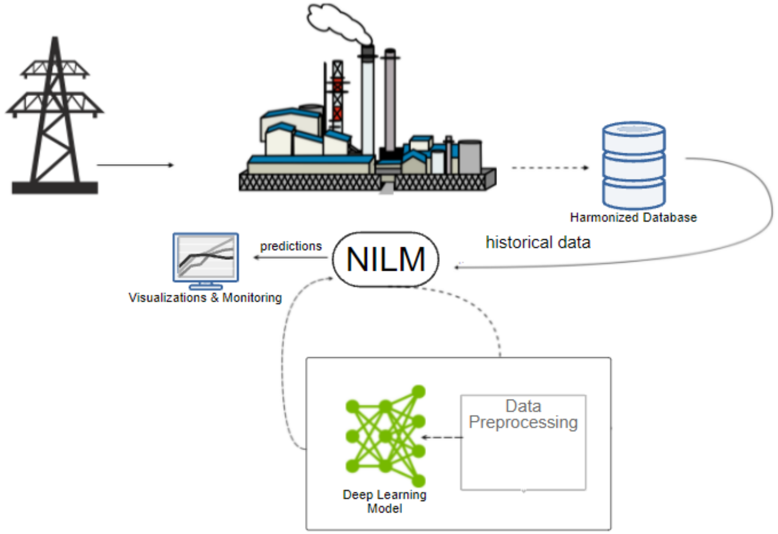
Industrial load Disaggregation

Disaggregation definition: The separation of an aggregate energy signal into appliance/ machine specific data

Industrial Load Disaggregation

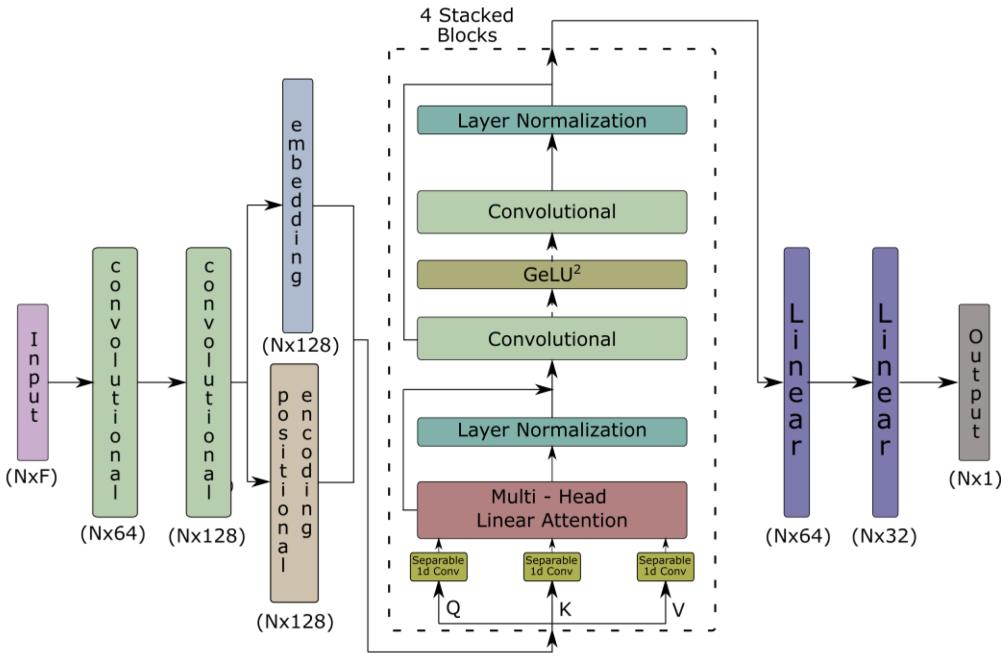
Industrial Disaggregation may be conducted on three different levels:

- Per machinery
- Per product
- Per production line



Large <u>savings potential </u>in the industrial sector
- Current applications mainly focused in the residential/ commercial sector

Suggested approach – Transformer NN



- Multi-head self-attention block captures long-term dependencies
- Multiple parallel attention layers utilized to preserve information in different temporal patterns
- Regular scale-dot product replaced with linear attention for computational time reduction

Industrial Load Disaggregation

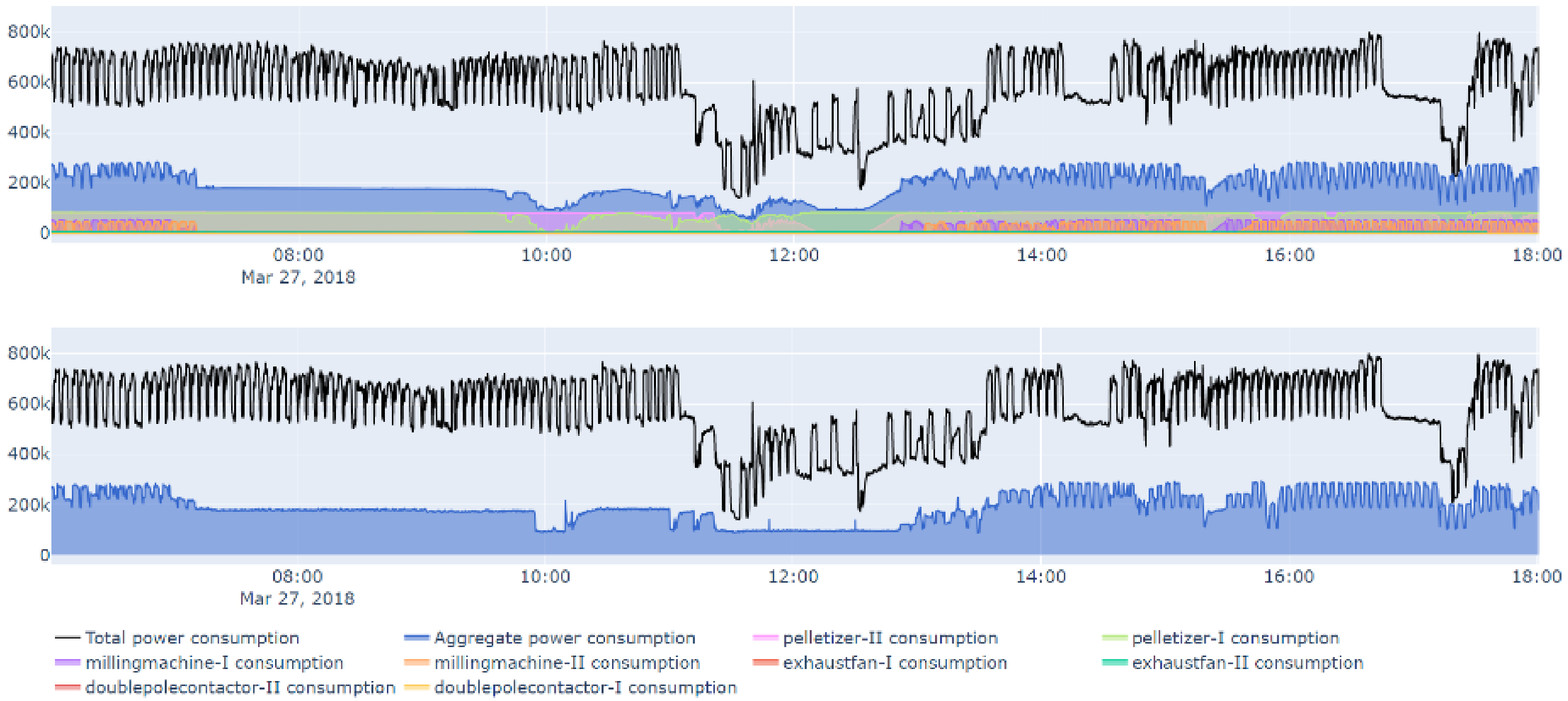
Suggested approach – Results

Method	Metric	IMDELD DPCI	IMDELD DPCII	IMDELD EFI	IMDELD EFII	IMDELD MMI	IMDELD MMII	IMDELD PI	IMDELD PII	Average	IMDELD per group DPCs	IMDELD per group EFs	IMDELD per group MMs	IMDELD per group Ps	Average
Industrial Transformer (proposed)	TECA (%)	**91.28**	**87.69**	**96.22**	**95.84**	**90.30**	**90.37**	**95.09**	**94.25**	**92.63**	**90.31**	**96.38**	**91.55**	97.02	**93.82**
	NDE	**0.062**	**0.155**	**0.030**	**0.035**	**0.062**	**0.055**	0.034	**0.047**	**0.060**	**0.081**	**0.033**	**0.047**	0.009	**0.043**
	SAE	**0.110**	**0.178**	**0.019**	**0.004**	**0.041**	0.083	**0.012**	**0.034**	**0.060**	**0.100**	**0.018**	**0.012**	**0.019**	**0.037**
	Time per epoch (s)	265.0	226.0	183.0	177.0	40.00	45.00	155.0	253.0	168.0	25.99	32.79	2.604	32.30	23.42
	Inference time (s)	19.28	16.43	13.42	13.18	3.124	3.483	11.44	18.18	12.32	25.99	32.79	2.604	32.30	23.42
S2P [21]	TECA (%)	90.11	85.59	95.77	95.57	85.46	85.40	93.88	93.71	90.68	87.11	93.27	84.97	**97.35**	90.67
	NDE	0.069	0.158	0.040	0.049	0.066	0.067	**0.033**	0.048	0.066	0.093	0.050	0.058	**0.005**	0.052
	SAE	0.151	0.233	0.022	0.006	0.092	0.092	0.055	0.057	0.089	0.197	0.042	0.067	0.025	0.083
	Time per epoch (s)	**23.00**	**24.00**	**23.00**	**23.00**	**7.000**	**7.000**	**23.00**	**23.00**	**19.13**	**23.00**	**24.00**	**7.000**	**24.00**	**19.50**
	Inference time (s)	**1.431**	**1.298**	**1.416**	**1.308**	**0.441**	**0.502**	**1.353**	**1.373**	**1.140**	**1.451**	**1.204**	**0.451**	**1.306**	**1.103**
S2S [21]	TECA (%)	56.32	50.23	62.02	60.49	60.41	76.60	56.59	54.55	59.27	54.93	62.04	36.19	57.81	52.74
	NDE	0.476	0.534	0.388	0.403	0.593	0.313	0.446	0.467	0.453	0.488	0.388	0.647	0.442	0.491
	SAE	0.207	0.253	0.037	0.052	0.653	0.428	0.087	0.083	0.225	0.213	0.045	0.213	0.090	0.140
	Time per epoch (s)	55.00	54.00	55.00	54.00	16.00	16.00	54.00	55.00	45.18	56.00	55.00	16.00	55.00	45.50
	Inference time (s)	1.623	1.550	1.674	1.540	0.524	0.546	1.561	1.664	1.335	1.824	1.777	0.561	1.922	1.521
WGRU [78]	TECA (%)	89.05	85.97	94.29	93.76	65.84	72.30	93.01	92.87	85.88	86.94	92.10	75.11	96.02	87.54
	NDE	0.063	0.169	0.036	0.040	0.216	0.162	0.040	0.058	0.098	0.087	0.035	0.138	0.009	0.067
	SAE	0.139	0.192	0.020	0.025	0.504	0.383	0.033	0.039	0.187	0.039	0.039	0.304	0.020	0.137
	Time per epoch (s)	92.00	91.00	92.00	91.00	28.00	27.00	91.00	92.00	75.55	90.00	91.00	27.00	91.00	74.75
	Inference time (s)	5.989	5.933	6.092	5.936	2.215	2.101	6.000	6.025	5.036	5.953	5.935	2.193	5.921	5.000
SAED-dot [43]	TECA (%)	88.84	86.87	93.63	94.42	84.11	84.46	94.81	93.03	90.02	87.71	95.59	83.25	96.55	90.77
	NDE	0.069	0.156	0.031	0.043	0.071	0.069	0.035	0.050	0.066	0.094	0.034	0.048	0.048	0.056
	SAE	0.165	0.190	0.004	0.012	0.185	**0.075**	0.023	0.060	0.089	0.177	0.008	0.178	0.038	0.100
	Time per epoch (s)	51.00	50.00	51.00	50.00	15.00	15.00	51.00	51.00	41.75	50.00	50.00	15.000	50.00	41.25
	Inference time (s)	3.085	3.108	2.967	2.923	1.055	1.048	2.928	2.928	2.505	3.047	2.944	1.043	3.035	2.517
SAED-add [43]	TECA (%)	88.53	86.57	95.81	95.30	78.54	82.91	94.98	93.31	89.49	87.51	94.45	88.50	96.60	91.76
	NDE	0.066	0.156	0.031	0.044	0.110	0.086	0.035	0.049	0.072	0.093	0.034	0.050	0.048	0.056
	SAE	0.168	0.196	0.004	0.022	0.304	0.111	0.017	0.062	0.111	0.185	0.021	0.080	0.035	0.080
	Time per epoch (s)	61.00	62.00	62.00	61.00	18.000	18.000	62.00	62.00	50.75	62.00	63.00	18.00	62.00	51.25
	Inference time (s)	4.275	4.374	4.153	4.149	1.384	1.433	4.231	4.265	3.533	4.361	4.440	1.421	4.190	3.603

- Tested on a real-life public industrial dataset (IMDELD), across 8 machines
- Results outperform other SoTA literature approaches with different deep learning architectures

Industrial Load Disaggregation

Suggested approach – Results



- Individual machines successfully disaggregated from the aggregate power signal

Industrial Load Disaggregation

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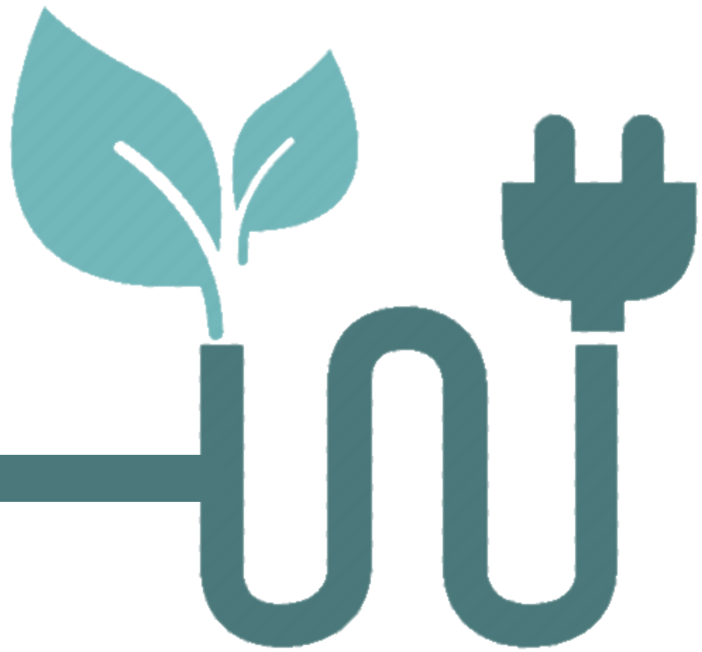
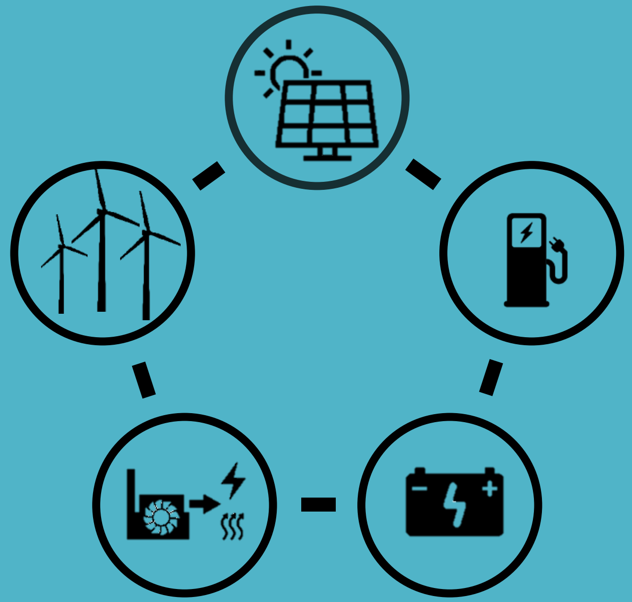
VPP Optimal Management



Business scenarios

- Optimal energy management of VPPs
- Resilient application of various DR schemes
- Provision of ancillary services through VPPs
- Cross-energy sector VPP formation (RES, ESS, EV chargers, CHP etc.)
- Flexibility exploitation through demand-side management in medium and large industrial applications
- Community-driven resilient microgrid planning and management

VPP Optimal Management



One Framework, several applications

01
Optimal Dispatch of diverse DERs/ RES

Power Grid
Storage
PV Farm
Wind Farm

02
Participation in Demand-Response Markets

Demand Response
Price Forecast

03
Incorporation of Electromobility

EV park

04
Real-time Monitoring and Control

Smart Metering
Control Centre

optimems

Microgrids 2.0 & VPPs brain

SmartHome Microgrid

58 Thin Film (CIS) panels
228o SW orientation/ 18o inclination
9.57 kWp

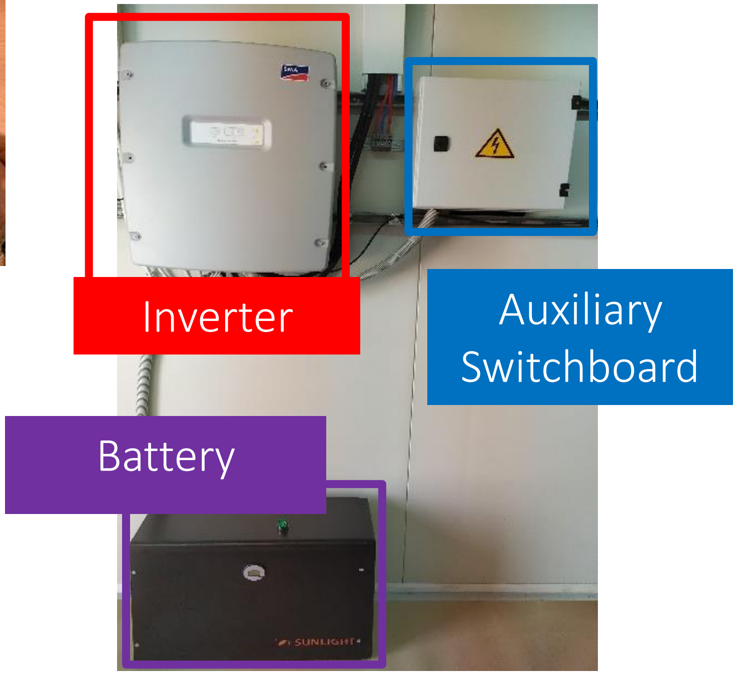
3ϕ inverter 10.0-3-M
2-MPPT channels

Modbus
TCP/IP

Distributed ESS Management

Energy management services for BESS

- Monitoring of facility assets, predictive maintenance
- Optimized energy/cost management Vs. occupant's comfort, offering various optimized options to the end-users



SUNLIGHT
Reliable Battery Solutions

TRL 7

Expanding to Cross-Sector Energy Utilization

Integration of Distributed Energy Resources targeting energy optimisation:

- All energy carriers in a single view
- Management of various assets, located in different sites
- Real-time depiction of active energy flows overview (e.g. electrical storage)
- Actual financial balances outline
- Historical and real-time forecasting performance evaluation
- Integration of electrical & thermal energy systems
- Application: Residential, Commercial & Tertiary Buildings

TRL 7

Optimems

Optimization of energy sources:

- Load
- RES
- Storage
- Energy prices

Optimization:

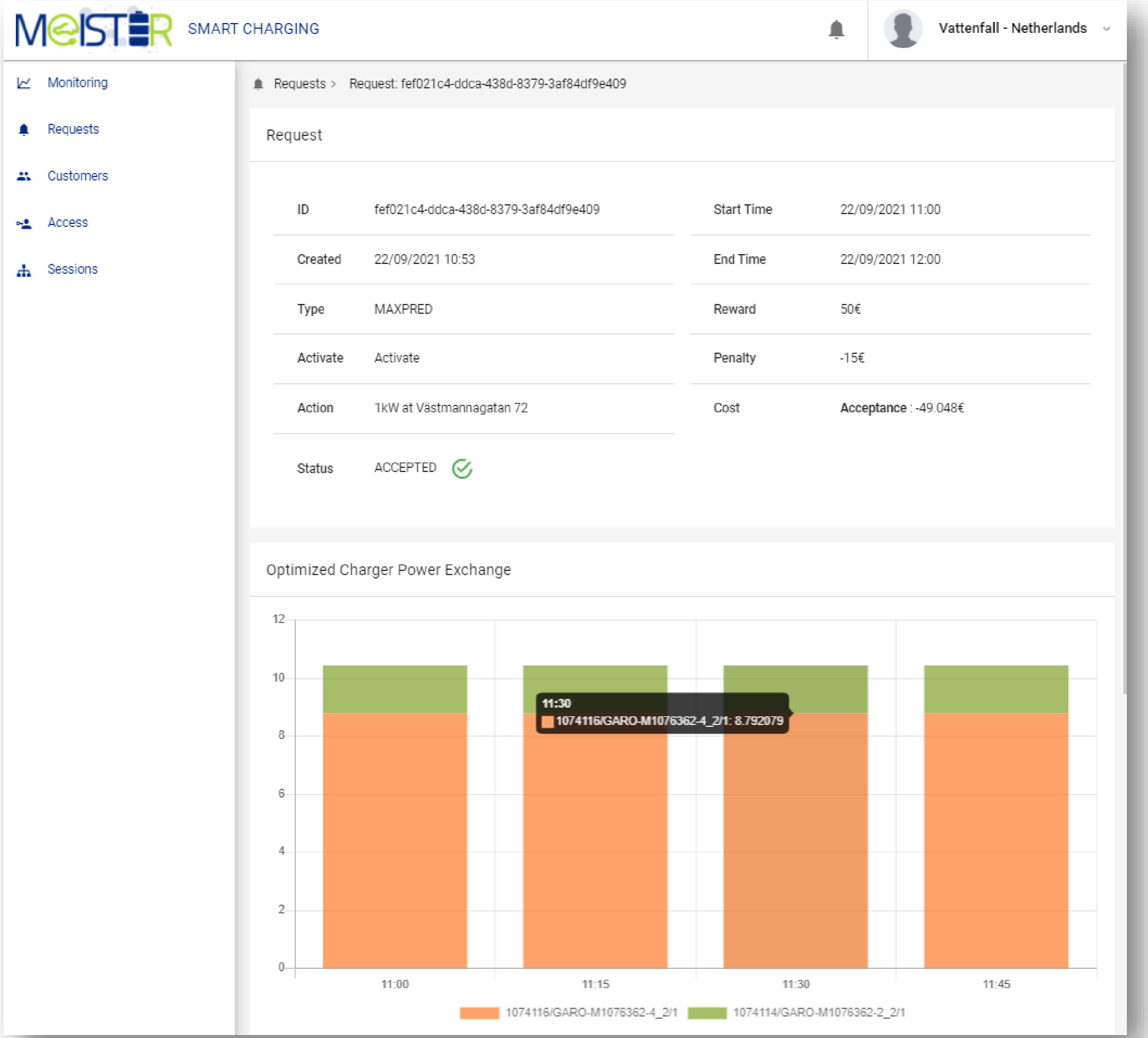
- What to do with energy generated by RES?
- When to charge or discharge the storage equipment?
- When to sell or buy energy from the Grid?
- When to shift loads?
- ...

TRL 7

MEISTER

Optimized VPP energy management for EV parking lots

- Optimal V1G and V2G charging schedule
- Implementation of Demand-Response signals (load dispatch type)
- Charging Sessions monitoring
- Dynamic Pricing integration



VATTENFALL

ELLEVIO

e.on

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Smart Grid

Scope: Provide added-value services to Distribution Grid

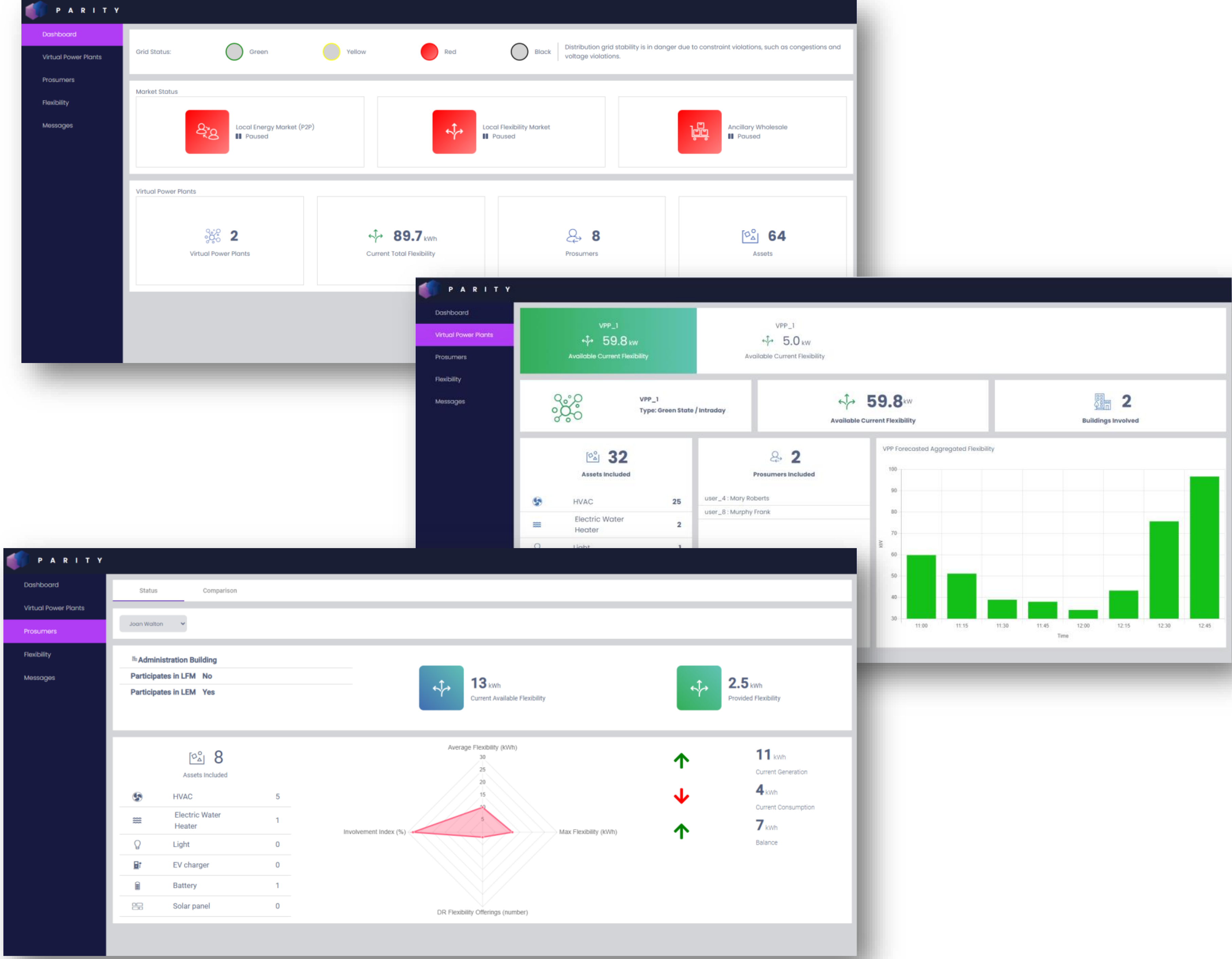
Beneficiaries: Aggregators, Prosumers, DSO

- Trade of electricity / flexibility automatically in a secure and optimized manner based on Grid state
- Optimal management of distributed energy resources
- Cross-sector energy sector optimal management (electric, thermal, gas)
- Predictive Maintenance in Distribution Grid assets (e.g. Transformers)

Smart Grid

PARITY

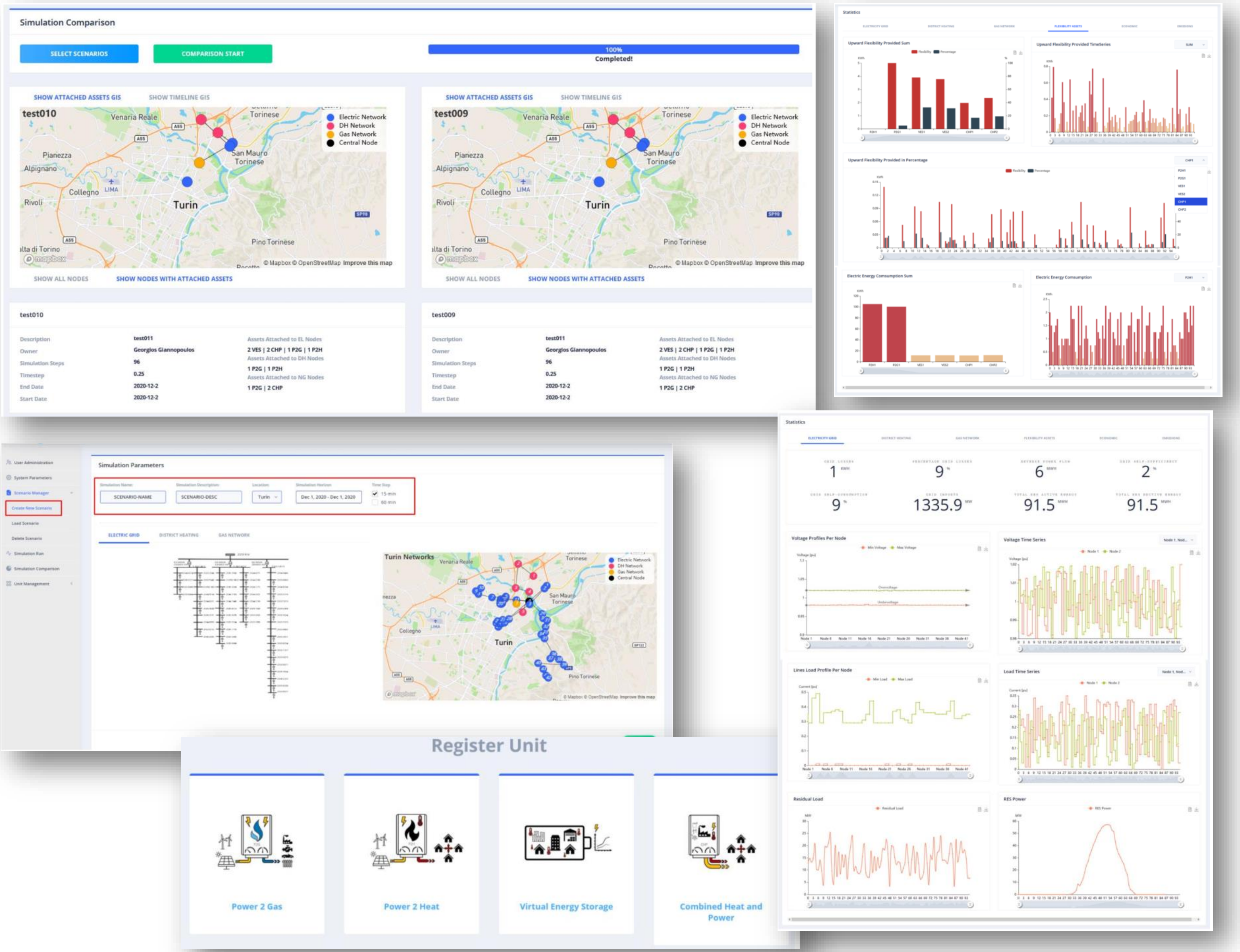
- Formation of dynamic VPPs
- Integration with a Local Flexibility Market to provide flexibility to DSO upon request (directly or through the market using price signals)
- Trading of excess aggregated flexibility to wholesale and ancillary markets, based on grid state
- Information views about each prosumer and optimal asset management
- Head-to-head comparison of prosumers' metrics



e.on HEDNO URBENER Energía

planet

- Real-time simulation of electric, natural gas and district heating network inter-coupled via Power-to-Gas, Power-to-Heat and Combined Heat & Power Flexibility Units
- Novel KPI-based assessment framework
- Scenarios Creator and Dynamic Comparison
- Distributed Simulations Orchestrator



POLITECNICO DI TORINO

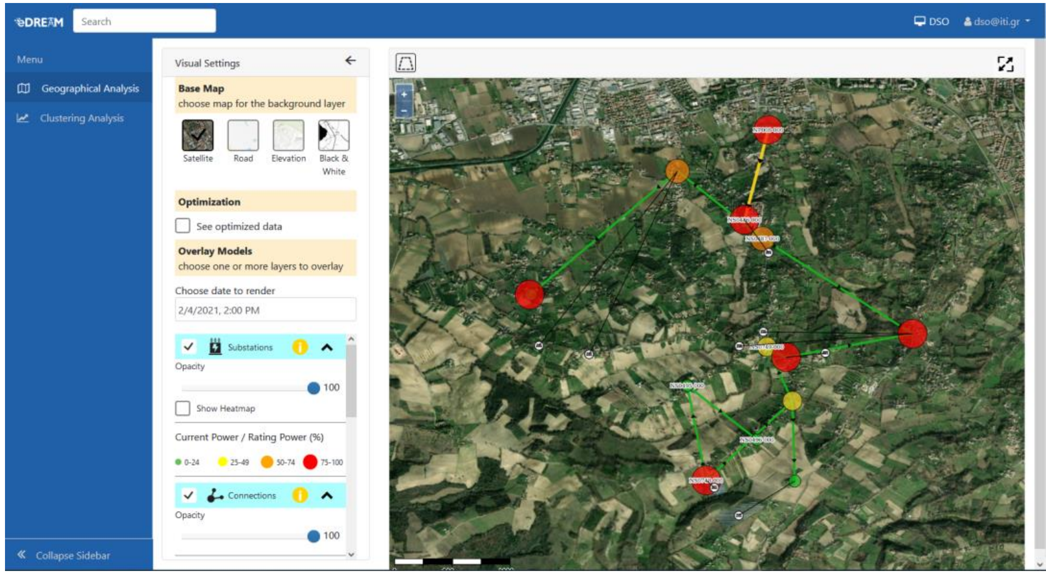
HIT HYPERTECH INNOVATIONS

Energy Efficiency at DN level

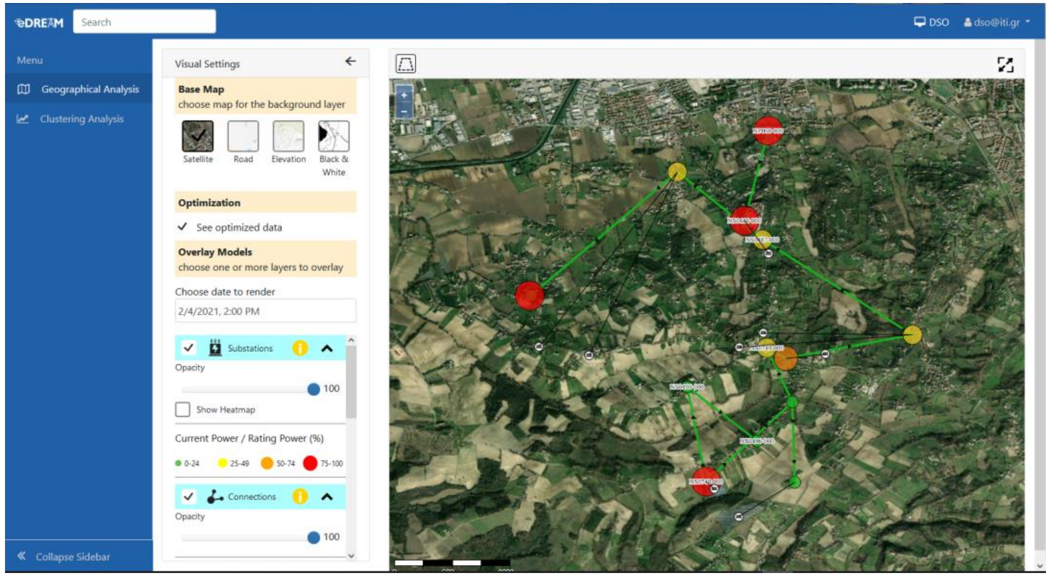
enabling new Demand REsponse Advanced, Market oriented and secure technologies, solutions and business models

- **Geographical representation** of the DN
- **Power flow depiction** along with critical levels of substations and feeders and connection points of RES/DER.
- **Objective**: loss minimization along with Voltage profile improvement, via DER utilization, i.e. RES adjustment / load flexibility.
- Congestion avoided

Before



After

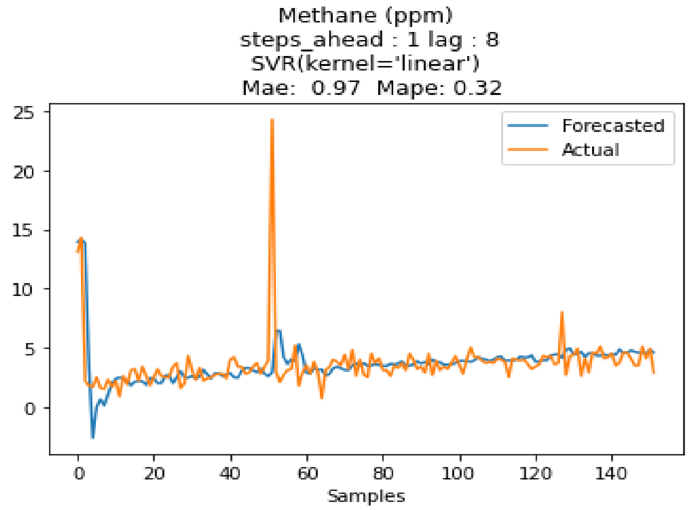


INTERPRETER project: Modular grid management solution

Predictive Maintenance on Transformers

The problem to be solved:

- Dynamic Assessment of T/F State of Health (SoH)
- Forecast diffused gases in T/F
- Minimize costly incidents(faults) and Maximize equipment lifespan



Core Technologies utilized:

- Timeseries analysis
- Data preprocessing
- Machine learning techniques
- Grid Search, Feature Selection
- Multi-objective Optimization

XFM-1	XFM-1/line4	XFM-1/line8	XFM-1/regulator
nan	nan	nan	nan
2012-06-25	nan	2012-06-29	nan
nan	nan	nan	2012-06-17
2012-06-29	nan	nan	2012-06-29
2012-06-29	2012-06-17	2012-06-17	2012-06-21

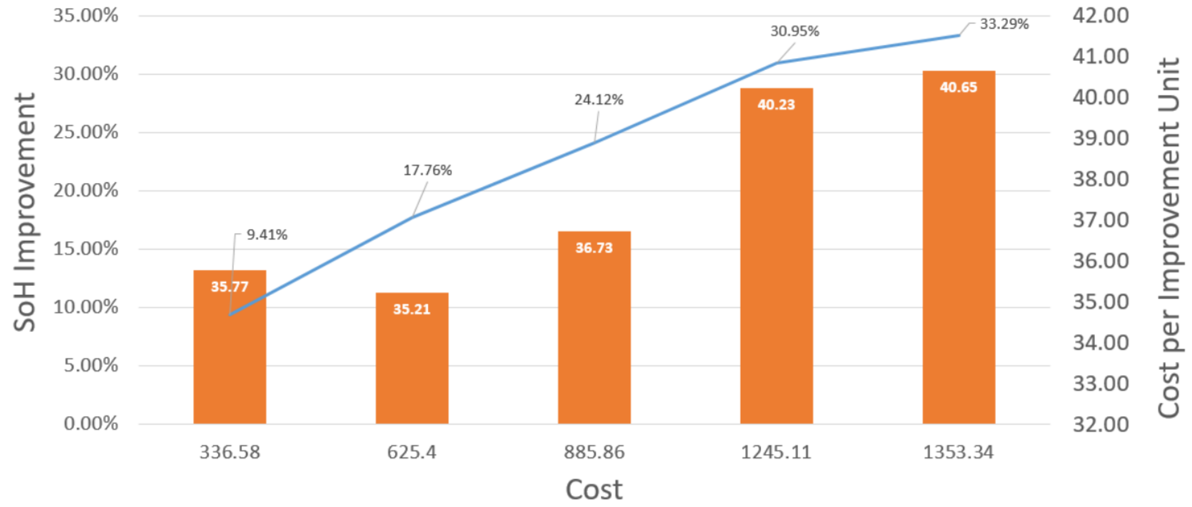
Grid Operators Support

INTERPRETER project: Modular grid management solution

Predictive Maintenance on Transformers

- Distribution Grid Modelling & Simulation
- Data from UK Power station transformers (2010-2015)
- Regression forecasting for diffused gases (multi-model)
- Use predictions to search for faults in the transformers and assess SoH
- Duval's Triangles & Pentagons
- Optimize faults to provide solutions

Achieves **over 32%** in the overall SoH improvement



Grid Operators Support

INTERPRETER project: Modular grid management solution

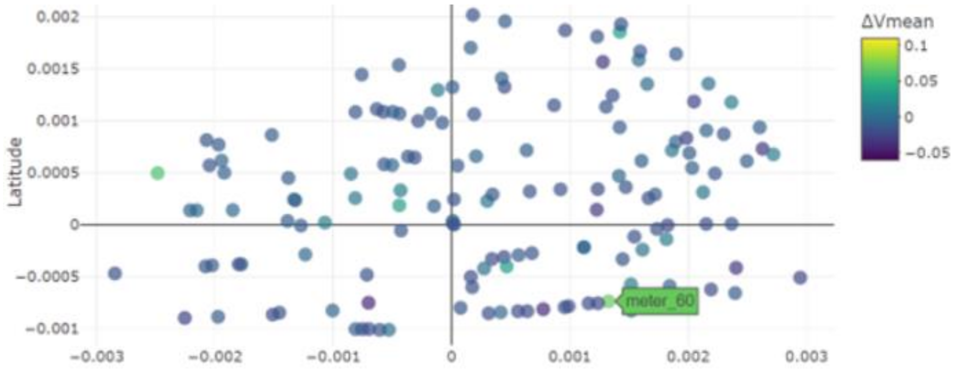
Non-technical losses detection

The problem to be solved:

- Provide support to DSO operation staff to locate non-technical losses
- Quantify losses at MV/LV transformer level
- Create a hybrid detection tool to identify
  - Clients with suspicious smart meter readings
  - Line sections with high losses

Core Technologies utilized:

- Machine learning techniques
- Timeseries analysis
- Data preprocessing
- Feature Selection
- Load-flow analysis



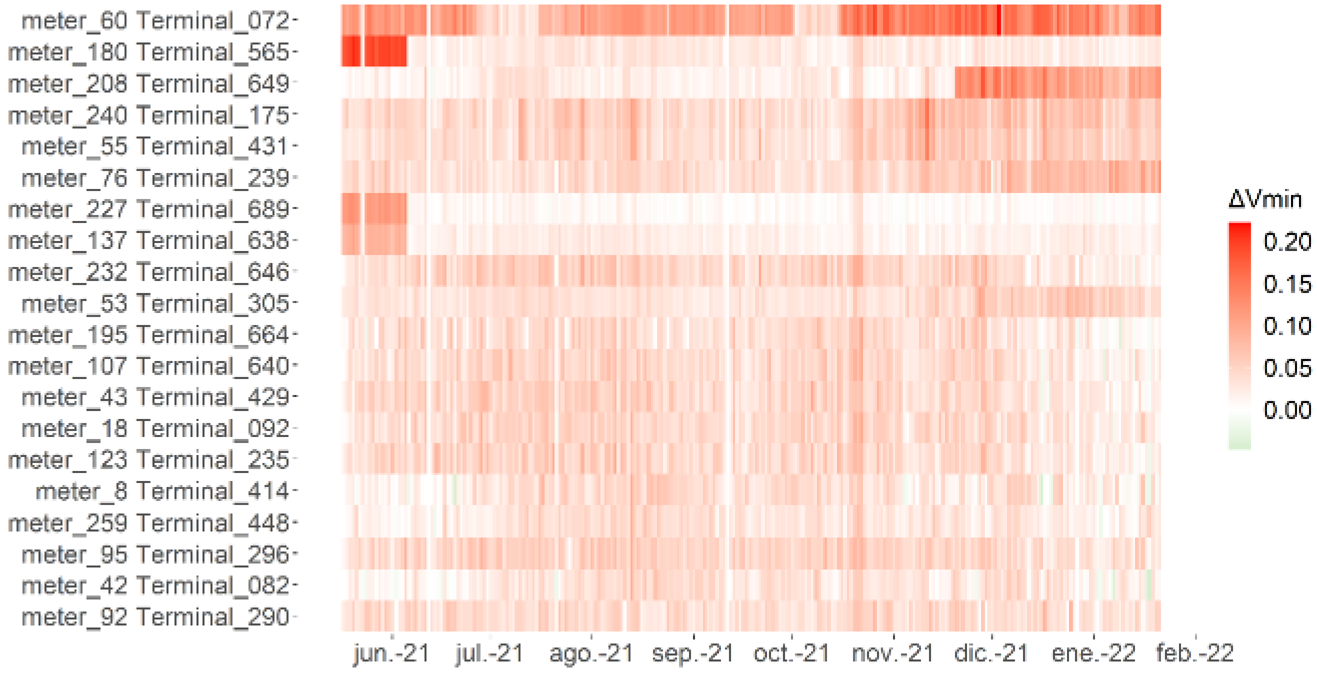
Spatio-temporal analysis of ΔVmean

Grid Operators Support

INTERPRETER project: Modular grid management solution

Non-technical losses detection

- Heatmap of top 20 locations with highest of Dvmin_max



Indicates the location of possible frauds
which are not related with the grid model

Grid Operators Support

Thank you

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