Edge Computing Platform (ECP) for Fault-Tolerant, Highly Reliable and Resilient Power Electronics in Prosumer Applications

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SMARTGYsum Project

CERGY PARIS UNIVERSITÉ

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- **PV-Battery System Modeling & Cost Assessment**
- **Joint Sizing Optimization and Economic Feasibility**
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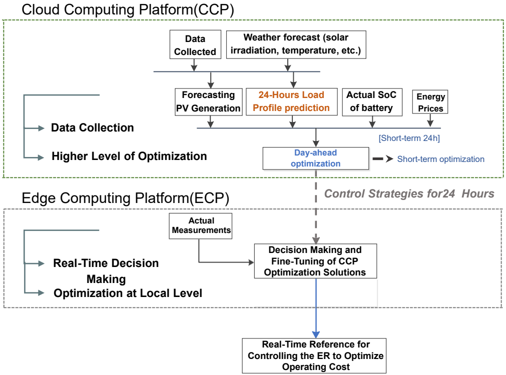
Introduction

Project Overview

Main objective:

- Develop an EMS for residential prosumer applications.
- Manage energy flows between PV, battery, loads, and grid.
- Combine cloud-level optimization with edge-level real-time control.
- Improve operational cost, battery usage, and system reliability.



Cloud Computing Platform(CCP)

Data Collected

Weather forecast (solar irradiation, temperature, etc.)

Forecasting PV Generation

24-Hours Load Profile prediction

Actual SoC of battery

Energy Prices

Data Collection

Higher Level of Optimization

[Short-term 24h]

Day-ahead optimization

Short-term optimization

Control Strategies for24 Hours

Edge Computing Platform(ECP)

Actual Measurements

Real-Time Decision Making

Optimization at Local Level

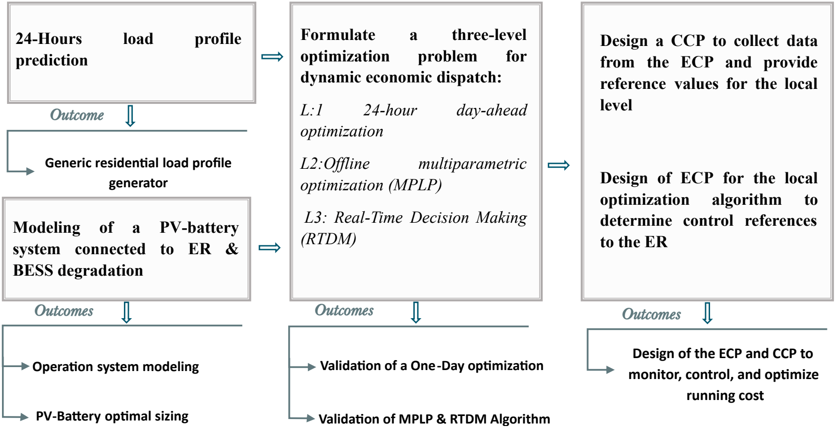
Decision Making and Fine-Tuning of CCP Optimization Solutions

Real-Time Reference for Controlling the ER to Optimize Operating Cost

Fig.1: Schematic representation of the proposed system architecture.

Introduction

Methodology



24-Hours load profile prediction

Outcome

Generic residential load profile generator

Modeling of a PV-battery system connected to ER & BESS degradation

Outcomes

- **Operation system modeling**
- **PV-Battery optimal sizing**

Formulate a three-level optimization problem for dynamic economic dispatch:

L:1 24-hour day-ahead optimization

L2:Offline multiparametric optimization (MPLP)

L3: Real-Time Decision Making (RTDM)

Outcomes

- **Validation of a One-Day optimization**
- **Validation of MPLP & RTDM Algorithm**

Design a CCP to collect data from the ECP and provide reference values for the local level

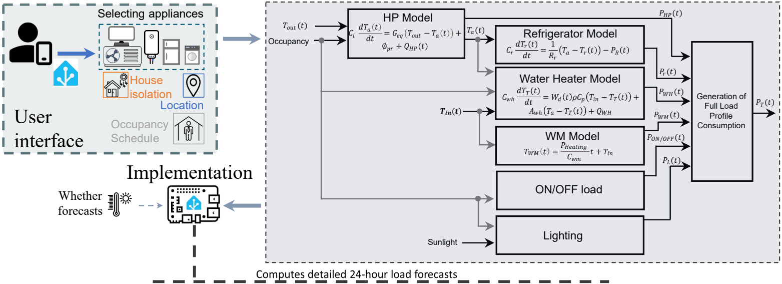
Design of ECP for the local optimization algorithm to determine control references to the ER

Outcomes

Design of the ECP and CCP to monitor, control, and optimize running cost

Load Profile Prediction

Overview & Implementation



Selecting appliances

House isolation

Location

Occupancy Schedule

User interface

Implementation

Whether forecasts

$T_{out}(t)$

Occupancy

HP Model

$$C_i \frac{dT_a(t)}{dt} = G_{eq}\left(T_{out} - T_a(t)\right) + \emptyset_{pr} + Q_{HP}(t)$$

$T_a(t)$

Refrigerator Model

$$C_r \frac{dT_r(t)}{dt} = \frac{1}{R_r}\left(T_a - T_r(t)\right) - P_R(t)$$

Water Heater Model

$$C_{wh} \frac{dT_T(t)}{dt} = W_d(t)\rho C_p\left(T_{in} - T_T(t)\right) + A_{wh}\left(T_a - T_T(t)\right) + Q_{WH}$$

$\boldsymbol{T_{in}(t)}$

WM Model

$$T_{WM}(t) = \frac{P_{Heating}}{C_{wm}} t + T_{in}$$

ON/OFF load

Lighting

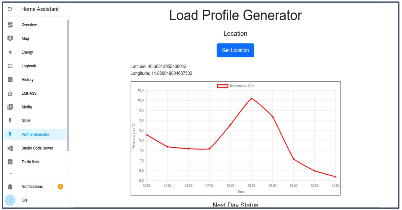
Sunlight

$P_{HP}(t)$, $P_r(t)$, $P_{WH}(t)$, $P_{WM}(t)$, $P_{ON/OFF}(t)$, $P_L(t)$

Generation of Full Load Profile Consumption

$P_T(t)$

Computes detailed 24-hour load forecasts

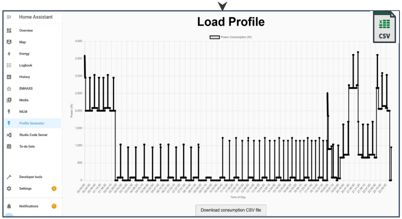


Load Profile Generator

Location

Latitude: 40.66813955408042
Longitude: 14.826049804687502

Next Day Status



Load Profile

Conceptual workflow for power consumption profile generation

PV-Battery System Modeling & Cost Assessment

Battery Degradation Cost Models

BESS degradation:

$$Q_{t,F} = Q_{t,F(\mathrm{cal})} + Q_{t,F(\mathrm{cyc})}$$

SoH-based:

$$C_{d,F}^{\mathrm{SoH}} = \sum_{t \in \Gamma} \frac{c_f E_b}{1 - SoH_f} \Delta SoH_{t,b}$$

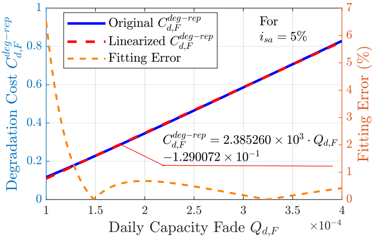
FEC-based:

$$C_{d,F}^{\mathrm{FEC}} = \sum_{t \in \Gamma} \frac{c_f E_b}{N_{\mathrm{cyc}}} \Delta FEC_t$$

Proposed:

$$C_{d,F}^{\text{deg-rep}} = c_f E_b \cdot \frac{i_{sa}}{(1 + i_{sa})^{D_b} - 1} \cdot \frac{1}{\gamma}$$

- SoH-based: direct SoH loss
- FEC-based: equivalent cycles
- Proposed: replacement-oriented cost



Linear approximation of degradation cost

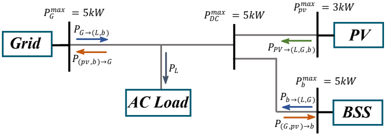
PV-Battery System Modeling & Cost Assessment

Day-Ahead Optimization Problem

$$\min \ C_{\text{daily}} = C_{\text{imp}} - C_{\text{exp}} + C_{\text{deg}}$$

s.t.

$$
\begin{aligned}
&P_L = P_{G\to L} + P_{b\to L} + P_{pv\to L}\\
&P_{pv} = P_{pv\to L} + P_{pv\to b} + P_{pv\to G}\\
&0 \le P_{G\to(L,b)} \le P_G^{\max}\\
&0 \le P_{(pv,b)\to G} \le P_G^{\max}\\
&0 \le P_{pv\to(L,b,G)} \le P_{pv}^{\max}\\
&0 \le P_{(G,pv)\to b} \le P_{b,ch}^{\max}\\
&0 \le P_{b\to(G,L)} \le P_{b,dch}^{\max}\\
&SoC_b^{\min} \le SoC_{t,b} \le SoC_b^{\max}\\
&P_{DC} \le P_{DC}^{\max}\\
&P_{(G,pv)\to b}\, P_{b\to(G,L)} = 0\\
&P_{G\to(L,b)}\, P_{(pv,b)\to G} = 0
\end{aligned}
$$



System power flow representation.

PV-Battery System Modeling & Cost Assessment

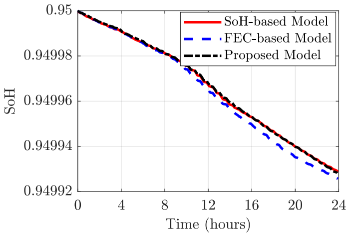
Main Results and Computational Comparison

Expected battery lifetime (winter case)

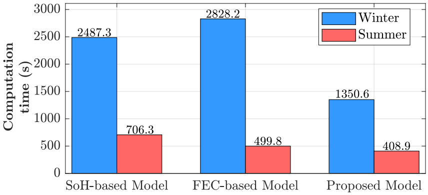
- **SoH-based:** 7.68 years
- **FEC-based:** 7.36 years
- **Proposed model:** 7.59 years

Interpretation

- The FEC-based model allows more aggressive cycling, leading to higher degradation and the shortest lifetime.
- The SoH-based model is more conservative and gives the longest lifetime.
- The proposed model provides a balanced compromise and also achieves the lowest computation time.



SoH evolution



Computation time

Joint Sizing Optimization and Economic Feasibility

Cost Function and Optimization Problem

Annualized cost

$$C_T = C_{\mathrm{Inv}} + C_{\mathrm{Rep}} + C_{\mathrm{Main}} + C_{\mathrm{Op}}$$

Replacement cost

$$C_{\mathrm{Rep},b} \propto \frac{i_{\mathrm{sa}}}{(1+i_{\mathrm{sa}})^{\frac{\mathrm{SoH}_i - \mathrm{SoH}_f}{A_b}} - 1}$$

Decision vector

$$X = [\, N_{pv},\ N_b,\ P_{t,*\to *}\,]^T$$

Optimization problem

$$\min_X \ C_T(X)$$

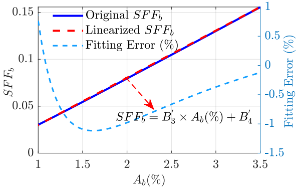
s.t.

Power balance and SoC constraints

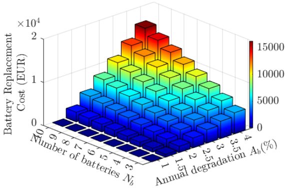
Grid / converter limits

$$N_{pv} \le \frac{S_{\mathrm{House}}}{S_{1,\mathrm{panel}}}$$

$$C_{\mathrm{Inv}} \le C_{\mathrm{Inv}}^{\max}$$



Linear approximation of SFF_b



Replacement cost variation with A_b and N_b

Joint Sizing Optimization and Economic Feasibility

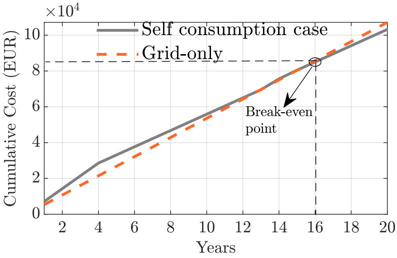
Optimal Sizing and Estimated Battery Lifetime

Mode	**Week**	$\mathbf{N_{pv}^{opt}}$	$\mathbf{N_{b}^{opt}}$	**Overall Cost**	$\mathbf{A_b}$ **(%)**	$\mathbf{D_b}$ **(yr)**
$\lambda = 0$	Low	25	7	248.14	1.60	12.50
$\lambda = 0$	Medium	16	3	20.33	1.33	15.00
$\lambda = 0$	High	24	5	35.81	1.58	12.60
$\lambda = 1$	Low	25	7	242.02	1.74	11.52
$\lambda = 1$	Medium	25	7	13.20	1.38	14.50
$\lambda = 1$	High	25	5	15.95	1.59	12.57

- Under grid-selling, the optimal PV size tends to reach its upper bound.
- The battery size remains adaptive depending on irradiance conditions.
- The estimated battery lifetime stays between about 11.5 and 15 years.

Joint Sizing Optimization and Economic Feasibility

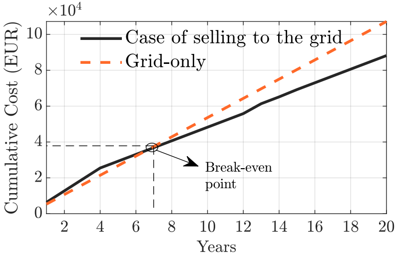
Sizing and Economic Results



(a) Payback curve for self-consumption

Key sizing results

- Under grid-selling, the optimal PV size reaches its upper bound.
- The battery size remains adaptive depending on irradiance conditions.
- Degradation-aware sizing avoids excessive battery oversizing.



(b) Payback curve for grid-selling

Economic interpretation

- Self-consumption: payback about 16 years.
- Grid-selling: payback about 7 years.
- Export revenues reduce total annual cost despite slightly higher degradation.
- The grid-selling mode provides the best economic trade-off.

Multiparametric Optimization

L1: Deterministic Day-Ahead Scheduling

Main idea

- 24-h deterministic scheduling used as global reference.
- Provides nominal dispatch and SoC targets for L2.
- Reformulated as LP for MPLP compatibility.

Complementarity and proof

$$P_{(G,pv)\to b}\,P_{b\to(G,L)} = 0$$
$$P_{G\to(L,b)}\,P_{(pv,b)\to G} = 0$$

- A proof shows that simultaneous opposite flows cannot be optimal.
- Hence, these constraints can be removed without changing the optimum.

Metric	**NLP**	**LP**	**MILP**
Solver	`fmincon`	`linprog`	`intlinprog`
Solver time (s)	483.83	0.0271	0.0281
Total cost (€)	31.7535	27.2756	27.2756
Deg. cost (€)	0.3111	0.3668	0.3668
Savings (€)	8.8214	13.2992	13.2992
Max sim. grid (kW)	5.99×10^{-5}	0	0
Max sim. batt. (kW)	4.03×10^{-4}	0	0

Multiparametric Optimization

L2: Offline MPLP under Uncertainty

Main idea

- A 4-hour MPLP is solved offline.
- First-step load, PV, and initial SoC are treated as parameters.
- The explicit solution gives affine laws over critical regions.

Compact MPLP form

$$\begin{aligned} \min_{x}\ & c^{\top}x \\ \text{s.t.}\ & Ax \le b + F\theta \\ & A_{eq}x = b_{eq} + F_{eq}\theta,\ x \ge 0 \end{aligned}$$

Outcome

- Real-time control only needs region identification and affine-law evaluation.
- L2 handles short-term uncertainty while L1 preserves the daily economic objective.

Active parameter vector

$$\theta = \begin{cases} [P_{L,1},\ P_{PV,1},\ s_0]^{\top}, & \text{daytime} \\ [P_{L,1},\ s_0]^{\top}, & \text{no-PV} \end{cases}$$

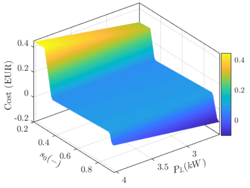
Uncertainty set

$$\Theta = \{\theta \mid \theta^{\min} \le \theta \le \theta^{\max}\}$$

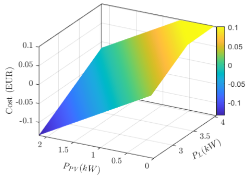
$$\begin{aligned} P_{L,1}^{\min} &= \hat{P}_{L,1}(1-\delta_L) \\ P_{L,1}^{\max} &= (1-\delta_L)\hat{P}_{L,1} + \delta_L P_L^{\max} \\ P_{PV,1}^{\min} &= \hat{P}_{PV,1}(1-\delta_{PV}) \\ P_{PV,1}^{\max} &= (1-\delta_{PV})\hat{P}_{PV,1} + \delta_{PV} P_{PV}^{\max} \\ s_0^{\min} &\le s_0 \le s_0^{\max} \end{aligned}$$

Multiparametric Optimization

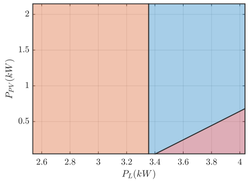
L2: Offline MPLP under Uncertainty



(a) $J(P_L, s_0)$ for $P_{PV} = 0.16\ \mathrm{kW}$



(b) $J(P_L, P_{PV})$ for $s_0 = 0.9$



(c) Projection of the CRs for the slice $s_0 = 0.90$

δ_L	δ_{PV}	Total number of critical regions	Computation time (s)
0.3	0.3	728	144.0
0.3	0.5	751	145.2
0.3	0.7	775	147.0
0.5	0.5	803	148.8
0.7	0.7	927	155.4
1.0	1.0	936	156.0

Impact of uncertainty levels on the explicit solution over the 4-hour moving-horizon study

Multiparametric Optimization

L3: Real-Time Decision Making

RTDM principle

- Build the current parameter vector $\hat{\theta}$.
- Identify the active critical region.
- Evaluate the affine law:

$$x^\star(\hat{\theta}) = F_i\hat{\theta} + g_i$$

- Apply the first-step control action.

Exemple:

$$\hat{\theta} = \begin{bmatrix}3.6238 & 0.1607 & 0.35\end{bmatrix}^\top$$

CR5 bounding box

$$\begin{aligned} 2.536741 \leq P_{L,1} &\leq 4.036541 \\ 0.048321 \leq P_{PV,1} &\leq 2.148121 \\ 0.301613 \leq s_0 &\leq 0.370853 \end{aligned}$$

Since $\hat{\theta}$ satisfies these bounds, it belongs to **CR5**.

Region 5 interpretation

- $P^\star_{PV\to L} = P_{PV,1}$
- $P^\star_{b\to L} = 57.6\, s_0 - 17.372899$
- $P^\star_{G\to L} =$ $P_{L,1} - P_{PV,1} - 57.6\, s_0 + 17.372899$
- No charging and no grid export

Obtained first-step control

$$x_1^\star(\hat{\theta}) = [0.6760,\ 0,\ 0,\ 0,\ 0.1607,\ 2.7871,\ 0]^\top\ \mathrm{k}$$

Multiparametric Optimization

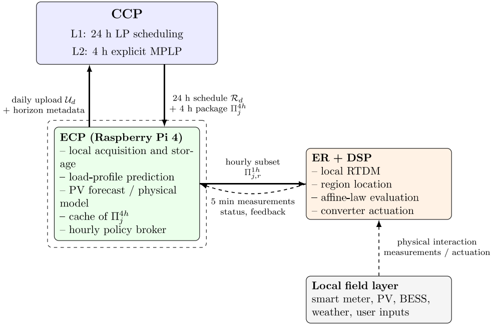
Conceptual Cloud/Edge Deployment Design

Role split

- **CCP:** 24-hour LP scheduling and 4-hour explicit MPLP generation
- **ECP:** local data, prediction, policy storage, and hourly policy transfer
- **ER:** real-time region identification and affine-law evaluation

Interest

- Reduces online computation burden
- Improves resilience through staged buffering
- Suitable for low-cost embedded implementation



CCP
L1: 24 h LP scheduling
L2: 4 h explicit MPLP

daily upload $\mathcal{U}_d$
+ horizon metadata

24 h schedule $\mathcal{R}_d$
+ 4 h package Π_j^{4h}

ECP (Raspberry Pi 4)
– local acquisition and storage
– load-profile prediction
– PV forecast / physical model
– cache of Π_j^{4h}
– hourly policy broker

hourly subset
$\Pi_{j,r}^{1h}$

5 min measurements
status, feedback

ER + DSP
– local RTDM
– region location
– affine-law evaluation
– converter actuation

physical interaction
measurements / actuation

Local field layer
smart meter, PV, BESS,
weather, user inputs

Proposed cloud/edge communication and execution architecture

Conclusion

Publications, Award, and Mobility

Secondments

- **S1.** May–August 2024, TalTech, Estonia.
- **S2.** September–November 2025, TalTech, Estonia.

Journal Articles

1. **J1.** C. E. S. Lekhel, R. Mbayed, O. Velihorskyi, O. Husev, and E. Monmasson, "Generic residential load profile generator based on weather data and occupancy," *Mathematics and Computers in Simulation*, vol. 237, 2025. DOI: `10.1016/j.matcom.2025.04.044`
2. **J2.** C. E. S. Lekhel, R. Mbayed, H. N. Hokmabad, O. Husev, O. Velihorskyi, and E. Monmasson, "Joint sizing and energy management optimization with dynamic battery lifetime modeling in residential PV–battery systems," *Renewable Energy*, vol. 260, 2026. DOI: `10.1016/j.renene.2026.125188`

Award

- **A1.** Second Prize Committee Paper Award, Renewable Energy and Energy Storage Systems track, IEEE IECON 2025.

Conference Articles

1. **C1.** C. E. S. Lekhel, R. Mbayed, O. Velihorskyi, O. Husev, and E. Monmasson, "Programme générateur d'un profil de charge journalier générique dans un contexte résidentiel en combinant les modèles physiques et des données météorologiques," *SGE 2025*, Toulouse, France, Jul. 2025. HAL: `hal-05506773`
2. **C2.** C. E. S. Lekhel, R. Mbayed, H. N. Hokmabad, O. Husev, O. Velihorskyi, and E. Monmasson, "A Comparative Study of Battery Degradation Cost Modeling in Residential PV-Battery Systems for Day-Ahead Optimization," *IECON 2025*, Madrid, Spain, 2025, pp. 1–6. DOI: `10.1109/IECON58223.2025.11221673`
3. **C3.** H. N. Hokmabad, C. E. S. Lekhel, T. H. Shahsavar, P. P. Vergara, O. Husev, and J. Belikov, "A Unified Hierarchical Digital Twin Platform for Synergistic Management of Low-voltage Electrical Network Components," *ISGT Europe 2025*, Valletta, Malta, 2025, pp. 1–5. DOI: `10.1109/ISGTEurope64741.2025.11305379`
4. **C4.** C. E. S. Lekhel, R. Mbayed, O. Velihorskyi, O. Husev, and E. Monmasson, "Multiparametric Optimization for Residential EMS with an Energy Router and Aging-Aware BESS Considering Variable Ranges for Prediction Accuracy," *Electrimacs 2026*, accepted.

Thank You

for your attention

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