On-line diagnosis and optimization of Energy Management Systems for Smart Buildings

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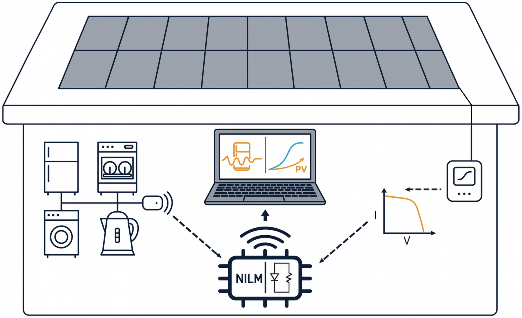
Results ⇒ SmartGySum Project Objectives



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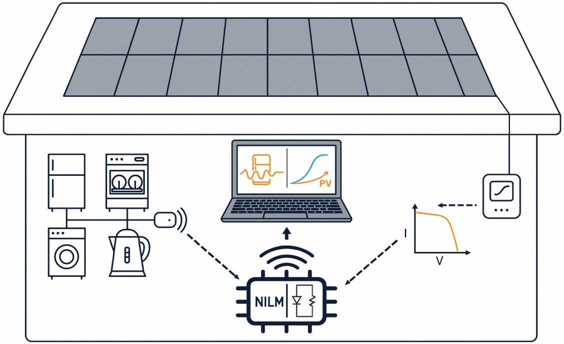
Part I: Demand-Side Intelligence: Non-Intrusive Load Monitoring

Part II: Supply-Side Intelligence: Robust PV Characterization

Part III: Integrated Demand-Supply Intelligence and Business Model

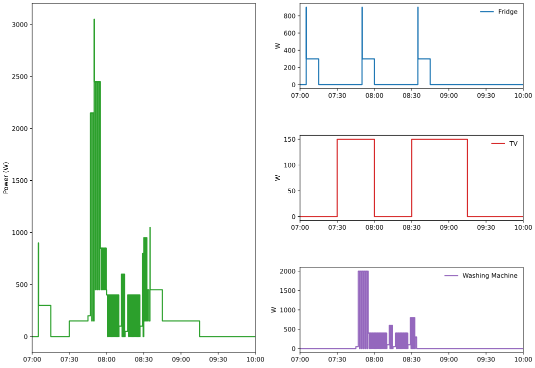


Part I: Demand-Side Intelligence: Non-Intrusive Load Monitoring

Part II: Supply-Side Intelligence: Robust PV Characterization

Part III: Integrated Demand-Supply Intelligence and Business Model

- Evaluation of CNN-NILM approaches in domain shifts.
- Identification of the key factors limiting robustness and generalization.
- Proposal of a new training-less NILM framework for real-time operation, and suitable for constrained edge hardware.
- Demonstration of strong accuracy and robustness in comparison with state-of-the-art methods across public datasets.



$$P(t) = \sum_{i=1}^{N} p_i(t) + \eta(t) \quad \Rightarrow \quad [\hat{p}_1(t), \ldots, \hat{p}_N(t)]$$

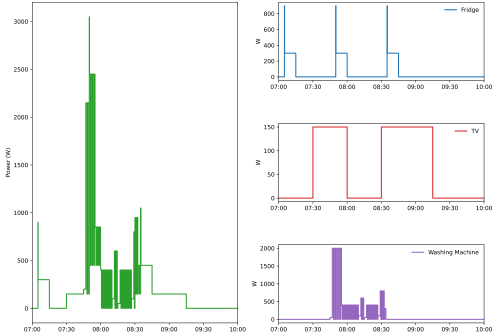
State of the Art

- **HMM / FHMM / AFHMM**
- **Optimization based**
- **Deep Learning**: Seq2Seq / Seq2Point CNNs, SSL, UDA
- **Training-less**: clustering, GSP

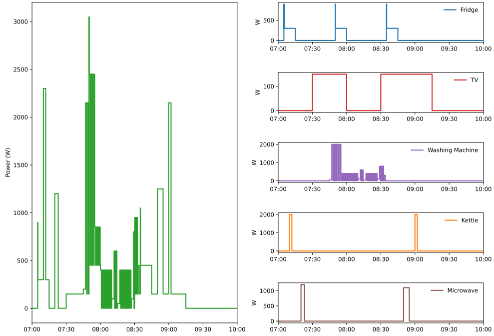
Limitations

- Needs sub-metered data for training / adaptation
- Poor generalization to unseen homes/appliances
- High compute/memory for real-time edge devices
- Sensitive to unknown appliances + noise

Domain shift → Degraded disaggregation



(a) Training Domain



(b) Test Domain

Sensitivity Analysis via First-Order Taylor Expansion

For single-appliance model $f_{\theta_i} : \mathbb{R}^W \to \mathbb{R}$, a small unknown load $\mathbf{U}$ perturbs the input $\mathbf{P}$:

$$f_{\theta_i}(\mathbf{P} + \mathbf{U}) \approx f_{\theta_i}(\mathbf{P}) + \nabla f_{\theta_i}(\mathbf{P})^\top \mathbf{U}.$$

Since $f_{\theta_i}(\mathbf{P}) \approx p_i$,

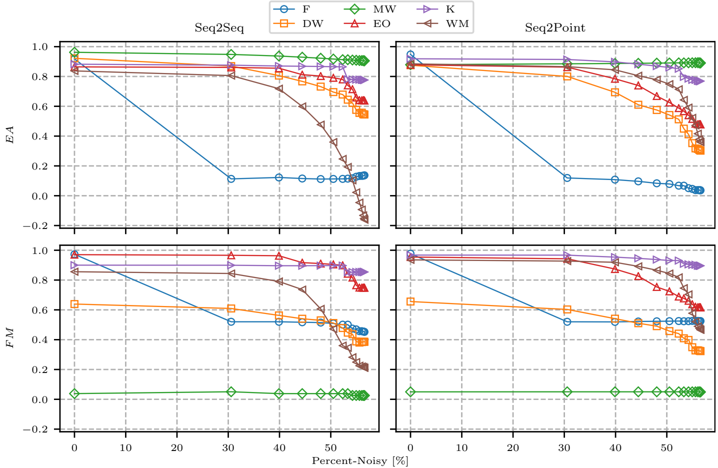
$$\Delta p_i = \hat{p}_i' - p_i \approx \nabla f_{\theta_i}(\mathbf{P})^\top \mathbf{U}, \epsilon^2 \approx \left(\nabla f_{\theta_i}(\mathbf{P})^\top \mathbf{U}\right)^2.$$

Key idea: extra error scales with unknown-load magnitude and model sensitivity $\|\nabla f_{\theta_i}(\mathbf{P})\|$.

Influence of Appliance Characteristics:

- **High-Power:** dominant signal $\Rightarrow$ lower gradient $\Rightarrow$ robust to moderate $\mathbf{U}$.
- **Multi-State:** subtle, transient patterns $\Rightarrow$ higher sensitivity $\Rightarrow$ moderate $\mathbf{U}$ can cause error.
- **Low-Power:** weak target, noise-susceptible $\Rightarrow$ large gradient needed $\Rightarrow$ even small $\mathbf{U}$ impacts error.

Experimental Verification



- low-power states or complex patterns ⇒ considerable deterioration **[Fridge (F), Washing Machine (WM), Dish Washer (DW)]**
- high power consumption or predictable patterns, ⇒ less affected by domain shift **[Kettle (K), Microwave (MW), Electric Oven (EO)]**

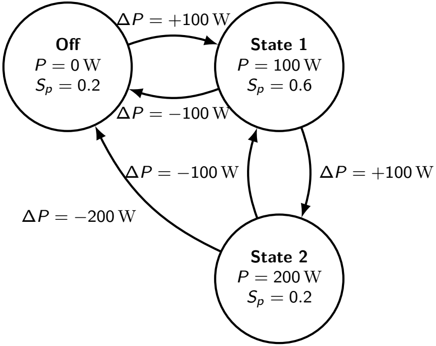


Figure: Finite State Machine Model

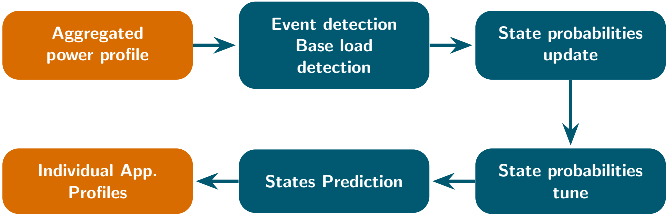


Figure: High Level Architecture O2RE Framework

O2RE: Online Real-Time Robust Non-Intrusive Load Monitoring for Edge Deployment

Event Detection, Base Load Detection (Module 1)

Edge Detection (3 points method)

$$\mu_P(t) = \frac{1}{3}\sum_{i=1}^{3} P(t - i\Delta t)$$

$$\sigma_P^2(t) = \frac{1}{3}\sum_{i=1}^{3} \left(P(t - i\Delta t) - \mu_P(t)\right)^2$$

Algorithm Base Load Estimation

$\alpha \leftarrow$ *User-defined* $\qquad \triangleright\ \alpha \in [0, 1]$
if $P(t) \leq B$ **then**
  $B \leftarrow P(t)$
else
  $\lambda \leftarrow \alpha \cdot \left(\frac{B}{P(t)}\right)^{(1-\alpha)}$
  $B \leftarrow B \cdot (1 - \lambda) + P(t) \cdot \lambda$
end if
return B

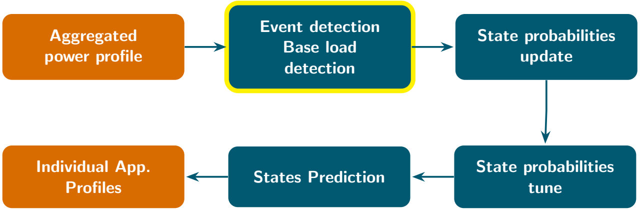
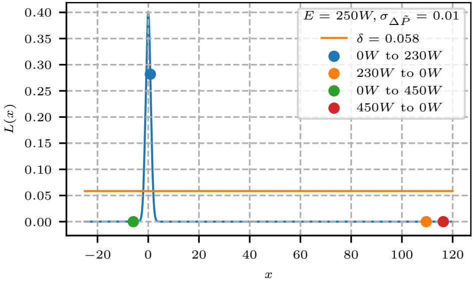


Figure: High Level Architecture O2RE Framework

State Probabilities Update (Module 2)



$$\Pr(T_{ijk} \mid E) = \frac{L(E \mid T_{ijk})\,\Pr(T_{ijk})}{\sum_{\substack{\forall i'j'k' \\ j' \neq k'}} L(E \mid T_{i'j'k'})\,\Pr(T_{i'j'k'}) + \mathrm{UTT}}$$

$$S'_{P_{i,j}} = \sum_{j \neq k} \Pr(T_{ikj} \mid E) \cdot S_{P_{i,k}} + \left(1 - \sum_{j \neq k} \Pr(T_{ijk} \mid E)\right) \cdot S_{P_{i,j}}$$

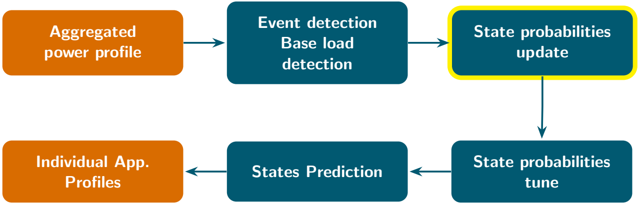


Figure: High Level Architecture O2RE Framework

State Probabilities Tuning

- *Motivation:* State probabilities S_P depend on edge detection; bad edge values can leave an appliance wrongly ON/OFF.
- *Goal:* Keep S_P robust to such anomalies.
- *When to tune:* if expected power exceeds the fluctuating part: $\mathbb{E}[P] > P_{\text{fluc}}$.
- *Fluctuating power:* $P_{\text{fluc}} = \max(0, \overline{P}_{\text{curr}} - B)$

$$\mathbb{E}[P] = \sum_{i=1}^{N} \sum_{j=0}^{M_i} S_{P_{i,j}} P_{i,j}$$

Update: adjust S_P to satisfy $\mathbb{E}[P] \leq P_{\text{fluc}}$ while staying close to the original S_P

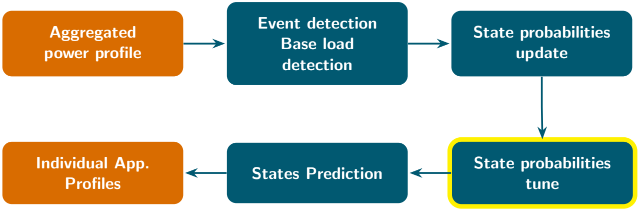


Figure: High Level Architecture O2RE Framework

States Prediction (Module 4)

Algorithm PBIL for appliance states prediction

Initialize: S_z, λ, p_m, G
$\vec{Pr}_i \leftarrow [S_{P_{i,0}}; \ldots; S_{P_{i,M_i}}]$
for $g \leftarrow 1$ **to** G **do**
    Generate a set *pop* of S_z samples from $\vec{Pr}$
    Set $\vec{B}$ to the best sample in *pop*
    for $i \leftarrow 1$ **to** N **do**
        $\vec{Pr}_i \leftarrow (1-\lambda)\,\vec{Pr}_i + \lambda\,\vec{B}_i$
    end for
    for $i \leftarrow 1$ **to** N **do**
        if $\mathrm{rand}(0,1) < p_m$ **then**
            $\vec{Pr}_i \leftarrow (1-\lambda)\,\vec{Pr}_i + \lambda\,\vec{M}_i$
        end if
    end for
end for
$S_{i,j} \leftarrow 0$
$\texttt{selected\_state}_i \leftarrow \mathrm{argmax}_j(\vec{Pr}_i)$
$S_{i,\texttt{selected\_state}_i} \leftarrow 1$
return S

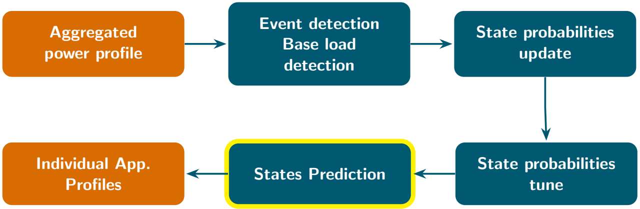
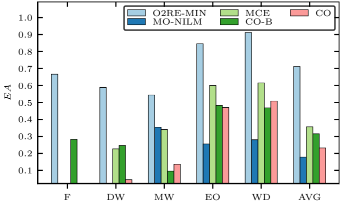
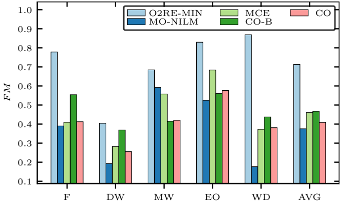


Figure: High Level Architecture O2RE Framework

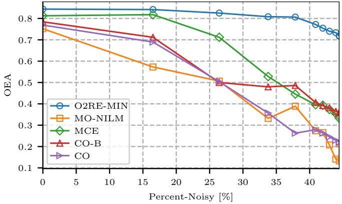
Performance Results



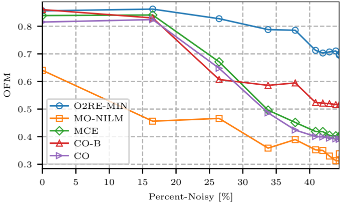
Estimation accuracy (Scenario 1: REDD-1, 96h)



F-measure (Scenario 1: REDD-1, 96h)



Overall Estimation Accuracy vs. noise



Overall F-measure vs. noise

Insights

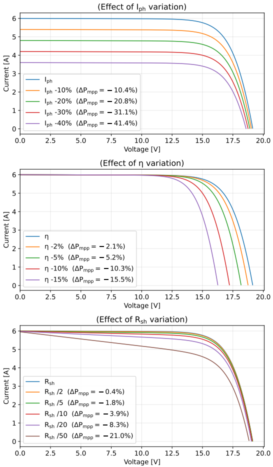
- O2RE consistently outperforms all competing algorithms across all scenarios.
- Competing algorithms show clear degradation as noise increases.
- O2RE remains stable and reliable even under heavy noise, with OEA and OFM staying above 0.7 even when noise exceeds 40 percent.

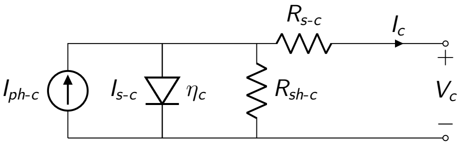
Part I: Demand-Side Intelligence: Non-Intrusive Load Monitoring

Part II: Supply-Side Intelligence: Robust PV Characterization

Part III: Integrated Demand-Supply Intelligence and Business Model

- Multi-objective framework combining static I–V and dynamic IS data for coherent PV parameter estimation.
- Introduction of a self-adapting procedure valid under uniform and mismatched conditions, using only I-V cuvers, enabling practical field deployment.
- Robust behaviour demonstrated under diverse mismatch patterns and operating conditions.
- Effective detection of degradation phenomena with improved stability compared to standard models.

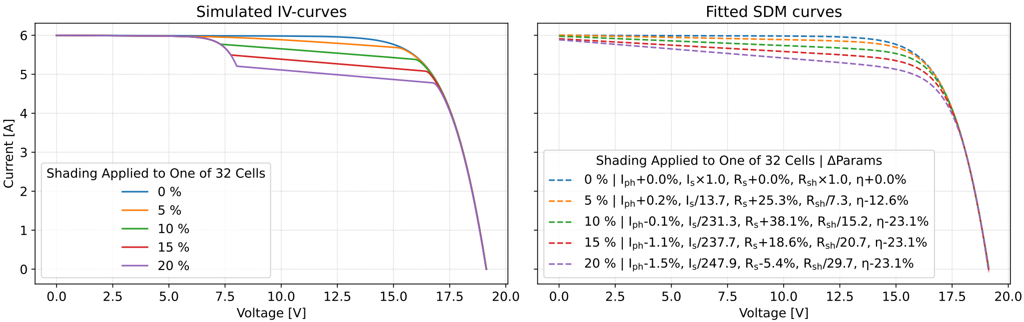




$$I_c = I_{ph\text{-}c} - I_{s\text{-}c}\left(\exp\left(\frac{V_c + I_c R_{s\text{-}c}}{\eta_c V_{th\text{-}c}}\right) - 1\right) - \frac{V_c + I_c R_{s\text{-}c}}{R_{sh\text{-}c}}$$

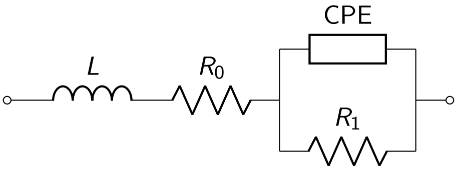
Scaled to a N_s-series module:

$$\begin{aligned} V_{th\text{-}m} &= N_s \cdot V_{th\text{-}c} \\ I_{ph\text{-}m} &= I_{ph\text{-}c} \\ I_{s\text{-}m} &= I_{s\text{-}c} \\ \eta_m &= \eta_c \\ R_{s\text{-}m} &= N_s \cdot R_{s\text{-}c} \\ R_{sh\text{-}m} &= N_s \cdot R_{sh\text{-}c} \end{aligned}$$

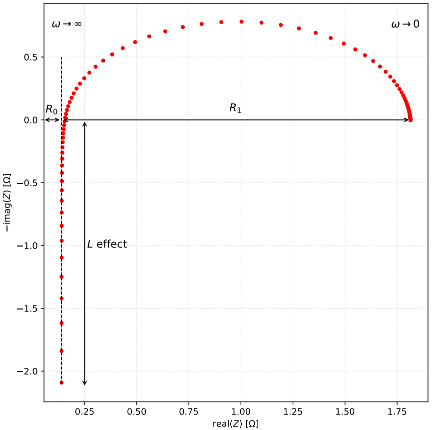


Effect of progressively shading a single cell in a 32-cell series string (2×16). Left: simulated $I-V$ (0–20% shading). Right: SDM fits with parameter changes vs. baseline.

Frequency Domain Analysis as a Complement



$$Z_{eq}(\omega) = j\omega L + R_0 + \frac{R_1}{(j\omega)^{\beta} Q R_1 + 1}$$



Garcia-Marrero et al., CPE-POWERENG (2023)

Multi-objective formulation

Objectives

$$f_1 = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{i,\exp} - I_{i,\mathrm{cal}}\right)^2}$$

$$f_2 = \sum_{i=1}^{M}\left[\frac{(Z'_{i,\exp} - Z'_{i,\mathrm{cal}})^2}{\sqrt{Z'^2_{i,\mathrm{cal}} + Z''^2_{i,\mathrm{cal}}}} + \frac{(Z''_{i,\exp} - Z''_{i,\mathrm{cal}})^2}{\sqrt{Z'^2_{i,\mathrm{cal}} + Z''^2_{i,\mathrm{cal}}}}\right]$$

Normalization (when converged)

$$\widetilde{f}_i(\mathbf{x}) = \frac{f_i(\mathbf{x}) - (\mathrm{ideal}_i - \epsilon)}{\mathrm{nadir}_i - (\mathrm{ideal}_i - \epsilon)}$$

Ideal: minimize f_1/f_2 separately. Nadir: fix $R_s = R_0^{id}$ when minimizing f_1 and $R_0 = R_s^{id}$ when minimizing f_2.

Decision variables (9)

$$\underbrace{I_{ph}, I_s, \eta, R_{sh}, R_s,}_{\text{SDM in } f_1} \quad \underbrace{R_0 (= R_s), R_1, L, \beta, Q}_{\text{CPE in } f_2}$$

Decomposition: R_s controls diversity & convergence; others control convergence. For fixed R_s, f_1 and f_2 can be optimized independently.

Proposed MOEA

1. Estimate *ideal* and *nadir* (swap R_s/R_0 across f_1, f_2).
2. *Early stage:* sample R_s; solve min $f_1 \mid R_s$ and min $f_2 \mid R_0 = R_s$; merge to seed population.
3. *Late stage:* NSGA-II on all variables; apply normalization once converged.

Tradeoff Solution Yields Stable, Meaningful Parameters

Table: **Independent optimization**

Condition		SDM (Mean Fitting Error : 0.85×10^{-2})						CPE (Mean Fitting Error : 0.05)				
$T[^\circ C]$	$G[W/m^2]$	$I_{ph}[A]$	$I_s[A]$	η	$R_s[\Omega]$	$R_{sh}[\Omega]$	$C[\mathrm{A/K^3}]$	$L_0[H]$	$R_0[\Omega]$	$R_1[\Omega]$	Q_1	β
30.67	535.39	2.83	0.22×10^{-8}	1.17	0.13	1×10^4	199.32	0.22×10^{-5}	0.17	3.04	0.19×10^{-3}	0.90
33.74	600.96	3.21	0.71×10^{-7}	1.37	0.08	1×10^4	3985.18	0.20×10^{-5}	0.16	2.75	0.37×10^{-3}	0.82
32.24	692.70	3.75	0.24×10^{-6}	1.48	0.06	190.02	1.70×10^4	0.19×10^{-5}	0.15	2.36	0.33×10^{-3}	0.86
33.71	758.06	4.16	0.36×10^{-6}	1.50	0.06	274.91	2.02×10^4	0.20×10^{-5}	0.15	2.06	0.37×10^{-3}	0.85
36.49	876.71	4.84	0.11×10^{-5}	1.57	0.06	1×10^4	3.92×10^4	0.19×10^{-5}	0.14	1.68	0.25×10^{-3}	0.93

Table: **Tradeoff solutions**

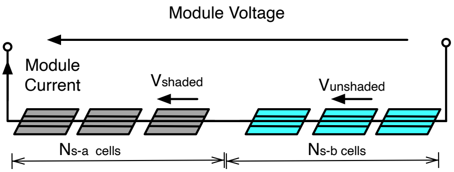
Condition		SDM (Mean Fitting Error : 0.03)						CPE (Mean Fitting Error : 0.06)				
$T[^\circ C]$	$G[W/m^2]$	$I_{ph}[A]$	$I_s[A]$	η	$R_s[\Omega]$	$R_{sh}[\Omega]$	$C[\mathrm{A/K^3}]$	$L_0[H]$	$R_0[\Omega]$	$R_1[\Omega]$	Q_1	β
30.67	535.39	2.83	0.17×10^{-9}	1.04	0.16	993.53	15.79	0.22×10^{-5}	0.16	3.04	0.19×10^{-3}	0.90
33.74	600.96	3.24	0.35×10^{-9}	1.06	0.15	99.92	19.97	0.20×10^{-5}	0.15	2.77	0.39×10^{-3}	0.82
32.24	692.70	3.83	0.19×10^{-9}	1.04	0.14	35.74	13.65	0.19×10^{-5}	0.14	2.38	0.36×10^{-3}	0.84
33.71	758.06	4.23	0.38×10^{-9}	1.06	0.14	40.53	21.45	0.21×10^{-5}	0.14	2.10	0.44×10^{-3}	0.83
36.49	876.71	4.96	0.50×10^{-9}	1.05	0.13	31.32	18.21	0.19×10^{-5}	0.13	1.74	0.35×10^{-3}	0.89

$$I_s = C\,T^3 \exp\left(-\frac{q\,E_g(T)}{k\,T}\right)$$

$$E_g(T) = E_g(0) - \frac{\alpha\,T^2}{T+\beta}$$

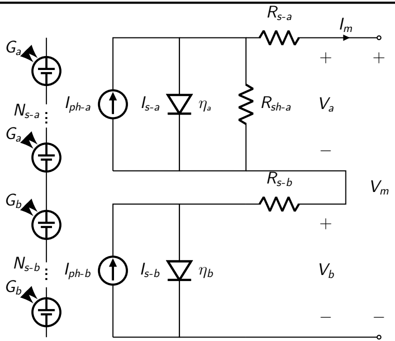
From SDM+CPE to IV-only (D-SDM)

- Multi-objective SDM+CPE improves coherence, but needs EIS hardware and Pareto threshold tuning.
- **Proposed solution: IV-only** method with more flexible structure and refined identification.
- The N_s cells of a **PV module** are divided into two groups **(*a* and *b*)**, capturing two irradiance levels (tradeoff: **Granularity** ↑ ⇒ **Complexity** ↑)



Two-irradiance levels assumption for a module with N_s cells. $N_s = N_{s\text{-}a} + N_{s\text{-}b}$

D-SDM: Double Single-Diode Model



Proposed **D-SDM** *electrical model*

D-SDM: Main Assumptions

- The entire module operates under a uniform cell temperature T_c, and $G_b > G_a$.
- The unshaded block assumes $R_{sh-b} \to \infty$.
- I_{s-c}, η_c, R_{s-c} do not depend on irradiance.

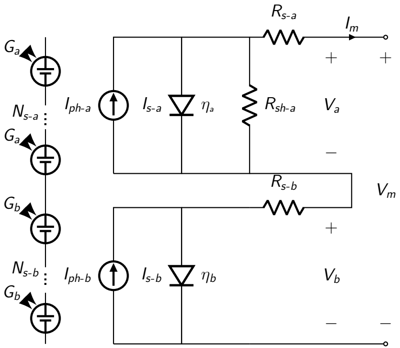
$$V_a = -I_m(R_{s\text{-}a} + R_{sh\text{-}a}) + R_{sh\text{-}a}(I_{ph\text{-}a} + I_{s\text{-}a}) - \eta_a V_{th\text{-}a}\, L_a$$

$$L_a = \mathcal{W}\left\{\frac{I_{s\text{-}a} R_{sh\text{-}a} \exp(\mathcal{S}_a)}{\eta_a V_{th\text{-}a}}\right\} \qquad \mathcal{S}_a = \frac{R_{sh\text{-}a}(-I_m + I_{ph\text{-}a} + I_{s\text{-}a})}{\eta_a V_{th\text{-}a}}$$

$$V_b = \eta_b V_{th\text{-}b} \ln\left(\frac{I_{ph\text{-}b} - I_m}{I_{s\text{-}b}} + 1\right) - I_m R_{s\text{-}b}$$

$$V_m = V_a + V_b$$

$$\vec{P} = [N_{s-a}, I_{ph-a}, I_{ph-b}, I_{s-c}, \eta_c, R_{s-c}, R_{sh-c}]$$



Proposed ***D-SDM*** *electrical model*

D-SDM parameter identification

- Use V_{exp} as input and compute I_m numerically
- Explicit voltage expressions allow direct evaluation
- **Binary search** computes I_m at each V_{exp} point
- **Only valid I–V points used** ($V_a > 0,\ V_b > 0$)

Binary search per point

- Initialize: $I_{\text{min}} = 0,\ I_{\text{max}} = \tau I_{\text{exp}}(i)$
- While $I_{\text{max}} - I_{\text{min}} > \epsilon$:
  - $I_{\text{mid}} = \frac{I_{\text{min}} + I_{\text{max}}}{2}$
  - Compute V_m at I_{mid}
  - If $V_m > V_{\text{exp}}(i)$: $I_{\text{min}} = I_{\text{mid}}$
  - Else: $I_{\text{max}} = I_{\text{mid}}$
- Final: $I_m(i) = \frac{I_{\text{min}} + I_{\text{max}}}{2}$

Monotonic I–V ensures convergence.

Error metric

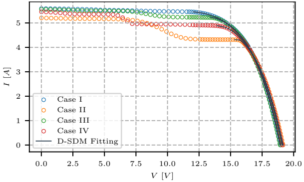
- Normalized area between experimental and modeled I–V (trapezoids)
- Promotes accuracy and largest valid curve segment

Optimization (DE)

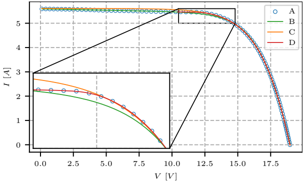
- DE/best/1/bin, $F = 0.8,\ Cr = 0.9,\ NP = 40$
- **D-SDM:** N_{s-a} treated as real
- **D-SDM-I:** real run → +5 random → re-run with integer repair

D-SDM Validation (Experimental Campaign)

(I) (II) (III) (IV)

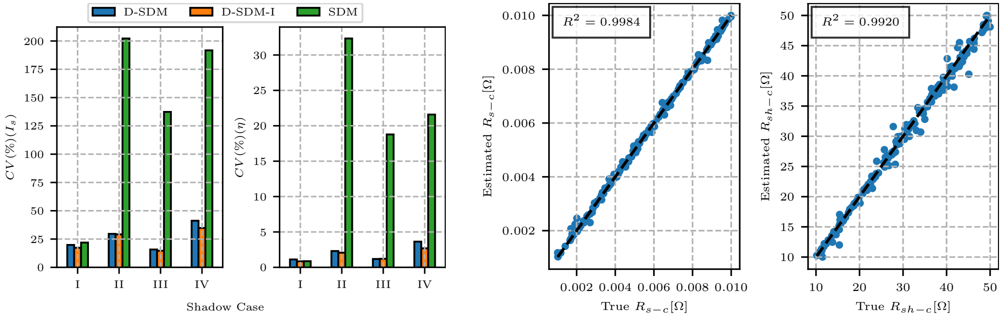


Fitting example



A. Experimental, B. SDM,
C. SDM ($0.8V_{mpp}$ to V_{oc}), D. D-SDM.

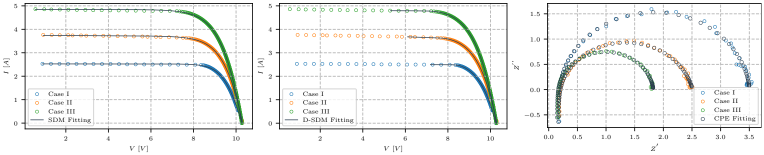
D-SDM validation (Mismatching scenarios)



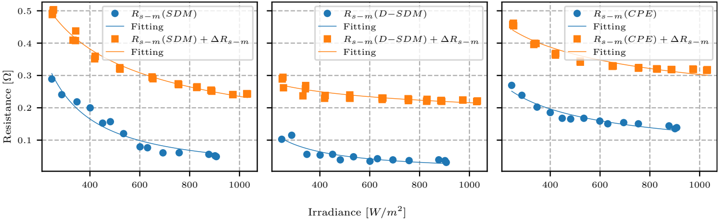
Findings. Experimental and simulated I–V curves under various mismatching patterns show that:

- D-SDM achieves **stable and consistent parameter identification** vs. standard SDM.
- Accurately estimates key physical parameters **(**I_s, η, $R_{s,c}$, $R_{sh,c}$**)**.
- Robust approach for **real PV monitoring**, requiring only I–V curves (no EIS hardware).

D-SDM validation (Estimation of R_s degradation)



SDM D-SDM CPE



Estimation of R_s degradation vs irradiance (SDM vs D-SDM vs CPE)

Key Insights

- Artificial series resistance added to emulate aging
- All methods detected resistance increase
- **SDM fluctuates** under varying irradiance → **less reliable**
- **D-SDM and CPE remain consistent** across conditions
- D-SDM achieves **high accuracy** with only I–V data

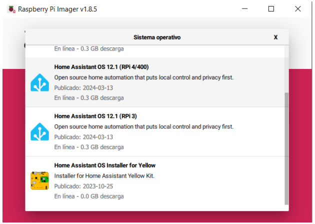
Part I: Demand-Side Intelligence: Non-Intrusive Load Monitoring

Part II: Supply-Side Intelligence: Robust PV Characterization

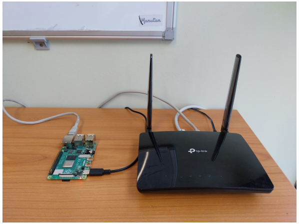
Part III: Integrated Demand-Supply Intelligence and Business Model

- Integration of O2RE-NILM and D-SDM PV characterization into a single edge-based monitoring platform.
- Demonstration of autonomous, privacy-preserving EMS operation using low-power embedded hardware.
- Validation that both demand- and supply-side intelligence can run concurrently in real environments.
- Proposal of a commercialization pathway enabling practical deployment and large-scale adoption.

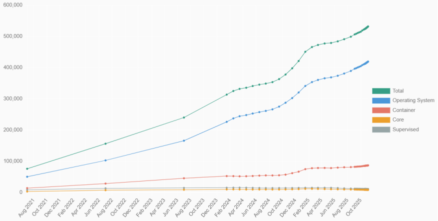
Practical deployment of O2RE and D-SDM



HA OS flashing



Pi as smart hub

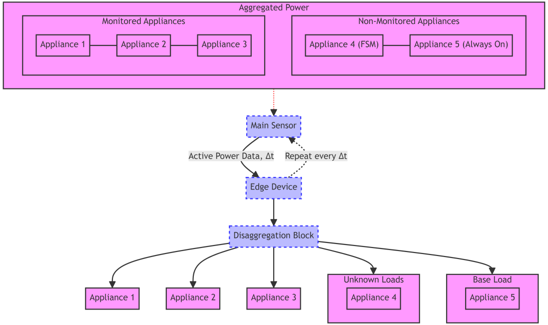


Active Home Assistant Installations

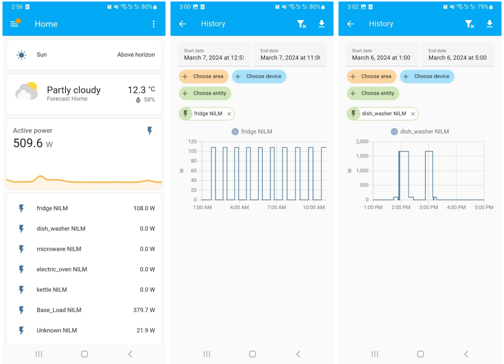
Why Home Assistant + Raspberry Pi?

- Realistic deployment for NILM and PV diagnostics
- Open-source platform with modular custom integration
- Fully local processing → privacy and no cloud dependence
- Raspberry Pi: low-cost, low-power, real-time capable
- Same device runs NILM + PV models → practical and scalable

O2RE-NILM: Practical Deployment



NILM prototype architecture: from aggregated power to appliance disaggregation

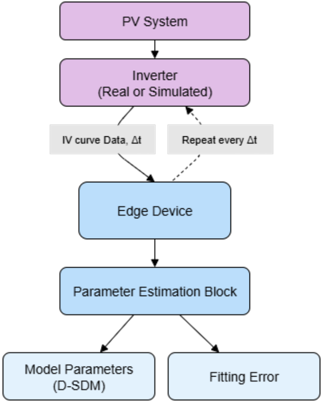


Real-time NILM outputs in Home Assistant

Unified edge platform (Home Assistant)

Garcia-Marrero, PhD thesis, CYU & UNISA (2025)

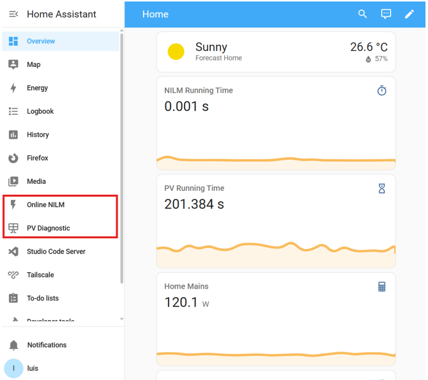
D-SDM PV parameter identification: Practical Deployment



Online PV parameter identification process

D-SDM PV add-on configuration

Real-Time Deployment Performance



Concurrent operation of NILM and PV add-ons in Home Assistant

NILM add-on

- Continuous operation with simulated & physical sensors
- Per-event processing time: **avg 0.004 s**, **max 0.132 s** (critical events: mean 0.071 s)
- Home Assistant remained responsive (no perceived lag)

D-SDM PV add-on

- IV-estimation runtime percentiles (s): **Q1 128.3**, **Median 234.3**, **Q3 390.4**, **P90 523.5**, **P95 566.4**
- Implied safe launch rates: **28** to **6.4 launches/h** (Q1→P95)
- Meets requirement: **1 IV-curve every 10 min**

Overall

- Concurrent NILM + PV analytics run reliably on a **Raspberry Pi 4**
- Suitable for continuous, edge-based energy monitoring

Business Model Proposal

Table: Lean Business Model Canvas for Integrated Real-Time Energy Intelligence (IREI)

Problem	**Solution**	**Unique Value Prop.**	**Unfair Advantage**	**Customer Segments**
Smart meter underused Cloud NILM: privacy + latency Smart plugs = costly	Local on-device NILM + PV diag. Free FSM mode + paid AI library Works inside Home Assistant	Real-time appliance detection No extra HW, privacy-first Native Home Assistant integration	Hybrid NILM (FSM + embeddings) Unique PV diagnostics (published) HA ecosystem access +1M users	Home Assistant users PV owners Installers, energy-savvy homes
Alternatives	**Key Metrics**	**High-level Concept**	**Channels**	**Early Adopters**
Smart plugs / CT clamps Cloud NILM apps	Accuracy & latency Free→Paid upgrades Active users	*"Unlock your smart meter. Real-time NILM + PV health, no extra hardware."*	Home Assistant community GitHub, forums, conferences	HA power users PV prosumers Energy geeks
Cost Structure R&D + ML training Embedded device integration Community + support Optional: OEM energy hub		**Revenue Streams** Free tier: FSM appliances €3–5 per appliance embedding download €5–7/mo Pro plan (AI insights + PV diag.) Optional plug-and-play NILM-PV hub		

***Winner of first place in the business canvas pitch competition in the frame of the SmartGySum project**

Journal Publications

J1 **L.E. Garcia-Marrero**, E. Monmasson, G. Petrone, “Online real-time robust framework for non-intrusive load monitoring in constrained edge devices,” **Applied Energy**, 2025.

J2 **L.E. Garcia-Marrero**, C.I. Pavón-Vargas, J.D. Bastidas-Rodríguez, E. Monmasson, G. Petrone, “Self-adaptive single-diode model parameter identification under small mismatching conditions,” **Renewable Energy**, 2025.

J3 **L.E. Garcia-Marrero**, G. Petrone, E. Monmasson, “Transfer capabilities of Seq2Seq and Seq2Point CNN architectures in Non-intrusive Load Monitoring with unseen appliances,” **Mathematics and Computers in Simulation**, 2025.

J4 M. Piliougine, **L.E. Garcia-Marrero**, K. Lappalainen, G. Spagnuolo, “Influence of the temperature on the intrinsic parameters of thin-film photovoltaic modules,” **Renewable Energy**, 2025.

J5 C. Pavón-Vargas, **L.E. Garcia-Marrero**, J.D. Bastidas-Rodríguez, R.A. Guejia-Burbano, G. Petrone, “Experimental Assessment of Partial Shading Detection in PV Panels Using Impedance Spectroscopy,” **IEEE Transactions on Industry Applications**, 2025.

J6 C. Pavón-Vargas, **L.E. Garcia-Marrero**, G. Petrone, “Dynamic Photovoltaic Modeling for Circuit-Emphasis Simulation,” **Renewable Energy** (submitted), 2025.

Conference Publications

C1 **L.E. Garcia-Marrero**, R.A. Guejia-Burbano, G. Petrone, M. Piliougine, E. Monmasson, "Identification of static and dynamic parameters of PV models through multi-objective optimization," **IEEE CPE-POWERENG**, 2023.

C2 **L.E. Garcia-Marrero**, M. Piliougine, G. Petrone, M. De Riso, P. Guerriero, E. Monmasson, "Challenges in photovoltaic parameter identification under mismatching conditions," **ICCEP**, 2023.

C3 **L.E. Garcia-Marrero**, G. Petrone, E. Monmasson, "Detection of Series Resistance Degradation in PV Modules Using Measured Current-Voltage and Frequency-Domain Impedance," **ICCEP**, 2025.

C4 C. Pavón-Vargas, **L.E. Garcia-Marrero**, G. Petrone, S. Curcio, "An enhanced single-diode model of photovoltaic panels for SPICE simulations," **ELECTRIMACS**, 2024.

C5 **L.E. Garcia-Marrero**, C. Pavón-Vargas, G. Petrone, E. Monmasson, "Advancements in Photovoltaic Research: Electro-Impedance Spectroscopy for PV Cell Characterization," **SPEEDAM**, 2024.

C6 M. De Riso, I. Matacena, P. Guerriero, S. Daliento, **L.E. Garcia-Marrero**, G. Petrone, "Dynamic Modeling of Si-based Photovoltaic Modules using Impedance Spectroscopy Technique," **ICCEP**, 2023.

C7 C. Pavón-Vargas, R.A. Guejia-Burbano, **L.E. Garcia-Marrero**, G. Petrone, "Impedance Spectroscopy for partial shading detection on series-connected PV panels," **SPEEDAM**, 2024.

Thank you for your attention

Feel free to ask any questions you may have