Comparative Analysis of the Energy Cost Assistant (ECA) vs. Standard Self-Consumption Optimization (OCO)

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1 Abstract

This paper examines the financial efficacy of the Energy Cost Assistant (ECA) algorithm compared to a standard inverter battery management strategy, referred to as "OCO" (baseline). Using a simulation-based approach on a curated sample of real photovoltaic (PV) systems, the study quantifies the potential reduction in electricity costs. The results demonstrate a consistent positive impact, with an average relative gain of 14.7% on the annual electricity bill, confirming that the ECA strategy consistently outperforms the baseline across diverse installation profiles.

2 Introduction

The objective of this study is to assess the financial benefit of the Energy Cost Assistant (ECA) in optimizing battery usage compared to a standard self-consumption optimization mode (OCO). While standard optimization focuses on maximizing the use of self-generated energy, the ECA is designed to further reduce costs by leveraging more sophisticated cost-based logic. This paper details the methodology, the assumptions underpinning the simulation, and the resulting financial gains.

2.1 Methodology and Pipeline

The study utilized a complex data pipeline to ensure that simulated scenarios mirrored real-world conditions. The process was divided into several key stages:

2.1.1 Sampling and Data Collection

The study began with a random sample of **350 PV systems** selected from three primary databases (Computation, Event, and ECA-state). The analysis covers a **complete one-year window**, spanning from May 2025 to May 2026. To ensure the simulation was grounded in reality, historical data—including PV production, load (consumption), and State of Charge (SOC)—were collected for each system.

2.1.2 Simulation Inputs

To replay the behaviour of a full year, a simulation model was employed that reproduces the operation of an inverter, battery, and associated energy transfers. To run such simulations, three data streams sourced from real installed systems were required.

- **Installation Data:** Battery specifications (capacity, power limits) and grid parameters (Feed-In limitations).
- **Forecasts:** The ECA relies on PV-production and consumption forecasts for the installation to generate optimizations. To mimic the system's real-world operation in the simulation, these historical forecasts need to be retrieved exactly as they were available at the time each optimization is computed. These forecasts must be cleaned to match the data that were available when the optimization was calculated, and, in some cases, they had to be approximated to fill gaps where forecast information was missing.

- **Tariffs:** Hourly purchase prices sourced from the respective energy providers linked to each system.

2.1.3 Simulation Execution

The simulation compared two strategies for every single system over a full year from May 2025 to May 2026:

1. **OCO (Baseline):** Standard inverter battery management without the ECA optimization
2. **ECA (Optimized Optimisation engine version available in May 2026):** Standard inverter battery management with the Energy Cost Assistant optimization on top of it.

The pipeline involved rigorous filtering to maintain data integrity. Systems were excluded if they had missing provider data, corrupted files, or if more than 10% of the forecast data required interpolation. Ultimately, **110 systems** successfully passed all validation steps and were simulated.

3 Results and Analysis

3.1 Financial Gain

- The performance was measured by calculating the absolute and relative difference in the annual electricity bill between the two strategies over a full year, since the ECA operates seasonally and a complete-year calculation is required for the results to be representative.
- **Average Relative Gain:** The ECA provided an average relative improvement of **14.7%** on the annual electricity bill.
- **Average Absolute Gain:** This corresponds to a mean saving of **58.41 €/year** per installation.
- **Consistency:** The study found that **no installation performed worse** under ECA than under OCO; even the lowest-performing system achieved a positive gain of 4.38 €/year.

3.2 Distribution and Variability

The results show a right-skewed distribution, meaning while most users see a steady gain, a few "best-case" installations experience significant savings. For example, the top 25% of installations saw a relative gain of over 15.9%. The variability (Standard Deviation of 45.94 €/year) suggests that the benefit of ECA is strongly dependent on the user's specific consumption profile, battery size, and tariff structure.

3.3 Assumptions and Limitations

To remain transparent, the following assumptions and limitations are noted:

3.3.1 Assumptions

- **Data Representativity:** It is assumed that the sample of 110 systems is representative of the broader population. The study attempted to validate this by comparing the average battery capacity of the sample which was comparable to the population.
- **Forecast Accuracy:** The simulation relies on the accuracy of the PV and Load forecasts. While a "quality filter" was applied to remove forecasts with $> 10\%$ interpolated data, any inherent error in the forecasting model is carried into the results.
- **Temporal Consistency:** The study assumes that the tariff structures and consumption patterns from the 2025-2026 window are applicable for evaluating future performance.

- **Algorithm version:** The study assumes that all the simulated systems use the latest version of the Energy Cost Assistant available in May 2026 with all the features activated.

3.3.2 Limitations

- **Sample Attrition:** There was a significant drop in the number of systems from the initial sample (350) to the final simulation (110). This attrition was caused by:
  - Missing Feed-in limitation data.
  - Corrupted installation files.
  - Errors during provider mapping and tariff data collection.
  - High interpolation rates in forecast files.
  - Changes in system configuration during the analysis period (e.g., tariff adjustments or alterations to the installation's size).
- **Geographic Concentration:** The sample is heavily weighted toward specific regions, with Austria (AT) representing 73 installations, followed by Sweden (SE) with 29. Results may vary in markets with significantly different tariff structures.
- **Edge Case Sensitivity:** Some relative gain percentages (e.g., 138.4%) are mathematically inflated because the baseline billing was very close to zero, making the relative percentage an unreliable metric for those specific cases.
- **Limited Presence of Flexible Feed-In Tariffs:** Within the sample, only a small proportion of installations have a flexible feed-in tariff. Consequently, the ECA's ability to optimize battery charge and discharge under such tariffs is not fully representative of the potential gains that could be realized as flexible feed-in tariffing becomes more widespread.

4 Conclusion

The study confirms that, over a **full year**, the Energy Cost Assistant (ECA) provides a clear financial advantage over standard self-consumption optimization. With a mean relative gain of 14.7%, the ECA effectively reduces the annual electricity bill for users without introducing the risk of financial loss compared to the baseline.