SATELLITE-BASED SOLAR NOWCASTING FOR ENERGY COMMUNITIES: AN AI-SUPPORTED FRAMEWORK FOR PV PANEL DETECTION AND PRODUCTION PREDICTION

Sead Mustafic[1], Irene Schicker[2], Lukas Prenner[3], Nikta Madjdi[2], Pascal Gfäller[2], Matthias Schlögl[2], Matthias Göbel[2], Petrina Papazek[2], Jasmina Hadzimustafic[2], Doris Oberleiter[3], Roland Perko[1]

Introduction

Energy communities enable collective renewable energy production and sharing but face challenges from PV production variability and grid balancing. The research project entitled *Satellite-based solar nowcasting for energy communities* (PV4C[4]) develops an AI-supported framework combining satellite-based PV detection with high-resolution solar nowcasting for community-level energy management. A core motivation of **energyfamily**, the application-oriented project partner, is to provide energy communities with accessible, automated forecasts that improve self-consumption, reduce grid dependency, and serve as a foundation for operational decision-making and strategic flexibility deployment.

The following technical objectives are presented within this work: (1) automated PV panel detection using deep learning on aerial imagery (20cm resolution), (2) ensemble nowcasting delivering 15-minute forecasts up to 12 hours ahead at 1km resolution, downscaled to rooftop level (10-50m), and (3) incorporation of all information into a web-based dashboard (cf. Figure 1).

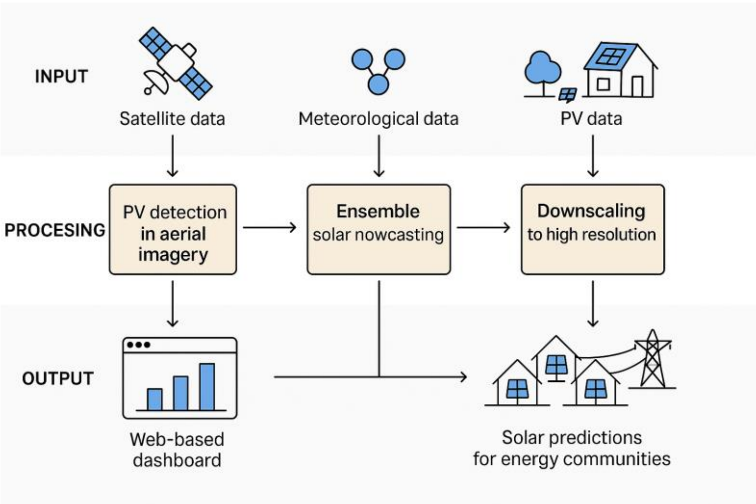

Figure 1: Workflow of solar nowcasting for energy communities.

Methodology

Data Integration: The framework combines Austrian BEV aerial photographs, European labeled PV datasets (BDAPPV, SolarDE, SolarDK), 270+ TAWES meteorological stations, CAMS radiation data, and real energy community production and consumption data from over 200 communities.

PV Panel Detection: Two complementary approaches were explored for PV panel detection: (1) Bounding-box detection using YOLO and the DEIM detector, and (2) Pixel-wise segmentation of individual installations and panels using U-Net, U-Net++, and SegFormer. In addition, a pretrained Mask R-CNN model from the GeoAI library was included for comparison and evaluation, providing both bounding boxes and instance-level segments. To further adapt the models to BEV data and Austrian conditions, an active learning strategy was applied to U-Net++ and SegFormer. In total, seven active learning cycles were conducted, including targeted manual adjustments after the first and fourth cycles to counteract model drift (i.e., by adding manually selected uncertain and misclassified samples).

Nowcasting: IrradPhyDNet combines PhyCells for PDE-approximation with ConvLSTM encoder-decoder architecture, trained on DSSF satellite data using timestep-dropout for missing frames. INCA+

[1] JOANNEUM RESEARCH, Graz, Austria, {firstname.lastname}@joanneum.at
[2] GeoSphere Austria, Vienna, Austria, {firstname.lastname}@geosphere.at
[3] EnergyFamily, Amstetten, Austria, {firstname.lastname} @energyfamily.at
[4] https://www.joanneum.at/digital/projekte/pv4c/ (accessed 20.01.2026).

integrates MTG satellite inputs (2km, 10-minute updates) with C-LAEF forecasts (1km, hourly). A Graph Neural Network models inter-site dependencies and productions for community predictions.

Dashboard: The PV4C dashboard serves as the central interface for energy communities and related stakeholders. It visualizes forecasted PV production at both rooftop and community level and supports decision-making through key features such as self-sufficiency and mismatch analytics, consumption and load forecasts, uncertainty visualization (e.g., ensemble spread), GDPR-compliant web-based tool designed to enable actionable insights for flexibility use, storage, and grid planning.

Results

PV Panel Detection: Evaluation results show that bounding-box–based detectors, despite their substantially larger architectures and higher training complexity, do not provide an advantage over the lighter segmentation models. U-Net, U-Net++, and SegFormer consistently produced more accurate PV segments and overall better performance. The pretrained Mask R-CNN model from the GeoAI library performed reasonably well on data like its original training domain, but its transfer to Austrian regions and BEV imagery led to noticeable performance degradation. This confirms that models trained on geographically or sensor-specific data suffer from reduced generalizability, even when extensive dataset merging and strong augmentation strategies are applied. The active-learning strategy proved to be an effective tool for improving model quality with comparatively little manual labeling effort. Iterative incorporation of uncertain and misclassified tiles led to substantial improvements in generalization and robustness.

Nowcasting Performance: IrradPhyDNet achieves lower MAE and higher equitable threat scores than INCA+ during summer under dynamic clouds. INCA+ excels in winter fog conditions. MTG integration improves spatial detail in cloud cover and radiation fields with better verification scores than legacy MSG. Initial PV production predictions with baseline model reveal high accuracy scores.

Energy Community Analysis: Real data reveals production-consumption temporal mismatch (midday PV peak vs. morning/evening consumption peaks), self-sufficiency ratios varying from 5:1 to zero, and critical ramp events concentrated mid-morning/midday. Member consumption patterns show high diversity, offering demand response opportunities.

Conclusions and Outlook

This work demonstrates how satellite remote sensing and AI address practical energy transition challenges. By automatically detecting PV installations and predicting production at high spatial-temporal resolution, energy communities become active participants in flexible, decarbonized energy systems. The multi-data integration verified against real operations provides robust forecasts for operational decision-making crucial for managing distributed generation while maintaining grid stability. The combination of scientific innovation and practical applicability ensures that energy communities and infrastructure operators alike benefit from more resilient and data-driven energy systems.

In future, the PV4C project focuses on PV panel detection in super-resolved Sentinel-2 imagery (based on the LDSR-S2 method) using spectral analysis, full ensemble implementation with uncertainty quantification, rooftop-level downscaling using digital surface models, GNN PV production validation, web platform integration with APIs, and comprehensive verification using probabilistic metrics.

Expected impacts include (1) scientific contributions in small-object detection methodologies for medium-resolution imagery and hybrid ML-physics nowcasting, (2) user-oriented, operational forecasting platform enabling Austrian energy communities to optimize self-consumption, increase resilience, and actively contribute to local grid stability, (3) Policy and planning support through reproducible, high-resolution evidence on distributed PV variability and ramp events, supporting infrastructure and flexibility investment decisions, and (4) commercial scalability to grid operators and energy service providers and regional flexibility markets across Austria and beyond.

Acknowledgments

This research was partly funded by the Austrian Space Applications Programme (ASAP) through the project PV4C (FFG project number 911917).