PREDICTIVE PV POWER GENERATION AND CONTROL IN COMPLEX BUILDING ENERGY SYSTEMS.

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Abstract

This paper discusses the application of smart metering devices and predictive control methods in building energy systems equipped with photovoltaic power plants (PVPP), battery energy storage systems (BESS), heat pumps, and flexible electrical appliances. The study focuses on the accuracy of forecasting electricity generation and consumption over time. It summarises the impacts of forecast inaccuracies on building energy management. The proposed system utilizes continuous monitoring of energy flows and short-term prediction algorithms based on historical operational and meteorological data. Special attention is devoted to the influence of weather change and stochastic consumer behavior on prediction accuracy. The analysis confirms that inaccurate forecasts combined with demand reduce the efficiency of BESS, heat pumps, and flexible appliances, reduce the utilization of local generation, and increase imports from the transmission grid. Even simple predictive methods can significantly improve energy management and support demand-side flexibility. Also, an experimental implementation in a facility equipped with multiple photovoltaic systems is presented here, demonstrating wider utilization of renewable energy and optimization of electrical appliances from the flexibility perspective.

Introduction

The development of smart energy systems and decentralized renewable energy sources (RES) fundamentally changes the way electricity is generated and consumed. A higher share of photovoltaics (PV), battery energy storage systems (BESS), and flexible appliances requires efficient energy management and the ability of accurate short-term prediction of electricity generation and consumption.

The basis of functional control is an accurate short-term forecast of energy generation and consumption along with continuous monitoring of equipment. Smart metering enables continuous collection of operational data in real time (generation, consumption, and energy flows within the facility). These data serve for the creation of predictive models utilizing meteorological data, measurement history, and artificial intelligence algorithms. However, prediction accuracy is mainly affected by weather variability, local shading, PV system sizing, and the stochastic nature of consumption [1-3].

An inaccurate prediction causes incorrect management of BESS (inefficient charging/discharging), reduces the utilization of generated solar energy, increases grid reliance, and worsens the overall operational efficiency. It thus negatively affects the control of heat pumps and flexible appliances dependent on the current energy balance of the facility.

Analysis

The Energo Lab of the Institute of Materials and Machine Mechanics of the Slovak Academy of Sciences (ÚMMS SAV) has built an extensive data-acquisition system on energy flows in the building and its surroundings, or the outdoor and indoor environments. Historically, many different systems have been installed, ranging from Siemens Simatic SCADA, through continuous recording of quantities using microcontrollers, sensors, and meters, to system solutions from equipment manufacturers (Schneider Insight Home and others). Within Energo Lab, other occasional measurement systems based on National Instruments systems, network analyzers, data loggers, or the above-mentioned microcontrollers with sensors and meters are also utilized. The basic measurement system for energy flow control is shown in the simplified block diagram of Energo Lab (Fig. 1). The abundance of different systems brings a challenge in system maintenance and in creating connections between individual systems. In this regard, microcontroller systems are the most flexible compared to complex system solutions. The data are subsequently network-aggregated into a control algorithm that determines the operation of flexible devices (BESS, inverters, heat pump, and other installed equipment).

The development of smart energy systems is significantly changing the way electrical energy is generated and consumed. It helps in real-time collection of operational data, providing detailed information on electricity generation, device consumption, and energy flows within the facility. The growing share of photovoltaic (PV) power plants, battery energy storage systems (BESS), and flexible appliances creates new requirements for the efficient management of energy flows in buildings, incorporating demand-side management and behavioral control capabilities. A key prerequisite for effective energy management is the ability to accurately forecast short-term electricity generation and consumption, as well as to establish feedback loops through the measurement and monitoring of device generation and consumption.

Inaccurate forecasting leads to suboptimal BESS management (inefficient charging/discharging), reduces the utilization of generated PV energy, increases grid reliance, and degrades overall operational efficiency. It also negatively impacts the operation of heat pumps and flexible appliances that are controlled based on the facility's energy status.

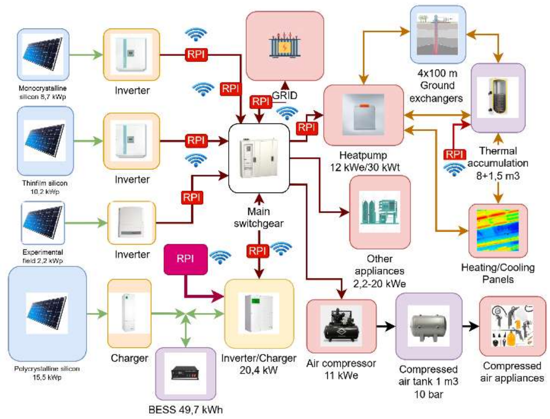

Fig. 1: Simplified energy diagram of Energo Lab

For the purposes of model evaluation and comparison, a prediction accuracy indicator *Δp*, was introduced. It is defined as the sum of positive and negative deviations (errors) between actual and predicted electricity generation, relative to the installed PV system capacity (1). The parameter *ΔE* expresses the generation error per time interval; positive values indicate generation exceeding the prediction, while negative values indicate the opposite. The parameter *Pinst* represents the installed capacity of the power plant.

$$\Delta p_- = \frac{\sum_{t=0}^{t=n} \Delta E_t^-}{P_{inst}} \quad \text{and} \quad \Delta p_+ = \frac{\sum_{t=0}^{t=n} \Delta E_t^+}{P_{inst}} \tag{1}$$

The subsequent analysis utilizes prediction horizons of T-1 h, T-24 h, and T-48 h, representing electricity generation forecasts generated 1, 24, and 48 hours prior to actual production, respectively. The analysis revealed that the average cumulative negative prediction errors for the T-1 h horizon reach approximately 8.0%, while the positive errors account for 9.8% of the estimated average annual PV system generation [4]. For the T-24 h prediction, the negative and positive errors reached approximately 13.3% and 13.4%, respectively (Table 1).

Accuracy Indicator	Preditcion T-1 h	Prediction T-24 h	Prediction T-48 h
Δp-	-96.97 kWh/kWp	-161.37 kWh/kWp	-183.76 kWh/kWp
Δp+	+119.26 kWh/kWp	+163.00 kWh/kWp	+168.01 kWh/kWp
RMSE	5.53%	7.37%	8.07%
Data availability	68.9%	76.5%	76.3%

Tab. 1: Annual model accuracy profile for the Solargis PV generation forecast
("Solar resource data © 2026 Solargis")

Table 1 highlights incomplete annual data availability. Overall measured data covered 86.2% of the year, with gaps primarily caused by plant shutdowns during power outages. Forecast data availability was 68.9% for T-1 h, and approximately 88.8% for both T-24 h and T-48 h. Prediction data gaps resulted mainly from internet disconnections caused by an unstable Wi-Fi modem. The lower availability of T-1 h data sets from its later implementation on July 24, 2025 (~20% data reduction) and the daily 5:00 AM start time of the earliest forecast. Monthly average hourly error analysis showed significantly higher, predominantly negative, prediction errors from April to October (Tab. 2). Conversely, winter months exhibited lower errors due to more stable weather and fewer variable clouds. During the growing season, elevated errors occurred mainly in the afternoon, shifting temporally with the solar position relative to the summer solstice. This deviation is likely caused by shading from trees on the west and building structures northwest of the PV system.

To quantify the stochastic nature of generation, the minimum and maximum predicted electricity generation parameters were also analyzed. The results (Table 2) showed that the accuracy of minimum generation predictions improves as the prediction horizon shortens. Conversely, the accuracy of maximum power predictions shows no significant improvement and, in some cases, even deteriorates (2026).

	2025														2026							
Month	May		June		July		September		Oktober		November		December		January		February		March		April	
AVE Error	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp	Positive kWh/kWp	Negative kWh/kWp
0:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5:00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6:00	0.01	-0.01	0.03	-0.01	0.02	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
7:00	0.03	-0.02	0.04	0.00	0.02	0.00	0.01	0.00	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	-0.01	0.02	-0.01
8:00	0.06	-0.07	0.02	-0.09	0.06	-0.03	0.03	-0.01	0.03	-0.03	0.04	-0.01	0.01	-0.01	0.01	-0.01	0.02	-0.02	0.04	-0.02	0.03	-0.04
9:00	0.07	-0.11	0.03	-0.21	0.04	-0.06	0.05	-0.01	0.08	-0.09	0.09	-0.04	0.07	-0.02	0.03	-0.03	0.08	-0.05	0.04	-0.05	0.04	-0.06
10:00	0.10	-0.12	0.04	-0.32	0.06	-0.07	0.07	-0.04	0.16	-0.14	0.11	-0.06	0.03	-0.04	0.06	-0.05	0.04	-0.07	0.04	-0.07	0.06	-0.14
11:00	0.11	-0.15	0.09	-0.44	0.09	-0.05	0.06	-0.10	0.16	-0.16	0.13	-0.09	0.04	-0.05	0.06	-0.07	0.03	-0.08	0.07	-0.08	0.07	-0.09
12:00	0.16	-0.17	0.03	-0.37	0.07	-0.06	0.09	-0.08	0.13	-0.21	0.13	-0.08	0.02	-0.05	0.04	-0.06	0.04	-0.06	0.11	-0.06	0.10	-0.22
13:00	0.16	-0.18	0.10	-0.26	0.04	-0.12	0.08	-0.08	0.14	-0.16	0.04	-0.07	0.03	-0.06	0.01	-0.05	0.05	-0.08	0.11	-0.08	0.11	-0.23
14:00	0.12	-0.12	0.08	-0.65	0.08	-0.10	0.10	-0.15	0.11	-0.15	0.01	-0.05	0.01	-0.03	0.02	-0.05	0.03	-0.05	0.10	-0.05	0.10	-0.18
15:00	0.11	-0.18	0.17	-0.30	0.08	-0.12	0.04	-0.11	0.04	-0.07	0.01	-0.01	0.00	0.00	0.01	-0.01	0.01	-0.11	0.04	-0.11	0.08	-0.18
16:00	0.08	-0.19	0.10	-0.28	0.28	-0.18	0.01	-0.09	0.01	-0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.09	0.02	-0.09	0.09	-0.15
17:00	0.09	-0.13	0.11	-0.23	0.02	-0.09	0.00	-0.10	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	-0.01	0.04	-0.07
18:00	0.04	-0.07	0.02	-0.15	0.01	-0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	-0.05
19:00	0.01	-0.03	0.00	-0.05	0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
20:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23:00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

-0.2 kWh/kWp 0.0 kWh/kWp +0.2 kWh/kWp

Tab. 2: Sample error map of T-24hr predictions for the period from May 1, 2025, to April 30, 2026

	Parameter	T-1Hour	T-24Hour	T-48Hour
2025 (april - december)	Maximum	7.49%	7.67%	7.75%
	Minimum	3.79%	5.23%	5.73%
2026 (january – april)	Maximum	6.22%	5.33%	4.74%
	Minimum	5.52%	7.36%	8.54%

Tab. 3: Exceedance frequency of predicted minimum and maximum generation, expressed as a percentage of the total number of forecasted values

The next part of the study analyzes the relationship between prediction accuracy and the total daily incident solar energy (Tab.4). The results show that the largest prediction errors occur at a daily global irradiation of approximately 2,000–5,000 Wh/m², with the maximum error recorded within the 3,000–4,000 Wh/m² interval. Such conditions are typical for partly cloudy days with broken cloud cover, during which it is highly challenging to accurately forecast short-term changes in solar irradiance intensity.

	May		June		July		September		Oktober		November		December		January		February		March		April		AVE		AVE
Wh/m²/day	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	ABS
0-1000	N/A	N/A	N/A	N/A	N/A	N/A	0.005	-0.019	0.004	-0.125	0.002	-0.058	0.003	-0.029	0.004	-0.042	0.001	-0.021	0.001	-0.014	0.000	0.000	0.020	-0.308	0.328
1000-2000	0.010	-0.108	N/A	N/A	0.013	-0.075	N/A	N/A	0.004	-0.086	0.011	-0.023	0.011	-0.051	0.001	-0.016	0.004	-0.004	0.000	0.000	0.000	0.000	0.054	-0.364	0.418
2000-3000	0.027	-0.081	N/A	N/A	0.032	-0.048	0.011	-0.074	0.028	-0.062	0.022	-0.044	N/A	N/A	0.010	-0.019	0.008	-0.031	0.006	-0.021	0.003	-0.041	0.146	-0.420	0.566
3000-4000	0.040	-0.099	N/A	N/A	N/A	N/A	0.014	-0.147	0.038	-0.128	0.037	-0.045	N/A	N/A	0.006	-0.025	0.008	-0.014	0.013	-0.080	0.009	-0.088	0.166	-0.626	0.792
4000-5000	0.028	-0.072	0.015	-0.052	0.013	-0.087	0.013	-0.109	0.023	-0.065	N/A	N/A	N/A	N/A	N/A	N/A	0.007	-0.028	0.006	-0.054	0.009	-0.037	0.114	-0.504	0.618
5000-6000	0.021	-0.094	N/A	N/A	N/A	N/A	0.026	-0.099	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.021	-0.083	0.005	-0.018	0.073	-0.294	0.367
6000-7000	0.049	-0.111	0.038	-0.072	0.027	-0.057	0.025	-0.048	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.019	-0.062	0.157	-0.349	0.506
7000-8000	0.046	-0.163	0.010	-0.342	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.024	-0.018	0.080	-0.522	0.602
8000-9000	0.094	-0.012	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.094	-0.012	0.106
9000-10000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.000	0.000	0.000

-0.15 kWh/kWp 0.0 kWh/kWp +0.15 kWh/kWp MIN MAX

Tab. 4: Table of the average positive and negative deviation in a given month as a function of the amount of incident solar energy on the PV power plant

Experiment

This section describes a predictive system implemented at the ÚMMS SAV facility, operating three PV plants (8.5, 10.5, and 15.5 kWp). The generated electricity powers flexible loads, including heat pumps, compressors, water heaters, and machinery.To maximize PV self-consumption, a BESS dynamically charges or discharges based on real-time building demand and main grid energy flows. Concurrently, a predictive demand-side management system allows operators to schedule flexible appliances using a 3-day energy forecast (Fig. 2). The operator selects the expected time interval for the operation of the given device (morning, afternoon, evening). The system evaluates the selection, recalculates the energy status, and the signaling displays the expected state (green – expected surpluses, blue – sufficient electrical energy, red – necessity of electricity supply from the grid).

Based on operational records, an analytical evaluation determined that from February to April 2026, predictive control enabled the utilization of approximately 167.64 kWh of electricity for electric vehicle charging and 311.62 kWh for heat pump operation. Other flexible devices utilized approximately 20–30 kWh of electricity optimized through generation forecasting. Based on average electricity prices for the facility, the total savings exceeded €120. For these applications, a baseline prediction is entirely sufficient and is available starting at €18/month [5]. Within the SPICE project, a prediction software based on open-source algorithms was developed; in its initial iteration, its RMSE error was 177% worse than the Solargis model. Subsequently, using a method developed by the Institute of Informatics of the ÚI SAV that combines difficulty, horizon, and regime weighting with piecewise losses, the model's underperformance was reduced to just 91%. Such a prediction is also sufficient for operations that do not engage in PV electricity trading. For PV operations featuring even smaller equipment with a flexible capacity of at least 10–20 kW and an annual consumption of >5 MWh (depending on the degree of flexibility), forecasting is definitively beneficial.

Fig. 2: Demand-side UI device for selecting the operational window while running appliances

Results and discussion

The study confirms that PV generation prediction accuracy is significantly influenced by local shading and meteorological stability. While shading can be largely mitigated using long-term historical data, eliminating errors from short-term cloud cover changes remains challenging. Higher short-term accuracy could be achieved via local meteorological sensors or data sharing from nearby PV systems [6].

Even a baseline generation forecast can significantly increase local PV self-consumption, particularly in facilities with flexible loads or energy storage. PV usability can be further enhanced by introducing additional flexible, surplus-consuming loads, such as:

- Nitrogen production and associated high-pressure compressor operation
- Intelligent low-pressure compressor operation with an air receiver
- Operational adjustment of experimental activities

Forecasting accuracy and computational algorithms can be continuously improved; expanding available datasets progressively enhances inputs for machine learning. However, the greatest challenge for intelligent control systems remains communication link stability and safeguarding devices against power outages. Rising computing capacity and AI-driven data analysis fuel the demand for highly accurate, high-sampling-frequency data. Intelligent microcontroller systems represent an ideal solution due to their flexibility, low power consumption, and edge-processing capabilities for larger architectures like the Cognitive Compute Continuum, which receives this data under the SPICE project. Through the Slovak Digital Innovation Center, ÚMMS SAV participates in Smart Grid Use Case no.3, optimizing energy management both technically and commercially for savings and profit. The core strength of this pilot lies in AI-driven generation and consumption prediction models.

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