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A multi-layer information model and adaptive algorithms for monitoring hybrid energy supply in IoT-based telecommunication networks

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Abstract: Most deployed energy-monitoring systems only measure electrical parameters and transmit them to a remote server, whereas equipment condition assessment and automatic optimisation remain undeveloped. This paper proposes the architecture and the mathematical model of a hybrid monitoring platform uniting IoT sensing, edge computing, cloud analytics and digital-twin technology in one six-layer framework. A multi-stage edge-side conditioning scheme is developed, the digital-twin state residual is introduced as a diagnostic feature for early fault detection, and an integral Energy Efficiency Index with a carbon-footprint model is formulated so that technical and environmental criteria are evaluated in one loop. The testbed on a 0.4 kV three-phase feeder and the 180-day dataset of 17 280 records collected on it are described. The deep-learning forecasting layer built on this architecture is treated in a companion study.

Keywords: energy monitoring, Internet of Things, edge computing, digital twin, Kalman filter, energy efficiency index, carbon footprint, predictive maintenance

1. Introduction

The rapid growth of electricity demand has made the efficient use of energy resources one of the most active research directions in power and information engineering. World final energy consumption is growing by 1.8–2.3 % per year, driven by industrial expansion, digital infrastructure and the proliferation of connected devices [1]. Real-time monitoring has therefore become a prerequisite rather than an optional feature of modern energy management.

Conventional equipment is oriented towards measuring voltage, current and power, and therefore only *records* consumption; the acquired data are used mainly for retrospective reporting, so energy waste is identified after it has occurred. The Internet of Things has advanced this field considerably [2], but in cloud-centric architectures the whole processing burden falls on a central server, which increases latency and creates a hard dependency on connectivity. Edge computing addresses exactly this problem [3].

Monitoring alone, however, is no longer sufficient. Recent studies indicate that it must be integrated with artificial intelligence and digital-twin technology [4], [5]. A digital twin is a virtual replica of a physical asset synchronised in real time, enabling state observation, “what-if” simulation and early fault prediction [5], [6]. In the power sector digital twins have mostly been applied to generation assets, whereas their integration into demand-side distributed monitoring remains insufficiently studied.

The scope of this paper is the computing platform itself: its layered structure, its operating algorithm, the

mathematical description of the measurement chain and the evaluation infrastructure on which it was deployed. The deep-learning forecasting layer that runs on top of the platform, together with its comparative evaluation and field results, is the subject of a companion study.

The contributions are: (i) a six-layer architecture unifying monitoring, digital-twin synchronisation and techno-environmental assessment; (ii) a multi-stage edge-side conditioning scheme; (iii) the digital-twin state residual as a diagnostic feature; and (iv) an integral Energy Efficiency Index (EEI) coupled with a carbon-footprint model.

2. Research methodology

Related Work and Problem Statement

Early monitoring devices were analogue and could not process large data volumes. Microcontroller platforms such as Arduino, Raspberry Pi and ESP32 later enabled accurate measurement with cloud storage, and current research is concentrated on edge computation, AI-driven analytics, digital twins, predictive maintenance and carbon-footprint tracking [4], [6].

Table 1 summarises a comparative analysis of existing solutions. None of the reviewed systems combines monitoring, forecasting, digital-twin synchronisation, integral energy-efficiency assessment and environmental-impact estimation within a single platform.

Table 1

Comparative analysis of existing energy-monitoring systems

System / approach	Real	Edge	Fore-	Digital	Effic.	Carbo
	time	comp.	cast	twin	index	n footpr.
Conventional SCADA	✓	—	—	—	—	—
Microcontroller IoT meters	✓	—	—	—	—	—



IoT with statistical forecasting	✓	—	⊖	—	—	—
IoT with machine learning	✓	⊖	✓	—	—	—
IoT with deep learning	✓	⊖	✓	—	—	—
Generation-side digital twins	✓	—	✓	✓	—	—
Proposed platform	✓	✓	✓	✓	✓	✓

✓— supported; ⊖— partially supported; — not supported.

The research problem is therefore stated as follows: *to develop a computing architecture and its mathematical model that provide real-time observation of energy consumption in a distributed IoT infrastructure, assessment of equipment condition through a digital twin, and integral evaluation of energy efficiency and environmental impact.*

System Architecture

The platform is intended not only to observe electricity consumption in real time, but also to assess the technical condition of the equipment and optimise energy use automatically. Functionally the architecture is divided into six layers (Fig. 1).

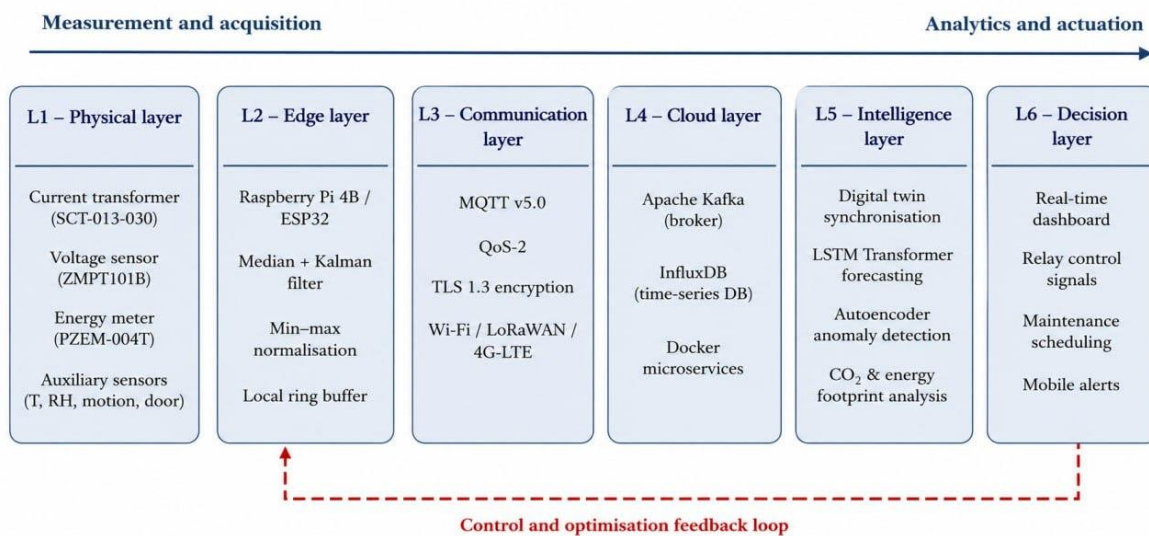


Fig. 1. Six-layer architecture of the proposed hybrid energy-monitoring platform. Solid arrows denote the data path; the dashed arrow denotes the control and optimisation feedback loop

L1 – physical layer contains the measurement chain: an SCT-013-030 current transformer, a ZMPT101B voltage sensor, a PZEM-004T energy meter and auxiliary temperature, humidity and motion sensors.

L2 – edge layer (ESP32 and Raspberry Pi 4B) performs primary conditioning – a median filter suppresses impulsive noise, a Kalman filter suppresses measurement noise – and writes normalised data to a local ring buffer that prevents data loss during outages.

L3 – communication layer transmits data over MQTT (QoS-2) with TLS 1.3 encryption [7] through Wi-Fi, LoRaWAN or 4G-LTE, and **L4 – cloud layer** distributes the stream by an Apache Kafka broker, stores it in InfluxDB and runs all services as Docker microservices.

L5 – intelligence layer performs digital-twin synchronisation, forecasting, anomaly detection and computation of the EEI and the carbon footprint, while **L6 – decision layer** visualises the results, issues relay control signals, updates the maintenance schedule and notifies the user.

Digital-Twin Loop

The digital twin is a mathematical model synchronised with the state vector of the physical asset with a synchronisation period of $\Delta t = 1$ s. Its discrete state model is

$$\hat{x}(t+1) = A\hat{x}(t) + Bu(t) + w(t), \quad (1)$$

where A is the system matrix, B the control matrix, $u(t)$ the control action and $w(t)$ the process noise. The mismatch between the asset and its twin is the residual norm

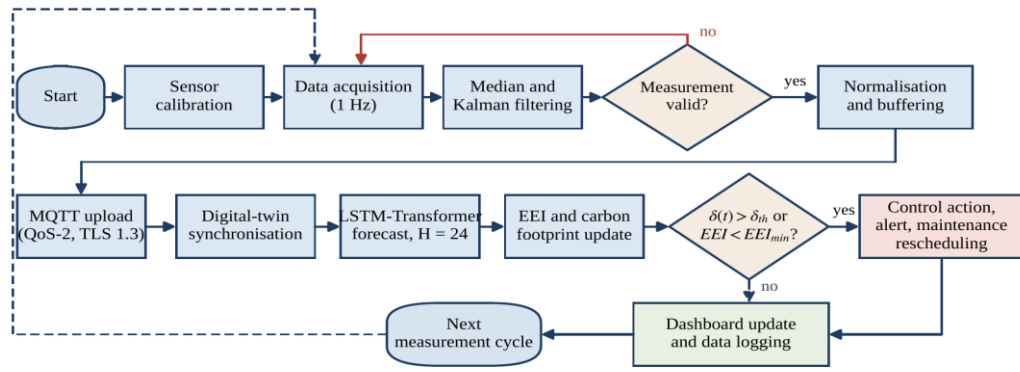
$$\delta(t) = \|x(t) - \hat{x}(t)\|_2. \quad (2)$$

If $\delta(t) > \delta_{th}$, the platform concludes that the technical condition of the equipment has changed and activates the predictive-maintenance module. The residual therefore acts as a model-based diagnostic feature: it reacts to parameter drift even while the measured power still lies inside its normal range, which is what makes early warning possible.

Operating Algorithm

The complete operating cycle is shown in Fig. 2 and formalised in Algorithm 1. It starts with sensor calibration, rejects invalid frames through a validity test, and closes with energy-efficiency evaluation and an anomaly check.





Solid lines: main data path; dashed lines: conditional transitions and cycle return.

Fig. 2. Block diagram of the operating algorithm. Solid lines denote the main data path; dashed lines denote conditional transitions and the return of the measurement cycle

Algorithm 1. Operating cycle of the platform

1. Calibrate the sensors; initialise the twin state $\hat{x}(0)$.
2. Acquire the frame z_k at 1 Hz, apply the median filter and the Kalman update (7); discard invalid frames.
3. Normalise by (8), buffer locally and publish over MQTT.
4. Synchronise the twin, compute $\delta(t)$ by (2), update the EEI by (9) and the carbon footprint by (10).
5. If $\delta(t) > \delta_{th}$ or $EEI < EEI_{min}$, solve(11) and issue the control action and the alert; update the dashboard and return to step2.

Mathematical Model of the Measurement Chain

For a single-phase circuit the active, apparent and reactive powers are

$$P = UI \cos \varphi, \quad S = UI, \quad Q = UI \sin \varphi, \quad (3)$$

where P is the active power (W), S the apparent power (VA), Q the reactive power (var), U and I the r.m.s. voltage and current, and φ the phase-shift angle. The power-triangle relation holds:

$$S^2 = P^2 + Q^2. \quad (4)$$

For a balanced three-phase load the active power is

$$P_{3\varphi} = \sqrt{3} U_L I_L \cos \varphi. \quad (5)$$

The energy consumed over an interval is obtained in integral form and, with step Δt , in discrete form:

$$E = \int_{t_1}^{t_2} P(t) dt = \sum_{k=1}^N P_k \Delta t. \quad (6)$$

At the edge node the measurement noise is suppressed by a Kalman filter [8]:

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-), \quad (7)$$

where K_k is the Kalman gain, z_k the measurement and H the observation matrix. Filtered values are then mapped to [0,1]:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}. \quad (8)$$

This ordering is essential: the median stage removes the impulsive outliers that would otherwise bias the Kalman innovation, so that the linear filter operates under the noise assumptions for which it is optimal. Its quantitative effect on forecasting accuracy is measured by the ablation study of the companion study.

Energy Efficiency Index and Carbon Footprint

The Energy Efficiency Index is defined as the ratio of ideal to actual consumption, the ideal value being computed from the nominal operating modes of the equipment:

$$EEI = \frac{E_{ideal}}{E_{real}}, \quad E_{ideal} = \sum_{i=1}^n P_{nom,i} t_i. \quad (9)$$

The platform operates at maximum efficiency as $EEI \rightarrow 1$; the optimisation module is triggered when $EEI < EEI_{min}$. The carbon footprint of the consumed electricity is estimated as

$$C_{CO_2} = k E, \quad (10)$$

where k is the emission factor of the supply mix (kg CO₂/kWh); $k = 0.468$ kg CO₂/kWh was adopted for the power system of Uzbekistan. Energy-use optimisation is posed as the constrained minimisation problem

$$\min_{\{E_i\}} \sum_{i=1}^n c_i E_i, \quad P_{min} \leq P_i \leq P_{max}, \quad EEI \geq EEI_{min}. \quad (11)$$

where c_i is the tariff coefficient of the i -th interval. Relations (9)–(11) place the technical, environmental and economic criteria in one loop, so that an optimisation decision can be justified in all three terms simultaneously.

Experimental Infrastructure and Dataset

A testbed connected to a 0.4kV three-phase network was assembled (Fig.3); the test object was a production area with a total installed capacity of 18.5 kW. Power-quality quantities were acquired in accordance with IEC 61000-4-30 [9] and the sensor interface followed IEEE 1451.0 [10]. The specification is given in Tab.2

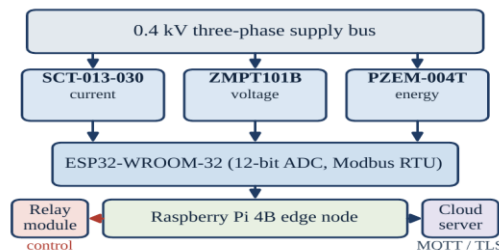


Fig. 3. Block diagram of the experimental testbed



Table 2

Technical specification of the experimental testbed

Component	Model / value	Characteristics
Current sensor	SCT-013-030	0–30 A, error $\pm 0.5\%$
Voltage sensor	ZMPT101B	0–250 V, error $\pm 0.4\%$
Energy module	PZEM-004T v3.0	Modbus RTU, 0–100 A
Microcontroller	ESP32-WROOM-32	240 MHz, 12-bit ADC
Edge node	Raspberry Pi 4B	4 GB RAM, Cortex-A72
Protocol	MQTT v5.0 / TLS 1.3	QoS-2, Wi-Fi 802.11n
Cloud server	Ubuntu 22.04 LTS	8 vCPU, 32 GB RAM, GPU T4
Software	PyTorch 2.1	Python 3.11, InfluxDB 2.7

Data were collected continuously over 180 days, from December 2025 to May 2026, at a primary sampling rate of 1 Hz and then aggregated into 15-minute intervals, yielding

17 280 records with seven features each (Table 3). The same dataset is used in the companion study.

Table 3

Statistical description of the dataset

Quantity	Mean	SD	Min.	Max.	Median
Active power P , kW	7.42	3.55	1.60	22.84	6.31
Voltage U , V	220.0	2.64	212.3	227.9	220.1
Current I , A	12.26	5.74	2.71	37.10	10.43
Power factor $\cos\phi$	0.895	0.041	0.702	0.972	0.905
Reactive power Q , kvar	3.71	1.92	0.58	12.44	3.12
Daily energy E , kWh	178.1	42.7	94.3	281.6	172.8

Fig.4 shows the mean daily load profiles for working days and weekends. The series exhibits pronounced daily and weekly periodicity: on working days a morning ramp is followed by a mid-day peak and a secondary afternoon peak, whereas weekend profiles are flatter and roughly 45 % lower in amplitude. This regular structure is what makes the series suitable for multi-step forecasting.

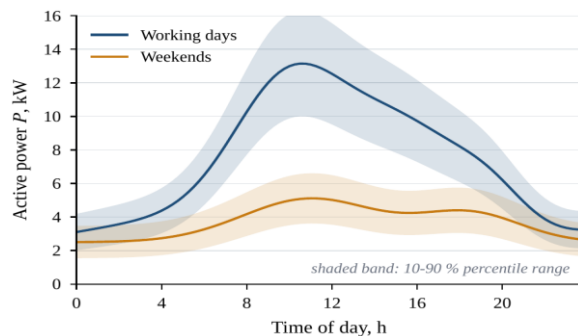


Fig. 4. Mean daily load profiles for working days and weekends; the shaded band denotes the 10–90 % percentile range

3. Conclusion

This paper has presented the architecture, the mathematical model and the experimental infrastructure of a hybrid digital-twin monitoring platform. The main outcomes are as follows.

1. A six-layer architecture was proposed in which measurement, edge conditioning, secure transport, cloud storage, intelligent analysis [11] and decision making are separated into explicit layers connected by a control feedback loop; the operating cycle was formalised as Algorithm 1.

2. A multi-stage edge-side conditioning scheme (median→Kalman→normalisation) was formulated and justified.

3. The digital-twin residual $\delta(t)$ was introduced as a diagnostic feature that reacts to parameter drift before it becomes visible in the measured power.

4. An integral EEI and a carbon-footprint model were combined with a tariff-aware optimisation problem, and a 180-day dataset of 17 280 records was collected on a 0.4 kV three-phase testbed.

A companion study builds a hybrid LSTM–Transformer forecasting model on this architecture, benchmarks it against eight reference algorithms, quantifies the contribution of every component by an ablation study and reports the energy and environmental results obtained at five types of facility.

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