

A Machine Learning, Internet of Things, and Techno-Economic Approaches for Solar-Powered Street Light

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Abstract- Street lighting consumes substantial electricity, and photovoltaic (PV) street lamps are increasingly promoted as a way to cut energy cost and emissions. Their performance, however, depends on weather, the dimming strategy, battery state of charge, and lamp condition, which makes prediction and monitoring central to reliable operation. This paper reviews three recent IEEE Access studies that address complementary parts of the problem: a comparison of five machine learning algorithms for predicting the operating status of PV streetlights, a year-long field trial and artificial-intelligence-assisted techno-economic analysis of a PV-integrated pedestrian streetlamp, and a vehicle-mounted Internet of Things device for mapping light intensity. The studies are summarised, compared on data, methods, and outcomes, and examined for internal consistency and transferability. The review finds that deep models give the highest reported accuracy but at much higher computational cost and on very small datasets, that compact neural networks combined with dimming-aware energy management achieve large grid-energy savings in field conditions, and that mobile sensing offers a scalable route to compliance checking but has not yet been validated against regulatory illuminance standards. Open gaps and research directions are outlined.

Keywords— solar street lighting, photovoltaic systems, machine learning, Internet of Things, light pollution, techno-economic analysis, literature review

I. INTRODUCTION

Street lighting underpins road safety, personal security, and night-time economic activity, yet it is also a large and continuous electrical load; the study in [2] cites a worldwide consumption of nearly 50 billion kWh per year for the sector. Photovoltaic (PV) street lamps, either stand-alone with battery storage or grid-connected, reduce this load and the associated emissions [1], [2]. Their energy yield, however, depends on irradiance, temperature, and shading, and the light they deliver drifts with lamp ageing, fixture soiling, and voltage changes [1]. Operators therefore need three capabilities: to size and operate the system so that the lamp is reliably powered, to predict its behaviour under varying conditions, and to verify in the field that the light delivered matches the standard it is meant to meet [3].

The light itself also has a cost. According to the literature summarised in [3], over 99% of Europe's population and about 80% of the global population live in areas affected by light pollution, and

consistent measurement methods are needed because different disciplines use different metrics and terminology. Surveys of machine learning in smart lighting have so far concentrated on user comfort and control [4], and systematic reviews of light-pollution measurement do not address PV-powered lamps specifically [5].

This paper reviews three recent IEEE Access studies that, taken together, cover the operational chain of PV street lighting. Nadweh et al. [1] compare five machine learning algorithms for predicting lamp operating status. Belloni et al. [2] report a year-long field trial of a PV-integrated lamp and use neural networks and a Python tool for energy and techno-economic forecasting. Alam et al. [3] present InLeR, a vehicle-mounted Internet of Things (IoT) device for mapping light intensity. The contributions of this review are:

- a structured, side-by-side summary of the data, methods, and results of the three studies;
- a consolidated view of the reported evidence on prediction accuracy, computational cost, energy savings, payback, and monitoring capability;

- a critical assessment of the internal consistency and transferability of the reported results; and
- a set of research gaps and directions that follow from the comparison.

The remainder of the paper is organised as follows. Section II describes the scope and method of the review. Section III covers system architecture and sizing, Section IV machine learning for performance prediction, Section V techno-economic and environmental evidence, and Section VI IoT-based monitoring. Section VII discusses the results critically, Section VIII outlines research gaps, and Section IX concludes.

II. SCOPE AND REVIEW METHODOLOGY

1. Selection of Studies

The three studies were chosen because they were published in IEEE Access in 2024–2025, concern street lighting with an emphasis on solar-powered lamps, and address different layers of the same problem, as shown in Fig.1. Additional works cited by the three studies are used only for context and are identified as such.

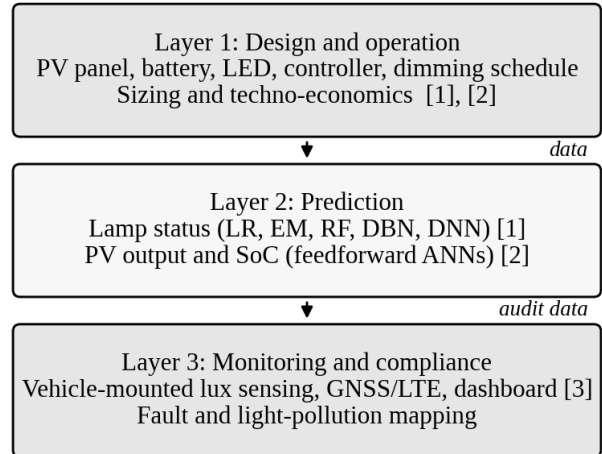


Fig.1. Three-layer view of the reviewed literature: design and operation, prediction, and monitoring.

2. Review Questions

Four questions guide the analysis: (i) which data and methods each study uses; (ii) which performance, cost, and environmental results it reports; (iii) how internally consistent and transferable those results are; and (iv) which gaps remain. Table I answers the first two questions and lists the principal limitations that Section VII examines.

Table 1: Summary of the Reviewed Studies

Ref.	Focus	Data and Setting	Methods	Principal Findings	Main Limitations
[1]	Predicting on/off status of PV streetlights from power and luminous flux	100-sample dataset, 10 lamps; field data (70%) and PVsyst simulation (30%); 5-min logging; three climate regions	LR, EM, RF, DBN, DNN trained in MATLAB; 70/15/15 split	DNN 97% accuracy and 2.5% error; DBN close behind; LR fastest and weakest; DNN costs 36.5× more energy per prediction than LR	Very small test set; text and figures disagree; emission figures implausible at case-study scale
[2]	Energy, economics, and AI-based forecasting of a PV-integrated lamp	Perugia field trial, Feb. 2023–Jan. 2024; simulation for Bolzano and Catania	Two feedforward ANNs, Coulomb counting, Python tool, 15-year NPV and payback model	72 kWh/yr load, 43% from grid; 93–95% less grid energy than HPS lamps; payback 11–14 yr at 120 €/MWh	Single prototype; high capital cost; payback driven by avoided lamp replacements

Ref.	Focus	Data and Setting	Methods	Principal Findings	Main Limitations
[3]	Mobile light-intensity monitoring for compliance and light pollution	Calibration with 247 points; field tests in Riyadh and AIUla	Three VEML7700 sensors, ESP32, LTE/GNSS, quadratic calibration, web dashboard	4 Hz sampling at 55 km/h; adjusted R ² of 1 after calibration; threshold maps of lux levels	No comparison with standards; one season; fault detection not validated

DNN: deep neural network; DBN: deep belief network; LR: linear regression; EM: expectation maximisation; RF: random forest; ANN: artificial neural network; NPV: net present value; HPS: high-pressure sodium.

III. SOLAR STREET LIGHTING SYSTEMS

1. System Architecture

Both [1] and [2] describe a PV street lamp as a PV generator, a charge controller, a battery, an LED luminaire with its driver, a pole, and a control system. Panels may be monocrystalline, polycrystalline, or amorphous silicon, and batteries lead-acid, lithium-ion, or LiFePO₄ [1]. In the conceptual design of [1], each lamp has its own panel and battery so that every luminaire operates independently off-grid.

The prototype of [2] differs in several respects. Flexible monocrystalline cells (200 W peak, 630 × 1800 mm) are wrapped around a 4 m aluminium pole; a 12.8 V, 36 Ah LiFePO₄ battery, about 0.46 kWh nominal by simple multiplication, sits inside the pole; and a dimmable 48 W LED module of 120 lm/W is used. The system is grid-assisted: when the state of charge (SoC) falls below 20%, the lamp draws the energy needed to keep minimum power from the grid. A maximum power point tracking (MPPT) charge controller and a battery management system complete the design. Because the cells cover a vertical cylinder they are never all irradiated at once, and the peak hourly production recorded was about 45 Wh despite the 200 W nameplate. An electrical performance analysis of a stand-alone PV-battery LED case study by the same group is given in [8].

2. Sizing and Operating Cost

Sizing and Operating Cost

Reference [1] gives a simple sizing chain: the number of poles is the street length divided by the pole spacing, total power is the lamp power times the number of poles, and daily energy is total power times the operating hours. For its 200 m case study (ten 100 W lamps at 20 m spacing, 10 h per night) the daily load is 10 kWh, or 1 kWh per pole. Battery capacity follows from daily energy and battery voltage:

$$C_B = E_{\text{day}} / V_B \quad (1)$$

which for 1 kWh at 12 V gives about 83.3 Ah per lamp. At 0.1 \$/kWh the equivalent grid cost is about 1 \$ per day [1]. Optimisation-based sizing, for example with genetic algorithms, has been applied to PV/battery street lighting in Oman [6], and a techno-economic analysis for Turkey identifies high up-front cost and variable sunshine as the main barriers to off-grid PV road lighting [7].

3. Dimming and Grid-Assisted Operation

Reference [2] shows that the energy balance is dominated by the dimming schedule. The lamp runs at 24 W (50% of maximum) until midnight, at 12 W (25%) from 00:00 to 04:00, and at 24 W until dawn, while the existing HPS luminaires on the same path run at full power all night. Measured illuminance on a 60-point grid was 4.6 lx minimum and 17.3 lx mean, above the 2 lx and 10 lx required for lighting class P2 of EN 13201. The scheduling time step was one hour although the controller supports 15 minutes. The hourly grid energy required when SoC is too low is computed as

$$E_{\text{grid}} = \sum_m N_m (T_{1,m}P_1 + T_{2,m}P_2 + T_{3,m}P_3) \quad (2)$$

where N_m is the number of days in month m , $T_{i,m}$ the nightly hours in dimming period i for which grid energy is needed, and P_i the lamp power in that period [2].

IV. MACHINE LEARNING FOR PERFORMANCE PREDICTION

1. Five-Algorithm Comparison

Problem Formulation: The task in [1] is binary classification of lamp state (on/off) from consumed power (W) and luminous flux density (lm/m^2), supplemented by daily-time and seasonal features. The dataset has 100 samples, split 70/15/15 into training, validation, and test sets after outlier removal or filling and standard normalisation, and models are implemented in MATLAB. Data are described as 70% field measurements and 30% PVsyst simulation from 50 lighting locations in three climate regions, logged every five minutes with Zigbee meters and LX-102 lux meters, both accurate to about $\pm 2\%$. Weather enters through the effective panel temperature,

$$T_{\text{eff}} = T_{\text{amb}} + ((NOCT - 20) / 800) \cdot G_{\text{poa}} \quad (3)$$

where T_{amb} is ambient temperature, $NOCT$ the nominal operating cell temperature, and G_{poa} the plane-of-array irradiance [1].

Algorithms and Settings: Linear regression (LR) models the lamp state as $Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + e_i$, with power X_i and illuminance Z_i (regularisation coefficient 10,000, 1,000 iterations). Expectation maximisation (EM) treats the state as a latent Bernoulli variable (100 iterations, tolerance 10^{-6} , three components). Random forest (RF) uses 400 trees of depth 40, 40% of features per split, and at least 8 samples per split. The deep belief network (DBN) and deep neural network (DNN) use four hidden layers of 100 and 50 units, learning rates of 10^{-4} and 3×10^{-4} , and 200 iterations [1].

Data Granularity: A separate analysis in [1] reports that moving from hourly to 15-minute data lowers the mean absolute error of power from 18.7 W to 16.4 W (about 12%), and 5-minute data reaches 15.9 W ($R^2 = 0.92$), while training time grows from 42 to

189 min. The paper does not state which model produced these figures.

2. Neural Networks in the Field Study

Reference [2] uses neural networks for a different target. Two networks are chained: ANN 1, from earlier work [9], estimates PV production from measured global horizontal radiation, and ANN 2, a feedforward network, estimates the PV voltage and current delivered after the MPPT regulator. With 80% of the data used for training and 20% for testing, the correlation coefficients are $R = 0.92$ for voltage and $R = 0.96$ for current at very low computational cost. Battery SoC is tracked by Coulomb counting, and a Python tool with a graphical interface accepts up to three dimming periods and returns battery voltage and current, lamp load, and the hourly energy that must come from the grid. Related work applies long short-term memory (LSTM) networks to weather-forecast-based control of autonomous street lighting [10].

The two studies are therefore complementary rather than competing: [1] predicts a discrete lamp state from load and light level, whereas [2] predicts continuous PV electrical output to drive an energy-balance simulation.

3. Reported Performance and Computational Cost

Table II collects the values read from the bar charts of [1]. The DNN and DBN lead on every metric, RF is third, and LR is last, as might be expected of a linear model fitted to a binary target. The text of [1] gives wider ranges for several values, for example 10–25% error for EM and 5–15% for RF.

Table 2: Reported Performance of the Five Algorithms [1]

Alg.	Acc. (%)	Err. (%)	Rec. (%)	F1	AUC
LR	82	17.5	70	0.70	0.70
EM	90	17.5	75	0.80	0.80
RF	90	10.0	80	0.85	0.90
DBN	96	2.5	90	0.90	0.95
DNN	97	2.5	95	0.95	0.98

On an AWS p3.2xlarge instance (NVIDIA V100 GPU, 64 GB RAM), training time, memory, and inference latency in [1] are 4.2 min, 1.8 GB, and 0.7 ms for LR; 41.7 min, 8.9 GB, and 1.5 ms for RF; and 153.8 min, 31.7 GB, and 22.4 ms for the DNN, with EM and DBN at 28.1 min, 5.3 GB, 2.1 ms and 127.4 min, 23.1 GB, 18.9 ms. The DNN is reported to use 36.5 times more energy per prediction than LR. Fig.2 summarises the accuracy results and the training-time figures.

V. TECHNO-ECONOMIC AND ENVIRONMENTAL EVIDENCE

1. Field Trial and Simulation in Italy

The monitored lamp in [2] consumed 72 kWh in a year; about 41 kWh (57%) came from PV and about 43% from the grid, mostly in winter. In summer the SoC varied between 40% and 100% with no grid supply, whereas in winter the on-period reached about 13 h and the battery was not self-sufficient for up to 150 h in January, against 35–45 h per month in summer. After tuning, the algorithm was run with weather data for Bolzano (north), Perugia (centre), and Catania (south).

Table III and Fig.3 show the results. Catania has the highest PV production but the lowest lamp consumption, because shorter nights give an on-period of 3,370 h per year against 3,780 h in Perugia and 4,100 h in Bolzano.

Table 3: Simulated Annual Results for One Solar Streetlamp [2]

Site	PV (kWh)	LED (kWh)	Grid (kWh)	Grid (%)	PbT (yr)
Bolzano	62.8	78.5	36.4	46	11–12
Perugia	70.7	72.2	31.4	43	11–12
Catania	83.3	61.1	21.7	35	13–14

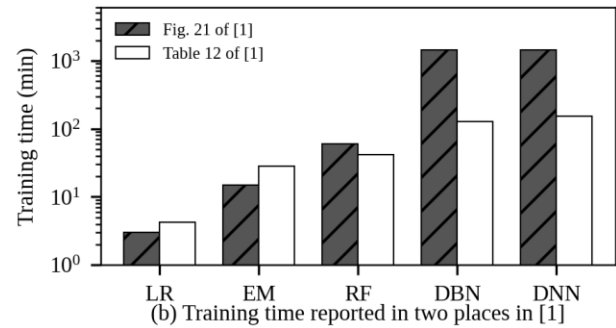
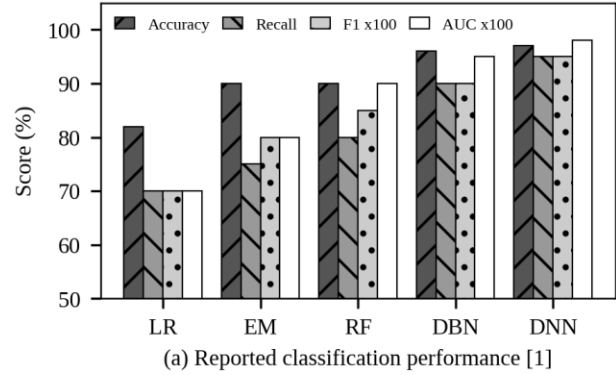


Fig.2. (a) Performance values reported in [1]; (b) training time as shown in Fig. 21 and in Table 12 of [1].

Reference [1] closes with deployment guidance: LR for arid sites with daily temperature change below 2 °C; DNN/DBN blends where relative humidity varies strongly (65–95%); RF with lidar-derived shadow maps in urban valleys; and DNN models only where a city has at least 10,000 lampposts. The reported results are not broken down by climate or city size, so this guidance appears to be informed judgement rather than a tested finding.

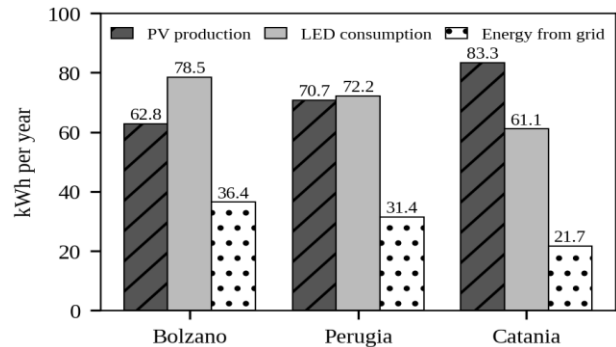


Fig.3. Simulated annual energy flows of one solar streetlamp at three Italian sites, from Table 1 of [2]. Replacing the ten HPS lamps of the path with the solar lamps cuts grid electricity from 4,961, 4,522, and 4,080 kWh per year to 363, 314, and 217 kWh in Bolzano, Perugia, and Catania, a saving of 93–95% [2].

Cost Model and Sensitivity

The economic model of [2] uses a 15-year horizon and a 5% discount rate. The solar lamp costs about 3,500 €, 2.3 times a standard lamppost; its battery is replaced every four years at 150 €; HPS lamps (24,000 h life) are replaced every 6–7 years, whereas the LED (over 100,000 h) is not. Grid electricity is priced at 0.12 €/kWh. The net present value is

$$NPV = \sum_{k=1}^{15} (C_{s,k} - C_{maint,k}) / (1 + r)^k - (I_0^{solar} - I_0^{std}) \quad (4)$$

where C_s is the annual cost saving, C_{maint} the maintenance cost, and I_0 the initial investment [2]. Annual savings are 464, 505, and 552 € for Catania, Perugia, and Bolzano, which for the ten-lamp path is about 50 € per lamp per year. Because this is far below the extra capital cost, break-even occurs through the avoided HPS replacements in years 6–7 and 12–14. At 120 €/MWh the payback is 11–12 years (Perugia, Bolzano) and 13–14 years (Catania), with NPV between 5,200 € and 6,130 €; at 180 €/MWh the payback is unchanged but NPV rises to 7,600–9,000 €; and at 550 €/MWh the payback falls to 5–7 years with NPV of 22,000–27,000 €. At an Italian carbon factor of 389 g CO₂eq/kWh the authors estimate avoided emissions of 1,560 kg (Catania), 1,700 kg (Perugia), and 1,856 kg (Bolzano) per lamp over its life.

System-Level Environmental Claims

The case study in [1] claims reductions of 70–80% in carbon emissions and energy consumption and 50–70% in light pollution, together with annual savings of 2 t of nitrogen oxides, 3.65 t of sulphur oxides, 0.5 t of PM_{2.5}, and 0.5 t of methane. The reference grid is assumed to be 60% natural gas, 20% coal, and 20% renewables, with emission factors from the IEA database. The authors attribute the light-pollution reduction mainly to full cut-off fixtures and dimming

controls rather than to PV supply. Section VII examines how these numbers relate to the scale of the case study.

VI. IOT-BASED MONITORING AND COMPLIANCE

1. Motivation and Related Work

Compliance checks on streetlights have traditionally relied on handheld lux meters, which are labour-intensive, measure in a single direction, and lack geotagging and real-time transmission [3]. Table 1 of [3] shows that most surveyed light-monitoring systems are fixed installations. Related approaches include a roof-mounted vehicle system for road-surface illuminance [11], a modular IoT sensor platform for light-pollution monitoring [12], and UAV-based photometric measurement [13].

2. Hardware and Firmware

The InLeR (Innovative Light Evaluation Rig) device in [3] uses an ESP32 controller and three VEML7700 ambient-light sensors facing upward, left, and right. The sensors share one I2C address and are therefore read through an I2C switching IC, one channel each. The VEML7700 was preferred to the LTR-329ALS and APDS-9306 for its range of 0.0036–120,000 lux, automatic gain control, and programmable integration time. Each sensor sits behind an epoxy-sealed Fresnel lens window; an LTE Cat 4 module with 3G/2G fallback and built-in GNSS provides connectivity and positioning; and an IP68 connector, a 5 V USB supply, and two neodymium magnets complete the enclosure. Firmware runs a sensing thread and a communication thread, starts logging only when a valid GPS fix exists, stores readings in JSON, and posts them to a server through a state machine that handles modem start-up, network registration, and retries.

3. Dashboard

The web dashboard maps readings along the route, colouring road sections blue below a user-set minimum, green within the band, and red above the maximum, with filters for minimum, maximum, and each sensor direction [3]. Thresholds can be changed after collection, so routes can be reclassified against different IES or CIE lighting categories. Sample data

from Riyadh and AlUla are published on Mendeley Data

(<https://data.mendeley.com/datasets/jsm2stkdpj/1>).

4. Calibration

Devices were calibrated in a $69.5 \times 38.5 \times 29$ cm matte-black foam-board chamber lit by an LED source driven from 2.50 V to 5 V in 0.01 V steps, against two handheld references (Extech SDL400 and PCE-172). The references agreed with slope 1 and intercept 0 and were averaged. Of 247 points, two outliers were removed. A linear fit left U-shaped residuals, so a quadratic term was added, giving an adjusted R^2 of 1 with both terms significant ($p < 0.001$); the linear and quadratic coefficient intervals were [1.393, 1.401] and [0.00040, 0.00043] for one device and [1.099, 1.103] and [0.00031, 0.00032] for the other, so each unit needs its own correction. Residual diagnostics gave a Durbin-Watson statistic of 1.226 and a condition number of 1.44×10^5 , which the authors attribute to using a variable and its square. Machine-learning calibration of low-cost light sensors is an alternative [14].

5. Field Deployment

The device was mounted on a car roof and powered from the USB port. In Riyadh and AlUla it sampled at 4 Hz, which at an average speed of 55 km/h gives one sample roughly every 3.8 m, comfortably finer than the 35–50 m streetlight spacing in Riyadh; readings were aggregated for two minutes before upload. The Riyadh maps separate dark, well-lit, and over-lit streets, and in AlUla four high-lux regions (A–D) were identified, with the densest clusters in a commercial zone. The authors report coverage of about 50 km at 50 km/h.

VII. CRITICAL DISCUSSION

1. Internal Consistency of Reported Results

Several figures in the reviewed studies cannot be reconciled with other statements in the same papers. The most important are listed below; none changes the overall ranking of the algorithms, but together they limit how far the numbers can be relied on.

- Battery and PV sizing in [1]. The text states a battery capacity of about 83,333 Ah, whereas

Table 11 lists 83.333 Ah and 1,000 Wh at 12 V corresponds to 83.3 Ah per lamp. Table 11 also gives total consumed power as 1 kWh where 1 kW is meant. In addition, a 100 W panel would have to deliver the lamp's 1 kWh daily load, which is 10 equivalent full-sun hours per day before losses, well above typical insolation; the paper presents no panel-count calculation for this.

- Accuracy and error in [1]. The text gives 85% accuracy for EM and 75% for LR, whereas Fig. 16 shows 90% and 82%. Accuracy and error rate do not sum to 100% for EM (90% and 17.5%), DBN, or DNN (97% and 2.5%, or 96% and 2.5%), and EM and LR have the same 17.5% error in Fig. 15 despite different accuracy.
- Training time in [1]. Fig. 21 gives 1,440 min for both DNN and DBN, 60 min for RF, and 3 min for LR, whereas Table 12 gives 153.8, 127.4, 41.7, and 4.2 min (Fig.2b). A network of four hidden layers of 50 units has only a few thousand parameters, so 31.7 GB of memory and hours of training on 100 samples are hard to reconcile and probably reflect implementation overhead rather than inherent model cost.
- Emission savings in [1]. The case study consumes 10 kWh per day, or about 3.65 MWh per year. A saving of 2 t of NO_x per year would imply about 0.5 kg per kWh, and 3.65 t of SO_x exactly 1 kg per kWh, whereas power-sector emission factors are of the order of grams per kWh or less. A unit slip is likely. Fig. 25 of [1] also refers to a 10 kW system, whereas the design load is 1 kW.
- Details in [2]. The case description refers to nine HPS luminaires and later to ten. The 121 W is called the total peak power but must be per luminaire, since $10 \times 121 \text{ W} \times 4,100 \text{ h}$ gives the 4,961 kWh of Table 2 for Bolzano. A rough check of the avoided CO₂ with the 15-year horizon, the 389 g/kWh factor, and the savings of Table 2 gives about 2.3–2.7 t per lamp rather than 1.6–1.9 t, so a different lifetime or baseline appears to have been used.

2. Dataset Size and Task Difficulty

The headline result of [1], 97% accuracy and 2.5% error, rests on a dataset of 100 samples from ten lamps. With a 15% test split there are 15 test

samples, so a single error changes accuracy by about 6.7 percentage points, and values such as 97% or 2.5% cannot come from one such split; the paper does not say whether repeated runs or a larger set were used. Table 9 of [1] also shows that every sample with 0 W consumed power has status off, so power may encode the label almost directly, which would make the classification task much easier than the text suggests. The learning curves of Fig. 19 extend to 10,000 data points, which is inconsistent with a 100-sample dataset. The paper further states that the models support early fault detection, but its labels are on/off status and no faulty-lamp data are shown.

3. Model Complexity versus Deployability

The comparison in [1] suggests that accuracy gains from deep models come with large cost increases, and the authors themselves recommend DNNs only for very large installations. The field work in [2] points the same way: two small feedforward networks with R of 0.92 and 0.96 were enough to drive a year-long energy simulation. The choice of model should therefore follow the prediction target and the available data. A further point is that LR in [1] fits a 0/1 target with a linear model (Eq. 13 of [1]), which may partly explain its weak results; logistic regression would be the natural baseline for a binary state.

4. Measurement Validity and Standards

Road-lighting classes such as P2 in EN 13201, used in [2], specify horizontal illuminance on the road

surface at grid points, which [2] measured with a luxmeter at 60 positions. The sensors of [3] instead record light incident at roof height from above, left, and right, and the paper does not map these readings to road-surface values; the vehicle-mounted system of [11] was designed for that purpose. The calibration in [3] covers about 0–500 lx in a dark chamber, the field tests cover one season, and the authors acknowledge that no municipal lux standard was available for a quantitative comparison. Fault detection, the other stated aim, is not validated against known faulty lamps, and the predictive-maintenance models are left to future work. InLeR is best seen as a data-collection platform that could supply the labelled data currently missing for the models of [1].

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Table IV condenses the gaps identified above. Two themes cut across them. First, the studies address different layers of the problem and different prediction targets, and no work yet links them: field-measured lux and fault labels from mobile audits could train lamp-status and degradation models, whose outputs in turn could adjust dimming schedules of the kind studied in [2]. Second, claims of accuracy and savings need transparent datasets, fixed metrics, and sensitivity analysis before they can guide procurement or standards.

Table 4: Research Gaps and Suggested Directions

Gap	Evidence in the Reviewed Studies	Suggested Direction
Small, non-public datasets for lamp-state prediction	100 samples and ten lamps in [1]; no fault labels	Release benchmark datasets with fault labels; report cross-validated results with confidence intervals
Inconsistent reporting of results	Text, figures, and tables disagree in [1] (Section VII-A)	Report fixed metrics once, with code and data, and state how each was computed
Different prediction targets across studies	Lamp status [1], PV voltage and current [2], lux [3]	Joint models of energy balance, lamp output, and fault state
Limited seasonal and climate coverage	One year at one site in [2]; one season in [3]	Multi-year, multi-climate trials with stratified evaluation

Gap	Evidence in the Reviewed Studies	Suggested Direction
Model complexity versus deployability	DNN: 31.7 GB, 22.4 ms in [1]; small ANNs suffice in [2]	Compact and edge-deployable models; cost-aware model selection
Measurement not linked to standards	Roof-level lux in [3]; road-surface grid in [2]	Map multi-direction lux to road-surface illuminance; validate on known faulty lamps
Economic analysis omits sensing and ML cost	Only electricity price varied in [2]	Include sensing and software cost; Monte Carlo on price, irradiance, and failure rates

IX. CONCLUSION

This review has compared three recent studies on solar-powered street lighting that cover prediction, system design and economics, and monitoring. Deep learning gives the best reported lamp-status accuracy but at much higher computational cost and on a dataset too small to support firm conclusions; compact neural networks combined with dimming and grid-assisted operation reduced grid electricity by 93–95% in a field-validated Italian case, though payback of 11–14 years at current prices depends on avoided lamp replacements and on the electricity price; and a low-cost vehicle-mounted device can map light levels over large areas but still has to be linked to regulatory illuminance measures and validated for fault detection. Future work should combine these layers, report results transparently, and test them across seasons and climates.

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