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Dirt Monitoring System for Solar Panel

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Abstract

This research presents a hybrid monitoring system designed to quantify solar panel dust accumulation and optimize maintenance schedules. By integrating nighttime Mie scattering in a dark-field environment with daytime DenseNet121 AI vision, the system effectively overcomes solar noise and provides robust spatial validation. Experimental results demonstrate an 85% AI classification accuracy and a high correlation (R2 = 0.971) between soiling levels and power loss, identifying a dynamic efficiency drop ratio of 1.183. Ultimately, the system utilizes an economic U-Curve optimization algorithm to identify the Global Minimum Cost, recommending the most profitable cleaning frequency to maximize energy yield and operational profitability.

1. Introduction

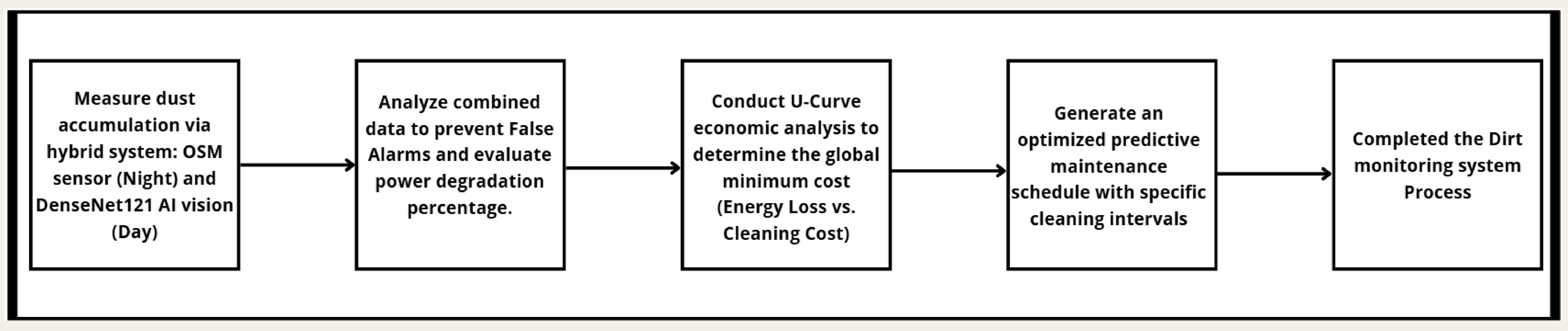


Figure 1. Project Overview.

The soiling effect on photovoltaic panels reduces energy yields by 10–30%, creating a critical maintenance trade-off for operators. Facilities must constantly balance the revenue lost from under-cleaning (production loss) against the wasted expenditures of over-cleaning (cleaning costs). To resolve this economic dilemma, this project introduces a monitoring system that links physical dust density to a financial engineering model. The objective is to pinpoint the exact economic break-even point, enabling a data-driven predictive maintenance strategy that minimizes total costs.

2. Methodology

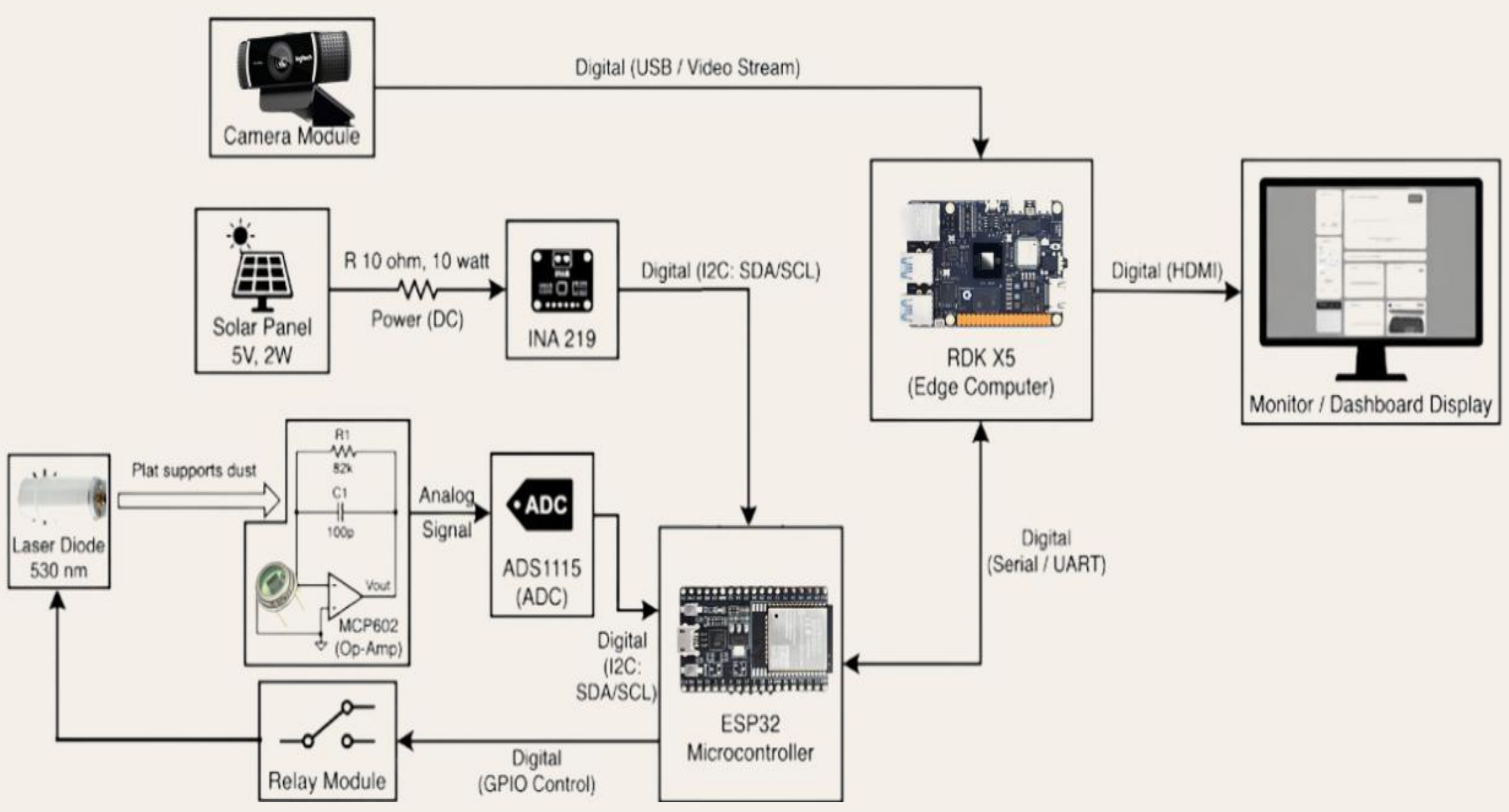


Figure 2. System Architecture.

The system runs microservices on an RDK X5 edge board, partitioned into two modes (Figure 2):

2.1 Nighttime Optical Sensing: To prevent solar saturation, a 550 nm laser (20° grazing angle) induces Mie scattering. A photodiode and TIA convert this scattered light into a dust-proportional voltage.

2.2 Daytime Vision & Power: A 45° camera utilizing DenseNet121 classifies soiling. Simultaneously, an INA219 sensor tracks power degradation, cross-validating visual data to account for environmental variables like dew.

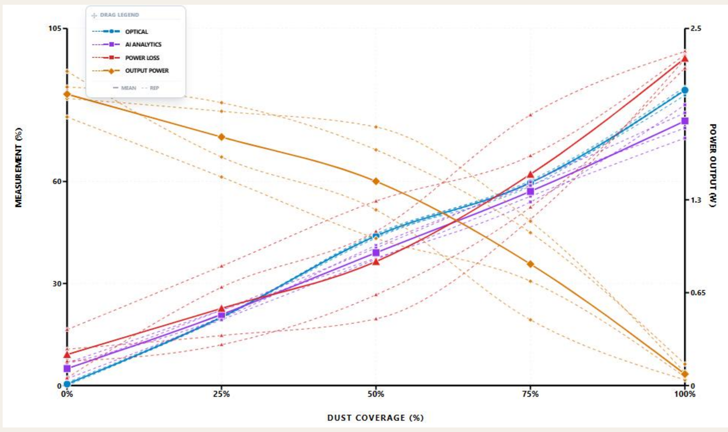
3. Results and Discussion

The DenseNet121 model achieved 85% accuracy for daytime visual validation, while the nighttime dark-field optical sensor delivered highly stable quantitative data. Together, they accurately capture the electrical impact of dust accumulation.

ระดับฝุ่นจำลอง	Optical sensor (%)					AI วิเคราะห์ภาพ (%)					กำลังไฟฟ้า (W)					Power loss (%)					Status ระบบ	ความสำเร็จ
ครั้งที่	1	2	3	4	เฉลี่ย (%)	1	2	3	4	เฉลี่ย (%)	1	2	3	4	เฉลี่ย (W)	1	2	3	4	เฉลี่ย (%)		
ระดับ 1: ฝุ่นเกาะ (0%)	0.38	0	0.88	0.5	0.44	6.45	6.65	2.01	4.83	4.99	2.09	2.01	2.2	1.88	2.045	7.11	10.7	2.22	16.44	9.11	Normal	☑
ระดับ 2: ฝุ่นเกาะ (25%)	20.29	19.96	20.29	19.84	20.095	19.89	22.15	19.33	22.21	20.9	1.98	1.92	1.6	1.46	1.74	12	14.7	28.89	35.11	22.67	Light Dirty	☑
ระดับ 3: ฝุ่นเกาะ (50%)	44.29	43.35	43.73	44.65	44.005	41.18	37.48	37.14	40.45	39.06	1.65	1.81	1.23	1.03	1.43	26.67	19.6	45.33	54.22	36.44	Light Dirty	☑
ระดับ 4: ฝุ่นเกาะ (75%)	60.31	59.84	58.66	59.6	59.6025	58.83	53.99	55.64	59.85	57.08	1.07	1.15	0.46	0.73	0.8525	52.44	48.9	79.56	67.56	62.11	Dirty	☑
ระดับ 5: ฝุ่นเกาะ (100%)	87.79	87.03	87.23	85.34	86.8475	75.73	82.56	72.76	80.19	77.81	0.15	0.09	0.04	0.06	0.085	93.33	96	98.22	97.33	96.22	Very Dirty	☑

Table 1: Empirical data of hybrid system performance

Analysis showed a strong linear correlation (R^2 = 0.971) between AI dust estimation and power loss. The regression established an Efficiency Drop Ratio of 1.183, meaning every 1% of dust degrades power by 1.183%



$$Cost_{Total}(f) = (Capacity \times Rate_{Clean} \times f) + \left[E_{Daily} \times \frac{\frac{(Dirt_{Optical} \times Ratio)}{Days_{Simulated}} \times 90}{2 \times 100 \times f} \right] \times 90 \times Price_{Energy}$$

$$Optimal\ Frequency = \underset{f \in \{1,2,...,15\}}{\arg\min}\ Cost_{Total}(f)$$

Figure 3. Dynamic correlation and Optimal maintenance frequency objective function.

Localized anomalies (e.g.,bird droppings) can cause optical sensor false alarms. However, cross-validation with AI spatial analysis and real power output successfully suppresses these errors, ensuring high system reliability

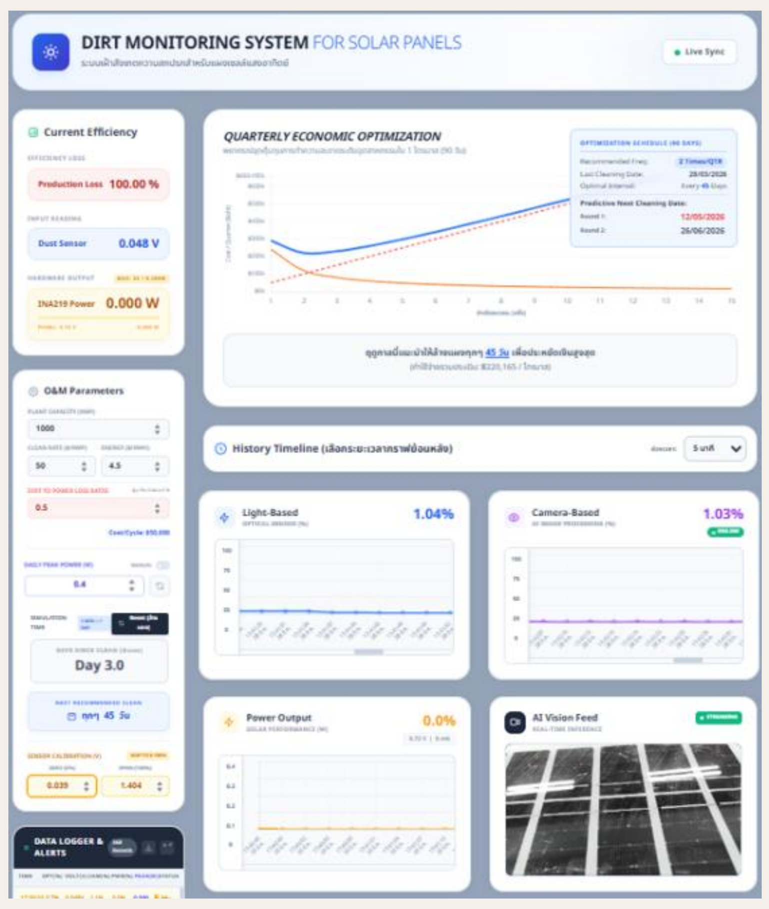


Figure 4. Smart UI for predictive maintenance scheduling Here.

The U-Curve analysis identifies the global minimum cost and the optimal maintenance frequency. The Smart UI then converts these insights into a predictive maintenance schedule to maximize long-term profitability.

4. Conclusion

This hybrid system effectively mitigates solar energy loss by integrating nighttime 550 nm laser sensing with daytime AI classification for continuous dust evaluation. By leveraging a U-Curve economic model, it delivers a dynamic, cost-optimized predictive maintenance strategy, maximizing both operational efficiency and long-term profitability for solar power plants.

References

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