

AI-Enabled Solar-Powered Smart Water Pumping System with CNN-LSTM-Based Predictive Energy and Water-Demand Management for Rural Communities

Abubakar Mohammed Baba¹, Ahmad Muhammad Bello^{2,3}, Zubairu Ibrahim¹, Lukman Salihu⁴, and Eeman Sani Abdu⁵

¹(Department of Computer Engineering, Kaduna Polytechnic)

²(Department of Electrical Engineering, Mewar University, India)

³(Department of Electrical and Electronics Engineering, Kaduna Polytechnic)

⁴(Computer Engineering Department, Kwara State Polytechnic)

⁵(Electrical and Electronics Engineering Department, Airforce Institute of Technology, Kaduna)

Abstract:

Solar-powered water pumping offers a sustainable water-supply option for rural communities with unreliable grid electricity, but conventional controllers react only to instantaneous tank-level conditions and cannot anticipate the mismatch between variable solar energy and changing water demand. This paper presents the design, implementation, and evaluation of an artificial intelligence (AI)-enabled solar-powered smart water pumping system with predictive energy and water-demand management. The prototype integrates a photovoltaic (PV) array with a maximum power point tracking (MPPT) pump controller, a submersible pump, water-level, flow, voltage and current sensors, an ESP32-based control unit, and GSM/IoT communication for remote monitoring and fault notification. A hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model forecasts solar-energy availability and water demand over a 24-hour horizon, and the forecasts are used for predictive pump scheduling, while dry-run, level and voltage protection remain rule-based. Tests carried out in Kaduna State, Nigeria, showed sensor errors of at most 3.0%, communication success rates of 90.0–100%, and a peak PV output of about 771 W. The model achieved R^2 values of 0.91 for solar-energy prediction and 0.88 for water-demand prediction. Compared with rule-based control, predictive control raised average water production from 3.42 to 3.92 m³/day (+14.6%), useful energy utilisation from 74.7% to 86.9%, and tank availability from 84.7% to 92.3%. The results demonstrate the feasibility of forecast-informed pumping in a unified, low-cost platform.

Keywords — Solar water pumping; Internet of Things (IoT); CNN-LSTM; predictive control; energy management; rural water supply.

I. INTRODUCTION

Access to reliable water underpins health, sanitation, agriculture, livestock production, and socioeconomic development. In many rural communities, however, inadequate water infrastructure and unreliable electricity continue to limit access. In Nigeria, rural water coverage remains substantially below urban coverage, and the provision of basic drinking-water services

remains a persistent challenge. Decentralised water-supply systems that are reliable, affordable, and sustainable are therefore needed.

Pumping water from boreholes and wells to storage or points of use requires a dependable energy source. Where grid electricity is unavailable or unreliable, diesel or petrol generators are commonly used, with attendant fuel and maintenance costs, noise, and emissions. Solar photovoltaic (PV) pumping provides an alternative

because electricity is generated locally without grid infrastructure [1], [2], and its suitability for irrigation, livestock, and community water supply, particularly in remote locations, is well established [3].

Solar pumping is nevertheless affected by variations in irradiance: PV output changes with time of day and weather, while water demand varies with household consumption, agricultural activity, and livestock needs. Effective operation therefore requires consideration of both available solar energy and anticipated water demand, rather than reliance on instantaneous conditions alone. Embedded systems and the Internet of Things (IoT) now allow sensing, communication, monitoring, and automated control to be integrated into pumping applications, and artificial intelligence (AI) can extend these capabilities by using historical and real-time data to forecast energy availability and water demand.

Conventional controllers respond only to present operating conditions and cannot anticipate reductions in available energy or increases in water requirements, which can cause inefficient pump operation and inadequate storage; IoT-based systems add remote monitoring and control but are not inherently predictive. This work addresses the problem by designing, implementing, and evaluating a functional prototype of an AI-enabled solar-powered smart water pumping system with predictive energy and water-demand management for rural communities.

The objectives were to: (i) design and implement a solar-powered pumping system with water-level and operating-parameter sensing; (ii) develop a microcontroller-based controller for automated pump management; (iii) develop an IoT platform for real-time monitoring; (iv) develop a CNN-LSTM model to forecast solar-energy availability and water demand; (v) integrate the model with the pump controller for predictive scheduling; and (vi) evaluate the prototype's monitoring, prediction, control, and pumping performance. The remainder of the paper is organised as follows: Section II reviews related work, Section III describes the system design and methodology, Section IV presents and discusses the results, and Section V concludes the paper.

II. LITERATURE REVIEW

A. Solar-Powered Water Pumping Systems

Solar-powered pumping has emerged as a sustainable alternative to diesel and grid-powered pumping in rural and off-grid settings. Declining PV module costs and growing environmental concern have accelerated its adoption for domestic, agricultural, and community supply [2]. Properly sized systems can reliably meet water demand while substantially reducing operating costs and greenhouse-gas emissions relative to diesel alternatives [4]. Performance depends on solar resource, pump selection, storage capacity, hydraulic head, and power-conditioning devices such as MPPT controllers. Most deployments, however, concentrate on energy generation and water delivery, with limited attention to intelligent operation and predictive management.

B. IoT-Based Monitoring in Water Systems

IoT-enabled water-management systems use sensors, microcontrollers, and communication networks to monitor water level, flow rate, pump status, pressure, and energy consumption. Real-time acquisition supports early fault detection, remote diagnostics, and automatic alerts, reducing downtime and maintenance cost, and GSM, Wi-Fi, and cloud-based platforms have been reported to improve operational efficiency. Most existing IoT-based pumping solutions, however, are limited to monitoring and notification, so operation remains reactive rather than proactive.

C. Rural Water Supply and Renewable-Energy Adoption

Inadequate infrastructure, unreliable electricity, high operating costs, and poor maintenance are recognised barriers to sustainable rural water provision. Solar pumping is widely promoted because it operates independently of the grid and removes fuel costs, and life-cycle comparisons indicate lower long-term cost and greater environmental benefit than diesel pumping. Many rural water projects nevertheless remain compromised by inadequate monitoring, delayed fault detection, and inefficient operation, which motivates intelligent water-management approaches.

D. Deep Learning for Energy and Demand Forecasting

Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architectures have outperformed conventional statistical approaches and standalone machine-learning models in forecasting solar irradiance, PV generation, and energy demand [5], [6]. The CNN component extracts local patterns from time-series data, while the LSTM component captures long-term temporal dependencies. Similar approaches have been applied to predict water consumption and demand fluctuations. Their integration into rural solar-powered pumping systems remains largely unexplored, and energy and demand forecasting are usually treated as independent problems.

E. Research Gap

The literature confirms the effectiveness of solar pumping, the value of IoT monitoring, and the strength of CNN-LSTM forecasting. Existing systems, however, either pump with solar energy without intelligent monitoring, add monitoring without predictive control, or apply forecasting without linking its output to pump scheduling. This work addresses the gap with a unified platform that combines solar generation, IoT monitoring, automated fault protection, and CNN-LSTM forecasting of solar energy and water demand for predictive pump scheduling.

III. SYSTEM DESIGN AND METHODOLOGY

An engineering design-and-development methodology was adopted covering the PV pumping system, the embedded monitoring and control subsystem, IoT connectivity, the CNN-LSTM prediction model, predictive pump scheduling, and prototype evaluation.

A. System Overview

The prototype comprises a PV array, an MPPT charge controller/pump inverter, a submersible DC pump, a rising main and overhead storage tank, a battery bank, water-level, flow, voltage and current sensors, an ESP32-based control unit, and a GSM/IoT communication module. Table I lists the main components.

TABLE I
MAIN HARDWARE COMPONENTS

Subsystem	Specification
PV array	2 × 450 W monocrystalline panels
Power conditioning	MPPT solar charge controller / pump inverter
Pump	Submersible DC water pump
Energy storage	12 V / 100 Ah deep-cycle battery
Sensing	Water-level, flow, voltage and current sensors
Control unit	ESP32-based microcontroller and control panel
Communication	GSM/IoT module with SIM data plan
Hydraulics	Rising main, fittings, overhead storage tank

B. PV Array and Pump Sizing

The PV capacity was determined from the pump rating, expected daily operating duration, solar resource, and system losses. The daily energy requirement is

$$E_L = P_L t \quad (1)$$

where E_L is the daily energy requirement, P_L the pump electrical power, and t the operating duration. Allowing for losses, the required PV energy and array capacity are

$$E_{PV} = E_L / \eta_s \quad (2)$$

$$P_{PV} = E_{PV} / H_s \quad (3)$$

where η_s is the overall system efficiency and H_s the equivalent peak-sun-hours at the site. The number of modules is

$$N_{PV} = P_{PV} / P_m \quad (4)$$

with P_m the rated power of one module, rounded up to the next whole number so that the array meets or slightly exceeds the requirement. For the pumping subsystem, the required flow rate follows from the daily volume V_d and pumping time t_p ,

$$Q = V_d / t_p \quad (5)$$

and the hydraulic power needed to lift water through the total head H (static head, friction losses, and any residual pressure) is

$$P_h = \rho g Q H \quad (6)$$

where ρ is the density of water and g the gravitational acceleration. With pump efficiency η_p , the pump input power is

$$P_{in} = P_h / \eta_p \quad (7)$$

The submersible pump was selected to match the required flow rate, head, and the electrical supply available from the PV subsystem.

C. Sensing and Microcontroller-Based Control

A water-level sensor in the overhead tank gives the instantaneous level, while flow, voltage, and current sensors measure operation at the pump. The ESP32 acquires the measurements and switches the pump on or off through a driver interface according to the programmed logic (Fig. 1): the pump starts when the level falls to the low threshold and no fault exists, stops at the high threshold, and is stopped with a fault flag and alert when low voltage or dry running is detected. The controller also prepares the measurements for transmission to the IoT platform and for use by the predictive model.

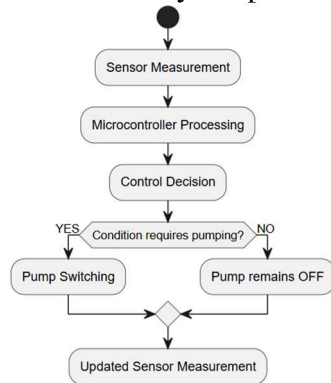


Fig. 1 Microcontroller-based monitoring and control flowchart.

D. IoT Monitoring Platform

The microcontroller transmits tank level, flow rate, PV voltage, PV current, pump status, and fault status through a wireless module to a monitoring platform that provides a remote view of the system. The time-stamped records also supply operational data for the predictive model. Local control and protection are retained at the microcontroller so that a temporary communication failure does not disable essential pump control and safety functions.

E. CNN-LSTM Prediction Model

Time-series data from the system were ordered by timestamp. The model inputs were solar irradiance, ambient temperature, tank water level, pump runtime, and time of day. The data were checked for missing, inconsistent, or erroneous observations, cleaned, converted into sequential samples, and normalised to improve training stability. A hybrid CNN-LSTM network (Fig. 2) was used: convolutional layers extract local features from the input sequences and LSTM layers learn

their temporal dependencies. The prediction relationship is

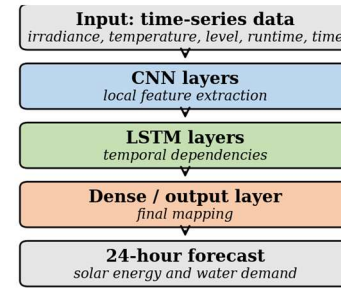


Fig. 2 CNN-LSTM architecture.

$$\hat{Y}_{t+k} = f(X_{t-n+1}, X_{t-n+2}, \dots, X_t) \quad (8)$$

where X is the sequence of input variables, n the input sequence length, k the prediction horizon, and $\hat{Y}$ the predicted output. The model predicts solar-energy availability and water demand for the following 24 hours. The dataset was split into training, validation, and test subsets; the training set was used for fitting, the validation set to guide hyperparameter selection with early stopping, and the test set was reserved for final evaluation.

F. Predictive Pump Scheduling

The forecast energy and demand are supplied to the pump controller together with the current tank level and energy (Fig. 3). Pumping is stopped when the tank reaches its upper level; it is started when current plus forecast solar energy is sufficient for the required pumping energy; and it is deferred when energy is insufficient but the stored volume remains above a safe reserve. If the level falls below the safe reserve, a priority override starts the pump regardless of the forecast to safeguard minimum supply. Pumping decisions therefore account for predicted as well as instantaneous conditions, which is expected to improve energy utilisation and reduce unnecessary cycling. Critical protections (dry-run, upper-level, and emergency shutdown) remain rule-based and independent of the model, and a rule-based fallback operates when no forecast is available.

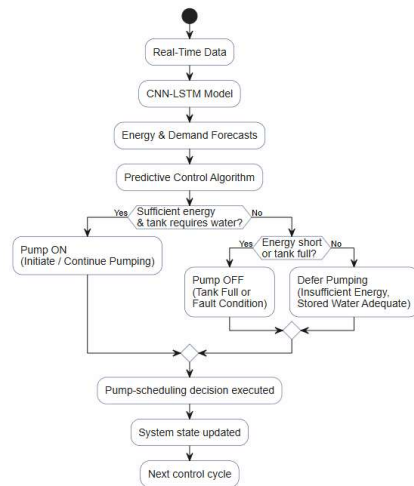


Fig. 3 Predictive pump-scheduling control flowchart.

G. Evaluation Procedures

The prototype was evaluated at Kaduna State, Nigeria. PV power was obtained from the measured voltage and current,

$$P_{PV} = V_{PV} I_{PV} \quad (9)$$

sensor accuracy was assessed against reference measurements using the percentage error, where X_m is the measured and X_r the reference value,

$$\% \text{ Error} = (|X_m - X_r| / X_r) \times 100 \quad (10)$$

the volume of water delivered was computed from the flow rate Q and pumping duration t ,

$$V = Qt \quad (11)$$

and the IoT communication success rate (CSR) from the numbers of messages received N_r and sent N_s ,

$$CSR = (N_r / N_s) \times 100 \quad (12)$$

Forecast accuracy on the test set was measured with the mean absolute error, root-mean-square error, and coefficient of determination,

$$\begin{aligned} \text{MAE} &= \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \\ \text{RMSE} &= \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \\ R^2 &= 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \end{aligned}$$

where y_i is the actual value, $\hat{y}_i$ the predicted value, $\bar{y}$ the mean of the observations, and n the number of observations. Finally, the predictive controller was tested against a conventional rule-based controller

under varying water level, predicted energy, and predicted demand.

IV. RESULTS AND DISCUSSION

A. Solar PV Performance

PV voltage, current, and power were monitored at different times of the day (Table II). Output rose from 314.2 W at 09:00 to a peak of about 771 W at 13:00 and then declined, consistent with the expected daily irradiance profile and confirming that the array can supply substantial power for daytime pumping. Output did not remain at nominal capacity because it depends on irradiance, module temperature, atmospheric conditions, orientation, wiring losses, and conversion efficiency, which is why forecast-based energy management is useful.

TABLE II
REPRESENTATIVE PV ELECTRICAL PERFORMANCE

Time	PV Voltage (V)	PV Current (A)	PV Power (W)
09:00	37.4	8.4	314.2
10:00	38.1	11.7	445.8
11:00	39.0	14.8	577.2
12:00	40.2	17.6	707.5
13:00	40.6	19.0	771.4
14:00	40.1	18.2	729.8
15:00	39.2	15.5	607.6
16:00	38.0	10.8	410.4

B. Sensor Accuracy

The sensors were compared with reference measurements (Table III). The largest error among the representative readings was about 3.0%, which is adequate for prototype-level monitoring and control. Accurate level sensing limits unnecessary pump operation and protects against dry running, and the flow sensor confirms that water is actually delivered while the pump runs.

TABLE III
SENSOR ACCURACY

Parameter	Reference	Sensor Reading	Error
Water level	1.25 m	1.22 m	2.4%
Water level	1.80 m	1.83 m	1.7%
Flow rate	10.0 L/min	10.3 L/min	3.0%
Flow rate	12.0 L/min	11.7 L/min	2.5%
PV voltage	38.0 V	37.5 V	1.3%
PV current	15.0 A	14.7 A	2.0%

C. Pumping Performance and Tank-Level Control

The pump was tested for operating durations of 30 to 120 minutes (Table IV). The average flow rate was approximately 11.2 L/min, and 1,416 L were delivered in 120 minutes. Variations in flow at some test points can be associated with changes in available solar power. The tank-level function operated according to its thresholds: the pump was off below the minimum level, on within the operating range, off when the upper threshold was reached, and on again after the level fell below the restart threshold. Pumping therefore followed water-level conditions rather than a fixed schedule, which suits rural supply where demand varies during the day.

TABLE IV
REPRESENTATIVE PUMPING PERFORMANCE

Duration	Avg. Flow (L/min)	Water Delivered (L)
30 min	10.6	318
45 min	11.0	495
60 min	11.2	672
90 min	11.5	1,035
120 min	11.8	1,416

D. IoT Communication Performance

Communication success rates ranged from 90.0% to 100% (Table V), showing that the key operating parameters reached the monitoring platform. Occasional losses may result from GSM network availability, signal strength, temporary interruptions, and delays. Because local sensing and control are retained on the microcontroller, a communication loss does not disable pump protection.

TABLE V
IoT COMMUNICATION PERFORMANCE

Parameter	Sent	Received	Success
Water level	30	28	93.3%
Flow rate	30	29	96.7%
PV voltage	30	29	96.7%
PV current	30	28	93.3%
Pump status	30	30	100%
Fault notification	10	9	90.0%

E. CNN-LSTM Prediction Performance

On the reserved test set (Table VI), the model reached $R^2 = 0.91$ for solar-energy prediction and

0.88 for water-demand prediction, indicating that it captured the main temporal patterns in the prototype data. The higher score for solar energy suggests that the solar-related inputs follow a more consistent pattern, whereas water consumption is influenced by changing usage patterns that are harder to learn from a small prototype dataset.

TABLE VI
CNN-LSTM PREDICTION PERFORMANCE

Prediction Variable	MAE	RMSE	R ²
Solar-energy prediction	0.084	0.118	0.91
Water-demand prediction	0.176	0.247	0.88

F. Predictive Versus Rule-Based Control

Table VII compares the predictive controller with conventional rule-based control. Predictive control raised average water production from 3.42 to 3.92 m³/day (about 14.6%), increased useful energy utilisation from 74.7% to 86.9%, and improved tank availability from 84.7% to 92.3%, while slightly reducing PV energy used (4.58 to 4.51 kWh/day), unnecessary pump runtime (3.1 to 2.2 min/day), and unnecessary pump cycles (7.0 to 5.7 per day). The gains arise because the controller anticipates solar availability and demand when choosing pumping periods instead of reacting to the present tank level. The AI model thus serves as a decision-support layer, while critical protections remain rule-based so that safe operation does not depend on the model.

TABLE VII
CONTROL-STRATEGY COMPARISON

Performance Indicator	Rule-Based	Predictive
Avg. water production	3.42 m ³ /day	3.92 m ³ /day
PV energy used	4.58 kWh/day	4.51 kWh/day
Useful energy utilisation	74.7%	86.9%
Unnecessary pump runtime	3.1 min/day	2.2 min/day
Tank availability	84.7%	92.3%
Unnecessary pump cycles	7.0 /day	5.7 /day

V. CONCLUSION

An AI-enabled solar-powered smart water pumping system integrating PV generation, automated pumping, sensor-based monitoring, IoT communication, and CNN-LSTM forecasting was designed, built, and evaluated as a prototype.

Sensor errors did not exceed 3.0%, communication success ranged from 90.0% to 100%, and the CNN-LSTM model achieved R^2 values of 0.91 (solar energy) and 0.88 (water demand). Forecast-informed scheduling outperformed rule-based control in water production, energy utilisation, tank availability, and pump cycling, demonstrating the technical feasibility of combining renewable energy, embedded control, IoT monitoring, and AI-based prediction for rural water supply. The reported results come from a prototype dataset and short test periods; future work should include long-term field trials under varying weather and demand, larger training datasets, and additional sensors, energy storage, and communication options to improve forecasting and robustness before wider deployment.

ACKNOWLEDGMENT

The authors thank the Tertiary Education Trust Fund (TETFund) for funding this work through its Institution-Based Research (IBR) intervention, and Kaduna Polytechnic for institutional support.

REFERENCES

- [1] S. S. Chandel, M. N. Naik, and R. Chandel, "Review of solar photovoltaic water pumping system technology for irrigation and community drinking water supplies," *Renew. Sustain. Energy Rev.*, vol. 49, pp. 1084–1099, 2015.
- [2] International Renewable Energy Agency (IRENA), *Solar Pumping for Irrigation: Improving Livelihoods and Sustainability*. IRENA, 2016.
- [3] K. Meah, S. Ula, and S. Barrett, "Solar photovoltaic water pumping—opportunities and challenges," *Renew. Sustain. Energy Rev.*, vol. 12, no. 4, pp. 1162–1175, 2008.
- [4] L. C. Kelley, E. Gilbertson, A. Sheikh, S. D. Eppinger, and S. Dubowsky, "On the feasibility of solar-powered irrigation," *Renew. Sustain. Energy Rev.*, vol. 14, no. 9, 2010, doi: 10.1016/j.rser.2010.07.035.
- [5] M. Husein and I.-Y. Chung, "Day-ahead solar irradiance forecasting for microgrids using a long short-term memory recurrent neural network: A deep learning approach," *Energies*, vol. 12, no. 10, p. 1856, 2019, doi: 10.3390/en12101856.
- [6] S. C. Lim, J. H. Huh, S. H. Hong, C. Y. Park, and J. C. Kim, "Solar power forecasting using CNN-LSTM hybrid model," *Energies*, vol. 15, no. 3, p. 1095, 2022, doi: 10.3390/en15031095.