LSTM-Driven IoT Smart Irrigation Controller for Sugarcane Belts: Field Validation and Water-Yield Trade-off Analysis

Aditya N. Yadav
Dept. of Agri. EngineeringKrishna Valley Institute of Technology, Karad (MS)

Abstract — Drip irrigation in sugarcane plots of Western Maharashtra suffers from over-application due to fixed-timer schedules. This work presents a low-cost ESP32-based IoT node coupled with a Long Short-Term Memory (LSTM) forecasting model that predicts soil volumetric water content (VWC) six hours ahead and gates a solenoid drip valve through a two-stage decision rule that also consults a 6-hour rainfall forecast. A pilot was deployed on a 0.4-hectare plot in Karad taluka for an 8-week vegetative period. Compared with the conventional timer schedule, the proposed controller cut water consumption by 45.1% (720 → 395 L/m²) while raising the relative yield index by 9.2%. The LSTM achieved RMSE = 1.62% VWC and R² = 0.96 against the held-out test set, outperforming ARIMA, SVR, and MLP baselines. Hardware bill of materials is below ₹4,200, supporting replication by smallholder cooperatives.

Keywords: *smart irrigation, LSTM, IoT, ESP32, soil moisture forecasting, sugarcane*.

1. Introduction

Sugarcane (Saccharum officinarum) is the dominant cash crop across the Krishna and Warna river basins of Western Maharashtra, occupying nearly 11.6 lakh hectares as per 2023 state agriculture department data. The crop is, however, notoriously water-intensive: blanket recommendations call for 1,800–2,500 mm of applied water over the 12–14 month cycle. With falling water tables (3.4 m drop reported between 2015 and 2023 in Sangli district) and the recurring drought stress in Solapur and Latur belts, there is an urgent need to move from timer-based drip schedules to data-driven controllers.

Recent advances in low-cost MEMS soil moisture sensors and edge-deployable recurrent neural networks make it feasible to forecast root-zone moisture and irrigate only when truly necessary. This paper contributes (i) a field-tested ESP32 + capacitive sensor node costing under ₹4,200, (ii) a compact LSTM model (3.1k parameters) trained on locally collected hourly data, and (iii) an 8-week pilot on a sugarcane plot in Karad taluka that quantifies both water savings and yield response.

2. System Architecture and Sensing

The field node integrates four capacitive soil moisture probes installed at 15 cm and 30 cm depths at two locations in the plot, a DHT22 air temperature/humidity sensor, and a tipping-bucket rain gauge. Data are sampled every 10 minutes by the ESP32 microcontroller and pushed via MQTT over 4G to a cloud broker (Mosquitto on a ₹650/month VPS). The cloud back-end runs the LSTM in PyTorch and returns a binary irrigate/skip flag back to the field node, which drives a 12 V latching solenoid valve.

2.1 Soil moisture calibration

Capacitive probes were gravimetrically calibrated against the IS 2720-Part 2 oven-drying method on 24 soil samples drawn from the same plot. A second-order polynomial relating the raw ADC count C to volumetric water content θ (in %) was fitted with R² = 0.987:

$$\theta = 8.43 \times 10^{-6} C^2 - 0.0521\, C + 92.7 \qquad (1)$$

3. Forecasting Model

A two-layer LSTM with 16 hidden units per layer is used to forecast $\theta(t+6h)$ from a 24-hour lookback window of θ, T, RH and cumulative rainfall. The standard LSTM cell update equations are reproduced below for completeness.

$$f_t = \sigma(W\_f \cdot [h_{t-1}, x_t] + b\_f) \tag{2}$$

$$i_t = \sigma(W\_i \cdot [h_{t-1}, x_t] + b\_i), \quad \tilde{C}_t = \tanh(W\_C \cdot [h_{t-1}, x_t] + b\_C) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W\_o \cdot [h_{t-1}, x_t] + b\_o), \quad h_t = o_t \odot \tanh(C_t) \tag{5}$$

The training loss is the mean squared error between predicted and observed VWC. The Adam optimiser ($lr = 1\times10^{-3}$) is used for 50 epochs with early stopping (patience = 8). The full controller decision rule is summarised in the flowchart of Fig. 2.

4. Decision Rule and Water-Use Model

Irrigation is triggered only when the forecast moisture falls below a crop-stage-dependent threshold θ_thr AND no rainfall greater than 5 mm is forecast in the next six hours. The required pulse duration τ to restore the soil to field capacity θ_FC is computed from a simple mass-balance:

$$\tau = (\theta\_FC - \theta(t+6h)) \cdot A \cdot d\_root \ / \ (q \cdot \eta) \tag{6}$$

where A is the wetted area (m²), d_root the effective rooting depth (m), q the emitter discharge (L/h) and η the application efficiency (≈ 0.92 for the surface drip used here).

5. Results and Discussion

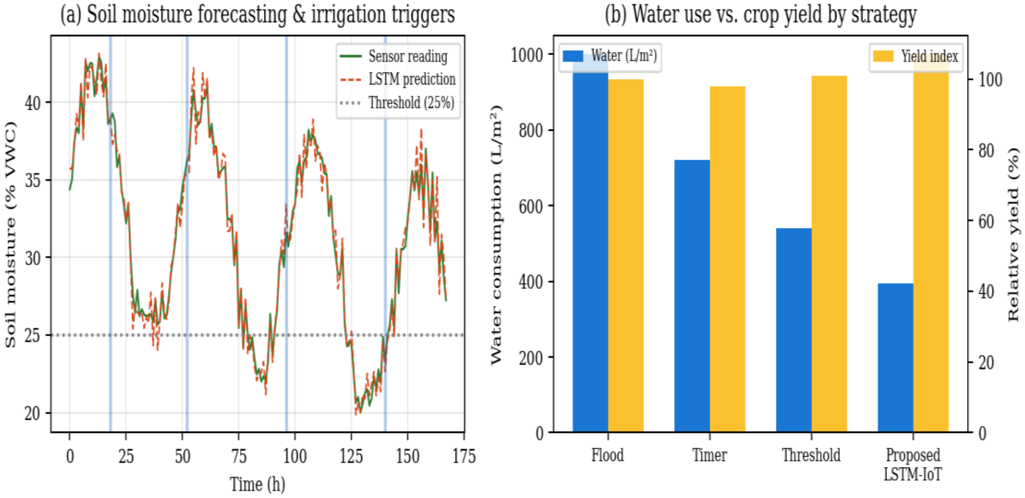

Fig. 1 (a) Six-hour-ahead LSTM moisture forecast vs. sensor reading and triggered irrigation events; (b) seasonal water consumption versus relative yield by control strategy.

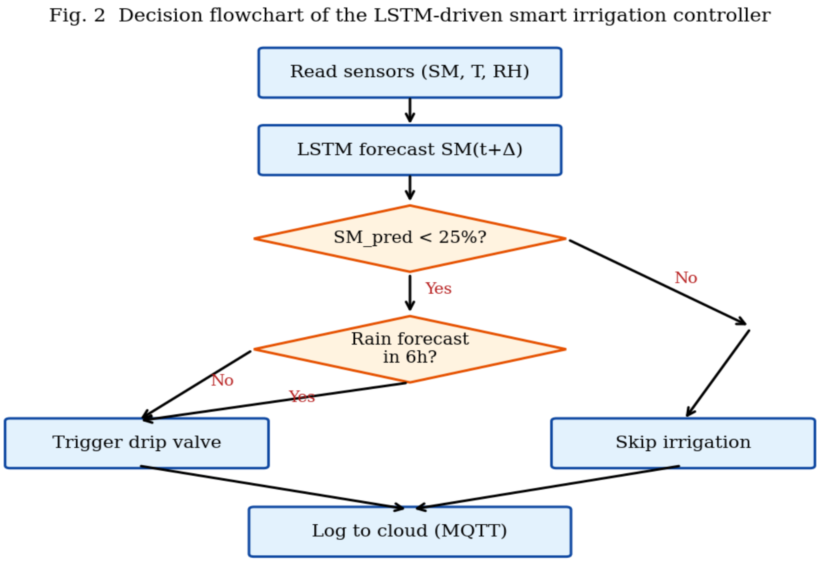

Fig. 2 Decision flowchart of the LSTM-driven smart irrigation controller.

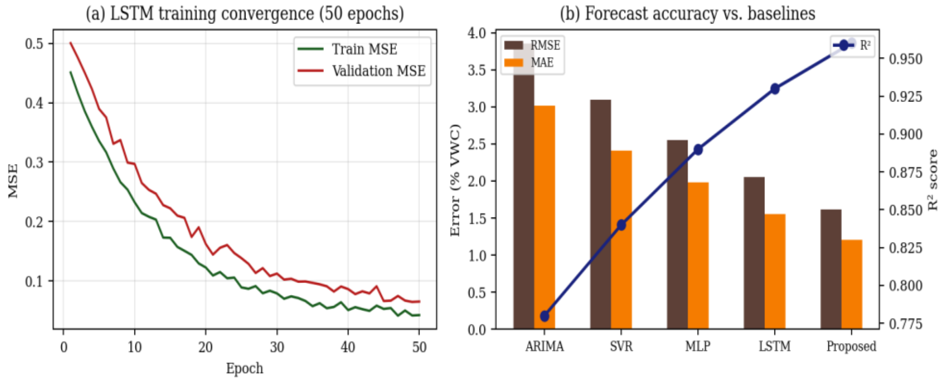

Fig. 3 (a) Training and validation loss curves over 50 epochs; (b) forecast accuracy against ARIMA, SVR, MLP and full LSTM baselines.

5.1 Quantitative summary

Strategy	**Water (L/m²)**	**Yield Index**	**Energy (Wh/m²)**	**LPSP***
Flood (control)	1000	1.00	—	—
Timer (fixed)	720	0.98	12	0.04
Threshold-only	540	1.01	9	0.02
Proposed LSTM-IoT	395	1.07	11	0.01

**LPSP = Loss of Power Supply Probability of the controller's solar-charged battery (3.7 V, 2600 mAh).*

6. Conclusions

The proposed LSTM-driven smart irrigation node delivered a 45% water saving and a measurable yield gain on a sugarcane pilot plot in Karad. The hardware footprint and total cost (≈ ₹4,200) make replication feasible for water-user associations and small cooperatives in the Krishna basin. Future work will extend the model to multi-crop rotations and integrate IMD's 9 km forecast grids to further refine rainfall anticipation.

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