

Extended Telemetry Reliability Analysis of a Solar-Powered IoT Smart Irrigation System

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Abstract

This study presents an extended audit of telemetry data quality and internal consistency from a stand-alone solar-powered smart irrigation prototype. Here, telemetry reliability refers to continuity, completeness, temporal comparability, and consistency with programmed rules; it does not imply traceable sensor measurement accuracy. The analysis uses an updated August export containing 602 additional observations and applies a reproducible audit workflow comprising continuity and completeness checks, five-minute temporal harmonization without interpolation, ceiling-aware soil-moisture analysis, and threshold-rule consistency checks. The combined dataset contained 12,025 unique timestamps from 1 July to 9 August 2026. Sampling gaps greater than 30 minutes formed 42 sessions, while ten core telemetry fields were simultaneously valid in 63.29% of records. The two soil-moisture channels produced 3,819 paired observations and 3,682 paired five-minute bins. The automatic and manual channels reached the 100% mapping ceiling in 71.25% and 46.35% of paired records, respectively, so the zero-point median daily difference primarily reflects censoring at the implemented scale. Across 3,789 valid battery-voltage and Energy Management System code pairs, threshold agreement was 99.60%. After 9 July, panel and battery voltage ranks were strongly associated ($\rho=0.995$), with a median offset of 0.06 V. These results support claims of telemetry availability, temporal comparability, voltage-channel coherence, and EMS rule consistency, but not measurement accuracy or irrigation, water, or energy efficiency because reference validation, pump-event history, and delivered-water records were incomplete or absent.

Keywords: data quality, Internet of Things, smart irrigation, soil moisture, solar energy.

INTRODUCTION

Smart irrigation combines sensors, embedded control, actuators, and communication to make watering decisions from measured conditions rather than from fixed schedules. In Internet of Things (IoT) implementations, soil moisture, temperature, humidity, and energy variables can be transmitted to a remote platform for monitoring and control. Solar supply is particularly relevant when a field installation must operate away from a stable utility connection. Al-Ali et al. (2020) integrated environmental sensing, renewable energy, and pump control in a solar-supported prototype, while Ramli and Jabbar (2022) demonstrated portable solar pumping with Blynk-based monitoring. Reviews likewise identify embedded controllers and networked sensors as recurring elements of smart irrigation architectures (Obaideen et al., 2022; Vallejo-Gomez et al., 2023).

Related embedded monitoring work has likewise emphasized the integration of sensors, communication, and automated control. Siskandar and Kusumah (2019) developed an aquaponic monitoring and control device, while Siskandar, Fadhil, et al. (2020) reported an Internet of Things-based automatic plant-watering system. Integrated greenhouse automation was subsequently demonstrated by Siskandar, Santosa, et al. (2022), and internet-based redox monitoring for aquaculture was developed by Siskandar, Wiyoto, et al. (2022). Wireless sensor-reading architectures for agricultural machinery were also reported by Siskandar, Mandang, et al. (2023a).

Further work extended embedded sensing and agricultural engineering to microcontroller-based light detection and solar tracking (Siskandar, Mandang, et al., 2023b), optical water-quality monitoring (Siskandar, Wiyoto, et al., 2023), and performance characterization of agricultural processing equipment (Siskandar, Kusumah, & Astuti, 2024). More recent studies applied embedded communication and actuator-control concepts to agricultural robotic platforms (Siskandar, Mandang, et al., 2025; Siskandar, Novianty, et al., 2025). These studies provide relevant examples of integrated sensing-to-control architectures; the present study differs by auditing whether the resulting telemetry is continuous, complete, temporally comparable, and internally consistent with programmed rules.

Beyond system architecture, sensor-data quality is itself a design concern. Fizza et al. (2022) proposed a smart-agriculture sensor-data quality model that separates dimensions such as completeness and accuracy, while Scholl et al. (2023) treated sensor data quality as a multidimensional construct that includes consistency and completeness. These approaches show that data presence or internal agreement should not be equated with measurement accuracy. In irrigation telemetry, this distinction is compounded by irregular cloud sampling, asynchronous channel updates, sensor saturation, and actuator events that may be shorter than the logging interval. Row-level summaries can therefore overweight high-frequency periods, interpolation can create observations that were never measured, and a plausible software state does not by itself prove physical actuation. These issues determine which engineering claims are supported: water saving requires recorded delivered-water volume, and energy efficiency requires validated and time-integrated energy data.

Soil-moisture sensing adds another measurement challenge. Low-cost capacitive sensors are attractive for automated irrigation because they are inexpensive and easy to interface, but their response depends on soil properties, installation, and calibration. Soil-specific calibration can substantially improve performance, while high water content can reduce discrimination near the wet end of the response range (Nagahage et al., 2019; Adla et al., 2020; Abdelmoneim et al., 2025). A mapped value of 100% is therefore a boundary of the implemented conversion, not automatically a gravimetric or volumetric water-content measurement. When many readings are pinned at that boundary, differences of means can be dominated by censoring rather than by a physically resolved moisture contrast.

The underlying final project developed a stand-alone solar-powered smart irrigation system using an ESP32, two series-connected 9 V solar panels, a solar charge controller, two series-connected 6 V batteries, two INA219 modules, a BH1750 light sensor, a DHT22 temperature-humidity sensor, two endpoint-mapped capacitive soil-moisture sensors, a relay-driven pump, and Blynk. Its thesis analysis used 11,423 records ending on 6 August 2026 and emphasized system implementation, descriptive telemetry, paired-pot moisture, and Energy Management System (EMS) code consistency. The August source file in the workspace was subsequently extended through 9 August 2026, which creates an opportunity for a journal analysis based on additional genuine observations and a different analytical question rather than altered or fabricated values.

Existing smart-irrigation studies commonly emphasize sensor integration, connectivity, monitoring dashboards, and irrigation control (Al-Ali et al., 2020; Ramli and Jabbar, 2022; Obaideen et al., 2022), whereas sensor-data-quality work has developed more general dimensions and quality models (Fizza et al., 2022; Scholl et al., 2023). This article does not propose a new universal quality score. Its methodological contribution is an auditable workflow for archived irrigation telemetry that jointly (i) quantifies continuity and cross-channel completeness, (ii) harmonizes unequal sampling intervals without interpolation, (iii) treats mapped soil-moisture ceilings as censoring rather than precise wetness values, (iv) checks recorded EMS states against firmware-derived voltage thresholds, and (v) separates verified telemetry relationships from unverified physical irrigation outcomes. This workflow is applicable to other IoT irrigation datasets in which cloud exports contain irregular timing, incomplete channels, or missing actuator or flow records. The article therefore asks three questions.

First, how does the extended dataset differ from the thesis cutoff in continuity and channel completeness? Second, what does a temporally harmonized and ceiling-aware analysis reveal about the automatic and manual soil-moisture channels? Third, how consistently do recorded EMS codes follow the programmed battery-voltage thresholds, and how closely do the two voltage channels track after the observed early-July regime change?

METHODS

System and Data Sources

The prototype was assembled during final-project activities at the National Research and Innovation Agency (BRIN), Indonesia. An ESP32 provided the embedded controller, analog inputs, I2C interfaces, and Wi-Fi connectivity (Espressif Systems, 2026). Two solar panels rated at 9 V were connected in series and routed through an INA219, a solar charge controller, and two 6 V, 4.5 Ah batteries connected in series as a nominal 12 V store. A second INA219 monitored the battery/load side; the INA219 is an I2C digital current/power monitor that also reports bus voltage (Texas Instruments, n.d.). The ESP32 read the BH1750, DHT22, and two DFRobot Gravity Waterproof Capacitive Soil Moisture Sensor channels (SEN0308), applied the irrigation and EMS rules, controlled a 12 V pump through a two-channel relay, and transmitted 13 telemetry channels to Blynk. Blynk virtual-pin datastreams were used for cloud monitoring and historical telemetry storage/export (Blynk, n.d.). One soil sensor was assigned to the automatically watered pot and the other to the manually watered pot. The physical integration is shown in Figure 1.

Scope of Telemetry Reliability and Sensor Validation

Three terms are separated throughout this study. Data completeness is the proportion of timestamps with valid values after the stated cleaning rules. Internal consistency is agreement among recorded fields or between recorded values and programmed rules, such as EMS-code agreement and voltage-channel co-movement. Measurement accuracy is the closeness of a sensor value to an independently validated reference. Only completeness and internal consistency are evaluated quantitatively here. Measurement accuracy is not claimed because the monitoring campaign did not include traceable reference measurements for the INA219 channels or gravimetric/volumetric reference water content for the soil sensors.

The two soil-moisture channels were converted from ESP32 ADC counts using project endpoint values SOIL_DRY=3456 and SOIL_WET=1648. The firmware applied a linear mapping from 3456 to 0% and 1648 to 100%, followed by a 0-100% clamp. These endpoints were empirical setup values rather than gravimetric or volumetric water-content calibration points. For qualitative interpretation the project treated values around 0-60% as dry and 60-100% as wet, while the automatic controller used hysteresis with pump start below 57% and pump stop at or above 65%. DFRobot specifies the waterproof capacitive sensor for 3.3-5.5 V operation and analog output (DFRobot, 2025), but the relationship between ADC output and true soil water content depends on soil properties, packing, installation depth, and sensor-specific calibration (Nagahage et al., 2019; Adla et al., 2020; Abdelmoneim et al., 2025). A mapped value of 100% is therefore treated as the conversion ceiling rather than as measured 100% water content.

For voltage and power telemetry, the INA219 provides digital bus-voltage, current, and power measurements through I2C and uses a 12-bit conversion architecture (Texas Instruments, n.d.). No independent multimeter or traceable reference comparison was performed for this prototype. Manufacturer specifications are therefore reported only as device characteristics and are not used as an experimental uncertainty estimate. Voltage results in this article are interpreted as internal channel tracking and firmware-rule consistency, not metrological accuracy.

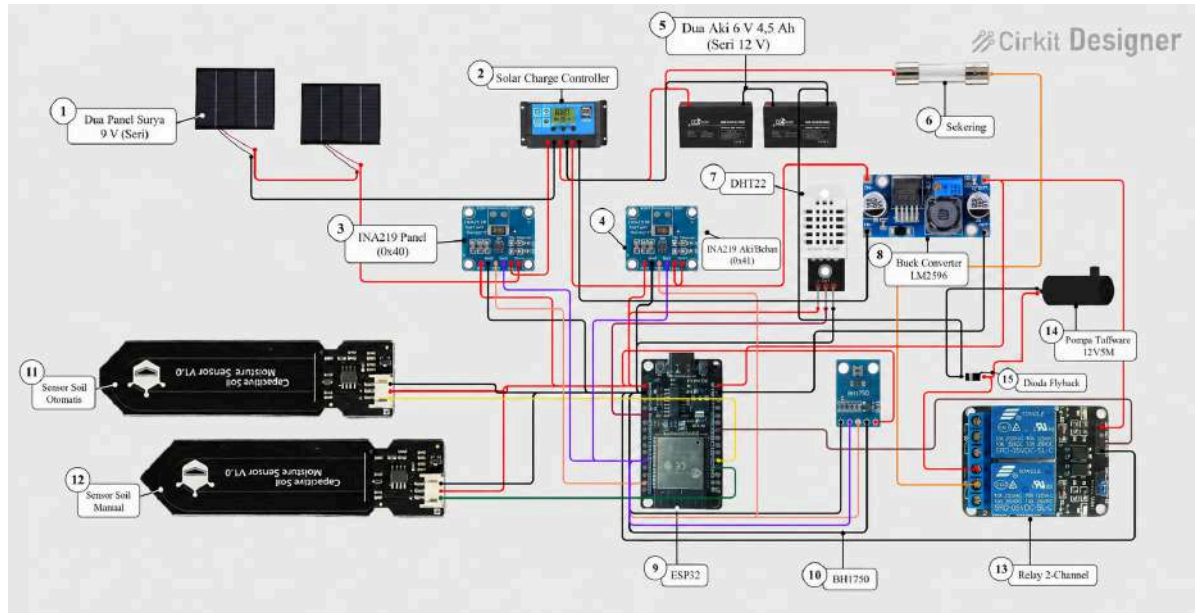


Figure 1. Hardware integration of the solar-powered IoT smart irrigation prototype.

Telemetry was sent to Blynk datastreams, where device values are timestamped and stored for historical retrieval (Blynk, n.d.). Two CSV exports were used: IOT TA data JULI_4086227_data.csv and IOT TA_4086227_data.csv. The July file contained 10,498 rows. The updated August file contained 1,527 rows, whereas the thesis cutoff used 925 August rows ending at 16:53 on 6 August. The journal analysis therefore includes 602 later records from 16:58 on 6 August through 19:35 on 9 August. The combined observation period spans 1 July 12:57 to 9 August 19:35, with timestamps reported as stored because the exported files do not specify a time zone. Analytical cleaning, aggregation, and visualization were performed on offline working copies in a spreadsheet workbook; the source CSV files were never overwritten.

Table 1. Differentiation of the journal dataset from the final-project analysis

Aspect	Final-project analysis	Journal analysis	Purpose
Observation window	1 Jul-6 Aug 2026	1 Jul-9 Aug 2026	Use the updated source export
Record count	11,423	12,025	Add 602 genuine observations
Temporal unit	Raw rows and hourly/daily summaries	Raw audit, five-minute bins, and daily paired summaries	Reduce unequal sampling weight
Primary lens	System performance description	Telemetry reliability and measurement limitations	Create analytical novelty
Missing values	No interpolation	No interpolation	Preserve traceability

Data Cleaning and Continuity Audit

Both files were parsed using month/day/year and 12-hour time, concatenated, sorted chronologically, and checked for duplicate timestamps. Values were retained as recorded except for rules that identified impossible or noncategorical readings in a separate analytical copy. Temperature at or below 0 deg C, relative humidity at or below 0%, and battery voltage at or below 0 V were set to missing. Pump Status values other than 0 or 1 and EMS Mode values other than the integer codes 0, 1, or 2 were also set to missing. Zero values in the other energy and light channels were retained because darkness, no current, or no measured power can be physically possible. Soil values within the

exported 0-100% mapping were retained, including the 100% boundary, and were flagged analytically as ceiling observations rather than deleted.

Continuity was evaluated from the difference between successive timestamps. Gaps greater than 10 minutes were counted as interruptions, and gaps greater than 30 minutes started a new analytical session. Calendar coverage was the number of dates containing at least one observation divided by the 40-day window. Channel completeness was the proportion of rows with a valid value after the stated cleaning rules. A strict core-completeness indicator required simultaneous valid values for the six energy channels, light, temperature, humidity, and automatic soil moisture.

Temporal Harmonization and Soil-Moisture Analysis

The July export was dominated by one-minute sampling and the August export by five-minute sampling. To avoid giving the more frequently sampled period disproportionate influence, the cleaned series was resampled to nonoverlapping five-minute bins using the arithmetic mean of available observations. Empty bins remained empty; no value was carried forward and no interpolation was performed. Daily paired summaries were calculated only for dates on which both soil channels were available. For each day, the median and mean were calculated for each pot along with the fraction of readings at 100%.

The automatic-minus-manual difference was reported at three levels: raw paired observations, paired five-minute bins, and daily summaries. A ceiling rate was calculated as the number of paired readings equal to 100 divided by the number of paired readings. The proportions below the pump-start threshold of 57% and within the programmed 57-65% hysteresis band were also tabulated. Daily medians were emphasized because they reduce the influence of unequal row counts and isolated changes; however, a daily median of 100% still indicates censoring and must not be interpreted as a precisely measured moisture level. Because the dataset contains only one automatic pot and one manual pot, these temporal summaries are not independent treatment replicates and no inferential treatment test is performed.

The two pots used the same type of growing medium and the same nominal sensor-placement procedure. Initial soil moisture was not standardized or equalized before monitoring. The manual pot was watered as needed, without a measured delivery volume. Consequently, automatic-minus-manual differences are interpreted descriptively as differences between two recorded channels and cannot be attributed solely to the irrigation method.

Voltage Tracking and EMS Consistency

For each record with valid battery voltage and an integer EMS code, the expected code was recalculated from the program thresholds: code 0 (NORMAL) for voltage at or above 12.2 V, code 1 (POWER-SAVING) for voltage from 11.8 V to below 12.2 V, and code 2 (PROTECTION) for voltage below 11.8 V. Agreement was the number of recorded codes equal to the expected code divided by all valid pairs. A 3 x 3 confusion matrix retained the direction of every mismatch. For mismatches, distance to the nearest threshold was used to identify observations that could be sensitive to small timing or measurement differences.

The source series showed a pronounced change between 1-7 July and the period beginning 9 July. Voltage tracking was therefore evaluated separately from 9 July onward. The analysis used the median signed difference, mean absolute difference, and Spearman rank correlation between simultaneously available panel and battery/load voltage. Rank correlation was selected because it assesses monotonic co-movement without assuming a linear error model. These statistics describe tracking between channels; they do not validate either INA219 against a traceable reference instrument. INA219-based measurements should be calibrated and validated against reference equipment before they support metrological or energy-efficiency claims (Prasetyawati et al., 2023).

RESULTS AND DISCUSSION

Extended Coverage, Sampling, and Completeness

The updated dataset contained 12,025 unique timestamps with no duplicate times. Observations were available on 36 of 40 calendar days; 4, 19, 20, and 21 July had no records. The chronological sequence contained 54 gaps longer than 10 minutes. Forty-one gaps exceeded 30 minutes, producing 42 sessions. The median interval was one minute in July and five minutes in August. These findings confirm that the dataset is an irregular collection of sessions rather than a continuously sampled 40-day time series.

The 602 added records represent 5.01% of the extended dataset and lengthen the record by approximately three days. Because they are concentrated in a five-minute regime, simply appending them to row-weighted averages would not make their temporal influence comparable with the one-minute July records. The five-minute transformation produced 5,390 observed bins across all channels. It therefore provides a differentiated analytical dataset with an explicit and reproducible time base, while preserving gaps as missing intervals.

Table 2. Completeness of the extended telemetry after analytical cleaning

Channel	Valid records (n)	Completeness (%)
Panel voltage	12,012	99.89
Panel current	11,995	99.75
Battery voltage	11,920	99.13
Panel power	11,957	99.43
Battery current	11,900	98.96
Battery power	11,878	98.78
Light	11,868	98.69
Temperature	7,626	63.42
Relative humidity	7,625	63.41
Automatic soil moisture	11,847	98.52
Pump status	8,812	73.28
Manual soil moisture	3,820	31.77
EMS mode	3,792	31.53

Six energy channels were 98.78-99.89% complete, and automatic soil moisture was 98.52% complete. In contrast, temperature and relative humidity were valid in only 63.42% and 63.41% of records after nonpositive readings were excluded. Manual soil moisture and EMS mode began later and were present in approximately one third of all timestamps. Only 7,611 records (63.29%) had simultaneous valid values for the ten predefined core channels. This strict figure shows why per-channel availability alone can overstate the number of records suitable for multivariable analysis.

The result also changes the interpretation of a dashboard. A channel may appear visually continuous because its own values are frequent, while a cross-channel calculation silently uses a much smaller intersection. Reporting the denominator for every analysis is consequently essential. The present article uses 12,025 for the raw audit, 3,819 for row-level paired soil analysis, 3,682 for paired five-minute soil bins, 25 for daily paired summaries, 3,789 for EMS validation, and 9,045 for post-9-July voltage tracking.

Ceiling-Aware Comparison of the Two Soil Channels

Both soil channels were simultaneously available in 3,819 records from 13 July 17:24 through 9 August 19:35. The raw automatic mean was 91.14%, compared with 89.09% for the manual channel, giving an automatic-minus-manual mean of 2.05 percentage points. The median difference was 0 because both distributions were frequently at the upper bound. Five-minute harmonization retained 3,682 paired bins and produced a similar mean difference of 2.16 points, indicating that the sign of the row-level difference was not created solely by the change in sampling interval.

Table 3. Ceiling-aware soil-moisture metrics for 3,819 paired records

Metric	Automatic pot	Manual pot
Mean (%)	91.14	89.09
Median (%)	100.00	97.00
Interquartile range (%)	81.00-100.00	80.00-100.00
Readings at 100%, n (%)	2,721 (71.25)	1,770 (46.35)
Readings below 57% (%)	0.13	0.24
Readings within 57-65% (%)	10.29	5.87

The automatic channel reached 100% in 71.25% of paired records, 24.90 percentage points more often than the manual channel. In August alone, the automatic ceiling rate was 99.80%, compared with 56.50% for the manual channel. Daily summaries were available on 25 dates. The median daily automatic-minus-manual median was 0 points, with an interquartile range of 0-6 points, although individual dates ranged from -19 to +22 points. Figure 2 shows that the apparent contrast changes by date and is often masked by ceiling behavior.

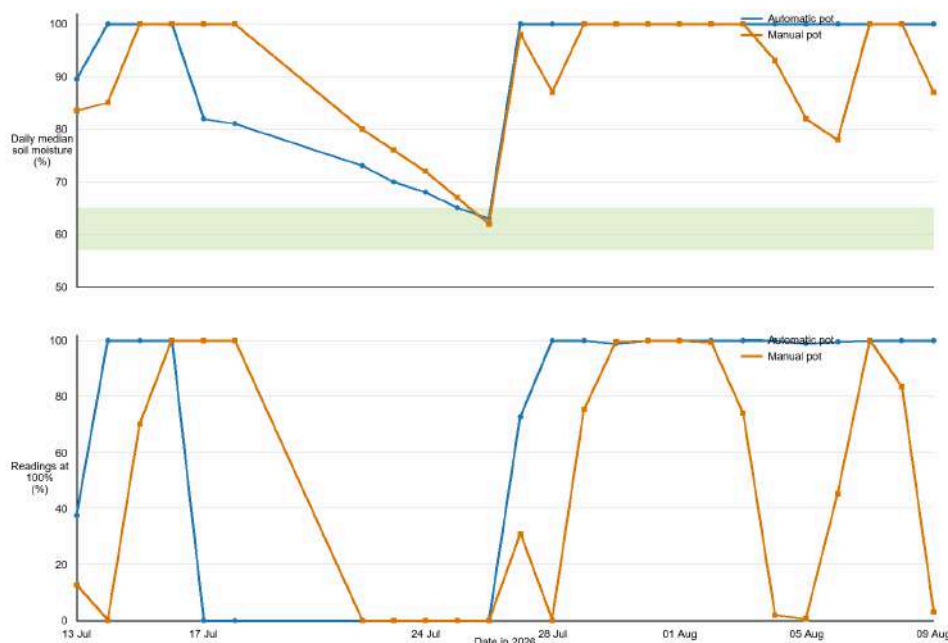


Figure 2. Daily paired soil-moisture medians and fractions at the 100% measurement ceiling.

These results support a measurement-quality conclusion rather than an agronomic-effect conclusion. The automatic channel was rarely below the 57% trigger and was mostly above the 65% stopping threshold, but the exported Pump Status contained no valid ON=1 history during the monitoring record. A separate functional test documented that the relay and pump could deliver water; however, that test does not establish the timing or frequency of pump activation during the telemetry period. Therefore time spent above or below a threshold cannot be causally assigned to recorded

pump events. Furthermore, only one pot represented each watering condition, manual watering volume was not logged, initial moisture was not standardized, and sensor readings were not validated against gravimetric water content during the monitoring period. Low-cost capacitive sensors can be useful after soil-specific calibration, but transfer across field conditions and discrimination at high moisture require validation (Adla et al., 2020; Abdelmoneim et al., 2025). The ceiling audit is therefore the key differentiated finding: a higher mapped average does not establish more effective watering when the measurement scale is repeatedly saturated.

Voltage Tracking and EMS Rule Reliability

After 9 July, 9,045 timestamps had both panel and battery/load voltage. The mean panel and battery/load voltages were 12.663 V and 12.719 V, respectively. Their median signed difference was 0.060 V and the mean absolute difference was 0.064 V. Spearman rank correlation was 0.995. This close co-movement indicates internally consistent channel tracking in the later regime, but it is not an accuracy statement because the two channels were not compared with a traceable meter and their measurement points are electrically different.

EMS validation used 3,789 records with valid battery voltage and an integer recorded code. Of these, 3,774 agreed with the threshold-derived code, for an overall agreement of 99.60%. Recorded code 0 matched expected NORMAL in 3,603 cases, code 1 matched expected POWER-SAVING in 25 cases, and code 2 matched expected PROTECTION in 146 cases. The remaining 15 pairs were mismatches; 6 of them (40%) were within 0.1 V of either 11.8 or 12.2 V. Asynchronous updates, firmware timing, and sensor variation are plausible explanations near boundaries, but the dataset cannot distinguish among them.

Table 4. Recorded versus threshold-derived EMS code

Recorded code	Expected 0	Expected 1	Expected 2	Row agreement (%)
0 (NORMAL)	3,603	4	2	99.83
1 (POWER-SAVING)	2	25	4	80.65
2 (PROTECTION)	0	3	146	97.99
Total	3,605	32	152	99.60

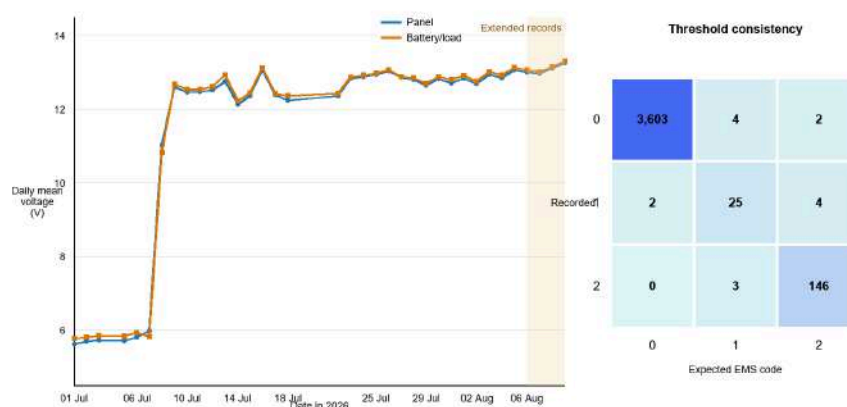


Figure 3. Daily voltage pattern, the extended observation window, and the EMS threshold-confusion matrix.

The class-specific result is important. NORMAL and PROTECTION had row agreements of 99.83% and 97.99%, whereas POWER-SAVING had 80.65%. The lower percentage for POWER-SAVING partly reflects its narrow 0.4 V band and small sample size of 31 recorded cases. A single delayed update near either boundary can change the expected class. Overall agreement alone should therefore be accompanied by the confusion matrix and denominators; otherwise the dominant NORMAL class can conceal weaker performance in a rare intermediate state.

The combination of a 0.064 V mean absolute channel difference and 99.60% rule agreement supports the narrower claim that recorded voltage behavior and EMS classification were internally coherent in the analyzed periods. It does not support energy savings. The dataset lacks validated current direction, integrated watt-hours, synchronized channel updates, and a separable energy record for the pump. Monitoring studies based on INA219 demonstrate the value of calibration and explicit uncertainty assessment (Prasetyawati et al., 2023). Without those steps, the scientifically defensible output is a reliability audit rather than an efficiency ratio.

Implications and Limitations

The extended analysis demonstrates a methodological distinction from the final-project report without altering any measurement. First, the source export was extended with 602 genuine observations. Second, the unit of analysis was changed from unequally spaced rows to five-minute bins and daily paired summaries. Third, the central outcome was changed from prototype description to an auditable telemetry data-quality assessment that separates completeness, internal consistency, and measurement accuracy. The workflow additionally exposes sensor ceilings and the evidence boundary between software-rule consistency and physical actuation. These transformations are reproducible and preserve the raw values; replacing observations or inventing treatment groups would undermine research integrity.

For system developers, the results identify concrete logging priorities. Pump events should be written on both state transitions with start time, stop time, duration, and delivered volume. Raw soil-sensor output and calibration endpoints should be stored alongside the mapped percentage so that ceiling behavior can be re-evaluated. Channel timestamps should be synchronized or accompanied by per-channel acquisition time. EMS code, threshold version, and firmware identifier should be retained per observation. Power studies should verify INA219 outputs against reference instruments and integrate signed power over time. These additions would connect controller behavior to water delivery, plant response, and energy use.

The study remains limited to one prototype, one automatically watered pot, and one manually watered pot. The same type of growing medium and nominal sensor-placement procedure were used, but initial moisture was not standardized; manual water was added as needed and its volume was not measured. With one pot per condition, temporal pairs do not constitute independent biological replicates, so the automatic-minus-manual comparison is descriptive only. Exact soil packing, drainage behavior, and plant-growth outcomes were not quantified in the telemetry. The automated pot has no independently logged pump-ON events in the Blynk history. The time zone is absent, and the early-July voltage regime changed without a configuration log. A large fraction of mapped soil values reached 100%, and environmental validity was limited by nonpositive DHT22 readings. Consequently, the findings cannot be generalized to crop yield, field-scale irrigation, water-use efficiency, battery autonomy, conversion efficiency, or causal treatment effects. Even with these limitations, the audit specifies what the available evidence can establish: the system produced a large traceable multichannel record, later voltage channels tracked closely, EMS coding was highly consistent with the programmed thresholds, and temporal harmonization did not reverse the small descriptive soil-channel difference.

Table 5. Verification status of the smart-irrigation causal chain

System link	Available evidence	Verification status	Permitted interpretation
Soil condition	Mapped soil-moisture telemetry; empirical endpoints 3456->0% and 1648->100%; control thresholds 57/65%	Telemetry available; physical moisture accuracy not independently validated	Supports analysis of recorded controller input values only

System link	Available evidence	Verification status	Permitted interpretation
Control decision	Firmware threshold and hysteresis logic; EMS rules also audited against voltage	Decision logic documented; irrigation-decision events not separately logged	Supports existence of the programmed rule, not event-by-event execution
Pump activation	Relay/pump operation demonstrated in a functional test; Blynk history contains no valid ON=1 events	Hardware function demonstrated; activation history during monitoring unverified	Pump-event timing and frequency cannot be estimated
Delivered water	No flow sensor or measured irrigation volume in the telemetry	Unverified	No water-use or irrigation-efficiency claim
End-to-end effectiveness	No synchronized soil -> decision -> pump -> water-delivery record	Unverified	Telemetry consistency must not be interpreted as irrigation-control effectiveness

CONCLUSION

This extended analysis evaluates telemetry data quality and internal consistency, not sensor metrological accuracy. The combined export contained 12,025 unique records through 9 August 2026, including 602 observations after the thesis cutoff. Irregular sampling produced 42 sessions; five-minute harmonization created 5,390 observed bins without interpolation, and only 63.29% of records had all ten core channels simultaneously valid. In 3,819 paired soil records, the automatic and manual channels reached the 100% mapping ceiling in 71.25% and 46.35%, respectively, so the zero-point median daily difference is dominated by censoring and the two-pot comparison remains descriptive. EMS codes agreed with voltage thresholds in 99.60% of 3,789 valid pairs, while post-9-July panel and battery/load voltages showed strong rank tracking and a small internal offset. The firmware-defined soil input and control thresholds are documented, and a separate functional test showed that the relay/pump could deliver water; however, the monitoring export did not contain valid pump-ON events or delivered-water measurements. Thus, the sensed-soil -> control-rule link is documented at the firmware/telemetry level, whereas the decision -> pump activation -> delivered water chain is not empirically verified for the monitoring period. The evidence supports claims of telemetry availability, temporal comparability, later-regime voltage coherence, and EMS rule consistency. It does not support claims of sensor measurement accuracy, causal irrigation treatment effects, water or energy efficiency, pump-event frequency, or improved plant growth. Future experiments should log synchronized state transitions, delivered-water volume, raw and reference soil measurements, calibrated signed energy, firmware versions, standardized initial pot conditions, and replicated growth outcomes.

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