



Data-Driven Evaluation of a Mamdani Fuzzy Duty-Cycle Controller for Solar Charging of a Lithium 18650 Battery-Powered Patient Monitor Prototype

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Abstract.

Purpose: Portable patient-monitor prototypes based on single-board computers require a stable energy source, whereas photovoltaic charging varies throughout the day. This study evaluates, from field measurements, how a Mamdani fuzzy inference system maps photovoltaic conditions to a duty-cycle charging command, how this decision layer compares with alternative decision methods, and what the available solar energy implies for a lithium 18650 battery-powered patient monitor prototype.

Methods: The open-circuit voltage (Voc) and short-circuit current (Isc) of a 10 W photovoltaic module were recorded on three days (74 records) through a 0.1 Ω shunt, and the shunt voltage was used to cross-check the current readings. Maximum available power was estimated with the datasheet fill factor. A two-input Mamdani controller with a complete nine-rule base (min-max inference, centroid defuzzification) generated a 0-100% duty-cycle command offline; the command was not applied to hardware as a PWM signal. The controller was benchmarked against a zero-order Sugeno system, a crisp rule-based system with the same rules, a proportional power map, and a fixed duty cycle using rule coverage, command variation, correlation with available power, robustness to simulated sensor error, rule-base completeness, and computation time.

Result: The Mamdani controller produced a decision for all records and over the whole operating envelope, whereas the crisp version decided only 50.0% of records and 71.5% of the envelope. Its command followed the estimated power (Spearman $\rho = 0.971$) and was smoother and less sensitive to sensor error (RMSE 4.58 percentage points) than the Sugeno (5.47) and crisp (9.27) variants. Estimated daily energy was 56.5-66.5 Wh, about five 18650 cells, but estimated power never reached the 17.116 W estimated load. One 3200 mAh cell provided an estimated 37.4 min battery-only runtime.

Novelty: The study provides an exploratory, data-driven evaluation that quantifies the quality of an interpretable Mamdani decision layer, namely its coverage, smoothness, robustness, and agreement with available power, against alternative decision methods, and places it within an energy evaluation of a patient-monitor prototype. It establishes a baseline for closed-loop hardware validation rather than evidence of charger performance or medical-device readiness.

Keywords: Mamdani fuzzy, Lithium 18650 battery, Patient monitor prototype, Solar charging, Duty cycle, Energy performance

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INTRODUCTION

Portable patient monitoring extends physiological observation beyond conventional bedside equipment. Raspberry Pi-based systems have been developed to acquire, process, display, and transmit vital signs such as heart rate and oxygen saturation [1], and low-cost Internet of Things (IoT) monitors have been deployed for remote cardiovascular follow-up in resource-limited settings [2]. Reviews of remote patient monitoring note that continuous operation depends on how the embedded platform manages its energy budget [3]. A single-board computer with an active display draws considerably more power than an ultra-low-power wearable node, so energy continuity becomes a design issue in its own right [3]. A single-board computer with an active display draws considerably more power than an ultra-low-power wearable node, so energy continuity becomes a design issue in its own right.

Energy harvesting has been studied as a way to prolong the operating time of healthcare electronics. A photovoltaic-powered wearable node combined a rechargeable lithium-ion battery and a charging controller

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for long-term monitoring [4], and design studies of wearable photovoltaic harvesting showed that panel orientation strongly affects the energy obtained [5]. Reviews of self-powered wearable and biomedical devices cover mechanical, thermal, radiofrequency, and solar sources [6], [7], [8]. At facility scale, photovoltaic systems have been proposed to secure electricity for health centers with unreliable grids [9], and battery-management strategies specific to healthcare devices have been reported [10]. These studies confirm the relevance of renewable supply for healthcare electronics, but they address either low-power nodes or entire facilities rather than a portable monitor drawing roughly 15-20 W.

The nonlinear current-voltage behaviour of photovoltaic modules and the variability of irradiance complicate charging control. Fuzzy logic controllers (FLCs) have been applied widely to maximum-power-point tracking (MPPT), where they adapt the perturbation step and track changing conditions faster than fixed-step perturb-and-observe or incremental-conductance methods [11], [12], [13]. In battery charging, FLCs have regulated a buck-converter solar charger while respecting battery voltage limits [14], have been combined with PI-regulated charging [15], have been tuned with a genetic algorithm to shorten charging time and reduce temperature rise relative to CC-CV charging [16], and have charged and balanced cells of different chemistries by adjusting only their membership functions [17]. Comparative studies also show that neural predictive and ANFIS-PI controllers can outperform conventional fuzzy and PID control in converter ripple and settling time when a plant model or training data are available [18], [19].

Lithium-ion charging requires an additional safety layer. Constant-current/constant-voltage (CC-CV) charging remains the benchmark because it balances charging time, efficiency, and battery life [20], and recent evaluations and microcontroller platforms continue to refine CC-CV variants [21], [22]. Experimental studies of 18650 cells show that voltage, current, and temperature must be supervised during charging [23]; high discharge currents shorten the time to thermal runaway and reduce usable capacity [24], [25], and the internal cell temperature can differ from what surface sensing suggests [26]. Fuzzy-assisted CC-CV charging has been implemented on an STM32 platform with an explicit termination current [27]. Consequently, an intelligent duty-cycle command should complement, rather than replace, a certified charger, battery-management system, current limitation, thermal monitoring, and overvoltage protection.

The controller in this study is based on fuzzy-set theory [28] and the Mamdani inference framework [29]. Mamdani and Sugeno inference have been compared directly for MPPT in islanded photovoltaic systems [30]. A recent review of photovoltaic fuzzy controllers reports that Mamdani systems remain the most widely adopted because of their simplicity and interpretability in applications with moderate response-time requirements, whereas Takagi-Sugeno and type-2 systems are preferred when faster convergence or explicit uncertainty modelling is needed [31]. Interpretability is also a main reason for using fuzzy rule-based systems in health-related applications, because each decision can be traced to a human-readable rule [32], [33]. A supervisory charging decision updated every few minutes for a medical-device prototype has a loose timing requirement, while the ability to inspect why the charging command changed is valuable. These considerations motivated the choice of Mamdani inference, but the choice still has to be supported by evidence that the fuzzy layer behaves better than simpler decision methods on the same data.

Earlier work by one of the authors implemented fuzzy charging and battery switching with a buck converter and reported an output power of 18.230 W, a 15.82 V peak response, and 1.15% overshoot [34]. That work addressed converter regulation in a photovoltaic battery-charging plant with IoT monitoring. The present study differs in three respects: the data come from a portable prototype intended for a Raspberry Pi-based patient monitor; the fuzzy layer is assessed with explicit decision-quality metrics and against alternative decision methods; and the available solar energy is related to an estimated patient-monitor load and to 18650 battery sizing.

Recent fuzzy photovoltaic charging studies indicate the current state of the art. A fuzzy-assisted perturb-and-observe charge controller with a buck converter reached about 96% efficiency under constant and step irradiance in simulation [35]; fuzzy MPPT combined with a PI voltage loop tuned by the jellyfish optimization algorithm improved power extraction, voltage stability, and settling time [36]; a hybrid fuzzy and perturb-and-observe tracker reduced oscillation around the maximum power point of a lithium battery-storage system [37]; and a fuzzy voltage-perturbation tracker was validated experimentally on a DSP platform [38]. Among these, the experimentally validated tracker and the genetic-algorithm-optimized lithium-ion charger provide the strongest evidence, because they were tested on hardware or compared directly with CC-CV charging. The main limitations of these studies are that most results were obtained in

simulation, that performance was reported with converter-level indices such as efficiency, settling time, and overshoot, and that the behaviour of the fuzzy rule base itself, namely its coverage, smoothness, and sensitivity to measurement error, was not examined. Reviews of fuzzy inference systems likewise compare Mamdani, Sugeno, and Tsukamoto methods mainly by accuracy and note that the choice of membership functions, rules, and defuzzification should be justified for each application [39], while reviews of photovoltaic supply for medical devices concentrate on cell materials, miniaturization, and implantable or wearable loads rather than on the charging decision of a portable monitor [40].

Table 1 summarizes the studies reviewed above. Patient-monitor studies [1], [2], [3] focus on sensing and communication without evaluating the energy supply; photovoltaic healthcare-harvesting studies [4], [5], [6], [7], [8], [40]. address low-power nodes; fuzzy photovoltaic and charging studies [11], [12], [13], [14], [15], [16], [17], [18], [19], [35], [36], [37], [38] report converter or MPPT performance without examining the decision layer itself; and battery studies [20], [21], [22], [23], [24], [25], [26], [27] characterize cells rather than application-level sizing. In short, a few researchers have focused on fuzzy MPPT and charging control at the converter level, and others on the energy supply of low-power medical nodes. There have been limited studies concerned with how an interpretable fuzzy decision layer behaves on field data, that is, whether its rules cover the operating conditions, how smoothly and robustly it responds, and whether its command follows the available power, within the energy context of a specific medical-device load. Therefore, this research intends to evaluate such a decision layer, as an exploratory three-day case study, for the solar charging of a lithium 18650 battery-powered patient monitor prototype. The objectives of this research are (i) to evaluate, in a reproducible and data-driven way, a two-input Mamdani duty-cycle decision layer with a complete rule base, using rule coverage, command variation, agreement with available power, robustness to sensor error, rule-base completeness, and computation time; (ii) to benchmark it on identical inputs against a zero-order Sugeno system, a crisp rule-based system with the same rules, a proportional power map, and a fixed duty cycle; and (iii) to relate the available solar energy to an estimated patient-monitor load and to first-order 18650 battery sizing. The fuzzy output was computed offline from measured data and was not applied as a hardware PWM signal; the results are therefore a baseline for subsequent closed-loop validation.

Table 1. Synthesis of related studies and the position of the present study

Ref.	Application and load	Control or decision method	Evaluation reported	Medical-load energy or battery sizing
[1]	Raspberry Pi portable health monitor	None (sensing and IoT)	Vital-sign acquisition and data transmission	Not evaluated
[2]	Arduino remote cardiovascular monitor	None (sensing and IoT)	Measurement accuracy with seven subjects	Not evaluated
[4]	Wearable sensor node with photovoltaic harvesting	Charging controller	Long-term node operation	Node level, low power
[5]	Wearable photovoltaic harvesting sleeve	None	Effect of panel orientation and curvature	Not evaluated
[10]	Battery system for healthcare devices	Active versus passive cell balancing	Energy saved per cycle	Battery level
[14]	Solar charger for VRLA battery	Dual fuzzy controller, buck converter	MPPT and battery voltage limits	Not evaluated
[15]	Photovoltaic battery charging	Fuzzy MPPT and PI charging control	Accuracy 92-96%, efficiency 76-83%	Not evaluated
[16]	Lithium-ion charging	Genetic-algorithm-optimized fuzzy control versus CC-CV	Charging time and temperature rise	Not evaluated
[19]	Lithium-ion charging with buck converter	PI, PID, FLC, ANN, and ANFIS	Overshoot and settling time	Not evaluated
[31]	Photovoltaic systems (review)	Mamdani, Takagi-Sugeno, and type-2 FLC	Comparative review	Not evaluated
This study	Raspberry Pi patient-monitor prototype, 10 W module, 17.116 W estimated load	Two-input Mamdani duty-cycle decision (offline) versus Sugeno, crisp, proportional, and fixed	Coverage, variation, robustness, completeness, energy, supply ratio	First-order 18650 sizing

METHODS

The research procedure consisted of four stages. First, the open-circuit voltage and short-circuit current of the photovoltaic module were measured on three days, and the current readings were cross-checked with the shunt voltage. Second, the available power, daily energy, panel utilization, and supply ratio were

estimated from the measured data. Third, the measured inputs were processed offline by a Mamdani fuzzy decision layer and by four baseline decision methods, and the outputs were compared with decision-quality indicators. Fourth, the energy results were related to the estimated load of the patient monitor and to first-order 18650 battery sizing. The fuzzy layer follows the standard Mamdani structure with min-max inference and centroid defuzzification [29], [31], [39], and the evaluation indicators were chosen to reflect the interpretability and reliability concerns raised for fuzzy rule-based systems [32], [33]. Compared with the authors' earlier fuzzy charging system [34], the present method differs in three respects: the inputs were limited to two quantities that can be measured without a charger in the loop (V_{oc} and I_{sc}), the rule base was completed to cover all nine input combinations, and the controller was benchmarked against alternative decision methods on identical data instead of being reported alone.

System architecture and design assumptions

The architecture is shown in Figure 1. A 10 W photovoltaic module supplies a voltage/current measurement stage and a DC-DC charging stage. A protected 18650 battery pack, which was not yet installed during this study and is treated here as a design scenario, is intended to supply a 5 V regulator connected to a Raspberry Pi 4, a TFT display, and a MAX30105 optical sensor. The Mamdani fuzzy controller processes the measured open-circuit voltage (V_{oc}) and short-circuit current (I_{sc}) and produces a normalized duty-cycle command. In this study the controller was executed offline in MATLAB on the measured data; its output was not applied to the converter as a real-time PWM signal. The dashed path in Figure 1 therefore represents the intended supervisory command whose decision behaviour is evaluated here, not a validated closed-loop regulator.

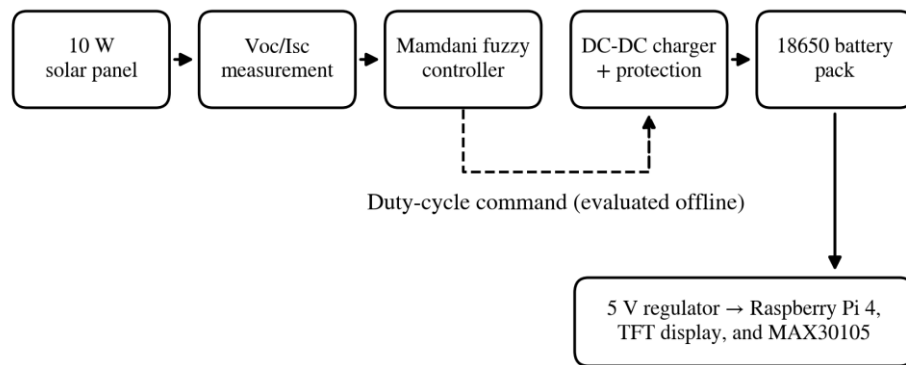


Figure 1. Research flowchart

Before conducting the electrical performance analysis, the physical prototype of the proposed solar charging system was prepared and tested under outdoor conditions. The prototype was designed as a portable enclosure equipped with an integrated photovoltaic panel, charging circuit, measurement module, and battery storage unit. The prototype configuration was intended to support field measurement of voltage, current, and charging performance while maintaining portability for patient monitor power-supply applications. Figure 2a shows the field-testing activity and the physical appearance of the developed prototype.

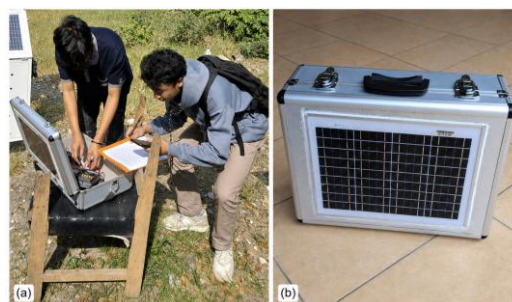


Figure 2. Physical prototype of the proposed portable solar charging system: (a) field testing and measurement setup, and (b) closed portable enclosure with integrated photovoltaic panel

The load values in Table 1 are design assumptions used for energy-performance analysis rather than simultaneous real-time measurements of each component. The Raspberry Pi 4 contribution was estimated from 5.1 V and 3 A, the TFT display from 5 V and 0.35 A, and the MAX30105 from 3.3 V and 0.02 A. The resulting design load was 17.116 W. A nominal DC conversion efficiency of 90% was used in the battery-runtime calculations. Because the load was estimated rather than measured, the supply-ratio analysis compares available power with an estimated load and does not demonstrate continuous real-world operation.

Table 2. System and load specifications used in the analysis

Component / quantity	Parameter	Value
Solar panel	Rated maximum power	10 W
Solar panel	V _{mp} / I _{mp}	18.0 V / 0.56 A
Solar panel	V _{oc} / I _{sc}	21.24 V / 0.57 A
Lithium 18650 cell	Nominal voltage / capacity	3.7 V / 3200 mAh
Lithium 18650 cell	Nominal energy	11.84 Wh
Raspberry Pi 4	Design voltage / current / power	5.1 V / 3.0 A / 15.30 W
TFT display	Design voltage / current / power	5.0 V / 0.35 A / 1.75 W
MAX30105	Design voltage / current / power	3.3 V / 0.02 A / 0.066 W
Total prototype load	Calculated design power	17.116 W
DC conversion stage	Assumed efficiency	90%

Experimental dataset and preprocessing

Field measurements were carried out on three consecutive days, 8, 9, and 10 October 2026, between 07:12 and 16:00 local time, giving 74 records (25, 29, and 20 records per day). The sampling interval was not uniform; it ranged from 4 to 60 min with a median of 27 min, and the actual time stamps were used in all energy calculations. Weather was noted at each record as clear or cloudy; 11 records were taken under cloud. Because the data cover three days in one season, the study is framed as an exploratory baseline case study, and the results do not describe seasonal or long-term performance.

For each record, V_{oc} was measured at the module terminals with the load disconnected. The module was then connected to a 0.1 Ω shunt resistor, which nearly short-circuits the module, and the current was read with a multimeter in series while the voltage across the shunt was read in millivolts. The current therefore corresponds to the short-circuit current I_{sc}. Voltages were read with a Sanwa CD800a (DC voltage accuracy $\pm(0.7\% + 3 \text{ digits})$) and currents with a ZOYI ZT102A (DC current accuracy $\pm(1.2\% + 3 \text{ digits})$). During the first morning, until 12:30 on 8 October, the current was read with the Sanwa CD800a on its 400 mA range ($\pm(2.2\% + 5 \text{ digits})$). The two readings were cross-checked through the effective shunt resistance, V_{shunt}/I, because validating sensor readings against an independent measurement is standard practice in low-cost photovoltaic monitoring [41], [42]. Over 60 consistent records this ratio was 0.1230 Ω , which corresponds to the 0.1 Ω shunt plus lead and contact resistance. Eight readings that saturated at the 400 mA limit were reconstructed as V_{shunt}/0.1230 Ω , and 6 records whose ratio deviated by more than 0.03 Ω , mostly under passing cloud when the two readings were not simultaneous, were retained and flagged. No other smoothing, interpolation, or outlier removal was applied.

Mamdani fuzzy logic controller

The fuzzy controller uses two inputs: V_{oc} and I_{sc}. I_{sc} is approximately proportional to irradiance and therefore indicates the available power, while V_{oc} decreases with cell temperature and very low irradiance. Each input was divided into Low, Medium, and High linguistic sets using triangular and trapezoidal membership functions whose parameters are listed in Table 3 and were set from the module datasheet and the observed operating range. The output universe ranged from 0% to 100% and contained four sets: Stop, Low, Normal, and Fast. The membership functions are presented in Figure 3. The crisp command was assigned to an operating mode using fixed thresholds: Stop below 20%, Low from 20% to below 45%, Normal from 45% to below 75%, and Fast from 75%.

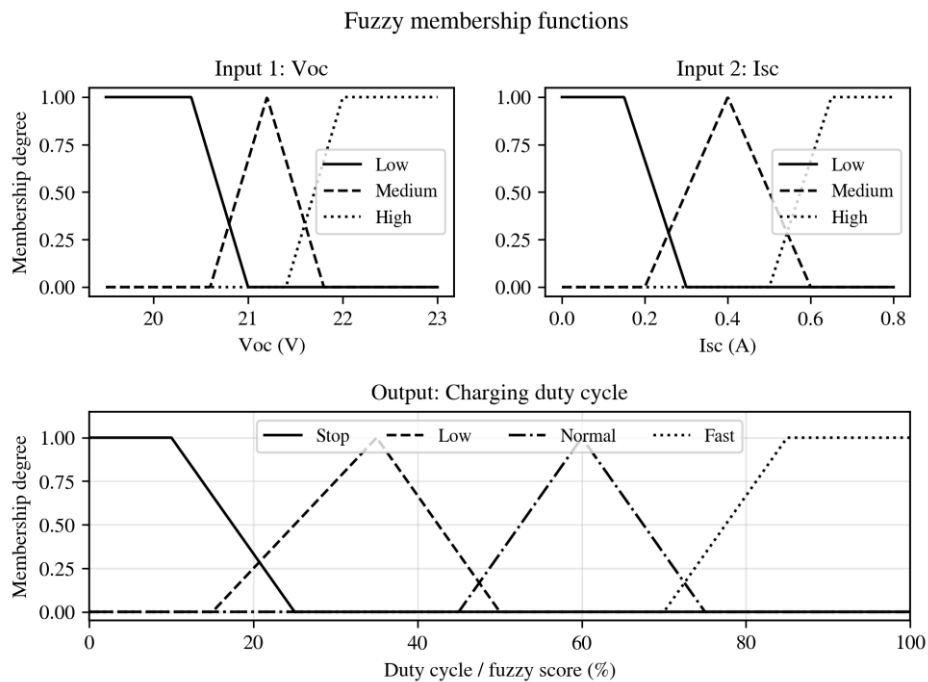


Figure 3. Membership functions of Voc, Isc, and the duty-cycle output

Table 3. Membership-function parameters of the Mamdani controller

Variable	Linguistic set	Shape	Parameters
Voc (V)	Low	Trapezoidal (left shoulder)	$[-, -, 20.4, 21.0]$
	Medium	Triangular	$[20.6, 21.2, 21.8]$
	High	Trapezoidal (right shoulder)	$[21.4, 22.0, -, -]$
Isc (A)	Low	Trapezoidal (left shoulder)	$[-, -, 0.15, 0.30]$
	Medium	Triangular	$[0.20, 0.40, 0.60]$
	High	Trapezoidal (right shoulder)	$[0.50, 0.65, -, -]$
Duty cycle (%)	Stop	Trapezoidal	$[0, 0, 10, 25]$
	Low	Triangular	$[15, 35, 50]$
	Normal	Triangular	$[45, 60, 75]$
	Fast	Trapezoidal	$[70, 85, 100, 100]$

For each rule, antecedent membership values were combined using the minimum operator. Consequent sets were clipped by the corresponding firing strength, aggregated using the maximum operator, and defuzzified using the centroid method:

$$\begin{aligned}
 \alpha_r &= \min(\mu_{_1}, \mu_{_2}, \dots, \mu_{_n}) \\
 \mu_{\text{agg}}(D) &= \max_r [\min(\alpha_r, \mu_r(D))] \\
 D^* &= \text{integral}[D \mu_{\text{agg}}(D) dD] / \text{integral}[\mu_{\text{agg}}(D) dD]
 \end{aligned}$$

The rule base is summarized in Table 4. It contains all nine combinations of the input sets, so at least one rule fires for every input within the operating range. Isc acts as the main indicator: weak irradiance leads to a Low command and strong irradiance to a Fast command. Voc acts as a correction: a Low Voc, which indicates a hot module or very weak light, lowers the command by one level, and Stop is issued only when both inputs are Low.

Table 4. Implemented fuzzy rule base

No.	Antecedent	Consequent
1	Isc Low AND Voc Low	Stop
2	Isc Low AND Voc Medium	Low
3	Isc Low AND Voc High	Low
4	Isc Medium AND Voc Low	Low
5	Isc Medium AND Voc Medium	Normal
6	Isc Medium AND Voc High	Normal
7	Isc High AND Voc Low	Normal
8	Isc High AND Voc Medium	Fast
9	Isc High AND Voc High	Fast

Because the rule base is complete and the neighbouring sets overlap, the command changes gradually between operating modes rather than switching abruptly at fixed thresholds. The fuzzy command is a supervisory set point only; an independent hardware protection circuit must provide a hard cut-off when cell voltage, pack current, or temperature exceeds the allowable limit.

Performance metrics

Estimated power was calculated from Voc and Isc with the datasheet fill factor. Daily energy was obtained by trapezoidal integration over the actual time stamps of each day. Panel utilization expressed the estimated power relative to the 10 W rating, and the supply ratio compared it with the 17.116 W estimated load.

$$P_{est,i} = FF \times Voc_i \times Isc_i, FF = 0.833 \quad (1)$$

$$E_{day} = \sum_i [(P_i + P_{(i-1)})/2] \times (t_i - t_{(i-1)}) \quad (2)$$

$$\text{Panel utilization}_i = 100 P_{est,i} / 10 \text{ W} \quad (3)$$

$$\text{Supply ratio}_i = 100 P_{est,i} / 17.116 \text{ W} \quad (4)$$

A supply ratio of at least 100% would indicate that the estimated available power equals or exceeds the estimated prototype load. Because both quantities are estimates, the supply ratio is a comparison against an estimated load; it does not demonstrate uninterrupted operation, because converter losses, start-up transients, battery state of charge, simultaneous charging and discharging behaviour, and component-level power variation were not measured.

Battery Runtime and Cell-Count Estimation

Battery-only runtime was estimated from the nominal energy of a 3200 mAh, 3.7 V cell and a 90% conversion efficiency. For N identical cells connected in parallel, runtime and current per cell were calculated using:

$$t_N = N E_{cell} \eta / P_{load} \quad (5)$$

$$I_{cell} = P_{load} / (\eta V_{nom} N) \quad (6)$$

The calculation assumes balanced cells with equal capacity and current sharing. It is a first-order sizing estimate and does not include usable depth of discharge, aging, temperature derating, wiring loss, regulator quiescent current, or the manufacturer-specified continuous discharge-current rating.

The daily energy was also expressed as the number of 3200 mAh cells it could recharge and as the corresponding operating time of the monitor, using an assumed charging efficiency of 90%:

$$N_{eq} = E_{day} \eta_{chg} / E_{cell} \quad (7)$$

$$t_{mon} = E_{day} \eta_{chg} \eta / P_{load} \quad (8)$$

Evaluation of the Fuzzy Decision Layer and Baseline Methods

Because the fuzzy output was computed offline, the evaluation focuses on the quality of the decision layer rather than on closed-loop converter dynamics. The same measured inputs (Voc, Isc) were passed to the proposed Mamdani controller and to four baseline decision methods: (i) a zero-order Sugeno system with the same membership functions and rules, in which each output set is replaced by a singleton at a

representative value (Stop 5%, Low 35%, Normal 60%, Fast 92.5%); (ii) a crisp rule-based system that applies the same nine rules with Boolean sets, in which an input belongs to a set when its membership degree is at least 0.5; (iii) a proportional power map, $D = \min(100\%, 100 P_{est}/10 \text{ W})$, representing a non-linguistic controller that follows available power; and (iv) a fixed 60% duty cycle representing an open-loop charger without adaptation. A PI controller was not included because a PI loop needs a converter and battery plant to act on and cannot be evaluated meaningfully from measured data without a validated plant model.

Seven indicators were computed. Rule coverage, Eq. (9), is the percentage of records for which at least one rule fired. Command variation was quantified within each day by the total variation, Eq. (10), the largest single step, and the number of switches between operating modes; where the crisp system produced no decision, the previous command was held. Agreement with the available power was measured by the Spearman rank correlation between the command and P_{est} . The weak-condition response, Eq. (11), is the percentage of records with P_{est} below 2.5 W (25% of the rating) that received a Low or Stop command. Robustness was assessed by Monte Carlo perturbation, Eq. (12): each record was perturbed 500 times with multiplicative Gaussian errors of 1% (one standard deviation) on V_{oc} and 2% on I_{sc} , and the root-mean-square deviation from the nominal command and the percentage of mode changes were recorded. These error levels were assumed; they are of the same order as the manufacturer-stated accuracies of the meters but were not derived from a calibration. Rule-base completeness was evaluated over 1,476 input combinations spanning V_{oc} 19.5-23.0 V and I_{sc} 0-0.8 A, and computation time per inference was measured.

$$\text{Coverage} = 100 N_{\text{fired}} / N \quad (9)$$

$$\text{TV} = \sum_i |D_i - D_{(i-1)}| \quad (10)$$

$$H = 100 |\{i: P_i < 2.5 \text{ W}, D_i < 45\% \}| / |\{i: P_i < 2.5 \text{ W}\}| \quad (11)$$

$$\text{RMSE} = \sqrt{(1/MN) \sum_k \sum_i (D_{k,i} - D_i)^2} \quad (12)$$

The analysis was implemented in MATLAB Online (MathWorks, accessed October 2026) without toolbox functions and was verified with an independent Python 3.11 implementation that uses the same membership functions, rules, operators, and defuzzification. The script and dataset are available from the corresponding author on reasonable request.

RESULT AND DISCUSSION

Open-Circuit Voltage and Short-Circuit Current

Figure 4 presents the measured profiles. V_{oc} remained within a narrow band, from 19.78 V to 22.73 V, with a mean of 21.26 V; it was slightly lower around midday, as expected from the temperature dependence of the cell voltage. The lowest value, 19.78 V at 12:00 on 10 October, coincided with a cloudy record.

I_{sc} followed the daily irradiance pattern. It ranged from 0.061 A to 0.725 A, with a mean of 0.375 A, and exceeded the datasheet value of 0.57 A in 15 records between about 10:00 and 12:30. The corresponding irradiance proxy reached about 1272 W/m². Values above the standard test condition are plausible in clear tropical midday conditions and under cloud-edge enhancement, but they also indicate that the module was operated outside its rated conditions during part of the day. Sharp drops of I_{sc} coincided with cloudy records.

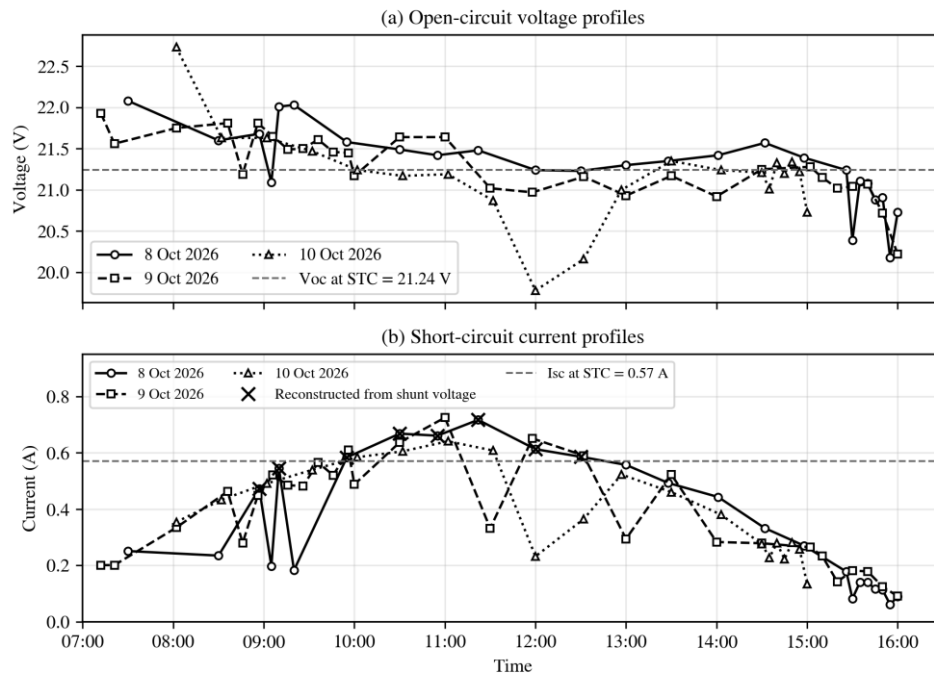


Figure 4. Measured profiles on the three days: (a) open-circuit voltage and (b) short-circuit current

Estimated available power and panel utilization

The estimated available power and the corresponding utilization of the 10 W rating are shown in Figure 5. Estimated power ranged from 1.03 W to 13.06 W, with daily means of 6.23 W, 6.83 W, and 6.98 W. Mean utilization was 66.7%. In 16 midday records the estimate exceeded the 10 W rating, which follows from I_{sc} values above the standard test condition and from the use of the 25 °C fill factor; these values should be read as upper bounds.

The estimated patient-monitor load was 17.116 W. The estimated power never reached this level; the supply ratio peaked at 76.3% and averaged 39.0%. Thus, under the conditions of the test days, the 10 W module can only supplement the battery and cannot supply the prototype load on its own, which makes the battery pack the primary energy source of the monitor.

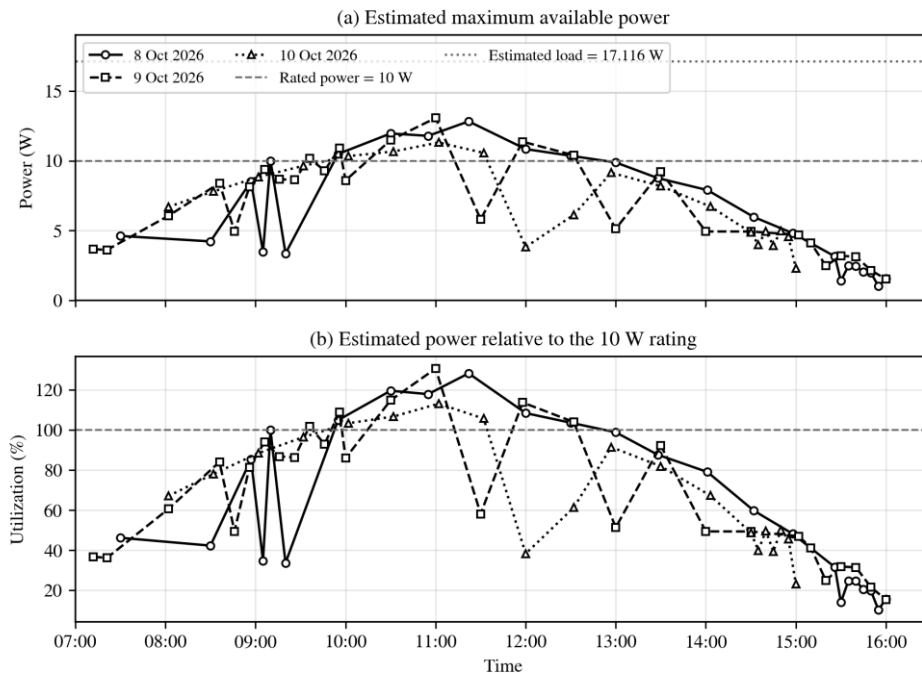


Figure 5. Estimated power: (a) maximum available power with the rated and estimated-load references and (b) utilization relative to the 10 W rating

Measurement consistency

Figure 6 compares the meter current with the shunt voltage for all records. Consistent records lie on a straight line through the origin with a slope of 0.1230Ω , confirming that the two independent readings agree. The eight readings recorded at the 400 mA limit lie above this line, which shows that the meter saturated while the shunt voltage continued to rise; these values were reconstructed from the shunt voltage. The 6 flagged records occurred mainly under passing cloud, when the current and the shunt voltage were read a few seconds apart.

These checks show that the I_{sc} values used in the analysis are internally consistent within the stated tolerance. They do not replace a calibration against a reference instrument, and future measurements should log voltage and current simultaneously with a data logger.

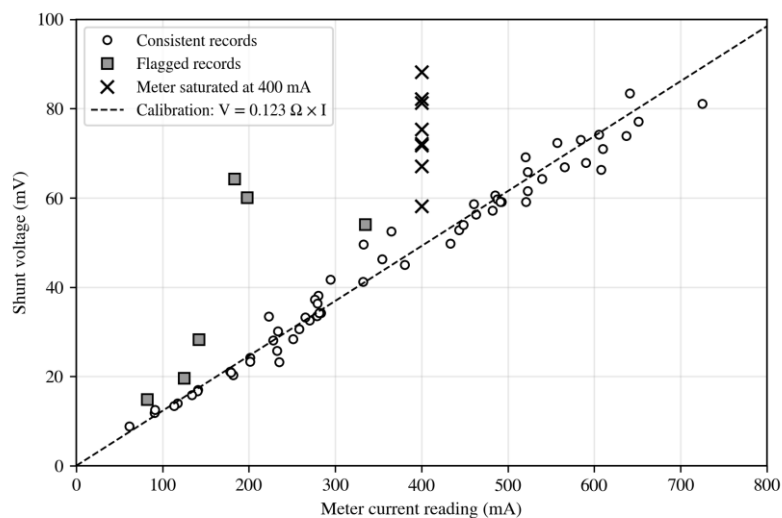


Figure 6. Cross-check between the meter current and the shunt voltage

Table 5. Summary of the measured and derived results for each day

Parameter	8 Oct 2026	9 Oct 2026	10 Oct 2026	All days
Records	25	29	20	74
Time window	07:30–16:00	07:12–16:00	08:02–15:00	-
Voc range (V)	20.18–22.08	20.22–21.93	19.78–22.73	19.78–22.73
Voc mean (V)	21.30	21.30	21.18	21.26
Isc range (A)	0.061–0.717	0.091–0.725	0.134–0.641	0.061–0.725
Isc mean (A)	0.349	0.384	0.395	0.375
Estimated power range (W)	1.03–12.82	1.53–13.06	2.31–11.31	1.03–13.06
Estimated power mean (W)	6.23	6.83	6.98	6.67
Estimated energy (Wh)	66.5	64.8	56.5	62.6 (mean)
Equivalent 18650 cells	5.05	4.93	4.29	4.76 (mean)
Equivalent monitor operation (h)	3.15	3.07	2.67	2.96 (mean)
Records with $P_{est} \geq 17.116$ W	0	0	0	0

Fuzzy controller response

The fuzzy-controller response is shown in Figure 7. The duty-cycle command ranged from 9.0% to 88.4%, with a mean of 54.7% and a median of 60.0%. Of the 74 records, 32 were classified as Normal, 18 as Low, 17 as Fast, and 7 Stop.

The command rose from Low or Normal in the early morning to Fast between about 10:00 and 12:30, when Isc was High, and fell to Low and Stop after 15:00. Cloudy records produced short dips, for example to 18% at 12:00 on 10 October. The 60% plateaus correspond to records in which the Medium-Medium rule dominated. The response therefore follows the available power in an interpretable way, but real-time PWM validation is still required before claiming optimal control.

Rule-activation statistics explain this behaviour. Rule 5 (Isc Medium and Voc Medium, Normal) fired most often (39 of 74 records), whereas Rule 7 (Isc High and Voc Low, Normal) fired in only 2 records with a maximum firing strength of 0.22. The strongest rule in each record had a mean firing strength of 0.55, and in 37 of 74 records no rule reached a firing strength of 0.5. Many commands were therefore produced by partial activation of overlapping rules, which is the situation in which fuzzy inference differs most from crisp rule evaluation.

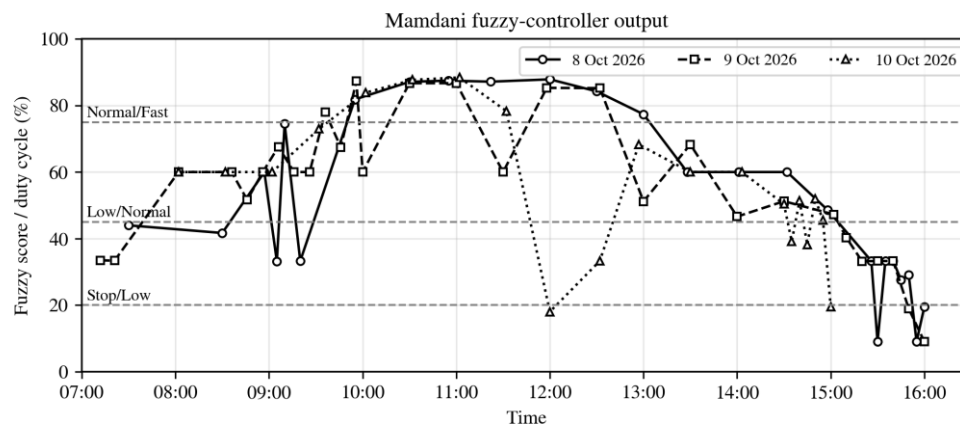


Figure 7. Mamdani fuzzy-controller output on the three measurement days

Benchmark against alternative decision methods

Table 6 and Figure 8 compare the decision methods on identical inputs. The Mamdani controller produced a decision for every record. When the same rules were evaluated crisply, no rule was satisfied in 37 of 74 records (50.0%), which equals the number of records in which no fuzzy rule reached a firing strength of 0.5, and under simulated sensor error the crisp system produced no decision in 47.7% of the perturbed cases. Over the operating envelope, at least one Mamdani rule fired for 100.0% of the input combinations, compared with 71.5% for the crisp system. All adaptive methods commanded Low or Stop in all 11 weak-condition records, whereas the fixed duty cycle did not.

Between the two fuzzy variants, the Mamdani controller produced a smoother command sequence than the zero-order Sugeno system: the total variation was 908.9 versus 1000.8 percentage points and the largest single step was 60.3 versus 69.0 percentage points. Its root-mean-square deviation under perturbation was also lower (4.58 versus 5.47 percentage points), while the rate of mode changes was similar (8.6% versus 8.0%) and both commands correlated strongly with the estimated power ($\rho = 0.971$ and 0.976). The Sugeno system was faster, about 41 μs against 63 μs per inference, because it avoids discretizing and integrating the output universe. At a decision interval of minutes, both costs are negligible, so the smoother and linguistically interpretable Mamdani output is the more suitable choice for this supervisory application, consistent with the trade-off described for photovoltaic fuzzy controllers [31].

The baselines clarify what the fuzzy layer contributes. The proportional power map correlates almost perfectly with P_{est} ($\rho = 0.995$) because it is a scaled copy of that estimate, and it is the least sensitive to sensor error (1.18 percentage points). However, it saturated at 100% whenever P_{est} exceeded 10 W, produced the largest total variation (1124.0 percentage points), and cannot express qualitative knowledge such as lowering the command when Voc indicates a hot module. The fixed duty cycle is perfectly stable but does not respond to any condition. Among the methods tested, the Mamdani controller combined complete coverage, close agreement with the available power, lower command variation than the Sugeno and proportional methods, and moderate sensitivity to sensor error.

Table 6. Benchmark of decision methods on identical inputs ($n = 74$)

Method	Coverage (%)	Total variation (pp)	Largest step (pp)	Mode switches	Spearman ρ	Noise RMSE (pp)	Mode change under noise (%)	Time (μs)
Mamdani FLC (proposed)	100.0	908.9	60.3	30	0.971	4.58	8.6	63
Zero-order Sugeno FLC	100.0	1000.8	69.0	31	0.976	5.47	8.0	41
Crisp rules (same rule base)	50.0	555.0	57.5	16	0.676	9.27	6.9	36
Proportional power map	100.0	1124.0	66.4	32	0.995	1.18	1.3	2.2
Fixed duty cycle (60%)	100.0	0.0	0.0	0	-	0.00	0.0	1.1

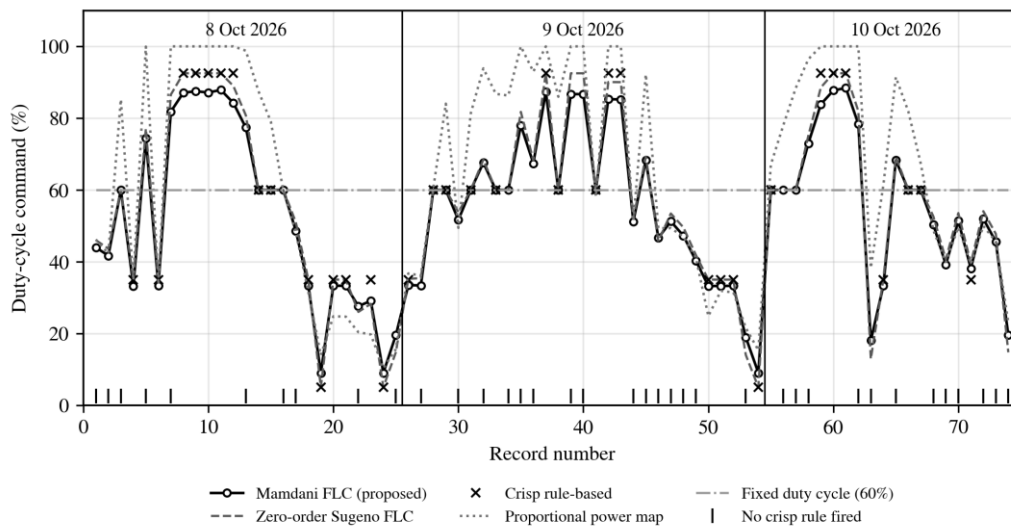


Figure 8. Duty-cycle commands of the Mamdani controller and the baseline decision methods computed from identical inputs

Estimated energy and load-equivalent supply

The estimated cumulative energy and supply ratio are presented in Figure 9. The estimated daily energy was 66.5 Wh, 64.8 Wh, and 56.5 Wh on the three days, with a mean of 62.6 Wh; the third day was shorter because measurements ended at 15:00. The cumulative curve crossed the nominal energy of one 11.84 Wh

cell between 09:08 and 09:38. With a charging efficiency of 90%, the mean daily energy corresponds to about 4.8 cells or about 3.0 h of monitor operation.

The cumulative value must not be interpreted as energy stored in the battery. It is an upper-bound estimate of the energy available at the maximum power point and does not include converter losses, maximum-power-point tracking error, battery acceptance, simultaneous load consumption, state-of-charge limits, or charging termination. The actual stored energy would therefore be lower and must be established by measuring battery-side voltage, current, state of charge, and temperature.

The supply ratio ranged from 6.0% to 76.3%, with a mean of 39.0%, and the 100% threshold was not reached in any record. The battery pack is therefore required not only to bridge cloudy intervals but to carry the monitor load throughout, with the module acting as a recharging source. Because the load is an estimate, these figures compare available power with an assumed demand and do not demonstrate continuous real-world operation of the monitor.

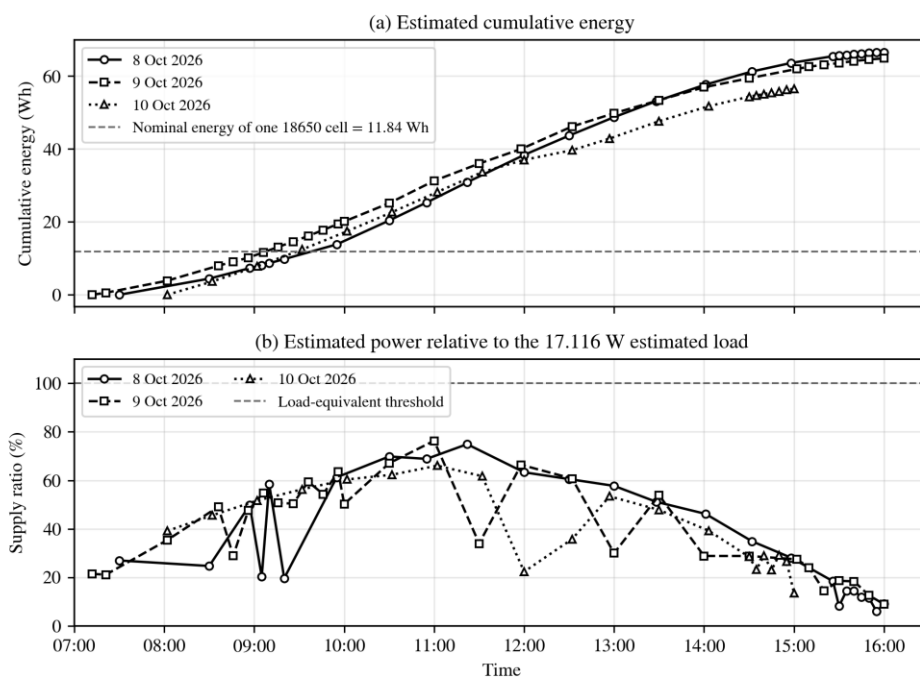


Figure 9. Energy and load adequacy: (a) estimated cumulative energy and (b) supply ratio relative to the 17.116 W estimated load

Effect of parallel cell count

Figure 10 presents the first-order battery-sizing results. A single 3200 mAh cell provides an estimated 37.4 min of battery-only operation at the 17.116 W design load and 90% conversion efficiency. The corresponding estimated cell current is 5.14 A, approximately 1.61 C for a 3.2 Ah cell. Whether this condition is acceptable depends on the continuous discharge-current rating, thermal behavior, cell condition, protection circuit, and voltage sag of the selected product; at this rate, rate-dependent capacity loss [25] and heating [24] would shorten the runtime further. These values are first-order estimates. No battery pack was installed in the prototype during this study; the battery results are design scenarios based on the nominal values of a 3200 mAh, 3.7 V 18650 cell, so temperature behaviour, state of charge, and converter efficiency were not measured and no safety or deployment claim is made.

Increasing the number of parallel cells increases nominal energy and runtime linearly while decreasing current per cell. Eight cells provide a nominal 94.72 Wh and an estimated runtime of 298.8 min, while reducing the calculated current to 0.64 A per cell. Parallel operation must use matched cells, appropriate fusing, balanced current paths, and a battery-management system designed for the selected configuration.

Under the measured conditions, recharging an eight-cell pack (94.72 Wh) from the 10 W module would require about 1.7 days of the mean estimated daily energy.

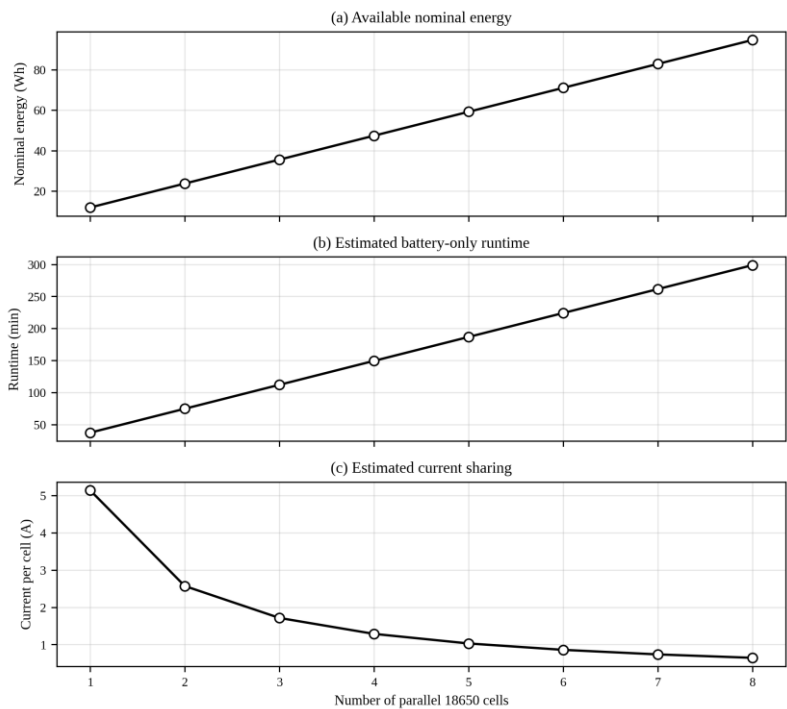


Figure 10. Effect of parallel 18650 cell count on nominal energy, estimated runtime, and current sharing

Table 7. Selected lithium 18650 battery-sizing scenarios

Parallel cells	Nominal energy (Wh)	Runtime (min)	Current per cell (A)	Approx. C-rate
1	11.84	37.4	5.14	1.61 C
2	23.68	74.7	2.57	0.80 C
4	47.36	149.4	1.28	0.40 C
8	94.72	298.8	0.64	0.20 C

Battery requirement for target runtime

The target-runtime analysis in Figure 11 predicts two parallel cells for approximately one hour, four cells for two hours, seven cells for four hours, thirteen cells for eight hours, twenty cells for twelve hours, and thirty-nine cells for twenty-four hours. These are theoretical minimums based on nominal energy and 90% conversion efficiency. A practical design requires additional margin for usable depth of discharge, capacity tolerance, aging, temperature, regulator losses, peak current, and reserve time.

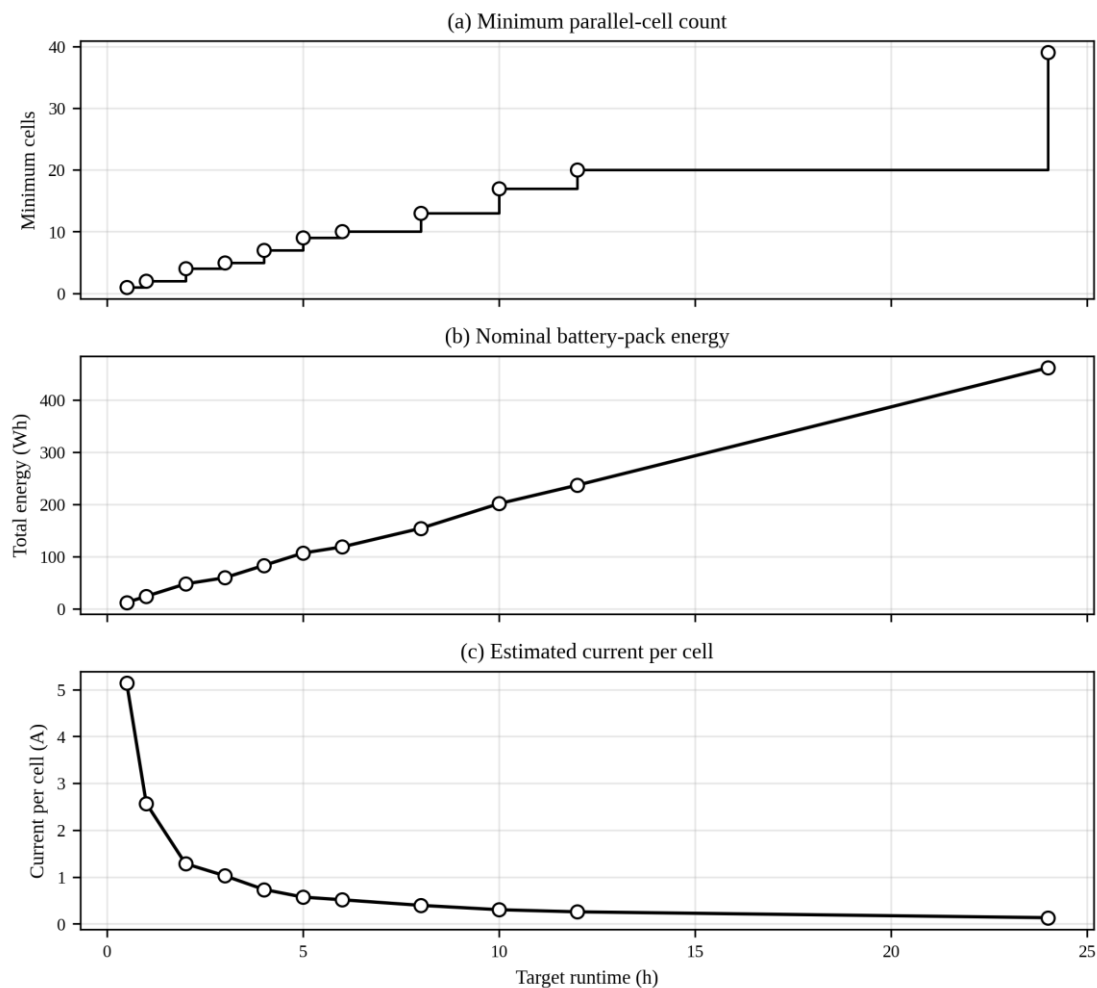


Figure 11. Battery-sizing estimates for target runtime: minimum cell count, nominal pack energy, and current per cell

Table 1 positions this study relative to the literature. Patient-monitor studies have concentrated on sensing, processing, and communication [1], [2], [3], whereas photovoltaic healthcare-harvesting studies target low-power wearable nodes [4], [5], [6], [7], [8]. A direct numerical comparison with those systems is not meaningful because their loads are far smaller than the 17.116 W estimated here; the comparison is one of scope, since none of them relates available photovoltaic energy to the load of a single-board-computer monitor. Fuzzy photovoltaic-charging studies differ in topology, battery chemistry, and evaluation method. Lopez Seguel and Seleme regulated a buck charger for VRLA batteries with a dual fuzzy controller [14], Khan et al. combined fuzzy MPPT with PI-regulated charging and reported 76-83% system efficiency [15], and Karolyi et al. optimized a fuzzy lithium-ion charger with a genetic algorithm and compared it with CC-CV charging [16]. More recent fuzzy charge controllers reported about 96% efficiency in simulation [35] and improved tracking on an experimental DSP platform [38]. Those studies evaluated closed-loop converter or battery behaviour, which the present data cannot do; conversely, they did not report rule coverage, robustness to sensor error, or a crisp-rule baseline on field data, which is what the present benchmark adds. Studies that compared fuzzy control with neural predictive or ANFIS-PI controllers reported better ripple and settling time for the learning-based methods [18], [19]; such controllers require a plant model or training data that a three-day dataset cannot provide, which is one reason an interpretable rule-based layer was chosen.

The authors' earlier fuzzy buck-converter work reported an output power of 18.230 W [34], whereas the mean estimated available power of the present 10 W module was 6.67 W. The systems differ in module rating, battery, load, irradiance, and test conditions, so this is not a performance comparison. The present study differs from that work in its data source, in the explicit evaluation of the decision layer against

alternative methods, and in relating the available energy to an estimated patient-monitor load and to 18650 battery sizing. At facility scale, photovoltaic supply for health centers has been motivated by unreliable grids [9]; the present results concern the much smaller problem of a single portable device, in which a 10 W module can recharge roughly five cells per clear day but cannot carry the monitor load directly.

The study has several limitations. It is an exploratory case study based on three days with irregular sampling intervals, and its results should not be generalized to seasonal or long-term performance. Only Voc and Isc were measured; the module was not operated at its maximum power point, and the available power was estimated with the datasheet fill factor, which overestimates power at high cell temperature. Current readings came from two meters, eight saturated readings were reconstructed from the shunt voltage, and the sensor-error model used in the robustness analysis was assumed rather than derived from calibration. The fuzzy output was computed offline; it was not applied to a converter as a PWM command, so closed-loop regulation was not demonstrated, the benchmark compares decision behaviour rather than harvested energy, and a PI controller could not be included without a plant model. Irradiance, panel temperature, converter efficiency, battery voltage, state of charge, cell temperature, and actual patient-monitor power consumption were not recorded. The battery calculations used nominal values without electrochemical or thermal models. Synchronous measurement of the module operating point, battery-side voltage, current, state of charge, temperature, irradiance, and the actual PWM signal is a prerequisite for any claim regarding charger performance, battery safety, or clinical readiness.

CONCLUSION

This exploratory study evaluated, from three days of field measurements on a 10 W photovoltaic module, a two-input Mamdani fuzzy duty-cycle decision layer for the solar charging of a lithium 18650 battery-powered patient monitor prototype. On identical inputs, the Mamdani layer produced a decision for every record and over the whole operating envelope, whereas the same rules applied crisply left half of the records undecided; its command followed the estimated available power closely; and it was smoother and less sensitive to sensor error than a zero-order Sugeno system, at a computational cost that is negligible for a supervisory decision updated every few minutes. These results support Mamdani inference as an interpretable supervisory layer for this application, but they characterize decision behaviour rather than closed-loop control. The energy evaluation showed that the module can deliver an estimated 56-67 Wh per clear day, enough to recharge about five 18650 cells, but never reached the estimated monitor load, so the battery pack must carry the load and a single 3200 mAh cell would provide well under one hour of operation. Future work should implement the controller as a real-time PWM command, compare it with PI and MPPT-based charging in closed loop, measure the module operating point, and record irradiance, converter efficiency, battery-side voltage, current, state of charge, temperature, and the PWM signal synchronously, together with a certified CC-CV charger and battery-management system.

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