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Enhancing Measuring Reliability: Calibration and Validation of IoT-based DC Power Logger

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ABSTRACT

A power logger is a device that has an electrical energy consumption monitoring function with an embedded data storage system to understand energy consumption patterns and improve the efficiency of energy usage. However, building meters without calibration causes inaccurate measurements and information. Therefore, the study proposed a simple method to enhance any system's measurement quality via an Internet of Things (IoT)-based DC Power Logger case. The IoT system built in the Blynk application enables the power logger to operate remotely and was integrated into a Google spreadsheet page to facilitate real-time data storage with an INA219 sensor as the measurement module. The calibration process of the power logger was conducted by comparing the measurement results obtained from the power logger with measurements obtained from a Sanwa multimeter with the best accuracy of ±7%. As a result, the calibration process ensures enhanced accuracy achieved following the calibration process was 99.86% for voltage measurement, and 98.37% for current measurement voltage drop-based.

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1. Introduction

The world's energy consumption is increasing significantly as a result of the increase in user demand for the support of life on earth [1]. The large amount of energy consumption requires a system that can monitor and control the flow of energy to maintain efficient use [2]. A power logger is a device that has an electrical energy consumption monitoring function with an embedded data storage system.
With considerable potential for use and relatively low development cost, an electrical energy monitoring system using IoT-based Arduino devices can be used to control and monitor energy use in the switchgear industry [3]. IoT-based power loggers can be used to collect and store data locally to observe energy patterns daily and determine the efficiency of energy consumption [4].
Implementing the INA219 sensor for current and voltage monitoring has become a popular choice for energy management devices, particularly in off-grid photovoltaic systems [5]. The sensor is utilized to monitor the battery charging and discharging cycles to gain some insight into energy production and consumption [6].

Besides industrial and domestic use, scientists, especially in physics research, often measure electrical quantities with large amounts of data, and the measurement results are not always whole numbers. Physicists measure electrical quantities using instruments such as voltmeters, ammeters, or instruments capable of measuring multiple quantities (multimeters). The measurement data recording may be done using written observation notes or electronic media. Thus, multimeters with data recording systems (data loggers) will make collecting data for experiments and scientific research easier. Zeleke [7] compared the effectiveness, accuracy, and quality of data generated by paper-based and automated methods. He concluded that automated (digitized) methods are more practical and can create higher-quality data than paper-based methods.

However, this facility impacts the high price of multimeters on the market. For more efficient data collection [8], and to prevent potential risk factors, IoT-based power loggers can be a solution. Adding IoT systems to power loggers can improve the performance of logging systems to make tools more mobile [9].

In summary, we aim to develop a simple and affordable system that uses a NodeMCU processor [10], Google spreadsheet as a data storage medium, and Blynk app as a remote control system. The combination of these features makes the IoT-based power logger more effective than a conventional power logger that does not take advantage of IoT technology [11]. A multimeter from Sanwa® is used to calibrate the system to ensure that it measures correctly and accurately.

2. Method

2.1. IoT-based DC Power Logger Design

The Internet of Things (IoT)-based direct current (DC) power logger is a measurement instrument that can store measurement data using the IoT system for remote operation. The DC power logger module was assembled with a NodeMCU as the central processing unit, an OLED screen as the display medium for measurement results, and an INA219 sensor as the measurement module. The INA219 provides a measurement range extending from 0 volts to 26 volts and an accuracy of 0.05% [12].

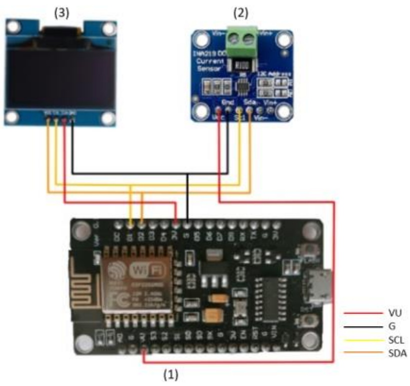

Fig. 1. Design of DC power logger circuit

Fig. 1 shows the basic circuit components of the DC power logger, with the applied microcontroller being the NodeMCU (1), the INA219 sensor (2) as the measurement input, and the OLED display (3) as the output medium. The DC power logger module was constructed on a printed circuit board (PCB) and was connected with two probe wires as a data retrieval module. The software system of the DC power logger, embedded in the Node MCU module, was compiled in the C++ programming language employing the ArduinoIDE application. The operational design of the DC power logger was intended to measure direct current (DC) in electrical circuits through the INA219 sensor. Data from the measurement was displayed on an OLED screen, and the logger interface was connected through the Blynk application to display and calibrate measurements. The DC power logger was also integrated with a data storage system (Google spreadsheet platform). As depicted in Fig. 2, the DC Power Logger performance flowchart commences upon initialisation, initiated by the activation of the DC Power Logger. Subsequently, the system connects with the WiFi network and the Blynk application system. The Blynk system is responsible for the visual representation and calibration of the measured data. Thereafter, the measurement results from the DC Power Logger are stored in a Google worksheet.

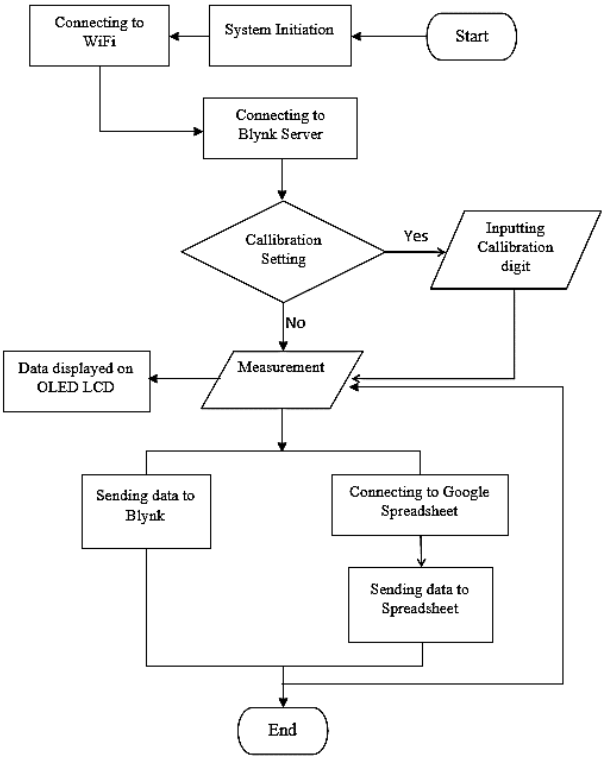

Fig. 2. Software design workflow

As a device that measures voltage, current, and power, it is imperative to calibrate this instrument to ensure its proper functioning and accuracy[13]. To assess the accuracy of the DC power logger, it is essential to compare the measurement results with those obtained from a standard meter like a multimeter. The comparison of the measurement results from the DC power logger and Sanwa® multimeter was used to measure the accuracy of the DC power logger and determine the measurement calibration variables. The multimeter from Sanwa is calibrated and measure with the best accuracy at ±7%. Multimeters from Sanwa are calibrated using precision instruments as part of their quality control process. The calibration is traceable to authorized institutions like AIST, JEMIC, CRL, and NIST, ensuring recognized standards are met.

2.1. Data Analysis Method

The data analysis process on the measurement results includes measurement of standard error, uncertainty, and accuracy. The uncertainty (ΔX) was determined by calculating the standard error [14] using Equation (1).

$$\Delta X = \frac{1}{\sqrt{n}} \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{1}$$

The standard error is calculated as follows: n represents the total number of data points in the sample, x_i represents the data sample value for i, and $\bar{x}$ represents the average value. $\frac{1}{\sqrt{n}}$ reduces the standar deviation by square root of the sample size, reflecting that larger sample provide more precise estimates

$\sum_{i=1}^{n}(x_i - \bar{x})^2$ is the sume of the squared differences between each data point and sample mean, measuring total variability in the data, and $n-1$ is the degree of freedom. The uncertainty (U) of the DC power logger is also affected by the accuracy of the INA219 sensor (ε_{sys}) of ±0.5% for each parameter [12], which is then applied to equation (2) for the total uncertainty [15].

$$U = \Delta X + \varepsilon_{sys} \tag{2}$$

The calculation of the accuracy of the measurement results is performed using the Equation (3), where $\bar{x}_i$ represents the average measurement result for i, and $\bar{x}_{ref}$ refers to the average measurement result of the instrument used as a reference.

$$Accuracy = \left(1 - \frac{\left|\bar{x}_i - \bar{x}_{ref}\right|}{\bar{x}_{ref}}\right)100\% \tag{3}$$

2.2. Calibration Method

Calibration was conducted by comparing the output of the instrument or sensor being tested with the output of a known-accuracy instrument where the same input (measured quantity) applied to both instruments [16]. The DC power logger calibration process comprises two stages: voltage calibration and current calibration. Data collection in the voltage calibration process involves measuring the voltage on the three measuring instruments utilizing a 4.7-Kohm and an indicator of a three-ohm LED lamp as load, with voltage supply ranging from 1V to 15V. Meanwhile, the current calibration entails collecting voltage drop data (shunt voltage) to adjust the current measurement process by an INA219 sensor. The current calibration data were collected using a 0.01ohm shunt resistor and a 12V LED lamp load, with supply voltages ranging from 7.7V to 9.1V. Current (I) measurements on the INA219 sensor were carried out following the Equation (4), Vshunt is defined as the shunt voltage value of the measurement results, and Rshunt is defined as the resistance value of the embedded resistor in the INA219 sensor module.

$$I = \frac{V_{shunt}}{R_{shunt}} \tag{4}$$

The voltage and current measurements were taken fifteen times at each voltage increment, with a ten-second interval between each measurement. The readings from the devices were then will be compared on a linear graph, yielding a linear equation for the calibration process . The linear equation then used as the calibration constant of the DC power logger registered by the Blynk application. The measurement data were displayed on the OLED screen, the Blynk application, and stored in the Google spreadsheet in real time. Fig. 3, shows the measurement reading and calibration interface of the Blynk application. From the Blynk application the measured raw data (V1, V2, V3, and V4) can be observed, the Data Logger button is connecting the Blynk application to data logging in google spreadsheet, and right below the button is the panel for applying the equation for calibration, then showing the calibrated measurement (V7, V8, V9).

Fig. 3. Example of measurement readout inside the Blynk system interface

2.3. Validation Method

The study used experimental validation, defined as generating scientific findings using computational methods on data from an experimental process [17]. The necessity of experimental validation in ensuring calibration model accuracy has been previously substantiated [18]. Thus, in this study, experimental validation was used to test the accuracy of the calibrated DC power logger. The validation process compared the calibrated DC power logger measurement results with those of a reference instrument to determine its advisability.

The experimental validation of the voltage measurement was conducted by measuring the voltage input by an adjustable power supply from 1 volt to 32 volts. The voltage measurement in this process utilized a 5.6-kohm resistor and a 3-volt LED lamp as the load, whereas the INA219 sensor was configured in a series with the voltage input and the load.

The experimental validation process on current measurement was done by measuring direct current utilizing a 3-volt LED lamp, 365-ohm resistor, and a 100-ohm multi-turn potentiometer with a voltage supply of 3 volts. The multi-turn potentiometer was set in 10 resistance increment stages. Each increment adds 10 ohms of resistance from the potentiometer, from 0 to 100 ohms. Each measurement in each stage of increment was repeated fifteen times with ten-second intervals for each data retrieved.

3. Results and Discussion

3.1. Calibration Result

The calibration process was executed through experimentation with the DC power logger to ascertain the voltage and current values. The voltage value was determined based on the bus voltage value, and the current value was derived from its shunt voltage value, following the INA219 sensor function.

3.1.1. Voltage Calibration Result

A comparative analysis of the (bus) voltage measurement results obtained from the DC power logger and the multimeter reveals a linear graph. Fig. 4 is illustrating the correlation between the two measurement devices, showing the regression equation $y_{\square} = 0.9975x + 0.0042$, , then employed to calibrate the DC power logger. This calibration equation was subsequently utilized in a new set of measurements. The graph shows that the results' coefficient of determination (R^2) is 1, indicating that the data comparison between the two measurements is 1:1, and the measurements made can be said to be correct and have similar values as the reference meter. Moreover, after calibration, the y-intercept value (3E-07) getting narrow to null indicates that the slope closes to 45°, as seen in the linear equation $y_o = 1x - 3E\text{-}07$.

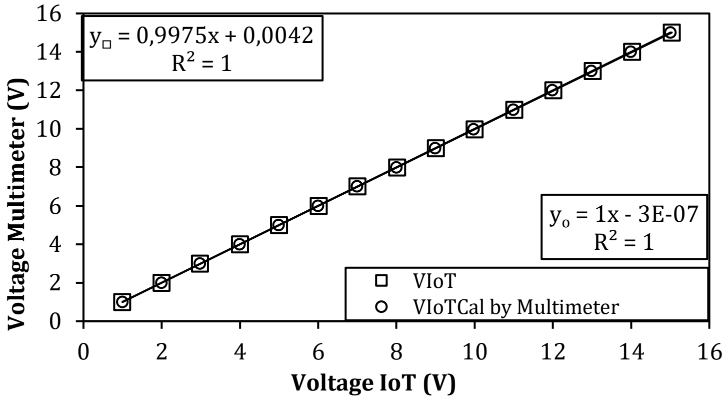

Fig. 4. Voltage calibration compared to a multimeter

The calibration procedure was implemented to enhance the accuracy of the IoT-based DC power logger. Prior to calibration, the accuracy was 99.73%, and after the calibration yielded a higher accuracy of 99.86% while the uncertainty remained the same. In other words, the calibration process resulted in an increase of 0.13% in accuracy, as presented in Table 1. **Table 1.** Voltage measurement calibrated by multimeter

No	Voltage (V)			Accuracy (%)		Total Uncertainty (V)	
	Multimeter	IoT		IoT		IoT	
		Before	After	Before	After	Before	After
1	0.999	0.995	0.997	99.661	99.833	0.008	0.008
2	1.990	2.001	2.000	99.446	99.486	0.013	0.013
3	3.000	2.985	2.981	99.491	99.383	0.017	0.017
4	3.996	4.001	3.996	99.859	99.995	0.021	0.021
5	4.987	5.005	4.996	99.649	99.815	0.026	0.027
6	5.999	6.013	6.003	99.766	99.946	0.031	0.032
7	7.001	7.011	6.997	99.858	99.952	0.036	0.036
8	7.991	8.022	8.006	99.608	99.807	0.041	0.041
9	8.998	9.011	8.993	99.850	99.946	0.046	0.046
10	9.981	10.000	9.979	99.807	99.985	0.050	0.050
11	10.984	11.015	10.992	99.711	99.923	0.056	0.057
12	12.000	12.016	11.990	99.867	99.918	0.061	0.062
13	12.998	13.020	12.992	99.830	99.952	0.065	0.065
14	14.000	14.028	13.997	99.800	99.980	0.071	0.072
15	15.000	15.040	15.007	99.733	99.956	0.075	0.076
Mean				99.729	99.858	0.041	0.041

Even a modest improvement in accuracy from calibration process is meaningful, because calibration process underpins the reliability, safety, compliance, and quality of measurement [19]. It's also implied from Table 1, that the uncertainty remains the same, because it includes other sources of variability that calibration alone cannot eliminate [20].

3.1.2. Current Calibration Result

The current calibration of the built DC power logger utilizing the multimeter involves the measurement of shunt voltage, leveraging the INA219 sensor's functionalities. The voltage drop of the embedded shunt resistor represented the shunt voltage. As demonstrated in Fig. 5, the difference between the measurements obtained by the IoT-based DC power logger is tenfold that of the multimeter, which deviates too much. Therefore, the full-scale calibration is indeed should be done to get the correct measurement of shunt voltage. The full-scale calibration was executed by employing the equation ($y_{\square}$ = 0.9975x + 0.0042) from the bus voltage calibration process, as depicted in Fig. 4, as the initial calibration step. The shunt voltage value obtained from the first calibration step was subsequently used to replace the x variable in the linear equation presented in Fig. 5, thus completing the full-scale calibration process and measuring any current.

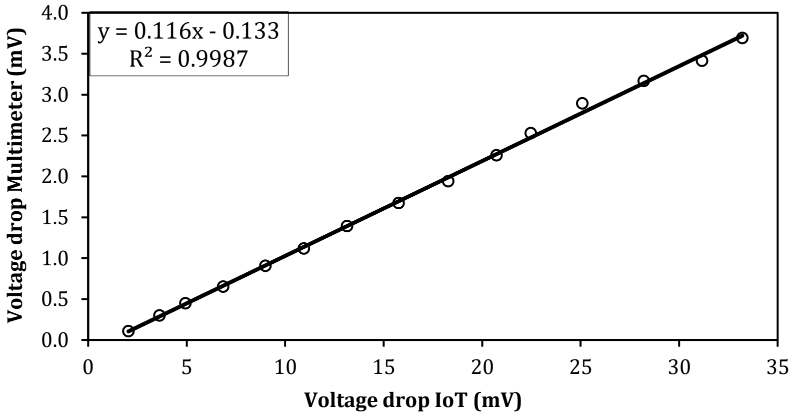

Fig. 5. Shunt voltage measurement result from IoT-based DC power logger and multimeter

Fig. 6 compares the full-scale calibrated shunt voltage value and the multimeter. After implementing the full-scale calibration process, the equation obtained from the graph shows the slope is close to 1, indicating the calibrated voltage drop value from the DC power logger is closely aligned with the measurement result from the multimeter [21]. By means, the full-scale calibration process was proved to get the exact shunt voltage and could accurately measure any current value. Table 2 shows the risen accuracy of voltage drop measurement of the calibrated Power Logger. The shunt voltage values that resulted from the uncalibrated IoT-based DC power logger show negative accuracy compared to the multimeter due to the IoT device was overestimating the voltage drop by a large margin compared to the reference multimeter [22]. Nevertheless, after calibration, the shunt voltage value accuracy rose to 98.37%, along with the uncertainty.

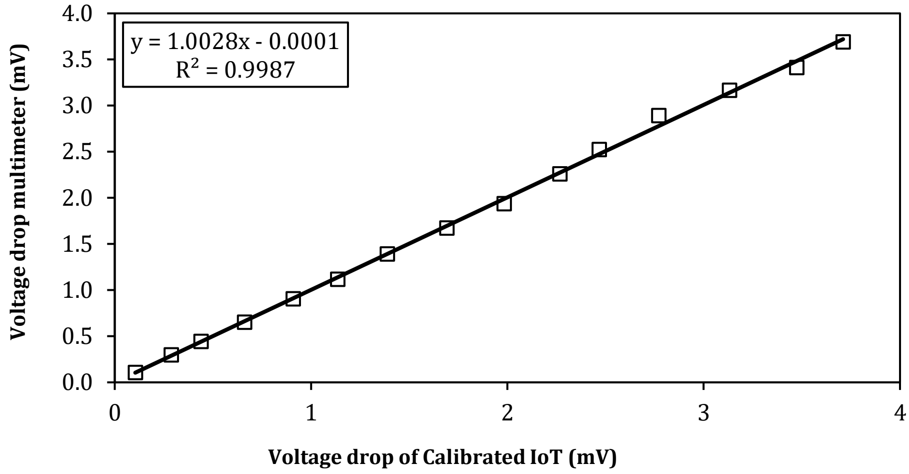

Fig. 6. The full-scale calibration result of shunt voltage

Table 2. The voltage drop measurement and full-scale calibration result

No	Voltage Drop(V)			Accuracy Power Logger (%)		Total Uncertainty (V)	
	Multimeter	IoT		IoT		IoT	
		Before	After	Before	After	Before	After
1	0.107	2.049	0.105	-1744.831	98.077	0.014	0.001
2	0.300	3.634	0.288	-1021.355	95.992	0.024	0.002
3	0.447	4.941	0.439	-913.907	98.339	0.031	0.003
4	0.653	6.862	0.661	-856.440	98.752	0.038	0.004
5	0.907	9.008	0.910	-798.683	99.654	0.051	0.005
6	1.120	10.959	1.136	-783.164	98.615	0.076	0.008
7	1.393	13.143	1.388	-747.527	99.633	0.071	0.008
8	1.673	15.761	1.691	-745.956	98.930	0.087	0.009
9	1.940	18.286	1.983	-746.468	97.765	0.098	0.011
10	2.260	20.744	2.268	-721.553	99.656	0.107	0.012
11	2.527	22.468	2.467	-692.736	97.649	0.220	0.025
12	2.893	25.094	2.771	-670.643	95.776	0.218	0.025
13	3.167	28.207	3.131	-694.113	98.885	0.147	0.016
14	3.413	31.167	3.474	-716.487	98.227	0.162	0.018
15	3.693	33.208	3.710	-702.430	99.549	0.174	0.020
Mean				-837.086	98.367	0.101	0.011

3.2. Experimental Validation Result

Experimental validation in this research defined the feasibility of the equation obtained from the calibration process for universal voltage and current measurement using the calibrated IoT-based system. The experimental validation was carried out by taking voltage and current measurements with different loads and ranges.

3.2.1. Experimental validation of Voltage measurement

The experimental validation process for the voltage measurement was conducted by measuring DC voltage with an LED lamp and a resistor as the load. The voltage was increased from 1V to 32V in increments of 1V, with 15 repetitions and a 10-second delay for each increment. This experiment also intended to assess the maximum voltage measurement possible by the DC power logger, exceeding the maximum voltage from the INA219 datasheet, which is 26 volts [12]. Voltage measurement was compared to the multimeter.

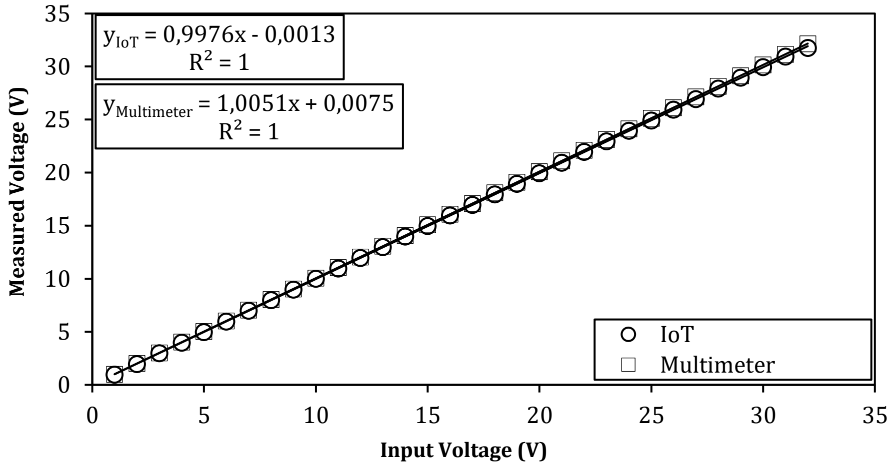

Fig. 7. The voltage measurement results from the validation process

The comparison of voltage measurement from three measuring instruments was shown inFig. 7. It can be seen that the voltage measurement result from the calibrated built system (y_{IoT}) is linear with two other measuring instruments and has the highest accuracy compared to the multimeter, as shown in Table 3.

Table 3. The voltage measurement results from IoT-based meter and multimeter

Input Voltage (V)	Voltage (V)			Accuracy (%)			Uncertainty (V)		
	Multimeter	IoT		Multimeter	IoT		Multimeter	IoT	
		Before	After		Before	After		Before	After
1	1.000	0.971	0.996	99.960	97.182	97.616	98.700	0.008	0.008
2	2.013	1.972	1.999	99.337	97.957	98.013	98.424	0.014	0.013
3	3.029	2.981	3.009	99.036	98.408	98.299	99.611	0.018	0.018
4	4.034	3.982	4.014	99.150	98.714	98.601	99.692	0.021	0.021
5	5.031	4.984	5.019	99.373	99.051	98.908	99.579	0.027	0.027
6	6.039	5.988	6.026	99.356	99.159	98.994	99.901	0.031	0.031
7	7.040	7.000	7.041	99.429	99.432	99.243	99.875	0.035	0.035
8	8.053	8.000	8.044	99.342	99.346	99.150	99.904	0.040	0.040
9	9.051	9.000	9.047	99.437	99.440	99.238	99.853	0.045	0.045
10	10.069	10.020	10.070	99.313	99.517	99.310	99.899	0.050	0.050
…	…	…	…	…	…	…	…	…	…
28	28.151	28.011	28.117	99.460	99.503	99.269	99.954	0.141	0.141
29	29.151	29.021	29.130	99.480	99.557	99.322	99.863	0.146	0.146
30	30.156	30.021	30.133	99.480	99.554	99.318	99.845	0.151	0.151
31	31.163	31.029	31.143	99.475	99.570	99.332	99.849	0.156	0.156
32	32.166	31.832	31.956	99.481	98.962	98.748	99.620	0.176	0.176
Mean				99.427	99.219	99.642	0.084	0.084	0.084

Obviously, it can be seen that the calibrated DC power logger achieves the highest accuracy (99.642%) compared to itself before calibration and the multimeter. Besides, the validation process demonstrates that the built system can measure voltage up to 32V, far beyond the limit specified in the datasheet. However, we found that the voltage measurement exhibited an anomaly in accuracy at more than 32V, with a slight decrease. Hence, to ensure the optimal functioning of the sensor and the IoT-based DC power logger, the voltage measurement was halted at 32V, which is not recommended to measure beyond the datasheet.

3.2.2. Experimental validation on current measurement

The objective was to assess its efficacy in measuring low current and current value changes in the presence of a minor change in resistance. After collecting data, the DC power logger was calibrated using the same method as in the initial experiment to ensure accuracy. The full-scale calibration process for current measurement was initiated by applying the equation from the previously conducted voltage calibration ($y_{\square} = 0.9975x + 0.0042$). Thereafter, the second step of calibration was performed using the equation derived from the comparison graph of the current measurement results obtained from the DC power logger and multimeter, as illustrated in Fig. 8. It can be seen that the current measurement values after calibration were better than before.

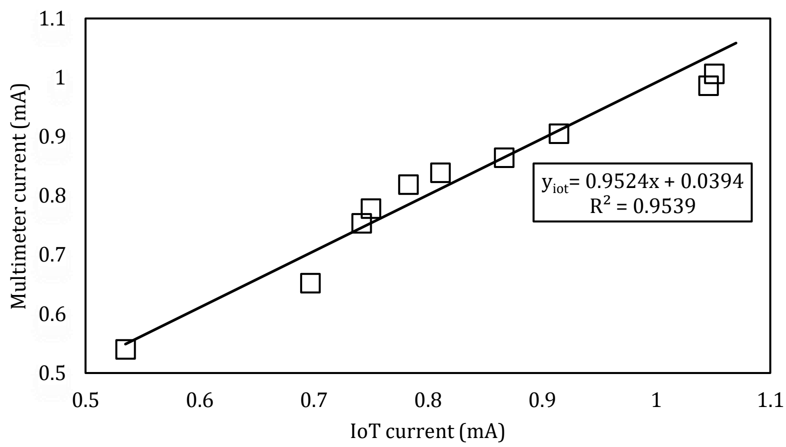

Fig. 8. Current measurement result from the DC power logger compared to the multimeter

The graphs demonstrated that the calibration process was suitable for current measurement by the IoT-based DC power logger and its capability of measuring current directly. However, the datasheet mentions that the current calibration procedure for the INA219 must be conducted for every alteration in measurement range and each application of a different shunt resistor during the measurement process [12]. This is due to the component's reliance on specific parameters that influence its accuracy. Furthermore, the validation shows that the current measurement using the DC power logger yielded 96.66% accuracy, as shown in Table 4.

Table 4. Current measurement results from both meters

	Multimeter	IoT		
No	**Current (mA)**		**Accuracy (%)**	**Uncertainty (+0.5%) (mA)**
1	0.535	0.540	98.957	0.017
2	0.697	0.652	93.528	0.025
3	0.742	0.753	98.546	0.013
4	0.750	0.778	96.255	0.017
5	0.783	0.819	95.412	0.022
6	0.811	0.839	96.527	0.021
7	0.867	0.864	99.706	0.019
8	0.915	0.905	98.828	0.021
9	1.046	0.986	94.224	0.022
10	1.051	1.006	95.671	0.018
11	1.070	1.117	95.593	0.020
	Mean		96.659	0.020

4. Conclusion

Calibration in every meter is crucial before measuring; however, there's little information on the INA219 power module calibration technique. Thus, this study shows a simple and accurate technique to calibrate and validate an IoT-based DC power logger using a standard multimeter. The results show that this process enhanced the IoT-based DC power logger's voltage and current measurement accuracy. The highest accuracy achieved in the IoT-based DC power logger following the calibration process was 99.86% for voltage measurement, and 98.37% for current measurement voltage drop-based. In addition, the validation process yielded an accuracy of 99.64% for the voltage measurement and also demonstrated the logger's capacity to measure up to 32 volts with a high degree of accuracy. Furthermore, the current validation process also shows that the direct measurement of current by the IoT-based DC power logger resulted in an average accuracy of 96.67%. Notably, the maximum current measurement capability of the IoT-based power logger has not yet been reached in this study. However, the minimum current measurement capability of the IoT-based power logger has been previously documented at 0.54 mA.

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