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RESEARCH ARTICLE

IOT-Based Electrical Energy Consumption Monitoring Application on Machine Tools

Putra Bismantolo[1,*], Kurnia Anggriani[2], Nurul Iman Supardi[3], Gusta Gunawan[4], and Emilio Oktori[5]

[1,3,5]Mechanical Engineering, Faculty of Engineering, University of Bengkulu, 38122, Indonesia
[2]Informatics, University of Bengkulu, 38122, Indonesia
[4]Civil Engineering, University of Bengkulu, 38122, Indonesia

*Corresponding email: putrabismantolo@unib.ac.id

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Abstract: The increasing demand for energy-efficient manufacturing processes has highlighted the importance of real-time monitoring systems in industrial environments. This study presents the development and implementation of an IoT-based application for monitoring electrical energy consumption on machine tools. By integrating smart sensors, microcontroller platforms, and cloud-based data visualization services, the system enables continuous tracking and analysis of electrical usage patterns. The application is designed to collect voltage, current, and power data in real-time, transmitting the information via Wi-Fi to a centralized server for storage and visualization. The proposed system was tested on various types of machine tools to evaluate its accuracy, responsiveness, and energy-saving potential. This study presents an overview of how the Internet of Things (IoT)-based application for monitoring electrical energy consumption on machine tools was developed for real-time measurements. The system integrates voltage and current sensors with a NodeMCU microcontroller, transmitting data to the Blynk platform for remote access and visualization. A functional prototype was successfully developed and tested under controlled conditions. Sensor readings were calibrated and compared with standard measuring instruments, resulting in a low error margin ranging from 0.01% to 0.59%. Energy consumption data collected from 1 to 25 seconds ranged from 6.92×10^{-5} kWh to 1.42×10^{-3} kWh, demonstrating the system's ability to capture detailed consumption patterns. The prototype is precise and responsive, showing significant potential for integration into predictive maintenance and energy efficiency initiatives in alignment with Industry 4.0.

Keywords: Blynk, Energy consumption, Internet of Things, Machine tools, Monitoring

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1 Introduction

In the current era of digital transformation, the application of the Internet of Things (IoT) in manufacturing enables real-time data acquisition, allowing manufacturers to make informed decisions that improve operational efficiency [1–4]. Machine tools, which consume significant amounts of electrical energy, are often insufficiently monitored despite being critical elements in production lines [5, 6]. Traditional monitoring methods are frequently inadequate in providing real-time operational visibility, resulting in wasted energy and increased operational costs [6, 7].

The Industry 4.0 paradigm integrates IoT, cloud computing, and cyber-physical systems to enable intelligent monitoring and automation [5,8,9]. Within this framework, IoT offers a promising solution for energy management by combining low-cost sensors, wireless communication, and cloud-based analytics [9, 10]. Such systems can monitor essential energy parameters—including voltage, current, power, and energy consumption (kWh)—which are crucial for optimizing machine performance and reducing electricity costs [2, 10, 11].

Previous studies have demonstrated the effectiveness of IoT technologies for machine condition monitoring. For example, Yang et al. [1] developed an IoT-based energy consumption monitoring and controlling system for smart manufacturing by integrating smart meters, sensors, and a cloud platform, showing that real-time energy tracking can significantly improve efficiency and reduce operational costs. Similarly, Gungor et al. [12] reviewed smart grid communication technologies and standards, highlighting that interoperability and reliable communication protocols are critical for enabling large-scale energy management. In another study, Lee et al. [13] proposed a predictive manufacturing framework that leverages big data analytics for machine health monitoring, and their results indicated that predictive approaches can effectively reduce downtime and enhance productivity. Ali et al. [14] conducted a comprehensive survey on IoT enabling technologies and protocols for smart manufacturing, concluding that lightweight communication protocols such as MQTT and CoAP, combined with edge computing, are essential for scalable and low-latency monitoring systems. Likewise, Prabha et al. [15] designed and implemented an IoT-based remote monitoring system for industrial equipment using embedded sensors and wireless communication, which successfully demonstrated real-time monitoring capabilities and improved fault detection. However, despite these advances, there is still a lack of real-time and precise energy monitoring systems specifically tailored for machine tools in manufacturing settings.

Therefore, the present study aims to develop an IoT-based application for real-time monitoring of machine tool energy consumption. The proposed system utilizes voltage sensors (ZMPT101B), current transformers (SCT013/TA12-200), a NodeMCU v3 microcontroller and the Blynk IoT platform [15, 16].

2 Research Method

To develop, implement and evaluate IoT energy monitoring systems for machine tools, this research utilized a prototyping design approach. The methodology consists of five key steps which are: system design, hardware realization, software design, calibration and validation, and data evaluation. The research flow chart is shown in Figure 1.

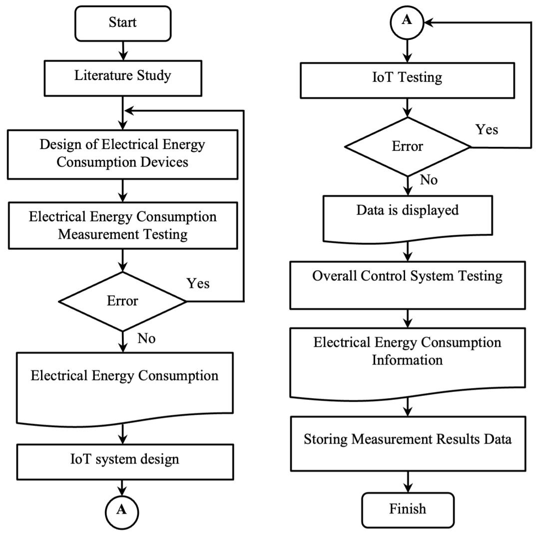


Figure 1: Research Flowchart

2.1 System Design

The system architecture integrates sensors, microcontrollers, communication modules, and a cloud-based dashboard to measure and visualize energy consumption Figure 2. The primary components include aurrent sensor (TA12-200) and a voltage sensor (ZMPT101B) to capture electrical parameters [17, 18]. a NodeMCU ESP8266 as the core microcontroller for data processing and Wi-Fi transmission [19, 20], and Real-Time Clock (RTC) DS3231 to maintain accurate time-stamping of data logs [21, 22]. Additionally, Blynk platform for IoT-based data visualization [23, 24].

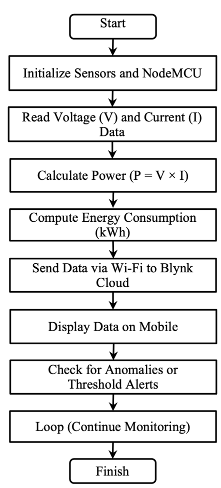


Figure 2: The tool works accompanied Flowchart

The system was intended to be inexpensive, scalable, and able to monitor in real time via a web interface or mobile application. Figure 3displays the application tools for monitoring wiring diagrams.

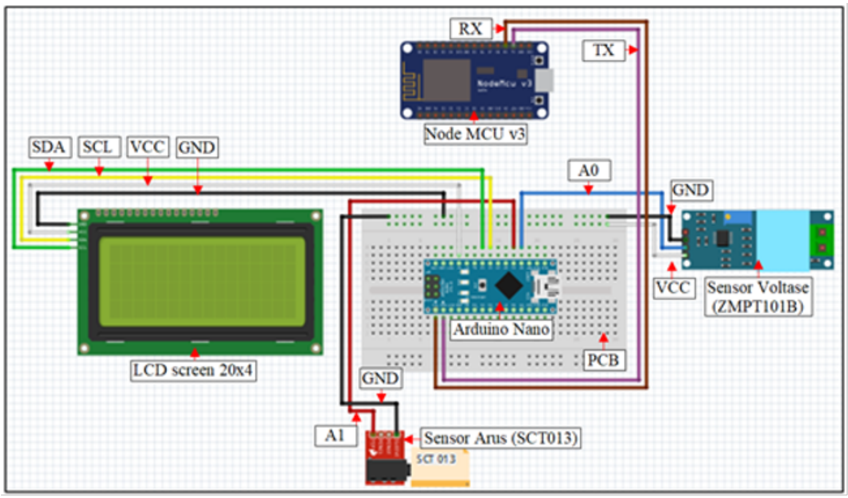


Figure 3: Wiring diagram monitoring application tools

2.2 Hardware and Software Development

The sensors were linked to the NodeMCU's analog input pins, which use equation 1 to compute power and carry out analog-to-digital conversion. P denotes power in watts (W), V denotes voltage in volts (V), and I denotes current in amperes (A).

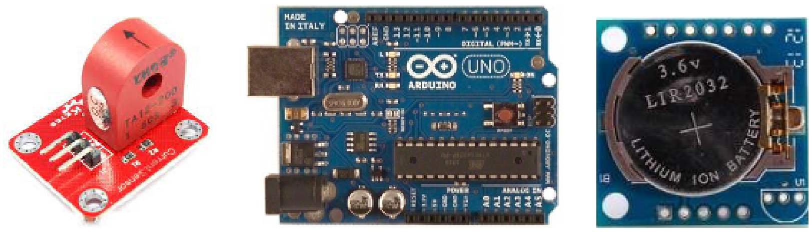
$$P = V \times I \tag{1}$$

Energy consumption was calculated using the trapezoidal numerical integration method over time. This is shown in equation 2.

$$E_{\text{kWh}} = \sum_{i=1}^{n} \left(\frac{P_i + P_{i-1}}{2} \right) \times \frac{\Delta t}{3600000} \tag{2}$$

is used to calculate the electrical energy consumption in kilowatt-hours (kWh) over a period of time based on discrete power measurements. In this calculation, P_i and P_{i-1} represent the instantaneous power values (in watts) at successive time intervals. The symbol Δt denotes the time interval between two measurements (in milliseconds). The expression $(P_i + P_{i-1})/2$ is used to compute the average power between two successive samples, while the division by 3,600,000 converts the resulting value from milliwatt-seconds into kilowatt-hours.

Arduino IDE was used to program the NodeMCU v3, incorporating libraries for RTC capabilities, Blynk cloud connectivity, and sensor reading [8, 9, 12]. Current sensor (TA12-200) Figure 4a, Arduino Uno Figure 4b, Real-Time Clock (RTC) DS3231 Figure 4c. Blynk receives real-time voltage, current, and energy data from the system via Wi-Fi on a regular basis. Figure 2 depicts the hardware sensor that was utilized.



(a) (b) (c)

Figure 4: The hardware sensor: (a) TA12-200, (b) Arduino Uno, (c) RTC DS3231

According to the integrated C/C++ code, a structured initialization and communication procedure is implemented to establish synchronization between the Arduino microcontroller and the sensor [6, 8, 9]. The first step in this procedure is to set the data transmission rate between the Arduino and the connected device by using the `Serial.begin(baud_rate)` function to configure the serial communication interface, which is essential for real-time debugging and monitoring. Next, the `pinMode(pin, mode)` function is then used to define the sensor's input pin, designating its particular digital or analog pin as an input in Figure 4 This enables data signals from the sensor to be received by the Arduino.

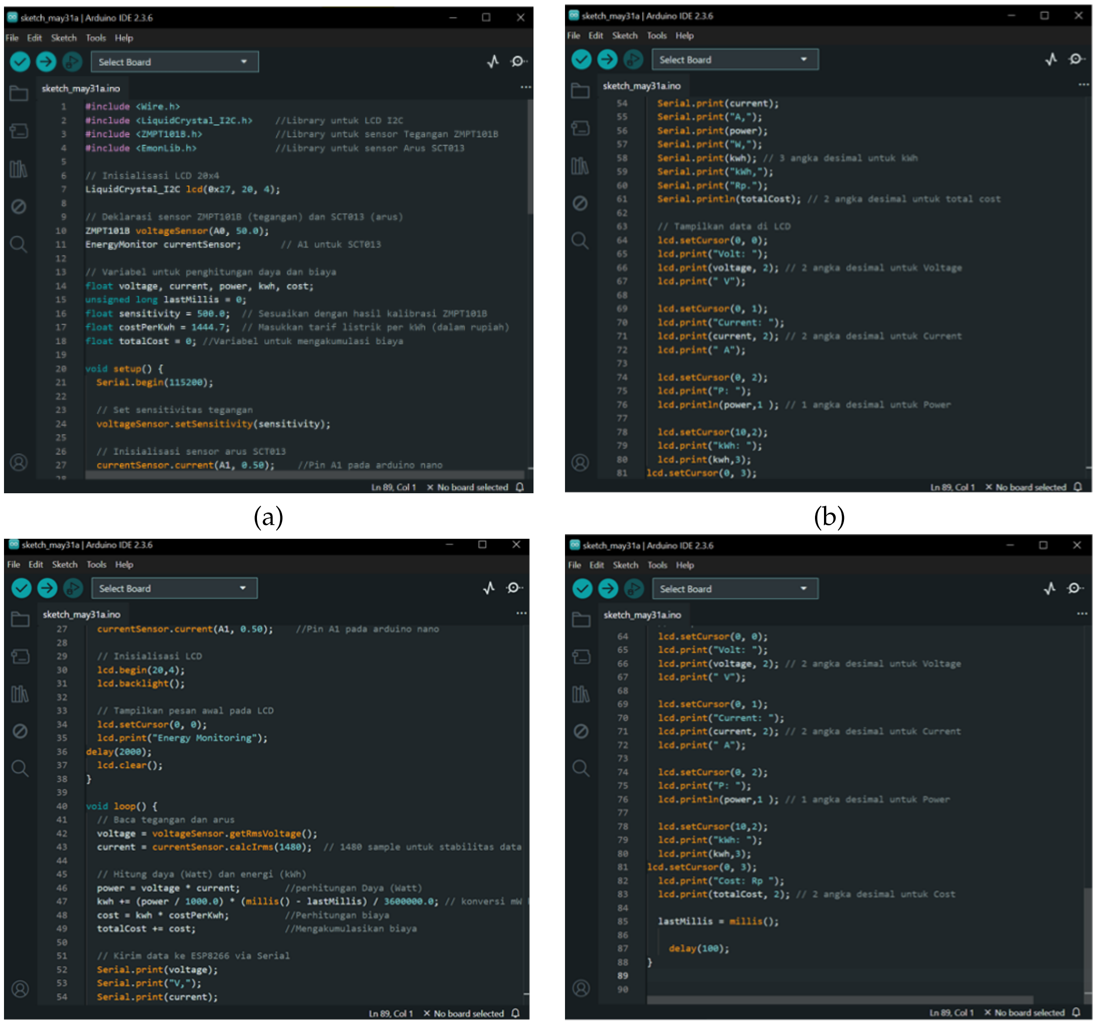
The Arduino constantly reads sensor data using either `analogRead(pin)` or `digitalRead(pin)` within the `loop()` function, depending on the kind of sensor [6,8]. After then, the values are processed or shown in real time. The relevant libraries are included and initialization procedures are carried out to establish connection with the sensor via its unique address if extra communication protocols (such as I2C or SPI) are being utilized. Time-based functions like `millis()` or `delay()` may be used to regulate the data sampling rate in order to guarantee synchronization correctness. For time-sensitive applications like motion detection, automation systems, and environmental monitoring, this guarantees that data collecting is carried out at regular intervals, Figure 5 illustrates this.

2.3 Calibration Process

Calibration was conducted by comparing sensor outputs with standard measuring instruments (clamp meter and multimeter). The relative error for each reading was calculated using equation 3.

$$\text{Error} = \left| \frac{\text{Sensor Reading} - \text{Standard Reading}}{\text{Standard Reading}} \right| \times 100\% \tag{3}$$

The formula is used to calculate the percentage error between a sensor's measured value and a reference or standard value. Sensor reading refers to the value measured by the device or system under evaluation, while the standard reading denotes the reference or true value, typically obtained from a calibrated instrument. The use of the absolute value ensures that the result is non-negative, representing the magnitude of the deviation regardless



(a) (b) (c) (d)

Figure 5: Synchronization code between the Arduino and the sensor

of direction. Multiplying by 100% expresses the error as a percentage, which facilitates easier interpretation and comparison. The error ranged from 0.01% to 0.59%, demonstrating the reliability of the measurement system for real-time monitoring tasks.

2.4 Testing and Data Collection

A milling machine was used to test the system (face milling operation on stainless steel 304). Energy usage was measured during a 25-second period, ranging from 6.92×10^{-5} kWh to 1.42×10^{-3} kWh. Every sensor reading was transmitted to the Blynk dashboard with a time stamp. Data collection and test data installation are illustrated in Figure 6.

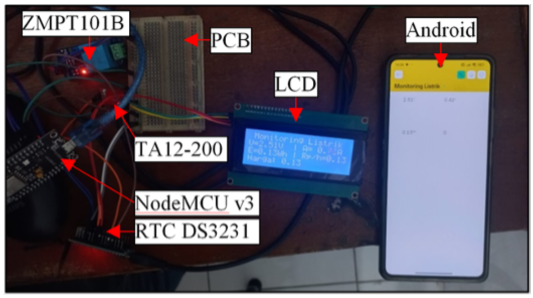


Figure 6: Installation of test data and data collection

The developed monitoring tool operates by capturing electrical parameters through voltage and current sensors, processing the signals with a NodeMCU ESP8266 microcontroller, and transmitting the data to the Blynk cloud platform for real-time visualization. The working principle is summarized as follows:

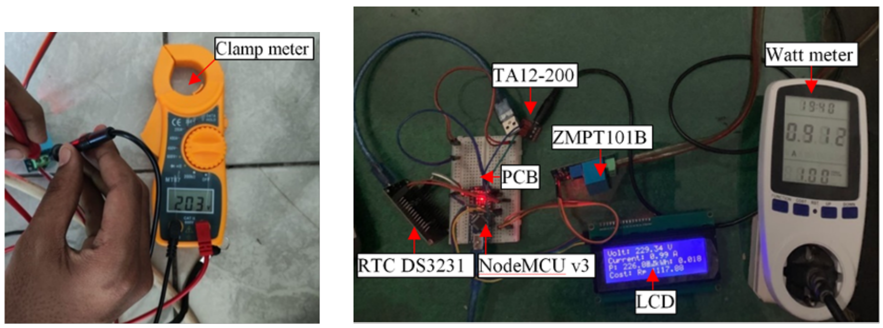
1. **Data Acquisition**
   The voltage sensor (ZMPT101B) and current sensor (TA12-200) continuously measure the electrical parameters from the machine tool.
2. **Signal Processing**
   The analog signals from the sensors are converted into digital values by the NodeMCU's ADC (Analog-to-Digital Converter). The microcontroller calculates power using $P = V \times I$ and integrates these values over time to obtain the total energy consumption in kilowatt-hours (kWh).
3. **Data Transmission**
   Processed data (voltage, current, power, and energy) are transmitted via Wi-Fi to the Blynk cloud server using the ESP8266 module.
4. **Cloud Storage and Visualization**
   The Blynk platform stores the data and provides a graphical interface accessible via smartphone or web dashboard. This allows users to monitor real-time energy consumption patterns.
5. **User Interaction**
   Operators can view energy usage trends, detect anomalies, and make informed decisions for predictive maintenance and energy efficiency improvements.

3 Results

In the present during a face milling operation, the created Internet of Things-based energy monitoring system was successfully installed and tested on a milling machine. Through the Blynk platform, the system showed that it was able to gather and send real-time data about voltage, current, power, and energy consumption.

3.1 Sensor Performance and Calibration Accuracy

Sensor outputs were compared against standard instruments (clamp meters and voltmeters) to assess measurement accuracy in Figure 5a. The calibration process yielded promising results, with the error rate ranging between 0.01% and 0.59%, validating the precision and reliability of the current and voltage sensors integrated in the system in Figure 5b This high accuracy ensures the system can be relied upon for energy diagnostics in an industrial environment. The installation process for the sensor performance and calibration accuracy installation is as shown in the Figure 7.



(a) (b)

Figure 7: Sensor Performance and Calibration Accuracy

The system used a one-second update rate when sending data to the Blynk platform. The dashboard gave consumers instant feedback via web and mobile applications by showing current, voltage, power, and total energy use. Through graphical display, users were able to identify patterns, anomalous oscillations, or spikes in electrical characteristics. The system's recorded energy usage during a 25-second test period under real load conditions ranged from 6.92×10^{-5} kWh to 1.42×10^{-3} kWh. This demonstrates that the system can identify slight increases in energy use, which is very helpful for intermittent or short-duration operations. The system's usefulness for industrial monitoring and possible cost-efficiency optimization is demonstrated by its precision and timeliness in gathering energy consumption data at this resolution. Table 1 displays the calibration results of Real-Time Monitoring between sensors and clamp ampere.

A comparison of the voltage readings obtained from 20 observations using a clamp meter and a voltage sensor is shown in the table. The goal is to compare the voltage sensor's accuracy and consistency to a reference device, which is well-known for its dependability in field measurements. With only little variations noted, the results show a high degree of agreement between the two measuring techniques. With an average error rate of roughly 0.24% for all 20 data points, the voltage sensor exhibits great precision under the measured conditions. Observations that are noteworthy include: With the voltage sensor measuring 226.40 V and the clamp meter measuring 225.03 V, observation 2 had the largest error, at 0.61%. Across several observations (9, 12, and 20), the lowest error was 0.01%, indicating nearly identical values from both sensors. Since the inaccuracy was less than 0.5% in 85% of the observations, the voltage sensor's dependability for real-world applications was confirmed. This research backs up the finding that the voltage sensor replicates voltages often recorded by a tang ampere with great fidelity. The sensor is appropriate for appli-

Table 1: Voltage comparison and error percentage

Data	V_{Sensor} (V)	$V_{\text{Clamp Meter}}$ (V)	Error (%)
1	225.04	224.8	0.11%
2	226.40	225.03	0.61%
3	225.37	224.66	0.32%
4	225.56	224.56	0.45%
5	224.87	225.22	0.16%
6	224.14	225.02	0.30%
7	224.12	224.74	0.27%
8	224.72	224.55	0.08%
9	224.66	224.64	0.01%
10	225.19	224.74	0.20%
11	224.92	225.22	0.13%
12	224.67	224.64	0.01%
13	223.39	224.72	0.59%
14	225.49	224.53	0.43%
15	225.00	225.16	0.07%
16	224.86	224.81	0.02%
17	225.04	225.28	0.11%
18	225.64	224.7	0.42%
19	224.19	225.29	0.49%
20	224.59	224.61	0.01%

cations needing accurate voltage monitoring, including embedded power systems, smart grid technologies, and electrical diagnostics, as seen by the low error margins.

The connection between current measurements made with a clamp meter and the outputs recorded by a current sensor is illustrated in the chart on Figure 8. Current in amperes is represented on the horizontal axis (x-axis), while sensor output values are displayed on the vertical axis (y-axis). The sensor output increases gradually in tandem with the current, demonstrating an exceptionally high linear correlation from the plotted data points. In particular, the sensor consistently increases by about 0.5 sensor units for every 1 ampere, demonstrating a dependable and proportionate response throughout the measured range. These findings confirm the sensor's suitability for use in accurate current measuring applications, including industrial automation, smart device load detection, and energy monitoring systems. Simple calibration is also made possible by the constant slope, which is essential for incorporation into embedded or Internet of Things-based monitoring applications.

3.2 Prototype Implementation

The Arduino-compatible hardware seen in Figure 9 was used to construct a working prototype on a breadboard. A NodeMCU microcontroller was linked to the sensor network, and Wi-Fi integration with the cloud was accomplished. An LCD display for local data readout and LED indicators to indicate operation status are features of the prototype. The device's small size allows it to be used in industrial settings with limited space.

The electrical characteristics are measured in detail over a 25-second period in the table, with particular attention paid to energy consumption in kWh and the associated monetary

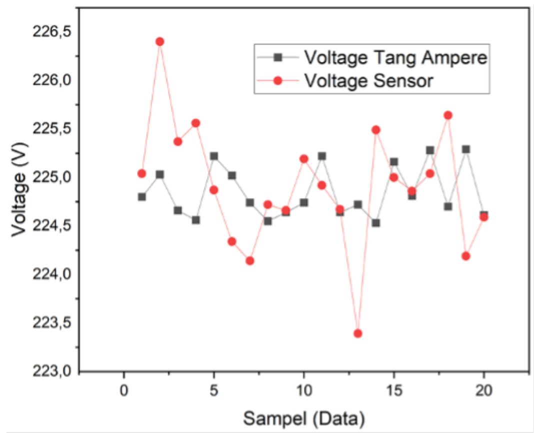


Figure 8: Result calibration between sensors versus clamp ampere

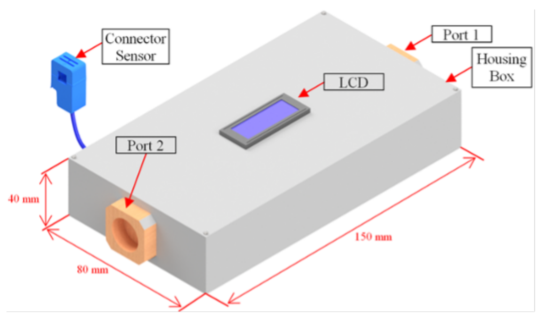


Figure 9: Prototype monitoring tool

cost in Indonesian Rupiah (Rp). This dataset is essential for assessing the financial impacts of electrical load utilization as well as evaluating operational efficiency in real time. According to Table 2, the energy consumption values increase steadily from 0.00 kWh at 0 seconds to 1.42×10^{-3} kWh at 25 seconds. This gradual accumulation indicates consistent power usage by the system, with power readings ranging approximately between 198 W and 358 W. These values illustrate typical patterns of low-to-medium electrical load consumption.

The dataset's real-time energy usage cost estimate is a crucial component. The total cost starts at Rp 0.000 and gradually increases to Rp 20.505 at the 25-second mark. A clear indicator for assessing cost effectiveness and budgeting in real-world applications, this linear cost trend shows a direct relationship with energy use. Several important conclusions include There was a noticeable price increase from Rp 0.999 to Rp 2.930 between the 1- and 3-second marks, suggesting a significant early usage. The cumulative cost hits Rp 7.934 at 10 seconds, which is over 40% of the final amount. This indicates that most of the energy was used during the first half of the observation period. Based on the data, the average energy cost rate is roughly Rp 14,440 per kWh, which is in line with the typical Indonesian residential or commercial electricity rates listed in Table 3.

Table 2: The energy consumption

Time (s)	Voltage (V)	Current (A)	Power (Watt)	kWh	Cost (Rp)
0.00	225.04	1.59	357.81	0.000000	0.000
1.00	226.40	1.08	249.04	0.000069	0.999
2.00	225.37	1.08	243.40	0.000138	1.998
3.00	225.56	0.96	216.54	0.000207	2.997
4.00	224.87	0.93	208.84	0.000276	3.996
5.00	224.14	0.93	208.64	0.000345	4.995
6.00	224.14	0.90	201.73	0.000414	5.994
7.00	224.72	0.93	208.21	0.000483	6.993
8.00	224.66	0.88	197.70	0.000552	7.992
9.00	225.19	0.88	198.17	0.000621	8.991
10.00	224.92	0.88	197.93	0.000690	9.990
11.00	224.67	0.90	202.20	0.000759	10.989
12.00	223.39	0.89	198.81	0.000828	11.988
13.00	225.49	0.93	209.71	0.000897	12.987
14.00	225.00	0.92	207.00	0.000966	13.986
15.00	224.86	0.90	202.37	0.001035	14.985
16.00	225.04	0.90	202.54	0.001104	15.984
17.00	225.64	0.92	207.59	0.001173	16.983
18.00	224.19	0.89	199.53	0.001242	17.982
19.00	224.59	0.91	204.38	0.001319	18.981
20.00	224.59	0.91	204.38	0.001396	19.980
25.00	224.59	0.91	204.38	0.001419	20.505

Table 3: Electricity tariffs in Indonesia

Gol	(VA)	kWh (Rp)
R-1/TR	900	1.352,00
R-1/TR	1.300	1.444,70
R-1/TR	2.200	1.444,70
R-2/TR	3.500–5.500	1.669,53
R-3/TR	6.600	1.669,53

This investigation emphasizes how well monitoring systems work when real-time kWh tracking and cost metering are integrated. This level of data granularity facilitates accurate forecasting, energy management, and optimization tactics in both commercial and residential contexts.

Figure 10 shows how the electrical power consumption (measured in watts) changed over a 25-second period. The y-axis shows the matching power values in watts, and the x-axis shows time in seconds. The power usage peaks at around 358 W at the start of the observation period (0 seconds), suggesting the first current surge that may have been caused by inrush current effects or system startup. When devices go from an idle to an active state, this phenomena frequently occurs in electrical systems.

After this first peak, power consumption sharply declines, stabilizing at 240 W after one second and falling to less than 210 W by five seconds. After this, there are little variations in

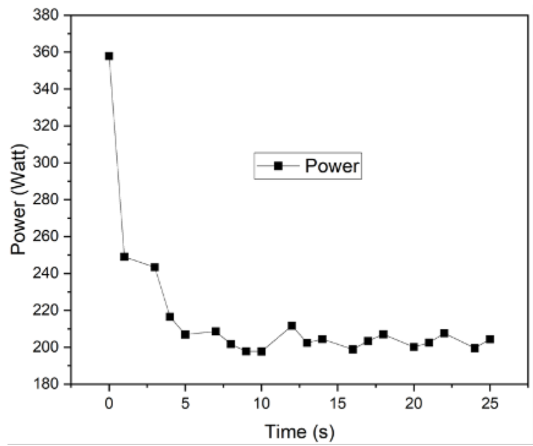


Figure 10: Result of electrical power consumption

power consumption but overall stability, with the consumption ranging from about 195 W to 210 W for the duration of the measurement. a sharp drop in power usage from the first peak during the first five seconds, of about 40%. After around seven seconds, the system reaches a constant operating condition, preserving power stability, a crucial component of effective energy use. The graph's latter section shows minimal variability, indicating a load that is well-regulated and limiting wasteful energy use. This trend analysis can help optimize start-up procedures or power management techniques in real-time systems and offers insightful information about the electrical load's dynamic behavior.

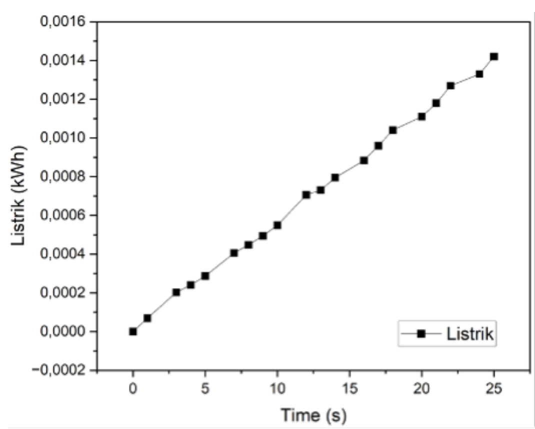


Figure 11: Result of the cumulative electrical energy consumption

Throughout a 25-second period in Figure 11, the cumulative electrical energy usage, expressed in kilowatt-hours (kWh), is plotted against time. The horizontal axis represents time in seconds, while the vertical axis shows the total energy consumed. In response to constant power demand, the energy consumption profile exhibits a steady increasing trend, reflecting typical cumulative behavior. The energy value begins at 0.00 kWh and rises gradually until it reaches approximately 0.00142 kWh at the 25-second mark.

An electrical load operating continuously during the recorded period is shown in this steady increasing trend. A rise in energy consumption that is almost linear, suggesting steady and continuous power use with little variation. A tiny rise in power seen in the related power-time graph, which corresponds to a slight acceleration in energy accumulation between 10 and 20 seconds. The system's low-to-moderate energy consumption, which is characteristic of tiny appliances or energy-efficient equipment, is confirmed by the ultimate cumulative energy value ($\sim 1.42 \times 10^{-3}$ kWh). This kind of data visualization is essential for energy efficiency monitoring and evaluation in real time. The graph's consistent slope indicates consistent consumption patterns, which is helpful for applications including demand forecasting, energy budgeting, and the development of intelligent power management systems.

3.3 Practical Implications

The prototype system is small, lightweight, and adaptable to various types of machine tools without requiring major modifications. Because it uses widely available components (NodeMCU, sensors, and open-source software), the system is both scalable and affordable for small and medium-sized manufacturing enterprises (SMEs). Even short machining operations contribute to meaningful energy consumption that can be monitored and analyzed for cost efficiency, as indicated by the recorded energy consumption values ranging from 6.92×10^{-5} kWh to 1.42×10^{-3} kWh. In the context of Industry 4.0, such fine-grained insights are essential because smart factories demand responsive automation systems and comprehensive operational visibility.

4 Discussion

The deployment of an Internet of Things-based monitoring system has shown great promise for improving industrial machine tool energy management. According to the findings, inexpensive sensors combined with a microcontroller and a cloud-based dashboard may very accurately deliver real-time information about electrical energy consumption. The calibration findings revealed a small error margin (0.01% to 0.59%) between sensor values and standard equipment. These outcomes attest to the system's dependability for accurate energy monitoring, even during brief operational periods. Detecting minute changes in energy use that could point to irregularities or inefficiencies requires this level of accuracy. For machine tool operations, real-time energy usage monitoring has several advantages. The Blynk platform gives operators and maintenance teams access to the most recent data, enabling prompt identification of unusual usage patterns. This lowers the chance of unplanned downtime by facilitating the early diagnosis of problems like overloading, mechanical wear, or electrical defects. Additionally, real-time monitoring allows:

1. More precise cost analysis for each operational cycle,
2. Implementation of energy-saving measures,
3. Improving the scheduling and maintenance of machines.

A real-time graphical user interface (GUI) for electrical energy usage monitoring is depicted in the figure; it was most likely created with an Internet of Things-based platform like Blynk. Along with a computed cost figure, the dashboard shows four important parameters: voltage, current, power, and total energy in kWh.

1. **Voltage:** The system records 232.67 V, which is within many countries' typical range for residential and business AC supplies.
2. **Current:** A comparatively low power consumption equipment or system is indicated by the load's real-time current draw of 1.02 A.
3. **Power:** The product of voltage and current yields the instantaneous power, which is 236.38 W and indicates a stable load functioning.
4. **Energy Consumption (kWh):** The accumulated energy usage at the point of observation is 0.01 kWh, reflecting recent or low-duration operation.
5. **Cost:** The calculated energy cost is displayed as Rp 234.94, highlighting the application's capability to convert energy data into a monetary metric, likely using a predefined tariff rate.

By providing a thorough and intuitive depiction of electrical indicators, this monitoring system helps end users assess consumption trends and related expenses effectively. The digital readouts guarantee accurate readings are displayed clearly, and the circular gauges offer user-friendly feedback on operational condition. In residential, commercial, or industrial contexts, these systems are essential for smart energy applications because they enable real-time diagnostics, efficiency evaluation, and well-informed energy management decisions. Real-time information on the machine tool's electrical energy consumption is displayed in this Blynk screenshot. The three primary parameters that are shown are current, power, and voltage. The specifics of every measured parameter are listed below. Figure 12 shows a voltage reading of 232.67 volts. In line with Indonesia's general electrical voltage standard, which is approximately 220-240 volts, this illustrates the voltage value flowing to the machine tool, which is rather stable. The power value that was recorded is 236.68 watts. The machine tool's electrical energy consumption in a specific time period is indicated by this power value.

5 Conclusion

An Internet of Things-based application for tracking machine tool electrical energy usage was successfully developed and put into use in this study. The system provides real-time data on voltage, current, power, and energy consumption by integrating inexpensive sensors, a NodeMCU microcontroller, and a cloud-based dashboard (Blynk). With calibration errors ranging from 0.01% to 0.59%, the results showed that the system is capable of measuring energy parameters with accuracy. Its sensitivity to small-scale energy changes common in machine operations was confirmed when the system recorded energy consumption figures ranging from 6.92×10^{-5} $kWhto1.42 \times 10^{-3}$ $kWhovera25 - secondtestwindow$.

Through the implementation of real-time monitoring, the system gives customers the ability to identify unusual patterns of use, enhance energy efficiency, and maybe lower operating expenses. The prototype is appropriate for wider implementation in small-to-medium industrial environments due to its low cost and portability, particularly in the context of Industry 4.0. Predictive analytics, wider machine compatibility, and extended field testing will be the main goals of future work to improve the system and guarantee its resilience in industrial environments.

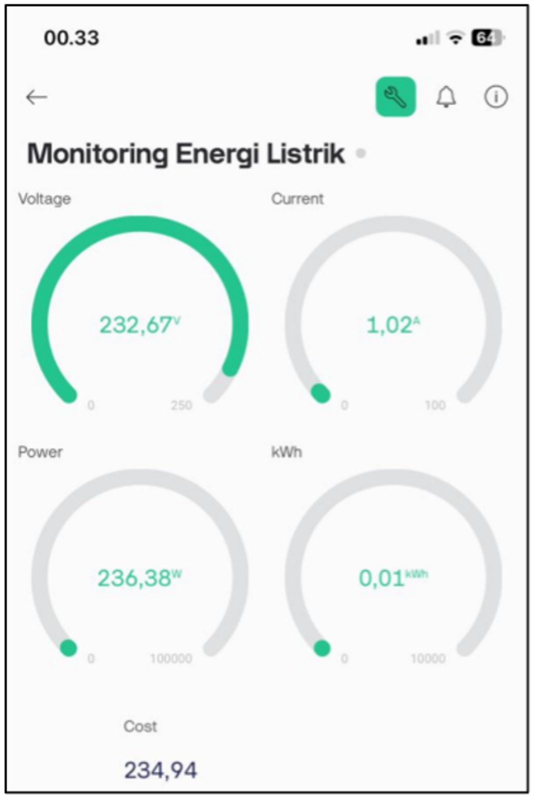


Figure 12: Blynk display on android

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