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Experimental Validation of an IoT-Based Sensor System for Real-Time Measurement of Tractor Performance Parameters

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Abstract: This article presents a detailed account of the design and development process of an Internet of Things (IoT)-based smart electronic system for the remote, real-time monitoring of important tractor performance parameters using embedded sensors. The proposed system includes three measurement modules, namely draft force, slip ratio, and fuel consumption, which were developed using ESP32 microcontrollers and a Wi-Fi network. The measurement process included a T12C pressure transducer, MPU6050 IMU sensor, and two YF-S401 flow sensors. The proposed system was tested through field experiments, and it was established that the two measurements were in close agreement with the results obtained through conventional measurement methodologies, thereby achieving accuracy levels of 96.81% in draft force, 97.35% in slip ratio, and 98.39% in fuel consumption. Thus, it can be established that the proposed system is effective in improving accuracy levels and facilitating decision-making.

Keywords: Internet of Things monitoring system; Draft force measurement; Tractor performance monitoring; Embedded sensor systems; Precision agriculture; Computational prediction model

1 Introduction

The increased pace of innovation in embedded systems technology, smart sensors, and the Internet of Things (IoT) has greatly influenced the monitoring and control functionality associated with modern mechanisms in diverse fields of engineering [1]. Agricultural tractors, one of the most widely used systems, require monitoring of important operating parameters to enhance their efficiency and prevent energy wastage [2]. The use of conventional mechanical systems, although popular, has limitations in terms of accuracy, lack of facilities related to real-time feedback, and difficulty in interfacing with digital monitoring systems.

From an electronics engineering perspective, the use of microcontroller-based systems, wireless communication modules, and multisensory data acquisition systems provides a reliable alternative to existing measurement systems [3]. The use of embedded systems, such as the ESP32, provides an efficient means of data processing and communication, as well as suitable interface connections for various data-measuring devices, which can be effectively applied in monitoring processes in fields [4]. In addition, the use of low-cost, high-performance sensors such as transducers, inertial measurement units (IMUs), and flow sensors facilitates the development of small systems that can continuously monitor the behavior of mechanical systems [5].

Monitoring the performance parameters of tractors, such as draft force, wheel slip ratio, and fuel consumption, is important for optimizing traction efficiency, reducing mechanical load, and improving fuel-use efficiency [6]. In the past, draft force performance parameter measurements depended on the use of a dynamometer, which is accurate but not connected and does not have the capability to monitor the values in real time [7]. Additionally, another significant performance parameter, the wheel slip ratio, has significant implications for monitoring the efficiency of traction and has been measured indirectly in the past based on manual estimations, which may have significant implications for accuracy, particularly in the case of soil [8]. Another significant performance parameter measured indirectly in the past, for which the implication for accuracy is considered, is dependent on weight within the context of using gravimetric systems to measure fuel.

Consequently, the application of electronics and IoT technology for the automation of measurements of parameters of interest to tractor performance has been recently demonstrated. For instance, the level of precision involved in the automatic slip and draft control system and electronic draft control monitor has been demonstrated to be higher than that achieved through manual measurements [9, 10]. The application of IoT technology also facilitates the easy transfer of information from the farm to the cloud monitor for action by the farm manager [11]. The application of an embedded system also enhances the application of decision-making algorithms, as demonstrated by Frikha et al. [12]

Previous systems mainly focused on single-parameter monitoring, such as draft force [9] or slip ratio [10], where, as the proposed system integrates multiple performance parameters into a unified IoT framework. Compared with existing approaches, the proposed system demonstrates improved measurement accuracy and real-time data transmission capabilities.

Despite these advances, the prevailing systems have limitations in terms of cost, power consumption, and appropriateness for the severe environmental conditions prevailing in field areas. In this context, designing a reliable, cost-effective, and real-time IoT-based electronic monitoring system capable of accurately measuring tractor performance parameters is challenging.

The present study meets this need by introducing and applying an integrated smart electronic system of embedded sensors, ESP32 microcontrollers, and cloud technology to monitor the draft force, wheel slip ratio, and fuel consumption with greater accuracy. in real time. The results demonstrate the possibility of using IoT-based embedded systems to optimize the measurement procedure of agricultural machine monitoring systems.

The key contributions of this study are as follows.

(1) Development of a cost-effective IoT technology-based embedded system for real-time measurement of the performance parameters of a tractor.

(2) Integration of different sensing technologies, such as draft force, slip ratio, and fuel consumption, into a single monitoring platform is also important.

(3) The proposed system was experimentally validated under actual conditions with high accuracy.

2 Methodology

2.1 System Architecture Overview

The smart monitoring system was designed as a distributed, sensor-based electronic platform with three independent measurement modules. The system architecture can be described as a three-layer framework: data acquisition (sensors), processing (ESP32), and communication (IoT cloud platform). The use of three independent ESP32 modules allowed for parallel processing, reduced signal interference, and enhanced system modularity and reliability during the field operations. The system comprises three independent measurement modules.

- A draft force measurement unit.
- A wheel slip ratio measurement unit.
- The fuel consumption measurement unit.

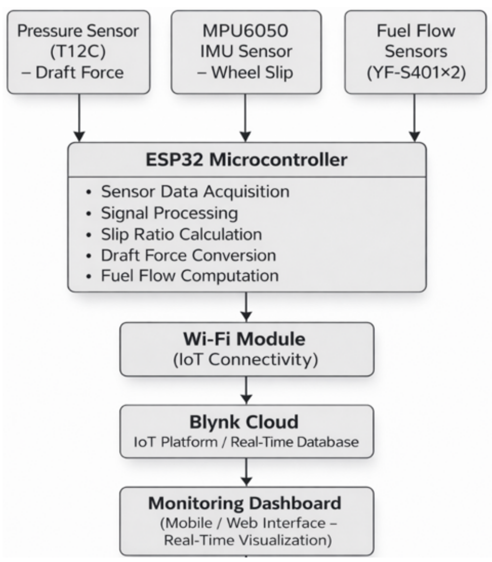


Figure 1. Architecture of the proposed Internet of Things (IoT)-based tractor-performance monitoring system

Each module comprised an ESP32 microcontroller responsible for data acquisition, processing, wireless communication, and cloud synchronization. An IoT dashboard was designed using the Blynk Cloud platform to display the operational data in real time, which were obtained from the microcontrollers.

Figure 1 shows the general design of the proposed IoT-based monitoring system.

2.2 Hardware Components

2.2.1 Sensors

Three types of embedded sensors were employed to measure the parameters of tractor performance:

(a) Pressure Sensor (T12C)

The T12C hydraulic pressure transducer was employed to sense the hydraulic pressure in a specially arranged cylinder to estimate the draft forces.

• Range: 0–250 bar.
• Output: Analog voltage proportional to the applied pressure.
• Application: Converts hydraulic pressure to draft force (kN).

(b) Inertial Measurement Sensor (MPU6050)

The speed was measured using a 6-axis IMU sensor (MPU6050 GY-521) for the features.

• Features: 3-axis accelerometer + 3-axis gyroscope.
• Communication: I2C.
• Application: Calculates the velocity of the translation used to determine the slip ratio.

(c) Fuel Flow Sensors (YF-S401)

Two Hall-effect flowmeters were placed in the fuel inlet and fuel return lines.

• Output: Pulse signal proportional to the flow rate.
• Application: The net fuel consumption is determined by subtracting the return flow from the inlet flow.

2.2.2 Microcontrollers (ESP32)

The measurement module was equipped with an ESP32 dual-core microcontroller, including:

• Integrated Wi-Fi for IoT connectivity.
• 12-bit ADC (Analog) for sensor signal conversion.
• Real-time processing for high-speed data operation.

The following three ESP32 modules were separately programmed:

• Draft force processing.
• Slip ratio estimation.
• Fuel flow calculation.

2.2.3 Power supply and enclosures

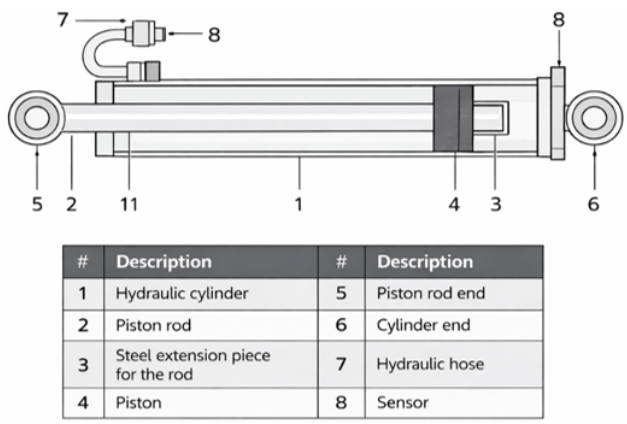
Each module was powered by a rechargeable lithium cell supplied at 3.3V.

All electronics were packaged inside specially designed enclosures made by 3D printing, which were aimed at:

• Protect components from dust, vibrations, and moisture.
• They provide easy access for charging and maintenance.
• It maintains stability during field operations.

2.3 System Implementation

2.3.1 Draft force measurement module



#	Description	#	Description
1	Hydraulic cylinder	5	Piston rod end
2	Piston rod	6	Cylinder end
3	Steel extension piece for the rod	7	Hydraulic hose
4	Piston	8	Sensor

Figure 2. A hydraulic cylinder with pressure sensor (T12C)

A hydraulic cylinder was installed between the tractor and auxiliary pulling tractor. The T12C sensor was positioned at the oil port of the hydraulic cylinder, as illustrated in Figure 2. The ESP32 continuously measured the analog pressure values and converted them into hydraulic force.

A three-stage conversion mechanism was adopted to convert the raw data obtained from the sensors into the corresponding pressure units. First, the raw digital value of 12 bits obtained from the ADC was converted into its corresponding voltage value (V) using Eq. (1), as follows:

$$V = \frac{ADC}{4095} \times V_{ref} \tag{1}$$

where, ADC refers to the raw integer value (0–4095) obtained from the sensor; V_{ref} refers to the reference voltage of the ADC, which was set to 5.00 V in this case. Subsequently, the obtained voltage value was converted into its corresponding pressure value in pascals (P) using the linear transfer function of the sensor, as expressed in Eq. (2).

$$\mathrm{P} = (V - V_{offset}) \times \mathrm{SF} \tag{2}$$

where, V_{offset} denotes the offset voltage of the sensor and the value of the output voltage at zero pressure; SF denotes the sensitivity factor, which is 400 in this case, as provided in the datasheet of the sensor. Finally, the obtained pressure values were converted from Pa to bars using Eq. (3), as follows:

$$P_{bar} = \frac{P}{10^5} \tag{3}$$

This conversion is based on the relationship that 1 bar is equal to 100,000 pascals. Calibration was performed by weighing the standardized weight values with respect to the sensor readings.

The pressure sensor was calibrated using a reference loading method with standardized weights using a hydraulic cylinder assembly. Calibration was performed at various points over a pressure range within which the pressure sensor operated properly. The calibration was performed at multiple load points. The measured hydraulic pressure was converted to the draft force using the following equation:

$$F = P \times A \tag{4}$$

where, F is the draft force (N), P the hydraulic pressure (Pa), and A the piston area of the hydraulic cylinder in square meters. The calculated force values were converted to kilonewtons (kN) for analysis. The calibration curve revealed a linear relationship between the sensor output and the load applied within this range. From the calibration results, a linear relationship can be established to relate the measured pressure to the applied load. This relationship is expressed by the following equation:

$$F = aP \times b \tag{5}$$

where, a and b are the calibration factors. From the calibration curve, it is clear that there is a high coefficient of determination, given that R^2 = 0.997. The deviation was within ±2%.

2.3.2 Slip ratio measurement module

The MPU6050 IMU was placed at the back of the operating seat to measure the linear acceleration. The ESP32 calculated:

• Theoretical velocity (V_t): obtained with the implement lifted.

• Practical velocity (V_p): obtained during soil penetration.

The slip ratio was then calculated in real time as follows [13]:

$$\text{Slip Ratio}(\%) = \frac{V_t - V_p}{V_t} \times 100 \tag{6}$$

All values were directly sent to the Blynk Cloud for real-time monitoring. The ESP32 microcontroller utilized the IMU data to calculate the theoretical velocity (V_t) with the implement raised and practical velocity (V_p) with the soil engaged. To reduce the effect of noise and drift associated with the accelerometer-based velocity calculation, a moving-average filter with a window size of ten samples was applied to the IMU acceleration signal prior to velocity estimation to reduce the high-frequency noise and mitigate the short-term drift effects. This approach is computationally efficient and suitable for real-time, embedded applications. The variables were used to compute the slip ratio in real time, with all data transmitted wirelessly to the Blynk Cloud dashboard for immediate monitoring (Figure 3).

Figure 3. Installation of the MPU6050 IMU module behind the operator's seat for real-time velocity and slip ratio measurement

2.3.3 Fuel consumption measurement module

In all measurement modules, the workflow included signal acquisition, signal conversion, calibration, digital processing by the ESP32, wireless transmission of the data, and real-time visualization of the results using the Blynk platform. The draft force module converts the hydraulic pressure into force, the slip ratio module calculates both the theoretical and practical speeds from the inertial IMUs, and the fuel module calculates the net volumetric flow from the inlet and return flow signals.

Two YF-S401 sensors were mounted, as illustrated in Figure 4.

• Sensor 1: Fuel inlet to the engine.

• Sensor 2: Fuel return line back to the tank.

The ESP32 calculated the pulses from each sensor to determine the flow rate based on the calibration constant (pulses/L) provided by the manufacturer.

The net fuel consumption was derived as follows:

$$Q_{\text{net}} = Q_{\text{inlet}} - Q_{\text{return}} \tag{7}$$

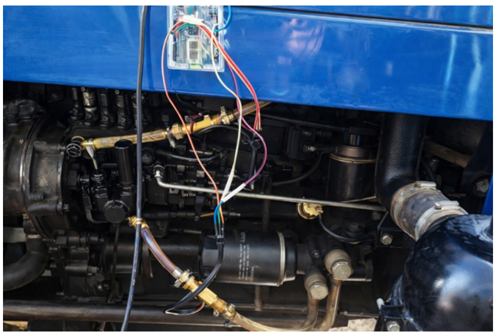


Figure 4. Integration of ESP32 and dual YF-S401 flow sensors for real-time fuel

The fuel density was set to 802 g/L to convert mass to volume.

Before the field tests, individual calibrations were conducted for each YF-S401 flow sensor. The sensor readings in terms of pulse signals were transformed into volumetric flow rates using the calibration coefficient provided by the manufacturer in pulses per liter. The ESP32 microcontroller processed the inlet and return fuel signals in a single acquisition cycle to facilitate the synchronized measurements. The net fuel consumption was determined based on the difference between the two flow rate measurements.

To validate the measurements, a gravimetric method with an external 5-L fuel tank was implemented. The fuel mass was measured using a high-precision balance before and after each experiment. The volume of the fuel was determined using the density of the standard fuel, which was 802 g/l. The measurements obtained using the sensor were in good agreement with the results obtained using the reference method, indicating that the proposed system provides reliable and accurate fuel consumption measurements.

2.4 Internet of Things Cloud Integration

Each ESP32 device was connected wirelessly to the central IoT dashboard through the Blynk.cloud platform.

The data were transmitted every 200–500 ms; therefore, visualization was near real-time. As shown in Figure 5, the IoT dashboard provides continuous monitoring of the draft force, wheel slip, and fuel.

The data acquisition system was designed using ESP32 microcontrollers and programmed to operate in a predetermined sampling loop. In the sampling loop, the pressure and fuel flow sensors were continuously sampled, and the processed data were sent to the Blynk cloud platform at intervals of 200–500 ms.

The IMU sensor used for the slip ratio estimation operated within the same acquisition framework. A moving average filter with a window size of ten samples was applied to reduce the measurement noise. Based on the system update interval, this corresponds to a filtering duration of approximately 2–5 s.

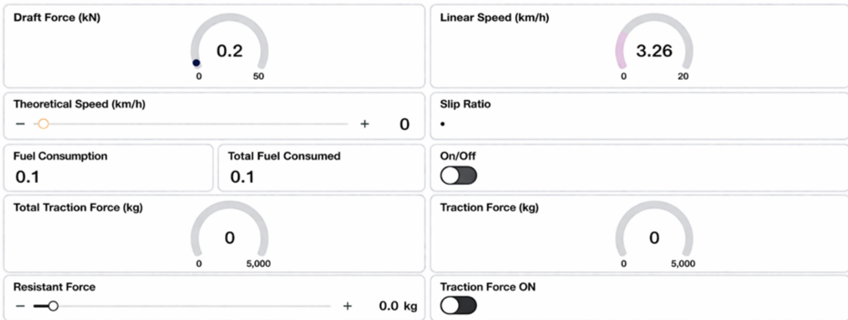


Figure 5. Internet of Things (IoT)-based dashboard interface on Blynk Cloud for real-time monitoring of tractor

Acceleration data from the IMU were recorded after a stationary initialization step to establish a zero-reference baseline for the velocity estimation. The filtered acceleration signal was numerically integrated over short-duration intervals corresponding to each experimental run. To reduce drift effects, the sensor was reinitialized before each test, and integration was limited to steady-state operation periods.

The synchronization of different measured parameters was achieved at the system level by utilizing separate ESP32 modules for each parameter measurement: draft force, slip ratio, and fuel consumption. Each of these modules operated within a single data acquisition loop, sending the measurements to an IoT platform.

All the sensor data were sampled at a frequency of 5 Hz. To ensure synchronization, each data packet was assigned a timestamp, and the data streams from the different modules were aligned during processing.

2.5 Field Experiment

2.5.1 Experimental site

- Location: Silty clay soil, Al-Mussaib region.
- The tractor used was a Massey Ferguson Xtra 470 (4WD).

Implements:

- Moldboard plow.
- Offset disc harrow.

The field plots were 100 m long, with a 20 m acceleration zone for speed stabilization.

The soil moisture was maintained at 18–20% during the trials.

2.5.2 Experimental procedure

(a) Draft force testing

- The tractor was pulled by an auxiliary tractor without connecting it to the implement to determine the resistance of motion.
- The implement was activated at the designated depths and speeds.
- Each measurement was performed three times to ensure accuracy.
- The draft force readings were compared with those of a mechanical dynamometer.

(b) Slip ratio testing

• The tractor was operated at its maximum speed, with the implement raised.
• The implementation was performed to measure the actual speed.
• The slip ratio was measured electronically, and its accuracy was verified using a stopwatch.
(c) Fuel consumption testing
• The External 5-L tank was filled with 4 L of fuel.
• The weights of the mice were measured before and after each run using a precision scale.
• The electronic and traditional measurements were compared.

Each experiment was performed in triplicate, and the values obtained were the average of the readings from the experiment to ensure accuracy.

2.5.3 Performance indicators

The key performance metrics were calculated using standard engineering equations [14].

Tractive efficiency:

$$TE(\%) = \frac{P_{FT}}{P_A} \times 100 \quad (8)$$

Field efficiency:

$$FE(\%) = \frac{P_p}{P_t} \times 100 \quad (9)$$

where,
• P_p = practical productivity;
• P_t = theoretical productivity.

Measurement reproducibility and reduction of random experimental errors were achieved by repeating each experimental condition three times for each sample. The final reported numbers represent the averages of the repeated measurements. The final data represented the mean of repeated measurements. The coefficient of variation derived from the repeated measurement method was $<3\%$, which is advantageous for the proposed monitoring system.

2.6 Measurement Uncertainty Analysis

The combined uncertainty was estimated using the root-sum-square method as follows:

$$U_c = \sqrt{u_1^2 + u_2^2 + u_3^2} \quad (10)$$

where, U_c is the combined uncertainty, and u_1^2, u_2^2, u_3^2 represent the contributions from sensor accuracy, ADC resolution, and calibration error, respectively.

These sensor-level uncertainties propagate to the final estimates of the draft force, slip ratio, and fuel consumption, and therefore affect the reported agreement with the conventional reference methods.

The uncertainty of the proposed measuring system was assessed by examining the sensor accuracy, analog-to-digital conversion resolution, and calibration error. Aggregate uncertainty was calculated using the root-sum-square approach.

The uncertainty analysis was further expanded to consider the incorporation of the last measured parameters of the system: the draft force, slip ratio, and fuel consumption.

The uncertainty in measuring the draft force is mainly related to the pressure sensor accuracy, calibration process, and uncertainties related to the hydraulic system parameters.

The uncertainty in measuring the slip ratio is related to the noise observed in the IMU sensor output, filtering processes, and numerical integration processes, which may cause deviations during the estimation process.

The uncertainty in measuring the fuel consumption is related to the flow sensor calibration process and some synchronization errors between the inlet and return flow signals.

The uncertainty analysis for the proposed system was determined using the root sum square (RSS) method, which considers the combined uncertainty related to each uncertainty source. The combined uncertainty of the proposed system remained within acceptable limits for measuring agricultural fields.

The propagation of measurement uncertainties to the derived parameters was also evaluated. Using the combined uncertainties of the sensors and calibration method, the estimated uncertainties in the derived parameters were within the ranges of ±3%, ±2%, and ±1.5% for the draft force, slip ratio, and fuel consumption, respectively. This demonstrates that the proposed system can be considered accurate for field applications.

The uncertainty analysis of the sensors used in the monitoring system is presented in Table 1.

Table 1. Measure uncertainty of the sensors used in the proposed monitoring system

Sensor	Range	Manufacturer Accuracy	Estimated Uncertainty
T12C pressure sensor	0–250 bar	±0.5%	±0.7%
MPU6050 IMU	±16 g	±0.3%	±0.6%
YF-S401 flow sensor	1–30 L/min	±1%	±1.3%

3 Results

The performance of the designed IoT-based smart electronic system for agriculture was tested for accuracy, responsiveness, and robustness through extensive field testing. These experimental results were validated by comparing them with traditional measurements to determine their reliability in verifying the functionality of the sensors and data acquisition modules integrated into the system.

3.1 IoT Data Transmission Performance

The response time of the IoT monitoring system was evaluated during field operations to determine its ability to communicate real-time measurement results from the tractor to a cloud monitoring platform. The average delay in transmitting the measurement values ranged between 200 and 500 ms and was mainly affected by factors such as network signal quality and wireless communication load during the experiment in an agricultural field.

The average transmission delays observed during the field experiments are listed in Table 2.

Table 2. Average data transmission delay of the Internet of Things (IoT) monitoring system

Parameter	Transmission Delay
Draft force	230 ms
Slip ratio	210 ms
Fuel consumption	240 ms

3.2 Effect of Speed on Draft Force

Table 3 shows the variation in the draft force with forward speed for both the implements. For the moldboard plow, the draft force measured by the smart system increased monotonically with increasing forward speed. The measured values increased from 19.46 kN at 3.84 km/h to 21.54 kN at 4.81 km/h. Similarly, for the conventional method, the measured values increased from 20.31 kN to 22.43 kN for the same range of forward speeds.

Table 3. Average data transmission delay of the Internet of Things (IoT) monitoring system

Implement Type	Speed (km/h)	Draft Force-Smart System (kN)	Draft Force-Traditional (kN)
Moldboard plow	3.84	19.74	20.31
Moldboard plow	4.81	21.54	22.43
Offset disc harrow	4.74	17.48	16.81
Offset disc harrow	6.75	19.46	18.60

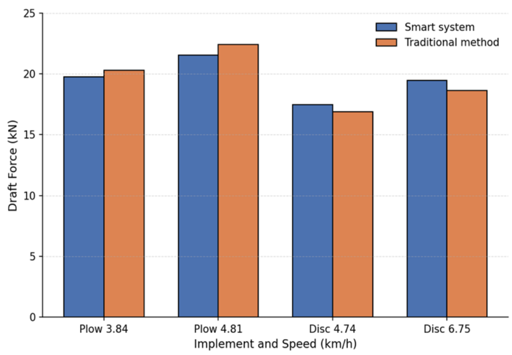


Figure 6. Draft force measured by the smart system and the traditional method at different speeds and implements

Similarly, for the offset disc harrow, the draft force measured by the smart system increased monotonically from 17.48 to 19.74 kN.

The results show that a positive correlation exists between the forward speed and draft force for both implements, as shown in Figure 6.

3.3 Empirical Draft Force Prediction Model

A regression model was developed using experimental draft force data collected from the tested operating speeds. In this study, a simple single-variable linear regression model was adopted to provide a computationally efficient approximation suitable for real-time field implementation. The model was intended as a supporting empirical predictor, rather than a generalized mechanistic model. Because the available dataset was limited to one site, one soil type, and two implements, the model should be interpreted as being condition-specific. Future work will extend the model by incorporating additional predictors, such as working depth, soil conditions, and implement type.

The draft force is expressed as:

$$D = a + bV \tag{11}$$

where, D is the draft force (kN); V is the tractor's forward speed (km/h); a and b represent the empirical coefficients obtained through the application of the least squares regression method. Table 4 lists the regression coefficients obtained from the experimental dataset.

Table 4. Regression coefficients of the draft force prediction model

Parameter	Value
a	14.72
b	1.38
R^2	0.96

The regression model showed good agreement with the experimental data, with R^2 = 0.96 and RMSE = 0.52 kN.

3.4 Effect of Speed on Wheel Slip Ratio

From the experimental results, it can be observed that the slip ratio of the wheel increases with the increase in the operating speed of the tractor, and this holds true for both the moldboard plow and offset disc harrow. Two methods were used to record the slip ratio: a smart IoT-based monitoring system and a conventional method using a stopwatch.

For the moldboard plow, the slip ratio values increased from 11.34% at a speed of 3.84 km/h to 14.31% at a speed of 4.81 km/h using the smart monitoring method, where as the conventional method recorded values increasing from 11.09% to 14.82% at the same speeds.

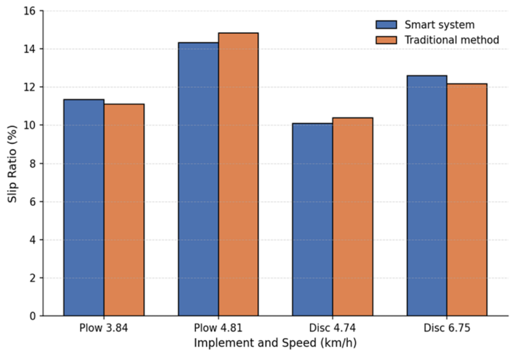


Figure 7. Wheel slip ratio measured by the smart system and the traditional method at different speeds and implements

For the offset disc harrow, the slip ratio values were observed to increase from 10.10% at 4.74 km/h to 12.60% at 6.75 km/h using the smart monitoring system, where, as the conventional method recorded slip ratio values increasing from 10.38% to 12.17%. The measured slip ratio values are listed in Table 5.

The relationship between the operating speed and slip ratio is illustrated in Figure 7.

Table 5. Wheel slip ratio at different speeds

Implement Type	Speed (km/h)	Slip Ratio-Smart System (%)	Slip Ratio-Traditional (%)
Moldboard plow	3.84	11.34	11.09
Moldboard plow	4.81	14.31	14.82
Offset disc harrow	4.74	10.10	10.38
Offset disc harrow	6.75	12.60	12.17

The slip ratios measured by the smart system were close to those obtained using the stopwatch-based method, confirming that the proposed IMU-based procedure was sufficiently sensitive to capture the increase in wheel slip with the operating speed.

3.5 Effect of Speed on Fuel Consumption

Fuel consumption per hectare was evaluated through field trials using the smart IoT monitoring system and the conventional method of gravimetric analysis.

Regarding the fuel consumption of the moldboard plow, the data provided by the smart IoT monitoring system showed that the fuel consumption per hectare decreased from 35.92 L/ha at 3.84 km/h to 33.34 L/ha at 4.81 km/h. Similarly, the conventional method of fuel consumption measurement showed a reduction in fuel consumption per hectare from 35.81 to 33.23 L/ha.

Regarding the fuel consumption of the offset disc harrow, the data provided by the smart IoT monitoring system showed that the fuel consumption per hectare decreased from 12.38 L per hectare at 4.74 km/h to 10.29 L per hectare at 6.75 km/h.

The measured fuel consumption values are presented in Table 6.

Table 6. Fuel consumption at different speeds

Implement Type	Speed (km/h)	Fuel Consumption-Smart (L/ha)	Fuel Consumption-Traditional (L/ha)
Moldboard plow	3.84	35.92	35.81
Moldboard plow	4.81	33.34	33.23
Offset disc harrow	4.74	12.38	12.29
Offset disc harrow	6.75	10.29	10.50

The relationship between the tractor speed and fuel consumption for both implements is illustrated in Figure 8.

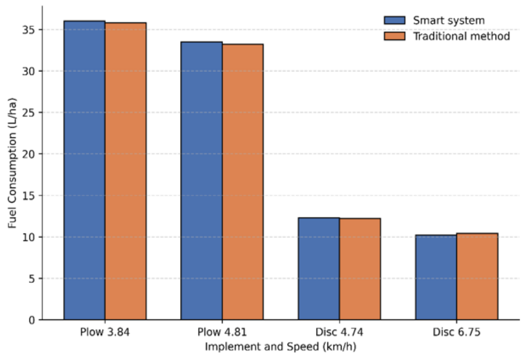


Figure 8. Fuel consumption measured by the smart system and the traditional method at different speeds and implements

The reduction in fuel consumption per hectare with an increase in speed indicated an increase in field productivity per unit of time, and the close agreement between the two methods validated the dual-sensor flow arrangement.

3.6 Statistical Validation of the Proposed Measurement System

To assess the dependability of the proposed monitoring system, a statistical error analysis was conducted by comparing the smart IoT-based measurements with the conventional measuring methods. The coefficient of determination (R^2), RMSE, and MAE were computed for each assessed parameter.

The accuracy of the proposed system was calculated based on the relative deviation between the smart monitoring system and conventional reference measurements, as follows:

$$\text{Accuracy}(\%) = 100 - \left(\frac{|M_s - M_r|}{M_r} \times 100\right) \quad (12)$$

where,

M_s: measurement from smart system;

M_r: reference measurement from conventional method.

A statistical comparison between the smart monitoring system and conventional measurement methods is presented in Table 7.

Table 7. Statistical accuracy evaluation of the proposed Internet of Things (IoT)-based measurement system

Parameter	R^2	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	Accuracy
Draft force	0.96	0.41 kN	0.32 kN	96.81%
Slip ratio	0.97	0.36%	0.28%	97.35%
Fuel consumption	0.98	0.24 L/ha	0.19 L/ha	98.39%

4 Discussion

The experimental results of this study confirmed the validity and efficacy of the proposed IoT-based monitoring system for measuring the most important parameters of tractor performance under real working conditions. The proposed IoT-based tractor performance monitoring system includes embedded sensors and wireless communication with cloud-based monitoring, enabling the real-time analysis of tractor working parameters. IoT-based monitoring systems have been implemented in smart agricultural systems to increase operational efficiency and enable better decision-making using data analysis [1, 4, 11].

4.1 Draft Force Behavior

The experimental results clearly show that the draft force increased with an increase in the working speed of the tractor for the moldboard plow and offset disc harrow. This may be explained by the increase in soil resistance when the working speed of the tractor increases, thus requiring a higher draft force. This finding is consistent with the relevant literature. It has been reported that soil penetration resistance increases with increasing working speed, which leads to higher traction requirements and draft force demands [15]. Similar observations have been recorded during research on the tilling mechanisms of agricultural fields, where, a linear relationship between the tractor speed and draft force was observed owing to soil displacement and friction forces between the tilling equipment and soil [14, 16].

Furthermore, the draft force is highly susceptible to different rates of variation in tractor operating speeds, particularly for cohesive soils, such as silty clay soils [17]. Experimental research on tractor dynamics has demonstrated significant variations in tractor loads and traction forces at different rates of variation in tractor speeds [18].

The similarity between the smart monitoring system and traditional dynamometer measurements confirmed the reliability of the proposed measurement approach. Similar observations have been recorded in research on electronic measurement systems, showing that electronic sensors can produce accurate measurements similar to those of traditional dynamometers when properly calibrated [19, 20].

Minor differences between the two methods may be related to pressure sensor calibration uncertainty, hydraulic response lag, and vibrations during field operation.

4.2 Wheel Slip Behavior

The experimental results revealed that the wheel slip ratio increased with increasing tractor speed for both implements. This behavior is mainly attributed to the higher tractive effort required at higher operating speeds. As the tractor velocity increased, the gap between the calculated wheel rotation speed and actual speed increased, thereby causing increased wheel slippage.

Previous studies have revealed similar trends in tractor-traction performance. Research on electric and conventional tractors has demonstrated that wheel slip increases when the operating speed and traction load increase, particularly during heavy tillage operations [6, 21]. In addition, theoretical analyses of tractor traction mechanics have indicated that slip ratios tend to increase significantly when the traction demand approaches the maximum allowable limit for wheel–soil interaction [22].

High wheel slips may affect the efficiency of the tractor, which may be reflected in terms of increased energy losses and reduced traction efficiency of the tractor. Experimental studies on tractor traction systems have shown that high slip rates reduce the efficiency of tractors and increase energy consumption [23, 24].

The results demonstrate that the IMU-based smart monitoring system can accurately measure slip ratios. Electronic measurement systems, such as the proposed system, have been successfully used to measure wheel slip and traction characteristics of tractors [25, 26].

The possible error sources in slip estimation include IMU drift, vibration-induced acceleration noise, and uncertainty in the transition between the raised and engaged operating conditions.

4.3 Fuel Consumption Behavior

Contrary to the behavior of the draft force and wheel slip, the results revealed that the fuel consumption per hectare decreased with an increase in the operating speed of the tractor. This is because tractors can cover a larger area in the same amount of time.

This finding is supported by the results of other studies on the operational efficiency of tractors. Studies on the performance of agricultural machinery have established that the optimal combination of tractor power and operating speed can improve agricultural productivity while reducing fuel consumption during tillage operations [27, 28].

Furthermore, research on tractor performance indicates that fuel efficiency can be enhanced when tractors operate within optimal parameters, specifically at 70%–80% of the engine's rated power. Under these conditions, the efficiency of the engine is maximized, thus reducing the fuel consumption per hectare [29, 30].

The high precision of the fuel consumption measurement of the smart monitoring system can be supported by the results obtained from the evaluation of the performance of the electronic fuel flow measurement system. The performance of the electronic fuel flow measurement system was evaluated, and it was found that the system could provide high-precision fuel consumption measurements [31].

Differences between the smart and conventional fuel measurements may arise from pulse quantization, sensor response time, and synchronization of the inlet and return-flow measurements.

4.4 Computational Model Interpretation

The proposed regression-based computational model can be used as a simple method for estimating the draft force as a function of the operating speed of a tractor. Based on the high coefficient of determination, the results show a high correlation between the operating speed and draft force under the experimental conditions.

Such computational prediction models can be very useful in assisting decision-making processes in precision agriculture systems. When integrated with IoT-based monitoring systems, the computational prediction model can assist the operator in estimating the power required during the operation of the tractor [1, 12].

The simplicity of the model affords fast computation, rendering it suitable for real-time field applications.

Although a linear regression framework was adopted in this study because of its simplicity, more advanced machine learning approaches could be adopted in the future to improve the accuracy of the predictions.

4.5 Limitations of the Proposed System

This validation was performed under a restricted set of conditions, including a single type of silty clay soil, a single experimental site, a single type of tractor, two types of implements, a restricted range of travel speeds, and three repetitions for each test condition. Therefore, the results obtained regarding the model performance and degree of accuracy in the measurements must be considered within the restricted conditions set for the test.

Notably, the proposed system has a usage time of 6–8 h using a rechargeable battery. This period is sufficient for most agricultural activities in the region. However, a more powerful battery or optimization technique may be necessary to improve the efficiency of the proposed system.

Improving the proposed system will involve improving the calibration of the sensors and implementing advanced machine-learning techniques to improve its accuracy.

5 Conclusions

This study presented the design and implementation of an IoT-based smart electronics system for monitoring tractor operational parameters, such as draft force, wheel slip ratio, and fuel consumption, using ESP32-based data acquisition systems.

Field tests resulted in high levels of accuracy for the designed system: 96.81% for draft force calculation, 97.35% for slip ratio calculation, and 98.39% for fuel consumption values compared to the traditional analysis using mechanical and gravitational methods. The results verified the appropriate use of the sensors (T12C, MPU6050, and YF-S401) and the effectiveness of the ESP32 microcontroller for data acquisition during field operations.

This system also exhibited responsiveness and stability for IoT data transmission ranging between 200 and 500 ms, which helped continuously monitor performance indicators during field operations. The draft force and slip ratio tended to increase with increasing tractor speed and decreased fuel consumption per hectare.

In general, an integrated IoT system may provide a cheaper option with scalability than classical mechanical measurement systems. The modularity of the proposed system facilitates its integration and extension for future analytical applications.

However, the system was evaluated under specific operating conditions, and its performance should be interpreted within the experimental scope.

The proposed system offers a cost-effective solution for the real-time monitoring of the performance of agricultural equipment. The integration of embedded sensors with IoT cloud platforms offers considerable potential for precision agriculture and future intelligent farm-management systems.

Author Contributions

Conceptualization, N.A.J. and H.F.M.; methodology, N.A.J.; software, R.A.O.; validation, N.A.J., R.A.O., and H.F.M.; formal analysis, H.F.M.; investigation, N.A.J. and R.A.O.; resources, H.F.M.; data curation, N.A.J.; writing—original draft preparation, N.A.J.; writing—review and editing, H.F.M.; visualization, R.A.O.; supervision, H.F.M.; project administration, H.F.M. All authors have read and agreed to the published version of this manuscript.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Nomenclature

D	Draft force
V	Tractor forward speed
S	Slip ratio
FC	Fuel consumption rate
T	Data transmission delay
R^2	Coefficient of determination
a	Regression model constant
b	Regression coefficient related to speed
Fs	Traction force measured by load sensor
ω	Angular velocity of tractor wheel
V_{ref}	ADC reference voltage
V_{offset}	Sensor offset voltage
SF	Sensor sensitivity factor
P	Pressure
P_{bar}	Pressure
A	Piston area
F	Draft force
V_t	Theoretical velocity
V_p	Practical velocity
M_s	Measurement from smart system
M_r	Reference measurement from conventional method
U_c	Combined uncertainty
u_1, u_2, u_3	Uncertainty components