Journal of Intelligent Systems and Control
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Evaluation of the Accuracy and Consistency of Variable Reluctance Sensors for Turbine Speed Monitoring in Steam Turbine Generator 1.0 at Tambak Lorok CCPP

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Received: 11-01-2024 **Revised:** 12-16-2024 **Accepted:** 12-23-2024

Citation: A. A. Hadi and A. A. Fikri, "Evaluation of the accuracy and consistency of variable reluctance sensors for turbine speed monitoring in steam turbine generator 1.0 at Tambak Lorok CCPP," *J. Intell Syst. Control*, vol. 3, no. 4, pp. 239–250, 2024. https://doi.org/10.56578/jisc030404.

Abstract: Accurate monitoring of turbine speed is essential for ensuring operational stability and efficiency in power generation systems, particularly within the context of low-carbon and renewable energy integration. This study evaluates the performance of three Variable Reluctance Sensors (VRSs)—VRS1, VRS2, and VRS3—used for real-time speed monitoring of the Steam Turbine Generator (STG) 1.0 at the Tambak Lorok Combined Cycle Power Plant (CCPP). The evaluation was conducted using statistical methods, including Root Mean Square Error (RMSE), standard deviation, and two-factor Analysis of Variance (ANOVA) without replication, to assess the accuracy and consistency of the sensors under varying operational conditions. The operational conditions were simulated through a motor controlled by a Variable Speed Drive (VSD), which allows for precise control over speed variations. The results indicate that the VRSs exhibit high accuracy and reliability, with RMSE values ranging from 0.08% to 0.28%. Among the three sensors, VRS3 demonstrated the highest performance, achieving minimal variability, with a standard deviation of 0.000 at a frequency of 50.00 Hz. ANOVA revealed no significant differences in performance between the three sensors (P-value = 1.000), suggesting uniformity in their measurement capabilities. These findings substantiate the suitability of VRSs for turbine speed monitoring in power plants, ensuring operational stability and supporting the integration of renewable energy technologies. The results reinforce the potential of VRSs as a reliable tool for improving the efficiency of sustainable energy systems.

Keywords: Variable Reluctance Sensor (VRS); Standard deviation; Root Mean Square Error (RMSE); Tambak Lorok Combined Cycle Power Plant (CCPP)

1 Introduction

Renewable energy is environmentally friendly and does not damage the surrounding environment, especially in standalone photovoltaic power plants [1]. However, its intermittent nature often challenges maintaining power quality and efficiency [2]. In particular, accurate monitoring of turbine speed plays a critical role in optimizing power plant performance and ensuring operational stability.

One of the crucial aspects in improving the performance of renewable energy plants is accurate monitoring of turbine speed [3]. Stable turbine speed is essential to ensure operational efficiency and the quality of power generated. Variations in turbine speed can cause instability in the electrical system, ultimately affecting the plant's overall performance [4]. Therefore, using appropriate sensors to monitor turbine speed becomes very important.

A CCPP is a power plant that integrates gas turbines and steam turbines to maximize energy efficiency by utilizing the residual heat from the gas turbine combustion process [5]. At the Tambak Lorok CCPP, the STG 1.0 plays a crucial role in converting the residual thermal energy into mechanical energy, which is then transformed into electricity through the steam turbine [6]. In typical operational conditions at CCPPs, the system operates at a frequency of 50 Hz, with the turbine spinning at approximately 3000 revolutions per minute (RPM). These conditions are essential for maintaining the stability and efficiency of the power plant. Monitoring turbine speed under these conditions ensures the system operates within the optimal performance range.

Monitoring turbine speed in real-time using VRSs is vital to ensure system stability and improve the reliability of energy conversion processes. This study evaluates the accuracy and consistency of VRSs under varying operational conditions, aiming to enhance the reliability of turbine speed monitoring systems in the context of renewable energy integration at the Tambak Lorok CCPP. Turbine speed, a critical parameter for ensuring system stability and efficiency, is monitored in real time using a VRS (The subgraph (a) of Figure 1). This sensor provides accurate data to support the control and optimization of turbine performance [7].

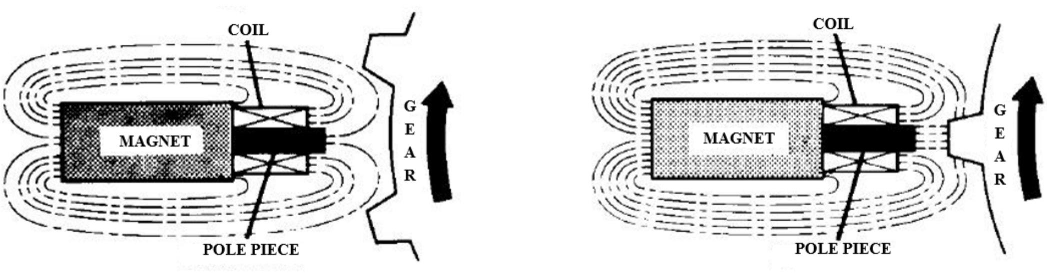
(a) (b)

Figure 1. (a) VRS; (b) Main components of VRS [8]

The main components of the VRS (The subgraph (b) of Figure 1) include the pole piece, which directs the magnetic field toward the metallic target; the coil, which induces electrical signals based on changes in the magnetic field; and the magnet, which generates the magnetic flux [9]. Potting protects the internal components from vibration and dust, while the shell provides mechanical protection [10]. The connector links the sensor to external systems, and the connector pins transmit the output signals from the coil to external cables [11].

The VRS operates by detecting changes in the magnetic field generated by a permanent magnet within the sensor, which is directed through the pole piece [9]. The basic operating principle of this sensor relies on the movement of a metallic target, such as gear teeth or a sprocket, passing through the pole piece [9]. During the detection process, two primary positions influence the magnetic flux: the high reluctance position (The subgraph (a) of Figure 2) occurs when the target teeth are not aligned with the pole piece, resulting in high magnetic reluctance [12]. This reduces the magnetic flux passing through the coil, causing the induced signal to weaken or even drop to zero [13].

At the low reluctance position (The subgraph (b) of Figure 2), the target teeth align with the pole piece, reducing magnetic reluctance and allowing the magnetic flux to flow more easily. This alignment generates a higher electrical voltage through pulses [14]. The resulting changes are induced into the coil, producing signals that indicate the target's positional changes.



(a) (b)

Figure 2. (a) High reluctance position; (b) Low reluctance position [15]

Inaccuracy in the VRS at STG 1.0 of the Tambak Lorok CCPP can lead to serious consequences, including turbine trips. In this system, six VRSs are utilized: three units for monitoring turbine speed and three others as safety trip sensors. A trip occurs if one of the sensors malfunctions or if the generated signal indicates that the turbine speed has fallen below the operational standard of 3000 RPM. This speed is a critical value that must be maintained to ensure turbine stability and safety.

In the STG 1.0 turbine system, the installed spur gear has 60 teeth [16]. The VRS is configured to detect changes in the magnetic field generated by these teeth as they rotate [17]. Each wave (1 Hz) produced by the VRS corresponds directly to one RPM of the turbine [18]. Therefore, a single pulse from the VRS represents one RPM.

The signal generated by the VRS, in the form of frequency, is processed by the MARK V system, equipped with three redundant processors (R, S, and T) to enhance system reliability. However, if two trip sensors fail or provide incorrect readings, the turbine will automatically shut down to prevent further damage. Therefore, accuracy testing of the VRS is crucial to ensure its proper functionality. During testing, a motor is used as the speed input, and the VRS output is tested with a multimeter to measure frequency (Hz). Meanwhile, the MARK V system calculates the speed percentage relative to the turbine's maximum value. This validation ensures the sensor operates optimally and prevents erroneous readings that could cause unexpected turbine trips.

This testing process enables the control system to monitor real-time changes in the turbine shaft's rotational speed. In the control room, the output signal from the VRS is displayed as the TNH parameter (turbine speed or turbine shaft speed), providing a visual representation of the turbine's speed. This parameter is shown in RPM, offering clear information about the turbine's operational status.

2 Literature Review

The turbine speed monitoring system is crucial in ensuring power plant operations' stability and efficiency, particularly in CCPPs. VRSs are widely used for their reliability and capability to detect turbine speed in real time. These sensors operate by converting changes in the magnetic field into electrical signals, which are then processed to produce accurate data for turbine control [19]. In an operational context, VRSs help prevent severe disruptions, such as turbine trips, when the speed falls below the operational standard.

To provide a clearer understanding of the strengths and weaknesses of VRSs relative to other sensor technologies, VRSs were compared with optical and capacitive sensors, as shown in Table 1. This comparison highlights their advantages, limitations, and relevance to turbine speed monitoring in renewable energy systems and power plant operations.

Table 1. Comparison of VRS, optical, and capacitive sensors

Sensor Types	Advantages	Limitations	Relevance to VRS
VRS	High reliability and real-time speed monitoring; tolerant to harsh environments (vibrations and dust).	Sensitive to extreme electromagnetic interference; possible requirements of a precise alignment for optimal performance.	Proven in CCPP applications (e.g., Tambak Lorok); consistent results in renewable energy systems.
Optical sensor [20]	High resolution in clean environments; non-contact measurement reduces wear and tear.	Prone to environmental factors like dust, moisture, and vibrations.	It offers complementary benefits but is less suited for harsh industrial environments.
Capacitive sensor [21]	Effective in high-temperature environments; capable of measuring small displacements precisely.	Requires frequent calibration; performance may degrade in highly dynamic or variable environments.	Suitable for specific scenarios but lacks the robustness of VRSs for turbine speed monitoring applications.

Previous research has highlighted the significant potential of VRSs in industrial applications. Zhang et al. [22] found that the accuracy of VRSs in industrial environments exhibited an error margin of only ±0.3%. Civera and Surace [23] demonstrated that environmental factors, such as high temperatures and vibrations, impact sensor accuracy in wind turbines but can be mitigated through additional mechanical protection. While these findings indicate promising performance, further research is needed to address challenges such as measurement variability under more complex conditions.

Several advanced technologies have been developed to enhance the accuracy and consistency of VRSs. Statistical analysis techniques, such as RMSE and standard deviation, have been employed to evaluate measurement accuracy [24]. Additionally, measurement validation through data comparison from multimeters, tachometers, and modern control systems like MARK V has become a standard practice to ensure data consistency. Modern control systems are also equipped with processor redundancies, such as the R, S, and T processors in MARK V, designed to improve system reliability in handling potential errors.

Nevertheless, several research gaps still need to be addressed. Studies of the impact of rotational frequency on the performance of VRSs in CCPP environments remain limited [25]. Additionally, research comparing the performance of various VRSs under uniform operational conditions is scarce. Advanced statistical analyses, such as ANOVA without replication, are also underutilized for evaluating measurement variations between sensors and measuring instruments [26]. These gaps highlight the need for further research to enhance the reliability of VRSs in power plant applications.

The accuracy and consistency of several VRSs for turbine speed monitoring applications in CCPPs were evaluated in this study. Using three VRSs (VRS1, VRS2, and VRS3), the measurement results from a multimeter, tachometer, and the MARK V control system were compared. Statistical analyses, including RMSE, standard deviation, and ANOVA, were employed to assess sensor performance comprehensively. The research provides empirical evidence that VRSs are a reliable solution for turbine speed monitoring, particularly in the Tambak Lorok CCPP. It enriches the related literature with a data-driven approach. The following is a summary of the state of the art, highlighting the technical and comparative aspects of research and applications of VRSs, as presented in Table 2.

Table 2. Related studies and research contributions concerning VRSs

No.	Researchers	Research Focus	Methods	Findings and Contributions
1	Zhang et al.	Evaluation of VRS accuracy in industrial environments	Error margin analysis	VRSs showed an error margin of $\pm 0.3\%$ in industrial settings, demonstrating reliable performance.
2	Civera et al.	Environmental effects (high temperatures and vibrations) on sensor accuracy in wind turbines	Experimental testing and mechanical protection	Environmental factors can be mitigated with additional mechanical protection to maintain sensor accuracy.
3	Liu et al.	Use of statistical methods to assess VRS accuracy	RMSE and standard deviation analysis	Statistical methods effectively evaluated VRS accuracy under various operational conditions.
4	Sugiyanto et al.	Impact of rotational frequency on VRS performance in CCPP environments	Frequency analysis and ANOVA	The need for further evaluation of frequency effects on sensor performance was highlighted.

3 Method

This study employs a comparative experimental method, an experimental approach focused on comparisons [27]. The technique aims to compare measurement results against specific standards or benchmarks to evaluate the accuracy of VRSs. In the testing, a 0.5 HP motor with speed adjustments via a VSD was used as the driver, while the VRS was positioned with a 0.10 mm gap. Testing was conducted at six speed variations: 500 RPM, 1000 RPM, 1500 RPM, 2000 RPM, 2500 RPM, and 3000 RPM. The sensor output was measured using a multimeter and the MARK V control system. The first stage involved comparing measurements from the multimeter with those from a tachometer to ensure data consistency, while the second stage compared MARK V results with the tachometer to evaluate system output accuracy. This approach ensures the sensor operates accurately, preventing reading errors when installed in turbine systems. The research flowchart is shown in Figure 3.

Table 3. List of tools and specifications

No.	Tools	Specifications
1	Electric Motor	Power: 0.5 HP; voltage: 220 V; speed: 3000 RPM [28]
2	Honeywell VRS	Model: magnetic speed sensor; Type: 3-wire sensor [8]
3	Multimeter	Type: digital; accuracy: $\pm 0.5\%$; voltage range: $0-600$ V [29]
4	Tachometer	Type: laser; range: 10-99999 RPM; accuracy: $\pm 0.05\%$ [30]
5	VSD	Type: FR-D700; frequency range: $0.5-60$ Hz; max power: 0.75 kW [31]
6	Miniature (MCB) Circuit Breaker	Type: 1P; max voltage: $230/400$ V; max current: 6-32 A [31]
7	Feeler Gauge	Thickness: $0.05-1$ mm; material: stainless steel [32]

3.1 Equipment Preparation

This testing was conducted at STG 1.0 of the Tambak Lorok CCPP, Semarang, on September 18, 2024. To ensure the smooth execution of the VRS testing process, various tools and materials were meticulously prepared. This preparation aimed to support the measurement of sensor accuracy using standardized methods. The list of tools used in this testing can be seen in Table 3.

3.2 Frequency Adjustment of VSD

In measuring the rotational speed of a motor controlled by a VSD, it is essential to understand the relationship between the supply frequency and the motor's synchronous speed. Synchronous speed, which is the speed at which the magnetic field rotates within the motor, depends on the number of magnetic poles in the motor and the supply frequency. This relationship shows that an increase in supply frequency can raise the motor's synchronous speed, while an increase in the number of magnetic poles can decrease the synchronous speed [33]. The synchronous speed (N_s) can be calculated using the following formula:

$$N_s = \frac{120f}{p} \tag{1}$$

Synchronous speed (N_s) is the rotational speed of the magnetic field inside a motor, expressed in RPM; it depends on the supply frequency (f) measured in Hertz (Hz), and the number of magnetic poles (p) in the motor. For the same supply frequency, a standard single-phase motor has two magnetic poles (p = 2), simplifying the formula to:

$$f = \frac{N_s}{60} \tag{2}$$

Using this equation, the appropriate frequency for each motor speed can be calculated, as presented in Table 4.

Table 4. VSD frequency settings at various motor speeds

RPM	Frequency (Hz)
500	8.33
1000	16.67
1500	25.00
2000	33.33
2500	41.67
3000	50

3.3 VRS Testing

Performance validation testing is a method to ensure that the sensor operates according to the performance standards established under various operational conditions [34]. This method includes systematic steps, such as initial sensor calibration, testing under multiple variables, and verifying measurement results against reference instruments. In VRS testing, the evaluation ensures the accuracy of motor speed readings across various RPM variations, as shown in Figure 4. The process began with ensuring that the MCB on the VSD module is in the OFF position to avoid the risk of short circuits or electrical accidents during installation. Next, the 0.5 HP single-phase motor cable was connected to the output terminal of the VSD module, and the VRS (magnetic speed sensor) was installed strategically to detect the rotor's rotation. A feeler gauge with a thickness of 0.10 mm ensures a precise distance between the sensor and the spur gear, allowing the sensor to detect changes in motor speed accurately.

After all components were installed, the output cable from the VRS was connected to the multimeter set to frequency measurement mode. This step is essential to validate the sensor's output signal against the speed parameters. Once the connection was checked, the MCB on the VSD module was activated to supply power to the system. The frequency of the VSD module was adjusted according to the predefined testing variables, such as 500 RPM, 1000 RPM, and up to 3000 RPM. At each frequency, the measurement results from the multimeter were compared with the values obtained using the tachometer to ensure data consistency and system accuracy.

The final testing stage involved recording all results in a table containing the frequency variables (Hz), motor speed values (RPM), and any deviations between the multimeter and tachometer measurements. The test data was analyzed using statistical methods such as RMSE to evaluate the accuracy and consistency of the VRS. This analysis ensures that the VRS performs according to the required standards for turbine speed monitoring systems. Furthermore, this method provides validation that can be applied to real-world operational systems.

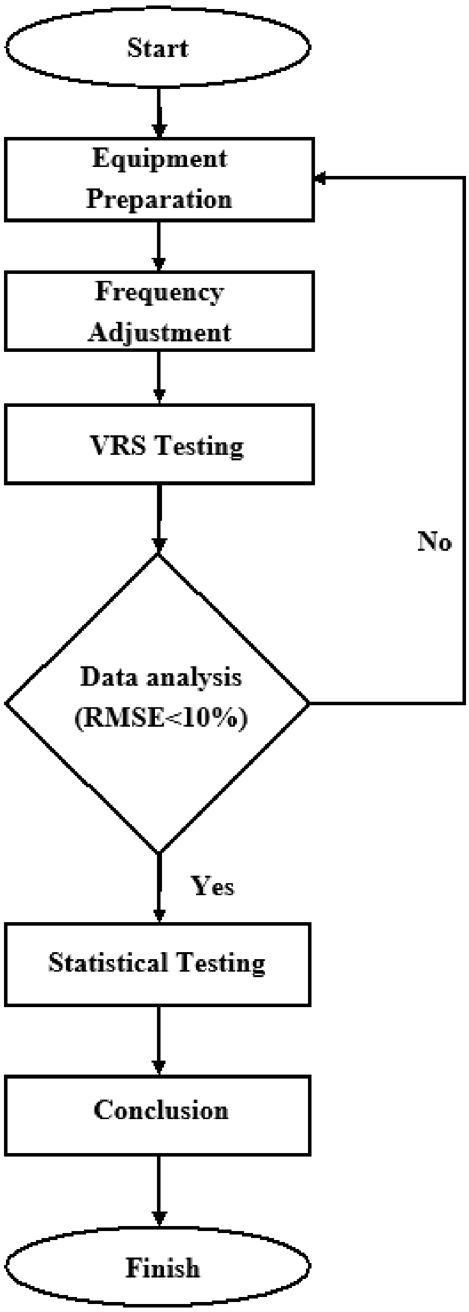


Figure 3. VRS testing flowchart

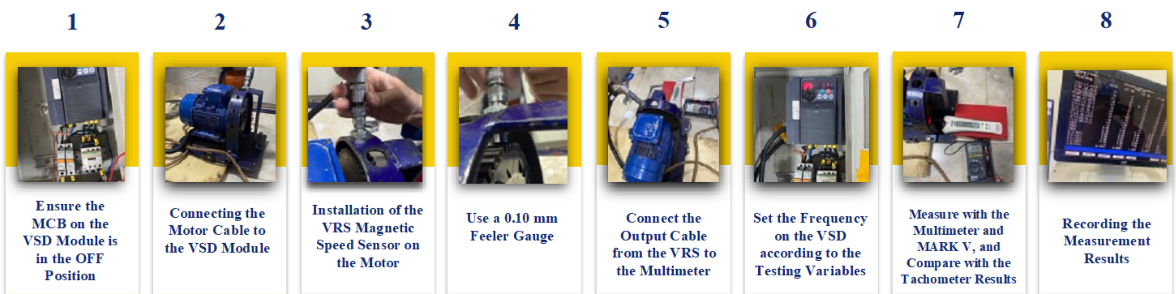


Figure 4. VRS testing diagram

3.4 Data Analysis and Statistical Testing

Measurements were taken using three VRSs. Data analysis was conducted by comparing the measurement results between the multimeter, tachometer, and Mark V with reference values. The following values were utilized for the data analysis.

a) RMSE (%)

RMSE calculates the difference between the values measured by the sensor (multimeter, tachometer, and Mark V) and the actual reference values. The RMSE calculation begins by finding the difference between the predicted values (sensor measurement results) and the actual values (reference values). These differences are then squared to avoid negative signs and give more weight to significant errors [26].

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{y_i} - \mathrm{\hat{y}_i})} \times 100\% \tag{3}$$

where, y_i is the reference value (the actual value or the value measured by the standard instrument), $\hat{y}_i$ is the value measured by the sensor, and n is the total number of measurements or data points used in the analysis.

b) Standard deviation

Standard deviation is used to measure the dispersion of measurement data from the average value [35] and is expressed by the following Eq. (4):

$$\sigma = \sqrt{\frac{\sum(\mathrm{x_i} - \overline{\mathrm{x}})^2}{\mathrm{n}}} \tag{4}$$

The measurement value (X_i) is the data obtained from the measurements; the average $(\bar{X})$ is derived from the measurement values; and the number of data points (n) is the total amount of data collected.

c) Two-factor ANOVA without replication

This test aims to identify whether there are significant differences in the motor speed readings produced by three types of sensors (VRS1, VRS2, and VRS3) and three measuring instruments (multimeter, tachometer, and MARK V). The results of this analysis are essential for evaluating the contribution of each factor to the data variability, whether from the sensor factor, the measuring instrument, or unidentified variations (residuals) [36]. Additionally, this method is highly relevant because it is efficient regarding resources and time, requiring no additional replications, making it suitable for the available data conditions.

4 Result

4.1 VRS1 Testing Result

The VRS1 testing results against the reference values show that all three measuring instruments, namely the multimeter, tachometer, and Mark V, produced values very close to the reference values at various VSD frequencies (Hz). VRS1 also demonstrated excellent performance, with the highest standard deviation of 0.635 at a frequency of 8.33 Hz and a minimum of 0.000 at 25.00 Hz. At the lowest frequency (8.33 Hz), the multimeter and tachometer recorded a value of 499.00 RPM, while Mark V recorded 500.10 RPM. As the frequency increased to 50.00 Hz, all instruments maintained good measurement consistency, with tiny variations from the reference values. The RMSE value for VRS1 also indicated very high accuracy, with a maximum value of only 0.22% at 8.33 Hz, which gradually decreased to a minimum of 0.00% at 25.00 Hz. The graph in Figure 5 illustrates the relationship between the VSD frequency, measurement results, and RMSE values, clearly showing that VRS1 provides excellent accuracy performance.

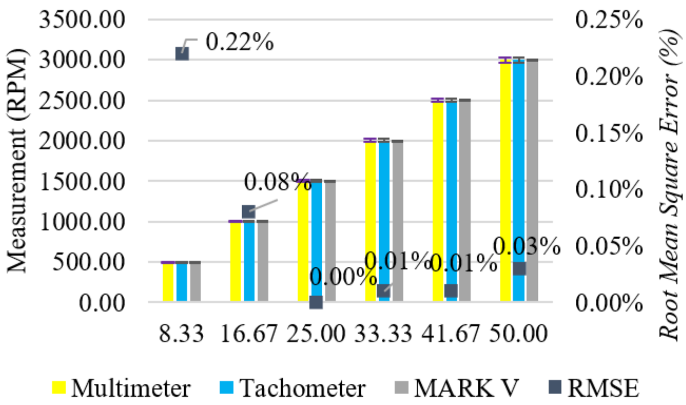


Figure 5. Comparison graph of the VRS1 measurement results with RMSE

4.2 VRS2 Testing Result

The VRS2 testing results show that measurements taken with the multimeter, tachometer, and Mark V were very close to the reference values at various VSD frequencies (Hz). VRS2 recorded the most significant variation, with a maximum standard deviation of 1.155 at 25.00 Hz. However, it still demonstrated consistency at specific frequencies, such as 16.67 Hz and 50.00 Hz ($\sigma = 0.000$). At the frequency of 8.33 Hz, there was a slight variation between the three instruments, with measurement values of 499.00 RPM (the multimeter), 500.00 RPM (the tachometer), and 500.40 RPM (the Mark V). However, these differences were still relatively small. At higher frequencies, the measurement results from all three instruments were almost identical to the reference values, such as at 50.00 Hz, which showed 3000 RPM. The RMSE values for VRS2 indicated high accuracy, with the lowest RMSE value reaching 0.00% at 16.67 Hz and 50.00 Hz, while the highest value was recorded at 8.33 Hz, at 0.28%. Overall, the test results in Figure 6 show that VRS2 provides consistent and accurate results with very low error rates.

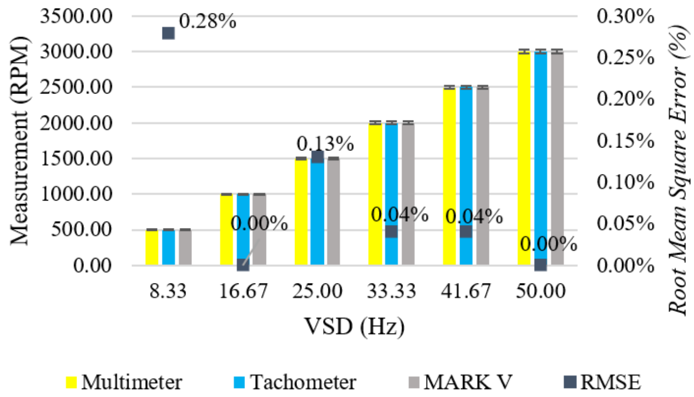


Figure 6. Comparison graph of the VRS2 measurement results with RMSE

4.3 VRS3 Testing Result

The VRS3 sensor testing results show that measurements with the multimeter, tachometer, and Mark V were almost identical to the reference values across all VSD frequencies (Hz), with minimal differences. VRS3 exhibited the most consistent performance among the three sensors tested, with a minimum standard deviation of 0.000 at 50.00 Hz and a maximum of 0.577 at 25.00 Hz. At 8.33 Hz, all three instruments measured 500.00 RPM (the multimeter), 500.00 RPM (the tachometer), and 500.10 RPM (the Mark V), while at higher frequencies, the measurements from all three instruments increasingly aligned with the reference values, such as at 50.00 Hz, which showed 3000.00 RPM. The RMSE values for VRS3 demonstrated excellent accuracy, with the lowest value of 0.00% at 50.00 Hz and the highest of only 0.08% at 16.67 Hz. Overall, the test results in Figure 7 indicate that VRS3 provides consistent and accurate measurements, with errors almost undetectable across the frequency range.

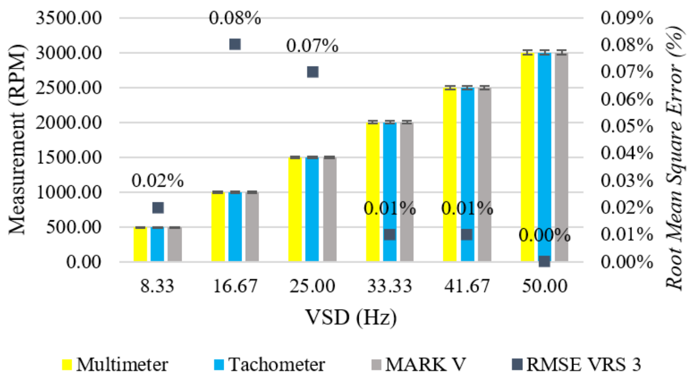


Figure 7. Comparison graph of the VRS3 measurement results with RMSE

The results show high accuracy and consistency among the sensors, with RMSE values ranging from 0.08% to 0.28%. VRS3 exhibited the best performance with minimal variability, achieving a standard deviation of 0.000 at

50.00 Hz. ANOVA confirmed no significant differences between the sensors or measuring instruments (P-value = 1.000).

However, it is essential to address potential sources of error that could influence sensor performance. Possible sources of error include environmental factors, such as temperature variations, mechanical vibrations, and electromagnetic interference, which may affect the accuracy of the VRS readings. Additional measures such as enhanced sensor shielding, improved mechanical mounting, and regular calibration should be implemented to mitigate these issues. Moreover, data redundancy using multiple sensors and advanced filtering algorithms can further minimize the impact of these errors on turbine monitoring accuracy.

4.4 Two-Factor ANOVA Without Replication

The results of the two-factor ANOVA without replication show no significant difference between the sensors used (VRS1, VRS2, and VRS3) or between the measuring instruments (the multimeter, tachometer, and MARK V), as shown in Table 5. The analysis results indicate that the sensors and measuring instruments provide consistent and accurate measurements, with no significant differences in motor speed readings across various VSD speed levels.

Table 5. Results of the two-factor ANOVA without replication test

Source of Variation	SS	df	MS	F	P-Value	F-Critical
Sensor (rows)	0.20	2	0.10	1.289-07	0.99	3.18
Tool (columns)	1.12	2	0.56	7.027e-07	0.99	3.18
Residual	39373062.88	49	803531.89			

The results of the analysis show insignificant variation between sensors (VRS1, VRS2, and VRS3) and measuring instruments (the multimeter, tachometer, and MARK V). The F-statistic values for the sensors (1.288e-07) and measuring instruments (7.027e-07) are much smaller than the F-critical value (3.186582), with P-values of 1.000 and 0.999999, respectively. Most of the data variation comes from the residuals, with a sum of squares (SS) value of 39373063.582 and a mean square (MS) value of 803531.895605, indicating that other factors dominate the total variation. In conclusion, the sensors and measuring instruments provide consistent and accurate measurement results, with no significant differences in motor speed readings across various VSD speed levels.

Although using two-factor ANOVA without replication is appropriate for this study, it is essential to acknowledge its assumptions and limitations. This method assumes that the data is normally distributed and the variances are homogeneous across groups without interactions between factors. These assumptions must be met to ensure the validity of the results. However, a limitation of this approach is the inability to detect variability within individual groups due to the absence of replications. Future studies could include additional replications or employ alternative statistical methods to validate the findings and account for potential intra-group variability.

5 Discussion

The results demonstrate that VRSs provide high accuracy and consistency in turbine speed monitoring, supporting power plants' operational stability and energy efficiency. These findings highlight the effectiveness of VRSs in enhancing the performance of renewable energy technologies, particularly in CCPP. Although this study focuses on three specific VRSs, the findings can be generalized to other VRS models and brands due to the similarity in their core operating principles, such as magnetic flux variation and electrical signal generation. Performance trends observed in this study, including high accuracy and low variability, are likely applicable to other VRS models. However, design, materials, and manufacturing standards variations could impact their performance in challenging environments. Future research could include comparative analysis across different VRS manufacturers and explore alternative sensor technologies, such as optical and capacitive sensors, to broaden the understanding of turbine speed monitoring systems.

Regarding environmental sustainability, integrating VRSs contributes to reducing energy losses and improving system efficiency, which directly minimizes greenhouse gas emissions. These sensors ensure that energy generated from renewable sources is utilized effectively by optimizing turbine performance, supporting global initiatives to transition to cleaner energy systems. Furthermore, this technology aligns with low-carbon building practices by improving the reliability of energy conversion systems and reducing reliance on fossil fuels.

Integrating VRSs specifically contributes to low-carbon infrastructure by optimizing the operational efficiency of renewable energy systems, such as wind and hydropower plants, thereby reducing greenhouse gas emissions. By improving turbine speed monitoring and minimizing energy losses, these sensors enable more effective utilization of clean energy sources. This aligns with global efforts to transition toward sustainable energy systems and supports the development of innovative grid technologies for low-carbon infrastructure. Additionally, the real-time data provided by VRSs enhances predictive maintenance, reducing the need for frequent manual interventions, which further minimizes the environmental impact of maintenance operations. These contributions emphasize the critical role of VRSs in achieving greater sustainability within renewable energy frameworks.

6 Conclusions

The testing results indicate that VRS demonstrates high accuracy and consistency in measuring motor speed, with minimal differences from the reference values, namely ±1 RPM at low frequencies (8.33 Hz) and a maximum RMSE value of 0.28% for VRS2. The testing method using the motor and VSD proved effective and consistent, as evidenced by the rotational speed values being very close to the reference, including at 50.00 Hz, where all instruments recorded 3000 RPM without deviation. The two-factor ANOVA without replication test supports the validity of the testing, with no statistically significant variation between the sensors (P-value = 1.000).

Although the results are promising, potential sources of error, such as environmental disturbances and sensor alignment issues, should be considered. Mitigation strategies, including regular sensor calibration, enhanced environmental protection, and redundant systems, are recommended to ensure the long-term reliability and accuracy of the VRSs in real-world applications. These findings have broader implications for the renewable energy sector. By providing accurate and reliable turbine speed monitoring, VRSs improve the stability and efficiency of energy conversion processes, which are critical for maximizing the output of renewable energy systems. Furthermore, their integration into smart grids based on the Internet of Things (IoT) could enhance predictive maintenance and system optimization, paving the way for more sustainable and efficient energy solutions. This research highlights the potential of VRSs as a pivotal component in achieving excellent reliability and performance in renewable energy infrastructure.

This study contributes to the broader field of renewable energy by demonstrating how VRSs can enhance the reliability and efficiency of turbine speed monitoring, which is critical for maximizing the performance of renewable energy systems such as wind, hydropower, and CCPPs. Moreover, these findings support the development of more stable and efficient energy conversion processes in power plants, reducing energy waste and supporting global efforts to transition toward sustainable energy systems. VRSs play a pivotal role in advancing clean energy technologies and optimizing power plant operations by ensuring operational reliability.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

The authors thank Singgih Dwi Prasetyo, S.T., M.T., our supervising lecturer, for his valuable guidance throughout this research. We also thank the Faculty of Vocational Studies, State University of Malang, for providing the facilities and support needed for this research—special thanks to the technical staff at CCPP Tambak Lorok for their assistance during the sensor testing process. Furthermore, we appreciate the insightful feedback from our colleagues, which contributed significantly to improving this research.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] R. Delfianti, B. Mustaqim, and Y. Afif, "Standalone photovoltaic power stabilizer using double series connected converter in sudden cloud condition," *Int. J. Integr. Eng.*, vol. 15, no. 4, pp. 281–291, 2023. https://doi.org/10.30880/ijie.2023.15.04.024

[2] N. Mlilo, J. Brown, and T. Ahfock, "Impact of intermittent renewable energy generation penetration on the power system networks–A review," *Technol. Econ. Smart Grids Sustain. Energy*, vol. 6, p. 25, 2021. https://doi.org/10.1007/s40866-021-00123-w

[3] A. Y. Jaen-Cuellar, D. A. Elvira-Ortiz, R. A. Osornio-Rios, and J. A. Antonino-Daviu, "Advances in fault condition monitoring for solar photovoltaic and wind turbine energy generation: A review," *Energies*, vol. 15, no. 15, p. 5404, 2022. https://doi.org/10.3390/en15155404

[4] A. T. W. K. Fahmi, K. R. Kashyzadeh, and S. Ghorbani, "A comprehensive review on mechanical failures cause vibration in the gas turbine of combined cycle power plants," *Eng. Fail. Anal.*, vol. 134, p. 106094, 2022. https://doi.org/10.1016/j.engfailanal.2022.106094

[5] W. Digwijaya, H. B. Tambunan, and A. D. Nugraha, "Power enhancement analysis from exhaust energy flow of an open cycle gas turbine power plant," in *2023 4th International Conference on High Voltage Engineering and Power Systems (ICHVEPS)*, Denpasar Bali, Indonesia, 2023, pp. 539–543. https://doi.org/10.1109/ICHVEPS58902.2023.10257363

[6] S. O. Oyedepo, B. A. Fakeye, B. Mabinuori, P. O. Babalola, and et al., “Thermodynamics analysis and performance optimization of a reheat–regenerative steam turbine power plant with feed water heaters,” *Fuel*, vol. 280, p. 118577, 2020. https://doi.org/10.1016/j.fuel.2020.118577

[7] S. Wang, C. Zheng, T. H. Ma, T. Y. Wang, S. Gao, and Q. Y. Dai, “Design and implementation of intelligent rolling bearing based on variable reluctance generator,” *IEEE Trans. Instrum. Meas.*, vol. 73, pp. 1–12, 2024. https://doi.org/10.1109/TIM.2024.3470982

[8] Honeywell, “Application note: VRS industrial magnetic speed sensors sensing and control,” 2012. https://prod-edam.honeywell.com/content/dam/honeywell-edam/sps/siot/ja/products/sensors/speed-sensors/common/documents/sps-siot-vrs-app-note-005934-2-en-ciid-44313.pdf

[9] P. Ripka, M. Mirzaei, and J. Blažek, “Magnetic position sensors,” *Meas. Sci. Technol.*, vol. 33, no. 2, p. 022002, 2021. https://doi.org/10.1088/1361-6501/ac32eb

[10] A. Manohar and S. Subramanian, “Environmental testing of outdoor electronic devices,” mastersthesis, Linköping University, 2024. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1905371&dswid=-8984

[11] A. Swain, E. Abdellatif, A. Mousa, and P. W. T. Pong, “Sensor technologies for transmission and distribution systems: A review of the latest developments,” *Energies*, vol. 15, no. 19, p. 7339, 2022. https://doi.org/10.3390/en15197339

[12] A. K. A. N. S. Amma, “Development of sensing techniques and sensing strategies to realize electric and magnetic field-based miniaturized angle sensors,” doctoralthesis, Macquarie University, 2023.

[13] V. Gurusamy, G. A. Capolino, B. Akin, H. Henao, R. Romary, and R. Pusca, “Recent trends in magnetic sensors and flux-based condition monitoring of electromagnetic devices,” *IEEE Trans. Ind. Appl.*, vol. 58, no. 4, pp. 4668–4684, 2022. https://doi.org/10.1109/TIA.2022.3174804

[14] C. Gong and F. Deng, “Design and optimization of a high-torque-density low-torque-ripple vernier machine using ferrite magnets for direct-drive applications,” *IEEE Trans. Ind. Electron.*, vol. 69, no. 6, pp. 5421–5431, 2021. https://doi.org/10.1109/TIE.2021.3090714

[15] Z. Y. Xu, T. Li, F. G. Zhang, Y. Zhang, D. H. Lee, and J. W. Ahn, “A review on segmented switched reluctance motors,” *Energies*, vol. 15, no. 23, p. 9212, 2022. https://doi.org/10.3390/en15239212

[16] J. G. Wang, Y. Tian, F. F. Dai, Y. J. Shen, Y. J. Yang, Q. Liu, and Y. J. Wu, “Local maximum synchrosqueezing reassigning chirplet transform and its application to gearbox fault diagnosis,” *Meas. Sci. Technol.*, vol. 35, no. 8, p. 086121, 2024. https://doi.org/10.1088/1361-6501/ad3a09

[17] Y. Koch, G. Martin, E. Kirchner, D. Quirnheim Pais, and R. Slatter, “Feasibility study of measuring instantaneous angular speed of helical gears with magnetoresistive sensors,” *Forsch. Ingenieurwes.*, vol. 86, pp. 451–459, 2022. https://doi.org/10.1007/s10010-022-00590-2

[18] H. Xiao, Z. W. Liu, R. Zhang, A. Kelham, X. Y. Xu, and X. Wang, “Study of a novel rotational speed amplified dual turbine wheel wave energy converter,” *Appl. Energy*, vol. 301, p. 117423, 2021. https://doi.org/10.1016/j.apenergy.2021.117423

[19] M. Oravec, P. Lipovský, M. Šmelko, P. Adamčík, M. Witoś, and J. Kwaśniewski, “Low-frequency magnetic fields in diagnostics of low-speed electrical and mechanical systems,” *Sustainability*, vol. 13, no. 16, p. 9197, 2021. https://doi.org/10.3390/su13169197

[20] P. W. Pong, A. M. Annaswamy, B. Kroposki, Y. Zhang, R. Rajagopal, G. Zussman, and H. V. Poor, “Cyber-enabled grids: Shaping future energy systems,” *Adv. Appl. Energy*, vol. 1, p. 100003, 2021. https://doi.org/10.1016/j.adapen.2020.100003

[21] J. Qin, L. J. Yin, Y. N. Hao, S. L. Zhong, and et al., “Flexible and stretchable capacitive sensors with different microstructures,” *Adv. Mater.*, vol. 33, no. 34, p. 2008267, 2021. https://doi.org/10.1002/adma.202008267

[22] J. Zhang, R. Xi, Y. He, Y. Sun, and et al., “A survey of mmWave-based human sensing: Technology, platforms and applications,” *IEEE Commun. Surv. Tuts.*, vol. 25, no. 4, pp. 2052–2087, 2023. https://doi.org/10.1109/COMST.2023.3298300

[23] M. Civera and C. Surace, “Non-destructive techniques for the condition and structural health monitoring of wind turbines: A literature review of the last 20 years,” *Sensors*, vol. 22, no. 4, p. 1627, 2022. https://doi.org/10.3390/s22041627

[24] T. O. Hodson, “Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not,” *Geosci. Model Dev. Discuss.*, vol. 15, pp. 5481–5487, 2022. https://doi.org/10.5194/gmd-15-5481-2022

[25] Y. Cheng, R. Azizipanah-Abarghooee, S. Azizi, L. Ding, and V. Terzija, “Smart frequency control in low inertia energy systems based on frequency response techniques: A review,” *Appl. Energy*, vol. 279, p. 115798, 2020. https://doi.org/10.1016/j.apenergy.2020.115798

[26] S. Shahub, S. Upasham, A. Ganguly, and S. Prasad, “Machine learning guided electrochemical sensor for passive sweat cortisol detection,” *Sens. Biosens. Res.*, vol. 38, p. 100527, 2022. https://doi.org/10.1016/j.sbsr

.2022.100527

[27] A. Saeed, A. Husnain, A. Zahoor, and R. M. Gondal, "A comparative study of cat swarm algorithm for graph coloring problem: Convergence analysis and performance evaluation," *Int. J. Innov. Res. Comput. Sci. Technol.*, vol. 12, no. 4, pp. 1–9, 2024. https://doi.org/10.55524/ijircst.2024.12.4.1

[28] R. G. Lawrence and K. K. Lobodovsky, "Motors, drives, and electric energy management," in *Energy Management Handbook (9th Edition)*. River Publishers, 2020, pp. 299–324.

[29] J. F. H. Castaño, "Calibration of handheld digital multimeters through digital image," in *Digital Image Processing-Latest Advances and Applications*, 2024, p. 85. https://doi.org/10.5772/intechopen.114861

[30] A. M. Zhang, S. Liu, Y. Ma, C. Hu, and Z. Y. Li, "Field tests on model efficiency of twin vertical axis helical hydrokinetic turbines," *Energy*, vol. 247, p. 123376, 2022. https://doi.org/10.1016/j.energy.2022.123376

[31] L. Huimin, "Design and implementation of the automatic sorting system based on PLC," in *2023 IEEE 3rd International Conference on Power, Electronics and Computer Applications (ICPECA)*, Shenyang, China, 2023, pp. 467–471. https://doi.org/10.1109/ICPECA56706.2023.10075963

[32] H. Algamaiah, N. Silikas, and D. C. Watts, "Polymerization shrinkage and shrinkage stress development in ultra-rapid photo-polymerized bulk fill resin composites," *Dent. Mater.*, vol. 37, no. 4, pp. 559–567, 2021. https://doi.org/10.1016/j.dental.2021.02.012

[33] W. Ji, F. Ni, D. G. Gao, S. H. Luo, Q. C. Lv, and D. Y. Lv, "Electromagnetic design of high-power and high-speed permanent magnet synchronous motor considering loss characteristics," *Energies*, vol. 14, no. 12, p. 3622, 2021. https://doi.org/10.3390/en14123622

[34] M. Pesenti, A. Antonietti, M. Gandolla, and A. Pedrocchi, "Towards a functional performance validation standard for industrial low-back exoskeletons: State of the art review," *Sensors*, vol. 21, no. 3, p. 808, 2021. https://doi.org/10.3390/s21030808

[35] I. Sutisna, "Statistika penelitian," *Universitas Negeri Gorontalo*, vol. 1, no. 1, pp. 1–15, 2020.

[36] Y. A. Winoko and M. K. Z. N. Junaidi, "Analisis pengaruh perubahan sudut penginjeksian bahan bakar terhadap kinerja mesin diesel untuk genset," *Briliant: Jurnal Riset dan Konseptual*, vol. 8, no. 2, pp. 490–495, 2023. https://doi.org/10.28926/briliant.v8i2.1217