Smart temperature and vibration monitoring device for small-scale fishing vessel engines

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Abstract. Monitoring engine condition parameters is crucial for ensuring efficiency and reliability of small-scale fishing vessels. However, existing monitoring device and their application remains limited and they are not extensively utilized for small-scale fishing vessels. This study aims to design and develops a real-time temperature and vibration monitoring device for small-scale fishing vessel propulsion. The proposed device integrates temperature and accelerometer sensors, with ESP32 serving as the main processor. Blynk was used as a real-time monitoring platform. The prototype was tested on a single-cylinder diesel engine by comparing its monitoring results with a standard measurement tool. A trial monitoring the parameters of a single-cylinder diesel engine was conducted for 30 min to assess accuracy by the Mean Absolute Percentage Error (MAPE) value. The results of the trial indicated that the device could effectively record temperature and engine vibration data with a MAPE value below 20%. This level of accuracy indicates the effectiveness of monitoring the performance parameters. The proposed monitoring device can offer notifications regarding the conditions of the small-scale fishing vessel propulsion engines.

1. Introduction

Degradation of engine performance can lead to significant operational failures and increased maintenance costs in fishing vessels. Therefore, it is crucial to select maintenance strategies that align with the characteristics of the engine and system conditions [1,2]. The maintenance and repair of industrial and marine systems have received significant attention over the past few decades owing to their high capital investment and demand for high availability. Determining an optimal maintenance policy that balances the costs of preventive maintenance and system failure is essential. Various efforts are continually made to collect and analyse data from past experiences to prevent risky situations and enhance system reliability, as well as to develop effective preventive maintenance planning [3]. Effective maintenance and condition monitoring are vital because 75% to 96% of maritime accidents are caused by human errors at three levels of behavior: knowledge-based, rule-based, and

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skill-based [4]. In addition, the complexity of ship engine maintenance activities onboard, where seafarers perform tasks under various maritime environmental conditions (such as extreme weather, ship movements, noise, and vibrations) and operational conditions (such as excessive workload and stress), adds to this challenge [5]. In such conditions, the ability of humans to manually obtain engine performance data is limited compared to automated systems. The large volume of data and complexity of engine parameters require fast and accurate analysis, which can exceed the cognitive capacity of human operators. Therefore, it is important to consider human-machine interaction to enhance machine safety [6].

Several studies have addressed the challenges of monitoring engine performance, emphasizing the importance of machine condition monitoring using Condition-Based Maintenance (CBM) methods. These methods integrate temperature, pressure, torque, and fuel flow data to enhance the engine reliability and efficiency [7]. Temperature monitoring is crucial to prevent engine damage caused by extreme exhaust gas temperatures. This technique employs advanced sensors to detect thermal overload conditions, ensuring that the engine operating temperatures remain within safe limits, thereby reducing the risk of wear and damage [8]. The exhaust gas temperature in internal combustion engines is also measured to evaluate measurement errors caused by radiation, conduction, and the dynamic response of thermocouples or platinum resistance thermometers when placed in the exhaust gas flow. This allows for a more accurate temperature estimation, contributing to a better engine performance evaluation and supporting the monitoring of ship operational performance and efficiency [9,10]. In addition to engine temperature monitoring, methods for monitoring engine performance using vibration signals have also been explored. Methods for diagnosing valve clearances in piston combustion engines using vibration signals are conducted by employing triaxial accelerometers mounted on the cylinder head of a 4-stroke 6-cylinder diesel engine [11], and misfire detection in engines using sound quality metrics from generated noise [12]. Internal MEMS (Micro Electro Mechanical Systems) accelerometers are also used to measure rotor vibration directly without requiring additional sensors on the stator [13].

The development of engine monitoring using sensors involves integrating Artificial Neural Networks, including artificial neural networks (ANN), K-nearest neighbors (KNN), Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), and Support Vector Machines (SVM), to model engine performance and detect faults. This integration enables more responsive and timely maintenance, minimizing the risk of operational failures, with accuracy rates ranging from 94% to 100% [7,11,12,14–16].

Another technology that has been utilized in machine condition monitoring is IoT, which can be employed to develop mathematical models based on monitoring data for diesel generator performance analysis, as well as fuzzy logic-based decision support systems to provide real-time warnings in critical situations [17]. The use of IoT can enhance maintenance efficiency and effectiveness and support predictive maintenance with higher reliability [16,17]. The integration of these technologies holds significant potential for improving machine reliability and operational efficiency as well as supporting more effective predictive maintenance.

Nevertheless, research has been conducted on the development of engine condition monitoring systems utilizing temperature and vibration sensors connected to IoT technology for small-scale fishing vessels under 5 GT and powered by single-cylinder diesel engine with less than 12 HP remains limited. Specifically, studies on the effective and efficient integration of multi-sensor systems for small fishing boats are sparse, despite the potential of such systems to combine temperature and vibration sensors into a single device that is easy to install and use on small vessels. Furthermore, infrastructure limitations in maritime environments often hinder the adoption of IoT technology and automation systems, highlighting the need for innovation in developing energy-efficient devices capable of

autonomous operation. Therefore, the aim of this study is to develop an automatic monitoring system for small-scale fishing boat engines using temperature and vibration sensors to record data in real time. This system aims to provide a more efficient solution for monitoring engine conditions in small fishing vessels, reducing the risk of damage, and enhancing operational efficiency. Identifying potential risks and their causes can help determine critical components, thereby enabling the implementation of mitigation measures to lower risk levels.

2. Material and Method

This study used two approaches. The first approach uses cyber-physical instrumentation. This involves designing an IoT-based real-time engine monitoring system capable of recording engine temperature and vibration. By leveraging the IoT technology, the system can continuously collect data from machines and transfer it directly to the monitoring platform.

The second approach utilizes Artificial Intelligence, specifically Artificial Neural Networks (ANN) [18]. In this approach, the collected machine data are used to analyse the condition of the machine. The ANN processes these data and produces accurate machine-condition predictions based on patterns identified from the received temperature and vibration data. This approach aids in the early detection of potential problems, allowing for more effective preventative maintenance [18,19].

The combination of these two approaches facilitates the development of systems that not only accurately monitor machine conditions in real time, but also provide in-depth analysis to support better and timely maintenance decisions.

The detailed research methodology applied in this study is outlined in the flowchart presented in Figure 1.

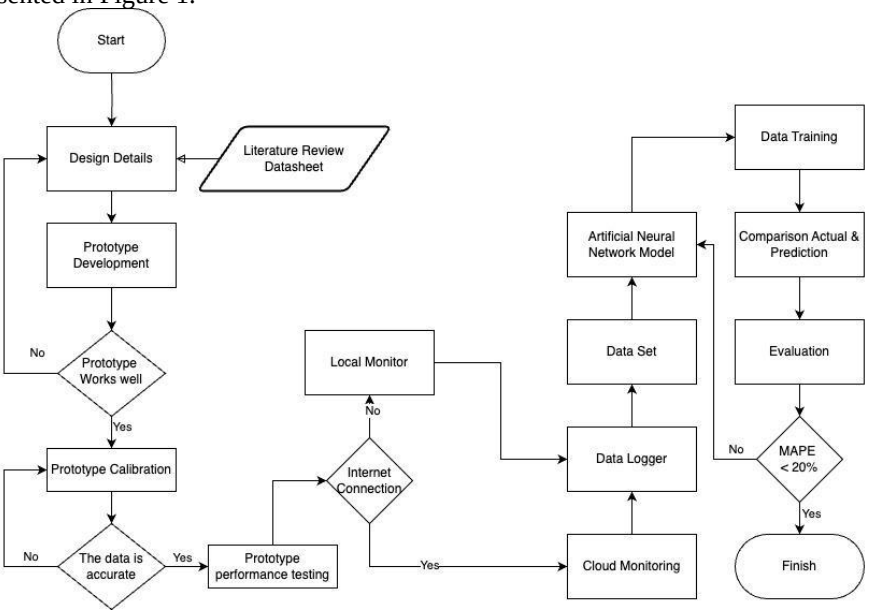


Fig 1. Flowchart Diagram of Research Methodology

In the detailed design phase, component selection was performed, the system was designed, and all necessary technical requirements were specified by referring to literature reviews and component datasheets. This step was conducted to ensure that the prototype

functioned correctly. The next phase involves prototype development, which includes assembling the components, developing the required software, and integrating the system into an internet network. The testing phase was conducted to verify that the prototype operated as expected. If the prototype does not perform as anticipated, further development will be undertaken to make improvements. Once the prototype operates satisfactorily, calibration is performed to ensure that all the sensors and systems within the prototype operate with the desired accuracy. The evaluation of the generated data is essential to confirm that the data produced are accurate.

During the prototype performance testing phase, system testing was conducted to ensure that the prototype functioned properly in a single-cylinder diesel engine. Simultaneously, Internet connectivity was tested to allow for online data monitoring. In the absence of an Internet connection, the prototype stored the data locally. The data from the prototype were then transmitted to a cloud-based monitoring system, enabling more comprehensive and real-time data analysis. The recorded data were subsequently compiled into a complete dataset, which was utilized for the analysis and model training processes.

In the second approach, Artificial Neural Networks (ANNs) were used for analyse the collected dataset. ANNs were chosen for their ability to identify patterns and make predictions based on data. The collected data were used to train an ANN model. This training process aims to enhance the accuracy of the model predictions. The ANN model utilized 512 neurons and applied the rectified linear unit (ReLU) activation function. The network was trained for 1000 epochs. In this study, 80% of the data were used for training. After the model was trained, the predicted machine conditions were compared with actual data. The purpose of this comparison was to evaluate the performance of the model and to ensure prediction accuracy. Finally, an evaluation phase was conducted to assess the overall process, including the prototype performance, data accuracy, and model prediction effectiveness. This evaluation is crucial for determining whether all research objectives have been met [7,20].

To evaluate the accuracy and suitability of the ANN model and prototype, performance indicators such as the Mean Absolute Percentage Error (MAPE) are used to assess the accuracy of both the model and the prototype.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{|A_t|} \times 100 \quad (1)$$

Where F_t is the measurement value of the prototype or the predicted value, A_t is the measurement value of the measuring instrument in period t or the actual value, and n is the number of measurement/data periods [21,22]. A smaller Mean Absolute Percentage Error (MAPE) value indicates better model performance; a reduced MAPE indicates that the prototype measurement results closely correspond to the actual values. A model is considered effective if its MAPE is less than 20% [22,23].

Figure 2 illustrates the hardware configuration and data flow process of the engine-monitoring system. The system utilizes a 5-volt battery as the power source to activate the ESP32. Two types of sensors were employed: an MLX90614 temperature sensor and a GY-521 vibration sensor. All data collected by these sensors were subsequently transmitted to the ESP32 TTGO T-SIM8000H microcontroller, which features GPRS communication capabilities. This microcontroller serves as the system processor, and manages and processes the data received from the sensors. The processed data are then sent to a data logger or a storage module. This data logger module is responsible for storing all the temperature and vibration data. In addition to local data storage, the system was equipped with cloud-based monitoring capabilities using the Blynk platform. This enables the real-time monitoring of temperature and vibration through devices such as laptops or smartphones.

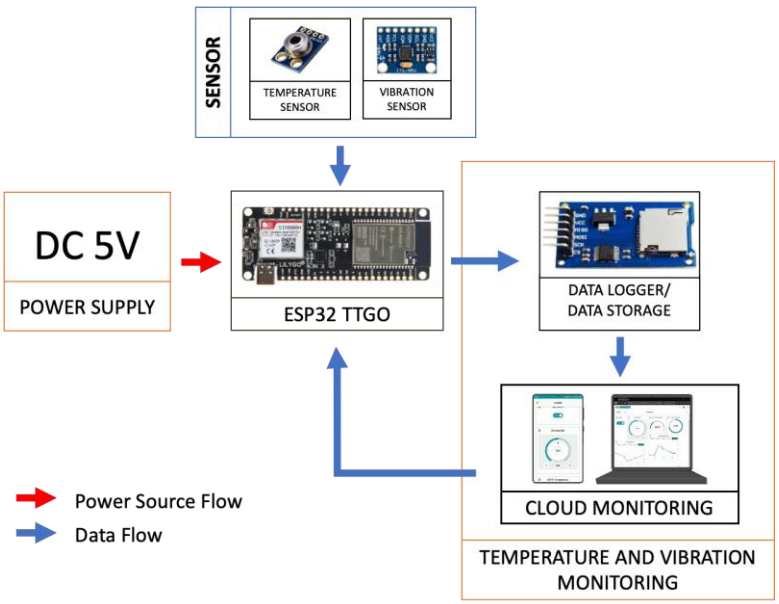


Fig 2. Hardware Block Diagram

3. Result and Discussion

The system was constructed by connecting the sensor components and other elements to the ESP32, following the wiring diagram illustrated in Figure 3. The entire system was assembled within a black enclosure to facilitate the operational processes. Subsequently, tests were conducted on a single-cylinder diesel engine operated under no-load conditions to verify and ensure the reliability and consistency of the measurements. During the testing phase, engine parameters such as temperature and vibration were periodically measured using a vibration-measuring device (vibration test) and infrared thermometer.

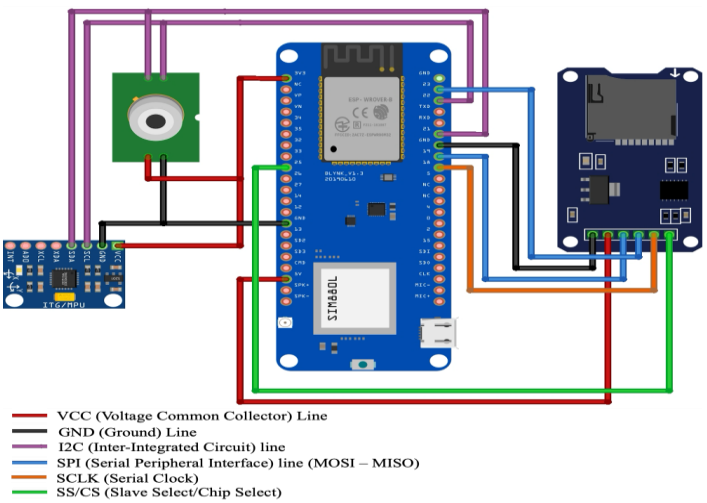


Fig 3. Wiring Diagram for Smart Temperature and Vibration Monitoring System (Schematic Made in Fritzing)

Figure 4 illustrates a prototype of a smart temperature and vibration device used for monitoring temperature and vibration parameters in small-scale fishing vessel engines. This system employs an Internet connection via GPRS signals, enabling real-time data transmission to the Blynk platform for immediate engine condition monitoring and historical data review.

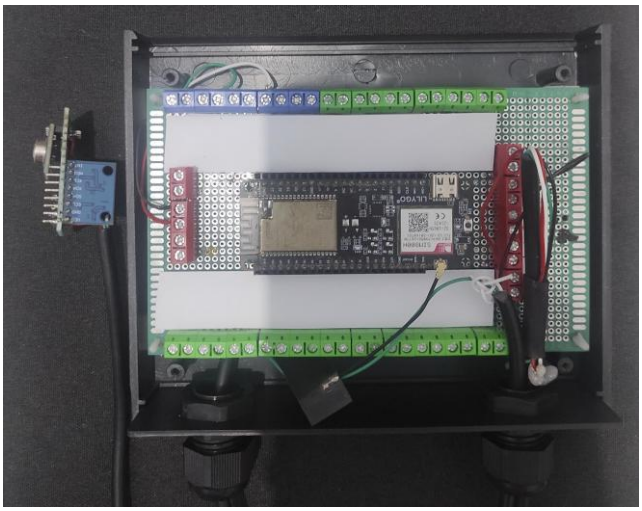
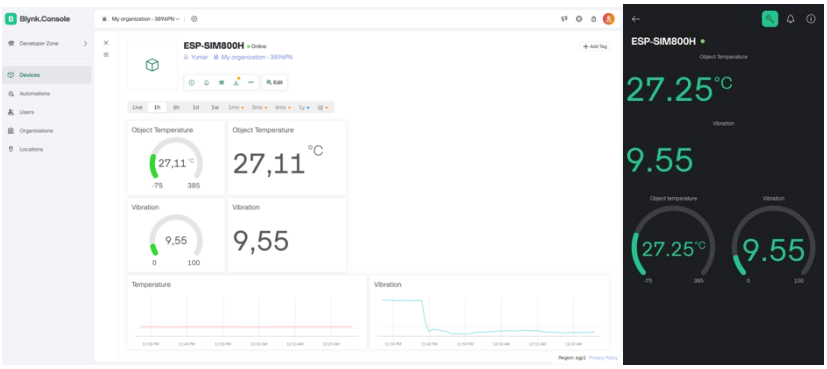


Fig 4. Prototype of Smart Temperature and Vibration Monitoring Device

During the development phase of the cyber-physical instrument, the Blynk platform was used to connect the monitoring devices to an online dashboard. This dashboard is designed to display measurement parameters, such as temperature and vibration sensor readings, enabling the real-time monitoring of engine parameters. This monitoring can be accessed through various devices, including computers, laptops, and smartphones, thereby enhancing the flexibility of engine parameter monitoring. The dashboard of this platform is shown in Fig. 5.



(a) and (b).

Fig 5. (a) Web Based Dashboard (b) Mobile Based Dashboard

The temperature and vibration sensors were tested using a prototype monitored under 'online' conditions on a Blynk platform dashboard. Figure 4 shows that the system operates effectively in an online state, with the temperature and vibration parameters being readable on the dashboard. The use of Blynk as an interface across various devices highlights its ease of access for monitoring machine conditions. As shown in Figure 5. A, the application

display on a computer or laptop facilitates machine monitoring through the panel, with measured temperature readings of 27.11°C and vibration readings of 9.55 m/s². Figure 5.b shows the display when accessed via a smartphone. This monitoring system exhibits flexibility in machine monitoring across different devices, thereby expanding the scope of machine observation.

Figure 6 illustrates the results of prototype testing on a single-cylinder diesel engine used as a propulsion system for a small-scale fishing vessel. In this test, the measurements obtained from the developed monitoring prototype were compared with those obtained using a vibration-testing device and infrared thermometer. This comparison yielded Absolute Percentage Error (APE) values, which were then averaged to calculate the Mean Absolute Percentage Error (MAPE).

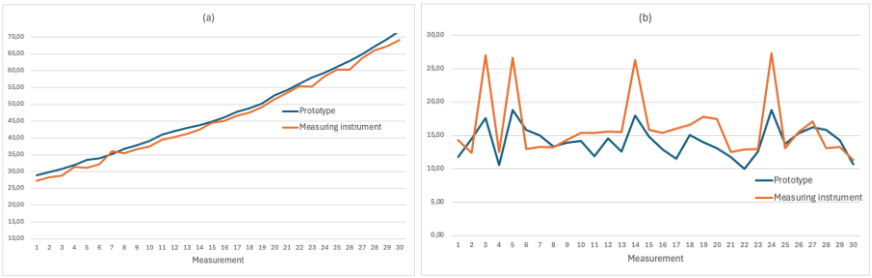


Fig 6. Graphics of Prototype Performance Test Results: (a) temperature and (b) vibration

For temperature measurements, the Mean Absolute Percentage Error (MAPE) obtained is 3.2%. This indicates that the prototype demonstrated a relatively high level of accuracy in temperature measurements, with an average absolute percentage error of 3.2%. Meanwhile, For vibration measurements, the MAPE value reached 18.6%. The vibration data exhibited more fluctuations than the temperature data. This is partly due to the nature of the vibration measurements, which can vary significantly in response to minor changes in the conditions. Therefore, it is evident that the prototype still exhibits variability in vibration measurement accuracy, with an average absolute percentage error of 18.6%.

There is a discrepancy between the prototype and the measurement instrument concerning the vibration measurements. The Absolute Percentage Error (APE) for vibration remained below 20%, with a Mean Absolute Percentage Error (MAPE) calculated at 18.6%. This indicates that although the prototype is capable of capturing general vibration trends, there is a greater level of error compared to temperature measurements.

ANN Model Development

The dataset utilized was derived from temperature and vibration measurements collected using a prototype device that served as the input layer. The machine condition, which was assessed based on the measured parameters, was used as the output. The accurate labelling of the output layer and partitioning of the dataset into training and testing sets ensured the accuracy of the model.

The details of the input layer dataset in the ANN analysis were temperature (°C) and vibration (m/s²). These inputs represent the temperature and vibration readings from sensors installed on the engine. The Output Layer (labels) consists of the machine condition, which is the target variable to be predicted by the ANN. The categories used for the machine's condition are normal (1) if the engine operates within normal parameters, warning (2) if the engine shows signs of potential issues that may require attention, and critical (3) if the engine is experiencing significant problems and may require immediate action. This dataset was

utilized by the ANN to learn the patterns of the input and output data for prediction purposes. The dataset was divided into two parts, 80% for the training set and 20% for the testing set. The Training Set was used to train the ANN, including a balanced representation of normal, warning, and critical conditions. The Testing Set was used to evaluate the ANN's performance on data that the model had not previously encountered.

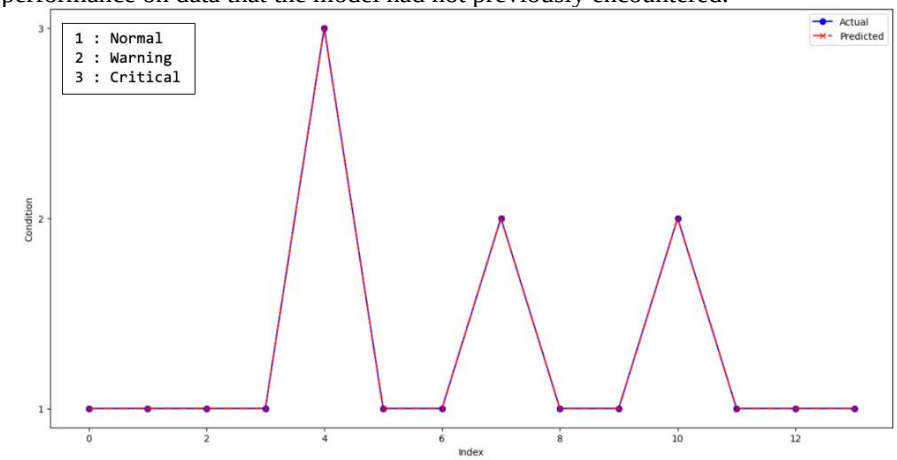


Fig 7. Comparison of Actual and Predicted Values

During the training phase, the Artificial Neural Network (ANN) received temperature and vibration data from the training set. The objective was to adjust the weights to minimize the error between the predictions and actual machine condition labels. The training process spanned 1000 iterations (or epochs), with each epoch representing a complete pass through the training set.

After undergoing 1000 epochs of training, the ANN achieved a 100% accuracy rate on the test data, as illustrated in Figure 7. This is evident from the line chart, which displays the results from the test set with two lines: a blue line representing the actual machine condition values, and an orange line representing the predicted values generated by the ANN. The closer these lines are to each other, the more accurately ANN predicts the condition of the machine. Therefore, this graph shows that the ANN provides predictions that closely align with the actual values, demonstrating the excellent performance quality of the developed model. Consequently, the ANN achieved a Mean Absolute Percentage Error (MAPE) of 0%, indicating that its predictions were highly accurate.

Achieving a Mean Absolute Percentage Error (MAPE) of 0%, this Artificial Neural Network (ANN) demonstrates an exceptionally high level of accuracy in its predictions. This indicates that the model does not produce significant errors in its estimations, where high accuracy is essential for preventing engine damage and ensuring safe and efficient operation. These results open up opportunities for the further application of ANN in machine condition monitoring systems, given their capability to effectively interpret and process sensor data.

4. Conclusion

A cyber-physical system for engine temperature and vibration monitoring was developed using the ESP32 TTGO and Blynk platforms. Prototype testing demonstrated good performance, with MAPE values below 20%. This indicates a satisfactory level of accuracy in monitoring and measuring the supporting parameters of the engine performance. The ANN Model Training Result shows an accuracy of 100% and Error Value (MAPE) of 0%,

indicating that the model has been trained well and performs very well in predicting machine conditions.

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