International Journal of Marine Engineering Innovation and Research, Vol. 11(2), Jun. 2026. 397-402
(pISSN: 2541-5972, eISSN: 2548-1479)

Intelligent Engine Mismatch Detection in Detroit Diesel Alusion DW.6WE Using Artificial Neural Networks

Ryan Yudha Adhitya[1*]
(Received: 10 April 2026 / Revised: 12 April 2026 / Accepted: 16 April 2026 / Available Online: 3 June 2026)

Abstract**—** The maritime industry plays an important role in global trade, especially in transporting goods between countries. The main engine is a key component that ensures a ship operates properly, so monitoring its condition is essential. Parameters such as main bearing temperature, exhaust gas temperature, and engine speed are used to evaluate engine health. However, preventive maintenance based on fixed schedules often fails to detect early damage. To address this, Artificial Neural Network (ANN) technology is used to analyze sensor data in real time. The data is sent to a PLC, processed by the ANN, and classified into Normal, Alert, or Danger conditions. This information is displayed visually and can be accessed by the ship's crew through the Node-RED platform using the Modbus TCP/IP protocol. The results show that the system achieves a classification accuracy of 94.11%, can trigger automatic alarms, and transmits data in real time via the MQTT protocol. This demonstrates that ANN is effective for building an intelligent and adaptive ship engine monitoring system.

Keywords— Artificial Neural Network, Main Engine, Real-Time Monitoring, PLC, Maritime Industry, Modbus TCP/IP, MQTT, Node-RED.

[*]*Corresponding Author: ryanyudhaadhitya@ppns.ac.id*

I. INTRODUCTION

The maritime industry plays a crucial role in international trade, particularly in transporting goods between countries. One of the most important components in ship operations is the main engine, which functions as the primary propulsion system. The performance and efficiency of the main engine strongly affect the reliability and safety of ship operations, making condition monitoring essential to prevent potential failures. During operation, the engine is subjected to high loads and continuous stress, which can lead to performance degradation [1][4][6][7] or damage. Key indicators such as main bearing temperature, exhaust gas temperature, and engine speed are commonly used to assess engine condition. Abnormal main bearing temperature may indicate excessive friction or poor lubrication, while abnormal exhaust gas temperature can signal overheating or gas leakage. In addition, improper engine speed, especially overspeed conditions, can accelerate wear and increase fuel consumption [9][10].

The main problem is that current monitoring practices for ship main engines are still largely based on periodic inspections, typically conducted on a weekly schedule. This approach is not effective for early fault detection because it cannot capture real-time anomalies that may occur between inspections. As a result, potential damage is often detected too late, leading to higher maintenance costs, unexpected downtime, and increased operational risks. Therefore, a more advanced and real-time monitoring system is required to detect early signs [14][15][16][17][18] of engine abnormalities and support timely decision-making.

To address this problem, Artificial Neural Network (ANN) technology is proposed as a solution for analyzing sensor data and identifying complex patterns in engine operation. ANN is capable of processing large amounts of data and providing more accurate detection of abnormal conditions compared to conventional methods [15]. By analyzing the relationship between parameters such as main bearing temperature, exhaust gas temperature, and engine speed, ANN can provide early warnings of potential failures. In addition, ANN systems are adaptive [19][20][21][22], as they can learn from historical data and improve their performance over time.

The novelty of this research lies in the integration of an Internet of Things (IoT)-based architecture with the implementation of an Artificial Neural Network directly on an industrial controller (PLC) for diesel engine monitoring. Unlike conventional approaches that rely on external computing systems, this study embeds intelligent data processing within the PLC, enabling real-time analysis, faster response, and seamless integration with existing industrial systems. The IoT architecture supports continuous data transmission, remote monitoring, and system scalability, making the proposed system more efficient, practical, and suitable for modern smart ship applications.

II. METHOD

2.1 System Block Diagram (Prototype)

The main engine is connected to three main sensors to collect system input parameter data, namely the main bearing temperature, exhaust gas temperature, and engine rotational speed. The position of the main bearing temperature sensor functions to measure the temperature of the main bearing in the crankshaft of the main engine,

Ryan Yudha Adhitya, Politeknik Perkapalan Negeri Surabaya, Email: ryanyudhaadhitya@ppns.ac.id

the exhaust gas temperature sensor is used to measure the output of combustion in the cylinder, and the rotary speed sensor to measure the rotational speed per minute (RPM) in the rotor of the main engine.

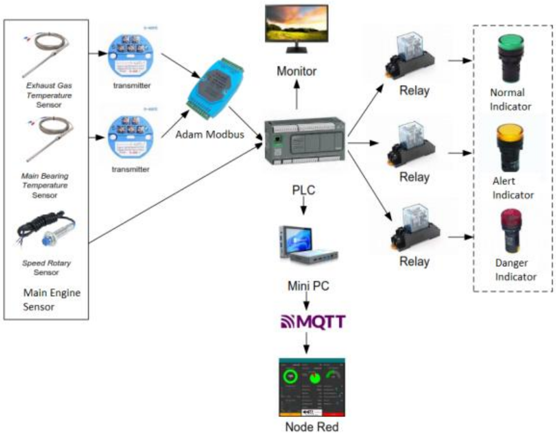


Figure 1. System Block Diagram

Information obtained from these three sensors is then received by the PLC [2][5] as input to be processed. The PLC functions as a controller that translates the readings from these sensors and forwards the processed information to take action according to the predetermined set point. One of the PLC outputs is connected to a relay to turn on an indicator light as a sign that the main engine is normal or abnormal and monitoring data can be viewed on the monitor. In addition, more detailed information will be stored in a data logger integrated with the Mini PC. This Mini PC not only functions to store data loggers but is also used to monitor the condition of the main engine via a web server (MQTT) [8] with a Node-Red [11] platform-based display.

2.2 Ship Main Engine Maintenance

Marine engine maintenance is performed daily, monthly, and annually to maintain optimal performance. Daily maintenance includes visual inspections of oil levels, temperatures, and pressures of key systems to detect potential problems early. Monthly maintenance includes filter cleaning, in-depth inspections of the lubrication and combustion systems, and analysis of key parameters. Annual maintenance includes comprehensive inspections, such as overhauling the main bearings, turbocharger, and fuel system. Parameter abnormalities can be caused by fuel contamination, poor lubrication, clogged injectors, or ineffective cooling, which can potentially increase exhaust gas temperatures, unstable oil pressure, and disrupt engine performance.

2.3 The Use of the Detroit Diesel Engine as a Prototype

Initial field studies for the installation of monitoring equipment on the main engine faced several practical challenges. One of the main obstacles was the limited time available for on-site activities, as the ship operates under a strict sailing and berthing schedule. This tight timeline restricted access for installation, calibration, and testing, making it difficult to conduct comprehensive data collection and system validation. All activities had to be carefully synchronized with the ship’s operational schedule to avoid disruption, which further reduced flexibility during the research process. This limitation is critical because accurate validation of the proposed neural network model requires balanced data covering all operating states. Without sufficient alert and danger data, the model’s ability to detect early faults and classify abnormal conditions may be less reliable [18].

The Detroit Diesel Alusion DW.6WE engine used as a prototype in this study is essentially identical in principle and technical characteristics to the ship's main engine. Both engines operate on the same internal combustion mechanism: air is compressed, fuel is injected, combustion occurs, and the resulting energy is used to generate mechanical power. Basic operating systems such as lubrication, cooling, and exhaust gas removal are also common to both types of engines. In terms of technical characteristics, the prototype engine has similar operating parameters, such as main bearing temperature, exhaust gas temperature, and engine rotational speed (RPM), which can be measured and analyzed in the same manner as a ship's engine. Despite differences in scale and power generation capacity, the prototype engine has similar operating parameters. Operational disturbance characteristics such as overheating, lubrication degradation, or overloading still provide similar technical responses and can be simulated in a laboratory environment.

Therefore, this prototype diesel engine is suitable for use as a representation of a ship's main engine in the context of research and development of neural network-based engine condition models [18]. The following is a table of specifications for the Detroit diesel 2 stroke diesel engine:

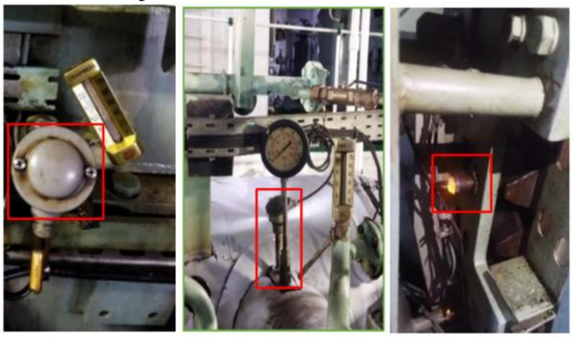
TABLE 1.
SPECIFICATIONS OF THE DIESEL ENGINE USED

Parameter	**Specification**
Type	Detroit Diesel Alusion DW.6WE
Bore	108mm
Stroke	127mm
Number of Cylinder	4
Firing order rh right rotation	1-3-4-2
Firing order rh left rotation	1-2-3-4
Number of main bearing	5
Ratio gearbox	1:95
Model	104 23100

Figure 2. Detroit Allusion DW.6WE Diesel Engine

2.4 Sensor Placement

The sensor installation locations are shown in Figure 3. All three sensors are calibrated using the direct comparison method, which involves comparing the readings of the measuring instrument with a standard or the sensor with the measuring instrument. The temperature sensor is calibrated with a thermogun and the rotational speed sensor with a tachometer.



(a) (b) (c)

Figure 3. Installation location of (a) main bearing temperature sensor, (b) exhaust gas temperature sensor and (c) RPM sensor

Figure 3 shows that the PT100 [3][12][13] temperature sensor is placed on the main bearing (figure 3(a)), on the exhaust gas duct (figure 3(b)) and the proximity sensor is placed near the engine shaft to detect rotation (figure 3(c)).

2.5 Dataset Creation

Data collection was conducted on April 28, 2025, at the Mechanical Engineering Laboratory of the Surabaya State Polytechnic of Shipping using a Detroit Diesel engine. The aim was to monitor the main bearing temperature, exhaust gas temperature, and measure the engine rotation speed in real-time using sensors, PLC, and the Python Platform. For temperature measurement, a PT 100 temperature sensor and a proximity-based speed sensor were used. The sensor readings were sent to the PLC and then saved to an Excel file using the library facilities available on the Python platform (pandas, openpyxl, and pycomm3). Measurements were carried out for 3 hours with 20-minute intervals. The following are the measurement results used for the validation process of the ANN predictor results.

TABLE 2.
ENGINE PERFORMANCE DATA THROUGH DIRECT MEASUREMENTS

Id	Main bearing temp. (°C) Thermogun	Exhaust gas temp. (°C) Thermogun	RPM Tacho	Information
1	30.5	30.7	0	No rotation
2	29.8	30.4	0	
3	29.9	30.5	601.9	
4	59.7	80.0	665.0	
5	62.7	83.3	718.7	
…	…	…	…	…
17	71.8	142.8	934.0	Alarm
18	71.9	142.9	932.0	
19	71.1	142.1	944.2	
20	71.1	142.1	952.8	Max. rotation
21	71.1	142.1	493.0	Lowest rotation
22	71.1	142.1	529.9	
23	70.7	129	533.3	

2.6 Artificial Neural Network

The artificial neural network used in this study has three main parameters (input vectors/input neurons): main bearing temperature, exhaust gas temperature, and RPM, one hidden layer, and three output vectors/output neurons: normal, alert, and danger conditions. The output neuron type used is binary classification as follows:

TABLE 3.
TARGET BINARY CLASSIFICATION OUTPUT NEURON

Parameter	Output 1	Output 2	Output 3
Normal	1	0	0
Alert	0	1	0
Danger	0	0	1

Based on Table 3, the labeling process is carried out according to identical criteria for each sensor condition. If the temperature and RPM sensors are normal, the target neuron output is [1 0 0]; if the sensor is in an alert condition, the target neuron output is [0 1 0]; and finally, if the sensor is in a dangerous condition, the target neuron output is [0 0 1]. The ANN training process enables the system to automatically predict engine conditions by updating the weight values in the hidden layer structure until they approach the target output or achieve the lowest RMSE value.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{1}$$

Where n is the number of training data, $\hat{y}_i$ is the predicted value, and y_i is the actual value. And here is the equation for updating weights in an artificial neural network:

$$\delta = (t - y) \cdot y \cdot (1 - y) \tag{2}$$

The neural network algorithm utilizes feedback techniques by calculating the deviation or error from the output layer to the previous layers with the aim of updating the network weights so that the model can learn and produce more accurate predictions in the next iteration. The t value is the target (actual value) as in table 3, the y value is the output of the neuron (prediction value) and $y.(1\text{-}y)$ is the derivative of the sigmoid activation function, and δ indicates how much and in what direction the changes need to be applied to the neuron weights.

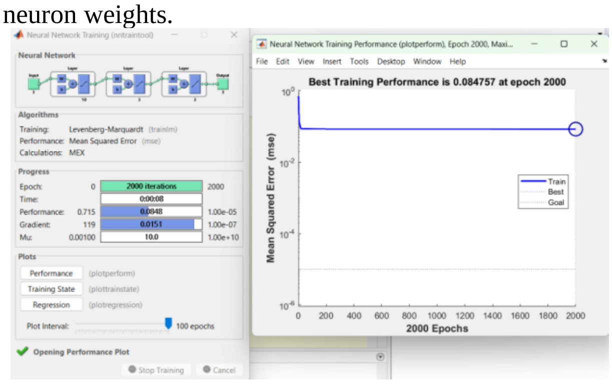


Figure 4. Training process using MATLAB's NN Toolbox

III. RESULT AND DISCUSSION

There are two types of testing in this study, namely partial sensor testing to determine the reliability of temperature and RPM sensor readings, as well as software testing which includes validation of ANN training results for diesel engine condition classification.

3.*1 PT100 sensor testing for Main Bearing Temperature*

Figure 5(a) shows the sensor installed on the engine block, which penetrates the crankshaft housing, to measure the main bearing temperature. Figure 5(b) shows the validation of the measurement results using a thermogun to compare the accuracy of the sensor values.

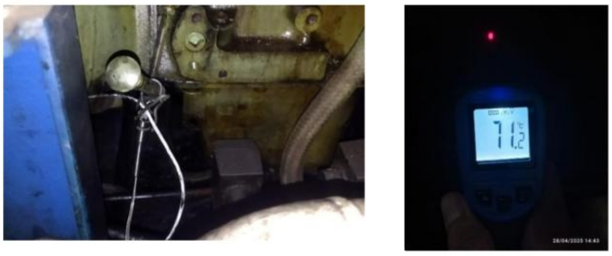


Figure 5. (a) PT100 Sensor (b) Thermogun Reading

The results of the PT100 sensor measurements with thermogun measuring instrument validation on the main bearing temperature parameter are listed in Table 4.

TABLE 4.
DATA FROM PT100 SENSOR AND THERMOGUN TEST RESULTS

Id	**PT 100 (^{o}C)**	**Thermogun (^{o}C)**	**Deviation**	**Error (%)**
1	70.5	71	0.5	0.7
2	65.6	71	5.4	7.6
3	68.3	71	2.7	3.8
4	70.1	71	0.9	1.2
5	66.8	71	4.2	5.9
6	67.5	71	3.5	4.9
7	66.7	71	4.3	6.0
8	65.4	71	5.6	7.8
9	70.3	71	0.7	0.9
10	69.8	71	1.2	1.6
Average Error (%)				4.0

Main bearing temperature testing was conducted by comparing the temperature sensor results to actual measurements using a thermogun. Table 4 shows that the actual value or measuring instrument reading was stable at 71^{o}C, while the sensor reading varied between 65.6^{o}C and 70.5^{o}C. The error rate ranged from 0.7% to 7.8%, with an average of 4%, still within the tolerance limit (below 5%).

3.2 PT100 sensor testing for Exhaust Gas Temperature

Figure 6(a) shows the sensor installed on the combustion flue of the cylinder block to measure the exhaust gas temperature. Figure 6(b) shows the validation of the measurement results using a thermogun to compare the accuracy of the sensor values.

The results of the PT100 sensor measurements with thermogun measuring instrument validation on the exhaust gas temperature parameter are listed in the following table 5:

Figure 6. (a) PT100 Sensor (b) Thermogun Reading

TABLE 5.
DATA FROM PT100 SENSOR AND THERMOGUN TEST RESULTS

Id	**PT 100 (^{o}C)**	**Thermogun (^{o}C)**	**Deviation**	**Error (%)**
1	135.7	142	6.3	4.4
2	136	142	6	4.2
3	133.9	142	8.1	5.7
4	138.2	142	3.8	2.6
5	140.8	142	1.2	0.8
6	130	142	12	3.5
7	125	142	17	11.9
8	132	142	10	7.0
9	140.6	142	1.4	0.9
10	139.1	142	2.9	2.0
Average Error (%)				4.3

Exhaust gas temperature testing was conducted by comparing the sensor measurements with the actual values from the thermogun. In Table 5, of the ten samples taken, the actual value remained constant at 142°C, while the sensor readings ranged from 125°C to 140.8°C. The resulting error rate ranged from 0.8% to a maximum of 11.9%, with an average of 4.3%, still within the tolerance limit. Thus, both temperature sensors showed moderate deviations, but were still acceptable in field measurements.

3.3 Proximity sensor testing as rotary speed

Proximity sensors work by detecting the presence of nearby metal objects without direct contact. For applications measuring revolutions (RPM), the sensor is mounted facing the gear and generates a pulse signal each time a gear passes in front of it. If there are 128 gears in one rotation, the sensor will generate 128 pulses in one complete rotation. Figure 7 shows the validation of measurement results using a tachometer to compare the accuracy of the sensor values.

Figure 7. (a) Proximity Sensor (b) Tachometer Reading

The results of proximity sensor measurements with thermogun measuring instrument validation on the rotation per minute (RPM) parameter are listed in table 6 as follows:

TABLE 6.
DATA FROM THE RESULTS OF TESTING THE PROXIMITY SENSOR AND TACHOMETER MEASURING INSTRUMENT

Id	RPM Sensor	Tachometer	Deviation	Error (%)
1	830.5	836	5.5	0.6
2	882.8	888	5.2	0.5
3	880.1	888	7.9	0.9
4	880.6	888	7.4	0.8
5	822.3	834	11.7	1.4
6	835.1	836	0.9	0.1
7	834.2	836	1.8	0.2
8	883.8	888	4.2	0.5
9	892	892	0	0
10	835.7	834	-1.7	0.2
Average Error (%)				0.8

Rotary speed testing was performed by comparing the rpm sensor readings with the actual tachometer readings. The average error was 0.8%, indicating that the proximity sensor generally exhibits fairly high accuracy, with a deviation of less than 1% from the actual value.

3.4 Artificial Neural Network Training

The results of applying the algorithm structure to the Artificial Neural Network are with 3 input neurons on the input layer, 10 hidden neurons on hidden layer 1, 2 hidden neurons on hidden layer 2 and 3 output neurons on the output layer. To obtain optimal performance, the RMSE parameter is used on the basis that the smallest RMSE value is the ANN structure with optimal accuracy. Observations are made by observing the number of epochs or iterations, namely for multiples of 500, 1000, 1500 and 2000 iterations. The following is a table of the training process with epoch variations:

TABLE 7.
RECAPITULATION OF TRAINING RESULTS WITH EPOCH OBSERVATIONS

Id	Epoch	MSE	RMSE	Information
1	500	0.0447	0.2114	MSE is quite low, the model starts learning
2	1000	0.0186	0.1363	Lowest MSE, but not consistent in later epochs
3	1500	0.1296	0.3600	There is an increase in MSE, and mild overfitting appears.
4	2000	0.0847	0.2911	The most stable model, optimal results for ANN training

The results of the artificial neural network (ANN) model training show that the 1000th epoch produced the lowest MSE value of 0.0186 with an RMSE of 0.1363. However, these values are inconsistent, as at the 1500th epoch the MSE increased to 0.1296 and the RMSE to 0.3600. This fluctuating increase indicates overfitting, a condition where the model over-adjusts to the training data and loses its ability to recognize patterns in new data. Meanwhile, at the 2000th epoch, the MSE value was recorded at 0.0847 and the RMSE at 0.2911. Although the MSE at the 2000th epoch was not as low as the 1000th epoch, it remained below the general tolerance limit (MSE < 0.1) and indicated more stable model performance. In this analysis, the RMSE serves to provide a more realistic picture of the average magnitude of the model error because its units are the same as the original data. Thus, RMSE facilitates interpretation of how far the predicted results deviate from the actual values. A moderate RMSE value at the 2000th epoch indicates that the model's predictions are quite close to reality. Therefore, the model at the 2000th epoch is considered to have the best balance between accuracy and stability, and is therefore selected as the best training result.

3.5 Feedforward ANN testing

To test the reliability of the designed ANN structure, real-time testing was conducted, with the hope that the final ANN structure would be able to predict unknown data with optimal accuracy. The data used consisted of 17 samples, with 11 normal class data, 5 alert class data, and 1 danger class data. With this data distribution, the proposed ANN system was able to correctly classify 16 data out of a total of 17. With a prediction error in the class that should have been included in the alert category, but the system predicted that it was still included in the normal category. Thus, the accuracy value obtained is:

$$\text{Accuracy} = \frac{\text{Number of correct prediction}}{\text{Total data}} x\ 100\% \tag{3}$$

$$\text{Accuracy} = \frac{16}{17} x100\%$$

$$\text{Accuracy} = 94{,}11\%$$

The prediction model used to classify engine conditions demonstrated quite good performance with an accuracy rate of 94.11%. Artificial neural network model embedded in a prommabale logic controller has successfully distinguished between normal, alert, and danger conditions accurately, especially under normal conditions.

The novelty of applying an Artificial Neural Network (ANN) as a predictor for ship engine performance with an accuracy of 94.11% lies in its ability to provide a highly reliable, data-driven approach for real-time condition monitoring and early fault detection. Unlike conventional methods that rely on periodic inspections or threshold-based alarms, this approach utilizes ANN to learn complex, nonlinear relationships between key engine parameters such as main bearing temperature, exhaust gas temperature, and engine speed. Achieving an accuracy of 94.11% demonstrates that the model is capable of classifying engine conditions (Normal, Alert, and Danger) with a high level of confidence, making it suitable for practical implementation in marine systems. Furthermore, the integration of ANN within an industrial control environment enables continuous analysis without the need for external computing systems, which enhances response speed and system reliability.

In relation to ship operations, this innovation significantly improves operational safety, efficiency, and maintenance strategies. With accurate real-time predictions, the system can provide early warnings of potential failures, allowing crew members to take preventive actions before serious damage occurs. This reduces unplanned downtime, lowers maintenance costs, and minimizes the risk of operational delays that could disrupt shipping schedules. In addition, the ability to continuously monitor engine health supports more efficient fuel usage and optimal engine performance. Overall, the implementation of ANN with high predictive accuracy contributes to smarter, more adaptive ship operations, aligning with the increasing demand for automation and digitalization in the maritime industry.

IV. CONCLUSION

A real-time monitoring system has been successfully designed by integrating temperature sensors for main bearing and exhaust gas temperatures as well as engine speed (RPM) sensors sent to the PLC as a data processor. The sensor validation value with the measuring instrument shows that the system built has a reading error percentage of no more than 5% and the ANN system built is able to produce an accuracy of 94.11% which indicates accurate ANN predictions for test data. Thus, this predictor can be used as a decision support system to ensure the ship operates safely and helps the crew determine further mitigation actions with more efficient techniques in terms of time and convenience.

ACKNOWLEDGEMENTS

Thank you to the Politeknik Perkapalan Negeri Surabaya for providing facilities for the publication of this article.

REFERENCES

[1] Design Of Real-Time Monitoring System For Performance Parameter And Alarm Of Main Engine Rv. Baruna Jaya III (DOI: https://10.1088/1755- 1315/1081/1/012024.
[2] DigiKey. (2024). Modicon M221 Programmable Logic Controllers. Diakses dari https://www.digikey.com/en/product-highlight/s/schneider-electric/modicon- m221-programmable-logic-controller
[3] Dzinavatonga, T., et al. (2023). Determination of Thermal Time Constant of a Pt100 Temperature Sensor in Still Oil Using the Time Derivative Method. Chemical Engineering & Technology. https://onlinelibrary.wiley.com/doi/full/10.1002/ceat.202200119Wiley Online Library
[4] Gordon, J. (2022). Understanding Diesel Engines: A Practical Guide. Wiley.
[5] Hackworth, J. R., & Hackworth, F. D. Jr. (2023). Programmable Logic Controllers. Pearson Prentice Hall.
[6] Harris, J. (2021). The Marine Diesel Engine: A Practical Guide to Understanding and Maintaining Your Engine. Adlard Coles Nautical.
[7] Hella. Checking the Exhaust Gas Temperature Sensor. Hella Techworld, https://www.hella.com/techworld/sg/technical/sensors-and-
[8] Hunkeler, U., Truong, H. L., & Stanford-Clark, A. (2019). MQTT-S—A publish/subscribe protocol for wireless sensor networks. 2008 3rd International Conference on Communication Systems Software and Middleware and Workshops, 791–798. IEEE.
[9] Hyulian, (2023). Digitalisasi Auxilary Engine Berbasis Standakone Scada Kapal Kontainer Dengan Metode Decision Tree C4.5 (Hyulian, 2023)
[10] Meyer, J. (2022). Marine Propulsion: A Guide to the Design and Operation of Marine Propulsion Systems. Springer.
[11] O'Grady, M. J., Langton, D., & O'Hare, G. M. (2017). Node-RED for rapid prototyping of context-aware applications. 2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), 1–4. IEEE.
[12] Saad, P. S. M., Abdul Halim, N. A. H., Zulkefle, H., Ahmad, N., & Sivaraju, S. S. (2024). Precision Temperature Measurement and Error Analysis for Three- Wire PT100 Resistance Temperature Detector (RTD) using LTSpice. Journal of Advanced Research in Fluid Mechanics and Thermal Sciences, 118(2), 148–159.https://doi.org/10.37934/arfmts.118.2.148159Semarak Ilmu
[13] Wang, W., Yang, M., Yu, L., & Liu, D. (2020). Design of PT100 High-Precision Temperature Measurement Systems Based on Third-Order Model. Ferroelectrics, 563(1), 118–127. https://doi.org/10.1080/00150193.2020.1760616
[14] Adhitya, R.Y.; Rinanto, N.; Sudibyo, R.W.; Wibowo, S.; Nuryanti; Purnomo, F.E.; Rusli, M.R.; Abadi, S.C.; Wiharya, C.; Afriansyah, F.L.; et al. State-of-Charge Estimation on Lithium-Ion 18650 Under Charging and Discharging Conditions: A Statistical and Metaheuristic Approach. World Electr. Veh. J. 2026, 17, 83. https://doi.org/10.3390/wevj17020083
[15] Adhitya, R.Y., Rinanto, N., Syafiuddin, Resmi, F., Arumsari, N., Sarena, S.T. (2025). Advanced Data Analytics for Maritime Energy Efficiency. In: Elsisi, M., Rinanto, N., Su, CL. (eds) Maritime Infrastructure for Energy Management and Emission Reduction Using Digital Transformation. Studies in Infrastructure and Control. Springer, Singapore. https://doi.org/10.1007/978-981-96-4438-4_4
[16] Syai'in, M., Adhitya, R., Soeprijanto, A., Rohiem, N., -, M., & Wang, Y. (2026). RNN-Driven Smart Water Quality Management for Vannamei Shrimp Aquaculture. International Journal of Robotics and Control Systems, 6(2). doi:https://doi.org/10.31763/ijrcs.v6i2.2363
[17] D. P. Riananda et al., "System Protection Analysis on 1kW Solar Charge Hybrid Inverter Using Adaptive Neuro-Fuzzy Inference System (ANFIS)," 2025 International Conference on Smart Computing, IoT and Machine Learning (SIML), Surakarta, Indonesia, 2025, pp. 1-6, doi: 10.1109/SIML65326.2025.11080910.
[18] N. P. Rahmawati, "Design of ANFIS system to detect the condition of generator set model P22-6 based on Omron CJ1M PLC", J. Soft Comput. Explor., vol. 5, no. 3, pp. 240-250, Sep. 2024.
[19] Adhitya, R.Y. et al. (2026). Optimizing Maximum Power Point Tracking (MPPT) Using Metaheuristic Approximation in Charging Condition. In: Elsisi, M., Amer, M., Rinanto, N., Su, CL. (eds) Advancements in Smart Energy Systems. Studies in Infrastructure and Control. Springer, Cham. https://doi.org/10.1007/978-3-032-17462-8_10.
[20] Adhitya, R.Y. et al. (2023). Rancang Bangun Aplikasi Intelligent Visual Scanner berbasis CNN untuk Identifikasi Cacat Pada Hasil Pengelasan. COMPLETE Journal of Computer, Electronic, and Teleommunication Vol. 4 No. 2. https://doi.org/10.52435/complete.v4i2.393.
[21] Sholahuddin Muhammad Irsyad, Khumaidi, A., Ryan Yudha Adhitya, Adi Rahmad Ramadhan, Dhika Arya Pratama, & Muhammad Jardin Saputra. (2025). Predicting Real Distance for Wheeled Soccer Robot using YOLO Architecture. International Journal of Informatics and Computation, 7(2), 806–821. https://doi.org/10.35842/ijicom.v7i2.200.
[22] Khumaidi, A., Muhammad, A. Y., Ryan Yudha Adhitya, Sholahudin Muhammad Irsyad, & Dhika Arya Pratama. (2025). Object Recognition in Robosoccer on Wheeled Using YOLO and ROS. International Journal of Informatics and Computation, 7(2), 779–792. https://doi.org/10.35842/ijicom.v7i2.199.