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## Automatic verification of wind test in DP annual trials using a rule-based expert system and LSTM network

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### Abstract

Dynamic Positioning (DP) systems play a critical role in maintaining vessel position and heading under challenging marine conditions. Among the standard DP performance trials, the wind sensors test verifies the redundancy and functionality of environmental inputs. Traditionally, such verification relies on human supervision and manual validation. This paper suggests an approach to automate the verification process using two methods: a rule-based expert system and a Long Short-Term Memory (LSTM) model. The expert system encodes domain knowledge through logical rules to detect test sequences, demonstrating accuracy in controlled scenarios. However, its limitations in adaptability, particularly due to its binary (yes/no) output, led to exploring a data-driven alternative. An LSTM-based model was developed and trained on synthetic data designed to simulate real-world sensors behavior and test conditions. Results show that the LSTM model effectively detects test sequences, achieving high classification accuracy. This study highlights the feasibility of automating DP trial verification and outlines the potential of LSTM models to generalize beyond fixed rule sets. While still in early stages, the machine learning approach presents a promising direction for future work aimed at broader scenario detection in autonomous DP assessment.

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*Keywords:* Dynamic Positioning; Maritime Systems; DP Trials; Rule-based expert system; LSTM network.

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### 1. Introduction

Dynamic Positioning (DP) systems are critical in offshore operations, enabling vessels to maintain their position and heading without anchoring. These systems combine control algorithms with sensors data to counteract environmental forces in real time. A comprehensive historical and technical overview of DP modeling and control is provided in [15], while recent surveys [9, 1] have reviewed traditional and modern DP control strategies, including model-based and intelligent approaches.

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To ensure the reliability of DP systems and to verify compliance with the standards required for different DP classes, annual trials are conducted, typically structured around Failure Modes and Effects Analysis (FMEA). This methodology is widely used to assess system vulnerabilities and prioritize preventive actions [14]. Its application in maritime operations has been explored in works such as [10, 3], and more recently in [16], who emphasize the importance of real-time data integration for enhancing safety and performance. Among these trials, the wind sensors test is particularly important, as it verifies not only the redundancy of environmental sensors but also the DP controller's ability to switch sensors priority automatically when conditions change.

Previous work [13] has shown that faults in the DP computer subsystem are both frequent and underrepresented in the existing literature. It was also noted that the control strategy employed by most DP systems incorporates wind information in a feedforward manner, where wind measurements directly influence control actions. This highlights the critical importance of accurate wind data and the potential impact of wind sensor failures on overall system performance. As the wind sensor test inherently verifies the DP controller's ability to respond to changes in sensor availability, it serves as a valuable opportunity to assess the reliability of the DP computer alongside the redundancy of environmental sensors.

Traditionally, such trials require human supervision and manual validation. However, with the increasing availability of real-time operational data, automating this verification process has become feasible. Expert systems (ES), particularly rule-based variants, have been applied in various domains to emulate human reasoning [8]. While effective in structured scenarios, these systems struggle with variability due to their reliance on predefined logic. To address these limitations, machine learning models such as Recurrent Neural Networks (RNNs) and their variant, Long Short-Term Memory (LSTM) networks, offer more robust alternatives. Designed for sequential data, LSTMs are capable of capturing long-term dependencies and complex temporal patterns [17].

This paper presents two approaches for the automatic detection of wind sensor test scenarios in DP trials: a rule-based expert system and an LSTM model trained on synthetic data. Section 2 outlines the problem context, starting with an overview of DP systems, the structure of annual trials, and the importance of wind sensor testing. Section 3 introduces the proposed detection methods: the expert system is detailed in Section 3.1, and the LSTM-based approach is presented in Section 3.2, including the design of the synthetic dataset and training procedure. Each method section includes implementation details and the corresponding detection results. The paper concludes with a summary of findings in Section 4, followed by perspectives for future work and extensions in Section 5.

## 2. Problem Statement

### 2.1. DP Overview

As per [11], a Dynamic Positioning (DP) system is a computer-controlled system designed to automatically maintain a vessel's position and heading in 3 degrees of freedom of surge, sway, and yaw (Fig. 1). This is accomplished through the synchronized use of the vessel's propellers and thrusters, which are guided by data from various sensors such as position reference sensors, wind sensors, and gyro-compasses. These sensors provide real-time information about the vessel's position and the environmental forces acting on it, such as wind, waves, and currents. The DP system employs advanced control algorithms and thrust allocation systems to interpret this data and continuously adjust the thrust output and angles, ensuring the vessel remains stable and accurately positioned despite external forces. This integration of sensors inputs with the controller enables precise and dynamic responses to varying environmental conditions, ensuring the vessel's position is maintained even under challenging circumstances.

The DP system is typically divided into three main subsystems according to [15]: the power, propulsion, and DP control systems. The power system includes all components necessary to supply the DP system with power, such as the power generation plant, power management system, and electric power distribution system. The propulsion system encompasses various types of thrusters, including conventional shaft-line propulsion systems, tunnel thrusters, and azimuth thrusters, which can produce thrust in any direction. The control system consists of hardware, software, and supporting systems that communicate with the other subsystems to maintain the vessel's position. This includes computer/joystick systems, sensors, position reference systems, and display panels.

As defined by the International Maritime Organization (IMO) in [7], DP systems are classified into three categories based on their reliability and redundancy. **Class DP1** has no redundancy, meaning a single fault can result in position

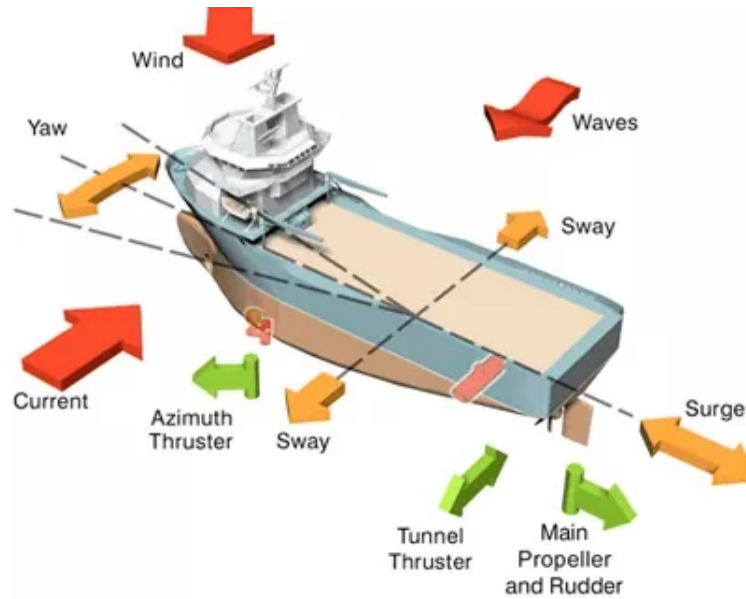


Fig. 1. External forces acting on a Dynamic Positioning vessel.

loss. **Class DP2** is designed to sustain operations if one active component fails, but it may fail if a static component, like cables or pipes, malfunctions. **Class DP3** offers the highest level of redundancy, enabling continued operation despite the failure of any component, including the loss of an entire compartment due to fire or flood. This classification ensures that the DP system's reliability aligns with the consequences of a loss of position-keeping ability, with more critical operations requiring more reliable systems.

## 2.2. Annual Trials

Given the critical role and complexity of DP systems in maintaining vessel position and safety, regular testing and validation are essential. This is achieved through DP annual trials, which are mandatory assessments designed to ensure the reliability and performance of DP systems under various operational conditions. These trials involve a series of tests to verify the integrity of the DP system, focusing on performance, protection, and detection attributes that are crucial for single-fault tolerance and post-failure DP capability. This reliability analysis of the Dynamic Positioning System (DPS) is performed through Failure Mode and Effect Analysis (FMEA) [10].

Initially, DP systems were tested frequently throughout the year, which was costly and inconvenient for vessel operators and their clients, and increased the risk of equipment damage. In response, industry guidelines were developed in the 1990s to standardize annual testing, culminating in [5], which mandates annual testing of all critical DP systems and components. This ensures that the DP system is maintained in good working order and documents the vessel's ability to keep position after single failures associated with its equipment class. Over time, the industry has evolved to enable remote trials, where an independent witness conducts oversight offboard (rather than being physically present), leveraging advancements in technology and operational practices

Following the guidelines of the International Marine Contractors Association (IMCA) in [6], initial DP FMEA proving trials are mandatory for a new build or major upgrade of the DP system, which involves a complete test of all systems and components to verify the vessel's ability to maintain position after single failures associated with its assigned equipment class. Subsequently, annual DP tests are conducted to ensure the system is maintained according to applicable guidelines and remains in good working order. These annual tests document the vessel's ability to keep position after single failures and validate the DP FMEA and operations manual. Additionally, a periodic test is performed every five years, consisting of a complete test of all systems and components to confirm the vessel's

position-keeping ability after single failures (Fig. 2). This periodic test does not necessarily replicate the original DP FMEA proving trials, as those may have included exploratory tests for validation purposes.

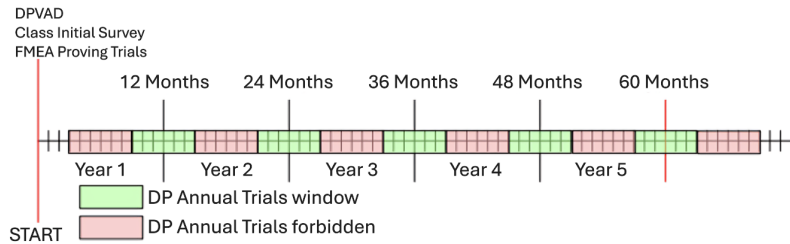


Fig. 2. Trials distribution for a vessel every 5 years [6].

Every DP trial includes two main categories of tests: DP Performance Trials and FMEA Redundancy Verification (RV) Trials. The DP Performance Trials aim to demonstrate the correct functioning of the dynamic positioning system, while the FMEA RV Trials ensure that the system installation conforms to the redundancy requirements of the DP Class. The DP Performance Trials are conducted annually to verify the system's functionality. In contrast, the FMEA RV Trials are subject to a rolling test schedule, meaning they are not performed every year. Instead, these tests are distributed such that all FMEA RV Trials are completed at least once within the five-year period between special surveys. Ultimately, all FMEA RV tests are performed during each five-year special survey.

### 2.3. Wind Sensors Test

One of the essential annual DP performance trials is the wind sensor test, which verifies the redundancy and reliability of the wind measurement system. On the tested vessel, the DP system includes two wind sensors (Wind 0 and Wind 1), and the DP computer uses wind data from one sensor at a time based on a predefined priority setting. This priority determines which sensor is used unless it becomes unavailable, in which case the system should switch automatically to the other. The test consists of four main steps:

1. Confirm system operation with all wind sensors online.
2. With Wind 0 prioritized, deselect Wind 0. The DP system should automatically switch its input to Wind 1. During this transition, monitor vessel performance and ensure no significant positional deviation occurs. Reinststate Wind 0 and verify environmental conditions have stabilized before proceeding.
3. With Wind 1 prioritized, deselect Wind 1. The DP system should automatically switch its input to Wind 0. During this transition, monitor vessel performance and ensure no significant positional deviation occurs. Reinststate Wind 1 and confirm environmental stability before proceeding.
4. Deselect all wind sensors. Monitor vessel performance and confirm that no significant positional deviation occurs. Reinststate all wind sensors.

Successfully completing DP trials, including the wind sensors test and other related evaluations, has traditionally depended on the coordinated efforts of the crew, supervised by an external witness, either onsite or remotely. This approach has been the standard practice for many years. However, with the rapid advancements in the maritime sector, particularly in dynamic positioning systems, and the growing influence of the data-driven industry, new opportunities have emerged to improve efficiency. Modern vessels are now equipped to capture and record data in real time, creating possibilities for innovative data-driven methods to monitor and verify these tests. The following section presents the proposed methods and the results obtained.

## 3. Methods and Results

Building on the wind sensors test steps described earlier, it is clear that the test follows a defined scenario, with the expected outcome being the priority changes, and the environmental stability, which is reflected in the vessel's

position stability. Consequently, the verification process can be divided into two main components. The first involves identifying the occurrence of the test scenario itself, while the second focuses on verifying the vessel's position stability during the detected test period.

In practice, once the scenario is successfully identified, the vessel's position stability can be evaluated by comparing its measured position against the desired (reference) position. Deviations must remain within predefined acceptable limits; thus, direct computation can determine whether the positional drift is valid or invalid. This section proposes and evaluates two methods for detecting the test scenario, establishing a framework for automated wind sensor test verification.

### 3.1. Rule-Based Expert System

Expert systems (ES) are a branch of applied artificial intelligence (AI) that originated in the mid-1960s. The main purpose of expert systems is to capture specialized human expertise and embed it within a computer system, allowing it to offer expert-level advice when required [8]. Once the knowledge is incorporated, the system is able to make inferences and draw conclusions from the stored information.

Among the different types of expert systems, rule-based systems are particularly significant [8]. These systems organize expert knowledge into structured rules, typically formatted as IF–THEN statements, which direct the system's reasoning and enable it to solve problems. Knowledge-based systems (KBS) follow a similar philosophy, aiming to emulate human reasoning within a computational framework, underscoring their close connection to the broader field of AI.

As noted in [2], rule-based systems are among the simplest forms of artificial intelligence. In these systems, knowledge is arranged into rule sets that specify what action to take or conclusion to reach under particular circumstances. This structure allows domain-specific human expertise to be transformed into an automated process. As highlighted in [2], these systems rely on a combination of assertions, statements representing the system's current knowledge, and rules that determine how the system should act when specific conditions are met, typically through IF-THEN logic.

As explained in [2], a typical rule-based system is composed of three fundamental elements:

- A set of facts, representing the initial state or relevant assertions within the system.
- A set of rules, linking conditions (the IF part) to corresponding actions (the THEN part). To maintain performance, it is important that the system includes only necessary and relevant rules.
- A termination criterion, which ensures the system concludes its process either by finding a solution or determining that no solution exists, preventing potential infinite loops.

To detect the wind sensors test scenario, a custom rule-based algorithm was developed based on the test procedure defined in Section 2.3. The rules are designed to mimic the decision-making process of a human operator by analyzing the real-time activation and deactivation status of wind sensors, along with priority assignments. The input consists of timestamped binary status logs for each wind sensor and a variable indicating the active priority. Logical rules are then applied to identify patterns that match the predefined sequence of the test.

In this study, the algorithm processes an event-based dataset, which captures discrete state changes over a 24-hour period. Unlike time-series data that records values at regular intervals, event-based logs only document moments when changes occur. The detection logic identifies transitions between relevant system states while ensuring that the expected timing constraints of the wind sensor test procedure are respected. The main detection steps are outlined in Algorithm 1.

To facilitate visualization, the event-based log was post-processed using zero-order hold interpolation, converting it into a time series format with a 1-minute resolution. This transformation allows for a clearer graphical representation without affecting the original detection process, as it was applied only after detection. Since event-based logs may contain multiple state changes occurring at the exact same timestamp, the conversion introduces a slight delay between such events to ensure they are visually distinguishable. This adjustment is solely for visualization purposes and has no impact on the accuracy or logic of the underlying detection.

Fig. 3 displays the detection output, where the highlighted segments correspond to identified test scenarios based on wind sensors status. The results align well with manually annotated trial events. A detailed view of one such detection is shown in Fig. 4, illustrating the behavior of the three key sensor signals during the test duration, with each point

on the plot presenting the value of a variable at that exact time. Although the changes appear to occur at 1-minute intervals due to the interpolation, they reflect actual sequential transitions captured in the original log. The regular spacing simply enhances readability and does not distort the underlying event sequence.

While the expert system demonstrated effective detection under standard test conditions, its performance is inherently limited by its reliance on predefined rules and binary decision logic, only producing a “yes” or “no” outcome. This rigid framework makes it challenging to identify situations that are close to, but not exactly, the defined test procedure, for example, when an operator initiates the test but omits a required step. Furthermore, extending the system to detect additional scenarios would significantly increase rule complexity, making development and maintenance more difficult. To address these limitations and explore a more adaptive, data-driven alternative, the following subsection presents the use of a Long Short-Term Memory (LSTM) model for scenario detection.

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### Algorithm 1: Sequence Detection

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**Input:** A dataset with timestamped rows (DateTime,  $v_1, v_2, v_3$ ) and a time limit  $\Delta t_{\max}$ .

**Output:** Detection of a predefined sequence within the dataset, respecting time constraints.

**Step 1: Preprocessing** (fill-forward)

**Step 2: Initialization**

Define the *target sequence* as a list of state vectors

Set the sequence index  $j \rightarrow 0$

**Step 3: Iterate Over Data**

**foreach** row  $i$  in the dataset (excluding the last row) **do**

- Extract *current\_time*  $\rightarrow$  timestamp of row  $i$ .
- Extract *next\_time*  $\rightarrow$  timestamp of row  $i + 1$ .
- Extract *current\_state*  $\rightarrow (v_1, v_2, v_3)$  from row  $i$ .
- Compute  $\Delta t \rightarrow (\text{next\_time} - \text{current\_time})$ .

**Sequence Matching:**

- **If** *current\_state* = *target\_sequence*[ $j$ ]:
  - **If**  $j = 0$ , record *starting\_time*  $\rightarrow$  *current\_time*.
  - **If**  $j$  is at the last step of the sequence:
    - \* Report successful detection between *starting\_time* and *current\_time*.
    - \* Reset  $j \rightarrow 0$ .
    - \* Continue to the next row.
  - **Else**, increment  $j \rightarrow j + 1$ .
  - **If**  $\Delta t > \Delta t_{\max}$ :
    - \* Reset  $j \rightarrow 0$  (time constraint violated).
- **Else** (state mismatch):
  - Reset  $j \rightarrow 0$ .

**End:** Print “End of Data”.

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### 3.2. Long-Short Term Memory (LSTM)

Sequences consist of data points arranged in a meaningful order, where information at one position provides context for others. Just as convolutional neural networks (CNNs) are designed to process grid-like data structures such as images, recurrent neural networks (RNNs) are specifically developed to handle sequential data. RNNs use cyclic connections between nodes to capture temporal dependencies, making them well-suited for tasks involving time series or ordered observations. However, standard RNNs often struggle to retain information over long sequences due to the vanishing gradient problem. To address this limitation, Long Short-Term Memory (LSTM) networks were proposed

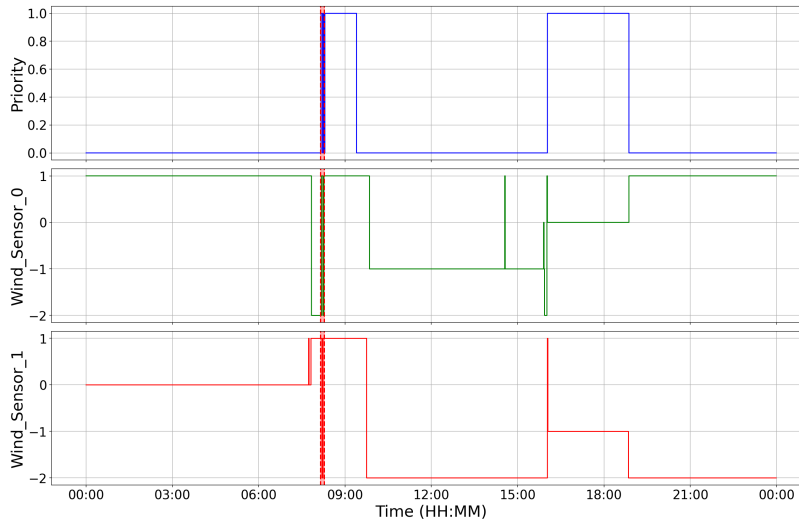


Fig. 3. Variables Over Time with Detected Sequence Highlighted

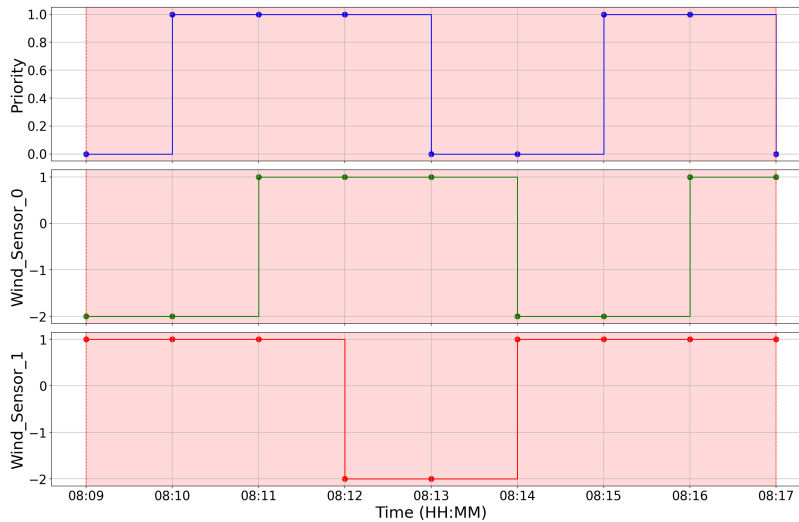


Fig. 4. Zoom-In on Detected Sequence

in [4], which enhance the RNN architecture by introducing memory cells capable of maintaining and regulating information over extended durations, enabling the learning of long-term dependencies more effectively.

A clear explanation of the long-term dependency problem inherent in RNNs, along with how LSTMs are specifically designed to overcome this challenge, is provided in [12]. Unlike standard RNNs, which struggle to retain information over extended sequences, LSTMs are inherently capable of preserving long-term dependencies as part of their core functionality. A detailed, step-by-step walkthrough of the internal mechanisms of LSTM layers, along with a discussion of various developed LSTM variants, is further offered in [12].

A Long Short-Term Memory (LSTM) model was implemented to detect wind sensor test scenarios from sequential data. Initially, the task was framed as a binary classification problem: normal operation (label 0), where wind sensor statuses change arbitrarily, versus a standard wind sensor test (label 1), following the prescribed sequence. With this setup, the model achieved 100% classification accuracy. While promising, this result was expected, as the same pattern had already been captured using a rule-based expert system. This outcome also demonstrated the LSTM model's ability to effectively replicate deterministic logic when trained on structured data.

To explore more nuanced behavior beyond this binary classification, we introduced a third label: near-test scenarios (label 2). These represent sequences that are close to valid tests but deviate slightly, often due to small procedural errors by human operators, something we observed in real trial logs. Unlike the official test steps, which are well-defined, near-test cases are less formal and not explicitly described in guidelines. Therefore, we generated these sequences synthetically by introducing minor variations, such as a single permutation of two consecutive steps, under the hypothesis that such deviations still resemble test behavior.

The complete synthetic dataset thus included three labeled classes: normal operation (0), test (1), and near-test (2), with diverse sensor activation patterns and durations to promote generalization. Additionally, we introduced a timing feature during preprocessing to encode the duration spent in each step, allowing the model to implicitly capture the time-based constraints that were explicitly handled in the expert system.

In this expanded three-class setup, the LSTM model still achieved a high classification accuracy of 97.88%, as illustrated by the confusion matrix in Fig. 5. The matrix shows strong diagonal dominance, indicating correct classification across all three classes: 299 out of 299 for normal operation, 292 out of 300 for standard tests, and 286 out of 297 for near-test sequences. The few misclassifications (primarily between labels 1 and 2) suggest a close proximity in behavior between valid and near-test scenarios, exactly the behavior we aimed to model by introducing the third class. This confirms the model’s ability to capture subtle sequence variations beyond rigid rule definitions, reinforcing its potential for flexible, real-world DP test detection.

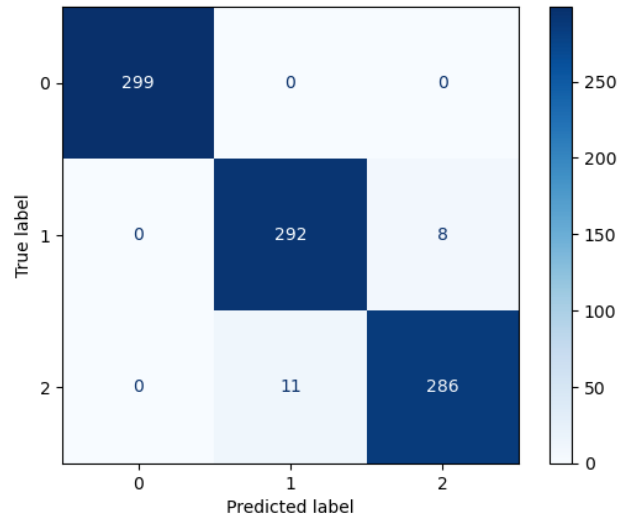


Fig. 5. LSTM Confusion matrix

#### 4. Conclusion

This paper presents an automated approach for detecting the wind sensors test scenario in Dynamic Positioning (DP) trials, based on two distinct methods: a rule-based expert system and a Long Short-Term Memory (LSTM) neural network. The expert system was implemented using domain-specific rules derived from the standardized test procedure, and it successfully detected the test scenario under controlled and clearly defined conditions. However, its reliance on fixed rules limits its flexibility and scalability, especially in the presence of deviations from the standard procedure.

To overcome these limitations, an LSTM-based approach was introduced and trained on synthetically generated data designed to replicate realistic operational scenarios. The model achieved high accuracy in detecting the test sequences, showing promise as a more adaptive and robust solution for automated trial verification. While the results are encouraging, the LSTM implementation represents an initial step in exploring data-driven methods for this application.

## 5. Perspective

Future efforts will pursue two main directions. First, the initial hypothesis on near-test detection will be extended to enhance the model's applicability in real-world conditions. While near-test scenarios were synthetically defined in the present study, the long-term objective is to enable the model to generalize beyond these predefined cases and identify a wider range of imperfect test executions, as commonly observed in practice. One promising avenue involves enabling the LSTM to process variable-length sequences using techniques such as masking and padding, though this adds complexity to the modeling process. Second, the system's capabilities will be expanded to detect additional test scenarios across the full suite of DP trials, with the goal of establishing a comprehensive and autonomous validation framework for maritime operations.

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