Northumbria Research Link

This paper appears in the ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering
DOI: 10.1115/OMAE2020-18844

REAL-TIME PREDICTION OF RELIABILITY OF DYNAMIC POSITIONING SUB-SYSTEMS FOR COMPUTATION OF DYNAMIC POSITIONING RELIABILITY INDEX (DP-RI) USING LONG SHORT TERM MEMORY (LSTM)

Charles Fernandez[1], Dr. Shashi Bhushan Kumar

DNV GL Oil and Gas Technology Centre,
Singapore

Prof. Wai Lok Woo, Dr. Rosemary Norman, Dr. Arun Kr. Dev[2]

Newcastle University,
Newcastle upon Tyne, NE1 7RU, UK

ABSTRACT

In this study, a framework using Long Short Term Memory (LSTM) for prediction of reliability of Dynamic Positioning (DP) sub-systems for computation of Dynamic Positioning Reliability Index (DP-RI) has been proposed. The DP System is complex with significant levels of integration between many sub-systems such as the Reference System, DP Control System, Thruster / Propulsion System, Power System, Electrical System and the Environment System to perform diverse control functions. The proposed framework includes a mathematical computation approach to compute reliability of DP sub-systems and a data driven approach to predict the reliability at a sub-system level for evaluation of model performance and accuracy. The framework results demonstrate excellent performance under a wide range of data availability and guaranteed lower computational burden for real-time non-linear optimization.

There are three main components of the proposed architecture for the mathematical formulation of the DP sub-systems based on individual sensor arrangements within the sub-system, computation of reliability of sub-systems and optimized LSTM deep learning algorithm for prediction of its reliability. Firstly, the mathematical formulation for the reliability of sub-systems is determined based on the series/parallel arrangement of the sensors of each individual equipment item within the sub-systems. Secondly, the computation of the reliability of sub-systems is achieved through an integrated approach during complex operation of the vessel. Thirdly, the novel optimized LSTM network is constructed to predict the reliability of the sub-systems while minimizing integral errors in the algorithm.

In this paper, numerical simulations are set-up using a state-of-the-art advisory decision-making tool with mock-up and real-world data to give insights into the model performance and validate it against the existing risk assessment methodologies. Furthermore, we have analyzed the efficiency and stability of the proposed model against various levels of data availability. In conclusion the prediction accuracy of the proposed model is scalable and higher when compared with other model results.

Keywords: Dynamic positioning systems, Station Keeping, Deep Learning, Long Short Term Memory, DP sub-system reliability, Forecasting, Decision making, Reliability Index.

1. INTRODUCTION

Dynamic Positioning (DP) systems have enabled the maritime, Oil and Gas industry to operate in deeper and deeper waters in search for resources to meet ever increasing energy demands. Loss of position or Loss of heading are considered to be serious incident / accident events in the context of the DP system. Loss of position / heading indicates that the vessel is not able to stay in the pre-defined stationary position or path. The loss of position may be due to drive off or drift off. The DP system consists of several sub-systems all of which contribute to the overall reliability. The Dynamic Positioning Reliability Index (DP-RI) indicates the quantitative reliability during complex marine operations [1]. The key elements for evaluating the performance of the system are its holding capability and reliability. The holding capability is measured through DP capability assessment. However, the reliability cannot be directly measured and calculated. The reason for this is that rules and guidelines doesn't specify the requirements for the level of reliability, they just provide minimum requirements for the reliability and safety of the vessels, equipment, persons and the environment [2]. One of the ways to ensure reliability is to provide redundancy in the design. Redundancy itself does not guarantee a sufficient level of reliability. The vessel's mission profile should determine what overall level of reliability should be attained to achieve the required vessel availability. Higher vessel availability can be achieved by the application of non-critical redundancy.

[1] Contact author: charles.fernandez@dnvgl.com
[2] Contact author: a.k.dev@newcastle.ac.uk

The most effective way to ensure good reliability is through design, for example by specifying high reliability components, carriage of critical spare parts and reducing the number of fault paths that lead to a loss of redundancy. Similarly, during in service operation, planned maintenance, condition monitoring and annual trials will contribute to ensuring sufficient reliability. Reliability is a product of the quality of equipment and suppliers selected, the competence of the engineers who design and build the DP vessel and competence of the crew and management who maintain and operate it [3]. The DP system of a vessel involves complex interactions between a large number of sub-systems. Each sub-system plays a unique role in the continuous overall DP function for safe and reliable operation of the vessel [4]. The DP system is divided into the following sub-systems in the DP-RI concept [1, 4]:

- Reference System (System A1)
- DP control system (System A2)
- Thrusters / Propulsion System (System A3)
- Power System (System A4)
- Electrical System (System A5)
- Environment System (System A6)
- Human / Operator Error System (System A7)

In Section 2 of this paper the authors present the current method of assessing the sub-system reliability and the application of LSTM followed by Section 3 in which the reliability modelling methodology is defined with sub-system architecture, modes of operation and criticality categorization among sub-system signals. Section 4 presents the experimental set-up for the reliability determination through mathematical calculation and reliability prediction through the LSTM model. In Section 5, the results and analysis of the effectiveness of the LSTM for the reliability prediction of sub-systems are discussed and validated. Finally, Section 7 is the conclusion on the effectiveness of proposed framework with LSTM for prediction of reliability of sub-systems and using it in a bottom-up approach for overall DP-RI prediction.

2. LITERATURE REVIEW

Recent developments in technology have contributed towards the optimal performance of DP systems with increased accuracy of positioning and faster response to the effects caused by the environmental conditions. This in-turn has resulted in the addition of sensors and equipment for redundancy leading to complex DP system design [5]. Redundancy does not in itself guarantee a sufficient level of reliability to necessarily lead to overall availability although it can contribute to availability if the redundant elements themselves are sufficiently reliable [2]. There are various factors that needs to be considered in the selection of DP control systems which include reliability and potential service life of components, subsystems and systems, sensor handling, sources of power, remote diagnostic capability, mathematical modelling, consequence analysis aligned with WCFDI and potential service life and obsolescence. This clearly indicates the reliability of sub-system is one of key aspect for DP control system and it plays vital role during complex operation.

Reliability of sub-systems is usually defined as the probability that a sub-system can perform a required function under given conditions for a given time interval [6]. Today industrial practice is that the sub-system reliability is a product of the quality of the equipment and suppliers selected, the competence of the engineers who design and build the DP vessel and the competence of the crew and management who maintain and operate it. DP vessels should ensure a required level of station keeping reliability before preparing for any operation.

DP rules and guidelines sometimes do not specify a level of reliability. When mentioned, it is in the context of the consequences of loss of position, then the DP vessel's availability to work can be related to the probability of losing fault tolerance [7]. DP related equipment should be selected on the basis of high reliability and resistance to internal and external influences which may reduce that reliability [2]. Modern DP vessels are complex machines with several layers of automation, integration between sub-systems, degrees of diversity and more fault tolerance enabling the following features [3]:

- Autonomy
- Diversity
- Decentralization
- Differentiation
- Orthogonality

Most of the shipyard's contractual position is to meet the class requirement, however the vessel owners should express the need for higher reliability for the sub-systems. The mission profile and desire to achieve greater availability may end up influencing the vessel operators and owner to exceed minimum requirement. This will lead to improvement in reliability, operability and maintainability. The sub-system reliability is achieved from component reliability which is choice of individual elements of equipment or software for prolonging mean time between failure (MTBF) [8].

Typically for Quantitative Risk Assessment (QRA) of DP systems, Fault Tree Analysis (FTA) will be developed considering the impact of the worst case failure. Following on from this, Bayesian networks are used for advanced offshore vessels for evaluating the reliability during the design stage, before the proving trial [6]. However, any of these methods does not guarantee the status of sub-systems and their reliability in all failure scenarios [9]. The risk analysis and the assessment just focus on the evaluation during the design stage and improve the design rather than supporting the operator during complex marine operations. Recently LSTM has been used for prediction within the maritime industry [10].Thus a new framework was developed to test its suitability for DP-RI.

3. METHODOLOGY

DP can be considered as a safety related system as it incorporates one or more electrical and/or electronic and/or programmable electronic devices for its control functions to keep the Equipment Under Control (EUC) during any undesirable event. Therefore, functional safety concepts could be easily applied to the DP system for the detection of a potentially dangerous condition resulting in the activation of a protective or corrective device or mechanism to prevent hazardous events arising or providing mitigation to reduce the consequence of the hazardous event. The application of IEC 61508 to DP systems is concerned with achieving functional safety, where unacceptable risk (loss of position) results in physical injury or damage to the health of people, either directly or indirectly [11].

The reliability of the sub-systems at a high level is calculated by using the principles of IEC 61508 which enabled to mathematically compute the approximate reliability to be used for most of QRA to improve the design by providing more redundancy [12]. With these calculations, the reliability reduces due to complexity and the greater the number of independent systems, the more likely it is that one or more will be unavailable in a given time period. These dis-advantages cannot be easily addressed with the current traditional method of reliability assessment. Therefore, it is necessary to develop a mathematical model which will enable accurate calculation of the reliability of sub-systems at any point in time and provide a solution for each of the items below [6]:

- Limiting the impact of the worst case failure to enhance post failure capability
- Optimizing equipment utilization
- Providing fault tolerance in the form of redundancy

3.1 Reliability Block Diagram

A reliability block diagram (RBD) presents a logical relationship of the system, sub-systems and components. A system can be modelled for reliability computation and analysis using block diagrams [12]. A DP system consists of sub-systems and components connected to perform given functions and maintain vessel position and heading. Due to the integration between sub-systems, it can become complex, making reliability analysis difficult. A mathematical model reduces the system to a graphical representation of the interconnection of its sub-systems. A typical reliability model can be represented as shown in Figure 1. These RBD can be used for mathematical calculation and prediction of the reliability of sub-systems.

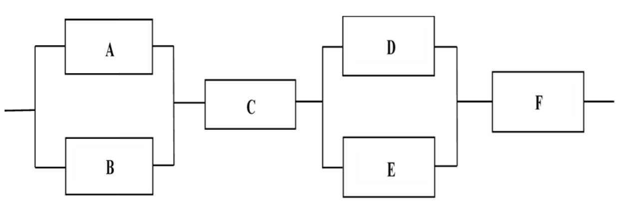

Figure 1. Typical Reliability Block Diagram of Complex System

3.2 Sub-System Architecture

The sub-systems can be represented through an RBD based on the system design architecture. The system architecture can be one of the below models [12]:

- Static System Models
- Series Model
- Parallel Model
- Stand-By System
- (K,n) System

Based on the system configuration, the sub-system reliability is calculated using the principle of probability theory. If the system has more than one function, each function must be considered individually, and a separate reliability block diagram has to be established for each system function. The system reliability can then be modeled using the reliability of the various sub-systems. The mathematical model can be used to assist in making changes to the system for reliability improvement. The model can be used to identify weak links in the system and to indicate where reliability improvement activities should be introduced. It can be used to determine test and maintenance procedures. Modeling of the system should be initiated as soon as preliminary designs are completed, and the model should be updated as design changes are made to the system.

3.3 Modes of Operation

A DP system operates in different modes during complex marine operations depending on the functionalities required by the vessel in one of the following modes [2, 3, 13]:

- Station Keeping
- Auto-Pilot mode
- Follow Target
- Joystick
- Auto Heading Auto track

The Operator and Captain would ensure that the sub-systems are arranged as per the operating manuals, instructions and based on experience for particular complex marine operations. From a functional safety perspective, the components within the sub-system will be operating in specific modes to fulfill the requirements of the safety related systems. The modes of operation for the components within the sub-systems will fall into one of the following modes for safety functions based on the vessel type and DP configuration [11, 14]:

- Low demand mode
- High demand mode
- Continuous Mode

3.4 Sub-System voting configuration

The sub-system architecture and modes of operation determine the component's configuration and voting group to prevent failure of a safety function in the case of accidental events. The sub-system and the components within the sub-system are grouped under one of the following voting configurations (in which "oo" stands for "out-of" to provide redundancy and reliability functionality [11, 12]:

- 1oo1
- 1oo2
- 1oo3
- 2oo2
- 2oo3

3.5 Critical, Non-Critical, Redundant or Non-Redundant grouping

In evaluation of DP system design it is often revealed that the common connection between the sub-systems intended to provide redundancy creates the probability for a fault to occur [8]. A fault in one redundant system can affect another independent system. Redundancy doesn't guarantee a high level of reliability therefore, it is evident that the fault tolerant concept needs to follow the above class requirements. The following arrangement can be found on typical DP vessels in order to achieve higher reliability and availability [3, 13, 15]:

- Critical Redundant
- Non-Critical Redundant
- Critical Non-redundant
- Non-Critical Non-redundant

3.6 Sub-System Equipment, Sensors and Criticality Definition

The mathematical computation model and prediction model for the reliability of the sub-system can be computed only when the system design assumptions and uncertainties are properly defined [16]. In this section, the vessel type, class, system set-up, sub-system configuration, critical, non-critical, redundant, non-redundant grouping and design boundary are defined for the experiment in the next section. The sub-system signals were identified and grouped across different categorizations, considering the design phase for evaluation. The grouping of the signals for the different sub-systems are presented in the following sections [17, 2, 3, 13, 15, 6]

The sub-systems component arrangement, architecture, voting group and criticality grouping are shown in Table 1 to Table 7.

Table 1: Reference System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
GYRO – 3 Unit (1oo3)		
Heading (deg)	Yes	Yes
Rate of Rotation (deg/min)	Yes	Yes
Yaw (%)	Yes	Yes
Preferred	No	No
Enable	No	No
Failure / Error	No	No
VESSEL REFERNECE UNIT – 4 Unit (1oo3)		
Roll (mm)	Yes	Yes
Pitch (mm)	Yes	Yes
Yaw (mm)	Yes	Yes
Preferred	No	No
Enable	No	No
Failure / Error	No	No
GLOBAL POSITIONING SYSTEM (GPS) - 3 Unit (1oo3)		
Vessel Speed (m/s)	Yes	Yes
Course Direction (deg)	Yes	Yes
Preferred	No	No
Enable	No	No
Failure / Error	No	No
DGPS – 2 Unit (1oo2)		
Relative Speed (m/s)	Yes	Yes
Relative Direction (deg)	Yes	Yes
Preferred	No	No
Enable	No	No
Failure / Error	No	No

Table 2: DP Control System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
GYRO – 3 Unit (1oo3)		
Operator Station (OS)	Yes	Yes
Power Supply (PS) Failure	Yes	Yes
Communication Failure	Yes	Yes
NETWORK DISTRIBUTION UNIT NDU – 6 Unit (1oo2)		
Network (Dual Network)	Yes	Yes
FIELD STATION FS – 6 Units (1oo2)		
Field Station (FS)	Yes	Yes
Input/Output Signal Failure	Yes	Yes
Input/Output Signal Failure	No	No
Input/Output Module Failure	Yes	Yes
Failure / Error	No	No
REDUNTANT CONTROLLER UNIT RCU – 6 Units (1oo3)		
Controllers (Triple Redundant)	Yes	Yes
Vessel Mode of Operation	Yes	Yes
Vessel Class (DP 3, DP 2 & DP1)	Yes	Yes
Rotation Center Position	Yes	Yes
Thruster Force Vector	Yes	Yes
Pitch	Yes	Yes
Roll	Yes	Yes
Vessel Model	Yes	Yes
Environmental Error	Yes	Yes
High Precision Control Mode	Yes	Yes
Current Position (deg)	No	Yes
Set Position (deg)	No	Yes
Allocation Mode	No	Yes
Moment (kNm)	No	Yes
Resultant Force (kN)	No	Yes
Resultant Direction (deg)	No	Yes
Required Force (kN)	No	Yes
Required Direction (deg)	No	Yes

Table 3: Thruster / Propulsion System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
THRUSTERS – 8 unit (1oo2)		
ANALOG CONTROL SIGNAL		
Azimuth Pitch Command (deg)	Yes	Yes
Azimuth Speed Command (rpm)	Yes	Yes
Torque Command (N)	Yes	Yes
Pitch Dev	Yes	Yes
Speed Dev	Yes	Yes
Torque Dev	Yes	Yes
Power Available (kW)	Yes	Yes
ANALOG MONITORING SIGNAL		
Power Used (kW)	Yes	Yes
Torque (N)	Yes	Yes
Current (A)	Yes	Yes
Voltage (V)	Yes	Yes
Speed (rpm)	Yes	Yes
Pitch Angle (deg)	Yes	No
Steering Oil Pressure (bar)	Yes	Yes
Azimuth Speed (RPM)	Yes	Yes
Azimuth Angle (deg)	Yes	Yes
Motor Speed (RPM)	Yes	Yes
Reserve Power Available (kW)	No	Yes
Hydraulic Oil Temperature (ºC)	No	No
Lube Oil Temperature (ºC)	No	No
Running Hours (hrs)	No	No
DIGITAL CONTROL SIGNAL		
Start	Yes	Yes

DESCRIPTION	CRITICAL	REDUNDANT
Stop	Yes	Yes
Connect	Yes	Yes
Dis-connect	Yes	Yes
Increase Load/Speed	Yes	Yes
Decrease Load/Speed	Yes	Yes
Local/Remote	No	No
Running	No	No
DIGITAL MONITORING SIGNAL		
Local	Yes	Yes
Remote	Yes	Yes
Running	Yes	Yes
Running Idle	No	No
Run Rated	No	No
Shutdown	Yes	Yes
Start Inhibit	No	No
System Ok	No	No
Circuit Breaker (CB) Opened	Yes	Yes
CB Closed	Yes	Yes
LO Tank Low	Yes	Yes
Hydraulic Pressure Low	Yes	Yes
Phase Fault Error	No	No
Emergency	Yes	Yes
VFD Interlock	Yes	Yes

Table 4: Power System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
ENGINE / GENERATOR – 8 unit (1oo2)		
ANALOG CONTROL SIGNAL		
Load Ref (KW)	Yes	Yes
Frequency Ref (Hz)	Yes	Yes
Re-active Load (kVAR)	Yes	Yes
Load Dev (KW)	Yes	Yes
Frequency Dev (Hz)	Yes	Yes
Voltage Dev	Yes	Yes
Load %	Yes	Yes
ANALOG MONITORING SIGNAL		
Load (kW)	Yes	Yes
Re-active Load (kVAR)	Yes	Yes
Current (A)	Yes	Yes
Voltage (V)	Yes	Yes
Power Factor	Yes	No
Frequency (Hz)	Yes	No
Fuel Rack Pos (%)	Yes	No
Field Current (A)	Yes	No
Speed (RPM)	Yes	No
SWBD Load (kW)	Yes	No
Winding Temperature U (ºC)	No	No
Winding Temperature V (ºC)	No	No
Winding Temperature W (ºC)	No	No
Engine Cylinder Temp 1 (ºC)	No	No
Engine Cylinder Temp 2 (ºC)	No	No
Engine Cylinder Temp 3 (ºC)	No	No
Engine Cylinder Temp 4 (ºC)	No	No
Engine Cylinder Temp 5 (ºC)	No	No
Engine Cylinder Temp 6 (ºC)	No	No
Engine Cylinder Temp 7 (ºC)	No	No
Engine Cylinder Temp 8 (ºC)	No	No

DESCRIPTION	CRITICAL	REDUNDANT
Fuel Oil Temp (ºC)	No	No
Lube Oil Temp (ºC)	No	No
Running Hours (hrs)	No	No
DIGITAL CONTROL SIGNAL		
Start	Yes	Yes
Stop	Yes	Yes
Connect	Yes	Yes
Dis-connect	Yes	Yes
Increase Load/Speed	Yes	Yes
Decrease Load/Speed	Yes	Yes
Local/Remote	No	No
Running	No	No
AVR Fail	Yes	Yes
DIGITAL MONITORING SIGNAL		
Local	Yes	Yes
Remote	Yes	Yes
Running	Yes	Yes
Running Idle	No	No
Run Rated	No	No
Shutdown	Yes	Yes
Droop Mode	No	No
Isoch Mode	No	No
AGS Mode	No	No
Start Inhibit	No	No
System Ok	No	No
CB Opened	Yes	Yes
CB Closed	Yes	Yes

Table 5: Electrical System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
SWITCHBOARD SWBD – 4 UNITS (1oo2)		
ANALOG MONITORING		
SWBD 1 Voltage (kV)	Yes	Yes
SWBD 1 Frequency (Hz)	Yes	Yes
SWBD 2 Voltage (kV)	Yes	Yes
SWBD 2 Frequency (Hz)	Yes	Yes
SWBD 3 Voltage (kV)	Yes	Yes
SWBD 3 Frequency (Hz)	Yes	Yes
SWBD 4 Voltage (kV)	Yes	Yes
SWBD 4 Frequency (Hz)	Yes	Yes
SWBD 1 Load (Kw)	No	Yes
SWBD 1 Spare Load (Kw)	No	Yes
SWBD 1 Load Percentage (%)	No	Yes
SWBD 2 Load (Kw)	No	Yes
SWBD 2 Spare Load (Kw)	No	Yes
SWBD 2 Load Percentage (%)	No	Yes
SWBD 3 Load (Kw)	No	Yes
SWBD 3 Spare Load (Kw)	No	Yes
SWBD 3 Load (%)	No	Yes
SWBD 4 Load (Kw)	No	Yes
SWBD 4 Spare Load (Kw)	No	Yes
SWBD 4 Load (%)	No	Yes
DIGITAL CONTROL SIGNAL		
SWBD1 Slave CB Connect	Yes	Yes
SWBD1 Slave CB Dis-Connect	Yes	Yes
SWBD1 Master CB Connect	Yes	Yes
SWBD1 Master CB Dis-Connect	Yes	Yes

DESCRIPTION	CRITICAL	REDUNDANT
SWBD2 Slave CB Connect	Yes	Yes
SWBD2 Slave CB Dis-Connect	Yes	Yes
SWBD2 Master CB Connect	Yes	Yes
SWBD2 Master CB Dis-Connect	Yes	Yes
SWBD3 Slave CB Connect	Yes	Yes
SWBD3 Slave CB Dis-Connect	Yes	Yes
SWBD3 Master CB Connect	Yes	Yes
SWBD3 Master CB Dis-Connect	Yes	Yes
SWBD4 Slave CB Connect	Yes	Yes
SWBD4 Slave CB Dis-Connect	Yes	Yes
SWBD4 Master CB Connect	Yes	Yes
SWBD4 Master CB Dis-Connect	Yes	Yes
DIGITAL MONITORING SIGNAL		
SWBD1 Earth Fault	Yes	Yes
SWBD 1 Blackout	Yes	Yes
SWBD 1 Dead Bus	Yes	Yes
SWBD 1 Slave CB Fault	Yes	Yes
SWBD 1 Master CB Fault	Yes	Yes
SWBD 2 Earth Fault	Yes	Yes
SWBD 2 Blackout	Yes	Yes
SWBD 2 Dead Bus	Yes	Yes
SWBD 2 Slave CB Fault	Yes	Yes
SWBD 2 Master CB Fault	Yes	Yes
SWBD 3 Earth Fault	Yes	Yes
SWBD 3 Blackout	Yes	Yes
SWBD 3 Dead Bus	Yes	Yes
SWBD 3 Slave CB Fault	Yes	Yes
SWBD 3 Master CB Fault	Yes	Yes
SWBD 4 Earth Fault	Yes	Yes
SWBD 4 Blackout	Yes	Yes
SWBD 4 Dead Bus	Yes	Yes
SWBD 4 Slave CB Fault	Yes	Yes
SWBD 4 Master CB Fault	Yes	Yes
UPS Fault	Yes	Yes
Open Bus Fault	Yes	Yes
Closed Bus Fault	Yes	Yes

Table 6: Environmental System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
WIND SENSOR – 3 Unit (1oo3)		
Relative Speed (A) m/s	Yes	Yes
Relative Direction (A) deg	Yes	Yes
Preferred (D)	No	No
Enable (D)	No	No
Failure / Error (D)	No	No
WAVE – 3 Unit (1oo3)		
Wave Drift - Force	Yes	Yes
Wave Momentum	Yes	Yes
Preferred (D)	No	No
Enable (D)	No	No
Failure / Error (D)	No	No
CURRENT – Model (1oo3)		
Current Speed (A) m/s	Yes	Yes
Current Direction (A) deg	Yes	Yes
Preferred (D)	No	No
Enable (D)	No	No
Failure / Error (D)	No	No

Table 7: Human / Operator Error System – Signal Configuration

DESCRIPTION	CRITICAL	REDUNDANT
DEXTIRITY (DEX)		
Level 1	Yes	Yes
Level 2	Yes	Yes
Level 3	Yes	Yes
DECISION (DEC)		
Level 1	Yes	Yes
Level 2	Yes	Yes
Level 3	Yes	Yes
DISTRACTION (DIS)		
Level 1	Yes	Yes
Level 2	Yes	Yes
Level 3	Yes	Yes
SITUATION AWARENESS (SA)		
Level 1	Yes	Yes
Level 2	Yes	Yes
Level 3	Yes	Yes
TANGIBLE EXTERNAL		
Weather	No	No
Technical failures	No	No
Temperature	No	No
Documentation	No	No
Design	No	No
INTANGIBLE EXTERNAL		
Relationship	No	No
Commercial Pressures	No	No
Financial	No	No
Culture	No	No
TANGIBLE INTERNAL		
Illness	No	No
Fatigue	No	No
Stress	No	No
Drugs	No	No
INTANGIBLE INTERNAL		
Dis-Orientation	No	No
Fixation	No	No
Visual Illusions	No	No
Denial	No	No
Memory	No	No

4. Experimental Set-Up

DP system is a composite entity with complex integration between sub-system comprising equipment, software, facilitates, materials, procedures and personnel. In this paper we have considered the analysis for the sub-systems from two different points of view [16]:

- Structural Focus
- Functional Focus

The reliability block diagrams are built as success oriented networks illustrating how the sub-systems operate as functional blocks to fulfil the overall DP system functional requirement [6, 7]. The structure of the RBD is described mathematically by structure functions. These structure function will be used to calculate the sub-system reliability.

The experimental set-up for the reliability calculation of the sub-systems was performed with the following parameters defined as common for the two approaches and validation [18]:

- System
- System Boundary
- Outputs
- Inputs
- Boundary conditions
- Support
- External Threats
    - Natural Environmental threats
    - Infrastructure threats and Social threats
    - Threats from other technical system

For this particular experiment, the data from a DP 3 vessel was used which was taken from a historical database during the annual trial and these samples are stored as time series with sample interval of 1 milli-second. The data was extracted for the period of the annual trial which was for one week and in addition, operation data for a period of two years was extracted. The sub-system signals were identified and grouped across different categorizations, considering the design phase for evaluation. The data was split into train and test for LSTM prediction and data was sorted to use for mathematical calculation. In this section the reliability of the seven sub-systems is calculated through mathematical computation through equation in next section and deep learning algorithm LSTM. The research framework of the experiment is shown in Figure 2 where the information from the sub-system level is carefully selected and diligently used for the calculation and prediction.

4.1 Mathematical Computation of DP Sub-System Reliability

The mathematical computation of reliability of DP sub-systems is highly dependent on the structural focus which is expressed through the RBDs. The structural physical architecture defines the basis system hierarchy of each of the sub-systems and the association of lower parts and components with higher level assemblies and systems. Once the structural aspects of the physical sub-system are defined then the functional focus is taken into consideration for the mathematical computation [16, 18, 8]. As shown in Figure 2, for mathematical computation, each sub-system is further divided into groups of equipment. The three main activities involved in the calculation of reliability of sub-systems are [19]:

- Reliability Block Diagram based on system configuration
- System Diagnostic based on voting group
- Pattern recognition for functional fault identification

The reliability of sub-systems can be calculated thought the below mathematical equation [20, 12]:

$$PFD_{SUB\text{-}SYSTEM} = PFD_{COMP1} + PFD_{COMP2} + \ldots\ldots + PFD_{COMPn}$$

Where

$PFD_{SUB\text{-}SYSTEM}$ → *Average probability of failure on demand for DP sub-system*

PFD_{COMP1} → *Average probability of failure on demand for components*

n → *Number of components in the sub-system*

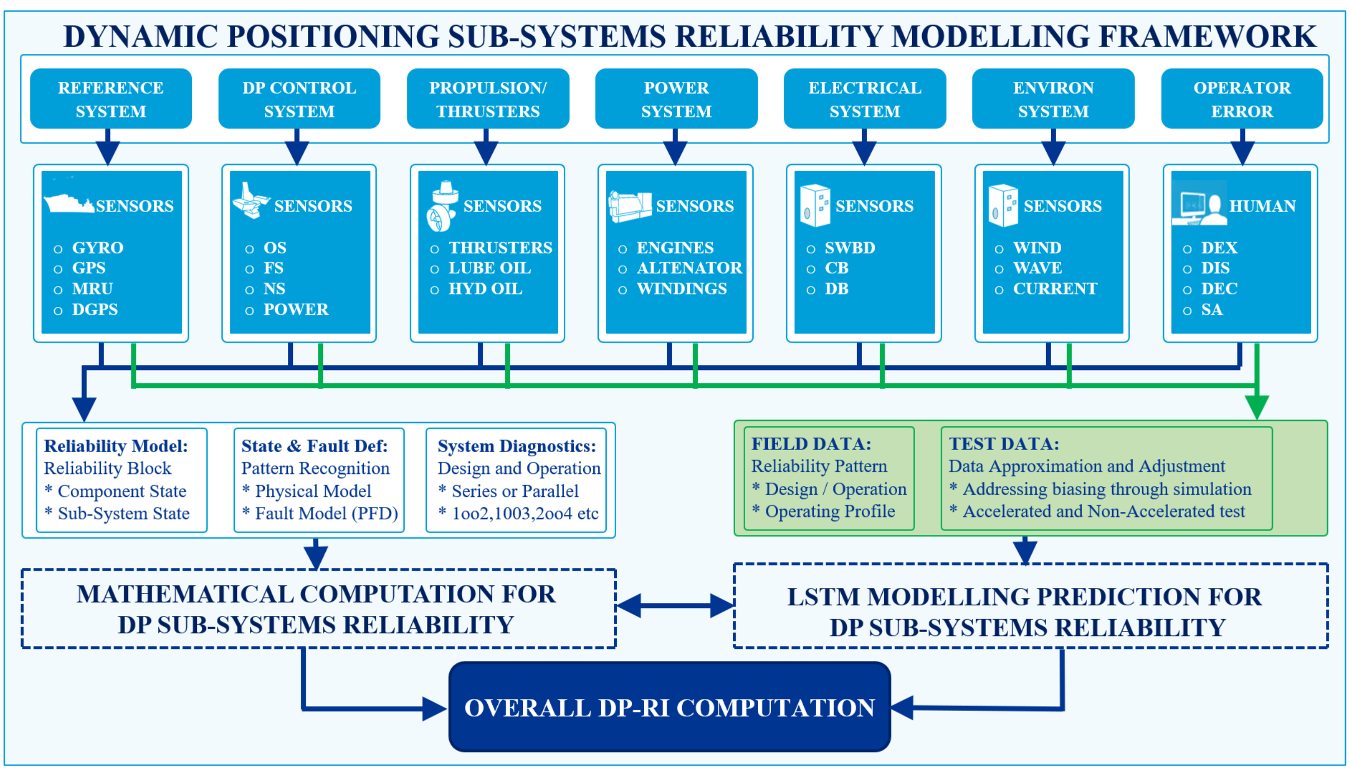

Figure 2. DP Sub-System Reliability Computation Framework

Note: The description of abbreviations is in Table 1 to 7

The arrangement and voting of components can in one of the following architectures, as shown in Figure 3,4 5, 6 & 7.

1oo1:

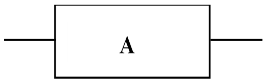

Figure 3 1oo1 architecture

$PFD_{AVG} = (\lambda_{DU} + \lambda_{DD})t_{CE}$

1oo2:

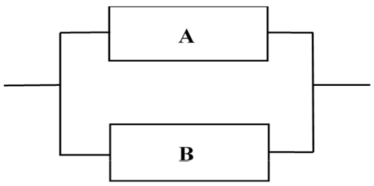

Figure 4 1oo2 architecture

$$PFD_{AVG} = 2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)$$

1oo3:

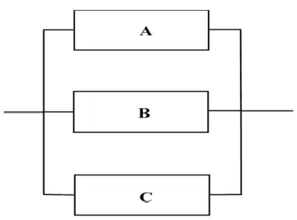

Figure 5 1oo3 architecture

$$PFD_{AVG} = 6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)$$

2oo2:

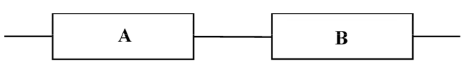

Figure 6 2oo2 architecture

$PFD_{AVG} = 2\lambda_D t_{CE}$

2oo3:

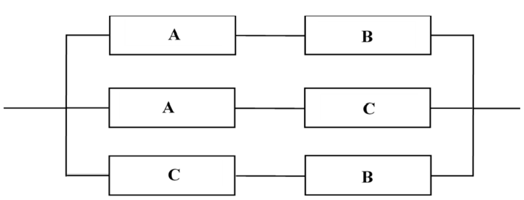

Figure 7 2oo3 architecture

$$PFD_{AVG} = 6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)$$

λ_{DU}→ Dangerous Undetected failure rate of a channel in a Subsystem
λ_{DD}→ Detected dangerous failure rate of a channel in a subsystem
t_{CE} → Calculate the channel equivalent mean down time
t_{GE} → System equivalent down time
β → The fraction of undetected failures that have a common cause
β_D → the fraction that have a common cause of those failures that are detected by the diagnostic tests
$MTTR$ → Mean time to restoration
MRT → Mean repair time
T_1 → Proof test interval
T_2 → Interval between demands

The system architecture / voting are used to calculate sub-system Reliability from Probability of failure on demand (PFD) [18, 12]:

Reference System (A1):

$PFD_{A1} = PFD_{GYRO} + PFD_{MRU} + PFD_{GPS} + PFD_{DGPS}$

$$PFD_{A1} = \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \{2\lambda_D t_{CE}\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\}$$

DP control System (A2):

$PFD_{A2} = PFD_{OS} + PFD_{NDU} + PFD_{FS} + PFD_{RCU}$

$$PFD_{A2} = \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \{6((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\}$$

Thruster / Propulsion System (A3):

$PFD_{A3} = PFD_{T1} + PFD_{T2} + PFD_{T3} + PFD_{T4} + PFD_{T5} + PFD_{T6} + PFD_{T7} + PFD_{T8}$

$$PFD_{A3} = \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\}$$

Power System (A4):

$PFD_{A4} = (PFD_{DG1} + PFD_{DG2}) + (PFD_{DG3} + PFD_{DG4}) + (PFD_{DG5} + PFD_{DG6}) + (PFD_{DG7} + PFD_{DG8})$

$$PFD_{A4} = \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \left\{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\right\} + \{2((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU})^2 t_{CE}t_{GE} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}(\frac{T_1}{2} + MRT)\}$$

Electrical System (A5):

$PFD_{A5} = PFD_{SWBD1} + PFD_{SWBD2} + PFD_{SWBD3} + PFD_{SWBD4} + PFD_{CB1} + PFD_{CB2} + PFD_{CB3} + PFD_{CB4}$

$$PFD_{A5} = \{(\lambda_{DU} + \lambda_{DD})t_{CE}\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE}\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE})\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE}\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE}\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE}\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE})\} + \{(\lambda_{DU} + \lambda_{DD})t_{CE}\}$$

Environmental System (A6):

$PFD_{A6} = PFD_{WIND} + PFD_{WAVE} + PFD_{CURRENT}$

$$PFD_{A6} = \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\}$$

Human / Operator Error (A7):

$PFD_{A7} = PFD_{DEX} + PFD_{DEC} + PFD_{S} + PFD_{DGPS}$

$$PFD_{A7} = \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\} + \left\{6\left((1-\beta_D)\lambda_{DD} + (1-\beta)\lambda_{DU}\right)^3 t_{CE}t_{GE}t_{G2E} + \beta_D\lambda_{DD}MTTR + \beta\lambda_{DU}\left(\frac{T_1}{2} + MRT\right)\right\}$$

Therefore, the overall reliability of DP system (DP-RI) is calculated as per equation (1):

$$PFD_{DP} = PFD_{A1} + PFD_{A2} + PFD_{A3} + PFD_{A4} + PFD_{A5} + PFD_{A6} + PFD_{A7} \quad (1)$$

4.2 LSTM prediction of DP Sub-System Reliability

Reliability prediction is becoming the most commonly used method in the oil and gas industry for predicting the reliability of complex systems [17, 21, 8]. For this specific application the research framework is defined in Figure 2. The DP sub-system data from the field and test simulations are used for training the deep learning algorithm LSTM for predicting the near future values.

The experimental set-up for the reliability prediction was based on the following parameters and boundaries, defined upfront to address the uncertainties through the key parameters [18]:

- Reliability Prediction uses (Why)
  - Reliability goal assessment
  - Mission Reliability Estimation
  - Prediction of Reliability performance
- Reliability Prediction in the system life cycle (When)
  - Operational Phase
- Factors to select Reliability Prediction method (What)
  - Product Technology
  - Consequence of failure
  - Failure criticality

The field data are directly extracted from the DP3 vessel for which the mathematical computation was performed using the RBD model. The LSTM model was developed for the reliability prediction and the field data of DP 3 vessel was used which was taken from a historical database during the annual trial was used to train the model. The test data was simulated to address bias for the missing system configuration. The reliability prediction through LSTM was performed with the information such as Reliability requirements, System Architecture, Operating environment, operating profile and failures, mechanism and causes were fed into the model to ensure that there will be the desired degree of precision in the prediction as per IEEE 1413 standard [18]. This is real-time prediction which involves the prediction of future system reliability based on the information of the current and past status of the sub-systems.

The LSTM model is a variant of Recurrent Neural Networks (RNN) which are application specific and use purpose-built memory cells to address time series prediction for sequential data [22, 23]. This unique attribute of LSTM supports the model to hold only relevant data and at the same time 'removing' or 'forgetting' in the memory cells which are regulated by structures called gates. Each of the memory cells have three gates maintaining and adjusting its cell state $s^{(t)}$:

- **Forget gate:** $f^{(t)}$ which defines what information is removed from the cell state
- **Input gate:** $i^{(t)}$ which specifies what information is added to the cell state
- **Output gate:** $o^{(t)}$ which specifies what information in the cell state is used.

The real-time sequential update formula is represented by

$$g^{(t)} = tanh\left(W_{gx}x^{(t)} + W_{gh}h^{(t-1)} + b_g\right)$$

Input Gate: $i^{(t)} = \sigma\left(W_{ix}x^{(t)} + W_{ih}h^{(t-1)} + b_i\right)$
Forget Gate: $f^{(t)} = \sigma\left(W_{fx}x^{(t)} + W_{fh}h^{(t-1)} + b_f\right)$
Output Gate: $o^{(t)} = \sigma\left(W_{ox}x^{(t)} + W_{oh}h^{(t-1)} + b_o\right)$
Cell State: $s^{(t)} = g^{(t)} \circledcirc i^{(t)} + s^{(t-1)} \circledcirc o^{(t)}$
Hidden Gate: $h^{(t)} = \tanh(s^{(t)}) \circledcirc o^{(t)}$
Output Layer: $y^{(t)} = \left(W_{hy}h^{(t)} + b_y\right)$

Where x^((t)) is the input vector for the time step t, W are the network weights, b are bias parameters, y is the output to be compared to observations, h is the hidden state, σ is the sigmoidal function, ⊚ is element wise multiplication and s is called the cell state of memory cells, which is unique to LSTM. The Root Mean Square Error (RMSE) represents the prediction accuracy and it is defined by [1]:

$$\boldsymbol{RSME} = \sqrt{\frac{1}{L}\sum_{j=1}^{L}(\boldsymbol{V_j} - \boldsymbol{\hat{V}_j})^2}$$

Where ∑ is summation, $\boldsymbol{L}$ is sample size, $\boldsymbol{V_j}$ is predicted values and $\boldsymbol{\hat{V}_j}$ is calculated or actual values.

The Correlation Coefficient (CC) represents the linear dependency of two random variables. The linear dependency is ***strong*** if CC is greater than 0.8 and ***weak*** if CC is less than 0.5.

$$\boldsymbol{CC} = \frac{\boldsymbol{Cov}\,(\boldsymbol{V},\widehat{\boldsymbol{V}})}{\sqrt{\boldsymbol{Var}\,(\boldsymbol{V})\boldsymbol{Var}(\widehat{\boldsymbol{V}})}}$$

Where $\boldsymbol{V}$ is predicted values, $\widehat{\boldsymbol{V}}$ is calculated or actual values, **Cov ()** is covariance and **Var ()** refer to the variance operator.

The Gated Recurrent Unit (GRU) is a simpler version of LSTM where the cellular state and the hidden state are combined which reduces the number of variables [24]. ELM provides a unified solution for a generalized feedforward network. In ELM, the input parameters, hidden node parameters are randomly generated, and output weights are computed analytically. The unique feature of ELM is high accuracy, minimal user intervention and real-time learning [24]. From Table 8 it is clearly evident that the performance indices of the LSTM model outperform the other deep learning algorithms that were tested. Therefore, LSTM was chosen for further research by optimizing for the activation function (ReLU) and hyperparameters (number of neurons = 400 , hidden layers = 6 and Learning rate = 0.3).

Table 8. Performance Analysis Results

SNo	MACHINE LEARNING	RSME	CC
1	LSTM	0.000713	0.9518
2	GRU	0.3078	0.8895
3	ELM	0.2578	0.8789

5. RESULTS AND ANALYSIS

In this section, we present the results of the reliability of DP sub-systems derived from two different methods: one through mathematical computation and another through the deep learning algorithm model. The Root Mean Square Error (RMSE) is used as the performance measure to compare the performance of prediction against mathematical calculation [1].

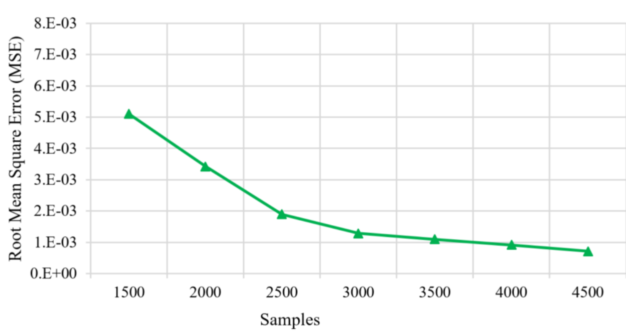

Figure 8 RMSE curve of LSTM with optimized hyperparameters

First, we present results of the reliability at sub-system level using the data collected from the same sources (vessel, configuration, period and mode of operation). A total of 4500 samples for each sub-system were collected and 3000 samples used in the training which was collected from the vessel during operational phase. The remaining data of 1500 samples were used for testing for each sub-system. In this experiment the comparison was performed in offline mode as online sequential operation was not possible to due to a confidentiality agreement and cybersecurity risks when interfacing the research laptop to the actual operational technology loop in the vessel.

The framework was developed for a DP 3 vessel where all the possible configurations, operation modes, voting logics and system architectures can be tested to evaluate the suitability for DP2 and DP1 vessels. As shown in the Table 9 and Figure 8, LSTM can predict the reliability of the DP-sub-system accurately under various conditions.

Table 9 DP sub-system reliability RSME

SNo	Number of Samples	RSME
1	1500	0.005102
2	2000	0.003428
3	2500	0.001895
4	3000	0.001289
5	3500	0.001099
6	4000	0.000919
7	4500	0.000713

In general, mathematical calculation involves huge computational effort and requires significant processing time, which limits its applicability for complex marine operations where the time for action is very limited. The deep learning algorithm LSTM provides a method for faster prediction of reliability of sub-systems and provides information directly during critical operations. Based on the type of Graphical Processing Unit (GPU) used in the Google Cloud Engine, the computation time will range from 30 minutes (8 GPUs, 96 GB GDDR5, 1 - 64 vCPUs,1-416 GB) to 8 hours (2 GPUs,16 GB GDDR5. 1 - 48 vCPUs, 1 - 312 GB). This supports the operator to make decisions at the right time more effectively.

Table 10 DP-RI calculation and prediction comparison

CASE	CASE ID IN IMCA DATABSAE	CAL VAL	LSTM
1	Year 2005 → 0501	70.1	70.3
2	Year 2006 → 0614	82.6	81.9
3	Year 2008 → 0892	60.4	60.9
4	Year 2009 → 0908	50.7	50.6
5	Year 2010 → 1047	34.5	33.9
6	Year 2011 → 1105	76.9	76.6
7	Year 2014 → 1431	56.1	55.9
8	Year 2015 → 1517	65.9	65.8
9	Year 2017 → 1787	48.4	48.6
10	Year 2018 → 18123	58.9	58.8

Secondly, in the research we present the results based on a cascaded bottom-up approach to evaluate the prediction at system level for DP-RI values. The results of the LSTM prediction for the DP-RI matched with the mathematical calculation as shown in Table 10 when the validation was performed for the 10 different case studies obtained from IMCA accident database [25]. In addition, LSTM showed improved results for the DP-RI when compared with its prediction at sub-system level. This is due to the fact that the model was able to train itself with the different data during the testing period for the unknown values and correct it with the approximations. Therefore, LSTM can be applied at system level for DP-RI prediction.

6. CONCLUSION

In this paper, we have investigated the performance of LSTM to predict the reliability for sub-systems of Dynamic Positioning. The proposed framework was effective as it included both a mathematical computation approach to compute reliability of DP sub-systems and a data driven approach to predict the reliability at a sub-system level. This provided a way to evaluate performance and accuracy of the model prediction against the mathematical computation. The data was collected from the vessel during annual trial phase for a period of one week and the previous two years operational data were taken from an event logger / historical station. The data from the first year of operation was used for training and the data from the second year was used for testing. The data is chosen such that the study covers all the different possible scenarios of operations. The framework can be used on any operational vessel to predict the reliability of sub-systems at any point in time during complex marine operations.

It must be noted that the work on prediction of reliability for sub-systems of DP using LSTM can be easily extended to the overall DP system for prediction for DP-RI. This will support in vessel performance analysis, operation planning and prescriptive solutions in the case of any failures in components during complex operations. Moreover, the features that are critical for each sub-system are selected based on the guidelines provided by IMCA, Classification societies such as DNV GL, ABS, LR etc. and DP system vendors. However, there is a need for a detailed study on the effects of individual sub-systems on overall performance during different configuration / operation modes/ voting logic throughout the life cycle of the DP system. Therefore, the ideal choice of critical signals and optimized deep learning algorithm for DP-RI prediction with prescriptive analytics will be a separate study topic for future work.

ACKNOWLEDGEMENT

The authors would like to thank DNV GL Singapore Pte Ltd and the Singapore Economic Development Board for providing the necessary funding / information required for this research work.

REFERENCES

[1] Fernandez Charles, Kumar Shashi Bhushan, Wai Lok Woo and Dev Arun Kr. "Dynamic Positioning Reliability Index (DP-RI) and Offline Forecasting of DP-RI During Complex Marine Operations." *Conference on Ocean, Offshore and Arctic Engineering, Volume 1: Offshore Technology,* Paper No. OMAE2018-77267, pp. V001T01A061 June 17-22, Madrid, Spain 2018. DOI:10.1115/OMAE2018-77267.

[2] DNV GL Recommended Practice. *"DNVGL-RP-E306: Dynamic Positioning vessel design philosophy guidelines"* July 2015.

[3] DNV GL Recommended Practice. *"DNVGL-RP-E307: Dynamic Positioning systems - operation guidance"* July 2015.

[4] Fernandez Charles, Kumar Shashi Bhushan, Wai Lok Woo and Dev Arun Kr. "Dynamic Positioning System: Systematic Weight Assignment for DP Sub-Systems Using Multi-Criteria Evaluation Technique Analytic Hierarchy Process and Validation Using DP-RI Tool with Deep Learning Algorithm." *Conference on Ocean, Offshore and Arctic Engineering, Volume 1: Offshore Technology Offshore Geotechnics,* Paper No. OMAE2019-95485, pp. V001T01A051 June 9-14, Glasgow, Scotland, 2019. DOI:10.1115/OMAE2019-95485.

[5] Bø Torstein I, Johansen Tor A, Sørensen Asgeir J, and Mathiesen Eirik. "Dynamic consequence analysis of marine electric power plant in dynamic positioning." *Elsevier Journal of Applied Ocean Research* Vol.57 (2016): pp.30-39. DOI:10.1016/j.apor.2016.02.004.

[6] Desai, Nitilaksh. "Dynamic Positioning: Method for Disaster Prevention and Risk Management." *Elsevier Journal of Procedia Earth and Planetary Science* Vol.11 (2015): pp.216-223. DOI:10.1016/j.proeps.2015.06.028.

[7] International Maritime Organization (IMO). "IMO: Msc.1/Circ.1580 Guidelines for Vessels and Units with Dynamic Positioning (DP) Systems." London SE1 7SR (2017).

[8] Vedachalam N and Ramadass G.A. "Reliability assessment of multi-megawatt capacity offshore dynamic positioning systems." *Elsevier Journal of Applied Ocean Research* Vol.57 (2017): pp.251-261. DOI: 10.1016/j.apor.2017.02.001.

[9] Junhai Cao, Qinqin Wang and Ying Shen. "Research on modeling method of complex system mission reliability simulation." *International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering,* INSPEC Number: 12882578 pp.307-311, June15-18, Chengdu, China 2012. DOI: 10.1109/ICQR2MSE.2012.6246242.

[10] Gao Miao, Shi Guoyou and Li Shuang. "Online Prediction of Ship Behavior with Automatic Identification System Sensor Data Using Bidirectional Long Short-Term Memory Recurrent Neural Network." *Multidisciplinary Digital Publishing Institute (MDPI) Articles on Sensors* Vol.18 (2018): pp.1-16 Basel, Switzerland. DOI:1 10.3390/s18124211.

[11] International Electrotechnical Commission (IEC). "IEC 61508 : Functional safety of Electrical/Electronic/Programmable Electronic Safety Related Systems Part 0 - 7" July 2010.

[12] Marvin Rausand and Arnljot Høyland. *"System Reliability Theory: Models, Statistical Methods, and Applications, 2nd Edition*." John Wiley and Sons, Hoboken, New Jersey (2004).

[13] DNV GL STANDARD. *"DNVGL-ST-0111: Assessment of station keeping capability of dynamic positioning vessels"* March 2018.

[14] International Electrotechnical Commission (IEC). "IEC 61511 Functional safety - Safety instrumented systems for the process industry sector Part 0 - 3" July 2016.

[15] Rokseth Børge, Utne Ingrid Bouwer and Vinnem, Jan Erik. "A systems approach to risk analysis of maritime operations". *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability,* Vol.231 (2016): pp.53-68. DOI: 10.1177/1748006X16682606.

[16] The Institute of Electrical and Electronics Engineers. *"IEEE Standard Framework for Reliability Prediction of Hardware"*. IEEE Standard 1413-2010 (Revision of IEEE Std 1413-1998), pp. 1-20 USA (2010). DOI: 10.1109/IEEESTD.2010.5446443.

[17] Mohan Anantharaman, T M Rabiul Islam, Faisal Khan, Vikram Garaniya and Barry Lewarn. "Data Analysis to Evaluate Reliability of a Main Engine." *The International Journal on Marine Navigation and Safety of Sea Transportation,* Vol.13 No.2 (2019): pp.403-407. DOI: 10.12716/1001.13.02.18.

[18] The Institute of Electrical and Electronics Engineers. *"IEEE Guide for Selecting and Using Reliability Predictions Based on IEEE 1413"*. IEEE Std 1413.1-2002, pp. 1-97 USA (2003). DOI: 10.1109/IEEESTD.2003.94232.

[19] Wang Zheng and Xie Liyang. "Dynamic Reliability Model of Components Under Random Load" *Journal on IEEE Transactions on Reliability,* Vol.57 No.3 (2015): pp.474-479. DOI: 10.1109/TR.2008.928184.

[20] Lina Sun, Ning Huang and Yanan Bai. "A new fractal based reliability model." *Second International Conference on Reliability Systems Engineering (ICRSE),* July 10-12 Beijing, China 2017. DOI: 10.1109/ICRSE.2017.8030781.

[21] Riedel G. J, Huesgen T. and Schmidt R. "Reliability prediction sensitivity analysis - How to perform reliability prediction time efficiently." *6th IET International Conference on Power Electronics, Machines and Drives (PEMD 2012),* pp. 1-6 March 27-29 Bristol, UK 2012. DOI: 10.1049/cp.2012.0326.

[22] Srivastava, Shikhar and Lessmann, Stefan. "A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data". *Elsevier Journal of Solar Energy,* Vol.162 No.1 (2018): pp.232-247. DOI: 10.1016/j.solener.2018.01.005.

[23] Rui Yang, Mengjie Huang, Qidong Lu and Maiying Zhong. "Rotating Machinery Fault Diagnosis Using Long-short-term Memory Recurrent Neural Network". *IFAC-PapersOnLine,* Vol.51 No.24(2018): pp.228-232. DOI: 10.1016/j.ifacol.2018.09.582.

[24] Naz Aqdas, Javed U.Muhammad, Javaid Nadeem, Saba Tanzila, Alhussein Musaed and Aurangzeb Khursheed 2019. "Short-Term Electric Load and Price Forecasting Using Enhanced Extreme Learning Machine Optimization in Smart Grids". *Multidisciplinary Digital Publishing Institute (MDPI) Journal of Energies,* Vol.12 No.5(2019): pp.866-896. DOI: 10.3390/en12050866.

[25] The International Marine Contractors Association (IMCA). *"Analysis of Station Keeping Incident Data 1993 - 2018"* March 2019.