Towards a model-based condition assessment of complex marine machinery systems using systems engineering

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Abstract

In the present paper, a systems engineering methodology is presented for the analysis and condition assessment of complex marine machinery systems. Two important characteristics of these systems are (i) that they comprise of a multitude of subcomponents which influence the overall system condition/performance and (ii) the continuously varying operating and environmental conditions. The methodology presented herein is capable to evaluate the system level effects of component degradation and faulty states under realistic system operation. By virtue of this, it is employed along with sensor signal data for the identification of degraded states and the allocation of the problem to specific system components. The modelling platform used in this work is the DNVGL COSSMOS (Complex Ship System Modelling & Simulation).

At the methodological level, an automated model-based sensitivity analysis is conducted with respect to a set of component degradation/failure modes. The latter is used along with a clustering algorithm for the precise allocation of the failure to specific components and system particulars. The selected case-study is the Diesel-electric marine propulsion system of a 2300 tonnes DWT (deadweight tonnage) anchor handling vessel embedded with its cooling network. Based on the results, the approach is capable to successfully identify faults at various subcomponents of the cooling network system including pumps, regulating valves, heat exchangers and piping. Due to the fact that the system is treated in an integrated manner, a fault can be identified in a component using sensor signals placed in other system locations.

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1. Background

Within the maritime industry there is a strong trend of machinery components and systems becoming more integrated and thereby also more complex. Advanced control and monitoring systems are enablers for safer, greener and smarter maritime transport of goods and people but also add to the level of complexity with regards to design, commissioning and operation. The key drivers behind this trend are stricter legislation related to emissions and the tough competitive market driving performance/cost optimization.

When different components and sub-systems from a multitude of suppliers are combined to fulfil one or more functions on board a ship, the need for increased multi-discipline knowledge and system understanding is obvious. It can be hard to determine and verify all possible failure modes and their effect, and thereby also the overall system reliability and safety. During operation, the increased level of integration and dependence of embedded control functions significantly escalates the level of information and possible failure scenarios that the operator needs to understand and handle. The fact that ship machinery systems are operated in a host of different working modes under continuously varying operating and environmental conditions further complicates the situation, and makes it hard to deal with process anomalies in an effective manner. Within this context, a systems engineering approach is required in order to achieve and document a safety level equivalent to the traditional and well proven designs.

One of the first studies on marine energy conversion systems dealing with the computer-aided design of the overall system is (Ito & Akagi, 1986). Later, in (Campora & Figari, 2003; Hansen, Adnanes, & Fossen, 2001; Jefferson, Zhou, & Hindmarch, 2003 ; Kyrtatos & Lambropoulos, 2000; Kyrtatos, Theodossopoulos, Theotokatos, & Xiros, 1999; Pedersen & Pedersen, 2012; Vrijdag, Stapersma, & Terwisga, 2009) process modelling approaches have been used for the analysis of marine propulsion systems. In (Dimopoulos, 2009; Dimopoulos, Kougioufas, & Frangopoulos, 2008; Tostevin & Nealy, 2003) the analysis and optimisation of generic marine energy production systems mostly focusing on steady-state synthesis, design and operation is presented. Moreover, in (Rüde, 2006) the cooling network of a conventional propulsion vessel with a four stroke Diesel engine has been modelled, the purpose of the analysis is the enhancement of safety and reliability studies.

COSSMOS (Dimopoulos, Georgopoulou, Stefanatos, Zymaris, & Kakalis, 2014; Dimopoulos & Kakalis, 2010; Kakalis & Dimopoulos, 2012) is DNVGL's model-based systems engineering simulation platform. What differentiates the aforementioned approaches from DNVGL COSSMOS is that each one of them is dedicated to a specific type of analysis for a specific system/component. On the other hand, COSSMOS is a generic marine machinery systems platform that is capable of performing steady-state and transient analysis as well as more complex tasks such as optimisation and parameter estimation for all machinery components that can be found on-board a vessel.

Another megatrend within the maritime industry is the remarkable growth in broadband satellite installations on board large ships over the past few years. Components and systems can be integrated with sensors that measure, log and send ashore operational system data. Access to comprehensive operational data from on board system sensors that is transferred to shore on a live basis will lead to tremendous opportunities for all stakeholders within the maritime industry to make shipping smarter, safer and more cost-efficient. This revolution in ship connectivity will enable the implementation of a host of new applications such as performance and environmental monitoring, energy efficiency optimisation, remote control/autonomy and condition monitoring (CM).

CM is the process of monitoring a set of parameters of condition in a system in order to identify a significant change that is indicative of a failure or a developing fault that is affecting it's function. Within the maritime industry the use of condition monitoring techniques to perform, for instance, condition based maintenance (CBM) on machinery components and systems is still very much in an infant stage. There are some early adopters within segments with high value vessels such as cruise and offshore but for most ships the on board maintenance tasks are carried out based on basis of either calendar or running hours (Coull, 2015). The need to stay competitive in a tough market is however pushing more and more ship owners and managers towards improving maintenance procedures, boosting uptime and cutting costs. The uptake of CBM is therefore expected to accelerate over the coming years.

Diagnostics and prognostics algorithms for implementing a condition monitoring system are based on one of two main approaches (G Manno, Knutsen, & Vartdal, 2014)

- A model-based (first principles physical model) approach (Isermann, 2011)
- A data-driven (statistical and data mining) approach (Baraldi, Maio, Genini, & Zio, 2015; Ge, Song, & Gao, 2013; Wang, 1999; Yin, Ding, Xie, & Luo, 2014)

One major challenge for the maritime industry is the lack of reliable statistical failure data for ship equipment similar to the OREDA database for the offshore industry (SINTEF, 2002). Additionally, machinery systems are run very differently from ship type to ship type and also under continuously varying operating and environmental conditions. These facts strongly support the use of model–based approaches within shipping since it requires knowledge about the physics and function of the system and not large amounts of previous failure data. In (Grimmelius et al., 1999) a comparison between data-driven and first principle model-based CM approaches is presented for two marine machinery case studies. The systems studied are: (i) a Diesel engine, using only the torsional vibration of the crank shaft, and (ii) a compression refrigeration plant, using many different sensors. Both CM approaches (data-driven and model-based) show promising results.

In (Monnin, Voisin, Leger, & Iung, 2011) and (Voisin, Medina-Oliva, Monnin, Leger, & Iung, 2013) a knowledge structuring scheme for achieving fleet-wide PHM utilizing both modelling and monitoring is proposed. Utilizing contextual information about the system and components by means of semantic modelling is identified as a key issue in order to allow for consideration of fleet component similarities and heterogeneities. Monitoring data from a given component are considered within their context and thereby enhancing the identification of the corresponding health condition. The fleet dimension can provide knowledge and data to improve both diagnostic and prognostic models. In the maritime sector a fleet could both be a ship owner fleet of typically 10 to a few hundred vessels or the entire fleet of a classification society such as DNVGL with a fleet of more than 13,000 vessels. Moreover, in (Grimmelius et al., 1999) the aspect of sensor redundancy using virtual sensing is investigated. Model-based technologies are a key enabler for virtual sensing / analytical redundancy (Chen & Patton, 1999). In (Blanke, 2001) a model-based methodology for the diagnosis of faults in ship propulsion systems and fault-tolerant control is presented. In this work mathematical models for ship speed, propeller and prime mover (i.e. Diesel engine) have been utilised. Diesel engines are among the most expensive, critical and maintenance intensive components on board the ship, and as a consequence many first principle condition monitoring approaches have been proposed in literature (Kouremenos & Hountalas, 1997; Watzenig, Sommer, &

Steiner, 2013). Although Diesel engine CM is a well investigated subject, there are less studies found for the auxiliary cooling network system or the Diesel engines and the other essential propulsion system equipment (such as frequency converters and electrical transformers in Diesel electric systems). One of the few works is (Twiddle & Jones, 2002) where a model-based CM approach for the cooling network of an on-shore Diesel generator has been developed.

During the recent years, DNVGL has initiated a number of projects in this area: COMPASS (Condition and operation monitoring for performance and ship safety), MODAM (Model based, data driven asset management) (DNVGL, 2015). “Nauticus Twinity” (Ludvigsen, Jamt, Husteli, & Smogeli, 2016) is a first DNVGL digital twin prototype (Glaessgen & Stargel, 2012; Tuegel, Ingraffea, Eason, & Spottswood, 2011). A digital twin, Figure 1, is a model of a physical asset, that encapsulates (i) an information/data model, (ii) a simulation model (e.g. COSSMOS) and model-based & data driven analytics, and (iii) possibly a dependability model and (iv) possibly a visualisation model. What makes a digital twin different from generic models is that they are specific to their physical counterparts. The digital twin model is specifically instantiated for the specific asset. Furthermore, it will follow its corresponding real life twin through its life cycle, through collecting sensor updates and history data. Any change on the physical asset must also be reflected in the model. As such, the digital twin is envisaged as a holistic simulation and analytics platform for performance, energy efficiency optimisation, classification services and condition monitoring.

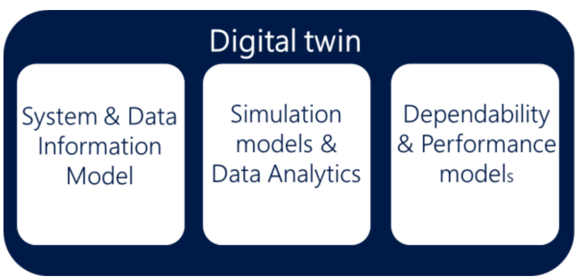

Figure 1. DNVGL Digital twin, MODAM project (DNVGL, 2015; G. Manno, et, & Al., 2015).

2. OUTLINE OF THE PROPOSED APPROACH

The ultimate goal of the work presented in this paper is to have a continuous health state monitoring of the subject cooling system that can support classification and predictive maintenance activities and enhance ship safety and reliability. A condition monitoring approach using first principle model-based analytics for the cooling network system is proposed. The digital twin of the propulsion system and its cooling network is developed in COSSMOS. Apart from the simulation model, a set of available sensor measurements have to be identified.

The approach is divided into two steps: (i) the binominal classification between failed and non-failed states and (ii) the specific failure identification on a system, subcomponent/location. The binominal classification procedure aims to compare system measurements with model results and class the system state between two different possibilities: failed or non-failed. If failed, the next step is to allocate the exact position of the failure. This is achieved by performing a holistic sensitivity analysis using the simulation model. The product of the sensitivity analysis (sensitivity maps) provides a quantitative behavioural analysis of the sensor variables with respect to an extensive envelope of system faults. Based on that, the failure pattern from the sensor readings can be matched to the pattern(s) of specific faults. In this work, an unsupervised type of neural network, the self-organising maps (SOM) (Kohonen, 2001) has been used for that purpose. The SOM task is to cluster the unknown failure pattern within clusters of failures that each one of them corresponds to a set of system failure modes (given by the sensitivity analysis). Although in literature a variety of neural networks have been used for condition monitoring and recognition of faults (Baraldi, Compare, Sauco, & Zio, 2013; Grimmelius et al., 1999; Schenk, Natale, Germond, Boss, & Lam, 2002), what differentiates this approach is that it utilises sensor signals along with the first principle sensitivity analysis results.

In the rest of the paper, the description of the under study system is presented in section 3. The modelling methodology is presented in section 4, and the detailed discussion of the binominal classification and the failure identification is given in sections 5 and 6. Two different case studies of failures at the cooling network are presented in section 7: (i) a fault (infraction) at the 3-way valve TCV65LT and (ii) a fault at the LT pump at the main engine (ME) cooling circuit.

3. SYSTEM UNDER STUDY

The chosen case-study for this work is a 2300 DWT anchor handling vessel built in 2009 and operated in the North Sea. The vessel has a twin screw conventional propulsion plant consisting of:

- Two 4.5 MW 4 stroke propulsion Diesel engines
- Two reduction gears each with a 3 MW Power Take-In (PTI) electric booster motor
- Two controllable pitch propellers with rudders

Vessel maneuverability and station-keeping capabilities are further enhanced by 4 separate thruster units:

- Two stern tunnel thrusters
- One bow tunnel thruster
- One bow retractable azimuth thruster

Power generation is achieved by two 5 MW shaft generators installed on front-end of the main engines and 4 equally sized 2.1 MW auxiliary Diesel generator sets. The propulsion and power system is designed to fulfill Class redundancy requirements but is also configured to provide the operator with large operational flexibilities.

The cooling of the vessel's main machinery equipment is divided into two separate freshwater (FW) cooling systems, FW cooling system No. 1 & No.2. Each FW cooling system is arranged for one main engine with shaft generator, reduction gear and PTI, two auxiliary generator sets and two thruster units. To the authors' knowledge this is the first time the entire cooling network of a Diesel electric system is modelled and assessed for condition monitoring purposes. The FW cooling system includes one main electrical circulation pump, engine driven pumps (for high and low temp systems), engine preheaters, valves and coolers. One 3-way regulating valve is arranged for each FW system with a set-point of 37°C. For each Diesel engine two additional 3-way regulating valves are installed. Crossover lines and one standby pump are arranged between FW Cooling Systems No.1 & No.2 with manual normally closed valves.

The system under study is FW Cooling System No.2 (starboard side) as illustrated in Figure 2.

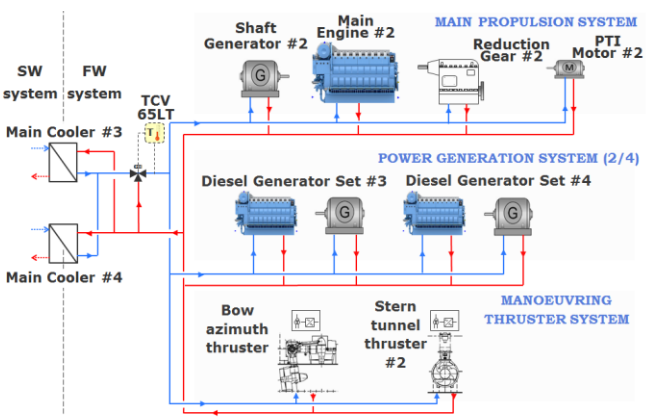

Figure 2. Illustration of FW Cooling System no.2. Propulsion, power and maneuvering system deposits heat to the FW system, which again deposits to a sea water (SW) system via 2 main coolers. The 3-way temperature controlled mixing valve (TCV65LT) maintains a given FW temperature of 37°C by mixing cold and warm water.

The Main Engine cooling system is divided into two sub-systems: a low temperature (LT) system and a high temperature (HT) system. Both sub-systems are equipped with a separate circulation pump. The LT system is used to provide fuel and lubrication oil cooling/heating and 2nd stage charge air cooling. The amount of cooling water flowing through the 2nd stage charge air cooler is regulated by a 3-way flow control valve. The valve PID controller is used to give a charge air temperature of 55°C. The HT system utilizes output cooling water from the LT system for 1st stage charge air cooling and cylinder block cooling. The system has a 3-way temperature controlled valve recirculating cooling water inside the HT system. The PID controller regulates the cooling water temperature coming out of the cylinder block to 90°C.

The cooling system is equipped with a limited number of sensors monitoring system temperatures, pressures, cooling water levels etc. Critical functions are protected by alarms. The complete FW system no.2 contains:

- 25 different plate coolers,
- 70-80 valves that can adjust cooling water flow (manually and automatically),
- Approximately 200 meters of cooling water pipe of varying diameter.

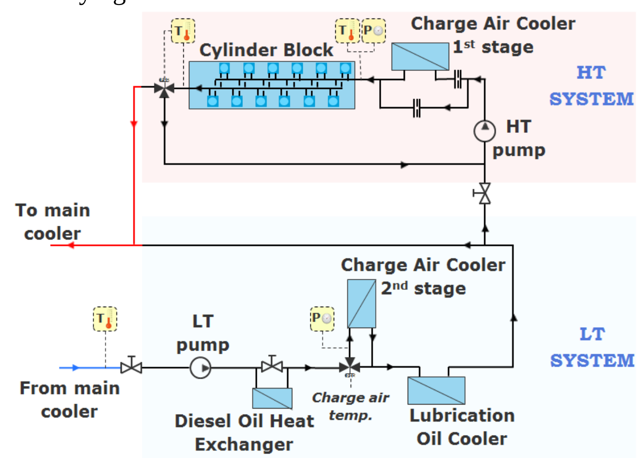

Figure 3. Illustration of Main Engine LT and HT sub-systems.

4. MODELLING APPROACH – DNVGL COSSMOS

Since 2008 DNVGL has introduced MBSE (Model Based Systems Engineering) for modelling, simulation and optimisation of integrated marine energy systems (Dimopoulos et al., 2014; Dimopoulos & Kakalis, 2010; Kakalis & Dimopoulos, 2012). This work has resulted in the modelling framework named as DNVGL COSSMOS. DNVGL COSSMOS (Figure 5) aims at being one tool providing model-based decision support on:

- Optimal design of on-board machinery with respect to energy efficiency, safety and cost effectiveness;
- Performance evaluation, diagnostics and operation optimisation under real-service conditions for the entire mission envelope of the machinery system; and
- Assessment of the potential, operational capabilities, and safety of new technologies.

As such, the COSSMOS modelling framework provides the user with the capability to define and analyse a wide range of system configurations, model their behaviour in terms of their physics processes (mechanical, electric, thermodynamic, heat transfer, fluid flow, etc.), and perform any model-based application of interest (simulation, optimisation, control, parameter estimation) under both steady-state (design/off-design conditions) and dynamic (time varying, transient operation) conditions.

The implementation of COSSMOS is done in gPROMS (PSE, 2016), an equation-oriented modelling language specially designed for process system modelling and simulation that can efficiently handle the numerical solution of highly complex non-linear PDAE (Partial Differential Algebraic Equation) systems in a variety of processes. The COSSMOS component models can be a phenomenological model based on first principles, detailed physical models or even correlations from experimental data.

A general description of the component model mathematical equations reads:

$$\frac{d\vec{Y}}{dt} = \vec{F}\left(\vec{Y}(t), \frac{d\vec{Y}}{dx_i}(t), \vec{u}(t), \vec{b}(t), t\right) \tag{1}$$

$$\vec{H}\left(\vec{Y}(t), \frac{d\vec{Y}}{dx_i}(t), \vec{u}(t), \vec{b}(t), t\right) = 0 \tag{2}$$

where t is the time, $\vec{Y} = (Y_1, \dots, Y_{N_Y})$, $\vec{u} = (u_1, \dots, u_{N_u})$ and $\vec{b} = (b_1, \dots, b_{N_b})$ are the vectors of differential variables, algebraic variables and parameters, respectively. The vectors $\vec{Y}$ and $\vec{u}$ constitute the process variables of the system. $\vec{F}$ and $\vec{H}$ are vector functions. The partial derivative base vector $\vec{x}$, is an appropriate distribution domain, usually expressing geometry dimensions (e.g. length, width, radius, etc.). The PDAE system is completed by the necessary initial and boundary conditions.

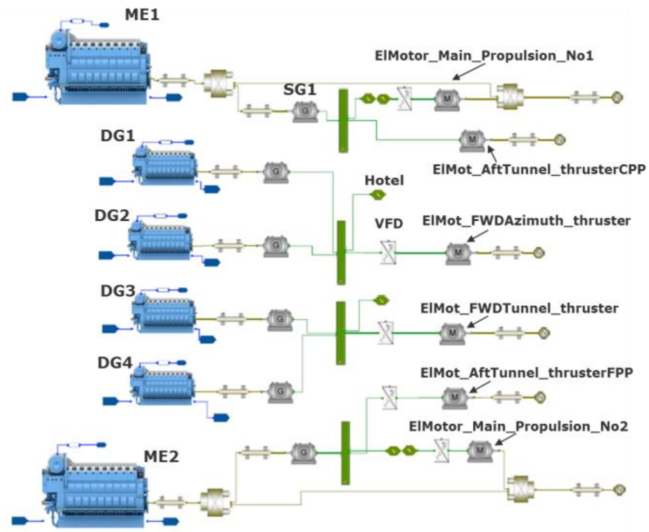

Figure 4. Propulsion system model in DNVGL COSSMOS. (Abbr.: ME=Main engine, SG=Shaft Generator, DG=Diesel Generator, VFD= Variable Frequency drive).

As in any model-based systems engineering approach, the overall system model is synthesized from coupling the individual component models as shown in Figure 5. In this work the vessel's propulsion system has been modelled; the model view from the COSSMOS GUI is presented in Figure 4. A schematic representation of the propulsion system with the cooling network is given in Figure 2. Moreover, the overall COSSMOS model: propulsion system and cooling network (starboard side) can be seen in Figure 6. The model comprises of approx. 14300 PDAE equations and 295 system components.

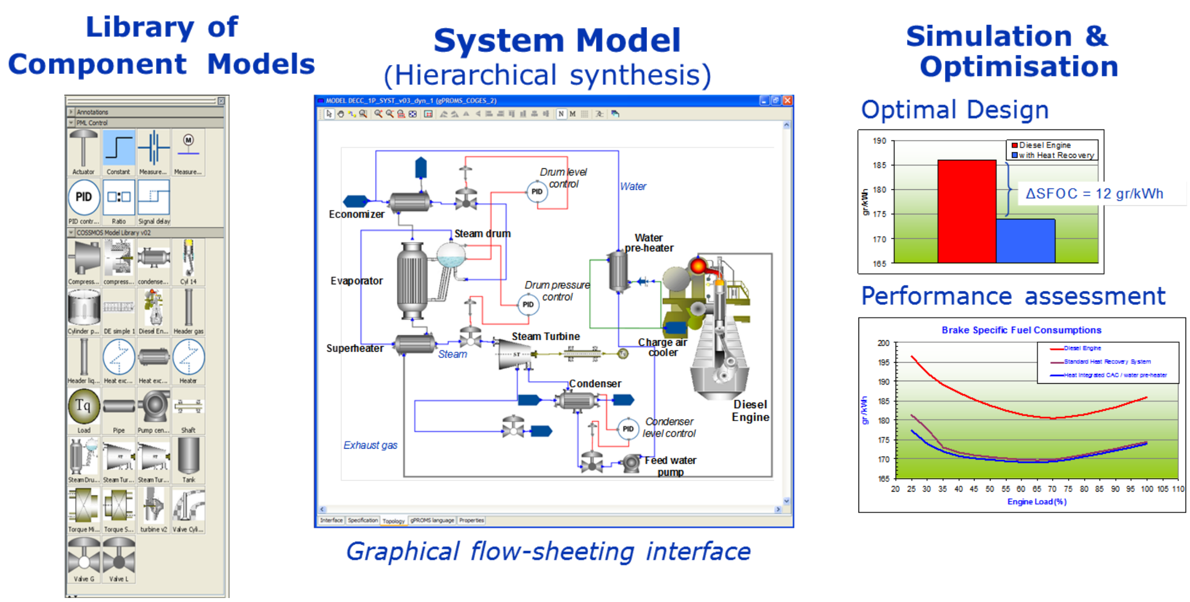

Figure 5. The DNVGL COSSMOS modelling framework.

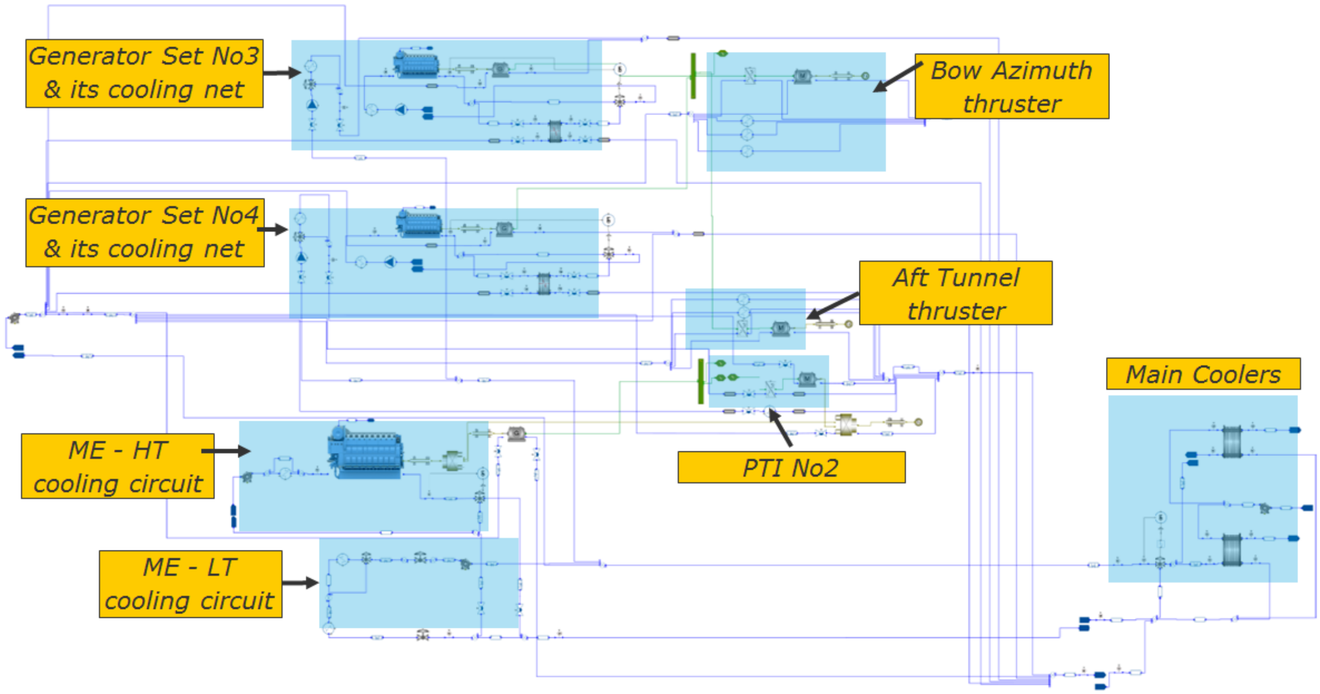

Figure 6. Overall COSSMOS model: propulsion system & cooling network (vessel's starboard side).

4.1. Model Calibration

The simulation model has been calibrated based on manufacturers' data. The comparison of results between the system operation at design conditions (black bars) and the model predictions (grey bars) can be found in Figure 7. These are indicative results and if the model is to be used in a real CM application a more exhaustive calibration procedure (through sensor data) has to be carried out. However, the simulation model is adequate for demonstrating the CM approaches presented in the current work.

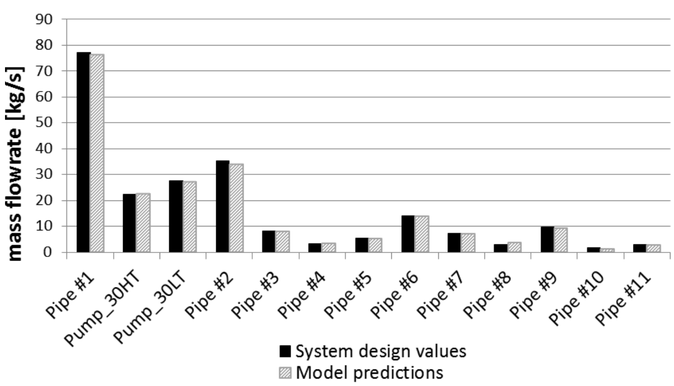

Figure 7. Comparison between system data (black bars) and model predictions (grey bars). The system positions corresponding to the quantities depicted in the x-axis can be found in Appendix I.

5. Binominal Classification Between Failed and Non-Failed System States

Let's assume the following fault detection problem: given the set of signal data in

Table 1, the engineer/analyst is asked to identify if this set of signals is corresponding to a degraded system condition (i.e. operation under the presence of fault or failure in the system). Based on the schematic of Figure 8: by using (i) a set of inputs (system operational data & sensor measurements that we have higher confidence in) and (ii) information about the condition of specific system parts (if a priori knowledge is available, e.g. amount of fouling at heat exchangers (HEXs), COSSMOS simulations can be carried out and the results can be used for benchmarking against the values of

Table 1 (signal measurements, column headers with grey background). In this example the inputs are the independent parameter values (

Table 1, white background), the benchmarking results are depicted in Figure 9 and Figure 10. From the differences between these one could assume that there is some kind of fault/degraded state in the LT circuit that affects (among other system variables) the TCV65LT stem position and the pump power.

In the discussion above the simulation model has been used for analysing the current system state by comparing with the "ideal" one (including HEX fouling) under the specific operating conditions. This is particularly useful when the system under study is at its infant life stage (where limited historical data exist). Moreover, it is also useful for systems with many independent parameters that influence the operation. In these cases there is a challenge in obtaining real-life data for all possible states (combinations of the independent parameters) that may be needed in order to create a good system representation. Critical and rare events can only be included in the database by using model-based simulations as it is done in this project. Consequently the use of simulations models is particularly important for filling these "gaps" of information in the real-life data.

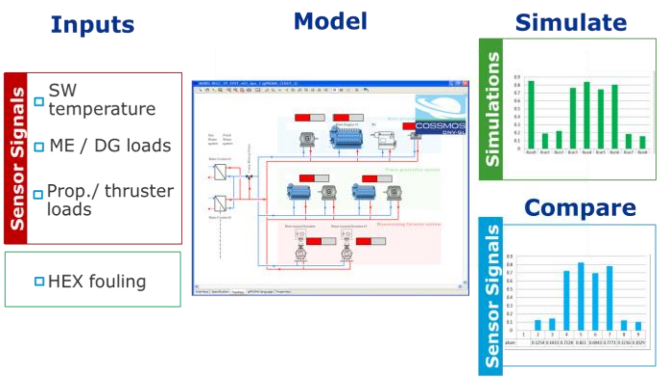

Figure 8. Methodology schematic. From left to right: Inputs to the COSSMOS model, COSSMOS simulation model, result comparison and benchmarking with sensor signals.

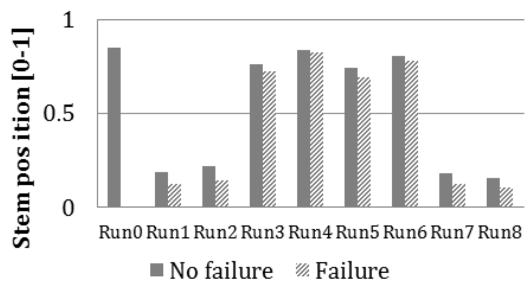

Figure 9. Comparison of TCV65LT stem position. Dark grey bars: values corresponding to a system without any fault. Light grey bars: set of data to be identified if correspond to a condition or not.

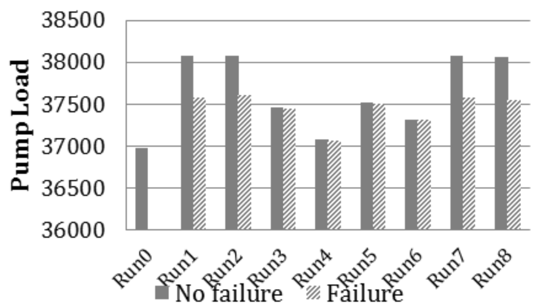

Figure 10. Comparison of LT pump loads (as in Figure 9).

Table 1. Propulsion system and cooling network TCV65LT valve and LT and pump signal data; Anchor handling (AH) mode. Input variables on left side (white background) and simulated variables on right side (grey background).

	Input variables							Output variables		
	Load ME 2	Load Azimuth Thruster [kW]	Load Tunnel Thruster3 Aft2 [kW]	Load PTI [kW]	El. demand STBD side (other) [A]	Central Cooler fouling	SW temperature	TCV65LT stem [0-1]	Pump LT Power [kW]	FW Temp ME inlet [C]
#1	20%	360	960	600	1000	No	15	0.13	37.58	88.1
#2	30%	360	960	600	1486	No	15	0.14	37.60	87.2
#3	20%	360	480	300	1486	Yes	32	0.72	37.44	88.1
#4	30%	360	480	300	1000	No	32	0.82	37.07	87.2
#5	20%	180	960	600	1000	Yes	32	0.69	37.50	88.1
#6	30%	180	960	300	1486	Yes	32	0.78	37.31	87.2
#7	20%	180	480	600	1486	No	15	0.12	37.57	88.1
#8	30%	180	480	600	1000	Yes	15	0.10	37.55	87.2

6. FAILURE IDENTIFICATION

Herein, the scope is to address the problem of locating the internal failure at the corresponding part of the system, extending the methodology described in section 5. The system's sensitivity map can be utilised for this purpose. DNVGL COSSMOS has the ability to perform automated sensitivity analysis using symbolic differentiation (Naumann, 2012). The step below are followed:

- Step 1: Perform Binominal classification analysis (as in paragraph 6). If it is identified that there is a hidden fault somewhere in the system, then:
- Step 2: Perform sensitivity analysis using the systems engineering model.
- Step 3: Cluster sensitivity analysis results into groups of faults.
- Step 4: Identify the group of faults that the specific fault pattern belongs to.

6.1. Sensitivity analysis map and sensitivity derivatives

In the sensitivity map, the sensitivity derivatives of selected system variables with respect to the model input parameters and independent variables are depicted. For condition monitoring, the selected system variables make sense to correspond to sensor measured variables (MV). In more detail, a non-linear differential and algebraic system of equations (like the COSSMOS model) that describes the dynamic behaviour of an engineering system can be written in the form:

$$R_i\left(x_j, \frac{dx_j}{dt}, y_l, u_m\right) = 0 \tag{3}$$

where $\vec{x}(t)$ and $\vec{y}(t)$ are the vectors of differential and algebraic variables respectively (both are unknowns to be determined by the simulation) and $\vec{u}(t)$ is the vector of the mathematical system input parameters that is a given function of time. The sensitivity derivative of a variable MV is a vector given by:

$$\left[\frac{\delta(MV)}{\delta x_j}\middle| \quad \frac{\delta(MV)}{\delta y_l}\middle| \quad \frac{\delta(MV)}{\delta u_m}\right]^T \tag{4}$$

The overall matrix comprises of M_{SV} columns, where M_{SV} is the number of the monitored variables. Each column vector element, shows how much the MV is affected by a perturbation in the corresponding system variable (x,y) or parameter (u). The system variables (x,y) and parameters (u) are related to a certain sub-component function and characteristics, and thus any possible failure mode of the sub-component will alter the their values by δx leading to a change in the MV. The sensitivity maps provide a holistic view of the internal system relations between MV and all the system variables and can be used to correlate the fault pattern ("fingerprint") to a specific matrix row[1] (i.e. variable (x,y) or parameter (u)); and consequently to a specific system component and failure mode. The advantage of using the sensitivity analysis approach is that it requires only one simulation of the system irrespective of the number of the system variables (x,y) or parameters (u) (and consequently the number of failures). This reduces computational requirements significantly.

In Figure 11, the sensitivity map for the cooling network is presented. The values are in log10 scale. The chosen MV variables are found in Table 2 (others could have been chosen as well).

[1] *If clustering has been applied before, then correlate to an agglomeration of matrix rows (that can be seen as very similar failures).*

Table 2. MV for the cooling network case.

1	Central cooler FW temperature OUT
2	DG3 cooler FW temperature before cooler
3	DG4 cooler FW temperature before cooler
4	TCV65HT stem position
5	DG3 cooler FW temperature after cooler
6	DG4 cooler FW temperature after cooler
7	ME pump_30HTpower
8	ME pump_30LTpower
9	LT circulation pump power
10	DG3 FW pump pressure
11	DG4 FW pump pressure

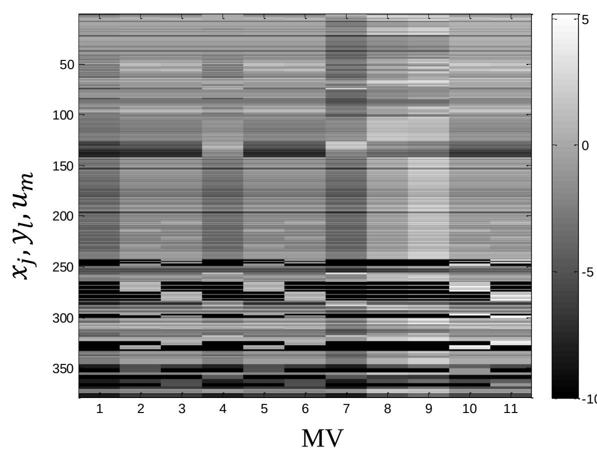

Figure 11. Sensitivity map: cooling network, AH mode. Values are in log10 scale: $\boldsymbol{log10}\left(\boldsymbol{abs}\left[\frac{\delta(MV)}{\delta x_j}\middle| \quad \frac{\delta(MV)}{\delta y_l}\middle| \quad \frac{\delta(MV)}{\delta u_m}\right]^T\right)$.

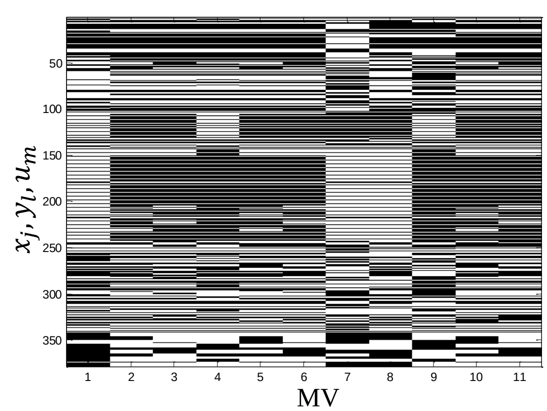

Figure 12. Sensitivity map: cooling network, AH mode. Sensitivity derivative signs: $\boldsymbol{sign}\left[\frac{\delta(MV)}{\delta x_j}\middle| \quad \frac{\delta(MV)}{\delta y_l}\middle| \quad \frac{\delta(MV)}{\delta u_m}\right]^T$, white: -1, black:+1.

7. CASE STUDIES

Two different cases of failures at the cooling network are studied. Case study 1 concerns a fault (infraction) at the 3-way valve TCV65LT, Figure 2 has been studied. In the second case study, a fault at the LT pump at the ME cooling circuit has been investigated (Figure 3).

7.1. 3-way regulation valve fault case study.

The Self-Organising Maps (SOM) (Kohonen, 2001), an unsupervised machine learning clustering method, has been utilised aiming to aggregate together system parameters/faults (i.e. the rows of sensitivity matrix), that have the same impact to the sensor readings. The SOMPY Python Library for Self Organizing Maps has been used for that purpose (Moosavi, 2016).

The data-set used to build the SOM was the sensitivity matrix (depicted in Figure 11). By using a 2-dimensional representation plane with a square topology (21x21 in size), the agglomerates of the parameters/faults can be seen in Figure 13 (left). Each cycle corresponds to the node of the SOM that has been best matched to a set/agglomerate of parameters/faults – the larger the cycle radius the more the system parameters/faults are associated with the corresponding node. On the right hand side of Figure 13 the U-Matrix [2], that gives insight into the local distance structures of the data set, is presented. The red areas represent divisions of the data set, while the dots are the nodes presented also in the left graph.

In Figure 21, the heat-maps of the sensor variables are depicted over the SOM. These heat-maps present the distribution of each sensor variable across the SOM node structure (21x21). By comparing them, interdependencies between sensors and sensor redundancies with respect to failures can be identified. For example, sensor variable 1 (LT FW temperature out of the central cooler) can differentiate mainly between parameters/failures that are located to the nodes of the upper right (blue, Figure 21) and lower-middle (red, Figure 21) part of the map.

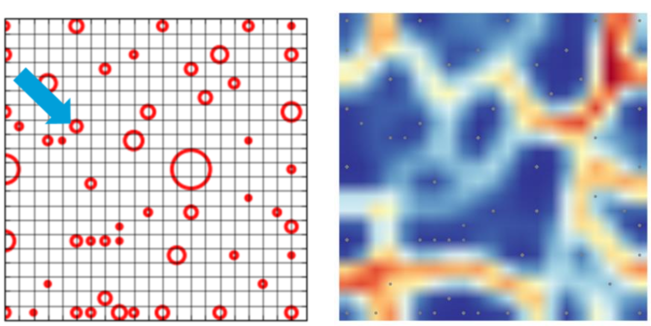

Figure 13. 3-way regulation valve fault case study: 2-dimensional representation plane (21x21) with the nodes (left). Corresponding the U-Matrix (right).

From the maintenance log of the vessel's cooling water system, it is known that there has been a fault at the 3-way valve TCV65LT, Figure 2. Unfortunately no real data were available for the time period of the fault. The simulation model has been used in order to simulate an infraction at the TCV65LT valve. Based on the sensor (

Table 1) readings (simulation with fault) the Binominal classification analysis (Step 1, section 5) has been carried out. The differences between the signals that correspond to the fault condition and the ones that correspond to the "non-fault" condition are depicted in Figure 14. These data are introduced to the clustering algorithm in order to be allocated in the best matching unit of the map in Figure 13. For this case, the best matching unit is the node (5,7) shown by the arrow in Figure 13 (left). Based on sensitivity matrix data, the components related to the faults/parameters that have been previously matched to node (5,7) are depicted in the Figure 15. The TCV65LT valve is one of them and consequently the approach has correctly identified the failed component between all the different (but influencing the sensor signal set) areas of the system (Figure 16).

In order to assess the SOM performance, as set of #40 different simulation cases has been used to create the true/false positive and true/false negative matrix of

Table **3**. The data set comprises of #20 different TCV65LT fault realisations (various infraction percentages, different SW and engine load conditions) and #20 system realisations without any fault at the TCV65LT valve. The latter includes the case where every component is working as new and other cases with faults/failures at components other than the TCV65LT valve. From the #20 system realisations that the TCV65LT valve has failed or degraded, #16 have been correctly identified, i.e. the sensor set signal was correctly matched to SOM node (5,7). For the rest #4 cases, the model prediction has allocated as best matching units the nodes (6,6) (three times) and (7,6) (one time). Although counted for false negatives, it is worth mentioning that the latter two nodes are at the vicinity of the correct node choice that is again node (5,7). In Figure 17, the orange-coloured highlighted area includes nodes that corresponding to the TCV65LT infraction fault, namely node (5,7) (16 true positive results of Table 3) and nodes (6,6) & (7,6) (four false negative cases of Table 3). In the same figure (Figure 17), the blue-coloured square areas correspond to the 20 true negative cases of Table 3.

Table 3. 3-way regulation valve case study: matching matrix that presents true/false positives and true/false negatives.

		Predicted	
		Failed	**Non-Failed**
Actual Class	**Failed**	16	4 (*)
	Non-Failed	0	20

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[2] https://en.wikipedia.org/wiki/U-matrix

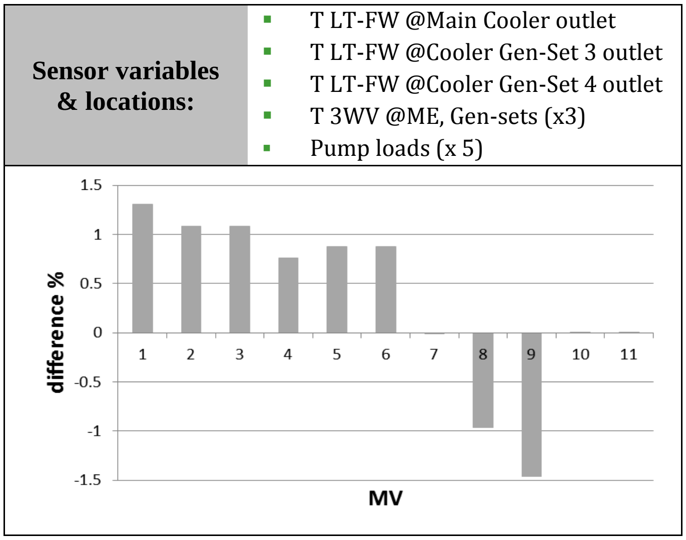

Figure 14. 3-way regulation valve fault case study; top: Sensor variables & locations. Bottom: Differences (%) between the signals that correspond to the fault condition and the ones that correspond to the "non-fault" condition.

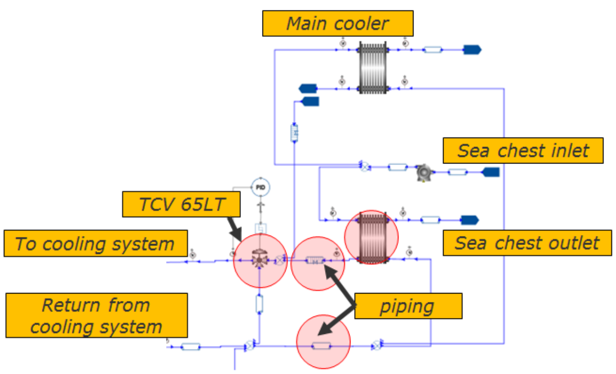

Figure 15. 3-way regulation valve fault case study: components related to the faults/parameters that have been previously matched to the node (5,7).

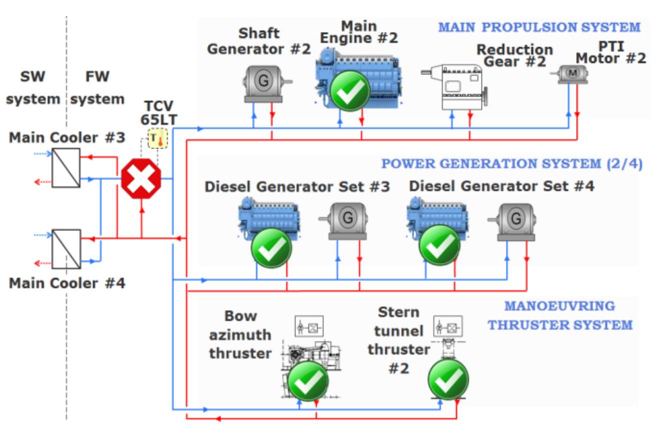

Figure 16. 3-way regulation valve fault case study: the approach has identified correctly the failed component

between all the different areas of the system which influence the sensors signal set values.

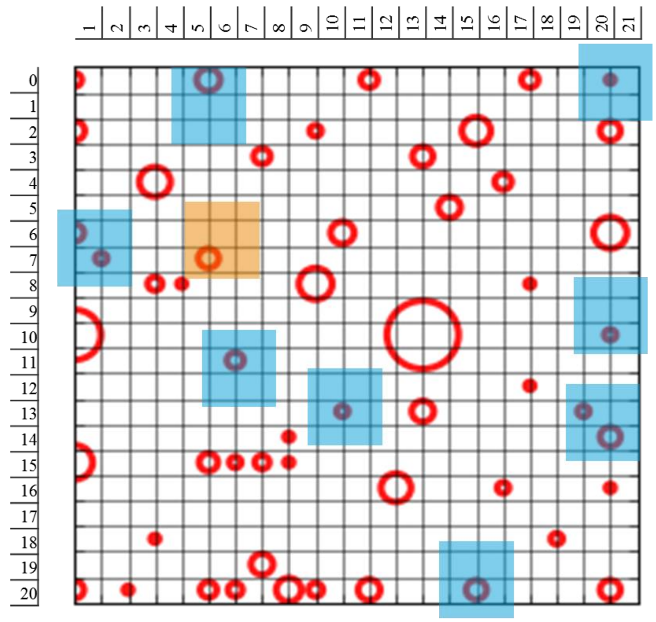

Figure 17. 3-way regulation valve case study: 2-dimensional representation plane with the SOM nodes. Orange-coloured nodes correspond to the TCV65LT infraction fault, namely node (5,7) (16 true positive results of Table 3) and nodes (6,6) & (7,6) (four false negative cases of Table 3). Blue-coloured square areas correspond to the 20 true negative cases of Table 3.

7.2. LT pump fault case study.

Like in the 3-way regulation valve fault case study, a SOM was built based on the sensitivity matrix depicted in Figure 11. By using the sensor set variables of Figure 18 (simulation with fault), the clustering model has been used to identify a fault at the LT pump at the ME (Figure 19). The fault has been successfully identified since it was best fitted to the node (5,16). In this node the failure of the LT ME pump has been allocated during the initial training of the model. In this case a smaller sensor set of six variables, Figure 18.

There are some interesting aspects in this case: (i) there is not any signal measurement placed on the pump where the fault has been identified and (ii) there is not any measurement directly at the LT ME circuit (apart from the temperature value at the exit of the central cooler). By using signal values at other positions the algorithm has managed to correlate them with this specific fault. Although a simple example, it indicates the potential of using simulation models with real signals so as to reason about faults in parts of the system where no real signals are available.

Sensor specific faults/failures could also be identified using the proposed methodology. Similarly to other system component faults/failures, when sensors faults/failures are under the CM scope, one could again utilise the fact that the pattern of a specific sensor fault may differ from other system or sensor fault patterns. To identify these patterns the sensitivity analysis and SOM approach described in this paper could be used.

In Figure 22, the heat-maps of the sensor variables are presented. These heat-maps show the distribution of each sensor variable across the SOM node structure (25x25). By comparing them, interdependencies between sensors, sensor redundancies with respect to failures and lack of sufficient sensors to monitor the entire set of possible system failure modes can be identified in a systematic way.

Sensor variables & locations:	▪ T LT-FW @Main Cooler outlet ▪ T LT-FW @Cooler Gen-Set 3 outlet ▪ T LT-FW @Cooler Gen-Set 4 outlet ▪ T 3WV @ME, Gen-sets (x3)

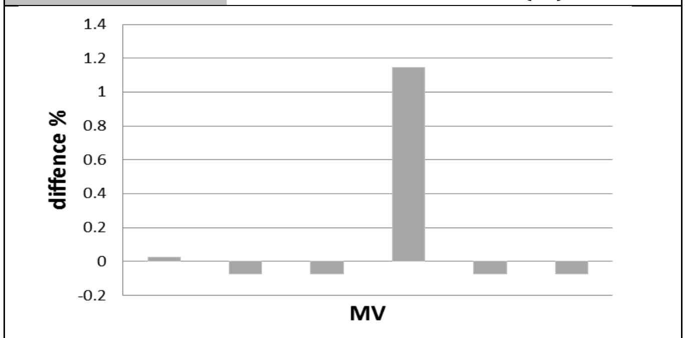

Figure 18. LT pump fault case study; left: Sensor variables & locations. Right: Differences (%) between the signals that correspond to the fault condition and the ones that correspond to the “non-fault” condition.

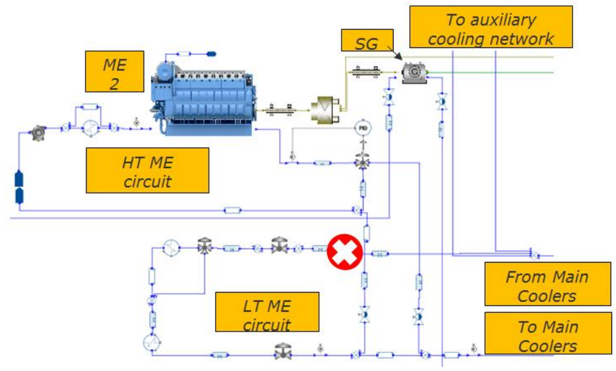

Figure 19. LT pump fault case study: detail of the ME circuit (ref. Figure 6). A fault at the LT ME pump is indicated.

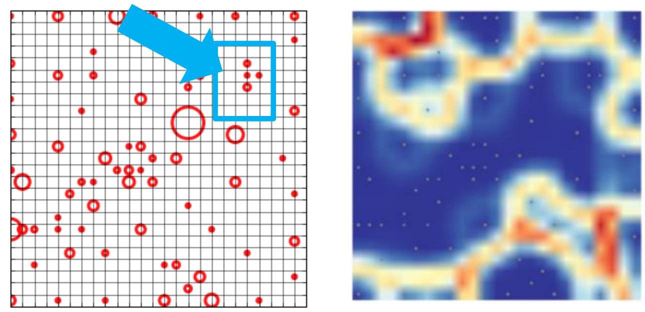

Figure 20. LT pump fault case study: 2-dimensional representation plane (25x25) with the SOM nodes (left). Corresponding the U-Matrix (right).

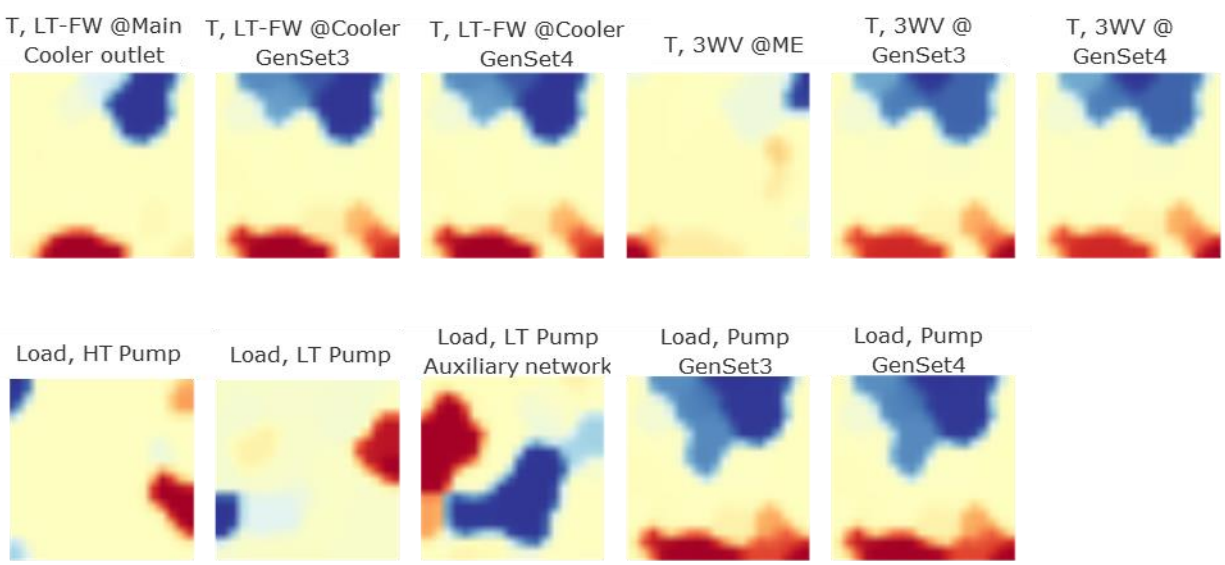

Figure 21. 3-way regulation valve fault case study: heatmaps of the sensor variables (Figure 14).

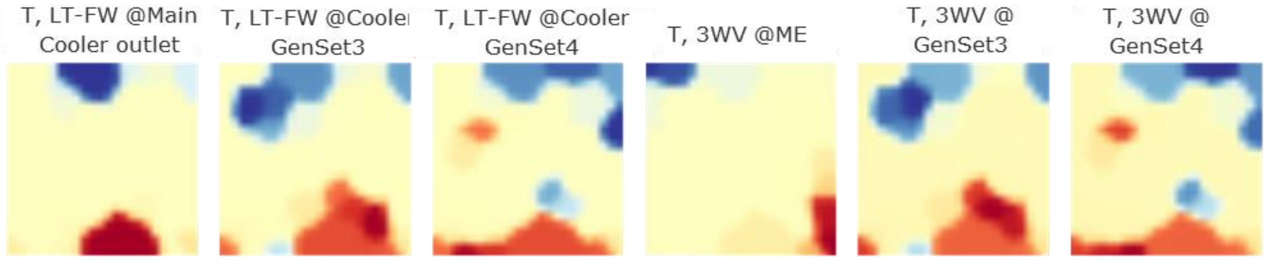

Figure 22. LT pump fault case study: heatmaps of the sensor variables (Figure 18).

8. CONCLUSION

By encapsulating model-based and data-driven analytics the DNVGL digital twin platform will enable new applications such as performance and environmental monitoring, energy efficiency optimisation, future classification services and potentially condition monitoring. The present paper describes a first principle digital twin of an anchor handling vessel's propulsion system along with its cooling network developed in DNVGL COSSMOS for condition monitoring purposes. After the model was built and tested, an extensive and automated sensitivity analysis with respect to possible system failures has taken place. The underlying benefit in this approach is that with a single simulation run the analyst obtains all failure patterns related to the system operation in that specific state. Based on this information, a SOM was used to cluster the sensor readings pattern (difference between nominal and actual sensor readings) with the model-based sensitivity results. By assigning the unknown failure pattern (from the sensor readings) to one of the clusters, the algorithm directly identifies the unknown fault to a single or a set of failure modes (that correspond to the specific cluster to which the unknown fault has been matched). The present case-studies have demonstrated the potential of the methodology. A powerful aspect of the approach is its ability to identify faults and failures in areas that are not directly subjected to measurements; by simply using signal values at other positions and employing first principle models, the algorithm is capable of correlating sensor readings with specific failures at other parts of the system.

Next steps will include the utilisation of the methodology along with real-life signal data. Aspects like signal filtering, sensor and model epistemic uncertainties will be also investigated. To the authors' view the current work is a first step towards a model-based prognostic tool for complex marine energy systems that will incorporate physics of failure with the exact current system condition to reason about possible system state under an envelope of possible future operational scenarios.

ACKNOWLEDGEMENT

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NOMENCLATURE & ABBREVIATIONS

AH	Anchor handling (vessel operating mode)
b	model parameters vector
CBM	Condition based maintenance
CM	Condition monitoring
COSSMOS	Complex Ship System Modelling & Simulation
COMPASS	Condition and operation monitoring for performance and ship safety
DG	Diesel generator
DWT	Deadweight tonnage
F	vector function describing the transient in time PDAE model equations
FW	Fresh water
GUI	Graphical user interface
H	vector function describing steady in time PDAE model equations
HEX	Heat exchanger
HT	High temperature (cooling network)
LT	Low temperature (cooling network)
MBSE	Model based system engineering
ME	Main engine
MODAM	Model based, data driven asset management
MV	Measured process variables
PDAE	Partial differential algebraic equations
PID	Proportional-integral-derivative control
PTI	Power take in
SOM	Self organising maps
SG	Shaft generator
STBD	Starboard side (vessel)
SW	Sea water
t	time
u	algebraic process variables vector
VFD	Variable frequency drive
x	differentiation domain
Y	differential process variables vector

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APPENDIX I

In the current appendix, namely in Figure 23, the system locations that correspond to the comparison of results presented in Figure 7 are depicted.

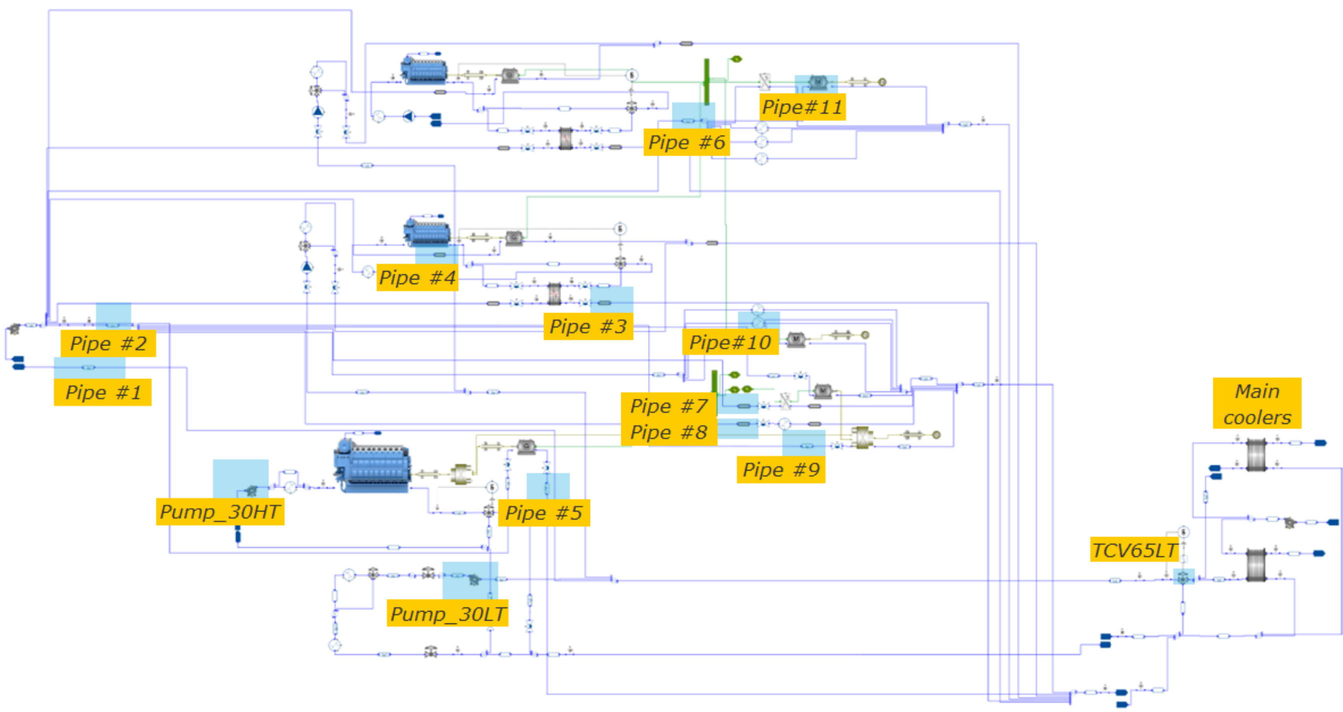

Figure 23. COSSMOS model: system locations for the comparison of results presented in Figure 7.