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A health-aware energy management strategy for autonomous ships power plants operation

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Abstract

Autonomous shipping developments have gathered increasing interest in the maritime industry. In this respect, innovative solutions are required to operate autonomous ships without the direct intervention of a human operator. This study focuses on the development of a health-aware energy management strategy for the operation of autonomous ship power plants. To enable autonomous decisions, it is essential to acquire sufficient situational awareness based on the health state of the machinery, using diagnosis and prognosis tools. In this respect, a dynamic Bayesian network (DBN) approach is adopted to calculate components and system reliability. The predictive information along with the operating profile are considered in an enhanced energy management strategy, to prolong the power plant's lifetime and avoid hazardous or degraded states whilst optimizing fuel consumption. To demonstrate the applicability of the proposed approach, a parallel hybrid power plant is selected as a case study. The investigated plant energy management is based on the equivalent consumption minimization strategy (ECMS). The results demonstrate that the most critical component is the engine while the electrical components have lower failure rates. By using the proposed strategy, the degradation of the engine can be attenuated, and the plant operation in safer regions can be achieved.

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Keywords: Autonomous ship, Hybrid propulsion, Energy management strategy, Prognostic decision-making, Dynamic Bayesian network;

1. Introduction

The ship power plant is one of the ship's critical systems, as it provides the power for the ship electrical propulsion demands. Nonetheless, in the case of the autonomous operation, limited or no crew is expected to be present onboard, as a result, the power plant must possess intelligent functionalities to operate without human intervention (Kooij et al., 2018). The technological breakthroughs in advanced automation nowadays can enable autonomous ships

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operations, as shipboard sensors and monitoring systems are widely installed. These systems can enable functionalities of intelligent monitoring and machinery health assessment (Bertram, 2016).

In the pertinent literature, several methodologies have been proposed for the intelligent monitoring of ship machinery, which can be applied to autonomous ship power plants. To estimate the probability of blackout in a cruise ship power, (Bolbot et al., 2021) have developed a methodology based on Fault Tree Analysis using virtual sensor measurements. (Eriksen et al., 2021) applied a modified FMECA to assess maintenance needs and reliability issues for an autonomous ship. (Abaei et al., 2022, 2021; BahooToroody et al., 2022) developed probabilistic reliability methods based on the Bayesian inference to assess the power plant of autonomous ships.

Nonetheless, apart from applying intelligent monitoring functionalities on the autonomous ship, it is crucial to integrate their input with the systems that are responsible for the performance control of the power plant. In the current literature, few studies integrate the real time health assessment in the power plant operation. (Johansen and Utne, 2022) have integrated online risk models using Bayesian networks for the supervisory risk control of an autonomous ship. (Tang et al., 2020) integrated battery prognostic models to estimate the battery degradation into the operation strategy of a hybrid ship power plant. (Hein et al., 2020) used a multi-objective optimisation for the energy management of a hybrid ferry considering battery degradation.

In this respect, this study aims to develop a health-aware energy management strategy for the operation of an autonomous ship hybrid power plant. To estimate the health state of the components and system, reliability is used as the health state metric. A decision-making approach is used as a trade-off between fuel consumption minimisation and system reliability maximisation.

2. Methodology

2.1. System description & modelling

For the application of the proposed methodology, a hybrid power plant of a pilot boat is chosen. Hybrid power plants can be good candidates for the autonomous ship offering redundancy since they have multiple components. In addition, hybridization can increase propulsion availability as well as improve maintainability (Geertsma et al., 2017). Propulsion availability is crucial for autonomous operation, as corrective actions cannot be performed without onboard engineers (AUTOSHIP, 2020).

The chosen hybrid power plant has a parallel hybrid architecture, where a diesel engine and an electric machine can provide propulsive power to the propeller coupled in a gearbox. The electric machine can be used either as a power take in (PTI) to provide propulsive power using the battery or as a power take off (PTO) to charge the battery using the engine. Table 1 presents the nominal characteristics of the hybrid power plant.

Table 1. System parameters

Component	Parameter	Value
Engine	Type	4 stroke, 8 cylinders
	Power MCR (kW)	423
	Speed MCR (RPM)	2100
Electric Machine	Nominal power (kW)	100
Battery	Type	Lithium ion
	Module capacity (Ah)	100
	Nominal Voltage (V)	12
	Number of modules	100

To calculate the fuel consumption for the diesel engine a fuel consumption map is utilised. Using data provided by the manufacturer, the fuel flow mass rate is calculated as a function of engine speed and power:

$$\dot{m}_f = f_{eng}\left(T_{eng}, \omega_{eng}\right) \tag{1}$$

For the electric machine, a quasi-static approach is adopted using the load correction factor provided by (McCarthy et al., 1990). Consequently, the power provided by the electric machine is given by:

$$P_{em} = \eta_{em}(P_{elec})\omega_{eng}T_{eng}, \quad P_{elec} \geq 0 \ (Motoring\ Mode) \tag{2}$$

$$P_{em} = \frac{1}{\eta_{em}(P_{elec})}\omega_{eng}T_{eng}, \quad P_{elec} < 0 \ (Generating\ Mode) \tag{3}$$

The battery is modelled using a first order equivalent circuit model (Onori et al., 2016). The battery SOC variation is given by (Planakis et al., 2021):

$$S\dot{O}C = -\frac{I_b}{Q_{max}} \tag{4}$$

Finally, to calculate the propeller load, the propeller law is used. To calculate the constant parameter kp, the engine torque and speed at the maximum continuous rating (MCR) are used. As a result, the propeller torque is expressed as:

$$Q_{prop} = k_p N_{eng}^2 \tag{5}$$

2.2. Energy management strategy

To find the optimal power allocation for the investigated hybrid power plant configuration, the equivalent consumption minimisation strategy (ECMS) is adopted. This strategy has already been applied to marine hybrid propulsion systems, demonstrating increased fuel savings, and sufficient robustness in unknown operating profiles, while achieving near optimal solutions for real time applications (Kalikatzarakis et al., 2018).

The principle behind this strategy is that an equivalent cost is assigned to the electrical energy of the battery to make it comparable to the fuel amount of the engine that either should be saved or be consumed (Onori et al., 2016). The global optimisation problem of finding the minimum fuel consumption is converted into an instantaneous optimisation problem, where the goal is to find the control input that minimises the equivalent fuel consumption. The equivalent fuel consumption is given by (Onori et al., 2016):

$$\dot{m}_{f,eqv}(t) = \dot{m}_f(t) + s(t)\frac{P_{bat}}{Q_{LHV}} \tag{6}$$

The equivalence factor is considered constant in this application, while it remains the same for both charging and discharging. The propulsion load, the propeller speed and the battery SOC are considered exogenous inputs to the problem, while the optimal control value is given by:

$$u^*(t) = \underset{u}{\operatorname{argmin}}\, \dot{m}_{f,eqv}\big(u, SOC, P_{prop}, \omega_{prop}\big) \tag{7}$$

The control variable in this application is the battery power command which then dictates the power setpoint to the other components in this hybrid power plant architecture. Various candidate solutions for the battery power command are created and the solution with the minimum value is selected in every timestep, subject to both equality and inequality constraints. The selected control value must satisfy the demanded power while ensuring that the performance limits of the components and the SOC are not violated.

2.3. Failure rate update model

The operating point of the components in the power plant can significantly affect the machinery's lifespan (Tang et al., 2020). As a result, a method is required to quantify the decrease of reliability in the current step based on the selected operating point, as well as to account for the influence of the past usage.

In this respect, the Weibull proportional hazard model (WPHM) is used, which considers the failure rate as a time dependent function, considering the effect of influencing variables using a covariate function. The WPHM is given by (Jardine et al., 1999):

$$\lambda(t, l) = \beta {\lambda_0}^{\beta} t^{\beta-1} g(l, \theta) \tag{8}$$

In this application, the covariate function depends on the load of the component. The covariate expressions which are followed also in this study are described extensively (Tsoumpris and Theotokatos, 2022).

2.4. Component and System reliability calculation

To calculate system reliability from the reliability of the components for the next timestep considering the influence of the current operating point, a dynamic Bayesian network (DBN) is used. Unlike, the Bayesian networks which can provide calculations for a specific time instant, the DBNs can capture the temporal dependencies of the network (Murphy, 2002). The joint probability distribution function of the DBN network from the previous time slice to the current time slice can be expressed as (Amin et al., 2018):

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{n} P\big(Z_{i,t}\big|Pa(Z_{i,t})\big) \tag{9}$$

The joint probability distribution function including all the timesteps takes the following form:

$$P(Z_{1:N}) = \prod_{t=1}^{N}\prod_{i=1}^{n} P\big(Z_{i,t}\big|Pa(Z_{i,t})\big) \tag{10}$$

In this study, the DBN is used with two time slices. The first time slice is fed with the current component reliability information whereas the next time slice is fed with the component reliability information considering the selected operating point. The root nodes in the DBN refer to the components while the probabilities in the conditional probability tables (CPT) are updated dynamically using a nonhomogeneous semi-Markov chain. In a homogeneous semi-Markov chain the transition probabilities are independent of time, whereas in the nonhomogeneous case the transition probabilities depend on the current state and the elapsed time (Salazar et al., 2017). The transition probabilities in this application refer to reliability and unreliability and they are calculated dynamically using the failure update model described in the previous section. Component reliability is calculated using the above expression:

$$R_i(t) = e^{-\int_0^t \lambda_i(t,l)dt} \tag{11}$$

Using this approach system reliability is estimated for the future timestep utilizing the information from the components' reliability and their operating point.

2.5. Decision-making method

The energy management strategy discussed earlier highlights the operating point with the minimum fuel consumption for the current timestep, whereas the DBN highlights the operating point with the highest system reliability. Nevertheless, the power plant must operate in a unique operating point which frequently does not coincide with the minimum fuel consumption and the maximum system reliability. As a result, a trade-off decision-making approach should be followed to select the final operating point as a compromise between the 2 objectives.

Furthermore, unlike design problems where the solution is found once, in this application the operating point must be selected for every timestep, with varying operating conditions and requirements, resulting in a multiobjective optimal control problem (Peitz and Dellnitz, 2018). Since system reliability and fuel consumption are significantly affected by the operating conditions and the current health of the system, the typical scalarization approach with fixed weights was not considered appropriate. A more sophisticated method called the reference or utopia point (Gambier, 2022; Peitz and Dellnitz, 2018) method was selected.

To apply this method, the Pareto front with the 2 objectives is created in every timestep. The underlying principle behind this method is that the distance to an infeasible target point T should be minimised that does not belong to the parent front J:

$$\min_u \bar{J}(u) = \min_u \|T - J(u)\| \tag{12}$$

In this study the Pareto front is created using the instantaneous fuel consumption as one objective and the system unreliability as the other objective for all the admissible control values of the operating point, satisfying the constraints dictated by the energy management strategy. The values of the objective functions are normalised to have an equal contribution to the infeasible target point which is the infeasible point that has both the lowest fuel consumption and system unreliability. Since the Pareto front gets updated in every timestep, the selected operating point is chosen based on the objective that has the most significant contribution based on the current operating conditions.

3. Case study Input

3.1. Operating Profile

In order to apply the proposed methodology to the examined hybrid power plant, the operating profile must be provided. Data from the actual operating profile of the pilot boat were collected, which however operates only with the diesel engine in the original design. The collected data account for 3 voyages, however, to highlight the effect of the proposed approach the operating time should be longer. As a result, the 3 voyages were put in random order with a random variation of the required speed setpoint, to create a half-month time operating profile closer to the real conditions.

In addition, as mentioned earlier the ECMS requires the specification of the equivalence factor, which depends on the operating profile. In this application, the equivalence factor is constant and is tuned based on the original operating profile using the 3 voyages sample and the shooting method approach (Onori et al., 2016).

3.2. Reliability input

The DBN requires the topology of the system in order to make computations. Figure 1 demonstrates the DBN structure for the investigated power plant. The root nodes represent the components, whilst the returning arcs indicate the temporal dependence.

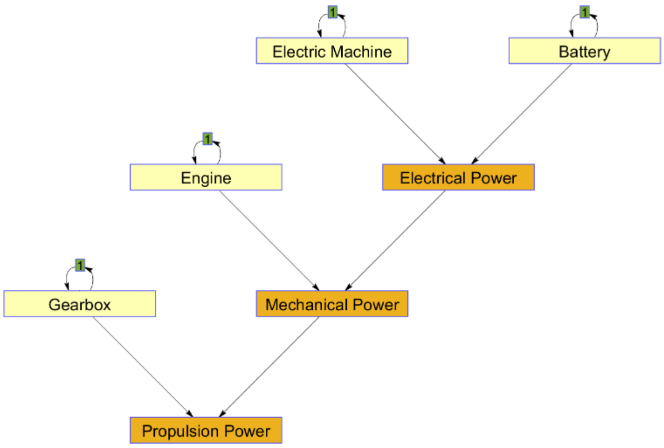

Figure 1. Developed dynamic Bayesian network structure

As for the failure rate data of the components, the OREDA database was used (SINTEF and NTNU, 2015) while the parameters of the Weibull distributions were set according to (Tsoumpris and Theotokatos, 2022).

4. Results & Discussion

The results presented in this section concern the half-month operating profile. It should be noted that the operating profile refers to actual operational time and not calendar time. The proposed health-aware energy management strategy is compared with the ECMS to highlight the differences between the two methods concerning system reliability and fuel consumption. The operating profile and the power setpoints are not presented, since there are too dense for the half-month operating profile, nonetheless, the SOC diagram is presented to understand the performance behaviour. Both methods are set with the target of keeping the SOC around 70%.

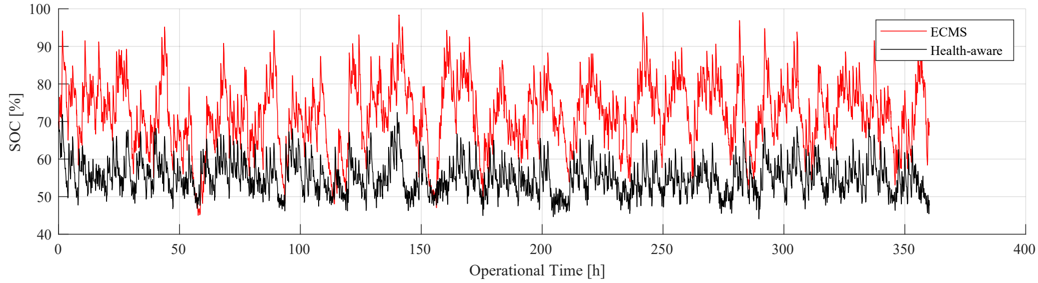

Figure 2. State of Charge (SOC) variation

Figure 3 presents the time variation of system reliability in the considered operating profile. It is inferred that using the proposed approach significant gains are achieved in the system reliability compared to ECMS, which focuses explicitly on the fuel consumption minimisation. The gains in the system reliability are more evident near the end of the operating period, which apart from the advantage of having higher propulsive availability for the autonomous operation, can help in prolonging the system lifetime expectancy reducing simultaneously the maintenance costs.

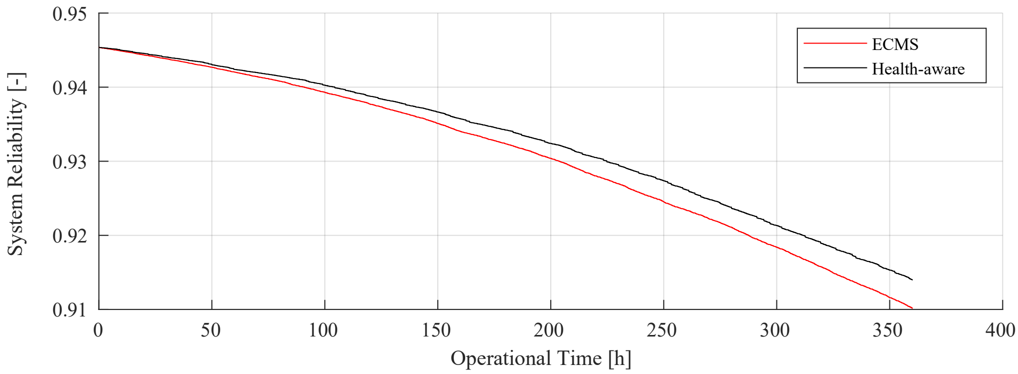

Figure 3. System reliability variation

As for the fuel consumption savings, both methods are compared with the baseline configuration of having only the diesel engine providing power to the propeller. By using only ECMS the fuel savings are around 16.8%, whilst using the health-aware energy management strategy the fuel savings are around 15.4%. Since health-aware energy management is a trade-off between system reliability maximisation and fuel consumption reduction, a small increase in fuel consumption is expected.

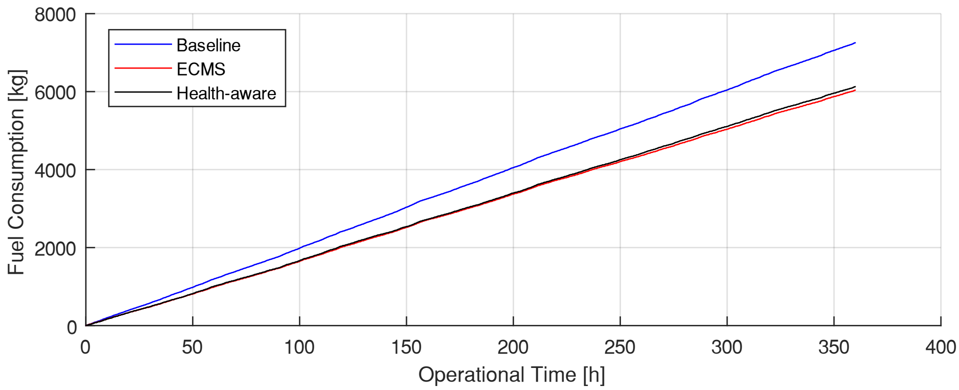

Figure 4. Total fuel consumption comparison

Finally, the most critical component in the power plant is found to be the engine, as it exhibits the highest failure rate. Figure 5 presents the variation of the engine reliability using the two methods as well as the engine reliability variation when the propeller load is only provided by the engine. It is inferred that using only the engine, its reliability decreases rapidly to very low values, whereas in the hybrid configuration engine reliability can achieve higher values. Moreover, with the health-aware energy management strategy engine reliability is slightly higher than using ECMS.

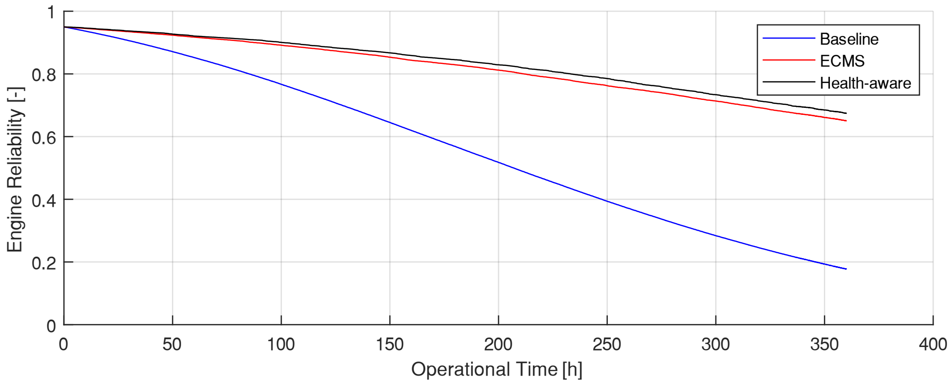

Figure 5. Engine Reliability variation

Overall using the health-aware energy management strategy, the operating points of the power plant are set to increase considerably system and component reliability, without influencing significantly fuel consumption.

5. Conclusion

This study demonstrated a health-aware energy management strategy that can be applied to the operation of autonomous ship power plants. Unlike, conventional ships where the energy management system focuses on fuel consumption minimisation and emissions reduction, this approach integrated the health state monitoring information for particular components and system reliability. The results demonstrate that the overall system reliability can be increased to prolong the system lifetime, while the engine, which is the most critical component in the power plant, can benefit by using this method to operate in regions to improve reliability.

The autonomous ship requires advanced monitoring capabilities to assess the health state of the machinery that can be integrated into the performance control. In this study, system reliability was chosen as the health metric, however, more sophisticated metrics can be included like the actual RUL, risk metrics etc.

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