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# A Comparison between Digital-Twin Based Methodologies for Predictive Maintenance of Marine Diesel Engine

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***Abstract*— An efficient operation of marine diesel engines, onboard ships, requires advanced monitoring and diagnostic techniques for early detection of faults and degradation in the propulsion or power generation system. This complex problem has been recently approached by digital-twin-based fault detection models. In this paper, we report on two methods for fault analysis on marine diesel engines exploiting (i) an Artificial Neural Network (ANN) combined with machine learning tools and (ii) a digital twin simulation model combined with a parameter estimator tool. In both cases, a digital twin model of the engine has been used for the generation of synthetic data, but in different simulation environments. These methodologies are applied to two distinct case studies, and their outcomes are discussed, focusing on the pros and cons. A proposal for a method combining the benefits of both is presented.**

***Keywords—diesel engines, performance monitoring, fault detection, condition-based maintenance, machine learning artificial neural networks, digital twin.***

## I. Introduction

The Predictive Maintenance (PM) approach aims at early fault identification in systems and component diagnostic, together with the monitoring of the degradation state and the prediction of possible future faults. The possibility of scheduling and targeting the maintenance activities in a proper and effective manner leads to several benefits, with an increase in system reliability, maximization of components uptime, and minimization of machine downtime [1], [2].

Generally, a component failure happens after a preliminary phase of incipient degradation during which one or more operating parameters start to deviate slightly from the expected values [3]. The duration of this phase ranges from months to a few minutes and, in the case of complex systems, such as the internal combustion engines (ICE), a prompt identification of such deviations requires measurements that are often impossible or at least very expensive. Additionally, among all measurable engine data, there is the problem of monitoring only those effectively prone to disclose possible faults. In this context, the digital twin approach is thought as a useful and promising technique to get an estimate of the engine working parameters, including those generally not accessible during normal running [4], [5], [6], [7]. This allows for the development of novel fault analysis techniques. Numerical simulation for the diagnostic analysis of a marine system is not yet widely used. The few existing studies mostly concern the influence of degradation of one or more components on the overall behavior of the examined system such as a marine gas turbine [8], a diesel engine [9], and its waste heat recovery system from exhaust gases [10]. In this paper, two methodologies, based on the digital twin concept, are presented. The first one employs an artificial neural network (ANN) regression model for estimating the process parameters in normal running conditions [11]. The measured real-time signal is compared with the optimal estimated value, and the deviation between them is used as an indicator of potential faults in the engines' system and components. The calibration and performance evaluation of the diagnostic model are conducted on synthetic fault data which are fault data generated through simulations by the digital twin of the engine in degraded conditions. The possibility of generating fault data from simulation models (synthetic fault data) is effective and useful in replacing fault data measured from a real engine (damaged in a controlled manner) [9], which would result somewhat dangerous and expensive. At the scope, the GT-Power tool is used as a simulation environment. Instead, the engine model in nominal conditions has been validated by means of real data collected from the field.

The second methodology combines a parameter estimation technique with a digital twin simulation model of the diesel engine [12]. This approach aims at identifying and quantifying the degradation level of engine components by matching the real-time signals with the simulated ones, minimizing their relative errors. This is achieved by means of the parameter estimation technique, by altering the degradation coefficients within the simulation model. At the scope, Matlab/Simulink toolboxes are used. Also in this case, the real-time signals of the degraded engine are synthetic data. The applications of such methods are carried out on two different engines: the G1716 produced by IFM- Isotta Fraschini Motori (a Fincantieri company) and the MAN 12V32/44CR four-stroke diesel engines. This paper presents the results obtained by the two case studies and provides a discussion of the pros and cons, boosting the development of both methods using their positive features.

## II. THE ANN DIAGNOSTIC MODEL

The first diagnostic model, presented herein, is based on the real-time comparison between actual measured signals and their estimated optimal values, which are generated by an Artificial Neural Network. Artificial Neural Networks (ANN) is a type of machine learning algorithm consisting of layers of interconnected nodes (neurons) that process and transmit information through weighted connections to make predictions or classifications. ANNs have gained significant attention as a promising approach to address modeling problems that include complex physical processes with nonlinear, high-order, and time-varying dynamics, such as those encountered in predictive maintenance strategies [7]. Indeed, when properly calibrated the ANNs have good computational efficiency. An ANN is here employed for the estimation of the optimal value of the diagnostic variable which is used as a reference for the diagnostic task. The engine's operational variables and environmental data are expected to be measured by sensors and acquired and organized by means of a so-called Data Gathering system (DGS). In this research, due to the lack of data from the field of a degraded engine, the GT-Power tool is used to generate the operational variables assuming controlled degradation types. The engine model implemented in GT-Power, operating in nominal condition was calibrated and validated against the field data of the real engine. A subset of the degraded signals (Predictors) is used as inputs to the ANN, which is trained on nominal condition data to output optimal values for the main engine's operational variables (diagnostic signals). The selection of the Predictors was based both on the outcomes of statistical analysis both on IFM experience. The deviation between the actual measured value and the estimated optimal value of the diagnostic signals serves as an indicator of how far the system is operating outside the normal condition. The diagnosis relies on defined thresholds based on anomalous running data simulated through simulation tools. In Figure 1, a scheme of the model is depicted.

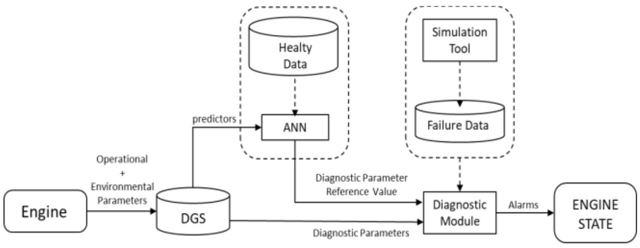
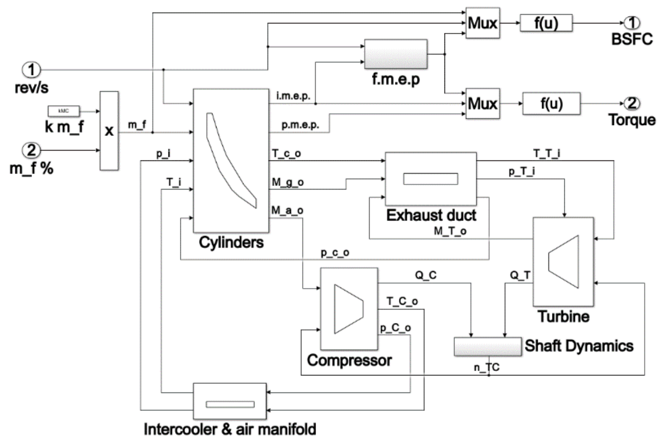



Fig. 1. Diagnostic model scheme

## III. THE PARAMETER ESTIMATION BASED DIAGNOSTIC MODELS

The second diagnostic model is based on the real-time comparison between actual measured signals and their simulated optimal values, which are generated by a digital twin simulation model of the engine, implemented in Simulink. The numerical simulation model of the diesel engine is organized in sub-modules each of them consisting of algebraic and differential equations that refer to the corresponding subsystem behavior. The arrangement of the engine blocks is shown in Figure 2.

A 0D filling and emptying approach is applied to each engine simulator block. The in-cylinder phenomena calculation is based on a fully thermodynamic actual cycle. A real gas model is used for the fluid properties calculation; specific internal energy and enthalpy are assumed to be functions of both fluid composition and temperature. The input variables to the engine simulator are the engine speed and the fuel mass flow rate. For the sake of synthesis, the reader can find the detailed description of the engine simulation model in [12], [13], [14]. In this research, the engine model implemented in Simulink, in nominal operations, was calibrated against the data reported in the project guide of the manufacturer.




Fig, 2. Block arrangement for the engine simulation model

In the same numerical model, a set of gain coefficients are introduced, aiming at modeling physical alterations (degradations) of mechanical components. In nominal operations, all these coefficients are defined by unitary value. Also, for this diagnostic model, the engine's operational variables and environmental data, are expected to be measured by sensors on the field. Due to the lack of data from the field of a degraded engine, in this case the degraded engine variables are simulated beforehand by using the same numerical model in Simulink, by altering in a controlled way, the gain coefficients. The deviation between the actual measured value (degraded variables) and the simulated optimal value is an offset that the parameter estimation method (optimization process) will minimize by altering the gain coefficients (parameters). At the scope, the parameter estimator toolbox of Simulink is used.

## IV. CASE STUDIES

The ANN diagnostic methodology is applied to the Isotta Fraschini Motori (IFM) G1716 diesel engine, originally employed for GENSET application.

TABLE I. ENGINE DETAILS

| Engine | G1716 | MAN 20V32/44CR |
|---|---|---|
| Cycle | 4 strokes | 4 strokes |
| Num. of Cylinders | 16 V | 20 V |
| Power | 1940 kW | 12000 kW |
| Speed | 1500 rpm | 750 rpm |
| Bore x Stroke | 170x185 mm | 320 x 440 mm |
| Mean effective pressure | 23.1 bar | 27.1 bar |
| Application | Genset | Propulsion |

The parameter estimation based diagnostic model is applied to a MAN 20V32/44CR marine diesel engine. The main specifications of the engines are shown in Table I [11],

[12]. For the training of the ANN and the test of the diagnostic model, it is used a dataset consisting in 4661 measurements. These data are collected with a sample time of 5s during about 6 hours of running on test bench in which the engine has been subjected to a specific and controlled operative profile characterized by different load regimes (from 0% to 100% and from 100% to 0%). In Figure 3 the density i.e. the number of instances in the Dataset referring to a specific power range is shown.

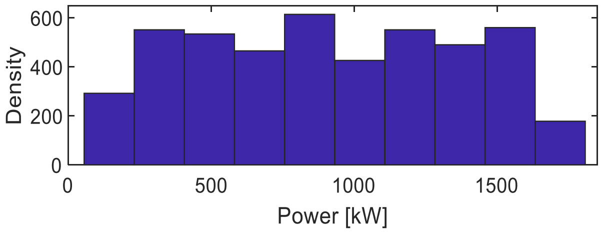



Fig. 3. Details of the tested load regimes

The measurements refer to 51 signals of sensors installed on the engine: only normal condition data are acquired. This data refers to specific environmental data, such as air temperature and freshwater temperature that are measured alongside. The ANN diagnostic model is tested on the detection of three possible faults: misfiring, intake valve seat fault, and turbine fault. These are selected from a priority list of relevant faults, identified by IFM manufacturer. In particular, the turbine fault is meant as a generic malfunction that causes a loss of turbine efficiency (e.g., turbine obstruction, damaged blades, dirt, etc.). Misfiring and intake valve seat fault was supposed to occur on cylinder 1 of the A bank (A1). For the case at hand, three diagnostic signals (variables) which has emerged as very good indicators for the engine operation and health state have been selected [11]: exhaust gas temperature of cylinder A1 (CGT), intake manifold temperature (IMT), and intake manifold pressure (IMP) of bank A.

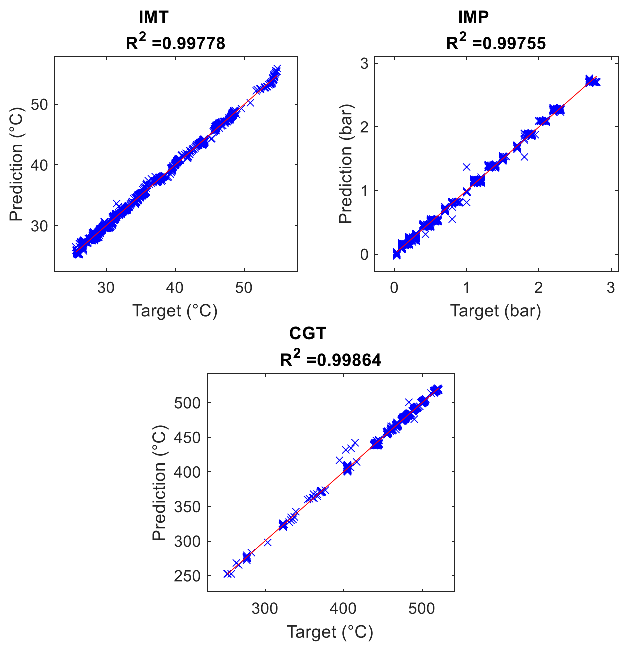



Fig. 4. Prediction performances of the ANN

Figure 4 shows the regressive performance of the network for the three different diagnostic signals of the engine in nominal conditions. All the diagnostic parameters are predicted with very good accuracy as indicated by a coefficient of regression R over 0.99. The percentage error of prediction is distributed almost normally around zero and it indicates that the model is not biased towards overestimating or underestimating the target variable. The calibration and validation of the MAN engine, implemented in Simulink, was carried out focusing on engine power and specific fuel consumption for different engine working conditions: engine load equal 100%, 85%, 75%, 65%, 50%, and 25% of Maximum Continuous Rating (MCR) at a constant speed (750 rpm) and variable speed. The comparisons between calculated and reference data, showed a good simulator accuracy, with errors less than 0.5% in the MCR engine load conditions, and less than 1% in the other examined engine working conditions.

A number of nine different degradations is considered, thus nine degradation coefficients (parameters) are implemented in the Simulink model, as reported in Table II [14], [15]. The diagnostic signals (i.e. variables) that are monitored are listed in Table III [16]: all variables that could be reasonably measured on the field are assumed.

TABLE II. DEGRADATION TYPES AND CORRESPONDING COEFFICIENTS

| **Simulation block** | **Degradation (Coefficient name)** |
|---|---|
| Intercooler | Intercooler fouling (d_in_p) |
| Intercooler | Efficiency reduction (d_in_eff) |
| Compressor | Dirty air filter (d_co_eff) |
| Compressor | Efficiency reduction (d_co_re) |
| Compressor | Mass flow reduction (d_co_m) |
| Shaft TG | Bearing deterioration (d_tg_cu) |
| Turbine | Efficiency reduction (d_t_re) |
| Turbine | Erosion or fouling of the blades (d_t_pa) |
| Cylinder | Fuel flow reduction (d_c_co) |

TABLE III. MONITORED ENGINE VARIABLES (I: INTERCOOLER, C: COMPRESSOR, D: DUCT, TEMP: TEMPERATURE, P: PRESSURE)

| **Intercooler (I) and Compressor (C)** | **Turbine (T) and exhaust duct (D)** | **Cylinder** |
|---|---|---|
| Outlet Temp. (I and C) | Outlet p (D and T) | Outlet Temp. |
| Torque (C) | Outlet Temp. (D and T) | Outlet p |
| Outlet p (C) | Torque (T) | Consumption |
| Speed rpm (C) | Speed rpm (T) | Engine torque |

## V. RESULTS

### *A. ANN + GT-Power*

The effect of faults on the engine behavior and the thermodynamic variables are investigated through GT-Power, an industry-standard engine performance 1D-CFD simulation tool. The engine model is built by using geometrical and real engine characteristic data and it is tuned and validated against experimental measurements from test bench tests. The faults are introduced by properly adjusting the tuning parameters in the engine model [11].

In Figure 5 it is possible to observe the deviation of the diagnostic parameter value from the normal condition for each fault occurrence. In general, the higher the power load, the higher the value and the range of deviation. Note that the considered faults do not exhibit common symptoms, thus this ensures that the diagnostic signals under consideration are adequate for fault diagnosis and there is no possibility of diagnostic ambiguity (i.e. a peculiar and exclusive behavior of the faults has been identified). The fault diagnostic is performed by calculating the percentage of deviation between the actual measured variables of the engine and their estimated optimal values generated by the ANN. If the percentage deviations of all diagnostic signals fall simultaneously within the fault boundaries, (identified by the engine loads and by the fault type, as shown in Figure 5), then the specific fault is detected by the system, and the corresponding alarm is raised.

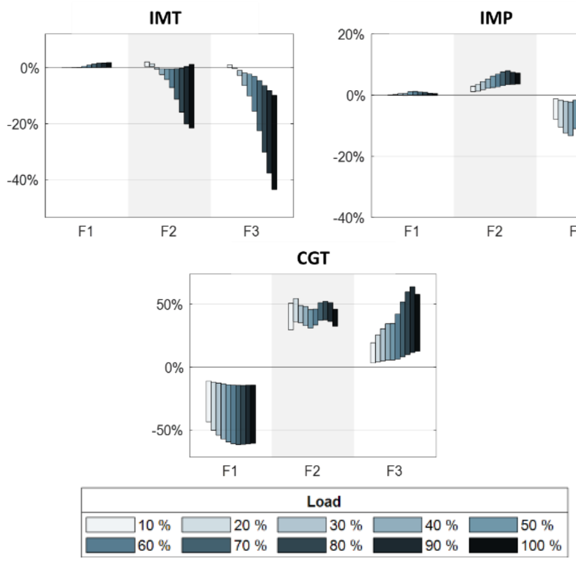



Fig. 5. Engine behavior under simulated misfiring (F1), valve leakage (F2), and turbine fault (F3)

Focusing on the misfiring fault type, 776 simulation instances, carried out in GT-power, are considered: 387 are associated with normal operating conditions, and 389 refer to fault occurrence. The results obtained from the application of the ANN fault analysis are presented in Figure 6 in the form of the confusion matrix, where F and H stay for fault and healthy, respectively.

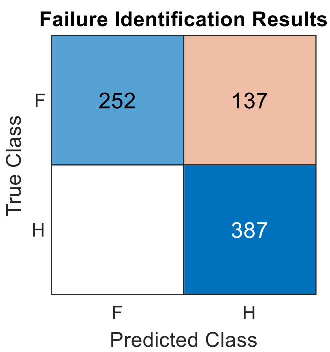



Fig. 6. Confusion matrix of the model's diagnosis

The ANN fault diagnostic correctly detected all 387 healthy instances, and no false alarm was raised. Among the expected fault cases, only 65% (i.e. 252 of the expected 389) were correctly detected, whereas the remaining fault cases were not identified. This could be imputed to the real data measured from the field affecting the training of the ANN. The measured signals and normal condition predictions could be affected by non-negligible noise due to sensors' precision, which may be responsible for the percentage deviation to fall outside thresholds, (i.e. the ANN may lack in perfectly tracking the optimal value of diagnostic signals).

### *B. Digital twin + Parameter estimation (PE)*

The degraded engine variables are obtained by the same numerical model of the engine in Simulink, by setting known values of the degradation coefficients. Several degraded cases were generated modifying one coefficient at a time and also two coefficients at the same time. These data are then inputted to the Parameter Estimation toolbox (PE) [12], [17]. The application of the parameter estimation to a sample set of monitored variables allows identifying the degraded component and its degradation level, causing that given realization of the monitored variables. In the optimization procedure, the degradation coefficients (parameters) vary until their value produces numerical outcomes matching with the input variables (degraded engine data). In Figure 7, the results for a sample case characterized by a single degradation are presented. The degraded scenario refers to a pressure loss at the intercooler (d_in_p) equal to 10%. Figure 7 shows the numerical iterations of the non-linear optimization routine, prior to converge. It is possible to observe how, during the whole iteration process, the most sensitive parameter is the one related to the pressure loss of the intercooler. After ten iterations, its value settles on 0.9 (i.e. corresponding to a 10% degradation), whereas all remaining coefficients provide almost unitary values (i.e. absence of corresponding degradation).

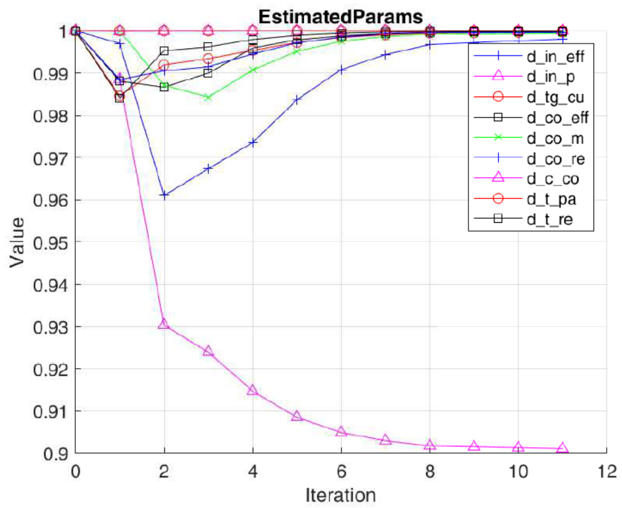



Fig. 7. Convergence plot for a single degradation scenario (d_in_p)

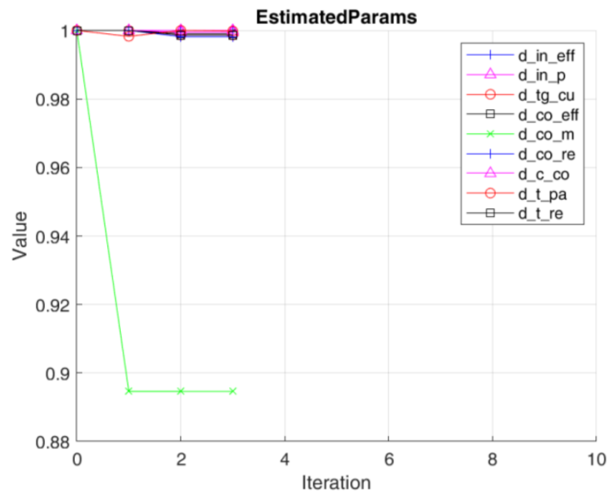



Fig. 8. Convergence plot for a single degradation scenario (d_co_m)

In Figure 8, the degraded scenario refers to a compressor mass flow reduction (d_co_m) equal to 10%. Also in this case, it is possible to observe how, during only three iteration process, the most sensitive parameter is the one related to the correct failure. Finally, the parameter estimation outcomes for a sample case involving two simultaneous degradations are presented. In this scenario, we expect a pressure loss at the intercooler (5% due to fouling of the air filter) and a problem on the turbine blades (10% loss due to fouling of the turbine blades). In Figure 9, it is possible noticing that, also in this case, the optimization procedure at convergence provides d_in_p= 0.95 and d_t_pa= 0.9 while all other coefficients remain unchanged.

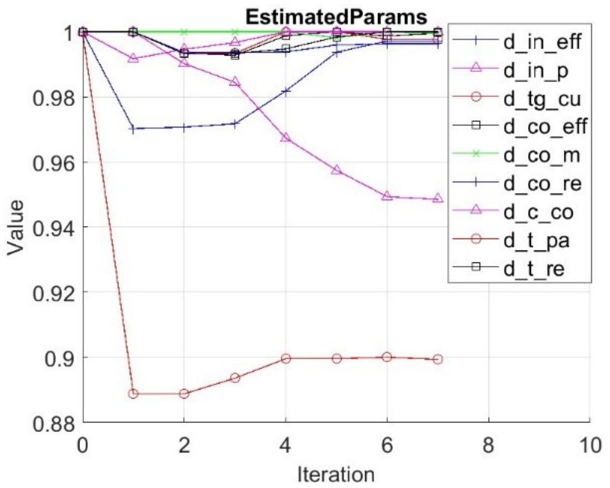



Fig. 9. Convergence plot for two degradations scenario (d_in_p and d_t_pa)

## VI. Discussion

The ANN and the PE methodologies showed promising outcomes regarding the fault analysis of marine diesel engines. This section provides a thoughtful discussion of the two case studies focusing on their positive aspects and limitations. The ANN, applied to the G1716 engine, benefits from the availability of several data from the field (i.e. signals affected by noise), in training the numerical model of the engine operating in nominal conditions. This gives the possibility of realizing a numerical model calibrated to the real engine. The analyzed faults relate to the three typical cases frequently observed on operating engines and exploit a direct correlation between each fault and the effects on a specific system variable. The possibility of generating degraded engine behavior in the GT-power environment ensures the generation of somewhat reliable synthetic data, although validation of such damage scenarios is not possible with real data from the field. On the other hand, the ANN model works with predefined thresholds for checking the offset between the nominal and the degraded engine variables, somewhat affecting the effectiveness of the fault analysis outcomes. The PE method applied to an engine model implemented in Simulink proves its effectiveness although limiting the whole analysis to the same simulation environment. Compared to the ANN technique it appears less mature meaning it has still room for development, regarding the applicability to real engine data. However, the possibility of handling more than one mechanical degradation at a time and the possibility of quantifying the degradation level prior to a major fault endorses further studies on the PE approach. For instance, the application of the PE method could be carried out to the G1716 engine, using the same input data by the ANN model, aiming at a validation through the comparison of the two method outcomes. This could be beneficial also for the further developments of the ANN method in better understanding the reasons behind the shortcomings in identifying all fault cases.

## VII. Conclusions

This paper presented two methodologies based on digital twin models for the fault analysis on marine diesel engines. Both methods proved their positive features through the applications to two different case studies based on available data. The ANN method was judged more mature, despite somewhat less accurate, because based on real data i.e. measured signals, thus affected by noise due to sensors' precision. The PE method resulted accurate and suitable for condition monitoring although less mature, since its outcomes were not affected by noisy measured signals. Future research will regard the application of ANN and PE methods to the same case study aiming at a direct comparison, enforcing further developments of both methodologies. Attention will be given to the degraded engine scenarios, attempting to a classification of the degradation levels. Indeed, the degradation level resulting from the PE application has currently no acknowledged physical meaning.

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## References


[1] A. Prajapati, J. Bechtel, and S. Ganesan, "Condition based maintenance: a survey," Journal of Quality in Maintenance Engineering, 18(4), 2012, pp. 384-400.

[2] N. Matulić, G. Radica, and S. Nižetić, "Engine model for onboard marine engine failure simulation," Journal of Thermal Analysis and Calorimetry, 141(1), 2020, pp. 119-130.

[3] S. Selcuk, "Predictive maintenance, its implementation and latest trends," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231(9), 2017, pp.1670-1679.

[4] C. S. Mishra, F. Ali, S. Adam, A. Tesfariam, A. Yemane, H. Amanuel, ... and Y. Alem, "Study of the Causes of Engine Failure in Ship and Maintenance Required to Prevent Engine Failure," International Journal of Contemporary Research and Review, 8(7), 2017, pp. 20218-20241.

[5] M. Acanfora, M. Altosole, F. Balsamo, L. Micoli, and U. Campora, "Simulation Modeling of a Ship Propulsion System in Waves for Control Purposes," Journal of Marine Science and Engineering, 10(1), 36, 2021.

[6] X. Song, H. Cai, T. Jiang, S. Schlegel, and D. Westermann, "Parameter Tuning for dynamic Digital Twin of Generation Unit in Power Grid," In 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe) , October 2021, pp. 01-06. IEEE.

[7] Í. A. Fonseca, H. M. Gaspar, P. C. de Mello, and H. A. U. Sasaki, "Standards-Based Digital Twin of an Experiment with a Scale Model Ship," Computer-Aided Design, 103191, 2022.

[8] M. Altosole, U. Campora, M. Martelli, and M. Figari, "Performance decay analysis of a marine gas turbine propulsion system," Journal of Ship Research, 58(3), 2014, pp. 117–129.

[9] R. Zaccone, M. Altosole, M. Figari, and U. Campora, "Diesel engine and propulsion diagnostics of a mini-cruise ship by using artificial neural networks," in Towards Green Marine Technology and Transport - Proceedings of the 16th International Congress of the International Maritime Association of the Mediterranean, IMAM 2015, 2015, pp. 593–602.

[10] M. Altosole, U. Campora, M. Laviola, and R. Zaccone," Deterioration effects on the performance of a steam plant for the waste heat recovery from a marine diesel engine," Ships and Offshore Structures, 14(8), 2019, pp. 867–878.

[11] M. Ceglie, F. Ferrante, and G. Giannino, "Employing Artificial Neural Network for Process Signal Estimation in the Monitoring of Smart Shipboard Diesel Engine Systems," In HSMV 2023, 2023, pp. 93-100. IOS Press.

[12] M. Altosole, F. Balsamo, M. Acanfora, L. Mocerino, U. Campora, and F. Perra, "A digital twin approach to the diagnostic analysis of a marine diesel engine," in Technology and Science for the Ships of the Future, 2022, pp. 198-206. IOS Press.

[13] G. Benvenuto, U. Campora, G. Carrera, and P. Casoli, "A two-zone diesel engine model for the simulation of marine propulsion plant transients," Proceedings of the MARIND, 98, 1998.

[14] M. Altosole, U. Campora, M. Figari, M. Laviola, and M. Martelli, "A diesel engine modelling approach for ship propulsion real-time simulators," Journal of Marine Science and Engineering, 7(5), 138, 2019.

[15] J. A. P. Rubio, F. Vera-García, J. H. Grau, J. M. Cámara, and D. A. Hernandez, "Marine diesel engine failure simulator based on thermodynamic model," Applied Thermal Engineering, 144, 2018, pp. 982-995.

[16] G. Benvenuto, U. Campora, M. Altosole, and F. Balsamo, "Numerical modelling and analysis of the ambient conditions influence on the performance of a marine diesel engine," in Maritime Technology and Engineering 5 Volume 2 , 2021, pp. 463-474. CRC Press.

[17] S. Rouquette, J. Guo, and P. Le Masson, "Estimation of the parameters of a Gaussian heat source by the Levenberg–Marquardt method: Application to the electron beam welding," International Journal of Thermal Sciences, 46(2), 2007, pp. 128-138.