System of Water Vehicle Power Plant Remote Condition Monitoring

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Abstract. Remote condition monitoring of water vehicles plays an important role in preventing potentially very expensive marine incidents and ensuring maximum efficiency of a ship’s operation and reliability with minimum maintenance downtime and repair costs. Concept of the condition-based approach to maintenance is today’s best practice, and it is becoming increasingly important to move from planned maintenance to condition-based maintenance, to reduce the increasingly high cost of maintaining a modern fleet. Onboard and remote monitoring is now an essential part of condition-based maintenance process to obtain the good quality data, correct analysis, and effective counteractive actions necessary for such an approach, and article presents the water vehicle power plant monitoring model developed by authors. Considered approach, coupled with preventive maintenance, saves shipowners time and money through early diagnosis of component failure or excess wear. Power plant of water vehicle comprises far more than just an engine with its auxiliary equipment but also other main propulsion blocks – in particular, thrusters. The result was the development of the Water Vehicle Condition Monitoring (WVCM) system, which enables to closely examine water vehicle equipment performance. A WVCM system comprises the following installed onboard: accelerometers, pressure and temperature transmitters, oil, fuel and exhaust monitoring units and a torque measurement system.

1. Introduction
Water vehicles management systems are changing to include proactive, condition-based maintenance, using good quality data from machinery health monitoring. So, maintenance strategies are moving away from reactive maintenance to proactive approaches that should see any deterioration before planned maintenance intervention. The modern maintenance strategy is based on a proper risk analysis and the correct implementation of condition-based maintenance practices, suitable work processes, tools, and good personnel skills [1]. Providing up-to-date and in-depth information about the water vehicle power plant condition, enables operators to assess risk far more accurately. The technical condition information is usually obtained from close inspections and functional tests, but condition-based maintenance strategy involves obtaining the real-time advice given by the advisory system and the monthly reports provided by the company’s experts [2]. Because if any significant wear or damage is detected early, the risk of consecutive damage is reduced, and continuous access to expert support advisory system enables the expert to support management decisions with reliable data and carefully plan water vehicle maintenance with minimum downtime and repair costs. This is important for all involved in maintenance management process and the overall operational efficiency and revenues will benefit. Onboard and remote monitoring is now playing an important role in supporting customers in the future, and as a logical supplement to the service agreements business.
The term water vehicle in this article means: container ships, general cargo ships, and multi-purpose dry cargo vessels.

Many publications are devoted to theoretical and practical issues of on-board control of the water vehicles machinery components technical condition [3, 4, 5, 6, 7, 8]. The following publications outline the impact of different service strategies on the machinery component operation efficiency [9, 10, 11, 12, 13]. Condition monitoring equipment, requirements for operation, methods of observation and research of water vehicles machinery components technical condition are described in the following publications [14, 15, 16, 17, 18, 19].

To ensure guaranteed and uninterrupted operation of the water vehicles, it is necessary to conduct not only onboard but also remote systematic monitoring [20] to identify the real technical condition of the machinery components and predict when the failure is going to occur to assign an appropriate mode of their operation.

2. Problem Definition
Across industry, many definitions are used when it comes to the different maintenance strategies. Water transport maintenance can be characterized by the two top level types of strategies: corrective maintenance (CM) and preventive maintenance (PM). CM is also called as reactive maintenance, and PM called proactive maintenance. Distinctive aspect of CM is that it is performed after a failure occurs either as Deferred CM or as Emergency Maintenance. CM can be the result of a deliberate run-to-failure strategy. PM can be aimed at preventing a failure, evaluating the risk of the failure occurring, or minimizing the consequence of the failure. PM is basically a type of maintenance that is done at a regular period while the equipment is still operating with the objective of reducing the possibility of failure or preventing failure. Distinctive aspect of PM is that it is performed before a failure occurs and consists of maintenance strategies like:

- Time-Based Maintenance (TBM),
- Risk-Based Maintenance (RBM),
- Failure-Finding Maintenance (FFM),
- Condition-Based Maintenance (CBM),
- Predictive Maintenance (PDM).

TBM refers to replacing or repairing the unit to restore its reliability at a regular time interval, or usage in any case of its condition. TBM assumes that the failure is age correlated and an obvious service life can be defined.

RBM is when you use a risk evaluation methodology to assign your limited maintenance resources to those assets that carry the most risk in case of a failure (risk = probability x consequence). With RBM, machinery components that has a higher risk and a very high consequence of failure would be subject to more frequent inspection and maintenance. Low risk machinery components may be inspected and maintained at a lower frequency and possibly with a smaller range of work. When shipowner implement a RBM process effectively it should have reduced the total risk of failure across machinery components in the most economical way.

FFM do not prevent failure but simply detect it. Once the failure is detected operator will have to repair it. FFM is conducted at fixed time intervals typically derived from legislation or risk-based approaches. FFM tasks are aimed at detecting hidden failures typically associated with protective functions.

CBM as a strategy looks for physical evidence that a failure is occurring or is about to occur. If evidence can be found that something is in the early stages of failure, it may be possible to take action to prevent it from failing completely and to avoid the consequences of failure. Most failure modes give some sort of warning that they are in the process of occurring. It is important to realize that CBM does not fix machinery and does not stop failures. CBM only lets you find some problems before they become a failure. For CBM to be as an effective strategy, is essential early maintenance intervention. This involves an effective data gathering, data analysis, decision making and definitively maintenance intervention.
Recently when experts spoke about PDM this was a synonym for CBM, but with the contemporary implementation of Applied Artificial Intelligence (AAI) and Machine Learning in lower costs equipment sensors there is appearing a difference between PDM and CBM. And the authors of the article can argue that PDM can be an extension, a more advanced approach compared to CBM where potentially many process parameters gained from intelligent sensors to determine if water vehicles machinery components are moving away from stable operating conditions and is heading towards failure. The PDM main task is to predict when the failure is going to occur and then determine the appropriate time for maintenance intervention.

Compulsory major overhaul intervals are stipulated by class – container ships, general cargo ships, and multi-purpose dry cargo vessels during CM might require a major overhaul which would involve dry-docking every five years, with intermediate survey between, regardless of its machinery components technical condition. But research of the authors of this article have shown that not all machinery components, based on their technical condition, require overhaul after a five-year period of operation [1, 2, 18, 20, 21]. And there is a sufficient safety margin of machinery components, which allows to extend the periods between major overhauls by 50 % from 5 to 7.5 years [1, 2, 20, 21]. A variety of factors are taken into consideration before approving a water vehicle for extended overhaul intervals.

It has been demonstrated that it is required to solve the problem of extending the periods between major overhauls, based on an accurate chronological determination of the water vehicle machinery components performance using the WVCM system and predicting the probable time of failure based on the PDM strategy.

3. Problem Solution

3.1. Water Vehicle Machinery Components Condition and Emissions Monitoring
Water vehicles machinery components fail due to different reasons and all failures are not the same. Machinery components fail or loses their usefulness when they stop functioning in the way they were designed for. This loss of usefulness is divided into three main categories:

- obsolescence,
- accidents,
- surface degradation.

Surface degradation of machinery components results in the machine’s loss of usefulness in the vast majority of cases and comprises mainly mechanical wear and corrosion. Every unexpected stop in operation, due to machinery components failures, has a significant influence on the water vehicles efficiency, repair and other costs, revenue, profits, and finally competitiveness. It is estimated that each water vehicle downtime costs ship operators around 25 thousand USD per hour or 600 thousand USD per day [21]. This is the reason why shipowners are constantly in search of ways to eliminate failures while keeping maintenance costs at the lowest possible level. This is the point where CBM acts as a basis for PDM strategy [22].

Proper Condition-Based Monitoring helps shipowners or operators to:

- decrease repair costs,
- reduce maintenance costs,
- increase water vehicle life,
- increase personnel safety,
- increase revenue,
- increase efficiency.

Water vehicles condition monitoring is a process of checking the status of the machinery components during its normal operation. It consists of data acquisition, data processing, and data comparison with trends, baseline, and representative data from similar components. Progress in electronics and software development are significantly changing machinery condition monitoring making it simpler to use and way more reliable.
Condition monitoring applies to many of applications: gearboxes, air conditioning, electric motors, fans, pumps, blowers, cranes, separators, gas turbines, steam turbines, water pumps, boilers, internal combustion engines and its auxiliary systems.

Regardless of application, to successfully implement a proper machinery condition monitoring strategy, it is essential to follow a structured approach in the following seven stages [23]:

1. compose of equipment register,
2. assessment of machinery components status and their criticality for the water vehicle operation,
3. identification of appropriate machinery component condition monitoring technique,
4. selection of available condition monitoring technologies,
5. installation of the condition monitoring system,
6. diagnostics data collection and data interpretation,
7. technical state prediction and maintenance tasks determination.

First stage aims to build a register of all water vehicle machinery components, and its usually includes: process drawings, wiring diagrams, correct details of each component (type, speed, power, etc.), component position for easy component finding, unique ID number of each component.

At second stage it is necessary to review of past machinery components failures, analysis of mean time between failures and mean time to repair, average costs of replacement or repair, cost of downtime, risk of subsequent damage. This information will help in the identification and selection of the right machinery component condition monitoring techniques and technologies.

The third stage is characterized by the choice of the correct techniques that are used for the assessment of machinery component condition, that are most frequently used: temperature monitoring, pressure monitoring, rotation speed monitoring, vibration monitoring, acoustics emission, ultrasound testing, oil analysis, fuel analysis, exhaust emissions analysis, motor condition monitoring and motor current signature analysis.

The fourth stage is characterized by the need to make a choice of available condition monitoring technologies. As authors noted in Problem definition, there is a wide range of available strategies for machinery condition monitoring. The best strategy of maintenance would be to use a combination of all described strategies to gain the best results. But, due to time and budget limitations, temperature measurements in combination with vibration diagnostics have proven to be the most effective condition monitoring technologies.

At fifth stage it is important to choose proper mounting method of sensors selected in the fourth stage. The proper installation of the condition monitoring sensors is important for its performance. Incorrect mounting will give diagnostics data that relates not only to a change in technical condition but also to the mounting of the sensor. Consequently, making the sensor’s data unreliable. Vibration sensors should be mounted in locations that provide the measurement of vertical, horizontal, and axial movement.

The sixth stage is the longest and most important, because it occurs during the communication of the running machinery components with the environment. Machinery components communicate through vibration signals generated while they are running. And it is important to understand vibration to be able to evaluate the machinery components technical condition. To translate signals of vibration into technical state condition vibration diagnostic tools are used, which composed of three main parts: sensors, data acquisition hardware, condition monitoring software. Condition monitoring software can be built for technical condition monitoring of specific machinery component or can be reconfigurable and consequently intend for complex machinery diagnostics applications. The most excellent software solutions offer direct connectivity and data transfer to distributed control systems. There are differences between condition monitoring software in terms of access to the data, it can be local-based with computer access or web-based software for remote condition monitoring.

Eventually, at seventh stage, it is necessary to interpret diagnostics data collected using the software tools described at previous stage and make a prediction of changes in technical condition. The most optimal way of doing it with automatic data using PDM strategy based on AAI, because it
can very reliably predict failure of various machinery components and set appropriate maintenance tasks.

Every condition or emissions monitoring strategy is based on the following conceptual information model shown in Figure 1.

![Figure 1. Conceptual information model of monitoring](image-url)

The organization of monitoring systems is based on general theoretical and methodological principles and shown in Figure 2 [24]:

1. Structural and organizational principle – a monitoring system of any level, being a multilevel hierarchical structure, should be built considering the interaction with higher systems and lower subsystems.

2. Functional principle – monitoring functions in time as an interconnected and interdependent system of continuous observation, assessment, predicting and management.

3. Learning principle – over time in the monitoring system, the quality of predictions and management efficiency should naturally improve, the monitoring system should be continuously improved over time and function as a "self-learning" system.

4. Spatial principle – the spatial structure of the information obtaining points system is formed depending on the monitoring technique and technologies.

5. Time principle – the frequency of observations and information collection in the monitoring system is completely determined by the dynamics of the observed processes.

6. Target Principle – every system of monitoring should be built considering the achievement of its goal - optimization of management, which achieving is based on predictive estimates of its development by making optimal control decisions and recommendations.

The purpose of condition and emissions monitoring is to provide the equipment control system with timely and reliable information that allows:

- assess markers of the condition and functional integrity of equipment,
- identify the reasons for changes in these markers and assess the consequences of such changes, as well as determine corrective actions,
- create prerequisites for determining actions to correct the emerging negative situations before damage is caused.

In this regard, the main tasks of monitoring the technical condition and emissions are:

- determination of the technical condition in which the equipment was in the past (genesis), is in the present (diagnosis) and will be in the future (prediction),
- search for a location and identification of failure sources,
- determination of the type of technical condition.

Figure 2. Organization principles of monitoring systems

In general, the monitoring block diagram is shown in Figure 3. It follows from this diagram that its main parts are an observation system (a system of points for acquiring information) and a control system (predictive diagnostic and control centers), interconnected by information transmission channels. Important elements of the monitoring structure are: systems of monitoring objects (water
vehicles, machinery, components; systems of production work that make up the production monitoring base (types of work that are used in organizing and conducting monitoring); systems of scientific and methodological developments (development of the entire complex of methods used in planning, organizing and functioning of monitoring, in carrying out production work, in analyzing and evaluating the results of observations, in predicting and issuing control decisions; technical support systems (equipment for observations and collection of primary information, sensors, indicators, technical means, laboratory equipment, computers and communication means, etc.).

3.2. The Development of the WVCM System

The basis of the organizational structure of condition and emission monitoring is an automated information system (AIS), which is created using computer tools (Figure 3).

The tasks of AIS monitoring consist of [25]:
- storage and retrieval of information about the technical condition of the water vehicle power plant,
- constant processing and evaluation of information,
- implementation of predictions of development and technical condition,
- solution of optimization problems for technical condition control.

This implies the AIS monitoring structure, which consists of four interconnected main blocks (Figure 4), each of which is aimed at solving one of the above tasks.

The first block of AIS is an automated information retrieval system (AIRS). This system is a computer-based database. All basic data about the monitoring object (including observational data) are sent to the AIPS system from the observation network, they are accumulated in the database, pre-processed, sorted and then used in all subsequent operations to assess and predict the technical condition.

The second block of AIS is the automated data processing system (ADPS). This system processes and evaluates the incoming information on monitoring the technical condition.

The third block of AIS is an automated predictive and diagnostic system (APDS). This block solves the issues of making repeated predictions in accordance with the functional monitoring scheme.
The fourth block is an automated control system (ACS) aimed at solving management problems and developing recommendations.

All four AIS units are connected to each other and form a single functioning WVCM system. The main issue in the organization of AIS is its information, technical and mathematical backing. Information backing forms the basis stored in the database for its subsequent analysis, processing, evaluation, multipurpose search, replenishment, and issuance. The technical backing of AIS is a set of hardware for storing and processing information, implemented on the basis of personal computers, as well as equipment for information networks and peripheral devices (network adapters, modems, etc.). AIS mathematical backing is based on the following program blocks: search with statistical data processing, predictive, diagnostic and optimization.

In this work, based on wavelet transform methods and applied artificial intelligence technologies, a model for processing (7) and predicting (6) water vehicles emissions and condition, and a functional structure of the system for automated control of the technical condition and emissions of water vehicle (Figure 5), has been developed.

The creation of a time series analysis model based on wavelet processing allows obtaining information about data with a lower error by reducing their fluctuations and by increasing the signal-to-noise ratio [26].

Studies have shown that the spectral density function of the analyzed signal is calculated based on the DFT coefficients of a samples sequence of length N:

\[ S(mn2\pi f_1) = \frac{1}{N} \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} x(k) e^{-\frac{m2\pi nk}{N}}, f_1 = \frac{F_s}{N} = \frac{1}{t_sN} \] (1)

where: \( x(k) \) – signal samples, \( t_s \) – sampling period (\( t_s \ll T_h \)), \( F_s \) – ADC sampling frequency, \( (F_h = 10f_1) \) – maximum spectrum frequency.

The maximum sampling period \( T_h \) is determined by the formula (2):

\[ T_h = \frac{1}{2F_h} = \frac{1}{20f_1} = 1000 \text{ seconds at } f_1 = 0.5 \cdot 10^{-4} \text{ Hz} \] (2)

Two AI predictive models with forward and backward linkages were investigated. The Artificial Neural Network (ANN) model with direct connections is selected according to the criterion of the lowest computational costs. The stages of the learning algorithm are shown by formulas (3), (4), (5).

The first stage of learning is “Outputs defining” conducted by direct pass:

\[ x_m = \begin{pmatrix} a(z_{m1}^T x_{m-1} + z_{o1}^j) \\ a(z_{m2}^T x_{m-1} + z_{o2}^j) \\ \vdots \\ a(z_{mam}^T x_{m-1} + z_{oam}^j) \end{pmatrix} \hfill \text{, } m = 1, 2, ..., n, \ x_0 = C_j(p) \] (3)

where: \( x_{m-1} \) - vector of ANNs m-layer coefficients, \( z_{m}^T \) and \( z_{o}^j \) – ANN weighting factors, \( \alpha(i) \) - scaling function, \( C_j(p) \) – approximating coefficients.

The second stage of learning is “Error detection” conducted by back pass:

\[ a_{m-1} = E_m z_m a_m, \quad m = n, n-1, ..., 2, \quad a_n = \alpha(k_n) - y \]

\[ k_m = E_m^T x_{m-1} + z_m = (k_{m1}, k_{m2}, ..., k_{man})^T \] (4)

where: \( E_m \) – m-neuron activation function, \( Z_m \) - synaptic coefficients vector.

The third stage of learning is “Correction of coefficients”:
\[ z_{ml}(k + 1) = z_{ml}(k) - q h_{ji}(k_{ml}) a_{ml} x_{m-1}, \quad l = 1, 2, ..., n \]

\[ z_{m0}(k + 1) = z_{m0}(k) - q Z_{m} a_{m}, \quad z_{m} = (z_{m1}, z_{m2}, ..., z_{ma_{m}}) \]

\[ \frac{\delta a^T(k_{ml})}{\delta k_{m}} = \text{diag} \left( \frac{\delta a(k_{1})}{\delta k_{m1}}, \frac{\delta a(k_{2})}{\delta k_{m2}}, ..., \frac{\delta a(k_{ma_{m}})}{\delta k_{ma_{m}}} \right) = Z_{m} \tag{5} \]

where: \( z_{ml} \) - synaptic coefficients, \( q \) and \( h_{ji} \) - correction factors, \( \alpha(i) \) - scaling function, \( a_{m} \) - error detected at second stage.

The recovery model of the output time series with a prediction of data changes for \( y \)-periods has the form:

\[ s(p + y) = \frac{1}{r} \left( u(p) \psi_{1}(2t - p) + \left( \sum_{i=2}^{5}(C_{i-1}) \psi_{i}(2^i t - p) \right) + C_{5} \psi_{6}(2^6 t - p) + C_{5}^{*} \psi_{6}(2^6 t - p) \right) \tag{6} \]

\[ s(p) = \frac{1}{r} \left( u(p) \psi_{1}(2t - p) + \left( \sum_{i=2}^{6}(C_{i-1}) \psi_{i}(2^i t - p) \right) + C_{6} \right) \tag{7} \]

where: \( u(p) \) - value of denoised \( x(p) \), \( \psi_{i}(p) \) - wavelet function, \( C_{i} \) - approximating coefficients.

Based on the developed predicting model (6) and the time series processing model (7), a structural diagram of the technical condition and emissions monitoring system model was developed (Figure 5).

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**Figure 5. Structural diagram of the technical condition and emissions monitoring system model (WVCM system)**

Figure 5 defines the processing model in the tasks of automated control and predicting using ANN technologies.

The problem of real-time control is specified at the algorithmic level by the complex distribution faults dynamics at the controlled object, the characteristics of sensors, means of processing and transmitting information, including the decision-making time at the highest system level [27]. To solve this problem, a subsystem of analysis and processing of the obtained experimental and calculated time
series of the vibration level is used. In this algorithm, prediction and reconstruction is based on regression analysis of approximating and detailing wavelet transform coefficients and on the use of ANN.

4. Summary
Analysis of the research results allows authors to assert that in the process of performing a major overhaul, the water vehicle is not in operation and operators will not receive their day-rate for the vessel. The total time required for major overhauling depends on many factors, such as time needed for dismounting, transportation, overhauling and mounting the machinery components. In this case it is 30 days. With day rate of 600 thousand USD, this represents a total cost of 18 million USD. Using the proposed approach, the second overhaul after 10 years of operation is unnecessary, so this 18 million USD can be considered as indirect savings.

The article demonstrates that as a result of using WVCM system with PDM strategy coupled with AAI, a reduction in maintenance costs is to be expected as in most cases the periods between major overhauls could be extended. In some cases, the periods between major overhauls are extended from five to seven and half years, so in the first 10 years, only one major overhaul is needed instead of the normal two. Furthermore, there is less risk of unexpected failures, which will also reduce maintenance costs.

With WVCM system, the operator might be allowed to major overhaul the water vehicle twice in 15 years, rather than three times. Water vehicle can now be maintained according PDM strategy, enables shipowners and operators to: base operational decisions on the known machinery components condition; assess the risks for upcoming contracts based on machinery components reliability; maximize the installation availability by performing overhauls only when needed, significantly reducing the likelihood of unscheduled breakdowns and maintenance errors; be well informed of faults before they lead to breakdowns; increase equipment lifetime by having real-time feedback on conditions that generate excess equipment wear; and reduce the total cost of ownership and maximize profitability.

In future study’s authors are planned to test the applicability of the PDM strategy coupled with AAI on transport inland vessels, passenger seagoing and inland vessel as well as on stationary power plants equipped with diesel generators.

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