8　船舶推進プラントとしての主機デジタルツインの開発

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1. Introduction

An intense pressure on the shipping industry to work towards greener shipping has been recently initiated by the regulatory framework imposed by the International Maritime Organisation (IMO). This is due to the continuously growing and intensifying shipping activity and concerns in the environmental issues. The initial IMO Strategy on Reduction of GHG Emissions from Ships introduced by MEPC72 (April 2018) require a 40% reduction of the CO_2 emission per transport work by 2030 and efforts towards a 70% reduction by 2050, compared to 2008. Besides, the strategy including a vision and target to reduce total annual GHG emissions at least by half by 2050 and zero emissions as soon as possible within this century was addressed as well. In response to this, the ship design is challenged by the continuously rising complexity. A number of solutions have been developed relating to propulsive and powering efficiencies improvement. Measures that positively affect the ship energy efficiency[1] include propeller-hull and propeller-rudder interaction optimization devices, hull attached energy saving devices, and bow optimized design. On the other hand, engine manufacturers have been introducing new engine designs combined with smart electronic systems providing flexible control and online tuning. In addition, the propulsion system composition is being gradually complicated with a diversity of energy sources, including liquefied natural gas (LNG) as fuel, fuel cells, hybrid systems, etc.[2-3] Apart from the design solutions, the energy and emission efficiencies during the operation of the ship are also crucial. In this respect, monitoring and processing of the propulsion system operating parameters is of great importance. The recent development in sensors and monitoring systems[4] provide a vast variety of data, which then can be used onboard or collected and processed at on-shore data centers[5]. Such digitalization of ship operations, which is also referred to digital-shipping, brought a number of new possibilities. The image of the digital-shipping ecosystem is outlined in Fig. 1. This includes ship operation and performance analysis systems[6-7], dynamic performance prediction and optimization[8], autonomous maneuvering control system[9], ship voyage optimization[10], condition-based maintenance system[11] and others. However, the common factor consolidating the above-mentioned technologies is that the comprehensive information about the present and future states of the propulsion system has to be available. Lately, another emerging technology, primarily related to the needs of the digital-shipping, a Digital Twin, has been introduced[12].

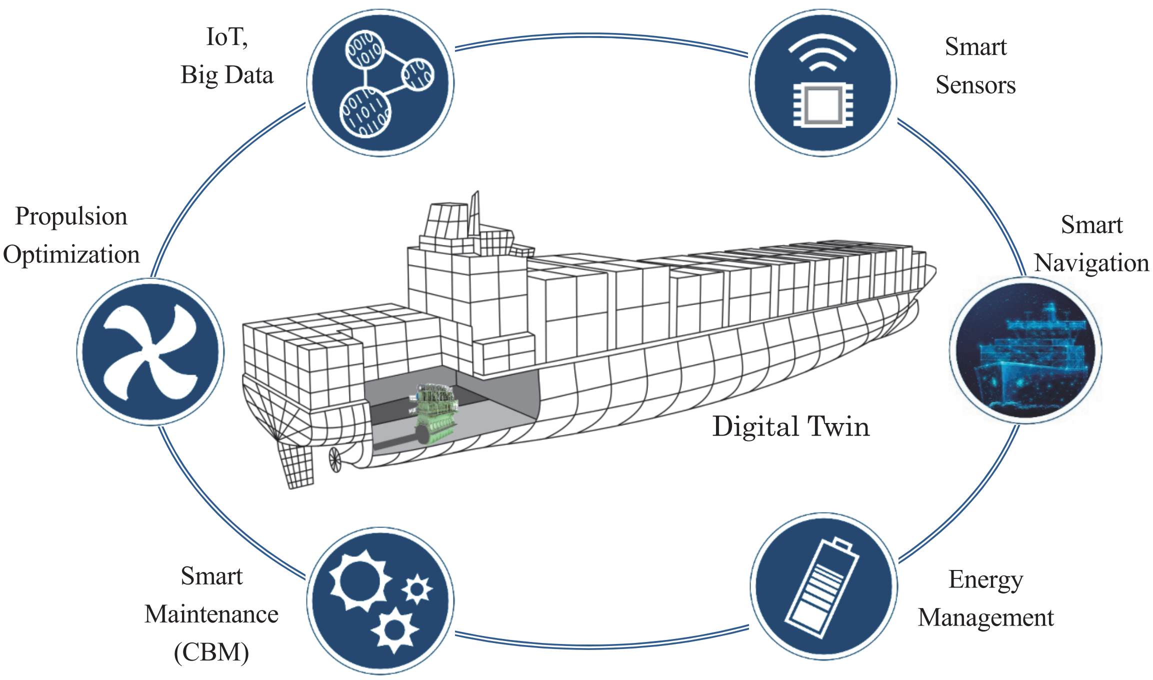

Fig.1 Image of the digital-shipping ecosystem

Digital Twin is a digital replica of a real ship or a particular subsystem which coexists with its physical counterpart and maps the dynamic behavior. In such a way, using the Digital Twin, any aspect of the real target can be explored through a digital interface. Thus, the Digital Twin combines real-time data obtained from the physical space and a set of dynamic models describing the physical counterpart in the cyberspace. A critical requirement for the Digital Twin is the need for the models to precisely reflect the characteristics intrinsic for the physical counterpart ensuring that the performance corresponded under all operating conditions and in real-time. Diesel engines remain an unavoidable part of the ship propulsion system, owing to their efficient conversion of fuel chemical energy into mechanical. Thus they are considered as a core part of the Digital Twin and the modelling of the Diesel engine is of prime interest.

2. Engine Models for Digital Twin

A generic ship propulsion system may be considered to be made of three main components: the engine producing the torque, the shaft transmitting the torque from the engine, and the propeller receiving the torque and delivering thrust to a hull. The vast majority of large merchant vessels are equipped with the two-stroke low-speed engines, thus the modeling of this type of propulsion and engine is considered in this work.

Diesel engines modeling has been evolving for many years since the development of computer simulation, and various model types can be distinguished, depending on their degree of complication: transfer function models, quasi-steady mean value models, and filling-emptying phenomenological models. The selection of a particular model is dictated by the requirements for the Digital Twin mentioned above – in-depth representation of the real phenomena and real-time execution time. Though, in the field of propulsion system simulation, a cycle-mean value (CMV) engine modeling approach has gained popularity[13-14].

In the CMV modeling approach, the engine is considered as a series connection of throttles through which flow takes place continuously disregarding the intermittent nature of the engine cylinder processes. In this respect, the model provides the engine-cycle-averaged temporal evolution of the engine operating parameters neglecting their in-cycle variation. The need for a more in-depth representation of the engine processes led to the development of the Combined-CMV modeling approach [15], where a detailed combustion model is used for representing the trapped part of the engine cycle and the CMV model employed for simulating the air and exhaust gas flows, as well as for the other engine components. However, on a par with the more detailed simulation, the model gained longer execution time intrinsic to the filling-emptying phenomenological models. Lately, the calculation scheme of the cycle evaluation has been improved providing for the real-time calculation[16]. In whole, the Combined-CMV approach is a suitable candidate for the Digital Twin of the propulsion system, and the details are discussed hereinafter.

3. Engine Physical Model

The model is composed of standalone blocks; each one is representing a particular system. Such modularity of the model composition provides a great flexibility where each sub-model can be easily replaced by a more detailed or simpler one without jeopardizing the integrity of the whole model. Furthermore, such an approach is beneficial when considering model parameters online tuning as discussed in the subsequent chapter.

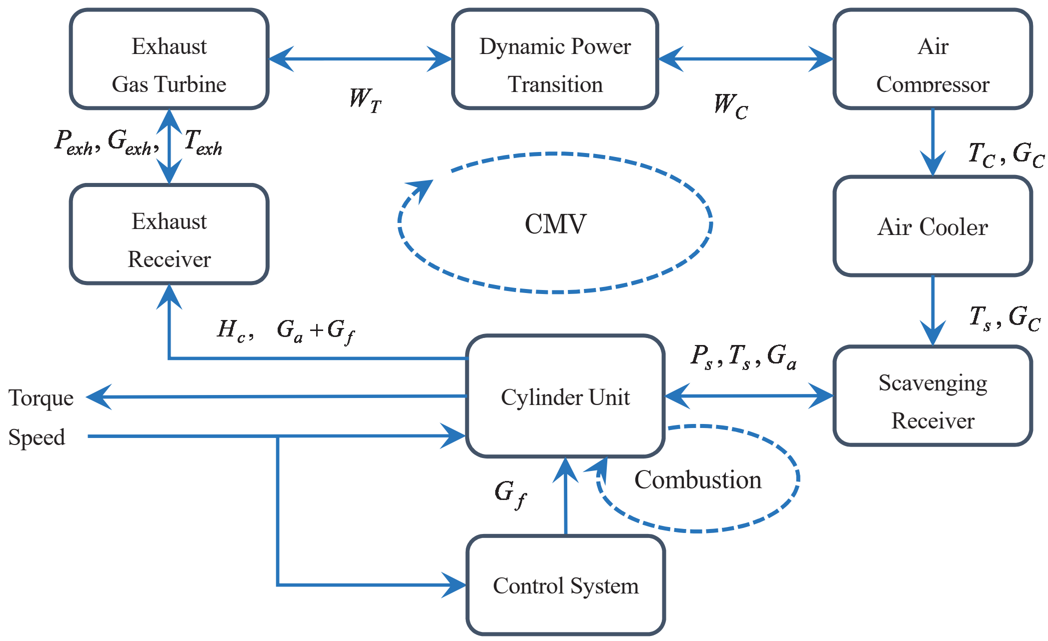

Fig.2 Composition of the engine Combined CMV model

Following the method of system analysis [17], the system under consideration is hierarchically decomposed to a number of lower-level entities. The information interface and physical variables are then determined to establish interconnections between the entities. Further, every entity is decomposed to a finite number of components which are described by the generic and reconfigurable mathematical models in terms of input/output relationships. Under the assumptions used in the CMV model, the engine is decomposed to a finite number of control volumes and resistance elements forming a lumped-parameter model. Figure 2 illustrates the component composition of the engine model. The engine is interfaced with the propeller by means of shaft rotational dynamics, expressed as:

$$2\pi I_e \frac{dn_e}{dt} = \theta_e - \theta_p \tag{1}$$

where θ_e and θ_p are the engine and propeller torques respectively, I_e is the total moment of inertia, and n_e is the engine rotational speed.

The engine torque is the result of brake mean effective pressure (BMEP) P_b developed in the cylinder volume V_s during one cycle:

$$\theta_e = \frac{P_b V_s}{2\pi} \tag{2}$$

From the above, it is clear that the objective of the engine model is to represent an external characteristic of the engine concerning the developed BMEP which generally is a function of the engine states such as rotational speed, air mass flow and fuel mass flow[18]. The fundamental equations, necessary to describe the states of the engine, can be obtained from the energy and mass conservation laws applied to the engine model components. The pressure and temperature in the air and exhaust receivers, respectively:

$$\begin{aligned} \frac{dP_s}{dt} &= \frac{R_a T_s}{V_{s.r}}\left(G_C - G_a\right) \\ T_s &= T_w + \eta_{ac}\left(T_C - T_w\right)\left(\widetilde{G}_C\right)^{\frac{1}{3}} \end{aligned} \tag{3}$$

$$\begin{aligned} \frac{dM_{exh}}{dt} &= G_a + G_f - G_{exh} \\ \frac{dT_{exh}}{dt} &= \frac{T_{exh}}{M_{exh}}\left(\frac{k_{exh} H_c}{C_{p.e} T_{exh}} - k_{exh} G_{exh} - \frac{dM_{exh}}{dt}\right) \\ P_{exh} &= \frac{M_{exh} R_{exh} T_{exh}}{V_{e.r}} \end{aligned} \tag{4}$$

Here it should be noted, that air temperature in the receiver T_s is slowly varying and thus considered constant and is obtained from the steady-state simulation of the air cooler.

As mentioned earlier, the central assumption in the CMV model is that the engine cylinder and turbine can be represented by the equivalent orifice, which produces the same mass flow rate for a given pressure ratio. The latter supposion allows employing a quasi-one-dimensional equation of flow through an orifice in the following form:

$$G = \mu\widetilde{A} \frac{P_{in}}{\sqrt{R_a T_{in}}} \sqrt{\frac{2k}{k-1}\left[\left(\frac{P_{out}}{P_{in}}\right)^{\frac{2}{k}} - \left(\frac{P_{out}}{P_{in}}\right)^{\frac{k+1}{k}}\right]} \tag{5}$$

here, $\mu\widetilde{A}$ is the effective equivalent area of the engine cylinder or turbine. It can be estimated using the instant areas or from the available experimental data. The subscript in/out stands for the inlet and outlet parameters of the considered element, correspondingly.

The fuel mass flow G_f is a part of mass conservation in the exhaust receiver and is evaluated with the assumption that the amount of fuel injected per cycle and cylinder $m_{f.c}$ is a linear function of engine speed and fuel pump rack position F_p, hence:

$$G_f = z_c m_{f.c0} n_e F_p \tag{6}$$

The energy flow rate H_c exiting the engine cylinder element is calculated by taking into consideration the energy conservation equation averaged over one engine cycle, thus:

$$H_c = G_a C_{p.a} T_s + G_f H_U - W_i - Q_w \tag{7}$$

Here the first member on the right hand side stands for the energy rate entering the cylinder with air; the second member is the total energy rate of injected fuel, W_i is the engine cylinder indicated work of one cycle and Q_w is the heat loss rate of one cycle.

In the former approach of CMV modeling, work done by the gas together with the heat loss was substituted by the proportionality coefficient ξ_a indicating remained fuel energy in the exhaust gas, that is:

$$G_f H_U - W_i - Q_w = \xi_a G_f H_U \tag{8}$$

and such approach allowed performing fast calculation of engine states without explicit consideration of combustion.

Though, the latter approach of Combined-CMV provides more accurate estimation of the engine performance, the calculation of combustion is a vulnerable point affecting the calculation speed of the whole model. Elaborating on this issue, the fast calculation scheme of engine cycle has been developed[16], and brief details are given in the subsequent chapter.

4. Modeling of the Engine Cycle

The full engine cycle consists of several stages such as gas exchange (fresh charge induction and combustion gas exhaust), compression, combustion and expansion. In the combined CMV model approach, the parameters characterizing the gas exchange part of the cycle are modelled as the continuous variables averaged over one cycle (as described hereinbefore). The parameters of the rest of the cycle are calculated considering a zero-dimensional thermodynamic approach applied to a stationary open system[15]. The heat input due to combustion is modeled using the classical approach utilizing the Wiebe[19] function. Similarly, the heat loss is considered based on the empirical correlation provided either by Woschni or Hohenberg[20]. The detailed elaboration on this part is out of scope of this paper.

The laws of conservation for mass and energy are considered assuming that a working medium is an ideal gas which state is homogeneous in space, changing with time. The 1st law of thermodynamics for such a system can be written in an integrated form considering a change of internal energy between two finite states:

$$U_2 - U_1 = -W_i + Q_f - Q_w, \quad \because W_i = \int_{V_1}^{V_2} p_c dV \tag{9}$$

The internal energy U can be evaluated from the average specific heat capacity $\widetilde{C}_v$ as a function of temperature and gas composition, hence:

$$U_1 = M_1 \widetilde{C}_v\Big|_1 T_1, \quad \because \widetilde{C}_v = f(r,T) \tag{10}$$

Since the state of gas at the end of the considered interval is unknown, the internal energy U can be obtained in terms of state at the beginning of interval. Assuming a small change of gas state and applying Taylor expansion, yields:

$$U_2 = M_2 \left(\widetilde{C}_v\Big|_1 + \frac{\partial \widetilde{C}_v}{\partial r}\Bigg|_1 \Delta r + \frac{\partial \widetilde{C}_v}{\partial T}\Bigg|_1 \Delta T \right) T_2, \quad \because T_2 = T_1 + \Delta T, \quad M_2 = M_1 + \Delta M \tag{11}$$

Under the same assumption, the work transmitted to the piston as a result of state transition can be approximated as:

$$\int_{V_1}^{V_2} p_c dV = \frac{p_{c1} + p_{c2}}{2} (V_2 - V_1) = \overline{p}_c \Delta V \tag{12}$$

The average pressure $\overline{p}_c$ (in the middle of the considered interval) can be evaluated from the ideal gas law considering the average parameters similarly:

$$\overline{p}_c = \frac{\left(M_1 + \frac{\Delta M}{2}\right)\left(T_1 + \frac{\Delta T}{2}\right)R}{V_1 + \frac{\Delta V}{2}} \tag{13}$$

As can be seen only states at the beginning of transition and increments are introduced in Eqs. (10), (11) and (13). Thus substituting Eqs. (10), (11) and (13) into Eq. (9), the transformation yields a quadratic equation with respect to the unknown temperature increment ΔT [21]:

$$a(\Delta T)^2 + b(\Delta T) + c = 0, \quad \Delta T = \frac{-b + \sqrt{b^2 - 4ac}}{2a} \tag{14}$$

Finally, starting from the initial state of gas at exhaust valve closed position and advancing the crankshaft by the angle $\Delta\varphi$, the new state of the working medium can be evaluated solving only the nonlinear algebraic equation (14):

$$T_{i+1} = T_i + \Delta T, \quad p_{c_{i+1}} = \frac{M_{i+1} R_{i+1} T_{i+1}}{V_{i+1}}, \quad \because M_{i+1} = M_i + \Delta M, V_{i+1} = V_i + \Delta V \tag{15}$$

Last but not least remark is that the presented calculation method preserves high accuracy at relatively large calculation step as compared to the Euler method. Furthermore, the calculation procedure allows flexible adjustment of the calculation step. Thus various stages of the cycle can be calculated with the variable step without loss of accuracy.

5. Engine Model Validity and Performance

5.1 Steady-state performance

The developed engine model has been validated against an actual marine two-stroke Diesel engine. The data were provided by the Mitsui E&S Machinery, where the test engine was run in a variety of loads. The specification of the test engine is given in Table 1.

Table 1. Test Engine Specification @ MCR

Engine Type	Mitsui-MAN 4S50ME-T9
No of Cylinders	4
Bore/Stroke, [mm/mm]	500/2214
Power, [kW]	7120
Speed, [rpm]	117
IMEP, [bar]	22
Scav. Air Pressure, [barA]	4.4
Air consumption, [Nm^3/h]	41000

Figure 3 depicts the results of a steady-state simulation of the Combined-CMV model, superimposed with the experimental data of the test engine. As can be seen, the well-tuned model provides fairly well agreement of the selected engine states such as air mass flow and pressure, turbine inlet and outlet temperatures, as well as specific fuel consumption. At the same time, the performance of the combustion model was also confirmed as illustrated by the traces of in-cylinder pressure.

5.2 Dynamic performance

One of the aims of the Digital Twin is the online monitoring and performance prediction of its physical counterpart. Thus, the real-time dynamic performance of the model employed in the Digital Twin is of great importance. However, the direct interface with the real engine restricts the freedom of the model performance elaboration and adjustment. Thus, the test was performed in an off-line manner, utilizing the concept of the Hardware in the Loop (HIL) test developed in the past [22].

The simple acceleration/deceleration tests were performed on the test engine in advance, and the required data were acquired with the high precision sampling at 100 Hz frequency. The virtual propulsion plant, incorporating the developed engine model has been implemented on a computation system controlled by the real-time operating system (RTOS).

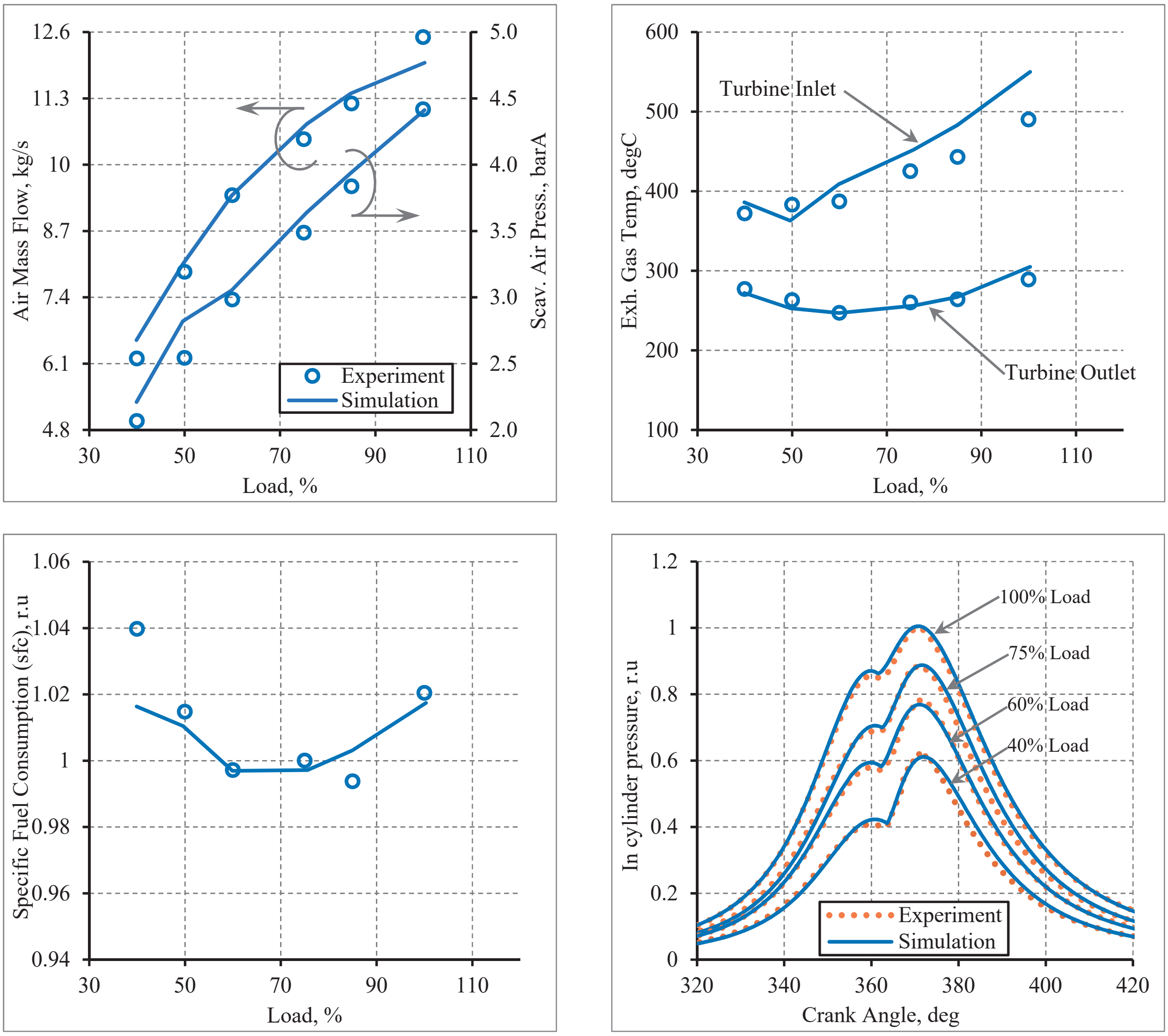

Fig. 3 Steady-state performance of the Combined-CMV model

The computation system was connected to the microprocessor controller by means of an analogue interface. The microprocessor controller was used to restore the data measured on the actual engine, thus acting as a virtual engine. The sampling frequency of RTOS running the propulsion plant model was set equal to that used in data acquisition, i.e. 100 Hz. The results obtained from the HIL co-simulation experiment are shown in Fig. 4. As can be seen, the model performs fairly well in a wide range of load but, there is still room for improvement as will be discussed later.

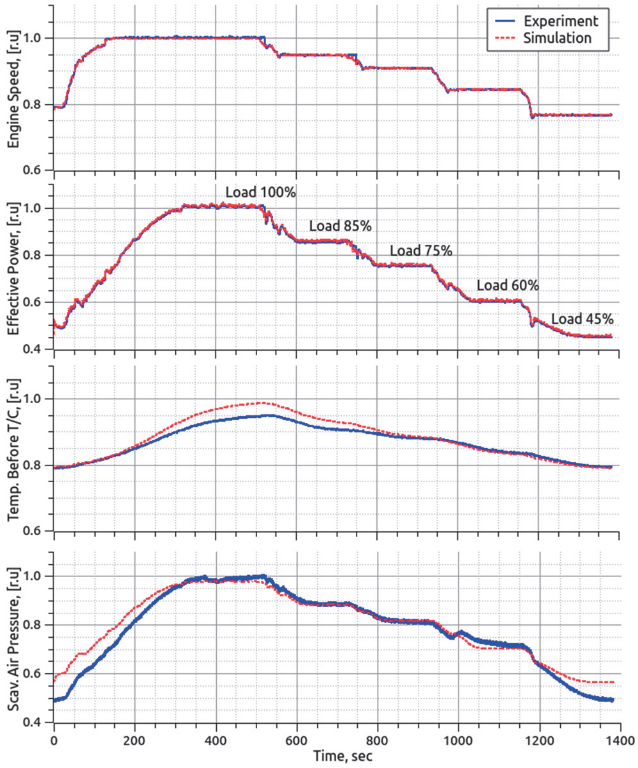

Fig. 4 HIL application of the engine Digital Twin

Another important point to be confirmed is the real-time performance of the engine model. This was also measured and Fig. 5 illustrates the results in terms of the time step scheduling error, which clearly proves the real-time ability of the developed model.

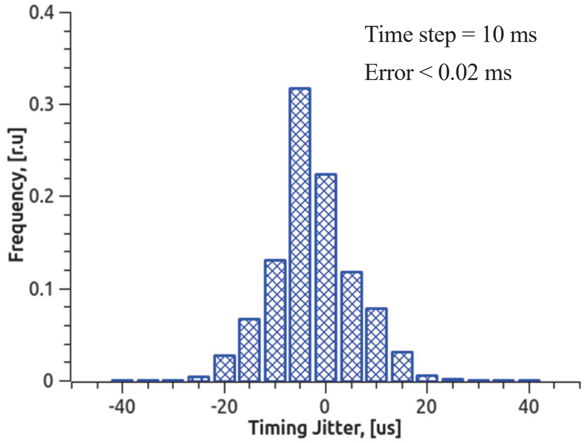

Fig. 5 Timing error of RTOS running the simulation

6. Problem of Model Adaptation

The results presented in the previous chapter justify the validity and performance of the developed engine model. At the same time, limited test data awareness should be kept in mind. This means that the limited number of test points and fixed environment conditions were used to tune and test the model. Whereas the operating range of the real ship is much wider, the model fidelity might be compromised. The above discussion set the problem of continuous adaptation for keeping a model up to date with the actual operating conditions of the real ship.

The performance of the model, in particular, depends on the set of tuning parameters and regression functions which are the part of the model components. Moreover, the Machine Learning (ML) techniques, which are a part of Artificial Intelligence (AI), can be used to tackle the task of updating the models. In general sense, the task of model learning can be viewed as a Tracking Filter consisting of the following key elements: 1) the underlying physics-based performance model of the component, 2) data-driven model (either a simple regression or sophisticated neural network), 3) operation data from multiple sensors, and 4) advanced ML technique for learning models to update the parameters in view of uncertainties. To demonstrate the Tracking Filter idea, let's consider a simple example – tuning the parameters of the air cooler model.

The turbocharger's compressor of the engine compresses air to the pressure required by the engine. As a result, the temperature of the air is increased following the adiabatic process, including constant compressor efficiency η_{ic} :

$$T_c = T_{amb}\left\{\frac{1}{\eta_{ic}}\left[\left(\frac{p_c}{p_{amb}}\right)^{0.286} - 1\right] + 1\right\} \quad (16)$$

In order to keep the density of scavenging air as high as possible an air cooler is installed between the compressor output and cylinders which model is based on the efficiency definition in the following form:

$$T_s = T_c - K_{ic}\left(T_c - T_{cw}\right) \tag{17}$$

The air cooler efficiency K_{ic} is usually considered constant, but it holds a certain relationship with the air mass flow G_C from the compressor. Moreover, the temperature of cooling water T_{cw} is not a constant. Therefore, the air cooler efficiency is assumed to be described by a second order polynomial:

$$K_{ic} = k_1 + k_2\,\tilde{n}_{tc}^2 \tag{18}$$

Here it should be noted that the air mass flow is not available as measurement, instead, the turbocharger relative rotational speed $\tilde{n}_{tc}$ is used.

Now the task is to recursively estimate the coefficients k_1 and k_2 in Eq. (18), which can be formulated as follows:

$$\frac{d\hat{\mathbf{x}}_i}{dt} = 0, \quad \because \hat{\mathbf{x}}(t_0) = \mathbf{x}_0$$
$$\hat{\mathbf{x}}_i = \hat{\mathbf{x}}_{i-1} + \mathbf{G}\left(T_s^{meas} - T_s^{pred}\right), \quad \because \hat{\mathbf{x}} = \left[k_1, k_2\right]^T \tag{19}$$

It is assumed here that the coefficients represent a slow varying dynamic process with the unknown initial conditions, and the estimation of the correction coefficient **G** can be accomplished with the application of an Unscented Kalman Filter (UKF) [23]. The exact mathematical formulation of UKF is not displayed in this paper; instead, the performance is studied through the calculating example.

For testing the Tracking Filter, the same data as in dynamic performance test were used. Figure 6 illustrates the perfect tracking performance of the scavenging air temperature as compared to the actual data. The performance of the Tracking Filter itself is shown in Fig. 7 depicting evaluation of the regression coefficients k_1 and k_2, which converge fast to the steady-state values.

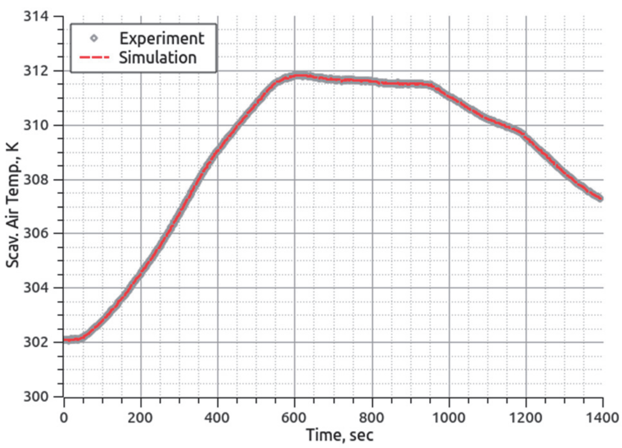

Fig. 6 Tracking of the scavenging air temperature

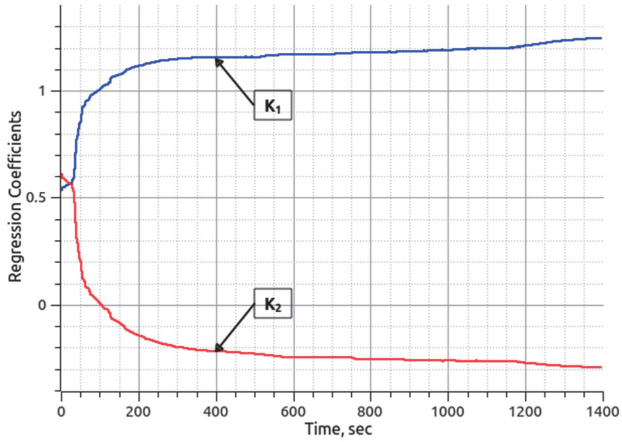

Fig. 7 Regression coefficients evaluation

7. Conclusion

Modeling of the diesel engine for the purpose of propulsion plant Digital Twin development is a crucial task affected by a trade-off between the in-depth representation of engine process, model fidelity and the execution time. Owing to the developed Combined-CMV approach with the special algorithm of the cycle evaluation, the great detailing and fast execution are now provided. At the same time, the concept of the Tracking Filter is proposed. This allows combining the physics-based models with the data-driven models and can provides the ultimate performance of the continuously matched model. Furthermore, the AI techniques are promising and powerful tools to be used in conjunction with the physics-based model to monitor and to continually update the Digital Twin. The latter is worth to be studied further.

Nomenclature

C_p specific heat at constant pressure, J/(kg K)
F_p fuel pump rack position
G flow rate, kg/s
H energy flow, W
I polar moment of inertia, kg m^2
H_U fuel lower heating value, J/kg
k specific heat ratio
M mass, kg
MCR maximum continuous rating
$m_{f.c}$ mass of fuel per cycle, kg
n rotational speed, rps
P pressure, Pa
Q heat rate, W
R gas constant, J/(kg K)
r.u. relative unit
T temperature, K
U internal energy, J
V volume, m^3
W power, W

z_c　number of cylinders

Greek symbols

ζa　proportion of fuel energy in the exhaust gas
μ　flow coefficient
η　efficiency
φ　crank-angle, deg
θ　torque, Nm
Δ　increment

Subscripts and superscripts

0　variable value at MCR
a　air
ac　air cooler
amb　ambient
c　cylinder
C　compressor
e　engine
exh　exhaust
T　turbine

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