MOSES Workshop: Modelling and Optimization of Ship Energy Systems

Ship Energy Systems Modelling: a Gray-Box approach

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Introduction

Ship Energy Systems Modelling
White Box Models | Black Box Models | Gray Box Models

Case Study
Introduction

Ship Energy Systems Modelling
White Box Models | Black Box Models | Gray Box Models

Case Study
Herbert Alexander Simon

Learning is any process by which a system improves performance from experience.

**Machine Learning** is about computer programs that automatically improve their performance through experience.

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**Statistics:**
- Inference from a sample

**Computer science:**
- Efficient algorithms to solve the optimization problem
- Representing and evaluating the model for inference
Introduction

Social media and networks

Mobile devices

Scientific instruments

Sensor technology and networks
Introduction

Ships Data Center

Meteorological Information
- Wind Direction
- Wind Speed
- Wave Direction
- Wave height
- Current velocity
- Current direction

Ship Information
- Engines
- Navigation
- Gearbox
- Generators
- Aux. engines
- Propellers
- Shaft line
- Electric Motor
- Rudders

Vessel Data – On Ship platform

Ships Data Center

Navigational data

Meteorological data

Machinery sensor data

Local data server

Operational Optimization
- Fleet Optimization
- Fleet Monitoring and Control
- Route Optimization
- Performance Management
- Decision Support Systems

Health Management
- Remote Machine Diagnostics
- Predictive maintenance
- Reliability and Redundancy
- Safety and Security Systems

Remote Control
- Operations Management
- Situational Awareness Interface
- Human Interaction Interface
- Remote Deep Sea Navigation

Situation Awareness
- Obstacle Detection
- Collision Avoidance
- Environmental Condition Monitoring

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Introduction

What to do with these data?

Aggregation and Statistics

Indexing, Searching, and Querying

Knowledge discovery (Data Mining, Statistical Modeling)
White, Black or Gray?

White Box Models are based on the knowledge of the physical underlying processes.
Physical problem not trivial to solve: 
i.e. evaluate the system health status by means of field measurements

Black box learning system able to learn from the available observation (on board sensor measures) of the system.
According to the Gray Box Model principles, an existing White Box Model is improved using data-driven techniques, either in order to calculate uncertain parameters or by adding a black-box component to the model output.

Gray Box Models allow exploiting both the mechanistic knowledge of the underlying physical principles and available measurements.
Introduction

Ship Energy Systems Modelling
The White Box Approach | The Black Box Approach | The Gray Box Approach

Case Study
Ship Energy Systems Modelling

The White Box Approach

Wind Resistance

Calm Water Hull Resistance

Waves Added Resistance

Fuel Consumption

Trade/route

Propeller Performance

Propulsion Plant
White Box Models describe the behaviour of the system based on governing physical laws of each components and taking into account their mutual interactions.

The higher the detail in the modelling of the physical equations which describe the different phenomena, the higher the expected **accuracy** of the results and the **computational time** required for the simulation.

**Open Water**

**Panel Method**

**CFD**

**Accuracy**

**Computational Time**
Mean Value Models

Accuracy

Computational Time
The White Box Approach

- Models rather tolerant to extrapolation
- Models do not require extensive amount of operational measurements
- Models that are computationally fast enough to be used for online optimisation
- Accuracy in the prediction can be relatively low, moreover in off design conditions.
- Availability of technical details are often not easy to get access to.
• Black Box Models (also known as data driven models), make use of statistical inference procedures based on historical data collection.

• These methods do not require any a-priory knowledge of the physical system and allow exploiting even measurements whose role might be important for the calculation of the predicted variables but might not be captured by simple physical models.

• The model resulting from a black-box approach is not supported by any physical interpretation and a significant amount of data (both in terms of number of different measured variables and of length of the time series) are required for building reliable models.
The Black Box Approach

Ship Energy Systems Modelling

- GPS
- Navigation systems
- Control systems

- Controllable Pitch Propellers
- Torque meters
- Steering systems

- Ballast management systems
- Oil separators
- Sewage/gray-water systems
- Ballast water treatment systems

- Reduction gears
- Transmissions

- Main propulsion diesel engines
- Ship's service diesel generators
- Emergency generators

- Gas turbine main engines
- Gas turbine generators
- Auxiliary gas turbines
- Gas turbine starting systems

- Waterjets
- Fin stabilizers
- Thrusters

- Tanks levels
- Fuel oil
- Lube oil
- Cargo
- Ballast

- Fuel flow meters

Other auxiliaries
- Waste heat boilers
- Chill water pumps
- Cathodic protection
- Feed & booster pumps
- Seawater service & fire pumps
- Deck equipment

Specialized equipment
- Fluid Analysis / SOS
- Visual (manual) inspections
- Additional / aftermarket sensors (bearing, oil condition, vibration, etc)

Compressors
- High pressure
- Medium pressure
- Low pressure
- De-ballast compressors

Reverse osmosis
- Steam evaporators

Air conditioning
- Refrigeration
The Black Box Approach

A set of data $D_n = \{(x_1, y_1), \ldots, (x_n, y_n)\}$, with $x_i \in \mathcal{X} \subseteq \mathbb{R}^d$ and $y_i \in \mathcal{Y} \subseteq \mathbb{R}$ are available from the automation system.

Each tuple $(x_i, y_i)$ is called **sample** and each element of the vector $x \in \mathcal{X}$ is called **feature**.

---

### Dataset

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<thead>
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<th>Name</th>
<th>Type</th>
</tr>
</thead>
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<td>Volume</td>
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<td>State</td>
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<td>Auxiliary electrical power output</td>
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<td>7</td>
<td>Shaft rpm</td>
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<td>Input</td>
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<tr>
<td>9</td>
<td>Ship draft (aft)</td>
<td>Input</td>
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<td>Ship generator power</td>
<td>Input</td>
</tr>
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<td>16</td>
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<td>18</td>
<td>Draft Starboard</td>
<td>Input</td>
</tr>
<tr>
<td>19</td>
<td>Sea Water Temperature</td>
<td>Input</td>
</tr>
<tr>
<td>20</td>
<td>CPP Setpoint</td>
<td>Input</td>
</tr>
<tr>
<td>21</td>
<td>CPP Feedback</td>
<td>Input</td>
</tr>
<tr>
<td>22</td>
<td>Fuel Density</td>
<td>Input</td>
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<tr>
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<td>Fuel Temperature</td>
<td>Input</td>
</tr>
<tr>
<td>24</td>
<td>Ambient Pressure</td>
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<td>25</td>
<td>Humidity</td>
<td>Input</td>
</tr>
<tr>
<td>26</td>
<td>Dew Point Temperature</td>
<td>Input</td>
</tr>
<tr>
<td>27</td>
<td>Rudder Angle</td>
<td>Input</td>
</tr>
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<td>28</td>
<td>Acceleration X Direction</td>
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<td>Acceleration Y Direction</td>
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<td>GyroZ</td>
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<td>Input</td>
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<td>35</td>
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<td>Input</td>
</tr>
<tr>
<td>38</td>
<td>True speed</td>
<td>Input</td>
</tr>
<tr>
<td>39</td>
<td>Beaufort</td>
<td>Input</td>
</tr>
</tbody>
</table>

**Table 3: Variable of Table 2 exploited to build the $D_n$.**
When inferring a model starting from a real system, the goal is to provide an approximation $M: x \rightarrow y$ of the unknown true model $\mathcal{G}: x \rightarrow y$.

The accuracy of the model $M$ as a representation of the unknown system $\mathcal{G}$ can be evaluated using different measures of accuracy.

Given a series of testing data $T_m = \{(x_1, y_1), \cdots, (x_m, y_m)\}$ the model will predict a series of outputs $\{(\hat{y}_1), \cdots, (\hat{y}_m)\}$ given the inputs $\{x_1, \cdots, x_m\}$.

Performance indicators:

\[
\text{MAE} = \frac{1}{m} \sum_{i=1}^{m} |y_i - \hat{y}_i| \\
\text{MSE} = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 \\
\text{REP} = 100 \sqrt{\frac{\sum_{i=1}^{m} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{m} y_i^2}}
\]

mean absolute error (MAE)

mean square error (MSE)

relative error percentage (REP)
The learning process for ML approaches usually consists of two phases:

(i) Training phase, a set of data is used to induce a model that best fits them, according to some criteria;

(ii) The trained model is used for prediction and control of the real system (feed-forward phase).

When targeting a regression problem, the purpose is to find the best approximating function \( h(x) \), where \( h: \mathbb{R}^d \to \mathbb{R} \).

During the training phase, the quality of the regressor \( h(x) \) is measured according to a loss function which calculates the discrepancy between the true and the estimated output \((y, \hat{y})\).
2-way data split

- Labelled data set
- Training set
- Test set
- Learning Method
- Accuracy estimate

3-way data split

- Labeled data set
- Training set
- Validation set
- Test set
- Learn model
- Select model
- Learned Model
The Black Box Approach: Cross Validation –

Labeled data set

Training set

Test set

Training set

Validation set

Learn model

Select model

Learned Model
Ship Energy Systems Modelling

The Black Box Approach: Model Selection

Machine Learning Algorithms

- Deep Learning
  - Deep Boltzmann Machine (DBM)
  - Deep Belief Networks (DBN)
  - Convolutional Neural Network (CNN)
- Stacked Auto-Encoders
- Random Forest
- Gradient Boosting Machines (GBM)
- Boosting
- Bootstrapped Aggregation (Bagging)
- AdaBoost
- Stacked Generalization (Blending)
- Gradient Boosted Regression Trees (GBRT)
- Radial Basis Function Network (RBFN)
- Neural Networks
  - Perceptron
  - Back-Propagation
  - Hopfield Network
  - Ridge Regression
  - Least Absolute Shrinkage and Selection Operator (LASSO)
  - Elastic Net
  - Least Angle Regression (LARS)
- Regularization
  - Cubist
  - One Rule (OneR)
  - Zero Rule (ZeroR)
- Repetitive Incremental Pruning to Produce Error Reduction (RIPPER)
- Logistic Regression
  - Ordinary Least Squares Regression (OLSR)
  - Stepwise Regression
  - Multivariate Adaptive Regression Splines (MARS)
  - Locally Estimated Scatterplot Smoothing (LOESS)
- Regression
- Instance Based
  - k-Nearest Neighbour (kNN)
  - Learning Vector Quantization (LVQ)
  - Self-Organizing Map (SOM)
  - Locally Weighted Learning (LWL)
- Clustering
  - k-Means
  - k-Medians
- Expectation Maximization
- Hierarchical Clustering

Bayesian
- Naive Bayes
- Averaged One-Dependence Estimators (AODE)
- Bayesian Belief Network (BBN)
- Gaussian Naive Bayes
- Multinomial Naive Bayes
- Bayesian Network (BN)

Decision Tree
- Classification and Regression Tree (CART)
- Iterative Dichotomiser 3 (ID3)
- C4.5
- C5.0
- Chi-squared Automatic Interaction Detection (CHAID)
- Decision Stump
- Conditional Decision Trees

Dimensionality Reduction
- Principal Component Analysis (PCA)
- Partial Least Squares Regression (PLSR)
- Sammon Mapping
- Multidimensional Scaling (MDS)
- Projection Pursuit
- Principal Component Regression (PCR)
- Partial Least Squares Discriminant Analysis
- Mixture Discriminant Analysis (MDA)
- Quadratic Discriminant Analysis (QDA)
- Regularized Discriminant Analysis (RDA)
- Flexible Discriminant Analysis (FDA)
- Linear Discriminant Analysis (LDA)
The Black Box Approach: Model Selection

**Hyper Parameters**

**Supported Vector Machines:**

\[ f(x) = w \cdot \phi(x) + b \]

\[ \min_{w, b, \xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i \]

\[ s.t. \quad y_i (w \cdot \phi(x_i) + b) \geq 1 - \xi_i \]

\[ \xi_i \geq 0, \quad i \in \{1, \ldots, n\} \]

\[ \min_{\alpha} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n} \alpha_i \]

\[ s.t. \quad 0 \leq \alpha_i \leq C \]

\[ \sum_{i=1}^{n} y_i \alpha_i = 0 \]

\[ f(x) = \sum_{i=1}^{n} y_i \alpha_i K(x_i, x_j) + b \]

\[ K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \]

In this case the hyper-parameters are two: \( C \) and the kernel hyperparameter \( \gamma \).
The Black Box Approach: Model Selection

Hyper Parameters

Kernel Regularized Least Squares (KRLS)

The equation indicating one of the output of a KRLS models is:

\[ f(x) = \sum_{i=1}^{n} \alpha_i K(x, x_j) \]

\[ \alpha^* = (Q + \lambda I)y; \quad K(x_i, x_j) = e^{-\frac{||x_i-x_j||^2}{2\sigma^2}}; \quad \gamma = 2\sigma^2 \]

\( \lambda \) : regulates the trade-off between the overfitting tendency, related to the minimization of the empirical error, and the under fitting tendency, related to the minimization of the complexity.
In this case the hyper-parameters are two: and \( \lambda \) and the kernal hyperparameter \( \gamma \).

Artificial Neural Network (ANN)

The universal approximation theorem states that a feed-forward network with a single hidden layer containing a sufficient number of neurons, can approximate any local continuous functions.
Such a network is called Multilayer Perceptron (MLP). The equation indicating one of the output of a MLP is:

\[ y_i = g \left( \sum_j w_{ij} f \left( \sum_k w_{jk} x_k \right) \right) \]

where \( g \) and \( f \) are in general non-linear but continuous functions.
To train this, the back-propagation algorithm is adopted in conjunction with gradient descend minimization.
In this case the hyper-parameter is only one: the number of neurons in the hidden layer.
The Gray Box Approach

Gray Box Models are a combination of White Box Models and Black Box Models. This requires to modify the Black Box Models to include the mechanistic knowledge of the system.

- Naive approach (N-GBM): the output of the WBM is used as a new feature that the BBM can use for training the model.

- The WBM can be seen as a function of the input $x$, and allows the creation of a new dataset.

$$D_{n}^{WBM} = \{(h_{WBM}(x_1), y_1), \ldots, (h_{WBM}(x_n), y_n)\}$$

**Dataset**

<table>
<thead>
<tr>
<th>Sample</th>
<th>Feature 1</th>
<th>Feature 2</th>
<th>…</th>
<th>Feature j</th>
<th>…</th>
<th>Feature d</th>
<th>Feature d + 1</th>
<th>Output Feature</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>$x_{11}$</td>
<td>$x_{12}$</td>
<td>…</td>
<td>$x_{1j}$</td>
<td>…</td>
<td>$x_{1d}$</td>
<td>$h_{WBM}(x_{1d+1})$</td>
<td>$y_1$</td>
</tr>
<tr>
<td>$i$</td>
<td>$x_{i1}$</td>
<td>$x_{i2}$</td>
<td>…</td>
<td>$x_{ij}$</td>
<td>…</td>
<td>$x_{id}$</td>
<td>$h_{WBM}(x_{id+1})$</td>
<td>$y_i$</td>
</tr>
<tr>
<td>$n$</td>
<td>$x_{n1}$</td>
<td>$x_{n2}$</td>
<td>…</td>
<td>$x_{nj}$</td>
<td>…</td>
<td>$x_{nm}$</td>
<td>$h_{WBM}(x_{nd+1})$</td>
<td>$y_n$</td>
</tr>
</tbody>
</table>
Case Study
Ship feature | Value | Unit
---|---|---
Deadweight | 47000 | [t]
Installed power (Main Engines) | 3840 (x2) | [kW]
Installed power (Auxiliary Engines) | 682 (x2) | [kW]
Shaft generator power | 3200 | [kg/h]
Exhaust boilers steam generators | 1400 | [kg/h]
Auxiliary boilers steam generators | 28000 | [kg/h]
Data available from 20/03/2012 to 03/10/2014

<table>
<thead>
<tr>
<th>Feature</th>
<th>Variable name</th>
<th>Unit</th>
<th>Feature</th>
<th>Variable name</th>
<th>Unit</th>
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<td>Time stamp</td>
<td>[t]</td>
<td>$x_{18}$</td>
<td>Sea depth</td>
<td>[m]</td>
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<tr>
<td>$x_2$</td>
<td>Latitude</td>
<td>[°]</td>
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<td>[°C]</td>
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<tr>
<td>$x_3$</td>
<td>Longitude</td>
<td>[°]</td>
<td>$x_{20}$</td>
<td>CPP Set point</td>
<td>[°]</td>
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<td>$x_4$</td>
<td>Auxiliary engines power output</td>
<td>[kg/h]</td>
<td>$x_{21}$</td>
<td>Fuel Density</td>
<td>[kg/m$^3$]</td>
</tr>
<tr>
<td>$x_5$</td>
<td>Shaft generator power</td>
<td>[kg/h]</td>
<td>$x_{22}$</td>
<td>Fuel Temperature</td>
<td>[°C]</td>
</tr>
<tr>
<td>$x_6$</td>
<td>Propeller shaft power</td>
<td>[kW]</td>
<td>$x_{23}$</td>
<td>Ambient Pressure</td>
<td>[bar]</td>
</tr>
<tr>
<td>$x_7$</td>
<td>Propeller speed</td>
<td>[rpm]</td>
<td>$x_{24}$</td>
<td>Relative Humidity</td>
<td>[%]</td>
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<td>Ship draft (fore)</td>
<td>[m]</td>
<td>$x_{25}$</td>
<td>Dew Point Temperature</td>
<td>[°C]</td>
</tr>
<tr>
<td>$x_9$</td>
<td>Ship draft (aft)</td>
<td>[m]</td>
<td>$x_{26}$</td>
<td>Shaft Torque</td>
<td>[kN m]</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td>Draft Port</td>
<td>[m]</td>
<td>$x_{27}$</td>
<td>Rudder Angle</td>
<td>[°]</td>
</tr>
<tr>
<td>$x_{11}$</td>
<td>Draft Starboard</td>
<td>[m]</td>
<td>$x_{28}$</td>
<td>Acceleration x Direction</td>
<td>[m/s$^2$]</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>Relative wind speed</td>
<td>[m/s]</td>
<td>$x_{29}$</td>
<td>Acceleration y Direction</td>
<td>[m/s$^2$]</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>Relative wind direction</td>
<td>[°]</td>
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<td>[m/s$^2$]</td>
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<td>[°]</td>
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<td>Roll</td>
<td>[°]</td>
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<tr>
<td>$x_{15}$</td>
<td>Speed over ground</td>
<td>[knots]</td>
<td>$x_{32}$</td>
<td>Pitch</td>
<td>[°]</td>
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<tr>
<td>$x_{16}$</td>
<td>Speed through water</td>
<td>[knots]</td>
<td>$x_{33}$</td>
<td>Yaw</td>
<td>[°]</td>
</tr>
<tr>
<td>$x_{17}$</td>
<td>CPP Feedback</td>
<td>[°]</td>
<td>$y$</td>
<td>Main engines fuel consumption</td>
<td>[kg/h]</td>
</tr>
</tbody>
</table>
Case Study

- **White Box Model**: the model is built based on a priori, mechanistic knowledge of $\mathbb{G}$ (numerical description of the body hull, propulsion plant configuration, design information of the ship).

- **Black Box Model**: the model is built based on a series of historical observation of $\mathbb{G}$ ($\mathbb{D}_n$).

- **Gray Box Model**: in this case the White Box Model and Black Box Model are combined in order to build a model that takes into account both a priori information and historical data $\mathbb{D}_n$ so to improve the performances of both the models.
Delivered power from trials @ different displacements.

Resistance prediction parameters tuning using real data from towing tank trials
(Ideal conditions: no wind, waves, trim, rudder, ...)

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The White Box Approach

Wind Resistance

Waves Added Resistance

Fuel Consumption

Trade/route

Calm Water Hull Resistance

Propulsion Plant

Propeller Performance

Case Study

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Case Study

The White Box Approach

- Resistance
  - Δ
  - trim
  - n
  - v
  - Pe
  - ηh
  - Rt

- Propeller
  - Pd
  - Qdo
  - ηo
  - Pdo

- Engine
  - Pb
  - Nb

- Shaftline
  - Ps_g
Case Study

Validation on “Calm Water Scenario”
Case Study

Validation on “Calm Water Scenario”

No. sample = 104 Mean error = -0.52558 [%]

No. sample = 104 Mean error = -5.9751 [%]
Validation on “Calm Water Scenario”

No. sample = 117  Mean error = -0.32124 [%]

No. sample = 117  Mean error = -5.972 [%]

Samples: 118  \( \Delta = 50800 \) [t]
Validation on “Calm Water Scenario”

![Graph showing power vs. speed]

Number of samples: 52, Mean error: -0.96196 [%]

Number of samples: 52, Mean error: -4.316 [%]
Case Study

Black and Grey Models comparison

(h) RF Shaft Torque  (i) RF Fuel Consumption

(b) RLS Shaft Torque  (c) RLS Fuel Consumption
Conclusions

• Data driven, or Black-Box Models can outperform state-of-the-art numerical, or White-Box, models which exploits the physical knowledge of the system in the task of predicting the fuel consumption of a naval propulsion plant.

• The Gray-Box models are able to exploit the advantages of two philosophy:
  1. Same performances of the black-box
  2. Requiring less historical data thanks to the knowledge embedded in the white box models.

• Feature ranking allows improving the understanding of Black- and Gray Box models as for these model physical principles are only partly accounted

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